Ecological Diversity in Hillsborough County, Florida: Correlations between Landscape Metrics and Socio-demographic Variables

David Godfrey
University of South Florida, davidjgodfrey@live.com

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Ecological Diversity in Hillsborough County, Florida: Correlations between Landscape Metrics and Socio-demographic Variables

by

David J. Godfrey

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Arts
Department of Anthropology
College of Arts and Sciences
University of South Florida

Major Professor: Lorena Madrigal, Ph.D.
Christian Wells, Ph.D.
Rebecca Zarger, Ph.D.

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Dedication

I would like to dedicate this thesis to everyone that made it possible and to everyone that may find it useful. I would particularly like to mention all of my professors from both James Madison University and the University of South Florida that have helped me get to this point in life. Additionally I would like to dedicate this thesis to my fellow USF graduate students and friends in Tampa that have helped make life more enjoyable in Tampa through playing tennis, going to the beach, and visiting Tampa’s diverse restaurants with me. I would also like to dedicate this thesis to my friends and family back home in Blacksburg, Virginia and elsewhere around the world that have provided additional encouragement and support.
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I would like to acknowledge Dr. Joni Downs and her course on environmental applications for GIS for inspiring the topic of this thesis. I would like to acknowledge Dr. Steven Reader for helping me to be more able to think as a GIS analyst rather than a GIS technician. I would like to thank Vincent Verweij for technical GIS advice. I would like to thank Drs. Christian Wells and Rebecca Zarger for their invaluable input as committee members with ideal academic backgrounds. Last but not least I would like to thank my advisor Dr. Lorena Madrigal for her mentorship over the past few years.
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Landscape metrics, a means of quantifying landscape attributes, are frequently used in landscape ecology to describe the spatial characteristics of a landscape, but they have been less often used in anthropology. Using geographic information system (GIS) software, this study tests a method that investigates statistical correlations between groundcover landscape metrics and socio-demographic variables in Hillsborough County, Florida. Statistically significant correlations were found, illustrating the potential utility of this exploratory method. Wealthier areas with fewer ethnic minorities tend to be more fragmented and diverse in terms of groundcover; these areas also tend to have a lower percentage of impervious surfaces. The method of analysis is critiqued and applications for the results are discussed with the hope that they might help guide municipal planners in designing better urban communities.
Chapter One: Introduction

Overview

This study investigates statistical relationships between eight landscape metrics and 28 socioeconomic and demographic variables in Hillsborough County, Florida (Figures 1 and 2). The purpose of this investigation was to use an exploratory method for developing research questions regarding human-environment relationships. Hillsborough County is a large county in terms of both area and population. It covers 1,020.21 square miles, making it the 12th largest in the state by area, although 215.31 square miles of that is water. Its population of 1,229,226 makes it the fourth most populous county in Florida. From a theoretical perspective, this study synthesizes elements of research programs and theories from anthropology, ecology, and geography, and seeks to test and critique an exploratory method of addressing the question of how humans and the environment are influenced by one another. This study also investigates how the developmental history of the Tampa Bay area has shaped present day landscape patterns and the distribution of different socio-demographic groups across the Tampa Bay area. This study was made possible by and relies heavily on the use of GIS software. The reliance on GIS has both strengths and weaknesses which are discussed below.
Figure 1. Hillsborough County highlighted in grey.
This research tests a method of identifying human-environmental relationships that may be ripe for further study. As with all GIS-based studies, this method is exploratory, as it merely identifies the presence of a correlation as well as whether it is a positive or negative correlation (Knigge and Cope, 2006). These relationships can then be interpreted in the broader context of anthropological work and used to guide future
studies that further explore these relationships using other more traditional anthropological methods.

This method may have many broader applications beyond those demonstrated in this study. For this reason, in addition to the results of the study being analyzed and interpreted, the method itself, as well as the use of GIS in social science, is critiqued. Attention is drawn to the strengths and weaknesses of studying human-environmental relationships using the proposed method of seeking correlations between landscape ground cover metrics and various types of human variables. With that in mind, suggestions for future applications of this method are also proposed.

Background on Landscape Metrics

The term landscape has many definitions, however for the purposes of this thesis it will be defined as “a piece of real world in which we are interested in describing and interpreting processes and patterns” (Farina, 2000:11). Landscape metrics are a way to quantify different aspects of the landscape. In this study individual census block groups make up the landscapes of interest. Landscape metrics are a means of describing the spatial distribution and configuration of different land cover patches in a landscape (McGarigal et al., 2002). For instance, a landscape metric known as patch density can describe how many different types of land cover occur within a landscape. Patch density is the number of different types of patches in a landscape normalized by the area of the landscape (McGarigal et al., 2002).
Landscape metrics are generally used by geographic information system (GIS) users in conjunction with the raster data model. In the raster data model, representations of the land are divided up into a grid, with each cell carrying a single value that describes something about that cell, such as elevation or soil type (Figure 3). Landscape metrics are widely used in landscape ecology to quantify the spatial characteristics of a landscape, but they have been less often used in anthropology, political ecology, and human ecology (Leitão et al., 2006).
Figure 3. Raster of a block group in southeastern Hillsborough County.

Different colors represent different ground cover types; contiguous areas of the same color are patches.

Thesis Organization

In the second chapter, relevant literature is discussed along with a brief history of the development of the Tampa Bay area. In the third chapter, the data and methods employed in this study will be presented and discussed. Additionally several hypotheses
will be proposed. In the fourth chapter, the results of this study will be provided and interpretations of the findings discussed. The concluding fifth chapter consists of a critique of the method used to obtain these findings along with a discussion of the applications of both the findings of this study and of the method employed.
Chapter Two: Literature Review

Several studies in the past have examined relationships between landscape metrics and different cultural variables. These prior studies served as a guide for designing and framing this study. Particularly important was the influence of Boucek and Moran (2004:30), who call for more research on using landscape metrics to study human-induced land cover change particularly in remote areas. Based on analysis of remotely sensed data such as satellite imagery (typically LANDSAT in the USA), landscape metrics allow for the study of areas that are difficult to access on the ground. While it is essential for anthropologists to be physically present in their study areas, preliminary research can identify study areas where visits will be most rewarding. The method that I describe in this thesis could allow researchers to identify patterns and locations that suggest further investigation. Additionally, this method offers a different perspective of a study area, making it possible to see patterns that might not otherwise be visible. From an anthropological perspective, it is important to study ground cover as it is through modifications of ground cover that humans make their greatest impact on a landscape (Boucek and Moran, 2004:24). For this reason, this study uses ground cover data and the landscape metrics based on them as the environmental component of the study.

As part of a method for modeling housing densities from LANDSAT imagery Hardin et al. (2008) compared landscape metrics and housing densities in Census blocks
in Terre Haute, Indiana. They employed Spearman’s rho to examine potential correlations between this variable and the following five landscape metrics: largest patch index, Shannon’s and Simpson’s diversity indices, and Shannon’s and Simpson’s evenness indices. Largest patch index measures what percentage of the landscape the largest patch makes up, the diversity indices measure how many different types of patches there are, and the evenness indices measure how evenly distributed the landscape is between the different types of patches. However, Hardin et al. (2008) sought to determine causation in addition to correlation between these variables. The method utilized in my study largely ends at finding correlations between variables, leaving finding causations to more traditional anthropological methods. Ethnography can engage local residents in the research and provide a nuanced look at why people live where they do. Ethnography also allows researchers to learn about how people feel about their situation, such as whether or not they enjoy living in a particular environment. Hardin et al. (2008) were particularly interested in determining what sort of housing density could be expected based on past land use, making their research question somewhat different than what was done in my study.

Perhaps the most similar study to my study was published by Schwarz 2010. In this study, Schwarz looked for correlations between and among a wide variety of landscape metrics, population-related indicators, and socioeconomic indicators at a city-wide level. She examined 231 different cities throughout Europe that had participated in a European Commission Urban Audit. Her aim was to identify indicators that could be used to determine urban form in European cities. Schwarz identified significant correlations between several landscape metrics and various population-related and
socioeconomic indicators. Unfortunately comparison between her findings and the findings of my study are difficult, because many of her variables are not quite the same and her study was conducted at a difference scale (city-wide using a land cover raster with 100 x 100 m resolution). However, it is encouraging that correlations were found, and Shwarz urges more research in this direction (2010).

Environment and Anthropology

The study of the relationship between humans and the environment is an integral part of anthropology. Ever since the days of Julian Steward and before, anthropologists have been interested in studying how the environment affects humans and vice versa. Julian Steward (1955) is best known for proposing that anthropologists study cultural ecology, a research orientation interested in investigating how a culture’s local environment impacts certain core cultural behaviors, particularly those related to subsistence and other economic activities.

