THESIS

MODELING POST-DISASTER PERMANENT HOUSING RECONSTRUCTION OUTCOMES IN THE U.S. USING RESOURCING FACTORS

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ABSTRACT

MODELING POST-DISASTER PERMANENT HOUSING RECONSTRUCTION OUTCOMES IN THE U.S. USING RESOURCING FACTORS

The residential housing stock in the U.S. is vulnerable to the rising frequency of weather-related hazards, exemplified by economic losses and social disruptions caused by recent billion-dollar events. Reconstruction of damaged residential housing is essential for the swift recovery and long-term resilience of communities. However, recovery is often delayed, and the outcomes are not uniform across disaster-affected regions of the U.S. which may be attributable to unequal access to reconstruction resources. Permanent housing reconstruction in the U.S. adopts a market-driven resourcing approach which is dependent on the availability of construction and capital resources. The availability of construction resources is determined by the capacity of the regional construction market to supply labor and material resources while the availability of capital resources is determined by the socioeconomic characteristics of households and the availability of federal grants for home repairs. Under a market-driven model, the socioeconomic characteristics of households, construction industry, and the federal government constitute three core resourcing forces, composed of various resourcing factors, that influence the availability and accessibility of capital and construction resources. Although the availability of resources is crucial for reconstruction, very few studies have quantitatively examined the influence of resourcing factors on residential reconstruction outcomes at a regional scale. As geographic regions of the U.S. vary in their socioeconomic conditions and construction capacity to supply resources, the influence of resourcing factors on reconstruction outcomes may also show regional variation. However, very few studies have explored the spatially varying influence of resourcing factors on reconstruction outcomes across disaster-affected regions. Using both aspatial and spatial statistical approaches, this study performs a quantitative analysis of post-disaster permanent housing reconstruction outcomes from the lens of resource availability and accessibility. Using Ordinary Least Square regression (OLS) and Geographically Weighted Regression (GWR) models, this study seeks to: (1) quantify the global relationships between socioeconomic, construction industry, and federal government resourcing factors and post-disaster permanent housing reconstruction outcomes at a regional scale in the U.S.; and (2) explore the spatially varying local relationships between resourcing factors and reconstruction outcomes. Over 600 counties hit by federally declared weather-related hazards, with substantial residential losses, between 2007-2015 are analyzed to establish the global relationships between resourcing factors and reconstruction outcomes. The Northeast Census Region of the U.S., hit by catastrophic weather-related hazards between 2011-2012 with unprecedented residential losses, is used as a case study region to explore the spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes. Findings from the OLS model reveal that availability of construction and capital resources, measured through socioeconomic and construction industry resourcing factors, significantly influence reconstruction outcomes in disaster-hit counties across the U.S. Findings from the case study of the Northeast Census Region, analyzed through the GWR model, reveal that the relationships between resourcing factors and reconstruction outcomes showed regional variation as a result of region-specific resourcing context. The findings of this study will help emergency planners, policymakers, contractors, homeowners, and reconstruction stakeholders in resource planning, policymaking, and decision-making through the identification of critical resourcing bottlenecks and their spatially varying influence across geographical boundaries.

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DEDICATION

To all the disaster-affected communities of the world

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I: INTRODUCTION

Housing, a cornerstone of American middle-class life, is the single biggest financial asset in American society with social, cultural, economic, and political importance. One of the hallmarks of the fabled 'American Dream' is homeownership—living in the single-family, owner-occupied housing units (Rohe et al., 2002). Homeownership is thought to foster life satisfaction, health, social involvement, security, and economic well-being of individuals (Yang & Li, 2010). The total number of occupied single and multifamily residential housing units in the U.S. was over 119 million in 2018, with owner-occupied units accounting for over 64% of total occupied housing units (U.S. Census Bureau, 2020e). While the large proportion of Americans prefer to own a house rather than rent (Rohe et al., 2002), the perils to the residential housing stock from the rising frequency of natural hazards is a growing issue to homeowners. The total residential damages due to various federally declared disasters that occurred between 2007 to 2015 have reached over $8 billion (FEMA, 2018). Disaster-related housing repair and reconstruction costs have been rising over the last decade, with repair costs reaching over $14 billion in 2017 (JCHS, 2018).

The residential housing stock is among the most vulnerable sectors to disasters in the U.S. as it constitutes a substantial portion of the built structures in any community (Comerio, 1997). The 2015 U.S. Natural Disaster Housing Risk Report released by a real estate tracking firm RealtyTrac (2015) highlighted that approximately 43% of the total single-family residential property in the U.S. with a market value of over 6 trillion are at high risk of damage from natural hazards. The varying geological conditions and weather patterns of the U.S. allow for multiple types of natural hazards (e.g., hurricanes, severe storms, flooding, wildfires, tornadoes, and earthquakes) across different geographical regions of the U.S. every year. For instance, in 2018, there were 14 separate billion-dollar weather and climate disasters in the U.S., such as Hurricane Michael, Hurricane Florence, Southeastern Tornadoes, and California Wildfires, to name a few (NOAA, 2019). The recent report released by the U.S. federal government—the Fourth National Climate Assessment-Volume II (U.S. Global Change Research Program, 2018)—pointed out that climate change has further led to the increase in both the frequency and intensity of weather-related events, exacerbating the existing vulnerabilities in communities. For instance, the American Society of Civil Engineers (ASCE) gave an overall grade of "D+" to existing U.S. infrastructures in its *2017 Infrastructure Report Card* (ASCE, 2017), which raised serious concerns of high risks of failure due to aging conditions. The rising frequency of natural hazards takes a heavy toll on the rehabilitation process of the aging and deteriorating infrastructures as additional federal investments are required for disaster-related repairs or reconstruction. At the same time, vulnerable populations such as low-income and marginalized communities have a lower capacity to prepare for and cope with disruptions caused by extreme weather events (U.S. Global Change Research Program, 2018). Ultimately, the interaction of these hazardous events with existing vulnerabilities in a geographic context results in severe physical and socioeconomic disruptions (Alexander, 1997). Because of the geographic discrepancies in the social and economic characteristics of the places and the households residing within them, some regions may be more susceptible to impacts than others (Cutter & Emrich, 2006).

Re-establishment of the damaged housing stock is a quintessential element of community recovery. Quarantelli (1995) conceptualized housing recovery as a multi-stage process consisting of four stages: emergency sheltering; temporary sheltering; temporary housing; and permanent housing. Post-disaster permanent housing reconstruction or residential reconstruction is the final stage of the overall housing recovery process, where homeowners carry out repairs or reconstruction of their damaged houses using personal capital resources supplemented by funds or assistance from the government or donor agencies. Permanent housing reconstruction not only helps individuals to resume their daily routines but also helps to achieve long-term resilience of communities and to build local capacities and economies (Charlesworth & Ahmed, 2015; Tran, 2015). Since permanent housing reconstruction is fundamental to achieving long-term community resilience, the U.S. National Disaster Housing Strategy (FEMA, 2009) has particularly emphasized building capacities for permanent housing in their comprehensive national disaster housing effort.

Accessibility and availability of resources (e.g., capital and construction resources) are central to residential reconstruction since it is a resource-driven process. Resourcing for permanent housing reconstruction broadly encompasses activities such as pre-disaster resource planning, resource procurement, supply-chain management, and post-disaster resource delivery to increase the flow and stockpiles of resources in the market (Chang, 2012). Resourcing for residential reconstruction is influenced by a multitude of factors such as government policies, funding practices, public-private interventions, and institutional arrangements (Mukherji, 2018). Permanent housing reconstruction in the U.S. uses a market-driven resourcing approach (Comerio, 1998) where availability and accessibility of capital and construction resources are fundamental to carry out repair or reconstruction works. Capital resources broadly comprise of public funds (e.g., federal grants and low-interest loans) and private finances (e.g., personal savings, private insurance, and disaster home loans) (Peacock et al., 2007) while construction resources comprise of labor and materials (Arneson et al., 2020). However, unlike government-driven reconstruction, where government agencies play a major role in funding housing reconstruction (e.g., China), the market-driven resourcing model heavily relies on homeowner's capital resources and market mechanisms while receiving limited financial assistance from the federal government agencies

(Comerio, 2014). For instance, a report released by RAND Gulf States Policy Institute on Post-Katrina Housing Market Recovery (McCarthy & Hanson, 2007) documented that access to private financing and the capacity of the construction sector were the two critical determinants of the housing recovery in the Mississippi coastal housing market following the 2005 Hurricane Katrina.

In a market-driven model, socioeconomic characteristics of households and construction market conditions influence the availability and accessibility of capital and construction resources, respectively, for permanent housing reconstruction (Chang-Richards et al., 2013). On the one hand, the socioeconomic status of households acts like a catalyst, either favoring or constraining homeowners to acquire capital resources. Inequities in the pre-disaster socioeconomic status of households lead to differential post-disaster housing recovery trajectories because of the disparities in their capacity to access capital resources (Peacock et al., 2014). On the other hand, as homeowners in the U.S. usually outsource the repair or reconstruction job to residential housing contractors (Zhang & Peacock, 2009), the upstream demand for the repair or rebuilding tasks must be met by the downstream supply of construction labor and materials. However, the capacity of the construction industry to supply resources is limited and is determined by the regional availability of labor and materials (Arneson, 2018).

Accessing resources for post-disaster residential reconstruction is complicated than in normal times because of the complex post-disaster environment (Davidson et al., 2007), supply-chain disruptions (Hallegatte, 2008), and time compression of urban activities (Olshansky et al., 2012). Resources are limited as homeowners in disaster-affected communities simultaneously compete for scarce capital and construction resources to repair or rebuild their houses. Pre-existing socioeconomic inequalities are exacerbated by disasters (Peacock et al., 2014), impeding the homeowner's ability to access capital resources. Furthermore, resource shortages and demand-surge are likely to occur as reconstruction demand outstrips the capacity of the regional construction industry to supply resources (Olsen & Porter, 2011). For instance, wage inflation for building contractors has been well documented following weather-related disasters in the U.S. (Ahmadi & Shahandashti, 2018a), and increases in labor wages have been considered as a driving force behind inflated post-disaster residential reconstruction costs (Olsen & Porter, 2013). Case studies have shown that permanent housing reconstruction is usually completed within two years after the disaster has struck (Wu & Lindell, 2004; Rathfon et al., 2013). However, the ripple effects of disasters such as supply-chain disruptions and time compression add additional constraints to resource acquisition and may prolong the recovery period (Chang et al., 2010), making households vulnerable to future hazards.

Since the impacts of disasters on the housing sector, and the subsequent recovery patterns within and across regions are not distributed equally (Finch et al., 2010), a regional perspective of housing recovery studies from the resourcing lens is essential to get a comprehensive picture of recovery patterns across regions and the driving forces behind those patterns. Regional development studies have highlighted the associations between geography and economic development (Gallup et al., 1999; Sachs, 2012) as economic activities are always tied with locations (Krugman, 1999). Just as the economic geography of the world is characterized by the uneven spatial distribution of development activities (Henderson et al., 2001), the geography of disaster recovery is shaped by regional discrepancies in pre-disaster social vulnerability (Cutter et al., 2003) and geographically varying construction capacity (Arneson, 2018). Such geographic variations are the driving forces of residential reconstruction, which may lead to unique outcomes across regions. As place-specific resourcing context shapes the reconstruction outcomes across regions, identification of the forces that influence reconstruction outcomes at a finer geographic resolution is fundamental to understand the differential recovery patterns across regions.

Problem Statement and Research Gaps

At a regional scale, three core ***resourcing forces*** influence post-disaster permanent housing reconstruction outcomes across regions: 1) socioeconomic characteristics of households (Peacock et al., 2007; Zhang & Peacock, 2009); 2) construction industry (Chang et al., 2012; Arneson et al., 2020); and 3) the federal government (Olshansky & Johnson, 2014). Each resourcing force is composed of one or multiple factors, defined in this study as ***resourcing factors***, which act as a catalyst that either favors or constrains homeowners to acquire capital and construction resources. Previous case studies have revealed that pre-disaster socioeconomic characteristics of households are important predictors of the residential reconstruction outcomes as the household's pre-disaster socioeconomic characteristics determine how easily they can access private and public capital resources. For instance, Cole (2003) analyzed household movements within and between the four phases of housing recovery conceptualized by Quarantelli (1995) and found that households with lower socioeconomic status faced delays in attaining permanent housing. Peacock et al. (2014) found that marginalized and low socioeconomic status households faced obstacles in acquiring financial resources for housing reconstruction in Miami-Dade County following the 1992 Hurricane Andrew. Recent studies have focused on the role of the construction industry in shaping residential reconstruction outcomes. For instance, Arneson et al. (2020) found that construction labor availability significantly influenced regional residential reconstruction outcomes following large-scale disasters in the U.S. While the temporal trajectories of reconstruction can be attributed to the influence of resourcing factors that either favor or constrain resources availability for residential reconstruction, the spatial disparities in recovery—such as the one noted by Cutter et al. (2006) following Hurricane Katrina in 2005—can be attributed to the geographically varying influence of resourcing factors on the reconstruction outcomes.

While existing literature has broadly discussed the underlying resourcing factors that drive residential reconstruction outcomes, two critical gaps remain in the literature. First, there is a lack of quantitative studies to understand the effects of the combination of socioeconomic, construction industry, and federal government resourcing factors on permanent housing reconstruction outcomes at a regional scale. Although previous qualitative case studies have highlighted the role of socioeconomic characteristics of the affected households for resource acquisition (Chang-Richards et al., 2013), there are limited quantitative studies that correlate socioeconomic characteristics with residential reconstruction outcomes at the regional scale. Furthermore, most of the social sciences literature focuses solely on socioeconomic factors that govern housing recovery (Peacock et al., 2014) while ignoring labor and material resources. Similarly, the focus of most of the construction science literature has been on labor and material resources (Chang et al., 2010) while largely ignoring the socioeconomic aspect of households. Qualitative case studies can provide meaningful insights into understanding the resourcing factors that influence reconstruction outcomes in various disaster stuck regions. However, quantitative approaches can provide a basis for testing hypotheses, develop a more generalized understanding of the recovery outcomes, establish empirical patterns, validate models, and inform policy (Chang, 2010).

Second, the role of geography has been largely ignored in existing literature dealing with residential reconstruction or resourcing. Regions with political or economic boundaries vary in their social, demographic, and economic attributes. Likewise, Arneson (2018) found that the construction capacity varies geographically across the U.S. economic regions. This has led the study to include geographical component when considering the issue of residential reconstruction outcomes, principally with the idea that the driving resourcing forces—socioeconomic characteristics and construction capacity—vary spatially across the U.S.

Research Goals

This research includes a quantitative study of permanent housing reconstruction through the lens of resource availability and accessibility in a market-driven resourcing environment at a regional level. The goal of this research is to quantify the relationships between resourcing factors—socioeconomic, construction, and federal government resourcing factors—and residential reconstruction outcomes at the regional level, and to explore how the relationships between resourcing factors and residential reconstruction outcomes vary across regions. Both aspatial and spatial statistical approaches are used to provide a comprehensive picture of the influence of resourcing factors on residential reconstruction outcomes at a regional scale. A global model, constructed using an aspatial statistical approach (e.g., Ordinary Least Squares regression), attempts to relate resourcing factors with reconstruction outcomes while a local model, constructed using a spatial statistical approach (e.g., Geographically Weighted Regression), attempts to explore the spatially varying relationships.

Research Questions

The study addresses the following research questions:

RQ 1: How do socioeconomic, construction industry, and federal government resourcing factors influence post-disaster permanent housing reconstruction outcomes at a regional scale?

An Ordinary Least Squares (OLS) regression model is utilized to quantify the relationships between resourcing factors and residential reconstruction outcomes using the federally declared disaster-affected U.S. counties as a geographical unit of analysis. Counties hit by single-event weather-related hazards between 2007-2015 with a high threshold of residential damages are included in the analysis. Counties hit by multiple disasters in the timeframe starting from two-years before a major disaster event to two years after a major disaster are not included to avoid the effects of multiple or overlapping hazard events. Using county-level data on various resourcing factors and reconstruction outcomes from the publicly available data sources, the relationship between socioeconomic, construction industry, and federal government resourcing factors and residential reconstruction outcomes is quantified. By incorporating disaster-affected counties across the U.S., this study empirically attempts to provide a general understanding of the influence of resourcing factors on residential reconstruction outcomes on a global scale. This research hypothesizes that regions with low pre-disaster availability of capital and construction resources will have more protracted post-disaster residential reconstruction trajectories.

RQ 2: How does the relationship between pre-disaster resourcing factors and post-disaster permanent housing reconstruction outcomes vary across regions?

The study incorporates location component or geography to answer this question by exploring the spatial heterogeneity in the relationships between resourcing factors and residential reconstruction outcomes. For example, this research hypothesizes that regional variation in the pre-disaster socioeconomic characteristics of homeowners and construction capacity may cause the influence of resourcing factors on reconstruction outcomes to vary across regions. A case study region and disaster time frame are selected, and spatial regression tools are utilized to explore the spatial variation in the relationships between resourcing factors and residential reconstruction outcomes. First, a global model is constructed for a case study region using Ordinary Least Squares (OLS) regression to describe the underlying resourcing factors that influence residential reconstruction outcomes. Second, a local model is constructed using Geographically Weighted Regression (GWR) which allows exploring the spatial heterogeneity in the regression equation

(Brunsdon et al., 1996). GWR is a spatial regression tool that functions inside a Geographic Information System (GIS) environment. The OLS and GWR models are compared to determine the best fit model that explains the relationships.

The research objectives for each research question are summarized in Table 1.

Table 1: Research objectives

Research Gaps	Research Question	Research Objectives
a) Limited quantitative studies to determine the influence of resourcing factors on residential reconstruction outcomes at a regional scale in the U.S. b) Limited understanding of the collective influence of socioeconomic characteristics of households, construction industry, and federal assistance on residential reconstruction outcomes	RQ 1: *How do socioeconomic, construction industry, and federal government resourcing factors influence post-disaster permanent housing reconstruction outcomes at a regional scale?*	a) Identify critical resourcing factors that influence housing recovery from the literature review b) Develop an OLS model to quantify the relationships between resourcing factors and residential reconstruction outcomes for disaster-affected counties across the entire U.S.
(a) Limited understanding of the influence of geography in shaping the resourcing environment across disaster-affected regions for permanent housing reconstruction (b) Limited studies investigating the spatial heterogeneity in the relationships between resourcing factors and residential reconstruction outcomes	RQ 2: *How does the relationship between pre-disaster resourcing factors and post-disaster permanent housing reconstruction outcomes vary across regions?*	a) Identify critical resourcing factors that influence housing recovery from the literature review b) Select a case study disaster-affected region c) Develop an OLS model to quantify the relationships between resourcing factors and residential reconstruction outcomes for the case study region d) Develop a GWR model to explore the spatially varying relationships between resourcing factors and residential reconstruction outcomes for the case study region

Contributions to the Body of Knowledge

This study contributes to the literature of post-disaster residential reconstruction resourcing in two ways. First, it introduces metrics to measure capital and construction resource availability and uses those metrics to quantitatively determine how resource availability influence reconstruction outcomes in a market-driven resourcing environment at a regional scale. Second, by introducing a spatial element in the statistical analysis, this study explores the spatial heterogeneity in the relationships between resourcing factors and residential reconstruction outcomes.

Policy Implications

Availability and accessibility of resources for residential reconstruction influences the decision-making process of households to rebuild or relocate (Nejat & Ghosh, 2016). Understanding households' decision-making process can help policymakers in formulating effective pre-disaster mitigation plans (Nejat et al., 2016). While statistical approaches such as OLS provides a global measure of the relationships between resourcing factors and residential reconstruction outcomes, the spatial heterogeneity is compromised in favor of average estimates across the entire region under observation. According to Ali et al. (2007, p. 300), "Policy design in a regional context requires explicit recognition of spatial heterogeneity in community characteristics as well as in the heterogeneity of how these characteristics impact the target variables." Statistically significant global variables that display high regional variability inform local policy (ESRI, 2020b). The use of GWR can, therefore, provide a robust basis for pre-disaster resource planning and development of local policies to improve the disaster-resilience of residential communities.

Organization of the Study

The thesis is organized into five chapters. Chapter I includes an introduction, problem statement, research gaps, research questions, and theoretical and practical contributions of the study. Chapter II is a literature review that discusses disaster recovery through a resourcing lens, highlights the U.S. reconstruction model, and explores various resourcing factors. Chapter III includes a description of the research methodology, data sources, and discusses the OLS and GWR method in detail. The results of the study are presented in Chapter IV. The thesis concludes with Chapter V, which discusses the findings and research implications.

CHAPTER II: LITERATURE REVIEW

Disaster Recovery: A resource-driven process

Disasters bring disruptions and damages to the social, built, economic, and natural environment. Post-disaster recovery can be conceptualized as a goal, phase or process which aims to return the community to regular routines (Lindell, 2013) by "restoring, rebuilding, and reshaping the physical, social, economic, and natural environment through pre-event planning and post-event actions" (Smith & Wenger, 2007, p. 238). Cheng et al. (2015) extended the concept of recovery by providing two different transitions following disruptions: returning to pre-disaster conditions or attaining a normal situation that would have existed if there was not a shock. Others have stated that recovery should return the community to a stable state (Chang, 2010), most preferably to a resilient state to prevent future hazards (Berke & Campanella, 2006; Cutter et al., 2013). However, the recovery outcomes depend on local social and economic context (Olshansky, 2005) and may vary depending on how communities define their recovery goals based on the existing situation, challenges, and priorities (FEMA, 2011). According to the U.S. National Disaster Recovery Framework (NDRF), a recovery process should encompass pre-disaster preparedness, mitigation, and capacity building to strengthen a community's resilience to withstand, respond, and recover from future hazards (FEMA, 2011). The NDRF's community recovery continuum comprises of four sequences of interdependent and concurrent activities that progress the community towards a successful recovery:

(a) Preparedness: This is an ongoing phase that includes activities to prevent expected threats such as pre-disaster recovery planning, mitigation planning, and resilience building.

(b) Short-term recovery: This phase is initiated after the impact and includes activities such as mass sheltering, debris removal, provision of emergency and temporary medical care, and assessment of risk and vulnerabilities. This phase usually lasts for days.

(c) Intermediate Recovery: This phase can last from weeks to several months and includes activities such as the provision of temporary housing, reestablishment of businesses, restoration of infrastructures, and development of mitigation plans.

(d) Long-term recovery: This phase usually lasts from months to several years and includes activities such as repair or reconstruction of residential housing and infrastructures, rebuilding local businesses and economies, and implementation of mitigation strategies.

Long-term recovery of the built environment is a resource-driven process (Olshansky, 2005). In their pioneering work—*Reconstruction Following Disaster*—Hass et al. (1977) proposed one of the earliest temporal and sequential models of the recovery process in the disaster literature, which they considered as an ordered, knowable, and predictable process. The model consists of four stages: (1) emergency period; (2) restoration period; (3) replacement-reconstruction period; and (4) commemorative, betterment and developmental reconstruction period. The *emergency period* is the initial coping period to the disruption of community activities and losses of life and property, which lasts for a few days to weeks. The *restoration period*, lasting for several months after the disaster, attempts to bring socioeconomic activities to relatively normal conditions through the restoration of transportation, utilities, infrastructure, and public services. The *replacement-reconstruction period*, which can last months, years, or decades, focuses on rebuilding capital stocks and socioeconomic activities to match pre-disaster levels. The *commemorative, betterment and developmental reconstruction period* includes improvement activities for the city’s future growth and may last for more extended periods than the previous phase. Hass et al. (1977) highlighted that availability of material, financial, and human resources are determinants of recovery outcomes. Communities with adequate access to resources will spend less duration completing each phase of recovery activities.

The linearity and phase occurrence of the Hass model has been contested by later studies in favor of a more realistic model portraying the complexities, unpredictability, non-linearity, and dynamism of post-disaster recovery (Quarantelli, 1982; Rubin et al., 1985; Berke et al., 1993; Jordan & Javernick-Will, 2013; Mahmoud & Chulahwat, 2018). In their case study of fourteen disaster-affected communities in the U.S., Rubin et al. (1985) found that the four recovery stages listed by Hass et al. (1977) are not necessarily orderly, may overlap, or can occur in different sequences. Rubin et al. (1985, p. 18) presented a conceptual framework of a recovery process that highlighted three elements of community recovery: "personal leadership," "capacity to act," and "knowledge of action." Availability of labor, material, and financial resources determines the capacity of local government and communities to act or carry out recovery over the long term (Rubin et al., 1985). Quarantelli (1982) studied disaster recovery from the perspective of patterns of sheltering and housing in three disaster-affected communities in Pennsylvania, Ohio, and Nebraska and highlighted that availability and accessibility of physical, monetary, and human resources were the key determinants of the housing recovery process. Recovery has also been considered as a social process that encompasses decision-making for the response, repair and reconstruction activities (Nigg, 1995; Mileti, 1999). Since communities are composed of various demographic and social groups, differences in resources accessibility among those groups influence the decision-making process for reconstruction (Nigg, 1995). Olshansky et al. (2012) viewed disaster recovery as a process compressed in time which makes it uniquely different from normal times. Since cities must be rebuild in a fraction of time it took to originally construct them, recovery activities are compressed in time and focused in space. As a result, resource availability becomes much more critical owing to the increasing and competing demand for limited resources.

