EVALUATING TEMPORAL AND SPATIAL LAND USE INFLUENCES AFFECTING NUTRIENT WATER QUALITY IN THE BISCAYNE BAY WATERSHED, FLORIDA

By

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To Florence and Judene

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LIST OF ABBREVIATIONS

AWMSI	Area weighted mean shape index
DCIA	Directly connected impervious area
HSR	High density single family residential
LDI	Landscape Development Intensity index
LIC	Low intensity commercial
LPI	Largest patch index
LSI	Landscape shape index
LSR	Low density single family residential
MDL	Minimum detection limit
MNN	Mean nearest neighbor
MPI	Mean proximity index
MPS	Mean patch size
MSR	Medium density single family residential
NSE	Nash-Sutcliffe Efficiency index
PBIAS	Percentage bias
PED	Pollutant empower density index
PSCoV	Patch size coefficient of variation
PSSD	Patch size standard deviation
RSR	Ratio of the root mean square error to the standard deviation of measured data
TIA	Total impervious area
UEV	Unit emergy value

Abstract of Dissertation Presented to the Graduate School
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Biscayne Bay, a tropical estuary along the southeastern Florida coastline, drains both the Miami metropolitan complex and South Dade Agricultural Area. Water management systems protect the watershed from seasonal floods but have also disrupted historical freshwater flows to the bay, which requires minimal phosphorus and nitrogen inputs. Watershed discharges therefore have a controlling influence on bay water quality and can degrade sensitive estuarine habitats.

To explore watershed land use and water quality variability, this study evaluated temporal and spatial land use influences on nutrient concentrations measured in canals discharging to Biscayne Bay. Disturbance indicators for 1995, 1999, and 2004 (landscape metrics, Landscape Development Intensity index [LDI], and imperviousness) suggested urban sub-basins were stable and characterized by complex residential areas, corresponding to greater anthropogenic intensity compared to agricultural and mixed land use sub-basins. Historical nutrient data (1992 to 2006), analyzed using multiple methods (trend analysis, load estimation, and a new water quality index), revealed water quality has generally improved. This improvement was likely a response to implementation of agricultural and urban best management practices as well as repair of leaky wastewater systems. The Pollutant Empower Density (PED) index assesses proportional impacts

from point source discharges and two discharge locations (MW04 and LR06) had the greatest potential to degrade Biscayne Bay water quality. Land use and water quality relationships were evaluated at multiple spatial extents (sub-basins, canal buffers, and site buffers) and regressions suggested nitrate/nitrite-nitrogen loads were most related to land use variables at the sub-basin level. Development patterns in a smaller zone (1000 m canal buffer) were important factors for total phosphorus loads, reflecting watershed nutrient transport processes.

Rapid urbanization is ongoing in south Florida and both the intensity and spatial distribution of land uses affect nutrient discharges that could alter Biscayne Bay. Disturbance indicators can link land use to water quality parameters for improved watershed management, such as increasing treatment efficiency of established pollutant-control strategies (e.g., detention and retention systems) and guiding zoning regulations. Combined assessment of multiple indicators also provides a more holistic interpretation of water quality, which is necessary for optimizing resources to preserve water quality.

CHAPTER 1
INTRODUCTION

Background

The south Florida landscape has changed dramatically in recent decades. Originally dominated by wetlands, pine forests, estuaries, bays, and hardwood hammocks, anthropogenic influences have transformed the region. Drainage projects, agriculture, and urban development have fragmented the landscape, threatened the Florida Everglades, fostered exotic species invasions, and impaired coastal resources (McPherson and Halley 1996) such as the Biscayne Bay, a tropical barrier-island estuary located along the southeastern Florida coastline (Figure 1-1). Surrounded by urbanized Miami-Dade to the north, Homestead to the west, and the Florida Keys to the south, Biscayne Bay is ecologically and economically important to the Miami metropolitan area because its tropical reefs and mangroves support numerous species (manatees, dolphins, wading birds etc.) as well as fishing and recreational industries (BBPI 2001). The state designated Biscayne Bay as an Outstanding Florida Water in 1978 to prevent environmental degradation but extensive development in its 2,500 km^2 watershed has altered the estuary. Problems include local fish extinctions, hypersalinity, algal blooms related to eutrophication, point source pollution, and seagrass deaths (Alleman et al. 1995).

A historical perspective of natural resource management in south Florida is required to understand water-related issues in the bay and elsewhere in the region. For example, the Everglades Reclamation program that began in 1906 sparked an intense real estate boom that laid the foundation for south Florida's future development. Over 5,000 years of accumulated peat deposits created a vast, 12,000 km^2 Everglades, but in the 20th century, drainage projects reduced this area to 6,000 km^2 (Gleason and Stone 1994). Local governments wanted to encourage settlement but could not afford to drain the land; instead, speculators bought millions

of acres of cheap land from the state, drained it, and attracted settlers (Hanna and Hanna 1948). Between 1910 and 1930, the population in three south Florida counties (Miami-Dade, Broward and Palm Beach) increased 165% and accelerated again after the Great Depression (1930s) and World War II (1939-1945). However, the Florida real estate crash in 1926, two deadly hurricanes in 1926 and 1928, and record floods in 1947 and 1948 slowed regional growth and shifted the focus to flood control (Schultz 1991).

Political pressure from concerned residents in the 1950s gave government agencies a mandate to prevent future flooding problems and to develop suitable drainage projects (Blake 1980). The new era of multipurpose water management thus attempted to control the hydrology of south Florida. Inland levees in Broward County, for example, helped to lower groundwater levels and improve development opportunities on former cypress and pine forests (Renken et al 2005). South Florida's population consequently doubled during the 1950s (724,000 to 1.5 million). Another important factor contributing to population growth during this period was the expansion of the transportation system. Three major highways that were built between 1930 and 1950 – U.S. Route 1, U.S. Route 27, and the Tampa-Miami (Tamiami) Trail – supported the extensive road network established in the 1950s and 1960s (Solecki and Walker 2001).

From 1900 to the early 1950s, agricultural production was predominantly responsible for land use conversions in the region but this pattern was beginning to change. Urban land uses in Miami-Dade and Broward Counties were increasing rapidly as "the demand to shift land to urban uses outweighed the demand to shift land to agricultural uses over a large area" (Solecki and Walker 2001). Agricultural production was still vital to the south Florida economy, however, as demand for winter vegetables and fruits grew in Northern and Midwestern states (Winsberg 1991). In addition, the Cuban Revolution (1959) increased tariffs on imported sugar and this

stimulated intensive sugar cane production in south Florida (Salley 1986). As the coast became more urbanized (1950-1970), farmers sought new agricultural land south of Lake Okeechobee in the Everglades Agricultural Area (EAA).

Two main factors have therefore driven land use change in south Florida from the 1970s to the present: increased migration and significant demand for Florida's agricultural produce (Walker et al. 1997). Although the overall population growth rate of south Florida has declined, absolute population growth in the region has continued to increase rapidly during the last 30 years; south Florida's population increased from 2.5 million in 1970 to more than 5 million in 2000. Northeastern and Midwestern states supplied the majority of new residents but immigrants from Caribbean and Latin American countries have also been substantial (Schultz 1991). From 1973 to1986, 28.3% of all land conversions were from agriculture to urban use (Solecki and Walker 2001) and the EAA has subsequently expanded deeper into the Everglades (Salley 1986). With intensive urbanization and agricultural operations, water consumption in south Florida has increased in recent decades and when coupled with hydrological modifications, this increased water demand has the potential to deteriorate water quality (McPherson and Halley 1996).

Land Use Analysis

Configuration and Composition

Dow (2000) defined human-dominated landscapes (e.g., the Biscayne Bay watershed) as complex mosaics where heterogeneous human activities gradually transform biophysical characteristics. For example, numerous studies have linked land use with water quality (e.g., Osborne and Wiley 1988; Johnson et al. 1997; Harman-Fetcho et al. 2005) as the proportion and spatial arrangement of land use and land cover (LULC) within watersheds can have significant impacts (e.g., Hunsaker and Levine 1995; Roth et al. 1996; Johnson et al. 2001). The field of landscape ecology provides a conceptual framework to understand these anthropogenic

influences because it is primarily concerned with land use patterns within defined areas, interactions among different landscape elements, and the effects of changes in the spatial heterogeneity complex over time (Risser et al. 1984; Haines-Young et al. 1994). German geographer Carl Troll originally developed the term "landscape ecology" in the 1930s and the discipline grew in Europe as a corollary to land planning (Schreiber 1990); beginning in the 1980s, landscape ecology became prevalent in the North American literature (Turner 2005).

A fundamental concept in landscape ecology is that patterns influence processes and several studies have emphasized methods to quantify spatial heterogeneity (e.g., Forman and Godron 1986; O'Neill et al. 1988; Turner and Gardner 1991). Metrics (variables) have been developed for landscape composition (relative amounts of different elements in the landscape) and configuration (arrangement of these elements) that aid analysis and interpretation of landscape processes (Turner 1989; Li and Wu 2004). The most widely used software package to calculate landscape metrics is FRAGSTATS (McGarigal and Marks 1995); several different categories of metrics can be calculated as FRAGSTATS generates values that can be useful to understanding changes occurring in an area such as a watershed. Patch Analyst (Elkie et al. 1999) uses a modified form of FRAGSTATS and provides an integrated user interface that enables metrics to be calculated for land use layers at both landscape and class levels within a Geographic Information System (GIS) software package, ArcGIS (ESRI 2005). GIS software, which can integrate multiple historical datasets (e.g., land use and water quality data), can be used to study ecological relationships within heterogeneous landscapes.

Hundreds of metrics can be obtained from temporal and spatial land use analyses utilizing mathematical operations in GIS. For a large dataset containing multiple variables, it is often easier to analyze this information if the number of variables is reduced to a smaller set of

components that retains all the important information. Principal Component Analysis (PCA) is a data reduction technique that identifies linear combinations of the original variables explaining all of the variance in a dataset (Nichols 1977; Bengraine and Marhaba 2003). These linear combinations, or principal components, describe variability in the dataset which are not directly measured. Factor analysis (FA) is another statistical procedure used with multi-variable datasets to identify factors contributing to the overall variance (McDonald 1985). The difference between PCA and FA is that while PCA attempts to simplify variable interpretation through data reduction, FA primarily focuses on identifying significant, underlying factors.

PCA and FA have been used together in land use analysis to elucidate historical or ongoing processes at different spatial extents, such as an entire landscapes or individual land use classes. For example, Ritters et al. (1995) calculated 55 landscape metrics for 85 LULC maps representing different U.S. physiographic regions to determine the best combination of metrics that describe landscape pattern and structure. Landscape metrics are often highly correlated because multiple variables can quantify the same phenomena but present the information in alternate forms (McGarigal and Marks 1995; Li and Wu 2004). Using correlation analysis, PCA, and FA, Ritters et al. (1995) reduced the initial set of 55 metrics to six factors, or composite variables, responsible for 87% of the variation in the dataset. Similarly, Cushman et al. (2008) analyzed LULC in eastern, central, and western U.S. regions and reduced both landscape (54 to 17) and class (49 to 24) level metrics into independent variables that described landscape configuration and structure. Other studies have calculated metrics and used PCA and FA to evaluate landscape structure at multiple scales (Griffith et al. 2000), to investigate development patterns in watersheds (Cifaldi et al. 2004; Kearns et al. 2005), and to assess the relationship between metrics and sediment contamination levels (Paul et al. 2002).

Emergy Index: Landscape Development Intensity

Emergy, or embodied energy, is a concept developed by H.T. Odum (Odum 1971; Odum 1996) that derived from decades of analysis on the differential ability of various forms of energy to do work (Brown and Ulgiati 2004). In the environmental context, available energy from sources such as the sun, wind, and rain are transformed within natural systems as it is used to maintain functional processes and/or to create new resources. However, energy is degraded during these transformations and the resultant forms of energy have unequal ability to do work (Odum 1996). To account for this variability, emergy analysis expresses different forms of energy within a system in units of solar emergy (the available solar energy used during energy transformations; solar emjoules) to assess the total amount of energy required to achieve a particular output. Emergy, in essence, "looks back upstream to record what energy went into the train of transformation processes" (Odum 1996).

Through emergy analysis, both natural and anthropogenic energy inputs required to generate products and services can be evaluated. Brown and Vivas (2005) explored this benefit of emergy analysis by developing a Landscape Development Intensity (LDI) index that analyzed human disturbance gradients within watersheds. The LDI index compares urban and agricultural areas based on energy signatures associated with land use classes that expanded on the earlier work of Brown (1980), and an evaluation of the relationship between development intensity and water quality in the St. Marks Watershed, Florida (Brown et al. 1998). Brown and Vivas (2005) evaluated the nonrenewable areal empower intensity (emergy per unit area per unit time) of various land uses using an area-weighted formula:

$$LDI_{Total} = \sum \% LU_i * LDI_i \qquad (1\text{-}1)$$

where LDI_{Total} is the LDI ranking for a landscape, $\%LU_i$ is the percent of the total area of influence in land use i, and LDI_i is the landscape development intensity coefficient for land use

i. Several other studies have utilized this LDI index to quantify disturbance gradients. Mack (2006) evaluated Ohio wetlands and found that the LDI index compared favorably with other assessment tools. In Florida, the LDI index was strongly correlated to a wetland biological integrity index (Reiss 2006; Reiss and Brown 2007). Lane and Brown (2006) determined that the LDI index explained more of the variation in benthic diatom species within Florida freshwater marshes compared to other landscape metrics (e.g., percent agriculture and percent urban).

As the LDI concept was applied under different conditions, an important emerging limitation of the index was that human disturbance intensity was not related to background conditions in the landscape. Another limitation was that each land use had predetermined LDI coefficients. Reiss et al. (2009) developed a revised LDI method to address these limitations. In the revised method, LDI values start at zero (i.e., nonrenewable empower intensity is equal to the renewable empower of the landscape unit), the overall impact of the nonrenewable empower intensity in a landscape is reduced as the background renewable empower intensity increases, and there is no maximum value. The following equation illustrates the revised LDI method:

$$LDI = 10 * \log_{10} (emPI_{Total} / emPI_{Ref}) \quad (1\text{-}2)$$

where LDI [unit less] is the Landscape Development Intensity index for a landscape, $emPI_{Total}$ [sej ha^{-1} yr^{-1}] is the total empower intensity (sum of renewable background empower intensity and nonrenewable empower intensity of land uses), and $emPI_{Ref}$ is the renewable empower intensity of the background environment within a particular landscape. For example, the renewable empower intensity of Florida is 1.97 E15 sej ha^{-1} yr^{-1} (Reiss et al. 2009). The total empower intensity ($emPI_{Total}$) was calculated as follows:

$$emPI_{Total} = emPI_{Ref} + \sum (\%LU_i * emPI_i) \quad (1\text{-}3)$$

where $\%LU_i$ is the percent of the total area in LULC class *i* and $emPI_i$ [sej ha^{-1} yr^{-1}] is the nonrenewable empower intensity for LULC class *i*.

Imperviousness

Urban development creates impervious surfaces that can have multiple hydrological, physical, and ecological effects within a watershed. Arnold and Gibbons (1996) described four qualities of imperviousness: (1) impervious surfaces contribute to hydrologic changes that impair water quality; (2) imperviousness is a characteristic of intensive land use activities; (3) impervious surfaces hinder pollutant processing by disrupting soil percolation; and (4) impervious surfaces efficiently transport pollutants into receiving waters. Studies have used impervious surfaces such as buildings, parking lots, and roads as a measure of the extent of development within landscapes and have linked these variables to overall water quality (e.g., McMahon and Cuffney 2000; Roy and Shuster 2009). Relatively low levels of watershed imperviousness can produce negative effects in aquatic systems; for example, Arnold and Gibbons (1996) characterized streams within watersheds containing <10% of impervious cover as protected, 10-30% as impacted, and greater than 30% as degraded. Linking an imperviousness threshold to water quality can be challenging, however, because many studies do not differentiate between total and effective impervious cover within watersheds (Brabec et al. 2002). Total impervious areas (TIA) include surfaces that may drain to pervious ground while effective impervious areas only include impervious cover directly connected to waterways. Using TIA instead of directly connected impervious areas (DCIA) in water quality investigations may therefore obscure the influence of land use changes (Alley and Veenhuis 1983). Reducing DCIA is an important component of low impact development (Wright and Heaney 2001) because it reflects the potential influence of human development on adjacent systems.

Land use analysis studies have estimated percent imperviousness for different land use classes (e.g., Stankowski 1972; Griffin 1980; Alley and Veenhuis 1983). Miami-Dade Department of Environmental Resources Management (DERM) developed percent imperviousness values for land uses classes within the Biscayne Bay watershed which can be used to calculate area-weighted imperviousness for LULC maps (DERM 2004). Quantifying development patterns by calculating disturbance indicators, such as watershed imperviousness, therefore has the potential to indicate the relative influence of land use classes on water quality.

Water Quality Analysis

Nutrient Enrichment

Phosphorus and nitrogen are essential nutrients for metabolic functions in living organisms and in aquatic environments, these nutrients stimulate overall productivity. However, excessive inputs of nitrogen and/or phosphorus can lead to over-enrichment, or eutrophication, of surface waters that produce problems such as algal blooms, decreased dissolved oxygen concentrations, and increased fish mortality (Carpenter et al. 1998; Smith 1998). Eutrophication ranks as the leading pollutant problem affecting the ability of U.S. surface waters to meet designated uses such as recreation, fishing, and irrigation (Howarth et al. 2002). Nutrients originate from both point (e.g., wastewater treatment plants) and nonpoint (e.g., agricultural and urban runoff) sources and watershed management plans often include strategies to mitigate inputs from all significant contributing factors. Water quality monitoring programs provide an opportunity to evaluate temporal variability and spatial variability in nutrient inputs within watersheds that enable managers to implement plans targeted to specific concerns. For example, management plans often include measures to control the nutrient limiting algal and aquatic plant growth. Limitation develops because metabolic processes require optimal nutrient ratios and the nutrient that is most scarce will regulate system productivity (Hecky and Kilham 1988).

In Biscayne Bay, the primary nutrient limiting autotrophic growth is phosphorus (Brand 1988; Kleppel 1996). Average phosphorus concentrations are low but variable throughout Biscayne Bay with the northern section typically having greater concentrations than the central and southern sections (Brand 1988; Alleman et al. 1995; Brand et al. 2002). Biscayne Bay is a natural oligotrophic estuary requiring minimal inputs of phosphorus and nitrogen to function; nutrient inputs from the watershed therefore have a controlling influence on water quality in the bay (Browder et al. 2005). Due to the difference in phosphorus concentrations in sections of the watershed, Brand (1988) found phytoplankton levels were five times greater in the north than in the south. Nitrogen may not be the limiting nutrient in the bay but elevated nitrate/nitrite concentrations (greater than 4 mg L^{-1}; Cheesman 1989) derived from agricultural and some urbanized areas in the watershed are a concern because artificially high nitrogen concentrations may have subtle ecological effects (Alleman et al. 1995), such as the bay being more susceptible to algal blooms.

Trends

Changes in land use, management practices, and environmental conditions may all lead to detectable differences in constituent concentrations over time at water quality monitoring sites. Both parametric and nonparametric techniques (Hirsch et al. 1982; Hirsch et al. 1991; Letttenmaier et al. 1991) are available to determine temporal changes in specific parameters of interest such as nutrients. However, long-term water quality datasets have several characteristics that can complicate trend analysis; there are frequently large gaps in the dataset, data are often skewed, censored data are prevalent (values less than the minimum detection limit; MDL), and chemical analytical techniques can improve over time producing multiple MDLs for the same parameter. Seasonality (Champley and Doledec 1997; Mcartney et al. 2003; Qian et al. 2007)

and discharge fluctuations (Alley 1988; Hirsch et al. 1991) are other factors that can significantly influence trend analysis.

USGS Estimate Trend (ESTREND; Schertz et al. 1991) includes both parametric (Tobit regressions) and non-parametric (uncensored/censored seasonal Kendall) methods to determine trends in constituent water quality data. Tobit regression uses a maximum likelihood estimation method to determine trends for parameters that contain greater than 5% censored data with multiple MDLs. The seasonal Kendall methods are suitable for parameters with less than 5% censored data (uncensored seasonal Kendall) and greater than 5% censored data at a single detection limit (censored seasonal Kendall). As watershed management plans become more refined to address specific concerns, trend analysis can provide important information on the relative success of such initiatives. Lietz (2000), for example, analyzed water quality data (1966 to 1994) at a site discharging to Biscayne Bay and found downward trends, indicative of improved water quality, for several parameters including total ammonia nitrogen and total phosphorus.

Loads

Different methods are available to quantify nutrients entering a water body depending on the objectives of a particular investigation. Concentration measurements are convenient for comparing field data to water quality criteria, loads assess the mass of constituents transported over time and help to quantify the total amount delivered, and yields estimate the mass of constituents delivered per unit area per unit time, which can help to assess best management practices (Christensen 2001). The total amount of nutrients entering Biscayne Bay is of particular concern and previous studies have quantified incoming nutrient loads. Lietz (1999) estimated nutrient loads to Biscayne Bay by analyzing nutrient concentrations and freshwater discharges and Caccia and Boyer (2007) developed a nutrient loading budget to the bay by analyzing canals

throughout the watershed. Both studies determined that nitrate/nitrite-nitrogen loads were elevated in the southern agricultural drainage areas while ammonia-nitrogen and total phosphorus loads were highest in the northern and central urban drainage areas.

The U.S. Geological Survey (USGS) developed the Load Estimator (LOADEST) model that has been specifically designed to estimate loads in streams and rivers (Runkel et al. 2004). The model is a publicly available FORTRAN program that uses linear regressions to estimate daily, monthly, seasonal, or annual loads and users have the ability to customize the model to fit particular objectives. Donato and MacCoy (2005), for example, used the LOADEST model to develop regression equations estimating total phosphorus loads, orthophosphorus loads, and suspended sediment in the lower Boise River. The authors concluded that LOADEST was a useful tool with good spatial and temporal resolution relative to phosphorus and suspended sediment.

LOADEST includes three methods to estimate loads, Maximum Likelihood Estimation (MLE), Adjusted Maximum Likelihood Estimation (AMLE), and Least Absolute Deviation (LAD). If the calibration dataset is uncensored, MLE (Cohn et al. 1989) is used for load estimation in LOADEST as follows:

$$\hat{L}_{MLE} = \exp\left(a_0 + \sum_{j=1}^{M} a_j X_j\right) g_m(m, s^2, V) \qquad (1\text{-}4)$$

where $\hat{L}_{MLE}$ is the load estimate using MLE, a_0 and a_j are maximum likelihood estimates, [g_m (m, s^2, V)] is the bias correction factor, which includes the number of degrees of freedom (m), the residual variance (s^2), and a function relating to the explanatory variables (V).

The Adjusted Maximum Likelihood Estimation (AMLE) method is used to estimate loads when the calibration dataset includes censored data. The AMLE method (Cohn 1988) is as follows:

$$\hat{L}_{AMLE} = \exp\left(a_0 + \sum_{j=1}^{M} a_j X_j\right) H(a, b, s^2, \alpha, \kappa) \tag{1-5}$$

where $\hat{L}_{AMLE}$ is the load estimate using AMLE, a_0 and a_j are maximum likelihood estimates adjusted for bias, and $H(a, b, s^2, \alpha, \kappa)$ is an approximate bias correction factor from Cohn et al. (1992).

MLE and AMLE both assume that model residuals are normally distributed. LOADEST includes the Least Absolute Deviation (LAD) method to estimate loads when the normality assumption is violated (Duan 1983; Powell 1984):

$$\hat{L}_{LAD} = \exp\left(a_0 + \sum_{j=1}^{M} a_j X_j\right) \frac{\sum_{k=1}^{n} \exp(e_k)}{n} \tag{1-6}$$

where $\hat{L}_{LAD}$ is the load estimate using LAD, a_0 and a_j are LAD regression model coefficients, e represents the residual error, and n is the number of uncensored calibration values. The flexibility of LOADEST and its ability to estimate loads when assumptions are violated enhances the utility of this program for water quality analyses.

Emergy Index: Pollutant Empower Density

The Pollutant Empower Density (PED) index is based on the concept that the effect of chemical stressors (metals, nutrients, etc.) in aquatic environments may be explained by their respective empower densities relative to background conditions. Each element has a unit emergy value (UEV) and this value increases as substances become more concentrated. Furthermore, for elements and compounds that are rare in nature, more energy is required to concentrate these

materials and this results in higher emergy/mass ratios (Brown and Ulgiati 2004). Metals, nutrients, and toxins generally have high UEVs and excess concentrations can alter critical ecosystem processes, which can lead to reduced ecosystem function. The LDI index is concerned with empower intensity (emergy per unit area per unit time) but the PED index focuses on empower density (emergy per unit volume per unit time). The PED index is calculated using the flux of pollutants and the background productivity of the reference environment:

$$PED = 10 * \log_{10} (emPD_{Total}/emPD_{Ref}) \quad (1\text{-}7)$$

where PED [unit less] is the Pollutant Empower Density index for an aquatic system, $emPD_{Total}$ is the total empower density [sej m^{-3} yr^{-1}] and $emPD_{Ref}$ is the background empower density [sej m^{-3} yr^{-1}]. The total empower density ($emPD_{Total}$) is calculated as follows:

$$emPD_{Total} = emPD_{Ref} + \sum emPD_i \quad (1\text{-}8)$$

where $emPD_i$ = empower density of pollutant *i* [sej m^{-3} yr^{-1}]. The annual empower density of pollutant *i* is calculated using the specific emergy of the appropriate nutrient and its annual flow weighted concentration.

Regression Analysis

Background

Regression analysis uses quantitative independent variables to explain variation in quantitative dependent variables. Linear regression models can be separated into two broad categories: simple regression models and multiple regression models. In simple linear regression models, the dependent variable (Y) is a direct function of an independent (or explanatory) variable (X). The following is the general equation for simple linear regressions:

$$Y = \beta_0 + \beta_1 X \quad (1\text{-}9)$$

where β_0 is the intercept and β_1 is the slope. For multiple linear regression models, multiple independent variables are used to predict the response of the dependent variable. Multiple

regression models enable researchers to explore phenomena that can be influenced by multiple factors, which offers an advantage over simple regression models. However, in regression analysis, the "typical goal is to build a model using the fewest variables to explain the greatest variability in the response, and to accurately parameterize regression coefficients for those variables" (Graham 2003). The general form of multiple linear regression models is as follows:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_{2...} + \beta_i x_i + \in \quad (1\text{-}10)$$

where Y is the dependent variable, β s are regression coefficients, Xs are explanatory or independent variables and ∈ is the random error term. Several issues exist with the use of multiple regression models, such as ensuring that explanatory variables are independent of each other (Johnston 1972; Mason 1975; Graham 2003). Variable selection (Hocking 1976; Thompson 1978) is another key component of model development as researchers often have concerns about the correct variables to use in various models. Finally, validation procedures evaluate the suitability and accuracy of regression models (Snee 1977).

Through multiple regression analyses and the increased availability of GIS software, many studies have correlated landscape characteristics to water quality parameters. For example, Hunsaker and Levine (1995) used regression models to link spatial and terrestrial processes to water quality in Illinois and Texas watersheds. Studies have also explored possible explanatory variables relating to land use and water quality at multiple spatial extents, including sub-basins (Mehaffey et al. 2005; Migliaccio et al. 2007), riparian zones (Silva and Williams 2001; Schiff and Benoit 2007), and monitoring site proximities (Bolstad and Swank 1997; King et al. 2005).

Variable Selection

Hocking (1976) reviewed numerous proposed variable selection methods for regression models. Predictor variables are often difficult to identify because researchers require data on a large set of potential variables that satisfy assumptions such as homoscedasticity. Collinear

variables (Johnston 1972; Mason 1975; Graham 2003) can result from incomplete sampling designs and can lead to problems with regression coefficients such as high variance (Hocking 1976). Thompson (1978) highlighted some sequential procedures that have been used to select independent variables, including forward ranking, backward ranking, forward selection, and backward elimination. Forward ranking involves assigning the highest rank to the independent variable with the smallest calculated variance ratio (F_s) and ranking additional variables based on comparisons of F_s values at each stage and critical F-values at a designated significance level. Independent variables with F_s values that are not significant are deleted from the regression equation; the forward ranking procedure therefore ranks independent variables from most important to least important. Conversely, the backward ranking procedure ranks independent variables in ascending order of importance. The forward and backward procedures may be expected to produce similar rankings but Abt (1967) cautioned that a set of independent variables may form an association or 'compound' that affects the variance of the dependent variable when one of the independent variables in the group is removed from the model. To avoid the possible effects of these compounds, Thompson (1978) recommended the combined use of both procedures (forward and backward) to select independent variables. The forward selection procedure is similar to the forward ranking method: the independent variable that is most highly correlated with the dependent variable is chosen first and subsequent variables are chosen based on correlation to the dependent variable, given previously selected variables. The backward elimination and backward ranking procedures produce identical rankings although calculated test statistics after the first step are not equal. Similar to the comparisons between the forward and backward ranking methods, backward elimination is favored over forward selection if correlations or possible compounds among independent variables exist (Mantel 1970).

Efroymson (1960) proposed an adaptation of the forward selection procedure that allows both the inclusion and removal of independent variables. This stepwise regression procedure enables researchers to identify variables that may no longer be necessary in the model and may eliminate the problem of compounds in the forward selection method (Thomas 1978). Studies have used stepwise regressions to select a sub-set of landscape attributes that had the most influence on historical land use patterns in Illinois (Iverson 1988), spatial land use variables that explained aquatic organism diversity in streams (Harding et al. 1998), and urbanization variables affecting stream ecological function (Chadwick et al. 2006). Stepwise regressions have also been used to develop multivariate regression models to predict constituent loads of targeted water quality parameters in response to changes in land use variables (e.g., Johnson et al. 2001; Jones et al. 2001; Paul et al. 2002). In addition, Mehaffey et al. (2005) used pairwise correlations and stepwise regressions to identify independent variables that were highly correlated to total nitrogen, total phosphorus, and fecal coliform bacteria in New York watersheds. Two landscape characteristics, percent agriculture development and percent urban development, explained 25 to 75% of the variation in the regression models (Mehaffey et al. 2005). Results such as these have clear management implications and can lead to improved strategies to mitigate threats to vulnerable water resources.

Model Validation and Assessment

After selecting independent variables, regression models need to be validated before being used because the goal of model development is to identify the best possible set of variables for a particular system. However, using the same set of data for model selection and inference, without model validation, can lead to unreliable models. Snee (1977) listed the following options to validate regression models: (1) compare the dependent variable and regression coefficients with physical theory; (2) collect new data to check predictions; (3) compare model results with

theoretical models and simulated data; (4) reserve a section of the available data to estimate model prediction accuracy. Collecting new data is the preferred method for validating regression models but this may not be a viable option in certain scenarios. Snee (1977) notes that splitting the data into an estimation dataset (for model coefficients) and a prediction dataset (to test model accuracy) can simulate the process of collecting new data.

Statement of Problem

Biscayne Bay requires substantial freshwater inputs to maintain its natural ecosystem processes but water management operations (canals, levees, pump sites, etc.) in south Florida have disrupted historical freshwater flows to the bay (Figure 1-2). In addition, urban development and agricultural development in the watershed have thrived on former wetlands as canals have lowered water tables (Parker et al. 1955), reducing watershed water storage and creating polluted discharges that degrade sensitive estuarine habitats (Browder et al. 2005). Numerous studies have analyzed the impact of agriculture on water resources in the Biscayne Bay watershed (e.g., Wang et al. 2003; Zhou et al. 2003) but over the last three decades, the predominant form of land use change has been the conversion of agricultural and natural areas to residential or urban complexes (Solecki and Walker 2001). Although researchers have addressed increasing population densities (e.g. Finkl and Charlier 2003; Renken et al. 2005) and the relative influence of land use and water management (e.g. Caccia and Boyer 2005) in south Florida, the spatial characteristics of land use change have not been quantified and linked to specific pollutants in the Biscayne Bay watershed.

According to Lausch and Thulke (2001), environmental protection requires a landscape-based approach that includes quantitative calculations of landscape structures, functions, and interactions:

Studying the landscape, its current state (structure) and its future changes (dynamics) enables understanding of the ecological mechanisms and processes that drives changes in the landscapes. Thus, the spatio-temporal analysis of landscape is a necessary basis for a mechanistic linkage between particular species or human being and the changing characteristics of the landscape.

Objectives

The overall objective of this research was to evaluate temporal and spatial land use influences on time series nutrient concentrations and loads measured in canals discharging to Biscayne Bay. To achieve this goal, land use indicators were used to quantify and compare human disturbance gradients in the watershed to historical water quality data. Specific objectives were as follows:

1) Quantify and compare three disturbance indicators (landscape metrics, LDI index, and percent imperviousness) in the Biscayne Bay watershed by analyzing five sub-basins representing agricultural, urban, and mixed land uses;

2) Evaluate nutrient water quality data at monitoring sites in the Biscayne Bay watershed by determining concentration trends, estimating annual loads, and calculating a pollutant index; and

3) Evaluate land use-water quality relationships in the Biscayne Bay watershed to determine if disturbance indicators within sub-basins, canal buffers, or site buffers explain more of the variability in nutrient loads at monitoring sites.

Significance of Study

The South Florida Water Management District (SFWMD) and the US Army Corps of Engineers manage a complex system of drainage canals, pumps, levees, and municipal well fields (Figure 1-3). Without these structures, the region could not adequately support an expanding population or protect urban complexes and agricultural fields from seasonal floods. Canals contain gated control structures that release excess water during the wet-season (May to November) and recharge groundwater during the dry season (November to May). Water-conservation areas also help with flood protection, groundwater recharge, and prevention of saltwater intrusion.

Water management practices, agricultural development, and increased urbanization have directly affected surface and groundwater systems in south Florida. For example, the canal conveyance system has altered the ecology of the region by accelerating freshwater flow from the Everglades to the Atlantic Ocean (Leach et al. 1972); freshwater inputs to Biscayne Bay have also been modified from natural pathways of continuous submarine discharges and overland sheet flow to periodic surface water releases at canal outlets (Langevin 2001). Ecological and hydrological processes within the bay and aquifer are directly and indirectly linked to population trends and land use dynamics within the region. Nineteen canals discharge into the bay and water quality in the bay has declined during the 20th century as south Florida's population has increased (Cantillo et al. 2000).

Canals bring pollutants from the watershed directly to the north, central, and south sections of Biscayne Bay with land use patterns (Table 1-1; Figures 1-4; 1-5; 1-6) influencing pollutant characteristics (Caccia and Boyer 2005). The heavily urbanized northern bay, which includes Miami Beach and several industrial complexes, struggles with sewage discharges, high nutrient loads, turbidity, and heavy metals (Alleman et al. 1995).The boundaries of the Biscayne National Park begin in the central bay – where problems such as solid wastes, metals, and fuel/oil pollution are prevalent – and extends to the relatively less developed southern bay, which receives discharges from agricultural runoff and toxic contaminants from the Homestead Air Force Base (Caccia and Boyer 2005). The characteristics of southern bay pollutants are changing however, as developers build new homes in Homestead at a rapid pace on former agricultural and sensitive lands.

