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Enhancing community flood resilience by incorporating landscape hydrological sensitivity and connectivity

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ABSTRACT

ENHANCING COMMUNITY FLOOD RESILIENCE BY INCORPORATING LANDSCAPE HYDROLOGICAL SENSITIVITY AND CONNECTIVITY

by
Wenlong Feng

Rapid urban expansion and dramatic climate change have significantly increased the intensity and frequency of floods worldwide. With rising flood risks, conventional flood defense strategies that rely on structural measures become ineffective. The present designations for flood-prone areas, such as FEMA’s flood maps, are becoming unreliable. Flood risk management is shifting toward enhancing community flood resilience, highlighting the importance of non-structural approaches. Landscape resilience has become a foundation of community flood resilience. However, past urban development typically undermined natural hydro-ecological functions and landscape resilience because of poor recognition of landscapes' ecological role, hydrological sensitivity, and hydrological connections. This study aims to enhance flood resilience by incorporating landscape hydrology concepts in flood management strategies. The study has two main objectives: first, to empirically examine the impacts of incongruent landscape alterations on flood losses and property values; second, to develop a proactive flood management strategy that integrates hydrological sensitivity.

The study first reviewed 31 hedonic pricing studies about floodplain’s impacts on property values in the United States. Subsequently, the effects of Hydrologically Sensitive Areas (HSAs) on property values were analyzed in Hillsborough and Montgomery, New Jersey, by hedonic pricing models. Moreover, the study employed multiple linear

regression models to analyze the impacts of impervious surface and development restriction areas on flood losses in the Raritan region from 2010 to 2020. This study also discussed the significance of HSAs for landscape resilience and provided suggestions on landscape planning, design, management, and flood insurance reformation.

The literature review of hedonic pricing studies revealed diverse patterns of floodplain impacts on property prices across the United States, with inland and 100-year floodplains having more adverse effects than coastal and 500-year floodplains. The study found that the impact of floodplains on property values was a compound effect of flood risk, insurance premiums, and local amenities. Hedonic pricing analysis in Hillsborough and Montgomery confirmed that properties in HSAs experience significant price discounts (-2%). The impact of HSAs on property values was independent of the impact of floodplains. The regression analysis in the Raritan River Basin region showed that increased impervious surfaces in landscapes lead to higher flood insurance claims, while effective land development restrictions reduce these claims.

These findings highlight the need for comprehensive flood risk assessments and better land use planning to enhance flood resilience. This research contributes valuable insights for policymakers, urban planners, and communities aiming to mitigate flood risks and build resilient landscapes.

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by
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CHAPTER 1

INTRODUCTION

1.1 Background

Floods are one of the most widely distributed and frequently occurring natural disasters across the world, causing numerous damages to property, disturbances of economic and social activities, and degradation of the natural environment (Flood Defenders, 2022; Jonkman et al., 2024; WMO, 2021). Nearly 41 million people in the United States live in the 100-year floodplain (Wing et al., 2018). According to the World Meteorological Organization's report (WMO, 2021), floods were the world's most frequent type of disaster, occupying 44% of record events in the past 50 years. These flood disasters caused 0.33 million deaths and $1.12 trillion in economic losses. Flood hazards affected over 2 billion people from 1998-2017. In 2017, flooding caused more than $ 60 billion in loss and 135 casualties in the United States, which was the severest in the 2007-2017 period (NOAA, 2017). 2021 was also a remarkable year of flood hazards. In the middle of July, extreme precipitation events and unprecedented flooding occurred in several European countries, causing more than two hundred mortalities and $11.8 billion in damage ("2021 European Floods," 2022). Between July 17 and 31, China's Hena Province experienced a catastrophic storm and flooding, resulting in nearly 400 deaths and approximately $12.7 billion in damage (Xinhua, 2021). New Jersey also suffered heavy rainfall and flooding from Hurricane Ida in early September, killing 29 people and causing over $8 billion in damage (NOAA, 2022).

Flood events have various causes, including storms, spring thawing, snowmelt runoff, coastal storm surges, and dams or levees breaking; storms are the main cause of most flood events. The ongoing climate change is increasing the global temperature, shifting the precipitation pattern, and raising sea levels, increasing the intensity and frequency of flood events worldwide (Banholzer et al., 2014; Kulp & Strauss, 2019; Liu et al., 2021). The northeastern US is projected to face more flood hazards in the future (Armstrong et al., 2014; Kirshen et al., 2008; Reidmiller et al., 2017; Wing et al., 2018).

Along with the increasing trend in flood events, there is considerable uncertainty in flood risk. Previous flood controls that heavily rely on structural measures (levees, dykes, and dams) have become less effective in facing unprecedented flood risks. As flood risks escalate, it is essential to implement more effective measures to help communities prepare for, mitigate the impacts of, and recover from floods. Enhancing community flood resilience has been suggested as one of the best strategies to deal with flood risk augmented by the uncertainty associated with climate change (Jongman, 2018; Liao, 2014; Zevenbergen et al., 2020). In 2020, the New Jersey Department of Environmental Protection (NJDEP) started the Protecting Against Climate Threats (PACT) initiative to reduce greenhouse gas and climate pollutant emissions and enhance the resilience of natural and built environments. The pace of this program was dramatically accelerated after the tragic flooding caused by Hurricane Ida in 2021 (CSG, 2022).

1.2 Flood Resilience Framework

1.2.1 Concept of flood resilience

Flood resilience is defined as the capacity of a community to absorb, recover from, and adapt to the adverse effects associated with flood events in a rapid time (Bulti et al., 2019). Since the resilience concept was introduced into disaster management, dozens of resilience measurement frameworks have been developed to evaluate resilience (Bulti et al., 2019; Cai et al., 2018; Nguyen & Akerkar, 2020). Most of these frameworks attribute resilience to the compound effect of society, economy, community, physical condition, resources, and infrastructure and develop various indices to evaluate resilience quantitively and qualitatively (Nguyen & Akerkar, 2020).

One popular resilience framework specific to community flood resilience is the '5C-4R' framework created by the Zurich Flood Resilience Alliance (Atreya & Kunreuther, 2020; Keating et al., 2014, 2017). The community's resilience is closely related to five sources of capital ('5C'): physical, natural, financial, human, and social capital (Keating et al., 2014, 2017). Atreya and Kunreuther (2020) add the political capital to this framework to characterize the community's ability to influence decisions and obtain and utilize outside resources to build resilience. Each source of resilience capital can be assessed with four properties: robustness, rapidity, redundancy, and resourcefulness ('4R'). To implement the framework, Keating et al. (2017) further specified 88 sources of resilience under '5C'. This resilience assessment framework and its variations have been used in at least 118 communities across nine countries (Campbell et al., 2019; Szoenyi et al., 2020).

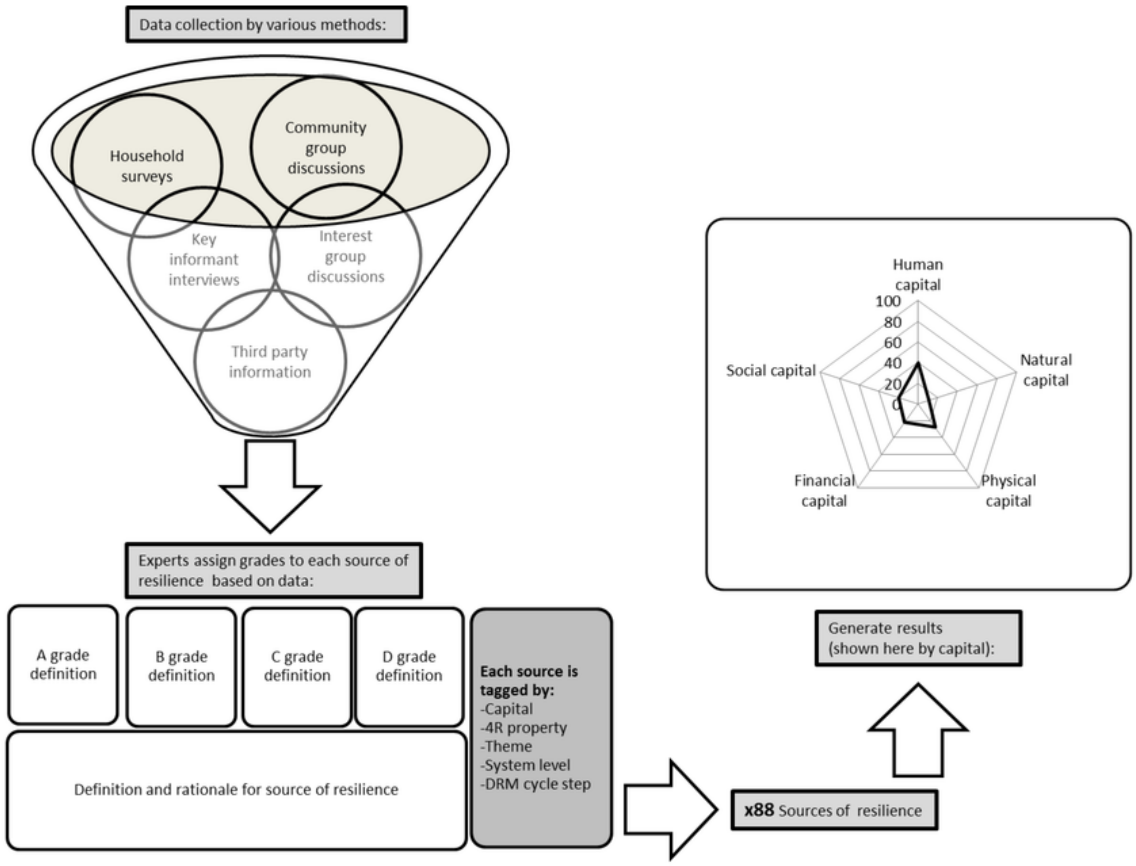

Figure 1.1 Zurich flood resilience measurement framework.
Source: Keating et al., 2017

1.2.2 Concept of landscape resilience

Landscape resilience is one dimension of the social-ecological system resilience. It is defined as the capacity of a landscape to maintain essential ecological functions, support robust native biodiversity, and uphold critical landscape processes over time under changing conditions and various stressors and uncertainties (Beller et al., 2015). This concept focuses on creating diverse, sustainable, and adaptable ecosystems that can long-term support both natural and human communities. Biodiversity, connectivity, adaptability, multifunctionality, and sustainability are key features of resilient landscapes (Ahern, 2013; Beller et al., 2015; Huang et al., 2022). Healthy and robust landscapes can provide essential ecosystem services, such as stormwater storage, habitats, clean water and air, fertile soil, and recreational opportunities.

Landscape resilience is a crucial foundation for building community flood resilience. It leverages natural processes to mitigate flood risks and enhances the community's ability to recover from flood events. By preserving and incorporating green infrastructure and natural resources, such as rain gardens, retention/detention basins, wetlands, forest lands, riparian buffers, and floodplains into landscape design, it is possible to enhance the ability of an area to absorb and manage floodwaters. Wetlands, rain gardens, and retention/detention basins absorb excess water during heavy rain events, enhance water infiltration, and slowly release it to streams, which helps to reduce the severity of floods (Acreman & Holden, 2013; Stefanakis, 2019). Riparian buffers, which are vegetated areas along waterways, can slow down water flow, trap sediments, and filter pollutants, improving water quality and reducing flood risks (Huang et al., 2022). Forest lands can intercept rainwater, increase evapotranspiration, and facilitate infiltration, temporarily storing stormwater and reducing runoff's peak flow, thereby mitigating the flood intensity (M. Kim et al., 2021; B. Zhang et al., 2015). Additionally, preserving and restoring floodplains allows rivers to overflow naturally, spreading out water and reducing the impact on developed areas (Huang et al., 2022; Palazzo & Wang, 2022). By integrating these systems into urban planning and landscape design, communities can create more resilient environments that protect against flooding and support ecological health.

1.2.3 Community rating system

In the United States, the Community Rating System (CRS) is a well-known practical community flood resilience assessment system (Atreya & Kunreuther, 2020; Highfield &

Brody, 2017; Sadiq et al., 2020; Tyler et al., 2019). The CRS was established in 1990 by the Federal Emergency Management Agency (FEMA) as an incentive program of the National Flood Insurance Program (NFIP), which encourages participating communities (i.e., municipalities or counties with land use regulatory authority) to implement more rigorous flood-prone area management. This program provides a 5-45% annual flood insurance discount to NFIP policy holders in those communities that successfully implement flood preparation, mitigation, and recovery measures.

CRS is a tool to boost community flood resilience comprehensively and contains several measures to enhance resilient landscapes. NFIP insurance specialists rate a community's CRS score based on credit activities that the community takes. Table 1.1 displays 19 credit activities and their corresponding maximum possible points, categorized into four classes: public information, mapping and regulations, flood damage reduction, and flood preparedness. Among these activities, open space preservation, floodplain mapping, floodplain management planning, and acquisition and relocation are measures to build resilient landscapes. The top three resilience activities with the highest possible points are building acquisition and relocation, higher regulatory standards, and open space preservation. Communities that invest more effort in these three activities tend to obtain higher CRS scores. As of 2017, over 22,200 communities across the United States participate in the NFIP, and nearly 1500 of them participate in the CRS (Sadiq et al., 2020). New Jersey has 109 communities participating in the CRS, and their average rate class is 7, indicating moderate resilience in general (FEMA, 2022).

Table 1.1 Credit Points Awarded for CRS Activities

Activity	Maximum possible points	% of communities credited
300 Public Information		
310 Elevation Certification	116	96
320 Map Information Service	90	85
330 Outreach Projects	350	93
340 Hazard Disclosure	80	84
350 Flood Protection Information	125	87
360 Flood Protection Assistance	110	41
370 Flood Insurance Promotion	110	4
400 Mapping & Regulations		
410 Floodplain Mapping	802	55
420 Open Space Preservation	2,020	89
430 Higher Regulatory Standards	2,042	100
440 Flood Data Maintenance	222	95
450 Stormwater Management	755	87
500 Flood Damage Reduction		
510 Floodplain Management Planning	622	64
520 Acquisition and Relocation	2,250	28
530 Flood Protection	1,600	13
540 Drainage System Maintenance	570	43
600 Flood Preparedness		
610 Flood Warning and Response	395	20
620 Levees	235	0.5
630 Dams	160	35

Source: FEMA

Previous studies suggest that participation in the CRS can effectively enhance community flood resilience, even though it is less comprehensive than those newly established flood resilience frameworks. Atreya and Kunreuther (2020) find that the CRS credit activities are associated with six types of community capital and a positive correlation between the CRS and the 6C-4R flood resilience measurement framework (a variation of the 5C-4R framework). A working paper (Michel-Kerjan et al., 2016) also mapped the CRS credit activities to 88 sources of resilience in the Zurich Flood Alliance's 5C framework. Participating in the CRS significantly reduces the mean flood damage, claims, and flood-related casualties (Highfield & Brody, 2017; Kousky & Michel-Kerjan, 2017; Petrolia et al., 2013; Zahran et al., 2008). Additionally, Burton (2015) suggests that participation in the CRS significantly improved the communities' recovery after Hurricane Katrina.

1.2.4 Limitations in current flood resilience frameworks

Although previous frameworks address various social, economic, human, and infrastructural factors relevant to flood resilience, there are several limitations in practices of fortifying resilience. Communities intensively adopt physical measurements (e.g., levees, dams, drainage systems, and stormwater management systems) to enhance flood resilience but seldom recognize the role of natural capital in increasing resilience (Mehryar & Surminski, 2021; Michel-Kerjan et al., 2016). Although disaster resilience frameworks regularly advocate anticipatory measures (i.e., risk assessment and risk reduction), most resources and funds are assigned to reactive measures (i.e., disaster response and recovery) in reality, which are highly inefficient for building long-lasting flood resilience (Mehryar & Surminski, 2021; Surminski & Thieken, 2017; Tanner et al., 2015).

Secondly, the CRS did not include a valid hydrological theory or model in its framework, which makes the evaluation of flood resilience in the CRS constrained by community administrational boundaries, ignores the connectivity among nearby communities, and distorts the continuous natural characteristics of flood over space.

Additionally, the CRS implementation depends on the FEMA floodplain maps delineating Special Flood Hazard Areas (SFHA, 100-year flood plains) in communities. However, the flood risk management and resilience measurement focus on floodplains fails to capture flood damage outside the floodplain and from local flood hazards caused by small storms. The present floodplain maps have coarse spatial resolution and incomplete coverage. FEMA floodplain map ignores small catchments (<10,000 km2) and only covers 30% of the length of rivers in the United States (Association of State Floodplain Managers, 2020; Wing et al., 2018). Several studies suggest that the 100-year floodplain did not capture about 25% of flood losses nationwide (Blessing et al., 2017; Highfield et al., 2013). In addition, the FEMA floodplain map is outdated in many areas and cannot accurately reflect the current flood risk. The NJDEP found that the existing flood hazard maps were based on outdated records and did not perform as expected in response to Hurricane Ida (CSG, 2022).

1.3 Landscape Hydrologic Sensitivity and Connectivity

1.3.1 Concept of variable source area hydrology

This study attempts to incorporate variable source area (VSA) hydrology into landscape planning, management, and design to enhance flood resilience. VSA hydrology is an extension of the saturation excess overland flow (runoff) process. Runoff has two primary mechanisms: infiltration excess overland flow and saturation excess overland flow. Infiltration excess overland flow describes the runoff generation process when precipitation intensity surpasses the soil's infiltration capacity (Horton, 1933, 1940). This process generally occurs in areas with very low soil infiltration capacity and little vegetation during highly intensive storm events. In contrast, saturation excess overland flow occurs when precipitation volume exceeds the soil's capacity to store water (Dunne et al., 1975; Hewlett & Hibbert, 1967; Hursh, 1944). Additional rainwater in saturated areas generates runoff. This process commonly occurs in humid, well-vegetated, topographically steep areas with high soil infiltration capacities and low soil capacity to store water. These areas typically have shallow soils or a high water table, indicating a propensity for saturation. Previous studies suggested that saturation excess overland flow is the dominant runoff mechanism within natural landscapes in the Northeast United States (Agnew et al., 2006; Anderson et al., 2015; Walter et al., 2003). VSA hydrology argues that the size of saturated areas for runoff generation varies with landscape wetness over time, and the variation occurs on multiple temporal scales ranging from a single storm to seasonal fluctuations (Dunne et al., 1975; Dunne & Black, 1970; Hewlett & Hibbert, 1967). During a period with abundant rainfall, the extent of saturation expands around saturation-prone areas, whereas the extent of saturation shrinks in a dry period.

1.3.2 Concept of hydrologically sensitive areas

Hydrologically Sensitive Area (HSA) is a crucial concept in VSA hydrology. It refers to a region within a watershed that has a higher propensity to generate runoff than other places (Agnew et al., 2006; Walter et al., 2000). HSAs commonly have direct hydrological links to surface waterbodies so that runoff from these areas can flow to perennial waterways in a short time, transporting water-borne pollutants and sediments to surface waterbodies (Walter et al., 2000). HSAs are usually delineated by the probability of soil saturation, which is significantly correlated with the soil topographic index. Therefore, many studies use the soil topographic index to derive the extent of HSAs (Agnew et al., 2006; Anderson et al., 2015; Qiu et al., 2014, 2020; Walter et al., 2000). As VSA hydrology defines, the extent of HSAs also varies recurrently over time following the soil wetness changes.

Incorporating the hydrological theory and models into the community flood resilience assessment and implementation has many benefits. The hydrological theory and models can make the resilience assessment more objective and scientifically defensible. Furthermore, they can help stakeholders identify critical areas, anticipate flood risk, and implement flood preparation and mitigation. Recent flood risk management efforts tend to control the flood event at the source. The HSA can help stakeholders find the source of surface runoff and improve the efficiency of flood risk management. Introducing the high spatial resolution maps of HSA into community resilience assessment would enhance open space preservation and provide prioritized locations for the acquisition and relocation measures.

Although studies have shown that HSAs are closely related to runoff generation, no study has connected the distribution of HSAs to flood damage and discussed how HSAs can be used to enhance community flood resilience. This study helps fill this research gap.

1.4 Research Objectives and Hypotheses

This study provides a proactive flood management strategy to enhance community flood resilience by incorporating landscape hydrological sensitivity and connectivity. The central hypothesis of this study is that landscape alterations dictated by human decisions are incongruent with the hydro-ecological function of the natural landscape as urbanization and associated infrastructure development fail to recognize such an ecologically functioning landscape and ignore landscape hydrological sensitivity and unique hydrological connections.

The objectives of the study are twofold. First is to examine the impacts of incongruent landscape alterations on community flood risk. Specifically, we empirically distinguished and tested the influence of landscape alterations in HSAs on property values and flood damage. There are two underlying hypotheses in this objective. Hypothesis 1 is that the home sale price implicitly incorporates the local hydrological sensitivity; the homes inside HSAs are subject to higher flood risks and are priced lower than their counterparts outside HSAs. Hypothesis 2 is that the encroachment of development into HSAs significantly increases flood risk, and so, structures in HSAs experience higher flood losses. The second objective is to develop a flood management framework that explicitly recognizes the landscape hydrological sensitivity and connectivity to enhance flood resilience. We discussed the significance of HSAs to landscape resilience and provided HSAs-oriented suggestions to enhance community flood resilience through building resilient landscapes.

CHAPTER 2

UNDERSTANDING THE FLOODPLAIN IMPACTS: A LITERATURE REVIEW

2.1 Introduction

Floods are the costliest natural hazards, causing numerous casualties and economic damages (Flood Defenders, 2022; NOAA, 2021). From 1970 to 2019, 44% of reported natural disasters across the globe were flood disasters, causing nearly 330,390 deaths and 1.12 trillion US dollars of economic losses (WMO, 2021). Over 2 billion people were affected by flood hazards from 1998-2017 (Wallemacq et al., 2018). In the United States, 90% of natural disasters are associated with flooding (GAO, 2005). About 41 million people in the United States are estimated to live in a floodplain with a probability of flooding of at least 1% annually (Wing et al., 2018). According to the natural hazard statistics of the National Oceanic and Atmospheric Administration (NOAA), flood hazards caused 2279 deaths and $193.80 billion of economic damages from 1997 to 2022. The costliest flood hazard in the past two decades happened in 2017, which caused more than $ 60 billion in loss and 135 casualties (NOAA, 2017). The exposure of properties and populations to flood hazards is increasing because of the population and economic growth in flood-prone areas, and the flood risk is expected to exacerbated by the sea-level rise and the increasing extreme precipitation events (Cigler, 2017; Wing et al., 2018).

Besides direct losses caused by flooding, people are also concerned with property value changes affected by flood risk. Housing properties are not only a component of personal wealth but also an important source of taxation for governments, playing a significant role in economic activities (N. Miller et al., 2011). Theoretically, prices of properties inside a floodplain are supposed to be lower than that of equivalent properties outside a floodplain as a result of a higher probability of exposure to flood hazards (Beltrán et al., 2018), as flood hazards can damage the structure of properties and facilities, undermine public services, and disorder local economy. The property price difference across floodplain borders reflects people's perspective on local flood risks. A clear impact of flooding on housing prices raises stakeholders' awareness of flood hazards and is often used in cost-benefit analyses of flood risk management. Because of the above significance, dozens of studies have been conducted to analyze flood risk in the estate market in different places since the 1980s. The foremost property-evaluating method employed in these studies is the hedonic pricing method (Beltrán et al., 2018; Daniel et al., 2009).