Disaster recovery has been studied through the lenses of various indicators, processes, or components. Chang (2010) used population recovery, business recovery, and economic recovery as indices to measure urban disaster recovery after the 1995 Kobe earthquake and identified spatial differences in the recovery outcomes. Lindell (2013) considered the recovery of households and businesses as two distinct types of social units for monitoring recovery. Jordan & Javernick-Will (2013) presented four types of indicators to measure recovery: economic, environment, infrastructure, and social. Infrastructure indicators include recovery of housing, infrastructures, and lifeline utilities. Norman (2006) formulated the integrated framework of community recovery encompassing social, economic, natural, and built environments. Among the five components of the built environment recovery following a disaster listed by Norman (2006)— residential housing, public buildings and assets, industrial and commercial buildings, rural infrastructure, and lifeline utilities—housing recovery is a crucial component of community recovery (Zhang & Peacock, 2009). Restoration of permanent housing is not only essential for the reestablishment of daily routines of households but also for the long term recovery of communities.

Resourcing Approaches for Permanent Housing Reconstruction

Housing recovery is a complex process which comprises of the recovery of both households (Quarantelli, 1995) and physical structure (Rathfon et al., 2013). Quarantelli (1995) conceptualized housing recovery as a multi-stage process consisting of four stages: emergency sheltering (unplanned shelter intended for a brief period during the peak of emergency); temporary sheltering (shelter in quarters with the provision of food and sleeping facilities intended for a temporary stay); temporary housing (transitional housing set in nonpreferred locations which also allows reestablishment of household routines), and permanent housing (permanent shelter either in the former location after reconstruction or resettlement in preferred locations). Permanent housing reconstruction, the final phase of the housing recovery process, is the long-term housing solution where individual homeowners or communities carry out repair and reconstruction of their damaged houses using capital resources such as personal funds, insurance payouts, or governmental assistance (Mukherji, 2018). While these four stages might be non-linear and overlapping (Bolin & Stanford, 1991), the ultimate path to achieve permanent housing requires homeowners to access capital resources to accomplish tasks related to each phase such as meeting basic life needs, completing damage assessments, and carrying out repairs or reconstruction (Zhang, 2006). Furthermore, housing recovery outcomes are determined by the sequences of household movements from one phase of sheltering and housing locations to the other, such as the transition of households from temporary housing to permanent housing. Availability of financial resources has direct impacts on the sequence of household movements towards permanent housing (Cole, 2003). Rathfon et al. (2013) integrated the recovery process of a physical building to the household recovery model conceptualized by Quarantelli (1995). The recovery of households and the residential building where they reside begin at the same time when the disaster strikes. The damage status of a building after a disaster determines the later recovery stages. Some houses undergo minor non-structural damages requiring minimum repairs, while others with moderate structural damages might need temporary shoring and structural retrofits. Houses with severe damage are demolished, and new structures are built. Since housing recovery culminates with the physical recovery of a residential building, availability of construction resources are crucial to accomplish reconstruction task.

Chang et al. (2010) defined *resourcing* for residential reconstruction as activities broadly encompassing pre-event planning, procurement, and delivery of resources along with the development of resource alternatives. Stakeholders such as homeowners, government agencies, donors, community-based organizations, construction sector, real estate sector, and insurance sector play an essential role in resourcing activities for residential reconstruction (Shafique & Warren, 2016). Depending on the interactions and influence of stakeholders into resourcing activities, Chang et al. (2010) highlighted four resourcing approaches for post-disaster permanent housing reconstruction—government-driven resourcing approach; market-driven resourcing approach; donor-driven resourcing approach; and owner-driven resourcing approach. Government agencies in a socialist market economy facilitate resources for housing reconstruction in a government-driven model. For instance, housing reconstruction following the 2008 Wenchuan earthquake in China was driven by the central government through policies to assist homeowners as well as through market interventions to control the supply-chain of construction resources (Chang et al., 2012). In a donor-driven model, national or international donor agencies handle housing reconstruction from its inception to delivery. An owner-driven model is a participatory approach where homeowners undertake reconstruction work themselves through the combination of technical and financial support provided by aid agencies. Finally, a market-driven model forces homeowners to rely on their personal funds, insurance, and market forces (e.g., real estate and construction market) to adjust and adapt after a disaster. Post-disaster permanent housing reconstruction in the U.S. adopts a market-driven model.

Permanent Housing Reconstruction in the U.S.

Permanent housing reconstruction in the U.S. can be described as the combination of the limited intervention model and the market model (Comerio, 1997). Unlike the government-driven model, where the government plays an active role in the overall reconstruction of private and public infrastructure, the U.S. model limits the obligations placed on the federal, state, and local government to assist in the physical establishment of permanent housing and mostly concentrates government resources for the recovery of public infrastructure. While the U.S. federal government provides early warnings for storms and floods, emergency response, and temporary shelters, a bulk portion of its capital funding is channelized for the restoration of public infrastructures (Comerio, 2014). Federal resources only provide minimal financial assistance in the form of home repair grants to homeowners while a significant chunk of the damage must still be covered through the homeowner's personal capital resources (FEMA, 2018). Market forces such as insurance, real estate, and construction industry are major determinants of the permanent housing recovery. Homeowners must rely on private capital such as property insurance and personal savings to fund housing repairs or reconstruction since government funding merely fills the gap in private resources. Private insurance is the primary source of funding for housing repairs and reconstruction in the U.S. (Wu & Lindell, 2004; Nejat & Ghosh, 2016).

Literature related to residential reconstruction in a market-driven resourcing environment can be divided into two categories: qualitative and quantitative. Qualitative studies include case studies discussing the role of market mechanisms, economic impacts, and bottlenecks for accessing resources for reconstruction. For instance, Comerio (1998) studied urban housing recovery following major disasters in the U.S. and found that residential insurance covered more than half of the total value of residential losses following the 1989 Hurricane Hugo, the 1992 Hurricane Andrew, and the 1994 Northridge Earthquake. Chang-Richards et al. (2013) studied the 2009 Victorian Bushfires in Australia and highlighted that local construction market conditions and socioeconomic status of households affected the availability of resources for permanent housing reconstruction.

Quantitative case studies have used conventional statistical approaches (e.g., linear regression) to predict housing recovery trajectories using a set of predictor variables. For instance, Zhang (2006) analyzed recovery processes of the 1992 Hurricane Andrew affected single-family households in Miami-Dade County, Florida, by regressing appraised building values on a set of predictor variables related to housing characteristics and neighborhood attributes (e.g., income, race, and ethnicity). Lu (2008) extended this study by analyzing single-family and multi-family housing recovery trajectories in Miami-Dade County. Similar to Zhang and his colleagues' study, appraised building values were used as an outcome variable, while housing attributes and neighborhood characteristics were assigned as predictor variables. Arneson et al. (2020) developed a quantitative model to predict permanent housing reconstruction outcomes at a regional scale in the U.S. by regressing building permits on variables such as pre-disaster labor availability, material availability, and federal grants.

Resourcing Forces and Factors

In a market-driven resourcing model, accessing capital and construction resources for rebuilding the damaged residential housing stock is crucial for homeowners. Under a time-compressed environment of capital depletion and recovery following large scale disasters, homeowners in a disaster-affected community simultaneously compete for scarce resources (Olshansky et al., 2012). Since homeowners themselves are accountable for repairing or rebuilding their damaged homes (Zhang & Peacock, 2009), homeowners having the most direct access to those finite resources can cope well with the housing repair and reconstruction task. Homeowners can supplement their private funds with reconstruction grants and loans from federal sources, such as the Federal Emergency Management Agency's (FEMA) Individuals and Household Program (IHP) and the U.S. Small Business Administration's (SBA) disaster loan program (FEMA, 2018), to procure construction resources for reconstruction. However, pre-existing socioeconomic status and regional construction market conditions act like a catalyst, either favoring or constraining homeowners' capacity to acquire capital and construction resources. The forces that influence resource availability and accessibility are termed as ***resourcing forces****,* shown in Figure 1. Case studies have shown that these forces fall into one of the three broad categories: socioeconomic characteristics of homeowners, construction industry, and the federal government. Each resourcing force is composed of one or multiple factors termed as ***resourcing factors***. Studying permanent housing reconstruction from the resourcing lens at a regional scale first requires understanding various resourcing factors that influence reconstruction outcomes.

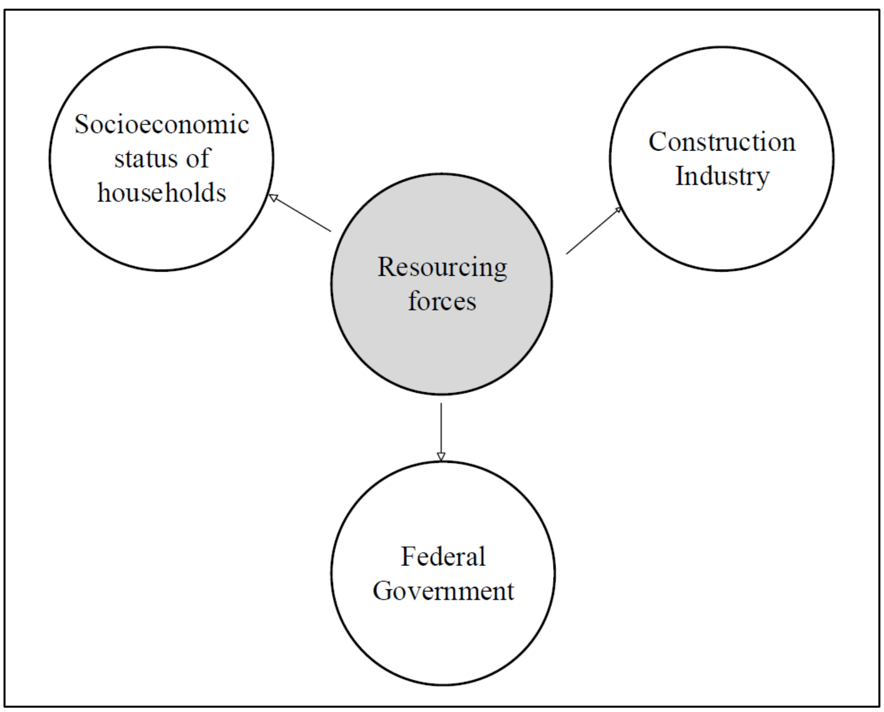

Figure 1: Three core resourcing forces. *Source: Author*

Socioeconomic Resourcing Factors

Disaster vulnerability and the ability of households to cope with and recover from a disaster are determined by their socioeconomic characteristics (Cutter et al., 2003). Case studies have shown that pre-existing socioeconomic characteristics of households such as income, age, and education influence the availability and accessibility of private and public capital resources for residential reconstruction (Bolin & Stanford, 1991; Fothergill & Peek, 2004; Peacock et al., 2007). Household's dependence on market forces for establishing permanent housing has predictable outcomes as higher socioeconomic status households take a speedy trajectory to recovery while low-income households are left behind (Bolin, 1993).

Low-income households are less likely to have access to the information and resources needed to restore permanent housing (Fothergill & Peek, 2004). Following Hurricane Katrina in 2005, pre-existing socioeconomic inequities resulted in differential recovery patterns among households of different socioeconomic classes in New Orleans (Finch et al., 2010). The most hardly hit were the low-income households in New Orleans, as they had a smaller percentage of flood insurance coverage and fewer resources to recover from Hurricane Katrina (Masozera et al., 2007). Conversely, higher-income neighborhoods showed accelerated housing recovery in Miami Dade County following the 1992 Hurricane Andrew and Galveston County following the 2008 Hurricane Ike (Peacock et al., 2014).

Households of ethnic and racial minority status have also historically faced challenges in accessing resources for housing reconstruction (Fothergill et al., 1999). Previous case studies have revealed that ethnic-minority households faced difficulties in accessing federal housing repair assistance following the Northridge Earthquake in 1994 (Bolin & Stanford, 1998; Kamel & Loukaitou-Sideris, 2004) and Hurricane Katrina in 2005 (Kamel, 2012). Furthermore, permanent housing reconstruction of African American households in New Orleans following the 2005 Hurricane Katrina was hindered by the discriminatory nature of the pre-Katrina housing market conditions to African Americans in terms of housing costs, access to housing finance and subsidies, coupled with lack of comprehensive insurance coverage and difficulties in accessing SBA loans (Bates, 2006; Pastor et al., 2006). Zhang & Peacock (2009) investigated housing recovery in minority neighborhoods in Miami-Dade County after Hurricane Andrew in 1992 and found that Hispanic and Black neighborhoods recovered slowly because of limited access to insurance. Similarly, elderly households and households with lower educational attainment are more likely to face difficulties in going through processes to receive federal assistance (Fothergill & Peek, 2004).

Additionally, using a quantitative case study of the community hit by a flood in Texas, Cole (2003) found that pre-disaster socioeconomic characteristics of households (e.g., household income and education) influenced the sequence of household movements in the housing recovery process. Low-income households and those lacking a high school diploma made slow progress towards permanent housing as they had limited financial resources to rebuild their houses (Cole, 2003).

Construction Industry Resourcing Factors

Reconstruction following a disaster is characterized by the heightened demand for construction activities which Olshansky et al. (2012, p. 173) termed as a "time compression" of recovery activities. Homeowners and the commercial sector compete for limited resources from the local construction market to carry out the reconstruction tasks, which results in a demand surge for construction resources. Demand surge further creates ripple effects by increasing the cost of repairs (Olsen & Porter, 2011). Moreover, large-scale disasters typically result in the disruption of local production, manufacturing capacity, and construction supply-chains, which has aggravating effects on the availability and accessibility of resources. Qualitative case studies by Chang et al. (2010) have documented the sluggish pace of housing reconstruction due to the shortage of construction labor and materials in the aftermath of the 2004 Indian Ocean Tsunami in Indonesia, the 2008 Wenchuan Earthquake in China, and the 2009 Victorian Bushfires in Australia.

Labor shortages are one of the major risks faced by the U.S construction companies employed in post-disaster reconstruction works (Tatum & Terrell, 2012). For instance, the shortages of labor were witnessed in the aftermath of the 2017 Hurricane Harvey in Texas, which impeded the reconstruction works (U.S. Chamber of Commerce, 2017). The regional availability of labor and materials is a key indicator of the capacity of the construction market to meet post-disaster reconstruction demand (Arneson, 2018). However, not all the regional construction markets have equal capacity to supply labor and materials owing to the regional availability of such resources. Additionally, disasters intensify the pre-existing skill shortages of the construction workforce which may delay reconstruction (Chang-Richards et al., 2017).

Federal Government Resourcing Factor

Under the housing assistance provisions of Section 408 of the Stafford Act, the Individuals and Households Program (IHP), administered by FEMA, provides disaster housing assistance to individuals and households (Lindsay, 2017). IHP provides financial assistance to eligible homeowners to repair or rebuild their houses. The factors that FEMA uses to determine potential IHP grants for affected individuals and households include cause of damage, damage concentration, degree of trauma, homeownership rate, special population, amount of insurance, and availability of aid programs (Reese, 2018). While the IHP grant provides funds that go directly to affected homeowners for housing repairs, it neither covers all the losses nor substitutes the homeowners' insurance (Lindsay, 2017; FEMA, 2018). As a result, homeowners must still rely on personal funds and insurance to carry out permanent housing reconstruction in the U.S. Moreover, the application process to receive IHP grants can be cumbersome for low-income and minority homeowners (Fothergill et al., 1999).

Although market mechanisms take precedence over federal assistance in the American scenario, the role of the U.S. federal government in permanent housing recovery cannot be underestimated, especially in cases of large-scale disasters. For instance, forty percent of the total expenditures for housing reconstruction in the city of Los Angeles, hit by the Northridge Earthquake in 1994, came in the form of grants and loans from federal sources such as FEMA, SBA, and Housing and Urban Development (HUD) (Comerio, 1997). Similarly, housing recovery in New Jersey following Hurricane Sandy in 2012 was significantly influenced by the availability of federal funding, particularly the individual assistance grant from FEMA (Cutter et al., 2014b; Nejat & Ghosh, 2016).

The Geography of Post-disaster Residential Reconstruction

Multiple regions in the U.S. are hit by disasters every year with varying magnitudes of residential damages across regions. Social vulnerabilities, disaster-related residential losses, and recovery patterns vary geographically among different social groups (Cutter et al., 2003). In her case studies of urban disasters, Comerio (1998, p. 45) used "local conditions" to evaluate housing losses and showed that pre-disaster local demographic, housing, social, and economic conditions are important predictors of reconstruction outcomes. Chang et al. (2012) studied resourcing issues through a comparative case study of three disaster-affected regions in Indonesia, China, and Australia and found that region-specific socioeconomic, cultural, and political environment influenced the availability of resources in those regions, producing different reconstruction outcomes. Furthermore, Arneson (2018) showed that the regional construction capacity of the residential construction industry varies across different U.S. regions. At a regional level, pre-disaster socioeconomic characteristics of households and construction industry resources shape the resourcing-context of each region, thereby making the reconstruction outcomes of each region distinct from the other. Since geographically specific resourcing factors shape the reconstruction outcomes across regions, the inclusion of 'geography' as an independent factor adds a new dimension to post-disaster housing reconstruction studies through the identification of region-specific resourcing issues.

Contrary to case studies conducted at a single geographic location, regional level studies tie observations to broader locations because of which the relationships between resourcing factors and reconstruction outcomes may not remain fixed over the entire region. Spatial non-stationarity is a situation where a simple global model cannot describe the relationship between any set of variables due to the variations in their relationships over space (Brunsdon et al., 1996). Moreover, unlike physical processes, social processes are often non-stationary (Fotheringham et al., 2002). In other words, the measurement of relationships between social factors may depend on the location where it was taken. For example, geographically varying socioeconomic status of households may cause its influence on housing reconstruction outcomes to vary across regions. Previous case studies have used conventional statistical approaches (e.g., multiple linear regression) to provide evidence of inequities of recovery outcomes across disaster-hit neighborhoods (Peacock et al., 2014). However, when studies are carried out at a regional scale, traditional linear regression is inadequate as it will assume that the relationships between resourcing factors and residential reconstruction outcomes will remain constant over the entire study region, thereby obscuring the spatial heterogeneity in the relationships.

Recent advances in technology, particularly Geographical Information System (GIS), have enabled the inclusion of spatial component in modeling relationships between variables which traditional regression methods cannot take into consideration. GIS integrates spatial or geographic data (e.g., information identifying the geographic location of features on Earth) and nongeographic data (e.g., a spreadsheet with data related to geographic features) into a single integrated system. Geographically Weighted Regression (GWR)—a spatial statistical technique that functions in a GIS environment—allows the magnitude and direction of the relationship between predictor and outcome variables to vary across space (Brunsdon et al., 1996). GWR can be a powerful tool to explore how resourcing factors influence residential reconstruction outcomes across geographical regions. Moreover, GWR vividly illustrates the patterns of spatially varying relationships in the form of maps, which helps inform local policy (Ali et al., 2007).

Besides the importance of location, the concept of *regional resilience* might be useful to help explain the significance of studying housing reconstruction outcomes at a regional level. Resilience has been interpreted in various ways by different disciplines such as disaster studies, engineering, psychology, and socio-ecological systems (Matyas & Pelling, 2014), thus making its definition quite elusive resulting from different epistemological orientations and methodological practices (Zhou et al., 2010). However, as highlighted by Zhou et al. (2010), the definition of resilience in the literature is chiefly concentrated on the ability of the system to withstand shocks as well as the ability of the system to bounce back to its initial conditions following perturbation. Bruneau et al. (2003) highlighted four properties of resilience: robustness (ability to withstand extreme event), rapidity (ability to recover quickly following an extreme event), redundancy (substitutability), and resourcefulness (ability to supply resources). Recent studies have also focused their attention on *regional economic resilience* (Christopherson et al., 2010; Martin, 2011), defined as the capacity of a regional economy to absorb shocks, adapt, and maintain acceptable growth path (Han & Goetz, 2015). Regions having limited reconstruction resources face a hard time to recover from a disaster. Vulnerability, on the other hand, is the susceptibility of a system to potential loss from shocks (Adger, 2006) and has intrinsic connections with resilience (Pendall et al., 2012). Households of low socioeconomic status are vulnerable to future hazards as they have limited access to capital resources to carry out reconstruction. Post-disaster reconstruction is a "patterned sequence" (Drabek, 1986, p. 66). Studying permanent housing reconstruction patterns on a regional scale by exploring the local relationships between resourcing factors and reconstruction outcomes can help improve the disaster-resilience of residential communities. Planners can facilitate long term housing recovery through prior identification of regions that are vulnerable to resourcing crisis in the aftermath of disasters.

Previous hazards and vulnerabilities studies have used U.S. counties as spatial units of analysis to explore the regional patterns of social vulnerability (Cutter et al., 2003) and geographical variability of community resilience (Cutter et al., 2014a). Counties are fundamental components of the disaster management system as they not only serve an important role in emergency management activities but are also the primary local administrative unit for emergency management agencies (Cutter et al., 2014a). Furthermore, each county has a unique resourcing environment shaped by its socioeconomic conditions and construction capacity. Regional level studies using counties as a geographical unit of analysis can help planners and policymakers to understand housing reconstruction patterns across regions and the driving resourcing factors behind those patterns.

Conclusion

Although qualitative case studies have highlighted various resourcing factors that influence residential reconstruction outcomes, there is a lack of quantitative studies combining socioeconomic, construction industry, and federal government resourcing factors and examining their effect on the regional outcomes of permanent housing. The role of geography in shaping reconstruction outcomes has been largely ignored in the existing literature. Understanding regional patterns of the residential reconstruction outcomes and the underlying resourcing factors influencing reconstruction outcomes across disaster-affected regions helps in the resource planning processes and implementation of policies at the local level. The following chapter discusses in detail about research design and methods to fulfill the targeted objectives.

CHAPTER III: DATA COLLECTION AND METHODOLOGY

The study uses both aspatial and spatial statistical approaches to answer each of the two research questions:

1) *How do socioeconomic, construction industry, and federal government resourcing factors influence post-disaster permanent housing reconstruction outcomes at a regional scale?* and

2) *How does the relationship between pre-disaster resourcing factors and post-disaster permanent housing reconstruction outcomes vary across regions?*

First, the relationships between resourcing factors (e.g., socioeconomic, construction industry, and federal government resourcing factors) and residential reconstruction outcomes were quantified by developing an Ordinary Least Squares (OLS) regression model. Counties were used as a spatial unit of analysis. Over 600 counties hit by various federally declared weather-related disasters from the year 2007 to 2015 were included in the analysis. The weather-related hazards included in this study were Hurricanes, Severe storms, Floods, and Tornadoes, as categorized by FEMA in their historical disaster declaration (FEMA, 2019). Counties with substantial residential damages related to owner-occupied housing units were selected for analysis based on the countywide Per Capita Impact Indicator threshold published by FEMA (FEMA, 2014b) for every federal fiscal year.

Second, the GIS-based Geographically Weighted Regression (GWR) model was developed to explore the spatially varying local relationships between resourcing factors and residential reconstruction outcomes. The Northeast Census Region of the U.S. was used as a case study region to build the GWR model due to unprecedented levels of residential damages between 2011-2012.

Also, the Northeast Census Region had contiguous disaster-affected counties with high per capita damage thresholds. An OLS model was developed to establish the global relationships between resourcing factors and residential reconstruction outcomes for the case study region. This was followed by the development of the GWR model to explore the spatial heterogeneity in the relationships between resourcing factors and residential reconstruction outcomes.

The Global OLS Model

Study Overview

A multi-step process was conducted for: (1) identification of study time frame; (2) selection of disaster-affected counties with residential losses; (3) selection of regression variables; (4) collection of data; and (5) development of OLS model. The study time frame was chosen from the year 2007 to 2015. Federally declared disaster-affected counties with per capita residential damages of owner-occupied housing units exceeding the countywide Per Capita Impact Indicator threshold published by FEMA for every federal fiscal year were included in the analysis. Counties hit by more than one major disaster within the two-year pre-disaster and two-year post-disaster timeframe (i.e., two years before the incidence of a major disaster to two years after a major disaster) were not included in the analysis. The predictor variables used in the regression model were the resourcing variables categorized into socioeconomic resourcing variables, construction industry resourcing variables, and federal government resourcing variable. For every federal disaster year *x,* socioeconomic and construction industry variables were recorded for the pre-disaster year *x-1*. The federal government resourcing variable was recorded for the disaster year *x*. The outcome variable was measured as the change in median home value from pre-disaster year *x-1* to post-disaster year *x+2* using a two-year reconstruction time frame. Data was collected from the publicly available data sources which included the U.S. Census Bureau's American

Community Survey (ACS) (U.S. Census Bureau, 2019a), U.S. Bureau of Labor Statistics (BLS) (U.S. Bureau of Labor Statistics, 2019), and FEMA (FEMA, 2014a).

