FLOOD-PROOFING COMMUNITIES WITH LAND USE PLANNING AND DESIGN

A Dissertation

by

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ABSTRACT

This dissertation evaluated how spatial patterns of pervious land cover moderate flood impacts in urban areas during an extreme rainfall event. First, it presented criteria to characterize hydrologic functions of natural landscape features through spatial metrics of size, proportion, abundance, and shape; second, it described improvements to measurements of flood risk and other context variables; third, it evaluated flood risk and severity of damage in urban neighborhoods using insurance and parcel data; and forth, it identified different design strategies that urban developers, communities and city planners could apply to mitigate flood damages or enhance community flood resilience.

Innovative methodological approaches to sampling and variable measurement were applied to analyze neighborhood-level damages of single-family residential properties covered by the National Flood Insurance Program in Harris County, Texas, at the time of Tropical Storm Allison (June 2001). A total of 68,351 insured properties comprised a sample of 532 neighborhoods in the study area. Risk, mitigation, socio-economic, hazard, and environmental context variables were included in statistical regression models as controls.

Results indicated that the hydrological functions of natural landscapes persist in urban areas. Wetlands, large pervious areas, cultivated agricultural parcels, and greenways and large urban parks of grass open space have important and statistically significant contributions to flood damage mitigation. Increasing some of these by 10% at neighborhood levels could have resulted in damage-cost reductions totaling over $100

million (USD 2001). Isolated patches of grass open space were found to increase flood risk, an indication that not all types of pervious areas can enhance flood resilience. Forested landscapes, however, were statistically insignificant.

Floods are frequent natural disasters that are often costly. While the potential hydrological benefits of pervious surfaces are generally understood, few studies have sought to evaluate the effects that the type, form, and structure of pervious areas may have on regulating the performance of cities with respect to floods. This dissertation's results can be used to assess the relative importance of pervious areas for flood mitigation and to qualify and estimate the potential economic consequences of some land-use decisions.

DEDICATION

To my parents,

Luis Lorente y Sánchez-Bravo and Aura Rodríguez de Lorente,

who have been role-models in life and an endless source of

love, support, encouragement and inspiration.

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NOMENCLATURE

ACV	Actual Cash Value
ASCE	American Society of Civil Engineers
ASFPM	Association of State Floodplain Managers
C-CAP	Coastal Change Analysis Program
CCCR	Canadian Center for Community Renewal
CRED	Centre for Research on the Epidemiology of Disasters
DFIRM	Digital Flood Insurance Rate Maps
EHLG	Environment Heritage and Local Government
EIA	Effective Impervious Area
FEMA	Federal Emergency Management Agency
FISRWG	Federal Interagency Stream Restoration Working Group
GEP	Google Earth Pro
GIMS	Geographic Information and Management System
GIS	Geographic Information Systems
GMM-Het	General Method of Moments with Heteroscedastic Errors
HCAD	Harris County Appraisal District
HCFCD	Harris County Flood Control District
HGAC	Houston-Galveston Area Council
LH	Likelihood of Damage Model in Half-Mile Areas
LM	Lagrange Multiplier

LQ	Likelihood of Damage Model in Quarter-Mile Areas
LPI	Large Patch Index
MAUP	Modifiable Areal Unit Problem
ML	Maximum Likelihood
NFIP	National Flood Insurance Program
NOAA	National Oceanic and Atmospheric Administration
NP	Number of patches
NRC	National Research Council
NRCS	Natural Resources Conservation Service
NWS	National Weather Service
OLS	Ordinary Least Squares
OPW	Office of Public Works
PLAND	Proportion of land
SAR	Spatial Autoregressive Models
SEM	Spatial Error Model
SES	Social-Ecological Systems
SH	Severity of Damage Model in Half-Mile Areas
SHAPE	Shape Index
SQ	Severity of Damage Model in Quarter-Mile Areas
SSURGO	Soil Survey Geographic Organization
StratMap	Strategic Mapping Program
TIA	Total Impervious Area

TNRIS	Texas Natural Resources Information System
TS	Tropical Storm
TSARP	Tropical Storm Allison Recovery Project
TWDB	Texas Water Development Board
UN-Habitat	United Nations Human Settlements Programme
UNFPA	United Nations Population Fund
USACE	United States Army Corps of Engineers
USDA	United States Department of Agriculture
USDC	United States Department of Commerce
VIF	Variance Inflation Factor
WBD	Watershed Boundary Dataset

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1. INTRODUCTION

Floods are the most frequent and one of the most expensive types of natural disasters worldwide (Centre for Research on the Epidemiology of Disasters [CRED], 2009). Despite a long tradition of flood hazard mitigation and adaptation strategies, property losses from flooding have been increasing for at least half a century. These increases have been attributed to the growth of impervious areas that alter the patterns of local landscape hydrological functions.

As urban areas grow and expand, the natural landscape is paved over, and wetlands, forests, grasslands, and agricultural areas are replaced with impervious surfaces. Large impervious areas prevent the natural absorption of flood waters through soils, and any added level of percent imperviousness seems to increase the potential for flooding, even exponentially (Paul & Meyer, 2001; Rogers & DeFee II, 2005; Shusher, Bonta, Thurston, Warnemuende, & Smith, 2005). Since the 1970s, urban areas around the world have grown faster than the population (UN-Habitat, 2008). This means that the predominant spatial pattern of urban growth is more sprawled than compact. With more sprawl, the impact of development on the hydrology of local places widens to regions, effectively increasing the susceptibility of more lands to floods. Furthermore, the expected impacts of future population growth along coastal areas, economic development, and climate change create great uncertainty about the urban adaptations needed for enhancing community resilience to floods.

Thus far, the current understanding of flood problems has led scientific inquiry to focus on the impacts of imperviousness. While the potential hydrological benefits of reducing impervious areas in landscapes are well documented, few studies have sought to evaluate the effects that pervious areas may have on counteracting the negative impacts of development, or regulating the performance of cities with respect to floods. If the hydrological function of landscapes is maintained by natural and ecological spaces in urban areas, there is a potential for attenuating floods and reducing associated impacts through land use planning and design. Furthering our understanding of the relationships between the ecological function of natural features in urban landscapes and flood impacts may be the missing component needed to help communities identify and act on the land use processes that can support their resilience to floods.

1.1 Research Purpose and Objectives

The main purpose of this dissertation study was to operationalize the concept of resilience for planning and design by investigating the extent to which the hydrological functions of natural landscape features are likely to reduce flood-related damages to residential property. The study focused on the spatial dimension of disaster resilience and, as such, was based on the idea that location, pattern, and context contribute to community resilience. Specifically, the central goal of this study was to identify key spatial metrics characterizing the hydrological function of pervious land cover, and test the effectiveness of these metrics with respect to flood damages. Two main research objectives were established to meet this goal:

1. Develop a theoretical conceptual model identifying and relating flood damage in urban areas as a function of spatially explicit pre-disaster attributes of community disaster resilience.
2. Empirically test the model by evaluating the hydrologic roles that the spatial arrangement of natural features of urban landscapes has on moderating flood damages in the context of other relevant risk, mitigation, socio-economic, and environmental variables.

The study used a hypothesis-testing framework to examine one basic question: *To what extent do type, form, and structure of pervious land cover in urban areas have an effect on flood damage?* The focus of the study was on assessed neighborhood property damages of single-family residential units actively participating in the National Flood Insurance Program (NFIP) in Harris County, Texas, when Tropical Storm Allison (TS Allison) impacted the area in June of 2001.

1.2 Research Significance

This research study and its findings are valuable for several reasons. First, the topic is timely. Floods are—and will continue to be—frequent and costly hazards. According to worldwide records (CRED, 2009), floods account for about 35% of damages associated with all extreme weather events. Furthermore, the number of flood events reported in the 2000s is about four times larger and five times more damaging on average, than the ones reported in the 1970s. Although improvements have been made in reducing the level of impact per event, the costs remain high in the billions of dollars.

Second, the geographic setting under study is representative of other regions where people live. Most of the seven-plus billion people in the world today are clustered along rivers and shores (United Nations Population Fund [UNFPA], 2011). In the United States, about 39% of the 2010 population lived in coastal shoreline counties, and these areas make up only about 10% of the total available land (excluding Alaska; National Oceanic and Atmospheric Administration [NOAA], 2013). Population growth estimates suggest that at least a hundred of these coastal shoreline counties (including Harris County) will practically double their 1980 population by 2020 (NOAA, 2013).

Third, this research fills a scientific knowledge gap about the hydrologic response of natural land cover in the context of floods. Thus far, most studies have focused on identifying the potential benefits of reducing the amount of impervious surfaces in the landscape (Arnold Jr. & Gibbons, 1996; Rogers & DeFee II, 2005; Shusher et al., 2005), and very few have sought to evaluate the possible practical implications that urban pervious land cover areas may have on regulating the hydrologic performance of cities with respect to floods.

Fourth, this research addresses an important need to operationalize the concept of resilience for land use planning. Almost any type of growth along coastal areas will result in adverse impacts to water-regulating ecosystems and an increased exposure of more people to flood hazards. Improving our understanding on the performance of the urbanized landscapes with respect to floods and translating that knowledge into local land use policy actions can help build community resilience and reduce flood risk.

Last, this research improves on the overall explained variance of current place-based flood damage assessment models by considering new landscape indicators of local hydrologic function, developing new measures of flood damage, refining measurement of related concepts, and addressing validity concerns associated with the quality and completeness of damage data from the NFIP.

1.3 Document Structure

This section (Section 1) outlines the need for improving flood damage assessment models to guide planning efforts for community flood resilience. Concepts of flood risk, mitigation, and disaster resilience are briefly discussed in Section 2 before a review of thematically related concepts of land use and landscape planning. Focusing on the spatial dimension of flood problems, Section 3 presents a conceptual model of community flood resilience as a loss function that integrates the theories and concepts reviewed in the previous section. Section 4 includes a detailed description of the methods, measures, and analytical procedures used to operationalize and test the model. The results of testing the model in neighborhoods of Harris County, Texas, after TS Allison in 2001 are presented in Section 5. Section 6 includes a discussion on the implications and benefits of adopting the proposed approach for assessing urban-scale outcomes of community disaster resilience. Last, Section 7 concludes this dissertation by summarizing results and guiding principles for urban land use planning and design, and outlining contributions, limitations, and future lines of research.

2. LITERATURE REVIEW

Adopting a resilience approach to tackling disasters is presumed to help communities understand the vulnerabilities, capacities, operations, and resources that may affect their susceptibility to hazards and associated impacts. This section covers the evolution of the concept of disaster resilience in the field of natural hazard mitigation, and demonstrates the relevance of a spatial approach to operationalize the concept for policy and land use planning and design.

2.1 Floods

Floods are hydrological events that temporarily cover land with water. Floods happen when the accumulation of water overflows the natural or artificial banks along river channels, shores, or barriers that keep land dry. They are often classified according to the main factor causing the flood, but can be further differentiated based on the nature of the mechanism that enables or intensifies the flood (see Table 1). Because floods result from many different circumstances, their characteristics can range from predictable to unpredictable, and from short to long duration.

From a landscape ecology perspective, hydrologic floods are desirable events. They maintain ecological connectivity in four ways: along the length of the floodplain, across the landscape (river-floodplain), vertically (river-groundwater), and over time with seasonal changes (Ward, 1989). Several landscape dynamics depend on floods to maintain their ecological integrity and productivity. Studies on river-floodplain ecology,

Table 1 Causes of floods.

Causes	Subcategory	Enabling mechanism (a); Intensifying factor (b)
Precipitation	Immediate effect (e.g., rain)	(a) Intense rainfall events; tropical storms; hurricanes (b) Climate change
	Delayed effect (e.g., hail, snow)	(a) Intense snowfall events; ice storms; hail storms; rapid snowmelt (b) Climate change
Rising waters	Sea water	(a) High tides; heavy wave action with high wind speeds; storm surges; hurricanes; tsunamis (b) Coastal erosion, subsidence, and loss of wetlands; sea level rise; poor mitigation; climate change
	Fresh water	(a) River bursts; raised water table levels; damming of water (by landslides or debris caught in bridges); glacial lake outbursts; ice jams (b) Storms; river-bank erosion; subsidence; loss of vegetation; poor mitigation
Poor drainage	Natural absorption	(a) Poor soil infiltration capacity; topography (low elevations and natural hollow areas) (b) Soil erosion; loss of vegetation; mudflows
	Anthropogenic prevention of natural absorption	(a) Large proportion of impervious surfaces; floodplain development; wetland loss; deforestation (b) Urbanization; population growth; poor land use planning; subsidence; liquefaction
Structural failure	Man-made retention structures (e.g., lakes, dams)	(a) Inadequate capacity levels; structural beach or collapse (b) Aging infrastructure; poor planning/maintenance; earthquakes
	Man-made drainage systems (e.g., water mains, sewers)	(a) Inadequate capacity levels; blockage or system collapse (b) Aging infrastructure; poor planning/maintenance; population growth; rain storms
	Defense structures (e.g., dikes, levees, canals)	(a) Breach or collapse of dikes; levees or canals (b) Aging infrastructure; poor planning/maintenance; erosion; tsunamis; hurricanes; earthquakes

(Sources: Doyle & Havlick, 2009; Du, FitzGerald, Clark, & Hou, 2010; Environment Heritage and Local Government [EHLG] and Office of Public Works [OPW], 2009; Kundzewicz, Hirabayashi, & Kanae, 2010; Pielke Jr. & Downton, 2000; Smith & Ward, 1998) for instance, point to the importance of annual floods in sustaining coastal habitats, building barrier islands, reducing coastal erosion, and decreasing groundwater salinization (Baldwin & Mitchell, 2000; Miller, Davis, Roelke, Li, & Driffill, 2009). Also, areas that are subject to frequent flooding owe their biodiversity in flora and fauna to this natural phenomenon. For example, studies on ecological responses to flooding have found that variability in flow quantity, frequency, duration, and seasonality facilitate seed dispersal and plant establishment, help fish migration, and regulate the amount of nutrients and organic resources that maintain the habitat and food webs for coastal species (Junk, Bayley, & Sparks, 1989; Miller et al., 2009; Poff et al., 1997).

Floods also help to maintain ecosystems that provide socially and economically valued services. Food and power production, water supply, and recreation opportunities are examples of ecosystem services that depend on healthy river ecosystems maintained by floods (Smith & Ward, 1998). Intentional flood pulses are even advocated in some areas as a restoration strategy for improving water quality and plant productivity, managing exotic species, and supporting overall biodiversity (Poff, 2002; Tiegs, O'leary, Pohl, & Munill, 2005).

Floods can also be unwelcome events. Damaging floods can cause loss of socially and economically valued habitat, environmental pollution, property destruction, social disruption, physical injury, illness, and even loss of life (see Table 2). Sometimes, the impacts are so devastating and costly that they extend well beyond the immediate community and are suffered for years after the event. The desirability for floods becomes an issue of contention in urbanized floodplains and coastal areas where aquatic

Table 2 Negative impacts of floods.

Economic Impacts	Social Impacts	Environmental Impacts
▪ Damage to lifeline infrastructure (transportation, communication network, and water, power, and sewer systems)	▪ Loss of life (drowning, water poisoning)	▪ Water quality and soil contamination: from sewage systems, livestock, and crops
▪ Damage to critical facilities (schools, chemical facilities, hospitals, police stations, fire stations)	▪ Injury (physical trauma, electrical injury, burns, hypothermia, disability)	▪ Pollution (chemicals from industrial sites, storage areas, punctured tanks, and damaged facilities)
▪ Damage to defense structures (levees, dams, dikes, channels)	▪ Health hazards (respiratory illness, poisoning, chronic diseases, exposure to water-borne diseases, animal bites)	▪ Air contamination from gas emissions, spills, explosions
▪ Residential losses (structural damages, internal finishes, contents)	▪ Mental health (psychological distress, shock)	▪ Animal displacement (domesticated and wild)
▪ Disruption of traffic and trade	▪ Increased hazard vulnerability of survivors	▪ Loss of rare and endangered species and/or introduction of exotic species
▪ Income losses: long-term closure of business and industry, days without work	▪ Disruption of living conditions (lack of clean water, unsanitary living conditions, overcrowding at evacuation sites)	▪ Damage to habitats, food chains, species diversity and stability
▪ Job losses (unemployment)	▪ Disruption of health services	▪ Morphological changes to natural amenities: bank erosion, land sliding, vegetation damage
▪ Disruption of business and farm operations	▪ Social disruptions (crime, suicide, malnutrition, increased vulnerability and poverty)	▪ Long-term impacts on ecosystem services
▪ Increased operational costs: fuel, time, taxes, repair/replacement of damages, debris removal, landfills	▪ Displacement of people and out-migration	▪ Damage to natural recreational resources
▪ Damage to archeological, touristic, recreational, and historical resources	▪ Disruption of community programs and cultural events	▪ Damage to natural scenic resources

(Sources: Doyle & Havlick, 2009; Du et al., 2010; EHLG and OPW, 2009; Federal Interagency Stream Restoration Working Group [FISRWG], 2001; Gautam & van der Hoek, 2003; Jha, Bloch, & Lamond, 2012; NOAA & Association of State Floodplain Managers [ASFPM], 2007; Smith & Ward, 1998) ecosystems and urban-human systems interact the most. One way to balance the ecological and societal values of floods is through land use planning. In order to guide development and planning practices in ways that are more aligned with sustainability goals, an understanding of flood risk becomes essential.

2.1.1 Community Flood Risk

A large volume of the hazards literature characterizes risk in terms of the likelihood of unwanted events with their associated consequences. Thus, flood risk is often estimated in monetary values as the product of the likelihood of flooding and the potential amount of flood-related damages. According to Crichton (1999), the convergence of three variables affects this equation at the community level: hazard, exposure, and vulnerability.

Hazard denotes a probability of occurrence for a threatening and potentially harmful natural event in a given area. For example, the 100-year floodplain defines an area of the landscape with a 1 in 100 chance of flood in a year's time. This probability changes with roads, culverts, gutters, and drainage systems that rapidly convey surface runoff to nearby channels (Booth & Jackson, 1997; Rogers & DeFee II, 2005). These channels are further affected by bridges, marinas, docks, etc. that constrict channel flow and provide barriers upon which debris can accumulate (Montz, 2000). Other ways in which urbanization has altered flood hazards is by building dams, channelizing streams, discharging wastewaters, compacting soils, draining wetlands, and removing or trampling vegetation (Alberti et al., 2007; Allan, 2004; Paul & Meyer, 2001).

Exposure represents the values, assets, and lives that are physically present at the location that may be affected by a harmful natural event. The rapid and sometimes unplanned expansion of urban areas often encroaches on hazard-prone locations (Hall & Ashley, 2008; Mileti, 1999). Since most urban areas in the world are located along major water bodies (UNFPA, 2011), then almost any form of urban expansion can lead to increased levels of hazard exposure. In the United States, for example, the sprawling pattern of low-density housing development increases the physical exposure of structural assets to floods much faster than it does the physical exposure of people.

Vulnerability indicates the susceptibility to loss due to a lack of strength or ability to withstand or avoid potential harm. When referring to people, vulnerability is often described in terms of socio-economic or demographic characteristics (Cutter, Boruff, & Shirley, 2003; Lindell & Perry, 2000; Morrow, 1999). For structures, vulnerability is defined in terms of design specifications, such as construction type, building materials, or adjustments (Birkmann, 2007; Lindell & Perry, 2000; Merz, Kreibich, Schwarze, & Thieken, 2010). Interactions between people and structures can also create patterns of vulnerability. For example, the use, quality, and structural characteristics of buildings produce differentiated markets of housing within the city. These markets change over time and space, which in turn also changes the spatial distribution of people with respect to hazards. As noted by Tobin and Montz (1994), for example, the relationship between disasters and property values is a negative one in the short term, but not in the long term.

While not necessarily life threatening, urban development can impose substantial costs that increase risk. For example, the overall costs and time required to access resources and services needed to adapt to, respond to, and recover from floods (e.g., emergency aid, food, materials, etc.) are greater for people living in more dispersed patterns of development than for those living in more clustered, mixed-use type settlements (Carruthers & Ulfarsson, 2003; Ewing, 2008). This suggests that the layout of cities can produce a spatial structure of risk that is not readily captured by either the physical exposure to hazards, the population fragility indicators, or the structural specifications alone.

2.1.2 Mitigation Strategies

Flood mitigation and adaptation strategies have a long tradition. From the oldest-known dam constructed in South of Cairo, Egypt (2900 B.C.), to today's complex mix of flood control management systems, society has attempted to eliminate or reduce risk by using different strategies (White, 2010; Wohl, 2000). These strategies are often classified as either structural or non-structural. Each approach has its pros and cons, as discussed subsequently below.

2.1.2.1 Structural Mitigation

Structural mitigation strategies are physical interventions to the built or natural environment of cities. The most prominent structural adaptations to flood risk are *hard measures* or concrete-type structures designed to reduce risk by controlling some aspect of the hazard (Gruntfest, 2000). Dams, for example, are large-scale hard structural measures that prevent flood damage by containing water and regulating its flow along a channel or river. Other structural defenses reduce flood risk by modifying landscape components, and these are often referred to as *soft measures*. Reshaping the landscape and restoring wetlands are some examples of soft structural adaptations to flood risk (Jha et al., 2012; Petry, 2002; Smith & Ward, 1998).

Traditionally, communities have found it easier to rely on hard structural measures than on any other form of mitigation. The performance of these structures with respect to flood hazards is relatively easy to quantify (Gruntfest, 2000), and their implementation does not require extensive change in human behavior (Birkland, Burby, Conrad, Cortner, & Michener, 2003) or controversial land use planning (Gruntfest, 2000). Also, some of these structures can support other community development goals. Dams, for example, can provide drinking water, hydro power, new access to irrigation, and diverse opportunities for recreation and tourism activities while also providing protection against floods (Birkland et al., 2003; Richter et al., 2010). However, there are disadvantages to a flood mitigation approach focused solely on hard structural defenses.

First, in controlling one aspect of the hazard, structural measures unintentionally change other aspects that increase flood risk (Benito & Hudson, 2010). Levees and channels, for instance, are built to augment a river's channel capacity and prevent water from overflowing. While these structures keep a greater volume of water away from people than the natural banks of the river, they also create bigger rivers with greater water roughness and speeds that increase the potential for damaging floods, especially downstream (Birkland et al., 2003). Second, hard mitigation structures generate a sense of complacency that leads people to underestimate their risk and lures them into further developing in hazard-prone areas (Jha et al., 2012; Mileti, 1999; Wohl, 2000). When flood inflows exceed designed capacity levels, structures fail or become overtopped, causing greater damages than if the area had been left unprotected and the structures had never been built (Birkland et al., 2003; Graham, 2000).

Third, outdated design specifications of aging and overburdened infrastructure further increase the potential for failures and losses. According to the American Society of Civil Engineers (ASCE, 2013), about 70% of all U.S. dams will exceed their life expectancy of 50 years by 2020. The construction, maintenance, and repair of these and other hard structural flood defenses often come at a high up-front cost. In some cases, the costs are so high that these flood protection measures are no longer an option for some communities (Graham, 2000; Mileti, 1999).

Finally, hard structural measures can adversely impact livelihoods of downstream communities. In a study of dam impacts on river-dependent economies, Richter et al. (2010) found that rivers subject to natural floods produce far more fish tonnage, have greater wildlife diversity, and provide communities with more income, food security, tourism, and flood-based agriculture opportunities than rivers with dams. Therefore, a full structural approach to flood mitigation is not broadly equitable or sustainable because in favoring one community, it hinders another.

The benefits of *soft* or nature-based structural approaches have also been explored. Wetland ecosystems have been particularly praised for the multiple ecosystem services they provide (Bolund & Hunhammar, 1999; Costanza et al., 1997; Woodward & Wui, 2001; Zedler & Kercher, 2005). Zedler (2003), for example, attributed 40% of the Earth's renewable ecosystem services to wetlands. Hey & Philippi (1995) estimated that roughly half of the wetland acreage drained since 1780 in the upper Mississippi Basin would have accommodated the excess waters from the disastrous 80-day flood of 1993 in Midwestern USA. Mitsch & Gosselink (2000) reviewed similar wetland studies and estimated that temperate-zone watersheds with a land cover of 3% to 7% in wetlands benefited from adequate flood control and water quality. Although using wetlands to restore ecosystem services seems to make sense, the reliability, feasibility, and success rate of restoring or preserving wetlands as flood control projects is still uncertain (Shultz & Leitch, 2003; Zedler & Kercher, 2005).

2.1.2.2 Non-Structural Mitigation

Non-structural mitigation approaches are not physical or built. These approaches include plans, strategies, and policies that attempt to reduce risk by guiding social-economic activities or people's behavior in ways that take floods into account (Gruntfest, 2000). Non-structural measures are classified as either *loss reduction strategies,* which include land use plans, development policies, preparedness plans, and forecasting programs, or *loss sharing methods,* which include insurance policies and disaster aid programs (Smith & Ward, 1998).

One promising non-structural measure for reducing flood risk is land use planning (Bechtol & Laurian, 2005; Burby, Deyle, Godschalk, & Olshansky, 2000;

Mileti, 1999). Communities rely on land use planning and regulation to determine the suitability for development (or conservation) of land exposed to hazards (Burby et al., 2000). Hence, a successful planning effort has the potential to provide long-term resilience to floods by keeping people away from hazard-prone areas, and by protecting the environmental quality and hydrological integrity of critical landscape features. However, a land use planning mitigation approach is most effective when used prior to development. Once development occurs, regulation is far less effective at achieving successful flood mitigation than other strategies focused on minimizing (rather than preventing) damages.

Also, even if a plan exists prior to development, there is much uncertainty about the effectiveness of plans and levels of implementation (Alfasi, Almagor, & Benenson, 2012; Brody & Highfield, 2005; Burby, Nelson, Parker, & Handmer, 2001). These uncertainties create legal challenges, such as lawsuits over property rights like *takings* that deter local governments from adopting new or strong land use regulations (Daniels & Lapping, 2005). Furthermore, plan and policy evaluations often require large amounts of data or analysis frameworks of several years (even decades) to capture the effects of planning on development practices. By the time issues are identified, the damage may already be irreversible or the institutional inertia may be too great to affect any meaningful change (Harries & Penning-Rowsell, 2011). As a result, non-structural mitigation measures alone are unlikely to produce sustainable land development or long-term resilient communities.

2.1.2.3 Integrated Approaches

An integrated approach to urban flood risk management combines structural and non-structural mitigation measures (Birkland et al., 2003; Jha et al., 2012; Petry, 2002). According to the World Bank's latest flood risk management guidelines, an ideal integrated mitigation program is one that balances the tradeoffs between different mitigation strategies in terms of cost effectiveness *and* robustness—i.e., ability to perform under varying levels of risk (Jha et al., 2012). Fig. **1** illustrates this idea.

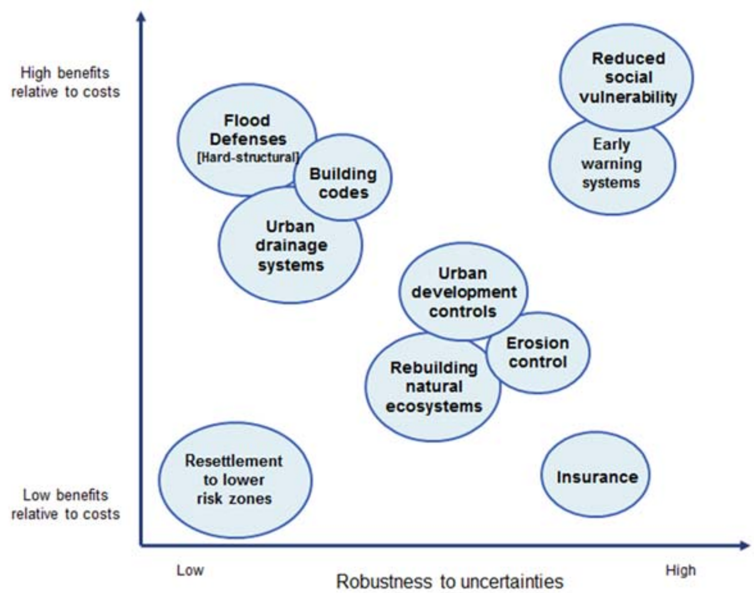


Fig. 1. Ranking of flood mitigation strategies based on Jha et al. (2012) (modified).

In general, structural measures tend to be more sensitive to changes in flood risk (i.e., less robust) and are relatively less expensive to set up (i.e., more cost effective) than non-structural measures. A number of authors have suggested that in order to achieve this goal of linking short-term objectives of cost effectiveness with long-term goals of robustness, disaster planning must first establish an operational bridge in between *disaster management activities* and *community planning* (Godschalk, 2003; Mileti, 1999; National Research Council [NRC], 2012; Pearce, 2003).

2.1.3 Disasters and Planning

The Federal Emergency Management Administration (FEMA) encourages communities to use the disaster management framework to plan for floods (Lindell, Prater, & Perry, 2006). Disaster management is the systematic application of policies, procedures, and practices aimed at helping communities deal with disasters. The prescribed sequence of disaster management activities involves four main stages: hazard mitigation, disaster preparedness, emergency response, and disaster recovery (Lindell et al., 2006). Mitigation and preparedness are pre-disaster planning activities that involve the implementation of structural and non-structural mitigation measures (EHLG and OPW, 2009; Lindell et al., 2006). Response and recovery are post-disaster planning activities comprised by tactical, short-term interventions directed at stabilizing the overall functioning of the system after disaster impact, or long-range programs strategically coordinated and designed to return the system to near pre-crisis conditions (Lindell et al., 2006). Once an acceptable level of recovery has been reached, the framework suggests a cyclical approach where the focus of management returns to (or is combined with) mitigation activities.

Traditionally, disaster management and community planning activities have not been linked or executed by the same people. Community-level planning has been identified as a participatory, comprehensive, bottom-up, long-range focused, and locally driven effort guided by urban planners (Ling, Hanna, & Dale, 2009; Pearce, 2003), whereas disaster planning has been historically a top-down effort, focused almost exclusively on post-disaster activities and carried out by higher levels of government through emergency response groups (Lindell et al., 2006). With the increased frequency of flood-related disaster events over the last two decades, their lack of integration has become an important issue (Burby, 2006; Haigh & Amaratunga, 2010; Hung, Shaw, & Kobayashi, 2010; O'Brien, O'Keefe, Rose, & Wisner, 2006; Pearce, 2003). If the way communities are developing is becoming a source of hazards or is placing more people and assets at risk (Burby, 2006), then it is a concern for disaster management. Conversely, if disasters can damage environmental assets, cause lower quality of life, or erase the benefits of urban investments and set back a community's growth by years if not decades (O'Brien et al., 2006), then it becomes a concern for community development.

Recently, the concept of disaster resilience has emerged as an alternative view of planning that fuses sustainable development goals with those of disaster management. A resilience approach to planning would require a careful understanding of community vulnerabilities, capacities, operations, and resources before developing strategies to lessen the impacts of disasters while ensuring that development efforts do not increase future susceptibility to hazards. Although the concept of resilience has not yet been operationalized for land use planning and design, it represents a potentially powerful tool for practitioners and local decision-makers.

2.2 Resilience

In facing a probable disaster event, there are at least two main positions that a community can take: shield from the blow, or (brace yourself to) take the blow. For many communities, the first position is preferable to the second, but choosing it may not be an option. Periodically, disaster strikes and cities get flooded. In the United States, mainly after Hurricane Katrina impacted the Louisiana region in 2005, it became clear that depending on systems of defense and hazard control was neither practical nor realistic, and that it is difficult (if not impossible) to prepare for all levels of hazard. This realization led to a paradigm shift in disaster planning. The planning goal was no longer to reduce the vulnerability of systems but rather to develop practical means for systems to cope with change and uncertainty (i.e., to prepare communities for taking the blow). For the past few years, planning practitioners, emergency managers, and local decision-makers have been tasked with finding ways to operationalize this goal and supplement traditional risk management programs with adaptation strategies that would enhance a community's resilience to floods. Yet, what is *resilience*?

2.2.1 Concept Definition

Resilience, broadly defined, is the capacity of a system to act upon the challenges imposed by adverse, and often expected forms of stress. Used to describe a variety of systems (e.g., natural, social, physical, etc.), the term has evoked a variety of meanings that are difficult to reconcile. For example, an ecological understanding of resilience points to the nonlinearities and irreversibilities of systems (Holling & Sanderson, 1996), whereas an engineer-based interpretation of resilience seeks balance, equilibrium, and predictability of operations (Bruneau et al., 2003; Kahan, Allen, & George, 2009). Moreover, meanings of resilience are also contested within fields. Disaster research, for example, has debated about possible taxonomies and conceptualizations of resilience (Gallopín, 2006; Tobin, 1999), suitable frameworks for analysis (Bruneau et al., 2003; Cutter et al., 2008; Zhou, Wang, Wan, & Jia, 2010), meaningful indicators (Cutter, Burton, & Emrich, 2010; Peacock, 2010), and whether resilience is an outcome or a process (Manyena, 2006).

Due to this lack of consensus, The National Academies brought together a group of scientists and professionals to help develop a definition of the concept for public policy and planning. They defined disaster resilience as "the ability to prepare and plan for, absorb, recover from or more successfully adapt to actual or potential adverse events" (NRC, 2012, p. 14). This definition suggests that there are at least three states of resilience: pre-disaster (to prepare and plan), during disaster (to absorb), and post-disaster (to recover and adapt). This pre-, during, and post-disaster characterization of resilience differs from most other definitions found in the literature, which refer almost exclusively to *bouncing back* capacities of a system, or the recovery actions taken after a disturbance occurs (for lists of definitions see Manyena, 2006; Norris, Stevens, Pfefferbaum, Wyche, & Pfefferbaum, 2008; Zhou et al., 2010). The emphasis that the National Academies' definition of resilience places on *proactive* and *adaptive* system behaviors indicates that the human dimension of disaster resilience is very strong, and the reference to the *absorbent* capacity of systems suggests that there are physical or ecological conditions that can moderate the system's performance during a disaster. The challenge, however, is to model resilience in ways that are relevant for local decision-makers and land use planning practitioners (Pickett et al., 2011). This process begins with measurement.

2.2.2 Measurement

Researchers who have theorized and explored the response of cities to disasters have identified several attributes to describe resilient systems (see Table 3). These characteristics are then used in assessments to meet one of two main goals: to understand the *resilience process* or to identify factors that may lead to *resilience outcomes*. Process-based studies of resilience offer guidelines for evaluating community planning processes, decisions, and operations in the context of disasters. The manual developed by the Canadian Center for Community Renewal (2000), for example, created a ranking system of decision-making processes to help rural communities identify which operations and investment decisions affected 23 characteristics of their resilience. Similarly, the U.S. Indian Ocean Tsunami Warning System Program (2007) developed an inter-agency planning tool aimed at identifying ways in which the dialogue and collaboration between different stakeholders affected eight principles of resilient operations. With a slightly different focus, Bruneau et al. (2003) created a conceptual framework based on four principles of resilience (robustness, rapidity, redundancy, and resourcefulness) and four dimensions of resilience (technical, organizational, social, and economic) to help decision-makers select quantitative measures of resilience. These

Table 3 Characteristics of resilient urban systems.

Characteristic	Description
Proactive	**Resilient systems** gather knowledge and use it to carry out multiple activities in anticipation of, and preparation for, changes. Changes can be either gradual (i.e., growth) or sudden (i.e., disasters).
Collaborative	**Resilient systems** provide opportunities and incentives for the support, participation, and collaborative work of multiple stakeholders.
Self-sufficient	**Resilient systems** are able to locally self-supply manufactured materials, as well as critical goods and services such as food, water, or energy. *Small ecological footprint* and being *carbon-neutral* are qualities of self-sufficient systems. Associated attributes include: 1) *Autonomous,* or the ability to operate without the interference of higher levels of government. 2) *Independent,* or the ability to cope *naturally* with internal elements.
Strong	**Resilient systems** use the physical health, strength, and capacity of social, natural, and artificial assets to withstand the shock of disasters. *Sense of community* and *social health* are qualities of strong human systems. Associated attributes include: 3) *Absorbent,* or the ability to mitigate consequences in place.
Robust	**Resilient systems** are able to perform well under different forms or levels of stress without suffering much degradation or experiencing despair, harm, or damage. Also referred to as *cohesion*.
Redundant/Diverse	**Resilient systems** have a great number and diverse set of resources that provide specific or similar functions. Thus, when disaster strikes, any one resource that suffers damage, failure, or degradation can be substituted by the function of another.
Efficient	**Resilient systems** take little time to use, or get access to, a resource once it has been impacted. The literature also uses *rapid* or *resourceful* to characterize this attribute. Associated attributes include: 4) *Restorative,* or the ability to remediate degraded functions and reconstruct them expeditiously.
Responsive/Adaptable	**Resilient systems** are *sensitive to feedback* and have the ability to detect and respond to changes generated from their constituent parts (social, economic, or ecological) or external conditions. Associated attributes include: 5) *Environmentally responsive,* or the ability to use ecological knowledge to develop integrated design solutions that work with (not against) nature.

(Sources: Bhamra, Dani, & Burnard, 2011; Bruneau et al., 2003; Canadian Centre for Community Renewal [CCCR], 2000; Godschalk, 2003; Kahan et al., 2009; Longstaff, Armstrong, Perrin, Parker, & Hidek, 2010; Newman, Beatley, & Boyer, 2012; Norris et al., 2008) types of assessments are mostly descriptive, so it is unknown whether or not the processes outlined in these studies are effective at enhancing resilient operations. Kahan et al. (2009), Longstaff et al. (2010), and the Bureau of Rural Sciences (2008) are other examples of process-based assessments of resilience.

Another group of studies sought to understand resilience through its outcomes. As of today, two main approaches have been used to achieve this goal: composite indices and system performance indicators.

2.2.2.1 Resilience Indices

Composite indices are an attempt to develop a universal metric of something that cannot be directly measured. A number of researchers have used composite indices to measure multiple dimensions of community disaster resilience (e.g., Cutter et al., 2010; Peacock, 2010; Sherrieb, Norris, & Galea, 2010; Somers, 2009). Authors often start by grouping relevant variables into a pre-defined set of resilience categories (e.g., technical, social, economic, institutional, etc.). Then, they follow a process of statistical variable reduction, scaling, and aggregation that results in one (or more) indices describing resilience in low-to-high scores of "success." These scores are descriptive but can gain meaning when validated against some measure of system performance with respect to disasters. For example, Peacock (2010) used flood-related deaths and property damages to assess the construct validity of indices of resilience.

While these types of indices provide valuable information on general levels of community resilience, they often exclude one major component of resilience: the ecological. A lot of resources available to communities are tied to the geographic setting in which they are built. For example, a community cannot survive if the local environment does not support some form of food production or economic use (e.g., timber, fisheries, etc.), or if it cannot provide enough clean air and water, and opportunities for social interaction and enjoyment (Bolund & Hunhammar, 1999; Chiesura, 2004; Cumming, 2011; Longstaff et al., 2010; Matsuoka & Kaplan, 2008). Even though studies recognize the importance of ecological factors for disaster resilience, they still exclude those factors from study, noting challenges with finding relevant ecological measures, or their focus on human-social systems.

Other limitations of indices-based studies relate the usability of the information they provide. For example, a measure of infrastructure resilience may be reduced to a count of schools, hotels, road miles, and similar type metrics. The index score could be the same whether a road is in good or bad condition, or whether said infrastructure is located in or out of floodplains. Furthermore, most indices are developed for county, regional, or national scales. The way land use planning affects change at broad scales is really made up of countless smaller changes at the site, neighborhood, and even landscape levels (Maruani & Amit-Cohen, 2007; Rodiek, 2010b). Thus, the information provided by a single regional resilience score can have limited effect on guiding local planning practices.

Last, index-based studies aim for comprehensiveness—i.e., their goal is to characterize resilience in ways that would be relevant to all-hazards, threats, stages of disaster, and for all types of communities. Yet, what makes a rural community resilient may not apply to an urban community. Also, it is possible that indices include variables that may support one aspect of resilience, but not another. For example, in the process of identifying important factors for carrying out disaster management activities, Peacock (2010) noted that "while the percentage of the labor force involved in construction may be important for the recovery phase, they will not necessarily be important for preparation planning activities" (p. 32). Similarly, indices could potentially include variables that are relevant for describing the resilience to one type of disaster, but not another. Maintaining connectivity of urban forested space, for instance, may be a good practice for flood mitigation, but not for fire mitigation. This suggests that it is not possible to develop one comprehensive measure of disaster resilience, and that scale, location, and hazard type matter for resilience.

2.2.2.2 Resilience Indicators

Another strategy to study resilience is evaluating the performance or behavior of a system with respect to desirable outcomes of resilience. Examples of indicators of resilient system behavior or functional performance include high policy adoption rates (Brody, Bernhardt, Zahran, & Kang, 2009), high capacity levels for autonomous decision-making within organizations (Somers, 2009), low vulnerability index scores (Collins, Carlson, & Petit, 2011; Sherrieb et al., 2010), low levels of utility service disruption (Rose & Lim, 2002), low levels of property damage (Brody, Zahran, Highfield, Grover, & Vedlitz, 2008; de Bruijn, 2005; Peacock, 2010; Veerbeek & Zevenbergen, 2009), and fewer associated deaths (Peacock, 2010).

Among these indicators, property damage is probably the most practical and common indicator of resilience. First, as a variable for analysis, property damage information is additive, easy to interpret, reasonably comprehensive, readily measurable, verifiable, and conceptually, it is clearly associated with disaster resilience. Resilient communities (i.e., well prepared and adapted to hazards) should not experience major impacts from disasters, and if they do, they should be low enough to result in short recovery times for people, businesses, and overall operations. Second, property damage information has several practical policy and management applications. For example, damage assessments can provide information on high vulnerabilities in the physical environment, such as low elevated buildings, that could be addressed preventatively before another disaster strikes (Aubrecht, Steinnocher, & Köstl, 2011; Merz et al., 2010). Property damage information is also valuable for risk mapping activities (Merz et al., 2010), as well as for evaluations of the potential benefits derived from mitigation investments, plans, and disaster management programs (Dawson et al., 2011; Jha et al., 2012). Finally, damage information can be used to further our theoretical understanding of resilience. For example, de Bruijn (2005) and Peacock (2010) used property damages to validate the effectiveness of conceptually developed resilience metrics and indices.

However, resilience goals are not just concerned with limiting property damages associated with disasters but also with limiting other types of impacts such as deaths, loss of government or business services, and environmental pollution. Therefore, an understanding of resilience as a loss function allows for the evaluation of only the system's physical resilience (of quantifiable assets), not its overall disaster resilience.

2.2.3 Physical vs. Spatial Resilience

The physical dimension of resilience refers to natural and built resources that support the adaptation of individuals and communities to floods (Paton, 2008). These resources include urban infrastructures, such as roads, residential housing, schools, police stations, and critical lifelines. Also, they include natural landscape features, such as wetlands, parks, greenways, riparian buffers, landscaped medians, and yards. Put together, these features make up the physical structure of cities. This physical environment provides the first line of defense and protection against disasters. Also, it provides the framework from which human aspects of resilience can unfold. A community's disaster resilience is based on the premise that these elements are *strong* (NRC, 2012; Norris et al., 2008).

