REDEVELOPMENT OF VACANT URBAN LAND:

PLANNING PERSPECTIVES ON DISASTER RECOVERY

A Dissertation

by

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ABSTRACT

After major disaster events, there is regularly a loss of population and increases in amounts of vacant land. Disaster recovery is notoriously uneven spatially, resulting in some neighborhoods lagging behind their neighbors during recovery. For such areas, disaster-induced vacant land can remain vacant many years after a hazard incident, sometimes never to fully recover.

The vacant properties and their redevelopment patterns are essential benchmarks for measuring recovery and community resilience. However, few studies have focused on the vacant land redevelopment process empirically after a disaster event occurs. The goal of this study is to identify factors facilitating or constraining the redevelopment of disaster-induced vacant land. The research questions include: (1) What are the differences in characteristics of disaster-induced and pre-existing vacant land and their respective redevelopment patterns? (2) How does the accumulation of vacant land affect redevelopment outcomes? and (3) What are the impacts of buyout programs on redevelopment outcomes?

One way to assess the redevelopment of vacant land is to compare systematic variations in redevelopment patterns across groups of neighborhoods and the characteristics of particular land parcels. This was accomplished by incorporating the longitudinal property tax records. Specifically, on Galveston Island and the Bolivar Peninsula in Texas, over 3,000 vacant lots emerged after Hurricane Ike.

For the first subsidiary question, this study employed an exploratory data analysis, case-control, and Propensity Score Matching methods to summarize the main characteristics of pre-disaster and disaster-induced vacant lots. Regarding the second and third subsidiary questions, this study employed three statistical models: logistic regression, Cox proportional hazards, and discrete time hazard models to capture the negative externalities of nearby vacant lots.

Results from this research could be used to find efficient ways of recognizing and managing properties and areas prone to redevelopment unevenness. The results showed that the negative externalities from vacant lots significantly discouraged land development within a 250-foot distance. Therefore, expediting redevelopment of both pre-disaster and post-disaster vacant lots is crucial to curtailing contagious negative externalities that will continuously interrupt redevelopment efforts. Planners and policymakers should make a concentrated effort to resolve long-existing vacant lots before and after a disaster event.

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Contributors

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NOMENCLATURE

ACS	American Community Survey
ADCIRC	ADvanced CIRCulation
AHP	Affordable Housing Program
AIC	Akaike Information Criterion
APA	American Planning Association
ATE	Average Treatment Effect
BCA	Benefit-Cost Analysis (or Cost-Benefit Analysis, CBA)
BIC	Bayesian Information Criterion
C-CAP	Coastal Change Analysis Program
CCD	Census County Division
CDBG	Community Development Block Grant
CDBG-DR	Community Development Block Grant - Disaster Recovery
CoE	Center of Excellence
DOAH	Department of Administrative Hearings
CRA	Community Reinvestment Act
FEMA	Federal Emergency Management Agency
GCAD	Galveston Central Appraisal District
GIS	Geographic Information System
HRRC	Hazard Reduction and Recovery Center
HUD	Department of Housing and Urban Development
IFG	Individual/Family Grant
IN-CORE	Interdependent Networked Community Resilience Modeling Environment
LDD	Limited Development District

LR	Likelihood Ratio
MHRP	Minimal Home Repair Program
MOE	Margin of Error
NFIP	National Flood Insurance Program
NHC	Natural Hurricane Center
NIST	National Institute of Standards and Technology
NOAA	National Oceanic and Atmospheric Administration
NSF	National Science Foundation
PD	Patch Density
PSM	Propensity Score Matching
SBA	Small Business Administration
SWAN	Simulating WAves Nearshore
TDR	Transferable Development Right
TOADS	Temporarily Obsolete Abandoned Derelict Sites
UGB	Urban Growth Boundary
UHD	Urban Homesteading Demonstration
USPS	United States Postal Service

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

On September 13, 2008, the eye of Hurricane Ike made landfall over the north end of Galveston Island, Texas, USA, with a 10 to 15 foot storm surge (Berg, 2009). While the seawall protected much of the city of Galveston from direct impact by the storm surge and wave action, a significant portion of the city still flooded. Bolivar Peninsula, a low-lying barrier land located northeast of Galveston Island, was the hardest hit community in Texas, due in large part to Ike's storm surge and battering waves. The surge and flooding resulted in extensive damage, forcing not only the relocation of many households, but also the abandonment of properties and generation of copious vacant land on both Galveston Island and Bolivar Peninsula.

Land left vacant after a disaster is an immediate and substantial phenomenon driven by physical damage to buildings and infrastructure. The intensification of social inequality and acceleration of urban decline can further obstruct recovery efforts (Peacock, Morrow, & Gladwin, 1997). Some neighborhoods lag behind their neighbors in regards to post disaster redevelopment (Hamideh, Peacock, & Van Zandt, 2018; Peacock, Van Zandt, Zhang, & Highfield, 2014), and consequently, vacant land can exist many years after a disaster event. Galveston Island and Bolivar Peninsula were no exception. By checking annual land-use transitions, the generation and recovery of vacant lots were identified before and after Hurricane Ike. More than half of the vacant lots were not redeveloped by 2017, nearly a decade after Hurricane Ike.

After Hurricane Ike, land that remained vacant added uncertainty with regards to reinvestment, slowing redevelopment. Vacant land is both a consequence of and trigger for urban decline (Dewar, 2006; Farris, 2001; Griswold & Norris, 2007; Han, 2014, 2017a, 2017b; Mikelbank, 2008; Newman & Saginor, 2014; Schilling & Logan, 2008; Shlay & Whitman, 2006; Skogan, 1990; Whitaker & Fitzpatrick IV, 2013; Zhang, 2012; Zhang & Peacock, 2009). Vacant land is known to be contagious, and empirical studies have connected degraded property values to adjacent vacant land (Griswold & Norris, 2007; Han, 2014, 2017a, 2017b; Mikelbank, 2008; Shlay & Whitman, 2006). Vacant land increases government expenditures because it can require government action such as increases in fire and police services, code enforcement, maintenance, foreclosure, and demolition costs associated with mitigating its negative effects on neighborhoods (Newman, Bowman, Lee, & Kim, 2016). These negative effects may increase the level of uncertainty in land development that impact on expected profits and drive developers to leave land vacant (Blair, Staley, & Zhang, 1996; Neutze, 1987; Titman, 1985). Therefore, revitalizing vacant land is vital to assuring sustainable urban development in terms of stabilizing tax bases, decreasing maintenance costs, and retaining the vibrancy of neighborhoods.

This research analyzes redevelopment of vacant lands after a major disaster event. Specifically, the research focuses on vacant lands that were once developed before a disaster event and became vacant due to disaster damage. In this case, post-disaster redevelopment can be understood in the context of resilience and disaster recovery. The argument is that an increase in vacant land slows down the disaster recovery process and negatively affects long-term redevelopment. So, this research asks, what factors facilitate or constrain the redevelopment of disaster-induced vacant land? In this research, annual property tax data is combined to create a longitudinal vacant land database. The spatial characteristics of pre- and post-disaster vacant land is then analyzed to contextualize the various types. Statistical analyses of longitudinal vacant land transitions are conducted to determine the probability of redevelopment, focusing on factors that usually hinder the recovery process. The redevelopment potential of vacant land is measured in terms of the type of land and duration left vacant. Findings from this research could be used to improve disaster recovery plans such as by identifying neglected areas that have a higher probability of long-term recovery issues and prioritizing reinvestment strategies following a major disaster.

Chapter 1 serves as an introduction to this study, including offering a brief explanation of the background, research questions, and research design based on the previous studies in the field of vacant land and disaster recovery research. Chapter 2 considers the existing research on vacant land, explaining its occurrence and proliferation through the concepts of natural vacancy rate, Neighborhood Change, and Broken Windows Theories. Chapter 2 also lists the various definitions of vacant land and their measurement in order to contextualize the various types. Chapter 3 explains the redevelopment of vacant land in the context of disaster recovery. Previous disaster recovery studies, particularly those analyzing recovery timelines and other factors, are described to provide a reference point for the duration of vacant land. Chapter 4 deals with the research design, including the study area, data collection and preparation, and data analysis methods. Chapter 5 and 6 present the results from the suggested exploratory analysis and statistical models. Chapter 7 is the conclusion chapter. It summarizes the key findings and related planning perspectives.

1.1 Research Questions based on Vacant Land Research

Definitions and measurements of vacant land vary by city and time. Definitions can be categorized by development status, either: 1) undeveloped land without any structures (Hearle & Niedercorn, 1964; Northam, 1971) or 2) pre-developed land with existing underutilized, unused, or abandoned structures (Accordino & Johnson, 2000; Bowman & Pagano, 2004; Coleman, 1982; Davidson & Dolnick, 2004; Greenberg, Popper, & West, 1990; Németh & Langhorst, 2014; Pagano & Bowman, 2000; Silverman, Yin, & Patterson, 2013). The latter definition incorporates the level of utilization, ranging from underutilized to abandoned. A multitude of elements are related to the utilization of structures, including whether the owner has stopped maintaining the property; refuses to meet the financial responsibilities of the property, such as paying property taxes and mortgage payments; and the property remains unused for an extended period of time (Hillier, Culhane, Smith, & Tomlin, 2003; Keenan, Lowe, & Spencer, 1999). Different definitions lead to different measures. Previous studies have measured the amount of vacant land in US cities at approximately 15% to 25%, based on survey results provided by city officials and residents (Hearle & Niedercorn, 1964; Newman, Bowman, et al., 2016; Northam, 1971; Pagano & Bowman, 2000). However, due to the lack of a unified definition of vacant land and differences in study area and timeframe, amounts of vacant land in different areas cannot be directly compared. Thus, a coherent and universal definition of vacant land is required to analyze the amount that appears in various US cities.

For most cities, transitory vacant land, a lot going from vacant to non vacant or vice versa, is not a serious issue, such as a vacant lot awaiting development or holding for sale. Conversely, land that remains vacant for "too long" is a significant problem, especially for slow-growing or depopulating cities (Bowman & Pagano, 2004). Little research has examined the effect of the duration land remains vacant on neighborhood redevelopment (Han, 2014), though many previous empirical studies have focused on the amount of and proximity to vacant land, in order to measure property devaluation in particular neighborhoods (Griswold & Norris, 2007; Han, 2014, 2017a, 2017b; Mikelbank, 2008; Shlay & Whitman, 2006). What remains unclear is how long is actually "too long" for a lot to remain vacant. The duration of vacant land (or delayed redevelopment) can serve as an indicator, demonstrating uncertainty in redevelopment attributed to the risk connected with reinvestment. An empirical study of the effects of the vacant land is needed to estimate the likelihood of redevelopment and level of negative effect on the neighborhood. The results could then be used to separate transitory and problematic plots of vacant land, as well as to identify neighborhoods prone to this type of problem.

1.2. Research Questions based on Disaster Recovery Research

The current body of disaster research has limitations due to the unpredictability of disaster occurrences, unavailability of experimental control, sampling bias, and perishable data conditions (National Research Council, 2006). Many research findings are based on cross-sectional and single case studies with small sample sizes and limited experiment designs (Bates & Peacock, 1987; Drabek, 2012; Rubin, Saperstein, & Barbee, 1985). In addition, little empirical research has focused on the redevelopment process and timeline before the 2000s (P. R. Berke, Kartez, & Wenger, 1993; Dynes, 1989; Passerini, 2000). Since the 2000s, researchers have focused on the level of recovery and recovery time, comparing physical conditions in pre- and post-disaster built environments (Stevenson, Emrich, Mitchell, & Cutter, 2010). For example, researchers have utilized changes in land use (Crawford et al., 2017; Zhang, 2012), video images (Curtis, Mills, Kennedy, Fotheringham, & McCarthy, 2007), property values (Bin & Kruse, 2006; De Silva, Kruse, & Wang, 2006; Hamideh et al., 2018; Peacock et al., 2014; Zhang & Peacock, 2009), and city-issued permits (Rathfon, Davidson, Bevington, Vicini, & Hill, 2013; Stevenson et al., 2010; Wu, 2004) to measure recovery outcomes.

While vacant land is known to have negative effects on neighborhood recovery outcomes, little academic work has considered vacant land after a disaster by estimating the negative impact of vacant land on recovery. Zhang (2012) studied the generation of vacant land after Hurricane Andrew in 1992 by estimating the probability of a residential parcel becoming vacant. The modeling result showed that the proximity to existing vacant lots can increase the likelihood of becoming vacant. This result implies that vacant land can spread. Crawford et al. (2017) measured a functionality change based on land use, structural damage, and repair status after an EF 4 tornado in 2011. Low-income and renter-oriented neighborhoods were more likely to have higher numbers of vacant lots. Despite the resulting damage and vacant land, how pre-disaster and disaster-induced vacant land slows down the recovery process is still in question. For example, the prevalence of vacant land may increase uncertainty about reinvestment that hinders redevelopment efforts and causes unevenness in terms of recovery (Blair et al., 1996; Neutze, 1987; Titman, 1985).

Vacant land can be remained undeveloped to promote urban resilience. For example, buyout programs are designed to acquire damaged or disaster exposed properties in flooding prone areas. The acquired properties can become public open spaces, green spaces, or flood storage areas. In this case, vacant land can contribute disaster mitigation by lessening expected damage due to future disaster events (Brody & Highfield, 2013). Unlike previous literature regarding vacant land in the context of urban decay and property abandonment, this perspective challenges the notion that long-lasting vacant land is a result of urban decline that should always be redeveloped. On the other hand, buyout land can be seen as randomly dispersed permanent vacant land in the middle of a neighborhood. Previous studies also highlighted the negative effects from buyout land regarding property value losses, crimes, and reinvestment in communities (Bukvic, Smith, & Zhang, 2015; U.S. Department of Housing and Urban Development, 2013).

The increasing occurrence of vacant land is common after catastrophic disasters. To mitigate the negative effects, redevelopment can be expedited through planning efforts. However, due to limitations in the previous research, several questions remain regarding finding efficient ways of recognizing and managing properties and areas prone to redevelopment unevenness.

Primary question:

What factors facilitate or constrain the redevelopment of disaster-induced vacant land?

Subsidiary questions:

- What are the differences in characteristics of disaster-induced and pre-existing vacant land and their respective redevelopment patterns?
- How does the accumulation of vacant land affect redevelopment outcomes?
- What are the impacts of buyout programs on redevelopment outcomes?

2. CHARACTERISTICS AND EFFECTS OF VACANT URBAN LAND

Because this research was designed to study large occurrences of vacant land and recovery post-disaster, it is essential to understand the definitions, characteristics, and adverse effects resulting from the presence of vacant land. First, this chapter reviews various definitions of vacant land. Many scholars have theoretically and empirically identified the definitions of vacant land that closely related to their causes and characteristics. Second, this chapter identifies the causes of vacant land in terms of external and global factors (i.e., deindustrialization, job loss, and outmigration) as well as internal and local factors (i.e., housing market failure in downtown areas, property tax, zoning, and annexation). In addition, this chapter introduces the concept of natural vacancy rates designed to explain the existence of vacancy regarding housing market fluctuation. Third, the neighborhood change theory and the broken windows theory are introduced with the recent empirical studies presenting the negative externalities from vacant land. Vacant land has been interpreted as both a trigger and a consequence of urban decline. Fourth, this chapter illustrates the ongoing efforts to identify the inventory of vacant land. The sources of vacant land data and their measurements were explained.

2.1. Definitions of Vacant Land

Various definitions exist for vacant land. Multiple definitions help to identify the differences between the types of vacant land in diverse urban contexts. However, the use of inconsistent definitions has hindered the coherent understanding of the amount and related implications. This inconsistency issue has been raised in earlier studies. When Barber (1938) pooled vacancy data from ‘real property inventories sponsored by the federal government’ and ‘private surveys conducted by local organizations', he noticed that federal vacancy data were more likely to include marginally livable dwelling units as vacant or occupied. Conversely, Barber (1938) found that local governments relied on realtors to collect vacancy data. Realtors tend to have a stricter view regarding undesirable residential structures and exclude marginally livable structures from their surveys than federal property assessors. This inconsistency in the definition of a livable housing unit made a noticeable difference between the two datasets. When comparing a city with both, local data consistently underestimated vacancy rates. As a result, the two datasets are not comparable. These kinds of inconsistency issues still exist (Bowman & Pagano, 2004; Newman, Bowman, et al., 2016): since the formation and type of vacant land can vary by city, there are many definitions and classifications of vacant land currently in use.

Schenk (1978) focused on the causal factors of vacant land, such as the excessive supply of unused land over the demand for development, and the unmatched land characteristics important for improvement. Unmatched land characteristics can include utilities, taxes, hazard risks, ownership, neighbors, and physical limitations such as size, slope, and shape. In the same vein, Northam (1971) categorized vacant land types as: 1) parcels considered remnant due to size and shape, 2) parcels with physical constraints, 3) cooperative reserve parcels, 4) parcels held for speculation, and 5) institutional reserve parcels.

The differences in definitions and classifications represent various symptoms as well. Vacant land can be seen as either greenfield or brownfield. Greenfield indicates undeveloped land in neighborhoods or urban fringe areas. Dead land or dead space (Coleman, 1982) is a traditional way of identifying derelict land that is unused and thus excluded from the real estate market. Brownfield indicates abandoned land mainly used as industrial sites (Kivell, 2002). Brownfield may be contaminated by abandoned and damaged structures (Alker, Joy, Roberts, & Smith, 2000). In general, the existence of damaged and abandoned buildings on contaminated land hinders revitalization efforts. Greenberg et al. (1990) identified Temporarily Obsolete Abandoned Derelict Sites (TOADS) including deferred maintenance and abandoned land and structures neglected by owners and residents as well as unused vacant land in urban fringe areas generated by urban expansion. Wasteland and derelict land (Kivell, 2002) are unused, damaged, and contaminated industrial land resulting from changes in the local economy. Zombie properties (Silverman et al., 2013) are vacant land in shrinking cities, including contaminated land and abandoned buildings, the presence of which can hinder redevelopment efforts.

Table 1 lists definitions of vacant land obtained from the literature. Vacant land can be identified by its structure type, level of usage, duration of vacancy, and upkeep of financial responsibilities. Each definition contains a unique mixture of aspects. For example, some earlier definitions only designated undeveloped land without any structures (Hearle & Niedercorn, 1964; Northam, 1971), while other definitions included pre-developed land with existing structures (Accordino & Johnson, 2000; Bowman & Pagano, 2004; Coleman, 1982; Davidson & Dolnick, 2004; Greenberg et al., 1990; Németh & Langhorst, 2014; Pagano & Bowman, 2000; Silverman et al., 2013).

Table 1. Aspects of Vacant Land from the Literature

Structure type	**Level of utilization**	**Minimum period**	**Financial responsibility**
(with, without, or once developed with) - Structures - Buildings (that can be) - Damaged - Destroyed - Demolished	- Undeveloped - Unused - Underutilized - Vacant - Abandoned	(properties should be vacant more than) - 60 days - 90 days - 120 days - 2 years (to be defined as vacant land)	(owners did not pay their property taxes or mortgage) - Tax delinquent - Foreclosure

The level of utilization is another key aspect of defining vacant land. It includes undeveloped (Davidson & Dolnick, 2004; Hearle & Niedercorn, 1964; Németh & Langhorst, 2014), unused (Bowman & Pagano, 2004; Davidson & Dolnick, 2004), underutilized (Baudry, 1991; Bowman & Pagano, 2000, 2004; Németh & Langhorst, 2014), vacant and abandoned land or properties (Accordino & Johnson, 2000; Bowman & Pagano, 2000). While undeveloped land directly relates to land without any improvements, other aspects are not clear, such as the presence of structures and any existing structures' physical status. For example, vacant land can indicate both empty land and buildings that are not being actively used. Structures on vacant land can be unused despite having no structural damage or may have damage ranging from boarded up windows to complete destruction.

Each local government has a different level of sensitivity concerning vacant land, and in general, transitory vacant land is not a serious issue. Accordingly, some definitions have included the minimum period of the land's unused or underutilized status, setting thresholds such as 60 to 120 days (Pagano & Bowman, 2000) and two years (Accordino & Johnson, 2000; United States General Accounting Office, 1978). Measurements of vacant land also affect aspects of vacancy period, the time during which a property lasts as unused. For example, the Department of Housing and Urban Development (HUD) Aggregated United States Postal Service (USPS) Administrative Data on Address Vacancies identifies units as vacant on a quarterly basis if residents fail to collect their mail for more than 90 days (U.S. Department of Housing and Urban Development, 2018). In this case, they measure vacant addresses for properties with buildings. Another example is measuring vacant land based on annually reported property tax records. In Texas, county tax offices issues properties' land uses each year (County of Galveston Office of Tax Assessor-Collector, 2020). Unlike the HUD-USPS address vacancies data, county tax offices in Texas identify properties without having a building as vacant lots. In this case, the duration of vacancy can only be measured on an annual basis.

Financial responsibility can also be used to determine vacancy and abandonment status, including whether owners pay their property taxes and make mortgage payments (Hillier et al., 2003). However, not all tax- and mortgage-delinquent properties are necessarily unused, abandoned, or damaged. Some tax-delinquent properties may not be notably different from tax-current lots (Whitaker & Fitzpatrick IV, 2013). Foreclosure is a transitory state existing between tax delinquency and tax lien sale, and may not properly represent the status of urban decline (Whitaker & Fitzpatrick IV, 2013). Regarding the status of financial responsibility, Apgar (2012) introduced the concept of the “underwater homeowner,” defining it as when the loan value exceeds the market value of the owner’s house. In such cases, underwater homeowners may consider defaulting on their mortgage, especially if they cannot sell their property or refinance their loan. Accordingly, underwater homeowners are less likely to have disaster insurance and to be qualified for SBA loans after disaster events (Comerio, 2014).

2.2. Causes of Vacant Land: Depopulation and Housing Market Fluctuation

Contextualizing the causes of vacant land is essential to understanding its characteristics. Loss of population has been reported widely as a predominant causal factor that increases the occurrence of vacant land (Hollander, Pallagst, Schwarz, & Popper, 2009; Wiechmann & Pallagst, 2012). In general, vacant land that was once developed and became vacant due to population loss can be seen as a sign of urban blight. In the US, these developed and abandoned vacant lands are often located in urbanized areas, since sprawl and the relative growth of suburbs prompted the outmigration from city centers.

Urban depopulation has a long history; it can be traced back to the Middle Ages and Early Modern period in Europe and Asia; more recently, it occurred in the US after the Second World War (Hollander et al., 2009). Sixteen of the 20 largest cities in the 1950s lost a significant amount of their population as a consequence of deindustrialization (Hollander et al., 2009). The terms “shrinking city” (Hollander et al., 2009) and “legacy city” (Mallach & Brachman, 2013) were coined to identify these areas of depopulation. The Shrinking Cities International Research Network defined a “shrinking city” as “a densely populated urban area with a minimum population of 10,000 residents that has faced population losses in large parts for more than two years and is undergoing economic transformations with some symptoms of a structural crisis” (Hollander et al., 2009. p. 6). Similarly, “legacy cities” were defined as cities “with populations less than 20 percent of peak but larger than 50,000” (Mallach & Brachman, 2013. pp. 2-3). Due to deindustrialization and subsequent job loss and outmigration, many depopulated cities now exist in the US.

In addition to deindustrialization, housing market failures in inner city residential areas, shortsighted municipal tax laws and zoning, and confusing property assessment and disposal procedures are also known to contribute to vacant land occurrences in urban areas (Accordino & Johnson, 2000; F. S. Alexander & Powell, 2011; Berkman, 1956; Bowman & Pagano, 2004; Hughes, 2000; McGovern, 2006; Pagano & Bowman, 2000). Another critical factor shaping the occurrence of vacant land is annexation (Bowman & Pagano, 2000; Newman, Bowman, et al., 2016). Unlike vacant land caused by depopulation, growing cities have expanded their urban boundaries to retain space for expected growth. In such cases, vacant land may exist in peripheral urban areas and indicate the capacity for future development.

The existence of vacant land can be interpreted in the context of housing market fluctuation and turnover in both supply and demand sides. Early housing vacancy studies attempted to find a natural vacancy rate, an inevitable rate that would bring equilibrium to the housing price adjustment mechanism (Blank & Winnick, 1953; Rosen & Smith, 1983; L. B. Smith, 1974). The housing price adjustment mechanism assumes that landlords try to maximize their revenue by filling their vacant units with renters. In the short term, the supply of new housing units is fixed, and landlords and renters try to find optimal rents. In such cases, a certain vacancy rate is expected. When there is no excess housing demand nor supply, rents are in equilibrium, and the natural vacancy rate represents frictions in the real estate market due to the decentralized housing market conditions between landlords and tenants. For example, every housing is unique in terms of its structural characteristics and its location, and landlords want to find the tenant who could pay the most. Tenants also have unique needs, and not all tenants will find an ideal housing. This conflict between landlords and tenants generates the natural vacancy rate.

Theoretically, fluctuations in the vacancy rate will converge on the natural vacancy rate. Thus, the natural vacancy rate can be used as a benchmark to compare vacancy rates. From 1930 to 1938, Blank and Winnick (1953) measured natural vacancy rates ranging from 1% to 7% in six US cities. Their research illustrated a convergence point between rent and occupancy ratio based on the annual urban residential vacancy data from Barber (1938). From 1961 to 1971, L. B. Smith (1974) measured natural vacancy rates ranging from 5% to 7.4% in five cities in Canada. He noted that the changes of rents depend on the vacancy rates, and rents changed quickly enough to keep up with fluctuating vacancy rates. Unlike these studies, from 1969 to 1980, Rosen and Smith (1983) found higher natural vacancy rates in 17 US cities, ranging from 5.5% to 16.7%, since they assumed rental units with excessive debt to be vacant units. Rosen and

Smith (1983) found that cities experiencing a higher degree of tenant turnover and rapid growth tended to have higher natural vacancy rates. Wheaton (1990) theoretically expanded the housing price adjustment mechanism by focusing on housing sales between buyers and sellers over housing rentals between landlords and tenants. The optimal number of vacant units was derived from the housing search process between buyers and sellers, and increases or decreases in vacancy rate were taken to signal adjustments in housing price. The supply side of housing units reacts relatively slower than does housing price change; accordingly, the number of vacant houses fluctuates until new units are built or demolished (Wheaton, 1990).

2.3. Vacant Land Theories: Occurrence and Proliferation of Vacant Land

The housing price adjustment mechanism and derived natural vacancy rates help explain why a city must have a certain number of vacant housings. Sternlieb, Burchell, Hughes, and James (1974) noted that market-based 'natural' vacancy rate theories tend to underestimate the factors affecting property owners' decisions regarding repairing, demolishing, rebuilding, or abandoning their properties. Especially in distressed urban areas, the occurrence of vacant land can be driven by individual landlords' or developers' decisions based on the profitability in land redevelopment (Sternlieb et al., 1974). For example, changes in job location, transportation, and income distribution can trigger social turnover and lower housing demand. In such cases, the occurrence of vacant land can be seen as a byproduct of neighborhood change (Featherman, 1977; Morgan, 1980) and a failure in redevelopment due to increased uncertainties in calculating the opportunity costs and expected yields of redevelopment (Blair et al., 1996; Neutze, 1987; Titman, 1985).

2.3.1 Neighborhood Change Theory

A neighborhood is a "natural area" that follows geographical and social relationship patterns. Robert Ezra Park (1952) argued that aspects of natural areas include discrete geographical spaces and residents with unique social, demographic, and ethnic compositions. Residents of natural areas demonstrate distinguishable behaviors, following their own particular social systems of rules, norms, and patterns of interaction. Residents select to live with a specific social group, which can in turn modify residents' behavior (Useem, Useem, & Gibson, 1960).

The invasion-succession model was designed to explain the demographic and socioeconomic changes in neighborhoods that result from migration (Robert Ezra Park, 1952). The invasion-succession model explains competition, confliction, and accommodation between migrating and existing residents. During the invasion-succession process, a "tipping point" may emerge where new residents overwhelm existing residents. Eventually, the new residents become the dominant group and the other residents are driven out (Schwirian, 1983). In the context of the invasion-succession model, three theories can be used to describe the neighborhood deterioration process in urban areas that generate once developed and now demolished vacant land or land with abandoned structures: Concentric Zone Theory, which views neighborhood change as an invasion of lower-status social populations (Robert E Park & Burgess, 1925); Sector Theory, which focuses on urban deterioration and consequent pull and push factors (Hoyt, 1939); and Stage Theory, which conceptualizes the collapse and renewal process of a neighborhood (Hoover & Vernon, 1959). These theories view the appearance of vacant land as a sign that property owners lack reinvestment decisions due to social issues like urban degradation, racial antagonism, and/or crime. Hoover and Vernon (1959) suggested five stages of the neighborhood lifecycle: development, transition, downgrading, thinning out, and renewal. During the shifts between each of these five stages, population, land use, and the quality of housing all fluctuate. Consequently, these shifts are often accompanied by widespread housing abandonment (Featherman, 1977; Morgan, 1980). In addition, these shifts are often derived from a "growth machine" (Molotch, 1976), in which directed urban growth in favor of select interest groups results in an uneven distribution of benefits throughout the neighborhood lifecycle process (Molotch, 1976).

2.3.2. Broken Windows Theory and Negative Externalities

J. Q. Wilson and Kelling (1982) presented Broken Windows Theory to explain why social disorder such as crime and vandalism is more likely to occur in distressed urban areas. Since the 1980s, its core idea that negative perceptions stemming from visible urban disorder may affect human behavior has offered a framework for connecting degraded urban built environments such as vacant land to the quality of life in adjacent neighborhoods (Garvin, Branas, Keddem, Sellman, & Cannuscio, 2013; Teixeira, 2016).

The existence of vacant land in the middle of a neighborhood is a visible symptom of urban decline (Dewar, 2006; Farris, 2001; Griswold & Norris, 2007; Han, 2014, 2017a, 2017b; Mikelbank, 2008; Newman & Saginor, 2014; Schilling & Logan, 2008; Shlay & Whitman, 2006; Skogan, 1990; Whitaker & Fitzpatrick IV, 2013; Zhang, 2012; Zhang & Peacock, 2009). Vacant land in a neighborhood spreads negative externalities (Bowman & Pagano, 2004); much research has tried to estimate the amount of such externalities by measuring property value decline. Hedonic price models were used in several studies to measure the effect of housing abandonment on housing prices (Mikelbank, 2008). Table 2 summarizes the estimated negative externalities as described in previous research on this topic.

Table 2. Negative Externalities as Estimated in Previous Studies

Authors	Study Area	Unit of Analysis	Negative Externalities
Temple University Center for Public Policy (2001)	Philadelphia, Pennsylvania (1984 to 2000)	Abandoned houses	One abandoned house reduced sales prices of other properties by $6,720 in a census block.
Immergluck and Smith (2006)	Chicago, Illinois (1997 to 1998)	Foreclosure of single-family houses	One foreclosure within a 1/8-mile distance resulted in a 0.9% to 1.1% decline in transaction value.
Shlay and Whitman (2006)	Philadelphia, Pennsylvania (2000 to 2001)	Abandoned properties	An abandoned home within a 450-foot distance decreased housing sales prices between $3,500 and $7,600. In a census block, one and five abandoned homes decreased housing sale prices $6,900 and $11,300, respectively.
Griswold and Norris (2007)	Flint, Michigan (2002 to 2005)	Residential structures and vacant residential lots	Within a 500-foot distance, one additional abandoned structure and one additional vacant lot reduced sales values by 2.27% and 1.5%, respectively.
Mikelbank (2008)	Columbus, Ohio (2006)	Vacancy, abandonment, and foreclosure	Within a 250-foot distance, one additional vacant/abandoned property reduced sales values by 3.5% to 4.0%, and one additional foreclosure reduced sales values by 2.1% to 3.1%.
Z. Lin, Rosenblatt, and Yao (2009)	Chicago, Illinois (1994 to 2006)	Foreclosures	Within a radius of 0.1km from a foreclosure, there was up to a 9.7% decrease in property values.
Whitaker and Fitzpatrick IV (2013)	Cuyahoga County, Ohio (2010 to 2011)	Tax delinquency, vacancy, and foreclosure	Within a 500-foot distance, one vacant, tax delinquent, or foreclosure home resulted in 1.8%, 1.5%, or 4.7% decrease in property sales values, respectively.
Han (2014)	Baltimore, Maryland (1991 to 2010)	Abandoned properties and foreclosures	One addition abandoned property located within a 250-foot distance reduced sales values by 0.5% (if abandoned for less than one year) to 0.9% (if abandoned for more than three years). One additional foreclosure within a 250-foot distance reduced sales values by 1.4%.

The Temple University Center for Public Policy (2001) reported that every year from 1984 to 2000, 1,348 properties were abandoned in Philadelphia, Pennsylvania. In 2001, there were 26,115 vacant houses and 30,729 vacant lots in the city. The results from multiple hedonic price models indicated that one additional abandoned house in a census block reduced the sales prices of other properties by $6,720. In neighborhoods with similar socioeconomic and housing characteristics, accessibility of financial resources and the number of houses facing financial burdens changed the occurrence of housing abandonment. For example, in each census tract, a 10% increase in the acceptance rate for home improvement loans and 10% decrease in conventional mortgage loan lenders reduced housing abandonment by 9% and 24%, respectively.

In their examination of Chicago, Illinois, Immergluck and Smith (2006) estimated decreases in property values due to 3,750 foreclosures in 1997 and 1998 by analyzing 9,600 single-family housing transactions in 1999. Each additional foreclosure within a 1/8-mile distance resulted in a 0.9% to 1.1% decline in transaction value. Each additional foreclosure within a 1/4-mile distance resulted in a 0.3% decline in transaction value. The negative externalities due to foreclosures were worse in low- and moderate-income neighborhoods. In low- and moderate-income census tracts, each additional foreclosure within a 1/8-mile distance resulted in a 1.4% to 1.8% decline in transaction value. The cumulative value loss due to one foreclosure ranged from $159,000 to $371,000. The total 3,750 foreclosures decreased citywide property values from $598 million to $1.39 billion.

Shlay and Whitman (2006) suggested a framework applying the number of abandoned properties in a census block, using the distance from abandoned housing by concentric 150-foot radius groups. The abandoned properties were divided by their land-use type, such as commercial, residential, and vacant lot. The results indicated that in Philadelphia, Pennsylvania, the existence of abandoned housing within a 450-foot distance decreased housing sales price from $3,500 to $7,600. For a census block, the housing sales price was devalued around $6,900 for one abandoned house and $11,300 for five abandoned houses.

Griswold and Norris (2007) assessed the number of abandoned single-family and multifamily residential structures, as well as the number of vacant residential lots, by 500-foot distance groups up to 1,500 feet. In Flint, Michigan between 2002 to 2005, there were over 5,000 vacant or abandoned housing units in over 44,000 residential properties. Based on 6,368 housing sales records, one additional abandoned structure and one additional vacant lot within a 500-foot distance reduced sales values by 2.27% and 1.5%, respectively.

Mikelbank (2008) separately estimated the effects of “vacancy and abandonment” and “foreclosure,” since both are likely to be located in a city center while foreclosures are often spread throughout a city. In Columbus, Ohio, for 9,046 single-family housing transactions in 2006, the number of vacant, abandoned, and foreclosed properties were calculated according to four concentric groups by increasing 250-foot radii. There were 4,152 vacant and abandoned properties and 6,083 foreclosure filings in 2006. The modeling results suggested that the negative effect was highly concentrated around vacant and abandoned properties rather than foreclosures. That negative effect covered up to a 500-foot distance for vacant/abandoned property and 1,000-foot distance for foreclosures. On average, within a 250-foot ring, one additional vacant/abandoned property reduced sales values by 3.5% to 4.0%, and one additional foreclosure reduces sales values by 2.1% to 3.1%.

Z. Lin et al. (2009) estimated diminishing negative externalities by increasing time and distance from foreclosures. The researchers randomly pulled 14,427 non-foreclosure owner-occupied properties from a pool of loans delivered to Fannie Mae in the Chicago Primary Metropolitan Statistical Area between 1994 and 2006. The most severe negative effect occurred within a 0.1km distance from a foreclosure, up to a 9.7% decrease in property value. The negative effect existed up to a 0.9km distance. In addition, even if a foreclosure was liquidated a few years before the sale, it also reduced property values. A negative effect still existed, a 4.0% decrease within a radius of 0.1km from the foreclosure if it was liquidated more than five years ago.

Whitaker and Fitzpatrick IV (2013) estimated the externalities due to property tax delinquency, vacancy, and foreclosure in Cuyahoga County, Ohio. Based on 1,3991 housing sales between 2010 and 2011, one vacant, tax delinquent, or foreclosed home within a 500-foot distance resulted in a 1.8%, 1.5%, or 4.7% decrease in property sales values, respectively. The negative effects from the combinations of tax delinquency, vacancy, and foreclosure were estimated separately. For example, a home could be “vacant, tax current, and non-foreclosed” or “occupied, tax delinquent, and non-foreclosed.” These two cases reduced nearby sales values by 1.8%.

Han (2014, 2017a, 2017b) illustrated the amount, distance, and duration of abandoned properties and foreclosures degrading nearby property values in Baltimore, Maryland. Property sales records and foreclosure filings were obtained for 1991 to 2010 and a longitudinal analysis applied; the authors then compared the repeat sales records for each house. The number of abandoned properties was calculated for each of four distance groups: 250 feet, 500 feet, 1,000 feet, and 1,500 feet. The duration of abandonment was organized into three groups: less than a year, one to three years, and more than three years. For one additional abandoned property located within a 250-foot distance, sales values were reduced by 0.5% if the property was abandoned for less than a year, 0.7% if abandoned for one to three years, and 0.9% if more than three years. Every additional foreclosure within a 250-foot distance reduced sales values by 1.4%. Han (2017a) presented the non-linear relationship between the number of abandoned properties within 250 feet and decreased property values. Han (2017b) then estimated the varying impact of housing abandonment due to differences in neighborhood characteristics.

In summary, vacant land can be seen as a type of neighborhood disorder, spreading negative externalities, which can be estimated by reduced property values (Griswold & Norris, 2007; Han, 2014, 2017a, 2017b; Immergluck & Smith, 2006; Z. Lin et al., 2009; Mikelbank, 2008; Shlay & Whitman, 2006; Whitaker & Fitzpatrick IV, 2013). Adjacent properties can give up on redevelopment and eventually become vacant land, due to decreasing property values. Based on property owners' and developers' rational decisions, the decreased profitability of housing can cause maintenance to be deferred (Sternlieb et al., 1974) and redevelopment can become an unfeasible option (Blair et al., 1996; Neutze, 1987; Titman, 1985). When the loan value exceeds the market value of a house, owners may consider defaulting on financial responsibilities such as property taxes and mortgages (Apgar, 2012). Eventually, decreased housing values can cause vacancies to proliferate.

Vacant land can generate a massive burden on the finances of local governments. For example, while the city of Dayton, Ohio had already spent $27 million to demolish abandoned structures, there were 4,159 abandoned structures listed in 2012. On average it takes $16,000 to demolish an abandoned structure (Hulsey, 2018). Apgar, Duda, and Gorey (2005) reviewed the direct municipal cost of foreclosure by addressing seven scenarios, including cost for demolition, conservation, crime, fire, trash, and direct property tax losses. The total municipal cost ranged from $27 to $34,199 due to vacancy status, demolition status, criminal activity, fire, and processing costs in Auction, Housing, and Demolition Court and the Department of Administrative Hearings (DOAH). Accordingly, due to shortages in tax revenue caused by increased maintenance costs, local governments often decrease investment in infrastructure such as water, electricity, gas, communications systems, and public transportation (Newman, Bowman, et al., 2016; Pearsall, Lucas, & Lenhardt, 2014; Shlay & Whitman, 2006). The reduced quality and number of public amenities then accelerates urban decline and the generation of vacant land (Leavitt & Saegert, 1988).

Lots that remain vacant for more than several years can be a significant urban problem (Bowman & Pagano, 2004). New vacant lots were found to be more likely to be redeveloped quickly than were long-vacant lots (Németh & Langhorst, 2014) because long-term vacant lots were more likely to contain multiple factors hindering their redevelopment. For example, in addition to the gap between land supply and demand, Schenk (1978) listed causal factors that related to undesirable characteristics of the vacant land, such as poor infrastructure, hazard risk, and physical limitations such as land size, slope, and shape. Broken Windows Theory explains why long-term vacant land often yields more adverse effects than does other transitory vacant land. Keizer, Lindenberg, and Steg (2008) focused on the visual symptom of social disorder, noting that negative perceptions from the built environment can increase the level of social disorder in adjacent areas. Long-term vacant land has generated negative perceptions for years, and can have more visible adverse conditions than new vacant land, since the physical conditions of vacant land degrade gradually due to deferred maintenance and ongoing abandonment.

Some empirical studies have noted that the existence and amount of vacant land in a neighborhood can increase the probability of land becoming vacant in cases where the vacancy is disaster-induced (Zhang, 2012), commercial and industrial land (I. K. Park & von Rabenau, 2015), and single-family residential land (Gu, Newman, Kim, Park, & Lee, 2019). The results of these studies imply that the duration of the vacancy can yield more vacant land within a neighborhood because long-vacant land often accumulates over time. However, little research has examined increasing negative externalities due to the duration of the vacancy itself, which can hinder neighborhood redevelopment (Han, 2014). Han (2014) showed that the duration of housing abandonment, especially when houses were abandoned more than three years, significantly devalued nearby properties. In turn, reduced property values may delay the redevelopment process.

2.4. Measures of Vacant Land

The amount of vacant land and housing vacancy rates have been estimated by the federal government and local organizations. Table 3 summarizes the sources of vacant land data. Before the 1940s, Barber (1938) presented housing vacancy rates in 64 US cities from 1930 to 1938, summarizing existing survey results. While there were few discrepancies in terms of defining "livable" vacant units, the estimated vacancy rates were based on structures where families were living or could live. The average urban vacancy rate was about 8% to 9% in 1932; it decreased to 2% to 3% by 1937. Since the 1940s, the US Census Bureau has provided housing vacancy data as the number of vacant and occupied housing units (U.S. Census Bureau, 2011, 2017g, 2018). Since 2008, the HUD Aggregated USPS Administrative Data on Address Vacancies has provided all USPS-identified vacant residential and commercial addresses. In addition, most local governments collect vacant land information through their land use and property tax records.

US Census data are designed to estimate the current use of residential housing units. Decennial Census, American Community Survey, and Housing Vacancy Survey data all consider housing to be vacant 'if no one is living in it at the time of the interview, unless its occupants are only temporarily absent' or 'entirely occupied by persons who have a usual residence elsewhere' (U.S. Census Bureau, 2011, 2017g, 2018). For example, if a housing unit is a summer house that is only occasionally occupied by temporary residents, this housing unit is counted as vacant.

Table 3. Sources of Vacant Land Data

Source	Definition of vacancy	Geographical unit	Time scale
US Census data - Decennial Census - American Community Survey (ACS) - Housing Vacancy Survey (HVS)	Vacant housing unit: - If no one is living in it at the time of the interview, unless its occupants are only temporarily absent - Entirely occupied by persons who have a usual residence elsewhere	Data aggregated to: - Blocks - Block groups - Census tracts (only Decennial Census data are block level)	Decennial data and annual data
HUD Aggregated USPS Administrative Data on Address Vacancies	Vacant address: - Addresses not collecting mail for 90 days or longer	Data aggregated to: - Census tracts	Quarterly data
Data from Local Governments - Land-use records - Property tax records - Foreclosure records	Vacant lot: - A small vacant tract of land suited for use as a building site (in Texas) - A lot with unpaid property taxes - A foreclosed lot	- Lot-level data	Annual data

Sources: U.S. Census Bureau (2011); Hegar (2014)

Conversely, this definition is not designed to include vacant land without a structure and vacant land with a profoundly damaged structure. Structures missing roofs, walls, windows, or doors and structures condemned or planned for demolition are not counted as vacant housing units (U.S. Census Bureau, 2011, 2017g, 2018). Moreover, since the definition relies on the occupancy status at the time of enumeration, such as the April 1st of every ten years for the decennial census (U.S. Census Bureau, 2011), a tax or mortgage-deferred unit or foreclosure unit can be marked as occupied if someone is still living in it at that time. Recent vacant land studies, such as Xie, Gong, Lan, and Zeng (2018) and Newman et al. (2019), used US Census data measuring vacant housing units.

