SHOEMAKER, DOUGLAS ALLEN. The Role of Spatial Heterogeneity and Urban Pattern in Modulating Ecosystem Services. (Under the direction of Ross Meentemeyer).

The shift of global populations to cities heralds a new epoch marked by human impact, the Anthropocene, and with it radical changes to the biosphere. Some of the most significant change has occurred in developing countries, where amenity migration to rural areas within commuting distance of expanding urban centers has fundamentally restructured the configuration, hydrology and ecologies of surrounding watersheds. The export of urbanization to the countryside is manifested by rapid conversions of greenfields to impervious covers designed for human use, conversions that have consumed and fragmented networks of green infrastructure supporting growing populations. While the benefits of urbanization to human populations have been substantial, the ability of novel and evolving landscapes to sustain the production of environmental services, such as the ability to purify water, sequester climate-changing carbon, and harbor biodiversity, is poorly understood and historically shown to be compromised. The pace of urbanization, and particularly the combinatorial effects of climate change and development-caused hydrological alteration, has made the task of managing landscapes for human well-being increasingly difficult. Given the persistence of land change drivers such as urban population growth, there is a critical need to describe the trajectory of land cover change using both theory and projection, and anticipate impacts associated with urban form in order to proactively respond to environmental vulnerabilities.

A socio-ecological systems approach to the challenge of sustainable environmental provisioning has facilitated efforts to understand the dynamics of co-evolving human and
environmental systems. However, a lack of concise theory regarding urban pattern and process, and the paucity of representative case study, has left the role of spatial structure in modulating ecosystem function largely unexplored. To overcome some of these challenges, I describe a series of three related studies where I used a novel integration of land change and ecosystem services simulations in order to map and measure the co-evolution of human and natural systems in transitioning socio-ecological landscapes (SEL), and generate ecosystem-scale cause and effect data. In the first study I used this data to estimate the costs of waterborne non-point source pollution, carbon sequestration, and land cover based revenues for a rapidly urbanizing model system over a 24 year period. I also compared the effect associated with alternative patterns of urban growth, contrasting sprawl, infill and de-regulated scenarios with business as usual trends to gauge the effectiveness of environmental planning paradigms, such as “smart growth”. In the second, I tested the capacity a leading theory to explain the role of spatial heterogeneity in modulating ecosystem function in urban systems, to induce the integrated simulation results. Using structural equation modeling to translate the conceptualizations of Alberti (2005) into testable hypotheses, I tested for direct, indirect and modulating effects of landscape composition, connectivity, form, and land use intensity on the production of NPSP and carbon storage. In the third I examined land cover projection data for the presence of patterns suggesting that landscapes evolved in predictable ways. Using a dynamic proxy to bridge human and environmental effect, I tracked the evolution of connectivity in urbanizing watersheds by holding magnitude of change constant for three pattern alternative, and analyzing spatial configuration using distance-based, structural and circuit-based methods. These methods represent a move to predictive, rather than reactive, analytical paradigm, and allow us to move beyond the focus of managing current problems.
They emphasize the utility of integrated urban growth-ecosystem service analyses in order to anticipate environmental trade-offs likely required by society. My findings emphasize the need for ecosystem service analyses to more adequately understand development tradeoffs in the metropolitan context. We conclude that not all urban growth impacts environments evenly, and that by controlling the compositional mix, configuration and connectedness, not just the amount of development, we can influence more benign environmental outcomes. To reduce environmental impacts regionally, planners are advised to manage amplifying effects of development by maintaining land cover diversity, and limiting the connectivity of developed land covers along hydrological gradients.
The Role of Spatial Heterogeneity and Urban Pattern in Modulating Ecosystem Services

by
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DEDICATION

I dedicate this dissertation to Adrienne Thompson in recognition of her unconditional support of both the researcher and the research.
BIOGRAPHY

Douglas Allen Shoemaker was born in Washington, DC, on August 26, 1962, first of three sons to Wayne and Joanne Shoemaker. Raised in a Levitt Town in the nearby suburbs of Maryland, Douglas cultivated a love for the outdoors on frequent hunting, hiking and fishing trips with his father and brothers.
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INTRODUCTION

The evolution of cities and associated urban forms have accelerated the advent of the Anthropocene, our current geologic epoch that references human dominance of many, if not most, biotic and abiotic domains (Ellis and Ramankutty 2007). Given this, and the fact that the majority of humans now live in or near cities (UN 2014), we find that roughly one-quarter of the planet’s net primary productivity is directly and indirectly managed by human activity servicing urban populations (Haberl et al. 2007). Growing urban populations are placing unprecedented demand on landscapes to not only provision us with food, fiber and fuel, and to clean our water and air, but provide places to live and work, places to stage our cultural practices and places to recreate (Grimm et al. 2008). These demands drive urbanization, a force that works mechanistically through conversions of greenfields to covers designed for human use. The combinatorial effects of urbanization have consumed arable land and habitat, reduced evapotranspiration and groundwater recharge, increased stormwater runoff, and made landscapes grayer, hotter, dryer and flashier (Eigenbrod et al., 2011; Revi et al. 2014). However the Earth’s resources are finite, as is the ability of ecosystems to deliver sustaining services. The conflict between land consumptions trends and ecosystem provisioning present a long-term challenge to sustaining human society (Cohen, 1995). Solutions to accommodate growth and ecosystem function will require trade-offs between human needs, economic well-being, and environmental quality (Foley et al. 2005).

Some of the most significant landscape change has occurred in developing countries, where Post-Industrial amenity migration to rural areas has resulted in development patterns that have fundamentally restructured the configuration, hydrology and ecologies of the
exurbs (Brown et al. 2008). Alberti (2005) posits that urban development pattern critically influences ecosystem function, and that detailed understanding regarding the nature of feedbacks between spatial structure and ecosystem services is needed to anticipate and minimize urbanization impacts. She adds (2010), “We do not know the effects of different urban forms, densities, land use mix, and alternative infrastructures. We do not know, for example, how clustered versus dispersed and monocentric versus polycentric urban structures differently affect ecological conditions.” In this vacuum of information, society has routinely exchanged environmental capacity for economic development with a poor understanding of which ecosystem services have been traded away, and at what cost (Polansky et al. 2013). In response, Bennett et al. (2015), Cadenasso (2007), Cumming (2011), Kaushal et al. (2015), Pickett et al (2004, 2011, 2014), Verberg et al (2006, 2009) and others have called for systematic studies of urban socio-ecological systems that explore the relationship between urban pattern and ecosystem function, and to generate theory robust enough to be applicable to cities worldwide and guide decision making. However, progress has been limited by either the lack of longitudinal case study adequate for representative analyses, or simulated data with realistic projections of spatial structure needed to conduct scenario analyses.

To test and generate theory regarding the effects of spatial heterogeneity in urban systems, I present a three part study which anticipates changes in ecosystem response associated with alternative futures of urban growth in Charlotte (NC), a study system representative of fast-growing urban areas in the Sunbelt. Data limitations were overcome using a novel integration of land change and ecosystem services simulations in order to map and measure the co-evolution of human and natural systems in socio-ecological landscapes.
Recent advances in land change modeling have improved simulations of the spatial structure of urban growth by moving to patch-based, multilevel modeling ([FUTURES] Meentemeyer et al. 2013). Similarly, the recent availability of ecosystem services mass-balance algorithms (Natural Capital 2014) allows regional estimates of ecosystem response by both estimating material fluxes and by placing a societally-relevant economic metric ($) on what in many cases are intrinsic values. The integration of these domains allowed for scenario development, using parameterization of FUTURES to produce alternatives, and a spatially-explicit contextualized ecosystem response.

The studies target the following questions: 1) can we anticipate the future response of endemic ecosystems to ongoing urban expansion? If so, what are some of the trade-offs between economic growth and the environment? 2) Urban expansion is widely implicated as a key driver of ecosystem degradation. Which aspect of urban pattern generates the greatest effect? 3) Environmental planning emphasizes managing connectivity between pollution-loading land covers and valued natural resources. However the location and strength of these connective gradients is often unknown. Can we anticipate regional effects by predictively mapping connections?

The analyses are presented in three chapters. In the first study I estimated the costs of water-borne non-point source pollution, carbon sequestration, and land cover based revenues for a rapidly urbanizing model system over a 24 year period. I also compared the effect associated with alternative patterns of urban growth, contrasting sprawl, infill and de-regulated scenarios with business as usual trends to gauge the effectiveness of environmental planning paradigms, such as “smart growth”. In the second, I tested the capacity of leading
theory, regarding the role of spatial heterogeneity in urban systems, to induce the integrated simulation results. Using structural equation modeling to translate the conceptualizations of Alberti (2005) into testable hypotheses, I tested for direct, indirect and modulating effects of landscape composition, connectivity, form, and land use intensity on the production of NPSP and carbon storage. In the third I examined land cover projection data for the presence of patterns suggesting that landscapes evolved in predictable ways. Using a dynamic proxy to bridge human and environmental effect, I tracked the evolution of connectivity in urbanizing watersheds by holding magnitude of change constant for three pattern alternative, and analyzing spatial configuration using distance-based, structural and circuit-based methods. Together, these studies reveal patterns and trends of coevolution in human and natural systems in our simulated study system.
CHAPTER 1: URBAN MODELING AND SCENARIO ANALYSIS OF THE EFFECTS OF METROPOLITAN STRUCTURE ON ECOSYSTEM SERVICES

1.1 Abstract

Expanding demand for exurban development is restructuring the urban-rural frontier, converting greenfields to impervious covers designed to accommodate human activity and shifting the burden of common-good ecosystem provisioning to fragmented networks of green infrastructure. The environmental response of transitioning landscapes to aggregated patterns of urbanization is understudied, and likely compromised as evidenced by increased environmental uncertainty. Planning approaches to retain green infrastructure networks and the ecosystem services they provide have focused on managing the spatial configuration of development pattern in attempt to reduce the low-density style of development (‘sprawl’) that dominates North American exurbia. However, we know little about the environmental performance of alternative patterns such as infill, and as a result, the trade-offs required by the implementation of such designs remain unclear to planners and policy makers. I tested the environmental performance of a suite of alternative development patterns using a novel integration of land change and ecosystem services simulations in order to map and measure the co-evolution of human and natural systems in socio-ecological landscapes. I assessed the landscape response to four scenarios of un-regulated and specific forms of urban build-out, estimating the biogeochemical balances of nitrogen (N) and phosphorus (P), carbon sequestration, and biodiversity, as well as monetary returns (i.e. expected rents, timber/crop revenues) to landowners across 37 urbanizing watersheds in the Charlotte, North Carolina metropolitan region (USA). Projections of future landscape patterns are estimated to greatly
increased exports of nutrient pollution, reduce terrestrial carbon stores, and lead to new disturbed habitat regimes. I found that while urban form and development rates influenced ecosystem service provision, no single urban form simultaneously reduced pollution, stored carbon, and retained sensitive habitat, a finding that underscores the difficulties likely to be encountered when balancing economic and environmental outcomes. Increased density yielded stronger financial returns to landowners as concentrated economic activity drove up land rents while minimizing broader pollution costs, as compared to a low-density status-quo. My findings emphasize the need for ecosystem service analyses to more adequately understand development trade-offs in the metropolitan context.

1.2 Introduction

In developed countries, amenity migration to rural areas within commuting distance of expanding urban centers has fundamentally restructured the configuration, hydrology and ecologies of surrounding watersheds through urbanization (Gosnell & Abrams, 2011; Taylor, 2011). Between 1950 and 2000 the US experienced a 500% increase in development at the urban fringe (Brown, Johnson, Loveland, & Theobald, 2005), much of it as sprawling development patterns that have been shown to exert high pressures on fragmented exurban ecosystems (Mentens, Raes, & Hermy, 2006). Urbanization works mechanistically through conversions of greenfields to impervious covers designed for human use, and is a direct impact which has consumed arable land, reduced evapotranspiration and groundwater recharge, increased stormwater runoff, and made landscapes grayer, hotter, dryer and flashier (Eigenbrod et al., 2011; Revi et al. 2014). This contrasts with the base condition where green infrastructure (GI), the network of natural and semi-natural areas generating ecosystem
services, sustains wellbeing by provisioning food, water, and raw materials, regulating climate and water flow, moderating extreme weather events, providing habitat that harbors both valued species and genetic diversity, and by providing opportunities for recreation, tourism, and aesthetic appreciation (Tzoulas et al., 2007).

Urbanizing areas are increasingly areas of environmental uncertainty, and evidence of green infrastructure overburdening includes the formation of urban heat islands (Voogt & Oke, 2003), increases in storm damage, flash flooding and the waterway impairment (Pyke et al. 2011), invasions of exotic alien species (McKinney, 2006), fish kill and algal bloom events (Bowen & Valiela, 2001), and non-attainment of air quality standards (Cardelino & Chameides, 1990), among others. As a consequence, many former ecosystem services – the common-good functions of ecosystems (e.g. water filtration, flood storage; MEA 2005) – have been replaced by engineered gray infrastructure (e.g. drains, pipes, water treatment plants, cisterns). This replacement typically comes at great cost, at inadequate capacities (Gaffield, Goo, Richards, & Jackson, 2003), and requires high levels of maintenance (NRC, 2000). Even when best engineering and management practices (BMPs) are employed, urbanization’s alteration of the physical factors underpinning ecosystem service provision, such as topography, biodiversity, soil capacity and biogeochemical cycling, have changed the fundamental assumptions of stationarity (i.e. that systems are varying continuously within a bounded middle ground) that guide management practices (Milly et al. 2008). These ongoing threats to resilience (Lawler et al. 2014) leave many urban areas lacking sustainable strategies for accommodating growth in the face of long-term climate change, changing urban patterns and forms, and population increase (Amin, 2013).
Planning approaches to retain green infrastructure networks, and the ecosystem services they provide, have focused on managing the spatial configuration of development pattern in attempt to reduce the low-density style of development (‘sprawl’) that dominates North American exurbia (Preuss & Vemuri, 2004). Sprawl is widely understood to fragment ecosystems through low density and disjunct growth (Ewing and Hamidi 2014, Theobald 2000) and the pattern it takes is associated with losses of agriculture productivity, accelerated climate change, increased childhood obesity, increased infrastructural costs, and increased vehicular miles traveled (Littman, 2015). Sprawl is also suggested as a driving factor compromising key ecosystem services, notably the storage of climate-changing carbon and the ability of landscapes to infiltrate and purify water (American Rivers, 2002; Beach 2001). Development alternatives such as Great Britain’s “Compact City” (Breheny, 1992) and the US’s “Smart Growth” programs (Duany, Speck, & Lydon, 2010) aim to limit these impacts with “infill” or “clustered” patterns that concentrate density around amenities or infrastructure to reduce land consumption and travel costs. Comparative studies have found smart growth programs effective in shaping design (Song, 2005); however, we know little about the environmental impacts of these alternative patterns (Preuss & Vemuri, 2004; Beach 2001) as progress has been limited by either the lack of longitudinal case study adequate for representative analyses, or simulated data with realistic projections of spatial structure needed to conduct scenario analyses. As a result, trade-offs required by the implementation of such designs remain unclear to planners and policy makers.

Anticipating the sustainability and performance of various development patterns is of increasing importance, and the subject of this study. I tested the environmental performance
of a suite of alternative development patterns in order to explore the spatial interactions between urban form and the generation of ecosystem services. Data limitations were overcome using a novel integration of land change and ecosystem services simulations in order to map and measure the co-evolution of human and natural systems in socio-ecological landscapes (SEL). Recent advances in land change modeling have improved simulations of the spatial structure of urban growth by moving to patch-based, multilevel multitemporal modeling ([FUTURES] Meentemeyer et al. 2013). Similarly, the recent availability of ecosystem services mass-balance algorithms (Natural Capital 2014) allows regional estimates of ecosystem response by both estimating material fluxes and by placing a societally-relevant economic metric ($) on what in many cases are intrinsic values. The integration of these domains allowed for scenario development using parameterization of FUTURES to produce alternatives, and a spatially-explicit contextualized ecosystem response.

Is there a possibility for more “environmentally benign” urban growth? Further, what are key trade-offs involved when we repurpose land from an environmental role to an economic one? To explore the impact of business-as-usual and alternative growth pattern on ecosystem services, I projected future development patterns and their impacts on green infrastructure over two decades (2006 – 2030) and across 37 watersheds (HUC-12 level; USGS 2006) in the Charlotte, North Carolina (USA) metropolitan region, which is one of the fastest growing and most urbanized regions in the Southeastern United States (Cohen, Hatchard, & Wilson, 2015). Using the FUTURES multi-level urban growth model (Meentemeyer et al. 2013), I simulated interactions between projected development pattern and green infrastructure based on five alternative urban forms (including a business-as-usual
scenario) proposed for a six-county Charlotte study area. Alternative development patterns were integrated with a suite of ecosystem service models, including Integrated Valuation of Ecosystem Services and Tradeoffs ([InVEST 3.1] Tallis et al 2013) and Southeast GAP Analysis Project Human Disturbance Index (USGS SEGAP 2011) to estimate green infrastructure performance, specifically landscape patterns’ generation of ecosystem services that purify water, sequester carbon, and harbor biodiversity in the face of urban change (as simulated between 2006 and 2030). Finally, in order to investigate the relationship between urban development and ecosystem services, I drew on work by Polasky et al. (2010) to compare urban form-related economic performance and landowner revenues with discounted cash flow models of the financial savings (or costs) related to the function of green infrastructure.

Controlling for climate, population increase and demand for land consumption, I explored how urban patterns functioned along five dimensions, including 1) reductions in remnant forest and farmland fragmentation; 2) lowered non-point source nitrogen and phosphorous pollution; 3) increased carbon sequestration rates; 4) increased revenues to landowners based on projected land rents and working lands revenues (e.g. timber, crops); and 5) increased habitat area for animals with low tolerance to human activity (vertebrates). Finally, I compare trade-offs between these five dimensions as revealed for each urban pattern, the findings of which can be used for land use planning processes and capital improvement program design.
1.3 Methods

Estimating the impact of projected urban patterns on a suite on indicators of water quality, carbon, habitat and landowner revenues required linking simulation models in a multistep process. Simulation modeling of land cover change has the potential to both generate cases studies and provide insights into ecosystem function beyond empiricism through their ability to undertake experiments in alternative futures (Rounsevell et al. 2012). First, I developed regional maps of starting (2006) and projected (2030) land cover based on business-as-usual and alternative pattern scenarios using a spatially explicit, population driven urban growth model. Next, maps for 2006 and 2030 were used as input into the InVEST Water Purification Nutrient Retention and Carbon Storage and Sequestration modules to assess the location, degree and costs of nutrient pollution exports as well as carbon sequestration associated with those landforms. Changes in habitat suitability for vertebrates was estimated for both time steps using a Human Disturbance Index from the SE GAP program. Revenues anticipated for urban, forested and agricultural land covers were estimated using data from Lubowski (2008) and adjusted for 2015 dollars. Results were aggregated at pixel, subwatershed and regional scales, and LSA performance was compared with the status quo trend.

