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Modeling the Impact of Land Cover Change on Non-point Source Nitrogen Inputs to Streams at a Watershed Level: Implications for Regional Planning

Dissertation

Presented in Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy in the Graduate School of the University of Cincinnati

by

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ABSTRACT

The objective of this research is to assess the impact of future land cover changes on nutrient enrichment of streams. It applies cellular automata (CA) – Markov chain model to simulate future land cover change and a GIS-based distributed cell-based model to predict non-point source nitrogen loadings to streams. The integration of the two models provides site-specific information on how the spatial location and extent of urban development can affect nitrogen pollution under dry, normal and wet conditions.

Two scenarios of land cover change, in particular, were examined. The baseline scenario (Scenario 1) involved only minor protection of environmentally sensitive areas. The open space conservation network scenario (Scenario 2) incorporated the principles of “green” infrastructure as outlined by the relevant literature. Scenario 2 was based on protection of riparian areas, floodplains, wetlands, urban open space, and areas with exceedingly shallow depth to seasonally high water table and bedrock. Increased setbacks, where appropriate, were considered. The impact of the projected land cover change under different development scenarios was then examined in terms of nitrogen delivery ratios, total loads and contributing areas. A spatial hydrological model of the watershed was developed under dry, normal and wet conditions. A non-linear regression model was applied to estimate nitrogen trapping efficiencies and delivery ratios based on field characteristics such as slope, saturated hydraulic conductivity, soil mean particle diameter, Manning’s roughness coefficient and length of flow. An attenuation factor taking into account cost distance to streams and decay constant was also incorporated into the model to account for transmission losses. Contributing areas of nitrogen delivery to streams were delineated based on the model results.
A significant proportion of impaired streams, lakes and estuaries in the United States are affected by the consequences of excess nutrient inputs to the soil and emissions of nitrogen compounds to the atmosphere. Excessive amounts of nitrogen (N) in soils, in the form of nitrate-nitrogen (NO$_3^-$-N) and ammonia-nitrogen (NH$_4^+$-N), result mainly from the application of artificial fertilizers and manure on agricultural fields. Dissolved by surface runoff, the inorganic N species are transported to rivers and can percolate to groundwater where they end up as a baseflow input to streamflow. In addition to agricultural inputs, emissions from internal combustion engines, power plants, and some industrial facilities produce large amounts of gaseous NO and NO$_2$. Nitrogen excess in soils can also enter the atmosphere through volatilization of ammonia and waste products of heterotrophic respiration. After chemical transformations in the atmosphere, nitrogen compounds re-enter the stream network via wet and dry deposition. Land use affects the movement of nitrogen in the environment. Nitrogen inputs are attenuated in agricultural and forested areas due to transmission losses resulting from deposition and transformation of nitrogen compounds as they move through the landscape from source areas to streams and lakes. Urbanized areas have reduced attenuation capacity due to imperviousness.

This research involves an assessment of the impact of future land cover changes on nutrient enrichment of streams. It applies cellular automata (CA) – Markov chain model to simulate future land cover change in combination with a GIS-based distributed cell-based model to predict non-point source nitrogen loadings to streams. The integration of the two models provides site-specific information on how the spatial location and extent of urban development can affect nitrogen pollution under dry, normal and wet conditions.
Two scenarios of land cover change, in particular, were examined. The baseline Scenario 1 involved only minor protection of environmentally sensitive areas. Scenario 2, based on an open space conservation network, incorporated the principles of “green” infrastructure as outlined by the relevant literature. Scenario 2 was based on protection of riparian areas, floodplains, wetlands, urban open space, and areas with exceedingly shallow depth to seasonally high water table and bedrock. Increased setbacks, where appropriate, were considered. The impact of the projected land cover change under different development scenarios was then examined in terms of nitrogen delivery ratios, total loads and contributing areas. A spatial hydrological model of the watershed is developed under dry, normal and wet conditions. A non-linear regression model is applied to estimate nitrogen trapping efficiencies and delivery ratios based on field characteristics such as slope, saturated hydraulic conductivity, soil mean particle diameter, Manning’s roughness coefficient and length of flow. An attenuation factor taking into account cost distance to streams and decay constant is also incorporated into the model to account for transmission losses. Contributing areas of nitrogen delivery to streams are delineated based on the model results.

The results of this research have been validated for the East Fork Little Miami River watershed, Ohio. The results include (1) projected land cover patterns for 2010, 2020 and 2030 under the two scenarios; (2) quantification of the surface runoff contribution to total nitrogen (TN) inputs to streams; (3) quantification and mapping of the long-term spatial variation in the effective or “contributing” land areas; (4) evaluation of the impact of urban development on nitrogen inputs and “contributing” areas. Results indicated that under the baseline scenario under dry conditions, although the urbanized areas constituted only 4 percent of the total watershed area, approximately 25 percent of the effective land area contributing to total nitrogen loadings
was urban. A future scenario suggested that urban growth without environmental constraints may lead to noticeable deterioration in the water quality parameters. However, the expected impact can be successfully mitigated if hydrological and ecological functions performed by natural systems are taken into consideration, and more specifically, if the open space conservation network is preemptively incorporated in the development process.
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Dedicated to my family
Replacement of vegetation with impervious surfaces as a result of urban development affects microclimate and hydrological regimes and induces changes in the spatial patterns of the non-point source pollution. Increased connectivity and higher hydraulic efficiency due to imperviousness can contribute to increased peak discharges of surface runoff usually accompanied by higher delivery ratios of pollutants to aquatic systems. The resulting nutrient and sediment export to water bodies, can then lead to accelerated eutrophication and water quality deterioration (USEPA 2001, Wickham et al. 2002, Tang et al. 2005, Carle et al. 2005). Despite the overall awareness of the linkages between urban development and its negative environmental consequences, projecting and quantifying the potential impact of land cover change in the long term is rarely taken into consideration in watershed land use decisions.

This thesis presents an integration of a cellular automata urban growth model with a non-point source pollutant loading model to predict changes in water quality as a result of urbanization. Future growth is projected with and without environmental constraints and the impact is examined through the concept of the contributing area. Contributing areas are defined
as areas that have higher delivery ratios of pollutants because of their soil properties, land use, vegetation and proximity to streams (Soranno et al. 1996). The green infrastructure literature provided the conceptual framework for defining the environmental constraints. For the purposes of this research, they included protection of riparian areas, floodplains, wetlands, urban open space, and areas with exceedingly shallow depth to seasonally high water table and bedrock. The behavior of the nutrient-contributing areas is investigated during low flow, normal and high flow conditions using a distributed cell-based model quantifying the interactions of soil, land use, vegetation, topography and distance to streams and their relationships to nutrient fate.

The link between urban growth projections, land cover change and environmental assessment is an area of research that is rapidly developing. Urban and transportation planners, and economists, have relied exclusively on economic theories such as utility maximization and discrete choice analysis to explain the drivers behind development decisions and link urban growth to land cover change. Alternately, environmental scientists, environmental engineers and epidemiologists have focused on compiling past and current data sets to determine the unintended impacts of those decisions upon natural systems and human health. To this respect, Arthur-Hartranft et al. (2003) noted that urban model predictions are often not “advanced beyond a qualitative look at development patterns.”

Recently, cellular automata (CA) models have been widely used to project future development patterns. Cellular automata are defined by their ability of self-reproduction in a cellular space according to simple transition rules accounting for neighborhood effects (Von Neumann and Burks 1966). Recently, efforts have been expanded in a direction which allows the integration of computer-based simulation and modeling of urban systems and environmental impact assessment and modeling (Yeh and Li 2001, Arthur-Hartranft et al. 2003, Wang et al.)
Yeh and Li (2001) developed a cellular automata model to represent sustainable urban growth. They used weights based on environmental criteria to assign an *environmental suitability score* for each cell subject to shift in land use (Yeh and Li 2001). Using these scores they were able to formulate alternative development scenarios and analyze the environmental impact of different urbanization patterns (Yeh and Li 2001: 739). Arthur-Hartranft *et al.* (2003) analyzed alterations in surface temperature and hydrologic response associated with the land cover change predicted by the SLEUTH urban growth model. The authors observed that because of an inability to use urban simulation models for environmental assessment, “coupling such work results is an enhancement of both efforts” (Arthur-Hartranft *et al.* 2003: 390). Another approach was offered by Yeo (2005) who used a distributed rainfall-runoff model and a multi-stage non-linear optimization to delineate land-use patterns that would guarantee land conservation at critical points in the watershed and minimize surface storm runoff.

The main objective of this research is to examine the impact of urban development on surface hydrology and nutrient export to streams. More specifically, this research aims at assessing to what extent changes in landscape characteristics resulting from land development would affect total nitrogen delivery to surface waters. The next sections further elaborate on the central concepts that outline the framework of this research.

1.1 The Concept of Development

The modern concept of development appeared after World War II and reflected the need for theoretical perspectives and models of development that reveal the transformation of principal actors, forms and objectives of development (Malizia and Feser 1999, Fritz 2004).
The earlier theoretical perspective on development defines it as a process of industrial modernization that spreads from developed to underdeveloped regions (Malizia and Feser 1999). Social aspects of development were not taken into consideration at that time (Fritz 2004). As a result, theorists largely consented on the structure of the process of modernization but disagreed on its consequences such as inequality in income distribution, resource depletion and industrial pollution (Malizia and Feser 1999).

In the 1950s and 1960s development was largely equated with growth (Malizia and Feser 1999, Fritz 2004). Development was defined as increase in per capita investment with anticipated improvement in all aspects of the social life. (Fritz 2004). This definition was at the core of growth pole theory, as well as other related theories such as staple theory, interregional trade theory and in recent times, neoclassical growth theory. In its general conception, the latter theoretical perspective asserted that growth in one area (locality or region) could have trickle-down effects for the surrounding regions and the benefits of development are multiplied by the consequential development of those regions (Edgington and Fernandez 2001, Fritz 2004). This theoretical perspective reflected to some extent the stable growth conditions in the world economy in the 1950s and 1960s when some of the largest development projects were completed.

In the late 1960s, theorists began to distinguish between development and growth. Increased awareness of the negative impacts of the current practices, including a widening income gap, increasing inequality and resource depletion and pollution prompted both theorists and practitioners to rethink the prevailing models and conceptions of development. The concept was redefined. In its new conception, growth was associated with quantitative change in the volume of production and services, whereas development was defined as a qualitative change in the
distribution of income (Malizia and Feser 1999). Development was redefined as a set of social rather than economic variables and was associated with employment opportunities, elimination of poverty, and fair distribution of income (Seers 1979, Malizia and Seers 1999, Fritz 2008).

Urban development is associated with conversion of land to uses that accommodate the functioning of the city (Wang and Vom Hofe 200). Planning initiatives today are focused on socioeconomic development which is defined as “a comprehensive economic, social, cultural and political process in a defined geographic area” (Fritz 2008: 8). As a planned process, socioeconomic development has three fields of action: creation of jobs through economic development, improvement of the quality of life and protection of disadvantaged populations and incorporation of the ideas of environmental sustainability into economic development projects (Fritz 2008). Urban sustainable development is a process of adjustment of these three fields of action to the evolution of cities (Campbell 1996). Urban growth refers to somewhat narrower idea most commonly understood as the evolution of the urban form, or the expansion of the physical boundaries of an urban core (Clarke and Gaydos 1998). In spite of these differences, urban growth and urban development will be employed interchangeably in this study.

In the decades following the World War II, urban growth in the United States is often referred to as ‘sprawl’. Sprawl is low-density, scattered, car-dependent development of land which consists for the most part of large-lot residential subdivisions, sizeable office and industrial parks, and vast retail centers (Randolph 2004:37). Urban Growth Boundary, Growth Management and Smart Growth are some of the policy instruments intended to promote land development that reduces the negative impacts of sprawl such as loss of prime agricultural land and degradation of natural resources (Randolph 2004).
1.2 Urbanization and Land Use/ Land Cover Change

Spatially, urban growth takes the form of disperse, seemingly inconsequential land cover and land cover changes accruing over time. These incremental changes often result in alterations of the hydrologic regime of watersheds, and affect their aquatic and riparian biota (U.S. Council for Environmental Quality 1993, USEPA 2000, Opaluch et al. 2006).

In the most general terms, the process of urbanization is the accommodation of a set of urban functions on existing land (Wang and Vom Hofe 2007). In the early stages of urbanization (i.e. the pre-industrial era), the physical features of land and the proximity to water determined where people would organize their settlements. In later stages, the urban function influences and controls the physical characteristics of the land (Wang and vom Hofe 2007). Land cover refers to the elements of the landscape such as forests, pasture, wetlands, water bodies or pavement. Land use is defined as the activities that occur on the landscape such as residential, commercial and industrial activities or public utilities and parks (Wang and Vom Hofe, 2007). Land cover and land use are distinguished based on classification schemes that apply different approaches. The discussion here is limited to the term land cover.

1.3 Non-point Source Pollution (NPS)

Anthropogenic activities in the past six decades have contributed to a more than a two-fold increase in nitrogen delivery to aquatic systems causing eutrophication and hypoxia with detrimental consequences for the health of ecosystems (Downing et al. 1999, Alexander et al. 2002, USEPA 1990). Nitrogen, mainly in the form of nitrate-nitrogen (NO$_3^-$-N) and ammonium-
nitrogen ($\text{NH}_4^+$-N) originates from both point and nonpoint sources. Point sources include localized discharges from waste-water treatment plants (WWTPs), livestock operations and some industrial activities. Nitrogen from nonpoint sources is introduced into aquatic systems by overland flow after rainfall events, a result of excess fertilizer runoff from applications on cropland fields and residential lawns, outfalls from combined sewer overflows, nitrogen fixation, atmospheric deposition and groundwater seepage (White and Hofschen 1996, Boring et al. 1998, Prasad et al. 2005, Sheeder et al. 2002). With the enactment of the U.S. Clean Water Act in 1972, and related federal and state regulations, pollution from point sources has been significantly reduced. Most point sources today, are subject to regulation, continuous monitoring and, if needed, treatment at the source, although they are still a significant source of nitrogen inputs to surface waters (Carpenter et al. 1998).

Nonpoint sources are still largely unmanaged and a cause for concern as they contribute approximately two-thirds of the total pollutant loads to surface waters in the conterminous United States (USEPA 1983, 1988, 1990, and 1996). Nutrient enrichment, primarily from phosphorus- and nitrogen-based fertilization compounds, is associated with widespread degradation of aquatic ecosystems, including eutrophication, depletion of dissolved oxygen which can cause fish kills, noxious algal blooms and losses of aquatic vegetation and biodiversity (USEPA 1990, Carpenter et al. 1998). The U.S. Environmental Protection Agency (USEPA 1996) estimated that approximately half of the impaired lakes, more than half of the impaired streams and most of the estuaries in the U.S. are disturbed by eutrophication to a certain degree (see also Carpenter et al. 1998). A study of 86 streams in the northeastern part of the U.S. found that in half, nitrogen fluxes from nonpoint sources accounted for approximately 90% of the total N inputs (Newman 1995). A recent study (Lee and Mankin 2007) found that the total
nitrogen exported across the Kansas border to the Gulf of Mexico was approximately 51,000 lb/yr, out of which 18 percent were introduced in the waterways by point sources and as much as 82 percent by non-point sources.

Surface runoff, atmospheric deposition and contribution from baseflow are major nonpoint sources of nitrogen inputs to surface waters. Runoff from agricultural and urban land is a primary source of nonpoint nitrogen pollution (Johnes 1996, Jordan et al. 1997, Johnes and Heathwaite 1997, Carpenter et al. 1998, Fenn et al. 1998, Jones et al. 2001). Air-borne nitrogen fluxes from a variety of sources can increase the total nitrogen (TN) inputs to streams via wet and dry deposition (Carpenter et al. 1998, Alexander et al 2002, Sheeder et al. 2002). Infiltration and leaching can carry nitrate to groundwater which, through the baseflow, can contribute significantly to the year-round nutrient enrichment of lakes, streams and reservoirs (Vanni et al. 2001).

Fertilization of agricultural fields is the single most important source of nitrogen fluxes to surface waters. It is estimated that crop uptake of nitrogen input in fertilizers accounts for no more than 18% of the total fertilizer application, resulting in as much as 170 kilograms per hectare per year in surplus nitrogen inputs on farmland (Carpenter et al. 1998). Depending on watershed characteristics such as soils and topography, nitrogen export from cropland to water may be as much as 40% of the total fertilizer inputs on loam and clay soils and 80% on sandy soils (Carpenter et al. 1998). Excess manure application on agricultural fields can also result in high levels of nutrient accumulation in soils. Surplus nitrogen, especially in dissolved forms easily leaches into surface waters or percolates into groundwater due to its low adsorption potential and high solvability (Harrison 2006). Factors including chemical form, process and rate of nutrient application, as well as season, plant cover, rainfall intensity, and time after application
are said to jointly determine the overall rate of nitrogen loss from agricultural fields to surface waters (Carpenter et al. 1998). Figure 1.1 displays the sources of the nitrogen inputs to streams.

**Nitrogen inputs to streams**

![Diagram of nitrogen inputs to streams]

Figure 1.1 Schematic representation of nitrogen inputs to streams

In addition to accumulating in soils, being washed-off by surface runoff and percolating to groundwater, reactive nitrogen (in the form of NO$_3^-$ and NH$_4^+$) present in soils can also enter the atmosphere through volatilization of ammonia and production by heterotrophic bacteria which reduce oxidized nitrogen to gaseous nitric oxide (NO), nitrous oxide (N$_2$O) and dinitrogen (N$_2$) (Allaby 2000, Harrison 2006, Carpenter et al. 1998). Both gaseous ammonia and nitrous oxide from agricultural ecosystems reach the aquatic environment via wet or dry deposition processes.
1.4  Contribution to NPS from Built-up Areas

While nonpoint source pollution from agricultural land has been the focus of a considerable number of studies and subject to a wide variety of control measures, nitrogen export from urbanized land is not extensively investigated and not well understood. Because fertilizer use on lawns and golf courses is not regulated or monitored, quantifying the extent of nitrogen loading from urban runoff has been less straightforward (Cutietta-Olson et al. 2007). Caraco and Cole (1999) found that human population density in watersheds explains a significant proportion of the variability in the amount of nitrogen carried in rivers. Sources of nitrogen losses to urban runoff include lawn fertilization, combined sewer overflows, ex-filtration from leaky septic systems and disturbances caused by construction sites and new urban development (White and Hofschen 1996, Carpenter et al. 1998).

Research has shown that nutrient export to streams is mitigated by densely vegetated land cover such as forests or shrubs (Wickham et al. 2002). On the other hand, urbanization tends to increase the magnitude of phosphorus and nitrogen loadings to streams partly because of increased connectivity and higher hydraulic efficiency due to imperviousness, and partly because it replaces the densely vegetated surfaces that can serve as sinks and attenuate the transmission of the pollutants in question (Wickham et al. 2002, Arthur-Hartranft et al. 2003, Yin et al. 2005, Khare et al. 2007). Wickham et al. (2002), estimated the risk of increasing phosphorus and nitrogen export and found that vulnerability to nutrient inputs proliferates more significantly when urbanization impinges upon forested areas compared to agricultural land.

1.5  Open Space Conservation

Historically, the origins of protected natural areas can be found in the United States during the second half of the 19th century when the first national parks and forests were designated
The Land and Water Conservation Fund (LWCF) established by the federal government in 1965 is a major funding source for acquisition of public lands designated exclusively as national parks (Randolph 2004). With the growing awareness of the importance of undisturbed natural open space for both recreation and for a wide variety of crucial services provided by natural systems, the notion of “open space” was extended from parks to a range of environmentally important areas such as urban forests, floodplains, wetlands and wildlife habitats (Randolph 2004). The 1992 Earth Summit officially recognized the significance of protected natural areas in the long-term ecosystem management (Crawford 2006). As a result, land conservation legislation has been strengthened worldwide (Crawford 2006).

The concept of *environmentally sensitive areas* was first defined in the United Kingdom in 1984 as a policy instrument inspired by the European Union (EU) legislation. The program, administered by the UK Ministry of Agriculture, provided incentives to farmers who protected areas with aesthetic or ecological value from disturbance by agricultural practices (Wilson et al. 2007). The program included financial assistance to compensate farmers who incurred financial losses as a result of reduced commercial farming due to voluntary participation in management practices aimed at preserving areas vulnerable to environmental degradation (Wilson et al. 2007). Similar funds were created in the United States under the Conservation Reserve Program (CRP) and the Conservation Reserve Enhancement Program (CREP) established by the U.S. Department of Agriculture (USDA) in 1985 and 1996, respectively (Dosskey 2001, Randolph 2004). In addition, in 1990 USDA established the Wetland Reserve Program (WRP) to provide financial and technical assistance to farmers who opted to restore wetlands on existing farm land (Randolph 2004).
Most state and local governments in the United States have established grant programs for land conservation. It has been recognized that it is important to both protect the areas that provide valuable natural services and ensure the connectivity of these areas. Connectivity in hydrological and ecological networks is an important factor that ensures their resilience to disturbance (Benedict and McMahon 2007). The network of environmentally sensitive areas has been described as “green infrastructure” (Benedict and McMahon 2007) and valued in terms of its significance for the overall quality of life as high as the traditional “grey” infrastructure composed of transportation corridors, telecommunications, water mains, and sewers (Randolph 2004). State growth management legislation that includes measures to protect environmentally sensitive areas and improve the quality of urban ecosystems has been adopted by thirteen states (Anthony 2004). In addition, the states of Florida, Georgia, and Maryland have adopted programs aimed at enhancing the connectivity of the protected areas as part of state-wide green infrastructure networks (Randolph 2004, Benedict and McMahon 2007).

Together with the federal and state grants for land acquisition and protection, land trusts administered by nonprofit conservation organizations, play an important role in protecting environmentally sensitive areas. Through conservation easements, land donations, and involvement of stakeholders, these nonprofit organizations managed to preserve nearly 6.2 million acres in the United States by the year 2000 (Randolph 2004: 84).

Despite its widely accepted use, the concept of environmentally sensitive areas is defined in various ways. The Dictionary of Geography provides the narrowest definition of the concept including only areas that are regulated by federal and state legislative acts:

“A fragile ecosystem area where the conservation or preservation of the natural environment is sustained by state controls and/or grants.”
The McGraw-Hill Dictionary of Architecture and Construction defines an environmentally sensitive area in a more comprehensive manner:

“A place that is vulnerable to a negative environmental impact, such as a flood plain, a wetland, an area where noise levels are excessively high, or an EPA-designated plant, fish, and animal habitat.”

The most comprehensive definition is given by Randolph (2004:110):

“Environmentally sensitive lands are those that exhibit certain hazards to development (e.g., floodplains, unstable slopes), are vulnerable to environmental impact (e.g., highly erodible soils, soils unsuitable for septic systems), provide resource value (e.g., prime agricultural lands, aquifer recharge areas), and have aesthetic or ecological values (e.g., wetlands, wildlife habitats).”

Randolph’s (2004) definition, together with Benedict and McMahon’s (2007) conceptualization of the green infrastructure network (further reviewed in Chapter 5), have been employed in identifying and delineating the open space conservation network that was incorporated in the cellular automata – Markov chains model of urban growth, presented in this research.

1.5.1 Urban Open Space

Urban open space includes parks, conservation easements, acquisitions, cemeteries, public and private undeveloped land, urban riparian areas, recreational areas and historic preservation sites. In addition to the ecological and hydrologic functions performed by natural areas, urban greenspace performs a number of social, aesthetic and economic functions (TPL 2008). Urban open space serves a hub for many species that have adapted to live in urban settings. Connecting the hubs through ecological corridors enables urban open space to become a part of the larger green infrastructure network. The urban forest in particular helps mitigate some of the effects of
the air pollution by absorbing considerable amounts of ozone and sulfur dioxide (TPL 2008). The Trust for Public Land (TPL) describes four important socio-economic functions of the urban open space: improving the assets of the local real estate market and increasing property values, attracting business entrepreneurs, bringing residents together, and providing space for community activities that help involve young people and prevent juvenile delinquency (TLP 2008).

1.6 Research Objectives

The overall objective of this dissertation is to construct an integrated framework for assessment of nitrogen loading to streams from planning scenarios represented by changes in the land cover. More specifically, the modeling framework is based on loose coupling of a GIS-based CA model using IDRISI GIS and Image Processing Software (Clark Labs, Clark University 2006) and a GIS-based non-point source (NPS) pollution model to assess future change in nitrogen loading resulting from land cover/land use change.

Two scenarios are explored. One is based on the continuation of current trends, while the second incorporates protection of environmentally sensitive areas. The results from both scenarios are used as inputs in the distributed cell-based, non-point source nutrient loading model. The impact of the projected land cover change under the development scenarios is examined in terms of nitrogen delivery ratios, total loads and contributing areas.

An important difference between nitrogen removal processes in agricultural and urban land is the nature of the “contributing” or source area. The “contributing” area is the source location that effectively contributes to runoff and nutrient loading to streams (Soranno et al. 1996). Source areas depend on soil properties, vegetation, topography, distance to streams, and the
amount of precipitation. The size of the effective land area on agricultural lands may vary seasonally. It also depends on the size of the event, size of the watershed and antecedent soil moisture conditions (Vanni et al. 2001, Seitzinger et al. 2002). Urbanized areas, however, were found to contribute effectively to nutrient loading regardless of distance to streams, season and/or amount of precipitation, as impervious surfaces increase hydraulic efficiency and direct storm water to the sewer network that is often directly connected to surface waters (Soranno et al. 2001, Khare et al. 2007). Soranno et al. (2001) found that during 1-year and 2-year storms, “only areas located at short distances to streams and urbanized areas contributed effectively to nutrient loading.”

Historically, the control of nonpoint source pollution has been hindered by several factors, including significant temporal and spatial variation, dispersed origins and the stochastic nature of many of the nitrogen input sources and contributing factors (i.e. precipitation). However, significant reduction in nitrogen concentrations in surface runoff can be achieved via the management nutrient sinks (White and Hofschen 1996, Carpenter et al. 1998, Boesch et al. 2001). It was estimated that approximately 90% of N inputs to streams comes from less than 10% of the land area during a few rainfall events of higher intensity (White and Hofschen 1996, Carpenter et al. 1998). Therefore, targeting remedial measures to source areas of N, that is, areas with high soil N concentrations and soils and land use characteristics that enhance erosion, surface runoff and leaching, would yield positive results in reducing non-point source pollution.

1.7 Research Questions

This research will address the following specific questions:

How can we model the land cover change in an expanding metropolitan area? Which contextual variables are useful in projecting the expected land cover change?
How can we account for the spatial variability in nitrogen inputs to streams? Is a spatially distributed model of nitrogen export to surface waters useful in understanding the spatial variability in nitrogen fluxes?

Can we successfully integrate a cellular automata urban growth/land cover change model with an environmental model to quantify TN losses associated with urban development? What spatial scale would make the results of the two models compatible?

How can we mitigate the impact of urban development on water quality alterations? Are the land cover changes less prone to increase N concentrations in streams and induce anticipated environmental impacts, if protection of environmentally sensitive areas is considered in land development planning?

What is the behavior of the TN contributing areas under different scenarios and climatic conditions (e.g., dry, normal and wet years)?

What are the implications of these results for urban planning and decision-making related to the future patterns of urbanization and the mitigation of its environmental consequences?

1.8 Limitations

Contributions of nitrogen from baseflow and groundwater are not considered in this research because of the soil characteristics of the study area, which contains mainly soils of SCS/NRCS hydrologic groups C and D, that is, soils with moderately-high and high runoff potential. Some of the dominant soils also contain a fragipan (that is, a hard pan, impermeable) layer which further inhibits the downward movement of water. The results from the proposed research can be considered empirically validated only for the East Fork Little Miami River watershed, Ohio.
2 LITERATURE REVIEW: URBAN SPATIAL ORGANIZATION, LAND COVER CHANGE AND ENVIRONMENTAL MODELING

This thesis focuses on the identifying inputs, source areas and transport mechanisms of non-point source nitrogen and examines their linkages to different land cover types. Hydrological concepts related to drainage area delineation, runoff-generating mechanisms and nutrient loadings are applied throughout this research. A basic understanding of the driving forces behind urbanization is also required to project land cover change into the future and examine how different land cover scenarios will impact water quality in the long run.

2.1 Spatial Urban Modeling

Studies of the urban systems are based on a variety of descriptive, analytical and simulation models largely developed to generalize the patterns of urban development as they emerged over
time. As the shape and form of cities changed, so did models of urban and regional theory. Just like the cities themselves, the models have evolved from simple logical structures to increasingly complex and differentiated abstractions of economic, social and land use processes and patterns (Knox 1994).

Computer-based urban simulation models first appeared in the 1960s but largely failed to assist planners in the decision-making process due to a number of shortcomings, including slow computers, tremendous data requirements, difficulties in data processing, loose approximation to real urban processes, poor representation of space and time dynamics and disconnect in algorithm development vs. application (Lee 1973, Batty 1994, Harris 1994, Lee 1994, Klosterman 2001a). The failures were considered to be both conceptual and technological (Torrens 2000). Some of the concerns put forward by critics of the “large-scale urban models” were addressed by the new generation of urban models that emerged in the 1970s (Wegener 1994, Batty 1994, Torrens 2000, Klosterman 2001a). Evolving microcomputer technology also encouraged improvements in three major ways: practicality (an effort was made towards meeting the everyday needs of the planning profession), programming of more sophisticated modeling techniques such as optimization and discrete choice analysis and attempts to incorporate space-time dynamics (Batty 1994), all of which required larger processing and memory capacity. Several new issues were investigated, including techniques of validation and calibration, disaggregation of large data sets and improved applicability to particular urban systems in specific locations.

The 1980s contributed to the urban dynamics modeling with new computer technologies, achievements in urban economics theory and the development of spatial analysis tools based on Geographic Information Systems (GIS) and Remote Sensing. Those contributions have radically
improved the ability of urban simulation models to represent a wide variety of urban phenomena (Torrens 2000, EPA 2000, Klosterman 2001a). The 1980s and 1990s also brought to life the idea of decision support systems as a technology-based support for planning decisions with improved linkages and capabilities for data compilation and analysis. The present era of communicative, collaborative and participatory planning made it clear that in spite of their advantages, purely technology-based approaches are no longer satisfactory tools for addressing the needs of the day. The planning support systems came to the fore in the 1990s as a response to the challenge of developing a more effective decision-making system by incorporating public involvement in real-time assessment of alternative solutions of a particular planning problem (Klosterman 2001a).

Geocomputation, as it emerged in the latter half of 1990s, presents a number of “pattern searching algorithms” (Atkinson and Martin 2001: 3) in both simulated and real urban settings and is the foundation of dynamic spatial models. Approaches to dynamic urban modeling now involve the use of fractal-based models, cellular automata and artificial neural networks. In this section, the emphasis is placed on modeling real cities using cellular automata as one of the most promising approaches to dynamic urban modeling.

2.1.1 Overview of Theoretical Approaches

Mathematical models as simplified representations of urban systems originated in the 1950s and five decades later continue to be a major research focus both in terms of theory and applications development. The theory and its applications have changed perspective, a change that has been referred to as different paradigms (Wu 1998b, Couclelis 2002), and Wu (1998b) described this transition as a movement from “cities as equilibrium systems” towards “cities as
evolutionary systems”. The latter refers to the *complexity theory approach*, which has inspired the most recent cellular automata, agent-based and hybrid models (Batty 1994, Torrens 2000, Couclelis 2002, Batty 2005).

### 2.1.1.1 Urban modeling and the static equilibrium approach

The concept of equilibrium in the exploration of cities was concomitant with earlier ideas of the city as a marketplace (the central place theory or Alonso’s bid rent function), as well as with the modern microeconomic theories of market equilibrium and economies of scale (Batty and Xie 2005). The early models of urban growth such as the large-scale urban models developed in the 1960s and 1970s were, by and large, consistent with the static equilibrium approach (Wu 1998, Batty and Xie 2005). They were informative and enriched in theories and ideas ranging from utility maximization and discrete choice analysis to input-output methodologies and various optimization techniques (Wegener 1994, Batty 1994, Klosterman 2005). These models were considered *comprehensive* because they incorporated all the elements of the urban system, including transportation flows, spatial interactions, housing markets, employment and residential mobility and land use change, which were modeled as subsystems under equilibrium conditions as well (Wegener 1994, Klosterman 2005). A basic assumption of these models was that economies and diseconomies of scale will produce regular patterns of urban growth based on agglomeration and dispersion. As a result, it was expected that these patterns can be accurately predicted by newer urban economic models (Batty and Xie 2005). The ultimate goal in modeling, as well as in its practical applications, was to bring the macro-system and its components into equilibrium by predicting and eliminating the factors that could potentially disturb it and lead to a disequilibrium state.
The advantage of this approach is that it is solidly grounded in urban economic theory, has a clear conception of the causal relationships that exist within the urban system and allows for the identification of the processes that govern the behavior of the urban system and its components. Many of these models such as IRPUD (Wegener et al. 1991), TRANUS (de la Barra 1989), and MEPLAN (Echenique et al. 1990) have received worldwide recognition by both academics and practitioners, and are still widely used in the planning practice. Yet, their main disadvantage was that they had no capabilities for dynamic modeling and visualization (Batty and Xie 1999, 2005, Torrens 2000, Couclelis 2002).

2.1.1.2 Urban modeling and the complexity theory approach

The ideas of the *complexity theory* are based on the premise that a system is seldom in a state of equilibrium. The system is dynamic, and therefore its components are in a state of constant change. Change is driven by macro-level forces (e.g., molecular interactions) as well as by macro-scale processes such as the constant arrangement and re-arrangement of individual entities (e.g., molecules in the physical space, or individuals making decisions in a social context) (Allen 1997). Complexity theory explains the evolution of a system as a process of spontaneous breaking, havoc, irreversibility, feedback, modulation, oscillation, emergence and self-organization (Krugman 1996, Holland 1998, Cross and Hohenberg 1993, Allen 1997, Couclelis 2002). The evolution of the city in this context is not viewed as a logical outcome of the interplay of market forces such as supply and demand. It is considered a set of alternative paths each of which may have been selected by chance as a result of a myriad of individual decisions that spontaneously occur in a self-organizing economy (Krugman 1996).
Complexity theory accepts that there are phase transitions in equilibrium systems that determine whether they will go through a perturbation phase or remain stable. When a system is stationary, minor oscillations may occur but if they do not reached a critical point in which the system’s spatial structure begins to disintegrate, the system is capable of preserving its homogeneous state (Prigogine 1997: ix, Cross and Hohenberg 1993). Major fluctuations above the threshold, a level at which the system can preserve its homogeneity at least in atomic terms, can break the system into a series of degenerate states (Cross and Hohenberg 1993). When this occurs, the system has reached what is termed its bifurcation point, a point of breakdown “at which new solutions to the evolution equations may emerge” (Prigogine, 1997: ix). The likelihood that a particular solution will emerge does not depend on past solutions but rather on the magnitude of the oscillation, and particularly on how far the perturbation has thrown the system from its previous equilibrium state (Allen 1997, Prigogine 1997, Cross and Hohenberg 1993, Boccara 2004). In a perfectly non-equilibrium pattern formation process or a fully non-linear regime (that is, far from the threshold), the system loses its capacity to restore its previous homogeneous state, and transcends into a new, irreversible state (Cross and Hohenberg 1993, Boccara 2004). At the same time, new structures emerge within the system (Holland 1998, Cross and Hohenberg 1993). The new structures have the potential to learn, respond, and adapt to the new condition through feedback loops (Prigogine 1997), which is termed “self-organization” (Resnik 1994, Krugman 1996) or “pattern formation” (Cross and Hohenberg 1993, Ball 1999). Ilya Prigogine, a Nobel laureate in chemistry and one of the pioneers of the complexity theory, describes this evolutionary process as “order through fluctuations” (Prigogine 1997: x).

The importance of the ideas brought about by complexity theory has been long recognized by the physical sciences. Research and experimentation has proven that these ideas are
applicable to the fields of social science, urban planning and economics as well. A new field called *econophysics*, which applies the methods of statistical mechanics used in physics to market analysis, has recently emerged (Mantegna and Stanley 2000). Complexity theory has found specific applications in urban planning as well. It has been recognized that complexity theory can bring invaluable insights to the conceptualization and modeling of urban growth (Krugman 1996, Allen 1997, Wu 1998, Couclelis 2002). These insights can be summarized briefly as follows:

- cities and regions do not emerge as a result of macro-level catalysis; they emerge as a result of self-organization based upon a multitude of micro-level interactions (Krugman 1996, Couclelis 2002);
- cities and regions are not congealed structures; they are dynamic systems that (1) change over time, and have (2) physical dynamics, i.e., they have the stochastic properties of non-linear systems (Prigogine 1997, Allen 1997);
- cities are irreversible changes to the environment;
- cities and regions respond to macro- and micro-level perturbations; these responses are not deterministic in nature, i.e. they may not necessarily be predicted based on past trends (Allen 1997);
- there are “different solutions to the evolution equation” (Prigogine 1997) which may include undesirable outcomes (i.e. sprawl) as well as desirable policies (i.e., smart growth, compact cities, sustainable urban development).

