INVESTING IN THE FUTURE FROM FLOODING: AN EXAMINATION OF FEDERAL HAZARD MITIGATION FUNDING ON OBSERVED FLOOD LOSSES ALONG THE GULF OF MEXICO

A Dissertation

by

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ABSTRACT

As coastal hazards, such as flooding, continue to grow in severity, the need to examine the influences federal mitigation expenditures has in relation to observable losses identified by the federal government becomes increasingly necessary. Hundreds of millions of dollars are invested into the United States coastal communities along the Gulf of Mexico for mitigation purposes, but we do not accurately understand how these funds influence damages caused by flooding events. This research addressing the lack of comprehensive knowledge by stating the following question: *To what degree are federal flood mitigation funds influencing observed flood losses as identified by FEMA and SBA in coastal watershed counties?* This question is answered by using panel data from 141 coastal counties over the 18 year span of 2002 to 2019 in a Spatial Error Regression model examining expenditures for flood-related mitigation strategies from the HMGP, FMA, and the number of identified mitigated properties from each of these federal programs. Models produced for HMGP funding showed no significance in reducing observable flood damages but was negative. Models produced for FMA funding showed no significance in reducing observable flood damages but was interestingly positive. The FMA model does provide a significant result after a 5-year lag prompting the need for future research to understand if it takes time for mitigation strategies to work after implementation. These results highlight the importance of examining how federal mitigation expenditures are currently influencing observable flood damages along the coastal counties of the Gulf of Mexico and offers perspectives of how these funds can be administered differently to significantly influence observable flood damages in communities that are deemed as high-risk for flooding.

DEDICATION

This dissertation is dedicated to my late father, Jeffrey Lewis Rainey, and my wife, Alexandra González Rainey.

My father indirectly taught me what it meant to be a great parent, to cherish all the little things in our life, and supported me in everything I did. From my days showing pigs in the stock show, to playing golf in high school, to all the science fair competitions, and to my days as a member in the Fightin' Texas Aggie Band, my father was always there to support me. No matter the challenge that came before me throughout my days in graduate school, I always relied on the words he wrote in a speech he gave to his Emmaus brothers titled "Perseverance." He said, "The Jeff Rainey's definition of perseverance is to never give up, to never lose hope, to never lose faith, to fight to the very end." Because of this speech he gave, I've embedded perseverance and grit into all that I set my mind on. Lastly, my father once told me before going to college, "You don't need a Ph.D. to live a happy life." Now that I have achieved this personal goal of mine, all I can say is that he was right.

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Contributors

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1. INTRODUCTION

1.1 Background

Gibert F. White, known as the “father of floodplain management,” once wrote, “floods are ‘Acts of God,’ but flood losses are largely Acts of man” (White, 1986 pg.12). Essentially, this statement recognizes the fact that flooding *is* a naturally occurring event but are created and mitigated by human decisions. Flooding is the most life-threatening (Stromberg, 2007) and, specifically in the United States (U.S.), costliest natural hazard (Gall et al., 2011 & Miller et al., 2008). It is expected that improper development and expansion throughout the floodplain will lead to more costly flooding events (Brody et al., 2007a). Just along the Gulf of Mexico, for example, Hurricane Katrina was the costliest natural disaster responsible for $16.2 billion in losses, and Hurricane Harvey was the second costliest natural disaster responsible for $8.9 billion in losses as identified by the National Flood Insurance Program. As the impacts of floods continue to occur, proactive strategies by way of mitigation to reduce the impacts of future events has never been more important. The U.S. federal government has a long history of providing financial support to localities for impact recovery after a major flood event. More recently, reducing the overall impacts from future flood events has become a primary objective, but little research has been done to better understand the effectiveness of mitigation initiatives and spending.

Flooding most commonly presents itself in two ways, the first of which is coastal flooding and the second is inland flooding. Coastal flooding is attributable to sea-level rise, tidal fluctuations and storm surge caused by tropical storms and hurricanes, whereas inland flooding is the result of river or stream overflow, excessive rainfall, or dam/levee failure. Urban flooding, as an additional term for flooding, has seen an increase in popularity in recent years and is broadly defined as “impacts from inundation exacerbated or caused by the human built environment” (Rainey et al., 2021). Unlike coastal and inland flooding, urban flooding is considered as being a human-made hazard and has been of concern for communities experiencing rapid expansion nationally. Winters et al. (2015) notes that urban flooding occurs in communities regardless of if they are within or outside the boundaries of a designated floodplain causing repetitive and costly impacts to those residing there.

Over time, humans have impaired the functionality of the natural environment by way of various alterations throughout the floodplain and, ultimately, their overall watersheds. These alterations include, but are not limited to, reducing open/green space, increases in impervious land cover, improper development design, and building in hazardous flood-prone regions. As the population and urban footprint by way of the previously stated alterations in the U.S. are expected to increase, particularly in coastal communities, the risk of flooding increases as well. All levels of government, relevant stakeholders, and individuals residing in current and future risky flood areas must heed the warnings and implement sound strategies that will mitigate the effects of future flood events. Local urban areas, particularly among coastal communities, will need to identify their respective opportunities and obstacles for implementing flood mitigation strategies. After every flooding event that creates significant amounts of damage, there are windows of opportunity to quickly address the problem and take the necessary actions to ensure the safety of our property from future hazards. As Beatley (2009) explains in his book, *Planning for Coastal Resilience*, common forms of obstacles faced by local communities are low importance given to hazard vulnerability, unwillingness to address large issues, limited resources, weak planning systems, political barriers, short timeframe for decision-making, protecting private property rights, and the perceptions of large upfront costs for unforeseeable long-term gains. While there are many forms of potential obstacles for implementing flood mitigation strategies at the local level, opportunities do arise. Collaboration within the local jurisdiction and the surrounding jurisdictions will create a more uniform community with identifiable goals being met with sound objectives. Expected changes made in one community will have a direct impact on the surrounding communities, more importantly the downstream neighbors.

Support/recovery and mitigation are two broad forms of financial assistance provided by multiple federal, state, and local government agencies to impacted communities, property owners, renters, and businesses. These funds are aimed towards people and property that have experienced a flooding event or has a high likelihood of experiencing flooding in the future. This research will focus primarily on the financial assistance programs provided at the federal level of the U.S. government, specifically programs within the Federal Emergency Management Agency (FEMA) and the Small Business Administration (SBA). In terms of support/recovery, financial assistance programs such as the National Flood Insurance Program (NFIP), Individual Assistance (IA), Public Assistance (PA), and SBA disaster loans are intended to alleviate the direct impacts made from a flooding event. Mitigation financial assistance programs, such as the FEMA Hazard Mitigation Assistance (HMA), which houses the Hazard Mitigation Grant Program (HMGP), the Flood Mitigation Assistance (FMA) grant program, and the Pre-Disaster Mitigation (PDM) grant program, are dispersed with the intention of reducing the risks of flooding from future events. Based on a congressional report, Rose et al. (2007) stated that for every $1 spent towards hazard mitigation $4 will be saved from future losses caused by natural hazards. This statement is misleading because the article and authors did not examine all available federal funding programs on direct losses. Instead, they focused on only HMGP funding and its influence on estimated damages from previous flooding events.

Studies have been done reporting the benefit-costs associated with federal mitigation funds using overestimating predictive loss models (NIBS, 2005 & 2019; Rose et al., 2007), localized mitigation policy implications (Brody et al., 2010; Highfield & Brody, 2012), and ecosystem response to mitigation activities (DeLaney, 1995; Dierauer et al., 2012). These prior studies fall short in articulating the effectiveness of federal mitigation funds on reducing actual reported losses across a larger scale. While there have been numerous studies conducted examining the impacts of flood damages on the built environment and how improper changes in the natural landscape led to larger flood losses, the cost effectiveness of mitigation funding and projects on direct losses from floods have not been researched extensively. As previously mentioned, the study by Rose et al. (2007) is a starting point in this area of research, but federal data has become publicly accessible in recent years and future studies no longer need to rely on estimated losses to determine the cost-effectiveness of mitigation funds and their associated projects.

1.2 Research Purpose and Objectives

As mentioned previously, flooding is a growing threat in the U.S., particularly in regions experiencing rapid development growth combined with the natural risk of experiencing flood-causing events. My research will address this issue by examining federal expenditures for flood mitigation and its influence on observed losses from flooding, that is, federal expenditures from programs identified by FEMA and the SBA.

The overall goal of this research is to assess the influence of mitigation funds and the number of identified properties that were mitigated on influencing losses from flooding. Accordingly, this dissertation will answer the following research question: *To what degree are* *federal flood mitigation funds influencing observed flood losses as identified by FEMA and SBA in coastal watershed counties?*

The specific research objectives are to:

1. Identify and examine the patterns of flood mitigation funds across the coastal watershed counties along the Gulf of Mexico.
2. Quantify the federal hazard mitigation assistance funding influences on observed flood damage using:
   i. Funding by hazard mitigation program:
      — Hazard Mitigation Grant Program (HMGP)
      — Flood Mitigation Assistance (FMA)
   ii. Number of properties mitigated as noted by FEMA by hazard mitigation program:
      — HMGP
      — FMA
3. Identify the policy implications and provide recommendations for federal mitigation spending to better protect at-risk communities from future flood events.

2. LITERATURE REVIEW

This section of the dissertation is a review of existing literature and their contributions towards creating a conceptual framework that will address the relationship between observed flood losses and mitigation funding. The literature helps recognize gaps in research and identifying key variables that will be used in the final models of this research. This section will cover current U.S. government agencies tasked with addressing the issue of flooding, federal support and recovery programs, federal mitigation and preparedness programs, mitigation strategies, built environment challenges, and followed by gaps in the literature.

2.1 U.S. Federal Government Programs to Address Flooding

2.1.1 Overview of Selected Federal Agencies

The Federal Emergency Management Agency is located under the U.S. Department of Homeland Security (DHS). The mission statement of FEMA is, "to lead America to prepare for, prevent, respond to and recover from disasters…" (FEMA, 2019a). FEMA has multiple federally administered financial programs in line with their mission statement that assist Americans in two broad categories: 1) support and recovery, and 2) mitigation and preparedness. For flood-related events, support and recovery funding programs are the National Flood Insurance Program (NFIP), Individual Assistance (IA) and Public Assistance (PA). FEMA identifies hazard mitigation as, "any action taken to reduce or eliminate long term risk to people and property from natural disasters" (FEMA, 2019b). At the time of this writing, mitigation and preparedness funding programs through FEMA are housed in Hazard Mitigation Assistance (HMA), which incorporates the Hazard Mitigation Grant Program (HMGP), the Flood Mitigation Assistance (FMA) grant program, and the Pre-disaster Mitigation (PDM) grant programs. Although not incorporated into this research due to its infancy, the newly established Building Resilient Infrastructure and Communities (BRIC) program will eventually replace the PDM program. A published FEMA brochure regarding flood insurance requirements for recipients of federal disaster assistance notes that homeowners and renters that receive federal disaster assistance must purchase and maintain flood insurance coverage (FEMA, 2020). Each of these previously mentioned federal programs are detailed further in Table 1.

The Small Business Administration (SBA), a separate federal government agency, works alongside FEMA during disasters to provide low-interest loans to businesses, renters, and homeowners in regions where Presidential Disaster Declarations are in place. If FEMA funding, either through the NFIP or IA, does not cover the immediate effects from a disaster, SBA provides disaster assistance in the form of low-interest loans. These loans are targeted for businesses, renters, and homeowners located in presidentially declared disaster regions. These disaster loans are applied for covering repairs and replacements of physically damaged property and to assist operating expenses for small businesses.

Table 1 Federal agency funding programs for flood-related events and disasters

Federal Agency	**Program Name**	**Disaster Declaration Needed**	**Funding Purpose**	**Type of Assistance**
FEMA	National Flood Insurance Program (NFIP)	No	Support and Recovery	Insurance
	Individual Assistance (IA)	Yes	Support and Recovery	Grant
	Public Assistance (PA): Section 406	Yes	Support and Recovery	Federal share of project
	Hazard Mitigation Grant Program (HMGP): Section 404	Yes	Mitigation and Preparedness	Grant; Federal share of project
	Flood Mitigation Assistance (FMA)	No	Mitigation and Preparedness	Grant
	Pre-Disaster Mitigation (PDM)	No	Mitigation and Preparedness	Grant

Table 1 Continued Federal agency funding programs for flood-related events and disasters

Federal Agency	Program Name	Disaster Declaration Needed	Funding Purpose	Type of Assistance
SBA	Disaster Loans	Yes	Support and Recovery	Loan

2.2 Support and Recovery Programs

2.2.1. National Flood Insurance Program (NFIP)

Enacted in 1968, the National Flood Insurance Act made flood insurance, otherwise known as the National Flood Insurance Program (NFIP), is available to property owners, renters, and businesses. The purpose of the NFIP is to provide Americans access to flood insurance that would financially assist policy holders from flooding events. Floodplain maps were then utilized in the U.S. to identify the Special Flood Hazard Area (SFHA) including the 100-year floodplain, which are areas having a 1% probability of inundation yearly. These hazardous areas serve as references for setting federal flood insurance requirements and local mitigation policies that are enforced by the Federal Emergency Management Agency (FEMA). Through the Flood Disaster Protection Act of 1973, one such requirement is the mandatory purchase of flood insurance for property with a federally-backed mortgage located in the SFHAs. Maximum financial coverage from the NFIP for homeowners are $250,000 for building damages and $100,000 for content damages. On the other hand, businesses with NFIP coverage can have a maximum coverage of $500,000 for building damages and $500,000 for personal property damages. Due to the regulatory caps on coverage, the losses from floods may exceed the maximum coverage allowance. Regrettably, some floodplain maps and hydraulic models are continually out of date due to various computing inputs, such as measurement errors in precipitation values and statistical assumptions, but also by the previously mentioned human influences in the built environment (Blessing et al., 2017). As found in studies such as Blessing et al. (2017), inaccuracies from former and current floodplain maps make identifying hazardous areas, communicating the risk to those residing there, and enforcing governmental policies ill-informed and more dangerous to those located in actual high-risk areas.

Flooding-related events covered by the NFIP continue to accrue debt each year. The Congressional Research Service (2019) reported that a total of $20.525 billion is owed from the NFIP to the U.S. Treasury as of December 2019. Recently, FEMA published their historical dataset of aggregate flood insurance claims between 1978 and 2018 at varying spatial scales. Researchers from the Risk Management and Decision Processes Center at The Wharton School of The University of Pennsylvania found that this data depicts an increased number of flood insurance claims and their subsequent value increasing over time (Bradt and Kousky, 2020). An average annual increase of $109 million, adjusted to 2018 dollars, per year from 1978 to 2018 was also noted in their study. These findings clearly show the disconnect between the original purpose of the NFIP, which is to provide flood insurance coverage on reasonable terms and for those that have need for such protection, and the actual flood losses being recorded nationally.

2.2.2 Individual Assistance (IA)

Individual Assistance (IA), administered by FEMA, becomes available to qualified renters and homeowners that reside in a county where a Presidential Disaster Declaration has been issued. IA funds are only available for items and specific needs not entirely met or not covered by insurance. Examples of qualified needs are temporary housing assistance, lodging expenses reimbursement, home repair, home replacement, and permanent or semi-permanent housing construction. Businesses and secondary homes are not eligible for IA funding. The maximum coverage for IA is $33,000, which is adjusted each year. Like the NFIP, damages that exceed the $33,000 are not accounted for and limits the true losses in a given flooding event.

2.2.3 Public Assistance (PA)

Public Assistance (PA) grant funds are administered by FEMA following a Presidential Disaster Declaration to "recipients", which are State, Territorial, or Tribal governments. The recipients then disperse these funds to qualified applicants, otherwise known as "sub-recipients". Applicants are only eligible by four key components: 1) must be a state, territory, tribe, local government, or private nonprofit organization; 2) must detail if funds will be towards a building, public works, system, equipment, or natural feature; 3) categorize the work as either Emergency (debris removal or emergency protective measures) or Permanent (restoration of roads/bridges, buildings/equipment, utilities, or water control facilities); and 4) detail costs of labor, equipment, materials, contract work, and direct and indirect administrative costs. At least 75% of the eligible cost with be covered by FEMA, and the recipient and sub-recipient will determine how the remaining share of no more than 25% will be covered.

2.2.4 Small Business Administration (SBA) Disaster Loans

The SBA provides loans, known simply as Disaster Loans, to assist in the support and recovery of an experienced disaster. A Presidential Disaster Declaration is needed for the activation of these funds. Homeowners and renters within the designated disaster declaration area are eligible for these loans up to $200,000 regardless of having flood insurance or not, whereas businesses may be eligible for up to $2 million. Serving as a loan, the recipients will receive the immediate short-term benefits but will be required to pay back what they owe to the SBA. Again, like the NFIP and IA, SBA disaster loans are capped at the previously mentioned amount, which suggests that damages can possibly be even greater than the amount allocated.

2.3 Mitigation and Preparedness Programs

2.3.1 Overview of FEMA Hazard Mitigation Assistance (HMA)

FEMA provides multiple preparedness and mitigation forms of federal funding to alleviate flooding in areas that apply and are considered high-risk. FEMA enforces a program called Hazard Mitigation Assistance (HMA), directed by the Federal Insurance and Mitigation Administration (FIMA), which encompasses the Hazard Mitigation Grant Program (HMGP), the Flood Mitigation Assistance (FMA) grant program, and the Pre-Disaster Mitigation (PDM) grant programs. Programs no longer administered through the HMA are the Repetitive Flood Claims (RFC) and the Severe Repetitive Loss (SRL) programs. The Biggert Water Flood Insurance Reform Act of 2012 eliminated the Repetitive Flood Claims (RFC) and Severe Repetitive Loss (SRL) programs, which were previous hazard mitigation programs overseen by FEMA as previously mentioned. The newly established Building Resilient Infrastructure and Communities (BRIC) program will eventually replace the PDM through amendments presented in the Disaster Relief and Recovery Act of 2018. Additionally, and discussed further in the Research Framework and Research Methodology chapters of this dissertation, PDM funding will not be included in this study simply for its lack of presence in the Gulf of Mexico when compared to HMGP and FMA funding. Presidential disaster declaration must be signed for the funding of HMGP to become available, but all the other programs solely depend on how much the U.S. Congress is willing to permit for each program in the federal budget. These programs are established to increase awareness of flood risk, reduce the impact of floods, determine the requirement or suggestion of obtaining insurance to property owners, deliver hazard mitigation assistance, and lessen the impacts made on natural and cultural resources from natural hazards.

Most recently, a study examined all three of mitigation funding programs, the HMGP, FMA, and PDM, and their relationships with “direct damages” expenditures from SHELDUS, a loss estimator application (Gall et al., 2020) in every parish of Louisiana. Solely exploratory in nature, this study refrained from conducting time series regression analysis because of the difficulty of obtaining the proper data to conduct such analysis. Because of this, Gall et al. (2020) reported the ratio comparison between the total amount of money identified as “direct losses”, “recovery” spending, and “mitigation” from the HMGP, FMA, and PDM. The results from Gall et al. (2020) showed that for every dollar for mitigation invested in a parish, residents will experience about $260 in “direct damages.” Gall et al. (2020) found that mitigation investments are insufficient in stabilizing and reducing future losses across Louisiana. This previously mentioned study directly contradicts a case study conducted by FEMA titled, “Losses Avoided from Hurricane Harvey in Texas.” The case study reported that more than $330 million in losses were avoided by investing $205 million in the elevation and acquisition of 1,618 properties over the years in the Harvey inundation area through Hazard Mitigation Assistance grant program funds. A ratio of 330:205 results in a Return on Investment (ROI) of 1.61, or $1.61 saved from mitigation funds. While this results seems promising, FEMA acknowledges that they did not account for observable losses but rather assigned an average of $184,871 per structure that was impacted. These two examples prove the difficulty in assessing the true effectiveness of mitigation funds on true losses related to flooding events.

2.3.2 Hazard Mitigation Grant Program (HMGP)

The process of the HMGP program is relatively straight forward: the local community that has been affected by the natural disaster submits an application to implement a mitigation strategy to FEMA who reviews it and determines whether or not the community is eligible for the available funds (Binder, 2014). If the community is eligible to receive a buyout then the process begins and FEMA works with the local government to carry out the buyout process (Binder, 2014). The monetary value that homeowners receive for their homes differ based on characteristics of the buyout, such as where the homeowner relocates to and if the buyout is individual or part of a group buyout project. The home owner receives the value of the home before the house was damaged and receives an additional 10% if homeowners are currently in a high-risk area, 5% if they stay in the same county when they relocate, and 10% if they are part of a group buyout (Maly and Ishikawa, 2013).

Group buyouts are preferable because they prevent the checkerboard pattern of the landscape. This checkerboard pattern occurs when there are individual houses bought out and the houses next to these bought out properties remain (Maly and Ishikawa, 2013). If there are multiple parcels acquired together then the potential to utilize the land in a productive manner is more probable. There are many aspects that drive homeowners to participate in the buyout process. Specifically, certain drivers, such as the FEMA cost benefit analysis (Fraser et al., 2003; Vries & Fraser, 2012), floodplain zone (Conrad et al., 1998; Maly & Ishikawa, 2013), distance to coast (Cheong, 2011), willingness of homeowner to participate and relocate (Vries & Fraser, 2006), previous damage (Conrad et al., 1998), income level (Conrad et al., 1998; Tate et al., 2016), and distance to parks, wetlands, or other open space (Zavar & Hagelman III, 2016; Maly & Ishikawa, 2013).

2.3.3 *Flood Mitigation Assistance (FMA)*

Secondly, the Flood Mitigation Assistance Grant program, as stated by FEMA, provides funding to states, local communities, and federally recognized tribes and territories for projects that are intended to reduce or eliminate the risk of repetitive flood damage from future events to buildings insured by the NFIP. This program is noted as being competitive amongst the applicants based on expected project impacts, eligibility, and cost-effectiveness of the overall project. Prior to disbursing these funds, FEMA requires that state, local, tribal, and territorial governments implement and enforce hazard mitigation plans.

2.3.4 *Pre-Disaster Mitigation (PDM)*

Lastly, the Pre-Disaster Mitigation (PDM) grant program, which, at the time of this writing, is being restructured into the Building Resilient Infrastructure and Communities (BRIC) program and will not be incorporated into this study, supports states, local communities, tribes, and territories as they envision and build hazard mitigation projects aimed to reduce risk from future disasters and natural hazards. A main reason for not including this program in this study is because it does not focus largely on specific flood mitigation efforts like the FMA. PDM offers funding that supports communities through the building process, enabling innovation for large projects, and promoting partnerships. This program, like the FMA program, is conducted through a competitive applicant process to ensure the desired mitigation project is cost-effective and aligns with the successful applicants' local hazard mitigation plan.

2.4 Built Environment Challenges

2.4.1 Land-use Change

Land-use change, in terms of urban expansion, are driving forces of more frequent and intense flooding events (Brody et al., 2006 and Brody et al., 2007b). Impervious surface practices are a direct result of expanding urban regions. Generally, impervious surfaces eliminate the effectiveness of soil permeability resulting in larger quantities of runoff (Kousky and Zeckhauser, 2006). The urban footprint is expected to increase from 3.1% to 8.1% (392,400 square kilometers) in the United States from 2000 to 2050 (Nowak and Walton, 2005). This urban sprawl is a direct consequence of population growth, poor land-use utilization, and inadequate planning policies (Djordjevic et al., 2011). Resource management and land use planning in the catchment area, security of natural and cultural values of floodplains and rivers, and the impact on the environment from structural and non-structural means are important aspects to consider when developing floodplain management policies (Correia et al., 1998). Brody et al. (2007a) studied eighty-five coastal watersheds across twelve years in Texas and Florida and found that increases in impervious surfaces resulted in significant increases in stream flow. Another study found that for every square meter of impervious surface added in the coastal counties of Texas resulted in approximately $3,602 of yearly property damages associated with flooding (Brody et al., 2007b). The expansion of impervious surfaces alters overall watershed area and floodplain dynamics. Jia et al. (2020) studied the China side of the Amur River Basin and found that 25% of the floodplain was lost between 1990 and 2018 due to agricultural and urban expansion. Although a foreign study, Jia et al. (2020) highlights important contributions to the effects that impervious surface expansion has on altering floodplain and wetland dynamics.

2.4.2 Development Density

High-density development, also known as compact development, and low-density development, also known as sprawling development, characterize the previously mentioned impervious surface land-use that will be used in this study. High-density development is more centralized and focuses on reducing the impacts made of natural landscapes. High-density development is classified by the National Oceanic and Atmospheric Administration (NOAA) Coastal Change Analysis Program (CCAP) as 30-sq-meter areas with more than 80% impervious surface coverage. Brody et al. (2011) found that high-density development resulted in a statistically significant decrease in flood losses from the NFIP between 2001 and 2005 across the 144 coastal county study area of the Gulf of Mexico. Low-density development increases the urban footprint across a wider region of the natural landscape when compared to high-density development. Low-density development is classified by the NOAA CCAP as 30-sq-meter areas with 21%-49% impervious surface coverage. Brody et al. (2011) also found that this type of development resulted in a statistically significant increase in flood losses between 2001 and 2005 across the coastal counties of the Gulf of Mexico. Breaking down the development density into low- and high-density categories dramatically influences previous models' interpretations of predicting flood losses (Brody et al. 2011), whereas using impervious surfaces collectively as a predictor of flood losses proved to be insignificant in the study conducted by Brody et al. (2012).

2.4.3 Wetland Alteration

Wetlands, specifically floodplain wetlands, serve as important ecological features in coastal regions and have been known to influence flood losses from storm surge or inland flooding events. Other than providing habitable environments for migratory and coastal species (Maltby et al., 1996; Maltby et al., 2013) and economic values through tourism (Emerton and Boss, 2004), this study will focus primarily on wetlands' physical influence on flooding. Through the hydrological cycle, wetlands contribute to increasing groundwater recharge rates, lowering flow rates, evaporation, and floods (Bullock and Acreman, 2003). Human intervention, by way of development and other uses, in wetland areas have led to dramatic changes in the hydrological cycle resulting in larger flood prone regions (Bullock and Acreman, 2003; Acreman and Holden, 2013).

In coastal regions, wetland alteration permits are granted for development projects that increase imperviousness and results in the expansion of urbanized areas (Bullock and Acreman, 2003). Under Section 404 of the Clean Water Act, the United States Army Corps of Engineers (USACE) maintains a variety of wetland alteration permit information. Permit types include Individual permits (IP), Letters of Permission (LOP), General Permits (GP), and Nationwide Permits (NP). IP are required when projects will result in significant impacts exceeding 0.5 acres across the wetland. Analyzed as a pattern of development, IP increases impervious surfaces through the construction of parking lots, roads, rooftops, etc. (Brody et al. 2008) and directly reduces wetlands' ability of collecting, storing, and discharging flood waters (Dunne and Leopold 1978; Paul and Meyer 2001). LOP are required for smaller projects that do not exceed 0.2 acres. GP are activity specific permits on a nationwide or regional basis. Examples of projects requiring GP are residential development or fill, road and bridge repair and construction, and utility work. Lastly, NP are issued only for specific projects that have "no more than minimal adverse effects on the aquatic environment, both individually and cumulatively" (Issuance of Nationwide Permits Notice 2005, p. 2023).

Analyzing 85 coastal watersheds from Texas and Florida over a 12-year period, Brody et al. (2007a) found that IP and GP led to a significant increase in flood losses, whereas LOP significantly reduced watershed flooding losses and NP had no significant effect. Interestingly, Reja et al. (2017) analyzed Section 404 watershed permits from 2008 to 2013 after Hurricane Ike and identified accelerated losses of natural wetlands in areas impacted after the major hurricane. More specifically, wetlands throughout the Texas counties of Galveston and Chambers were negatively impacted by increases in wetland permits when compared to counties that did not experience Hurricane Ike (Reja et al. 2017). This study also found that wetland permits, particularly after Hurricane Ike, occurred in undeveloped regions further eliminating the natural processes that wetlands provide in alleviating flood impacts. Geographically, the number of wetland alteration permits found within the 100-year floodplain from Reja et al. (2017) were shown to be insignificant in predicting wetland development.

2.5 Environmental Influences

2.5.1 Floodplain Area

Establishing boundaries of any kind, particularly for watershed management, is a key component when addressing environmental related issues, such as flooding (Randolf, 2003). The coastal watershed counties identified by the National Oceanic and Atmospheric Administration (NOAA) are preferred for this study because these counties are chosen based on their ecological and physical characteristics rather than administrative, political, or jurisdictional boundaries (Williams et al. 1997). More specifically, water flow of any kind, be it a result of fluvial or pluvial events, responds only to the makeup of the land it encounters, not where the ZIP code boundary or the county boundary has been designated. Mentioned further in the study area selection of this dissertation, NOAA details two selection criteria for identifying what they have deemed as "coastal watershed counties": "(1) at a minimum, 15 percent of the county's total land area is located within a coastal watershed or (2) a portion of or an entire county accounts for at least 15 percent of a coastal USGS 8-digit cataloging unit" (NOAA, 2019). This numbered cataloging code used by NOAA, otherwise known as a hydrologic unit code (HUC), are delineated watershed boundaries based on surface hydrologic features created by the United States Geological Survey (USGS). Regarding NOAA's selection criteria for coastal watershed counties using the HUC-8, this digit level is classified as drainage sub-basins (8-digit) consisting of watersheds (10-digit) and sub-watersheds (12-digit). It is not beneficial for this study to use smaller coastal HUC levels other than HUC-8 to identify coastal watershed counties, specifically HUC-10 or HUC-12. These considerably smaller watershed boundaries do not recognize their associated, more complete watersheds upstream (Maidment and Djokic, 2000) and are not considered "true" or "head" watersheds (Seaber et al., 1987). Furthermore, sub-basins along the coastal United States, according to NOAA (2019), are incredibly vital environmental regions due to their ability of absorbing and draining surface water back to the ocean while also serving as a habitable area for a variety of species, including humans. In a prior study, Brody et al. (2007a) used total watershed area as a control variable in predicting watershed alteration and watershed flooding. While this study showed that total watershed area was insignificant, it failed to incorporate more context into watershed area. Where Brody et al. (2007a) used total watershed area, this study will calculate the percentage watershed area within the previously defined coastal watershed counties.