1.3.1 The Study System

My study system falls within six counties (Cabarrus, Mecklenburg, Iredell, Rowan, Stanly, and Union) located in the Piedmont region of the Southeastern US, and is part of the “Charlanta” megaregion (Florida, Gulden, and Mellander 2008) (Figure 1A). This region is North Carolina’s most urban, and projected to grow an additional 1.2 million people (50%)
by 2030 (North Carolina State Demographics Office 2009). In the 19th and early-20th centuries, the region was largely bereft of forest due to plantation agriculture, but the agricultural abandonment associated with the regions’ decline in the textile industry lead to widespread reforestation (American Forest 2010). Today, approximately 25% of the region’s landscape is urban, 25% agricultural, and over 50% is forested with Oak/Hickory/Pine upland forests connected by 2nd and 3rd order stream networks (Figure 1B). With the ascension of Charlotte as an international banking center and the resulting population influx, the need for housing drove widespread conversions of forest and farmland to sprawling development patterns (Graves & Smith, 2010).

Despite having the same of the strictest floodplain protection ordinances in the state, Mecklenburg County experienced 100-year floods in 1995, 1997, 2006, 2008 and 2011 (Charlotte-Mecklenburg Storm Water Services, 2015). During this same period, the region was found to be developing 30 acres per day (Meentemeyer et al. 2013). But floods were not the only water management problem. The region’s primary source of drinking water and electric power, the Catawba River, was named America’s Most Endangered River in 2008 by American Rivers, who cited climate change, sedimentation and sewer overflows as the system’s biggest challenges (American Rivers, 2013). Public interest in sustainable landscapes is found in two concurrent, but independent, regional visioning exercises: Mecklenburg Counties “Livable Communities” program (2013) and Centralina Council of Government’s CONNECT Our Future program (2011).

To explore the effects of urban and exurban growth in Charlotte I selected thirty-seven sub-watersheds (HUC-12) within the region along an urban-rural gradient that is
representative of fast growing and unconstrained urban regions throughout the US (Figure 1B). My choice of sub-watersheds as the unit of analysis – rather than jurisdictional (i.e. municipal boundary) or demographic (i.e. census) units – reflects my goal of measuring effects at ecologically relevant scales, with the understanding that results can later be aggregated at other specified extents once processed. I excluded three subwatersheds directly adjacent to reservoirs along the impounded Catawba River, which reduced the complexity introduced into hydrological modeling by non-gradient flows. The study system’s 346,000 ha extent was extended by 1,000 meter buffers to reduce boundary effects in simulation modeling.

1.3.2 Urban Growth Projections

FUTURES provides a dynamic, spatially explicit raster modeling framework for simulating realistic spatial structures of per-capita land consumption and settlement patterns. FUTURES is comprised of three interacting sub-models that represent key domains of land change processes: i) where development is likely to occur, ii) how much land area will convert during an interval of analysis, and iii) the spatial configuration of landscape change that emerges given historical precedent and stochasticity underlying human agency. The POTENTIAL sub-model (i) constructs the development suitability of a cell based on the relationship between land change and key socio-economic, environmental, and infrastructural factors. The use of multilevel logistic regression incorporated structure (e.g., jurisdictional, administrative, census geographies) to account for variation in higher level social and policy factors (e.g., land use policies and cultural perspectives), thereby minimizing assumptions of spatial stationarity (Pan & Bilborrow, 2005; Overmars & Verburg, 2006). The DEMAND
sub-model (ii) projects land demand of a region based on historical observation of per-capita land consumption, and RGS is a Region Growing Simulator (iii) that emulates the dynamic process of land change based upon a stochastic site selection process and a discrete patch-based region growing algorithm. The RGS simulates the conversion of undeveloped lands as development events, or “patches”, whose distribution of size and shapes matched those recorded 1996-2006 by the Landsat satellite. Only new development converting greenfields (forest, agriculture) change: previously existing development, and undeveloped forest and agricultural classes are static. FUTURES projections where dynamic and spatially interactive as they included a “development pressure” feedback loop, where patches simulated by RGS are allowed to influence neighboring undeveloped lands, thereby alters the likelihood of development in the POTENTIAL sub-model for the next step. Development pressure is estimated using a distance decay model, and has been shown to be statistically predictive of future development (Dorning et al., 2015; Meentemeyer et al. 2013).

In anticipation of FUTURES modeling, inputs quantifying the amount and structure of land use change were needed to parameterize and calibrate the model. In analyzing historical satellite imagery, Meentemeyer et al. (2013) estimated the conversion rate of 35 ha per day in the region between 1985 and 1996, and 32.5 ha per day between 1996 and 2006. Using mapped conversions, I made extrapolations of historical per capita land consumption (PCLC) trends, based on estimates of population growth provided by the NC Office of State and Budget Management (2012), projected the demand (i.e. number and area) for development (land conversion events) each year. New development was excluded from areas with known protection (e.g. parks, conservation easements) as of 2006. Given this
parameterization, I applied a calibrated FUTURES model to simulate annual business-as-usual change 2006 to 2030. From an output of 50 stochastic runs per landscape treatment, I report mean values on a random selection of 10. Using a back casting method, Meentemeyer et al. (2013) estimated accuracy of the projections at 86.7%, with error distributed along a gradient of underestimation in more urban areas and overestimations in rural areas.

The native output of FUTURES is a binary, raster map of developed/undeveloped land at the 30 meter resolution. I re-classified the single development class into four intensity classes using a scoring scheme based on three parameters determined to be significant predictors in the development of the FUTURES generalized linear model, including development pressure, road density and slope (Meentemeyer et al. 2013). Grid-based values for the three were then divided into quartiles and scored 1-4 with higher values inferring increased suitability for intensive development, after which they were summed, and the result was divided again into quantiles and scored 1 to 4. This datum was treated to an unsupervised classification: intensity was awarded based on context and expert knowledge of the region, and resulted in a plausible land cover map (Figure 1C “BAU”).

For this study, I assumed that any areas undeveloped by 2030 maintained the same land cover classes as used in the National Agricultural Statistical Services (NASS) Cropland Data Layer (CDL) in 2011, which represents a conservative projection of the agricultural landscape. I also assumed that no forest would be converted into row-crop agriculture, as well as no agricultural abandonment leading to new forests. I also assumed that once developed, land cover classes could not revert to undeveloped types.
1.3.3 Alternative urban pattern scenarios

I produced a series of scenarios suggested as sustainability solutions by the region’s envisioning programs to compare with the benchmark “business-as-usual” and each other. Suggested alternatives were deregulated growth, with expectations for dispersed, low intensity development, and infill or cluster growth, the expectation of compact and high intensity growth around existing infrastructure. However, in translating these narratives into mapped parameters I used the opportunity to make two key choices: modeled growth would be “bottom-up” rather than prescriptive or expert-based, and that I would disentangle the effects of configuration and composition through a factorial research design. The former recognizes the current absence of policy or ordinance sufficient to shift aggregated pattern in this strong property rights state. The latter allows us to explore whether it is the location of new development, or the composition, which modulates the generation of ecosystem services.

With this rationale I developed four pattern alternatives (Figure 1C) to compare with business-as-usual. I designed the first factor pair to isolate the effects of configuration. I held population growth, per capita land consumption, and patch size and shape distributions constant, and created “Sprawl” and “Infill” patterns by adjusting a site suitability parameter (“INCENTIVE”; Meentemeyer et al. 2013). INCENTIVE modifies the evenness of the development suitability surface, and parameterization flattening the suitability surface (in the case of sprawl) effectively increased the likelihood of survival and emergence of dispersed development events. In the obverse, parameterization making the suitability surface peakier
increased survival near places already highly suitable, thus clustering development events closer to, for example, transportation infrastructure.

I designed the second factor pair to isolate the role of composition. I held dispersion, population growth and patch size and shape distributions constant, and created “Increase Density” and “Decrease Density” pattern by altering PCLC. Increase Density simulated the effect of intensifying human activity on developed lands, perhaps through ordinance, whereas Decrease Density simulates a deregulatory environment. Reducing PCLC in the case of Increase Density places more individuals on less land, in effect upzoning lands, resulting in a reduction of greenfield conversions as compared to status quo. Increasing per capita land consumption means each individual in situ uses more land, and simulates more greenfield conversions along patterns referenced by the historical (1996-2006) trend, an effect likened to low density zoning, or absence of zoning ordinance.

While I applied five INCENTIVE treatments to the projections, I report on widest range values, 0.25 for Sprawl and 4.0 for Infill. Similarly, I developed five land intensity treatments and report on widest range values, 40% above and below business-as-usual per capita land consumption. To account for stochastic effects designed to mimic landowner behavior, the four pattern alternatives and business-as-usual treatments were iterated 10 times, and generated 50 regional map projections for evaluation (Figure 1C, single run illustrated).

1.3.4 Water Purification modeling

Land covers both contribute and retain on-site soluble nonpoint source pollutants (NPSP) loads, such as lawn chemicals or depositions of atmospheric pollution, up to a
dynamic threshold bounded by the amount of impervious surface, the topography-influenced speed of water, the porosity of soil, the metabolism of vegetation and climate (the combination of heat and humidity determining how well things evaporate). When those dynamic thresholds are exceeded, exported pollutants follow hydrological gradients downhill to the next area where they may be retained, passed-on or amplified. Green infrastructure has a wide capacity to purify incident rainfall and runoff without human intervention when present.

I modeled this process for the study area using the “Water Purification Nutrient Retention” module, a spatially-explicit eco-hydrological model within InVEST 3.1. I estimated per-pixel annual nitrogen (N) and phosphorous (P) pollutant balances (loading, retention and export) based on projected land cover and soil porosity, with annual climate and geophysical characteristics held constant. The Water Purification Nutrient Retention module is comprised of three sub-models employed in sequence: an eco-hydrological water yield model, a process-based nutrient cycling model, and an economic valuation model. The data needed for the water yield model, (annual precipitation, potential evapotranspiration, plant available water content, root restricting layer depth, watershed and sub-watershed boundaries) was acquired from various sources (Appendix B, Tables 1 & 2). Landcover maps were prepared as noted above. I chose a value of Zhang’s Constant value of 8 to reflect the relative evenness of precipitation throughout the year, a choice consistent with recommendations for temperate climates. I held annual rainfall and potential evapotranspiration components (annual mean temperature, annual mean relative humidity)
constant, but allowed plant available water content and root restricting layer depth to change when projected to develop.

Urban and agricultural land covers are significant sources of NPSPs, and the magnitude of loading varies by crop. My maps contained 50 cover types, including four urban types and four forest types, to which I appended empirically determined evapotranspiration coefficients, nutrient loading and vegetative filtering data added to each (Recknow 1980; Appendix B Table 2). For each pixel I estimated landcover supplied loads of N and P, as well as loading passed from upslope exports, retention, and exports in kg yr-1 cell-1. Soils were assumed to not saturate their ability to uptake nutrient loading. The Water Purification Nutrient Retention module only measures terrestrial water and non-point source nutrient balances; no subsurface contributions or in-stream processes are considered. Following Polasky et al. 2010) nutrient balances are not tracked in water bodies, and all exports are assumed to be delivered to the mouth of the watershed. Thus, the biogeochemical balances of all subwatersheds are considered independent.

I estimated hydrological gradients using biophysical factors and excluded engineered stormwater infrastructure in order to reveal ecosystem function, acknowledging a lack of information regarding the location and performance of such infrastructure in both 2006 and in projections. This choice is analogous to the use of total impervious area (TIA) by hydrologist rather than effective impervious area (EIA) when estimating regional runoff (Brabec 2002). The use of TIA has been shown to overestimate runoff volumes and infiltration (Alley and Veenhuis, 1983), however these bias may be offset by large
proportions of unconnected imperious areas (Brabec 2012) such as those observed in the study area.

Currently, non-point source pollution is not monitored or treated in the study area, however, to assess a value to N and P exports I used a fee schedule from nearby watersheds as a proxy. North Carolina’s Division of Mitigation Services administers a voluntary Nutrient Offset Program in the Neuse and Tar-Pamlico basins east of the study area. This program applies a fee schedule to non-point source nutrients N and P using an “Actual Cost Method” to estimate the cost of mitigating these pollutants (NCDENR 2015). Fees vary by area, and I took the average which billed N at a rate of $43.85 kg yr\textsuperscript{-1} ha\textsuperscript{-1}, and P at $524.30 kg yr\textsuperscript{-1} ha\textsuperscript{-1}, values held constant throughout. I assumed a linear change in purification services between 2006 and 2030, and estimated the present value of 24 years of aggregated pollution offset fees using a discounted (4%) cash flow model. All estimations are developed on an annual basis, and significant intra-annual variability, such as nutrient pulses during the growing season, is unaccounted for in the modelling.

1.3.5 Carbon sequestration

Forest and other vegetative covers use photosynthesis to actively remove atmospheric carbon and store it in tissues and soil-building organic debris, a service that in part mitigates climate-changing greenhouse gas production. I estimated both the amount and societal value of carbon sequestration by regional land covers using the InVEST Carbon Storage and Sequestration module. Estimates of stored carbon (Mg/ha) for above- and below-ground biomass stocks, soil and dead wood stocks were estimated for 2006 and 2030 scenarios using empirically derived land cover class associations (Appendix B Table 2). To facilitate
comparisons, I assumed no losses of carbon due to timber harvests over the period of analysis, or the growth of new trees, holding carbon stored in soils and biomass constant at 2011 values.

Carbon sequestration is the difference between starting and projected stocks, I used the social value of carbon sequestration at $60.00 USD per Mg, a conservative value also used in a recent ecosystem service assessment of Wake County NC (Schmidt 2012) to report dollar values. The social cost of carbon represents the marginal damage incurred for each additional ton of carbon released into the atmosphere (Ackerman and Stanton 2012). I assumed a linear change in carbon over the period of analysis, and report PV of 2030 carbon sequestration using discounted (4%) cash flow modeling.

1.3.6 Urban Biodiversity

Changes in land cover have direct implications for biodiversity (Seto et al. 2012), and urban land covers favor habitat generalists, colonizers and other species while excluding habitat specialists. In the study area “Urban Adopters” (McKinney 2008) include invaders such as coyote (Canis latrans; Wine et al. 2015) as well as many culturally and economically significant game animals such as white-tailed deer (Odocoileus virginianus). “Urban Avoiders” include forest interior birds and woodland salamanders such as the spotted (Ambystoma maculatum). The degree of intolerance for human associated disturbances is a synoptic habitat indicator developed by the USGS SE GAP (2011) as part of their effort to predict species distributions for 602 native vertebrates. The “Human Disturbance Index” (high, medium and low tolerance, and intolerant) is based on road density and development intensity covers, and while the GAP program uses the indicator to mask distributions relative
to specific species, it is used here to interactively map change introduced by projected
development pattern and facilitating post hoc assessment. Monetary values for the different
types of habitat have not been estimated, and as a consequence are not included in monetary
analyses.

1.3.7 Returns to Land Owners

Many aspects of economic development are founded in land systems. Land covers
generate income to land owners in the form of timber and agricultural production for
managed greenfields, and rents in urban areas. Forests, croplands and pastures can,
depending on management, deliver both private revenues and generate common good
ecosystem services. In contrast, development typically exchanges non-rival service goods
provided by the green infrastructure for exclusive rents. To investigate the relationship
between land-derived revenues and service provisioning by green infrastructure, I compared
returns to landowners to assessed ecosystem service valuations using discounted cash flow
models.

I estimated annual average returns to landowners for 2006 and for projected
landscapes using data from Lubowski et al. (2008) that matches land use/land cover to
revenues per unit arear. Lubowski et al. estimated cropland values from averaged county-
level market net returns for 21 crops; pasture returns from soil productivity data from NRI
and prices from NASS; timber revenues for aggregated forest types based on state and
regional prices, yields, costs and area; and urban returns based on median values of new
development, less structure, annualized at 5%. Estimates of per area urban returns for higher
or lower intensities in the increase density and decrease density alternative are unknown: in
order to compare plausible outcomes, urban land covers were weighted by a factor of 1.4 and 0.6 respectively. I converted annual returns estimated for 1988-1992 (the latest period of analysis) to 2015 dollars using a range of indicators (Williamson, 2015) and applied them to 2006 and projected landscapes on a pixel-level basis. In all cases pixel values were summed and aggregated for each subwatershed, and a discounted (4% annually) cash flow model generated present value (PV) of 2030 patterns.

1.4 Results

1.4.1 Historical and business-as-usual mapping

I mapped regional land covers in 2006 from three forms of data: Landsat TM satellite imagery, aerial orthophotography and light detection and ranging data (LiDAR; for a full description of methodologies see Meentemeyer et al. 2013). Mapping revealed 21.7% developed land covers, 52.7% forested, 7.5% cropland and 17.4% pasture lands in 2006 (Figure 1.2 B; Table 1.1). Overall classification accuracy was 86%. Population for the study area in 2006 was 1,177,507 (Census Bureau 2015), a per capita consumption rate of 0.064 developed hectares per person (Table 1.1).

Population in the study system was expected to grow 26% to 1.48 million over the next three decades (North Carolina State Demographics Office 2012). Extrapolating business as usual trends, I anticipated a per capita land consumption rate of 0.23 developed hectares (0.56 acres) by 2030. Business as usual serves as a benchmark for comparison of competing alternatives. Projections of business as usual growth estimated that by 2030 the landscape would be composed of 51.9% developed land covers, 31.5% forested, 5.2% cropland and 11.0% pasture lands (Figure 1.1C, Table 1.1) which represents a substantial restructuring of
the landscape to one dominated by low density development and associated high tolerance habitat. Conversions outpaced population growth which was estimated at 1,483,291 individuals, an increase of 26.0% over 2006, with per capita land consumption roughly doubling to 0.12 hectare per person. Associated with this change were increases in nutrient pollution loading, 22% and 30% percent for P and N respectively, and the landscape lost an average of 2,771,448 metric tons of carbon representing costs to society of $105,604,827 (Table 1.1).