The hedonic pricing method is one of the most commonly used economic approaches for goods and services evaluation. Lancaster's consumer theory (Lancaster, 1966) and Rosen's model (Rosen, 1974) are two main theoretical sources of this method. They consider the price of a good as an aggregated price of its inherent attributes. These attributes are objectively measurable and affect the utility or satisfaction of the good. The hedonic pricing method regresses the sellable price of a good against its attributes. Although individual attributes are not selling in the market, their implicit prices can be estimated through their coefficients in the hedonic regression. For residential properties, attributes analyzed in a hedonic pricing model generally consist of structural, locational, and neighborhood attributes (Aladwan & Ahamad, 2019; Chau & Chin, 2003). Structural attributes describe the physical configuration of housing properties, such as living areas and room numbers. Locational attributes refer to characteristics related to the site of properties, such as block number, aesthetic view, and proximity to local amenities.

Neighborhood attributes reflect the surrounding conditions of properties, including socio-economic variables, public services and facilities, and other externalities such as crime rates, noise conditions, and air pollution. When the hedonic pricing method is employed to evaluate ecosystem or environmental services, the housing attributes related to physical environmental characteristics are sometimes specifically separated from location and neighborhood attributes as environmental attributes. For hedonic pricing studies in the flood hazard field, housing attributes related to the floodplain designation, flood insurance rate, or flood damage are introduced into the analysis in addition to former housing attribute categories(Beltrán et al., 2018; Gibson & Mullins, 2020).

Most flood-related studies using the hedonic pricing method analyze the impact of floodplains on property prices. More than 80% of the previous flood-related hedonic pricing studies were conducted in the United States, and they predominantly use the Flood Insurance Rate Maps (FIRMs) designated floodplain as a flood-related attribute in analysis (Beltrán et al., 2018; Daniel et al., 2009). The FIRMs are official maps delineating flood-prone areas at the United States community level, drawn and maintained by the Federal Emergency Management Agency (FEMA). They are designed to implement the National Flood Insurance Program (NFIP) regulations and requirements. Flood-prone areas in these flood maps are classified into two main classes: the 100-year floodplain and the 500-year floodplain. The former delineates areas with an annual flooding probability of no less than 1%, and the latter represents additional areas with an annual flooding probability between 0.2% and 1%. The 100-year floodplain is further split into the A zone (including A, AE, AH, AO, AR, and A99) and the V zone (i.e., V and VE). Compared to the A zone, the V zone is subject to additional hazards associated with storm waves. The NFIP designates all

100-year floodplains as the Special Flood Hazard Areas (SFHA). Within the SFHA, homeowners who finance their purchase via federally regulated lenders must purchase flood insurance through the NFIP. local land use authorities are required to implement stringent floodplain regulation in these areas. Outside the SFHA, the NFIP does not have a mandatory regulation requirement but encourages the State and local governments to implement floodplain management based on local conditions. Therefore, the floodplain impact on property values is a compound effect of flood risk and flood insurance premiums (Bin et al., 2008; de Koning et al., 2019).

After over three decades of study, researchers have found that the impact of floodplains on property values varies over space and time. Daniel et al. (2009) investigated the economic impacts of flood risk on housing values through meta-analyzing 19 hedonic pricing studies in the U.S. between 1987 and 2008. They found that house prices within the 100-year floodplain varied between -52% and +58% relative to house prices outside the floodplain, with an average value of -0.6%. The actual occurrence of a flood or changes in disclosure rules can slightly affect house prices. The marginal willingness to pay for reduced risk exposure increased over time but was slightly lower in areas with higher per capita income. The authors also highlighted the importance of distinguishing between positive amenities (e.g., scenic views) and negative risks (e.g., flood risk) associated with proximity to water. Beltrán et al. (2018) reviewed 37 papers of flood-related hedonic pricing studies before 2013 across the globe, and they found that the magnitude of the floodplain impact ranges from -75.5% to +61.0%. The meta-regression analysis of this paper suggested that the properties in the 100-year floodplain generally experience a price discount, with an overall estimation of this price discount for a meta-analysis of -4.6%.

However, significant variations in the price impact existed between inland and coastal regions. Properties exposed to inland flooding have a price discount of -5.6%, while those exposed to coastal flooding enjoy a price premium of +13.4% (Beltrán et al., 2018). The meta-analysis also identified publication bias in studies related to coastal flooding. Studies showing significant positive effects of coastal location on property values were more likely to be published, contributing to an overrepresentation of such findings in the literature. Beltrán et al. (2018) attributed the positive correlation between property prices and coastal floodplain location to omitted variable bias rather than a true lack of price discount for flood risk. This study also summarized the temporal variation of the price discount for floodplain properties. It is more pronounced immediately following a flood event and tends to decrease over time as the memory of the flood fades and properties are repaired or improved.

This chapter reviewed the flood-related hedonic pricing studies published in peer-reviews journals by 2023. The reviewed studies were analyzed and summarized from three aspects: variable selection, modeling methods, and patterns in floodplain impacts on property values. The factors affecting the floodplain impact were discussed in this study. At the end of this chapter, limitations on previous flood risk economic impact studies are also pointed out.

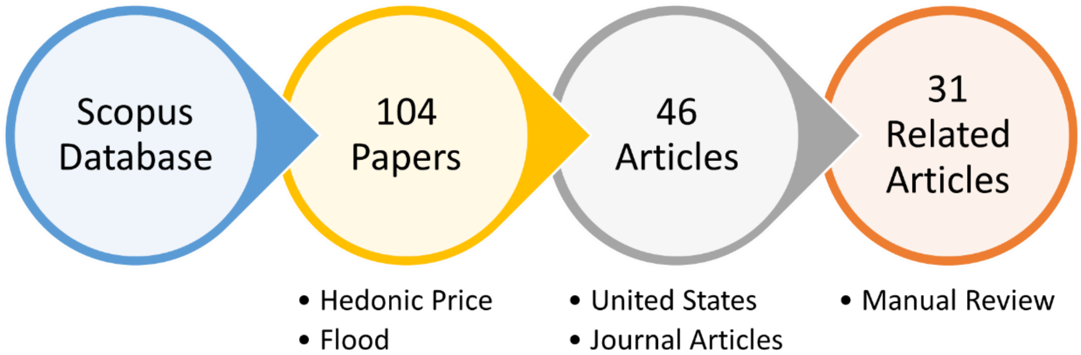

Figure 2.1 Flow chart of literature search.

2.2 Literature Searching Method

This literature review focused on hedonic pricing studies about the impact of floodplains in the United States. We used the Scopus database to search for papers related to hedonic pricing method applications in the flood hazard field before May 2023. Our paper search has three steps. First, we searched for “Hedonic price” and “flood” in titles, keywords, and abstracts of papers. The initial search found 104 papers, subsequently filtered to peer-reviewed journal articles in the United States by setting the Scopus searching conditions. Forty-six articles passed the filtering and were then manually reviewed. During the manual review, we kept articles that explicitly related to the hedonic pricing method and the floodplain impact and filtered off review papers and meta-analysis studies from the review list. Finally, we refined the list to thirty-one studies, as shown in Table 2.1. The following sections summarize our findings in detail.

Table 2.1 List of Reviewed Journal Articles on Flood-Related Hedonic Pricing Studies

No.	Papers	Locations	Research period
1	Atreya & Ferreira, 2015	Albany, Georgia	1985-2007
2	Atreya et al., 2013	Dougherty County, Georgia	1985-2004
3	Bakkensen et al., 2019	Florida State	2002-2012
4	Bin & Kruse, 2006	Carteret County, North Carolina	2000-2004
5	Bin & Landry, 2013	Pitt County, North Carolina	Sep 1992 - Aug 2008
6	Bin & Polasky, 2004	Pitt County, North Carolina	1992-2002
7	Bin et al., 2008	Carteret County, North Carolina	2000-2004
8	Chandra Putra, 2017; Chandra-Putra & Andrews, 2020	Monmouth County, New Jersey	2010-2015
9	de Koning et al., 2018	Pitt County, North Carolina	1992 - 2002
10	de Koning et al., 2019	Beaufort, North Carolina	2001 -2004
11	Donnelly, 1989	La Crosse, Wisconsin	Jan 1984 - Dec 1985
12	Fonner et al., 2022	Orting, Washington	2005-2017
13	Fu et al., 2016	Tampa-St. Petersburg Metropolitan Area	By 2015
14	Gibson & Mullins, 2020	New York City, New York	2003-2017
15	Hennighausen & Suter, 2020	Boulder County, Colorado	2009-2017
16	Kousky & Walls, 2014	St. Louis County, Missouri	2008-2012
17	Lee & Li, 2009	College Station, Texas	By 2006
18	Livy, 2023	Hamilton County, Ohio	2009-2017
19	Meldrum, 2016	Boulder County, Colorado	1995-2012
20	Miller & Pinter, 2022	Benton County, Oregon; Boulder County, Colorado; Cass County, North Dakota	2009-2013
21	A. Morgan, 2007	Santa Rosa County, Florida	Jan 2000 - Dec 2006
22	J. D. Morgan et al., 2022	Pinellas County, Florida	2000 - 2015
23	Netusil et al., 2019	Portland, Oregon	1988-2014
24	Pope, 2008	Wake County, North Carolina	Jan-Sep in 1995 and 1996
25	Posey & Rogers, 2010	St. Louis County, Missouri	2000-2007
26	Qiu et al., 2006	St. Louis, Missouri	Jan 2000- Sep 2001
27	Shilling et al., 1989	Baton Rouge, Louisiana	Dec 1982 - Feb 1984
28	Shultz & Fridgen, 2001	Fargo-Moorhead Metropolitan	1995-1998
29	Troy & Romm, 2004	California State	1997-1999
30	Zhang & Leonard, 2019	Fargo-Moorhead Metropolitan	2007-2013
31	Zhang, 2016	Fargo-Moorhead Metropolitan	2000-2013

2.3 Variables in Hedonic Models

2.3.1 Response variable

Almost all reviewed studies used the single-family home sale price as the response variable for hedonic pricing models. Most reviewed studies used the semi-log function in modeling, i.e., the natural logarithm of selling price is the main format of response variables. Only Donnelly (1989) and J. D. Morgan et al. (2022) used the untransformed sale price as the response variable. In a hedonic pricing model that uses the semi-log function, a coefficient of an explanatory variable can be converted to a percentage change in sale prices by Equation (2.1).

$$\%\ change\ in\ sale\ price = (\exp(Estimated\ Coefficient) - 1) \times 100\% \qquad (2.1)$$

2.3.2 Explanatory variables

The explanatory variables of hedonic pricing models in previous studies are very diverse. Nearly 190 kinds of explanatory variables are found in the reviewed papers, and these variables were coarsely grouped into structural, location, neighborhood, and environmental characteristics. Sirmans et al. (2005) provide a more detailed classification system for explanatory variables, including eight categories: structural characteristics, internal features, external features, natural environment characteristics, neighborhood and location characteristics, public service characteristics, marketing characteristics, and financial issues. We modified this classification system to describe explanatory variables in the reviewed studies. Variables are first grouped into property characteristics, community characteristics, natural environment characteristics, and flood-related characteristics. The property characteristics are divided into three sub-classes, and the community characteristics are split into four. Table 2.2 shows 43 commonly used variables in groups of community, environmental, and property characteristics.

Table 2.2 Common Variables of Community, Environmental, and Property Characteristics

Groups	Variable categories	Variables	Counts	Paper No.
Community Characteristics	Economic	Local median household income	5	[1], [2], [8], [20], [29].
Community Characteristics	Facility	Distance to nearest highway / major road	12	[1], [2], [3], [5], [6], [7], [9], [15], [16], [17], [19], [29].
Community Characteristics	Facility	Distance to the nearest park, recreation forest, or game land	11	[1], [2], [3], [5], [6], [7], [9], [16], [17], [24], [28].
Community Characteristics	Facility	Distance to the nearest downtown area (CBD)	9	[5], [6], [7], [9], [19], [20], [23], [29], [30].
Community Characteristics	Facility	Distance to the closest railroad	7	[1], [2], [3], [5], [6], [9], [19].
Community Characteristics	Facility	Distance to the closest airport	5	[3], [5], [6], [9], [30].
Community Characteristics	Facility	Distance to the closest school	4	[1], [2], [8], [17].
Community Characteristics	Facility	Dummy variable for abutting park	3	[17], [30], [31].
Community Characteristics	Facility	Dummy variable for abutting golf course	3	[28], [30], [31].
Community Characteristics	Neighborhood	City/Township	4	[4], [6], [7], [15].
Community Characteristics	Neighborhood	Census tract	3	[3], [21], [24].
Community Characteristics	Social	Percent of nonwhite	4	[1], [2], [4], [24].
Environment Characteristics	Environmental	Distance to nearest stream/creek/river	10	[1], [2], [3], [5], [6], [8], [9], [12], [19], [26].
Environment Characteristics	Environmental	Distance to the nearest coastline	5	[3], [8], [13], [22], [29].
Environment Characteristics	Environmental	Distance to closest lake/waterbody	5	[1], [2], [15], [22], [24].
Environment Characteristics	Environmental	Elevation of structure	5	[1], [2], [12], [13], [15].
Environment Characteristics	Environmental	Dummy variable for abutting river	3	[28], [30], [31].
Environment Characteristics	Environmental	Dummy variable for abutting coastline	3	[7], [8], [22].
Property Characteristics	Housing information	Dummy variable for vacant home	3	[5], [6], [9].
Property Characteristics	Structural	Property age	26	[2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [15], [17], [18], [19], [20], [21], [22], [23], [24], [25], [27], [28], [30], [31].

Table 2.2 Common Variables of Community, Environmental, and Property Characteristics (continued)

Groups	Variable categories	Variables	Counts	Paper No.
Property Characteristics	Structural	Total structure square footage (living area)	25	[2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [15], [16], [18], [19], [20], [21], [23], [25], [27], [28], [29], [30], [31].
Property Characteristics	Structural	Lot size	22	[1], [2], [4], [5], [7], [9], [10], [11], [12], [13], [15], [16], [19], [20], [23], [24], [26], [27], [28], [29].
Property Characteristics	Structural	Number of bathrooms	17	[3], [4], [6], [7], [12], [13], [17], [18], [20], [21], [24], [25], [26], [28], [29], [30], [31].
Property Characteristics	Structural	Number of bedrooms	16	[1], [2], [3], [6], [9], [10], [12], [15], [17], [19], [20], [21], [26], [29], [30], [31].
Property Characteristics	Structural	Condition of buildings (quality)	8	[5], [6], [8], [9], [15], [19], [22], [24].
Property Characteristics	Structural	Dummy variable for Brick Exterior	8	[1], [2], [5], [6], [9], [18], [22], [24].
Property Characteristics	Structural	Dummy variable of air-conditioning (AC)	8	[1], [2], [8], [11], [18], [28], [30], [31].
Property Characteristics	Structural	Dummy variable of fireplace	7	[5], [6], [8], [9], [11], [30], [31].
Property Characteristics	Structural	Dummy variable for new home	6	[6], [7], [12], [21], [24], [29].
Property Characteristics	Structural	Size of garage	6	[11], [24], [26], [28], [30], [31].
Property Characteristics	Structural	Number of floors (stories)	5	[18], [22], [25], [30], [31].
Property Characteristics	Structural	Size of heated area	5	[1], [2], [17], [22], [24].
Property Characteristics	Structural	Number of Full bathrooms	4	[1], [2], [15], [19].
Property Characteristics	Structural	Dummy variable of hardwood floor	4	[5], [6], [9], [24].
Property Characteristics	Structural	Dummy variable of garage	4	[1], [2], [15], [19].
Property Characteristics	Structural	Type of Structural foundation	4	[8], [22], [30], [31].
Property Characteristics	Structural	Number of half-bathrooms	3	[1], [2], [19].
Property Characteristics	Structural	Number of fireplaces	3	[1], [2], [24].
Property Characteristics	Structural	Dummy variable for Gas heating	3	[5], [6], [9].
Property Characteristics	Structural	Dummy variable for basement	3	[15], [18], [19].
Property Characteristics	Structural	Dummy variable of deck	3	[8], [30], [31].
Property Characteristics	Temporal	Sale year	12	[1], [2], [3], [4], [7], [11], [18], [20], [21], [23], [30], [31].
Property Characteristics	Temporal	Sale month (month-year)	5	[8], [18], [19], [30], [31].

Note: The paper number refers to the sequence numbers in Table 2.1.

2.3.2.1 Property characteristics. Property characteristics are the physical configuration, selling information, and other housing attributes related to specific houses, including structural, temporal, and housing information subclasses. It is the largest and most frequently used variable group in hedonic pricing modeling. There are 25 variables in this group used in at least three studies, including the top three frequently used variables (age of property, squared footage, and lot size). Structural variables refer to the physical configuration of a house, such as the number of bedrooms, number of bathrooms, lot size, square footage, and stories. Temporal variables relate to the sale date of a property, such as sale year, sale month, and temporal trend of prices. Housing information contains other property attributes, such as the property tax and dummy variables for the home vacancy, owner-occupied house, and conventional financing.

2.3.2.2 Community characteristics. Community characteristics depict the economic, social, and demographic conditions surrounding a house, further classified into neighborhood, facility, social, and economic variables. It is the second largest variable group, including 12 commonly used variables. The neighborhood variable indicates a house's position or administrative region designations, such as block number, census tract, and tax district. The neighborhood variable is often used to denote the spatial fixed effects. The facility variable depicts the accessibility of a house to nearby infrastructures and public services, such as distances to the closest highway, railway, commercial district, school, and park. Social variables are attributes that relate to the demographic features of a community, such as the percentage of vacant houses, the percentage of nonwhite population, and the total household size of a community. Economic variables consist of various economic indicators for a community, including local property tax rate, total rent, percent of owner-occupied housing, and median household income.

2.3.2.3 Environmental characteristics. Environmental characteristics reflect the natural amenities and disamenities near a house. They are the smallest variable group, with only six commonly used variables. Most variables in this group vary over space, so they are often shown in some format of proximity to natural surroundings, such as the distance to the closest stream and the distance to the nearest waterfront. However, flood-related hedonic pricing studies seldom use environmental variables to assess air quality, noise, water quality, biodiversity, and aesthetic views.

2.3.2.4 Flood-related characteristics. The flood-related characteristic is an iconic explanatory variable group for flood-related hedonic pricing studies. The reviewed studies apply 26 kinds of flood-related variables (Table 2.3). Only one-third of these variables are used in more than two studies. This group of variables can be generally split into two subtypes. One subtype is the flood-prone area designation, such as floodplains, flood zones, inundation areas, and the distance to floodplains. Another subtype is the variable indicating certain events or factors that can affect the floodplain impact, such as major flood events, flood damage, flood insurance reformation, and flood risk information disclosure. According to reviewed studies, dummy variables for the floodplain designation and home sales after flood events are the most frequently used flood-related variables.

Table 2.3 Flood-Related Variables

Variables	Counts	Variables	Counts
Dummy variable for 100-year floodplain	22	Dummy variable for Sandy flooding	1
Dummy variable for 500-year floodplain	15	Dummy variable for a sale after a levee setback	1
Dummy variable for a sale after a major flood /hurricane event	10	Dummy variable for the new floodplain	1
Dummy variable for inundation	4	Dummy for sale after the issue of the new floodplain maps	1
Dummy variable for flood zone A / AE	4	Average flood damage by census block	1
Years after the local flood event	3	Distance to the 100-year floodplain (buffer rings)	1
Dummy variable for floodplain (merge 100-year and 500-year floodplains)	3	Product of a floodplain and property's tax liability	1
Dummy variable for property built after FIRM /NFIP	3	Dummy variable for near-miss (properties in a floodplain but not inundated)	1
Flood depth	3	Dummy variable for sale after an elevated river level (non-destructive flood) event	1
Dummy variable for flood zone V / VE	2	Dummy variable for flood insurance	1
Dummy variable for a sale after the hurricane cluster event	1	Annual flood insurance payment	1
Dummy variable for the old floodplain	1	Dummy variable for property in 100-year floodplain built before FIRM	1
Dummy variable for sale after the passage of the Biggert-Waters Act (raise of flood insurance premium)	1	Dummy variable for sales within a month after Hurricane Sandy	1

2.4 Modeling Methods

The early stage of the hedonic pricing method uses multiple linear regressions to estimate property sale prices (e.g., Donnelly, 1989; A. Morgan, 2007; Shilling et al., 1989). With the development of the hedonic pricing method, a couple of modeling techniques were applied to hedonic pricing analysis, especially the difference-in-differences framework and spatial analysis models (Table 2.4). We discussed these methods in the following subsections.

Table 2.4 Modeling Methods of Reviewed Articles on the Hedonic Pricing Model

Papers	Multiple Linear Regression	Difference-in-Difference	Spatial Fixed Effect	Spatial autoregressive model	Spatial error model	Spatial autoregressive lag and error model (SARAR)	R Squared
Atreya & Ferreira, 2015		✓	✓				0.320~0.331
Atreya et al., 2013		✓				✓	*
Bakkensen et al., 2019		✓	✓				*
Bin & Kruse, 2006	✓						0.650~0.690
Bin & Landry, 2013		✓			✓		*
Bin & Polasky, 2004	✓						*
Bin et al., 2008	✓				✓		*
Chandra Putra, 2017	✓	✓		✓	✓		0.628~0.646
de Koning et al., 2018		✓		✓			*
de Koning et al., 2019	✓						*
Donnelly, 1989	✓						0.838
Fonner et al., 2022		✓				✓	0.890
Fu et al., 2016				✓	✓		*
Gibson & Mullins, 2020		✓	✓				*
Hennighausen & Suter, 2020		✓	✓				0.775~0.776
Kousky & Walls, 2014			✓				0.729
Lee & Li, 2009				✓			0.963~0.987
Livy, 2023			✓				*
Meldrum, 2016				✓			*
Miller & Pinter, 2022	✓	✓					0.513~0.707
A. Morgan, 2007			✓				*
J. D. Morgan et al., 2022		✓			✓		0.48
Netusil et al., 2019	✓						0.502~0.508
Pope, 2008		✓	✓				0.92-0.93
Posey & Rogers, 2010	✓			✓			0.883
Qiu et al., 2006	✓						0.524
Shilling et al., 1989	✓						0.77~0.78
Shultz & Fridgen, 2001	✓		✓				0.78
Troy & Romm, 2004	✓	✓					0.765~0.767
Zhang & Leonard, 2019		✓			✓		0.751~0.764
Zhang, 2016		✓		✓			0.5616~0.755
Count	12	15	9	7	6	2	

2.4.1 Multiple linear regression

Multiple linear regression is a basic and frequently used modeling technique in hedonic pricing modeling. Over one-third of reviewed studies use multiple linear regression as their base model because it is easy to implement. This approach analyzes the collective influence of structural, locational, and neighborhood attributes on real property prices. Its general formula is described in Equation (2.2)

$$\boldsymbol{y} = \boldsymbol{X\beta} + \varepsilon \tag{2.2}$$

Where $\boldsymbol{y}$ is a vector of home sale prices, $\boldsymbol{X}$ represents a matrix of property attributes, $\boldsymbol{\beta}$ denotes a vector of coefficients of the explanatory variable, and ε is an independent random error term. The ordinary least square (OLS) and the maximum likelihood estimation (MLE) are frequently used fitting methods for multiple linear regression. Although the original format of the multiple linear regression does not consider the spatial dependence and temporal variation in property prices, it can easily integrate with the spatial fixed effect technique and the difference-in-difference framework to improve model performance.