Like watershed area, it is important to understand the area where flooding has a higher likelihood of occurring, more commonly referred to as floodplains. As mentioned previously in the NFIP section, floodplains serve as geographic markers of flood risk that informs community residents and influences local planning initiatives and flood mitigation policies. FEMA regulates insurance rates and enforces the purchase of flood insurance policies through a Flood Insurance Rate Map (FIRM). The Special Flood Hazard Area (SFHA) further breaks up the floodplain into separate zones dependent upon the risk severity or type of flooding in each area. Simply, FEMA uses the 100-year floodplain, an area with a 1 percent chance of flooding yearly, and the 500-year floodplain, an area with a 0.2 percent annual chance of flooding, as metrics to determine who should be required to purchase flood insurance. Homeowners with a federally-backed mortgage are required to purchase and maintain flood insurance if they reside within the 100-year floodplain. Incorporating floodplain area has proven to be an important control variable in prior studies when predicting flood losses. For example, Brody et al. (2011 & 2013) and Highfield and Brody (2017) found that using the floodplain area percentage within their study area at the county scale is significant in predicting flood losses. Similarly, Brody et al. (2012) observed significant results at predicting flood losses by using the percentage area of a county that is not considered within the floodplain.

2.5.2 Precipitation and Number of Storm Events

Precipitation is an important predictor of flooding and flood losses and should not be overlooked. Further discussed in the study area portion of this dissertation, the Gulf of Mexico is prone to many forms of flood hazards, heavy precipitation events included. Different storm-induced rainfall calculations have been incorporated into many studies focusing on flood losses. Examples of these calculations are reporting the positive significance of the number of times precipitation levels exceeded the 75th percentile (Brody et al. 2011; Brody et al. 2012; Brody et al.

2013), mean precipitation (in inches) by Highfield and Brody (2017), and total annual wet days (Brody et al. 2007a) have on predicting flood losses.

Along the Gulf of Mexico, especially the direct coastal regions, flood-inducing storm events are of great concern when considering flood losses. Storm events that take the form of fluvial, rivers exceeding capacity due to excessive rainfall, and pluvial, a flood event independent of a water body overflowing, need to be accounted for in studies such as this. In the same way that moderate to extreme precipitation events can cause flooding within inland and coastal communities, storm surge events, as an example, inundate the landscape from the ocean. High winds from tropical storms and hurricanes can essentially push coastal waters inland resulting in property damage and even loss of life. In prior studies examining coastal development and flood losses, the number of storm surge events have been significant predictors of flood losses (Brody et al. 2011; Brody et al. 2012; Brody et al. 2013; Highfield and Brody, 2017). This study expands on prior research in that storm events classified as Coastal Flood, Flash Flood, Flood, Heavy Rain, High Surf, Hurricane (Typhoon), Storm Surge/Tide, and Tropical Storm are utilized to account for coastal and inland flooding events.

2.6 Socioeconomic

2.6.1 Housing and Income

Housing and income are important information when analyzing and predicting flood losses. Flood losses from the NFIP, IA, PA, and SBA disaster loans are focused primarily on homeowners and businesses. The number of homes in an area and the population income has been shown in prior studies to be influential predictors of flood loss. As more individuals and more costly built structures are exposed to the risk of flooding, flood losses are expected to rise. The number of housing units in a study area has shown to be a significant predictor of flood loss (Brody et al., 2011; Brody et al., 2012; Brody et al., 2013; Highfield and Brody, 2017). Median home value, used by Brody et al. (2013), was also a significant predictor of flood losses. In terms of population income, median household income (Brody et al. 2011; Brody et al. 2007a; Highfield and Brody, 2017) and per capita income (Brody et al., 2012) are significant predictors of flood losses. Interestingly, median household income showed a positive relationship with flood losses, that is that flood losses increased as median household income increased. The median household income has also been shown as a positive but insignificant predictor of the local community participating in the Community Rating System (CRS), which is described in the following sections (Landry and Li, 2012; Li and Landry, 2018).

2.6.2 Presidentially Declared Disasters

Dependent upon the severity of the natural hazard, in this case flooding, and in accordance with the Robert T. Stafford Disaster Relief and Emergency Assistance Act, the governor of each state has the option to declare affected or potentially affected counties as disaster areas. Once the states' governor certifies this declaration, the President of the United States can officially declare individual or grouped counties as Presidentially Declared Disaster areas. This designation opens various form of federal aid, and, in the case of flooding, access to funds within the Individual Assistance (IA) program, Public Assistance (PA) program, SBA Disaster Loans, and the Hazard Mitigation Grant Program (HMGP) become available. There are many incident types of disaster declarations, but for the purposes of this study only Coastal Storms, Dam/Levee Breaks, Flood, Hurricane, Severe Storm(s), Tsunami, and Typhoons will be examined. This is an important control variable as many of the observed flood loss and HMGP information would not be accessible without the approval of a Presidential Disaster Declaration. At the time of this study there has been no research conducted on the number of presidentially declared disasters in a county being used as a predictor of observed flood loss.

2.6.3 Community Rating System (CRS)

The Community Rating System (CRS) is a credit program used by FEMA through the NFIP to award participating communities with varying levels of insurance premium reductions when they implement and maintain, at the very least, minimum mitigation standards. While not directly related to the federal mitigation funds in this research, the CRS is an important program to highlight about how specific mitigation activities, like open space protection and structure elevations, make a big difference in observed flood losses. In a way, the CRS is a form of mitigation that is separate from the mitigation spending variable used in this research. These participating communities voluntarily join the CRS and implement sound flood mitigation strategies that go above and beyond the minimum standards set forth by FEMA. Discounts in flood insurance premiums paid by policy holders are granted and appropriately scaled to those communities that have garnered higher CRS scores. Table 2 details further the CRS scores and their associated flood insurance premium discounts for policy holders within participating communities. Broadly, these credit accumulations are across four categories composed of multiple flood mitigation activities. The four categories are Public Information, Mapping and Regulations, Flood Damage Reduction, and Flood Preparedness. Based on the listed CRS activities performed within each category, the maximum number of points a community can achieve is 12,654 (FEMA: NFIP CRS, 2018).

Table 2 CRS Credit Points Earned, Classification Awarded, and Premium Reductions

Score Class	Credits (Points)	Discount in SFHA (percentage)	Discount in non-SFHA (percentage) **
1	4,500+	45	10
2	4,000-4,499	40	10
3	3,500-3,999	35	10
4	3,000-3,499	30	10
5	2,500-2,999	25	10
6	2,000-2,499	20	10
7	1,500-1,999	15	5
8	1,000-1,499	10	5
9	500-999	5	5
10	0-500	-	-

"**Preferred Risk Policies are available only in B, C and X Zones for properties that are shown to have a minimal risk of flood damage. The Preferred Risk Policy does not receive premium rate credits under the Community Rating System because it already has a lower premium than other policies. The Community Rating System credit for AR and A99 Zones are based on non-Special Flood Hazard Areas (non-SFHAs) (B, C and X Zones)."

Early studies by Brody et al. (2012) found that calculating CRS scores from county floodplain planning and management mitigation (Activity 510) were insignificant in predicting flood losses. While the previously mentioned study found the CRS Activity 510 score to be an insignificant predictor of flood loss, Highfield and Brody (2017) found that the CRS participation has a significant effect of reducing insured flood losses. Communities in their study participating in the CRS have a 41.6% reduction in flood claims when compared to communities of similar characteristics not participating in the CRS. Participation in the CRS at the parcel level has even been shown to significantly reduce flood losses (Highfield et al. 2014). Michel-Kerjan and Kousky (2010) identified that communities participating in the CRS can significantly reduce flood claim amounts at a Class 5 level or better.

2.7 Gaps in the Literature

Rose et al. (2007) was directed by Congress and FEMA to address the cost effectiveness of HMA projects in relation to estimated losses from natural hazards. Based on all identified natural hazards, their findings were that every $1 spent towards hazard mitigation $4 will be saved from future losses. Although this claim seems positive, the study does not accurately depict the cost-benefit of hazard mitigation funding towards actual reported losses from natural hazards, particularly flooding. Out of the three available funding types under HMA at the time, only HMGP funding was assessed and only projects with detailed reports, which was less than 3% of the total reported projects, were analyzed. The analysis by Rose et al. (2007) used the FEMA software program HAZUS Multi-Hazard (MH) estimation model to calculate the potential losses from natural hazards. A more recent report updating the original findings from the 2007 article was published by the National Institute of Building Sciences (NIBS) Multi-hazard Mitigation Council (MMC) in 2019 at the direction of the U.S. Congress. This updated report, entitled *Natural Hazard Mitigation Saves: An Independent Study to Assess the Future Savings from Mitigation Activities*, found that federal grant funding for mitigation efforts would result in $6 saved for every $1 spent. More specifically towards flooding, this updated report identified a $7 to $1 ratio for federally funded riverine flooding mitigation costs (NIBS, 2019).

In 2012, Hurricane Sandy impacted the northeastern region of the United States, causing more than $71 billion in estimated damages and claimed 157 lives. Federal funding immediately went towards HMGP buyout projects throughout the New England states and research assessing the effectiveness of these projects towards future hazards followed suit and continue today (Binder, 2014). Most recently, Hurricane Harvey wrecked the Texas coast and produced record-breaking levels of precipitation throughout the Houston area, the fourth largest city in the United States.

Houston, the State of Texas, and the United States are scrambling to determine how to prevent a disaster like this from happening in regions that are typically prone to flooding. There is a disconnect between local enforcers and government officials concerning urban development and the impacts it has on processes within socio-economic and ecological regimes (Eakin et al., 2010).

While there have been multiple studies on various aspects of the buyout system from the HMGP and flood damage costs associated with NFIP claims (Maly & Ishikawa, 2013; Tate et al., 2016; Vries & Fraser, 2006), **very few studies have looked at other funding alternatives, such as FMA funding, when pertaining to flooding-specific hazards, and their effects on NFIP, IA, PA, or SBA funding, to potentially reduce or eliminate flood impact costs and property damage.** These alternative forms of funding are considered mitigation strategies and have the potential to create a more resilient community and nation to these devastating natural disasters. In addition, federal funding for support and recovery is massive in comparison to funding for preparedness and mitigation strategies. **Research is needed to understand how federal mitigation funding from multiple federal mitigation programs influence non-estimated, observable losses caused by floods.**

3. RESEARCH FRAMEWORK

This section of the dissertation will detail the conceptual model of the research and provide insightful information about the dependent, independent, and various control variables selected for this research. The conceptual model describes the relationship between hazard mitigation funding and observed flood losses. Measurable hypotheses for each variable are listed further noting their respective relationship with observed flood losses.

3.1 The Conceptual Model

The conceptual model for this research is presented in the following figure (1) showing the different models being examined based on the independent variable and the relationship between selected variables on the dependent variable. The dependent variable in this research is observed flood losses. The primary research focus is to identify how selected federal mitigation funding, environmental control and socioeconomic control variables influence observed flood losses.

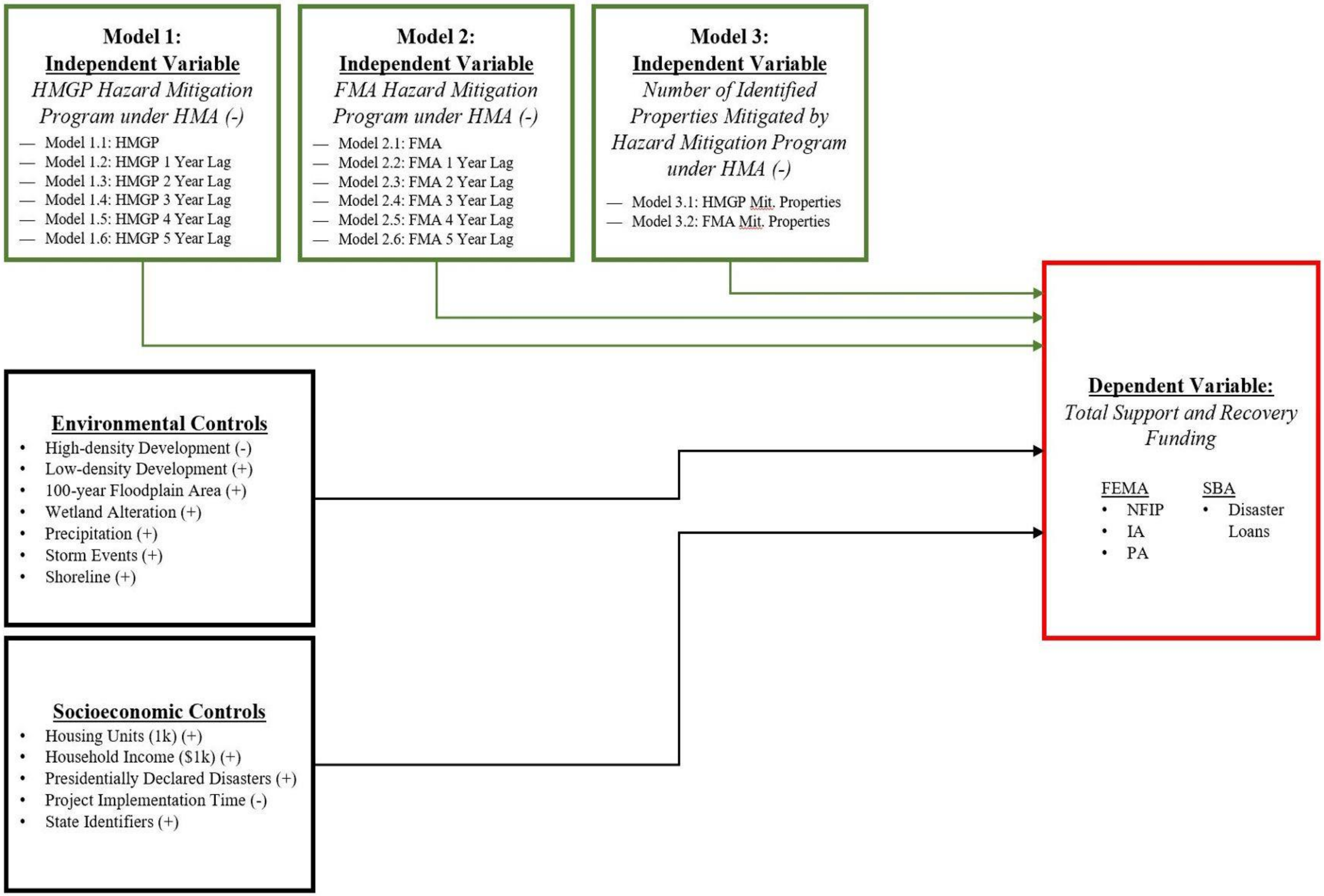

Figure 1 Conceptual Model

3.2 Dependent Variable: Flood Damage

The *dependent variable* for this study is flood losses from federal payouts associated with support and recovery from FEMA and the Small Business Administration (SBA) (see Table 1). Funds that support immediate recovery from flood events through FEMA include the NFIP, Individual Assistance (IA) and Public Assistance (PA). The SBA administers disaster loans that can be awarded to homeowners and businesses needing additional funds that flood insurance fails to meet. As shown in the conceptual model above, observed flood loss is the dependent variable (far right of Figure 1) for the study. This variable will capture the culmination of all previously identified support and recovery funding provided by the federal government for flooding events. These losses include structural and content losses from homes and businesses throughout the study area.

3.3 Independent Variables: Mitigation Funding

The *independent variables* are gathered from multiple programs administered by FEMA deemed as "mitigation and preparedness." These programs are encapsulated under the Hazard Mitigation Assistance (HMA) Grants and, for the purposes of focusing on flood mitigation for this study, are further broken down into the Hazard Mitigation Grant Program (HMGP) and the Flood Mitigation Assistance (FMA) grant program. The third HMA program that is currently in effect at FEMA is the Pre-Disaster Mitigation (PDM) but will not be incorporated into this study. An explanation as to why PDM will not be examined in this study will be addressed further in the data analysis portion of the Research Methodology chapter of this dissertation. The two programs that are no longer operational under the federal government for mitigation and preparedness assistance, Repetitive Flood Claims (RFC) and Severe Repetitive Loss (SRL), will also not be included within the HMA datasets. As depicted in the upper portion of Figure 1, the independent variable has been broken down into three separate models that will be analyzed in this study. Multiple explanatory analyses will be conducted investigating the statistical effects of HMGP mitigation funds in model 1, the statistical effects of FMA mitigation funds in model 2, and the third model using total number of identified properties mitigated between each of the previous mitigation programs on observed flood losses. Each of these models are expected to significantly reduce observed flood losses across the coastal Gulf of Mexico at the county-level.

3.3.1 Hazard Mitigation Program Under HMA Hypotheses

Each of the HMA programs and their associated funds distributed for mitigation projects will be separated individually. Separating will highlight the effectiveness of each mitigation program under the HMA.

Hypothesis 1: Counties that receive **larger amounts of mitigation funds from HMGP** will experience significantly **lower** amounts of observed flood losses.

Hypothesis 2: Counties that receive **larger amounts of mitigation funds from FMA** will experience significantly **lower** amounts of observed flood losses.

3.3.2 Number of Properties Mitigated Hypothesis

Each project uniquely identified by the HMA programs detail the initial number of properties the proposed project will mitigate as well as the final number of properties that were mitigated. These numbers represent properties that should no longer experience risk from natural hazards, or, at the very least, experience low levels of risk.

Hypothesis 3: Counties with **more identified properties that were mitigated through HMGP** will experience significantly **lower** amounts of observed flood losses.

Hypothesis 4: Counties with **more identified properties that were mitigated through FMA** will experience significantly **lower** amounts of observed flood losses.

3.4 Environmental Control Variables

Indicated on the left-hand side of Figure 1, environmental controls include high- and low-density development, 100-year floodplain area, HUC-8 watershed area, wetland alteration, precipitation, and storm surge. These variables, as shown in the literature review, are factors that influence flood damage. High-density development patterns in the study area are expected to significantly decrease flood losses. Low-density development patterns, increases in floodplain and watershed area, increases in wetland alterations, increases in precipitation, larger numbers of flood-related storm events, and the county being located along the coastline is expected to result in significantly more observed flood losses.

3.4.1 High-density Development Hypothesis

High-density development is a form of development pattern that reduces urban sprawl and lessens the risk and exposure to flooding threats. Homes and business considered high-density development are less likely to experience losses from floods possibly seen in more sprawled, low-density regions.

Hypothesis 5: Counties with higher percentages of high-density development will experience significantly **lower** amounts of observed flood losses.

3.4.2 Low-density Development Hypothesis

Low-density development, opposite of high-density development, is a development pattern that increases impervious surface coverage over a wider region. This type of urban expansion will not only increase exposure to more flooding events but also costlier flood damages.

Hypothesis 6: Counties with higher percentages of low-density development will experience significantly **higher** amounts of observed flood losses.

3.4.3 Floodplain Area Hypothesis

The 100-year floodplain is primarily used as a flood risk indicator and serves as a means of identifying structures that should be required to own NFIP policies in the anticipation of flooding. Counties in the study area that have lower percentage areas of the 100-year floodplain should be at a low level of risk from flooding and their associated damages.

Hypothesis 7: Counties with higher 100-year floodplain area percentages will experience significantly **higher** amounts of observed flood losses.

3.4.4 Wetland Alteration Hypothesis

Altering wetlands directly impacts natural ecosystem hydrology and influences flood damages. As shown in the literature review, increases in wetland alterations lead to increases in flood damages.

Hypothesis 8: Counties with higher amounts of wetland alteration percentages will experience significantly **higher** amounts of observed flood losses.

3.4.5 Precipitation Hypothesis

Flood intensity is calculated by precipitation recordings. More precipitation creates flooding conditions in the study area and has been shown through prior studies to be a significant predictor of flood losses.

Hypothesis 9: Counties that have a larger annual precipitation accumulation will experience significantly **higher** amounts of observed flood losses.

3.4.6 Number of Storm Events Hypothesis

Storm events are calculated by the total number of flood-related events across the study period. More storm events across the study area have been shown to be a significant predictor of flood losses. Storm event identifiers used in this study include Coastal Flood, Flash Flood, Flood, Heavy Rain, High Surf, Hurricane (Typhoon), Storm Surge/Tide, Tropical Storm.

Hypothesis 10: Counties that have a greater number of storm events, particularly coastal counties, will experience significantly **higher** amounts of observed flood losses.

3.4.7 Shoreline Identifier Hypothesis

Shoreline identifiers are included to signify counties that are considered shoreline as opposed to counties that are termed coastal counties. Shoreline counties that have a portion of their boundary as the Gulf of Mexico are susceptible to all relevant flood-related event types, whereas more inland counties are not as exposed to coastal-based flooding events, like storm surge.

Hypothesis 11: Counties that are considered shoreline counties along the Gulf of Mexico will experience significantly **higher** amounts of observed flood losses.

3.5 Socioeconomic Control Variables

Lastly, as shown on the left-hand side of Figure 1, socioeconomic control variables include number of housing units, household income, the number of Presidentially Declared Disasters, mitigation project implementation time, and unique state identifiers. It is expected that increases in the number of housing units, greater household income, increases in Presidentially Declared Disasters, and counties within all state identifiers will result in a significantly higher amount of observed flood losses, whereas longer mitigation project implementation times will result in lower amounts of observed flood losses.

3.5.1 Housing Units Hypothesis

Detailed in the literature review, the population along the coastal U.S. is increasing resulting in an increase in the number of housing units. More housing units throughout the study area results in more cases of structural and content flood losses which, in turn, results in greater amounts of flood losses.

Hypothesis 12: Counties that have more housing units on average will experience significantly **higher** amounts of observed flood losses.

3.5.2 Median Household Income Hypothesis

Median household income is used to account for the general capacity in which residents choose where they live. Lower income families may have no choice but to live in cheaper, and typically more risky areas to flooding. Higher household income may show that people can afford to live in more expensive households and can choose their level of risk from flooding more so than lower income families.

Hypothesis 13: Counties that have a higher median household income will experience significantly **higher** amounts of observed flood losses.

3.5.3 Number of Presidentially Declared Disasters Hypothesis

When a disaster is expected or has occurred from a natural hazard, state governors and President of the U.S. have the option to declare specific counties as qualified to receive federal funding from multiple federal programs. The programs only activated when a Presidentially Declared Disaster is in effect are IA, PA, HMGP, and SBA disaster loans, detailed in Table 1.

Hypothesis 14: Counties that have more Presidentially Declared Disasters on average will experience **higher** amounts of observed flood losses.

3.5.4 Project Implementation Time Hypothesis

Mitigation projects vary in size and scope. Similarly, it is assumed that larger and more complex mitigation projects take the longest to be fully implemented. For example, funding for hazard mitigation plans may not take as much funding or time compared to the installment of stormwater drainage systems. For this study, the amount of time, in years, it takes for a mitigation observation to be considered "complete" by FEMA is an interesting control variable for determining effects on observable flood losses.

Hypothesis 15: Counties that have longer Project Implementation Times will experience **lower** amounts of observed flood losses.

3.5.5 State Identifiers Hypotheses

State control variables are used to account for each state's differences in governmental policies, state spending, infrastructure soundness, and environmental and socioeconomic conditions that are not uniquely addressed as individual control variables in this study. The six states in this study are different in many ways but share one common attribute, they are all coastal states that are exposed to increased risks associated with flood-producing hazard events.

Hypothesis 16: Counties located within the state of Alabama will experience **higher** amounts of observed flood losses when compared to counties in Texas.

Hypothesis 17: Counties located within the state of Florida will experience **higher** amounts of observed flood losses when compared to counties in Texas.

Hypothesis 18: Counties located within the state of Georgia will experience **higher** amounts of observed flood losses when compared to counties in Texas.

Hypothesis 19: Parishes located within the state of Louisiana will experience **higher** amounts of observed flood losses when compared to counties in Texas.

Hypothesis 20: Counties located within the state of Mississippi will experience **higher** amounts of observed flood losses when compared to counties in Texas.

4. RESEARCH METHODOLOGY

4.1 Study Area and Spatial Sample Frame

The study area for this proposed research is the Gulf of Mexico coastal watershed counties of the U.S., as identified by NOAA, due to their proximity to the coast and their susceptibility to multiple forms of flooding hazards. The NOAA Office for Coastal Management identifies two different classifications for coastal counties, one being “coastal shoreline” (Figure 2) and the other as “coastal watershed counties” (Figure 3). While coastal shoreline counties (Figure 2) may experience larger effects from storm surge, they are not experiencing the full extent of coastal hazards that are more prevalent in upstream counties. When a major flooding event occurs, or a Presidential Disaster Declaration is issued, the coastline counties are not the only beneficiaries of federal assistance funds. Using only coastal shoreline counties will not be an accurate representation of assistance funds and their influence on observed flood losses. Coastal watershed counties are preferred for this study because coastal hazards and changes in land use and water quality at this scale impact coastal ecosystems more directly than simply just coastal shoreline counties. Also, coastal hazards impact larger, and more inland regions other than the coastal shoreline counties.

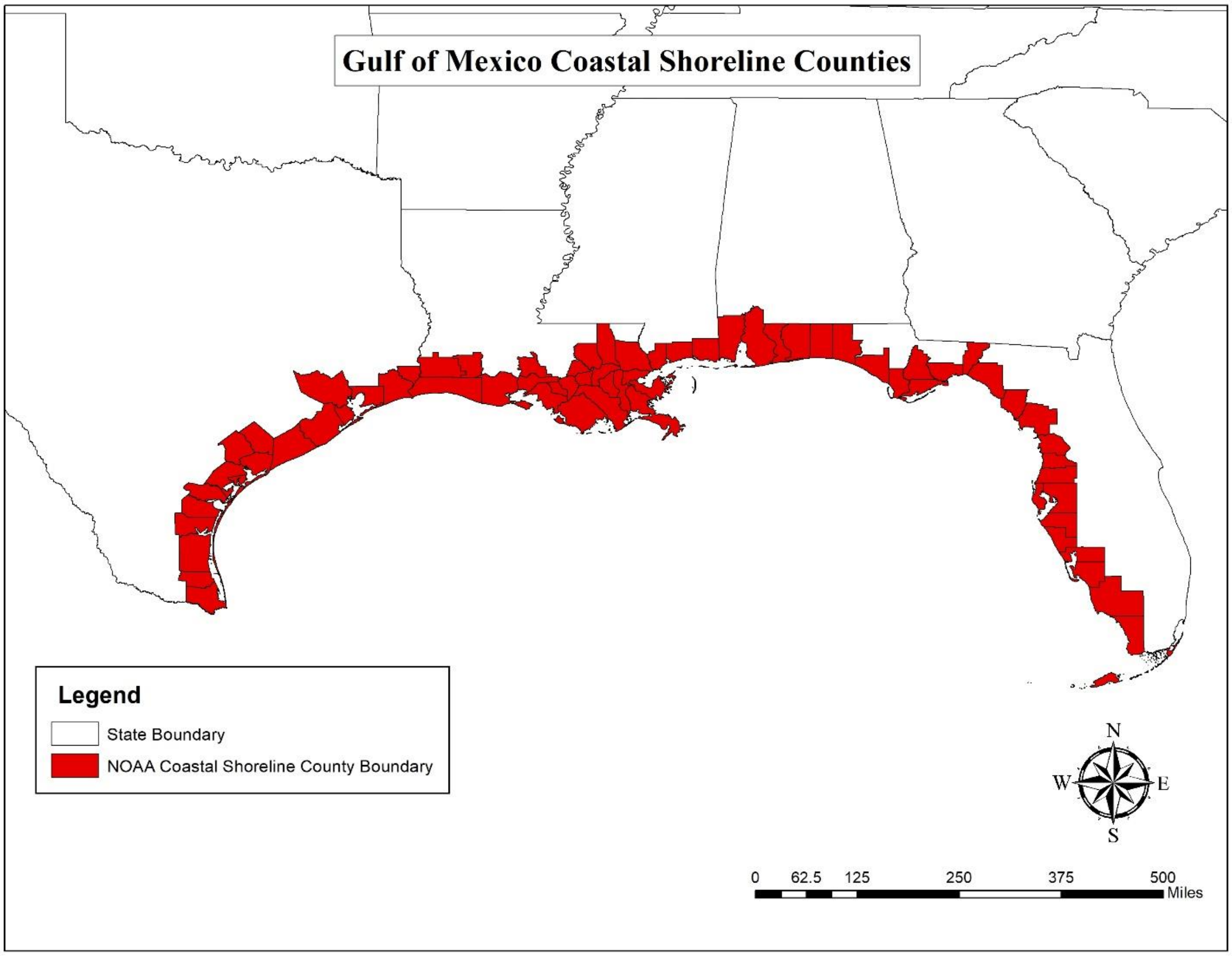

Figure 2 NOAA identified coastal shoreline counties for the Gulf of Mexico

NOAA has defined 145 coastal watershed counties along the Gulf of Mexico using a particular selection criteria. The selection criteria NOAA uses for determining coastal watershed counties must account for one of the following: "(1) at a minimum, 15 percent of the county's total land area is located within a coastal watershed or (2) a portion of or an entire county accounts for at least 15 percent of a coastal USGS 8-digit cataloging unit" (NOAA, 2019). Due to limited data availability discussed in the next section results in 141 of the 145 NOAA defined coastal watershed counties used in this study. Data collected for the study sample will be aggregated to the 141 NOAA defined coastal watershed counties along the Gulf of Mexico (see Figure 3).