1.4.2 Regional Responses to Alternative Urban Pattern Scenario

Table 1.1 aggregates the differential response of green infrastructure to simulated urban pattern alternatives (Figure 1.1 C). All projections of future landscape patterns are estimated to increased exports of nutrient pollution, reduce terrestrial carbon stores, and lead to new disturbed habitat regimes (Figures 1.2, 1.3). I found that while urban form and development rates differentially influenced ecosystem service provision, no single urban form simultaneously reduced pollution, stored carbon, and retained sensitive habitat. Increased density yielded stronger financial returns to landowners as concentrated economic activity drove up land rents while minimizing broader pollution costs, as compared to a low-density business-as-usual (Figure 1.4).

In the first comparison pair, where configuration was adjusted and composition was held constant, the sprawl alternative resulted in less N and P NPSP exports than Infill (and all other alternatives except increase density), an effect estimated to save $16.5 million over the period of analysis (Figure 1.2). While all alternatives were predicted to lose stored carbon by 2030, sprawl retained significantly more than business-as-usual, and the other scenario in
which population growth and per capita land consumption was held constant, Infill. However sprawl converted the most “intolerant habitat” of all scenarios (Figure 1.3) and was expected to generate slightly less revenue for landowner (Figure 1.4).

Infill clustered growth around previously developed and thereby retained the maximum area of habitat for human-intolerant species. It also generated slightly more landowner revenues. However this alternative was the second highest polluter, behind Decrease Density, and lost the most the most carbon of all alternatives considered. The Infill alternative increases the contiguity of impervious surfaces, reducing opportunities for the absorption or uptake of nutrient pollution. Infill sequesters less carbon because it converts relatively more forest (Table 1.1). Forests store more carbon than cropland and pasture greenfields, and in this historically agricultural landscape, the fast growing forests of the Southeast are found proximal to development due to decades of urban-driven agricultural abandonment.

In the second factorial pair where configuration was held constant, Increase Density polluted less than Decrease Density, and compared with other scenarios, sequestered the most carbon, generated the most revenues, and was the second highest conserver of habitat for intolerant species behind infill (Figure 1.3). The decrease in per capita land consumption resulted in fewer greenfield conversions, and this alternative was estimated to avoid over $70 million of costs associated with offsetting NPSP and carbon emissions as compared to business-as-usual (Figure 1.4) most likely because growth occurred without aggregating impervious surfaces. Revenues increased 17.6% over business-as-usual, reflecting the estimated intensification of human activity generation within constrained expansion.
Increasing per capita land consumption has the effect of increasing greenfield conversions without concurrent increases in intensity, making it unsurprising that the Decreasing Density alternative generated the highest environmental costs (Figure 1.4), second highest loss of habitat for intolerant species, and the lowest returns to landowners (Table 1.1), for the services examined. However more carbon was retained in this alternative than Infill as the historical trend in pattern was somewhat dispersed from existing development, and thereby converted less forest. The decrease in returns to land owners simulates the effect of diluting human activity.

1.4.3 Landowner revenues and trade-offs

One way to examine trade-offs is to compare environmental costs with landscape generated revenues. When estimated revenues are compared with the suite of examined environmental costs, the increase density alternative had the highest monetary performance (Figure 1.4). However, the increase density alternative polluted the least and sequestered the most carbon, and at $1,047 million in ecosystem services costs, conserved the second highest amount of habitat for human intolerant species (Figure 1.5). This compares favorably with decreased density, which polluted the second most and generated the least revenue to landowners. Sprawl performed unexpectedly well, incurring the second lowest ecosystem services costs. The enigma is infill. Infill represents the primary planning tool underpinning many smart growth-type development, but these result indicate it is the prime polluter, possibly due to consolidation of impervious surfaces, and consumer of carbon, most often in form of urban fringe trees and their rich soils. That said, modest increases over status quo in land owner revenues place it behind increase density as the second highest monetary
performer (Figure 1.4). Finally, infill conserved the highest amount of habitat for human intolerant species, 16,000 ha more on average than increase density. If these lands were valued at $250,000 per hectare, or about $102,000 per acre, the monetary performance would be even.

1.4.4 Nested Analyses: Subwatershed Responses to Alternatives

Regionally, scenarios that isolated landscape configuration (i.e. sprawl and infill) were not found to differ significantly from business-as-usual in how green infrastructure mediated biogeochemical balances (Table 1.1). To investigate further I looked at these balances at subwatershed scales. Of the 37 subwatersheds in the region, 18 exported significantly (p = 0.05) more or less nitrogen than the benchmark business-as-usual; similarly 17 were significantly different for phosphorus exports, and 14 for carbon sequestration (Figure 1.5). In most cases subwatershed responses offset each other when aggregated regionally, obscured the effect of configuration oriented alternatives on the green infrastructure services.

When I control for magnitude of change on specific subwatersheds, I found 56% demonstrated sensitivity to configuration for one indicator, 48% to two and 27% to all three (Figure 1.6). This analysis reveals that location, rather than composition, is a key determinant as to whether a sustainability-oriented urban pattern prescription pollutes more or less a laissez-faire approach.

1.5 Discussion

Anticipating the aggregated impacts that emerge from individual development events has constituted a key challenge to planners and environmental management, and in this
absence of understanding, society has leaned heavily on site-level building codes and local ordinance to protect common pool resources. This research suggests that while composition of new development remains important, the specifics of how development is spatially configured across a landscape has consequences for water quality, retention of climate-changing carbon, and habitat for charismatic animals. It’s not just what it is, it’s where it is.

To be clear, all alternative futures tested resulted in more pollution, losses of carbon, and irreparable changes to habitat as compared with a fixed starting point. Simulations of projected urban growth estimate that by 2030 nutrient pollution exports to surface waters across the region may increase over 65%; that we will lose over 2 million metric tons of stored carbon from our forests and soils, and we will flip the composition of landscape from one dominated by low human disturbance habitat to one of overwhelmingly high disturbance. The clearest signal comes from the loss of forests, and landscapes where they are lost incur the highest ecosystem services costs. Forests add moderate amounts of P and N to the landscape, but by storing carbon in wood and debris, their metabolic uptake, evapotranspiration and possibly flow-slowing width along hydrological gradients modulate the regulation of nutrient export and carbon loss. In contrast to the environmentally dreary prognosis is the likelihood that landowners will be making much more money, the region generating more than 24 times current returns as conversion replaces low-yielding forests and pastures for high yield urban covers.

Given this significance of configuration, is there a possibility of benign urban growth through planning? No single urban form simultaneously reduced pollution, stored carbon, and retained sensitive habitat, but the study clarifies three points: 1) the need to recognize
combinatorial effects of composition, configuration, and time; 2) the fallacy of “one size fits all”; and 3) the utility of spatially explicit analyses.

First, there is a need for systemic understanding the combinatorial effects of composition, configuration, and time. The estimated impacts of development pattern were generated from interactions of land use composition (specific land use / land cover and magnitude of change) and configuration (location and geographic context), and time (when did it happen, aggregated effect), and each of these dimensions should be managed to produce desired effects, not just composition which is the typical planning tool represented by zoning. Moreover, these key factors (composition, configuration and time) are not independent, and are instead highly path dependent given a starting time step and trajectory. New development fits into existing patterns of growth, and can aggregate to new pattern or condition the fate of undeveloped areas. Bendor et al. (2013) found that relatively low amounts of urban growth made woodland owners in rural communities more inclined to sell land to developers.

“One size fits all” prescriptions, such as deregulation or infill are demonstrated to have the unintentional effect of increasing N pollution in more than half of the subwatersheds in the region, while at same time decreasing pollution, the desired effect, in one-third. In similar fashion, these results “flip” for a low density sprawl prescription, and for P and carbon to a lesser extent. I found landscape structure and configuration was a major driver of nutrient export, and flip-flop patterns of contrary response is due to configurational sensitivity of green infrastructure to development, leading to the conclusion that “place matters”, specifically the location of new development along eco-hydrological gradients.
Third, that in all cases the explicit consideration of scale is warranted, as development events are unique in time and space, but frequently aggregate to form patterns that transcend jurisdiction. In this study a simple regional aggregation of impacts masked the differential, and frequently counter-indicated responses of individual subwatersheds. Given that environmental impacts of pattern follow natural gradients and ignore jurisdiction, I suggest acquiring a synoptic understanding of the context and topology of the landscape matrix as part of regional planning. Ultimately planning for such a limited suite of ecosystem services is far from responsible, however I found certain urban patterns such as Increasing Density retained green infrastructure function better than others while accommodating projected population growth, suggesting a pragmatic way forward to limit impacts associated with development and maximize sustainability.

1.6 Conclusion

I used an integration of spatial modeling throughputs to estimate green infrastructure services in a complex, urbanizing landscape at two time steps. Projections of future landscape patterns are estimated to greatly increased exports of nutrient pollution, reduce terrestrial carbon stores, and lead to new human disturbed habitat regimes. Loss of forest is insinuated as a leading driver of nutrient pollution export. Subwatershed exhibited differential responses to alternative land system architectures, and both composition and configuration influenced landscape performance. Monetary analyses suggest land cover generated revenues are adequate to offset some environmental costs, but non-substitutable goods such as habitat remain outside of costs comparisons. I suggest that analyses leading to sustainable landscape solutions are necessarily spatial, that place matters especially in the
context of biophysical gradients, and that representation of both composition and configuration of land covers are needed to develop effective strategies to maintain water quality in the future. Finally, for landowners and local governments, my work suggests that increased density also increases financial returns in the face of reduced pollution costs.

Tables

Table 1.1 Ecosystem Services Associated with Landscape Composition, Pattern and Change (2006-2030). Business-as-usual (BAU) is taken as the mean values of 10 model runs. All other values are given as percentage change from BAU.

<table>
<thead>
<tr>
<th>Land Cover (ha)</th>
<th>Start period (2006)</th>
<th>BAU</th>
<th>Sprawl</th>
<th>Infill</th>
<th>Increase Density</th>
<th>Decrease Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Development (change)</td>
<td>75,208</td>
<td>179,874</td>
<td>-4,247</td>
<td>3,384</td>
<td>-19,007</td>
<td>18,816</td>
</tr>
<tr>
<td>Forest (change)</td>
<td>182,633</td>
<td>109,048</td>
<td>1,065</td>
<td>-3,989</td>
<td>15,345</td>
<td>-13,443</td>
</tr>
<tr>
<td>Cropland (change)</td>
<td>25,815</td>
<td>17,855</td>
<td>453</td>
<td>730</td>
<td>1,342</td>
<td>-1,446</td>
</tr>
<tr>
<td>Pasture (change)</td>
<td>60,348</td>
<td>37,751</td>
<td>2,685</td>
<td>-68</td>
<td>4,027</td>
<td>-3,847</td>
</tr>
</tbody>
</table>

| Social Metrics          | Estimated Population (change) | 1,177,507 | 1,483,291 | -34 | -182 | -466 | -465 |
| Per Capita Land Consumption (ha/person) | 0.0639 | 0.1213 | 0.1184 | 0.1236 | 0.1085 | 0.1340 |

| Carbon                  | Carbon Sequestration 2006-2030 (change) | 48,873,449 | 46,102,001 | 199,617* | -791,436* | 492,908* | -470,460* |
| Present Value SCC 2006-2030 (thousands $USD) | na | $-105,605 | $7,612* | $30,156 | $18,780* | $17,925* |

| Nitrogen (kg)           | Annual N Loading (change) | 1,173,997 | 1,436,385 | -11,108 | 23,585 | -46,154 | 44,137 |
| Annual N Retention      | 806,358 | 820,105 | 2,854 | -12,172 | 1,336 | -4,209 |
| Annual N Export         | 367,638 | 616,279 | -13,962 | 35,758 | -47,490* | 48,346* |
| N Accumulated Exports 2006-2030 | na | 11,807.0 | 167.54 | 429,091 | 569,883 | 580,157* |
| Present Value of Offset costs N 2006-2030(Millions $USD) | na | $328,883 | $-4,667 | $11,952 | $15,874* | $16,160* |

31
Table 1.1 Continued

<table>
<thead>
<tr>
<th>Phosphorus (kg)</th>
<th>Annual P Loading††</th>
<th>Annual P Retention</th>
<th>Annual P Export</th>
<th>P Accumulated Exports 2006-2030</th>
<th>Present Value Offset cost 2006-2030 (Millions $USD)</th>
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<tr>
<td></td>
<td>190,264</td>
<td>128,496</td>
<td>61,768</td>
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<td></td>
<td>248,491 (30.6%)</td>
<td>139,382 (8.5%)</td>
<td>109,109 (76.6%)</td>
<td>2,050,513</td>
<td>682.995</td>
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<td>-2,688 (-1.1%)</td>
<td>376 (0.27%)</td>
<td>-3,064 (-2.8%)</td>
<td>-36,768 (-1.8%)</td>
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<td>7,217 (2.9%)</td>
<td>-685 (-0.49%)</td>
<td>7,903 (7.2%)</td>
<td>94,833* (4.6%)</td>
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<td>-10,187 (-4.1%)</td>
<td>-1,252 (-0.90%)</td>
<td>8,935 (8.2%)</td>
<td>-107,216* (-5.2%)</td>
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<td>9,637 (3.9%)</td>
<td>616 (0.44%)</td>
<td>9,022</td>
<td>108,258* (5.3%)</td>
<td>36.059*</td>
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<table>
<thead>
<tr>
<th>Habitat (Ha)</th>
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<td>High Tolerance Habitat</td>
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<td>194,482 (507%)</td>
<td>11,412 (-62.6%)</td>
<td>83,792 (-47.7%)</td>
<td>56,670 (-54.2%)</td>
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<tr>
<td></td>
<td>-7,858 (-4%)</td>
<td>2,322* (20%)</td>
<td>19,584* (23%)</td>
<td>14,048* (-25%)</td>
<td></td>
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<tr>
<td></td>
<td>-8,385 (-4%)</td>
<td>-2,584* (-23%)</td>
<td>- *</td>
<td>25,002* (44%)</td>
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</tr>
<tr>
<td></td>
<td>18,888.1* (3%)</td>
<td>1,554.67* 14%</td>
<td>8,386.37* (-8%)</td>
<td>8,947* (16%)</td>
<td></td>
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<td></td>
<td>15,612.51* 8%</td>
<td>1,209.65* (-11%)</td>
<td>6,948.44* (-8%)</td>
<td>-7,454.42 (-13%)</td>
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<th>Returns to Land Present Value Revenues 2006-2030 (Millions $USD)</th>
<th>$970.34</th>
<th>$23,937.55</th>
<th>$311.94</th>
<th>$4,204.27*</th>
<th>$5,619.96*</th>
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<tr>
<td></td>
<td>$-389.14 (-1.6%)</td>
<td>$311.94 (1.3%)</td>
<td>$4,204.27*</td>
<td>$5,619.96*</td>
<td>$-23.5%</td>
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Figure 1.1 Charlotte Metropolitan Study System. A) Charlotte NC is part of the Char-lanta megalopolis. B) 37 HUC-12 digit subwatersheds sampled along an urban gradient extending from more urbanized west to the more rural east. C) detail of business-as-usual (BAU) and alternative futures projected for the region.
Figure 1.2 Scenario analyses of ecosystem service (ES) costs 2006-2030 in $USD (2015). Costs are the present value of aggregated pollution offset fees and terrestrial carbon losses estimated using a discounted (4%) cash flow model.
Figure 1.3 Scenario analyses of habitat area projections for 2030. Habitat was classified using the human disturbance index (USGS SEGAP 2011)
Figure 1.4 Scenario analyses of ecosystem services costs and projected returns to landowners attributed to land cover revenues 2006-2030 in $USD (2015). Revenues are the aggregated annual returns of rents, timber sales and agricultural yields estimated using data from Lubowski et al. (2008). Present value is estimated using a discounted (4%) cash flow model. Environmentally adjusted revenues are the present value of projected land cover revenues minus the present value of aggregated pollution offset fees and terrestrial carbon losses (Figure 2).
Figure 1.5 Local change in ecosystem services attributed to land cover configuration.

Symbolization indicates response “flipped” from positive to negative (as compared to status...
quo) based on development configuration. Ecosystem service are exports of A) Nitrogen and B) Phosphorus in kg yr\(^{-1}\) ha\(^{-1}\); C) is Carbon storage in Mg yr\(^{-1}\) ha\(^{-1}\).

Figure 1.6 Subwatershed sensitivity to configuration. Of the 37 HUC-12 subwatersheds, 18 exported significantly (p = 0.05) more or less nitrogen than the benchmark business-as-usual; similarly 17 were significantly different for phosphorus exports, and 14 for carbon sequestration. 56% demonstrated sensitivity to configuration for one indicator, 48% to two and 27% to all three.
CHAPTER 2: STRUCTURAL EQUATION ANALYSIS OF THE ROLE OF URBAN PATTERN IN GENERATING ECOSYSTEM SERVICES

2.1 Abstract

Development pattern, such as urban sprawl, has been widely implicated in driving environmental degradation and compromising ecosystem resilience. However, a lack of concise theory regarding urban pattern and process, and the paucity of representative case study, has left the role of spatial structure in modulating ecosystem function largely unexplored. I tested the capacity of leading theory to explain the role of spatial heterogeneity in modulating urban ecosystem function by first translating a conceptual model of urban impact into a testable structural equation model (SEM). This step distinguished four spatial pattern domains rendered as latent variables representing composition, configuration, connectivity, and land use intensity. I then examined model response to estimates of non-point source pollution (N, P) and carbon storage generated by scenarios of urban growth in the rapidly developing Charlotte (NC) region over a 24 year interval. This data was generated using a novel integration of land change and ecosystem services simulations. I statistically evaluated correspondence between simulated estimates and latent variables and iteratively arrived at a model ($r^2_{adj} = 0.79$) that found heterogeneity in composition most influential ($\beta_{std} = -0.58$) in the generation of nutrient non-point source pollution (NPSP), followed by connectivity ($\beta_{std} = 0.28$) and heterogeneity of configuration ($\beta_{std} = -0.15$). Land use intensity, a measure of local change, had insignificant direct effect, but moderated all other effects. Purification function varied with the configuration of new development, evidence that ecosystem resilience was spatially conditioned. To reduce NPSP regionally, planners are
advised to manage amplifying effects of greenfield conversions by maintaining land cover diversity, and limit the connectivity of developed land covers along hydrological gradients.