As agricultural and natural areas are converted to urban uses, understanding the spatial and temporal characteristics of critical pollutant sources will be key to mitigating environmental

contaminants. Watershed managers therefore need to consider both ‘obvious’ and ‘subtle’ effects of human activities. Obvious effects include hydrological impairment due to increased impervious surfaces while subtle effects include time lags, biological legacies, and cumulative impacts (McDonnell and Pickett 1997). By incorporating concepts from landscape ecology and hydrology within GIS applications, watershed analysis may reveal critical, subtle effects that are not reflected in raw water quality data. Canals, for example, function as point source discharges to Biscayne Bay and reflect complex interactions between urban and agricultural elements within the watershed. Biophysical data can indicate the source of contaminants but water quality management and conservation plans require detailed analyses focused on underlying pollutant processes.

The Biscayne Bay watershed in south Florida has undergone rapid transformation in the 20th century and development patterns as well as agricultural operations will continue to influence land use dynamics. In addition, the Comprehensive Everglades Restoration Plan will eventually affect the quantity and quality of freshwater discharges to Biscayne Bay (USACE and SFWMD 1999; Browder et al. 2005). Understanding the context of environmental change throughout the watershed is therefore crucial to the long-term health and protection of Biscayne Bay.

Scope of Study

This study included temporal statistical analyses on land use and water quality data from sites within the Biscayne Bay watershed (Figure 1-1) to evaluate the impact of anthropogenic activity. GIS data layers (SFWMD 2009) for the watershed boundary, land use/land cover (LULC) for three different years (1995, 1999, and 2004) (Figures 1-4; 1-5; 1-6), and monitoring site locations were used to calculate anthropogenic disturbance indicators at different spatial extents in five sub-basins. Class categories in the LULC layers were based on the SFWMD

modified version of the Florida Land Use and Cover Classification System (FLUCCS), which was originally developed by the Florida Department of Transportation (FDOT 1999). Historical (1992 to 2006) nutrient water quality data from monitoring sites within these five sub-basins were used to evaluate water quality and to identify significant correlations between land use variables and selected parameters (nitrate/nitrite-nitrogen, total ammonia nitrogen and total phosphorus). Water quality datasets were statistically evaluated using trend analysis techniques that are available in the US Geological Survey (USGS) add-in package ESTREND and SPLUS software. Load estimations were completed using LOADEST (Load Estimator) from USGS. Stepwise multiple regression models were used to determine the relative contribution of specific land use classes to water quality data and to predict water quality impacts in the watershed in response to future land use change.

Table 1-1. Land use/land cover data for the Biscayne Bay watershed (1995, 1999, and 2004).

Land use/Land cover class	1995 (%)	1999 (%)	2004 (%)
Natural land/water	31.9	32.2	30.0
Improved pastures	1.5	0.7	0.5
Low intensity pastures	1.1	0.1	0.1
Medium intensity recreational, open space	4.8	4.9	4.9
Tree crops	5.0	5.6	6.3
Row crops	10.2	8.9	7.3
High intensity agriculture	0.1	0.0	0.0
High intensity recreational	1.7	1.9	2.0
Low density single family residential	5.2	4.6	4.6
Medium density single family residential	16.8	16.9	18.1
High density single family residential	1.8	2.5	3.1
Institutional	1.9	2.5	2.7
Low density multifamily residential	3.3	3.7	4.0
High intensity transportation	3.5	3.5	3.6
Low intensity commercial	3.0	4.2	4.6
Industrial	6.3	6.0	6.6
High intensity commercial	1.1	0.8	0.9
High density multifamily residential	0.8	0.8	0.8

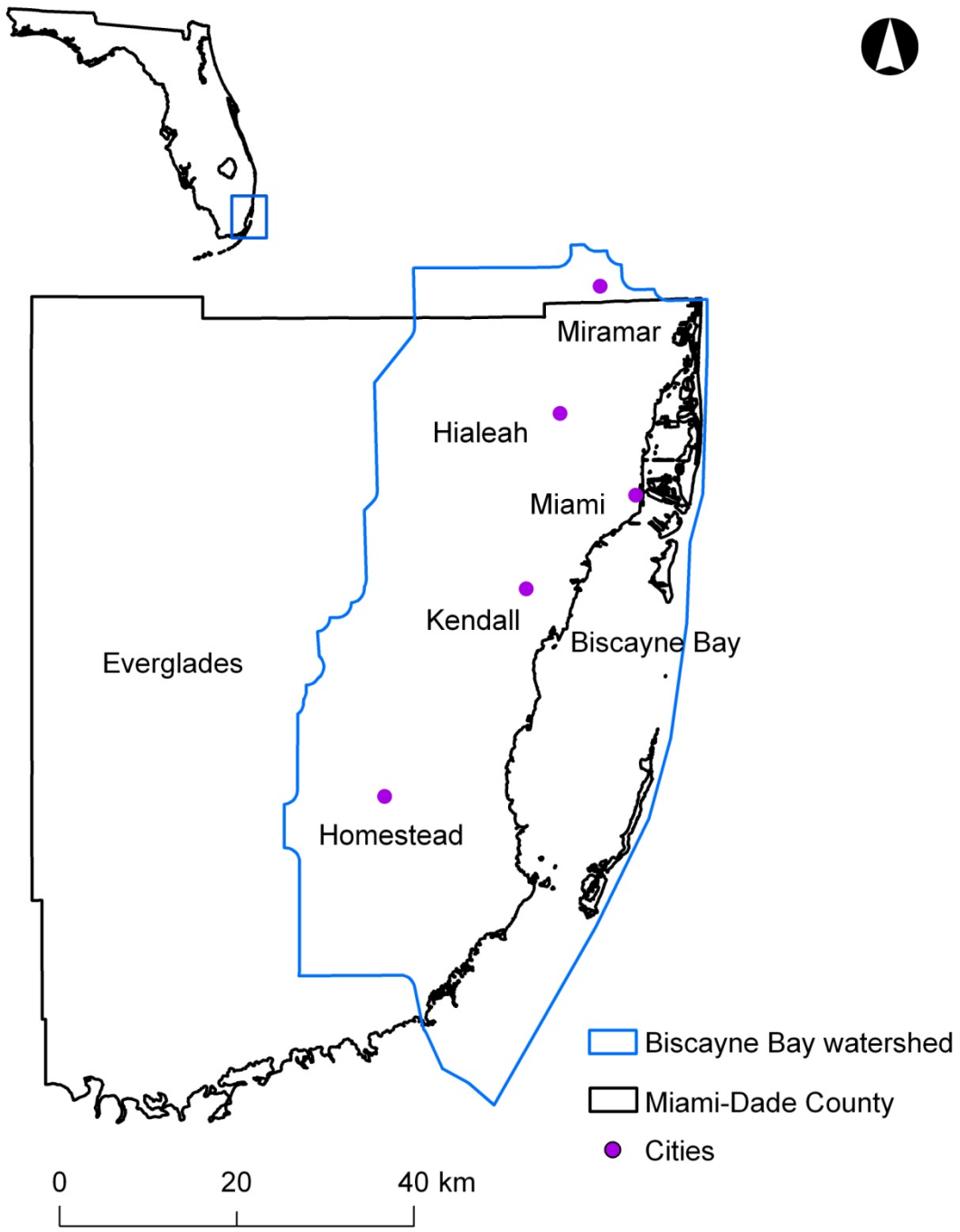


Figure 1-1. Biscayne Bay watershed in southeastern Florida.

A) 

B) 

Figure 1-2. Examples of water management systems in south Florida. A) Canal. B) Flow control structure (S194) operated by the South Florida Water Management District.

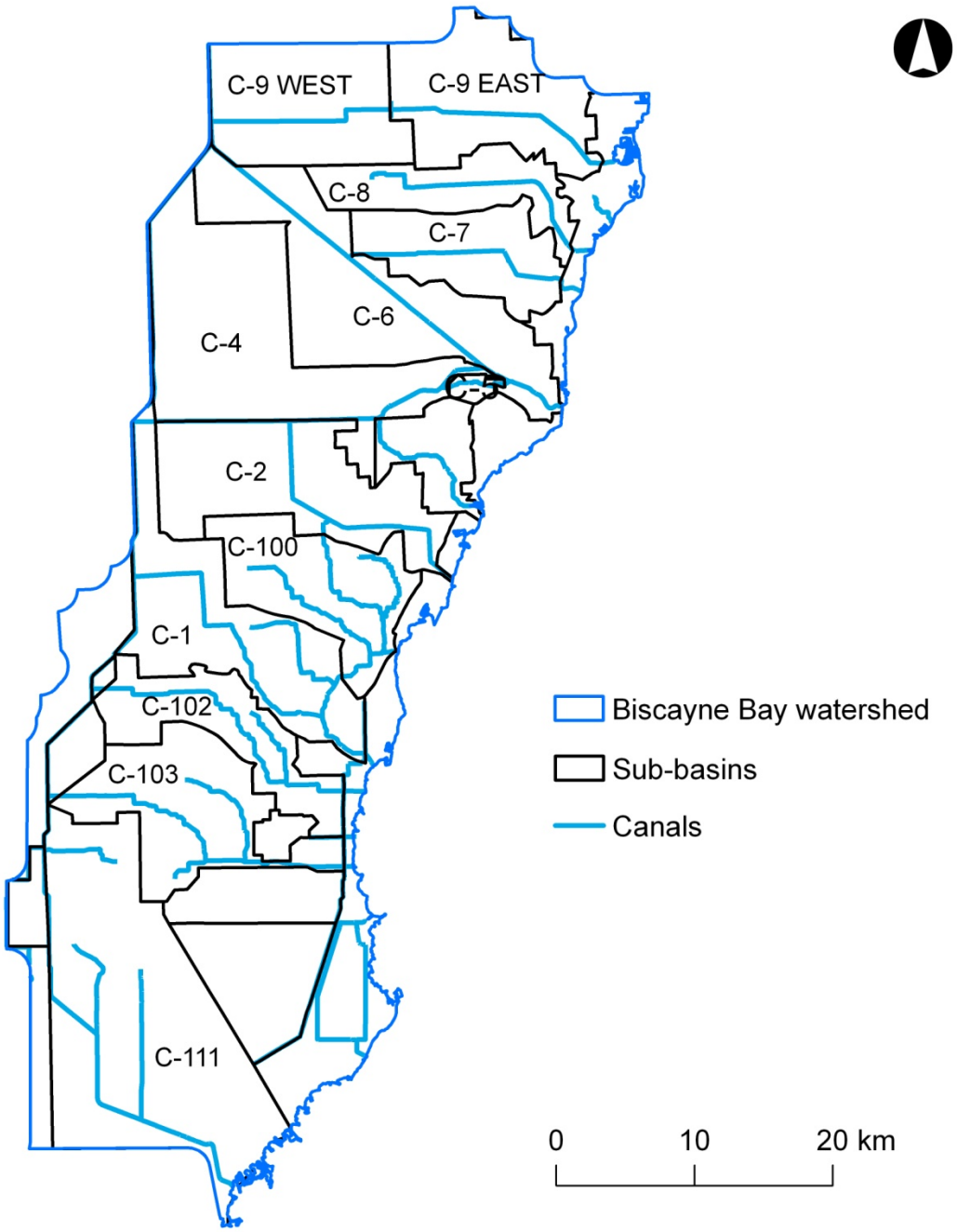


Figure 1-3. Canals and drainage sub-basins in the Biscayne Bay watershed.

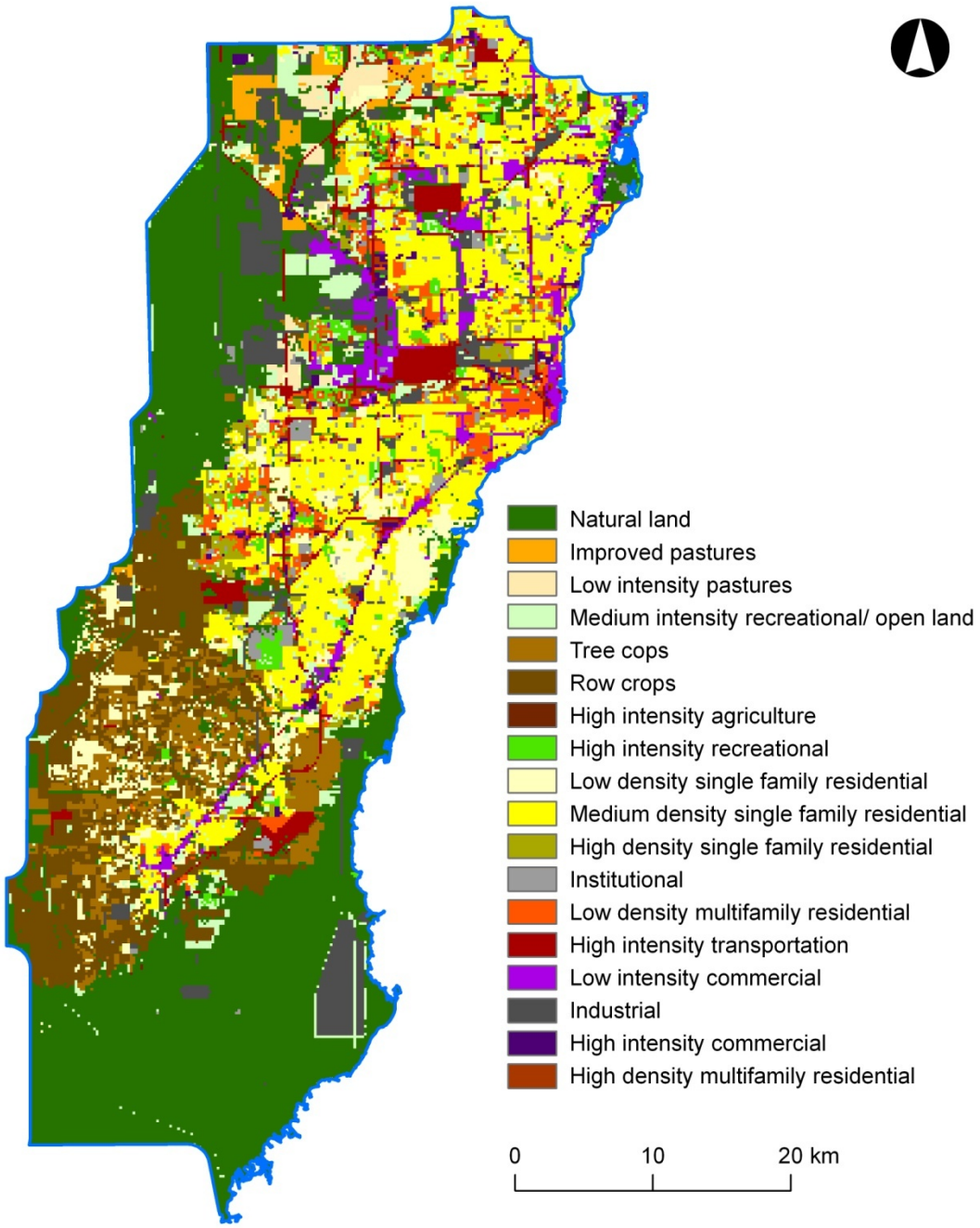


Figure 1-4. Watershed land use/land cover map (1995). Land use/land cover data from the South Florida Water Management District (SFWMD 1995).

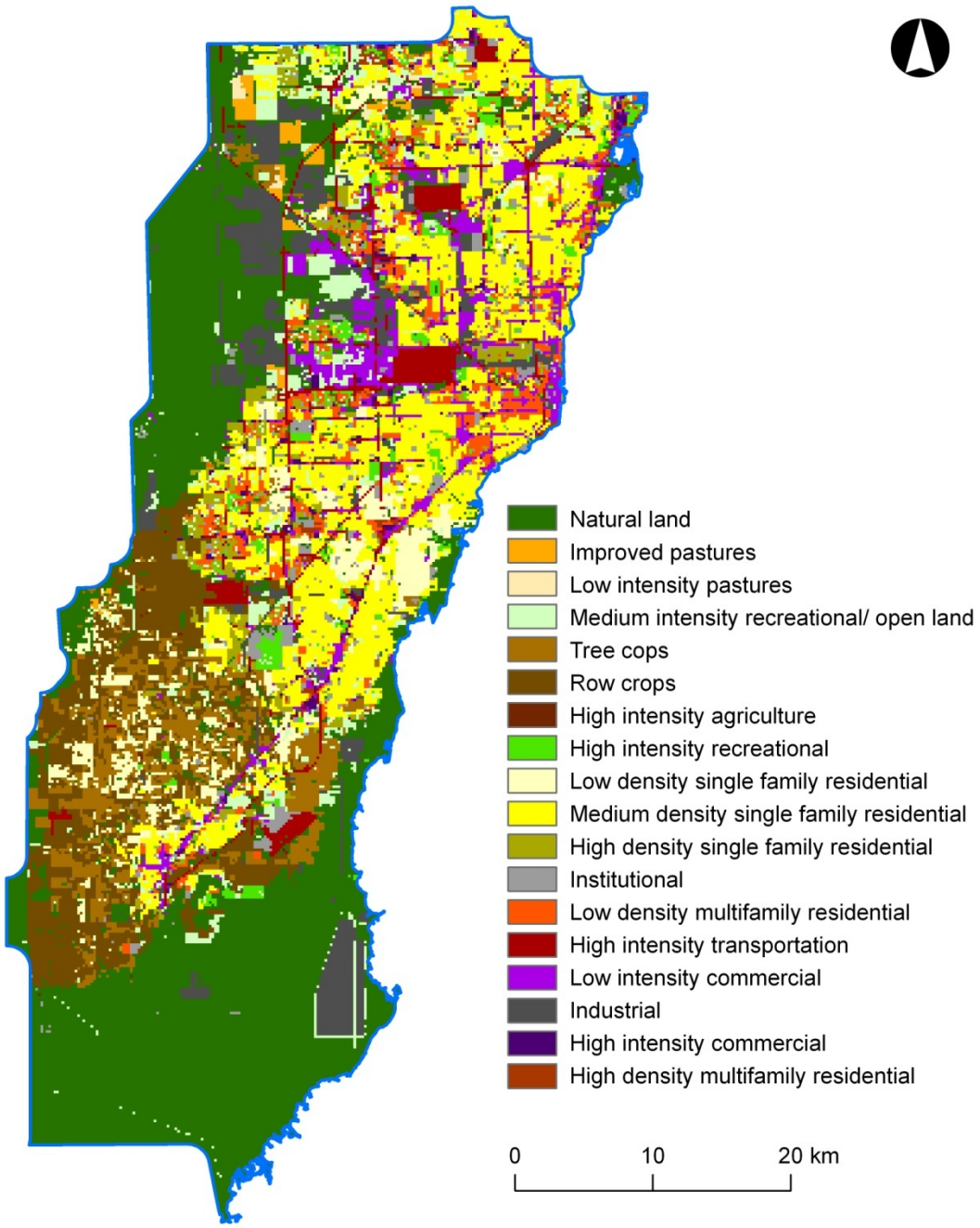


Figure 1-5. Watershed land use/land cover map (1999). Land use/land cover data from the South Florida Water Management District (SFWMD 1999).

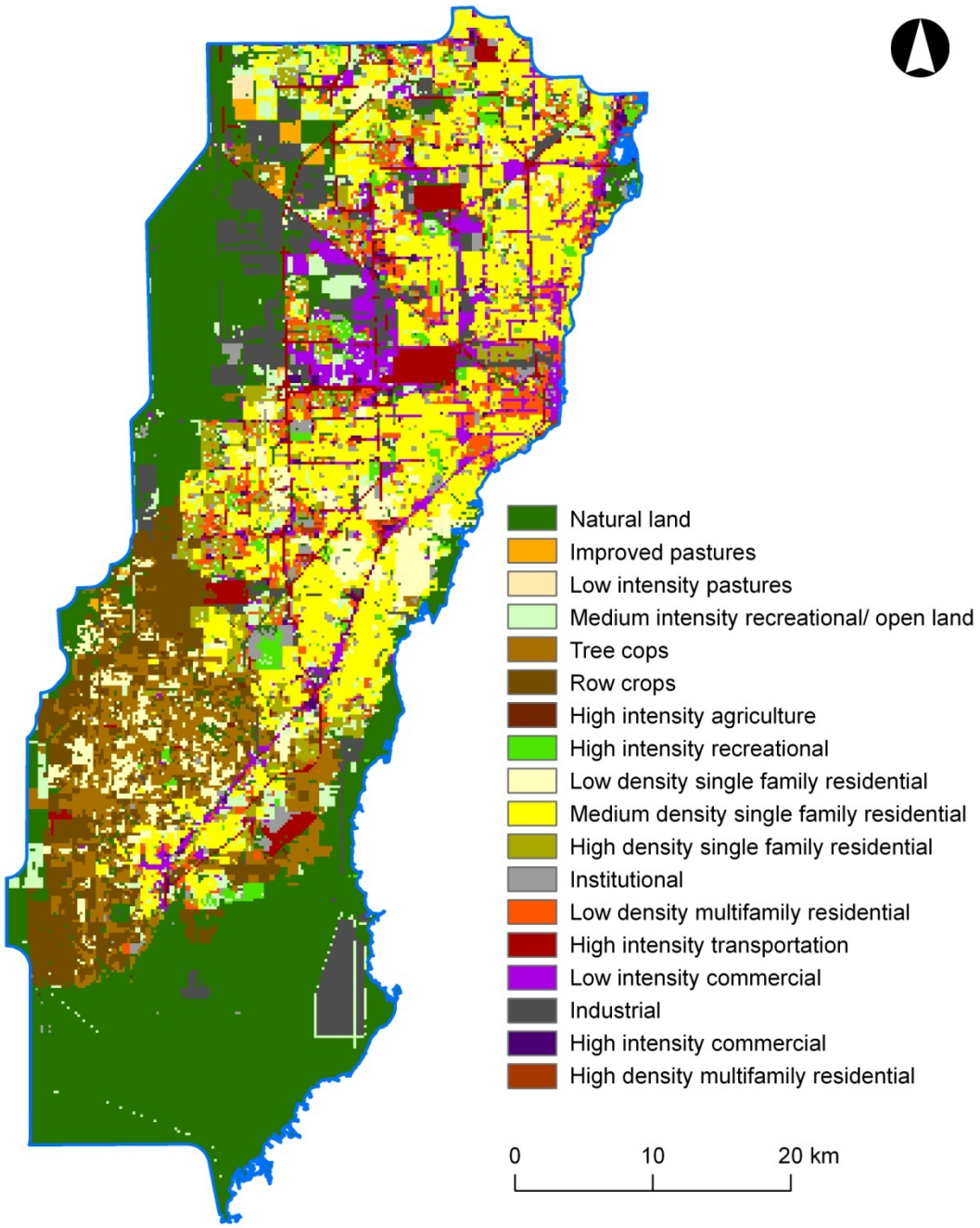


Figure 1-6. Watershed land use/land cover map (2004). Land use/land cover data from the South Florida Water Management District (SFWMD 2004).

CHAPTER 2
EVALUATING LAND USE CHANGE (1995 TO 2004) USING MULTIPLE DISTURBANCE INDICATORS IN THE BISCAYNE BAY WATERSHED, FLORIDA

Introduction

Variability, in terms of extent and intensity of human land uses, creates disturbance gradients that can potentially alter processes such as nutrient cycling, energy flows, and pollutant export (Newcombe 1977; Turner 1989; McDonnell et al. 1997; Alberti et al. 2007). Landscape ecology provides a conceptual framework to understand anthropogenic influences by focusing on land use patterns, interactions among different landscape elements, and the effects of changes in the spatial heterogeneity complex over time (Risser et al. 1984; Haines-Young et al. 1994). A fundamental concept in landscape ecology is that patterns influence processes; thus, several studies have provided methods to characterize spatial heterogeneity (e.g., Forman and Godron 1986; O'Neill et al. 1988; Turner and Gardner 1991). Geographic Information System (GIS) software is an important tool in this process because it allows for complex computational analyses in a relative simple and time efficient manner. GIS software also enables the integration of multiple historical datasets (e.g., digital land use data), which create opportunities to study temporal patterns in heterogeneous landscapes. Hundreds of metrics (or landscape variables) can be obtained from temporal and spatial land use analyses utilizing mathematical operations in GIS. However, specific metrics have been developed for both landscape composition (relative amounts of different elements in the landscape) and configuration (arrangement of these elements) that can be used to assess and compare landscape processes (Turner 1989; Li and Wu 2004).

Human disturbance gradients have also been quantified using landscape indices to assess relative impact (e.g., McMahon and Cuffney 2000; Wang et al. 2008). One such index is the Landscape Development Intensity (LDI) (Brown and Vivas 2005) which considers nonrenewable

energy use among land use and land cover (LULC) classes. The LDI index is based on emergy, a concept developed by systems ecologist H.T. Odum (Odum 1971; Odum 1996) that derived from decades of analysis on the differential ability of various forms of energy to do work (Brown and Ulgiati 2004). Emergy is a useful concept in environmental accounting because it measures the amount of energy that is directly and/or indirectly associated with both natural and anthropogenic products and services. Emergy, in essence, "looks back upstream to record what energy went into the train of transformation processes" (Odum 1996) to produce specific landscape features. Thus, LULC classes (e.g., row crops and commercial areas) have characteristic energy transformations that can be described by the change in energy that has occurred due to landscape disturbance (Odum 1996; Brown and Vivas 2005). Several studies have utilized the LDI index to quantify disturbance gradients such as Mack (2006), who evaluated Ohio wetlands and concluded the LDI index compared favorably with other assessment tools. In Florida, the LDI index was strongly correlated to a wetland biological integrity index (Reiss 2006; Reiss and Brown 2007) and Lane and Brown (2006) determined that the LDI index explained more of the variation in benthic diatom species within freshwater marshes compared to other landscape metrics (e.g., percent agriculture land use and percent urban land use). As the LDI concept was applied under different conditions, important limitations of the index were that human disturbance intensity was not related to background conditions and LDI coefficients were restricted to a predetermined set of LULC classes. A revised LDI method (Reiss et al. 2009) addressed these issues.

In addition to landscape metrics and indices, another common measurement used to evaluate LULC characteristics and associated impacts is imperviousness. Arnold and Gibbons (1996) described four qualities of imperviousness: (1) impervious surfaces contribute to

hydrologic changes that impair water quality; (2) imperviousness is a characteristic of intensive land use activities; (3) impervious surfaces hinder pollutant processing by disrupting soil percolation; and (4) impervious surfaces efficiently transport pollutants into receiving waters. Studies have used impervious surfaces such as buildings, parking lots, and roads as a measure of the extent of development within landscapes and have linked these variables to overall water quality (e.g., McMahon and Cuffney 2000; Roy and Shuster 2009). Relatively low levels of watershed imperviousness can produce negative effects in aquatic systems; for example, Arnold and Gibbons (1996) characterized streams within watersheds containing <10% of impervious cover as protected, 10-30% as impacted, and greater than 30% as degraded. Linking an imperviousness threshold to water quality can be challenging, however, because many studies do not differentiate between total and effective impervious cover within watersheds (Brabec et al. 2002). Total impervious areas (TIA) include surfaces that may drain to pervious ground while effective impervious areas only include impervious cover directly connected to waterways. Using TIA instead of directly connected impervious areas (DCIA) in water quality investigations may therefore obscure the influence of land use changes (Alley and Veenhuis 1983). Reducing DCIA is an important component of low impact development (Wright and Heaney 2001) because it reflects the potential influence of human development on adjacent systems.

Indicators provide information on the condition of landscapes (Dale 2001; Bolliger 2007) and multiple indicators addressing different aspects of land use change can help to reveal broader impacts of human disturbance. Although previous studies have compared the efficacy of multiple indicators (e.g., McMahon and Cuffney 2000; Gergel et al. 2002), there has been no study comparing landscape metrics, the LDI index, and DCIA. Landscape metrics and percent imperviousness have been used extensively to investigate human impacts (e.g., Ritters et al.

1995; Arnold and Gibbons 1996; Alberti et al. 2007) but the LDI index is a relatively new index that can potentially provide unique information to help managers monitor and evaluate the effects of land use change.

An ideal location for evaluating these indicators together is south Florida because rapid land use transformations in recent decades have impacted its native ecosystems (McPherson and Halley 1996; Solecki and Walker 2001) and both urban and agricultural development continues to influence critical areas such as Biscayne Bay, the receiving water body for the Miami metropolitan area. Biscayne Bay is both ecologically and economically important to the region because its tropical reefs and mangroves support various species (manatees, dolphins, wading birds, etc.) as well as fishing and recreational industries (BBPI 2001; Browder et al. 2005). Human-dominated landscapes, such as the Biscayne Bay watershed, are complex mosaics where heterogeneous human activities gradually transform biophysical characteristics (Dow 2000) and understanding the context of environmental changes throughout the watershed is crucial to the long-term health and protection of the bay. Thus, the goal of this study was to quantify and compare three disturbance indicators (landscape metrics, LDI index, and percent imperviousness) in the Biscayne Bay watershed by analyzing five sub-basins representing agricultural, urban, and mixed land uses for 1995, 1999, and 2004. Specific objectives were as follows: (1) quantify human disturbance indicators in the five sub-basins, (2) determine if selected disturbance indicators provide contrasting information, and (3) evaluate how these indicators could potentially influence watershed management decisions.

Methods

Study Area

Biscayne Bay, a barrier-island subtropical estuary, includes the federally protected Biscayne National Park and is located along the southeastern Florida coastline. Extensive urban

and agricultural development in the watershed (2,500 km^2) have thrived on former wetlands as canals have lowered water tables (Parker et al. 1955), reducing watershed water storage and creating polluted discharges that degrade sensitive estuarine habitats (Browder et al. 2005). The watershed is primarily located in Miami-Dade County, which includes the city of Miami, but the northern section extends into Broward County; the western boundary of the watershed lies adjacent to the Florida Everglades and the Everglades National Park.

The South Florida Water Management District (SFWMD) sub-divided the watershed into several sub-basins based on major canal structures. Five sub-basins (Figure 2-1) were selected based on data availability and these sub-basins represented different types of LULC within the watershed, including agricultural, urban, and mixed-land use. C-9 East (118 km^2; referred to as C-9 hereafter), C-8 (71 km^2), and C-7 (82 km^2) sub-basins are located in the northern section of the watershed, which is primarily characterized by urban land uses. In the central section of the watershed, the C-1 (117 km^2) sub-basin includes extensive urban and agricultural land uses and was selected as an example of a mixed land use sub-basin. The C-103 (113 km^2) sub-basin, located in the southern section of the watershed within the South Dade Agricultural Area, is dominated by agricultural land uses such as row and tree crops. Analyses were limited to sub-sections of both C-1 and C-103 sub-basins to correspond with locations of water quality monitoring stations.

Land Use Data

LULC GIS data layers were obtained from SFWMD for three separate years: 1995 (scale - 1: 40000), 1999 (1: 40000) and 2004 (1: 12000). SFWMD created all three layers by photo-interpreting aerial photography and digital orthophotographic quarter quadrangles (DOQQs). Each layer used a modified form of the Florida Land Use and Cover Classification System (FLUCCS; FDOT 1999) as SFWMD FLUCCS codes primarily use community level classes to

identify vegetation. To simplify analysis, land use classes were aggregated into 18 natural, agricultural, and urban classes (Table 2-1). Vector LULC data were converted to raster format for spatial analysis using a common scale (190 x 190 meters grid cell size). To ensure the accuracy of LULC data for each of the three years obtained (1995, 1999, and 2004), DOQQs corresponding to the timeline of the data layers were retrieved from the Land Boundary Information System (LABINS) of the Florida Department of Environmental Protection. Quality assurance/quality control involved comparing DOQQs depicting actual LULC within a particular year to assigned LULC classes in corresponding GIS layers. Any GIS classifications that were inconsistent with DOQQs for each of the three data layers were corrected to reflect actual LULC throughout the watershed.

Landscape Metrics

FRAGSTATS (McGarigal and Marks 1995), a software package developed to calculate landscape metrics, generates values for several different categories of metrics that can be useful to understanding LULC changes in watersheds (Table 2-2). Patch Analyst (Elkie et al. 1999), a modified version of FRAGSTATS designed specifically as an ESRI ArcGIS extension tool, provides an integrated user interface that enables metrics to be calculated for LULC layers at both landscape and class levels. Landscape-level metrics calculate values with all classes included (e.g., mean patch size within a watershed) while class-level metrics calculate values for specific classes (e.g., mean patch size of row crops). Patches are contiguous cells containing single LULC classes grouped together (e.g., row crop areas and commercial areas) (O'Neill et al. 1997) and for each of the three LULC layers (i.e., 1995, 1999, and 2004), 17 landscape metrics and 13 class metrics were calculated for the entire Biscayne Bay watershed (Table 2-2). Metrics were calculated on a watershed level to identify important variables throughout the watershed and then applied to the five selected sub-basins as an analytical dataset. Area-weighted metrics

(e.g., patch richness density) were preferred to absolute metrics (e.g., patch richness) to compare data from the five sub-basins. Metrics were tested for normality using the Shapiro-Wilk W test for normality with a p-value < 0.05 (Shapiro and Wilk 1965; Royston 1983). Most metrics deviating from a normal distribution were either log or square root transformed to improve normality; metrics containing percentage data were arcsin-square root transformed.

For large datasets containing multiple variables, it is often easier to analyze this information if the number of variables is reduced to a smaller set of components that retains all the important data. Principal Component Analysis (PCA) is a data reduction technique that identifies linear combinations of the original variables explaining all of the variance in a dataset (Nichols 1977; Bengraine and Marhaba 2003). These linear combinations, or principal components, describe variability in the dataset which are not directly measured. Factor analysis (FA) is another statistical procedure used with multi-variable datasets to identify factors contributing to overall variance (McDonald 1985). The difference between PCA and FA is that while PCA attempts to simplify variable interpretation through data reduction, FA primarily focuses on identifying significant, underlying factors.

Pair-wise correlation coefficients were calculated for transformed landscape and class metrics to eliminate redundancy, with only one metric in a correlated pair of metrics included in further analysis if Pearson coefficients were greater than 0.90 (Ritters et al. 1995). Significant landscape and class metrics were then identified for the Biscayne Bay watershed using a correlation matrix to conduct PCA and FA in S-Plus 8.0 (Insightful Corporation 2007). In a correlation matrix, the mean of eigenvalues (a measure the variance explained by each principal component) is one and principal components with above average eigenvalues explain more of the overall variance (Burstyn 2004). The number of principal components with eigenvalues

greater than one therefore determined the number of factors to use in FA. To aid interpretation, FA included a varimax rotation to reveal metrics that had the strongest correlations, or loadings, for identified factors across the three different LULC layers (1995, 1999, and 2004).

LDI Index

The LDI Index was evaluated on a sub-basin level because it measures the intensity of land use activities within a specific area. Data required to calculate LDI index values for Biscayne Bay sub-basins included LULC GIS layers, areas for each LULC class, nonrenewable empower intensity (emergy per time per area) values for LULC classes, and the renewable empower intensity of the background area. The first step in the LDI calculation process was to sum the areas of each LULC class and express these values as a percent of the total landscape area. LULC percentages were then multiplied by their respective nonrenewable empower intensity values for Florida (Table 2-3). Finally, LDI index values were calculated using Equation 2-1:

$$LDI = 10 * \log_{10} (emPI_{Total} / emPI_{Ref}) \quad (2\text{-}1)$$

where LDI [unit less] is the Landscape Development Intensity index for sub-basins, $emPI_{Total}$ [sej ha^{-1} yr^{-1}] is the total empower intensity (sum of renewable background empower intensity and nonrenewable empower intensity of land uses), and $emPI_{Ref}$ is the renewable empower intensity of the background environment (Florida = 1.97 E15 sej ha^{-1} yr^{-1}). The total empower intensity ($emPI_{Total}$) was calculated as follows:

$$emPI_{Total} = emPI_{Ref} + \sum (\%LU_i * emPI_i) \quad (2\text{-}2)$$

where $\%LU_i$ is the percent of the total area in LULC class *i* and $emPI_i$ [sej ha^{-1} yr^{-1}] is the nonrenewable empower intensity for LULC class *i*.