2.4.2 Spatial analysis models

Real property values typically have significant spatial dependence. The price of a house is often affected by prices of nearby properties, and closer properties have greater impacts. This phenomenon makes the estimation of a multiple linear regression bias and inefficient. Spatial analysis techniques are used to resolve spatial dependence in modeling. Among reviewed studies, the spatial fixed effects technique and the spatial regression are frequently used spatial modeling techniques. The spatial regression includes the spatial autoregressive model and the spatial error model.

2.4.2.1 Spatial fixed effects. A spatial fixed effect model is a statistical approach to analyze data incorporating spatial dependencies. It assumes that observations in close geographic proximity may have similar characteristics or behaviors. In this model, specific effects or characteristics are associated with individual spatial units (e.g., regions, census tracts, or neighborhoods) and are considered fixed over time. This approach is often used to capture unobserved heterogeneity specific to each location. Equation (2.3) shows a formula of a spatial fixed effect model.

$$y_i = \boldsymbol{X_i}\boldsymbol{\beta} + S_i + \varepsilon_i \tag{2.3}$$

Where, y_i is the predicted variable of the i-th observation (home sale price), $\boldsymbol{X_i}$ represents explanatory variables (property attributes) of the i-th observation. $\boldsymbol{\beta}$ represents coefficients of explanatory variables. S_i stands for the spatial fixed effect of the i-th observation. It is usually an indicator variable for a spatial unit (e.g., block, tract, and county). The spatial effect is assumed constant within a spatial unit but varies among different spatial units. From the modeling view, the spatial fixed effect variable can be treated as a categorical variable expressed by a set of dummy variables.

Nine of the reviewed studies used the spatial fixed effects technique (Atreya & Ferreira, 2015; Bakkensen et al., 2019; Gibson & Mullins, 2020; Hennighausen & Suter, 2020; Kousky & Walls, 2014; Livy, 2023; A. Morgan, 2007; Pope, 2008; Shultz & Fridgen, 2001) The spatial units used in these studies include geographic regions in a state, Core

Based Statistical Areas, counties, municipalities, census tracts, census blocks, tax lots, and tax districts.

2.4.2.2 Spatial autoregressive model and spatial error model. A spatial autoregressive model is a statistical model used to analyze spatial data that exhibits spatial autocorrelation. It considers the dependency between observations in neighboring locations by incorporating a lagged term of the dependent variable. A formula of a spatial autoregressive model is Equation (2.4).

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \varepsilon \tag{2.4}$$

Where, $\boldsymbol{W}\boldsymbol{y}$ is the spatial lag term. $\boldsymbol{W}$ is the spatial weight matrix reflecting the strength of the relationship between locations. A weight matrix can be constructed according to contiguity or distance. Neighbor within a distance, Nearest-Neighbors, Inverse Distance Weighting, and semi-variograms are common methods for building a spatial weight matrix. ρ is the coefficient of the spatial lag term. Because of the spatial lag term, a spatial multiplier should be applied when interpreting the coefficients of the explanatory variables. The spatial multiplier equals $1/(1-\rho)$.

In a spatial error model, the error term of the regression equation is assumed to be spatially correlated. Therefore, it incorporates a spatially lagged term in errors. Its formula follows Equation (2.5).

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{u}, \boldsymbol{u} = \lambda \boldsymbol{W}\boldsymbol{u} + \varepsilon \tag{2.5}$$

Where, $\boldsymbol{u}$ is an additional error term that captures the uncorrelated variation. λ is the spatial autoregressive coefficient in the error term. The spatial error model allows for analyzing spatial dependencies and spatially correlated variations not captured by the explanatory variables. In contrast to the spatial autoregressive model, the spatial error model does not need a spatial multiplier when interpreting coefficients of explanatory variables.

Among reviewed papers, six studies used the spatial autoregressive model (Atreya et al., 2013; Chandra Putra, 2017; J. S. Lee & Li, 2009; Posey & Rogers, 2010; L. Zhang, 2016), and five studies used the spatial error model (Bin & Landry, 2013; Chandra Putra, 2017; de Koning et al., 2018, 2019; J. D. Morgan et al., 2022; L. Zhang & Leonard, 2019). The spatial autoregressive and spatial error methods can be implemented simultaneously in one model, called spatial autoregressive with additional autoregressive error structure (SARAR). Three studies used the SARAR model to analyze the property prices under the flood hazard impact (Atreya et al., 2013; Fonner et al., 2022; Fu et al., 2016).

2.4.3 Difference-in-differences

The difference-in-differences (DiD) is a quasi-experimental statistical technique used to compare the difference in outcomes between treatment (e.g., floodplain) and control groups before and after an intervention (e.g., flood event) is implemented. This approach can isolate the effect of treatment. The basic format of a DiD framework in a flood-related hedonic pricing regression is Equation (2.6).

$$y = \boldsymbol{X\beta} + \gamma(Floodplain) + \tau(Post) + \theta(Floodplain \times Post) + \varepsilon \tag{2.6}$$

Where, y is a home sale price, $\boldsymbol{X}$ stands for a vector of property attributes, $Floodplain$ is a dummy variable indicating a home in a floodplain, $Post$ is a dummy variable indicating a home sale after a flood event, $Floodplain \times Post$ represents the interaction term of the floodplain dummy and flood event dummy, and ε is the error term. $\boldsymbol{\beta}$ represents a vector of coefficients corresponding $\boldsymbol{X}$. Coefficient γ is the treatment effect coefficient, representing the difference in the sale price between properties inside and outside a floodplain before a flood event. Coefficient τ is the coefficient for time effect, representing the average change in sale price for properties outside a floodplain through a flood event. Coefficient θ is the interaction term coefficient, representing the difference in pre-post sale price changes between floodplain properties and non-floodplain properties. If θ is significantly different from zero, the flood event changes the floodplain's impact on property values.

Fifteen studies used a DiD technique in their hedonic pricing regressions. Each of these studies used the presence of floodplain as a treatment of properties in the difference-in-differences framework. Properties outside a floodplain are the control group. Most studies analyzed changes in property prices before and after a flood event or a storm. (Atreya et al., 2013; Atreya & Ferreira, 2015; Bakkensen et al., 2019; Bin & Landry, 2013; Chandra Putra, 2017; de Koning et al., 2018; Gibson & Mullins, 2020; R. G. Miller & Pinter, 2022). Three studies examined changes before and after certain policies were implemented (Gibson & Mullins, 2020; Pope, 2008; Troy & Romm, 2004). The DiD framework was also used to compare the impacts of other hazard area designations, such as inundated areas and hurricane evacuation zones, with the floodplain impact (Atreya & Ferreira, 2015; Hennighausen & Suter, 2020; J. D. Morgan et al., 2022).

2.5 The Floodplain Impact on Property Values

Intuitively, properties in floodplains should suffer a discount effect on sale prices, as properties in floodplains are exposed to a higher risk of flood hazard than comparable properties outside floodplains. Some early studies estimate this discount effect ranging from 4% to 12% (Bin & Polasky, 2004; Donnelly, 1989; Shilling et al., 1989; Shultz & Fridgen, 2001; Troy & Romm, 2004). However, the pattern of the floodplain impact on property values is not universally negative over space and time. Through reviewing 19 studies in the United States before 2009, Daniel et al. (2009) found that the 100-year floodplain has an effect ranging from -52% to +58% on house prices, and their meta-analysis suggests that a 0.01 increase in the annual probability of flooding is associated with a 0.6% decrease in house prices. Beltrán et al. (2018) analyzed 37 studies worldwide before 2018. They found that the floodplain impact lies between -75.5% and +61.0%, and their meta-analysis result suggests that properties in a 100-year floodplain in the inland region have a price discount of 4.6%. According to our reviewed journal articles (Table 2.5), the floodplain impact in the United States ranges from -48% to +61%. The detailed spatial and temporal patterns of the floodplain impact are complicated and even counterintuitive in some places, reflecting a diversity of flood risk perspectives in the real estate market. The following three subsections describe patterns in the floodplain impact from spatial, temporal, and other aspects.

Table 2.5 The Floodplain Impact on Property Values

Papers	Overall Impact	Pre-event Impact	Post-event Impact	Events	Coast / Inland
Atreya & Ferreira, 2015		Insignificant	Floodplain × Inundated: -48% Near-miss: insignificant Inundated ×No Floodplain: -36%	1994 flood caused by tropical storm Alberto	Inland
Atreya et al., 2013		100-year floodplain: -9% 500-year floodplain: insignificant	100-year floodplain: -32% to -44% 500-year floodplain: -23%	1994 flood caused by tropical storm Alberto	Inland
Bakkensen et al., 2019		In never-hit counties, A Zone price relative to X Zone price: +4.4% to +16.5% In near-miss counties, A Zone price relative to X Zone price: +4.7% to +8.3%	In never-hit counties, A Zone price relative to X Zone price: +9.4% to +18.8% In near-miss counties, A zone price relative to X Zone price: -3.3% to +2.2%	Hurricane cluster period from Aug 2004 to Oct 2005	Florida
Bin & Kruse, 2006	100-year floodplain: -5.6% to +10% V Zone: +26.5% to +61% 500-year floodplain: -5% to -10.3%				Coast
Bin & Landry, 2013		Insignificant	All floodplain: -5.7% to -8.8% 100-year floodplain: -8.8% to -13% 500-year floodplain: insignificant	Hurricane Fran and Hurricane Floyd	Inland
Bin & Polasky, 2004	100-year floodplain: -5.7%	100-year floodplain: -3.8%	100-year floodplain: -8.4%	Hurricane Floyd	Inland
Bin et al., 2008	100-year floodplain: -7.8% 500-year floodplain: -6.2%				
Chandra Putra, 2017; Chandra-Putra & Andrews, 2020	A Zone: -21.6% V Zone: +11.7% X Zone: -3.6%	A Zone: -26.7% A Zone × owner occupied: -9.4% V Zone: +8.0% V Zone × owner occupied: +48.8% X Zone: +6.4% X Zone × owner occupied: -2.2%	A Zone: -35.4% V Zone: -18.1% X Zone: +0.2%	Hurricane Sandy	Coast
de Koning et al., 2018	All floodplains: -5% to -6.3%			Hurricane Fran and Hurricane Floyd	Inland
de Koning et al., 2019	100-year floodplain: -32.1% 500-year floodplain: -24.6%				Coast
Donnelly, 1989	All floodplains: -12%				Inland

Table 2.5 The Floodplain Impact on Property Values (continued)

Papers	Overall Impact	Pre-event Impact	Post-event Impact	Events	Coast / Inland
Fonner et al., 2022		100-year floodplain: -3% 500-year floodplain: -3.5%	100-year floodplain: -3% 500-year floodplain: +1.8%	2014 Levee setback	Inland
Fu et al., 2016	100-year floodplain: +3.5% to +8.4%				Coast
Gibson & Mullins, 2020			Avg. inundation inside 100-year floodplain: -7% Avg. inundation outside 100-year floodplain: -5.5%	Hurricane Sandy	Coast
Hennighausen & Suter, 2020		100-year floodplain Overall: -6.1% 100-year floodplain × inundated: -10% Near-miss: -4.1% 500-year floodplain: insignificant	100-year floodplain Overall: -6.1% 100-year floodplain × inundated: -17.3% Near-miss: insignificant 500-year floodplain: +4% to +4.6%	2013 Flood event	Inland
Kousky & Walls, 2014	100-year floodplain: -0.68% (insignificant)				Inland
Lee & Li, 2009	Flood control detention basin: -3.5% Multi-use detention basin: +$2,489				Inland
Livy, 2023	100-year floodplain: -12.7% 500-year floodplain: -17.6%		100-year floodplain: -19.2% 500-year floodplain: insignificant	Elevated river level	Inland
Meldrum, 2016	100-year floodplain: -14% (Condo); insignificant (standalone)				Inland
Miller & Pinter, 2022		100-year floodplain: -6.1% to -9.4% 500-year floodplain: -4.8% to -7.3%	100-year floodplain: -9.4% to -15.7% 500-year floodplain: -1% to +0.6%	Local flood events	Inland
A. Morgan, 2007	100-year floodplain: +27.5%	100-year floodplain: +32.1%	100-year floodplain: +15.7%	Hurricane Ivan	Coast
J. D. Morgan et al., 2022	100-year floodplain: -$5,887.92 100-year floodplain × evacuation zone: -$11,162.47				Coast

Table 2.5 The Floodplain Impact on Property Values (continued)

Papers	Overall Impact	Pre-event Impact	Post-event Impact	Events	Coast / Inland
Netusil et al., 2019	100-year floodplain × tax lot: -8.6% 100-year floodplain × building footprint: -21.5% 500-year floodplain: insignificant				Inland
Pope, 2008	A Zone: -2% (insignificant)	Insignificant	A Zone: -4.3% X Zone: insignificant	1996 NC Residential Property Disclosure Act	Inland
Posey & Rogers, 2010	100-year floodplain: -8.6%				Inland
Qiu et al., 2006	All floodplains: -4.7% to -5.6%				Inland
Shilling et al., 1989	All floodplains -8%				Inland
Shultz & Fridgen, 2001		100-year floodplain: -$8,890 500-year floodplain: +$3,100	100-year floodplain: -$ 10,241	1997 Flood event	Inland
Troy & Romm, 2004		Insignificant	100-year floodplain: -4.3%	1998 CA Natural Hazard Disclosure Law (AB 1195)	California
Zhang & Leonard, 2019	100-year floodplain: -4.8% 500-year floodplain: insignificant	100-year floodplain: -3.6% to -12.2%	100-year floodplain: -18.9% to -27.4%	2009 Major Flood, 2010 non-major flood, 2011 non-major flood, and the first two years after the 2011 flood.	Inland
Zhang, 2016		100-year floodplain: -3.9% to -6%	100-year floodplain: -10.1% to -30.2%	2009 Major Flood	Inland

2.5.1 Spatial patterns of the floodplain impact

2.5.1.1 Patterns between coastal and inland properties. The floodplain impact has different patterns in coastal and inland areas. The price discounts of floodplain properties in coastal areas are generally smaller than in inland areas, and floodplain properties adjacent to the waterfront even have a price premium over non-floodplain properties. Eight studies in our review list (see Table 2.5) were conducted in coastal areas, suggesting a floodplain impact on home sale prices between -35.5% and +61%. Several studies find properties in high flood-risk zones (100-year floodplains), especially in the V Zone, have higher prices (ranging from +2.9% to +61%) than comparable properties outside floodplains (Bin & Kruse, 2006; Chandra Putra, 2017; Fu et al., 2016; A. Morgan, 2007). On the one hand, most of these studies believe that coastal amenities or other unobserved factors related to the proximity to the coast and the frontage of waterbodies may overwhelm the negative effect of flood risk, resulting in positive coefficients of floodplain dummy variables (Bin & Kruse, 2006; Chandra Putra, 2017; Fu et al., 2016). On the other hand, A. Morgan (2007) suggests that home price premiums in high flood-risk areas are caused by flood insurance premium subsidies that reduce the perceived risks and expected flood losses in floodplains. By adding independent variables in modeling to control coastal amenities, three studies successfully identified a negative floodplain impact on property prices (between -32.1% and -2.9%) in the high flood-risk zones (Bin et al., 2008; de Koning et al., 2019; J. D. Morgan et al., 2022).

In contrast, the pattern of the floodplain impact in inland areas is relatively straightforward. Properties in 100-year floodplains in inland areas generally undertake a price discount from 3% to 48%, which is consistent with people's expectations of the influence of flood risk and flood insurance premiums on property prices. Twenty-one studies in our list were conducted in the inland region. Eleven studies distinguish a significant overall price discount (from -4.7% to -21.5%) for floodplain properties across their study period (Bin & Polasky, 2004; de Koning et al., 2018; Donnelly, 1989; Hennighausen & Suter, 2020; Livy, 2023; Meldrum, 2016; Netusil et al., 2019; Posey & Rogers, 2010; Qiu et al., 2019; Shilling et al., 1989; L. Zhang & Leonard, 2019). Twelve studies analyze changes in the floodplain impact before and after a storm, a flood event, a floodplain conservation project, or a floodplain information disclosure policy (Atreya &

Ferreira, 2015; Atreya et al., 2013; Bin & Landry, 2013; Bin & Polasky, 2004; de Koning et al., 2018; Fonner et al., 2022; Hennighausen & Suter, 2020; Livy, 2023; R. G. Miller & Pinter, 2022; Pope, 2008; Shultz & Fridgen, 2001; L. Zhang, 2016; L. Zhang & Leonard, 2019). Most of these studies suggest that the property price discounts in 100-year floodplains were enlarged after a flood event, and the post-flood price discounts compared to non-floodplain properties range from -8.4% to -48%. However, R. G. Miller & Pinter (2022) found that post-flood price changes of properties in 100-year floodplains were insignificant in Benton County, Oregon, and Cass County, North Dakota. They attribute the insignificant property price changes in Benton County to a substantial pre-flood property price discount in 100-year floodplains (-9.4%) and less damages from the 2012 storm in Oregon, while they attribute the insignificant property price changes in Cass County to a broad discussion about the Fargo-West Fargo Flood Control Project causing local homebuyers not to emphasize the floodplain designation of their homes.

2.5.1.2 The pattern among flood zones. The floodplain impact also varies among different flood zones. The FEMA classifies floodplains into 100-year floodplains and 500-year floodplains, and 100-year floodplains are further split into A and V flood zones which represent the most hazardous portions (due to flowing waters or wave action) of riverine and coastal floodplains, respectively. The 500-year floodplain is also denoted as the X flood zone. As the V Zone abuts the waterfront and is exposed to coastal waves, properties suffer more flood risks than in the A Zone. Based on the level of flood risk and the mandatory requirement of flood insurance in the 100-year floodplain, the property price in V Zone should be lower than the price of a comparable property in A Zone, the property price in A Zone should be lower than the price of a comparable property in the 500-year floodplain, and floodplain properties should have a price discount compared to non-floodplain properties. This pattern is generally correct in most studies. However, there are some exceptional cases in reality.

In the coastal region, coastal amenities often outweigh the flood risk and the flood insurance premium in high flood-risk areas, leading to a property price premium in V Zone and some parts of A Zone (Bin & Kruse, 2006; Chandra Putra, 2017; Fu et al., 2016; A. Morgan, 2007). The magnitudes of floodplain coefficients follow the level of flood risk when controlling for coastal amenities in the model (Bin et al., 2008; de Koning et al., 2019; J. D. Morgan et al., 2022). In contrast, the impact of the 500-year floodplain on property prices is usually negative because this type of floodplain is away from coastal amenities and still suffers a moderate risk of flood hazards (Bin et al., 2008; Bin & Kruse, 2006; Chandra Putra, 2017; de Koning et al., 2019).

In the inland region, the property price discount is usually higher in the 100-year floodplain than in the 500-year floodplain (Atreya et al., 2013; Bin & Landry, 2013; Hennighausen & Suter, 2020; R. G. Miller & Pinter, 2022; Pope, 2008; Shultz & Fridgen, 2001; L. Zhang & Leonard, 2019). However, Fonner et al. (2022) found that the effect of the 100-year floodplain on property prices was close to the effect of the 500-year floodplain before a floodplain restoration project in Orting, Washington. Livy (2023) also suggested no significant difference between the 100-year floodplain and 500-year floodplain impacts before a non-destructive flood event. Only Bakkensen et al. (2019) found a significant inverse pattern of floodplain impacts between A Zone and X Zone. They compared the differences between the effects in A Zone and X Zone in Florida State before and after a hurricane cluster period (2004-2005). Their results show properties had higher prices in A

Zone than in X Zone before the 2004-2005 hurricane season. After the hurricane season, the property price premium in A Zone over X Zone was reduced by 5.1 to 8.0 percentage points in counties adjacent to hurricane-hit counties (near-miss counties) but slightly increased (≤5%) in counties not adjacent to hurricane-hit counties (never-hit counties).

The pattern of the 500-year floodplain impact is ambiguous in inland areas. The impact of the 500-year floodplain on home prices ranges from -23% to +4.6%. Shultz & Fridgen (2001) found that home prices were, on average, $3,100 higher in 500-year floodplains than outside floodplains before the 1997 flood event in Fargo-Moorhead Metropolitan. Atreya et al. (2013) did not find a significant pre-flood impact but a post-flood home price discount of -23% in the 500-year floodplain in Dougherty County, Georgia. In contrast, Hennighausen & Suter (2020) found no significant pre-flood impact but a post-flood home price premium of 4% to 4.6% in the 500-year floodplain in Boulder County, Colorado. Similarly, two studies suggest that the negative pre-flood effects in the 500-year floodplain in several places were weakened after local flood events (Livy, 2023; R. G. Miller & Pinter, 2022). Besides flood events, a floodplain restoration project also changed the impact of the 500-year floodplain from a home price discount to a price premium (Fonner et al., 2022). In addition, several studies suggest no significant impact of the 500-year floodplain on property prices in some places (Bin & Landry, 2013; Netusil et al., 2019; Pope, 2008; L. Zhang & Leonard, 2019).

2.5.1.3 The pattern between inundated and non-inundated areas. Floodplains are conceptual designations of flood-prone areas that do not represent the actual extent of inundation. Home buyers may be more sensitive to the costs related to flooding in actual flooded areas than in a designated floodplain generally. Therefore, the impact of floodplains on property values also varies between inundated and non-inundated places within a floodplain. Previous studies suggest that properties in directly flooded areas inside a floodplain have lower sale prices than non-flooded properties in the same floodplain (near-miss property) after flooding. Atreya & Ferreira (2015) analyzed the interaction effect of floodplain and inundation on housing prices in Albany, Georgia, and found properties in inundated areas within the 100-year floodplain had a price discount of 48% compared to equivalent properties in non-inundated areas outside the 100-year floodplain immediately after the Tropical Strom Alberto. However, near-miss properties did not have a significant price discount after the storm. Hennighausen & Suter (2020) also found a similar pattern in Boulder County, Colorado. Their result shows that inundated properties inside 100-year floodplains had a price discount of 17.3% after the 2013 major flood, while near-miss properties had an insignificant price premium (1.1%) after the flood event.

However, the pattern of flooded property prices outside the floodplain is blurry. Atreya & Ferreira (2015) found a significant property price discount of -36% in inundated areas outside the 100-year floodplain, which is 11 percentage points lower than the price discount in inundated areas inside the floodplain. Gibson & Mullins (2020) found a significant price discount for flooded properties outside the 100-year floodplain in New York City after Hurricane Sandy, which is not significantly different from the price discount for flooded properties inside the floodplain. In contrast, Hennighausen & Suter (2020) did not find a significant price discount for inundated properties outside floodplains.

Previous inundation records may also affect the property price responses to the floodplain map update. In 2013, the FEMA updated floodplain maps in New York City. Gibson & Mullins (2020) found that issuing new floodplain maps decreased prices of

Hurricane Sandy flooded properties by 2.9% while decreasing non-flooded property prices in the new designated floodplain by 11%. The larger price changes in non-flooded properties may be attributed to a pre-existing price discount for flooded properties before the floodplain map update.