The HUD Aggregated USPS Administrative Data on Address Vacancies reflects all USPS-identified residential and commercial addresses. HUD aggregates USPS data on the census tract level for public dissemination. The identification of vacant addresses is based on whether residents' mail is collected. If a resident has not collected their mail for 90 days or longer, the mailing address is considered a vacant address (U.S. Department of Housing and Urban Development, 2018). Newman, Gu, Kim, and Li (2016) and Wang and Immergluck (2019) used the vacant addresses to capture the patterns of vacant land in various US cities and regions.

The vacant addresses data has limitations. Addresses under construction, demolition, or that are not likely to be active for some time (such as some abandoned addresses) are considered "no-stat" rather than vacant (U.S. Department of Housing and Urban Development, 2018). Growing areas and areas in decline tend to have higher rates of no-stat addresses. In severely distressed areas where demolition is ongoing, the total count of addresses will decrease if demolished buildings are not replaced by new construction. As a result, USPS vacant addresses cannot be used directly to measure the existence of undeveloped land and vacant land with damaged structures. In addition, since these data rely on residents collecting their mail, high vacancy rates might exist in neighborhoods with substantial numbers of recreational housing units (U.S. Department of Housing and Urban Development, 2018).

Local governments' land-use records represent lot usage, categorizing lots as single-family residential, multifamily residential, industrial, commercial, and vacant. In such cases, the resolution of vacant land data obtained from land use records is higher than aggregated data obtained from the US Census and HUD-USPS. While US Census and HUD-USPS data identify vacant units and addresses, land-use records tend to identify vacant lots without buildings. For example, the Property Classification Guide from the Texas Property Tax Assistance Office recommends identifying vacant lots as those which are idle, unused, or underutilized, with only nominal improvement value (Hegar, 2014). However, local governments can use different approaches to identifying vacant lots because of variations in tax structure and development plans (Bowman & Pagano, 2004).

Property tax records indicating the foreclosure and tax-delinquent status for each lot can also be used to identify vacant land in destressed urban areas. For example, I. K. Park and von Rabenau (2015) analyzed the tax-delinquent and abandonment statuses of industrial and commercial properties in Cuyahoga County, Ohio. They identified tax-delinquent properties those owned by individuals owing more than 60% of taxes at the settlement deadline. A property was considered abandoned when its tax delinquency lasted more than three years. However, not all tax-delinquent or foreclosure properties are unused, damaged, or vacant (Whitaker & Fitzpatrick IV, 2013). For example, some may not be visually different from tax-current lots. While foreclosure properties are frequently vacant and abandoned, foreclosure properties comprise only a small portion of vacant land. Whitaker and Fitzpatrick IV (2013) noted that vacant homes were four times more common than foreclosure homes, and 88% of foreclosure homes were tax-current in Cuyahoga County, Ohio. Most foreclosure homes have never been tax delinquent because lenders and mortgage providers prioritize tax payment (Whitaker & Fitzpatrick IV, 2013). Many studies have used the property tax records to identify foreclosure or tax delinquent lots based on the local government’s land use records and lot boundaries (Griswold & Norris, 2007; Han, 2014, 2017a, 2017b; Immergluck & Smith, 2006; Z. Lin et al., 2009; Mikelbank, 2008; Shlay & Whitman, 2006; Whitaker & Fitzpatrick IV, 2013).

Table 4. Occupant and Vacant Housing Units per US Census Data

Year	Housing Type	Number of Units	% Vacant	% Vacant by Type
2000	Total housing units	115,904,641		-
	Occupied housing units	105,480,101	91.0	-
	Vacant housing units	10,424,540	9.0	-
	For rent	2,614,652	-	25.1
	Rented or sold, not occupied	702,435	-	6.7
	For sale only	1,204,318	-	11.6
	For seasonal, recreational, or occasional use	3,578,718	-	34.3
	For migrant workers	25,498	-	0.2
	Other vacant	2,298,919	-	22.1
2010	Total housing units	131,704,730	-	-
	Occupied housing units	116,716,292	88.6	-
	Vacant housing units	14,988,438	11.4	-
	For rent	4,137,567	-	27.6
	Rented, not occupied	206,825	-	1.4
	For sale only	1,896,796	-	12.7
	Sold, not occupied	421,032	-	2.8
	For seasonal, recreational, or occasional use	4,649,298	-	31.0
	For migrant workers	24,161	-	0.2
	Other vacant	3,652,759	-	24.4
2017	Total housing units	137,407,308	-	-
	Occupied housing units	120,062,818	87.4	-
	Vacant housing units	17,344,490	12.6	-
	For rent	2,897,808	-	16.7
	Rented, not occupied	626,594	-	3.6
	For sale only	1,239,933	-	7.1
	Sold, not occupied	685,541	-	4.0
	For seasonal, recreational, or occasional use	5,704,328	-	32.9
	For migrant workers	40,870	-	0.2
	Other vacant	6,149,416	-	35.5

Source: 2000 Decennial Census Table H3: Occupancy Status and H5: Vacancy Status (U.S. Census Bureau, 2000b, 2000c); 2010 Decennial Census Table H3: Occupancy Status and H5: Vacancy Status (U.S. Census Bureau, 2010e, 2010f); ACS Table B25002:Occupancy Status and B25004: Vacancy Status (U.S. Census Bureau, 2017a, 2017b)

Table 4 illustrates the inventory of vacant housing units in the US based on the 2000 and 2010 Decennial Census data and 2017 ACS data. The number of vacant units was continuously increased from 10.4 million (9.0%) in 2000, 15.0 million (11.4%) in 2010, to 17.3 million (12.6) in 2017 in accordance with the definition used by the US Census. The US Census designed six categories of vacant housing units (U.S. Census Bureau, 2020a). In 2000, among the 15.0 million vacant units, 34.3% were defined as secondary homes for occasional use. The rest were related to rental homes: 25.1% vacant rental units. The other category of vacant units comprised 22.1% of the total. It included those held by an estate, abandoned properties, and units kept vacant for reasons related to family, legal proceedings, repair, or foreclosure. In 2010, the rented or sold, not occupied category was divided into the rented, not occupied and the sold, not occupied categories. While the number of vacant units was increased by 4.6 million between 2000 and 2010, the general trend of the categories of vacant housing units has remained. On the other hand, while the number of vacant units was increased by 2.4 million between 2010 and 2017, the other category of vacant units were significantly increased, from 3.7 million to 6.1 million.

Table 5 shows the inventory of vacant addresses in the US based on the USPS-HUD data as of March 2010. Unlike the land-use survey results and census-based vacant housing units, only 3.1% and 7.0% of the residential addresses were counted as vacant or no-stat. The reason for the relatively low number of approximately 4 million vacant addresses, may be related to differences in definitions used by the two. For example, while the US Census assigned all secondary homes as vacant units, the USPS-HUD vacant addresses were related solely to whether the mail was being collected (U.S. Department of Housing and Urban Development, 2020). Residential addresses can be classified as no-stat for many reasons relying on mail careers' decisions. For example, it includes urban residential addresses that are unlikely to be occupied anytime soon and rural residential addresses that appear vacant for over 90 days. Accordingly, there were many no-stat residential addresses in both growing and declining areas. Since the no-stat residential addresses represent the inactive residential addresses, the sum of vacant addresses and no-stat address may also represent the conceptual amount of housing vacancy. In this case, there were 13.3 million (10.1% of total residential addresses) vacant residential addresses and no-stat residential addresses in March 2010. This number was not very different from the number of vacant housing units, 15.0 million (11.4% of total housing units), in the 2010 US Decennial Census based on April 1, 2010. Besides, the previous land use survey results by Newman, Bowman, et al. (2016) noted that an average of 16.7% of the land area was vacant in 124 cities with populations over 100,000.

Table 5. Occupant and Vacant Addresses in the US

Housing Type	Number of Addresses	% Vacant
Total addresses	149,211,545	-
Residential addresses	132,071,403	-
Residential occupied addresses	118,778,909	89.9
Residential vacant addresses	4,068,223	3.1
No-stat residential addresses	9,224,271	7.0
Business addresses	10,991,662	-
Business occupied addresses	8,033,299	73.1
Business vacant addresses	1,150,679	10.5
No-stat business addresses	1,807,684	16.4
Other addresses	6,148,480	-
Other occupied addresses	6,146,164	100.0
Other vacant addresses	1,986	0.0
No-stat other addresses	330	0.0

Source: U.S. Department of Housing and Urban Development (2018), USPS-HUD March 2010

3. DISASTER RECOVERY AND VACANT LAND REDEVELOPMENT

The primary topic of this research, disaster-induced vacant land and its effect on redevelopment, touches upon three areas of disaster studies: 1) resilience in terms of recovery from disaster events, 2) the progress of recovery and associated timeline, and 3) population loss and vacant land. This chapter provides synopses of the topics most relevant to each of these areas. In addition, this chapter includes 4) programs and policies for the redevelopment of vacant land, and discusses 5) where this study could be adopted in the context of community resilience models.

Vast quantities of literature have focused on the level of resilience during disaster recovery and the associated recovery timeline. This research focuses primarily on the occurrence and duration of vacant land after disaster events. A review of the literature allowed for a consideration of vacant land in the context of the disaster recovery process; it hinders redevelopment efforts and facilitates unevenness in recovery; however, it also mitigates future disaster losses. Therefore, disaster-induced vacant land can be an indicator of initial damage and uncertainty in the redevelopment process.

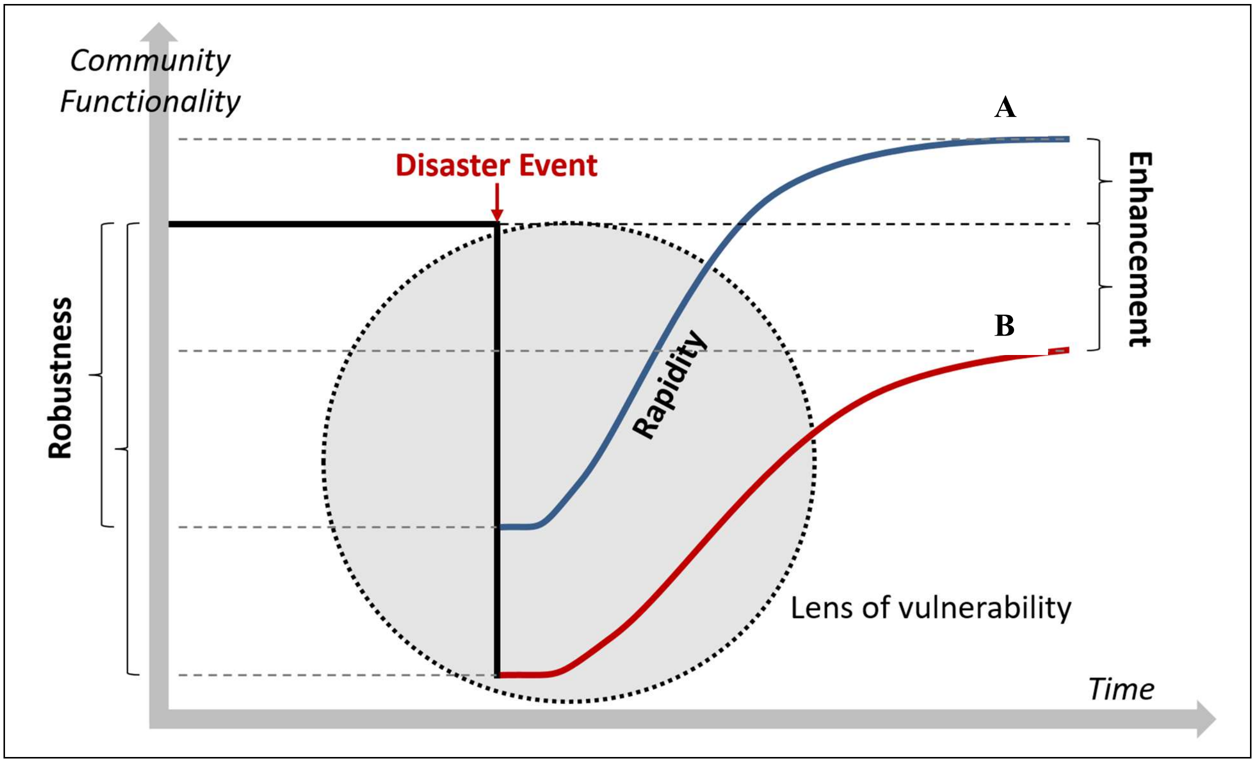
3.1. Resilience and Disaster Recovery

Sustainability, resilience, and vulnerability are highly related concepts that can be used to portray a community's status regarding a disaster event. In the early 1980s, sustainability and sustainable development were used to conceptualize the goal of interactions between nature and society, and society's capacity to serve as a means of "meeting fundamental human needs while preserving the life-support systems of planet Earth" (Kates et al., 2001. p. 642). For every community, sustainability is a desirable goal. Resilience is a required component in a sustainable community. Holling (1973) used the word “resilience” to represent ecosystem recovery. Specifically, resilience indicates an ability to absorb disturbances without rearranging the original structure and function of a system (Beatley, 2012; Gunderson, 2001; Holling, 1973). The amount of disturbance a system can endure and still return to the initial status is an indication of the system’s robustness (Gunderson, 2001). Resilience can also represent the speed at which the system is able to return to the initial status (Buckle, 2006), as well as the capacity to build resilience superior to the initial resilience status after a disturbance (Beatley, 2012). These elements can be summarized in three dimensions: robustness, rapidity, and enhancement.

Since the 1930s, many researchers have attempted to define the stages of disaster management (Neal, 1997). In general, disaster recovery is one of the four key stages of disaster management, along with mitigation, preparedness, and response (Godschalk, Brower, & Beatley, 1989). Since the preparedness and response stages tend to focus on imminent health and safety issues, the mitigation and recovery stages are known to be especially efficient in building resilience (Beatley, 2012). For example, during the recovery stage, which often lasts from months to decades after a disaster event, a damaged society confronts the prevailing consequences of the disaster. For them, adopting mitigation strategies can often be a more compelling option than the others available (Beatley, 2012; Paton & Johnston, 2017).

Figure 1 indicates a conceptual model of disaster recovery and community functionality, demonstrating how three dimensions of resilience, such as robustness, rapidity, and enhancement, can be identified in the disaster recovery process, as well as how the vulnerability of a community affects it. Vulnerability can be defined as the comprehensive conditions of physical, social, economic, and environmental factors or processes that affect the susceptibility of an individual, community, asset, or system to loss from hazard impact (UNSDR, 2019). Paton and Johnston (2017) viewed resilience as a remedy for vulnerability because resilience outcomes help to preserve community resources after disaster events. The vulnerability of a community has an influence on the resistance of the initial level of decreased functionality (robustness), the speed of the recovery process (rapidity), and the enhanced level of functionality over the pre-disaster status (enhancement). For example, Line A indicates a more resilient community with less initial loss of functionality, faster recovery, and to an extent that surpassed the initial functionality status. On the other hand, Line B indicates a community with more initial loss of functionality, slower recovery, and did not recovered to the pre-disaster level functionality.

Figure 1. Community Functionality after Disaster Events



Reprinted from Bruneau et al. (2003)

The goal of the recovery process should be enhanced resilience in order to minimize future loss of life and damage to property (P. R. Berke & Campanella, 2006). Resilience and vulnerability rely on a community's social decisions (Beatley, 2012). A disaster can be seen as a social event; the impact of a hazard can only be considered a disaster if that impact disrupts social functions and networks of social interactions (Paton & Johnston, 2017; Peacock et al., 1997). Enhanced resilience does not occur by chance, due to every community's uniquely complicated societal mechanisms (Paton & Johnston, 2017). In addition, the uncertainty associated with estimating the level of a future disturbance inhibits recognition of the necessity of effective enhanced resilience (Paton & Johnston, 2017). Limited knowledge and power differences among multiple interest groups (Forester, 1988) also deteriorate the resilience of neglected households.

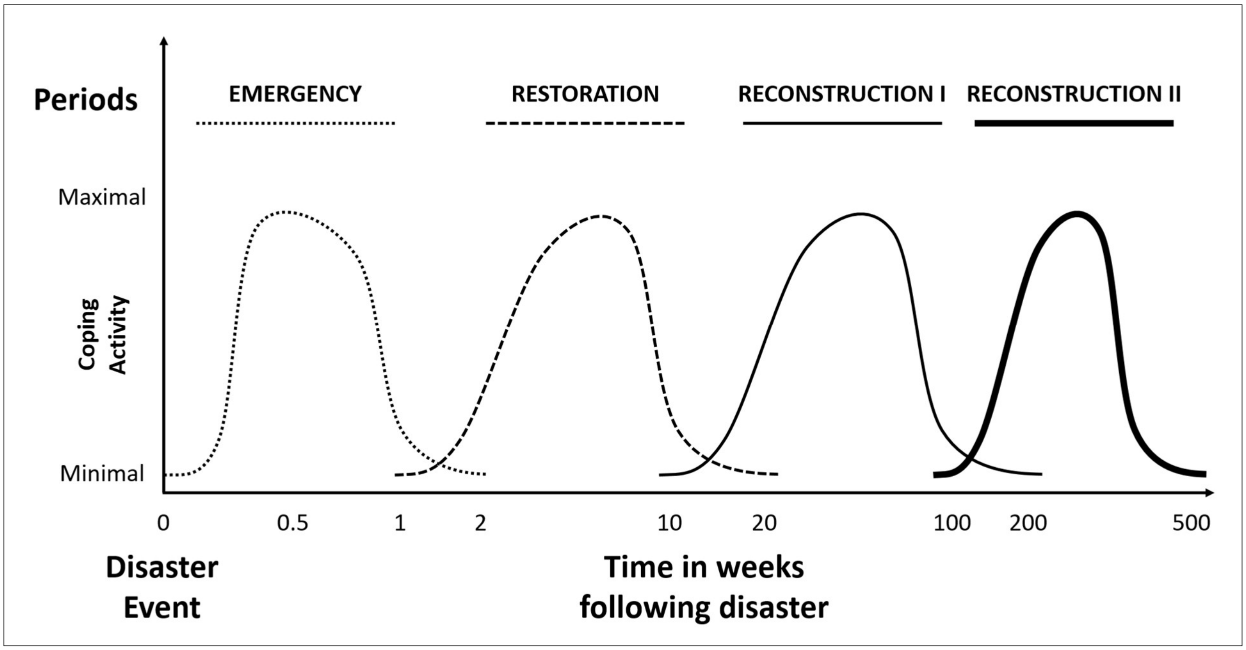
The recovery stage refers to long-term actions designed to build enhanced resilience. However, after a disaster event, making decisions related to comprehensive recovery may be difficult due to a lack of time. In addition, most governing institutions prefer to return to pre-disaster status, due to a tradition of pragmatism in planning and policy implementation (Gunderson, 2001). An optimization approach in planning practices assumes the initial status as a reference point to which a community should strive to return (Walker & Salt, 2012). Vested interest groups also prefer a status quo policy because it ensures the maintenance of their status (Gunderson, 2001). In general, the recovery process tends to exacerbate inequity by polarizing the level of accessibility to resources, hindering power relationships, and obstructing bureaucratic processes (Olshansky, Hopkins, & Johnson, 2012).

3.2. Recovery Progress after Disaster Event

Achieving an equal or better level of economic function by reconstructing damaged buildings and communities is typically a primary goal of disaster recovery (Olshansky, 2005). A well-organized planning intervention enhances the public confidence in transparency, accountability, and efficiency of recovery efforts (Federal Emergency Management Agency, 2011b). Identifying the progress being made by recovery efforts can aid in identifying the most appropriate time for each planning intervention (Mader & Tyler, 1991). However, predicting recovery progress can be challenging because progress can be uneven; some neighborhoods may recover speedily while others lag behind (Van Zandt et al., 2012).

To predict the progress of a recovery effort, Haas, Kates, and Bowden (1977) and Rubin et al. (1985) suggested two distinct paradigms for recovery timelines. Haas et al. (1977) proposed an “ordered, knowable, and predictable” (p. 261) recovery timeline with four distinctive periods that follow a chronological order. Figure 2 presents the “Wave Chart” (Haas et al., 1977, p. 4) illustrates these four periods, using a logarithmic scale of time. The four periods include: 1) the emergency itself (in days or weeks), 2) restoration (usually a few months), 3) replacement reconstruction (up to two years), and 4) commemorative, betterment, and developmental reconstruction periods (up to ten years).

Figure 2. Wave Chart: Four Periods and Timings



Reprinted from Haas et al., 1977.

In opposition to this ordered and sequential recovery timeline, Rubin et al. (1985) suggested a more complex measure that focuses on the time necessary for each recovery period. For example, initial disaster response activities must be enacted to begin the recovery process. The time required for the initial disaster response activities varies by disaster type, damage, and the resources available to each neighborhood and household. Differences in completion of the initial disaster response can hinder the general recovery progress. In other words, "no noticeable pattern of progress is discernable with respect to the recovery process as it goes on in communities across the U.S." (Rubin et al., 1985, p. 59). For example, Javernick-Will, Chinowsky, and Senesi (2010) noted how the time required for the initial response activities can affect the timeline of the recovery process. They measured the recovery periods after three earthquakes: Kobe, Japan in 1995; Izmit, Turkey in 1999; and Bhuj, India in 2001. The start times of the initial disaster response activities were similar, despite these earthquakes occurring in three different countries.

For instance, search and rescue activities began one to two days after each earthquake. Conversely, due to differences in damage level and resources available for disaster response, the starting points of each recovery period were different. It took two weeks in Japan, six weeks in India, and two months in Turkey to begin recovery activities.

Sheltering and housing patterns are examples of non-sequential recovery progress. Quarantelli (1982) explained recovery progress by identifying four types of housing: emergency shelter, temporary shelter, temporary housing, and permanent housing. During a recovery period, disaster victims do not follow a sequential order such as linear movement from emergency shelter to permanent housing. Instead, disaster victims may progress through different types of shelter and housing before settling into something permanent. Consequently, post-disaster shelter and housing activities can be seen as concurrent and overlapping recovery efforts. In addition, Sutphen (1983), Bolin (1993), L. Johnson (1999), and Javernick-Will et al. (2010) all noted non-sequential recovery progress due to disaster victims being at different points in the recovery process.

In sum, previous studies have indicated that housing repair and rebuilding activities can last from a year to a decade after a disaster event (Haas et al., 1977; L. A. Johnson & Hayashi, 2012; Kimura, 2007; Mader & Tyler, 1991). The ordered and sequential recovery timeline provided by Haas et al. (1977) offers a predictable overview of the entire recovery process. For example, the American Planning Association (APA) and the Federal Emergency Management Agency (FEMA) produced reports on the disaster recovery framework that adopted an ordered and logarithmic recovery timeline comprised of short-term (several days), intermediate (weeks to months), and long-term (months to years) recovery stages (Federal Emergency Management Agency, 2011b; Schwab, 2014). Green, Bates, and Smyth (2007) recognized five mutually exclusive and sequential stages of redevelopment after a disaster event: (1) 'vacant lot' as an initial stage; (2) 'no visible signs of recovery' stage with debris and without repair; (3) 'debris removal and gutting' stage without repair; (4) 'repair without occupancy' stage; and (5) 'occupancy' stage when all repairs done and property is inhabited. Haas et al. (1977) also identified five factors that can affect recovery progress: availability of external resources, national leadership, having a recovery plan in place before the disaster, community consensus, and wide dissemination of information. However, this approach has been challenged due to the lack of social interactions, such as structural inequities in neighborhoods and regions, conflicts between stakeholders, delays in political decision making process, and inefficiency and inaccuracy in measuring damage and distributing resources (P. Berke & Beatley, 1997).

Conversely, the concurrent and non-linear recovery timeline provided by Rubin et al. (1985) emphasizes the flexibility of recovery activities by focusing on damage, recovery efforts, and resources. In the same vein, minority communities (Bolin & Stanford, 1991), family lifecycle and income (Bolin, 1982; Peacock et al., 1997; Phillips, 1993; Quarantelli, 1995), tenure status for both renters (Quarantelli, 1995; Tafti & Tomlinson, 2013) and owners (Nejat & Damnjanovic, 2012), redlining by language barrier and realtor racism (Bolin, 1994; Phillips, 1993), accessibility to external resources (Bolin, 1986; Bolin & Bolton, 1986; Bolin & Stanford, 1991; Haas et al., 1977), accessibility to community networks (Perry & Mushkatel, 2008), carrying insurance and eligibility of government loans (Comerio, 1997), and repair and reconstruction processes including damage evaluation and obtaining permits (Mitrani-Reiser, 2007) were all known to either facilitate or disturb recovery progress. These factors are also highly correlated with one another, and can aggravate recovery efforts. For example, high-income households tend to have more personal resources to facilitate recovery, as well as greater access to disaster assistance (Bolin, 1982), while low-income households (who are often comprised of minorities, the elderly, and renters) are at greater risk of failing to recover (Peacock et al., 1997; Quarantelli, 1995). Market-based recovery policies (Peacock et al., 1997) and ongoing social change such as ethnic segregation and an aging population (Quarantelli, 1995) can also exacerbate inequity among disaster victims.

Comparing the statuses of built environments pre- and post-disaster is the most common quantitative measure used to identify the progress of recovery (Stevenson et al., 2010). For example, researchers have utilized land-use changes from vacant to developed land (Crawford et al., 2017; Zhang, 2012), visual changes in buildings attributable to repair and rebuilding efforts (Curtis et al., 2007; Jarmin & Miranda, 2009), changes in property values (Bin & Kruse, 2006; De Silva et al., 2006; Hamideh et al., 2018; Peacock et al., 2014; Zhang & Peacock, 2009), and building and repair permits issued (Rathfon et al., 2013; Stevenson et al., 2010; Wu, 2004) to identify recovery status. In addition, the population index (Hirayama, 2000), New Orleans index (Liu & Plyer, 2009) and recovery indicator (Chang, 2010) have all been designed to systematically track recovery progress, including population dislocation, housing damage, new constructions and repairs, number of businesses and sales, school enrollment, availability of schools and childcare, and gross regional product. However, many of the research findings on disaster recovery have been based on single case studies, and the results derived difficult to generalize due to the small sample size and limitations in experiment design (Bates & Peacock, 1987; Drabek, 2012; Rubin et al., 1985). A comprehensive operational definition that measures the progress of recovery has yet to be established (Rubin, 2009).

3.3. Population Loss and Vacant Land after Disaster Event

Loss of population and massive amounts of vacant land have repeatedly emerged after major disaster events (Y. S. Lin, 2009; Milch, Gorokhovich, & Doocy, 2010; Mitchell, Esnard, & Sapat, 2011; Perkins, 1996; S. K. Smith & McCarty, 2011). Population loss and housing vacancy occur simultaneously after disaster events, at least until damaged residential buildings are either repaired or demolished and rebuilt (Rathfon et al., 2013). As discussed in the previous chapter, loss of population is a predominant causal factor for the occurrence of vacant land (Hollander et al., 2009; Wiechmann & Pallagst, 2012). Accordingly, estimating the population that moved away and residential properties left vacant can both be essential to measure the initial vacant land and progress of vacant land recovery.

A number of terms have been used to indicate population loss after disaster events, such as dislocation, displacement, and migration. Migration after a disaster event is more likely to be considered permanent after an initial voluntary or forced move (Kliot, 2004). Oliver-Smith (2006) noted that "forced migration involves moving further away, to different environments and for longer periods of time, if not permanently" (Oliver-Smith, 2006, p. 4). Therefore, long-lasting vacant land that generated after disaster events can be seen as a result of migration.

The most remarkable factor incorporates an element of coercion (i.e., whether disaster victims chose to move or were forced) to compare migration and dislocation (Esnard & Sapat, 2014). Migration includes a voluntary choice to either return or stay (Hunter, 2005; Myers, Slack, & Singelmann, 2008). For example, Hunter (2005) described migration as "resultant of environmental hazards rang[ing] across a continuum from forced to voluntary … the association between migration and environmental hazards varies by context, hazard type, and household characteristics" (Hunter, 2005, p. 16). Conversely, dislocation (and displacement) are more commonly used in disaster research, emphasizing the forced removal of households and businesses mainly because of damage to building structures and infrastructure losses (Lindell & Prater, 2003; Xiao & Van Zandt, 2012).

The push and pull factors are derived to explain the factors shaping population loss (Davenport, Moore, & Poe, 2003; Hunter, 2005; Myers et al., 2008; Yonetani and IDMC, 2015). Push factors are reasons why people have to leave their homes; initially, they tend to lead to dislocation and displacement due to reactive and immediate survival responses. Pull factors are reasons why people are driven to leave their homes; they lead to migration motivated by the desire to seek a better quality of life and greater opportunities. In real-world setting, however, push and pull factors tend to be mixed with varying perceptions of disaster damage (Kirschenbaum, 1996). For example, Myers et al. (2008) noted that "initial migration is indeed forced, though the decision to return to the place of origin may become a more individualistic cost-benefit analysis as time progresses" (Myers et al., 2008, p. 274). Oliver-Smith (2006) stated that "displacement can be temporary or permanent, voluntary or involuntary, and may be a response to both physical and economic harm" (Oliver-Smith, 2006, p. 4).

Structural damage and infrastructure disruption in residential buildings are predominant factors affecting the probability of population loss, and consequently, the occurrence of vacant land. For example, Krishnamurthy (2012) noted that "in reality, whether disaster-related migration is forced or voluntary depends on the magnitude of the event" (Krishnamurthy, 2012, p. 105). Similarly, residents of highly damaged buildings were found to be more likely to be dislocated (Y. S. Lin, 2009; Milch et al., 2010; Myers et al., 2008; Perkins, 1996; S. K. Smith & McCarty, 2011). Infrastructure disruption and subsequent utility losses are other key factors increasing population loss; they include loss of water, electricity, gas, communication, and public transportation (Bukvic et al., 2015; Chatterjee & Mozumder, 2015; Lindell, Prater, & Perry, 2006; Peacock, Dash, & Zhang, 2007; S. K. Smith & McCarty, 2011).

Population loss may be driven not only by structural damage, but also by social factors related to social vulnerability, such as ethnicity, income, and tenure. People decide to move based on their available resources and socioeconomic conditions. In other words, decisions are made based on whether someone can leave rather than whether they should leave. For example, disaster victims cannot leave if they cannot find affordable places to relocate, even though their dwellings may have suffered substantial building damage (Comerio, 1997; Levine, Esnard, & Sapat, 2007; Lindell et al., 2006; Lindell & Prater, 2003). On the other hand, tenants had to leave regardless of the physical damage to their residences when owners evict entire groups of tenants from partially damaged complexes (Comerio, 1997; Perkins, 1996). Previous studies identified that racial and ethnical minorities, low-income individuals, and tenants living in densely developed areas are more likely to have to leave their homes (Fussell & Harris, 2014; Y. S. Lin, 2009; Milch et al., 2010; Myers et al., 2008; Zhang & Peacock, 2009). Consequently, disaster events can trigger social change, increased community vulnerability (Drabek, 2012), and socioeconomic inequality (Dynes, 1989; Peacock et al., 1997). Neighborhoods that suffer urban issues before disaster events are more likely to experience hardship afterwards, and disaster events accelerate the speed of urban decline (Davis, 1986).

Social vulnerability was related to individual, household, and community capacity to withstand and respond to disaster events. Social vulnerability was measured through several indices, such as the Social Vulnerability Index (Cutter, Boruff, & Shirley, 2003), Vulnerability Score, Disaster Preparedness Index, Disaster Resilience Index (Simpson & Katirai, 2006), and Center for

Hazards Research and Policy Department Model (Simpson & Human, 2008). Factors shaping social vulnerability can also be related to dislocation outcomes; however, not many studies have compared social vulnerability assessments in hurricane-prone coastal regions (Levine et al., 2007). Van Zandt et al. (2012) emphasized the relationship between the lower levels of social vulnerability and delayed recovery, including later evacuation, sustained damage, and lack of resources.

Kliot (2004) stated that population loss is "often an indicator of the breakdown of social resilience" (Kliot, 2004. p. 86). Initial population loss due to disaster damage can trigger a cascading adverse effect, such as in the case of decreasing neighborhood vitality that includes property abandonment and vacant land. For example, disaster events can trigger widespread unemployment and subsequent reduced income levels (Hori & Schafer, 2010). Dolfman, Wasser, and Bergman (2007) noted that the adverse effects on the labor market resulted $2.2 billion loss in wages during the first ten months after hurricane Katrina resulting from job and population loss. Reduced income levels can then lead to failures to pay rent or mortgage payments (Lindell et al., 2006). Business failures are also related to population loss and the deterioration of socioeconomic conditions. For instance, business failures rooted in both physical damage and market shrinkages stem from population and job loss (Krishnamurthy, 2012; Lindell et al., 2006; Lindell & Prater, 2003; Xiao & Van Zandt, 2012). Eventually, widespread vacancy and abandonment undermine local governments' long-term urban development plans due to decreases in the tax base and increases in maintenance costs (Newman, Bowman, et al., 2016; Pearsall et al., 2014).

Redevelopment of vacant land is relying on property owners' reinvestment decisions (Blair et al., 1996; Featherman, 1977; Morgan, 1980; Neutze, 1987; Sternlieb et al., 1974; Titman, 1985). In the same vein, while the initial post-disaster vacant land is mainly triggered by disaster damage, the recovery of disaster-induced vacant land depends on owners' decisions (Myers et al., 2008) and their available resources (Comerio, 1998; Peacock et al., 1997). Therefore, the loss of population and resultant vacant land will obstruct recovery efforts by increasing uncertainty in owners' decision-making related to repair and redevelopment (Blair et al., 1996; Neutze, 1987; Titman, 1985).

3.4. Programs and Policies for the Redevelopment of Vacant Land

Disasters have prompted changes in land use regulations, public policies, and building codes by offering a "window of opportunity" within which there is a greater potential to solve social problems that exist post-disaster (Passerini, 2000). This is because disaster-affected communities are more likely to favor the adoption of hazard mitigation strategies and be open for options to safely, rather than quickly, rebuild (D. C. Alexander, 1993; Mader & Tyler, 1991). However, in many cases, damaged communities have not fully utilized this opportunity to build resilience beyond that of their pre-disaster status (D. C. Alexander, 1993; Passerini, 2000). First of all, financial resources comprise the most critical factor determining community recovery (Peacock et al., 2007). Many communities are hindered in their recovery efforts by a lack of resources (Peacock et al., 1997). A compression of time and space also triggers disorganized urban development and under-researched decisions (Olshansky et al., 2012). Moreover, as time passes, governmental organizations tend to lose interest in recovery, and consequently reduce the amount of resources allocated (D. C. Alexander, 1993). Some recovery plans take more time to apply, especially hazard mitigation plans designed to reduce the risk to life and property. Fading recovery efforts can undermine these long-term recovery plans. For example, accepting revised land-use plans, adopting reinforced building codes, and creating open spaces for setbacks and buffers can become infeasible due to the time required (Mileti, 1999).

3.4.1 Funding Sources for Housing Recovery

Comerio, Landis, and Rofe (1994) listed certain federal and local financial sources for disaster victims' housing recovery. These sources can be divided into two major sections: private and public (Bolin & Stanford, 1991; Comerio, 1997; Peacock et al., 2007; Quarantelli, 1982; Sutley & Hamideh, 2017; Wu, 2004; Wu & Lindell, 2004). Especially, Wu and Lindell (2004) organized the major funding sources as outlined in Table 6 (Wu & Lindell, 2004. p. 70):

Table 6. Funding Sources for Housing Recovery

Private	Personal savings
	Insurance
Public	Small Business Administration (SBA): low-interest loans
	Federal Emergency Management Agency (FEMA): Minimal Home Repair Program (MHRP) and Individual/Family Grant (IFG)
	U.S. Department of Housing and Urban Development (HUD): Community Development Block Grant (CDBG) and HOME Investment Partnerships Program under Affordable Housing Programs (AHP)

Adapted from Wu and Lindell (2004)

Private sources consist of personal savings, insurance, commercial loans, and funds from friends and family members. Among these private sources, insurance payouts used to provide the largest financial portion of housing reconstruction resources. For example, funds from private insurance were responsible for approximately 65% of the total reconstruction after the 1994 Northridge earthquake in Los Angeles, California (Wu, 2004). Ideally, households with private resources sufficient to accomplish recovery do not have to rely on public resources. In such cases, policies and incentives provided by federal and local governments may have little influence on housing reconstruction. However, socioeconomically vulnerable households are more likely to suffer from a lack of private resources, and thus must be supported by public resources (Peacock et al., 1997). Public funding comes from several areas such as the SBA's low-interest loans, FEMA's Minimal Home Repair (MHR) and IFGs, and HUD's HOME and CDBGs. The SBA provides the Disaster Loan Program to support uninsured property owners and those without sufficient resources from insurance to allow for repairs. The MHR provides small grants for minor repairs to housing owners who do not have sufficient resources from insurance. The IFG offers aid for home repair to victims ineligible for other federal resources. HUD's CDBG and HOME give grants to local governments for reconstruction and mortgage assistance to low- and moderate-income neighborhoods (Wu, 2004). In addition to these federal funding sources, some state governments also offer funding programs for housing recovery (Schwab, 2014; Zhang & Peacock, 2009).

The federal sources listed above are designed to support households that do not, on their own, have access to sufficient recovery resources. However, minorities, renters, and low-income households are more likely to experience a shortage of funds for housing repair and redevelopment (Kamel & Loukaitou-Sideris, 2004; Peacock et al., 1997; Rubin et al., 1985). For example, housing owners tend to have better federal resources for repairing and rebuilding than do owners of second homes and renters (Bolin, 1993; Comerio, 1997; Hamideh et al., 2018; Olshansky, Johnson, Horne, & Nee, 2008). SBA loans estimate the amount of money needed based on the housing owner's credit and value of the property (Kamel & Loukaitou-Sideris, 2004; Schwab, 2014). Insurance also favors affluent households living outside of flood-prone areas, while minority households living inside of flood-prone areas are discriminated against in terms of obtaining adequate insurance (Peacock et al., 1997).

Local governments also rely on federal sources for disaster recovery in the public sector. Public sector recovery such as lifeline infrastructure, including electricity, water, roads, schools, and hospitals, is interdependent with household recovery (Comerio, 2014). Recovering disrupted infrastructure is especially important to stabilizing household dislocation (Bukvic et al., 2015; Chatterjee & Mozumder, 2015; Lindell et al., 2006; Peacock et al., 2007; S. K. Smith & McCarty, 2011). FEMA's Public Assistance Grant Program and Hazard Mitigation Grant Program are major sources for local governments seeking funds to repair damaged infrastructure and adopt mitigation strategies (Schwab, 2014). Accordingly, local governmental efforts regarding demolition and re-habitation depend heavily on federal and state laws and funding regulations (Hummel, 2015). Federal funding is more likely to be a top-down process beginning with a presidential declaration of disaster (Schwab, 2014).

3.4.2. Recovery Policies for Vacant Urban Land

A government's recovery policies demonstrate how they are preparing for future disaster events. In the US, such policies rely on the private property market (Peacock et al., 1997), and assume that homeowners will mainly utilize private funding sources with some federal support such as SBA loans and FEMA grants, and renters will find alternative rental homes (Comerio, 1998). However, as Comerio (2014) noted, the private property market may not be able to adapt in post-disaster situations, especially since the 2008 financial crisis. For example, in 2012, the number of homeowners whose mortgages exceeded their home values was 10.8 million, and this was approximately 14.7% of all homeowners (Svenja Gudell, 2013). These homeowners, that used to be identified as “underwater” homeowners, are less likely to have disaster insurance, and may not qualify for SBA loans (Comerio, 2014). Accordingly, many of this type of homeowner are more likely to give up on repair or redevelopment after disaster events.

The prevalence of housing abandonment and vacant land can lead to major losses in nearby property values (Griswold & Norris, 2007; Han, 2014; Immergluck & Smith, 2006; Z. Lin et al., 2009; Mikelbank, 2008; Shlay & Whitman, 2006; Temple University Center for Public Policy, 2001; Whitaker & Fitzpatrick IV, 2013). Decreased property values weaken the housing market and further increase uncertainty in terms of repair and redevelopment. Since housing repair and rebuilding can cake take up to a decade (Haas et al., 1977; L. A. Johnson & Hayashi, 2012; Kimura, 2007; Mader & Tyler, 1991), finding an alternate home is not necessarily an option for homeowners who lose their homes and renters who were removed from their rentals. Moreover, previous study results have indicated ongoing hardships with regards to low-income renters. Since multi-family rental units were found to be less likely to be repaired within a short period of time, it is more challenging to find an affordable rental unit for a low-income renter (Comerio et al., 1994). In extreme cases, some landlords evicted low-income renters because of their late rental payment (Bolin & Stanford, 1998) and fabricate or exaggerate building damage (Bolton, 1993) after disaster events. Recovery policies should be able to support these socioeconomically vulnerable households to reverse declining urban conditions due to disaster events.

Hazard events can only become disasters when societies build hazard-prone communities (Beatley, 2012; Paton & Johnston, 2017). Disaster-induced vacant land that was once developed for residential, commercial, or industrial use are losses in both economic and social capital. Conversely, disaster-induced vacant land in flood-prone areas provide enhanced resilience if used to protect developed areas. In this context, disaster-induced vacant land in flood-prone areas can be a suitable disaster mitigation strategy. For example, as Brody, Highfield, and Kang (2011) noted, open space protection such as setbacks, buffers, and retention and detention ponds are avoidance strategies known to significantly reduce flood loss. Assignment of setbacks and buffer areas are non-structural mitigation methods that reduce flood damage without substantial structural investment. Retention and detention ponds provide run-off management that supports the natural function of water storage and prevents flooding. In addition, these open-space protection methods increase pervious surfaces in urban areas, reducing flooding from surface run-off.

The open space protection strategies listed above correspond to sustainable vacant land management solutions such as "smart decline" and "right-sizing." Smart decline is designed for shrinking cities. It suggests to decline growth-driven planning strategies and to promote planning for the people who will remain. Smart decline strategies include acquiring vacant land, promoting agricultural land uses, memorializing remnant buildings, offering open spaces, and de-annexation (Popper & Popper, 2002). Right-sizing is focusing on urban greening strategies through collaborating neighborhood planning, including a green infrastructure program and plan that managed by a land bank. Specifically, right-sizing strategies include de-annexation, decommissioning surplus public infrastructure and services, moratorium on public investments, privatizing public services, and adopting urban growth boundaries (Schilling & Logan, 2008). Popper and Popper (2002) and Schilling and Logan (2008) have all suggested smart decline and right-sizing as alternative sustainable solutions for neglected neighborhoods that could replace traditional intervention methods. Disaster-induced vacant land can offer spaces for the greening strategies in smart decline and right-sizing.

Until the late 1970s, federal policies focused on using direct intervention methods to support the private housing market (Newman et al., 2019). Disaster assistance policies were not designed to provide funding to homeowners (Comerio, 2014). The Community Reinvestment Act of 1977 was the first to support community reinvestment by counteracting disinvestment attributable to redlining. In addition, the Urban Homesteading Demonstration program was designed to retain original residents after redevelopment. However, the program itself had only a marginal impact on stabilizing residents' mobility (Varady, 1984). For example, urban renewal programs tend to increase the supply of vacant land available for redevelopment. However, since at that time urban renewal programs did not require reuse plans, cities with a low demand for development were prone to high levels of vacant land after massive demolitions (Hollander, 2018). Alternatively, smart decline and right-sizing contribute to the reduction of vacant land through strategic reuse plans, demolishing abandoned structures in order to increase greenspace and green infrastructure (Foo, Martin, Wool, & Polsky, 2013; Németh & Langhorst, 2014; Popper & Popper, 2002; Schilling & Logan, 2008; Silverman et al., 2013), finding temporary uses for vacant land (Németh & Langhorst, 2014), and adopting design solutions to mitigate negative externalities (Ryan, 2012). In addition, when vacant land is reused in a manner that increases greenspace, it yields benefits beyond flood mitigation, including increased property values near the edge of the greenspace, as well as enhanced natural habitat protection, water quality, and recreation opportunities (Brody & Highfield, 2013).

