URBAN PATTERNS AND FLOOD DAMAGE IN TEXAS COASTAL WATERSHEDS

A Dissertation

by

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ABSTRACT

This study develops a framework to conceptualize and measure multiple urban patterns and examines their relationship with flood damage in Texas coastal watersheds. Development and flood damage impacts are analyzed over a ten year period in 916 watersheds that overlap Texas' 41 coastal watershed counties using the USGS National Hydrography Dataset. A cross sectional time series regression model is used to determine how changes in these patterns influence the amount of flood damage that occurs in the study area.

Results from the study provide clarity on how different dimensions of urbanization are related to flood damage. Using six landscape metric measurements for three different levels of urban land cover and two measures of residential property location in relation to the rest of the watershed, regression analyses conclude that most urban pattern metrics are significant in influencing the degree of flood damage at a watershed scale. Specifically, increases in percentage of impervious surface increases flood damage, as do most other metrics as they pertain to expansiveness of impervious surface across the landscape. Two metrics (Mean Shape and Average Distance of Residential Property to Water) did not behave as hypothesized; it is believed that mean patch shape was incorrectly hypothesized, and the metric representing average distance to water was measured inappropriately.

The results of the models and the significance and direction of the independent and control variables all provide evidence of the need to take urban form and environmental factors into consideration and an ecosystem-based approach should be taken when engaging in policy and planning activities to reduce residential property damage from flood events.

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1. INTRODUCTION

1.1. The Problem

Floods are one of the most expensive and lethal hazards in the United States (U.S.), and the impact they have on the economy and society indicates a lack of progress in determining where and how humans choose to live and place property. From 1996 to 2007, flooding caused almost $2 billion damage annually to insured residential properties in the U.S. (Brody, Peacock and Gunn 2012) and 987 people were killed (National Weather Service 2016). In Texas, higher amounts of flood damage were recorded than in any other U.S. state partly because of the frequency and intensity of flooding along the Texas coast (Zahran et al. 2009). Also, Texas has consistently ranked as the state with the highest number of flood fatalities annually and has the highest total number of flood fatalities from 1959 to 2005 (Ashley and Ashley 2008). The damage due to flooding along the Texas coast necessitates further investigation into how development decisions contribute to flood damage.

The rapid development that has occurred in coastal areas over the past 40 years has led to increased levels of flood damage due to placement of property in flood-prone areas and alterations to natural hydrology. The human population in U.S. coastal counties increased by 34.8 million people (39 percent) from 1970 to 2010, and is projected to increase by another 10 million people by 2020 (Crossett et al. 2013). Currently, 23 of the 25 most populated counties in the U.S. are found in coastal areas (Crosset 2005). In Texas, the population found within coastal counties doubled to over 6 million people from 1970 to 2010, and this same region is projected to exceed 7 million people by 2020 (Crossett et al. 2013). To accommodate this growth, a large number of homes have and will be built along the coast. Approximately 65,000 building permits for residential properties were issued annually in coastal parts of Texas between 1999 and 2003 (Crosset 2005). The rapid rate of expected growth coupled with the historical flood losses observed along the Texas coast indicates that flood damage can be expected to increase if current trends in construction remain unchanged. To prevent future flood losses, a better understanding of how urban development patterns are related to flood damage within coastal watersheds is needed.

Flooding is a function of how much water enters a landscape area relative to how efficient the landscape is at either storing or releasing the water. Factors that determine efficiency include topography, soil type, land cover type, and other natural landscape features. When more water enters a landscape area than the landscape can store or release, flooding occurs. Smith and Ward (1998) identify four different ways flooding can occur from a landscape perspective: Flooding due to poor drainage of the landscape area (low relief), overspill from small streams/artificial channels into adjacent areas, large rivers flooding into adjacent floodplains, and coastal flooding (storm surge, extreme high tides, and deltaic flooding) (Smith and Ward 1998, Douglas et al. 2008).

Regardless of the type of flood, if lives and property are located in landscape areas prone to flooding, flood damage can occur. While the risks and costs associated with flooding may or may not be known by those that live in flood-prone areas (Kreibich et al. 2005), the economic and social benefits of living in the flood plain have long since been realized (White 1937), and these benefits precipitate the development of residential homes so people can live in the areas where they work and play (Burton, Kates and White 1968).

Despite all evidence that living in flood-prone areas can cause damage to lives and property, human occupancy in flood prone areas continues because perceived benefits outweigh the perceived risks (Loucks and Stedinger 2007). Riverine and coastal areas provide access to food, water and transportation that has sustained both small communities as well as large regions that depend on these resources to support agriculture and manufacturing industries. In all likelihood, people will continue to inhabit flood prone areas for the foreseeable future and flood reduction strategies will have to be employed to mitigate damage. A better understanding of how different urban development patterns influence flood damage can guide future planning efforts that allows the benefits of living near these areas to be maintained while simultaneously reducing risks from flooding and flood damage.

1.2. Research Purpose and Objectives

Different fields of research have approached the problem of flooding and flood damage differently. Some approach the problem by attempting to clarify how natural and man-made features influence flood variables like height, volume and rate of change; while others approach the problem by analyzing how land use and policy decisions influence flood damage. There are potential gaps in both these methods because land use decisions influence both flooding and flood damage, and identifying how urban development patterns are related to both can be difficult to conceptualize and measure when conducting analyses.

This dissertation provides a review of the literature on how urbanization influences flooding and flood damage, and presents a research methodology guided by the literature that utilizes landscape ecology methods to better understand how different dimensions of urbanization influence flood damage in Texas coastal watersheds. A suite of "urban pattern metrics" are applied to conceptualize several different aspects of urbanization and are incorporated in 18 regression analyses to identify how each metric is related to flood damage. Results of the regression analyses provide a better understanding of the numerous ways urbanization has modified the Texas Coast, provides evidence for differentiating between urban land cover and urban land use when considering how development is related to socio-ecological processes, and estimates the contribution of different dimensions of urban development to flood damage in Texas coastal watersheds.

From a spatial perspective, the field of landscape ecology provides a robust number of metrics that can successfully measure dimensions of urban patterns as well as other environmental variables that influence flooding; including land cover, land use, precipitation, soil characteristics, basin morphometry, and many others (Leitão et al. 2006). Many of these variables are utilized to gain a better understanding of how urbanization influences the socio-ecological process that results in flood damage.

There are two ways urban patterns can influence flood damage; indirectly through the alteration of hydrology, and directly through the placement of lives and property in flood-prone areas. To date, there has been little to no research conducted that operationalizes these dimensions of urbanization and estimates their respective contributions to flood damage. By utilizing existing urban pattern metrics identified in the literature, as well as developing new ones, this study answers the research question, "How are urban patterns related to flood damage in Texas coastal watersheds?"

1.3. Dissertation Structure

This dissertation is structured in the following manner. This first section provides an introduction to the issue of flooding in the U.S. The second section provides a review of the literature as it relates to studies that have analyzed how different aspects of urbanization are related to flooding and flood damage; how urbanization has been conceptualized and quantified spatially; and a brief introduction to landscape ecology and spatial analysis with a specific overview of several landscape metrics that have been applied to urban landscape measurement as it relates to flood damage. The third section provides an overview of the research framework, which includes the conceptual model, overview of dependent, independent and control variables, and presents the research hypotheses. The fourth section presents the research methodology, which includes information on the study area and sample selection, how variables were conceptualized and measured, model selection and diagnostics, and known validity threats. Section five presents the results from the regression analyses and provides a summary of how the variables behaved compared how they were hypothesized, and presents four example watersheds in the study period to compare and contrast specific urban pattern metrics and their change over time. The sixth section provides a discussion of the results, comparisons across models, and implications for policy, planning, and the application of the results that support environmental literacy efforts. Finally, the last section of the dissertation provides concluding thoughts and suggestions for future research.

2. LITERATURE REVIEW

Due to the interdisciplinary nature of this study, a thorough review of the literature on how urbanization is related to flooding and flood damage is presented, pulling from several different fields of study and ranges from theory and research that focus on imperviousness and hydrology, to how urban patterns have been measured and correlated to social and ecological processes. Additionally, this review provides a brief overview of several metrics that may be useful at capturing different dimensions of urbanization that are related to flooding and flood damage. The first section focuses on literature from diverse fields of study that have sought to identify how urbanization is related to flooding and flood damage. This includes studies that focus on how impervious surface and stormwater management are related to flooding from a hydrologic modelling perspective, as well as several fields related to urban studies (economics, planning, natural hazards, etc.) that have provided a diversity of studies that look at the spectrum of how and why people live in flood-prone areas, as well as the various consequences of living in these areas.

Next, this literature review discusses how urban patterns have been conceptualized, operationalized, and categorized in the recent urban studies and landscape ecology literature. The multiple studies from various fields also provide an excellent overview of the different definitions of urbanization, as well as specific aspects of it (specifically, the concept of sprawl).

Finally, this review describes several landscape and spatial metrics that have the potential to effectively measure aspects of urbanization that are related to flooding and flood damage. Few of these have been utilized for the purposes of measuring urbanization as a land cover, and fewer still have been used to directly analyze the relationship between urbanization and flood damage.

2.1. Influence of Urbanization on Flooding and Flood Damage

Different aspects of urbanization can influence both flooding and flood damage. This section provides a review of the literature on how 1) flooding and flood damage have been defined, 2) urbanization has influenced flooding, and 3) urbanization has influenced flood damage. For the purposes of this section, urbanization has been broadly defined as not only the land cover or land use, but also as policies and strategies that may guide land cover and land use conditions (planning, insurance schemes, low impact development and smart growth techniques, etc.). A more detailed review of how urbanization has been defined in terms of its operationalization, measurement, and classification can be found in the next section of this literature review.

2.1.1. Defining Flooding and Flood Damage

From a landscape ecology perspective, flooding is a natural phenomenon influenced by topographical, climatic, and other environmental variables, and only results in damage when humans attempt to occupy areas prone to flooding (White 1937, Mileti 1999). While flooding can be quantified by height, volume, rate, and other measurements, flood damage can be calculated in terms of costs and is often quantified in terms of lives lost and damage to property. Costs can also include monetary and non-monetary damages that are the result of both direct and indirect impacts (Smith and Ward 1998, Gall, Borden and Cutter 2009).

It is challenging to identify precisely how human occupancy of flood-prone areas is related to flood damage because methods quantifying flooding are not standardized. This is due to the fact that "flooding" can be measured and defined differently depending on context (Pielke 1999). For example, flooding, flood risk, and flood damage have different meanings in different fields of study, and policy or decision-makers may use these terms differently than scientists. Green, Tunstall, and Fordham (1991) examined groups of engineers, planners, citizens, and researchers to identify whether there was a significant difference in their perception of flood risk. The authors concluded that there is a significant difference in the colloquial definition of terms among the groups, which can be problematic when collaboration and transfer of information is required to identify flood problems and develop solutions.

Flooding in terms of hydrologic response can be measured numerous ways; including flood volume and rate, frequency of events, efficiency of the watershed to move stormwater downstream, how quickly a hydrologic system can fill with water, and numerous other measurements. In their review of the literature, Olden and Poff (2003) examined flood variables used in 20 different studies and found there were only four principal components of the 171 variables that accounted for 75% of the variability. This indicates that even though there are numerous different ways to measure flooding, there are only a few key measurements that effectively represent what exactly a flood is.

Flood damage can be more difficult to define than flooding, as there are numerous ways flooding can impact human lives and property. Monetary costs can include direct damage to property, and non-monetary costs may include how the health of individuals is impacted by a flood (both mental and physical health), as well as loss of non-monetary goods like memorabilia (Green and Penning-Roswell 1989). Additionally, direct and indirect costs can be both economic and non-economic; indirect monetary costs could include the cost to evacuate a storm and stay at a hotel, to the loss of income from not being able to return to work after a storm (Gall et al. 2009). Indirect non-monetary costs can include the long-term emotional impacts caused by the experience (Green and Penning-Roswell 1989).

2.1.2. Urbanization and Flooding Studies

Impervious Surface

Impervious surface can influence different measures of flooding, including the magnitude, frequency, duration, timing, and rate of change (Richter et al. 1996). Additionally, patterns of impervious surface relative to the watershed landscape and hydrologic features can exacerbate or ameliorate flooding, and are dependent on spatial factors like how far upland the impervious surface is, or whether or not the impervious surface is directly connected to hydrologic channels (Jacobson 2011). Channelization can simultaneously reduce flooding for adjacent properties while increasing downstream flooding (White 2008). Shallow, small-scale channelization like neighborhood stormwater ditches can quickly exceed their capacity during extreme or long periods of rainfall, or when they are not properly maintained (Smith and Ward 1998, Center for Neighborhood Technology 2013). Flood control structures like dams, dikes, and levees can reduce flood damage, but run the risk of having additional lives and property placed in flood-prone areas in the event these devices fail or encounter a rainfall event beyond the level anticipated and incorporated in to the design (Burby et al. 1999, Brody, Highfield and Kang 2011).

The effects of urbanization on flood pulses have been understood for quite some time. Urbanization of catchments can result in increased flood peaks and decreased lag time to reach those peaks (Leopold 1968, Seaburn 1969). Urbanization can result in hydrologic alteration by increasing amounts of impervious surface (Shuster et al. 2005, Jacobson 2011) inadvertently fragmenting hydrologic networks by placing patchy development outside of urban areas (Brody, Carrasco and Highfield 2006), or through the use of purposeful and engineered structures (Hopkinson and Day 1980).

When landscapes become urbanized, pervious natural areas are replaced with impervious ones (Shuster et al. 2005). The two most significant ways impervious surfaces influence flooding is through decreasing infiltration rates and increasing surface runoff (Ogden et al. 2011). Increases in impervious surface are also related to decreased levels of rainfall infiltration into the soil (Dunne and Leopold 1978, White and Greer 2006) as well as increased surface runoff rates from the lower frictional resistance compared to natural landscapes (Paul and Meyer 2001, Kousky and Zeckhauser 2006). These changes have the potential to increase peak discharge levels (Brezonik and Stadelmann 2002) as well as cause peak discharge points to be reached more rapidly (Hirsch et al. 1990).

The impacts of urbanization on landscapes can be very significant as modifications to hydrology are made to support population growth. Zhang and Wang (2007) studied a heavily urbanizing 3800 square kilometer area in China and found that between 1988 and 2003, almost 58% of the water area had been converted to other land use types and almost 43% of other land use types had been converted to water, indicating significant modifications to the hydrology of the region.

Different patterns of impervious surface can influence hydrologic parameters differently. The total impervious area (TIA) of a catchment has been found to influence hydrology differently than the effective impervious area (EIA) or the directly connected impervious area (DCIA) (Alberti et al. 2007). Lee and Heaney (2003) compared total imperviousness and DCIA to flood variables in a small basin using data over a 52 year period. They found that even though DCIA only accounted for 44% of the land cover for the site, it contributed to 72% of the total runoff over the 52 year period. In almost 57% of the rainfall events, DCIA was the singular source of runoff, meaning that during the smaller storms, the landscape was able to adequately handle precipitation by allowing it to infiltrate into the soil, be stored as surface water, or evaporate.

Hood, Clausen, and Warner (2007) examined how low impact development (LID) strategies can reduce flooding when compared to traditional residential development. They defined LID as development that allows soil infiltration to occur, as opposed to traditional strategies where the goal is to move stormwater rapidly away from a site. Hood and colleagues also found that LID strategies reduced overall peak flows, as lengthened the time it took to reach peak flows. However, the impact LID had on peak flows was greatly diminished during extreme events (rainfall over 25 mm or an event lasting longer than four hours), but was still found to be more efficient at ameliorating flooding when compared to traditional development.

There are other studies that signify the complexity of measuring the relationship between impervious surface and flood regimes. Rose and Peters (2001) compared flooding in watersheds that had varying levels of urbanization and discovered that topography played a much more significant role in determining runoff coefficients than impervious surface. They also found that watersheds with higher elevations and higher reliefs had higher runoff coefficients than lower watersheds with lower reliefs. Additionally, runoff coefficients did not vary significantly among watersheds of varying urbanization. However, they did find that for the largest streamflow events, peak flows were 30% - 100% higher in urbanized watersheds when compared to less-urbanized watersheds, and the stormwater receded between one and two days quicker in urbanized watersheds when compared to less-urbanized watersheds (Rose and Peters 2001). Saghafian and colleagues (2008) found that there are hydrologically significant areas in watersheds such as upland subwatersheds and hillslopes where land use changes influence hydrology more than others, which indicates that watersheds with the same amount of impervious surface located in different areas will influence hydrology differently.

Stormwater Management

Increases in the size of urban areas result in increased levels of stormwater runoff (Arnold and Gibbons 1996). Anthropogenic modification of topography can be used to construct simple artificial waterways like ditches, canals and channels; or can create complex and elaborate stormwater conveyance systems that mimic natural hydrologic features like lakes and wetland networks. Channelization can be used to quickly move large amounts of stormwater downstream until it connects with streams or rivers, but may result in overall increases in downstream flooding (Rose and Peters 2001). More sophisticated stormwater conveyance systems can also be used to divert water into natural landscape areas that either trap or store and slowly release water so it does not contribute to downstream flooding, but these systems may be limited in the amount of water they are able to effectively divert (Cohen and Brown 2007). However, it is important to understand how both of these methods regulate flooding in context with the urban pattern metrics that are utilized in this study.

Anthropogenic channelization represents one way humans modify the topography of a watershed. Graf (1977) identified the creation of artificial drainage as an important factor to consider beyond impervious surface when looking at how urbanization influences surface runoff and downstream flooding. Artificial drainage channels are oftentimes created to manage the incredible amount of stormwater runoff that is generated in urban areas (White 2008). Channelization within a watershed is often characterized as drainage density, which is the ratio of length of streams to the area of the catchment (Paul and Meyer 2001). Similar to impervious surface area, drainage density may also influence flooding at different scales. While the use of artificial drainage may reduce flooding in some urban areas by quickly moving stormwater downstream, it may also contribute to flooding in areas farther down the watershed (Meyer et al. 2001).

Anthropogenic channelization and impervious surface area have been linked to changing flood regimes. Ogden and colleagues (2011) examined an urbanized catchment near Baltimore, Maryland to understand how urbanization variables like drainage density and impervious surface were related to flood peaks, runoff volumes, and runoff efficiency. They concluded that increased drainage density significantly increased peak discharges. Also, they found that peak flows are highly sensitive to rainfall rates in watersheds with high levels of imperviousness.

More complex stormwater management systems can mimic natural hydrologic features for the purpose of storing and regulating the release of stormwater back into the natural hydrology of a watershed. This can include retention or detention basins that behave similar to small lakes or ponds, as well as distributed stormwater conveyance systems that function similar to wetland networks. Constructed stormwater conveyance systems are part of a suite of distributed stormwater management practices (DSMPs) that can be employed to create an "absorbent city" and reduce flooding by mimicking natural hydrologic patterns (White 2008). There is evidence that these DSMPs can reduce flooding.

Cohen and Brown (2007) found that constructed stormwater conveyance systems could mimic the function of a hierarchical wetland system. They determined that such a system could improve both water quantity and quality; where flows would be reduced by 31%; and 36% and 27% of sediment and phosphorus could be removed through the system, respectively.

The aforementioned hierarchical stormwater system and other DSMPs have been proposed as the key to solving stormwater issues that have increased from growning amounts of urban impervious surface (Freni and Oliveri 2005). In their study, Freni and Oliveri (2005) identified how DSMPs influence several hydrologic parameters to determine their effectiveness at reducing flooding. They found that disconnecting impervious area from larger drainage systems and handling it locally was the most effective means to reducing flood peak flows. They surmise that in locations where disconnection was not possible, detention ponds could be used to slowly release stormwater into larger drainage systems.

2.1.3. Urbanization and Flood Damage Studies

Urbanization can influence flooding through increased levels of impervious surface and alterations to natural hydrology, but urbanization can also result in flood damage directly. Damage to property caused by floods are the result of the way societies choose where development occurs and how it is designed (Mileti 1999, Freeman, Keen and Mani 2003, Benson and Clay 2004). As such, numerous studies that analyze the connection between urbanization and the extent of flood damage focus on property located in flood-prone areas. Property in low-lying areas, near rivers and streams, or downstream of water bodies are at greater risk of flooding than property in other parts of a watershed. In coastal areas, flooding is especially a concern due to the potential impact of storms that can cause damage by creating tidal surges as well as by releasing large quantities of precipitation onto areas with naturally poor drainage (Costanza et al. 2008). In many cases, these flood-prone areas are delineated using FEMA's designated special flood hazard areas (SFHA), but recent work has begun to look at urban flooding outside of these areas (Center for Neighborhood Technology 2013).

Without structural controls in place, properties located in flood-prone areas are susceptible to flooding; and unless flood-proofing strategies have been implemented, flood damage of some sort can occur (Lind 1967, Birkland et al. 2003, Hansson, Danielson and Ekenberg 2008). Planned, high-density development can improve quality of life and protect the environment (Calthorpe 1993), but high-density development in flood-prone areas can increase a community's exposure to flood hazards (Stevens, Song and Berke 2010, Burby 2001). Land use policies that prevent development in flood-prone areas or restrict it to low density development and require flood-proofing strategies can reduce the overall exposure of properties to flood damage (White 2008).

Flooding due to Location

It is estimated that there are over six million buildings located within the FEMA Special Flood Hazard Area (Burby 2001; p. 111). Research indicates that even properties outside of these areas are at risk for severe and repetitive flooding (Brody et al. 2012b). The presence of these properties in flood-prone areas has not only resulted in property damage, but has also resulted in reductions in property values and other financial losses.

Using a hedonic price model to estimate the effects of flood hazards on residential property values, Bin and Polasky (2004) found that homes in flood-prone areas had lower property values than those outside of flood-prone areas. Additionally, the price of homes sold after major storm events was lower in flood-prone areas than comparable homes located outside of flood-prone areas. Bin, Kruse, and Landry (2008) also used a hedonic price model to estimate the effect of flood hazards on coastal property values, and concluded that even when controlling for amenities available nearby (measured as distance to coastal water), homes in flood-prone areas had lower values than homes outside of flood-prone areas. Daniel, Florax, and Rietveld (2009) conducted a meta-analysis of data from 19 different studies and found that in a given year, a one-percent increase in probability of flooding resulted in a .06 decrease in property value.

The amenity that Bin, Kruse and Landry (2008) identify in their analysis is supported by information found in a Congressional Budget Office (2007) study that concluded overall property values of homes in SFHAs was contingent on the value of the land independent of the value of the structure placed on the land. In other words, property values in coastal areas are high because of their location on the coast and regardless of whether the home is flood-prone. Conversely, in inland areas properties that have incurred flood damage have lower values than inland properties that have not had flood damage (Congressional Budget Office 2007).

Holoway and Burby (1990) studied how flood hazard variables were related to residential property values by examining a sample of properties located in floodplain areas. They found property protected by flood control structures had a higher value than property not protected. Additionally, the value of properties located in cities that had experienced a recent flood event was lower than the value of properties located in cities that had not experienced a recent flood event. Another important finding was that the land use regulations required by the National Flood Insurance Program were found to affect property value. Lots zoned for larger parcels were found to be of less value per unit area than lots zoned for smaller ones. Lots located in communities that required building homes one foot above the base flood level were less expensive than lots built in communities that did not require it.

The Center for Neighborhood Technology (2013) conducted one of the few studies related urban development to flood damage with a focus on the failure of stormwater conveyance and drainage systems. From 2007 to 2011, flood damage data from FEMA's National Flood Insurance Program and sewer and drain backup claims from other insurance providers was analyzed at the zip code level for Cook County, Illinois. This data was then paired with social survey data to better understand the prevalence of urban flooding. Summary statistics showed that on average, one out of every six properties flooded during the study period. Residents self-reported supplementary survey data that revealed 70 percent of respondents had flooded three or more times in the past five years, and twenty percent had flooded at least 10 or more times (Center for Neighborhood Technology 2013).

One of the most important findings of the study is that of the 96 zip code areas studied, the areas with the highest amount of claims paid out had little to no federally-designated floodplain area present within their boundaries (Center for Neighborhood Technology 2013). This is strong evidence that urban flooding can be a chronic problem regardless of whether or not it is located in flood-prone areas.

Policies and Planning that Reduce Flood Damage

Throughout the history of floodplain management in the U.S., there are several strategies that have been adopted at different levels of government that have been implemented in an attempt to reduce flood damage. These strategies include:

1. structural controls like dams, dikes and levees (managing the water to prevent encroachment into floodplain areas);

2. land use/building restrictions (elevating homes, flood-proofing, and zoning);

3. insurance and disaster relief assistance (damage still occurs but the financial cost to the individual is minimized); and

4. stormwater and land use strategies that maintain or create natural hydrologic features that reduce flood damage to the surrounding urban and suburban areas (White 2008).

There is disagreement in the literature on the effectiveness of these strategies, as many of them have had unintended consequences. For example, structural controls and insurance and disaster relief assistance can reduce perceived risks and increase encroachment into floodplain areas (Brody et al. 2011b).

In 1958, White and colleagues studied 17 cities in the U.S. to analyze the change in occupancy of floodplains after flood control structures were put in place and found that there was an increase in properties located in these areas. In 1986, Montz and Gruntfest looked at nine of these same cities to determine whether federal floodplain regulations had further influenced development in these areas. They found that although participation in the NFIP has occurred, actual adoption of many of the requirements has not occurred in the communities that have seen high levels of population growth. (Montz and Gruntfest 1986).

Holoway and Burby (1993) studied how NFIP requirements and floodplain boundaries influence patterns of development. They argued that NFIP requirements may reduce flood damage by requiring buildings to be constructed to a certain elevation, but will not necessarily drive development outside of the floodplain. They proposed that low impact development strategies should be employed in floodplains to ensure that encroachment into these areas is limited.

Patterson and Doyle (2009) tested whether NFIP policies led to reduced development in floodplains. By looking at temporal and spatial changes to development in three regions of North Carolina, the authors found evidence that two of the regions had some success in reducing exposure of property within the 100 year floodplain, and the coastal region was very successful at reducing exposure. However, a spatial analysis indicated that exposure of property immediately outside of the 100 year floodplain increased significantly.

Brody and colleagues (2007) identified how planning and development patterns were related to flood damage caused by hurricanes along the Florida coast. They found that planning for flood hazards reduced flood damage (as seen through higher community rating system scores), and development that altered wetlands and hydrologic networks resulted in increased flood damage.

Policies that regulate urban design standards can ensure that development in flood-prone areas is kept to a minimum. In a study of 318 New Urbanist developments in the United States, Stevens, Song and Berke (2010) found that the probability of these developments being placed in flood-prone areas decreased as the presence of floodplain development restrictions increased.

Burby (2005) looked at how planning was related to insured flood losses for the United States between 1994 and 2000, and found that states that required hazard mitigation planning of their communities had significantly lower weather-related insured losses than states that did not require it, even though the effect was minimal when looked at from an actual dollar value. The author notes that one possible reason this effect was minimal was that planning does not mean that activities were actually implemented; and although a plan was in place, it does not account for the pre-existing built environment characteristics of the landscape.

2.2. Urbanization from a Spatial Perspective

2.2.1. Quantification of Urban Patterns

The process of how urbanization occurs from a spatial perspective has evolved over the past 70 years. Once thought of as simply the location and concentration of human populations, our understanding of urbanization has expanded as numerous fields of study have sought to identify the causes, consequences, and conditions of urbanization (Tisdale 1942, Galster et al. 2001).

From a spatial perspective, urbanization is related to both flooding *and* flood damage. Urbanization can influence flooding because it frequently results in increases in impervious surface which can alter the hydrology of a watershed (Arnold and Gibbons 1996, Shuster et al. 2005). Urbanization can also result in direct modification of hydrology through the creation of artificial channels used for stormwater management or structures utilized in large-scale floodplain management strategies (White 2008). These two aspects of urbanization influence where and to what degree flooding occurs in a watershed, but are only *indirectly* related to flood damage.

Flood damage only occurs when lives or property are placed in flood-prone areas. As opposed to land cover which influences flooding, Urbanization as *land use* represents the exposure of lives and property to damage if it is located in areas where flooding can occur (Brody et al. 2011a).

Identifying how urbanization is related to flood damage requires measuring different dimensions of urbanization spatially to differentiate what degree of flood damage is due to alterations in hydrology versus how much is due to exposure. These spatial measurements of urbanization can be described as urban patterns (Alberti 1999). Urban patterns can be classified into three categories (adapted from Alberti et al. 2007):

1. those that represent quantity of a particular land cover type;
2. those that represent the spatial arrangement of a particular land cover type relative to itself and to other landscape features; and
3. those that represent land use intensity

These three components of urbanization provide a framework for which urban pattern variables can be related to flood damage. Quantity of land cover type measures urbanization as impervious surface, and as well as the location of impervious surface relative to itself and other landscape features which influence how urbanization alters the hydrology of a watershed. Land use intensity represents the density of lives and property in urban areas that are located in areas prone to flooding. Utilizing all three of these categories of urban patterns allow for the generation of urban pattern metrics that are based on previous research. However, this study expands on previous research by creating new measures that are based on the literature from two different fields; those found in hydrology, and those found in hazard analysis and management.

Urban patterns have been quantified and measured in several academic fields, including landscape ecology and urban studies. While some studies have looked at urbanization as one of many land cover types across a landscape, others look at more specific land cover or land use patterns that are specific to the problem being studied. This section 1) provides a brief introduction to terminology in landscape ecology and the use of landscape metrics; 2) describes how urban patterns have been defined, measured and categorized; and 3) explains how urban patterns have been linked to ecological and socio-ecological processes.

2.2.2. Studies Measuring Sprawl and Classifying Urban Patterns

Landscape ecology is the study of linking patterns to processes at various landscape scales (Turner, Gardner and O'Neill 2001). Successful linking of patterns to processes requires both an understanding of the landscape or spatial metrics being used to measure landscape structure as well as an understanding of the ecological phenomenon being studied. Researchers that employ landscape and other spatial metrics from numerous fields of study have called for context to be provided to determine the appropriateness of metrics used to correlate patterns to processes (Corry and Nassauer 2005, O'Neill et al. 1988, Galster et al. 2001, Turner 2005, Li and Wu 2004, Jaeger et al. 2010b, Herold, Goldstein and Clarke 2003, Gustafson 1998). It is therefore important to understand not only how urbanization is linked to flooding and flood damage, but also how urban patterns have been conceptualized, measured, and categorized in the existing literature prior to determining which urban pattern metrics may be most appropriate.

Although not ubiquitous in the literature, many studies in quantitative geography have approached the measurement of urban patterns from a perspective of efficiency, where there is a continuum of development patterns that, when efficient, provide some sort of economic, social, or environmental benefit. When measuring urbanization, inefficient patterns can be classified as sprawl (Ewing 2008) or an undesirable pattern of growth (Theobald 2005). Torrens (2008) identifies several categories that sprawl may refer to, including: costs and benefits; growth, decentralization, and density, social/quality of life aspects, and environmental aspects. While sprawl is a difficult concept to conceptualize and measure, theoretical and empirical articles discussing sprawl are a major cornerstone to the larger body of research that looks at urbanization as a spatial science.

Jaeger and colleagues (2010b) outline 13 suitability criteria that should be used when determining how to operationalize and measure sprawl. After identifying several unique dimensions of sprawl, they applied these suitability criteria to determine the appropriateness of current measurement methods. In a following article, the authors applied the suitability criteria to four proposed measures of sprawl and surmised that these new measurements were more robust due to the validation tests they applied to them. The four metrics they proposed included: 1) degree of urban dispersion, 2) total sprawl, 3) degree of urban permeation of the landscape, and 4) sprawl per capita (Jaeger et al. 2010a).

Galster and colleagues (2001) bring context to the argument of what is and is not sprawl by operationalizing eight different dimensions of sprawl as defined by the literature and then proceeded to test these measures on 13 urbanized areas in order to determine whether lower scores would represent less sprawl and higher scores would indicate higher amounts of sprawl. By measuring the eight dimensions and comparing to maps of the study sites, the authors validated their metrics and concluded that specific aspects of urbanization being captured included land use density, concentration, continuity, clustering, centrality, nuclearity, mixed uses, and proximity. Cutsinger and colleagues (2005) expanded Galster and colleagues' (2001) study to operationalize 12 different dimensions of land use patterns and utilized 16 different metrics to measure land use patterns for 50 of the largest cities' extended urban area (EUA). After analyzing descriptive statistics and conducting a factor analysis, they found that there were seven factors that explained 94% of the variation in the indices. The authors identified these categories as containing metrics that represented density/continuity, proximity (both housing to housing and housing to jobs), job concentration, mixed use, housing centrality, nuclearity, and housing concentration.

Jaret and colleagues (2009) summarized several studies that attempted to conceptualize and measure sprawl, but focused on studies that viewed sprawl as a land *use* issue and failed to incorporate numerous studies that also conceptualize sprawl as land *cover*. Alberti (1999) identified four different aspects of urbanization, including urban form, density, grain, and connectivity. Alberti and colleagues (2007) later built upon this framework to propose that the four aspects of urban patterns that are linked to ecological health in different ways include land use intensity, land cover composition, landscape configuration, and connectivity of impervious area. Herold, Goldstein, and Clarke (2003) looked at 72 years of spatial data to develop several urban pattern metrics and found that both topography as well as planned urban growth boundaries influenced spatial patterns of development. These measures of urbanization can also be used to predict future urban growth scenarios and estimate future resource needs (Sudhira, Ramachandra and Jagadish 2004, Herold et al. 2003).

One of the most comprehensive reviews of the quantification of urban form was conducted by Clifton and colleagues (2008) who, after reviewing the literature from several disciplines, determined there were five categories that effectively classified different perspectives across disciplines when quantifying urban form. These include: landscape ecology, economic structure, surface transportation, community design, and urban design. From their review they also determined that while there has been major technological advances that allow for more detailed quantification of urbanization, standardizing how different components are operationalized and measured could further allow comparison across study sites and research disciplines.

Depending on the situation, many urban pattern metrics or a single metric may be useful at answering a specific research question. To generally describe urbanization across a landscape, Lu and Weng (2006) incorporated land cover data and population density data to describe five different types of urbanization within their study area: low-, medium-, high-, and very high-residential urban areas; and commercial/ industrial/ transportation urban areas. In contrast, Theobald (2005) proposed a single urban sprawl metric that summarizes numerous levels of development densities present on a landscape while also accounting for the edge contrast among each density level. Using this metric, the author measured residential housing density change from 1980 to 2000 and estimated that while urban and suburban housing densities (parcels .68 hectares and smaller) will increase to 2.2% per year by 2020, exurban development (parcels larger than .68 hectares) will expand by 14.3% for the same time period.

Tsai (2005) proposed four different measurements that quantify urban form on a continuum of compactness versus sprawl. These four measurements characterize different dimensions of urbanization and include: metropolitan size, activity intensity, distribution of activities across urban area, and how well high-density areas are clustered among one another. While Tsai's (2005) study does not go into the validity assessment that others do for the proposed variables, it does utilize a Moran's I function to address the spatial dependence that occurs when analyzing landscapes.