2.5.2 Temporal pattern of the floodplain impact

The floodplain impact on property values is not temporally constant (Atreya et al., 2013; Bakkensen et al., 2019; Netusil et al., 2019). In a long-term period, the floodplain impact can be affected by various events (e.g., natural hazards, floodplain map updates, and flood insurance reformations) and the tendency of flood memory fading, resulting in an oscillating pattern (Netusil et al., 2019). However, most previous studies focused on analyzing the floodplain impact variations several years before and after a flood or hurricane event. Many studies suggest that a major flood event or a hurricane can either cause a new property price discount or enlarge a pre-existing property price discount in the 100-year floodplain(Atreya et al., 2013; Atreya & Ferreira, 2015; Bin & Landry, 2013; Bin & Polasky, 2004; Chandra Putra, 2017; Hennighausen & Suter, 2020; Shultz & Fridgen, 2001; L. Zhang, 2016; L. Zhang & Leonard, 2019). In some coastal areas, storm events can reduce the property price premium in the V Zone or even convert the price premium to a price discount (Chandra Putra, 2017; A. Morgan, 2007). However, relatively lower severity flood events did not exacerbate the pre-event price discount in the 100-year floodplain but caused a decay of the pre-event price discount in the 500-year floodplain impact (Livy, 2023; R. G. Miller & Pinter, 2022). A hurricane or a major flood event may also affect places near the hazard zone. Bakkensen et al. (2019) found that hurricanes caused home prices in A Zone to decrease by 5.1% to 8% relative to X Zone in counties adjacent to hurricane-hit counties in Florida. This indirect impact decays with the increased distance to the hazard zone. A Zone home prices in counties far from hurricane-hit counties barely changed relative to X Zone home prices after the 2004 -2005 hurricane season.

However, these post-flood effects fade with time and are short-lived. Several studies suggest that the price discount in the floodplain gradually diminishes after a major flood event and may return to the pre-flood level in a few years (Atreya et al., 2013; Atreya & Ferreira, 2015; Bin & Landry, 2013; R. G. Miller & Pinter, 2022; L. Zhang, 2016; L. Zhang & Leonard, 2019). The effect of a non-destructive flood event has an even shorter life, which can disappear in a few months (Livy, 2023). From a long-term view, multiple flood events and other factors can cause the oscillation in the floodplain impact. Even though housing prices in the 100-year floodplain relative to the 500-year floodplain oscillated downward for four years after the 2004-2005 hurricane in Florida clustered period, Bakkensen et al. (2019) found that they started to bounce back after 2009.

2.5.3 Other floodplain impacts

Several other factors affect the floodplain impact besides spatial and temporal factors. First, disclosing flood risk information to home buyers can reduce home prices in the 100-year floodplain. Pope (2008) found that a property price discount of -4.3% occurred in the 100-year floodplain in Wake County, North Carolina, after implementing the Residential Property Disclosure Act. Similarly, Troy & Romm (2004) found that the 100-year floodplain impact changed from no insignificant effect to a significant price discount of -4.3% in California State after the 1998 California Natural Hazard Disclosure Law took effect.

Second, preserving and restoring environmental amenities in floodplains can mitigate the negative impacts of flood-prone areas on property values. Kousky & Walls (2014) found that floodplain conservation (e.g., greenway) can diminish the negative impact of floodplains on property values. They analyzed property prices in the Meramec Greenway in St. Louis County, Missouri, and found a weak and insignificant discount effect (-0.68%) in 100-year floodplains, even though two previous studies suggest a significant price discount in 100-year floodplains in nearby places (Posey & Rogers, 2010; Qiu et al., 2019). In College Station, Texas, Lee & Li (2009) found that properties near a flood control detention basin are 3.5% cheaper than properties not close to a detention basin, while properties near a multi-use detention basin with a recreational park have an average price premium of $2,489. Fonner et al. (2022) investigated home sale price changes before and after a floodplain restoration project in Orting, Washington. They found that post-event home sale prices in 500-year floodplains increased 5.3 percentage points from the pre-event prices, although the home sale prices in 100-year floodplains did not significantly change after the restoration.

Third, the type of residential properties can affect their price response to the floodplain designation. Meldrum (2016) found that condominiums in 100-year floodplains in Boulder County, Colorado, have a price discount of -14%, whereas standalone properties do not have a significant discount in floodplains.

Fourth, the floodplain impact can be more substantial for lower-priced homes than higher-priced homes. Zhang (2016) used a spatial quantile regression approach to analyze hedonic home prices from 2000 to 2013 in Fargo-Moorhead Metropolitan. The author found that lower quantile homes had more pre-event price discounts in floodplains than higher quantile homes, and the 2009 major flood event caused more price decreases for lower quantile homes than higher quantile homes.

Finally, the floodplain property designation approach can affect the floodplain impact. Netusil et al. (2019) compared two approaches for floodplain property designation in an urban watershed around Johnson Creek in Oregon with repeated home sale data between 1988 and 2014. One approach uses the building footprint to overlap the floodplain extent, while the other uses the tax lot extent to overlap the floodplain extent. They found that the building footprint approach released a more substantial home price discount (-21.5%, on average) in a 100-year floodplain than the tax lot approach (-8.6%, on average).

2.6 Discussion

Previous studies display diverse patterns in the floodplain impact, suggesting that the floodplain impact not only reflects the effects of flood risks and flood insurance but also tangles with other factors. The purpose of the floodplain designation is to reflect the flood risk of properties and facilitate the implementation of the NFIP. Therefore, the floodplain impact naturally consists of the adverse effects of higher flood risks and mandatory flood insurance premiums on property prices. However, these adverse effects did not always lead to a significant property price discount in floodplains; even price premiums existed in some places. There were some factors related to floodplains that reduce or compensate for the adverse effects of flood risks and insurance premiums. One usually referred factor is the unobserved amenity related to the proximity of the waterfront (especially coastlines). Properties near the waterfront enjoy better aesthetic views, convenient access to recreational water, and pleasant natural environments, which benefit housing prices and offset part or even all adverse effects caused by flood risks and flood insurance. These amenities generally increase inversely to the distance to waterbodies or coastlines. Therefore, more amenities often tangle with high flood-risk areas. This phenomenon is pronounced in coastal areas, leading to a housing price gradient inverse to the flood-risk levels (Bin & Kruse, 2006; Fu et al., 2016; A. Morgan, 2007). Although the effect of amenities near the coastline is potent, it can be effectively isolated in the hedonic pricing model by adding independent variables reflecting the proximity to the waterfront (Bin et al., 2008; J. D. Morgan et al., 2022). However, in inland areas, the beneficial effect of amenities near the waterfront is minor and only appears in the prices of properties immediately adjacent to the riverfront (Shultz & Fridgen, 2001; L. Zhang, 2016; L. Zhang & Leonard, 2019). Most studies did not find that unobserved inland floodplain amenities blur the adverse effects of flood risks and flood insurance premiums. Therefore, the amenity effect can explain only a part of the patterns in the floodplain impact. Researchers tend to isolate the amenity effect from the adverse effects of floodplains to determine the effect of flood risks.

The perception of flood risks is another significant factor that drives the changes in the floodplain property price. The more flood risk people perceived, the more pronounced an adverse floodplain impact on prices is obtained. The perception of flood risks originates from the probability of flooding and the flood insurance premiums in the floodplain. However, it is influenced by obtained flooding information, people's attention, and specific flood insurance policies. Home buyers would not have price discrimination against floodplain properties without enough information on the properties' flood risk (Pope, 2008; Troy & Romm, 2004). Floods and hurricanes can evoke people's awareness of flood hazards, increasing price discounts for floodplain properties after flooding (e.g., Atreya et al., 2013; Bin & Landry, 2013; Zhang & Leonard, 2019). However, as time passes, people's memories of the flood fade, and their perception of flood risk decays until the next flood (Atreya et al., 2013; Bin & Landry, 2013; L. Zhang & Leonard, 2019). Therefore, regular publicity and education of flood risks to stakeholders in the floodplain is necessary.

People also update their perception of flood risk based on where flooding occurred (Atreya & Ferreira, 2015; Hennighausen & Suter, 2020). Inundated areas in the floodplain confirm and foster people’s high flood-risk perception about the floodplain, leading to a more pronounced property price discount after the flooding. Non-inundated areas in the floodplain are contrary to the expectation of higher flood risk, and people degrade the perceived flood risk in these areas after flooding, resulting in insignificant price differentials between floodplain properties and non-floodplain properties. This kind of post-flood adjustment in the perceived flood risks may reflect the local facts or be misled by a singular flood event. Exaggerated flood risks in the 100-year floodplain may not cause serious consequences, whereas omitting flood risks will likely cause heavy losses in the long run. Authorities need to update floodplain maps and publicize flood risk information in time to avoid mistake adjustments in the perceived flood risks.

Flood insurance policies also affect the perception of flood risks. To some extent, the flood insurance premium is a flood risk reminder for homeowners in flood-prone areas. Raising flood insurance premiums and updating floodplain maps can increase the perceived flood risks, thereby reducing floodplain property prices (Gibson & Mullins, 2020). Subsidizing flood insurance premiums undermines the reminder effect of flood insurance and reduces homeowners’ perceived flood risks, even though it can increase the take-up rate (A. Morgan, 2007). Most flood insurance is paid through the homeowner's mortgage payment (along with taxes and regular home insurance), making the risk reminder less apparent. The lack of flood insurance requirement is one reason causing low perceived flood risks in the 500-year floodplain, which makes the 500-year floodplain impact on home prices ambiguous (Bin & Landry, 2013; Hennighausen & Suter, 2020; Pope, 2008; Shultz & Fridgen, 2001). The same point would apply for homeowners in the 100-year floodplain who do not have a mortgage and therefore do not have a flood insurance requirement. It is worth analyzing how to maintain necessary perceived flood risks for stakeholders in the floodplain by manipulating the flood insurance premium rate.

Almost all previous studies use the FEMA floodplain designation in modeling, as it is the standard way to delineate flood-prone areas. However, this designation has several limitations. First, over 25% of flood losses across the United States occurred outside the designated 100-year floodplains (Blessing et al., 2017; Brody et al., 2013; Highfield et al., 2013). This phenomenon may reduce the price differentials between floodplain properties and non-floodplain properties. In part, this finding is because the spatial coverage of FEMA floodplain maps is incomplete. The current floodplain maps cover only about one-third of the length of streams and 46% of the length of coastlines in the United States (Association of State Floodplain Managers, 2020; Wing et al., 2018). Many places may not have usable floodplain maps to delineate flood-prone areas. At last, many floodplain maps are not frequently updated. Although floodplain maps should be updated every five years, over half were not validated or updated as of 2017 (Kelly, 2017). Climate change is shifting the precipitation pattern in the United States, leading to dramatic changes in the distribution and intensity of flood events (Kunkel et al., 2013; Singh et al., 2013; Swain et al., 2020).

Outdated floodplain maps are likely inconsistent with reality, causing distortions in floodplain impact estimations. Besides urging timely updates for floodplain maps, researchers may consider using alternative indicators for flood risks in future studies to cope with the challenge of climate change.

Many studies suggest spatial dependence exists in home sale prices (e.g., Atreya et al., 2013; Bin & Landry, 2013; Zhang, 2016). That is, a property's price is correlated with prices of nearby properties. The spatial lag term coefficients in our reviewed studies that use spatial regressions (see Table 2.4) are all positive, meaning properties with similar prices tend to be spatially clustered. On one hand, the sale price of a property often refers to nearby property prices, such as prices of comparable homes in the same communities tend to be similar. On the other hand, factors affecting property prices, such as structural configurations and environmental amenities, tend to cluster geographically. The hedonic pricing model will be biased and inefficient when omitting the spatial dependence on property prices. Researchers should use spatial modeling techniques when the spatial autocorrelation is significant in model residuals to get an accurate and precise model estimation. One frequently used spatial modeling technique is the spatial fixed effects because it can control unobserved, time-invariant heterogeneity across spatial units and mitigate omitted variables bias. However, the spatial fixed effects approach simplifies the responses within individual spatial units, which cannot reflect the detailed spatial dependence among properties within the spatial units. The spatial fixed effects model may be biased near the edge of a spatial unit. In addition, spatial relationships may be sensitive to the geographic or analytical scales of observations, requiring a careful selection of the size of spatial units. In contrast, the spatial regression model can depict the spatial dependence with a finer resolution and is more efficient than the spatial fixed effects model. Spatial regression models have flexibility in specifying the spatial relationship through various spatial weight matrices. The spatial regression model can also handle observations near the edge of spatial units that may be problematic for the spatial fixed effect model. However, less than half of the reviewed studies use spatial regression, suggesting the recognition of spatial dependence in property prices still can be improved.

Previous studies have some limitations in the settings of study areas. Most of the reviewed studies were conducted at the community level. Only Bakkensen et al. (2019) and Troy & Romm (2004) conducted their studies at the state level. Most studies assume that the floodplain impact on property prices is uniform across the study area. Very limited studies addressed the variations in the floodplain impact among different places. However, researchers have found that a spatial dependence of flood risks exists in the United States (Quinn et al., 2019). It will likely cause a spatially dependent pattern in the floodplain impact on a broad scale (e.g., at the regional level). The wide value range of the floodplain impact in the reviewed studies also suggests a pattern of spatial heterogeneity. However, the estimation of floodplain impact in each study can be directly compared because of different modeling structures and explanatory variables. Beltrán et al. (2018) and Daniel et al. (2009) derived overall estimations of the floodplain impact through the meta-analysis. However, using a single value to represent the floodplain impact across a broad region would still be somewhat arbitrary. Hedonic pricing studies will be needed to reveal future floodplain impact changes over space. The common variables described in section 4 can help researchers determine the variable set in future studies.

Previous studies made great efforts to analyze floodplain impact changes following specific flood events but seldom explored the long-term patterns. With the rapid climate change, long-term variations in flood hazards and risks will be obvious, which may lead to substantial changes in the floodplain impact. Revealing a long-term trend beyond the short-term oscillations in the floodplain impact could be an essential topic in future hedonic pricing studies.

Few studies explicitly considered the effects of property sale rates in the hedonic pricing analyses nor explored the variation in floodplain property sale rates before and after floods. The effects of floodplain property sale rates were under-studied in the United States. Although previous hedonic pricing studies did not experience a problem of scarcity of floodplain property sales, property sale rate changes in floodplains are worth analyzing as they can also reflect people's perspectives on flood risks.

2.7 Conclusion

This chapter reviews the findings in thirty-one peer-reviewed journal articles on flood-related hedonic pricing studies in the United States. Previous articles suggest a diverse pattern of the floodplain impact over space and time with an impact value range of -48% to +61%. On the spatial scale, three major patterns in the floodplain impact are summarized: coastal vs. inland, the 100-year floodplain vs. the 500-year floodplain, and inundated vs. non-inundated. The pre-flood and post-flood patterns and the decay of the floodplain impact are summarized on the temporal scale. In general, inland floodplains have more adverse effects on property prices than coastal floodplains; the 100-year floodplain has more adverse effects on property prices than the 500-year floodplain; coastal 100-year floodplain properties can have a price premium relative non-floodplain properties when not isolating local amenities from the floodplain impact; flood and hurricane events foster the adverse impact on home prices in the 100-year floodplains; and the post-event floodplain impact decays with time and diminishes in few years. The floodplain impact is the composite effect of flood risks, flood insurance premiums, and amenities in floodplains, and the perceived flood risk of stakeholders directly influences it.

Several limitations exist in previous studies. First, less than half of the reviewed studies addressed the spatial dependence on the floodplain impact. Second, previous studies depend on the FEMA floodplain designation, which is becoming increasingly inaccurate and outdated during climate change, and in some cases may assume incorrectly that homes are outside of the floodplain because FEMA has not mapped floodplains for that area. Third, the reviewed studies focus on the floodplain impacts at an individual community level. There is a lack of studies exploring floodplain impacts over a broad geographic scale. Finally, the temporal analysis in previous studies mainly focuses on short-term oscillations but seldom detects long-term changes. Future hedonic pricing studies on floodplain impact can contribute to exploring spatial patterns in floodplain impact on the regional scale and analyzing long-term trends in floodplain impact under climate change. The findings in this review study provide a baseline for future hedonic pricing model research, which aims to understand the long-term impacts of floodplains on property values and develop effective management strategies for reducing flood risks.

CHAPTER 3

EXAMINING THE IMPACT OF HYDROLOGICAL SENSITIVITY AND CONNECTIVITY ON PROPERTY VALUES

3.1 Introduction

The FEMA 100-year floodplain is the standard way for high flood-risk zone delineation and plays an irreplaceable role in flood management and enhancing flood resilience. However, several limitations of the 100-year floodplain designation are found in practice. First, the coverage of present floodplain maps is incomplete. The FEMA floodplain map ignores small catchments (<10,000 km^2) and only covers 30% of the length of rivers and 46% of coastlines in the United States (Association of State Floodplain Managers, 2020; Wing et al., 2018). About 25% of flood losses across the United States occurred outside the designated 100-year floodplain (Blessing et al., 2017; Highfield et al., 2013). Although the FEMA is required to update floodplain maps every five years, floodplain designation is outdated in many areas and cannot accurately reflect flood risks under climate change. The out-of-date flood hazard maps did not perform as expected in response to Hurricane Ida in New Jersey (CSG, 2022). In addition, the 100-year floodplain only delineates high flood-risk areas but fails to depict the hydrological sensitivity and connection of the local landscape. This leads to the construction of flood resilience constrained by community administrational boundaries, hindering cooperation among nearby communities in flood management. Without cognition of landscape hydrological connectivity, current flood management invests most resources in physical measures (e.g., levees and dams) but seldom uses natural capital (e.g., land conservation) to foster resilience (Mehryar & Surminski, 2021; Michel-Kerjan et al., 2016).

This study used hydrological sensitive areas (HSAs) to overcome these limitations and improve conventional floodplain delineation. The HSA is a concept of the variable source area (VSA) hydrology theory, which refers to the area where the soil is readily saturated and generates the major portion of runoff during precipitation (Anderson et al., 2015; Qiu et al., 2014; Singh, 2021; Walter et al., 2002). It reflects the hydrological sensitivity and connectivity of the local environment. Any landscape changes incongruent with the natural hydro-ecological functions in this area will increase the flood risk. Incorporating the HSA into community flood resilience establishment can provide a more objective and scientifically defensible view of flood risks and help stakeholders combine flood management measures in the upland and downstream.

This study examined the impacts of the development encroachment in HSAs on flood risk. Specifically, we empirically tested the influence of landscape alterations in HSAs on home sale prices. The hypothesis underlying this objective is that home sale prices already implicitly incorporate the local hydrological sensitivity. Because urbanization and associated infrastructure development fail to recognize the landscape's ecological function and ignore the landscape's hydrological sensitivity and connectivity, landscape alterations dictated by human decisions undermine the hydro-ecological function of the natural landscape. Properties inside HSAs are subject to higher flood risks and are expected to be priced lower than the equivalent properties outside of HSAs.

3.2 Study Area, Data, and Method

3.2.1 Study area

This study analyzed property records in Hillsborough Township and Montgomery Township, two municipalities in Somerset County, New Jersey. The study area map is displayed in Figure 3.1. The south branch and mainstream of the Raritan River, the Millstone River and its Royce Brook and Beden Brook tributaries, the Rocky Hill Ridge, and the Sourland Mountain surround these two communities. The total area of these townships is about 87.6 square miles (226.88 km^2), with a population of approximately 67,000. According to the New Jersey Parcel and MOD-IV data, a compilation of tax assessment data for all properties, there are 22,502 properties in the study area, and 14,555 are registered as one-family properties. About 8.06 square miles (about 20.88 km^2) in this area are Special Flood Hazard Areas (SFHA). Most regular floodways are distributed along the South Branch Raritan River, the Raritan River, the Millstone River, and the Neshanic River. The rest of the SFHAs are located along ten smaller streams in this region.

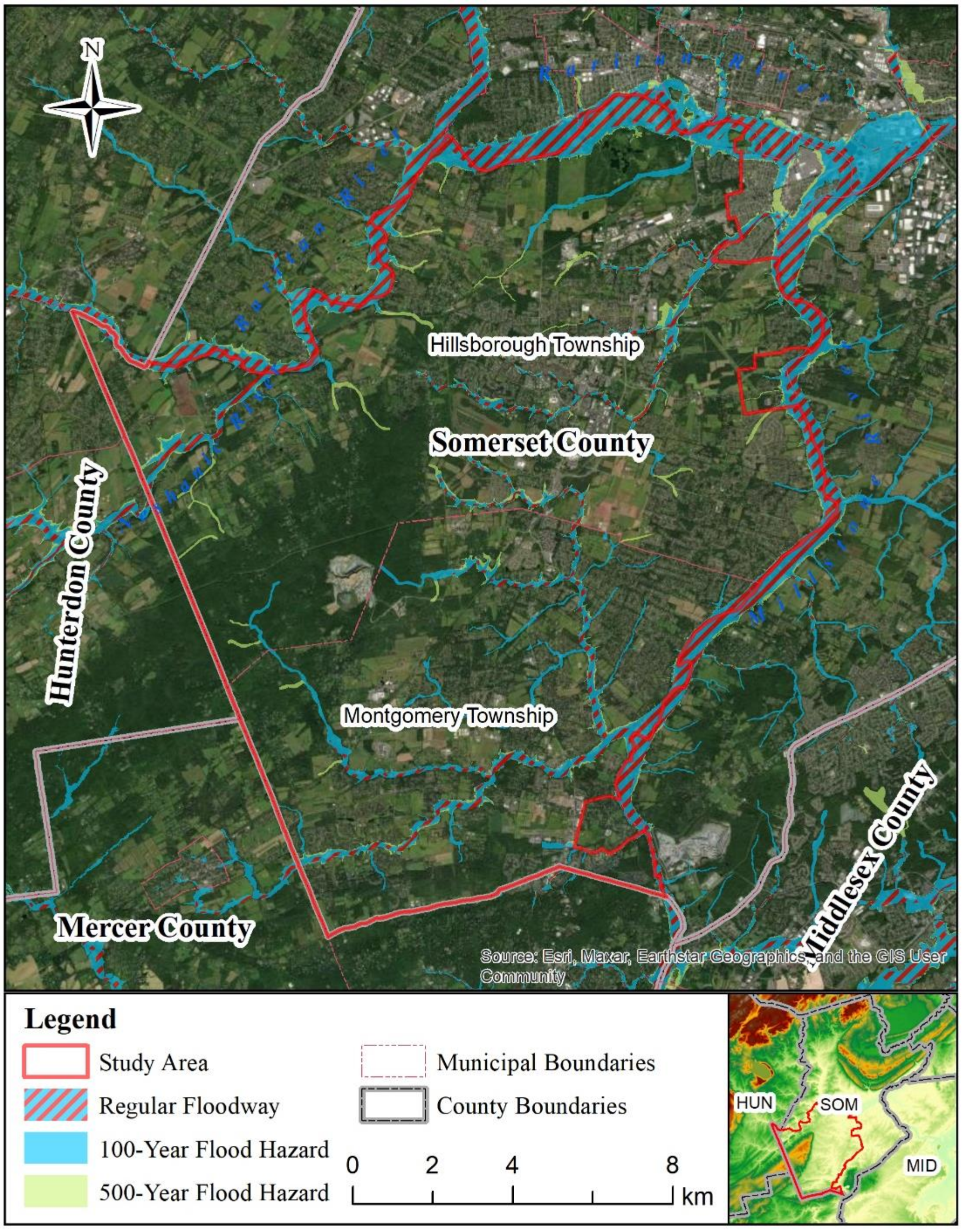

Figure 3.1 Floodplains and Hydrologically Sensitive Areas in Hillsborough and Montgomery, NJ.