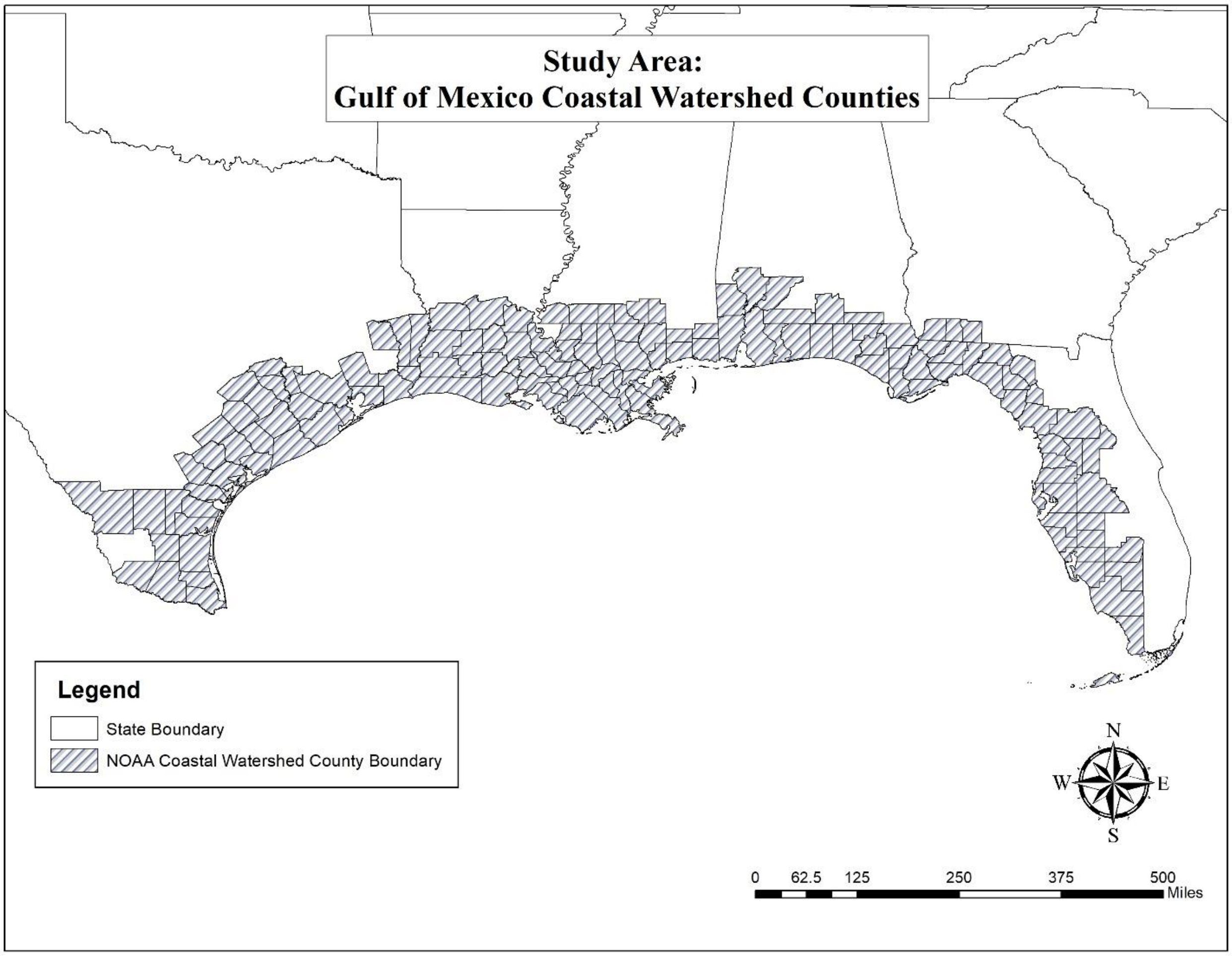

Figure 3 Study area; the 141 coastal watershed counties along the Gulf of Mexico

4.2 Study Timeframe Availability

The study timeframe from the coastal watershed counties of the Gulf of Mexico will span 18 years, from 2002 to 2019, where observed flood loss information, mitigation information, and control variable information have the same data availability. Table 3 details the timeframe and scale availability of each component of the dependent and independent variables. Counties omitted from this study for lack of control variable information consist of Sabine and West Feliciana of Louisiana and Jim Hogg and Live Oak of Texas. This procedure reduced the number of coastal watershed counties to 141 across an 18-year timeframe resulting in 2,538 observations. The county level was chosen as the unit of analysis for this study because many types of mitigation are intended to affect larger regions than their immediate surroundings where the mitigation project was implemented. Another important factor in choosing the county level as the unit of analysis was that all dependent and independent variables contain this level of specification. Total mitigation funding from each of the federal mitigation programs were aggregated to their respective county and year where a project was implemented. Counties and years that had no mitigation spending were given values of zero.

Table 3 Data timeframe and scale availability

Federal Agency	Program Name	Timeframe Available	Scales
FEMA	National Flood Insurance Program (NFIP)	Nationwide 1978 – 2020	Parcel (up to 2014), City, County
	Individual Assistance (IA)	DR Required 2002 - 2020	City, zip, county, state
	Public Assistance (PA): Section 406	DR Required 1998 - 2020	County, state
	Hazard Mitigation Grant Program (HMGP): Section 404	DR Required 1989 - 2020	City, zip, county, state
	Flood Mitigation Assistance (FMA)	1989 - 2020	City, zip, county, state
SBA	Disaster Loans https://www.sba.gov/document/report-sba-disaster-loan-data	DR Required 2001 – 2020	City, zip, county, state

"DR" – Major Disaster Declaration

4.3 Conceptual Measurement and Variable Operationalization

4.3.1 Dependent Variable: Observed Flood Losses Descriptive Statistics

The dependent variable, *observed flood losses*, are measured in dollars, and encompass the total insured losses from the NFIP, and losses from IA, PA, and SBA disaster loans. This variable is aggregated to the county scale between 2002 and 2019. Data from the NFIP are made up of both structural and content losses from floods. Information from IA, PA, and SBA were gathered based on the recorded disaster declaration number associated with a flood-related event (e.g., Coastal Storm, Flood, Hurricane, and/or Severe Storm). Pairing these data with the disaster declaration number associates the hazard event type and the date with each observation and was aggregated to its respective year between 2002 and 2019. Disaster declaration hazard event types that were kept in this analysis were any observations associated with Coastal Storm, Dam/Levee Break, Flood, Hurricane, Severe Storm(s), Tsunami, and/or Typhoon. Rather than using previous methods of estimation models to calculate flood damage, this ratio scale variable contains true observed flood losses by each county inflation adjusted to 2019 dollars using the Consumer Price Index (CPI). Table 4 shows the descriptive statistics for the dependent variable, the observed flood losses across NFIP, IA, PA, and the SBA. The 141 counties across 18 years that leads to 2,538 unique observations reports a mean of $35,378,547 with a standard deviation of $488,303,220. The minimum amount of money distributed to the study area is $0.00 and the maximum value collected was $17,960,155,136 from Orleans Parish, Louisiana in 2005. To ensure a normal distribution among the total observed loss values, mathematically accounting for the natural log of the variable will create a normal distribution of the values.

Table 4 Total Observed Flood Loss Descriptive Statistics

Variable	Obs.	Mean	St. Dev.	Min.	Max.
Total Observed Loss	2,538	$35,378,547	$448,303,220	$0.00	$17,960,155,136
Logged Observed Loss	2,538	9.70	5.98	1	23.61

4.3.2 Independent Variable Sample Descriptive Statistics

As described in the Conceptual Model (Figure 1), the independent variables are split between three separate model analyses. The first and second model analyses examines total allocated funding for each of the flooding-specific HMA programs administered by FEMA, the HMGP and the FMA. The third analysis examines the number of properties mitigated as identified by each of the HMA programs administered by FEMA, again, the HMGP and the FMA.

Initially, mitigation funding across HMGP and FMA was to be examined as a lump sum, but after careful analysis, heavy differences between both federal programs were present which led to the decision that they should be mutually exclusive of one another in the final models. The major identifiable difference, statistically, consisted of the average amount of money spent by each program across this studies time frame. The mean dollar amount spent out of the HMGP and FMA was $258,619 and $10,665, respectively. Same can be said about the average number of properties mitigated with HMGP and FMA reporting 1.287 and 0.067, respectively. Splitting these two programs into their own respective variables proved to be more effective and efficient in determining the unique effects each of them have on observed flood losses.

4.3.2.1 <u>Model 1: HMGP Spending</u>

Adjusted for inflation using Consumer Price Index (CPI) 2019 dollars, this ratio scale set of HMGP spending is aggregated to the county scale yearly. Only mitigation observations that are associated to individual counties and are considered “completed” are included in this research. To ensure that only flood related mitigation activities are examined in this study, a list of acceptable and declined mitigation activities was made to separate them from other natural hazard mitigation efforts. A comprehensive list of acceptable and declined mitigation activities can be found in Tables A.1 & A.2 in Appendix A.

Aside from Model 1 that looks at HMGP spending on observable flood losses by each year the money was finalized in, Models 1.2, 1.3, 1.4, 1.5, and 1.6 are HMGP spending lagged by one year up to five years of lag, respectively. Lagging this independent variable will provide insight into how mitigation spending influences observable flood losses over time from a given year. For example, HMGP spending in Model 1.2 has a one-year lag, that is that spending creates an effect after a one year timeline. Model 1.3, a two-year lag, adjusts and determines the effects HMGP spending has after two years of establishment. Model 1.4 is a three-year lag, and so on and so forth. Lagging variables in regression analysis, particularly time series panel models, are used to alleviate autocorrelation in the residuals as a robust alternative. The method of lagging variables takes the true value from the time in which it is observed and models its influence over the number of lags associated with it (Beck and Katz, 2011; Shumway and Stoffer, 2006). More specifically, lagging variables can determine if time plays a role in its initiation. It can answer the question of how many years does it take for a variable to begin influencing the dependent variable in the model. This dissertation examines the independent variable lag of HMGP spending across 1, 2, 3, 4, and 5 years. One to five years are chosen because of the lack of its use in the research of hazard mitigation in the subject of social sciences.

Table 5, below, shows the descriptive statistics of this variable and its log-transformation to ensure a normal distribution of values. Of the 2,538 unique observations across 141 counties and 18 years, the average HMGP spending is $258,619 with a standard deviation of $3,310,930. The range of HMGP spending across this area and timeframe is $0.00 as the minimum and $147,109,760 as the maximum from Harris County, Texas in 2014.

Table 5 Descriptive Statistics for Model 1 of the independent variable

Variable	Obs.	Mean	St. Dev.	Min.	Max.
HMGP Spending	2,538	$258,619	$3,310,930	$0.00	$147,109,760
Logged HMGP Spending	2,538	3.221	4.586	1	18.807

4.3.2.2 Model 2: FMA Spending

Like the HMGP model discussed previously, the FMA spending model examines only mitigation observations as identified by FEMA in their HMA open source data set that are both associated to a single county and are considered "complete" to exclude projects that have not been fully implemented. Again, a comprehensive list of acceptable and declined mitigation activities for this research can be found in Tables A.1 & A.2 in Appendix A. To reiterate the separation between the HMGP and FMA programs from the HMA program administered by FEMA, the HMGP spending is more reactionary in areas that have experienced Presidentially Declared Disasters whereas FMA is considered pre-event spending. The project amounts are adjusted for inflation using 2019 dollars and are aggregated to the county scale yearly.

As mentioned in the previous HMGP spending section regarding the application of lagging variables, Models 2.2, 2.3, 2.4, 2.5, and 2.6 are FMA spending lagged by one year up to five years of lag. Model 2.2 is a one-year lag, Model 2.3 is a two-year lag, and so on and so forth. Lagging this variable, like the HMGP spending variable, can show how it influences observed flood losses after a certain number of years depending on the number of lags that are associated with it.

Table 6, below, shows the descriptive statistics of this variable and its log-transformation to ensure a normal distribution of values. Of the 2,538 unique observations across 141 counties and 18 years, the average FMA spending is $10,665 with a standard deviation of $110,715. The range of FMA spending across this area and timeframe is $0.00 as the minimum and $2,747,206 as the maximum from Pasco County, Florida in 2009.

Table 6 Descriptive Statistics for Model 2 of the independent variable

Variable	Obs.	Mean	St. Dev.	Min.	Max.
FMA Spending	2,538	$10,665	$110,715	$0.00	$2,747,206
Logged FMA Spending	2,538	1.272	1.744	1	14.826

4.3.2.3 <u>Model 3: Mitigated Properties from HMGP & FMA</u>

Lastly, the third analysis, measured in individual units, is a ratio scale variable depicting the *number of properties mitigated* across the two previously mentioned HMA programs throughout the study area. Again, this variable only includes mitigation observations that are associated to a single county and that has been deemed "completed" by FEMA. Table 7, below, shows the descriptive statistics of both variables used in this model. Of the 2,538 unique observations across 141 counties and 18 years, the average number of mitigated properties under HMGP are 1.287 with a standard deviation of 18.071, and the average number of mitigated properties under FMA are 0.067 with a standard deviation of 0.809. The range of HMGP mitigated properties are 0 as the minimum and 629 as the maximum from Harris County, Texas in 2014, and the range of FMA mitigated properties are 0 as the minimum and 28 as the maximum from Pinellas County, Florida in 2003.

Table 7 Descriptive Statistics for Model 3 of the independent variable

Variable	Obs.	Mean	St. Dev.	Min.	Max.
Mitigated HMGP Properties	2,538	1.287	18.071	0	629

Table 7 Continued Descriptive Statistics for Model 3 of the independent variable

Variable	Obs.	Mean	St. Dev.	Min.	Max.
Mitigated FMA Properties	2,538	0.067	0.809	0	28

4.3.3 Control Variables

The following section will cover the previously mentioned control variables utilized in each of the models and the methods in which they were collected, manipulated, and measured. The control variables being used in this dissertation are development density (low- and high-density development) percentage, the 100-year floodplain area percentage, wetland alteration area percentage, average precipitation, number of storm events, binary shoreline identifier, number of housing units, average household income, number of Presidentially Declared Disasters, project implementation time, and individual binary state identifiers.

4.3.3.1 Development Density

High- and low-density development, as an environmental control, is measured as the percentage of the county landscape identified through the NOAA CCAP as a ratio scaled variable. To reiterate the definition of low- and high-density development in this study, high-density development is a 30-meter-squared area that has >80% of impervious surface coverage, and low-density development is a 30-meter-squared area having 21-49% of impervious surface coverage. NOAA CCAP reports development characteristics across the coastal United States at four different points of time. The years where values of development are gathered are 2001, 2006, 2010, and 2016. For this research, values of each development type are taken from the preceding dates available for each of the yearly observations. For example, a county observation for the year of

2005 will be associated with the values from the NOAA CCAP in 2001, and a county observation for the year of 2010 will be associated with the values from the NOAA CCAP in 2010. Utilizing the Geographic Information System (GIS) spatial analytical software, ArcMap, the 30-meter-squared pixels representing both high- and low-density development are intersected by each county boundary and summed together to equal the total number of 30-meter-squared pixels located within each county from the study area. The resulting number is converted to calculate the total area measured in square meters. The total area of both low- and high-density development, measured in square meters, is divided by the total county area, also measured in square meters. This calculation reports the percentage of each development type found within each of the study area counties. Table 9 reports the descriptive statistics from each of the development variables. The average percentage of high-density development equals 0.592, whereas the average percentage of low-density development equals 4.302. The county reporting the maximum percentage area of high-density development is Harris County, Texas with 10.625%, and the county reporting the maximum percentage area of low-density development is Pinellas County, Florida with 28.022%.

4.3.3.2 Floodplain Area

The *100-year floodplain area* is measured by calculating the percentage of the floodplain located in each county of the study area through the FEMA National Flood Hazard Layer and FEMA Q3 Flood Data. The selected floodplains for this study were high risk flood zones (A, AE, A1-30, AH AO, AR, and A99) and high risk coastal area flood zones (V, VE, V1-30). The areas are collectively considered as the 100-year floodplain, being the area with the highest risk, or of having a 1% chance of experiencing a flood event. Areas that are not included in this analysis are moderate to low risk areas (B, C, and shaded- and unshaded-X) and undetermined risk areas (D). The data from the FEMA National Flood Hazard Layer and the FEMA Q3 Flood Data are simply snapshots from when floodplain maps were created for each county and unfortunately, not analyzed on an annual basis. The total area of the floodplain would be divided by the total area of each county to understand the 100-year floodplain percentage. The original 145 coastal watershed counties/parishes that NOAA identified are reduced to the final study area of 141 coastal watershed counties/parishes here because Sabine Parish and West Feliciana Parish of Louisiana and Jim Hogg County and Live Oak County of Texas do not have any available floodplain information. Table 9 details the descriptive statistics of this variable. The average percentage of the 100-year floodplain in the study area was 38.29%. Pike County, Mississippi contained the minimum value of the 100-year floodplain area percentage at 8.16%, and Plaquemines Parish, Louisiana reported the maximum percentage area at 98.96%.

4.3.3.3 Wetland Alteration

The wetland alterations are measured as an annual average percentage change in the natural landscape between both palustrine wetlands and estuarine wetlands. Taken from the same data set where development density was gathered, the NOAA CCAP analyzes wetlands and identifies multiple types from 2001, 2006, 2010, and 2016. These types are palustrine forested wetland, palustrine scrub/shrub wetland, palustrine emergent wetland, estuarine forested wetland, estuarine scrub/shrub wetland, estuarine emergent wetland, palustrine aquatic bed, and estuarine aquatic bed. Using the same methods from the development density section, the area from each of the wetland types are calculated, aggregated together, and then converted to depict the area percentage that these selected wetlands that are accounted for in each county of the study area. The values, like the development density variable, are taken from the preceding dates available for each of the yearly observations. To gather the percentage change in wetlands, the date in which a value was recorded is subtracted from the previous year available. For example, an observation taken in 2008 will receive the values from the preceding year available, which is 2006, and then subtracted by the next available year from NOAA CCAP, which is 2001, to acquire the percentage change between each year. Observations taken between 2002 and 2005 will report a 0% change in wetland area because they are taking the values representing 2001 and being subtracted by the values representing 2001. The descriptive statistics in Table 9 report an average wetland loss of 0.084%. The minimum value shows a 2.861% loss of wetlands from Cameron Parish, Louisiana during this study timeframe, and the maximum value shows an increase of wetlands by 2.184% in St. Mary Parish, Louisiana.

4.3.3.4 <u>Precipitation</u>

Precipitation levels obtained by PRISM Climate Group is a ratio scaled variable measured as an average amount of rainfall in each county annually. The PRISM Climate Group gathers climate data, covering a 30 meter squared area grid cell, and develops various spatial climate dataset models, one of which is yearly average rainfall. Yearly datasets of average rainfall were downloaded from the PRISM website and uploaded into the GIS spatial analytical software, ArcMap. The measurable values collected from each study area county were then converted to inches to represent the average annual rainfall (in inches) from each county between 2002 – 2019. Table 9 highlights the descriptive statistics of this variable in the models. From the 2,538 unique observations across 141 counties and 18 years, the average annual rainfall is 56.19 inches with a standard deviation of 15.756. The minimum rainfall observation across the study area is 9.109

inches from Starr County, Texas in 2011 and the maximum rainfall observation is 104.455 inches from Orange County, Texas in 2017.

4.3.3.5 Number of Storm Events

The *number of storm events* was gathered from the NOAA National Centers for Environmental Information National Weather Service (NWS) storm events database and measured as an aggregate. Potential flood-inducing storm events gathered include Coastal Flood, Flash Flood, Flood, Heavy Rain, High Surf, Hurricane (Typhoon), Storm Surge/Tide, Tropical Storm. These records are only documented if the weather event has sufficient intensity and can cause loss of life, injuries, significant property damage, and/or disruption to commerce. As shown in the descriptive statistics in Table 9, the average number of these flood-related storm events are 2.052 during the 18-year period across the 141 study area counties/parishes. The maximum number of storm events observed in a single county was 45 and that was in Walton County, Florida in 2014.

4.3.3.6 Shoreline Identifier

It is important to account for counties/parishes that reside along the coastline. These counties/parishes that have any portion of their jurisdictional boundary consisting of the shoreline are directly threatened by storm surge from hurricane force winds and any other coastal flood hazard that more inland areas do not experience. Of the 141 coastal watershed counties/parishes serving as the study area, this binary variable reports that 48.2% are considered shoreline counties along the Gulf of Mexico (Table 9).

4.3.3.7 Housing Units

The *number of housing units* is measured, in the thousands, as the number of homes as identified from the U.S. Census Bureau. Using the American Community Survey, the 5-year Estimates from 2010, 2015, and 2019 are best when precision is important and when 1-year estimates are not available. Observations during and before the year 2010 will retain the housing information from the 2010 5-year estimate, observations from 2011 to 2015 will retain the housing information from the 2015 5-year estimate, and the observations from 2016 to 2019 will retain the housing information from the 2019 5-year estimate. Measuring this variable in the thousands makes the regression coefficient results easier to interpret in relation to flood loss. The average number of housing units across the study area is 67.168(k) with a maximum value of 1,768.096(k) from Harris County, Texas (Table 9).

4.3.3.8 Household Income

Like the housing unit variable previously mentioned, the *median household income* is measured in dollars (in thousands) from the U.S. Census Bureau American Community Survey 5-year Estimates from 2010, 2015, and 2019. Observation values were appointed similarly to the housing unit variable in terms of yearly allocations. Using the median rather than the average household income is simply because it is a more accurate measure of income across a region. The median value is also not affected by extremely high or low income outliers. Again, this variable is measured in the thousands making the regression coefficient results easier to interpret. As seen in Table 9, the average median household income (in thousands) across the study area and 18-year period is $44.343. The minimum median household income value recorded, $19.595(k), is from

Brooks County, Texas, and the maximum value recorded, \$97.743(k), is found in Fort Bend County, Texas.

4.3.3.9 Presidentially Declared Disasters

Presidentially Declared Disasters are measured as the total number of these experienced by each county across the study area. FEMA notes the number of disasters declared and the type of disaster associated with each. Only flood-related Presidentially Declared Disasters, such as Flood, Coastal Flood, Flash Flood, Severe Storm(s), Tropical Storm/Depression, and Hurricane are included in this analysis. As shown in Table 9, the average number of declared disasters across the study area and timeframe of this study is 0.745. Most counties across any given year do not experience a presidentially declared disaster, but Saint Bernard Parish, Lafourche Parish, Jefferson Parish, Saint Charles Parish, and Plaquemines Parish of Louisiana each experienced the maximum number of declared disasters, 5, in 2005 alone.

4.3.3.10 Project Implementation Time

As stated previously regarding *project implementation time*, only mitigation projects considered “complete” by FEMA are incorporated into this study, and it is interesting to note the time (in years) it took to complete each effort from their original “start date.” By separating the two mitigation programs administered under FEMA, there is a distinct difference between the average and maximum project implementation time as shown in Table 9. The average time, in years, for HMGP projects to be complete is 1.014 as opposed to the average time for FMA projects at 0.067. Most projects in both programs are considered complete within the first year of their funding allocation and are given values of 0. The maximum project implementation time for HMGP and FMA is 14 and 6, respectively.

4.3.3.11 State Identifiers

Using state control variables account for the broader differences between each Gulf of Mexico state. With the study area spanning 141 counties across 6 states, it is worth noting how many counties make up the study area within each of the 6 states. Alabama – 8 counties accounting for 5.67% of the total study area, Florida – 42 counties, the largest number out of the study area, accounting for 29.78% of all counties, Georgia – 3 counties making up 2.13% of the study area, Louisiana – 37 counties accounting for 26.24%, Mississippi – 12 counties making up 8.51% of the study area, and lastly, Texas – 39 counties contributing to 27.66% of the study area, the second largest contribution of coastal watershed counties along the Gulf of Mexico. To avoid perfect collinearity between each of the dummy variables comprising the states, the Texas identifier will be omitted from the analysis. Omitting Texas from the model changes the interpretation of the model results by comparing each states' coefficient to the Texas identifier.

4.4 Data Analysis

Following the information provided in this chapter, Table 8 (below) is a summary of each of the previously discussed variables used in this research and their unique descriptors. This table details each variable source, measurement scale, temporal resolution, and hypothesized effect on the dependent variable.

Table 8 Variables and their operational definition

Variable	Description	Source	Scale	Temporal	Effect
Dependent Variable					
Flood Losses	Total observed flood losses ($) for each county (2002-2019)	FEMA, SBA	Ratio	Annual	N/A
Independent Variables					
HMA Program Spending	Total allocated spending by hazard mitigation program	FEMA	Ratio	Annual	-
Number of Mitigated Properties	Total number of properties mitigated from each HMA program	FEMA	Ratio	Annual	-
Environmental Controls					
High-Density Development	Average percentage of landscape designated high-density development	NOAA CCAP	Ratio	Annual	-
Low-Density Development	Average percentage of landscape designated low-density development	NOAA CCAP	Ratio	Annual	+
100-Year Floodplain Area	Average percentage of floodplain within study area	FEMA NFHL	Ratio	Invariant	+
Wetland Alteration	Average percentage landscape change from wetlands	NOAA CCAP	Ratio	Annual	+
Precipitation	Average precipitation level reported across county	PRISM	Ratio	Annual	+
Storm Events	Number of flood-related storm events in each county	NOAA NWS	Ratio	Annual	+
Shoreline	Identifier if county is a coastline county or not	NOAA	Binary	Invariant	+
Socioeconomic Controls					
Housing Units	Number of structures and homes	U.S. Census	Ratio	Annual	+
Household Income	Average dollar value of income by household	U.S. Census	Ratio	Annual	+
Presidentially Declared Disasters	Total number of declared disasters	FEMA	Ratio	Annual	+
Project Implementation Time	Length of time for mitigation projects to be implemented	FEMA	Ratio	Annual	-
State Identifier	Alabama, Florida, Georgia, Louisiana, Mississippi, Texas	NOAA	Binary	Invariant	+

To reiterate, the proposed research question is: *to what degree are federal flood mitigation funds reducing observed direct coastal flood losses identified by FEMA and SBA?* To effectively address this research question, and to ensure the best unbiased linear estimates, I will explore the data using descriptive statistics (Table 9) and utilizing a variety of regression diagnostic methodologies for panel data. The panel data in this study is considered balanced, which means that every panel subject (i.e., county) has the same time identifier (i.e., years). The list of diagnostics that are applied for this study are testing for and remedying multicollinearity, using a fixed effects or random effects model based on the Hausman Test, serial correlation, cross-sectional dependence, spatial autocorrelation, and heteroskedasticity. These diagnostic techniques will guide the decision of model selection for this study. Panel data differs from time-series or cross-sectional datasets in that multiple panel members (i.e., counties) are measured over time (i.e., years).

Table 9 Descriptive Statistics for all variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Total Flood Loss (2019$)	2,538	$35,378,547	$448,303,220	$0.00	$17,960,155,136
Logged Total Flood Loss	2,538	9.70	5.98	1	23.61
Model 1					
HMGP Spending (2019$)	2,538	$258,619	$3,310,930	$0.00	$147,109,760
Logged HMGP Spending	2,538	3.221	4.586	1	18.807
Model 2					
FMA Spending (2019$)	2,538	$10,665	$110,715	$0.00	$2,747,206
Logged FMA Spending	2,538	1.272	1.744	1	14.826
Model 3					
Mitigated HMGP Properties (#)	2,538	1.287	18.071	0	629
Mitigated FMA Properties (#)	2,538	0.067	0.809	0	28
Low – Density Dev. (%)	2,538	4.302	4.035	0.315	28.022
High- Density Dev. (%)	2,538	0.592	1.219	0.008	10.625
Floodplain Area (%)	2,538	38.299	24.139	8.159	98.962
Wetland Alteration (%)	2,538	-0.084	0.314	-2.861	2.184

Table 9 Continued Descriptive Statistics for all variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Precipitation (in.)	2,538	56.194	15.756	9.109	104.455
Storm Events (#)	2,538	2.052	3.297	0	45
Shoreline (Y/N)	2,538	0.482	0.499	0	1
Housing Units (1k)	2,538	67.168	158.505	0.247	1768.096
Median Household Income ($1k)	2,538	44.343	10.298	19.959	97.743
Declared Disasters (#)	2,538	0.745	1.071	0	5
HMGP Implementation Time (years)	2,538	1.014	2.437	0	14
FMA Implementation Time (years)	2,538	0.067	0.48	0	6
Alabama Identifier (Y/N)	2,538	0.057	0.231	0	1
Florida Identifier (Y/N)	2,538	0.298	0.457	0	1
Georgia Identifier (Y/N)	2,538	0.021	0.144	0	1
Louisiana Identifier (Y/N)	2,538	0.262	0.44	0	1
Mississippi Identifier (Y/N)	2,538	0.085	0.279	0	1
Texas Identifier (Y/N)	2,538	0.277	0.447	0	1

4.4.1 Multicollinearity

Correlation analyses ensures that the collected dependent and independent variables maintain a linear relationship. Multicollinearity is when multiple independent variables are highly correlated to one another and can create difficulties in determining the most valuable independent variables. Correlation coefficient matrixes were used to test for multicollinearity (Figure B.1 and Figure B.2 in Appendix B). No significantly high correlations were found, meaning multicollinearity was not an issue in this study.

4.4.2 Serial Correlation

Models examining cross sectional time-series data can be influenced by serial correlation where standard errors become biased, and the regression results can be less efficient (Drukker 2003). A test for serial correlation was developed by Drukker (2003) for the use of the statistical software program, STATA. All models reported that serial correlation was not significant and absent.