Impacts of urbanization on land cover and hydrology can be significant. In Zhang and Wang's (2007) study of an urbanizing landscape, almost 58% of the water area had been converted to other land use types and almost 43% of other land use types had been converted to water. Burchfield and colleagues (2003) converted aerial photographs from 1976 and 1992 to raster grids in order to measure and understand changes in urban patterns between the two time periods for the entire continental U.S. They found that while residential land increased by 47.3% during the study period, the population only grew 17.1%. In their study on the form and growth of cities, (Schneider and Woodcock 2008) found that there were four ways urbanization occurred; low levels of growth that included infilling, high levels of growth with rapid infilling, sprawling growth with high levels of dispersion and low population densities, and extremely rapid and haphazard growth represented by high levels of land use conversion and high density levels.

Burchfield and colleagues (2003) identified how potential differences in how urbanization is defined and measured can lead to different calculations and ultimately different conclusions on the composition of the urban area. The authors compared their findings to other studies that have estimated the total percentage of urbanization for the continental U.S. and found that their estimate of 1.9% total urban area was slightly lower than the U.S. Census estimate of 2.5% in 1990, as well as the 2.9% estimate made in the U.S. Department of Agriculture's Natural Resource Inventory for 1992. Burchfield and colleagues articulate that the difference between their estimate and the one made by the U.S. Census is that the U.S. Census Urbanized Area and Urban Place designations can include open space within their boundaries. The authors explain the difference between their estimate and the one made in the Natural Resources Inventory is due to a similar issue, where fragmented development adjacent to an urban area may be included in the analysis, which also includes the open space in between the two patches.

There are a number of studies that have analyzed the spatial configuration of urbanization to better understand different types of urban patterns. Ji and colleagues (2006) calculated landscapes at the county, metropolitan, and city levels to assess how land cover change had occurred. They found that over a 30 year period, much of the urban area had been converted from non-forested rangeland areas. While metric focus was on vegetative cover, the metrics did lead the authors to believe that landscape metrics of larger spatial units (county and metropolitan areas) were more effective at measuring land use change than metrics calculated of smaller units of analysis.

Seto and Fragkias (2005) studied four cities in southern China over an 11 year period using landscape metrics at three levels of analysis. The authors concluded that using landscape metrics at different buffer zone levels is a superior method to understanding urban expansion rather than just looking at urban growth rates. Additionally, the use of metrics can provide clarity to the underlying social, economic and political processes that drive development. The authors also concluded that urban patterns metrics can successfully quantify rapid changes to urbanization over short temporal periods, which can be important in places like China where many cities are undergoing this type of rapid transformation (Schneider and Woodcock 2008).

Within urban areas, urban patterns can change as spatial scale and distance from the urban core changes. Luck and Wu (2002) used several landscape metrics to measure urban form and found that not only were most of them robust to changing spatial scales, they were also able to effectively measure different urban patterns as land cover diversified and distance from the urban core increased.

2.3. Landscape and Spatial Metrics

2.3.1. Landscape and Spatial Metrics Background

A brief overview of the terms associated with landscape ecology and the measurement of spatial patterns is necessary in order to better understand how urban patterns have been measured and correlated to social and ecological phenomenon. These terms deal with the format of the spatial data, ways in which different spatial data are described, as well as the components of a landscape.

Land cover can be represented as different class types. For example, there can be one or several types of vegetation, depending on how and for what purpose the classes are generated. Each class type can be represented as patches that differ by size, location, and spatial arrangement; and the together create the mosaic for a given landscape being analyzed (Turner et al. 2001, McGarigal, Cushman and Ene 2012). The quantity, location, and spatial arrangement of land cover classes can be quantified using landscape metrics that are specific to measuring a particular patch, the pattern of a single land cover class, or the relationship of all classes found on a given landscape. Landscape metrics that calculate quantities are considered compositional metrics and do not change based on the spatial location of the class types. Configurational metrics are used to quantify spatial relationships relative to other patches, class types, or other landscape features (Leitão et al. 2006).

The suite of landscape metrics available makes it difficult to determine which may be most appropriate, and may compel researchers to attempt to use all of them without fully understanding the underlying mathematics (Li and Wu 2004). Cushman, McGarigal and Neel (2008) recognized that multiple landscape metrics may be necessary in landscape analysis due to the numerous dimensions they may measure. To select the correct type and number of landscape metrics to be used in an analysis, validity tests should be conducted to ensure metrics are conceptually linked to ecological patterns or processes, analyses are conducted at the appropriate scale, and that unnecessary metrics are not included in the analysis (Cushman et al. 2008).

Landscape analysis in landscape ecology and related fields has sought to answer multiple questions on how landscapes are structured and how this structure is related to ecological processes or other social and environmental variables. In their meta-analysis of 478 articles that discussed landscape metrics or landscape indices, Uuemaa and colleagues (2009) found that there were seven categories of research being conducted in the field. These include the following:

1. the selection/use/misuse of metrics;
2. biodiversity/habitat analysis;
3. water quality studies;
4. temporal analyses of landscapes;
5. quantification of urban landscapes;
6. landscape aesthetic; and
7. planning/management/monitoring of landscapes.

While the authors provide evidence that the publication of articles quantifying urban has increased over the past decade, there is still notably an absence articles of linking patterns to socio-ecological processes.

Landscape ecology emerged as a field of study to better understand the implications of changing landscape patterns on ecological processes (Turner et al. 2001). Urban ecology has recently emerged as a sub discipline that explicitly looks at how landscape changes due to urbanization are related to ecological processes, but have primarly focused on ecosystem condition and function (see Alberti 1999, Alberti 2005 for a summary of studies). Few have sought to link urban patterns to socio-economic consequences, and fewer still have attempted to identify how urban landscape patterns are related to flood damage.

Use of landscape metrics to measure urban patterns has been attempted in both conceptualizing urban patterns, as well as the linking of these patterns to flood damage. Herold, Scepan, and Clarke (2002) used several Fragstats metrics to characterize urban landscapes including fractal dimension, patch density, standard deviation of patch size, edge density, area weighted mean patch fractal dimension, and contagion. They used these metrics on pre-defined urban landscapes to measure the dominant urban class (commercial, high-density residential, and low density residential). They found that most of the metrics were distinct from one another on different landscapes, and that the metrics were especially useful at analyzing land use change over time.

When analyzing insured flood loss data from 2001-2004 for 144 coastal counties in the Gulf of Mexico, Brody and colleagues (2011a) found that landscape metrics that calculated Total Area/Proportion of high intensity development and low intensity development were significantly related to flood damage. As the proportion of high-intensity development increased, flood damage was found to decrease. Conversely, as proportion of low-intensity development increased, flood damage was found to increase. (Brody et al. 2011a)

Brody, Kim and Gunn (2012a) studied specific landscape metrics calculated in Fragstats (Total Class Area, Number of Patches, Patch Density, Proximity, and Connectance) of different intensities of development to determine their relationship to flood damage. They found that the total amount of high intensity development was inversely related to flood damage, while total amount of low intensity development was positively related to flood damage. Increased numbers of low intensity and medium intensity development patches led to greater amounts of flood damage. Additionally, high intensity development that was highly connected led to increased amounts of flood damage.

One of the greatest limitations of these two studies is the measurement of urban patterns does not allow for the distinction of whether these patterns represent impervious surface or exposure of property. Without utilization of metrics that capture these distinct dimensions or urbanization, it is difficult to understand what level of damage is due to increasing amounts and complexity of patterns of impervious surface, and how much damage is due to the placement of property in flood-prone areas.

3. RESEARCH FRAMEWORK

3.1. Conceptual Model

Urbanization is related to both flooding and flood damage. Modification of the landscape can impact natural hydrologic functioning of a watershed, which can alter flood regimes. Additionally, urbanization that occurs in flood-prone areas can result in property being exposed to flooding. Property in low-lying areas, near rivers and streams, or downstream of water bodies are at greater risk of flooding than property in other parts of a watershed (Brody, Highfield and Kang 2011).

This research sought to identify how various urban patterns are related to residential property flood damage across the Texas coast. Urban patterns have multiple dimensions; in the case of flood damage, land cover patterns that measure the amount and spatial arrangement of impervious surface relative to hydrology can measure the influence these patterns can have on flooding, which is indirectly related to flood damage. Other urban pattern metrics measure land use, and these measurements capture the intensity of development as the amount of property located in a particular area, as well as the spatial location and whether the property is located in a flood-prone area.

Land cover urban pattern metrics selected for this study measure impervious surface and reflect their use in the literature as they are related to influencing flood regimes and stormwater runoff. The primary measurement in the literature is TIA which has been shown to increase flood peaks and reaching those peaks more rapidly (Leopold 1968, Seaburn 1969, Alberti et al. 2007).

Configurational metrics utilized in this study help differentiate TIA and EIA/DCIA in each watershed (see Lee and Heaney 2003). The less contiguous impervious surface area is, the more natural area will be able to slow runoff and provide opportunity for absorption into the soil (Ogden et al. 2011). The literature provides evidence of such patterns being included in process-based hydrologic models and evidence that such patterns are important contributors to altering flood regimes. Additional metrics that capture the fragmentation, expansiveness and uniformity of patches of impervious surface, as well as the distance between patches, provide the opportunity to see if there are other impervious surface configurations that influence flood damage. Six urban land cover metrics are utilized in this analysis.

Land use metrics utilized in this study also reflect findings from the literature. Height and distance are the two spatial dimensions that reflect exposure of property to flooding. Two simple but critical metrics that capture the relationship of where residential properties are located relative to flood-prone areas of the watershed include the average distance of residential property to flood-prone areas (streams, outlets, coastline, etc.), and the average elevation of residential properties. These simple metrics allow for the measurement of urban land use intensity and spatial configuration relative to each unique watershed.

These eight urban pattern metrics that reflect land cover and land use were used to determine the influence of urbanization of flood damage in Texas coastal watersheds. As seen in Figure 1, land cover urban patterns influence hydrology directly, and flood damage indirectly. Urban land use metrics that represent residential property exposure are directly related to flood damage. Table 1 presents the dependent and independent variables and their hypothesized relationship to residential property flood damage.

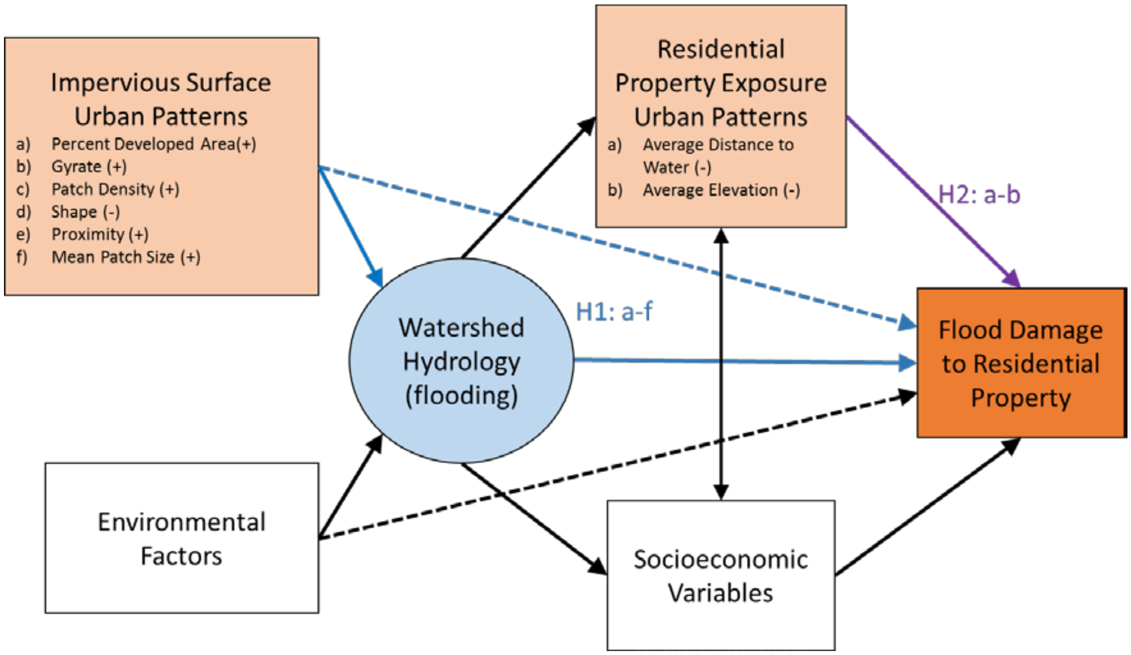

Figure 1: Conceptual Model

3.2. Dependent Variable

Flood damage occurs when there is flooding in locations where there is something to damage like lives or property. There are four ways to mitigate such impacts; either avoid the impact by preventing lives and property from being placed in flood-prone areas, reduce the potential for impact through design modifications intended to manage the hydrology (like engineered structures), modify built features (like raised homes), or offset the impact through monetary relief (like insurance or government relief) (Randolf, 2004). As mentioned in Section 2.1.1., there are numerous ways to quantify the impacts of flooding, and even damage in dollars is difficult to quantify because of the lack of uniformity across geography and time. For the purposes of this research, data from FEMA's National Flood Insurance Program (NFIP) is utilized for the purposes of quantifying residential property damage in dollars. NFIP was established in 1968 and is one of many methods the U.S. government attempts to offset damage from flooding. Participation in NFIP occurs at the community level, and eligibility of individuals is dependent on the community adopting a minimum set of development standards within the identified flood risk boundary. Individual policy and claim data can be scaled up to the watershed for the purposes of measuring total insured annual flood damage.

Table 1: Independent Variables and Expected Relationship with Dependent Variable

	Variable Name	Expected Relationship with Flood Damage
Urban Patterns	Percent of Developed Area (High, Medium and Low Intensity)	+
	Mean Gyrate Value of Developed Area Patches (High, Medium and Low Intensity)	+
	Patch Density of Developed Area (High, Medium and Low Intensity)	+
	Mean Shape Value of Developed Area Patches (High, Medium and Low Intensity)	-
	Mean Proximity Value of Developed Area Patches (High, Medium and Low Intensity)	+
	Mean Patch Size of Developed Area (High, Medium and Low Intensity)	+
Control Variables	Average Distance of Homes to Water	-
	Average Elevation of Homes	-
	Mean Slope	-
	Drainage Density	-
	Percent Upland Vegetation	-
	Percent Wetland	-
	Precipitation	+
	Mean KSAT Value of Soil	-
	Mean Hydrologic Capacity of Soil	+
	Residential Property Age	+
	Number of Policies	+

3.3. Independent Variables

Urban patterns have multiple dimensions; depending on the context, patterns that measure how urban land cover and urban land use intensity are spatially arranged over a landscape may or may not be useful in determining how urban patterns are related to socio-ecological processes (Alberti et al. 2007, Galster et al. 2001). To understand the impact of urbanization on flood damage at a landscape scale, urban patterns can be conceptualized two ways. Urban land cover that represents patterns of impervious surface across a landscape influence hydrology, and urban land use intensity that represents development density influences exposure of property to flooding. For the purposes of this study, Landscape metrics that are traditionally used to measure land cover are used exclusively to measure patterns of impervious surface. Based on the literature, the intensity of land use in either flood-safe or flood-prone areas determines whether lives and property are exposed to floods. Two urban land use intensity metrics that measure degree of exposure are also reviewed.

There are two difficulties with selecting landscape metrics that may contribute to flooding and flood damage. First, there are very few landscape metrics that have been used to measure urban patterns, and even fewer of these have been used to relate urban patterns to flood damage. Second, there are countless landscape metrics available for use. While many of these metrics may be successful at completely explaining a land cover pattern, many also only measure distinct dimensions and require the combination of multiple metrics to paint a clear picture of the pattern across a landscape. This combination of multiple metrics can lead to confusing and confounding results that can often only be explained after the measurement has already occurred. The following eight land cover metrics presented and discussed on how they are related to flood damage based on existing literature.

Total Class Area (TCA) measures the area of a particular land cover type, and is used to determine the Percent Area by dividing CAP by total area of the landscape (watershed).

This metric has been used to estimate the impact of intensity development on flood damage, where it was found that increases in CAP of high intensity development resulted in reductions in flood damage, while increases in CAP of low intensity development resulted in increases in flood damage (Brody et al. 2011a). However, when used to measure imperviousness, TCA and CAP/Percent Area essentially measure total impervious area (TIA), which has been shown to increase flood peaks as well as reduce the time it takes to reach those peaks (Leopold 1968, Seaburn 1969, Alberti et al. 2007).

Leitao and colleagues (2006) argue that CAP/Percent Area is one of the most important variables when describing landscapes, as it provides basic information about the composition of the landscape and can also provide context when used in conjunction with configurational landscape metrics.

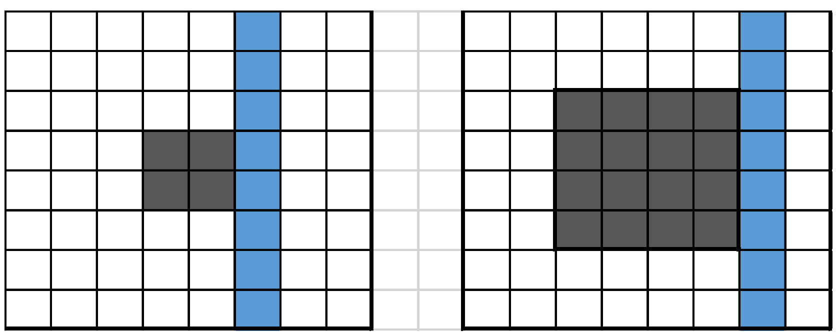

Figure 2: Example of Percent Class Area

Percent Area can be calculated both by summing the area of a given class type within a landscape and dividing it by the area of the landscape. In Figure 2, the patch in the landscape to the right adjacent to water has a greater value than the patch in the landscape on the left.

Patch number (PN) is the total number of patches of a given land cover type on a specified landscape. By itself, PN of impervious surface land cover does not have any predicted relationship with flooding or flood damage. However, when combined with

Percent Area, it could provide clarification for how broken up impervious surface land cover is on a given landscape, which may indicate that there are pervious land covers in between impervious surface patches. PN may distinguish the TIA from directly connected impervious area (DCIA) or effective impervious area (EIA), which have been shown to contribute to runoff more significantly than TIA. If this is the case, then increased PN would indicate decreased DCIA and EIA and result in overall reductions to stormwater runoff (Lee and Heaney 2003).

To further understand how "broken up" impervious surfaces are across a landscape, two other metrics may be used. Mean Patch Size is the total area of all patches of a given class type, divided by the total number of patches of that class type. Patch Density (PD) is the number of patches per unit area within a given landscape. It is difficult to estimate how these metrics would interact with one another in an analysis, but each could be used to measure patches of impervious surface to determine whether they will behave more like TIA or like DCIA or EIA.

It is recommended that PN and PD are combined with other metrics like Mean Patch Size, Class Proportion, Radius of Gyration, and Patch Shape to provide a clearer picture of the connectivity, complexity and overall distribution of patches of a given class type across a landscape (Leitão et al. 2006).

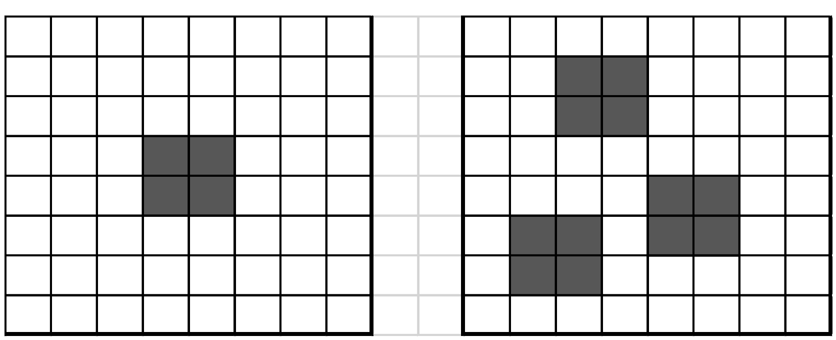

Figure 3: Example of Patch Number

Patch Number is simply the number of patches on a landscape. Although the patches are all the same size, the Patch Number for the landscape on the right in Figure 3 than the Patch Number on the landscape to the left.

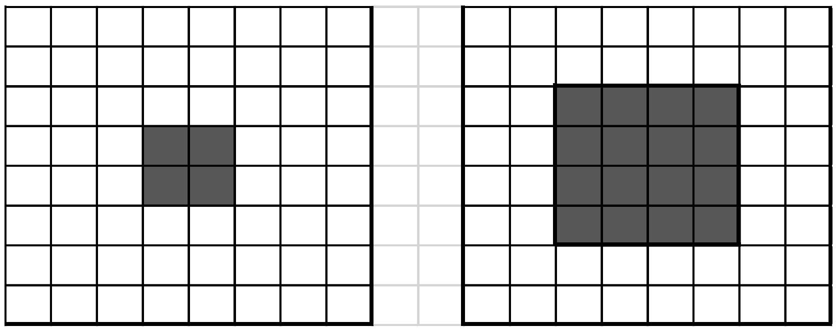

Figure 4: Example of Mean Patch Size

As seen in Figure 4, while both the landscapes above have the same Patch Number, the Mean Patch Size of the landscape to the right is larger than the Average Patch Size of the landscape to the left. With a single patch, it is easy to see that the Total Class Area is also larger in the landscape to the right. As the Patch Number increases, Mean Patch Size becomes a better descriptor of how large patches are of a given class type across the landscape.

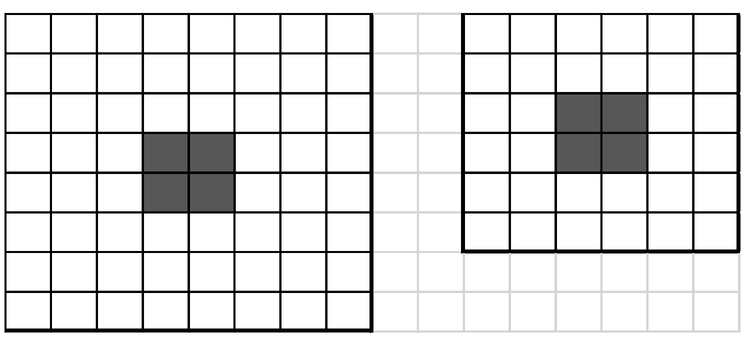

Figure 5: Example of Patch Density

Patch Density takes into account the total area of the landscape. As seen in Figure 5, the Patch Number and Mean Patch Size are the same, but because the landscape to the right is smaller, the Patch Density value is higher.

Shape is a standardized measure of how complex a patch is, or how far it stretches across a landscape relative to its size. This allows Shape to provide information on the compactness of a patch or patches of a given land cover type where compact patches will have values close to 1.0, and more complex patches will have higher Shape values (Leitão et al. 2006). Mean Shape is the result of averaging all Shape values across a landscape.

If Mean Shape is used to calculate impervious surface, then as Mean Shape complexity increases, the amount of perimeter that is connected to pervious land cover would also increase, which would allow for stormwater runoff to be absorbed. Mean Shape could also identify transportation networks on the landscape with adjacent artificial stormwater conveyance systems designed to quickly move water downstream.

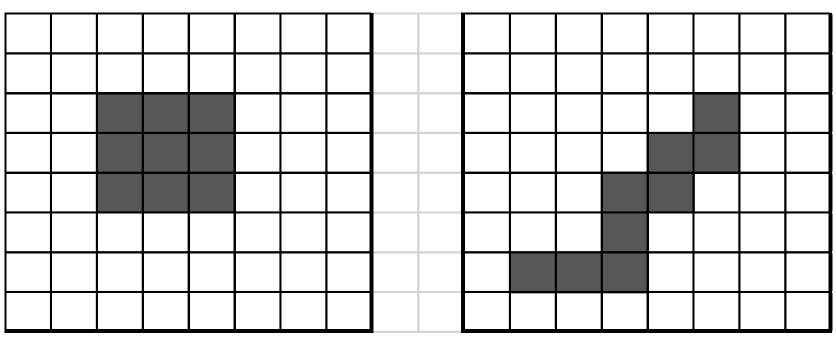

Figure 6: Example of Shape

While both patches in the two landscapes in Figure 6 have the same amount of area (nine cells), the patch to the right has a much higher perimeter to area ratio, indicating that its shape is more complex. (12 cell sides exposed in the patch to the left versus 20 sides exposed in the patch to the right).

Gyrate (or Radius of Gyration) is a measure of how expansive or compact a patch is. As seen in Figure 7, the center of a patch can be found and used to measure and average the distance between the centroid and all cells within the patch. Fragstats can calculate an Area-weighted Mean Gyrate value, which sums Gyrate values for all patches of a given class type and divides it by the area of the given class type. When Gyrate measures impervious surface land cover, increases in Gyrate are expected to increase stormwater runoff. Mean Gyrate is calculated by taking the average Gyrate value for all patches of a particular land cover type within the landscape.

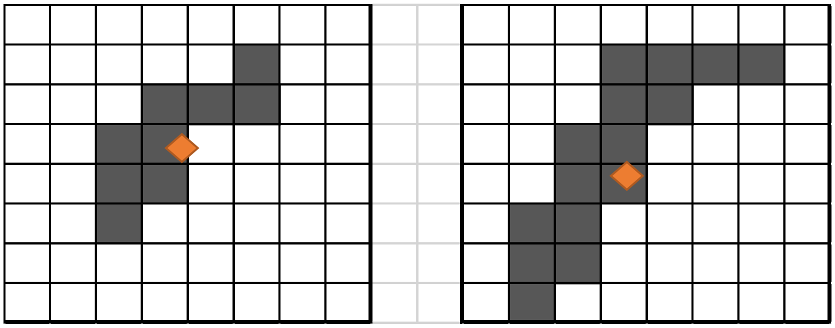

Figure 7: Example of Gyrate

The patch in the landscape to the right of Figure 7 has a larger Gyrate value because it covers more total area than the patch to the left, and the distal cells in the patch to the right are farther away from the patch centroid (orange diamond) than the distal cells of the patch to the left.

Proximity is a measurement that describes the size of patches within a landscape, as well as the distance of these patches from one another. Typically, the metric is used to estimate patch isolation from a focal patch where larger patches closer to the focal patch would yield a higher value, and smaller patches further away from would yield a lower value (Leitão et al. 2006). When Proximity measures impervious surface land cover, increases would indicate that patches are "broken up" which would reduce stormwater runoff. Mean Proximity is calculated by taking the average Proximity value for all patches within a landscape.

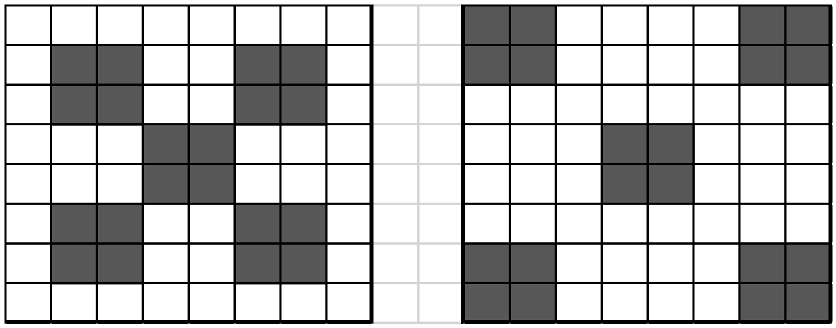

Figure 8: Example of Proximity

Landscapes with a single focal patch and no surrounding patches have a value of zero, as additional patches enter the landscape and are found closer to the focal patch, Proximity increases. In Figure 8, the landscape to the left has a higher Proximity value than the landscape to the right.

Property in low-lying areas, near rivers and streams, or downstream of water bodies are at greater risk of flooding than property in other parts of a watershed (Brody, Highfield and Kang 2011). Other metrics that estimate exposure of property to flood impacts need to be included to effectively capture other dimensions of urban patterns in order to determine the impact of urbanization on flood damage. Urban pattern metrics that represent the level of exposure for residential properties in the watershed can be calculated using the density-weighted distance of residential property to flood-prone areas (streams, outlets, coastline, etc.), as well as a density-weighted calculation of the average relative elevation of properties within the watershed.

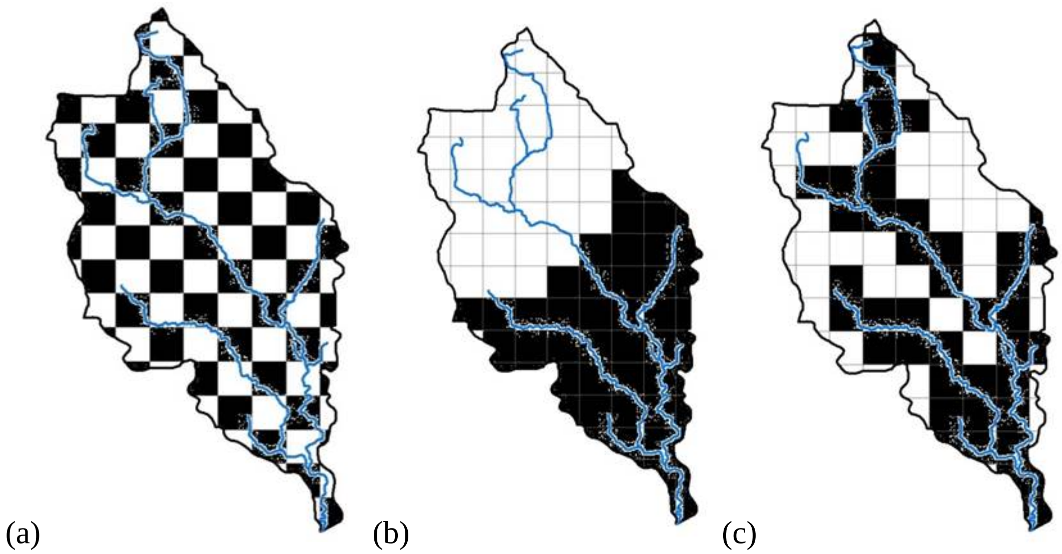

Figure 9: Example to Conceptualize Average Distance to Water and Average Elevation

The three watersheds in Figure 9 have identical perimeters, streams, and amount of area blacked out representing presence of property. However, while (a) has an equally distributed pattern, (b) and (c) are both aggregated in flood prone areas, which means they may be more susceptible to flooding and incur flood damage. Due to the elevation differences in a watershed, (b) would indicate properties are located in low-lying areas and result in more flood damage. The properties in (c) would have low values for distance to water, which would also lead to higher amounts of flood damage.

3.4. Control Variables

3.4.1. Basin Morphometrics

There are numerous studies that have quantified basin morphometrics and stream characteristics for the purpose of classifying basin types regionally and estimating different aspects of flooding in ungauged locations (Helsel and Hirsch 2002). These metrics have roots in quantitative geography but have been adopted into the field of hydrologic analysis and many have shown to be fairly accurate in estimating flooding. These metrics make ideal control variables for this research and can only be utilized due to the units of analysis being conducted at the watershed scale. Additionally, there are several environmental, policy, and structural variables that can be used as control variables.

Horton (1945) was the first to attempt the quantification of key basin characteristics that could be used to estimate surface runoff. These basin morphometrics often utilized simple measures like channel length to basin area ratio or number of streams as a proxy when estimating stream flow characteristics. This work is some of the first in quantitative geography, and despite it not having a direct link to landscape ecology, the use of metrics to look at hydrological processes is very similar to the use of landscape metrics that are used to look at other ecological processes. Other important basin metrics include average slope and drainage density. Average slope determines how quickly water flows down the watershed. Drainage density is the length of all streams in a watershed divided by the total area of the watershed and has been positively correlated with increased rates of runoff and reducing local impacts from flash flooding, but could increase flood waters in downstream areas (Patton 1988, Youssef, Pradhan and Hassan 2011).

3.4.2. Wetlands

In the hydrologic cycle, vegetation can slow the accumulation of runoff into downstream areas during moderate all events. While upland vegetation can reduce runoff efficiency

of surface flows, wetlands are important to consider as a distinct vegetation type due to their adjacency to stream networks and coastal areas which allows them to store and absorb large quantities of water that might otherwise flood into developed areas.
This service, however, is influenced by many other variables. For example, wetlands may play an important role in regulating flooding, but this may be dependent of the season, amount of precipitation, and available storage capacity of the wetland.
Wetlands regulate flooding and potentially reduce flood loss by storing excess rainfall which may slow stream flow rates enough to allow for absorption into the ground and evapotranspiration to occur before the water reaches developed areas. In a given watershed, the two locations where wetlands are most efficient at conducting this process is in the headwaters of the watershed, which can capture initial rainfall; and in floodplains, which can capture stream flows as they accumulate further down the watershed (Bullock and Acreman 2003).

There is evidence to suggest that the type of wetland may not matter in determining how effective it is in regulating flooding. Macreadie and colleagues (1982) found that increases in wetland area (regardless of type) resulted in in lower base flows and lower flood peaks. However, location of the wetland and the storage capacity may be significant. Burke (1969) that found drained peatlands reduced flooding to a greater extent than undrained peatlands. Ogawa and Male (1986) sought to identify the level of flood reduction capability based on wetland size, number, and location upstream or downstream, and came up with conflicting results. This irregular estimation of wetland's ability to reduce flooding is due to the fact that wetlands in different locations may provide different levels of service (Mitsch and Gosselink 2007).

3.4.3. Precipitation

Precipitation is one of the most critical variables to consider when looking at flooding and flood damage because flooding cannot occur without precipitation that eventually turns into runoff. Indeed, Pielke and Downton (2000) found that both precipitation duration and depth are related to flood loss. In Pielke and Downton (2000), ten different measurements of precipitation were compared to determine which ones best explained flood damage in the U.S. It was found that rainfall duration far exceeded all other precipitation measurements in its ability to explain flood damage to different regions of the U.S.

There are four elements of precipitation that are directly related to the hydrology of a basin; depth (quantity), duration (length of time that rainfall occurs), intensity (rate of quantity over duration), and the spatial distribution (in relation to the catchment) (Bras 1990). It is evident how each element is related to the different types of flood events mentioned above. Large quantities of rainfall can overwhelm a channel, leading to overspill. A long duration of rainfall can increase groundwater levels and fill ponds, contributing to water-table flooding. Rainfall intensity can cause rainfall ponding, sheetwash flooding, failure of stormwater systems, or other flash flood events.

Precipitation may result in flood damage due to the placement of property in flood prone areas, but it has also been shown to influence where urban patterns emerge. Parthasarathy and colleagues (1987) explain that flooding occurs in a given geography when the rainfall exceeds the climatic average rainfall for the area, which will influence social and economic patterns that result in the evolution of urban form that adjusts to these patterns.

3.4.4. Soil

Infiltration of rainfall into the ground can alleviate flooding until either the rainfall rate exceeds the absorption rate into the soil, or until the soil becomes saturated entirely from the surface level to the groundwater level. Determinants of infiltration rates include soil texture and the level of moisture present prior to a rainfall event (Saxton and Shiau 1990). In addition to type of soil and moisture levels, infiltration rates can vary based on different rainfall, but this effect may be negated during heavy rainfall events

(Moldenhauer and Long 1964). Absorption of rainfall is ultimately determined by the constancy of precipitation, infiltration capacity of the soil type, and depth of soil until water table is reached (Morel-Seytoux 1978).