3.2.2 Home sales and property data

We collected and analyzed property sale records, structural characteristics, and neighborhood and environmental conditions of single-family homes in the study area. The explored variables are shown in Table 3.1. They are common property characteristic variables used in hedonic pricing analysis for flood-related studies. The sale price, deed date, parcel area, property class, building class, construction year, property age, and parcel location were extracted from a GIS data layer of Parcels and MOD-IV Composite records of Somerset County. This GIS layer was provided by the New Jersey Department of the Treasury and maintained by the New Jersey Office of GIS. It was downloaded from the New Jersey Geographic Information Network (NJGIN) Open Data portal. During the data preprocessing, only records for residential (Code 2) and farmland (Code 3A) properties were used. As the most recent deed date in the MOD-IV records is in 2021, and the property market changed substantially during and after the COVID-19 pandemic, we only used property sale records between 2010 and 2020 to explore the market response in the most recent consistent period. This period includes one severe flood, associated with the remnants of Hurricane Irene in 2011, but precedes the next severe flood period associated with Hurricane Ida in 2021. To ensure arm's length transactions, sale records with a price lower than $50,000 were filtered out. Sale prices were subsequently adjusted by the U.S. Bureau of Labor published consumer price index (CPI) for housing to reduce the impact of inflation. After the inflation correction, records of properties with sale prices in the top or bottom 2.5 percent tile were also removed to avoid extreme home sale cases. In this study, we assumed the deed date was the sale date, and the property age at sale was the deed date minus the construction year. Any records with a deed date before the construction year were removed from our analysis, as they contained potential data errors. The parcel acreage was calculated from the shape area in the GIS layer, as MOD-IV missed the acreage for many parcels.

Structural characteristics used in this study were collected from property record cards provided by municipal governments. These characteristics include bedroom number, bathroom number, living area footage, story (floor) number, presence of brick exterior, air-conditioning, fireplace, basement, hardwood floor, and garage. Property record cards were matched with parcels and MOD-IV records via a GIS PIN (property identification number) generated from block, lot, and qualification numbers. A few GIS PINs have more than one property card matched. We removed property records corresponding to these PINs from the analysis to avoid mistakes during sale data matching. Furthermore, any property records that have missing values were dropped out of the analysis. After these data filtering processes, 5024 parcel records were reserved for further analysis.

Neighborhood and environmental conditions, including distances to the nearest open space, stream, water body, highway, and bus stop, and the presence of floodplains, were derived from several geographic datasets provided by the NJGIN Open Data and the FEMA (Table 3.1). We used ArcMap 10.8 to prepare these geographic data. The "generate near table" tool calculated Euclidian distances from parcel centroids to the nearest open space, stream, waterbody (lake), highway, and bus stop. These distances were initially calculated in feet and then converted to meters. The highways defined in this study refer to roads above the county 500 route level, and so local roads were not defined as a factor, as all homes fronted on local streets at a minimum.

The presence of homes in floodplains was identified by intersecting parcel polygons with designated 100-year floodplains and 500-year floodplains. Homes in 100-year floodplains were assigned 1 in FD100 and 0 for homes outside 100-year floodplains. Similarly, homes in 500-year floodplains were assigned 1 in FD500 and 0 for homes outside floodplains. The FEMA Flood Insurance Rate Maps (FIRMs) for the study area provide floodplain mapping for all major rivers and their tributaries, and they were adopted in 2016.

Besides the neighbor and environmental variables described in this section, the presence of homes in Hydrologically Sensitive Areas was also analyzed in this study. This variable is explained in detail in the next section.

Table 3.1 Variables Explored in the Hedonic Pricing Study

Variable Name	Definition	Data Source
Price	Deed prices of properties	NJ Parcels and MOD-IV data
Adj_Price	Deed prices adjusted by the Consumer Price Index	Adjusted by the Consumer Price Index from the U.S. Bureau of Labor
Ln_Price	Log-transformed Adj_Price	
Bed	The number of bedrooms in a property	Property Record Cards
SQ_Bed	Squared term of bedroom numbers	
Bath	The number of bathrooms in a property	Property Record Cards
SQ_Bath	Squared term of bathroom numbers	
LArea	The size of living areas (sq. meters)	Property Record Cards
Ln_LArea	Log-transformed living areas	Property Record Cards
LotSize	The acreage of a parcel lot	NJ Parcels and MOD-IV data
Ln_LotSize	Log-transformed LotSize	
Age	The age of a property at sale	NJ Parcels and MOD-IV data
SQ_Age	Squared term of property age	
BE	Dummy variable for the presence of a Brick Exterior	Property Record Cards
AC	Dummy variable for the presence of an air-conditioning	Property Record Cards
FP	Dummy variable for the presence of a fireplace	Property Record Cards
Stry	Number of floors (stories)	Property Record Cards
Bsm	Dummy variable for the presence of a basement	Property Record Cards
FHW	Dummy variable for the presence of a hardwood floor	Property Record Cards
Gar	Dummy variable for the presence of a garage	Property Record Cards
Ln_D2OpenS	Log-transformed distance to the nearest park, conservation area, forest, game land, or other open space (meters)	"State, Local and Nonprofit Open Space of New Jersey," NJDEP
Ln_D2Stream	Log transformed distance to nearest stream/creek/river (meters)	"National Hydrography Dataset Streams and Waterbodies 2015 for New Jersey", NJDEP

Table 3.1 Variables Explored in the Hedonic Pricing Study (Continued)

Variable Name	Definition	Data Source
Ln_D2Waterb	Log-transformed distance to nearest lake/waterbody (meters)	"National Hydrography Dataset Streams and Waterbodies 2015 for New Jersey", NJDEP
Ln_D2HW	Log-transformed distance to nearest highway / major road (meters)	"Road Centerlines of NJ -Next Gen 911", NJOGIS
Ln_D2BusS	Log-transformed distance to the nearest bus stop (meters)	"Bus Stops of NJ Transit by Line," NJ Transit
FD100	Dummy variable for a property located in the 100-year floodplain	National Flood Hazard Layer, FEMA
FD500	Dummy variable for a property located in the 500-year floodplain	National Flood Hazard Layer, FEMA
HSAs_TWI_105	Dummy variable for a property located in HSAs. The threshold is TWI > 10.5	Derived from DEM of NJ
HSAs_STI_105	Dummy variable for a property located in HSAs. The threshold is STI > 10.5	Derived from DEM of NJ
HSAs_TWI_110	Dummy variable for a property located in HSAs. The threshold is TWI > 11	Derived from DEM of NJ
HSAs_STI_110	Dummy variable for a property located in HSAs. The threshold is STI > 11	Derived from DEM of NJ
HSAs_TWI_115	Dummy variable for a property located in HSAs. The threshold is TWI > 11.5	Derived from DEM of NJ
HSAs_STI_115	Dummy variable for a property located in HSAs. The threshold is STI > 11.5	Derived from DEM of NJ

3.2.3 The hydrological sensitive areas

This study aims to examine the impacts of HSAs on property prices. Figure 3.1 displays a view of HSAs in the study area. To determine whether homes are in HSAs, we used the 10-m resolution HSAs generated by Qiu et al. (2020). This dataset of HSAs was derived by a two-fold process. First, a soil topographic index (STI) or a topographic wetness index (TWI) was calculated from a digital elevation model and soil transmissivity to depict the hydrological sensitivity of landscapes. A higher index value implies a higher propensity for generating and accumulating runoff. The STI and TWI follow the theory of VSA hydrology and are calculated using Equation (3.1) (Anderson et al., 2015; Qiu et al., 2014; Walter et al., 2002):

$$STI = \ln\left(\frac{\alpha}{\tan(\beta)}\right) - \ln(K_s D) = TWI - \ln(K_s D) \tag{3.1}$$

Where α is the upslope contributing area per unit contour length, β is the surface slope, K_s is the soil saturated hydraulic conductivity, and D is the soil depth from the top to the restrictive layer. α and β were calculated from the DEM data, while K_s and D were extracted from the SSURGO data. The term $\ln\left(\frac{\alpha}{\tan(\beta)}\right)$ is also known as the TWI. After deriving topographic indices, the HSAs were extracted by the index value thresholding. The areas with STI or TWI values greater than the given threshold value were assigned to HSAs. Qiu et al. (2020) used the FEMA's 100-year floodplain data as a reference to determine the threshold values in five water regions of New Jersey, and their recommendation for the threshold values of STI and TWI were both 11 in the Raritan Region.

In this study, we analyzed six layers of HSAs derived from the TWI and STI with threshold values of 10.5, 11.0, and 11.5, respectively. These raster layers of HSAs were converted to vector polygon layers. Homes in HSAs were subsequently identified by intersecting their parcel extents with HSAs polygons. The intersection results were recorded by HSAs dummy variables, with 1 indicating homes inside HSAs and 0 for outside HSAs.

3.2.4 Modeling methods

This study employed the hedonic pricing method to examine whether HSAs influence the home sale price. The hedonic pricing method is frequently used to evaluate the influence of non-market environment conditions and ecosystem service on real estate prices. A hedonic pricing model is a function of property characteristics, and its conceptual format is as Equation (3.2):

$$p = f(x_1, x_2, \cdots, x_i) \tag{3.2}$$

Where, p is the property price (the dependent variable), commonly in nature logarithmic transformation format; $x_1, x_2, \cdots, x_i$ are characteristics (independent variables) affecting property values, including structural variables, location and neighborhood variables, and natural environment variables. Structural variables describe the configuration of properties, such as the number of bedrooms and bathrooms, building age, lot size, and square footage (Aladwan & Ahamad, 2019; Sirmans et al., 2005). Location and neighborhood variables reflect the value of property position, including the proximity to surrounding amenities and facilities, neighborhood land use situation, community attributes, and public services (Bin et al. 2008; Bin and Landry 2013; Shultz and Fridgen 2001). Natural environment variables represent characteristics provided by natural surroundings, such as waterfront and scenic views (Nicholls & Crompton, 2018; Sirmans et al., 2005). In previous hedonic pricing studies related to flood hazards, the floodplain designation was commonly used to indicate high flood-risk areas (Atreya & Ferreira, 2015; Bin et al., 2008; Qiu et al., 2006). This study used HSAs to supplement the conventional floodplain approach in delineating flood-prone areas. Both HSAs and FEMA 100-year floodplains were included in the modeling.

The impacts of HSAs on home sale prices were preliminarily examined by two hedonic pricing regressions depicted in Equations (3.3) and (3.4). The first model, Equation (3.3), treated variables of floodplains and HSAs independently, without considering the interaction of these variables. However, a substantial amount of HSAs spatially overlap floodplains. Therefore, the impact of HSAs likely interacts with the impact of floodplains. The second model, Equation (3.4), adopted a Difference-in-Difference framework similar to the framework of Atreya & Ferreira (2015) to quantify the effect of interaction between floodplains and HSAs.

$$\ln p_i = \alpha + \boldsymbol{\beta X_i} + \gamma_1 FD_i + \gamma_2 HSA_i + \varepsilon \tag{3.3}$$

$$\ln p_i = \alpha + \boldsymbol{\beta X_i} + \gamma_1 FD_i + \gamma_2 HSA_i + \gamma_3 FD_i \times HSA_i + \varepsilon \tag{3.4}$$

Where i is the index for the properties; the dependent variable, $\ln p_i$, is the natural logarithm of the CPI-adjusted home sale price for property i; α is the intercept; $\boldsymbol{X_i}$ is a vector of control variables representing the characteristics of property i; $\boldsymbol{\beta}$ is a vector of the regression coefficients corresponding to property characteristic variables; FD_i and HSA_i are dummy variables indicating whether property i intersects with floodplains or HSAs; $FD_i \times HSA_i$ is a dummy variable indicating whether property i is in both floodplains and HSAs; the coefficients γ_1, γ_2, and γ_3, represent the impacts of floodplains, HSAs, and their interaction term on the property sale price, respectively.

This study fitted the prior two models with the help of a forward stepwise regression method. The explored variables in Table 3.1 are not entirely mutually independent, so using them all would generate unstable coefficient estimations and cause a severe overfitting problem. A forward stepwise variable selection method can reduce the overfitting problem in multiple regression. In this method, the Ordinary Least Squares (OLS) regression starts with a model that only contains a constant term and then adds the most promising independent variable to the model step by step based on some predetermined criterion. In each step, the independent variable that can achieve the minimum mean squared error in the cross-validation was added to the model. Iterations of adding independent variables will end after adding all variables or meeting the requirement of variable number. The stepwise regression technique provides a variable subset of structural, neighborhood, and environmental characteristics except for the HSA designation. A manual tuning for selecting the best HSA threshold then follows the stepwise process. The most promising HSA threshold was determined by comprehensively considering the mean square error and R-squared in the cross-validation. Stepwise regression is implemented through the Mlxtend library and Scikit-learn package in Python, and subsequent manual tuning is implemented through the Statsmodel package in Python (Pedregosa et al., 2011; Raschka, 2018; Seabold & Perktold, 2010).

In addition to the OLS regression, this study fitted the second model (Equation (3.4)) with spatial regression. Many studies suggest that property prices have significant spatial dependence, which means the price of a property is correlated with its nearby property prices, resulting in biased and inefficient OLS estimations (Atreya et al., 2013; Bin & Landry, 2013; L. Zhang, 2016). Therefore, this study tested the spatial autocorrelation among residuals of the second model through Global Moran's I. Four spatial weight matrices built from queen contiguity (QC), inverse distance weighting (IDW), k-nearest neighbor (KNN), and the kernel method were applied to Moran’s I test, respectively, to get a robust result about the spatial dependence.

After testing the spatial autocorrelation, Lagrange Multiplier (LM) tests for the spatial lag model and the spatial error model were conducted to determine which one is the proper format of spatial regression for this study. Structures of a spatial lag model and a spatial error model are shown in Equations (3.5) and (3.6), respectively.

$$\boldsymbol{y} = \rho\boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{3.5}$$

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{u}, \boldsymbol{u} = \lambda\boldsymbol{W}\boldsymbol{u} + \boldsymbol{\varepsilon} \tag{3.6}$$

Where, $\boldsymbol{y}$ is a vector of log-transformed home sale prices, ρ is the coefficient of the spatial lag term, $\boldsymbol{W}$ is the spatial weight matrix representing the weight for the influence of neighboring observation, $\boldsymbol{X}$ is the matrix of independent variables, $\boldsymbol{\beta}$ is a vector of coefficient corresponding to $\boldsymbol{X}$, $\boldsymbol{u}$ is the regression residuals which influence by spatial dependency, λ is the coefficient of the residual autoregressive term, and $\boldsymbol{\varepsilon}$ is the error term following a normal distribution. The spatial lag model explicitly models the spatial dependency in home prices as an explanatory variable. In contrast, the spatial error model focuses on capturing spatial patterns in the residuals and assumes the independent variables are exogenous and not influenced by spatial dependencies. This study used GeoDa software to implement Moran's I test, Lagrange Multiplier test, and spatial regression (Anselin et al., 2006).

3.3 Results

The summary of input variables for the final model after the forward stepwise regression and manual tuning is shown in Table 3.2. Eighteen independent variables were used in the modeling. Based on the average R squared score in the cross-validation and the AIC score in the OLS model, the HSAs_STI_105 is the most promising variable for the HSAs designation. We use HSAs to represent HSAs_STI_105 in the following. The average value of home sale prices is $ 664,072.11, and 13.35 for the log-transformed home sale prices (dependent variable). The average bedroom number is 3.86. The average bathroom number is 3.18. The average living area of a home is 260 m^2. The mean acreage of parcels (lot size) is 0.42 acres and -1.33 for the log-transformed lot size. The average age of homes is 28.45 years. The average story number of homes is 1.88. About 95% of properties have air conditioning. Nearly 87% of properties have a fireplace. More than 54% of properties have a basement. Only 5.5% of properties are inside the 100-year floodplain, while 48% are inside or contiguous to the HSAs, providing evidence of the far larger extent of runoff risk to homes using the HSAs. Properties inside the 100-year floodplain and the HSAs occupy nearly 4% of analyzed properties. The average values of log-transformed distances to the nearest bus stop, stream, and open space are 8.44, 5.22, and 5.05, respectively.

Table 3.2 Basic Statistics of Variables in the Hedonic Pricing Modeling

Variables	Mean	Std	Max	Min
Ln_Price	13.3526	0.3347	14.0174	12.3799
Bed	3.8635	0.7310	8	0
Bath	3.1813	0.9133	8	0
Age	28.4484	26.2951	314	0
AC	0.9461	0.2259	1	0
FP	0.8674	0.3391	1	0
Stry	1.8857	0.3175	3	1
Bsm	0.5414	0.4983	1	0
LArea	260.0835	83.0818	809.3713	55.7418
SQ_Bed	15.4606	5.7514	64	0
SQ_Bath	10.9548	6.6787	64	0
SQ_Age	1500.6069	4406.8725	98596	0
Ln_LotSize	-1.3331	0.8938	3.0285	-4.6396
Ln_D2BusS	8.4434	0.7712	9.6524	4.5919
Ln_D2Stream	5.2249	0.7588	6.6698	-0.2637
Ln_D2OpenS	5.0491	1.0536	6.9715	1.5409
FD100	0.0555	0.2290	1	0
HSAs	0.4809	0.4997	1	0
FD100×HSAs	0.0392	0.1941	1	0

The OLS model results are shown in Table 3.3. Model 1 was built from Equation (3.3), and Model 2 was built from Equation (3.4). These two have similar R-squared scores, root mean squared errors (RMSE), and coefficients of most independent variables. Both models have an R-squared score close to 0.8 and an RMSE of 0.1512. All coefficients of independent variables are statistically significant, except the coefficient of FD100×HSAs. The coefficient of the bedroom number is 0.1176, which is nearly nine times the coefficient of the squared bedroom number, suggesting that an increase in bedroom number can result in a home price rise when the number of bedrooms is lower. The coefficient of the squared bedroom number is -0.013, indicating that the impact of bedroom number on home prices follows a convex curve. For example, with other home characteristics being equivalent, prices of homes with two bedrooms are 8.18% higher than those with one bedroom, but prices of homes with five bedrooms are merely 0.06% higher than those with four bedrooms.

Similarly, the curve of the impact of bathroom numbers on home prices is also convex. Prices of homes with two bathrooms can be 3.72% higher than those with one bathroom, while prices of homes with four bathrooms are 0.49% higher than those with three bathrooms. In contrast, the impact of property age on home sale prices is a concave curve because the coefficient of squared age is positive. When the property age is less than 148 years, a year increase in the age can lead to a price discount, but the magnitude of this discount is gradually diminished with the age increase. Further increases in the property age can result in a price premium as the property's historic value increases.

Increasing the size and elevation of a property can positively affect the home price. Each additional floor can yield about a 6.2% increase in the home price. For every additional square meter of living space, house prices will rise by 0.2%. A 1% increase in lot size results in a 0.045% increase in home prices. Complete amenities also raise the value of a home. The presence of air-conditioning, fireplace, and basement can increase home sale prices by 6.77%, 4.26%, and 6.37%, respectively.

In addition to physical configurations, environmental conditions significantly affect house values. Proximity to transportation facilities can increase the value of a house. A 1% decrease in distance to the nearest bus stop raises house prices by 0.032%. Riparian amenities may slightly increase home prices in the study area, with a 0.019% increase for every 1% decrease in the distance to the nearest stream. However, homes away from open spaces in this study area tend to have slightly higher prices. Every 1% increase in distance to the nearest open space increases house prices by 0.008%.

The most obvious differences between Model 1 and 2 are the coefficients of FD100, HSAs, and their interaction term. In Model 1, the impact of the 100-year floodplain on home prices is -5.55%, while the impact of the HSAs is -2.43%. In Model 2, comparing properties outside the 100-year floodplain and HSAs, properties inside the 100-year floodplain but outside HSAs have a price discount of 6.82%, properties inside HSAs but outside the 100-year floodplain have a price discount of 2.53%, and properties inside both HSAs and the 100-year floodplain have a price discount of 7.36%. Because the interaction term coefficient of FD100 and HSAs is insignificant, there is no significant joint effect of the 100-year floodplain and HSAs, implying that the impact of the 100-year floodplain is independent of the impact of HSAs.

Table 3.3 Results of OLS Models

	Model 1			Model 2		
Variables	Coef	Std err	P-val	Coef	Std err	P-val
Intercept	12.8194	0.053	0.000	12.818	0.053	0.000
Bed	0.1176	0.017	0.000	0.1177	0.017	0.000
Bath	0.0602	0.012	0.000	0.0599	0.012	0.000
Age	-0.0078	2.27E-04	0.000	-0.0078	2.28E-04	0.000
AC	0.0655	0.011	0.000	0.0655	0.011	0.000
FP	0.0418	0.007	0.000	0.0417	0.007	0.000
Stry	0.0601	0.008	0.000	0.0603	0.008	0.000
Bsm	0.0618	0.004	0.000	0.0618	0.004	0.000
LArea	0.002	4.72E-05	0.000	0.002	4.72E-05	0.000
SQ_Bed	-0.013	0.002	0.000	-0.013	0.002	0.000
SQ_Bath	-0.0079	0.002	0.000	-0.0079	0.002	0.000
SQ_Age	2.63E-05	1.11E-06	0.000	2.63E-05	1.11E-06	0.000
Ln_LotSize	0.0451	0.003	0.000	0.045	0.003	0.000
Ln_D2BusS	-0.0317	0.003	0.000	-0.0316	0.003	0.000
Ln_D2Strea	-0.0195	0.003	0.000	-0.0193	0.003	0.000
Ln_D2OpenS	0.0077	0.002	0.001	0.0076	0.002	0.001
FD100	-0.0571	0.011	0.000	-0.0706	0.018	0.000
HSAs	-0.0246	0.005	0.000	-0.0256	0.005	0.000
FD100×HSAs				0.0198	0.021	0.336
R-squared	0.7958			0.7959		
RMSE	0.1512			0.1512		

The spatial autocorrelation test result is shown in Figure 3.2. In each sub-figure, the x-axis represents the OLS residual value, and the y-axis represents the spatial lag term of residuals based on a spatial weight matrix. The Moran's I statistics were computed using four different spatial weight matrices. The Moran's I score obtained with the QC weight matrix is 0.248, indicating a relatively strong clustered pattern in the Model 2 residuals. However, Moran's I test using the QC weight matrix removed isolated parcels, which may overestimate the spatial autocorrelation. In contrast, the IDW weight matrix yields a Moran's I score of 0.144, suggesting a lower degree of spatial clustering. The KNN weight matrix results in a Moran's I score of 0.179, reflecting a moderate level of spatial autocorrelation. Similarly, Moran's I score obtained with the kernel weight matrix is 0.175.

All four scores are positive and significant at 0.01 level, suggesting the spatial clustered pattern in the OLS residual is robust. We subsequently conducted LM tests and LM robust tests for the spatial lag model and the spatial error model with the KNN weight matrix, and the test results were all significant at 0.01 level. Therefore, we built both spatial regression models.