Imperviousness

The Miami-Dade Department of Environmental Resources Management (DERM) developed DCIA reference values for land uses classes within the county (Table 2-3) to evaluate

pollutant loading estimates under alternate scenarios (DERM 2004). DERM calculated these reference values using aerial maps and measuring the total imperviousness area within typical land uses occurring in basins throughout the county. DERM DCIA values for various land uses were used to estimate percent imperviousness in each of the five sub-basins and for each LULC layer (1995, 1999, and 2004). The sub-basin level was used for imperviousness evaluation to compare DCIA values across the five sub-basins.

Results

Landscape Metrics

Several pairs of metrics were significantly correlated (greater than 0.90) at both landscape and class levels. At the landscape level, PCA was performed on 11 of the 17 metrics calculated and three principal components had eigenvalues greater than one. After varimax rotation and FA, these three factors accounted for 76% of the cumulative variation of the selected parameters for the entire Biscayne Bay watershed. Metrics with the highest loadings for the first factor, interpreted as patch size variability, were mean patch size (MPS; 0.92) and patch size standard deviation (PSSD; 0.91). The largest patch index (LPI; -0.94) and landscape shape index (LSI; 0.86) had the highest loadings for the second factor, patch diversity. Patch complexity was the third and final factor at the landscape level and included patch size coefficient of variation (PSCoV; 0.84) and area weighted mean shape index (AWMSI; 0.77) (Figure 2-2).

Among the 18 land use classes (Table 2-1), the two most dominant classes – in terms of relative area and distribution – within the five sub-basins were row crops and medium density single family residential (MSR). Only PCA and FA results for metrics in these two classes are reported to limit analysis to dominant classes in the sub-basins. For row crops, PCA was performed on 9 of the 13 class-level metrics calculated and two principal components had eigenvalues greater than one. FA revealed these two factors accounted for 66% of the spatial

variability in row crops (Figure 2-3). The first factor, patch fragmentation, included mean proximity index (MPI; 0.93), PSSD (0.93), AWMSI (0.87), and PSCoV (0.86). Edge density (ED; 0.80) and landscape percentage (%LAND; 0.80) both had high loadings for the second factor, patch distribution. For MSR, PCA was performed on 8 of the 13 class-level metrics and FA identified three factors that were responsible for 80% of the cumulative variance (Figure 2-4). MSR factors were interpreted as patch complexity (PSCoV, 0.96; AWMSI, 0.88; and class area [CA], 0.84), patch area (LPI, 0.99 and %LAND, 0.88), and patch fragmentation (mean nearest neighbor [MNN], -0.56 and MPS, 0.55).

LDI Index and Land Use Percentages

LDI values for all five sub-basins ranged from 25.4 to 31.0 (Figure 2-5), which reflects a substantial difference in the level of anthropogenic disturbance as 25.4 is approximately four times greater than 31.0 on the logarithmic LDI scale. In 2004, MSR (37.6%), high intensity transportation (14.4%), and low intensity commercial (LIC; 10.2%) land use classes dominated the C-8 sub-basin, which produced the highest LDI value (31.0). No other 2004 land use class in the C-8 sub-basin had a land use percentage that was greater than 10%. Between 1995 and 2004, C-9, C-8, and C-7 land uses were primarily MSR (35.9 to 51.7% in C-9, C-8, and C-7), LIC (8.0 to 11.7% in C-8 and C-7), and high intensity transportation (14.4 to 15.5% only in C-8) (Tables 2-4; 2-5; 2-6). From 1995 to 2004, LDI values in the three urban sub-basins (29.6 to 31.0) were greater than the mixed land use (C-1; 27.7 to 28.5) and agricultural (C-103; 25.4 to 26.2) sub-basins. LDI values in both C-1 and C-103 sub-basins reflect the highest increase in the magnitude of anthropogenic development intensity (Figure 2-5) across the five sub-basins for the study period.

In C-1, the mixed land use sub-basin, both row crops and MSR land use percentages were 20% or greater for 1995, 1999, and 2004 LULC layers. Only one other land use class, high

density single family residential (HSR) in 2004, was greater than 10% between 1995 and 2004 in the C-1 sub-basin. Row crops decreased from 27.6% in 1995 to 21.6% in 2004, MSR increased from 19.7% to 23.4%, and HSR also increased from 5.0% to 12.6%.

Four land use classes accounted for greater than 76% of LULC in C-103, the agricultural sub-basin, from 1995 to 2004: tree crops, row crops, low density single family residential (LSR), and MSR (Tables 2-4; 2-5; 2-6). During the study period, row crops declined (22.8% to 12.2%) in C-103 while tree crops (26.7% to 32.5%) and the residential classes (LSR and MSR) increased (26.8% to 31.4%). Increased residential land use in the C-103 sub-basin from 1995 to 2004 corresponded to an increase in LDI values (25.4 to 26.2).

Imperviousness

For all five sub-basins, percent imperviousness values for 2004 were greater than both 1995 and 1999 values (Figure 2-5). DCIA was greatest in the three urban sub-basins and values in C-8 and C-7 for all three LULC layers were greater than 30%. Imperviousness in C-8 and C-7 changed minimally from 1995 to 2004 as values ranged from 33.2% to 35.8%, the highest in this study. In the mixed sub-basin, C-1 (18.2% to 23.3%), DCIA was lower than in the three urban sub-basins and C-103 (13.6% to 16.8%), primarily an agricultural sub-basin, had the lowest overall values. The greatest changes in DCIA during the study period occurred in the C-1 (5.0%) and C-103 (3.2%) sub-basins (Figure 2-5). DCIA and LDI values for all five sub-basins had a positive linear relationship, with an R^2 value of 0.97 (Figure 2-5).

Discussion

Landscape Metrics

Similar to McGarigal and Marks (1995) and Li and Wu (2004), many of the landscape metrics were highly correlated. Using PCA and FA, patch size variability, patch diversity, and patch complexity were identified as significant factors contributing to overall spatial variability

at the landscape-level (i.e., considering all LULC classes) for all sub-basins in the Biscayne Bay watershed. The first factor, patch size variability, included both MPS and PSSD and indicated patch size distribution among LULC classes varied significantly in sub-basins throughout the watershed (Figure 2-2). Between 1995 and 2004, MPS and PSSD values suggested that there was great variability in patch sizes in the five study sub-basins. For C-103, the agricultural sub-basin, an increase in PSSD (+0.7 km^2) suggests that smaller patches were being created although several large patches remained intact. Conversion of agricultural and natural areas to residential or urban complexes has been the predominant form of land use change during the last three decades in south Florida (Solecki and Walker 2001) and this is becoming increasingly evident in C-103. However, not all agricultural areas in C-103 have been developed for other uses. Row crops in C-103 have been converted as residential areas expand but this is only occurring in limited sections of the sub-basin, thereby leaving large tree crop patches undeveloped. In C-1, the mixed land use sub-basin, PSSD has actually declined (-0.3 km^2) during the study period because the conversion of agricultural areas is occurring in multiple areas throughout the sub-basin.

The second landscape-level factor, patch diversity, included both LPI and LSI metrics and continued to highlight the contrast between C-103 and C-1 (Figure 2-2). LPI is a percentage measure of class dominance as it assesses the size of the largest single patch relative to total sub-basin area and LSI reflects patch shape complexity and edge density (McGarigal and Marks 1995). In C-103, LPI increased between 1995 and 2004 (7.8 to 23.0) and for the same period in C-1, LPI declined (24.5 to 19.1). As row crops were being converted to different land uses in C-103, tree crops became the largest contiguous land use areas because residential development did not reduce tree crops. Row crops have been similarly converted to residential land uses (MSR

and HSR) in C-1 but LPI values in this sub-basin still reflect large row crop patches. Therefore, as row crops declined in C-1 in favor of MSR and HSR, there was a corresponding decline in LPI values. The largest patch in all three urban sub-basins was MSR but LPI values changed the least in the urbanized sub-basins, with both C-9 and C-8 having some of the lowest LPI values. The lower LPI values for C-9 and C-8 indicated these sub-basins had a greater diversity of urban land uses compared to C-7, which was more homogenous and dominated by MSR. C-9 and C-103 had similar values for the LSI metric although dominant land use classes in these sub-basins were different and this may have been due to increasingly fragmented landscapes. Fragmentation leads to increasing amounts of edge (McGarigal and Marks 1995) and in C-9, improved pastures have been drastically reduced (5.5 to 0.76 km^2) and splintered as MSR and low intensity multifamily residential land use classes have increased.

The third landscape-level factor was patch complexity and included both PSCoV and AWMSI (Figure 2-2). PSCoV is dependent on both PSSD and MPS and in the five sub-basins, PSCoV was correlated (greater than 0.90) to PSSD. Consequently, sub-basin relationships discussed earlier for PSSD in the first factor, patch size variability, were similar to PSCoV. Both PSCoV and PSSD were included in the analysis because when considering the entire Biscayne Bay watershed, these two metrics were not correlated. AWMSI assesses the irregularity of patch shapes, with lower values indicating uniform shapes (McGarigal and Marks 1995). C-1 and C-9 had similar AWMSI values, with C-8 having the lowest values compared to the other sub-basins. Although C-7 generally had the highest AWMSI values, the greatest change occurred in C-103 (2.23 to 3.18). Row crops generally have uniform shapes in the landscape and as row crops declined in C-103 and MSR and LSR increased, this may have potentially led to greater patch shape irregularity in C-103.

Row crops and MSR were the most widely distributed land use classes throughout the five sub-basins and only factors for these two classes were considered. Row crops were primarily found in C-1 and C-103 while MSR was a common feature in all five sub-basins. Fragmentation and patch distribution factors revealed the spatial configuration of row crops within C-1 and C-103 sub-basins (Figure 2-3). MPI, PSSD, and PSCoV values indicated large row crop patches occurring closer together are more prevalent in C-1 and edge densities suggested a greater distribution of LULC classes between row crops in C-103. Therefore, row crops have smaller areas and are more fragmented in C-103 compared to C-1. MSR had three factors controlling spatial variability in the five sub-basins: patch complexity, area, and fragmentation (Figure 2-4). Generally, MSR patches in urban sub-basins were larger, more complex (i.e., considering size, shape, and area) and had greater connectivity than in C-1 and C-103. The urban center of the Biscayne Bay watershed includes C-9, C-8, and C-7 sub-basins whereas C-1 and C-103 are at the fringes of urban development. Fragmentation is generally low in urban centers because of the concentration of urban land uses (such as MSR) and urban fringes typically exhibit a greater degree of fragmentation as the process of urbanization occurs (Herold et al. 2003; Weng 2007). After PCA and FA, factors for row crops (66%) and MSR (88%) had different variability and this may be due to the generally stable nature of urban sub-basins during the study period, compared to land use changes occurring in C-1 and C-103.

LDI Index and Imperviousness

The three urban sub-basins (C-9, C-8, and C-7) had relatively little change in their LDI values compared to C-1 and C-103 (Figure 2-5). Brown and Vivas (2005) described LDI values as representing a combination of several anthropogenic influences occurring in developed landscapes such as pollutants in both air and water, physical landscape damage, and environmental modifications (e.g., hydrological impairment leading to increased flooding risk).

Therefore, in the three urban sub-basins, dominant land use classes such as MSR and low intensity commercial (LIC) did not change substantially from 1995 to 2004 and resulted in LDI values that remained relatively constant.

The agricultural sub-basin, C-103, had the lowest overall LDI values but the conversion of row crops to residential uses (LSR and MSR) – especially between 1999 and 2004 – increased development intensity at a rate similar to the mixed land use sub-basin, C-1 (Figure 2-5). Westward residential development in C-1, from the coastal areas inland, has led to the gradual decline of row crops and the concurrent expansion of both MSR and HSR land use classes. Interestingly, although residential areas increased in both C-103 and C-1 from 1995 to 2004, the types of residential development occurring in these sub-basins were different. LSR and MSR increased in C-103 but in C-1, MSR and HSR land use classes were most responsible for the decline in row crops. LSR has a lower development intensity (i.e., less nonrenewable energy use per unit area) than HSR and as row crops become replaced by residential land uses, the LDI index indicates that C-1 is gradually attaining the characteristics of the three urban sub-basins.

The strong correlation between DCIA and LDI values (Figure 2-5) suggests both indicators provided similar information regarding the intensity of human disturbance in the five sub-basins. The LDI is a continuous index evaluating both urban and agricultural land uses (Brown and Vivas 2005) while DCIA primarily reflects the impact of watershed urbanization. The LDI index, by incorporating anthropogenic intensity associated with agricultural land uses, has the potential to provide a more consistent link between all aspects of human disturbance and resultant ecosystem effects. For example, DCIA percentages in agricultural areas are minimal and may not accurately reflect the extent of human involvement required to sustain agricultural production or potential pollutants that could be generated. The LDI index is therefore useful in

evaluating the impact of a broad range of land uses on adjacent systems, such as the biological community structure in Florida wetlands (Reiss et al. 2009).

DCIA is an integrative measure that can be used to evaluate various aspects of urban development contributing to the increased distribution of impervious surfaces (Arnold and Gibbons 1996). As a result, DCIA for the five sub-basins reflected changes in the distribution of urban land use classes from 1995 to 2004. Predictably, the three urbanized sub-basins had greater DCIA values than C-1 and C-103 (Figure 2-5). DCIA changed the least in the urbanized sub-basins, which would indicate that C-9, C-8, and C-7 have already been extensively developed and additional modifications to these sub-basins would not necessarily lead to changes in DCIA. Both C-1 and C-103, in contrast, had agricultural, natural, and open land areas at the beginning of the study period and increased urbanization in these sub-basins led to the creation of more impervious surfaces. The three urbanized sub-basins are less likely to be substantially modified by increased DCIA percentages because of their already well-developed characteristics but this may not apply in C-1 and C-103. The greater rate of DCIA changes in C-1 and C-103 could potentially affect water resources as new urban development projects continue to expand into previously pervious areas.

Management Implications

The disturbance indicators suggested that the three urban sub-basins were relatively stable and dominated by complex MSR patches that corresponded to a greater degree of anthropogenic intensity compared to the mixed land use and agricultural sub-basins. Similarly, Lee et al. (2009) determined that in areas where urban land uses represent the largest patch, water quality declines. Water quality issues in the northern Biscayne Bay watershed, where the urban sub-basins are located, include sewage discharges, high nutrient loads, turbidity, and heavy metals (Alleman et al. 1995) and are unlikely to be altered by land use changes that do not fundamentally shift

overall landscape characteristics. Mitigating impacts from existing land use influences, such as MSR, in these sub-basins through best management practices (BMPs) would help to alleviate established water quality issues. Retrofitting of stormwater outfalls and the construction of grassed swales and French drains have been utilized to intercept the first flush of pollutants (i.e., first inch of runoff) in the Biscayne Bay watershed (Alleman et al. 1995). These pollutant-control strategies have improved water quality discharges to the bay but increased treatment efficiency could be obtained by using disturbance indicators to target urban complexes with a greater proportion of intensive land use activities located in hydrologically sensitive areas.

Unlike the urban sub-basins, critical issues in both C-1 and C-103 were changes in the composition and spatial distribution of residential and agricultural land use classes. In C-1, MSR and HSR land use classes extended further inland and replaced row crops and this has led to changes in the landscape structure of C-1. Numerous studies have linked land use with water quality (e.g., Osborne and Wiley 1988; Johnson et al. 1997; Harman-Fetcho et al. 2005), as the proportion and spatial arrangement of LULC within watersheds can have significant influences on water resources (e.g., Hunsaker and Levine 1995; Roth et al. 1996; Johnson et al. 2001). Furthermore, in C-1, the increased development intensity associated with MSR and HSR land use classes, compared to row crops, also affects the type of possible pollutants. A landfill and possibly a wastewater treatment plant at the furthest point downstream in C-1 influence pollutant characteristics from this sub-basin (Meeder and Boyer 2001; Caccia and Boyer 2005) but upstream land use changes could still increase pollutant loads discharged to Biscayne Bay. New residential developments are also a concern in C-103, along with increased agricultural land (tree crops) that could potentially contribute additional pollutants.

Watershed managers can therefore use information provided by disturbance indicators to identify and evaluate the mechanisms of land use change and forecast impacts on water quality (Roy and Shuster 2009). Dispersed urban landscape patterns have been linked to degradation of water quality (Lee et al. 2009) and it has been shown that development patterns within landscapes typically affect the extent of anthropogenic influences on biophysical processes (Alberti 2005). C-1 and C-103 sub-basins have experienced the greatest increase in LDI and DCIA values during the study period but landscape metrics indicate that compact (HSR) development patterns are more prevalent in C-1 compared to C-103, where low intensity development is relatively scattered. Watershed managers therefore need to consider both 'obvious' and 'subtle' effects of human activities. Obvious effects include hydrological impairment due to increased imperviousness while subtle effects include underlying factors such as cumulative impacts (McDonnell and Pickett 1997). LDI and DCIA values provide an overall view of watershed development but the location of intensive land uses compounds the threat to water resources. Landscape metrics describing spatial configurations therefore complement LDI and DCIA values by providing information on watershed development that might not be immediately apparent.

Watershed management strategies for assessing developing sub-basins can include all three disturbance indicators. Similar to C-1 and C-103, LDI values below 30.0 and DCIA values below 25% (Figure 2-5) reflect sub-basins that are not completely urbanized. Identifying important landscape metrics contributing to overall spatial distribution in these sub-basins helps to reveal factors that can influence water quality. Disturbance indicators can therefore be used together to develop watershed policies that address specific relationships between land use and water quality. Implications for municipality zoning regulations in urbanizing sub-basins include

promoting MSR and HSR development, as opposed to LSR, at greater distances from aquatic corridors (Schiff and Benoit 2007). Implementing BMPs in these critical areas would also aid zoning regulations and reduce hydrologic impacts of gradually increasing LDI and DCIA values.

Conclusion

During the period of analysis (1995 to 2004), all three disturbance indicators revealed different levels of anthropogenic disturbance among urban (C-9, C-8, and C-7), mixed land use (C-1), and agricultural (C-103) sub-basins. Landscape metrics provided information on influential land use classes within the five sub-basins and spatial processes occurring over time that have contributed to variability at the landscape and class levels. In contrast, DCIA and LDI values provided similar information on the intensity of human disturbance; urban sub-basins were the most disturbed but the greatest changes occurred in C-1 and C-103. Residential and agricultural land use classes were most responsible for the variability in C-1 and C-103 as the proportion of residential areas increased and row crops declined. Although residential areas in C-1 and C-103 both increased, these sub-basins featured different development patterns. Medium density single family residential (MSR) and high density single family residential (HSR) land use classes increased in C-1 while MSR and low density single family residential (LSR) increased in C-103. HSR and LSR land use classes represent different levels of human intensity and indicate C-1 was becoming increasingly urbanized through compact development.

Disturbance indicators can provide complementary information for watershed management decisions regarding water quality. Strategies to reduce the impacts of existing land use influences such as detention systems are necessary for sub-basins that are highly developed and display little variability for disturbance indicators. In urbanizing watersheds, however, disturbance indicators are likely to reveal the effects of incremental land use changes and potential impacts on water resources. Planning initiatives such as zoning regulations are critical

because the spatial distribution of intensive land uses and impervious surfaces can adversely affect watershed hydrology, especially in urbanizing watersheds. Rapid urbanization is ongoing in south Florida and further research is needed to explore the relationship between land use characteristics and water quality variables, such as constituent loads, to link development patterns to quantifiable effects in the watershed and in Biscayne Bay.

Table 2-1. Description of land use/land cover classes.

Land use/Land cover class[1]	Description
Natural land/water	Forest; wetland; rangeland
Improved pastures	Improved pastures
Low intensity pastures	Unimproved pastures; woodland pastures
Medium intensity recreational, open space	Community recreational facilities; open land; disturbed land
Tree crops	Groves; orchards; nurseries; vineyards
Row crops	Field crops
High intensity agriculture	Feeding operations; specialty farms
High intensity recreational	Golf courses; parks; zoos
Low density single family residential	Less than two dwelling units per acre
Medium density single family residential	Two to five dwelling units per acre
High density single family residential	Greater than five dwelling units per acre
Institutional	Government; educational; religious; medical
Low density multifamily residential	Multiple dwelling units (less than three stories)
High intensity transportation	Airports; highways; port facilities
Low intensity commercial	Mixed use commercial; professional services
Industrial	Mineral processing; chemical processing; utilities
High intensity commercial	Retail sales; shopping centers
High density multifamily residential	Multiple dwelling units (greater than three stories)

[1]FDOT (1999).

Table 2-2. Description of landscape metrics.

Category	Metric	Description
Area	Class area	Sum of patch areas (C)[1]
	Percentage of landscape	Percentage of landscape covered (C)
	Largest patch index	Percentage of landscape comprised by the largest patch (L or C)
Density and Size	Mean patch size	Mean patch size (L or C)
	Patch size coefficient of variation	Coefficient of variation (L or C)
	Patch size standard deviation	Standard deviation of patch areas (L or C)
	Patch richness density	Variety of patch types relative to area (L)
Edge	Edge density	Perimeter of adjacent patches with different land uses relative to area (L or C)
Shape	Area weighted mean shape index	
	Area weighted mean patch fractal dimension	Shape complexity; increases with irregular shapes (L or C)
	Landscape shape index	
Isolation and Interspersion	Mean nearest neighbor distance	Mean distance between similar patch types (L or C)
	Mean proximity index	Mean distance between similar patch types within a search radius (L or C)
	Interspersion juxtaposition index	Relative adjacency of patch types (L or C)
Diversity	Shannon's diversity index	
	Shannon's evenness index	
	Simpson's evenness index	Relative patch diversity (L)
	Modified Simpson's diversity index	
	Modified Simpson's evenness index	

[1]C indicates metric calculated at the class level and L indicates landscape level.

Table 2-3. Land use/land cover coefficients for Landscape Development Intensity (LDI) index and percent imperviousness.

Land use/Land cover class	Non-renewable empower intensity (E15 sej ha^{-1} yr^{-1})[1]	Directly Connected Imperviousness %
Natural land/water	0.00	0.00
Improved pastures	2.02	0.00
Low intensity pastures	3.38	0.00
Medium intensity recreational, open space	6.06	0.00
Tree crops	7.76	0.00
Row crops	20.30	0.00
High intensity agriculture	50.40	0.00
High intensity recreational	123.00	0.00
Low density single family residential	197.50	30.00
Medium density single family residential	658.33	38.00
High density single family residential	921.67	38.00
Institutional	4,042.20	27.33
Low density multifamily residential	4,213.33	38.00
High intensity transportation	5,020.00	53.00
Low intensity commercial	5,173.40	45.00
Industrial	5,210.60	45.00
High intensity commercial	8,372.40	53.00
High density multifamily residential	12,771.67	38.00

[1] LDI Coefficients from Reiss et al. (2009); sej ha^{-1} yr^{-1} = solar emjoules (the available solar energy used during energy transformations) per hectare per year. DCIA coefficients from DERM (2004).

Table 2-4. Land use/land cover data for five study sub-basins in the Biscayne Bay watershed.

Land use/Land cover class	1995 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	7.1	5.3	2.0	7.6	5.7
Improved pastures	4.6	2.1	0.1	0.3	0.8
Low intensity pastures	1.2	0.4	0.0	0.3	0.0
Medium intensity recreational, open space	9.5	8.2	5.1	5.9	4.7
Tree crops	0.2	0.2	0.0	6.8	26.7
Row crops	0.1	0.0	0.0	27.6	22.8
High intensity agriculture	0.0	0.0	0.0	0.2	0.4
High intensity recreational	4.1	2.1	2.3	3.5	1.0
Low density single family residential	1.9	5.1	1.3	5.1	14.0
Medium density single family residential	43.3	35.9	51.7	19.7	12.7
High density single family residential	1.2	1.2	2.1	5.0	0.6
Institutional	3.3	4.2	6.4	4.8	1.0
Low density multifamily residential	6.8	3.1	7.6	2.5	2.4
High intensity transportation	5.4	15.5	3.7	3.3	2.1
Low intensity commercial	3.7	8.0	8.9	2.3	3.6
Industrial	3.8	7.7	5.7	3.6	0.6
High intensity commercial	2.1	0.6	1.9	1.2	0.5
High density multifamily residential	1.7	0.5	1.0	0.4	0.3

Table 2-4. Continued.

Land use/Land cover class	1999 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	7.0	5.5	1.9	4.8	4.6
Improved pastures	1.7	0.4	0.0	0.0	0.2
Low intensity pastures	0.4	0.2	0.0	0.0	0.0
Medium intensity recreational, open space	9.9	5.9	4.5	6.3	4.5
Tree crops	0.2	0.2	0.0	6.6	28.2
Row crops	0.0	0.0	0.0	23.5	20.0
High intensity agriculture	0.0	0.0	0.0	0.1	0.2
High intensity recreational	4.4	2.1	2.9	3.9	1.1
Low density single family residential	0.2	4.7	0.7	4.2	15.4
Medium density single family residential	43.9	36.7	48.8	21.1	12.7
High density single family residential	2.1	1.8	2.0	9.1	1.6
Institutional	4.6	4.8	6.8	5.6	1.7
Low density multifamily residential	7.4	4.3	8.3	2.9	2.9
High intensity transportation	5.2	14.6	3.4	3.3	1.7
Low intensity commercial	4.7	10.1	11.6	2.6	3.9
Industrial	4.4	7.9	5.9	3.9	0.7
High intensity commercial	2.1	0.4	2.0	1.5	0.6
High density multifamily residential	1.7	0.7	1.2	0.5	0.2

Table 2-4. Continued.

Land use/Land cover class	2004 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	5.3	4.8	1.8	3.0	2.7
Improved pastures	0.6	0.5	0.0	0.0	0.1
Low intensity pastures	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	9.4	4.9	4.7	5.6	4.4
Tree crops	0.1	0.1	0.0	5.2	32.5
Row crops	0.0	0.0	0.0	21.6	12.2
High intensity agriculture	0.0	0.0	0.0	0.1	0.1
High intensity recreational	4.6	2.1	2.9	4.0	1.1
Low density single family residential	0.1	4.2	0.6	3.0	15.6
Medium density single family residential	44.6	37.6	48.9	23.4	15.8
High density single family residential	2.6	1.8	1.4	12.6	2.4
Institutional	4.7	5.1	6.6	5.5	1.8
Low density multifamily residential	8.6	4.9	8.6	3.6	3.4
High intensity transportation	5.0	14.4	3.3	3.3	1.8
Low intensity commercial	5.7	10.2	11.7	2.7	4.4
Industrial	5.0	8.2	6.1	4.4	0.7
High intensity commercial	2.1	0.4	2.0	1.6	0.7
High density multifamily residential	1.5	0.7	1.2	0.5	0.2

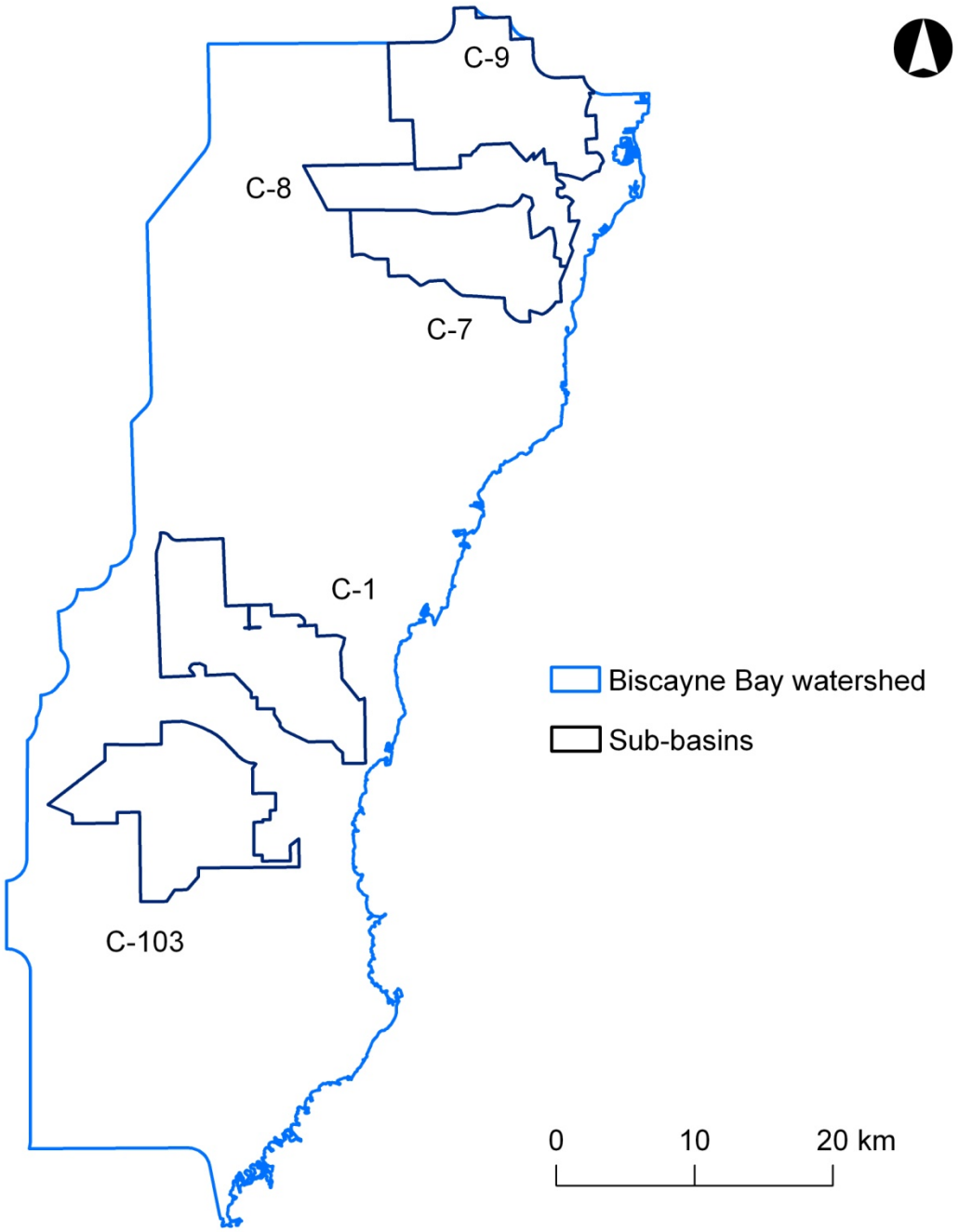
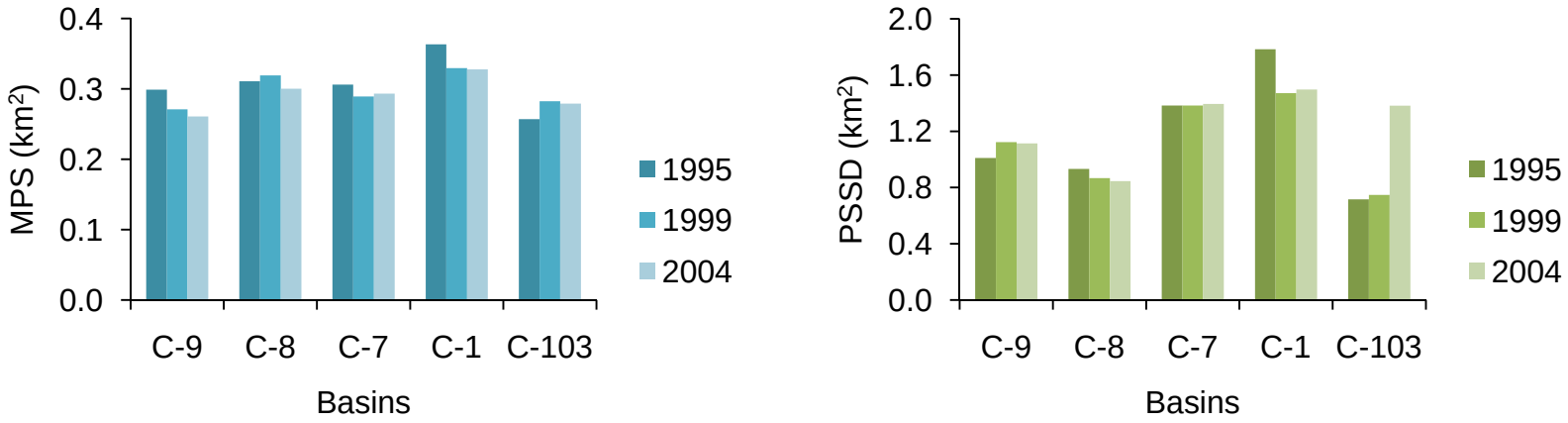
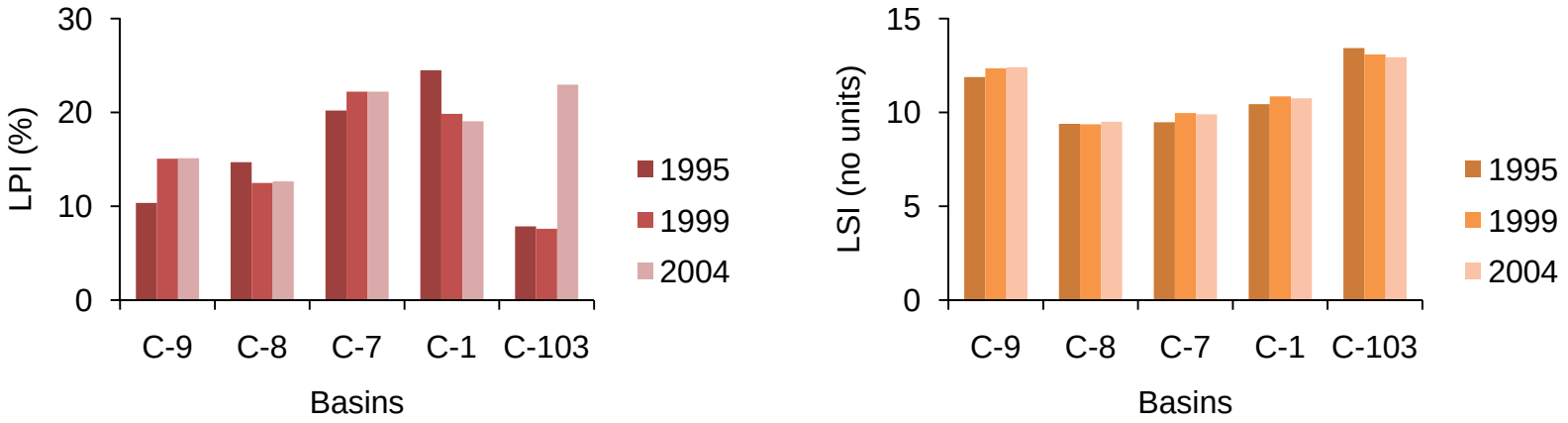


Figure 2-1. Five study sub-basins in the Biscayne Bay watershed.