3.4.5. Residential Property Age

Residential property age is included to control for design standards that have evolved over time, including being built at higher elevations as well as improved materials that may reduce amount of building damage. Age of homes has been shown to be significantly related to flood damage, albeit in a non-liner fashion (Highfield, Peacock and Van Zandt 2010).

3.4.6. Number of Insurance Policies

Including the number of insurance policies in this analysis provides multiple benefits to the analysis. The inclusion of the number of policies per watershed provides a control for the total amount of damage based on claims, where watersheds with more policies may have higher counts of claims than watersheds with lower number of policies. Also, number of insurance policies was found to be highly correlated to number of residential properties in each watershed, so number of policies serves as a proxy and number of residential properties was not included to prevent multicollinearity issues.

3.5. Research Hypotheses

1. Urban patterns that represent impervious surface are significantly related to flooding and flood damage; specifically:

    a. Increases in Percent Area of impervious surface will result in significant increases in flood damage.

    b. Increases in the Radius of Gyration of impervious surface will result in significant increases in flood damage.

    c. Increases in Patch Density of impervious surface will result in significant increases in flood damage.

    d. Increases in Shape complexity of impervious surface will result in significant decreases in flood damage.

    e. Increases in the Proximity value of impervious surface will result in significant increases in flood damage.

    f. Increases in Mean Patch Size of impervious surface will result in significant increases in flood damage.

2. Urban patterns that represent the level of exposure of housing units to flooding are significantly related to flood damage; specifically:

    a. Increases in the average distance of housing units to hydrology will result in significant decreases in flood damage.

    b. Increases in the average elevation of housing units will result in significant decreases in flood damage.

4. RESEARCH METHODOLOGY

4.1. Study Area

The Texas Coast is an ideal study area for several reasons. First, flooding is arguably a greater problem here than most other places due to the high amounts of monetary damage and lives lost on a regular basis (Ashley and Ashley 2008). Additionally, this study area provides a great representation of both urban and rural watersheds; as well as variability in topography, soil type and average precipitation.

The Texas Coast has a diversity of development levels ranging from highly urbanized areas within Harris and Galveston Counties, to sparsely populated areas like Kennedy and Kleberg Counties. The entire study area can be classified as having a subtropical climate (Angelovic 1976), and due to its proximity to the Gulf of Mexico and Atlantic Ocean, is frequently impacted by atmospheric patterns that result in the formation of tropical storms and hurricanes. These storms can bring large amounts of precipitation to flood-prone areas, and can exacerbate coastal flooding with heavy winds that contribute to storm surge (Smith and Ward 1998).

Texas has vastly different average annual rainfall levels ranging from less than 22 inches per year at the southern part of the state, to over 54 inches per year at the eastern part of the Gulf Coast (Oregon State University, 2011). Additionally, much of this precipitation comes from extreme events like tropical storms and hurricanes. On average, a storm hits the Texas Coast every 1.5 years.

The frequency and intensity of storms and rainfall events has caused Texas to consistently rank as the state with the highest number of flood fatalities annually and have the highest total number of flood fatalities from 1959 to 2005 (Ashley and Ashley, 2008). In terms of insured flood damage, Texas ranks second in the nation for the state for both the largest number of closed NFIP claims and total NFIP payments (in dollars) between January 1978 to August 30 2012 (FEMA, 2013).

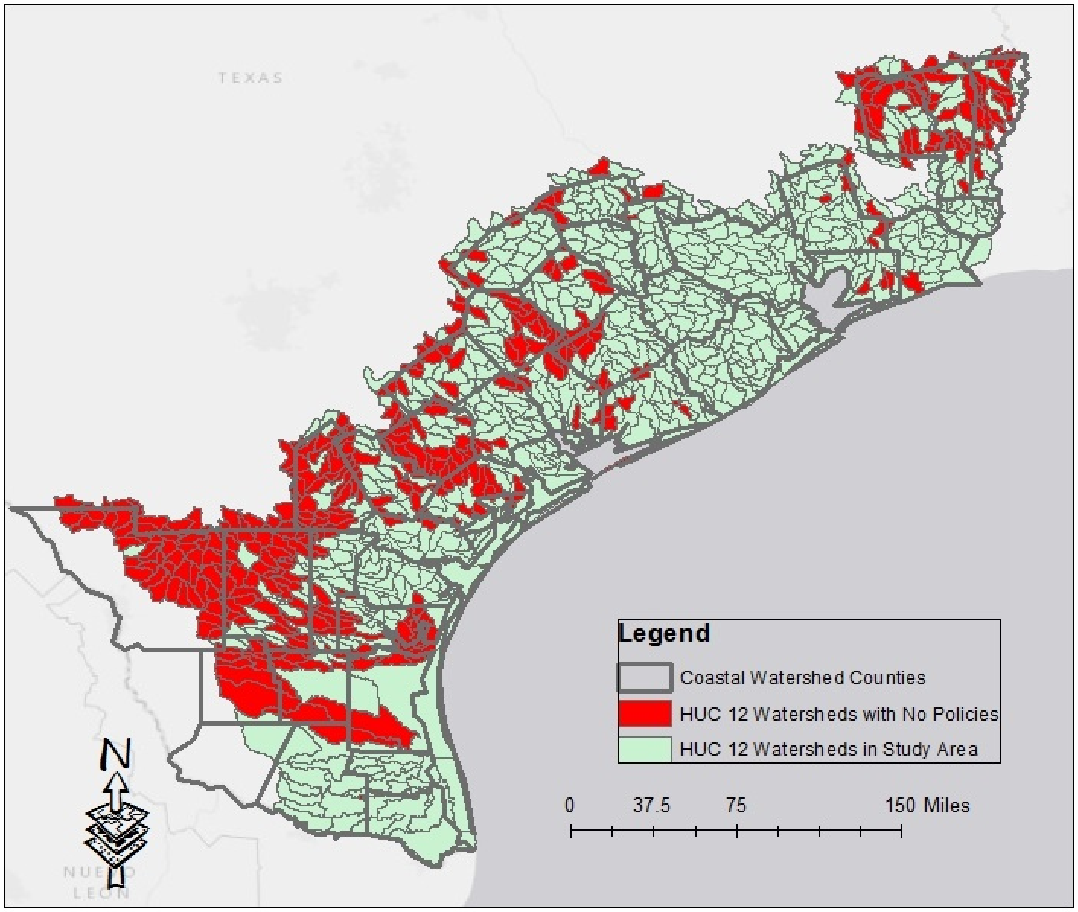

Figure 10: Study Area with 12th Order Watersheds

4.2. Sample Selection

The units of analysis include 12th order watersheds (based on the USGS Hydrological Unit Code (HUC)) found within or connected to Texas' 41 coastal watershed counties, as defined by the National Oceanic and Atmospheric Administration (NOAA) (Crossett et al. 2013), and exclude watersheds that are adjoining to Mexico or Louisiana. Figure 10 displays the 916 12th order watershed in the study area. Several of the watersheds have no flood insurance policies, which means they cannot have flood insurance claims.

However, as flood insurance is required on homes located in designated flood zones with mortgages from federally insured lenders (FEMA, 2011). The lack of policies indicates that there are either no homes in these watersheds, or there are homes that are owned outright. These watersheds are included in the analysis because they are believed to still contain important information that should be considered in modelling. In total, the 916 watersheds over the ten year period result in a total of 9,160 observations.

4.3. Concept Measurement

4.3.1. Dependent Variable – Flood Damage

The dependent variable, estimated damage to buildings with flood insurance, is from FEMA's National Flood Insurance Program and contains parcel level residential property data for the study area from January 2000 to December 2009. Data used for this study is limited to estimated damage to buildings (not contents). This was used instead of the amount paid out in claims, which is limited to $250,000 for residential properties. This data was aggregated yearly to the 12th order watershed level to generate the total amount of estimated building damage per year per watershed. This variable was then log transformed to better approximate a normal distribution. Table 2 presents an overview of average annual damage per watershed, as well as total annual damage for the study area. For context, Figure 11 displays the number of claims per watershed for the entire study period.

Table 2: Descriptive Statistics for Total Flood Damage in Dollars by Year

Year	Mean	Standard Deviation	Max	**TOTAL BUILDING DAMAGE**
2000	$12,851.65	$113,148.30	$2,056,493.00	$5,595,477.00
2001	$1,562,335.00	$8,038,872.00	$91,500,000.00	$689,000,000.00
2002	$186,668.70	$1,101,373.00	$16,800,000.00	$83,500,000.00
2003	$75,081.12	$492,986.00	$7,715,395.00	$37,700,000.00
2004	$25,565.12	$111,698.60	$1,356,786.00	$13,100,000.00
2005	$71,740.25	$627,951.50	$10,700,000.00	$37,300,000.00
2006	$113,787.20	$766,109.60	$16,200,000.00	$60,900,000.00
2007	$56,508.44	$476,556.80	$9,937,265.00	$29,500,000.00
2008	$3,093,744.00	$27,800,000.00	$532,000,000.00	$1,590,000,000.00
2009	$250,414.00	$2,621,618.00	$54,900,000.00	$125,000,000.00

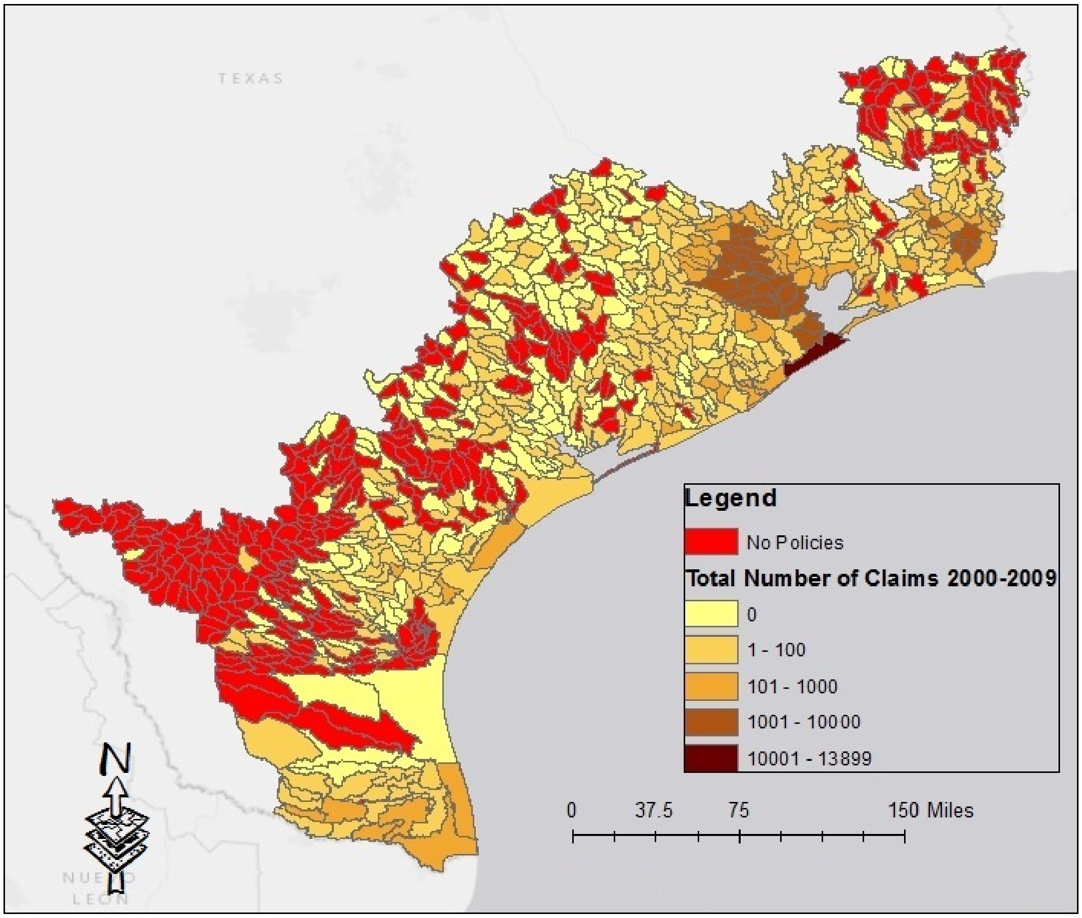

Figure 11: Total Number of Claims for Study Area from 2000-2009

4.3.2. Independent Variables – Land Cover Pattern Metrics

The Coastal Change Analysis Program (CCAP)'s Land Cover Classification Scheme provides raster layer data for land cover types derived through remote sensing. Land cover data is available for 1996, 2001, 2006, and 2011 and provides consistent land cover classification schemes over all four time periods that allows for comparison across time.

Land cover data was used in Fragstats version 4 (McGarigal, Cushman and Ene 2012) to derive land cover metrics for multiple land cover types. Independent variables that represent different aspects of urban patterns utilized high, medium and low intensity development land covers. High intensity development (HID) land cover includes areas covered by concrete, asphalt and other constructed materials that account for 80 to 100 percent of the land cover. Medium intensity development (MID) land cover includes landscapes covered by 50 to 79 percent constructed materials, and low intensity development (LID) land cover includes landscapes covered by 21-49 percent constructed materials. Fragstats was also used to calculate metrics for other natural land cover types, and are described below in appropriate sections.

Six landscape metrics were calculated to calculate different dimensions of urban pattern for the three different intensity development land cover types; percent area, mean patch area, mean gyrate, patch density, proximity and shape. These 18 metrics were calculated for 1996, 2001, 2006 and 2011 for 916 landscapes using polygons representing watersheds at the twelve-digit Hydrologic Unit Code (HUC) from the National Hydrography Dataset (NHD). Between years were imputed assuming a consistent annual change between years of available data.

Percent Class Area

Percent Class Area (Percent) creates a ratio of total area of a particular class type to the total area of the landscape. Increases in impervious surface reduce infiltration and increase surface runoff, which can cause flood waters to accumulate more rapidly and increase flood peaks. When controlling for flood exposure using other variables, increased quantities of impervious surface are expected to increase flood magnitudes which will lead to increased flood damage. Fragstats calculates Percent Class Area as:

$$PercentClassArea = \frac{\sum_{j=1}^{n} a_{ij}}{A}$$

Where i is the land cover type, j is the patch number, a_{ij} is the area of patch j for the i^{th} land cover type, and A is the total landscape area (Leitão et al. 2006). It is hypothesized that as percent urban area increases, flood damage will increase (H1a).

Mean Gyrate

Mean Gyrate (or Radius of Gyration) is a measure of how expansive or compact a patch is. Fragstats can calculate the Mean Gyrate value, which is the average Gyrate value for all patches of a given class type. When Gyrate measures impervious surface land cover, increases in Gyrate are expected to increase stormwater runoff. Fragstats calculates Mean Gyrate as:

$$MeanGYRATE = \frac{\sum_{r=1}^{z} \frac{h_{ijr}}{z}}{n}$$

Where h_{ijr} is the distance in meters between cell *ijr* and the centroid of patch *ij* based on cell-center to cell-center distance, *z* is the number of cells in parch *ij* and *n* is the number of patches in the landscape (Leitão et al. 2006). Mean Gyrate is measured in meters. It is hypothesized that as Mean Gyrate increases, flood damage will increase (H1b).

Patch Density

Patch Density is simply the number of patches of a particular class divided by the area of the landscape. By itself, patch density of impervious surface land cover does not have any predicted relationship with flooding or flood damage. However, when combined with Percent Area, it could provide clarification for how broken up impervious surface land cover is on a given landscape, which may indicate that there are pervious land covers in between impervious surface patches. PN may distinguish the TIA from directly connected impervious area (DCIA) or effective impervious area (EIA), which have been shown to contribute to runoff more significantly than TIA. If this is the case, then increased PN would indicate decreased DCIA and EIA and result in overall reductions to stormwater runoff (Lee and Heaney 2003).

To further understand how "broken up" impervious surfaces are across a landscape, two other metrics may be used. Average Patch Size (APS) is the total area of all patches of a given class type, divided by the total number of patches of that class type. Patch Density (PD) is the number of patches per unit area within a given landscape. It is difficult to estimate how these metrics would interact with one another in an analysis, but each could be used to measure patches of impervious surface to determine whether they will behave more like TIA or like DCIA or EIA. Fragstats calculates Patch Density as:

$$PatchDensity = \frac{PN}{A}$$

Where PN is the Patch Number, A is the landscape area (Leitão et al. 2006). It is hypothesized that as Patch Density increases, flood damage will increase (H1c).

Mean Shape

Mean Shape is a standardized measure of how complex a patch is, or how much of its perimeter is adjacent to other land cover types relative to its size. As patch shape becomes more complex, the amount of perimeter that is connected to pervious land covers increases, indicating that increasing shape would result in reductions to stormwater runoff. Fragstats calculates Shape as:

$$MeanSHAPE = \frac{\dfrac{p_{ij}}{\min p_{ij}}}{n}$$

Where i is the patch type, j is the patch number, p_{ij} is the current perimeter of patch ij and min p_{ij} is the minimum perimeter of patch ij if all cells were perfectly clustered. Mean Shape is a unitless measurement (Leitão et al. 2006). It is hypothesized that as Mean Shape increases, flood damage will decrease (H1d).

Mean Proximity

Mean Proximity is a measurement that describes the size of patches within a landscape, as well as the distance of these patches from one another. Typically, the metric is used to estimate patch isolation from a focal patch where larger patches closer to the focal patch would yield a higher value, and smaller patches further away from would yield a lower value (Leitão et al. 2006). When Mean Proximity measures impervious surface land cover, increases would indicate that patches are “broken up” which would reduce stormwater runoff. Fragstats calculates Mean Proximity as:

$$MeanPROXIMITY = \frac{\sum_{j=1}^{n}\sum_{i=1}^{n}\dfrac{a_{ij}}{h_{ij}^{2}}}{n}$$

Where i is the patch type, j is the patch number, and h_{ijs} is the distance from patch ij to another patch ij within the landscape (Leitão et al. 2006). Higher values of Mean Proximity indicate patches are closer together. Mean Proximity is dimensionless. It is hypothesized that as Mean Proximity increases, flood damage will increase (H1e).

Mean Patch Size

Mean Patch Size is the area of all patches summed for each watershed, and then divided by the number of patches. Fragstats calculates Mean Patch Size as:

$$MeanPatchSize = \frac{\sum_{j=1}^{n} a_{ij}}{n}$$

Where i is the patch type, j is the patch number, a_{ij} is the area of patch ij, n_i is the number of patches in the landscape of patch type i. Mean Patch Size is measured in square meters (Leitão et al. 2006). It is hypothesized that as Mean Patch Size increases, flood damage will increase (H1f).

4.3.3. Independent Variables – Land Use Exposure Metrics

There are two spatial metric variables proposed that may estimate the level of property exposed to flooding at the watershed scale; average distance of residential property to flood features (AV_DIST) and average elevation of residential property (AV_ELEV). Block-level U.S. Census data were used to identify the number of housing units in a given block. Using tools within Arc Toolbox, as well as hydrology and elevation data from the National Hydrography Dataset (NHD), the following metrics were calculated for each watershed.

Proximity of Residential Property to Hydrology

Distance to flood features are calculated as:

$$AV\_DIST = \frac{\sum_{n=1}^{N} P_n * D_{nf}}{N}$$

Where P_n is the number of residential properties at point n, D_{nf} is the distance between point P_n and the target flood feature. The points within the landscape are numbered 1,2,…,n,…,N. This equation will be used to determine distance to multiple exposure factors, including distance to watershed mouth/shoreline, distance to stream, and distance to any water feature. Increasing AV_DIST is expected to result in decreased exposure to flooding. As AV_DIST increases, flood damage is expected to decrease.

While most landscape metrics only utilize two-dimensional measurements, there is opportunity to expand the field into three dimensions as well as increasing the use of functional metrics that assign values based on other landscape features like elevation, soil, etc. that can better capture the different dimensions of watersheds (Blaschke and Strobl 2003, Ward 1989). Flood damage can also occur beyond simple distance from flood-prone features. On a three-dimensional landscape, landscape metrics can also be calculated to estimate flood exposure of residential properties where properties at lower elevations are more exposed to flooding than properties at higher elevations. Average distance of residential property to water is measured in meters. It is hypothesized that as averaged distance of residential property to water increases, flood damage will decrease (H2a).

Elevation of Residential Property

Average Elevation of Property are calculated as:

$$AV\_ELEV = \frac{\sum_{n=1}^{N} P_n * E_n}{N}$$

Where P_n is the number of residential properties at point n that occupies the same space as E_n which is the elevation. The points within the landscape are numbered 1,2,…,n,…,N. Increasing AV_ELEV results in decreased exposure to flooding. It is hypothesized that as AV_ELEV increases, flood damage will decrease (H2b).

For both AV_DIST and AV_ELEV, *P* was calculated for each census block by calculating the number of homes per unit area, clipping the census block polygons to within HUC 12 polygons, and then recalculating the number of homes based on the new are of the polygon. This essentially only effected census blocks that bordered HUC 12 boundaries; all census blocks completely contained within HUC 12 boundaries retained original number of properties. Centroids of the new census block polygons were generated for the purpose of identifying n points. For AV_DIST, distance from each centroid to water features from all water features in the NHD dataset (in meters) was calculated to populate D_{nf}. For AV_ELEV, elevation (in feet) was calculated by overlaying census block centroid points on the digital elevation model data available in the NHD dataset and values were assigned to E_n.

All urban pattern metrics were derived from datasets that only had data from specific years. Land cover data was available for 1996, 2001, 2006 and 2011, and block-level housing data was available from the U.S. Census from 2000 and 2010. Due to this limitation, between years data was imputed assuming a constant annual rate of change to each variable.

4.3.4. Control Variables

There are several environmental variables that influence watershed hydrology and flooding. The proposed environmental control variables all measure two basic aspects of watershed hydrology; how much water enters a watershed (precipitation), and where and how long it stays before leaving the watershed. While there are several other ways that water can leave a watershed (evaporation, etc.), the proposed control variables primarily focus on absorption into soil and morphometric features that regulate movement of water downstream to the next watershed or to open ocean.

Average Slope

Average slope was calculated using digital elevation model (DEM) data from the National Hydrography Dataset and ArcGIS software to create a layer that represented the angle of slope in degrees. This layer was aggregated at the watershed level to calculate the average slope in degrees. Higher Average Slope values would result in runoff moving quicker down the watershed. It is hypothesized that as average slope increases, flood damage will increase.

Drainage Density

Drainage density was calculated using polyline data and watershed boundary data from the National Hydrography Dataset and ArcGIS software to measure the total length of streams (in kilometers) as well as the watershed area (in square kilometers). Increases in Drainage Density are rates of runoff and reducing local impacts from flash flooding, but could increase flood waters in downstream areas. It is hypothesized that as Drainage Density increases, flood damage will decrease.

Soil Water Capacity

Soil water capacity was calculated using data from the Natural Resources Conservation Service (NRCS)'s Digital General Soil Map of the United States (STATSGO2) and NRCS's Soil Data Viewer. Soil water capacity values were calculated for the different soil types in each watershed and averaged based on the proportion of each soil type in a given watershed. The resulting variable is the average available water capacity value in inches. This value represents quantities of soil that can store water, which would represent areas that are more prone to flooding. Increased soil storage capacity may indicate water being held within the landscape instead of infiltrating into groundwater or flowing downstream. It is hypothesized that as AWC increases, flood damage will increase.

Hydrologic Conductivity

Hydrologic Conductivity was calculated using data from the Natural Resources Conservation Service (NRCS)'s Digital General Soil Map of the United States (STATSGO2) and NRCS's Soil Data Viewer. KSAT values were calculated for the different soil types in each watershed and averaged based on the proportion of each soil type in a given watershed. The resulting variable is the average KSAT value in inches per second representing infiltration rate. The slower water infiltrates into the soil, the more it has the potential to pool and cause flooding. It is hypothesized that as KSAT increases, flood damage will decrease.

Precipitation

Precipitation was calculated using Oregon State University PRISM Climate Groups data that contained raster data at the 30 m resolution of annual rainfall amounts. These values were averaged for each watershed to calculate the average annual rainfall in millimeters. It is hypothesized that as precipitation increases, flood damage will increase.

Upland Vegetation

Upland vegetation is an aggregated percent of land cover that is described by the CCAP Land Cover Classification scheme that includes Grassland and Forest land cover types that have vegetation that accounts for greater than 20 percent of the total vegetation coverage. Vegetation types include Grassland/Herbaceous, Deciduous Forest, Evergreen Forest, and Mixed Forest. These land cover types were aggregated and the percentage of these land covers consisted of the total area of each watershed was calculated. It is hypothesized that as percent upland vegetation increases, flood damage will increase.

Wetlands

Wetlands, as described by the CCAP Land Cover Classification Scheme, includes multiple wetland types that account for at least 20 percent of the total vegetation coverage. Wetland types include Palustrine Forested Wetland, Palustrine Scrub/Shrub Wetland, Palustrine Emergent Wetland, Estuarine Forested Wetland, Estuarine Scrub/Shrub Wetland, and Estuarine Emergent Wetland. These land cover types were aggregated and the percentage of these land covers consisted of the total area of each watershed was calculated. It is hypothesized that as percent wetland area increases, flood damage will increase.

Average Age of Homes

Average age of homes was calculated using the National Flood Insurance Program's Policy Dataset. Point level data were aggregated to the watershed scale to calculate average age homes covered by a flood insurance policy. It is hypothesized that as Average Age of Homes increases, flood damage will increase.

Number of Flood Insurance Policies

Number of flood insurance policies was calculated using the National Flood Insurance Program's Policy Dataset. Point level data were aggregated to the watershed scale to calculate the total number of policies per watershed. Watersheds with zero policies were excluded from the regression analyses. It is hypothesized that as Number of Flood Insurance Policies increases, flood damage will increase.

4.4. Data Analysis

Data analysis to test the relationship between urban patterns and flood damage in Texas coastal watersheds consisted primarily of the use of multivariate regression analyses, after analyzing the data statistically and visually (see Table 3 for summary statistics and Appendix 1 for Figures 20-59 which are maps showing change of urban patterns over study area). Justification for analytic approach, model selection, and diagnostics is discussed in the next section, and is followed by identification of known threats to the interpretability and generalizability of this study.

4.4.1. Statistical Analysis of the Relationship between Urban Patterns and Flood Damage

Due to the availability of annual data throughout the study period, a cross-sectional time series regression analysis was chosen. However, there were several potential issues that were addressed through model selection and regression diagnostics to determine whether basic regression assumptions were met and ensure models provide reliable results. The following includes information on the model selection and diagnostic criteria.

Table 3: Summary Statistics for Independent Variables

Variable	Source	Mean	Std. Dev.	Min	Max
Percent HID	CCAP	1.213286	3.692091	0	29.9179
Percent MID	CCAP	3.016324	7.154743	0	45.4069
Percent LID	CCAP	3.65418	5.595132	0.00906	39.1009
Gyrate HID	CCAP	24.48826	18.5768	0	435.6562
Gyrate MID	CCAP	27.59226	9.038397	0	86.2631
Gyrate LID	CCAP	29.4085	8.126735	15.625	84.19839
Proximity HID	CCAP	11.08399	47.88308	0	542.1953
Proximity MID	CCAP	31.50651	103.8411	0	1265.247
Proximity LID	CCAP	27.99658	179.8943	0.0026	3417.354
Shape HID	CCAP	1.041675	0.360446	0	3.3722
Shape MID	CCAP	1.214418	0.144801	0	1.8586
Shape LID	CCAP	1.248642	0.101354	1	1.886
Mean Patch Size HID	CCAP	0.543888	0.634765	0	8.4724
Mean Patch Size MID	CCAP	0.632669	0.707017	0	5.5168
Mean Patch Size LID	CCAP	0.59052	0.590356	0.1133	6.5411
Patch Density HID	CCAP	1.090301	2.306753	0	14.91492
Patch Density MID	CCAP	2.369795	3.405064	0	19.07696
Patch Density LID	CCAP	5.206582	5.827601	0.04862	34.4842
Average Elevation	US Census	3489.521	3355.741	0	18906.49
Av. Distance to Water	US Census	414.2382	213.9089	0	1805.128
Mean Slope	NHD	0.550779	0.576391	0.033981	3.699681
Drainage Density	NHD	0.545188	0.235798	0	2.09515
Soil Water Capacity	USGS	0.266354	0.162393	0	1.266795
KSAT	USGS	9.114925	15.14483	0	229.3172
Precipitation	PRISM	1131.215	378.302	322.7832	2160.662
Percent Upland Veg.	CCAP	56.94348	24.637	.0103	98.2366
Percent Wetland	CCAP	14.06645	16.18545	0.0263	83.5503
Age	FEMA	24.66714	10.35409	0	108
Total Number Policies	FEMA	707.7175	2275.289	1	28757

Multicollinearity among Landscape Metrics

Landscape metrics, like many ecological measurements, can be highly correlated due to different measurement of the same (or similar) construct being quantified (Leitão et al. 2006, Smith et al. 2009). Use of such variables in a single regression model can result in incorrect model parameterization and reduce statistical power of the overall model as well as otherwise significant predictor variables (Graham 2003). While there are several options for addressing this issue, the simplest method that has been employed in the literature is to isolate collinear variables and analyze them in separate models (Brody et al. 2012a). This method was employed in the current study to examine six different landscape metrics for three different land cover classes, resulting in 18 regression models. The two proposed urban pattern metrics that measured land use intensity and spatial location (not land cover) were in all 18 models, as they were not correlated with any of the urban land cover metrics. Collinearity diagnostics on each of the 18 models found no multicollinearity issues present.

Spatial Autocorrelation

Spatial autocorrelation can occur when measurements of variables are taken for each unit and values are similar or otherwise related to nearby or adjacent units (Dale and Fortin 2014). When observations are not independent spatially, regression assumptions are violated and can bias standard errors and reduce efficiency of estimated coefficients (Anselin 2007). Shehata and Mickaiel (2012) developed a routine for use in Stata statistical software package (StataCorp 2011) to determine the presence of spatial autocorrelation in cross-sectional time series data. Results indicated that there was spatial autocorrelation was not a concern (see Appendix 3). Due to the computational intensity of running the program on the data, only one “example” regression analysis was used (percent area of High Intensity Development).

Serial Correlation

Serial correlation in regression models that utilize cross sectional time series datasets can bias standard errors and cause overall results to be less efficient (Drukker 2003). This is due to error terms of observations being dependent over time, which violates model assumptions (Wooldridge 2015). Drukker (2003) developed a routine for use in Stata statistical software package version 11 (Statacorp 2011) to execute the Wooldridge (2002) test for serial correlation. The test was run on all 18 models, and results indicated the models were absent of serial correlation.

Cross-sectional Dependence

Cross-sectional dependence is a third type of correlation issue that is similar to spatial autocorrelation, but more general in that it looks for correlations between observations in a given time period due to the presence of unobserved common factors, which may or may not be related to spatial dependence (De Hoyos and Sarafidis 2006). The presence of cross-sectional dependence may also lead to biased standard errors (Driscoll and Kraay 1998). For panel datasets, where the number of observations is larger than the number of time periods (*N>t),* three tests are proposed by Hoyos and Sarafidis (2006) who developed a statistical routine using Stata statistical software version 11 (StataCorp 2011) to implement the Pearson's (2004) test, Friedman's (1937) test, and Frees' (1995) test to determine the presence of cross-sectional dependence in time series models. Results from all three tests for the 18 models indicated that cross-sectional dependence was present in all models which led to the use of robust standard errors in the regression analyses.

Heteroskedasticity

Heteroskedasticity violates the assumption that there is constant variance in the error terms, and is doubly of concern in cross sectional time series models due to the potential for non-constant variance across observations, as well as within the same observation over time (Baltagi, Song and Kwon 2009). Visual analysis and the Breusch-Pagan /

Cook-Weisberg test for heteroscedasticity available in the Stata version 11 (StataCorp 2011) indicated that the error terms in all 18 regression models lack constant variance across observations, which further supported the use of robust standard errors in the final regression models.

4.5. Validity Threats

There are many threats to the validity of the results from the regression analyses presented in Section 5. Most of these pertain to the nature of spatial data the use of existing and available datasets. This section provides a brief overview of many of the known validity threats that can only be recognized and were not able to be addressed in the research design.

4.5.1. Dependent Variable – Flood Damage

While flooding can be quantified by height, volume, rate, and other measurements, flood damage can be calculated in terms of costs and is often quantified in terms of lives lost and damage to property. These can include monetary and non-monetary damages and can be the result of both direct and indirect impacts (Smith and Ward 1998, Gall et al. 2009).

It is challenging to identify precisely how human occupancy of flood-prone areas is related to flood damage because methods quantifying flooding are not standardized. This is due to the fact that “flooding” can be measured and defined differently depending on context (Pielke 1999). For example, flooding, flood risk, and flood damage have different meanings in different fields of study, and policy or decision-makers may use these terms differently than scientists. Green, Tunstall, and Fordham (1991) examined groups of engineers, planners, citizens, and researchers to identify whether there was a significant difference in their perception of flood risk. The authors concluded that there is a significant difference in the colloquial definition of terms among the groups, which can be problematic when collaboration and transfer of information is required to identify flood problems and develop solutions.

Flooding in terms of hydrologic response can be measured numerous ways; including flood volume and rate, frequency of events, efficiency of the watershed to move stormwater downstream, how quickly a hydrologic system can fill with water, and numerous other measurements. In their review of the literature, Olden and Poff (2003) examined flood variables used in 20 different studies and found there were only four principal components of the 171 variables that accounted for 75% of the variability. This indicates that even though there are numerous different ways to measure flooding, there are only a few key measurements that effectively represent what exactly a flood is.

Flood damage can be more difficult to define than flooding, as there are numerous ways flooding can impact human lives and property. Monetary costs can include direct damage to property, and non-monetary costs may include how the health of individuals is impacted by a flood (both mental and physical health), as well as loss of non-monetary goods like memorabilia (Green and Penning-Roswell 1989). Additionally, direct and indirect costs can be both economic and non-economic; indirect monetary costs could include the cost to evacuate a storm and stay at a hotel, to the loss of income from not being able to return to work after a storm (Gall et al. 2009). Indirect non-monetary costs can include the long-term emotional impacts caused by the experience (Green and Penning-Roswell 1989).

There are numerous issues with utilizing FEMA insured flood damage data that limits the results of the analysis. For example, only insured homes are included which means that there are numerous other homes that may have been impacted by flooding whose property damage will not be included in the analysis.

There are also potential data quality issues with the FEMA data. A study conducted by the Congressional Budget Office (2007) found that when looking at FEMA's NFIP data, many of the addresses (41 percent) were unable to be matched to corresponding property value data. The company that provided the property value data estimated that incorrect coding of the data could lead to up to a 50% matching failure rate (Congressional Budget Office 2007).