Accordingly, one way communities have enhanced their disaster resilience is by reinforcing the physical environment with means of protection. Yet, an interventionist approach to hazard mitigation has brought to light several poorly understood connections between natural hazards and land development. Mileti (1999), for example, argued that losses from hazards are symptoms of much broader societal problems that cannot be tackled with technological or site-based solutions alone. According to Mileti, effective hazard mitigation can only happen with the integration of mitigation practices into all aspects of community development. This suggests that disaster resilience is not just about flood-proofing structures but also about community land use practices and policies as well. Similarly, Bull-Kamanga et al. (2003) raised some central questions about the built environment and disaster risk. They argued that disaster risk in urban areas is the result of the accumulation of different types of vulnerabilities that overlay one another (e.g., congestion, unemployment, poverty, etc.). Therefore, the accumulation of disaster risk is not evenly distributed across an urban system, and its distribution is produced not only by the spatial concentration of hazards but also by complex social, economic, and environmental interactions with the built environment. This suggests that elements of the built (and natural) environment that help communities prosper can also put people at a high risk of hazards. Also, it suggests that the spatial arrangement of cities has an impact on flood losses in the short term and on community disaster resilience over time.

Using spatial theoretical principles developed in landscape ecology, Cumming (2011) offered the concept of *spatial resilience* to describe resilience in terms of spatial patterns and effects. According to Cumming, just as pattern-function relationships are suitable for describing the integrity of ecological systems, they are also suitable for describing the integrity of social systems. Therefore, another way of enhancing community disaster resilience is by preventing the critical loss of desirable attributes in the spatial distribution of land uses in an urban system. Since the spatial arrangement of physical features (social and ecological) seems to play a role in the overall resilience of urban systems, then "good" practices in land use planning and design are essential to achieve disaster resilience goals. The research challenge is finding suitable indicators and reliable metrics to characterize good land use planning practices for resilience.

2.3 Land Use Planning

Concerns about how to improve quality of life by modifying urban form are not new. In the 1970s, the debate on desirable physical properties and qualities of the built environment centered on the suburbs. By this time, sprawl had become the predominant form of development in North America. The negative social, economic, and environmental impacts of this low-density, dispersed, and auto-dependent residential type of development triggered a growing call to examine the existing paradigm of land development. Smart Growth and New Urbanism movements emerged as counter-measures of sprawl. Smart Growth proponents focus on city-wide planning strategies to reduce land consumption and environmental impacts. Some of their policies to combat sprawl call for exclusive farm-use zones, investments on land preservation, urban growth boundary regulations, and tax incentives for cluster developments or high residential densities (Daniels & Lapping, 2005). New Urbanists, on the other hand, narrow the scale of intervention and focus on reviving pre-sprawl neighborhood development practices to foster a sense of community (Duany, Plater-Zyberk, & Speck, 2000; Godschalk, 2003). Their design principles support compact development with higher residential densities than typical suburbs, mixed land uses (residential, commercial, and civic), street network accessibility, public open space, and pedestrian scale design (Jabareen, 2006). The argument of New Urbanism is that urban design can help create "good" sustainable places (i.e., safe, accessible, vibrant, environmentally-friendly, and aesthetically pleasing neighborhoods that reduce auto use, promote healthy lifestyles, and reinforce sense of place). Since then, a growing body of literature focusing on testing the validity of design-based solutions for improving quality of life has emerged.

2.3.1 Urban Form and Livability

One area of urban design research has focused on providing the "proof of goodness" of the promoted virtues of neighborhood form. The effects of New Urbanist designs on travel behavior (Joh et al., 2008; Khattak & Rodriguez, 2005), obesity and sedentary lifestyles (Giles-Corti & Donovan, 2002; Heinrich et al., 2008), and sense of place and community life (Brown & Cropper, 2001; Rogers & Sukolratanametee, 2009) have been widely documented. While the benefits of New Urbanism seem to have significant support in the literature, studies have also yielded conflicting results. For example, Joh et al. (2008) noted that urban designs associated with more walking are not necessarily related to less driving. Part of the reason for the inconsistency of results is attributed to poor application of design principles in practice, limited data availability, and limitations associated with measurement—i.e., robustness of metrics used to describe urban form (Jabareen, 2006; Owens, 2005). Other scholars argue that the cause for discrepancies is rooted in the conflicting rhetoric of sustainability vs. livability. Neuman (2005), for instance, asserted that just as high densities make a case for sustainability, lower densities make it for livability. Studies on the desire and benefit of having access to natural areas partially support this claim. While the search for open space may drive some people to build "out in the country," the process of development often destroys the very features they seek to access (Kaplan & Austin, 2004).

Another line of neighborhood research has focused on understanding human behavior in hazardous conditions. These studies include concerns with the valuation of natural amenities in the context of risk (Bin, Crawford, Kruse, & Landry, 2008), market effects on property values located in hazard-prone environments (Tobin & Montz, 1994; Zhang, Hwang, & Lindell, 2010), and levels of preparedness and evacuation readiness of people exposed to hazards (Kusenbach, Simms, & Tobin, 2010; Lindell & Prater, 2002). In an effort to incorporate this knowledge into planning, subsequent studies have expanded interpretations from these human behavior studies and linked them to the form of the built environment. For instance, social cohesion is considered a key variable in hazard preparedness and community readiness (Mishra, Mazumdar, & Suar, 2010; Paton & Johnston, 2001). Since it is said that New Urbanist designs promote social interaction, then the leap is made to suggest that this type of development contributes to individual and community preparedness.

More recently, the promise of sustainable urban forms has drawn attention to their role in improving urban ecosystem services, reducing vulnerability to floods, and fostering disaster resilience (Bull-Kamanga et al., 2003; Cadenasso & Pickett, 2008; Colding, 2007; Moffatt & Kohler, 2010; White, 2010). A fraction of this body of research has studied the relationships between neighborhood design and hazards. Stevens, Berke & Song (2010), for example, examined New Urbanist projects in the United States and found that, while designs may reduce flood hazards by maximizing open space through reduced building footprints, they may also increase hazard exposure with greater densities in hazard-prone locations. Also, Yang (2009) evaluated the designs of two neighborhoods in The Woodlands, Texas, in terms of levels of imperviousness and runoff and found that a landscape ecologically-based design approach had better flood mitigation performance than a conventional approach. Even though the importance of incorporating ecological knowledge into land use planning has long been recognized—e.g., seminal works by Ian McHarg's (1992) *Design with Nature* originally published in 1969, and Eugene Odum's (1969) *Strategy of Ecosystem Development*—empirical evaluations of the performance of neighborhood development with respect to flood hazards are scarce.

2.3.2 Landscape Pattern and Ecological Function

Another major area of urban and landscape research is aimed at identifying aspects of urban development that have a detrimental impact on environmental quality. Questions about habitat fragmentation—not just in terms of physical alteration to the size and level of isolation of patches of habitat but also in terms of functional changes to the transfer of energy, matter, water, and species—have been the primary concern behind many competing models of landscape ecology (Alberti & Marzluff, 2004; Cumming, 2011; Grimm, Grove, Pickett, & Redman, 2000; Pickett et al., 2011; Turner, 2005). The challenge for this field has been identifying and developing appropriate metrics for quantifying habitat (i.e., patch) and spatial heterogeneity, at scales that are relevant for the viability of species, or ecological functions of interest (Li & Wu, 2004; McGarigal, 2015).

At least two major conceptualizations of landscapes have been used to address this need: the island biogeographic model and the landscape mosaic model. The island biogeography model (MacArthur & Wilson, 1967) is a dichotomous conceptualization of space where habitats are studied in isolation of their context. Patches of habitat are either present or not, and any interactions among patches are assumed to only be affected by the travel distance between them, not by what lies between them. In contrast, a landscape mosaic model (Dramstad, Olson, & Forman, 1996) takes into account the presence of other types of patches and their role in facilitating or obstructing flows of movement between the patches of focal interest. Both models have supported the development of numerous spatial metrics used by empirical research to characterize the composition and configuration of landscapes. Composition refers to non-spatial characteristics of landscapes, such as the relative abundance of one or more land cover types. Configuration, on the other hand, refers to the spatial arrangement in which different land cover types brand the landscape, and metrics often require spatial information such as edge, area, or number of adjacencies for calculation.

2.3.2.1 Impervious Land Cover

Landscape studies are dominated by composition analyses of impervious areas. Examples of urban impervious areas include roads, rooftops, parking lots, or sidewalks (see reviews by Booth & Jackson, 1997; Brabec, Schulte, & Richards, 2002; Paul & Meyer, 2001; Schueler, 1994; Shusher et al., 2005). Precipitation that falls onto these areas cannot infiltrate directly into the ground; instead, water is redirected to flow toward drainage outlets from where it is rapidly conveyed into streams. Studies evaluating indicators of watershed hydrological function have demonstrated how increased levels of imperviousness contribute to the degradation of streams and wetlands (Arnold Jr. & Gibbons, 1996; Lee et al., 2006), the reduction of soil infiltration and saturation capacities (Booth & Jackson, 1997; Leopold, 1968), and the increase of peak flow discharges, runoff volumes, and streamflow variability—i.e., hydrological flashiness (Rogers & DeFee II, 2005; Weng, 2001; Yang, 2009).

Landscape configuration studies of land cover are less common (e.g., Alberti et al., 2007; Lee, Hwang, Lee, Hwang, & Sung, 2009; Rogers & DeFee II, 2005). These studies have confirmed and further described the impacts of imperviousness using spatial configuration metrics. For example, Alberti et al. (2007) studied 42 sub-basins in the Puget region and found that while increased levels of imperviousness (i.e., proportion of impervious areas) had a significant negative effect on in-stream biotic integrity overall (R^2=0.61), five metrics of spatial configuration measures of imperviousness (relating patch size, connectedness, diversity, and levels of aggregation) were generally better predictors (R^2 from 0.63 to 0.67). Similarly, with respect to flood hazards, Rogers and DeFee II (2005) found that road edge density (a spatial configuration metric) was a slightly better predictor of watershed residual flows than overall percent road.

While imperviousness is a fairly straightforward metric, its measurement is not without debate. The literature stresses the difference between two types of impervious surface areas: total and effective. Total impervious area (TIA) refers to all types of impervious surfaces regardless of their location in the landscape. Effective impervious area (EIA) is more selective than TIA and only refers to impervious areas that are hydrologically connected to each other and the urban drainage system. Thus, a driveway draining onto a road would be included for measurement, whereas a roof draining onto a lawn would not. The importance of making this distinction when modeling floods is that TIA tends to overestimate soil infiltration rates and runoff volumes, especially for watersheds consisting of mostly residential land uses, and EIA tends to underestimate runoff volumes for watersheds consisting of a mix of more intense land uses—i.e., commercial and industrial (Alley & Veenhuis, 1983). Another point of contention is the method used for quantifying impervious areas. With varying levels of precision and accuracy, imperviousness has been measured with fixed scores for census, land use, or zoning categories (Booth & Jackson, 1997), areas from roads and land parcels (Rogers & DeFee II, 2005), and pixel values from remote-sensed data (Slonecker, Jennings, & Garofalo, 2001). Since the accuracy of these estimation methods has not been systematically tested, it is uncertain how the choice of technique affects measurement. Still, most studies use a remote-sensed approach, carefully outlining the limitations imposed by data selection (type, resolution, and source), project constraints, and rationale for pixel interpretation.

2.3.2.2 Natural Land Cover

Another landscape approach to study flood hazards is through pervious land cover. Pervious areas, such as greenways, riparian zones, local forests, and even yards, are important features of landscapes that determine how water moves through the local system (FISRWG, 2001; Law, Cappiella, & Novotney, 2009). Each type of natural land cover provides a specific set of pathways for the continuous transfer of water from the atmosphere, onto the surface, through the ground, and eventually back again into the atmosphere. According to principles of landscape ecology, the processes behind these water transfers can be tied to physical characteristics of natural land cover and their spatial organization (Alberti et al., 2007; Alberti & Marzluff, 2004).

Studies evaluating the role of pervious landscapes on the severity of flood impacts are very few. Lorente (2011) study is probably the first to evaluate the relationships between natural landscape features and flood impacts on a local scale. This work used a combination of landscape composition and configuration metrics to examine the role that different types of pervious land cover had in mitigating property damages due to floods in 40 neighborhoods of Texas after TS Alison in 2001. The novelty of this study was its focus on ecological indicators of resilience, its scale of analysis, and its methodological approach applied to a single disaster event. To assure the independence of each neighborhood and the non-overlapping of information, the study adopted circles of 1/2-mile radius, centered in and totally inscribed in a grid that was traced over the landscape beginning from a random point. The results of this pilot study showed that greater proportions of wetland areas, as well as larger, rounder, and more clustered patches of pervious land, significantly reduced flood damages to residential property. Other studies published in the following years applied different aspects of this methodology, adapting it to diverse aims and to the data available. Some of these studies, for example, evaluated property flood damages using like measures for pervious land cover (Brody & Gunn, 2013; Brody, Peacock, & Gunn, 2012), with similar methodological approaches at the same scale of analysis (Brody, Blessing, Sebastian, & Bedient, 2013; Highfield, Brody, & Blessing, 2014), applied to the same natural disaster event and general area of disaster impact (Brody, Sebastian, Blessing, & Bedient, 2015).

While most of these studies shared similarities in approach, data sources, and concept measures, they had limited success in providing consistent results with respect to usually strong predictors of flood loss, like precipitation, floodplain exposure, wetlands, slope, and property values. Part of the reason for these mixed results may be due to differences in research design, but another part may be due to measurement validity issues. For example, all of these studies used dollar amounts of insurance claims paid per household under NFIP as a measure for residential flood damages. Since 1994, maximum coverages for residential buildings and contents are $250,000 and $100,000, respectively. If combined, the largest possible damage any given household could have is $350,000, yet these studies reported a maximum range of values per household of claim payments up to 2.25 times greater than the combined estimated program maximum. Similar questions with the range of other model variables (e.g., zero values for year-built, or for assessed property values), as well as concerns with overlapping spatial data collected for adjacent cases, and the temporal resolution of data sources (e.g., evaluating damages with property data produced up to 10 years after the studied disaster) suggest that measurement problems may be the cause for the variability in the reported results. Thus, the relationships between the spatial arrangement of natural landscapes and flood damages remains unclear, and the underlying assumption that more natural space will reduce flood impacts is still in need of further exploration.

2.4 Summary

The cumulative impact of more frequent and severe disaster events has made it clear that relying on systems of defense is neither practical nor realistic. For the past 10 to 15 years, the discussion on disasters has shifted from a focus on engineered solutions of hazard control, to socio-economic strategies of risk reduction. However, despite these advancements, the current approach of flood management does not seem to keep up with the pace at which flood risk increases. Floods remain the most frequent and one of the costliest types of natural disaster events in the world.

Recently, new understandings of disaster resilience have led researchers to an evaluation of landscapes. Most landscape-based studies on flood hazards have examined the relationships between urban impervious surfaces and ecosystem performance (Brody et al., 2008; Sung & Li, 2010; Yang, 2009), and a fraction of these studies have narrowed the scope of analysis and addressed the relationships between the spatial configuration of urban development and ecosystem function (Alberti et al., 2007; Rogers & DeFee II, 2005). Together as a group, these studies argue the same point: increases in impervious surface areas have a cumulative effect on the water balance of landscapes that typically results in deeper inundation levels, expanded flood risk areas, and damaging floods. This chain reaction starts with the alterations of the hydrological cycle imposed by the built environment, which means that a significant reduction in flood damages may be achieved through urban design choices alone. Therefore, in order to reduce the cost of associated damages, impervious surface areas must be minimized, redesigned, reduced, or even transformed back to pervious (natural) land areas. But to what type of pervious area? And how big or connected should these areas be?

Thus far, research has disproportionally focused on one side of the story (i.e., assessing the benefits of reducing the land take of built-up areas), but we know much less about the ecological performance of natural features of the landscape with respect to flood hazards. This suggests that there is still a gap of knowledge in our current understanding (and measurement) of flood resilience concepts. This dissertation aims to fill this gap.

3. THEORY

After identifying the knowledge gap left by the current understanding of disaster resilience, this section presents a new conceptual model for analyzing resilience as a loss function. Specific hypotheses are listed for each major factor known to (or expected to) affect flood impacts to residential property. Basic risk, mitigation, socio-economic, hazard, and environmental control variables are also outlined.

3.1 Knowledge Gap

A generic understanding of community disaster resilience seems to involve two major components: risk and protection. While theoretical frameworks of resilience are very diverse in their presentation and intellectual origin (see Appendix A), they all seem to consider groups of negative (or risk) factors, and positive (or protection) factors that, processed in some way, result in desirable outcomes of resilience (see Fig. **2**).

The negative or risk factors of disaster resilience refer to conditions that make individuals or households vulnerable to harm, or susceptible to damage from disasters. From a socio-economic perspective, some conditions that increase flood risk include people's unfamiliarity with flood hazards (Elmer, Thieken, Pech, & Kreibich, 2010; Peacock, Brody, & Highfield, 2005), low index scores of community vulnerability/capacity indicators (Birkmann, 2007; Cutter et al., 2010; Norris et al., 2008; Peacock, 2010), and low levels of risk perception (Paton, Smith, Daly, & Johnston, 2008; Peacock et al., 2005; Rogers, 1998) or disaster preparedness

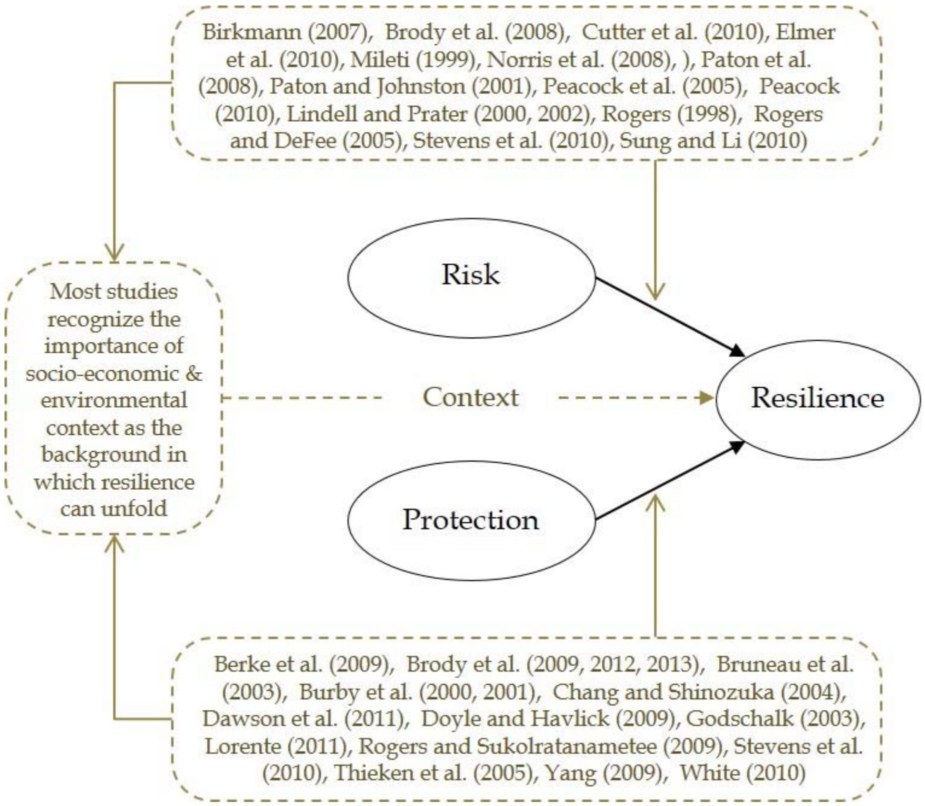


Fig. 2. General risk-protection understanding of disaster resilience.

(Lindell & Prater, 2000, 2002; Paton & Johnston, 2001). From a physical perspective, the amount or spatial distribution of impervious land cover (Brody et al., 2008; Rogers & DeFee II, 2005; Sung & Li, 2010) and the geographic exposure to hazards (Brody et al., 2008; Mileti, 1999; Stevens et al., 2010) are considered two strong indicators of high flood risk. The general agreement in the literature is that factors that increase flood risk also increase the incidence of resilience deficit outcomes, and that this result is indicative of low levels of (or capacity for) disaster resilience.

In contrast, positive or protective factors of resilience refer to conditions that help people to avoid, cope with, and recover from disasters. Some studies linking outcomes of resilience with protective factors have evaluated the quality and scope of community plans (Burby et al., 2000; Godschalk, 2003; White, 2010), the effectiveness of policy tools and mitigation strategies (Brody et al., 2009; Burby et al., 2001; Dawson et al., 2011; Stevens et al., 2010), the implementation of sustainable development practices (Berke, Song, & Stevens, 2009; Rogers & Sukolratanametee, 2009; Yang, 2009), and local capacity indicators (e.g., index score studies mentioned for risk factors). From a physical perspective, studies have also linked protection factors with flood resilience by evaluating the performance of flood defenses (Doyle & Havlick, 2009; FEMA, 1997; U.S. Army Corps of Engineers [USACE], n.d.), buildings (Thieken, Müller, Kreibich, & Merz, 2005), lifeline infrastructures (Bruneau et al., 2003; Chang & Shinozuka, 2004), and pervious land cover with respect to disaster impacts (Brody et al., 2013; Brody et al., 2012; Lorente, 2011). While methodological and analytical differences among these studies may have led to some contradictory results, the general direction of this body of work suggests that local environmental assets and a mix of hazard mitigation and adaptation strategies can reduce flood risk and associated negative outcomes, and that such reductions are indicative of increased levels of (or capacity for) disaster resilience.

Studies that view resilience as a process have framed concepts of risk and protection in the context of disaster management activities (Paton, 2008; Peacock, 2010; Tobin, 1999) or processes of ecosystem dynamics (S.L. Collins et al., 2011; Holling, 2001). These frameworks first identify sequential stages of system functioning and then define metrics that would best describe characteristics of the system at each stage of operation. The main criticism of these types of frameworks is that they are set in a vacuum, paying little attention to interactions with the local spatial environment. In an effort to ground the concept of disaster resilience, researchers have included physical or geographic components to conceptual frameworks (e.g., Cutter et al., 2008; Zhou et al., 2010). However, integrating the complexities of disasters and human-social systems with a spatial-ecological understanding of place requires a new framework for analysis.

A first approach to integrate social, environmental, and spatial aspects of resilience was formalized by an understanding of cities as Socio-Ecological Systems [SES] (Moffatt & Kohler, 2010; Pickett et al., 2011). Proponents of SES suggest a highly contextualized understanding of resilience, not just within specific system boundaries, scales of analysis, and types of disturbance (Carpenter, Walker, Anderies, & Abel, 2001) but also in terms of key relationships that link social and ecological systems. While most SES conceptualizations of resilience identify elements of the local spatial environment that affect resilience, they do not specify how. One way to further our understanding of disaster resilience is by differentiating types of place-based, functional roles that different elements of the physical context of communities have during a disaster event.

3.2 Conceptual Model

This study examined the differentiation of environmental context factors that affect community resilience to floods by the hydrological function they play during a disaster event.

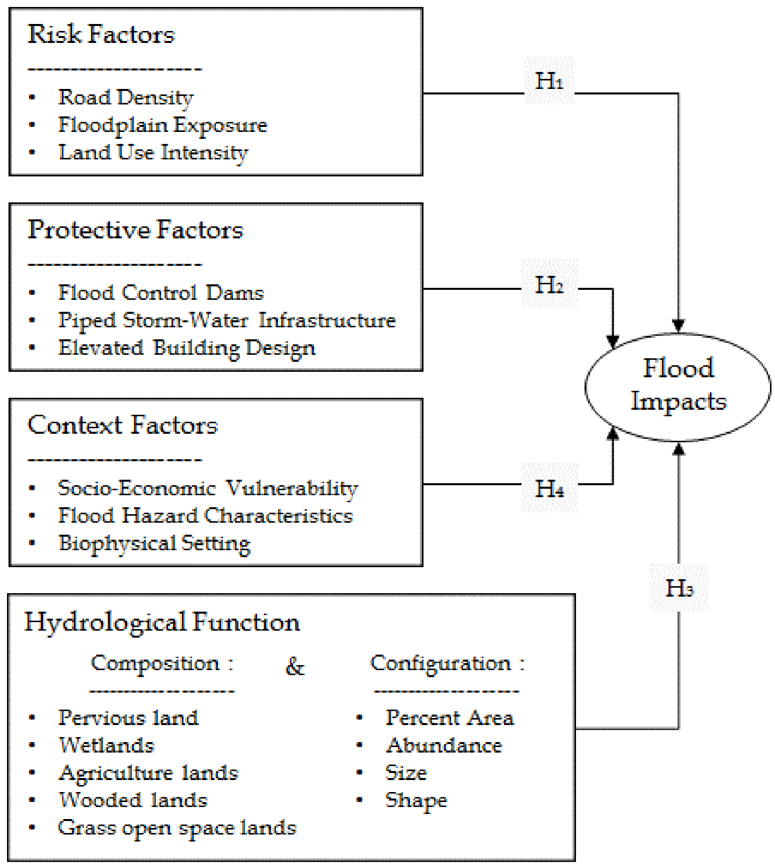


Fig. 3. Proposed risk-protection-function understanding of community flood resilience.

With the argument that nearly all elements, relationships, and regimes that describe the resilience of systems have spatial locations and spatial attributes, landscape ecologist have suggested the analysis of resilience through spatial patterns and effects (Alberti & Marzluff, 2004; Cumming, 2011; Grimm et al., 2000). The conceptual model proposed in this study is based on these ideas (see Fig. **3**) and suggests that community flood resilience is as much tied to an inventory balance of system weaknesses or vulnerabilities (i.e., H_1 risk factors) and system strengths or capacities (i.e., H_2 protective factors), as it is tied to important local landscape patterns of hydrological function (i.e.,

H_3 factors) within a specific context (i.e., H_4 factors). Accordingly, this study first identified and measured a number of representative indicators for each factor of resilience and then tested the degree to which each indicator increased or decreased the probability and severity of flood impacts. Descriptions of these factors and their expected association with flood damages to residential property are discussed next.

3.2.1 Risk Factors

A review of the literature brings out three ways in which communities increase flood risk. The first is through the effects that urban development has on flood *hazards*. Among the characteristics of urban development that influence flood hazards the most, imperviousness has the greatest impact. According to Arnold Jr. & Gibbons (1996), for example, a watershed with just 10 to 20% of impervious area can experience almost double the amount of surface runoff. However, the impacts of imperviousness are not evenly distributed across space. Most studies point to roads as the most prevalent type of impervious surface in urban landscapes (Arnold Jr. & Gibbons, 1996; Schueler, 1994; Shusher et al., 2005), except in areas dominated by commercial, industrial, and institutional land uses where the proportion of land dedicated to parking lots and rooftops may be greater than the land dedicated to roads (Rogers & DeFee II, 2005; Tilley & Slonecker, 2007; Washburn, Yancey, & Mendoza, 2010).

The second factor is through the production of conflicting land uses in hazard-prone locations, effectively increasing *exposure*. Critical facilities or high-density residential developments in the 100-year floodplain, for example, are problematic

(Mileti, 1999; Stevens et al., 2010). As a regulatory standard, the 100-year floodplain is used in the United States to denote zones that are considered to be most exposed to flood hazards, and property owners with a standing mortgage on a structure located in these zones are required to purchase flood insurance.

The third factor is the production of socio-economic *vulnerabilities*. As a place-based concept, vulnerability refers to susceptibilities that are ingrained in the spatial make-up of cities.[1] Vulnerable populations, for example, are often located in areas deemed least desirable (fringe, flood-prone, heavily industrialized, or degraded areas), and in buildings with the least technological dependability (e.g., mobile homes) (Kusenbach et al., 2010; Maantay & Maroko, 2009).

Guided by this evidence, this study tested whether high levels of risk, as reflected by greater levels *road density, floodplain exposure* and *land use intensity*, increased the likelihood and severity of residential property damage from flood events (**Hypotheses 1.1**, **1.2** and **1.3)**.

3.2.2 Protective Factors

Non-structural and structural mitigation strategies make up the tool set of coping mechanisms currently available to communities for managing flood risk. Overall, these mitigation strategies rely on an understanding of flood problems in terms of *sources* (i.e., where the water comes from), *pathways* (how and where water flows), and *receptors*

[1] Social and structural types of vulnerability are considered part of context and protective factors.

(who and what can be impacted by water). Therefore, an analysis of community protective measures against flood impacts should consider at least three mitigation measures, one for each type of mitigation strategy.

Dams are probably the most prominent mitigation strategy used to affect *sources* of flood hazards. According to the U.S. Army Corps of Engineers (USACE, n.d.), for every dollar spent in building and maintaining these types of structures, approximately $6 in potential damages has been saved. With respect to flood mitigation interventions on *pathways*, communities are often served by two types of drainage systems that redirect the flow of surface runoff away from people and assets: an underground system, designed to convey surface runoff from small, frequent events through a network of pipes; and an overland system of streams, ditches, and canals, designed to handle excess runoff from severe, less frequent events that cap the underground system. Even though a piped storm-water system is likely to overflow onto roads and low-lying areas during extreme events, these systems are still able to remove a considerable amount of water from the surface and away from people and property. Last, with respect to potential impacts on property or *receptors*, the general premise is that structures that are built or designed in a way that takes into account the impacts of floods are more resistant than those without these hazard adjustments. This is supported by findings from Kreibich et al. (2005), who reported that building precautionary measures such as elevated structures, water barriers, waterproof sealing, and safe-guarding reduced the damage ratio for buildings in urban areas around the Elbe river in Germany by 46% to 53%.

Based on this evidence, this study tested whether high levels of protection, as reflected by the *presence of up-stream dams*, *lengthy piped storm-water sewer infrastructure* and *elevated building design*, reduced the likelihood and severity of property damages (**Hypotheses 2.1**, **2.2** and **2.3)**.

3.2.3 Context Factors

Risk and protection components of community disaster resilience are not set in a vacuum. These elements are regulated by other much broader factors that cannot be easily changed by human interventions or policies—factors that are part of weather conditions, or part of the context in which a community is set in time and space. These factors can be grouped into one of three groups: socio-economic factors, flood hazard factors, and environmental factors. Environmental factors can be further specified in two separate groups: biophysical factors (often accounted for in the literature) and hydrological function indicators (this dissertation's contribution).

3.2.3.1 Socio-Economic Factors

Key factors behind risk perception and hazard adjustment behaviors are *socio-economic* characteristics. Decades of research have found a positive relationship between people's adoption of hazard adjustments and demographic characteristics across a wide variety of disaster agents, including seismic hazards (Lindell & Prater, 2000), hurricanes (Peacock et al., 2005), and hazardous facilities (Rogers, 1998). Groups of people considered to be most vulnerable to impacts of disasters include the elderly, children, poor or single-parent households, ethnic or linguistic minorities, people with disabilities or mental illness, and the homeless among others (Cutter et al., 2003; Lindell & Perry, 2000; Morrow, 1999). Accordingly this study tested the extent to which high levels of *social vulnerability* were correlated with the likelihood and severity of property damages (**Hypothesis 3.1**).

3.2.3.2 Flood Hazard Factors

The main factors influencing property damages from flood disaster events are associated with characteristics of the flood hazard itself. For example, Thieken et al. (2005) found that in the aftermath of a severe flood event in Germany, high losses and loss ratios were caused by higher water-depth levels, longer flood durations, faster flow velocities, and higher levels of contamination. Elmer et al. (2010), in a follow up study on the same area, found highly significant positive correlation between loss and flood recurrence intervals. These and other characteristics of floods are generally measured using stream flow data and are related to the intensity of precipitation (Pielke Jr. & Downton, 2000). Accordingly, this dissertation tested the degree to which areas that receive greater concentrations of *rainfall* during a disaster event will be more likely to experience flood impacts and severe damage to residential property (**Hypothesis 3.2**).

Also, the general placement of natural or built overland drainage systems can be a factor in predicting structural losses from floods. Urban developments located in areas where there is a greater density of streams are more exposed to flood hazards than areas with fewer overland drainage—both stream and open channels can eventually overflow and cause damage to nearby properties. Accordingly, this study tested the degree to which urban areas with a *lengthy overland stream drainage network* will experience a higher-than-average likelihood and severity of property damage (**Hypothesis 3.3**).

3.2.3.3 Biophysical Factors

Biophysical factors include local landscape conditions of soils and pervious land cover. Water infiltration through lower soil layers is a process regulated by soil texture (percentage of sand, silt, and clay), land form, topography, groundwater levels, and climate (Allan, 2004; FISRWG, 2001; McAlpine & Wotton, 2009; Pickett et al., 2011). References to drainage classifications of soils often consider the combined effect that local landscape conditions have on the soil's ability to transfer water downward. The class roughly indicates the degree, frequency, and duration of wetness, which is information often used by planners and developers to make decisions on the potential of soils for various land uses. Reference to poor drainage, for example, means that the soil is frequently and periodically saturated and may have limited to no capacity for handling excess surface runoff generated during a disaster event. Therefore, the expectation is that areas characterized by *poorly drained soils* will experience a higher-than-average likelihood and severity of property damage from floods (**Hypothesis 3.4**).

3.2.4 Hydrologic Function Indicators

The hydrological function of different types of pervious land cover can be a factor in regulating the performance of places with respect to floods. Hydrological functions that are of particular interest during a disaster event include water soil infiltration, storage, surface distribution, and interception. If ecologically sound, natural landscape features in urban areas have the potential to attenuate floods by supporting one or more of these functions.

Table 4 Main hydrologic roles of natural landscapes during extreme rainfall events.

Hydrologic function	Agriculture	Wetlands	Grass open space	Woody lands
Landscape infiltration	X	X	X	X
Landscape water storage	X	X		
Surface distribution		X	X	
Interception of precipitation		X		X

While considered separate, hydrologic landscape functions are often realized simultaneously (with various degrees of efficiency) by all types of pervious areas. Since ecological processes are tightly linked with elements of the landscape mosaic (Pickett et al., 2011; Turner, 2005), then distinct characteristics of natural land cover (e.g., type, abundance, size, shape, and distribution) are expected to alter the natural flow of water in ways that can either intensify or reduce the potential for local impacts from floods. Accordingly, this study identified physical and spatial characteristics specific to four dominant types of pervious land cover—agriculture, wetlands, grass open space, and woody lands—that are known to (or expected to) have a role in the hydrological performance of landscapes during extreme rainfall events (see Table 4). A more specific discussion of these relationships is provided next.

3.2.4.1 Landscape Infiltration

Large areas of pervious land cover have the potential to improve the landscape's performance with respect to floods. Water from precipitation that accumulates on the surface is initially stored on the upper layers of the soil, where it moves vertically into deeper layers of the soil or horizontally across other upper layers of soils (FISRWG, 2001; Marsh, 2005). The rate at which water breaks through the upper layers of soils is regulated by surface characteristics of land cover. Since all types of pervious areas allow for some level of surface water removal through soil infiltration, then the general expectation is that larger amounts of *pervious land cover* will reduce the likelihood and severity of residential property damage from flood events (**Hypothesis 4.1**).

3.2.4.2 Landscape Water Storage

Wetlands and agricultural areas are natural features of landscapes that can enhance the overall water storage capacity of the system. Wetland ecosystems are considered the top provider of flood attenuating ecosystem services in urban areas for two main reasons (Bolund & Hunhammar, 1999; Costanza et al., 1997; Troy & Wilson, 2006). First, wetland soils and vegetation are particularly adapted to manage saturated conditions, which gives them the ability to slow down and store large amounts of water runoff; second, they gradually release any excess water back into the system over a prolonged period of time, thereby diminishing the potential impacts of disasters (Mitsch & Gosselink, 2000). The abundance, size, position, type, and spatial arrangement of wetlands has been linked to a landscape's ability to provide effective water quality protection, flood attenuation and storage, and wildlife habitat (Hey & Philippi, 1995; Mitsch & Gosselink, 2000; Zedler, 2003; Zedler & Kercher, 2005).

Empirical flood assessments, for example, have found that wetland alterations of more than 0.5 acres—measured by the number of approved permits under Section 404 of the Clean Water Act—increase peak annual flows in watersheds (Highfield & Brody, 2006) and property damages at the county level (Brody et al., 2008). Wetland size and shape are also considered important predictors of hydrological function and ecosystem health. The notion that large patches of wetlands provide better hydrological services and habitat than small ones, for example, is the basis for wetland compensatory mitigation banking policy (Lorente, 2005). Also, certain shape configurations of wetlands can augment wetland hydrological functions. Elongated shapes, for example, can increase flow travel time and dissipate the energy of storm-water pulses (France, 2003). Also, interlinked wetlands or chains of wetland patches along streams can provide supplemental water storage and ecological benefits to those of isolated, large patches (Dramstad et al., 1996). Accordingly, this dissertation tested the degree to which increased *wetland acreage*, *patch size*, and *elongated shapes* reduced the likelihood and severity of property damage (**Hypotheses 4.2, 4.3,** and **4.4**).

In contrast, the role of agricultural lands with respect to flood disasters is not clear. Land used for agricultural purposes—cultivated lands for crops or pasture and hay—is often found in large parcels that occupy most of the land of many developed catchments (Allan, 2004). On one hand, agricultural management practices have the potential to increase overland runoff and exacerbate flood impacts due to the reduced soil infiltration rates and water storage capacities of compacted soils (O'Connell, Ewen, O'Donnell, & Quinn, 2007). On the other hand, agricultural land is designed and prepared for handling some level of water runoff and preventing crops from being lost due to excessive soil saturation. From a landscape ecology perspective, the land form of agricultural areas is essentially a large bowl, maybe leveled or sunk 1 to 4 feet below ground level, with plowing trenches at the bottom that allow for a quick distribution of water across the entire area. Even though the presence of agriculture in floodplains may be undesirable from other perspectives (e.g., water quality, wildlife habitat, and biodiversity) and a crop may be lost during a disaster event, any patches of agricultural land within an urban system have the potential to remove large volumes of water from the surface and protect adjacent property from flooding. Since there is little variability in the size, shape, and distribution of agricultural patches at an urban scale of analysis, this study tested the degree to which the *abundance of agricultural patches* in the landscape reduced the likelihood and severity of residential property damage from floods (**Hypothesis 4.5**).

3.2.4.3 Water Surface Distribution

Grass open space—such as stream corridors, undeveloped parcels, rangelands, greenways, parks, road easements, or connected yards—may reduce the adverse impacts of floods by allowing the distribution of surface water over the expanse of pervious landscapes. If ecologically intact, the leaves of grasses could capture as much precipitation as forest canopy—in other words, 10 to 20% of average annual precipitation (FISRWG, 2001). However, in an urban environment, these landscapes are seldom undisturbed. Therefore, from a hydrologic perspective, some of the most valuable properties of grass open space in urban areas are related to patch size, shape and their abundance.

When dedicated to recreational land uses, large tracts of grassed lands often include some impervious surfaces that may increase runoff. However, these areas are also equipped with landscape design elements, such as swells, drains, or sunk-in areas, that can manage some excess surface runoff. Elongated shapes of grass open space may be indicative of protected greenways and riparian areas. Narrow strips of vegetated cover over the length of a stream, for example, are considered important for reducing sediment input and pollutants, moderating temperatures for aquatic species, stabilizing stream banks, reducing the speed of surface runoff, and absorbing the impact of rising water levels (Allan, 2004; FISRWG, 2001; Osborne & Kovacic, 1993; Semlitsch & Bodie, 2003).

Considering the different types of land uses often assigned to grass open space, this study tested whether *large patch sizes, elongated shapes* and *their abundance* reduced the likelihood and severity of property damage (**Hypotheses 4.6**, **4.7** and **4.8**).

3.2.4.4 Interception of Precipitation

Canopy interception and transpiration of rainfall are two hydrological functions of woody plants presumed to buffer flood-generating rainfall and reduce runoff peaks. Factors that regulate these functions include general characteristics of plant materials at the site level (e.g., type, species, age, leave density, etc.), and regional conditions of soils, climate, and landscape setting (Farley, Jobbágy, & Jackson, 2005; Hümann et al., 2011; McAlpine & Wotton, 2009). Coniferous forests, for example, can intercept up to 28% of average annual precipitation levels, twice as much as deciduous forests which intercept up to 13% (FISRWG, 2001). The water storage capacity of forests is further improved by interactions with soils. Intensive rooting trees, for example, can break soil layers and create more gaps for water storage. Also, the transpiration of tree stands increases soil moisture deficits which, in turn, improve the soil's water-holding capacity (Hümann et al., 2011). According to Farley et al. (2005), the afforestation of grasslands and shrublands can reduce mean annual runoff by 44% and 33%, respectively. However, the effects of afforestation on flood runoff volumes are variable. Trees and vegetation along roads, for example, can increase the rates of water runoff because urban trees often have low stem densities (Pickett et al., 2011) and subsoil layers are too compacted for adequate water infiltration (Hümann et al., 2011; Shusher et al., 2005). Also, Calder & Aylward (2006) pointed out that the negative impacts of forest management activities on soils (e.g., logging, road construction, drainage, etc.) make plantation forests less efficient at water infiltration and storage than undisturbed forests, and that their overall performance may be easily overridden in prolonged, high-intensity storm events.

While the presence of canopy may reduce some amount of surface runoff, it is the presence of both canopy and undisturbed ground cover—not just canopy—that has the potential to afford some level of protection from floods. Accordingly, this study tested the extent to which the *abundance of undisturbed woody lands* (i.e., canopy in undeveloped parcels) reduced the likelihood and severity of residential property damage from flood events (**Hypotheses 4.9**).

3.3 Hypotheses Summary

Based on the literature, this study identified nine indicators of landscape hydrological function (see Table 5) that are hypothesized to increase community disaster resilience by reducing the negative impacts associated with floods. Also, it identified additional indicators of risk, protection and context that are known to, or expected to have a moderating effect on flood impacts (see Table 6).

Table 5 Hypotheses relating landscape hydrological functions and flood impacts.

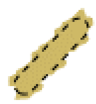
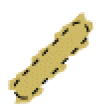
Natural Feature	Hydrologic Role	Types of landscape patterns: Reduce flood damages	Types of landscape patterns: Exacerbate flood damages	Description	Land Cover Characteristics
All	Infiltration	%	%	Percent area	Total pervious land cover.
Wetlands	Infiltration, Storage, Distribution, Interception	%  	%  	Percent Area Size Shape	Large isolated wetlands, or elongated wetlands in a riparian setting have greater hydrologic value than small isolated wetlands, or compact wetlands in riparian settings.
Agriculture lands	Storage			Abundance	Agriculture parcels are often large, with little variability of size, shape, or distribution.
Grass open space	Distribution	  	  	Size Shape Abundance	Few, large patches of grass open space refer to rangelands or urban parks. Few, elongated shapes of grass open space refer to riparian zones, easements, and connected landscapes of undeveloped land.
Woody lands	Interception	%	%	Percent Area	Total area of undeveloped land with woody plants.

Table 6 Summary of hypothesis.

Components of community disaster resilience Hypotheses	H_i	Expected associations with property damage Likelihood	 Severity
<u>Risk Factors</u>			
1) High road density	1.1	+	+
2) High floodplain exposure	1.2	+	+
3) High land use intensity	1.3	+	+
<u>Protective Factors</u>			
4) Presence of dams	2.1	-	-
5) Pipelines of storm-water infrastructure	2.2	-	-
6) Elevated building design	2.3	-	-
<u>Context</u>			
Socio-economic condition			
7) High levels of social vulnerability	3.1	+	+
Flood hazard factors			
8) High precipitation intensity	3.2	+	+
9) Lengthy overland stream network	3.3	+	+
Biophysical setting			
10) Poor soil drained capacity	3.4	+	+
<u>Hydrologic Function Indicators</u>			
Landscape infiltration			
11) Percent area pervious land cover	4.1	-	-
Landscape water storage			
12) Percent area wetlands	4.2	-	-
13) Large wetland patch sizes	4.3	-	-
14) Elongated wetland patches	4.4	-	-
15) Abundance of agricultural patches	4.5	-	-
Surface distribution			
16) Large patches of grass open space	4.6	-	-
17) Elongated patches of grass open space	4.7	-	-
18) Abundance of patches of grass open space	4.8	-	-
Interception of precipitation			
19) Percent area undisturbed woody lands	4.9	-	-

4. METHODS

The methodological approach used in this study is explained in five sub-sections. The first outlines the approach used for empirical evaluation of community flood resilience, and it includes information about the area of study, unit of analysis, scale, data sources, record selection, and sampling. The second describes the measurement of relevant concepts as listed in Section 3: Theory. The third explains applied spatial and statistical analytical procedures. Finally, the fourth and fifth sub-sections provide a descriptive analysis of measures and a validity assessment of the study, respectively.