4.4.3 Hausman Test

The Hausman test is used in panel data analysis to test for endogeneity and for a correlation between predictor variables and the error term. The null hypothesis of a Hausman Test is that random effects are the preferred model, and the alternative hypothesis is the model should be conducted using fixed effects. All models in this study underwent the Hausman Test and resulted in the application of random effects on all models.

4.4.4 Cross-sectional Dependence

A third type of correlation test is cross-sectional dependence. Cross-sectional dependence is when correlations between observations occur due to common factors that are unobserved (De Hoyos and Sarafidis 2006). Biased standard errors may influence model results if cross-sectional dependence is found and not remedied. De Hoyos and Sarafidis (2006) employs three different tests for panel data where the number of observations is larger than the number of time periods, which is true in the case of this study. The three different tests for cross-sectional dependence in time series models through the statistical software program STATA are the Pearson's test, Friedman's test, and Frees' test. All three tests were run on all models in this research and resulted in the presence of cross-sectional dependence further enforcing the use of robust standard errors in the final model.

4.4.5 Heteroskedasticity

To ensure that the data used in each model are homoscedastic and not heteroscedastic (that is when the error terms in the data are inconsistent and violates the assumption of constant variance), a Breusch-Pagan/Cook-Weisberg test for heteroskedasticity was conducted. The heteroskedasticity test results were significant across all models leading to the use of robust standard errors in the final model selection.

4.4.6 Spatial Autocorrelation

Spatial autocorrelation is present when multiple independent variables are correlated based on related experiences and can be problematic when studying areas that can be influenced by surrounding observations. Spatially, counties within the study area that are closer may experience similar values from the selected variables than counties that are further away. Tobler’s first law of geography states that “everything is related to everything else, but near things are more related than distant things.” A spatial panel autocorrelation test using an inverted weight matrix developed by Shehata and Michaiel (2012) for STATA showed that spatial autocorrelation is significant in all models resulting in the use of robust standard errors in the final model. The same test by Shehata and Michaiel (2012) reports the significance of running and LM Lag (Robust) model or a LM Error (Robust) model. Both model preferences were significant in this test, but the LM Error (Robust) was shown to be more significant in all models (Figure B.3, B.4, B.5, and B.6 in Appendix B) and would be utilized in this study.

4.4.7 *Final Model Selection*

Results from the examination and testing of multicollinearity, the Hausman Test, serial correlation, cross-sectional dependence, heteroskedasticity, and spatial autocorrelation previously mentioned led the final model selection that estimates a spatial error model with the inclusion of robust standard errors and random effects.

4.5 Validity Threats

This study recognizes limitations and is not free of validity threats that should be addressed through future research. This dissertation only addresses threats that pertain to internal validity, external validity, construct validity, and any reliability threats in the collected and analyzed data (Cook, Campbell & Day 1979). This section details the known validity threats to this research design that were not able to be addressed.

4.5.1 *Internal Validity*

Internal validity is described as controlling or strengthening variable selections and methodologies used in collecting the data being analyzed.

In terms of mitigation, the study also does not take into consideration pre-existing structural or non-structural hazard mitigation measures located within the study area. Types of pre-hazard mitigation measures include local, state, or federally funded mitigation projects, such as funds from the U.S. Department of Housing and Urban Development (HUD) to the Texas General Land Office (GLO) Community Development and Revitalization program, other federal agency programs, or regional-based mitigation activities performed by private citizens investing in hazard mitigation for their personal property.

While the mitigation dataset acquired from FEMA and used in this study provides beneficial information across all HMA programs, such as amount of funds dispersed, which programs were responsible for each project, the type(s) of project(s) performed, the number of properties mitigated by the project, the expected benefit-cost ratio of each project, and which communities benefited from these funds, it is difficult to separate most values to conduct a more thorough study of federal mitigation spending. For example, each value in the dataset is unique based on a recorded project identifier. Although the project identifier is uniquely recorded, the type of project performed within each project identifier, specifically in this dataset, are individually and collectively listed. This, in turn, means that the funds allocated for each project identifier cannot be further split between the type of project conducted unless the project identifier only notes one type of mitigation project. Those values where multiple mitigation practices are identified in a single project identifier would be better utilized if FEMA could split the project identifier further based on mitigation project type and the amount of funds granted for each. In doing this, not only would the data be more diverse, but it would allow future research to examine the impact of selected mitigation practices and the amount of funds granted for each across the study area. Another issue regarding project identifiers, many observations were considered "statewide" disbursements and some observations were listed across multiple counties benefiting from these funds. To ensure only one county was being represented in this study, only observations with one unique county identification was included. Future research should break down mitigation project type and the amount of spending that went to individual counties when they are grouped together in the obtained dataset.

From the selected HMA programs administered by FEMA, only HMGP is activated where there is a Presidentially Declared Disaster, and all other programs function off a rigorous application cycle before funds are distributed. The mitigation projects and funds under HMGP are only directly related to areas that have been deemed to have experienced a declared disaster and are not capable of responding to more acute hazard events. Unlike HMGP, the FMA grant program is only awarded through an application cycle annually. The application process for this program requires cooperation from higher systems of government and many weighted factors. The award distribution may be more biased to the selected applicants based on many aspects, including having the ability to create a more effective application, having a foreseeably higher benefit-cost ratio from the projected funds and mitigation practices selected, and may not be awarded to those communities that are in the most need of federal mitigation funds.

4.5.2 External Validity

External validity, unlike internal validity, relates to how applicable and generalizable results are to being translated into another context or in the real world.

One such threat to external validity is aggregating variable inputs to the county scale. Aggregating these variables to this scale risks losing data accuracy and more defined detail in the data otherwise seen in local-level study areas. On the other hand, the research findings at the county scale can be externalized to the national level more easily resulting in future research and policy implications across a wider and more generalizable scale.

The data sources used in this study are not considered to be a complete set to accurately account for total observed flood losses and mitigation funding. While FEMA and SBA are more commonly known, there are approximately six additional federal agencies that provide sources of funding to alleviate the effects from flood events. While noting these additional agencies is important, data availability is limited, and they will be the focus for future research at the conclusion of this current project. With this current research project being directed towards direct losses experienced by FEMA and SBA, it would be advantageous for future research to examine all avenues of federal funding to determine the near full extent of federal payouts and their effects on true observed flood losses.

4.5.3 Construct Validity

Construct validity revolves around the question of did the study measure what it was designed to measure. The best method of controlling construct validity has occurred through the literature review by taking proven methodologies and results from previous research and extrapolating them into this study.

Certain funds are only administered when there is a Presidentially Declared Disaster in effect. The IA, PA, and SBA disaster loans are examples of this, whereas the NFIP is only applicable to those that have flood insurance policies. While the NFIP can capture non-disaster and declared disaster events, it is only accounting for individuals and businesses that have purchased flood insurance. The IA, PA, and SBA disaster loans are only capturing observed flood losses when a declared disaster occurs and not during a smaller, more acute flood event may happen.

4.5.4 Reliability Threats

Reliability of data and measurement tools are important factors when making assumptions or explaining research results to a broader audience. Human error in data collection and processing, as an example, is a threat that many studies must correct for as best they can.

Data obtained by FEMA, this includes all NFIP, IA, PA, HMGP, and FMA data, is collected and input by hand manually. This type of methodology runs the risk of human error and must be recognized. All data collected for this study was thoroughly examined, cleaned, and interpreted without creating threats to reliability.

5. EXPLORING THE SPATIAL AND TEMPORTAL PATTERNS OF OBSERVED FLOOD LOSSES AND THE FEDERAL MITIGATION INDEPENDENT VARIABLES

This Chapter consists of two main sections that further examine the observed flood losses (dependent variable) and the federal mitigation independent variables within the 141 coastal watershed county study area along the Gulf of Mexico. Each of the variables are characterized spatially and temporally by informative basic descriptive statistics and graphics.

5.1 Descriptive Temporal and Spatial Analysis of Observed Flood Losses

5.1.1 Temporal Observed Flood Loss Analysis

The total amount of observed losses from flooding for every coastal watershed county by each federal program (NFIP, IA, PA, and SBA) gathered for this study and adjusted to 2019 dollars is further described in Table 10. The year with a maximum of over $43.6 billion was 2005, and the total losses from 2002 to 2019 are over $89.6 billion. Interestingly, each of these programs that account for flood-related observable losses report multiple years of federal expenses reaching from the tens of millions well into the billions. The NFIP alone, which is the flood insurance program for homeowners and businesses administered by FEMA, shows six years of at least one billion dollars of observable losses due to flood-related events (2004, 2005, 2008, 2016, 2017, and 2019).

Table 10 Total Yearly Observed Flood Loss (2019 $) from each Federal Program

Year	Total NFIP Loss	Total IA Loss	Total PA Loss	Total SBA Loss	Total Losses Summed
2002	$398,202,637	$69,615,550	$88,410,981	$157,643,295	**$713,872,461**
2003	$100,964,451	$83,784,114	$34,858,543	$25,928,947	**$245,536,055**
2004	$1,981,639,850	$781,770,420	$1,602,949,839	$1,648,622,574	**$6,014,982,647**

Table 10 Continued Total Yearly Observed Flood Loss (2019 $) from each Federal Program

Year	Total NFIP Loss	Total IA Loss	Total PA Loss	Total SBA Loss	Total Losses Summed
2005	$8,966,173,774	$8,678,433,767	$15,634,322,540	$10,391,804,937	**$43,670,734,656**
2006	$138,779,575	$26,715,293	$131,563,878	$63,629,881	**$360,688,630**
2007	$60,053,563	$13,474,291	$15,974,240	$29,952,885	**$119,454,979**
2008	$3,193,329,379	$868,407,860	$2,007,312,797	$994,436,635	**$7,063,486,697**
2009	$255,645,655	$4,574,414	$47,787,391	$2,157,391	**$310,164,851**
2010	$25,784,866	$10,764,770	$30,563,394	$1,464,279	**$68,577,308**
2011	$37,174,907	$1,822,432	$17,522,818	$535,667	**$57,055,823**
2012	$302,550,208	$129,454,058	$309,407,823	$143,105,128	**$884,517,220**
2013	$55,126,365	$1,387,367	$54,741,642	$1,703,082	**$112,958,457**
2014	$1,206,680	$51,921,149	$147,608,558	$57,905,487	**$258,641,873**
2015	$498,557,668	$33,662,158	$34,494,361	$63,924,581	**$630,638,762**
2016	$3,560,937,075	$542,237,800	$467,225,129	$1,600,806,237	**$6,171,206,243**
2017	$9,813,206,414	$1,863,182,723	$2,179,231,648	$4,943,229,515	**$18,798,850,564**
2018	$273,536,984	$0	$26,251,632	$680,342	**$300,468,959**
2019	$1,105,337,124	$166,730,901	$1,030,284,282	$1,598,249,089	**$3,900,601,451**

The previous table can be better visualized with the use of informative bar graphs, Figures 4 and 5. The first of which (Figure 4) details the total yearly observed flood losses (in 2019$ billions) from 2002 to 2019. As mentioned in the previous table, there are multiple years with over $1 billion in observable flood losses, the greatest of those being 2004, 2005, 2008, 2016, and 2017. These years coincide with major flood-related events and disasters, such as 2004 when four named hurricanes made landfall in Florida, in 2005 with Hurricane Katrina, and Hurricane Harvey in 2017. While there were many more billions of dollars of loss from different programs at each level of government, these numbers only reflect losses accounted for by the NFIP, IA, PA, and SBA.

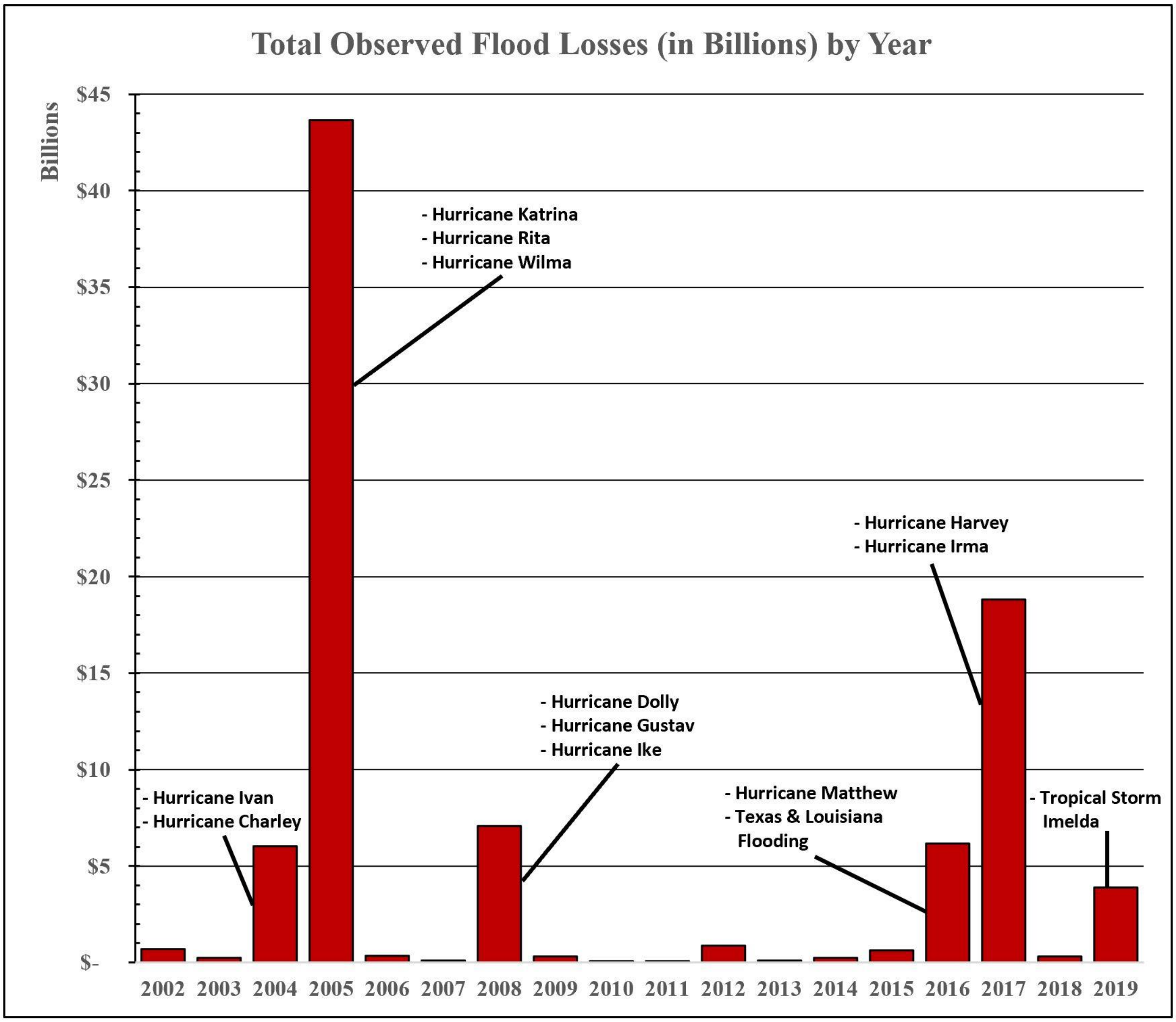

Figure 4 Total Observed Flood Losses (in Billions) by Year

The following bar graph, Figure 5, is a more detailed image of Figure 4 as shown before. Where Figure 4 simply illustrates the total observable flood losses across all the federal programs analyzed in this study, Figure 5 displays a more detailed infographic as to how much money each of the federal programs spent during a given year towards flood-related events. It is interesting to note that the IA and SBA programs increase relative to the increases in NFIP expenditures. A great comparison can be made between the losses observed in 2005 and 2017. In 2005, Hurricane

Katrina created catastrophic damage due to the failure of multiple levee systems, whereas Hurricane Harvey caused widespread flooding from excessive inundation in 2017. The largest difference between these two dates is the amount of PA expenses in 2005 and the NFIP expenses in 2017. This observation suggests that more structural assistance was provided because of Hurricane Katrina, whereas an increase in NFIP losses coincides with the widespread inundation from rainfall by Hurricane Harvey.

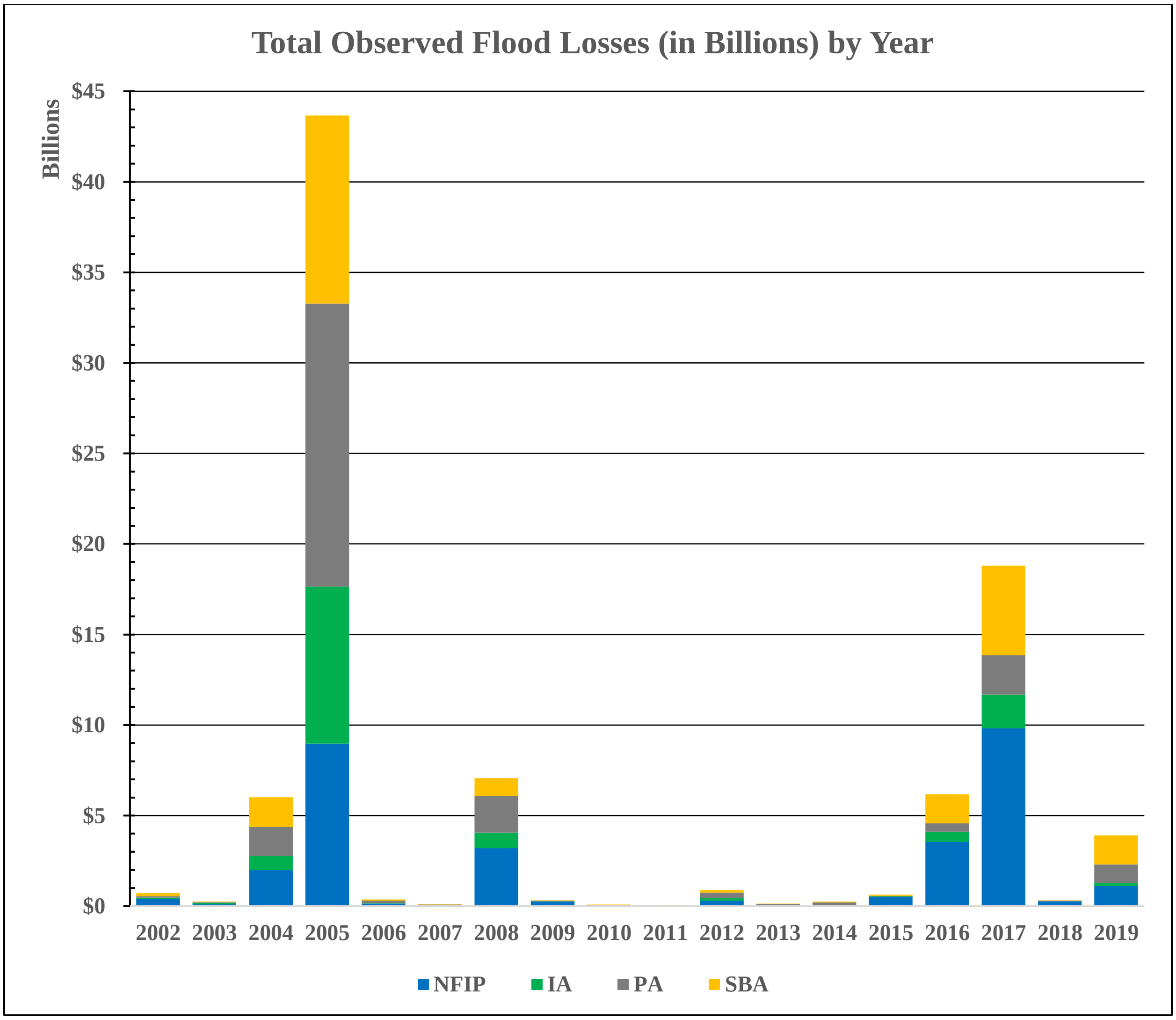

Figure 5 Total Observed Flood Losses (in Billions) by Year from NFIP, IA, PA, and SBA

5.1.2 Spatial Observed Flood Loss Analysis

In terms of observed flood losses across the Gulf of Mexico coastal watershed county study area, a spatial depiction of losses provides interesting insights (Figure 6). Figure 6 is measured in the millions adjusted to 2019 dollars. The dispersal of observable flood losses is quite representative of areas that experience higher frequencies and more extreme flood related events. Clearly, more populated counties, such as Harris County in Texas and Orleans and Saint Bernard Parishes in Louisiana, display larger amounts of observable losses from flooding events over the timeframe of this study. Areas that experience little to no observable flood losses include areas such as central and southern coastal Texas and the middle of the Florida panhandle. Counties and parishes considered direct shoreline areas also experience larger amounts of observable flood losses as compared to the more inland regions due to their increased exposure to storm surge and coastal rainfall events.

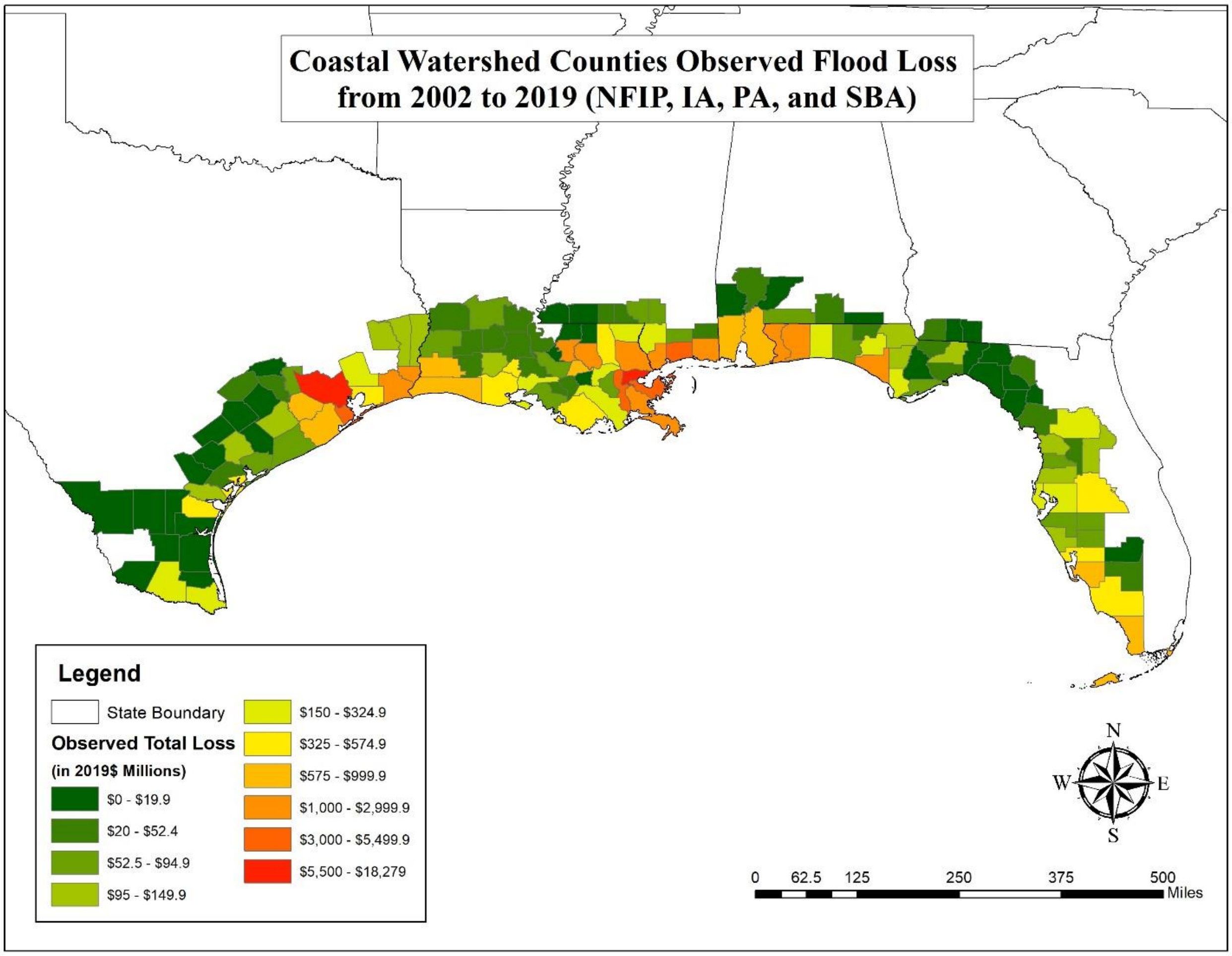

Figure 6 Total Observed Flood Losses across the Study Area

5.2 Descriptive Temporal and Spatial Analysis of Mitigation Independent Variables

5.2.1 Temporal HMGP and FMA Spending Analysis

Temporally, Figure 7 details the total amount of mitigation spending, in millions, for mitigation projects listed as "complete" from each of the federal programs used in this study. When compared to the total amount of funds distributed from the HMGP, FMA pales in comparison throughout the study period. Both federal programs report "completed" flood-related mitigation projects for coastal watershed counties along the Gulf of Mexico below the $20 million mark from 2002 to 2013. The cost of "completed" mitigation projects rose drastically in 2014 and incrementally decreasing over the next few years. Whereas observable flood losses are consistent with the number and magnitude of major flooding events in any given year, HMGP and FMA spending does not accurately represent when a major flooding event occurred. Rather, many mitigation funded projects by the HMGP and FMA programs take multiple years to be fully executed in the real world and become usable in this study.

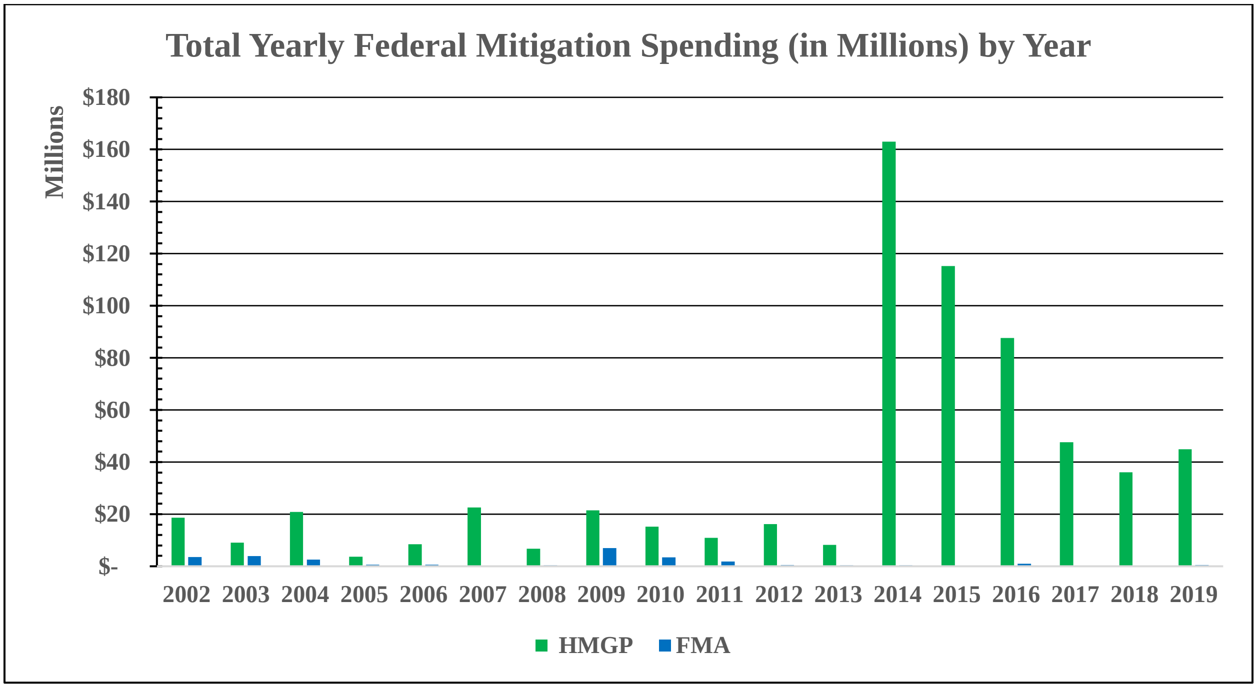

Figure 7 Total Yearly Federal Mitigation Spending (in Millions) by Year

Gaining a better understanding of where federal mitigation spending is being spent temporally, Figure 8 (below) is the same information as the previous figure except for splitting the yearly funding further by state. The Gulf of Mexico coastal watershed counties are found within Alabama, Florida, Georgia, Louisiana, Mississippi, and Texas. Most notably, Texas is the sole recipient of HMGP funds for "completed" mitigation projects during 2014, 2015, 2016 and 2019.

Compared to the amounts that represent HMGP, FMA funds for “completed” mitigation projects can be found primarily in Florida, particularly in 2003, 2009 and 2010. Based on the information provided, coastal watershed counties in Texas received little-to-no FMA funds for mitigation projects considered to be “complete.”