4.5.2. Independent and Control Variables – Spatial Data

There are threats to validity due to the use of spatial land cover data as well, and can be categorized as either data quality problems or unit selection problems. Data quality problems include issues with the data before measurement takes place, like how the data is stored (vector vs. raster), the grain size of the data, or how the aerial imagery is converted into different class types. Unit selection problems include how the researcher chooses to measure the landscape features/patterns, which are entirely dependent on how features within a landscape are aggregated or zoned, how the measurement of the landscape occurs within the geographic information system, and landscape scale choice.

There are also concerns with spatial autocorrelation and inference of the data. Another way to think of this is that data quality pertains to the reliability of the measures, the unit selection problems relate to the validity of the measures. Reliability may only be noted as a limitation to this study as all of the data comes from pre-existing datasets. However, recognizing the validity issues can improve the measurement and the inference of the metrics. When paired with statistical tests that assist with determining validity, knowledge of the processes that the metric is supposed to represent, as well as a firm understanding of how the variable is measured can guide decision-making on how to measure, as well as what scale should be used.

While many of these are related to both the reliability *and* validity of landscape measures/geographic metrics, some are inherent in how the data is made available publicly, and some are related to how the data are analyzed. By understanding these issues, many of the validity issues can be addressed, even if the reliability ones can only be mentioned as limitations to the study.

When measuring landscape metrics, grain (cell) size can have a significant effect. In a study that looked at the same landscape with artificially increased grain size, it was found that some metrics (configurational) changed significantly, while others (compositional) did not have a major change (Wickham and Rhitters 1995). Another study found there were three different categories of metrics that had either a predicted change as grain size changed, no change as grain size changed, or an unpredicted change as grain size changed (Wu, Shen, Sun and Tueller (2002). Based on the results of both studies, it seems it is extremely difficult to make any generalizations on how grain size has any consistent effect on metric measurement.

Another issue with using existing datasets is the thematic resolution, which refers to the conversion process that occurs when an aerial image is converted into a raster dataset. Classes are determined by color interpretation, and based on the thematic resolution selected, an aerial photo may be classified into any number of classes. This “spatial filtering” can have significant implications on landscape metrics. Grain size may have a similar effect as changing the number of classes (Buyantuyev, Wu, and Gries 2010). NOAA CCAP provides documentation of this process and claims that data from 1996, 2001, 2006 and 2011 have all undergone the same data conversion procedures which should provide consistency across the study period.

Another threat to validity is the issue of the Modifiable Areal Unit Problem (MAUP). Statisticians have dealt with MAUP long before landscape ecology and quantitative geography emerged as their own fields. Simply stated, the MAUP is error that may exist due to a choice of units of analysis that are selected. MAUP poses a threat to the validity of the measurements taken, as they may not accurately represent the construct intended.

Jelinski and Wu (1996) and Dark and Bram (2007) both provide detailed reviews of the MAUP in the fields of landscape ecology and quantitative geography, respectively.

There are some options to addressing the MAUP, including selecting appropriate units of analysis (Openshaw 1984, Hay et al. 2001), and conducting analyses at different spatial scales and comparing the results to determine an appropriate spatial scale (Jelinski and Wu 1996, Dark and Bram 2007). Ecological analyses where hydrologic function is a primary factor may benefit from a watershed scale approach as this is a natural landscape unit that encloses many ecosystem functions as well as the fact that there are numerous methods existing in the literature to measure hydrologic functions of basins that may be used as control variables (Brody, Highfield and Thornton 2006, Montgomery, Grant and Sullivan 1995).

5. ANALYSIS OF URBAN PATTERNS IN TEXAS COASTAL WATERSHEDS

5.1. Regression Analysis of Urban Patterns on Flood Damage

Using the variables and model selection and diagnostics presented in the previous section, a total of 18 regression models were run to isolate the unique contribution to flood damage of each urban land cover metric. The results can be classified into three different sets of models where six landscape metrics were calculated for high-intensity, medium-intensity and low-intensity development land cover types. Average distance of residential property to water and average elevation of residential property were included in all eighteen models as they are not correlated with the 18 urban land cover metrics, and allow urban patterns that measure land use to be differentiated between land cover. Table 4 presents summary results of how each urban landscape metric behaved in its respective model. For the purposes of explaining how the models support or reject the eight hypotheses in this dissertation, the first six that are related to urban land cover metrics are presented first, and the last two are discussed briefly along with control variables for each group of models. This section concludes with a summary of all models and general trends identified.

Table 4: Significance of Land Cover Urban Patterns and Flood Damage

Metric Type	High Intensity Dev.	Medium Intensity Dev.	Low Intensity Dev.
Percent Area	.2162***	.2192***	.3425***
Mean Patch Size	.893***	1.5846***	1.5936***
Mean Gyrate	.0194*	.06***	0.02237
Mean Shape	.8613***	3.613***	3.867***
Mean Proximity	0.0016	.0044**	.0017*
Patch Density	.8019***	.6099***	.3184***

Notes: *** p<.01; **p<.05; * p<.1.

Control variables not included in table.

5.1.1. Overall Significance of Urban Patterns and Flood Damage

All but two of the land cover urban pattern metrics were significant in their respective models and behaved consistently across low, medium and high intensity development land cover types, which contrasts with previous research that have used similar metrics to determine how urbanization is related to flood damage. Additionally, all but one of the metrics behaved as hypothesized; indicating that the metrics are in-fact representative of the dimensions of urbanization that were presented in Section 3. However, one of the variables, mean patch shape, was statistically significant across all three land cover types and had the opposite relationship as hypothesized. Initially, it was thought that increases in mean patch shape signified increased adjacency to natural land cover types which were thought to result in reduced flood damage, but it more likely represents the overall diffusion of urban patches across the landscape regardless to what is other nearby.

There were two independent variables representing urban patterns that did not behave as hypothesized; Mean Shape and Average Distance of Residential Property to Water. It is believed that Mean Shape was incorrectly conceptualized in Section 3, which led to an incorrect hypothesis on the relationship between the metric and flood damage. While increases in the value of Mean Shape may indeed represent greater adjacency to natural area (which could lead to decreased flood damage), it is believed that the metric by itself represents an overall diffusion of urbanization across the landscape which is why it is positively related to flood damage.

The relationship between Average Distance of Residential Property to Water and flood damage was inconsistent among the 18 models, and was not always significant. There is no doubt that distance to water must be related to flood damage, but due to the behavior of this metric across all models may indicate that the variable was measured inappropriately. The water features that were used to measure distance included rivers, ocean, and lakes/ponds. It may be that this was an incorrect method, as there may be many water features that despite their proximity to residential property, have no hydrologic connection.

Two variables, Mean Gyrate and Mean Proximity, did not have statistically significant results across all three urban land cover types, indicating that these patterns may be ecologically significant for some types of urban land cover, but not others.

In summary, the results of the 18 regression models support Hypotheses 1a, 1b, 1c, 1e and 1f. When controlling for where residential properties are located relative to the hydrology of the watershed, the models show that regardless of urban land cover intensity, increases in Percent Area, Mean Gyrate, Mean Proximity, Mean Patch Size, Mean Shape, and Patch Density all result in increased flood damage.

5.1.2. Urban Patterns and Flood Damage for High Intensity Development

The first group of models include the six metrics as they measure High Intensity Development, which is characterized as developed area that is 80% - 100% impervious surface. All six models had Wald $\chi 2$ values that indicated the models were significant, and explained between 39.9% and 43.5% of the variance in flood damage (see Table 5).

Average Elevation of Residential Property had a negative and statistically significant relationship ($p<.01$) with flood damage in all six models, which supports the hypothesis that increased elevation of residential property results in reduced flood damage (H2a). Surprisingly, Average Distance of Residential Property to Water had a positive relationship that was statistically significant in five of the six models, meaning there was no evidence to support the hypothesis that increased distance from water results in reduced flood damage (H2b).

Almost all control variables were statistically significant in the model, except for Drainage Density and Percent Wetland Area, which were not significant in the models that included Patch Density. KSAT was not statistically significant in any of the models. In the models where Drainage Density was statistically significant, it did not behave as hypothesized and indicated that increased Drainage Density resulted in increased flood damage. As the variable is used in hydrological studies, it represents the ability of a basin to shed runoff and take it downstream, which would reduce flooding adjacent to streams. The unexpected relationship may be due to water being carried quickly downstream but results in flood damage in low-lying areas.

Table 5: Urban Patterns and Flood Damage for High Intensity Development Model Results

	Model 1 Beta	Model 2 Beta	Model 3 Beta	Model 4 Beta	Model 5 Beta	Model 6 Beta
Average Elevation	-0.0000788***	-.0000823***	-.0000897***	-0.0000843***	-.0000989***	-.0000517***
Average Distance to Water	.0005462*	.0006208**	.0007767***	.0007887***	.0008109***	.0002778
Drainage Density	.7247746*	.6905499**	.8360754**	.904937***	.8564902**	.2937147
Mean Slope	-.6671163***	-.6224565***	-.6179397***	-.6634136***	-.6211789***	-.6441542***
Soil H20 Capacity	3.535359***	3.939757***	4.28765***	4.274824***	4.414332***	2.510036***
KSAT	.0076134	.0077067	.0068079	.0065081	.0063827	.0067394
Precipitation	.002191***	.002192***	.0022043***	.0022077***	.0022436***	.0021024***
Total Number Policies	.0004682***	.0005692***	.0005956***	.0005878***	.0005956***	.0001994*
Age of Homes	.0292481***	.0279605***	.0286515***	.0267802***	.0315922***	.0270579***
Percent Upland Veg.	-.0361313***	-.0412901***	-.0440906***	-.044343***	-.0438976***	-.0259978***
Percent Wetland	-.0215532***	-.0296154***	-.0314814***	-.0329876***	-.0305543***	-.0094644
Percent Area HID	**.2162*** **					
Mean Patch Size HID		**.893*** **				
Mean Gyrate HID			**.0194* **			
Mean Shape HID				**.8613*** **		
Mean Proximity HID					**0.0016**	
Patch Density HID						**.8019*** **
Constant	.6536493**	.7127151*	.6547115	0.320277	.8997368**	.238305
R-squared	.4046	0.4087	.4054	0.4092	.3992	.4351
Wald χ 2	948.69***	1081.26***	1054.65***	1110.15***	1033.33***	1260.19***

Notes: *** p<.01; **p<.05; * p<.1.

5.1.3. Urban Patterns and Flood Damage for Medium Intensity Development

The second group of models include the six metrics as they measure Medium Intensity Development, which is characterized by development that is 50% to 79% impervious surface cover. All six models had Wald χ 2 values that indicated the models were significant, and explained between 40.2% and 46.2% of the variance in Flood Damage (see Table 6).

As with the first group of models, Average Elevation of Residential Property had a negative and statistically significant relationship with flood damage in all six models, which provides additional support to Hypothesis 2a. Average Distance of Residential Property to Water did not indicate consistent relationship across the metrics, as five of the six had a positive relationship, one had a negative relationship, and only three of the models were statistically significant at the $p<.1$ level.

Also similar to the first set of models, almost all control variables were statistically significant except for KSAT which was again not significant in any of the models. In this set of models, Drainage Density and Wetlands was not statistically significant in the Patch Density model, and Wetlands was also not significant in the Percent Medium Intensity Development model. Drainage Density was again positively related to flood damage, opposite of how the variable was hypothesized.

Table 6: Urban Patterns and Flood Damage for Medium Intensity Development Model Results

	Model 1 Beta	Model 2 Beta	Model 3 Beta	Model 4 Beta	Model 5 Beta	Model 6 Beta
Average Elevation	-0.0000608***	-.000065***	-.0000836***	-.0000821***	-.0000917***	-.0000419***
Average Distance to Water	.0003467	.0003742	.0006656**	.0006639**	.0006743**	-.0000807
Drainage Density	.4523807	.6002163*	.8451657**	.7743822**	.8213399**	-.0172183
Mean Slope	-.6455901***	-.5872697***	-.5746023***	-.6013098***	-.6298708***	-.6339043***
Soil H20 Capacity	2.852825***	3.653409***	4.157429***	4.180018***	4.23124***	1.976165***
KSAT	.0078647	.008161	.0081684	.007609	.0067157	.0104676*
Precipitation	.0021531***	.0021878***	.0022071***	.0021983***	.0022502***	.0021001***
Total Number Policies	.0002723**	.0004234***	.0005682***	.0005651***	.0005146***	.0002744***
Age of Homes	.0281402***	.028215***	.0278645***	.0267721***	.0308282***	.023648***
Percent Upland Veg.	-.0286542***	-.0351929***	-.0403599***	-.039485***	-.0418575***	-.0161887***
Percent Wetland	-.010485	-.0176036**	-.0251492***	-.0251639***	-.0272552***	-.0015202
Percent Area MID	**.2192*** **					
Mean Patch Size MID		**1.5846*** **				
Mean Gyrate MID			**.06*** **			
Mean Shape MID				**3.613*** **		
Mean Proximity MID					**.0044** **	
Patch Density MID						**.6099*** **
Constant	.2637986	-.15991	-.7422311	-3.427797***	.7952579**	-.5395698
R-squared	.4226	.4254	.4145	0.4147	.4018	.4619
Wald χ 2	1102.62***	1193.15***	1129.19***	1141.22***	994.32***	1822.16***

Notes: *** p<.01; **p<.05; * p<.1.

5.1.4. Urban Patterns and Flood Damage for Low Intensity Development

The third and final set of models include the six metrics as they measure Low Intensity Development, which is characterized by development that is 21% to 49% impervious surface cover. All six models had Wald χ 2 values that indicated the models were significant, and explained between 40.12% and 45.8% of the variance in Flood Damage (see Table 7).

As with the first two groups of models, Average Elevation of Residential Property had a negative and statistically significant relationship with flood damage in all six models, meaning all 18 models provide support to Hypothesis 2a. Similar to the second set of models, Average Distance of Residential Property to Water did not indicate consistent relationship across the metrics, and four of the models were statistically significant at the $p<.1$ level.

Also similar to the first two sets of models, almost all control variables were statistically significant except for KSAT which was again not significant in any of the models. Again, the variables Drainage Density and Percent Wetland Area was not statistically significant in all models, including the Patch Density model. Only one of the models had the variable Drainage Density behave as hypothesized (Patch Density), and in that model the variable was not statistically significant.

Table 7: Urban Patterns and Flood Damage for Low Intensity Development Model Results

	Model 1 Beta	Model 2 Beta	Model 3 Beta	Model 4 Beta	Model 5 Beta	Model 6 Beta
Average Elevation	-.0000469***	-.000075***	-.0000938***	-.0000873***	-.0000964***	-.0000473***
Average Distance to Water	-.000028	.0004606*	.000789***	.0006972**	.0007377***	.0001563
Drainage Density	.1901577	.8136365**	.9192363***	.9757701***	.8437059**	.1627321
Mean Slope	-.6598262***	-.6368883***	-.6286834***	-.6704827***	-.6270867***	-.7352352***
Soil H20 Capacity	2.781968***	4.406019***	4.554562***	4.486233***	4.530876***	2.309741**
KSAT	.0080028	.0092051	.0077469	.009609	.0067279	.0089517
Precipitation	.0019371***	.0020401***	.0021954***	.0021513***	.0022196***	.0021714***
Total Number Policies	.0003082***	.0005793***	.0006099***	.0005973***	.0005949***	.0002657***
Age of Homes	.0259469***	.0276317***	.031162***	.0292292***	.03727***	.0266217***
Percent Upland Veg.	-.0233359***	-.0365318***	-.423377***	-.0387384***	-.0432955***	-.0225736***
Percent Wetland	-.0146053**	-.0337753***	-.0330439***	-.0343937***	-.0306811***	-.0055913
Percent Area LID	**.3425*** **					
Mean Patch Size LID		**1.5936*** **				
Mean Gyrate LID			**0.02237**			
Mean Shape LID				**3.867*** **		
Mean Proximity LID					**.0017***	
Patch Density LID						**.3184*** **
Constant	.0542098	.0569298	.1789061	-4.032054***	.8760479**	-.6691641*
R-squared	.4582	.4228	.4012	.4078	.4020	.4503
Wald χ 2	1326.37***	1108.11***	1035.68***	1074.82***	1030.28***	1498.45***

Notes: *** p<.01; **p<.05; * p<.1.

5.2. Control Variables

Almost all of the control variables behaved as hypothesized, and most were statistically significant across all models. Basin metrics (mean slope and drainage density) behaved as hypothesized in all models. Mean slope was statistically significant in all models. As mean slope increased (signifying increased runoff) flood damage decreased. Drainage Density was statistically significant in 13 of the 18 models. As drainage density increased (indicating a larger stream network relative to the watershed area), flood damage increased.

Soil variables were not as effectives as expected in the regression models. Although KSAT did behave as hypothesized, it was not statistically significant in any of the models. In contrast, Soil AWC behaved as hypothesized, was statistically significant in all 18 models, and was by far the most influential variable in all the models. Precipitation also behaved as hypothesized, was statistically significant in all models, and indicated that increased in precipitation indeed result in increased in flood damage.

Vegetation variables (percent Upland Vegetation and percent Wetlands) both behaved as hypothesized, indicating that increases in these types of vegetation result in reduced flood damage. Percent upland vegetation was statistically significant in all models, and Percent wetlands was significant in 14 of the 18 models.

Lastly, Age of Homes behaved as hypothesized and results from all 18 models indicated that older homes had more damage than newer homes. Age of Homes was statistically significant in all 18 models.

5.3. Urban Land Cover Pattern Examples from Houston

The world's population continues to grow especially in coastal areas. If future development mimics existing population density trends, there will be three times as much urban area as there was in 2000 by 2030 (Seto, Güneralp and Hutyra 2012). As of

2010, the Houston-Galveston region had 5.7 million residents, and is expected to increase to 9.8 million people by 2040 (Houston Galveston Area Council 2014). In U.S. Census statistics show that in 2010 Houston had a population density of 3, 371.7 people per square mile, and ranked as the fourth largest incorporated place in the U.S., while ranking 171st in population density. The growth experienced during the study period covered in this research provides an opportunity to look at urban land cover change. Although the study area stretches across the Texas coast, growth in Houston has been pronounced and provides context for the measurement and change of urban land cover metrics. Four example watersheds are discussed, and data is provided in Tables 9 and 10 on actual urban land cover metric measurements, as well, policy, demographic and flood damage data from 2001 and 2008, which were the two years in the study period that had the greatest amount of damage (see Table 2). Although there were other flood events during these years, the majority of damage occurring in these two years is due to the impact of tropical storms/hurricanes; Tropical Storm Alison in 2001, and Hurricane Ike in 2008. Due to the limited years of visual data, maps are provided for each of the watersheds from years 2001 and 2011. The maps of 2011 are not representative of change from 2001 to 2008; they are being used due to a lack of visual data from 2008, and should only be used as a comparison to the 2001 maps to provide clarity on overall urban land cover change within each of the watersheds.

It should also be noted that differences in flood damage are likely more related to the climatological differences between the two storms, and not differences in the urban pattern metrics. The differences between Tropical Storm Allison and Hurricane Ike can be seen in the data from those years. In 2001, the study area experienced $689 million in insured flood damage to residential properties, and had an average 1194.8mm in annual precipitation among the watersheds. In contrast, 2008 experienced $1.59 billion in insured flood damage to residential properties, and watersheds had an average 790mm fall within their boundaries. The primary difference between the two storms was that flooding due to Tropical Storm Allison in 2001 was largely precipitation-based, and much of the flood damage from Hurricane Ike in 2008 was due to storm surge in watersheds adjacent to the coast.

5.3.1. Upper Greens Bayou

Upper Greens Bayou watershed is north of Houston, spanning the northern part of Beltway 8 and has part of the George W. Bush International Airport in its northern section. The watershed experienced modest growth in urban land cover between 2001 and 2008, with HID increasing from 12.83% to 14.92%, MID increasing from 16.16% to 19.4% and LID increasing from 16.19% to 18.57%. There were 21,674 homes in the watershed in 2001, and aproximately 4700 homes were added to the watershed by 2008. However, the number of NFIP flood policies *decreased* from 3472 to 1821, resulting in the number of policies per home dropping from .16 to .07.

In 2001, Upper Greens Bayou had $36.2 million in damage, which was the second highest amount among the four watersheds and contains roughly 5.3% of the total damage for the study area that year. There was 1787.7 mm of rainfall in the watershed that same year, about 593 mm more than the average across the study area. In 2008, the watershed had $4.3 million in damage, only .2% of the total damage that occurred across the study area that year. There was 1257 mm of rainfall in 2008, about 468 mm more than the average across the study area that year. The amount of damage per home was $1,668.54 for 2001 and $163.38 per home in 2008.

There are similar quantities of MID and LID in the Upper Greens Bayou watershed, with MID growing at a slightly higher rate from 2001 to 2008. Despite the increases in area for these two land cover types, Mean Gyrate and Mean Shape stayed relatively the same. However, Mean Gyrate actually decreased for HID land cover, and at the same time Mean Shape for HID stayed fairly similar to previous measurement. This is likely due to the addition of separate HID patches on the landscape, as exemplified by the increase of HID Patch Density from 6.08 to 8.2 At the same time, Patch Density for MID and LID increased indicating additional patches were being created as opposed to existing patches getting larger. The only change in Mean Proximity worth noting is that HID patches changed from 126.13 to 105.212, indicating that HID patches are located closer to one another in the 2008 landscape.

Figure 12 presents the land cover for the watershed in 2001, and you can see changes in land cover in Figure 13 with visible changes highlighted in yellow circles. There are four locations in the watershed where significant development occurs. Of particular concern is the large circle at the easternmost part of the watershed which is where all water from the watershed flows towards as it exits the watershed mouth and enters the next downstream watershed. As such, this area may be particularly prone to flooding as stormwater and runoff accumulates and potentially overspills or expands into the floodplain. The other two lower circles in Figure 13 highlight other areas where large patches of vegetation have been replaced with various amounts of HID, MID and LID land cover. The fourth circle in the upper-left part of the watershed point out where Other, Wetland, and Upland Vegetation land covers have been replaced with MID and LID development. The Other land cover classification is actually various types of agricultural land covers that have been reclassified.

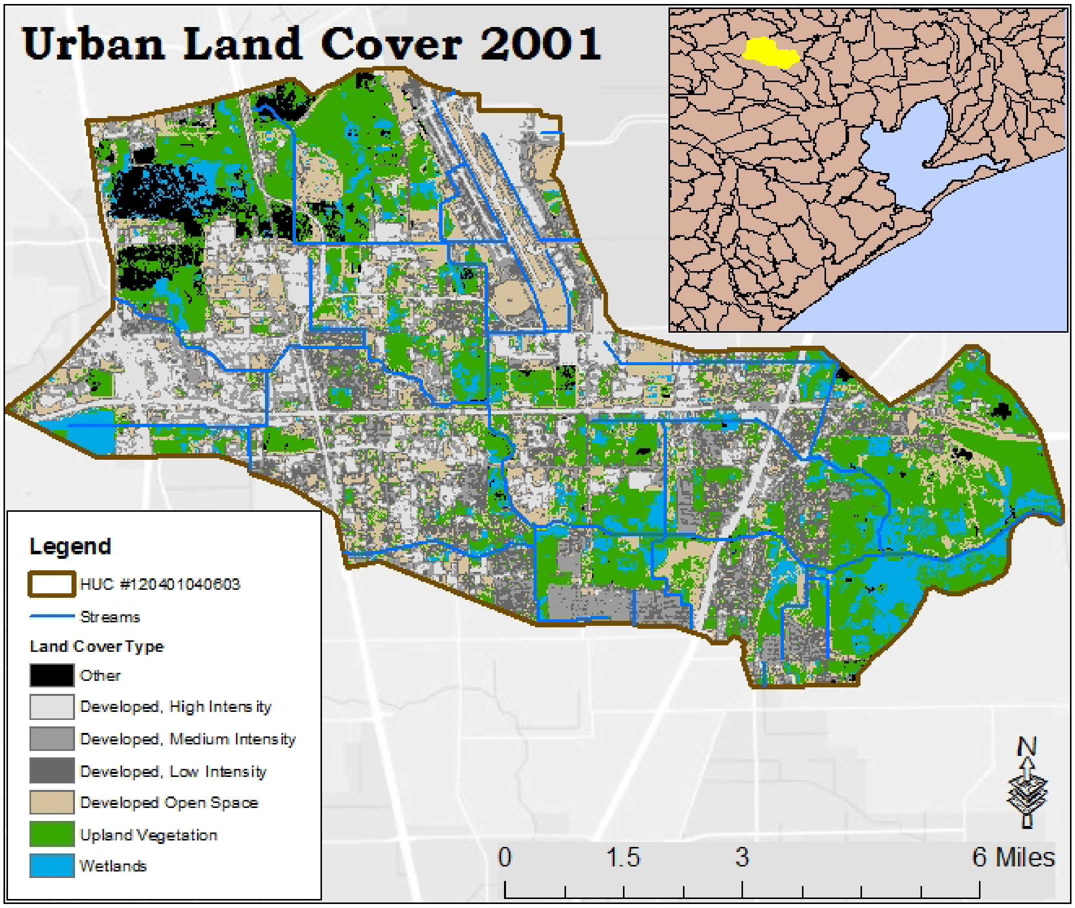

Figure 12: Upper Greens Bayou (North Houston) Land Cover in 2001

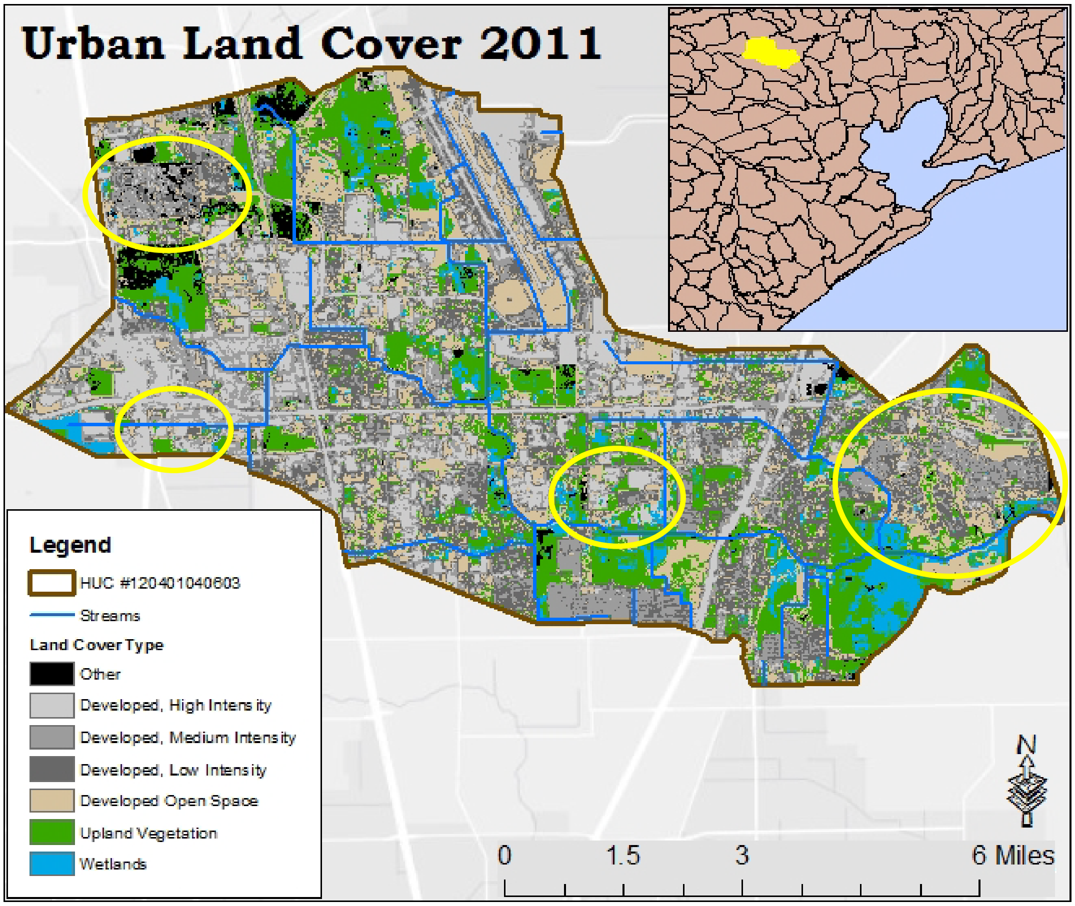

Figure 13: Upper Greens Bayou (North Houston) Land Cover in 2011

5.3.2. Country Club Bayou

Country Club Bayou is located just south Downton Houston, and provides a good representation of a highly urbanized watershed. Overall, the watershed experienced only slight changes to the amount of development contained within its boundaries, with HID increasing from 28.94% to 29.92%. MID and LID both decreased, from 45.4% to 45.07% and 15.85% to 15.65%, respectively. These numbers provide a good comparison among the three different Urban Land Cover types, with HID having a 2:1 ratio with LID, and MID having a 3:1 ratio with LID. Aproximately 12,500 additional homes were added to the watershed from 2001 to 2008, resulting in a total 124,328 homes. The number of policies per home increased during this time resulting an estimated number of homes covered growing from 9.52% to 10.17%.

In 2001, Country Club Bayou had $79.9 million in insured residential property damage, was the watershed with the most losses among the four examples and accounted for approximately 11.6% of the total damage for the study area that year. The watershed experienced 1850.7 mm of rainfall, about 655 mm more than the average for the study area, and observed approximately $714.25 of damage per home. There was about $3.2 million in flood damage to insured residential buildings in 2008, and the watershed experienced precipitation levels about 435 mm higher than the average for the study area that year.

Similar to Percent Area, MID patches had higher values of Mean Patch Size, Mean Gyrate and Mean Shape than HID or LID patches. This trend makes sense as larger patches will have greater distances from the center of the patch to the perimiter (expansiveness) as well as potential for greater patch complexity due to patch size increase while grain size of the patches stays the same. Despite these differences, the changes from 2001 to 2008 were relatively modest for these variables. There was significant changes to Mean Proximity, as MID patches decreased from 898.34 to 858.78, and HID patches increased from 519.3 to 540.89. This means that at the landscape scale, MID patches across the landscape grew closer together, and the average distance among all HID patches grew further apart.

Through visual analysis qualitative patterns emerge, and some of the quantifiable metrics are demonstrated. Figure 14 presents the land cover for the watershed in 2001, and you can see changes in land cover in Figure 15 with visible changes highlighted in yellow circles. Country Club Bayou provides an excellent representation of typical urban patterns in a heavily urbanized watreshed with HID land cover spiderwebbing across the landscape, both connecting other HID areas as well as cutting through larger MID land cover patches. Within each of the MID patches, there are numerous smaller LID patches scattered about. There is actually little land cover change in the watershed, except for the two areas circled in yellow in Figure 15 where there is evidence of converting upland vegetation to urban land cover. In the larger vegetation patch in the southwest part of the watershed, the top right portion of that patch was converted to HID and MID area. In the second smaller circle, there is MID and other developed open space replacing what once was another small patch of upland vegetation. In the larger circle, there is also evidence of the removal of MID land cover that has been replaced by a large patch of developed open space.

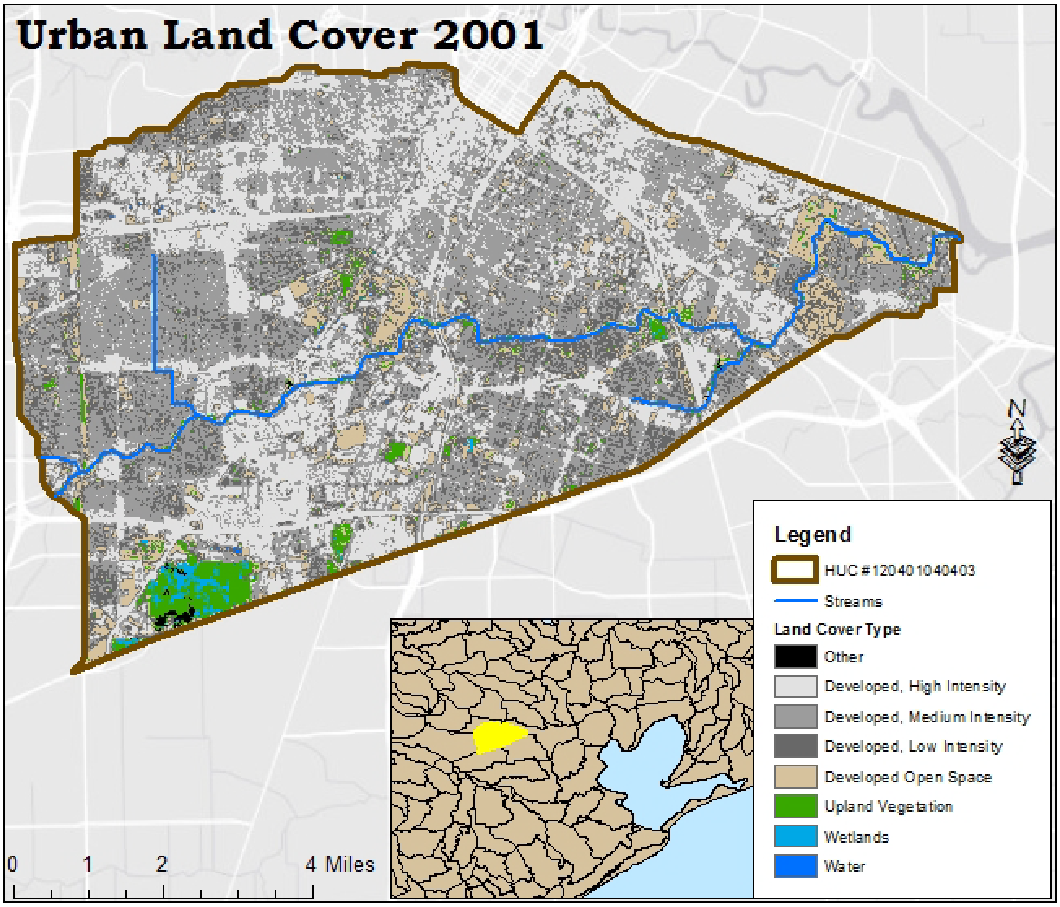

Figure 14: Country Club Bayou (South Downtown Houston) Land Cover 2001

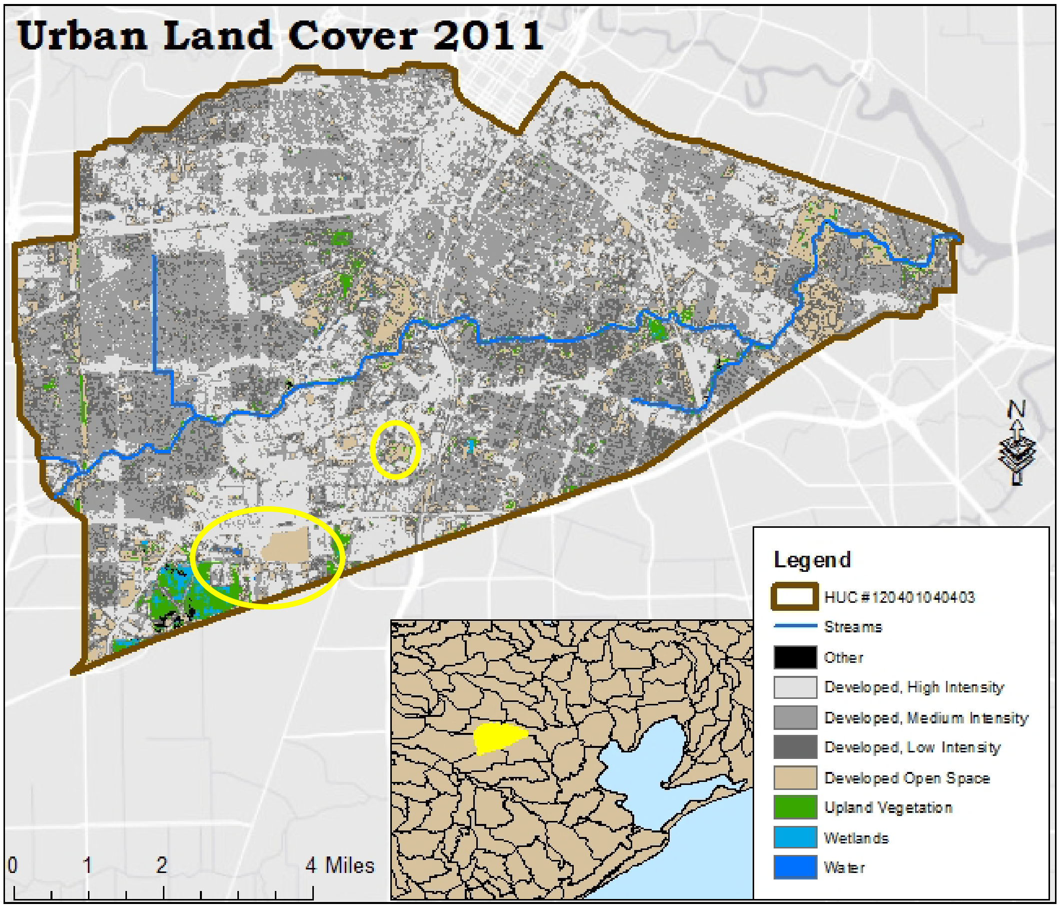

Figure 15: Country Club Bayou (South Downtown Houston) Land Cover 2011

5.3.3. Frontal Galveston Bay

Frontal Galveston Bay watershed is located further south of Houston than Country Club Bayou, and spans a large part of the southernmost part of Beltway 8. The watershed experienced fairly significant increases in development from 2001 to 2008, with HID nearly doubling from 2.7% to 4.48%, MID growing from 13.24% to 18.38%, and LID increasing from 12.93% to 16.54%. During this same time, the number of homes increased by nearly 14,500; from 25,208 to 39,641. Policies per home decreased, with an estimated 29.2% of homes having flood insurance policies in 2001 and 23.93% of homes having policies in 2008.