The latest developments in the simulation and modeling of urban environments are related to various applications of cellular automata, artificial neural network and agent-based modeling techniques, all of which are well-known examples of some recent applications of the science of
complexity (Couclelis 2002). The most important contribution of those models, developed in the 1990s, is the incorporation of stochastic temporal dynamics in the process of urban spatial evolution (Clarke et al. 1997, Couclelis 1997). Cellular automata (CA) models allow for spatially explicit representation of urban processes on a spatially referenced cellular lattice at small-scale time steps governed by specific transition rules (Torrens 2000, Yeh and Li 2001), while agent-based models derived global interactions from the behavior of individual agents facing a number of discrete choice possibilities (Noth et al. 2000). The strengths of both approaches have been reinforced by the introduction of hybrid multi-agent cellular automata models.

2.1.2 Conceptualization of Urban Simulation Using CA

In discrete mathematics and physics, the concept of cellular automata is associated with the theory of continuous dynamic systems (Ilachinski 2001). Since their introduction in the physical sciences as a result of the work of Alan Turing in the 1930s, and Stanislaw Ulam and John von Neumann in the 1940s and 1950s, cellular automata (CA) models have been assigned a wide variety of computational tasks involving spatio-temporal dynamics of natural and mechanical systems (Wolfram 2002). They have been used to build theories and investigate various phenomena such as the behavior of reaction-diffusion systems in physics and chemistry, the construction of sequences in genetic algorithms (Ilachinski 2001, Boccara 2004) and the behavior of lattice gases in hydrodynamics (Wolfram 1986). Other applications of the CA models include animal and plant populations, HIV and immune system responses, “artificial life”, robotics, finance and urban growth simulations.

Pure CA models, regardless of their field of application, are based on the interaction of five components: the grid space composed of cells, the neighborhood, the cell states subject to
transition, and the *transition rules* themselves (Torrens 2000, Singh 2003, Sietchiping 2004). The grid space, known as “the lattice”, is one-dimensional, two-dimensional (or, more recently, three-dimensional) surface with “crystalline” structure (Von Neumann and Burks 1966:132) that serves as a hypothetical representation of the study area. The “cell” or the “automaton” is a discrete variable that represents the structural units of the lattice. Von Neumann and Burks (1966: 132) describe the self-reproductive cell in which:

“Each lattice point of this crystal will be able to assume a finite number of different states (say $N$ states) and its behavior will be described (or controlled) by an unambiguous *transition rule*, covering all transitions between these states, as affected by the states of the immediate neighbors.”

The objective of each cellular automata model is “the formalization of the spatial and the temporal relations” (Von Neumann and Burks 1966:132). In other words, CA is based on micro-level interactions between the structural units than can simulate the “logical and constructive universality of self-reproduction” (Von Neumann and Burks 1966: 132). The “cell state” is a description of the cell characteristics subject to change. The change occurs according to specific transition rules (Von Neumann and Burks 1966). Transition rules are mathematical expressions that define pattern formations through dynamic change of the cell state at a specific time step. Apart from the mathematical formulation, change of the cell state also depends on the states of surrounding cells, known as “the neighborhood”. The neighborhood is represented as either Neumann’s (a five-cell structure where the cells on the diagonals are not taken into consideration) or Moore’s (a nine-cell structure where the cells on the diagonals are taken into account) configurations (Wolfram 1994).
2.1.3 Limitations of CA Application in Urban Modeling

The formal mathematical rules that govern cellular automata in physical and biological systems are not directly applicable to urban simulation models (Torrens 2000). The main question is whether the complex nature of human decision-making and human-environment interactions can be reduced to the simple cell-state transition functions (Couclelis 1997, Torrens 2000, Torrens and O’Sullivan 2001). In general terms, this question reveals the dichotomy between reductionism and synthesis (Torrens 2000). According to Holland (1998), reductionism is a scientific approach based on the understanding that complex phenomena can be built and explained by the interactions between their basic micro-level constituent elements, or building blocks. Synthesis is an a priori deductive approach to reasoning where characteristics of individual elements are derived from the macro-level theories (Cullen 1984).

Are reductionist theories directly applicable to urban phenomena? Is it possible that the main strength of CA models, their simplicity, could also be one of their most important disadvantages? Addressing these issues has resulted in integrating the basic CA framework with other techniques such as fuzzy logic control (Wu 1998a), artificial neural networks (Li and Yeh 2001, 2002) or Markov chain analysis (IDRISI Andes v15.00) which, can each be incorporated to govern the transition rules, with the expectation to achieve a more realistic representation of urban dynamics.

In its classical mathematical formulation, CA models operate in an infinite and unconstrained space. This assumption is not applicable to urban dynamics simulations where only a finite number of cells undergo transition depending on the growth rate specific to the study area and the transition potential (Singh 2003, IDRISI Andes v15.0). Also, in classical CA models, there is no consideration of geographical location (Singh 2003) or understanding of the
sequential and hierarchical nature of human interactions with complex environments (Torrens 2001). In conventional CA models, transitions occur synchronously, such that the rate of change for all cells on the lattice is the same (Stevens 2005, Torrens 2000). Urban growth, however, often does not follow a synchronous pattern (Stevens 2005). Different locations and urban centers experience different growth rates – a dynamic that has not yet been well represented with CA models. Recent research efforts have focused on developing asynchronous dynamics of urban growth (Portugali 2000).

Concerns have been raised also that the conventional CA models do not account for spatial heterogeneity (Torrens 2001) since in its initial state the lattice contains only identical cells. In dynamic urban simulations the initial cell states are not identical. In the simplest case, there are two cell-states that represent urban and non-urban land uses. In more complex cases, the cell-states may correspond to several land use/land cover classes.

The modifiable areal unit problem (MAUP), which accounts for the effect of partitioning the areal units and specify the level of spatial resolution, may also positively affect the modeling results (Wong and Lee 2005). Geographic research has collected persuasive evidence of the omnipresence of MAUP in spatial data representations and analysis. The compatibility of CA models with the raster data structure also makes them more vulnerable to the modifiable areal unit problem. The level of spatial resolution and methods of defining the neighborhood in CA are conducive to propagating MAUP in the modeling results (Torrens 2000).

Despite these limitations, there is little doubt within the research community that CA models are one of the most successful and promising techniques for dynamic urban systems simulations. Better use of GIS functionalities, disaggregation of the land cover/land use classes beyond the dichotomy urban/non-urban, and the coupling of the simple transition rules of CA with other
analytical approaches have contributed in recent years towards overcoming some of these limitations.

2.1.4 Classification of Urban Cellular Automata Models

Cellular automata models have been classified according to their behavior, compatibility with GIS, purpose of use and computational techniques imbedded in their transition rules. In his well-known paper, “Universality and Complexity in Cellular Automata”, first published in 1984, Stephen Wolfram (1994) develops a four-level classification of cellular automata models describing their general behavior on one- and two-dimensional lattices. According to this classification, the first level cellular automata result in a uniform surface where all cells attain identical values. At the second level, the pattern formation exhibits periodic fluctuations in a time-dependent manner. At the third level the pattern formation ranges from “highly irregular” to “rather regular” configurations (Wolfram 1994). Finally, at the forth level the pattern formation evinces ordered, non-repetitive and highly complex behaviors that result in regular, long-lasting configurations (Wolfram 1994). The urban cellular automata models evidently belong to the last category of models because of their ability to simulate well-defined, structured, time-dependent, recurring (persistent or spontaneous) patterns of urban growth.

2.1.4.1 Compatibility of cellular automata with GIS

It has been acknowledged that cellular automata are well-suited to represent geographic processes because of the similarities between a two-dimensional lattice and a raster grid. A raster grid is a representation of the geographic space in the form of cells or pixels with a predetermined spatial resolution (e.g., 10 m). Torrens (2003) lists a number of reasons for which cellular automata can be useful in simulating urban systems: (1) several characteristics of the
urban systems such as land use, concentrations of employment location and population change can all be modeled as automata; (2) cells can provide good approximations to represent traffic analysis zones, property boundaries, and links and nodes in transportation systems; (3) the neighborhoods as part of the cityscape can be successfully simulated by the neighborhoods of cells on the cellular lattice; (4) the concepts of urban theory such as spatial interaction and gravity models can be successfully incorporated in the transition rules. Despite these similarities between cellular automata and the raster-based GIS, the difficulties of coupling the two cannot be overstated.

One of the most difficult tasks in developing dynamic urban simulations is the transformation of the initial space as it exists in cellular automata into a geographic space. The difficulties stem mainly from the fact that the existing Geographic Information Systems are designed to store, retrieve, represent and visualize geographic data, but are not functional in terms of supporting dynamic simulations (Longley and Batty 1996, Batty et al. 1999). A geographic information system essentially combines a database structure with cartographic routines that allows the display, management and analysis of data based upon location and attribute (Heywood et al. 1998). With a few exceptions (IDRISI, PCRaster), the available proprietary and open-source GIS packages lack capabilities for incorporating time-dependent dynamics. Thus, data representations within GIS are fixed in time (Longley and Batty 1996a).

In recent years, GIS has incorporated some advanced options such as generation of dynamic networks and simulation of multi-modal structures. Even these rather limited applications of time-dependent dynamics within GIS have encountered significant challenges. A key problem is related to the existing vector data structures in GIS. Non-topological vector data structures are simple data structures that have mostly drafting applications. They are fast and easy to retrieve,
but lack information on spatial relationships and connectivity, and therefore have limited analytical functionality (Curtin 2007). A topological data structure stores information about spatial relationships, recognizes points and lines of connectivity, and thus eliminates redundancy and gaps within the data. Figure 2.1 and Table 2.1 illustrate the difference between non-topological and topological data structures. Figure 2.1 presents four segments of a network. Table 2.1 summarizes the non-topological and topological attributes of this network.

**Figure 2.1 Schematic vector network representations and reference polygons**

The non-topological data structure includes only $x, y$ coordinates of each node on the grid, but does not provide indication on how the segments are connected. The topological data structures contain information on the direction of movement and additional information on location characteristics such as the names of the polygons it intersects. Until the introduction of the shapefile by ESRI in the mid-1990s, the usefulness of the non-topological data structures was limited only to computer-aided drafting applications (Curtin 2007). The TIGER data files maintained by the Census Bureau use encoding that enforces the topological data structure.
Overall, GIS developers have been successful in incorporating temporal dynamics in network analysis. But can this success be translated into urban simulation and CA modeling with GIS?

Table 2.1 Attributes of non-topological and topological data structures

<table>
<thead>
<tr>
<th>Non-topological Data Structure</th>
<th>Topological Data Structure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node</td>
<td>Segment</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
</tr>
</tbody>
</table>

A pure cellular automata model is an evolutionary framework where processes are time-dependent. The lattice *per se*, however, is not a geographic space and is not primarily designed to support and represent geographic data. Spatial data in GIS has three fundamental characteristics: an attribute (a thematic dimension), time of occurrence (a temporal dimension) and a geographic location (a spatial dimension) (Heywood et al. 1998). Location can be relative (the cell placement on the \( n \)th column and \( m \)th row within the array of cells) or absolute (expressed in terms of \( x, y \) coordinates or latitude/longitude) (Heywood et al. 1998). Cellular automata work with the attribute values of the cells (i.e., the cell-states) but not with their locational characteristics. The neighborhood as defined in CA cannot be considered a locational characteristic in purely geographic terms.

In recent years, urban simulation modelling has had success with running vector-based cellular automata such as “the graph-cellular automata” suggested by O’Sullivan (2001) and the “irregular cellular automata” (Stevens 2005). However, the majority of studies have focused on running cellular automata in a raster data space. A raster data model has several characteristics that makes it compatible with a cellular automata model: two-dimensional arrays composed of pixels (square cells), a single attribute value assigned to each cell, and capabilities for
formalisation of the CA algorithm using geo-computational methods such as geo-algebra (Takeyama and Couclelis 1997, Batty et al. 1999, O’Sullivan 2001). Geo-algebra is a form of raster math applied in urban growth modeling (Takeyama and Couclelis 1997). The main problem with raster data models stems from the process of data encoding. Raster datasets can be enormous in size, which creates significant data storage demands and can hinder computations based on complex algorithms. Batty et al (1999: 210) note that “CA models have usually been developed in software which is not adapted to deal with extensive lattices such as those that characterize real urban systems of interest.”

Cellular automata models in their original form have been developed using ordinary computer languages such as Visual C++ which have greater flexibility and functionality than the modeling languages used in GIS such as Avenue script (ArcView), or Microsoft Visual Basic for Applications (ArcGIS). The macro language used in GIS is less efficient in computing algorithms (Ungerer 2000), but offer some advantages that include building CA within a raster dataspace and using the analytical capabilities of GIS such as database queries, a raster calculator, distance and context operators (Batty and Xie 2005, IDRISI Andes v15.0).

In general, there are three levels of potential integration of GIS with models programmed within a different operating system: loose coupling, partial and complete integration (Tim and Jolly 1994, Saunders and Maidment 1996). Loose coupling occurs when GIS and the model run on separate platforms and do not have a common interface (Saunders and Maidment 1996). Some of the inputs that the model requires are processed within GIS. At the more advanced level of partial integration, GIS and the model can interact through a common interface (Saunders and Maidment 1996). Finally, at the level of complete integration, the model is developed on the GIS platform and is fully operational within the GIS environment taking advantage of all the GIS
functionalities for data analysis, modeling and forecasting (Tim and Jolly 1994, Saunders and Maidment 1996).

2.1.4.1.1 Loose coupling

Most of the cellular automata models for urban applications have been constructed using the loose coupling approach. When it comes to integrating CA and the GIS, this approach has some advantages and disadvantages. The main advantage is that both the GIS and CA remain fully operational on their own platforms, and their full functionality as separate technologies is maintained (Sietchiping 2004). Only specific functions (such as distance and overlay) are executed depending on the modeling and computational tasks. Shortcomings of this approach include that the capabilities of the two modeling systems cannot be fully utilized and their application in urban growth simulations is limited only to specific tasks.

Clarke’s UGM (Urban Growth Model) and SLEUTH (Slope, Land cover, Exclusion area, Urban extent, Transportation network, Hillshade) are examples of loosely coupled GIS with a CA model (Clarke and Gaydos 1998). UGM and its upgraded version SLEUTH are written in Visual C++ modeling language and run on a UNIX platform (Dietzel and Clarke 2006, Sietchiping 2004). Clarke’s models forecasts land cover change using five coefficients: “slope resistance, road gravity, breed, diffusion and spread” (Clarke and Gaydos 1998). The slope coefficient reflects the influence of local topography. The proximity–to-roads coefficient reflects road-driven urban expansion. High values of this coefficient, for example, are found with the simulation of the recent land development around Atlanta (Yang and Lo 2003). Spread is associated with development at the urban fringe and most notably with sprawl (Theobald 2001).
Breed and diffusion are used to forecast new development. Breed is related to randomly scattered new urban patches. Diffusion occurs when the land around a newly developed patch is rapidly urbanized (Clarke and Gaydos 1998, Sietchiping 2004, Dietzel and Clarke 2006).

Clarke’s models have a long list of applications which include testing theories of urban growth (Dietzel et al. 2005), examining the potential of using landscape metrics to model urban growth (Harold et al. 2005), and various regional applications for forecasting land use change and examining policy implications (Esnard et Yang 2002, Arthur-Hartranft et al. 2003, Jantz et al. 2003, Sietchiping 2004). Dietzel and Clarke (2006) list five reasons for which SLEUTH has been successfully applied in several urban growth simulations: (a) the model is a public domain and easily available at no cost; (b) it can be implemented to any region given data availability; (c) its theoretical and empirical foundation is explicitly formulated, documented and recognized; (d) it can project urban growth based on urban/non-urban categorization or with a number of land use classes; (e) it is supported by a well-established discussion forum.

The Dynamic Urban Evolutionary Model (DUEM) (Batty et al. 1999) is another example of successful urban simulation model based on cellular automata dynamics that has incorporated limited GIS capabilities. The model is written in Visual C++ and runs under the Windows 95/NT operating system (Batty et al. 1999). The model simulates five classes of land use activities: residential land use (P), manufacturing (E), commercial and services activities (S), roads (R), and vacant land (V). DUEM is designed to simulate these five classes simultaneously. Its parameters need to be adjusted if transitions to urban land use class only have to be simulated (Batty et al. 1999). The general parameters of the model include “distance, direction, density and transition”, which are activated through the module Rules and need to be developed for each land use category separately (Batty et al. 1999). The model applies a linear decay function with a
probability of land use transition decreasing by a rate of 0.8 per unit pixel. Batty et al. (1999) acknowledge that this assumption is conservative, and if not relaxed, the model tends to produce “highly compact growth” patterns due to the rapidly declining transition potential.

The direction of the transitions is also assumed to be symmetrical, meaning that the likelihood that the cell will transition is the same in all directions (Batty et al. 1999). The default assumptions are that there should be at least 80% residential land in the neighborhood in order for a cell to transition to residential, 15-25% of commercial or industrial land in cell to transition to either of those two uses (Batty et al. 1999). The model has been very helpful in examining hypothetical patterns of growth including diffusive “successive waves of development”, “dispersed settlements”, and random growth patterns (Batty et al. 1999).

2.1.4.1.2 Partial integration

Partial integration between CA and GIS has been difficult because of problems related to data interchange and compatibility (Sietchiping 2004). Incompatible data structures may pose significant problems in the process of file transfer and conversion. A successful example of partial integration of CA and GIS is LEAM (Land-Use Evolution and Impact Assessment Model) (Sun et al. 2005). The CA-component of LEAM is developed using the STELLA modeling environment. The GIS-component of LEAM is based on the Spatial Modeling Environment (SME), a spatial modeling system developed at the University of Maryland by Maxwell and Constanza (1997). In LEAM, STELLA is used to construct the cellular automata model while the Spatial Modeling Environment allows for “assembling and linking the cellular models spatially across the lattice” (Sun et al. 2005). SME can transfer the STELLA code into a C++ code, which eliminates the problem of developing separate file conversion protocols. As a result, LEAM
results can be visualized (both as maps and animation), exported and further analyzed in a number of different formats including GIS and image processing (Sun et al. 2005). A model of partial integration between CA and GIS, SimLand, has been developed by Wu (1998d). The model has a common graphic user interface (GUI) which allows interactive transfer of inputs and outputs between GIS and CA environments for either data processing or dynamic change routines (Wu 1998d).

2.1.4.1.3 Full integration

The major advantage of the geographic information systems is their ability to represent georeferenced data at various scales (from regional to local to pixel) and therefore allow for “real-world” examination of a multitude of factors that determine land use/land cover change. GIS applications in land cover / land use change has been limited because of difficulties that arise from handling temporal dynamics in the general GIS environment. For this reason, most cellular automata models for simulation of urban spatial structures were developed outside the GIS environment.

With the advance of Geo-science information technologies and geo-computational methods, there has been a renewed interest in tight coupling of the CA models with GIS. Full integration of CA and the GIS has been achieved through the use of a macro language which extends the functionality of the existing GIS environment to incorporate time-dependent dynamics (Takeyama and Couclelis 1997). The logic of this approach presumes that CA routines can be implemented or programmed directly into GIS. The concepts of “geo-algebra” and “map dynamics” have been used to describe enhanced GIS functionality, which makes it possible to
execute all pre-processing and analytical functions under the same operating system (Couclelis 1997, Takeyama and Couclelis 1997).

IDRISI developers have come a long way in overcoming those challenges, and modern software offers several modules and models for dynamic simulation of land cover / land use change. The modules within the general IDRISI environment include CELLATOM which is a purely cellular automata model, CA_MARKOV which combines cellular automata with Markov chain analysis. Land Change Modeler (LCM) and GEOMOD are extensions of IDRISI GIS software. LCM allows evaluation of land cover transitions, construction of probability matrices based on logistic regression or neural networks, prediction of change and impact assessment. GEOMOD is a raster-based model of land use/ land cover change which uses four decision rules to allocate land cover transitions (Pontius and Chen 2006). The four decision rules include persistence, regional stratification, neighborhood constraint and suitability, but they are not formulated as CA rules.

Ping et al. (2002) developed a cellular automata model which adopts the functionality of the relational databases in the GIS environment to simulate dynamic spatial interactions. The research applies an innovative approach to identifying CA neighborhoods in which the definition of “a neighbor” includes not only geographic proximity but also “attribute correlation” (Ping et al. 2002). The spatial relationships between cells are defined at three levels: adjacency, extended neighborhood and spatial separation (Ping et al. 2002). Thus, the neighborhood definition is extended beyond its locational characteristics so as to include the human knowledge of essential attributes that determine selection of a cell’s neighbor (Ping et al. 2002).
2.1.5 An Outline of Urban CA Applications

In recent years, CA models for urban simulations have found numerous applications in practically every research area in the field of urban planning, including travel demand, land use change, urban growth, gentrification, employment and residential mobility, analysis of locational decisions by firms and households, and more (Torrens 2000). As Torrens (2000) observes, the wide variety of applications is partly due to the weaknesses of earlier large-scale models. Researchers focused on the CA models in their explorations of the urban space because, for the most part, the models were capable of answering a number of previously intractable research tasks, such as modeling of spatial dynamics, simulation of micro-levels relationships and interactions, capacity to predict emergent patterns and advance innovative techniques for micro-level representation, and visualization and animation of urban processes (Torrens 2000, Sietchiping 2004).

Torrens and O’Sullivan (2001) refer to three non-mutually exclusive fields of application of urban CA models: examination of implications of complexity for urban studies, experimentation with hypothetical ideas about cities, and applications in operational and decision-making context. CA models have also been categorized according to their application to real or hypothetical cities (Sietchiping 2004).

The identification of different types of urban CA models according to their application can be useful in answering important questions related to the context in which the models were applied or the tasks for which they have most successfully been used. A review of recent applications of urban CA models suggests that a classification based on applications related to the explorations of urban theories, analysis of urban morphology and structure, validation and calibration of the urban CA models, orientation towards the planning practice, and the possible
ways of integrating the urban CA model with other models (e.g., atmospheric, hydrology/water quality, ecological, socio-spatial, etc.) can bring useful insights.

2.1.5.1 Exploration of urban theories as they are implemented in urban CA models

More than a decade ago, Batty and Longley (1994) proposed a model of cities based on principles used in statistical physics to explain the “fractal growth phenomenon”, that is, the formation of particle clusters from random movement and agglomeration in two-dimensional space. More specifically, they adopted a principle known as “diffusion-limited aggregation” and applied this principle to describe the “fractal geometry” of cities, i.e. a dendritic, tree-like pattern constructed around the “central business district” (Vicsek 1991, Makse et al. 1995). The model explained how cities arose from random, unsynchronized and arbitrary decisions of a multitude of local agents (Batty and Longley 1994, Peterson 1996). Batty and Longley (1994) emphasized that these seemingly disordered patterns are controlled by what they called “a deeper order”, or the ability of the cities to organize and re-organize (or, “self-organize”) themselves from “the bottom-up”.

In order to test hypotheses about the “edge city” formation, Batty (2001) used agents operating in a cellular space to simulate two models, “a random proportionate growth” model and “a disaggregate growth” model. He argued that both models generated “polynucleated urban landscapes” which comprised both long-standing spatial structures and emerging nodes. He pointed out that there is both continuity and adaptability in urban structures formation which have not been discussed satisfactorily in urban literature. Urban theory, according to Batty, looks at urban growth in one of three ways: growth as a result of some locational or other localized advantage that reinforces itself through a positive feedback, growth that occurs as a completely
random process, and growth that occurs in proportion to previous stages of development and accumulated economies of scale (Batty 2001).

Batty contends that there is a fourth step to this reasoning, which is that “growth is proportionate to size but the rate of growth is random, thus ensuring that there will be no ultimate, unchanging state” (Batty 2001: 641). His view is consistent with the fundamentals of complexity theory which asserts that a system is never in complete equilibrium; it undergoes a number of phase transitions, and every state of the system is only a temporary condition. His modeling approach to urban growth from “the bottom-up” is based on three principles: highest disaggregation possible of micro-activities so that individual decisions are appropriately emphasized; change results from multiple individual decisions taken simultaneously at these micro-levels; and the necessity of some information on the exchange of resource flows between individuals and the system (Batty 2001: 643). From this perspective, the appearance of poly-nucleated urban structures, also defined as “edge cities,” on the simulated map is a rule rather than an exception.

A group of physicists from Boston University developed a mathematical model of a physical expansion of the urban structures which also simulates the rank-size distribution of cities (Makse et al. 1995, 1998, Peterson 1996). The rank-size rule states that the population of each city in the region can be estimated if the rank of the city and the population of largest urban center are given (Kaplan et al. 2004). The model is based on the principle of “correlated percolation in a presence of a gradient” which, according to the authors, would better explain the fractal growth of cities than the diffusion-limited aggregation model of Batty and Longley (Makse et al. 1995, 1998). The authors observed also that the model proposed by Batty and Longley would allow growth to occur only in the periphery of cities and would not adequately explain the scaling (or, the rank-
size) distribution of individual towns as distance from the central business district (CBD) increased. The model developed by Hernan Makse and his colleagues, takes into account population density and its decreasing gradient as the radial distance from the CBD increases.

According to Makse et al. (1995), growth does not occur in a completely random fashion since there is a correlation between developed and undeveloped units. The presence of a developed unit increases the probability of adjoining or contiguous development. Therefore, there is a physical relationship based on correlations between the probabilities of development (or “occupancy’), which can explain the irregular morphology of cities like Berlin and London (Makse et al. 1995, 1998). The authors used a fixed density gradient and different degrees of correlation to describe the variability in the rank-size distribution of cities and towns surrounding the metro areas (Makse et al. 1995).

Charles Dietzel and his colleagues from the University of California, Santa Barbara, introduced “a more formal theory of spatio-temporal urban growth dynamics” (Dietzel et al. 2005: 233). The theory, based on the concepts of “diffusion” and “coalescence,” explains the outward expansion of cities as a cyclical stochastic process which begins with random “seeding” or diffusion of urban nuclei throughout available cellular space (Dietzel et al. 2005). As the urban landscape becomes more and more fragmented, with a great number of scattered urban centers throughout the entire region, a second process develops in which urban areas begin to grow within each other. As a result of this process of coalescence, the nearest-neighbor distance decreases and some urban areas fuse. The overall number of urban areas goes down as they grow in size. As a result, there is a change in the size-rank distribution of cities, known also as “scaling up” (Dietzel et al. 2005).
The theory has been tested for the Houston Metropolitan Area. The distribution of density metrics of the urban patches is established as a measure of the presence of diffusive processes. A decreasing with distance from a set urban core density is an indication that urban expansion follows a pattern of agglomeration which is consistent with the process of coalescence (Dietzel et al. 2005). Twelve metrics of urban patch density and proximity have been tested. Four metrics, including nearest-neighbor distance, number of contiguous urban areas (or patches) within a given region, density of contiguous urban areas and average size proved to be particularly useful in identifying the processes of diffusion and coalescence (Dietzel et al. 2005).

The theories and ideas presented above describe in detail the spatial dynamics of urban change, but to a certain extent, they are disconnected from the traditional socio-economic models of cities that dominated urban planning and urban geography for nearly five decades (Batty 2002, Dietzel et al. 2005). Urban CA models have proven to be very successful in generating spatial patterns of development with high accuracy, but it has been contended that their ability to incorporate “causality” or explanation of the forces driving urban growth, is rather narrow (Cheng and Maser 2004). In addition, the interpretation of results from such models becomes problematic when different processes are represented by spatially similar urban growth patterns (Cheng and Maser 2004).

Engelen et al. (1995, 1997) developed “a dynamic modeling framework” based on CA that is capable of integrating the influences of a wide variety of phenomena that operate on different spatiotemporal scales. The model is particularly suitable (but computationally demanding) for representation of urban dynamics at a regional scale (Engelen et al. 1995). It consists of macro- and micro-level components. The macro-level component is based on three sub-components: environmental, economic and social. Environmental dynamics is formulated qualitatively as
expert knowledge about possible changes in climate and hydrology. Social dynamics take into account population and employment projections. Economic development is simulated as an input-output sub-model that feeds data to the modeling framework at each iteration (Engelen et al. 1995).

Export demand, local consumption and land use demand link the macro- and micro-level components. The macro-level component, for example, computes growth coefficients based on population change and employment projections, which are then used to estimate the amount of additional space required to accommodate new residential and industrial/commercial development (Engelen et al 1995). The land cover change demand is then translated in a micro-level model based on CA. The cellular automata model allocates demand based on “locational” (proximity) and “intrinsic” (physio-graphic) suitability designed for a circular neighborhood of 113 cells (Engelen et al. 1995).

The research of Engelen et al. (1995, 1997) has shown that CA models can represent complex social environments by integrating components that are traditionally found in the earlier operational urban models. These studies have also shown that CA models for urban simulations can benefit from transition rules based on socio-economic parameters since they can incorporate “real-world” policies, plans, and investment projects.

2.1.5.2 Analysis of urban morphology and structure

Andersson et al. (2002) used several methods from statistical physics to produce hypothetical urban forms and examine the morphological organization of urban systems. The research examined the effect of distance interactions, birth and loss of activities, shape and radius of neighborhoods, discontinuities and phase transitions in behavior, sensitivity to neighborhood
influence and density of urban cells on tree-like structures representing urban form. The analysis of global-local interactions indicates disappearance of a bulk of dendritic structures as global influences are reduced and only local actions are taken into account (Andersson et al. 2002).

Manrubia et al. (2000) applied a CA-based reaction-diffusion model to examine the morphological properties of cities. The model builds upon Zipf’s law which states that the rank of a city is inversely proportional to its population (Manrubia et al. 2000). The model is applied to hypothetical cities representing the differences between American, European and African urban settlements. The rationale is that cities “close to saturation” like cities in Europe exhibit different dynamics in their morphological organization than cities in a process of formation such as those in Africa (Manrubia et al. 2000). The research provides evidence that an increase in population size does not change the rank-size distribution that is subject to power-laws. Manrubia et al. (2000) also observe that changes in geographical boundaries may change city morphology, but the rank-size distribution remains constant.

Wu (1998b) creates a CA modeling framework called “a cellular automatic city” to generate a polycentric hypothetical city. Four simulations are run that are based on a qualitative (such as land use categories) and quantitative (such as population densities) variables. Three of them resulted in monocentric cities, while only the fourth produced a polycentric urban structure. Wu (1998b) explains the formation of sub-components in urban spatial structure with the “disutility effect” resulting from increasing population densities and the pull effect of local amenities. The formation of new urban cores was consistently found in areas that have recently experienced rapid increase in population density and higher land development intensity (Wu 1998b: 742).

Herold et al. (2005) adapted a number of spatial metrics borrowed from landscape ecology to examine the fractal dimensions of the urban form. The authors use remote sensing data and
suggest the development of two categories of spatial metrics: those specific to the built environment and those specific to vegetative cover because of unique spectral characteristics of both classes. Spatial metrics, which are statistical measures for identification of patterns of clustering or dispersion, allow for detailed investigation of urban morphology and structure at different scales (Herold et al. 2005). The authors emphasized that current research is still largely based on statistical tools developed in landscape ecology, and there is a need to develop specific metrics or “signatures corresponding to specific urban processes” (Herold et al. 2005: 394) that would better serve urban analysis.

Cheng and Masser (2004) developed “a project-based cellular automata” that incorporates both the “top-down” and the “bottom-up” approaches in urban growth modeling. The simulation framework is based on global and local patterns. An interesting element of this framework is that it works in units that are common to real planning practice: “project planning”, “site-selection”, “local growth”, and “temporal control” (Cheng and Masser 2004). “Project-planning” in this framework is planning future demand for land based on social and economic characteristics of the region. The “site-selection” process builds upon a number of factors and constraints derived from land suitability analysis, institutional development, and the demographic and economic structure of the region (Cheng and Masser 2004). The last two phases – “local growth” and “temporal control” – are modeled as “bottom-up” processes consistent with the complexity theory. The morphology of the urban form resulting from the simulation can be described as “diffusive, concentric, road-influenced and leapfrog in nature” (Cheng and Masser 2005: 172). The dispersive and road-influenced patterns of development found by Cheng and Masser (2005) are consistent with the findings of Clarke and Gaydos (1998), Yang et Lo (2003) and others. The concentric type of development confirms the results from the simulations of the mono-centric
city (Wu 1998). “Leapfrog” development is presumably a scattered form of new urban
development.

2.1.5.3 Approaches to validation and sensitivity analysis of the urban CA models

Model parameters should be calibrated and validated to ensure that findings are valid and
reliable. In physical models, which are based on mathematical principles, the calibration requires
finding the most appropriate coefficients for each algorithm. Coefficients can be derived from
previous studies in regions with similar physiographic characteristics, or by observing the
fluctuations of a selected indicator for which both simulated and observed data are available.
Sensitivity analysis determines which parameter or coefficient has the strongest influence on the
modeling results. Usually models are calibrated for a certain interval of time. Validation requires
a calibrated model to be run for a subsequent period of time and observed and simulated results
to be compared.

The calibration and validation of urban CA models differs in several important ways from
the calibration and validation of physically-based models (e.g., hydrologic/ water quality
models). Models parameters in physically-based models are derived as a function of the laws of
physics. Urban development is not just a physical process of land conversion, but also a social
and economic process (Batty et al. 1999). In addition, it is a spatial process and the calibration
process needs to take into account both the number of pixels that have transitioned and their
location. For this reason, the parameter space of urban CA models is intricate and not easy to
estimate (Dietzel and Clarke 2004).

Research has shown that spatial resolution and the number of land use classes used in the
simulation effort affect urban CA models results. Dietzel and Clarke (2006) calibrated the
SLEUTH model for several land use categories and compared the results with a simulation based on the crude dynamics of urban and non-urban land. The results indicated that the urban/non-urban model produced substantial growth at the periphery, while the disaggregated model generated a random and dispersed pattern of growth throughout the entire study area (Dietzel and Clarke 2006). The study also indicated that all variables used in quantifying the impact of urbanization, including total urbanized area, number of urban patches, rate of growth and total amount of land conversions had lower values when the disaggregated dataset was used. Dietzel and Clark (2006: 98) explained this result with the “explicit link between the likelihood of urbanization, and the type of land use that will be converted to urban”, and cautioned that models based on oversimplified dichotomy urban/non-urban may not produce reliable results since they ignore essential elements of land use change dynamics. They also observed that the results have major implications for planning decision support in general and planning support systems in particular because of the major role that land use planning and zoning rules play in actual planning practice (Dietzel and Clarke 2006).

In order to examine the effect of spatial scale on modeling results, Dietzel and Clarke (2004) derived different sets of parameters for each calibration run with four levels of spatial resolution. The study determined that the parameter with the highest sensitivity to spatial resolution is the slope, since a change in the resolution of the elevation layer alters the values of the slope layer (Dietzel and Clarke 2004). The authors observed that the difficulties of calibrating an urban CA model at various scales increase when a mixture of land use categories is transitioned simultaneously.

Kocabas and Dragicevic (2006) examined the combined effect of neighborhood size and scale on the output of the urban CA model. They found that neighborhood type (circular or
rectangular), neighborhood size (in terms of simple and complex configurations) and spatial resolution significantly affect the output of CA models. Cross-tabulations of maps produced by CA at different spatial resolutions clearly indicated that there was a significant level of discrepancy in the model outputs (Kocabas and Dragicevic 2006). The magnitude of the inconsistencies increased with pixel size. The results showed that there were not major discrepancies between the maps produced at spatial resolutions of 50 m and 100 m, but the output generated at a coarser resolution, such as 500 m, tended to be in significant disagreement with the first two outcomes (Kocabas and Dragicevic 2006).

Menard and Marceau (2005) developed thirty different scenarios to investigate the sensitivity of geographic cellular automata to different spatial scales and neighborhood designs. Four pixel sizes, ranging from 30 to 1000 m, and six neighborhood shapes were included in the analysis. The simulation was performed for real cities in southwest Quebec, Canada. Each model was run ten times to ensure the reliability of results. The results indicated greater similarities between the outcomes of the different scenarios in the earlier time period than after an extended number of iterations. For example, if the forest cover is considered, the discrepancy between the modeling results in the short-run and long-run may differ by orders of magnitude (Menard and Marceau 2005). The study found that: (1) cell size has to be carefully selected and should be in accordance with the size of the area that has been modeled; (2) even insignificant changes in cell size may alter the output considerably; (3) neighborhood design has less impact on the model output than on spatial resolution. Menard and Marceau (2005) have observed some important aspects of the threshold effect. They illustrated that effect by examining the changes that occur in simulated mean forest area. Within a certain range of the pixel size – for example, 50 to 100 m – the values of the simulated mean forest area time series fluctuate in a very narrow range. When
the simulation hits a threshold value, there is an abrupt change in the curve slope and a noticeable difference in the simulated mean forest area because the pixel size affects the distribution of each specific land cover class (Menard and Marceau 2005).