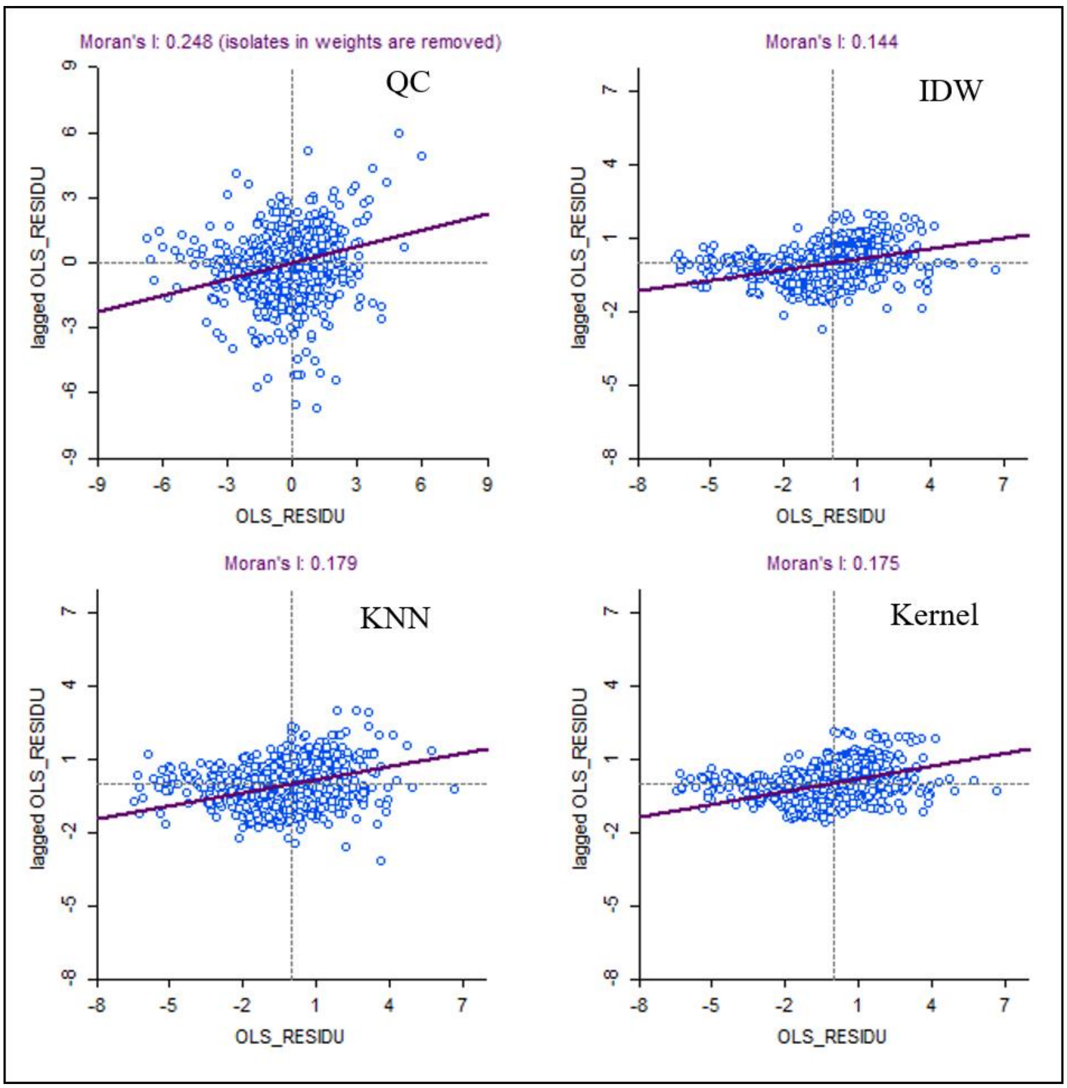

Figure 3.2 Spatial autocorrelation tests for the OLS residuals. Four kinds of spatial weight matrices are used in the test. QC represents queen contiguity, IDW represents inverse distance weight, KNN represents k-nearest neighbor, and Kernel refers to the kernel method.

The results of spatial regression models are shown in Table 3.4. Both spatial regression models significantly improve explanatory power compared to the OLS models. The spatial lag model has an R-squared score of 0.8231 and an RMSE of 0.1408. Similarly, the R-squared score and RMSE of the spatial error model are 0.8196 and 0.1422, respectively. The coefficient of spatial lag term (ρ) and the coefficient of spatially autocorrelated errors (λ) are both positive and significant at the 0.01 level, indicating positive spatial spillover effects. These results suggest that higher-priced homes will increase the prices of their nearby homes. Although the spatial regression models use more independent variables than the OLS models, the coefficients of the shared independent variables in these models are not fundamentally different from those in the OLS model, except for slight changes in magnitude. One thing needs to be mentioned. Coefficients in the spatial lag model should be multiplied by $1/(1-\rho)$ when interpreting the total effects of individual independent variables (C. W. Kim et al., 2003; L. Zhang, 2016). In the spatial lag model, the coefficients of HSAs and FD100 are -0.0153 and -0.0609, suggesting home price discounts of 2.1% and 8.82%, respectively. In the spatial error, the coefficients of HSAs and FD100 are -0.0198 and -0.0647, suggesting home price discounts of 1.96% and 6.27%, respectively. Similar to the OLS models, the coefficients of FD100×HSAs in the spatial lag and spatial models are insignificant, indicating no significant joint effect between HSAs and FD100 in spatial models.

Table 3.4 Results of Spatial Regression Models

	Spatial Lag			Spatial Error		
Variables	Coef	Std err	P-val	Coef	Std err	P-val
Intercept	9.0529	0.155	0.000	12.9550	0.065	0.000
Bed	0.1006	0.016	0.000	0.0776	0.017	0.000
Bath	0.0606	0.011	0.000	0.0628	0.012	0.000
Age	-0.0059	2.27E-04	0.000	-0.0078	2.45E-04	0.000
AC	0.0871	0.010	0.000	0.0617	0.010	0.000
FP	0.0249	0.007	0.000	0.0331	0.007	0.000
Stry	0.0613	0.008	0.000	0.0651	0.008	0.000
Bsm	0.0564	0.004	0.000	0.0497	0.004	0.000
LArea	0.0016	4.60E-05	0.000	0.0017	4.83E-05	0.000
SQ_Bed	-0.0113	0.002	0.000	-0.0092	0.002	0.000
SQ_Bath	-0.0074	0.001	0.000	-0.0070	0.002	0.000
SQ_Age	1.99E-05	1.07E-06	0.000	2.69E-05	1.14E-06	0.000
Ln_LotSize	0.0389	0.003	0.000	0.0505	0.004	0.000
Ln_D2BusS	-0.0227	0.003	0.000	-0.0317	0.005	0.000
Ln_D2Strea	-0.0123	0.003	0.000	-0.0149	0.004	0.000
Ln_D2OpenS	0.0054	0.002	0.008	0.0080	0.003	0.008
FD100	-0.0609	0.016	0.000	-0.0647	0.017	0.000
HSAs	-0.0153	0.004	0.000	-0.0198	0.005	0.000
FD100×HSAs	0.0252	0.019	0.187	0.0167	0.020	0.401
ρ	0.2799	0.011	0.000			
λ				0.4330	0.018	0.000
R-squared	0.8231			0.8196		
RMSE	0.1408			0.1422		

A dummy variable indicating homes in 500-year floodplains (FD500) and a dummy variable for the interaction of 500-year floodplains and HSAs (FD500 × HSAs) were added to Model 2 (OLS), spatial lag model, and spatial error model to analyze the effect of 500-year floodplains. Model results (Table 3.5) show that the p-values of coefficients for FD500 and FD500 × HSAs are all above 0.05, indicating an insignificant effect of FD500. Adding FD500 to models did not change the impact of HSAs.

Table 3.5 Comparison of Coefficients for HSAs and the 500-Year Floodplain

	OLS		Spatial Lag Model		Spatial Error Model	
Variables	Coef	P-val	Coef	P-val	Coef	P-val
FD500	-0.0217	0.311	-0.0029	0.884	0.0047	0.828
HSAs	-0.0260	0.000	-0.0158	0.000	-0.0201	0.000
FD500 × HSAs	0.0243	0.357	0.0309	0.206	0.0128	0.620

3.4 Discussion

All models in this study have an R-squared value above 0.79, indicating good accuracy of their results. Although these models have different variable structures, their estimations of the effects of the shared independent variables are very similar, reflecting the robustness of the model results.

Most estimations of independent variable effects are coherent with intuitions. The impact of the bedroom and bathroom numbers follow a convex curve. These findings can be explained by the fact that more rooms in a home will reduce the size per room when the living area is stable, which may be less suitable for living. The concave curve of the age effect reflects both home depreciation and the value of historic buildings. The story number, the size of the living area, and the lot size are all positively correlated with home prices. This is coherent with the intuition that larger-size properties have higher prices. The air-conditioning system, fireplace, and basement can improve the living quality of a home, so the presence of these amenities results in positive coefficients in models. Homes close to bus stops can enjoy the convenience of public transportation, which results in higher home prices. Riparian areas can provide aesthetic views and recreational amenities to nearby properties, so the home price increases when close to a stream. However, the coefficient of the distance to the nearest open space differs from the estimation in some previous studies (Atreya et al., 2013; Bin & Polasky, 2004; J. S. Lee & Li, 2009). This difference may be due to the housing market in the study area valuing privacy over easy access to public open spaces.

This study used the 100-year floodplain and HSAs to indicate flood-prone areas. All models find negative and significant impacts of the floodplain and HSAs on home values. The FEMA's 100-year floodplain is a well-known flood-prone area designation with a mandatory flood insurance requirement for homes with federally backed mortgages. Therefore, homes in the 100-year floodplain have lower prices than homes outside this region. The estimated impact of the 100-year floodplain in this study ranges from -5.6% to -8.8%, consistent with the estimations (-4% to -12%) in previous hedonic pricing studies (Bin & Polasky, 2004; Donnelly, 1989; Shilling et al., 1989; Shultz & Fridgen, 2001; Troy & Romm, 2004).

In contrast to the floodplain, the public is unfamiliar with the concept of HSAs and seldom knows the precise location of these areas. However, the results of this study confirm that home prices are implicitly affected by HSAs, revealing a significant adverse impact of HSAs on home prices. The magnitude of the HSA impact is around -2%, smaller than that of 100-year floodplains, but it affects 48% of homes analyzed in this study. Floodplains are mainly clustered along streams, whereas HSAs are dispersed in every neighborhood of the study area. Using HSAs to supplement the 100-year floodplain in delineating flood-prone areas will greatly expand people's awareness of flood risks, especially those not directly associated with well-known rivers and streams.

Model results also suggest that the impact of HSAs is independent of the impact of the 100-year floodplain. This may be attributed to the differences in the delineating approaches of floodplains and HSAs. The floodplain designation depends on records of submerged places in past flood events, which does not consider the hydrological connectivity between the upper land and downstream. In contrast, HSAs are derived from the local landscape with soil topographic index, which naturally contains the hydrological connectivity in the landscape. Although these two kinds of areas overlap in many locations, they are derived independently. Flood records focus on water levels near rivers and streams but poorly capture many depression terrains suffering pluvial and flash floods in the landscape. HSAs can fill the blanks of flood-prone areas.

The 500-year floodplain is a conventional method to delineate flood-prone areas outside the 100-year floodplain. However, the study results show that the efficacy of the 500-year floodplain in raising awareness of flood risk is not comparable with the impact of HSAs. On the one hand, the space coverage of the 500-year floodplain is limited. Merely 4.8% of analyzed properties are in the 500-year floodplain, most distributed along streams and lakes. On the other hand, the 500-year floodplain delineates areas with medium or low flood risks based on historical records, whereas HSAs depict many high flood-risk areas in a landscape. Improving flood risk management in HSAs may foster community flood resilience more efficiently than in the 500-year floodplain.

Although this study confirms the impact of HSAs, there are some limitations in the methodology. One limitation is that this study uses a binary designation for HSAs and assumes that the flood risk is higher inside HSAs than outside. However, the spatial distribution of flood risk is continuous, and outside properties close to HSAs may not suffer a very different flood risk level than properties within HSAs. The binary designation may cause people to underestimate the flood risk outside HSA boundaries. Unlike the 100-year floodplain, HSAs do not have a clear probability of flood hazard occurrence due to a lack of field observation records. Future studies should analyze the relationship between soil topographic index and flood risk and use a gradient designation of flood-prone areas.

Another drawback of this study is that the relationship between HSAs and flood losses is not examined. A direct linkage between HSAs and flood insurance claims can make the inference of HSAs indicating flood-prone areas more compelling. However, we cannot extract flood insurance claims in HSAs, as the FEMA withholds the precise location information for flood insurance claims in its open data. Further, as houses outside of the 100-year floodplain are not required to have flood insurance, few flood insurance claims would be expected in HSAs that are not also within the 100-year floodplain. Using the housing price discount as a proxy for flood losses is an acceptable compromise, although it is also affected by various factors unrelated to flood risks. Future studies can analyze the effect of land use in HSAs on flood insurance claims at the census tract or county level.

Finally, this study only uses the KNN weight matrix to fit spatial regressions. This weight matrix is arbitrary and may not precisely reflect the spatial structure in home sale prices. The study only analyzed a part of property records between 2010 and 2020. After data pre-processing and trimming, many isolated parcels are reserved in the data for modeling. If using the QC weight matrix, the spatial model has to remove all the isolated parcels from modeling, which occupies a substantial portion of input data. Using either the IDW matrix or the kernel matrix will suffer from a problem of excessive bandwidth caused by parcels far away from their neighbors. The symmetric KNN weight matrix is a relatively rational approach to fit spatial regressions to the entire data. The performance of spatial models is significantly better than the OLS models, proving the rationality of the KNN weight matrix to some extent. A possible improvement in spatial modeling for this problem is using geostatistical models (kriging), which are applications of Gaussian Process regression in spatial modeling.

On a final note, this study did not evaluate changes in housing prices within the study period, treating the entire period from 2010 to 2020 as a single cohort. Therefore, pricing impacts of Hurricane Irene (2021) are note evaluated.

3.5 Conclusions

This study used linear and spatial hedonic pricing models to examine the impact of hydrological sensitive areas (HSAs) on home prices in Hillsborough Township and Montgomery Township in Somerset County, New Jersey. Model results confirm the hypothesis that properties in HSAs exhibit an adverse effect of higher flood risks on their sale prices. Both the OLS and spatial models suggest a significant price discount (-2%) of homes in HSAs, and this adverse impact is independent of the effect of floodplains.

By making the public aware of HSAs, the awareness of flood risks can be substantially extended beyond the conventional floodplains. Introducing HSAs in flood-prone area delineation can overcome the lack of records of pluvial and flash flood areas and improve the efficiency of flood risk management. HSAs also reflect flood source areas, which can guide land use and conservation in a landscape and help residents choose favorable home locations. New Jersey communities are working on improving flood resilience in the landscapes (Maslo et al., 2023). The findings in this study can facilitate this landscape resilience project.

This study has several limitations that need to be addressed in the future. First, the HSA used in this study is a binary designation and does not have a specific probability of flood occurrence, which is not convenient for quantifying the flood risk. Second, this study used home price discounts as the proxy for flood losses, the price discounts may be affected by factors unrelated to flood risks. Finally, the spatial weight matrix in spatial regression models of this study is an arbitrary setting, although it obtained significant spatial dependence in home prices.

CHAPTER 4

ESTIMATING THE IMPACTS OF IMPERVIOUS SURFACES AND LAND DEVELOPMENT RESTRICTIONS ON FLOOD LOSSES

4.1 Introduction

Flood risk variation is not only related to climate change but also attributed to urbanization (Hodgkins et al., 2019). Rapid urbanization has profoundly altered natural landscapes and water flow patterns (Arnold Jr. & Gibbons, 1996; Shuster et al., 2005; Tollan, 2002). As cities expand, transforming permeable surfaces into impervious ones reduces the land's ability to absorb rainfall, thereby increasing surface runoff. This phenomenon often overwhelms urban drainage systems, leading to more frequent and severe flooding (W. Zhang et al., 2018; Q. Zhou et al., 2019). Additionally, urban development frequently intrudes into floodplains, reducing their natural capacity to manage floodwaters (Andreadis et al., 2022; Gori et al., 2019). The loss of green spaces and wetlands during urbanization further exacerbates this issue (Brody et al., 2017; Narayan et al., 2017; Vázquez-González et al., 2019). In addition, climate change introduces more intense and unpredictable weather patterns, contributing to heavier rainfall events (Marvel et al., 2023). Consequently, urban areas are highly vulnerable to flooding, substantially challenging infrastructure, public safety, and economic stability. Understanding the impact of land use on flood losses is crucial for developing effective flood risk management strategies and mitigating future flood damage.

Increases in impervious surfaces can lead to increases in the velocity and volume of surface runoff and decreases in infiltration (Arnold Jr. & Gibbons, 1996; Lin et al., 2015; J. D. Miller et al., 2014; Shuster et al., 2005; Q. Zhou et al., 2019). This can lead to higher peak flows and shorter lag time to peak flow, triggering flash floods and urban flooding (Burns et al., 2005; Hodgkins et al., 2019; Yan et al., 2020; Q. Zhou et al., 2019). Furthermore, the reduction in natural infiltration reduces groundwater recharge and increases surface runoff, contributing to erosion and water pollution (Arnold Jr. & Gibbons, 1996; Shuster et al., 2005). Besides the size of impervious surfaces, the development patterns also affect flood losses. The clustered, high-density urban development pattern, associated with well stormwater drainage systems, can reduce flood damage, while the development pattern characterized as low-density, haphazard, and outward from urban centers leads to a substantial increase in flood losses (Brody et al., 2011, 2014; Y. Lee & Brody, 2018).

Open space and green infrastructure can significantly mitigate flood risk. Research indicates that incorporating green infrastructure, such as permeable pavements, green roofs, rain gardens, and urban forests, significantly enhances stormwater management by increasing infiltration and reducing runoff (Gill et al., 2007, p. 20; H. Kim et al., 2016; Sohn et al., 2021; Tollan, 2002). Open spaces, including parks and wetlands, act as natural buffers, absorbing excess water during heavy rainfall events. Studies show that these areas can lower peak discharge rates and volume, decreasing the strain on conventional drainage systems and reducing the likelihood of flooding (Brody et al., 2015, 2017; Narayan et al., 2017; Vázquez-González et al., 2019). The ecosystem services provided by these green infrastructures, including water purification, groundwater recharge, and biodiversity conservation, further contribute to their effectiveness in flood risk reduction (Brody et al., 2015; Highfield & Brody, 2013; Stefanakis, 2019). As such, integrating open spaces and green infrastructure into urban landscapes is increasingly recognized as a sustainable and cost-effective strategy for flood risk management.

To protect important natural and environmental resources and against haphazard land developments, the State of New Jersey has implemented five key land use programs: steep slope ordinance, stream corridor ordinance, open space preservation, farmland preservation, and wetlands protection. These programs were developed based on New Jersey's Water Quality Management Planning rule (NJAC 7:15), Stormwater Management rules (NJAC 7:8), Flood Hazard Area Control Act rules (NJAC 7:13), Freshwater Wetlands Protection Act (NJAC 7:7A), the Green Acres rules (NJAC 7:36) and farmland preservation policy. They have significantly contributed to reducing impervious surfaces and preserving green spaces. The steep slope ordinance limits construction on steep terrains, preventing erosion and runoff that would otherwise increase impervious surfaces. Stream corridor ordinances safeguard waterways by maintaining buffer zones, which help filter pollutants and manage stormwater. Open space and farmland preservation initiatives protect large tracts of land from development, ensuring that natural landscapes and agricultural areas remain intact, thereby minimizing urban sprawl and creating impervious surfaces. Wetlands protection ordinances preserve critical ecosystems that naturally manage water flow and quality, reducing the necessity for artificial drainage solutions. Collectively, these ordinances help maintain ecological balance, support biodiversity, and enhance the resilience of New Jersey's environments against urbanization pressures.

Hydrologically Sensitive Areas (HSAs) generate most stormwater runoff in watersheds and significantly affect the local hydrological cycle and water quality (Dahlke et al., 2013; Qiu et al., 2014, 2019; Walter et al., 2000; Y. Zhou et al., 2022). Protecting the natural function of HSAs will effectively improve stormwater management and water quality, frosting healthy and resilient watersheds. However, Qiu et al. (2014) found that current land use controls only protected 44-64% of municipal HSAs in three municipalities in New Jersey's Raritan Water Region, and they suggested that land use planning should incorporate the concept of HSAs. On the other hand, the significance of HSAs in flood risk management is not widely recognized, resulting in a lack of motivation among stakeholders to protect these areas. Few studies have analyzed the impact of impervious surfaces and land development restrictions in HSAs on flood damage.

This study intends to fill the knowledge gap on the impact of land use patterns in HSAs on flood damage. We hypothesize that impervious surfaces and land development restrictions in HSAs have a greater impact on flood losses than in other areas. This study uses the flood insurance claims in the Raritan Water Region of New Jersey from 2010 to 2020 as a case study. Correlations between flood losses and impervious surfaces within municipal boundaries, HSAs, and the 100-year floodplain were compared. Correlations between flood losses and land development restriction areas within municipal boundaries, HSAs, and the 100-year floodplain were also compared. The impacts of impervious surfaces and land development restrictions on flood losses were further analyzed via linear regressions, respectively, incorporating essential environmental and socioeconomic variables.

4.2 Data and Methods

4.2.1 Study area

The study area is the spatial extent of municipalities within and contiguous to the Raritan Water Region. There are 120 municipalities spatially overlapping with the Raritan Water Region. Figure 4.1 displays the spatial extent of 108 of them that were analyzed in this study. The Raritan Water Region is one of five water resource management regions designated by the New Jersey Department of Environmental Protection (NJDEP). It is located in central New Jersey, a transition zone from the highlands to the coastal plains. The Raritan region is about 3,271 km^2 large and contains watersheds in the Raritan River basin and the Arthur Kill watershed. The Raritan River and the Millstone River are major streams in this region.

Flooding has been a persistent problem in the Raritan region, impacting local communities for centuries. One of the most significant flooding events happened during Hurricane Floyd in 1999, which caused severe damage in many places, such as Bound Brook and Manville. This flood event highlighted the vulnerability of this region to major storm events. Hurricane Irene hit this region in 2011 and caused significant flooding, particularly affecting New Brunswick and Sayreville. More recently, in 2021, Hurricane Ida led to severe flooding in this region, breaking previous records set by Hurricane Floyd. Towns such as Manville, New Brunswick, Somerville, and South Bound Brook experienced extreme flood damage, with the Raritan River cresting at unprecedented levels. Since the 1990s, many efforts have been made to mitigate flooding in this region, including projects like the Green Brook Flood Control Project. These projects aim to manage and reduce flood risks through various engineering and environmental measures. However, flood control structures are inefficient in addressing the rising flood risk. Historical responses to flooding in this region have evolved from retreat and recovery to proactive resilience-building strategies. These include removing vulnerable floodplain-based structures, changing land use practices, and improving communication and evacuation planning.

Figure 4.1 Regional map of municipalities in the analysis of land use impact on flood losses

4.2.2 Flood insurance claims

This study used the payment amount in National Flood Insurance Program (NFIP) claims to reflect flood losses. The NFIP in the United States is a federal program established by the National Flood Insurance Act, passed in 1968. It aims to reduce the impact of flooding on private and public structures by providing affordable insurance to property owners, renters, and businesses. This program was initially administered by the Department of Housing and Urban Development and subsequently transferred to the Federal Emergency Management Agency (FEMA) when it was established in 1979. Property owners in Special Flood Hazard Areas (SFHA) with mortgages from federally regulated or insured lenders are required to purchase and maintain flood insurance during the life of the loan. NFIP policies cover property and contents damage up to specific levels; homes with greater damages will only receive reimbursement to those limits, with the remainder being the property owner's responsibility. However, there is no mandatory flood insurance requirement for properties outside the SFHA or for properties lacking such mortgages. Therefore, the NFIP-insured properties are concentrated in the SFHA. The NFIP payment is a commonly used indicator for flood losses, although it only reflects covered flood damages on insured properties (Brody et al., 2014, 2017). Unfortunately, there is no database of total flood losses, even for those properties submitting NFIP loss claims.