Designing a local hazard mitigation plan before a disaster occurs is the starting point for open space protection efforts. Growth management plans such as adopting Urban Growth Boundary (UGB) and Limited Development District (LDD) methods can be used to control development in disaster-prone areas. Down-zoning, such as gradually decreasing the density of developed areas, and Transferable Development Right (TDR) that allow for trading unused development capacity can be used to mitigate flood damage in pre-developed disaster-prone areas. These growth management plans may have a negative side effect that increases land prices due to the reduced supply of land (Blair et al., 1996). However, these efforts also reduce risk by relocating people away from vulnerable areas, enhancing community resilience. To minimize the expected side effects, community-level decisions should be made that consider other citywide policies such as land-use plans, zoning, and building codes (Brody et al., 2011).

Vacant land can promote post-disaster resilience when it remains as vacant. In comparison to redeveloped land, vacant land (as an open space) contributes disaster mitigation by lessening expected damage due to future disaster events. Buyout programs can be a solution for adopting open space protection methods in post-disaster conditions to support disaster victims and to reduce future disaster losses. Buyout programs are designed to purchase properties in flooding prone areas and demolish structures on the acquired properties. The purchased properties become public open spaces, green spaces, or flood storage areas. Accordingly, buyout programs can help communities facing a high risk of disaster events by reducing the impact of future disasters. Federal Emergency Management Agency (2020a) noted that local officials decide to request a fund from the state to purchase substantially damaged properties after a presidentially declared disaster. FEMA allocates the fund through its Hazard Mitigation Grant Program, and the fund covers 75% of any buyout cost. The rest of the cost is paid by either or both the state and the local government. Besides, after the 1998 Midwest floods, Congress enabled FEMA to have administrative authority over CDBG funds for land buyouts from HUD (Gotham, 2014). In addition, the Community Development Block Grant Disaster Recovery (CDBG-DR) program administrated by the U.S. Department of Housing and Urban Development (HUD) can also be used for buyout programs (U.S. Department of Housing and Urban Development, 2013) for both residential and commercial properties. In this case, a local government, such as a city or a county, should apply for the CDBG property acquisition program to acquire properties 1) located in designated areas; 2) damaged 51% or more based on the pre-flood fair market value of the structure; or 3) suffering a healthy/safety risk. Besides, most buyout programs target low-moderate income households whose income is less than 80% of the local area median income.

Both FEMA and CDBG-DR funded buyout programs offer the post-disaster fair market property values for the acquisition of real properties. For the owners of eligible properties, the participation of buyout programs is voluntary. The owners can also argue that their damage level is not reached to the required standard if they don't want to participate. However, much of the fight was triggered when some of the owners wanted to participate the buyout program while others didn't want. Acquired properties become permanent vacant lands in the middle of neighborhoods. While buyout programs encourage resettlement in the community instead of out-migration, the loss of population is inevitable after most residents participate in buyout programs. Therefore, some property owners may not want buyouts in their neighborhoods because the acquired properties could drive down their property values and diminish the tax base of their community. In the same vein, the U.S. Department of Housing and Urban Development (2013) noted that changes in the property value due to the nearby buyouts could be positive or negative, depending on the nature of the housing market following demolition and redevelopment. To lessen the adverse effects, the New York State's buyout program after Hurricane Sandy incentivizes local relocation and collective group participation—agree to move as a whole block—by offering an additional 5% and 10% bonus, respectively (Kaplan, 2013). However, Bukvic et al. (2015) noted that residents in Hurricane Sandy-affected communities prefer to make relocation decisions independently from the rest of their community. This tendency may lead randomly distributed vacant lots, a “Swiss cheese” pattern, that can undermine resilience in neighborhoods in terms of real estate value, crime, utility disruption, and investment in the community. Besides, there were inequality issues in the distribution of buyout resources. Latino and elderly households received a lower amount of acquisition funds than the assessed home value (Muñoz & Tate, 2016). Accordingly, property acquisition programs should effectively engage stakeholders by considering their diverse contexts and needs (Bukvic et al., 2015).

3.4.3. Vacant land Recovery in Local Governments and Communities

For local governments, reshaping citywide policies can be a way to support neglected neighborhoods and stabilize the housing market (Shlay & Whitman, 2006). The collapse of the American housing market in 2008 resulted in massive foreclosures and widespread property abandonment (Crump et al., 2008; Immergluck, 2008). Many depopulated cities showed visible symptoms of urban decline, such as high unemployment, poverty, and crime rates, and visible increases in vacant and abandoned land (Wiechmann & Pallagst, 2012). Many local municipalities designed policies to overcome these increases in vacant land and the subsequent negative externalities (Accordino & Johnson, 2000). Several Rust Belt cities adopted early warning systems that indicate properties at risk of vacancy or abandonment (Hillier et al., 2003). Urban revitalization strategies for vacant land such as rehabilitation incentives and land bank programs, as well as regulations like aggressive code enforcement, sanctions, tax foreclosure, and eminent domain, can also be adopted to revitalize local housing markets (Accordino & Johnson, 2000).

While urban recovery policies are designed to build better cities, sometimes recovery outcomes obtained from a particular policy can be incomplete and even contradictory, especially in response to the various viewpoints of particular interest groups. For example, the mandatory flood insurance offered by the National Flood Insurance Program (NFIP) for buildings in flood-prone areas drives down potential premium prices that a private insurance company would impose to cover the high risk of flooding (Bonnie Kristian, 2017). While NFIP insurance was designed to increase the level of resilience, it also led to a decrease in adaptive capacity by encouraging floodplain construction. This unintentional and undesirable effect is known as perverse incentives. Using adaptive governance and capacity concepts can be a way of overcoming perverse incentives (Adger, Hughes, Folke, Carpenter, & Rockström, 2005; Walker & Salt, 2012). In terms of policy implementation, Folke et al. (2002) suggested preparing for sudden and abrupt changes rather than focusing on developing optimal management and technical solutions. For example, policymakers should expect and be prepared for uncertainty, focus on flexibility and diversity in management options, and thoroughly monitor resilience outcomes (Folke et al., 2002). Adger et al. (2005) emphasized social resilience in policy implementation, such as networking and collaboration among institutions, robust governance systems, the offering of diverse choices in terms of livelihood, promoting social reorganization, and reserving assets for building buffers against extreme events. Walker and Salt (2012) highlighted the elements of resilience and adaptability in social-ecological systems, such as diversity in all forms, modularity of components, redundancy and overlap in governance, tightness of feedback, and social capital including social networks, trust, and leadership.

Often, the future of a neighborhood is dictated by economic and political forces outside that neighborhood (Downs, 2010). Previous studies have noted that restoring a community's social fabric (P. R. Berke & Campanella, 2006) and obtaining participation and support from local stakeholders for plan-making and implementation (Burby, 2003) are known factors necessary to gaining access to local knowledge (Zaferatos, 1998) and guiding government officials to follow community-based decisions rather than those made by technical experts from the outside (Burby, 2003).

In the same vein, communities designed planning processes to manage excessive vacancies after disaster events. Irazábal and Neville (2007) described the grassroots planning process in New Orleans, Louisiana. They emphasize on a community-based participatory planning process in reconstruction after Hurricane Katrina. In pre-Katrina New Orleans, the planning process can be summed up as a 'development-at-any-cost' environment (Irazábal & Neville, 2007). Since the 1960s, New Orleans lost 30.3% of its peak population (Irazábal & Neville, 2007). Accordingly, the city was willing to establish any projects to revitalize their economic condition regardless of their long-term benefits (Irazábal & Neville, 2007). The city was relying on short-lived and issue-based coalitions in planning that hindered to recognize systemic community agendas and to share policy problems and solutions (Burns & Thomas, 2006). After Hurricane Katrina destroyed approximately 80% of the city, it took ten months to establish a unified planning process for damaged neighborhoods while the city still lost half of its pre-Katrina population (Colten, Kates, & Laska, 2008; Robert William Kates, Colten, Laska, & Leatherman, 2006). The city's planning consultants were more interested in rebuilding 'high ground' areas over inundated areas where pre-Katrina African-American neighborhoods located (Robert William Kates et al., 2006). In addition, there were many obstacles in the recovery process hindering redevelopment efforts (Green et al., 2007). Some temporary housings were located outside of the city, so residents could not access their homes for repair. Rental vouchers were not working well due to the shortage of rental housing units in the city. Basic homeowners' insurance did not cover flood damage. The distribution of the Road Home grants, a federal home repair grants for moderate- and low-income homeowners, took at least one year after Katrina. Accordingly, communities, especially for marginalized communities, had to take an active role in conducting autonomous recovery efforts. The informal recovery activities include community design center, public housing coalitions, anarchist health center, cooperative grocery, and non-profit 'house gutting' organizations (Irazábal & Neville, 2007). However, these participatory planning activities had to rely on the recovery plans from city and federal governments because communities cannot rebuild life-supporting physical infrastructures by themselves, such as levees, utilities, and public transits (Irazábal & Neville, 2007).

3.5. Community Resilience Model

Notably, among the topics related to disaster recovery, the redevelopment of vacant land is one of the least studied (P. R. Berke et al., 1993; Dynes, 1989; Passerini, 2000; Zhang & Peacock, 2009). After the 2010s, researchers have focused on the empirical parcel level analysis regarding the vacancy and recovery after disaster events. Zhang (2012) focused on the occurrence of vacant lots in Miami-Dade County, Florida, before and after Hurricane Andrew in 1992. The study results indicate that vacancy and abandonment substantially increased after Hurricane Andrew, and more importantly, both spread over time, especially in marginalized neighborhoods such as low-income, renter-oriented, and racial and ethnic minority neighborhoods (Zhang, 2012). Rathfon et al. (2013) identified the redevelopment trend of damaged residential units by utilizing remote sensing data and building permit data. Overall, around 20% buildings were repaired 12 months after Hurricane Charley, and the percentage reached 80% and 90% at 24 months and 36 months. Crawford et al. (2017) estimated the redevelopment of vacant lots after the 2011 Tuscaloosa, Alabama tornado using the functionality change category. Overall, 28% of the parcels remained vacant (i.e., fall in negative functionality) five years after the tornado. High income, high percentage of owned homes, and homes with mortgage tend to lead a lower number of vacant parcels. However, findings from these studies are focusing on the generation of vacant lots rather than redevelopment (Zhang, 2012), testing the measurements and derived redevelopment trends (Rathfon et al., 2013), and based on an explanatory case study without using statistical modeling methods (Crawford et al., 2017).

The Center of Excellence for Risk-Based Community Resilience Planning (CoE) is a National Institute of Standards and Technology (NIST) funded multi-university multidisciplinary research center headquartered at Colorado State University. The goal of the center is to develop the measurement sciences to support community resilience assessment and risk-informed decisionmaking (Van de Lindt, Van de Lindt, Peacock, & Mitrani-Reiser, 2018). To accomplish this goal, measurement science is implemented in a community resilience modeling environment called the Interdependent Networked Community Resilience Modeling Environment (IN-CORE). IN-CORE assesses community resilience planning and recovery strategies for disaster events. Users include researchers, government officials, planners, and community stakeholders seeking to estimate the impact of natural hazards on communities. This is accomplished by employing various hazard scenarios, built environment settings, and socioeconomic conditions. The estimated results indicate resilience outcomes based on community decisionmaking. Therefore, IN-CORE can guide communities in reducing the impact of extreme hazards and rapidly recovering from disasters. For example, IN-CORE enables local decisionmakers to assess and model the physical and socioeconomic systems of a community to minimize post-disaster disruption and recovery time for homes, businesses, schools, and utilities, based on algorithms developed from experts in engineering, economics, data and computing, and the social sciences.

The findings from this study regarding predictors of long-existing vacant land will contribute the algorithms used by IN-CORE. By implementing the land redevelopment prediction algorithm, estimating the extended loss of housing and population will serve as a key index for the sustained loss of community performance. In addition, comparing systematic variations in vacant land redevelopment patterns across groups of neighborhoods will identify vacancy-prone areas that require a concentrated recovery effort. This algorithm is particularly necessary for marginalized communities because they are likely to already suffer symptoms of urban decline, including high unemployment, poverty, and crime rates, and visible increases in vacant and abandoned lands. IN-CORE supports endangered communities by providing a science-based approach to identifying spatial problems and testing planning solutions. Using IN-CORE, the ability to provide information about delayed recovery outcomes in declining neighborhoods will help local decisionmakers to test and optimize their disaster preparedness and recovery planning scenarios.

4. RESEARCH DESIGN

4.1. Research Strategy

The main question of this study was to find the factors facilitating or constraining the redevelopment of disaster-induced vacant land. Three sub-research questions were designed to compare systematic variations in redevelopment patterns across groups of neighborhoods and the characteristics of particular land parcels. Table 7 lists the questions, hypotheses, and analytical methods.

Table 7. Research Questions, Hypotheses, and Analytical Methods

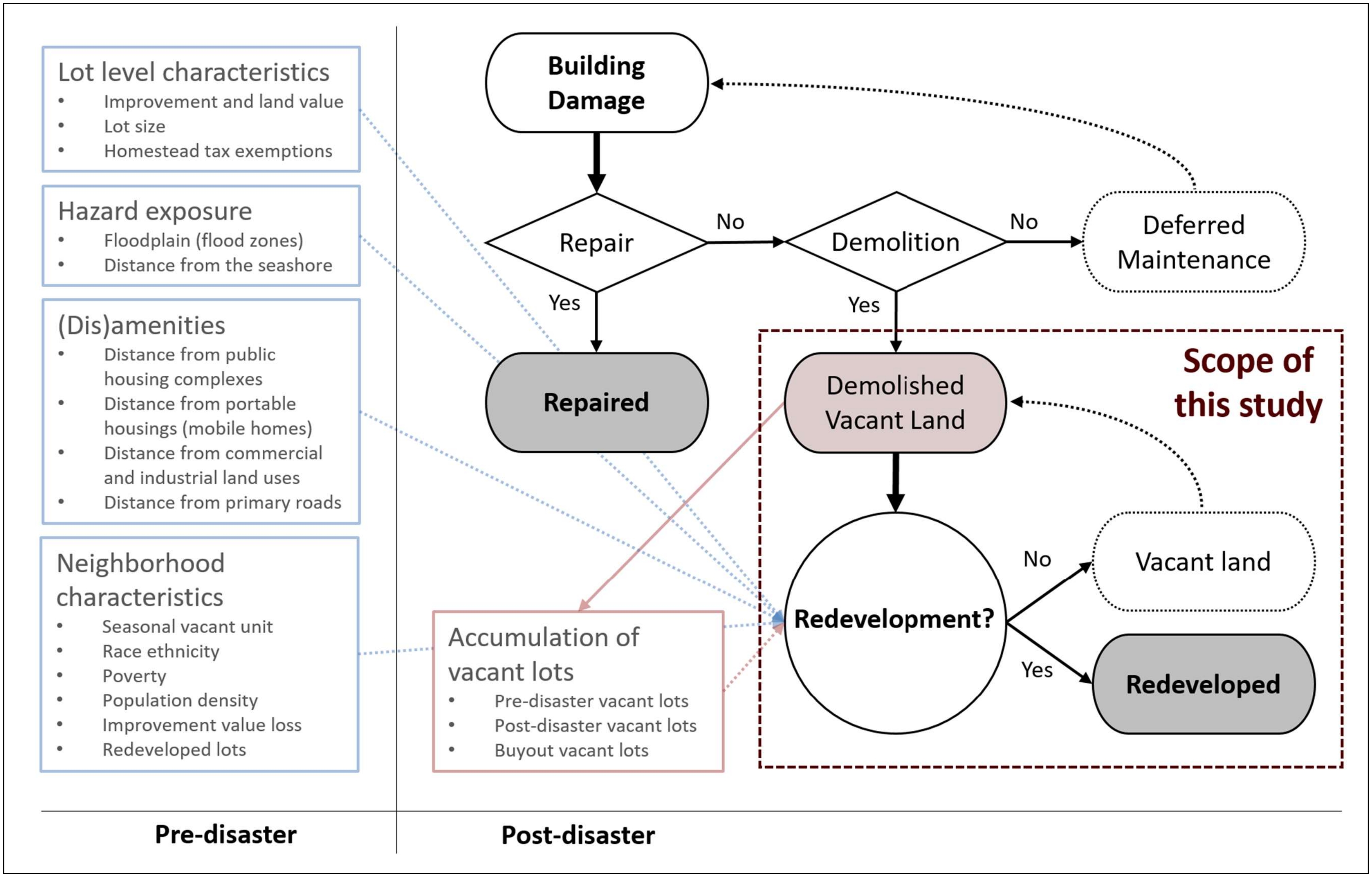
Main question	Sub-question	Hypothesis	Analytical method
What factors facilitate or constrain the redevelopment of disaster-induced vacant land?	(1) What are the differences in characteristics of disaster-induced and pre-existing vacant lands and their redevelopment patterns?	Disaster-induced vacant lots are redeveloped faster than pre-existing vacant lots.	Exploratory analysis, case-control study, PSM, and logistic regression model
	(2) How does the accumulation of vacant land affect redevelopment outcomes?	Accumulation of vacant land decreases the chance of redevelopment in a neighborhood.	Statistical analysis: cross-sectional and survival data analysis
	(3) What are the impacts of buyout programs on redevelopment outcomes?	Acquired vacant land by buyout programs is associated with a decreased likelihood of redevelopment in a neighborhood	Test the significance of buyout factors with the established models

The first sub-question was designed to uncover what happens to occupied and vacant lands when a disaster hits, and how such properties change after a disaster. An exploratory analysis was conducted to determine the longitudinal patterns of land use for both Galveston county and the study area, Galveston Island and Bolivar Peninsula.

The findings from analyses to answer the first sub-question were used to contextualize the types of vacant land. The case control study method was also employed to help determine if disaster exposure was associated with redevelopment outcomes between disaster-induced and pre-existing vacant lands. Then, propensity score matching (PSM) method and logistic regression model were tested, including physical characteristics (size and shape) and economic characteristics (improvement value, land value, and ownership). For the redeveloped lots, their durations of vacancy were also illustrated to represent the speed of redevelopment between these two groups.

Figure 3 shows the conceptual framework of post-disaster housing redevelopment. According to the damage status, a damaged building can be considered temporarily protected, repaired, or demolished. The longitudinal land use records allowed this study to identify the demolished lots from those that had become vacant. The scope of this research is tracking the redevelopment outcomes of these disaster-induced vacant lots. The redeveloped lots were identified when vacant lots changed to other land uses. For these vacant and redeveloped lots, vacancy duration was measured by tracking changes in land use over time; the duration of vacancy was the time that elapsed before redevelopment.

Figure 3. Conceptual Framework of Post-disaster Housing Recovery



The second sub-question estimated the negative spillover effects that emerged from various types of accumulated vacant land. The prevalence of vacant land was expected to hinder redevelopment efforts and extend the duration of the land's unused or underutilized status. The longitudinal land use records provided an opportunity to model unevenness in recovery, focusing on the characteristics of vacant land that facilitate or constrain redevelopment. A review of modeling methods was included to address the duration of vacant land. Vacancy duration within the study area exhibited two features: a finite period when the vacant land was redeveloped before the end of the observation phase, and a right-censored period for "not redeveloped" land that the duration could not be directly measured; this specifics when the land remained vacant at the end of the observation period. A number of approaches were used to analyze this type of data, including: 1) modeling the occurrences of redevelopment based on the end of the observation time using logistic regression models, and 2) survival data analysis and survival models estimating the probability of redevelopment over time.

The third sub-question was designed to determine what might be done in terms of the redevelopment of long-vacant land. Notably, this question focused on federal buyout programs. In addition to their direct effects benefitting damaged properties, this study estimated whether buyout properties actually hindered or promoted redevelopment outcomes in adjacent areas by escalating or de-escalating negative externalities.

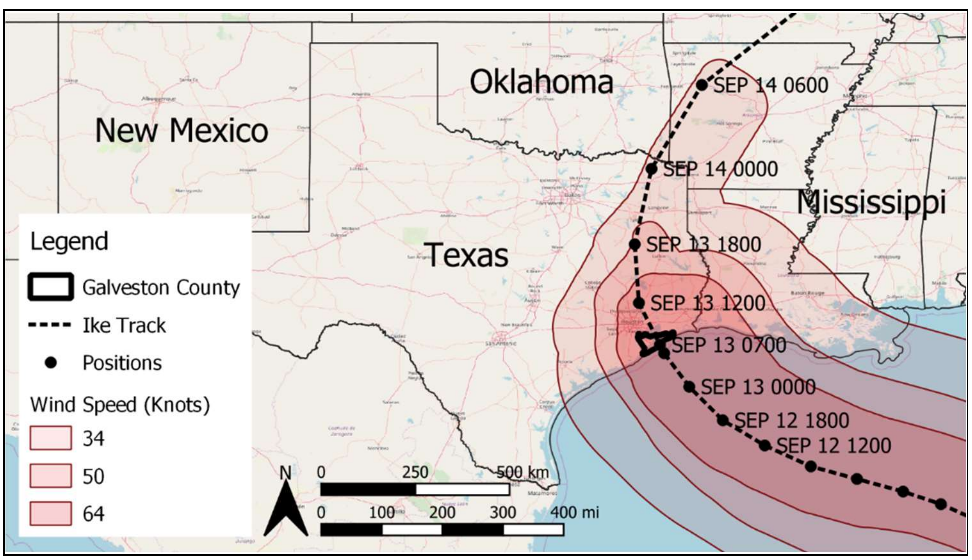
First, this chapter describes the study area, Galveston Island and Bolivar Peninsula Census County Divisions (CCDs) in Galveston County, Texas. Secondly, the information collection and data preparation procedures are explained, including sources and management methods. These three questions were resolved by mianly incorporating annual property tax records and US

Census data to identify neighborhood characteristics. The last section of this chapter explains the data analysis methodology.

4.2. Study Area

In early September 2008, Hurricane Ike caused devastating damage along the US coastline even before its landfall, due to its enormous size and 110 mph (95 knot) maximum sustained winds (Berg, 2009). Figure 4 illustrates the coastline area impacted by Hurricane Ike from Corpus Christi, Texas to New Orleans, Louisiana. On September 13, the eye of Hurricane Ike landed over the north end of Galveston Island in Galveston County, Texas. At the same time, the large wind field pushed water towards the Texas coastline.

Figure 4. Hurricane Ike's Track

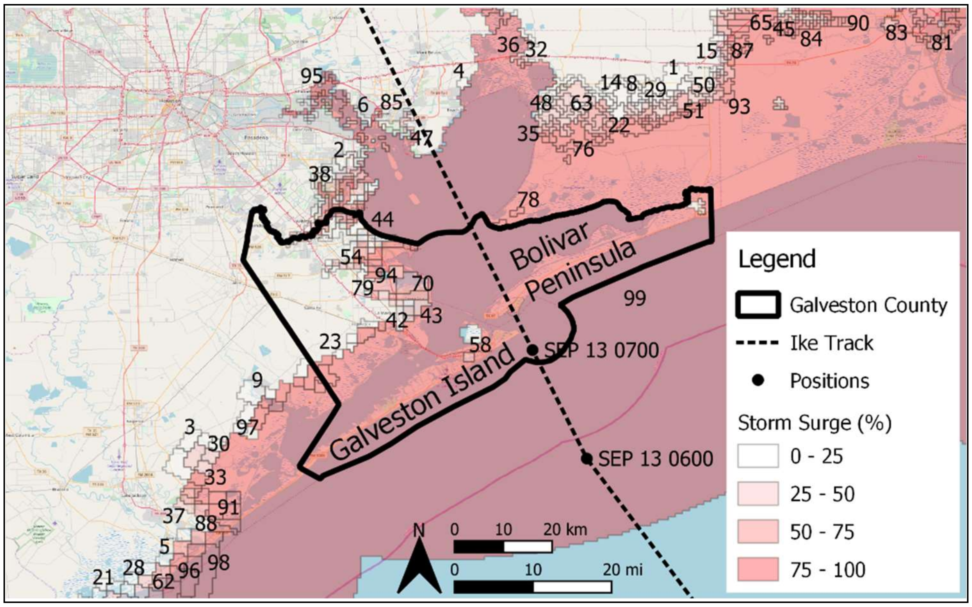


Sources: Tropical Cyclone Best Track NHC (2008b); TIGER/Line Shapefiles, U.S. Census Bureau (2000i); OpenStreetMap contributors (2020)

Figure 5 indicates the storm surge probability calculated by the National Hurricane Center (NHC) about an hour before its landfall (6 AM, September 13, 2008) (NHC, 2008a). The NHC recommended preparing for an extreme surge event, even though the chances were only around 5% to 10% that the event would occur. The southeast part of Galveston County had a 99% chance at that time. Eventually, at least four feet of water covered all of the Bolivar Peninsula in Galveston County, in addition to wave action. The highest storm surge was 15 to 20 feet on the Bolivar Peninsula. While the seawall protected much of the city of Galveston from direct impact by the storm surge and accompanying waves, a significant part of the area still eventually flooded. The Hurricane Ike Tropical Cyclone Report from the NHC (2008) noted that "significant storm surge and wave damage occurred along an extensive section of the upper Texas and southwestern Louisiana coast, with the worst devastation on the Bolivar Peninsula and parts of Galveston Island" (NHC, 2008a. p. 10).

Property Claim Services at the Insurance Services Office and National Flood Insurance Program estimated the overall insured damage in Texas, Louisiana, and Arkansas to be $14.76 billion. Since each inland flood and storm surge has a $250,000 cap, the total damage was calculated by doubling the initial estimate, which was $29.52 billion (Berg, 2009). Hurricane Ike became the second-costliest in US history at the time, after Hurricane Katrina in 2005 (Berg, 2009). In 2018, Hurricane Ike ranked sixth after Katrina (2005), Harvey (2017), Maria (2017), Sandy (2012), and Irma (2017) (NHC, 2018).

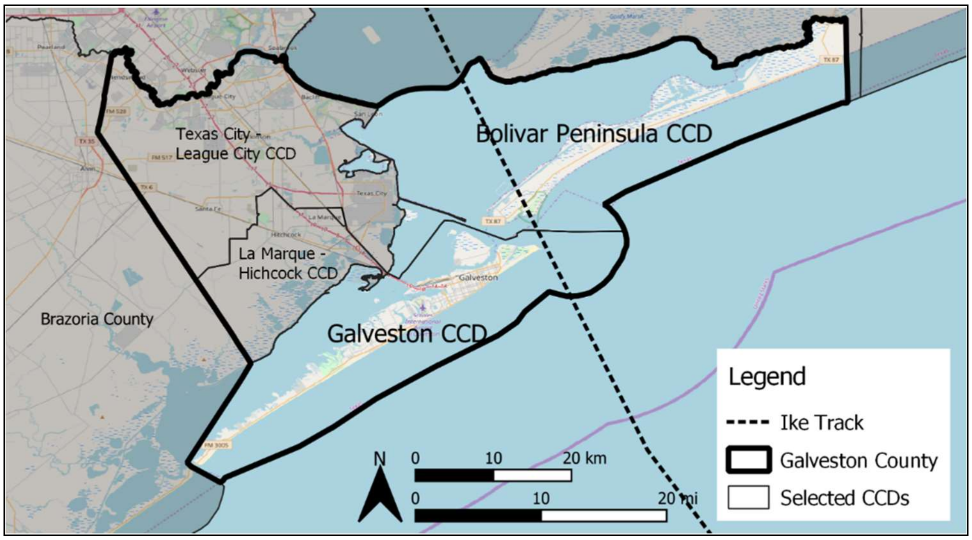
Figure 5. Probability of Ike Storm Surge at 6 AM, September 13, 2008



Sources: Probabilistic Storm Surge Forecasts, NHC (2008a); Tropical Cyclone Best Track NHC (2008b); TIGER/Line Shapefiles, U.S. Census Bureau (2000i); OpenStreetMap contributors (2020)

Because the research questions were designed to study the redevelopment of disaster-induced vacant land, Hurricane Ike damage and recovery during the following 10 years made it an ideal case for a longitudinal approach. As the NHC noted, Galveston Island and the Bolivar Peninsula were devastated by Hurricane Ike's strong winds and surge. Almost all of the structures on Bolivar Peninsula were completely destroyed from their foundations up. Two CCDs were selected in Galveston County to serve as the study area: Galveston and the Bolivar Peninsula. Figure 6 shows the designated study area in Galveston County. The combination of wind, surge, and wave action resulted in varying levels of housing damage in these CCDs. Consequently, neighborhoods in both exhibited various patterns of vacant land and redevelopment outcomes. By reviewing annual land use changes for each lot in the study area before and after the hurricane event, this study was able to clearly specify the relationships among redevelopment outcomes and a variety of factors, as well as identify pre-existing and disaster-induced vacant lands. The ten-year period after the event showed a significant amount of vacant land, enabling this study to observe and assess the progress of redevelopment.

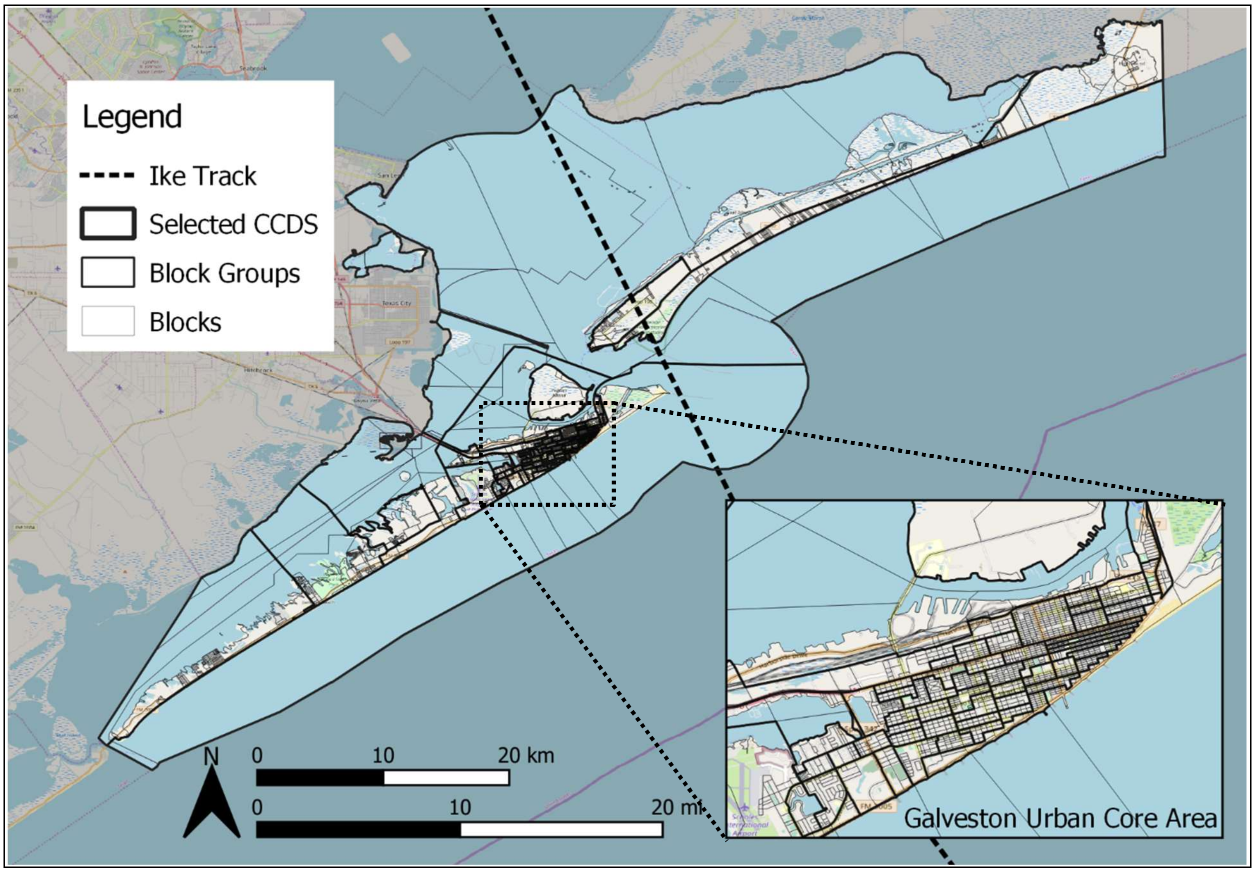
Figure 6. Study Area: Galveston and Bolivar Peninsula CCDs



Sources: Tropical Cyclone Best Track NHC (2008b); TIGER/Line Shapefiles, U.S. Census Bureau (2000i); OpenStreetMap contributors (2020)

The study area included different development types and neighborhoods, from the high-density urban core of the city of Galveston to low-density residential areas on the Bolivar Peninsula. Figure 7 indicates the US Census Small-Area Geography, including blocks and block groups. There were 2,568 blocks and 71 block groups within the study area. Hamideh et al. (2018) divided this same study area into three groups, based on housing submarkets: urban core, Galveston Island vacation residences, and Bolivar vacation homes. Galveston Island has an urban core, an historical heart of the community with single family owner-occupied units and rental housing protected by a 10 mile-long seawall (Hamideh et al., 2018). Due to the relatively high residential density, the urban core has a somewhat smaller block group than the other areas do. While a quarter of the housing units in the urban core were vacant before Hurricane Ike, about half were vacant in the vacation areas and most vacant units were intended for seasonal vacation use (Hamideh et al., 2018). Because the study area included different patterns of development, this study was able to include a variety of neighborhood and property characteristics in terms of redevelopment outcomes.

Figure 7. US Census Geography: Block Groups and Blocks in the Study Area



Sources: Tropical Cyclone Best Track NHC (2008b); TIGER/Line Shapefiles, U.S. Census Bureau (2000i); OpenStreetMap contributors (2020)

The populations of Galveston Island and Bolivar Peninsula CCDs show a parabolic trajectory, increasing for a time and now decreasing, though the population of Galveston County has continuously increased (see Table 8). Before the 1900s, the population of the Galveston Island

CCD comprised most of the population of Galveston County. Galveston County has been growing due to the Texas oil boom that initiated inland development (including the construction of oil refineries in Texas City). The Great Galveston Hurricane in September 1900 also triggered inland development because the storm caused overwhelming damage, including at least 6,000 fatalities and 3,636 homes destroyed on Galveston Island (Cline, 1900; Larson, 2000).

Table 8. Historic Population Levels

	Galveston County	Galveston Island CCD	Bolivar Peninsula CCD
1890	31,476	29,084*	-
1900	44,116	37,789*	756
1910	44,479	36,981*	710
1920	53,150	44,255*	317
1930	64,401	52,938*	767
1940	81,173	60,862*	1,359
1950	113,066	66,568*	1,242
1960	140,364	67,175*	1,694
1970	169,812	61,809*	2,424
1980	195,738	62,395	2,670
1990	217,399	60,054	2,807
2000	250,158	58,789	3,853
2010	291,309	48,728	2,417
2017	321,184	50,720	2,190
	(**)	(284)	(543)

Sources: Texas Almanac: City Population History from 1850 to 2000 (Texas Almanac, 2020); 1900 Census of Population and Housing, Texas, Table 5 (U.S. Census Bureau, 1900); 1920 Census of Population and Housing, Texas, Table 53 (U.S. Census Bureau, 1920); 1950 Census of Population and Housing, Texas, Table 26 (U.S. Census Bureau, 1950); 1960 Census of Population and Housing, Table 25 (U.S. Census Bureau, 1960); 1990 Census of Population and Housing, Table 8 (U.S. Census Bureau, 1990); Decennial Census Table P1: Galveston County (U.S. Census Bureau, 2000e, 2010h); ACS Table B01003: Galveston County (U.S. Census Bureau, 2017d); Decennial Census Table P1: Galveston CCD and Bolivar Peninsula CCD (U.S. Census Bureau, 2000d, 2010g); ACS Table B01003: Galveston CCD and Bolivar Peninsula CCD (U.S. Census Bureau, 2017c)
Note: the number in parentheses is the margin of error (MOE).
*Galveston population **This estimate is controlled to be equal to a fixed value, so it has no sampling error. A statistical test for sampling variability is not appropriate.

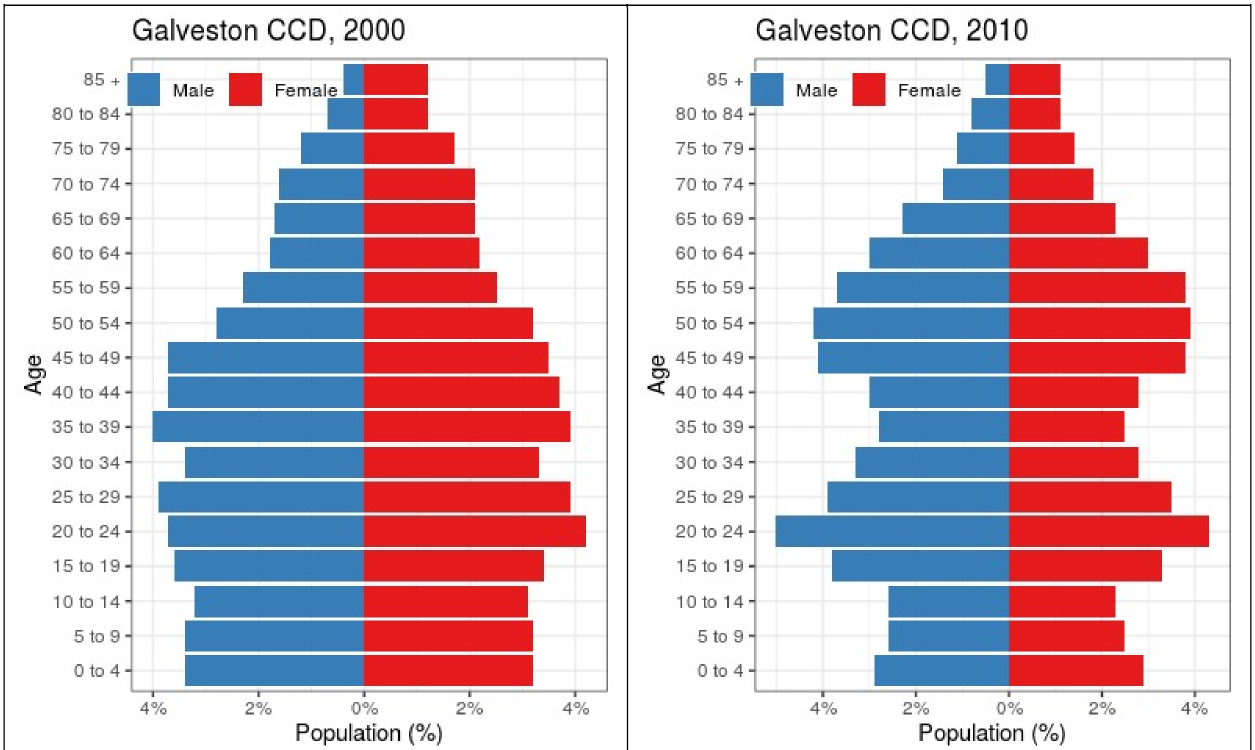
The population of Galveston Island CCD peaked in 1960. At that point, it began decreasing due to declining entertainment and manufacturing sectors. The population of Galveston Island CCD had been decreasing gradually until 2000, when Hurricane Ike intensified the population loss. Between 2000 and 2010, approximately 10,000 people left the Galveston Island CCD. Based on the estimated population in 2017, the Galveston Island CCD satisfies both the definition of a shrinking city, "a densely populated urban area with a minimum population of 10,000 residents that has faced population losses in large parts for more than two years and is undergoing economic transformation with some symptoms of a structural crisis" (Hollander et al., 2009. p. 6), and a legacy city "with populations less than 20 percent of peak but larger than 50,000" (Mallach & Brachman, 2013. pp. 2-3).

The population of the Bolivar Peninsula CCD increased after construction of Texas State Highway 87 in the 1930s. Public ferries have connected the Bolivar Peninsula to Galveston Island since 1933 (Daniels, 1985). In 1971, Crystal Beach was incorporated, making it the most populated community on the Bolivar Peninsula (Daniels, 1985). The population decreased drastically according to the 2010 Census, mainly because of the catastrophic destruction caused by Hurricane Ike in 2008. Hurricane Ike's storm surge destroyed approximately 85% of the structures on the eastern end of the peninsula. Before Hurricane Ike, there were many small houses listed at prices around $100,000. Relatively expensive homes replaced them after the surge wiped out the peninsula (Rita, 2013).

Population loss between 2000 and 2010 in Galveston Island and Bolivar Peninsula CCDs affected the distribution of age groups. Figures 8 and 9 illustrate their population pyramids. From 2000 to 2010, the Galveston Island CCD lost a great portion of its population who were between 25 and 44 years of age. The population group between 20 and 24 years of age decreased from 4,617 to 4,494, though enrollment at Texas A&M University-Galveston increased from 1,363 in the fall of 2000 (Texas A&M University at Galveston, 2014) to 1,869 in the fall of 2010 (Texas

A&M University, 2010). Bolivar Peninsula CCD appeared more like a retirement or summer home area in terms of the population pyramids for 2000 and 2010, although the age group of 60 years and over decreased in 2010. Table 9 indicates the race and ethnicity distribution in the study area. On Galveston Island CCD, the percentages are as follows: 45.9% White only, 30.8% Hispanic, and 18.3% Black only population. In the Bolivar Peninsula CCD, the most dominant population is White only, which comprises 81.2% of the total.

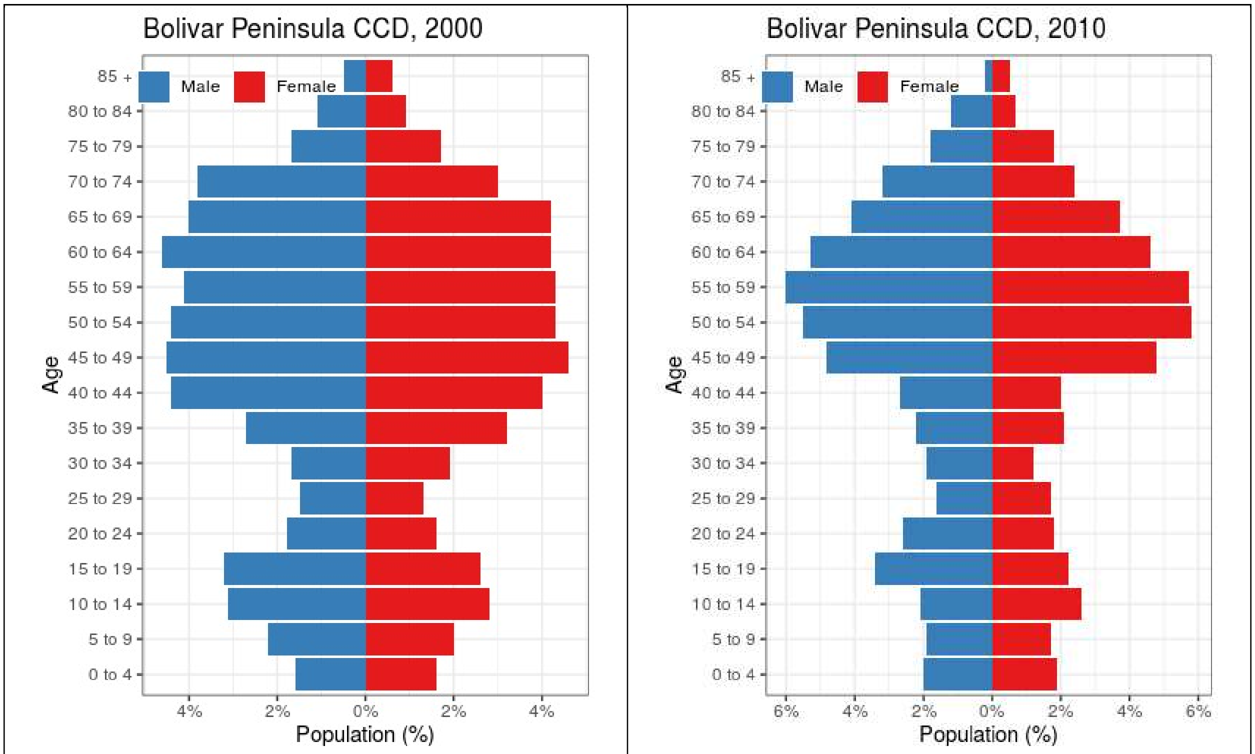
Figure 8. Population Pyramids for Galveston CCD



(a) **(b)**

Sources: Decennial Census Table QT-P1: Galveston CCD and Bolivar Peninsula CCD (U.S. Census Bureau, 2000h); Decennial Census Table QT-P1: Galveston CCD (U.S. Census Bureau, 2010l)
These graphs were made using population pyramid data and R Script for the US, States, and Counties 1970 – 2017 (Rosenheim, 2020).