2.2 Introduction

Worldwide, human well-being depends on a wide suite of services provided by functioning ecosystems (UN, 2005). Growing urban populations, obligate on the stable generation of these services both in situ and in the urban footprint (Rees and Wakernagel 2008), are particularly vulnerable when these benefits breakdown in response to sudden or chronic landscape change (Smith et al. 2009; Collins et al. 2011). Urbanization, a term here used to describe the pattern and process of anthropocentric growth manifested as conversion of greenfields to development (Ewing 2002; Ewing and Hamidi, 2014), is the primary agent of landscape change worldwide (Haddad et al., 2015). Urbanization has been shown to change the state factors underpinning ecosystem function (Eigenbrod et al., 2011; Revi et al. 2014), and made urban and periurban landscapes places of environmental uncertainty (Voogt & Oke, 2003; Pyke et al. 2011; McKinney, 2006; Bowen & Valeila 2001).

In contrast to these risks, the advantages created by urban development (e.g. housing, economic opportunity) make urbanization the dominant land change trend for the foreseeable future (Glaser 2011). The trade-offs presented by positive and negative aspects of urbanization represent a dilemma to decision makers and planners charged with simultaneously accommodating growth while conserving the environmental aspects of public health (Wu & Wu, 2013). Given that trajectories of environmental impact associated with urban expansion are likely to continue (Lawler et al. 2014), then it becomes productive to explore the role of spatial heterogeneity, not just magnitude of change, in the generation
ecosystem services. A process-based understanding of the relationship between landscape heterogeneity and ecosystem provisioning is needed to provide the basis from which trade-offs and alternative strategies can be evaluated (Turner MG et al. 2013). Given that few studies to date have used alternative futures of growth to project local- to regional-scale ecosystem response to urban growth, with the notable exception of Nelson et al.(2009), anticipating (and avoiding) the indirect, combinatorial and accumulated environmental impacts remains a key challenge to sustainable development (United Nations, 2013).

Despite the growing number of models relating urban pattern to landscape performance (e.g. Ramalho and Hobbs 2011; for a review, Wu 2014) concise theory regarding the nature of spatial heterogeneity is needed to guide studies of urban pattern and process, and inform the management of ecosystem services (Turner et al. 2013). Conceptually, the relationship between spatially heterogeneity and ecological response is long established (Pickett and Cadenasso 1995; Wiens 2002). The widest application of this concept has focused on the role of fragmentation in compromising ecosystem function (Theobald, 2003; Zhou, Huang, Pickett, & Cadenasso, 2011). However, operational definitions of fragmentation have been fraught with ambiguity: fragmentation is alternately considered a mechanism and effect of urbanization. When distinguished from the effect of land cover or habitat loss (Smith et al. 2009) fragmentation can infer variety of composition, complexity of configuration, losses of connectivity or combinations of all three (Didham, Kapos, & Ewers, 2012). Lindenmayer and Fisher (2006) call fragmentation the “panchreston problem”, and blame the overly-broad and often vague usage of the term for shrouding
specific mechanisms of harmful effect, hampering the development of management strategies to manage deleterious effect.

Among other conceptualizations of spatial heterogeneity, structural changes in composition (e.g. land cover type and proportion) has also been widely assumed to drive ecosystem function (Lautenback et al. 2011). However, configuration (e.g. size, shape and connectivity) is theorized to play an important role also (Petrosillo, Zaccarelli, & Zurlini, 2010), and evidence of the importance of connectivity is mounting as seen in analysis of agricultural systems (Mitchell et al. 2013). This illustrates the need to disentangle heterogeneity, composition, and configuration in order to understand which types and amounts of spatial heterogeneity that promote sustainability (Turner MG et al. 2013).

In their conceptual model of urban ecosystem impact, Alberti et al. (2003, 2005) provided a degree of disentanglement by orienting fragmentation as a mechanism of ecosystem impact driven by pattern domains within spatial heterogeneity. Much like Fahrig and Nuttle (2005), Alberti et al. distinguish between heterogeneity of composition (land use diversity [sic]) and configuration (urban form [sic]). Alberti et al. also include pattern domains connectivity and land use intensity, theorizing that in urban systems these aspects of development pattern are critical to ecosystem function. However, the theory implicit in this conceptual model remain largely untested, due in part to a lack of case studies with adequate controls to isolate pattern (Alberti 2010), a lack of clear, landscape driven meaningful responses, and entanglement of correlated and replicated behavior of the landscape metrics.

The goal of this study was to identify and test the pattern domains of spatial heterogeneity suggested by Alberti et al. and examine their role the production of ecosystem
services in an urbanizing region, estimating how development pattern and associated fragmentation may effect water purification and carbon sequestration. In a case study of projected growth for rapidly expanding Charlotte NC I asked:

1) Are ecosystems sensitive to urban pattern independent of magnitude of change? If I isolate fragmentation as mechanism (rather than an effect or response) by using landscape simulations to control for land cover loss, can then I then quantify a response uniquely linked to spatial heterogeneity?
2) What aspects of spatial heterogeneity effect ecosystem service production? Does test data support the decomposition of spatial heterogeneity into pattern domains relevant to the system? Which metrics best describe those domains?
3) What is the strength and directionality of effect between hypothesized pattern domains and ecosystem services?

To explore the role of urban pattern in ecosystem function I first summarized and translated the conceptualizations of Alberti et al. (2003, 2005) into a causal diagram for testing using structural equation modeling. This step generated testable hypotheses by decomposing heterogeneity into structural types associated with fragmentation, and formalizing suspected relationships between these types and simulated landscape effect using latent variables. I then conducted structural equation analyses by challenging the hypotheses with ecosystem response data simulated for a rapidly urbanizing region using an integrated urban growth ([FUTURES] Meentemeyer et al. 2012) and ecosystem services models ([InVEST 3.1] Natural Capital, 2014). Specifically, carbon storage and non-point source nitrogen and phosphorus pollution in the fast growing Charlotte (NC) metropolitan region
were estimated from land cover simulations for the interval 2006-2030. Scenario simulation
design referenced status quo trends to control for magnitude of change or dispersion of new
growth, generating a dataset of ecosystem response representative of a range of plausible
growth outcomes. Analyses were conducted at a HUC-12 subwatershed extents (USGS
2006), allowing us to sample pattern and effect along the regional urban to rural gradient. I
tested the directionality and overall strength of hypothesized linkages between pattern
domains and ecosystem response, and explored variation in response attributed to spatial
configuration, an indicator of spatial resilience. From this study I hope to identify the
characteristics of spatial heterogeneity that will enhance or impede production of different
ecosystem services (Turner et al. 2013).

2.3 Methods

2.3.1 The development of a structural equation model

Alberti et al. (2003, 2005) introduced an influential conceptual framework for the
study of urban land systems that related urban form to ecosystem function, and proposed that
pattern, working through mechanisms such as fragmentation, impacted ecosystem function.
Alberti posited that pattern components salient to landscape-scale effect were land use
heterogeneity, land use connectivity, land use intensity, and urban form, and ecosystem
responses included nutrient cycling, biodiversity, disturbance, and primary productivity. I
translated this conceptualization into its simplest prediction, holding aside functional
dimensions of fragmentation and choosing nutrient cycling as a response, to specify a
structural equation causal diagram linking pattern with ecosystem response (Figure 2.1).
SEM is a method is used to infer causality between (Hair 2011) allowing researchers to test
theory and concepts (Pearl 2009) and examine model fit for developed hypotheses. SEM facilitates the translating scientific ideas into testable form (Grace et al 2006) by using graphic diagramming to both hypothesize linkages (“paths”) between variables, and ultimately to estimate the strength, directionality and significance of those effects. SEM also accommodates collinearity between variables, and allowed us to statistically evaluate correspondence between latent variables and response variables generated from My data, a useful characteristic in this study were I expected landscape metrics to produce multiple quantification of pattern, e.g. the obverse relationship between cohesion and dispersion (Li & Wu, 2004; McGarigal, Cushman, Neel, & Ene, 2002). The development of the causal diagram was an opportunity to summarize, translate and formalize conceptualizations of theory in a format that was initially noncommittal as to the particulars of functional form (Grace et al. 2012).

In translating the Alberti et al. model, isolating domains that comprise structural fragmentation required classifying heterogeneity as conceptualized into types. Following Fahrig and Nuttle (2005) I interpreted Land Use Heterogeneity and Urban Form as descriptions of heterogeneity of composition and heterogeneity of configuration, respectively (Figure 2.1). In the former, concept of diversity is useful to describe both richness of patch types, and the relative evenness or dominance of a patch mosaic. For the latter, the degree of dispersion, interspersion or aggregation describe a landscape texture that considers isolation, cores, and contrasts. Given these two perspectives of the same landscape, encroaching urbanization is expected to fragment greenfield composition, decreasing richness and evenness with delirious effect on an ecosystem’s ability to store carbon and purify water with
infiltration, evapotranspiration and vegetative uptake (H1, Figure 2.1). Fragmentation of greenfield configuration is anticipated to create landscapes that are more dispersed and less patch isolation, changes whose effect on carbon and nutrient cycling is unclear (H2, Figure 2.1).

Urbanization is also expected to increase overall connectivity between developed and undeveloped covers as greenfields are dissected with impervious covers along functional gradients (e.g. hydrological) which may place net nutrient loaders proximal to stream and other water features, reducing opportunities for infiltration and vegetative uptake, increasing export (H3, Figure 2.1). The intensification of land use associated with urban forms is in many cases a disturbance (e.g. soundscapes Barber et al., 2011) that goes beyond the state change that occurs with land conversion, and is often accompanied by land covers that dramatically change the nature of stored carbon (Raciti, Hutyra, Rao, & Finzi, 2012) and load nutrients in the form of waste, fertilizers, and atmospheric deposit of air pollution (H4, Figure 2.1).

2.3.2 Study System

The greater Charlotte (NC) metropolitan area is North Carolina’s most urbanized region, experiencing rapid growth in both population and development over the past three decades, with roughly a third of total land area indicated as developed land covers in 2006 (Figure 2A, B; Meentemeyer et al. 2013). The region projected to grow an additional 1.2 million people (50%) by 2030 (North Carolina State Demographics Office 2009), yet recent remote sensing analyses of the fast growing region (Figure 2B) revealed significant private woodlands (regional canopy coverage > 25%) at or behind the urban frontier, one of the
highest in the nation for medium to large cities (American Forests 2010). The region sits at a mean elevation of 218 m, and the rolling terrain reaches a maximum 289 m, and is naturally forested with mixed deciduous/coniferous and Oak/Hickory/Pine upland types, and the clay soils are mostly prime farmland, but highly erodible. I selected 37 HUC 12 sub-watersheds along an urban gradient, and the 346,000 ha extent was extended by 1,000 meter buffers to reduce boundary effects in analysis.

In preparation of analyses I mapped the region at five roughly decadal time steps 1976-2006 using historical Landsat MS and TM satellite imagery, aerial orthophotography and LiDAR data (Meentemeyer et al. 2013). Classification was conducted using vegetation-impervious surface-soil (VIS) subpixel unmixing, a methodology shown to be effective in mapping heterogeneous urban landscapes (Lee and Lathrop 2005; Gluch and Ridd 2010). Land cover classes for the region were taken from Singh et al. (2012) and included development, managed clearings, forest, farmland, water and barren land.

2.3.3 Data Development: Urban Pattern Scenarios

Simulation modeling of land cover change has the potential to both generate cases studies and provide insights into ecosystem function beyond empiricism through their ability to undertake experiments in alternative futures (Rounsevell et al. 2012). To generate a representative sample of subwatersheds that exhibit a plausible range of fragmentation and urban pattern I used the future urban-regional environment simulation ([FUTURES] Meentemeyer et al. 2013; Appendix A) to generate land cover scenarios for two series of controlled complexity experiments designed to isolate composition and configuration. FUTURES is a dynamic, patch-based stochastic model that reliably simulates urban structure.
and fragmentation (Meentemeyer et al. 2013). Series 1 held the area changed by 2030 constant (relative to Status Quo) over 30 stochastic iterations but alters a dispersion parameter to produce scenarios of Infill growth or Sprawl. Series 2 holds the dispersion parameter constant relative to Status Quo over 30 stochastic iterations but increases the amount of growth to produce scenarios of Increase Density or Reduce Density (Meentemeyer et al. 2013, Dorning et al. 2015). In all cases, only developed land cover classes (high, medium, low, developed open space) change: all other land covers not converted to development are held constant including croplands (USDA-NASS 2012) and forest canopy (Singh et al. 2014).

Each FUTURES realization of landscape has a unique frontier of urbanization, a unique distribution of population and unique configuration of habitat attributes. I located the frontier each alternative by locating areas of projected new development between 2006 and 2030 using a moving window analyses that area of change in a 1 km$^2$ neighborhood, an extent found to be a significant predictor of new development (Meentemeyer et al., 2013). I also developed pixel-based population density maps using dasymetric mapping techniques (Sleeter and Gould 2007) to integrate extrapolations of census-based population with maps of future development.

Landscape analysis was conducted for the 10 randomly selected runs from five scenarios, e.g. Status Quo, Infill, Sprawl, Increase Density, and Reduce Density. Four landcover-based patch types were considered: developed, forest, high intensity agriculture (croplands), and low intensity cropland (pasture, hayfields). FRAGSTATS (McGarigal 2002)
was used to generate compositional, configurational and connectivity metrics (Appendix C Table 1).

2.3.4 Data Development: Ecosystem Services

Eco-hydrological modeling was performed using the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Water Purification module and the data referenced in Appendix B Table 1. InVEST is a tool for ecosystem service assessment to support environmental decision-making developed in 2007 by Stanford University, the World Wide Fund for Nature and the Nature Conservancy and features a suite of models designed to quantify ecosystem service at landscape scales. I used the Water Purification module to model per 30 m pixel balances (Kg ha\(^{-1}\) yr\(^{-1}\)) of nitrogen (N) and phosphorus (P). Water Purification is comprised of three sub-models employed in sequence: an eco-hydrological water yield model, a process-based nutrient cycling model, and an economic valuation model. InVEST reduces all bio-physical processes into one land cover class dependent export coefficient, and in this way generalizes local effects that may be relevant to how nutrient cycles operate on a specified landscape. Estimations are developed on an annual basis, and significant intra-annual variability, such as nutrient pulses during the growing season, is unaccounted for in the modelling. In-stream processes, and point source pollution, are not considered by the model, and for this study I held climate variables constant over the analysis interval. I estimated the amount of carbon sequestration by regional land covers using the InVEST Terrestrial Carbon model. Estimates of stored carbon (Mg/ha) for above-
and below-ground biomass stocks, soil and dead wood stocks for using empirically derived land cover class associations (Appendix B Table 2).

I integrated FUTURES and InVEST modules by passing inputs of alternative land cover maps. The study extent contained 50 cover types, including four urban types and four forest type, to which I appended empirically determined evotranspiration coefficients, nutrient loading and vegetative filtering data added to each (Recknow 1980; Appendix B Table 1). Agricultural land covers are primary sources of NPSPs, and the magnitude of loading varies by crop. To capture field-level agricultural covers I used the National Agricultural Statistical Services (NASS) Cropland Data Layer (CDL) for 2011 at a native resolution of 30 m.

My unit of analysis was the HUC-12 subwatershed, and there are 37 within the study area that fall along a polycentric urban gradient. As the stochastic land change model iterates 10 times per treatment, I selected a central response rather than means, as many of the responses are non-continuous indices and proportions. This resulted in \( n = 185 \). A detailed description of land change and ecosystem services models applied is presented in Appendices A, B.

2.3.5 Testing the structural equation model

I tested whether data supported the hypothesis implicit in the causal diagram (Figure 1) by developing an initial SEM populated with indicators I thought would best characterize the latent variables (Figure 2.3; Appendix D Table 1). I standardized the data based on standard deviations to allow comparison between the varieties of raw units (percentages, continuous indices, and measures), facilitating the interpretation of beta coefficients, and
illustrating relative influence of partial regression coefficients on pathways. My observed effects was specified as annual mean exports of N and P by subwatershed (Kg ha\(^{-1}\) yr\(^{-1}\)), and carbon storage by subwatershed (Mg ha\(^{-1}\) yr\(^{-1}\)). Landscape pattern indicators were generated from projected landscape pattern using FRAGSTATS (McGarigal 2002), and I modeled the urban frontier and population density specifically for this analysis (Table 2.1). I include the covariate latent variable “Physical”, populated by values from a flow accumulation model (GRASS, 2006), to control for hydrological gradients, and test whether findings were confounded by one subwatershed being steeper, or more hydrologically connected, than another.

Following guidelines suggested by Grace et al. (2012), I evaluated the initial, over-specified structural equation diagram represented by Figure 3 using WarpPLS (Kock 2013) SEM software. WarpPLS is based on partial least squares regression (PLS) and has the unique ability to identify non-linear relationships between latent variables and adjust path coefficients to reflect fit. Prior to analyses all data was standardized based on standard deviations to allow comparison between the varieties of raw units and to facilitate the interpretation of beta coefficients, illustrating relative influence of partial regression coefficients on pathways. I developed a specific SEM by iteratively removing non-significant variables and paths (Grace 2010) and exploring alternative linkages including moderated effects.

2.4 Results

2.4.1 Land cover mapping and projections of alternative futures of urban growth
I mapped regional land covers in 2006 from three forms of data: Landsat TM satellite imagery, aerial orthophotography and light detection and ranging data (LiDAR; for a full description of methodologies see Meentemeyer et al. 2013). Mapping revealed 21.7% developed land covers, 52.7% forested, 7.5% cropland and 17.4% pasture lands in 2006 (Figure 2.2 B; Table 2.1). Overall classification accuracy was 86%. Population for the study area in 2006 was 1,177,507 (Census Bureau 2015), a per capita consumption rate (PCLC) of 0.064 developed hectares per person (Table 2.1).