In more recent times anthropologists have begun studying how both the local environment and political power structures interact with people, a research orientation known as political ecology (Paulson et al., 2003). Political ecologists have called for multi-scalar research; something that the research method used in this study could be used for (Paulson et al., 2003). Political ecologists with a biological orientation have called for increased attention to be paid to environmental aspects of health inequalities, wishing to give these problems a spatial dimension (Huss-Ashmore, 2000; Leatherman
and Thomas, 2001). Methods such as the one proposed in this study would be a useful exploratory method in helping political ecologists identify potential areas for further research. It has been said that “ecology is inherently political” (Robbins, 2011:3). By examining the human socio-demographic aspect of the environment, this study allows a look at how ecology is political.

**Environment and Health**

Anthropologists are becoming increasingly interested in studying the interactions between the environment, different health outcomes, human behaviors, and socioeconomic variables. Sir Michael Marmot’s (2007) well-designed study of British civil servants clearly documented the positive correlation between socioeconomic status and health status. Marmot discovered that every step up in the socioeconomic ladder generally was accompanied by improved health. In other words, upper level administrators were healthier than mid-level office clerks who in turn were healthier than janitors. While Marmot’s study was conducted in the United Kingdom, he notes that it is also true globally (Marmot, 2007:1158). Marmot (2007:1159) also notes a similar correlation between education and health status.

Possible reasons for this correlation are discussed by Jonathan Wells (2010). Wells discusses how living conditions can have multigenerational effects on health status through various mechanisms including epigenetic changes. An epigenetic change alters the structure of a DNA molecule without changing the genetic makeup, but still potentially activating or deactivating a gene (Wells, 2010). Evidence exists that these effects can be passed down through generations, although conclusive experiments in
humans are difficult to conduct for ethical reasons (Bollati and Baccarelli, 2010). Human growth and development, especially at the fetal stage, are particularly impacted by stress, poor nutrition, contaminants, and other detrimental outside effects (Schell, 2010; Wells, 2010). Other anthropologists have documented the relationship between stress and poor health, noting that some environments are more stressful than others (Gravlee, 2009; Himmelgreen et al., 2004; Madrigal et al., 2009; Madrigal et al., 2011).

Himmelgreen et al. found a positive correlation between body mass index (BMI) and length of stay in Puerto Ricans relocating to the United States mainland (2004). Himmelgreen et al. note that changes in diet and activity are largely responsible for the increase in BMI; these changes are due to a variety of biological, cultural, and psychological factors. As far as relevance to this study, new environments on the mainland have an effect on these factors, leading to the change in BMI. BMI is an important health indicator, as many health problems stem from obesity (Pollard, 2008). Madrigal et al. (2011) reached similar conclusions as Himmelgreen’s research team in a meta-analysis of studies examining BMI and blood pressure of populations from the South Asian diaspora. Immigrants find themselves in situations that may be better in some regards and worse in other regards relative to their living situation in their country of origin. My study investigates the types of environments associated with different socio-demographic groups, which are in turn correlated with different health outcomes (Marmot, 2007; Wells, 2010).

Ecological surroundings can also impact health via racism. Clarence Gravlee wrote a 2009 article describing how the culturally constructed notion race can have biological manifestations, despite having no genetic basis. Since genetics are not related
to race, it is through environmental and cultural factors that “race becomes biology” (Gravlee, 2009:47). One chief environmental factor that affects biology is stress; stress can be caused by racism, unpleasant surroundings, poor nutrition, environmental pollution, and a variety of other sources. This study investigated what groups of people tend to live in what types of environment. One would expect that people of higher socioeconomic status would tend to live in more pleasant environments.

Another study on how stress can impact human biology was conducted by Madrigal et al. (2009) and investigated hypertension in Africans and those of African ancestry. Some groups of African-Americans are known for high rates of hypertension. However Madrigal et al. found that many African groups and diasporic Africans do not have high rates of hypertension. The cultural milieu (including both blatant and subtle racism) many individuals of African ancestry in the United States experience may instead explain the higher levels of stress and resultant health problems including hypertension in this group. This cultural milieu exists partly in a physical environment, explaining why environment has more influence on hypertension than genes in this population. A goal of this study was to investigate the extent of environmental segregation. While de jure housing segregation is largely a thing of the past in the United States, de facto segregation may continue to exist (see Stretesky and Lynch 2002 for a discussion of segregation in Tampa). Additionally, the GIS methodology may find application in other countries where segregation is explicitly institutionalized. Segregation can also exist between classes in addition to between ethnic groups. The Residential Income Segregation Index score for the City of Tampa, which makes up a substantial portion of Hillsborough County, increased from 19 to 29 from 1980 to 2010, indicating that
segregation along class lines is on the rise in the study area (Taylor and Fry, 2012). The Residential Income Segregation Index, developed by Pew Research, measures diversity in terms of income in residential tracts. Thus it was expected that different ethnic groups and social classes would tend to live in different types of landscapes.

Research has been conducted on the various other ways that local environments impact their residents. Cummins et al. (2005) studied how the neighborhood environment affected self-perception of health. These authors found that in neighborhoods in England and Scotland poor self-perceptions of health had significant associations with a number of variables describing neighborhoods including poor physical quality residential environment, a left wing political climate, low political engagement, high unemployment, lower access to private transportation, and lower amounts of wealth invested in a means of transportation (Cummins et al., 2005).

Another study conducted in the Netherlands found that neighborhood character could impact physical activity levels (van Lenthe et al., 2005). They found interesting patterns where more disadvantaged people were more likely to walk or ride a bicycle to work or a store but were less likely to engage in physical activity during leisure time. These authors also noted that more disadvantaged neighborhoods tended to be less conducive to physical activity during leisure time, encouraging people to primarily engage in physical activity when shopping or traveling to work (van Lenthe et al., 2005).

In a study conducted in 82 California counties Wang et al. (2007) found that living in a neighborhood with lower overall socioeconomic status was associated with a higher mean body mass index (BMI). Interestingly, they also found that in women, higher BMI values were also associated with living where there was a greater density of small
grocery stores and where chain grocery stores were in closer proximity (Wang et al., 2007).

An Australian study investigated sedentary behavior in the form of television and computer use in children as it related to data on the local environment collected using GIS (Veitch et al., 2012). Veitch el al. found that living near a park with a water feature was negatively correlated with playing computer or videogames. Additionally they found that greater park area was negatively correlated with television use. As noted by William Leonard (2010), sedentary behavior is on the rise in modernizing societies due to technological innovations. Sedentary behavior contributes to many health problems, particularly in conjunction with the readily available high energy food sources in many areas (Leonard, 2010).

*Health and Socioeconomic Dimensions of Impervious Surfaces*

Several studies have also documented correlations between the percentage of impervious surfaces and various socioeconomic variables. Impervious surfaces are surfaces nearly impenetrable by water, such as parking lots, roads, and buildings. Impervious surfaces have been shown to be a primary factor in increasing the average land surface temperature (LST) of an area as they tend to absorb more of the sun’s warmth than vegetation does (Huang et al., 2011). Huang et al. noted that in Baltimore, MD average LST was higher in areas “characterized by low income, high poverty, less education, more ethnic minorities, more elderly people and greater risk of crime” (2011:1753). Very similar findings were made by Jenerette et al. (2007) in Phoenix, AZ. Urban areas of unnaturally high LSTs (known as urban heat islands or UHIs) have been
implicated in playing a role in heat wave deaths in urban areas, making their study particularly important (Gabriel and Endlicher, 2011; Rosenthal, 2010).

Impervious surfaces themselves were correlated with socioeconomic status in two Massachusetts studies; while in most of the state there was a negative correlation; gentrification has led to a positive correlation between these variables in Boston (Ognea-Himmelberger et al., 2009; Ognea-Himmelberger et al., 2012). A study of cities in southeastern Australia found a negative correlation between percent impervious and home ownership and income (Luck et al., 2009). As my study includes variables measuring income, poverty, education, ethnicity, and age in addition to percent impervious surfaces, it was expected that correlations would be found between these variables.

Mechanisms behind Human-Environmental Correlations

When it comes to interpreting relationships between the environment and different human variables, Verheij et al. (1999) noted that there are two different mechanisms than can cause these relationships. First there is the breeder mechanism, where the environment causes its inhabitants to exhibit certain characteristics. This mechanism is sometimes called a causation mechanism, as the environment is causing the characteristics to be exhibited.

Second there is the drifter or selection mechanism, where people exhibiting certain set of characteristics are attracted to certain environments (Verheij et al., 1999). In this case, rather than the environment causing certain characteristics, it selects for certain characteristics. These two mechanisms are very important to bear in mind when
interpreting results such as those that were provided by this study. However this is a unidirectional way of thinking about human-environmental interactions. In addition to being influenced by the environment, humans exert their own influence on the local environment, modifying it in both intended and unintended ways.

De Vries et al. (2003) carried out a study with these mechanisms in mind that had similar elements to my study. Using raster data of Dutch neighborhoods the authors determined the percentages of green space and water that was present in each neighborhood studied. Since the authors hypothesized that the causation mechanism was responsible for the resident’s characteristics, the authors used these environmental variables as their independent variable and various socioeconomic, demographic, and health-related variables as their dependent variables to conduct multiple regression analyses. The authors found a particularly strong association between green space and health for women and the elderly; green space also seemed to have a greater impact on people with less education. The authors also noted that having gardens of any kind also had a positive effect on one’s health.