2.1.5.4 Applications oriented towards the planning practice

Planning support systems (PSS) entered the field of urban planning in the late 1980s. Generally, planning support systems (PSS) can be defined as a nested structure of techniques which provide a holistic approach to decision-making in planning. Yet, the definition of PSS is rarely debated. The authors agree that it involves two basic components: information technologies (Geographic Information Systems, in particular, but also other computer-aided modeling techniques) integrated with the planning’s specific aims and tasks (Klosterman 2001a, Geertman and Stillwell 2004). Hopkins et al. (2005: 599) define planning support systems “as tools and techniques to enhance the effectiveness of planning through information technologies.” Geertman and Stillwell (2004: 293) emphasize, however, that “it is not so much the technology, with its capabilities and restrictions that dictates the support function performed by the PSS, but the specific needs of the planning context in which the PSS is designated to operate.” In this context, it is not difficult to distinguish PSS, designed purposely for the tasks and objectives of planning from GIS, which is a general use computer technology (Geertman and Stillwell 2004). It is also commonly understood that planning support systems differ from spatial decision support systems (SDSS) in that they tend to encompass a broader vision of long-term planning strategies while SDSS are usually focused on immediate localized solutions (Geertman and Stillwell 2004). The planning support systems have three major components: relational databases, models and capabilities for visualization (Klosterman and Brail 2001).
Engelen et al. (1997) proposed a modeling framework which integrates components of planning support systems such as GIS-based data structures with “a constrained cellular automata model”. The model was applied to the city of Cincinnati and in a separate case study a hypothetical Caribbean island. The simulation framework examining the impact of climate change on the coastal and inland development of a Caribbean island is a particularly useful example of the application of cellular automata in a decision-making process. The inputs for the cellular automata (the micro-scale model) are developed at the macro-scale based on four components: meteorological, demographic, economic, and land area requirement. The four components are interlinked and determine demand of land for various economic activities such as tourism, agriculture, exports, shopping and manufacturing (Engelen et al. 1997). The probability of transition is defined as a function of the suitability of each cell for a particular land use, its accessibility and the influence of the neighborhood defined as a circular configuration of 113 cells (Engelen et al. 1997). The framework allows planning practitioners to simulate different scenarios with emphasis on the consequences of climate change. More specifically, the authors studied the impact on the land use patterns of coastal areas and the economy of an increase in average temperature by 2°C and the sea level by 20 cm (Engelen et al. 1997). Some constraints regarding the use of cellular automata models as decision support tools in planning are also discussed. They include but are not limited to: a lack of adequate software, a need for highly specialized technical skills, the “normative” nature of planning decisions which is not always compatible with the analytical structure of the simulation, and insufficient knowledge about the impact of the spatial scale on the modeling results (Engelen et al. 1997).

Sun et al. (2005) suggest an integrated framework incorporating a CA-based model as “a comprehensive urban planning support system.”
Model (LEAM) framework consists of a land use change component combined with an impact assessment and a feedback component. The land use change dynamics are modeled with a cellular automata routine. The routine allows for the incorporation of different assumptions and policies. The impact assessment component consists of several sub-models that provide evaluation of air quality, water quality, travel demand and housing values. Finally, planners and decisions makers can use a feedback loop to evaluate alternatives and help adjust policies and plans according to the desired outcomes (Sun et al. 2005).

Yeh and Li (2001) successfully integrated GIS software (ARC/INFO GRID) with a cellular automata model to simulate different land consumption scenarios. They emphasized that the GIS/CA integration makes the simulations more realistic and useful for the planning practice (Yeh and Li 2001: 734). The focus of the study links urban growth to some measures of sustainability such as protection of prime agricultural land, wetlands, water bodies, etc. The model is used to generate seven scenarios of urban growth. Three scenarios are based on various degrees of dispersion and four are based on different types of compact urban configurations. The compact urban structures were further sub-divided into monocentric and polycentric.

Finally, multi-criteria evaluation is used to introduce environmental constraints for both monocentric and polycentric urban organization. The dispersed forms of urban development did not include environmental considerations (Yeh and Li 2001). The different scenarios are evaluated based on an environmental index defined as a cost function and an agglomeration index defined as a ratio of the area and perimeter of the urban patches. Normalization by area is performed to force the environmental cost index between zero and one. The assumption is that the closer the value is to unity, the higher the environmental cost, while the lower the value of the agglomeration index, the greater the dispersal of urban development (Yeh and Li 2001). The
model indicated that compact development significantly reduces environmental costs (Yeh and Li 2001).

Yantz et al. (2003) used the SLEUTH urban growth model (Clarke and Gaydos 1997) to develop three scenarios of future urban development in the Baltimore – Washington metropolitan area. The scenarios included continuation of existing trends, a “smart growth” scenario with a higher level of protection of resources, and “an ecologically sustainable” scenario with rigorous protection of environmentally sensitive areas and restriction on substantial new development projects (Yantz et al. 2003). The scenarios created the framework for decision support of regional management plans and future planning practices regarding the Chesapeake Bay watershed. Yantz et al. (2003) emphasized the importance of visualizing the modeling results which drew public attention (the results were publicized by Washington Post and other media) and fostered a dialogue about future paths of development based on diminished loss of valuable ecological services provided by undisturbed natural areas.

As part of the European Commission’s MOLAND (Monitoring Land Use Dynamics) project, Barredo et al. (2004) ran a CA-based model of urban expansion of Lagos, the capital of Nigeria, which is one of fastest growing cities in the developing world. The study illustrates the usefulness of growth projections for megacities of the Third World experiencing erratic population growth and uncontrolled land consumption. With a current population of 12 million, Lagos was projected to expand to 27 million in 2020 occupying an area of almost 1,000 square kilometers (Barredo et al. 2004). Given the inadequate infrastructure and the lack of basic services, such an explosive growth poses insurmountable difficulties for city management. The authors emphasized that because of overwhelming poverty, environmental aspects of sustainability are hardly ever addressed. Major efforts are primarily invested in sustaining basic
facilities such as water supply, electricity generation and waste disposal (Barredo et al. 2004). The CA model constructed by Barredo et al. (2004) captures the complexity of this environment and is capable of adequately representing the dominant “bottom-up” growth that occurs spontaneously around Lagos. The results of the model have important implications for the future planning of the overall distribution of city services.

Along the same line of inquiry, Sietchiping (2004) suggested use of the Informal Settlement Growth Model (ISGM) which contributed to better understanding of the origins and distribution of unplanned settlement in Yaounde, Cameroon. ISGM is a cellular automata model written as a Visual Basic macro and executed in a GIS environment. Given that nearly 80 percent of the urban growth in the developing world is unplanned, the uncontrolled emergence of informal settlements “will also make the sustainable organization of the built environment more complex” (Sietchiping 2004: 2). Therefore, the use of a CA-based model to closely follow the pattern of spread of the informal settlements could be an invaluable planning tool in support of the city management practices.

Cellular automata models have also been used as decision support tools for marketing operations (Benati 1997). Benati (1997) used a two-dimensional discrete lattice representing the market space of a product to simulate the behavior of two competitors involved in choosing a business location. Benati (1997) found that the model based on cellular automata routines is capable of distinguishing self-organizing behaviors which cannot be identified otherwise using conventional micro-economic approaches based on supply and demand.

Yang and Lo (2003) linked the SLEUTH urban growth model (Clarke and Gaydos 1998) to a landscape change model (Clarke 1997) to identify the best possible scenario for the future development of Atlanta, Georgia. Three scenarios have been proposed and investigated. The first
scenario simply extrapolated current trends of “rampant” development at the urban fringe into the future (Yang and Lo 2003). This type of development, as shown by modeling results, would cause a drop in the number of urban patches as infill development takes place. Another consequence would be an almost complete loss of forested and open space areas due to expansion by sprawl. The second scenario envisioned a slight increase in the area of the road network as well as establishment of riparian setbacks, protection of wetlands and limited development in the floodplains. The outcomes of this scenario showed an improvement of open space preservation and a decreased tendency towards agglomeration (Yang and Lo 2003). Finally, the preferred pattern of urban development was simulated under the third scenario. As a result of growth management activities, the total amount of newly developed land was significantly reduced, green space increased by almost 30 percent and all of the ecologically important areas were protected (Yang and Lo 2003).

2.1.5.5 Integration of urban CA models with impact assessment models

This section summarizes the use of cellular automata models to develop inputs for different types of environmental models. Arthur-Hartranft et al. (2003) examined the modifications in vegetative cover, surface temperature and runoff resulting from simulated expansion of urbanized land in southeastern Pennsylvania. SLEUTH urban growth model (Clarke and Gaydos 1997) was used to generate different scenarios of land cover alteration ranging from high impact development to more environmentally tolerant options that not only preserve but even extend vegetative cover. The study found that the most significant changes in radiant surface temperature and moisture (measured in terms of evapotranspiration fraction) occur when development proceeds without environmental considerations. The results also indicated that if
secondary forest re-growth would have occurred simultaneously and at the same rate as new development, there would be a decrease in temperature and increase in moisture (Arthur-Hartranft et al. 2003).

The land cover change images generated with the SLEUTH model were also used as an input in a hydrological model based on runoff ratio. The hydrological model was used to develop “an index of runoff response” under typical and atypical antecedent moisture conditions and investigate losses in the overall moisture storage due to urbanization. The study outlined important aspects of how the coupling of an urban CA model with environmental models could facilitate sustainable decisions regarding pace, scope, patterns and physical location of future urban development (Arthur-Hartranft et al. 2003).

Clemonds et al. (2004) used the SLEUTH model to examine the land cover change in the Houston Metropolitan Area and analyze the propagation of “heat islands” or areas where radiant surface temperature increases sharply as result of the adjacent built-up environment. Cogan et al. (2004) integrated the SLEUTH model with a wildlife habitat model to predict the impact of urban development on biodiversity. Hester and Feller (2002) explored the impact of land cover change in the Middle Rio Grande Basin of New Mexico on groundwater quantity and quality.

Platt (2006) used a cellular automata model of urban development in conjunction with a conceptual model for selecting primary areas for forest thinning with the objective to reduce damage from wildfire in the fire-prone areas of Boulder County, Colorado. The combined WHAMED (Wildfire Hazard Mitigation and Exurban Development) model was implemented in the SELES (Spatially Explicit Landscape Event Simulator) modeling environment. The output of the cellular automata model was used to generate “priority areas” for wildfire protection according to criteria outlined by the community protection zone (CPZ) and the wildland – urban
The results of the study were useful for understanding patterns of future urbanization, how they might affect the fire-prone areas in the study region, where the mitigation efforts should be targeted and where financial resources should be allocated.

In Section 4 of this Chapter, urban CA models have been classified according to their compatibility with GIS and the various applications to which they have subject. In the last part of Section 4, the urban CA models will be categorized according to the transition rules applied.

2.1.6 A Taxonomy of Urban CA Transition Rules


2.1.6.1 Deterministic approaches

Conventional CA transition rules have always been deterministic in nature (Torrens 2000). As urban CA transition rules diversified, both deterministic and probabilistic approaches to modeling the behavior of the automaton were applied (Engelen et al. 1997, Clarke and Gaydos 1997, Torrens 2000, Platt 2006). In deterministic urban CA applications, the transition potential of a cell is defined by a cumulative score obtained on the basis of suitability, proximity or accessibility factors (Yeh and Li 2001, Barredo et al. 2004). The transition potential is typically expressed as a coefficient or a score between 0 and 1, or 0 and 100. Whether or not a cell would
transition depends on a given threshold value based on either expert knowledge, analysis of historical trends or a random factor (Yeh and Li 2001).

2.1.6.2 Probabilistic approaches

The probabilistic approach is typically based on a statistical procedure that allows the development of a probability surface on which the likelihood that a particular cell would transition to a different land cover/land use class depends. Barredo et al. (2004) have recast the initial scores obtained as a result of suitability, proximity and policy analysis using a stochastic process. As a result, they obtained a probability distribution based on a modified extreme value technique. Some initial suitability scores were rescaled using a probabilistic function in order to fit an empirical distribution (Barredo et al. 2004). The fitting process required modification of the initial values: some were changed only slightly while others were significantly stretched (Barredo et al. 2004).

Verburg et al. (2004) and Platt (2006) used logistic regression to estimate the probability that a cell will undergo a transition. In order to account for spatial interactions at various distances, Verburg et al. (2004) introduced the concept of “the enrichment factor”, a measure of neighborhood characteristics similar to the location quotient in urban geography. The enrichment factors are then used as independent variables in maximum likelihood estimation. The WHAMED model (Platt et al. 2004) applies logistic regression to estimate the probability of development in fire-prone areas of Boulder County, Colorado. The independent variables used in the model include zoning regulations, slope, distance to streams, developed land and roads and density of structures. A cell will go through a transition if its assigned value is less than the probability of development given in the model (Platt 2006).
Dendoncker et al. 2007 compared the results of binary and multinomial logistic regression with a *Bayesian Maximum Entropy (BME)* approach. The logistic regression models estimate the likelihood of occurrence as a categorical response (yes/no). The categorical response was estimated for each land use class on a pixel by pixel basis of a size of 1.1 km (Dendoncker et al. 2007). Despite the large size of the pixel, the cells do not actually coincide with real-world geographic entities such as neighborhoods or municipalities. The study found that the logistic regression does not adequately represent spatial patterns of land use distribution. For example, if two regions have similar percentage of each land use class but different spatial patterns of land use allocation, the logistic regression would yield the same coefficients for both regions whereas the Bayesian method would take into account the spatial context and provide different types of spatial predictions for each region (Dendoncker et al. 2007).

2.1.6.3 Application of fuzzy membership functions

Wu (1998c) developed “a fuzzy-logic-controlled cellular automata” to predict loss of rural land due to urban development. Wu (1998c) argues that transition rules based on mathematical functions can adequately represent natural systems, but are not well-suited to define the complex nature of human decision-making. He suggests a fuzzy set theory as more useful in defining transition rules in urban CA models than a deterministic system of equations. The fuzzy logic approach uses logical statements instead of mathematical symbols and is much more transparent and understandable than conventional approaches. Fuzzy set operators such as “IF” and “AND” statements are then used to establish relationships within a set of variables (Wu 1998c).

Shi and Pang (2000) developed a vector-based cellular automata model using transition rules based on a series of “IF-THEN” statements. The model based on spatial and temporal
interactions successfully simulated population movement. The study illustrates the utility of using simple transition rules to model irregular and self-modifiable spatial object (Shi and Pang 2000).

Liu and Phinn (2005) used fuzzy membership functions to create transition rules for a CA-based model of urban growth applied to a study area in Australia. An innovative feature of this model was its ability to simulate different rates of urban transitions simultaneously. Liu and Phinn (2005) develop five membership functions to characterize five different dynamics of urban development: basic, rapid, lingering, new and no development. The authors argue that one of the advantages of using fuzzy set approaches in defining transition rules of cellular automata is that they make the modeling process closer to human decision-making (Liu and Phinn 2005).

2.1.6.4 Multi-criteria Evaluation (MCE)

Wu and Webster (1998: 103) incorporated the principles of multi-criteria evaluation (MCE) into an urban CA model in order to set apart “nondeterministic, multi-dimensional and multi-level transition rules.” The authors argue that the integration of CA with MCE provides decision-makers with a real-world tool to examine the evolution of the city under different conditions and scenarios brought to light by an analytical framework of multi-criteria weights (Wu and Webster 1998). In their investigation of sustainable urban growth, Yeh and Li (2001) used multi-criteria evaluation techniques to generate a composite environmental score based on distance-decay functions giving specific weights to a number of environmental factors. They emphasize the importance of using MCE because it allows for standardization of a set of scores that may be measured on different scales (Yeh and Li 2001: 739). The inputs for the CA_Markov module in IDRISI, used in this research, are created using the MCE procedure.
The MCE approach sets apart the data-driven CA models such as those based on spatial metrics, from the knowledge-driven CA simulation (Jiao and Boerboom 2006). The difference will be illustrated by the following example. Almost every CA model includes road-influenced development where the suitability score of a cell depends on its close proximity to the road. The process of multi-criteria evaluation allows for a simultaneous assessment of several factors that would influence road-related development such as proximity to areas of increased population and employment density, or distance to water bodies and streams located in the area. Multi-criteria evaluation would also allow the protection of environmentally sensitive areas designated by federal, state or local regulations.

2.2 Watershed Hydrology and Transport of Constituents

Since the 1970s, physically-based hydrologic simulation models have increasingly been used to analyze short- and long-term effects of changes in hydrologic conditions on pollutant loadings and assess the impact of various management practices. Non-point source (NPS) pollution, associated with multiple diffuse sources, was identified as a primary cause of water quality deterioration (USEPA 1990).

2.2.1 Modeling Effects of Urbanization on Watershed Hydrology

Both empirical studies and simulation models have shown that an increase in impervious surface as a result of urbanization alters both annual and seasonal water balance which can lead to larger volumes and higher frequencies of discharge, higher flow velocities, modification of stream morphology and erosion, impaired groundwater recharge, alteration of water quality parameters, and degradation of stream habitats (Chow et al. 1988, Yoder 1995, Maidment 1993,
PGC 1999). Studies have shown that for undeveloped land, surface runoff usually does not exceed 30 percent of the total annual precipitation (PGC 1999). Urban development, particularly when associated with inappropriate site design, may result in an increase of surface runoff to over 50 percent of the total annual precipitation (PGC 1999). Pre- and post-development storm hydrographs, as shown on Figure 2.1, illustrate the impact of urbanization on the peak flows and the rates of flow discharge and recession. The hydrographs indicate that urban development generates larger volumes of direct runoff, and steeper and faster peak discharges. By creating a connected network of impervious surfaces (such as roads, driveways and parking lots) urban development decreases the time of concentration, that is, the time that a droplet at the farthest point of the watershed travels to the watershed outlet (Chow et al. 1988, Maidment 1993, PGC 1999).

Figure 2.2 Pre- and post-development hydrographs
There is also an increase in the frequency of occurrence of extreme runoff events due to increased hydraulic efficiency. Higher flow velocities affect stream banks stability, contributing to channel erosion and potential to transport sediment and pollutants (Haan et al. 1994). Recent studies suggest that even low levels of imperviousness (such as 10 percent) can lead to stream channel instability (Booth and Reinelt 1993), increase surface water temperature, which can result in distressed habitats and loss of biodiversity (Yoder 1995).

The source area concept has important implications for risk management and planning practices since it allows for identification of “hydrologically sensitive areas” and designation of “critical management zones” where measures can be applied to prevent the transport of contaminants to perennial water bodies (Walter et al. 2000). Areas with increased interflow levels, elevated water table, soils with shallow depth and/or fragipan that provide little additional storage capacity, poorly and very poorly drained soils as well as impervious surfaces should mostly be considered as runoff-generating areas (Chow et al. 1988, McGrath et al. 2007).

2.2.2 Nitrogen Cycle and Nitrogen Sources

The nitrogen cycle consists of five major chemical transformations of nitrogen: fixation, uptake, mineralization, nitrification and denitrification (Scarborough 2000, Harrison 2006). Fixation is the process in which the triple bond in the molecule of the inert gaseous dinitrogen (N\textsubscript{2}) (the gas that makes up approximately 80% of the Earth’s atmosphere) is broken by either biochemical or high-energy physical processes (Harrison 2006). Biochemical fixation includes metabolic reduction by nitrogen fixing bacteria, such as actinomycetes and cyanobacteria (Pidwirny 2006). The structure of dinitrogen can also be broken by the electricity released in thunderstorms by lightning, by high temperature resulting from forest fires and volcano eruptions.
or by industrial operations involving high-energy, high-temperature processes such as fossil fuel combustion (Carpenter et al. 1998, Harrison 2006). As a result of these processes, the molecule of N\textsubscript{2} splits into free atoms that can react readily with either hydrogen or oxygen. The process of nitrogen fixation most commonly results in the production of ammonium ion (Pidwirny 2006).

Organisms and plants need nitrogen to build proteins, amino acids and nucleic acids (Harrison 2006). With the exception of a few microorganisms, those plants and organisms cannot take nitrogen directly from the atmosphere. They need nitrogen in the mineral form of either inorganic nitrate (NO\textsubscript{3}\textsuperscript{−}) or ammonium (NH\textsubscript{4}\textsuperscript{+}). Nitrate is the main source of nutrients for plants (Harrison 2006). Animals consume living and dead organic matter to obtain the nitrogen necessary to support their metabolic processes (Pidwirny 2006). Nitrogen mineralization is the process in which organic nitrogen is reduced to inorganic nitrogen in the form of ammonium ion (NH\textsubscript{4}\textsuperscript{+}) and amino nitrogen (-NH\textsubscript{2}) (Scarborough 2000). The process is carried out by a special class of microorganisms (mainly bacteria and fungi) called decomposers. Ammonium from decomposition, under aerobic conditions, is oxidized to nitrite (NO\textsubscript{2}\textsuperscript{−}) and nitrate (NO\textsubscript{3}\textsuperscript{−}) in a process called nitrification (Harrison 2006, Scarborough 2000). The energy-yielding process occurs only in oxygen-saturated environments such as surface soil layers, sediments and running waters (Harrison 2006, Scarborough 2000).

The process of nitrification has implications for non-point source pollution in many aspects. Soil organic matter and clay particles are negatively charged and absorb positively charged ammonium ions (Harrison 2006). The bond between positively and negatively charged particles prevents ammonium nitrogen from being leached during rainfall events (Harrison 2006). Negatively-charged clay particles anionic nitrate which are carried out by the surface runoff or
leach through the soil decreasing its fertility and contributing to nutrient over-enrichment of surface and groundwater resources (Harrison 2006).

Under anaerobic conditions, nitrates are reduced to dinitrogen gas and nitrous oxide in a process called denitrification (Harrison 2006, Scarborough 2000). This is one of the processes through which nitrogen is removed from ecosystems (Harrison 2006). The process of denitrification occurs in wetlands and riparian areas where the saturated soil creates the necessary anaerobic conditions. Leaching of nitrates under natural conditions will occur predominantly from forested lands depending on the amount of organic matter available, usually decomposing leaf biomass. Those amounts are generally considered background concentrations and in waters unaffected by anthropogenic contributions they rarely exceed 1 mg/L (Harrison 2006).

The most significant inputs are associated with the application of commercial fertilizers on agricultural lands. The second most important contributor of nitrogen to surface waters is atmospheric deposition. Total load from urban runoff is less adequately characterized. Some studies suggest that it may contribute up to 50% of the nitrogen export from agricultural lands (Scarborough 2000). Other sources include leachate from septic system, and contributions from baseflow generated from groundwater.

2.2.3 The Effects of Land Cover Change on Nitrogen Cycling

In the past three decades, research efforts related to nonpoint source water pollution focused predominantly on contributions to loading from agricultural land. As a result, a wide range of agricultural best management practices including tillage, filter strips for manure/fertilizer applications and a number of conservation practices (over 100 practices can be simulated with
SWAT) have been developed and implemented with the objective of reducing the contribution of nutrient loadings from cropland to surface waters (Lee and Mankin 2007).

A study by Kirkby et al. (2000) examined the impact of land cover change on nitrate concentrations in the Ipswich Watershed, Massachusetts. The study found that a modeled 12 km$^2$ residential development at the estuary of the river has contributed to a significant increase of NO$_3^-$ concentrations. Another study (Waschbusch et al. 1999) concluded that phosphorus from fertilized lawns could be an important contributor to nutrient enrichment of the surface waters in watersheds. Caraco and Cole (1999) regressed population density on nitrate export and provided an estimate of per capita nitrogen release of 1.85 kg/yr. There is little doubt that with accelerated population growth and intensified economic activities, direct nitrogen inputs to the environment from anthropogenic sources will continue to amplify (Alexander et al. 2002).

Soranno et al. (1996) observed that although agricultural and urban lands may contribute similar amounts of nutrients, “they are qualitatively different in their linkage to surface waters and response to precipitation” (Soranno et al. 1996: 875). Differences have been observed in terms of “contributing area”, response to the magnitude of rainfall events, types of nutrients and whether they are transported in dissolved or particulate form (Omernik 1976, Clesceri et al. 1986, Soranno et al. 1996, Jordan et al. 1997, Vanni et al. 2001, Jones et al. 2001). “Contributing area” is the source area that effectively contributes to runoff and nutrient enrichment of streams (Soranno et al. 1996). On agricultural lands, as the source area decreases, contribution also decreases and at a certain distance it may approach zero (Soranno et al. 2001). The size of the contributing area on agricultural lands may vary seasonally and also by dry to wet year. Imperviousness in urbanized areas prevents infiltration and because of the shorter concentration times transmission losses are negligible. For this reason built-up areas were found to contribute
effectively to loading regardless of season and amount of precipitation (Soranno et al. 2001). Nitrogen fluxes from disturbed watersheds can vary significantly (Omernik 1976, Soranno et al. 1996, Vanni et al. 2001). Empirical models based on statistical relationships between land cover categories (e.g., urban, agricultural and forested land) and nutrient fluxes show significant temporal and spatial variation (Jordan et al. 1997, Jones et al. 2001, Vanni et al. 2001, Caraco and Cole 2003). Literature also suggests that in smaller watersheds similar distributions of land cover categories may result in significantly different nutrient fluxes or in-stream concentrations (Kirkby et al. 2000, Vanni et al. 2001, Seitzinger et al. 2002). Predictions may vary within a wide range of values and sometimes in orders of magnitude.

2.3 Conclusion

This chapter presented an overview of the existing theory and applications of the urban CA models. It began with a brief discussion of the theoretical underpinnings that lie behind the urban cellular automata models. More specifically, it describes two influential schools of thought in building operational urban models: the view of the city as a static system vs. the view of the city as a dynamic system. The overview of the urban simulation literature focused primarily on the applications of cellular automata in urban growth modeling. Discussion of compatibility with the GIS, and approaches towards the definition of the transition rules has been presented. The second part of the literature review examined issues related to the hydrology of watersheds, nitrogen cycle and transport of inorganic nitrogen species in urbanizing watersheds.

Because of their ability to incorporate time-dependent dynamics, cellular automata models have become a primary tool of urban growth modeling. This research builds upon the existing knowledge on the application of cellular automata in dynamic urban simulations. In selecting the
modeling approach, the limitations of the CA applications were also considered. The literature indicated that tighter coupling with GIS could enhance the capabilities of CA for real-world planning applications as the strengths of both approaches can be incorporated. More specifically, GIS allows for the addition of wide range of factors, physical as well as socioeconomic, to the modeling framework, and make it possible for the cellular automata to operate in a referenced geographic space. A modeling framework with enhanced GIS capabilities facilitates disaggregation of land cover classes to more than two categories (e.g., urban and non-urban), and incorporation of real-world planning tools (e.g., zoning ordinances and growth management strategies) into the simulation. For this reason, the IDRISI Andes Edition, v15.0 (Clark Labs, Clark University 2006) was selected as the most appropriate modeling environment for this research.

The review of the literature also indicated that there was a gap between urban growth simulation and environmental modeling. The results of the urban growth models were used mostly for visualization and qualitative examination of future development patterns. With a few exceptions, studies that attempted to quantify the impact of the land cover changes resulting from urbanization on environmental conditions were rarely undertaken. This research fits in this niche by integrating a cellular automata – Markov chain model of urban growth with a nitrogen loading model. The combination of urban dynamics simulation and environmental modeling is a relatively new field of research, and given the importance of the changing environmental conditions today, studies based on such an approach, can bring useful insights into better understanding of how urban development affects natural environment.

In recent years, there has been an increasing amount of work focusing on linking optimal land use allocation to environmental conditions to provide a practical framework for future land
use decision-making (Yeo 2005, Wang et al. 2004). Database support, modeling support, and visualization support are the three fundamental components of a planning support system, and all three of them have been developed as part of this research. These components can evolve into a practical tool that links the academic exercise in environmental modeling and urban simulation to the planning practice with the objective to guide and facilitate land use decision-making.
CHAPTER 3

3 METHODOLOGY

The methodological framework presented in this research includes a dynamic land cover change simulation model, a spatial hydrological model, and a spatially distributed nitrogen export model. It is based on an integrated approach towards environmental assessment of future development decisions which includes examining the spatial interaction between land cover and water quality, identifying contributing areas, evaluating the impact of projected land cover change on the long-term nitrogen inputs to streams, and discussing the implications of the results for regional planning and watershed land use decisions.

The land cover change model projects landscape alterations in the study region by 2030. The projections are based on two scenarios. Scenario 1 is a continuation of the current trends and involves only limited environmental constraints. Scenario 2 incorporates an extended network of protected environmentally sensitive areas. The environmentally sensitive areas are defined as areas in which disturbance can lead to rapid deterioration of their natural functions, or instigate
hazards such as floods, landslides, and water quality problems (Walter et al. 2000, Mayhew 2004, Crawford 2006). The environmentally sensitive areas excluded from development under Scenario 2 include floodplains, wetlands, areas with exceedingly shallow depth to seasonally high water table and bedrock, very poorly drained soils and steep slopes. A distributed cell-based model has been developed to quantify the impact of the landscape disturbance on total nitrogen loadings resulting from non-point source pollution. The model is sensitive to changes in the landscape since it takes into account several landscape features such as soil thickness and saturated hydraulic conductivity, geology and vegetative cover.

Figure 3.1 presents the modeling framework and its inputs and outputs.

FLOW-CHART OF MODELS, INPUTS AND OUTPUTS

Figure 3.1 Conceptual framework
3.1 A Cellular Model of Land Cover Change

This section presents a cellular model of urban growth that builds upon a variety of well-established and novel approaches. It incorporates Markov chain analysis to examine past changes in land cover/land use and construct transition probability matrices. It also applies a multi-criteria evaluation based on such traditional and well-established planning techniques as suitability, accessibility and demographic analyses. Finally, it uses the outcomes of these techniques as an input into a cellular automata model that predicts future spatial patterns and landscape organization. Because such models are built upon a variety of techniques, Torrens and O’Sullivan (2001: 164) suggest modified urban cellular automata models to be simply defined as “cellular models” as they depart from the traditional CA structure and create some doubt “as to whether urban CA actually constitute CA at all.”

It has been argued that in spite of the success of the CA models in simulating urban spatial structures, their ability to incorporate causality is rather limited, and therefore the interpretation of results becomes quite difficult as empirically similar patterns can be produced by conceptually different processes (Cheng and Masser 2004). The model discussed in this chapter is not intended to provide explanation of the complex patterns of urban expansion resulting from explicit locational choices of firms and households. Implicitly, however, it accounts for those choices, since it is based on the changing patterns of population and employment densities during the study period. The process of multi-criteria evaluation (MCE) takes into consideration residential and employment mobility between 1990 and 2000 by assigning higher weights to the areas that have experienced higher growth rates. Other factors, such as proximity to roads and water bodies, slope and environmentally sensitive areas were also included in the MCE analysis.
3.1.1 Cellular Automata

A cellular automata model is a spatially explicit model (Berger et al. 2001b). A spatially explicit model is defined as having a geo-referenced framework where change of geographic attributes such as location and/or distance implies changes in the model results (Berger et al. 2001b). In sum, “a spatially explicit model modifies the landscape on which it operates” (Berger et al. 2001b:12).

The four components of a cellular automata model include cells whose behavior is under investigation, the framework through which they cooperate, rules for their interactions at the micro-level and rules for their responses to the influences and controls from the macro-level. In this framework, the environment is usually represented by a lattice of cells or other spatially defined fields with specific characteristics such as land value, employment and population density, labor markets and proximity to socially and economically significant places and networks (Berger et al. 2001a). The transition rules are expressed by mathematical functions that solve different decision-making problems by satisfying some end conditions and constraints.

A cellular automata model represents spatio-temporal dynamics of the land use/land cover change as a function of the following variables:

\[
\text{LU/LC change} = f(S_n, C_{k,t}, N_{k,t}, R_k) \quad (3.1)
\]
Figure 3.2 Conceptual representation of a cellular automata model

Where \( S_n \) is the cell space (lattice or raster) of \( n \) number of cells; \( C_{k,t} \) represents a combination of attributable cell states \( k \) that can be assigned to each cell at each time step \( t \); \( N_{k,t} \) is the neighborhood of adjacent cells in which each cell is in one of the possible states \( k \), where \( k = 1, 2, 3, \ldots, n \); and \( R_k \) is a set of transition rules that determines whether or not a cell moves to any of the states \( k \) or remains unchanged (Torrens 2000, Singh 2003).

In an urban simulation model, the cell space \( S_n \) is a raster or lattice of the urban area. Various cell states are expressed as land use/land cover categories. The propensity of each cell to undergo transition is defined by its suitability for a specific use. The suitability of a cell can be expressed either as a score (as in purely deterministic models), or as a probability function (as in models with a stochastic component). In deterministic models, the composite final score of each cell (i.e. its aptitude for change) is determined by overlaying the individual suitability scores of each cell at time \( t \). In stochastic models, the potential of each cell to undergo transition and the rate of change is expressed as a probability function:

\[
\text{Prob}[C_{k,t+n}] = f(C_{k,t}, N_{k,t}, R_k, S_{k,t})
\]  

(3.2)

where \( \text{Prob}[C_{k,t+n}] \) is the likelihood that a cell will change to a state \( k \) at time \( t+n \), \( C_{k,t} \) is the state of a cell at time \( t \); \( N_{k,t} \) are the states of the neighborhood cells at time \( t \); \( R_k \) are the transition rules formulated for the model; and \( S_{k,t} \) is the potential of a cell to transition to state \( k \) at time \( t \), based on suitability analysis and expressed as a probability function. Logistic regression, fuzzy stochastic logic, Markov transition probabilities, and neural networks have
been used to develop land cover change probability functions (IDRISI Andes v15.0, Wu 1998c, Li and Yeh 2002).

Most urban cellular automata models work with only two categories, urban and non-urban land, because of the complexity of simulating several land cover categories at once. Dietzel and Clarke (2006) discussed the significance of including disaggregated land cover categories in the simulation and the implications of disaggregation for the CA model results. They compared the output from a simulation based on the dynamic change of non-urban to urban land with the results from a separate run of the SLEUTH model calibrated for several land use categories. Dietzel and Clark (2006: 98) emphasized that disaggregating land use/land cover classes in running urban CA simulations is important because location and type of land use/land cover can explain to a certain extent the probability that cells from a particular class would transition to built-up areas. Dietzel and Clarke (2006) cautioned that models based on oversimplified dichotomy urban/non-urban may be biased since they ignore essential elements of the land use change dynamics such as local land use planning and zoning.

Cellular automata – Markov chains (CA_MARKOV) module in IDRISI Geographic Information Systems and Image Processing software, Andes edition v15.0 (Clark Laboratories, Clark University, 2007) has been used to project future changes in the landscape as a result of urban development. The module allows the simultaneous simulation of a group of land use/land cover categories. The module uses Markov transition probability matrices to determine the number of cells from each land cover category that would be converted to any other land cover category. The transition probabilities are estimated using the module MARKOV incorporated in IDRISI (Clark Labs, Clark University 2006). The location of the cells subject to transition is determined on the basis of suitability scores determined by multi-criteria evaluation (MCE). The
In each land cover class included in the simulation. The CA_MARKOV module also requires a basis land cover image, the number of iterations and contiguity filter which down-weighs the suitability scores of randomly located isolated cells that do not belong to any of the nearby clusters of similar land cover cells (Clark Labs, Clark University 2006).

\subsection{Markov Transition Probabilities}

A Markov chain is a stochastic sequence in which random variables $Z_1, Z_2, Z_3, \ldots$ move from one state to another or remain in their previous state according to fixed conditional probabilities (Grinstead and Snell 1997). A Markov system consists of two components: a distribution vector $\mathbf{x}$ with a finite number of states

$$
\mathbf{Z} = \{z_1, z_2, z_3, \ldots\}
$$

and a probability vector or a transition matrix $\mathbf{p}$ which denotes the probability of shifting from state $x_i$ to state $x_j$ (Grinstead and Snell 1997). The entries of the transition matrix are non-negative and sum to 1 (Waner and Costenoble 2007). The Markov process differs from the independent Bernoulli trials. It is based on the assumption that a system acquires a specific state given its current or previous states. In other words, the outcome of one trial may influence the outcome of any subsequent trial (Grinstead and Snell 1997). It is assumed that the future and past states are independent from the current state. Formally, a Markov transition probability is expressed as:

$$
p_{ij}(Z_{i+1} = z \mid Z_i = z_i, \ldots, Z_j = z_j) = p_{ij}(Z_{i+1} = z \mid Z_i = z_i) \quad (3.1)
$$
By using transition probabilities, a random walk over \( n \) number of time steps can be set up through the distribution matrix. If \( P \) is a transition probability matrix, then the \( p_{ij}^{(n)} \) entry of the matrix \( P^n \) denotes the conditional probability that the Markov process with an initial state \( z_i \) will reach state \( z_j \) after an \( n \)-step transition:

\[
p_{ij}^{(n)} = \sum_{k=1}^{z} p_{ik} p_{kj}
\]

(3.2)

where \( 0 < x < n \), \( Z \) is a distribution vector, \( p_{ik} \) and \( p_{kj} \) are conditional probabilities of transitioning to states \( i, k \) and \( j \) after \( n \) time steps (Grinstead and Snell 1997). In the random walk process, the product of the conditional probability of each event is accumulated (Waner and Costenoble 2007). The distribution vector after one step equals \( Z*P^{(1)} \). After two steps, the distribution is determined by \( (Z*P^{(1)})*P^{(2)} \) or \( Z*P^{2} \). After three steps, the resulting distribution vector is \( [(Z*P^{(1)})*P^{(2)}]*P^{(3)} \) or \( Z*P^{3} \). Therefore, after \( n \) steps, the distribution is \( Z*P^n \) (Waner and Costenoble 2007) If the Markov process returns the initial distribution vector, the Markov system is said to be in a steady state (Waner and Costenoble 2007).

Equation 3.3 establishes the probability \( p_{im} \) of land cover category \( i \) at time step \( m \).

\[
(p_m = z_{i_0 i_1} z_{i_1 i_2} + z_{i_1 i_2} z_{i_2 i_3} + z_{i_2 i_3} z_{i_3 i_4} + \ldots z_{i_{m-1} i_m}) \quad \ldots \quad (3.3)
\]

The entry \( p_{im} \) of the \( P^{(n)} \) transition probability matrix is obtained by multiplying the conditional probability that a cell in a category \( i \) would change to a category \( m \) after \( n \) time steps. If we have a vector \( z \) for \( k \) number of land cover classes and a transition probability matrix obtained from historical data, the Markov process results in a sequence of distribution vectors of all transitions between different land cover categories at each time step. The probability that a cell (a pixel) in the raster dataset will transition to urban is estimated by the product of the
conditional probabilities that any of the other cell states would occur. The initial Markov transition probabilities applied in this research were obtained using the 1992 and 2001 NLCD datasets. A specific Markov chain matrix was derived for each ten-year land cover projection.