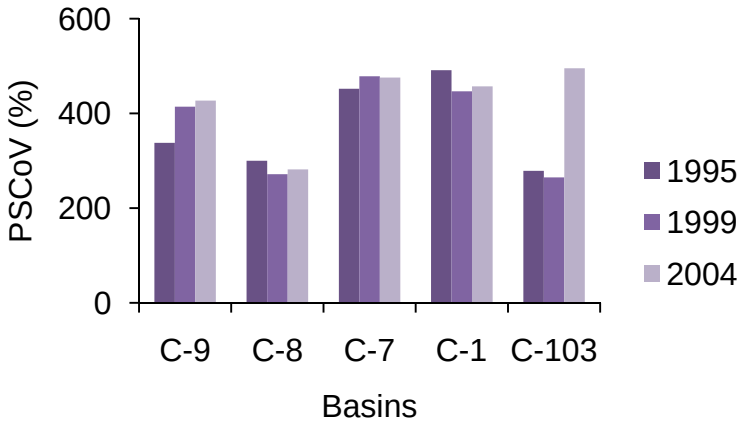


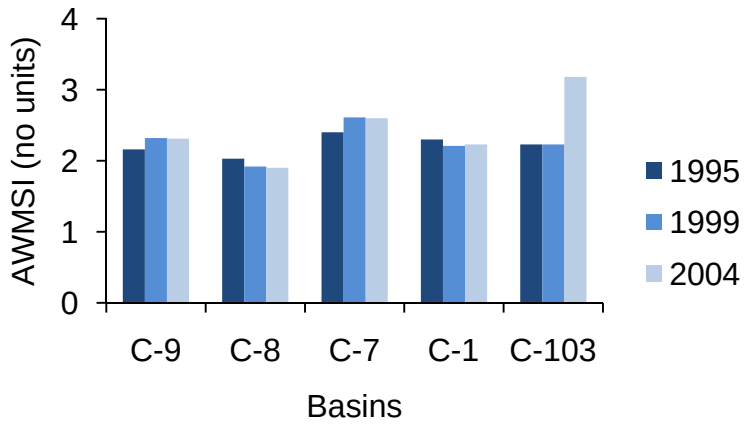
A)



B)

Figure 2-2. Landscape-level factors describing spatial variability in the Biscayne Bay watershed. A) Factor 1 (Mean Patch Size [MPS] and Patch Size Standard Deviation [PSSD]). B) Factor 2 (Largest Patch Index [LPI] and Landscape Shape Index [LSI]). C) Factor 3 (Patch Size Coefficient of Variation [PSCoV] and Area Weighted Mean Shape Index [AWMSI]).





C)

Figure 2-2. Continued.

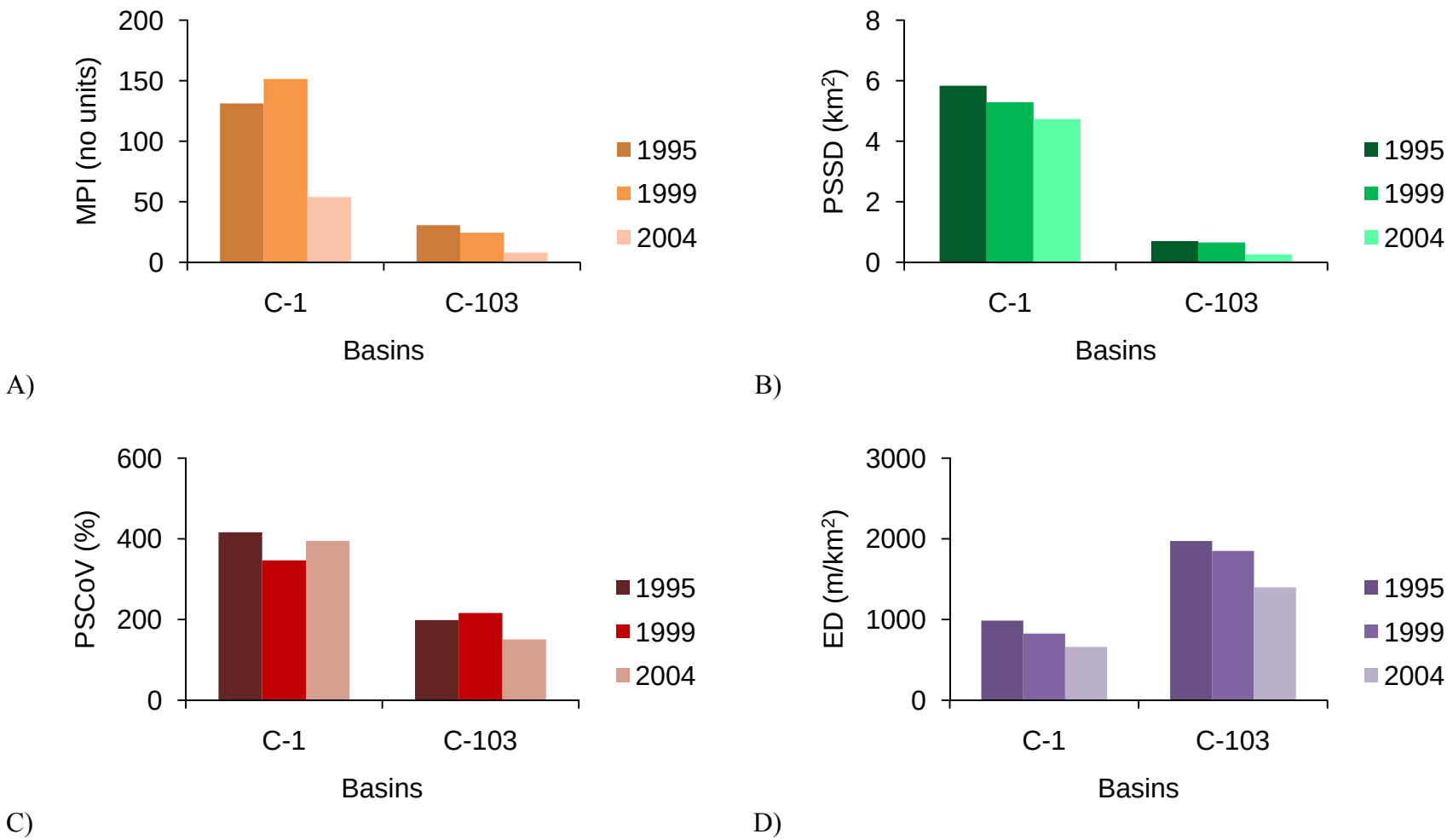


Figure 2-3. Selected class-level metrics for row crops in the Biscayne Bay watershed. A) Mean Proximity Index (MPI). B) Patch Size Standard Deviation (PSSD). C) Patch Size Coefficient of Variation (PSCoV). D) Edge Density (ED).

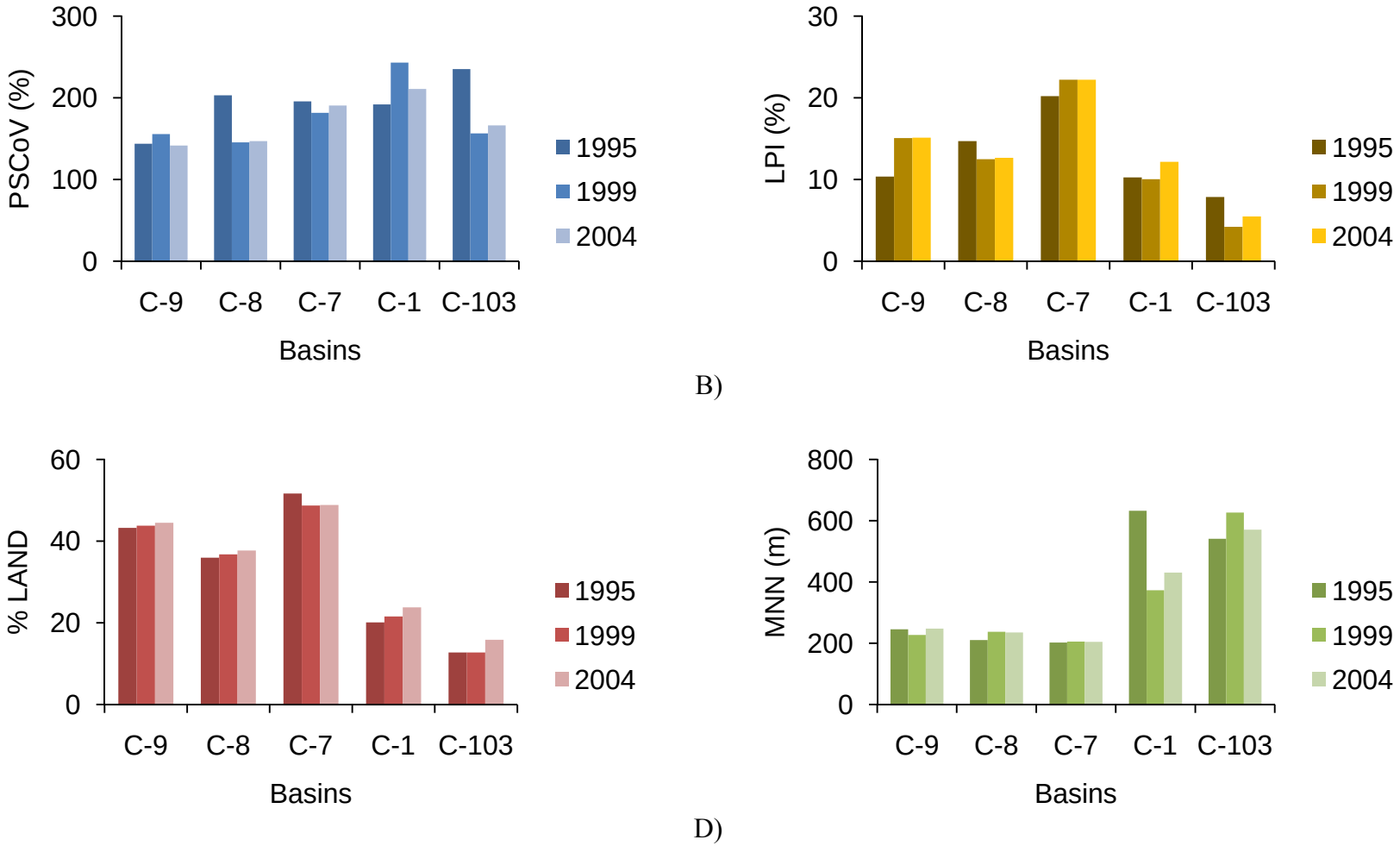


Figure 2-4. Selected class-level metrics for medium density single family residential (MSR) land use class in the Biscayne Bay watershed. A). Patch Size Coefficient of Variation (PSCoV). B) Largest Patch Index (LPI). C) Percent Landscape (%LAND). D) Mean Nearest Neighbor (MNN).

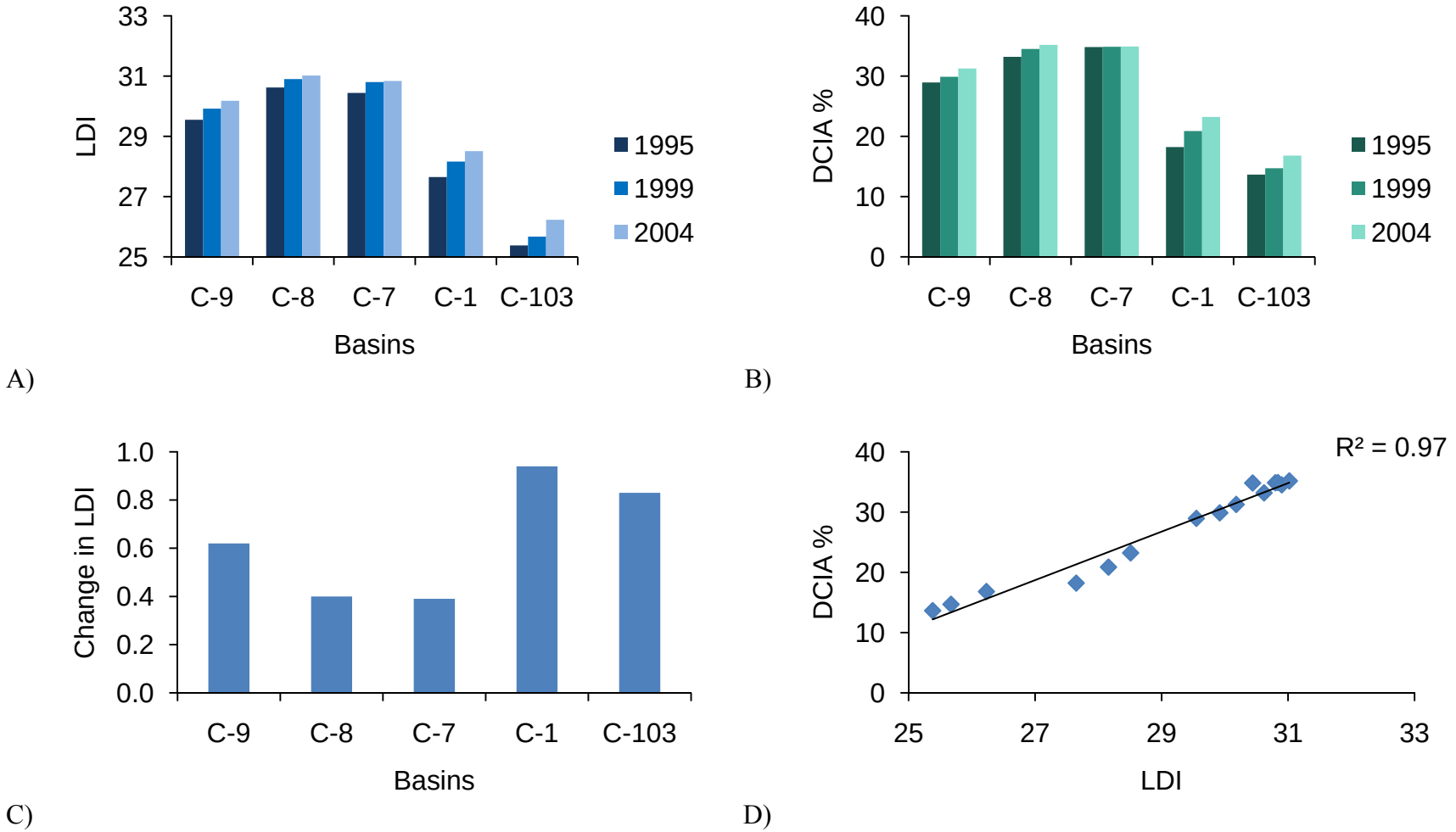


Figure 2-5. Landscape Development Intensity (LDI) index values and Directly Connected Impervious Area (DCIA) percentages for five study sub-basins in the Biscayne Bay watershed. A) LDI index values. B) DCIA percentages. C) Change in LDI values from 1995 to 2004. D) Relationship between LDI values and DCIA percentages.

CHAPTER 3
NUTRIENT DISCHARGES TO BISCAYNE BAY, FLORIDA (1992 TO 2006): WATER QUALITY TRENDS, LOADS, AND A POLLUTANT INDEX

Introduction

Phosphorus and nitrogen are essential nutrients for aquatic productivity but excessive nutrient inputs can lead to over-enrichment, or eutrophication, of surface waters that produce problems such as algal blooms, decreased dissolved oxygen concentrations, and increased fish mortality (Carpenter et al. 1998; Smith 1998). Eutrophication ranks as the leading pollutant problem affecting the ability of U.S. surface waters to meet designated uses such as recreation, fishing, and irrigation (Howarth et al. 2002).

As watershed management plans become more refined to address specific concerns, different methods can be used to evaluate nutrient water quality in both healthy and impaired systems. Parametric and nonparametric trend analysis techniques, for example, can provide important information on temporal changes in nutrient concentrations (Hirsch et al. 1982; Hirsch et al. 1991; Letttenmaier et al. 1991). However, long-term water quality datasets have several characteristics that can complicate trend analysis; there are frequently large gaps in the dataset, data are often skewed, censored data are prevalent (values less than the minimum detection limit; MDL), and chemical analytical techniques can improve over time producing multiple MDLs for the same parameter. Seasonality (Champley and Doledec 1997; McCartney et al. 2003; Qian et al. 2007) and discharge fluctuations (Alley 1988; Hirsch et al. 1991) are other factors that can significantly influence trend analysis. Although concentration measurements are convenient for comparing field data to water quality criteria, additional methods are available to quantify nutrients, such as loads and yields. Loads assess the mass of constituents transported over time and help to quantify the total amount delivered and yield measurements estimate the mass of

constituents delivered per unit area per unit time, which can help to assess best management practices (Christensen 2001).

Another aspect of water quality management is the acknowledgement that chemical stressors that are dispersed in water can have cumulative and deleterious effects in downstream locations far removed from primary pollutant sources (Carpenter et al. 1998; Howarth et al. 2002). A Pollutant Empower Density (PED) index can be used to assess the potential impact of these pollutants released over time in aquatic systems. The PED index addresses environmental effects of dissolved stressors such as nutrients by analyzing their respective emergy per unit time per unit volume (empower densities) relative to background conditions. Emergy is the amount of energy that is directly and/or indirectly required to provide a given flow or storage of energy or matter (Odum 1996). Therefore, the PED index describes the change in energy that has occurred in aquatic systems due to the influence of pollutant discharges. Every element (e.g., nitrogen and phosphorus) has an associated emergy per mass ratio, or unit emergy value (UEV), and as dissolved substances become more concentrated, UEVs increase because energy is required to concentrate materials. For elements and compounds that are rare in nature, more energy is required to concentrate these materials and this results in higher UEVs (Brown and Ulgiati 2004). Nutrients generally have high UEVs and excess concentrations can alter critical ecosystem processes, which can lead to reduced ecosystem function.

Analyzing water quality using multiple methods enables watershed managers to develop and implement specific plans targeting factors affecting water resources. Trend analysis and nutrient quantification methods have been used extensively in water quality studies (e.g., Hirsch et al. 1982; Runkel et al. 2004; Qian et al. 2007) but the PED index is a new, exploratory assessment tool to evaluate the potential impact of known pollutant discharges (Mark Brown,

personal communication). The PED index is especially relevant to sensitive aquatic systems experiencing greater anthropogenic influences, such as Biscayne Bay, a natural oligotrophic estuary in southeastern Florida.

Biscayne Bay requires minimal inputs of phosphorus and nitrogen to function and thus watershed nutrient inputs have a controlling influence on bay water quality (Browder et al. 2005). The primary nutrient limiting autotrophic growth in Biscayne Bay is phosphorus (Brand 1988; Kleppel 1996) and average phosphorus concentrations are low but variable throughout the bay, with the northern section having greater concentrations (0.008 to 0.020 mg L^{-1}) than other areas (<0.008 mg L^{-1}) (Alleman et al. 1995). Due to these phosphorus concentration differences, Brand (1988) found phytoplankton levels were five times greater in the north than in the south. Nitrogen may not be the limiting nutrient in the bay but elevated nitrate/nitrite concentrations (>4 mg L^{-1}; Cheesman 1989) derived from agricultural and some urbanized areas in the watershed are a concern because artificially high concentrations may have subtle ecological effects (Alleman et al. 1995), such as making the bay more susceptible to algal blooms.

Changes in land use, management practices, and environmental conditions may all lead to detectable differences in nutrients transported to Biscayne Bay. Lietz (2000), for example, analyzed water quality data (1966 to 1994) at a site discharging to the bay and found downward trends, indicative of improved water quality, for several parameters including total ammonia nitrogen and total phosphorus. The total amount of nutrients entering Biscayne Bay is of particular concern and previous studies have quantified incoming nutrient loads. Lietz (1999) estimated nutrient loads to Biscayne Bay by analyzing nutrient concentrations and freshwater discharges and Caccia and Boyer (2007) developed a nutrient loading budget to the bay by analyzing canals throughout the watershed. Both studies determined that nitrate/nitrite-nitrogen

loads were elevated in the southern agricultural drainage areas while ammonia-nitrogen and total phosphorus loads were highest in the northern and central urban drainage areas. Canal discharges are therefore important factors influencing Biscayne Bay water quality and the goal of this study was to evaluate historical nutrient water quality data from 1992 to 2006 at six monitoring sites located near the outlets of canals discharging to the bay. Quantifying the effects of continued urban and agricultural development in the watershed is important for adaptive management of the bay and thus specific objectives included the following: (1) determine nutrient concentration trends during the study period; (2) estimate annual nutrient loads from six canals in the watershed; and (3) use the PED index to assess the proportional impact of nutrient discharges from various canals.

Methods

Study Area

Biscayne Bay is a barrier-island subtropical estuary that is located along the southeastern coastline of Florida and includes the federally protected Biscayne National Park. Designated as an Outstanding Florida Water, Biscayne Bay requires substantial freshwater inputs to maintain its natural ecological balance; however, water management operations in south Florida have disrupted historical freshwater flows to the bay. For example, the canal conveyance system has accelerated freshwater flow from the Everglades to the Atlantic Ocean (Leach et al. 1972) and freshwater inputs to Biscayne Bay have been modified from natural pathways of continuous submarine discharges and overland sheet flow to periodic surface water releases at canal outlets (Langevin 2001). Canals function as point source discharges to Biscayne Bay and reflect complex interactions between urban and agricultural elements within the watershed. Nineteen canals discharge into the bay and water quality has declined during the 20th century as south Florida's population has increased (Cantillo et al. 2000).

The Biscayne Bay watershed is primarily located in Miami-Dade County, which includes the city of Miami, but the northern section extends into Broward County. The western boundary of the watershed lies adjacent to the Florida Everglades and the Everglades National Park. The South Florida Water Management District (SFWMD) and the US Army Corps of Engineers manage a complex system of drainage canals, pumps, levees, and municipal well fields in the watershed. Without these structures, the region could not adequately protect urban complexes and agricultural fields from seasonal floods. Canals contain gated control structures that release excess water during the wet season (May to November) and recharge groundwater during the dry season (November to May).

Water quality and flow data from six monitoring sites near the outlets of six separate canals were used in this study (Figure 3-1). Sites SK02, BS04, LR06, BL03, and MW04 were the primary focus of the study and the sixth site, AR03, was used as a reference or baseline. Selected canals were located in sub-basins containing different types of land use/land cover (LULC) such as agricultural, urban, and mixed-land uses. SK02, BS04, and LR06 are located on the C-9, C-8, and C-7 canals, respectively; these canals are in the northern section of the watershed, which is primarily characterized by urban land uses. BL03 is on the C-1 canal, located in the central section of the watershed surrounded by extensive mixed (urban and agricultural) land uses. MW04 is on the C-103 canal in the South Dade Agricultural Area, a region dominated by agricultural land uses such as row and tree crops. AR03, located on C-111, is surrounded by wetlands in the extreme southern section of the watershed.

Water Quality Data

Miami-Dade County Department of Environmental Resources Management (DERM) collects monthly grab samples from water quality monitoring sites throughout Biscayne Bay and in watershed canals. DERM uses EPA methods 353.2, 350.1, and 365.1 to analyze water quality

samples for nitrate/nitrite-nitrogen (NO_X-N), total ammonia nitrogen (NH_3-N), and total phosphorus (TP) respectively. NO_X-N, NH_3-N, and TP concentrations from 1992 to 2006 for each of the six monitoring sites used in this study were obtained from DERM. Each of the six monitoring sites had associated flow sites and daily flow data were obtained from SFWMD to estimate nutrient loads. SFWMD uses wireless communications systems to remotely monitor and record flow data through existing structures. Water quality and flow data flagged for violating quality control criteria were excluded from analysis.

Trend Analysis

USGS Estimate Trend (ESTREND; Schertz et al. 1991) is an application extension for S-Plus 8.0 (Insightful Corporation 2007) that includes both parametric (Tobit regressions) and non-parametric (uncensored/censored seasonal Kendall) methods to determine trends in constituent water quality data. Tobit regression uses a Maximum Likelihood Estimation (MLE) method to determine trends for parameters that contain greater than 5% censored data with multiple MDLs. The seasonal Kendall methods are suitable for parameters with less than 5% censored data (uncensored seasonal Kendall) and greater than 5% censored data at a single detection limit (censored seasonal Kendall).

ESTREND was used to analyze nutrient concentration trends at the water quality monitoring sites. For the period 1992 to 2006, trend analysis was performed separately at each site on monthly NO_X-N, NH_3-N, and TP concentrations. To account for seasonality in trend analysis, wet (May 27th to November 7th) and dry (November 8th to May 26th) seasons were defined in ESTREND based on an evaluation of historical rainfall in south Florida (Qian et al. 2007). Nutrient data from Miami-Dade DERM were not flow adjusted because SFWMD regulates flow within the six study canals, thereby deviating from natural discharge patterns characteristic of unaltered systems (Hirsch et al. 1991).

Only Tobit regression was used for trend analysis on NO_X-N, NH_3-N, and TP concentrations because more than 5% of the data at each study site were censored at multiple detection limits. In Tobit regression, censored data are not assigned values; instead, values for censored data are predicted based on the distribution of known values (Schertz et al. 1991). Constituents were log transformed prior to the Tobit procedure and seasonal terms (sine and cosine of yearly cycle) were included for constituents. Studentized residuals below -3 or above 3 for NO_X-N, NH_3-N, and TP concentrations at each site were considered outliers and excluded from trend analysis. Finally, the Tobit procedure in ESTREND calculated trend slopes that indicated the rate of change of each nutrient over time and results were evaluated using a significance level of $p < 0.1$.

Nutrient Loads

The U.S. Geological Survey (USGS) developed the Load Estimator (LOADEST) model that has been specifically designed to estimate loads in streams and rivers (Runkel et al. 2004). The model is a publicly available FORTRAN program that uses linear regressions to estimate daily, monthly, seasonal, or annual loads and users have the ability to customize the model to fit particular objectives. LOADEST primarily uses the Adjusted Maximum Likelihood Estimation (AMLE) method to estimate loads but if the calibration dataset is uncensored, the MLE method is used. However, both methods assume that model residuals are normally distributed. LOADEST also includes the Least Absolute Deviation (LAD) method to estimate loads when the normality assumption is violated. The flexibility of LOADEST and its ability to estimate loads when assumptions are violated enhances the utility of this program for water quality analyses.

LOADEST was used to estimate annual nutrient loads (1992 to 2006) from the six sites using monthly NO_X-N, NH_3-N, and TP concentrations daily flow data. Nutrient and flow data for

each of the six sites were utilized as LOADEST calibration datasets to develop separate regression models estimating NO_X-N, NH_3-N, and TP loads. LOADEST gives users the option of selecting a regression model for load estimations or allowing the program to select the best model from a set of predefined models. The latter option was chosen in this study to identify the best available regression models for each constituent at each of the six sites. To select the best models, LOADEST calculated model coefficients for several predefined regression models using each calibration dataset and models with the lowest Akaike Information Criterion values (Judge et al. 1988) were selected for load estimations.

NO_X-N, NH_3-N, dissolved inorganic nitrogen (NO_X-N plus NH_3-N), and TP load estimates from LOADEST were evaluated by calculating Nash-Sutcliffe efficiency (NSE) coefficients (Nash and Sutcliffe 1970), comparing daily load estimates to actual loads at monitoring sites on days where both nutrient concentrations and flow data were available. NSE was calculated using Equation 3-1:

$$\text{NSE} = 1 - \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{mean}\right)^2}\right] \tag{3-1}$$

where n is the number of values, Y^{obs} and Y^{sim} are measured and simulated values, respectively, and Y^{mean} is the mean of measured values. NSE coefficients range from $-\infty$ to 1 (1 being a perfect model fit) and coefficients above zero indicate acceptable model performance. Negative values indicate that simulated values from a model are less efficient than using the mean of the measured values, representing unacceptable model performance (Moriasi et al. 2007).

Pollutant Index

The PED index uses empower density (emergy per unit volume per unit time) values to provide a relative indicator of ecological stress because thermodynamic principles guide

ecosystem organization. According to the 4th law of thermodynamics, the maximum power principle (Lotka 1922), systems organize to increase efficiency and hierarchical relationships involve energy transfers and positive feedback loops (Odum 1996). Emergy signatures for ecosystems are therefore associated with the level of structural organization and can be used as a reference to evaluate ecological integrity (Campbell 2000). For example, Bastianoni (1998) defined pollution in terms of emergy flows and system organization, noting that pollutants cause an increase in emergy flows and a corresponding decrease in ecosystem efficiency. There is a temporal dimension to pollution because ecosystems are dynamic networks and increased emergy flows, due to factors such as additional nutrient inputs, inevitably lead to reorganization efforts that attempt to maximize newly available resources. Depending on the range of species that can exploit these new resources, overall structural complexity within ecosystems could possibly decline. Coral reefs and seagrass communities in Biscayne Bay, for example, are susceptible to increased nutrient concentrations (Brand et al. 2002).

The PED index is calculated using the flux of pollutants and the background productivity of the reference environment. Campbell et al. (2000) used nine energy sources to derive emergy signatures for three different types of estuaries. Literature values for these nine energy sources that could be applied to Biscayne Bay were used to calculate the reference empower density (Table 3-1). In emergy analysis, all contributing energy sources are converted and expressed in units of solar emergy (the available solar energy used during energy transformations; solar emjoules [sej]) to assess the amount of emergy associated with each source [sej yr^{-1}]. However, all emergy values were not added to determine the background empower density of Biscayne Bay. Adding all the emergy values would lead to an overestimation of background conditions because individual inputs may not be independent (e.g., energy inputs from wind and tides)

(Odum 1996; Campbell et al. 2000). To address this potential problem, the following procedure was implemented: (1) all emergy values were calculated; (2) the highest emergy value was identified; (3) energy inputs were evaluated to determine if adding particular emergy values would avoid the problem of overestimation; and (4) the background empower density [sej m^{-3} yr^{-1}] was determined using the highest emergy value by itself or with another emergy value that was derived from a sufficiently different energy source. The PED was calculated using Equation 3-2:

$$PED = 10 * \log_{10} (emPD_{Total}/emPD_{Ref}) \quad (3\text{-}2)$$

where PED [unit less] is the Pollutant Empower Density index for Biscayne Bay, $emPD_{Total}$ is the total empower density [sej m^{-3} yr^{-1}] and $emPD_{Ref}$ is the background empower density [sej m^{-3} yr^{-1}]. The total empower density ($emPD_{Total}$) is calculated as follows:

$$emPD_{Total} = emPD_{Ref} + \sum emPD_i \quad (3\text{-}3)$$

where $emPD_i$ = empower density of pollutant *i* [sej m^{-3} yr^{-1}]. The annual empower density of pollutant *i* is calculated using the specific emergy of the appropriate nutrient and its annual flow weighted concentration. For example, the empower density of NO_X-N was calculated using Equation 3-4:

$$emPD \text{ of } NO_X\text{-}N = (\text{specific emergy of N}) * (\text{annual } NO_X\text{-N load/annual discharge volume}) \quad (3\text{-}4)$$

The specific emergy for nitrogen (7.02E+12 sej g^{-1}) was used to calculate PED values for both forms of nitrogen (NO_X-N and NH_3-N); the specific emergy for phosphorus (1.08E+11 sej g^{-1}) was used for TP. Annual PED values (1992 to 2006) at each of the six sites were calculated separately for NO_X-N, NH_3-N, and TP.

Results

Trend Analysis

Table 3-2 summarizes ESTREND results for NO_X-N, NH_3-N, and TP at the six study sites using the Tobit procedure and a significance level of $p < 0.1$. During the study period (1992 to 2006), five sites had significant annual trends for NO_X-N. SK02 and AR03 had significant negative (i.e., downward) trends while LR06, BL03, and MW04 had significant positive (i.e., upward) trends. BS04 had no significant trend for NO_X-N. For NH_3-N, there were four sites with significant trends: BS04, LR06, and AR03 (all negative) and BL03 (positive). SK02 and MW04 exhibited no significant trends for NH_3-N. Only BS04 and MW04 had significant positive trends for TP during the study period. SK02, LR06, BL03, and AR03 all had no significant trends for TP.

Nutrient Loads

Annual discharges associated with the six sites are shown in Figure 3-2. Average NSE coefficients for nutrient loads at the six sites, when comparing measured loads to LOADEST simulated results, were 0.59 (NO_X-N), 0.61 (NH_3-N), 0.72 (NO_X-N plus NH_3-N), and 0.70 (TP) (Table 3-3; Figure 3-3). Median annual NO_X-N loads from 1992 to 2006 indicated MW04 (157,248 kg yr^{-1}) had substantially larger values than the other five sites: BL03 (81,888 kg yr^{-1}), SK02 (79,658 kg yr^{-1}), LR06 (48,907 kg yr^{-1}), BS04 (35,056 kg yr^{-1}), and AR03 (2,434 kg yr^{-1}) (Figure 3-4). Median annual NH_3-N loads were greatest for LR06 (105,022 kg yr^{-1}), with SK02 (61,247 kg yr^{-1}), BL03 (46,644 kg yr^{-1}), BS04 (26,204 kg yr^{-1}), AR03 (3,943 kg yr^{-1}), and MW04 (1,168 kg yr^{-1}) having lower loads (Figure 3-4). Combined median annual NO_X-N plus NH_3-N loads for AR03 (6, 376 kg yr^{-1}) were substantially less than MW04 (158,127 kg yr^{-1}), LR06 (145,854 kg yr^{-1}), SK02 (136,227 kg yr^{-1}), BL03 (136,026 kg yr^{-1}), and BS04 (57,035 kg yr^{-1}) (Figure 3-4). For TP, median annual loads for LR06 (4,738 kg yr^{-1}), SK02 (2,816 kg yr^{-1}), BS04

(2,288 kg yr^{-1}), BL03 (1,196 kg yr^{-1}), and AR03 (211 kg yr^{-1}) all had greater estimated loads than MW04 (155 kg yr^{-1}) (Figure 3-4).

Pollutant Index

Table 3-1 lists the energy sources and relevant literature values used to calculate the background empower density of Biscayne Bay (3.17E+11 sej m^{-3} yr^{-1}). Organic matter (measured as total organic carbon) in the canals had the highest emergy value (5.16E+20 sej yr^{-1}) and was combined with the chemical potential energy in groundwater (1.83E+19 sej yr-1) to determine the background empower density. Chemical inputs from groundwater to Biscayne Bay are temporally different from organic matter inputs from the canals and therefore emergy values for both of these sources were not expected to lead to an overestimation of background conditions.

PED index values are shown in Figure 3-5. For NO_X-N, MW04 (average: 18.47) consistently had the highest PED from 1992 to 2006. PED values began to decline at MW04 in 2001 but remained elevated compared to the other four sites. The reference site, AR03 (4.61), had the lowest PED for NO_X-N during the study period. LR06 (9.96), BL03 (9.87), BS04 (8.91), and SK02 (8.62) all had similar PED values for NO_X-N. For NH_3-N, LR06 (12.96) had the greatest PED but declined between 2002 and 2006. MW04 (2.34) had lower NH_3-N PED values than AR03 (5.49) while BS04 (8.13), BL03 (8.05), and SK02 (7.87) all had similar values. PED values for TP were much lower than those for nitrogen (both NO_X-N and NH_3-N). LR06 (0.06) had the highest PED values for TP but declined from 1992 to 1997 and then stayed relatively constant from 1998 to 2006. BS04 (0.03) had the second highest PED for TP and increased from 1999 to 2006. SK02 (0.02), BL03 (0.01), MW04 (0.01), and AR03 (0.01) all had similar PED values for TP (Figure 3-5).