Status quo serves as a benchmark for comparison of competing alternatives. Projections estimated that by 2030 the landscape would be composed of 51.9% developed land covers, 31.5% forested, 5.2% cropland and 11.0% pasture lands (detail, Figure 2.2C; Table 2.1) which represents a restructuring of the landscape to one dominated by low density development and associated high tolerance habitat. Conversions were expected to outpaced population growth, which was estimated at 1,483,291 individuals, an increase of 26.0% over 2006, with PCLC roughly doubling to 0.12 hectare per person. Associated with this change were increases in nutrient pollution loading, 22% and 30% percent for P and N respectively, and the landscape lost an average of 2,771,448 metric tons of carbon (Table 2.1).

In the first comparison pair, where configuration was adjusted and magnitude of change was held constant, the sprawl alternative resulted in less N and P NPSP exports than Infill (and all other alternatives except increase density; detail Figure 2.2C). While all alternatives were predicted to lose stored carbon by 2030, sprawl retained significantly more than status quo, and the other scenario in which population growth and PCLC was held constant, Infill. Infill clustered growth around previously developed, however this alternative
was the second highest polluter, behind Decrease Density, and lost the most the most carbon of all alternatives considered.

In the second factorial pair where configuration was held constant, Increase Density polluted less than Decrease Density, and compared with other scenarios, sequestered the most carbon. The decrease in per capita land consumption resulted in fewer greenfield conversions. Decreasing Density alternative generated the second highest amount of NPSP, yet more carbon was retained in this alternative than Infill

2.4.2 Structural Equation Analysis

Model-data discrepancies led us to revise my initial SEM over a series of steps before reaching a final form (Figure 2.4). This model accounted for 79% of the variance in simulated non-point source nutrient pollution using metrics of pattern from land cover maps. In PLS SEM fit may be assessed using Tenehause’s goodness of fit index (GoF; Tenenhause et al. 2005), and at 0.878, the model’s explanatory power is high according to thresholds published by Wetzels et al. (2009). Due to high collinearity (0.994) responses N Export and P Export were combined into a single reflexive latent variable N, P Exports. Intensity was not found to be significant as a direct effect as hypothesized in Figure 2.1, but was influential on overall model fit as a moderating effect (dashed arrows). In testing the proposition that terrains had controlling response, the physical control was found to exert non-significant effect, providing confidence that observed variation is not due to hydro-topographical characteristics. In an intermediate SEM Carbon Storage was significantly influenced by terrain and removed for the balance of analyses.
Definitions of land cover heterogeneity was best supported by the variable Shannon Diversity Index SHDI. Heterogeneity of form was supported by suite of variables, including disjunct core area density (DCAD), contrast weighted edge density (CWED, aggregation index (AI), cohesion, and percent like adjacencies (PLADJ).

Non-linear relationships characterized relationships between latent variables. Heterogeneity had a strong overall negative influence on NPSP exports ($\beta = -0.58$; Figure 2.4) but plots of direct effect reveal the directionality and strength of the path varies based on the degree of heterogeneity along an urban gradient (Figures 2.5 A, 2.5 B), where higher values are indicative of increasing evenness. In subwatersheds dominated by specific land covers (e.g. low HETERO) nutrient exports are predicted to be higher, but decrease sharply and significantly with increased heterogeneity before increasing again in the areas of highest evenness (Figure 5 B). The density of subwatersheds to the right of the plot reflects the mosaic of farm, forests and developed covers characteristic to the region.

Connectivity exerts a positive but weaker ($\beta = 0.28$, Figure 2.4) influence on N, P Exports than Heterogeneity, but the generally linear trend is inflected upward at higher levels of connectedness (Figure 26 A). Connectivity is quantified as the accumulated annual runoff index reported as a subwatershed mean (Natural Capital 2014; Appendix B), and because land cover-based evapotranspiration coefficients (Kc), and soil-based plant available water content (PAWC) and root restricting layer depth (RRLD) are adjusted with each modeled simulation (reflecting greenfield conversion to impervious surfaces), the use of runoff index dynamically contextualizes connectedness along a functional gradient. However, it does not correlate ($r = 0.017$) with my physical control, Flow Accumulation (FAC), which is a hydro-
topographical gradient which does not consider land cover-based water yield. In all cases, precipitation and climatic conditions were held constant.

At lower levels of connectedness, represented as a downward concavity I interpret to reflect a dampened trend of nutrient pollution, then inflects upward late in midrange, symmetrically accelerating as Connectivity reached high levels (Figure 2.5 E). Moderation by Intensity differs from the case before, and rather that running roughly parallel with the best fit trend instead continues linearly, the “high” case amplified pollution at midrange connectivity where the overall and “low” conditions had slowed pollution. At its broadest, the gap between “high” and “low” intensity represented an increase of 28% in nutrient pollution, connectivity held constant.

Form is a formative latent variable composed of indices found to statistically describe the most abstract of the five latent variables. Chosen variables fell into three form pattern dimensions: 1) Core metrics, as exemplified by disjunct core area density (DCAD); 2) Edge metrics, with contrast weighted edge density; and 3) Dispersion metrics, with aggregation index (AI), cohesion and percent like adjacency (PLADJ). Analysis of indicator weights found all significant at a p = 0.05, with the negative influence of DCAD and CWED offsetting the positive influence of AI, Cohesion and PLADJ. Together, they describe a landscape where higher values are highly dispersed and low contrast, and low values are more interspersed with higher contrasts. With this basis, I interpret the direct effects as a downward convex where increased dispersion reduces nutrient pollution (Figure 2.7 A) but the path is weakly significant (2.7 B).
Those trends reverse when the moderating effects of Intensity are considered. The concave upward relationship exhibits a damping at midrange values, as well as a performance gap where “high” Intensity values predict more nutrient pollution that “low” values. Statistically, significance values are unavailable for moderating plots.

2.4.3 Spatial Resilience

Hollings (1996) described ecological resilience “as the magnitude of disturbance a system can absorb before the system changes its structure” which Adger (2003) interpreted as “the ability to persist and the ability to adapt.” Cumming (2011) adapted the concept to spatially explicit analyses noting, “Spatial resilience can thus be seen as an interplay… between spatial attributes of the system and the different system constituents that are typically included in definitions of resilience.” Applying these concepts to this analysis of pattern and process, I was able assign the pattern domains Heterogeneity, Connectivity and Form as spatial attributes, Nutrient Export as a system constituent, and Intensity, as used in this study, as a disturbance manifested by greenfield conversions. Thus, if the amount of Intensity (e.g. “high” or “low” disturbance) doesn’t change the exports of nutrients at a point in a spatial domain, then that may describe a spatially resilient condition. Places where “high” Intensity results in more exports than “low” at a similar spatial value, indicates a loss of resilience, or a resilience gap. The place where “high” and “low” Intensity cross or diverge may be described as a resilience threshold. I measured the leverage of modulating latent variable Intensity on subwatershed nutrient exports for the three spatial heterogeneity domains using WarpPLS. This phenomena is illustrated as “high” and “low” trend lines in Figures 2.8, 2.9 and 2.10.
In Figure 2.8, reading left to right along gradient of Connectivity, I encountered a resilience threshold at around 7.42 m$^3$/ha, indicating that at low levels of runoff, subwatersheds export NPSP to the same degree whether disturbance is high or low. Beyond this point the ability of subwatersheds to retain NPSP diverges to a maximum resilience gap at 7.68 m$^3$/ha of runoff, and converges once again as the subwatershed becomes very urbanized.

In Figure 2.9, now reading right to left along a decreasing gradient of Heterogeneity (which I interpret as moving from areas of high land cover diversity, such as peri-urban areas with combinations of forests, farms and development, to subwatersheds dominated by urban or rural covers) I immediately pass a threshold extrapolated to SHDI = 1.36, indicating a subwatershed nutrient export response is sensitive to decreasing heterogeneity. “High” and “Low” Intensity diverge to maximum resilience gap at around SHDI =1.0, and eventually converge as “low” becomes meaningless and the subwatershed becomes very urbanized.

Changes in Form, Figure 2.10, reading left to right with Form increase, exhibits no distinct threshold and instead maintains a resilience gap throughout until increasing subwatershed urbanization makes “low” meaningless.

2.5 Discussion

2.5.1 Summary

In this study I developed 5 alternative scenarios of urban expansion that simulated varying degrees of fragmentation in an historical (2006) landscape over 24 year interval. I estimated the ecosystem response, quantified as stored carbon and water purification at each 30 m pixel, of 37 HUC-12 subwatersheds along an urban gradient, and used the data to test
the effects of spatial heterogeneity in the simulated system. I used SEM to translate Alberti et al. (2003, 2005) conceptual model of urban pattern and process into a series of testable hypotheses based on heterogeneity domains. After serially revising an initial, over-specified SEM, I arrived at a parsimonious SEM model ($R_{adj}^2 = 0.79$). I found that simulation data supported analyses decomposing spatial heterogeneity into three pattern domains: heterogeneity of composition, heterogeneity of configuration and connectivity. A fourth, land use intensity, measured as the frontier of greenfield conversion, was found to modulate the effect of the other three, and was not statistically significant predictor of direct effect.

Parameterization of the land cover heterogeneity latent variable was best supported by the variable Shannon Diversity Index SHDI. Heterogeneity of form was supported by suite of variables, including disjunct core area density (DCAD), contrast weighted edge density (CWED, aggregation index (AI), cohesion, and percent like adjacencies (PLADJ). Connectivity was supported by a hydrological run off index ($m^3/ha$). Commonly used indicators, such a patch metrics, population density and % abundance (PLAND) were dropped during SEM model revisions due insignificant effect or cross-variable loading. The ecosystem response of carbon storage was significantly associated with topography, and consequently dropped from analyses due to lack of independence.

I found that the generation of NPSP (N, P) exports in an urbanizing landscape was directly influenced by 1) the degree of heterogeneity in land cover composition, 2) increases in connectivity between land covers, and 3) the form or texture of landscapes. The insignificance of variables quantifying relative area of covers, such as PLAND or patch metrics, suggest that pattern is a better predictor of altered ecosystem function than
magnitude of urban covers. Unlike many SEMs, the WarpPLS software allows analyses of non-linear relationships between latent variables, a feature that revealed complex effects along spatial gradients (Figures 5C, D, I). Decomposition of point values found that in many cases uneven effect was associated with a given subwatershed’s location on an urban gradient. Decreasing levels of compositional heterogeneity, associated with losses of land cover diversity, are associated with increased NPSP exports. Higher pollution exports are anticipated when land covers are highly connected along hydrological gradients. In terms of variation of configuration, coarse landscapes generate less NPSP than smoother ones. The influence of all three of these levels of spatial heterogeneity was modulated by the degree of land cover change experienced by subwatersheds over the 24 year interval. Areas with high change amplified the influence of land cover heterogeneity, connectivity and form, increasing NPSP exports as compared to low change. Overall I found over half of NPSP to be associated with composition, one-third to connectivity, and one-fifth to configuration.

2.5.2 Theory development

The data from the simulated study system supported the conceptualizations of Alberti et al. with the possible exception of land use intensity, to which I determined a modulating rather than direct effect. This however could be attributed to the ways in which I translated the concepts into formulaic hypotheses. Alberti et al. also intended their framework to be applicable to number of socio-ecological urban pattern-process effects, and I chose to examine one, nutrient and material cycling, to reduce complexity. However, the discrimination of explicit pattern domains within encompassing ideas such as spatial
heterogeneity and fragmentation has potential to disentangle some of the confounding effects cited by Lindenmayer and Fisher (2006). Based on this study, I can recommend that fragmentation analyses consider dimensions of compositional diversity, spatial configuration, and connectivity independently, and independent of, magnitude of change.

I posit that socio-ecological landscapes co-evolve thorough human and environmental system interaction; however it is not a zero-sum game. Not all development impacts equally, and 1) pattern is a better predictor of environmental effect that magnitude of change; 2) that among influencing pattern domains, connectivity has a more significant effect that configuration, but not as much as heterogeneity of composition; and 3) that contextual factors such as the spatio-temporal location of change modulates environmental impacts of land use patterns. It is equally important to note that these sorts of conclusions are unlikely to be drawn from aspatial analyses, and that full spatial interaction between cause and effect are likely required in order to render the complex non-linear relationships that govern environmental response in heterogeneous environments.

2.5.3 Implications for management

Understanding the mechanisms behind synergies and tradeoffs among ecosystem services can help identify ecological leverage points where small management investments can yield substantial benefits (Bennett et al. 2009). For environmental planners, this research provides some disentanglement as to what types and amounts of spatial heterogeneity that promote ecosystem services, such as water purification. I find that not all urban growth impacts environments evenly, and that by controlling the compositional mix, configuration and connectedness of development we can influence more benign environmental outcomes.
However, it is at best unwise to plan for a single ecosystem service, an example in this study system noting highly diverse landscapes would likely extirpate forest interior birds native to the region (USGS SEGAP 2011). Further, this study is agnostic on the political and social trade-offs needed to apply suggested solutions such as promoting land cover diversity.

That said, I find evidence of the loss of spatial resilience in the simulated study system. Treating Intensity as a disturbance component reveals that, for a given location on the attribute of a pattern domain, subwatersheds have a wide range of NPSP outcomes. Subwatersheds with diverse land covers or reduced connectedness along hydrological gradients (e.g. via isolation by vegetative buffers) are projected to pollute less when undergoing greenfield conversions. Resilience is the analytical basis for societal norms regarding sustainability (Pizzo 2015), and indicators of reduced capacity in environmental due to development may be at odds with notions regarding sustainable economic development (Redman 2014).
Table 2.1 Simulated Environmental Response to Scenarios of Change (2006-2030). Status quo is taken as the mean values of 10 model runs. All other values are given as percentage change from Status quo. * Significant at p= 0.05

<table>
<thead>
<tr>
<th>Land Cover (ha)</th>
<th>Start period (2006)</th>
<th>Status Quo</th>
<th>Sprawl</th>
<th>Cluster</th>
<th>Increase Density</th>
<th>Decrease Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Development (change)</td>
<td>75,208</td>
<td>179,874 (139.2%)</td>
<td>-4,247 (-2.4%)</td>
<td>3,384 (1.9%)</td>
<td>-19,007 (-10.6%)</td>
<td>18,816 (10.5%)</td>
</tr>
<tr>
<td>Forest (change)</td>
<td>182,633</td>
<td>109,048 (-40.3%)</td>
<td>1,065 (1.0%)</td>
<td>-3,989 (-3.7%)</td>
<td>13,545 (12.4%)</td>
<td>-13,443 (12.3%)</td>
</tr>
<tr>
<td>Cropland (change)</td>
<td>25,815</td>
<td>17,855 (-30.8%)</td>
<td>453 (2.5%)</td>
<td>730 (4.1%)</td>
<td>1,342 (7.5%)</td>
<td>-1,446 (-8.1%)</td>
</tr>
<tr>
<td>Pasture (change)</td>
<td>60,348</td>
<td>37,751 (-37.4%)</td>
<td>2,685 (7.1%)</td>
<td>-68 (0.2%)</td>
<td>4,027 (10.7%)</td>
<td>-3,847 (-10.2%)</td>
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</thead>
<tbody>
<tr>
<td>Population</td>
<td>1,177,507 (26.0%)</td>
<td>1,177,507</td>
<td>1,483,291 (26.0%)</td>
<td>-34</td>
<td>-182</td>
<td>-466</td>
<td>-465</td>
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<tr>
<td>Population</td>
<td>Per Capita Land Consumption (ha/person)</td>
<td>0.0639</td>
<td>0.1213</td>
<td>0.1184</td>
<td>0.1236</td>
<td>0.1085</td>
<td>0.1340</td>
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<tbody>
<tr>
<td>Carbon</td>
<td>48,873,449</td>
<td>46,102,000 (5.67%)</td>
<td>199,617* (7.2%)</td>
<td>-791,436* (28.6%)</td>
<td>492,908* (17.8%)</td>
<td>-470,460* (17.0%)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Nitrogen (kg)</th>
<th>Annual N Loading †† (change)</th>
<th>Start period (2006)</th>
<th>Status Quo</th>
<th>Sprawl</th>
<th>Cluster</th>
<th>Increase Density</th>
<th>Decrease Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nitrogen</td>
<td>1,173,997 (22.3%)</td>
<td>1,436,385 (22.3%)</td>
<td>-11,108 (-0.8%)</td>
<td>23,585 (1.6%)</td>
<td>-46,154 (-3.2%)</td>
<td>44,137 (3.1%)</td>
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<tr>
<td>Nitrogen</td>
<td>Annual N Retention</td>
<td>806,358</td>
<td>820,105 (1.7%)</td>
<td>2,854 (0.3%)</td>
<td>-12,172 (-1.5%)</td>
<td>1,336 (-0.2%)</td>
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<tr>
<td>Nitrogen</td>
<td>Annual N Export</td>
<td>367,638</td>
<td>616,279 (67.6%)</td>
<td>-13,962 (-2.3%)</td>
<td>35,758 (5.8%)</td>
<td>-47,490* (7.7%)</td>
<td></td>
</tr>
<tr>
<td>Phosphorus (kg)</td>
<td>Annual P Loading †† (change)</td>
<td>Start period (2006)</td>
<td>Status Quo</td>
<td>Sprawl</td>
<td>Cluster</td>
<td>Increase Density</td>
<td>Decrease Density</td>
</tr>
<tr>
<td>Phosphorus</td>
<td>190,264 (30.6%)</td>
<td>248,491 (-1.1%)</td>
<td>-2,688 (-2.9%)</td>
<td>7,217 (-4.1%)</td>
<td>-10,187 (-3.9%)</td>
<td>9,637 (3.9%)</td>
<td></td>
</tr>
<tr>
<td>Phosphorus</td>
<td>Annual P Retention</td>
<td>128,496</td>
<td>139,382 (8.5%)</td>
<td>376 (0.27%)</td>
<td>-685 (-0.49%)</td>
<td>-1,252 (0.44%)</td>
<td></td>
</tr>
<tr>
<td>Phosphorus</td>
<td>Annual P Export</td>
<td>61,768</td>
<td>109,109 (76.6%)</td>
<td>-3,064 (-2.8%)</td>
<td>7,903 (7.2%)</td>
<td>-8,935 (-8.2%)</td>
<td></td>
</tr>
</tbody>
</table>

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Figure 2.1 Graphic diagramming of causal relationships referencing the simple translation of the Alberti et al. conceptual model (2005) used to develop a series of hypotheses exploring the relationship between urban pattern components of fragmentation and environmental effect. Ovals represent latent variable conceptualizations of urban landscape pattern and response. Single-headed arrows denote linkages (“paths”) between variables, and ultimately to estimate the strength, directionality and significance of influence on nutrient and material cycling. Double headed arrows denote likely correlations between endogenous latent variables. Error terms (ε) infer influences of factors uncorrelated with predictors. Labeled linkages constitute hypotheses by which pattern components may be effected and are described in the text.
Figure 2.2 Study System. A) Charlotte NC is part of the Char-lanta megalopolis. B) 37 12-digit subwatersheds sampled along an urban gradient extending from more urbanized west to the more rural east. C) detail of alternative futures projected for the region.
Figure 2.3 Initial “over-specified” structural equation model used to test causal diagram (Fig. 1).