Land cover change is a complex process that involves multi-level social, economic and environmental factors (Monroe and Muller 2007). Most commonly, land cover change is analyzed and modeled at a regional level. However, landscape alterations occur locally, and by its nature, land cover change is a localized process (Monroe and Muller 2007). Yet, its driving forces and impacts, especially in the long run, are better understood at a regional level.

Multi-criteria evaluation is a decision-making process driven by objective specification. Multi-criteria evaluation is particularly useful when social and biophysical factors need to be considered (Munasinghe and Douglas 2007). MCE can incorporate objectives that are hierarchical in nature, does not require specific types of criteria (factors could be quantitative as well as qualitative), and uses relative weighting with respect to different priorities (Munasinghe and Douglas 2007). The usefulness of integrating cellular automata with multi-criteria evaluation was illustrated by the Wu and Webster (1998) who simulated urban expansion using MCE to assign factor weights derived from possible planning policies and understanding of the planning process.

The multi-criteria evaluation is conducted in three steps: (i) identification of the possible factors determining land cover change; (ii) selection of criteria to represent the hierarchical relationships between these factors in accordance with the simulation objectives; and (iii) computation of weighted average as a function of desirability (Clark Labs 2007). In general, factors account for the suitability, neighborhood, and accessibility effects (Jiao and Boerboom 2006). Local field characteristics such as soil properties, slope and elevation are usually
considered in assigning suitability scores. Accessibility is measured in terms of proximity to urban centers, water/sewer districts, schools, major and minor roads. The neighborhood effect is accounted for as proximity to different types of residential and commercial development. Multi-criteria evaluation can be performed in IDRISI Geographic Information Systems and Image Processing Software (Clark Labs 2006) using the MCE and Decision Wizard modules. The IDRISI MCE procedures used in this research are discussed in further detail in Chapter 4.

3.2 A Distributed Cell-based Model of Nitrogen Export

Assessing the impact of dispersed runoff-contributing areas can play an important role in nonpoint source pollution management and control (Phillips 1989). Research has shown that source areas of nutrient loadings are often small portions of the watershed. In order to improve the understanding of nutrient-contributing areas, the cell-based model developed in this research quantifies interactions between nutrient loss and field characteristics such as soil, land use, topography and distance to streams.

3.2.1 Assumptions

The cell-based model of nitrogen export incorporates the following assumptions:

1. There is a strong positive correlation between runoff and stream nitrogen export in both undeveloped and developed watersheds, and therefore

2. Nutrient export from each land use/land cover type increases linearly with the size of the contributing area which may or may not be equivalent to the aggregate area of that particular land use/land cover class.
3. Not all areas within a specific land cover type contribute equally to N loading. The method applied in this research accounts for source areas, sinks and attenuation factors that affect nutrient transport.

4. Contributing areas depend on two types of factors: constant and variable. Constant factors relate to physiographic characteristics such as soil, topography, location relative to streams, presence of riparian buffers and percentage of impervious surfaces which remain relatively unchanged over time. Variable factors depend on precipitation patterns, antecedent soil moisture conditions, application of best management practices and development patterns which may change over short periods of time.

5. Effective land areas exhibit higher variability in agricultural, forest and undisturbed lands. Urbanized land, due to cumulative inputs from impervious surfaces, is assumed to contribute effectively to loading regardless of distance to streams, season and/or amount of precipitation.

7. Parameters and uncertainties do not depend on the grid-cell size for either the urban simulation or the nutrient export model.

3.2.2 Model Synopsis

The model conceptualization is based on a previous study conducted by Levine et al. in 1993 and partially included in the IDRISI’s UNITAR Workbook, *Volume 6: Applications in Hazard Assessment and Management* (UNITAR 2007). The model has the following components: (i) a spatial hydrological model of the watershed based on DEM derived stream network that reflects stream network densities during dry, normal and wet conditions; (ii) a grid of the TN nitrogen export potential based on the nitrogen export coefficients derived from the literature; (iii) a non-linear regression model that estimates the retention (or trapping) efficiency
of each cell based on soil type and soil permeability, slope and vegetative cover; (iv) estimation of delivery ratios; (v) incorporation of an attenuation factor based on travel time and nitrogen decay coefficient to determine what amount of total nitrogen exported from each cell effectively reaches the stream network.

The trapping efficiencies show the percent of sediments and nutrients that are physically retained in each cell of the raster dataset (UNITAR 2007). Delivery ratios show the percent of TN that is carried away by the overland flow (Levine et al 1993). Thus, the sum of the trapping efficiency and the delivery ratio is 100% (UNITAR 2007). Once the trapping efficiency of each cell is established through a non-linear regression model, its delivery ratio is found by subtracting the trapping efficiencies from one (UNITAR 2007). A cost distance to streams layer based on velocity of unconcentrated flow has also been derived. The cost distance function gives the travel time through the watershed accounting for differences in hydraulic roughness of different land covers. The approximate velocities of unconcentrated flow given by Chow et al. (1988) as a function of slope and vegetative cover were used in the derivation of the travel time. The travel time is multiplied by a decay constant to account for nonconservative transport assuming first-order kinetics (White and Hofschen 1996, Wang et al. 1999, Alexander et al. 2000, 2001). Detailed discussion of model inputs, structure and results is presented in Chapter 6.

3.2.3 Identification of Contributing Areas

The distributed cell-based model of nitrogen export is a spatially explicit model that allows the identification of TN contributing areas, the areas that actively export nutrients to the stream network. The model is able to capture changes in the extent of contributing areas during dry, normal and wet conditions. It also accounts for contributions from agricultural, built-up and
forested areas. When precipitation occurs during dry periods, agricultural land will absorb most of the incoming moisture and thus only areas in immediate proximity to streams would become contributing areas. Impervious surfaces have low attenuation potential and therefore, they will contribute consistently to surface runoff regardless of frequency, amount or intensity of precipitation.

3.3 Study Area

The purpose of this research is to examine the impact of land cover/land use change on the nutrient loadings entering the East Fork Little Miami River (EFLMR). The EFLMR watershed is part of the rapidly developing region around the City of Cincinnati. Therefore, the cellular automata model for projecting urban growth has been applied to the Greater Cincinnati area with the assumption that processes occurring on a larger scale affect the rate of development in the EFLMR watershed. Two study areas, at regional and watershed level, were identified for the purposes of this research.

3.3.1 Study area at Regional Level

The study area at the regional level includes the fifteen counties of the Cincinnati-Middletown, OH-KY-IN Metropolitan Statistical Area:

Boone County, KY; Bracken County, KY; Campbell County, KY; Gallatin County, KY; Grant County, KY; Pendleton County, KY; Kenton County, KY;

Hamilton County, OH Brown County, OH; Butler County, OH; Clermont County, OH; Warren County, OH;

Dearborn County, IN; Franklin County, IN; Ohio County, IN.

(Source: http://www.bls.gov/oes/current/msa_def.htm#17140)
In addition to the counties that are currently part of the Cincinnati-Middletown, OH-KY-IN Metropolitan Statistical Area, twelve other counties were included at the fringes to account for the so-called edge effect (Zhang and Chen 2000, Wong and Lee 2005). The edge effect is associated with the modified dynamics at the boundaries of the study area where the spatial characteristics of the landscape structure change (Wong and Lee 2005).

Figure 3.3 Map of the study area (Data source: USGS)
3.3.2 Study area at Watershed Level

The East Fork Little Miami River watershed, which covers approximately 506 square miles (1,313 square kilometers) in the southeastern part of the Little Miami River sub-basin (HUC # 05090202) was selected. The East Fork Little Miami River originates north of New Vienna at an elevation of 1140 feet above the sea level and drops to 492 feet at its confluence with the Little Miami River (CCOEQ, 2000). The average change in longitudinal slope is 7.6 feet per mile. The confluence of the East Fork Little Miami River and the Little Miami River occurs 3.5 miles south of Milford, east of the City of Cincinnati.

Topographically, the watershed is subdivided into two sub-watersheds. The drainage area of the lower East Fork Little Miami River lays almost entirely in Clermont County, OH, and covers an area of 320 square miles (830 square kilometers). This part of the watershed is a rapidly urbanizing area due to its proximity to Cincinnati. The primary land uses, however, are still agricultural, pasture, forest and low density rural residential with the exception of scattered commercial development along highways.

Figure 3.4 Location of the East Fork Little Miami River watershed in Ohio (Data source: USEPA)
The eastern portion of the watershed is split between Brown, Clinton and Highland counties, Ohio. The headwaters’ total drainage area is approximately 195 square miles (506 square kilometers) of which 29% fall in Brown, 33.8% in Clinton and 34% in Highland county (CCOEQ, 2005). Agricultural and forest land cover around 80 percent of the watershed based on the 1992 National Land Cover Data obtained through the Multi-Resolution Land Characteristics Consortium (MRLC 1992). Residential, commercial and industrial development account for less than 20 percent and are clustered around small communities such as New Vienna, Lynchburg and Fayetteville (MRLC 1992; CCOEQ 2000).

The eastern part of the East Fork Little Miami River watershed is characterized by steeper topography and variations in elevation. The western part is flatter, consisting mainly of gently rolling hills and wider floodplain (CCOEQ, 2000). The average monthly precipitation is 3.5
inches (CCPEQ, 2000). The spring and the summer are the wettest seasons with approximately 60 percent of the total annual precipitation.

The parent material below the glacial till and the soil cover consists mainly of shale substrates (CCOEQ, 2000). The dominant soil associations are Clemont-Avonburg-Rossmoyne (OH042) and Rossmoyne-Avonburg-Bonnell (OH051) which account for 54.27 and 32.12 percent of the soils in the watershed respectively (180,249 acres). Rossmoyne-Eden-Cincinnati association (OH052) and Miami -Miamian – Xenia (OH040) cover 3.4 and 3.23 percent respectively. Fincastle-Brookston-Miamian (OH038) constitutes 1.15 percent or 3,730 acres. Stream network and reservoirs cover 2.076 acres or 0.64 percent of the watershed area.

Avonburg series are somewhat poorly drained and exhibit seasonal wetness. Although Cincinnati and Rossmoyne soils are relatively well drained, they contain a fragipan clay layer between loess and glacial till that inhibits downward movement of water and contributes to the formation of perched water tables above it. In sloping landscapes, the lateral subsurface flow that develops above the fragipan layer affects the transport of dissolved and suspended constituents to surface and groundwater (Calmon, 1997; CSWCD, 2002). Subsurface drainage is not efficient for Clermont and Avonburg soils (CSWCD, 2002).
CHAPTER 4

4  SCENARIO 1: MODELING LAND COVER CHANGE AS A CONTINUATION OF CURRENT TRENDS

Alterations of the landscape due to urban development have a profound effect on the natural systems and the vital functions on which many plants and living organisms depend. These changes also affect the effectiveness of the natural services that are particularly important to city dwellers, such as decrease of surface stormwater runoff, groundwater purification, water resources protection against sedimentation, nutrient enrichment and contamination and presence of landscapes with aesthetic and recreational value.

This chapter presents a cellular automata model of urban growth that simulates changes in the landscape as a result of the polycentric development of the urban system. The model takes into account the amount of land that has transitioned from each land cover class during a specific period of time, the change of population and employment densities during the same period, the areas that have experienced the highest rates of growth and accessibility in terms of proximity to roads and previously developed land. The model introduces different patterns of development
related to different degrees of protection of environmentally sensitive areas such as riparian zones, wetlands, steep slopes susceptible to erosion hazards, shallow depth to water table, shallow depth to bedrock, non-compressive soil foundations, etc. The model was used to examine two scenarios. The first scenario excluded from development only areas situated in immediate proximity to water bodies and streams and on slopes above 25 percent. The second scenario took into consideration a variety of environmental factors such as protection of the existing urban open space, increased width of riparian setbacks, protection of the 100-year floodplain, setting up buffers around areas where shallow water table is present, and excluding from development areas on slopes higher than 15 percent.

### 4.1 Materials and Methods

#### 4.1.1 Data Inputs and Data Processing

Land cover/land use data for 1992 and 2001, soil characteristics, demographic and employment data for 1990 and 2000, and the major roads network constitute the main datasets required to prepare the inputs for the CA_MARKOV model.

#### 4.1.2 Land Cover/ Land Use Data

Land cover/land use data were obtained from the Multi-Resolution Land Characteristics Consortium (USGS 2003) which provides 1992 and 2001 National Land Cover Dataset (NLCD) in grid format. Table 4.1 presents the classification schemes for the two datasets. Table 4.1 indicates how the 1992 and 2001 classifications schemes were reclassified for the purposes of the simulation. Figures 4.1 and 4.2 display the reclassified land cover images for 1992 and 2001.
Table 4.1 Reclassification of the 1992 and 2001 NLCD classification schemes

<table>
<thead>
<tr>
<th>New coding</th>
<th>1992 scheme</th>
<th>2001 scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>Open water</td>
<td>Open water</td>
</tr>
<tr>
<td>Woodland/Open space</td>
<td>Deciduous Forest</td>
<td>Deciduous Forest</td>
</tr>
<tr>
<td></td>
<td>Evergreen Forest</td>
<td>Evergreen Forest</td>
</tr>
<tr>
<td></td>
<td>Mixed Forest</td>
<td>Mixed Forest</td>
</tr>
<tr>
<td></td>
<td>Urban/Recreational Grasses</td>
<td>Open Space</td>
</tr>
<tr>
<td>Cropland</td>
<td>Pasture/Hay</td>
<td>Pasture/Hay</td>
</tr>
<tr>
<td></td>
<td>Row Crops</td>
<td>Cultivated Crops, Barren Land</td>
</tr>
<tr>
<td>Wetlands</td>
<td>Woody Wetlands</td>
<td>Woody Wetlands</td>
</tr>
<tr>
<td></td>
<td>Emergent Herbaceous Wetlands</td>
<td>Emergent Herbaceous Wetlands</td>
</tr>
<tr>
<td>Urban</td>
<td>Low Intensity Residential</td>
<td>Developed, Low Intensity</td>
</tr>
<tr>
<td></td>
<td>High Intensity Residential</td>
<td>Developed, Medium Intensity</td>
</tr>
<tr>
<td></td>
<td>Commercial/Industrial/Transp</td>
<td>Developed, High Intensity</td>
</tr>
</tbody>
</table>

Figure 4.1 Map of the reclassified 1992 land cover (Data source: USGS)
4.1.2.2 Soils Data

The STATSGO database with the soil attributes for the study area was downloaded from the USGS Soil Data Mart. The database contains information on land productivity and habitat potential categorized as good, fair, poor and very poor. The prime agricultural land was derived based on good productivity for grain cultivation. The soils that have good and fair potential to support wetland habitats were extracted and the layer was intersected with the existing wetlands layer derived from the NLCD dataset. Thus it became possible to categorize the existing wetlands according to wetland and wildlife supporting conditions. The STATSGO database was also used to identify areas with seasonally high water table and water table depth annual
minimum. Floodplains were delineated based on flooding frequency observed as both dominant condition and maximum. Areas susceptible to erosion hazard were determined based on the slope gradient dominant component. Areas with shallow depth to bedrock were also designated based on the information contained in the STATSGO database. The different types of areas that need to be protected from encroachment from development because of the specific conditions and the hazards they may pose, if disturbed, to both natural and built environments constitute the environmentally sensitive areas.

4.1.2.3 Roads

Proximity to roads is one of the most common factors included in the simulation of urban growth. The road network for the study area was obtained from the USGS Seamless Server - National Atlas Roads database. The database includes major roads and ferry crossings. Detailed street information is not available through the server (USGS 2008). The file is based on the 1:2,000,000-scale Digital Line Graph (DLG) data produced by the USGS (USGS 1999 Metadata). The file was initially projected in latitude/ longitude. It was re-projected in UTM, zone 17.

4.1.2.4 Population and Employment Data

Population and employment data for 2000 and boundary files by census tracts were obtained for the U.S. Bureau of the Census. The 1990 demographic and employment data and boundary files at census tract level were downloaded from the National Historical Geographic Information System (NHGIS) database maintained by the Minnesota Population Center at the University of Minnesota (MPC 2004). 1990 employment data were also obtained from the Bureau of Transportation Statistics (BTS) – Census Transportation Planning Package (CTPP) which
contains data that can be used for calculation of the traffic flows based on place of residence and place of work.

4.1.2.5 Perennial Streams Network

The perennial streams and rivers dataset for the study region in a vector format was obtained from the USGS National Hydrography Dataset (NHD). The NHD is a DLG file that contains information about surface water features excluding reservoirs, lakes, ponds, and wetlands. The dataset was originally projected in latitude/longitude and re-projected to UTM.

4.1.2.6 National Elevation Dataset (NED)

The National Elevation Dataset (NED) for the study area at 1 arc-second (approximately 30 m) resolution was downloaded from the USGS Seamless Data Server. The data is originally projected in Albers Equal Area Conic Projection USGS Version and re-projected in UTM. The elevation layer was used to derive a slope layer for the study area using the Surface – Slope Tool in ArcGIS©. All layers described above were rasterized using a cell size of 30 meters.

4.2 Past Trends in Land Development

This section describes how changes in population spatial distribution and employment locational dynamics affect the land use/land cover patterns in the study area between 1990 and 2000. It presents facts and graphics related to the rates of land consumption and loss of productive agricultural land and natural resources.
4.2.1 Changes in Population and Employment Dynamics

Between 1990 and 2000, the total population of the study areas has increased by 267,507 persons (US Bureau of the Census 1990, 2000). During the same period of time, the overall employment in the region increased from 741,149 to 949,856, or by 208,707 workers (28.16 percent). Over the study period, from 1990 through 2000, the spatial distribution of the population and employment in the study area also changed. The maps of population density and employment density changes, as shown on Figures 4.4 and 4.5, clearly indicate that throughout the study period the City of Cincinnati continued to lose residents and jobs while the periphery gained both employment and population.

An earlier study of the locational patterns of employment at the Greater Cincinnati area confirmed the general pattern of deconcentration of manufacturing and service-oriented jobs (Mitsova-Boneva et al. 2006). The study included the eight most rapidly growing counties in the Greater Cincinnati area: Hamilton, Butler, Warren, and Clermont counties in Ohio, Kenton, Campbell and Boone counties in Kentucky, and Dearborn county in Indiana.

A comparison of total employment distribution between 1990 and 2000 by standard deviation clearly indicates a trend towards dispersion of employment. The total employment distribution by standard deviation (as shown on Figure 4.5) reveals that jobs in 1990 were primarily concentrated within the loop of Interstate 275, a major highway that runs through the southern portions of Ohio and Indiana, and the northern part of Kentucky.
Figure 4.3 Map of population density change between 1990 and 2000 (persons/sq km) (Data sources: U.S. Census Bureau, NHGIS)
Figure 4.4 Map of employment density change between 1990 and 2000 (persons/sq km) (Data sources: U.S. Census Bureau, NHGIS)
Figure 4.5 1990 Total employment distribution by standard deviation (Data source: BTS)

Figure 4.6 2000 Total employment distribution by standard deviation (Data source: U.S. Census Bureau)
Figure 4.7 1990 manufacturing employment distribution by standard deviation (Data source: BTS)

Figure 4.8 2000 Manufacturing employment distribution by standard deviation (Data source: U.S. Census Bureau)
Figure 4.7 illustrates that, in the year 2000, census tracts with high employment concentrations are scattered throughout the entire study area, including large portions of Dearborn County in Indiana, Butler, Warren and Clermont counties in Ohio, and Campbell and Kenton counties in Kentucky. It is also important that most of the census tracts with employment declining as much as two or more standard deviations below the mean are increasingly found in Hamilton County which indicates that jobs are drifting away from the City of Cincinnati (Mitsova-Boneva et al. 2006).

This trend is particularly pronounced with regard to changes in manufacturing employment distribution between 1990 and 2000. Figure 4.8 makes it evident that in 1990 all manufacturing employment in the Greater Cincinnati area was concentrated at a few locations found predominantly within the I-275 loop, mostly in Norwood, and along interstates 75 and 71. It is also clear that in 1990 the central business district (CBD) was still a major center of manufacturing employment. The remaining areas have virtually no manufacturing jobs (Mitsova-Boneva et al. 2006).

By 2000, as shown on Figure 4.9, manufacturing employment has moved almost completely from its previous locations to the outer rings of the Greater Cincinnati area. By the turn of the century, major manufacturing centers could no longer be found in close proximity to the City of Cincinnati. Areas near the Cincinnati-Northern Kentucky (CVG) airport, and in Dearborn County, Indiana, have witnessed significant increases in manufacturing employment which is now equivalent to more than two standard deviations above the mean (Mitsova-Boneva et al. 2006). Manufacturing employment with significant numbers of workers is currently found in several census tracts in Butler, Warren and Clermont counties in Ohio, Boone County in Kentucky, and to a lesser extent Hamilton, OH, and Campbell and Kenton, KY.
Figure 4.9 1990 service employment distribution by standard deviation (Data source: BTS)
Figure 4.10  2000 service employment distribution by standard deviation (Data source: U.S. Census Bureau)

In sum, from highly concentrated activity within a few spatial units in 1990, manufacturing has become widely dispersed, deconcentrated activity located predominantly in the outer rings of the metropolitan area. In the last decade of the 20th century, the number of service-oriented jobs in the eight most rapidly growing counties of the study area has increased dramatically. From 283,068 in 1990 the service employment has reached 460,634 employees in 2000, which is an increase by 177,566 jobs or 62.73 percent.

Figures 4.10 and 4.11 depict the changing patterns of service employment distribution between 1990 and 2000. In 1990, more than 80 percent of the total service employment was located within the I-275 loop. During the same period of time, the spatial units of analysis that contained service employment were less than 25 percent. They included the Central Business District, Northgate, Beechmont, Norwood, Kenwood and Florence/Erlanger. Similarly to the manufacturing employment, service-oriented activities were dispersed throughout almost all census tracts in the study area.

The number of service providers within each spatial unit has also increased significantly. Contrary to manufacturing and retail employment, in 2000, major centers of service employment are also found within the central city. In summary, service employment exhibits trends of scattering similar to the general trend of employment dispersion in the region, but there are also signs of reversal of the trend of decentralization resulting in significant concentration of workers within specific spatial units.
4.2.2 Changes in Landscape as a Result of Urban Development

The changes in employment spatial distribution and related changes in population movement and land use allocation have resulted in significant alterations of the regional landscape. The analysis of the gains and losses of different types of land cover between 1992 and 2001 indicated that the built-up had increased by nearly 120,000 hectares or approximately 10 percent (as shown on Figures 4.12 and 4.13). The analysis of the past trends of change was performed using the tools of the IDRISI’s Land Change Modeler (Clark Labs, Clark University, 2006).

![Change Analysis](image)

Figure 4.11 Gains and losses of different types of land cover between 1992 and 2001 (in hectares)
Graphs 4.12 and 4.13 indicate that built-up area is mostly increasing by encroaching on agricultural land, and to lesser extent to woodland and open space. The woodland/open space category is both gaining and losing area. The losses can primarily be attributed to the expansion of built-up area. The gains are likely due to reforestation of protected open space areas as well as to secondary forest re-growth on land that has been cleared but not yet developed. Figure 4.13 depicts the net change in the areas pertaining to different land cover classes between 1992 and 2001. Agricultural land, both cropland and pasture, has lost approximately 140,000 hectares. The loss exceeds by 20,000 hectares the amount of land that has been built during the study period. This is likely land that is no longer used for agriculture but has not yet been built up.
Urban development not only encroaches on cropland and pasture, but it also results in significant losses of prime agricultural land. Figure 4.14 shows to what extent the prime agricultural land in the study areas has been affected by the spatial expansion of urban land. The analysis indicates that the fastest land conversion occurs in northeast direction where significant proportion of the prime agricultural land in the study region is found. Figure 4.15 provides a generalized expression of this trend. Between 1992 and 2001 approximately 5 percent of the most productive agricultural land in the region has been lost due to the process of urbanization.
Figure 4.14 The extent of urbanized land on prime agricultural land in 2001 (Data source: USGS)
The trend analysis of the direction of the change associated with conversion of agricultural land confirmed the results from the net change analysis and the examination of the growth areas identified by changes in population and employment densities. Global trend analysis is an interpolation technique that allows the identification of a non-random component in a surface (Johnston et al. 2001). The cubic trend interpolation that was used here is associated with fitting a polynomial through the observed points. If the line-of-best fit had a slope of zero, no-trend would be represented (Johnston et al. 2001). Our analysis indicated increase in values in the northeast direction. Therefore, the data seemed to indicate a trend strongly associated with this direction as shown on Figure 4.16. The *Spatial Trend of Change* tool in IDRISI’s Land Change Modeler was used to derive the graphic representation of the trend.

Other areas that have experienced losses during the period of study are the areas covered by wetlands. The analysis of the net changes in land cover between 1992 and 2001 clearly indicate that the urban land in the study area has expanded significantly at the expense of valuable productive land and other natural resources.
Urban development also results in sizeable fragmentation of agricultural and forested land. The fragmentation of agricultural land (shown on Figure 4.18) although significant has less important ecological implications that fragmentation of forested land that provides habitats to a number of endemic species. Figure 4.19 indicates that large forested areas are still preserved in Indiana and Northern Kentucky parts in the region, but forested habitats and almost completely lost in the Ohio portion of the study area. The images displayed on figures 4.18 and 4.19 are based on a byte data type (with values between 0 and 255) and therefore, the color-coding as shown on the legends of the two maps just indicates a significant variety of patch sizes.
Figure 4.17  Fragmentation of agricultural land

Figure 4.18  Fragmentation of forested areas
Dividing the landscape into smaller, isolated pieces of land affects resource availability (Benedict and McMahon 2006). In addition, fragmentation increases the distances between undisturbed habitats and affects the ability of the animal populations to move, feed, and maintain genetic diversity (Benedict and McMahon 2006).

Loss of habitats, fragmentation, loss of prime agricultural land, reduction of the quality and extent of the leaf canopy are some of the changes that have been observed in the study area as a result of the urban development.

4.3 Model Structure and Model Steps

The CA_MARKOV (Cellular Automata – Markov Chains) module within IDRISI Geographic Information Systems and Image Processing software (Clark Labs, Clark University 2006)A model of land cover/land use change has been used to project future land cover change. The module requires the following inputs: a land cover image from which future change will be projected, a Markov transition probabilities matrix, a suitability image for each land cover/land use class considered for change, the number of iterations, and a contiguity filter for the cellular automata.

In this study, the USGS National Land Cover Datasets for 1992 and 2001 were used as basic land cover images. Both images were reclassified to obtain five land cover classes: urban, woodland, cropland, wetlands and water bodies. The CA_MARKOV module also requires as an input a file containing Markov transition probabilities which determine the likelihood that each cell of a particular land cover class will transition to any other land cover class (Clark Labs, Clark University 2006). The MARKOV module in IDRISI was run to create the Markov transition areas file that was used as an input to the cellular automata model. On an aggregate level, the Markov transitional probabilities matrix also determines the total number of cells
Apart from a transition probability value, each cell is assigned a suitability score using multi-criteria evaluation (MCE) procedure. MCE is an aggregation method that allows for reclassification and weighing of the input variables. The Markov transition probabilities matrix determines the number of cells from each land cover class that would transition to any other land cover class, while MCE determines where transitions would occur. MCE, as applied in IDRISI Decision Wizard, is based on a number of constraints and factors. Constraints are the areas excluded from further modification. Factors are inputs variables that determine the level of suitability of each cell for a particular objective. In this context, existing roads can be considered a constraint since they are not subject to further development. Composite maps resulting from the MCE were developed for the five land cover categories. Another input variable for the IDRISI’s CA_MARKOV module is the specification of the number of iterations which is normally based on the approximate number of years between the first and the second land cover images (Clark Labs, Clark University 2006). Finally, the module involves the specification of a weighing contiguity filter. The filter assigns lower weights to pixels that have high suitability scores but are not in close proximity to the existing constellations of cells of the same land cover class. Suitable pixels are converted to a specific land cover only if they are in relative proximity to an area of that land cover class (Clark Labs, Clark University 2006). The down-weighing does not surpass 90 percent which provides each floating pixel a chance to be assigned a class even if it is not located in close proximity to an existing cluster of cells of the same land cover class.

During each iteration, each land cover class becomes consecutively a host category (Clark Labs, Clark University 2006). The amount of area within the host class that is to be converted
into any other land cover class is given by the Markov transition probabilities areas (Clark Labs, Clark University 2006). A multi-objective land allocation (MOLA) procedure is used to discriminate among the competing classes and allocate land within the host category to the “claimant” land cover classes (Clark Labs, Clark University 2006). At the end of the specified number of iterations, a new land cover/land use map is created. Figure 4.19 presents a diagram of the data requirements, model inputs, model steps, and the model output.

![Figure 4.19 Model structure and model steps](image)

4.4 Scenario 1: Continuation of Current Trends

The overall model objective is to project land cover change in the Greater Cincinnati area until the year 2030. The model projections are executed in increments of approximately 10 years because of the limitations imposed by the Markov transition probability matrix. The matrix contains probabilities of transition based on the land cover change observed during the period of study. The land cover change maps generated by the model are then used as an input in a cell-
based model of nitrogen loading to examine changes in water quality in the East Fork Little Miami River watershed.

4.4.1 Markov Transition Probability Matrices

The Markov transition probability matrix establishes the number of cells within each land cover class that would transition to any other land cover class during the simulation period. The matrix is based on the observed frequencies of transition between land cover classes of the earlier and the later land cover images obtained from the 1992 and 2001 USGS National Land Cover Datasets (NLCD). The Markov transition probabilities were derived using the MARKOV module of IDRISI GIS and Image Processing Software (Clark Labs, Clark University, 2006). Table 4.2 contains the Markov transition probabilities matrix. The matrix indicates that there is, for example, 17.2 percent chance that agricultural land would transition to secondary forest regrowth areas and open space, and 12.5 percent that it will transition to urban land. Approximately 15.1 percent of the woodland/open space, according to the matrix, will transition to land for agricultural uses, and 8.3 percent to urban uses.

Table 4.2 Markov transition probabilities based on reclassified 1992 and 2001 land cover images

<table>
<thead>
<tr>
<th>Given:</th>
<th>Probability of changing to:</th>
<th>Water (1)</th>
<th>Woodland (2)</th>
<th>Cropland (3)</th>
<th>Wetland (4)</th>
<th>Urban (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1 Water</td>
<td>.7871</td>
<td>0.11</td>
<td>0.04</td>
<td>0.01</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>Class 2 Woodland</td>
<td>.0046</td>
<td>0.15</td>
<td>0.17</td>
<td>0.08</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>Class 3 Cropland</td>
<td>.0033</td>
<td>0.69</td>
<td>0.00</td>
<td>0.12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class 4 Wetland</td>
<td>.053</td>
<td>0.00</td>
<td>0.11</td>
<td>0.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class 5 Urban</td>
<td>.0045</td>
<td>0.58</td>
<td>0.18</td>
<td>0.97</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4.3 describes the Markov transition areas (i.e., the number of cells, not just the frequencies, of each land cover class that are expected to transition to any other land cover class). The transition areas file is used as an input into the cellular automata model.

Table 4.3 Markov transition areas based on reclassified 1992 and 2001 land cover images

<table>
<thead>
<tr>
<th>Cells in:</th>
<th>Expected to transition to:</th>
<th>Wa</th>
<th>Wood</th>
<th>Cropl and</th>
<th>Wet</th>
<th>Urban</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>ter 1</td>
<td>land 2</td>
<td>land 3</td>
<td>tland 4</td>
<td>5</td>
</tr>
<tr>
<td>Class 1 Water</td>
<td></td>
<td>21</td>
<td>31421</td>
<td>12682</td>
<td>54</td>
<td>10445</td>
</tr>
<tr>
<td>Class 2 Woodland</td>
<td></td>
<td>27</td>
<td>46611</td>
<td>93060</td>
<td>16</td>
<td>50764</td>
</tr>
<tr>
<td>Class 3 Cropland</td>
<td></td>
<td>22</td>
<td>11794</td>
<td>47858</td>
<td>48</td>
<td>85713</td>
</tr>
<tr>
<td>Class 4 Wetland</td>
<td></td>
<td>15</td>
<td>7286</td>
<td>27</td>
<td>7</td>
<td>3157</td>
</tr>
<tr>
<td>Class 5 Urban</td>
<td></td>
<td>15</td>
<td>28986</td>
<td>21036</td>
<td>43</td>
<td>19367</td>
</tr>
</tbody>
</table>

The model adjusts the probability matrix as the simulation progresses into the future. Table 5 illustrates the Markov transition probabilities based on the 2001 land cover image and the projected land cover for the year 2010. The contiguity filter included in the CA_MAKOV module of IDRISI (Clark Labs 2006) down-weighs cells that are not in close proximity to a particular land cover class. As the number of projected periods increases, the probability that cells of a particular land cover class would transition to the same land cover class slightly increases.

Table 4.4 Markov transition probabilities based on 2001 land cover and projected 2010 land cover

<table>
<thead>
<tr>
<th>Given:</th>
<th>Probability of changing to:</th>
<th>Wat</th>
<th>Wood</th>
<th>Cropland</th>
<th>Wetland</th>
<th>Urban</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>er 1</td>
<td>land 2</td>
<td>land 3</td>
<td>tland 4</td>
<td>an 5</td>
<td></td>
</tr>
<tr>
<td>Class 1 Water</td>
<td>79</td>
<td>0.99</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>Class 2 Woodland</td>
<td>04</td>
<td>0.00</td>
<td>0.87</td>
<td>0.08</td>
<td>0.00</td>
<td>0.04</td>
</tr>
<tr>
<td>Class 3 Cropland</td>
<td>13</td>
<td>0.00</td>
<td>0.11</td>
<td>0.79</td>
<td>0.04</td>
<td>0.09</td>
</tr>
<tr>
<td>Class 4 Wetland</td>
<td>34</td>
<td>0.00</td>
<td>0.30</td>
<td>0.05</td>
<td>0.63</td>
<td>0.00</td>
</tr>
<tr>
<td>Class 5 Urban</td>
<td>34</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.99</td>
</tr>
</tbody>
</table>
As the simulation proceeds into the future, the rate of transition during the next 10-year period to urban land given that the “feeding” cell is either woodland or cropland remains relatively constant, but the transitions to other classes that had low values in the previous period were slightly lowered as illustrated by tables 4.5 and 4.6. In other words, the rate of transition to urban land and to other land cover classes stabilizes at different levels. The results indicate that one needs to proceed with caution when simulation is extended too far into the future.

Table 4.5  Markov transition probabilities based on projected 2010 and 2020 land cover images

<table>
<thead>
<tr>
<th>Given:</th>
<th>Probability of changing to:</th>
<th>Wat</th>
<th>Woo</th>
<th>Cro</th>
<th>Wet</th>
<th>Urb</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>er 1</td>
<td>dland 2</td>
<td>pland 3</td>
<td>and 4</td>
<td>an 5</td>
<td></td>
</tr>
<tr>
<td>Class 1 Water</td>
<td>89</td>
<td>0.99</td>
<td>0.00</td>
<td>01</td>
<td>00</td>
<td>0</td>
</tr>
<tr>
<td>Class 2 Woodland</td>
<td>05</td>
<td>0.00</td>
<td>0.94</td>
<td>28</td>
<td>01</td>
<td>14</td>
</tr>
<tr>
<td>Class 3 Cropland</td>
<td>13</td>
<td>0.00</td>
<td>0.04</td>
<td>0.86</td>
<td>0.00</td>
<td>0.09</td>
</tr>
<tr>
<td>Class 4 Wetland</td>
<td>33</td>
<td>0.00</td>
<td>0.04</td>
<td>0.00</td>
<td>0.94</td>
<td>0.00</td>
</tr>
<tr>
<td>Class 5 Urban</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 4.6  Markov transition probabilities based on projected 2020 and 2030 land cover images

<table>
<thead>
<tr>
<th>Given:</th>
<th>Probability of changing to:</th>
<th>Wat</th>
<th>Woo</th>
<th>Cro</th>
<th>Wet</th>
<th>Urb</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>er 1</td>
<td>dland 2</td>
<td>pland 3</td>
<td>and 4</td>
<td>an 5</td>
<td></td>
</tr>
<tr>
<td>Class 1 Water</td>
<td>98</td>
<td>0.99</td>
<td>0.00</td>
<td>01</td>
<td>01</td>
<td>0</td>
</tr>
<tr>
<td>Class 2 Woodland</td>
<td>06</td>
<td>0.00</td>
<td>0.94</td>
<td>20</td>
<td>00</td>
<td>02</td>
</tr>
<tr>
<td>Class 3 Cropland</td>
<td>12</td>
<td>0.00</td>
<td>0.04</td>
<td>0.87</td>
<td>0.00</td>
<td>0.08</td>
</tr>
<tr>
<td>Class 4 Wetland</td>
<td>32</td>
<td>0.00</td>
<td>0.03</td>
<td>12</td>
<td>01</td>
<td>0.94</td>
</tr>
<tr>
<td>Class 5 Urban</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

The Markov transition probabilities matrix establishes the amount of land that would transition to a different land cover class during the projection period, but it cannot determine the spatial distribution of these transitions. The Multi-criteria evaluation procedure in IDRISI is used
to assign each cell a suitability score that determines which cell would transition to a different land cover class during the projection period.