Discussion

Trends

During the period of analysis (1992 to 2006), the majority of NO_X-N, NH_3-N, and TP concentrations decreased or exhibited no change at the six water quality monitoring sites, with only six instances of significantly ($p < 0.1$) increasing trends (Table 3-2). Temporal changes in nutrient concentrations are important but specific water quality standards determine the significance of increasing or decreasing trends. The U.S. Environmental Protection Agency (USEPA) proposed nutrient criteria guidelines for nationwide ecoregions (USEPA 2000) and has allowed individual states to develop and implement specific criteria that reflect local conditions. The Florida Department of Environmental Protection (FDEP) is currently developing statewide nutrient criteria for surface waters, including streams/canals in ecoregion XIII (southern Florida coastal plain) where the Biscayne Bay watershed is located (FDEP 2009). Watershed nutrient criteria following USEPA guidelines is therefore not yet available but Abbott (2005) described water quality targets for NO_X-N (0.05 mg L^{-1} in Biscayne National Park) and NH_3-N (0.05 mg L^{-1} throughout the bay; 0.01 mg L^{-1} within Biscayne National Park). The Miami-Dade County water quality standard for NH_3-N in surface waters is 0.5 mg L^{-1} and the USEPA nutrient criteria recommendations for ecoregion XII (southern coastal plain; directly adjacent to ecoregion XIII) for total nitrogen concentrations is 0.9 mg L^{-1}. The USEPA recommendation for TP in ecoregion XII is 0.04 mg L^{-1}. Surface water quality standards in Miami-Dade County and USEPA ecoregion XII nutrient criteria were used to evaluate concentration trends at the six monitoring sites.

Trend analysis results were somewhat different from other Biscayne Bay water quality reports identifying possible areas of concern in the watershed. Factors that may have contributed to different results include variability in trend analysis methods (e.g., not accounting for

changing minimum detection limits over time) and contrasting study periods. For example, Abbott (2005) evaluated long-term (1991 to 2003) water quality data at 13 sites throughout the watershed, including five of the sites analyzed in this study, and concluded that nitrogen concentrations were generally increasing and TP concentrations were declining. Trend analysis results at site MW04, located in the C-103 sub-basin, corresponded with data from Abbott (2005) for both NO_X-N (increasing trend) and NH_3-N (no trend) but TP concentrations had a significant ($p < 0.1$) increasing trend from 1992 to 2006 (Table 3-2). Factors that may be contributing to gradually increasing TP concentrations include a wastewater treatment plant located upstream from MW04 and increasing (26.8% to 31.4%) low and medium density single family residential land use classes in the C-103 sub-basin between 1995 and 2004 (SFWMD 1995; SFWMD 2004). Median TP concentrations at MW04 and AR03 (reference site) however, were the lowest for all sites and far below the recommended TP criteria in ecoregion XII (Table 3-4). Additional phosphorus inputs in south Biscayne Bay could produce an ecosystem shift from benthic autotrophs (i.e., seagrasses and macroalgae) to phytoplankton, as has already occurred in the north (Brand et al. 2002), but low TP concentrations at MW04 suggest that an increasing trend will not likely contribute to water quality problems in the immediate future.

Site BL03, in the C-1 sub-basin, had a significant ($p < 0.1$) increasing trend for NO_X-N and was the only site with a significant ($p < 0.1$) increasing trend for NH_3-N concentrations. NO_X-N concentrations at BL03 were among the highest in the study (Table 3-4) and although NH_3-N concentrations did not exceed county standards (0.5 mg L^{-1}), multiple factors influence nitrogen concentrations at BL03, including fertilizer applications in upstream agricultural areas. In addition, a cause for concern at BL03 is the influence of the nearby South Dade Landfill. Environmental issues associated with landfills include leachate formation and its potential to

affect both surface and groundwater (El-Fadel et al. 1995; Kjeldsen et al. 2002). Alleman (1990) and Meeder and Boyer (2001) have found elevated ammonia concentrations in canals adjacent to the landfill, including C-1, after evaluating water quality in the area. In addition, McKenzie (1983) monitored wells within the landfill and determined ammonia concentrations were greatest beneath recent waste deposits during the dry season, indicating active organic matter decomposition. The South Dade Wastewater Treatment Plant (SDWWTP) is another potential source of ammonia but it uses deep well injection to dispose effluents underground and monitoring data suggests that it is not affecting ammonia concentrations in surface or groundwater (Alleman 1990). The SDWWTP could be a concern, however, as ammonia was found in shallow monitoring wells after only 11 years of the first effluent injection, contradicting estimates suggesting a 343-year period for upward migration (McNeill 2000; Brand et al. 2002).

Loads

Similar to Lietz (1999) and Caccia and Boyer (2007), annual nutrient loads at the six monitoring sites during the study period revealed higher NO_X-N loads in the southern section of the watershed and higher NH_3-N and TP loads in the northern and central areas (Figure 3-4). Downstream water flow in canals transport pollutants from the watershed directly to the north, central, and south sections of Biscayne Bay with land use patterns influencing pollutant characteristics (Caccia and Boyer 2005). Nutrient loads from the watershed therefore reflect widespread agricultural production in the south as well as urban and residential land use classes in the north. As described in the previous section, the South Dade Landfill and SDWWTP are located in the central watershed and these two facilities are potential nutrient sources influencing water quality at site BL03.

NO_X-N loads from site MW04, located on the C-103 canal, were the highest for all sites (Figure 3-4), which is similar to the results from other water quality studies throughout the entire

watershed (Scheidt and Flora 1983; Cheesman 1989; Alleman et al. 1995). Agricultural production is a dominant influence in the C-103 sub-basin as row and tree crops accounted for approximately 45% of total land use in 2004 (SFWMD 2004). Local environmental characteristics and land use practices therefore combine to influence nutrient loads from MW04 and the C-103 canal. For example, Orth (1976) analyzed groundwater samples wells within the C-103 sub-basin and found NO_X-N concentrations ranging from 3 mg L^{-1} to 10 mg L^{-1}, which were likely influenced by fertilization rates, inappropriate irrigation, and leaching caused by high permeability soils with low water-holding capacity (Li 2000; Li and Zhang 2002). Furthermore, high water tables in the watershed enable nitrogen-enriched groundwater to degrade water quality in the canals and eventually Biscayne Bay (Langevin 2000).

Although MW04 had the highest loads among all sites, NH_3-N loads at this site were the lowest in the study (Figure 3-4). Scheidt and Flora (1983) also reported low NH_3-N concentrations in the C-103 canal and Caccia and Boyer (2007) determined that NO_X-N contributed 95% of dissolved inorganic nitrogen (NO_X-N plus NH_3-N) inputs from canals in the southern region of the watershed to the bay. MW04 had the lowest median NH_3-N concentration during the study period (Table 3-4) among the six sites analyzed and this suggests that compared to NO_X-N, NH_3-N concentrations have been historically low in the C-103 sub-basin.

Site LR06, located on the C-7 canal, had the highest median concentrations and annual loads for both NH_3-N and TP (Figure 3-5). The heavily urbanized North Bay, which receives canal discharges from C-9, C-8, and C-7 canals, has historically struggled with sewage discharges, high nutrient loads, turbidity, and heavy metals (Alleman et al. 1995). Land use data from 2004 revealed medium intensity single family residential (48.9%) and low intensity commercial (11.7%) areas dominated the C-7 basin (SFWMD 2004). Between 1920 and 1955,

raw wastewater was released into several northern canals, including C-7 (Wanless 1976), which was identified as a conveyor transporting sewage-contaminated discharges to Biscayne Bay (McNulty 1970). Raw wastewater is no longer discharged into the C-7 canal but Alleman et al. (1995) suggested stormwater runoff and leaks associated with sewage systems were likely factors contributing to ongoing pollutant problems. SK02 (C-9 canal) and BS04 (C-8 canal) also had elevated NH_3-N and TP loads compared to the reference site, although loads at these sites were lower than LR06.

Pollutant Index

Annual nutrient loads at the six monitoring sites fluctuated greatly but corresponding PED index values were less sensitive, exhibiting a damped response to nutrient fluxes (Figure 3-5). An important factor contributing to this difference is that the PED index uses the logarithmic decibel scale to represent the intensity of discharged pollutants relative to reference conditions in aquatic systems. The decibel scale has been previously used in the development of a human disturbance index (Reiss et al. 2009) to evaluate the impact of anthropogenic influences. Brown and Vivas (2005) introduced the Landscape Development Intensity index (LDI) to investigate the effect of human activities on adjacent systems but an important limitation of the index was that disturbance intensity was not related to background conditions. Reiss et al. (2009) revised the LDI index to address this issue, enabling background conditions to regulate the effects of disturbances. Similarly, the PED index assesses the ability of pollutants to affect aquatic system productivity when considering baseline system properties.

PED index values for the six monitoring sites in the Biscayne Bay watershed suggest that canal discharges from two sites (MW04 and LR06) provide a greater proportional impact in the bay compared to the other sites (Figure 3-5). Site MW04 consistently produced the highest annual PED values for NO_X-N but PED values for NH_3-N and TP at MW04 were the lowest

among all sites (including the reference site, AR03), which suggests that NO_X-N dominates nutrient inputs from MW04. However, PED values for NO_X-N at MW04 began a general decline in 2001 and this could be indicative of improved best management practices or land use changes occurring in the drainage sub-basin, C-103. From 1999 to 2004, row crops declined (20% to 12.2%) in C-103 while tree crops (28.2% to 32.5%) and single family residential land use areas (28.1% to 31.4%) increased (SFWMD 2009). Tree crops and residential developments correspond to relatively lower NO_X-N canal concentrations than row crops and this may have contributed to lower PED values between 2001 and 2006.

Site LR06 had the highest PED index values for NH_3-N and TP (Figure 3-5). Similar to MW04, general water quality improvement at LR06 also occurred during the study period. PED values for NH_3-N at LR06 eventually declined to a point where they were similar to values from SK02, BS04, and BL03; furthermore, PED values for TP at LR06 declined substantially from 1992 to 1997, before leveling out in subsequent years. Drainage and sewer improvement projects have helped to lower pollutant discharges from LR06 but additional measures are necessary to control nutrient export to the bay. Brand et al. (2002) conducted nutrient bioassays throughout the bay and found that at the mouths of some northern canals, including C-7 where LR06 is located, the ecosystem is actually nitrogen limited; the bay is typically phosphorus limited because calcium carbonate chemically scavenges phosphorus from water due to groundwater inputs moving through limestone and calcareous sediments in shallow surface water. Localized saturation of calcium carbonate in northern Biscayne Bay therefore reflects historical and substantial phosphorous inputs from urbanized sub-basins. Similar to annual nutrient loads, PED values for NH_3-N also provide evidence of another localized issue in the watershed as the mixed land use site, BL03, consistently had similar values to the more urban sub-basins, SK02 and

BS04. The South Dade Landfill and possibly the SDWWTP are important factors influencing the water quality of adjacent canals.

Management Implications

Trend analysis, load estimation, and the PED index can be used together to provided a more holistic interpretation of water quality (Figure 3-6), which is necessary for optimizing resources to meet watershed management goals. An extensive period of record (e.g., 10 years) is required to detect statistically significant changes in water quality and thus trend analysis can be used to evaluate existing management strategies to determine if constituent trends are improving over time or getting worse. In addition, results from trend analysis can help to forecast future conditions when considering historical patterns. Both loads and the PED index are useful indicators to determine relative pollutant contributions from multiple sites but the PED index provides an ecological assessment of discharges relative to receiving systems. Loads and the PED index can be calculated annually but comparisons over time would provide additional insight into pollutant dynamics.

Trend analysis results suggest that water quality is generally improving throughout the Biscayne Bay watershed and pollutant loads and the PED index indicate that canal discharges are coupled with land use activities in adjacent drainage areas. However, development patterns are not the only concern for watershed managers because proposed projects under the Comprehensive Everglades Restoration Plan will affect the quantity and quality of freshwater flows to the bay. Projects include rerouting canal discharges to coastal wetlands and recycling wastewater to supplement freshwater inflows to the bay; however, proposed criteria for recycled water that would provide protection for the bay may not be easily attainable (Browder et al. 2005).

In the Biscayne Bay watershed, therefore, there is an urgent need for assessment tools that can be used to guide management initiatives regarding water quality discharges to the bay. The PED index can be used to evaluate potential ecological impacts associated with discharges from specific water quality monitoring sites. Creating a separate PED index for individual pollutants reveals watershed distribution and also provides a relative indication of energy-based ecological stress associated with pollutants. The PED index can therefore provide a link between watershed processes and subsequent pollutant discharges, which can be used to identify watershed locations that may disproportionately affect the ecological health of the bay.

The PED index may also be useful in a variety of watersheds because data needed to calculate emergy signatures are available through published reports pertaining to particular aquatic ecosystems. Emergy values have been calculated for different types of estuaries (Campbell 2000), subtropical springs (Collins and Odum 2000), subtropical lakes (Brown and Bardi 2001) and coral reefs (McClanahan 1990). The PED index is not limited to a particular type of system or region and can be used to assess the proportional impact of pollutant discharges from multiple sources.

Conclusion

Nutrient water quality data (1992 to 2006) from six water quality monitoring sites in the Biscayne Bay watershed were evaluated using multiple analytical methods (trends, loads, and the PED index) and although areas of concern were identified, water quality has generally improved during the study period. Trend analysis results indicate that nutrient (NO_X-N, NH_3-N, and TP) concentrations declined or exhibited no change at most of the six water quality monitoring sites. NO_X-N and NH_3-N concentrations increased during the study period at site BL03 and upstream agricultural influences, along with a nearby landfill and possibly a wastewater treatment plant, are factors contributing to nitrogen concentrations at BL03. For nutrient loads, the monitoring

site in the southern, agricultural section of the watershed (MW04) consistently produced greater NO_X-N loads than monitoring sites in the urbanized northern section of the watershed (SK02, BS04, and LR06), where NH_3-N and TP loads were greatest. Compared to nutrient loads, PED index values for the monitoring sites were more consistent during the study period and pollutant discharges from two sites (MW04 and LR06) had the greatest potential for impact in the bay.

The PED index is a new analytic tool to assess the intensity of discharged pollutants relative to the background productivity of aquatic systems. All ecosystems rely on fundamental energy relationships and the PED index can be used to identify pollutant discharges that could disrupt energy flows and impair aquatic health. The index can be applied in a broad range of aquatic systems because the volume of incoming pollutants can be quantified and background productivity can be calculated. Results from studies investigating additional pollutants beyond nutrients in different types of aquatic systems will contribute to the continued development of the PED index.

Table 3-1. Energy sources and conversion factors used to calculate background productivity (emergy signature) for Biscayne Bay.

Energy Source[1]	Energy (J yr^{-1})[2]	Transformity (sej J^{-1})	Emergy (sej yr^{-1})
Sunlight	4.39E+18	1	4.39E+18
Wind	1.16E+17	1496	1.74E+20
Rain, Chemical	5.29E+15	18199	9.62E+19
Tide	8.96E+14	24259	2.17E+19
Estuary Waves	7.69E+15	30550	2.35E+20
Geologic Uplift	2.50E+12	34377	8.59E+16
Ground Water, Chemical	4.47E+14	41000	1.83E+19
River (Canals), Chemical	6.17E+15	48459	2.99E+20
River (Canals), Organic matter[3]	1.73E+14	2.98E+06	5.16E+20

[1] Calculations for each energy source taken from Odum (1996) and Cambell (2000). Biscayne Bay area and average depth from Dame et al. (2000). Average of insolation from Fend et al. (2003). Wind gradient and diffusion coefficient for Tampa Bay (Odum 1996). Rainfall estimates and wave data from Buchanan and Klein (1976). Tide data from Lee and Rooth (1976). Geologic uplift (heat flow per area) from Odum (1996). Groundwater inputs from Radell and Katz (1991) and Langevin (2001). Chemical and organic matter input from Alleman et al. (1995) and Lietz (2000).

[2] J yr^{-1} = joules per year; sej J^{-1} = solar emjoules per joule; sej yr^{-1} = solar emjoules per year.

[3]Organic matter in canals refers to total organic carbon concentration.

Table 3-2. Trend analysis results for nutrient concentrations at six water quality monitoring sites in the Biscayne Bay watershed.

Constituent	Site	Observations	Trend (%)	p value	Significance ($p < 0.1$)
NO_X-N	SK02	142	-5.47	0.00	decreasing
	BS04	88	-0.63	0.31	none
	LR06	149	1.97	0.01	increasing
	BL03	149	4.48	0.00	increasing
	MW04	138	2.07	0.00	increasing
	AR03	150	-3.01	0.08	decreasing
NH_3-N	SK02	154	-1.11	0.64	none
	BS04	149	-2.80	0.09	decreasing
	LR06	151	-4.75	0.00	decreasing
	BL03	153	13.20	0.00	increasing
	MW04	153	0.55	0.73	none
	AR03	145	-7.72	0.00	decreasing
TP	SK02	141	1.01	0.27	none
	BS04	150	2.69	0.00	increasing
	LR06	153	1.03	0.15	none
	BL03	155	-0.47	0.74	none
	MW04	147	4.55	0.00	increasing
	AR03	151	1.42	0.36	none

Table 3-3. Average Nash-Sutcliffe Efficiency (NSE) coefficients for six water quality monitoring sites in the Biscayne Bay watershed after comparing LOADEST simulated loads to measured loads (1992 to 2006).

Site	NO_X-N	NH_3-N	NO_X-N plus NH_3-N	TP
SK02	0.41	0.76	0.72	0.38
BS04	0.20	0.66	0.46	0.87
LR06	0.73	0.41	0.71	0.92
BL03	0.49	0.38	0.72	0.50
MW04	0.83	0.54	0.84	0.65
AR03	0.88	0.88	0.88	0.88
Average	0.59	0.61	0.72	0.70

Table 3-4. Summary statistics for nutrient concentrations (1992 to 2006) and flow data at six water quality monitoring sites in the Biscayne Bay watershed.

Constituent	Site	Min[1] (mg L^{-1})	Mean (mg L^{-1})	Median (mg L^{-1})	Max[2] (mg L^{-1})	Mean Annual Discharge (m^3 s^{-1})
NO_X-N	SK02	0.010	0.224	0.210	0.680	8.88
	BS04	0.010	0.222	0.200	1.750	3.40
	LR06	0.020	0.271	0.280	0.530	3.87
	BL03	0.010	0.288	0.245	1.010	6.00
	MW04	0.010	2.200	2.250	4.640	1.41
	AR03	0.010	0.049	0.040	0.230	1.14
NH_3-N	SK02	0.008	0.124	0.070	0.540	
	BS04	0.008	0.111	0.070	0.410	
	LR06	0.010	0.390	0.370	0.930	
	BL03	0.008	0.086	0.030	0.400	
	MW04	0.008	0.025	0.020	0.100	
	AR03	0.008	0.051	0.040	0.240	
TP	SK02	0.001	0.010	0.008	0.170	
	BS04	0.003	0.018	0.015	0.170	
	LR06	0.004	0.024	0.022	0.170	
	BL03	0.001	0.007	0.005	0.170	
	MW04	0.001	0.006	0.004	0.048	
	AR03	0.001	0.006	0.004	0.170	

[1]Water quality targets: NO_X-N (0.05 mg L^{-1} in Biscayne National Park); NH_3-N (0.01 mg L^{-1} within Biscayne National Park; 0.05 mg L^{-1} throughout the bay; 0.5 mg L^{-1} for surface waters in Miami-Dade County); total nitrogen (0.9 mg L^{-1} for ecoregion XII, southern coastal plain); TP (0.04 mg L^{-1} for ecoregion XII).
[2]Minimum detection limits (MDLs) were used as maximum concentrations for censored data. MDLs for censored TP data during the study period included 0.17 mg L^{-1}.

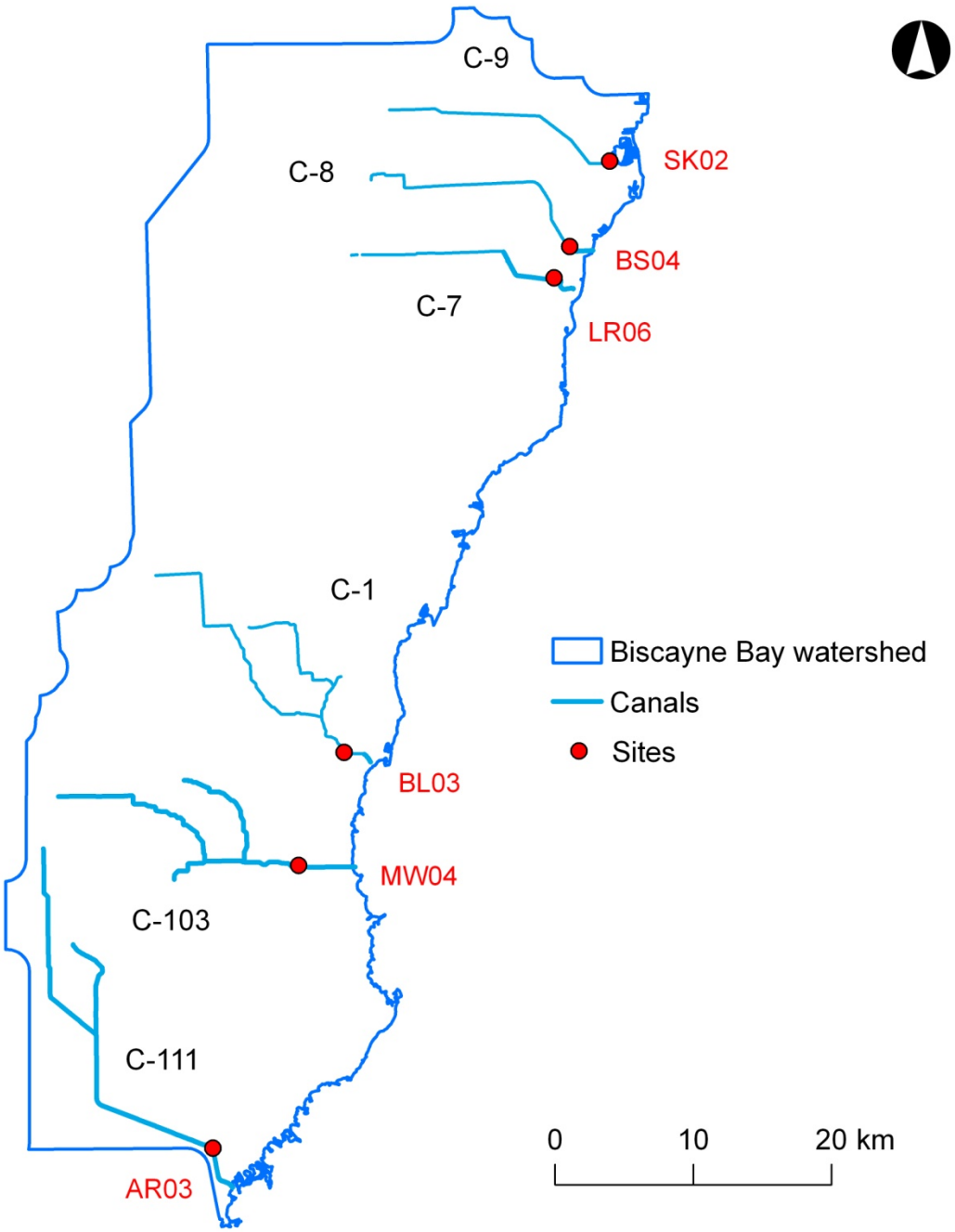


Figure 3-1. Six water quality monitoring sites in the Biscayne Bay watershed.

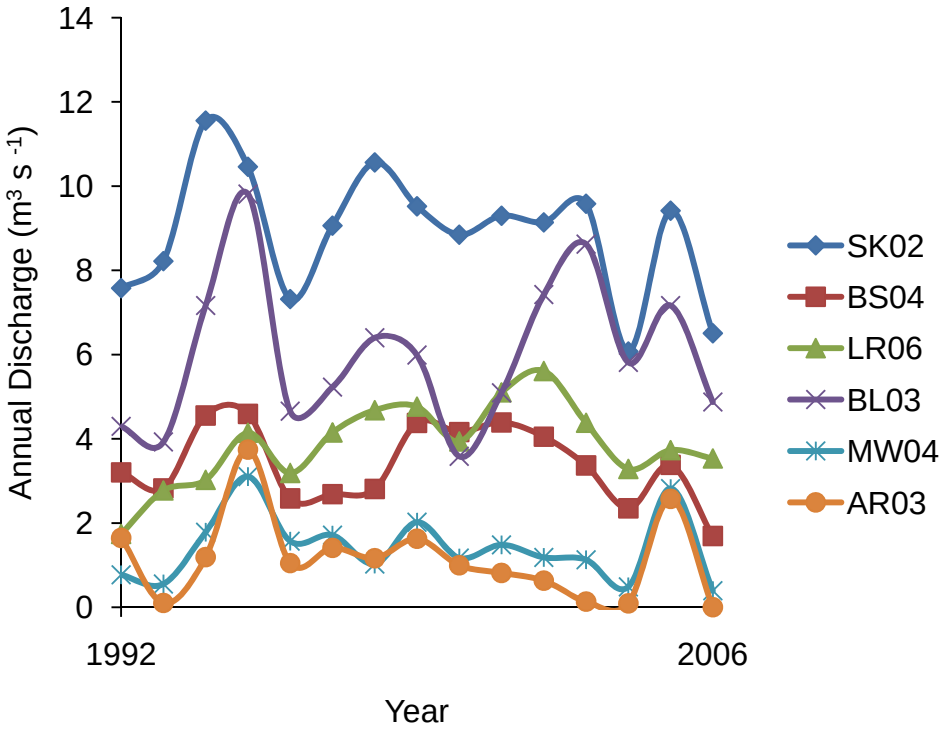


Figure 3-2. Annual discharge (1992 to 2006) from six water quality monitoring sites in the Biscayne Bay watershed.

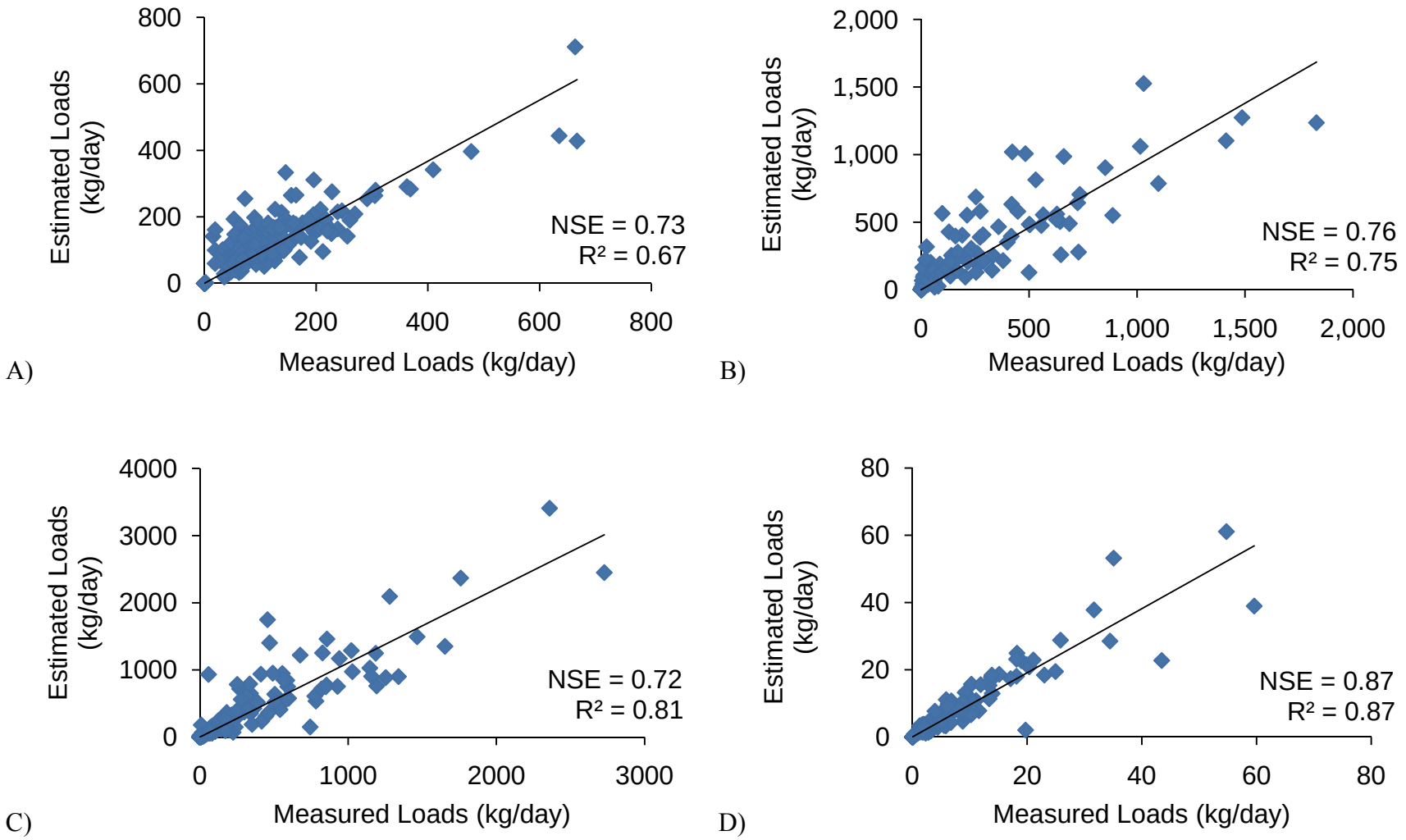
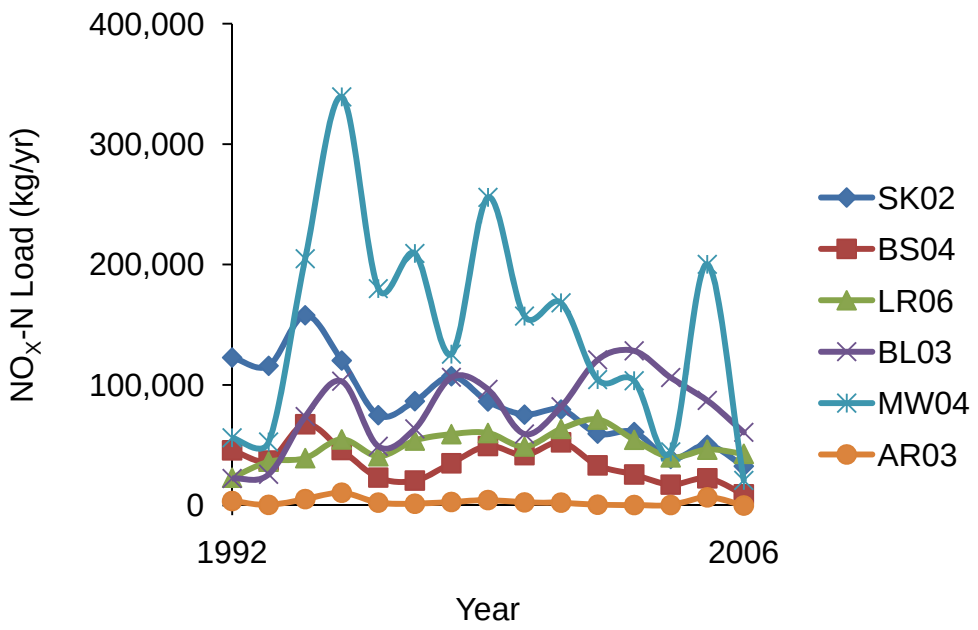
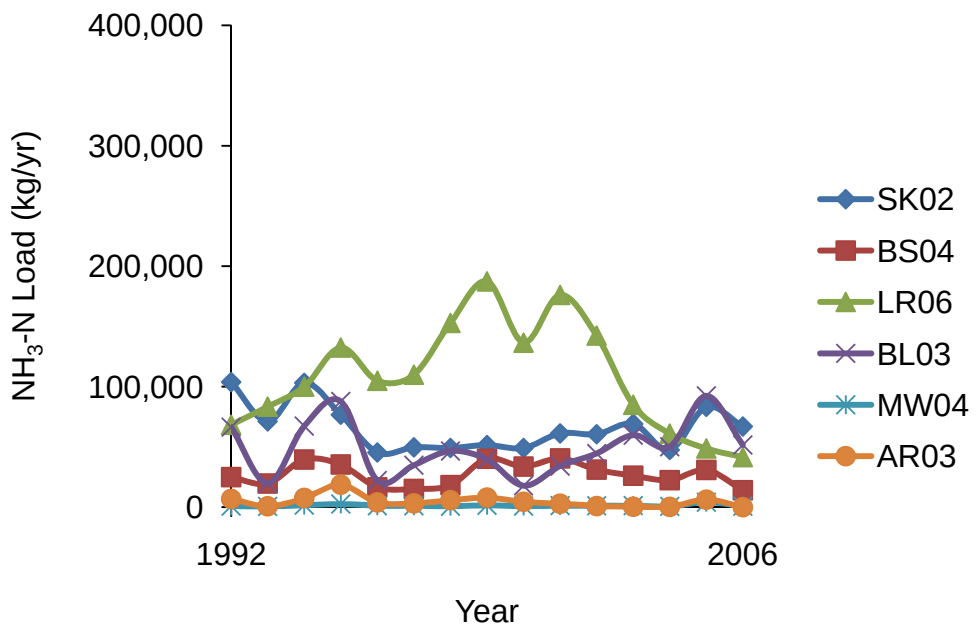


Figure 3-3. Nash-Sutcliffe Efficiency (NSE) coefficients for selected water quality monitoring sites in the Biscayne Bay watershed after comparing LOADEST simulated loads to measured loads (1992 to 2006). A) NO_X-N loads at LR06. B) NH_3-N loads at SK02. C) NO_X-N plus NH_3-N loads at BL03. D) TP loads at BS04.