Figure 9. Population Pyramids for the Bolivar Peninsula CCD



(a)	(b)

Sources: Decennial Census Table QT-P1: Galveston CCD and Bolivar Peninsula CCD (U.S. Census Bureau, 2000h); Decennial Census Table QT-P1: Bolivar Peninsula CCD (U.S. Census Bureau, 2010k)
These graphs were made using population pyramid data and R Script for the US, States, and Counties 1970 – 2017 (Rosenheim, 2020).

Table 9. Race and Ethnicity in the Study Area

2010 Decennial Census data	**Galveston Island CCD**	**Bolivar Peninsula CCD**
Total	48,728	2,417
Not Hispanic or Latino	33,729	2,064
White alone	22,370 (45.9%)	1,962 (81.2%)
Black or African American alone	8,909 (18.3%)	16 (0.7%)
American Indian*	207 (0.4%)	35 (1.4%)
Asian alone	1,490 (3.1%)	18 (0.7%)
Native Hawaiian**	23 (0.0%)	0 (0.0%)
Some other race alone	44 (0.1%)	2 (0.1%)
Two or more races	686 (1.4%)	31 (1.3%)
Hispanic or Latino	14,997 (30.8%)	353 (14.6%)

Sources: Decennial Census Table DP1: Galveston CCD and Bolivar Peninsula CCD (U.S. Census Bureau, 2010c)
*American Indian or Alaska Native **Native Hawaiian and Other Pacific Islander alone

Tables 10 and 11 identify the housing characteristics and structural units in the study area. Between 2000 and 2010 the population decreased by about 10,000 in the Galveston Island CCD, and similarly, the number of occupied units decreased from 24,540 to 20,435. The number of housing units slightly increased from 31,926 to 33,542, mainly because the number of vacant units increased for seasonal use, rent, and sale. This result implies that the housing market in the Galveston Island CCD leaned toward a vacation rental market. The number of "other: vacant" units also increased. This category represents abandoned properties and units kept vacant for reasons related to family, legal proceedings, repair, foreclosure, or held in estate. In the Bolivar Peninsula CCD, the number of housing units decreased significantly, whether total, occupied, or vacant. Overall, in 2010, the percentages of vacant housing units were 39.1% and 59.3% for each CCD, which were substantially higher than the national average, 12.6%. In terms of housing structure, Bolivar Peninsula is a single-family oriented residential community; 82.3% of housing units were single family detached. Conversely, in the Galveston CCD, 58.3% of housing units were single family detached.

Table 10. Housing Characteristics in the Study Area

	Galveston Island CCD in 2000	Galveston Island CCD in 2010	Bolivar Peninsula CCD in 2000	Bolivar Peninsula CCD in 2010
Housing unit	31,926	33,542	5,425	2,707
Occupied	24,540	20,435	1,801	1,101
Owner	10,987 (44.8%)	9,943 (60.9%)	1,512 (84.0%)	890 (80.0%)
Renter	13,553 (55.2%)	10,492 (39.1%)	289 (16.0%)	211 (19.2%)
Vacant	7,386	13,107	3,624	1,606
For rent	2,654 (35.9%)	3,385 (25.0%)	162 (4.5%)	106 (6.6%)
For sale only	396 (5.4%)	990 (7.6%)	75 (2.1%)	75 (4.7%)
Rented or sold*	289 (3.9%)	284 (2.1%)	36 (1.0%)	8 (0.5%)
For seasonal**	3,276 (44.4%)	5,343 (40.8%)	3,252 (89.7%)	1248 (77.7%)
For migrant***	2 (0.0%)	8 (0.1%)	1 (0.0%)	0 (0.0%)
Other vacant	769 (10.4%)	3,207 (24.5%)	98 (2.7%)	169 (10.5%)

Sources: Decennial Census Table QT-H1: Galveston CCD and Bolivar Peninsula CCD (U.S. Census Bureau, 2000g, 2010i, 2010j)
*Rented or sold, not occupied; ** For seasonal, recreational, or occasional use *** For migratory workers

Table 11. Occupied Housing Units by Structure Type in the Study Area

	Galveston Island CCD in 2010	Bolivar Peninsula CCD in 2010
1, detached	58.3% (2.1)	82.3% (8.1)
1, attached	2.2% (0.5)	0.2% (0.4)
2 apartments	4.7% (0.9)	1.1% (1.7)
3 or 4 apartments	5.5% (1.3)	0.0% (3.0)
5 to 9 apartments	6.9% (1.4)	0.0% (3.0)
10 or more apartments	21.5% (1.7)	0.7% (1.2)
Mobile home or other	0.9% (0.4)	15.6% (7.8)

Sources: ACS Table S2504: Galveston CCD and Bolivar Peninsula CCD (U.S. Census Bureau, 2010c)
Note: the number in parentheses is the margin of error (MOE).

Table 12. Median Household Income

Year	Galveston County	Galveston Island CCD	Bolivar Peninsula CCD
2000	62,410	43,642	50,369
2010	65,409 (1,795)	41,074 (2,436)	47,745 (12,513)
2017	65,702 (1,802)	43,033 (2,522)	49,737 (23,428)

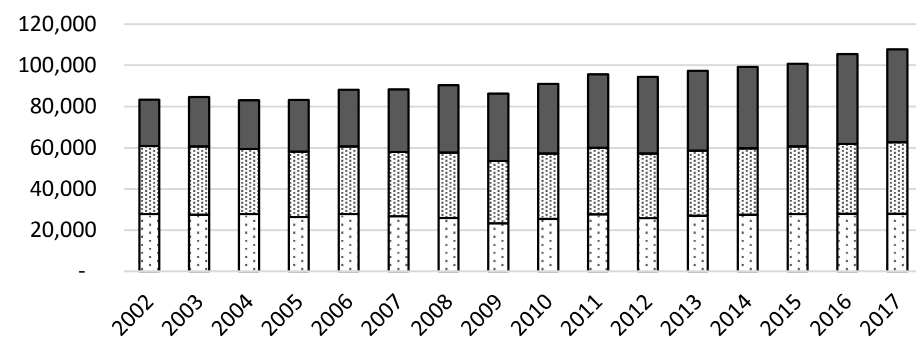
Sources: Decennial Census Table P53: Galveston County (U.S. Census Bureau, 2000f); ACS Table S1903: Galveston County (U.S. Census Bureau, 2010b, 2017f); Decennial Census Table P53: Galveston CCD and Bolivar Peninsula CCD; ACS Table S1903: Galveston CCD and Bolivar Peninsula CCD (U.S. Census Bureau, 2010a, 2017e)
Note 1: in 2017 inflation-adjusted dollars per the Consumer Price Index Calculator, U.S. Bureau of Labor Statistics (https://www.bls.gov/data/inflation_calculator.htm)
Note 2: the number in parentheses is the margin of error (MOE).

In Table 12, the median household incomes listed are inflation-adjusted in dollar amounts for 2017. The median incomes in both CCDs were lower than those of Galveston County. Note that the Bolivar Peninsula CCD had a larger margin of error than did the other areas. Still, Bolivar Peninsula CCD had a higher median income than did Galveston Island CCD.

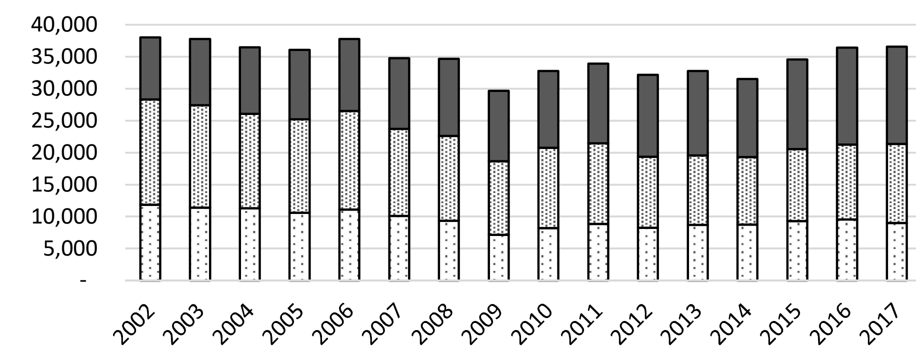
Figure 10 illustrates the annual number of jobs in the county and study area. In 2009, the number of jobs in Galveston County slightly decreased, probably due to the economic recession and damage from Hurricane Ike. The county lost 3,996 jobs (a 4.4% decrease) between 2008 and 2009. The loss of jobs in the Galveston and Bolivar Peninsula CCDs was more severe than in other areas of the county. The Galveston CCD lost 5,006 jobs (a 14.4% decrease) and the Bolivar Peninsula CCD lost 367 jobs (a 61.6% decrease) during the same period. According to the Jobs by NAICS Industry Sector (U.S. Census Bureau, 2020b), between 2008 and 2009, the Galveston CCD lost 2,358 jobs in the Education Services sector and 1,108 jobs in the Accommodations and Food Services sector. In the Bolivar Peninsula CCD, 131 jobs in the Construction sector, 89 jobs in the Retail Trade sector, and 67 jobs in the Accommodations and Food Services sector disappeared between 2008 and 2009.

Figure 10. Number of Jobs between 2002 to 2017

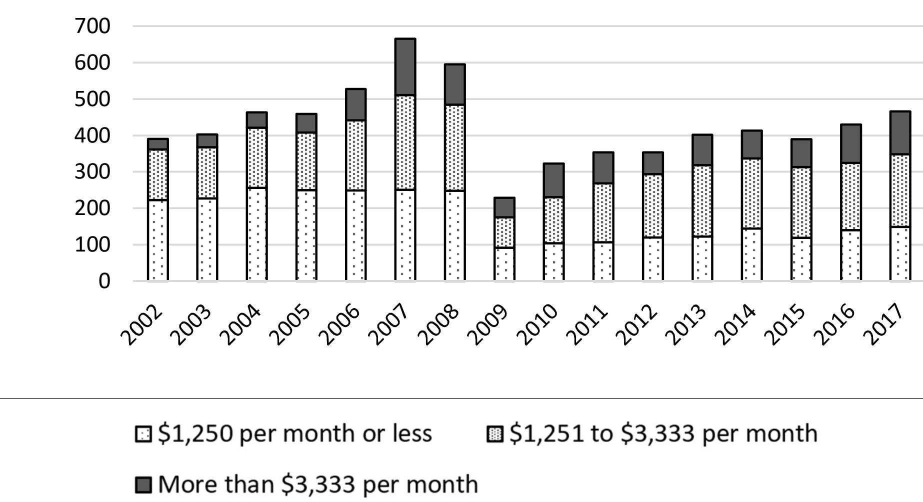
Galveston County



Galveston CCD



Bolivar Peninsula CCD



Source: OnTheMap, a web-based reporting application (U.S. Census Bureau, 2020b)

Table 13 shows the inflow and outflow of job counts. Between 2008 and 2009, the Galveston CCD lost 3,814 workers who had previously been employed and lived in the Galveston CCD (static). At the same time, the Bolivar Peninsula lost 281 workers who lived outside (inflow) and 86 who were employed and lived in the Galveston CCD (static).

Table 13. Inflow/Outflow Job Counts

	Galveston CCD			Bolivar Peninsula CCD		
	Inflow	**Static**	**Outflow**	**Inflow**	**Static**	**Outflow**
2007	20,445	14,338	12,057	517	149	653
2008	20,545	14,144	12,492	454	142	692
2009	19,353	10,330	12,455	173	56	697
2010	22,121	10,684	11,684	230	93	582
2017	23,944	12,652	11,860	359	107	553

Source: OnTheMap, a web-based reporting application (U.S. Census Bureau, 2020b)
Note: Inflow includes workers employed in the selected area but living outside; static is those employed and living in the selected area, and outflow is those living in the selected area but employed outside.

4.3. Data Collection

The credibility of a study improves when external researchers participate in reviewing, critiquing, extending, and reproducing its scientific claims. Shared research data and methodologies can be used to verify the results described in published articles (Stone, 1995). This enables other researchers to extend their research with a more coherent employment of research methods (King, 1995) and prevents cumbersome and repetitive work (Freese, 2007). Disaster research can also benefit from sharing research outcomes. Hazard research tends to have limitations due to its unpredictable occurrences, unavailability of experimental controls, sampling biases, and perishable data conditions (National Research Council, 2006). Sharing research data and methodologies facilitates researchers conducting longitudinal and multi-hazard research and overcoming such limitations. However, as Munafò et al. (2017) noted, only a limited number of researchers share their research outcomes, due to vested interests and a lack of incentives to engage in sharing. To enhance the credibility of this research and facilitate data sharing, this study applied an automated data cleaning and analytical workflow using Stata (StataCorp, 2017a) and a do-file, a text file designed to instruct Stata by executing the commends stored in that file.

Standardized data management is required to efficiently share and replicate research outcomes. Standards include archiving materials, data, and methodologies at the time of publication (Freese, 2007). As an example of an appropriate data management process, Mason and Wiggins (2010) suggested five steps, the acronym for which is OSEMN: 1) Obtaining, 2) Scrubbing, 3) Exploring/visualizing, 4) Modeling, and 5) iNterpreting data. In addition, J Scott Long (2009), Gentzkow and Shapiro (2014), and Lowndes et al. (2017) have all suggested guidelines for data management, including automating the research process, clearly describing the unique identification variables and unit of analysis, recording metadata and workflow via a codebook and research log, organizing data based on normalized files with key variables, and keeping data under version control. This study followed the suggested data management methods to enhance the reproducibility of research for open data and open science.

This section focuses on the process for obtaining and scrubbing the data. Table 14 lists the data sources consisting the influential factors in Figure 3, Conceptual Framework. Researchers in the field of disaster recovery often compare properties' physical conditions before and after a disaster to identify vacant land (Bin & Kruse, 2006; Chang, 2010; Curtis et al., 2007; De Silva et al., 2006; Hamideh et al., 2018; Hirayama, 2000; Jarmin & Miranda, 2009; Liu & Plyer, 2009; Peacock et al., 2014; Rathfon et al., 2013; Stevenson et al., 2010; Wu, 2004; Zhang & Peacock, 2009). For example, Zhang (2012) identified vacant lots based on changes in the land use code, such as "if a lot was in residential use but changed to vacant land, it was considered [as] becoming vacant" (Zhang, 2012. p. 1091). In the same vein, this research identified the spatial disparity of emergent vacant lots after Hurricane Ike by using the annual land use data from the property tax records from Galveston Central Appraisal District (2019). In addition, the land-use related amenities and disamenities factors and the neighborhood level damage and redevelopment trend factors were also derived from the property tax records.

Table 14. Data Sources

Name	Data Source	Variable Group
Property tax records	• Galveston Central Appraisal District (GCAD) parcel shapefiles with detailed lot information	• Lot level characteristics • Accumulation of vacant lots • (Dis)amenities
Floodplain and water areas	• FEMA Flood Map Service Center • U.S. Census Tiger/Line Shapefiles	• Hazard exposure
U.S. Census data	• Decennial Census data in 2000 (aggregated to census block groups)	• Neighborhood characteristics
Others	• City of Galveston • U.S. Census Tiger/Line Shapefiles	• (Dis)amenities

Floodplain and water areas were used to identify the level of hazard exposure. FEMA flood zone data and U.S. Census Tiger/Line Shapefiles were utilized with the locations of each lot based on the property tax records (Federal Emergency Management Agency, 2020b; U.S. Census Bureau, 2010m). Lots located in the high risk flood zones and the close in distance from seashores were considered as exposed to future disaster losses. In the same vein, U.S. Decennial Census data in 2000 were used to provide the components of recovery factors regarding pre-disaster socioeconomic characteristics. The Census data were aggregated to census block groups. For the disamenity factors, the distances from pre-disaster public housing complexes and major roads were calculated using the data from the City of Galveston and U.S. Census Tiger/Line Shapefiles (Housing Authority of Galveston, 2009; U.S. Census Bureau, 2010d).

This research targets residential lots in the Galveston and Bolivar Peninsula CCDs in Galveston County, Texas. The Galveston Central Appraisal District (GCAD) annually publishes lot-level data with property tax information. The data file format is the ESRI shapefile, a geospatial vector data format that includes multiple shapes and related data attributes. The shapefile data exists for each year from 2005 to 2019. However, the shapefile data in 2005 and 2006 did not contain data attributes such as land use type and property value. The data in 2018 and 2019 were also limited since these shapefiles did not contain the land use type variable due to the recent transition of the GCAD database. For these reasons, these four years of data were excluded from the research. Each year, appraised property values are based on the January 1 market values; residents can appeal their appraised values until mid-May (County of Galveston Office of Tax Assessor-Collector, 2020). In general, GCAD uploads the shapefile data around mid-July. Thus, decreases in property values due to Hurricane Ike in September 2008 were reflected in the 2009 property tax data. Accordingly, the shapefile data contained two years of data before the hurricane that showed pre-disaster conditions (2007 and 2008), one year of data immediately after Hurricane Ike that indicated direct hurricane damage (2009), and eight years of data demonstrating the progress of recovery (2010 to 2017).

Unlike using cross-sectional or solely post-disaster data, this research was able to distinguish pre-disaster urban development and post-disaster recovery patterns. The methodological advance of longitudinal data is especially important for a vacant land study because it enabled the present research to control for different occurrence types of vacant land, such as preexisting vacant land before the observation period, newly generated vacant land before the hurricane, and disaster-induced vacant land right after the hurricane. The analysis further controlled for the vacant land types necessary for appropriately specified models. Specifically, comparing recovery patterns by different vacant land type was required to answer the first subsidiary research question regarding the differences in characteristics of disaster-induced and pre-existing vacant land and related redevelopment patterns.

The GCAD property tax data were ideal because of the depth of the information collected. Each shapefile from the GCAD has a dBase file (*.dbf) containing the data attributes for each lot. Table 15 includes a description of these attributes. Each year, a dBase file is generated that contains approximately 156,000 to 167,000 lots in Galveston County and approximately 30 variables. There were 10 variables for numeric values such as property values and land area, and 20 string variables for text characters such as lot identification, owners' names and addresses, and land use types. Since 2011, the data have contained the FLAGS variable, which presents detailed lot-level characteristics. The FLAGS variable enabled this study to track lots that participated in the federal buyout program since early 2010. These advantages made the GCAD data better suited for this study than other regions with a history of disaster damage and resulting vacant land.

Table 15. Description of Data Files from GCAD

File Name	Format	Unit of analysis	Key variabl e	# of observations (rows)	# of variables (columns)	# of string variables	# of numeric variables
parcels_2007.dbf	dBase	parcel/lot	XREF	156,259	28	18	10
parcels_2008.dbf	dBase	parcel/lot	XREF	158,192	28	18	10
parcels_2009.dbf	dBase	parcel/lot	XREF	159,446	28	18	10
parcels_2010.dbf	dBase	parcel/lot	XREF	160,699	27	17	10
parcels_2011.dbf	dBase	parcel/lot	XREF	161,338	28	18	10
parcels_2012.dbf	dBase	parcel/lot	XREF	161,079	29	18	11
parcels_2013.dbf	dBase	parcel/lot	XREF	162,108	30	19	11
parcels_2014.dbf	dBase	parcel/lot	XREF	162,801	29	18	11
parcels_2015.dbf	dBase	parcel/lot	XREF	164,345	29	18	11
parcels_2016.dbf	dBase	parcel/lot	XREF	165,967	28	18	10
parcels_2017.dbf	dBase	parcel/lot	XREF	166,918	27	18	9

Source: Galveston Central Appraisal District Shape File (Galveston Central Appraisal District, 2019)

Table 16. Number of Lots in the Study Area

File Name	Format	Unit of analysis	# of observations (rows)	Change	Change (%)
parcels_2007_inSA.dbf	dBase	lot	45,499		
parcels_2008_inSA.dbf	dBase	lot	45,637	138	0.30%
parcels_2009_inSA.dbf	dBase	lot	45,758	121	0.27%
parcels_2010_inSA.dbf	dBase	lot	46,458	700	1.53%
parcels_2011_inSA.dbf	dBase	lot	46,508	50	0.11%
parcels_2012_inSA.dbf	dBase	lot	45,913	-595	-1.28%
parcels_2013_inSA.dbf	dBase	lot	45,887	-26	-0.06%
parcels_2014_inSA.dbf	dBase	lot	45,844	-43	-0.09%
parcels_2015_inSA.dbf	dBase	lot	45,847	3	0.01%
parcels_2016_inSA.dbf	dBase	lot	45,991	144	0.31%
parcels_2017_inSA.dbf	dBase	lot	45,871	-120	-0.26%

Source: Galveston Central Appraisal District Shape File (Galveston Central Appraisal District, 2019)

The property tax records from GCAD contain a key variable, XREF, that can be used to identify each lot. The XREF variable contains 15 digits of numbers. However, it is not a unique identifier; it includes duplicate and missing observations. For example, in the 2007 data, the XREF variable incorporated approximately 5,000 duplicate and 500 missing observations. This was about a 3.6% of the total number of observations. Table 16 shows the number of lots within the study area. Every year, the number of lots slightly increased or decreased by around 1.5% from the previous year.

A new identification variable was designed based on the lots in the 2007 data. For example, integers from 1 to 156,260 were assigned for each lot in the 2007 data. To create longitudinal land use records by lot, the center points of each lot in the 2007 data were spatially joined with the subsequent annual data from 2008 to 2017. After the spatial joining process, years of lot data were consolidated into one file. The longitudinal data contained the unique identification variable based on the center points of lots in the 2007 data. The shapefile data included some technical errors, such as slivers and overlaps. For example, many lot boundaries overlapped with US Census geographical boundaries. Using the center points of each lot as reference points mitigated these minor locational errors. Finally, the lots within the study area, both the Galveston Island and Bolivar Peninsula CCDs, were extracted for the analysis. This process was conducted using QGIS, an open-source geographic information system (GIS) application (QGIS Development Team, 2020).

The full list of land use categories used in the GCAD data are illustrated in Table 17. The Texas Property Tax Assistance Property Classification Guide (Hegar, 2014) indicates the definitions of vacant lots, such as the ‘C1, Vacant’ category, which represents small vacant tracts of land most suited for use as building sites. In general, these lots are idle tracts in some stage of development or awaiting construction. If a lot is at least as valuable without the improvements and a lot is unused, it is identified as a ‘C1, Vacant’ lot. The land use codes in the data follow the Texas Property Classification Guide except in the tax exempt case. The GCAD prefers to use separate codes for tax exempt properties for each type of land use. For example, GCAD has created the

‘C9, Vacant, tax exempt” category to differentiate untaxed vacant lots. Except the tax exempt vacant lots (C9), the unused lots with nominal improvements were identified as C1, Vacant in the study area.

Table 17. Land Use Categories in the GCAD Property Tax Data

Category	Code	Description
Single family residential	A1	Single family residential
	A2	Single family residential, mobile home
	A3	Single family residential, condominium
	A9	Single family residential, tax exempt
Multi-family residential	B1	Multi-family residential
	B2	Multi-family commercial
	B9	Multi-family, exempt
Vacant	C1	Vacant platted lot
	C9	Vacant platted lot, tax exempt
Acreage	D1	Acreage, ranch land
	D3	Acreage, farmland
	D4	Acreage, undeveloped
	D5	Acreage, non-qualifying agriculture use
	D9	Acreage, tax exempt
Farm and ranch	E1	Farm and ranch improvements
	E9	Farm and ranch improvements, tax exempt
Commercial and industrial	F1	Commercial
	F2	Industrial
	F9	Commercial, tax exempt
Utility	J1	Water system
	J2	Gas distribution system
	J3	Electric company
	J4	Telephone company
	J5	Railroad
	J6	Pipeline
	J9	Utility, tax exempt
Inventory	O1	Inventory, vacant land
	O2	Inventory, single family residential

In addition to the C1 and C9 vacant lots, there are other types of vacant land, such as farm and ranch lots without improvements (all D-category lots) and residential inventory lots (all O-category lots). Because this study focused on the redevelopment of disaster-induced vacant land and related negative externalities, agricultural lots were not considered vacant. Residential inventory lots such as ‘O1, Inventory, vacant land’ and ‘O2, Inventory, single family residential’ indicate properties held as inventory if they are under the same ownership and located in the same subdivision or development, have never been occupied, and are held for sale (Hegar, 2014). Accordingly, a Category O lot can also be identified as a vacant lot when it is left undeveloped (O1) or developed and held for sale (O2). Thus, O1 and O2 lots were reviewed in the present research, along with C1 and C9 vacant lots.

Table 18 lists the concepts of dependent and independent variables based on Figure 3, Conceptual Framework. From the longitudinal property tax records, the dependent variables were derived through changes in land use categories. For example, the generation of vacant lots was identified when residential lots changed to vacant lots over time. The duration of vacancy was then assessed for these newly generated vacant lots. Session 4.4.1 contains more detailed information about this procedure.

The component of independent variables identified by the literature review that contribute to mediating or stimulating residential redevelopment and disaster recovery. These independent variables were categorized into six groups: lot-level characteristics, hazard exposure, distance from amenities and disamenities, neighborhood characteristics, accumulation of vacant lots, and vacant area. In addition to the property tax records (Galveston Central Appraisal District, 2019), the study acquired a variety of spatial datasets from the Federal Emergency Management Agency (2020b) and US Census Bureau (U.S. Census Bureau, 2000a, 2000i, 2010d, 2010m). The datasets were cleaned and spatially joined with the information on disaster-induced vacant lots using QGIS (QGIS Development Team, 2020) and NNJoin Plugin (Tveite, 2020), a nearest neighbor join and distance calculation program.

Table 18. Concepts of Variables

Category	Variable	Description	Data Source
Dependent variable	Vacant lot	Lot was for residential use and changed to vacant before and after Hurricane Ike	GCAD
Lot level characteristics	Improvement value	Unit: USD	GCAD
	Land value	Unit: USD	GCAD
	Lot size	Unit: square feet	GCAD
	Homestead tax exemption	Homestead tax exemption lots (owner occupied lots)	GCAD
Hazard exposure	Floodplain	Categorical flood zones: 0.2, X, AE, and VE	FEMA Flood Map Service Center
	Distance from the seashore	Distance from any water areas; Unit: feet	Tiger/Line Shapefiles
Distance from (dis)amenities	Public housing complexes	Distance from pre-disaster public housing complexes; Unit: feet	City of Galveston
	Portable housing lots	Distance from 'A2 portable housing' lots; Unit: feet	GCAD
	Commercial lots	Distance from 'F1 commercial' lots; Unit: feet	GCAD
	Industrial lots	Distance from 'F2 industrial' lots; Unit: feet	GCAD
	Major roads	Distance from major roads; Unit: feet	Tiger/Line Shapefiles
Neighborhood characteristics	Seasonal vacant unit	Percentage of seasonal vacant units; Unit: %	2000 Decennial Census
	Black, non-Hispanic	African American population; Unit: %	2000 Decennial Census
	Hispanic	Hispanic population; Unit: %	2000 Decennial Census
	Poverty	Percentage of persons in poverty; Unit: %	2000 Decennial Census
	Population density	Population density; Unit: person per square mile	2000 Decennial Census; Tiger/Line Shapefiles
	Improvement value loss	Percentage of value loss before and after Hurricane Ike (2008 and 2009); Unit: %	GCAD
	Redeveloped lots	Percentage of redeveloped lots between 2009 and 2017; Unit: %	GCAD
Accumulation of vacant lots	Number of vacant lots	Number of vacant lots	GCAD
Vacant area	% of vacant area	Percentage of vacant area based on Landscape Shape Index provided by FRAGSTAT	GCAD
	Patch Density of vacant area	Patch Density of vacant area based on Landscape Shape Index provided by FRAGSTAT	GCAD

The lot level characteristics include each lot's pre-disaster (and pre-vacancy) values, size, and homestead tax exemption status obtained from the longitudinal property tax records. These lot-level characteristics are known to facilitate vacant lots' redevelopment outcomes. For example, higher-value, properly-sized, and owner-occupied vacant lots tend to be redeveloped at a faster rate. In terms of disaster recovery, these factors were also expected to expedite the redevelopment outcomes of disaster-induced lots.

The hazard exposure category has two variables: a categorical variable indicating the flood zones in which each vacant lot was located, and a variable calculated by the straight-line distance between each vacant lot and the nearest seashore (or any water area). These two variables were derived to indicate the level of flood hazard using FEMA Flood Map (Federal Emergency Management Agency, 2020b) and area hydrography shapefiles from the US Census TIGER/Line Shapefiles database (U.S. Census Bureau, 2010m).

The variables for distances from amenities and disamenities were designed to control for contextual urban land development factors. Distances from pre-disaster public housing complexes (Hamideh & Rongerude, 2018), portable housing, commercial (Shultz & King, 2001; Song & Knaap, 2004; Yoon, 2018) and industrial lots (Shultz & King, 2001; Song & Knaap, 2004), and major roads variables were expected to hinder or stimulate residential development. The major roads variable utilized State Highway 87 and Termini-San Luis Pass Road, which pass through the entire Galveston Island and Bolivar Peninsula areas.

To evaluate differences among demographic, race/ethnic, income, and population density as they relate to redevelopment outcomes, this study included variables derived from the 2000 Decennial Census before the disaster event. The longitudinal property tax data were spatially joined with the census block group geographic layers to obtain the geographic identifiers for each lot. Then, the socioeconomic information from the Decennial Census was joined through those block group geographic identifiers. There were 71 block groups in the study area. The census block group data enabled this study to capture homogeneous neighborhood-level characteristics (Van Zandt et al., 2012). The variables for percentage of loss of improvement value and percentage of redeveloped lots were derived from the longitudinal parcel data to indicate the general tendency of redevelopment outcomes.

Because this research focuses on the proliferation of vacant land and resultant negative externalities, the variables indicating the accumulation of vacant land were derived using four concentric rings of radii around each observation, increasing the radii by 250 feet for each. These variables offered insight into negative externalities in terms of their cumulative effects within certain distances from vacant lots (Griswold & Norris, 2007; Han, 2017a; Immergluck & Smith, 2006; Z. Lin et al., 2009; Mikelbank, 2008; Shlay & Whitman, 2006). Specifically, identifying the amount and number of vacant lots was achieved by using QGIS. After that, the percentage of vacant area and patch density were estimated by the Landscape Shape Index through FRAGSTATS, a spatial pattern analysis program (McGarigal, Cushman, & Ene, 2012). Using these indices allowed this study to estimate the effects of vacant area and fragmentation while controlling for other factors. For example, clustered vacant lots may generate more adverse effects on redevelopment than fragmented vacant lots. Three types of vacant lots were separately processed for these variables, such as pre-disaster, post-disaster, and buyout lots.

4.4. Data Preparation and Analysis

4.4.1. Identification of Vacant Land and Vacancy Duration

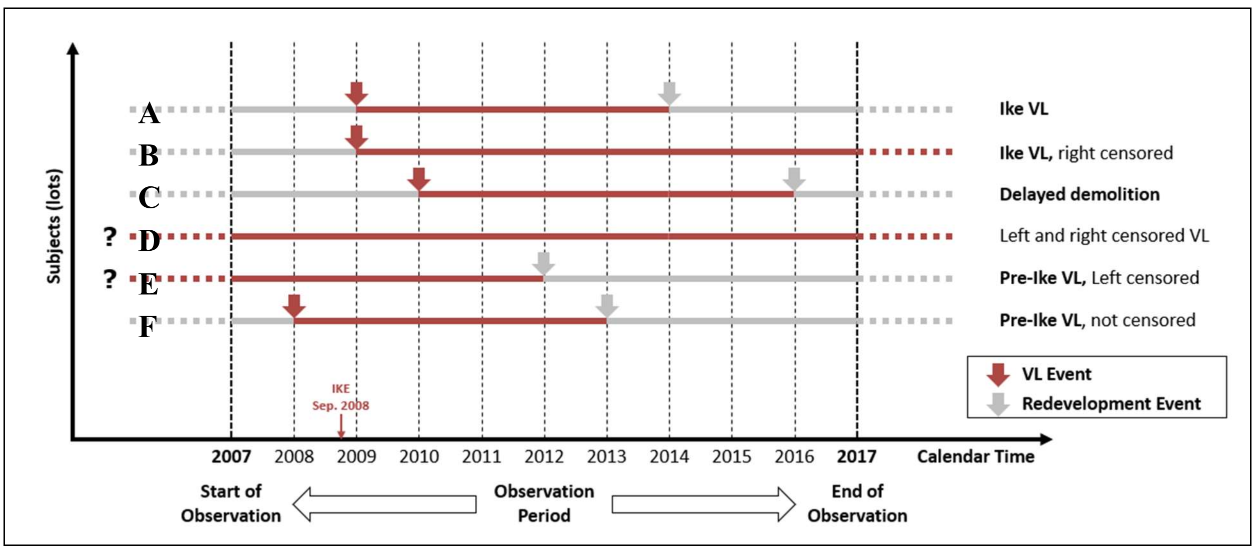
This section describes the major steps used to analyze the consolidated vacant land data. The data were imported to Stata, a statistical data management and analysis program, for data preparation and analysis. The steps followed for data preparation and analysis were recorded using a Do-file Editor, a Stata-integrated text editor for programming. The list of commands was saved in several text files, following the data management guidelines provided by J Scott Long (2009), Mason and Wiggins (2010), Gentzkow and Shapiro (2014), and Lowndes et al. (2017). These guidelines facilitate the review and sharing of the workflow employed in this study.

The data preparation process was designed to identify the spatial locations of vacant land parcels before and after Hurricane Ike. The first step was measuring the vacant land and vacancy duration over time. The definition of vacant land included several aspects, such as structure type, utilization, minimum period, and maintenance of financial responsibilities. Following the land use codes employed in Texas (Hegar, 2014), the existence of a structure was used when measuring vacancy (Hearle & Niedercorn, 1964; Northam, 1971). For example, a vacant lot was considered undeveloped land if it had no structures or the land was at least as valuable without the improvements. In such cases, redevelopment was a critical factor differentiating vacant land from occupied land with buildings.

Figure 11 illustrates the operational definitions of vacant land and vacancy duration. Each line in the graph indicates a lot and its time series of vacancy status from 2007 to 2017. Grey lines are occupied lots and red lines are vacant. The figure includes six examples of vacant land patterns. The first and second examples are disaster-induced vacant lots, lots developed before Hurricane

Ike that had buildings that were then demolished in 2009. The Line A lot is a disaster-induced vacant lot. This lot was occupied before Hurricane Ike (in 2007 and 2008) and became vacant after Hurricane Ike (in 2009 to 2013). This lot was redeveloped in 2014; thus the duration of vacancy was five years. The Line B lot is another example of a disaster-induced vacant lot. Like the Line A lot, this lot became vacant after Hurricane Ike. However, the lot remained vacant during the observation period (right censored). The duration of vacancy could be presented as 8+ years, or as undeveloped within the research period. The third example is a delayed demolition lot. Unlike the Lines A and B lots, the Line C lot became vacant in 2010. However, it is unclear whether the cause of vacancy was damage from Hurricane Ike.

Figure 11. Measures of Vacant Lots and Vacancy Durations



Note: VL stands for vacant lot.

Land made vacant from flood and surge damage caused by Hurricane Ike was distinguished from preexisting vacant land through the use of pre- and post-Ike land-use types. Lines D, E, and F, indicate vacant lots that existed before Hurricane Ike. The Line D lot is a lot that was vacant during the entire observation period. In the study area, some of these vacant lots usually included wetlands and partially submerged land. The Line E lot was vacant until being redeveloped in 2012. For the Lines D and E vacant lots, the durations of vacancy could not be directly measured (left censored). The Line F lot was occupied in 2007 and became vacant in 2008. This lot represents a pre-disaster vacant lot that was used as a benchmark to distinguish differences in redevelopment patterns and the characteristics of disaster-induced and pre-existing vacant land.

Three assumptions were made to identify vacant lots and their vacancy durations. First, this study assumed all newly generated vacant lots in 2009 were the product of Hurricane Ike. Because the surge covered most of the study area, new vacant lots were more likely to be related to damage from flooding. Second, this study assumed that information in the property tax records was maintained for each year. Because the property tax records were updated annually, this study could not measure changes in land use occurring within a fiscal year. For example, after Hurricane Ike in September 2008, if a damaged residential lot was demolished and redeveloped before January of 2009, the lot was marked as a residential lot in the 2008 and 2009 records. The third assumption regards subdivision. This study tracked changes in land use based on the center points of each lot in the 2007 shapefile data. Subdivision of a lot can be an issue when measuring the longitudinal land use changes. For example, a large undeveloped lot tended to be split into two or more lots to be sold and developed individually. To capture the longitudinal parcel data with homogeneous physical characteristics over time, such as size, shape, and location, this study excluded the subdivided lots.

4.4.2. Data Analysis

The goal of this research was to understand the underlying factors that facilitate or constrain the redevelopment of disaster-induced vacant land. Accordingly, the patterns of disaster-induced vacant lots and trends of redevelopment needed to be thoroughly analyzed. The first sub-question was answered by an exploratory analysis and case control study. The exploratory analysis included a longitudinal inventory of vacant land and redevelopment trends. In addition, like Han's vacant land studies on threshold effects (Han, 2017a) and social dynamics (Han, 2017b), a time series analysis of the annual redevelopment trend for spatially aggregated groups illustrated differences in the degree of impact of influential factors on redevelopment among the various study neighborhoods.

In the study area, vacant land was categorized according to lots that were vacant prior to Hurricane Ike and disaster-induced vacant lots subsequent to Hurricane Ike. For the disaster-induced vacant lots, the level of damage dictated the probability of being vacant. Disaster-induced vacant lots were recorded in the 2009 tax data immediately after Hurricane Ike struck in September 2008. Conversely, pre-existing vacant lots could have been generated many years before the first available tax records in 2007. Many of these pre-existing vacant lots had physical constraints on development (e.g., size, shape, unmatched land cover such as wetlands and unconsolidated shores) (Northam, 1971; Schenk, 1978). Therefore, disaster-induced vacant lots had to be distinguished from pre-existing vacant lots to compare patterns of redevelopment. In addition, among the pre-existing vacant lots, the vacant lots that occurred just before Hurricane Ike, between 2007 and 2008, were identified as pre-disaster vacant lots to compare redevelopment outcomes by the disaster exposure.

The case-control method was used to examine whether there was a significant difference between pre-disaster and disaster-induced vacant lots in terms of redevelopment speed. Table 19 presents the case-control study concept. The case control method is used widely in epidemiological studies (N. E. Breslow, 1996; Ernster, 1994).

In this study, the exposed group was disaster-induced vacant lots, and the unexposed group was pre-disaster vacant lots. The cases were redeveloped lots and the controls were remnant vacant lots after a lapse of years. The odds ratio indicates the strength of the association between the vacant lots' disaster exposure status and their redevelopment outcomes. In this case, the estimated odds ratio represents a measure of the odds of redevelopment in the exposed group as compared to those of the unexposed group.

Table 19. Case-Control Study

	Case (redeveloped lots)	**Control** (remnant vacant lots)	**Total**
Exposed (Disaster-induced vacant lots)	a	b	a + b
Unexposed (Pre-existed vacant lots)	c	d	c + d
Total	a + c	b + d	a + b + c + d

Due to the lack of random sampling, comparison of the redevelopment outcomes might yield biased results when the case study data contains underlying factors shaping redevelopment decisions (Rosenbaum & Rubin, 1983). For example, cases and controls were sampled at different rates between the exposed and unexposed groups and some lots with specific characteristics might have become redeveloped more frequently. Therefore, the propensity-score matching (PSM) method was tested to control for underlying factors and different sampling rates of these vacant lots. The estimated average treatment effect (ATE) indicates the average difference between the treatment group (i.e., disaster-induced vacant lots) and control group (i.e., pre-disaster vacant lots) in the population.

Cepeda, Boston, Farrar, and Strom (2003) compared the logistic regression and PSM methods with regards to bias, precision, and empirical power when specific characteristics of observations affected the outcome and probability of exposure. Based on Monte Carol simulations, PSM showed more overall empirical power than did logistic regression. Especially of note, PSM produced less biased estimates over logistic regression, controlling for imbalances between groups when there were less than seven observations per each controlled characteristic. Conversely, when there were more than eight observations per each controlled characteristic, the logistic regression yielded more empirical power.

The longitudinal and spatial land use data also enabled further analytical capabilities to highlight systematic variations in redevelopment patterns and factors shaping the progress of redevelopment. While the occurrence of disaster-induced vacant lots was clearly driven by hurricane damage, many underlying factors appeared to have consequences for their redevelopment outcomes. The second and third sub-questions were designed to identify factors facilitating or inhibiting redevelopment outcomes. The second sub-question focused on the accumulation of vacant lots. Increasing the level of negative externality due to the accumulation of vacant lots was expected to hinder redevelopment in adjacent areas. The third sub-question addressed the effect of buyouts on redevelopment outcomes.

To find answers to the second and third sub-questions, statistical models that included influential and control factors were required. Several modeling approaches were used to best exploit the available longitudinal vacancy and redevelopment data. First, the occurrence of redevelopment was estimated through logistic regression model. For vacant lots, redevelopment was identified as a dummy variable: "1" for redeveloped lots and "0" for remnant vacant lots for every year after their occurrence. In this case, the multiple redevelopment dummy variables were calculated by elapsed years. For the last period, the logistic regression model estimated the probability of redevelopment during 8 years after Hurricane Ike. This study individually addressed each variable group and included them in a full model to determine how they might relate to redevelopment outcomes. All models were estimated by Stata 15 (StataCorp, 2017a) with the 'estout' command that generates regression tables in Stata (Jann, 2005).

Unlike separately modeling the occurrence of redevelopment and period of vacancy, a survival analysis enabled a holistic estimation while controlling for annual trends and considering influential factors for both time-varying and time-invariant covariates. The Cox proportional hazards and discrete time hazard models were employed for the survival analysis.

The Cox model focuses on estimating the effects of the covariates and avoid estimating the baseline hazard function. Without the baseline hazard function, the probability distribution of the time to the event (i.e., the shape of the hazard over time) could have any shape and was assumed to be the same for every observation (Cox, 1972; Finlay & Agresti, 1986; Singer & Willett, 1993). The basic Cox model treats time as continuous. However, due to the inherent limitation of the annually collected property tax data, the redevelopment time data could not yield specific redevelopment times that could be seen as continuous time; this issue is called tied survival times. In the Cox model, the Breslow approximation method (N. Breslow, 1974) was used to address the tied survival times in the calculation of the log of partial likelihood. This approximation method is preferred when the number of events is relatively smaller than the size of the observation group (Cleves, Gould, Gould, Gutierrez, & Marchenko, 2008).

The concept of discrete time was used because the exact redevelopment time was not obtainable from annual property tax records. The discrete-time hazard model addresses the problem of tied event times data (DeMaris, 2004). When the model has many time-varying covariates, the discrete time hazard model is preferred over the Cox model (DeMaris, 2004). Logit and complementary log-log transformations are the most commonly used link functions for discrete-hazard models (Singer, Willett, & Willett, 2003). Discrete time survival models with both link functions can be estimated by the maximum likelihood method.