Rectangle represent endogenous measures and indices quantified from the simulation data: multiple indices contribute to composite latent variables. Responses include non-point source (NPSP) exports of N and P, as well as C storage. A terrain control was added to test for effects associated with topographic hydrology.
Figure 2.4 Revised SEM found to be consistent with the data. Standardized coefficients are indicative of path strengths. Coefficients with asterisk (*) are not significant at $p = 0.05$. In the case of the physical control, non-significant effect provides confidence that observed variation is not due to terrain characteristics. The latent variable “intensity” was more influential on overall model fit as a moderating effect (dashed arrows) than as a direct effect.
Figure 2.5 Non-linear relationship between pattern domain “heterogeneity of composition” and nutrient exports.
Figure 2.6 Non-linear relationship between pattern domain “connectivity” and nutrient exports.
Figure 2.7 Non-linear relationship between pattern domain “Form” and nutrient exports.
Figure 2.8 Detail of plot suggesting resilience gap associated with increasing connectivity. The effects of connectivity are moderated by land use intensity, and the difference between “high” and “low” reveal resilience thresholds and gaps.
Figure 2.9 Detail of plot suggesting resilience gap associated with change in land cover heterogeneity. The effects of heterogeneity are moderated by land use intensity, and the difference between “high” and “low” reveal resilience thresholds and gaps.
Figure 2.10 Detail of plot suggesting resilience gap associated with changes in landscape texture. The effects of form are moderated by land use intensity, and the difference between “high” and “low” reveal resilience thresholds and gaps. Form maintains resilience gap.
CHAPTER 3: THE COEVOLUTION OF CONNECTIVITY IN SOCIO-ECOLOGICAL LANDSCAPES

3.1 Abstract

In urbanizing areas, breaking connectivity between developed and natural land covers is the primary tool for controlling non-point source pollution, flooding and environmental degradation. However, connectivity as a planning tool is rarely used due to difficulties in quantification and interpretation, leaving planners in the dark as to sustainability outcomes of design choices. In this paper we describe a suite of generalizable connectivity metrics that estimate effective distance, effective flow and distance weighted flow (DWF) between selected land cover types using digital maps and circuit theory. We use these metrics to compare future alternative futures of growth for the rapidly urbanizing Charlotte NC region. Within a GIS we created circuits from field representations of landscapes by configuring pixels as network nodes, specifying urban land covers as current sources and surface waters as sinks, and connecting them by along gradients of interests, in this case surface hydrology. Controlling for the amount of growth, we found a trivariate relationship between land cover composition, connectivity and change in the simulated study system. The combined effect of compositional change and the propinquity imposed by land scarcity generates a distinct threshold between peri-urban and urban classifications. This implies a successional effect where composition shifts directionally as subwatersheds move along the gradient of change. Despite stochastic effects mimicking landowner truculence, the response of alternative growth patterns designed to reduce connectedness was found to be significant; however the recommendation as to which alternative to employ varies with the subwatershed’s location.
on the gradient of change. For rural and peri-urban subwatersheds exhibiting increased conversions, Infill was less connected than Business as Usual and Sprawl alternatives. For urban watersheds Sprawl reduced connections most. For planners interested in managing connectivity as a mean of avoiding environmental uncertainty, placing parks, greenspace and vegetative buffers in urbanized areas is likely to reduce connectivity as compared to Infill. Infill patterns where found to be influential in limiting connectivity in rapidly urbanizing subwatershed. Managing connectivity and the rate of change is suggested as way to maintain a land cover mosaic with maximum diversity.

3.2 Introduction

In developed countries, societal demand for multifunctional landscapes, those that provide natural amenities within commuting distance, is restructuring rural and ex-urban landscapes through urbanization (Gosnell & Abrams, 2011; Taylor, 2011). Between 1950 and 2000 US experienced a 500% increase in development at the urban fringe (Brown, Johnson, Loveland, & Theobald, 2005), generating novel socio-ecological landscapes conceptualized as Exurbia (Taylor, 2014). Urbanization works mechanistically through conversions of greenfields to impervious covers designed for human use, and is a direct impact which has consumed habitat, reduced evapotranspiration and groundwater recharge, increased stormwater runoff, and made landscapes grayer, hotter, dryer and flashier (Eigenbrod et al., 2011; Revi et al. 2014). Conversions aggregate into development patterns that fragment natural and agricultural landscape mosaics, bringing people, pollution sources, invasive plants and animals geographically closer to wild lands and supporting ecosystems (Sanderson et al., 2002). While the benefits of urbanization have been substantial (Glaeser,
the tradeoffs of a fragmented and highly connected landscapes have been exposure to natural hazards (Moritz et al., 2014; Moss, Alldredge, & Pauli, 2015), increased frequency of biological invasions (Meentemeyer, Haas, & Václavík, 2012), and degradation of water quality (Walsh, Roy, & Feminella, 2005). The pace of change, and particularly the combinatorial effects of climate change and development-caused hydrological alteration, has made the task of managing landscapes for human well-being increasingly difficult (Milly et al., 2008). With the acceptance of the coupled nature of human and environmental systems, there is a call to understand both the trajectory of land cover change and its implications in order to proactively respond to environmental vulnerabilities (Kaushal et al., 2015).

Few theories capable of synthesizing the coevolution of human and environmental land systems have emerged to explain or predict the trajectories of ecosystem development in urbanizing regions (Kaushal et al., 2015; McDonnell & Pickett, 1990). Individually, however, idea that regions change in predictable patterns has generated many theories in both urban and ecological domains (McHale et al., 2015). Cities in particular are well studied, with a number of influential theories such as von Thunen’s economic model of the spatial dependencies between the central city and agricultural lands, the Chicago School’s concentric ring model (Burgess, 1925) and Hotelling’s location model based on the completion of firms (1929), among others. Similarly, ecologists have developed theories to explain the spatial heterogeneity observed in environmental systems, and these include both static (Clement, 1916) and dynamic (Gleason, 1917) community secession models, models that structure composition based on disturbance (Randall Hughes, Byrnes, Kimbro, & Stachowicz, 2007). However, a spatio-temporal understanding combinatorial effects of socio-
ecological systems poses unique challenges. Coevolution is a defining characteristic of complex adaptive systems (Anderson, 1999), and Wu and David (2002) cite the sheer complexity of socio-ecological systems as a barrier to analysis. Rounsevell (2012) suggests scenario simulation as a way resolve complexity and overcome the lack of empirical study needed to provide comparative analyses. Despite the availability of spatially-explicit urban growth simulation models (Jantz, Goetz, & Shelley, 2004), studies of ex-urban environmental trajectories to date have mostly been retrospective, as in the case study of urbanization in Puget Sound (WA) by Hepinstall-Cyerman et al. (2009).

To explore for systemic pattern indicative of trends in socio-ecological landscape evolution, we designed a series of tests to estimate the connectivity response of urban and exurban landscapes to urbanization. Connectivity is broadly understood as the mechanism through which human and natural systems exchange materials flows (Mitchell, Bennett, & Gonzalez, 2013), and as such is synoptic metric to bridge the human, ecological and hydrological domains. High connectivity between urban land covers and surface waters is a key driver of urban stream syndrome (USS) a condition characterized by changes in stream geomorphology, increased flooding, and high levels of non-point source pollution (Walsh et al., 2005). The location and magnitude of connectivity has major implications for environmental, resilience, and conservation planning (Collinge, 1996; Pickett, Cadenasso, & McGrath, 2013). We tested three scenarios of plausible development patterns for the rapidly urbanizing Charlotte (NC) metropolitan area over a 24 year period using a population-based, spatially explicit regional growth simulator (Meentemeyer et al. 2013). To facilitate comparison, the absolute area of new development for the region was held constant in each
scenario; however we varied the dispersion of development pattern to generate a representative sample of exurban growth generalizable to different geographic extents. The scenarios referenced business-as-usual trends, as well as infill and sprawling development patterns. In order to estimate the degree of connectedness within our simulated landscapes we measured connectivity in three unique ways: using structural methods based on the landscape patch mosaic model distance-based cost surface, and electric circuit-based methods.

What sorts of patterns can be expected in a rapidly restructuring exurban landscape? Planning strategies designed to limit environmental impact, such as low impact development or smart growth (Duany, Speck, & Lydon, 2010), anticipate that the configuration development takes (e.g. clustering or infill) can improve water quality (Pyke et al., 2011). Comparative studies have found smart growth programs effective in shaping design (Song, 2005); however, we know little about the environmental impacts of these alternative patterns (Preuss & Vemuri, 2004; Beach 2001). Needed are predictive frameworks that allow us to move beyond designing plans today to solve yesterday’s problem (Taylor 2005 in Davoudi et al. 2012) and instead preemptively and systematically respond to future environmental challenges (Kaushal et al., 2015).

3.3 Methods

3.3.1 Study area

The greater Charlotte (NC) metropolitan area is North Carolina’s most urbanized region, experiencing rapid growth in both population and development over the past three decades, with roughly a third of total land area indicated as developed land covers in 2006 (Figure 3.1 A, B; Meentemeyer et al., 2013). The region projected to grow an additional 1.2
million people (50%) by 2030 (North Carolina State Demographics Office 2009), yet recent remote sensing analyses of the fast growing region revealed significant private woodlands (regional canopy coverage > 25%) at or behind the urban frontier, one of the highest in the nation for medium to large cities (American Forests 2010). The region sits at a mean elevation of 218 m, and the rolling terrain reaches a maximum 289 m, and is naturally forested with mixed deciduous/coniferous and Oak/Hickory/Pine upland types, and the clay soils are mostly prime farmland, but highly erodible. For my unit of analysis I selected 37 HUC 12 sub-watersheds along an urban gradient, and the 346,000 ha extent was extended by 1,000 meter buffers to reduce boundary effects in analysis.

In preparation for simulation analyses I mapped the region at five roughly decadal time steps 1976-2006 using historical Landsat MS and TM satellite imagery, aerial orthophotography and LiDAR data (Meentemeyer et al. 2013). Classification was conducted using vegetation-impervious surface-soil (VIS) subpixel unmixing, a methodology shown to be effective in mapping heterogeneous urban landscapes (Lee and Lathrop 2005; Gluch and Ridd 2010). Land cover classes for the region were taken from Singh et al. (2012) and included development, forest, cropland, pasture/managed clearing and water.

Mapping of land cover in 2006 revealed 21.7% developed land covers, 52.7% forested, 7.5% cropland and 17.4% pasture lands in 2006 (Figure 3.1B; Table 3.1). Overall classification accuracy was 86% (Meentemeyer et al., 2013). Population for the study area in 2006 was 1,177,507 (Census Bureau 2015), and per capita land consumption (PCLC) was a mean of 0.09 developed hectares (0.22 acres) per person (Table 3.1).
3.3.2 Data Development: Human dimensions of the socio-ecological landscape

Simulation modeling of land cover change has the potential to both generate cases studies and provide insights into ecosystem function beyond empiricism through their ability to undertake experiments in alternative futures (Rounsevell et al. 2012). To generate a representative sample of subwatersheds that exhibit a plausible range of fragmentation and urban pattern I used the future urban-regional environment simulation (FUTURES; Meentemeyer et al. 2013) to generate land cover scenarios for a controlled complexity experiments designed to isolate composition and configuration. FUTURES is a dynamic, patch-based stochastic model that reliably simulates urban structure and fragmentation (Meentemeyer et al. 2013). I held the area changed by 2030 constant (relative to Business as Usual) over 5 stochastic iterations but altered a dispersion parameter to produce scenarios of Infill growth or Sprawl (Meentemeyer et al. 2013, Dorning et al. 2015). In all cases, only developed land cover classes (high, medium, low, developed open space) change: all other land covers not converted to development are held constant including croplands (USDA-NASS 2012) and forest canopy (Singh et al. 2014).

Each FUTURES realization of landscape has a unique frontier of urbanization, a unique distribution of population and unique configuration of habitat attributes. I located the frontier for each alternative, or “Momentum” by locating areas of projected new development between 2006 and 2030 using a moving window analyses that area of change in a 1 km² neighborhood, an extent found to be a significant predictor of new development (Meentemeyer et al., 2013). I also developed pixel-based population density maps using
dasymetric mapping techniques (Sleeter and Gould 2007) to integrate extrapolations of census-based population with maps of future development.

Landscape analysis was conducted for 5 randomly selected runs from 3 scenarios, e.g. Business as Usual, Infill, Sprawl. Four landcover-based patch types were considered: developed, forest, high intensity agriculture (croplands), and low intensity cropland (pasture, hayfields). FRAGSTATS (McGarigal 2002) was used to generate compositional, configurational and connectivity metrics (Appendix A Table 1).

3.3.3 Estimating Connectivity

We estimated connectivity for a range of simulated landscapes projected for the study system using spatial pattern methods based on the landscape patch mosaic model (McGarigal, Cushman, Neel, & Ene, 2002), overlay analyses of a cost distance surface, and electric circuit-based methods (McRae, Dickson, Keitt, & Shah, 2008). Connectivity in landscapes has not been precisely defined ((Tischendorf & Fahrig, 2000; McGarigal et al., 2014), but conceptually requires first identifying discrete units of interest, perhaps states or aggregates of states such as patches, a matrix between the two, and in some cases, information as to dispersal ability of phenomena under consideration (Calabrese & Fagan, 2004). In spatial pattern analyses, connectivity may be structural or functional, and the distinction between these depends largely on specific knowledge of the study system: in the absence of dispersal ability information, algorithms estimate the structural continuity of patch types (McGarigal et al., 2014).

In contrast to the patch-mosaic model, landscapes can be conceptualized as graphs, or networks composed on nodes representing patches or points of interest, and edges
representing intermodal paths, lengths of which may be measured units relevant to the study system (Bunn, Urban, & Keitt, 2000). Graph theory metrics estimate the intermodal distances along connecting edges, is often used to measure connectivity in hydrological networks, or terrestrial systems of nodes and linkages (Larsen, Choi, Nungesser, & Harvey, 2012; Urban & Keitt, 2001). Graph theory has been applied to estimating cost-weighted distances in rasters, where cell centers represent nodes linked in field representation (Framstad et al. 2012 in GRASS Development Team, 2015). Cost distance algorithms then generate a surface based on accumulated cost of moving across an impedance (or permeability) the matrix defined by phenomena of interest. In many cased cost distance surfaces are utilized in optimizing routines to identify the “least cost path”, but they may also be used in overlay analyses to measure relative or functional distances.

Circuit theory analysis is another application of graph theory, and makes the intuitive analogy between connectivity in landscape and movement of charge through an electrical circuit (McRae & Beier, 2007; McRae, Dickson, Keitt, & Shah, 2008). In a raster application, circuit theory treats cells in a landscape as electrical nodes connected to neighboring cells by resistors, with resistance values determined by user-supplied values in the matrix. Potential is generated by assigning patches or cells as current sources and sinks, and a circuit is created by connecting the two by a resistance matrix. Current and voltage values are determined at each cell using Ohm’s Law. Circuit theory is unique in that when all possible paths among patches are treated as resistors connected in parallel, a measure of effective cumulative resistance decreases with increasing numbers of paths.
We estimated structural connectivity in landscape pattern is using FRAGSTATS “contagion” metric (McGarigal et al., 2014). Contagion measured the physical contiguity of patches, increasing as patches become more aggregated (Schumaker 1996). We estimated the contagion of five classes of land cover patches aggregated on a four-neighbor rule: urban, forest, cropland, pasture and surface water. Contagion metrics are unmapped, and were reported in tabular form (Table 3.1).

A cost distance surface was generated and mapped in ArcGIS 10.3 using Spatial Analyst tools “Cost Distance” (ESRI 2015). Source input were pixels classified as surface water, and the impedance matrix was the hydrological runoff index unique to each scenario run. Each runoff index uniquely contextualizes the geography of built and natural land covers (including the presence of impervious surfaces), slope, soil conditions, rooting depth, vegetation status and type for annual estimates of precipitation, temperature and potential evapotranspiration. I report the mean cost distance for each urban pixel in a given scenario run using overlay analyses of the cost distance within a GIS (Table 3.1).

I used Circuitscape 4.0 in “advanced mode” to estimate current and voltage in the simulated landscapes (McRae & Shaw, 2009). I first created a potential by assigning each urban pixel source a 1 amp current, and designation each surface water pixels as a sink, and then completed the circuit by connecting sources and sinks via hydrological runoff indexes. Circuitscape generates maps of current and voltage, which I interpreted as Effective Flow and Effective Distance flowing Cowley, Johnson & Pocock (2015). I also multiplied the two map products to produce Distance Weighted Flow (DWF) and report the means for each landscape scenario in Table 3.1.
3.4 Results

3.4.1 Simulated landscapes

Population in the study system was expected to grow 26% to 1.48 million over the next three decades (North Carolina State Demographics Office 2012). Extrapolating historical trends, we anticipated a per capita land consumption rate of 0.23 developed hectares (0.56 acres) by 2030. Anticipated PCLC varied widely between subwatersheds, ranging from 0.06 in the urbanized subwatershed 23 to 0.53 in rural subwatershed 11. Based on PCLC demand, the Business as Usual scenario estimated that by 2030 the landscape would be composed of 51.9% developed land covers, 31.5% forested, 5.2% cropland and 11.0% pasture lands (Figure 3.1 D; Table 3.1). Based on back-casting validation procedures, overall accuracy was estimated at 86%, and figure of merit, a measure of statistical agreement between observed and simulated change, was 13.6%. Meentemeyer et al. (2013) report FUTURES slightly overestimates development in rural areas and underestimates in more urban settings. Overall, the anticipated doubling of developed covers represents a fundamental restructuring of the urban-rural interface.