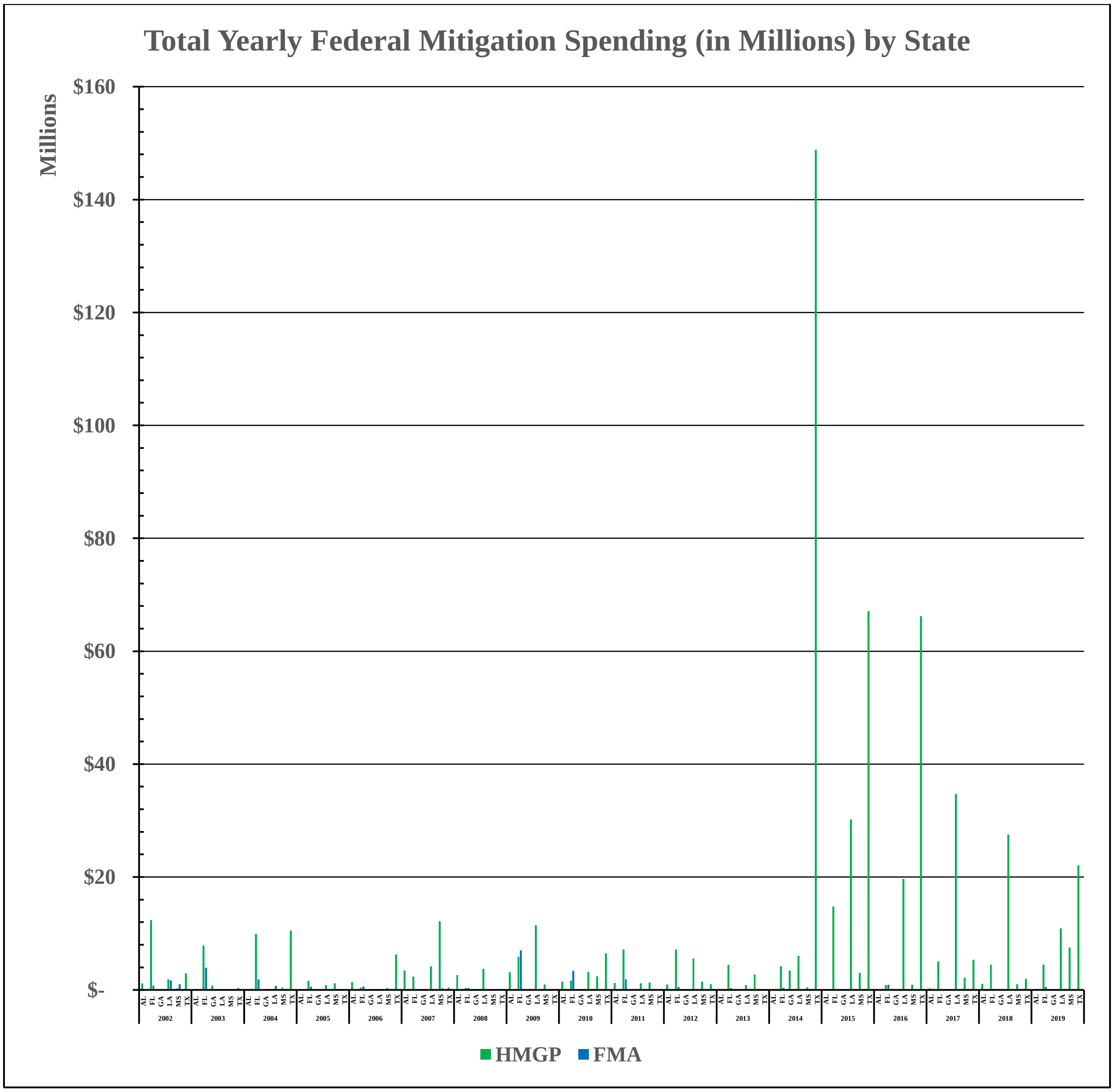

Figure 8 Total Yearly Federal Mitigation Spending (in Millions) by State

5.2.2 Spatial HMGP and FMA Spending Analysis

Spatially, HMGP spending (Figure 9) for “completed” mitigation projects between 2002 and 2019 are like the previous map of observable flood losses across the Gulf of Mexico coastal watershed counties. Where larger amounts of flood losses are identified, HMGP funds look to be focused on those counties that were heavily impacted. Nearly all highly populated and direct coastline counties show some form of HMGP representation except for the central Texas coastline and the northern section of Florida just before the panhandle. More populated counties in Texas, such as Harris County and Jefferson County, and Louisiana, such as Saint Tammany Parish, Jefferson Parish, and Terrebonne Parish, report the largest amounts of HMGP spending across the study period. The dispersal of HMGP spending correlates with the spatial figure of observable flood losses previously presented.

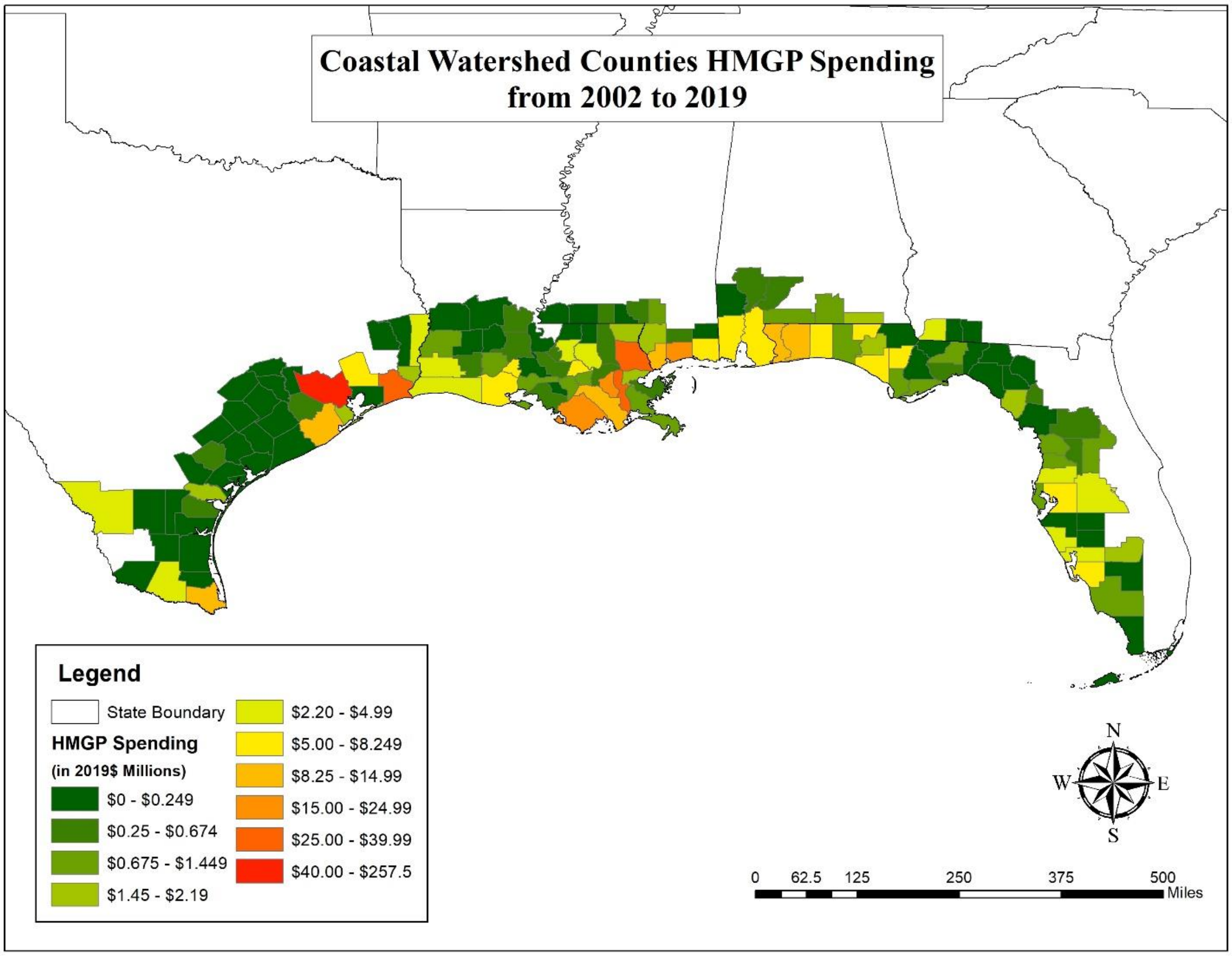

Figure 9 Total HMGP Spending across the Study Area

On the other hand, FMA spending (Figure 10) for "completed" mitigation projects depicts a different spatial picture. The majority of FMA funds are throughout the coastal watershed counties of Florida and parishes of southeastern Louisiana. This is not to say that counties outside of these reported areas do not receive any form of FMA support, only that FMA projects that were considered "complete" by this study's standards were primarily in these two areas. When compared to the previous figure, FMA mitigation funding is not as equally dispersed in areas that experience larger amounts of observable flood losses. The heavy differences shown between the

HMGP and FMA maps highlight concerns as to why FMA mitigation spending is more selective whereas the HMGP mitigation funds are more like the observable flood losses figure.

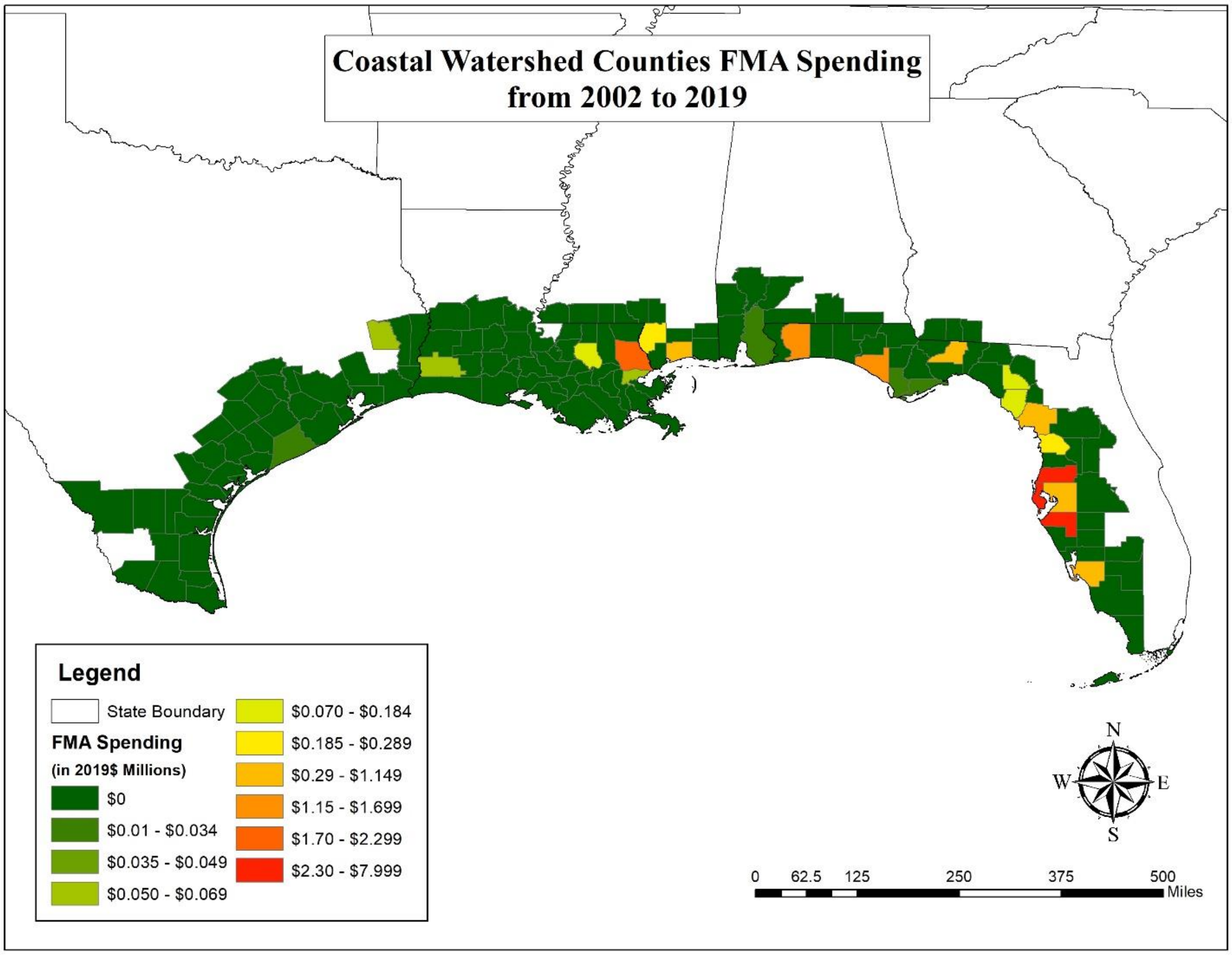

Figure 10 Total FMA Spending across the Study Area

5.2.3 Analysis of the Number of Mitigated Properties from HMGP and FMA

The number of mitigated properties identified by HMGP (Figure 11) and FMA (Figure 12) are similar, spatially, to that of the total spending figures previously discussed from each of the federal programs. Mitigated properties will only be identified in areas where funding has been dispersed. More simply, just because a coastal watershed county receives mitigation funds from either of these programs does not guarantee that properties will be directly mitigated and accounted for. It can be shown that coastal watershed counties receiving larger amounts of funds from "completed" mitigation projects report increased amounts of identified mitigated properties. For the HMGP mitigated properties figure, it is more relatable to the observable flood losses figure than the FMA mitigated properties figure. Analyzing the coastal watershed county study area between 2002 and 2019, the maximum number of mitigated properties in a single county for HMGP is 1,488 and FMA is 60.

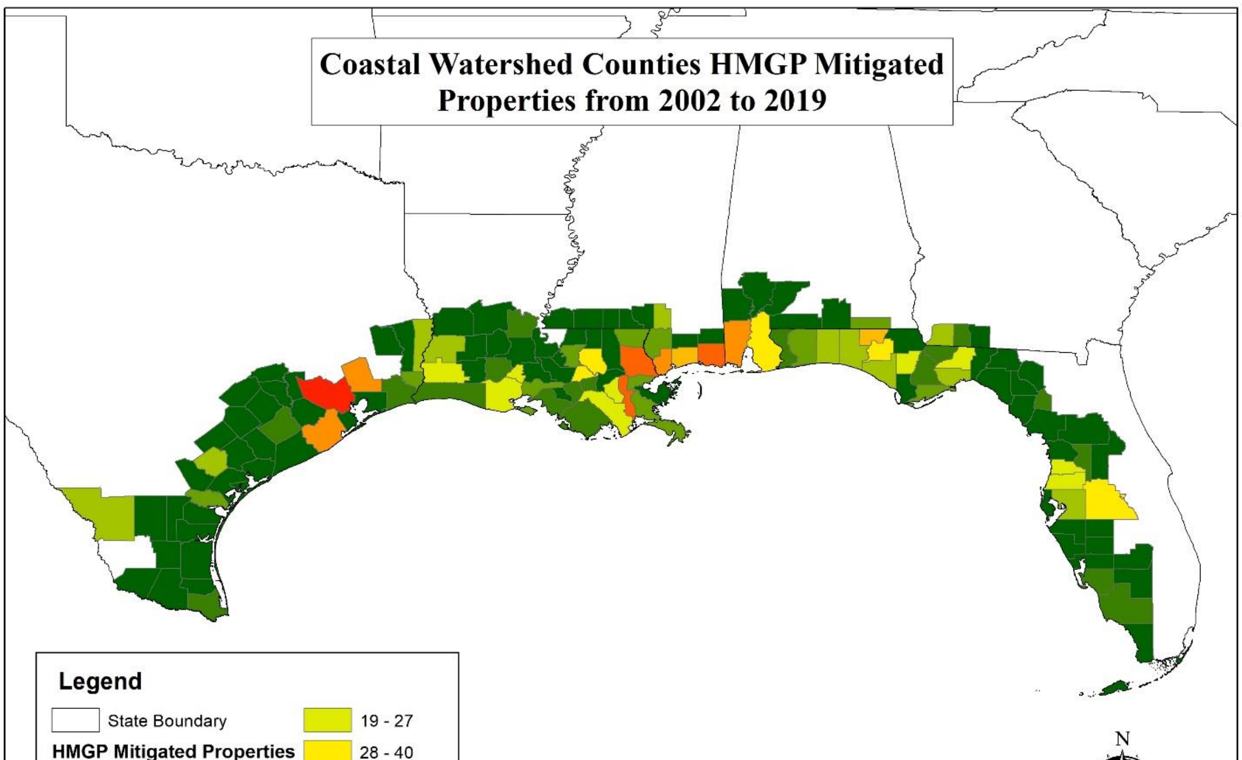

Figure 11 Total Number of HMGP Identified Mitigated Properties across the Study Area

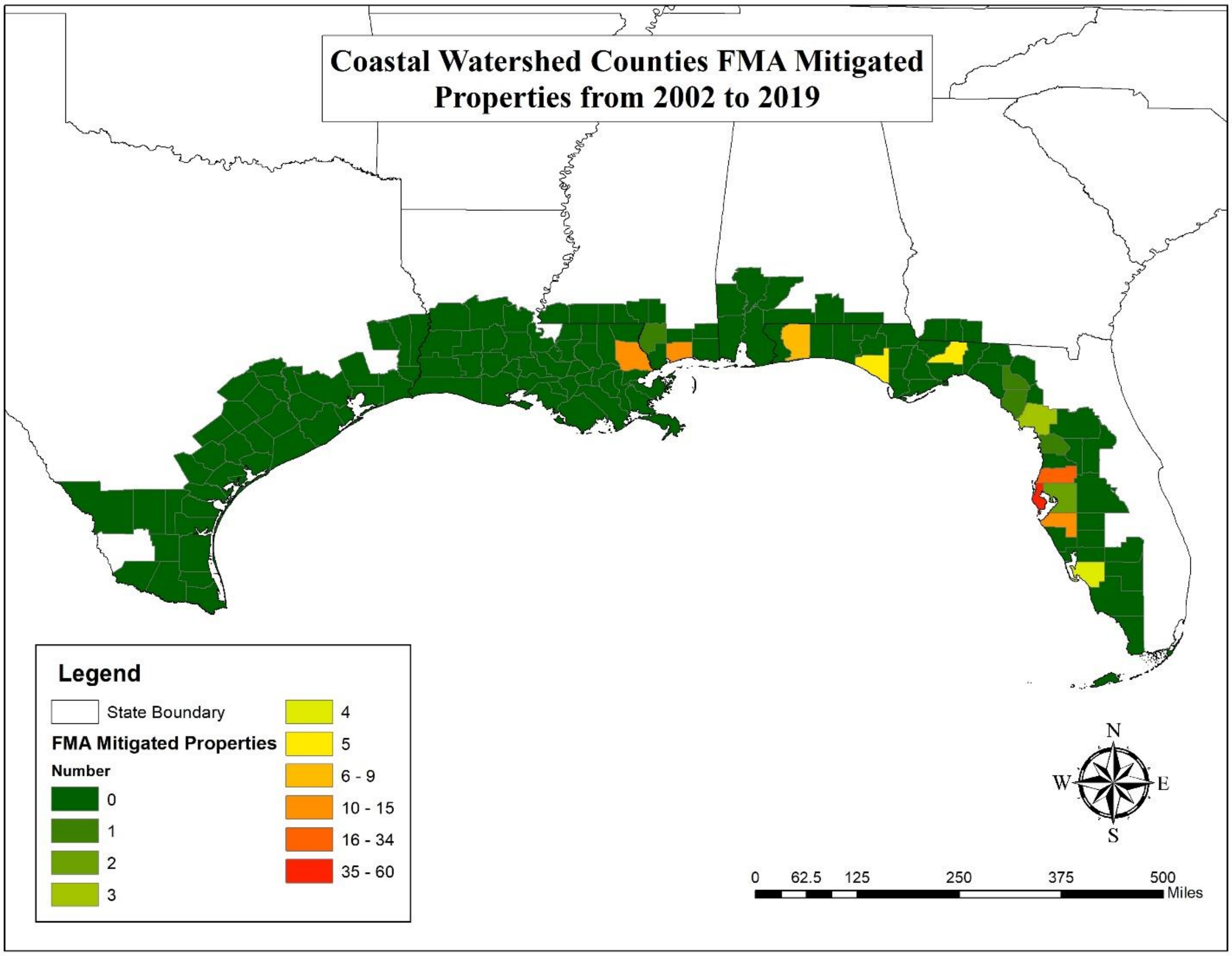

Figure 12 Total Number of FMA Identified Mitigated Properties across the Study Area

6. EXPLAINING THE EFFECT OF FEDERAL HAZARD MITIGATION FUNDING AND THE NUMBER OF MITIGATED PROPERTIES ON OBSERVED FLOOD LOSSES

As described in Chapter 4 of this dissertation, it is necessary for spatial regression models (spatial error models in this case as mentioned in the Final Model Selection portion of Chapter 4) to use additional measures to examine the effects the independent variables have on the dependent variable, which is observable flood losses. The independent variables for this dissertation are split between three model groupings. The independent variable for Model 1 is HMGP spending and its yearly lag up to five years, Model 2 is FMA spending and its yearly lag up to five years, and Model 3 is the number of mitigated properties from HMGP and FMA. Additional control variables, individually characterized in Chapter 4, are also examined in each of the models to identify their effects on observable flood losses.

6.1 Modelled Results for Spatial Error Regression Model 1 (HMGP Spending)

The spatial panel error regression model results for the HMGP spending independent variable that makes up Model 1 are detailed in Table 11. The independent and control variables selected in this model explained between 41.02% and 41.28% of the variance. The R-squared-Within value is reported in this research because it depicts how well the explanatory variables account for changes in observed flood losses within each of the counties over time. The values from R-squared-Between reports how well the explanatory variables account for differences in the observed flood losses between the study area counties. The R-squared-Overall is a weighted average of the within and between values. A negative, non-significant constant was also created by this model. The natural log of HMGP spending has a negative coefficient effect on the natural log of observed flood losses when holding other variables constant but is not statistically significant at any level. This reported coefficient supports half of *Hypothesis 1* in that increased HMGP spending will result in a statistically significant reduction in observed flood losses. Due to these variables being transformed into natural logs, the correct interpretation of this coefficient result is considered log-log. More simply, a percentage point increase in HMGP spending creates a percentage decrease in observed flood losses. The exact percentage decrease in observed flood losses depends entirely on the value of the reported coefficient. As lags are incorporated into the natural log of HMGP spending, none of the reported coefficients are statistically significant. A 3-year and 5-year lag shows negative effects (albeit, statistically insignificant at the .05 level) on observed flood losses.

The regression output for the sub-models that make up Model 1 are nearly identical in their coefficient value, identical in the coefficient direction, and identical in their statistical significance. Knowing this, only the results for the remaining explanatory variables from Model 1.1 are reported.

Environmental explanatory variable coefficient results examined in this research support the findings previously identified in studies noted throughout Chapter 2: Literature Review of this dissertation. A percentage point increase in high-density development in a county has a negative effect on observed flood losses, but is not statistically significant, which does not support *Hypothesis 5*. Low-density development, on the other hand, shows that a percentage increase in a county results in a statistically significant ($p<0.001$) increase in observed flood losses and supports *Hypothesis 6*. Larger 100-year floodplain area percentages show the expected effect on observed flood losses, but is not statistically significant, which does not support *Hypothesis 7*. A percentage gain in wetlands reduces observed flood losses but does not support *Hypothesis 8* because it is not statistically significant. If the percentage area of wetlands were to decrease from alteration, the direction of the resulting coefficient would then be reversed. The resulting coefficient for precipitation, measured in inches, supports *Hypothesis 9* in that more rainfall results in larger and significant ($p<0.001$) observed flood losses. An increase in the number of storm events supports *Hypothesis 10* with an expected significant ($p<0.001$) increase in observed flood losses. Lastly, for the environmental explanatory variables from the sub-models in Model 1, a county or parish that has a shoreline along the Gulf of Mexico has a positive and statistically significant ($p<0.01$) influence on observed flood losses, supporting *Hypothesis 11*.

The socioeconomic explanatory variables and their hypothesis results are the last section of variables to cover from Model 1. Housing units increase, measured in $1 thousand, does not support *Hypothesis 12* because it is not statistically significant. Likewise, increased median household income does not support *Hypothesis 13* because it was not statistically significant, even though it did support the expected coefficient direction. The number of presidentially declared disasters supports *Hypothesis 14* in that it has a significantly ($p<0.001$) positive effect on observed flood losses. *Hypothesis 15* is not supported in this research, that is the time to implement HMGP projects, measured in years, has a positive effect on observed flood losses and is insignificant. The state control variables in the model indicate the influence of a state jurisdiction on observed losses. When compared to counties within the state of Texas, counties or parishes located in Alabama ($p<0.001$), Florida ($p<0.001$), Georgia ($p<0.05$), Louisiana ($p<0.01$), and Mississippi ($p<0.05$) each had negative and significant influences on observed flood losses, which runs counter to *Hypothesis 16, 17, 18, 19,* and *20* respectively. As mentioned previously, all coefficient results from Model 1 and its associated sub-models can be found below in Table 11.

Table 11 Spatial Error Model 1 (HMGP) Regression Results on Observable Flood Losses

Variable	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 1.5	Model 1.6
Log Flood Losses						
Log HMGP	-0.026					
Log HMGP – 1-Year Lag		0.033				
Log HMGP – 2-Year Lag			0.041			
Log HMGP – 3-Year Lag				-0.034		
Log HMGP – 4-Year Lag					0.068	
Log HMGP – 5-Year Lag						-0.046
Low-Density Development	***0.327	***0.326	***0.325	***0.328	***0.327	***0.325
High-Density Development	-0.523	-0.498	-0.497	-0.519	-0.508	-0.499
100-Year Floodplain Area	0.011	0.011	0.011	0.011	0.012	0.011
Wetland Alteration	-0.241	-0.255	-0.246	-0.237	-0.218	-0.259
Precipitation	***0.117	***0.119	***0.118	***0.117	***0.118	***0.119
Storm Events	***0.146	***0.145	***0.147	***0.146	***0.146	***0.147
Shoreline	**1.117	**1.105	**1.102	**1.124	**1.092	**1.131
Housing Units	0.005	0.005	0.005	0.005	0.005	0.005
Household Income	0.013	0.015	0.014	0.014	0.012	0.015
Presidentially Declared Disasters	***2.670	***2.662	***2.662	***2.669	***2.677	***2.661
HMGP Proj. Implementation Time	0.092	-0.078	-0.076	0.083	-0.073	0.037
Alabama	***-3.171	***-3.279	***-3.295	***-3.147	***-3.371	***-3.125
Florida	***-3.216	***-3.294	***-3.289	***-3.228	***-3.327	***-3.218
Georgia	*-2.529	**-2.591	**-2.592	*-2.536	**-2.627	*-2.528
Louisiana	**-2.002	**-1.980	**-1.987	**-1.982	**-2.035	**-1.957
Mississippi	*-1.854	*-1.956	*-1.963	*-1.849	*-2.034	*-1.831
Texas (Omitted / Base Category)	-	-	-	-	-	-
Constant	-0.234	-0.419	-0.378	-0.301	-0.341	-0.385
R-squared: Within	0.4104	0.4107	0.4107	0.4118	0.4102	0.4128
R-squared: Between	0.6875	0.6854	0.6871	0.6849	0.6900	0.6810
R-squared: Overall	0.4798	0.4794	0.4798	0.4801	0.4802	0.4799
N	2,538	2,538	2,538	2,538	2,538	2,538
Number of Groups (counties)	141	141	141	141	141	141
Panel Length (years)	18	18	18	18	18	18

Notes: + p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001

6.2 Modelled Results for Spatial Error Regression Model 2 (FMA Spending)

The spatial panel error regression model results for the FMA spending independent variable that makes up Model 2 are detailed in Table 12. The independent and control variables selected in this model explained between 41.11% and 41.65% of the variance, that is the R-squared: Within value identified in the spatial error model, in observed flood losses across the coastal watershed counties of the Gulf of Mexico. A negative, non-significant constant was also created by this model. The natural log of FMA spending surprisingly has a positive coefficient effect on the natural log of observed flood losses when holding other variables constant but is not statistically significant at any level. This reported coefficient does not support *Hypothesis 2* in that increased FMA spending will result in a statistically significant reduction in observed flood losses. Due to these variables being transformed into natural logs, the correct interpretation of this coefficient result is considered log-log. More simply, a percentage point increase in FMA spending creates a percentage increase in observed flood losses. The exact percentage increase in observed flood losses depends entirely on the value of the reported coefficient. As lags are incorporated into the natural log of FMA spending, all but one of the reported coefficients are not statistically significant. An interesting point is that a 5-year lag of FMA spending reports a statistically significant ($p<0.01$) negative effect on observed flood losses. This would imply that FMA spending that has been in effect for 5 years results in a percentage reduction in observed flood losses, which would then support *Hypothesis 2* for this model.

Like Model 1 that was previously mentioned, the regression output for the sub-models that make up Model 2 are nearly identical in their coefficient value, identical in the coefficient direction, and identical in their statistical significance. Knowing this, only the results for the remaining explanatory variables from Model 1.1 will be reported in the writing of this dissertation.

The environmental explanatory variables included in this research produces coefficient directions, being positive or negative influences on observed flood loss, like the studies that had examined them previously identified in Chapter 2: Literature Review of this dissertation. A percentage point increase in high-density development in a county has a negative effect on observed flood losses, which is what was expected, but is not statistically significant, which does not support *Hypothesis 5*. Low-density development, on the other hand, shows that a percentage increase in a county results in a statistically significant ($p<0.001$) increase in observed flood losses and supports *Hypothesis 6*. Larger 100-year floodplain area percentages show the expected effect on observed flood losses but is not statistically significant, which does not support *Hypothesis 7*. A percentage gain in wetlands reduces observed flood losses but does not support *Hypothesis 8* because it is not statistically significant. If the percentage area of wetlands were to decrease from alteration, the direction of the resulting coefficient would then be reversed. The resulting coefficient for precipitation, measured in inches, supports *Hypothesis 9* in that more rainfall results in larger and significant ($p<0.001$) observed flood losses. An increase in the number of storm events supports *Hypothesis 10* with an expected significant ($p<0.001$) increase in observed flood losses. Lastly, for the environmental explanatory variables from the sub-models in Model 2, a county that is considered of having a shoreline along the Gulf of Mexico has a positive and statistically significant ($p<0.01$) influence on observed flood losses, supporting *Hypothesis 11*.