This study tested both transformations with binary variable indicating time periods. The logit transformation is the most commonly used link function (Cox, 1972; Singer et al., 2003). The estimated coefficients based on the logit link function can be directly interpreted in terms of proportional odds. The complementary log-log transformation retains the proportional hazards assumption also applied for the Cox model: a hazard ratio of each explanatory variable is constant over time (Singer et al., 2003). The complementary log-log transformation works better for the interval censored data (Singer et al., 2003) like the annual tax records for this study. The estimated coefficients from the complementary log-log transformation can also be directly interpreted in terms of hazard ratios, same as the Cox models. While the complementary log-log model is asymmetrical (sharply increases near 1) and closely related to continuous time models, however, the complementary log-log model closes to the logit model when the probability of an event is small.

Technically, this study utilized logistic regression and complementary log-log regression by 'logit' and 'cloglog' commends in Stata (StataCorp, 2017a) with assuming non-frailty (i.e., unobserved individual heterogeneity). First, the survival dataset was reorganized to have one observation for each period per each lot until a lot was redeveloped (or remained vacant until the last period). An interval identification variable was created to identify the sequence of redevelopment periods from the period 1 to the period 8. Then, a period-specific censoring indicator was created to differentiate the redevelopment and buyout lots from the other right-censored lots that remained vacant.

The modeling results indicated reasons why many lots remained vacant while others were redeveloped. The findings could be used to inform planning practitioners by identifying high risk areas in terms of long-existing vacancies and delayed redevelopment. The estimated results can also be used to prioritize neighborhoods in need of government support and reverse declining urban conditions.

5. REDEVELOPMENT PATTERNS OF VACANT LAND AFTER HURRICANE IKE

This chapter provides an exploratory analysis comparing systematic variations in redevelopment patterns of vacant lots across Galveston County, Texas. The first sub-question of this research, what are the differences in the characteristics of disaster-induced and pre-existing vacant land, will first be assessed according to each type of vacant land's respective redevelopment patterns. This is addressed by comparing vacant lots in Galveston County, both inside and outside of the study area.

There are three reasons why this sub-question needs to be studied. First, the duration of vacancy is a key factor dividing between a transitory vacant lot and a lot that remains vacant for too long. What remains unclear is how long is too long for a lot to remain vacant. The exploratory analysis of the longitudinal land use changes indicated the remnant vacant lots in the context of the general redevelopment patterns in the study area. Second, little empirical research has focused on the redevelopment time after a disaster event. The longitudinal redevelopment outcomes were used to identify similarities and differences between the disaster-induced and pre-existing vacant lots after a disaster event. Then, redevelopment outcomes for the pre-existing vacant lots were used as a benchmark for evaluating the recovery speed of disaster-induced vacant lots. Third, little academic work has considered the negative impact of vacant lots on recovery. The results of this exploratory analysis constructed an initial examination of redevelopment outcomes for the empirical studies regarding the second and third sub-questions. In summary, by comparing the longitudinal records of disaster-induced and pre-existing vacant land, this study explored what happens to occupied and vacant land when a disaster strikes, and how such properties subsequently redevelop.

This chapter describes patterns in the redevelopment outcomes of disaster-induced and pre-disaster vacant lots in Galveston County. First, longitudinal property data are examined to address issues regarding divided and merged lots during the research period (from 2007 to 2017). Next, the land uses in Galveston County are described both outside and within the actual study area (Galveston Island CCD and Bolivar Peninsula CCD) where damage occurred due to Hurricane Ike. Based on the primary land use transition patterns, further analysis is focused on vacant lots that were single family lots prior to Hurricane Ike. Then, the redevelopment outcomes of the disaster-induced and pre-disaster vacant lots are statistically compared. The comparison of redevelopment outcomes allows for the consideration of vacant lots within the context of the disaster recovery process. In other words, the redevelopment outcomes from pre-disaster vacant lots serve as a benchmark for a review of the effects of disaster events on redevelopment patterns. The results indicate that a greater number of disaster-induced vacant lots were redeveloped. Conversely, in terms of the redeveloped lots, the disaster-induced vacant lots lagged in time related to redevelopment, when compared to their annual redevelopment rates. This delay in redevelopment time implies that disaster events facilitate unevenness in recovery, and planning efforts should target early redevelopment similar to what can be seen with pre-disaster vacant lots.

5.1. Issues Related to Subdivision: Divided or Merged Lots

To clean the data and allow for longitudinal assessment, it was assumed that the boundary of each lot was maintained over time. Using QGIS and Stata, the annual data for 2008 to 2017 were spatially joined with the 2007 data to consolidate the years of parcel information into a single longitudinal data file (QGIS Development Team, 2020; StataCorp, 2017a). For the spatial joining method, the center points of each parcel (or centroids) in the 2007 data were used as reference points, and annual data from 2008 to 2017 were extracted based on the center points of each parcel in the 2007 data. The subdivision of parcels was somewhat problematic when tracking the longitudinal information for divided and merged parcels after 2007. For example, if two parcels that shared borders and were owned by the same person were merged in 2008, the longitudinal data would include duplicate information for these parcels in the 2008 records. If a parcel was divided into several parcels in 2008, the longitudinal data could only track information for one of the many separate parcels. Thus, divided and merged parcels that changed their boundaries were identified and excluded before conducting further analyses.

To identify divided and merged parcels, this study reviewed changes in annual parcel size. If a parcel's size decreased or increased more than 5% over that of the previous year, the parcel was assumed to have a boundary change. This 5% buffer was established to absorb minor technical errors when recording parcel boundaries, such as with slivers and overlaps. Compared to other land use studies that define subdivisions as the splitting of a parcel into two or more parcels (Irwin, Bell, & Geoghegan, 2003; B. Wilson, 2009; B. Wilson & Song, 2010), this 5% rule offers a more sensitive measure of subdivision identifying both divided and merged parcels. Table 20 lists the number of parcels with changed boundaries between the first and last years of the observation period, 2007 and 2017, respectively.

Table 20. Parcels with Boundary Changes between 2007 and 2017

	Total	Not changed in 2017	Changed in 2017
Galveston County			
Total parcels in 2007	156,256	146,831 (93.97%)	9,425 (6.03%)
'A1, Single Family' lots in 2007	94,950	91,920 (96.81%)	3,030 (3.19%)
'C1, Vacant' lots in 2007	34,926	31,156 (89.21%)	3,770 (10.79%)
Inside the study area			
Total parcels in 2007	45,497	42,383 (93.16%)	3,114 (6.84%)
'A1, Single Family' lots in 2007	24,071	22,975 (95.45%)	1,096 (4.56%)
'C1, Vacant' lots in 2007	13,645	12,309 (90.21%)	1,336 (9.79%)
Outside the study area			
Total parcels in 2007	110,587	104,448 (94.30%)	6,311 (5.70%)
'A1, Single Family' lots in 2007	70,879	68,945 (97.27%)	1,934 (2.73%)
'C1, Vacant' lots in 2007	21,281	18,847 (88.56%)	2,434 (11.43%)

The issues regarding the subdivision of parcels were more of a concern for the vacant lots. In Galveston County, 6.03% of the total volume of parcels changed boundaries during the 10-year period. For single family lots in 2007, only 3.19% had changed boundaries in 2017. However, for vacant lots in 2007, the percentage of boundary changes was 10.79%. The percentages of lots changing boundaries remained consistent inside and outside the study area.

Developers and property owners can request permission to divide or merge with neighboring parcels. Because vacant lots are potential building sites, they are more likely to experience boundary changes during the development process than are single family lots. For example, a large vacant parcel is more likely to be reapportioned into two or more lots to be developed and sold individually. In the same way, a small vacant lot is more likely to be combined with nearby lots. As a result, among the 34,926 vacant lots in 2007, 10.79% (3,770 lots) were divided or merged by 2017. Among these lots, 708 were divided (18.78% of the total 3,770) and 3,062 were merged (81.22% of the total 3,770). Based on the 2007 data, the median sizes of the divided and merged lots were 28,573 sq. ft. (0.66 acres) and 6,749 sq. ft. (0.15 acres), respectively.

To control for issues regarding divided and merged lots, this study excluded all lots with boundary changes. However, it should be noted that this may have resulted in a degree of underestimation of the development outcomes because merging and dividing lots tends to accompany development efforts addressing unsuitable lot size. Therefore, the results of this study should be interpreted conservatively, especially regarding the amount of overall development occurring during the observation period.

5.2. Changes in Land Use and Inventory of Vacant Land

Table 21 indicates the land use codes and related information for Galveston County in 2007. In terms of the number of parcels, 'A1, Single Family Residential' and 'C1, Vacant' lots represented 62.6% and 21.2% of the total parcels in the county, respectively. Because A1 and C1 lot sizes tend to be smaller than other parcels, these lots comprised 16.6% and 7.3% of the total plotted areas in the county, respectively. In Galveston County, agricultural parcels (D1 to D9) represented 122,996 acres, 59.0% of the total plotted area.

Table 22 indicates the land use codes for the study area in 2007. In terms of the number of parcels, 'A1, Single Family Residential' and 'C1, Vacant' lots comprised 54.2% and 29.0% of the total parcels in the county, respectively. The sizes of these A1 and C1 lots tended to be relatively smaller than others in the county, 0.14 and 0.15 acres as compared to 0.19 and 0.17 acres, respectively. However, the distribution of C1 lot sizes was positively skewed due to the presence of large C1 lots, often over 10 acres. Because of these larger C1 lots, the aggregated land areas were similar; the A1 and Cl lots represented approximately 8.40% and 8.36% of the total plotted area, respectively. Agricultural parcels (D1 to D9) comprised more than half of the total plotted area (34,268 acres, or 62.5%).

In Galveston County and the study area, 'C1, Vacant' lots take 7.3% and 8.36% of the total plotted area, respectively. Considering that the national average was about 16.7% (Newman, Bowman, et al., 2016), their pre-disaster vacant areas were relatively smaller than the mean vacant areas of 124 US cities with populations over 100,000.

In the 2007 data, there were 28 land use codes. The present research grouped these land use codes into 17 revised codes (see Tables 21 and 22). The revised codes were designed to clarify annual transitions in land use. Agricultural, farm and ranch, and utility parcels were aggregated by group either because they were not related to the research questions or the number of observations was substantially smaller than those of the other codes. In addition, since 2008, new land use codes appeared in the data. These included 20 observations in 2017 in the county (one L9, two M3, four S, and 13 XV parcels) and three observations in 2017 in the study area (one L9 and two XV). According to the Texas Property Tax Assistance Property Classification Guide (Hegar, 2014), the L, M, S, and X codes represent personal property, mobile homes, special inventory, and exempt property, respectively. These 20 lots with new land use codes have little or no impact on this research due to their low number of observations comparted to the total number of lots. Besides, the definition of other land uses did not change during the research period.

Table 21. Galveston County Land Use Types

Category	Code	Revised code	N	Area (acre)	Med. size (acre)	Description
Total	-	-	146,831	208,521	0.19	-
Single family residential	A1	A1	91,920	34,705	0.19	Single family residential
	A2	A2	2,562	2,663	0.36	Single family residential, mobile home
	A3	A3	121	183	0.12	Single family residential, condominium
	A9	A9	226	203	0.21	Single family residential, tax exempt
Multifamily residential	B1	B1	1,266	212	0.12	Multifamily residential
	B2	B2	510	841	0.27	Multifamily commercial
	B9	B9	119	54	0.14	Multifamily, exempt
Vacant	C1	C1	31,156	15,260	0.17	Vacant
	C9	C9	2,204	2,629	0.23	Vacant, tax exempt
Agricultural	D1	D1-5	2,437	51,893	5.52	Acreage, ranch land
	D3		236	24,630	26.07	Acreage, farmland
	D4		12	123	12.55	Acreage, undeveloped
	D5		1,392	25,203	9.22	Acreage, non-qualifying ag. use
	D9	D9	492	21,148	9.58	Acreage, tax exempt
Farm and ranch	E1	E1-9	292	2,115	6.18	Farm and ranch improvements
	E9		5	118	12.42	Farm and ranch imp., tax exempt
Commercial and industrial	F1	F1	5,241	7,502	0.34	Commercial
	F2	F2	156	3,869	3.16	Industrial
	F9	F9	1,074	10,227	0.83	Commercial, tax exempt
Utility	J1	J1-9	1	0	0.29	Water system
	J2		8	10	0.37	Gas distribution system
	J3		274	897	1.17	Electric company
	J4		16	11	0.67	Telephone company
	J5		5	228	9.66	Railroad
	J6		4	15	2.76	Pipeline
	J9		4	5	1.20	Utility, tax exempt
Inventory	O1	O1-2	3,186	733	0.18	Inventory, vacant land
	O2		19	2	0.09	Inventory, single family residential
Missing*	-	-	1,893	3,044	0.24	-

* Parcels without land use code information

Table 22. Study Area Land Use Types

Category	Code	Revised code	N	Area (acre)	Med. size (acre)	Description
Total	-	-	42,383	54,813	0.14	-
Single family residential	A1	A1	22,975	4,605	0.14	Single family residential
	A2	A2	198	50	0.16	Single family residential, mobile home
	A3	A3	51	121	1.04	Single family residential, condominium
	A9	A9	93	67	0.14	Single family residential, tax exempt
Multifamily residential	B1	B1	839	89	0.12	Multifamily residential
	B2	B2	216	242	0.24	Multifamily commercial
	B9	B9	28	35	0.38	Multifamily, exempt
Vacant	C1	C1	12,309	4,581	0.15	Vacant
	C9	C9	722	1,411	0.19	Vacant, tax exempt
Agricultural	D1	D1-5	826	15,450	1.00	Acreage, ranch land
	D3		0	0	0	Acreage, farmland
	D4		7	57	5.52	Acreage, undeveloped
	D5		596	10,987	7.98	Acreage, non-qualifying ag. use
	D9	D9	148	7,774	8.24	Acreage, tax exempt
Farm and ranch	E1	E1-9	23	230	7.21	Farm and ranch improvements
	E9		0	0	0	Farm and ranch imp., tax exempt
Commercial and industrial	F1	F1	1,460	1,846	0.24	Commercial
	F2	F2	42	374	1.46	Industrial
	F9	F9	429	4,934	0.65	Commercial, tax exempt
Utility	J1	J1-9	1	0.29	0.29	Water system
	J2		1	0.003	0.003	Gas distribution system
	J3		7	11	1.70	Electric company
	J4		10	7	0.75	Telephone company
	J5		0	0	0	Railroad
	J6		0	0	0	Pipeline
	J9		2	2	0.87	Utility, tax exempt
Inventory	O1	O1-2	665	131	0.14	Inventory, vacant land
	O2		18	2	0.09	Inventory, single family residential
Missing*	-	-	717	1,805	0.39	-

* Parcels without land use code information

The Texas Property Tax Assistance Property Classification Guide (Hegar, 2014) suggests differentiating between ‘O1, Inventory, Vacant Land’ and ‘O2, Inventory, Single Family Residential’ lots. If a vacant lot is held by a developer or builder, the lot is identified as O1 or O2. The O2 category was implemented to identify developed residential lots held for sale from undeveloped O1 lots. However, almost all inventory lots were categorized as O1 lots in the data. For example, in Galveston County in 2007, there were 19 O2 lots and 3,186 O1 lots. The number of O2 lots was zero in 2017. Accordingly, O1 and O2 lots were aggregated into O1-2 lots.

The patterns of land use change in Galveston County, Texas, are illustrated in Figures 12 and 13. In each figure, three Sankey diagrams present the proportional flow rates of the transitions in land use. The three sub-figures, (a), (b), and (c), identify land use transitions in the pre-disaster period, disaster event period, and post-disaster period, respectively. Because the last sub-figure, indicating the post-disaster period, presents the changes in land use between multiple years, some parcels changed their land use multiple times during this period. In this type of case, this sub-figure does not indicate the intermediate land uses.

The unit of analysis is the number of parcels. These Sankey diagrams were made using Python 3.6 (van Rossum & Drake, 1995) in Google Colaboratory (Google, 2020) and Plotly (Plotly Technologies Inc., 2015), a Python-based open-source graphing library and data visualization tool. An example of the Python code appears in Appendix 9.1.

Figure 12. Land Use Transitions in Galveston County

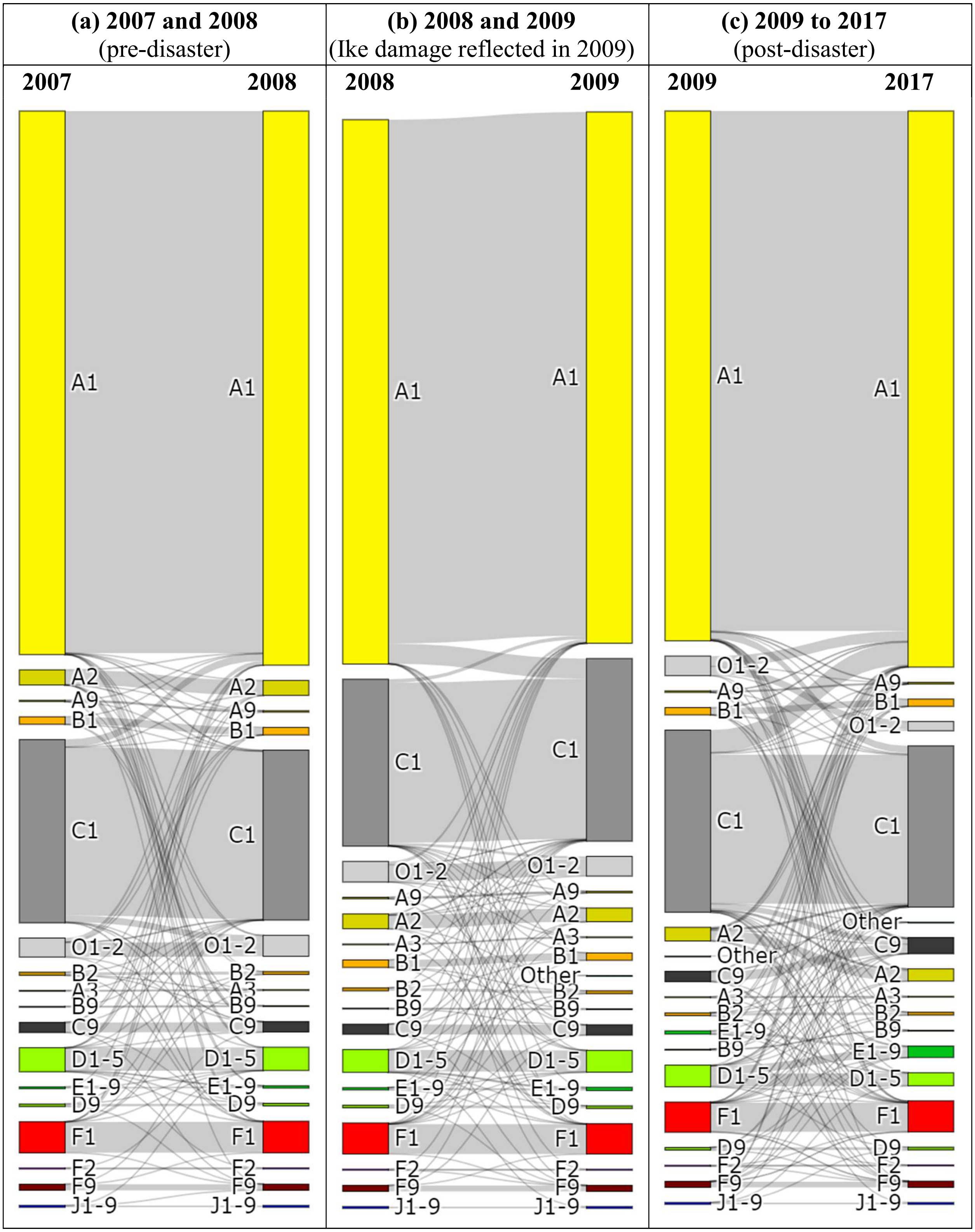


Figure 13. Land Use Transitions in Galveston County: Parcels with Changed Land Uses

(a) 2007 and 2008 (pre-disaster)	**(b) 2008 and 2009** (Ike damage reflected in 2009)	**(c) 2009 to 2017** (post-disaster)

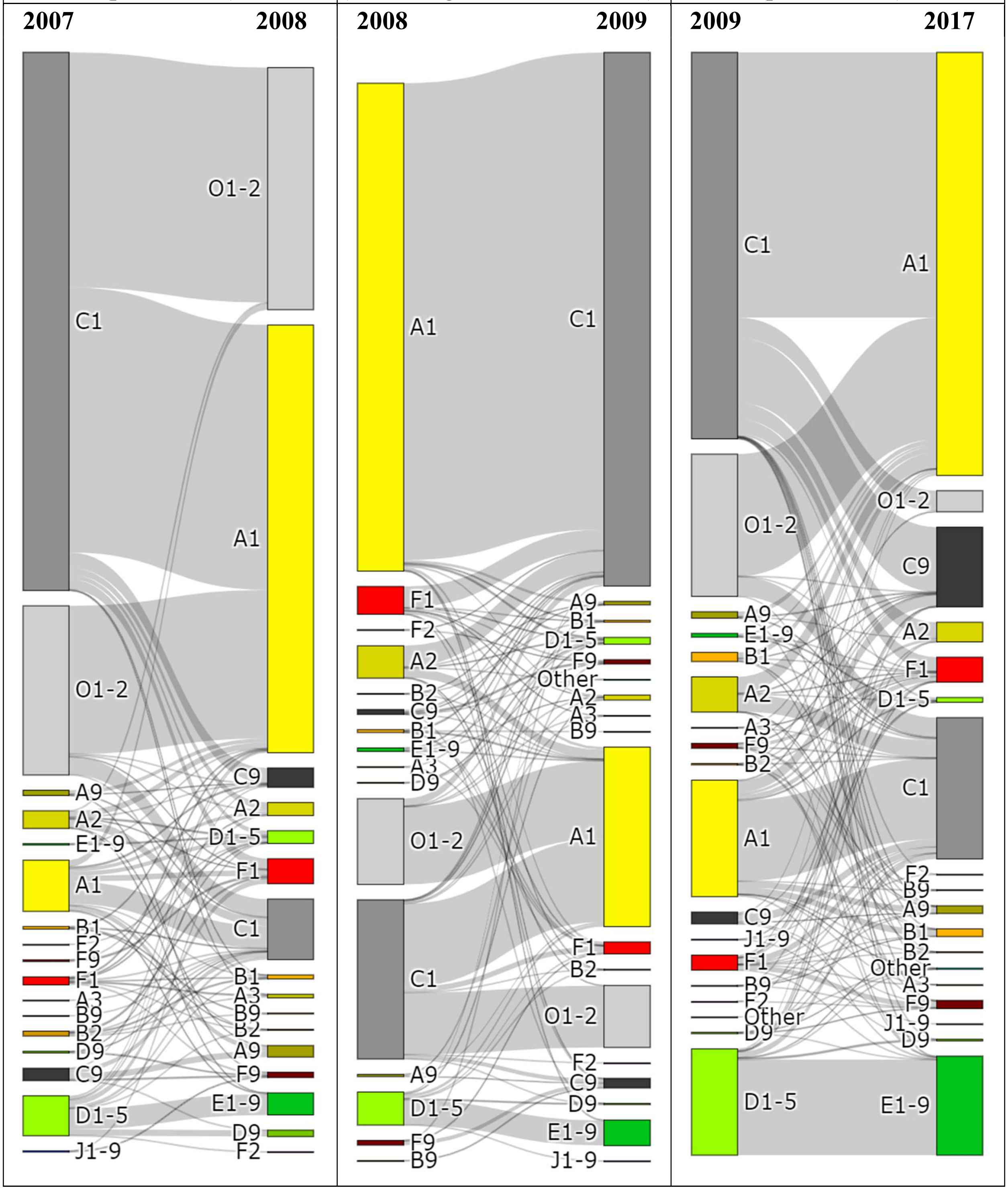


Figure 12 identifies the composition of all land uses in Galveston County. Because many parcels maintained their land use during each of the three periods, the flow of parcels with changed land uses did not stand out. For example, in the pre-disaster period, almost all 'A1, Single Family' lots in 2007 remained A1 lots in 2008. In the disaster period, the figure shows that some of the A1 lots changed to 'C1, Vacant' lots. In Galveston County, 3,441 A1 lots became C1 lots in 2009, 3.7% of the total 93,697 that were Al lots in 2008. In the post-disaster period, there was a flow of C1 to A1 lots that represents recovery outcomes, as well as development efforts.

While Figure 12 includes all parcels, Figure 13 only represents parcels with changed land uses; parcels maintaining the same land use were excluded from Figure 13. For example, as can be seen in Figure 12, many lots remained A1 lots during the entire observation period; these were not included in Figure 13. Accordingly, lots with changed land uses are emphasized by their relative number of transitions.

Figure 13 illustrates that during the pre-disaster period, there were three major transition patterns: 'C1 to A1', 'C1 to O1-2,' and 'O1-2 to A1 (basically vacant to non-vacant).' As described in Table 22, the 'C1, Vacant' category represents small vacant tracts of land most suited for use as building sites. These three major patterns show that the redevelopment of vacant lots from 'C1, Vacant' to 'A1, Single Family Residential' could be temporarily categorized as 'O1-2, Vacant Land Inventory' lots held by developers for sale.

Hurricane Ike considerably changed the patterns of land use transition, as reflected in Figure 13(b), which shows the disaster event period: about a half of the total land use transitions was related to non-vacant to vacant. In the pre-disaster period, a small number of 'A1, Single Family Residential' lots became 'C1, Vacant' lots (170, 0.18% of the total A1 lots in 2007). Conversely, many new A1 to C1 lots were recorded in the 2009 tax data following Hurricane Ike's landfall in September 2008. Unlike the pre-disaster period, the A1 to C1 pattern shows approximately one-half the total land use changes between 2008 and 2009. Because C1 lots are unused lots without improvements, these A1 to C1 vacant lots were considered disaster-induced vacant lots: single family lots that became vacant due to damage caused by Hurricane Ike.

In Figure 13(c), which illustrates the post-disaster period between 2009 and 2017, the land use transitions proceeded similarly to those in the pre-disaster period, except for the increase in 'C1 Vacant' to 'C9, Tax Exempt Vacant' types. The C1 to A1 change included both recovery efforts and new developments. There were 3,922 lots that changed from C1 to A1 between 2009 and 2017. Among these, 1,221 were recovered disaster-induced vacant lots that were single family lots in 2008 (31.1% of the 3,922 C1 to A1 lots). Many 'C1, Vacant' lots changed to 'A1, Single Family' lots because disaster-induced A1-oriented vacant lots were more likely to be redeveloped as A1 lots.

After Hurricane Ike, Galveston County was one of the top two participants in FEMA's buyout program, garnering $102.7 million from their Hazard Mitigation Program (ABC13, 2011). By April 6, 2011, Galveston County had purchased 338 properties and planned to own more (ABC13, 2011). The FEMA grant paid 75% of the pre-disaster fair market value for the structure and land, and state funding was allocated to make up the remaining 25% (Moore, 2010). The number of buyout lots was 514 in 2011; that number increased until 2013, when it reached 656 lots. Among these 656 buyout lots, 649 were categorized as 'C9, Tax Exempt Vacant' lots and owned by Galveston County or Galveston City. Many buyout lots were disaster-induced vacant lots. Among the 656 buyout lots, 439 were disaster-induced vacant lots that were A1 lots in 2008 and C1 lots in 2009.

In the pre-disaster and disaster periods, the C1 to O1-2 transition represents inventory lots held by developers for sale. Figure 13(c) presents the changes in land use between 2009 and 2017; thus, transitions from C1 to O1-2 and A1 lots were identified as C1 to A1 lots. For example, 168 C1 lots in 2009 became O1-2 lots in 2013 and A1 lots in 2017. Nevertheless, the annual number of new O1-2 lots decreased significantly after Hurricane Ike. In the pre-disaster period, 1,144 lots became O1-2 lots between 2007 and 2008. During the eight years after Hurricane Ike (2009 to 2017), only 100.4 lots became O1-2 lots per year, on average. The reduction in C1 to O1-2 transitions since 2009 could have been caused by the decreased number of property development projects following the 2008 housing crisis.

Similar to Figures 12 and 13, Figures 14 and 15 present land use transitions in the study area. The transition patterns in the study area resemble those of Galveston County, except for the increased flow rates from A1 to C1 in the disaster period. In both figures, the increased ratios of disaster-induced vacant lots demonstrate the concentration of single family lots that were severely damaged and or demolished. The Galveston Island and Bolivar Peninsula CCDs were devastated by Hurricane Ike's wind and surge. From 2008 to 2009, 3,441 'A1, Single Family' lots became 'C1, Vacant' lots in Galveston County; approximately 3,100 of those were located in the study area. In the same vein, 645 buyout lots were located in the study area, among the total 656 buyout lots in Galveston County. This research focused on redevelopment efforts regarding these disaster-induced vacant lots that were pre-disaster single family lots.

Figure 14. Land Use Transitions in the Study Area

(a) 2007 and 2008 (pre-disaster)	**(b)** 2008 and 2009 (Ike damage reflected in 2009)	**(c)** 2009 to 2017 (post-disaster)

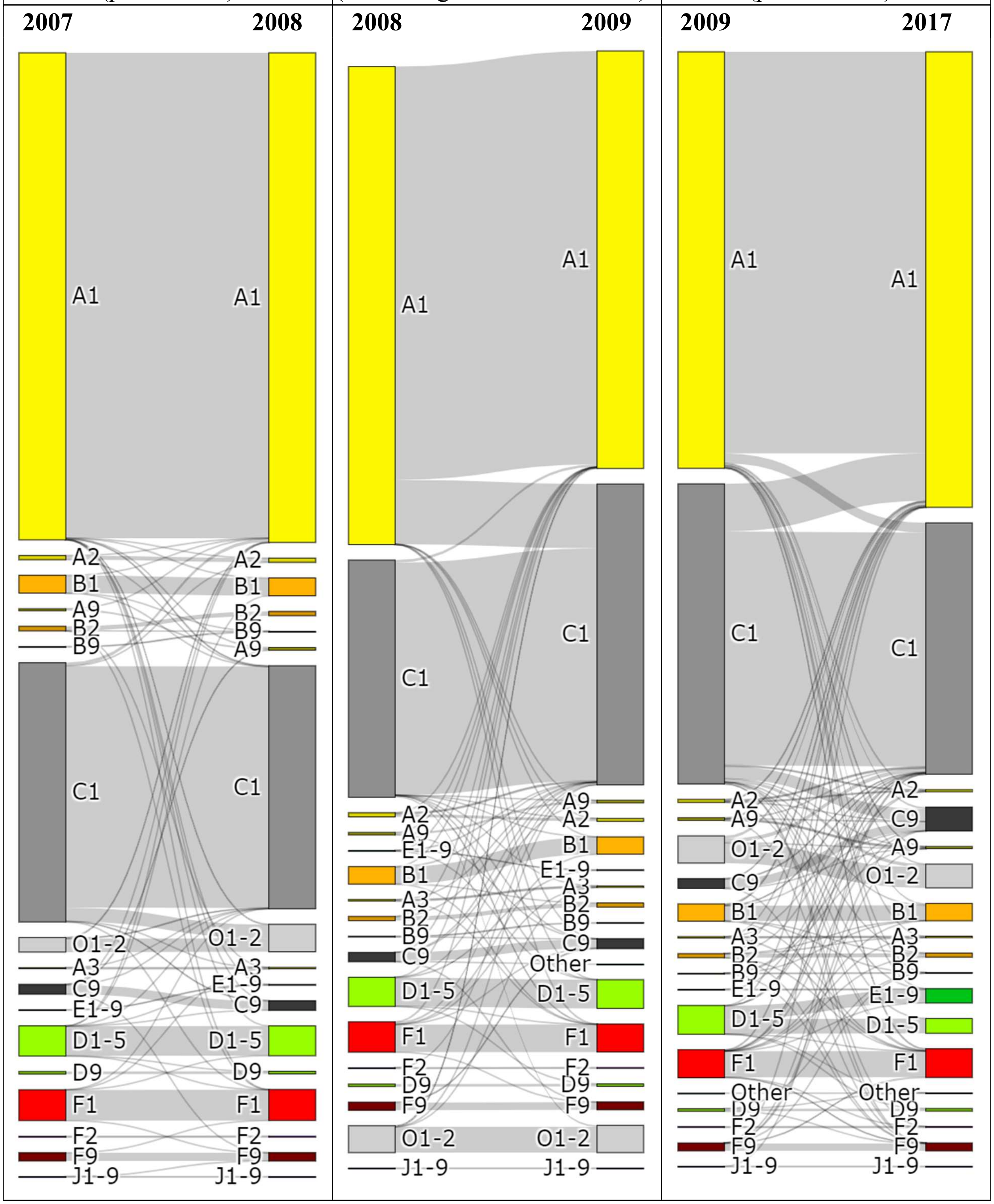


Figure 15. Land Use Transitions in the Study Area: Parcels with Changed Land Uses

(a) 2007 and 2008 (pre-disaster)	**(b)** 2008 and 2009 (disaster event in 2009)	**(c)** 2009 to 2017 (post-disaster)

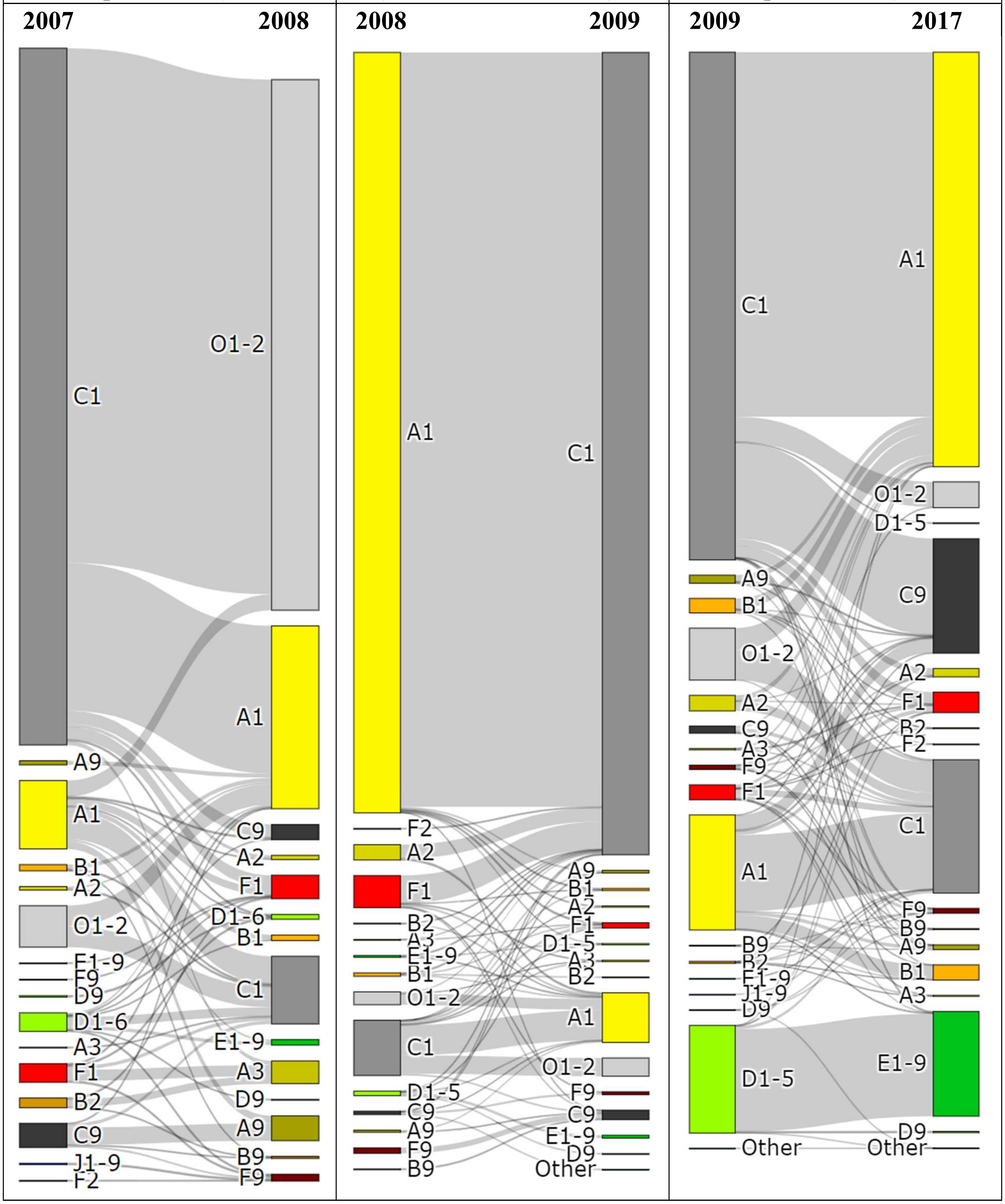


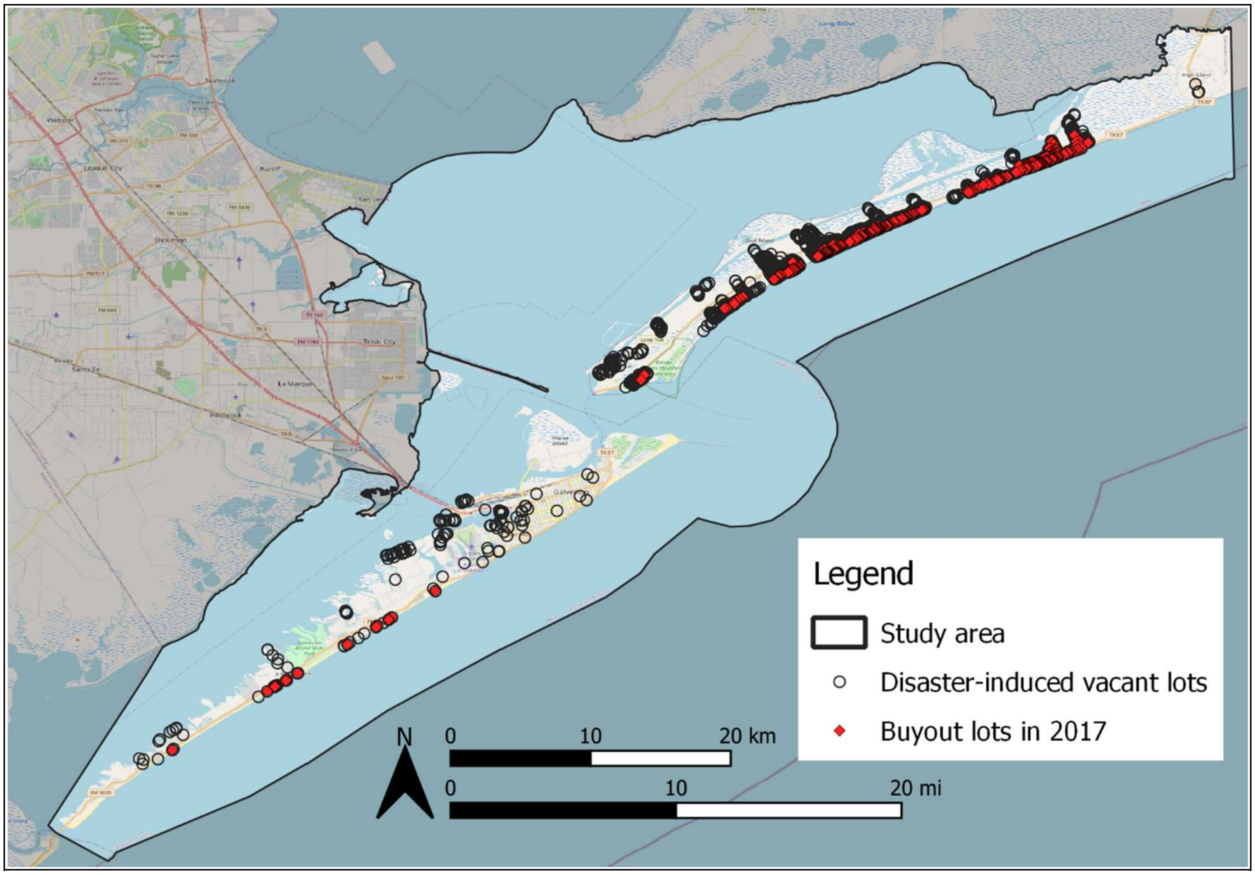
Table 23 lists the descriptive statistics for the disaster-induced vacant lots. In the study area, the average pre-disaster improvement value was higher than that outside of the study area. Conversely, the average land value was lower than that outside of the study area. Overall, the average total property value was higher in the study area. In terms of redevelopment status, the 2017 data indicated that 36.3% of the disaster-induced vacant lots in the study area became A1 lots. Outside of the study area, the percentage of redeveloped lots was lower; 28.5% became A1 lots. Similarly, 48.1% of lots remained C1 vacant lots in the study area, while 62.8% of lots remained C1 vacant lots outside of the study area. Among the disaster-induced vacant lots, all buyout lots were located inside the study area; 439 disaster-induced vacant lots became buyout lots and were recategorized as C9 lots.

Table 23. Disaster-Induced Vacant Lots

	N	Mean (median) property value* in 2008	Land use in 2017	Buyouts in 2017
Galveston County	3,441	Land: $18.8k (7.7k) Imp.: $69.8k (55.3k) Total: $88.6k (68.5k)	A1: 1,221 (35.48%) C1: 1,705 (49.55%) C9: 461 (13.40%) Other: 54 (1.57%)	439** (12.76% of 3,441 lots)
Inside the study area	3,100 (90%)	Land: $17.7k (7.5k) Imp.: $73.7k (59.0k) Total: $91.4k (70.9k)	A1: 1,124 (36.26%) C1: 1,491 (48.10%) C9: 450 (14.52%) Other: 35 (1.12%)	439** (14.16% of 3,100 lots)
Outside the study area	341 (10%)	Land: $28.9k (16.5k) Imp.: $34.1k (25.3k) Total: $62.9k (43.9k)	A1: 97 (28.45%) C1: 214 (62.76%) C9: 11 (3.23%) Others: 19 (5.56%)	None

Note: single family lots (land use code: A1) in 2008 that became vacant lots (land use code: C1) in 2009
* Land: land value; Imp.: improvement value; Total: total value (land value plus improvement value)
** Among the 439 lots, 436 were categorized as ‘C9, Tax exempt’

Figure 16. Disaster-Induced Vacant Lots inside the Study Area

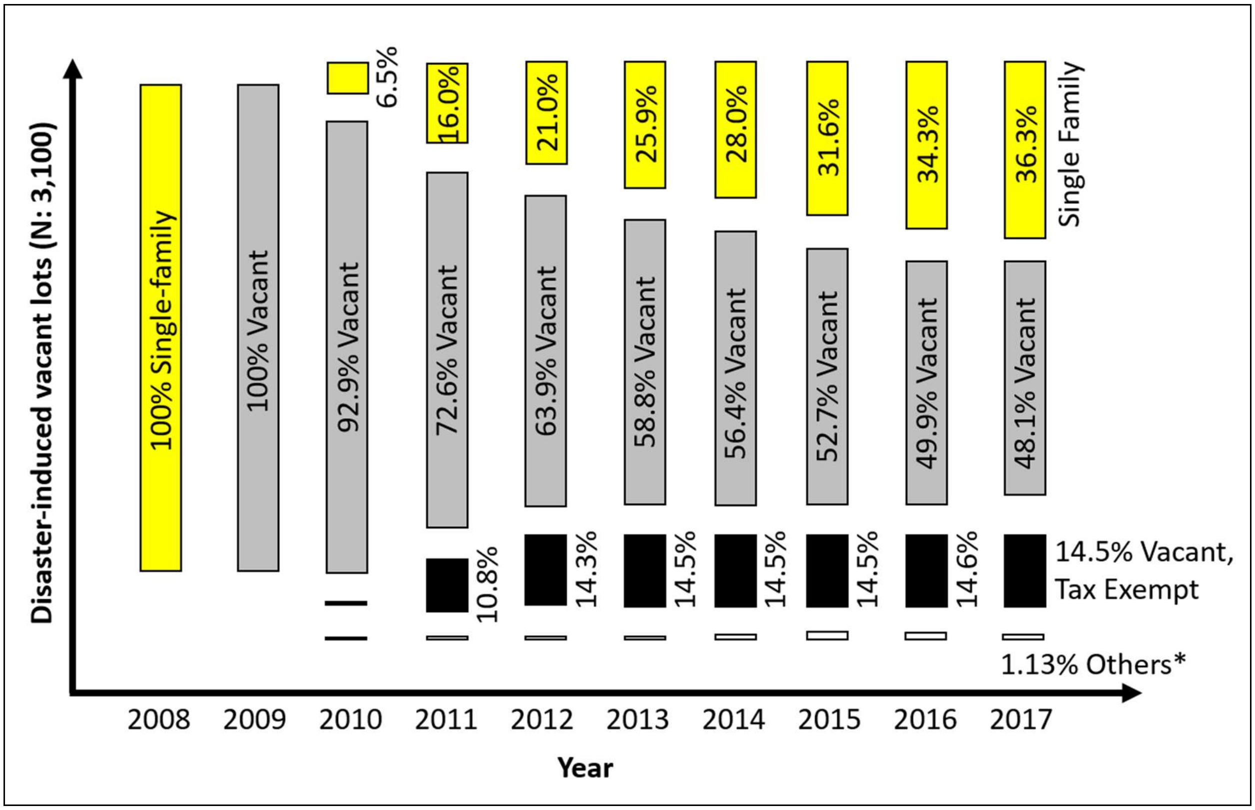


Sources: TIGER/Line Shapefiles, U.S. Census Bureau (2000i); OpenStreetMap contributors (2020)

Figure 16 and 17 show the locations of disaster-induced vacant lots inside the study area, and their redevelopment trajectory. Note that these figures are based on the lots transitioning from C1 to A1 during the disaster event period (2008 to 2009). Because these lots were designated as ‘A1, Single Family’ lots before Hurricane Ike, most of the redeveloped lots returned to A1 status. Only 1.1% of the lots were redeveloped for other land uses: 22 portable home, eight commercial, four vacant land inventory, and one multifamily. Eight years after Hurricane Ike, more than half of the disaster-induced lots remained ‘C1, Vacant’ lots (48.1%) or ‘C9 Tax Exempt Vacant’ lots (14.5%, mainly buyout lots). The redevelopment outcomes were concentrated in the second year after Hurricane Ike (i.e., 2011). In 2011, the percentage of single family lots increased by 9.5

points over the previous year (i.e., 2010). After that, the redevelopment speed gradually slowed. The buyout lots were first reflected in 2011. The percentage of buyout lots increased until 2013 and remained unchanged.