The time frame was restricted from 2007-2015 due to data availability and study framework. A total of three ACS datasets from the U.S. Census Bureau were used in this study: ACS 1-year estimates, ACS 3-year estimates, and ACS 5-year estimates. ACS 1-year estimates were available starting from the year 2005 while ACS 3-year estimates and ACS 5-year estimates were available since 2007 and 2009 respectively (U.S. Census Bureau, 2019c). Residential damages data was available from FEMA for all the disaster-affected counties starting from the year 2005. The first disaster year was chosen as the year 2007 to determine if counties were hit by more than one major disaster two years prior to it (i.e., between 2005 and 2006). The final disaster year was chosen as 2015 since the change in median home value for 2015 was measured from 2014 to 2017. The ACS 5-year estimates were available until the year 2017. Finally, an OLS regression model was built, and the relationships between resourcing factors and reconstruction outcomes were quantified.

Data Collection

Disaster-related Data

Disaster-related data such as disaster declaration number, disaster category, date of incidence, and declared counties were obtained from the Disaster Declarations Summary Dataset, publicly available from the FEMA website (FEMA, 2019). Damages data for the owner-occupied housing units were collected from the Archived Housing Assistance Program Data, also publicly available from the FEMA website (FEMA, 2014a). For this study, only owner-occupied housing units were used for analysis as homeowners usually carry out reconstruction tasks by investing their capital resources (Zhang, 2006). According to FEMA, renters are not eligible for home repair assistance grant provided by FEMA under IHP since they do not own the structure (FEMA, 2014a).

Disaster-related data and their sources are summarized in Table 2.

Table 2: Disaster-related data

Dataset	Description	Data availability	Description	Time frame	Source
Disaster Declarations Summary	Lists all federally declared disasters with attributes such as disaster number, declaration date, incident type, incident begin and end date, and declared counties/area	County-level	Disaster number, date of incidents, incident type, and affected counties were key indicators collected from this database.	2007-2015	(FEMA, 2019)
Archived Housing Assistance Program Data	Lists residential damages and Individuals and Households Program (IHP) grant data with attributes such as total inspected houses, damages amount, and total approved IHP amount for homeowners	County-level	Disaster number, affected cities at a zip code level for each county, damages amount, and total approved IHP amount were key variables collected from this dataset. Zip code level data for each county were aggregated to obtain the county-level damage and IHP grant data.	2007-2015	(FEMA, 2014a)

Predictor Variables

Three principal categories of predictor variables were collected for this study—socioeconomic resourcing variables, construction industry resourcing variables, and federal government resourcing variable.

First, county-level data for socioeconomic resourcing variables were collected for the time frame 2006-2014 from ACS 1-year estimates, ACS 3-year estimates, and ACS 5-year estimates, publicly available from the U.S. Census Bureau. For every federal disaster year *x* beginning from the year 2007 to 2015, socioeconomic variables were collected for the pre-disaster year *x-1*. The year 2006 was the first pre-disaster year for this study, while the year 2014 served as the last pre-disaster year. Socioeconomic resourcing variables included indicators such as income, educational attainment, unemployment rate, and mortgage status. The 'Income' variable was defined as the median household income of owner-occupied households in U.S. dollars. Educational attainment represented the percentage of owner-occupied households with the educational attainment of bachelor's degree or above. Unemployment rate indicated the percentage of the population over 16 years and above who were not employed. Mortgage status was defined as the percentage of owner-occupied housing units with unpaid home mortgages. These socioeconomic variables, selected from the literature review, acted as a resourcing catalyst that either favored or constrained homeowners' capacity to acquire capital resources. Hence, they are indicators of broader capital resource availability for homeowners. The study hypothesized that income and educational attainment acted as positive catalysts, while unemployment rate and mortgage status acted as negative catalysts for availability and accessibility of capital resources. The variables of this category are summarized in Table 3.

Table 3: Socioeconomic resourcing variables

Variable	Symbol	Definition	Data availability	Time frame	Dataset	Source
Income	INCOME	Median household income of owner-occupied householders in U.S. dollars	County-level	2006-2014	Year 2006: ACS 1-year estimates Year 2007-2008: ACS 3-year estimates Year 2009-2014: ACS 5-year estimates	(U.S. Census Bureau, 2020d)
Educational attainment	EDUCATION	Percentage of owner-occupied householders with a bachelor's degree or above education	County-level	2006-2014	Year 2006: ACS 1-year estimates Year 2007-2008: ACS 3-year estimates Year 2009-2014: ACS 5-year estimates	(U.S. Census Bureau, 2020f)
Unemployment rate	UNEMP	Percentage of the population of age 16 years and over who are unemployed	County-level	2006-2014	Year 2006: ACS 1-year estimates Year 2007-2008: ACS 3-year estimates Year 2009-2014: ACS 5-year estimates	(U.S. Census Bureau, 2020a)
Mortgage status	MORTGAGE	Percentage of owner-occupied housing units with unpaid home mortgages.	County-level	2006-2014	Year 2006: ACS 1-year estimates Year 2007-2008: ACS 3-year estimates Year 2009-2014: ACS 5-year estimates	(U.S. Census Bureau, 2020b)

Second, data for construction industry resourcing variables were collected for the time frame 2006 to 2014 from the Quarterly Census of Employment and Wages dataset, publicly available from the BLS (U.S. Bureau of Labor Statistics, 2019). For every federal disaster year *x* beginning from the year 2007 to 2015, construction resourcing variables were collected for the pre-disaster year *x-1*. Location Quotient (LQ) of economic indices of the North American Industry Classification System (NAICS) based regional construction sector was used to measure construction resourcing factors. NAICS is the standard used by the statistical agencies of the U.S. federal government to analyze data related to the U.S. market economy by grouping sectors based on the similarity of their production processes (U.S. Census Bureau, 2017). Industry LQ quantifies how concentrated an industry (e.g., number of construction establishments or employment) is within a region compared to the national level (Bureau of Economic Analysis, 2018).

Construction resourcing variables included two categories: labor resources and material resources. Availability of labor resources was measured through the *employment* metric using LQ of annual average employment count of the NAICS Sector 238 industry. NAICS Sector 238 comprised of establishments involved in performing specific activities related to building construction which included exterior activities (e.g., site preparation) and interior activities (e.g., painting, electrical, and plumbing). NAICS 238 included the following sub-sectors: Foundation, Structure, and Building Exterior Contractors (NAICS 2381); Building Equipment Contractors (NAICS 2382); and Building Finishing Contractors (NAICS 2383) (U.S. Bureau of Labor Statistics, 2020b). General contractors typically subcontract residential construction related works to establishments belonging to Sector 238. Besides, homeowners also hire specialty trade contractors for residential repair or reconstruction works (U.S. Bureau of Labor Statistics, 2020b).

Availability of material resources was measured through the *establishment* metric using LQ of annual average wholesale establishments of the NAICS Sector 423. NAICS Sector 423 represented merchant wholesalers engaged in the wholesale of durable goods. NAICS Sector 423 included merchant wholesalers selling construction materials such as Lumber and wood (NAICS 42331), Masonry (NAICS 42332), and Roofing and siding (NAICS 42333) (U.S. Bureau of Labor Statistics, 2020a).

Construction labor and material resourcing factors, represented by the LQ of economic indices of NAICS based industry sectors, were used to indicate regional labor and material availability. Availability of labor and materials is crucial for residential reconstruction in a market-driven resourcing environment (Arneson et al., 2020). The study hypothesized that labor and material resourcing factors would positively influence residential reconstruction outcomes. The study used the LQ metric of the NAICS industry since previous quantitative studies have used the LQ metric as indicators of construction market conditions. For instance, Arneson (2018) used employment and wages LQ as economic indicators of the residential construction industry. Ahmadi & Shahandashti (2018b) used LQ of construction establishments, employment, wages, and contributions of the residential construction sector as indicators of pre-disaster construction market conditions. The variables of this category are summarized in Table 4.

Table 4: Construction industry resourcing variables

Variable	Symbol	Definition	Data availability	Time frame	Dataset	Source
Construction Labor	LQ_EMP	Location Quotient of the annual average employment of the specialty trade contractors (NAICS 238)	County-level	2006-2014	Quarterly Census of Employment and Wages (QCEW), U.S. Bureau of Labor Statistics	(U.S. Bureau of Labor Statistics, 2019)
Construction Material	LQ_WHOLESALE	Location Quotient of the annual average wholesale establishments of durable goods (NAICS 423)	County-level	2006-2014	Quarterly Census of Employment and Wages (QCEW), U.S. Bureau of Labor Statistics	(U.S. Bureau of Labor Statistics, 2019)

Lastly, county-level data for the federal government resourcing variable was obtained for disaster year *x* from the Archived Housing Assistance Program Dataset, publicly available from the FEMA website (FEMA, 2014a). The federal government resourcing variable was measured as the housing assistance grant in dollars approved under FEMA IHP. Eligible homeowners who have uninsured or underinsured disaster-related losses receive financial assistance from the IHP. It was hypothesized that the availability of the IHP grant would have a positive influence on residential reconstruction outcomes. The description of this variable is provided in Table 5.

Outcome Variable

Post-disaster permanent housing reconstruction outcomes were measured as the percent change in median home values of owner-occupied housing units from pre-disaster year *x-1* to post-disaster year *x+2* for every federal disaster year *x* under study. Data for median home value was collected from the U.S. Census Bureau's ACS 1-year estimates, ACS 3-year estimates, and ACS 5-year estimates for the year 2006-2017. The two year reconstruction time frame was chosen because case studies have highlighted that a major portion of the housing reconstruction is usually accomplished within two years of the disaster incidence (Zhang, 2006; Rathfon et al., 2013; Arneson et al., 2020). For instance, Zhang (2006) found that it took two years for single-family housing to recover in Miami-Dade County following the 1992 Hurricane Andrew. Similarly, around 90% of the housing stock was recovered within two years following Hurricane Charley in 2004 (Rathfon et al., 2013). Furthermore, Comerio (1998, p. 26) listed five criteria for a successful housing recovery where she stated that *"Rebuilding and/or repairs must take place within two years."*

Previous case studies have used individual home values to model long-term housing recovery trajectories following disasters in the U.S. (Zhang & Peacock, 2009; Peacock et al., 2014;

Hamideh et al., 2018). The median home value was used in this study since the analysis was carried out at a county-level. It was expected that homeowners with easy access to capital and construction resources would be able to repair or rebuild their houses quickly, thereby improving home value growth rates following the damages caused by disasters. The description of this variable is provided in Table 6.

Table 5: Federal government resourcing variable

Variable	Symbol	Definition	Data availability	Time frame	Dataset	Source
Federal housing assistance grant	IHP	The total dollar amount approved under FEMA's IHP program (in hundred thousand of dollars)	County-level	2007-2015	Archived Housing Assistance Program Data	(FEMA, 2014a)

Table 6: Outcome variable

Variable	Symbol	Definition	Data availability	Time frame	Dataset	Source
Reconstruction outcomes	%ΔReconstruction	Percent change in median home value from pre-disaster year *x-1* to post-disaster year *x+2*	County-level	2006-2017	Median home values were collected from ACS datasets depending upon the following data availability years: Year 2006: ACS 1-year estimates Year 2007-2008: ACS 3-year estimates Year 2009-2015: ACS 5-year estimates	(U.S. Census Bureau, 2020c)

Data Analysis

Data analysis steps included: (1) selection of disaster-affected counties; and (2) development of the OLS regression model. Counties were used as a geographical unit of analysis for this study since counties were the smallest unit of analysis considering data availability. For instance, construction industry data from the BLS were available at the county level. Although damages data were available from FEMA at the zip code level, socioeconomic data from the ACS dataset and construction industry data from BLS was not available at the zip code level.

Four criteria were used to select the disaster-affected counties included in this study: 1) the counties had federal disaster declaration status; 2) the counties were hit by weather-related disasters of the following categories: Hurricanes, Severe storms, Floods, and Tornadoes; 3) the counties had residential damages recorded by FEMA with per capita damages equal to or exceeding the Per Capita Impact Indicator threshold published by FEMA for every federal fiscal year; 4) the counties were not hit by more than one major disaster in a period starting from two years before a major disaster to two years after a major disaster.

Only weather-related disasters such as Hurricanes, Severe storms, Floods, and Tornadoes were included as it accounted for more than 90% of the residential damages in counties under this study. Also, the types of residential damages were similar as a result of these events. County-level per capita damage was calculated for each county for each federal disaster year using equation 1.

$$Per\ capita\ damage_x^i = \frac{Total\ countywide\ damages\ in\ U.S.dollars}{Total\ countywide\ population\ in\ owner{-}occupied\ housing\ units} \qquad 1$$

where,

$Per\ capita\ damage_x^i$ is the per capita damage for county i in federal disaster year x

The flow chart of the county selection process is shown in Figure 2.

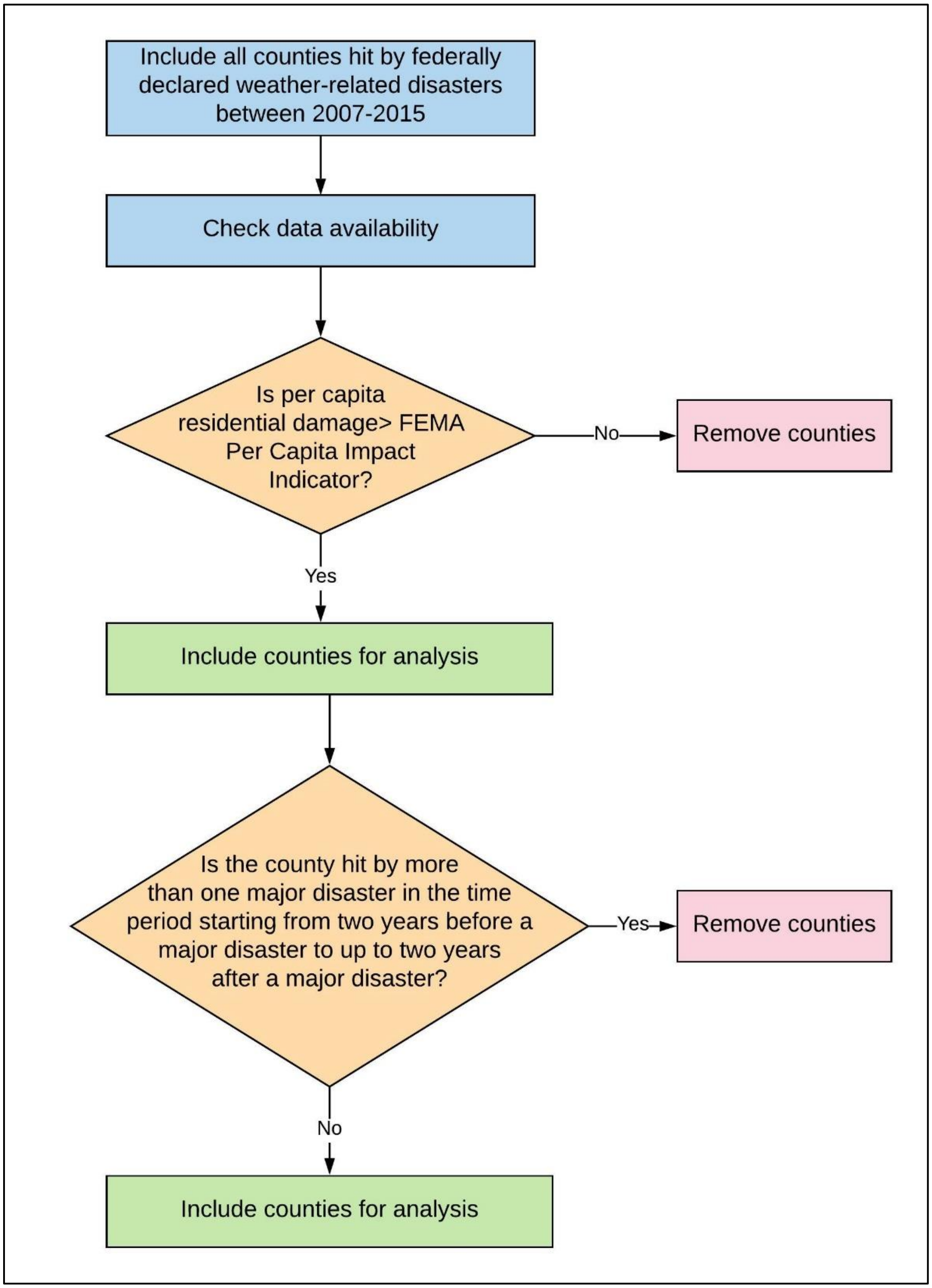

Figure 2: County selection flowchart. *Source: Author*

Per capita damage of each county was compared with countywide Per Capita Impact Indicator published by FEMA for each federal fiscal year. If the per capita damage of a county for a federal disaster year *x* was more than the Per Capita Impact Indicator for that year, the county was included in the analysis. FEMA uses a Per Capita Impact Indicator threshold to indicate that the disaster is of such size and magnitude that it warrants federal assistance. Per Capita Impact Indicator is published by FEMA for every federal fiscal year based on the Consumer Price Index (CPI), as shown in Table 7. Counties with missing data were not included in the analysis. Counties hit by more than one disaster in a period starting from two years before the incidence of a major disaster to two years after a major disaster were discarded to eliminate the effects of preceding or succeeding disasters on resource availability and residential reconstruction outcomes. Ahmadi & Shahandashti (2018b) used a similar approach to eliminate the effects of multi-events on the regression model when counties from multiple years were aggregated together. If the same county was hit more than once with at least two years gap after the date of incidence of a major disaster, it was considered as a separate unit.

Table 7: Per Capita Impact Indicator. *Source: (FEMA, 2014b)*

Fiscal year	**Countywide Per Capita Impact Indicator**
2006	\$2.94
2007	\$3.05
2008	\$3.11
2009	\$3.28
2010	\$3.23
2011	\$3.27
2012	\$3.39
2013	\$3.45
2014	\$3.50
2015	\$3.56

Ordinary Least Squares (OLS) regression model was used to quantify the relationships between resourcing variables and reconstruction outcomes. Existing studies have used linear modeling techniques to model housing recovery using a set of socioeconomic variables (Zhang & Peacock, 2009; Lu, 2008) or construction variables (Arneson et al., 2020). OLS is a generalized linear modeling technique that uses a set of predictor variables to predict the best behavior of the outcome variable (Hutcheson, 2011). The OLS model for examining the influence of resourcing factors on reconstruction outcomes is specified in equation 2.

$$\%\Delta Reconstruction_i = \beta_o + \sum_k \beta_k Socioeconomic_{ik} + \sum_l \beta_l Construction_{il} + \sum_m \beta_m Federal_{im} + \varepsilon_i \qquad 2$$

where,

$\%\Delta Reconstruction_i$ is the outcome variable, measured as a percent change in median home value from pre-disaster year *x-1* to post-disaster year *x+2* at county *i*

$Socioeconomic_{ik}$ represents socioeconomic resourcing variables measured at county *i* for pre-disaster year *x-1*

$Construction_{il}$ represents construction resourcing variables measured at county *i* for pre-disaster year *x-1*

$Federal_{ik}$ represents federal government resourcing variable measured at county *i* for disaster year *x*

β_o represents intercept

β_k , β_l, and β_m represent the regression coefficients associated with socioeconomic, construction, and federal government resourcing variables respectively

ε_i are the residuals of the OLS regression

OLS regression was performed in the SPSS software package Version 25.0 (IBM Corp, 2017). The OLS model was checked for linearity, normality, homoscedasticity, and multicollinearity using statistical tests.

The Local GWR Model

Study Overview

A multi-step process was used to build the local GWR model which included: (1) selection of study region; (2) selection of study timeframe; (3) organization of data in GIS software; (4) development of a global OLS model for the study region; (5) development of a local GWR model for the study region, and (6) mapping GWR coefficients using GIS-based maps. The Northeast Census Region of the U.S., comprising of eight disaster-affected states, was chosen as the case study region and the analysis was done for the federal disaster year 2011 and 2012. The case study approach was adopted since the local model could not be built for the whole U.S. because of the lack of contiguity across all the disaster-affected counties. The Northeast Census Region was hit by some of the catastrophic disasters in the history of the U.S. between 2011 and 2012, such as Hurricane Irene, Tropical Storm Lee, and Hurricane Sandy, with residential losses exceeding billions of dollars. The OLS model was built to quantify the global relationships between predictor and outcome variables. The predictor variables were the resourcing variables categorized into the socioeconomic and construction industry variables. Socioeconomic and construction industry resourcing variables were recorded for the pre-disaster year. The outcome variable was the change in median home value from pre-disaster to post-disaster period. Data was collected from the publicly available data sources which included the U.S. Census Bureau's ACS (U.S. Census Bureau, 2019a), BLS (U.S. Bureau of Labor Statistics, 2019), and FEMA (FEMA, 2014a).

Geographically Weighted Regression

OLS is a global model that provides a single regression equation to represent the relationship between variables of interest. The parameters of OLS are referred to as global parameters as they represent the average effect across space under a spatial context (Ali et al., 2007). One of the drawbacks of OLS is the assumption that the measurement of the relationship between predictor and outcome variable is uniform for the entire region being studied. However, spatial data may not always follow this assumption. In reality, the relationship between the predictor and outcome variable may vary across space—a phenomenon called spatial non-stationarity (Fotheringham et al., 2002). Using OLS for data with spatial attributes might hide possible regional variation in the relationships between predictor and outcome variables. To account for a local relationship, OLS could be run separately for each location. Using this method, however, results in a smaller sample size and generates a large standard error for the regression coefficients (Slagle, 2007). An alternative approach called Geographically Weighted Regression (GWR) assumes that the measurement of the relationship varies geographically and hence can be used to evaluate the spatial heterogeneity in the relationships between predictor and outcome variables (Fotheringham et al., 2002).

GWR allows for spatial variability in the relationships that are measured. For each geographic location in the data, GWR estimates a separate model with local parameter estimates using a differential weighting scheme. GWR is based on Tobler's First Law of Geography, which states that "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236). For example, when an observation is done at arbitrary point *i,* locations near to *i* have a greater influence on that observation than distant locations. In GWR, the influence of data surrounding a regression point *i* is weighted such that the data further away from

i will have comparatively less influence than those near to i (Fotheringham et al., 2002). Hence, GWR expands the OLS model by allowing parameters to be determined locally by using the weighing method that is dependent on location. Parameters from the GWR results can be mapped to display spatial variability on a geographical scale.

GWR equation is an extension of the OLS equation and can be specified as:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \qquad 3$$

where,

y_i is the outcome variable at point i (i=1,2,3…., n)

(u_i, v_i) are the coordinates of i

$\beta_0(u_i, v_i)$ is the intercept for i

$\beta_k(u_i, v_i)$ is the regression coefficient for the k^{th} covariate at i

x_{ik} is the value of k^{th} predictor variable at i

The parameter β can be expressed in the following $n \times k$ matrix form:

$$\beta = \begin{bmatrix} \beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \cdots & \beta_k(u_1, v_1) \\ \beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \cdots & \beta_k(u_2, v_2) \\ \cdots & \cdots & \cdots & \cdots \\ \beta_0(u_n, v_n) & \beta_1(u_n, v_n) & \cdots & \beta_k(u_n, v_n) \end{bmatrix}$$

The rows in the above matrix denote the parameters for each point and are estimated by equation 4 (Fotheringham et al., 2002):

$$\beta(i) = (X^T W_i X)^{-1} X^T W_i Y \qquad 4$$

where,

X is the argument matrix

W_i is N * N diagonal matrix that contains the geographical weights for point *i*

$$W(i) = \begin{bmatrix} w_{i1} & 0 & 0 \\ 0 & \dots & 0 \\ 0 & 0 & w_{in} \end{bmatrix}$$

Y is the vector of the values of the outcome variable.

In GWR, a spatial kernel is placed around each data point *i* (as shown in Figure 3), and the surrounding observations are weighted using a *distance-decay function.*

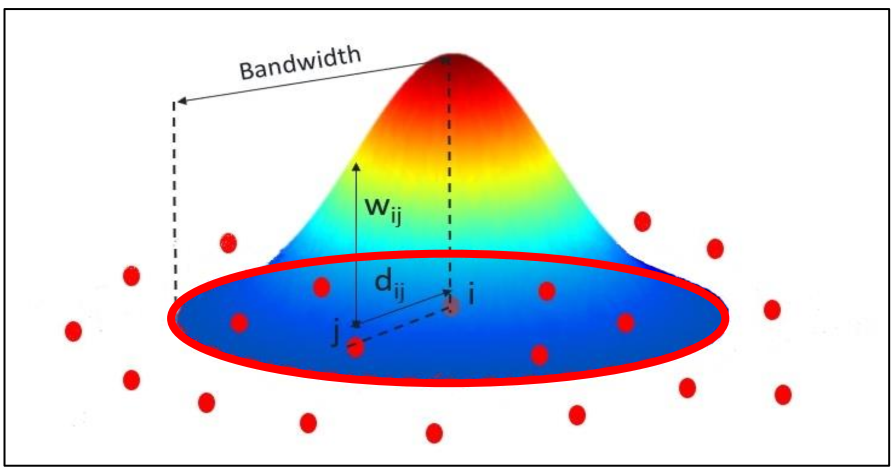

Figure 3: GWR spatial parameters. *Source: Author*

Two common distance-decay functions used in GWR are Gaussian distance function and Bisquare distance function. In a gaussian distance function, the weighing of neighboring points at *j* on the point of observation *i* will decrease exponentially according to a Gaussian curve as the distance between the points *i* and *j* increases. Bisquare distance function is similar to the Gaussian distance function, i.e., the weights decrease as the distance increases. However, if the distance from i to j is greater than a threshold distance or bandwidth, the weight of observations at j is excluded.