The socioeconomic explanatory variables and their hypothesis results are the last section of variables to cover from Model 2. Housing units increase, measured in $1 thousand, does not support *Hypothesis 12*. Likewise, increased median household income does not support *Hypothesis 13* because it was not statistically significant even though it did support the expected coefficient direction. The number of presidentially declared disasters supports *Hypothesis 14* in that it has a significantly ($p<0.001$) positive effect on observed flood losses. *Hypothesis 15* is not supported in this research, that is the time to implement FMA projects, measured in years, has a negative effect on observed flood losses and is insignificant. Although, the 5-year lag model, Model 2.6, the time to implement FMA projects variable reported a significant (p<0.01) and positive influence on observed flood losses. The coefficient direction reported runs counter to the theory that mitigation projects under the FMA that take longer to implement will result in a decreased amount in observed flood losses. When compared to counties in the state of Texas, counties or parishes located in Alabama (p<0.001), Florida (p<0.001), Georgia (p<0.01), Louisiana (p<0.01), and Mississippi (p<0.05) each had significant influences on observed flood losses but were negative, which does not support *Hypothesis 16*, *17*, *18*, *19*, or *20* respectively. As mentioned previously, all coefficient results from Model 2 and its associated sub-models can be found below in Table 12.

Table 12 Spatial Error Model 2 (FMA) Regression Results on Observable Flood Losses

Variable	**Model 2.1**	**Model 2.2**	**Model 2.3**	**Model 2.4**	**Model 2.5**	**Model 2.6**
Log Flood Losses						
Log FMA	0.020					
Log FMA – 1-Year Lag		0.023				
Log FMA – 2-Year Lag			-0.087			
Log FMA – 3-Year Lag				-0.046		
Log FMA – 4-Year Lag					0.007	
Log FMA – 5-Year Lag						**-0.177
Low-Density Development	***0.329	***0.324	***0.326	***0.322	***0.325	***0.321
High-Density Development	-0.496	-0.516	-0.501	-0.511	-0.509	-0.481
100-Year Floodplain Area	0.011	0.011	0.011	0.011	0.011	0.010
Wetland Alteration	-0.247	-0.233	-0.244	-0.242	-0.239	-0.296
Precipitation	***0.118	***0.118	***0.117	***0.116	***0.118	***0.117
Storm Events	***0.147	***0.146	***0.146	***0.148	***0.146	***0.147
Shoreline	**1.129	**1.101	***1.121	**1.099	**1.109	**1.112
Housing Units	0.005	0.005	0.005	0.005	0.005	0.005
Household Income	0.014	0.014	0.015	0.016	0.014	0.018
Presidentially Declared Disasters	***2.666	***2.667	***2.675	***2.669	***2.665	***2.633
FMA Proj. Implementation Time	-0.220	0.081	0.255	0.334	0.054	**0.605
Alabama	***-3.202	***-3.222	***-3.199	***-3.185	***-3.216	***-3.169
Florida	***-3.227	***-3.284	***-3.230	***-3.249	***-3.265	***-3.206
Georgia	**-2.550	**-2.566	**-2.553	**-2.542	**-2.562	**-2.552
Louisiana	**-1.984	**-1.980	**-1.964	**-1.941	**-1.980	**-1.928
Mississippi	*-1.894	*-1.901	*-1.873	*-1.851	*-1.899	*-1.850
Texas (Omitted / Base Category)	-	-	-	-	-	-
Constant	-0.3361	-0.364	-0.292	-0.347	-0.365	-0.423

Table 12 Continued Spatial Error Model 2 (FMA) Regression Results on Observable Flood Losses

Variable	Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 2.5	Model 2.6
R-squared: Within	0.4111	0.4120	0.4120	0.4134	0.4113	0.4165
R-squared: Between	0.6845	0.6862	0.6849	0.6869	0.6856	0.6840
R-squared: Overall	0.4795	0.4806	0.4803	0.4818	0.4799	0.4834
N	2,538	2,538	2,538	2,538	2,538	2,538
Number of Groups (counties)	141	141	141	141	141	141
Panel Length (years)	18	18	18	18	18	18

Notes: + p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001

6.3 Modelled Results for Spatial Error Regression Model 3 (HMGP & FMA Mitigated Properties)

The spatial panel error regression model results for the number of mitigated properties identified under the HMGP and FMA independent variable, respectively, that makes up Model 3.1 and Model 3.2 are detailed in Table 13. The independent and control variables selected in this model explained 41.01% and 41.13% of the variance in Model 3.1 and Model 3.2, respectively, that is the R-squared: Within value identified in the spatial error model, in observed flood losses across the coastal watershed counties of the Gulf of Mexico. A negative, non-significant constant was also created by this model. When holding all other variables included in these models' constant, neither the number of HMGP nor FMA mitigated properties report statistically significant coefficients. It is interesting to note that the number of mitigated properties from HMGP produces a negative coefficient when the number of FMA mitigated properties produces a positive coefficient. While the independent variables are not naturally logged like the previous two model explanations, the correct interpretation of these variables coefficient results are considered log-level because of the dependent variable, observed flood loss, being naturally logged. More simply, a unit increase in the number of mitigated properties from HMGP or FMA creates a percentage increase in observed flood losses. The exact percentage increase in observed flood losses depends entirely on the value of the reported coefficient and simply multiplying it by 100. Knowing this information, both *Hypothesis 3* and *Hypothesis 4* are not supported in this research.

Like Model 1 and Model 2 before, the regression coefficient outputs from the explanatory variables from Model 3.1 and Model 3.2 are nearly identical in coefficient number but they are identical in their coefficient direction and significance. Because of this, the following explanatory variable information will be interpreted from both models in a singular manner.

The environmental explanatory variables show only four hypotheses being supported from the reported coefficient outputs. A percentage point increase in high-density development in a county has a negative effect on observed flood losses, which is what was expected, but is not statistically significant, which does not support *Hypothesis 5*. Low-density development, on the other hand, shows that a percentage increase in a county results in a statistically significant ($p<0.001$) increase in observed flood losses and supports *Hypothesis 6*. Larger 100-year floodplain area percentages show the expected effect on observed flood losses but is not statistically significant, which does not support *Hypothesis 7*. A percentage gain in wetlands reduces observed flood losses but does not support *Hypothesis 8* because it is not statistically significant. If the percentage area of wetlands were to decrease from alteration, the direction of the resulting coefficient would then be reversed. The resulting coefficient for precipitation, measured in inches, supports *Hypothesis 9* in that more rainfall results in larger and significant ($p<0.001$) observed flood losses. An increase in the number of storm events supports *Hypothesis 10* with an expected significant ($p<0.001$) increase in observed flood losses. Lastly, for the environmental explanatory variables from Model 3, a county that is considered of having a shoreline along the Gulf of Mexico has a positive and statistically significant ($p<0.01$) influence on observed flood losses, supporting *Hypothesis 11*.

The socioeconomic explanatory variables report only two hypotheses being supported and are the last section of variables to cover from Model 3. Housing units increase, measured in $1 thousand, supports *Hypothesis 12* in Model 3.1 (HMGP mitigated properties) by being positive and statistically significant ($p<0.05$), but not significant in Model 3.2 (FMA mitigated properties). Likewise, increased median household income does not support *Hypothesis 13* because it was not statistically significant even though it did support the expected coefficient direction. The number of presidentially declared disasters supports *Hypothesis 14* in that it has a significantly ($p<0.001$) positive effect on observed flood losses. *Hypothesis 15* is not supported in this research for either of the models examining the number of HMGP or FMA mitigated properties, that is the time to implement HMGP or FMA projects, measured in years. The HMGP model (Model 3.1) for project implementation time shows a positive and insignificant effect on observed flood losses, and the FMA model (Model 3.2) for project implementation time shows a negative and insignificant effect on observed flood losses. When compared to counties within the state of Texas, counties or parishes located in Alabama ($p<0.001$), Florida ($p<0.001$), Georgia ($p<0.05$), Louisiana ($p<0.01$), and Mississippi ($p<0.05$) each had significant influences on observed flood losses but were negative, which does not support *Hypothesis 16*, *17*, *18*, *19*, or *20* respectively. As mentioned previously, all coefficient results from Model 2 and its associated sub-models can be found below in Table 13.

Table 13 Spatial Error Model 3 (HMGP & FMA Mitigated Properties) Regression Results on Observable Flood Losses

Variable	**Model 3.1**	**Model 3.2**
Log Flood Losses		
Mitigated HMGP Properties	-0.001	
Mitigated FMA Properties		0.098
Low-Density Development	***0.325	***0.327
High-Density Development	-0.516	-0.505
100-Year Floodplain Area	0.011	0.011
Wetland Alteration	-0.245	-0.245
Precipitation	***0.117	***0.118
Storm Events	***0.147	***0.147
Shoreline	**1.105	**1.131
Housing Units	*0.005	0.005
Household Income	0.013	0.014
Presidentially Declared Disasters	***2.668	***2.666
HMGP Proj. Implementation Time	0.052	
FMA Proj. Implementation Time		-0.230
Alabama	***-3.220	***-3.203
Florida	***-3.238	***-3.227
Georgia	*-2.544	**-2.551
Louisiana	**-2.003	**-1.979
Mississippi	*-1.889	*-1.895
Texas (Omitted / Base Category)	-	-
Constant	-0.257	-0.344
R-squared: Within	0.4101	0.4113
R-squared: Between	0.6897	0.6843
R-squared: Overall	0.4801	0.4796
N	2,538	2,538
Number of Groups (counties)	141	141
Panel Length (years)	18	18

Notes: + p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001

6.4 Summary of Regression Results

In summary, the regression results from Model 1, Model 2, and Model 3 show similar effects among the explanatory variables, but with some notable variations. The results from each regression model represent the expected relationship or influence on observed flood losses based on the independent variable holding all others constant. The R-squared: Within values reported explain the variation in the dependent variable from each model. First and most importantly, the expected relationship between HMGP spending, FMA spending, and the number of mitigated properties from each of these mitigation programs shows interesting coefficient outputs. Model 1 does not support *Hypothesis 1* for HMGP spending because it was not statistically significant even though it had a negative relationship with observed flood losses. Model 2 does not support *Hypothesis 2* for FMA spending except for the 5-year lagged variable. The regression results produced a positive relationship between FMA spending and observable flood losses, but only the 5-year lag of FMA spending supports *Hypothesis 2* by having a highly significant and negative relationship with observed flood losses. Model 3 does not support *Hypothesis 3* or *Hypothesis 4*, that is the number of mitigated properties under HMGP and FMA, respectively, because neither were significant. Like the coefficient outputs from Model 1 and Model 2, HMGP mitigated properties shows a negative nonsignificant relationship with observed flood losses whereas FMA mitigated properties shows a positive nonsignificant relationship.

Second, environmental explanatory variables in this research show that higher values in low-density development, higher values of precipitation, larger number of storm events, and being considered a shoreline county produced highly significant and positive influences on observed flood losses. These results from each model support *Hypothesis 6*, *Hypothesis 9*, *Hypothesis 10*, and *Hypothesis 11*.

Lastly, socioeconomic explanatory variables show that having higher values of housing units and larger number of Presidentially Declared Disasters indicate a highly significant and positive relationship with observed flood losses. These two variables in these models support *Hypothesis 12* and *Hypothesis 14*. While these two variables were the only ones able to support their associated hypotheses, it is interesting to note that, when compared to counties within the state of Texas, counties and parishes within Alabama, Florida, Georgia, Louisiana, and Mississippi were significant but did not have the hypothesized relationship on observed flood losses.

7. DISCUSSION

In this section of the dissertation, I discuss the exploratory data analysis from spatial and temporal figures and the results from the panel data spatial error regression models by addressing the explanatory data analysis. This chapter will conclude with additional policy implications and recommendations based on the findings from this research.

7.1 Discussion of Exploratory Analysis

As shown in Chapter 5 of this research, the results of the exploratory analysis of federal mitigation spending and the number of identified mitigated properties from the HMGP and FMA on observable flood losses along the Gulf of Mexico coastal watershed counties reveal several findings worthy of discussion. First are the temporal characteristics of the observable flood losses compared to the HMGP and FMA spending and second are the spatial characteristics between the observable flood losses and HMGP and FMA spending.

First, in discussing the temporal characteristics of the observable flood losses compared to the HMGP and FMA spending, the most obvious observation is that observable flood losses vary over time and typically accrue larger amounts of loss around a major flooding event within a given year. Unlike observable flood losses being correlated with major flooding events, HMGP and FMA spending do not signify when a major flood event occurred. Rather, federal mitigation spending signifies that heavy losses were experienced in any given area at some point in time because it takes many years for some mitigation observations to be considered “complete,” that is where the funds from a given observation are being fully utilized. Temporally, when looking at the dispersal of mitigation funds from HMGP and FMA, neither of these programs should be used to determine when a major flooding event occurred. With many yearly observations reaching over $1 billion, the largest amounts of observable flood losses occurred in 2005 (over $40 billion) and 2017 (over $15 billion). While observable flood losses reach well into the multiple of billions for each year in this study timeframe, HMGP and FMA only display multiple millions in federal mitigation spending.

Lastly, in discussing the spatial characteristics between the observable flood losses and HMGP and FMA spending, there are a couple similarities and differences to address. The spatial distribution of observable flood losses coincides with highly populated counties and parishes along the Gulf of Mexico. These areas are not only highly populated but are at higher levels of risk from flood-related events. HMGP spending, which is only activated in areas that have received a presidential disaster declaration, has similar characteristics to the spatial depictions of observable flood losses. This signifies that federal mitigation spending from the HMGP are going directly to the areas that experience larger amounts of observable flood losses. On the other hand, FMA spending, which is administered through a competitive application process and can only be awarded under certain limitations, depicts a different spatial picture. The majority of FMA funds are shown to be primarily situated in central-Florida counties, particularly Pasco, Pinellas, and Manatee. These counties surround the Tampa region, which are major tourist hotspots. This, of course, raises concerns as to why much of the FMA funds are localized and not similar in their distribution like the HMGP. While not addressed directly in this research, it would be worth exploring why certain areas receive FMA funds and others do not.

In summary, the federal mitigation spending observations classified as “completed” from HMGP and FMA are more reactionary and take large amounts of time for total implementation.

From the timeframe used in this research, highly populated coastal watershed counties within Florida, Louisiana, and Texas received the largest amounts of funding from HMGP when compared to FMA. Unlike the HMGP, which is widely dispersed across the study area, the FMA funds are primarily located throughout Florida. The total amount of federal spending from the HMGP is significantly more than the observed federal spending from the FMA. Counties that receive larger amounts of losses and mitigation funds are typically highly populated, but the maps generated in this study could also be explained by the technical capacity and available resources available to these communities to apply for and receive mitigation funding. HMGP is directed specifically to areas that have been under a disaster declaration, but FMA is more free-for-all with certain limitations. Clearly, from the maps presented in Chapter 5, HMGP follows where larger amounts of observable flood losses occur, but FMA is not as evenly dispersed and seems to be highly selective.

7.2 Discussion of Explanatory Analysis

The results of this research as shown in Chapter 6 led to supporting 6 out of the 21 hypotheses proposed. The models presented express interesting characteristics and relationships worthy of further consideration, especially those related to mitigation spending programs, number of mitigated properties from each program, and select explanatory variables.

In summary, when using a spatial error regression model for the purposes of this research, the primary independent variables of HMGP spending, FMA spending, and the number of mitigated properties from both HMGP and FMA shows insignificant effects on observed flood losses. By looking at the year in which the spending from either program was made, not incorporating the lagging effects, the final regression models indicate that, when holding all other variables constant, HMGP spending and the number of mitigated properties under the HMGP produced a negative effect while FMA spending and the number of mitigated properties under the FMA produced a positive effect on observed flood losses. These results alone are insignificant and produce minimal percentage point differences on observed flood losses, but they provide the grounds to further advance our knowledge of how mitigation spending has been conducted in the past and creates an opportunity for more beneficial federal and local policy changes. As lags are included on the independent variables for mitigation spending, the results from both Model 1 and Model 2 remain inconclusive. Only a 5-year lag under FMA produced a statistically significant output that supports its hypothesis of increases in FMA spending significantly decrease observed flood losses. This result would imply that after 5 years of project completion, FMA spending would have a statistically significant and negative effect on observed flood losses. Another point about the inconclusiveness of mitigation spending is the changing coefficient signs as the lag increases. In the HMGP model, for example, the original coefficient with no lag showed a negative influence on observed flood losses. A one-year, two-year, and four-year lag resulted in a positive sign, while a three-year and five-year lag resulted in a negative sign. This finding would imply that HMGP spending with no lagging effects, as well as HMGP spending that has been in effect for 3 and 5 years, report a percentage reduction in observed flood losses. In the FMA model, the original coefficient with no lag showed a positive influence on observed flood losses. When incorporating the lags, a one-year and four-year lag resulted in a positive sign, while a two-year, three-year, and the statistically significant 5-year lag resulted in a negative sign.

Theoretically, these two federal programs serve different purposes and are only activated or disburse their funds under certain conditions. Firstly, HMGP is only activated after a presidential disaster declaration and can only be directed to counties where the declaration is in effect. This would imply that only counties that have experienced flooding events destructive enough to warrant a presidential disaster declaration can experience mitigation funding from this program. On the other hand, FMA is conducted through a competitive application process to reduce flooding impacts on communities that participate in the NFIP. While both programs offer the same mitigation measures, the disbursement of funds are drastically different and the communities that receive these funds may not be the most deserving.

The model analyzing HMGP spending resulted in an insignificant, but negative coefficient on observed flood losses. This result is promising in that with increased flood mitigation spending there should be a negative influence on flood losses. While the insignificance of this variable is concerning, this output implies that spending from the HMGP reduces flood losses in the areas that experience presidential disaster declarations. The finances from HMGP are already focused on areas that have experienced a major disaster, but the overall HMGP spending for mitigation measures, or the selected mitigation measures themselves have little effect on the observed flood losses in these areas.

The model analyzing FMA spending, similarly to the results from HMGP, resulted in an insignificant, but positive coefficient on observed flood losses. This result raises serious concerns because this implies that observed flood losses increases as spending increases from the FMA. To reiterate, FMA finances are only disbursed after local communities have gone through a competitive application process detailing their risk of flooding, the mitigation measure they will deploy, and the cost-benefit the spending will have on future flood risk. Although not addressed in this study, community dynamics, such as wealth and economic importance, could play a role as to where this money is being directed and its true effectiveness at reducing flood risk and losses. The results from this study clearly show that, not only is non-lagged FMA spending insignificant, but it also increases observed flood losses. When incorporating yearly lags into the models, the 5-year lag produces a negative and statistically significant influence on observed flood losses. The application process used by the FMA clearly is ineffective, at least in the non-lag and the one-through four-year lag, at addressing or reducing the observed losses and risk of flooding in the coastal areas along the Gulf of Mexico.

The model analyzing the number of mitigation properties by both the HMGP and FMA showed the same results as the two previous mitigation spending models. Mitigated properties identified under the HMGP were insignificant but negatively influencing observed flood losses, and mitigated properties identified under the FMA were insignificant but positive. These inconclusive results do not provide much information about where improvements could be made, but initial policy recommendations can guide future research, mitigation spending and the number of mitigated properties to be more cost effective.

In summary, this study is the first of its kind in examining the effects mitigation funds have on historical observable flood losses in the coastal watershed study area along the Gulf of Mexico. Prior studies fall short when compared to this research because they only examined the mitigation expenditures from HMGP and applied models that generated hypothetical losses from flooding events rather than actual observed losses from federal administrations, such as FEMA and SBA. In the context of mitigation, specifically federal spending and the number of properties that have been repurposed for mitigation purposes, this study and its results do not support the current use of mitigation spending to significantly reduce or eliminate future observable flood losses. Aside from the results presented in the previous chapter, the current federal mitigation programs do not distribute their funds in a consistent fashion and focus on different aspects of mitigation from one another. For example, the HMGP can only be activated and distributed to areas where a presidential declaration has been issued and the funds can only be used for mitigation purposes from the specified disaster event. The FMA funds, on the other hand, do not require a presidential disaster declaration to become activated, but rather force localities to compete for these funds through a highly competitive application process. This does not necessarily mean that the most deserving or highest risk communities receive these FMA funds for mitigation purposes. The largest difference between these two programs is that HMGP targets regions directly impacted by a major natural disaster whereas FMA is more open to any community willing to apply for the available funds. Theoretically, the direct targeting of HMGP funds to areas that are affected by disaster events should directly influence observable flood losses in future events, but that is not what is found in this study's results. This would imply that the type of mitigation projects HMGP funds are directed towards are ineffective, such as funding for non-structural mitigation measures. It would be foolish to think that mitigation and the funds that the federal government provides for these measures do not matter in the grand scheme of reducing flood losses. The results of this study would rather suggest that efforts of mitigation under the current system for both HMGP and FMA are not being utilized to their full potential, or the effectiveness of completed mitigation projects occurs beyond a five-year period.

7.3 Federal Hazard Mitigation Spending Recommendations

The relationship between observed flood losses and federal mitigation spending and the number of properties mitigated, as shown in this research, highlighted important insights into the ineffectiveness of mitigation spending conducted in the past. Additionally, possible policy implications have been mentioned based on the results of this study. The insignificance and inconsistent results of mitigation spending on observed flood losses requires serious attention through additional research and policy recommendations. Millions of taxpayer dollars are spent yearly to combat the growing threat of flooding in the coastal communities of the Gulf of Mexico, but, more importantly, the damage costs associated with flooding continue to rise into the billions year after year. The results of this research benefits policies that can be implemented at the federal and county level, both of which are highlighted below.

7.3.1 Recommendations at the federal level

Federal-level recommendations address the support and recovery programs that account for observed flood losses as well as the proactive programs that account for mitigation. Due to the HMGP, FMA, NFIP, IA, and PA programs being administered by FEMA alongside disaster loans from the SBA, addressing policy recommendations at the federal level are critical to understanding and correcting the inefficiencies of mitigation spending found in this research.

Flood mitigation spending should be viewed as an investment into flood-prone communities that would eventually lead to decreasing losses experienced by flooding events. Methodically investing mitigation spending in areas that need it the most will create a better return on investment rather than throwing or granting vast sums of money at the issue. Increasing the amount of federal mitigation spending, as approved by Congress, paired with a deeper understanding of proven and effective mitigation techniques are necessary in combating the rising costs of flood losses. A method of achieving this would be to take success stories from areas under certain environmental and socioeconomic characteristics and encourage similar communities to strive for similar results with the assistance of these federal mitigation programs. Another key recommendation for the disbursal of federal mitigation funds should be to enforce a reasonable timeframe for county officials where all mitigation money must be spent ensuring the greatest return on investment.

Presidential disaster declarations can be easily relied upon and utilized to inform policy makers where high flood risk communities are located. The current and future federal programs can be more proactive rather than reactive to future flooding events by directing federal mitigation spending to these specific areas. It is important to note that counties that have not yet received presidential disaster declarations does not mean that there is no potential for a disaster in the future. While presidential disaster declarations are designated to entire counties, it would be advantageous to be able to focus the direction of federal mitigation spending into more localized areas that will benefit the most or create the greatest return on investment. Currently, once a county is considered a declared disaster area, federal funding granted can be used for any purpose seen fit by the respective regional government. Converting presidential disaster declarations to areas such as the city boundary, ZIP code, or watershed boundary, although a watershed is not considered a singular jurisdictional boundary, would enhance the effectiveness of federal spending for mitigation and support purposes after a disastrous flooding event.

Most local communities must have an up-to-date hazard mitigation plan before they can receive federal aid in the form of support and recovery or mitigation. Hazard mitigation plans are used as guides for the local communities to consider and implement mitigation techniques and encourage development styles most suitable for the environment in which they reside. At the federal level, it would be beneficial to enforce local hazard mitigation plan documents to incorporate multi-use mitigation strategies, ultimately eliminating a one-size-fits-all mitigation approach. The federal government can provide the necessary aid while the local communities must take initiative by analyzing their current environmental situations and provide actionable recommendations that federal aid can be used for.

The current use of the competitive application process for the disbursement of FMA funds should be restructured to be easily accessible to communities that may not have a competitive application but need federal aid more based on a predefined rubric or grading system. This federal program currently uses a cost-benefit analysis to factor which communities or individual groups need federal mitigation money more. Obviously, using current cost-benefit analyses presents major biases to moderate - high-income communities where property value is higher than that of low-income communities. The development of a more inclusive, non-biased cost-benefit calculator will yield in reducing flood risk and observable flood losses from communities that are more vulnerable to these events.

The NFIP, currently used as an identifier of risk from flooding and provides basic coverage in the event of a flooding event. With support from FEMA mitigation programs, the NFIP should begin removing individuals from properties within the immediate 100-year floodplain, widen the area where it is required to own flood insurance, and discourage future buyers from purchasing high-risk property by declining insurance or any form of federalized incentive. To the first point, the floodplain is in a constant state of change depending on the land-use and development pattern in the surrounding areas. Areas considered risky can become even more risky as time goes on and areas not considered risky can expect to become risky if environmental conditions are right. It is not feasible for the federal government or private entity to continue providing insurance when it is a certainty that a property will experience a flood event. In conjunction with mitigation programs and spending, systematically and responsibly begin removing more vulnerable property and families out of highly hazardous areas and into areas where their vulnerability can be better managed. Secondly, property owners that reside within the 100-year floodplain and have a federally-backed mortgage are required to own flood insurance. This area is considered small when comparing to other nations that live with the constant threat of flooding. The NFIP should reform the minimum floodplain area requirement to own flood insurance to at least the 500-year floodplain or even begin incorporating the mapping of the 1,000-year floodplain. Lastly, as we see losses from flooding rising over the years, buyers looking to purchase property in high flood risk areas should not be afforded the opportunity to purchase flood insurance because the likelihood of incurring flood damages and receiving mitigation funds would be inevitable. While considered extreme, the federal government should respectively draw a theoretical line that will deny the purchase of flood insurance if the prospective buyer truly understands the risks and can handle the costs from flooding events themselves.

7.3.2 Recommendations at the county level

Based on this study's spatial scale, policy recommendations at the county level are also critical to ensure that impacted communities receive federal funding quickly and that the major flood risk concerns are being addressed through proper mitigation measures. County officials are far more knowledgeable about the unique threats of flooding or the environmental makeup of local communities than the federal government.

First, it can take years for mitigation efforts to be successfully implemented once federal aid has been granted and disbursed to the county level. The average number of years it takes for mitigation projects to be fully funded and implemented are 1.014 years for HMGP projects and 0.067 years for FMA projects. Although these seem relatively short timeframes, the maximum years for project completion under the HMGP was 14 years and for the FMA was 6 years. While this study did its best to ensure that only observations included in the study were considered complete and fully implemented, it is still crucial to develop a method at the local level that fast tracks federal aid to alleviate the effects and future costs of flooding.

Secondly, local communities within these counties should continue to encourage and require continual updates of their respective hazard mitigation plans. Through these plans, local communities can outline areas of interest that are considered high risk and where mitigation measures should be implemented. The initiative of local communities to assess their own environments and their relationships with different forms of floods can influence the type of decisions made to combat future risk and losses. The Gulf of Mexico represents many different types of regional and environmental characteristics, but the one constant is the increase in development that leads to greater losses from flooding. Returning local communities back to native characteristics, such as incorporating native vegetation and environmental conditions will assist in alleviating the damages experienced by floods. Take Houston for example, an area that was once a swamp is now experiencing rapid development where wetlands are being removed at a considerable rate. Reincorporating native environmental characteristics to the current conditions of the built environment may create a more natural association with flooding rather than a nuisance. Based on the guidelines presented in these mitigation plans, local communities can focus the received federal spending in areas deemed highly vulnerable and are considered low income. Developers should abide by regulations limiting urban sprawl and focusing on building more densely, especially in areas experiencing population growth. Community awareness should constantly be promoted by local communities based on the goals and objectives listed in the hazard mitigation plans. Creating general awareness can lead to better responses from flood events and can encourage local assistance through charitable giving and direct communication through open forums.

Lastly, while floodplain maps are generally produced by the federal government, regional officials at the county level should be held responsible for the generation and distribution of floodplain maps based on a uniform set of standards in a timely manner. Future floodplain mapping should be highly-detailed and begin accounting for all environmental and human characteristics. The built environment, not just locally but also in surrounding regions, impacts the direct and downstream floodplain in undisputable ways. Generating more accurate flood maps at the county level for local populations to visualize, and for the federal government to base their requirements on, should be enforced immediately. Floodplain maps that are updated frequently by the local emergency management department, once a year as an example, will lead to the proper enforcement of local and federal development policies as well as determining where federal mitigation allocations and where specific mitigation strategies will have the greatest effect in reducing observable flood losses.

8. CONCLUSIONS

8.1 Research Summary

To reiterate, the research question to this dissertation is as follows: *To what degree are federal flood mitigation funds influencing observed flood losses as identified by FEMA and SBA in coastal watershed counties?* In summary, federal mitigation spending from FEMA, being split between HMGP and FMA in the confines of this research, proved to be highly inconclusive and insignificant as a predictor of observable flood losses across the coastal watershed counties of the Gulf of Mexico. Theoretically, it can be assumed that investing larger amounts of money for mitigation efforts would then lead to the reduction of observable flood losses. This research, based on the model results, has rejected this theory due to the insignificance reported from both mitigation programs administered by FEMA. Although both mitigation programs from FEMA were insignificant in this study, HMGP was producing a negative effect on observable flood losses and, more interestingly, FMA was producing a positive effect. Being a novel study examining the influence federal flood mitigation funds have on observed flood losses, it is premature to directly state that federal flood mitigation funding is wholly ineffective. Rather, this study suggests that the current administrative system in which these funds are being allocated and implemented are ineffective at influencing observed flood losses from the programs within FEMA and the SBA.