While the assumption may be that green space increases health by increasing physical activity, some studies have been unable to find significant correlations between green space and physical activity levels (Hillsdon et al., 2006). This suggests that other factors may be at play, such as socioeconomic status, age, or the ability to exercise equally well in areas or facilities not classified as green spaces. Essentially, one must bear in mind that the health benefits or detriments of a landscape are not exclusively based on opportunities for physical activity, but are rather much more complex, likely including factors such as stress as mentioned previously by Cummins et al. (2005), Gravlee (2009),
and Madrigal et al. (2009). Clearly the environment influences humans in many ways, making its study an important endeavor for anthropologists.

Relevant Local Research

Former University of South Florida graduate student Alec Foster (2010) completed a master's thesis on what Tampa residents thought of the urban forests. He wanted to find out whether Tampa residents valued the trees in Tampa as well as how much they would pay for the quantity of trees to increase. He found that in general Tampa residents appreciated the trees and were willing to pay for an increase in trees in their city. There were also found positive associations between being willing to pay for more trees and income and education. In a study published in 2009, Landry and Chakraborty documented the socioeconomically unequal distribution of street trees in Tampa. They found that areas of Tampa with more African-Americans, low income residents, or renters tended to have fewer street trees.

Research has also been conducted in the Tampa Bay area on resident perceptions of water resources. Larsen and Zarger (2012) interviewed residents, finding that many were deeply bothered by the loss of water resources. Water resources in Hillsborough County take a number of forms, including streams, lakes, wetlands, retention ponds, and the Hillsborough River, which meanders its way through the county and drains into Tampa Bay. Water is a precious commodity in Florida, as various communities battle against each other and the agriculture industry for water sources (Zarger et al., 2010).
Drought conditions, new real estate developments, and increasing water demands for municipal and agricultural purposes have all led to the depletion of the underground water aquifers that feed Hillsborough County’s water resources. Thus Hillsborough County has been seeing its water resources diminishing or disappearing, making them all the more valuable. This localized evidence suggests that elsewhere people may recognize the importance of their natural surroundings and have strong personal connections to local landscapes, even in urban areas where such connections may be assumed to be not present.

The general socio-demographic makeup of Hillsborough County according to the 2010 US Census is as follows. The total population of the county is 1,229,226. Fifty-one percent of the population reported gender as female, while 49 percent was male, making it roughly even. Twenty-five percent of the population reported being Hispanic or Latino. Twelve percent of homes in Hillsborough County were vacant. The average household size was 2.62. Median household income was $50,195. Fifteen percent of the population was living below the poverty level.

Figure 4. Ethnic makeup of Hillsborough County.
The Developmental History of Hillsborough County.

Parts of Hillsborough County have been occupied (and as a result modified) continuously since prehistory, with much of this occupation centering near the mouth of the Hillsborough River in Tampa Bay (Johnson, 2007). Fort Brooke was a US Army outpost constructed in 1823 that was of critical importance during the Seminole Wars (Johnson, 2007). The fort also served as a trading outpost and center of economic activity.

What would eventually become Tampa grew relatively slowly until the arrival of the railroad in 1884. The railroad facilitated the shipment of both goods and people in and out of the Tampa area (Johnson, 2007). The 1890s brought even greater change with the Cuban Revolution and the Spanish-American War, as Tampa was strategically positioned as a sizeable port near Cuba. These events brought an influx of American troops and Cuban immigrants and contributed to further urbanizing the area (Johnson, 2007). Cigar factories owned by entrepreneurial Cuban-Americans and operated with Cuban-American labor sprang up in Ybor City and West Tampa; cheap housing was constructed to house the workers.

World War I spurred on an even greater increase in the development of Hillsborough County as infrastructure was enhanced and urban areas expanded (Johnson, 2007). The flat land and sandy beaches were particularly useful for aviation purposes. During the Great Depression, Tampa attracted even more people as those without work sought warm climates like Southern California and Florida (Rogers, 1996).
However pollution was also beginning to be a problem. Inadequate flushing Hillsborough’s waterways due to ecological damage done by development projects began to cause a buildup of pollutants in Hillsborough County (Derr, 1989; Goodwin, 19991). One major ecological blow was the creation of manmade islands and peninsulas such as the Davis Islands to create waterside real estate properties (Egozcue, 2001).

MacDill Air Force Base was created shortly before World War II and greatly increased both the population and prominence of Hillsborough County. Parts of Hillsborough County were used for bombing runs by aircraft and for testing of chemical and other types of weapons; unfortunately many of these weapons are still stored in Hillsborough County to this day (Johnson, 2007). Hillsborough County rapidly grew after World War II as the Cold War military presence, the draining of swamps, and an increase in economic activity spurred on the development of the county. With air conditioning becoming more commonplace in the 1950s, Hillsborough County became a popular destination for vacationers and retirees, many of whom were former soldiers fondly remembering their stationing in Tampa (Egozcue, 2001; Johnson, 2007).

The Port of Tampa has also played a significant role in the development and ecology of Hillsborough County. The Port of Tampa is one of the primary industrial ports in the Southeastern United States; it is ranked number one in Florida and twentieth in the United States in terms of total cargo tonnage (American Association of Port Authorities, 2010). The Port of Tampa’s prominence is in part due to the lucrative phosphate mining industry of West Central Florida, including Hillsborough County itself (Egozcue, 2001; Johnson, 2007). Phosphate mining has caused considerable ecological damage in terms of both the mining itself and the byproducts of the mining process, most notably the
immense gypsum stacks that are ecological ticking time bombs (Egozcue, 2001). Phosphate is prepared for use as fertilizer in the southern portions of Hillsborough County and then exported around the world.

Florida is inseparably associated with oranges and the fruit industry, and Hillsborough County is no different. Unfortunately this puts a strain on local water resources. Hillsborough County largely consists of karst terrain, which consists of limestone bedrock amenable to cavern formation (Egozcue, 2001). When the underground water aquifer is full, buoyancy keeps the ground above the caverns from caving in. However when the water table is lowered, whether it is due to drought conditions not allowing the aquifer to be recharged or to excessive drawing of water from wells, buoyancy decreases and often leads to a cave-in and the subsequent formation of a sinkhole (Ford and Williams, 1989).

The agriculture industry, the phosphate mining industry, and all other water consumers compete for water resources in Hillsborough County and surrounding areas, leading to the frequent appearance of sinkholes (Egozcue, 2001). A great deal of water is occasionally used agriculturally in winter to stave off frosts; unfortunately this is also the dry season in Florida and can result in a dramatic lowering of the water table (Egozcue, 2001). Many of these sinkholes become ponds. Further erosion and changing water levels in the aquifer can result in rapid appearance or disappearance of lakes and ponds (Ford and Williams, 1989). Sinkholes and the appearance or disappearance of water features are difficult for geologists to forecast, as oftentimes drilling a well in one part of the water aquifer may result in geological or hydrological change miles away.
The urban development history of Hillsborough County provides the backdrop for this study. The county was relatively rapidly developed and used with little concern for the natural environment. The people of Hillsborough County now live with this legacy; however measures could be taken to ensure that future municipal and other developments are conducted in an ecologically sound fashion and that what natural resources that are left are preserved if not expanded.
Chapter Three: Hypotheses, Data, and Methods

Hypotheses

Based on the preceding literature review the following hypotheses are proposed. Hypothesis #1 is that different ethnic groups and social classes would live in divergent landscape types. In other words, significant correlations should be found between socio-demographic variables measuring ethnicity and one or more of the landscape metric variables; similarly significant correlations should be found between variables measuring social class and any of the landscape metric variables. This would indicate a correlation between place of habitation of different socio-demographic groups and certain landscape types.

Hypothesis #2 is that wealthier individuals would tend to live in more ecologically diverse environments. Some research has shown that more ecologically diverse environments are regarded as more aesthetically pleasing. A study by Dramstad et al. (2006) found a statistically significant preference in participants for landscapes with greater ground cover diversity and heterogeneity as well as landscapes that contained water resources. A study by Alister Scott (2002) also found that landscape diversity was perceived as a positive attribute; however he noted there were many other factors also at play when people were assessing the attractiveness of a landscape. Similarly a study
conducted in the Washington DC area found that landscape diversity was valued in more urban parts of the study area but was of lesser importance in more rural areas (Geoghegan et al., 1997). Based on these studies it is thus hypothesized that those of higher socioeconomic status would live in more diverse and even environments less dominated by a single type of ground cover.

Hypothesis #3 is that those of higher socioeconomic status would live in landscapes that included a greater percentage of water resources compared to those of lower socioeconomic status. This is based on the value placed on water resources by residents of the Tampa Bay area as found by Larsen and Zarger (2012).

Hypothesis #4 is that there are correlations between percent impervious surfaces and at least some socioeconomic variables as found in previous studies (Huang et al., 2011; Jenerette et al. 2007; Ogneva-Himmelberger et al., 2009; Ogneva-Himmelberger et al., 2012; Luck et al., 2009). My study includes nearly all of the socioeconomic variables for which correlations were found with impervious surfaces; it also includes a number of other variables. Thus this study also contributes to the body of research involving impervious surfaces.