### 4.4.2 Multi-Criteria Evaluation (MCE)

The Multi-Criteria Evaluation procedure is a method of data aggregation based on reclassification and weighing of a number of variables that are believed to constitute the driving forces behind the transitions. It requires recasting of a set of variables in the form of factors and constraints. The constraints in MCE exclude areas from development. The factors are used to designate developable areas.

#### 4.4.2.1 Constraints

Constraints in MCE are Boolean images in which the land that cannot further transition into any of the classes is given a value of 0, while the all the remaining cells are assigned a value of 1. The CA_Markov module requires as an input a raster group file that contains an MCE image for all the land cover classes on which the simulation is based. In order to meet the requirement, MCE procedures with appropriate factors and constraints were run for urban land cover, cropland and woodland/open space, and wetlands and open water. Actual suitability composite scores were developed for cropland, woodland/open space and built-up area. In order to meet the requirement of the CA-MARKOV module, MCE procedures were also created for wetlands and water bodies as well. The challenge with the last two categories was to define their constraints and factors in a way that would prevent the modification of their boundaries during simulation, while the built-up expanded and the woodland and cropland areas were re-adjusted accordingly.
Scenario 1, which extends the current trends into the future, is based on a minimal set of constraints. Land that has already been converted to urban uses including the road network, could not be considered for further transitioning and therefore was excluded from development. Perennial streams and rivers were excluded from development as well. The 2001 NLCD dataset was reclassified to extract the built-up area and the water bodies as separate Boolean layers. The road network layer from the USGS National Roads Atlas was also reclassified as a Boolean image. Finally the perennial stream network obtained from the USGS National Hydrography Dataset (NHD) was also acquired and transformed into a Boolean constraint. Another constraint factor considered is slope. Building regulations normally restrict construction on steep slopes (such as slopes exceeding 25 percent) because of the hazards that this type of development may cause such as slope instability and landslides. The hazards usually include erosion, slope instability, and increased potential for landslides. They also impose additional costs to developers. In the first scenario, based on minimal protection of environmentally sensitive areas, patches of land on slopes exceeding 25 percent were excluded from urban development. Additionally, areas on slopes above 40 percent were excluded from transitions to cropland. Transitions to woodland/open space were not restricted based on the slope factor. The slope layer derived from the National Elevation Dataset using the Surface Tools in ArcGIS© was reclassified as two Boolean images based on 25 and 40 percent slopes. After all constraints were derived as separate images, the OVERLAY by multiplication procedure in IDRISI was used to combine them in a composite constraint image.

Figures 4.21 and 4.22 present the constraining layers used in the 2010 land cover change simulations. The first image (Figure 4.21) displays the excluded areas based on already developed land, water bodies and areas where the slope exceeds 25 percent. On the second image
(Figure 4.22) the constraining layer includes already developed areas, water bodies and areas where the slope exceeds 40 percent. The second layer was used in the MCE analysis of cropland since agricultural activities can be developed on slopes higher than 25 percent but no more than 40 percent since the higher the slope the higher the erosion potential. No slope restrictions were involved in the MCE analysis for woodland.

Figure 4.20 Constraining layer based on 25 percent slope where 0 indicates exclusionary zones and 1 areas suitable for development
Figure 4.21 Constraining layer based on 40 percent slope where 0 indicates zones excluded from agricultural activities

The only difference between Figures 4.21 and 4.22 is that constraining criteria for developing the image on Figure 4.21 included areas with slopes exceeding 25 percent, while the constraining criteria for image 4.22 included slopes exceeding 40 percent. The first image was used in the urban growth simulation, while the second was applied to the simulation of the cropland area change. Similar constraining layers were developed for the 2020 and 2030 simulations. They differ from the images presented on Figures 4.21 and 4.22 only in the extent of the urban development.

4.4.2.2 Factors

Factors are input variables on which the composite suitability score of each cell is based on. Scenario 1, described as a continuation of current trends, is based on five factors:
- distance to areas that have experienced considerable increase in population between 1990 and 2000,
- distance to areas that have experienced substantial growth in employment,
- distance to roads,
- slopes below 25 percent, and
- proximity to streams.

Areas that have recently experienced substantial increases in population and employment are obviously more attractive for developers. These areas were identified based on the population and employment density layers as shown on figures 4.3 and 4.4. Census tracts with increase in population density of more than 300 persons per square kilometers (2.5 standard deviations above the mean) or increase in employment density by more than 180 persons per square kilometer (2.5 standard deviations above the mean) were extracted and a new layer of areas attractive to developers was created. Histograms of population and employment densities are shown on figures 4.22 and 4.23. The simulation is based on the assumption that there is an increased likelihood that new development would occur in relatively close proximity to these areas.
In order to examine how far development can spread from existing urban areas, a layer of the transition from all land cover categories to urban land between 1992 and 2001 was created.
(Figure 4.24). The layer was reclassified to obtain a Boolean image of change from all to urban land. In addition, a layer of Euclidean distance from the 1992 urban land category was created. The Euclidean distance file was entered as input to the HISTO module in IDRISI, while change from all to urban land was used as a mask. The resulting histogram (Figure 4.24) shows the frequency of change depending on distance from already developed land. The histogram indicates that there is a high frequency of change, or conversion to urban uses, in the initial 500 meters from developed land. As the distance from urban land increases, the frequency of change sharply declines to the point where it drops to almost zero at approximately 2.5 kilometers.

Proximity to roads is an important factor since it determines how far development can spread from an existing urbanized area. The feasibility of new development depends on whether
it is close to the existing road network, and for this reason it is one of the most commonly used variables in urban simulation models. Areas in close proximity to streams and water bodies are usually associated with higher housing values because of the amenities they offer (e.g., more open space and recreational facilities) (Bosch et al. 2003).

Once the factors were specified, the DISTANCE module in IDRISI was used to create Euclidean distance layers for each factor. The factors were standardized to a continuous scale of a byte-level range of 0 – 255 to ensure maximum differentiation (Clark Labs, Clark University 2006). The purpose of the standardization process is to convert the incongruent measurement units associated with each factor into comparable suitability scores (Clark Labs, Clark University 2006). After the standardization, a fuzzy membership function is applied to each factor. The FUZZY sub-routine incorporated into the Decision Wizard module in IDRISI requires the specification of a fuzzy membership function that can have nine different combinations of shape and type (Clark Labs, Clark University 2006).

The fuzzy membership function rescales the suitability scores based on selected criteria, prior knowledge, or inputs from stakeholders. The fuzzy membership includes monotonically increasing, monotonically decreasing, and symmetric functions and each of these functions can be represented as sigmoidal, J-shaped or linear (Clark Labs, Clark University 2006). Figure 4.25 illustrates an example of monotonically increasing sigmoidal function which is one of the nine possible combinations of the fuzzy membership function shape and type. Each function requires the specification of control points, that is, the points at the beginning and the end of the curve. The control points are expressed in metric units. The rescaling criteria applied to each factor are discussed below.
Euclidean distance to areas with increased population and employment density of more than 300 persons per square kilometer was rescaled as a fuzzy monotonically decreasing J-shaped function because this function closely matches the form of the histogram presented on Figure 4.23. The control points were set from 30 to 2500 meters to accommodate the range indicated by the graph shown on Figure 4.24. The same fuzzy membership function was applied to rescale proximity to roads. The control points for proximity to roads were set to 20 and 1000 meters, respectively. The outer control point of 1000 m was chosen since the graph on Figure 4.24 indicates that the most suitable areas lie within approximately a 1000-meter distance to roads. A J-shaped distance decay function is appropriate for these three criteria according to the graph presented on Figure 4.25. Figure 4.25 presents an example of a J-shaped fuzzy membership function.
After steep slopes were masked out with the constraint layer, the slopes ranging from 1 to 25 percent were rescaled using monotonically decreasing linear function. A simple linear decay function is appropriate with this criterion since suitability decreases as the steepness of the slopes increases.

![Fuzzy monotonically decreasing J-shaped function as applied in IDRISI's Decision Wizard](image)

**Figure 4.26 FUZZY monotonically decreasing J-shaped function as applied in IDRISI's Decision Wizard**

The last criterion included in the suitability analysis was proximity to streams. A minimal riparian setback of 30 meters (1 cell in the raster dataset) was applied and set as the first control point. After a certain distance (which could be approximately 800 or 1000 meters from the stream) the suitability may neither decrease nor increase (Clark Labs, Clark University 2007). This situation is best represented by a monotonically increasing sigmoidal function which levels at a certain suitability value. The function was applied to rescale distance to streams. The rescaling of factors used so far was consistent with defining the most suitable areas for urban development. After all the constraints and factors for a particular type of transition are assembled.
and an overlay operation is performed, the multi-criteria evaluation (MCE) procedure is completed. The resulting image shows the suitability of each cell for a specific type of land conversion, including expansion of the built-up area.

Similar MCE procedures were completed also for the other types of transitions including transition to cropland and transition to woodland/open space. The factors were rescaled in a similar way, only in the opposite direction. For example, the suitability scores for forest and cropland increase as the distance from the built-up area increases. However, the distance to streams fuzzy membership function remained constant in all three types of transitions because proximity to water bodies is equally important for urban development, agriculture and forested habitats. In IDRISI, the multi-objective land allocation (MOLA) procedure is used to determine the land areas allocated to each of the claimant classes.

4.4.3 Validation

Kappa statistics is a commonly used statistical indicator for assessing the level of agreement between the cell values of two datasets. It is a nonparametric correlation technique applied to nominal variables. The method is based on the pixel by pixel agreement between the observed data and the modeled result. For example, if we have a 2 x 2 table in which the cell are A, B, C, and D, the Kappa statistic is calculated as follows: (i) find agreement, \( a = (A + D) \); (ii) calculate the expected behavior value given by \( e = (A+B)(A+C)+(C+D)(B+D) \); (iii) calculate Kappa as \( k = a + e / 1 - e \) (Raleigh, personal communication).

When a perfect agreement on a pixel by pixel basis is observed, the Kappa statistic is close to 1. When the agreement is random, the statistic yields close to zero values (Monserud and Leemans 1992, Prasad and Iverson 2000). A Kappa statistic value below 0.4 indicates very poor to poor agreement. Values between 0.4 and 0.55 are associated with a good agreement within the
comparison matrix. Values between 0.7 and 0.85 indicate a very good agreement. An excellent agreement is assumed if $k > 0.85$ (Prasad and Iverson 2000).

![Image of 2001 observed and projected land cover data layers](image)

**Figure 4.27 2001 observed and projected land cover data layers**

In order to assess the validity of the CA-MARKOV results, land cover change between 1992 and 2001 was also projected. The validity of the model results have been verified by comparing the projection land cover image for 2001 with the existing 2001 land cover map. Figure 4.29 displays the two maps.

The VALIDATE tool in IDRISI was used to obtained the Kappa statistics values based on the comparison of the two layers. Figure 4.30 shows the results of the VALIDATE procedure for the five land cover classes used in the simulation.
The results indicate that the model predicts accurately 74.43 percent the location of the pixels of each land cover class. The overall Kappa statistics is 0.7 which shows a very good agreement. Kappa statistics was separately calculated for the agreement between observed and
projected built-up areas. The results from the VALIDATE module in IDRISI for urban land only (Figure 4.32) show that the model predicts accurately the location of 87.68 percent of the urban pixels. The overall Kappa statistics is 0.75 which indicates a very good agreement between the observed and projected data layers.

In addition to the Kappa statistics the CROSSTAB module in IDRISI was used to examine the spatial cross correlation between the actual and the modeled maps (Clark Labs 2006). Spatial cross correlation is based on the spatial (i.e., the x, y location) and non-spatial attributes of the maps. The results from the spatial cross correlation are presented in Table 4.7.

**Table 4.7 Results from the spatial cross correlation**

<table>
<thead>
<tr>
<th>Category</th>
<th>KIA</th>
<th>Category</th>
<th>KIA</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.9994</td>
<td>0</td>
<td>0.9901</td>
</tr>
<tr>
<td>1</td>
<td>0.9665</td>
<td>1</td>
<td>0.9631</td>
</tr>
<tr>
<td>2</td>
<td>0.9778</td>
<td>2</td>
<td>0.9720</td>
</tr>
<tr>
<td>3</td>
<td>0.9473</td>
<td>3</td>
<td>0.6493</td>
</tr>
<tr>
<td>4</td>
<td>0.6673</td>
<td>4</td>
<td>0.5590</td>
</tr>
<tr>
<td>5</td>
<td>0.9108</td>
<td>5</td>
<td>0.9073</td>
</tr>
</tbody>
</table>

Overall Kappa 0.9768

The Kappa indices of agreement (KIA) for woodland (category 2), and built-up areas (category 5) is above 0.85 which indicates excellent agreement. The Kappa index of agreement for (category 3) yields a result that is within the range of what is considered to be a very good agreement. Category 0 is not meaningful. The only exception is the wetland areas (category 4) which a relatively low KIA. This is to be expected since the total number of pixels classified as wetlands is very low and the degree of dispersion of those pixels is high.
4.4.4 Results

Figures 4.26, 4.27 and 4.28 depict the increase of the built-up area during the projection period, 2001 - 2030. Under the current scenario, the CA_MARKOV model predicts that between 2001 and 2010 the existing built-up area would increase by another 10 percent approximately. Estimates based on the model predictions indicate that between 2010 and 2020 the urban land would increase by another 8 percent, and some additional 7 percent will be added to the urbanized areas between 2020 and 2030. All simulation results indicate that the direction of change would remain constant, that is, development primarily moves in northeast direction.

The usefulness of the Kappa statistic when applied to urban simulation results has raised some questions. The most problematic issue, as seen by many, is related to the fact that the pixel-by-pixel agreement does not account for patterns or locational distributions (Torrens and O’Sullivan 2001, Barredo et al. 2004). Also, this method applied to land cover classes with a low number of pixels may not generate meaningful results, especially if the pixels are scattered (Barredo et al. 2004). It is recommended that the method is used in combination with other statistical methods in order to better evaluate the modeling results. Despite its limitations, the Kappa statistics method is widely used in global vegetation change and other land cover...
Figure 4.30  Projected land cover: 2010

Figure 4.31  Projected land cover: 2020
Figure 4.32  Projected land cover: 2030
CHAPTER 5

5 SCENARIO 2: INCORPORATING ENVIRONMENTAL CONSTRAINTS INTO A CELLULAR AUTOMATA MODEL OF LAND COVER CHANGE

This chapter presents an urban simulation scenario which incorporates an open space conservation network. Incorporating a green infrastructure network into a cellular automata model of urban growth is a challenging task that became possible as a result of the modeling capabilities of the IDRISI Geographic Information Systems.

5.1 The “Green” Infrastructure Concept

The pace of land consumption in the United States in the past fifty years and its impact on the existing natural resources has prompted new land use planning approaches. Arendt (1996) introduced the concept of conservation design and outlined the principles of establishing green space networks. Arendt (1999) proposed conservation subdivision design as an alternative to the conventional large housing lots subdivision design which often encroaches on prime agricultural land, destroys natural features and fragments existing habitats. The open space conservation subdivision design principles suggested by Arendt (1999) include narrower driveways and
streets, T-shaped turning driveways instead of conventional cul-de-sac, conservation of the existing green space, compact lots, and community septic systems. Arendt’s approach does not restrict the allowable amount of development but it places it at sites where the impact of new construction will be minimal (Pal 2005). Pal (2005) developed a “creative site design” based on suitability analysis that identifies areas minimizing surface runoff and suggested clustering of the new housing units in these areas in order to decrease runoff volumes and protect natural features, factors that are not usually accounted for in conventional design.

Green infrastructure is a relatively new concept used to describe the interdependence of land conservation and land development (Benedict and McMahon 2006). Green infrastructure refers to the “interconnected network of natural areas and other open spaces that conserves natural ecosystem values and functions, sustains clean air and water, and provides a wide array of benefits to people and wildlife” (Benedict and McMahon 2006:1). Benedict and McMahon (2006) suggest that efforts to create green infrastructure begin preemptively, before development has occurred. Green infrastructure also requires development of partnerships with stakeholders that will ensure the implementation and maintenance of ecological networks in the future.

A green infrastructure network consists of riparian areas, floodplains, aquifer recharge zones, wetlands, forested areas and areas that provide refuge for wildlife habitats. Steep slopes contributing to erosion should also be conserved, protected, and otherwise stabilized (USEPA 2005). The conservation measures should be extended to both undisturbed natural areas and areas subject to redevelopment with natural features that provide ecological, aesthetic and recreational services (Arendt 1996, USEPA 2005). Benedict and MacMahon (2006) use the notions of hubs, sites and links to describe the basic components of a green infrastructure network. Hubs include sizeable undisturbed areas such as public and private conservation lands,
federal and state reserves, wilderness areas, and large urban open spaces. Sites are defined as relatively small areas with important ecological functions, mainly in the urban context. Links are the ecological pathways that bind the elements of the network together (Benedict and MacMahon 2006). The Maryland GreenPrint Program (Maryland Department of Natural Resources 2001), the Florida Statewide Greenways System Planning Project (FDEP/UFL 1994), and the Southern Rockies Wildlands Network Vision (Southern Rockies Ecosystem Project 2003) are examples of proposed green infrastructure networks.

5.1.1 Riparian Buffers

A riparian buffer is a complex ecosystem that provides a vital link between stream and terrestrial ecosystems (USEPA 2008, CRWP 2006, Eikaas 2005). Riparian buffers are characterized with unique flora and fauna and serve as both hubs for wildlife habitats and ecological corridors. Sediment trapping, nutrient retention, cooling of stream waters and support for wildlife habitats are some of the most important functions of vegetated riparian buffers confirmed by a number of site-scale studies and technical reports (Heraty 1993, Osborne and Kovacic 1993, Schueler 1995, Dosskey 2004, Eikaas et al. 2005). The canopy of the forested riparian buffers, for example, prevents direct sunlight from reaching the stream waters and moderates the stream temperature fluctuations (Osborne and Kovacic 1993, Leavitt 1998). Vegetated buffers trap significant amounts of sediment, nutrients, heavy metals and other toxic compounds (Osborne and Kovacic 1993). Disturbances affecting these services may have destructive consequences for the integrity of both aquatic and terrestrial ecosystems (Leavitt 1998). The criteria for establishment of vegetated riparian buffers depend primarily on the functions required.
5.1.1.1 Evaluation of Riparian Buffer Functions According to Land Cover

Field studies indicate that stream buffers in forested, agricultural and urban areas do not function in identical ways (Osborne and Kovacic 1993, Barling and Moore 1994, Leavitt 1998). Undisturbed forested riparian areas provide the highest quality of ecological services, support abundance of plant and animal species and can minimize the impact of logging operations in forestlands (Barling and Moore 1994). The recommended width for stream buffers in forest areas ranges from 30 to 50 m (Barling and Moore 1994).

Agricultural riparian buffer are designed to intercept agricultural runoff and reduce the amount of pollutants including nutrients (e.g., phosphorus, ammonium, nitrate nitrogen), pesticides, and pathogens that may reach the stream network (Dosskey 2001, Grismer et al. 2003). Several programs of the U.S. Department of Agriculture (USDA) such as the Conservation Reserve Program (CRP) and the National Conservation Buffer Initiative (NCBI) promote conservation efforts and provide guidelines and financial support to farmers for developing riparian buffers on farmland (Dosskey 2001).

The alteration of the landscape due to the conversion of undeveloped land to urban uses induces changes in stream morphology, hydrologic cycle, evapotranspiration and stream biotic communities (Leavitt 1998). Impervious surfaces usually cover as much as 40 to 50 percent of the urban areas (Benedict and McMahon 2006) and have major impact on the hydrological conditions in urban watersheds (Chow et al. 1988). As a result, urban streams have considerably higher flow rates than the streams in forest and agricultural areas. The change in stream flow regime is caused by direct conversion of rainfall to runoff without storage, and increased hydraulic efficiency due to artificial channelization of stormwater runoff (Chow et al. 1988).
Both factors result in higher volumes and peak discharges of surface runoff which have a detrimental effect on the stability of urban streams (Booth and Jackson 1997).

Urban stream banks are more vulnerable to erosion processes, and downcutting and widening is common in urban streams that are not otherwise channelized (Leavitt 1998). One of the requirements for the installation of riparian buffers in urban watershed is to maintain a sheet flow conditions over a distance of 150 feet for pervious areas and 75 feet for impervious areas (CWP 2002). However, because of the amount of runoff and the flow velocity, the stormwater runoff in urban areas is channelized quickly, and even the physical integrity of riparian buffers in urban watersheds is difficult to maintain. Schueler (1995) estimates that only 10 percent of the total generated surface runoff reach the urban riparian buffer as unconcentrated or laminar flow. The remaining 90 percent of the urban stormwater runoff enters the buffer as concentrated flow and “cross it in an open channel or an enclosed storm drain pipe” (Schueler 1995: 155).

As a result of channelization of flow in urban watersheds, the ability of the riparian buffer to filter pollutants is downgraded and there is a need for structural stormwater practices to protect the stream water quality (CWP 2002). Conversely, the width of riparian buffers in urban watersheds becomes an important issue to consider. Yu et al. (1992) examined the removal rates of several pollutants in grass filter strips of different sizes (75 and 150 feet, respectively) that were used to treat runoff from a large commercial parking lot. The study found that longer flow paths through the vegetated filter increase the removal rates as much as 30 percent for specific pollutants. The 150-feet filter strip removed 84 percent of the sediment, 20 percent of dissolved inorganic nitrogen, 40 percent of total phosphorus, 50 percent of extractable lead and 55 percent of extractable zinc (Yu et al. 1992). The shorter filter removed approximately 50 percent of the total suspended solids and extractable zinc, but was found to export nitrate-nitrite, lead and most
considerably, phosphorus (Yu et al. 1992, USEPA 2005c). This indicates that the capacity of a swale is related to length of swale, which, therefore, is a critical design factor.

5.1.1.2 Evaluation of Buffer Widths According to Function

Width, total area and vegetation impact the effectiveness of the natural services provided by riparian buffers (CRWP 2006). Osborne and Kovacic (1993) and CRWP (2006) conducted thorough literature reviews on the functions of riparian buffers and their dependence on width, coverage and type of vegetative cover. A riparian buffer provides five particularly important services, including flood management, sedimentation / erosion control, provision of habitat, cooling and regulation of water quality.

Flood hazard management. Zoning regulations routinely incorporate riparian setbacks to protect floodplains from encroachment of development (CRWP 2006). Floodplains are low-lying areas adjacent to streams with extent that is derived from the frequency of occurrence and probability-based limits of the area covered by floodwaters (Chow et al. 1988). Flood magnitudes are estimated based on return periods of 2, 5, 10, 25, 50 and 100 years. The extent of the area that has a probability of 1 percent of being flooded is known as the 100-year floodplain.

Floodplains contribute to the connectivity of stream channels, allow recharge of the underlying alluvial aquifers, and facilitate temporary storage that allow for gradual recession and infiltration of floodwaters (CRWP 2006). Development on floodplains limits not only the ability of riparian buffers to perform their natural services, but may even result in failure of some of the flood control structures. A study of the 1993 levee failures on the Missouri River found that approximately 75 percent of the failures occurred in areas where the riparian buffer widths were below 100 m (300 feet) (CRWP 2006).
Sedimentation/erosion control. Clearing of riparian vegetation and wooded debris from both stream channels and stream banks can accelerate erosion (Barling and Moore 1994). Scouring that occurs in the streambed can contribute to lateral channel migration, channel widening and abnormal sedimentation (CRWP 2006). Vegetative cover decreases the runoff velocity as it increases the hydraulic roughness of the flow surface (Barling and Moore 1994). A wider buffer zone leads to a longer travel time which obstructs the flow transport capacity and stimulates deposition. The process of deposition does not affect the volume of runoff flow but causes reduction in concentration and mass of constituents (Dosskey 2001). Finer particles are carried longer distances by the overland flow because they are suspended for longer periods and settle gradually (Dosskey 2001). Barling and Moore (1994) observe that the sediment particle size and runoff event determine the trapping efficiencies of the vegetative filters. They estimated optimal trapping distances depending on sediment particle size and their respective settling time. At a flow rate of 1.02 liters/sec/m, they suggest an optimal buffer width of 3 meters for sand particles, 15 meters for silt, and 122 meters for clay particles (Barling and Moore 1994). Mankin et al. (2007) examined the impact of the buffer width on the removal rates for suspended solids and nutrients. The study found that established riparian buffers with widths between 8 and 16 meters can effectively eliminate 99.7% of the mass and 97.9% of the concentration of total suspended solids depending on the infiltration rates (Mankin et al. 2007).

Field studies have found that the forest cover of riparian buffers is more effective in preventing erosion than the grassed filters in two ways: the stabilizing effect of the tree roots on the stream banks and the continuous supply of coarse wooded debris which play an important role in in-stream sediment deposition (CRWP 2006). Overall, headwater streams should have higher density of wooded debris than the downstream portions of the rivers (CRWP 2006).
Grassed buffers were found to have higher sediment trapping efficiencies than forested buffers capable of retaining as much as 8,000 cubic meters of sediment per streambank kilometer (Trimble 1997). Osborne and Kovacic (1994) report results from a number of controlled experiments that suggest that the ability of the filters to remove suspended solids may be reduced over longer periods of time because of accumulation and loss of effectiveness.

**Nutrients removal.** Numerous studies have examined the trapping efficiencies of riparian buffers and vegetated filter strips for phosphorus and nitrogen (Osborne and Kovacic 1994, Dosskey 2001, CRWP 2006, Mankin et al. 2007).

Riparian vegetation can process nitrogen in several forms. The processes of bio-assimilation that contribute to nitrogen removal include seasonal uptake and recycling by riparian plants and micro-organisms, and reduction of nitrates to dinitrogen gas and nitrous oxide in a process called *denitrification* which usually takes place in saturated horizons of the riparian soils (Osborne and Kovacic 1994, Harrison 2006, CRWP 2006, Triska 2007). Triska et al. (2007) investigated the processes of depletion of dissolved inorganic nitrogen in four hydrologically connected zones: subsurface flow between the edge of riparian zone and the streambank, alluvial groundwater, hyporeic zone, and open channel. The study found that the processes of nitrogen assimilation in surface and alluvial groundwater are influenced by the extent of the hyporeic zone and the hydrological connectivity of headwater streams (Triska et al. 2007). A significant portion (up to 90 %) of the inorganic nitrogen species are removed in the first 15 meters of the riparian buffer (Mankin et al. 2007). Several studies have found almost complete removal of phosphorus and substantial removal of nitrates at relatively narrow widths of the riparian buffers (Osborne and Kovacic 1994, Dosskey 2001, Mankin et al. 2007). A comparative analysis of buffer widths and type of vegetation reported in the literature indicates that widths in the range of 10 to 50 meters.
can remove between 33 and 100 percent of nitrate–nitrogen from subsurface flow, whereas
widths ranging from 5 to 50 meters can remove between 50 and 98 percent of nitrate-nitrogen in
the surface runoff (Osborne and Kovacic 1994). Mankin et al. (2007) report that relatively
narrow strips of 8 to 16 meters can remove 92.1% (mass) and 44.4% (concentration) for total N,
and 91.8% and 42.9% for total P, respectively. The results also indicate that more than 90
percent of total P and N removal are associated with infiltration rates (Mankin et al. 2007).
Triska et al. (2007) report that hydrogeochemical interactions including surface and subsurface
flow paths, biology and micro-biology, geo-morphological setting, and ion exchange play an
important role in the processes of nitrogen removal. The buffer width, however, is not the only
factor that determines the effectiveness of the riparian buffer (Desbonnet et al. 1994, CRWP
2006). Sandy soils require buffer widths between 25 and 175 meters to achieve 90 percent
assimilation of nitrogen, whereas loamy sand textures can achieve similar efficiency within 15
meters of a riparian buffer system (CRWP 2006).

**In-stream temperature control.** Surface water has a low level albedo ($\alpha = 0.06$) which
implies that significant fraction of the incoming solar radiation is absorbed rather than reflected
(Chow et al 1988). For this reason, direct sunlight has direct impact on in-stream temperature,
especially in shallow headwater streams. Several studies reviewed by Osborne and Kovacic
(1993), Leavitt (1998) and Wenger (1999) found direct relationship between streams shading and
stream temperature. Overall, the riparian vegetation affects the near stream microclimate by
reducing evaporation and convection, moderating stream temperature, and eliminating extreme
fluctuations in daily and seasonal in-stream temperature values (Leavitt 1998). Forested
vegetative cover also decreases the temperature of the alluvial groundwater which supplies
cooler input to the stream (Wenger 1999). The lack of forested riparian buffers can significantly
increase stream temperature (Osborne and Kovacic 1993, Leavitt 1998, Cappiella and McNeal 2007). A study of the effect of riparian buffers on stream temperature in Georgia, cited by Wenger, found a difference of 15 degrees Centigrade between the shaded segments of a stream and those exposed to direct sunlight.

Headwater streams are more vulnerable to inputs from direct solar radiation because of their relatively shallow depths (Cappiella and McNeal 2007). Direct inputs from incoming solar radiation have less impact on deeper perennial streams and as a result, the influence of vegetative cover may in some cases be reduced. Other factors such as inputs from groundwater, ambient air temperature depending on season, time of day and latitude, the extent and quality of the leaf canopy, runoff contribution and releases from impounded water may significantly affect in-stream temperature (CRWP 2006, Wenger 1999). Stream temperature and shading affect the production of blue-green algae and concentrations of dissolved oxygen that can cause eutrophication and disrupt spawning of fish species (CRWP 2006) A number of studies report on the sensitivity of many fish communities to even slight fluctuations in stream temperature (Wenger 1999). Osborne and Kovacic (1993) report that stream temperature can be efficiently stabilized by a riparian buffer that is 10 to 30 m wide. A study by Barton et al. (1985) conducted in Ontario, Canada, showed that a 1 km long riparian buffer wide 140 m (459 ft) can effectively maintain a maximum water temperature of 22 degrees Centigrade (as cited by CRWP 2006). The study also presented evidence that the buffer width could be reduced to 50 m (164 ft) with a twofold increase in buffer length (CRWP 2006).

**Biodiversity.** Due to proximity to water and abundance of nutrients and organic matter, riparian areas have the potential to develop remarkable ecological diversity (Wenger 1999, CRWP 2006). Riparian vegetation has unique functions in aerating the soil, preventing
streambank erosion and supporting enormous variety of plants and animals. A number of studies reviewed by Leavitt (1998) indicated that the loss of riparian vegetation increased the primary production and biomass in streams, which negatively affects native species. Studies reviewed by Wenger (1999) and CRWP (2006) confirm that the core habitat requirements of a number of terrestrial species extend beyond the widths set up to support basic riparian buffer functions. Buffer widths of 142 to 289 m are, for example, necessary to support core habitats for amphibians and reptiles (Wenger 1999). Buffers up to 100 m are usually established to support bird habitats (CRWP 2006). Figure 5.1 is a summary of the estimated by various studies effective setbacks widths necessary to maintain specific buffer functions

![Figure 5.1 Estimated effective buffer widths (in meters) with regard to different functions (adapted from Leavitt 1998)](image)

5.1.2 **Slope**

The inclination of the terrain and internal structure of the particle mass are important considerations in site development (Marsh 1983). Soil materials may be affected by failures at different angles depending on compaction, vegetative cover and average water content (Marsh 1983). Coarse materials such as sand and gravel are less influenced by the presence of vegetation
and subsurface flow than fine clays. Unconsolidated clay material with high water content may rupture at relatively low angles (Marsh 1983). Despite these differences, the angle of terrain inclination provides a general indication of suitability for development. Most building codes limit residential development to slopes up to 25 percent, septic systems to up to 15 percent, streets to 17% depending on the speed limits, highways to 4 percent, and industrial sites to less than 3 percent slope (Marsh 1983). Steep slopes are particularly susceptible to erosion which requires specific erosion control measures to be applied on upslope areas (USEPA 2005).

The slope angle also affects the effectiveness of the vegetated riparian buffers. USEPA (2008c) recommends slopes no greater than 15 percent for the installation of vegetative filter systems. Terrains with slopes that exceed 15 percent are conducive to concentrated flow that can effectively circumvent the filtering systems (CWP 2002, Grismer et al. 2003, USEPA 2005).

USDA – National Resource Conservation Service provides the following minimum requirements for the width of the vegetative filter strips: 25 ft for slopes 1 – 3 percent, 35 ft for slopes 4 – 7 percent, and 50 ft for slopes 8 – 10 percent. (USDA – NRCS 2004). Trimble and Sartz (1957) developed a model to estimate the approximate width of riparian setbacks in forested areas to protect streams from sedimentation resulting from logging operations. They suggested a minimum width of 25 feet (7.62 m) that was extended by 2 feet (0.61 m) with every 1 percent increase in slope. The model indicated that a slope of 4 percent would require a buffer of 33 feet (10.1 meters), a slope of 30 percent would yield a buffer of 85 feet (25 meters), and a maximum buffer width of 165 ft (50 m) should be established in areas with a 70 percent slope.

5.1.3 Wetlands

Wetlands are considered “waters of the United States and as such are afforded protection under the Clean Water Act (CWA)” (USEPA 2005a). Similarly to riparian areas, wetlands
provide ecological, hydrologic and pollution abatement functions. They improve water quality by intercepting surface runoff and allowing sufficient detention time so that polluting constituents such as sediment, phosphorus, nitrogen, pesticides, heavy metals and toxics are removed (USEPA 2005a).

Wetlands are particularly vulnerable to development. Measures for protecting wetlands include setbacks, permit requirement, downstream liability, and restoration (CSWCD 2007). The Ohio EPA has classified wetlands in three categories depending on their quality and the services they provide. Category 1 wetlands are considered low-quality wetlands with minimal functions in support of aquatic habitat and streams integrity. For this type of wetlands, specific setbacks are not required (CSWCD 2007). Category 2 wetlands support higher levels of ecological diversity including threatened and endangered species. These types of wetland system are relatively degraded but are still capable of performing a number of wetland functions (CSWCD 2007). The recommended setback for category 2 wetlands is 75 feet (23 m). Category 3 wetlands have intact biodiversity and enormous potential for supporting biodiversity and streams integrity. The recommended buffer for this type of wetland is 150 ft (46 m) (CSWCD 2007). The factors described in the introductory section of this chapter have been taken into consideration when the MCE procedure for the second urban growth scenario was developed.

5.2 Scenario 2: Incorporating an Open Space Conservation Network in CA

The objective of this scenario is to examine the impact of incorporating environmental constraints on the patterns of land cover change simulated with a cellular automata model. Markov transition probabilities and transition areas used in the second scenario are similar to those used in the Scenario 1, and for this reason will not be discussed in further detail here.
5.2.1 Open Space Conservation Network in the Study Region

Environmentally sensitive areas are areas that can undergo rapid degradation or trigger hazards if disturbed (Walter et al. 2000, Randolph 2004). For example, development in areas with shallow water table can disrupt groundwater recharge and increase vulnerability to contamination. Steep slopes pose severe erosion hazards and can easily give way if developed without additional measures for stabilization. Poorly and very poorly drained fine particle soils are not particularly appropriate for construction projects because they are susceptible to failures even at relatively low inclinations (Marsh 1983). Wetlands are another example of environmentally sensitive areas.

Figures 5.1 and 5.2 present a set of environmentally important factors that have been considered in the suitability analysis scores for Scenario 2. Figure 5.1 indicates that the eastern part of the study region (where the East Fork Little Miami River watershed is located) is almost completely covered by poorly and very poorly drained soils. The southern, Kentucky, part of the study region is characterized by shallow depth to bedrock. The western part is particularly vulnerable because of the combination of erosion hazard and exceedingly shallow depth to seasonally high water table. Most development in the past decades has occurred in northeast direction, as discussed in the previous chapter, where environmentally sensitive areas are present to a lesser extent. The northern part of the region is hosting, however, the most productive agricultural land in the region, as shown on Figure 5.2.
Figure 5.2 Environmentally sensitive areas (Data source: USGS)
Figure 5.3 Map of prime agricultural land (Data source: USGS)

Wetlands are areas particularly sensitive to the alterations of the landscape caused by urban development because of the abundance of wildlife and plants that they support. Wetlands provide a number of environmental services which include sediment and nutrient control, stormwater...
runoff mitigation, groundwater recharge and streambank stabilization (Beneduct and McMahon 2006).

**Figure 5.4 Map of wetlands and floodplains(Data source: USGS)**
Most of the wetlands in the study region are located in close proximity to the floodplains, as shown on Figure 5.3. Most of them are located in close proximity to the built-up areas. Figure 5.4 shows that wetlands are scattered throughout the entire study region which requires the concerted efforts of several authorities to ensure protection of their integrity.

5.2.2 Multi-Criteria Evaluation (MCE)

The MCE procedure involved in the second scenario incorporated an increased number of constraints and factors. In addition to roads, built-up areas and water bodies that were included as constraints in Scenario 1, the second scenario excluded from development the 100-year floodplains, wetlands, urban open space and slopes above 15 percent. Other environmentally sensitive areas such as exceedingly shallow depth to seasonally high water table and bedrock were also included in the MCE procedure as constraining features. In addition to the factors considered in Scenario 1, four new factors were added to the suitability analysis. They included distance to shallow water table, distance to urban open space, distance to wetlands, and distance to floodplains. Their rescaling is discussed in more detail below.