4.1 General Research Approach

This study used an explanatory research approach to examine the role that natural features of landscapes have on flood damages to residential property. A single rain-driven flood disaster event was chosen for study to allow for an in-depth investigation of factors that may affect flood impacts at the neighborhood scale over a wide area of impact. Also, by evaluating the localized impacts of a single major flood event, the study was able to control for the moderating effects of disaster-specific characteristics (such as duration and intensity of flood event), as well as regional ecological conditions (e.g., seasonal soil saturation or drought conditions) that would be difficult to measure (or account for statistically) in a multi-year, multi-disaster, regional study.

The sampling of neighborhood cases was carefully specified to allow independent measurement of all data, for all cases, and at two scales of analysis. Metrics derived from landscape analyses were used on quantitative methods to report on actual observations of property damage associated with TS Allison in the Houston area.

This research was also cross-sectional, meaning it studied the problem at a single point in time. Descriptive causal inference from the results was possible only by using a valid, well-documented theoretical framework, by collecting data on predicting factors with a temporal resolution that would describe the system's condition prior to (or at the time of) disaster, and by using statistical models of multiple regression.

4.1.1 Study Area

Harris County is located in a low-lying coastal area of Texas by the Gulf of Mexico where hurricanes and flood events are common. In June 2001, the area was hit by the most devastating rainfall event in the state of Texas, TS Alison. The storm's trajectory started in the Gulf of Mexico, first moving north across the county, and then moving back south into the region again before continuing a northeast path across the nation toward the East Coast. This behavior resulted in five consecutive days of continuous rainfall in the Houston area, from June 5 to June 9. In some areas of the county, the intensity of the rainfall was as high as 28 inches of rain during a 12-hour period, about 80% of the area's average annual rainfall (Tropical Storm Allison Recovery Project [TSARP], 2002). Official reports indicated that TS Allison affected more than 2 million people, flooded about 1,000 residences, caused 22 fatalities, and generated over $5 billion (USD 2001) in property damage in Harris County alone (TSARP, 2002; U.S. Department of Commerce [USDC], NOAA, & National Weather Service [NWS], 2001).

From a landscape perspective, Harris County is also an interesting case study because it has been under intense pressure from urbanization for years. Between 1990 and 2000, for example, Harris County experienced a 20% increase in population (US Census Bureau, 2000). Also, the way development shapes the landscape is very unique. The state of Texas follows a bottom-up approach to land use planning where local jurisdictions are not required to adopt a legally binding, prescriptive comprehensive plan. Consequently, the distribution of urban growth is generally scattered and only planned within the boundaries of subdivision development projects. Furthermore, Harris County is the jurisdiction with the most flood policies in Texas; at the time of TS Allison, for example, this county accounted for more than 33% of all flood insurance policies in the state, and 65% of all state claims associated with the storm. Thus, the localized impact of TS Allison over the study area and the unregulated fragmentation of landscapes made Harris County an ideal case study to consider a wide range of landscape patterns with respect to disaster impacts.

4.1.2 Unit and Scale of Analysis

The target population of study was single-family residential properties in Harris County, Texas that were actively participating in NFIP during TS Allison in June 2001. Considering that these records were available for individual address locations, the data were kept securely and were aggregated into groups of NFIP policies to preserve the confidentiality of individual records. Thus, the unit of analysis for study became the physical space around clusters or neighborhoods of NFIP properties.

An understanding of neighborhoods in terms of physical characteristics is not new. The concept of physical neighborhood units has a long tradition in guiding land development and planning policy practices (Duany et al., 2000; Lawhon, 2009; Park & Rogers, 2014). Generally, broad neighborhood scales (e.g., census track boundaries, zip codes, or transportation access zones) are suited for the analysis of social services, economic opportunities, and networks, whereas narrow scales (e.g., census blocks, block-groups, housing clusters, or circular-buffered areas) are suited for analyses on predictable social encounters or the physical use of space (Chaskin, 1997; Kearns & Parkinson, 2001; Park & Rogers, 2014). Since this dissertation is about flood damages to residential property (not ecological floods), the most appropriate scale of analysis was a narrow scale that studied and tested environmental factors possibly associated with damages within neighborhoods of NFIP properties. However, there is no single, generalizable functional narrow scale at which to study the physical conditions of neighborhoods, and the choice of scale may force the aggregation of data into zones that are inconsistent with the scale and purpose of study. This problem is also known as the modifiable areal unit problem (MAUP), which can affect the magnitude of measures and the reliability of correlation and regression coefficients that guide policy decisions (Wu, 2004; Zhang & Kukadia, 2005).

The challenge was to minimize the impact of MAUP by defining the spatial extent of neighborhoods of NFIP properties with a shape and a size appropriate for studying the physical use of space, and the effectiveness of policy decisions of residential development on flood mitigation. This study achieved this by:

1. Using circular areas to represent the physical space of neighborhoods. Circular shapes are important in spatial data analyses because they comply with a basic understanding of geography about the influence of relative distances of pixel data within units of analysis—in other words, Tobler's first law of geography, which states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236).
2. Delineating neighborhood circular boundaries using one fixed size for all shapes to provide equal representation of spatial data for all cases (i.e., no one spatial unit is larger or smaller than another).
3. Sizing the spatial extent of neighborhoods using a radius distance with practical applications for land use planning and development—an area of 1/4-mile or 5-minute walk radius (Duany et al., 2000; Hasan, Ahmad, & Hadiuzzaman, 2014).
4. Defining two scales of analysis for neighborhoods. As some effects of the environment could manifest only at a larger scale of analysis, the model and results obtained for the 1/4-mile neighborhood were contrasted with a similar analysis carried independently on a larger unit of 1/2-mile radius, that is, four times the area of the smaller one.
5. Avoiding any overlap of circular areas in either of the alternatives to prevent double-counting pixels of spatial data from adjacent areas—this is an

important consideration that ensures the independent measurement of all spatial variables, for all cases, and at both scales of analysis.

Additional benefits to this approach relate to measurement. Landscape metrics (i.e., variables characterizing land cover patterns) are highly sensitive to boundary changes in the *shape* and *scale* (Botequilha Leitão, Joseph, Ahern, & McGarigal, 2006; McGarigal, 2015; Wu, 2004). Using circles to describe all boundaries alleviates the metrics' sensitivity to shape, and using two scales of analysis allows for testing the robustness of metric scores at the locations of interest. The implementation of these strategies is discussed next.

4.1.3 Data Sources and Temporal Resolution

The primary source of data for this study was collected by NFIP under FEMA. The NFIP maintains two separate databases: one on policies, and another on claims. Together, NFIP policy and claim records provide the most complete information available today on flood-related damages in the United States.

Data on land use/land cover collected by the Coastal Change Analysis Program (C-CAP) under NOAA were also important; as well as property parcel data collected by the Harris County Appraisal District (HCAD). Since the temporal resolution of the parcel data was for 2005 (four years after the disaster event under study), additional land use data collected by Google Earth Pro (GEP) as historic imagery were needed to derive a new parcel dataset for 2001 (see Appendix B for details on this process).

Table 7 Data source descriptions.

Data	Sources	Format	Date
Flood insurance records: policies and claims	FEMA NFIP 1998-2008 (restricted access)	Tabular	2001
Land cover data	NOAA C-CAP http://www.csc.noaa.gov/digitalcoast/	Raster 30mx30m	2001
Property and land use data	HCAD http://pdata.hcad.org/GIS/	Tabular and vector	2005*
Historic land use	GEP http://earth.google.com	Image	12/31/2001
Disaster data and floodplains	TSARP HCFCD www.hcfcd.org/tsarp.asp	Image and vector	2001
Hydrology	USDA NRSC WBD datagateway.nrcs.usda.gov	Vector	2008**
Soils	USDA NRCS SSURGO http://websoilsurvey.sc.egov.usda.gov	Tabular and vector	2002
Dams	USACE http://nid.usace.army.mil/	Tabular	2013***
Infrastructure	GIMS http://www.gims.houstontx.gov	Vector	2011***
Boundaries and water features	HGAC https://www.h-gac.com	Vector	Various**
Roads	StratMap TINRIS TWDB https://tnris.org	Vector	2011***
Socio-economic data	US Census Bureau http://factfinder.census.gov/	Tabular and vector	2000

* The county appraisal office lost all parcel data for years prior to 2005. The land use designation of all properties with a year-built of zero, or greater than 2000, was visually verified using 2001 historic imagery from Google Earth Pro. In cases where properties were demolished or remodeled between 2001 and 2005, the median assessed property value of neighboring properties was used to describe the property's value at the time of disaster.

** The completeness and alignment of vector features were verified using 2001 historic imagery from Google Earth Pro. When needed, spatial data were re-categorized or digitized to generate a new map of features in existence at the time of disaster.

*** These data contained year-built information allowing the selection of features by date.

Other secondary data needed for study were collected from eight different agencies and programs that produce and distribute data (see Table 7): (a) TSARP under Harris County Flood Control District (HCFCD); (b) Watershed Boundary Dataset (WBD) managed by the United States Department of Agriculture (USDA) and the Natural Resources Conservation Service (NRCS); (c) Soil Survey Geographic (SSURGO) database; (d) USACE; (e) City of Houston's Geographic Information and Management System (GIMS); (f) the Houston Galveston Area Council (HGAC); (g) the Texas Strategic Mapping Program (StratMap) of the Texas Natural Resources Information System (TNRIS), a division of the Texas Water Development Board (TWDB); and (h) United States Bureau of the Census.

When available, date information was used to select features or records in existence at the time of disaster. When unavailable, the completeness and alignment of vector features were verified using 2001 historic imagery from Google Earth Pro. Also, in those cases, spatial information was re-categorized, digitized, or reformatted to generate a new accurate map of 2001 features.

4.1.4 Accuracy and Reliability of Data

Any type of spatial analysis requires associating data with specific locations on a map. Before summarizing flood damages at the neighborhood level, NFIP policy records had to be mapped (i.e., geo-located) and then linked with parcel data of the corresponding property. An accurate policy-parcel match is one where the geographic placement of an NFIP record falls completely within the boundaries of the parcel's polygon shape with the land use and tax information of the insured property.

If parcel and policy data were complete and correctly specified, then a standard process of geocoding would generally be enough. However, during the course of this research, it became apparent that the accuracy of geocoded matches was affected by the completeness of NFIP database extractions, the number of valid NFIP records, the quality of geographic information specified for all NFIP records (i.e., latitude and longitude information), the temporal resolution of parcel data, the quality of parcel maps, and the constraints and default settings of available spatial analytical software. Prior to correction, for example, 65% of confirmed NFIP records would have been associated with the wrong parcel, and at least 11% of all records for study (or 17% of all associated damages) would have been placed in the wrong county altogether. Also, prior to restricting the selection of policy records to strictly single-family residential properties, this study would have included a small number of cases that reported damage claims beyond the maximum coverage limit of $250,000 by a factor of 3.15 (in the case of multifamily and other residential structures), or by a factor of 120 (in the case of condos). Appendix B provides additional information on data quality issues, their potential impacts on study results, and the steps taken to overcome them and ensure measurement accuracy.

4.1.5 Record Selection

The NFIP databases include records for different types of policies. Policies can be issued for individual properties or groups of properties, dedicated to residential or non-residential land uses, and contained coverage for buildings and/or contents. At the time of TS Allison, for example, 98% of all policies had building coverage, and 92% of these were issued for single-family residential buildings.

To measure flood damages to residential property, this study restricted the types of NFIP records to policies that were for individual properties, in good standing (i.e., no canceled entries), issued for single-family residential structures, and for building damage coverage. These restrictions increased the validity of the study in several ways (see Table 8). First, removing canceled policies cleaned out the data from invalid or void records. Second, using only the building property damage data allowed for a valid comparison between data points because while flood damage to contents can provide additional information about the impacts of floods to households, the value of contents varies considerably by household characteristics and in relation to the value of buildings (Grigg & Helweg, 1975). Also, modeling the factors that affect the types, values, and susceptibility to damage of household contents was beyond the scope of this research.

Third, policies for condominiums, multifamily structures, other-residential, and non-residential properties are subject to different policy rules that can overestimate property damages and bias results. For example, the NFIP offers a maximum of $250,000 of building coverage for residential properties, but this maximum does not apply to multifamily structures or residential condo policies, which can expand their

Table 8 NFIP record selection and validation process.

Selection Steps	Policies	Claims
1. Disaster NFIP data (Texas)		
Existing policy records at the time of Tropical Storm Allison	355,202	25,306
Completeness: 96% of claim records had a policy match in provided datasets.		
2. Record selection (Texas)		
Individual policy records in good standing of single-family residential structures insured for building property damage	319,707	21,427
3. Records geographically relevant (Harris County, Texas)		
Records inside the county by zip code and geographic boundary	118,279	17,299
4. Exclusion of unusable NFIP data		
Content validation: incomplete or invalid records		
- Duplicate records (invalid data)	(4,568)	(115)
- Descriptive or unknown address (not geocodable)	(2,881)	-
- Wrong address (errors, address does not exist)	(973)	(55)
	(8,422)	(170)
Land use verification: not single-family residences		
- Apartments or multifamily structures	(1,178)	(181)
- Mobile homes or trailer parks	(225)	(53)
- Not a home (commercial, religious, or school property)	(286)	(71)
- Vacant lot (not developed as evident in historic imagery)	(82)	(15)
	(1,771)	(320)
5. Multiple NFIP policies for the same property*		
Excess number of policies and claims	(553)	(34)
6. Target Population (Validated Database)		
Single-family homes with relevant and valid policies and/or claims	**107,533**	**16,775**
(*Percentages of #3, initially selected and geocoded records*)	*(90.9%)*	*(97.0%)*

* Parcels can have multiple NFIP policies, one for each building within the property used/held for residential, business or farming purposes. These records were excluded from total policy/claim counts because they referred to the same property, but their data on flood property damages were aggregated at the parcel level.

coverage to include other elements, such as shared carports, club houses, pool equipment, elevators, and similar type elements (some of these coverages have changed since 2012). While these items may be important amenities for a residential complex, they are not an integral part of the residential unit itself and add uncertainty to the analyses.

Last, non-single-family residential policies (even if very few) are not evenly distributed (within or among counties); they are clustered in urbanized regions or business districts. These clusters would most likely generate data outliers that can drive the linear relationship found in statistical analyses and lead to wrong conclusions. Thus, restricting the selection of records was an important methodological step to improve the validity of property damage measures.

4.1.6 Sampling

A systematic spatial sampling framework was used to sample neighborhoods of NFIP properties. This method was guided by superimposing arbitrarily a regular grid over the study area's polygonal region. Each grid cell had to accommodate circular areas of 1/4-mile and 1/2-mile radii drawn from the same grid centroids. Also, the spacing of the grid had to ensure independence of measurement of all spatial data collected on cases adjacent to each other. Therefore, the size of the grid was specified to maintain a generous gap between adjacent 1/2-mile circular areas. A number of cases only captured NFIP properties in the gaps between circular areas or in the space between 1/4-mile and 1/2-mile circular areas, but not within the 1/4-mile circles. These cases were considered incomplete and were not included for study. Other cases captured at least one NFIP property within the 1/4-mile radius neighborhoods. Since some of the data collected for neighborhoods related to averages and median values, a minimum of three NFIP properties could be required for variable computations. However, this study used a more conservative approach by selecting a minimum cluster of at least five NFIP properties. A total of 540 neighborhood cases met this requirement and were initially selected for study.

4.1.7 Data Integration

The integration and analysis of all geographic datasets was facilitated by defining a common coordinate framework for all spatial data (vector and raster). The Albers Equal Area Conic projection, 1983 datum with linear units in meters was selected as the most appropriate coordinate system for the study for several reasons: (a) it is suitable for regions predominantly east-west in extent and located in middle latitudes; (b) it preserves area and direction properties of spatial features, over distance or shape properties; (c) it allows the integration of data with FRAGSTATS, a software used to measure landscape metrics that requires raster data cell sizes in meters; and (d) the majority of the data are already produced on this projection which reduces the chance of introducing error through coordinate system transformations. Further analytical integration of data was achieved using ArcGIS v.10.2 software, as well as Geospatial Modelling Environment v.0.7.3.0, Microsoft Excel 2010, GeoDa v.1.6.7, GeodaSpace v.1.0, and Gretl v.1.9.92.

4.2 Resilience as a Loss Function

Disaster resilience is best understood through consequences. Estimating and understanding the causes of potential flood damages is a federal, state, and local planning problem that gained particular importance following the implementation of the Flood Insurance Act of 1968. Although a concern with the physical consequences of disasters would not lead to a comprehensive evaluation of resilience, a property damage approach is still valuable in that it relates to the basis from which other forms of resilience can unfold. Furthermore, dealing with the physical impacts of disasters represents a critical stage in the recovery process, and low levels of physical loss are indicative of a community's ability to withstand the impacts of disasters, thereby displaying high levels of adaptation and disaster resilience.

Thus far, flood resilience assessments have evaluated damage-causing factors by differentiating between risk-impact and protective-resistance model parameters (see review by Merz et al., 2010). These studies have based their evaluations on estimated or actual flood damage data. In the absence of actual damage data, studies have estimated flood damages by assuming a level of impact for all properties under specific hydrologic what-if scenarios. When actual damage data are available (e.g., insurance records, or household surveys), the accuracy of damage estimations is improved. For regional flood damage assessments, the general approach has been to use the information on available cases to measure flood damages for zones. One limitation of this approach is that it assumes that the damage on a few properties accurately represents the damage on all properties within that zone. For example, $100,000 of property damage in a neighborhood of 100 homes, where 40 properties have insurance and filed damage claims will assume an average damage per home 2.5 times lower than the actual average damage suffered by each insured home. To address this limitation, this study was restricted to only insured properties because they make the only set of cases with full information concerning damage intensity or absence of damage.

Another important characteristic of flood resilience assessments is the choice of damage function. The relative influence of risk, protection, and context factors is often tested using multivariate analyses where a choice is made between absolute or relative functions (see Fig. **4**). Absolute damage functions specify damage amounts in raw monetary values, for example, Euros or U.S. dollars. The advantage of this approach is that it does not require additional detailed information on property values, a type of data that may be very difficult to obtain. Hence, a number of studies have used absolute damage functions to evaluate factors affecting property damages (e.g., Brody et al., 2013; Brody & Gunn, 2013; Brody et al., 2012; Brody et al., 2015; Highfield et al., 2014; Kreibich et al., 2005; Peacock, 2010; Thieken et al., 2005). While informative and easy to interpret, model results vary strongly depending on the value of the damaged object under evaluation (Merz et al., 2010; Messner & Meyer, 2006). Furthermore, an aggregated measure of absolute damages does not allow for gauging the severity of that damage. For example, an average damage of $10,000 may be a very high price tag for a home-owner whose property is worth $80,000, but the same damage on a property worth $1,000,000 is almost negligible. Also, an assessed damage of $10,000 in an area where the cost of living is very high may not be as significant as if that same damage were to happen in a community where it may represent a larger portion of the household's income. Pielke Jr. & Downton (2000), for example, pointed out that when evaluating absolute flood damages in the United States from 1930 to 2000, the trend is increasing, but when evaluating those same damages relative to measures of local wealth, the trend is flat.

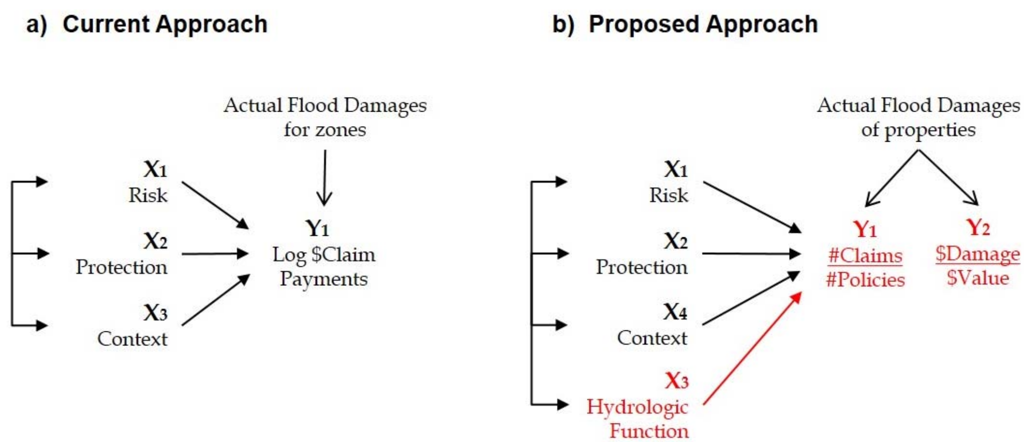


Fig. 4. Current and proposed approaches to model flood-damage-causing factors.

Considering the limitations of absolute measures of damage, other flood impact assessments have used relative measures (e.g., Kreibich et al., 2005; Lorente, 2011; Michel-Kerjan & Kousky, 2010; Thieken et al., 2005). This study followed these types of studies and tested two relative measures of flood damage: probability of suffering any damage, measured as a proportion of insured properties reporting flood damages; and severity of damage, measured as a ratio between assessed damages and their respective property values. Detailed descriptions of these and other measures used for hypotheses testing are provided next.

4.3 Measurement

A set of 21 measures, including two dependent variables, was collected for each neighborhood case. The specification of these measures was subject to data availability, resolution, scale of analysis, and study constraints.

4.3.1 Flood Damage

The *likelihood* and *severity* of flood damage, the two dependent variables for the study, were measured using flood insurance records of residential property from the NFIP, and property value data from HCAD. The likelihood of flood damage was calculated using aggregated counts of flood policies and claims of single-family residential properties, such that for a neighborhood *i*:

$$L_i = \frac{C_i}{P_i}(100),$$

where L_i is the likelihood of flood damage in the neighborhood, C_i is the number of NFIP claims for flood damage filed by single-family properties in the neighborhood, and P_i is the number of NFIP policies issued for single-family units in the neighborhood. The severity of flood damage was calculated as an average of property damage and value ratios, such that for a neighborhood *i*:

$$S_i = \frac{\sum_{j=1}^{P_i}\left(\frac{D_j}{V_j}\right)}{P_i} (100),$$

where S_i is the severity of flood damage in the neighborhood, D_j is the assessed property flood damage for a single residential unit in 2001 dollar amounts of actual cash value (ACV), V_j is the corresponding total assessed property value for the same property in 2001 dollar amounts, and P_i is the number of NFIP policies issued for single-family units in the neighborhood.

Actual cash and appraised values were preferred over replacement or market values because they reflect similar depreciated values of property and materials at the time of disaster, whereas "replacement values usually involve some form of improvement" (Merz et al., 2010, p. 1700). Flood damages in NFIP databases are recorded in dollar amounts at the time of damage; therefore, an extraction by date ensured an accurate representation of property damage data in 2001 dollars. Assessed property values were recorded in 2005 dollar amounts. These data were adjusted for inflation by consumer price index correction factors to 2001 dollars. Additionally, the validity of 2005 land use codes was verified using tabular parcel data on year-built, and when needed, codes were modified to represent 2001 land development conditions represented in historic photographic imagery from Google Earth Pro (12/31/2001). Detailed information on parcel data verification and adjustments is provided in Appendix B. The neighborhood's median assessed property value (of single-family residential properties) was assigned to 1,641 parcels that lacked property value information—about 0.01% of the 107,533 NFIP policies in the county. This value was considered the best approximation to describe the type, condition, and value of the property value at the time of disaster.

Five neighborhoods with more than half of the parcels missing property values were excluded from analyses of flood damage severity because with fewer known property values, the median estimation was considered less reliable. Consequently, 535-cases were used for the analysis of *severity of damage*, while a complete set of 540-cases was maintained for the analysis of *likelihood of damage*.

4.3.2 Flood Risk Factors

Road density was measured as road length per single-family residential unit in the neighborhood (m/unit). Considering that area measures of pervious land cover and impervious land cover are perfectly negatively correlated and can lead to severe multicollinearity problems in statistical analyses, this study developed a measure of road density not based on land cover classes. Since 90.1% of all residential parcels in sampled neighborhoods referred to single-family residential units, this metric was considered appropriate. The highest resolution of road network data available for the study area was produced by the StratMap section of the TNRIS, a division of the TWDB. City streets, as well as local, neighborhood, and rural roads (category A4 in Census Feature Class Codes), with a year built of 2001 or earlier were extracted for analysis. Major interstate and state highways were excluded from analysis because these road features are often designed with setbacks and water retention areas that modify the impact of imperviousness. The length (m) of A4 road features was divided by the number of single-family residential parcels in the neighborhood. This metric was log transformed to avoid extreme range of values relative to other metrics in the study, and to reduce the spread of values that may exacerbate problems with model heteroscedasticity.

Floodplain exposure was calculated as the percent area of the neighborhood located within the boundaries of the 100-year floodplain. The delineation of floodplains was based on advanced Digital Flood Insurance Rate Maps (DFIRMs) produced by FEMA. A version of floodplain maps in force at the time of disaster was available through the TSARP under HCFCD.

Land use intensity was calculated as the percent area of the neighborhood comprised by commercial, industrial, and institutional land uses. Land use data were derived from HCAD. The temporal resolution of these data was verified and adjusted based on historic imagery for 2001 from GEP.

4.3.3 Flood Protection Factors

The *presence of flood protection dams* was recorded in a dichotomous variable, where a value of 1 indicated the presence of upstream dams in the neighborhood's watershed, zero otherwise. Therefore, any neighborhoods located geographically to the side or above a dam structure were coded zero, and any neighborhood located in the basin immediately below the dam were coded 1. Data on dams were available from the

USACE. Features with primary or secondary uses of flood protection, and with a year built of 2001 or earlier, were extracted for analysis. Watershed boundaries were based on the most up-to-date WBD managed by the USDA and NRCS. The relative location of dams with respect to neighborhoods was specified in a geographic information system (GIS) environment and joined to neighborhood units.

The *availability of storm-water infrastructure* was measured in meters of underground storm-water pipelines and then divided by the square root of neighborhood area (m) to make the metric comparable across scales of analysis. Detailed data on storm-water infrastructure were derived from 181 separate files from the City of Houston's GIMS that were merged in a GIS environment. Main pipeline features with a year built of 2001 or before were extracted for measurement.

Elevated building designs were assessed using descriptive information available on single-family properties with NFIP policies. A neighborhood's overall vulnerability to flood damage associated with building design was measured as a ratio between the total number of NFIP buildings with split levels designs or with two or more floors and the total number of NFIP buildings, multiplied by 100 to make it a percentage value. A total of 89 cases (of 107,533) were missing building design information. These records were coded as one-story buildings, the most common type of single-family residential design in Harris County (69% of all insured single-family properties).

4.3.4 Context Factors

4.3.4.1 Socio-Economic Conditions

Neighborhood *percent minority population* information was measured using parcel land use data from HCAD, 2000 census block-group demographic information from the U.S. Census Bureau, and GIS techniques. In an effort to improve on the accuracy of commonly used area-weighted population estimation techniques, this study adopted a cadastral-based expert dasymetric system to disaggregate census block-group population data into finer scales of analysis (e.g., Maantay & Maroko, 2009). This technique assumes that all residential tax parcels within a census block-group accurately represent total counts of census households. Since 93% of all housing units in Harris County, Texas, were occupied in 2000 (US Census Bureau, 2000), this assumption was considered appropriate. As such, ratios of population per household and non-white population per household were assigned to each residential parcel. Neighborhood percent minority population was then calculated as the sum of non-white population/household, divided by the sum of population/household, multiplied by 100 to make it a percentage value.

4.3.4.2 Flood Hazard Factors

Precipitation intensity was calculated as cumulative 5-day precipitation in inches. Data on precipitation levels associated with TS Allison were available as a detailed image of local precipitation patterns from June 5 to June 9 of 2001 produced by the TSARP under HCFCD. These data were mapped at a scale of 30-m raster grid cells, and the pixel precipitation values were aggregated and joined to neighborhood units.

The *length of overland stream network* was measured using hydrologic vector data available for major rivers from HGAC. The temporal resolution of these data was verified and adjusted based on historic imagery for 2001 from GEP. Network length (i.e., streams, open ditches, and canals) was measured in meters and then divided by the square root of neighborhood area (m) to make the metric comparable across scales of analysis.

4.3.4.3 Biophysical Context

Neighborhood *poor soil drainage capacity* was calculated as the percent area comprised of poorly-drained or very-poorly-drained soil classes. Measures of soil drainage capacity are based on natural dominant drainage soil classes specified in the SSURGO database, the most detailed county-level data on soils. The natural undisturbed drainage condition of soils has seven classifications, from very-poorly-drained to excessively-drained. The two lowest classifications (i.e., very-poorly-drained and poorly-drained) describe soil types where water moves so slowly that the soil is wet at shallow depths periodically, or almost permanently. Also, these soils have free water at shallow depths, an indication of low or very low hydraulic conductivity.

4.3.5 Hydrological Function Indicators

Land cover information was derived from the 2001 NOAA C-CAP dataset. The C-CAP dataset differentiates 24 land cover types, 21 of which were present in the study area. Hydrological function indicators were described using landscape composition and configuration metrics calculated for four land cover types: wetlands, agriculture lands, grass open space, and woody lands.

4.3.5.1 Land Cover Types

Wetland areas were measured by aggregating eight land cover types describing palustrine and estuarine, tidal and non-tidal wetlands. *Agriculture lands* included planted and cultivated land cover types. A visual check of the C-CAP land cover classification against photographic historic imagery revealed that park areas, undeveloped residential parcels, and residential yards were classified as either grassland or open space land cover. This may be the result of overlapping pixel classification schemes. For example, C-CAP data describe grassland land cover as areas dominated by over 80% of herbaceous vegetation, and open space land cover as areas containing more than 80% of managed grasses and low-lying vegetation. Therefore, grassland and open space land cover types were aggregated to describe *grass open space*. The C-CAP classification of forested landscapes can also be misleading. Since remote-sensed data only describes what can be seen from above the ground, not what is on the ground, there is a potential for classifying dense canopy areas covering roads and other impervious areas as forested landscapes. To avoid overestimating the amount of forested land cover, woody lands were measured by crossing land cover data with land use parcel information. Four land cover types containing descriptions for tree canopy in any successional stage were combined—from shrubs and young trees, to established deciduous, evergreen, and mixed forests. Pixels of woody land cover types located in undeveloped parcels were kept for analysis. The remaining five land cover types were classified as either water (open water and unconsolidated shore land cover types representing large and small water areas) or urban areas (high-, medium-, and low-intensity land cover types). Measures of pervious land cover were calculated by aggregating the new land cover classifications of wetlands, agriculture lands, grass open space, and woody lands.

With the new land cover classifications, two categorical map images were produced: one was a binary map of two land cover classes differentiating between pervious and non-pervious areas, and the other was a categorical map of six land cover classes differentiating wetlands, agriculture lands, grass open space, woody lands, and urban and water areas. These images were then used for deriving spatial metrics describing the hydrological functions of natural landscape features in urban areas.

4.3.5.2 Spatial Metrics

Landscape spatial metrics were derived following a number of steps. First, neighborhood circular areas of 1/4-mile and 1/2-mile radii were used to extract land cover information from C-CAP raster images for all 540 neighborhoods. A Python-based script was developed to ensure that these image extractions contained an additional border of at least two pixels in depth around the circular boundary. A landscape border is an essential requirement for the unbiased calculation of most spatial metrics, especially at narrow scales of analysis. In the absence of a border, analytical software will take two default actions: (a) it will assume that all edge cells are adjacent to a contrasting land cover type, which will result in an overestimation of perimeter-based spatial metrics; and (b) it will exclude all edge cells and use their attribute information to inform the calculation of adjacency-based spatial metrics for interior cells, thereby reducing the effective size of the landscape under study and the amount of information available for describing the neighborhood.

Second, patches of pervious areas were defined using the 8-cell neighbor rule. The 30 m x 30 m resolution of C-CAP data tends to oversimplify the shape of landscape components that are ecologically relevant for study, such as wetlands or green corridors. The 8-neighbor rule was chosen, because it allows for some level of variation on the minimum size of landscape components by considering cells of the same class that are diagonally or orthogonally adjacent to each other as one patch unit.

Third, a number of class-level spatial metrics were computed in FRAGSTATS 4.2.1 (McGarigal, Cushman, & Ene, 2012) using the images with two and six land cover classes. None of these classes were specified as background because doing so could significantly bias the calculation of metrics. While the software can generate hundreds of landscape metrics, a good portion of these are redundant because they use the same primary information (patch size, area, edge, or adjacency), or because they present the same information in alternative ways (McGarigal, 2015). Several studies have tested and evaluated groups of metrics in an effort to identify an ideal set of meaningful measures for characterizing ecological processes (e.g., Botequilha Leitão et al., 2006; Frank, Fürst, Koschke, & Makeschin, 2012). However, there is little agreement on the choice of individual metrics due to differences in study constraints (e.g., data resolution, or scale of analysis), analytical specifications (e.g., boundaries, borders, or ecological process being measured), investigation focus (i.e., ecological or spatial process of research interest), and criteria—or lack thereof—for variable selection.

The selection of spatial metrics for this study was based on theory, research objectives, interpretability, and practicality of use for statistical analysis. Specifically:

1. Metrics corresponding to landscape patterns functionally meaningful for hydrological processes (i.e., infiltration, storage, run-off distribution, or interception) were selected for evaluation.
2. Area-weighted metrics were selected for measures that summarize size and extent of patch patterns across all patches at the class level because these metrics emphasize the role of larger patches over small ones. From a hydrological perspective, large patches of pervious land provide more opportunities for water infiltration than small patches.
3. Standard mean metrics were selected to summarize shape patch patterns across all patches at the class level because the hydrological importance of corridor-type patches (e.g., riparian buffers) is best described by the prevalence of elongated shapes, not the shape of the largest patch.

4. When multiple landscape metric options were available, priority was given to metrics that described spatial configuration as a relative measure to some other characteristic of the neighborhood (e.g., percent), or to metrics that could be parameterized easily with respect to neighborhood size. This criterion was added to facilitate comparisons between different scales of analysis (i.e., 1/4-mile and 1/2-mile buffered areas) and to avoid mixing very large values with very small ones in regression models—a condition that can exacerbate model heteroscedasticity or have an effect similar to data outliers and lead to wrong conclusions.

Four different types of landscape metrics were selected: proportion of land (PLAND), number of patches (NP), large patch index (LPI), and shape index (SHAPE). PLAND is a basic landscape composition metric that measures the proportional abundance of a specific land cover class in the landscape (%). This metric was calculated for pervious areas, wetlands, and woody lands. NP is a simple measure of the extent of subdivision or fragmentation that refers to the abundance of certain types of landscape features (count). This metric was calculated for agriculture and grass open space. LPI is a configuration metric that describes the spatial dominance by measuring the percent area comprised by the largest patch of a specific land cover type (%). Last, SHAPE is a spatial configuration metric that compares a patch's perimeter against the perimeter of a square of equal area. This metric was calculated for wetlands and grass open space. All of these metrics were extracted at the class level to avoid the influence of dominant urban land cover types in the calculation of metrics. Detailed descriptions and formulae of the final set of variables selected for study are listed in Appendix C.

4.4 Analytical Procedures

This study used ordinary least squares (OLS) and spatial autoregressive methods (SAR) to test the hypotheses relating factors of neighborhood context, risk, protection, and hydrological function with respect to flood property damage. The first goal of analysis was to specify four separate multivariate linear regression models using OLS estimators, one for each dependent variable at each scale of analysis. These models are referred to as *LQ*, *LH*, *SQ*, and *SH*, where *L* and *S* describe the dependent variables *likelihood of damage* and *severity of damage*, and *Q* and *H* describe neighborhood scales as either *1/4-mile* or *1/2-mile*, respectively. It is important to note that all variables were extracted for both scales of analysis, and that, to avoid collinearity, the two levels of measurement were considered independently during the analytical process.

Since the expectation is that location and scale matter in the evaluation of flood impacts, a second goal of analysis was to test whether or not there was a spatial pattern of influence that jointly affected neighborhoods under investigation. This process began with the specification of a spatial weight matrix, which was then used to test for spatial autocorrelation in OLS model residuals. Once the presence of a spatial structure in the data was confirmed, the third aim of analysis consisted of choosing the most appropriate spatial econometric model for estimating flood impacts as a function of a number of explanatory variables. This process was guided by an evaluation of different spatial regression estimation methods. Among alternative models that define structures of spatial dependence, the multivariate spatial error regression model based on General Method of Moments for Heteroscedastic Errors (GMM-Het) estimators was considered the most suitable (see section 4.4.3). The following sub-sections include detailed descriptions of the steps taken to perform these analytical procedures.

4.4.1 OLS Regression Models

The specification of OLS regression models started with general checks of variable specifications and linear relationships. Statistical linear models are sensitive to drastic differences in the ranges of values between variables, as well as the spread of these values within the variable's range. For example, comparing a variable ranging from 0 to 500,000 against a variable ranging from 0.0 to 0.4 is problematic; the distance between these points in statistical space, not just their values, can drive the linear relationship found in models and lead to erroneous conclusions, or cause severe heteroscedasticity. Similarly, heavily skewed variables can affect the efficiency of coefficient t-statistics.

Therefore, one way to avoid these problems and improve on the validity and efficiency of statistical models is to ensure that the values of all variables fall within a similar range, and that any extremely skewed variable (relative to the distribution of all other variables) is adjusted or transformed. Accordingly, this study (when needed) multiplied or divided by a constant the value of variables to adjust for neighborhood area or its square root as a distance reference standard. The benefits of these adjustments are threefold. First, they allow for the direct comparison of area-based and length-based metrics between models derived at different scales; second, they adjust the range of values proportionally to the neighborhood size and scale of analysis; and third, they preserve the actual value of measurements. Only when these adjustments were not possible was variable transformation considered.

The mathematical expression of OLS models is such that:

$$y = \propto + \sum_{i=1}^{n} X_i \beta_i + u \,,$$

where the dependent variable y is explained by the sum of the constant term α, the sum of the products between X_i independent variables and their respective coefficients β_i, and an error term u. The efficiency of OLS models is based on assumptions of independence and constant variance of error terms. Other assumptions, such as model linearity, and normality and homoscedasticity of model residuals need not be exact, but as approximate as possible. Accordingly, subsequent steps of model specification included standard checks of linear relationships with correlation matrices, multicollinearity (Variance Inflation Factor [VIF] <2.00, and model condition numbers),[2] and regression residuals.

All variables under consideration were added into models in blocks representing resilience factors (Models 1 to 3), except in the case of hydrological function indicators.

[2] With spatial data, even if VIFs are small, model condition numbers can be large. According to Anseling and Rey (2014), conditions numbers greater than 30 or 50 can be problematic.

Considering the collinearity of landscape metrics, hydrological function indicators were introduced in four smaller separate sub-groups (Models 4 to 7). The resulting models were:

- Model 1 Risk Factors (three variables).
- Model 2 Risk and Protection Factors (six variables).
- Model 3 Risk, Protection, and Context Factors (10 variables).
- Model 4 Basic model with PLAND (11 variables).
- Model 5 Basic model with agriculture NP, woody lands PLAND, grass open space NP and LPI, and wetlands SHAPE (15 variables).
- Model 6 Basic model with grass open space SHAPE and wetlands PLAND (12 variables).
- Model 7 Basic model with grass open space SHAPE and wetlands LPI (12 variables).

The four most-specified models (Models 4 to 7) allowed the separation of correlated variables and provided a robust measurement of the impact of each hydrological function indicator on flood impacts. These models were run for each dependent variable (*L* and *S*) and for each scale of analysis (*Q* and *H*). All models were run using Robust Heteroscedastic Errors to account for model heteroscedasticity that resulted, in part, from differences in the internal distribution of values within model variables. This adjustment of heteroscedasticity was preferred over model heteroscedastic adjustments that impose a transformation of all variables to make them more normal.

4.4.2 Spatial Data Analysis

In the presence of spatial dependence, OLS estimations are inefficient because regression residuals are not independent nor have a constant variance. To test the degree to which features with similar location share similar value attributes, this study used the Global Moran's I statistic. Specifically, Moran's I tests the null hypothesis of spatial randomness against the alternative hypothesis of spatial structure. The mathematical expression for this index is such that:

$$I = \left[\frac{\sum_i^n \sum_j^n w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_i^n (y_i - \bar{y})^2}\right] \Big/ \left[\frac{\sum_i^n \sum_j^n w_{ij}}{n}\right]$$

$$\text{for } i \neq j,$$

where w_{ij} refers to an *n* by *n* spatial weight matrix that formalizes what is meant by spatial similarity between pairs of observations; y_i and $\bar{y}$ are the observed and mean values in the *i*th location, respectively; and *n* is the total number of observations. Similar to a correlation coefficient, the Moran's I index varies from -1.0 to +1.0. A key component for the functionality of the spatial autocorrelation analysis, and subsequent spatial regression analyses, is the spatial weight matrix. These weights define the geographic structure between observed neighborhood cases. The matrix can be created based on distances, boundary contiguity, or number of nearest neighbors using the projected point location of cases (i.e., neighborhood centroids) on the map. Taking into account the uneven distribution of cases across the county, the phenomenon under study, and the scale of analysis, a distance-based spatial weight matrix was considered most appropriate. One limitation of this type of matrix is that it can identify “islands,” or cases without neighbors, for which a spatial similarity statistic cannot be calculated and the cases need to be removed.

Table 9 NFIP data samples for regression analyses with each dependent variable.

	y=Likelihood of damage			y=Severity of damage		
Data Aggregation	Cells	Policies	Claims	Cells	Policies	Claims
Population	1,183	107,533	16,775	1,183	107,533	16,775
Initial Sample						
-Cases for 1/4-mile	540	18,394	2,668	540	18,394	2,668
-Cases for 1/2-mile	540	68,613	10,200	540	68,613	10,200
Data analysis restrictions						
-Cases for 1/4-mile	(8)	(96)	(19)	(13)	(181)	(81)
-Cases for 1/2-mile	(8)	(262)	(36)	(13)	(697)	(336)
Final Sample						
-Cases for 1/4-mile	532	18,298	2,649	527	18,213	2,587
		17.0%	*15.8%*		*16.9%*	*15.4%*
-Cases for 1/2-mile	532	68,351	10,164	527	67,916	9,864
		63.6%	*60.6%*		*63.2%*	*58.8%*

After a sensitivity analysis of the lag influence of the dependent variables, a zonal structure of 3,280 meters or 12 cells was selected for the spatial weight matrix. This spatial structure identified eight island cases, which were removed from further analysis (see Table 9). With shorter distances (of 4-cell or 8-cell zones), the number of island cases was larger (36 and 17, respectively). Also, when using more restrictive weight matrices, the Lagrange multiplier (LM) tests would suggest the use of spatial lag regression models over spatial error models. A spatial error model is preferred because it does not require the use of a modified version of the dependent variable (or *y_lag*) to explain the dependent variable. The need for an *y_lag* statistical adjustment suggests that the scale at which the structure of spatial dependence is being defined is smaller than the scale at which it functions. In spatial error models, the structure of spatial dependence is incorporated in the error term, which suggests that the auto-correlation of OLS model residuals is likely the result of heterogeneity in observational units and sampling patterns, or a missing variable with spatially distinct effects. Therefore, the choice was made to use a spatial error regression model based on a 12-cell spatial weights matrix.