Figure 17. Redevelopment Trajectory of Disaster-Induced Vacant Lots



*Other: 22 mobile home, 8 commercial, 4 vacant land inventory, and 1 multifamily

5.3. Comparison of Redevelopment Patterns

To compare them to the redevelopment outcomes of disaster-induced vacant lots, pre-disaster vacant lots were identified based on their land use transition. The disaster-induced vacant lots were ‘A1, Single Family’ lots that changed to ‘C1, Vacant’ lots between 2008 and 2009. Correspondingly, the lots changing from A1 to C1 between 2007 and 2008 were identified as pre-disaster vacant lots. Because the data began in 2007, the period between 2007 and 2008 offered the only available information on pre-disaster land use. These pre-disaster vacant lots were divided into two groups, based on their location: outside or inside the study area. Table 24 presents the number of pre-disaster and post-disaster vacant lots. There were 107 pre-disaster vacant lots, 78 outside the study area and 29 inside.

Table 24. Redevelopment Statuses of Disaster-Induced and Pre-Disaster Vacant Lots

	Total	Redeveloped (cases)	Not redeveloped (controls)	Odds Ratio
Unexposed: pre-disaster vacant lots	107	29 (27.10%)	78 (72.90%)	1.63**
Outside the study area	78	21 (26.92%)	57 (73.08%)	1.64*
Inside the study area	29	8 (27.59%)	21 (72.41%)	1.59
Exposed: disaster-induced vacant lots				
Inside the study area	3,100	1,169 (37.71%)	1,931 (62.29%)	NA

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The redevelopment statuses of these disaster-induced and pre-disaster vacant lots were determined based on their annual land use transition after becoming vacant. Accordingly, until 2017, pre-disaster vacant lots' redevelopment statuses could be measured up to nine years, from 2008 to 2017. Conversely, disaster-induced vacant lots' redevelopment statuses could be measured up to eight years, from 2009 to 2017. To compare redevelopment statuses within the same period of time, this study used redevelopment outcomes after eight years for both disaster-induced and pre-disaster vacant lots. For example, for pre-disaster vacant lots, redevelopment status was determined through 2016.

Changes in land use determined the redevelopment status during these eight years. The present study identified lots as redeveloped when vacant lots became recategorized for other land uses, except ‘C9, Tax Exempt Vacant’ and ‘O1-2, Vacant Land Inventory.’ For example, if a vacant lot changed its land use to a non-vacant land use type such as ‘A1, Single Family,’ this lot was identified as redeveloped. As discussed in the previous section, most of the redeveloped disaster-induced vacant lots were returned to their pre-disaster land-use, ‘A1 Single Family.’ In the same vein, for the 107 pre-disaster vacant lots, 29 were redeveloped and 26 returned to being A1 lots. The other three lots changed to ‘A2, Mobile Home’ lots.

Moreover, a vacant lot could change its land use more than once during the eight-year research period. In such cases, this study identified the first land use change as the redevelopment outcome. There were a total of 3,207 pre-disaster and disaster-induced vacant lots; 1,198 were redeveloped at least once (29 pre-disaster vacant lots and 1,169 disaster-induced vacant lots). Among the 1,198 that were redeveloped, 25 became vacant and 18 became vacant but were then redeveloped.

For the disaster-induced vacant lots, 37.71% were redeveloped during the eight-year period. For the pre-disaster vacant lots, approximately 27% to 28% were redeveloped. This result may indicate that disaster-induced vacant lots were more likely to be redeveloped than were pre-existing vacant lots because of financial support for housing redevelopment. A case-control method was used to examine the difference between the pre-disaster and disaster-induced vacant lots in terms of redevelopment outcomes. The case-control data were used to determine the ratio of the odds of redevelopment for disaster-induced vacant lots to the odds of redevelopment for pre-disaster vacant lots. The odds ratios present the odds of being redeveloped in the total county area, outside the study area, and inside the study area. The odds of being redeveloped were 1.63

higher for disaster-induced (i.e., the exposed group) lots than for pre-disaster (i.e., the unexposed groups) lots. However, the Chi-squared test results, which tested against an odds ratio of 1, were not significant for the pre-disaster vacant lots in the study area and were marginally significant at the 10% level for pre-disaster vacant lots outside the study area. The insignificant *p*-value indicates that disaster exposure was probably not related to redevelopment outcomes. Overall, disaster-induced vacant lots were significantly associated with redevelopment outcomes at the 5% level.

The case study data allowed for the odds ratio to be measured without controlling for factors shaping redevelopment decisions. However, with the underlying factors left unaddressed, comparison of the redevelopment outcomes might yield biased results. In observational studies, exposed and unexposed groups are often different in terms of their characteristics, due to the lack of random sampling (Rosenbaum & Rubin, 1983). Here, cases and controls were sampled at different rates between the exposed and unexposed groups. Some lots with specific characteristics might have become vacant more frequently, which also might have affected their redevelopment outcomes. For example, previous studies have indicated that owner-occupied, higher-value, and properly-sized vacant properties tend to be redeveloped at a faster rate. Table 25 presents the descriptive statistics for lot-level characteristics. The table was based on the 2007 data, and accordingly it shows descriptive statistics for both disaster-induced and pre-disaster vacant lots before they became vacant. In the study area, the vacant lots had a more than two times higher median improvement value, $56.2k, than that of outsides the study area, $17.6k. Table 25 also presents statistics related to lot size and homestead tax exemption. Lots that are too small or too large are known to hinder redevelopment efforts. Vacant lots outside and inside the study area had similar median lot sizes, around 7,000 sq. ft. Homestead tax exemption was used as a dummy variable to indicate owner-occupied residential properties that exempted part of their property value from taxation. These owner-occupied residential lots tended to be redeveloped at a faster rate than were the other vacant lots. For lots outside and inside the study area, 16.67% and 11.22% receiving the Homestead tax exemption were assumed owner-occupied. Some vacant lots had zero land value or zero improvement value. Zero-value lots were excluded from the analysis; a total of 39 lots, 31 disaster-induced vacant lots and eight pre-disaster vacant lots, fell into this category.

Table 25. Pre-vacancy Descriptive Statistics

Variable	N	Mean	Median	Std. Dev.	Min.	Max.
Total						
Land value ($)	3,207	17,190	7,000	29,622	0	511,620
Improvement value ($)	3,207	69,714	55,520	56,458	0	437,050
Lot size (sq. ft.)	3,207	11,712	6,900	20,916	1,044	355,402
Homestead tax exemption	3,207	0.1135	0	0.3173	0	1
Outside the study area						
Land value ($)	78	33,414	7,645	77,268	1,150	511,620
Improvement value ($)	78	38,427	17,620	64,030	0	437,050
Lot size (sq. ft.)	78	21,618	7,071	48,116	2,885	333,853
Homestead tax exemption	78	0.1667	0	0.3751	0	1
Inside the study area						
Land value ($)	3,129	16,785	6,880	27,307	0	295,100
Improvement value ($)	3,129	70,494	56,230	56,045	0	434,860
Lot size (sq. ft.)	3,129	11,465	6,900	19,720	1,044	355,402
Homestead tax exemption	3,129	0.1122	0	0.3156	0	1

Std. Dev.: Standard Deviation; Min.: Minimum; Max.: Maximum; sq. ft.: square feet

The propensity-score matching (PSM) method was used to control for the differences in characteristics of these vacant lots. This method utilizes an average of the redevelopment outcomes of similar lots to impute the missing potential outcomes attributable to such characteristics. The average treatment effect (ATE) obtained from the PSM estimator indicated the average difference between the treatment group (i.e., disaster-induced vacant lots) and control group (i.e., pre-disaster vacant lots) in the population. For the binary redevelopment outcomes for each vacant lot (1 for redeveloped and 0 for not redeveloped), the ATE can be interpreted as the difference in probability between the two groups. Table 26 presents the estimated ATEs from two PSM estimators using a one-to-one match (PSM 1) and one-to-three matches (PSM 2) per observation. The treatment of interest was the disaster-induced vacant lots versus the pre-disaster vacant lots, and the outcome of interest was their redevelopment status after the eight-year research period. Note that the number of observations slightly decreased after excluding the lots with zero land or improvement value.

The propensity score calculated the similarities among vacant lots by using estimated treatment probabilities. Logistic regression is a commonly used method for predicting the probability of an event for PSM. Accordingly, the accuracy of a PSM relies on the selected covariates. In this study, the PSM model utilized covariates for land value, improvement value, lot size, and Homestead exemption. Because the land value, improvement value, and lot size variables were positively skewed, they were transformed using a natural logarithm function. The first ATE coefficient, PSM 1 Coef., was based on a one-to-one match; one vacant lot was matched with the vacant lot in the opposite treatment group with the closest propensity score. The second ATE coefficient, PSM 2 Coef., was based on a one-to-three match; one vacant lot was matched with three vacant lots in the opposite treatment group. In general, matching with more neighbors reduces the variance of the estimator, but can also increase bias (Statacorp, 2017b).

The PSM results indicated from 0.23 to 0.34 ATEs for the disaster-induced vacant lots, as compared to the pre-disaster vacant lots. All PSM results were significant at the 99% level. On a percent scale, the chance of redevelopment was higher by 23 to 34 percentage points for the disaster-induced vacant lots as compared to the pre-disaster vacant lots.

Table 26. Probability of Redevelopment Determined by the PSM Method

	Total	Redeveloped	Not redeveloped	PSM 1 ATE Coef. [95% CI]	PSM 2 ATE Coef. [95% CI]
Control group: pre-disaster vacant lots	99	22 (22.22%)	77 (77.78%)	0.28*** [0.2035 0.3634]	0.23*** [0.1091 0.3536]
Outside the study area	76	20 (26.32%)	56 (73.68%)	0.24*** [0.1508 0.3389]	0.24*** [0.1694 0.3205]
Inside the study area	23	2 (8.70%)	21 (91.30%)	0.31*** [0.2149 0.4015]	0.34*** [0.2933 0.3850]
Treatment group: disaster-induced vacant lots					
Inside the study area	3,069	1,155 (37.63%)	1,914 (62.37%)	-	-

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Coef.: Coefficient

In addition to PSM, logistic regression can be used to test the differences between disaster-induced and pre-disaster vacant lots. Because the control group (i.e., total pre-disaster vacant lots) had 99 observations, logistic regression was more likely to yield better empirical power when measuring the difference in redevelopment outcomes (Cepeda et al., 2003). Table 27 shows the results from three logistic regression models after controlling for lot-level characteristics (similar to the PSM method). The first model, Logit 1, estimated the effects of lot-level characteristics and served as a base model. Like the PSM method, land value, improvement value, and lot size were log-transformed to reduce skewness. The second model, Logit 2, used a dummy variable to estimate the effect of the total pre-disaster vacant lots (1 for pre-disaster vacant lots and 0 for disaster-induced vacant lots), after controlling for lot-level characteristics. The third model, Logit 3, estimated the effects of the pre-disaster vacant lots using two dummy variables: outside the study area (1 for pre-disaster vacant lots outside the study area and 0 for other vacant lots) and inside the study area (1 for pre-disaster vacant lots in the study area and 0 for other vacant lots).

Table 27. Probability of Redevelopment Determined by Logistic Regression

	Logit 1 Coef. (OR)	**Logit 2 Coef. (OR)**	**Logit 3 Coef. (OR)**
Lot-level characteristics			
Land value in 2007 (USD, log transformed)	0.0836* (1.0872)	0.0907** (1.0949)	0.0922** (1.0965)
Improvement value in 2007 (USD, log transformed)	0.3607*** (1.4343)	0.3453*** (1.4124)	0.3439*** (1.4104)
Lot size in 2007 (sq. ft., log transformed)	-0.1413** (0.8682)	-0.1398** (0.8695)	-0.1444** (0.8656)
Homestead tax exemption in 2007 (dummy variable)	0.1796 (1.1967)	0.1920* (1.2116)	0.1932* (1.2132)
Pre-disaster dummy variables			
Pre-disaster vacant lots (total)		-0.4077 (0.6652)	
Pre-disaster vacant lots (outside the study area)			-0.1942 (0.8235)
Pre-disaster vacant lots (inside the study area)			-1.4703* (0.2299)
Constant	-0.8701	-0.8279	-0.7849
N	3,168	3,168	3,168
LR Chi^2	120.20	122.90	126.18
Prob. > Chi^2	0.001	0.001	0.001
Pseudo-R^2 *(McFadden's)*	0.029	0.029	0.030
Pseudo-R^2 *(Cragg & Uhler's)*	0.051	0.052	0.053
Pseudo-R^2 *(McKelvey & Zavoina's)*	0.063	0.063	0.067

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Coef.: Coefficient; OR: Odds ratio

While the three models' likelihood ratio (LR) Chi-squared test statistics showed that the models were statistically significant at the 99% level, the models had very low rates of explained variation. The overall pseudo R-squared values were around 3% to 7% for all three models. A pseudo R-squared indicates a quantified predictive accuracy of single redevelopment event as the strength of association between the dependent variable and selected covariates (Heinzl, Waldhör, & Mittlböck, 2005). In general, using R-squared to nonlinear models causes some issues. For example, R-squared values can lie outside of the 0 to 1 interval and decrease as covariates are added (Cameron & Windmeijer, 1997). This study also listed alternative R-squared type goodness-of-fit summary statistics (i.e. Cragg & Uhler's and McKelvey & Zavoina's R-squared) using 'fitstat' command in Stata (J. Scott Long & Freese, 2000). These low rates of pseudo R-squared values indicated that the lot-level characteristics and cause of vacancy, whether disaster-induced or not, were not enough to explain the variance in redevelopment outcomes. Therefore, the logit models presented here should not be used to predict the probability of redevelopment outcomes. The purpose of these logit models was to check the reliability of the relationships among pre-disaster vacant lots and redevelopment outcomes after controlling for lot-level characteristics. The LR Chi-squared test statistics with the pre-disaster vacant lots' dummy variables were higher than those for the base model, Logit 1.

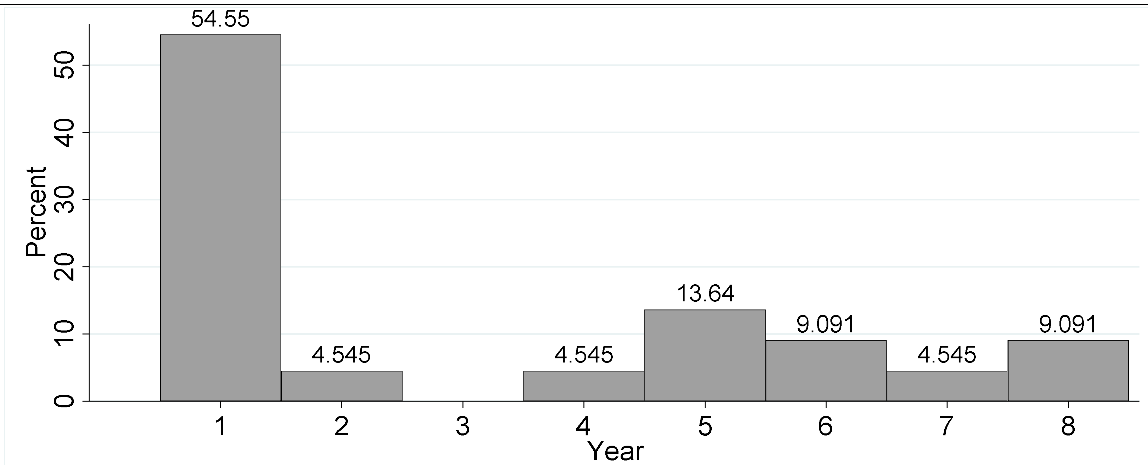
The lot-level characteristics were significant at the 90% level for all three models, except for the Homestead tax exemption variable in Logit 1 (its *p*-value was 0.118). This result implies that lot-level characteristics, which were known to expedite or hinder the redevelopment of general vacant lots, also influenced the disaster-induced vacant lots. Both pre-vacancy land value and improvement value were positively related to the probability of redevelopment. The lot size variable was significant for all three models at the 95% level, indicating that the larger vacant lots were less likely to be redeveloped.

The ATE coefficients from the PSM method indicated a significant difference between the pre-disaster vacant lots (both inside and outside the study area) and disaster-induced vacant lots at the 99% level. Conversely, the Logit 2 model indicated that the redevelopment outcomes for the total pre-disaster vacant lots might not be significantly different from those of the disaster-induced vacant lots. In the Logit 2 model, the dummy variable indicating the total pre-disaster vacant lots was slightly non-significant at the 90% level (its *p*-value was 0.111). The Logit 3 model showed that only the pre-disaster vacant lots in the study area were significantly different from the other vacant lots (its *p*-value was 0.050). In other words, only the pre-disaster vacant lots in the study area were less likely to be redeveloped than the other vacant lots.

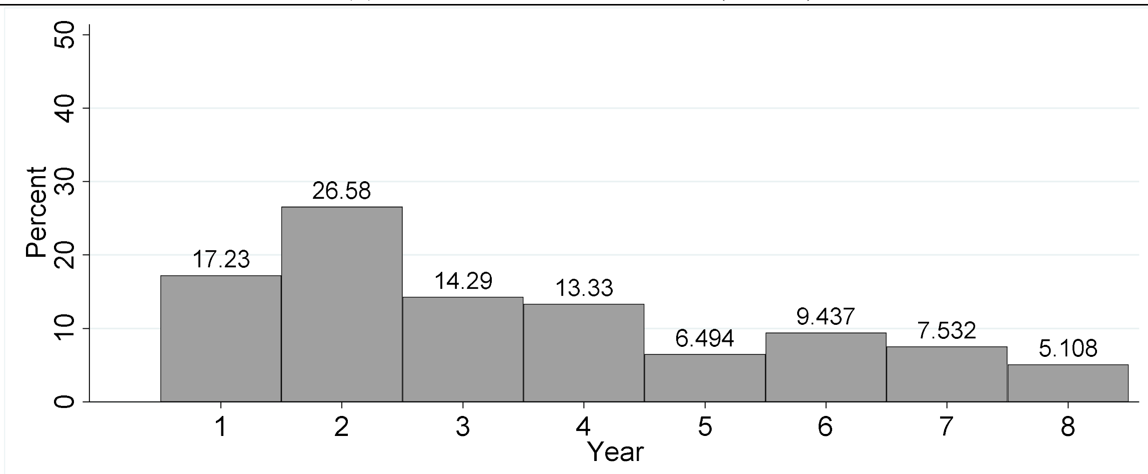
Overall, both the PSM and logistic regression models implied that the disaster-induced vacant lots had a higher probability of redevelopment than did the pre-disaster vacant lots. Unlike pre-disaster vacant lots, disaster-induced vacant lot owners may receive insurance payouts and disaster assistance from federal and local governments, likely resulting in a higher probability of redevelopment. In the same vein, Hurricane Ike may also affected the pre-disaster vacant lots' redevelopment outcomes. While the pre-disaster vacant lots were not directly damaged by Hurricane Ike, extensive damage in neighborhoods and emerged vacant properties can increase the levels of uncertainty in land development. Besides, the results also indicate that the redevelopment factors identified from previous vacant land studies can be applied to disaster-induced vacant lots, such as property value, lot size, and ownership.

To compare their annual redevelopment patterns, Figure 18 presents vacant lots' annual redeveloped patterns, including both pre-disaster and disaster-induced vacant lots. While a higher percentage of disaster-induced vacant lots was redeveloped during the eight years following vacancy, the annual redevelopment patterns present an opposing view. Figure 18(a) shows the annual redevelopment rate based on 22 redeveloped pre-disaster vacant lots, 20 lots from outside the study area and two lots from inside. Figure 18(b) shows the annual redevelopment rate based on 1,155 redeveloped disaster-induced vacant lots.

Figure 18. Annual Redevelopment Patterns of Redeveloped Vacant Lots



(a) Pre-disaster vacant lots (n = 22)

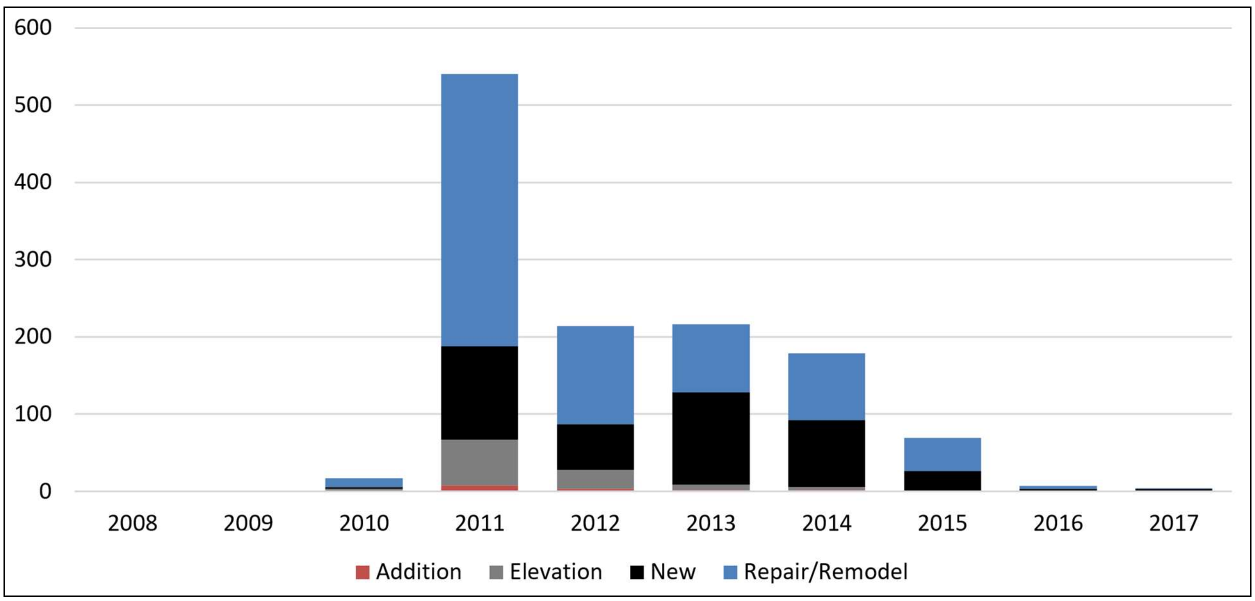


(b) Disaster-induced vacant lots (n = 1,155)

Regarding the pre-disaster vacant lots, about half were redeveloped within one year of becoming vacant (54.55% of vacant lots were redevelopment in the first year). Conversely, the disaster-induced vacant lots show a lagging, flattened redevelopment pattern; their redevelopment outcomes were comparable during the first four years, and peaked in the second year after becoming vacant (17.23% in the first year and 26.58% in the second year).

The difference between the two annual redevelopment patterns may emphasize the unevenness in disaster recovery. Disaster-induced vacant lots could be redeveloped similarly to pre-disaster vacant lots. Unlike the owners of pre-disaster vacant lots, the owners of post-disaster vacant lots were faced unexpected expenditures for redevelopment. On the other hand, the owners of disaster-induced vacant lots could apply insurance payouts and disaster assistance.

Figure 19. CDBG-DR Funded Residential Building Permits in Galveston



Note: the data were collected by an Open Records Request through the Public Records Center for the City of Galveston (City of Galveston, 2020).

Providing immediate disaster relief and recovery assistance would facilitate early redevelopment of disaster-induced vacant lots. For example, Figure 19 shows the annual number of CDBG-DR funded residential building permits by permit type in the City of Galveston. The majority of

CDBG-DR permits were issued between 2011 and 2015, two years and eight years after Hurricane Ike. While the distribution of CDBG funds is just a part of recovery issues, the number of CDBG-DR permits peaked in 2011, similar to when the redevelopment of disaster-induced vacant lots peaked (the second property tax period after Hurricane Ike, from mid-2010 to mid-2011).

Redevelopment time can be defined as the years of vacancy before redevelopment. In the study area, redevelopment took a mean 3.48 years and median 3 years after becoming vacant. However, both pre-disaster and disaster-induced vacant lots were affected by the housing market crisis of 2008. For pre-disaster lots, the recession started with the first year after becoming vacant. The disaster-induced lots might become vacant between early September 2008 (when Ike made landfall) and June 2009, when the tax appraisal period concluded. Accordingly, the disaster-induced vacant lots suffered due to the recession from the beginning. Therefore, the redevelopment trend seen in this study should not be considered a general redevelopment outcome that can be applied to other disaster events.

These redevelopment outcomes should be interpreted conservatively. First, this study excluded lots with size changes, either due to merger or division. In addition, the number of pre-disaster vacant lots was very small, especially as compared to the disaster-induced vacant lots: 22 versus 1,150, respectively. However, comparing the redevelopment outcomes allowed for the identification of similarities and differences between the two types of vacant lot. In terms of redevelopment, the disaster-induced vacant lots shared some characteristics with general vacant lot redevelopment factors. However, the delayed and dispersed annual redevelopment pattern implies that the disaster-induced vacant lots should be understood in the context of the disaster recovery process. In this case, redevelopment outcomes for the pre-disaster vacant lots can serve as a benchmark for evaluating their recovery speed. For example, the redevelopment time distribution that heavy-tailed and peaked in the second year after the disaster event might be expedited by planning efforts, either minimizing the disaster response phase or facilitating the dispersal of disaster recovery relief.

6. FACTORS SHAPING VACANT LAND REDEVELOPMENT

The previous chapter compared the redevelopment patterns between disaster-induced and pre-disaster vacant lots. In terms of the redevelopment outcomes, disaster-induced vacant lots were more likely to be redeveloped than pre-disaster vacant lots. Conversely, for the redeveloped lots, disaster-induced vacant lots show a lagging, flattened redevelopment pattern. In other words, the annual redevelopment outcomes after Hurricane Ike were relatively delayed. This unevenness in disaster recovery has hindered early recovery of vacant lots.

This chapter focuses on disaster-induced vacant lots and the second and third sub-questions of this research, which touch upon the relationships among vacant land, buyout lands, and redevelopment outcomes:

- How does the accumulation of vacant land affect redevelopment outcomes?
- What are the impacts of buyout programs on redevelopment outcomes?

Accordingly, the primary subject of this chapter is the length of time before disaster-induced vacant lots are redeveloped. The length of time differentiates the vacant lots that remains vacant for “too-long” from the transitory vacant lots. This study estimated the annual redevelopment probabilities to emphasize the effect of the duration land remains vacant. This study also estimated negative effects from adjacent vacant lots. The presence of both pre-disaster and disaster-induced vacant lots were expected to delay the redevelopment process in nearby areas. Similarly, buyout lots were also expected to hinder redevelopment outcomes. Government purchase of vacant lots is assumed to help mitigate repetitive losses due to disasters, but they become permanently vacant after the buyout process. These permanent vacant lots are known to increase uncertainty regarding redevelopment in nearby areas by reducing property values and deteriorating the vitality of neighborhoods (Bukvic et al., 2015; U.S. Department of Housing and Urban Development, 2013).

Statistical analyses were performed to estimate the adverse effects of vacant lots. First, logistic regression models were used to determine the factors shaping redevelopment outcomes during the eight-year period after Hurricane Ike (i.e., 2009 to 2017). Second, Cox proportional hazards and discrete time hazard models were used to explore the negative effects of vacant lots accumulating nearby and how they may change over time. The statistical modeling results showed that all types of vacant lots, whether pre-disaster, disaster-induced, or buyout, hindered redevelopment outcomes. The effective distance of adverse effects from vacant lots was 250 feet, which was relatively smaller than those measured in previous studies examining property value losses.

6.1. Redevelopment Factors

Table 28 presents the descriptive statistics for the characteristics of disaster-induced vacant lots in the study area. There were 3,100 disaster-induced vacant lots. As with the previous analysis in Chapter 5, lots showing zero values for pre-disaster land or improvement values were excluded from the data; a total of 21 lots fell into this category, due to their improvement values being listed as zero in the 2008 data. Thus, analyses were conducted using 3,079 disaster-induced vacant lots.

Table 28. Descriptive Statistics

Variable	N	Mean	Median	Std. Dev.	Min.	Max.
Dependent variable						
Redevelopment outcome	3,079	0.38	0	0.48	0	1
Lot-level characteristics						
Land value ($)	3,079	17,348	7,450	26,899	50	295,100
Improvement value ($)	3,079	74,227	59,470	57,979	25	546,680
Lot size (sq. ft.)	3,079	11,383	6,910	19,298	1,550	355,510
Homestead tax exemption	3,079	0.11	0	0.32	0	1
Hazard exposure						
Floodplain (flood zone)						
0.2: minimal hazard	1	-	-	-	-	-
X: moderate hazard	2	-	-	-	-	-
AE: 100-yr coastal	673	-	-	-	-	-
VE: 100-yr coastal w/waves	2,403	-	-	-	-	-
Distance from the seashore	3,079	752	592	589	1	3,873
Distance from (dis)amenities						
Public housing complexes	3,079	78,398	77,466	27,691	973	154,827
Portable housing lots	3,079	1,795	1,043	2,420	24	25,666
Commercial lots	3,079	1,214	1,075	951	15	7,431
Industrial lots	3,079	20,006	19,089	12,879	181	86,779
Major roads	3,079	1,546	1,347	1,309	82	11,337
Neighborhood characteristics						
Seasonal vacant units (%)	3,079	88	92	12	0	93
Black, non-Hispanic (%)	3,079	0.89	0.51	3.60	0	50
Hispanic (%)	3,079	4.90	3.90	4.70	2.90	52
Poverty (%)	3,079	11	9.90	4.50	2.60	62
Pop. density (sq. mi.)	3,079	248	182	783	35	14,010
Imp. value loss (%)	3,079	77	83	14	11	83
Redeveloped lots (%)	3,079	38	44	12	0	100
Accumulation of vacant lots						
# of pre-disaster vacant lots						
0 to 250 feet	3,079	6.00	5	4.60	0	27
250 to 500 feet	3,079	16.00	14	11.00	0	56
500 to 750 feet	3,079	23.00	20	16.00	0	91
750 to 1,000 feet	3,079	28.00	26	19.00	0	114
# of buyout lots in 2013						
0 to 250 feet	3,079	1.50	0	2.60	0	16
250 to 500 feet	3,079	2.70	1	4.00	0	31
500 to 750 feet	3,079	3.70	2	5.30	0	35
750 to 1,000 feet	3,079	4.40	2	5.90	0	40
Vacant area within 250 feet						
Pre-disaster area (%)	3,079	28	26	18	0	93
Pre-disaster area PD	3,079	314	309	172	0	976
Buyout area (%)	3,079	9	0	15	0	100
Buyout area PD	3,079	79	0	111	0	826

Std. Dev.: Standard Deviation; Min.: Minimum; Max.: Maximum; sq. ft.: square feet

The dependent variable identified the redevelopment outcome within the research period; it was a dummy variable coded "1" for redeveloped and "0" for remaining vacant until 2017. As defined in Chapter 5, a lot was identified as redeveloped when a vacant lot changed its land use to a non-vacant type. Among the 3,079 disaster-induced vacant lots, 38% were redeveloped by 2017 (i.e. 1,161 lots). The duration of all disaster-induced vacant lots remaining vacant was then measured. A total of 439 disaster-induced vacant lots became buyout vacant lots between 2011 and 2013.

The independent variables were categorized into six groups: lot-level characteristics, hazard exposure, distance from amenities and disamenities, neighborhood characteristics, accumulation of vacant lots, and vacant area. The independent variables were selected based on previous vacant land and disaster recovery research.

The pre-disaster lot-level characteristics were based on 2008 data recorded just before Hurricane Ike. The mean pre-disaster land and improvement values displayed a right-skewed distribution; thus, the mean values substantially exceed the median values. Similarly, the distribution of lot sizes was skewed to the right due to some large vacant lots. The 1^{st} percentile lot size was 2,497 sq. ft., median was 6,910 sq. ft., and 99^{th} percentile lot size was 82,516 sq. ft. For the statistical analysis, these right-skewed variables were natural log transformed to reduce their skewness. Homestead tax exemption was used to indicate owner-occupied residential properties; 11% of lots received the Homestead tax exemption, reducing their taxable property value before Hurricane Ike. These lot-level characteristics are known to affect vacant lots' redevelopment outcomes. For example, higher-value, properly-sized, and owner-occupied vacant lots tend to be redeveloped at a faster rate. In terms of disaster recovery, these factors were also expected to affect the redevelopment outcomes of disaster-induced lots.

The hazard exposure category contained two variables: the flood zones and distance between each vacant lot and the nearest seashore. The disaster-induced vacant lots were mainly located in two FEMA flood zones: areas with a 1% or greater annual chance of flooding (coded as AE), and areas with an additional hazard associated with storm waves in addition to a 1% or greater annual chance of flooding (coded as VE) (Federal Emergency Management Agency, 2020c).

Both AE and VE zoning indicate high-risk areas (i.e., base flood or 100-year flood areas) known as Special Flood Hazard Areas, mandating the purchase of flood insurance by any federally regulated financial institution. In other words, per the Flood Disaster Protection Act of 1973 and National Flood Insurance Reform Act of 1994, flood insurance must be retained for the life of the loan for any building in these areas (Federal Emergency Management Agency, 2011a). Only three lots were located in the 0.2 and X zones, representing areas of minimal (i.e., outside of the 500-year flood area) and moderate flood hazard areas (i.e., between the 100-year and 500-year flood areas). Because the target of this study is disaster-induced vacant lots, most of the lots examined were located in high-risk areas, either AE or VE. The variable for straight-line distance from the seashore was also designed to indicate the level of flood hazard. The US Census TIGER/Line Shapefiles database offers area hydrography shapefiles (U.S. Census Bureau, 2010m). This file contains area hydrography, featuring areas covered by ponds, lakes, oceans, rivers, streams, and canals. The unit of distance for the variable was feet. For example, a disaster-induced vacant lot was 752 feet away from the nearest water area, on average. This distance variable was transformed using a natural logarithm function to control for positive skewness and decrease the marginal effect as the distance increased.

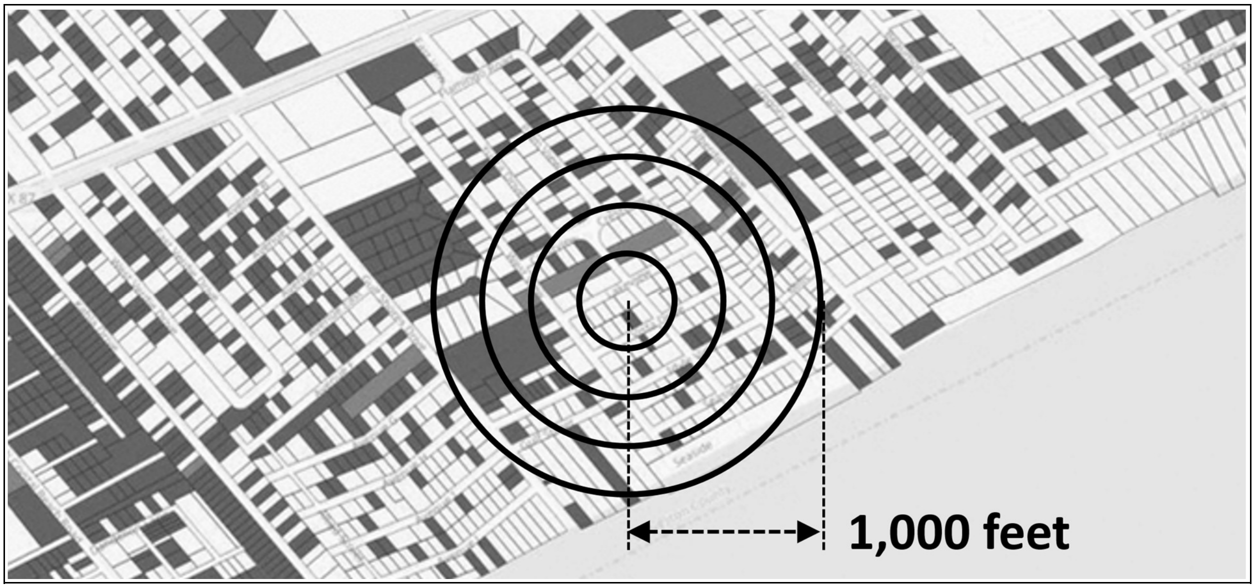
The variables for distances from amenities and disamenities were designed to control for contextual urban land development factors. Distances from pre-disaster public housing complexes (Hamideh & Rongerude, 2018), portable housing lots, and industrial lots were expected to decrease redevelopment outcomes in nearby areas (Shultz & King, 2001; Song & Knaap, 2004). Conversely, distances from commercial lots (Song & Knaap, 2004) and major roads may have had a non-linear relationship in terms of land development. For example, commercial lots, especially when they are of a neighborhood scale, can positively influence housing values and stimulate residential development (Shultz & King, 2001; Yoon, 2018).

The Housing Authority of Galveston (2009) indicated four public housing sites in 2008: Cedar Terrace (136 units), Magnolia Homes (133 units), Oleander Homes (196 units), and Palm Terrace (332 units). Similarly, there were 223 portable housing lots in 2008 (i.e., land use code 'A2, Single family residential, mobile home' lots): 209 lots on the Bolivar Peninsula and 14 lots in the city of Galveston. Commercial lots were well-dispersed across the entire study area (1,619 lots with the land use code 'F1, Commercial'), while industrial lots were clustered in the harbor area near the downtown (44 lots with land use code 'F2, Industrial'). For each disaster-induced vacant lot, straight-line distances were calculated to the nearest public housing site and portable housing, commercial, and industrial lots. The major roads variable calculated the distance from State Highway 87 and Termini-San Luis Pass Road, which pass through the entire Galveston Island and Bolivar Peninsula areas. Overall, this study included five distance variables regarding amenities and disamenities. The unit of distance for these variables was feet. The variables were also transformed using a natural logarithm function, due to their positive skewness. The log transformation also addressed diminishing marginal effects by increasing the distance from the source.

Seven variables were selected to control for the neighborhood-level characteristics affecting redevelopment outcomes. The Decennial Census 2000 data were used to indicate the block group level-socioeconomic characteristics. These characteristics included the percentage of seasonal vacant units, percentage of minority population (African Americans and Hispanic or Latino), percentage of persons living in poverty, and population density. The variables for percentage of loss of improvement value and percentage of redeveloped lots were derived from the longitudinal parcel data. For each single-family lot, the percentage of decrease in improvement value between 2008 and 2009 was calculated. Then, this percentage of value loss was aggregated into census block groups to indicate the mean hurricane damage to single-family units for each neighborhood. In addition, for each census block group, the percentage of redeveloped lots was calculated based on the number of redeveloped lots out of the total number of disaster-induced vacant lots present during the research period. Accordingly, this variable indicated the general tendency of redevelopment outcomes.

Similar to Mikelbank (2008) and Han (2017a), the numbers of both pre-disaster vacant and buyout lots were calculated according to four concentric circles, increasing the radii by 250 feet for each. Figure 20 presents an example of the four concentric distance groups: 250 feet, 500 feet, 750 feet, and 1,000 feet. Because the mean single-family lot size was around 6,100 sq. ft. (0.19 acres), a 250-foot radius could include two to four nearby single-family lots on both sides. The number of pre-disaster vacant lots was based on the 'C1, Vacant' code in the 2008 data (Hegar, 2014). Because the buyout lots were assigned between 2011 and 2013, the number of buyout lots was based on the 2013 data.

Figure 20. Four Concentric Circles



In addition to the numbers of vacant and buyout lots, this study included the percentages of vacant and buyout areas and their patch densities within a 250-foot distance from each disaster-induced vacant lot. This was accomplished using FRAGSTATS version 4.2.1 (McGarigal et al., 2012) and the FRAGSTATS metrics of percentage of landscape (PLAND) and patch density (PD). Han (2014) identified that the vacant lots within the 250-foot distance have the most dominant adverse effect among the suggested distance groups. The 250-foot distance was also stood out in the preliminary modeling results testing the variable for the number of vacant lots for each distance group; the number of vacant lots within the 250-foot distance was the only significant variable among the four concentric distance groups.

The percentages of vacant and buyout areas were calculated based on the area covered by 'C1, Vacant' lots and designated buyout lots, divided by the total parcel area. Accordingly, non-parcel areas like streets and open water areas were not included in this calculation. One patch of vacant area identified vacant lots sharing boundaries (i.e., attached to one another). The patch densities of the vacant and buyout areas presented the number of patches in a per unit area of 100 hectares (equal to 0.3861 square miles or 247.1 acres). Therefore, patch density identified the extent of fragmentation of the patch type. On average, within a 250-foot distance from a disaster-induced vacant lot, 28% and 9% of the area were either pre-disaster vacant or buyout lots, respectively.

A logistic regression model is a cross-sectional type of analysis that estimates the probability of an event at a specific point in time. For example, in the present research, the redevelopment outcome was the dependent variable; the logistic regression model estimated the probability of redevelopment between 2009 and 2017. Alternatively, a survival analysis was used to study the redevelopment outcomes in terms of the duration of vacancy. In this case, the dependent variable was constructed by a person-period structure (Cleves et al., 2008; Mills, 2010). The dependent variable was transformed into a lot-period structure, indicating the years of vacancy of each lot.

Using the survival analysis method enabled full exploitation of the longitudinal data. Specifically, it allowed for the inclusion of time-varying covariates, as well as time-invariant covariates (Finlay & Agresti, 1986; Singer & Willett, 1993). For example, the number of vacant lots changed drastically between 2008 and 2017. The logistic regression model could not include the changing number of vacant lots as time-varying covariates. Instead, the percentages of improvement value loss and redeveloped lots were included as proxy factors for disaster damage and redevelopment outcomes per block group. The survival analysis was used to estimate the annual number of vacant lots before and after the disaster event. Table 29 presents the time-dependent covariates included in the survival analysis. The variables for the number of post-disaster vacant lots and buyout lots presented the increased number of lots beyond the number of pre-disaster vacant lots. For example, in 2008, there was a mean of 6 vacant lots within a 250-foot distance. These 2008 vacant lots were identified as the pre-disaster vacant lots. In 2009, the number of vacant lots increased by 8.25, in addition to the previous 6, on average. The increased number of vacant lots was identified as the post-disaster vacant lots in 2009. Similarly, the area and patch density of post-disaster vacant lots were calculated based on the value changes in pre-disaster area and patch density.