The gaussian distance function is given by equation 5 (Brunsdon et al., 1998):

$$w_{ij} = exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right) \quad 5$$

where,

w_{ij} is the weight of observation j at regression point i

d_{ij} is the Euclidean distance between i and j

b is the bandwidth

The bisquare distance function is given by equation 6 (Brunsdon et al., 1998):

$$w_{ij} = \left[1 - \left(\frac{d_{ij}}{b}\right)^2\right]^2 \ (if\ d_{ij} < b) \quad 6$$

$$w_{ij} = 0 \ (if\ d_{ij} > b)$$

where,

w_{ij} is the weight of observation j at regression point i

d_{ij} is the Euclidean distance between points i and j. Points closer to i have greater influence than more distance points, and points outside the bandwidth are not weighted.

b is the bandwidth

Bandwidth is the amount of distance decay in the *kernel* which provides an estimate of the number of nearest observations and determines the local sample size to estimate the model for a particular location. Bandwidth determines the size of the kernel. There are two types of kernels: fixed and adaptive. The fixed kernel provides constant bandwidth for each data point *i* so that the kernel captures only the neighbors within that bandwidth. It is useful for sample points that are reasonably regularly spaced. The adaptive kernel allows the size of the bandwidth to vary across space so that the same number of neighbors is captured by the kernel for each point *i*. Methods for determining the kernel bandwidth in GWR includes Akaike Information Criterion (AICc) or Cross-Validation (CV) (Wheeler & Páez, 2010). No standard method exists for selecting a bandwidth when using counties as spatial units in a GWR model (Siordia et al., 2012). However, using an adaptive kernel that minimizes the AICc is common. Additionally, variation in the size of counties and sparseness of counties in most parts of the U.S. can be adjusted using an adaptive bandwidth.

Spatial Unit of Analysis

Counties were used as the spatial unit of analysis for GWR. In addition to the data availability factor, the choice of using counties as a spatial unit of analysis was vital for the implications of this research in informing local policy. Counties are the primary local administrative units for national emergency management authorities (Cutter et al., 2014a). Waugh (1994) highlighted that county governments in the U.S. are the most rational hosts for emergency management compared to municipal and state governments because of its close proximation to natural hazards, close political and administrative ties to the state government, easy access to state's resources, strong representation of local interests, collaborative environment for decision making, and a platform for planning and managing reconstruction resources. Furthermore, previous GWR studies have used the U.S. counties as a spatial unit of analysis to explore the spatially varying relationships across counties (Voss et al., 2006; Siordia et al., 2012; Gebreab & Diez Roux, 2012; Chi et al., 2013; Hipp & Chalise, 2015). Because of the unique demographic, social, economic, housing characteristics, and construction capacity of counties, local associations between resourcing factors and residential reconstruction outcomes can be captured better at the county level using GWR and hence is a vital resource for planners and policymakers.

Study Region and Time Frame

The selection of the study time frame and disaster-affected case study region was the first step in developing the GWR model. Since this study used pre-disaster and post-disaster time frames for each county, multiple-year disaster-affected counties could not be aggregated together. GWR estimates the regression coefficient of each county using data from the neighboring counties. Aggregating random multi-year disaster-affected counties results in the estimation of some of the local coefficients using data from the post-disaster time frame. This violated the assumption of this study that resource availability was measured at the pre-disaster time frame. As a result, it was necessary for all counties used in the GWR model to have the same pre-disaster baseline year.

The case study region was chosen based on two criteria: (1) contiguity of disaster-affected counties; (2) data availability. First, since counties were used as a spatial unit of analysis, contiguity across counties was crucial (Partridge et al., 2008; Siordia et al., 2012). It was because GWR estimates local regression coefficients by weighing all observations according to their spatial proximity to the regression point. Also, resource availability in the counties adjacent to the disaster-affected county is vital during major reconstruction works. As GWR requires more features for best results (ESRI, 2020b), a study region was selected such that it covered a minimum of 100 counties. Second, data availability was a critical factor since data related to resourcing variables used in the model must be available for all the counties in the study region.

The spatial patterns of residential damages across various U.S. regions from the year 2007 to 2015 were studied to find the case study region. From the residential losses and data availability point of view, the Northeast Census Region of the U.S., which was hit by various federally declared disasters between 2011-2012, was found to be the most suitable region to construct the GWR model. The year 2011-2012 was one of the worst years in the history of the U.S. in terms of disaster events and residential losses. Also, the year 2011 had relatively more number of contiguous disaster-affected counties between 2007-2015. The spatial patterns of residential damages across various regions of the U.S. during the year 2011 and 2012 is shown in Figure 4.

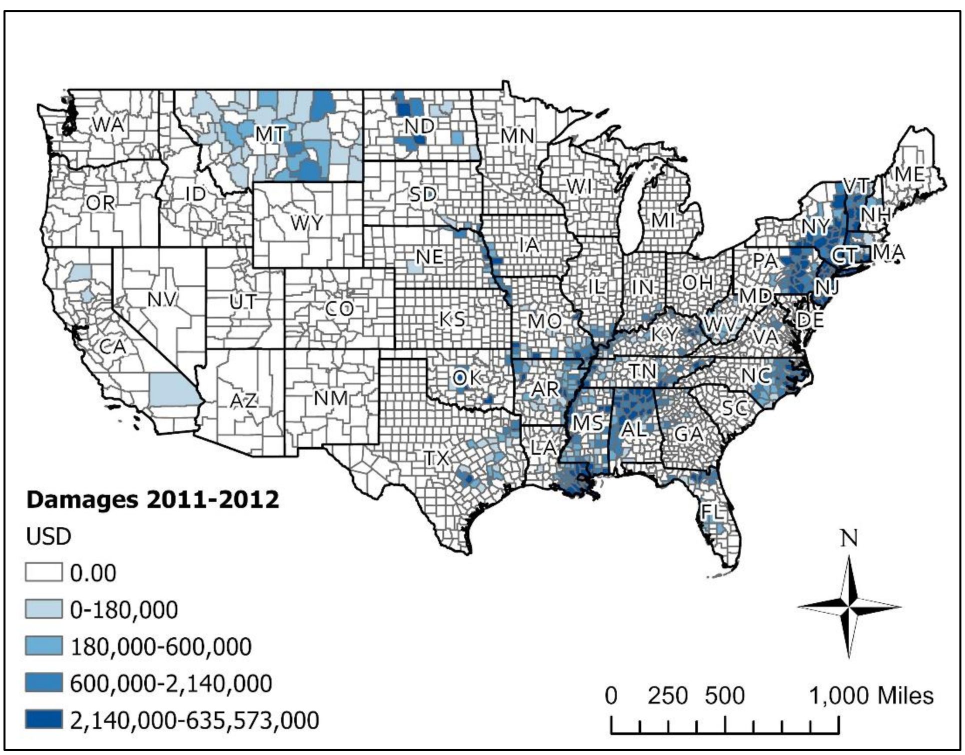

Figure 4: Spatial distribution of residential damages for owner-occupied housing units. *Source: Author*

From Figure 4, it was observed that there was an adequate number of contiguous disaster-affected counties on the east coast clustered together across eight states sharing contiguous borders. The disaster affected states include Connecticut, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. The Northeast Census Region (excluding the state of Maine) had an average per capita residential damage of $57.5 during the year 2011-2012. Counties of the Northeast Census Region had substantial residential damages compared to other regions during the year 2011-2012 due to some of the devastating weather-related events such as Hurricane Irene (2011), Tropical Storm Lee (2011), and Hurricane Sandy (2012). For instance, in 2011, the total residential damages in the Northeast Census Region was $738 million, accounting for over 49% of the total residential damages in the U.S. that occurred during the year 2011. In 2012, the total residential damages in this region were $2.5 billion, accounting for over 88.91% of the total U.S. losses that occurred in 2012. Data related to resourcing variables was also available for the counties of the Northeast Census Region. The other advantage lied in its geographical boundary as the Northeast Census Region is one of the five census divisions of the U.S., as shown in Figure 5. Census regions aggregate states or counties that are roughly similar in terms of historical development, demographic characteristics, economy, and provides a broader geographical framework for statistical analysis (U.S. Census Bureau, 2018). Because of the catastrophic events that brought substantial residential losses to counties sharing contiguous borders across the eight states, the Northeast Census Region provided a prime study area for the examination of the spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes.

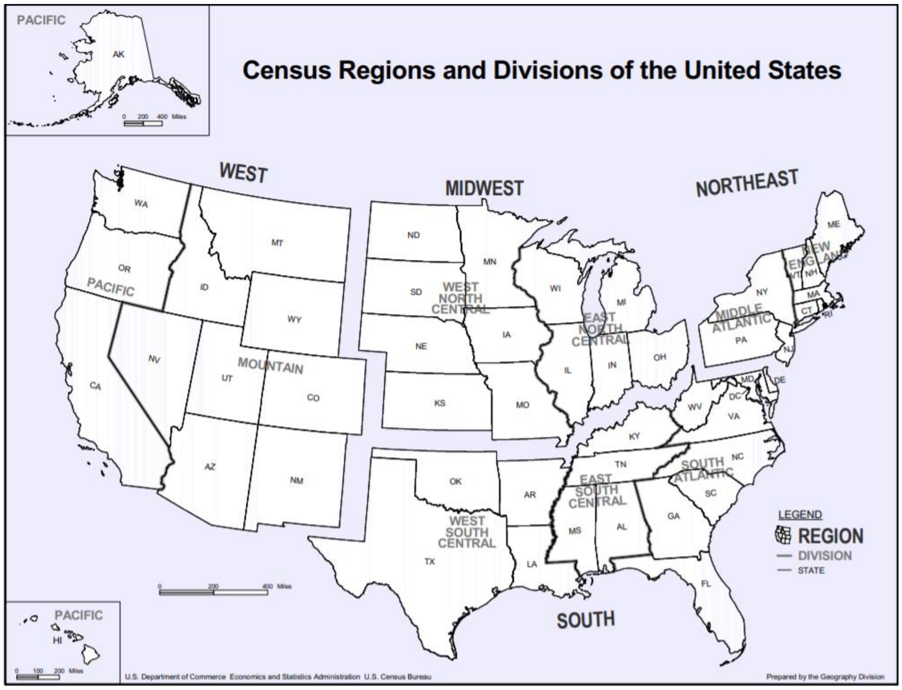

Figure 5: Census divisions of the U.S. *Reprinted from Census Regions and Divisions of the United States, by U.S. Census Bureau. Retrieved January 15, 2020, from http://webarchive.loc.gov/all/20130107113900/http://www.census.gov/geo/www/us_regdiv.pdf*

Study Region Overview

The study area comprised eight disaster-affected states of the Northeast Census Region—Connecticut, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. Various federally declared weather-related disasters hit these states during the years 2011 and 2012, which included Hurricane Irene (2011), Tropical Storm Lee (2011), and Hurricane Sandy (2012). Counties of the state Maine were excluded as it was not hit by any disasters in 2011 and 2012. The average per capita residential damage for this region during 2011-2012 was $57.49. The year 2010 was taken as the baseline year for measuring pre-disaster resources capacity for all the counties in the study region. Out of 210 counties of the disaster affected states in the Northeast Census Region, 194 counties were included in the study due to data availability. The spatial distribution of damages in the Northeast Census Region during the year 2011-2012 is shown in Figure 6.

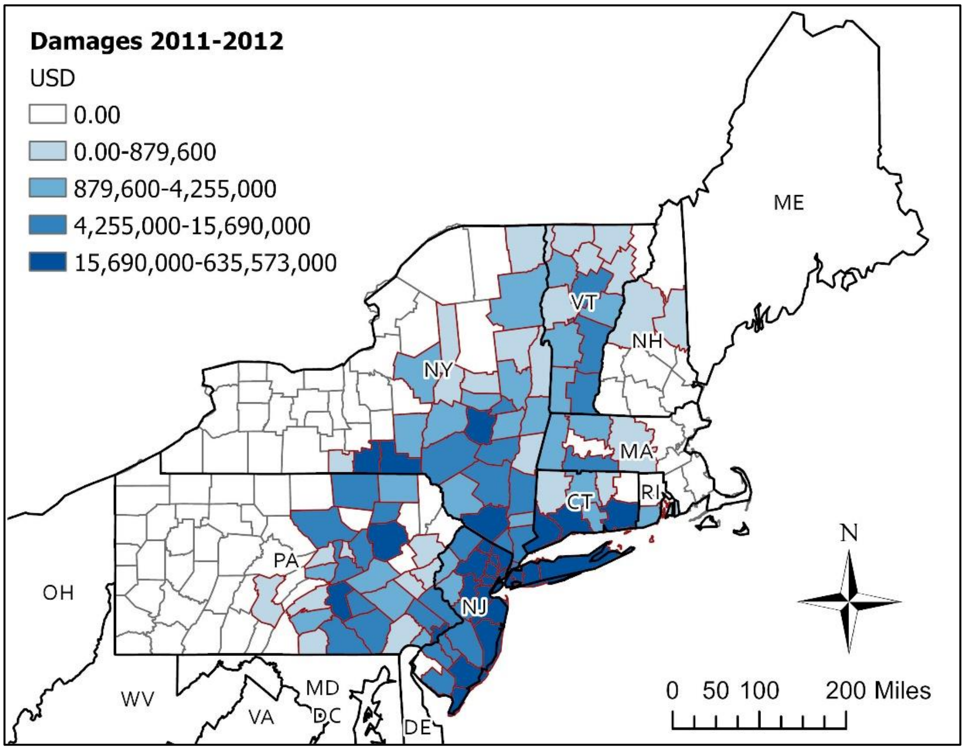

Figure 6: Spatial distribution of residential damages in the Northeast Census Region. *Source: Author*

Data Collection

Disaster-related data

Disaster-related data such as declaration number, disaster type, date of incidence, and declared counties were obtained from the Disaster Declarations Summary Dataset, publicly available from the FEMA website (FEMA, 2019). Damages data such as the number of houses inspected and residential losses were collected for the years 2011 and 2012 from the Archived Housing Assistance Program Data, also publicly available from the FEMA website (FEMA, 2014a). GIS shapefiles of counties of the study region were collected from the *Topographically*

Integrated Geographic Encoding and Referencing (TIGER) files available from the U.S. Census Bureau (U.S. Census Bureau, 2019b). The summary of disaster and residential damages related data is provided in Table 8.

Table 8: Disaster-related data

Dataset	Description	Data availability	Description	Time frame	Source
Disaster Declarations Summary	Lists all federally declared disasters with attributes such as disaster number, declaration date, incident type, incident begin and end date, and declared counties/area	County-level	Disaster number, date of incidents, incident type, and affected counties were key indicators collected from this database.	2011-2012	(FEMA, 2019)
Archived Housing Assistance Program Data	Lists residential damages and Individuals and Households Program (IHP) grant data with attributes such as total inspected houses, damages amount, and total approved IHP amount for owners and rents.	County-level	Disaster number, affected cities at a zip code level for each county, damages amount, and total approved IHP amount were key variables collected from this dataset. Zip code level data for each county were aggregated to obtain the county-level damage and IHP grant data.	2011-2012	(FEMA, 2014a)

Predictor Variables

Two principal categories of predictor variables were collected for this study—socioeconomic resourcing variables and construction industry resourcing variables. The federal government resourcing variable was not considered for this study since it used a common pre-disaster baseline year (i.e., 2010). The federal grant, however, was available only for a disaster year (i.e., after the disaster has occurred). First, data for socioeconomic resourcing variables were collected for the pre-disaster year 2010 from the publicly available dataset provided by the U.S. Census Bureau's ACS 5-year estimates. Socioeconomic resourcing variables included socioeconomic indicators of owner-occupied households such as income, educational attainment, and mortgage status. The 'Income' variable was defined as the median household income of owner-occupied households. Educational attainment represented the percentage of owner-occupied households with the educational attainment of bachelor's degrees or above. Mortgage status was defined as the percentage of owner-occupied housing units with unpaid home mortgages. These variables acted as a resourcing catalyst that either favored or constrained homeowners' capacity to acquire capital resources and broadly measured pre-disaster capital resource availability for homeowners. The study hypothesized that income and educational attainment acted as a positive catalyst, whereas mortgage status acted as a negative catalyst. The summary of socioeconomic predictor variables is provided in Table 9.

Table 9: Socioeconomic resourcing variables

Variable	Symbol	Definition	Data availability	Time frame	Dataset	Source
Income	INCOME	Median household income of owner-occupied householders in U.S. dollars	County-level	2010	ACS 5-year estimates	(U.S. Census Bureau, 2020d)
Educational attainment	EDUCATION	Percentage of owner-occupied householders with a bachelor's degree or above education.	County-level	2010	ACS 5-year estimates	(U.S. Census Bureau, 2020f)
Mortgage status	MORTGAGE	Percentage of owner-occupied housing units with unpaid home mortgages.	County-level	2010	ACS 5-year estimates	(U.S. Census Bureau, 2020b)

Second, data for construction industry resourcing variables were collected for the pre-disaster year 2010 from the Quarterly Census of Employment and Wages (QCEW) data publicly available from the BLS (U.S. Bureau of Labor Statistics, 2019). Construction resourcing variables included: (1) LQ of annual average establishments of NAICS Sector 238 industry; (2) LQ of annual average employment of NAICS Sector 23 industry; and (3) LQ of annual average wholesale establishments of NAICS Sector 423 industry. NAICS Sector 23 represented the construction sector, comprising establishments mainly engaged in buildings, utilities, and infrastructure construction. NAICS 238 represented specialty trade contractor subsector that comprised of establishments primarily involved in building construction. The specialty trade contractor subsector consisted of the following industry groups: Foundation, Structure, and Building Exterior Contractors (NAICS 2381); Building Equipment Contractors (NAICS 2382); and Building Finishing Contractors (NAICS 2383) (U.S. Bureau of Labor Statistics, 2020b). NAICS Sector 423 represented merchant wholesalers engaged in wholesaling durable goods, which also comprised of establishments selling construction materials such as Lumber and wood merchant wholesalers (NAICS 42331), Masonry material merchant wholesalers (NAICS 42332), and Roofing and siding merchant wholesalers (NAICS 42333) (U.S. Bureau of Labor Statistics, 2020a). The construction employment data from the NAICS Sector 23 and the establishment data from the NAICS 238 sector were used because of the data availability as GWR requires data from all the counties of the study region. BLS employment data for the NAICS ‘three-digit’ subsectors were missing for most counties in the study region. Moreover, as the Northeast Census Region sustained unprecedented levels of residential losses, it was expected that construction labor resources would play a crucial role in reconstruction. The summary of construction industry predictor variables is provided in Table 10.

Table 10: Construction industry resourcing variables

Variable	Symbol	Definition	Data availability	Time frame	Dataset	Source
Construction Labor Employment	LQ_EMP	Location Quotient of the annual average employment of the construction sector (NAICS 23)	County-level	2010	Quarterly Census of Employment and Wages (QCEW), U.S. Bureau of Labor Statistics	(U.S. Bureau of Labor Statistics, 2019)
Construction Labor Establishments	LQ_EST	Location Quotient of the annual average establishments of the specialty trade contractors (NAICS 238)	County-level	2010	Quarterly Census of Employment and Wages (QCEW), U.S. Bureau of Labor Statistics	(U.S. Bureau of Labor Statistics, 2019)
Construction Material Wholesale Establishments	LQ_WHOLESALE	Location Quotient of the annual average wholesale establishments of durable goods (NAICS 423)	County-level	2010	Quarterly Census of Employment and Wages (QCEW), U.S. Bureau of Labor Statistics	(U.S. Bureau of Labor Statistics, 2019)

Outcome Variable

Reconstruction outcomes were measured as the change in median home value from pre-disaster to post-disaster period. For counties that were hit by disasters in the year 2011, the reconstruction outcomes were measured as the change in median home values from the year 2010 to 2013, using a two-year reconstruction time frame. For counties that were hit by disasters both in 2011 and 2012, the reconstruction outcomes were measured as the change in median home value from the year 2010 to 2014 to provide one additional year for reconstruction. The description of the outcome variable is provided in Table 11.

Table 11: Outcome variable

Variable	Symbol	Definition	Data availability	Time frame	Dataset	Source
Reconstruction outcomes	%ΔReconstruction	For counties hit by disasters in 2011: Percent change in median home value from the pre-disaster year 2010 to the post-disaster year 2013 For counties hit by disasters in 2011 and 2012: Percent change in median home value from the pre-disaster year 2010 to the post-disaster year 2014	County-level	2010-2014	ACS 5-year estimates	(U.S. Census Bureau, 2020c)

Data Analysis

A multi-step process was conducted to analyze data which included: (1) importing and organizing data in GIS software: (2) development of the global OLS model for the case study region; and (3) development of the GWR model. ArcGIS Pro 2.4 software (ESRI, 2020a) was used for data analysis. First, a datasheet was created in Excel containing all the counties of the study region with their respective predictor and outcome variables. Using ArcGIS Pro, the excel datasheet was linked to county shapefile by using the *Add Join* tool from the Geoprocessing toolbox. *Add Join* tool joins a feature class to excel table based on a common field. Geographic Identifiers (GEOID) was used as a common field to join each county-level data with their respective county shapefile. GEOIDs provide unique code to each administrative, legal, and statistical geographic areas for which the data is tabulated by the Census Bureau (U.S. Census Bureau, 2019b).

Second, the OLS model was developed to establish a global relationship between resourcing variables and residential reconstruction outcomes for the study region. OLS was considered the first step in the modeling process because of three reasons: 1) to select the optimum model for GWR analysis with significantly correlated predictor and outcome variables; 2) GIS toolbox in ArcGIS Pro software does not provide statistics of Variance Inflation Factor (VIF) to access multicollinearity for the GWR model; 3) GWR results can be compared with OLS to decide the best fit model.

The global OLS model is specified using equation 7.

$$\%\,\Delta Reconstruction_i = \beta_o + \sum_k \beta_k Socioeconomic_{ik} + \sum_l \beta_l Construction_{il} + \varepsilon_i \qquad 7$$

where,

$\%\Delta Reconstruction_i$ is the outcome variable, measured as a percent change in median home value from: (1) pre-disaster year 2010 to post-disaster year 2013 at county *i* for counties hit by disasters in the year 2011; (2) pre-disaster year 2010 to post-disaster year 2014 at county *i* for counties hit by disasters in the year 2011 and 2012

$Socioeconomic_{ik}$ represents socioeconomic resourcing variables measured at county *i* for the pre-disaster year 2010

$Construction_{il}$ represents construction resourcing variables measured at county i for the pre-disaster year 2010

β_o represents intercept

β_k and β_l represents the regression coefficients associated with socioeconomic and construction resourcing variables respectively

ε_i are the residuals of the OLS regression

Different combinations of variables used in OLS regression models were compared using the OLS diagnostic report from ArcGIS Pro software. OLS diagnostic report was assessed to check regression coefficients, probability or robust probability, adjusted R-squared values, and Akaike Information Criterion (AICc). Predictor variables with Variance Inflection Factor (VIF) greater than 7.5 was removed from the regression model as variables associated with large VIF are redundant. Statistical significance of the model was assessed through Joint F-statistic and Joint Wald Statistic tests. Joint Wald Statistic was used to determine the overall model significance if the Koenker (BP) statistic was significant. The Koenker (BP) statistic was used to assess if the model's predictor variables had a consistent relationship with the outcome variable across the study region counties. When the Koenker (BP) statistic is statistically significant (p-value <0.05 for a 95 percent confidence level), the relationship between variables indicates non-stationarity (ESRI, 2020c). The Jarque-Bera statistic was used to determine if the residuals were normally distributed. A statistically significant Jarque-Bera statistics show that the residuals are not normally distributed, and key variables are absent from the model (ESRI, 2020c).