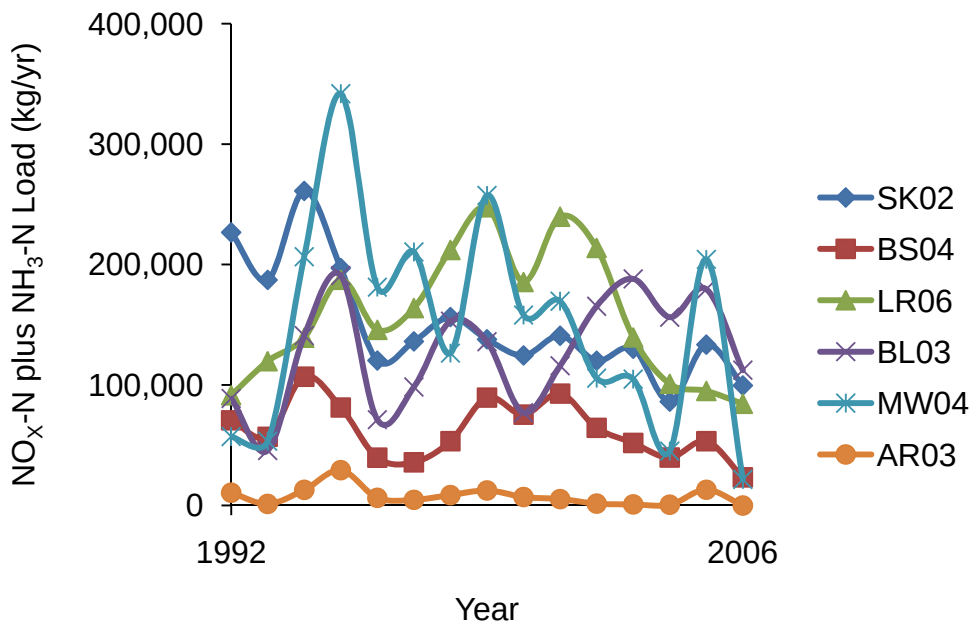


A)

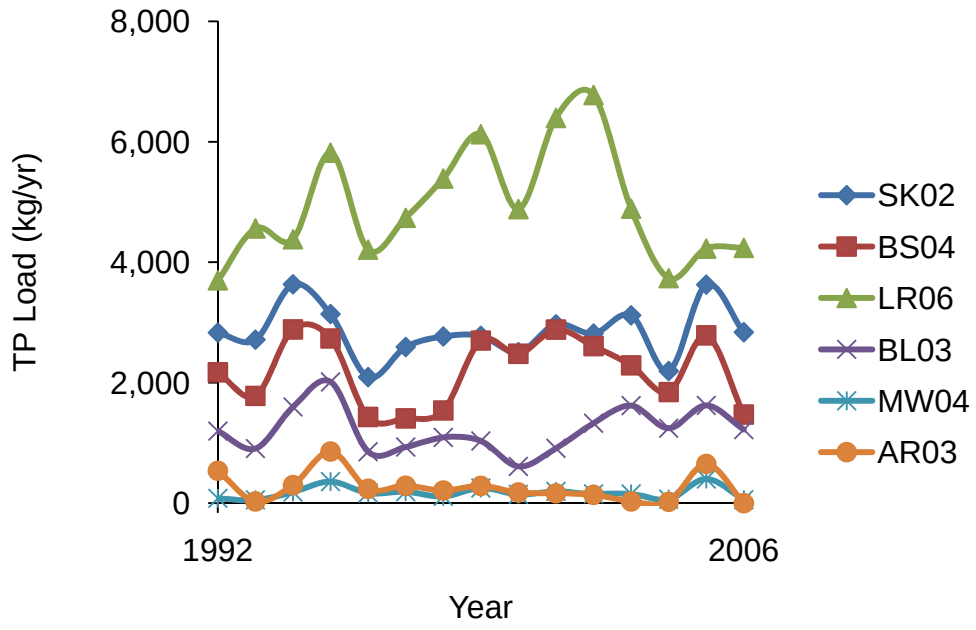


B)

Figure 3-4. Estimated annual nutrient loads (1992 to 2006) at six water quality monitoring sites in the Biscayne Bay watershed. A) NO_X-N. B) NH_3-N. C) NO_X-N plus NH_3-N. D) TP.

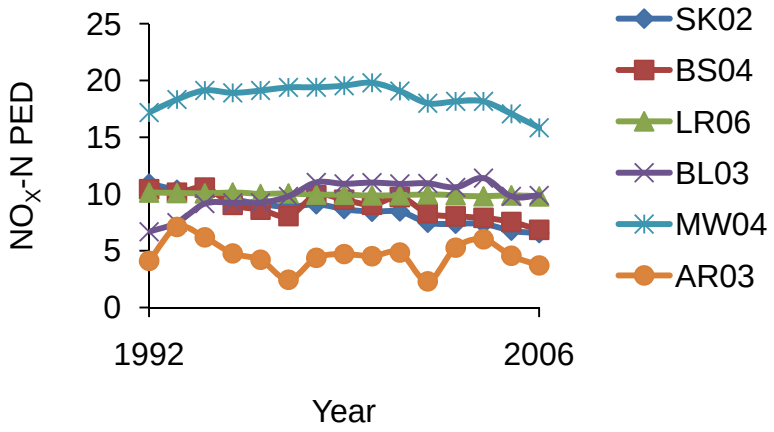


C)

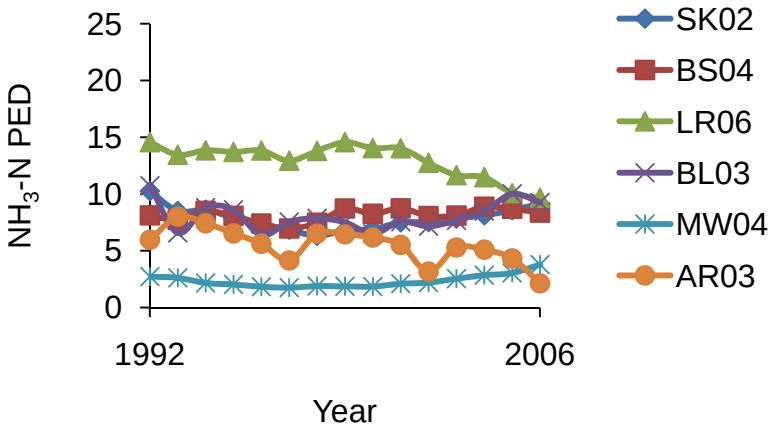


D)

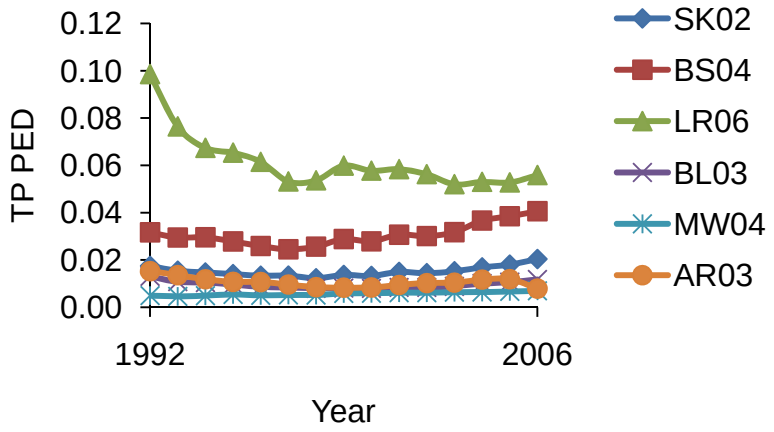
Figure 3-4. Continued.



A)



B)



C)

Figure 3-5. Pollutant Empower Density (PED) index values (1992 to 2006) at six water quality monitoring sites in the Biscayne Bay watershed. A) NO_X-N. B) NH_3-N. C) TP.

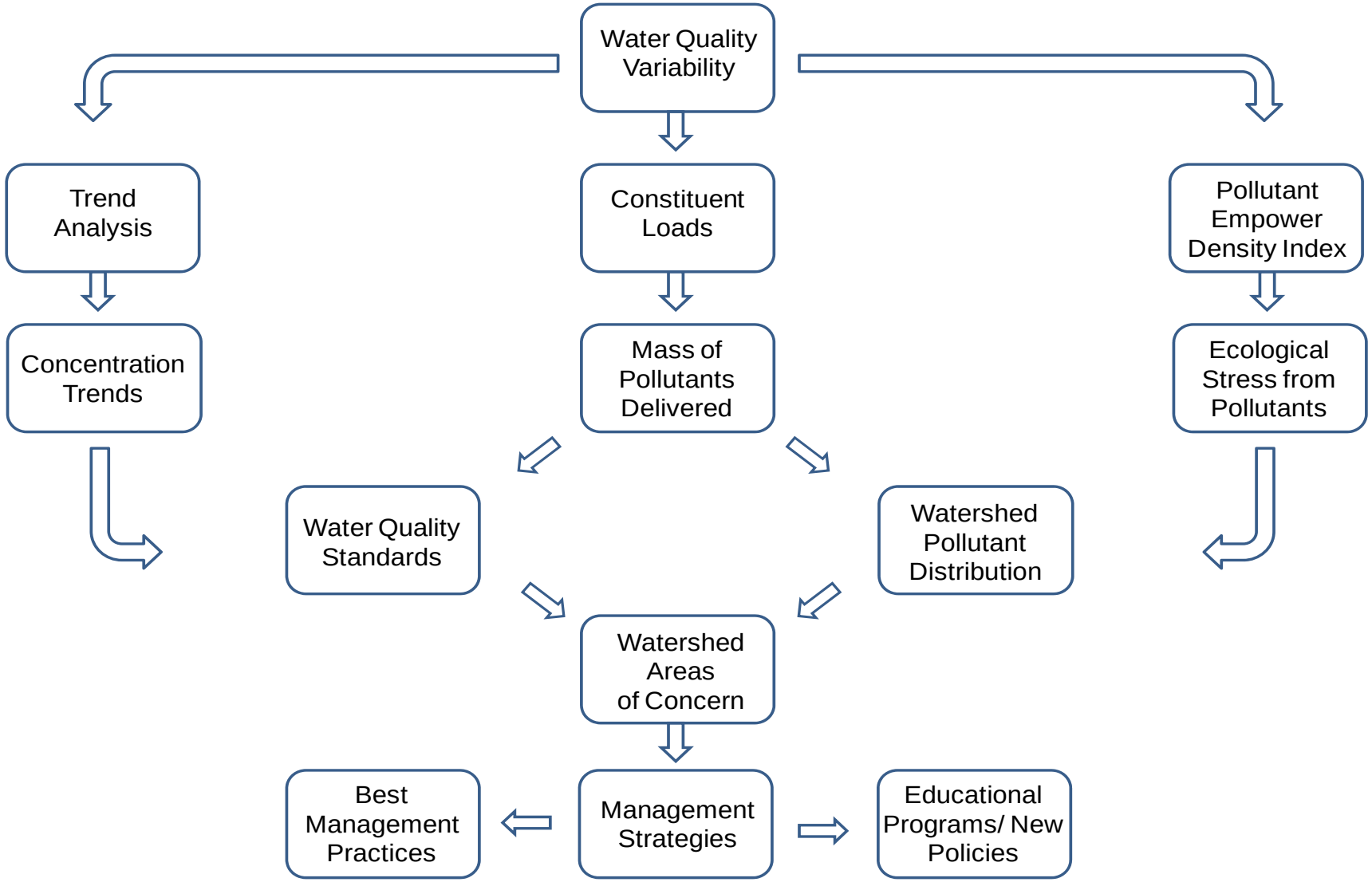


Figure 3-6. Flow chart illustrating the combined use of trend analysis, load estimation, and the Pollutant Empower Density index to evaluate water quality variability in watersheds.

CHAPTER 4
LAND USE INFLUENCES (1995 TO 2004) AFFECTING NUTRIENT WATER QUALITY IN THE BISCAYNE BAY WATERSHED, FLORIDA

Introduction

Geographic information system (GIS) software and increasingly available land use data facilitates watershed analysis linking indicators of landscape condition to water quality parameters (e.g., Hunsaker and Levine 1995; Johnson et al. 2001; Kearns et al. 2005). Intensive land use activities affect hydrological, biological, chemical, and geomorphic aspects of aquatic systems (Arnold and Gibbons 1996; Gergel et al. 2002; Alberti 2005). Several indicators can be used to evaluate anthropogenic influences within watersheds including landscape metrics (Forman and Godron 1986; Turner 1990; Li and Wu 2004), disturbance gradients (McMahon and Cuffney 2000; Brown and Vivas 2005; Wang et al. 2008), and the extent of impervious surfaces (Arnold and Gibbons 1996; Brabec et al. 2002; Roy and Shuster 2009). Landscape metrics quantify spatial configuration and composition (McGarigal and Marks 1995) and have been used to investigate development patterns in watersheds (Kearns et al. 2005; Cifaldi et al. 2004), landscape characteristics influencing sediment contamination levels (Paul et al. 2002), and the effect of land use distribution on water quality (Lee et al. 2009).

To evaluate the effects of land use activities on adjacent systems, Brown and Vivas (2005) developed the Landscape Development Intensity (LDI) index to quantify disturbance gradients based on nonrenewable energy use and emergy analysis. Emergy (Odum 1971; Odum 1996) measures the amount of energy that is directly and/or indirectly associated with both natural and anthropogenic products and services. Human-dominated landscapes feature greater nonrenewable energy use than natural areas and the LDI index provides a relative indication of the extent of nonrenewable energy use associated with landscape disturbances (Odum 1996; Brown and Vivas 2005). Reiss (2005), Mack (2006), and Reiss and Brown (2007) have all used

the LDI index to assess landscape conditions and Reiss et al. (2009) utilized an updated LDI index to evaluate the effect of human disturbances on Florida wetlands.

Imperviousness is another important environmental indicator because it is associated with intensive land use activities and contributes to hydrologic changes that can degrade water quality (Arnold and Gibbons 1996; Brabec et al. 2002; Schiff and Benoit 2007). Watershed imperviousness values can describe either total impervious areas (TIA), which include surfaces that may drain to pervious ground, or directly connected impervious areas (DCIA) that drain directly to aquatic systems (Brabec et al. 2002). Watershed imperviousness values using TIA therefore include connected (DCIA) and unconnected surfaces which could underestimate the impact of changes in land use activities and subsequent hydrological effects (Alley and Veenhuis 1983; Brabec et al. 2009). Roy and Shuster (2009) therefore identified DCIA measurements as factors that can be integral to watershed management plans.

Numerous studies have used GIS technology and regression analyses to link land use indicators to water quality parameters at multiple spatial extents, including sub-basins (Mehaffey et al. 2005; Migliaccio et al. 2007), riparian zones (Silva and Williams 2001; Schiff and Benoit 2007), and monitoring site proximities (Bolstad and Swank 1997; King et al. 2005). Investigations using regression analyses identify important explanatory and independent variables (Johnston 1972; Mason 1975; Graham 2003) and consequently variable selection procedures influence model development and reliability. The stepwise procedure allows both the inclusion and removal of independent variables during model development to identify the most important variables (Efroymson 1960; Thomas 1978) and has been widely used in regression analyses. Iverson (1988) used stepwise regressions to select a sub-set of landscape attributes that had the most influence on historical land use patterns in Illinois, Harding et al. (1998) identified

land use variables that explained aquatic organism diversity in streams, and Chadwick et al. (2006) investigated urbanization variables affecting stream ecological function. Stepwise regressions have also been used to develop multivariate regression models to predict constituent loads of targeted water quality parameters in response to changes in land use variables (e.g, Johnson et al. 2001; Jones et al. 2001; Paul et al. 2002). After selecting variables, validation procedures (Snee 1977; Moriasi et al. 2007) help to assess the suitability of developed models. Although collecting new data is the preferred method for validating regression models, Snee (1977) notes that splitting the data into an estimation dataset (for model coefficients) and a prediction dataset (to test model accuracy) can simulate the process of collecting new data.

Linking land use variables to specific response criteria such as constituent nutrient loads has clear management implications and can lead to improved strategies to combat threats to vulnerable water resources. For example, Biscayne Bay is an oligotrophic estuary that drains the Miami metropolitan area and is sensitive to watershed land use activities, including extensive agricultural and urban development. Thus, the goal of this study was to evaluate land use-water quality relationships in the Biscayne Bay watershed from 1995 to 2004 at eight water quality monitoring sites considering three different spatial extents: sub-basins, canal buffers, and site buffers. Specific objectives included the following: (1) quantify human disturbance indicators using land use/land cover (LULC) data and GIS spatial analysis; (2) estimate nutrient loads at water quality monitoring sites; (3) develop and validate multivariate regression models to identify significant land use variables influencing nutrient loads; and (4) determine if disturbance indicators within sub-basins, canal buffers, or site buffers explain more of the variability in nutrient loads at monitoring sites during the study period.

Methods

Study Area

Biscayne Bay is a barrier-island subtropical estuary that is located along the southeastern coastline of Florida and includes the federally protected Biscayne National Park. Designated as an Outstanding Florida Water, Biscayne Bay requires substantial freshwater inputs to maintain its natural ecological balance; however, water management operations (canals, levees, pump sites, etc.) in south Florida have disrupted historical freshwater flows to the bay. Extensive urban and agricultural development in the watershed (2,500 km^2) have thrived on former wetlands as canals have lowered water tables (Parker et al. 1955), reducing watershed water storage and creating polluted discharges that degrade sensitive estuarine habitats (Browder et al. 2005). The watershed is primarily located in Miami-Dade County, which includes the city of Miami, but the northern section extends into Broward County; the western boundary of the watershed lies adjacent to the Florida Everglades and the Everglades National Park.

Hydrological connectivity may be a significant factor affecting water quality in the watershed and eight monitoring sites with adequate data were identified and used in this study. Selected sites were located upstream from canal outlets to avoid tidal influences that could potentially affect water quality measurements. In addition, the eight sites were located in areas of the watershed with contrasting LULCs such as agricultural, urban, and mixed-land uses. Land use and water quality relationships were investigated at the eight sites considering sub-basins, canal buffers (Tables 4-1; 4-2; 4-3; Figure 4-1), and proximity buffers (Tables 4-4; 4-5; 4-6; Figure 4-2), with the latter two considered at the following distances: 500, 1000, and 1500 meters. Selected sites were associated with a total of five canals, with three canals (C-9, C-1, and C-103) having two sites each (one upstream and one downstream) and two other canals (C-8 and

C-7) with only downstream sites. C-8 is a headwater canal and no flow data was associated with the upstream site for C-7 during the study period.

The C-9 East (118 km^2; referred to as C-9 hereafter), C-8 (71 km^2), and C-7 (82 km^2) sub-basins are located in the northern section of the watershed, which is primarily characterized by urban land uses. In the central watershed, the C-1 (117 km^2) sub-basin includes extensive mixed (urban and agricultural) land uses. The C-103 (113 km^2) sub-basin, located in the southern section of the watershed within the South Dade Agricultural Area, is dominated by agricultural land uses such as row and tree crops. Analysis was limited to sub-sections of both C-1 and C-103 sub-basins to correspond with locations of upstream and downstream monitoring sites. For sub-basins with both upstream and downstream sites (C-9, C-1, and C-103), canal buffers covered the distance between the two sites. Canal buffers in sub-basins with only downstream sites (C-8 and C-7) started at the most upstream point of the major canal and continued to the downstream site. Proximity buffers for the eight sites were located upstream of each site to evaluate water quality and LULC influences (Figure 4-2).

Land Use Data

LULC GIS data layers of the Biscayne Bay watershed were obtained from SFWMD for 1995 (scale - 1: 40000), 1999 (1: 40000), and 2004 (1: 12000). SFWMD created all three layers by photo-interpreting aerial photography and digital orthophotographic quarter quadrangles (DOQQs). Each layer used a modified form of the Florida Land Use and Cover Classification System (FLUCCS; FDOT 1999) as SFWMD FLUCCS codes primarily use community level classes to identify vegetation. Land use classes in this study were aggregated into 18 natural, agricultural, and urban classes to simplify analysis and LULC data were converted to raster format for spatial analysis using a common scale (190 x 190 meters grid cell size). To ensure LULC data accuracy, DOQQs corresponding to the timeline of the LULC data were retrieved

from the Land Boundary Information System (LABINS) of the Florida Department of Environmental Protection. DOQQs were then compared to LULC data and any assigned classes that were inconsistent with actual conditions were corrected to reflect LULC throughout the watershed.

Landscape Metrics

The most widely used software package to calculate landscape metrics is FRAGSTATS (McGarigal and Marks 1995), which generates values for several different categories of metrics that can be useful to understanding changes occurring in a watershed. Patch Analyst (Elkie et al. 1999), a modified version of FRAGSTATS designed specifically as an ESRI ArcGIS extension tool, provides an integrated user interface that enables metrics to be calculated for LULC layers at both landscape and class levels. Landscape metrics calculate values with all classes included (e.g., mean patch size within a watershed) while class metrics calculate values for specific classes (e.g., mean patch size of row crops). Contiguous cells from the same land use classes were considered patches in this study.

For each of the three LULC layers (i.e., 1995, 1999, and 2004), 17 landscape metrics and 13 class metrics were calculated for the entire Biscayne Bay watershed. Area-weighted metrics (e.g., patch richness density) were preferred to absolute metrics (e.g., patch richness) to compare data from sub-basins and buffers. Metrics were tested for normality using the Shapiro-Wilk W test for normality with a p-value <0.05 (Shapiro and Wilk 1965; Royston 1983). Most metrics deviating from a normal distribution were either log or square root transformed to improve normality; metrics containing percentage data were arcsin-square root transformed. Pair-wise correlation coefficients were calculated for transformed landscape and class metrics to eliminate redundancy, with only one metric in a correlated pair of metrics selected if Pearson coefficients were greater than 0.90 (Ritters et al. 1995).

Principal component analysis (PCA) and factor analysis (FA) were then used to further reduce the number of landscape and class metrics (e.g., Ritters et al. 1995; Cushman et al. 2008). PCA and FA have been used together in land use analysis to investigate landscape structure at different spatial extents (Griffith et al. 2000) and to study development patterns in watersheds (Cifaldi et al. 2004; Kearns et al. 2005). PCA simplifies variable interpretation through data reduction (Nichols 1977; Bengraine and Marhaba 2003) and FA identifies significant, underlying factors contributing to overall variance (McDonald 1985). Using a correlation matrix to conduct PCA and FA in S-Plus 8.0 (Insightful Corporation 2007), significant landscape and class metrics were identified for the Biscayne Bay watershed. Principal components, which are linear combinations of the original metrics, explain all the variance within a dataset and eigenvalues measure the variance explained by each principal component. In a correlation matrix, the mean of eigenvalues is one and principal components with above average eigenvalues explain more of the overall variance (Burstyn 2004). The number of principal components with eigenvalues greater than one therefore determined the number of factors to use in FA. To aid interpretation, FA included a varimax rotation to reveal metrics that had the strongest correlations, or loadings, for identified factors across the three different LULC layers (1995, 1999, and 2004).

Landscape Development Intensity Index

Data required to calculate LDI index values for Biscayne Bay sub-basins included LULC GIS layers, areas for each LULC class, nonrenewable empower intensity (emergy per time per area) values for LULC classes, and the renewable empower intensity of the background area. The first step in the LDI calculation process was to sum the areas of each LULC class and express these values as a percent of the total landscape area. LULC percentages were then multiplied by their respective nonrenewable empower intensity values for Florida. Equation 4-1 illustrates the revised LDI method (Reiss 2009):

$$LDI = 10 * \log_{10} (emPI_{Total} / emPI_{Ref}) \quad (4\text{-}1)$$

where LDI [unit less] is the Landscape Development Intensity index for sub-basins, $emPI_{Total}$ [sej ha^{-1} yr^{-1}] is the total empower intensity (sum of renewable background empower intensity and nonrenewable empower intensity of land uses), and $emPI_{Ref}$ is the renewable empower intensity of the background environment (Florida = 1.97 E15 sej ha^{-1} yr^{-1}). The total empower intensity ($emPI_{Total}$) was calculated as follows:

$$emPI_{Total} = emPI_{Ref} + \sum (\%LU_i * emPI_i) \quad (4\text{-}2)$$

where $\%LU_i$ is the percent of the total area in LULC class *i* and $emPI_i$ [sej ha^{-1} yr^{-1}] is the nonrenewable empower intensity for LULC class *i*. For each of the three LULC layers, LDI values were calculated for each sub-basin, canal buffer, and monitoring site buffer.

Imperviousness

Percent imperviousness is a key environmental indicator and multiple studies have estimated percent imperviousness associated with different land use classes (e.g., Stankowski 1972; Griffin 1980; Alley and Veenhuis 1983). Miami-Dade County Department of Environmental Resources Management (DERM) developed total impervious area (TIA) and directly connected impervious area (DCIA) reference values for various land uses classes to evaluate pollutant loading estimates under alternate scenarios (DERM 2004). Reference values were calculated using aerial maps and measuring impervious areas within typical land use classes throughout the county. DERM DCIA values for defined land use classes were used to estimate percent imperviousness for 1995, 1999 and 2004 in each of the five sub-basins, canal buffers, and monitoring site buffers.

Water Quality Data

Monthly nitrate/nitrite-nitrogen (NO_X-N), total ammonia nitrogen (NH_3-N), and total phosphorus (TP) concentrations from 1992 to 2006 at the eight water quality monitoring sites

(Table 4-7) were obtained from Miami-Dade County Department of Environmental Resources Management (DERM). Grab samples from sites throughout Biscayne Bay and in watershed canals were analyzed at DERM using EPA methods 353.2, 350.1, and 365.1 for NO_X-N, NH_3-N, and TP, respectively. To estimate nutrient loads, daily flow data (1992 to 2006) from flow sites associated with each of the monitoring sites were obtained from SFWMD (Table 4-7). SFWMD uses wireless communications systems to remotely monitor and record flow data through existing structures. Water quality and flow data flagged for violating quality control criteria were excluded from analysis.

Nutrient Loads

The U.S. Geological Survey (USGS) developed the Load Estimator (LOADEST) model that estimates constituent loads in streams and rivers (Runkel et al. 2004). The model is a publicly available FORTRAN program that uses linear regressions to estimate daily, monthly, seasonal, or annual loads and users have the ability to customize the model for specific conditions. The Adjusted Maximum Likelihood Estimation (AMLE) method is used if the calibration dataset is censored and the Maximum Likelihood Estimation (MLE) method is used if the calibration dataset is uncensored. However, both methods assume that model residuals are normally distributed. The Least Absolute Deviation method is used to estimate loads when the normality assumption is violated.

LOADEST was used to estimate annual nutrient loads from selected water quality monitoring sites using monthly NO_X-N, NH_3-N, and TP concentrations from DERM and daily flow data from SFWMD. Loads were estimated for the period 1992 to 2006 at eight sites that had available water quality and flow data. To isolate nutrient loads from specific sub-basins or canals, loads at downstream sites were adjusted to remove nutrient inputs from upstream sources. Nutrient load estimates from LOADEST were evaluated by calculating Nash-Sutcliffe efficiency

(NSE) coefficients (Nash and Sutcliffe 1970), comparing daily load estimates to actual loads at monitoring sites on days where both nutrient concentrations and flow data were available. NSE was calculated using the following formula:

$$\text{NSE} = 1 - \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{mean}\right)^2}\right] \tag{4-3}$$

where n is the number of values, Y^{obs} and Y^{sim} are measured and simulated values, respectively, and Y^{mean} is the mean of measured values. NSE coefficients range from - ∞ to 1 (1 being a perfect model fit) and coefficients above zero indicate acceptable model performance. Negative values indicate that simulated values from a model are less efficient than using the mean of the measured values, representing unacceptable model performance (Moriasi et al. 2007).

Stepwise Regressions

Combined land use variables from 1995 and 1999 were used with LOADEST nutrient loads in stepwise regressions to calibrate models predicting (1) NO_X-N, (2) total inorganic nitrogen (NO_X-N plus NH_3-N), and (3) TP loads. Stepwise regressions were performed separately for LULC data from sub-basins, canal buffers (500, 1000, and 1500 m), and site buffers (500, 1000, and 1500 m). Three-year average annual nutrient loads at each site were used in stepwise regressions to correspond to LULC data (i.e., 1994 to 1996 loads for 1995 and 1998 to 2000 loads for 1999). Land use variables included landscape metrics, class metrics, LDI values, and DCIA percentages. After conducting PCA and FA on metrics for the entire Biscayne Bay watershed, the metric with the highest loading for each identified landscape and class-level factor was chosen to represent that factor in stepwise regressions. Variables for stepwise regression models included the same set of landscape-level metrics, albeit with different land use data corresponding to sub-basins, canal buffers, and site buffers. Class-level metrics included in

stepwise regressions, however, were based on the area and distribution of each class relative to the total area of sub-basins, canal buffers, and site buffers. Stepwise regressions included combined land use data for 1995 and 1999 and thus each class in the sub-basin and canal buffer datasets had 10 values for each variable – one value for each of the five sub-basins or canals in each year; for the site buffers, each class had 16 values (because of the eight sites) for each variable. To maximize the predictive power of regression equations, class metrics included in stepwise regressions were limited to classes that had at least four values greater than 10% of the total areas for sub-basins and canal buffers. Similarly, class-level criteria for site buffers limited metrics to classes with at least six values greater than 10%. Therefore class metrics were only included in stepwise regressions for classes with approximately 40% or more of their areal percentages exceeding 10% of the total areas for sub-basins, canal buffers, and site buffers.

Two types of stepwise regressions were used to determine which models best predicted nutrient loads considering different spatial extents: (1) forward stepwise regressions only and (2) a combination of both forward and backward stepwise regressions (Thomas 1978). All variables were included in the initial model for forward stepwise regressions before the final model was determined for the sub-basins, canal buffers, and site buffers. For stepwise regressions in both directions (forward and backward), pair-wise correlation coefficients were calculated for all remaining land use variables and if any two variables were highly correlated (greater than 0.90), only one variable from that pair was included in the initial model.

Moriasi et al. (2007) reviewed hydrological model evaluation techniques and determined that NSE coefficients of at least 0.5 represented satisfactory model performance, with values greater than 0.75 indicating very good performance. In addition to NSE coefficients, Moriasi et al. (2007) also recommended two quantitative statistics to evaluate model performance, percent

bias (PBIAS) and the ratio of the root mean square error to the standard deviation of measured data (RSR). PBIAS assesses the average tendency of simulated data to exhibit underestimation (positive PBIAS values) or overestimation (negative PBIAS values) bias (Gupta et al. 1999):

$$\text{PBIAS} = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)*100}{\sum_{i=1}^{n} Y_i^{obs}} \tag{4-4}$$

where PBIAS is the deviation of simulated values (Y^{sim}) relative to measured values (Y^{obs}). RSR provides a standardized error index of model performance (Moriasi et al. 2007):

$$\text{RSR} = \frac{\text{RMSE}}{\text{STDEV}_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}\right]}{\left[\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{mean}\right)^2}\right]} \tag{4-5}$$

where RMSE is the root mean square error, STDEV_{obs} is the standard deviation of measured values, Y^{obs} are measured values, Y^{sim} are simulated values, and Y^{mean} is the mean of measured values. Overall, NSE coefficients greater than 0.5, RSR values less than or equal to 0.7, and PBIAS values within ±70% indicate satisfactory model performance. Land use-water quality regression models were validated using 2004 land use data and average nutrient loads from 2003 to 2005. PBIAS and RSR values were calculated for regression models with NSE coefficients greater than 0.5 to evaluate model efficiency.

Results

Landscape Metrics

After identifying and removing metrics from highly correlated (greater than 0.90) metric pairs, PCA was performed on 11 of the 17 landscape metrics calculated. Three principal components had eigenvalues greater than one and after FA, three factors accounted for 76% of the cumulative variation in landscape metrics for the entire Biscayne Bay watershed. Metrics with the highest loadings for the first factor, interpreted as patch size variability, were mean

patch size (MPS; 0.92) and patch size standard deviation (PSSD; 0.91). The largest patch index (LPI; -0.94) and landscape shape index (LSI; 0.86) had the highest loadings for the second factor, patch diversity. Patch complexity was the third and final factor at the landscape level and included patch size coefficient of variation (PSCoV; 0.84) and area weighted mean shape index (AWMSI; 0.77). PCA and FA results on class metrics are reported for only the four classes that satisfied the minimum distribution criteria to be included in stepwise regressions: natural land cover, row crops, medium intensity single family residential (MSR), and low intensity commercial (LIC) (Table 4-8).

LDI and Imperviousness

Average LDI values for the three urbanized sub-basins, C-7 (30.7), C-8 (30.9), and C-9 (29.9) were greater than the mixed land use (C-1; 28.1) and agricultural (C-103; 25.8) sub-basins. The overall average LDI value for the five sub-basins was 29.1, with C-8 (31.0) having the single highest value and C-103 (25.4), the lowest (Table 4-9). DCIA values in the five sub-basins exhibited a similar pattern to the LDI index as C-8 (35.2%) and C-103 (13.6%) had the highest and lowest values, respectively.

For all canal buffers, C-7, C-8, and C-9 LDI values continued to be greater than those for C-1 and C-103. The C-7 (500 and 1000 m) and C-8 (1500 m) canal buffers had maximum LDI values while C-103 had the lowest values for all three buffer distances (Table 4-9). However, LDI values for the different buffers (500, 1000 and 1500 m) at each canal were similar: C-9 (29.6; 29.9; 29.9), C-8 (30.6; 30.9; 31.0), C-7 (31.1; 31.0; 30.9), C-1 (29.1; 28.8; 28.5), and C-103 (25.6; 25.9; 26.5). C-103 had the lowest DCIA values for all buffer distances (10.0%; 11.9%; 13.9%) while C-7 had the highest value for the 500 m (36.1%) distance and C-8 had the highest values for both the 1000 m (36.0%) and 1500 m (36.9%) buffers.

Average LDI values for monitoring site buffers were lower than both the sub-basins and canal buffers (Table 4-9). MW04, a monitoring site in the C-103 sub-basin, had the lowest LDI values in the 500 m (6.9) and 1000 m (6.9) buffers. The lowest LDI value in the 1500 m buffer was from BL12 (10.5), located in the C-1 sub-basin. SK02 (C-9) had the highest LDI values in the 500 m (33.6), 1000 m (33.0), and 1500 m (31.7) buffers. DCIA values for C-103 monitoring sites, MW04 and MW13, were zero for both the 500 m and 1000 m buffers. BL12 (C-1) also had a zero value for DCIA in the 500 m buffer. LR06 (C-7) had the greatest value in the 500 m (38.0%) buffer while BS04 (C-8) had the highest DCIA values in the 1000 m (37.9%) and 1500 m (37.5%) buffers.

Loads and Stepwise Regressions

Comparing measured loads to LOADEST simulated results at the eight monitoring sites produced the following average coefficients: NO_X-N (NSE: 0.52; R^2: 0.60); NO_X-N plus NH_3-N (NSE: 0.75; R^2: 0.85); and TP (NSE: 0.64; R^2: 0.58) (Table 4-10). Estimated annual loads from LOADEST for each site are listed in Table 4-11.

For stepwise regressions, landscape metrics with the highest loadings for each of the three factors were MPS, LPI, and PSCoV; these metrics, along with LDI and DCIA, were selected as landscape variables for sub-basins, canal buffers, and site buffers. Row crops and MSR classes met the distribution criteria to be included in all stepwise regressions for the sub-basins, 1000 m canal buffer, 1500 m canal buffer, and 1000 m site buffer. Additional classes were needed for the 500 m canal buffer (natural land cover), 500 m sites buffer (natural land cover; LIC), and 1500 m sites buffer (natural land cover; LIC).

Regression models selected using the forward stepwise procedure generally had greater NSE coefficients after validation compared to models selected from stepwise procedures in both directions (Tables 4-5; 4-6). Using forward and backward stepwise regression, the sub-basins

regression model (NSE: 0.69; R^2: 0.43; RSR: 0.55; PBIAS: -50.89%) was the best predictor of NO_X-N loads (Table 4-12) and the NSE coefficient (greater than 0.5), RSR value (less than 0.7), and PBIAS value (within ± 70%) all indicated satisfactory model performance. The regression model for the sub-basins (Equation 4-6) was as follows:

$$\text{Log } (NO_X\text{-N load}) = 7.9182 - 0.0982 \text{ (LDI)} - 0.0115 \text{ (LPI)} \quad (4\text{-}6)$$

There were no positive NSE coefficients for NO_X-N plus NH_3-N loads in the sub-basins, canal buffers, or site buffers after validation. However, several regression models had positive NSE coefficients for TP loads and evaluation statistics indicated that TP regression models performed better than models for NO_X-N loads. Models with NSE coefficients greater than 0.75, RSR values less than 0.50, and PBIAS values less than ± 25% indicate very good performance (Moriasi et al. 2007) and using forward stepwise regression, the 1000 m canal buffer model (NSE: 0.90; R^2: 0.89; RSR: 0.31; PBIAS: 7.92%) for TP loads was the only model to satisfy these criteria (Table 4-13). The regression model for the 1000 m canal buffer (Equation 4-7) was as follows:

$$\text{TP load} = 190.4019 \text{ (MSR LPI)} - 610.2028 \quad (4\text{-}7)$$

Discussion

Land Use Variables and Nutrient Loads

Evaluating land use-water quality relationships within multiple spatial extents enhances the applicability of human disturbance indicators to aquatic environments by exploring spatially explicit effects (Sponseller et al. 2001; Kearns et al. 2005). Land use variability is reflected in the biological, chemical, and physical condition of aquatic environments but the relative impact of human influences is mediated by watershed characteristics that affect pollutant transport efficiency. Strayer et al. (2003) showed that watershed size was an important factor regulating LULC influences on stream ecosystems, riparian buffers have been suggested as key elements to

protect water quality (Schlosser and Karr 1981; Sponseller et al. 2001; Gergel et al. 2002), and other studies have stressed the influence of entire watersheds (Hunsaker and Levine 1995; Roth et al. 1996; Migliaccio et al. 2007). In the Biscayne Bay watershed, stepwise multivariate regressions revealed spatially explicit land use variables that were indicators of nutrient loads at eight canal monitoring sites, such as LDI values and MSR metrics.