4.4.3 Spatial Error Regression Models

The mathematical expression of a spatial error regression model is such that:

$$y = \propto + \sum_{i=1}^{n} X_i \beta_i + (\lambda W u + \varepsilon),$$

where the OLS error term is modified by the spatial autoregressive parameter λ according to the specification of weights matrix W and an idiosyncratic error ε. There are a number of statistical techniques available for the estimation of the autoregressive parameter that are applicable to the type of model produced in this study. In the absence of guidelines, the choice on the most appropriate technique was based on a comparison of spatial parameter lambda (λ) estimates and standard errors, and their impact on model pseudo-R^2 scores. The estimate that led to the highest pseudo-R^2 was the Maximum Likelihood (ML) method. This method was initially selected; however, after implementation, model diagnostics revealed strong evidence of remaining heteroscedasticity. These types of results supported using GMM-Het rather than ML. Therefore, among alternative models, the multivariate spatial error regression model based on GMM-Het estimators was considered the most suitable.

The same models that were run using OLS regression methods were run again using spatial error autoregressive methods. These models were then used to test the central hypothesis that hydrologic function indicators have a moderating effect on flood damages to residential property at the neighborhood level. Even though all hypotheses were stated with one direction of association (positive or negative), two-tail tests were used to assess the significance of model coefficients because it is more conservative, in the sense that it provides less power to detect an effect. Model performance indicators (i.e., pseudo-R^2 scores) and statistical significance of estimated coefficients were noted and compared across scales for each dependent variable. Standardized coefficients were calculated on all models to allow effect-size comparisons of model coefficients, and the relative contribution of different factors of resilience was assessed by adding groups of variables to the models and noting changes in pseudo-R^2 scores.

4.5 Descriptive Analysis and Diagnostics

This study analyzed 532 neighborhoods in Harris County, Texas, comprised of 68,351 single-family residential properties with NFIP policies at the time TS Allison impacted the area in 2001. A total of 10,164 of those properties, located in 382 sampled neighborhoods, suffered flood damages that totaled over $307 million (USD 2001). Of all policies-in-force at the time of disaster, 15% had claims for property damages, for an average of $30,224. Overall, the data revealed well-distributed variations in the measures of interest, which supports using multiple linear regressions. In general, 1/4-mile neighborhood analyses had more cases with contrasting characteristics than 1/2-mile analyses. Table 10 lists the percent number of cases with information on a given variable, and Table 11 lists variable statistics for 1/4-mile and 1/2-mile neighborhoods.

Average values in all variables were very similar for both scales of analysis (see Table 11). For example, for all insured properties at both scales of analysis, there was, on average, a 15% chance of being impacted by floods, and for that damage to correspond, on average, to 4% of the assessed value of all insured properties. These values are also very similar to those for the entire population of Harris County. For instance, the average *likelihood of damage* for all NFIP policies in Harris County was 15.6% (16,775 claims/107,533 policies), and the average *severity of damage* was 4.1%.

Since the generalizability of regression model results is tied to how well samples represent the population, the similarity in the average value for the dependent variables across both scales of analysis, and between sample and population values suggest that the findings are generalizable to all NFIP properties identified in Harris County (i.e., the population under study). The variables with noticeable differences in average values between 1/4-mile and 1/2-mile scales (i.e., storm-water pipes, overland streams, and number of patches of agriculture and grass open space) were carefully reviewed, and the

Table 10 Cases capturing contrasting information in relevant variables.

Variables	1/4-mile neighborhoods *# Cases*	*%*	1/2-mile neighborhoods *# Cases*	*%*
Reporting property damage	278	52.3	382	71.8
Risk Factors				
* Located in the floodplain	299	56.2	422	79.3
* With any intense land uses	438	82.3	521	97.9
* Protected from floods by dams	177	33.3	177	33.3
Protection Factors				
* With storm-water piped infrastructure	224	42.1	252	47.4
* Containing buildings with elevated designs	398	74.8	487	91.5
* With overland streams and drains	340	63.9	479	90.0
* Containing poorly drained soils	353	66.4	425	79.9
Hydrological Function Indicators				
* With pervious areas	531	99.8	532	100.0
* With agricultural lands	100	18.8	144	36.5
* With woody lands	375	70.5	491	92.3
* With grass open space	527	99.1	532	100.0
* With wetlands	235	44.2	375	70.5

N=532

Table 11 Summary statistics for 1/4-mile and 1/2-mile neighborhood analyses.

Variable*	1/4-mile neighborhoods Mean	Median	Range			Std. Dev.	1/2-mile neighborhoods Mean	Median	Range			Std. Dev.	Units
Likelihood of damage	14.74	1.52	0	to	100	24.90	14.77	4.55	0	to	100	21.79	Proportion
Severity of damage**	4.17	0.02	0	to	62.09	9.22	4.20	0.29	0	to	53.91	8.74	Percent property value
Road density	3.12	3.00	2.08	to	4.96	0.52	3.11	3.02	2.27	to	5.50	0.45	Normalized (ln)[A]
Floodplain exposure	21.59	2.39	0	to	100	32.04	21.69	8.47	0	to	100	27.08	Percent area
Land use intensity	11.76	7.35	0	to	72.05	13.34	12.35	9.65	0	to	54.52	10.63	Percent area
Dams	0.33	0.00	0	to	1	0.47	0.33	0.00	0	to	1	0.47	1/0
Storm-water pipes	1.29	0.00	0	to	7.61	1.94	2.40	0.00	0	to	13.78	3.33	Normalized [A]
Elevated bg. design	28.27	16.67	0	to	100	28.94	28.41	18.71	0	to	100	26.01	Percent buildings
Minority pop.	31.99	24.39	1.55	to	100	24.67	32.06	24.66	1.88	to	99	24.07	Percent population
Precipitation	16.00	16.37	2.3	to	31	5.88	16.00	16.38	2.3	to	31	5.88	Inches
Overland streams	6.76	0.69	0	to	109.56	17.71	13.28	1.58	0	to	121.84	23.79	Normalized [A]
Poor soil drainage	41.36	23.05	0	to	100	42.47	41.42	32.19	0	to	100	38.48	Percent area
Pervious PLAND	25.09	18.19	0	to	91.23	22.08	27.73	23.57	0.53	to	87.12	20.31	Percent area
Agriculture NP	0.52	0.00	0	to	16	1.63	2.01	0.00	0	to	49	4.63	Count
Woody lands PLAND	6.50	1.23	0	to	71.35	10.93	7.43	3.25	0	to	63.48	9.91	Percent area
Grass open sp. NP	9.19	8.00	0	to	36	5.39	34.35	33.00	4	to	84	15.09	Count
Grass open sp. LPI	8.15	4.41	0	to	72.24	10.75	5.98	3.71	0	to	45.15	6.72	Percent area
Grass open sp. SHAPE	1.27	1.23	0	to	3.57	0.30	1.25	1.24	1	to	2.63	0.15	Index
Wetlands PLAND	3.00	0.00	0	to	60.89	8.13	3.67	0.33	0	to	50.31	7.93	Percent area
Wetlands LPI	2.35	0.00	0	to	60.89	7.01	2.40	0.13	0	to	41.25	6.00	Percent area
Wetlands SHAPE	0.54	0.00	0	to	3.20	0.64	0.88	1.05	0	to	4.97	0.65	Index

* *N*=532 for all variables except Severity of damage** which was calculated with *N*=527.
bg. = building; pop. = population; sp. = space; PLAND = proportion of land; NP = number of patches; LPI = largest patch index.
[A] Variables measured in linear meters (m) were normalized by the square root of the neighborhood's area (m2).

differences in ranges were found to be primarily the result of wider geographic scales of analysis that were able to capture more dispersion in the data.

The total area of neighborhoods examined in this study was 27,046 hectares (ha) for 1/4-mile cases (104.4 mi^2 or 6.1% of the county's area), and 108,201 ha for 1/2-mile cases (417.8 mi^2 or 24.5% of the county's area). The largest shares of land at both scales of analysis described in 30m grid cells were allocated to urban land uses & roads (72% and 75%, respectively, for 1/4- and 1/2-mile neighborhoods). Among pervious land cover types, grass open space was the most prevalent (13.5% and 14%, respectively), followed by woody lands (6.5% and 7.5%, respectively), wetlands (3% and 4%, respectively), and agriculture lands (2% and 3%, respectively). Interestingly, only one case in the study of 1/4-mile neighborhoods did not have any type of pervious land cover, as recorded by C-CAP data of 30 m x 30 m pixels. Since the lack of pervious land cover is still valuable information, this case was retained.

Model diagnostics for initial OLS regression models revealed strong evidence of heteroscedasticity and borderline levels of model collinearity (see OLS regressions and tests results in Appendix D). In general, lower levels of heteroscedasticity were found in 1/4-mile radius neighborhood models than in 1/2-mile models. Lower levels of heteroscedasticity were also found in models for *likelihood of damage* than in models for *severity of damage*. Similarly, lower levels of collinearity were found in 1/4-mile models than in 1/2-mile models, but without noticeable differences between likelihood and severity models. Even though VIF values for all variables were maintained below a value of 2.0, all models revealed evidence of border high collinearity, especially in 1/2-

mile models. Still, OLS model multicollinearity condition numbers in 1/4-mile and 1/2-mile analyses remained within the suggested cut-off values of 30 and 50 needed for spatial regressions (Anselin & Rey, 2014). The impacts of scale on model collinearity make sense. Measures of local environmental conditions collected for cases of 1/2-mile radius tend to be more similar to regional average conditions than the measures collected for cases of 1/4-mile radius. Consequently, in 1/2-mile analyses there are fewer cases with contrasting information than in 1/4-mile analyses, and the overall variability of values across all cases is reduced. With wider scales of analysis (e.g., 1, 1.5, or 2 mile radius areas) the impacts on model collinearity can only be exacerbated, as a number of environmental measures will tend to provide redundant information.

Highly significant heteroscedasticity tests are often found when regression residuals are autocorrelated. This was confirmed with the Global Moran's I statistical tests (pseudo-p<.000), which indicated that the pattern of damage (as represented in the most-specified regressions, Models 4 to 7) is not compatible with spatial randomness, and that there is a general pattern of spatial clustering in the data. Overall, lower Moran's I scores were found in 1/4-mile models than in 1/2-mile models, and in regression models for *likelihood of damage* than in models for *severity of damage*. Further diagnostics of spatial dependence consistently led to the specification of spatial error regression (SER) models as the proper alternative to adjust for the autocorrelation of residuals (see Moran's I and Lagrange multiplier test results in Appendix D). An exploration of the most suitable estimation method for spatial error parameters initially led to ML methods (see lambda estimation comparison tables in Appendix D); however, diagnostics of SER regression results with ML estimation revealed strong evidence of remaining heteroscedasticity, which argued in favor of using GMM-Het over ML (Anselin & Rey, 2014). Therefore, the regressions with both dependent variables (i.e., *likelihood of damage* and *severity of damage*), for Models 1 to 7, at both scales of analysis (i.e., 1/4-mile and 1/2-mile) were re-run following recommended adjustments. The results from these final regression analyses are presented in Section 5: Results.

4.6 Validity Assessment

The cross-sectional nature of this study is in essence a one-group post-test-only research design. The lack of a control group or pretest observations poses internal validity threats. However, the extensive background knowledge (empirical and theoretical) already available on how the variables included in the study behave provided the basis for causal inference. Also, the study made careful note of the temporal resolution of data and ensured that all the independent variables represented accurately the physical and socio-economic landscape of the study area for the year of the disaster event. Furthermore, the robustness of measures was confirmed with regression analyses in an area four times larger than the 1/4-mile radius neighborhoods of focal interest.

4.6.1 Statistical Conclusion Validity

Given the large sample of cases (N=532 for dependent variable *likelihood of damage*, and N=327 for dependent variable *severity of damage*), the probability of Type I or Type II errors is low; that is, the spatial regression analyses had enough statistical power to identify significant relationships between the dependent variables and the independent variables.

4.6.2 External Validity

The similarity in the average values of the dependent variables for the population and for the samples in 1/4-mile and 1/2-mile radius neighborhoods suggests that the results from either sample can be generalized to other groups or populations of interest within Harris County for TS Allison.

4.6.3 Internal Validity

The availability of geographic-based information and analysis tools allowed this study to find opportunities for integrating a greater number of influencing factors. Except for conceptual models, most assessments can only include a few of these parameters. While this research is no exception, the large sample of cases allowed the specification of a flood damage assessment model with the most comprehensive set of relevant independent variables to date. Nonetheless, several considerations were taken into account to increase internal validity.

First, this study focused on a single flood disaster event, TS Allison, which allowed controlling for the possible influence of other flood causing factors such as strong winds or surge events. Second, this study included several community-moderating variables to account for those factors not directly related to the physical form of the built environment that may influence the dependent variables. Third, multicollinearity was avoided in the selection and measurement of independent variables and in the specification of regression analyses. Since multicollinearity may lead to unstable regression coefficients with inconsistent signs of association and large standard errors (Cohen, Cohen, West, & Aiken, 2003), the measurement of related concepts (e.g., perviousness and imperviousness) was carefully defined so that each independent variable conveyed unique information not contained by other factors for the prediction of the dependent variables. This is an important consideration when using land cover data where the sum of all land cover types equals a constant (i.e., the total area under study). While most statistical packages will identify redundant independent variables, they will not catch the effect of land cover data redundancy since these concepts are not introduced into regression models as categorical variables but as separate continuous variables (e.g., area or percent area values). Last, this study included a thorough check of data completeness and quality to ensure measurement and temporal validity of all variables.

4.6.4 Construct Validity

The measurement of two important parameters of flood damage studies was further specified to improve on our current understanding of flood resilience.

Most damage assessment studies measure flood loss by combining insured claim payments of damages to residential buildings and contents. This study sought to further improve the generalizability of flood assessment analyses by restricting the selection of policy records to only property damages to single-family residential structures, and by using the value claim payments are based on. The NFIP registers the total building damage value in ACV amounts "that would be payable to the insured under the policy for damages to the main building if there were an unlimited dollar amount of coverage for covered items and no policy deductible" (FEMA, 2015, pp. 4-202). This value was considered an accurate assessment of actual flood damages.

Similar improvements were sought for soil measures. Soil infiltration capacity was measured using drainage classification groups rather than average porosity or permeability rates of the top layers of soil profiles. The advantage of soil drainage classification is that it incorporates a number of conditions that affect soil infiltration capacities, and it has clear applications for land use planning and design. These classifications of soils are used by planners and designers for site analyses and the evaluation of suitable areas for development.

5. RESULTS

5.1 Empirical Results

Results from spatial error regression (SER) models indicated that several hydrological function indicators act to reduce the adverse impacts of flooding, even when controlling for risk, mitigation, and other context variables. Table 12 shows the effects of adding groups of variables into regression models for *likelihood of damage* in 1/4-mile radius neighborhoods (results for *severity of damage* are presented in Appendix D). The first two groups of variables in Table 12 correspond to addition of control variables related to flood risk (Model 1) and flood protection factors (Model 2). Model 3 corresponds to the addition of control variables for socio-economic, hazard, and ecological contexts.

The next four models expand on ecological context factors in Model 3. Models 4 to 7 present the addition of variables that measure the hydrological function of landscapes with similar yet complementary measures.[3] For example, in Model 4, an increase in the area of pervious land was significantly associated with a reduction in the likelihood and severity of flood damage to insured properties during TS Allison (pervious PLAND, $p<.01$, **Hypothesis 4.1**). In fact, based on standardized betas, this variable ranked above all flood protection variables in models for *likelihood of damage*, and above most protection variables in models for *severity of damage*.

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[3] As mentioned in Section 4 Methods, these variables could not be added together into the same regression model due to their collinearity.

Table 12 Spatial error regression models explaining the likelihood of flood damage in 1/4-mile neighborhoods.

SEM GMM-HET	*y* = Likelihood of damage											
	Model 1 Risk Factors				Model 2 Risk and Protection				Model 3 Risk, Protection, and Context			
Model	(LQ1)				(LQ2)				(LQ3)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-15.298	-0.004	5.83	***	-15.784	-0.004	6.20	**	-46.200	-0.003	7.66	***
Road density	7.756	0.163	2.01	***	7.791	0.164	2.03	***	7.552	0.159	1.88	***
Floodplain exposure	0.221	0.285	0.03	***	0.227	0.291	0.03	***	0.212	0.273	0.03	***
Land use intensity	0.079	0.042	0.08	*.332*	0.084	0.045	0.08	*.332*	0.075	0.040	0.08	*.327*
Dams					8.029	0.152	2.99	***	5.539	0.105	2.57	**
Storm-water pipes					-0.075	-0.006	0.48	*.876*	-0.315	-0.025	0.44	*.472*
Elevated bg. design					-0.083	-0.097	0.03	***	-0.089	-0.104	0.03	***
Minority pop.									0.005	0.004	0.05	*.927*
Precipitation									1.811	0.428	0.24	***
Overland streams									0.075	0.054	0.06	*.215*
Poor soil drainage									0.079	0.135	0.02	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass open sp. NP												
Grass open sp. LPI												
Grass open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
Lambda λ	0.640	0.640	0.04	***	0.608	0.608	0.04	***	0.441	0.441	0.06	***
pseudo-R2	0.136				0.216				0.425			

N=532. SEM = spatial error model; GMM-Het = general method of moments for heteroscedastic errors; L = likelihood of damage; Q = quarter-mile neighborhoods.
b.g. = building; pop. = population; sp. = space; PLAND = proportion of land; NP = number of patches; LPI = largest patch index.
****p* <.01, ***p* <.05, **p* <.10 for two-tail tests. For directional hypotheses, a less-restrictive one-tail significance tests may be applied by dividing reported *p*-values by 2.

Table 12 Continued.

SEM GMM-HET	*y* = Likelihood of damage															
	Model 4 HFI Part 1				Model 5 HFI Part 2				Model 6 HFI Part 3				Model 7 HFI Part 4			
Model	(LQ4)				(LQ5)				(LQ6)				(LQ7)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	b	beta	s.e.	*p*
constant	-44.925	-0.001	7.65	***	-46.056	0.001	7.53	***	-39.145	-0.001	7.88	***	-38.704	-0.001	7.97	***
Road density	8.890	0.187	1.88	***	7.579	0.159	1.94	***	7.855	0.165	1.86	***	7.770	0.163	1.86	***
Floodplain exposure	0.217	0.280	0.03	***	0.217	0.279	0.03	***	0.224	0.288	0.03	***	0.225	0.289	0.03	***
Land use intensity	0.017	0.009	0.08	*.829*	0.047	0.025	0.08	*.554*	0.048	0.026	0.08	*.532*	0.049	0.026	0.08	*.527*
Dams	5.260	0.100	2.53	**	5.382	0.102	2.52	**	5.001	0.095	2.53	**	5.048	0.096	2.52	**
Storm-water pipes	-0.750	-0.058	0.45	*	-0.375	-0.029	0.46	*.418*	-0.606	-0.047	0.44	*.168*	-0.610	-0.047	0.44	*.166*
Elevated bg. design	-0.091	-0.106	0.03	***	-0.082	-0.096	0.03	***	-0.087	-0.101	0.03	***	-0.087	-0.101	0.03	***
Minority pop.	0.003	0.003	0.05	*.945*	0.001	0.001	0.05	*.977*	0.006	0.006	0.05	*.902*	0.006	0.006	0.05	*.908*
Precipitation	1.745	0.412	0.24	***	1.758	0.415	0.24	***	1.793	0.424	0.24	***	1.794	0.424	0.24	***
Overland streams	0.094	0.067	0.06	*.104*	0.076	0.054	0.06	*.186*	0.104	0.074	0.06	*	0.103	0.073	0.06	*
Poor soil drainage	0.079	0.135	0.02	***	0.077	0.131	0.02	***	0.082	0.140	0.02	***	0.082	0.140	0.02	***
Pervious PLAND	-0.127	-0.112	0.04	***												
Agriculture NP					-0.660	-0.043	0.36	*								
Woody lands PLAND					-0.012	-0.005	0.08	*.877*								
Grass open sp. NP					0.351	0.076	0.17	**								
Grass open sp. LPI					-0.110	-0.048	0.06	*								
Grass open sp. SHAPE									-5.377	-0.064	1.84	***	-5.573	-0.066	1.86	***
Wetlands PLAND									-0.220	-0.072	0.10	**				
Wetlands LPI													-0.270	-0.076	0.11	**
Wetlands SHAPE					-1.630	-0.042	1.32	*.217*								
Lambda λ	0.444	0.444	0.06	***	0.433	0.433	0.06	***	0.431	0.431	0.06	***	0.431	0.431	0.06	***
pseudo-R2	0.431				0.440				0.437				0.438			

N=532. SEM = spatial error model; GMM-Het = general method of moments for heteroscedastic errors; L = likelihood of damage; Q = quarter-mile neighborhood. b.g. = building; pop. = population; sp. = space; PLAND = proportion of land; NP = number of patches; LPI = largest patch index.
****p* <.01, ***p* <.05, **p* <.10 for two-tail tests. For directional hypotheses, a less-restrictive one-tail significance tests may be applied by dividing reported *p*-values by 2.

A more in-depth analysis of pervious land cover (Models 5 to 7) revealed the importance of greenways and wetlands for reducing flood impacts to property. For example, an increase in the prevalence of elongated shapes of grass open space was significantly associated with a reduction in the likelihood and severity of flood damage (grass open space SHAPE, $p<.01$, **Hypothesis 4.7**). Also, an increase of wetland area (wetland PLAND) and an increase in the area of the largest patch of wetland (wetland LPI) were also significantly associated with reductions in the likelihood and severity of flood damage ($p<.05$, **Hypotheses 4.2** and **4.3**).

The mitigating effects of increases in area of large parks were found to significantly, albeit in weak associations, for reducing the likelihood and severity of flood property damage, (grass open space LPI, $p<.10$, **Hypothesis 4.6**). In contrast, increases in isolated patches of grass open space (grass open space NP) were significantly associated with the increased likelihood ($p<.05$) and—in a weaker predictor—severity of flood damage ($p<.10$, **Hypothesis 4.8**).

Considering the general large size of agricultural parcels, the effects of multiple parcels of agricultural land are not very easily captured in a 1/4-mile neighborhood. Still, an additional unit of an agricultural patch of land had a marginally significant effect in reducing the *likelihood of damage* (agriculture NP, $p<.10$), but no significant effect on *severity of damage* (**Hypothesis 4.5**). The effects of wetland shape were generally not significant in 1/4-mile analyses, but clearly significant in 1/2-mile analyses ($p<0.05$). Therefore, this variable was considered to partially support the stated hypothesis (wetland SHAPE, **Hypothesis 4.4**). A variable that plainly did not have a significant effect on either measure of flood impacts was total forested areas (woody lands PLAND, **Hypothesis 4.9**). Overall, of the nine expected associations between hydrological function indicators and flood impacts, regression results in 1/4-mile radius neighborhoods supported seven hypotheses with respect to *likelihood of damage*—six of which (except for agriculture NP) were also supported with respect to *severity of damage*—one hypothesis was considered to be partially supported, and another one was not supported in any regression model.

Several risk, protection, and other contextual variables in the models were also found to be significant predictors of flood impacts. As expected, risk factors related to increases in road density and floodplain exposure significantly increased the likelihood and severity of flood damage (p<.01, **Hypotheses 1.1** and **1.2**). These factors had the second and third largest standardized betas in all regression models. This finding indicates the strongest predictors of flood property damages were the risk factors.

Neighborhoods located in watersheds with flood protection dams were significantly more likely to have a greater likelihood of flood damage, and flood damage severity (p<.05, **Hypothesis 2.1**). At first glance, this result seemed counterintuitive, but the shape of the landscape below these structures is the original floodplain—i.e., a "landscape bowl," naturally designed to receive run-off waters from the surrounding land. Without the dams, however, flood impacts would likely had been more extreme. Also among protection factors, elevated building designs were found to be significantly associated with reduced flood impacts in both types of models (p<.01, **Hypothesis 2.3**).

This variable had a weaker effect (i.e., smaller beta coefficient) on observed property damages in the models for *likelihood of damage* than in models for *severity of damage*.

As expected, baseline environmental context variables had moderating effects on flood property damages. For example, an increase in the area of poorly drained soils was significantly associated with the increased *likelihood of damage* ($p<.01$), and to a lesser extent, the *severity of damage* ($p<.10$, **Hypothesis 3.4**). Aside from the spatial parameter λ for error adjustments, precipitation was by far the most powerful predictor in all models, where increasing amounts of rainfall resulted in significantly more properties being impacted by floods, and in more severe damages to property ($p<0.01$, **Hypothesis 3.2**), even controlling for drainage network structures.

The effects of storm-water pipe infrastructure were seldom marginally significant and inconsistent in regression models for both dependent variables. Thus, the results did not support the stated hypothesis (**Hypothesis 2.2**). Overland stream network was marginally significant ($p<0.10$), and in models where it was not significant it maintained close to marginal levels of significance with p-value differences in the hundredth level (1/2-mile models) or thousandth level (1/4-mile models). While there may be some partial correlation effects causing these slight changes, the relationships between lengthy overland streams and flood impacts seem consistent, and therefore, the variable was considered to provide partial support of the stated hypothesis (**Hypothesis 3.3**). Two variables of interest that clearly did not have a significant effect on measures of flood damage were high land use intensity (**Hypothesis 1.3**) and percent minority population (**Hypothesis 3.1**). Overall, of the 10 expected associations between flood impacts and risk, protection, and context factors, regression results in 1/4-mile neighborhoods supported six hypotheses with respect to both dependent variables, while one hypothesis was considered partially supported, and another three were not supported.

The robustness of fully specified regression model results (i.e., Models 4 to 7) was further confirmed by comparing them against results obtained from parsimonious regression models (see Appendix D). After removing non-significant variables (i.e., land use intensity, storm-water pipes, minority population, and woody lands PLAND), model coefficients only changed by less than half a standard error, and generally maintained or strengthened their levels of significant association. Also, model fit scores were changed negligibly (mostly in the thousandth level). Since the relevance of all variables are clearly supported by theory, and the differences between fully-specified and parsimonious regression models were minimal, fully-specified models were retained for further discussion and interpretation.

5.2 Model Quality

Classic measures of model fit suggested that regression models in 1/4-mile radius neighborhoods accounted for a greater level of explained variance in *likelihood of damage* (pseudo-$R^2 \approx 0.44$) than in *severity of damage* (pseudo-$R^2 \approx 0.38$). Initially, the regression models for both dependent variables behaved similarly. For example, results from Type-1 models with risk factors explained 11% and 14% of the variance in the models for *likelihood of damage* (Model LQ1) and *severity of damage* (Model SQ1), respectively. With the introduction of protection factors, the explained variance in

Type-2 models was practically doubled in regressions for both dependent variables (pseudo-R^2=0.22 in Model LQ2, and pseudo-R^2=0.21 in Model SQ2). Among context factors introduced with Type-3 models, measures for soils seem to create a gap of 5 points of explained variance between Model LQ3 and Model SQ3. This gap was slightly larger by one or two extra percentage points of explained variance with the introduction of additional landscape hydrological function indicators. This suggests that ecological context indicators (in particular soils) are an important component of flood resilience, and that the added contribution of hydrologic indicators, while not particularly large, can help further characterize the resilience of communities to floods.

One way to evaluate the robustness and reliability of regression results for 1/4-mile radius neighborhoods is to run the same regression models for selected locations using a wider neighborhood scale. Regression results for Types-1 through 7 models in 1/2-mile radius neighborhoods with each dependent variable are provided in Appendix D. Given that all variables were defined in relative terms with respect to neighborhood area (for percent area values) or its area's square root (for a distance reference standard), regressions with the same set of variables derived at different scales were directly comparable. A variable that is only significant in one scale of analysis but not another suggests that, while influential, the measure may not be very reliable due to potential problems with partial correlations or levels of model collinearity.

After an evaluation of regressions for *likelihood of damage* at both 1/4-mile and 1/2-mile radius scales (see Table 13 and parsimonious regression model results in Appendix D), two of 7 significant hydrological function indicators were considered important but less reliable: grass open space LPI and wetland SHAPE. In addition, after an evaluation of models for *severity of damage*, three of 7 significant hydrological function indicators were considered important yet less reliable as well: agriculture NP, grass open space LPI, and grass open space SHAPE. A summary of all regression results in terms of significant or non-significant findings, and whether or not these findings supported the hypotheses stated in Section 3: Theory of this dissertation, is provided in Table 13.

Table 13 also provides an overall assessment of the relative importance of independent variables with respect to each dependent variable. Whether or not a statistical result supported a stated hypothesis, this assessment was based on rankings of independent variable standardized coefficients across all models. Any significant variables that maintained a 1st to 4th ranking across all models were considered to be of high importance. Subsequent significant variables that shifted between 5th and 6th rankings were considered to be of medium importance, and significant variables that fluctuated between rankings two levels apart, or variables that yielded inconsistent results of significance were considered to be of low importance. Since hydrological factors further describe the potential effects of pervious land areas, their evaluation was tied to the ranking of pervious areas in Type-4 models. A discussion on the potential implications of these results is provided in Section 6: Discussion.

Table 13 Summary of findings from all spatial error regression models.

	Risk Factors				Risk and Protection				Risk, Protection, Context				Model 4 HFI Part 1			
	Likelihood		Severity		Likelihood		Severity		Likelihood		Severity		Likelihood		Severity	
Variables	(LQ1)	(LH1)	(SQ1)	(SH1)	(LQ2)	(LH2)	(SQ2)	(SH2)	(LQ3)	(LH3)	(SQ3)	(SH3)	(LQ4)	(LH4)	(SQ4)	(SH4)
Road density	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Floodplain exposure	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Land use intensity	n.s.	+	n.s.	n.s.	n.s.	+	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Dams					+	+	+	+	+	+	+	+	+	+	+	+
Storm-water pipes					n.s.	+	n.s.	n.s.	n.s.	+	n.s.	n.s.	--	+	--	n.s.
Elevated bg. design					--	--	--	--	--	--	--	--	--	--	--	--
Minority pop.									n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Precipitation									+	+	+	+	+	+	+	+
Overland streams									n.s.	n.s.	+	n.s.	n.s.	n.s.	+	+
Poor soil drainage									+	+	+	+	+	+	+	+
Pervious PLAND													--	--	--	--
Agriculture NP																
Woodlands PLAND																
Grass open sp. NP																
Grass open sp. LPI																
Grass open SHAPE																
Wetlands PLAND																
Wetlands LPI																
Wetlands SHAPE																
Lambda	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Pseudo-R2	0.14	0.14	0.11	0.12	0.22	0.26	0.21	0.24	0.42	0.51	0.37	0.41	0.43	0.51	0.37	0.40

L = likelihood of damage; S = severity of damage; Q = quarter-mile radius neighborhoods; H = half-mile radius neighborhoods.
HFI = Hydrological Function Indicators; PLAND = proportion of land; NP = number of patches; LPI = largest patch index.
b.g. = building; pop. = population; sp. = space; n.s. = non-significant.

Table 13 Continued.

	Model 5 HFI Part 1				Model 6 HFI Part 1				Model 7 HFI Part 1				Overall Assessment		
	Likelihood		Severity		Likelihood		Severity		Likelihood		Severity		Supports	Relative Importance*	
Variables	(LQ5)	(LH5)	(SQ5)	(SH5)	(LQ6)	(LH6)	(SQ6)	(SH6)	(LQ7)	(LH7)	(SQ7)	(SH7)	Hypothesis	L	S
Road density	+	+	+	+	+	+	+	+	+	+	+	+	Yes	High	High
Floodplain exposure	+	+	+	+	+	+	+	+	+	+	+	+	Yes	High	High
Land use intensity	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	No	-	-
Dams	+	+	+	+	+	+	+	+	+	+	+	+	No	Medium	Medium
Storm-water pipes	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	--	n.s.	n.s.	n.s.	--	n.s.	No	-	-
Elevated bg. design	--	--	--	--	--	--	--	--	--	--	--	--	Yes	Medium	High
Minority pop.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	No	-	-
Precipitation	+	+	+	+	+	+	+	+	+	+	+	+	Yes	High	High
Overland streams	n.s.	n.s.	+	n.s.	+	+	+	+	+	n.s.	+	+	Partial	Low	Low
Poor soil drainage	+	+	+	+	+	+	+	+	+	+	+	+	Yes	High	Medium
Pervious PLAND													Yes	Medium	Medium
Agriculture NP	--	--	n.s.	--									Partial	Low	Low
Woodlands PLAND	n.s.	n.s.	n.s.	n.s.									No	-	-
Grass open sp. NP	+	+	+	+									No	Medium	Medium
Grass open sp. LPI	--	n.s.	--	n.s.									Partial	Low	Low
Grass open SHAPE					--	--	--	--	--	--	--	n.s.	Partial	Low	Low
Wetlands PLAND					--	--	--	--					Yes	Medium	Medium
Wetlands LPI									--	--	--	--	Yes	Medium	Medium
Wetlands SHAPE	n.s.	--	n.s.	n.s.									Partial	Low	Low
Lambda	+	+	+	+	+	+	+	+	+	+	+	+			
Pseudo-R2	0.44	0.53	0.38	0.43	0.44	0.52	0.38	0.41	0.44	0.52	0.38	0.41			

L, likelihood of damage; S, severity of damage; Q, quarter-mile radius neighborhoods; H, half-mile radius neighborhoods.
HFI, Hydrological Function Indicators; PLAND, proportion of land; NP, number of patches; LPI, largest patch index.
b.g. building; pop., population; sp., space; n.s., non-significant.
* Assessment of all statistically significant variables whether or not they supported stated hypotheses.

6. DISCUSSION

As described in Section 3: Theory, features of the landscape mosaic are tightly linked to ecological processes (Alberti & Marzluff, 2004; Cumming, 2011; Grimm et al., 2000; Pickett et al., 2011; Turner, 2005). Based on this premise, specific physical and spatial characteristics of landscapes were hypothesized to affect the hydrological function of neighborhoods, as well as the flood damage to property.

This study's results suggest that natural features of landscapes played a statistically significant role in regulating the hydrological function of neighborhoods in Harris County, Texas, during TS Allison. By extending these results to patterns of neighborhood growth and development, it follows that some design considerations can be adopted to modify the probability of flood damage and the severity of economic impacts to residential properties in neighborhoods or, scaled up through analysis of land cover, larger areas and even the entire county. The findings from this research support the notion that natural space in urban areas can help reduce the risk of flood damage to property, and that communities can enhance their resilience to floods through careful land use planning and design.

6.1 Hydrological Function Indicators

6.1.1 Landscape Infiltration

Large areas of pervious land cover can improve the landscape's performance with respect to floods. For example, the average likelihood of damage for the entire population of insured single-family residential properties in Harris County was 15.6% (i.e., the percent of NFIP housing inventory that suffered flooding damage). Based on regression coefficients (Model LQ4), a 10% increase in pervious area could have reduced the likelihood of flood damage to these properties by nearly 1.3 points, on average. While the effect may not seem large at first glance, a 1.3-point reduction in the likelihood of damage actually means that instead of 15.6%, only 14.3% of insured single-family homes in Harris County would have been damaged. That is a reduction of 1,366 homes, or about 8.1% of all claims in the county associated with the storm.

The interpretation of regression results of percent pervious area for severity of damage (i.e., the percent impact on the economic value of NFIP insured housing inventory) also suggests important implications. Based on regression coefficients (Model SQ4), a 10% increase in pervious areas could have reduced the severity of damage by nearly 0.5 points, on average. A 0.5-point reduction in the severity of damage means that instead of 4.1%, only 3.6% of the total economic value of insured single-family residential properties in Harris County would have been damaged. Considering that the total assessed damage for insured residential properties in the county was $476 million (USD 2001), the 0.5-point reduction would have resulted in a savings of $55.8 million, or about 11.7% of the total economic damage to insured properties.

Table 14 Flood mitigation effects of hydrological function indicators.

Δ	Indicator*	Likelihood of damage: Impacted homes	Likelihood of damage: Number of claims	Severity of damage: $ Millions in property damage	Severity of damage: Economic impact to insured inventory
10%	Pervious LAND**	- 1,366	- 8.1%	$ - 55.8	- 11.7%
1 unit	Agricultural NP	- 710	- 4.2%	$ - 16.0	- 3.4%
1 unit	Grass open sp. NP	+ 378	+ 2.3%	$ + 15.8	+ 3.3%
10%	Grass open sp. LPI	- 1,183	- 7.1%	$ - 52.3	- 11.0%
1 unit	Grass open sp. SHAPE***	- 5,782	- 34.5%	$ - 251.6	- 52.8%
10%	Wetland PLAND	- 2,366	- 14.1%	$ - 102.2	- 21.5%
10%	Wetland LPI	- 2,903	- 17.3%	$ - 117.3	- 24.6%

* Coefficients from models LQ5 and SQ5 for likelihood of damage and severity of damage, respectively.
** Coefficients from models LQ4 and SQ4 for likelihood of damage and severity of damage, respectively.
*** Coefficients from models LQ6 and SQ6 for likelihood of damage and severity of damage, respectively.

Pervious areas and other statistically significant hydrological function indicators could have helped mitigate damages from TS Allison for thousands of single-family residential properties in Harris County, with mitigated values totaling over $100 million (USD 2001). As shown in Table 14, the flood mitigation effects of each indicator are listed in terms of number of impacted homes and percent change in the number of insurance claims (based on regression results for *likelihood of damage*), and in terms of millions of dollars and percent change in economic impacts to insured inventory of single-family residential property (based on regression results for *severity of damage*). The monetary reduction of pervious areas, for example, is comprised by the 1,366 undamaged homes (first column) that, at $30,000 of average damage each, would sum $41.0 million. The remaining $15.8 million represents a reduction in all the other damages. The other cases are similar, except for one. In the agricultural case, homes may be valued below the urban average, because they are in the periphery of Houston where property values are comparatively low.

Note that not all of these variable effects are additive since some of these variables were collinear and could not be included in the same regression model. The potential benefit of any two effects can be added only if both variables appear in the same regression model.

6.1.2 Landscape Water Storage

The notion that wetlands and agricultural areas can enhance the overall water storage capacity of the system is supported by results from this study. Restoring wetlands or creating conditions to further expand the size of existing wetlands may be the least expensive land use strategy (in terms of land area requirements) with the largest potential effects in reducing the negative impacts of floods.

A 10% increase in wetland acreage in Harris County (or a 10% increase in the largest wetland in a neighborhood) would have roughly doubled the reductions in the number of single-family residential claims and associated damages attained by increasing all pervious land cover by the same percentage. However, since wetland areas in Harris County occupy a smaller area of land in a neighborhood than all pervious land, on average, the actual land area affected by a 10% increase in wetland acreage would be smaller than a 10% increase in all pervious land acreage. Furthermore, with that smaller area, wetlands are nearly twice as effective as all pervious land at reducing the number of cases of damaged single-family residential properties, as well as the economic damages to properties. These results corroborate previous findings relating the importance of wetland area and wetland large patch index (Lorente, 2011) and wetland alterations for flood mitigation (Brody et al., 2008; Highfield & Brody, 2006), and they support the general assumption of wetland mitigation banking policy that larger wetland ecosystems provide better ecological services (Lorente, 2005). Also, considering the usual small size of wetlands (34% of wetlands are described by 1 to 3 pixels of land cover data, i.e., 0.09 to 0.27 ha or 0.22 to 0.67 acres), it is not surprising that the variable of wetland SHAPE measured in 30-m grid cells yielded inconsistent results. Still, the fluctuating significance levels on this variable suggest that convoluted shapes of wetlands, as exemplified by large wetlands in 1/2-mile radius analyses (Appendix D), are effective at absorbing the impact of floods. Also, the fluctuating results suggest a potential issue with measurement, in that the shape of wetlands may be truncated or split by the 1/4-mile radius neighborhood boundary, but not by the 1/2-mile radius boundary.

A unit change in agricultural NP would also result in millions of dollars saved in single-family residential property damages due to floods. Even though agricultural areas and their water management systems can easily be overwhelmed during an extreme rainfall event, agricultural landscapes in Harris County are able to reduce the volume of water reaching adjacent property and associated damages. The average mitigation effect per impacted home may be less than the savings associated with other land cover types, but that may simply be the effect of low or stagnant property values associated with areas farther out from the traditional Houston urban zone. Nonetheless, an important implication of this finding is that it identifies a value for flood attenuation services of agricultural land in urban areas (i.e., land actively used for agriculture with maintained drainage systems). Communities seeking to integrate agricultural land uses into the urban fabric could use this information to adjust purchase development rights, impact fees, or conservation agreements.

6.1.3 Water Surface Distribution

The hydrological function indicator with the largest effect on flood impacts per unit change is the grass open space shape index; however, affecting a unit change on this index may not be so easily achieved. For example, to change SHAPE from a value of 1 to 2 with 30m pixels, a one-pixel patch (SHAPE = (120*.25)/ $\sqrt{900}$ = 1) would have to be converted into a four-pixel patch arranged diagonally (SHAPE = (480*.25)/ $\sqrt{3{,}600}$ = 2), or into a 14-pixel patch arranged orthogonally (SHAPE = (900*.25)/ $\sqrt{12{,}600}$ = 2). The sensitivity of SHAPE values to pixel resolution and arrangement may be part of the reason why this variable lost strength and statistical significance at the 1/2-mile scale of analysis. Still, the high significance levels of this indicator in models LQ6 and SQ6 suggest that the presence of elongated landscapes of grass open space with a lot of perimeter relative to area, probably along streams or other urban amenities (independent of the effects of these features), can significantly reduce the impacts of floods on adjacent property. The elongated shape of these landscapes likely facilitates the flow and distribution of surface runoff over a wide area of pervious surface that enables the direct transfer of water into soils. Also, a greater proportion of perimeter length relative to area suggests that allowing natural space to follow the contour of landscapes is more ecologically beneficial than restricting shapes to an urban grid.

Other important characteristics of grass open space landscapes relate to their distribution. Unexpectedly, an additional unit patch of grass open space significantly increased the overall impacts of floods. This result for grass open space NP suggests that not all pervious areas in Harris County are equally beneficial in creating flood-resilient communities, and that some patterns of development can actually increase risk of damage even if they comply with a mandated percent area of pervious land. When examining the land uses associated with the relative abundance of patches of grass open space land cover, this result makes sense. On average, about half of a community's pervious land cover is comprised by grass open space. When this proportion of land is divided into few land cover patches, it often refers to large parks or connected tracks of undeveloped land that allow the distribution of surface water across a large area before coming into contact with property. In contrast, when the same amount of land is divided into multiple isolated patches of grass open space (0.3 ha or 0.74 acres on average), these areas lose hydrological value. According to Shusher et al. (2005), pervious areas that are intermixed or proximate to development often have compacted soils that infiltrate slowly and saturate quickly as a result of construction activities. Therefore, it is not surprising that during a major rainfall event these compacted areas would function as extensions of impervious areas, thereby expanding the runoff-producing area.

Connecting scattered patches of grass open space to create bigger patches of land may be a strategy to improve the hydrological performance of places with respect to floods. However, based on the results from grass open space LPI and agricultural NP, the beneficial effects of a larger patch of pervious land may be related not just to more area of pervious land but to additional elements of water management design as well. Large urban parks and agricultural lands often incorporate improvements such swells, drains, or sunk-in areas that can help manage excess surface runoff on-site. Therefore, one way to increase the resilience of communities with numerous isolated patches of grass open space is to connect these patches of pervious land, and maybe even restore some areas with extremely compacted soils and/or add water management design elements to manage some amount of excess runoff on-site.