Holding population growth, PCLC demand and therefore area of conversions constant with those of Business as Usual, we varied dispersion parameters for new growth 2007-2030 to project alternative futures of land cover, Infill and Sprawl (Figure 3.1 D). While the proportions of greenfield converted varied little between Business as Usual and Sprawl, the Infill scenario converted relatively more forests (Table 3.1). As much of the forest in the region is regeneration, urban growth clustered near extant development has the potential to
offset regional gains in forest covers generated by urbanization-influenced agricultural abandonment.

3.4.2 Unsupervised classification of subwatersheds into typologies

Through mapping we observed that urban patterns in the study area are polycentric and complex. To facilitate interpretation of subsequent analyses we clustered land cover scenarios for each of the 37 subwatersheds (n = 555) into a typology set representative of settlement characteristics in North American metropolitan areas (i.e. “urban”, “peri-urban”, “rural”). Based on relative area of projected developed, forested and agricultural (i.e. aggregated cropland and pasture) land covers in the Business as Usual scenario, we used unsupervised k-means methods to identify three clusters (CCC = 4.132) of subwatersheds that we subsequently labeled “Urban”, “Peri-Urban” and “Rural” types based on our interpretation of aerial imagery (Figure 3.1 C). Of the 37 subwatershed simulated, 13 were classified as Urban, 17 as Peri-Urban and 7 as Rural.

3.4.3 Mapping the gradient of land conversion

Each realization of a scenario has a unique gradient associated with conversion to built land cover types. We mapped this gradient of change, or “Momentum”, for each alternative by locating areas of projected new development between 2006 and 2030 using a moving window analyses that area of change in a 1 km² neighborhood (Figure 3.2 A), an extent found to be a significant predictor of new development (Meentemeyer et al., 2013). The amount of anticipated change varied by subwatershed and scenario, and a best fit trend line (r²= 0.345) shows maximum change in subwatersheds with moderate population density, a proxy for urban density, and a slowing of change with increased population density (Figure
3.3 B). Visual analysis indicates that the frontier of development is uneven, with areas of high change skirting existing development particularly to the east and north of Charlotte.

3.4.4 Mapping connectivity using Flow, Effective Distance, and DWF

Analyses of the circuit created by urban current sources, surface water sinks, and the conductive network represented by the hydrological runoff index we predicted the strength of projected urban-water connections using current (i.e. Flow). Our projections rendered complex patterns of high Flow values in steeper and more urbanized headwater reaches of first and second order streams (Figure 3.3 A). For a given land cover pattern, these areas collect and funnel connectivity between urban and water covers. Areas with diverse covers, flatter topography and low stream density exhibited low Flows (Figure 3.4 inset, Figure 3.6 inset).

We mapped the highest values of Effective Distance (i.e. voltage) proximal to current sources, diminishing in anisotropic patterns that reflected the structure of the underlying conductive surface (Figures 3.4, 3.5 and 3.6 inset). Rapid voltage declines reflecting shorter effective distances occurred in areas locally dominated by urban land cover and characterized by high runoff, itself indicative of contiguous impervious surfaces, steep slopes, or both (Figure 3.5 inset). Gradual declines indicating longer urban-water distances are likely due to the combinatorial effects of reduced or discontinuous impervious surfaces, the presence of shallower slopes, or the presence of vegetative covers that impede surface runoff (Figures 3.4, 3.6 inset).

The patterns of DWF differ from both Effective Distance and Flow, and areas with high values represent strong linkages between urban covers and water, and likely target areas
where connection effects could be amplified. DWF may be useful in forecasting the location of future hotspots less suitable for urban development due to extreme connectivity with surface waters.

3.4.5 Comparing indices: How connectivity varies along an urban gradient

To better understand the relationship between urban expansion and landscape connectivity we compared structural, circuit and cost-based connectivity metrics for each scenario realization along a proxy for the urban gradient, Momentum. The relationship between Flow and Momentum is characterized by a distinct trend (Figure 3.3 B, top). The strength of connection increases as the degree of land coverts to development, even beyond and inflection to a point around 58% where Momentum retrogrades, likely in response to scarcity of available land to develop. The location of typologies along this trend provides independent support for our cluster analyses: simple urban forms could be similarly classified by composition or by their spatial structure along a trajectory of change.

The relationship between the structural connectivity metric contagion and Momentum is characterized by a trend similar to that of Flow (Figure 3.3 B, middle). Higher contagion values are indicative of high interspersion with high contrast, which in many cases describes fragmentation (Larsen et al. 2012), and our population of subwatersheds exhibited increased contagion with increased Momentum until a point of inflection at between 50% and 60%. From there contagion continues to increase, but Momentum becomes retrograde reflecting the increasing scarcity of undeveloped land. The alignment of typologies along this trend is also similar.
On average, the cost distance between surface waters and urban land covers was varied little between all typologies (Figure 3.3 B, bottom). However, Momentum did vary significantly by type, with the greatest change predictably occurring in urban and peri-urban types (Table 3.1). Heteroscedasticity in the plot signals the zero-sum trade between new development and forested and agricultural covers (Lambin & Meyfroidt, 2011) with Momentum bounded by scarcity of developable land.

3.4.6 The role of scenario spatial configuration in connectivity

We performed a nested analysis of three subwatersheds along the continuum of change and looked specifically at how the spatial configurations of Business and Usual, Sprawl or Infill scenarios influenced connectedness. As described above, climate, population growth, PCLC, area of conversion (barring minimal stochastic effects) were held constant between scenarios. Also recall, for this study, connectivity is associated with watercourse impairment. Sampling subwatersheds from along the trend, we selected subwatershed 4 as a rural exemplar, subwatershed 2 as a subwatershed at the point of inflection, and subwatershed 20 as an urban exemplar (Figures 3.4, 3.5 and 3.6).

In rural subwatershed 4, Sprawl and Business as Usual patterns significantly increased connectivity between urban land covers and surface water as compared to Infill (Figure 3.4, Table 3.1). This pattern was exhibited by all rural subwatersheds sampled. Inset maps of DWF, a metric useful for visualizing the intersection of land cover configuration and connectivity, illustrate that in clustering growth leaves much of the subwatershed undisturbed by development. This is the basis for many “smart growth” planning strategies.
In urban subwatershed 20, Infill significantly increased connectivity compared to other scenarios, the obverse of the effects observed in rural subwatersheds (Figure 3.5, Table 3.1). This pattern was exhibited by all urban subwatersheds. For peri-urban subwatershed 2 where over 50% of the landscape was expected to be converted to development, Business as Usual increased connectivity most (Figure 3.5, 3.6; Table 3.1). Overall, for peri-urban subwatersheds, the effects of scenario configuration was mixed.

3.5 Discussion

In our simulated system of urban and exurban landscapes we compared three connectivity metrics, two commonly used, and introduced a third. Each measured connectivity independently, with cost distance based on a weighted proximity to water, contagion base on interpatch contiguity, and Flow based on probabilistic connectivity between current sources (urban) and sinks (surface water). The corroboration between Contagion and Flow ($r = 0.75$) provide some support for our observations.

There is a trivariate relationship between land cover composition, connectivity and change in these projected landscapes (Figure 3B). In this simple system, the supply of land is finite, and much like a mass balance equation, land is therefore “conserved”. It follows that land cover change in the form of greenfield conversions can only proceed to a limit, beyond which scarcity of developable land reduces its rate. Thus, Momentum was similar in areas compositionally classified as urban or rural, the former not changing having already exhausted developable land and the not having been visited by the urban frontier. The combined effect of compositional change and the propinquity imposed by land scarcity generates a distinct threshold between peri-urban and urban classifications. This implies a
successional effect where composition shifts directionally as subwatersheds move along the gradient of change. Put more simply, rural watersheds undergoing conversion evolve to peri-urban, and urban forms ultimately as they become more connected. Increases in connectivity push areas over the threshold.

Temporal scale is a significant factor, and given the short (i.e. 24 year) interval of analyses, this interpretation of the relationship between connectivity and change gives rise to conceptualizations of coevolution in human and natural systems driving what may be thought of as a Clementian ecological succession model (1916). However, the time frame of analysis, and historical record of PCLC driving it, is likely inadequate for long term prediction. Further, our model may not be realistic due to heuristics that do not allow reverse or alternate transitions. A continued emphasis on understanding the causes, patterns and drivers of coevolution at different scales is likely to result in mature theories of landscape transformation (McHale et al., 2015). Likewise, an intermediate disturbance characteristic is identified: the greatest diversity in subwatersheds was observed at moderate rates of change (20-30%). However, this rate of change would only be realistic or sustainable over time if our model supported reverse or alternative transitions.

3.5.1 Implications for management

Efforts to measure and manage runoff processes have relied on assessments of impervious surfaces as proxies for a causal mechanism (Brabec, 2009). In intensively urbanized areas, stormwater drainage conducted by piped infrastructure is considered directly connected, or effective imperviousness (EIA; Ally and Veenhuis 1983) and is thought to be a better predictor of impairment (Brabec 2002). However, in rapidly urbanizing areas such as
Charlotte (NC) over one-third of all urban land cover is “managed clearing” with no associated stormwater infrastructure (Singh, Vogler, Shoemaker, & Meentemeyer, 2012). There, a 2012 study found 81% of the County’s watersheds “impaired” and “not clean enough for their intended use…” (LUESA 2012). Impairment associated with urban expansion has been routinely observed in peri-urban and rural areas where presence of stormwater infrastructure is irregular (Burns et al., 2005; Bernhardt & Palmer, 2007), as well as in cases of deforestation for development (Stephens et al., 2002 VB; Booth 2005 VB) suggesting that unconnected impervious may also significant mechanism of impact (Brabec 2009). In practice, aggregating connected and unconnected measures of impervious surfaces into a total impervious metric (TIA) comprises a pragmatic approach (Brabec 2002). The circuit-based approach presented here, which allowed continuous mapping of connectivity, was useful for visualizing the location and magnitude of flows as defined. DWF is a unique product that can guide LID. Looking at insets one can see (Figures 3.4 B, 3.5 B, 3.6 B) that the brightest colors are places where special consideration is needed.

Even with stochastic effects mimicking landowner truculence, the response of alternative growth patterns designed to reduce connectedness was found to be significant; however the recommendation as to which alternative to employ varies with the subwatershed’s location on the gradient of change. For rural and peri-urban subwatersheds exhibiting increased conversions, Infill was less connected than Business as Usual and Sprawl alternatives. For urban watersheds Sprawl reduced connections most. For planners interested in managing connectivity as a mean of avoiding environmental uncertainty, placing parks, greenspace and vegetative buffers in urbanized areas is likely to reduce
connectivity as compared to Infill. Infill patterns were found to be most use in limiting connectivity in rapidly urbanizing subwatershed. Managing connectivity and the rate of change is suggested as way to maintain a land cover mosaic with maximum diversity.

Tables

Table 3.1 Landscape Composition, Pattern and Change by Urbanization Typology (2006-2030). Business as Usual (BAU), Sprawl and Infill are mean values of 5 model runs. \( \Delta \) = percentage change from 2006. MOM = momentum, or neighborhood index of new development. CD = cost distance, nominal meters. I = Flow, nominal amperage. V = Effective distance, nominal volts. DWF = Distance Weighted Flow, unitless. CONT = contiguity, or patch-based proximity.

* Significant at p= 0.05

<table>
<thead>
<tr>
<th>Scenario</th>
<th>( \Delta ) ha Dev*</th>
<th>( \Delta ) ha Forest*</th>
<th>( \Delta ) ha Cropland*</th>
<th>( \Delta ) ha Pasture*</th>
<th>MOM</th>
<th>CD</th>
<th>CONT</th>
<th>I</th>
<th>V</th>
<th>DWF</th>
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<tr>
<td>Urban Cluster</td>
<td>BAU</td>
<td>-2.271 (-69%)</td>
<td>-62 (-64%)</td>
<td>-250 (-59%)</td>
<td>385.8</td>
<td>2.1</td>
<td>68.7</td>
<td>9.9</td>
<td>5.0</td>
<td>50.4</td>
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<td></td>
<td>Sprawl</td>
<td>-2.273 (-65%)</td>
<td>-58 (-65%)</td>
<td>-237 (-57%)</td>
<td>384.3</td>
<td>1.6</td>
<td>68.6</td>
<td>9.9</td>
<td>5.0</td>
<td>49.8</td>
</tr>
<tr>
<td></td>
<td>Infill</td>
<td>-2.270 (-71%)</td>
<td>-82 (-74%)</td>
<td>-385 (-67%)</td>
<td>440.8</td>
<td>2.4</td>
<td>72.7</td>
<td>10.1</td>
<td>5.1</td>
<td>53.9</td>
</tr>
<tr>
<td>Peri-urban Cluster</td>
<td>BAU</td>
<td>-2.388 (-39%)</td>
<td>-293 (-40%)</td>
<td>-866 (-45%)</td>
<td>372.2</td>
<td>3.8</td>
<td>43.7</td>
<td>2.8</td>
<td>3.6</td>
<td>26.0</td>
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<tr>
<td></td>
<td>Sprawl</td>
<td>-2.297 (-38%)</td>
<td>-233 (-38%)</td>
<td>-726 (-39%)</td>
<td>350.5</td>
<td>3.2</td>
<td>41.7</td>
<td>3.1</td>
<td>3.4</td>
<td>23.0</td>
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<td>-2.235 (-37%)</td>
<td>-333 (-37%)</td>
<td>-952 (-46%)</td>
<td>366.0</td>
<td>5.4</td>
<td>46.3</td>
<td>2.2</td>
<td>3.5</td>
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<td>Rural Cluster</td>
<td>BAU</td>
<td>-591 (-13%)</td>
<td>-286 (-17%)</td>
<td>-576 (-20%)</td>
<td>160.1</td>
<td>1.7</td>
<td>32.5</td>
<td>6.2</td>
<td>2.0</td>
<td>8.8</td>
</tr>
<tr>
<td></td>
<td>Sprawl</td>
<td>-761 (-17%)</td>
<td>-350 (-20%)</td>
<td>-546 (-20%)</td>
<td>182.9</td>
<td>2.8</td>
<td>31.0</td>
<td>6.0</td>
<td>2.0</td>
<td>8.7</td>
</tr>
<tr>
<td></td>
<td>Infill</td>
<td>-430 (-10%)</td>
<td>-156 (-9%)</td>
<td>-387 (-14%)</td>
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<td>34.3</td>
<td>5.9</td>
<td>1.7</td>
<td>8.0</td>
</tr>
</tbody>
</table>
Figures

Figure 3.1 Study System. A) Charlotte NC is part of the Char-lanta megalopolis. B) 37 12-digit subwatersheds sampled along an urban gradient extending from more urbanized west to the more rural east. C) Given the polymorphic development pattern, we plotted the urban gradient using a ternary profile of developed, forested and agricultural land covers. Within the gradient,
subwatersheds fall into three distinct clusters: urban, peri-urban and rural. D) Detail of alternative growth patterns used in analyses.

Figure 3.2 The frontier of urbanization 2006-2030 for a single Business as Usual scenario realization. The relationship between change in subwatersheds and projected population density. The locations of projected greenfield conversions were mapped using 1 km² moving window analyses, an extent found to be a significant predictor of new development in a previous study.
Figure 3.3 Estimated Flow in the study area (A). Plots illustrate the relationship between connectivity measures (cost distance, contagion and Flow) and land cover change (Momentum).
Figure 3.4 Connectivity in a rural subwatershed 4. A) Maps of connectivity metrics, B) impact of scenarios on connectivity, C) detail of DWF.
Figure 3.5 Connectivity in an urban subwatershed 20. A) Maps of connectivity metrics, B) impact of scenarios on connectivity, C) detail of DWF.
Figure 3.6 Connectivity in a peri-urban subwatershed 2. A) Maps of connectivity metrics, B) impact of scenarios on connectivity, C) detail of DWF.
CONCLUSION

In these studies I found that not all urban growth impacts environments evenly, and that by controlling the compositional mix, configuration and connectedness, not just the amount of development, we can influence more benign environmental outcomes. My results indicate that all projected landscape patterns were estimated to increase exports of nutrient pollution, reduce terrestrial carbon stores, and lead to new disturbed habitat regimes. Of land pattern alternatives considered, no single urban form simultaneously reduced pollution, stored carbon, and retained sensitive habitat, a finding that underscores the difficulties likely to be encountered when balancing economic and environmental outcomes. However, increased land use density yielded stronger financial returns to landowners as concentrated economic activity drove up land rents while minimizing broader pollution costs.

Which aspect of urban pattern generates the greatest effect? Analyses of spatial pattern found that heterogeneity in composition most influential in the generation of nutrient non-point source pollution, followed by connectivity and heterogeneity of form. Land use intensity, a measure of local change, had insignificant direct effect, but moderated all other effects. The insignificance of variables quantifying relative area of covers suggest that pattern is a better predictor of altered ecosystem function than magnitude of urban covers.

Can we anticipate regional effects by predictively mapping connections? Analyses of simulation data found a trivariate relationship between the rate of greenfield conversion, subwatershed composition and connectivity. Given a simple classification scheme, subwatersheds followed a simple successional progression along a gradient of change, with
rural compositions of development, agriculture and forest giving way to peri-urban compositions, and then to urban. When this directionality is understood, connectivity was found increase throughout the compositional range even as conversion slowed due to land scarcity. Maps generated by using circuit-based metrics may be useful in siting low impact development (LID).

These findings represent a move to predictive, rather than reactive, analytical frameworks that have the potential to move beyond designing plans today to solve yesterday’s problem and instead preemptively and systematically respond to future environmental challenges. They emphasize the utility of integrated urban growth-ecosystem service analyses in order to anticipate environmental trade-offs likely required by society. My findings emphasize the need for ecosystem service analyses to more adequately understand development tradeoffs in the metropolitan context. To reduce environmental impacts regionally, planners are advised to manage amplifying effects of development by maintaining land cover diversity, and limiting the connectivity of developed land covers along hydrological gradients.
REFERENCES


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Saura, S., & Rubio, L. (2010). A common currency for the different ways in which patches and links can contribute to habitat availability and connectivity in the landscape. Ecography, 33(July 2009), 523–537. doi:10.1111/j.1600-0587.2009.05760.x


APPENDIX A

Urban Growth Projections

I hypothesized that the location and spatial configuration of anticipated growth would greatly influence results, and in response rejected urban growth model platforms that depicted change on a pixel-by-pixel basis (e.g. SLEUTH). FUTURES is a multilevel modeling framework that simulates the emergence of development “patches” using three sub-models that project 1) the location (POTENTIAL sub-model), 2) the quantity (POPULATION DEMAND sub-model), and 3) the spatial pattern (PGA sub-model) of urban growth using a patch growing algorithm that combines field and object-based representations of change. The PGA incorporates a stochastic algorithm designed to mimic human agency, and is therefore probabilistic for the typical 50 run treatment. In this study a single realization for 2030 given status-quo population growth (North Carolina State Demographics Office 2012) was used as the comparator (Figure 2B).