Furthermore, Spatial Autocorrelation (Global Moran's I) tool (ESRI, 2020d) was used to determine if the residuals were clustered or random. A statistical method called *Spatial Autocorrelation* tests a variable's association with itself across space (Legendre, 1993). It occurs when data with similar values tend to cluster together rather than provide a random distribution in space. Positive spatial autocorrelation shows similar values clustered together. Negative spatial autocorrelation shows dissimilar values located near similar values. When there is no statistically significant spatial pattern, the spatial autocorrelation would be zero. Global Moran's I statistic was used to measure spatial autocorrelation whose value range from -1 to +1. When the value approaches near to 1.0 or -1.0, a significant spatial autocorrelation is present. A value closer to 0 indicates no spatial autocorrelation. The presence of spatial autocorrelation violates the assumption that the observations are independent of one another and indicates that the model may include spatially varying relationships. After accounting for possibilities of spatial non-stationarity due to the presence of spatial autocorrelation and confirmation with Koenker (BP) statistical analysis, the variables were entered in the GWR model. Only those predictor variables that were significantly correlated with the outcome variable were included in the GWR model. The GWR model is specified by equation 8:

$$\%\Delta Reconstruction_i = \beta_o(u_i, v_i) + \sum_k \beta_k(u_i, v_i) Socioeconomic_{ik} + \sum_l \beta_l(u_i, v_i) Construction_{il} + \varepsilon_i \quad 8$$

where,

(u_i, v_i) are the coordinates of the centroid of the county i

$\beta_o(u_i, v_i)$ is the intercept for county i

$\beta_k(u_i, v_i)$ and $\beta_l(u_i, v_i)$ are the regression coefficients associated with socioeconomic and construction resourcing variables respectively. The regression coefficients are a function of geographical coordinates (u_i, v_i)

ε_i are the residuals

Model Selection Parameters

ArcGIS Pro offers three types of GWR models—Continuous (Gaussian), Binary (Logistic), and Count (Poisson) (ESRI, 2020b). A continuous model type is used when the outcome variable can take a wide range of values. Binary model type is used when the outcome variable takes the binary form, such as ones and zeros, to denote success/failure or presence/absence. Count model type is used when the outcome variable represents the number of occurrences of an event such that the values are non-negative and does not contain decimals.

In ArcGIS Pro-environment, bandwidth is called a *neighborhood* whose shape and extent are analyzed based on two parameters: (1) Neighborhood Type, and (2) Neighborhood Selection Method (ESRI, 2020b). Neighborhood Type can be selected based on either *Number of Neighbors* (similar to adaptive kernel) or *Distance Band* (similar to Fixed kernel). Next, the Neighborhood Selection Method determines the parameters for selecting the size of the neighborhood which is classified into three types—*Golden search*, *Manual interval*, and *User-defined*. *Golden search* and *Manual interval* method are based on minimizing the Akaike Information Criterion (AICc). *Golden search* determines the best values for fixed or adaptive kernels by finding the maximum and minimum distances and testing the AICc at various distances incrementally between them. ArcGIS Pro provides two types of distance-decay function or weighing scheme—Gaussian and Bisquare (ESRI, 2020b). In a Gaussian weighting scheme, a weight of one is assigned to one of the regression features such that the weights for the surrounding features exponentially decrease as the distance from the regression feature increase. Bisquare weighting scheme works similarly as Gaussian scheme with an exception that the influence of features lying outside of the specified neighborhood on the target feature will be null.

The model selection parameters are shown in Table 12. For this study, the model type was *Continuous* since the dependent variable encompassed a wide range of values. Bandwidth selection was made using the *Number of Neighbors* criteria or *Adaptive Kernel* to account for the variation of the size of counties. The *Golden search* method was used to determine the optimal size of the bandwidth which is based on minimizing the AICc. *Bisquare* weighing scheme was used to ensure that only the neighboring counties lying in close proximation to the disaster-affected counties contributed to the estimation of regression coefficients. The spatial autocorrelation of GWR residuals was tested using Global Moran's *I* index. The GWR model was compared to the OLS model using AICc score. The lower AICc and higher R-squared suggest better fitting of the GWR model (Fotheringham et al., 2002). Finally, the GWR coefficients were mapped using ArcGIS Pro and the results were analyzed.

Table 12: GWR model selection parameters

Parameter	Selection	Justification
Bandwidth	Number of neighboring counties	Accounts for the differing size of counties
Bandwidth type	Adaptive	
Optimum bandwidth	Minimization of AICc	Model with minimum AICc is the best fit model (Fotheringham et al., 2002)
Local weighing scheme	Bisquare	Counties falling outside the specified bandwidth are assigned zero weights

CHAPTER IV: RESULTS

This chapter presents the results of the Global OLS model and the local GWR models. The analysis is divided into two parts. The first part discusses the results of the Global OLS regression model for multi-year disaster-affected counties. The second part discusses the findings of the local GWR model constructed for the case study region. The results of OLS and GWR models are presented and compared. Finally, the local parameter estimates are mapped and analyzed.

The Global OLS Model

Descriptive Statistics

Table 13 presents the descriptive statistics of each variable using 621 disaster-affected counties of the U.S. between 2007-2015. These counties incurred substantial residential damages with per capita residential damages of owner-occupied housing units exceeding countywide Per Capita Impact Indicator published by FEMA for every federal fiscal year. Counties that were hit by more than one disaster in a period starting from two years prior to the major disaster to two years after the major disaster were removed from the analysis. This was done to remove the effects of multiple or overlapping hazard events on pre-disaster resource availability and post-disaster reconstruction outcomes. The average growth rate in median home value from pre-disaster year to post-disaster year for counties under the study was 4.63% with minimum and maximum values of -14.09% and 24.02%, respectively. The average median household income was $56,217. Median household income varied from $31,140 to $137,984 with a standard deviation of $13,568 in the counties under study. The average percentage of owner-occupied households with the educational attainment of a bachelor's degree or higher was 24.98%. The average unemployment rate of the population over 16 years was 7.59%. The average percentage of owner-occupied households with a mortgage status was 61.01%. Finally, the average LQ of construction employment (NAICS 238) was 0.96 while the average LQ of material wholesale establishments (NAICS 423) was 0.90. The average FEMA IHP grant was over $3 million.

Table 13: Descriptive statistics

Variable	Min.	Max.	Mean	S.D
IHP	8,161.51	118,533,102	3,161,980	10,232,019.55
INCOME	31,140.00	137,984.00	56,216.66	13,567.53
EDUCATION	8.12	82.20	24.98	10.71
MORTGAGE	35.37	86.00	61.01	9.77
UNEMP	2.10	19.50	7.59	2.37
LQ_EMP	0.08	6.15	0.96	0.49
LQ_WHOLESALE	0.15	2.44	0.90	0.31
%ΔRECONSTRUCTION	-14.09	24.02	4.63	5.94

OLS Results

Table 14 highlights the ANOVA results, which show the overall fit of the regression equation with the data. The p-value associated with the F value was statistically significant ($p < 0.05$) which showed that the regression model significantly predicted the outcome variable. In other words, the results indicated an overall model fit.

Table 14: ANOVA Results

Model	Sum of Squares	df	Mean Square	F value	p-value
Regression	6863.066	7	980.438	39.909	0.000*
Residual	15059.467	613	24.567		
Total	21922.533	620			

Table 15 shows the summary statistics of the OLS results.

Table 15: OLS results summary

Variable	Coefficient	Std. Error	t value	Pr (>|t|)	VIF
Intercept	28.228	1.735	16.266	0.000000*	-
IHP	0.001	0.002	0.467	0.640	1.065
INCOME	-0.0001729	0.00	-5.621	0.000000*	4.396
EDUCATION	0.097	0.034	2.828	0.005*	3.409
MORTGAGE	-0.246	0.031	-7.960	0.000000*	2.309
UNEMP	-0.666	0.091	-7.329	0.000000*	1.170
LQ_WHOLESALE	3.044	0.679	4.483	0.000000*	1.144
LQ_EMP	1.057	0.431	2.454	0.014*	1.117
Adjusted R-Squared		0.305	Std. Error of the Estimate		4.956
Multiple R-Squared		0.313	Durbin-Watson		1.438

** indicates a statistically significant value $p < 0.05$*

The adjusted R-squared value was 0.305, which showed that the model accounted for around 31% of the variance in median home value growth rates through resourcing variables. The coefficients denote a change in median home value growth rates from the pre-disaster period to the post-disaster period for one unit of change in the predictor variable while other predictor variables are held constant. *EDUCATION* (0.097), *LQ_WHOLESALE* (3.044), and *LQ_EMP* (1.057) showed a positive and statistically significant correlation (p-value<0.05) with median home value growth rates (*%ΔRECONSTRUCTION*). This showed that an increase in the pre-disaster educational attainment of households positively influenced post-disaster median home value growth rates. Construction material and labor availability were the positive drivers of reconstruction outcomes. For instance, an increase in pre-disaster LQ of construction labor in the disaster-affected county by 0.1 would increase the median home value growth rates by 0.11%. An increase in pre-disaster LQ of wholesale establishments of durable goods by 0.1 would increase the median home value growth rates by 0.30%. *INCOME* (-0.0001729), *MORTGAGE* (-0.246), and *UNEMP* (-0.666) showed a negative and statistically significant relationship (p-value<0.05) with median home value growth rates. An increase in pre-disaster median household income, unemployment rate, or households with unpaid home mortgages negatively influenced the median home value growth rates. FEMA IHP grant was positively correlated with reconstruction outcomes (β=0.001). However, the relationship was not statistically significant (p-value=0.640).

The results generalized the influence of resourcing factors on residential reconstruction outcomes at a regional scale. Pre-disaster construction labor and material availability significantly and positively influenced post-disaster residential reconstruction outcomes in the disaster-affected counties under study. Pre-disaster socioeconomic characteristics of households such as educational attainment acted as a positive catalyst while unpaid mortgage status and unemployment acted as a negative catalyst for accessing capital resources by homeowners. As a result, higher educational attainment positively drove median home value growth rates while mortgage status and unemployment rate impeded the growth rates. Counterintuitively, income showed a negative correlation with reconstruction outcomes. FEMA IHP grant had a positive correlation with reconstruction outcomes as expected. However, it did not show a statistically significant relationship.

Diagnosis of Model Assumptions

The assumptions of the linear regression model are linearity, multicollinearity, homoscedasticity, and normality. These assumptions were tested using diagnostic plots of the residuals and statistical tests.

Linearity

Figure 7 shows the scatterplot of the standardized residuals vs. the fitted values. The residuals were well dispersed around the mean of zero, and no patterns were detected.

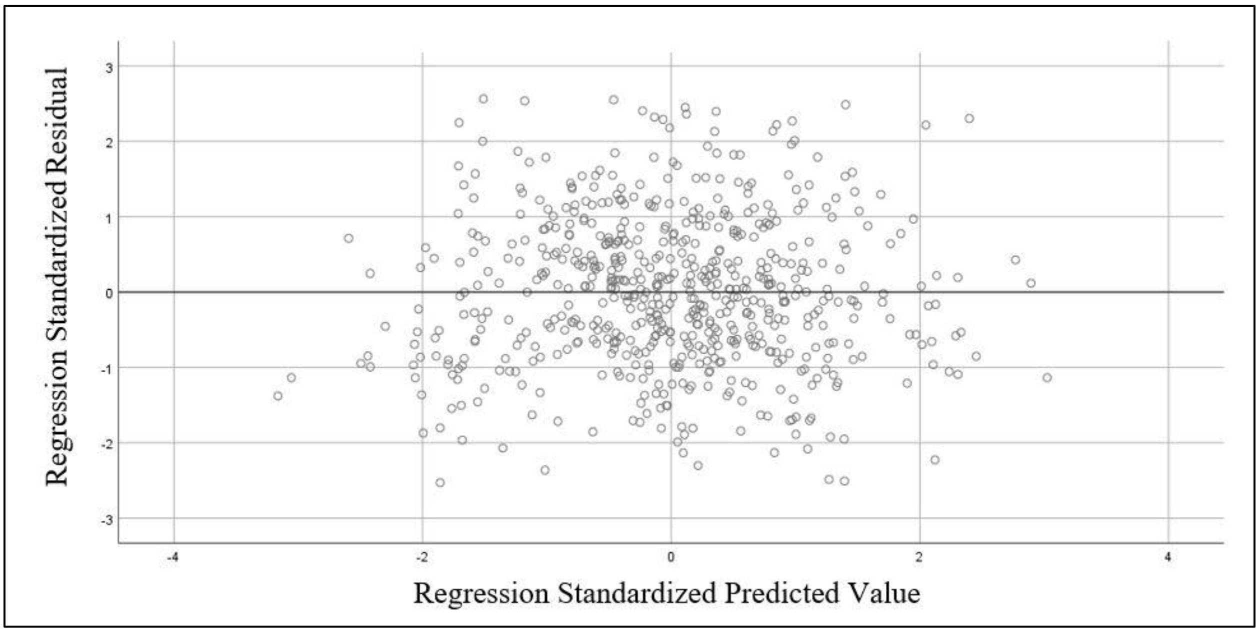

Figure 7: Scatter plot of standardized residuals

Multicollinearity

Multicollinearity occurs when the predictor variables in a regression model are highly correlated (Thompson et al., 2017). The presence of multicollinearity reduces the precision of the estimation of coefficients, makes it very sensitive to small changes in the model, and makes it difficult to assess the relative importance of predictor variables in explaining the variation caused by the outcome variable. Variance Inflation Factor (VIF) was used to test the multicollinearity. A VIF greater than 10 indicates the presence of multicollinearity (Woodward et al., 1994). The VIF for each predictor variable was calculated and shown in Table 15. The VIF's for each predictor variable was found to be less than five, which indicated that no multicollinearity was present.

Normality

One of the assumptions of the linear regression is that error (residuals) follows a normal distribution. The Normal probability plot or a P-P plot was generated to test the normality of the residuals, where the observed cumulative distribution function (CDF) of the standardized residual was compared with the expected CDF of the normal distribution. The P-P plot given in Figure 8 shows that the points cluster around the horizontal line indicating the normality of residuals. Besides, the Shapiro-Wilk test and the Anderson-Darling test was used to test the normality of residuals. The null hypothesis of these tests was the normal distribution of the residuals. A p-value below 0.05 results in null hypothesis rejection. The summary of the Shapiro-Wilk test and the Anderson-Darling test is shown in Table 16. The null hypothesis was not rejected for the OLS model in both the tests.

Table 16: Normality tests

Shapiro-Wilk test		**Anderson-Darling test**	
W-value	p-value	A-value	p-value
0.99529	0.05593	0.54089	0.1646

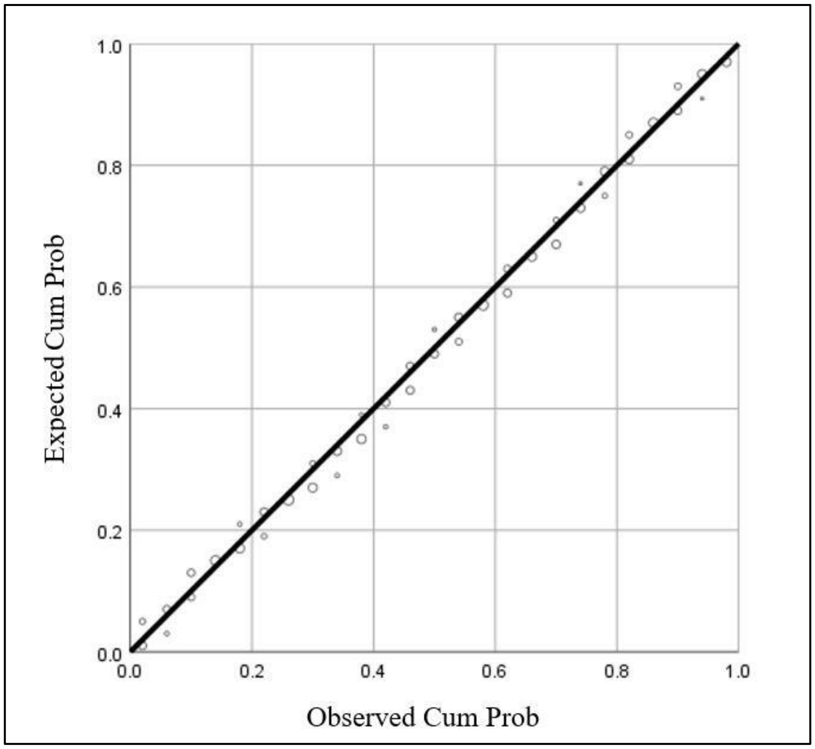

Figure 8: Normal P-P plot of standardized residual

Homoscedasticity

In multiple linear regression, the error term must be the same across all values of the independent variables, the condition called homoscedasticity. Heteroscedasticity is the violation of homoscedasticity that arises when the size of the error term varies across values of an independent variable. Homoscedasticity was tested using the Breusch-Pagan (BP) test. A null hypothesis of this test was that the variance for all observation was the same. A p-value less than 0.05 results in the rejection of the null hypothesis. The results of the BP test are shown in Table 17. The null hypothesis for this test was not rejected for the OLS model. The scale-location plot of the residuals is shown in Figure 9 which shows the random spread of the residuals. The average magnitude of the standardized residuals was not found to be varying as a function of the fitted values. This further substantiates the absence of heteroscedasticity in the model.

Table 17: Homoscedasticity test

Studentized Breusch-Pagan test		
BP value	df	p-value
10.48	7	0.163

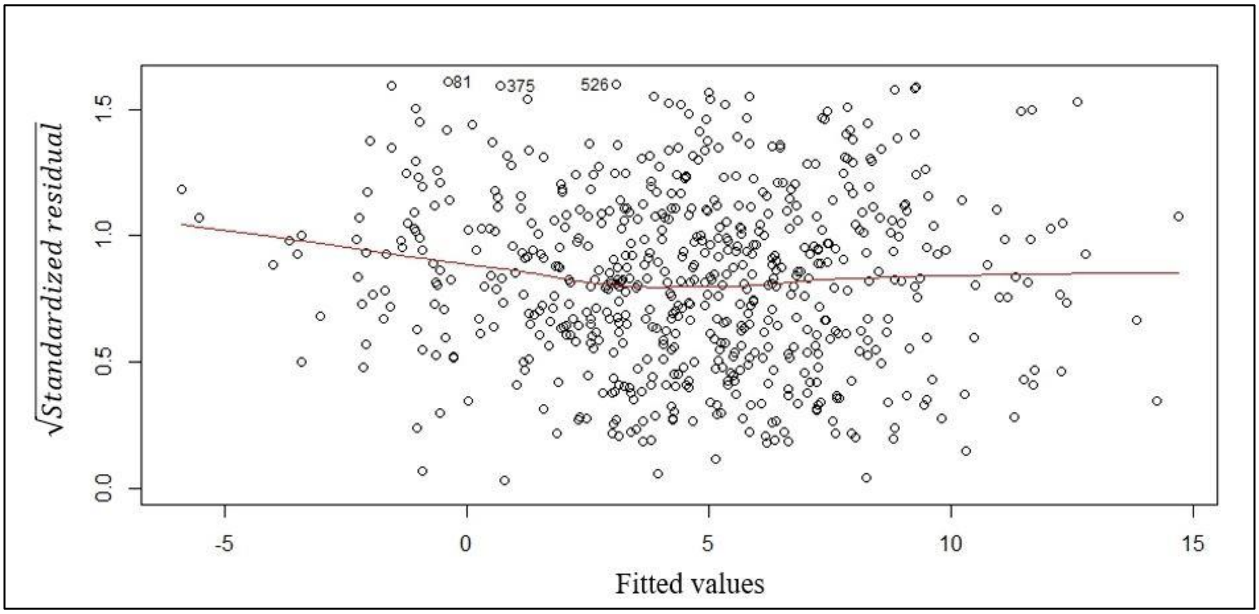

Figure 9: Scale-location plot

The Local GWR Model

Descriptive Statistics

The descriptive statistics of each variable from the 194 counties of the Northeast Census Region is shown in Table 18. The average median home value growth rate from the pre-disaster period to the post-disaster period for this region from 2010 to 2014 was 0.84%. This was less than the average growth rate in median home value for the contiguous U.S. from 2010 to 2014, i.e., 2.8%. The growth rate in pre-disaster median home values from 2009 to 2010 for the study region was 2.5%, while the average annual growth rate in post-disaster median home values from 2010 to 2014 was 0.17%. The trajectory of home value growth rates for the study region is shown in

Figure 10. The annual growth rates started to drop, starting from the disaster year 2011 and continued till 2013. The annual growth rates started to climb from the year 2014. The effect of the catastrophic events on the home value trajectory is visible from the figure. The average median income for owner-occupied households in the study region was $66,358 with a standard deviation of $17,502 during the pre-disaster year 2010. Counties in the study region varied to a good extent in terms of median household income. The average percentage of owner-occupied households with the educational attainment of a bachelor's degree or above was 31.07% in 2010, while the average percentage of households with unpaid home mortgages was 63.24%. The average LQ of material wholesale establishments was 0.78 in the year 2010. The average LQ of construction employment and establishments in the study region was 0.92 and 1.12, respectively, during the year 2010. The average LQ of the construction establishments of specialty trade contractors in the study region was higher than the LQ of the whole U.S. (i.e., 1). This highlights that the regional construction market had a higher concentration of establishments related to specialty trade contractors compared to the national average.

Table 18: Descriptive statistics

Variable	Min.	Max.	Mean	S.D
INCOME	36,163.00	134,116.00	66,358.48	17,501.78
EDUCATION	11.09	82.04	31.07	11.84
MORTGAGE	39.11	78.10	63.24	7.78
LQ_WHOLESALE	0.09	1.52	0.78	0.27
LQ_EMP	0.30	3.33	0.92	0.35
LQ_EST	0.17	2.47	1.12	0.32
%ΔRECONSTRUCTION	-16.36	17.90	0.84	7.63

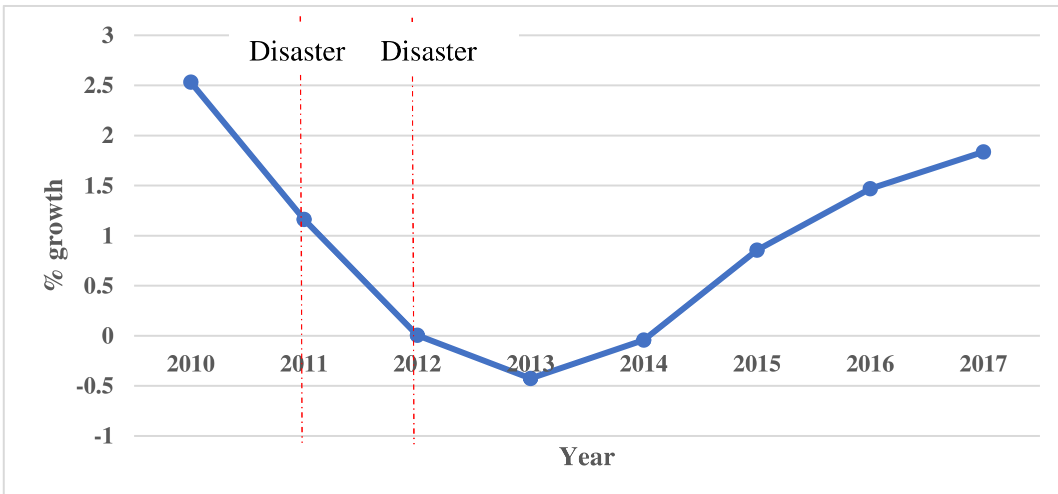

Figure 10: Annual median home value growth rate trajectory in the Northeast Census Region

Exploratory Spatial Analysis of Resource Availability

The spatial distribution of the three construction industry resourcing variables (i.e., LQ of wholesale establishments, LQ of construction employment, and LQ of construction establishments) is shown in Figure 11, Figure 12, and Figure 13, respectively. The spatial patterns show that the availability of construction resources varied across the study region counties. The spatial heterogeneity in the distribution of construction resources aligns with the findings of Arneson (2018) that construction capacity varies geographically across the U.S. regions because of the regional supply chain availability of labor and materials. Compared to the spatial patterns of material wholesale establishments and construction employment, it was observed that most of the counties in the study region had LQ for construction establishments greater than 1, revealing the higher concentration of pre-disaster construction establishments.