5.2.2.1 Constraints

Building a constraining layer requires the identification of the areas that will be excluded from development. The constraints incorporated in Scenario 2 include wetlands, floodplains, perennial streams, rivers and water bodies, areas with shallow water table, urban open space, roads, already built-up areas and slopes exceeding 15 percent. The wetlands layer was extracted from the 2001 National Land Cover Dataset (USGS 2003). The water bodies layer included
reservoirs, lakes and ponds and was also obtained using the same dataset. The stream network of the study region was obtained from the USGS Hydrography dataset. The creation of individual layers of roads, built-up areas and slopes has already been discussed in the previous chapter. Floodplains and areas with seasonally high water table were extracted from the STATSGO Digital Soils Database. A layer containing urban open space areas in the study region has been obtained from the Cincinnati Area Geographic Information Systems (CAGIS). The urban open space covered by this layer includes conservation easements, public and private school properties, golf clubs, cemeteries, state parks, wildlife areas, forests, scenic parks, camp areas, bike trails, nature centers, conservancy districts, preserves, rest areas, playfields, and other designated greenspace (CAGIS 2006). Table 5.1 presents an overview of the datasets and data sources.
<table>
<thead>
<tr>
<th>Factors</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Data Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance to roads</td>
<td>up to 2500 m to major roads</td>
<td>0 - 400 m to all roads</td>
<td>ISGS Seamless Data Server - major highways</td>
</tr>
<tr>
<td></td>
<td>Graph of extent of development</td>
<td>IDRISI Tutorial</td>
<td>Distance to roads layer was created using the DISTANCE function in IDRISI. The linear function was modified to monotonically decreasing J-shaped distribution using the FUZZY function in IDRISI Decision</td>
</tr>
<tr>
<td>Distance to streams</td>
<td>50 - 1000 m</td>
<td>EPA</td>
<td>USGS Seamless Data Server - Hydrography</td>
</tr>
<tr>
<td>Wetlands</td>
<td>n/a</td>
<td>100 meters</td>
<td>OEPA, EPA, Yang &amp; Lo 2003</td>
</tr>
<tr>
<td></td>
<td>OECD, EPA</td>
<td>Intersect wetland and soil layers. For reclassification in 3 categories - STATSGO component table: wetland habitat potential and wetland wildlife potential</td>
<td></td>
</tr>
<tr>
<td>Shallow water table</td>
<td>n/a</td>
<td>shallow water table</td>
<td>Soil Data Mart STATSGO Database</td>
</tr>
<tr>
<td>Urban open space</td>
<td>n/a</td>
<td>all protected</td>
<td>From STATSGO &quot;muaggatt&quot; table, extract features with &quot;frequent&quot; and &quot;occasional&quot; flooding frequency</td>
</tr>
<tr>
<td>Slope</td>
<td>less than 25%</td>
<td>less than 15%</td>
<td>USGS Seamless Data Server - National Elevation Dataset 30 m</td>
</tr>
<tr>
<td></td>
<td>IDRISI Tutorial</td>
<td>The slope layer has been derived from the elevation dataset using the SLOPE function in ArcGIS Spatial Analyst</td>
<td></td>
</tr>
</tbody>
</table>
Figure 5.5 allows a comparison of the constraining Boolean images used in the continuation of current trends scenario and the scenario that incorporates green infrastructure components. The values of 0 on both images indicate areas that are excluded from urban development. The areas that can undergo future development are assigned the value of 1.

Figure 5.5 Constraining layers for Scenario 1 (left) and Scenario 2 (right)

5.2.2.2 Factors

A set of nine different factors was considered in developing Scenario 2. They include the factors that have already been discussed in the previous chapter as part of Scenario 1, and additional four environmentally-based factors. A complete list of the factors used in Scenario 2 is presented below:

- distance to areas that have experienced considerable increase in population between 1990 and 2000,
- distance to areas that have experienced substantial growth in employment
- distance to roads,
- slopes below 15 percent,
- proximity to streams,
- proximity to shallow water table,
- proximity to floodplains,
- proximity to wetlands, and
- proximity to urban open space.

Euclidean distances to roads and areas with increased population and employment density were rescaled using the same fuzzy membership functions as described under Scenario 1. Monotonically decreasing linear function was applied to rescale the slope from 1 to 15 percent. Euclidean distance to wetlands and areas with shallow water table were rescaled using also the monotonically decreasing linear fuzzy membership function. The control points for both layers were set at 50 and 1000 meters. Monotonically increasing sigmoidal function was used to rescale distance to streams and floodplains. Control points of 100 and 2000 meters were defined for the first layer, and 50 to 1000 meters were applied to the second layer based on suggested riparian setbacks identified in the first section of this chapter. Finally, fuzzy monotonically decreasing J-shaped function with control points of 1 to 2000 was applied to the rescaling of the Euclidean distance to urban greenspace areas.

Similar to scenario 1, MCE procedures based on factors and constraints were performed for the remaining four land cover classes. The constraining layer of Scenario 2 was used in the MCE assessment for those four layers as well. The slope constraint for cropland transitions was changed to 40 percent, similarly to Scenario 1. The fuzzy membership functions for the other factors including proximity to roads, streams and built-up areas were kept the same as those applied to Scenario 1.
5.2.3 Results

Figures 5.6, 5.7 and 5.8 display the CA_MARKOV simulation results based on the factors and constraints of Scenario 2.

Figure 5.6  Land cover projection with environmental constraints: 2010
Figure 5.7  Land cover projection with environmental constraints: 2020

Figure 5.8  Land cover projection with environmental constraints: 2030
The comparison of results between Scenario 1 and Scenario 2 reveals that there is only a slight decrease in the overall extent of development using environmental constraints. This result is to be expected since the total amount of pixels that will transition to urban land is determined by the Markov transitional areas defined by the probability matrix. The slight decrease can be explained with the other claimant categories, especially woodland / open spaces, which were given higher priority in the environmentally protected areas. In other words, when competing to claim a pixel, the urban land cover class may be in some instances in slight disadvantage compared to other categories. The results from the simulation of land cover change based on Scenario 2 also indicate that development is clustered near roads which leave fairly large undisturbed areas, especially in the southern part where shallow depth to bedrock is frequently present. Figures 5.6 through 5.8 also show that there is more open space within the urban areas and around surface waters which provides opportunities for reduction of sedimentation and nutrient enrichment of water bodies, runoff control, shading and cooling of streams, and allocation of sufficient areas that can support habitats.
6 A CELL-BASED MODEL FOR EXPLORING SPATIAL VARIABILITY IN NITROGEN DELIVERY TO STREAMS

Chapter 6 provides a detailed discussion of the distributed cell-based nitrogen export model. Section 1 of this chapter presents some conceptual approaches towards the identification of hydrological units and contributing areas. Section 2 outlines model inputs and data processing. Section 3 identifies the major steps in the modeling procedure which include developing a spatial hydrological model of the watershed and applying a distributed cell-based model of nitrogen export. The distributed model is estimated using a non-linear regression technique which quantifies the impact of field characteristics such as soil permeability, topography and distance to streams on the TN delivery ratios.

6.1 Identifying the contributing areas

Research suggests that not all areas in the watershed are contributing equally to pollutant loadings. Source areas of non-point source pollution are often relatively small portions of the watershed (Phillips 1989, Levine et al. 1993, Soranno et al. 1996). Different types of land use
activities, slope steepness, soil characteristics and distance to streams are some of the factors that
determine how much of the sediment and nutrients available for transport would actually reach
the streams. Therefore, assessing the impact of those often dispersed runoff- and nutrient-
contributing areas can play an important role in the nonpoint source pollution decrease.

6.1.1 Rainfall-runoff models

Studies have found that there is a direct relationship between runoff-generating mechanisms,
runoff volumes and the amount of pollutants that are loaded into the water bodies (Phillips 1989,
Alexander et al. 2002, Migliaccio et al. 2007). The primary runoff-generating mechanisms that
directly affect the transport of constituents include infiltration-excess mechanism consistent with
the Hortonian overland flow, saturation-excess mechanism consistent with the variable source
area (VSA) concept, or statistically derived equations based on regression analysis or other
statistical techniques (Chow et al. 1988, Johnson et al. 2003, Borah and Bera 2003, Borah and

Infiltration-excess overland flow model is based on Horton’s infiltration equation which
states that “infiltration begins at some rate \( f_0 \) and decreases exponentially until it reaches a
constant rate \( f_c \)” (Chow et al. 1988: 109). Horton’s equation is derived from Richard’s equation
(which is the governing equation for unsteady unsaturated flow in a porous medium) by
assuming constant hydraulic conductivity and constant soil water diffusivity (Chow et al. 1988).
According the infiltration-excess overland flow model, the amount of the generated surface
runoff depends on landscape and soil characteristics that determine the infiltration capacity of the
ground (Chow et al. 1988, Johnson et al. 2003). Infiltration-excess overland flow (runoff) occurs
when the infiltration capacity of the soil is lower than the precipitation rate. The Hortonian infiltration equation is given by:

\[ f(t) = f_c + (f_0 - f_c)e^{-kt} \quad (6.1) \]

where \( f_0 \) is the initial infiltration rate, \( f_c \) is the constant infiltration rate, and \( k \) \([T^{-1}]\) is a decay constant (Chow et al. 1988). For nearly five decades, it was considered the governing equation of the runoff processes. It is still the prevailing mechanism in areas with medium and high precipitation rates where naturally occurring conditions (such as predominant soils of hydrologic groups C and D), alterations in the landscape structure due to urbanization (such as increased amount of impervious surfaces), or excessive irrigation contribute to lower infiltration capacity of the ground (Chow et al. 1988, Borah and Bera 2003, Johnson et al. 2003, Lyon et al. 2004). One supposition of the Hortonian model is that infiltration-excess runoff generation processes are dependent on existing land use and soil type but independent of location (Lyon 2004). A basic assumption of the model is that runoff is produced at any point of the entire generating area (Chow et al. 1988, McDonnell 2003, Lyon et al. 2004).

More recent studies indicated that the Hortonian runoff concept is not applicable to the runoff generation processes in humid regions of the US, namely the Northeast and the Pacific Northwest where occasional flashy releases of significant amounts of storm runoff that are not proportional to the average rainfall intensities (Frankenberger et al. 1999, Walter et al. 2000, McDonnell 2003, Agnew et al. 2006). This type of runoff-generating mechanism known as saturation-excess overland flow lies behind the variable source area (VSA) concept, first suggested by J.D. Hewlett in the 1980s (Chow et al. 1988). It is a typical phenomenon in humid areas where the soil is already saturated due to excessive subsurface flow or storage of “old” water. Under these conditions, even precipitation events of low duration and intensity may cause
significant amount of surface runoff (Chow et al. 1988, McDonnell 2003). Hewlett observed that there is discernable spatial and temporal variability of the runoff-generating sources (Chow et al. 1988). He hypothesized that not all areas (as in the Hortonian model) are equally prone to become saturated and generate runoff. Some landscape features such as available water storage capacity, the presence of shallow depth bedrock or fragipan, local topography, and changes in hydraulic transmissivity and hydraulic gradient are important factors in determining which areas in the watershed are more prone to generate runoff. Frankenberger et al. (1999) found that areas with increased interflow levels, elevated water table, soils with shallow depth and/or fragipan that provide little additional storage capacity should mostly be considered as runoff-generating areas. With any additional precipitation input, the saturated area grows in extent, increasing the area generating runoff, and contracts under dry conditions since the interflow decreases (Chow et al. 1988, Frankenberger et al. 1999). The saturation-excess overland flow model also gives priority to total rainfall volume over rainfall intensity which controls the Hortonian model. Chow et al. (1988) summarize the differences between the two models in the following way: the Hortonian overland flow is based on saturation “from above by infiltration” whereas the saturation-excess overland flow is based on saturation “from below by subsurface flow” (p. 131).

The Hydrologic Simulation Program – FORTRAN (HSPF) uses the infiltration-excess mechanism (namely, the Philip’s equation) to simulate overland flow. The widely used Soil Conservation Service curve-number (SCS-CN) method model is largely based on the assumptions of the Hortonian model. The method implicitly assumes that infiltration excess is the primary runoff mechanism. Each combination of land use and soil class is assigned a curve number (CN) which is necessary to calculate the maximum retention potential $S$ which is then
used to calculate the depth of excess precipitation or direct runoff. Maidment (2002) has developed a distributed cell-based version of the SCS model.

Lyon et al. (2003) develop a modified version of the traditional SCS-CN method for watersheds where VSA concept is applicable. A spatially distributed topographic index is first created which is then combined with the traditional SCS-CN method to evaluate the probability of saturation for a given area. This new approach is called the distributed CN–VSA method (Lyon et al. 2003), and has been tested in the north-eastern USA where the generation of saturation-excess overland flow results from accumulated shallow interflow.

An example of saturation-excess mechanism is the Soil Moisture Routing (SMR) model which was designed specifically for the simulation of hydrologic responses in the northeast part of the United States. TOPMODEL (Beven and Kirkby 1979) also simulates dynamic hydrological responses based on the variable source area concept.

In humid regions, the variable source area concept has important implications for risk management and planning practices since it allows for identification of “hydrologically sensitive areas” and designation of “critical management zones” where measures can be applied to prevent the transport of contaminants to other perennial water bodies (Walter et al. 2000).

Referring to recent studies, McDonnell (2003) suggests that the hydrologic response in terms of generated runoff does not always follow fluctuations (rise and fall) of the water table. He also casts doubt on the assumption that the pattern of soil moisture distribution depends on the surface topography. The bedrock topography rather than the surface topography plays prominent role in routing the subsurface flow downhill (McDonnell 2003: 1871). Another VSA assumption challenged by recent studies is that the process of saturated-excess overland flow is driven by the soil mantle volume only. Some investigators suggest that contributions from
baseflow are also part of that process (McDonnell 2003). McDonnell (2003) argues that a new concept is emerging viewing watersheds as “a series of cryptic reservoirs that have coupled unsaturated and saturated zones, explicit dimensions and porosities, and that connect vertically and laterally in time and space in linear and non-linear ways” (p. 1872).

6.1.2 Identifying Contributing Areas of Nonpoint Source Pollution

Knowledge of the appropriate runoff-generating mechanism is essential in identifying the areas that most contribute to non-point source pollution (Chow et al. 1988, Bull et al. 2003). In general, there are two main approaches in spatially explicit modeling: as discrete objects and as a continuous spatial framework (Berger et al. 2001). The first approach assumes that spatial variability in watershed response can be explained successfully by splitting a catchment into smaller drainage areas whose response to watershed conditions can then be aggregated to represent the response of a larger geographic unit (Hornberger and Boyer 1995). If the appropriate scale is applied, the distributed drainage areas can bring insights about the spatial heterogeneity of hydrological responses within the watershed. The second approach assumes that the geographic space (i.e., the study area) can be represented as a continuous spatial framework or lattice composed of cells at a certain spatial resolution (i.e. the size of the cell used in the modeling process). This approach does not take into consideration the physical characteristics (such as elevation, slope, and stream network) that are used in discrete objects modeling to delineate drainage areas. It, rather, takes into consideration the geographic extent and the scale at which the processes occur. When using the second approach, it is therefore important to make sure that the selected cell size is consistent with both the geographic extent of the study area and the scale at which the environmental processes under investigation occur (Berger 2001).
Maidment (1996) suggests typical ranges of cell size of digital elevation models for various watersheds (Maidment 1996). Dividing the total study area by one million is one way to obtain the appropriate cell size (Maidment 1996).

Flügel (1995, 1997) introduced the concept of the Hydrological Response Units (HRUs) to describe the distributed discrete entities or drainage areas that comprise the watershed. HRUs are assumed to have similar hydrological dynamics due to similarities of their geomorphological properties (Flügel 1995, Hornberger and Boyer 1995, Srinivasan et al. 2000, Bull et al. 2003). The geographic extent of the HRUs can vary from a sub-basin to a small drainage site. How the hydrological response units are defined depends on the conceptualization and the applications of a specific hydrological model (Srinivasan et al. 2000).

Bull et al. (2003) developed the concept of hydrologically similar surfaces (HYSS) described as “[a]n area with a particular set of surface characteristics which defines the distribution and pattern of one-dimensional hydrological response” (p. 2). The concept is particularly useful for semi-arid and arid environments dominated by the Hortonian overland flow where key runoff-producing areas depend on soil type and slope, and transmission losses are significant (Bull et al. 2003). HYSSs are predicted from field data using GIS techniques by examining spatial variability in geology, land use and slope. Rainfall data is not included since sensitivity analysis indicated that such data had limited effect on the HYSS classification (Bull et al. 2003).

Commonly used input parameters for characterization of the discrete distributed entities within a watershed are physical properties such as elevation, slope, land cover classes, soil characteristics, or any combination of them (Bull et al. 2003). Flügel (1995, 1997) used rainfall distribution, land use, unsaturated zone, bedrock, slope and aspect to define the HRUs. The
watershed delineation tool in BASINS (USEPA 2000) uses an overlay of land use and soil to define the hydrological response units used as input in HSPF and SWAT models.

Sensitivity analysis in some studies also indicates that the spatial aggregation of input parameters can affect the simulation of the watershed response. Fitzhugh and Mackay (1999) and Bingner et al. (1997) have shown that defining HRUs on a finer or coarser scale has an impact on the simulated flow and sediment yield. In an attempt to define the smallest significant unit of hydrological response Wood et al. (1990) introduced the concept of the representative elementary area (REA). REAs cover an area of approximately 1 square kilometer within which it is believed that heterogeneity is not statistically significant (Hornberger and Boyer 1995). The problem of the spatial resolution of the HRUs is yet to be resolved (Hornberger and Boyer 1995). Because of the uncertainty surrounding the distributed modeling structure, Beven (1993) once even argued that “the application of distributed hydrological models is more an exercise in prophecy than prediction” (p. 41).

It has been recognized that runoff is the primary mechanism of sediment and nutrient transport (Alexander et al. 2002, Migliaccio et al. 2007). Obviously, areas that are prone to producing higher runoff volumes are also those that will contribute mostly to pollutant loadings. Spatial variability in nutrient transport affects the site-to-stream loadings as well as downstream loadings at outlet (Phillips 1989, Pionke et al. 1997). Identification of nutrient-contributing areas is critical for evaluating management and control options that can effectively reduce nonpoint source pollution (Phillips 1989, Soranno et al. 1996, Pionke 1997, Chaubey and Ward 2006).

The extent of the runoff- and nutrient-contributing areas (known also as runoff-producing or source areas) is controlled by soils, topography, groundwater levels, rainfall intensity and duration, and antecedent soil moisture conditions (Wood et al. 1990, Flügel 1995 & 1997, Liu
2000, Maidment 2002, Bull et al. 2003). Although it has been recognized for quite some time
that nutrient export is a dynamic, non-linear and spatially variable process (Soranno et al. 1996,
Liu 2000, Alexander et al. 2002), the spatial distribution of nutrient-contributing areas in a
watershed is yet to be understood. Studies confirm that the extent of the primary source areas of
pollutant loadings is often a small percentage of the total watershed area, with spatial variability
that is significantly correlated with precipitation (Soranno et al. 1996).

Soranno et al. (1996) developed a distributed model for nonpoint source phosphorus
loading to surface waters using geographic information systems. The investigators examined a
scenario in which the urbanized land in the watershed would increase by 80% (from 9 %
currently to 16 % in a thirty-year period). They found potentially slight increase in annual P
loadings but significant deterioration in water quality. Soranno et al. (1996) also estimated the
contributing areas in the watershed. They examined the spread of nutrient contributing areas
under different land use scenarios and during low-runoff, high-runoff, and baseline years. They
found consistently that agricultural watersheds tend to attenuate runoff and nutrient delivery
better than urbanized areas (Sorrano et al. 1996). For example, during low-runoff years
significant contribution to loading came only from urban areas and areas at short distance to
streams while in agricultural and vegetated areas most of the phosphorus was attenuated before
reaching the tributaries (Soranno et al. 1996). The investigators also found that during the low-
runoff year, even though only 9 percent of the watershed was urbanized, approximately fifty
percent of contributing land area was urban (Soranno et al. 1996). These findings supported the
assumption that land use patterns in the contributing areas may not coincide with the land use
patterns in the watershed as a whole.
A number of recent studies of nonpoint source pollution have applied GIS techniques using the cell-based approach (Levine et al. 1993, Liu 2006, Maidment 2002, Yeo 2005). Liu (2000) developed a cell-based approach to examine how spatial aggregation affects the relationship between IBI/QHEI and land use. He investigated three different models of spatial aggregation (to basin, to upstream contributing areas, and distance decay) and found that the highest R square value was obtained for the model based on a cell-based distance decay function (Liu 2000).

Yeo (2005) developed an integrated hydrological land use optimization (IHLUO) model using spatial resolution at a 30-meter cell size. The model investigates the relationship between land use and watershed hydrology in terms of peak discharge and examines the impact of different land use patterns on stormwater runoff. The model provides site-specific policy recommendations with regard to stormwater management based on optimal distribution of land development and land conservation.

Levine et al. (1993) applied a GIS-based model to estimate the annual loadings of sediment and nutrients to the surface water of twelve watersheds in the Lake Ray Roberts Drainage Basin, Texas. The modeling procedure, which is also useful in examining contributing areas, is implemented in five consecutive steps. Annual export coefficients obtained from the literature are applied to each land use category to evaluate the potential for phosphorus and nitrogen detachment, i.e., the amount of pollutants available for transport (Levine et al. 1993). An empirical statistical model is applied to obtain an estimate of the cells “trapping efficiencies” (i.e., the amount of nutrients trapped into the cell), and “delivery ratios” (i.e., the proportion of sediments and nutrients that are effectively carried out to surface water by overland flow) (Levine et al. 1993, UNITAR 2007). The empirical model is based on soil characteristics, slope and vegetative cover (Levine et al. 1993). Finally, the model estimates what proportion of
sediment and nutrients carried out by overland flow reaches the outlet of the watershed and contributes to overall pollutant loading. The calculation is based on the percent of sediments and nutrients that are retained in each consecutive cell as they are carried from the most distant cells to the stream. Those percentages constitute the “total flow path delivery ratios” (Levine et al. 1993, UNITAR 2007). The total amount of pollutant reaching the outlet of the watershed is calculated by summing over the loadings of the contributing cells. The procedure developed by Levine et al. (1993) is included in the IDRISI workbook Applications in Hazard Assessment and Management (UNITAR 2007). While the method for calculating total nitrogen export ratios used in this research is adapted from Levine et al. (1993), the distributed nitrogen export model is an original contribution of this research.

In order to improve the understanding of nutrient-contributing areas, the cell-based model developed in this research quantifies interactions between nutrient loss and field characteristics such as soil, land use, topography and distance to streams.

6.2 Model Inputs and Data Processing

Model inputs include slope (in radians), saturated hydraulic conductivity, soil mean particle diameter, length of flow, Manning’s roughness, approximate velocities of unconcentrated runoff flow through various landscapes, and N decay coefficient. The inputs were not readily available in the original datasets downloaded from the USGS and USEPA websites. The initial data which included topography, soils, and land cover /land use were further processed to prepare the inputs for the model. Stream network and slope were derived from the Digital Elevation Model (DEM). Land use/land cover data were used to assign the Manning’s roughness coefficients. Saturated
hydraulic conductivity and the mean particle diameter were derived from the SSURGO database and published soil surveys.

6.2.1 Digital Elevation Model (DEM)

Digital elevation models (DEM) in both vector and grid format were downloaded from the EPA website using BASINS Web Data Download Tool. The DEM data sets were projected in North American Datum of 1983 (NAD83) which uses the spheroid Geodetic Reference System of 1980 (GRS80). In order to be used in further hydrological analysis, the data were re-projected to Universal Transverse Mercator (UTM) coordinate system Zone 17. The spatial resolution of this data is 30 m (1 arc second). Spatial resolution is the extent of land area covered by each pixel in the raster file (Letsinger et al. 2007). The DEM shapefile of the watershed was used with the Manual Delineation Tool of BASINS to create a boundary shapefile for the East Fork Little Miami River watershed. The DEM grid file and the National Hydrography Dataset (05090202NHD) were then used with the Automatic Delineation Tool to derive the land and stream network segmentation within the watershed.

In addition, the USGS National Elevation dataset (NED) at 1/3 arc second (10 m) spatial resolution in grid format was downloaded from the USGS Seamless Data Resource Center. NED has a Geographic projection (latitude/longitude), and elevation units are in meters. The horizontal datum is NAD83, and the vertical datum for this dataset is NAVD88 (USGS 2006). The NED dataset was used for a more detailed and precise encoding of the streamlines in the watershed.
6.2.2 Soils

Digital soil information for Clermont, Clinton, Highland, Brown, and Warren counties, Ohio were downloaded from the Ohio Department of Natural Resources (ODNR). The data were made available in October 2006 as a part of Ohio’s Statewide Digital Soils Information (SDSI) Project and incorporate the most current changes to the soil taxonomic classifications and correlations as provided by the ODNR’s Division of Soil and Water Conservation, and the Ohio Agricultural Research and Development Center at the Ohio State University (ODNR 2006). The original data are obtained from Soil Survey Geographic (SSURGO) database published in June 2006 (ONDR 2006). The spatial data is available in ESRI© shapefile format with Geographic projection, re-
projected to UTM zone 17. The soil attribute data are provided in Microsoft Access database format. Using the available soil characteristics data, the shapefiles were joined to the database to create three additional data files in vector format: soils taxonomic classification, physical and engineering properties and water features.

Figure 6.2 Map of the mean particle diameter (mm) (Data sources: ODNR, USGS)

In addition, two new attributes were computed and added to the attribute tables. The saturated hydraulic conductivity originally given in micrometers per second was converted to centimeters per hour and added to the database. Data to derive the mean particle diameter (mpd) was not found in the SSURGO database. Published soil surveys of Clermont, Brown, Clinton and Highland counties were used to obtain data on the soil particle size distribution. The soil shapefile was converted to several floating point raster grids based on these attributes. The grid cell size is the same as that of the elevation grid at 30 meters.
6.2.2  **Land cover / Land use**

The Geographic Information Retrieval Analysis System (GIRAS) is a land use data compiled by NASA high-altitude missions in the late 1970s (Saunders and Maidment, 1996). This data is available through BASINS Wed Data Tool. It provides reference to the land use conditions in the 1980s. More recent land use data was obtained from the Multi-Resolution Land Characteristics Consortium (MRLC) which provides 1992 and 2001 National Land Cover Dataset (NLCD) in grid format. The data were converted to a shapefile and re-projected from Albers Equal Area Conic Projection USGS Version to UTM zone 17.
A new attribute for the Manning’s roughness coefficient is added to the land use datasets using ESRI© ArcGIS Field Calculator. The attribute is used with the ESRI© ArcGIS Conversion Tool to create a raster of the vegetative which is considered an independent variable in the nonlinear regression model used to obtain estimates of the field retaining efficiency. Each land use/land cover category was also assigned a nitrogen export coefficient using ESRI© ArcGIS Field Calculator function.

![Manning's Roughness Coefficient Map](image)

Figure 6.4 Map of the Manning's roughness coefficient (Data sources: USGS, Engman 1986, Chow et al. 1988)

The Manning roughness coefficients used in this study were obtained from Applied Hydrology (Chow et al. 1988) and Distributed Hydrologic Modeling Using GIS (Vieux 2005).
Table 6.1  Manning roughness coefficients for natural streams and flood plains

<table>
<thead>
<tr>
<th>Land cover</th>
<th>Manning’s roughness coefficients (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>0.001</td>
</tr>
<tr>
<td>Pavement</td>
<td>0.011</td>
</tr>
<tr>
<td>Barren</td>
<td>0.02</td>
</tr>
<tr>
<td>Cultivated / Pasture</td>
<td>0.24</td>
</tr>
<tr>
<td>Wetlands</td>
<td>0.4</td>
</tr>
<tr>
<td>Forest</td>
<td>0.8</td>
</tr>
</tbody>
</table>

Source: Chow et al. 1988, Engman 1986

6.3 Method

The method employed in this study consists of a spatial hydrological model of the watershed and a cell-based nitrogen loading model.

A spatial hydrological model applies the laws of physics and hydrodynamics to study watershed hydrology and represents the transport of sediment and pollutants “by means of locationally referenced data” (Maidment 1996). The use of Digital Elevation Model (DEM) in watersheds delineation is now a routine procedure in several Geographic Information Systems packages such as BASINS (USEPA 2000), ESRI© ArcGIS Spatial Analyst, and ArcHydro (Maidment 2002).

Assessing the extent and spatial distribution of dispersed runoff-contributing areas can play an important role as part of nonpoint source pollution management practices. Research efforts over the past three decades have proven that spatial variability in watershed response can be successfully described if a catchment is subdivided into smaller geographical units with specific physiographic properties whose response to watershed conditions can then be aggregated to represent the response of a larger geographic unit. If appropriate scale is applied, those distributed entities can bring insights about the spatial heterogeneity of hydrological responses within the watershed.
Research has shown that primary sources of nutrient loadings are often small portions of the watershed which may constitute only a small percentage of the entire catchment area. In order to improve the understanding of nutrient-contributing areas, the cell-based model developed in this research quantifies the interactions between nutrient loss and field characteristics such as soil, land use, topography and distance to streams. The model is implemented in five consecutive steps: (1) data pre-processing; (2) creating a spatial hydrological model; (3) deriving the nitrogen export potential based on N export coefficients obtained from the literature; (4) estimating cell
retention efficiencies and delivery ratios; (5) applying an attenuation factor based on cost-distance and N decay coefficient, and (6) calculating the total N loadings from non-point sources.

Developing a spatial hydrological model with ArcGIS involves the following steps: (1) pre-processing the elevation data to remove “pits” or “sinks” (i.e., errors occurring in the data), (2) calculating the flow direction based on the elevations of the eight neighborhood cells (four cells on the perpendicular axes, and four on the diagonals); (3) calculating flow accumulation based on the number of cells that flow into each lower elevation cell; (4) identifying the flow accumulation threshold; (5) calculating the raster stream network and converting it to a feature class; (6) identifying the stream link, that is, assigning a value to each stream segment; (7) delineating subwatersheds (Letsinger et al. 2007). The density of the stream network is calibrated for a low-runoff, a high-runoff and a baseline year.

The nitrogen export potential of each cell in the raster dataset, representing the watershed, is calculated based on nitrogen export coefficients derived from the literature. A non-linear regression model based on soil characteristics, slope and vegetative cover gives an estimate of the retention efficiency of each cell. The model determines what percent of the nitrogen available for transport will be retained on site and what percent will leave each cell carried out by the overland flow. In the next step, an attenuation factor is used based on travel time and nitrogen decay coefficient to determine how much of the nitrogen exported from each cell will effectively reach the stream network. The resulting maps indicate the spread of contributing areas during dry, normal and wet periods. Previous findings support the assumption that land use patterns in the contributing areas may not coincide with the land use patterns in the watershed as a whole.
6.4 Results and Discussion

This section presents the results from applying the distributed cell-based model of nitrogen export to the East Fork Little Miami River watershed. The modeling process consists of two steps: (1) construct a spatial hydrological model of the watershed, and (2) developing a non-linear regression model to estimate the trapping efficiency of each cell in the raster dataset based on field characteristics, convert the trapping efficiencies into delivery ratios, apply the delivery ratios to the TN available for detachment, calculate the transmission losses using an attenuation factors, and estimate the total nitrogen loadings.

6.4.1 A Spatial Hydrological Model

A spatial hydrological model applies the laws of physics and hydrodynamics to study watershed hydrology and represents the transport of sediment and pollutants “by means of locationally referenced data” (Maidment 1996). The use of DEMs in watersheds delineation is now a routine procedure in several Geographic Information Systems packages such as BASINS (USEPA 2000), ESRI© ArcGIS Spatial Analyst, and ArcHydro (Maidment 2002).

The modeling procedure involves the following steps: (1) pre-processing the Digital Elevation Model to remove “pits” or “sinks” (i.e., errors occurring in the dataset), (2) calculating the flow direction based on the spot elevations of the eight neighborhood cells (four cells on the perpendicular axes, and four on the diagonals); (3) calculating flow accumulation based on the number of cells that flow into each lower elevation cell; (4) identifying the flow accumulation threshold; (5) calculating the raster stream network and converting it to a feature class; (6) identifying the stream link, that is, assigning a value to each stream segment; (7) delineating subwatersheds and catchments (Letsinger et al. 2007).
6.4.2 Preprocessing the Digital Elevation Models

Sampling inaccuracies and rounding effects may sometimes introduce bias and errors in Digital Elevation Models (DEMs) (Letsinger et al. 2007). The most common type of error found in a digital elevation model is a “sink” or a depression defined as a cell or a cluster of cells where the flow direction is undetermined due to the fact that all neighboring cells have higher elevations than the processed cell (ESRI ArcMap 9.2 Desktop Help 2006, Letsinger et al. 2007). In order to produce a consistent stream network using hydrology algorithms in Spatial Analyst the “sinks” that interfere with simulation of surface hydrology need to be removed. Sinks cause discontinuities in the derived drainage network (Letsinger et al. 2007). The presence of sinkholes is a valid assumption only in karst areas which are internally drained through cracks and crevices as the carbonate bedrock (mostly dolomite and limestone) dissolves under the influence of rainwater (Hauwert et al. 2006, Mark 1988, Letsinger et al. 2007). Karst landscapes are not present in the East Fork Little Miami watershed, and therefore, in order to complete the delineation of the stream network and drainage areas, “sinks” were removed through an iterative process using the “Fill” function in Spatial Analyst. During the “Fill” process the sink cell is assigned the value of its lowest neighbor and flow is directed towards that cell.

The stream network derived from DEM needs to be compared with officially available hydrograph data because of potential errors. The errors consist of disconnected streams, loops and streams draining into a wrong river basin. Two techniques are currently applied to correct for those errors. Both techniques requires converting existing hydrograph data into a grid and either
“burn it in” to the DEM by encoding zeros at the streamline level (Maidment 1996); or, “re-
condition” the DEM by smoothing the landscape surface around the streams so that the elevation
decreases gradually towards the level of the stream (Maidment 2002, Yeo 2005).

6.4.1.2 Watershed Delineation

Watershed delineation involves constructing a grid of flow direction, constructing a grid of
flow accumulation, determining the drainage area threshold, defining the order of individual
stream links, locating the outlet point for each link, and delineating the drainage area for each
outlet point (Maidment 1996).

Flow direction. The grid of flow direction represents the movement of pollutants over space
and is therefore an important aspect of non-point source pollution modeling (UNITAR 2007).
Different models apply different algorithms to calculate a grid of flow direction. The flow
direction function in ArcGIS is based on the eight-direction pour point model in which elevations
of the eight neighboring cells are compared and water flow is directed towards the neighboring
cell with the lowest elevation (ESRI ArcMap 9.2 Desktop Help). The directions specified by this
model are north, northeast, east, south east, south, southwest and northwest. Other models, such
as the FLOW module in IDRISI, allow for the calculation of flow direction in terms of azimuthal
distance in degrees, in the range of 0° to 360° clockwise (UNITAR 2007). The FLOW module in
IDRISI assigns flow directions in degrees where, for example, 360° are assigned to the North
direction, 315° to the northwest direction, 270° to the west direction, 225° to the southwest, 180°
to the south, 115° to the southeast, 90° to the east, and 45° to the northeast (UNITAR 2007).

Flow accumulation. Once the flow direction grid is derived from the digital elevation model,
a grid of flow accumulation is constructed based on the number of cells upstream of a given cell.
In a raster data structure, upstream drainage area consists of cells whose flow accumulation does not exceed a specified number of cells called “a threshold”. The paths formed by cells whose flow accumulation exceeds that threshold (usually those with the lowest elevation values) are defined as streams (ESRI 2007, Maidment 1996, 2002). The higher the threshold (or, the number of cells that flow into each cell based on the direction of flow), the lower the density of the streams, while the lower the threshold, the higher the density of the stream network.

Different approaches have been used to calibrate the threshold for the flow accumulation grid. Letsinger et al. (2007) used GPS data to compare derived stream network with existing tributaries mapped in the field. If existing streams mapped with a GPS device are not present in the computed stream network, a lower threshold is defined. The procedure is repeated until mapped channels appear on the stream network based on the flow accumulation algorithm. Levine et al. (1993) used observed nutrient loadings to identify the density of the stream network. Their approach is based on the assumption that the variation in the stream network density affects each cell delivery ratio and, therefore, the total flow path delivery ratio (UNITAR 2007). The threshold of the stream network density is derived by approximating the calculated load to the observed data (UNITAR 2007).