6.1.4 Interception of Precipitation

Woody lands was the only hydrological indicator evaluated in this study that was not significant in any statistical model. One potential reason for this result may be due to specific characteristics of plant materials that regulate water transfers at the site level in Harris County (i.e., type, specie, age, leaf density, etc.). Since the measure of woody lands was constructed by combining data from four land cover types containing tree canopy in any successional stage—from shrubs and young trees, to mature deciduous, evergreen, and mixed forests—it is possible that effects of one type of woody plant material counteracted the effects of another, thereby moderating or even nullifying the effect of forests as a whole. Alternative explanations could be that urban forested landscapes in Harris County are just inefficient ecosystems at water infiltration and storage—as suggested by Hümann et al. (2011)—or that their overall performance is easily overridden in prolonged, high-intensity storm events like TS Allison but not in low-intensity yet more frequent storm events (Calder & Aylward, 2006).

6.2 Other Factors

Soil drainage capacity, as measured in this study by soil drainage group classifications, had a consistent significant effect in all models. By considering the combined effect of land cover characteristics with soils, communities in Harris County have an opportunity to further increase their resilience to floods. For example, in cases where poorly drained soil classifications relate to clay-type soils, communities could consider dedicating these areas for building structures while setting aside better drained soil areas for pervious land cover. In cases where poorly drained soils refer to saturated soils, the restoration or creation of wetlands would be a better alternative. Overall, urban areas with greater proportions of poor or very poor drainage classification of soils should consider compensating the reduced hydrological performance of these areas with a greater proportion of undeveloped pervious landscapes.

Additional considerations to improve the hydrological performance of places with respect to flood disasters relate to the placement of urban developments in the landscape. As expected, neighborhoods containing large proportions of land in the 100-year floodplain or lengthy overland stream networks (e.g., LQ6 and SQ6 models) significantly increased the likelihood and severity of flood damage in neighborhoods. Also, based on regression results, neighborhoods of single-family residences in Harris County located below dams were 5.3% more likely to be flooded than other areas of the landscape (e.g., LQ4). As effective as these structural solutions have been in protecting people living in hazard-prone locations from the most frequent floods, their designs were based on limited historic storm data. In the face of more urban development and more frequent and extreme rainfall events, the overall effectiveness of dams is reduced, if not at times reversed. The breaching in 2015 of at least 11 dams in South Carolina, for example, show how structural design limitations paired with record rainfall can lead to disaster and extend its impacts beyond the duration of the event (Yan & Sanchez, 2015). But even if dams are not breached, the geomorphology of the landscape below these structures is shaped to receive waters from the original river basin. During an extreme rainfall event like TS Allison, these areas may flood whether there is a flood protection dam in the watershed or not. Urban development should be avoided in these areas, as well as in floodplains where the likelihood and severity of damages are also significantly greater than in other parts of the landscape.

With respect to specific characteristics of the built environment, road density and building designs also have significant effects on flood damages to insured property (see Table 15). A 10% increase of neighborhood road density across Harris County could have resulted in $33.5 million (USD 2001) in additional property damage to insured single-family residences, or a 7% increase in the overall economic impact of floods on those structures. Note this effect is independent of, and additional to, the effects of pervious land area described in Section 6.1. Communities with high levels of road density should consider the redistribution of services within the community to reclaim some road areas as pervious landscapes. Also, in areas where communities have been successful in relocating neighborhoods out of the floodplain, abandoned roads should be removed in order to further improve the hydrological performance of those areas.

Table 15 Flood mitigation effects of built environment factors.

Δ	Indicator*	Likelihood of damage: Impacted homes	Likelihood of damage: Number of claims	Severity of damage: $ Millions in property damage	Severity of damage: Economic impact to insured inventory
10%	Road density	+ 911	+ 5.4%	$ + 33.5	+ 7.0%
10%	Elevated bg. design	- 978	- 5.8%	$ - 54.6	- 11.5%

* Coefficients from models LQ4 and SQ4 for likelihood of damage and severity of damage, respectively

Other development-related interventions that can improve the hydrological performance of places involve the design of buildings. However, elevated building design in Harris County is highly correlated with median income (r^2=0.62, p<0.000), and it is possible the magnitude of this effect is strongly associated with the spatial distribution of expensive properties located in the traditional urban Houston zone (similar case to agricultural NP as described in Section 6.1.2, but opposite effect). The challenge for development is creating an affordable housing product with an elevated design. The NFIP or cities could develop a financial lending program to target the elevation of buildings in the most hazard-prone areas. Also, cities should provide density bonuses and other incentives to facilitate production of elevated building design developments.

Three variables were not significant in most statistical models: land use intensity, storm-water pipes, and minority populations. A visual check of neighborhoods with large proportions of intense land uses revealed that these types of parcels often include water management improvements to handle some levels of water runoff on-site. With respect to storm-water pipes, a reason for insignificant and inconsistent results may be related to the design of storm-water infrastructure in Harris County. In central areas of the county—where the city of Houston is located—the connectedness of storm-water infrastructure suggests that there is a city-wide system designed to manage and evacuate water for a wide region. Further away from the county center, this system becomes more localized and dependent on overland stream drainage networks. In some areas, the only sections of storm-water pipes correspond to connections that allow an overland canal or ditch to continue under a road crossing. Therefore, this measure may need further refinement for an accurate evaluation. Lastly, the measure for social vulnerability in terms of proportion of minority population was not significant in any of the models. A potential reason for this result may be that the spatial distributions of minority populations in Harris County are intermixed, so that the flood disaster impacted all population groups indiscriminately. Other measures for social vulnerability should be considered in future studies.

6.3 Policy Implications and Recommendations

Overall, greater proportions of pervious land can mitigate the negative impacts of floods. In order to improve the hydrological performance of existing development, local planning agencies should target land acquisition programs or pervious land restoration projects that connect existing isolated patches of grass open space with other patches of pervious land. The focus of these programs should be the creation of large, elongated patches of grass open space that can also function as urban amenities for recreational use (e.g., bike trails and pedestrian ways).

For example, the potential benefits of implementing different land restoration projects in a neighborhood of Harris County located out of the 100-year floodplain is illustrated in Fig. **5**. In this example, properties at the end of six cul-de-sacs would be targeted for demolition to expand the width of an existing utility setback and create a green corridor of grass open space with enough continuous pervious area to provide flood attenuation services. Also, properties and vacant lots adjacent to the largest patch of open space (at the bottom of the image) would be selected for pervious land restoration projects to create a larger area for water distribution. Another land use intervention illustrated in this example is the creation of a wetland feature within an existing patch of grass open space—historic imagery from 1995 indicates that this location of the landscape formerly contained wetlands.

Together, these interventions total an increase of 20 pixels or 1.80 hectares (or 4.45 acres) of pervious land. If these new pervious areas were to be added to the neighborhood without any regard to their type or placement on the landscape, the potential reductions of flood impacts would be moderate, 4.3% points for *likelihood of damage* and 4.7% points for *severity of damage* (Models LQ4 and SQ4). As mentioned in the results, the greatest benefits can be achieved when the placement of new pervious space is carefully thought out to follow landscape ecology principles and support one or more landscape hydrological functions (Models 5 to 7).

Before **After**

2001 land cover conditions in a 1/4-mile neighborhood of Harris County, Texas.

Land use interventions restoring grass open space and wetlands are indicated with dark green and dark blue pixels, respectively.

Note: There are a few months of discrepancy between the 2001 C-CAP land cover data and Google Earth Pro's historic imagery of 12/31/2001. During that time, some grass open space areas became developed. The land use interventions evaluated on this example are based on the C-CAP land cover data which describes land use conditions at the time of the disaster event and before development occurred.

Fig. 5. Example of potential land use interventions for improving the hydrological performance of neighborhoods.

Table 16 Potential reductions on flood impacts associated with the example of land use interventions.

Flood impacts	Model No.	Observed value	Before	After		
			Predicted value (a)	Predicted value adjusted (b)	Difference (a-b)	Reductions on flood impacts
Likelihood						
	LQ4	12.33	10.38	9.93	0.45	4.3%
	LQ5	12.33	9.31	6.98	2.33	25.1%
	LQ6	12.33	10.36	7.21	3.15	30.4%
	LQ7	12.33	10.37	7.13	3.24	31.2%
Severity						
	SQ4	1.06	3.55	3.38	0.17	4.7%
	SQ5	1.06	3.36	2.65	0.70	21.0%
	SQ6	1.06	3.54	2.27	1.27	35.8%
	SQ7	1.06	3.54	2.25	1.28	36.3%

L = likelihood of damage; Q = quarter-mile neighborhoods; S = severity of damage.

Table 16 summarizes the potential benefits of different land use interventions. Using the models to predict observed values yield slightly different numbers (with a maximum distance of 2 points). By strategizing the placement of new pervious areas in ways that expand the largest patch of grass open space, connect isolated patches of grasslands, or increase the shape of a wetland feature (Models LQ5 and SQ5), the flood attenuation capacity of the landscape can increase. In fact, the reductions of the *likelihood of damage* can increase by a factor of 6, from 4.3% up to 25% (see last column on Table 16). Similarly, reductions of the *severity of damage* can increase by a factor of 5. The greatest flood attenuation benefits can be achieved when the placement of new pervious space creates greenway areas of continuous grass open space, and when wetland features can be restored or created (Models LQ6, LQ7, SQ6, and SQ7). With a spatial arrangement as specified in Figure 5, neighborhoods can reduce their likelihood and severity of damage by 30% and 36%, respectively.

Also important to reduce the potential impacts of flood is to target the relocation of properties in the 100-year floodplain and in watersheds right below dam structures. The NFIP could use the results from this study to further specify premium rates for properties located in high-risk areas.

Other capital improvement programs should target the conversion of impervious areas in ways that would allow the expansion of wetlands, greenways, or large urban parks, especially in areas with well-drained soils. An assessment of soil conditions is essential for further improving the effectiveness of flood mitigation projects with pervious areas. Densely urban areas with interspersed patches of green space should consider the enlargement of pervious areas, as well as the restoration of compacted soils and the implementation of water management design features to handle some level of excess runoff on-site.

With respect to new development, neighborhood designs should consider placing structures in poorly drained soils composed of clay-type soils, while setting aside areas with well drained soils for pervious landscapes. Even though clay-type soils are not ideal for building foundations, there are several engineer solutions that can be applied to account for these types of soil conditions. Whenever possible, the configuration of pervious landscapes should follow the contours of landscapes and form large patches (i.e., at least 4.05 ha or 10 acres) of pervious lands. Priority should be given to the preservation of active agricultural parcels and naturally occurring wetlands with conservation or transfer development right agreements. Housing should be arranged in ways that allow for a larger proportion of pervious space in back-yards that, when connected to neighboring yards, create bigger pervious landscapes. To ensure the performance of these backyard areas, development should include storm-water infrastructure, and/or on-site water management features to help handle some excess runoff. Also, communities should provide density bonus incentives to encourage the development of elevated building designs. In cases when compromises must be made, communities or the NFIP could use the results from this study to establish compensatory fees to account for reductions in the hydrological capacity of places.

7. CONCLUSIONS

Much of the social and economic investments of communities have already taken place in coastal areas and other hazard-prone locations. Thus, the question for decision-makers and practitioners is no longer strictly about how to control or eliminate flood risk. They also must consider what can be done to develop society's capacity to recognize, manage, and cope with any potential disruptions associated with hazards within timeframes that allow ecosystems and society to adapt to (or catch up to) changes in risk. A key point is how to measure, manage, and reduce flood risks in already populated areas with limited intervention possibilities and/or with high urbanization pressure. To address this question, it has been recognized that community planning and disaster management need to come together, and the concept of resilience has emerged as a guiding principle for societal planning and policy making.

7.1 Summary of Research

In order to operationalize the concept of resilience for land use planning and design, this research identified physical characteristics of neighborhood environments that can influence the risk of flood damage to single-family residential properties, using an approach that endows future urban planners with some guides and criteria to minimize that risk. The most appropriate size of neighborhood is one with practical applications for land use planning and design. According to the planning literature, physical circular-buffered areas of 1/4-mile or 5-minute walk radius describe the minimum size of neighborhood suited for analyses on mobility and the physical use of space (Chaskin, 1997; Duany et al., 2000; Hasan et al., 2014; Kearns & Parkinson, 2001; Park & Rogers, 2014). Housing density is another important characteristic defining the physical space of neighborhoods (Dempsey et al., 2010; Owens, 2005; Park & Rogers, 2014). The amount of land occupied by clusters of homes can vary depending on local settlement patterns, the terrain, and the complexity of street networks. For example, Owens (2005) reported that, on average, residential clusters of about 86 homes accurately represented neighborhoods in New England, and that these areas generally occupy less than 75 acres (or 30 hectares). In Harris County, Texas, a subdivision (or group of small subdivisions) of 94 residential homes generally corresponds to an area of 1/4-mile radius (50 hectares). These areas include housing, access roads, and public services. Therefore, a 1/4-mile radius size was considered suitable for describing neighborhoods of fully documented cases of insured single-family residential properties.

A total of 540, 1/4-mile radius circles sampled from Harris County captured clusters of at least 5 correctly geocoded insured single-family residential properties. These circular areas were centered in and totally inscribed in a 1-mile grid that was traced over the landscape beginning from a random point. To assure the robustness of measures without losing independence of measurement (i.e., non-overlapping spatial data for all cases), this research also adopted wider circles of 1/2-mile radius sharing the same center of 1/4-mile circles areas. Property damages measured as *likelihood of damage* and *severity of damage* were then explained using different metrics that were defined and calculated for the two scales of analysis. Due to data availability and analytical restrictions, 532 neighborhood cases were evaluated for *likelihood of damage*, and 527 cases were evaluated for *severity of damage*. The suitability of a 1/4-mile radius neighborhood size over alternative larger neighborhood sizes was further confirmed with regression diagnostic tests indicating lower levels of model collinearity in 1/4-mile analyses than in 1/2-mile analyses. Also, a lag analysis of the dependent variables (for distances of 1, 1.5 and 2 miles) indicated that somewhere between 1.5 and 2 mile radius areas the effect of neighborhoods is lost.

Overall, the results provided a general assessment of flood attenuation services of pervious land cover in Harris County, and a close examination of the potential mitigating effects of four dominant types of natural land cover in urbanized areas: wetlands, agriculture lands, grass open space, and woody lands. Such information can help identify "good" landscape forms—that is, spatial solutions that integrate concepts of risk, ecology, and development in future planning for new landscapes, and for the people who live (and will live) in these regions. Ultimately, this information can help to determine whether urban systems can be formed in a way that gives sustainability a better chance while providing livable environments that are resilient to disasters. This is an important issue because floods are one of the costliest as well as the most-frequent type of natural disaster. Over the past 50 years, property losses from flooding have been increasing, largely due to development in hazard-prone areas. As cities grow and expand, a better understanding of the tradeoffs between new development and the local capacity of landscapes to handle floods can help communities determine the most suitable uses of land and the best land use strategies to enhance their flood resilience.

Some of the study results are in accordance with well-documented expectations of flood risk (i.e., the negative impacts of road density and floodplain exposure on flood loss) and flood mitigation factors (i.e., the limited performance of dams during major disasters and the benefits of elevated building designs). The general notion that more pervious areas mitigate the negative impacts of floods was confirmed for most types of natural land cover. However, this study also showed that not all pervious areas in Harris County are equally beneficial in creating flood-resilient communities, and that some patterns of development—such as isolated patches of grass open space—can actually increase risk of damage even if they comply with a mandated percent area of pervious land. The lack of significance of woody lands was somewhat surprising because of the expectation that precipitation interception and soil infiltration of forested landscapes would reduce runoff. This may be one indication that not all types of trees in Harris County have a significant role in flood attention services, or that the role of forests is just not perceptible during extreme rainfall events.

Communities seeking to improve their resilience to floods can use a number of strategies related to the planning and design of pervious landscapes. For example, maintaining or rehabilitating wetlands is probably the best approaches to mitigate for floods. A 10% increase in wetland acreage in Harris County (or a 10% increase in the largest wetland size in every neighborhood) could have protected over 2,300 single-family residential homes—equaling a 14% reduction in the total number of insurance claims associated with TS Allison—or could have saved over $102 million (USD 2001) in associated property damages—equaling a 21% reduction in total economic impacts associated with the same storm. These savings are roughly double the reductions in the number of single-family residential claims and associated damages attained by increasing all other types of pervious land cover by the same percentage. These results suggest that the protection and enhancement of naturally occurring wetlands should be a priority of communities that are exposed to flood hazards. Further improving wetlands in terms of size and shapes following the natural contours of landscapes should also be considered in cases where land use conditions allow for it. The added flood mitigation effects of greenway areas of grass open space can further improve the hydrological performance of communities with respect to floods. Therefore, communities should also provide buffer upland areas around wetlands to help absorb the impacts of floods. These areas can also serve as urban natural amenities (e.g., bike trails, pedestrian ways, etc.).

Other ways in which communities can increase their resilience to floods is by retaining agricultural parcels and incorporating large urban parks. Many types of pervious areas, when located in well-drained soils, have the potential to further increase local flood attenuation services. Communities and developers should make an effort to restore or enlarge wetlands when possible, use poorly-drained clay-type soils for building structures, and set aside areas with well-drained soils for pervious landscapes. Even though clay-type soils are not ideal for building foundations, there are several engineer solutions that can be applied to account for these types of soil conditions. These recommendations are in accordance with Ian McHarg's (1992) composite map approach to Master Planning, which highlights the value of incorporating ecological knowledge among the usual engineering, socio-economic, and aesthetic criteria when developing a development plan. Neighborhood designs should also aim for clustered developments, or the management of front and rear setbacks that allow for the creation of corridors of green space. As also suggested by proponents of Socio-Ecological Systems (e.g., Cadenasso & Pickett, 2008; Moffatt & Kohler, 2010; Pickett et al., 2011), these areas should be supplemented with on-site water management features to handle excess runoff. Additionally, new development should offer affordable housing with elevated building designs located along an efficient network of roads, since excess lengths of local roads can significantly increase the likelihood and severity of flood damage to single-family residential properties.

For existing developments, land acquisition programs should target the conversion of abandoned roads and other types of impervious surfaces to pervious areas in ways that would allow the enhancement of wetlands, parks, or greenways. Also, local planning agencies should consider the relocation of communities in floodplains and basin areas below dam structures to other areas of the landscape where the risk of damage is minimized. Last, the NFIP should actively encourage or require the purchase of flood insurance for structures located below dams or similar flood mitigation structures with limited design capacities.

7.2 Theoretical and Practical Contributions

An important finding of this dissertation is that the hydrological function of landscapes still persists in natural spaces within urban areas, even at scales as narrow as 1/4-mile radius areas. While the ecological value of large undisturbed natural ecosystems have long been recognized—e.g., John Muir's environmental activism in late 1800s that resulted in the establishment of the first national parks and the subsequent protection of multiple wilderness sites in the U.S.—urban natural spaces have not received the same level of legal or research attention. Understanding the physical and economic value of hydrological functions provided by natural features of urban landscapes has several benefits. First, this information can provide legal backing for the protection of still-undeveloped natural space. The protection of wetland ecosystems, for example, has been particularly hindered by a lack of scientific information tying the provision of ecosystems services with wetland spatial characteristics at specific sites.

Second, it also provides a scientific basis for ecologically-based land use planning and design decisions. According to Ndubisi (2002), the design, planning, and management of landscapes depends on how people "understand, evaluate, and interpret landscapes." By identifying a direct economic value of the spatial arrangement of natural features in the context of development, ecological design criteria can be more easily incorporated into traditional cost-benefit analyses guiding development decision-making processes. Third, it provides an understanding of how to restore or enhance the provision of ecological services in urban areas. Since societal risk from flood hazards is increasing at a faster pace (even exponential) than society's ability to respond to new conditions (Rogers & DeFee II, 2005), finding a tool to counteract the negative impacts of development and increasing levels of risk offers tremendous opportunities for improving community adaptation rates to new conditions.

Last, a valuation of flood attenuation services of natural features of landscapes provides a bargaining tool with which communities can evaluate tradeoffs between development investments and landscape conservation. As Rodiek (2010a, 2010b) pointed out in reviews of the previous 20 years of scientific evidence, human environments reflect conflicts between ecosystem values, land uses, and perceived and assigned values of land and its character. Within these conflicts, choices are made either to support urban growth or to conserve natural and ecological space. Both options cannot be maximized at a given location, but compromises can be made so that both objectives can coexist within the larger context of a landscape. This suggests that there are interdependent urban functions and human values tied to form, and that this form requires careful planning. A major challenge for planning is to identify attributes in the distribution of urban land uses that contribute to enhancing the resilience of communities with respect to disasters such as floods, and then use this information to allow for urban growth in a way that landscape hydrological functions are not impaired.

Thus far, research has focused primarily on assessing the impacts of impervious surfaces, but we know much less about the ecological performance of natural features of landscapes with respect to flood hazards. The few studies that have explored the effects of pervious areas have had limited success in terms of consistency of results. This suggests that there is still a gap of knowledge in our current understanding (and measurement) of flood resilience concepts. This study addresses this gap by incorporating landscape ecological knowledge into flood damage assessment models; refining the measurement of flood loss, soils, and other key indicators of resilience for empirical analysis; using an innovative methodological approach for the analysis of data; and addressing validity concerns associated with the quality and completeness of insurance data from NFIP.

Specifically, this study makes theoretical contributions to our current understanding of flood resilience by:

- Bringing forward the importance of environmental context to the evaluation of community flood resilience.
- Quantifying hydrological landscape function using spatial metrics that relate landscape design principles with the ecological functions of natural features of landscapes.

Practical contributions of this dissertation to the NFIP and for professional planners and designers concerned with enhancing community resilience to floods include:

- Operationalizing the concept of flood disaster resilience for land use planning and design by providing specific land use guides and criteria that can help communities to minimize the risk of flood property damage.
- Valuing the flood attenuating services of natural features of landscapes at a local scale. For instance, part of the challenge for the legal protection of wetlands has been identifying their flood attenuating value at specific sites; thus, this research fills an important gap.

- Providing a basis for on-site compensatory flood mitigation where capital improvement programs or new development could account for local reductions in the hydrological performance of places.
- Providing decision-makers and practitioners information to help formulate comparative assessments of community resilience to floods at the neighborhood level.
- Providing design and planning practitioners with meaningful information about the relative performance of different spatial-ecological characteristics of urban natural spaces with respect to flood damages.
- Providing a basis for improving the effectiveness of the NFIP by incorporating new evaluations of flood risk and by identifying ways to balance individual and community responsibilities in building urban resilience to floods.

Also, this study makes analytical and methodological contributions to flood damage assessment studies using NFIP flood insurance data by:

- Isolating the potential effects of a well-specified type of flood policy (only single-family residential records with building coverage were selected for study), and removing biases caused by duplicate policies (removed), coding errors (removed), incomplete records (removed), and multiple policies per property (aggregated at the parcel level).
- Verifying the correct geographic location of flood insurance records in a way that guarantee a perfect spatial match with the tax-parcel polygon of the

insured property, a condition that ensures the validity of results and the expansion of variables for study. Prior to correction of geocoding errors in the original NFIP databases, at least 11% of all records for study (or 17% of associated damages) would have been placed in the wrong county altogether.

- Using the total assessed damage as a measure for actual flood damages to minimize bias due to values that are cut-off by deductible and coverage limits, or that include other reimbursements to policy holders for various account activities.
- Using the total number of insured single-family properties as the population of study, which allows an individual analysis of cases with full information concerning damage intensity or absence of damage.
- Including the evaluation of cases without damage (i.e., insured single-family residences that did not file a claim for property damages) as part of the relevant information about flood risk and damage assessments.
- Introducing the proportion of policies that suffered any damage as a frequency-like measure of probability or likelihood of flood damage, along with a more traditional measure of severity of flood loss (i.e., the ratio of damages over property value) to further confirm relevant measures of flood resilience.
- Introducing a measure of soils not yet used in flood damage assessments (i.e., soil drainage groups), that has a significant and reliable behavior across

scales of analysis and has direct and practical applications for land use planning and design.

- Producing regression models that can be directly compared, even across scales of analysis, given the normalization of all variables with respect to characteristics of the neighborhood under study.
- Testing the robustness of regression results using two scales of analysis, one of 1/4-mile radius neighborhoods that approximates the size of a subdivision of 94 homes, and another 1/2-mile scale (four times larger) of neighborhoods sharing the same center.
- Ensuring the independence of measurement of all spatial data for all cases at both scales of analysis.
- Improving the specification of flood damage assessment models by incorporating information on spatial dependence with spatial error models.
- Evaluating a large number of cases (532 neighborhoods in Harris County, Texas, that included 68,351 single-family insured residential properties, or about 64% of all NFIP policies available in the area at the time of TS Allison in 2001), which allowed the most comprehensive specification of flood damage regression models to date.
- Including up to 15 conceptually different independent variables, all with unique contributions to the prediction of the dependent variables.
- Improving the percent explained variance of comparable flood damage assessment models. Data depuration and the new selection of variables and

definition of metrics allowed a substantial improvement over previous analyses;[4] the new regression models account for 43% and 51% of explained variance (*likelihood of damage* models for 1/4-mile and 1/2-mile radius areas, respectively) and 37% and 41% of explained variance (*severity of damage* models for 1/4-mile and 1/2-mile radius areas, respectively).

Additional lessons learned during the course of this study relate to the use of specialized software. As noted throughout Section 4: Methods and Appendices B and D, default settings of various programs (i.e., ArcGIS v.10, FRAGSTATS 4.2.1, GeoDa 1.6.7, and GeodaSpace 1.0) are not always appropriate and could lead to biased measurements and statistical results. In many instances, it was necessary to design, prove, and apply totally new scripts to clean and integrate data from different sources, and/or to ascertain the correct treatment of data when processed through various analytical software packages. Also, careful attention should be paid to understanding how implementing seemingly straightforward commands in software can affect analytical outcomes.

7.3 Study Limitations and Future Research

While perhaps useful for grounding a political agenda, the concept of resilience is only practical for policy, planning, and management if it is quantifiable. This study

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[4] Studies with 1/2-mile radius zones in the Houston area, but with different sampling methods and variables, attained 25% of variance explained in flood losses for damages accumulated over an 11-year period of disasters (Brody et al., 2013) and 12% in flood losses for TS Allison (Brody et al., 2015).

used an understanding of resilience as a loss function, which only allows for the evaluation of the system's physical resilience (of quantifiable assets), not for its overall disaster resilience. Thus, further research is needed to take into account other social and ecological impacts of floods. Also, resilience as a loss function only examines resilience to a specific time and situation (i.e., the disaster event). Further research is needed to assess the resilience of communities during the processes of short-term and long-term recovery.

Even though the results of this study are not affected by the number of cases captured per neighborhood (dependent variables are quotients similar to probabilities), the study may have missed some locations where damages occurred but for which there was no information to derive the probability or severity of flood impacts. For example, even though Harris County had the greatest NFIP market saturation of all counties in the state of Texas (i.e., 33% of all flood insurance policies in the state at the time of TS Allison were in Harris County), on average, only 43% of all single-family residences located in 1/4-mile neighborhoods with more than 90% of the area in the 100-year floodplain had NFIP policies. The rate of NFIP market saturation dropped to 14% for neighborhoods with a 10% or less area in floodplains. Therefore, one way to expand this research is to include other sources of flood damage information that describe the impacts on uninsured buildings.

The cross-sectional nature of this study is in essence a one-group post-test-only research design. One way to further expand the generalizability of results is to apply the same flood damage assessment presented in this dissertation for the same region but with respect to other major flood disaster events, such as Hurricane Ike in 2008 or the Memorial Day weekend floods in 2015. A comparison of results from different major disaster events could provide a basis for assessing how well communities in the region of Harris County have adapted to flood hazards. Also, an evaluation of yearly minor flood disaster events and improvements on data resolution could lead to new insights on the relative performance of natural features of landscapes with respect to floods at narrow scales of analysis. The application of the model to other coastal areas within the Gulf Coast with similar ecoregion conditions and NFIP market saturation could lead to the generalization of results by ecoregion. If the impacts of development can be linked to the local hydrological performance of places, then developers and communities can benefit from better understanding the tradeoffs of altering the size, shape, and distribution of specific natural features of landscapes.

Other potential expansions of this study could involve the specification of other structures of risk not readily captured by population facility indicators or structural conditions alone. If we can more thoroughly understand the physical vulnerability of places, then we will be able to better explain why some systems (whether neighborhoods, communities, or entire cities) are more at risk to disasters than others, and then plan or design accordingly. Also, by extracting capacity factors affected by the spatial structure of cities, we will be able to develop evidence-based land-use strategies that enhance the hydrological response of urban systems with respect to floods.

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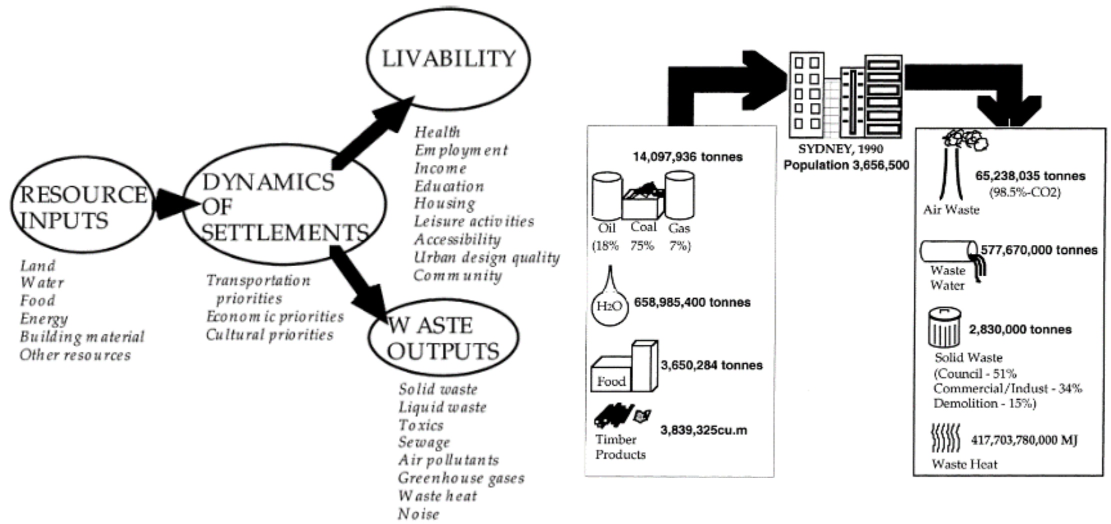
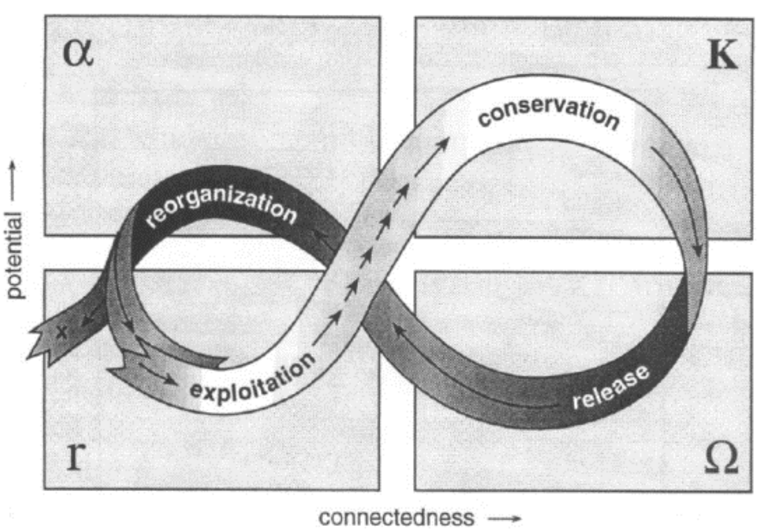
APPENDIX A

Graphic summary of disaster resilience conceptual models.



Newman (1999) Extended Human Settlements Metabolism (EHSM) model and application.
Reprinted with permission.



Holling (2001) ecological adaptive cycle framework.
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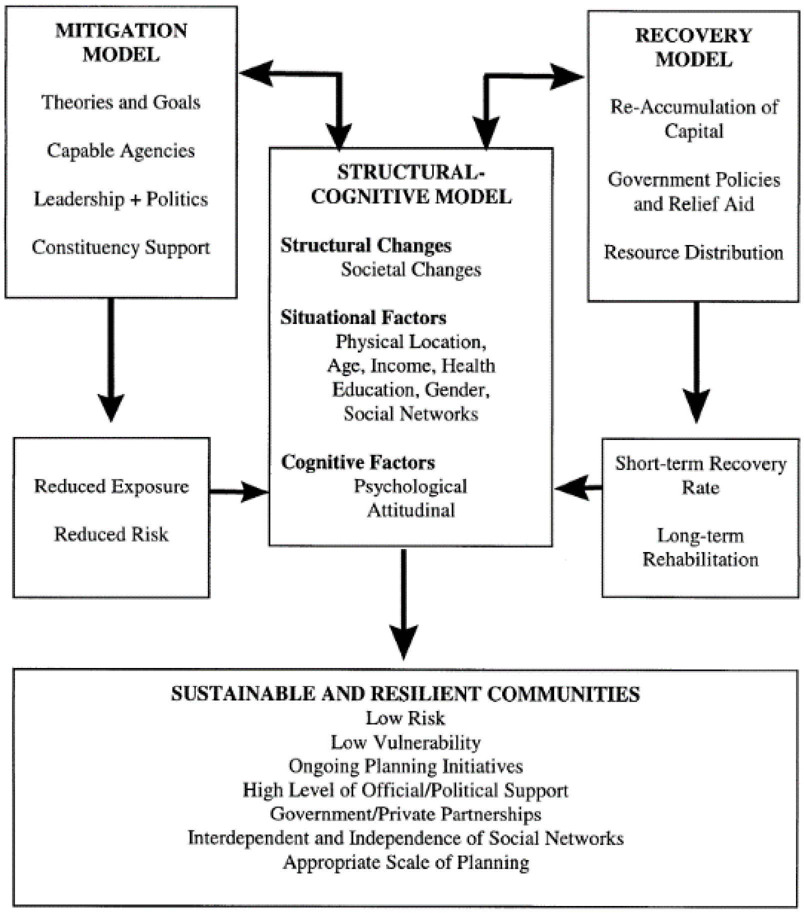
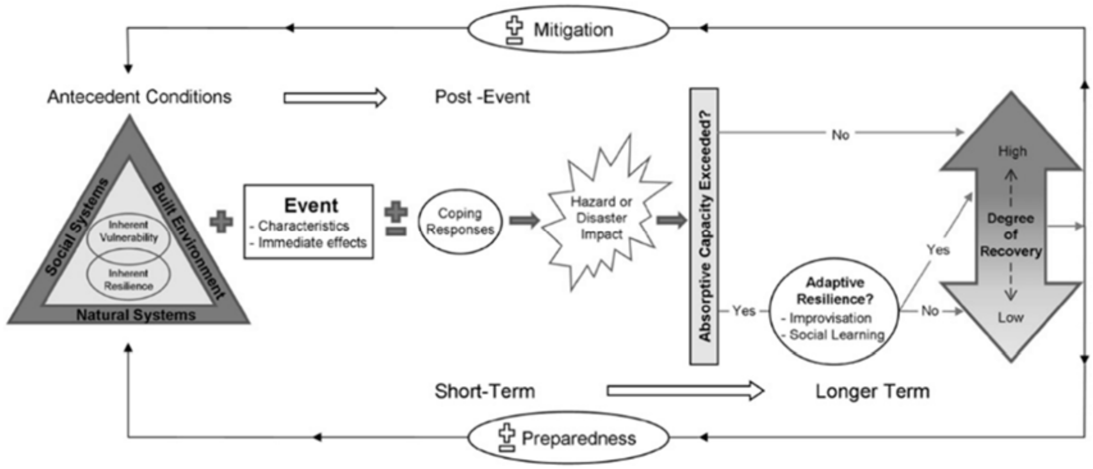


Tobin (1999) Sustainable and resilient communities in hazardous environments.
Reprinted with permission.

Peacock (2010) Community Disaster Resilience Framework (CDRF). Government publication in the public domain.



Cutter et al. (2008) Disaster Resilience Of Place (DROP) model.
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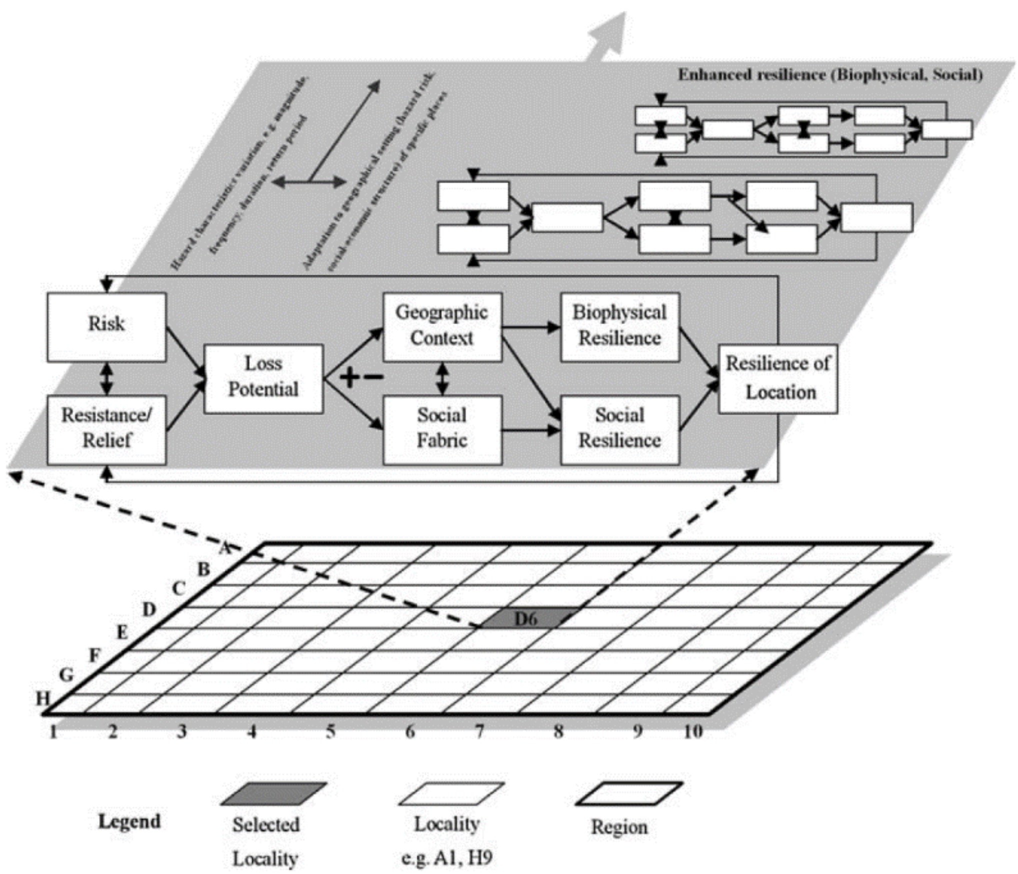

Zhou et al. (2010) Disaster Resilience of Loss-Response of Location (DRLRL) model.
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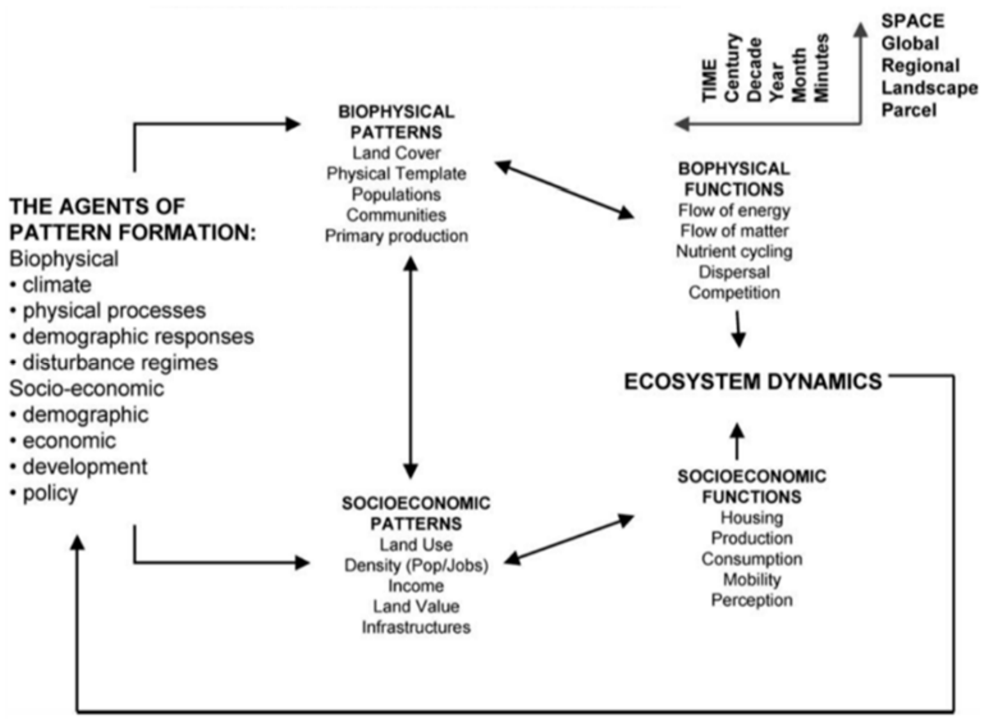

Albeti and Marzluff (2004) urban patterns and processes framework.
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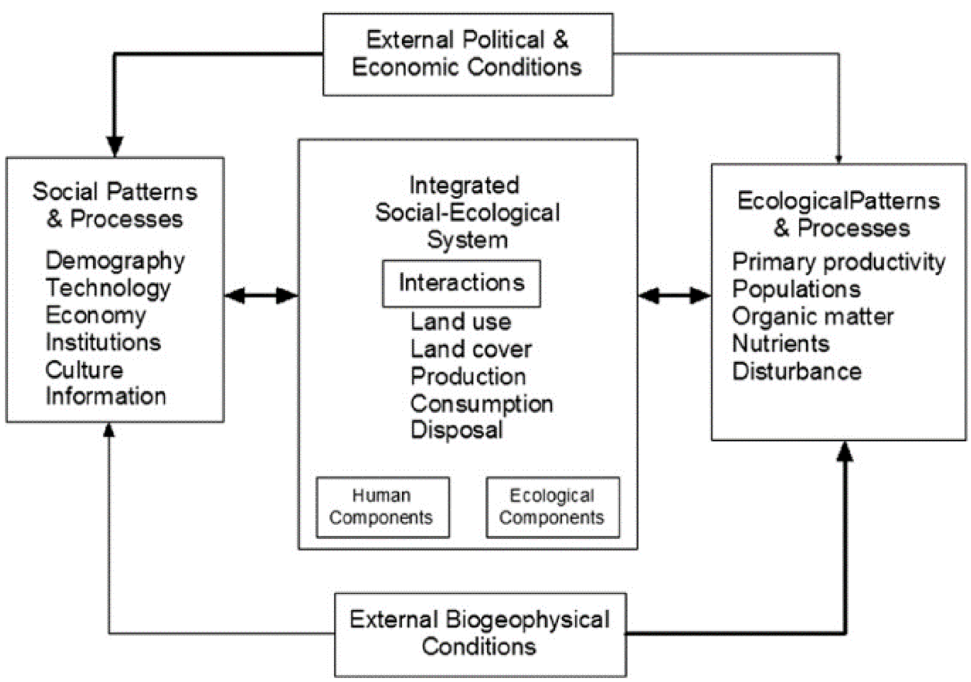
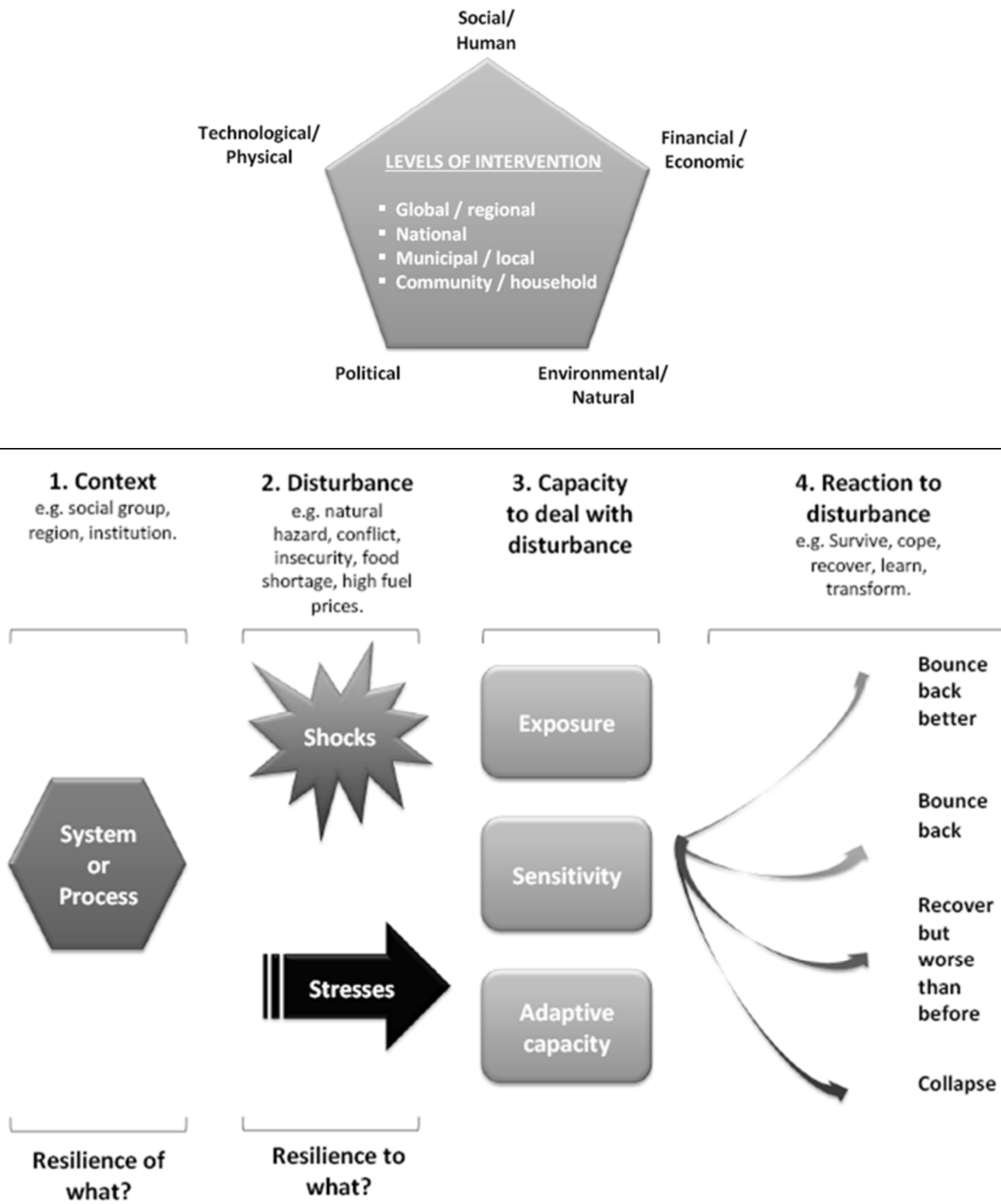


Pickett et al. (2011) human ecosystem model template.
Reprinted with permission.