A total of 6 out of 21 hypotheses were confirmed by using multiple spatial error models that incorporated robust standard errors and random effects with observable flood losses from the NFIP, IA, PA, and SBA as the dependent variable. While none of the confirmed hypotheses were from the independent variables, the mitigation spending factors from HMGP and FMA, there is still a world of research left to properly understand the effects that mitigation spending has on observable flood losses. This study has left more questions than it did answers for individuals and communities that are directly at risk or at future risk of flooding.

8.2 Limitations

There are limitations, briefly mentioned in the validity threats section, that this study must acknowledge to ensure that the reader, and any future research being based on this study's approach and findings, understands what has yet to be accounted for to ensure unbiased results.

The first major limitation of this research is the calculation of flood losses by using the NFIP, IA, PA, and SBA as proxies for real losses caused by flooding events. Each of these programs serve different functions from one another and some are only activated under certain circumstances. The NFIP, for example, has two key issues for being used as an identifier of risk and accounting for true losses from flooding. These issues are 1) that it is not being used properly to identify all properties that are at all levels of risk of flooding, and 2) that it has a financial cap for properties that take out a claim. Currently, only homes and businesses that are located within the Special Flood Hazard Area (SFHA) are required to own flood insurance, but that has been shown to be lightly enforced and flood hazard maps are highly inaccurate. As to the second point, there is a $350,000 cap on homeowner claims and $500,000 cap on business claims. These financial caps, although large, may not report the actual total cost of loss from property and content damage because damages can easily surpass these financial caps during extreme events, like Hurricane Katrina or Hurricane Harvey. For properties that were damaged and not covered through insurance, they would then become financially responsible for fixing all damages through means other than relying on grants or loans from the federal government. The flip side to these limitations from the NFIP is that any costs that were not covered through insurance could be covered by other federal programs, such as the IA and SBA disaster loans. As mentioned previously, the activation of IA, PA, or SBA funds require the county where funding will be directed for support and recovery to be declared a disaster area from the president of the United States.

Second, the NFIP, IA, PA, and SBA disaster loans are not a complete dataset of observable flood losses or flood mitigation spending that can be identified at the federal level. Federal agencies that have programs in place to financially support property owners and local jurisdictions from flood events can also be found in the United States Department of Housing and Urban Development (HUD), the United States Army Corps of Engineers (USACE), the United States Department of Agriculture (USDA), the Environmental Protection Agency (EPA), and the National Oceanic and Atmospheric Administration (NOAA).

Third, the hazard mitigation programs from FEMA used in this study are implemented differently from one another and are intended to address flood mitigation in different fashions. The HMGP becomes activated after a presidentially declared disaster and will only be awarded to those select counties that receive this declaration status. The FMA does not need a presidential disaster declaration but is instead awarded only through a highly competitive application process that details a high benefit-cost potential for the intended mitigation project and is expected to reduce flood risk properties identified by the NFIP. With FMA being awarded through a competitive application process, this could imply that communities that are wealthier, can communicate their issues more effectively, and potentially are not as deserving may receive these benefits. Low income communities with higher risk of experiencing flood events that are more deserving of these federal mitigation funds may be limited in receiving any form of financial assistance.

Fourth, this research, being scaled to the county level, eliminates vital details that could be picked up at a smaller level of analysis, such as city boundary, ZIP code, or Census block group.

Although the available mitigation spending data is uniformly given at the county scale, identifying methods to analyze this data at a smaller scale would be beneficial for future studies. Details and other control variables not accounted for in this research include flood mitigation practices already in place and the associated spending amounts for each of those observations prior to this study's timeframe. This vital information could also support key assumptions about the impacts that flood mitigation practices and spending have on observable flood losses.

Lastly, the overall analysis in which this study was conducted has limitations of its own as well. Mitigation observations collected and reported by FEMA are not necessarily clean cut. Heavy data scrubbing was conducted to obtain straightforward and concise information useful in answering the research questions presented for this study. Much of the information was compounded and made data collection and interpretation quite difficult. Detailing the amount of mitigation money awarded to certain jurisdictions were easily understood, but the available data sets have much more insightful information to better understand not only how different mitigation spending amounts influence observable flood losses but how the specific types of mitigation practices can have their own effects. The timeframe of this study is just but a brief snapshot in time when flooding has a long history of inflicting lasting damages, particularly in the U.S. A longer research timeframe could better detect the impacts of mitigation strategies currently in place and how to implement future mitigation strategies most effectively. This study serves as a starting point to truly understand how federal mitigation spending influences observable flood losses in the watershed counties along the Gulf of Mexico.

8.3 Future Research

This research not only contributes to the theory of mitigation as a major influencer of influencing observable flood loss, but also opens the door to a realm of research that has yet to be fully explored. Future research is necessary to better understand how federal mitigation spending has been conducted in the past, how it is being utilized in the present, and how to use mitigation spending and specific mitigation project types more effectively in the future. Each of these prelisted necessities will assist federal agencies, decisionmakers, and local officials in reaching the goal of reducing and/or eliminating risk from natural hazards, specifically flooding in this case.

To begin, it would be more beneficial to analyze federal mitigation spending at a more detailed spatial scale other than the county level. Spending that originates from the federal level reaches multiple scales in terms of political jurisdictions. Some spending is designated to the state to do as they wish, while other observations can be directed to the city or even the ZIP code level. The complexities and influences of cross-regional mitigation spending from the federal government, such as multiple jurisdictions receiving forms of monetary assistance that are considered as a singular observation, make research difficult to assess how spending is actually being used and if it is effective in its mission. It would benefit this area of research to monitor who controls the money after being distributed by the federal government and where exactly this money is directed and implemented at the lowest possible spatial scale.

Splitting this study further into two distinct research areas where one will focus on broader applications of federal mitigation spending across diverse coastal regions of the United States, like this study, and the other should focus in on more finite areas, such as individual watersheds or within developing or already developed cityscapes. The reasoning behind this is to address flooding and federal hazard mitigation spending across two different theoretical lenses. One is to analyze observable flood losses and federal mitigation spending across larger areas, such as individual states, the entire Gulf of Mexico, the eastern seaboard of the United States, etc. The second focus should be to investigate the impacts of observable flood losses and federal mitigation spending at more localized areas. More localized areas can shed light as to what types of mitigation works for areas with similar characteristics and what types of mitigation are not suitable for the challenge at hand. There is no one-size-fits-all when it comes to mitigation. Instead, mitigation should be adaptable to the specific challenge and area in which it will be implemented.

Examining mitigation project types more thoroughly, such as unique mitigation measures or grouping them based on structural and non-structural forms of mitigation, can better assist local and federal policy decision makers as to selecting the most appropriate and effective mitigation method and their associated costs to reduce or eliminate risks and observable losses associated with flooding.

This study, in terms of the literature review, was the first to utilize lags to better understand the effects federal hazard mitigation spending has on observable flood losses over periods of time. To better understand how time can play a role in mitigation spending, developing theoretical assumptions that would reinforce the application of incorporating lags on federal mitigation spending is necessary. Doing this will help to understand how federal mitigation spending affects observed flood losses over time after application. For example, lags can help identify how long it takes for different types of mitigation programs, project types, and size of mitigation measure to take effect in the area which it was applied. In the case of this study, it was used to identify if mitigation spending created any more or any significant effect on observable flood losses.

Future research would benefit by addressing individual mitigation-specific program effects on individual flood risk support and recovery programs. This study, spearheading research in the realm of mitigation spending, examined all available federal programs in a broad manner. Splitting the federal programs will lead to a better assessment of the unique effects from these mitigation programs on support and recovery programs. For example, HMGP effects on the NFIP will simplify and more accurately detail the effects being experienced rather than lumping all support and recovery programs together.

There are more federal programs that have incorporated mitigation or support and recovery programs for natural hazards that were not incorporated into this study but are worth consideration for future research. Other than the programs from FEMA and SBA, which were used for this study, I have identified five other federal agencies that have multiple programs offering financial assistance in both mitigation and support and recovery capacities. These federal agencies are the United States Department of Housing and Urban Development (HUD), the United States Army Corps of Engineers (USACE), the United States Department of Agriculture (USDA), the Environmental Protection Agency (EPA), and the National Oceanic and Atmospheric Administration (NOAA). Bringing each of these agencies and their respective mitigation or support and recovery programs that focus on natural hazards, particularly flooding, will create a more accurate portrayal of how effective these programs are at achieving their intended objectives.

Lastly, other than the inclusion of current and future federal agencies and their associated programs that provide flood-prone communities with the finances for after-the-fact support and recovery or mitigation assistance, future research should include other explanatory variables that were not measured in this study. Variables, such as pre-existing mitigation measures, other significant environmental influencers, and more socioeconomic influencers, should be identified, considered, and utilized in the research that is to follow. Pre-existing mitigation measures can include structural and non-structural methods, but individuals in communities that participate in the NFIP are eligible to receive certain discounts on their flood insurance premiums dependent upon their Community Rating System (CRS) score. A better CRS score is given to communities that address flood risk at a high level within their local communities by implementing and bolstering hazard mitigation plans, developing and upkeeping sound mitigation measures, and enforcing more strict building codes to alleviate the costs from future flooding events. As the spatial scale of this study is more defined, incorporating a CRS score directly to a local community can assist in understanding how flood risk and observable flood losses are being treated at a more local level.

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APPENDIX A

Table A.1 List of Accepted FEMA Hazard Mitigation Activity Codes

Accepted Mitigation Activity Codes
90.4: Mitigation Plan - Local Multi-Hazard Mitigation Plan
90.6: Mitigation Plan - State Multi-Hazard Mitigation Plan
91.1: Local Multi-Hazard Mitigation Plan
91.2: Local Multi-Hazard Mitigation Plan - NEW
91.3: Local Multi-Hazard Mitigation Plan - UPDATE
91.4: Local Multijurisdictional Multi-Hazard Mitigation Plan - NEW
91.5: Local Multijurisdictional Multi-Hazard Mitigation Plan - UPDATE
92.1: State Multi-Hazard Mitigation Plan
92.2: State Multi-Hazard Mitigation Plan - UPDATE
93.1: Tribal (Local) Multi-Hazard Mitigation Plan
93.3: Tribal Multi-Hazard Mitigation Plan - UPDATE
93.5: Tribal Multijurisdictional Multi-Hazard Mitigation Plan - UPDATE
94.1: Tribal Multi-Hazard Mitigation Plan
95.1: FMA or CRS Plan
95.2: Planning Related Activities
96.1: Public Awareness and Education (Brochures, Workshops, Videos, etc.)
97.1: Expanded Mitigation Strategies - PILOT
100.1: Public Awareness and Education (Brochures, Workshops, Videos, etc.)
101.1: Professional Education (Building Inspectors, Architects, Engineers, Contractors, etc.)
103.1: Feasibility, Engineering and Design Studies
104.1: Developing, Implementing and Enforcing Codes, Standards, Ordinances and Regulations
105.1: Applied Research and Development in the Building Sciences
106.1: Other Non-Construction (Regular Project Only)
106.2: Other Non-Construction
200.1: Acquisition of Private Real Property (Structures and Land) - Riverine
200.1A: RETRO - Acquisition of Private Real Property (Structures and Land) - Riverine
200.2: Acquisition of Private Real Property (Structures and Land) - Coastal
200.3: Acquisition of Public Real Property (Structures and Land) - Riverine
200.4: Acquisition of Public Real Property (Structures and Land) - Coastal
200.5: Acquisition of Vacant Land
201.1: Relocation of Private Structures - Riverine
201.2: Relocation of Private Structures - Coastal
201.3: Relocation of Public Structures - Riverine
201.4: Relocation of Public Structures - Coastal
202.1: Elevation of Private Structures - Riverine
202.1A: RETRO - Elevation of Private Structures - Riverine
202.2: Elevation of Private Structures - Coastal
202.2A: RETRO - Elevation of Private Structures - Coastal
202.3: Elevation of Public Structures - Riverine
202.4: Elevation of Public Structures - Coastal
203.1: Wet Floodproofing Private Structures - Riverine
203.2: Wet Floodproofing Private Structures - Coastal
203.3: Wet Floodproofing Public Structures - Riverine
203.4: Wet Floodproofing Public Structures - Coastal
204.1: Dry Floodproofing Private Structures - Riverine (Commercial)
204.3: Dry Floodproofing Public Structures - Riverine
204.4: Dry Floodproofing Public Structures - Coastal
207.1: Mitigation Reconstruction - PILOT
207.1A: RETRO - Mitigation Reconstruction - PILOT

207.2: Mitigation Reconstruction
300.1: Vegetation Management - Natural Dune Restoration
300.4: Vegetation Management - Non Coastal Shoreline Stabilization
301.1: Shoreline Stabilization (Riprap, etc.)
303.1: Wetland Restoration/Creation
303.2: Floodplain and Stream Restoration
400.1: Utility Protective Measures (Electric, Gas, etc.)
400.1A: RETRO - Utility Protective Measures (Electric, Gas, etc.)
401.1: Water and Sanitary Sewer System Protective Measures
401.1A: RETRO - Water and Sanitary Sewer System Protective Measures
402.1: Infrastructure Protective Measures (Roads and Bridges)
402.2: Roads and Bridges - Post-wildfire erosion and flood protection
403.1: Stormwater Management – Culverts
403.1A: RETRO - Stormwater Management – Culverts
403.2: Stormwater Management – Diversions
403.2A: RETRO - Stormwater Management - Diversions
403.3: Stormwater Management – Flap gates/Floodgates
403.3A: RETRO - Stormwater Management – Flap gates/Floodgates
403.4: Stormwater Management - Detention/Retention Basins
403.4A: RETRO - Stormwater Management - Detention/Retention Basins
403.5: Floodwater Storage and Diversion
403.7: Low Impact Development (LID) / Green Infrastructure (GI)
404.1: Localized Flood Control System to Protect Critical Facility
405.1: Other Minor Flood Control
405.1A: RETRO - Other Minor Flood Control
500.1: Flood Control - Floodwall
500.2: Flood Control - Berm, Levee, or Dike
500.2A: RETRO - Flood Control - Berm, Levee, or Dike
500.3: Flood Control - Dam
501.1: Other Major Structural Projects
600.1: Warning Systems (as a Component of a Planned, Adopted, and Exercised Risk Reduction Plan)
601.1: Generators
601.2: Generators - Regular
602.1: Other Equipment Purchase and Installation
700.1: Management Costs - Salaries
700.2: Management Costs - Equipment
700.3: Management Costs - Office Space Rental
700.4: Management Costs - Supplies
701.1: Technical Assistance - Outreach/Training
701.2: Technical Assistance - Application Development/Review
701.3: Technical Assistance - Salaries & Expenses
800.1: Miscellaneous
900.1: Hazard Identification
904.1: Advanced Assistance
904.2: Advance Assistance (FMA and PDMC)
CRS Plan
FMA Plan
Other Plan
Repetitive Loss Plan

Table A.2 List of Rejected FEMA Hazard Mitigation Activity Codes

Declined Mitigation Activity Codes
103.2: Feasibility, Engineering, and Design Studies - Safe Rooms
200.6: Acquisition of Private Real Property (Structures and Land) - Landslide
200.8: Acquisition of Private Real Property (Structures and Land) - Snow Avalanche
205.1: Retrofitting Private Structures - Wildfire
205.6: Structural Retrofitting/Rehabilitating Public Structures - Seismic
205.7: Retrofitting Private Structures - Wind
205.7A: RETRO - Retrofitting Private Structures - Wind
205.8: Retrofitting Public Structures - Wind
205.8A: RETRO - Retrofitting Public Structures - Wind
206.1: Safe Room (Tornado and Severe Wind Shelter) - Private Structures
206.1A: RETRO - Safe Room (Tornado and Severe Wind Shelter) - Private Structures
206.2: Safe Room (Tornado and Severe Wind Shelter) - Public Structures
206.2A: RETRO - Safe Room (Tornado and Severe Wind Shelter) - Public Structures
300.2: Vegetation Management - Wildfire
300.8: Vegetation Management - Post-wildfire burn area restoration
302.1: Landslide Stabilization - Structural
304.2: Post Wildfire Reforestation

APPENDIX B

Data Analysis Results

Figure B.1 Pairwise Correlation with Logged HMGP Spending on Logged Observed Losses

```
. pwcorr ln_rtotalloss ln_rhmgp ccaplowprcnt ccaphighprcnt fldareaprcnt ccapwetlandchangeprcnt avprecip stormevents shoreline housingunits1k medianincome1
> k disasevents mitprojecttime ALbinary FLbinary GAbinary LAbinary MSbinary TXbinary, sig star(.05)
```

	ln_rto~s	ln_rhmgp	ccaplo~t	ccaphi~t	fldare~t	ccapwe~t	avprecip
ln_rtotall~s	1.0000						
ln_rhmgp	0.1285* 0.0000	1.0000					
ccaplowprcnt	0.2860* 0.0000	0.1881* 0.0000	1.0000				
ccaphighpr~t	0.2619* 0.0000	0.1818* 0.0000	0.7918* 0.0000	1.0000			
fldareaprcnt	0.1827* 0.0000	0.0688* 0.0005	0.0704* 0.0004	0.0688* 0.0005	1.0000		
ccapwetlan~t	-0.0641* 0.0012	-0.0842* 0.0000	-0.1683* 0.0000	-0.1743* 0.0000	-0.1415* 0.0000	1.0000	
avprecip	0.2996* 0.0000	0.2220* 0.0000	0.1719* 0.0000	0.0345 0.0827	0.2648* 0.0000	-0.0142 0.4740	1.0000
stormevents	0.2596* 0.0000	0.0611* 0.0021	0.1308* 0.0000	0.2031* 0.0000	-0.1117* 0.0000	0.0013 0.9483	0.1145* 0.0000
shoreline	0.2494* 0.0000	0.1479* 0.0000	0.2769* 0.0000	0.2677* 0.0000	0.5020* 0.0000	-0.2030* 0.0000	0.0849* 0.0000
housingun~1k	0.2288* 0.0000	0.1744* 0.0000	0.5956* 0.0000	0.8550* 0.0000	-0.0178 0.3689	-0.1637* 0.0000	-0.0022 0.9132
medianinc~1k	0.2269* 0.0000	0.1554* 0.0000	0.2760* 0.0000	0.2742* 0.0000	0.2963* 0.0000	-0.1771* 0.0000	0.1401* 0.0000
disasevents	0.5233* 0.0000	-0.0023 0.9077	0.0120 0.5471	0.0025 0.9007	0.1085* 0.0000	0.0167 0.4012	0.0555* 0.0052
mitproject~e	0.1466* 0.0000	0.8597* 0.0000	0.1916* 0.0000	0.2066* 0.0000	0.1294* 0.0000	-0.0961* 0.0000	0.2148* 0.0000
ALbinary	-0.0426* 0.0321	0.0828* 0.0000	-0.0763* 0.0001	-0.0753* 0.0001	-0.2153* 0.0000	0.0202 0.3095	0.1059* 0.0000
FLbinary	-0.0468* 0.0185	-0.0127 0.5225	0.1553* 0.0000	0.0066 0.7389	0.0831* 0.0000	-0.0237 0.2320	0.1010* 0.0000
GAbinary	-0.0940* 0.0000	-0.0349 0.0784	-0.0436* 0.0279	-0.0513* 0.0098	-0.1645* 0.0000	0.0273 0.1686	-0.0342 0.0851
LAbinary	0.1633* 0.0000	0.0708* 0.0004	0.1100* 0.0000	0.0450* 0.0234	0.4905* 0.0000	-0.0412* 0.0381	0.2867* 0.0000
MSbinary	0.0015 0.9384	0.0672* 0.0007	-0.0175 0.3776	-0.0823* 0.0000	-0.2301* 0.0000	0.0238 0.2317	0.2076* 0.0000
TXbinary	-0.0644* 0.0012	-0.1225* 0.0000	-0.1886* 0.0000	0.0599* 0.0025	-0.2954* 0.0000	0.0264 0.1832	-0.5550* 0.0000

	storme~s	shorel~e	housi~1k	media~1k	disase~s	mitpro~e	ALbinary
stormevents	1.0000						
shoreline	0.0674* 0.0007	1.0000					
housingun~1k	0.2351* 0.0000	0.2176* 0.0000	1.0000				
medianinc~1k	0.0550* 0.0055	0.3851* 0.0000	0.2221* 0.0000	1.0000			
disasevents	0.0692* 0.0005	0.0741* 0.0002	0.0073 0.7130	0.0312 0.1162	1.0000		
mitproject~e	0.0614* 0.0020	0.1504* 0.0000	0.1739* 0.0000	0.2081* 0.0000	-0.0064 0.7480	1.0000	
ALbinary	0.0540* 0.0065	-0.1140* 0.0000	-0.0333 0.0931	-0.1609* 0.0000	0.0217 0.2739	-0.0026 0.8967	1.0000
FLbinary	0.0481* 0.0153	0.1009* 0.0000	0.1202* 0.0000	-0.0338 0.0886	0.0137 0.4917	-0.0709* 0.0004	-0.1570* 0.0000
GAbinary	-0.0462* 0.0199	-0.1423* 0.0000	-0.0491* 0.0134	-0.1212* 0.0000	-0.0466* 0.0190	-0.0412* 0.0380	-0.0362 0.0685
LAbinary	-0.1235* 0.0000	0.1018* 0.0000	-0.0980* 0.0000	0.0985* 0.0000	0.1100* 0.0000	0.1620* 0.0000	-0.1463* 0.0000
MSbinary	-0.0468* 0.0185	-0.1418* 0.0000	-0.0844* 0.0000	-0.1394* 0.0000	-0.0475* 0.0167	-0.0056 0.7760	-0.0748* 0.0002
TXbinary	0.0916* 0.0000	-0.0257 0.1964	0.0616* 0.0019	0.1251* 0.0000	-0.0908* 0.0000	-0.0626* 0.0016	-0.1517* 0.0000

	FLbinary	GAbinary	LAbinary	MSbinary	TXbinary
FLbinary	1.0000				
GAbinary	-0.0944*	1.0000			
	0.0000				
LAbinary	-0.3819*	-0.0879*	1.0000		
	0.0000	0.0000			
MSbinary	-0.1953*	-0.0450*	-0.1819*	1.0000	
	0.0000	0.0235	0.0000		
TXbinary	-0.3959*	-0.0912*	-0.3688*	-0.1886*	1.0000
	0.0000	0.0000	0.0000	0.0000	

Figure B.2 Pairwise Correlation with Logged FMA Spending on Logged Observed Losses

```
. pwcorr ln_rtotalloss ln_rfma ccaplowprcnt ccaphighprcnt fldareaprcnt ccapwetlandchangeprcnt avprecip stormevents shoreline housingunits1k medianincome1k
>  disasevents mitprojecttime ALbinary FLbinary GAbinary LAbinary MSbinary TXbinary, sig star(.05)
```

	ln_rto~s	ln_rfma	ccaplo~t	ccaphi~t	fldare~t	ccapwe~t	avprecip
ln_rtotall~s	1.0000						
ln_rfma	0.0547*	1.0000					
	0.0058						
ccaplowprcnt	0.2860*	0.2163*	1.0000				
	0.0000	0.0000					
ccaphighpr~t	0.2619*	0.1648*	0.7918*	1.0000			
	0.0000	0.0000	0.0000				
fldareaprcnt	0.1827*	0.0130	0.0704*	0.0688*	1.0000		
	0.0000	0.5122	0.0004	0.0005			
ccapwetlan~t	-0.0641*	-0.0496*	-0.1683*	-0.1743*	-0.1415*	1.0000	
	0.0012	0.0125	0.0000	0.0000	0.0000		
avprecip	0.2996*	0.0238	0.1719*	0.0345	0.2648*	-0.0142	1.0000
	0.0000	0.2310	0.0000	0.0827	0.0000	0.4740	
stormevents	0.2596*	0.0286	0.1308*	0.2031*	-0.1117*	0.0013	0.1145*
	0.0000	0.1498	0.0000	0.0000	0.0000	0.9483	0.0000
shoreline	0.2494*	0.1321*	0.2769*	0.2677*	0.5020*	-0.2030*	0.0849*
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
housingun~1k	0.2288*	0.1252*	0.5956*	0.8550*	-0.0178	-0.1637*	-0.0022
	0.0000	0.0000	0.0000	0.0000	0.3689	0.0000	0.9132
medianinc~1k	0.2269*	0.0476*	0.2760*	0.2742*	0.2963*	-0.1771*	0.1401*
	0.0000	0.0166	0.0000	0.0000	0.0000	0.0000	0.0000
disasevents	0.5233*	-0.0049	0.0120	0.0025	0.1085*	0.0167	0.0555*
	0.0000	0.8061	0.5471	0.9007	0.0000	0.4012	0.0052
mitproject~e	0.0481*	0.8987*	0.2328*	0.1831*	0.0200	-0.0621*	0.0073
	0.0153	0.0000	0.0000	0.0000	0.3149	0.0017	0.7145
ALbinary	-0.0426*	-0.0295	-0.0763*	-0.0753*	-0.2153*	0.0202	0.1059*
	0.0321	0.1368	0.0001	0.0001	0.0000	0.3095	0.0000
FLbinary	-0.0468*	0.1847*	0.1553*	0.0066	0.0831*	-0.0237	0.1010*
	0.0185	0.0000	0.0000	0.7389	0.0000	0.2320	0.0000
GAbinary	-0.0940*	-0.0230	-0.0436*	-0.0513*	-0.1645*	0.0273	-0.0342
	0.0000	0.2468	0.0279	0.0098	0.0000	0.1686	0.0851
LAbinary	0.1633*	-0.0642*	0.1100*	0.0450*	0.4905*	-0.0412*	0.2867*
	0.0000	0.0012	0.0000	0.0234	0.0000	0.0381	0.0000
MSbinary	0.0015	-0.0200	-0.0175	-0.0823*	-0.2301*	0.0238	0.2076*
	0.9384	0.3144	0.3776	0.0000	0.0000	0.2317	0.0000
TXbinary	-0.0644*	-0.0867*	-0.1886*	0.0599*	-0.2954*	0.0264	-0.5550*
	0.0012	0.0000	0.0000	0.0025	0.0000	0.1832	0.0000

	storme~s	shorel~e	housi~1k	media~1k	disase~s	mitpro~e	ALbinary
stormevents	1.0000						
shoreline	0.0674*	1.0000					
	0.0007						
housingun~1k	0.2351*	0.2176*	1.0000				
	0.0000	0.0000					
medianinc~1k	0.0550*	0.3851*	0.2221*	1.0000			
	0.0055	0.0000	0.0000				
disasevents	0.0692*	0.0741*	0.0073	0.0312	1.0000		
	0.0005	0.0002	0.7130	0.1162			
mitproject~e	0.0275	0.1286*	0.1344*	0.0370	-0.0018	1.0000	
	0.1668	0.0000	0.0000	0.0621	0.9271		
ALbinary	0.0540*	-0.1140*	-0.0333	-0.1609*	0.0217	-0.0200	1.0000
	0.0065	0.0000	0.0931	0.0000	0.2739	0.3138	
FLbinary	0.0481*	0.1009*	0.1202*	-0.0338	0.0137	0.1887*	-0.1570*
	0.0153	0.0000	0.0000	0.0886	0.4917	0.0000	0.0000
GAbinary	-0.0462*	-0.1423*	-0.0491*	-0.1212*	-0.0466*	-0.0206	-0.0362
	0.0199	0.0000	0.0134	0.0000	0.0190	0.3003	0.0685
LAbinary	-0.1235*	0.1018*	-0.0980*	0.0985*	0.1100*	-0.0692*	-0.1463*
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0005	0.0000
MSbinary	-0.0468*	-0.1418*	-0.0844*	-0.1394*	-0.0475*	-0.0289	-0.0748*
	0.0185	0.0000	0.0000	0.0000	0.0167	0.1452	0.0002
TXbinary	0.0916*	-0.0257	0.0616*	0.1251*	-0.0908*	-0.0863*	-0.1517*
	0.0000	0.1964	0.0019	0.0000	0.0000	0.0000	0.0000

	FLbinary	GAbinary	LAbinary	MSbinary	TXbinary
FLbinary	1.0000				
GAbinary	-0.0944*	1.0000			
	0.0000				
LAbinary	-0.3819*	-0.0879*	1.0000		
	0.0000	0.0000			
MSbinary	-0.1953*	-0.0450*	-0.1819*	1.0000	
	0.0000	0.0235	0.0000		
TXbinary	-0.3959*	-0.0912*	-0.3688*	-0.1886*	1.0000
	0.0000	0.0000	0.0000	0.0000	