**Landscape Metric Variables**

The ground cover layer being measured using landscape metrics categorized the landscape into one of 30 different ground cover types in 30 m$^2$ cells (Figure 4). This
raster layer was produced by the Florida Fish and Wildlife Conservation Commission and is available through the Florida Geographic Data Library (FGDL).

Figure 5. Ground cover raster used for calculating landscape metrics. Note areas excluded for lacking residential parcels.

Eight landscape metrics were examined in this study. While there are many more landscape metrics, many are redundant and many are not appropriate for this study. All
landscape metrics selected were acceptable for comparing landscapes of different sizes, which is necessary since block groups vary in area. The following landscape metrics were used:

1. Patch density (PD) is a measure of landscape diversity that indicates the number of patches in a landscape, with this number then being normalized using the area of the landscape (McGarigal et al., 2002). As a reminder, patches are contiguous areas of the same ground cover type. This metric expressed in the units number per 100 hectares. Patch density is a basic measure of how fragmented a landscape is.

2. Largest patch index (LPI) measures what percentage of area the largest patch in the landscape takes up (McGarigal et al., 2002). It is calculated by dividing the area of the largest patch by the area of the landscape and multiplying by 100. It measures how dominated the landscape is by the largest patch.

3. Mean patch size (AREA_AM) is an area-weighted mean representing average patch size in a landscape (McGarigal et al., 2002). It is measured in map units, in this case square meters. It is another measure of landscape fragmentation.

4. Patch richness density (PRD) is calculated as the number of different patch types in a landscape divided by the landscape area times 10,000 and 100 (McGarigal et al., 2002). Like patch density, it is also expressed in the units number per 100 hectares. In addition to patch richness density, two more complex landscape metrics that measure diversity will also be used.

5. and 6. The Simpson’s diversity index (SIDI) was used as well as the Simpson’s evenness index (SIEI) (McGarigal et al., 2002). The Simpson’s diversity index is generally regarded as superior to patch richness density as it less apt to be skewed by a
few rare groundcover types. Simpson’s diversity index is equivalent to the probability that two randomly selected pixels will be of different types. Simpson’s evenness index is simply Simpson’s diversity index divided by the number of different types of patches. As suggested by Yue et al., Shannon’s diversity index and Shannon’s evenness index were not used due to the number of ground cover classes being under 100 (1998). The reason for this is that Shannon’s diversity index and Shannon’s evenness index are more vulnerable to yielding inaccurate results if there are rare ground cover classes present; however this effect is mitigated as the number of ground cover classes increases. The two Simpson’s indices are less vulnerable to this bias.

7. and 8. Two additional landscape metrics were also computed at the class level: percent impervious surface and percent water resources. These variables indicate what percent of the landscape is occupied by these classes of ground cover.

**Socioeconomic and Demographic Variables**

The unit of analysis in this study was the Census block group with a sample size of n = 100. 2010 Census data are now available (also via the Florida Geographic Data Library), making this research relatively current. Block groups are ideal units of study as they are the smallest geographic subdivision for which current demographic data are readily available.

Twenty-eight socioeconomic and demographic variables were correlated with the aforementioned landscape metrics. These variables can be divided into four general
categories: age-related, ethnicity-related, economically-related, and education-related, and health-behavior-related. The age-related variables include median age as well as percentages of people in different age ranges. The ethnicity-related variables consist of percentages of different ethnic groups. Economically-related variables include variables relating to income and poverty levels.

Additionally a variable based on average expenditure on sporting goods was included. The sole education-related variable was percent of the population with a Bachelor’s degree. Many of these categories overlap to varying degrees, but by pulling them apart a more nuanced look can be obtained. These variables cast a broad net, with a great deal of data being obtained. Taken as a whole, these variables allowed for a detailed look at a wide variety of human-environment relationships from a political-ecologic perspective.

Data for 17 socio-demographic variables were obtained from the 2010 Census. Data for an additional 10 socio-demographic variables were obtained from the U.S. Census Bureau’s 2006-2010 American Community Survey. Additionally, data for one economic variable concerning expenditures on sporting goods were derived from the Bureau of Labor’s 2006 and 2007 Consumer Expenditure Surveys. All of the aforementioned variables are listed below:

**2010 Census-derived variables (17)**

PCT_WHITE - White percentage of total population  
PCT_BLACK - Black percentage of total population  
PCT_AMERI - American Indian or Alaska native percentage of total population
PCT_ASIAN - Asian percentage of total population
PCT_HAWN - Native Hawaiian and other Pacific Islander percentage of total population
PCT OTHER - Other race percentage of total population
PCT_MULTI - Percentage of total population that is two or more races
PCT_HISP - Hispanic percentage of total population
PCT_OVER18 - Percent of the population over the age of 18
PCT_VACANT - Percentage of housing units that are vacant
PCT_18_21 – Percent of population 18-21 years old
PCT_MNRTY - Percent of the minority population
MED_AGE - Median age of both sexes
PCT_25ABV - Percent of the population over the age of 25
PCT_65ABV - Percent of the population over the age of 65
AVE_HH_SZ - Average household size
AVE_FAM_SZ - Average family size

2006-2010 American Community Survey derived variables (10)
MED_INCOME - Median household income
MEDFINCOME - Median family income in the past 12 months (in 2010 inflation-adjusted dollars)
MEDOOHVAL - Median value (dollars) of owner-occupied homes
PCT_NOTWEL - Percent of population that Speaks English "not well"
PCT_NOTATA - Percent of population that Speaks English "not at all"
PCT_BACHLR - Percent of population that has a bachelor’s degree
PCT_POV - Percent below poverty

PCT_RU50 - Percent of population with ratio of income to poverty level under .50

PCT_R50_9 - Percent of population with ratio of income to poverty level from .50 to .99

PCT_R125AB - Percent of population with ratio of income to poverty level above 1.25


AVG_SPORTS - Average amount spent on sports/recreation/exercise equipment

GIS and Statistical Methods

All geographic data were projected using the Albers Conical Equal Area projection, a projection that ensures mapped area is proportional to the same area in the physical world. A projection is a means of portraying the three dimensional world on a two dimensional surface. Using a land use vector data layer published by the University of Florida GeoPlan Center and available through the FGDL, all residential and vacant residential land use types were selected. Vector data can be defined as geographic data in the form of points, polygons, or lines that represent spatial features.

This layer was then spatially joined to the Hillsborough County Census 2010 block group layers with joins occurring where at least one residential polygon was wholly contained in a block group, creating a layer of suitable block groups (Figure 5). This eliminates very irregular block groups such as the one that is equivalent to the boundaries
of MacDill Air Force Base, a critical military base which occupies the southern portion of a peninsula jutting into Tampa Bay.

Figure 6. Hillsborough County divided into block groups. Excluded block groups in black.
The aforementioned ground cover raster layer from the Florida Fish and Wildlife Conservation Commission of Hillsborough County was then clipped by the vector data layer of suitable block groups thus creating a separate raster layer for each block group (Figure 6). Clipping is a geoprocessing function that eliminates all areas in the input layer that do not overlap with the clipping layer. A random sample of 100 block groups was then created for this study.

Figure 7. Raster overlaid with block groups for clipping.
At the core of this study was FRAGSTATS 3.4, a software program developed at the University of Massachusetts that allows the user to compute various landscape metrics (McGarigal et al., 2002). Using ArcGIS these block group rasters were then converted to ASCII format, allowing them to be read by FRAGSTATS (Figure 7). For each of the 100 block groups in the sample the values for each of the landscape metric variables were then calculated using FRAGSTATS.
Figure 8. Block group raster converted to ASCII format. Each number represents a different ground cover type.

Each block group’s raster layer had an ID number that corresponded with a 2010 Census block group. Each block group’s associated socioeconomic and demographic
variables of interest were obtained and entered into SPSS along with the corresponding landscape metrics. Due to the high number of statistical tests in this study, the Bonferroni correction was applied to adjust the alpha level for determining statistical significance of correlations. The Bonferroni correction reduces the likelihood of finding statistical correlations that are due purely to chance, an occurrence that increases in likelihood as the number of statistical tests being performed increases (Field, 2009). Using the standard alpha level of .05 and given that there were 228 statistical tests conducted, the alpha level was corrected to 0.0002 (Field, 2009).

Statistical correlations were then calculated between these landscape metrics and the various socioeconomic and demographic variables associated with the Census block groups. Both Spearman’s rank correlation coefficient (Spearman’s rho, abbreviated $r_s$), and the Kendall rank correlation coefficient (Kendall’s tau, abbreviated $\tau$) were used. Spearman’s rho has been used in similar studies to identify correlations between landscape metrics and various other variables (Hardin et al., 2008; Kearns et al., 2005; Schwarz, 2010; Uuemaa et al., 2005; Uuemaa et al., 2009).