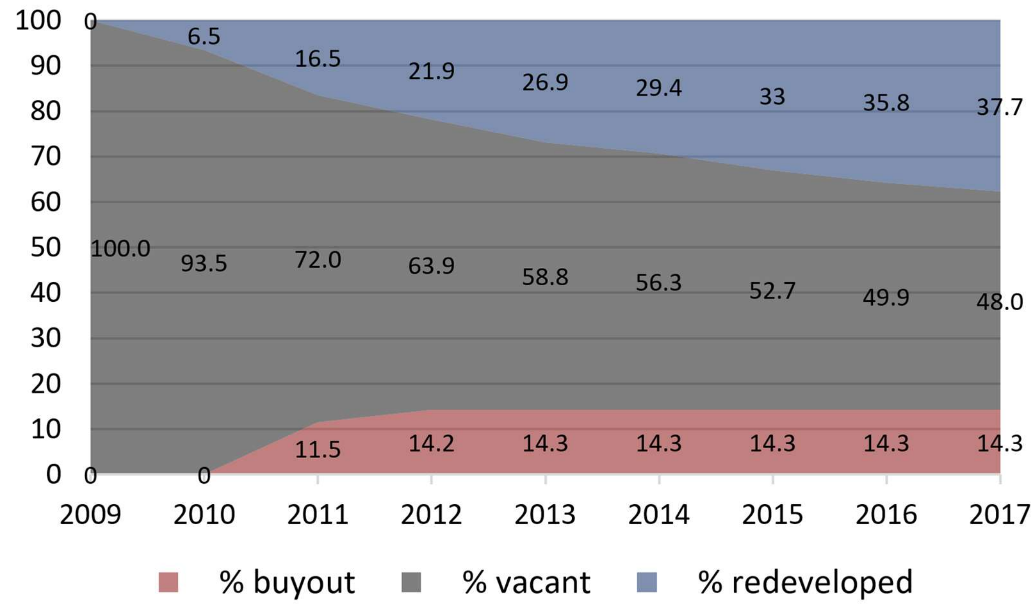
Table 29. Time-Dependent Covariates for Survival Analysis

Calendar Year	2009	2010	2011	2012	2013	2014	2015	2016	2017
Years after Ike (periods)	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Accumulation of vacant lots									
# of post-disaster vacant lots									
0 to 250 feet	8.25	8.06	6.13	4.97	4.32	3.88	3.37	2.97	2.67
250 to 500 feet	17.11	16.84	12.76	10.27	8.64	7.59	6.25	5.29	4.60
500 to 750 feet	22.58	22.16	16.75	13.33	11.22	9.83	7.97	6.64	5.77
750 to 1,000 feet	25.89	25.36	19.19	15.12	12.80	11.17	8.87	7.24	6.15
# of buyout lots									
0 to 250 feet	0.00	0.00	1.17	1.48	1.50	1.50	1.50	1.50	1.50
250 to 500 feet	0.00	0.00	2.13	2.72	2.76	2.76	2.76	2.76	2.76
500 to 750 feet	0.00	0.00	2.92	3.73	3.76	3.76	3.77	3.77	3.77
750 to 1,000 feet	0.00	0.00	3.42	4.41	4.45	4.45	4.45	4.45	4.45
Vacant area within 250 feet									
Post-disaster area (%)	45.10	45.37	33.95	27.60	23.97	21.82	19.16	17.18	15.65
Post-disaster area PD	-36.4	-20.6	6.66	17.36	15.11	18.26	16.51	18.57	17.77
Buyout area (%)	0.00	0.00	7.22	9.04	9.14	9.14	9.14	9.14	9.14
Buyout area PD	0.00	0.00	68.89	78.94	79.75	79.75	79.70	79.70	79.70

6.2. Modeling the Redevelopment Outcomes

A survival analysis focuses on events occurring over time (Finlay & Agresti, 1986). For example, this study modeled how long it would take for disaster-induced vacant lots to be redeveloped. Accordingly, in the longitudinal data, each lot consisted of an observation of the length of time until the redevelopment occurred. Figure 21 presents a summary of the annual redevelopment outcomes based on the 3,079 observations used for the logistic regression models. The data began with the 100% vacant lots in 2009; then, there was a gradual increase in redeveloped lots. After 2010, some lots became buyout lots. Overall, 37.7% of the lots were redeveloped, 48.0% remained vacant, and 14.3% remained vacant as buyout lots.

Figure 21. Redevelopment Outcomes



Calendar Year	2009	2010	2011	2012	2013	2014	2015	2016	2017
Year after Ike	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
% redeveloped	0.0	6.5	16.5	21.9	26.9	29.4	33.0	35.8	37.7
% vacant	100.0	93.5	72.0	63.9	58.8	56.3	52.7	49.9	48.0
% buyout	0.0	0.0	11.5	14.2	14.3	14.3	14.3	14.3	14.3

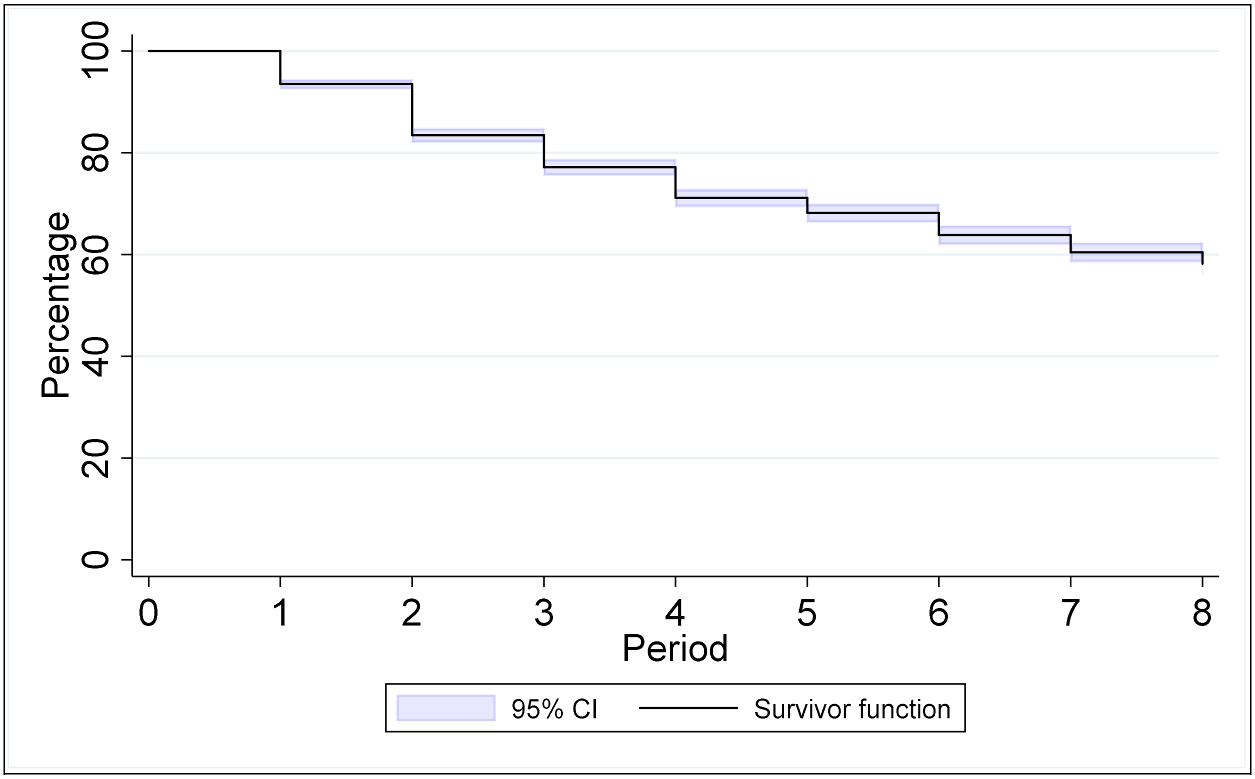
Note: the number of observations was 3,079.

There are two main issues with the longitudinal data regarding the length of redevelopment time limited the statistical analysis. First, because 48.0% of lots were vacant in 2017, the actual time of redevelopment could not be observed (i.e., right-censoring). Analyzing data using only fully observed data can result in the biased estimations of parameters (Finlay & Agresti, 1986). In addition, the length of time for buyout-processed lots needed to be differentiated from other remnant vacant lots because their probability of redevelopment became zero after the land acquisition process. Second, this study addressed the accumulation of vacant lots and vacant areas that changed over time. Therefore, the analysis needed to address time-dependent covariates as well as time-invariant covariates. The survival analysis enabled this study to address censored observations and include time-dependent covariates (Singer & Willett, 1993; Singer et al., 2003). The buyout lots were also treated as censored observations; they were coded as vacant lots, and their length of time ended when they became acquired. Table 30 and Figure 22 show the Kaplan-Meier survival estimates using the survival data addressed. The survival rate provided an estimate of the likelihood that a vacant lot would not experience a redevelopment event.

Table 30. Kaplan-Meier Survival Function

Interval	Period	At risk	Events	Censored	Survival Rate
2009 to 2010	1	3,079	199	0	0.9354
2010 to 2011	2	2,880	310	351	0.8347
2011 to 2012	3	2,219	167	82	0.7719
2012 to 2013	4	1,970	154	4	0.7115
2013 to 2014	5	1,812	76	0	0.6817
2014 to 2015	6	1,736	110	0	0.6385
2015 to 2016	7	1,626	86	0	0.6047
2016 to 2017	8	1,540	59	1,481	0.5816

Figure 22. Kaplan-Meier Survival Estimate



For the preliminary analysis, the logistic regression and Cox proportional hazard models were tested. First, the logistic regression models estimated the occurrence of redevelopment outcomes as a dummy variable: "1" for redeveloped lots and "0" for remnant vacant lots. Then, the Cox proportional hazard models estimated the hazard ratios indicating how often a redevelopment event occurred. The modeling results were illustrated in Chapter 8, Appendix session 9.2 and 9.3 for the logistic regression models and the Cox regression models. In summary, the results from these two types of models resemble that of the discrete time hazard models explained below. This study selected the discrete time hazard model as the final modeling method because it comprehensively addresses the censoring and the tied survival times issues.

The discrete time hazard model is an extended version of the proportional hazards model used to analyze discrete time data (i.e., tied survival times) (Singer & Willett, 1993). This study tested a logit and a complementary log-log transformations to retain the proportional hazards assumption in the Cox model (Singer et al., 2003). In this case, the estimated coefficients from both transformations can also be directly interpreted in terms of odds ratios and hazard ratios, respectively. The discrete-time hazard model using the logit transformation allows this study to understand the modeling coefficients more intuitively. The complementary log-log transformation is reputed to work better for the interval censored data and when the outcome is very rare (Singer et al., 2003).

The variables used for the preliminary models were applied to the discrete time hazard model. Like the preliminary logistic regression models, each group of independent variables was separately tested by the proportional hazards models. The tested modeling results were illustrated in Chapter 8, Appendix session 9.4. In summary, the significant explanatory variables in the preliminary models also significantly influenced the proportional hazards models.

Table 31 presents the discrete time hazards modeling results using the logit transformation (Model 1 to Model 3) for predicting the probability of redevelopment. The complementary log-log transformation closes to logit transformation when the probability of an event is small. Accordingly, the modeling results from the complementary log-log transformation close to those from the logit transformation. The complementary log-log transformation modeling results were presented in Chapter 8, Appendix session 9.5.

Table 31. Discrete Time Hazard Model: Logit Transformation (Odds Ratio)

Model:	Model 1	Model 2	Model 3
Time			
Period 2 (2010 to 2011)	1.818***	1.663***	1.440***
Period 3 (2011 to 2012)	1.246**	1.090	0.874
Period 4 (2012 to 2013)	1.321**	1.131	0.859
Period 5 (2013 to 2014)	0.694***	0.581***	0.428***
Period 6 (2014 to 2015)	1.097	0.899	0.638***
Period 7 (2015 to 2016)	0.922	0.736*	0.505***
Period 8 (2016 to 2017)	0.660***	0.516***	0.348***
Lot-level characteristics			
Land value (log)	1.060	0.950	0.934
Improvement value (log)	1.341***	1.338***	1.340***
Lot size (log)	3.509	1.090	2.105
(Lot size (log))^2	0.938	0.989	0.977
Homestead tax exemption	1.210**	1.230**	1.182*
Hazard exposure			
Floodplain: VE	0.967	0.923	0.992
Dist. to the seashore (log)	1.294	1.322	1.147
(Dist. to the seashore)^2	0.985	0.984	0.991
Dist. to (dis)amenities (log)			
Public housing complexes	1.367**	1.502**	1.306
Portable housing lots	0.979	0.922**	0.929*
Commercial lots	2.109*	2.672**	2.233*
(Commercial lots)^2	0.941*	0.921**	0.936*
Industrial lots	1.322	1.171	0.819
(Industrial lots)^2	0.981	0.988	1.007
Major roads	4.139**	3.975**	1.435
(Major roads)^2	0.920	0.928	0.993
Neighbor. characteristics			
Seasonal vacant units (%)	0.986**	0.993	0.989*
Black, non-Hispanic (%)	0.984	0.985	0.972
Hispanic (%)	0.999	0.987	0.987
Poverty (%)	0.996	1.003	1.001
Pop. density (sq. mi., log)	0.901	1.038	0.919
Imp. value loss (%)	0.997	0.996	1.004
Redeveloped lots (%)	1.033***	1.029***	1.028***
Accumulation of vacant lots			
# of pre-disaster vacant lots			
0 to 250 feet		0.940***	0.994
250 to 500 feet		1.006	1.003
500 to 750 feet		1.004	1.005
750 to 1,000 feet		0.994*	0.995
# of post-disaster vacant lots			
0 to 250 feet		0.857***	0.971*
250 to 500 feet		1.042***	1.040***

Model:	Model 1	Model 2	Model 3
500 to 750 feet		0.999	0.998
750 to 1,000 feet		1.000	0.999
# of buyout lots			
0 to 250 feet		0.915***	0.892***
250 to 500 feet		1.045***	1.014
500 to 750 feet		1.005	1.004
750 to 1,000 feet		0.997	0.995
Vacant area within 250 feet			
Pre-disaster area (%)			0.978***
Pre-disaster area PD			1.001***
Post-disaster area (%)			0.964***
Post-disaster area PD			1.001***
Buyout area (%)			0.984**
Buyout area PD			1.002**
Constant	<0.001***	<0.001***	<0.001**
N (lots)	3,079	3,079	3,079
LR Chi^2	436.05	641.74	807.63
Pseudo-R^2 *(McFadden's)*	0.052	0.076	0.096
AIC	8079.28	7897.59	7743.70
BIC	8318.99	8230.10	8122.61

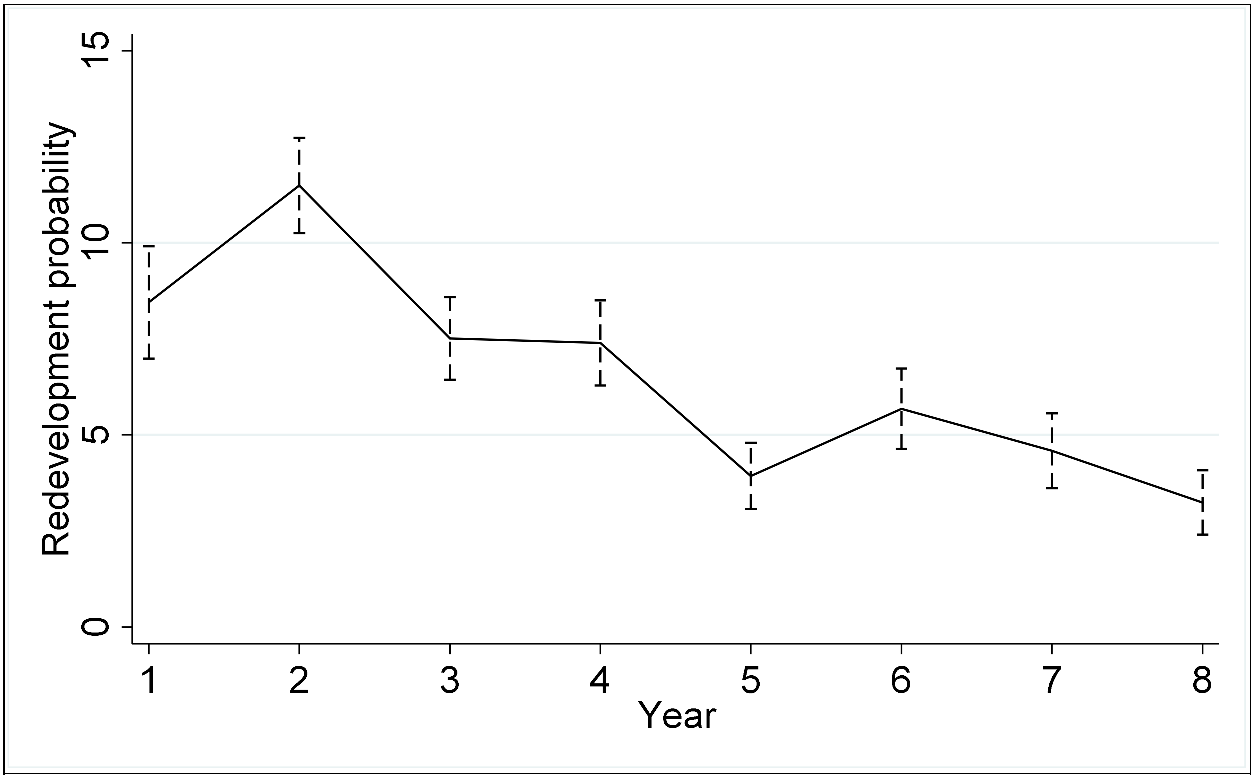
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Model 1 tested the baseline explanatory variables. For Model 2 and Model 3, each tested a group of time-varying (variables related to the post-disaster vacant lots and buyout lots) and time-invariant (variables related to the pre-disaster vacant lots) covariates regarding the accumulation of vacant lots. In addition to the baseline explanatory variables, Model 2 tested the number of vacant lots by the vacancy types. Model 3 included the vacancy area variables. Note that the relatively lower pseudo-R^2 values were due to the censored observations in the survival data (Royston & Sauerbrei, 2004). In the present research, including explanatory variables enhanced the rates of explained variation, as can be seen through the increased LR Chi-squared and R-squared values and the decreased AIC and BIC values.

Odds ratios indicate how often a redevelopment event occurred, corresponding to the explanatory variable. An odds ratio close to 1 means that the explanatory variable did not affect the redevelopment outcome. If the odds ratio is less than or greater than 1, the explanatory variable was associated with a decreased or increased chance of redevelopment, respectively. Test results of statistical significance are noted by the number of stars (i.e., *, **, and *** for $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively) next to the odds ratios.

Unlike the preliminary models, these models included dummy variables capturing the influence of each period. The first period was omitted (the baseline period). Accordingly, the following Period variables estimated the odds ratios versus the first period. Except for Periods 3 and 4, the other periods were significant at the 99% level in Model 3. The Period 3 and 4 variables were not significant compared to Period 1, the base period. On the other hand, the differences between Period 2 and Period 3 and between Period 2 and 4 were significant at the 99% level (tested by the 'lincom' command in Stata 15). This result implies that each period affected redevelopment outcomes, even after controlling for the influence of other explanatory variables. Figure 23 illustrates the estimated probability of redevelopment by each period, based on Model 3. The figure implies that the probability of redevelopment (i.e., the probability of a disaster-induced vacant lot to be redeveloped in the given period) was high in the second period, and then significantly declined after the third period; the redevelopment of disaster-induced vacant lots was peaked in the second period, and it became less feasible three or more years after the disaster event. The overall effect of the period variables was tested using the 'test' command, and it was statistically significant at the 99% level.

Figure 23. Estimated Probability of Redevelopment: Annual Probability



Overall, the preliminary and discrete time hazard models yielded almost identical results in terms of the accumulation of vacant lots. The distance from vacant lots is a critical factor. Some previous research has emphasized far-reaching adverse effects in terms of property value losses up to 328 feet (i.e., 0.1 km) (Z. Lin et al., 2009), 450 feet (Shlay & Whitman, 2006), 500 feet (Griswold & Norris, 2007; Whitaker & Fitzpatrick IV, 2013), and 660 feet (i.e., 1/8-mile) (Immergluck & Smith, 2006). However, in terms of the redevelopment of disaster-induced vacant lots, only vacant lots within a 250-foot distance appeared to have a significant adverse effect on the chance of redevelopment. This 250-foot distance corresponds with the distance terms used by Han (2014) and Mikelbank (2008). In other words, considering the mean size of single-family residential lots, only two to four nearby side-by-side lots affected the redevelopment outcome of each disaster-induced vacant lot.

While previous literature has focused on the existence and number of vacant properties, the difference between Model 2 and Model 3 implied that the percentage of vacant area should be examined, as well as the number of vacant lots. In Model 3, as with the other explanatory variables, the percentage of pre-disaster and post-disaster areas had a significant and negative effect on redevelopment outcomes, while the numbers of pre-disaster and post-disaster vacant lots became insignificant or less significant. In other words, within the 250-foot distance, the percentages of pre- and post-disaster vacant areas were expected to decrease the redevelopment outcomes. In Model 3, the odds of redevelopment decreased by 2.2%, 3.6%, and 1.6% for every 1% point increase in the pre-disaster, post-disaster, and buyout vacant areas, respectively. For the buyout lots, both the number and area variables were significant at the 99% and 95% levels. In Model 3, the odds of redevelopment decreased by 10.8% for every one additional buyout lot. The number of post-disaster vacant lots variable in Model 3 was significant at the 90% level, however, testing the effect of this variable can be considered as a one-tailed test. In this case, the odds of redevelopment decreased by 2.9% for every one additional pre-disaster lot.

Besides, based on Model 2, the number of post-disaster vacant lots and buyout vacant lots from 250 feet to 500 feet away may have had some positive effect on redevelopment outcomes. The number of post-disaster vacant lots from 250 feet to 500 feet distance was significant in Model 2 and Model 3 at the 99% level. This may correspond with previous literature that emphasized the positive effects of open and green space in neighborhoods. On the other hand, the number of buyout lots from 250 feet to 500 feet distance became insignificant in Model 3.

Regardless of the source of vacancy, the fragmentation of vacant land increased the probability of redevelopment. This implies that the clustering of vacant lots could also be a key factor shaping redevelopment of neighborhoods. The patch density of the pre-disaster, post-disaster, and buyout areas had a significant effect on redevelopment outcomes; an increase in patches (i.e., more fragmented vacant areas) tended to increase the probability of redevelopment. In other words, after controlling for number and size of vacancy, scattered vacant areas could increase the probability of redevelopment of nearby areas up to the 250 feet distance.

Like the preliminary models, the improvement value and percent of redeveloped lots in block groups had significant and positive effects on redevelopment outcomes at the 99% level. The pre-disaster (and pre-vacancy) improvement value can be seen as an index of housing owner's resource and attachment as well as a reference of restoration aids. Vacant lots with higher pre-disaster improvement values located in a block group with other redeveloped lots were more likely to be redeveloped. Based on literature, testing the effect of housing ownership can be considered as a one-tailed test. The homestead tax exemption variable had significant coefficients larger than 1, indicating that the probability of redevelopment likely increased for pre-disaster owner-occupied lots. In the same vein, the percentage of seasonal vacant units showed significant negative effects on redevelopment outcomes based on a one-tailed test.

The distance from commercial lots variable and its squared term variable were marginally significant at the 90% level in Model 3 (as in the preliminary models), meaning an inverted U-shaped curve, indicating adverse effects on nearby lots as well as lots located far away from commercial areas. The distance from major roads variable was significant in Model 1 and Model 2 with its squared term. Without the squared term, the distance from major roads variable indicated a positive relationship, meaning that major roads had a negative effect on redevelopment outcomes in nearby areas. However, the major roads variables were not significant in Model 3.

In Model 3, the distance from the portable housing lots variable had a 0.055 *p*-value, meaning that this variable was significant at the 90% level. Its estimated effect on redevelopment outcomes was not consistent with general expectations; the exponentiated coefficient of this variable implies that the increased distance from portable housing lots may have decreased the probability of redevelopment. While the variable itself is marginally significant, its relative magnitude on redevelopment outcomes was limited: the expected redevelopment probability was 8.0% when the distance was 100 feet, 7.0% for the median distance (976 feet), and 6.0% for the 10,000-foot distance.

Along with the other independent variables, hazard exposure factors and neighborhood socioeconomic characteristics were not significant in the logit, Cox, and discrete time hazard models. Almost all disaster-induced vacant lots were located in high-risk areas, either AE or VE zones. The difference between the AE and VE zones was an additional hazard due to storm waves, which did not create a significant contrast in terms of redevelopment outcomes. In the same vein, all disaster-induced vacant lots were fairly adjacent to the seashore. Galveston Island and Bolivar Peninsula are waterfront areas, and the maximum distance from the seashore for the study parcels was 3,873 feet; all lots were located less than ¾ of a mile from the seashore. This study cannot confirm the significance of neighborhood socioeconomic characteristics such as the percentages of racial and ethnic groups, number of individuals living in poverty, and population density. As seen in Figure 16, most of the disaster-induced lots were located outside the downtown area. Thus, block group level data may not have worked well, due to the block groups being quite large.

As this study was most interested in negative externalities from nearby vacant lots, the estimated redevelopment probabilities (i.e., the probability of a disaster-induced vacant lot to be redeveloped in the given period) were illustrated in Figure 24 by the levels of pre-disaster, post-disaster, and buyout vacant areas: 10%, 30%, and 50% as minor, moderate, and severe levels of vacancy. The overall probabilities peaked in the second period. After the second period, values tended to decrease over time, with minor fluctuations. The nearby vacant areas substantially attenuated the probability of redevelopment, regardless of the source of the vacancy. For example, if a lot is located in areas with over 50% post-disaster vacancy, the estimated annual redevelopment probabilities were considerably flattened; they never exceeded 10% during the entire study period. For example, right after Hurricane Ike, the 2009 data indicated that 1,474 disaster-induced vacant lots (47.9% of the total 3,079) were located in areas with over 50% post-disaster vacancy. Even after eight years of redevelopment time, the 2017 data indicated that 89 lots (2.9% of the total 3,079) were still located in areas with over 50% post-disaster vacancy. For the entire study period, of the 89 lots located in the severe vacancy areas, only 12.3% were redeveloped.

Figure 24. Estimated Probability of Redevelopment: Vacant Area Variables

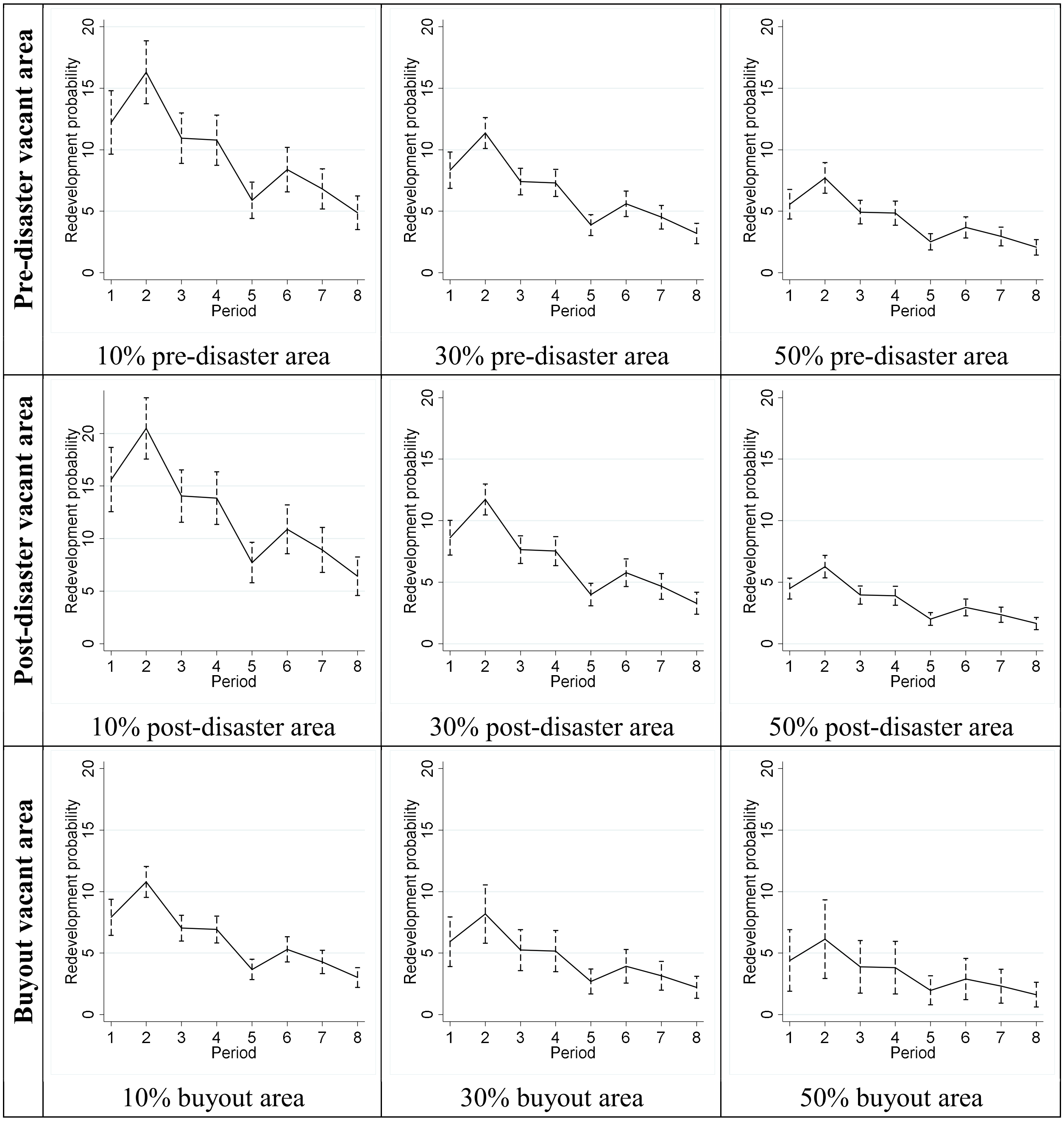
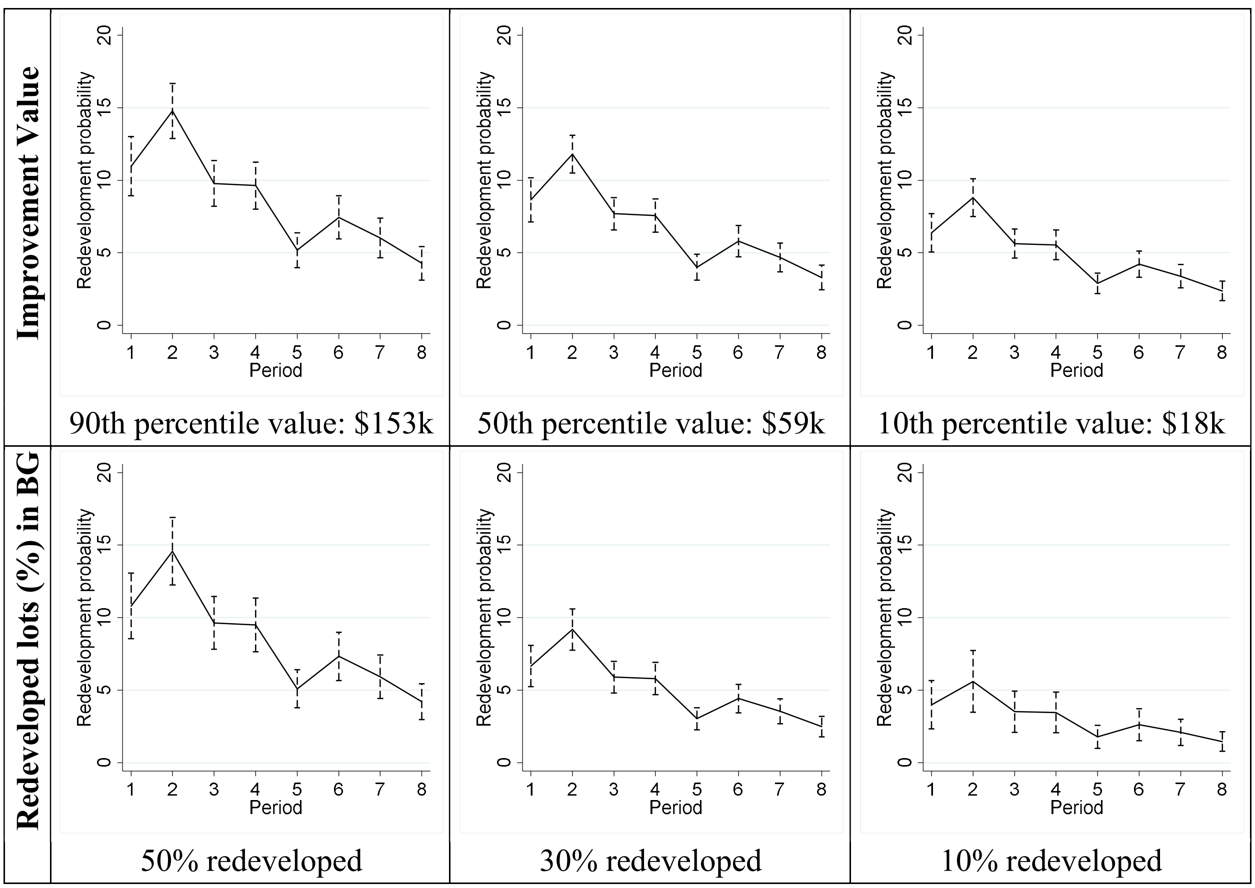


Figure 25 shows the estimated redevelopment probabilities by pre-disaster improvement value and the percentage of redeveloped disaster-induced vacant lots per block group. These explanatory variables were significant at the 99% level for all modeling methods: logit, Cox, and discrete time hazards models. Based on Model 3, a lot with a 90th percentile pre-disaster improvement value (i.e., $ 153k) had a 14.7% peak redevelopment probability in the second period. Conversely, a lot with the 10th percentile pre-disaster improvement value (i.e., $18k) had an 8.8% peak redevelopment probability in the second period. Vacant lots located in block groups with high percentages of redevelopment were more likely to be redeveloped. The 50% redeveloped block groups had 14.6% of the peak redevelopment probability, while the 10% redeveloped block groups had 5.6% of the peak redevelopment probability.

Figure 25. Estimated Probability of Redevelopment: Explanatory Variables



7. CONCLUSION

7.1. Findings and Planning Perspectives

7.1.1. Integration of Vacant Land and Disaster Recovery Studies

The main focus of this discussion is vacant land generated after a major disaster event and how its existence can threaten the viability of urban communities. Vacant land is a chronic issue for urban areas in decline in the United States, and often is negatively perceived. Land vacated due to disaster events can have both positive and negative implications for urban resilience; however, in terms of post-disaster redevelopment, vacant land is usually viewed as a negative outcome because damaged urban areas are at risk of not being redeveloped to their pre-disaster state. Therefore, this study focused on the negative impacts of vacant land on disaster recovery, and disaster recovery was analyzed in the context of vacant land redevelopment.

Negative externalities from vacant land and spreading urban blight in marginalized neighborhoods are currently the major points of interest in vacant land research. Because massive amounts of vacant land are regularly formed after disaster events, negative externalities from clustered post-disaster vacant land must be measured and addressed to counteract risks emerging in post-disaster urban environments. To this end, vacant land regeneration strategies can be applied as a part of disaster mitigation and recovery plans, in order to identify where vacant land will be generated, mitigate negative externalities, and expedite recovery outcomes.

Previous urban decline and vacant land studies have emphasized the negative externalities resulting from vacant land. The number of and distance from vacant lots are factors known to decrease property values and the chance of land development. However, much past research has used cross-sectional analysis to estimate the impact of vacancies on reducing property values. No previous studies have identified the attenuating adverse effects on vacant land redevelopment by comparing their grouped distances from the subject property. Also, previous studies have not explored how the size and fragmentation of vacant land might influence the development of nearby properties, instead using the number of vacant properties alone to measure the aggregated effect of vacancy. Therefore, it remains unclear whether nearby vacant land reduces the chance of land development.

Previous studies on disaster recovery have explored redevelopment outcomes in terms of the level of recovery and recovery time, comparing physical conditions in pre- and post-disaster built environments. Conversely, how pre-disaster and disaster-induced vacant land slows the recovery process is still in question. Little academic work has considered the various types of vacant land that existed before a disaster event and substantially accumulated after the disaster event as a key indicator shaping recovery outcomes. This study was designed to estimate the long-term effect of a disaster event on the redevelopment of vacant land; this study focused on disaster recovery in terms of the duration of vacancy and probability of vacant residential properties becoming redeveloped.

This study was most interested in the accumulation of vacant land and subsequent redevelopment outcomes. The overarching question was finding factors facilitate or constrain the redevelopment of disaster-induced vacant land. Specifically, on Galveston Island and the Bolivar Peninsula in Texas, over 3,000 vacant lots emerged after Hurricane Ike. By tracking these disaster-induced vacant lots, this study identified factors either facilitating or constraining their redevelopment outcomes. To be specific, three subsidiary questions were addressed regarding: 1) the differences in characteristics of disaster-induced and pre-existing vacant land and their respective redevelopment patterns, 2) the accumulation of vacant land and redevelopment outcomes, and 3) the impacts of buyout programs on redevelopment outcomes. For the first subsidiary question, this study employed the case-control and PSM methods, as well as an exploratory data analysis to summarize the main characteristics of pre-disaster and disaster-induced vacant lots and their redevelopment outcomes. Regarding the second and third subsidiary questions, several statistical modeling methods were employed to capture the time-varying and time-invariant characteristics of nearby vacant lots after controlling for the other explanatory variables obtained from the previous literature.

For the first subsidiary question, this study found that disaster-induced vacant lots showed a delayed and dispersed redevelopment pattern as compared with pre-disaster vacant lots. While the disaster-induced vacant lots shared some characteristics with general vacant lot redevelopment factors (i.e., land and improvement values, lot size, and tenure), the disaster-induced vacant lots should be understood in the context of the disaster recovery process. The delayed and dispersed redevelopment time highlights the uneven recovery common after disaster events. The pre-disaster vacant lots can serve as a benchmark for evaluating their recovery speed; the redevelopment pattern of the disaster-induced vacant lots might be expedited by planning efforts, such as reducing the disaster response time or expediting the disaster recovery relief.

For the second and third subsidiary questions, this study utilized several statistical models: logistic regression, Cox proportional hazards, and discrete time hazard. The logistic regression model treats longitudinal redevelopment outcomes like cross-sectional data. It was used to estimate the probability of redevelopment during the eight-year study period as a binary outcome: whether a vacant lot had been redeveloped or not. The Cox proportional hazards and discrete time hazard models were employed to address the time-varying covariates, as well as to estimate the duration of vacancy instead of the binary redevelopment outcome. Especially, the annual recovery period dummy variables in the discrete time hazard models indicated that the redevelopment of disaster-induced vacant lots became less feasible, especially three or more years after the disaster event.

Research methods from previous urban decline and vacant land studies were applied to estimate the probability of redevelopment after a disaster event. For example, as described in Table 2, adverse effect of vacant land have been estimated in various urban settings and measurements. As in Mikelbank (2008) and Han (2014), the types of vacant lot and distances from vacant lots by concentric and increasing 250-foot circles yielded different levels of impact on nearby properties. In terms of redevelopment outcomes, only vacant lots within 250 feet significantly affected nearby lots while many previous research has emphasized far-reaching adverse effects in terms of property value losses: 328 feet (i.e., 0.1 km) (Z. Lin et al., 2009), 450 feet (Shlay & Whitman, 2006), 500 feet (Griswold & Norris, 2007; Whitaker & Fitzpatrick IV, 2013), and 660 feet (i.e., 1/8-mile) (Immergluck & Smith, 2006).

All of the tested modeling methods showed similar results in terms of the significance of variables addressing the accumulation of vacant lots. The percentage of vacant area and patch density, calculated by the extended use of landscape indices (McGarigal et al., 2012), became significant predictors; between the number and percentage of area variables, the latter worked better for explaining negative externalities. The percentage of pre-disaster, post-disaster, and buyout area variables indicated a significant and substantial adverse effect on redevelopment outcomes at the 95% and 99% levels. According to the discrete time hazards model with the logit transformation, a 1% point increase in pre-disaster, post-disaster, and buyout vacant areas within the 250-feet distance decreased the relative chance of redevelopment by 2.2%, 3.6%, and 1.6%, respectively. In addition, the numbers of post-disaster and buyout lots were also significant at the 90% and 99% levels; the odds of redevelopment decreased by 2.9% and 10.8% for every one additional post-disaster or buyout lot, respectively. These results emphasize the importance of addressing the pre-existed vacant lots as well as the disaster-induced vacant lots as soon as possible to mitigate the adverse effects and expedite the speed of recovery. Regarding the buyout lots, more attention should be given to mitigating the adverse effects from the permanent vacant lots in high risk areas. The modeling results also suggests that the fragmentation of vacant areas is positively related to the chance of redevelopment when all other variables remain the same; clustered vacant lots could decrease the probability of redevelopment of nearby areas up to the 250 feet distance.

7.1.2. Planning Perspectives on Disaster Recovery

The main contribution of this research is its bridging of vacant land and disaster studies in the field of urban resilience, connecting findings and solutions from vacant land studies to disaster mitigation and recovery planning. Vacant lots can be contagious, especially clusters remaining vacant for long periods of time. However, the negative externalities of vacant land comprise one of the least studied topics related to risks emerging in post-disaster urban environments. The prevalence of vacant land increases uncertainty with regards to reinvestment, hindering redevelopment efforts and exacerbating unevenness in recovery. To counteract these negative externalities, vacant land regeneration strategies must be integrated into disaster mitigation and recovery plans. Concentrated efforts to do so across pre- and post-disaster planning for urban vacant land will improve the rapidness of recovery and level of recovery outcomes.

Estimating the factors hindering or facilitating redevelopment outcomes allows for the identification of neighborhoods prone to long-term vacancy, as well as the design of more efficient disaster mitigation and recovery plans. In other words, the specific characteristics of residential lots and neighborhoods affect redevelopment outcomes. This is especially true for long-term vacant land, which can be one of the best metrics for measuring risk to community resilience. Municipalities should identify and manage both pre-existing and post-disaster vacant lots. Local disaster mitigation and recovery plans should target neighborhoods with clusters of long-term vacancies.

The redevelopment of disaster-induced vacant lots touches upon three aspects of resilience: robustness in terms of the occurrence of vacant lots after a disaster event, the rapidity associated with the speed of redevelopment, and enhancement as a result of redevelopment outcomes and buyouts. First, this study categorized the types of vacant lots as pre-disaster, post-disaster, and buyout, and separately tested their adverse effects. The modeling results indicated that the post-disaster vacant lots in nearby areas, in addition to the other types of vacant lots, reduced the probability of redevelopment. This implies that preventing the occurrence of vacant lots is also important to attenuating the negative externalities during recovery, as well as stimulating early redevelopment. Because the occurrence of disaster-induced vacant lots was exclusively related to physical damage and neighborhood characteristics (Zhang, 2012), disaster mitigation and preparation strategies designed to lessen the immediate and direct impact could also contribute the long-term recovery.