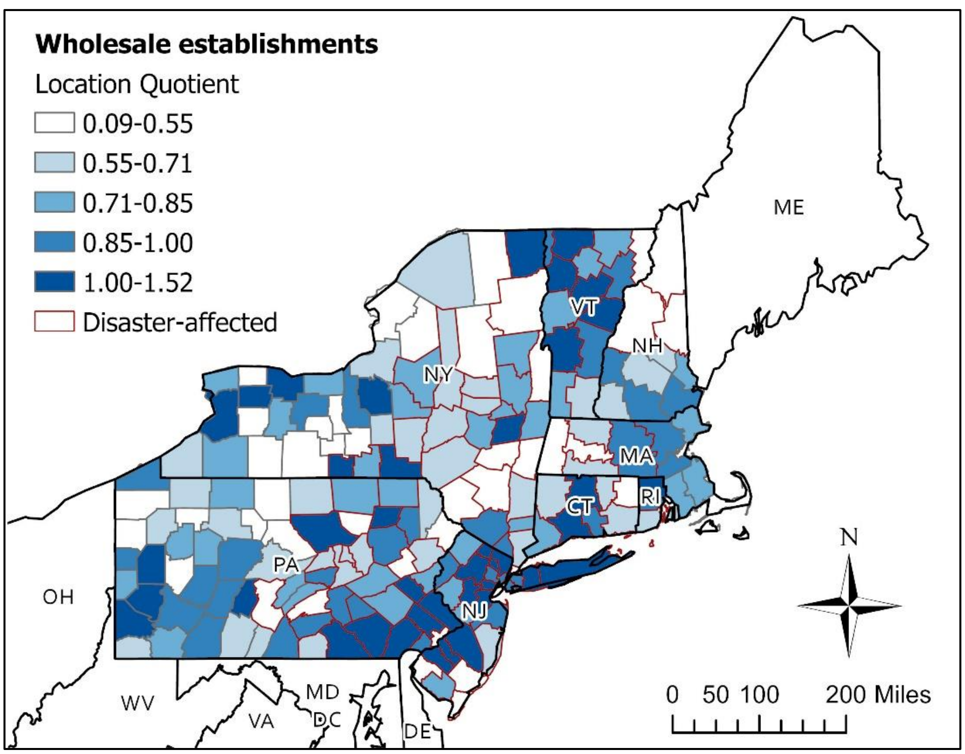

Figure 11: Spatial distribution of LQ of wholesale establishments

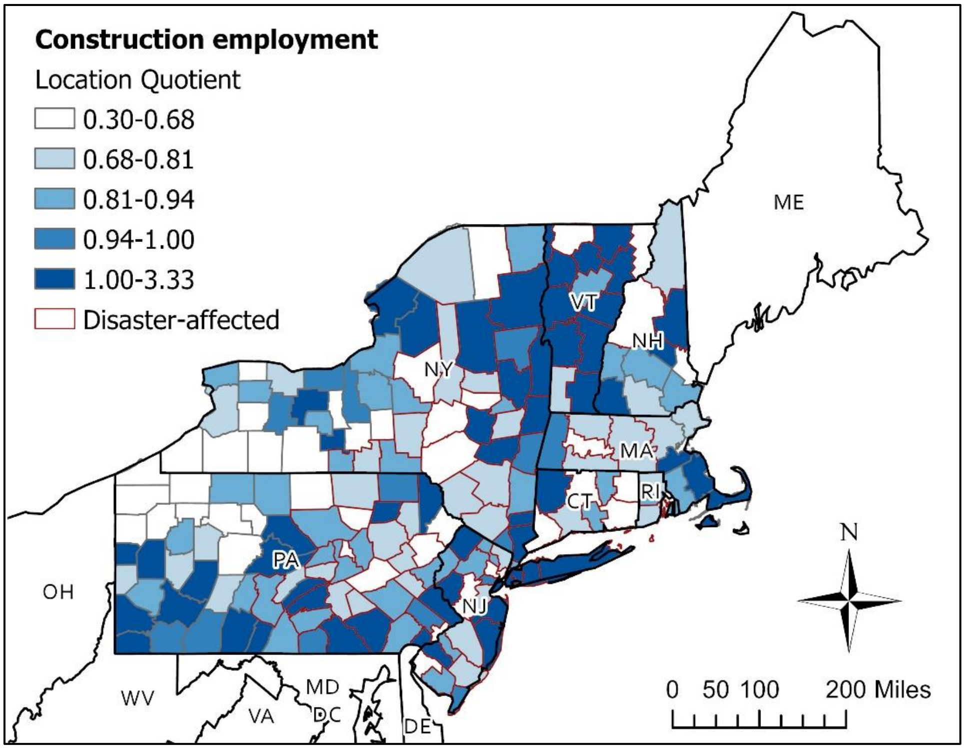

Figure 12: Spatial distribution of LQ of construction employment

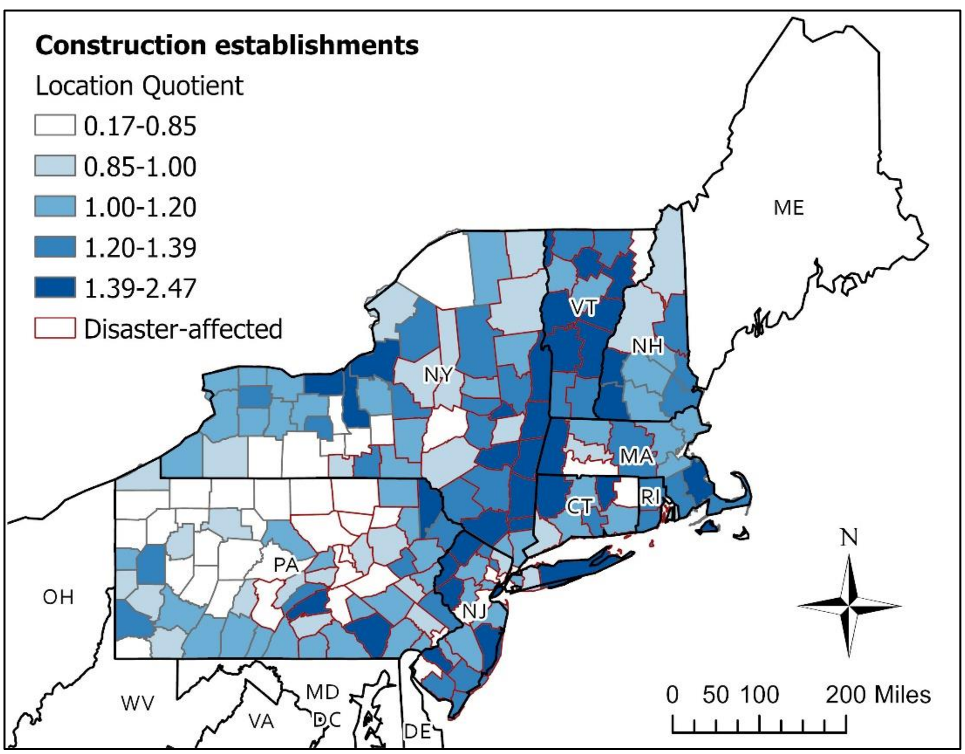

Figure 13: Spatial distribution of LQ of construction establishments

The spatial distribution of the three socioeconomic resourcing variables (i.e., median household income, mortgage status, and educational attainment) is shown in Figure 14, Figure 15, and Figure 16, respectively. The spatial patterns show distinct geographic variations of the socioeconomic characteristics of households. Most of the counties located near the east coast were urban counties and part of the Metropolitan Statistical Areas (MSAs) located in this region. High-income homeowners and households with higher educational attainment were found to be concentrated near the east coast. Also, counties closer to the east coast had higher percentage of households with home mortgages.

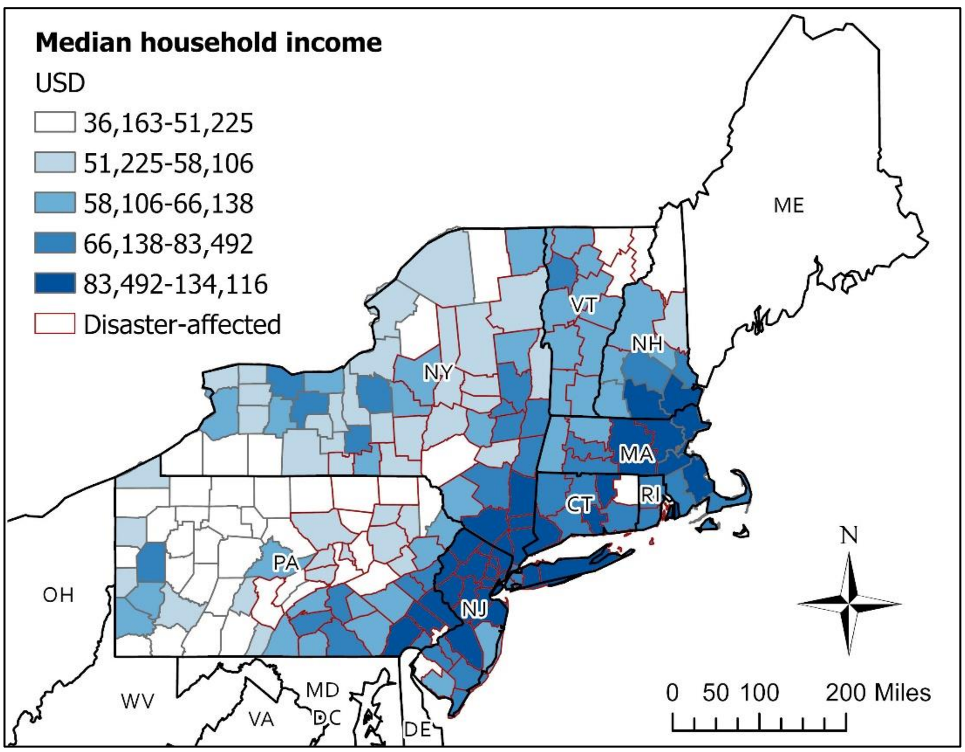

Figure 14: Spatial distribution of median household income

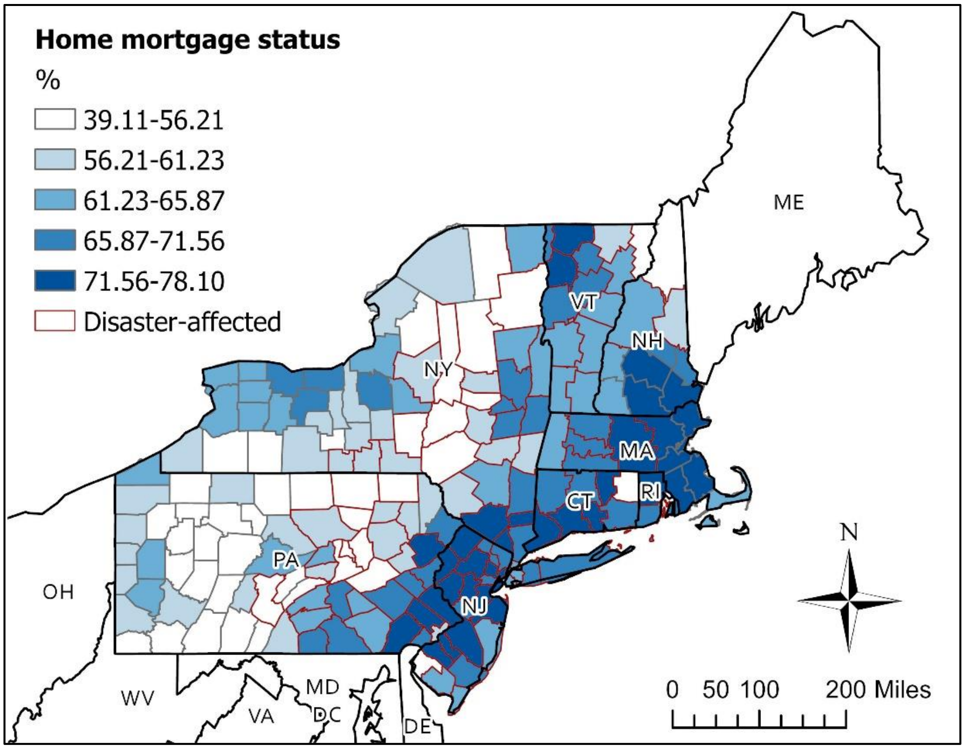

Figure 15: Spatial distribution of % of households with a home mortgage

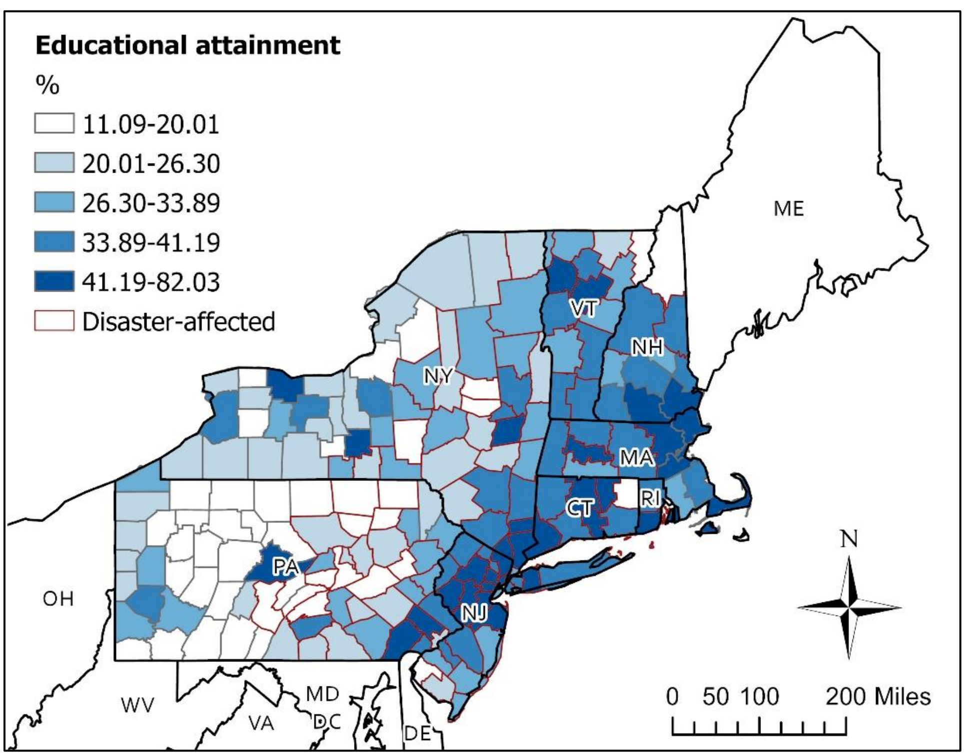

Figure 16: Spatial distribution of % of households with bachelor's degree or above education

OLS Results

The statistical output of the variables from the OLS is shown in Table 19. The adjusted R^2 value was 0.59, which meant that the model was able to explain around 59% of the variance in post-disaster median home value growth rates through construction and capital resourcing factors. The adjusted R-squared value indicated a relatively good model fit of the OLS model. The coefficients denote a change in median home value growth rates from the pre-disaster period to the post-disaster period for one unit of change in the predictor variable while holding other predictors in the model constant. Educational attainment of households (β=0.18), LQ of construction employment of NAICS Sector 23 (β=2.71), and LQ of material wholesale establishments of NAICS Sector 423 (β=5.73) had a positive and statistically significant relationship (p-value<0.05) with reconstruction outcomes (%Δ*RECONSTRUCTION*). An increase in pre-disaster construction labors, material wholesale establishments, or households with at least a bachelor's degree education had a positive effect on median home value growth rates. Median household income (β=-0.000338*)*, mortgage status (β=-0.28), and LQ of construction establishment of NAICS 238 (β=-3.84) had a negative and statistically significant correlation (p-value<0.05) with reconstruction outcomes (%Δ*RECONSTRUCTION*). An increase in pre-disaster median household income, construction establishments, or unpaid home mortgages had a negative effect on median home value growth rates.

Joint F-statistics and Joint Wald Statistics were statistically significant which indicated a significant linear relationship between the predictor variables and the outcome variable. The Jarque-Bera Statistic was not statistically significant, which meant that the residuals were normally distributed, the model was not biased, and all the key variables were included in the model. Koenker (BP) statistic was statistically significant for this model which meant the relationships exhibited signs of spatial nonstationarity. In other words, the relationships between resourcing factors and reconstruction outcomes varied across the study region counties. No multicollinearity was present as all the variables had a VIF less than 7.5.

The spatial distribution of standardized residuals of the OLS model, shown in Figure 17, indicates a clustered pattern. Table 20 shows the Spatial Autocorrelation results which yielded a Global Moran's *I* index of 0.279 with a z-score of 7.614. The results indicate the presence of spatial autocorrelation among the standardized residuals of the OLS model.

Table 19: OLS Results Summary

Variable	Coefficient	Std Error	t-Statistic	Probability	Robust SE	Robust t	Robust P	VIF
Intercept	32.602623	3.549344	9.185534	0.000000*	4.423302	7.370652	0.000000*	-
INCOME	-0.000338	0.000051	-6.622205	0.000000*	0.000044	-7.676860	0.000000*	6.400528
EDUCATION	0.188404	0.067848	2.776871	0.006047*	0.065134	2.892579	0.004277*	5.166328
MORTGAGE	-0.282665	0.086816	-3.255922	0.001352*	0.107444	-2.630802	0.009223*	3.658551
LQ_EMP	2.716352	1.300069	2.089390	0.038018*	1.367653	1.986141	0.048475*	1.671244
LQ_EST	-3.842435	1.629274	-2.358372	0.019377*	1.657074	-2.318808	0.021475*	2.155797
LQ_WHOLESALE	5.739948	1.461583	3.927212	0.000128*	1.400411	4.098758	0.000067*	1.233631
Number of observations			194	**Akaike's Information Criterion (AICc)**				1177.722
Multiple R-Squared			0.599005	**Adjusted R-Squared**				0.586139
Joint F-Statistic			46.556695	**Prob (>F), (6187) degrees of freedom**				0.000000*
Joint Wald Statistic			407.580251	**Prob (>chi-squared), (6) degrees of freedom**				0.000000*
Koenker (BP) Statistic			13.845754	**Prob (>chi-squared), (6) degrees of freedom**				0.031407*
Jarque-Bera Statistic			0.416062	**Prob (>chi-squared), (2) degrees of freedom**				0.812182

* indicates a statistically significant p-value ($p< 0.05$)

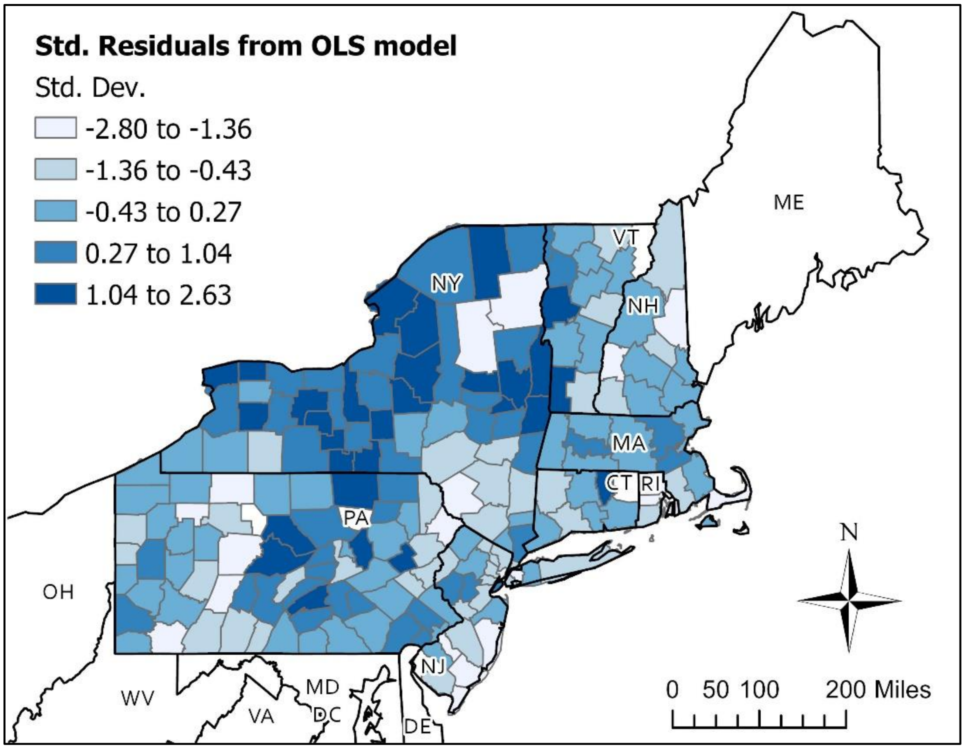

Figure 17: Spatial distribution of OLS standardized residuals

Table 20: Global Moran's I Summary for OLS standardized residuals

Parameter	**Value**
Moran's Index	0.279382
Expected Index	-0.005181
Variance	0.001397
z-score	7.614237
p-value	0.000000

GWR Results

The variables *INCOME*, *EDUCATION*, *MORTGAGE*, *LQ_EST*, *LQ_EMP*, and *LQ_WHOLESALE* were used to construct the GWR model as they had statistically significant correlations with reconstruction outcomes. The GWR model used 61 neighbors from each of the 194 regressed polygons. The results of the GWR is given in Table 21. While the OLS model (R-squared=0.59) obscured a geographic distribution of local associations between resourcing factors and housing reconstruction outcomes, GWR unmasked the local relationships and explained 80% (Adjusted R-Square = 0.80) of the variation in median home value growth rates. The AICc value of the GWR model was 1087.82.

Table 21: GWR results

Parameter	Estimate
R-squared	0.8604
Adjusted R-squared	0.7952
AICc	1087.82
Sigma-Squared	11.84
Sigma-Squared MLE	8.09
Effective degrees of freedom	132.60

Figure 18 shows the distribution of standardized residuals for the GWR model which indicates a random pattern. The Global Moran's *I* index was 0.041046 with a z-score of 1.24, as shown in Table 22. Given the z-score of 1.24, the pattern was random. In other words, no spatial autocorrelation was present.

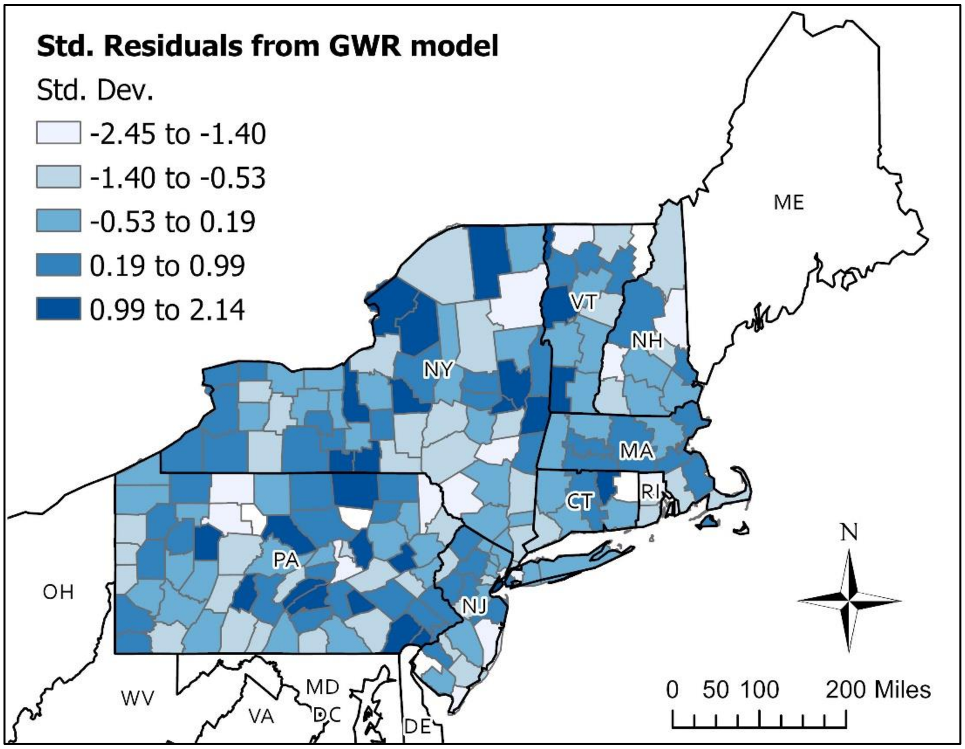

Figure 18: Spatial distribution of GWR standardized residuals

Table 22: Global Moran's I Summary for GWR standardized residuals

Parameter	**Value**
Moran’s Index	0.041046
Expected Index	-0.005181
Variance	0.001398
z-score	1.236449
p-value	0.216292

Table 23 shows the comparison between OLS and GWR model. The GWR model was a better fit than the OLS model. First, the adjusted R-Squared increased from 0.59 in the OLS model to 0.80 in the GWR model. Second, the AICc of the GWR model was smaller compared to the OLS model. Finally, no spatial autocorrelation was present in the GWR model which indicated that the GWR model was properly conducted.

Table 23: Comparison between OLS and GWR models

Parameter	OLS model	GWR model
Adjusted R-Squared	0.59	0.80
Akaike's Information Criterion (AICc)	1177.722	1087.82
Moran's I	0.279382	0.041046
Spatial autocorrelation of standardized residuals	Yes	No

The GWR model constructed separate regression equations for each county of the study region, thereby producing R-Squared value and local coefficients for each of the regressed counties. Table 24 shows the summary of the GWR parameters. The change in both the magnitude and direction of coefficients indicated that the relationships between resourcing factors and reconstruction outcomes varied across the study region counties.