This study analyzed FEMA NFIP redacted claims for 2010 to 2020, which were extracted from the OpenFEMA Dataset in April 2022. The payment amount of each flood insurance claim is the sum of the amount paid on the building claim, contents claim, and increased cost of compliance claim. All payment values were adjusted to payments in 2020 through the Consumer Price Index (CPI). As FEMA did not disclose the information of the reported city, the payment amounts were initially aggregated to census tracts and subsequently summarized to specific municipalities through overlapping census tracts with municipality boundaries in ArcMap. Small municipalities that share a census tract with their neighbor townships were excluded from further analysis. Finally, the insurance claim aggregation suggests that property owners from 108 municipalities received flood insurance payments from 2010 to 2020. To reduce the effect of municipality size on flood losses, we calculated the flood insurance payment per hectare (loss per hectare) in every municipality from 2010 to 2020. The loss per hectare was further transformed by natural logarithms before statistical analysis.

4.2.3 Flood-prone areas

The flood-prone areas comprised the Hydrologically Sensitive Areas (HSAs) and the 100-year floodplain. This study analyzed land use impacts on flood losses in HSAs, floodplains, and flood-prone areas, respectively. The HSAs were derived from a digital elevation model and soil hydraulic conductivity of New Jersey through the same method described in Qiu et al. (2020), as discussed in Chapter 3. The spatial resolution of this dataset is 10 meters. HSAs are denoted by pixel value 1, and non-HSAs by 0. The extent of 100-year floodplains, Special Flood Hazard Areas, were extracted from the FEMA's National Flood Hazard Layer (NFHL). The floodplain extent was converted from a vector layer to a binary raster layer with a resolution of 10 meters to facilitate subsequent spatial overlay processing and statistical analysis. The raster layer of flood-prone areas was merged from binary raster layers of HSAs and the floodplain through the mosaic method. The percentages of each municipality's HSAs, floodplains, and flood-prone areas were derived by the zonal mean method, respectively.

Figure 4.2 displays the spatial distribution of FEMA floodplains and HSAs along a tributary (Pike Run and its upper streams) of the Millstone river in Montgomery, New Jersey. Designated 100-year floodplains are immediately adjacent to streams. Although parts of HSAs overlap floodplains, many HSAs are away from streams in topographic converged areas with a relatively thin soil layer. These areas may not be exposed to fluvial floods but are likely to be disturbed by pluvial floods.

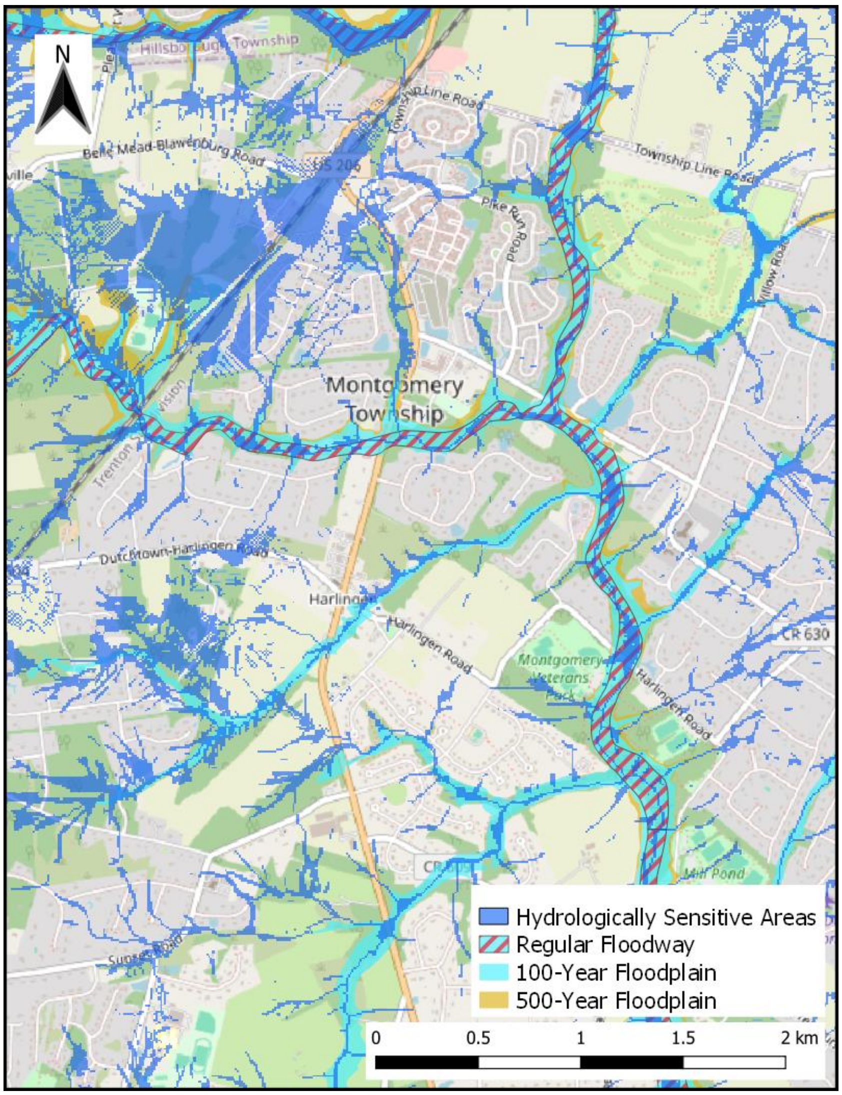

Figure 4.2 Floodplains and Hydrological Sensitive Areas along a tributary of the Millstone River in Montgomery, New Jersey.

4.2.4 Impervious surfaces

The impervious surfaces in the study area were derived from the impervious surfaces in 2015 provided by the NJDEP, derived from digital imagery, LiDAR point clouds, and vector data sets, including land use/land cover, road centerlines, and hydrographic features. This dataset delineated boundaries of buildings, roads, and other paved or highly compacted impervious features, such as parking lots, sidewalks, and driveways, in New Jersey. We first converted all impervious surfaces to a raster dataset (10-meter resolution) and clipped it to the study area. The rasterized impervious surfaces were subsequently intersected with the extent of HSAs, floodplains, and flood-prone areas using the raster calculator. Finally, the percentages of impervious surfaces in each municipality's administrative boundaries, flood-prone areas, HSAs, and floodplains were derived by the zonal mean method, respectively.

4.2.5 Development restrictions

Five land use programs are implemented to regulate urban developments, preserve open lands, and reduce adverse impacts of urbanization on environmental quality, including steep slope ordinance, stream corridor ordinance, open space preservation, farmland preservation, and wetlands protection. Of these, the steep slope ordinances were adopted by municipalities in response to State regulatory requirements that lapsed in 2016 through a change in New Jersey's Water Quality Management Planning rule (NJAC 7:15). Stream corridor protection ordinances are required to be adopted under the State's stormwater management regulations. Open space and farmland programs are joint and voluntary efforts of State, county and municipal governments with non-profit land trusts. Wetlands protection requirements are State regulations, implemented by the NJDEP.

The steep slope ordinance originally was designed to regulate development on areas with significant slopes to prevent soil erosion, manage stormwater runoff, and maintain natural topography. The ordinance was based on requirements in the old version of New Jersey's Water Quality Management Planning rule (NJAC 7:15). Some municipalities that adopted the model ordinance have retained the ordinance. It controls different land use activities based on slope ranges, such as 15% to 20%, 20% to 25%, and above 25%. Although steep slope ordinances in municipalities in the study area are not fully identical, urban development in areas with a slope of no less than 20% is prohibited (Noblejas, 2008). This study derived the steep slope areas (slope ≥20%) from a DEM in 2016 provided by the NJDEP. As the horizontal spatial resolution of this DEM is 10 feet, the raster layer of steep slope areas was resampled to the 10-meter resolution using the nearest-neighbor method.

The stream corridor ordinance is designed to protect the ecological integrity of waterways by regulating activities within designated buffer zones around streams and rivers. This ordinance typically requires maintaining vegetated riparian buffers, which help filter pollutants, manage stormwater, and provide habitat for wildlife. New Jersey's Stormwater Management rules (NJAC 7:8), the Flood Hazard Area Control Act rules (NJAC 7:13), and the Pollutant Discharge Elimination System rules (NJAC 7:14) have specific requirements for stream corridor regulations. The buffer range of steam corridors is 300 feet for Category One streams, 150 feet for trout production and maintenance streams, stream segments flowing through documented habitats for threatened or endangered species, and stream segments flowing through acid-producing soils, and 50 feet for all other surface water bodies (Kruger, 2008). If slopes steeper than 15% are in the designated width, the riparian buffer should be extended to include the entire sloped area and the buffer range can be extended to 300 feet at maximum. Additionally, stream corridors shall cover the entire floodway area. We initially created riparian buffers according to the NJDEP’s Surface Water Quality Classification, Landscape 3.3 data for habitats, and Potential Acid Producing Soils data. The steep slopes (≥15%) near streams were extracted by intersecting a 300-foot riparian buffer zone with sloped areas (polygons) derived from the DEM. Floodway areas were extracted from the NFHL. Riparian buffers, riparian steep sloped areas, and floodway areas were finally merged into stream corridors.

Open space programs are designed to preserve and manage undeveloped land for environmental protection, recreation, and historic preservation. Typical open space properties include parks, conservation areas, preserves, historic sites, recreational fields, beaches, etc. The NJDEP established the Green Acres program (N.J.A.C. 7:36) in 1961 to preserve open spaces in New Jersey. Local and county governments also protect many open spaces either in collaboration with or separate from the Green Acres program. The NJDEP has created a geography dataset, ‘State, Local and Nonprofit Open Space of New Jersey,’ to record various open spaces in the state.

Farmland preservation in New Jersey involves a program to protect agricultural lands from development and maintain the state's farming heritage. This is achieved by purchasing development rights from landowners, which ensures the land remains managed so that it is available for agriculture. The program is administered by the New Jersey State Agriculture Development Committee (SADC) and includes measures of purchasing development easements, designating agricultural development areas, and providing municipal planning incentive grants. Counties, municipalities and non-profit lands trusts also are involved in the program. These efforts help to maintain New Jersey's agricultural industry, protect natural resources, and prevent urban sprawl. The area of preserved farmlands was derived from a vector geographic dataset, 'Preserved Farmland of New Jersey,' produced by the SADC.

Freshwater wetland preservation in New Jersey is managed under the New Jersey Freshwater Wetlands Protection Act (NJAC 7:7A), which aims to protect these critical ecosystems. Any development or alteration in freshwater wetlands requires a permit from the NJDEP. Developers may need to create or restore wetlands to offset any permitted impacts. The wetland preservation program helps protect water quality, prevent flooding, and maintain biodiversity. This study used the 2012 wetlands layer derived from the NJDEP's land use/ land cover data to approximately represent the extent of wetland protection.

The above development restriction areas were converted to binary raster layers and merged using ArcGIS. The percentages of development restriction areas in administrative boundaries, flood-prone areas, HSAs, and floodplains of each municipality were respectively derived by the zonal mean method.

4.2.6 Physical and socioeconomic variables

This study also analyzed relationships between flood loss and several physical and socioeconomic variables frequently appearing in previous studies (Brody et al., 2011, 2014; Y. Lee & Brody, 2018). These variables include the average slope (%), mean saturated soil hydraulic conductivity (μm/s), housing value density ($\$/m^2$), mean household income ($), percent of high school graduates or higher, and percentage of non-Hispanic white population in municipalities. The average slope was derived from the NJDEP's DEM in

2016. The mean saturated soil hydraulic conductivity was derived from the Gridded Soil Survey Geographic Database (gSSURGO) produced by the United States Department of Agriculture's Natural Resources Conservation Service. The housing value density equals the sum of residential property sale prices divided by the sum of residential parcel areas in a municipality, calculated from the parcels and MOD-IV composite data published by the New Jersey Office of GIS. The housing value density values were further transformed by the natural logarithm in subsequent statistical analysis. The mean household income values in municipalities were derived from the American Community Survey (ACS) 5-year estimates from 2010 to 2020. The income data were initially adjusted by the CPI and subsequently averaged for the study period. The natural logarithm-transformed income data were further analyzed. The percentage of high school graduates or higher and the percentage of the non-Hispanic white population in each municipality were averaged from the ACS 5-year estimates from 2010 to 2020.

4.2.7 Statistical analysis

The statistical analyses implemented in this study include the correlation analysis and the multiple linear regression. Table 4.1 lists eighteen variables analyzed in this study. Pearson's correlation coefficient was calculated for each pair of these variables. The result of the correlation analysis was subsequently used to guide the independent variable selection for the multiple linear regression.

Eight multiple linear regression models were built to examine the impacts of land use on NFIP flood loss payments. The dependent variable was each model's log-transformed flood insurance payment per hectare (Ln_LPH). Four regression models used the percentages of impervious surfaces in the administrative boundaries, flood-prone areas, HSAs, and the 100-year floodplain as independent variables, respectively. The other four regression models used the percentages of development restriction areas in the administrative boundaries, flood-prone areas, HSAs, and the 100-year floodplain as independent variables, respectively. The rest of the independent variables were selected based on the correlation analysis result and the Variance Inflation Factor to reduce the multicollinearity effects in modeling.

Table 4.1 List of Variables in the Analysis for Land Use Impacts on Flood Losses

Variables	Descriptions
Ln_LPH	Natural log-transformed flood losses per hectare
FPA	% of flood-prone areas in a municipality
HSA	% of Hydrologically Sensitive Areas in a municipality
FDP	% of 100-year floodplains in a municipality
IS_MUN	% of impervious surfaces in a municipality
IS_FPA	% of impervious surfaces in flood-prone areas of a municipality
IS_HSA	% of impervious surfaces in the HSA of a municipality
IS_FDP	% of impervious surfaces in the floodplain of a municipality
DR_MUN	% of development restriction areas in a municipality
DR_FPA	% of development restriction areas in flood-prone areas of a municipality
DR_HSA	% of development restriction areas in the HSA of a municipality
DR_FDP	% of development restriction areas in the floodplain of a municipality
Ln_HVD	Natural log-transformed housing value density ($ per square meter)
KSAT	Mean saturated soil hydraulic conductivity (μm per second)
SLOPE	Mean terrain slope (%)
Ln_INCOME	Natural log-transformed mean household income
HIGHSCH	% of the population that has a high school education or above
WHITE	% of the non-Hispanic white population

4.3 Results

4.3.1 Variable statistics

Table 4.2 displays the basic statistics of eighteen variables analyzed in the study. The natural logarithm-transformed flood loss per hectare (Ln_LPH) ranges from 1.618 to

10.913, with an average value of 5.663. The mean value of natural logarithm-transformed housing value density (Ln_HVD) is 4.717. The mean value of natural logarithm-transformed household income (Ln_INCOME) is 11.781. The mean of the population with a high school education (HIGHSCH) and above is 91.785%. The average percentage of the non-Hispanic white population (WHITE) is 61.794%. The mean saturated soil hydraulic conductivity (KSAT) ranges from 7.181 μm/s to 77.955 μm/s, with an average value of 26.855 μm/s. The mean slope value (SLOPE) ranges from 3.26% to 15.71%, with an average value of 6.748%.

Among three area designations related to flood risk, the average percentages of flood-prone areas, HSAs, and the 100-year floodplain in municipalities are about 19.1%, 12.1%, and 11.1%, respectively. Only 26 of the 108 municipalities have more than 25% of their area in flood-prone areas. The average percentage of impervious surfaces in the entire municipal boundaries is about 32%, higher than that of impervious surfaces in flood-prone areas (23.1%). This difference suggests a higher development density outside flood-prone areas than inside it. The average percentage of impervious surfaces in HSAs is 25.7%, but 14.8% in the 100-year floodplain, indicating a lower development density in floodplains than in HSAs. The average percentage of development restriction areas in municipalities is 34.8%, while 65.8% in flood-prone areas, suggesting that land use controls protect more portions within than outside of flood-prone areas. The average percentages of land use control areas in HSAs and the 100-year floodplain are 57.4% and 79.6%, respectively, suggesting a more stringent development restriction in the floodplain than in HSAs.

Table 4.2 Basic Statistics of Variables in the Analysis for Land Use Impacts

	Mean	Std	Min	25%	50%	75%	Max
Ln_LPH	5.663	2.2294	1.618	3.9233	5.6593	7.3658	10.9128
FPA	19.0871	11.0956	2.9709	10.5154	16.5039	24	57.552
HSA	12.1153	7.2625	2.2019	6.0046	11.3009	16.3876	33.6451
FDP	11.0682	8.5995	0	4.7229	8.7801	15.1984	51.8329
IS_MUN	32.049	19.3813	4.4683	16.423	27.4713	47.8159	77.8885
IS_FPA	23.1019	18.3422	1.3943	7.7087	17.812	34.9004	75.567
IS_HSA	25.7115	19.44	1.396	9.7014	20.4207	40.3651	76.4725
IS_FDP	14.8414	15.9374	0	2.9396	9.3546	21.0372	80.5848
DR_MUN	34.7746	14.5677	5.0696	23.7082	35.9076	46.4619	64.85
DR_FPA	65.839	21.1923	10.0237	49.9358	70.7369	82.7915	96.5249
DR_HSA	57.4123	23.2834	7.6852	38.5235	62.6265	77.5026	95.8446
DR_FDP	79.5647	25.997	0	75.9861	91.0344	95.3568	99.9442
Ln_HVD	4.7172	1.3197	0.1655	4.1511	4.929	5.6608	6.851
KSAT	26.8551	16.7572	7.1806	14.6366	21.2553	33.0771	77.9553
SLOPE	6.7484	2.8561	3.2599	4.5955	5.7224	8.3264	15.7101
Ln_INCOME	11.7805	0.3851	10.8685	11.5214	11.7881	12.0556	12.6347
HIGHSCH	91.7854	6.496	63.6909	89.8523	94.1545	95.8682	98.6364
WHITE	61.7935	23.5361	2.1032	49.3389	68.6947	80.4711	91.3065

4.3.2 Correlation analysis result

Figure 4.3 displays a heatmap of the correlation coefficient of each pair of variables. Ln_LPH is significantly correlated with most variables except DR_FDP and KSAT. It has positive correlations with FPA, HSA, FDP, IS_MUN, IS_FPA, IS_HSA, IS_FDP, and Ln_HVD, while negative correlations with SLOPE, Ln_INCOME, HIGHSCH, WHITE, DR_MUN, DR_FPA, and DR_HSA.

The extent of the correlation between flood losses and impervious surfaces varies across areas. The correlation between Ln_LPH and IS_MUN is about 0.57, which is stronger than the correlations between Ln_LPH and impervious surfaces in flood-related areas (IS_FPA, IS_HSA, and IS_FDP), suggesting that impervious surfaces inside and outside flood-prone areas increase flood loss. In addition, the correlation between Ln_LPH and IS_HSA is around 0.4, which is slightly stronger than the correlation between Ln_LPH and IS_FDP (0.32), indicating that impervious surfaces in HSAs are associated with greater flood losses than those in the 100-year floodplain.

Similar patterns are found in DR_MUN, DR_FPA, DR_HSA, and DR_FDP. Ln_LPH correlates more strongly with DR_MUN (-0.39) than with DR_FPA (-0.29), DR_HSA (-0.3), and DR_FDP (nearly zero), suggesting that land use control areas inside and outside flood-prone areas decrease flood loss. Ln_LPH has a moderate correlation with DR_HSA but no significant correlation with DR_FDP, suggesting that flood losses are more sensitive to the variation of land use control areas in HSAs than in the 100-year floodplain.

The correlation heatmap also shows strong correlations among independent variables. The independent variables in this study can be separated into three groups based on correlations and variable types. The first group includes FPA, HSA, and FDP. The second group contains impervious surface variables and land use control variables. The third group consists of Ln_INCOME, HIGHSCH, and WHITE. Variables within the same group are strongly correlated and reveal similar impacts on flood loss. Therefore, only one variable in each group should be selected for modeling to reduce the multicollinearity problem. SLOPE and Ln_HVD were used in modeling because they have relatively weaker correlations with other independent variables and reflect different impacts on flood loss. After several experiments, FDP, WHITE, SLOPE, and Ln_HVD were finally selected as the fixed variable combination for modeling, along with the impervious surface and land use control variables.

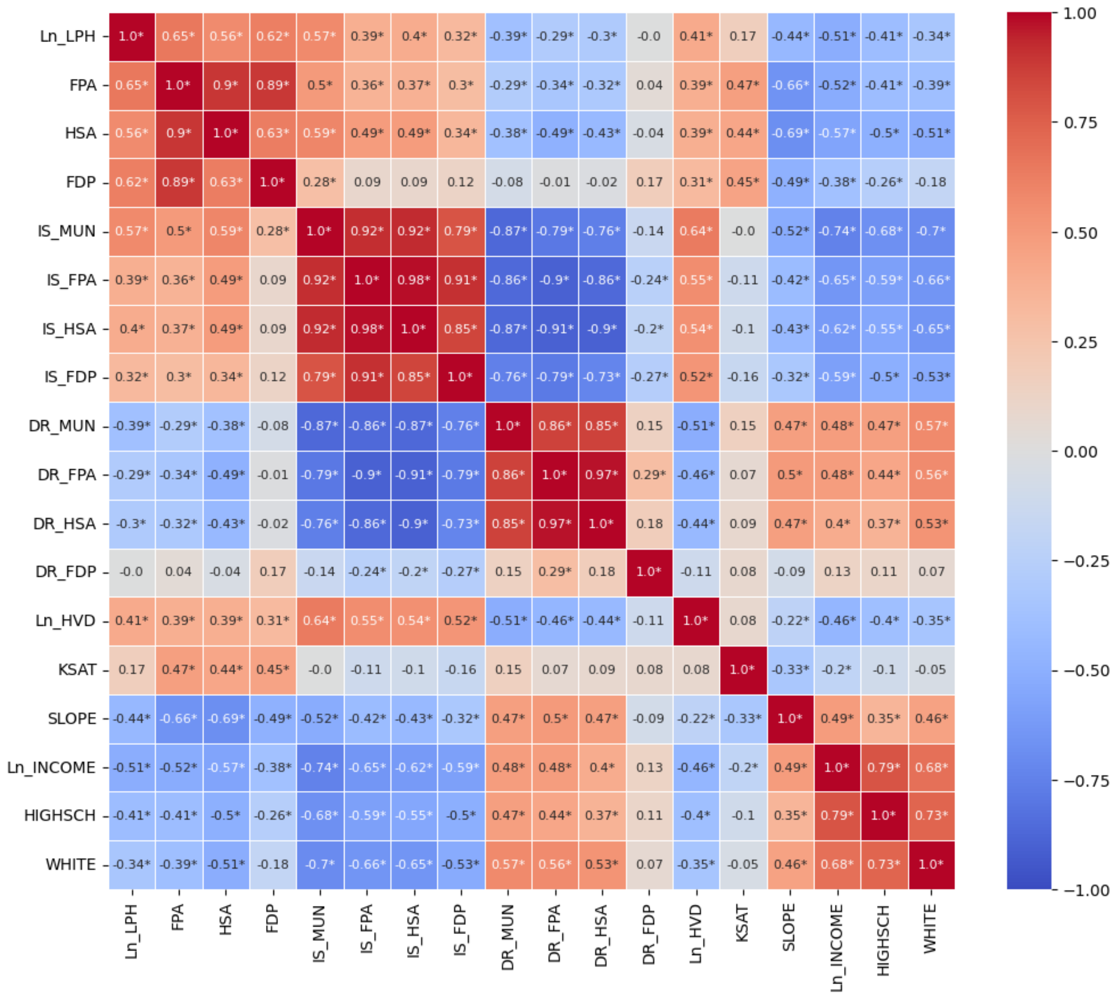

Figure 4.3 Heatmap of pairwise correlations among variables. Correlation values are filled in the grids. * indicates the correlation that is significant at the 0.05 level.