PCA and FA analyses identified landscape-level metrics that were most responsible for watershed LULC variability and these indicators, along with LDI values, were important variables for NO_X-N loads. The sub-basins regression model, including both LDI and the largest patch index (LPI) values at the landscape-level, was the best predictor of NO_X-N loads (Table 4-12) in the study (Figure 4-3). Brown and Vivas (2005) suggested that the LDI index represents aggregate land use influences such as pollutants (e.g., in air and water) and physical landscape alterations that reflect the extent of anthropogenic disturbance. Landscape composition is an important factor because the LDI index measures disturbance gradients by evaluating nonrenewable energy use per unit area in LULC classes. During the study period (1995 to 2004), medium intensity single family residential (MSR) land use percentages in the three urban sub-basins (C-9, C-8, and C-7) ranged from 35.9 to 51.7% and in C-1 (mixed land use sub-basin), MSR and row crops were also widespread (45.1% to 47.3%). In C-103 (agricultural sub-basin), four land use classes were responsible for greater than 76% of the total land use: tree crops, row crops, low intensity single family residential, and MSR. The urban sub-basins therefore had greater LDI values because extensive urban land use classes, such as MSR, are characterized by greater non-renewable energy use per unit area than agricultural land uses. LOADEST results further indicated that C-1 and C-103 contributed greater NO_X-N loads to the bay than the urban

sub-basins and this suggests that in the sub-basin regression model, agricultural land use is a strong predictor of NO_X-N loads.

In the Biscayne Bay watershed, agricultural activity is generally located in the central and southern sub-basins while the well-developed urban core is found in northern sub-basins. Increasing urbanization has reduced the relative proportion of agriculture in the watershed but overall, agricultural land use is still much more extensive in central and southern urbanizing sub-basins such as C-1 and C-103. Therefore, NO_X-N loads are substantially larger in areas away from the urban core, such as the South Dade Agricultural Area, and this produces an increasing NO_X-N gradient from the north to the south. Conversely, LDI index values are greater in the north and this sharp distinction contributed to LDI values being negatively associated with NO_X-N loads. LPI values at the landscape-level are also negatively associated with NO_X-N loads because this indicator reflects landscape connectivity, the percentage of the total landscape area comprised of the largest land use patch (McGarigal and Marks 1995). The types of land use (indicated by LDI) and their relative dominance (indicated by LPI) both influence NO_X-N loads within the sub-basins.

In contrast to NO_X-N, class-level metrics had strong relationships with TP loads. The regression model for the 1000 m canal buffer was the best predictor of TP loads and the only variable included in this model was LPI for the MSR class (Figure 4-4). The MSR class had the largest patch in all three urban sub-basins but agricultural classes were dominant in C-1 (row crops) and C-103 (tree crops); complex MSR patches (i.e., considering size, shape, and area) were therefore not as prominent in C-1 and C-103. Due to the limestone geology and soil types in south Florida, phosphorus does not transport as easily through the watershed as nitrogen (Li 2000; Brand et al. 2002; Li and Zhang 2002) and as a result, TP loads were more closely related

to human disturbance indicators at a smaller spatial extent (1000 m canal buffer) compared to NO_X-N loads (sub-basin level). The 1000 m canal buffer highlighted the effects of land use variability on TP loads. For example, MSR LPI values in the 1000 m canal buffers between 1995 and 2004 for the urban canals (MSR LPI: 10.0 to 27.5; TP: 1,550 kg yr^{-1} to 5,467 kg yr^{-1}) exceeded corresponding values for C-1 and C-103 (MSR LPI: 3.1 to 7.7; TP: 84 kg $yr^{-1}$to 886 kg yr^{-1}). TP loads are generally higher in the northern, more urbanized area of the watershed and as urbanizing sub-basins such as C-1 and C-103 become more developed, subsequent increased TP loads could pose a threat to Biscayne Bay.

Uncertainty Analysis

Water quality models help decision makers develop measures addressing water resource policy, management, program evaluation, and regulation (Beck 1987; Sharpley et al. 2002). Uncertainty inherent in water quality samples, load estimations, and model output can all affect the success of initiatives to improve or protect water resources. For example, uncertainty is introduced into water quality sampling through flow data measurement, sampling techniques, preservation protocols, and laboratory analysis. Harmel et al. (2006) estimated cumulative probable uncertainties for measured streamflow (±10%), NO_3-N (±17%), NH_4-N (±31%) and TP (±30%) under typical scenarios (including moderate to extensive quality control/quality assurance procedures) based on a review of published data. Results suggested that models providing output data within 10 to 31% of these measured values would be within average uncertainty ranges (Harmel et al. 2006). After reviewing model evaluation techniques for measured data with typical uncertainty estimates, Moriasi et al. (2007) recommended NSE, RSR, and PBIAS quantitative statistics to assess model performance.

LOADEST (Runkel et al. 2004) was used to estimate nutrient loads at the eight monitoring sites and these load estimates were then used with human disturbance indicators in additional

regressions to identify important land use variables influencing water quality data in the Biscayne Bay watershed. Errors in estimated nutrient loads from LOADEST could add to the overall error in subsequent regression models describing land use-water quality relationships and this was the primary reason for comparing measured loads to simulated estimates. In addition, land use data in each sub-basin were compared to aerial maps to improve the quality of land use variables used in regression models. Monthly water quality data and daily flow data associated with each monitoring site were also reviewed carefully to identify and exclude flagged values, such as data violating quality control criteria.

Several factors can complicate constituent load estimations including deviations from normality, censored data, and retransformation bias (Runkel et al. 2004) but regression models in LOADEST incorporate features such as bias corrections (Cohn et al. 1992) to increase the validity of simulated data. However, studies have still noted problems with constituent load estimations in LOADEST. Clark (2003) suggested that because LOADEST does not account for hysteresis effects (different constituent concentrations at similar discharge rates), measured loads after rapid changes in streamflow may produce inaccurate simulations. Donato and MacCoy (2005) discussed large errors in daily load estimates due to unusually high flows but conceded that simulations over longer time periods (e.g., seasonal or annual) reduced overall model inaccuracies because LOADEST estimates were more representative of measured data under typical system conditions. To increase the accuracy of load estimates for 1995, 1999, and 2004 that were used in stepwise regressions, LOADEST was used to estimate annual nutrient loads over a longer timescale (1992 to 2006). Load comparisons between measured and simulated data suggested LOADEST reasonably modeled the variability in nutrient loads across the eight monitoring sites (Table 4-10).

The NSE index was used to evaluate the goodness-of-fit between measured loads and LOADEST data as well as to validate land use-water quality models. Although R^2 values were calculated as a comparison to NSE coefficients, they were not used to determine the accuracy of regression models because R^2 values are only based on consistency between measured and predicted data, thereby producing high correlation coefficients for models that vastly overestimate or underestimate nutrient loads (Krause et al. 2005). However, the NSE index can also overestimate larger values in a time series because differences between measured and predicted data are squared (Legates and McCabe 1999). The NSE index is also sensitive to other factors such as sample size and outliers but despite these disadvantages, the NSE index has been applied to numerous models because of its flexibility as a goodness-of-fit statistic (McCuen et al. 2006).

Management Implications

Canals draining agricultural or highly urbanized sub-basins in the Biscayne Bay watershed typically contain elevated inorganic nitrogen (NO_X-N and NH_3-N) levels (Alleman et al. 1995). For example, Scheidt and Flora (1983) and Cheesman (1989) described high NO_X-N concentrations in the C-103 canal that were related to agricultural activity. The sub-basin regression models reflected the influence of agriculture in the watershed as an important land use variable. Although low LDI index values correspond to greater NO_X-N loads in this study, this suggests that LDI values should not be used alone as a water quality indicator because natural areas, with much lower NO_X-N loads, would also have low LDI values. The LDI index should therefore be used with additional assessment tools to evaluate the overall impact of human disturbances (e.g., Mack 2006; Reiss et al. 2009).

In south Florida, plans to reduce nitrate loading from agriculture sources in the Biscayne Bay watershed require an understanding of the unique hydrology and soil types in the region. For

example, high permeability soils which do not retain water leads to nitrogen leaching (Li 2000; Li and Zhang 2002) and elevated water tables cause nitrogen-enriched groundwater to enter Biscayne Bay through canal discharges (Langevin 2000). Li and Zhang (2002) discussed technologies that can help to reduce the impact of agricultural production in south Florida, such as crop-specific fertilizers, slow release fertilizers, and soil organic amendments (e.g., cover crops and compost).

For phosphorus, additional inputs to the bay concern watershed managers because it is the primary nutrient limiting autotrophic growth (Brand 1988; Kleppel 1996). Phosphorus concentrations are generally higher in the northern bay (Alleman et al. 1995; Caccia and Boyer 2005), where phytoplankton levels can be five times greater than the south (Brand 1988). Model evaluation indicated that the strongest relationship between TP loads and watershed land uses occurred in the 1000 m canal buffer. These results suggest that development patterns along the canals were important factors contributing to the variability in TP loads. Watershed management plans focused on development patterns within canal (1000 m) buffers could therefore potentially reduce phosphorus discharges to the bay. Several strategies could be implemented such as zoning policies developed specifically for new residential developments within 1000 m of canals in urbanizing sub-basins such as C-1 and C-103. In the watershed, urban stormwater treatment already includes retention systems in housing developments to preventing the first flush of pollutants after storm events from entering canals and detention systems (e.g., grassed swales and French drains) have also been utilized to intercept pollutants (Alleman et al. 1995). Targeting these management practices within critical buffer areas and implementing additional measures, such as increased use of riparian buffers, could improve overall treatment efficiency. Development patterns regulate the effects of anthropogenic influences on natural resources

(Alberti 2005) and increased urbanization throughout the watershed will likely increase TP loads if specific strategies are not implemented in hydrologically sensitive regions such as 1000 m canal buffers.

Conclusion

In the Biscayne Bay watershed (1995 to 2004), three human disturbance indicators (landscape metrics, LDI index, and imperviousness) associated with eight water quality monitoring sites at multiple spatial extents (sub-basins, canal buffers, and site buffers) were analyzed with annual nutrient loads to determine land use factors that influenced water quality variability. The LDI index and metrics at the landscape level (largest patch index [LPI]) and class level (LPI for medium density single family residential [MSR] class) were identified as land use variables with the strongest relationships to estimated loads from the monitoring sites. The sub-basin regression model was the best predictor of annual NO_X-N loads in the watershed and included both LDI and LPI variables, indicating that the relative distribution of dominant land use classes influences NO_X-N loads. TP loads were more closely related to human disturbance indicators at a smaller spatial extent (1000 m canal buffer), which is a function of nutrient transport processes in the watershed. The land use variable included in the 1000 m canal buffer (MSR LPI) model suggests that urban development patterns in this buffer zone are important factors for TP loads discharged from the watershed. The LDI index has been applied under various environmental settings to evaluate human disturbance gradients and results from this study suggest that LDI values can be included as one indicator in an overall assessment of water quality. The LDI index, which quantifies the intensity of land use activities within watersheds, can be used with landscape metrics that evaluate spatial patterns to link land use development to water quality parameters.

Table 4-1. Land use/land cover data (500 m canal buffer).

Land use/Land cover class	1995 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	18.0	7.6	4.1	8.9	9.4
Improved pastures	1.7	1.0	0.0	0.6	1.2
Low intensity pastures	0.4	0.0	0.0	0.7	0.0
Medium intensity recreational, open space	9.8	4.4	3.7	8.5	6.1
Tree crops	0.6	0.0	0.0	3.6	21.8
Row crops	0.0	0.0	0.0	18.8	34.2
High intensity agriculture	0.0	0.0	0.0	0.3	0.1
High intensity recreational	4.8	1.0	1.1	0.7	0.0
Low density single family residential	2.5	5.8	2.5	4.9	10.2
Medium density single family residential	36.3	41.7	55.3	23.1	6.2
High density single family residential	0.0	0.4	1.1	6.0	0.0
Institutional	1.5	5.4	8.0	5.0	1.4
Low density multifamily residential	7.5	3.2	7.5	4.1	2.5
High intensity transportation	5.4	15.0	1.1	5.2	3.9
Low intensity commercial	3.5	8.6	3.9	3.2	1.7
Industrial	5.0	4.8	3.7	4.6	0.1
High intensity commercial	2.3	0.4	5.0	1.8	0.6
High density multifamily residential	0.8	0.6	3.0	0.0	0.5

Table 4-1. Continued.

Land use/Land cover class	1999 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	18.9	8.6	2.3	6.6	6.9
Improved pastures	3.1	0.0	0.0	0.0	0.6
Low intensity pastures	0.0	0.0	0.0	0.1	0.0
Medium intensity recreational, open space	7.5	2.0	2.5	8.6	5.8
Tree crops	0.4	0.0	0.0	3.3	22.4
Row crops	0.0	0.0	0.0	17.0	32.6
High intensity agriculture	0.0	0.0	0.0	0.0	0.0
High intensity recreational	5.6	1.0	1.6	0.9	0.2
Low density single family residential	0.0	6.4	1.8	3.1	11.7
Medium density single family residential	32.0	41.7	50.2	22.5	6.2
High density single family residential	1.2	0.2	1.8	10.8	1.5
Institutional	2.9	6.4	8.9	6.0	1.8
Low density multifamily residential	8.9	6.0	6.4	4.9	4.2
High intensity transportation	3.9	12.2	3.2	5.2	3.5
Low intensity commercial	4.8	9.8	8.7	3.6	1.8
Industrial	7.9	4.8	3.9	4.7	0.3
High intensity commercial	1.2	0.0	5.7	2.3	0.3
High density multifamily residential	1.7	0.8	3.0	0.4	0.0

Table 4-1. Continued.

Land use/Land cover class	2004 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	15.4	8.0	2.3	5.5	3.4
Improved pastures	3.1	0.0	0.0	0.0	0.2
Low intensity pastures	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	7.3	2.4	3.2	7.0	6.4
Tree crops	0.4	0.0	0.0	3.0	30.2
Row crops	0.0	0.0	0.0	13.8	17.0
High intensity agriculture	0.0	0.0	0.0	0.0	0.0
High intensity recreational	6.4	0.8	1.8	1.0	0.5
Low density single family residential	0.0	6.2	1.8	1.9	12.7
Medium density single family residential	34.4	42.5	50.2	25.1	11.4
High density single family residential	1.2	0.2	1.1	14.1	4.0
Institutional	2.5	6.6	8.4	5.8	2.1
Low density multifamily residential	10.2	6.0	7.1	6.1	4.7
High intensity transportation	4.1	12.0	3.4	5.1	3.5
Low intensity commercial	4.6	9.6	8.9	3.6	2.8
Industrial	8.5	4.8	3.0	5.4	0.3
High intensity commercial	1.0	0.0	5.5	2.4	0.3
High density multifamily residential	0.8	0.8	3.2	0.3	0.5

Table 4-2. Land use/land cover data (1000 m canal buffer).

Land use/Land cover class	1995 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	14.6	4.8	2.9	7.9	7.9
Improved pastures	1.4	1.4	0.0	0.6	0.8
Low intensity pastures	0.6	0.0	0.0	0.4	0.0
Medium intensity recreational, open space	12.2	3.9	5.6	7.1	6.0
Tree crops	0.3	0.0	0.0	4.7	20.6
Row crops	0.0	0.0	0.0	19.5	32.1
High intensity agriculture	0.0	0.0	0.0	0.3	0.1
High intensity recreational	6.0	1.7	1.5	1.3	0.3
Low density single family residential	2.9	5.7	1.6	5.2	10.3
Medium density single family residential	34.5	42.0	53.2	25.3	9.4
High density single family residential	0.2	0.6	2.2	5.3	0.7
Institutional	1.8	5.8	6.9	6.5	1.9
Low density multifamily residential	7.4	3.4	8.4	3.1	2.2
High intensity transportation	5.1	14.4	1.7	4.4	4.2
Low intensity commercial	4.3	8.4	4.2	2.5	2.6
Industrial	5.0	5.9	4.9	3.9	0.1
High intensity commercial	2.3	0.9	3.4	1.7	0.5
High density multifamily residential	1.3	0.8	3.5	0.2	0.3

Table 4-2. Continued.

Land use/Land cover class	1999 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	14.4	5.3	2.1	5.3	7.2
Improved pastures	2.4	0.0	0.0	0.0	0.4
Low intensity pastures	0.0	0.0	0.0	0.1	0.0
Medium intensity recreational, open space	10.5	2.9	4.3	7.6	5.1
Tree crops	0.2	0.0	0.0	4.7	22.3
Row crops	0.0	0.0	0.0	16.4	28.8
High intensity agriculture	0.0	0.0	0.0	0.1	0.0
High intensity recreational	7.3	1.0	1.8	1.5	0.4
Low density single family residential	0.0	5.1	1.0	4.2	11.1
Medium density single family residential	30.9	42.1	49.4	24.6	10.0
High density single family residential	1.5	0.1	2.1	10.9	2.1
Institutional	3.8	6.1	8.7	7.2	2.6
Low density multifamily residential	8.7	6.6	7.6	4.2	3.0
High intensity transportation	5.2	12.9	3.0	4.3	3.4
Low intensity commercial	4.9	10.9	8.1	3.1	2.7
Industrial	6.7	5.6	4.9	3.3	0.2
High intensity commercial	1.3	0.2	3.8	2.1	0.7
High density multifamily residential	2.3	1.0	3.2	0.5	0.2

Table 4-2. Continued.

Land use/Land cover class	2004 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	11.8	4.5	2.1	4.1	4.7
Improved pastures	2.2	0.0	0.0	0.0	0.1
Low intensity pastures	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	10.0	3.0	4.7	6.5	5.6
Tree crops	0.2	0.0	0.0	3.3	28.2
Row crops	0.0	0.0	0.0	14.2	17.2
High intensity agriculture	0.0	0.0	0.0	0.2	0.0
High intensity recreational	7.5	0.9	2.1	1.5	0.5
Low density single family residential	0.0	5.0	1.1	2.2	11.9
Medium density single family residential	32.6	42.4	49.7	27.7	14.3
High density single family residential	1.5	0.2	1.0	14.0	3.7
Institutional	3.6	6.4	8.4	7.1	2.4
Low density multifamily residential	9.7	7.3	7.8	5.1	3.4
High intensity transportation	5.2	12.8	3.1	4.2	3.6
Low intensity commercial	5.3	10.5	8.4	3.1	3.1
Industrial	7.3	5.6	4.8	4.0	0.2
High intensity commercial	1.2	0.2	3.5	2.2	0.8
High density multifamily residential	1.8	1.1	3.4	0.5	0.4

Table 4-3. Land use/land cover data (1500 m canal buffer).

Land use/Land cover class	1995 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	10.6	4.5	2.5	7.2	8.0
Improved pastures	1.8	1.3	0.0	0.6	0.6
Low intensity pastures	1.7	0.0	0.0	0.3	0.0
Medium intensity recreational, open space	10.9	3.6	5.8	6.9	5.2
Tree crops	0.2	0.0	0.1	5.5	20.3
Row crops	0.0	0.0	0.0	21.0	27.8
High intensity agriculture	0.0	0.0	0.0	0.2	0.1
High intensity recreational	7.2	1.9	1.6	2.9	0.6
Low density single family residential	2.9	5.0	1.5	4.9	11.6
Medium density single family residential	37.7	42.6	52.6	25.7	11.1
High density single family residential	0.4	0.6	1.9	4.4	0.7
Institutional	1.6	5.6	5.4	6.0	2.0
Low density multifamily residential	6.7	3.5	8.1	2.5	2.4
High intensity transportation	5.4	14.6	3.6	4.3	4.6
Low intensity commercial	4.6	9.3	5.3	2.2	3.4
Industrial	4.9	6.0	5.8	3.6	0.6
High intensity commercial	2.3	1.0	3.1	1.4	0.7
High density multifamily residential	1.1	0.3	2.6	0.4	0.3

Table 4-3. Continued

Land use/Land cover class	1999 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	10.9	4.1	1.9	4.9	7.7
Improved pastures	2.2	0.0	0.0	0.0	0.2
Low intensity pastures	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	9.9	3.4	4.5	7.9	4.3
Tree crops	0.1	0.0	0.0	5.7	21.3
Row crops	0.0	0.0	0.0	17.1	25.3
High intensity agriculture	0.0	0.0	0.0	0.1	0.0
High intensity recreational	7.3	1.3	2.8	3.3	0.5
Low density single family residential	0.0	4.2	1.0	3.6	12.5
Medium density single family residential	35.4	42.5	48.7	26.0	11.5
High density single family residential	2.5	0.3	1.8	9.4	1.9
Institutional	3.9	6.0	7.2	6.6	3.0
Low density multifamily residential	8.2	6.0	8.6	3.2	2.7
High intensity transportation	4.6	14.8	3.1	4.3	3.7
Low intensity commercial	5.7	11.0	9.5	2.7	3.8
Industrial	5.9	5.1	5.1	2.8	0.6
High intensity commercial	1.2	0.3	3.2	1.6	0.8
High density multifamily residential	2.2	1.0	2.4	0.6	0.2

Table 4-3. Continued.

Land use/Land cover class	2004 Land use/Land cover (%)				
	C-9	C-8	C-7	C-1	C-103
Natural land/water	9.0	3.2	1.9	3.3	5.2
Improved pastures	1.5	0.0	0.0	0.0	0.1
Low intensity pastures	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	9.7	2.9	4.5	6.5	4.8
Tree crops	0.1	0.0	0.0	4.0	26.9
Row crops	0.0	0.0	0.0	15.0	15.5
High intensity agriculture	0.0	0.0	0.0	0.2	0.0
High intensity recreational	7.4	1.2	2.9	3.4	0.6
Low density single family residential	0.0	4.1	1.1	2.1	12.9
Medium density single family residential	36.6	42.8	48.8	29.0	15.3
High density single family residential	2.7	0.3	1.1	13.0	2.8
Institutional	3.5	6.1	7.0	6.5	2.9
Low density multifamily residential	8.9	7.1	8.9	4.0	3.2
High intensity transportation	4.5	14.5	3.1	4.3	3.9
Low intensity commercial	6.2	11.0	9.7	2.8	4.2
Industrial	6.8	5.1	5.3	3.6	0.6
High intensity commercial	1.3	0.7	3.1	1.7	0.9
High density multifamily residential	1.8	0.9	2.5	0.6	0.2

Table 4-4. Land use/land cover data (500 m water quality monitoring site buffer).

Land use/Land cover class	1995 Land use/Land cover (%)							
	SK09	SK02	BS04	LR06	BL12	BL03	MW13	MW04
Natural land/water	69.2	0.0	0.0	0.0	0.0	9.1	23.1	0.0
Improved pastures	23.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity pastures	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	0.0	7.7	0.0	0.0	0.0	0.0	0.0	0.0
Tree crops	0.0	0.0	0.0	0.0	0.0	36.4	38.5	61.5
Row crops	0.0	0.0	0.0	0.0	100.0	0.0	38.5	38.5
High intensity agriculture	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High intensity recreational	0.0	7.7	18.2	18.2	0.0	0.0	0.0	0.0
Low density single family residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium density single family residential	0.0	7.7	72.7	72.7	0.0	0.0	0.0	0.0
High density single family residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Institutional	0.0	7.7	0.0	0.0	0.0	0.0	0.0	0.0
Low density multifamily residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High intensity transportation	0.0	23.1	9.1	9.1	0.0	0.0	0.0	0.0
Low intensity commercial	0.0	30.8	0.0	0.0	0.0	0.0	0.0	0.0
Industrial	7.7	0.0	0.0	0.0	0.0	54.5	0.0	0.0
High intensity commercial	0.0	15.4	0.0	0.0	0.0	0.0	0.0	0.0
High density multifamily residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 4-4. Continued.

Land use/Land cover class	1999 Land use/Land cover (%)							
	SK09	SK02	BS04	LR06	BL12	BL03	MW13	MW04
Natural land/water	46.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Improved pastures	23.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity pastures	7.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	7.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Tree crops	0.0	0.0	0.0	0.0	0.0	27.3	61.5	61.5
Row crops	0.0	0.0	0.0	0.0	100.0	0.0	38.5	38.5
High intensity agriculture	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High intensity recreational	0.0	7.7	9.1	0.0	0.0	0.0	0.0	0.0
Low density single family residential	7.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium density single family residential	0.0	0.0	63.6	53.8	0.0	0.0	0.0	0.0
High density single family residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Institutional	0.0	7.7	18.2	0.0	0.0	0.0	0.0	0.0
Low density multifamily residential	0.0	15.4	9.1	30.8	0.0	0.0	0.0	0.0
High intensity transportation	0.0	23.1	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity commercial	0.0	46.2	0.0	15.4	0.0	0.0	0.0	0.0
Industrial	7.7	0.0	0.0	0.0	0.0	72.7	0.0	0.0
High intensity commercial	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High density multifamily residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 4-4. Continued.

Land use/Land cover class	2004 Land use/Land cover (%)							
	SK09	SK02	BS04	LR06	BL12	BL03	MW13	MW04
Natural land/water	30.8	0.0	0.0	0.0	0.0	9.1	0.0	0.0
Improved pastures	7.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity pastures	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	15.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Tree crops	0.0	0.0	0.0	0.0	0.0	18.2	61.5	100.0
Row crops	0.0	0.0	0.0	0.0	100.0	0.0	38.5	0.0
High intensity agriculture	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High intensity recreational	0.0	7.7	9.1	0.0	0.0	0.0	0.0	0.0
Low density single family residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium density single family residential	7.7	0.0	63.6	53.8	0.0	0.0	0.0	0.0
High density single family residential	23.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Institutional	0.0	7.7	18.2	0.0	0.0	0.0	0.0	0.0
Low density multifamily residential	7.7	15.4	9.1	30.8	0.0	0.0	0.0	0.0
High intensity transportation	0.0	23.1	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity commercial	0.0	46.2	0.0	15.4	0.0	0.0	0.0	0.0
Industrial	7.7	0.0	0.0	0.0	0.0	72.7	0.0	0.0
High intensity commercial	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High density multifamily residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 4-5. Land use/land cover data (1000 m water quality monitoring site buffer).

Land use/Land cover class	1995 Land use/Land cover (%)							
	SK09	SK02	BS04	LR06	BL12	BL03	MW13	MW04
Natural land/water	30.0	5.0	0.0	2.5	5.0	23.3	12.5	15.0
Improved pastures	32.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity pastures	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	0.0	2.5	0.0	0.0	0.0	0.0	0.0	0.0
Tree crops	0.0	0.0	0.0	0.0	5.0	58.1	40.0	50.0
Row crops	0.0	0.0	0.0	0.0	87.5	0.0	47.5	35.0
High intensity agriculture	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High intensity recreational	0.0	5.0	2.3	0.0	0.0	0.0	0.0	0.0
Low density single family residential	5.0	0.0	0.0	5.0	2.5	0.0	0.0	0.0
Medium density single family residential	5.0	40.0	86.4	55.0	0.0	0.0	0.0	0.0
High density single family residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Institutional	0.0	2.5	2.3	2.5	0.0	0.0	0.0	0.0
Low density multifamily residential	0.0	0.0	0.0	30.0	0.0	0.0	0.0	0.0
High intensity transportation	2.5	12.5	4.5	0.0	0.0	0.0	0.0	0.0
Low intensity commercial	0.0	17.5	2.3	5.0	0.0	0.0	0.0	0.0
Industrial	25.0	0.0	0.0	0.0	0.0	18.6	0.0	0.0
High intensity commercial	0.0	15.0	2.3	0.0	0.0	0.0	0.0	0.0
High density multifamily residential	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 4-5. Continued.

Land use/Land cover class	1999 Land use/Land cover (%)							
	SK09	SK02	BS04	LR06	BL12	BL03	MW13	MW04
Natural land/water	7.5	10.0	0.0	0.0	5.0	18.6	0.0	15.0
Improved pastures	32.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity pastures	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	10.0	0.0	0.0	0.0	0.0	7.0	0.0	0.0
Tree crops	0.0	0.0	0.0	0.0	5.0	46.5	57.5	55.0
Row crops	0.0	0.0	0.0	0.0	87.5	0.0	42.5	30.0
High intensity agriculture	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High intensity recreational	0.0	7.5	0.0	0.0	0.0	0.0	0.0	0.0
Low density single family residential	10.0	0.0	0.0	0.0	2.5	0.0	0.0	0.0
Medium density single family residential	17.5	5.0	86.4	57.5	0.0	0.0	0.0	0.0
High density single family residential	2.5	0.0	0.0	2.5	0.0	0.0	0.0	0.0
Institutional	0.0	2.5	4.5	2.5	0.0	0.0	0.0	0.0
Low density multifamily residential	10.0	30.0	4.5	17.5	0.0	0.0	0.0	0.0
High intensity transportation	0.0	15.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity commercial	0.0	27.5	4.5	20.0	0.0	0.0	0.0	0.0
Industrial	5.0	0.0	0.0	0.0	0.0	27.9	0.0	0.0
High intensity commercial	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High density multifamily residential	0.0	2.5	0.0	0.0	0.0	0.0	0.0	0.0

Table 4-5. Continued.

Land use/Land cover class	2004 Land use/Land cover (%)							
	SK09	SK02	BS04	LR06	BL12	BL03	MW13	MW04
Natural land/water	0.0	10.0	0.0	2.5	5.0	23.3	7.5	5.0
Improved pastures	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity pastures	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	10.0	0.0	0.0	0.0	0.0	7.0	0.0	0.0
Tree crops	0.0	0.0	0.0	0.0	10.0	25.6	52.5	92.5
Row crops	0.0	0.0	0.0	0.0	70.0	16.3	40.0	2.5
High intensity agriculture	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High intensity recreational	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0
Low density single family residential	7.5	0.0	0.0	5.0	15.0	0.0	0.0	0.0
Medium density single family residential	25.0	7.5	86.4	55.0	0.0	0.0	0.0	0.0
High density single family residential	35.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Institutional	0.0	2.5	4.5	2.5	0.0	0.0	0.0	0.0
Low density multifamily residential	15.0	30.0	4.5	30.0	0.0	0.0	0.0	0.0
High intensity transportation	0.0	15.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity commercial	0.0	27.5	4.5	5.0	0.0	0.0	0.0	0.0
Industrial	7.5	0.0	0.0	0.0	0.0	27.9	0.0	0.0
High intensity commercial	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High density multifamily residential	0.0	2.5	0.0	0.0	0.0	0.0	0.0	0.0

Table 4-6. Land use/land cover data (1500 m water quality monitoring site buffer).

Land use/Land cover class	1995 Land use/Land cover (%)							
	SK09	SK02	BS04	LR06	BL12	BL03	MW13	MW04
Natural land/water	20.8	5.9	0.0	1.0	2.0	38.4	8.9	26.7
Improved pastures	26.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity pastures	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	3.0	4.0	0.0	0.0	0.0	4.0	0.0	1.0
Tree crops	0.0	0.0	0.0	0.0	5.0	47.5	33.7	31.7
Row crops	0.0	0.0	0.0	0.0	89.1	0.0	46.5	37.6
High intensity agriculture	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
High intensity recreational	2.0	12.9	1.0	0.0	0.0	0.0	0.0	0.0
Low density single family residential	15.8	0.0	1.0	3.0	3.0	0.0	5.9	0.0
Medium density single family residential	8.9	39.6	85.9	52.5	0.0	0.0	0.0	0.0
High density single family residential	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0
Institutional	0.0	2.0	6.1	4.0	0.0	0.0	0.0	0.0
Low density multifamily residential	2.0	0.0	0.0	26.7	0.0	0.0	0.0	0.0
High intensity transportation	2.0	5.9	2.0	0.0	0.0	0.0	5.0	3.0
Low intensity commercial	0.0	18.8	2.0	10.9	0.0	0.0	0.0	0.0
Industrial	18.8	1.0	0.0	0.0	0.0	10.1	0.0	0.0
High intensity commercial	0.0	8.9	2.0	0.0	0.0	0.0	0.0	0.0
High density multifamily residential	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 4-6. Continued.

Land use/Land cover class	1999 Land use/Land cover (%)							
	SK09	SK02	BS04	LR06	BL12	BL03	MW13	MW04
Natural land/water	16.8	8.9	0.0	1.0	4.0	27.3	0.0	34.7
Improved pastures	17.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity pastures	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	9.9	2.0	0.0	0.0	1.0	13.1	1.0	0.0
Tree crops	0.0	0.0	0.0	0.0	10.9	44.4	42.6	33.7
Row crops	0.0	0.0	0.0	0.0	82.2	0.0	47.5	29.7
High intensity agriculture	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
High intensity recreational	2.0	11.9	0.0	0.0	0.0	0.0	0.0	0.0
Low density single family residential	18.8	0.0	0.0	0.0	1.0	0.0	5.9	0.0
Medium density single family residential	19.8	21.8	83.8	51.5	0.0	0.0	0.0	0.0
High density single family residential	1.0	0.0	1.0	3.0	0.0	0.0	0.0	0.0
Institutional	0.0	4.0	6.1	3.0	0.0	0.0	0.0	0.0
Low density multifamily residential	5.9	20.8	6.1	19.8	0.0	0.0	0.0	0.0
High intensity transportation	1.0	6.9	0.0	0.0	0.0	0.0	3.0	2.0
Low intensity commercial	3.0	21.8	3.0	21.8	0.0	0.0	0.0	0.0
Industrial	2.0	1.0	0.0	0.0	0.0	15.2	0.0	0.0
High intensity commercial	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High density multifamily residential	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 4-6. Continued.

Land use/Land cover class	2004 Land use/Land cover (%)							
	SK09	SK02	BS04	LR06	BL12	BL03	MW13	MW04
Natural land/water	6.9	9.9	0.0	1.0	2.0	17.2	6.9	31.7
Improved pastures	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Low intensity pastures	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium intensity recreational, open space	0.0	1.0	0.0	0.0	13.9	13.1	0.0	0.0
Tree crops	10.9	0.0	0.0	0.0	3.0	31.3	40.6	56.4
Row crops	0.0	0.0	0.0	0.0	68.3	8.1	43.6	9.9
High intensity agriculture	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
High intensity recreational	18.8	9.9	1.0	0.0	11.9	0.0	5.9	0.0
Low density single family residential	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Medium density single family residential	22.8	22.8	83.8	51.5	0.0	0.0	0.0	0.0
High density single family residential	20.8	0.0	0.0	2.0	0.0	15.2	0.0	0.0
Institutional	3.0	4.0	3.0	21.8	0.0	0.0	0.0	0.0
Low density multifamily residential	0.0	20.8	6.1	4.0	0.0	0.0	0.0	0.0
High intensity transportation	2.0	7.9	0.0	0.0	0.0	0.0	3.0	2.0
Low intensity commercial	3.0	21.8	0.0	0.0	0.0	0.0	0.0	0.0
Industrial	7.9	1.0	6.1	19.8	0.0	15.2	0.0	0.0
High intensity commercial	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
High density multifamily residential	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 4-7. Summary statistics for nutrient concentrations (1992 to 2006) and flow data at eight water quality monitoring sites in the Biscayne Bay watershed.