Department for International Development (2011) DFID resilience framework.
Government publication in the public domain.

APPENDIX B

This dissertation used secondary data from several large databases (see Table 7 in Section 4 Methods). In particular, three databases were used to extract data for the dependent variables:

- Flood insurance policies from the National Flood Insurance Program (NFIP), maintained by the Federal Emergency Management Agency (FEMA).
- Flood damage claims, also from NFIP and maintained by FEMA.
- Parcel data on land use and tax-assessed property values maintained by the Harris County Appraisal District (HCAD).

Data from these sources was directly obtained from an individual database to generate variables for study (e.g., parcel land use classification, an independent variable), or the data from multiple databases was combined to create new measures (e.g., *property damage per property value*, a dependent variable).

Prior to analysis, information from these databases needed to be placed accurately on a map so that each policy and associated claims (represented by points) would be spatially matched with the parcel with the tax record of the corresponding insured property (represented by polygons). For any empirical assessment, the accuracy of the source data directly affects the validity of the outcomes. This is compounded when matching information across multiple databases, for example, matching data about NFIP policies and claims for properties with their corresponding HCAD property values and land uses.

Data Quality Issues

In the course of this research, a number of data and operational issues were identified as serious threats to the study's internal validity. Failure to address these threats would result in questionable, even inaccurate empirical outcomes, and the process of addressing these threats collectively represented over three years of effort for the researcher. This section describes these issues and how they were addressed.

1. Completeness of NFIP Databases

As mentioned above, the NFIP under FEMA maintains two separate databases: one on flood policies, and another on damage claims due to floods. These databases have different fields that can be used for extracting records associated with disasters, and the choice of fields has important research implications.

This dissertation received three different extractions of 2001 NFIP policy records for the area and disaster of study:

- The first extraction was based on year and geocoded information (i.e., extractions by map), and included 117,847 NFIP records that represented all policies in Harris County, Texas for 2001. After a careful evaluation of incongruous results it became apparent that this extraction of policy records only matched 53% of all reported claims associated with Tropical Storm Allison in the study area, and that a number of NFIP records were from other counties and even other states.

- The second extraction was provided for the year of the disaster under study, 2001, and it included over 3.5 million records that represented all policies in Texas for 2001. Since NFIP policies can have policy contract terms of 1-year (the majority) and 3-years, this extraction missed a substantial number of policies-in-effect at the time of disaster that were issued 6 months to three years prior to January 1st, 2001, the cutoff date used for data extractions. Consequently, only 86% of all actual reported claims associated with TSA in the study area had a policy match.
- The third and final extraction was provided for all records available in 11 years of data for the state of Texas, about 6 million records. A careful sub-extraction of 355,202 NFIP records in Texas associated with TSA was based on policy term and policy issued dates. This extraction allowed a 96% match of all state claims in 2001 associated with the storm.

After the first extraction, it became apparent that the spatial information of NFIP records was wrongly specified, and that any analysis of NFIP policies would require a process of record geocoding based on address descriptive information on insured properties.

2. Number of valid NFIP records

Databases contained numerous errors—such as, duplicate records, blanks, and null values—that could substantially alter policy counts, case sampling, and neighborhood flood damage estimations. Duplicated records, cancelled entries, policies without a property's physical address, and policies with a non-existent address were removed to address these errors (about 7% of extracted records for study).

3. Quality of geographic information of NFIP records

NFIP databases contain geocoded information for each insured property (i.e., latitude and longitude information). However, as mentioned above, the spatial information on these records was wrongly specified. After extensive data cleaning and re-geocoding of NFIP records associated with TSA listed in local zip codes (135,973 records), this study confirmed the presence of 107,533 valid NFIP policies-in-force in Harris County, Texas at the time of Tropical Storm Alison.

The implications of using wrongly specified geocoded information for data analysis cannot be understated, especially for narrow scales of analysis like this study. For example, prior to correction, 65% of confirmed records would have been associated with the wrong parcel, and at least a 10% (or 15% of all residential damages) of all records for the study would have been placed in the wrong county altogether.

4. NFIP policy coding errors for Single-Family Residential

Some of the NFIP single-family policies were found on non-residential parcels. Broader categories of NFIP policies include: buildings (residential and non-residential), residential condominium (to insure common property), and contents. Building policies are further classified as single- or multi-family, individual condo units, manufactured homes, or as non-residential buildings (e.g., commercial, schools, churches, etc.). At the time of Tropical Storm Allison, 92% of policies and claims in Texas were coded for single-family residential buildings. However, a number of these policies were found on parcels for apartment style buildings/condos, trailer/mobile homes, or properties owned by religious groups, schools, and other organizations.

This study used a supervised geocoding process to match policies with the appropriate parcel shape. The land use and year-built information was revised on all matches. In cases where there were mismatches, other information was used to identify the source of the mismatch, including Google Earth's historic imagery (12/31/2001), and the Harris County Tax Appraisal database on last year sold and ownership history. Any NFIP records not located in single-family residential parcels were removed.

5. Multiple NFIP policies for the same property

The NFIP writes one policy per building. If a single-family residential parcel has multiple buildings, the property owner can have multiple NFIP policies, one for each building (e.g., pool houses with in-law suite, garages, or any other structures used or held for residential, business or farming purposes). This issue could affect metrics such as neighborhood policy counts (which in turn affects the total number of neighborhood cases that can be selected for study), and the dependent variable for severity of flood damage (i.e., flood property damage/assessed property value) in 36% of neighborhoods (194 of the 540 cases of 1/4-mile neighborhoods for study) where there were clusters of properties with multiple NFIP policies.

Policies referring to structures other than the actual home structure were excluded from neighborhood policy counts, because they referred to the same property. However, since all the structures on a parcel are included in the assessment of the property value, data on flood coverage and damages from these supplemental policy records were retained and aggregated at the parcel level.

6. Using 2005 parcel data for describing 2001 land use

According to the HCAD office, all original spatial and tabular parcel data files for years prior to 2005 was corrupted and lost. The oldest parcel data files available are for 2005. In order to create a relevant parcel dataset for 2001, the land use of parcels with *blank* land use codes, tax exempt codes, or with improvements built/remodeled on or after 2001 were verified using Google Earth Pro's historic imagery (12/31/2001).

Since the final extraction of NFIP records are of single-family residential structures, any parcel polygon in which they are geocoded is assumed to be of a single-family residential home—unless there is clear evidence indicating different as noted on issue 4. This assumption helped create a new land use map for 2001. Initially, the land use codes for the new 2001 map were created using the 2005 land use codes, but some values were updated based on three criteria:

- In cases where historic imagery showed evidence that the lot was undeveloped in December 2001 (after TS Allison), the land use code was updated from *residential* to *vacant*, and the land value information removed.

- In cases where there was a structure in December 2001, but this structure was significantly remodeled or re-built between 2002-2005, the land use code was left intact, but its property value was set to equal the neighborhood's median property value as the best approximation of the actual property value at the time of disaster.
- In cases where there was a structure in December 2001, but this structure (that had a NFIP policy record in 2001) was later demolished, the land use code was updated from *tax-exempt* or *vacant* to *residential*, and its property value was set to equal the neighborhood's median property value as the best approximation of the actual property value at the time of disaster.

All assessed property values were corrected for inflation to better reflect 2001 values and match the temporal resolution of all other data.

7. <u>Tax records vs. land use information</u>

HCAD data specifies the land use and property values for tax-paying properties; however, a lot of homes may be listed as tax exempt because the property owner received an exemption, or because the property was demolished or set as vacant.

Tax exempt properties often include government, charitable, religious, historical, and school buildings, community housing, as well as open space lands (e.g., parks and setbacks), but they may also include some residential properties—e.g., property owners over-65 years of age, or with a disabilities, or over-55 years of age as a surviving spouse, or 100% disabled veterans. Vacant properties include undeveloped land (most cases), as well as a few properties with improvements, but uninhabited. However, just because a parcel is coded as tax-exempt or vacant does not preclude it from having an insurable residential property. Excluding policy records that fall on these types of land uses would have reduced the total number of neighborhood cases, and affected the number of valid policy counts in 24% of the neighborhood under study (132 out of 540 cases of 1/4-mile neighborhoods).

All parcel records with tax-exempt and vacant land uses in sampled areas were verified using tabular tax record information and historic imagery from Google Earth (12/31/2001). In cases where an NFIP policy was placed on a parcel without property values, it was initially assumed that (in 2001) it belonged to a single-family residential unit. If according to historic imagery this structure existed in 2001, and if based on tax records this structure was not owned by a school district, religious organization, etc., then the land use code was updated from *tax-exempt* to *residential*, and its property value was set to equal the neighborhood's median property value as the best approximation of the actual property value at the time of disaster.

8. <u>One "mega-parcel" with multiple tax accounts for different properties</u>

In Harris County's Tax Appraisal original spatial data, there are cases in which parcels were not individually delineated, but instead one "mega-parcel" was drawn and multiple identical shapes of the same parcel were stacked one of top of another. If a mega-parcel included (say) 100 homes, the same polygon shape was copied one hundred times to describe each home's tax account in the mega-parcel. This can be a significant problem for sampling and matching parcels (polygons) with policies/claims (data points), because geocoding will place an NFIP policy point at the centroid of the parcel's polygon shape. If a mega-parcel has multiple homes with policies, then all policy points will be clustered at the centroid. The sampling of cases using 1/4-mile or 1/2-mile neighborhoods can either take them all as part of the neighborhood, thereby overestimating policy counts and damages, or it can miss them all altogether and underestimate policy counts and associated damages.

Another problem with mega-parcels is operational. In ArcGIS, when joining parcel information to NFIP policy data points, the program will assign to all points the information associated with the "top" shape, or it will assign to each point the information associated with all parcel polygons in which it falls. If (say) 30 NFIP policy points fall in a mega parcel of 100 vertically stacked parcel polygon shapes, the software can either: 1) produce 30 identical matches, where all 30 NFIP records are assigned the property information of the top polygon shape (whatever that may be); or 2) produce 30 * 100 = 3000 matches. Both matches will have important implications for measurement. The first one will artificially reduce the variability of flood damage and property value information within the neighborhood, and the second (the program's default setting) will grossly exaggerate the number of cases, which in-turn overestimates neighborhood policy counts and estimated damages.

Figure B-1 below illustrates two examples of mega parcels with multiple policies for different homes. This figure was obtained by merging the parcel data polygons with the NFIP data points. The green parcels correspond to insured properties, and the yellow ones are uninsured or undeveloped properties. Ideally, each residential parcel should be delineated individually from its neighboring lots, and if it has a policy, it should have its own point associated with it. However, as explained above HCAD sometimes groups parcels into large mega parcels encompassing several lots. In these cases, the process of geocoding becomes inefficient, it can either:

- Locate all policies contained in mega parcel at the centroid of that polygon shape (left in Figure B-1).
- Distribute policies of insured structures at different locations within the mega parcel's shape (right in Figure B-1).

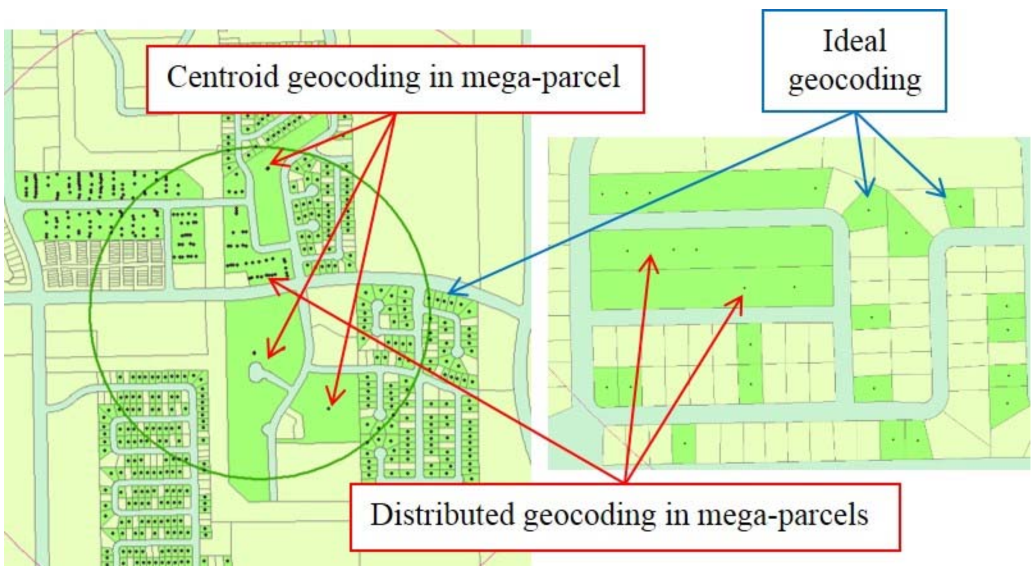


Fig. B-1. Example of geocoding results when matching NFIP records (points) with the corresponding tax parcel account (green polygon), and the issue with mega parcels (green polygons stacked one on top of another with multiple points located at the centroid or distributed across the shape).

To address this issue, it was necessary to “fish out” the polygons of parcels corresponding to insured properties, and supervise the matching process of points to parcels in ArcGIS to ensure and accurate match of policies with parcels.

9. <u>Vertical stacking of parcel polygons for multiple tax accounts</u>

HCAD original spatial data, parcels that have more than one land use are described by stacking multiple identical shapes of the same parcel one of top of another. The same problems listed for mega-parcels apply. Since the top polygon shape may be one of a secondary land use or a *blank* land use (error?), it is also possible that NFIP records are incorrectly removed from study because the program produced an invalid match with the polygon shape of the non-residential parcel.

ACCOUNT	Mailto	Site_addr_	Site_addr1	Site_add_1	State_Clas	Yr_Impr	Total_Appr
0411100000021	[redacted]	19870 CYPRESS CHURCH	CYPRESS	77433	1D1		1733
0411100000024	[redacted]	19870 CYPRESS CHURCH	CYPRESS	77433	A1	1998	606765

Fig. B-2. Example of a parcel address with two parcel polygon shapes, each with a different designated land use, one residential (A1) and the other agricultural (1D1).

Addressing this issue required identifying parcels among the 107,533 geocoded NFIP policy records that had more than one policy (see Figure B-2). At each location, tax records with a matching address and residential land use were retained, all others were removed to ensure a one-to-one match when joining the datasets in ArcGIS.

10. Horizontal stacking of parcel shapes for multiple tax accounts

Another way HCAD spatial data records multiple land uses at a given address is by subdividing the parcel into multiple sub-parcels. When geocoding NFIP policy points, the policy location information may fall in the sub-parcel that does not have the residential tax record, but instead the sub-parcel with records for *blanks* or another land use. Policy points that fall on these types of parcels may end up being excluded from the study, because they did not belong to parcels coded as single-family structures. The placement of all policies points falling in non-residential parcels was verified so that they were placed in the parcel shape containing residential tax record information.

11. NFIP policies without a parcel match

HCAD spatial data appears to have some missing shapes (384 out of 107,533 policy locations). When geocoding policies into parcels, some of these policies were not associated with a parcel polygon. To address this, tabular records were checked to confirm land use codes, and year-built and ownership information. When needed, data was verified using historic imagery from Google Earth (12/31/2001). Also, newer versions of parcel maps were used to add missing parcel shapes to the map.

13. ArcGIS limitations for joining large datasets

ArcGIS appears to be unable to fully merge the tax spatial and tabular information together. The program joins about 70% of the information records accurately, but for the remaining 30% of the joins, the program assigns the same tabular record to a number of spatial shapes. While this may be the impact of a temporary software bug, the result was a file with a few groups of hundreds of parcels with identical tax record information. The software seemed to have a limit on the number of records that it could effectively join; maybe there were too many records in the county for the program to handle (over 1.2 million parcel polygon shapes in Harris County, Texas). To address this, the tax spatial data was broken down into smaller files, and tabular information was joined to each file. All relevant files (those with policies) were then merged together into one single file.

APPENDIX C

Table C-1 Variable descriptions.

Variables	Descriptions
Dependent Variables	
Likelihood of Damage	Proportion of insured single-family homes that filed a claim.
Severity of Damage	Proportion of the property value that was damaged by flood.
Risk Factors	
Road density	Road length per single-family units (m/un), log transformed.
Floodplain exposure	Percent area in the 100-year floodplain (%).
Land use intensity	Percent area dedicated to intense land uses (%).
Protective Factors	
Dams	Presence of upstream flood protection dams (1/0).
Storm-water pipes	Length of pipe drainage network divided by a constant to adjust for a square standard of neighborhood size (proportion).
Elevated building designs	Percent buildings in neighborhoods with elevated designs.
Context Factors	
Minority population	Percent non-white population (%).
Precipitation	Precipitation intensity (in).
Drainage network	Length of overland drainage network divided by a constant to adjust for a square standard of neighborhood size (proportion).
Poorly drained soils	Percent area comprised by poorly drained soils (%).
Hydrologic Function Indicators	
PLAND	Percent area comprised by a specific land cover class (%). Calculated for total pervious areas, wetlands, and woody lands.
LPI	Percent area comprised by the largest patch of a specific land cover class (%). Calculated for wetlands and open grass lands.
SHAPE	Proportion of similarity between a patch's perimeter and that of a square with the same area. Calculated for wetlands and open grassed lands.
NP	Number of patches of the land cover types of interest (count). Calculated for agriculture and open grass lands.

Likelihood of Flood Damage

$$L_i = \frac{C_i}{P_i}(100)$$

i, neighborhood i
C_i, number of NFIP claims for flood damage filed by single-family properties
P_i, number of NFIP policies issued for single-family units

Proportion of insured single-family homes filing claims for flood property damage.

Unit: percent (%)
0 ≤ Likelihood ≤ 100

Severity of Flood Damage

$$S_i = \frac{\sum_{j=1}^{P_i}\left(\frac{D_j}{V_j}\right)}{P_i}(100)$$

i, neighborhood i
D_j, assessed property flood damage for a single-family residential unit j in 2001 dollar amounts of actual cash value (ACV)
V_j, assessed property value in 2001 dollar amounts of the corresponding property j
P_i, number of NFIP policies issued for single-family units

Proportion of the single-family property damaged by flood.

Unit: percent (%)
0 ≤ Severity ≤ 100

Road Density

$$RoadDty_i = \frac{RDTY_i * 7.9248}{SFR_i}$$

i, neighborhood i
$RDTY_i$, road segments (m)
SFR, count of single-family residential units

Road length per housing unit.

Units: meters per unit (m/un)
0 < RDmt2pSFR

Floodplain Exposure

$$hF100yr\_pt_i = \frac{FP_i}{A_i}$$

i, neighborhood i
FP_i, area (m^2) located in floodplains
A_i, neighborhood area (m^2)

Percent area located in the 100-year floodplain.

Units: percent (%)
$0 \leq$ hF100yr_pt ≤ 100

Land Use Intensity

$$LuseInt\_pt_i = \frac{LU_i}{A_i}$$

i, neighborhood i
LU_i, area (m^2) in intense land uses
A_{ni}, neighborhood area (m^2)

Percent area comprised by commercial, industrial, and institutional land uses.

Units: percent (%)
$0 \leq$ LuseInt_pt ≤ 100

Dams

$$FloodDam_i = 1 * FD_i$$

i, neighborhood i
FD_i, 1 if upstream dam, 0 otherwise

Presence of upstream flood protection dams in the neighborhood's watershed.

Units: 1/0
0 – FloodDam - 1

Storm-Water Infrastructure

$$aPipes\_m_i = \frac{\sum_{j=1}^{n} PIPE_i}{\sqrt{A_i}}$$

n_i, neighborhood i
$PIPE_i$, combined length (m) of j storm-water pipe segments in the neighborhood
A_{ni}, neighborhood area (m^2)

Length (m) of major and minor streams divided by a constant to adjust for a square standard of neighborhood size and make metric comparable across scales.

Units: proportion (per neighborhood side length)
$0 \leq$ aPipes_m

Elevated Building Designs

$$2PFloors\_pt_i = \frac{bn_i}{BN_i}$$

i, neighborhood i
bn_i, number of NFIP buildings with elevated designs
BN_i, number of NFIP buildings

Percent buildings in neighborhoods with elevated designs.

Units: percent (%)
0 ≤ 2PFloors_pt ≤ 100

Percent Minority Population

$$hMrity\_pt_i = \frac{\sum_{j=1}^{n}\left(\frac{NW_j}{HH_j}\right)}{\sum_{j=1}^{n}\left(\frac{POP_j}{HH_j}\right)}$$

i, neighborhood i
j, residential parcels in the neighborhood
NW, total count of census non-white population assigned to *j*
HH, total count of census households assigned to *j*
POP, total count of census population assigned to *j*

Using parcel and census blockgroup data, equals the sum of (non-white population/household), divided by the sum of (population/household), and multiplied by 100.

Units: percent (%)
0 ≤ hMrity_pt ≤ 100

Precipitation Intensity

$$ppt5d_i = \frac{\sum_{j=1}^{n} R_j}{N_i}$$

i, neighborhood i
R_j, cumulative 5-day rainfall in pixel j
N_i, number of rainfall pixels in neighborhood

Cumulative 5-day precipitation in inches.

Units: inches of rainfall (")
0 ≤ ppt5d

Drainage Network

$$aDraiNet\_m_i = \frac{\sum_{j=1}^{n} L_j}{\sqrt{A_i}}$$

i, neighborhood i
L_j, combined length (m) of major or minor stream segment j
A_i, neighborhood area (m^2)

Length (m) of major and minor streams divided by a constant to adjust for a square standard of neighborhood size and make metric comparable across scales.

Units: proportion (per neighborhood side length)
0 ≤ aDraiNet_m

Soil Drainage Capacity

$$SoilD\_pt_i = \frac{SD_i}{A_i}$$

i, neighborhood i
SD_i, area (m^2) of poorly drained soils
A_i, neighborhood area (m^2)

Percent area comprised by poor or very poor drained soils classes.

Units: percent (%)
0 ≤ SoilD_pt ≤ 100

Composition: Percent Area

$$PLAND_i = \frac{\sum_{j=1}^{n} a_{kj}}{A_i} (100)$$

i, neighborhood i
k, land cover class of interest
a_{ki}, area (m^2) of patch j of land cover class type k
A_i, neighborhood area (m^2)

Percent area comprised by a specific land cover class. Calculated for pervious areas, wetlands, and woody lands.

Units: percent (%)
0 ≤ PLAND ≤ 100

Configuration: Size

$$LPI_i = \frac{max(a_{kj})_{j=1}^{n}}{A_i}(100)$$

i, neighborhood i
k, land cover class of interest
a_{ki}, area (m^2) of patch j of land cover class type k
A_i, neighborhood area (m^2)

Percent area comprised by the largest patch of a specific land cover class (%). Calculated for wetlands and open grass lands.

Units: percent (%)
$0 \leq LPI \leq 100$

Configuration: Shape

$$SHAPE_k = \frac{.25\, p_{kj}}{\sqrt{a_{kj}}}$$

$$SHAPE\_MN_i = \frac{\sum_{j=1}^{n} SHAPE_k}{n_k}$$

i, neighborhood i
k, land cover class of interest
p_{ki}, perimeter (m) of patch j of land cover class type k
a_{kj}, total area (m^2) of patch j of land cover class type k
n_k, number of patches of land cover class type k

Proportion of similarity between the perimeter of a patch (or sum of perimeters if more than one) divided by the perimeter of a square of equal area. Score increases with patch meandering or complexity (similitude to a natural limit or fractal). Calculated for wetlands and grasslands.

Units: score
0 for blanks, $1 \leq SHAPE$

Composition: Abundance

$$NP_i = n_k$$

i, neighborhood i
k, land cover class of interest
n_k, number of patches type k

Number of patches of the land cover types of interest. A score of zero is assigned when the land cover type is not present in the neighborhood. Calculated for agriculture and open grass lands.

Units: score
0 for blanks, $1 \leq NP$

APPENDIX D

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Table D-1 Summary statistics for 1/4-mile (Q) and 1/2-mile (H) neighborhood analyses.

	1/4-mile neighborhoods						1/2-mile neighborhoods						
*Variable**	*Mean*	*Median*	*Range*			*Std. Dev.*	*Mean*	*Median*	*Range*			*Std. Dev.*	*Units*
Likelihood of damage	14.74	1.52	0	to	100	24.90	14.77	4.55	0	to	100	21.79	Proportion
Severity of damage**	4.17	0.02	0	to	62.09	9.22	4.20	0.29	0	to	53.91	8.74	Percent property value
Road density	3.12	3.00	2.08	to	4.96	0.52	3.11	3.02	2.27	to	5.50	0.45	Normalized (ln)[A]
Floodplain exposure	21.59	2.39	0	to	100	32.04	21.69	8.47	0	to	100	27.08	Percent area
Land use intensity	11.76	7.35	0	to	72.05	13.34	12.35	9.65	0	to	54.52	10.63	Percent area
Dams	0.33	0.00	0	to	1	0.47	0.33	0.00	0	to	1	0.47	1/0
Storm-water pipes	1.29	0.00	0	to	7.61	1.94	2.40	0.00	0	to	13.78	3.33	Normalized [A]
Elevated bg. design	28.27	16.67	0	to	100	28.94	28.41	18.71	0	to	100	26.01	Percent buildings
Minority pop.	31.99	24.39	1.55	to	100	24.67	32.06	24.66	1.88	to	99	24.07	Percent population
Precipitation	16.00	16.37	2.3	to	31	5.88	16.00	16.38	2.3	to	31	5.88	Inches
Overland streams	6.76	0.69	0	to	109.56	17.71	13.28	1.58	0	to	121.8 4	23.79	Normalized [A]
Poor soil drainage	41.36	23.05	0	to	100	42.47	41.42	32.19	0	to	100	38.48	Percent area
Pervious PLAND	25.09	18.19	0	to	91.23	22.08	27.73	23.57	0.53	to	87.12	20.31	Percent area
Agriculture NP	0.52	0.00	0	to	16	1.63	2.01	0.00	0	to	49	4.63	Count
Woody lands PLAND	6.50	1.23	0	to	71.35	10.93	7.43	3.25	0	to	63.48	9.91	Percent area
Grass/open sp. NP	9.19	8.00	0	to	36	5.39	34.35	33.00	4	to	84	15.09	Count
Grass/open sp. LPI	8.15	4.41	0	to	72.24	10.75	5.98	3.71	0	to	45.15	6.72	Percent area
Grass/open sp. SHAPE	1.27	1.23	0	to	3.57	0.30	1.25	1.24	1	to	2.63	0.15	Index
Wetlands PLAND	3.00	0.00	0	to	60.89	8.13	3.67	0.33	0	to	50.31	7.93	Percent area
Wetlands LPI	2.35	0.00	0	to	60.89	7.01	2.40	0.13	0	to	41.25	6.00	Percent area
Wetlands SHAPE	0.54	0.00	0	to	3.20	0.64	0.88	1.05	0	to	4.97	0.65	Index

* N=532 for all variables except Severity of damage; **N=527.

Bg. Building; pop, population; PLAND, proportion of land; NP, number of patches; LPI, largest patch index.

[A] Linear meters (m) normalized by the square root of the neighborhood's area.

Table D-2 OLS Regression models for likelihood of damage (L) in 1/4-mile neighborhoods (Q).

	y = Likelihood of flood damage partial models 1/4-mile											
OLS Model		(LQ1)				(LQ2)				(LQ3)		
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-16.067	0.001	7.01	**	-11.007	0.002	7.37		-42.996	0.001	7.32	***
Road density	7.584	0.158	2.39	***	7.065	0.147	2.40	***	6.931	0.145	1.98	***
Floodplain exposure	0.233	0.298	0.04	***	0.235	0.300	0.04	***	0.221	0.283	0.03	***
Land use intensity	0.177	0.094	0.09	*	0.147	0.078	0.10		0.085	0.045	0.08	
Dams					10.801	0.203	2.25	***	7.269	0.137	2.10	***
Storm-water pipes					-1.248	-0.096	0.46	***	-1.067	-0.082	0.39	***
Elevated bg. design					-0.181	-0.208	0.03	***	-0.118	-0.136	0.03	***
Minority pop.									0.023	0.022	0.04	
Precipitation									1.796	0.427	0.16	***
Overland streams									0.043	0.031	0.07	
Poor soil drainage									0.069	0.116	0.02	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
R-squared	0.139				0.236				0.430			
Adjusted R-squared	0.134				0.227				0.419			
Log-likelihood	-2425				-2393				-2315			
Akaike info criterion	4858				4800				4652			
Breusch-Pagan	87	*p*	*0.000*		148	*p*	*0.000*		178	*p*	*0.000*	
Koenker	38	*p*	*0.000*		73	*p*	*0.000*		114	*p*	*0.000*	

N=532, Heteroscedasticity-robust standard errors variant HC1, VIF variables <2.00, ****p* <.01, ***p* <.05, **p* <.10.

Table D-2 Continued.

	y = Likelihood of flood damage full models 1/4-mile															
OLS Model		(LQ4)				(LQ5)				(LQ6)				(LQ7)		
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	
constant	-42.516	0.000	7.27	***	-45.378	0.001	7.25	***	-35.499	0.000	7.64	***	-34.901	0.001	7.69	***
Road density	8.363	0.175	2.02	***	7.559	0.158	2.08	***	7.731	0.161	1.96	***	7.587	0.158	1.96	***
Floodplain exposure	0.222	0.284	0.03	***	0.229	0.293	0.03	***	0.235	0.300	0.03	***	0.236	0.301	0.03	***
Land use intensity	0.025	0.013	0.08		0.035	0.018	0.08		0.041	0.022	0.08		0.044	0.023	0.08	
Dams	6.928	0.130	2.09	***	7.074	0.133	2.04	***	6.328	0.119	2.11	***	6.434	0.121	2.10	***
Storm-water pipes	-1.465	-0.113	0.41	***	-0.988	-0.076	0.42	**	-1.414	-0.109	0.40	***	-1.419	-0.109	0.41	***
Elevated bg. design	-0.116	-0.134	0.03	***	-0.104	-0.120	0.03	***	-0.114	-0.131	0.03	***	-0.114	-0.132	0.03	***
Minority pop.	0.022	0.022	0.04		0.008	0.008	0.04		0.019	0.019	0.04		0.020	0.019	0.04	
Precipitation	1.738	0.413	0.16	***	1.768	0.420	0.16	***	1.768	0.420	0.16	***	1.768	0.421	0.16	***
Overland streams	0.062	0.044	0.06		0.041	0.029	0.06		0.087	0.061	0.07		0.085	0.060	0.07	
Poor soil drainage	0.068	0.115	0.02	***	0.063	0.108	0.02	***	0.072	0.122	0.02	***	0.072	0.122	0.02	***
Pervious PLAND	-0.114	-0.102	0.05	**												
Agriculture NP					-0.938	-0.061	0.39	**								
Woody lands PLAND					-0.021	-0.009	0.08									
Grass/open sp. NP					0.433	0.094	0.19	**								
Grass/open sp. LPI					-0.057	-0.025	0.07									
Grass/open sp. SHAPE									-6.373	-0.075	2.13	***	-6.581	-0.077	2.16	***
Wetlands PLAND									-0.312	-0.104	0.10	***				
Wetlands LPI													-0.370	-0.106	0.11	***
Wetlands SHAPE					-2.465	-0.063	1.43	*								
R-squared	0.436				0.445				0.443				0.444			
Adjusted R-squared	0.425				0.429				0.430				0.431			
Log-likelihood	-2312				-2308				-2309				-2309			
Akaike info criterion	4648				4648				4644				4643			
Breusch-Pagan	179	*p*	*0.000*		181	*p*	*0.000*		190	*p*	*0.000*		189	*p*	*0.000*	
Koenker	115	*p*	*0.000*		116	*p*	*0.000*		120	*p*	*0.000*		119	*p*	*0.000*	

N=532, Heteroscedasticity-robust standard errors variant HC1, VIF variables <2.00, ****p* <.01, ***p* <.05, **p* <.10.

Table D-3 OLS Regression models for likelihood of damage (L) in 1/2-mile neighborhoods (H).

	y = Likelihood of flood damage partial models 1/2-mile											
OLS Model		(LH1)				(LH2)				(LH3)		
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-10.524	0.001	7.66		-7.624	0.002	6.69		-38.006	0.001	5.86	***
Road density	4.893	0.101	2.57	*	5.567	0.115	2.28	**	4.948	0.102	1.72	***
Floodplain exposure	0.256	0.315	0.04	***	0.256	0.315	0.04	***	0.242	0.299	0.03	***
Land use intensity	0.365	0.177	0.09	***	0.212	0.103	0.09	**	0.091	0.044	0.07	
Dams					11.999	0.257	1.89	***	8.224	0.176	1.76	***
Storm-water pipes					-0.284	-0.043	0.23		0.026	0.004	0.18	
Elevated bg. design					-0.226	-0.266	0.03	***	-0.137	-0.162	0.03	***
Minority pop.									0.049	0.053	0.03	
Precipitation									1.675	0.454	0.13	***
Overland streams									0.022	0.024	0.04	
Poor soil drainage									0.083	0.145	0.02	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
R-squared	0.149				0.295				0.519			
Adjusted R-squared	0.144				0.287				0.509			
Log-likelihood	-2351				-2301				-2199			
Akaike info criterion	4709				4616				4420			
Breusch-Pagan	85	*p*	*0.000*		137	*p*	*0.000*		156	*p*	*0.000*	
Koenker	39	*p*	*0.000*		82	*p*	*0.000*		105	*p*	*0.000*	

N=532, Heteroscedasticity-robust standard errors variant HC1, VIF variables <2.00, ****p* <.01, ***p* <.05, **p* <.10.

Table D-3 Continued.

	y = Likelihood of flood damage full models 1/2-mile															
OLS Model		(LH4)				(LH5)				(LH6)				(LH7)		
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-38.104	0.001	5.87	***	-40.382	0.001	5.96	***	-36.963	0.000	8.01	***	-35.625	0.001	8.09	***
Road density	5.522	0.114	1.86	***	4.919	0.102	1.96	**	6.511	0.134	1.77	***	5.940	0.123	1.75	***
Floodplain exposure	0.242	0.298	0.03	***	0.254	0.313	0.03	***	0.256	0.315	0.03	***	0.254	0.312	0.03	***
Land use intensity	0.061	0.029	0.08		0.065	0.032	0.08		0.011	0.006	0.07		0.030	0.014	0.07	
Dams	8.034	0.172	1.78	***	8.202	0.176	1.73	***	7.198	0.154	1.76	***	7.311	0.157	1.76	***
Storm-water pipes	0.007	0.001	0.18		-0.063	-0.010	0.18		-0.030	-0.005	0.18		-0.016	-0.002	0.18	
Elevated bg. design	-0.139	-0.164	0.03	***	-0.114	-0.135	0.03	***	-0.137	-0.162	0.03	***	-0.139	-0.164	0.03	***
Minority pop.	0.048	0.052	0.03		0.049	0.054	0.03		0.043	0.047	0.03		0.044	0.048	0.03	
Precipitation	1.660	0.450	0.13	***	1.592	0.431	0.12	***	1.665	0.451	0.13	***	1.658	0.449	0.13	***
Overland streams	0.024	0.026	0.04		0.009	0.010	0.04		0.036	0.039	0.04		0.032	0.035	0.04	
Poor soil drainage	0.083	0.145	0.02	***	0.072	0.126	0.02	***	0.091	0.159	0.02	***	0.091	0.159	0.02	***
Pervious PLAND	-0.033	-0.031	0.04													
Agriculture NP					-0.289	-0.061	0.12	**								
Woody lands PLAND					0.000	0.000	0.09									
Grass/open sp. NP					0.200	0.138	0.05	***								
Grass/open sp. LPI					0.002	0.001	0.08									
Grass/open sp. SHAPE									-2.952	-0.019	4.06		-2.913	-0.019	4.05	
Wetlands PLAND									-0.332	-0.122	0.09	***				
Wetlands LPI													-0.377	-0.104	0.11	***
Wetlands SHAPE					-2.542	-0.075	1.18	**								
R-squared	0.519				0.541				0.530				0.528			
Adjusted R-squared	0.509				0.527				0.519				0.517			
Log-likelihood	-2199				-2187				-2193				-2194			
Akaike info criterion	4422				4405				4412				4414			
Breusch-Pagan	156	*p*	*0.000*		145	*p*	*0.000*		156	*p*	*0.000*		156	*p*	*0.000*	
Koenker	106	*p*	*0.000*		108	*p*	*0.000*		105	*p*	*0.000*		105	*p*	*0.000*	

N=532, Heteroscedasticity-robust standard errors variant HC1, VIF variables <2.00, ***p <.01, **p <.05, *p <.10.

Table D-4 OLS Regression models for severity of damage (S) in 1/4-mile neighborhoods (Q).

	y = Severity of flood damage partial models 1/4-mile											
OLS Model		(SQ1)				(SQ2)				(SQ3)		
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-6.902	-0.014	2.84	**	-4.540	-0.011	2.62	*	-14.206	-0.009	2.68	***
Road density	2.870	0.159	0.97	***	2.603	0.144	0.92	***	2.511	0.139	0.81	***
Floodplain exposure	0.076	0.256	0.02	***	0.078	0.263	0.01	***	0.067	0.227	0.01	***
Land use intensity	0.031	0.044	0.04		0.021	0.029	0.04		0.004	0.005	0.03	
Dams					4.088	0.204	0.88	***	2.882	0.144	0.85	***
Storm-water pipes					-0.559	-0.114	0.15	***	-0.511	-0.104	0.14	***
Elevated bg. design					-0.073	-0.223	0.01	***	-0.056	-0.171	0.01	***
Minority pop.									0.008	0.020	0.02	
Precipitation									0.558	0.351	0.07	***
Overland streams									0.042	0.079	0.03	
Poor soil drainage									0.020	0.089	0.01	**
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
R-squared	0.112				0.227				0.376			
Adjusted R-squared	0.106				0.218				0.364			
Log-likelihood	-1876				-1840				-1783			
Akaike info criterion	3760				3693				3588			
Breusch-Pagan	138	*p*	*0.000*		274	*p*	*0.000*		412	*p*	*0.000*	
Koenker	23	*p*	*0.000*		51	*p*	*0.000*		98	*p*	*0.000*	

N=527, Heteroscedasticity-robust standard errors variant HC1, VIF variables <2.00, ****p* <.01, ***p* <.05, **p* <.10.