In addition to using Spearman’s rho, this study also used Kendall’s tau, which makes fewer assumptions regarding the nature of the data, making it a more accurate assessor of correlation (Howell, 1997). Preliminary analysis of the data showed that the data were not normally distributed, so Pearson’s correlation was not used. Correlations that were significant with both Spearman’s rho and Kendall’s tau were regarded as particularly important.
Chapter Four: Results and Interpretation

Results

Nineteen of the 228 tests for correlation proved to be significant with the corrected alpha level of 0.0002. All tests that were significant for Kendall’s tau were also significant for Spearman’s rho. Since Kendall’s tau is a more conservative test it is generally the case that significant Kendall’s tau correlations will also be significant Spearman’s rho correlations; however there can be occasions where this is not the case. In all cases correlations for Spearman’s rho tests were substantially stronger than for Kendall’s tau tests. Median family income and median household income were both significantly positively correlated with Simpson’s diversity index ($\tau = 0.340 / r_s = 0.494$ and $\tau = 0.319 / r_s = 0.457$ respectively), and Simpson’s evenness index ($\tau = 0.328 / r_s = 0.486$ for median family income, $\tau = 0.306 / r_s = 0.443$ for median household income), while being significantly negatively correlated with percent high impact urban ground cover ($\tau = -0.256 / r_s = -0.390$ for median family income, $\tau = -0.264 / r_s = -0.377$ for median household income). See Tables 1 and 2 for more details.

The average amount spent on sporting goods was significantly positively correlated with Simpson’s diversity index ($\tau = 0.357 / r_s = 0.511$), and Simpson’s evenness index ($\tau = 0.346 / r_s = 0.496$), while being significantly negatively correlated
with largest patch index ($\tau = -0.274 / r_s = -0.404$) and percent high impact urban ground cover ($\tau = -0.301 / r_s = -0.435$). See Tables 1 and 2 for more details.
Table 1. Economically-related Kendall's Tau Correlations. Significant correlations are highlighted in grey. Variable definitions are available in the Appendix.

<table>
<thead>
<tr>
<th></th>
<th>AVE_HH_SZ</th>
<th>AVE_FAM_SZ</th>
<th>Median_Inc</th>
<th>MEDFINCOME</th>
<th>MEDOOHVAL</th>
<th>PCT_POV</th>
<th>PCT_RU50</th>
<th>PCT_R50_9</th>
<th>PCT_R125AB</th>
<th>AVG_SPORTS</th>
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<td>-.119</td>
<td>.065</td>
<td>.088</td>
<td>.124</td>
<td>-.062</td>
<td>-.092</td>
<td>-.050</td>
<td>.063</td>
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<td>-0.235</td>
<td>-.226</td>
<td>-.21</td>
<td>.117</td>
<td>.130</td>
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<td>-.128</td>
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<td>-.051</td>
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<td>.022</td>
<td>.008</td>
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</tr>
<tr>
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<td>-.111</td>
<td>-.221</td>
<td>-.222</td>
<td>-.120</td>
<td>.145</td>
<td>.14</td>
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<td>-.152</td>
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<td>-.2</td>
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<td>.0008</td>
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<td>.0036</td>
<td>.1659</td>
<td>.0017</td>
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<td>-.264</td>
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<td>.136</td>
<td>.157</td>
<td>.083</td>
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<td>.5452</td>
<td>.0002</td>
<td>.0001</td>
<td>.0023</td>
<td>.0480</td>
<td>.0235</td>
<td>.2309</td>
<td>.0246</td>
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Table 2. Economically-related Spearman's Rho Correlations. Significant correlations are highlighted in grey. Variable definitions are available in the Appendix.

<table>
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<th></th>
<th>AVE_HH_SZ</th>
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<th>MEDOOHVAL</th>
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<th>PCT_RU50</th>
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<th>AVG_SPORTS</th>
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<tr>
<td><strong>Correlation</strong></td>
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<td>-0.184</td>
<td>0.099</td>
<td>0.128</td>
<td>0.190</td>
<td>-0.087</td>
<td>-0.127</td>
<td>-0.068</td>
<td>0.074</td>
<td>0.131</td>
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<tr>
<td><strong>Sig. (2-tailed)</strong></td>
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<td>0.0662</td>
<td>0.3278</td>
<td>0.2062</td>
<td>0.0589</td>
<td>0.3907</td>
<td>0.2088</td>
<td>0.5018</td>
<td>0.4640</td>
<td>0.1922</td>
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<td>0.113</td>
<td>-0.353</td>
<td>-0.335</td>
<td>0.312</td>
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<tr>
<td><strong>Sig. (2-tailed)</strong></td>
<td>0.4747</td>
<td>0.2609</td>
<td>0.0003</td>
<td>0.006</td>
<td>0.0016</td>
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<td>0.0481</td>
<td>0.5151</td>
<td>0.0552</td>
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<tr>
<td><strong>AREA_AM</strong></td>
<td>Correlation</td>
<td>0.188</td>
<td>0.247</td>
<td>-0.084</td>
<td>-0.073</td>
<td>-0.183</td>
<td>0.009</td>
<td>0.018</td>
<td>0.018</td>
<td>-0.003</td>
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<tr>
<td><strong>Sig. (2-tailed)</strong></td>
<td>0.0616</td>
<td>0.0131</td>
<td>0.4064</td>
<td>0.4683</td>
<td>0.0683</td>
<td>0.9270</td>
<td>0.8601</td>
<td>0.8625</td>
<td>0.9733</td>
<td>0.1967</td>
</tr>
<tr>
<td><strong>PRD</strong></td>
<td>Correlation</td>
<td>-0.307</td>
<td>-0.157</td>
<td>-0.327</td>
<td>-0.326</td>
<td>-0.155</td>
<td>0.216</td>
<td>0.217</td>
<td>0.079</td>
<td>-0.234</td>
</tr>
<tr>
<td><strong>Sig. (2-tailed)</strong></td>
<td>0.0019</td>
<td>0.195</td>
<td>0.0009</td>
<td>0.0009</td>
<td>0.1232</td>
<td>0.306</td>
<td>0.0301</td>
<td>0.4361</td>
<td>0.0192</td>
<td>0.0007</td>
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<td><strong>SIDI</strong></td>
<td>Correlation</td>
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<td>-0.103</td>
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<td>0.494</td>
<td>0.328</td>
<td>-0.259</td>
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<td>0.321</td>
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<tr>
<td><strong>Sig. (2-tailed)</strong></td>
<td>0.3942</td>
<td>0.3076</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0009</td>
<td>0.0993</td>
<td>0.0022</td>
<td>0.2035</td>
<td>0.0011</td>
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<tr>
<td><strong>SIEI</strong></td>
<td>Correlation</td>
<td>0.074</td>
<td>-0.108</td>
<td>0.443</td>
<td>0.486</td>
<td>0.325</td>
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<td><strong>Sig. (2-tailed)</strong></td>
<td>0.4631</td>
<td>0.2855</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0010</td>
<td>0.0173</td>
<td>0.0054</td>
<td>0.2579</td>
<td>0.0028</td>
<td>0.0000</td>
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<tr>
<td><strong>PCT_Impervious</strong></td>
<td>Correlation</td>
<td>-0.137</td>
<td>0.059</td>
<td>-0.377</td>
<td>-0.39</td>
<td>-0.292</td>
<td>0.189</td>
<td>0.232</td>
<td>0.109</td>
<td>-0.23</td>
</tr>
<tr>
<td><strong>Sig. (2-tailed)</strong></td>
<td>0.1737</td>
<td>0.5605</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0032</td>
<td>0.0594</td>
<td>0.0204</td>
<td>0.2821</td>
<td>0.0211</td>
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<tr>
<td><strong>PCT_Wet</strong></td>
<td>Correlation</td>
<td>-0.068</td>
<td>-0.148</td>
<td>0.244</td>
<td>0.262</td>
<td>0.182</td>
<td>-0.056</td>
<td>-0.152</td>
<td>0.038</td>
<td>0.096</td>
</tr>
<tr>
<td><strong>Sig. (2-tailed)</strong></td>
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<td>0.1410</td>
<td>0.0145</td>
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<td>0.1318</td>
<td>0.7109</td>
<td>0.3414</td>
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</table>
As far as ethnicity was concerned, correlations involving the percent white and percent black variables were nearly mirror images. Percent black was significantly positively correlated with largest patch index (τ = 0.256 / rs = 0.371) and was significantly negatively correlated with Simpson’s diversity index (τ = -0.297 / rs = -0.418) and Simpson’s evenness index (τ = -0.288 / rs = -0.410). Percent white had a negative correlation with largest patch index (τ = -0.251 / rs = -0.363) and positive correlations with the Simpson’s diversity index (τ = 0.283 / rs = 0.400) and the Simpson’s evenness index (τ = 0.278 / rs = 0.394). See Tables 3 and 4 for more details.