Regarding the rapidity of redevelopment, recovery efforts in terms of the expedited distribution of disaster relief after Hurricane Ike may not have been enough to expedite recovery. Political factors hindered the distribution process of government funding for private housing (Moss, Schellhamer, & Berman, 2009; Olshansky & Johnson, 2017; Olshansky et al., 2008). Many previous studies have highlighted delays in the process for insurance payouts and federal funding after Hurricanes Andrew (Peacock et al., 1997; Zhang & Peacock, 2009), Katrina (Fussell & Harris, 2014; Gotham, 2014; Green et al., 2007; Olshansky & Johnson, 2017; Sapat, Li, Mitchell, & Esnard, 2011), and Ike (Bedient & Blackburn, 2012; Sapat et al., 2011). In terms of patterns of redevelopment, disaster-induced vacant lots could be redeveloped similarly to pre-disaster vacant lots. Considering that about half of pre-disaster vacant lots were redeveloped within a year after becoming vacant, providing immediate disaster relief and recovery assistance would facilitate early redevelopment of disaster-induced vacant lots.

Previous studies have suggested disproportionate recovery by marginalized households and neighborhoods. The modeling results also indicated that pre-disaster improvement value and block group-level percentages for seasonal vacant unit variables influenced the speed of redevelopment. Housing recovery is a market-driven process (Peacock et al., 1997; Zhang & Peacock, 2009). Insurance payouts and public resources rely on the pre-disaster value of property, and thus owners of low-value housing units may not have sufficient resources to recover. A previous household survey indicated that about a half of homeowners did not have flood insurance after Hurricane Ike (Peacock, Dash, Zhang, & Van Zandt, 2018; Peacock et al., 2014; Van Zandt et al., 2012). Even for households with insurance, debates regarding the source of damage (i.e., wind or flood) hindered the insurance payout process (Hamideh, 2015). More substantial flood requirements after Hurricane Ike also increased redevelopment costs (Peacock et al., 2014). In accordance with Hamideh et al. (2018), neighborhoods with a high percentage of seasonally vacant units (meaning vacation housing submarket areas) also suffered delayed redevelopment.

Buyout programs have both positive and negative effects. By acquiring damaged properties to support disaster victims, buyout programs create permanent greenspaces out of high-risk properties in flood-prone areas. Accordingly, the vacant land acquired will eventually enhance disaster resilience. Besides, buyout lots can be reused as permanent green spaces, and it will increase property values near the edge of the greenspace (Brody & Highfield, 2013). Negative side effects of buyout programs have also been identified, such as reducing property values, providing little investment for public infrastructure and private rebuilding in depopulated communities, crime, and inequality in the property evaluation process (Bukvic et al., 2015; Muñoz & Tate, 2016; U.S. Department of Housing and Urban Development, 2013).

Unlike pre- and post-disaster vacant lots, buyouts tended to generate randomly distributed permanent vacant lots in a “Swiss cheese” pattern through “checkerboard” participation (Bukvic et al., 2015; McLeman, 2011). This pattern undermines the viability of neighborhoods and their resilience. Consequently, remaining residents face difficulties with recovering (Bukvic et al., 2015). In this regard, more attention should be given to mitigating the adverse effects of buying out vacant lots. Incentive strategies have been used to promote group relocation (as in when entire blocks of homeowners decide to leave), in-county relocation (for homeowners deciding to relocate within their home county), and participation from residents of high-vulnerability areas to lessen the side effects of buyouts in New York State after Hurricane Sandy (Kaplan, 2013).

The findings from this research correspond with those of previous studies. The negative externalities from all types of vacant lots triggered the emergence of marginalized neighborhoods suffering long-existing vacancy issues; the modeling results showed that the negative externalities from vacant lots significantly discouraged land development within a 250-foot distance. The examination of pre-disaster vacant lots showed that neighborhoods suffering from urban vacancy issue before a disaster event were more likely to experience hardship afterward. Post-disaster vacant lots illustrated that a disaster event could accelerate the speed of urban decline. Buyout lots as randomly generated permanently vacant lots in the middle of a neighborhood could substantially increase uncertainty in terms of land development. Clustered (attached side by side) vacant lots decrease the chance of redevelopment. For all of these cases, vacant lots could be seen as a symptom, result, and trigger of urban decline before and after a disaster event.

Disaster-affected communities are more likely to favor options to safely, rather than quickly, rebuild (D. C. Alexander, 1993; Mader & Tyler, 1991). In the same vein, disasters have prompted a "window of opportunity" to address land use regulations, public policies, and building codes; there is a greater potential to solve social problems that exist before disasters (Passerini, 2000). However, there are limitations. Governmental organizations tend to lose interest in recovery as time goes, and consequently reduce the amount of resources allocated (D. C. Alexander, 1993). Fading recovery efforts can undermine some recovery plans that take more time to apply, such as accepting revised land-use plans, adopting reinforced building codes, and creating open spaces for setbacks and buffers (Mileti, 1999). A compression of time and space also hinders organized recovery efforts (Olshansky et al., 2012). Therefore, planners and policymakers should make a concentrated effort to resolve long-existing vacant lots before a disaster event and prepare for disaster-induced vacant lots following a disaster.

Expediting redevelopment of both pre- and post-disaster vacant lots is crucial to curtailing contagious negative externalities that will continuously interrupt redevelopment efforts. For example, as discussed in Chapter 3.4., identifying vulnerable social groups and gaps in recovery resources (Beatley, 2012; Paton & Johnston, 2017; Peacock et al., 1997; Shlay & Whitman, 2006); utilizing disaster mitigation and vacant land management strategies prior to disaster events (Brody & Highfield, 2013; Folke et al., 2002; Peacock et al., 1997); and following up on community-based decisions to overcome a "development-at-any-cost" environment (P. R. Berke & Campanella, 2006; Brody et al., 2011; Burby, 2003; Downs, 2010; Irazábal & Neville, 2007; Zaferatos, 1998) will help communities facing issues resulting from both disasters and vacant lands.

Identifying households at risk of long-existing vacancy is the starting point for promoting redevelopment after disaster events. Distressed households (i.e., minorities, renters, and low-income households) are more likely to locate inside of flood-prone areas and experience a shortage of resources for housing repair and redevelopment (Bolin, 1993; Comerio, 1997; Hamideh et al., 2018; Kamel & Loukaitou-Sideris, 2004; Olshansky et al., 2008; Peacock et al., 1997; Rubin et al., 1985; Schwab, 2014). The modeling results showed that the property improvement value, homestead tax exemption, and percentage of seasonal vacant units as well as the clustered pre-and post-disaster vacant lots can be used as indicators to determine the vulnerable households and neighborhoods regarding long-existing vacancy issues. Like the early warning system indicating properties at risk of housing abandonment in the Philadelphia Neighborhood Information System (Hillier et al., 2003), government organizations can identify vacancy-prone neighborhoods by utilizing the readily available property tax records and Census data. To manage excessive vacancies after disaster events, vacant land management strategies can be used, such as regulations (e.g., aggressive code enforcement, sanctions, tax foreclosure, eminent domain, and demolishing abandoned structures) as well as revitalization strategies (e.g., promoting agricultural land uses, open spaces, de-annexation, urban growth boundaries, rehabilitation incentives, land bank programs, finding temporary uses for vacant land, and adopting design solutions) (Foo et al., 2013; Németh & Langhorst, 2014; Popper & Popper, 2002; Ryan, 2012; Schilling & Logan, 2008; Silverman et al., 2013).

Prior to disaster events, local disaster mitigation plans should target marginalized neighborhoods with substantial clusters of vacant land, which are prone to long-term post-disaster vacancies. FEMA's multi-hazard mitigation planning guidance (FEMA, 2008) lists six key elements of local mitigation plans: planning process, risk-assessment, mitigation strategies, coordination of local mitigation planning, plan maintenance process, and severe repetitive loss strategies. In the planning process, public involvement should include planning for the reuse of existing and acquired vacant land. For example, vacant land can be reused for open space protection strategies such as setbacks, buffers, and retention and detention ponds. Potential vacant land hotspots (i.e., neighborhoods with clustered vacant land that are likely to suffer from delayed redevelopment) can be identified when conducting local risk assessments regarding concentrations of and changes in land use. Vacant land management and regeneration strategies should be integrated into mitigation strategies. The plan maintenance process must include trends in vacant land inventory and redevelopment outcomes, using annual property tax records to monitor and engage lagging neighborhoods in redevelopment. Severe repetitive loss strategies can also benefit from historical property tax records, which can be used to identify high-risk areas. In addition, negative externalities from the acquisition of flood prone properties should be considered in a manner that minimizes uncertainty in redevelopment for the remaining properties in high-risk areas.

7.2. Limitations and Future Research

This study has several limitations. The first is the exclusion of boundary-changed lots found in the land development process. Because this study dropped the boundary-changed lots, the sample profile did not capture a full representation of disaster-induced vacant lots and their redevelopment outcomes. The sampling strategy was designed to utilize vacant lots generated after a disaster event. In terms of experimental control, a unique dataset was created from parcels in which the pre-disaster land use was known, duration of vacancy measurable, and exposure to urban and economic conditions over time after becoming vacant similar. This sampling strategy was driven by capturing the longitudinal parcel data with homogeneous physical characteristics over time, such as size, shape, and location, as well as practical reasons for divided and merged parcels such as accessibility and measurement issues. Boundary-changed lots tend to accompany development efforts addressing unsuitable lot size. Excluding these lots may have resulted in a degree of underestimation of redevelopment outcomes. In other words, regarding the overall redevelopment outcomes, the results from this study should be interpreted conservatively. This limitation may also have affected the modeling results. For example, previous vacant land studies have emphasized too small or too large vacant lots because their unsuitable lot size hindered their development. However, as with the other explanatory variables, parcel size and its squared term became insignificant in the statistical models. Negative effects of an unsuitable lot size may become diluted due to the boundary-changed lots being excluded. Future research should address this subdivision issue regarding vacant land recovery after disaster events.

The second limitation is related to the 2008 housing market crisis. Because disaster-induced lots were identified by 2009 property tax records, from the beginning, their redevelopment outcomes were affected by the nation-wide collapse of the housing bubble (Hamideh et al., 2018).

Accordingly, the overall recovery trajectories, including the ratio of redevelopment outcomes and duration of vacancy, should not be considered a general picture of post-disaster vacant land recovery. Previous studies have also found ambiguity and uncertainty in measuring and predicting redevelopment trends after a disaster event; reconstruction can last from a year to a decade after a disaster (Haas et al., 1977; Javernick-Will et al., 2010; L. A. Johnson & Hayashi, 2012; Kimura, 2007; Mader & Tyler, 1991). In the same vein, after Hurricane Ike in 2008, the longitudinal land use data showed that only about half of the disaster-induced vacant lots were redeveloped by 2017.

The third limitation is the lot-level information regarding disaster relief and recovery aid. To comprehensively understand redevelopment outcomes, a future study should develop a longitudinal dataset, including recovery resources and times required for each redevelopment process, such as inspections, insurance payouts, aid, loans, and building permits. A cost effectiveness study should capture the dynamic nature of post-disaster property redevelopment decisionmaking. A semi-Markov model could be used to simulate time to buyout or redevelopment events (or time remaining vacant). Among various cost effectiveness studies, cost/benefit analysis could be used to quantify the estimated economic benefits such as increases in the property tax revenue for local governments and decreases in negative externalities from vacant land as opposed to costs regarding disaster relief and recovery aid. This model would be useful for providing guidance for the future use of disaster recovery resources for repair, redevelopment, and buyouts in regions with recurring natural disasters.

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9.1. Sankey Diagram Python Code

```
# import settings
import json, urllib
import plotly.graph_objects as go
import pandas as pd

# Upload my file
from google.colab import files
uploaded = files.upload()

# Test the data
ike_df = pd.read_csv('/content/filename.csv')
ike_df.head()

# draw Sankey diagram
ike_df = pd.read_csv('/content/filename.csv')

data_trace = dict(
    type='sankey',
    domain = dict(
      x =  [0,1],
      y =  [0,1]
    ),
    orientation = "h",
    valueformat = ".0f",
    node = dict(
      pad = 10,
      thickness = 30,
      line = dict(
        color = "black",
        width = 0.5
      ),
      label =  ike_df['Node, Label'].dropna(axis=0, how='any'),
      color = ike_df['Color']
    ),
    link = dict(
      source = ike_df['Source'].dropna(axis=0, how='any'),
      target = ike_df['Target'].dropna(axis=0, how='any'),
      value = ike_df['Value'].dropna(axis=0, how='any'),
  )
)
```

```
layout =  dict(
    title = "",
    height = 900,
    width = 350,
    font = dict(
      size = 14
    ),
)

fig = go.Figure(data=[go.Sankey(data_trace)], layout=layout)
fig.show()
```

9.2. Logistic Regression Model

Table 32 shows the odds ratios obtained from the logistic regression analysis. Eight logistic regression models were run using different sets of independent variables. From Logit 1 to Logit 6, each model tested a group of independent variables, as follows: 1) lot-level characteristics, 2) hazard exposure, 3) distance from amenities and disamenities, 4) neighborhood characteristics, 5) accumulation of vacant lots, and 6) vacant area. Logit 7 included all independent variables. For the 3,079 disaster-induced lots, the pseudo-R^2 values (McFadden; Cragg & Uhler; McKelvey & Zavoina) ranged from 0.107 to 0.233 for all variables included in Logit 7. Including all independent variables enhanced the rate of explained variations that could be seen through the increased LR Chi-squared and decreased AIC and BIC values. The Logit 8 model was designed to estimate the effects of the independent variables after excluding buyout lots. In this case, the number of observations was 2,640, after removing the buyout lots.

Table 32. Logistic Regression Model (Odds Ratio)

	Logit 1	Logit 2	Logit 3	Logit 4	Logit 5	Logit 6	Logit 7	Logit 8
Lot-level characteristics								
Land value (log)	1.093**						1.063	1.085
Improvement value (log)	1.414***						1.368***	1.435***
Lot size (log)	6.849*						2.377	4.437
(Lot size (log))^2	0.895**						0.954	0.923
Homestead tax exemption	1.282**						1.254*	1.300**
Hazard exposure								
Floodplain: VE		0.738***					0.964	0.977
Dist. to the seashore (log)		2.048**					1.102	1.100
(Dist. to the seashore)^2		0.950**					1.002	0.998
Dist. to (dis)amenities (log)								
Public housing complexes			1.185**				1.654**	1.767***
Portable housing lots			1.187***				0.958	0.941
Commercial lots			2.682**				3.415**	3.919**
(Commercial lots)^2			0.930*				0.903**	0.894***
Industrial lots			32.71***				0.998	1.132
(Industrial lots)^2			0.815***				0.995	0.986
Major roads			48.74***				1.773	2.275
(Major roads)^2			0.759***				0.984	0.965
Neighbor. characteristics								
Seasonal vacant units (%)				0.997			0.984*	0.983**
Black, non-Hispanic (%)				0.992			0.969	0.969
Hispanic (%)				1.015			1.028	1.024
Poverty (%)				1.004			1.008	1.004
Pop. density (sq. mi., log)				0.871			0.710	0.739
Imp. value loss (%)				1.002			1.002	1.001
Redeveloped lots (%)				1.058***			1.049***	1.046***
Accumulation of vacant lots								
# of pre-disaster vacant lots								
0 to 250 feet					0.948***		1.005	1.010
250 to 500 feet					0.997		0.993	0.995
500 to 750 feet					1.006		1.004	1.004
750 to 1,000 feet					1.007*		0.995	0.995
# of buyout lots in 2013								
0 to 250 feet					0.797***		0.824***	0.888**
250 to 500 feet					1.040**		1.015	0.995
500 to 750 feet					0.997		1.004	0.994
750 to 1,000 feet					0.987		0.997	1.000
Vacant area within 250 feet								
Pre-disaster area (%)						0.981***	0.989***	0.989***
Pre-disaster area PD						1.000	1.000	1.000
Buyout area (%)						0.960***	0.977***	1.006
Buyout area PD						1.001	1.002***	1.002**
Constant	0.001***	0.067***	0.001***	0.130**	0.809***	1.166	0.001**	0.001***
N	3,079	3,079	3,079	3,079	3,079	3,079	3,079	2,640
LR Chi^2	118.19	32.87	169.47	189.78	176.63	185.74	437.95	317.56
Pseudo-R^2 *(McFadden)*	0.029	0.008	0.042	0.047	0.043	0.046	0.107	0.088
(Cragg & Uhler)	0.051	0.014	0.073	0.081	0.076	0.080	0.181	0.152
(McKelvey & Zavoina)	0.062	0.020	0.084	0.094	0.096	0.098	0.233	0.175
AIC	3,974	4,055	3,929	3,907	3,922	3,905	3,714	3,375
BIC	4,010	4,080	3,983	3,955	3,976	3,935	3,932	3,587

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The test results of statistical significance are noted by the number of stars (i.e., *, **, and *** for $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively) next to the odds ratios. The statistical significance presents the probability of finding an odds ratio due to chance alone. For example, a small *p*-value indicates that there is a small probability that this odds ratio could be observed by chance alone. If the *p*-value is equal to or less than the cutoff value (usually 0.05), the odds ratio is considered statistically significant.

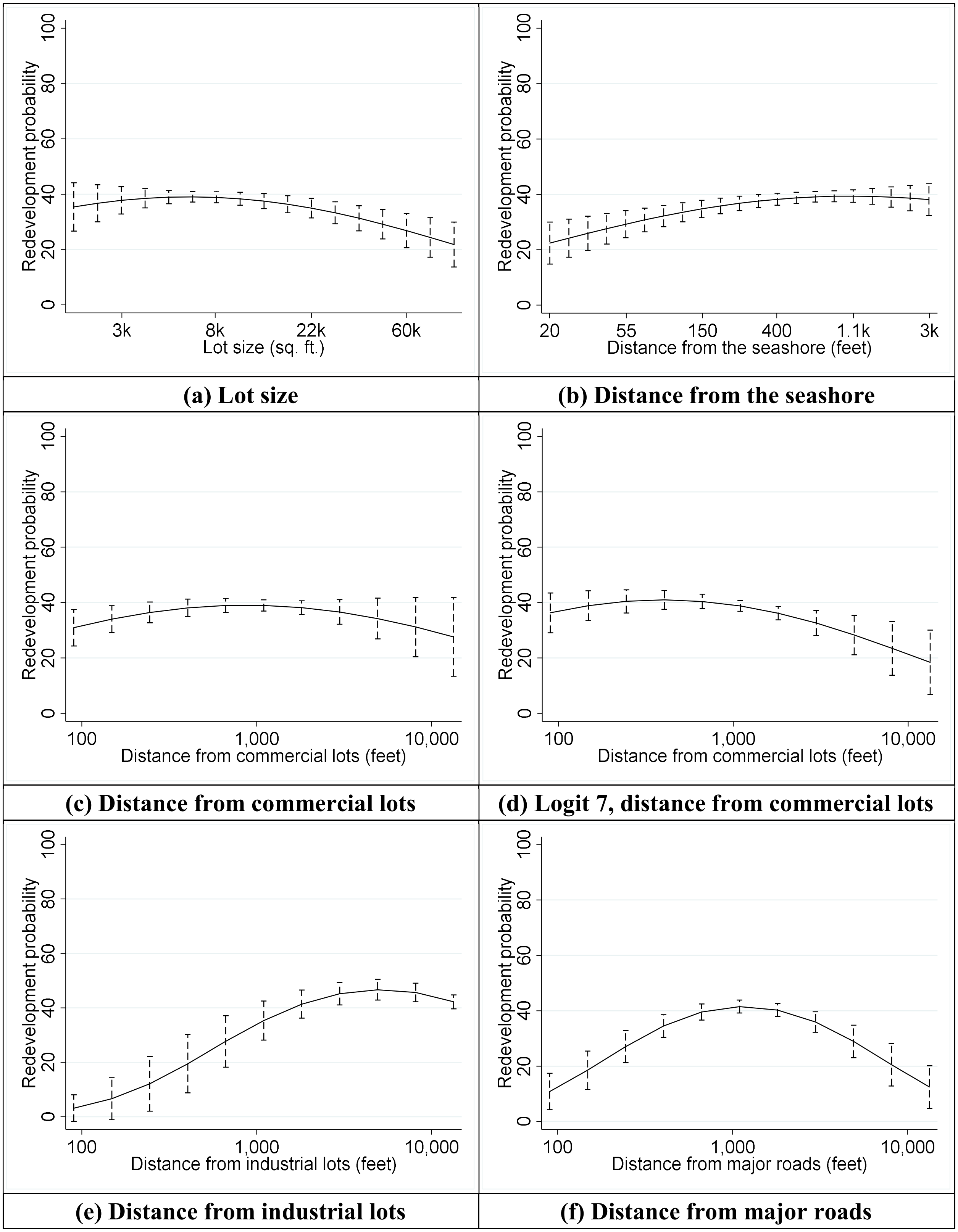
The Logit 1 model tested the variables related to lot-level characteristics, such as land and improvement values, lot size, and Homestead tax exemption. The land and improvement values and Homestead tax exemption variables had significant coefficients larger than 1, indicating that the probability of redevelopment likely increased for pre-disaster owner-occupied lots with higher property values. The squared term of the lot size variable was added to the original lot size variable. These two variables demonstrated a non-linear relationship with the probability of redevelopment. Figure 26 shows the predicted probability of redevelopment for these non-linear factors. Figure 26(a) indicates the decreased probability of redevelopment for lots that were too small or too large, demonstrated by an inverted U-shaped curve. In the Logit 7 and Logit 8 models, however, only the improvement value and Homestead tax exemption variables remained significant.

The hazard exposure factors in the Logit 2 model indicated that vacant lots in VE zones (i.e., high-risk areas with the additional hazard of storm waves) would have a lower chance of redevelopment than lots in mainly AE zones (also high-risk areas, but without storm waves). This was a dummy variable identifying the lots located in VE zones because most disaster-induced lots were located in either AE or VE zones. While both AE and VE zones indicate high-risk areas, chances of additional storm waves in VE zones could have negatively affected redevelopment outcomes. Nearness to the seashore or other water area also had a negative effect on redevelopment outcomes, which was illustrated by its squared term (see Figure 26(b)). However, these hazard exposure variables were not significant in the Logit 7 and Logit 8 models.

The squared variables were tested for the distance to amenities and disamenities variables in the Logit 3 model. The selected squared variables showed significance at the 90% level or higher. The modeling results indicated that disaster-induced vacant lots near public housing complexes were less likely to be redeveloped. Commercial and industrial lots and major roads may also have decreased the probability of redevelopment for nearby vacant lots, up to a 1,000-foot distance (i.e., 0.19 miles or 305 meters) (see Figures 26(c), (e), and (f)). In the Logit 7 and Logit 8 models, public housing complexes and commercial lots remained significant to the other independent variables. Figure 26(d) shows the distance from commercial lots and predicted probabilities of redevelopment, based on the Logit 7 model. The distance from commercial lots gave an inverted U-shaped curve, indicating a non-linear adverse effect on nearby lots, as well as lots located far away from commercial areas.

Among the neighborhood characteristics, the percentage of redeveloped lots was the only significant variable in the Logit 4 model. This variable was also significant in the Logit 7 and Logit 8 models, suggesting that the recovery trend of a neighborhood could be positively related to individual vacant lots' redevelopment outcomes. With the other independent variables, the percentage of seasonal vacant units became significant at the 90% and 95% levels in the Logit 7 and Logit 8 models, respectively. This variable indicated block groups with high levels of seasonal vacation housing (Hamideh et al., 2018). Vacant lots located in areas with seasonal vacation housing submarkets tended to have a lower chance of redevelopment.

Figure 26. Predictive Probability of Redevelopment: Non-linear Explanatory Variables



(a) Lot size

(b) Distance from the seashore

(c) Distance from commercial lots

(d) Logit 7, distance from commercial lots

(e) Distance from industrial lots

(f) Distance from major roads

Note: dotted lines indicate 95% confidence intervals.

The Logit 5 model reaffirmed the findings of previous literature. There was a negative spillover effect from vacant lots that decreases the chance of redevelopment, both pre-disaster and buyout. In addition, the results imply that the distance from vacant lots is a critical factor. In terms of the size of the adverse effects, for every one additional pre-disaster or buyout lot, the odds of redevelopment decreased by 5.2% or 20.3%, respectively. The number of pre-disaster vacant lots from 750 to 1,000 feet and number of buyout lots from 250 to 500 feet also showed positive and significant relationships in the Logit 5 model. However, they became insignificant with the other independent variables in the Logit 7 and Logit 8 models.

The Logit 6, Logit 7, and Logit 8 models implied that the percentage of vacant area should be examined as well as the number of vacant lots. In the Logit 6 model, the percentages of pre-disaster and buyout vacant areas were both significant at the 99% level. In this model, the odds of redevelopment decreased by 1.9% and 4% for every 1% point increase in the pre-disaster vacant area and buyout area, respectively. In the Logit 7 and Logit 8 models, as with the other explanatory variables, the percentage of pre-disaster area had a significant and negative effect on redevelopment outcomes, while the number of pre-disaster vacant lots became insignificant. Both the percentage of buyout area and number of buyout lots were significant in the Logit 7 model. However, only the number of buyout lots had a significant effect in the Logit 8 model, after excluding the buyout-processed disaster-induced lots from the analysis.

The Logit 7 and Logit 8 models implied that the patch density of the buyout area had a significant effect on redevelopment outcomes. For both models, an increase in patches of buyout lots, meaning more fragmented buyout areas, tended to increase the probability of redevelopment. In other words, after controlling for number and size, buyout lots being attached to one another (or being adjacent to one another) could decrease the probability of redevelopment of nearby areas.

9.3. Cox Proportional Hazards Model

The Cox model was designed to focus on estimating the effects of the covariates and avoid estimating the baseline hazard function. Accordingly, the probability distribution of the time to the event (i.e., the shape of the hazard over time) could have any shape and was assumed to be the same for every observation (Cox, 1972; Finlay & Agresti, 1986; Singer & Willett, 1993). Besides, due to the annually reported property tax data, the Breslow approximation method (N. Breslow, 1974) was used to address the tied survival times in the calculation of the log of partial likelihood.

Table 33 presents the results from the Cox models. Five Cox models were run using the different sets of explanatory variables. Like the logistic regression models, the Cox models included both continuous and dichotomous explanatory variables. In addition, the Cox models also tested time-dependent variables, as well as time-invariant variables. The Cox 1 model tested the explanatory variables used for the logistic regression models, except for the vacant lot related variables. Each of the Cox 2 to Cox 4 models tested a group of time-varying and time-invariant covariates regarding the accumulation of vacant lots. The Cox 5 model included all explanatory variables. Table 33 also includes the logistic regression results from Table 32 (the Logit 7 and Logit 8 models) to compare the significant explanatory variables and their *p*-values to those of the Cox models.

Table 33. Cox Proportional Hazards Model (Hazard Ratio)

Model:	Cox 1	Cox 2	Cox 3	Cox 4	Cox 5	Logit 7	Logit 8
Lot-level characteristics							
Land value (log)	1.055				0.942	1.063	1.085
Improvement value (log)	1.317***				1.309***	1.368***	1.435***
Lot size (log)	3.089				1.934	2.377	4.437
(Lot size (log))^2	0.944				0.980	0.954	0.923
Homestead tax exemption	1.181*				1.152	1.254*	1.300**
Hazard exposure							
Floodplain: VE	0.965				0.986	0.964	0.977
Dist. to the seashore (log)	1.270				1.128	1.102	1.100
(Dist. to the seashore)^2	0.986				0.993	1.002	0.998
Dist. to (dis)amenities (log)							
Public housing complexes	1.340**				1.270	1.654**	1.767***
Portable housing lots	0.981				0.938*	0.958	0.941
Commercial lots	1.965*				2.033*	3.415**	3.919**
(Commercial lots)^2	0.947*				0.944*	0.903**	0.894***
Industrial lots	1.310				0.822	0.998	1.132
(Industrial lots)^2	0.981				1.007	0.995	0.986
Major roads	3.997**				1.460	1.773	2.275
(Major roads)^2	0.920*				0.990	0.984	0.965
Neighbor. characteristics							
Seasonal vacant units (%)	0.990*				0.993	0.984*	0.983**
Black, non-Hispanic (%)	0.987				0.977	0.969	0.969
Hispanic (%)	1.000				0.991	1.028	1.024
Poverty (%)	0.997				1.002	1.008	1.004
Pop. density (sq. mi., log)	0.936				0.941	0.710	0.739
Imp. value loss (%)	0.998				1.003	1.002	1.001
Redeveloped lots (%)	1.027***				1.023***	1.049***	1.046***
Accumulation of vacant lots							
# of pre-disaster vacant lots							
0 to 250 feet		0.940***		0.980	0.997	1.005	1.010
250 to 500 feet		1.010*		1.009*	1.002	0.993	0.995
500 to 750 feet		1.004		1.005	1.004	1.004	1.004
750 to 1,000 feet		0.999		0.997	0.996	0.995	0.995
# of post-disaster vacant lots							
0 to 250 feet		0.875***		0.950***	0.976		
250 to 500 feet		1.048***		1.044***	1.035***		
500 to 750 feet		1.001		1.001	0.998		
750 to 1,000 feet		1.006*		1.004	0.999		
# of buyout lots							
0 to 250 feet		0.924***		0.868***	0.904***	0.824***	0.888**
250 to 500 feet		1.045***		1.018	1.013	1.015	0.995
500 to 750 feet		0.989		0.997	1.003	1.004	0.994
750 to 1,000 feet		0.983*		0.986	0.995	0.997	1.000
Vacant area within 250 feet							
Pre-disaster area (%)			0.979***	0.980***	0.980***	0.989***	0.989***
Pre-disaster area PD			1.001***	1.000*	1.001***	1.000	1.000
Post-disaster area (%)			0.976***	0.973***	0.968***		
Post-disaster area PD			1.002***	1.001***	1.001***		
Buyout area (%)			0.981***	0.995	0.986**	0.977***	1.006
Buyout area PD			1.001	1.002***	1.001**	1.002***	1.002**
N	3,079	3,079	3,079	3,079	3,079	3,079	2,640
LR Chi^2	290.94	254.58	279.98	420.94	623.75	437.95	317.56
R^2	0.126	0.121	0.137	0.179	0.253	-	-

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; For the Cox models, R^2 computed using Royston and Sauerbrei's method.

Royston and Sauerbrei (2004) designed a new measure of R-squared statistic for censored survival data to deal with the fact that the settling of censored data substantially decreases measures of explained variation. The concept of explained variation is a modified version of O'Quigley, Xu, and Stare's method (2005), which was rooted in Nagelkerke's (1991) likelihood-ratio statistic-based measurement. The Royston and Sauerbrei R-squared statistics were measured by STR2D, a Stata module for computing explained variations in survival models (Royston, 2006, 2011). In the present research, including explanatory variables enhanced the rates of explained variation, as can be seen through the increased LR Chi-squared and R-squared values. With 3,079 disaster-induced lots, the R-squared value was 0.253 for all variables included in the Cox 5 model.

The hazard ratios in Table 33 indicate how often a redevelopment event occurred, corresponding to the explanatory variable. A hazard ratio close to 1 means that the explanatory variable did not affect the redevelopment outcome. If the hazard ratio is less than or greater than 1, the explanatory variable was associated with a decreased or increased chance of redevelopment, respectively. Test results of statistical significance are noted by the number of stars (i.e., *, **, and *** for $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively) next to the hazard ratios.

Some of the significant explanatory variables in the logistic regression models also influenced redevelopment outcomes. The variables of improved value and percentage of redeveloped lots in block groups had hazard ratios higher than 1, indicating a positive relationship. They were significant at the 99% level, meaning vacant lots with higher improvement values located in a block group with other redeveloped lots were more likely to be redeveloped. Conversely, the other variables in the distance from amenities and disamenities and neighborhood characteristics groups lost their significance in the Cox models, especially to the other independent variables.

For example, unlike the Logit 7 and Logit 8 models, distances from public housing complexes and commercial lots and the percentage of seasonal vacant units in block groups were not significant at the 95% level in the Cox 5 model.

In terms of the accumulation of vacant lots, the Cox models tested both time-varying and time-invariant covariates. The variables for the number of pre-disaster lots, percentage of pre-disaster area, and patch density of pre-disaster area were time-invariant covariates; these variables did not change over time. The other variables regarding post-disaster vacancy and buyout were time-varying variables that changed over time. For example, in the Logit models, the number and area of buyout lots were based on the 2013 data, after the buyout process was completed.

Between the number of vacant lots and percentage of vacant area, the vacant area variables remained significant to the other explanatory variables for both pre- and post-disaster vacant lots. Similar to the logit models, the number and percentage of pre-disaster vacant areas within a 250-foot distance were expected to decrease redevelopment outcomes when tested separately in Cox models 2 and 3. In Cox models 4 and 5, however, only the area variable remained significant. In the same vein, the percentage of post-disaster area within a 250-foot distance remained significant to the other independent variables in the Cox 5 model. The number of post-disaster vacant lots reduced in significance compared to the other variables. The hazard ratios in the Cox 5 model indicated that a 1% point increase in pre- and post-disaster vacant areas decreased the hazard (i.e., chance of redevelopment) by approximately 2.0% and 3.2%, respectively.

For buyout lots within a 250-foot distance, both the number and area variables had adverse effects that were significant at the 95% level. One additional buyout lot and a 1% point increase in the buyout area were estimated to decrease the hazard ratio (i.e., the chance of redevelopment) by 9.6% and 1.4%, respectively. Besides, the existence of one buyout lot increased the buyout area within the 250-foot distance by around 8.0% point, on average.

In the Cox 5 model, all patch density variables based on pre-disaster, post-disaster, and buyout lots were significant at the 95% level or higher. An increase in patches of vacant area indicated the fragmentation of land. The results suggest that the more fragmented the vacant areas, the better the chance of redevelopment, regardless of the source of vacancy. In addition to the adverse effects of increasing number and area of vacant lots, the clustering of vacant lots could also be a key factor hindering redevelopment outcomes.

Similar to the logit models, the "up to 250 feet" distance dictated the adverse effects from vacant lots. However, the coefficient of the variable for the number of post-disaster vacant lots from 250 to 500 feet was higher than 1 and significant at the 99% level in the Cox 2, Cox 4, and Cox 5 models. This implies that some of the new vacant lots after Hurricane Ike may have had positive effects on redevelopment outcomes when they were located between 250 and 500 feet away. The other variables for the number of vacant lots from 250 to 500 feet, whether pre-disaster or buyout lots, also presented positive and significant effects in the Cox 2 and Cox 4 models. However, these variables became insignificant to the other explanatory variables in the Cox 5 model.

9.4. Discrete Time Hazard Model: Testing Variable Groups

Table 34. Variables Groups in Discrete Time Hazard Model: Logit Transformation (Odds Ratio)

Model:	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Time								
Period 2 (2010 to 2011)	1.746***							
Period 3 (2011 to 2012)	1.178							
Period 4 (2012 to 2013)	1.227*							
Period 5 (2013 to 2014)	0.634***							
Period 6 (2014 to 2015)	0.979							
Period 7 (2015 to 2016)	0.808							
Period 8 (2016 to 2017)	0.577***							
Lot-level characteristics								
Land value (log)		1.112***						
Improvement value (log)		1.486***						
Lot size (log)		4.186*						
(Lot size (log))^2		0.920*						
Homestead tax exemption		1.194*						
Hazard exposure								
Floodplain: VE			0.813***					
Dist. to the seashore (log)			2.315***					
(Dist. to the seashore)^2			0.928***					
Dist. to (dis)amenities (log)								
Public housing complexes				1.173**				
Portable housing lots				1.161***				
Commercial lots				2.520**				
(Commercial lots)^2				0.938**				
Industrial lots				10.194***				
(Industrial lots)^2				0.874***				
Major roads				22.829***				
(Major roads)^2				0.799***				
Neighbor. characteristics								
Seasonal vacant units (%)					0.992			
Black, non-Hispanic (%)					0.988			
Hispanic (%)					0.979			
Poverty (%)					1.000			
Pop. density (sq. mi., log)					1.039			
Imp. value loss (%)					1.003			
Redeveloped lots (%)					1.039***			
Accumulation of vacant lots								
# of pre-disaster vacant lots								
0 to 250 feet						0.935***		0.975*
250 to 500 feet						1.012**		1.012**
500 to 750 feet						1.004		1.005
750 to 1,000 feet						0.998		0.995
# of post-disaster vacant lots								
0 to 250 feet						0.865***		0.946***
250 to 500 feet						1.055***		1.055***
500 to 750 feet						1.002		1.004
750 to 1,000 feet						1.008**		1.008**

Model:	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
# of buyout lots								
0 to 250 feet						0.934***		0.862***
250 to 500 feet						1.051***		1.017
500 to 750 feet						0.987		0.994
750 to 1,000 feet						0.985		0.980**
Vacant area within 250 feet								
Pre-disaster area (%)							0.980***	0.981***
Pre-disaster area PD							1.001***	1.000
Post-disaster area (%)							0.982***	0.972***
Post-disaster area PD							1.002***	1.001***
Buyout area (%)							0.986***	0.998
Buyout area PD							1.000	1.002***
Constant	0.069***	<0.001***	0.009***	<0.001***	0.025***	0.093***	0.146***	0.172***
N (lots)	3,079	3,079	3,079	3,079	3,079	3,079	3,079	3,079
LR Chi^2	120.97	205.52	20.01	148.08	186.22	297.44	219.70	458.92
Pseudo-R^2 *(McFadden's)*	0.014	0.024	0.002	0.018	0.022	0.035	0.026	0.054
AIC	8348.35	8259.80	8441.32	8323.24	8283.10	8181.89	8247.62	8032.40
BIC	8410.21	8306.20	8472.25	8392.84	8344.97	8282.41	8301.75	8179.33

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 35. Variable Groups in Discrete Time Hazard Model: Complementary Log-Log Transformation (Hazard Ratio)

Model:	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Time								
Period 2 (2010 to 2011)	1.704***							
Period 3 (2011 to 2012)	1.171							
Period 4 (2012 to 2013)	1.218*							
Period 5 (2013 to 2014)	0.641***							
Period 6 (2014 to 2015)	0.980							
Period 7 (2015 to 2016)	0.813							
Period 8 (2016 to 2017)	0.585***							
Lot-level characteristics								
Land value (log)		1.105***						
Improvement value (log)		1.469***						
Lot size (log)		4.025*						
(Lot size $(\log))^2$		0.922*						
Homestead tax exemption		1.185*						
Hazard exposure								
Floodplain: VE			0.819***					
Dist. to the seashore (log)			2.281***					
(Dist. to the $\text{seashore})^2$			0.929***					
Dist. to (dis)amenities (log)								
Public housing complexes				1.165**				
Portable housing lots				1.155***				
Commercial lots				2.474**				
(Commercial $\text{lots})^2$				0.939**				
Industrial lots				9.326***				
(Industrial $\text{lots})^2$				0.878***				
Major roads				21.253***				
(Major $\text{roads})^2$				0.804***				

Model:	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Neighbor. characteristics								
Seasonal vacant units (%)					0.993			
Black, non-Hispanic (%)					0.987			
Hispanic (%)					0.977			
Poverty (%)					1.000			
Pop. density (sq. mi., log)					1.065			
Imp. value loss (%)					1.002			
Redeveloped lots (%)					1.036***			
Accumulation of vacant lots								
# of pre-disaster vacant lots								
0 to 250 feet						0.937***		0.976*
250 to 500 feet						1.011**		1.011**
500 to 750 feet						1.003		1.005
750 to 1,000 feet						0.999		0.995
# of post-disaster vacant lots								
0 to 250 feet						0.870***		0.948***
250 to 500 feet						1.052***		1.052***
500 to 750 feet						1.001		1.003
750 to 1,000 feet						1.008**		1.008**
# of buyout lots								
0 to 250 feet						0.936***		0.869***
250 to 500 feet						1.049***		1.016
500 to 750 feet						0.988		0.995
750 to 1,000 feet						0.986		0.981**
Vacant area within 250 feet								
Pre-disaster area (%)							0.981***	0.982***
Pre-disaster area PD							1.001***	1.000
Post-disaster area (%)							0.983***	0.974***
Post-disaster area PD							1.002***	1.001***
Buyout area (%)							0.987***	0.998
Buyout area PD							1.000	1.002***
Constant	0.067***	<0.001***	0.009***	<0.001***	0.023***	0.089***	0.137***	0.161***
N (lots)	3,079	3,079	3,079	3,079	3,079	3,079	3,079	3,079
LR Chi^2	120.97	205.59	20.11	148.17	187.04	297.44	218.44	458.01
Pseudo-R^2 *(McFadden's)*	0.014	0.024	0.002	0.018	0.022	0.035	0.026	0.054
AIC	8348.35	8259.73	8441.21	8323.15	8282.28	8181.89	8248.89	8033.32
BIC	8410.21	8306.13	8472.15	8392.75	8344.14	8282.41	8303.02	8180.24

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

9.5. Discrete Time Hazard Model: Results from Complementary Log-Log Transformation

Table 36. Discrete Time Hazard Model: Complementary Log-Log Transformation (Hazard Ratio)

Model:	C. log-log 1	C. log-log 2	C. log-log 3
Time			
Period 2 (2010 to 2011)	1.756***	1.604***	1.397***
Period 3 (2011 to 2012)	1.229*	1.075	0.875
Period 4 (2012 to 2013)	1.303**	1.117	0.861
Period 5 (2013 to 2014)	0.701***	0.588***	0.441***
Period 6 (2014 to 2015)	1.091	0.892	0.644***
Period 7 (2015 to 2016)	0.918	0.734*	0.514***
Period 8 (2016 to 2017)	0.663***	0.521***	0.359***
Lot-level characteristics			
Land value (log)	1.053	0.949	0.934
Improvement value (log)	1.331***	1.326***	1.329***
Lot size (log)	3.247	1.094	1.975
(Lot size (log))^2	0.941	0.989	0.980
Homestead tax exemption	1.193*	1.206**	1.161
Hazard exposure			
Floodplain: VE	0.964	0.922	0.985
Dist. to the seashore (log)	1.291	1.316	1.147
(Dist. to the seashore)^2	0.984	0.984	0.991
Dist. to (dis)amenities (log)			
Public housing complexes	1.360**	1.491***	1.309*
Portable housing lots	0.980	0.925**	0.931**
Commercial lots	2.028*	2.498**	2.135*
(Commercial lots)^2	0.944*	0.927**	0.940*
Industrial lots	1.368	1.211	0.860
(Industrial lots)^2	0.979	0.986	1.004
Major roads	4.281**	4.063**	1.500
(Major roads)^2	0.916*	0.925	0.988
Neighbor. characteristics			
Seasonal vacant units (%)	0.987**	0.994	0.990*
Black, non-Hispanic (%)	0.984	0.985	0.972
Hispanic (%)	0.997	0.988	0.988
Poverty (%)	0.995	1.002	1.000
Pop. density (sq. mi., log)	0.934	1.066	0.950
Imp. value loss (%)	0.997	0.996	1.003
Redeveloped lots (%)	1.029***	1.026***	1.025***
Accumulation of vacant lots			
# of pre-disaster vacant lots			
0 to 250 feet		0.943***	0.995
250 to 500 feet		1.006	1.002
500 to 750 feet		1.003	1.004
750 to 1,000 feet		0.995*	0.996
# of post-disaster vacant lots			
0 to 250 feet		0.863***	0.973*
250 to 500 feet		1.040***	1.038***
500 to 750 feet		0.998	0.998
750 to 1,000 feet		1.001	0.999

Model:	C. log-log 1	C. log-log 2	C. log-log 3
# of buyout lots			
0 to 250 feet		0.918***	0.899***
250 to 500 feet		1.042***	1.014
500 to 750 feet		1.005	1.004
750 to 1,000 feet		0.996	0.995
Vacant area within 250 feet			
Pre-disaster area (%)			0.979***
Pre-disaster area PD			1.001***
Post-disaster area (%)			0.966***
Post-disaster area PD			1.001***
Buyout area (%)			0.984***
Buyout area PD			1.002**
Constant	<0.001***	<0.001***	<0.001**
N (lots)	3,079	3,079	3,079
LR Chi^2	436.99	645.40	812.40
Pseudo-R^2 *(McFadden's)*	0.052	0.076	0.096
AIC	8078.33	7893.92	7738.92
BIC	8318.05	8226.43	8117.83

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$