The output of FUTURES is a binary map of developed/undeveloped. For this study I assumed any areas undeveloped by 2030 maintained the same land cover classes as 2011. I also assume that once developed, land cover classes could not revert to undeveloped types. I re-classified the single 2030 development class into four intensity classes used in USDA-NASS cropland data using a scoring scheme based on three parameters determined to be significant predictors in the development of the FUTURES generalized linear model: Development pressure, road density and slope (Meentemeyer et al. 2013, unpublished communication). Grid-based values for the three were 1) divided into quantiles and scored 1-4 with higher values inferring increased suitability for intensive development, 2) added
together using map algebra, and 4) the result dived into quantiles and scored 1 to 4. This
datum was treated to an unsupervised classification: intensity was awarded based on context
and expert knowledge of the region, and resulted in a plausible land cover map (Figure 2B).
APPENDIX B

Water Purification and Valuation modeling

Eco-hydrological modeling was performed using the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Water Purification module and the data referenced in Table 1. InVEST is a tool for ecosystem service assessment to support environmental decision-making developed in 2007 by Stanford University, the World Wide Fund for Nature and the Nature Conservancy and features a suite of models designed to quantify ecosystem service at landscape scales. I used the InVEST 3.1 Water Purification module (Sharp et al. 2015) which is comprised of three sub-models employed in sequence: an eco-hydrological water yield model, a process-based nutrient cycling model, and an economic valuation model. While we examine the balances of phosphorous (P) in the system, nitrogen (N) balances may be estimated using the same methods. I here provide an overview of the sub-models.

The addition of climatological data to the flow accumulation surfaces underlying erosion models generate water yield surfaces (Zhang et al. 2012), inputs that, when linked to process-based nutrient cycling models incorporating ecological parameters, such as the soil-based plant available water capacity (PAWC), and landcover-based nutrient flux coefficients, generate estimations of nutrient loading and retention on a per-pixel basis (Tallis et al. 2013). Informed by DEM-derived geomorphology, pixels aggregated on topographic configuration (e.g. downslope flow accumulation) estimates nutrient export to surface waters, which are further aggregated by catchment or watershed (Bia et al. 2013).

Eco-hydrological Water Yield
The overall model is based on the Budyko curve (1974) and annual precipitation. Annual water yield per pixel $Y(x)$ is understood as the precipitation less the fraction of water that undergoes evapotranspiration, and is defined as:

$$Y(x) = \left(1 - \frac{AET(x)}{P(x)}\right) \cdot P(x)$$  \hspace{1cm} (1)

Where $AET(x)$ is actual evapotranspiration at $x$, and $P(x)$ is annual precipitation.

The evapotranspiration partition may be estimated as:

$$\frac{AET(x)}{P(x)} = \frac{1 + \omega(x)R(x)}{1 + \omega(x)R(x) + \frac{1}{R(x)}}$$  \hspace{1cm} (2)

where $R(x)$ is the dimensionless Budyko Dryness index, defined as:

$$R(x) = \frac{K_c(\ell_x) \cdot ET_0(x)}{P(x)}$$  \hspace{1cm} (3)

where $K_c$ is an land cover class evapotranspiration modifier for land cover $L_x$ and $ET_0$ is potential evapotranspiration.

and $\omega(x)$ is a modified dimensionless ratio of plant accessible water storage to expected annual precipitation, defined as:

$$\omega(x) = Z \frac{AWC(x)}{P(x)}$$  \hspace{1cm} (4)

where $Z$ is Zhang’s Constant (Zhang et al. 2001), a seasonality index were higher values indicate evenness in annual precipitation, and $AWC(x)$ is the volumetric (mm) plant available water content defined as:

$$AWC(x) = f(\text{plant available water content, root restricting layer depth})$$
The data needed for this model, (annual precipitation, potential evapotranspiration, plant available water content, root restricting layer depth, watershed and sub-watershed boundaries) was acquired from various sources (Table 1) and reprojected to NAD 83 SPC 3200 (NC). Root restricting layer depth and plant available water content was assumed to be zero in urban areas, including developed open space. I chose a value of Zhang’s Constant value of 8 to reflect the relative evenness of precipitation throughout the year, a choice consistent with recommendations for temperate climates. The land cover data for 2011 and 2030 passed to the water yield model was prepared as described in the previous section. All analysis was conducted at the native land cover resolution, 30 m.

*Process-based Nutrient Cycling*

Informed by topographical flow gradients, the InVEST first estimates per-pixel adjusted nutrient load values $ALV_x$ and then estimates how much load is either retained or carried out by surface flows to adjacent downstream pixels. The first step is defined as:

$$ALV_x = HSS_x \cdot pol_x$$

Where $HSS_x$ is a hydrological sensitivity index at $x$, described as:

$$HSS_x = \frac{\lambda_x}{\lambda_W}$$

Where $\lambda_x$ is the runoff index at $x$, defined as:

$$\lambda_x = \log \left( \sum_{u} Y_u \right)$$
where $\sum_{U} Y_u$ is the sum of water yield along a flow path above pixel $x$, and $\overline{\lambda_W}$ is the mean runoff index per watershed;

$pol_x$ is an empirically-determined land cover nutrient export coefficient.

In the second step, the model uses a flow accumulation (FAC) surface generated internally from a hydrologically-conditioned digital elevation model to track $ALV_x$, retention (e.g. $ALV_x \times pol_x$), and downstream outflows (e.g. $ALV_x \times (1 - pol_x)$). The model does not account for saturation of uptake. The model then aggregates the loading that reaches the stream at pixel, sub-watershed and watershed levels.

New data needed for this model included a hydrologically conditioned DEM, a threshold accumulation value, and a water purification threshold look up table. The DEM was prepared using GRASS GIS r.fill and r.carve modules, and tested for its ability to generate a flow accumulation surface in advance of use in InVEST. A threshold accumulation value of 1000 cells was used to generate the stream network from the FAC. I used a default water purification threshold value of 1 kg yr-1 to represent the critical annual nutrient loading allowed for the HUC 8 watershed. Water yield ($Y(x)$) and land covers for 20 and 2030 passed to this model were prepared as previously described.

**Economic estimation of ecosystem services**

To estimate the value of P retention by the landscape, ignoring “allowable” nutrient export, the net above-threshold retention at a given pixel ($net_x$) is defined as:

$$net_x = retained_x - \frac{thresh}{contrib}$$
Where retainedx is per-pixel nutrient retention, thresh is total allowed annual load, and contrib is the number of pixels on the landscape. Nutrient loads below threshold levels are not credited. Pixel values are then aggregated at watershed or other scale of interest. The monetary value of avoided water treatment costs provided by soil and vegetative retention at the sub-watershed extent (wp_Valuex) is estimated by:

$$wp_{Value_x} = Cost(p) \times retained_x \times \sum_{t=0}^{T-1} \frac{1}{(1 + r)^t}$$

where $Cost(p)$ is annual treatment costs ($/kg), T is time span under consideration, and r is discount rate.

\[ \sum_{t=0}^{T-1} \frac{1}{(1 + r)^t} \]

is the basic net present value formula that values an investment based on discounted flows of future payment, with money being worth more now than in the future a standard assumption in investment.

To estimate this value, we developed a water purification valuation look up table based on fees assessed in watersheds east of the study area. North Carolina’s Division of Mitigation Services administers a voluntary Nutrient Offset Program in the Neuse and Tar-Pamlico basins east of the study area. This program applies a fee schedule to non-point source nutrients N and P using an “Actual Cost Method” to estimate the cost of mitigating these pollutants (NCDENR 2015). Fees vary by area, and I took the average which billed N at a rate of $43.85 kg yr\(^{-1}\) ha\(^{-1}\), and P at $524.30 kg yr\(^{-1}\) ha\(^{-1}\), values held constant throughout. I assumed a linear change in purification services between 2006 and 2030, and estimated the present value of 24 years of aggregated pollution offset fee.
s using a discounted (4%) cash flow model. All estimations are developed on an annual basis, and significant intra-annual variability, such as nutrient pulses during the growing season, is unaccounted for in the modelling.

Model limitations

InVEST reduces all bio-physical processes into one land cover class dependent export coefficient, and in this way generalizes local effects that may be relevant to how nutrient cycles operate on a specified landscape. Estimations are developed on an annual basis, and significant intra-annual variability, such as nutrient pulses during the growing season, is unaccounted for in the modelling. In-stream processes, and point source pollution, are not considered by the model.
Table 1. Data used in eco-hydrological and nutrient cycling modeling.

<table>
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<th>Data Source</th>
<th>Description</th>
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<th>Notes</th>
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<tr>
<td>Soil Depth (BDMA)</td>
<td>Soil depth at which pedogenesis is in progress (modified from USDA Soil Survey Database)</td>
<td>Meters above sea level</td>
<td>From NC-Northeast Project, hydrologically conditioned.</td>
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<td>Soil Porosity</td>
<td>Soil porosity at a location of interest</td>
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</tr>
<tr>
<td>Water Flow</td>
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</tr>
<tr>
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# APPENDIX C

Carbon Storage and Sequestration Modeling

## Tables

Table 1. Empirical estimates of terrestrial carbon pools (Mg/ha) for land cover classes in the study area. These estimates were applied in the InVEST 3.1 Carbon Storage and Sequestration module.

Adapted from Schmidt (2012).

<table>
<thead>
<tr>
<th>Above</th>
<th>Below</th>
<th>Soil</th>
<th>Dead</th>
<th>Landcover Class</th>
<th>Sources</th>
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<tbody>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>Open Water</td>
<td>N/A</td>
</tr>
<tr>
<td>n/a</td>
<td>3.0</td>
<td>78.0</td>
<td>n/a</td>
<td>Developed OS</td>
<td>Pouyat, 2006 (park soil)</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>144.0</td>
<td>n/a</td>
<td>Low Intensity Developed</td>
<td>Pouyat, 2006 (residential soil)</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>33.0</td>
<td>n/a</td>
<td>Medium Intensity Developed</td>
<td>Pouyat, 2006 (residential soil)</td>
</tr>
<tr>
<td>n/a</td>
<td>6.6</td>
<td>82.0</td>
<td>n/a</td>
<td>High Intensity Developed</td>
<td>Pouyat, 2002 (urban soil)</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>14.3</td>
<td>n/a</td>
<td>Bare Soil</td>
<td>Han, 2007</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>Quarry/Strip Mine/Gravel Pit</td>
<td>N/A</td>
</tr>
<tr>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>So. Appalachian Granitic Dome</td>
<td>N/A</td>
</tr>
<tr>
<td>95.8</td>
<td>20.1</td>
<td>41.1</td>
<td>16.5</td>
<td>Atlantic Coastal Plain Dry-Mesic Oak Forest</td>
<td>JE Smith, 2006 Oak-pine (all pools)</td>
</tr>
<tr>
<td>89.0</td>
<td>18.7</td>
<td>143.5</td>
<td>16.9</td>
<td>Atlantic Coastal Plain Mesic Hardwood-Mixed Forest</td>
<td>JE Smith, 2006 Oak-hickory (all pools)</td>
</tr>
<tr>
<td>88.9</td>
<td>18.7</td>
<td>55.8</td>
<td>19.5</td>
<td>So. Piedmont Dry Oak-(Pine) Forest - Hardwood</td>
<td>JE Smith, 2006 LLP (all pools)</td>
</tr>
<tr>
<td>95.8</td>
<td>20.1</td>
<td>41.1</td>
<td>16.5</td>
<td>So. Piedmont Mesic Forest</td>
<td>JE Smith, 2006 LLP (all pools)</td>
</tr>
<tr>
<td>85.0</td>
<td>17.9</td>
<td>66.2</td>
<td>23.1</td>
<td>Evergreen Plantations</td>
<td>JE Smith, 2006 LLP (all pools)</td>
</tr>
<tr>
<td>86.0</td>
<td>18.1</td>
<td>66.2</td>
<td>23.1</td>
<td>So. Piedmont Dry Oak-(Pine) Forest - LLP Modifier</td>
<td>JE Smith, 2006 Oak-pine (all pools)</td>
</tr>
<tr>
<td>87.0</td>
<td>18.3</td>
<td>66.2</td>
<td>23.1</td>
<td>Atlantic Coastal Plain Upland LLP Woodland</td>
<td>JE Smith, 2006 (above); Saugier, 2001 (below); Lorenz and Lal, 2009 (soil)</td>
</tr>
<tr>
<td>88.9</td>
<td>18.7</td>
<td>55.8</td>
<td>19.5</td>
<td>So. Piedmont Dry Oak-(Pine) Forest - Mixed</td>
<td>JE Smith, 2006 (above); Saugier, 2001 (below); Lorenz and Lal, 2009 (soil)</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td>Successional Shrub/Scrub</td>
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</tr>
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<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---------------------------</td>
<td>---</td>
</tr>
<tr>
<td>3.1</td>
<td>0.2</td>
<td>117.0</td>
<td>n/a</td>
<td>(Clear Cut)</td>
<td>JE Smith, 2006 (above); Saugier, 2001 (below); Lorenz and Lal, 2009 (soil)</td>
</tr>
<tr>
<td>2.6</td>
<td>0.2</td>
<td>117.0</td>
<td>n/a</td>
<td>(Other)</td>
<td>JE Smith, 2006 (above); Saugier, 2001 (below); Lorenz and Lal, 2009 (soil)</td>
</tr>
<tr>
<td>2.6</td>
<td>0.2</td>
<td>117.0</td>
<td>n/a</td>
<td>Grassland/Herbaceous</td>
<td>Paul, 1999 (above and 21% below); USDA-ARS (conventional till soil)</td>
</tr>
<tr>
<td>2.6</td>
<td>0.2</td>
<td>117.0</td>
<td>n/a</td>
<td>Grassland/Herbaceous (Other)</td>
<td>USDA-ARS (conventional till); Paul (conventional till); Han, 2005 (above and 21% below)</td>
</tr>
</tbody>
</table>
APPENDIX D

Structural Equation Modeling (SEM)

Tables

Table 1. Data used in analysis of pattern domains. In most cases, percentages, indices and relative measures are used in order to compare sub-watersheds of different sizes.

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Metric</th>
<th>Description</th>
<th>Units</th>
<th>Comment</th>
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</thead>
<tbody>
<tr>
<td>Magnitude Change, Composition</td>
<td>Δ PLAND [1, 2, 3, 4, 5]</td>
<td>Change in Percentage of Class Area</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Δ CA [1, 2, 3, 4, 5]</td>
<td>Change in Class Area</td>
<td>HA</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PLAND [1, 2, 3, 4, 5]</td>
<td>Percentage of landscape by load class</td>
<td></td>
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<tr>
<td></td>
<td>DOM</td>
<td>Dominance</td>
<td></td>
<td>Measure of evenness.</td>
</tr>
<tr>
<td></td>
<td>SHDI</td>
<td>Shannon Diversity Index</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Configuration</td>
<td>LSI, nLSI</td>
<td>Landscape Shape Index, normalized Landscape Shape Index</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ED</td>
<td>Edge Density</td>
<td></td>
<td>Internal border used: edge density reports edge length on a per unit area basis that facilitates comparison among landscapes of varying size</td>
</tr>
<tr>
<td></td>
<td>PDEN</td>
<td>Patch Density</td>
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<td></td>
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<tr>
<td></td>
<td></td>
<td>Isolation/Proximity</td>
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</tr>
<tr>
<td></td>
<td>CONTAGION</td>
<td>Adjacency</td>
<td></td>
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<tr>
<td>Intensity</td>
<td>POPDEN</td>
<td>Population Density</td>
<td>Mean</td>
<td></td>
</tr>
<tr>
<td>-------------</td>
<td>--------</td>
<td>--------------------</td>
<td>------</td>
<td></td>
</tr>
<tr>
<td>POP</td>
<td>POP</td>
<td>Population by sub-watershed</td>
<td>Sum</td>
<td></td>
</tr>
<tr>
<td>MOMENTUM</td>
<td>MOMENTUM</td>
<td>Urban land cover intensity</td>
<td>% 1 km(^2)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Connectivity</th>
<th>CWED</th>
<th>Contrast Weighted Edge Density</th>
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</thead>
<tbody>
<tr>
<td>Cohesion</td>
<td>Cohesion measures the physical connectedness of a patch type, increasing as patches become more aggregated. It is computed based on the perimeter (Pi) and area (ai) of each patch i and the total area (A) and number of patches (n) in the landscape (Schumaker 1996):</td>
<td></td>
</tr>
<tr>
<td>AI</td>
<td>AI is maximal when the cells of a patch type are configured as a single, compact mass. It is constructed from the ratio of the number of shared edges (adjacencies) between pixels of a patch type (gij) to the maximum possible number of adjacencies between pixels of that patch type (He et al. 2000):</td>
<td></td>
</tr>
<tr>
<td>Contagion</td>
<td>Total Edge Contrast Index</td>
<td>Mean</td>
</tr>
<tr>
<td>-----------</td>
<td>---------------------------</td>
<td>------</td>
</tr>
<tr>
<td>TECI</td>
<td>Contrast Weighted Edge Density</td>
<td></td>
</tr>
<tr>
<td>CWED</td>
<td>Patch Shape Index</td>
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<td>CA [1, 2, 3, 4, 5]</td>
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<td>Mean</td>
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<td>FAC</td>
<td>Flow Accumulation Model</td>
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<td>Phosphorus export</td>
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<tr>
<td>N Export</td>
<td>Nitrogen export</td>
<td>Kg·ha⁻¹·yr⁻¹</td>
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<tr>
<td>C storage</td>
<td>Carbon storage</td>
<td>Mg·ha⁻¹·yr⁻¹</td>
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</table>

Contagion is a measure of overall landscape clumpiness computed across all patch types (j and k). Inversely related to edge density, it is highest when patch dispersion and interspersion are both low, resulting in a high proportion of like adjacencies and an inequitable distribution of unlike adjacencies, respectively (Li and Reynolds 1993).