During the year of Tropical Storm Allison the watershed had $30.5 million in flood damage to insured residential buildings, and 1962.8 mm of precipitation; aproximately 768 mm more than the average for the study area. Average damage per home in 2001 was $1,210.48. In 2008, residental buildings suffered 2.23 million in insured property damage caused by floods and 475 mm more precipitation than the average for the study area. Average damage per home in 2008 was only $56.19.

The changes in urban land cover metrics for Frontal Galveston Bay provide an example of how to determine whether growth is occurring due to existing patches growing larger or through the development of new patches. Mean Gyrate values of HID, MID and LID all decrease, while Mean Proximity all increase, which at first provides evidence that existing patches of all three types are getting larger, and growing closer together. However, Mean Patch Size and Patch Density tell the other part of the story. Mean Patch Size decreases from 2001 to 2008 for all three Urban Land Cover types, and Patch Density increases. This is strong evidence that there are more patches per unit area for each of the urban land cover types, which is also reducing the average size of all urban patches across the landscape.

Figure 16 presents the land cover for the watershed in 2001. There are four locations highlighted in Figure 17 that show how land cover is evolving in the Frontal Galveston Bay watershed. The easternmost (smallest) and westernmost (largest) circles show where vast quantities of Other (agricultural) land cover have been converted to various amounts of HID, MID, LID and developed open space. The topmost circle shows where previous developed open space has been converted to mostly MID and some areas of HID. Development in the centermost circle is the result of converting Wetland and Upland Vegetation land covers to MID and LID land covers.

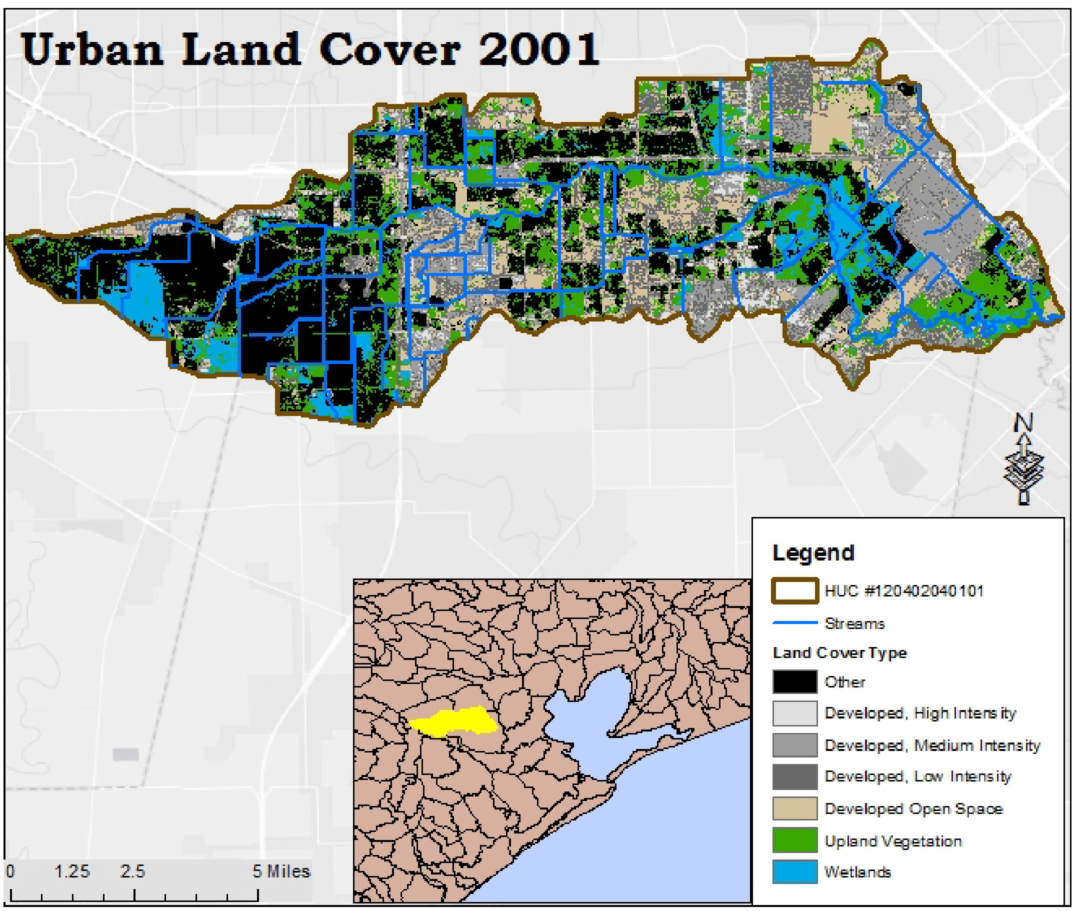

Figure 16: Frontal Galveston Bay (South Houston) Land Cover 2001

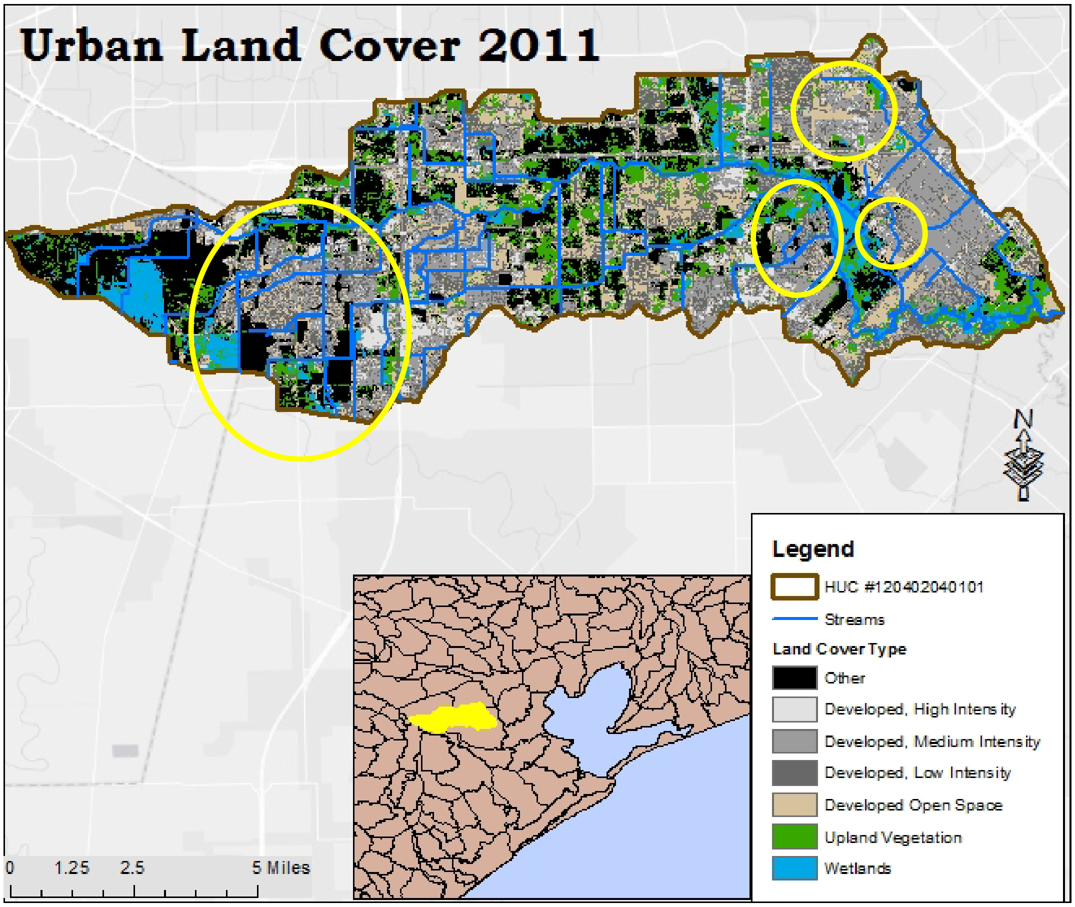

Figure 17: Frontal Galveston Bay (South Houston) Land Cover 2011

5.3.4. Dickinson Bayou

Dickinson Bayou watershed is located southeast of Houston, approximately halfway between Houston and Galveston Island. Although it is adjacent to the westernmost shores of Galveston Bay, its hydrology actually drains southeast towards Texas City. The watershed had fairly significant increases in development from 2001 to 2008, with HID increasing from 1.19% to 2.13%, MID nearly doubling from 4.78% to 8.08%, and LID increasing from 10.28% to 12.84%. The number of homes grew from 12,308 to 17, 906. The number of policies per home decreased, from .338 to .268.

In 2001, there was about $21.2 million in flood damage to insured residential buildings in Dickinson Bayou. The watershed had nearly twice as much rainfall as the average across the study area, with a total of 2025 mm. There was an estimated $1,724.31 of damage per home that same year. In 2008, there was over $69.47 million in flood damage to insured residential buildings, aproximately 4.4% of the total damage that year. There was 1193.8 mm of rainfall in the watershed, about 404 mm above the average for the study area.

Medium Intensity Development metrics had the most interesting changes between 2001 and 2008. The amount of MID area doubled, and due to MID Patch Density almost doubling from 5.56 to 9.08, it would seem that it was due to separate MID patches being developed. However, Mean Patch Size increased, meaning that old and new MID patches were larger in 2008 than just the patches found in 2001. Mean Proximity for MID patches increased, indicating that even though overall Patch Size was larger, the new patches were developed in other parts of the landscape away from existing MID patches.

Figure 18 presents the land cover for the watershed in 2001. All yellow circles Figure 19 point out areas that were once vegetation or agriculture that have been replaced mostly with MID or LID suburban developments. The rightmost circle has what can visibly be seen as a large-scale LID suburban development. In the same circle, there is a small patch of HID land cover is a part of Clear Creek Independent School District's Education Village, a 144 acre PK-12 facility that was developed in 2009 after the flooding that occurred in the watershed the previous year.

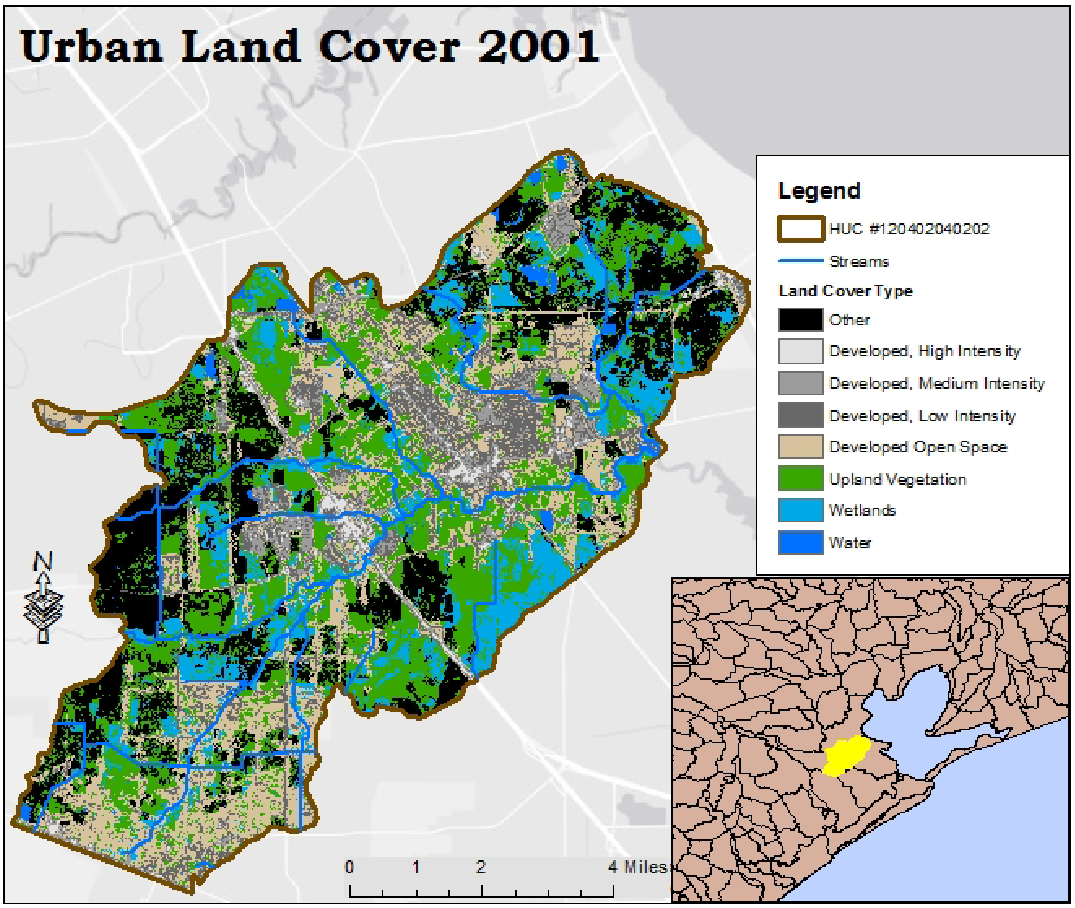

Figure 18: Dickinson Bayou Land Cover 2001

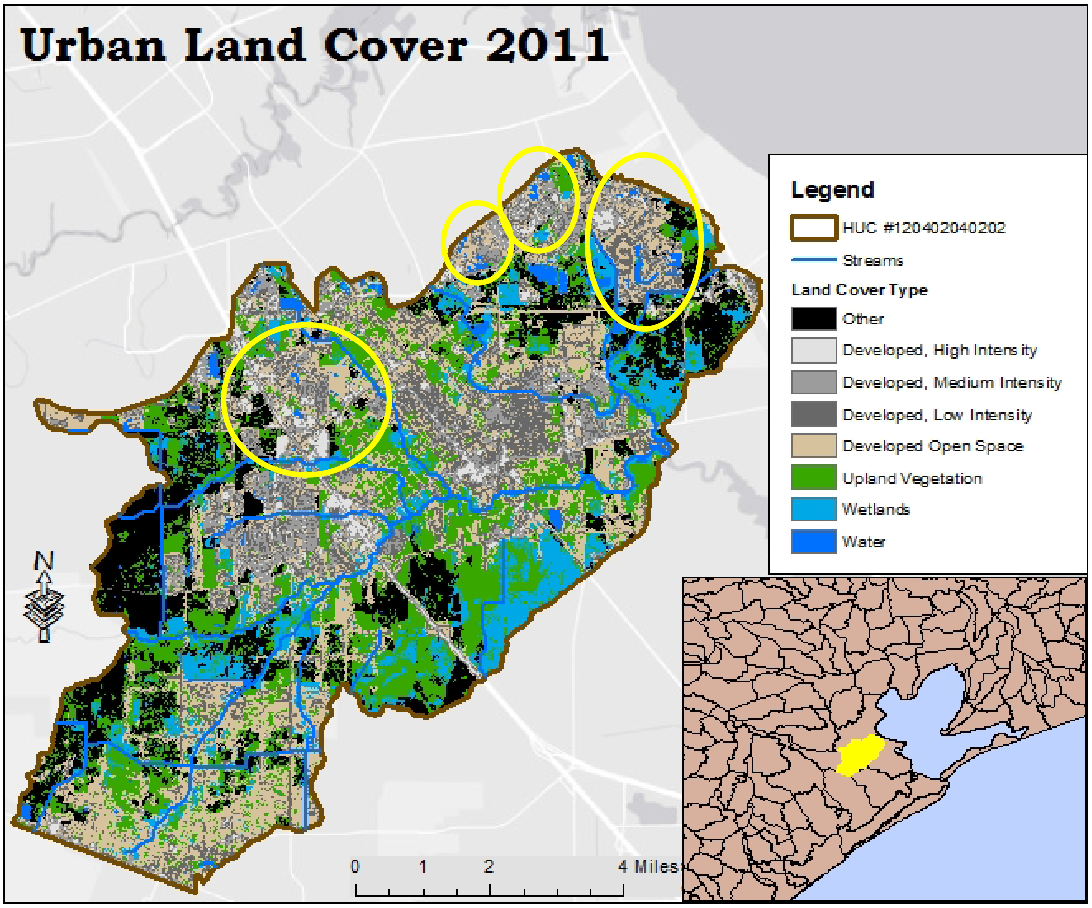

Figure 19: Dickinson Bayou Land Cover 2011

5.3.5 Patterns across Watersheds and Time

Comparison of the metrics from the four example watersheds across time allows us to make some generalizations about the evolution of urban form in cities with large urban footprints that are experiencing continued growth. For reference, Table 8 presents Urban Land Cover metrics from all four watersheds for 2001 and 2008, with 2008 numbers either being in blue or red indicating increases or decreases in the metric, respectively. Generally speaking, Percent Area increased in all four watersheds, except in Country Club Bayou which is located in the center of the city and was already significantly developed. As cities and regions grow, this increase in impervious surface is expected. In many of the watersheds, especially where there is already lower levels of High Intensity Development, Medium and Low Intensity Development seem to be the preferred style of development.

Mean Gyrate and Mean Shape decreased for nearly all Urban Land Cover types in all four watersheds from 2001 to 2008. As a measure of how expansive and complex the patches are, these decreases initially indicates that patches are becoming more compact and uniform over time. However, when you look at other metrics, specifically Mean Patch Size and Patch Density, another story is told. Patch Density, which measures the number of patches divided by the area of the watershed, consistently increases in nearly all land cover types in all watersheds indicating that existing patches are not growing, but new patches are being added. This can heavily influence metrics like Mean Gyrate and Mean Shape. Mean Patch Size also suffers from this fate, as most of the metrics for each land cover type gets smaller due to new smaller patches being included in the analysis on the landscape.

Table 8: Urban Land Cover Metrics for Example Watersheds in Houston Area

Name	Urban Land Cover Type	Percent Area		Mean Gyrate		Mean Shape		Mean Proximity		Mean Patch Size		Patch Density	
		2001	2008	2001	2008	2001	2008	2001	2008	2001	2008	2001	2008
Country Club Bayou	HID	28.940	29.917	34.819	34.821	1.120	1.251	519.295	540.888	2.142	2.218	13.511	13.489
	MID	45.407	45.073	40.095	39.779	1.448	1.443	898.341	858.782	4.028	3.819	11.272	11.802
	LID	15.849	15.651	28.145	27.897	1.276	1.272	13.775	13.523	0.556	0.546	28.512	28.677
Upper Greens Bayou	HID	12.828	14.921	44.738	40.822	1.308	1.278	126.134	105.212	2.110	1.806	6.080	8.271
	MID	16.162	19.397	36.503	36.210	1.380	1.381	45.118	44.406	1.020	1.032	15.853	18.795
	LID	16.185	18.574	31.717	31.078	1.324	1.315	23.653	24.073	0.772	0.740	20.967	25.081
Frontal Galvest on Bay	HID	2.697	4.475	26.946	25.800	1.154	1.146	4.437	5.472	0.562	0.549	4.799	8.130
	MID	13.240	18.378	38.323	36.998	1.373	1.377	46.422	76.084	1.664	1.597	7.955	11.512
	LID	12.929	16.539	35.135	33.701	1.374	1.363	23.488	27.393	0.854	0.813	15.133	20.315
Dickins on Bayou	HID	1.193	2.133	27.727	25.681	1.185	1.167	4.550	4.059	0.530	0.461	2.252	4.602
	MID	4.775	8.083	35.265	34.569	1.381	1.375	11.150	17.726	0.858	0.888	5.564	9.083
	LID	10.282	12.840	32.823	31.812	1.342	1.340	47.964	40.961	0.849	0.758	12.116	16.922

One of the most significant patterns that emerge from examining the four example watersheds is the relationship between precipitation and damage. Three of the watersheds (Country Club Bayou, Upper Greens Bayou and Frontal Galveston Bay) are all located relatively inland, and flood damage can be seen to increase with annual precipitation. However, in Dickinson Bayou watershed in 2001, the watershed had the most amount of precipitation out of the four watersheds, and resulted in the smallest amount of damage that year. Also, in 2008 Dickinson Bayou had the least amount of precipitation that year, but resulted in over 15 times as much damage as any of the other example watersheds. This exemplifies how precipitation can play an important role in flood regimes in inland watersheds, but watersheds adjacent to the coast have additional variables to consider when linking urban patterns to flood damage.

6. DISCUSSION

6.1. Discussion of Regression Analysis

The results from the 18 regression models provide a great deal of opportunity to discuss several topics. This section will go into further detail about how each of the six urban land cover metrics and two urban land use metrics behaved, and how this may be interpreted for real-world application. A brief discussion then occurs about the results from many of the control variables. This section concludes with a discussion of how the results could be incorporated into planning and policy decision-making, as well as their application in education and outreach activities focused on increasing environmental literacy and systems thinking.

6.1.1. Interpretation of Percent Urban Land Cover

Many of the landscape metrics are unitless and dimensionless, which means that understanding their relationship to flood damage is limited to only the directionality and significance of their regression coefficients. However, the overall composition of urban land cover across the watershed, measured by the percentage of area covered by a given land cover type, does allow for marginal effects to be estimated. While controlling for exposure of property to flooding, a one percent increase in high intensity development results in a 24.14% increase in residential property damage. One percent increase in medium intensity developed area results in a 24.5% increase residential property damage. Finally, a one percent increase in area of low intensity development results in a 40.85% increase residential property damage.

These effects indicate that despite controlling for placement of property in flood-prone areas, increases in impervious surface still contribute to increases in flood damage. However, it is important to point out that as land cover type increases in imperviousness, (low intensity development to high intensity development), there is an increased marginal effect on flood damage. One percent of High Intensity Development results in a much lower increase in flood damage as does a one-percent increase in Low Intensity Development. From a practical standpoint, this is an important finding. High and Medium Intensity Development typifies a more efficient urban design, where homes are located in closer proximity and can reduce costs related to municipal services, as well as reduce potential flood impacts on a greater number of homes by placing these structures in ecologically-sound places relative to a watershed's hydrology.

6.1.2. Interpretation of Mean Patch Size

Where Percent Area measures the overall quantity of urban land cover, Mean Patch Size looks at the average size of urban land cover across the watershed. While marginal effects are not easily inferred from the models, there are general trends that have important implications. Increases in Mean Patch Size for Low, Medium and High Intensity Development all resulted in increases in flood damage. However, the coefficients for Medium Intensity Development and Low Intensity Development were almost twice the amount as the High Intensity Development, indicating that increases in size for Medium and Low Intensity Development patches increase flood damage much greater than increases in Mean Patch Size for High Intensity Development. Similar to Percent Area, the coefficients for Mean Patch Size across the three levels of impervious surface suggest that when considering how urban areas grow, that more efficient urban design may be the best option when trying to reduce flood damage for communities.

6.1.3. Interpretation of Mean Gyration

Mean Patch Gyration is an average of how expansive or compact urban land cover patches are in each watershed. Although the unit is dimensionless, comparing the coefficients across the three different urban land cover types again provides clarity on how the configuration of urban land cover can influence flood damage. The coefficient for Mean Gyrate of Medium Intensity Development patches is three times as much as the coefficient for Mean Gyrate of High Intensity Development patches, indicating that increases the areas that typify this type of land cover (i.e. suburbs) increase flood damage to a greater degree than increases in a more compact design pattern. Mean Patch Gyration of Low Intensity Development land cover was not significant.

6.1.4. Interpretation of Mean Shape

Mean Patch Shape is conceptually similar to Mean Patch Gyration, but in its calculation it measures adjacency to other patch types. It was incorrectly hypothesized that increases in Mean Patch Shape of urban land cover would result in decreases in flood damage because as Mean Patch Shape increases, it indicates that the patch shares a longer amount of perimeter with other land cover types. There are two possibilities for why the variables did not behave as hypothesized. First, Mean Patch Shape like Mean Patch Gyration measures expansiveness, but does so by calculating cell perimeters that are adjacent to non-similar land covers instead of averaged distance to the center of the patch. So utilizing Mean Patch Shape without controlling for Mean Patch Gyration may have resulted in the metric behaving how Gyrate was predicted to. Another possibility is that, especially for High Intensity Development, the non-similar land cover that it was adjacent to was not open space, but instead other levels of development (Medium or Low) which would mean increases in Mean Patch Shape would not lead to decreases in flood damage due to adjacency to open space.

All three coefficients for Mean Patch Shape were positive and significantly related to flood damage. However, the coefficients for Medium and Low Intensity Development were about four times as large as the coefficient for High Intensity Development. This was not similar to the results from Mean Patch Gyration, indicating that Mean Patch Shape was measuring something else beyond how expansive the patch was. The coefficients further support the use of compact, efficient design to minimize the potential for flood damage.

6.1.5. Interpretation of Mean Proximity

Mean Proximity of urban land cover patches indicates how far apart all patches of a given land cover type are to one another within the specified landscape. It is another dimensionless metric and so its interpretation is also limited. Mean Proximity was only significant when measuring Medium and Low Intensity Development, indicating that the measure may not be important when looking at how distance between patches of High Intensity Development can influence flood damage. A potential reason for this could be that High Intensity Development patches seldom occur near one another, because instead they are connected as a single patch. This is in contrast to patches of Medium and Low Intensity Development, which represents suburban and rural areas that are typically associated with leapfrogging and disjointed, unplanned development (Brody, Kim and Gunn, 2012).

6.1.6. Interpretation of Patch Density

Patch Density is a ratio of the number of patches to the area within a landscape. In contrast to Mean Patch Size, Patch Density measures nothing about the size of individual patches, but instead represents the overall patchiness of a landscape. Patch Density of urban land cover was positively related to flood damage and significant in all models, and the coefficients suggest that patches of increased imperviousness have increased effects. This seems in contrast to the other variables that indicate compact urban form may not increase flood damage as much as suburban or rural types of development. By itself, there is limited ability to interpret why the models behaved this way. Combining it with other metrics like Percent Area or Mean Patch Size might have provided greater insight into how it is related to flood damage when measuring urban land cover, and future research designs should attempt to look at such relationships while avoiding issues with multicollinearity.

6.1.7. Interpretation of Urban Land Use Metrics

Inclusion of urban pattern metrics that quantify land use provided a control that allowed urban land cover metrics to perform consistently across different levels of land cover. Average Elevation of Residential Properties was negatively related to flood damage and significant in all models. The use of such a metric does not necessarily provide new insights into how flood damage occurs; it is already well-documented that properties at lower elevations are more susceptible to flood damage than properties at higher elevations. However, the inclusion of such a variable does allow for a better conceptual understanding of how urbanization is related to flood damage. In contrast to previous research that found increases in High Intensity Development resulted in reduced flood damage and increases in Low Intensity Development resulted in increased flood damage (Brody et al. 2011), the inclusion of a separate urban land use variable allowed analyses to distinguish between effects from urban land cover (imperviousness) and urban land use (location of property relative to the watershed).

Unfortunately, Average Distance of Residential Property to Water did not behave as expected. It had varying relationships to flood damage across the 18 models, and some were significant and some weren't. This may be due to incorrect measurement, where distance was determined to the closest water feature, regardless of type. This means that if there was a large pond or any other water feature in the National Hydrography Dataset, distance to this feature is given the same importance as distance to a river or the open ocean. Examples of this would be proximity to stormwater detention basins and artificial drainage channels, which may explain why increased distance from these features resulted in increases in flood damage. Proximity to such features may actually be reducing damage due to stormwater management measures.

Potentially related and similarly curious is that Drainage Density, which indicates the overall ability of the watershed to carry runoff downstream, was also incorrectly hypothesized. Increased Drainage Density was found to result in increases in flood damage in many of the models, which runs counter to the literature. There could perhaps be some relationship between the two variables that is not visible through statistical diagnostics, or it could be that efforts should have been made to distinguish artificial versus natural water features from NHD dataset was used to measure both variables. Future research could measure distance to specific water feature types to determine why this occurred and would also provide additional land use metrics for representing urban patterns at the watershed scale.

6.1.8. Missing Relationships among Independent Variables

While there was much success with the inclusion of urban land use variables to better demonstrate the relationship between urban land cover patterns and flood damage, due to statistical limitations, the analysis was conducted as a separate 18 regression models and therefore failed to identify if and how urban land cover metrics might have interacted with one another. The issue of multicollinearity is already an identified problem in statistical analysis of landscape metrics (Graham 2003), but statistical options for allowing several of these variables to be included in the same model would have made interpretation of each of the models even more difficult. Now that there is a better understanding of how these metrics are related to flood damage, key metrics should be selected and included in statistical modeling efforts that attempt to explain interactions. A prime example of this is the Percent Area urban land cover variable which has been identified as the foundation for which other metrics should be related to due to it being a compositional metric that allows for a better interpretation of metrics that measure land cover configuration.

Where land cover metrics of a particular type (High, Medium or Low Intensity Development) may interact with one another, the analysis selected for this dissertation also fails to account for the interactions across levels of impervious surface. Looking at descriptive statistics of the variables and maps displaying change of different urban land cover metrics over the study period, there is evidence of some sort of an urban evolution where Low Intensity Development evolves into Medium Intensity Development, Medium Intensity Development evolves into High Intensity Development, and High Intensity Development can only grow larger. This process deserves further analysis as how these transitions occur is also important in understanding how urban patterns are related to flood damage.

6.1.9. Interpretation of Control Variables

There were a number of variables that performed as hypothesized that are worth noting as they should be considered when using watershed-scale planning and management. This section is divided into metrics that can be classified as basin metrics and precipitation, and other land cover metrics that represent vegetation.

Basin Characteristics and Precipitation

Drainage density, which is the ratio of length of streams to the watershed area, describes the extent of the stream network over the watershed and has been shown to increase flooding (Giannoni et al. 2003, Hollis 1975). While drainage density is used in models to estimate flood risk (Youssef et al. 2011), this study is unique as it identifies drainage density as also being positively related to observed flood damages. Mean slope also behaved as hypothesized, and similar to drainage density, it has a rich history in the literature as being negatively related to flooding and is used frequently in hydrologic modeling (Carpenter et al. 1999). Its use in this study provide additional support for analyzing flood damage at the watershed scale while utilizing multiple basin metrics.

Precipitation was positively related to flood damage and statistically significant in all models. While this may seem to be obvious, there are flooding and flood damage studies that have found it difficult to utilize total annual precipitation as a control for rainfall and instead utilize other methods like counts of number of months average rainfall for the study area was exceeded (Brody et al. 2011a, see Pielke and Downton 2000 for a review of several different methods for measuring precipitation).

Vegetation and Wetlands

The use of other land cover variables like upland and wetland vegetation in the analyses provide additional evidence of the benefits of utilizing social, economic and environmental variables in landscape analysis of socio-ecological systems. This author has found in previous research that wetlands significantly reduce flood damage (Brody et al. 2012a), and has expanded such models to demonstrate how upland vegetation can also play a role in reducing flood damage. Amount of upland vegetative land cover may represent how as a land cover it influences hydrology related to flooding, or it might represent patterns of land use where increases in amount of vegetation may signify reduced urbanization of the overall watershed.

6.2. Implications of Example Watersheds from Houston Area

One of the reasons that watersheds around the Houston area were selected was to examine changes in urban patterns in an area that is known for its low population density and would assumingly have patterns that typified this type of development. From a metric standpoint, Patch Density combined with Percent Area are probably the two metrics that can best be utilized as early predictors for landscape-scale sprawl. In the four examples, all but one of the urban land cover classes experienced increases in Patch Density, and with Percent Area also increasing for almost every urban land cover type, indicates that while there is growth, it is not occurring adjacently to existing urban land cover.

Another important finding is the metrics from the highly urbanized watershed of Country Club Bayou. The ratio of 2:3:1 regarding HID, MID and LID land cover is a good baseline for comparing existing or future growth scenarios in different areas. If you want a watershed like one in downtown Houston, then these ratios can be the target. If you want a different type of watershed, then you might consider different ratios of urban land cover types.

The difference between flooding from precipitation and flooding from storm surge, and the implications for resulting flood damage is exemplified between the three Houston watersheds and the Dickinson Bayou watershed located closer to the coast. Some of the urban land cover patterns in the Dickinson Bayou watershed resulted in lower flood damages due to precipitation, but did not help reduce damage from storm surge. This is important to consider when developing watersheds as there may not be one single preferred landscape urbanization method to adopt when trying to reduce flood damage.