Percent minority was similar to percent black except with even stronger correlations with largest patch index (τ = 0.317 / rs = 0.455), Simpson’s diversity index (τ = -0.380 / rs = -0.528), and Simpson’s evenness index (τ = -0.366 / rs = -0.516); additionally there was a significant positive correlation with percent high impact urban ground cover (τ = 0.292 / rs = 0.423). See Tables 3 and 4 for more details.
Table 3. Ethnicity-related Kendall’s Tau Correlations. Significant correlations are highlighted in grey. Variable definitions are available in the Appendix.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Correlation Coefficient</th>
<th>Sig. (2-tailed)</th>
</tr>
</thead>
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<td>PD</td>
<td>Correlation Coefficient</td>
<td>Sig. (2-tailed)</td>
</tr>
<tr>
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<td>0.185 -0.188 .021 .080 -0.008 -0.007 -0.086 .032 -0.155 -0.009 -0.035</td>
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<td>-.251 0.256 -.073 -.074 .003 0.192 .123 0.216 0.317 0.085 0.011</td>
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<tr>
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<td>.000 .000 .302 .276 .973 .005 .074 .001 .0000 .222 .885</td>
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<tr>
<td>LPI</td>
<td>Correlation Coefficient</td>
<td>Sig. (2-tailed)</td>
</tr>
<tr>
<td></td>
<td>-0.178 0.178 -.022 -.056 .084 .085 .081 .080 .183 .015 -.002</td>
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<tr>
<td>AREA_AM</td>
<td>Correlation Coefficient</td>
<td>Sig. (2-tailed)</td>
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<td>.118 .109 .495 .623 .618 .015 .304 .002 .009 .149 .681</td>
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<td>PRD</td>
<td>Correlation Coefficient</td>
<td>Sig. (2-tailed)</td>
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<td>0.283 -0.297 .079 .117 .039 -0.215 -.073 -.053 -0.024 -0.38 -0.164 -0.053</td>
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<td>PCT_Impervious</td>
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<td>Sig. (2-tailed)</td>
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<td></td>
<td>.046 -.066 .042 .171 .051 -.063 .023 .004 -.069 .064 .038</td>
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<td>.508 .341 .561 .014 .525 .363 .745 .957 .320 .373 .608</td>
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Table 4. Ethnicity-related Spearman’s Rho Correlations. Significant correlations are highlighted in grey. Variable definitions are available in the Appendix.

<table>
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<th>Variable</th>
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<th>PCT_Ameri</th>
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<th>PCT_Hawn</th>
<th>PCT_Other</th>
<th>PCT_Multi</th>
<th>PCT_Hisp</th>
<th>PCT_Mnrtys</th>
<th>PCT_Notwel</th>
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No significant correlations were found involving any of the age-related or education-related variables (see Tables 5-8 for more details).

Table 5. Age-related Kendall's Tau Correlations. Variable definitions are available in the Appendix.

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Table 6. Age-related Spearman's Rho Correlations. Variable definitions are available in the Appendix.
Table 7. Education-related Kendall's Tau Correlations.  
Variable definitions are available in the Appendix.

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**Evaluating the Hypotheses**

The general hypothesis was that significant correlations would be found between at least some of the landscape metrics of the ground cover and at least some of the socio-demographic variables. This hypothesis was clearly supported by the 19 significant correlations found.

Hypothesis #1 was that different ethnic groups and social classes would live in divergent landscape types. This hypothesis was also supported to some extent. In terms of socioeconomic status, correlations between income and the landscape as well as correlations between sporting goods expenditures and the landscape lend support for this hypothesis. The correlations between the landscape and three of the ethnicity variables (percent white, percent black and percent minority) lent support for this part of the hypothesis. Significant correlations were not found for some ethnic variables, such as percent Hispanic.

Hypothesis #2 was that individuals of higher socioeconomic status would live in more diverse and even environments less dominated by a single type of ground cover. This hypothesis was also supported, as significant positive correlations were found between the variables measuring wealth and variables measuring landscape diversity.

Hypothesis #3 postulated that those of higher socioeconomic status would live in landscapes that included a greater percentage of water resources. No significant correlations were found with the percent water resource variable, meaning that this hypothesis was not supported.
Hypothesis #4 stated that correlations between percent impervious surfaces and at least some socioeconomic variables would be found. Support was also found for this hypothesis with percent impervious surface significantly correlating with median household income, median family income, average expenditure on sporting goods, and percent minority. The correlation with percent minority was positive, while the other three significant correlations were negative.

Based on these results, the following initial interpretations can be made. Incomes tend to be higher in areas with more diverse ground cover types; additionally in areas where incomes are higher landscapes (block groups) tend to have patches that are more even in size rather than being dominated by a single large patch.

A landscape’s percent impervious surface was negatively correlated with income. High impact urban ground covers include streets and parking lots; apartment complexes are often in high impact urban areas.

As one might expect, the average amount spent on sporting goods had similar correlations with the landscape as that of median income, however correlations were even stronger. Research has shown that wealthier families tend to be able spend more money on sporting goods than poorer families (Federico et al., 2009; Kirk et al., 1997; Scheerder et al., 2011). However, since the correlations between landscape diversity and amount spent on sporting goods are even stronger than the correlations between landscape diversity and median income; this suggests that those who live in more diverse landscapes tend to spend more money on sporting goods regardless of their income. It may be the case that more diverse landscapes offer a greater variety of outdoor recreation activities. If this is so, this could then translate into more money being spent on sporting
goods. Future ethnographic research in Hillsborough County could investigate whether or not this is the case.

In terms of ethnicity, minorities tend to live in areas with a similar relationship to the environment as those of lower incomes: landscapes dominated by a single larger patch, with overall lower diversity in ground cover types and a larger percentage of high impact urban ground cover. Given the negative effects of impervious surfaces on a population and the environment, this is an important discovery that will be discussed in detail below.

**Interpretation of Results**

Several interpretations of the results obtained may be made. The historical background of the Tampa Bay area may shed light on why no significant correlations were found between percent water features and socio-demographic variables. First, due to the nature of karst terrain, many water features are transient. The transient nature of Florida’s lakes and ponds is further increased by the extensive use of the Florida aquifer for agricultural, industrial, and consumer use, particularly in winter. Home locations may not necessarily be predicated on where lakes and ponds are, as these may rapidly appear or disappear.

Secondly, many of the water features in the Tampa Bay area are polluted; negating the positive attributes of living near water features (Figure 8). Some water features are of course still fairly unpolluted in appearance (Figure 9). It is likely that
enough of a balance is struck between polluted and unpolluted water features that no significant correlations were found.

Figure 9. Muscovy ducks in a retention pond experiencing an algal bloom. Algal blooms often arise from an overabundance of phosphates due to fertilizer runoff. Photograph by David Godfrey.
The theme of landscape diversity being positively correlated with income suggests that more affluent people tend to live in more ecologically diverse areas. Affluent housing developments featuring ponds, swamps, forested areas, green spaces, and so forth would rate higher in terms of landscape diversity than apartment complexes consisting largely of impervious surfaces or subdivisions consisting largely of small cinderblock homes with little ecological variety. It may also suggest that in Hillsborough County at least wealthier individuals tend to live in more suburban or rural areas featuring a greater degree of ecological variety. It should be noted that while these
correlations were statistically significant, they were not extremely strong. This is due to other factors aside from landscape type that influence where people live. Instances such as higher income individuals living in expensive upscale urban areas and lower income individuals living in inexpensive rural areas reduce the strength of these correlations.

Nevertheless, it seems evident that there is a tendency for different socioeconomic groups and ethnic groups to live in different landscapes. This hearkens back to the issue of breeder mechanisms and drifter mechanisms discussed in the literature review (Verheij et al., 1999). Do these groups tend to live in their particular environments because the environment shaped them so (breeder mechanism), or were these groups attracted or compelled to live their particular environments (selector mechanism)? Unfortunately, this study merely indicates a correlation exists, but not why.

However, given the developmental history of Hillsborough County, possible explanations can be put forth. Those of lower incomes are financially restricted to living in affordable areas. It may not be the case that poorer people consciously choose to live in areas with more impervious surfaces or with less landscape diversity; rather these areas may instead be the most affordable or nearest to place of work. Thus a drifter mechanism may be the best way to describe the human-environmental relationship in Hillsborough County. Ethnographic research in Hillsborough County could investigate why people choose to live where they do. Interview questions could be included regarding water features, impervious surfaces, and landscape diversity.

For a breeder mechanism to be at work, something about a particular landscape in Hillsborough County would have to shape people in terms of socioeconomic status. It is difficult to think of a situation in which this would be the case; however there may be at
least one scenario in which a breeder mechanism could be at work. Pollutants such as lead and arsenic are known to have negative health impacts on individuals, including developmental effects (Schell, 2010). Lead from older houses painted with lead paint or from automobile exhaust can enter the body through, orally, or dermally (Schell, 2010). Research has shown that lower income housing areas are more likely to have lead paint than higher income housing areas (Jacobs et al., 2002; Tong et al., 1996). The negative health effects of pollutants can be life-long. Pollutants are not always physical materials; light and noise pollution may also be considered (Schell, 2010). Individuals who are living in a landscape with higher levels of pollutants and who are suffering from the negative health effects would be more disadvantaged and subsequently potentially have lower socioeconomic status (Brooks-Gunn and Duncan, 1997; Needleman et al., 1990; Tong et al., 1996). It may be possible that certain landscape types are more amenable to the buildup of pollutants. Areas with impervious surfaces are often such a place; these areas are typically urban, have poor drainage, and experience more engine exhaust (Barnes et al., 2000). These environmental stressors may be linked to epigenetic changes that are passed down from generation to generation; these epigenetic changes may in turn be related to poor health (Wells, 2010).