Table 24: Summary of local GWR coefficients in the Northeast Census Region

Parameter	OLS	GWR	
		Min.	**Max.**
R-Squared	0.59 (Adjusted)	0.23 (Local)	0.89 (Local)
β_{k1} (INCOME)	-0.000338	-0.000414	0.000542
β_{k2} (EDUCATION)	0.188404	-0.53	0.55
β_{k3} (MORTGAGE)	-0.282665	-0.90	0.55
β_{l1} (LQ_EMP)	2.716352	-2.00	11.61
β_{l2} (LQ_EST)	-3.842435	-11.06	3.95
β_{l3} (LQ_WHOLESALE)	5.739948	-4.90	12.59

Local R-Squared Estimates for the GWR Model

Figure 19 highlights the distribution of local R^2 across the study region counties. The local R-Squared varied from 0.23 to 0.89 across the study region counties. The median local R^2 for the disaster-hit counties in the Northeast Census Region was 0.70, while the lower and upper quartile was 0.62 and 0.78, respectively. The GWR model had a strong explanatory power (local R^2 greater than 0.70) in more than 50% of the disaster-hit counties of this region. The counties in New Jersey hit by Hurricane Sandy in 2012 had local R^2 ranging from 0.65 to 0.84. While the OLS model had estimated a single R^2 value for the entire study region, the GWR model revealed the spatial variation of the local R^2. The GWR model seemed less able to explain the observed reconstruction outcomes in the counties not affected by disasters. The spatial patterns of local R^2 highlighted that socioeconomic and construction industry resourcing variables were the drivers of the residential reconstruction outcomes in the study region.

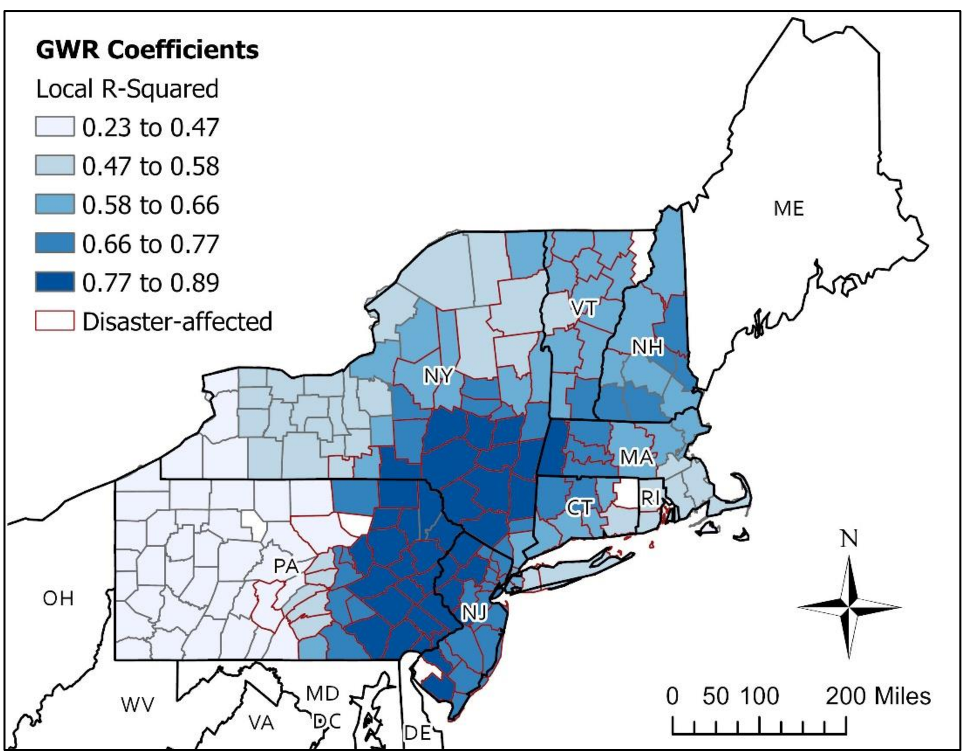

Figure 19: Spatial distribution of local R-squared

Local Estimates for INCOME

Figure 20 shows the spatial distribution of local GWR coefficients for *INCOME*. The range of GWR coefficients in the study region varied from -0.000414 to 0.000542. Except for a few disaster-affected counties in Massachusetts, New York, and Rhode Island states, most of the disaster-affected counties showed a negative range of GWR coefficients for *INCOME.* The negative correlation between *INCOME* and reconstruction outcomes can be attributed to the spatial distribution of median income across the study region where disaster-affected urban counties near to the east coast had high values of median income compared to rural counties in the west.

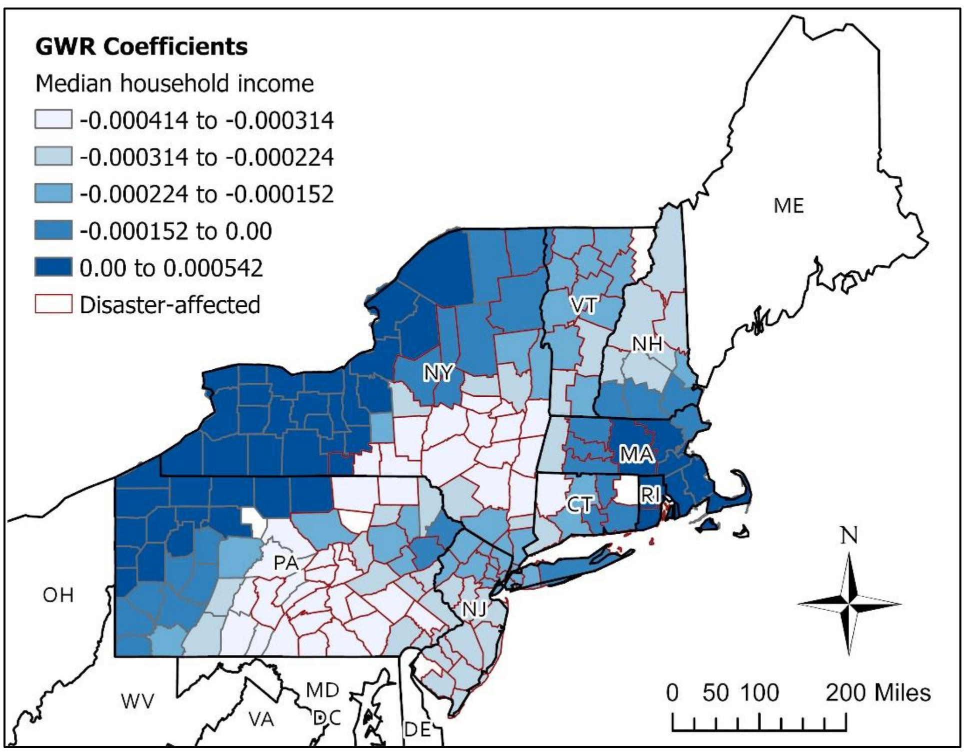

Figure 20: Spatial distribution of GWR coefficients for INCOME

Local Estimates for EDUCATION

The spatial distribution of local GWR coefficients for *EDUCATION* is shown in Figure 21. The global coefficient for *EDUCATION* in the entire study region was 0.18, as given by the OLS model. However, the GWR coefficients varied from -0.53 to 0.55 in the study region. The median GWR coefficient for *EDUCATION* in the disaster-affected counties was 0.25, while the lower and upper quartile was 0.019 and 0.30 respectively. More than 50% of the disaster-hit counties had a GWR coefficient greater than 0.25. Only 22% of the disaster-affected counties had a negative range of GWR coefficients. Among the top 25% of the counties with GWR coefficients greater than 0.30, most of the counties were from Pennsylvania state. The findings show that the influence of educational attainment on reconstruction outcomes varied across the study region counties, while most disaster-affected counties showed a positive range of GWR coefficients.

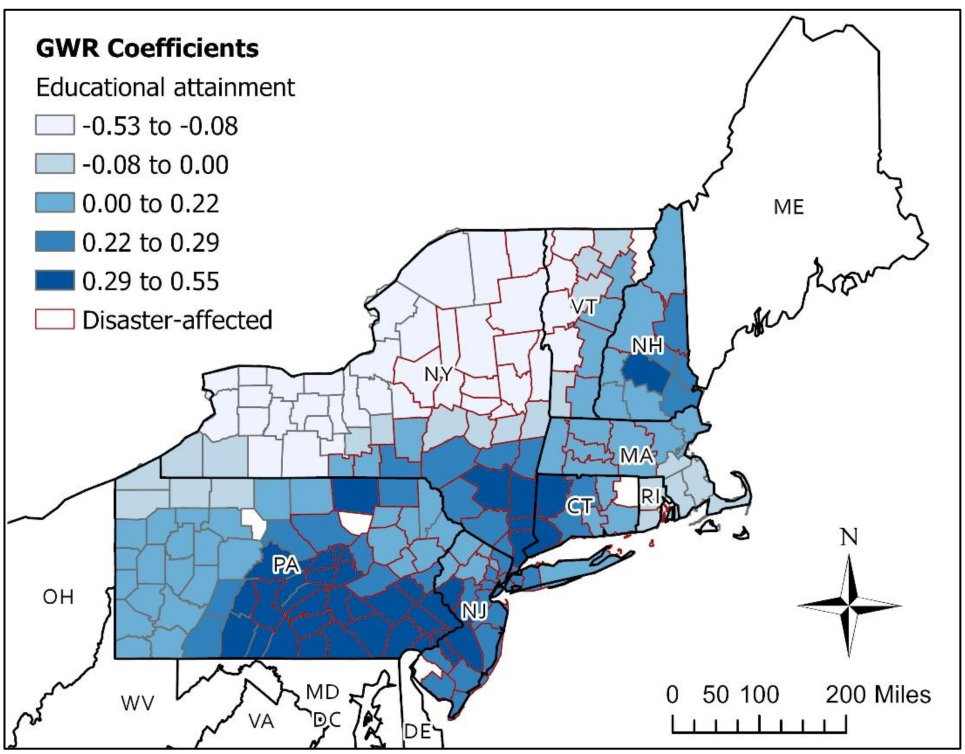

Figure 21: Spatial distribution of GWR coefficients for EDUCATION

Local Estimates for MORTGAGE

Figure 22 shows the spatial distribution of local GWR coefficients for *MORTGAGE*. The GWR coefficients varied from -0.90 to 0.55 across the study region. The median GWR coefficient for *MORTGAGE* in disaster-affected counties was -0.35. The lower quartile was -0.14 while the upper quartile was -0.48. In more than 75% of the disaster-hit counties, *MORTGAGE* showed a negative range of GWR coefficients. The spatial patterns of the home mortgage status (Figure 15) showed that counties near to the east coast had a higher percentage of households with unpaid home mortgages. The GWR model showed a strong range of negative correlations between *MORTGAGE* and reconstruction outcomes in counties near to the east coast. To test the relationships between the percentage of households with a home mortgage and local GWR coefficients for *MORTGAGE*, a Pearson correlation test was conducted using 97 disaster-affected counties of the study region with local GWR coefficients ranging from 0.00 to -0.90. The results of the test are presented in Table 25. A significant negative relationship was found between the percentage of households with a mortgage status *MORTGAGE* and local GWR coefficients for mortgage status β_{k3} *(MORTGAGE)* [r(97)=-0.223, p=0.05]. This shows that counties with a higher percentage of unpaid home mortgages were associated with lower GWR coefficients for *MORTGAGE* (i.e., coefficients approaching negative values). The findings reveal that the home mortgage status had a spatially varying influence on reconstruction outcomes with most disaster-affected counties showing a negative range of local correlations with reconstruction outcomes.

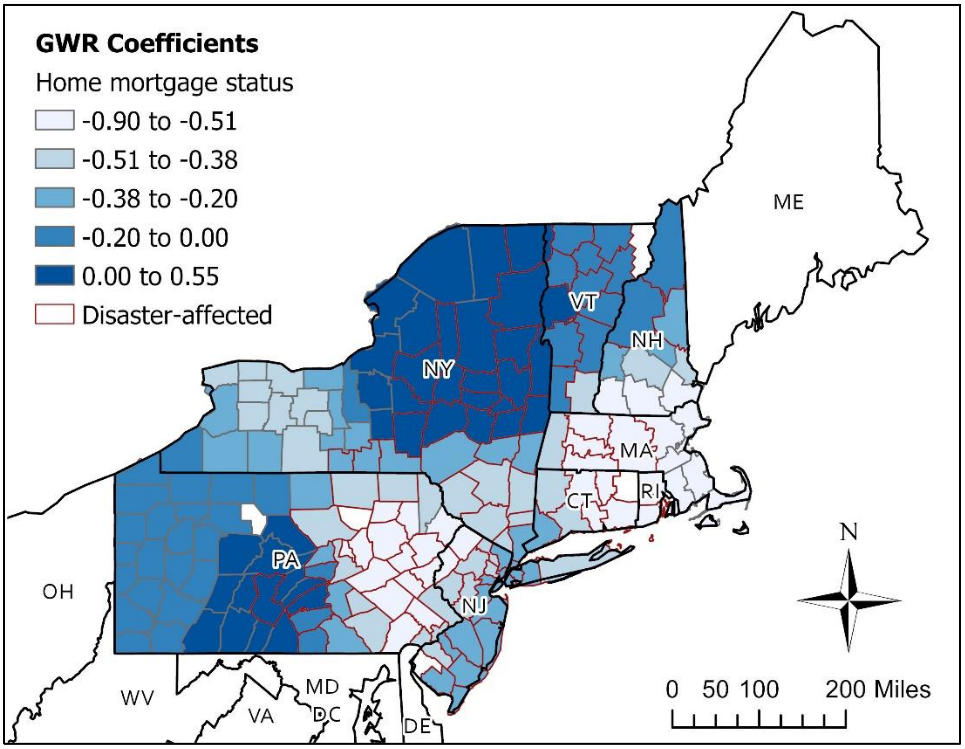

Figure 22: Spatial distribution of GWR coefficients for MORTGAGE

Table 25: Pearson Correlation Test

		MORTGAGE	β_{k3} (*MORTGAGE*)
MORTGAGE	Pearson Correlation	1	-0.223**
	Sig. (2-tailed)		0.028
	N	97	97
β_{k3} (*MORTGAGE*)	Pearson Correlation	-0.223**	1
	Sig. (2-tailed)	0.028	
	N	97	97

**. Correlation is significant at the 0.01 level (2-tailed).

Local Estimates for LQ_WHOLESALE

Figure 23 shows the spatial distribution of local GWR coefficients for *LQ_WHOLESALE*. GWR coefficients for *LQ_WHOLESALE* varied from -4.90 to 12.59 in the study region. The median GWR coefficient for the disaster-affected counties was 2.71. The lower and upper quartile was 0.66 and 7.07. More than 75% of the disaster-affected counties had a positive range of local GWR coefficients for *LQ_WHOLESALE* greater than 0.66. The upper quartile counties with the GWR coefficient of more than 7.07 were mostly from New York and Vermont state. The positive correlations showed that the availability of construction material resources positively affected reconstruction outcomes in the study region. In contrast, counties that were not affected by disasters had negative correlations since those regions had comparatively less demand for construction materials compared to disaster-affected counties.

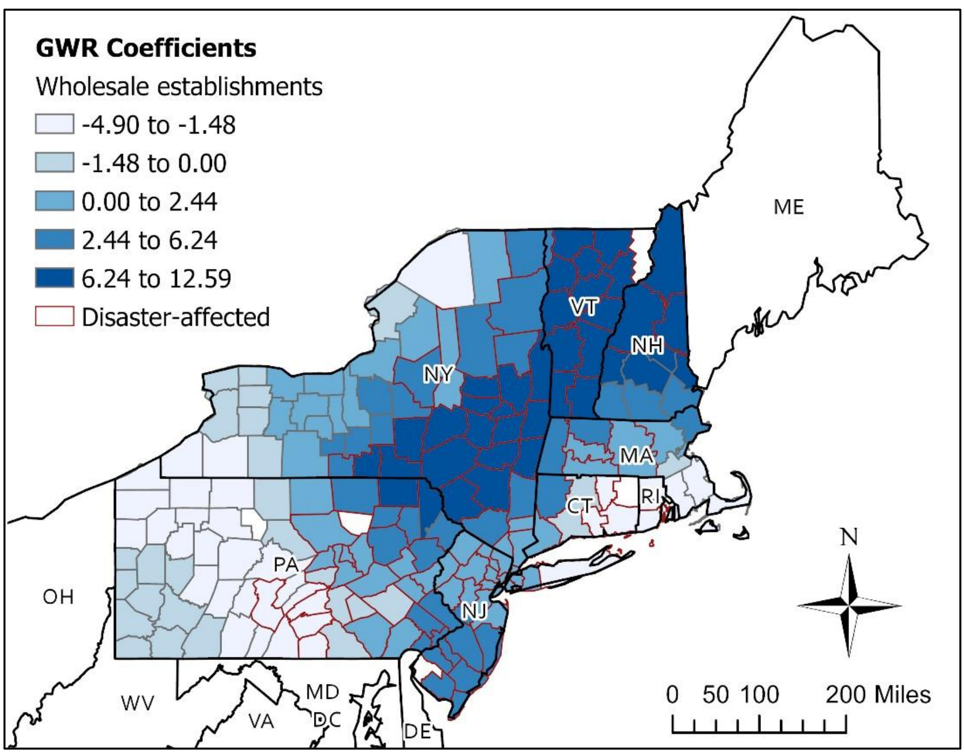

Figure 23: Spatial distribution of GWR coefficients for LQ_WHOLESALE

Local Estimates for LQ_EMP and LQ_EST

The spatial distribution of GWR coefficients for construction employment and establishments is shown in Figure 24 and Figure 25, respectively. The GWR coefficients for *LQ_EMP* varied from -2.0 to 11.61 in the study region counties. The median GWR coefficient for disaster-affected counties was 3.12, with a lower and upper quartile value of 1.72 and 5.15, respectively. This shows that most of the disaster-hit regions showed a positive range of GWR coefficients for *LQ_EMP*. However, most of the disaster-affected counties had a negative rage of GWR coefficients for *LQ_EST* (Median= -4.15, Q_1= -3.27, Q_3 =-5.72). The negative correlations can be attributed to the higher concentration of pre-disaster construction labor establishments in the study region (LQ>1) related to specialty trade contractors.

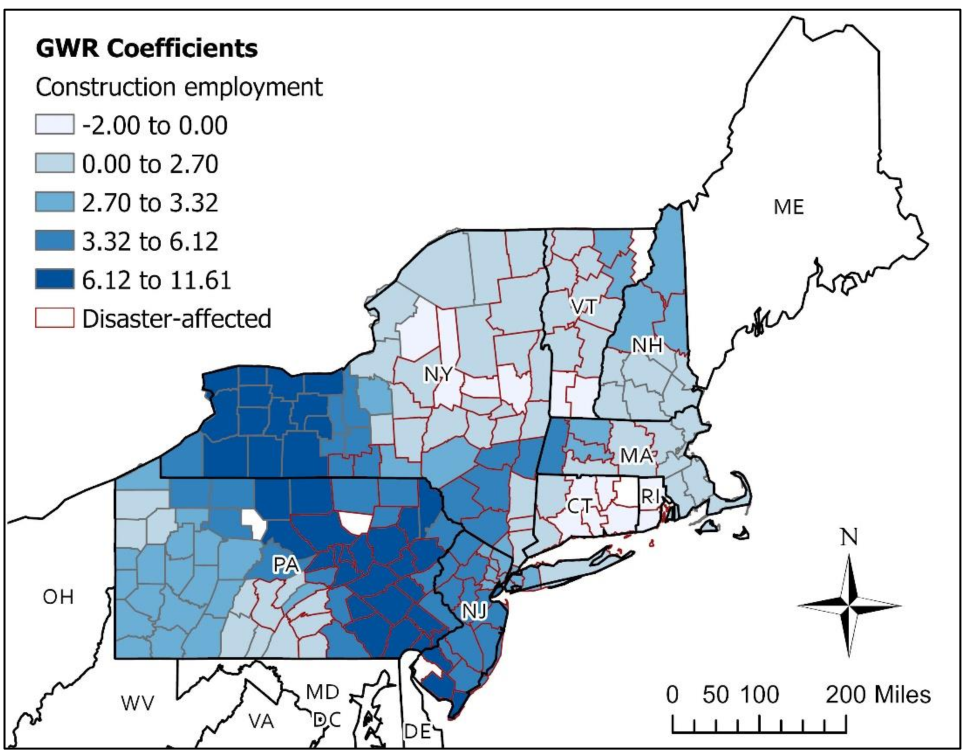

Figure 24: Spatial distribution of GWR coefficients for LQ_EMP

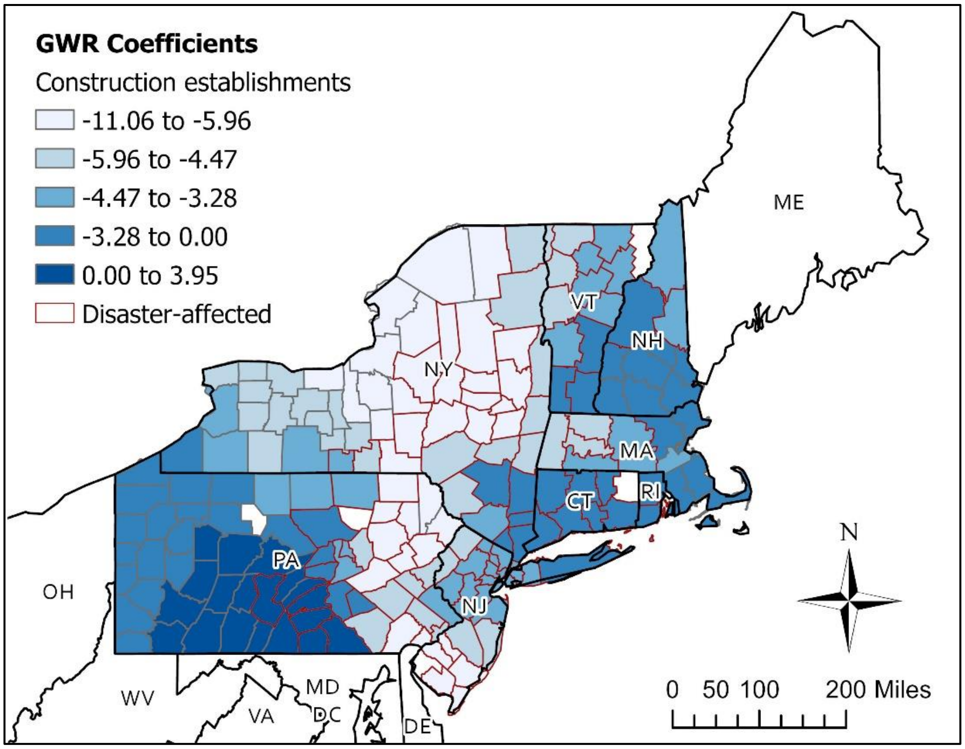

Figure 25: Spatial distribution of GWR coefficients for LQ_EST

An *Optimized Hotspot Analysis* (ESRI, 2020e) was run in ArcGIS Pro to detect statistically significant spatial clusters of high values (e.g., hot spots) and low values (e.g., cold spots) of LQ of construction establishments. Optimized hotspot analysis uses optimal settings to produce hotspot analysis results. The output feature class of this analysis are Gi Bin interval (shown in Figure 26) and Gi-Z score (shown in Figure 27). Statistically significant clusters of high concentration of construction establishments (90% confidence interval, z-score>1) were found in the regions with negative GWR coefficients. In contrast, a cluster of counties with a low concentration of construction establishments was detected in the regions with positive GWR coefficients. The negative range of GWR coefficients in the study regions can be attributed to clusters of counties with a saturated construction establishments market.