Constituent	Site	Min[1] (mg L^{-1})	Mean (mg L^{-1})	Median (mg L^{-1})	Max[2] (mg L^{-1})	Mean Annual Discharge (m^3 s^{-1})
NO_X-N	SK09	0.010	0.055	0.050	0.200	5.88
	SK02	0.010	0.224	0.210	0.680	8.88
	BS04	0.010	0.222	0.200	1.750	3.40
	LR06	0.020	0.271	0.280	0.530	3.87
	BL12	0.010	0.022	0.010	0.480	6.00
	BL03	0.010	0.288	0.245	1.010	6.00
	MW13	0.010	0.065	0.030	2.410	0.69
	MW04	0.010	2.200	2.250	4.640	1.41
NH_3-N	SK09	0.010	0.204	0.200	0.430	
	SK02	0.008	0.124	0.070	0.540	
	BS04	0.008	0.111	0.070	0.410	
	LR06	0.010	0.390	0.370	0.930	
	BL12	0.020	0.332	0.340	0.820	
	BL03	0.008	0.086	0.030	0.400	
	MW13	0.008	0.230	0.205	0.600	
	MW04	0.008	0.025	0.020	0.100	
TP	SK09	0.010	0.006	0.005	0.040	
	SK02	0.001	0.010	0.008	0.170	
	BS04	0.003	0.018	0.015	0.170	
	LR06	0.004	0.024	0.022	0.170	
	BL12	0.001	0.009	0.005	0.210	
	BL03	0.001	0.007	0.005	0.170	
	MW13	0.001	0.007	0.004	0.170	
	MW04	0.001	0.006	0.004	0.048	

[1]Water quality targets: NO_X-N (0.05 mg L^{-1} in Biscayne National Park); NH_3-N (0.01 mg L^{-1} within Biscayne National Park; 0.05 mg L^{-1} throughout the bay; 0.5 mg L^{-1} for surface waters in Miami-Dade County); total nitrogen (0.9 mg L^{-1} for ecoregion XII, southern coastal plain); TP (0.04 mg L^{-1} for ecoregion XII).
[2]Minimum detection limits (MDLs) were used as maximum concentrations for censored data. MDLs for censored TP data during the study period included 0.17 mg L^{-1}.

Table 4-8. Class-level factors and metrics describing spatial variability in the Biscayne Bay watershed.

Class	Factor 1[1]	Factor 2	Factor 3
Natural land cover	MPS (0.96) LPI (0.92) PSSD (0.87) CA (0.80)	LSI (0.81) PSCoV (0.73) AWMSI (0.65)	ED (0.92) IJI (-0.80) %LAND (0.76)
Row crops	MPI (0.93) PSSD (0.93) AWMSI (0.87) PSCoV (0.86)	ED (0.80) %LAND (0.80)	N/A
MSR	PSCoV (0.96) AWMSI (0.88) CA (0.84)	LPI (0.99) %LAND (0.88)	MNN (-0.56) MPS (0.55)
LIC	MPI (0.93) AWMSI (0.92) PSCoV (0.91) MPS (0.90) CA (0.87)	%LAND (0.84) LPI (0.79)	N/A

[1]Metric loadings for each factor after principal component analysis and factor analysis. Metrics: mean patch size (MPS); largest patch index (LPI); patch size standard deviation (PSSD); class area (CA); mean proximity index (MPI); area weighted mean shape index (AWMSI); patch size coefficient of variation (PSCoV); landscape shape index (LSI); edge density (ED); % landscape (%LAND); interspersion and juxtaposition index (IJI); mean nearest neighbor (MNN).

Table 4-9. Summary statistics for Landscape Development Intensity (LDI) index values and Directly Connected Impervious Area (DCIA) percentages (1995 to 2004) considering multiple spatial extents in the Biscayne Bay watershed.

Spatial extent	LDI			DCIA		
	Min	Mean	Max	Min	Mean	Max
Sub-basins	25.4	29.1	31.0	13.6	27.0	35.2
Canals (500 m)	25.1	29.2	31.3	10.0	26.6	36.1
Canals (1000 m)	25.5	29.3	31.2	11.9	27.0	36.0
Canals (1500 m)	26.2	29.4	31.2	13.9	27.5	36.9
Stations (500 m)	6.9	22.0	33.6	0.0	18.4	38.0
Stations (1000 m)	6.9	21.9	33.0	0.0	18.1	37.9
Stations (1500 m)	10.5	24.1	31.7	0.3	17.7	37.5

Table 4-10. Average Nash-Sutcliffe Efficiency (NSE) coefficients for eight water quality monitoring sites (1992 to 2006) in the Biscayne Bay watershed after comparing LOADEST simulated loads to measured loads.

Site	NO_X-N	NO_X-N plus NH_3-N	TP
SK09	0.74	0.86	0.57
SK02	0.41	0.72	0.38
BS04	0.20	0.46	0.87
LR06	0.73	0.71	0.92
BL12	0.30	0.86	0.58
BL03	0.49	0.72	0.50
MW13	0.45	0.84	0.61
MW04	0.83	0.84	0.65
Average	0.52	0.75	0.64

Table 4-11. Median annual loads (1992 to 2006) at eight water quality monitoring sites in the Biscayne Bay watershed.

Site	Basin	NO_X-N (kg/yr)	NO_X-N plus NH_3-N (kg/yr)	TP (kg/yr)
SK09	C-9	13,161	56,559	1,099
SK02	C-9	79,658	136,227	2,816
BS04	C-8	35,056	57,035	2,288
LR06	C-7	48,907	145,854	4,738
BL12	C-1	1,572	49,172	562
BL03	C-1	81,888	136,026	1,196
MW13	C-103	615	5,744	63
MW04	C-103	157,248	158,127	155

Table 4-12. Validation results for NO_X-N stepwise regression models (forward and backward selection and forward direction only) using three quantitative statistics.

Spatial extent	Forward and Backward			Forward Only		
	NSE	RSR[1]	PBIAS	NSE	RSR	PBIAS
Sub-basins	0.69	0.55	-50.89	0.55	0.67	-117.81
Canals (500 m)	-6.57			0.40		
Canals (1000 m)	-0.36			0.41		
Canals (1500 m)	0.39			0.55	0.67	-109.73
Stations (500 m)	-3.84			-22.28		
Stations (1000 m)	-0.52			-0.49		
Stations (1500 m)	-8512.37			-33.84		

[1]Ratio of the root mean square error to the standard deviation of measured data (RSR) values were only calculated for regression models with Nash-Sutcliffe Efficiency (NSE) coefficients greater than 0.5. Percentage bias (PBIAS) values were only calculated for RSR values less than 0.7.

Table 4-13. Validation results for TP stepwise regression models (forward and backward selection and forward direction only) using three quantitative statistics.

Spatial extent	Forward and Backward			Forward Only		
	NSE	RSR[1]	PBIAS	NSE	RSR	PBIAS
Sub-basins	0.79	0.46	-47.37	0.69	0.56	-119.14
Canals (500 m)	0.98	0.13	61.34	0.98	0.13	61.34
Canals (1000 m)	-4.76			0.90	0.31	7.92
Canals (1500 m)	0.38			0.67	0.57	-45.00
Stations (500 m)	0.72	0.53	-37.64	0.57	0.66	33.15
Stations (1000 m)	0.82	0.42	61.71	0.66	0.58	56.27
Stations (1500 m)	-0.55			0.47		

[1]Ratio of the root mean square error to the standard deviation of measured data (RSR) values were only calculated for regression models with Nash-Sutcliffe Efficiency (NSE) coefficients greater than 0.5. Percentage bias (PBIAS) values were only calculated for RSR values less than 0.7.

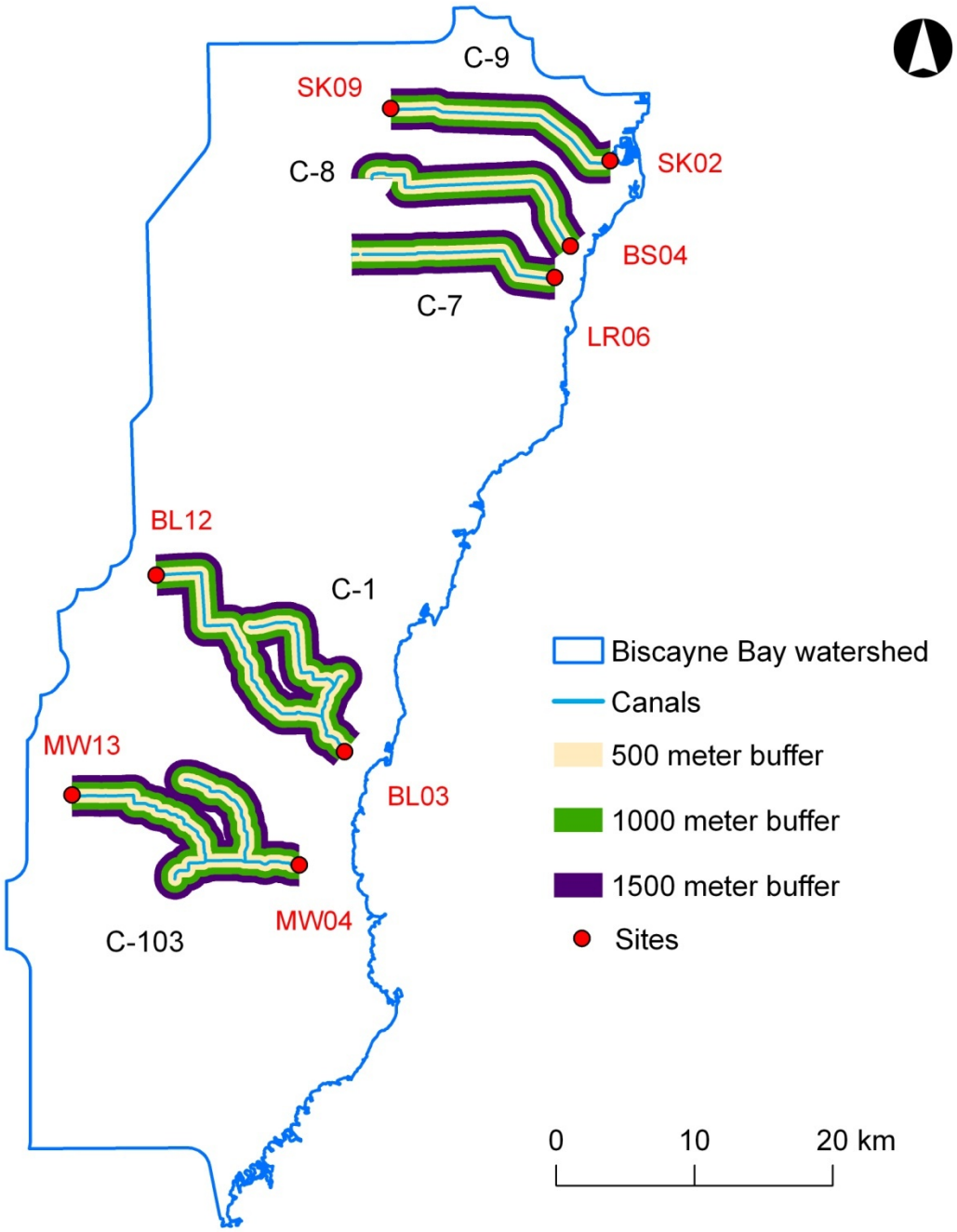


Figure 4-1. Buffers (500, 1000, and 1500 m) for five canals in the Biscayne Bay watershed.

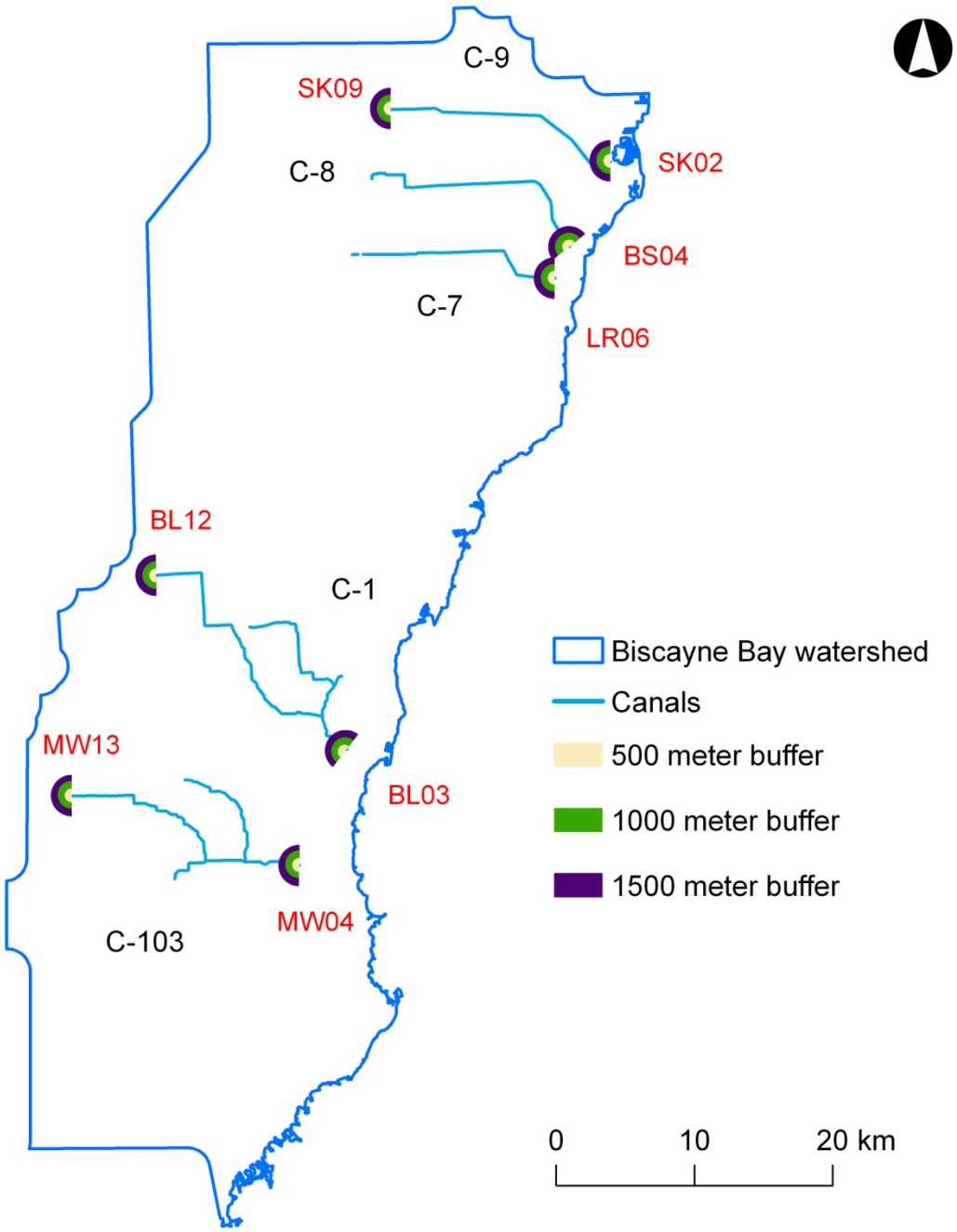
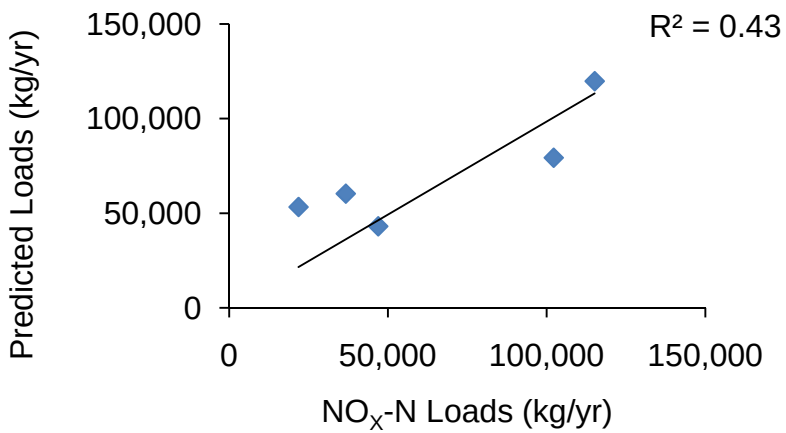
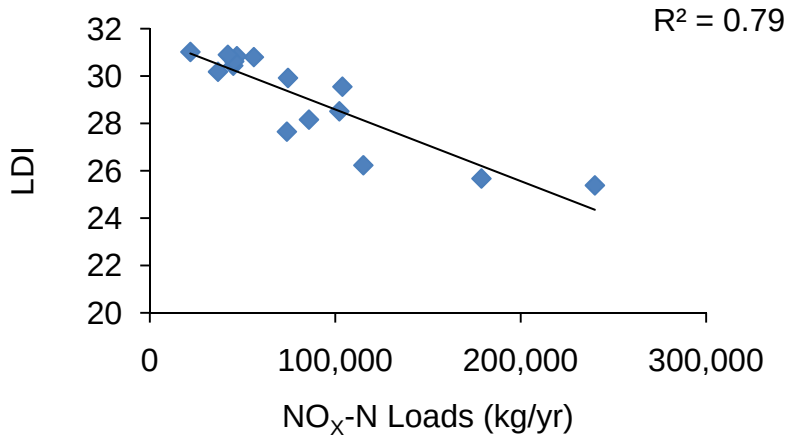


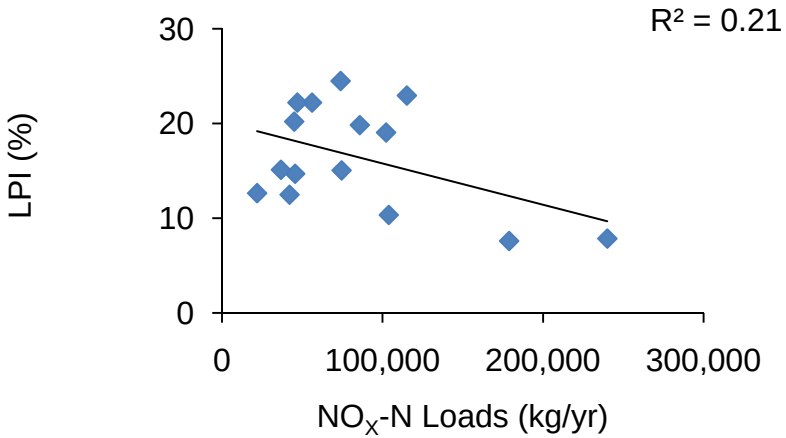
Figure 4-2. Buffers (500, 1000, and 1500 m) for eight water quality monitoring sites in the Biscayne Bay watershed.



A)

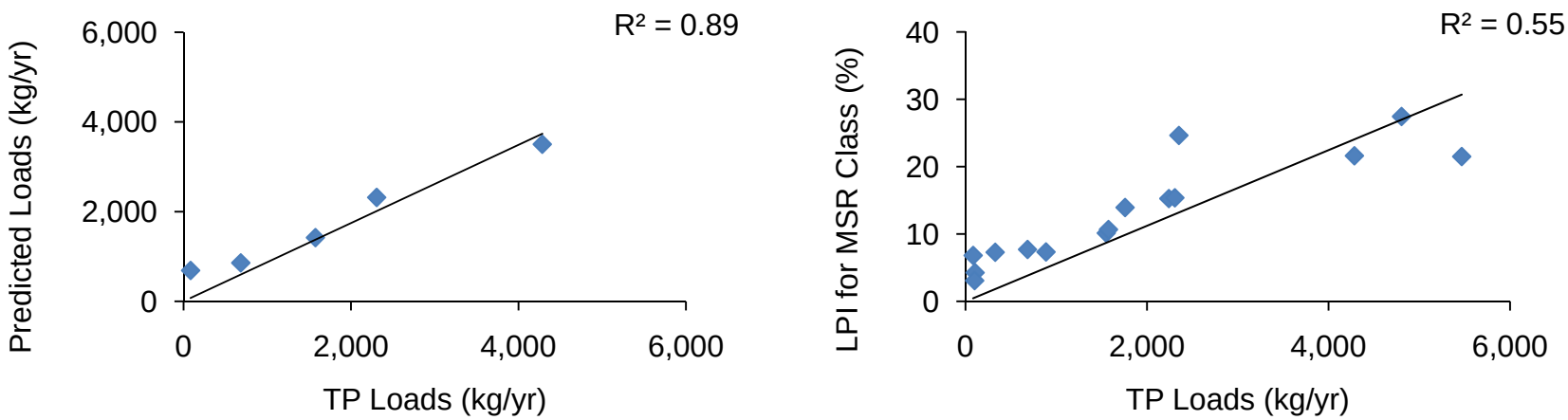


B)



C)

Figure 4-3. Land use variables influencing NO_X-N loads in the Biscayne Bay watershed. A) Predicted loads (2004) for the sub-basins regression model compared to LOADEST NO_X-N loads. B) Landscape Development Intensity Index (LDI) values and LOADEST NO_X-N loads (1995 to 2004) in the five study sub-basins. C) Largest Patch Index (LPI) metric percentages and LOADEST NO_X-N loads (1995 to 2004) in the five study sub-basins.



A) B)

Figure 4-4. Land use variables influencing TP loads in the Biscayne Bay watershed. A) Predicted TP loads (2004) for the 1000 m canal buffer regression model compared to LOADEST TP loads. B) Largest Patch Index (LPI) metric percentages for medium density single family residential (MSR) class and LOADEST TP loads (1995 to 2004) in the 1000 m canal buffers.

CHAPTER 5
SUMMARY

The predominant form of land use change in south Florida in recent decades has been the conversion of agricultural and natural areas to residential or urban complexes (Solecki and Walker 2001) and land use influences, along with watershed management practices, directly affect water resources such as Biscayne Bay, which drains the Miami metropolitan area. Biscayne Bay requires minimal inputs of phosphorus and nitrogen to function and thus watershed nutrient inputs have a controlling influence on bay water quality (Browder et al. 2005). Spatial characteristics of land use change have not been quantified and linked to specific pollutants in the watershed and therefore the overall objective for this study was to evaluate temporal and spatial land use influences on time series nutrient concentrations and loads measured in canals discharging to Biscayne Bay. Specific objectives and results are summarized below.

Objective 1

- Evaluate three disturbance indicators (landscape metrics, Landscape Development Intensity [LDI] index, and percent imperviousness) in the Biscayne Bay watershed for 1995, 1999, and 2004. Specific objectives: (1) quantify disturbance indicators in five sub-basins representing agricultural, urban, and mixed land uses; (2) determine if selected disturbance indicators provide contrasting information; and (3) evaluate how these indicators could potentially influence watershed management decisions.

- All three disturbance indicators revealed different levels of anthropogenic disturbance among urban (C-9, C-8, and C-7), mixed land use (C-1), and agricultural (C-103) sub-basins.

- Landscape metrics provided information on influential land use classes within the five sub-basins such as medium density single family residential (MSR) and row crops. LDI and DCIA values both provided similar information regarding the intensity of human disturbance; urban sub-basins were the most disturbed but the greatest changes occurred in C-1 and C-103.

- Overall, disturbance indicators suggested that the three urban sub-basins were relatively stable and dominated by complex MSR patches that corresponded to a greater degree of

anthropogenic intensity compared to the mixed land use and agricultural sub-basins, which were urbanizing through the conversion of row crops to residential uses.

- LDI values below 30.0 and DCIA values below 25% reflect sub-basins that are not completely urbanized. In these developing sub-basins, disturbance indicators can provide complementary information for watershed management decisions regarding water quality because LDI and DCIA values provide an overall view of watershed development but landscape metrics describe spatial configurations that could compound the threat to water resources.

- Implications for municipality zoning regulations in urbanizing sub-basins include promoting MSR and HSR development, as opposed to LSR, at greater distances from aquatic corridors. Implementing BMPs in these critical areas would also aid zoning regulations and reduce hydrologic impacts of gradually increasing LDI and DCIA values.

Objective 2

- Evaluate historical nutrient water quality data from 1992 to 2006 at six monitoring sites located near the outlets of canals discharging to the bay. Specific objectives: (1) determine nutrient concentration trends during the study period; (2) estimate annual nutrient loads from six canals in the watershed; and (3) use the PED index to assess the proportional impact of nutrient discharges from various canals.

- The majority of NO_X-N, NH_3-N, and TP concentrations decreased or exhibited no change at the six water quality monitoring sites, with only six instances of significantly ($p < 0.1$) increasing trends. LR06, BL03, and MW04 all had increasing NO_X-N trends, BL03 was the only site with an increasing NH_3-N trend, and both BS04 and MW04 had increasing TP trends.

- Only MW04 had median inorganic nitrogen concentrations (2.27 mg/L) that exceeded USEPA Southern Coastal Plain (ecoregion XII) criteria for total nitrogen (0.9 mg/L). The median NH_3-N concentration at BL03 (0.03 mg/L) was below Miami-Dade County surface water standard (0.5 mg/L). Median TP concentrations at BS04 (0.015 mg/L) and MW04 (0.004 mg/L) were both below ecoregion XII criteria for TP (0.04 mg/L).

- Annual nutrient loads at the six sites revealed higher NO_X-N loads in the southern section of the watershed and higher NH_3-N and TP loads in the northern and central areas.

- Annual nutrient loads fluctuated greatly but corresponding PED index values were less sensitive, exhibiting a damped response to nutrient fluxes. PED index values suggest that canal discharges from two sites (MW04 in the C-103 sub-basin and LR06 in the C-7 sub-basin) provide a greater proportional impact in the bay compared to other sites.

- In the Biscayne Bay watershed, there is an urgent need for assessment tools that can be used to guide management initiatives regarding water quality discharges to the bay. The PED index is a new analytic tool that can be used to evaluate the potential impact of

canal discharges because it provides a relative indication of ecological stress associated with pollutants that could disrupt energy flows and impair aquatic health.

- Trend analysis (concentration trends), load estimation (mass of pollutants delivered), and the PED index (ecological stress from pollutants) can be used together to provide a more holistic interpretation of water quality, which is necessary for optimizing resources to meet watershed management goals.

Objective 3

- Evaluate land use-water quality relationships in the Biscayne Bay watershed from 1995 to 2004 at eight water quality monitoring sites considering sub-basins, canal buffers, and site buffers. Specific objectives: (1) quantify human disturbance indicators; (2) estimate nutrient loads at monitoring sites; (3) develop and validate multivariate regression models; and (4) determine if disturbance indicators within sub-basins, canal buffers, or site buffers explain more of the variability in nutrient loads at monitoring sites.

- The LDI index and metrics at the landscape level (largest patch index [LPI]) and class level (LPI for MSR class) were identified as land use variables with the strongest relationships to estimated loads from monitoring sites.

- The sub-basin regression model was the best predictor of annual NO_X-N loads in the watershed and included both LDI and LPI variables. The types of land use (indicated by LDI) and their relative dominance (indicated by LPI) influence NO_X-N loads.

- TP loads were more closely related to human disturbance indicators at a smaller spatial extent (1000 m canal buffer), which is a function of nutrient transport processes in the watershed. The land use variable included in the 1000 m canal buffer (MSR LPI) model suggests that urban development patterns in this buffer zone are important factors for TP loads discharged from the watershed.

- Additional phosphorus inputs to the bay concern watershed managers because it is the primary nutrient limiting autotrophic growth. Watershed management plans focused on development patterns within canal (1000 m) buffers could therefore potentially reduce phosphorus discharges to the bay.

- Results from this study suggest that LDI values can be included as one indicator in an overall assessment of water quality. The LDI index, which quantifies the intensity of land use activities within watersheds, can be used with landscape metrics that evaluate spatial patterns to link land use development to water quality parameters.

Research Synthesis

Anthropogenic activity in south Florida, as well as other coastal communities, is continually changing, with dramatic population growth and land use development producing

temporal changes in water quality that can alter ecosystem functionality in receiving waters such as Biscayne Bay. After analyzing land use and nutrient water quality data in the Biscayne Bay watershed, research results indicated that the intensity of land uses, nutrient transport processes, and the distribution of land uses close to surface water conveyance systems were the most influential factors affecting nutrient water quality during the study period.

The process used in this study to identify important watershed factors influencing water quality variability can be applied to other aquatic ecosystems and watersheds (Figure 5-1). First, identifying possible areas of influence (e.g., sub-basins and buffer zones) enables land use data within specific locations to be evaluated relative to associated water quality data. Analysis of land use within defined areas includes quantifying the intensity and spatial distribution of land uses. The LDI index and percent imperviousness are examples of indicators providing information on the intensity of land uses while landscape metrics reveal the composition and configuration of land uses. Together, these indicators describe land use variability within defined areas. Linking land use characteristics to water quality data also requires that land use influences are hydrologically isolated. Methods of isolating land use include using buffers that are upstream of water quality monitoring sites. Trend analysis, load estimation, and the PED index are all examples of analytical methods that describe water quality variability at monitoring sites. Linking data describing land use and water quality variability through procedures such as stepwise regressions reveals important factors influencing water quality. Figure 5-1 includes examples of different indicators and methods and is intended to be a general guideline for evaluating land use-water quality relationships, not an exhaustive description of all possible procedures. Thus, Figure 5-1 provides a starting point for evaluating land use-water quality relationships and would be modified depending on data availability and management objectives.

Aquatic ecosystems and watersheds have specific natural and anthropogenic influences that combine to create unique systems with characteristic features. Hydrological connectivity, soils, pollutant sources, land use variability, and management practices are all factors that can influence nutrient discharges from watersheds. Evaluating particular systems using the overall process previously outlined (Figure 5-1) will likely reveal influential factors that contrast with results from the Biscayne Bay watershed. Identifying and addressing local factors contributing to water quality variability is a key aspect of effective watershed management strategies that can ultimately protect vulnerable water resources.

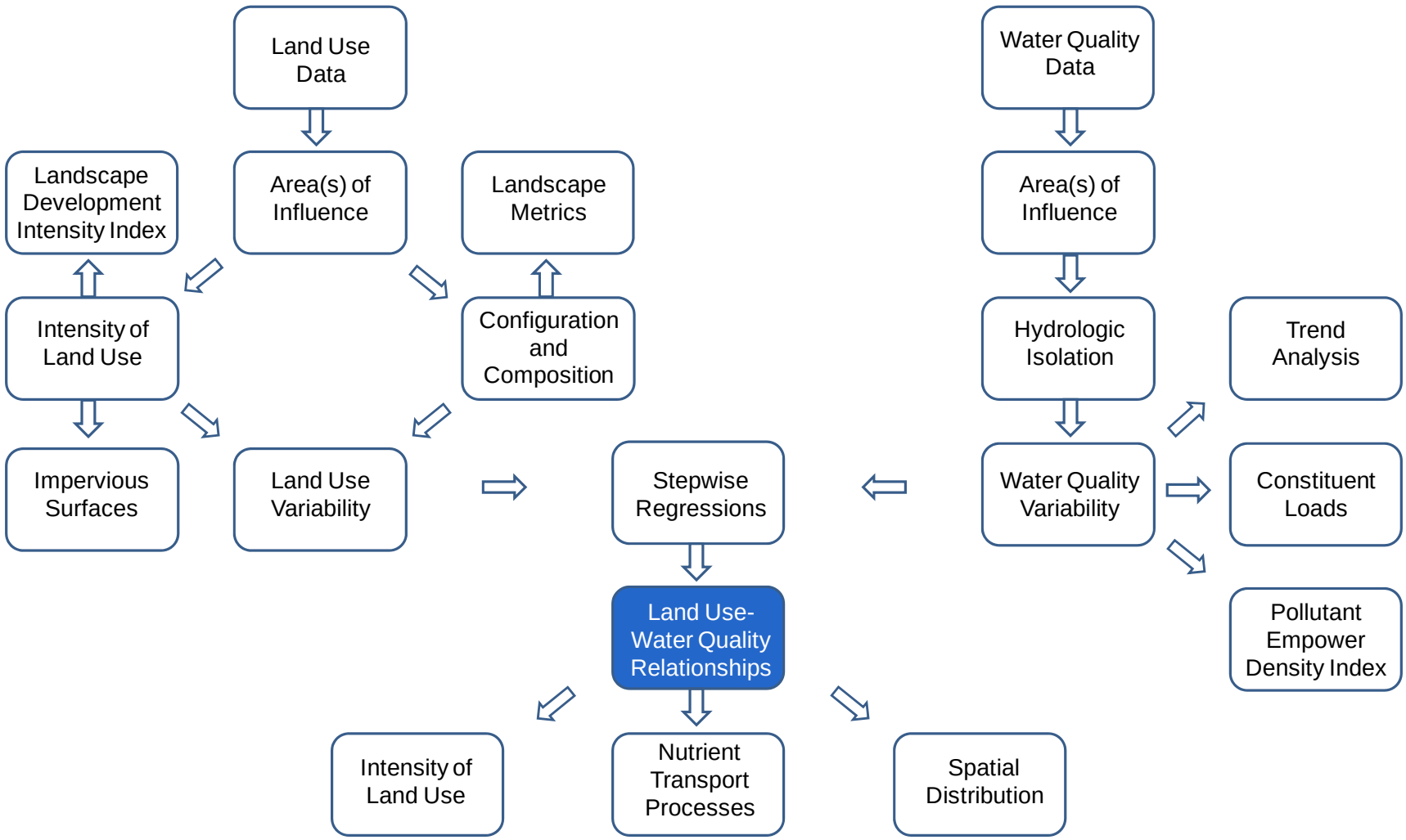


Figure 5-1. Flow chart illustrating an overall process that can be used to evaluate land use-water quality relationships in watersheds.

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BIOGRAPHICAL SKETCH

Richard O. Carey was born in Jamaica. As a small child, he exhibited a natural tendency to lead, had a keen sense of understanding, and thus was regularly assigned leadership roles within his age cohort. He excelled both academically and athletically during his preparatory school years, receiving awards for his endeavors. Successful in his high school entrance examination, he was awarded a place at one of Jamaica's most prestigious institutions – Wolmer's Boys' School – in the capital city of Kingston. Richard participated in several extra-curricular activities while in high school, including playing for Wolmer's football teams.

In his quest for higher education after graduating from high school, Richard chose to attend the University of Miami, where he read for a Bachelor of Science degree in Biology. Richard's curiosity and love for nature then led him to the University of Georgia, where he earned a Master of Science degree in Conservation Ecology and Sustainable Development from the Odum School of Ecology. The University of Florida's Interdisciplinary Ecology Ph.D. program at the School of Natural Resources and Environment allowed him to explore his interests further as he investigated anthropogenic influences affecting natural resources.

After receiving his Ph.D., he intends to develop research programs evaluating ecological stressors in urbanized and degraded areas while providing opportunities for others within his professional capacity.