6.3. Application of Findings

Both the findings of this research as well as the methods utilized to measure different components of urbanization may be applied to real-world activities. These include changes to state and federal policy, local-level land use decision-making, and educational efforts that increase understanding of social, ecological, and economic phenomenon so people can make more-informed decisions.

6.2.1. Policy and Planning

One of the clearest ways the results from this study could be applied to policies is through the FEMA's NFIP. As mentioned in Section 3.4, while flood insurance policies and claims come from individuals, ability to participate occurs at the community level. In 1990, FEMA developed the Community Rating System (CRS), which provides insurance discounts of up to 45% as incentives to residents of communities that conduct additional flood risk reduction activities (Brody et al. 2011b). Existing flood risk reduction measures in CRS include preserving open space in the floodplain, maintaining drainage systems, and either relocating or modifying existing flood-prone structures to reduce their exposure to future flood events. The results of this study both support existing design standards but could also inform additional ones that address overall configuration of urban area within a watershed. This is especially relevant in Texas as many localities are limited in their ability to effectively plan from a regulatory standpoint (Brody et al. 2012a), and the CRS program may provide the impetus for creative solutions at the community level to overcome these obstacles.

There are three main findings from this research that could guide CRS design standards. First, increases in impervious surface result in increases in flooding, so attempts should be made to minimize the ratio of impervious area to watershed area. Such a standard would not only reduce flood damage, but could improve water quality and ecosystem health which have been found to be negatively correlated to increases in impervious surface (Schueler, Kumble and Heraty 1992). In many areas where there is already high levels of imperviousness or demand for urbanization, a separate set of standards may be appropriate. As indicated in this study, increases in flood damage are smaller from a percent increase in high intensity development than a percent increase in low intensity development, so such watersheds identified as urban should limit low intensity development, while ensuring adequate development and maintenance of artificial drainage systems. Additionally, limiting hydrologic connectivity of landscape patches in such watersheds has the potential to protect water quality and minimize flooding as well (Jackson and Pringle 2010).

Another design standard supported by this research is placing development in areas of higher relative elevation within the watershed. While erroneous measurement prevented distance to water from being negatively correlated to flood damage, development in higher parts of the watershed will frequently result in development away from hydrologic features. Burton, Kates and Snead (1969) provide a sensible framework for determining where to construct property that is adapted here to address flood risk reduction of all property within a watershed. Three categories of development include water-based, water-oriented and footloose; where water-based development requires direct connection to water or the floodplain, water-oriented development requires proximity to water or the floodplain which may in order to provide an economic or other benefit, and footloose development that is coincidentally located near water or the floodplain but provides no benefit, and perhaps even results in an increased cost of some sort. Businesses located on or near water may have an economic reason to do so, and arguably residences located on or near water may be justified by improving quality of life. However, there is much development that occurs at lower elevations either in or near the floodplain that is “footloose” and only located there because the flood-prone land is less expensive than land in other locations. Zoning in flood-prone areas could be adopted that takes the residence or business intent into consideration.

The third recommended design standard is related to the existing standard of protecting open space. Specifically, this research demonstrated the importance of preserving natural space in key hydrological areas. A one-percent increase in upland vegetation or wetlands reduced flood damage anywhere from 2-6% in the models, and preserving such areas protects normal hydrologic function and preserving wetlands especially ensures development does not occur in low-lying flood-prone areas. A prime example of this occurring was in Figure 12 and 13 in Upper Greens Bayou where a large amount of upland vegetation located on the east side of the watershed near its outlet was converted to Medium and Low Intensity Development.

Outside of CRS activities, local planning at the watershed scale may provide assistance land use decision-making due to the nature of watershed planning being inherently community-driven that requires interjurisdictional coordination and input from diverse stakeholders and interests groups. While this may make for a more complicated process, it does provide an opportunity for science-based decision-making through learning and consensus-building activities. Watershed-based planning may also overcome some of the regulatory obstacles found in Texas, where watershed planning is seemingly being embraced there are numerous watershed protection plans being implemented or developed, with 28 watershed protection plans being sponsored by Texas State agencies, and 12 plans being sponsored by third-parties (Texas State Soil and Water Conservation Board 2016).

The above strategies for adopting landscape designs that result in reduced flood damage (and other ecological benefits) should be pursued, but there is a larger policy issue that also needs to be addressed. There are underlying policies at different levels of government that are indirectly responsible for the existing urban patterns present in coastal watersheds (Burby 1998). Federally-subsidized flood insurance and disaster relief may provide financial relief from the impacts of floods, but it also subsidizes risk which prevents more appropriate (less exposed) urban patterns from emerging should those incentives not be in place. At the local level, a greater focus is placed on economic development rather than infrequent flooding events that may only impact isolated pockets of the community. This results in businesses and homes being developed in low-value, flood-prone areas, betting immediate economic gains against unforeseen future economic losses.

One solution that addresses both issues is presented by Burby (2006) is to provide flood insurance at the community level, which would then cause municipal and state governments to pick up a portion of the flood damage costs. This would then incentivize municipal and state governments to adopt hazard mitigation strategies. Another option would be to require everyone to obtain flood damage. When paired with basing premiums on the risk of flooding within a given watershed, such a policy would result in communities sharing risk locally and may increase community participation in local planning efforts. Examples of such potential costs can be seen in Table 9 in Appendix 2 with the amount of damage per home in the four example watersheds.

There are other crude solutions that range from a pure market perspective (abolishing subsidized flood insurance and financial relief) to a strong state perspective (outlawing development in flood-prone areas completely) that are not feasible due to the economic and social justice issues that plague them. Providing education and increasing awareness are of flooding and strategies for reducing impacts is another potential solution. While there is incredible debate on the effectiveness of such strategies and strong arguments why limits to human rationality prohibits knowledge gain from resulting in action, it is still a commonly employed strategy for attempting to reduce flood impacts.

6.2.2. Education

The watershed scale planning approach, as well as the use of metrics that are correlated to complex socio-ecological processes can be used to increase literacy and foster informed decision-making by community members who engage in participatory planning activities. Urban pattern metrics, like landscape and other spatial metrics, have the potential for conveying complex socio-ecological processes that can then be utilized in participatory planning activities (Leitão et al. 2006). While the metrics utilized in this study need to undergo additional validation tests, they do have the potential to convey concepts to a non-technical audience who nevertheless need such information to support science-based decision-making. In combination with case studies that describe the effectiveness of low-impact development and other best management practices, such metrics could make the science easier to understand how to plan in ways that reduce flood damage and achieve other planning objectives.

Using such metrics to explain and represent complex socio-ecological processes does not need to occur only within a planning framework. There is opportunity to utilize such metrics in existing formal and informal watershed education activities that are already being conducted by formal educators in the classroom environment, as well as by informal educators who work for state agencies and non-profit organizations across the U.S. While many of these trainings discuss anthropogenic influences on water quality, utilizing such metrics to explain other economic and social impacts should be just as important. Geographic Information Systems are being increasingly used in such efforts (Ramasubramanian 2010, Lo, Affolter and Reeves 2002), and there is incredible opportunity to include the principles of holistic landscape ecology that seek to acknowledge humans as key players in both the causes and consequences regarding landscape transformation.

7. CONCLUSIONS

7.1. Research Summary

This research has confirmed that urban patterns are significantly related to flood damage in Texas coastal watersheds. Further, it confirms that metrics that represent patterns of impervious surface are consistent regardless of low, medium or high intensity development when urban patterns that represent flood exposure are included in the analysis. These results are based on a ten year period of rapid development across the study area.

Seven of the eight research hypotheses were confirmed utilizing cross sectional time series regression models that looked at six distinct landscape metrics hypothesized to represent land cover patterns on three different intensities of impervious surface, and two metrics that measured the relative placement of residential properties within a given watershed. These metrics can be used to further policy and planning activities that lead to flood resilient designs of urban areas, and educational efforts that increase literacy on how landscape variables and urbanization influence flooding in various types of watersheds.

7.1.1. Use of Metrics in Flood Damage Studies

This research built upon previous studies that looked at how urban development patterns are related to flood damage by including more explicit variables that not only measured land cover, but also land use intensity. The results of the study show that it is more than just urban land cover that influences flood damage, and that while land cover may represent some aspect of land use, more spatially-explicit metrics are available and should be used in analysis and planning.

7.1.2. Use of Metrics in Planning and Policymaking

This research also showed the benefits of utilizing watershed scale variables in the analyses, which is arguably a more appropriate unit of analysis and allows for basin morphometrics to be utilized. Multijurisdictional planning at the watershed scale has gained traction over the past decade, as it allows for ecological processes to be taken into consideration as well consensus being built through collaboration and participatory planning input. This research supports the use of both urban pattern metrics as well as other watershed-scale metrics in planning and policy activities that take flood damage of residential property into consideration.

7.1.3. Use of Metrics in Education and Environmental Literacy

The use of urban land cover and land use metrics in education activities could be expanded in an effort to increase understanding of social, economic and ecological principles as they pertain to urban environments. Simple measurements of the landscape have the potential to convey complex processes, and applying this concept to the human development of the landscape may facilitate understanding of the impacts human have on the environment.

7.2. Future Research

This research contributes to both the theory of urban landscape ecology and practice of ecosystem-based planning and management, but there are still avenues that need to be explored in future research. First, there is a need to continue correlating urban patterns to social, economic and ecological processes. Validity testing needs to be conducted to ensure metrics are indeed measuring what we think they are measuring if they are to be used when considering the design of communities and cities. This validity testing also needs to occur at different spatial scales, both with the size of the land cover data, as well as the size of the watershed as changes in both have ecological implications, and valid metrics at one scale may lead to inappropriate development patterns if employed at a different scale.

Second, the analyses used in this study were selected to address the issue of multicollinearity that is common among regression models that consider multiple landscape metrics. This difficulty of analyzing multiple urban pattern metrics in a combined prevented this research from fully understanding how different metrics may relate to one another as the each account for similar but subtle differences in urban design. The most obvious example of this is the combination of both compositional and configurational metrics. In this study, percent urban land cover may account for the amount of impervious surface, but combining this metric with others like Gyrate or Shape would allow it to serve as a control variable and may provide a better understanding of how the configuration of land cover influences flood damage. In fact, the incorrect hypothesis of the relationship between Mean Shape and flood damage is a perfect example of why combining metrics would be beneficial. In this research, Mean Shape was shown to have a positive relationship with flood damage, which contradicted hypothesis 1d. With the inclusion of a metric that accounted for the overall diffusion of urban land cover, Mean Shape may have indeed behaved as hypothesized. Future research should seek to better understand how these metrics relate to one another to achieve a more nuanced understanding of how land use patterns are related to socio-ecological processes.

Finally, this research discussed the potential for the use of such metrics in improving literacy and understanding of complex socio-ecological processes that occur at a landscape scale, but future human dimensions research should be conducted that tests the viability of this claim. Such tests should not be undertaken until several other validity issues are addressed and a suite of urban pattern metrics have been verified scientifically so there is confidence that the metrics are indeed related to hypothesized socio-ecological processes.

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APPENDIX 1

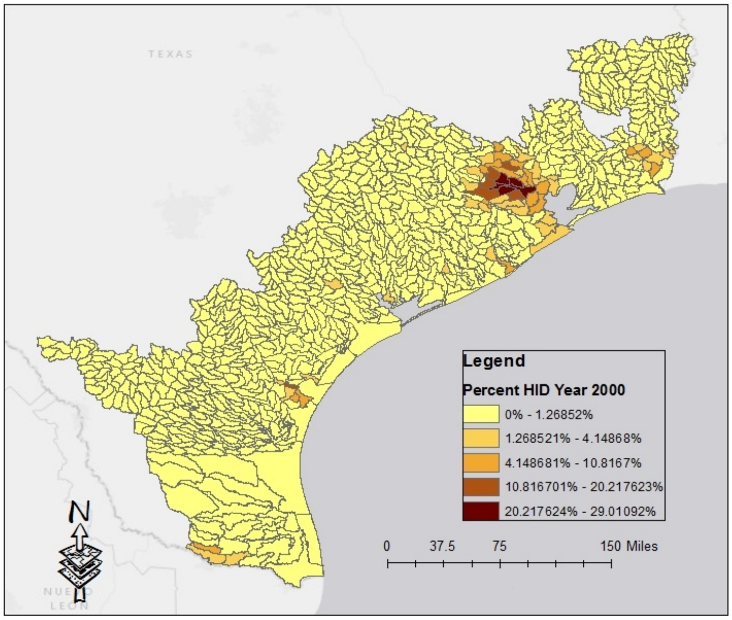

Figure 20: Percent High Intensity Development in Year 2000

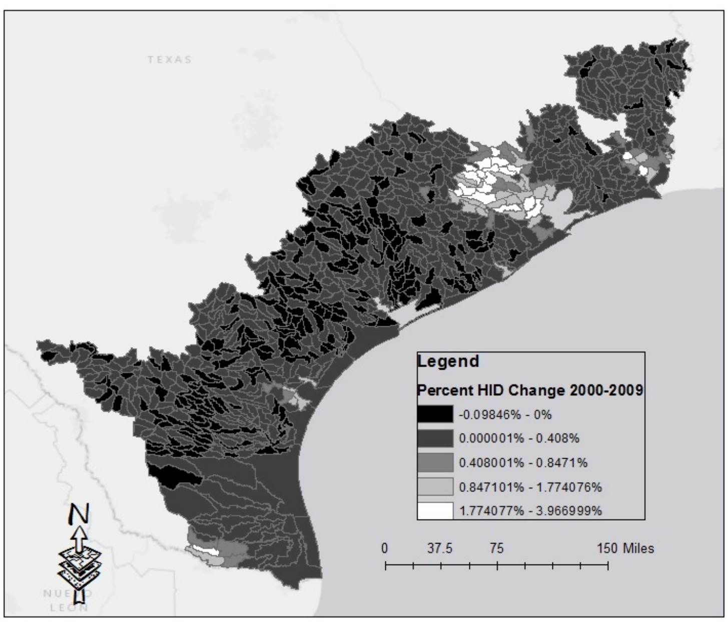

Figure 21: Change in Percent High Intensity Development from 2000 to 2009

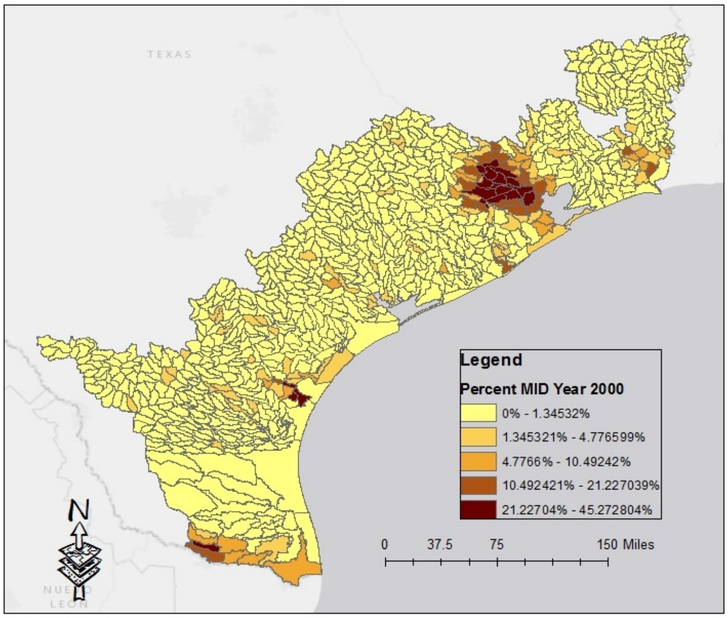

Figure 22: Percent Medium Intensity Development in Year 2000

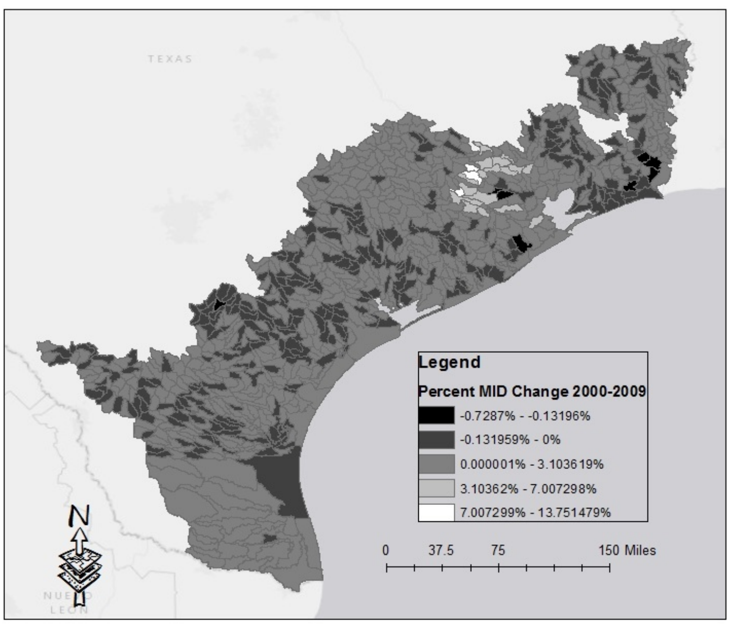

Figure 23: Change in Percent Medium Intensity Development from 2000 to 2009

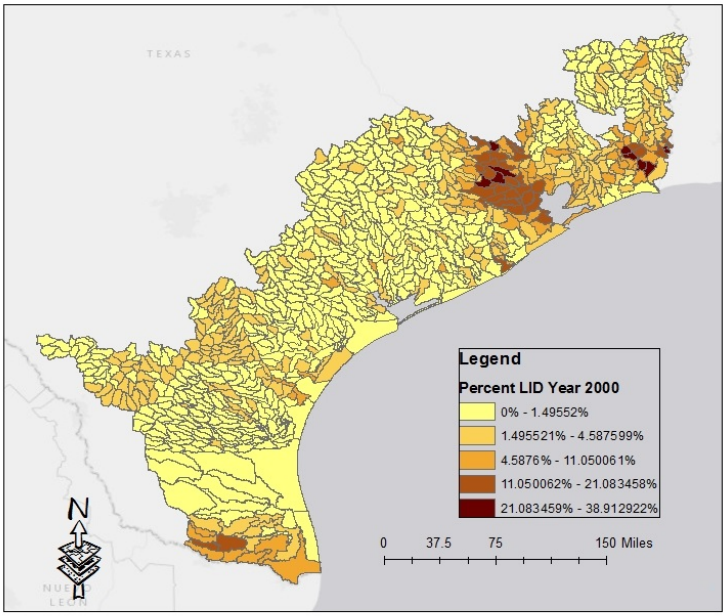

Figure 24: Percent Low Intensity Development in Year 2000

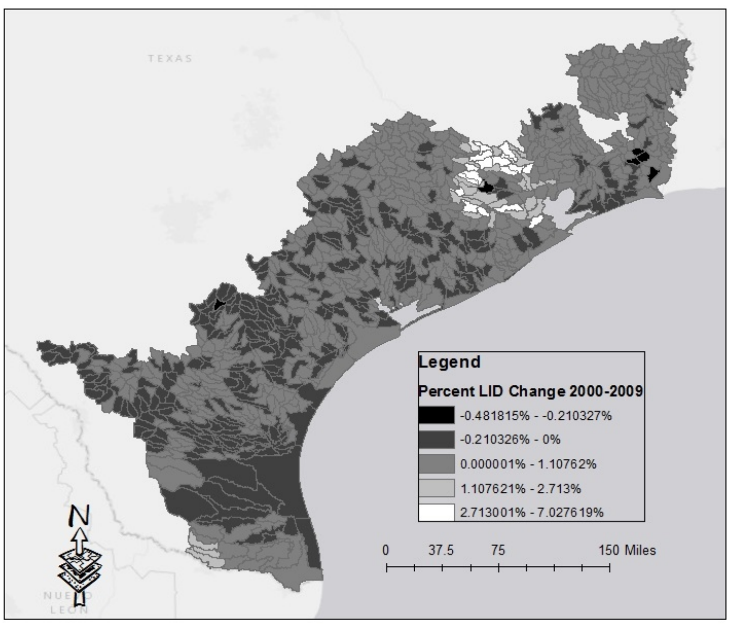

Figure 25: Change in Percent Low Intensity Development from 2000 to 2009

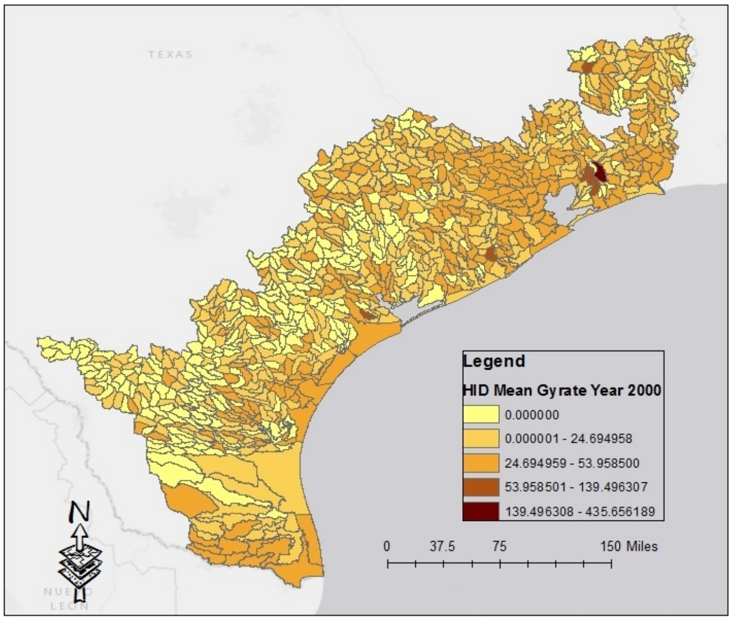

Figure 26: Mean Gyrate Value of High Intensity Development Patches in Year 2000

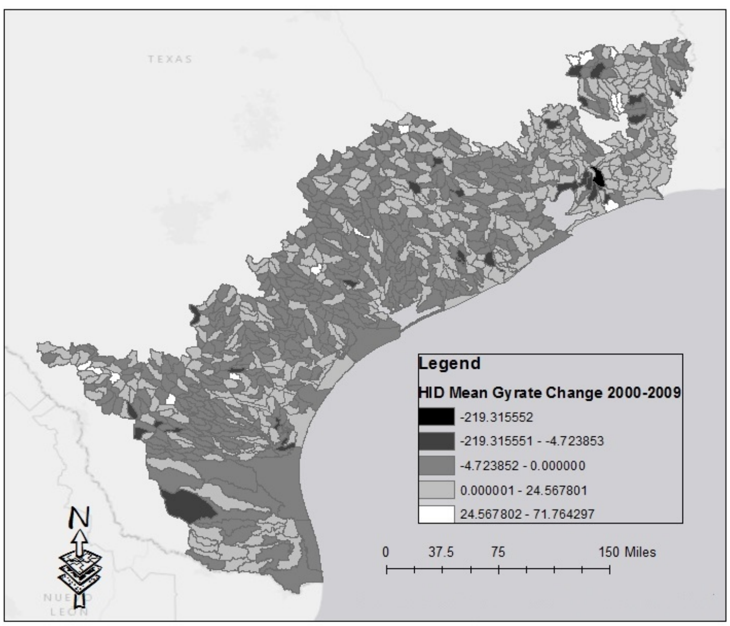

Figure 27: Change in Mean Gyrate Value of High Intensity Development Patches from 2000 to 2009

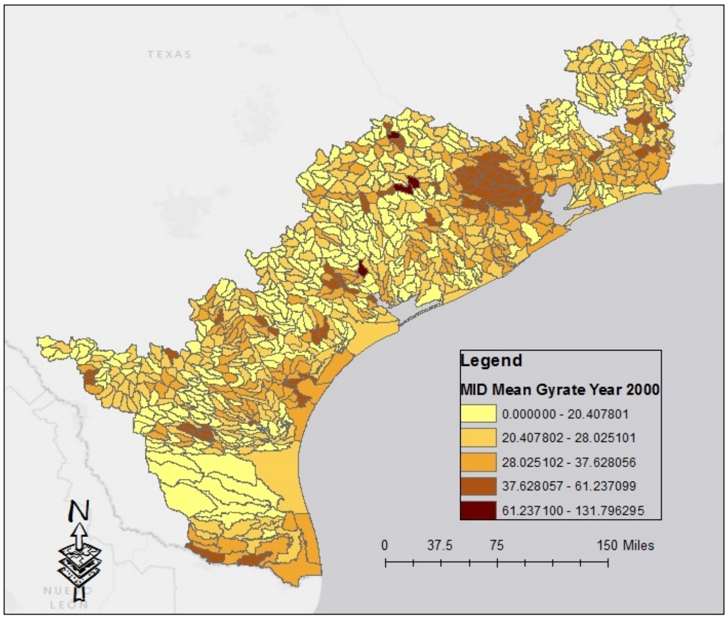

Figure 28: Mean Gyrate Value of Medium Intensity Development Patches in Year 2000

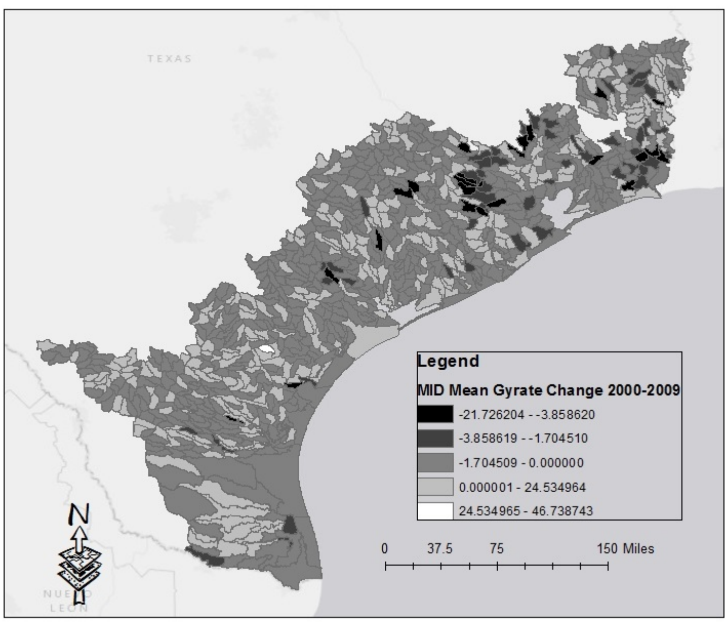

Figure 29: Change in Mean Gyrate Value of Medium Intensity Development Patches from 2000 to 2009

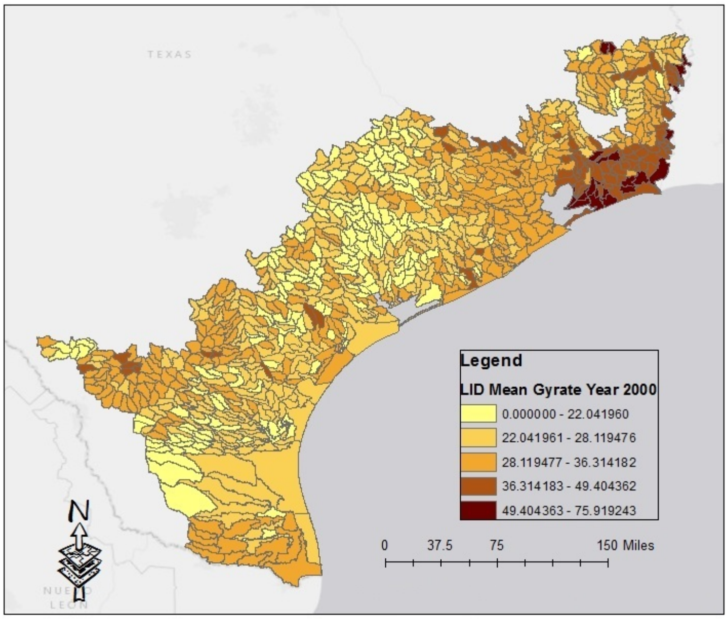

Figure 30: Mean Gyrate Value of Low Intensity Development Patches in Year 2000

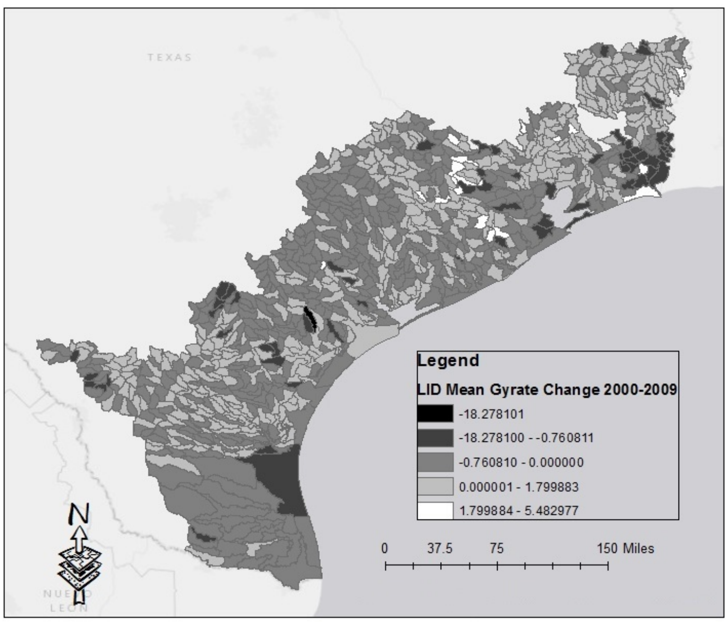

Figure 31: Change in Mean Gyrate Value of Low Intensity Development Patches from 2000 to 2009

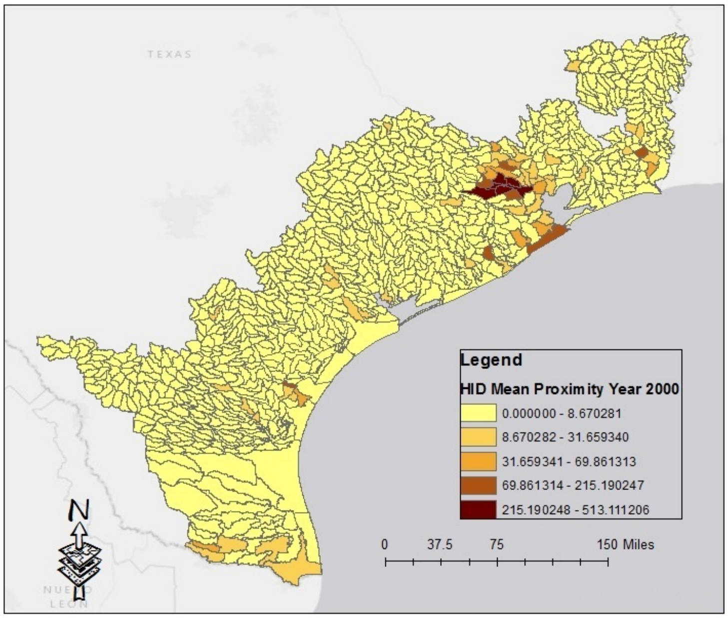

Figure 32: Mean Proximity Value of High Intensity Development Patches in Year 2000

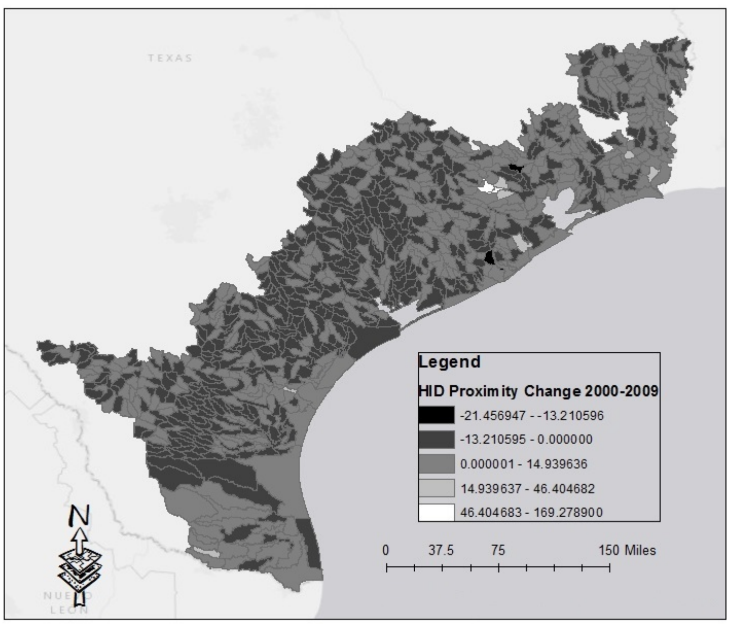

Figure 33: Change in Mean Proximity Value of High Intensity Development Patches from 2000 to 2009

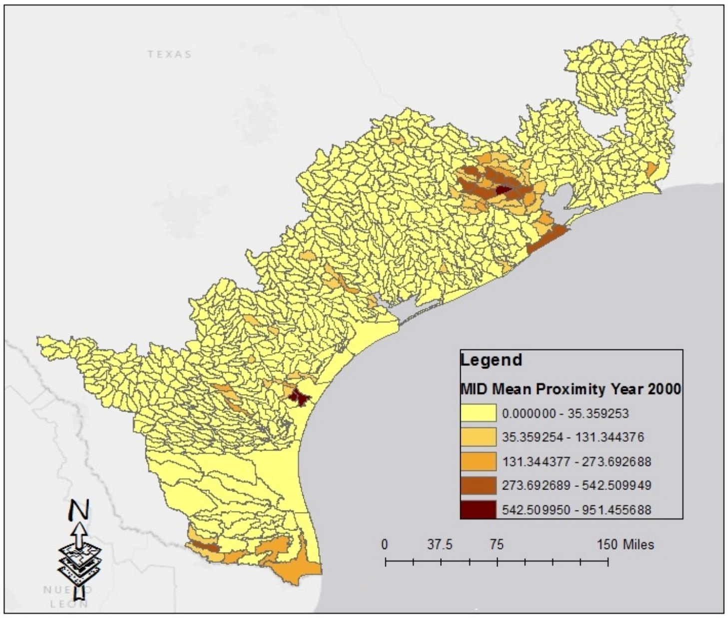

Figure 34: Mean Proximity Value of Medium Intensity Development Patches in Year 2000