Identification of contributing areas of non-point source pollution during average flow, high flow and low flow years is among the objectives of this research. Previous studies have shown that the extent of those areas changes with wet and dry years (Soranno et al. 1996). During storm events of higher intensity, a network of temporary streams capable of mobilizing and washing off sediments and nutrients also occurs in the watershed (UNITAR 2007). The model used here assumes that the density of the stream network does not remain constant as changes occur during high flow and low flow years. The density of the temporary stream network varies also
seasonally with the higher occurrence of temporary stream networks during the spring season (as a result of snow melting, higher frequency of rainfall events, and increased soil moisture) and decreased stream network density during the dry summer months. The calibration of the density of the stream network to the average flow, low flow and high flow years was completed using BASINS-HSPF. BASINS-HSPF allows the calibration of the simulated flow using observed USGS streamflow data. Table 6.2 presents the observed flow data obtained from USGS and the summary statistics calculated on the basis of that data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Observed flow (cfs)</th>
<th>Summary statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>197</td>
<td>640</td>
<td>Mean: 62.54</td>
</tr>
<tr>
<td>198</td>
<td>501</td>
<td>Median: 51.50</td>
</tr>
<tr>
<td>199</td>
<td>626</td>
<td>Standard Error: 38.37</td>
</tr>
<tr>
<td>198</td>
<td>479</td>
<td>Mode: 69.00</td>
</tr>
<tr>
<td>199</td>
<td>609</td>
<td>Standard Deviation: 51.64</td>
</tr>
<tr>
<td>198</td>
<td>620</td>
<td>Sample Variance: 274.34</td>
</tr>
<tr>
<td>199</td>
<td>658</td>
<td>Kurtosis: 1.35</td>
</tr>
<tr>
<td>198</td>
<td>610</td>
<td>Skewness: 0.64</td>
</tr>
<tr>
<td>199</td>
<td>610</td>
<td>Range: 89.86</td>
</tr>
</tbody>
</table>

Sorranno et al. (1996) used a threshold of one standard deviation above and below the mean annual flow to distinguish high and low flow years, respectively. Since high and low flow years
are defined in a statistical sense researchers usually use as many years of stream flow data as are available. This approach requires that watershed conditions remain stationary (i.e., they do not change much) over the period of record (Buchberger 2007, personal communication). The impoundment of Harsha Lake on the East Fork of the Little Miami River in 1978 may have influenced (reduced) the natural stream flow. For this reason the period 1978 – 2003 was selected to calculate the summary statistics necessary to determine the high and low flow years. The year 1991 was assumed to be representative for normal flow conditions as it is close to the mean annual flow during the period of study. The year 1987 is selected as a low flow year and the year 1996 represents a high flow year since the mean annual flow for those two years is two standard deviations below and above, respectively, the mean for the period of study. Lower threshold values were identified for wet conditions and higher threshold values were identified for dry (summer) and normal conditions.

6.5 Nitrogen Loading Model

The nitrogen loading model consists of the following steps:

- estimate the total amount of nitrogen per cell that is available for transport;
- calculate the retention efficiency of each cell based on field characteristics;
- convert trapping efficiencies to delivery ratios;
- multiply the result from the first step by the delivery ratios;
- estimate an attenuation factor based on cost-distance to streams;
- estimate TN loadings and convert them to concentrations; and
locate and map the contributing areas.

6.5.1 Estimating the Total Amount of TN Available for Transport

Nitrogen, mainly in the form of nitrate-nitrogen (NO$_3^-$-N) and ammonium-nitrogen (NH$_4^+$-N), is transported to rivers by overland flow during rainfall events. The amount of nutrients that reach streams depends on nutrient availability, detachment, and deposition during nutrient transport (USEPA 2002). Nitrogen export potential is the amount of nitrogen available for transport from each individual cell in the raster database. It is determined on the basis of empirically-derived coefficients obtained from the literature (Rekhow et al. 1980, Clesceri et al. 1986, Loehr et al. 1989, Frink 1991, Dodd et al. 1992, Mcfarland and Hauck 2001, Lin 2004).

Nutrient export coefficients are an approximation of the potential mass of nitrogen or phosphorus that are yielded per unit area per unit time (most commonly, kg/ha/yr) depending on land use/land cover type and soil characteristics (Wickham et al. 2003). Nutrient export coefficients sometimes have limited transferability because of the site-specific variables used in their estimation such as precipitation patterns, soil characteristics, best management practices and percentage of the different types of land use/land cover (Mcfarland and Hauck 2001). Nutrient export coefficients are empirically derived from observed data using statistical approaches such as multiple regression (Mcfarland and Hauck 2001), or are estimated “as risk where lack of monitoring data prevents empirical estimation” (Wickham et al. 2003, p. 193). They are used in estimating nutrient loads with the assumption that each land use activity has “a specific rate of nutrient export” under certain meteorological and geographic conditions (McFarland & Hauck 2001).

The literature reports a wide range of export coefficients for any specific land use/land cover class. Nutrient export coefficients are given for the three major land use/land cover classes,
agricultural land, forest and developed land (Rast and Lee 1983, Clesceri et al. 1986, Dodd et al. 1986, Mcfarland and Hauck 2001), as well as for various land use categories such as row crops, non-row crops, pasture, feedlots and manure storage, mixed agriculture, wooded areas, golf courses, residential, commercial and industrial land use (Reckhow et al. 1980, Loehr et al. 1989).

The comprehensive study of Reckhow et al. (1980) presents a series of tables with export coefficients obtained from various sources in more than 20 states, mostly in the Midwest and the Northeast of the United States. Data from Texas, Oregon, Washington and Florida are also available. Reckhow et al. (1980) report average values and ranges for total nitrogen (TN) (in kg/ha/yr) for seven different land use/land cover classes: forested, row crops, non-row crops, pasture, feedlot/manure, mixed agriculture and urban. For almost all of those categories specific values for Ohio are also reported. Loehr et al. (1989) compiled a table of ranges of export coefficients for total nitrogen and total phosphorus in nine categories similar to those reported by Reckhow et al. (1980). In more recent efforts, Frink (1991) and Dodd et al. (1992) reviewed a significant number of publications to obtain export coefficients for the three major land use land cover classes. Table 6.3 below summarizes some of the nitrogen export coefficients reported in the literature.

<table>
<thead>
<tr>
<th>Land Use Category</th>
<th>Average</th>
<th>Min.</th>
<th>Max.</th>
<th>Median</th>
<th>Low (25%)</th>
<th>High (75%)</th>
<th>Standard Deviation</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>2.86</td>
<td>1.38</td>
<td>0.26</td>
<td>0.26</td>
<td>0.38</td>
<td>0.69</td>
<td>0.30</td>
<td>Reckhow et al. 1980</td>
</tr>
<tr>
<td>Forest - Eastern US</td>
<td>3.00</td>
<td>0.3</td>
<td>0.69</td>
<td>0.26</td>
<td>0.30</td>
<td>0.30</td>
<td>0.30</td>
<td>Rast and Lee 1983</td>
</tr>
<tr>
<td>Forest</td>
<td>2.33</td>
<td>0.00</td>
<td>0.30</td>
<td>0.30</td>
<td>0.00</td>
<td>0.30</td>
<td>0.00</td>
<td>Loehr et al. 1989</td>
</tr>
<tr>
<td>Forest</td>
<td>2.86</td>
<td>0.00</td>
<td>0.30</td>
<td>0.30</td>
<td>0.00</td>
<td>0.30</td>
<td>0.30</td>
<td>Clesceri et al. 1986</td>
</tr>
<tr>
<td>Forest/wetland</td>
<td>3.00</td>
<td>0.00</td>
<td>0.30</td>
<td>0.30</td>
<td>0.00</td>
<td>0.30</td>
<td>0.30</td>
<td>Dodd et al. 1992</td>
</tr>
<tr>
<td>Forest</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>1.00</td>
<td>1.00</td>
<td>Frink 1991</td>
</tr>
<tr>
<td>Land Use</td>
<td>Export Coefficient Mean</td>
<td>Export Coefficient Median</td>
<td>Reference</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>-----------------</td>
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<td>--------------------</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AGRICULTURE</td>
<td></td>
<td></td>
<td>Reckhow et al.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mixed Agriculture</td>
<td>6.53</td>
<td>1.50</td>
<td>1980</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural/Agriculture</td>
<td>5.00</td>
<td></td>
<td>Rast and Lee 1983</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural cropland</td>
<td>2.10</td>
<td>9.60</td>
<td>Loehr et al. 1989</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agricultural</td>
<td>69.00</td>
<td>4.8</td>
<td>Clesceri et al. 1986</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>0.80</td>
<td>2.60</td>
<td>Frink 1991</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>URBAN</td>
<td></td>
<td></td>
<td>Reckhow et al.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>97.00</td>
<td>8.47</td>
<td>1980</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residential</td>
<td>0.00</td>
<td>3.00</td>
<td>Loehr et al. 1989</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commercial</td>
<td>90.00</td>
<td>1.00</td>
<td>Loehr et al. 1989</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industrial</td>
<td>90.00</td>
<td>4.00</td>
<td>Loehr et al. 1989</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>0.60</td>
<td>8.00</td>
<td>Frink 1991</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mixed</td>
<td>0.00</td>
<td>1.00</td>
<td>Mcfarland &amp; Hauck 2001</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Developed</td>
<td>50.00</td>
<td>0.50</td>
<td>Dodd et al. 1992</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PASTURE</td>
<td></td>
<td></td>
<td>Reckhow et al.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pasture</td>
<td>65.00</td>
<td>0.85</td>
<td>1980</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pasture</td>
<td>0.20</td>
<td>4.00</td>
<td>Loehr et al. 1989</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forage Fields</td>
<td>40.00</td>
<td>5.00</td>
<td>Mcfarland &amp; Hauck 2001</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BARREN</td>
<td></td>
<td></td>
<td>Loehr et al. 1989</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Barren</td>
<td>0.50</td>
<td>6.00</td>
<td>Frink 1991</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rangeland</td>
<td>0.51</td>
<td></td>
<td>Levine et al. 1993</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wetlands</td>
<td>3.33</td>
<td></td>
<td>Dodd et al. 1992</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The annual average export coefficients for forest, mixed agriculture, developed land and pasture, used in this study, were obtained from the data compiled by Reckhow et al. (1980).

These data were selected for several reasons: first, the reports geographically cover the study area; second, the size of the watersheds for which export coefficients were derived is commensurable with the size of the study area; and third, recent studies confirm the validity of
these data (Wickham et al. 2003). Export coefficients for barren land and rangeland were obtained from Frink (1991) and Levine et al. (1993) respectively.

<table>
<thead>
<tr>
<th>Land Use Category</th>
<th>Nitrogen export (kg/ha/yr)</th>
<th>Nitrogen export cell size 10m (g/cell/yr)</th>
<th>Nitrogen export cell size 20m (g/cell/yr)</th>
<th>Nitrogen export cell size 30 m (g/cell/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>2.86</td>
<td>28.6</td>
<td>114.4</td>
<td>260.0</td>
</tr>
<tr>
<td>Cropland</td>
<td>16.53</td>
<td>165.3</td>
<td>661.2</td>
<td>1502.7</td>
</tr>
<tr>
<td>Urban</td>
<td>9.97</td>
<td>99.7</td>
<td>398.8</td>
<td>906.4</td>
</tr>
<tr>
<td>Pasture</td>
<td>8.65</td>
<td>86.5</td>
<td>346.0</td>
<td>786.4</td>
</tr>
<tr>
<td>Barren</td>
<td>9.51</td>
<td>95.1</td>
<td>380.4</td>
<td>864.5</td>
</tr>
<tr>
<td>Wetlands</td>
<td>4.40</td>
<td>44.0</td>
<td>176.0</td>
<td>400.0</td>
</tr>
</tbody>
</table>

In order to be used in the raster-based model, the units of the reported coefficients were converted from kg/ha/yr to g/cell/year as explained by Levine et al. (1993). Table 6.4 shows the results of this conversion for 10m, 20m and 30m cell size in the raster database. Some researchers report differences in nutrient loadings during low-runoff and high-runoff periods. Soranno et al. (1996) found lesser variation in nutrient loadings between different land-use scenarios than between high- and low-runoff years. Jensen et al. (1998) and Xue et al. (1998) observed positive correlation between higher rainfall intensity and higher nutrient loads. Lower values for total nitrogen export (0.10-0.60 kg/ha/yr) during the low-runoff season compared to a high-runoff season (2.00-14.00 kg/ha/yr) were also reported (Jeje 2006).
6.5.2 Trapping (Retention) Efficiency and Delivery Ratios

The export coefficients approach assumes that during a precipitation event all the cells within the same land use activity will deliver the same amount of nutrients to the streams in the watershed. In fact, certain amount of nutrients is retained on the slopes, in the floodplain (Cashman 1997), or leaches below the root zone (USEPA 2002). The nitrogen delivery ratio determines the amount of nutrient that is actually transported through the landscape and reaches the outlet. It is defined as:

\[
\text{Nitrogen delivery ratio} = \frac{\text{Nitrogen load at basin outlet (tons)}}{\text{Nitrogen available for transport off fields (tons)}}
\]

Estimating nitrogen delivery ratios using this method is not that straightforward as it may appear. Monitoring data on detachment rates of total nitrogen from each type of land use activity are rarely available (Cashman 1997). Potential loads are usually an approximation of the actual loads since the compilation of such datasets is often time- and resource-consuming. Explaining some of the factors that affect the accuracy of the above approach to the delivery ratio estimation, Cashman (1997) observes that transport rates cannot be easily verified “because the processes occur over time scales that might range from hours (during a single event) to decades” (p. 15).

Levine et al. (1993) investigated a vast number of vegetated filter strip or buffer strip studies to construct models that describe trapping (or retention) efficiencies based on field characteristics. The independent variables in the models include vegetative cover, soil characteristics, slope and length of flow (Levine et al. 1993). Based on the analysis of this group of studies, Levine et al. (1993) suggested estimating the nitrogen delivery ratios as the percent of
total nitrogen that is exported from each cell in the watershed. As such, it is estimated by subtracting the retention or removal efficiency of each cell from 1 (Levine et al. 1993, UNITAR 2007).

\[
\text{Nitrogen delivery ratio} = 1 - \text{the trapping efficiency of the cell (in percent)}
\]

For the purposes of this research, I adopt the approach suggested by Levine et al. (1993). The cell nitrogen export ratio is therefore defined as percent of the total available nitrogen that is physically exported from each cell in the raster dataset. The trapping or retention efficiency is the percent of the available total nitrogen that is deposited on the landscape and in the channels, or that leaches below the root zone and reaches the groundwater. The sum of both equals the export coefficient for each type of land use activity.

The studies reviewed by Levine et al. (1993) also identify the parameters that were found to impact substantially the movement of water, sediment and nutrients in overland flow. Several physically-based simulation models including ANSWERS (Beasley et al. 1980), AGNPS (Young et al. 1989), and CREAMS (Knisel et al. 1980) use these parameters to simulate sediment and nutrient runoff from agricultural fields and evaluate the relative impacts of the applied management practices. According to this body of literature, the retention efficiency of each cell in the raster dataset depends on the landscape and soil characteristics such as vegetative cover, slope length and steepness, hydraulic conductivity, soil particle size and distance to streams.

Two statistical approaches were considered to model the behavior of variables: Poisson rate model and a nonlinear regression model. Using linear regression analysis was deemed unwise for two reasons: first, the univariate analysis revealed some data limitations, and second, the
mathematical structure applied in the analysis had to incorporate “the inherent non-linearity of many physical systems” (Klemes 1983).

6.5.3 Poisson Rate Model

Poisson rate regression is typically used when the response variable is a count. It is the simplest form of a log-linear model. The study area contains a number of cells of each type of land that release a specific amount of nutrients each year as shown in Table 6.7. For this reason, the Poisson rate model was considered appropriate. If we assume that Poisson variable $Y_i$ denotes the number of responses associated with some factor $t_i$ (usually time or area), then the random variable $R_i$ can represent the rate for the $i^{th}$ observation in the following form:

$$R_i = \frac{Y_i}{t_i}$$  \hspace{1cm} (6.2)

where the count $Y_i$ has a Poisson distribution with a mean $\mu_i$ (Agresti 2002).

The response count can then be written as (Kleile 2003):

$$E[R_i] = \frac{\mu_i}{t_i}$$  \hspace{1cm} (6.3)

The log-linear model can then be represented as (Agresti 2002):

$$\log e \left( \frac{\mu_i}{t_i} \right) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_p x_{ip}$$  \hspace{1cm} (6.4)

Which is equivalent to (Agresti 2002):

$$\log e \mu_i - \log e t_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_p x_{ip}$$  \hspace{1cm} (6.5)

In SAS the adjustment factor $-\log e t_i$ is coded as offset.

The model can be represented also as (Kleile 2003):
\[ \mu = te^{\alpha + \beta x} \quad (6.6) \]

for any fixed \( x \).

When fitting a statistical model it is important to know how well the data fits a selected model. The goodness-of-fit of the Poisson rate models is related to the general approach of verifying the goodness-of-fit in generalized linear models. A measure of the goodness-of-fit in generalized linear model is the deviance (Agresti 2002). The deviance is the likelihood ratio statistics for testing the hypothesis that all parameters in the saturated model (not in the reduced model) are equal to zero (Agresti 2002).

\[ D_{\text{reduced model}} = -2 \log \Lambda (M, S) = -2[L_{\text{reduced}}, L_{\text{saturated}}] = 2[L_{\text{saturated}}, L_{\text{reduced}}] \quad (6.7) \]

The deviance has an approximate chi-square distribution with degrees of freedom equal to the difference between the total number of levels (categories) of the explanatory variable and the number of parameters in the reduced model, when there is a large set of observations for each level of the explanatory variable (Agresti 2002). The model is considered of reasonably good fit when the deviance ratio (i.e., the deviance divided by the number of degrees of freedom) is between 1 and 2 (Kleile 2003). Table 6 presents the inputs for the Poisson rate regression model.

In order to prepare the spatial data for this type of analysis, the raster datasets of the slope (in radians), saturated hydraulic conductivity (cm/h), and mean particle diameter (mm) were superimposed using the OVERLAY function in ESRI’s Spatial Analyst to create a composite variable that represent different categories of field characteristics – from steeper, impermeable slopes to flatter, more permeable flood plain. Table 6.6 presents the characteristics of the thirteen categories created using the overlay function.
### Table 6.5 Data inputs for Poisson rate regression model

<table>
<thead>
<tr>
<th>VALUE</th>
<th>Slope in radians</th>
<th>Ksat (cm/h)</th>
<th>MPD (mm)</th>
<th>COUNT</th>
<th>Mean TN Export (g/cell/yr)</th>
<th>Mean TN Export (kg/cell/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.3140 to 0.8199</td>
<td>0 to 3.9046</td>
<td>0</td>
<td>33376</td>
<td>796.22</td>
<td>0.796</td>
</tr>
<tr>
<td>2</td>
<td>0.2442 to 0.3140</td>
<td>3.9046 to 7.8092</td>
<td>0 to 0.0098</td>
<td>steeper, impermeable</td>
<td>7573</td>
<td>775.97</td>
</tr>
<tr>
<td>3</td>
<td>0.1919 to 0.2442</td>
<td>7.8092 to 11.7138</td>
<td>0.0098 to 0.0196</td>
<td>437064</td>
<td>801.80</td>
<td>0.802</td>
</tr>
<tr>
<td>4</td>
<td>0.1570 to 0.1919</td>
<td>11.7138 to 15.6185</td>
<td>0.0196 to 0.0294</td>
<td>89477</td>
<td>784.30</td>
<td>0.784</td>
</tr>
<tr>
<td>5</td>
<td>0.1221 to 0.1570</td>
<td>15.6185 to 19.5231</td>
<td>0.0294 to 0.0392</td>
<td>324473</td>
<td>833.10</td>
<td>0.833</td>
</tr>
<tr>
<td>6</td>
<td>0.1047 to 0.1221</td>
<td>19.5231 to 23.4277</td>
<td>0.0392 to 0.0490</td>
<td>6408</td>
<td>709.79</td>
<td>0.710</td>
</tr>
<tr>
<td>7</td>
<td>0.0872 to 0.1047</td>
<td>23.4277 to 27.3323</td>
<td>0.0490 to 0.0588</td>
<td>65877</td>
<td>794.51</td>
<td>0.795</td>
</tr>
<tr>
<td>8</td>
<td>0.0698 to 0.0878</td>
<td>27.3323 to 31.2369</td>
<td>0.0588 to 0.0686</td>
<td>300097</td>
<td>826.50</td>
<td>0.827</td>
</tr>
<tr>
<td>9</td>
<td>0.0523 to 0.0698</td>
<td>31.2369 to 35.1415</td>
<td>0.0686 to 0.0882</td>
<td>89142</td>
<td>801.20</td>
<td>0.801</td>
</tr>
</tbody>
</table>

A program written in SAS has given the following estimates for the Poisson rate regression:

### Table 6.6 SAS output from the Poisson rate model

Poisson Rate Regression  
Explanatory Variable: Composite surface characteristics  
Response Variable: Mean nitrogen loss (kg/cell/yr)

The GENMOD Procedure

Model Information

<table>
<thead>
<tr>
<th>Data Set</th>
<th>WORK.DATA1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distribution</td>
<td>Poisson</td>
</tr>
<tr>
<td>Link Function</td>
<td>Log</td>
</tr>
<tr>
<td>Dependent Variable</td>
<td>TNloss</td>
</tr>
<tr>
<td>Offset Variable</td>
<td>Log_case</td>
</tr>
</tbody>
</table>

Number of Observations Read 13  
Number of Observations Used 13
Criteria For Assessing Goodness Of Fit

<table>
<thead>
<tr>
<th>Criterion</th>
<th>DF</th>
<th>Value</th>
<th>Value/DF</th>
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<tbody>
<tr>
<td>Deviance</td>
<td>11</td>
<td>27.3499</td>
<td>2.4864</td>
</tr>
<tr>
<td>Scaled Deviance</td>
<td>11</td>
<td>27.3499</td>
<td>2.4864</td>
</tr>
<tr>
<td>Pearson Chi-Square</td>
<td>11</td>
<td>235.4422</td>
<td>21.4038</td>
</tr>
<tr>
<td>Scaled Pearson X2</td>
<td>11</td>
<td>235.4422</td>
<td>21.4038</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-</td>
<td>-26.2949</td>
<td></td>
</tr>
</tbody>
</table>

Algorithm converged.

Analysis Of Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>DF</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Wald 95% Confidence Limits</th>
<th>Chi-Square</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1</td>
<td>-13.4476</td>
<td>0.9839</td>
<td>-15.3759 -11.5193</td>
<td>186.82</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Compos</td>
<td>1</td>
<td>0.2611</td>
<td>0.1354</td>
<td>-0.0042 0.5265</td>
<td>3.72</td>
<td>0.0538</td>
</tr>
<tr>
<td>Scale</td>
<td>0</td>
<td>1.0000</td>
<td>0.0000</td>
<td>1.0000 1.0000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NOTE: The scale parameter was held fixed.

Letting Log_\(e\) (number of counts or cells in each category) be the offset, I obtain the following parameters from the SAS output:

\[
\hat{\alpha} = -13.4476 \quad \hat{\beta} = 0.2611
\]

Thus, the estimated Poisson rate model becomes:

\[
Log_\(e\) \hat{\mu}_i - Log_\(e\) t_i = -13.4476 + 0.2611x_i
\]  \quad (6.8)

for \( i = 1, 2, 3, \ldots, 13 \).

The deviance is 27.35 based on 11 degrees of freedom, which results in a deviance ratio of 2.4864. The ratio is slightly above 2 but still close enough to conclude that the Poisson rate model fits the grouped data reasonably well.

Although the Poisson rate regression model indicated a good fit to the grouped data, it was left out from further consideration because the grouped data may not reflect accurately the watershed conditions and, thus, introduce bias in the modeling results.
6.5.4 A Non-Linear Regression Model

A nonlinear regression model differs from a linear in that the curve it produces is segmented (Bates and Watts 1988) and its derivatives contain one or more of the model parameters (Schabenberger and Pierce 2002). Non-linear models are not to be mistaken with quadratic and cubic polynomials which produce curvilinear graphs but their derivatives depend only on the independent variable and do not include parameters (Schabenberger and Pierce 2002). Non-linear models are useful when constraints need to be built into the model and when the parameters can be interpreted directly with regard to the processes under study (Schabenberger and Pierce 2002). These models are particularly suitable for representing biological and physical processes as differential equations conceptualizing such processes can be easily built within a non-linear regression model (Schabenberger and Pierce 2002). Another difference between linear and non-linear models is that the number of parameters in the model may exceed the number of independent variables (Neter et al. 1996).

In its general form, the non-linear regression model is similar to a linear regression model:

\[
Y_i = f(X_i, \gamma) + \varepsilon_i
\]

(6.9)

where \( Y_i \) is the response variable, \( f(X_i, \gamma) \) denotes the non-linear response function, \( X_i \) is the vector of observations on the predictor variables, \( \gamma \) being the parameter vector (which in a linear regression model is given by \( \beta \)), and \( \varepsilon_i \) represents the error term (Neter et al. 1996). Most commonly a non-linear regression model takes an exponential form.

Typically, solving non-linear regression expression requires the use of numerical search procedures for estimating both the least squares and the maximum likelihood solutions since finding analytical solutions as in a linear regression model may not be possible. The first step in fitting a nonlinear model is initializing the parameters. The software performs a number of
iterations trying to improve the fit of the model by adjusting the parameters (Bates and Watts 1988, Schabenberger and Pierce 2002). Parameters change during each iteration until the model converges which means that further improvement of the fit is not feasible (Schabenberger and Pierce 2002). When the model converges after only a few iterations, this is an indication that “the linear approximation model is a good approximation to the non-linear model” (Neter et al. 1996: 546).

Non-linear regression models are notorious for problematic convergence (Neter et al. 1996). Meeting the convergence criterion is an indicator of a good fit of the model. The coefficient of multiple determination ($R^2 = \frac{SSR}{SSTO}$) is not useful in the assessment of a non-linear regression model as the total sum of squares $SSTO$ may not necessarily equal the sum of the error sum of squares $SSE$ and the regression sum of squares $SSR$ (Neter et al. 1996). The F-ratio, however, holds. It tests the null hypothesis that all partial slopes are simultaneously equal to zero. If the null hypothesis holds, the F-ratio is approximately one. When the alternative hypothesis is true, the F-ratio is greater than one. Therefore, we reject the null hypothesis for large values of F (Kleile 2003). The SAS program for estimating the non-linear regression model used in this research is included in Appendix B. The model uses the Gauss-Newton fitting algorithm.

Levine et al. (1993) used published records from 13 vegetated filter-strip studies to estimate a nonlinear regression model describing the trapping efficiency of each cell.

The estimated model is given in the following form (Levine et al. 1993):

\[
TN_{\text{trapped}} = \frac{1}{1 + e^{(-10.14 + 0.016d + 26.83θ - 4.58\ln(n) + 2.87\ln(mpd) + 1.47dn - 1.63dθ)}} 
\]

where

\[
191
\]

(6.10)
$TN = \text{total nitrogen retention efficiency,}$

$d = \text{distance of flow through the cell (meters),}$

$mpd = \text{soil mean particle diameter (mm),}$

$n = \text{Manning's roughness coefficient (unitless),}$

$\theta = \text{theta, slope steepness angle (radians)}$

The structure of the model forces values between 0 and 1, which corresponds to the proportion of nutrients retained in each cell as a result of its field characteristics. For the purposes of this research, I have used a slightly modified version of the model structure suggested by Levine et al. (1993). However, when applied to the data from the East Fork Little Miami River watershed the model did not converge. Several variations of the above model were considered, including a model with the saturated hydraulic conductivity as an additional variable. The SAS output below presents the results for the converged non-linear regression model based on the data from the East Fork Little Miami River watershed.

<table>
<thead>
<tr>
<th>Iter</th>
<th>b1</th>
<th>b2</th>
<th>b3</th>
<th>b4</th>
<th>b5</th>
<th>b6</th>
<th>Sum of Squares</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-9.8600</td>
<td>2.1800</td>
<td>-5.3300</td>
<td>3.7500</td>
<td>-15.7300</td>
<td>0.1600</td>
<td>138.9</td>
</tr>
<tr>
<td>1</td>
<td>-8.2713</td>
<td>2.1800</td>
<td>-5.3300</td>
<td>4.6925</td>
<td>-15.7300</td>
<td>0.1600</td>
<td>138.1</td>
</tr>
<tr>
<td>2</td>
<td>-8.2713</td>
<td>2.1800</td>
<td>-5.3300</td>
<td>4.6925</td>
<td>-15.7300</td>
<td>0.1471</td>
<td>138.1</td>
</tr>
<tr>
<td>3</td>
<td>-8.2713</td>
<td>2.1800</td>
<td>-5.3300</td>
<td>4.6925</td>
<td>-17.0519</td>
<td>0.1471</td>
<td>136.7</td>
</tr>
<tr>
<td>4</td>
<td>-8.9155</td>
<td>2.1800</td>
<td>-5.3300</td>
<td>4.6925</td>
<td>-17.0519</td>
<td>0.1550</td>
<td>136.5</td>
</tr>
<tr>
<td>5</td>
<td>-8.7498</td>
<td>2.1800</td>
<td>-5.3300</td>
<td>4.9295</td>
<td>-17.0519</td>
<td>0.1550</td>
<td>136.4</td>
</tr>
<tr>
<td>6</td>
<td>-9.0820</td>
<td>2.1800</td>
<td>-5.3300</td>
<td>4.9295</td>
<td>-17.0519</td>
<td>0.1550</td>
<td>136.4</td>
</tr>
<tr>
<td>7</td>
<td>-9.0007</td>
<td>2.1800</td>
<td>-5.3300</td>
<td>4.9295</td>
<td>-17.0519</td>
<td>0.1550</td>
<td>136.4</td>
</tr>
<tr>
<td>8</td>
<td>-8.9942</td>
<td>2.1800</td>
<td>-5.3300</td>
<td>4.9295</td>
<td>-17.0519</td>
<td>0.1550</td>
<td>136.4</td>
</tr>
</tbody>
</table>

NOTE: Convergence criterion met.
Method                     Newton
Iterations                      8
Subiterations                   2
Average Subiterations        0.25
R                        1.959E-6
PPC(b1)                  4.865E-6
RPC(b1)                  0.000726
Object                   8.708E-8
Objective                136.4259
Observations Read             502
Observations Used             502
Observations Missing            0

NOTE: An intercept was not specified for this model.

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>F Value</th>
<th>Pr &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>1</td>
<td>250.4</td>
<td>250.4</td>
<td>919.61</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Error</td>
<td>501</td>
<td>136.4</td>
<td>0.2723</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uncorrected Total</td>
<td>502</td>
<td>386.8</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NOTE: The (approximate) Hessian is singular.

The estimated model is:

\[ \text{TN}_{\text{trapped}} = \frac{1}{(1 + \exp(-8.99 + 2.18 \text{slope} - 5.33 \text{ksat} + 4.93 \ln(Mn) - 17.05 \ln(mpdp) + 0.155 \text{len} \cdot Mn + 1.63 \text{len} \cdot \text{slope}))} \]

where

\( \text{TN}_{\text{trapped}} = \) total nitrogen trapping efficiency

\( K_{\text{sat}} = \) saturated hydraulic conductivity (cm/h)

\( \text{len} = \) distance of flow through the cell (meters)

\( mpd = \) soil mean particle diameter (mm)

\( Mn = \) Manning's roughness coefficient (unitless)

\( \text{slope} = \) slope steepness angle (in radians)

The SAS output indicates that the model convergence has been achieved after eight iterations. The model has converged quickly which shows that the non-linear regression model can be reasonably approximated by a linear model. The F-ratio given by SAS is 919.61 with a p-
value of 0.0001 which suggests that the null hypothesis stating that the partial slopes are equal to zero can be rejected at virtually any significance level. Also, the mean square error $MSE = 0.2723$ is very low. Overall, the results indicate that the estimated model fits the data reasonably well.

The results indicate that increases in slope would increase the trapping efficiency, which is consistent with the findings of Levine et al. (1993: 62) who construed that steeper slopes reduce the cell delivery ratio. The inverse relationship between the cell trapping efficiency and saturated hydraulic conductivity is not completely logical from hydrologic standpoint. It would rather be expected that the trapping efficiency would increase as the saturated hydraulic conductivity increases. The observed effect, however, can be explained by the fact that soils with low hydraulic conductivity such as clays and clay loams are predominantly found on the steeper slopes of the watershed which is consistent with the finding on the effect of the slope mentioned above. The direct relationship between the cell trapping efficiency and Manning’s roughness coefficient is consistent with the expectation that lower trapping efficiency would result from lower $n$. For example, concrete has the lowest Manning’s roughness coefficient, and therefore the lowest trapping efficiency. The effect of the mean particle diameter is consistent with the effects of slope and saturated hydraulic conductivity.

Since each of the input variables was in the form of floating point raster datasets, equation (6.11) was applied using the Raster Calculator under the Spatial AnalystToolbar. The equation was entered step by step in the form of multiple expressions. Each step produced a temporary image which was then used as an input for the subsequent step.

Figures 6.6 and 6.7 show the final maps of trapping efficiencies and delivery ratios.
Figure 6.6  Map of the trapping efficiencies for total nitrogen

Figure 6.7  Map of total nitrogen delivery ratios
6.5.5 Total Flow Path Nitrogen Delivery Ratio

In step 3, each cell in the watershed was assigned a potential nitrogen export value based on the existing nitrogen export coefficients. Step 4 linked the potential export values to soil and landscape characteristics and based on retention efficiencies converted the potential nitrogen export values into delivery ratios, i.e. the percent of the available for transport nitrogen that leaves each cell. Step 5 involves GIS-based analysis to estimate how much of the nitrogen “escaping” each cell will reach the streams effectively contributing to loading. This step is conceptually different from what has been proposed by Levine et al. (1993).

Levine et al (1993) estimated the total flow path nitrogen delivery ratios by multiplying the value of the export coefficient of each cell by the cell’s delivery ratios. In order to account for the length of flow through the field, the delivery ratio of the “receiving” cell are multiplied by the delivery ratio of the “feeding” cell, and a new value to the “feeding” cell is assigned (UNITAR 2007). For example, if the receiving cell has a value of 0.3, and the receiving cell – a value of 0.5, the two values are multiplied, and the feeding cell is assigned a value of 0.15 to account for the loss occurring during transport. The process is inverse because the computation “starts at the watershed outlet and works up slope following the direction of flow” (UNITAR 2007: 87).

In this study, an attenuation factor representing the non-conservative transport of a pollutant is calculated by multiplying travel time by a decay constant (White and Hofschen 1996):

Total flow path nitrogen delivery ratio = (1 – the trapping efficiency of the cell (in percent))* attenuation parameter
Conservative transport is implied for nutrients that are carried by overland flow in sediment-bound forms. Nonconservative transport is present when nutrient concentrations decrease as the travel time increases (White and Hofschen 1996, USEPA 2004). Research has also shown that the amount of nitrogen delivered to a point downstream is an exponential function of travel time and a decay coefficient.

In a first-order reaction, the initial concentration of a substance declines proportionally at a constant rate of loss of that substance in a given period of time (White and Hofschen 1996, Wang et al. 1999, Alexander et al. 2000, 2001). A first-order reaction can be written as:

\[
[A] = [A_0] \exp(-Kt) \quad (6.12)
\]

where,

\(A_0\) is the initial concentration of the substance of interest,

\(K\) is a decay constant, and \(t\) is travel time.

The attenuation parameter, \(g_{ij}\) is based on first order kinetics):

\[
g_{ij} = \exp(-K_{ij}t_j) \quad (6.13)
\]

where \(K_{ij}\) is a decay constant \([T^{-1}]\) for the pollutant at location \(j\); and \(t_j\) is the travel time \([T]\).

The travel time of the overland flow between two points in the watershed is derived from the known length of flow and empirical estimate of velocity (Chow et al. 1988, White and Hofschen 1996). If \(L\) denotes the distance between two points on the flow path and the velocity along that path is \(v(l)\), the travel time is estimated from the following relationship (Chow et al. 1988):

\[
t = \int_0^L \frac{dl}{v(l)} \quad (6.14)
\]
If a constant velocity in an increment of length $\Delta l_i$ is assumed, where $i = 1, 2, 3, \ldots n$ then the travel time is given by (Chow et al. 1988):

$$t = \sum_{i=1}^{n} \frac{\Delta l_i}{v_i} \quad (6.15)$$

Chow et al. (1988) provide approximate average velocities of for concentrated and unconcentrated runoff flow for different land cover types and slopes. Table 6.7 provides estimates of approximate average velocities of runoff flow for unconcentrated and concentrated flow. The unconcentrated flow condition is found in a watershed before the accumulation of the overland flow in a channel occurs (Chow et al. 1988).

Table 6.7 Approximate average velocities of runoff flow in m/h (adapted from Chow et al. 1988)

<table>
<thead>
<tr>
<th>Description of water course</th>
<th>Slope in percent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 to 3</td>
</tr>
<tr>
<td>Unconcentrated</td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>13.8</td>
</tr>
<tr>
<td>Pasture</td>
<td>22.8</td>
</tr>
<tr>
<td>Cropland</td>
<td>27.6</td>
</tr>
<tr>
<td>Pavement</td>
<td>78</td>
</tr>
<tr>
<td>Concentrated</td>
<td></td>
</tr>
<tr>
<td>Natural channel undefined</td>
<td>18</td>
</tr>
</tbody>
</table>
Figure 6.8 Travel time estimated as a cost distance to streams (in hours)

The average velocity of flow through each cell was calculated based on the land cover class and slope using the values obtained from Table 6.7. The travel time from each cell to the tributary was derived by dividing the distance to streams by the average velocity. In order to account for the synchronized influence of slope and land cover, the distance to stream was calculated as a cost-distance function and not as Euclidean distance.

The travel time to the watershed outlet determines which part of the watershed will contribute to surface water flow under various rainfall durations and intensities. The lines that delineate areas having equal time of flow to the watershed outlet are called isochrones (Chow et al. 1988). Those lines also define the boundaries of contributing areas. The spread of contributing areas depend on the rainfall duration and intensity (Chow et al. 1988). Examining contributing areas in terms of rainfall duration and intensity is beyond the scope of this research. However, approach accounts indirectly for precipitation conditions by identifying contributing
areas during low-runoff, average and high-runoff years. This is accomplished by adjusting the drainage network density and calculating what percent of each land use/land cover category contributes mostly to runoff under typical and atypical conditions.