Future studies investigating pollutant levels in different landscapes could be conducted in Hillsborough County to shed more light on this issue. Such a study might not be so different from this one, as it would likely include finding correlations between different landscape metrics and pollutant levels. Such a study would probably fall more within the purview of environmental science, as expertise would be required in proper sampling of pollutant levels. This aforementioned scenario is a possible way in which a
breeder mechanism could be in effect as far as determining who lives where; however in general it seems most reasonable to assume that individuals live in a given environment out of choice or necessity via the selector mechanism.

The correlations found between percent impervious surfaces and several socio-demographic variables (median household and median family income, amount spent on sporting goods, and percent minority) lend support to previous studies. The results of this study suggest that in Hillsborough County lower income individuals may be more likely to live in areas with more impervious surfaces such as apartment complexes, while higher income individuals may be more likely to live in areas with less impervious surfaces and a more ecologically diverse setting. Similar correlations were found between percent impervious surfaces and income and percent impervious surfaces and percent minority.

The correlation between percent impervious surfaces and amount spent on sporting goods was also very interesting. There are a number of sports that are played on impervious surfaces; popular outdoor examples include street hockey, basketball, and tennis. Buildings can also be impervious surfaces so therefore virtually any indoor sport may be played on impervious surfaces. With a large number of popular sports being played on impervious surfaces, why is there a negative correlation between percent impervious surfaces and amount spent on sporting goods?

There are a number of reasons for why this may be the case. First of all, costs for different types of sports can vary considerably. Boats and fishing gear cost significantly more than a basketball. It may be the case that sporting goods used on impervious surfaces are on average less expensive than those used on other types of surfaces.
Another possible explanation is that correlation may simply be due to higher income people tending to live where impervious surface percentage is lower. People with higher incomes have more money to spend on sporting goods as well as on other leisure items. Even within the same sport, an individual with higher income would be able to afford higher quality and more expensive items than an individual with lower income (Federico et al., 2009; Kirk et al., 1997; Scheerder et al., 2011).

Another unfortunate possibility is that individuals living in areas with more impervious surfaces are simply less involved in recreation activities. These individuals may have less leisure time or fewer accessible recreation facilities for participating in sports. Ethnographic research in Hillsborough County could examine if this is the case.

It should be mentioned that people do not necessarily always use recreational facilities in their own block group. For instance, there are few ice rinks in Hillsborough County, so individuals have to travel from all over the county to be able to play ice hockey or to go ice-skating. By the same token, individuals may not necessarily want to or be able to use recreational facilities located in their block group. This makes the second and third explanations that were previously mentioned previously stronger arguments than the first explanation. In all likelihood, the correlation probably exists due to some or all of these explanations. Ethnographic research could be conducted on this topic in order better determine the relationship between landscape and sporting goods expenditures with the aforementioned possible explanations as guides for writing interview questions.

It should be noted that no significant correlations were found for any of the age-related variables (percent over 18, percent 18-21, median age, percent above 25, percent
above 65) or the one education-related variable (percent of population with bachelor’s degree). The reason no significant correlations were found for age may be fairly easily explained, as every ethnic group and socioeconomic group has members of all ages. For instance, while there may be many very wealthy elderly people in Hillsborough County, there are a sufficient number of very poor elderly people in Hillsborough County as well.

What about the lack of significant correlations between the landscape metric variables and the percent bachelor’s degree variable (Tables 7 and 8)? One explanation may be that due to the presence of the very large University of South Florida as well as other smaller colleges and universities in Hillsborough County bachelor’s degrees are common across many ethnic and socioeconomic groups. Whether someone has a bachelor’s degree or not is very vague, as a wide variety of bachelor’s degrees exist. In general, holders of bachelor’s degrees must not have a particular affinity for certain landscapes, nor are they compelled to live in certain landscapes for financial or other reasons. It would be interesting to see if this lack of significant correlations was true for more advanced degrees.

In general, correlations between landscape metrics and socio-demographic variables were not particularly strong. The three strongest correlations found were between percent minority and Simpson’s diversity index ($\tau = -0.380 / r_s = -0.528$), percent minority and Simpson’s evenness index ($\tau = -0.366 / r_s = -0.516$), and average expenditure on sporting goods and the Simpson’s diversity index ($\tau = 0.357 / r_s = 0.511$). While landscape type may play some role in where people live, there are of course other factors. For instance, as mentioned in the literature review, the City of Tampa continues to be somewhat segregated (Stretesky and Lynch, 2002; Taylor and Fry, 2012). Many
individuals may wish to continue to live in the same area partly due to the social capital accumulated in their neighborhood in the form of friends and family (Greenbaum et al., 2008). Social capital is derived from the network of relationships upon which people rely for support. As Greenbaum et al. found in Tampa, it is more advantageous to improve existing communities than to disperse residents amongst several other communities (2008). This study suggests one way in which this may be done.

However, it seems to be the case that for whatever reason, these areas tend to share certain landscape types. The validity of these correlations is enhanced by the Bonferroni-corrected alpha levels, which makes it much less likely that these correlations are entirely due to chance. While in some cases the manifestations of what different landscape types look like is not noticeable to someone standing on the ground, in many cases it is. For instance, a landscape with a high percentage of impervious surfaces looks very different than one with a low percentage of impervious surfaces. People are therefore apt to be aware of what kind of landscape they are living in or potentially deciding to live in, at least to a certain extent.

In summary, 19 statistically significant correlations were found, with these correlations involving economic, ethnic, and health-related variables. In general, as percent minority increases, median incomes decrease, and sporting goods expenditures decrease, landscapes become less ecologically diverse and have a greater percent of impervious surfaces.
Chapter Five: Critique, Applications and Conclusion

Critique of Method

This study is not without limitations, most of which are common to many GIS-based studies. Chief among these is the modifiable areal unit problem (MAUP) (Wong, 2008). The block groups divide the county up into a number of different polygons. The data aggregated within each block group depends on how the block group boundary is drawn; as each boundary is moved the data within are changed, sometimes dramatically. The political practice of gerrymandering is an instance in which the MAUP is manipulated for political gain. In gerrymandering, a political party redraws the boundaries of electoral districts so as to enhance party strength by concentrating supporters in certain districts or by dispersing rival parties’ supporters amongst several electoral districts. Florida’s 3rd congressional district was until 2013 one infamous example of a gerrymandered congressional district. The long snake-like district meandered through several counties and urban centers in order to gather together the desired constituency (Figure 10) (Mixon and Upadhyaya, 1997). Similarly researchers could draw boundaries for study areas in such a way as to increase chances of producing the kind of results they would like to see. Drawing boundaries for study areas can be an ethical quandary.
Figure 11. Florida 3rd congressional district outlined in red.

Ways in which to minimize the effect of the MAUP include repeating studies at different scales and in different locations. If a pattern holds true at different scales then more trust may be put in its accuracy. Similarly, some patterns may be tested for existence in different areas; if the same pattern continues to emerge in various geographic locations or using different aggregations of data more credence can be given to the pattern (Wong, 2008). Researchers must remain mindful of the MAUP, allowing it to contextualize the results of their studies. Additionally it is best to use data aggregated at
the finest grain that is practical. In this case, the census block group was the smallest socio-demographic unit for which quality data were readily available.

Closely related to the MAUP is the issue of ecological fallacy (Wong, 2008). Aggregated data speak for the population as a whole, not for individuals. For instance, a few very wealthy individuals may live in a very poor block group. The correlations found in this study are merely tendencies found in the population. The ecological fallacy should always be kept in mind when interpreting results of GIS-based studies. One cannot make assumptions about an individual based on the population.

As with any study, the findings from this study are only as strong as the data on which they are based. In this study, data from several local, state, and federal agencies were integrated. As the data are secondary data, one cannot be completely sure of their reliability. Researchers must strive to use the best data available; additionally as better data become available studies should be repeated to see if different results are found.