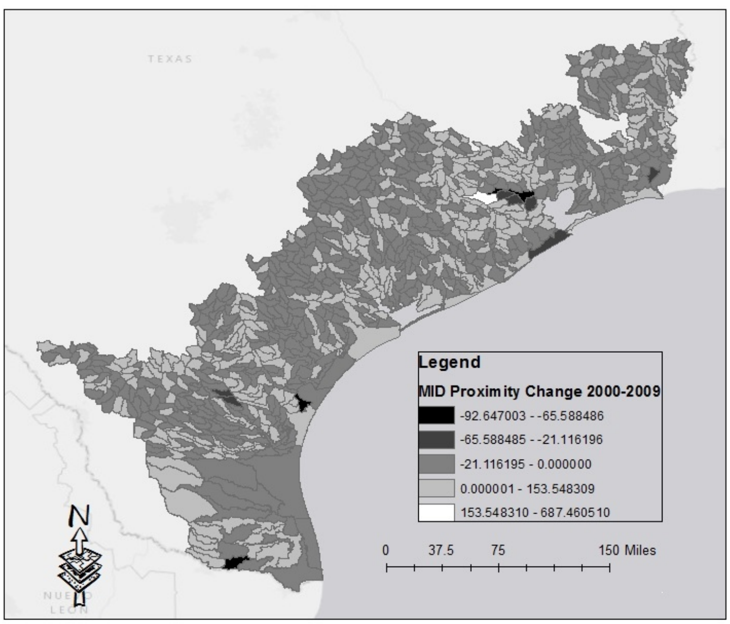

Figure 35: Change in Mean Proximity Value of Medium Intensity Development Patches from 2000 to 2009

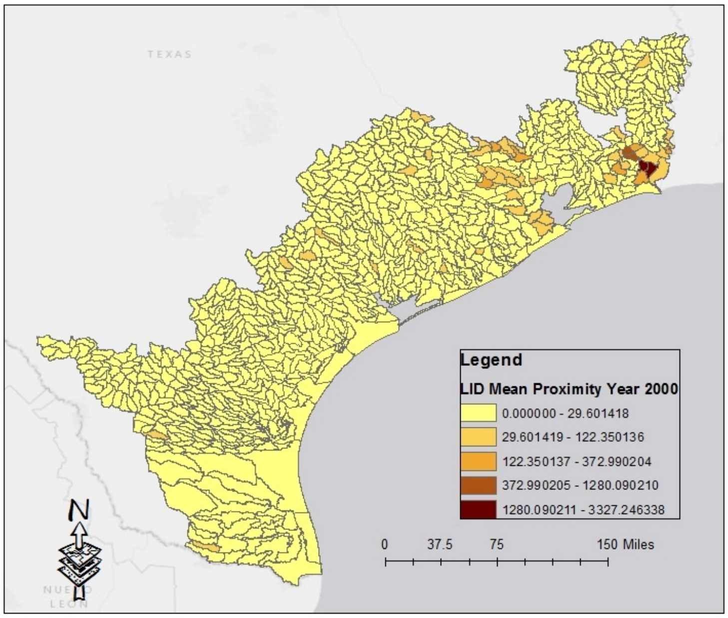

Figure 36: Mean Proximity Value for Low Intensity Development Patches in Year 2000

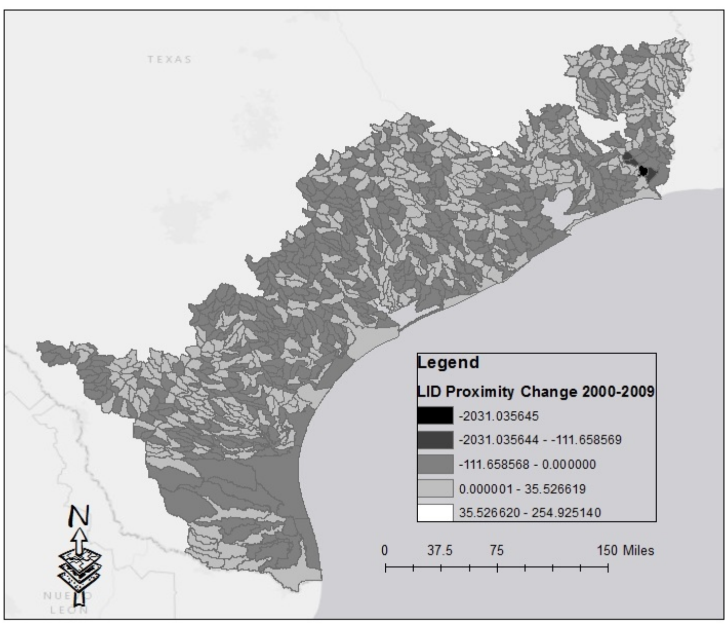

Figure 37: Change in Mean Proximity Value for Low Intensity Development Patches from 2000 to 2009

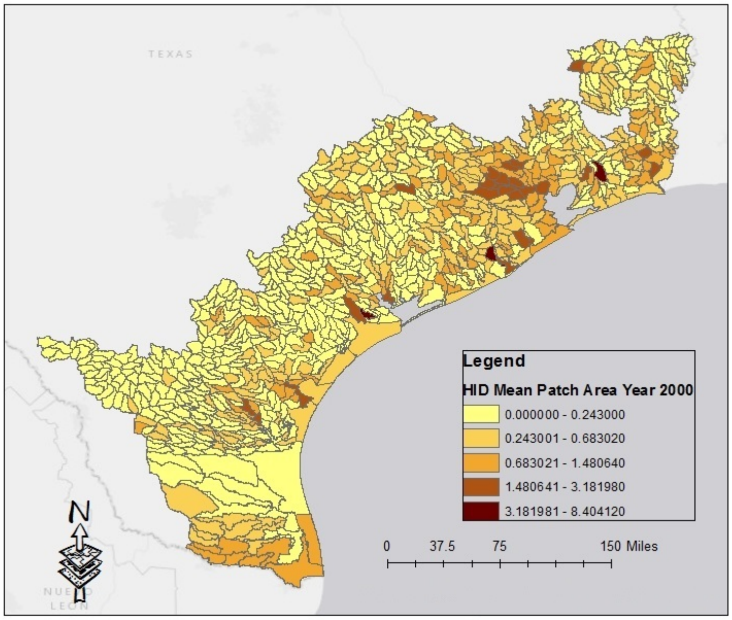

Figure 38: Mean Patch Area Value for High Intensity Development Patches in Year 2000

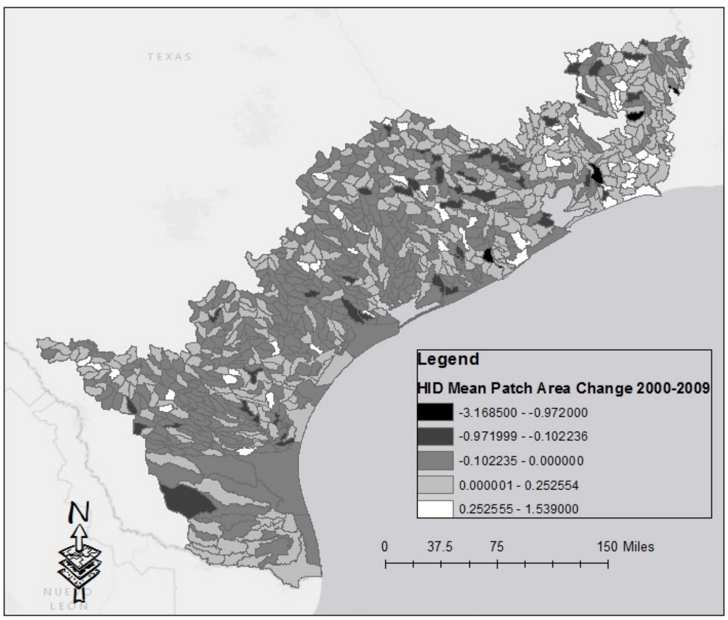

Figure 39: Change in Mean Patch Area Value for High Intensity Development Patches from 2000 to 2009

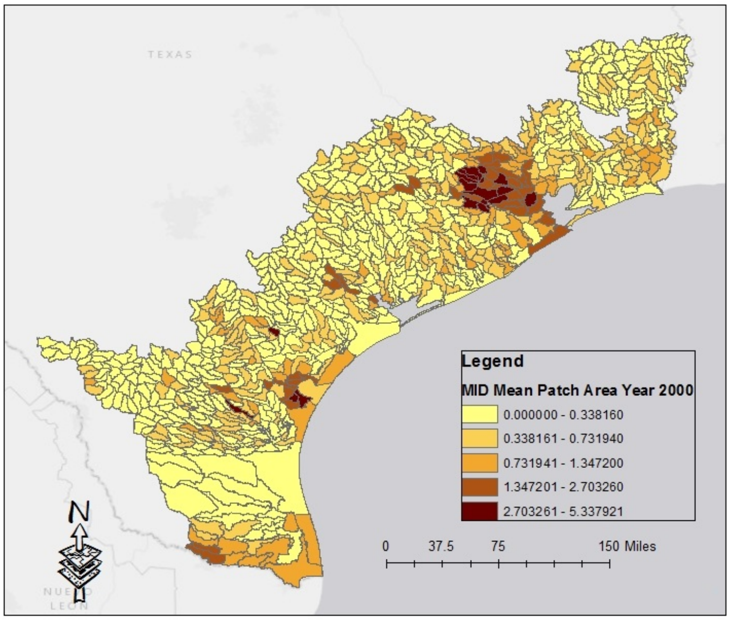

Figure 40: Mean Patch Area Value for Medium Intensity Development Patches in Year 2000

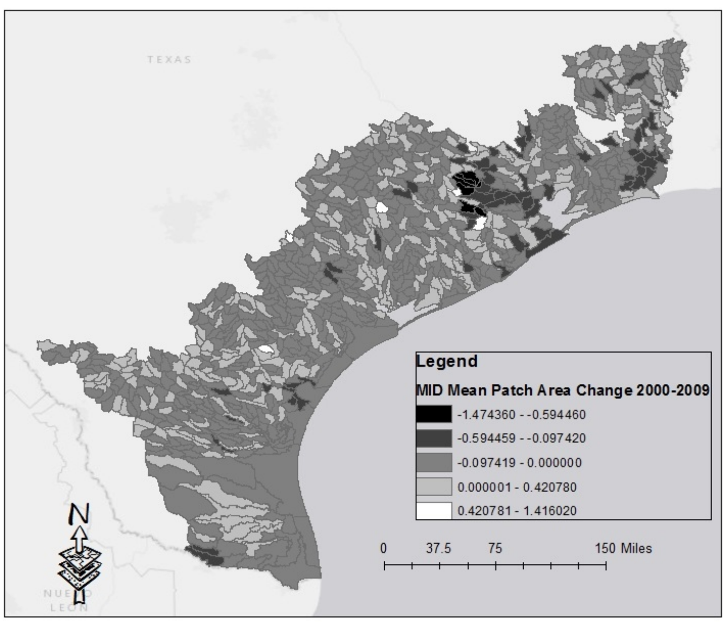

Figure 41: Change in Mean Patch Area Value for Medium Intensity Development Patches from 2000 to 2009

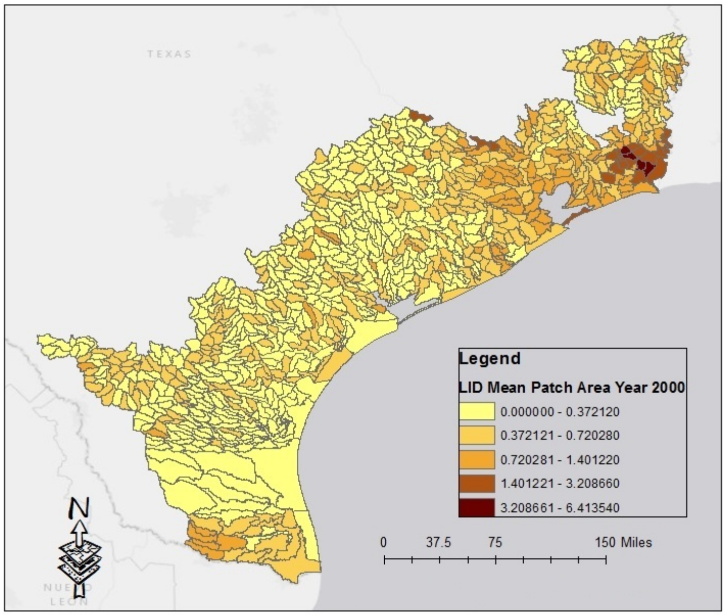

Figure 42: Mean Patch Area Value for Low Intensity Development Patches in Year 2000

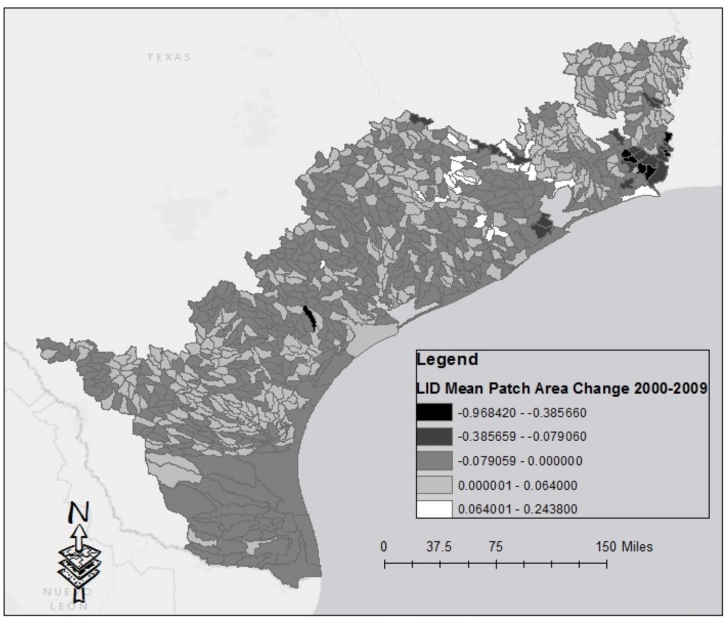

Figure 43: Change in Mean Patch Area Value for Low Intensity Development Patches from 2000 to 2009

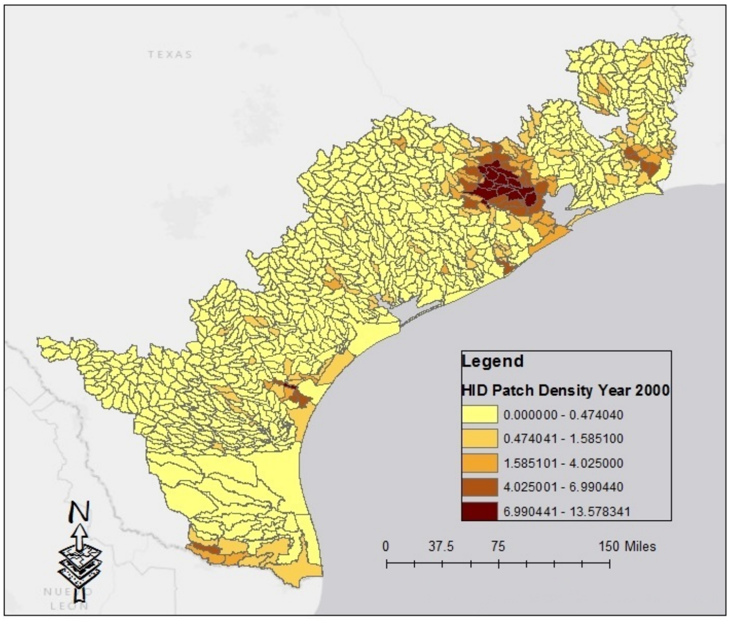

Figure 44: Patch Density Value for High Intensity Development in Year 2000

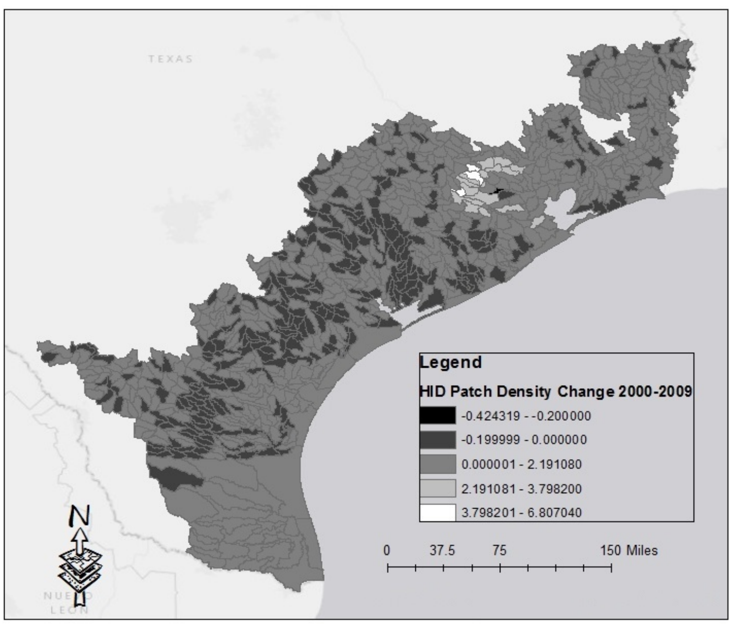

Figure 45: Change in Patch Density Value for High Intensity Development from 2000 to 2009

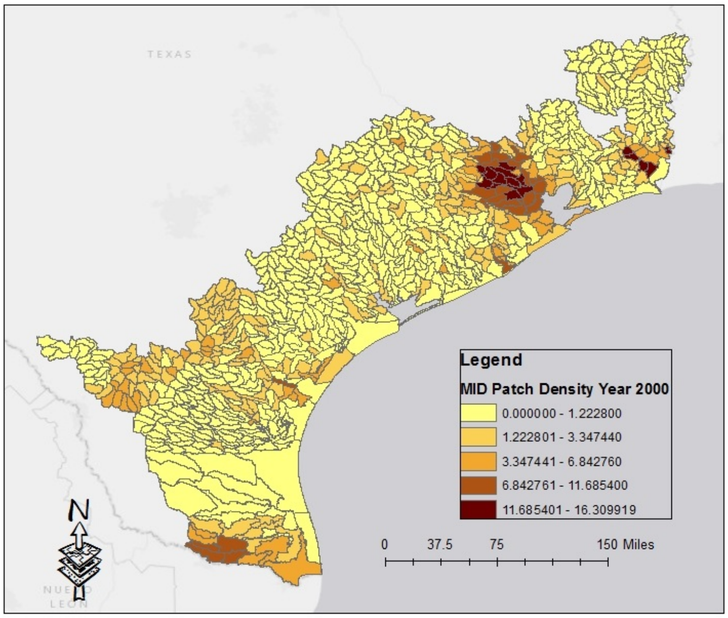

Figure 46: Patch Density Value for Medium Intensity Development in Year 2000

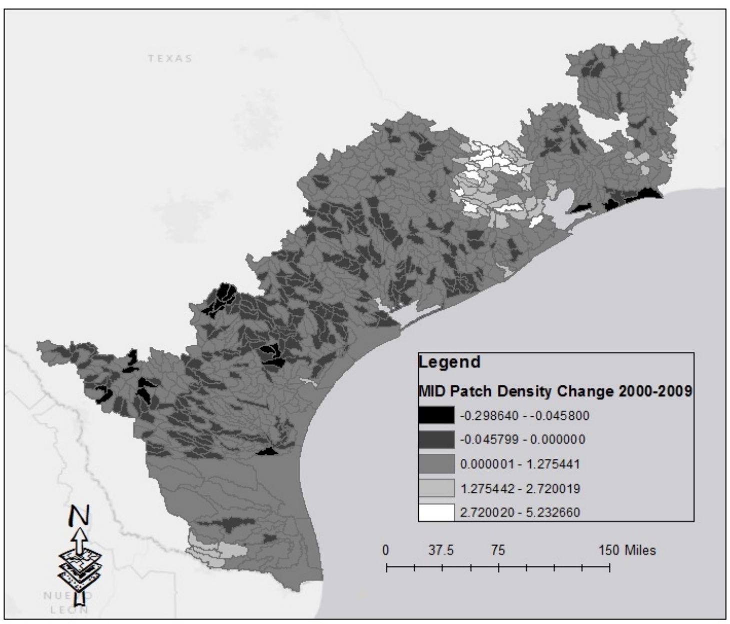

Figure 47: Change in Patch Density Value for Medium Intensity Development from 2000 to 2009

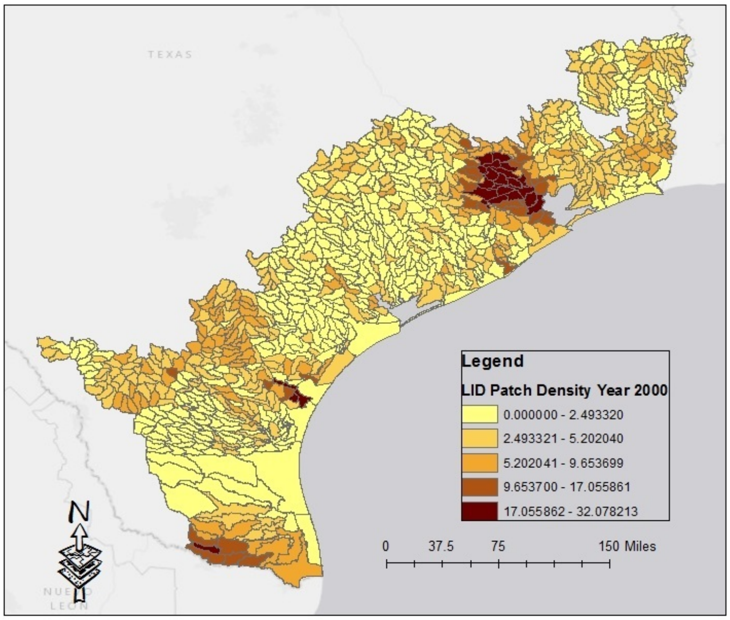

Figure 48: Patch Density Value for Low Intensity Development in Year 2000

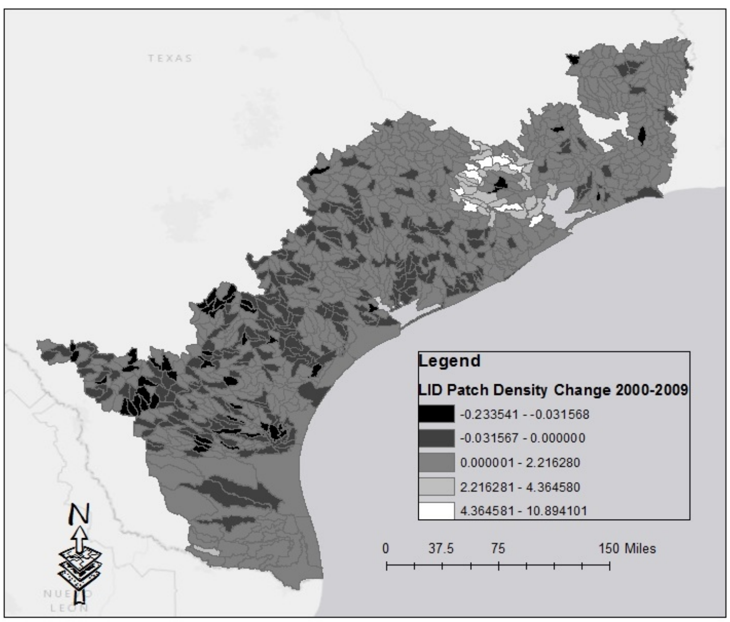

Figure 49: Change in Patch Density Value for Low Intensity Development from 2000 to 2009

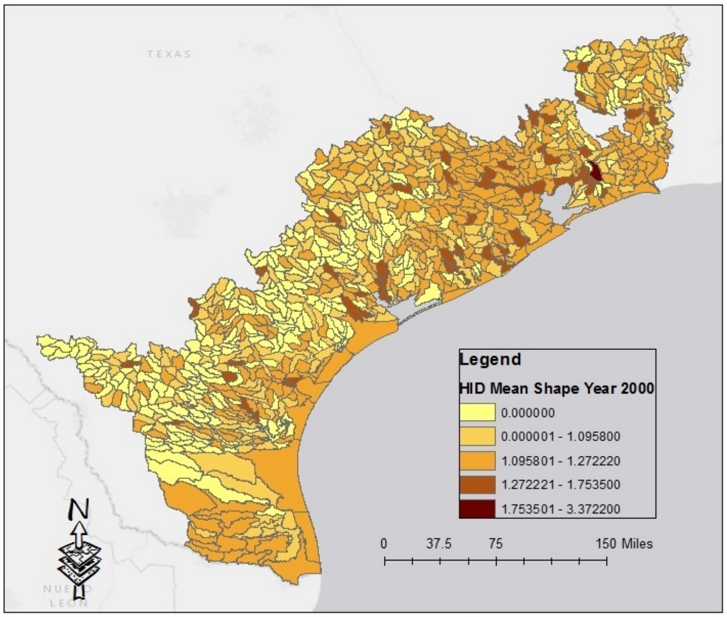

Figure 50: Mean Shape Value for High Intensity Development Patches in Year 2000

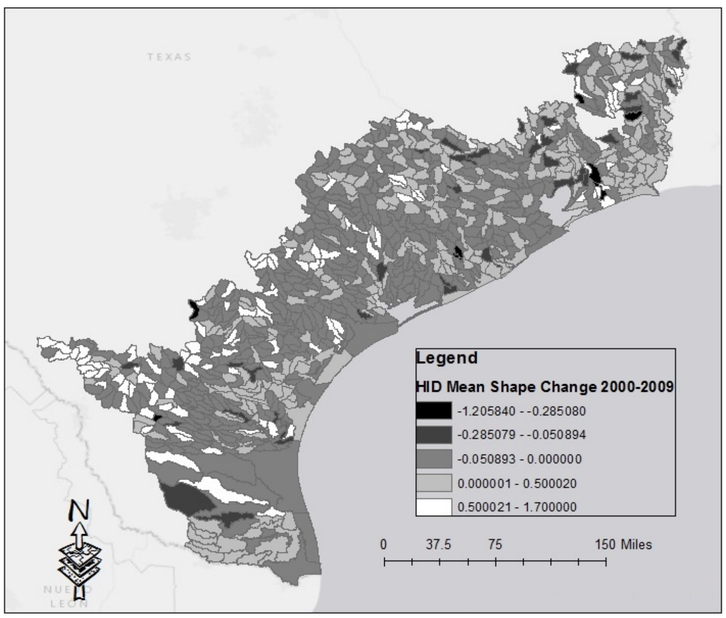

Figure 51: Change in Mean Shape Value for High Intensity Development Patches from 2000 to 2009

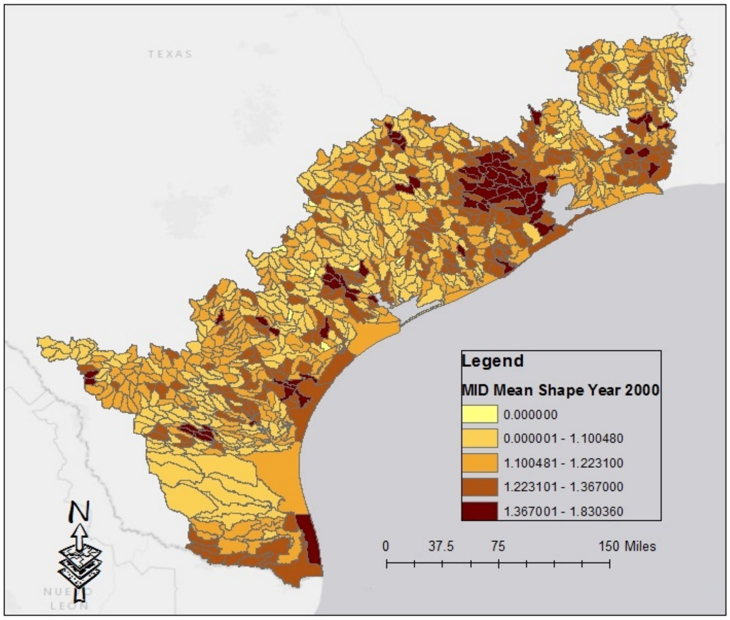

Figure 52: Mean Shape Value for Medium Intensity Development Patches in Year 2000

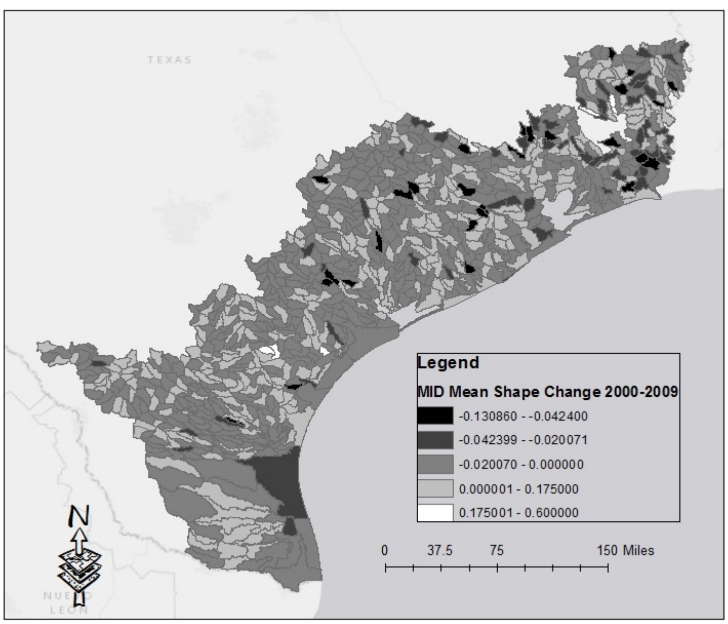

Figure 53: Change in Mean Shape Value for Medium Intensity Development Patches from 2000 to 2009

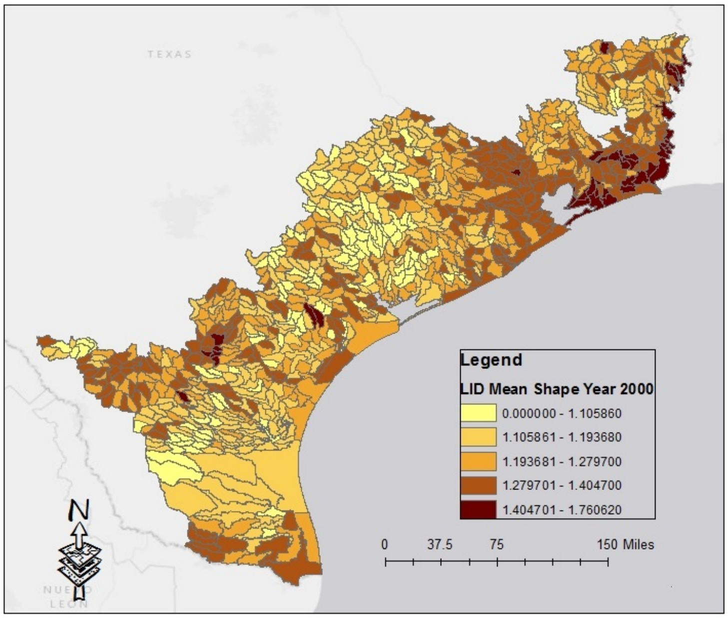

Figure 54: Mean Shape Value for Low Intensity Development Patches in Year 2000

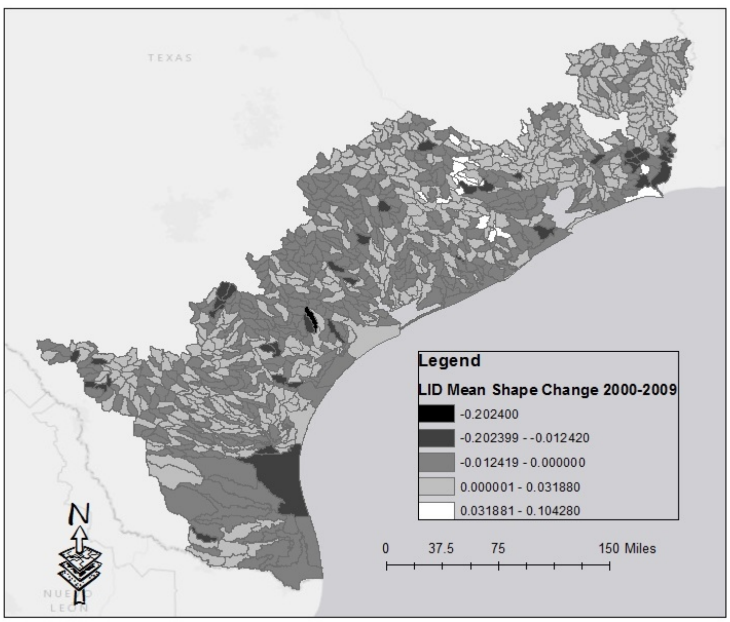

Figure 55: Change in Mean Shape Value for Low Intensity Development Patches from 2000 to 2009