Table D-4 Continued.

	y = Severity of flood damage full models 1/4-mile															
OLS Model		(SQ4)				(SQ5)				(SQ6)				(SQ7)		
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-14.127	-0.010	2.68	***	-14.964	-0.008	2.68	***	-11.314	-0.010	3.05	***	-11.196	-0.009	3.07	***
Road density	2.939	0.162	0.79	***	2.606	0.144	0.80	***	2.751	0.152	0.79	***	2.713	0.150	0.80	***
Floodplain exposure	0.067	0.228	0.01	***	0.069	0.234	0.01	***	0.072	0.242	0.01	***	0.072	0.242	0.01	***
Land use intensity	-0.014	-0.019	0.03		-0.007	-0.010	0.03		-0.010	-0.014	0.03		-0.009	-0.013	0.03	
Dams	2.782	0.139	0.85	***	2.856	0.142	0.83	***	2.635	0.131	0.84	***	2.659	0.132	0.84	***
Storm-water pipes	-0.626	-0.128	0.15	***	-0.463	-0.094	0.16	***	-0.633	-0.129	0.15	***	-0.633	-0.129	0.15	***
Elevated bg. design	-0.056	-0.169	0.01	***	-0.053	-0.162	0.01	***	-0.055	-0.167	0.01	***	-0.055	-0.168	0.01	***
Minority pop.	0.007	0.019	0.02		0.004	0.010	0.02		0.006	0.015	0.02		0.006	0.016	0.02	
Precipitation	0.541	0.341	0.07	***	0.544	0.343	0.07	***	0.549	0.346	0.07	***	0.549	0.346	0.07	***
Overland streams	0.048	0.090	0.03		0.041	0.077	0.03		0.054	0.101	0.03	*	0.054	0.101	0.03	*
Poor soil drainage	0.020	0.089	0.01	**	0.018	0.079	0.01	*	0.021	0.094	0.01	**	0.021	0.093	0.01	**
Pervious PLAND	-0.033	-0.078	0.02	*												
Agriculture NP					-0.284	-0.049	0.14	**								
Woody lands PLAND					-0.015	-0.017	0.03									
Grass/open sp. NP					0.148	0.085	0.08	*								
Grass/open sp. LPI					-0.022	-0.025	0.03									
Grass/open sp. SHAPE									-2.399	-0.075	0.87	***	-2.432	-0.076	0.88	***
Wetlands PLAND									-0.092	-0.082	0.04	**				
Wetlands LPI													-0.106	-0.081	0.05	**
Wetlands SHAPE					-0.163	-0.011	0.65									
R-squared	0.380				0.387				0.386				0.387			
Adjusted R-squared	0.367				0.369				0.372				0.372			
Log-likelihood	-1781				-1778				-1779				-1779			
Akaike info criterion	3587				3589				3583				3583			
Breusch-Pagan	409	*p*	*0.000*		407	*p*	*0.000*		418	*p*	*0.000*		418	*p*	*0.000*	
Koenker	95	*p*	*0.000*		96	*p*	*0.000*		94	*p*	*0.000*		94	*p*	*0.000*	

N=527, Heteroscedasticity-robust standard errors variant HC1, VIF variables <2.00, ****p* <.01, ***p* <.05, **p* <.10.

Table D-5 OLS Regression models for severity of damage (S) in 1/2-mile neighborhoods (H).

	y = Severity of flood damage partial models 1/2-mile											
OLS Model		(SH1)				(SH2)				(SH3)		
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-6.443	-0.016	3.94		-5.013	-0.013	3.46		-15.121	-0.012	3.46	***
Road density	2.307	0.117	1.34	*	2.530	0.129	1.23	**	2.407	0.122	1.05	**
Floodplain exposure	0.094	0.284	0.02	***	0.095	0.288	0.02	***	0.088	0.265	0.02	***
Land use intensity	0.106	0.127	0.04	**	0.050	0.060	0.04		0.012	0.014	0.04	
Dams					4.496	0.237	0.78	***	3.105	0.164	0.76	***
Storm-water pipes					-0.176	-0.066	0.09	*	-0.074	-0.027	0.08	
Elevated bg. design					-0.088	-0.257	0.01	***	-0.059	-0.171	0.01	***
Minority pop.									0.024	0.066	0.02	
Precipitation									0.522	0.348	0.06	***
Overland streams									0.015	0.040	0.02	
Poor soil drainage									0.029	0.124	0.01	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
R-squared	0.128				0.270				0.424			
Adjusted R-squared	0.123				0.262				0.413			
Log-likelihood	-1840				-1793				-1731			
Akaike info criterion	3689				3601				3484			
Breusch-Pagan	209	*p*	*0.000*		322	*p*	*0.000*		414	*p*	*0.000*	
Koenker	36	*p*	*0.000*		60	*p*	*0.000*		89	*p*	*0.000*	

N=527, Heteroscedasticity-robust standard errors variant HC1, VIF variables <2.00, ****p* <.01, ***p* <.05, **p* <.10.

Table D-5 Continued.

	y = Severity of flood damage full models 1/2-mile															
OLS Model		(SH4)				(SH5)				(SH6)				(SH7)		
Variables	*b*	*beta*	*s.e.*		*b*	*beta*	*s.e.*		*b*	*beta*	*s.e.*		*b*	*beta*	*s.e.*	
constant	-15.101	-0.011	3.46	***	-15.798	-0.010	3.52	***	-15.407	-0.012	4.63	***	-15.162	-0.012	4.69	***
Road density	2.298	0.117	1.10	**	2.051	0.104	1.23	*	2.746	0.139	0.99	***	2.619	0.133	1.00	***
Floodplain exposure	0.088	0.266	0.02	***	0.093	0.283	0.02	***	0.091	0.277	0.02	***	0.091	0.275	0.02	***
Land use intensity	0.017	0.021	0.04		0.019	0.022	0.04		-0.006	-0.007	0.04		-0.002	-0.002	0.04	
Dams	3.140	0.166	0.78	***	3.098	0.163	0.75	***	2.892	0.153	0.76	***	2.914	0.154	0.75	***
Storm-water pipes	-0.070	-0.026	0.08		-0.095	-0.035	0.08		-0.086	-0.032	0.08		-0.082	-0.031	0.08	
Elevated bg. design	-0.058	-0.170	0.01	***	-0.051	-0.147	0.01	***	-0.059	-0.171	0.01	***	-0.059	-0.172	0.01	***
Minority pop.	0.025	0.066	0.02		0.024	0.064	0.02		0.022	0.060	0.02		0.023	0.062	0.02	
Precipitation	0.525	0.350	0.07	***	0.486	0.324	0.06	***	0.523	0.349	0.06	***	0.521	0.347	0.06	***
Overland streams	0.015	0.039	0.02		0.009	0.023	0.02		0.018	0.048	0.02		0.017	0.046	0.02	
Poor soil drainage	0.029	0.123	0.01	***	0.024	0.101	0.01	**	0.031	0.132	0.01	***	0.031	0.132	0.01	***
Pervious PLAND	0.006	0.015	0.02													
Agriculture NP					-0.119	-0.061	0.05	**								
Woody lands PLAND					0.027	0.030	0.04									
Grass/open sp. NP					0.085	0.145	0.03	***								
Grass/open sp. LPI					0.002	0.001	0.03									
Grass/open sp. SHAPE									-0.236	-0.004	1.88		-0.202	-0.003	1.88	
Wetlands PLAND									-0.083	-0.075	0.05	*				
Wetlands LPI													-0.091	-0.062	0.06	
Wetlands SHAPE					-0.674	-0.049	0.46									
R-squared	0.424				0.447				0.428				0.427			
Adjusted R-squared	0.412				0.431				0.415				0.414			
Log-likelihood	-1731				-1720				-1729				-1730			
Akaike info criterion	3486				3473				3484				3485			
Breusch-Pagan	418	*p*	*0.000*		402	*p*	*0.000*		422	*p*	*0.000*		421	*p*	*0.000*	
Koenker	90	*p*	*0.000*		88	*p*	*0.000*		86	*p*	*0.000*		87	*p*	*0.000*	

N=527, Heteroscedasticity-robust standard errors variant HC1, VIF variables <2.00, ****p* <.01, ***p* <.05, **p* <.10.

Table D-6 Spatial autocorrelation diagnostics of fully-specified OLS regression models 4 to 7 for likelihood of damage (L) and severity of damage (S).

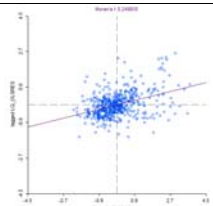
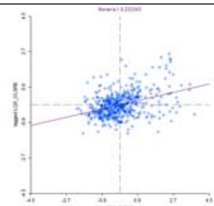
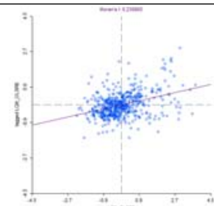
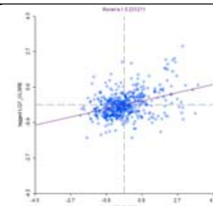
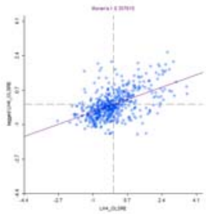
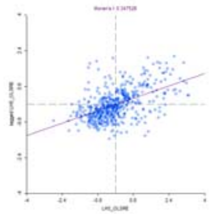
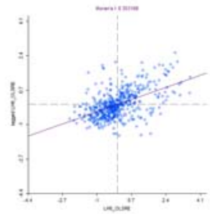
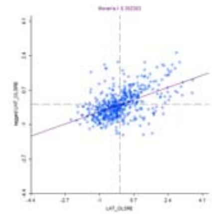
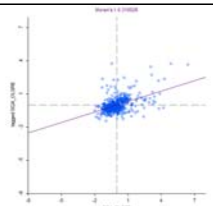
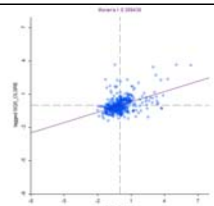
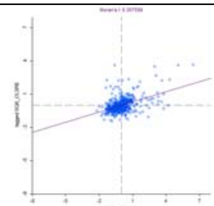
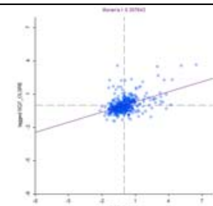
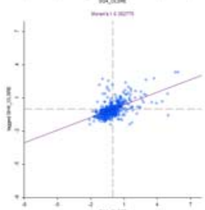
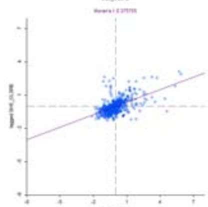
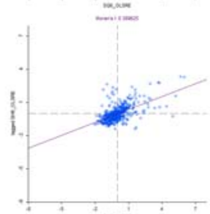
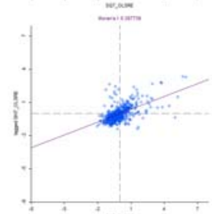
Likelihood of damage	Model 4	Model 5	Model 6	Model 7
1/4-mile				
1/2-mile				
Severity of Damage	**Model 4**	**Model 5**	**Model 6**	**Model 7**
1/4-mile				
1/2-mile				

Table D-7 Collinearity diagnostics of fully-specified OLS regression models 4 to 7 for likelihood of damage (L) in 1/4-mile neighborhoods (Q) and 1/2-mile (H) neighborhoods.

	y = Likelihood of Flood Damage							
	1/4-mile VIF values				1/2-mile VIF values			
OLS Model	(LQ4)	(LQ5)	(LQ6)	(LQ7)	(LH4)	(LH5)	(LH6)	(LH7)
Road density	1.334	1.338	1.215	1.204	1.360	1.391	1.223	1.179
Floodplain exposure	1.369	1.384	1.406	1.406	1.385	1.402	1.416	1.413
Land use intensity	1.340	1.349	1.221	1.212	1.543	1.481	1.333	1.299
Dams	1.435	1.438	1.457	1.448	1.620	1.603	1.649	1.648
Storm-water pipes	1.300	1.363	1.226	1.226	1.092	1.097	1.085	1.083
Elevated bg. design	1.261	1.297	1.262	1.261	1.363	1.403	1.359	1.359
Minority pop.	1.377	1.414	1.384	1.384	1.391	1.403	1.394	1.394
Precipitation	1.144	1.164	1.120	1.120	1.159	1.188	1.175	1.175
Overland streams	1.487	1.491	1.533	1.523	1.523	1.558	1.545	1.538
Poor soil drainage	1.355	1.380	1.363	1.361	1.507	1.601	1.524	1.528
Pervious PLAND	1.625				1.649			
Agriculture NP		1.190				1.304		
Woody lands PLAND		1.440				1.544		
Grass/open sp. NP		1.289				1.256		
Grass/open sp. LPI		1.162				1.131		
Grass/open sp. SHAPE			1.123	1.125			1.141	1.142
Wetlands PLAND			1.273				1.323	
Wetlands LPI				1.220				1.225
Wetlands SHAPE		1.398				1.389		
Condition number	25.59	28.31	28.53	28.45	30.16	34.36	41.72	41.61

N=532.

Table D 8 Collinearity diagnostics of fully-specified OLS regression models 4 to 7 for severity of damage (S) in 1/4-mile neighborhoods (Q) and 1/2-mile (H) neighborhoods.

	y = Severity of Flood Damage							
	1/4-mile VIF values				1/2-mile VIF values			
OLS Model	(SQ4)	(SQ5)	(SQ6)	(SQ7)	(SH4)	(SH5)	(SH6)	(SH7)
Road density	1.329	1.333	1.200	1.191	1.352	1.393	1.208	1.172
Floodplain exposure	1.339	1.356	1.385	1.381	1.360	1.381	1.398	1.392
Land use intensity	1.336	1.344	1.218	1.208	1.543	1.485	1.334	1.299
Dams	1.434	1.433	1.448	1.443	1.608	1.591	1.632	1.633
Storm-water pipes	1.300	1.366	1.225	1.224	1.089	1.093	1.083	1.081
Elevated bg. design	1.258	1.292	1.258	1.258	1.363	1.400	1.359	1.359
Minority pop.	1.377	1.421	1.388	1.384	1.397	1.409	1.404	1.400
Precipitation	1.146	1.169	1.121	1.121	1.159	1.187	1.175	1.175
Overland streams	1.443	1.451	1.465	1.464	1.488	1.523	1.505	1.502
Poor soil drainage	1.351	1.375	1.360	1.358	1.498	1.590	1.517	1.521
Pervious PLAND	1.634				1.641			
Agriculture NP		1.190				1.303		
Woody lands PLAND		1.444				1.544		
Grass/open sp. NP		1.299				1.260		
Grass/open sp. LPI		1.175				1.131		
Grass/open sp. SHAPE			1.116	1.118			1.140	1.140
Wetlands PLAND			1.258				1.314	
Wetlands LPI				1.216				1.223
Wetlands SHAPE		1.406				1.390		
Condition number	25.72	28.43	28.59	28.53	30.28	34.57	41.60	41.50

N=527.

Table D-9 Spatial Autoregressive Model (SAR) diagnostics of fully-specified OLS regression models 4 to 7 for likelihood of damage (L) in 1/4-mile neighborhoods (Q) and 1/2-mile (H) neighborhoods.

	y = Likelihood of flood damage 1/4-mile							
OLS Model	(LQ4)		(LQ5)		(LQ6)		(LQ7)	
	Value	*Prob.*	*Value*	*Prob.*	*Value*	*Prob.*	*Value*	*Prob.*
Moran's I (error)	0.25	0.000	0.25	0.000	0.23	0.000	0.23	0.000
z-score	9.336		9.208		8.814		8.260	
Lagrange Multiplier (lag)	73.05	0.000	70.21	0.000	69.07	0.000	69.27	0.000
Robust LM (lag)	1.03	0.310	3.63	0.057	3.70	0.054	3.68	0.055
Lagrange Multiplier (error)	81.54	0.000	71.08	0.000	69.54	0.000	69.78	0.000
Robust LM (error)	9.53	0.002	4.50	0.034	4.17	0.041	4.22	0.040
Lagrange Multiplier (SARMA)	82.57	0.000	74.71	0.000	73.24	0.000	73.47	0.000

Table D-9 Continued.

	y = Likelihood of flood damage 1/2-mile							
OLS Model	(LH4)		(LH5)		(LH6)		(LH7)	
	Value	*Prob.*	*Value*	*Prob.*	*Value*	*Prob.*	*Value*	*Prob.*
Moran's I (error)	0.36	0.000	0.35	0.000	0.35	0.000	0.35	0.000
z-score	13.110		12.601		12.962		12.777	
Lagrange Multiplier (lag)	146.90	0.000	139.90	0.000	141.03	0.000	141.75	0.000
Robust LM (lag)	2.59	0.107	4.03	0.045	2.50	0.114	2.75	0.095
Lagrange Multiplier (error)	166.94	0.000	157.66	0.000	162.82	0.000	162.02	0.000
Robust LM (error)	22.63	0.000	21.78	0.000	24.29	0.000	23.02	0.000
Lagrange Multiplier (SARMA)	169.53	0.000	161.69	0.000	165.32	0.000	164.77	0.000

Table D-10 Spatial Autoregressive Model (SAR) diagnostics of fully-specified OLS regression models 4 to 7 for severity of damage (S) in 1/4-mile neighborhoods (Q) and 1/2-mile (H) neighborhoods.

	y = Severity of flood damage 1/4-mile							
OLS Model	(SQ4)		(SQ5)		(SQ6)		(SQ7)	
	Value	*Prob.*	*Value*	*Prob.*	*Value*	*Prob.*	*Value*	*Prob.*
Moran's I (error)	0.32	0.000	0.31	0.000	0.31	0.000	0.31	0.000
z-score	11.259		11.180		11.303		11.611	
Lagrange Multiplier (lag)	121.24	0.000	120.51	0.000	118.77	0.000	118.98	0.000
Robust LM (lag)	2.45	0.118	4.92	0.265	4.67	0.036	4.76	0.029
Lagrange Multiplier (error)	129.90	0.000	122.98	0.000	121.52	0.000	121.55	0.000
Robust LM (error)	11.10	0.000	7.39	0.007	7.42	0.006	7.33	0.007
Lagrange Multiplier (SARMA)	132.34	0.000	127.90	0.000	126.19	0.000	126.31	0.000

Table D-10 Continued.

	y = Severity of flood damage 1/2-mile							
OLS Model	(SH4)		(SH5)		(SH6)		(SH7)	
	Value	*Prob.*	*Value*	*Prob.*	*Value*	*Prob.*	*Value*	*Prob.*
Moran's I (error)	0.38	0.000	0.38	0.000	0.39	0.000	0.39	0.000
z-score	13.487		13.599		14.310		13.572	
Lagrange Multiplier (lag)	173.36	0.000	166.46	0.000	173.28	0.000	172.99	0.000
Robust LM (lag)	3.56	0.059	4.69	0.030	2.12	0.145	2.41	0.127
Lagrange Multiplier (error)	188.17	0.000	181.34	0.000	194.97	0.000	193.09	0.000
Robust LM (error)	18.37	0.000	19.57	0.000	23.82	0.000	22.51	0.000
Lagrange Multiplier (SARMA)	191.73	0.000	186.03	0.000	197.09	0.000	195.49	0.000

Table D-11 Comparison of lambda estimates of fully-specified OLS regression models 4 to 7 for likelihood of damage (L) in 1/4-mile neighborhoods (Q) and 1/2-mile (H) neighborhoods.

	(LQ4)			(LQ5)			(LQ6)		
Estimation Method	*lambda*	*s.e.*	*R2*	*lambda*	*s.e.*	*R2*	*lambda*	*s.e.*	*R2*
GM	0.4150		0.431	0.3947		0.439	0.3944		0.437
GMM Hom errors[1]	0.4330	0.043	0.431	0.4198	0.043	0.439	0.4175	0.044	0.437
GMM Het errors	0.4438	0.058	0.431	0.4332	0.057	0.440	0.4311	0.059	0.437
GMM Het errors 1c	0.4452	0.058	0.431	0.4350	0.057	0.439	0.4328	0.059	0.437
GMM Het errors Iterated	0.4468	0.058	0.430	0.4376	0.057	0.438	0.4356	0.059	0.435
ML[2]	0.4439	0.051	0.523	0.4342	0.051	0.524	0.4307	0.051	0.521

	(LH4)			(LH5)			(LH6)		
Estimation Method	*lambda*	*s.e.*	*R2*	*lambda*	*s.e.*	*R2*	*lambda*	*s.e.*	*R2*
GM	0.4967		0.509	0.4861		0.533	0.4982		0.521
GMM Hom errors[1]	0.5333	0.037	0.509	0.5173	0.037	0.533	0.5266	0.038	0.521
GMM Het errors	0.5978	0.048	0.509	0.5770	0.047	0.533	0.5922	0.049	0.521
GMM Het errors 1c	0.6088	0.047	0.505	0.5855	0.047	0.530	0.6026	0.049	0.518
GMM Het errors Iterated	0.6188	0.047	0.500	0.5928	0.047	0.528	0.5297	0.037	0.520
ML[2]	0.5813	0.042	0.654	0.5687	0.043	0.663	0.5736	0.043	0.658

[1] Default setting GeodaSpace.
[2] Default setting GeoDa.

Table D-12 Comparison of lambda estimates of fully-specified OLS regression models 4 to 7 for severity of damage (S) in 1/4-mile neighborhoods (Q) and 1/2-mile (H) neighborhoods.

	(SQ4)			(SQ5)			(SQ6)		
Estimation Method	*lambda*	*s.e.*	*R2*	*lambda*	*s.e.*	*R2*	*lambda*	*s.e.*	*R2*
GM	0.4665		0.367	0.4582		0.376	0.4599		0.374
GMM Hom errors[1]	0.4850	0.036	0.367	0.4760	0.036	0.376	0.4780	0.037	0.374
GMM Het errors	0.4964	0.070	0.369	0.4901	0.070	0.377	0.4889	0.072	0.376
GMM Het errors 1c	0.4983	0.070	0.367	0.4920	0.070	0.376	0.4907	0.071	0.374
GMM Het errors Iterated	0.5013	0.069	0.364	0.4946	0.069	0.373	0.4939	0.071	0.371
ML[2]	0.5236	0.046	0.520	0.5173	0.046	0.521	0.5178	0.046	0.519

	(SH4)			(SH5)			(SH6)		
Estimation Method	*lambda*	*s.e.*	*R2*	*lambda*	*s.e.*	*R2*	*lambda*	*s.e.*	*R2*
GM	0.4964		0.403	0.4947		0.431	0.5080		0.410
GMM Hom errors[1]	0.5305	0.033	0.403	0.5185	0.034	0.431	0.5342	0.033	0.410
GMM Het errors	0.5907	0.054	0.404	0.5698	0.054	0.432	0.5868	0.054	0.411
GMM Het errors 1c	0.5978	0.053	0.397	0.5734	0.053	0.428	0.5923	0.053	0.405
GMM Het errors Iterated	0.6084	0.052	0.387	0.5792	0.052	0.422	0.5997	0.052	0.398
ML[2]	0.6384	0.038	0.616	0.6236	0.039	0.623	0.6389	0.038	0.620

[1] Default setting GeodaSpace.
[2] Default setting GeoDa.

Table D-13 Spatial error regression models (SEM) explaining the likelihood of flood damage (L) in 1/4-mile neighborhoods (Q).

	y = Likelihood of damage											
SEM GMM-HET	Model 1 Risk Factors				Model 2 Risk and Protection				Model 3 Risk, Protection, and Context			
Model	(LQ1)				(LQ2)				(LQ3)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-15.298	-0.004	5.83	***	-15.784	-0.004	6.20	**	-46.200	-0.003	7.66	***
Road density	7.756	0.163	2.01	***	7.791	0.164	2.03	***	7.552	0.159	1.88	***
Floodplain exposure	0.221	0.285	0.03	***	0.227	0.291	0.03	***	0.212	0.273	0.03	***
Land use intensity	0.079	0.042	0.08		0.084	0.045	0.08		0.075	0.040	0.08	
Dams					8.029	0.152	2.99	***	5.539	0.105	2.57	**
Storm-water pipes					-0.075	-0.006	0.48		-0.315	-0.025	0.44	
Elevated bg. design					-0.083	-0.097	0.03	***	-0.089	-0.104	0.03	***
Minority pop.									0.005	0.004	0.05	
Precipitation									1.811	0.428	0.24	***
Overland streams									0.075	0.054	0.06	
Poor soil drainage									0.079	0.135	0.02	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
Lambda λ	0.640	0.640	0.04	***	0.608	0.608	0.04	***	0.441	0.441	0.06	***
pseudo-R2	0.136				0.216				0.425			

N=532, Spatial Errol Model (SEM), General Method of Moments for Heteroscedastic errors (GMM-HET).
L, likelihood of flood damage; Q, quarter-mile neighborhoods; PLAND, proportion of land; NP, number of patches; LPI, largest patch index.
****p* <.01, ***p* <.05, **p* <.10.

Table D-13 Continued.

	y = Likelihood of damage															
SEM GMM-HET	Model 4 HFI Part 1				Model 5 HFI Part 2				Model 6 HFI Part 3				Model 7 HFI Part 4			
Model	(LQ4)				(LQ5)				(LQ6)				(LQ7)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-44.925	-0.001	7.65	***	-46.056	0.001	7.53	***	-39.145	-0.001	7.88	***	-38.704	-0.001	7.97	***
Road density	8.890	0.187	1.88	***	7.579	0.159	1.94	***	7.855	0.165	1.86	***	7.770	0.163	1.86	***
Floodplain exposure	0.217	0.280	0.03	***	0.217	0.279	0.03	***	0.224	0.288	0.03	***	0.225	0.289	0.03	***
Land use intensity	0.017	0.009	0.08		0.047	0.025	0.08		0.048	0.026	0.08		0.049	0.026	0.08	
Dams	5.260	0.100	2.53	**	5.382	0.102	2.52	**	5.001	0.095	2.53	**	5.048	0.096	2.52	**
Storm-water pipes	-0.750	-0.058	0.45	*	-0.375	-0.029	0.46		-0.606	-0.047	0.44		-0.610	-0.047	0.44	
Elevated bg. design	-0.091	-0.106	0.03	***	-0.082	-0.096	0.03	***	-0.087	-0.101	0.03	***	-0.087	-0.101	0.03	***
Minority pop.	0.003	0.003	0.05		0.001	0.001	0.05		0.006	0.006	0.05		0.006	0.006	0.05	
Precipitation	1.745	0.412	0.24	***	1.758	0.415	0.24	***	1.793	0.424	0.24	***	1.794	0.424	0.24	***
Overland streams	0.094	0.067	0.06		0.076	0.054	0.06		0.104	0.074	0.06	*	0.103	0.073	0.06	*
Poor soil drainage	0.079	0.135	0.02	***	0.077	0.131	0.02	***	0.082	0.140	0.02	***	0.082	0.140	0.02	***
Pervious PLAND	-0.127	-0.112	0.04	***												
Agriculture NP					-0.660	-0.043	0.36	*								
Woody lands PLAND					-0.012	-0.005	0.08									
Grass/open sp. NP					0.351	0.076	0.17	**								
Grass/open sp. LPI					-0.110	-0.048	0.06	*								
Grass/open sp. SHAPE									-5.377	-0.064	1.84	***	-5.573	-0.066	1.86	***
Wetlands PLAND									-0.220	-0.072	0.10	**				
Wetlands LPI													-0.270	-0.076	0.11	**
Wetlands SHAPE					-1.630	-0.042	1.32									
Lambda λ	0.444	0.444	0.06	***	0.433	0.433	0.06	***	0.431	0.431	0.06	***	0.431	0.431	0.06	***
pseudo-R2	0.431				0.440				0.437				0.438			

N=532, Spatial Errol Model (SEM), General Method of Moments for Heteroscedastic errors (GMM-HET); HFI, Hydrologic Function Indicators.
L, likelihood of flood damage; Q, quarter-mile neighborhoods; PLAND, proportion of land; NP, number of patches; LPI, largest patch index.
***p <.01, **p <.05, *p <.10.

Table D-14 Spatial error regression models (SEM) explaining the likelihood of flood damage (L) in 1/2-mile neighborhoods (H).

	y = Likelihood of damage											
SEM GMM-HET	Model 1 Risk Factors				Model 2 Risk and Protection				Model 3 Risk, Protection, and Context			
Model	(LH1)				(LH2)				(LH3)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-15.132	0.021	5.79	***	-16.621	0.014	5.77	***	-45.872	0.009	6.53	***
Road density	7.705	0.159	1.92	***	8.193	0.169	1.96	***	7.404	0.153	1.71	***
Floodplain exposure	0.217	0.267	0.03	***	0.223	0.275	0.03	***	0.215	0.265	0.03	***
Land use intensity	0.131	0.063	0.07	*	0.119	0.058	0.07	*	0.082	0.040	0.07	
Dams					7.254	0.155	2.73	***	5.613	0.120	2.42	**
Storm-water pipes					0.366	0.055	0.20	*	0.342	0.052	0.18	*
Elevated bg. design					-0.122	-0.144	0.03	***	-0.115	-0.135	0.03	***
Minority pop.									0.024	0.026	0.05	
Precipitation									1.733	0.469	0.24	***
Overland streams									0.038	0.042	0.03	
Poor soil drainage									0.087	0.152	0.02	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
Lambda	0.759	0.759	0.03	***	0.727	0.727	0.04	***	0.585	0.585	0.05	***
pseudo-R2	0.136				0.260				0.509			

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
L, likelihood of flood damage; *H*, half-mile neighborhoods.
***p <.01, **p <.05, *p <.10.

Table D-14 Continued.

	y = Likelihood of damage															
SEM GMM-HET	Model 4 HFI Part 1				Model 5 HFI Part 2				Model 6 HFI Part 3				Model 7 HFI Part 4			
Model	(LH4)				(LH5)				(LH6)				(LH7)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-45.374	0.010	6.53	***	-45.840	0.012	6.41	***	-39.418	0.011	7.65	***	-38.920	0.011	7.70	***
Road density	8.491	0.175	1.77	***	7.306	0.151	1.78	***	8.076	0.167	1.75	***	7.752	0.160	1.76	***
Floodplain exposure	0.219	0.270	0.03	***	0.223	0.275	0.03	***	0.229	0.282	0.03	***	0.227	0.280	0.03	***
Land use intensity	0.025	0.012	0.07		0.054	0.026	0.07		0.030	0.015	0.07		0.044	0.021	0.07	
Dams	5.305	0.114	2.42	**	5.747	0.123	2.41	**	4.639	0.099	2.40	*	4.784	0.103	2.41	**
Storm-water pipes	0.308	0.047	0.18	*	0.214	0.032	0.18		0.267	0.040	0.18		0.280	0.042	0.18	
Elevated bg. design	-0.117	-0.138	0.03	***	-0.101	-0.120	0.03	***	-0.115	-0.136	0.03	***	-0.116	-0.136	0.03	***
Minority pop.	0.023	0.025	0.05		0.034	0.037	0.05		0.020	0.022	0.05		0.022	0.024	0.05	
Precipitation	1.696	0.459	0.25	***	1.638	0.444	0.23	***	1.728	0.468	0.26	***	1.719	0.466	0.25	***
Overland streams	0.044	0.048	0.03		0.032	0.035	0.03		0.056	0.061	0.03	*	0.051	0.056	0.03	
Poor soil drainage	0.086	0.151	0.02	***	0.078	0.136	0.02	***	0.095	0.167	0.02	***	0.094	0.165	0.02	***
Pervious PLAND	-0.085	-0.080	0.04	**												
Agriculture NP					-0.314	-0.066	0.10	***								
Woody lands PLAND					-0.035	-0.016	0.08									
Grass/open sp. NP					0.155	0.107	0.05	***								
Grass/open sp. LPI					-0.025	-0.008	0.07									
Grass/open sp. SHAPE									-5.482	-0.036	3.25	*	-5.354	-0.035	3.24	*
Wetlands PLAND									-0.311	-0.114	0.09	***				
Wetlands LPI													-0.326	-0.090	0.10	***
Wetlands SHAPE					-2.465	-0.073	1.09	**								
Lambda	0.598	0.598	0.05	***	0.577	0.577	0.05	***	0.592	0.592	0.05	***	0.590	0.590	0.05	***
pseudo-R2	0.509				0.533				0.521				0.519			

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
HFI, Hydrologic Function Indicators; *L*, likelihood of flood damage; *H*, half-mile neighborhoods.
****p* <.01, ***p* <.05, **p* <.10.

Table D-15 Spatial error regression models (SEM) explaining the severity of flood damage (S) in 1/4-mile neighborhoods (Q).

	y = Severity of damage											
SEM GMM-HET	Model 1 Risk Factors				Model 2 Risk and Protection				Model 3 Risk, Protection, and Context			
Model	(SQ1)				(SQ2)				(SQ3)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-5.974	-0.018	2.14	***	-5.620	-0.017	2.20	**	-14.786	-0.013	2.66	***
Road density	2.631	0.145	0.73	***	2.618	0.145	0.73	***	2.508	0.139	0.69	***
Floodplain exposure	0.077	0.260	0.01	***	0.078	0.264	0.01	***	0.066	0.225	0.01	***
Land use intensity	0.010	0.015	0.03		0.011	0.016	0.03		0.009	0.012	0.03	
Dams					2.983	0.149	1.11	***	2.312	0.115	1.05	**
Storm-water pipes					-0.132	-0.027	0.17		-0.171	-0.035	0.16	
Elevated bg. design					-0.041	-0.125	0.01	***	-0.046	-0.141	0.01	***
Minority pop.									-0.015	-0.039	0.02	
Precipitation									0.603	0.380	0.12	***
Overland streams									0.049	0.091	0.03	*
Poor soil drainage									0.018	0.081	0.01	*
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
Lambda	0.625	0.625	0.06	***	0.582	0.582	0.06	***	0.489	0.489	0.07	***
pseudo-R2	0.110				0.210				0.366			

N=527, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
S, severity of flood damage; *Q*, quarter-mile neighborhoods.
***p <.01, **p <.05, *p <.10.

Table D-15 Continued.

SEM GMM-HET	y = Severity of damage															
	Model 4 HydroFI Part 1				Model 5 HydroFI Part 2				Model 6 HydroFI Part 3				Model 7 HydroFI Part 4			
Model	(SQ4)				(SQ5)				(SQ6)				(SQ7)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-14.370	-0.013	2.64	***	-14.915	-0.011	2.70	***	-12.020	-0.012	2.84	***	-11.908	-0.012	2.87	***
Road density	3.022	0.167	0.68	***	2.489	0.138	0.68	***	2.633	0.146	0.68	***	2.601	0.144	0.68	***
Floodplain exposure	0.069	0.232	0.01	***	0.067	0.228	0.01	***	0.072	0.243	0.01	***	0.072	0.243	0.01	***
Land use intensity	-0.013	-0.018	0.03		0.001	0.001	0.03		-0.002	-0.003	0.03		-0.001	-0.002	0.03	
Dams	2.209	0.110	1.04	**	2.235	0.111	1.03	**	2.112	0.105	1.02	**	2.128	0.106	1.02	**
Storm-water pipes	-0.331	-0.068	0.16	**	-0.174	-0.036	0.16		-0.269	-0.055	0.16	*	-0.268	-0.055	0.16	*
Elevated bg. design	-0.047	-0.142	0.01	***	-0.043	-0.133	0.01	***	-0.044	-0.136	0.01	***	-0.044	-0.136	0.01	***
Minority pop.	-0.016	-0.041	0.02		-0.016	-0.040	0.02		-0.016	-0.041	0.02		-0.015	-0.040	0.02	
Precipitation	0.579	0.365	0.12	***	0.582	0.367	0.12	***	0.598	0.377	0.12	***	0.599	0.377	0.12	***
Overland streams	0.056	0.105	0.03	**	0.050	0.094	0.03	**	0.059	0.110	0.03	**	0.059	0.110	0.03	**
Poor soil drainage	0.018	0.081	0.01	*	0.017	0.078	0.01	*	0.019	0.087	0.01	*	0.019	0.086	0.01	*
Pervious PLAND	-0.048	-0.113	0.02	***												
Agriculture NP					-0.138	-0.024	0.13									
Woody lands PLAND					-0.015	-0.018	0.03									
Grass/open sp. NP					0.136	0.079	0.08	*								
Grass/open sp. LPI					-0.045	-0.051	0.02	*								
Grass/open sp. SHAPE									-2.166	-0.067	0.69	***	-2.214	-0.069	0.70	***
Wetlands PLAND									-0.088	-0.078	0.04	**				
Wetlands LPI													-0.101	-0.077	0.04	**
Wetlands SHAPE					-0.224	-0.015	0.53									
Lambda	0.496	0.496	0.07	***	0.490	0.490	0.07	***	0.489	0.489	0.07	***	0.489	0.489	0.07	***
pseudo-R2	0.369				0.377				0.376				0.376			

N=527, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
HydroFI, Hydrologic Function Indicators; *S*, severity of flood damage; *Q*, quarter-mile neighborhoods.
****p* <.01, ***p* <.05, **p* <.10.

Table D-16 Spatial error regression models (SEM) explaining the severity of flood damage (S) in 1/2-mile neighborhoods (H).

SEM GMM-HET	*y* = Severity of damage											
	Model 1 Risk Factors				Model 2 Risk and Protection				Model 3 Risk, Protection, and Context			
Model	(SH1)				(SH2)				(SH3)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-7.906	-0.002	3.11	**	-8.105	-0.006	3.10	***	-17.710	-0.005	3.83	***
Road density	3.124	0.159	1.07	***	3.269	0.166	1.09	***	3.044	0.155	0.97	***
Floodplain exposure	0.088	0.268	0.01	***	0.090	0.274	0.01	***	0.083	0.250	0.01	***
Land use intensity	0.038	0.045	0.04		0.032	0.038	0.04		0.018	0.021	0.03	
Dams					3.021	0.159	1.05	***	2.345	0.124	1.04	**
Storm-water pipes					0.085	0.032	0.07		0.083	0.031	0.07	
Elevated bg. design					-0.052	-0.150	0.01	***	-0.051	-0.147	0.01	***
Minority pop.									-0.001	-0.002	0.02	
Precipitation									0.598	0.399	0.14	***
Overland streams									0.021	0.057	0.01	
Poor soil drainage									0.024	0.105	0.01	**
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
Lambda	0.691	0.691	0.04	***	0.652	0.652	0.05	***	0.581	0.581	0.06	***
pseudo-R2	0.120				0.243				0.408			

N=527, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
S, severity of flood damage; *H*, half-mile neighborhoods.
****p* <.01, ***p* <.05, **p* <.10.

Table D-16 Continued.

	y = Severity of damage															
SEM GMM-HET	Model 4 HFI Part 1				Model 5 HFI Part 2				Model 6 HFI Part 3				Model 7 HFI Part 4			
Model	(SH4)				(SH5)				(SH6)				(SH7)			
Variables	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*	*b*	*beta*	*s.e.*	*p*
constant	-17.533	-0.004	3.81	***	-17.743	0.000	3.71	***	-15.026	-0.003	4.44	***	-14.918	-0.003	4.49	***
Road density	3.425	0.174	1.00	***	2.941	0.149	1.03	***	3.311	0.168	0.98	***	3.192	0.162	0.99	***
Floodplain exposure	0.084	0.255	0.01	***	0.086	0.260	0.01	***	0.088	0.267	0.01	***	0.087	0.263	0.01	***
Land use intensity	-0.002	-0.003	0.04		0.012	0.014	0.04		-0.001	-0.001	0.03		0.004	0.005	0.03	
Dams	2.259	0.119	1.03	**	2.373	0.125	1.03	**	2.003	0.106	0.99	**	2.058	0.109	0.99	**
Storm-water pipes	0.070	0.026	0.07		0.039	0.014	0.07		0.058	0.022	0.07		0.064	0.024	0.07	
Elevated bg. design	-0.051	-0.150	0.01	***	-0.045	-0.131	0.01	***	-0.050	-0.147	0.01	***	-0.051	-0.147	0.01	***
Minority pop.	-0.001	-0.002	0.02		0.003	0.007	0.02		-0.003	-0.009	0.02		-0.002	-0.005	0.02	
Precipitation	0.585	0.390	0.14	***	0.556	0.371	0.13	***	0.599	0.399	0.14	***	0.593	0.396	0.14	***
Overland streams	0.023	0.062	0.01	*	0.018	0.049	0.01		0.027	0.074	0.01	**	0.026	0.070	0.01	*
Poor soil drainage	0.024	0.105	0.01	**	0.020	0.087	0.01	*	0.027	0.118	0.01	**	0.027	0.116	0.01	**
Pervious PLAND	-0.030	-0.069	0.02	*												
Agriculture NP					-0.131	-0.067	0.04	***								
Woody lands PLAND					-0.001	-0.001	0.03									
Grass/open sp. NP					0.064	0.109	0.03	**								
Grass/open sp. LPI					-0.026	-0.019	0.03									
Grass/open sp. SHAPE									-2.320	-0.038	1.39	*	-2.224	-0.036	1.39	
Wetlands PLAND									-0.113	-0.102	0.05	**				
Wetlands LPI													-0.110	-0.075	0.05	**
Wetlands SHAPE					-0.721	-0.052	0.44									
Lambda	0.591	0.591	0.05	***	0.570	0.570	0.05	***	0.587	0.587	0.05	***	0.584	0.584	0.05	***
pseudo-R2	0.404				0.432				0.411				0.410			

N=527, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
HFI, Hydrologic Function Indicators; *S*, severity of flood damage; *H*, half-mile neighborhoods.
****p* <.01, ***p* <.05, **p* <.10.

Table D-17 Example of sensitivity analysis models 4 to 7 of full vs. various parsimonious spatial error model (SEM) results for likelihood of damage (L) in 1/4-mile radius neighborhoods (Q).

SEM GMM-HET	Full Model 4 all variables			Parsimonious Model v.1 without 3 variables			Parsimonious Model v.2 without 4 variables			Parsimonious Model v.3 without 5 variables		
	y = Likelihood of damage											
Model	(LQ4)			(LQ4)			(LQ4)			(LQ4)		
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-44.925	7.65	***	-45.103	7.40	***	-47.046	7.32	***	-48.618	7.34	***
Road density	8.890	1.88	***	9.058	1.82	***	9.174	1.81	***	9.309	1.83	***
Floodplain exposure	0.217	0.03	***	0.217	0.03	***	0.217	0.03	***	0.241	0.03	***
Land use intensity	0.017	0.08	0.83									
Dams	5.260	2.53	**	5.254	2.53	**	4.996	2.55	**	5.746	2.54	**
Storm-water pipes	-0.750	0.45	*	-0.739	0.46	0.11						
Elevated bg. design	-0.091	0.03	***	-0.092	0.03	***	-0.089	0.03	***	-0.080	0.03	***
Minority pop.	0.003	0.05	0.94									
Precipitation	1.745	0.24	***	1.750	0.25	***	1.756	0.25	***	1.793	0.25	***
Overland streams	0.094	0.06	0.10	0.093	0.06	0.11	0.094	0.06	0.10			
Poor soil drainage	0.079	0.02	***	0.079	0.02	***	0.081	0.02	***	0.078	0.02	***
Pervious PLAND	-0.127	0.04	***	-0.130	0.04	***	-0.112	0.04	***	-0.100	0.04	**
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE												
Lambda	0.444	0.06	***	0.444	0.06	***	0.459	0.06	***	0.455	0.06	***
pseudo-R2	0.431			0.431			0.423			0.422		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
***p <.01, **p <.05, *p <.10.

Table D-17 Continued.

SEM GMM-HET	y = Likelihood of damage											
	Full Model 4 all variables			Parsimonious Model v.1 without 3 variables			Parsimonious Model v.2 without 4 variables			Parsimonious Model v.3 without 5 variables		
Model	(LQ5)			(LQ5)			(LQ5)			(LQ5)		
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-46.056	7.53	***	-46.674	7.29	***	-47.666	7.22	***	-48.733	7.25	***
Road density	7.579	1.94	***	7.981	1.88	***	8.040	1.88	***	8.189	1.90	***
Floodplain exposure	0.217	0.03	***	0.216	0.03	***	0.216	0.03	***	0.236	0.03	***
Land use intensity	0.047	0.08	0.55									
Dams	5.382	2.52	**	5.399	2.50	**	5.223	2.50	**	5.794	2.49	**
Storm-water pipes	-0.375	0.46	0.42	-0.338	0.46	0.46						
Elevated bg. design	-0.082	0.03	***	-0.084	0.03	***	-0.082	0.03	***	-0.075	0.03	***
Minority pop.	0.001	0.05	0.98									
Precipitation	1.758	0.24	***	1.767	0.24	***	1.768	0.25	***	1.791	0.24	***
Overland streams	0.076	0.06	0.19	0.072	0.06	0.21	0.074	0.06	0.20			
Poor soil drainage	0.077	0.02	***	0.077	0.02	***	0.078	0.02	***	0.075	0.02	***
Pervious PLAND												
Agriculture NP	-0.660	0.36	*	-0.709	0.34	**	-0.681	0.34	**	-0.739	0.34	**
Woody lands PLAND	-0.012	0.08	0.88									
Grass/open sp. NP	0.351	0.17	**	0.344	0.17	**	0.364	0.16	**	0.374	0.16	**
Grass/open sp. LPI	-0.110	0.06	*	-0.116	0.06	*	-0.106	0.06	*	-0.094	0.06	*
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE	-1.630	1.32	0.22	-1.822	1.34	0.17	-1.732	1.33	0.19	-1.644	1.34	0.22
Lambda	0.433	0.06	***	0.433	0.06	***	0.439	0.06	***	0.435	0.06	***
pseudo-R2	0.440			0.439			0.437			0.436		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
***p <.01, **p <.05, *p <.10.