Since this study relied heavily on U.S. Census data, many of the critiques of the U.S. Census Bureau’s methods are also applicable here (Driscoll-Derickson, 2009; Alexander et al., 2010; Schwede, 2010; Swanson and Walashek, 2011). One of the main criticisms leveled against the U.S. Census Bureau is regarding their view of race and ethnicity (Baer et al., 2012; Lee et al., 2001; Griffith et al., 2011). The U.S. Census groups people into a few categories that are based on a few phenotypic or geographic traits under the assumption that these traits are proxies for distinct populations. For instance, those who are from or whose ancestors are from Asia are all lumped into the same category, despite the world’s largest continent possessing a great deal of cultural and genetic diversity.
Africa is treated similarly, despite Africa possessing the greatest amount of genetic diversity of any continent and similarly possessing significant cultural diversity (Campbell and Tishkoff, 2008). Those who are of African ancestry that are the descendants of slaves are also not distinguished from those who have arrived from Africa much more recently despite also possessing significant genetic and cultural differences (Madrigal and Barbujani, 2007; Tishkoff et al., 2009). The continents do not exist in isolation; there has been significant gene flow and cultural exchange between the continents making them unsuitable as a means of apportioning human diversity (Madrigal and Barbujani, 2007). One of the many uses of the U.S. Census dataset is for drawing the boundaries of electoral districts. Gerrymandering politicians often seek to draw electoral districts along ethnic boundaries that are most apt to favor themselves. It is unfortunate that what could be and still is a very valuable source of data is somewhat tainted by ulterior motives of a political nature.

It is hoped that the U.S. Census Bureau will amend its methods in order to better study human diversity; it would be interesting to see how any changes made might affect the results of this study if it were to be repeated. While there are some indications that changes are afoot in the U.S. Census’ methods (Dade, 2012), the issue is highly political and therefore unpredictable.

However, these limitations should not discourage the use of GIS in scientific research; GIS methods and their results just need to be critically examined. GIS is a powerful tool that allows for time-efficient and cost-efficient analysis of spatial data. In many cases, as in this study, GIS allows for analyses that simply would not be possible any other way. Another advantage of this method is that it can be deployed remotely.
Researchers hoping to work in a distant location could use this method as part of their preliminary research, saving more time at the research site for tasks that require physical presence. In a time when budgets are being cut and results are expected quickly, GIS methods can allow researchers budgeting time and money to use both more efficiently (Hardin et al., 2008; Knigge and Cope, 2006).

This study was conducted using data and software available for free to university faculty and students and in some cases available for free to the general public. This particular method can effectively identify correlations or the lack thereof which can then be used to help create research questions for further interviews, focus groups, surveys and other research methods. It is an exploratory method, and as such it generates more questions than it answers.

Applications

Local knowledge regarding human-environment interactions may be one useful reservoir of information that can be accessed to enhance the applicability of the study results. Anthropologists could use the results of this or similar exploratory studies to frame questions and stimulate discussions with local residents regarding these interactions. Political ecology suggests that human interactions with the environment, including how people are arranged in an environment, are politically influenced. This study examines politically significant human variables, such as age, ethnicity, and wealth,
and how they relate to the environment. The environment has been operationalized and quantified in the form of landscape metrics.

Existing literature regarding studies in Hillsborough County and elsewhere support many of the findings in this study. For instance, areas that have higher percentages of impervious surfaces were in fact positively correlated with areas that have higher percentages of lower income individuals, a finding consistent with those obtained by Jenerette et al. (2007), Luck et al. (2009), and Huang et al. (2011). Studies conducted in the Tampa Bay area such as Landry and Chakraborty (2009), Foster (2010), Zarger et al. (2010), Larsen and Zarger (2012), lend quantitative and qualitative support for there being important connections between local residents and their environment, with people being alarmed by degradation of their surroundings. Thus the findings of this study and studies building upon this study may be able to have useful real world applications.

The results of this study can have at least two different applications. First, the results of the analysis and their interpretation can shed light on how municipal planners in Hillsborough County can design new communities or improve existing ones. This study demonstrates what types of landscape may be more desirable; municipal planners can then consider if they wish to apply these landscape types to more communities. Anthropologists could also consult residents of these areas to determine if suggested changes were indeed desired. Of course correlation is not causation. This method alone could not determine whether the poor live in areas with low patch richness density because they are poor or that they are poor because they live in low patch richness density areas. Additionally, the statistically significant correlation between these variables could be a red herring, with some other factor being the cause. The natural
environment is an open system, making controlled experiments difficult and often unethical to conduct. However further research using various other methods could help determine the cause of the correlation and whether or not it is important. Poverty is of course a multi-faceted issue and therefore improved landscape designs alone are not sufficient to solve this complex problem.

Second, this study demonstrates a method that could be applied to other locales at the same scale. The significant correlations for Hillsborough County, Florida would not necessarily hold true for Hillsborough County, New Hampshire due to differing ecologies. However, the method may be able to determine the significant correlations particular to Hillsborough County, New Hampshire, which could then be further studied and the results used to inform decisions there. This method could be applied virtually to any residential area in the world, assuming appropriate census and ground cover data are available.

I will now discuss more specifically potential applications for each of the findings of this study. In terms of water resources, no significant correlations were found. This may be due the transient nature of Florida water resources due to the karst terrain and over-pumping of the Florida Aquifer. It may also be due to a sufficient amount of water features being too polluted or poorly managed to be considered attractive assets. Either way, the importance of water management and sound water policy is evident. Cleaning up Hillsborough County’s water resources would do much to improve both their aesthetic appearance and their ecological health. Future studies should consider water resource quality; for instance many aesthetically unappealing retention ponds littered with trash can be seen while driving around Hillsborough County.
What applications do the correlations between landscape diversity and indicators of wealth have? The answer to the poverty issue is not simply to plant more trees and create some ponds and wetlands in poorer neighborhoods. Poverty is a complex condition that stands at the confluence of many different factors. However, there is the potential that certain landscape types may be more polluted than others. The negative health effects of pollution present obstacles for those living in poverty. Of course the negative health effects of pollution are not pleasant for anyone, regardless of their socio-demographic profile. It would be ideal to improve everyone’s quality of life, regardless of who they are. Further studies identifying landscape types that tend to have higher levels of pollution could allow municipal planners the ability to minimize the creation of these landscapes or to replace existing unhealthy landscapes with more healthful alternatives.

Applications based on the findings regarding impervious surfaces are similar. This study supports the general consensus in the scientific community that artificial impervious surfaces have a negative impact on the environment, including the people living in it (Jenerette et al. 2007; Rosenthal, 2010; Gabriel and Endlicher, 2011; Huang et al., 2011). Construction and remodeling efforts in Hillsborough County and elsewhere should make every effort to replace impervious surfaces with pervious alternatives, of which there are a number.

Further research should also be conducted to investigate the accessibility of recreational facilities for those living in areas with a higher percentage of impervious surfaces. If accessibility is poor, efforts could be made to create recreation facilities in these areas. A longitudinal study investigating how these efforts affected the amount of money spent on sporting goods would be an excellent endeavor.
Modified versions of this method could also be deployed in other ways. For instance it would be very interesting to investigate if this method can identify significant correlations at other scale levels, such as comparing entire counties or states (or similar administrative divisions in other countries) instead of the relatively small block groups. Studies such as those by Griffith et al. (2000) suggest that some landscape metrics may actually remain fairly consistent at various scales.

One could also search for significant correlations between landscape metrics and other issues with a spatial dimension using this same method. For instance, this method could be applied to malaria, dengue fever, and other health problems that have an ecological dimension. For instance, landscape configurations particularly amenable to malaria transmission could potentially be identified.

Lastly, while this study is cross-sectional, one could conduct a similar study longitudinally by seeing if changes in different landscape metrics are correlated with changes in different human variables. Computers and GIS technology have only recently become powerful enough to conduct studies such as this. There are many different applications for this technology yet to be explored. It is an exciting time to be on the frontier of science and technology.

Conclusion

This study demonstrates an exploratory method for identifying correlations between landscape configuration and assorted socio-demographic variables. While the
results can be interpreted based on current scholarly literature, a more thorough investigation in Hillsborough County using other methods would shed more light on the correlations, particularly regarding causation. Traditional anthropological methods like ethnography could be employed to parse out these relationships, with researchers living in different landscape configurations and interviewing residents regarding their relationship with the landscape.

Nevertheless, this exploratory method offers a time and cost-efficient way of identifying potential human-environmental relationships. It has the benefit of being readily applicable to a variety of places, as human-environment relationships are apt to vary from place to place. The correlations found in this study are not likely to be universal; this method must be redeployed in each locale of interest. This method can also be adapted to investigate other types of human-environment relationships aside from those between socio-demographic variables and landscape configuration variables.

Lastly, this study also contributed to the body of literature regarding the effects of impervious surfaces on humans. The findings of this study corroborate findings from earlier studies that suggest that in general, impervious surfaces have a negative impact upon the landscape, including the people living in it. Municipal planners and developers should take this into account when designing new communities or developments or when revitalizing old ones (Arnold and Gibbons, 1996; Tennis et al., 2004).

Advances in technology have allowed architects and city planners to reduce the percentage of impervious surfaces in a landscape. For instance, rooftop gardens can transform a building from an impervious surface to a pervious surface. Likewise, the invention of various types of permeable pavement has allowed certain sidewalks, parking
lots, and roads to not be considered impervious surfaces, as water is able to flow through the pavement to the soil below. These technologies may help mitigate some of the ill effects of impervious surfaces. In conclusion, it is hoped that this study will facilitate the advancement of the understanding of how humans interact with their planet.
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