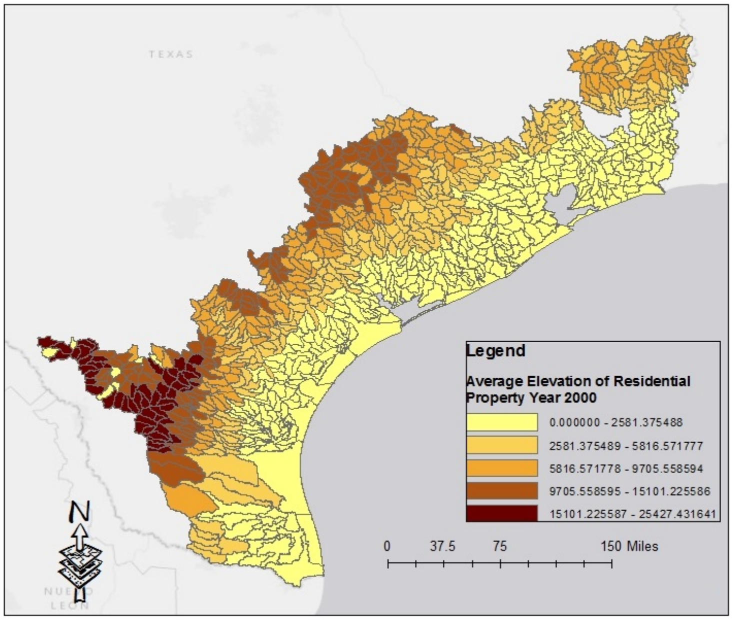

Figure 56: Average Elevation of Residential Property in Year 2000

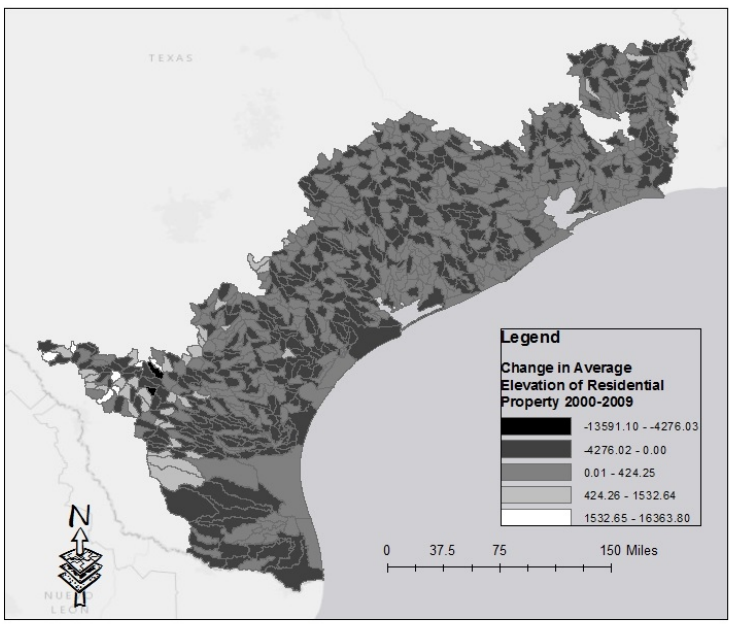

Figure 57: Change in Average Elevation of Residential Property from 2000 to 2009

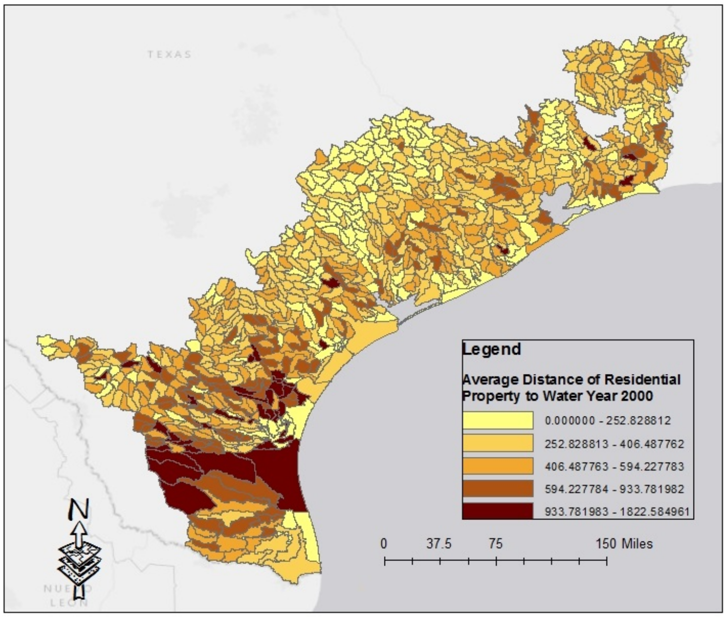

Figure 58: Average Distance of Residential Property to Water in Year 2000

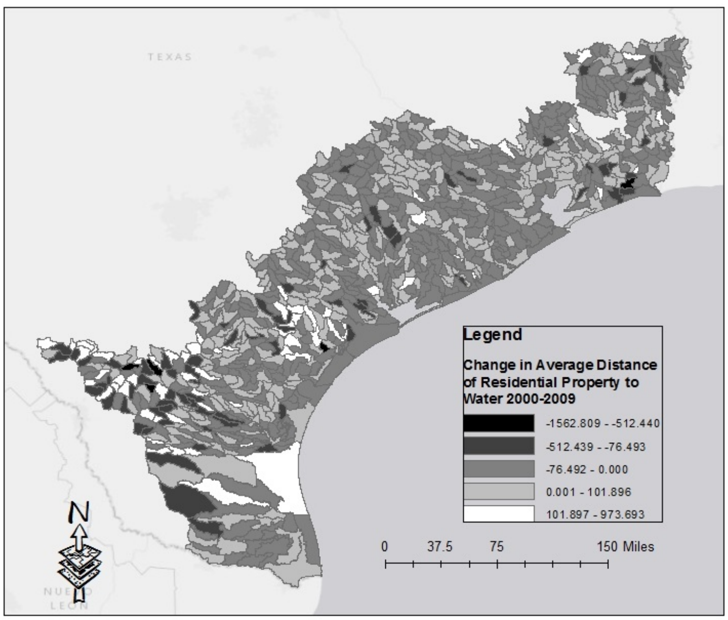

Figure 59: Change in Average Distance of Residential Property to Water from 2000 to 2009

APPENDIX 2

Table 9: Damage and Policy Data for Example Watersheds in Houston Area

Name		Country Club Bayou	Upper Greens Bayou	Frontal Galveston Bay	Dickinson Bayou
HUC		120401040403	120401040603	120402040101	120402040202
Total Bldg. Damage	2001	$79,904,726.00	$36,163,929.00	$30,513,902.00	$21,222,794.00
	2008	$3,204,856.00	$4,298,459.00	$2,227,491.00	$69,474,508.00
Number Homes	2001	111872	21674	25208	12308
	2008	124328	26309	39641	17906
Number Claims	2001	1905	898	1345	275
	2008	458	234	493	548
Number Policies	2001	10656	3472	7360	4164
	2008	12647	1821	9486	4795
Policies per Home	2001	0.095251716	0.160191935	0.291970803	0.338316542
	2008	0.101722862	0.069215858	0.239297697	0.267787334
Damage per Home	2001	$714.25	$1,668.54	$1,210.48	$1,724.31
	2008	$25.78	$163.38	$56.19	$3,879.96

APPENDIX 3

```
  Ho: Error has No Spatial AutoCorrelation
  Ha: Error has    Spatial AutoCorrelation

- GLOBAL Moran MI            =  -0.0037     P-Value > Z(-0.576)
0.5645
- GLOBAL Geary GC            =   0.9747     P-Value > Z(-2.663)
0.0078
- GLOBAL Getis-Ords GO       =   0.0208     P-Value > Z(0.576)
0.5645
- Moran MI Error Test        =   0.0705     P-Value > Z(11.334)
0.9438
- LM Error (Burridge)        =   0.2824     P-Value > Chi2(1)
0.5951
- LM Error (Robust)          =   0.0329     P-Value > Chi2(1)
0.8560
```

```
  Ho: Spatial Lagged Dependent Variable has No Spatial
AutoCorrelation
  Ha: Spatial Lagged Dependent Variable has    Spatial
AutoCorrelation

- LM Lag (Anselin)           =   0.2675     P-Value > Chi2(1)
0.6050
- LM Lag (Robust)            =   0.0179     P-Value > Chi2(1)
0.8935
```

```
  Ho: No General Spatial AutoCorrelation
  Ha:    General Spatial AutoCorrelation

- LM SAC (LMErr+LMLag_R)     =   0.3004     P-Value > Chi2(2)
0.8605
- LM SAC (LMLag+LMErr_R)     =   0.3004     P-Value > Chi2(2)
0.8605
```

APPENDIX 4

```
. xtreg  log_totdmgbld pct_HID av_elev_new av_distH20 drain_dens mean_slope SoilH2OCap
ksat Precip_ tot_nu
> m_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0290                         Obs per group: min =        10
       between = 0.6592                                        avg =      10.0
       overall = 0.4046                                        max =        10

                                                Wald chi2(12)      =    948.69
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     pct_HID |   .2162206    .058611     3.69   0.000     .1013451    .3310961
 av_elev_new |  -.0000788   .0000141    -5.58   0.000    -.0001065   -.0000511
  av_distH20 |   .0005462   .0002741     1.99   0.046     8.96e-06    .0010835
  drain_dens |   .7247746   .3511013     2.06   0.039     .0366287     1.41292
  mean_slope |  -.6671163    .092349    -7.22   0.000     -.848117   -.4861157
  SoilH2OCap |   3.535359   .5943735     5.95   0.000     2.370409     4.70031
        ksat |   .0076134   .0073185     1.04   0.298    -.0067305    .0219573
     Precip_ |    .002191   .0001469    14.92   0.000     .0019031    .0024789
 tot_num_pol |   .0004682   .0001169     4.01   0.000     .0002391    .0006972
         age |   .0292481   .0036314     8.05   0.000     .0221308    .0363654
pct_upland~g |  -.0361313    .003998    -9.04   0.000    -.0439672   -.0282954
 pct_wetland |  -.0215532   .0071756    -3.00   0.003     -.035617   -.0074893
       _cons |   .6536493   .3793572     1.72   0.085    -.0898772    1.397176
-------------+----------------------------------------------------------------
     sigma_u |  1.6360363
     sigma_e |  2.7575473
         rho |  .26035382   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld pct_MID av_elev_new av_distH20 drain_dens mean_slope SoilH2OCap
ksat Precip_ tot_nu
> m_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
```

```
Group variable: UID                              Number of groups   =       916

R-sq:  within  = 0.0308                          Obs per group: min =        10
       between = 0.6873                                         avg =      10.0
       overall = 0.4226                                         max =        10

                                                 Wald chi2(12)      =   1102.62
corr(u_i, X)   = 0 (assumed)                     Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     pct_MID |   .2192165   .0276614     7.93   0.000     .1650013    .2734318
 av_elev_new |  -.0000608   .0000134    -4.55   0.000     -.000087   -.0000346
  av_distH20 |   .0003467   .0002585     1.34   0.180    -.0001599    .0008533
  drain_dens |   .4523807   .3355032     1.35   0.178    -.2051934    1.109955
  mean_slope |  -.6455901   .0887368    -7.28   0.000     -.819511   -.4716692
  SoilH2OCap |   2.852825   .5999662     4.75   0.000     1.676913    4.028737
        ksat |   .0078647   .0069172     1.14   0.256    -.0056928    .0214223
     Precip_ |   .0021531   .0001438    14.97   0.000     .0018712    .0024349
 tot_num_pol |   .0002723   .0001087     2.50   0.012     .0000592    .0004855
         age |   .0281402   .0035448     7.94   0.000     .0211926    .0350878
pct_upland~g |  -.0286542   .0037874    -7.57   0.000    -.0360775   -.0212309
 pct_wetland |   -.010485   .0069292    -1.51   0.130     -.024066    .0030961
       _cons |   .2637986   .3740214     0.71   0.481      -.46927    .9968672
-------------+----------------------------------------------------------------
     sigma_u |  1.5569252
     sigma_e |  2.7572678
         rho |  .24175994   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld pct_LID av_elev_new av_distH20 drain_dens mean_slope SoilH2OCap
ksat Precip_ tot_nu
> m_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                    Number of obs      =      9160
Group variable: UID                              Number of groups   =       916

R-sq:  within  = 0.0315                          Obs per group: min =        10
       between = 0.7458                                         avg =      10.0
       overall = 0.4582                                         max =        10

                                                 Wald chi2(12)      =   1326.37
```

```
corr(u_i, X)   = 0 (assumed)                   Prob > chi2       =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     pct_LID |   .3425344   .0409977     8.35   0.000     .2621804    .4228883
 av_elev_new |  -.0000469   .0000123    -3.82   0.000    -.0000709   -.0000228
  av_distH20 |   -.000028   .0002335    -0.12   0.904    -.0004857    .0004296
  drain_dens |   .1901577   .2933579     0.65   0.517    -.3848133    .7651287
  mean_slope |  -.6598262   .0811093    -8.14   0.000    -.8187975   -.5008549
  SoilH2OCap |   2.781968   .5335015     5.21   0.000     1.736324    3.827612
        ksat |   .0080028   .0061109     1.31   0.190    -.0039743      .01998
     Precip_ |   .0019371   .0001396    13.88   0.000     .0016635    .0022107
 tot_num_pol |   .0003082    .000079     3.90   0.000     .0001533    .0004631
         age |   .0259469    .003451     7.52   0.000     .0191831    .0327107
pct_upland~g |  -.0233359   .0034812    -6.70   0.000     -.030159   -.0165128
 pct_wetland |  -.0146053   .0059978    -2.44   0.015    -.0263607   -.0028499
       _cons |   .0542098   .3606321     0.15   0.881    -.6526162    .7610358
-------------+----------------------------------------------------------------
     sigma_u |  1.3545733
     sigma_e |  2.7558624
         rho |  .19458512   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  AREA_MNHID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_ to
> t_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0280                         Obs per group: min =        10
       between = 0.6672                                        avg =      10.0
       overall = 0.4087                                        max =        10

                                                Wald chi2(12)      =   1081.26
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
  AREA_MNHID |   .8930567   .2596498     3.44   0.001     .3841525    1.401961
 av_elev_new |  -.0000823   .0000144    -5.71   0.000    -.0001105    -.000054
  av_distH20 |   .0006208   .0002806     2.21   0.027     .0000709    .0011707
  drain_dens |   .6905499   .3392269     2.04   0.042     .0256775    1.355422
  mean_slope |  -.6224565   .0925028    -6.73   0.000    -.8037586   -.4411545
  SoilH2OCap |   3.939757   .5606309     7.03   0.000     2.840941    5.038573
        ksat |   .0077067   .0074208     1.04   0.299    -.0068378    .0222512
     Precip_ |    .002192   .0001476    14.86   0.000     .0019028    .0024812
 tot_num_pol |   .0005692   .0001127     5.05   0.000     .0003483    .0007902
         age |   .0279605   .0036993     7.56   0.000     .0207099    .0352111
pct_upland~g |  -.0412901   .0039884   -10.35   0.000    -.0491073   -.0334729
 pct_wetland |  -.0296154   .0069662    -4.25   0.000    -.0432689   -.0159619
       _cons |   .7127151   .3813887     1.87   0.062     -.034793    1.460223
-------------+----------------------------------------------------------------
     sigma_u |   1.623582
     sigma_e |   2.757678
         rho |  .25740341   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  AREA_MNMID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_ to
> t_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0280                         Obs per group: min =        10
       between = 0.6946                                        avg =      10.0
       overall = 0.4254                                        max =        10

                                                Wald chi2(12)      =   1193.15
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  AREA_MNMID |   1.584616   .2011167     7.88   0.000     1.190435    1.978798
 av_elev_new |   -.000065    .000014    -4.63   0.000    -.0000926   -.0000375
  av_distH20 |   .0003742   .0002687     1.39   0.164    -.0001524    .0009008
  drain_dens |   .6002163   .3208696     1.87   0.061    -.0286767    1.229109
  mean_slope |  -.5872697   .0886483    -6.62   0.000    -.7610171   -.4135223
  SoilH2OCap |   3.653409   .5289206     6.91   0.000     2.616744    4.690074
        ksat |    .008161     .00682     1.20   0.231    -.0052059     .021528
```

```
     Precip_ |   .0021878   .0001453    15.06   0.000     .0019031    .0024725
 tot_num_pol |   .0004234   .0001071     3.95   0.000     .0002134    .0006333
         age |    .028215   .0035749     7.89   0.000     .0212083    .0352218
pct_upland~g |  -.0351929   .0037724    -9.33   0.000    -.0425866   -.0277992
 pct_wetland |  -.0176036   .0068385    -2.57   0.010    -.0310069   -.0042003
       _cons |   -.015991   .3826283    -0.04   0.967    -.7659286    .7339467
-------------+----------------------------------------------------------------
     sigma_u |  1.5403035
     sigma_e |  2.7576614
         rho |  .23779491   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  AREA_MNLID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_ to
> t_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0273                         Obs per group: min =        10
       between = 0.6905                                        avg =      10.0
       overall = 0.4228                                        max =        10

                                                Wald chi2(12)      =   1108.11
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  AREA_MNLID |   1.593586   .3210227     4.96   0.000     .9643934    2.222779
 av_elev_new |   -.000075   .0000137    -5.48   0.000    -.0001018   -.0000482
  av_distH20 |   .0004606   .0002774     1.66   0.097     -.000083    .0010043
  drain_dens |   .8136365   .3193804     2.55   0.011     .1876624    1.439611
  mean_slope |  -.6368883   .0917313    -6.94   0.000    -.8166784   -.4570981
  SoilH2OCap |   4.506019   .4946518     9.11   0.000     3.536519    5.475519
        ksat |   .0092051   .0072745     1.27   0.206    -.0050527    .0234629
     Precip_ |   .0020401   .0001484    13.75   0.000     .0017493    .0023309
 tot_num_pol |   .0005793   .0001062     5.45   0.000     .0003711    .0007874
         age |   .0276317   .0035892     7.70   0.000     .0205969    .0346665
pct_upland~g |  -.0365318   .0038187    -9.57   0.000    -.0440163   -.0290474
 pct_wetland |  -.0337753   .0070283    -4.81   0.000    -.0475504   -.0200002
       _cons |   .0569298   .3852967     0.15   0.883    -.6982378    .8120975
-------------+----------------------------------------------------------------
```

```
     sigma_u |   1.548739
     sigma_e |   2.757688
         rho |  .23977688   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  GYRATE_MNHID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_
> tot_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0273                         Obs per group: min =        10
       between = 0.6625                                        avg =      10.0
       overall = 0.4054                                        max =        10

                                                Wald chi2(12)      =   1054.65
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
GYRATE_MNHID |   .0194094   .0110428     1.76   0.079    -.0022342    .0410529
 av_elev_new |  -.0000897   .0000153    -5.85   0.000    -.0001197   -.0000596
  av_distH20 |   .0007767   .0002869     2.71   0.007     .0002143     .001339
  drain_dens |   .8360754   .3417994     2.45   0.014      .166161     1.50599
  mean_slope |  -.6179397   .0938221    -6.59   0.000    -.8018277   -.4340518
  SoilH2OCap |    4.28765   .5334103     8.04   0.000     3.242185    5.333115
        ksat |   .0068079   .0076133     0.89   0.371    -.0081139    .0217296
     Precip_ |   .0022043   .0001478    14.91   0.000     .0019145     .002494
 tot_num_pol |   .0005956   .0001154     5.16   0.000     .0003695    .0008217
         age |   .0286515   .0040186     7.13   0.000     .0207752    .0365278
pct_upland~g |  -.0440906   .0040463   -10.90   0.000    -.0520213   -.0361599
 pct_wetland |  -.0314814   .0071252    -4.42   0.000    -.0454464   -.0175163
       _cons |   .6547115   .4075161     1.61   0.108    -.1440053    1.453428
-------------+----------------------------------------------------------------
     sigma_u |  1.6373491
     sigma_e |  2.7576541
         rho |  .26064793   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  GYRATE_MNMID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_
```

```
> tot_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0274                         Obs per group: min =        10
       between = 0.6775                                        avg =      10.0
       overall = 0.4145                                        max =        10

                                                Wald chi2(12)      =   1129.19
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
GYRATE_MNMID |   .0599965   .0123334     4.86   0.000     .0358234    .0841695
 av_elev_new |  -.0000836   .0000152    -5.50   0.000    -.0001134   -.0000538
  av_distH20 |   .0006656    .000281     2.37   0.018     .0001148    .0012163
  drain_dens |   .8451657   .3291088     2.57   0.010     .2001243    1.490207
  mean_slope |  -.5746023    .092732    -6.20   0.000    -.7563537   -.3928509
  SoilH2OCap |   4.157429   .5164154     8.05   0.000     3.145273    5.169584
        ksat |   .0081684   .0073779     1.11   0.268     -.006292    .0226288
     Precip_ |   .0022071   .0001452    15.20   0.000     .0019226    .0024916
 tot_num_pol |   .0005682   .0001115     5.10   0.000     .0003497    .0007867
         age |   .0278645   .0036386     7.66   0.000     .0207329    .0349961
pct_upland~g |  -.0403599   .0040715    -9.91   0.000      -.04834   -.0323798
 pct_wetland |  -.0251492   .0069488    -3.62   0.000    -.0387687   -.0115298
       _cons |  -.7422311   .4898482    -1.52   0.130    -1.702316    .2178538
-------------+----------------------------------------------------------------
     sigma_u |  1.5934154
     sigma_e |  2.7574724
         rho |  .25032694   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  GYRATE_MNLID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_
> tot_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0274                         Obs per group: min =        10
       between = 0.6555                                        avg =      10.0
```

```
       overall = 0.4012                                        max =        10

                                                Wald chi2(12)      =   1035.68
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
GYRATE_MNLID |   .0223659   .0155552     1.44   0.150    -.0081216    .0528535
 av_elev_new |  -.0000938   .0000147    -6.39   0.000    -.0001227    -.000065
  av_distH20 |    .000789   .0002971     2.66   0.008     .0002066    .0013714
  drain_dens |   .9192363    .341625     2.69   0.007     .2496636    1.588809
  mean_slope |  -.6286834   .0976559    -6.44   0.000    -.8200855   -.4372813
  SoilH2OCap |   4.554562   .5270377     8.64   0.000     3.521587    5.587537
        ksat |   .0077469   .0078021     0.99   0.321    -.0075449    .0230387
     Precip_ |   .0021954   .0001492    14.71   0.000     .0019029    .0024878
 tot_num_pol |   .0006099   .0001173     5.20   0.000       .00038    .0008397
         age |    .031162   .0037826     8.24   0.000     .0237483    .0385757
pct_upland~g |  -.0423377   .0041465   -10.21   0.000    -.0504646   -.0342108
 pct_wetland |  -.0330439   .0076585    -4.31   0.000    -.0480544   -.0180334
       _cons |   .1789061   .5373455     0.33   0.739    -.8742718    1.232084
-------------+----------------------------------------------------------------
     sigma_u |   1.646592
     sigma_e |  2.7576959
         rho |   .2628175   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  PROX_MNHID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_ to
> t_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0276                         Obs per group: min =        10
       between = 0.6524                                        avg =      10.0
       overall = 0.3992                                        max =        10

                                                Wald chi2(12)      =   1033.33
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
```

```
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  PROX_MNHID |   .0016288   .0027753     0.59   0.557    -.0038106    .0070682
 av_elev_new |  -.0000989   .0000152    -6.50   0.000    -.0001287    -.000069
  av_distH20 |   .0008109    .000293     2.77   0.006     .0002367    .0013852
  drain_dens |   .8564902   .3528358     2.43   0.015     .1649448    1.548036
  mean_slope |  -.6211789    .095261    -6.52   0.000    -.8078871   -.4344708
  SoilH2OCap |   4.414332   .5529303     7.98   0.000     3.330608    5.498055
        ksat |   .0063827   .0075917     0.84   0.400    -.0084967    .0212621
     Precip_ |   .0022436   .0001483    15.13   0.000     .0019529    .0025342
 tot_num_pol |   .0005956   .0001186     5.02   0.000     .0003631    .0008281
         age |   .0315922   .0037742     8.37   0.000      .024195    .0389895
pct_upland~g |  -.0438976   .0042891   -10.23   0.000     -.052304   -.0354911
 pct_wetland |  -.0305543   .0074061    -4.13   0.000      -.04507   -.0160387
       _cons |   .8997368   .3918131     2.30   0.022     .1317971    1.667676
-------------+----------------------------------------------------------------
     sigma_u |  1.6494785
     sigma_e |  2.7576322
         rho |  .26350571   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  PROX_MNMID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_ to
> t_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0282                         Obs per group: min =        10
       between = 0.6560                                        avg =      10.0
       overall = 0.4018                                        max =        10

                                                Wald chi2(12)      =    994.32
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  PROX_MNMID |   .0043848   .0021121     2.08   0.038     .0002452    .0085244
 av_elev_new |  -.0000917   .0000168    -5.47   0.000    -.0001245   -.0000589
  av_distH20 |   .0006743   .0003045     2.21   0.027     .0000776     .001271
  drain_dens |   .8213399    .357044     2.30   0.021     .1215464    1.521133
```

```
  mean_slope |  -.6298708   .0943912    -6.67   0.000    -.8148741   -.4448675
  SoilH2OCap |    4.23124   .5643191     7.50   0.000     3.125194    5.337285
        ksat |   .0067157   .0074432     0.90   0.367    -.0078727    .0213041
     Precip_ |   .0022502   .0001481    15.19   0.000     .0019599    .0025406
 tot_num_pol |   .0005146   .0001012     5.08   0.000     .0003163     .000713
         age |   .0308282   .0037738     8.17   0.000     .0234317    .0382247
pct_upland~g |  -.0418575   .0047789    -8.76   0.000    -.0512239   -.0324912
 pct_wetland |  -.0272552   .0079296    -3.44   0.001    -.0427969   -.0117135
       _cons |   .7952579   .4033603     1.97   0.049     .0046862     1.58583
-------------+----------------------------------------------------------------
     sigma_u |  1.6443653
     sigma_e |  2.7576915
         rho |  .26229408   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  PROX_MNLID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_ to
> t_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0275                         Obs per group: min =        10
       between = 0.6571                                        avg =      10.0
       overall = 0.4020                                        max =        10

                                                Wald chi2(12)      =   1030.28
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  PROX_MNLID |   .0016548   .0008883     1.86   0.062    -.0000863     .003396
 av_elev_new |  -.0000964   .0000146    -6.61   0.000     -.000125   -.0000679
  av_distH20 |   .0007377   .0002822     2.61   0.009     .0001846    .0012908
  drain_dens |   .8437059   .3472639     2.43   0.015     .1630811    1.524331
  mean_slope |  -.6270867   .0947889    -6.62   0.000    -.8128695    -.441304
  SoilH2OCap |   4.530876   .5276109     8.59   0.000     3.496778    5.564974
        ksat |   .0067279   .0075863     0.89   0.375     -.008141    .0215968
     Precip_ |   .0022196   .0001474    15.06   0.000     .0019308    .0025084
 tot_num_pol |   .0005949   .0001144     5.20   0.000     .0003707    .0008192
         age |   .0313292    .003727     8.41   0.000     .0240244    .0386341
pct_upland~g |  -.0432955   .0040321   -10.74   0.000    -.0511983   -.0353926
```

```
 pct_wetland |  -.0306811   .0071966    -4.26   0.000    -.0447862    -.016576
       _cons |   .8760479   .3854671     2.27   0.023     .1205463     1.63155
-------------+----------------------------------------------------------------
     sigma_u |  1.6424494
     sigma_e |  2.7575912
         rho |  .26185725   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  SHAPE_MNHID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_ t
> ot_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0278                         Obs per group: min =        10
       between = 0.6684                                        avg =      10.0
       overall = 0.4092                                        max =        10

                                                Wald chi2(12)      =   1110.15
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 SHAPE_MNHID |   .8613019   .0884868     9.73   0.000      .687871    1.034733
 av_elev_new |  -.0000843   .0000145    -5.83   0.000    -.0001126   -.0000559
  av_distH20 |   .0007887   .0002857     2.76   0.006     .0002288    .0013486
  drain_dens |    .904937   .3375417     2.68   0.007     .2433673    1.566507
  mean_slope |  -.6634136   .0946721    -7.01   0.000    -.8489675   -.4778597
  SoilH2OCap |   4.274824   .5190708     8.24   0.000     3.257464    5.292184
        ksat |   .0065081   .0077343     0.84   0.400    -.0086508    .0216669
     Precip_ |   .0022077   .0001464    15.08   0.000     .0019208    .0024946
 tot_num_pol |   .0005878   .0001139     5.16   0.000     .0003646     .000811
         age |   .0267802   .0034989     7.65   0.000     .0199224    .0336379
pct_upland~g |   -.044343   .0039994   -11.09   0.000    -.0521817   -.0365044
 pct_wetland |  -.0329876   .0070576    -4.67   0.000    -.0468202    -.019155
       _cons |   .3207277   .3759666     0.85   0.394    -.4161533    1.057609
-------------+----------------------------------------------------------------
     sigma_u |  1.6268514
     sigma_e |  2.7576635
         rho |  .25817522   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. xtreg  log_totdmgbld  SHAPE_MNMID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_ t
> ot_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0281                         Obs per group: min =        10
       between = 0.6771                                        avg =      10.0
       overall = 0.4147                                        max =        10

                                                Wald chi2(12)      =   1141.22
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                  (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 SHAPE_MNMID |   3.612976    .534552     6.76   0.000     2.565273    4.660678
 av_elev_new |  -.0000821   .0000144    -5.69   0.000    -.0001104   -.0000539
  av_distH20 |   .0006639   .0002723     2.44   0.015     .0001302    .0011977
  drain_dens |   .7743822   .3350955     2.31   0.021     .1176071    1.431157
  mean_slope |  -.6013098    .091892    -6.54   0.000    -.7814149   -.4212048
  SoilH2OCap |   4.180018   .5137551     8.14   0.000     3.173076    5.186959
        ksat |    .007609   .0073259     1.04   0.299    -.0067495    .0219676
     Precip_ |   .0021983   .0001451    15.15   0.000     .0019139    .0024827
 tot_num_pol |   .0005651   .0001107     5.11   0.000     .0003481     .000782
         age |   .0267721   .0035077     7.63   0.000     .0198971     .033647
pct_upland~g |   -.039485    .003927   -10.05   0.000    -.0471818   -.0317881
 pct_wetland |  -.0251639   .0069925    -3.60   0.000     -.038869   -.0114587
       _cons |  -3.427797   .7171677    -4.78   0.000     -4.83342   -2.022174
-------------+----------------------------------------------------------------
     sigma_u |  1.5965969
     sigma_e |  2.7576298
         rho |  .25105486   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  SHAPE_MNLID av_elev_new av_distH20 drain_dens mean_slope
SoilH2OCap ksat Precip_ t
> ot_num_pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916
```

```
R-sq:  within  = 0.0279                         Obs per group: min =        10
       between = 0.6657                                        avg =      10.0
       overall = 0.4078                                        max =        10

                                                Wald chi2(12)      =   1074.82
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 SHAPE_MNLID |   3.866982   .9743478     3.97   0.000     1.957295    5.776669
 av_elev_new |  -.0000873   .0000141    -6.17   0.000    -.0001151   -.0000596
  av_distH20 |   .0006972   .0002903     2.40   0.016     .0001284    .0012661
  drain_dens |   .9757701   .3303426     2.95   0.003     .3283105     1.62323
  mean_slope |  -.6704827   .1004027    -6.68   0.000    -.8672683   -.4736971
  SoilH2OCap |   4.486233   .5144668     8.72   0.000     3.477897     5.49457
        ksat |    .009609   .0078181     1.23   0.219    -.0057141    .0249322
     Precip_ |   .0021513    .000146    14.73   0.000     .0018651    .0024376
 tot_num_pol |   .0005973    .000114     5.24   0.000     .0003738    .0008208
         age |   .0292292   .0037246     7.85   0.000     .0219291    .0365292
pct_upland~g |  -.0387384   .0039162    -9.89   0.000    -.0464141   -.0310627
 pct_wetland |  -.0343937   .0074503    -4.62   0.000     -.048996   -.0197914
       _cons |  -4.032054   1.135815    -3.55   0.000    -6.258211   -1.805897
-------------+----------------------------------------------------------------
     sigma_u |  1.6221611
     sigma_e |  2.7572779
         rho |  .25712427   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  pdHID av_elev_new av_distH20 drain_dens mean_slope SoilH2OCap
ksat Precip_ tot_num
> _pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0323                         Obs per group: min =        10
       between = 0.7070                                        avg =      10.0
       overall = 0.4351                                        max =        10

                                                Wald chi2(12)      =   1260.19
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

```
                                 (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       pdHID |   .8019101   .0877249     9.14   0.000     .6299725    .9738477
 av_elev_new |  -.0000517    .000013    -3.98   0.000    -.0000772   -.0000263
  av_distH20 |   .0002778   .0002499     1.11   0.266     -.000212    .0007677
  drain_dens |   .2937147   .3238038     0.91   0.364    -.3409291    .9283586
  mean_slope |  -.6441542   .0868286    -7.42   0.000    -.8143352   -.4739731
  SoilH2OCap |   2.510036   .5896598     4.26   0.000     1.354324    3.665748
        ksat |   .0067394   .0064263     1.05   0.294    -.0058559    .0193347
     Precip_ |   .0021024   .0001428    14.72   0.000     .0018225    .0023822
 tot_num_pol |   .0001994   .0001016     1.96   0.050     3.12e-07    .0003984
         age |   .0270579   .0034722     7.79   0.000     .0202526    .0338632
pct_upland~g |  -.0259978   .0035759    -7.27   0.000    -.0330065   -.0189891
 pct_wetland |  -.0094644   .0066237    -1.43   0.153    -.0224466    .0035178
       _cons |    .238305   .3658158     0.65   0.515    -.4786808    .9552908
-------------+----------------------------------------------------------------
     sigma_u |  1.4941173
     sigma_e |   2.756816
         rho |  .22704343   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  pdMID av_elev_new av_distH20 drain_dens mean_slope SoilH2OCap
ksat Precip_ tot_num
> _pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0323                         Obs per group: min =        10
       between = 0.7517                                        avg =      10.0
       overall = 0.4619                                        max =        10

                                                Wald chi2(12)      =   1822.16
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                 (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       pdMID |   .6099323   .0421672    14.46   0.000     .5272862    .6925785
```

```
 av_elev_new |  -.0000419   .0000132    -3.17   0.002    -.0000679    -.000016
  av_distH20 |  -.0000807   .0002264    -0.36   0.722    -.0005245    .0003631
  drain_dens |  -.0172183   .2848598    -0.06   0.952    -.5755333    .5410967
  mean_slope |  -.6339043   .0821101    -7.72   0.000    -.7948372   -.4729714
  SoilH2OCap |   1.976165   .5209977     3.79   0.000     .9550283    2.997302
        ksat |   .0104676   .0061073     1.71   0.087    -.0015025    .0224376
     Precip_ |   .0021001   .0001384    15.18   0.000     .0018289    .0023713
 tot_num_pol |   .0002744   .0000767     3.58   0.000     .0001241    .0004247
         age |    .023648   .0033595     7.04   0.000     .0170635    .0302325
pct_upland~g |  -.0161887   .0035707    -4.53   0.000    -.0231871   -.0091903
 pct_wetland |  -.0015202   .0063175    -0.24   0.810    -.0139022    .0108618
       _cons |  -.5395698   .3762029    -1.43   0.152    -1.276914    .1977744
-------------+----------------------------------------------------------------
     sigma_u |  1.3477218
     sigma_e |  2.7571012
         rho |  .19286065   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xtreg  log_totdmgbld  pdLID av_elev_new av_distH20 drain_dens mean_slope SoilH2OCap
ksat Precip_ tot_num
> _pol age pct_uplandveg pct_wetland, vce(robust)

Random-effects GLS regression                   Number of obs      =      9160
Group variable: UID                             Number of groups   =       916

R-sq:  within  = 0.0315                         Obs per group: min =        10
       between = 0.7331                                        avg =      10.0
       overall = 0.4503                                        max =        10

                                                Wald chi2(12)      =   1498.45
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

                                (Std. Err. adjusted for 916 clusters in UID)
------------------------------------------------------------------------------
             |               Robust
log_totdmg~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       pdLID |   .3183937   .0280613    11.35   0.000     .2633946    .3733929
 av_elev_new |  -.0000473   .0000142    -3.33   0.001    -.0000751   -.0000195
  av_distH20 |   .0001563   .0002568     0.61   0.543     -.000347    .0006595
  drain_dens |   .1627321   .3150673     0.52   0.606    -.4547885    .7802527
  mean_slope |  -.7352352   .0873382    -8.42   0.000    -.9064148   -.5640555
  SoilH2OCap |   2.309741   .5221321     4.42   0.000     1.286381    3.333101
        ksat |   .0089517   .0062515     1.43   0.152    -.0033011    .0212044
     Precip_ |   .0021714   .0001425    15.24   0.000     .0018921    .0024507
```

```
  tot_num_pol |   .0002657   .0000992     2.68   0.007     .0000713      .00046
          age |   .0266217   .0035318     7.54   0.000     .0196995    .0335438
 pct_upland~g |  -.0225736   .0038357    -5.89   0.000    -.0300914   -.0150558
  pct_wetland |  -.0055913   .0065713    -0.85   0.395    -.0184709    .0072883
        _cons |  -.6691641   .4045276    -1.65   0.098    -1.462024    .1236955
-------------+----------------------------------------------------------------
      sigma_u |  1.4097744
      sigma_e |  2.7574233
          rho |  .20722506   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```