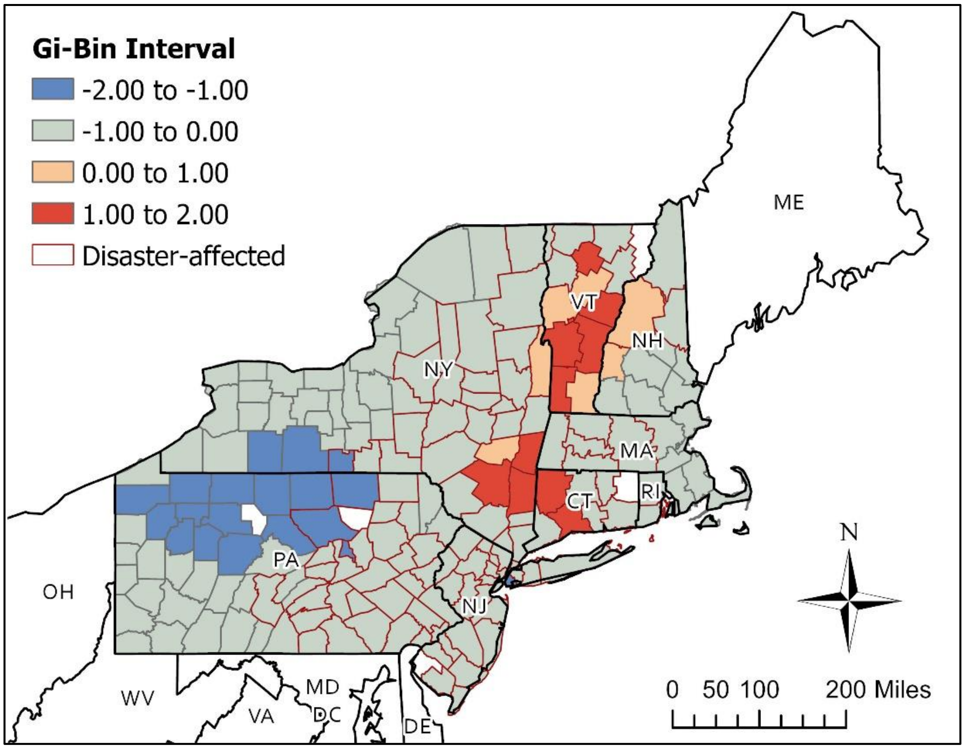

Figure 26: Gi-Bin Interval for LQ_EST

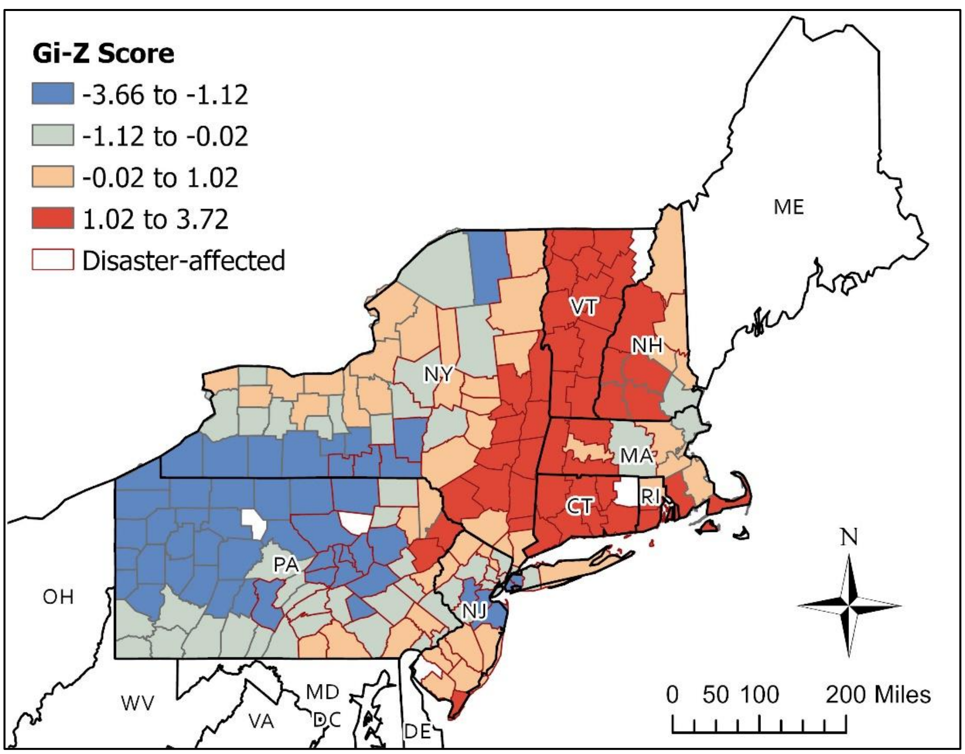

Figure 27: Gi-Z score for LQ_EST

Chapter Summary

This chapter quantified both the global and local relationships between resourcing factors and residential reconstruction outcomes using OLS and GWR statistical modeling approaches. The findings from the Global OLS model constructed by using 621 disaster-affected counties across the U.S. highlighted that pre-disaster socioeconomic and construction resourcing factors significantly influenced post-disaster residential reconstruction outcomes. The case study of the Northeast Census Region, hit by catastrophic disasters between 2011-2012, revealed that the relationships between the resourcing factors and reconstruction outcomes varied across the study region counties.

CHAPTER V: DISCUSSION AND CONCLUSION

This study has quantified the global relationships between socioeconomic, construction industry, and federal government resourcing factors and post-disaster permanent housing reconstruction outcomes at the regional level in the U.S. Using a case study of a disaster-affected region, this study has also quantified the local relationships between pre-disaster resourcing factors and post-disaster permanent housing reconstruction outcomes along with exploring the spatial heterogeneity in their relationships. The results of this study provide insight into the role of construction and capital resource availability for long-term housing recovery.

Discussion

The findings of the global OLS model using data of over 600 disaster-affected counties showed that construction labor and material resourcing factors were significantly and positively correlated with residential reconstruction outcomes. Construction resourcing factors are the indicators of pre-disaster labor and material resources availability. These findings are consistent with the observations of previous studies, which concluded that the availability of labor and materials are the drivers of residential reconstruction in a market-driven model (Chang-Richards et al., 2013; Arneson et al., 2020). However, the findings of this study have particularly highlighted the significance of the availability of specialty trade contractors for residential reconstruction in the U.S. context. Specialty trade contractors (NAICS 238) undertake the repair, restoration, rehabilitation or reconstruction activities related to residential buildings such as foundation and framing works, roofing, electrical, plumbing, flooring, and painting. While the general contractor typically subcontracts residential construction related works to establishments belonging to Sector

238, homeowners are equally likely to hire specialty trade contractors for post-disaster repair or reconstruction works (U.S. Bureau of Labor Statistics, 2020b).

A recent study by Arneson et al. (2020) revealed that the availability of labor resources is critical for swift residential reconstruction in the U.S. However, the capacity of regional construction market to supply resources to meet the heightened reconstruction demand is limited and is determined by the regional availability of labor and materials (Arneson, 2018). A survey conducted by Associated General Contractors of America (AGC) in 2017 highlighted that skilled labor shortage, particularly craft workers, was the major issue faced by 70% of the contractors in the U.S. (AGC, 2017). Moreover, inflation in labor wages, caused by lack of availability of labor, has been considered as the driving force behind the increase in residential reconstruction costs following major disasters (Olsen & Porter, 2013). Residential framing, masonry, and roofing contractors are vulnerable to wage changes following weather-related disasters in the U.S. (Ahmadi & Shahandashti, 2018a). While the construction labor market has received much attention from existing demand surge studies (Döhrmann et al., 2017), the findings of this study reveal that the availability of material resources is equally essential for swift residential reconstruction. Lack of availability of labor and material resources delays the residential reconstruction while creating ripple effects such as demand surge. Efforts should be made towards narrowing down existing market capacity gaps. This could be made possible by providing training and employment to local labor forces.

The socioeconomic characteristics of households broadly measure the availability of capital resources for reconstruction. Socioeconomic resourcing factors are the catalysts that either favor or constrain homeowners for acquiring capital resources. The findings show that the educational attainment of households was positively and significantly correlated with residential reconstruction outcomes. For instance, an increase in the pre-disaster percentage of households with higher educational attainment (e.g., bachelor's degree or above) positively influenced residential reconstruction outcomes. The findings are consistent with the case study by Cole (2003), which showed that households with limited education background face a hard time returning to permanent housing following disasters because of obstacles to access resources. Education levels of households not only enhances their disaster-preparedness but also provides them opportunities to seek out and utilize resources for reconstruction (Fothergill & Peek, 2004). Home mortgage status had a negative and statistically significant correlation with reconstruction outcomes. An increase in the pre-disaster percentage of households with unpaid home mortgages negatively affected reconstruction outcomes. Unpaid home mortgage adds additional financial burden to homeowners to acquire capital resources for reconstruction (Binder & Greer, 2016). The unemployment rate was negatively and significantly related to reconstruction outcomes which were intuitive. Income, however, had a statistically significant and negative correlation with reconstruction outcomes. The negative correlation can be explained based on the sequence of movement of households following a disaster (Cole, 2003), and also the development patterns and damage levels across disaster-hit regions (Hamideh et al., 2018). In her empirical study of the housing recovery process following disasters, Cole (2003) found that households with higher income exhibited a delayed housing recovery trajectory which she attributed to the *freedom of movement*. For example, Cole (2003) highlighted that households with high incomes were more likely to rent apartments and live in vacant summer homes or travel trailers. In contrast, low-income households may not have alternative permanent housing choices than to repair or rebuild their homes using personal savings and insurance. Hamideh et al. (2018) studied recovery trajectories of owner-occupied housing units in Galveston, Texas, following the 2008 Hurricane

Ike and found that high-income neighborhoods in some regions suffered higher levels of damages and exhibited slower recovery. They attributed the negative correlation between median household income and recovery to differences in development patterns across regions and the magnitude of damages. For instance, some of the high-income neighborhoods may be located near to the coasts and might suffer higher levels of damages during a storm surge.

The federal housing assistance grant was positively correlated with reconstruction outcomes but not found to be statistically insignificant. This could be because the federal grant only provides minimum financial assistance to homeowners. The findings align with the existing studies that homeowners still need to rely on personal savings and private insurance to repair or rebuild their damaged houses (Zhang & Pecock, 2009; Arneson et al., 2020)

When housing recovery studies focus on the regional scale, the role of geography cannot be ignored. Each region is unique in its demographic, socioeconomic, and market characteristics that shape the reconstruction outcomes of each region. Existing case studies have hinted that variations in housing recovery outcomes can be attributed to geographically varying resourcing environment across disaster-hit regions (Comerio, 1998; Chang et al., 2012). However, there is little quantitative evidence to suggest that the influence of resourcing factors varies from one disaster-affected region to others. While the *Research Question 1* of this study established the global relationships between resourcing factors and residential reconstruction outcomes, the R-Squared value of 0.30 may have compromised the possible geographical variation in favor of average estimates of parameters for the entire U.S. regions. However, *Research Question 1* established some of the key resourcing factors that were found to be significant on a global scale. These factors could be tested to determine if the magnitude and direction of relationships vary across regions. This would address one of the critical gaps in the literature by introducing geographical component in the quantitative analysis of post-disaster residential reconstruction. The goal of *Research Question 2* was to explore the spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes. Since aspatial statistical approaches such as OLS could not account for the spatial variation, the study used GIS-based spatial statistical approaches such as GWR.

GWR places spatial kernel on resources located nearby disaster-affected counties and uses a distance-decay function to weigh the relative influence of those resources on reconstruction outcomes. Contiguity across disaster-affected counties is essential when polygons shapefiles representing counties are used as the spatial unit of analysis. Since disasters hit not every county of the U.S., the GWR model could not be created for the whole U.S. A study region was required such that it covered a large number of contiguous disaster-affected counties located in states sharing contiguous borders. From the exploratory spatial analysis of the counties hit by disasters between 2007 to 2015, the Northeast Census Region was found to the ideal region for testing the spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes. The Northeast Census Region had more than a hundred contiguous disaster-affected counties, hit by some of the catastrophic disasters in the history of the U.S. between 2011-2012 (e.g., the 2012 Hurricane Sandy). The other advantage lied in its geographical boundary as the Northeast Census Region is one of the five census divisions of the United States. Census regions are large units comprised of states or counties that are roughly similar in terms of historical development, demographic characteristics, economy, and provides a broader geographical framework for statistical analysis (U.S. Census Bureau, 2018). This helped to avoid the problem of creating hypothetical political or geographic boundaries to run the analysis which may not be practical in a real-world policy scenario.

The findings from the case study of the Northeast Census Region showed that pre-disaster construction and capital resource availability significantly influenced post-disaster residential reconstruction outcomes. All the predictor variables were found to be statistically significant. The OLS model explained 59% of the variation in the changes in median home value growth rates through construction and socioeconomic resourcing factors, leaving the remaining 41% unexplained. Availability of pre-disaster construction labor and material were the drivers of residential reconstruction in the Northeast Census Region which were consistent with the findings of the global model from *Research Question 1*. Educational attainment was positively correlated with reconstruction outcomes, while median household income, home mortgage status, and construction labor establishments were negatively correlated. The findings from the two global models showed a negative correlation between income and reconstruction outcomes, which was counterintuitive. However, GWR can open a new window into understanding the spatially varying nature of the relationship.

One of the drawbacks of the global OLS model is the assumption that the relationships between predictor and outcome variables are uniform for the entire region under study. The statistical test, however, provided evidence of the presence of spatial non-stationary in the OLS model. Spatial non-stationary occurs when the relationships between predictor and outcome variables do not remain constant over the entire region under study. Findings from the GWR model reveal that the relationships between resourcing factors and reconstruction outcomes varied across the study region counties. Compared to the OLS model, the GWR model was able to explain over 80% of the variation in median home value growth rates through construction and socioeconomic resourcing factors. Detection of spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes is consistent with the conclusions from previous studies that location-specific resourcing context leads to unique reconstruction outcomes across regions (Comerio, 1998; Chang et al., 2012). Existing studies have already established that pre-disaster socioeconomic characteristics of households (Peacock et al., 2014) and regional construction capacity (Arneson et al., 2020) are important predictors of post-disaster reconstruction outcomes. However, existing studies provide a limited understanding of the presence of spatial inequalities and its role in distorting long-term recovery outcomes across regions. Spatial inequalities are manifested in the form of geographical discrepancies in the socioeconomic characteristics of households and construction capacity. Disasters magnify pre-existing socioeconomic inequalities (Bolin & Stanford, 1991), whereas compression of reconstruction activities in space (Olshansky et al., 2012) constrains the capacity of the regional construction market to supply labor and material resources (Arneson, 2018). Spatial inequalities and time compression result in a unique resourcing environment for each disaster-hit region. This study provides quantitative evidence of the geographic distortion of reconstruction outcomes as a result of the spatially varying influence of resourcing factors.

In contrast to the two global OLS models created under this study, the GWR model captured the local relationships between resourcing factors and reconstruction outcomes at the county-level. By introducing GWR-based resourcing maps, this study has helped in understanding the spatial patterns of reconstruction outcomes as a result of spatially varying influence of resourcing factors. The spatial patterns of relationships were consistent with the conclusions from the OLS results. For instance, GWR map produced a positive range of local coefficients for construction employment and material wholesale establishments in most of the disaster-affected counties of the Northeast Census Region, with some counties showing strong positive correlations (e.g., β ranging from 6.12 to 11.61 for construction employment and β ranging from 6.24 to 12.59

for material wholesale establishments). An increase in pre-disaster construction labor or material resources in counties showing strong positive correlations had a greater positive impact on reconstruction outcomes. Educational attainment had a positive range of GWR coefficients for most of the disaster-affected counties of the study region while home mortgage status had a negative range of coefficients. Median household income, however, had a negative range of GWR coefficients for most of the disaster-affected counties of the study region. Construction labor establishments had negative correlations with reconstruction outcomes for most of the disaster-affected regions. The negative correlations can be attributed to the high concentration of construction establishments in the disaster-affected counties (LQ > 1). Also, it implies that increment in labor employment positively drives reconstruction outcomes rather than increasing the number of establishments. A comparison between the OLS and GWR model showed that GWR was a better fit model in describing the relationships between resourcing factors and reconstruction outcomes in the Northeast Census Region.

Theoretical Contributions

Social sciences literature on housing recovery has long been discussing the role of households' pre-disaster demographic and socioeconomic characteristics on long-term housing recovery (Bolin, 1993). The notion of 'resourcing' for post-disaster housing reconstruction in a market-driven resourcing environment has recently garnered attention from researchers (Chang-Richards et al., 2013; Arneson et al., 2020). Case studies have provided qualitative evidence of the delays in permanent housing recovery as a result of the lack of availability of reconstruction resources (Chang et al., 2010). The research questions asked in this study contributes to the literature of post-disaster housing reconstruction in a market-driven resourcing environment in several ways. For instance, this study incorporates both the socioeconomic characteristics of households and construction market factors into developing a comprehensive quantitative resourcing model for residential reconstruction at a regional scale. The resourcing factors used in this study are indices to track and measure broader capital and construction resource availability for residential reconstruction. Existing qualitative studies have suggested that *local resourcing conditions* distort housing recovery outcomes across the disaster-affected regions (Comerio, 1998; Chang et al., 2012). This study has provided quantitative evidence of the distortion of recovery outcomes as a result of spatially varying influence of resourcing factors across regions. This study goes beyond conventional statistical approaches (e.g., OLS) to incorporate GIS-based GWR statistical approaches to explore the spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes. The findings of this study provide new insights into understanding the differential housing recovery from the lens of geographically varying influence of socioeconomic and construction resourcing factors.

Practical Implications

This study has important practical implications that will help policymakers, city planners, contractors, homeowners, and reconstruction stakeholders in planning and decision-making processes to improve the resilience of residential communities to natural hazards. First, the findings of the global OLS model of this study will help reconstruction planners in identifying critical resourcing catalysts that drive the reconstruction outcomes at a regional level. For instance, the findings highlighted that the availability of specialty trade contractors was significant for the progress of the housing reconstruction. Lack of labor not only delays the reconstruction but also generates ripple effects such as demand surge. Planners and policymakers can take pre-disaster mitigation steps by narrowing down existing capacity gaps in regional construction markets. Similarly, unpaid home mortgages add financial strain to homeowners and may constrain them from accessing capital resources for rebuilding. The findings of this study will help government agencies to focus on programs that will assist homeowners in home mortgage payments following disasters.

Second, this study showed that socioeconomic characteristics of households and construction market conditions are important predictors of reconstruction outcomes in a market-driven model. The findings will help planners and policymakers to consider socioeconomic characteristics of households and regional construction market conditions into resource planning. The GWR maps developed by this study is a powerful analytical tool that fosters decision-making process. For instance, results from the OLS model assume uniform relationships between predictor and outcome variables. As resources are limited, allocating resources equally to the entire region may not sound pragmatic. However, GWR maps can reveal the spatial variation in the relationships across disaster-affected counties. Some regions may show strong correlations, while others may show weaker correlations. Hence, by using GWR-based resourcing maps, mitigation planners, policymakers, and reconstruction stakeholders can develop mitigation strategies by focusing on vulnerable regions. Vulnerable regions are those that show strong positive or negative correlations depending on the nature of the relationships. This will not only help to reduce time and resources in pre-disaster mitigation planning but also to facilitate the decision-making process.

Third, exploration of the spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes aid in developing local policy mechanisms. Standard regional analysis (e.g., using OLS) may produce misleading results in the policymaking context. As a result, GWR has been considered an effective tool for improving regional analysis and real-world policy applications (Ali et al., 2007) as it accounts for the spatial heterogeneity in the relationships (ESRI, 2020b). The findings from the GWR analysis of this study will help regional scientists working in disaster mitigation to understand the spatial patterns of the recovery outcomes as a result of spatially varying influence of resourcing factors. This will enable the development of disaster mitigation policies at the local level by addressing the local resourcing needs of homeowners and mitigating bottlenecks that affect long-term housing recovery.

Fourth, reconstruction contractors also operate from distant locations by mobilizing resources located outside of the disaster-affected regions. Most of the existing studies have ignored the importance of resource sharing across regions or the role of stakeholders operating from distant regions. The GWR model used in this study takes into account the resources located in neighboring regions into consideration. The findings of this study will call attention to multi-stakeholder collaboration from neighboring regions for resource mobilization.

Finally, GWR-based maps can quickly disseminate the resourcing vulnerabilities of regions to homeowners, which can help them in the decision-making process to rebuild or relocate. Availability of capital resources is one of the major determining factors in influencing the household's decision to rebuild or relocate (Nejat & Ghosh, 2016). However, the findings of this study show that it is also essential to consider the spatially varying patterns of relationships. Resourcing factors showing strong influence in one region may not show the same degree of influence in other regions. Hence, by using GWR-based resourcing maps, homeowners can quickly identify the resourcing bottlenecks prevalent within the geographic boundaries and adopt necessary proactive steps to respond to future disasters.

Limitations of the Study

One of the major limitations of this study was the availability of data from the U.S. Census Bureau. ACS 5-years estimates dataset contains the socioeconomic and demographic data for the entire U.S. counties. However, ACS 5-years estimates were only available from the year 2009 to

2010. For counties hit by disasters before 2009, the data was acquired from ACS 3-years, and ACS 1-year estimates. However, ACS 3-years estimates, and ACS 1-years estimates did not provide data for the entire U.S. counties. As a result, data could not be obtained for some disaster-hit regions. The other limitation was the data availability from the BLS. Although BLS provides county-level data on market indices, data was not available for all the U.S. counties, especially for three-digit and four-digit industry subsectors (e.g., NAICS 23611). Although the GWR model has the potential to unravel spatial heterogeneity in the relationships between variables in other disaster-affected regions of the U.S., the model could not be created due to lack of contiguous disaster-hit regions and data availability at the county-level. In order to use GWR for other regions of the U.S., a more refined geographical scale such as census blocks will have to be used.

Future Study

Future studies can explore the spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes in disaster-affected regions at a much fine geographic scale such as blocks or census tracts. Inclusion of resourcing factors such as availability of personal savings or property insurance might provide an answer to some of the unexplained causes. Future studies can examine the influence of resourcing factors on reconstruction outcomes for public infrastructure reconstruction. Finally, the methodology used in this study can be expanded to include other factors (e.g., climate change, urban growth, and real estate markets) to analyze long-term housing recovery.

Conclusion

Within the existing limited literature on resourcing for residential reconstruction in a market-driven resourcing environment, very few studies have quantitatively examined the influence of construction and capital resource availability on post-disaster residential reconstruction outcomes at a regional scale. Two research goals were formulated to address critical gaps in the literature related to residential reconstruction in a market-driven resourcing environment: (1) quantify the global relationships between resourcing factors and residential reconstruction outcomes at the regional scale, and (2) explore the spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes. This study incorporated both aspatial and spatial statistical approaches to answer each of the two research questions.

The goal of the first research question of this thesis was to develop a general resourcing model for residential reconstruction by quantifying the global relationships between resourcing factors and residential reconstruction outcomes at a regional scale. This study used U.S. counties that were hit by federally declared weather-related disasters between 2007 to 2015 as a spatial unit of analysis to conduct regional-scale studies. Using county-level data on various resourcing factors (i.e., socioeconomic, construction industry, and federal government resourcing factors) and reconstruction outcomes, this study used OLS regression to quantify the relationships between resourcing factors and reconstruction outcomes. A total of 621 counties were included in the regression model. These counties incurred substantial residential damages with per capita damages exceeding the Per Capita Impact Indicator threshold determined by FEMA for every federal fiscal year. The predictor variables were the socioeconomic, construction industry, and federal government resourcing factors. Socioeconomic resourcing factors represented socioeconomic characteristics of owner-occupied households which included variables such as median household income, educational attainment, unemployment rate, and home mortgage status. Construction industry resourcing variables were represented by location quotient of labor employment (NAICS 238 industry) and material wholesale establishments (NAICS 423 industry). The federal government resourcing variable was represented by the housing assistant grant provided under the

FEMA IHP program for homeowners. For every federal disaster year *x*, socioeconomic and construction resourcing variables were recorded for the pre-disaster year *x-1* while the IHP grant was collected for the disaster year *x*. The residential reconstruction outcomes were measured as the percent change in median home value from the pre-disaster year *x-1* to post-disaster year *x+2* using a two-year reconstruction time frame. The findings reveal that the socioeconomic and construction industry resourcing factors significantly influenced residential reconstruction outcomes in the U.S.

The goal of the second research question was to explore the spatial heterogeneity in the relationships between resourcing factors and residential reconstruction outcomes using a case study region. The study region comprised eight contiguous disaster-affected states of the Northeast Census Region of the U.S. between 2011-2012 (e.g., Connecticut, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont). The state of Maine was not included as it was not hit by any disasters between 2011-2012. The year 2010 was considered as the pre-disaster baseline year to study the influence of pre-disaster resource availability on reconstruction outcomes in the counties hit by disasters during the years 2011 and 2012. Socioeconomic resourcing variables (e.g., income, educational attainment, and mortgage status) and construction resourcing variables (e.g., construction labor employment, labor establishments, and material wholesale establishments) were the predictor variables. The federal housing repair grant was not used as a resourcing variable since resource availability was measured for the pre-disaster year in the GWR model. The construction employment data from the NAICS Sector 23 and the establishment data from the NAICS 238 sector were used. For counties hit by disasters in 2011, the reconstruction outcomes were measured as the percent change in median home values from the year 2010 to 2013. Some counties were hit by disaster both in 2011 and 2012. For those counties, the change in home values was measured from 2010 to 2014. The OLS model was created to establish global relationships between resourcing factors and reconstruction outcomes for the case study region. This was followed by the development of the GWR model to explore the spatial heterogeneity in the relationships between resourcing factors and reconstruction outcomes. The findings show that the relationships between resourcing factors and reconstruction outcomes varied across the counties of the Northeast Census Region.

The measure of the influence of construction and capital resource availability on reconstruction outcomes through global statistics (e.g., OLS) may help decision-makers in assessing the critical resourcing bottlenecks for housing reconstruction. However, inferences solely based on global results may not be suitable in specific local settings as revealed by the case study carried out under this thesis. This study addresses a critical gap in housing reconstruction literature by determining how region-specific resourcing context *globally* and *locally* drive residential reconstruction outcomes across disaster-affected regions. Local parameter maps can be a powerful tool for decision-makers to identify regions vulnerable to resourcing crisis for post-disaster permanent housing reconstruction and can assist them in developing robust post-disaster resource planning and policy mechanisms.

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