The travel time raster file is then multiplied by the decay coefficient $K$. Values for $K$ for nitrogen were found to be in the following ranges: from 0.03-0.2 [d$^{-1}$] typical for NH$_3$ ≥ NO$_3$ transformation, to 0.2-10.0 [d$^{-1}$] (NO$_2$ ≥ NO$_3$) (White and Hofscben 1996). The United States Environmental Protection Agency (USEPA 2004) reported a decay coefficient of 0.3842 [d$^{-1}$] for total inorganic nitrogen for flow rate of less than 1000 cubic feet per second. After a sensitivity analysis which indicated that the decay rate affects the overall model performance, a decay coefficient of 0.2 [d$^{-1}$] was selected and uniformly applied throughout the study area. Thus, the attenuation parameter $g_{ij}$ took the form of:

$$g_{ij} = \exp(-0.2t_j) \quad (6.16)$$

where $t_j$ is the travel time assigned to each cell in the watershed.

An attenuation parameter grid is created from the travel time grid using Formula (7). In order to obtain the proportion of nitrogen loading, that is, nitrogen reaches the stream network, the attenuation parameter grid is multiplied by 1 minus trapping efficiency.
Figure 6.9 Contributing land areas and estimated TN export per cell during dry periods.
The result indicates the proportion of total nitrogen that each cell delivers to the water body after the attenuation parameter is taken into consideration. Figures 6.11, 6.12 and 6.13 display the contributing areas during low, average, and high flow years together with the estimated delivery ratio for each cell.

The results indicate that urban areas consistently contribute to nitrogen loadings under all types of precipitation conditions. During low runoff periods the contributing areas constitute approximately 11.1 percent of the watershed area, or 142 out of 1,280 square kilometers. During average flow periods the percentage area of the watershed contributing effectively to loadings is
approximately 15.4 percent, or 197 square kilometers. The results show that during wet periods only 22.4 percent of the watershed area was contributing to the total nitrogen loadings. Table 6.8 summarizes the results from the analysis of the contributing areas.

Table 6.8 Size of contributing areas under different rainfall conditions

<table>
<thead>
<tr>
<th>Type of precipitation conditions</th>
<th>Contributing areas in m²</th>
<th>Contributing urbanized areas in m²</th>
<th>Contributing areas as proportion of total watershed area</th>
<th>Proportion urban land in contributing area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry</td>
<td>140,897,242</td>
<td>36,526,320</td>
<td>0.111</td>
<td>0.249</td>
</tr>
<tr>
<td>Normal</td>
<td>212,145,453</td>
<td>38,487,762</td>
<td>0.154</td>
<td>0.203</td>
</tr>
<tr>
<td>Wet</td>
<td>298,314,312</td>
<td>41,508,000</td>
<td>0.224</td>
<td>0.151</td>
</tr>
</tbody>
</table>
The urbanized areas contributing to total nitrogen loadings were approximately one fourth of the total contributing area under dry conditions. This percentage drops to 19.5 percent under average precipitation conditions, and 14.5 percent under wet conditions.

Figures 6.11, 6.12 and 6.13 provide an illustration of how the contributing areas during low flow, normal flow and high flow relate to each other. The maps show how contributing areas expand as the stream network density increases. Figure 6.14 allows a comparison of the difference in extent between contributing areas under different conditions. The extent of contributing areas under baseline conditions involves the extent of the areas under dry conditions.
and the supplementary areas activated as a result of the higher volume of runoff following increased precipitation. The extent of contributing areas during wet conditions includes the contributing areas under dry conditions plus those under the average conditions plus the additional areas mobilized as a result of the higher rainfall intensity.

6.5.6 Total Nitrogen Loading

Total nitrogen loadings are estimated by multiplying the raster representing the amount of total nitrogen available for transport with the raster datasets representing delivery ratios for dry, normal and wet conditions respectively. Figures 6.11, 6.12 and 6.13 illustrate the amount of TN nitrogen delivered to the water bodies from each cell in the raster dataset.

Table 6.9 displays estimates for the average annual cell nitrogen loading under different conditions. The results indicate that the wet conditions increase the overall nitrogen loading to streams.
Figure 6.12 illustrates the extent of the contributing areas under different conditions.
Table 6.9 Average TN export rates under wet, dry and average conditions

<table>
<thead>
<tr>
<th>Type of precipitation conditions</th>
<th>Total nitrogen export kg/cell/yr</th>
<th>Total nitrogen export kg/ha/yr</th>
<th>Total nitrogen export kg/km²/yr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry</td>
<td>0.0958</td>
<td>1.0640</td>
<td>106.3965</td>
</tr>
<tr>
<td>Normal</td>
<td>0.1083</td>
<td>1.2032</td>
<td>120.3243</td>
</tr>
<tr>
<td>Wet</td>
<td>0.1221</td>
<td>1.3564</td>
<td>135.6372</td>
</tr>
</tbody>
</table>

The sensitivity of the overall model was examined by applying three values of the decay coefficient (K): 0.2 [d⁻¹], 0.3842 [d⁻¹], and 0.5 [d⁻¹]. The effect of the decay rate (K) on the overall model results was shown to be significant since the percent change on the mean model predictions was in the range of 10 to 15 percent. The value of 0.2 [d⁻¹] was chosen since the model yielded the closest to the observed data results.

A comparison between observed and simulated values shows that the model predictions are close or within the same range as the measurements. The model slightly under-predicts the observed values, which is to be expected since the model accounts only for non-point source pollution and does not include other sources such as contributions from wastewater treatment plants, accidental effluents, or atmospheric fallout.

6.6 Applying the Model to the Projected Land Cover

The main objective of this research is to examine the alterations in non-point source nitrogen loadings in relation with the changes in the landscape occurring as result of urban development. The land cover change model incorporated two scenarios: a scenario based on the continuation of
the current trends and a scenario with an extensive open space conservation network. The study region for the urban growth was projected included not only the East Fork Little Miami watershed, but also the entire OH-KY-IN Cincinnati-Middleton MSA. The cell-based nitrogen loading model was run for both scenarios assuming dry, wet and normal precipitation conditions using the methodology described in the previous section.

Both scenarios indicated that by the 2030, if the rate of development were the same, there would be considerable expansion of the total nitrogen contributing areas. Figures 6.15 and 6.16 below show the extent of the TN contributing areas for Scenario 1 and Scenario 2 respectively, under dry conditions.

Figure 6.13 Contributing areas and delivery ratios under dry conditions: Scenario 1
Although the incorporation of the open space conservation network does modify the shape and extent of contributing areas, it has an impact on the effectiveness of nitrogen removal, and therefore, affects the total amount of inorganic nitrogen species that enter the surface water.

Figure 6.14 Contributing areas and delivery ratios under dry conditions: Scenario 2

The cell-based model of nitrogen loading indicates that there will be at least 30 percent increase in the total nitrogen loadings by the 2030 if the current pace of land development continues. The results from the analysis are summarized in Table 6.10. The results indicate that under the second scenario as much as 50 percent of these additional expected nitrogen inputs could be reduced if the green infrastructure principles are applied. Under the average precipitation conditions (Figures 6.15 and 6.16) the expected increase of the total nitrogen loadings would be approximately 49.5 percent. Imposing environmental constraints on future
land development would decrease the TN loads by nearly 27.5 percent under dry conditions and by 29 percent under wet conditions. Nutrient removal is only one of the numerous hydrological, ecological and water quality services that riparian setbacks and other environmentally important areas can provide.

<table>
<thead>
<tr>
<th>Climates conditions</th>
<th>TN Loadings and Size of Contributing areas:</th>
<th>TN Loadings and Size of Contributing areas:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Land cover 2030 Scenario 1</td>
<td>Land cover 2030 Scenario 2</td>
</tr>
<tr>
<td>Number of cell in contributing areas</td>
<td>717273</td>
<td>470747</td>
</tr>
<tr>
<td>Size of contributing areas (ha)</td>
<td>64554.57</td>
<td>42367.23</td>
</tr>
<tr>
<td>Mean TN loading (cell/g/yr)</td>
<td>186.87</td>
<td>177.57</td>
</tr>
<tr>
<td>Mean TN loading (kg/ha/yr)</td>
<td>2.08</td>
<td>1.97</td>
</tr>
</tbody>
</table>
Figure 6.15 Contributing areas and delivery ratios under normal precipitation conditions: Scenario 1
The model also shows that under wet conditions, when the urbanized areas in the watershed increases significantly (to approximately 24 percent), the cell-based nitrogen loading model indicates no difference in the total nitrogen loadings between the two land cover change scenarios. This is due to the increased imperviousness and connectivity between as a result of the urban development as well as to the fact the watershed consists primarily of poorly and very poorly drained soils. Figure 6.17 presents the contributing areas of nitrogen loadings under wet conditions that are characterize both Scenario 1 and Scenario 2.
The behavior of the nutrient-contributing areas is investigated during low flow, normal and high flow conditions using a distributed cell-based model quantifying the interactions between nutrient loss and field characteristics such as soil, land use, vegetation, topography and distance to streams. Results indicated that under the contributing areas comprised between eleven and twenty three percent of the total watershed area depending on the moisture conditions. Under dry conditions urban land was found to represent approximately one fourth of the effective land area contributing to total nitrogen loadings is, while the urbanized areas constituted only 4 percent of the total watershed area. The results from the study have implications for the effectiveness of the nonpoint source management practices which will be improved if they are targeted to the source areas of nitrogen pollution.
CHAPTER 7

7 INTEGRATING SENSITIVE AREAS PROTECTION INTO REGIONAL DEVELOPMENT PLANNING: POLICY IMPLICATIONS AND BENEFITS

Regional development planning recognizes the necessity to look at cities and their surrounding areas holistically and beyond existing jurisdictional boundaries, since many of the processes that shape the economic future and determine the quality of life, happen at scales that may not coincide with the existing administrative boundaries. Regional development transcends territorial boundaries and refers to the multitude of interactions that cities develop with their hinterlands. It encompasses individuals who, and systems that, directly or indirectly interact with each other in a larger spatial context. The trends and patterns of urbanization, the nature of economic activities, land management practices, land use planning and conservation efforts vary across regions due to differences in physiographic conditions, and social and economic contexts.

Complexity theory has brought to light the idea that outcomes of development depend on micro-scale interactions resulting from a myriad of individual decisions. Regional development planning helps us understand the impact of these micro-level interactions at the macro-level. In this research, an attempt to combine and employ the strengths of both approaches has been made.
The cellular automata model of urban growth, presented in this dissertation, is consistent with the ideas of the complexity theory and the need to go beyond territorial boundaries to understand micro-level developments. The cell-based model of nutrient export integrated with a cellular automata model of land cover change provides site-specific information on the impact of urban development on important environmental indicators. The major strength of this approach is that it allows adjustment to policies of future development with regard to expected environmental consequences at the regional level. The knowledge of how anticipated urban development affects important water quality indicators can become the focal point of a number of urban environmental planning initiatives. The information obtained from the two models can be useful to planning decision-making in many respects, including comprehensive land use planning, zoning and stormwater management practices. This chapter explores various planning and policy implications of the results of both models in further detail.

The chapter is organized as follows. The first section examines the importance of integrating the environment into urban development policies in the long run, while the second section focuses on the benefits of integrating an open space conservation network in urban development plans and policies. The third section of this chapter discusses the importance of the contributing source areas for non-point source control measures.

7.1 Why Integrate the Environment into Regional Development Planning?

Most commonly, regions are defined as distinctive geographic entities based on proximity and some form of economic integration. The early definitions of the region represented it as a trading area with “an inner radius sufficient to render the production profitable” (Lösch 1938: 99). The export base theory of the 1950s redefined the concept emphasizing that “the unifying cohesion to a region, over and beyond geographic similarities, is its development around a
common export base” (North 1955: 346). In short, the concept focused on the distinction between regional economic activities oriented to export markets and those producing for local markets. Another regional theorist of the 1950s, Charles Tiebout, disagreed with the export base theory, stating that the export base is merely one aspect of a general theory of short-run regional income determination (Tiebout 1956). Other activities such as business investment, government expenditures, and the volume of residential construction may have the same impact on regional income as exports. Thus, the definition of the region was expanded beyond the geographic division of labor to incorporate some social and political interactions. In the same vein, Hirschman (1958) offered a fuller concept of the region by adding political and social dimensions to it. He argued that the growth poles, or regional growth centers that drive the economic development in the region by producing “trickle-down” or multiplicative effects, were determined not only by the free interplay of market forces but also by the regional allocation of public investment. Hirschman alluded to the social cohesiveness and political identity of a region that go beyond its geographical and economic components.

The urban simulation models that entered planning practice in the 1960s (Klosterman 2001a, Torrens 2000), as discussed in Chapter 2, were mostly large-scale metropolitan land use/transportation models, applied in regional context. Cellular automata models projecting future patterns of urbanization were also applied exclusively to metropolitan regions such the San Francisco Bay area (Clarke et al. 1997), the Chicago area (Xian et al. 2000), the New York metropolitan region (Esnard and Yang, 2002), the Santa Barbara region (Herold et al. 2002), Lisbon and Porto, Portugal (Silva and Clarke, 2002), the Baltimore/Washington metropolitan area (Jantz et al. 2003), the Atlanta metropolitan area (Yang and Lo 2003), and the Houston metropolitan area (Oguz et al. 2004).
The results of these simulations suggest that the trend of land conversion to urban uses will not be reversed in the near future. Even the implementation of state growth management strategies is not expected to reduce dramatically sprawl and other undesirable phenomena associated with urban development (Anthony 2004). Projections of urban populations worldwide confirm the outcomes of the models and statistical analyses. The Cities Alliance, for example, in its 2007 report, estimates that today half of the world’s population lives in urban settlements. In addition, it is expected that over the next three decades cities worldwide will absorb most of the projected urban population growth of more than 2 billion people (Cities Alliance 2007). Cities and highly urbanized regions have been held responsible for many of the negative consequences of development, including exacerbated social inequality, pollution, resource depletion, and environmental degradation (Cities Alliance 2007).

The impact of cities and urbanized metropolitan regions on the environment is evident at global, regional and local levels. Urbanized areas are not antithetical to the environment. The image of the region and its competitiveness in modern globalized markets depends on its economic and financial infrastructure as much as on its “environmental credentials”, that is, its water resources, greenspace and air quality (Cities Alliance 2007). The past has taught us that “an ad hoc approach to environmental issues is fragmentary, expensive and inefficient” (Cities Alliance 2007:12). A prosperous and marketable city has the ability to integrate environmental planning considerations into its comprehensive plans, zoning ordinances, and other regulatory mechanisms (Cities Alliance 2007).
7.2 Significance of the Open Space Conservation Network

The results of this research indicate that projected urban development will affect considerably the environmentally sensitive areas in the study region. Figure 7.1 has been derived by intersecting the environmentally sensitive areas layer with the projected urban growth layer for the year 2030.

Figure 7.1 Environmentally sensitive areas affected by projected urban development under Scenario 1 for 2030
Table 7.1 Summary statistics of projected land cover change in the study area by the year 2030

<table>
<thead>
<tr>
<th>Category</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total area (ha)</td>
<td>1,417,024</td>
</tr>
<tr>
<td>Total urban area (ha)</td>
<td>438,874</td>
</tr>
<tr>
<td>Percent urban land</td>
<td>0.3097</td>
</tr>
<tr>
<td>Total sensitive areas (ha)</td>
<td>379,485</td>
</tr>
<tr>
<td>Percent sensitive areas</td>
<td>0.2678</td>
</tr>
<tr>
<td>Urban development in the sensitive areas (ha)</td>
<td>108,989</td>
</tr>
<tr>
<td>Percent urban development in sensitive areas</td>
<td>0.2483</td>
</tr>
<tr>
<td>Percent disturbed sensitive areas</td>
<td>0.2872</td>
</tr>
</tbody>
</table>

Table 7.1 provides an overview of the summary statistics of the projected change in land cover under Scenario 1. The results indicate that approximately 30 percent of the study area will be urbanized by the year 2030. Under Scenario 1, nearly 24.8 percent of the projected urban development by the year 2030 will happen in environmentally sensitive areas. Thus, under this scenario, urbanization is expected to affect 28.7 percent of the existing environmentally important areas such as floodways, wetlands, existing urban open space, areas potentially vulnerable to accelerated erosion, and areas with exceedingly shallow depth to seasonally high water table. These results show dramatic improvement under Scenario 2 since environmentally sensitive areas are protected from encroachment by urban expansion by setbacks and exclusion from development. Although Scenario 2 may seem unrealistic to a certain extent, it shows that it is indeed possible to build and incorporate a green infrastructure network into development plans at a regional level. The results from the application of the nitrogen loading model to the projected land cover indicate that protecting environmentally important areas can reduce non-point source TN by approximately 49 percent during normal flow years, by 27 percent during low flow years, and by 29 percent during high flow years.
The economic impact of the green infrastructure is beyond the scope of this research. It is, however, widely acknowledged that it is more cost efficient for a city to protect and maintain high quality ecosystems than build expensive infrastructure facilities to provide some of the same services than are occurring naturally in undisturbed habitats, or cover the damage from the failures of such facilities (CRWP 2006). The State of Massachusetts, for example, opted for the purchase of the full title and easements of 8,500 floodplain wetlands in the upper Charles River instead of a proposed engineering project. The purchase was at a cost of $10 million and proved to be a better alternative to the $100 million in engineering improvements such as construction of upstream levees and flood control reservoirs (CRWP 2006). It is expected that maintaining the floodplain wetlands in the upper Charles River would provide economic benefits equivalent to $27 million dollars (CRWP 2006). It is estimated that this is the value of the annual flood damage that would have resulted from the wetland loss (CRWP 2006).

The benefits of the “green infrastructure” approach have been recognized by the nation’s mayors who passed a policy resolution at their 2006 annual meeting in which they recognized that as a result of accelerated land conversion to urban uses valuable natural resources have been lost, which hampered the ability of natural systems to reduce volume and peak discharges of stormwater, perform water treatment functions, contribute to groundwater recharge and carbon sequestration, and provide wildlife habitat.

The U.S. Conference of Mayors (2006) emphasized the need for protection and restoration of natural systems that perform “many of the same functions as traditionally built infrastructure, often at a fraction of the cost” (U.S. Conference of Mayors 2006). Estimates given by the General Accounting Office, the US Environmental Protection Agency and the American Society of Civil Engineers indicate that over the next 20 years there will be a $1 trillion dollar deficit in
drinking and wastewater infrastructure (U.S. Conference of Mayors 2006). Some of the functions performed by this infrastructure can be successfully replaced by the services provided by natural systems. Nitrogen removal processes, for example, occur at higher rates in riparian and wetland areas. The protection of such areas from encroachment by urban development can improve water quality and reduce costs for stormwater treatment.

Local governments have at their disposal several planning tools that can help construct, operate and maintain the “green” infrastructure network. They include comprehensive plans, zoning and subdivision regulations, transportation plans, and the local annual budget (Benedict and McMahon 2006). More than 30 local municipalities in the State of Ohio, for example, have adopted regulations to protect riparian and wetland setbacks (CRWP 2006). Nationwide, thirteen states have adopted growth management strategies intended to reduce sprawl, promote land conservation and protect environmentally important areas (Anthony 2004).

It is not sufficient, however, to protect isolated patches of environmentally important areas. The “green infrastructure” approach emphasizes the importance of connectivity for the effective control of hydrological and ecological processes (Benedict and McMahon 2007). The Florida Statewide Greenways Project (DEP 1994) has pioneered the green infrastructure network approach. Under the project, several priority areas that can serve as ecological hubs were identified, and, based on analysis of the landscape attributes, physical linkages or ecological corridors were delineated to connect the hubs (DEP 1994, Benedict and McMahon 2007).

Acquisition through easements or full title rights, water rights, special area zoning, transferable development rights, specific water quality standards for designated areas, wetland restoration, wide-ranging watershed planning, and outreach programs are some of the local
government planning instruments for wetland and riparian area protection suggested by USEPA (2005).

The cellular automata model of land cover change can be used to generate different scenarios of urban growth. A public discussion of these scenarios involving stakeholder participation can bring awareness of the expected change and valuable inputs to the planning process. The model can be used to resolve conflicts of interests in land development and build consensus among stakeholders about the future patterns and directions of urban development, if visions differ. The model can also easily incorporate growth management strategies, zoning ordinances or other regulatory tools that may influence the patterns and pace of urban development.

The cell-based model of nutrient loading is a helpful tool to examine a particular aspect of the environmental impact of proposed plans of development. In this research the model has been applied to total nitrogen loadings, but with slight modifications it can also be useful for estimating total phosphorus loadings. These results can be further incorporated in rapid and strategic environmental assessments, and analyzed with the objective of identifying the optimal future scenario which minimizes the negative consequences of urban development.

7.3 Significance of Contributing Areas for Non-point Source Pollution Management

Higher levels of dissolved oxygen, deeper light penetration and lower levels of plant and algal biomass, were observed in highly eutrophic estuaries following reduction of P and N inputs (Mallin et al 2005). These results indicate that eutrophication can be effectively reversed within short periods of time if appropriate measures targeted at source areas of N export are in place. Studies have shown that control over pollutants originating from non-point sources, “be they
from agriculture, atmospheric deposition, or urban runoff, cannot be adequately controlled at their sources” (Boesch et al. 2001). Combining input controls with management methods targeted to increase the extent of nutrient sinks through expansion of riparian buffers and wetland restoration can result in improved effectiveness of remedial measures designed to reverse eutrophication and other forms of non-point source pollution (NRC 1993, NRC 1994, Carpenter et al. 1998, Boesch et al. 2001).

The results from this research can be the focus of site-specific management guidelines based on the identification of source areas that effectively contribute to N loading from surface runoff and atmospheric deposition. They provide insights into the extent of contributing areas, the relationship to land use, the effect of terrain and soil properties that increase/decrease delivery ratios, the shape and location of contributing areas, the response to climatic changes, and the contributions from built-up areas and atmospheric deposition. The results from this research can be the focus of site-specific management guidelines based on the identification of source areas that effectively contribute to N loading from surface runoff.

Extent of contributing areas. The findings confirm results from previous studies (Levine et al. 1993, Soranno et al. 1996) that nutrient export from each land use type does not increase linearly with the area of a specific land use (e.g., agriculture, urban, etc.) (Soranno et al. 1996). The results suggest that even during an above normal rainfall year only a certain percentage of the watershed area (not exceeding 25 percent) contributes actively to loading. This percentage is even lower during below normal and average rainfall years. The cost-effectiveness of the best management practices would increase if, for managers, instead of treating the entire watershed area, they can target their efforts only to source areas which contribute the most to nutrient loadings.
**Shape and location of contributing areas.** The model results (figures 6 and 7) show that contributing areas are mostly irregular in shape, which confirms the findings by Levine et al. (1993). The study also found that the contributing areas may not be immediately adjacent to the streams (Figure 7), as also suggested by Levine et al. (1993). Approximately 85 percent of the expected contributing areas lie in close proximity to perennial streams, and another 15 percent are not immediately adjacent to them. This result can be explained by the relative importance of the stream network density. As the stream network density increases, the total mobilization of pollutant mass also increases. The irregular shape of the contributing areas is an important factor in watershed management which relies extensively on riparian buffers and setbacks in order to protect these vital ecosystems. Buffers are usually based on fixed widths (i.e., distance from the streambank). The findings suggest that the variable buffer width approach as described by Xiang and Stratton (1996), Phillips (1996), and Polyakov (2005) is better suited to reflect the irregular shape of the contributing areas.

**Relationship to land use.** The results from the nutrient loading model also help develop better understanding of the spatial relationships between land use and water quality. Research has consistently shown that annual fluxes of dissolved and airborne nitrogen per unit watershed area (export coefficients) vary in orders of magnitude between watersheds with similar land uses. A number of studies suggest that the percentage of agricultural, urban and forested land within the watershed can explain some of the variability of water quality parameters, but much remains to be investigated (Vanni et al. 2001, Soranno et al. 1996). The results of this study confirm that surface roughness (as reflected by land cover) is a significant factor in estimating total N loading, but, because nitrogen moves through the landscape in mostly soluble forms, the overall effect of
the Manning’s roughness coefficient is less for nitrogen than for nutrients that are transported in sediment-bound form such as phosphorus (Levine et al. 1993).

Effect of terrain and soil properties. The delivery ratios approach, suggested by Levine et al. (1993), allows the incorporation of landscape attributes such as slope and soil characteristics in the total N loads estimation, thus adjusting the export coefficients for each land use to the specific physical conditions in the watershed. The model results suggest that the saturated hydraulic conductivity of the soil and the attenuation factor (estimated as the exponent of the travel time multiplied by the decay constant) have the most significant effect on the total nitrogen loadings and contributing areas. It is also important to indicate that the travel time is estimated as a cost distance to streams in order to account for the influence of the trapping efficiencies of the preceding cells as nitrogen compounds move through the landscape.

Response to changes in climatic conditions. The model accounted for alterations in total nitrogen loadings and contributing areas under dry, normal and wet conditions. The model shows how increased density of the stream network (as a result of higher precipitation rates), increases the extent of the contributing areas, thus mobilizing additional TN inputs to the surface water. Year-round variation of nitrogen loadings is beyond the scope of this research but as part of future research efforts, the suggested approach can be adjusted to reflect seasonal variability as well.

Contributions from urbanized areas. The study showed that urbanized areas may constitute up to 25 percent of the total contributing areas during dry conditions, although only 4 percent of the watershed was built-up. During an average rainfall year, approximately 19 percent of the contributing areas are urban. During wet conditions the proportion of the urbanized areas contributing to loadings drops to 15 percent, which can be explained by the absolute increase in
the total extent of the source areas. The results are consistent with the findings reported by Soranno et al. (1996) who also suggest that urbanized areas are substantial part of the total contributing area. The relatively high contribution from urbanized areas compared to the actual extent of urban land use can be explained by the lack of transmission losses due to imperviousness. In agricultural or forested areas, nutrients are deposited in the soil and decomposed as they are transported through the landscape by the overland flow.

Applying the nutrient loading model to future land cover change scenarios suggested that urban growth without environmental constraints may lead to noticeable deterioration in the water quality parameters. The exclusion of riparian areas, floodplains and floodways, wetlands, steep slopes and other sensitive areas from development, and applying wider buffers to protect those areas, resulted in reduction of the predicted TN loadings. This result combined with the delineation of the contributing areas, can assist in developing site design and management practices to control stormwater runoff and NPS pollution.

7.4 Conclusions

There are a large number of variables that play into a formal planning process. This includes different types of land use which are varying extents and connectivities amongst each other, proximities to regulated streams and rivers, societal goals for land development and commerce. All these factors and objectives must be balanced within some type of framework, preferably at least semi-quantitative.

Incremental changes to the landscape that occur on an ongoing basis (a relatively fast temporal scale), are usually looked at with hindsight, rather than a proactive, prognostic approach that incorporates variability in the physical and biological aspects of an area of interest to model potential outcomes in a way that is not only quantifiable, but also realistic and graphic.
This contributes to a potentially more effective spatial planning process such that post-modern attributes of contemporary planning practice are re-linked to a spatial planning process by providing pictorial representations of planning scenarios that are more or less immediately recognizable by laypeople (stakeholders), yet these images are based on a specific quantitative methodology that is grounded in the primary literature. Furthermore, this process is necessarily multidisciplinary. This thesis is an interdisciplinary work, as its goal is to synthesize the broad influences that bear upon modern planning practice, and hopefully advance the knowledge in the field.

The impact of urbanization on environmental quality is often felt and can be better understood at a regional level. If examined at a local scale, the impacts may not be significant. Yet, the incremental changes that slowly occur as the land cover changes have cumulative effects. Those effects may not be detectable at a micro-scale, but can be quite noticeable at a regional level.
8 CONCLUSIONS

The objective of this research is to construct a framework for evaluating the impact of land cover change on water quality. The framework consists of five components: review of the relevant theoretical background and research, the use of GIS-based software (IDRISI Andes v.15.0) and its modules to build land cover change projections until the year 2030, development of scenarios and the examination of impact of those scenarios on nitrogen inputs to streams, as well as the examination of TN contributions from atmospheric deposition. The last chapter of this dissertation returns to the research questions stated in the Introduction, summarizes the results from the projections and analysis, outlines what the author believes is the contribution of this research, and provides some directions for future investigations.
8.1 Revisiting the Research Questions

Six specific research questions were defined in the Introduction to this dissertation to evaluate the functions of the models developed. In this section, the answers to these questions are briefly summarized.

How can we model the land cover change in an expanding metropolitan area? What variables do we use to study these changes?

The expected changes in the land cover of the Greater Cincinnati metropolitan area were analyzed using a cellular automata – Markov chain model. Land cover change was projected exploring two scenarios: continuation of current trends and incorporation of environmental constraints. Growth areas defined on the basis of employment and population density change, proximity to roads and developed land, and proximity to streams and environmentally sensitive areas are the variables incorporated in the cellular automata – Markov chain model to project land cover change. Both scenarios suggested that the process of rapid urbanization in the area will continue. This finding is consistent with the results from a recent study which compared the urbanization patterns in 49 states over a 15-year period. The study concluded that there was little evidence that the observed trends of urban expansion would be reversed in the near future (Anthony 2004).

How can we assess the impact of the land cover changes on the non-point source nitrogen pollution? Is the application of a cell-based, distributed model of nitrogen loading useful in this assessment?

The existing physically-based hydrological/water quality models have not be used to evaluate the impact of the land cover change projections on nutrient loadings because most of them work at different spatial resolution than the cellular model of urban growth. It was assumed
that a nutrient loading model that works at a pixel level would be more compatible with the cellular model that projects urban growth on a pixel-by-pixel basis. The model estimates the trapping efficiency and the delivery ratio of each cell accounting simultaneously for soil characteristics and vegetative cover. The soil component of the model remains constant, while the vegetative cover component represented as a Manning’s roughness coefficient assigned to each cell is variable and reflects land cover changes. Therefore, the model has the potential to assess the difference in nitrogen loadings associated with land cover change.

Can we successfully integrate a cellular automata urban growth/land cover change model with an environmental model to quantify TN losses associated with urban development? What spatial scale would make the results of the two models compatible?

The results indicate that the models can be successfully integrated on a pixel-by-pixel basis. This means that the transition of every pixel to a different land cover class can be evaluated in terms of its nitrogen delivery ratios, which is expected to improve the accuracy of the modeling results.

How can we mitigate the impact of the expected land cover change on TN inputs to streams? What is the utility of incorporating the green infrastructure approach in the modeling framework?

The cell-based model of nutrient delivery indicated that the protection of riparian areas, floodplains, wetlands, areas with exceedingly shallow depth to seasonally water table and bedrock, and other environmentally sensitive areas can have an impact on the total nitrogen delivery rates. Denitrification occurs in soils that are waterlogged and oxygen depleted due to the fact that water fills in the spaces between soil particles (Sirivedhin and Gray 2006). Denitrification occurs in groundwater, wetlands, and some soils in the riparian areas where
heterotrophic bacteria are present (Sirivedhin and Gray 2006). Therefore, the results of this study substantiate the assumption that the protection of these areas can reduce TN inputs to rivers and streams.

What is the behavior of the TN contributing areas under different scenarios and climatic conditions?

This question is important because such knowledge would help watershed managers and planners to target the measures of non-point source pollution control to the source areas. The results from the study suggest that the contributing areas are irregular in shape and do not always coincide with the buffer zones that are often constructed to protect stream water quality. The model results indicate that the contributing areas expand and contract depending on precipitation conditions. It also became obvious that urbanized areas can become a significant proportion of the total contributing area even if they are only a small percent of the total watershed area.

What are the policy implications and benefits of linking an urban growth model with a model of environmental impact assessment?

The sixth question requires a discussion of how transportable the study results are to the planning process. Chapter 7 argues that the models developed in this research can serve the planning practice in many different ways including future land use plans development based on visualization of projected urban growth. The results from this research, if incorporated in a planning process, can provide information on the expected changes in water quality and facilitate the dialogue with the stakeholders on protecting environmentally sensitive areas.

8.2 Research Contribution

This research develops a functional and effective quantitative framework that can assist decision-makers in their environmental assessment of projected land cover changes resulting
from urban development. A set of factors, constraints and probabilities that underpin projected land cover change, are successfully estimated and validated based on observed data. The procedure incorporates in a structured fashion the natural and developed components of the land developed unique algorithms to present in a graphic format different scenarios of land cover change.

The overview of the relevant literature has shown that there is still a gap between urban growth simulation and environmental modeling, and that the simulation of urban growth dynamics rarely goes beyond visualization and qualitative examination of future development patterns. By integrating a cellular automata – Markov chain model of urban growth with a nitrogen loading model, this research contributes to better understanding of how the environmental impact of the land cover changes resulting from urbanization can be quantified. The integration of urban dynamics simulation and environmental modeling is a relatively new line of scientific inquiry. Given the importance of the changing environmental conditions today, studies that take into account both urban growth factors and environmental impacts can help identify strategies that would be most effective in sustaining the vital functions provided by natural systems as cities expand.

This research also fits recent efforts focusing on linking optimal land use allocation to environmental conditions. It has not been intended to provide a practical framework developed as a planning support system for future land use decision-making. However, by incorporating the three key components of the planning support system such as database support, modeling support, and visualization support, this research has the potential to evolve into a practical tool that can guide and facilitate future land use decisions by linking environmental modeling to urban simulations.
One of the strengths of the cellular automata model of land cover change based on Markov transition probabilities and multi-criteria evaluation is that it can operatively incorporate factors (e.g., distance to streams or roads) and constraints (e.g., existing urban area, surface water, transportation surfaces), and then connect and collect new and potential land uses to build corridors and nodes of “green” undeveloped areas of high environmental quality. This set of techniques can formalize the structure of conservations easements by avoiding present-time piecemeal or opportunistic (which are randomly distributed donations of land or endowment purchases) and help guide the sequencing and arrangement of land acquisition plans, floodplain zoning, parks and trails planning and zoning, to not only protect existing natural areas, but also to realistically deal with typically haphazard approaches to planning (sprawl, etc.) with specific functions can be easily integrated into the simulation framework. For municipalities that require comprehensive planning that accounts for present and future environmental regulations, this type of modeling and prediction will play a significant role in illustrating the probable outcomes of different land use choices upon expanding the extent of green infrastructure and the numerous ecosystem-level services that are provided by such area.

The cell-based method of quantifying nutrient loads also provides site-specific information on source areas of nutrient enrichment. The proposed approach also differs from the traditional export coefficient approach as well as from the either highly-parameterized models (i.e., HSPF), and also pushes beyond spatially-lumped models of water quality. It takes into account attenuation factors such as soil type, topography, distance, hydraulic conductivity and soil particle size distribution which affect the transport of nutrients over the landscape. The model accounts for spatial variation in these factors, and is scalable to the various scales of spatial resolution that can sometimes make working these datasets problematic. Yet, once this approach
is published as a protocol, it will be relatively easy to use since it does not require sophisticated technical knowledge and all of the input datasets are available from public domain sources.

GIS and hydrological techniques were integrated to develop a distributed, cell-based model of nutrient loading at the spatial scale of a watershed (560 sq. mi.; ~1000 sq. km). SAS (SAS Institute, Inc.) codes for a Poisson rate and non-linear regression models were developed to quantify TN trapping efficiencies on a pixel-by-pixel basis. One unique aspect of this algorithm is that the potential for changing climatic conditions to affect change in pollutant loadings is automatically accounted for. With cities and regions attempting to plan for and adapt to current or predicted climate change, this type of algorithm will be effective in illustrating the impact of land use choices in context of environmental change at the largest scales (i.e., climate (rainfall) forcing of non-point pollution processes). Ultimately, the graphic users interface that is the end product of these algorithms can increase the capacity of the proposed simulation framework to incorporate important factors in growth and for stakeholders to select those scenarios with minimal impact on the environment, if they so choose. The approach described within this thesis is scalable, and provides visualization that facilitates dialogue with stakeholders in either a watershed setting or overall regional planning process.

8.3 Directions for Future Research

Throughout this research, several questions remained unanswered, either because they were beyond the scope of its objectives, or because they were too challenging to tackle simultaneously with the model calibration, validation and application. The suggestions for future research are related to some of those unanswered questions that, to a certain degree, would also determine the uncertainty in the modeling results.
It would be interesting, for example, to examine the sensitivity of the modeling results to spatial resolution. In this research, a spatial resolution of 30 meters was uniformly applied for all datasets. It remains unclear how changes in the spatial scales would affect urban growth projections, contributing areas of TN pollution and total TN loadings. A further investigation in this direction would provide valuable insights about the level of uncertainty in the modeling results.

The incorporation of a more sophisticated set of factors, constraints and probabilities into the cellular model of urban growth may increase the accuracy of projections. Applying artificial neural networks, for example, instead of fixed Markov probabilities, is another venue of future research that may improve the adaptability and versatility of data inputs and outputs.

The modeling framework can be used to examine how effective different growth management strategies are at local level and compare their overall impact on the process of urbanization. Rendering the modeling framework operational so that the outputs of the land cover change model can automatically enter the nutrient loading model is a future direction of research that can transform the outcomes of this investigation into a planning support system.

The economic benefits of conserving environmentally sensitive areas have been beyond the scope of this research. The quantification and valuation of the tangible and intangible benefits associated with the services provided by natural systems is also a promising venue for future research.
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