4.3.3 Regressions of impervious surface impacts

Table 4.3 displays variable coefficients and model performance of four regressions for impervious surface impacts. The R-squared values of these regressions range from 0.475 to 0.560. The M1 model, which used IS_MUN, has the highest R-squared value, while the M4 model, which used IS_FDP, has the lowest R-squared value. M2 and M3 have similar model performance, with an R-squared value around 0.5. The coefficient of IS_MUN is 0.0639, suggesting that a 1% increase in impervious surfaces in municipal boundaries is associated with a 6.4% increase in flood losses per hectare between 2010 and 2020. The coefficient of IS_FPA is 0.0312, suggesting that a 1% increase in impervious surfaces in flood-prone areas is associated with a 3.1% increase in flood losses per hectare. The coefficient of IS_HSA is 0.0339, suggesting that a 1% increase in HSAs is associated with a 3.4% increase in flood losses per hectare. The coefficient of IS_FDP is 0.014 but insignificantly different from zero. The FDP coefficients in all impervious surface impact regressions are significant, ranging from 0.1296 to 0.1448, suggesting that a 1% increase in the 100-year floodplain increases the flood losses per hectare by around 13.5%. The coefficients of SLOPE, Ln_HVD, and WHITE are insignificant at the 0.05 level and inconsistent across these four regressions.

Table 4.3 Coefficients of Variables in Models for Impervious Surface Impacts

	M1	M2	M3	M4
Intercept	1.7672*	3.0818***	2.8343***	3.9064***
IS_MUN	0.0639***			
IS_FPA		0.0312**		
IS_HSA			0.0339***	
IS_FDP				0.0140
FDP	0.1345***	0.1421***	0.1448***	0.1296***
SLOPE	0.0340	-0.0240	-0.0122	-0.0617
Ln_HVD	-0.0989	0.1358	0.1140	0.2501*
WHITE	0.0097	-0.0031	-0.0016	-0.0105
R-squared	0.560	0.495	0.504	0.475
RMSE	1.473	1.576	1.562	1.608

Note: * indicates a coefficient significant at the 0.1 level; ** indicates a coefficient significant at the 0.05 level; *** indicates a coefficient significant at the 0.01 level.

4.3.4 Regressions of development restriction impacts

Table 4.4 shows variable coefficients and model performance of the regressions for development restriction impacts. Among these four models, the DR_MUN (M5) model has the highest R-squared value of 0.505, while the DR_FDP (M8) has the lowest R-squared value of 0.474. M7 and M6 perform slightly better than M8, with R-squared values of 0.486 and 0.481, respectively. The coefficient of DR_MUN is the only significant coefficient at the 0.05 level among the development restriction variables, with a value of -0.0431, suggesting that a 1% increase in development restriction areas within municipal boundaries is associated with a 4.3% decrease in flood losses per hectare between 2010 and 2020. The coefficient of DR_HSA is -0.0175 and significant at the 0.1 level, suggesting that a 1% increase in development restriction areas in HSAs is expected to decrease flood losses per hectare by about 1.8%. The coefficients of DR_FPA and DR_FDP are insignificant at any level. The coefficients of FDP across models for development restriction impacts are all significant at the 0.01 level, ranging from 0.1299 to 0.1480, which are consistent with the coefficients of FDP in models for impervious surface impacts. The coefficient of Ln_HVD is only significant in the M8 model, with a value of 0.3012, suggesting that a 1% increase in housing value density ($ per square meter) increases flood losses per hectare by around 0.3%. The coefficients of SLOPE and WHITE are also insignificantly different from zero in models for land use control impacts.

Table 4.4 Coefficients of Variables in Models for Land Use Control Impacts

	M5	M6	M7	M8
Intercept	5.2211***	4.8771***	4.7217***	4.6035***
DR_MUN	-0.0431***			
DR_FPA		-0.0176		
DR_HSA			-0.0175*	
DR_FDP				-0.0059
FDP	0.1480***	0.1430***	0.1433***	0.1299***
SLOPE	0.0130	-0.0104	-0.0079	-0.0753
Ln_HVD	0.1206	0.2131	0.2090	0.3012**
WHITE	-0.0057	-0.0093	-0.0093	-0.0133
R-squared	0.505	0.481	0.486	0.474
RMSE	1.561	1.598	1.591	1.610

Note: * indicates a coefficient significant at 0.1 level; ** indicates a coefficient significant at 0.05 level; *** indicates a coefficient significant at 0.01 level.

4.4 Discussion

The correlation analysis suggests that impervious surfaces and development restriction areas significantly correlate with flood loss. Increases in impervious surfaces in a municipality can significantly increase flood losses per hectare, while increases in development restriction areas can significantly decrease flood losses per hectare. The intensity of correlations for flood losses with impervious surfaces and land use control areas varies across flood-prone areas, HSAs, and the floodplain. The flood losses per hectare more strongly correlate with the percentages of impervious surfaces and development restriction areas in municipal boundaries than those in flood-prone areas. This implies that the flood loss per hectare is related to impervious surfaces and land use control areas in flood-prone areas and those outside. Meanwhile, the flood losses per hectare more closely correlate with the percentages of impervious surfaces and development restriction areas in HSAs than those in the floodplain, implying that impervious surface and land use control areas in HSAs have more impacts on flood losses than those in the floodplain.

The results of regression models are consistent with the findings in the correlation analysis. The coefficient of IS_MUN is significant and positive, suggesting that impervious surfaces in a municipality increase flood losses per hectare. In contrast, the coefficient of DR_MUN is significant and negative, suggesting that development restriction areas in a municipality reduce flood losses per hectare. The coefficient of IS_MUN is nearly twice the coefficients of IS_FPA and IS_HSA. Similarly, the coefficient of DR_MUN is about twice the coefficients of DR_FPA and DR_HSA. This implies that flood losses per hectare are more sensitive to variations in municipalities' impervious surfaces and development restriction areas than those in flood-prone areas. The coefficients of IS_FDP and DR_FDP are insignificantly different from zero. In contrast, the coefficient of IS_HSA is positive and significant at the 0.05 level. The coefficient of DR_HSA is negative and significant at the 0.1 level, suggesting that flood losses per hectare are more sensitive to the variations in impervious surfaces and development restriction areas in HSAs than those in the floodplains. The insignificant coefficients of impervious surfaces and land use control areas in the floodplain may be attributed to relatively good land conservation in the floodplain. In most municipalities, the percentage of impervious surfaces in the floodplain is below 20%, while the percentage of development restriction areas is above 75%. Most runoff in the floodplain originates from upper land, whereas runoff generated from local impervious surfaces occupies a small portion.

Although the correlation and regression analyses do not suggest that flood loss is more sensitive to impervious surfaces and development restrictions in HSAs than those in other areas, it does not imply that the land use impact on flood losses is the same within or outside HSAs. The bias in the flood loss data may distort the results of this study. Because only mortgaged properties in the 100-year floodplain have a mandatory requirement of flood insurance, insured properties are concentrated in the floodplain. Many flood damages outside the floodplain were not recorded in the NFIP claims. This bias can cause an underestimation of the impact of land use in HSAs on flood loss. Even though the bias exists, the analyses in this study suggested that the percent of impervious surfaces in HSAs had a greater impact on flood losses per hectare than the percent of impervious surfaces in the floodplain. Future studies need to address the bias in flood loss data. One strategy can be collecting additional data to reflect flood losses outside the floodplain, including inferred losses through mapping of actual flood extent (e.g., using orthophotography gathered during flood peaks) against home locations. Another strategy is to analyze the precise location of individual flood insurance claims to identify the impact of land use in HSAs on flood losses.

4.5 Conclusions

This study used correlation analysis and linear regression to examine the impacts of impervious surfaces and development restriction areas on flood losses across the entire municipality, and within flood-prone areas, HSAs, and the 100-year floodplain of each municipality. The results suggested that a 1% increase in a municipality's impervious surfaces correlates to a 6.4% increase in flood insurance claim payments per hectare from 2010 to 2020, and a 1% increase in the municipality's development restriction areas correlates to a 4.3% decrease in flood insurance claim payments per hectare. However, model results did not provide evidence to support that impervious surfaces and land use control areas in HSAs have greater impacts on flood losses than those in other areas. This result did not imply that the impacts of land use in HSAs are no different than those outside HSAs, as the flood insurance claims fail to reflect flood damages outside the floodplain.

CHAPTER 5

DEVELOPING PROACTIVE STRATEGIES TO ENHANCE COMMUNITY FLOOD RESILIENCE

5.1 Flood Resilience

Resilience refers to the capability of a system to return to an equilibrium state after an external disturbance, whereas the resistance concept aims to prevent changes in system function (Irwin et al., 2016). The concept of resilience was first introduced to the field of ecosystem and ecology (Holling, 1973) and evolved into several other areas, including psychology, engineering, economy, public health, and social science(Bahadur & Pichon, 2017; McClymont et al., 2020). Different disciplines have various definitions of resilience, which can be summarized into three different frameworks (Disse et al., 2020; Nofal & van de Lindt, 2020; Zevenbergen et al., 2020):

(1) Engineering resilience refers to a system's ability to reduce the probability of failure, reduce the consequence during failure, and rapidly recover to the pre-disturbance state or equilibrium (bouncing back).

(2) Ecological resilience refers to a system's capacity to withstand or absorb disturbance and maintain the system's function under a wider range of disturbances.

(3) Socio-ecological resilience refers to a system's ability to anticipate, absorb, recover from, and reorganize in response to recurrent disturbance. The system with socio-ecological resilience will continuously learn, adapt, and transform to accommodate the gradual external stresses (e.g., climate change) and shocks on it.

Engineering resilience is usually applied in technological systems (e.g., buildings and infrastructures) to reflect the stability of the system functions, which emphasizes the return to the pre-disturbance state, whereas ecological resilience is used to cope with the complex and dynamic systems that have multiple equilibrium states to persistent the system function. The socio-ecological resilience is developed from ecological resilience, which additionally acknowledges the adaptive capacity of complex systems to adjust to long-term changes like climate change. As flooding engages with various socio-economic and environmental factors and its intensity and frequency are affected by the changing climate, community flood resilience is a kind of social-ecological resilience, referring to the capacity of a community to accommodate, recover from, and adapt to the adverse effects associated with flood events. Flood resilience does not guarantee the absence of any flood losses but rather emphasizes mitigation of flood impacts, rapid recovery from disturbances, and continued adaptation to future threats (Bulti et al., 2019).

Numerous resilience frameworks have been developed to evaluate and guide resilience establishment from various aspects (Bulti et al., 2019; Cai et al., 2018; Nguyen & Akerkar, 2020). Most of them recognize that community resilience is a comprehensive capability involving society, economy, human resources, physical condition, natural resources, and infrastructure components (Nguyen & Akerkar, 2020). A representative framework is the Zurich flood resilience ('5C-4R') framework. It attributes the community's resilience to five sources of capital ('5C'): physical, natural, financial, human, and social capitals (Keating et al., 2014, 2017). Physical capital refers to the built environment and infrastructure of a community; natural capital denotes the natural resource base, e.g., land, water, and biological resources; financial capital refers to financial resources to foster community resilience to future hazards; human capital refers to the education, skills, and health of household members; social capital refers to the cooperative and mutually beneficial social relationships, networks, and close social bonds. The natural capital greatly depends on the landscape's resilience, which is the foundation of community resilience.

5.2 Resilient Landscape

A resilient landscape is one that maintains essential ecological functions, supports robust native biodiversity, and upholds critical landscape processes over time, even amid changing conditions and various stressors. Resilient landscapes play a pivotal role in flood resilience by incorporating nature features into water flow management and flood mitigation (Huang et al., 2022; Lafortezza et al., 2018; Luo et al., 2023; Palazzo & Wang, 2022). Flood risks can be substantially reduced by emphasizing the natural functions of the landscape. For example, wetlands absorb excess rainwater and reduce the speed of runoff. Floodplains provide areas for rivers to overflow safely, thus lowering the risk of flooding in populated areas. Riparian buffers, with their vegetation, trap sediments, and filter pollutants, improving water quality and preventing soil erosion. Nature-based solutions, such as rain gardens, green roofs, bioswales, bio-detention basins, and permeable pavements, integrate green and blue infrastructures in landscapes. They significantly improve stormwater storage, soil water recharge, and evapotranspiration relative to traditional development and stormwater management approaches, thereby slowing down runoff and reducing the burden of sewer discharge systems. These natural and semi-natural systems reduce the severity and frequency of floods, protect infrastructure, and support quicker recovery post-flooding, making communities more resilient. Meanwhile, these systems also provide multiple ecosystem services, such as habitats, clean water and air, cooling effects, and aesthetic values, to foster biodiversity and sustainability in landscapes (Beller et al., 2015).

Landscape resilience is commonly achieved through the planning, management, and design of landscapes. Landscape planning involves the master plan of development and municipal land use ordinances, controlling the macro-scale land use. Landscape planning should preserve and restore natural habitats and ensure connectivity between them to allow species movement and adaptation (Ahern, 2013; Huang et al., 2022; Qiu et al., 2014). Sustainable management practices that use native plants help maintain the health and functionality of the landscape (Beller et al., 2015). Thoughtful landscape design that incorporates green infrastructure and low-impact development techniques further enhances water management and reduces urban runoff (Huang et al., 2022; Palazzo & Wang, 2022; Van Long et al., 2020). Building a resilient landscape cannot occur without the engagement of local communities in these processes. Their participation ensures that the landscapes meet their needs and fosters a sense of ownership and responsibility. This holistic approach not only mitigates flood risks but also promotes ecological health and community well-being, creating a robust foundation for long-term resilience.

5.3 Significance of the HSAs to Resilient Landscape

HSAs are critical components in the design and management of resilient landscapes. Because HSAs have a high propensity to saturation and direct hydrological connections to surface water bodies, they indicate the sources areas of runoff in landscapes (Agnew et al., 2006; Walter et al., 2000). Our study has found that flood risk inside HSAs is higher than outside. These areas can delineate susceptible areas to floods, especially for pluvial flooding. Land development should avoid HSAs. As HSAs are often in topographically converging areas, encroaching on these areas will likely induce dramatic increases in runoff, leading to severe flood damage. Another significance of HSAs to a landscape is their hydrologic linkage to surface water bodies. Water-borne pollutants and sediments in these areas can rapidly move to surface water bodies with rainwater runoff. Finally, many HSAs overlap with wetlands, riparian zones, floodplains, and other regions with high water tables or frequent water flow, which play a vital role in maintaining ecological balance and hydrological function. By preserving the natural hydrologic function in HSAs and detaining or retaining runoff within these areas, communities can enhance their resilience to climate change, mitigate the effects of extreme weather events, and ensure the sustainability of water resources.

In the context of resilient landscapes, HSAs can help stakeholders identify flood-prone areas in addition to the 100-year floodplain and evade high-risk regions. Land use planners and managers can use HSAs to set up a priority for property acquisition and relocation. Thoughtful landscape designs can apply green infrastructures near and within HSAs to detain runoff from these areas, thereby reducing the severity of floods. Preserving these areas from development can benefit the water quality and biodiversity of a landscape. These areas support biodiversity by providing essential habitats and corridors for wildlife, contributing to the overall health of the ecosystem. Moreover, HSAs can improve the aesthetic and recreational value of landscapes, offering green spaces that enhance the quality of life for local populations. Effective management and conservation of HSAs are therefore crucial for building landscapes that are not only resilient to environmental stresses but also capable of supporting human well-being and ecological integrity over the long term.

5.4 Suggestions for Building Resilient Landscape

As the critical role of HSAs in landscape resilience, stakeholders of land use and flood risk management have to emphasize the preservation and restoration of these areas and apply natural-based solutions to regulate and treat stormwater in these areas proactively. Our suggestions for flood resilience strategies based on the concept of HSAs are comprised of four primary components. First, in the landscape planning phase, the extent of HSAs needs to be accurately mapped out and publicized to draw stakeholders' attention to these areas. The master plan and municipal ordinances should be revised to prohibit new constructions in HSAs and their adjacent areas. Restoration plans should be made for developed HSAs to gradually restore the landscape to its natural condition.

Second, in the landscape design phase, buffers and stormwater retention / detention / infiltration basins should be designed for HSAs. Because HSAs are active source areas of runoff, we suggest surrounding each HSA with vegetated buffers (woodlands or grasslands) to detain runoff and filter pollutants and sediments (Kato & Huang, 2021; M. Kim et al., 2021; Luo et al., 2023; Van Long et al., 2020). Direct hydrologic connections between HSAs and surface water bodies should be restricted to slow runoff velocity, while indirect connections through green infrastructures can be restored and maintained (Luo et al., 2023). Green spaces, such as forests and grasslands, can be maintained or created at the upstream areas of HSAs to reduce water flows into them, while bio-detention basins and wetlands can be built at the downstream areas of HSAs to temporally store runoff generated from them and slowly release water into the hydrological network (Kato & Huang, 2021). Meanwhile, the connectivity among green spaces should be enhanced as much as possible to increase the water storage capacity and wildlife habitats(M. Kim et al., 2021; Luo et al., 2023).

Third, in the landscape management phase, local communities should use native plants adapted to local conditions to build and maintain green infrastructures to enhance the sustainability of the landscape. In an urban landscape, grey infrastructures, such as buildings, sewer systems, and roads, near HSAs should be retrofitted with green infrastructure and other low-impact development techniques to reduce their impacts on the natural functions of HSAs. In a rural landscape, the best management practices of fertilizer and pesticides should be implemented in agriculture fields, and buffers should be set around fields in order to prevent non-point pollution to HSAs.

Last but not least, FEMA should incorporate the concept of HSAs into its work, including the National Flood Insurance Program (NFIP). The present flood insurance program focuses on floodplain losses, which only reflect the losses of fluvial and coastal floods. The insurance program did not cover numerous losses caused by pluvial floods (Rosenzweig et al., 2018). The NFIP's flood maps are incomplete and outdated, so many property owners in HSAs are unaware of the flood risk they face. Including properties in HSAs in the NFIP can, on the one hand, provide financial support for recovery after floods; on the other hand, insurance premiums can persuade property owners to avoid HSAs. The concept of HSAs can also improve the performance of the NFIP’s Community Rating System in flood mapping, open space preservation, and property acquisition and relocation. Including HSAs in the flood mapping can greatly extend stakeholders’ awareness of flood risk. Preserving HSAs as open spaces can reduce property flood exposure and avoid future flood losses. Vulnerable properties needed for acquisition within floodplains can be efficiently identified with the help of HSAs. HSAs maps can also help people evade high-risk areas during property relocation.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

In this dissertation, we sought to provide a proactive strategy to enhance community flood resilience by incorporating landscape hydrological sensitivity and connectivity. The central hypothesis posited that landscape alterations driven by human decisions are often incongruent with the natural hydro-ecological functions, leading to increased flood risks. The study reviewed hedonic pricing studies on floodplain impact in the United States, examined the effects of landscape alterations in Hydrologically Sensitive Areas on property values, assessed the impacts of impervious surfaces and development restrictions (both regulatory and land preservation) in landscapes on flood losses, discussed the significance of incorporating HSAs in building resilient landscapes, and finally provided suggestions to improve flood resilience.

Our research provided significant insights into the relationship between landscape alterations, flood risks, and property values. Key findings include:

(1) The review of 31 peer-reviewed articles revealed diverse patterns of floodplain impacts on property prices, influenced by factors such as spatial location (coastal vs. inland, 100-year vs. 500-year floodplain) and temporal aspects (pre-flood vs. post-flood events). The floodplain impact on property values is the compound result of flood risks, insurance premiums, and local environmental amenities (e.g., shore proximity), varying from -48% to +61% over space and time. People's perceived flood risk directly affected this impact. Due to a lack of information, people are often exposed to flood risks without knowing it.

(2) The empirical analysis in Hillsborough and Montgomery Townships, New Jersey, confirmed that properties within HSAs experienced a significant price discount (-2%) compared to those outside HSAs. This impact was almost independent of the floodplain's impact, implying that HSAs imposed additional flood risks on properties within these areas.

(3) The empirical study in the Raritan region, New Jersey, found that increases in impervious surfaces in landscapes were associated with higher flood insurance claim payments per unit area, while increased land use control areas correlated with lower claim payments per unit area. However, the impacts of these factors within HSAs were not significantly different from those in other areas, indicating potential limitations in the flood insurance claims data in reflecting actual flood damages. Improved flood loss data (e.g., losses beyond flood insurance maximums, and non-insured losses) would likely increase the robustness of these findings.

These findings are significant for several reasons. First, they provide empirical evidence supporting the hypothesis that landscape alterations induce increases in flood risk. Second, the identification of HSAs extends flood risk awareness beyond conventional floodplain boundaries, offering a more effective approach to flood risk management. Moreover, the correlation between impervious surfaces, land use controls, and flood losses highlights the importance of effective land use planning and regulations in mitigating flood risks. These contributions are crucial for developing more effective flood management strategies. Realizing the importance of landscape management to flood risk management, we proposed a proactive strategy to enhance community flood resilience by incorporating the protection and regulation of HSAs in creating and maintaining resilient landscapes. Suggestions were provided on aspects of landscape planning, landscape design, landscape management, and flood insurance reformation.

While this study provided important insights, several limitations were identified. First, the binary designation of HSAs lacked specific probabilities of flood occurrence, like the 100-year floodplain. HSAs delineate the areas with a high probability of becoming saturated, but this probability is not equal to the flooding probability. Second, this study could not find clear evidence of the impact of HSAs imposed on flood losses due to a lack of precision location tags of flood claims and limited data on flood losses outside the 100-year floodplain. Moreover, the effects of HSAs' spatial configuration and connectivity on flood resilience were not analyzed in the study. Further research could address these limitations by developing more granular flood risk metrics, collecting more comprehensive flood loss data, and analyzing the land use and land cover patterns in landscapes.

Future studies should focus on exploring spatial and temporal patterns in HSA's impacts at different scales to improve our understanding of the role of HSAs in flood resilience and water resource management. Besides, incorporating HSAs in flood risk modeling will have significant implications for urban planning and flood risk management.

In conclusion, this dissertation has demonstrated the critical need for incorporating landscape hydrological sensitivity and connectivity into flood management strategies. By enhancing our understanding of the impacts of landscape alterations and providing a framework for more effective flood resilience, this research offers valuable insights for policymakers, urban planners, and communities aiming to mitigate flood risks and build resilient landscapes.

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