Table D-17 Continued.

	y = Likelihood of damage											
SEM GMM-HET	Full Model 4 all variables			Parsimonious Model v.1 without 3 variables			Parsimonious Model v.2 without 4 variables			Parsimonious Model v.3 without 5 variables		
Model		(LQ6)			(LQ6)			(LQ6)			(LQ6)	
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-39.145	7.88	***	-39.673	7.68	***	-41.748	7.55	***	-43.965	7.48	***
Road density	7.855	1.86	***	8.261	1.82	***	8.444	1.81	***	8.667	1.83	***
Floodplain exposure	0.224	0.03	***	0.223	0.03	***	0.222	0.03	***	0.246	0.03	***
Land use intensity	0.048	0.08	0.53									
Dams	5.001	2.53	**	5.000	2.53	**	4.750	2.53	*	5.629	2.52	**
Storm-water pipes	-0.606	0.44	0.17	-0.557	0.44	0.21						
Elevated bg. design	-0.087	0.03	***	-0.089	0.03	***	-0.086	0.03	***	-0.076	0.03	***
Minority pop.	0.006	0.05	0.90									
Precipitation	1.793	0.24	***	1.808	0.24	***	1.807	0.25	***	1.840	0.25	***
Overland streams	0.104	0.06	*	0.102	0.06	*	0.103	0.06	*			
Poor soil drainage	0.082	0.02	***	0.082	0.02	***	0.084	0.02	***	0.080	0.02	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE	-5.377	1.84	***	-5.515	1.85	***	-4.966	1.80	***	-4.464	1.75	**
Wetlands PLAND	-0.220	0.10	**	-0.231	0.10	**	-0.216	0.10	**	-0.174	0.10	*
Wetlands LPI												
Wetlands SHAPE												
Lambda	0.431	0.06	***	0.431	0.06	***	0.445	0.06	***	0.442	0.06	***
pseudo-R2	0.437			0.437			0.430			0.428		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
***p <.01, **p <.05, *p <.10.

Table D-17 Continued.

	y = Likelihood of damage											
SEM GMM-HET	Full Model 4 all variables			Parsimonious Model v.1 without 3 variables			Parsimonious Model v.2 without 4 variables			Parsimonious Model v.3 without 5 variables		
Model	(LQ7)			(LQ7)			(LQ7)			(LQ7)		
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-38.704	7.97	***	-39.236	7.76	***	-41.345	7.62	***	-43.615	7.53	***
Road density	7.770	1.86	***	8.178	1.82	***	8.368	1.81	***	8.605	1.83	***
Floodplain exposure	0.225	0.03	***	0.224	0.03	***	0.223	0.03	***	0.248	0.03	***
Land use intensity	0.049	0.08	0.53									
Dams	5.048	2.52	**	5.054	2.52	**	4.793	2.53	*	5.644	2.52	**
Storm-water pipes	-0.610	0.44	0.17	-0.560	0.44	0.20						
Elevated bg. design	-0.087	0.03	***	-0.089	0.03	***	-0.086	0.03	***	-0.076	0.03	***
Minority pop.	0.006	0.05	0.91									
Precipitation	1.794	0.24	***	1.810	0.24	***	1.808	0.25	***	1.841	0.25	***
Overland streams	0.103	0.06	*	0.101	0.06	*	0.102	0.06	*			
Poor soil drainage	0.082	0.02	***	0.082	0.02	***	0.083	0.02	***	0.080	0.02	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE	-5.573	1.86	***	-5.721	1.87	***	-5.159	1.82	***	-4.628	1.77	***
Wetlands PLAND												
Wetlands LPI	-0.270	0.11	**	-0.281	0.11	**	-0.265	0.11	**	-0.224	0.11	**
Wetlands SHAPE												
Lambda	0.431	0.06	***	0.431	0.06	***	0.445	0.06	***	0.442	0.06	***
pseudo-R2	0.438			0.438			0.431			0.429		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
****p* <.01, ***p* <.05, **p* <.10.

Table D-18 Comparison of full vs. parsimonious spatial error model (SEM) results: models 4 to 7 for likelihood of damage (L) in 1/4-mile radius neighborhoods (Q).

	y = Likelihood of damage											
SEM GMM-HET	Model 4 Full			Model 4 Parsimonious			Model 5 Full			Model 5 Parsimonious		
Model	(LQ4)			(LQ4)			(LQ5)			(LQ5)		
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-44.925	7.65	***	-47.046	7.32	***	-46.056	7.53	***	-47.666	7.22	***
Road density	8.890	1.88	***	9.174	1.81	***	7.579	1.94	***	8.040	1.88	***
Floodplain exposure	0.217	0.03	***	0.217	0.03	***	0.217	0.03	***	0.216	0.03	***
Land use intensity	0.017	0.08	*0.83*				0.047	0.08	*0.55*			
Dams	5.260	2.53	**	4.996	2.55	**	5.382	2.52	**	5.223	2.50	**
Storm-water pipes	-0.750	0.45	*				-0.375	0.46	*0.42*			
Elevated bg. design	-0.091	0.03	***	-0.089	0.03	***	-0.082	0.03	***	-0.082	0.03	***
Minority pop.	0.003	0.05	*0.94*				0.001	0.05	*0.98*			
Precipitation	1.745	0.24	***	1.756	0.25	***	1.758	0.24	***	1.768	0.25	***
Overland streams	0.094	0.06	*0.10*	0.094	0.06	*0.10*	0.076	0.06	*0.19*	0.074	0.06	*0.20*
Poor soil drainage	0.079	0.02	***	0.081	0.02	***	0.077	0.02	***	0.078	0.02	***
Pervious PLAND	-0.127	0.04	***	-0.112	0.04	***						
Agriculture NP							-0.660	0.36	*	-0.681	0.34	**
Woody lands PLAND							-0.012	0.08	*0.88*			
Grass/open sp. NP							0.351	0.17	**	0.364	0.16	**
Grass/open sp. LPI							-0.110	0.06	*	-0.106	0.06	*
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE							-1.630	1.32	*0.22*	-1.732	1.33	*0.19*
Lambda	0.444	0.06	***	0.459	0.06	***	0.433	0.06	***	0.439	0.06	***
pseudo-R2	0.431			0.423			0.440			0.437		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
****p* <.01, ***p* <.05, **p* <.10.

Table D-18 Continued.

	y = Likelihood of damage											
SEM GMM-HET	Model 6 Full			Model 6 Parsimonious			Model 7 Full			Model 7 Parsimonious		
Model	(LQ6)			(LQ6)			(LQ7)			(LQ7)		
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-39.145	7.88	***	-41.748	7.55	***	-38.704	7.97	***	-41.345	7.62	***
Road density	7.855	1.86	***	8.444	1.81	***	7.770	1.86	***	8.368	1.81	***
Floodplain exposure	0.224	0.03	***	0.222	0.03	***	0.225	0.03	***	0.223	0.03	***
Land use intensity	0.048	0.08	*0.53*				0.049	0.08	*0.53*			
Dams	5.001	2.53	**	4.750	2.53	*	5.048	2.52	**	4.793	2.53	*
Storm-water pipes	-0.606	0.44	*0.17*				-0.610	0.44	*0.17*			
Elevated bg. design	-0.087	0.03	***	-0.086	0.03	***	-0.087	0.03	***	-0.086	0.03	***
Minority pop.	0.006	0.05	*0.90*				0.006	0.05	*0.91*			
Precipitation	1.793	0.24	***	1.807	0.25	***	1.794	0.24	***	1.808	0.25	***
Overland streams	0.104	0.06	*	0.103	0.06	*	0.103	0.06	*	0.102	0.06	*
Poor soil drainage	0.082	0.02	***	0.084	0.02	***	0.082	0.02	***	0.083	0.02	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE	-5.377	1.84	***	-4.966	1.80	***	-5.573	1.86	***	-5.159	1.82	***
Wetlands PLAND	-0.220	0.10	**	-0.216	0.10	**						
Wetlands LPI							-0.270	0.11	**	-0.265	0.11	**
Wetlands SHAPE												
Lambda	0.431	0.06	***	0.445	0.06	***	0.431	0.06	***	0.445	0.06	***
pseudo-R2	0.437			0.430			0.438			0.431		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
***p <.01, **p <.05, *p <.10.

Table D-19 Comparison of full vs. parsimonious spatial error model (SEM) results: models 4 to 7 for likelihood of damage (L) in 1/2-mile radius neighborhoods (H).

	y = Likelihood of damage											
SEM GMM-HET	Model 4 Full			Model 4 Parsimonious			Model 5 Full			Model 5 Parsimonious		
Model	(LH4)			(LH4)			(LH5)			(LH5)		
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-45.374	6.53	***	-43.766	6.46	***	-45.840	6.41	***	-44.329	6.26	***
Road density	8.491	1.77	***	8.676	1.69	***	7.306	1.78	***	7.585	1.67	***
Floodplain exposure	0.219	0.03	***	0.221	0.03	***	0.223	0.03	***	0.223	0.03	***
Land use intensity	0.025	0.07	*0.73*				0.054	0.07	*0.45*			
Dams	5.305	2.42	**	5.237	2.41	**	5.747	2.41	**	5.683	2.39	**
Storm-water pipes	0.308	0.18	*				0.214	0.18	*0.23*			
Elevated bg. design	-0.117	0.03	***	-0.125	0.03	***	-0.101	0.03	***	-0.112	0.03	***
Minority pop.	0.023	0.05	*0.66*				0.034	0.05	*0.49*			
Precipitation	1.696	0.25	***	1.714	0.25	***	1.638	0.23	***	1.675	0.24	***
Overland streams	0.044	0.03	*0.16*	0.042	0.03	*0.17*	0.032	0.03	*0.31*	0.029	0.03	*0.35*
Poor soil drainage	0.086	0.02	***	0.085	0.02	***	0.078	0.02	***	0.077	0.02	***
Pervious PLAND	-0.085	0.04	**	-0.099	0.04	***						
Agriculture NP							-0.314	0.10	***	-0.362	0.10	***
Woody lands PLAND							-0.035	0.08	*0.68*			
Grass/open sp. NP							0.155	0.05	***	0.151	0.05	***
Grass/open sp. LPI							-0.025	0.07	*0.73*	-0.037	0.07	*0.61*
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE							-2.465	1.09	**	-2.743	1.09	**
Lambda	0.598	0.05	***	0.598	0.05	***	0.577	0.05	***	0.578	0.05	***
pseudo-R2	0.509			0.508			0.533			0.531		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
****p* <.01, ***p* <.05, **p* <.10.

Table D-19 Continued.

SEM GMM-HET	Model 6 Full			Model 6 Parsimonious			Model 7 Full			Model 7 Parsimonious		
	y = Likelihood of damage											
Model	(LH6)			(LH6)			(LH7)			(LH7)		
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-39.418	7.65	***	-37.607	7.61	***	-38.920	7.70	***	-36.934	7.67	***
Road density	8.076	1.75	***	8.232	1.71	***	7.752	1.76	***	7.981	1.72	***
Floodplain exposure	0.229	0.03	***	0.231	0.03	***	0.227	0.03	***	0.229	0.03	***
Land use intensity	0.030	0.07	*0.65*				0.044	0.07	*0.52*			
Dams	4.639	2.40	*	4.529	2.39	*	4.784	2.41	**	4.682	2.40	*
Storm-water pipes	0.267	0.18	*0.14*				0.280	0.18	*0.12*			
Elevated bg. design	-0.115	0.03	***	-0.122	0.03	***	-0.116	0.03	***	-0.124	0.03	***
Minority pop.	0.020	0.05	*0.69*				0.022	0.05	*0.67*			
Precipitation	1.728	0.26	***	1.752	0.26	***	1.719	0.25	***	1.746	0.25	***
Overland streams	0.056	0.03	*	0.055	0.03	*	0.051	0.03	*0.10*	0.050	0.03	*0.12*
Poor soil drainage	0.095	0.02	***	0.095	0.02	***	0.094	0.02	***	0.094	0.02	***
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE	-5.482	3.25	*	-6.028	3.22	*	-5.354	3.24	*	-6.043	3.22	*
Wetlands PLAND	-0.311	0.09	***	-0.339	0.09	***						
Wetlands LPI							-0.326	0.10	***	-0.361	0.10	***
Wetlands SHAPE												
Lambda	0.592	0.05	***	0.591	0.05	***	0.590	0.05	***	0.588	0.05	***
pseudo-R2	0.521			0.522			0.519			0.519		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
****p* <.01, ***p* <.05, **p* <.10.

Table D-20 Comparison of full vs. parsimonious spatial error model (SEM) regression results: models 4 to 7 for severity of damage (S) in 1/4-mile radius neighborhoods (Q).

	y = Severity of damage											
SEM GMM-HET	Model 4 Full			Model 4 Parsimonious			Model 5 Full			Model 5 Parsimonious		
Model		(SQ4)			(SQ4)			(SQ5)			(SQ5)	
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-14.370	2.64	***	-15.405	2.62	***	-14.915	2.70	***	-15.730	2.65	***
Road density	3.022	0.68	***	2.961	0.63	***	2.489	0.68	***	2.510	0.65	***
Floodplain exposure	0.069	0.01	***	0.068	0.01	***	0.067	0.01	***	0.067	0.01	***
Land use intensity	-0.013	0.03	*0.69*				0.001	0.03	*0.98*			
Dams	2.209	1.04	**	2.098	1.04	**	2.235	1.03	**	2.119	1.03	**
Storm-water pipes	-0.331	0.16	**				-0.174	0.16	*0.29*			
Elevated bg. design	-0.047	0.01	***	-0.043	0.01	***	-0.043	0.01	***	-0.040	0.01	***
Minority pop.	-0.016	0.02	*0.39*				-0.016	0.02	*0.40*			
Precipitation	0.579	0.12	***	0.566	0.12	***	0.582	0.12	***	0.568	0.11	***
Overland streams	0.056	0.03	**	0.056	0.03	**	0.050	0.03	**	0.050	0.03	*
Poor soil drainage	0.018	0.01	*	0.018	0.01	*	0.017	0.01	*	0.017	0.01	*
Pervious PLAND	-0.048	0.02	***	-0.036	0.01	**						
Agriculture NP							-0.138	0.13	*0.28*	-0.150	0.12	*0.21*
Woody lands PLAND							-0.015	0.03	*0.61*			
Grass/open sp. NP							0.136	0.08	*	0.144	0.07	*
Grass/open sp. LPI							-0.045	0.02	*	-0.039	0.02	*
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE							-0.224	0.53	*0.67*	-0.184	0.54	*0.73*
Lambda	0.496	0.07	***	0.509	0.07	***	0.490	0.07	***	0.494	0.07	***
pseudo-R2	0.369			0.358			0.377			0.374		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
****p* <.01, ***p* <.05, **p* <.10.

Table D-20 Continued.

	y = Severity of damage											
SEM GMM-HET	Model 6 Full			Model 6 Parsimonious			Model 7 Full			Model 7 Parsimonious		
Model	(SQ6)			(SQ6)			(SQ7)			(SQ7)		
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-12.020	2.84	***	-13.308	2.80	***	-11.908	2.87	***	-13.198	2.82	***
Road density	2.633	0.68	***	2.720	0.64	***	2.601	0.68	***	2.694	0.64	***
Floodplain exposure	0.072	0.01	***	0.071	0.01	***	0.072	0.01	***	0.071	0.01	***
Land use intensity	-0.002	0.03	*0.95*				-0.001	0.03	*0.97*			
Dams	2.112	1.02	**	1.995	1.02	*	2.128	1.02	**	2.006	1.02	**
Storm-water pipes	-0.269	0.16	*				-0.268	0.16	*			
Elevated bg. design	-0.044	0.01	***	-0.041	0.01	***	-0.044	0.01	***	-0.041	0.01	***
Minority pop.	-0.016	0.02	*0.38*				-0.015	0.02	*0.39*			
Precipitation	0.598	0.12	***	0.583	0.12	***	0.599	0.12	***	0.583	0.12	***
Overland streams	0.059	0.03	**	0.059	0.03	**	0.059	0.03	**	0.059	0.03	**
Poor soil drainage	0.019	0.01	*	0.019	0.01	*	0.019	0.01	*	0.019	0.01	*
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE	-2.166	0.69	***	-1.920	0.64	***	-2.214	0.70	***	-1.970	0.65	***
Wetlands PLAND	-0.088	0.04	**	-0.081	0.04	**						
Wetlands LPI							-0.101	0.04	**	-0.094	0.04	**
Wetlands SHAPE												
Lambda	0.489	0.07	***	0.501	0.07	***	0.489	0.07	***	0.501	0.07	***
pseudo-R2	0.376			0.366			0.376			0.366		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
****p* <.01, ***p* <.05, **p* <.10.

Table D-21 Comparison of full vs. parsimonious spatial error model (SEM) regression results: models 4 to 5 for severity of damage (S) in 1/2-mile radius neighborhoods (H).

SEM GMM-HET	Model 4 Full			Model 4 Parsimonious			Model 5 Full			Model 5 Parsimonious		
	y = Severity of damage											
Model		(SH4)			(SH4)			(SH5)			(SH5)	
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-17.533	3.81	***	-17.312	3.85	***	-17.743	3.71	***	-17.667	3.71	***
Road density	3.425	1.00	***	3.419	0.92	***	2.941	1.03	***	3.043	0.92	***
Floodplain exposure	0.084	0.01	***	0.085	0.01	***	0.086	0.01	***	0.086	0.01	***
Land use intensity	-0.002	0.04	*0.95*				0.012	0.04	*0.75*			
Dams	2.259	1.03	**	2.217	1.02	**	2.373	1.03	**	2.338	1.01	**
Storm-water pipes	0.070	0.07	*0.32*				0.039	0.07	*0.59*			
Elevated bg. design	-0.051	0.01	***	-0.051	0.01	***	-0.045	0.01	***	-0.046	0.01	***
Minority pop.	-0.001	0.02	*0.97*				0.003	0.02	*0.90*			
Precipitation	0.585	0.14	***	0.584	0.13	***	0.556	0.13	***	0.562	0.13	***
Overland streams	0.023	0.01	*	0.023	0.01	*	0.018	0.01	*0.18*	0.018	0.01	*0.19*
Poor soil drainage	0.024	0.01	**	0.024	0.01	**	0.020	0.01	*	0.020	0.01	*
Pervious PLAND	-0.030	0.02	*	-0.032	0.01	**						
Agriculture NP							-0.131	0.04	***	-0.138	0.04	***
Woody lands PLAND							-0.001	0.03	*0.98*			
Grass/open sp. NP							0.064	0.03	**	0.063	0.02	**
Grass/open sp. LPI							-0.026	0.03	*0.44*	-0.028	0.03	*0.37*
Grass/open sp. SHAPE												
Wetlands PLAND												
Wetlands LPI												
Wetlands SHAPE							-0.721	0.44	*0.10*	-0.772	0.45	*
Lambda	0.591	0.05	***	0.589	0.05	***	0.570	0.05	***	0.571	0.05	***
pseudo-R2	0.404			0.406			0.432			0.432		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
****p* <.01, ***p* <.05, **p* <.10.

Table D-21 Continued.

	y = Severity of damage											
SEM GMM-HET	Model 6 Full			Model 6 Parsimonious			Model 7 Full			Model 7 Parsimonious		
Model	(SH6)			(SH6)			(SH7)			(SH7)		
Variables	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*	*b*	*s.e.*	*prob.*
constant	-15.026	4.44	***	-14.821	4.50	***	-14.918	4.49	***	-14.644	4.55	***
Road density	3.311	0.98	***	3.305	0.93	***	3.192	0.99	***	3.224	0.94	***
Floodplain exposure	0.088	0.01	***	0.089	0.01	***	0.087	0.01	***	0.087	0.01	***
Land use intensity	-0.001	0.03	*0.97*				0.004	0.03	*0.90*			
Dams	2.003	0.99	**	1.954	0.99	**	2.058	0.99	**	2.004	0.99	**
Storm-water pipes	0.058	0.07	*0.42*				0.064	0.07	*0.37*			
Elevated bg. design	-0.050	0.01	***	-0.050	0.01	***	-0.051	0.01	***	-0.050	0.01	***
Minority pop.	-0.003	0.02	*0.88*				-0.002	0.02	*0.93*			
Precipitation	0.599	0.14	***	0.597	0.14	***	0.593	0.14	***	0.594	0.13	***
Overland streams	0.027	0.01	**	0.027	0.01	**	0.026	0.01	*	0.026	0.01	*
Poor soil drainage	0.027	0.01	**	0.027	0.01	**	0.027	0.01	**	0.027	0.01	**
Pervious PLAND												
Agriculture NP												
Woody lands PLAND												
Grass/open sp. NP												
Grass/open sp. LPI												
Grass/open sp. SHAPE	-2.320	1.39	*	-2.424	1.40	*	-2.224	1.39	*0.11*	-2.383	1.41	*
Wetlands PLAND	-0.113	0.05	**	-0.116	0.05	**						
Wetlands LPI							-0.110	0.05	**	-0.116	0.05	**
Wetlands SHAPE												
Lambda	0.587	0.05	***	0.584	0.05	***	0.584	0.05	***	0.582	0.05	***
pseudo-R2	0.411			0.413			0.410			0.413		

N=532, Spatial Errol Model (SEM), General Method of Moments (GMM) for Heteroscedastic errors (HET).
****p* <.01, ***p* <.05, **p* <.10.

Table D-22 Example of endogeneity diagnostics of OLS regression residuals: model 4 for likelihood of damage (L) in 1/4-mile neighborhoods (Q).

Q_RoadDty_ln	Q_hF100yr_pt	Q_LuseInt_pt	Q_FloodDam	Q_aPipes_m	Variables
1.0000	0.1449	0.2427	-0.0025	-0.1674	Q_RoadDty_ln
	1.0000	-0.1229	-0.0389	-0.0083	Q_hF100yr_pt
		1.0000	0.0754	0.1534	Q_LuseInt_pt
			1.0000	0.0849	Q_FloodDam
				1.0000	Q_aPipes_m

Q_2PFloors_pt	Q_hMrity_pt	Q_ppt5d	Q_aDraiNet_m	Q_SoilD_pt	Variables
0.0064	-0.1048	0.0285	0.1675	0.0020	Q_RoadDty_ln
-0.0214	0.1081	0.0076	0.4802	-0.0638	Q_hF100yr_pt
-0.0862	0.0285	0.0951	-0.1086	0.0280	Q_LuseInt_pt
-0.0814	0.0683	0.0213	0.1515	0.4968	Q_FloodDam
-0.0323	0.2185	0.0008	-0.0313	-0.0495	Q_aPipes_m
1.0000	-0.3963	-0.1669	0.1226	-0.0433	Q_2PFloors_pt
	1.0000	0.2806	0.0818	0.0219	Q_hMrity_pt
		1.0000	0.0654	0.0397	Q_ppt5d
			1.0000	0.0101	Q_aDraiNet_m
				1.0000	Q_SoilD_pt

Q_PLAND	uhat_LQ4	Variables
0.2928	-0.0000	Q_RoadDty_ln
0.1611	-0.0000	Q_hF100yr_pt
-0.3315	0.0000	Q_LuseInt_pt
-0.1056	0.0000	Q_FloodDam
-0.4173	0.0000	Q_aPipes_m
0.1106	-0.0000	Q_2PFloors_pt
-0.1528	-0.0000	Q_hMrity_pt
-0.1578	0.0000	Q_ppt5d
0.2157	-0.0000	Q_aDraiNet_m
-0.0407	0.0000	Q_SoilD_pt
1.0000	-0.0000	Q_PLAND
	1.0000	uhat_LQ4S

N=532; 5% critical value (two-tailed) = 0.0850.

Table D-23 Correlation coefficients used for specification of OLS regression models.

Q_RoadDty_ln	Q_hF100yr_pt	Q_LuseInt_pt	Q_FloodDam	Q_aPipes_m	Variables
1.0000	0.1433	0.2341	-0.0029	-0.1715	Q_RoadDty_ln
	1.0000	-0.1222	-0.0344	-0.0088	Q_hF100yr_pt
		1.0000	0.0803	0.1592	Q_LuseInt_pt
			1.0000	0.0879	Q_FloodDam
				1.0000	Q_aPipes_m

Q_2PFloors_pt	Q_hMrity_pt	Q_ppt5d	Q_aDraiNet_m	Q_SoilD_pt	Variables
0.0013	-0.1084	0.0217	0.1652	0.0016	Q_RoadDty_ln
-0.0212	0.1072	0.0138	0.4805	-0.0608	Q_hF100yr_pt
-0.0815	0.0326	0.0976	-0.1077	0.0290	Q_LuseInt_pt
-0.0787	0.0674	0.0289	0.1489	0.4973	Q_FloodDam
-0.0290	0.2211	0.0041	-0.0308	-0.0490	Q_aPipes_m
1.0000	-0.3934	-0.1622	0.1218	-0.0373	Q_2PFloors_pt
	1.0000	0.2762	0.0851	0.0170	Q_hMrity_pt
		1.0000	0.0594	0.0495	Q_ppt5d
			1.0000	0.0073	Q_aDraiNet_m
				1.0000	Q_SoilD_pt

Q_PLAND	Q_AgNP	Q_WdyPLAND	Q_OpenNP	Q_OpenLPI	Variables
0.2977	0.1393	0.2276	0.1818	0.1048	Q_RoadDty_ln
0.1500	0.0851	0.0802	0.0044	0.0462	Q_hF100yr_pt
-0.3397	-0.1624	-0.2781	-0.0412	-0.1237	Q_LuseInt_pt
-0.1170	-0.0798	-0.0002	0.0734	-0.0112	Q_FloodDam
-0.4200	-0.1713	-0.2700	-0.3058	-0.2062	Q_aPipes_m
0.0982	0.0145	0.1269	-0.1261	0.0414	Q_2PFloors_pt
-0.1541	-0.0498	-0.1451	0.0495	-0.0736	Q_hMrity_pt
-0.1691	-0.1301	-0.0143	0.0612	-0.1386	Q_ppt5d
0.2104	0.0003	0.1318	0.0322	0.1196	Q_aDraiNet_m
-0.0434	-0.1167	0.0090	0.1061	-0.0171	Q_SoilD_pt
1.0000	0.4304	0.6596	0.2203	0.4965	Q_PLAND
	1.0000	0.2873	0.0472	0.0807	Q_AgNP
		1.0000	0.1774	0.0329	Q_WdyPLAND
			1.0000	-0.1201	Q_OpenNP
				1.0000	Q_OpenLPI

Q_WetSHAPE	Q_OpenSHAPE	Q_WetPLAND	Q_WetLPI	Q_Likelihood	Variables
0.1794	0.0749	0.1748	0.1458	0.2262	Q_RoadDty_ln
0.1071	0.0923	0.2831	0.2707	0.3143	Q_hF100yr_pt
-0.2422	-0.1216	-0.2227	-0.2076	0.0968	Q_LuseInt_pt
-0.0290	-0.0666	-0.1130	-0.0945	0.2174	Q_FloodDam
-0.2308	-0.2614	-0.1742	-0.1584	-0.0869	Q_aPipes_m
0.1600	0.0625	0.0993	0.0850	-0.2325	Q_2PFloors_pt
-0.1708	-0.0423	-0.0946	-0.0837	0.2013	Q_hMrity_pt

Table D-23 Continued.

Q_WetSHAPE	Q_OpenSHAPE	Q_WetPLAND	Q_WetLPI	Q_Likelihood	Variables
0.0184	-0.0717	-0.0204	-0.0187	0.4741	Q_ppt5d
0.1214	0.1542	0.2890	0.2696	0.2178	Q_aDraiNet_m
0.0509	-0.0437	0.0075	0.0088	0.2043	Q_SoilD_pt
0.4973	0.3906	0.5201	0.4754	-0.0591	Q_PLAND
0.2361	0.0766	0.1935	0.1632	-0.1038	Q_AgNP
0.4257	0.0450	0.3150	0.2706	0.0147	Q_WdyPLAND
0.2598	-0.1201	0.0305	0.0277	0.2014	Q_OpenNP
0.0521	0.6184	-0.0219	-0.0382	-0.0635	Q_OpenLPI
1.0000	0.0910	0.5451	0.5130	0.0020	Q_WetSHAPE
	1.0000	0.0724	0.0425	-0.0607	Q_OpenSHAPE
		1.0000	0.9733	-0.0022	Q_WetPLAND
			1.0000	-0.0098	Q_WetLPI
				1.0000	Q_Likelihood

Q_Severity	H_RoadDty_ln	H_hF100yr_pt	H_LuseInt_pt	H_FloodDam	Variables
0.2221	0.7783	0.1492	0.1663	-0.0029	Q_RoadDty_ln
0.3031	0.1470	0.9499	-0.0701	-0.0344	Q_hF100yr_pt
0.0460	0.1364	-0.1282	0.8039	0.0803	Q_LuseInt_pt
0.2312	0.0026	-0.0478	0.1305	1.0000	Q_FloodDam
-0.1193	-0.1508	-0.0018	0.2002	0.0879	Q_aPipes_m
-0.2504	0.0164	-0.0131	-0.1514	-0.0787	Q_2PFloors_pt
0.1793	-0.0998	0.0954	0.1009	0.0674	Q_hMrity_pt
0.4152	0.0513	0.0139	0.1524	0.0289	Q_ppt5d
0.2338	0.1211	0.4153	-0.0903	0.1489	Q_aDraiNet_m
0.1976	0.0362	-0.0784	0.0847	0.4973	Q_SoilD_pt
-0.0147	0.2620	0.1220	-0.4039	-0.1170	Q_PLAND
-0.0738	0.1566	0.0804	-0.2012	-0.0798	Q_AgNP
0.0415	0.2333	0.0879	-0.3006	-0.0002	Q_WdyPLAND
0.2335	0.2170	-0.0018	-0.0394	0.0734	Q_OpenNP
-0.0423	0.0751	0.0154	-0.1207	-0.0112	Q_OpenLPI
0.0519	0.2086	0.1174	-0.2937	-0.0290	Q_WetSHAPE
-0.0511	0.0422	0.0622	-0.1255	-0.0666	Q_OpenSHAPE
0.0115	0.1811	0.2675	-0.2707	-0.1130	Q_WetPLAND
0.0074	0.1505	0.2607	-0.2568	-0.0945	Q_WetLPI
0.9177	0.2102	0.2871	0.1686	0.2174	Q_Likelihood
1.0000	0.2227	0.2879	0.1166	0.2312	Q_Severity
	1.0000	0.1554	0.1759	0.0026	H_RoadDty_ln
		1.0000	-0.0941	-0.0478	H_hF100yr_pt
			1.0000	0.1305	H_LuseInt_pt
				1.0000	H_FloodDam

H_aPipes_m	H_2PFloors_pt	H_hMrity_pt	H_ppt5d	H_aDraiNet_m	Variables
-0.0268	-0.0066	-0.1124	0.0216	0.1268	Q_RoadDty_ln
-0.0117	-0.0268	0.1052	0.0141	0.4731	Q_hF100yr_pt

Table D-23 Continued.

H_aPipes_m	H_2PFloors_pt	H_hMrity_pt	H_ppt5d	H_aDraiNet_m	Variables
0.1367	-0.1145	0.0360	0.0978	-0.1210	Q_LuseInt_pt
-0.0495	-0.0664	0.0640	0.0293	0.2011	Q_FloodDam
0.1255	-0.0246	0.2274	0.0046	0.0234	Q_aPipes_m
-0.0830	0.9275	-0.4073	-0.1624	0.1336	Q_2PFloors_pt
0.0268	-0.4340	0.9873	0.2765	0.0993	Q_hMrity_pt
-0.0138	-0.1904	0.2817	1.0000	0.0820	Q_ppt5d
-0.0548	0.0920	0.0842	0.0593	0.7851	Q_aDraiNet_m
-0.1625	-0.0349	0.0073	0.0497	-0.0138	Q_SoilD_pt
-0.1700	0.1028	-0.1674	-0.1693	0.1172	Q_PLAND
-0.0605	0.0066	-0.0544	-0.1303	-0.0224	Q_AgNP
-0.1055	0.1207	-0.1544	-0.0141	0.0718	Q_WdyPLAND
-0.0279	-0.1169	0.0548	0.0613	0.0622	Q_OpenNP
-0.0554	0.0514	-0.0853	-0.1387	0.0386	Q_OpenLPI
-0.1961	0.1574	-0.1806	0.0184	0.1322	Q_WetSHAPE
-0.0570	0.0610	-0.0432	-0.0722	0.1011	Q_OpenSHAPE
-0.1336	0.1152	-0.1049	-0.0206	0.2429	Q_WetPLAND
-0.1310	0.1033	-0.0924	-0.0188	0.2384	Q_WetLPI
-0.0080	-0.2581	0.2066	0.4746	0.2023	Q_Likelihood
-0.0399	-0.2703	0.1857	0.4157	0.2327	Q_Severity
-0.0647	0.0015	-0.1027	0.0513	0.1172	H_RoadDty_ln
-0.0150	-0.0189	0.0929	0.0142	0.4823	H_hF100yr_pt
0.1518	-0.1670	0.1054	0.1528	-0.0975	H_LuseInt_pt
-0.0495	-0.0664	0.0640	0.0293	0.2011	H_FloodDam
1.0000	-0.0788	0.0313	-0.0134	-0.0506	H_aPipes_m
	1.0000	-0.4503	-0.1906	0.1177	H_2PFloors_pt
		1.0000	0.2820	0.0969	H_hMrity_pt
			1.0000	0.0820	H_ppt5d
				1.0000	H_aDraiNet_m

H_SoilD_pt	H_PLAND	H_AgNP	H_WdyPLAND	H_OpenNP	Variables
0.0058	0.2567	0.1501	0.2145	0.1469	Q_RoadDty_ln
-0.0402	0.1133	0.0674	0.0605	0.0125	Q_hF100yr_pt
0.0274	-0.3784	-0.1808	-0.2903	-0.0588	Q_LuseInt_pt
0.5451	-0.1764	-0.1111	-0.0030	0.0961	Q_FloodDam
-0.0712	-0.4354	-0.2026	-0.3030	-0.3077	Q_aPipes_m
-0.0562	0.0912	0.0755	0.1308	-0.1320	Q_2PFloors_pt
0.0307	-0.1213	-0.0706	-0.1222	0.0910	Q_hMrity_pt
0.0543	-0.1756	-0.1349	0.0153	0.1611	Q_ppt5d
0.0292	0.1467	0.0147	0.1335	0.0872	Q_aDraiNet_m
0.9665	-0.0857	-0.1741	-0.0009	0.1196	Q_SoilD_pt
-0.0265	0.8877	0.4334	0.6234	0.1504	Q_PLAND
-0.1269	0.4784	0.7791	0.2745	0.0599	Q_AgNP
0.0322	0.6053	0.3325	0.8830	0.1439	Q_WdyPLAND
0.1245	0.2363	-0.0005	0.1871	0.7997	Q_OpenNP

Table D-23 Continued.

H_SoilD_pt	H_PLAND	H_AgNP	H_WdyPLAND	H_OpenNP	Variables
-0.0141	0.3464	0.0667	0.0449	-0.1172	Q_OpenLPI
0.0698	0.5364	0.2555	0.4688	0.2484	Q_WetSHAPE
-0.0479	0.3182	0.0843	0.0549	-0.0767	Q_OpenSHAPE
0.0243	0.5005	0.2058	0.3444	0.0411	Q_WetPLAND
0.0287	0.4571	0.1861	0.3032	0.0395	Q_WetLPI
0.2215	-0.0727	-0.1345	0.0283	0.2706	Q_Likelihood
0.2198	-0.0219	-0.1056	0.0611	0.2986	Q_Severity
0.0344	0.3075	0.1854	0.2841	0.2103	H_RoadDty_ln
-0.0647	0.1114	0.0622	0.0802	0.0002	H_hF100yr_pt
0.0831	-0.4599	-0.2330	-0.3509	-0.0706	H_LuseInt_pt
0.5451	-0.1764	-0.1111	-0.0030	0.0961	H_FloodDam
-0.1750	-0.1864	-0.0582	-0.1573	-0.0375	H_aPipes_m
-0.0457	0.0790	0.0599	0.1171	-0.1462	H_2PFloors_pt
0.0214	-0.1350	-0.0753	-0.1351	0.0914	H_hMrity_pt
0.0546	-0.1759	-0.1352	0.0153	0.1613	H_ppt5d
0.0030	0.1060	-0.0218	0.0962	0.0958	H_aDraiNet_m
1.0000	-0.0774	-0.1929	0.0181	0.1330	H_SoilD_pt
	1.0000	0.5338	0.7014	0.1969	H_PLAND
		1.0000	0.3556	0.0124	H_AgNP
			1.0000	0.1727	H_WdyPLAND
				1.0000	H_OpenNP

H_OpenLPI	H_WetSHAPE	H_OpenSHAPE	H_WetPLAND	H_WetLPI	Variables
0.0732	0.1544	0.0671	0.1936	0.1332	Q_RoadDty_ln
0.0297	0.0493	0.0167	0.2449	0.2163	Q_hF100yr_pt
-0.1430	-0.1835	-0.2120	-0.2438	-0.2128	Q_LuseInt_pt
-0.0563	0.0151	-0.1230	-0.1284	-0.1215	Q_FloodDam
-0.2043	-0.2097	-0.2673	-0.1722	-0.1326	Q_aPipes_m
0.0882	0.1181	0.0367	0.0914	0.0572	Q_2PFloors_pt
-0.0929	-0.0259	-0.0608	-0.0859	-0.0750	Q_hMrity_pt
-0.1676	-0.0089	-0.1945	-0.0104	-0.0249	Q_ppt5d
0.0689	0.1114	0.0003	0.2190	0.1732	Q_aDraiNet_m
-0.0603	0.0929	-0.0632	0.0088	0.0190	Q_SoilD_pt
0.4296	0.3871	0.3635	0.5111	0.4429	Q_PLAND
0.0603	0.1828	0.0965	0.2903	0.2240	Q_AgNP
0.0454	0.3099	0.0881	0.3361	0.2473	Q_WdyPLAND
-0.0988	0.2356	-0.0229	0.0494	0.0352	Q_OpenNP
0.8173	0.0851	0.4608	-0.0076	-0.0138	Q_OpenLPI
0.0981	0.5885	0.0701	0.5715	0.5058	Q_WetSHAPE
0.5738	0.1067	0.5412	0.0838	0.0510	Q_OpenSHAPE
-0.0066	0.3365	0.0117	0.8721	0.8385	Q_WetPLAND
-0.0206	0.3208	-0.0043	0.8308	0.8465	Q_WetLPI
-0.1281	-0.0039	-0.1262	-0.0067	-0.0287	Q_Likelihood

Table D-23 Continued.

H_OpenLPI	H_WetSHAPE	H_OpenSHAPE	H_WetPLAND	H_WetLPI	Variables
-0.1017	0.0270	-0.0842	0.0161	0.0016	Q_Severity
0.0741	0.1597	0.0623	0.2376	0.1673	H_RoadDty_ln
0.0181	0.0696	0.0259	0.2566	0.2311	H_hF100yr_pt
-0.1574	-0.2588	-0.2250	-0.2962	-0.2661	H_LuseInt_pt
-0.0563	0.0151	-0.1230	-0.1284	-0.1215	H_FloodDam
-0.0474	-0.1913	-0.0781	-0.1402	-0.1181	H_aPipes_m
0.0964	0.1314	0.0494	0.1011	0.0795	H_2PFloors_pt
-0.1039	-0.0366	-0.0627	-0.0960	-0.0832	H_hMrity_pt
-0.1677	-0.0093	-0.1952	-0.0106	-0.0251	H_ppt5d
0.0666	0.1286	0.0491	0.2005	0.1678	H_aDraiNet_m
-0.0597	0.1090	-0.0637	0.0190	0.0306	H_SoilD_pt
0.4147	0.5037	0.4131	0.5833	0.5114	H_PLAND
0.0945	0.2289	0.1641	0.3060	0.2527	H_AgNP
0.0763	0.3973	0.1446	0.3784	0.2865	H_WdyPLAND
-0.1435	0.2776	-0.1647	0.0506	0.0248	H_OpenNP
1.0000	0.1392	0.5498	-0.0050	-0.0116	H_OpenLPI
	1.0000	0.1741	0.4533	0.4348	H_WetSHAPE
		1.0000	0.0412	0.0204	H_OpenSHAPE
			1.0000	0.9488	H_WetPLAND
				1.0000	H_WetLPI

H_Likelihood	H_Severity	Variables
0.1598	0.1619	Q_RoadDty_ln
0.3179	0.3100	Q_hF100yr_pt
0.0778	0.0366	Q_LuseInt_pt
0.2863	0.2786	Q_FloodDam
-0.0435	-0.0866	Q_aPipes_m
-0.2832	-0.2755	Q_2PFloors_pt
0.2858	0.2581	Q_hMrity_pt
0.5253	0.4390	Q_ppt5d
0.2045	0.1994	Q_aDraiNet_m
0.2462	0.2303	Q_SoilD_pt
-0.0974	-0.0439	Q_PLAND
-0.1195	-0.0875	Q_AgNP
-0.0209	0.0181	Q_WdyPLAND
0.2054	0.2404	Q_OpenNP
-0.0589	-0.0388	Q_OpenLPI
-0.0354	0.0142	Q_WetSHAPE
-0.0734	-0.0599	Q_OpenSHAPE
-0.0586	-0.0326	Q_WetPLAND
-0.0567	-0.0292	Q_WetLPI
0.8838	0.8199	Q_Likelihood
0.8545	0.8990	Q_Severity
0.1891	0.2048	H_RoadDty_ln

Table D-23 Continued.

	H_Likelihood	H_Severity	Variables
	0.3214	0.3209	H_hF100yr_pt
	0.1679	0.1217	H_LuseInt_pt
	0.2863	0.2786	H_FloodDam
	-0.0334	-0.0663	H_aPipes_m
	-0.3019	-0.2944	H_2PFloors_pt
	0.2899	0.2636	H_hMrity_pt
	0.5260	0.4397	H_ppt5d
	0.2407	0.2513	H_aDraiNet_m
	0.2640	0.2523	H_SoilD_pt
	-0.1137	-0.0498	H_PLAND
	-0.1607	-0.1291	H_AgNP
	0.0020	0.0513	H_WdyPLAND
	0.2702	0.2974	H_OpenNP
	-0.1335	-0.1128	H_OpenLPI
	-0.0285	0.0157	H_WetSHAPE
	-0.1348	-0.0990	H_OpenSHAPE
	-0.0514	-0.0144	H_WetPLAND
	-0.0593	-0.0216	H_WetLPI
	1.0000	0.9377	H_Likelihood
		1.0000	H_Severity

N=540, 5% critical value (two-tailed) = 0.0844.