Figure B.3 HMGP SPREGREXT Results

```
. * 1
. spregrext $ylist $xlist, nc(141) wmfile(C:\Users\jlrai\Desktop\Dissertation\Data\Boundaries\weights1
> 41.dta) model(sar) zero lmspac lmhet lmnorm diag test

==============================================================================
*** Binary (0/1) Weight Matrix: 2538x2538 - NC=141 NT=18 (Non Normalized)
==============================================================================

==============================================================================
* Spatial Panel Random-Effects Lag Regression (SAR)
==============================================================================
  ln_rtotalloss = wly_ln_rtotalloss + ln_rhmgp + avprecip + fldareaprcnt + ccaplowprcnt +
                 ccaphighprcnt + ccapwetlandchangeprcnt + housingunits1k + medianincome1k +
                 stormevents + disasevents + shoreline + ALbinary + FLbinary + GAbinary + LAbinary
                 + MSbinary + TXbinary + mitprojecttime
------------------------------------------------------------------------------
  Sample Size        =        2538   |   Cross Sections Number   =         141
  Wald Test          =   2924.1976   |   P-Value > Chi2(19)      =      0.0000
  F-Test             =    153.9051   |   P-Value > F(19 , 2378)  =      0.0000
 (Buse 1973) R2      =      0.6607   |   Raw Moments R2          =      0.9066
 (Buse 1973) R2 Adj  =      0.6381   |   Raw Moments R2 Adj      =      0.9003
  Root MSE (Sigma)   =      3.5992   |   Log Likelihood Function =  -6983.9540
------------------------------------------------------------------------------
- R2h= 0.5163   R2h Adj= 0.4839  F-Test =   141.44 P-Value > F(19 , 2378)0.0000
- R2v= 0.6316   R2v Adj= 0.6070  F-Test =   227.22 P-Value > F(19 , 2378)0.0000
------------------------------------------------------------------------------------------
         ln_rtotalloss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
ln_rtotalloss          |
     wly_ln_rtotalloss |   .1225251   .0051187    23.94   0.000     .1124876    .1325626
              ln_rhmgp |  -.0361348   .0335255    -1.08   0.281     -.101877    .0296074
              avprecip |   .0629697   .0077271     8.15   0.000     .0478172    .0781223
          fldareaprcnt |   .0118376   .0125016     0.95   0.344    -.0126776    .0363528
          ccaplowprcnt |    .353392   .0913004     3.87   0.000     .1743554    .5324286
         ccaphighprcnt |  -.4214714   .4327979    -0.97   0.330    -1.270172    .4272289
ccapwetlandchangeprcnt |  -.1941682    .272666    -0.71   0.476     -.728856    .3405196
        housingunits1k |   .0025379   .0025093     1.01   0.312    -.0023827    .0074585
        medianincome1k |  -.0133373   .0157833    -0.85   0.398    -.0442876    .0176131
           stormevents |   .1381098   .0264381     5.22   0.000     .0862657    .1899538
           disasevents |   1.405143   .0880984    15.95   0.000     1.232385      1.5779
             shoreline |   .9825997   .4965164     1.98   0.048     .0089499    1.956249
              ALbinary |  -5.597275   2.608781    -2.15   0.032      -10.713   -.4815551
              FLbinary |  -5.786798   2.435834    -2.38   0.018    -10.56338   -1.010219
              GAbinary |  -4.148452    2.82893    -1.47   0.143    -9.695877    1.398973
              LAbinary |  -6.526019    2.41461    -2.70   0.007    -11.26098    -1.79106
              MSbinary |  -4.489189   2.560902    -1.75   0.080    -9.511021    .5326431
              TXbinary |  -3.429782   2.468394    -1.39   0.165    -8.270208    1.410645
        mitprojecttime |   .0603458   .0629579     0.96   0.338    -.0631122    .1838038
                 _cons |   2.900884   2.642791     1.10   0.272    -2.281529    8.083297
------------------------------------------------------------------------------------------
  Rho Value  =  0.1225        Chi2 Test =   572.977   P-Value > Chi2(1)  0.0000
------------------------------------------------------------------------------

==============================================================================
*** Spatial Panel Aautocorrelation Tests
==============================================================================
  Ho: Error has No Spatial AutoCorrelation
  Ha: Error has    Spatial AutoCorrelation

- GLOBAL Moran MI           =  -0.0461     P-Value > Z(-3.431)    0.0006
- GLOBAL Geary GC           =   1.0192     P-Value > Z(1.191)     0.2337
- GLOBAL Getis-Ords GO      =   0.2041     P-Value > Z(3.431)     0.0006
------------------------------------------------------------------------------
- Moran MI Error Test       =  -0.5265     P-Value > Z(-39.469)   0.5985
------------------------------------------------------------------------------
- LM Error (Burridge)       =  10.4886     P-Value > Chi2(1)      0.0012
- LM Error (Robust)         = 103.7289     P-Value > Chi2(1)      0.0000
------------------------------------------------------------------------------
  Ho: Spatial Lagged Dependent Variable has No Spatial AutoCorrelation
  Ha: Spatial Lagged Dependent Variable has    Spatial AutoCorrelation

- LM Lag (Anselin)          =   9.2386     P-Value > Chi2(1)      0.0024
- LM Lag (Robust)           = 102.4789     P-Value > Chi2(1)      0.0000
------------------------------------------------------------------------------
  Ho: No General Spatial AutoCorrelation
  Ha:    General Spatial AutoCorrelation

- LM SAC (LMErr+LMLag_R)    = 112.9675     P-Value > Chi2(2)      0.0000
- LM SAC (LMLag+LMErr_R)    = 112.9675     P-Value > Chi2(2)      0.0000
------------------------------------------------------------------------------
```

Figure B.4 FMA SPREGREXT Results

```
. spregrext $ylist $xlist, nc(141) wmfile(C:\Users\jlrai\Desktop\Dissertation\Data\Boundaries\weights1
> 41.dta) model(sar) lmspac lmhet lmnorm diag test

==============================================================================
*** Binary (0/1) Weight Matrix: 2538x2538 - NC=141 NT=18 (Non Normalized)
==============================================================================

==============================================================================
* Spatial Panel Random-Effects Lag Regression (SAR)
==============================================================================
  ln_rtotalloss = w1y_ln_rtotalloss + ln_rfma + avprecip + fldareaprcnt + ccaplowprcnt +
                ccaphighprcnt + ccapwetlandchangeprcnt + housingunits1k + medianincome1k +
                stormevents + disasevents + shoreline + ALbinary + FLbinary + GAbinary + LAbinary
                + MSbinary + TXbinary + mitprojecttime
------------------------------------------------------------------------------
  Sample Size       =        2538   |   Cross Sections Number   =         141
  Wald Test         =   2922.3001   |   P-Value > Chi2(19)      =      0.0000
  F-Test            =    153.8053   |   P-Value > F(19 , 2378)  =      0.0000
 (Buse 1973) R2     =      0.6606   |   Raw Moments R2          =      0.9065
 (Buse 1973) R2 Adj =      0.6379   |   Raw Moments R2 Adj      =      0.9003
  Root MSE (Sigma)  =      3.5999   |   Log Likelihood Function =  -6984.1513
------------------------------------------------------------------------------
- R2h= 0.5167   R2h Adj= 0.4844  F-Test =   141.67 P-Value > F(19 , 2378)0.0000
- R2v= 0.6322   R2v Adj= 0.6076  F-Test =   227.82 P-Value > F(19 , 2378)0.0000
----------------------------------------------------------------------------------------
           ln_rtotalloss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------------+--------------------------------------------------------------
ln_rtotalloss            |
       w1y_ln_rtotalloss |   .1227244   .0051247    23.95   0.000     .1126751    .1327736
                 ln_rfma |   .0290492   .0961209     0.30   0.763    -.1594403    .2175387
                avprecip |   .0628048   .0076623     8.20   0.000     .0477793    .0778303
            fldareaprcnt |   .0119297   .0124807     0.96   0.339    -.0125446    .0364039
            ccaplowprcnt |   .3536978   .0910583     3.88   0.000      .175136    .5322597
           ccaphighprcnt |  -.3983398   .4307513    -0.92   0.355    -1.243027    .4463471
  ccapwetlandchangeprcnt |  -.1974942   .2728189    -0.72   0.469    -.7324818    .3374934
          housingunits1k |   .0023988   .0025046     0.96   0.338    -.0025127    .0073103
          medianincome1k |  -.0126213   .0156195    -0.81   0.419    -.0432506    .0180081
             stormevents |   .1398243   .0264059     5.30   0.000     .0880433    .1916053
             disasevents |   1.402526   .0881776    15.91   0.000     1.229613    1.575439
               shoreline |    .970396   .4956513     1.96   0.050    -.0015574    1.942349
                ALbinary |  -5.663249   2.602983    -2.18   0.030     -10.7676   -.5588975
                FLbinary |  -5.791985   2.431172    -2.38   0.017    -10.55942   -1.024548
                GAbinary |  -4.163827   2.823766    -1.47   0.140    -9.701125     1.37347
                LAbinary |  -6.537929   2.409653    -2.71   0.007    -11.26317    -1.81269
                MSbinary |   -4.54526   2.555655    -1.78   0.075    -9.556803    .4662826
                TXbinary |  -3.440121   2.463965    -1.40   0.163    -8.271862    1.391621
          mitprojecttime |  -.2355621   .3536746    -0.67   0.505    -.9291047    .4579804
                   _cons |   2.804557   2.634927     1.06   0.287    -2.362434    7.971548
----------------------------------------------------------------------------------------
  Rho Value  =  0.1227        Chi2 Test =   573.496   P-Value > Chi2(1)  0.0000
------------------------------------------------------------------------------

==============================================================================
*** Spatial Panel Aautocorrelation Tests
==============================================================================
  Ho: Error has No Spatial AutoCorrelation
  Ha: Error has    Spatial AutoCorrelation

- GLOBAL Moran MI            =  -0.0459     P-Value > Z(-3.413)    0.0006
- GLOBAL Geary GC            =   1.0191     P-Value > Z(1.181)     0.2376
- GLOBAL Getis-Ords GO       =   0.2031     P-Value > Z(3.413)     0.0006
------------------------------------------------------------------------------
- Moran MI Error Test        =  -0.5289     P-Value > Z(-39.645)   0.5969
------------------------------------------------------------------------------
- LM Error (Burridge)        =  10.3835     P-Value > Chi2(1)      0.0013
- LM Error (Robust)          = 103.3716     P-Value > Chi2(1)      0.0000
------------------------------------------------------------------------------
  Ho: Spatial Lagged Dependent Variable has No Spatial AutoCorrelation
  Ha: Spatial Lagged Dependent Variable has    Spatial AutoCorrelation

- LM Lag (Anselin)           =   9.3403     P-Value > Chi2(1)      0.0022
- LM Lag (Robust)            = 102.3283     P-Value > Chi2(1)      0.0000
------------------------------------------------------------------------------
  Ho: No General Spatial AutoCorrelation
  Ha:    General Spatial AutoCorrelation

- LM SAC (LMErr+LMLag_R)     = 112.7119     P-Value > Chi2(2)      0.0000
- LM SAC (LMLag+LMErr_R)     = 112.7119     P-Value > Chi2(2)      0.0000
------------------------------------------------------------------------------
```

Figure B.5 HMGP Mitigated Properties SPREGREXT Results

```
. spregrext $ylist $xlist, nc(141) wmfile(C:\Users\jlrai\Desktop\Dissertation\Data\Boundaries\weights141.dta) model(sar) zero
> lmspac lmhet lmnorm diag test

==============================================================================
*** Binary (0/1) Weight Matrix: 2538x2538 - NC=141 NT=18 (Non Normalized)
==============================================================================
==============================================================================
* Spatial Panel Random-Effects Lag Regression (SAR)
==============================================================================
  ln_rtotalloss = wly_ln_rtotalloss + numberOfFinalProperties + avprecip + fldareaprcnt + ccaplowprcnt + ccaphighprcnt +
                  ccapwetlandchangeprcnt + housingunits1k + medianincome1k + stormevents + disasevents + shoreline +
                  ALbinary + FLbinary + GAbinary + LAbinary + MSbinary + TXbinary + mitprojecttime
------------------------------------------------------------------------------
  Sample Size         =        2538   |   Cross Sections Number   =        141
  Wald Test           =   2921.0304   |   P-Value > Chi2(19)      =     0.0000
  F-Test              =    153.7384   |   P-Value > F(19 , 2378)  =     0.0000
 (Buse 1973) R2       =      0.6605   |   Raw Moments R2          =     0.9065
 (Buse 1973) R2 Adj   =      0.6378   |   Raw Moments R2 Adj      =     0.9002
  Root MSE (Sigma)    =      3.6007   |   Log Likelihood Function =  -6984.4405
------------------------------------------------------------------------------
- R2h= 0.5170   R2h Adj= 0.4848  F-Test =   141.88 P-Value > F(19 , 2378)0.0000
- R2v= 0.6317   R2v Adj= 0.6071  F-Test =   227.35 P-Value > F(19 , 2378)0.0000
------------------------------------------------------------------------------------------
           ln_rtotalloss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------------
ln_rtotalloss            |
       wly_ln_rtotalloss |   .1224336   .0051301    23.87   0.000     .1123737    .1324935
 numberOfFinalProperties |  -.0018964   .0043715    -0.43   0.664    -.0104688    .0066761
                avprecip |   .0631342   .0077331     8.16   0.000     .0479698    .0782986
            fldareaprcnt |   .0119724    .012455     0.96   0.337    -.0124513    .0363961
            ccaplowprcnt |   .3503815   .0910499     3.85   0.000     .1718361    .5289268
           ccaphighprcnt |  -.4074952   .4314097    -0.94   0.345    -1.253473    .4384829
  ccapwetlandchangeprcnt |  -.1909168   .2727444    -0.70   0.484    -.7257583    .3439247
          housingunits1k |   .0025397   .0025062     1.01   0.311    -.0023749    .0074544
          medianincome1k |  -.0126076   .0157469    -0.80   0.423    -.0434866    .0182715
             stormevents |   .1397008   .0264267     5.29   0.000      .087879    .1915225
             disasevents |   1.405459   .0881612    15.94   0.000     1.232578     1.57834
               shoreline |   .9599803   .4942205     1.94   0.052    -.0091673    1.929128
                ALbinary |  -5.662382   2.598329    -2.18   0.029    -10.75761   -.5671572
                FLbinary |  -5.805254   2.426677    -2.39   0.017    -10.56388   -1.046632
                GAbinary |  -4.155639   2.818333    -1.47   0.140    -9.682284    1.371005
                LAbinary |  -6.518108   2.405705    -2.71   0.007     -11.2356   -1.800611
                MSbinary |   -4.53267   2.550998    -1.78   0.076    -9.535081    .4697408
                TXbinary |  -3.421489     2.4592    -1.39   0.164    -8.243887    1.400909
          mitprojecttime |   .0052189   .0335614     0.16   0.876    -.0605937    .0710315
                   _cons |   2.820848   2.632307     1.07   0.284    -2.341007    7.982703
------------------------------------------------------------------------------------------
  Rho Value  =  0.1224        Chi2 Test =    569.573   P-Value > Chi2(1)  0.0000
------------------------------------------------------------------------------
==============================================================================
*** Spatial Panel Aautocorrelation Tests
==============================================================================
  Ho: Error has No Spatial AutoCorrelation
  Ha: Error has    Spatial AutoCorrelation

- GLOBAL Moran MI            =  -0.0461     P-Value > Z(-3.432)    0.0006
- GLOBAL Geary GC            =   1.0191     P-Value > Z(1.180)     0.2380
- GLOBAL Getis-Ords GO       =   0.2042     P-Value > Z(3.432)     0.0006
------------------------------------------------------------------------------
- Moran MI Error Test        =  -0.5309     P-Value > Z(-39.801)   0.5955
------------------------------------------------------------------------------
- LM Error (Burridge)        =  10.4965     P-Value > Chi2(1)      0.0012
- LM Error (Robust)          = 104.7331     P-Value > Chi2(1)      0.0000
------------------------------------------------------------------------------
  Ho: Spatial Lagged Dependent Variable has No Spatial AutoCorrelation
  Ha: Spatial Lagged Dependent Variable has    Spatial AutoCorrelation

- LM Lag (Anselin)           =   9.3910     P-Value > Chi2(1)      0.0022
- LM Lag (Robust)            = 103.6276     P-Value > Chi2(1)      0.0000
------------------------------------------------------------------------------
  Ho: No General Spatial AutoCorrelation
  Ha:    General Spatial AutoCorrelation

- LM SAC (LMErr+LMLag_R)     = 114.1241     P-Value > Chi2(2)      0.0000
- LM SAC (LMLag+LMErr_R)     = 114.1241     P-Value > Chi2(2)      0.0000
------------------------------------------------------------------------------
```

Figure B.6 FMA Mitigated Properties SPREGREXT Results

```
. spregrext $ylist $xlist, nc(141) wmfile(C:\Users\jlrai\Desktop\Dissertation\Data\Boundaries\weights141.dta) model(sar) zero
> lmspac lmhet lmnorm diag test

==============================================================================
*** Binary (0/1) Weight Matrix: 2538x2538 - NC=141 NT=18 (Non Normalized)
==============================================================================
==============================================================================
* Spatial Panel Random-Effects Lag Regression (SAR)
==============================================================================
  ln_rtotalloss = wly_ln_rtotalloss + numberOfFinalProperties + avprecip + fldareaprcnt + ccaplowprcnt + ccaphighprcnt +
               ccapwetlandchangeprcnt + housingunits1k + medianincome1k + stormevents + disasevents + shoreline +
               ALbinary + FLbinary + GAbinary + LAbinary + MSbinary + TXbinary + mitprojecttime
------------------------------------------------------------------------------
  Sample Size         =        2538   |   Cross Sections Number   =         141
  Wald Test           =   2923.8544   |   P-Value > Chi2(19)      =      0.0000
  F-Test              =    153.8871   |   P-Value > F(19 , 2378)  =      0.0000
 (Buse 1973) R2       =      0.6607   |   Raw Moments R2          =      0.9066
 (Buse 1973) R2 Adj   =      0.6380   |   Raw Moments R2 Adj      =      0.9003
  Root MSE (Sigma)    =      3.5993   |   Log Likelihood Function =  -6983.8376
------------------------------------------------------------------------------
- R2h= 0.5166   R2h Adj= 0.4843  F-Test =   141.64 P-Value > F(19 , 2378)0.0000
- R2v= 0.6323   R2v Adj= 0.6077  F-Test =   227.85 P-Value > F(19 , 2378)0.0000
------------------------------------------------------------------------------------
           ln_rtotalloss |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------
ln_rtotalloss            |
       wly_ln_rtotalloss |   .1227322   .0051237    23.95   0.000     .1126848    .1327796
 numberOfFinalProperties |   .0905115   .1067646     0.85   0.397    -.1188499    .2998728
                avprecip |   .0626555   .0076637     8.18   0.000     .0476274    .0776837
            fldareaprcnt |   .0118548   .0124852     0.95   0.342    -.0126283    .0363379
            ccaplowprcnt |   .3520609   .0911242     3.86   0.000     .1733697     .530752
           ccaphighprcnt |  -.4035785   .4309073    -0.94   0.349    -1.248571    .4414143
  ccapwetlandchangeprcnt |  -.1965195   .2726539    -0.72   0.471    -.7311833    .3381444
          housingunits1k |   .0024303   .0025058     0.97   0.332    -.0024835    .0073441
          medianincome1k |  -.0122482   .0156272    -0.78   0.433    -.0428925    .0183961
             stormevents |   .1401693   .0264041     5.31   0.000     .0883918    .1919468
             disasevents |   1.402359   .0881531    15.91   0.000     1.229494    1.575223
               shoreline |   .9729534   .4957785     1.96   0.050     .0007506    1.945156
                ALbinary |  -5.654175   2.604395    -2.17   0.030    -10.76129    -.547056
                FLbinary |  -5.780995   2.432513    -2.38   0.018    -10.55106   -1.010929
                GAbinary |  -4.155156   2.825316    -1.47   0.142    -9.695494    1.385182
                LAbinary |  -6.524261   2.410999    -2.71   0.007    -11.25214   -1.796383
                MSbinary |  -4.536918   2.557049    -1.77   0.076    -9.551194    .4773587
                TXbinary |  -3.436151   2.465307    -1.39   0.164    -8.270525    1.398222
          mitprojecttime |  -.2129543   .1913876    -1.11   0.266    -.5882581    .1623495
                   _cons |   2.825341   2.634517     1.07   0.284    -2.340846    7.991528
------------------------------------------------------------------------------------
  Rho Value  =  0.1227      Chi2 Test =   573.784   P-Value > Chi2(1)  0.0000
------------------------------------------------------------------------------
==============================================================================
*** Spatial Panel Aautocorrelation Tests
==============================================================================
  Ho: Error has No Spatial AutoCorrelation
  Ha: Error has    Spatial AutoCorrelation

- GLOBAL Moran MI            =  -0.0458     P-Value > Z(-3.405)    0.0007
- GLOBAL Geary GC            =   1.0190     P-Value > Z(1.180)     0.2381
- GLOBAL Getis-Ords GO       =   0.2026     P-Value > Z(3.405)     0.0007
------------------------------------------------------------------------------
- Moran MI Error Test        =  -0.5266     P-Value > Z(-39.479)   0.5984
------------------------------------------------------------------------------
- LM Error (Burridge)        =  10.3339     P-Value > Chi2(1)      0.0013
- LM Error (Robust)          = 103.0069     P-Value > Chi2(1)      0.0000
------------------------------------------------------------------------------
  Ho: Spatial Lagged Dependent Variable has No Spatial AutoCorrelation
  Ha: Spatial Lagged Dependent Variable has    Spatial AutoCorrelation

- LM Lag (Anselin)           =   9.3231     P-Value > Chi2(1)      0.0023
- LM Lag (Robust)            = 101.9961     P-Value > Chi2(1)      0.0000
------------------------------------------------------------------------------
  Ho: No General Spatial AutoCorrelation
  Ha:    General Spatial AutoCorrelation

- LM SAC (LMErr+LMLag_R)     = 112.3300     P-Value > Chi2(2)      0.0000
- LM SAC (LMLag+LMErr_R)     = 112.3300     P-Value > Chi2(2)      0.0000
------------------------------------------------------------------------------
```

Figure B.7 HMGP Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7234.0141
Iteration 1:   Log-pseudolikelihood = -7006.1799
Iteration 2:   Log-pseudolikelihood = -6982.8695
Iteration 3:   Log-pseudolikelihood = -6982.5836
Iteration 4:   Log-pseudolikelihood = -6982.5834

SEM with random-effects                         Number of obs =       2538

Group variable: fips                         Number of groups =        141
Time variable: dateActual                        Panel length =         18

R-sq:    within  = 0.4104
         between = 0.6875
         overall = 0.4798

Log-pseudolikelihood = -6982.5834
                                    (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
ln_rhmgp	-.0261305	.0322581	-0.81	0.418	-.0893553	.0370943
avprecip	.1165493	.0121775	9.57	0.000	.0926818	.1404168
fldareaprcnt	.0110617	.0095135	1.16	0.245	-.0075844	.0297079
ccaplowprcnt	.3270087	.0904758	3.61	0.000	.1496794	.5043379
ccaphighprcnt	-.5232705	.4213012	-1.24	0.214	-1.349006	.3024647
ccapwetlandchangeprcnt	-.2413636	.3062003	-0.79	0.431	-.8415052	.3587781
housingunits1k	.0048646	.0025184	1.93	0.053	-.0000715	.0098006
medianincome1k	.0127816	.014479	0.88	0.377	-.0155968	.04116
stormevents	.1461767	.0428103	3.41	0.001	.0622701	.2300833
disasevents	2.670146	.1378305	19.37	0.000	2.400003	2.940289
shoreline	1.11695	.3709811	3.01	0.003	.3898404	1.84406
ALbinary	-3.170792	.614932	-5.16	0.000	-4.376037	-1.965548
FLbinary	-3.216365	.4856189	-6.62	0.000	-4.168161	-2.26457
GAbinary	-2.529355	.9968297	-2.54	0.011	-4.483105	-.5756047
LAbinary	-2.00237	.6740187	-2.97	0.003	-3.323423	-.6813177
MSbinary	-1.85395	.8829891	-2.10	0.036	-3.584577	-.1233234
mitprojecttime	.0918539	.0546629	1.68	0.093	-.0152833	.1989912
_cons	-.2339052	.8552565	-0.27	0.784	-1.910177	1.442367
Spatial						
lambda	.5158852	.0177787	29.02	0.000	.4810396	.5507307
Variance						
ln_phi	-1.850713	.2115238	-8.75	0.000	-2.265292	-1.436134
sigma2_e	12.38886	.5332777	23.23	0.000	11.34366	13.43407

Figure B.8 HMGP One-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7235.3236
Iteration 1:   Log-pseudolikelihood = -7007.9257
Iteration 2:   Log-pseudolikelihood = -6983.7064
Iteration 3:   Log-pseudolikelihood = -6983.3824
Iteration 4:   Log-pseudolikelihood = -6983.3822

SEM with random-effects                          Number of obs =       2538

Group variable: fips                          Number of groups =        141
Time variable: dateActual                         Panel length =         18

R-sq:     within  = 0.4107
          between = 0.6854
          overall = 0.4794

Log-pseudolikelihood = -6983.3822
                                   (Std. Err. adjusted for 141 clusters in fips)

------------------------------------------------------------------------------------------
                         |               Robust
            ln_rtotalloss |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------------+---------------------------------------------------------------
Main                      |
              ln_rhmgp_l1 |   .0333198   .0314867     1.06   0.290    -.0283931    .0950327
                 avprecip |    .118589   .0121368     9.77   0.000     .0948014    .1423766
             fldareaprcnt |   .0112804   .0095845     1.18   0.239    -.0075049    .0300657
             ccaplowprcnt |   .3260217   .0891646     3.66   0.000     .1512623    .5007811
            ccaphighprcnt |  -.4979624   .4195368    -1.19   0.235    -1.320239    .3243147
 ccapwetlandchangeprcnt   |  -.2422368   .3103588    -0.78   0.435    -.8505288    .3660552
           housingunits1k |   .0048729   .0025312     1.93   0.054    -.0000881     .009834
           medianincome1k |   .0145591   .0145014     1.00   0.315    -.0138631    .0429813
              stormevents |   .1454777   .0423479     3.44   0.001     .0624773    .2284782
              disasevents |   2.662391   .1385587    19.21   0.000     2.390821    2.933961
                shoreline |   1.105086   .3740075     2.95   0.003     .3720447    1.838127
                 ALbinary |  -3.278546   .6117838    -5.36   0.000     -4.47762   -2.079472
                 FLbinary |  -3.293603   .4898889    -6.72   0.000    -4.253768   -2.333439
                 GAbinary |   -2.59072   .9951994    -2.60   0.009    -4.541275   -.6401653
                 LAbinary |  -1.979681   .6775105    -2.92   0.003    -3.307578   -.6517852
                 MSbinary |  -1.956102   .8849682    -2.21   0.027    -3.690608   -.2215962
       mitprojecttime_l1  |  -.0780911   .0622809    -1.25   0.210    -.2001594    .0439772
                    _cons |  -.4192352   .8576771    -0.49   0.625    -2.100251    1.261781
--------------------------+---------------------------------------------------------------
Spatial                   |
                   lambda |   .5157237    .017699    29.14   0.000     .4810343     .550413
--------------------------+---------------------------------------------------------------
Variance                  |
                   ln_phi |  -1.839099   .2103636    -8.74   0.000    -2.251404   -1.426794
                 sigma2_e |   12.39162   .5305446    23.36   0.000     11.35177    13.43146
------------------------------------------------------------------------------------------
```

Figure B.9 HMGP Two-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood =  -7234.478
Iteration 1:   Log-pseudolikelihood = -7006.9705
Iteration 2:   Log-pseudolikelihood = -6983.6637
Iteration 3:   Log-pseudolikelihood = -6983.3916
Iteration 4:   Log-pseudolikelihood = -6983.3915

SEM with random-effects                          Number of obs =       2538

Group variable: fips                           Number of groups =        141
Time variable: dateActual                          Panel length =         18

R-sq:    within  = 0.4107
         between = 0.6871
         overall = 0.4798

Log-pseudolikelihood = -6983.3915
                                 (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
ln_rhmgp_l2	.0413765	.0384619	1.08	0.282	-.0340074	.1167605
avprecip	.1181436	.0120623	9.79	0.000	.094502	.1417852
fldareaprcnt	.0113665	.0095919	1.19	0.236	-.0074333	.0301663
ccaplowprcnt	.3253319	.08919	3.65	0.000	.1505226	.5001412
ccaphighprcnt	-.4968366	.4200538	-1.18	0.237	-1.320127	.3264538
ccapwetlandchangeprcnt	-.246397	.3122255	-0.79	0.430	-.8583478	.3655537
housingunits1k	.0048245	.0025131	1.92	0.055	-.0001011	.0097501
medianincome1k	.0137584	.0145182	0.95	0.343	-.0146967	.0422136
stormevents	.1467831	.0427854	3.43	0.001	.0629253	.230641
disasevents	2.661507	.1380823	19.27	0.000	2.39087	2.932143
shoreline	1.101581	.3743808	2.94	0.003	.3678082	1.835354
ALbinary	-3.294854	.6097121	-5.40	0.000	-4.489868	-2.09984
FLbinary	-3.288975	.4915979	-6.69	0.000	-4.252489	-2.325461
GAbinary	-2.591609	1.000109	-2.59	0.010	-4.551787	-.6314318
LAbinary	-1.987053	.678802	-2.93	0.003	-3.317481	-.6566258
MSbinary	-1.962791	.8991782	-2.18	0.029	-3.725148	-.2004342
mitprojecttime_l2	-.0757998	.0737189	-1.03	0.304	-.2202861	.0686866
_cons	-.3781627	.8505849	-0.44	0.657	-2.045279	1.288953
Spatial						
lambda	.5152742	.0177639	29.01	0.000	.4804576	.5500908
Variance						
ln_phi	-1.847186	.2094885	-8.82	0.000	-2.257776	-1.436596
sigma2_e	12.3975	.5321456	23.30	0.000	11.35452	13.44049

Figure B.10 HMGP Three-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7233.9011
Iteration 1:   Log-pseudolikelihood = -7007.4868
Iteration 2:   Log-pseudolikelihood = -6983.7538
Iteration 3:   Log-pseudolikelihood = -6983.4613
Iteration 4:   Log-pseudolikelihood =  -6983.461

SEM with random-effects                          Number of obs =       2538

Group variable: fips                          Number of groups =        141
Time variable: dateActual                         Panel length =         18

R-sq:    within  = 0.4118
         between = 0.6849
         overall = 0.4801

Log-pseudolikelihood = -6983.4610
                                   (Std. Err. adjusted for 141 clusters in fips)

------------------------------------------------------------------------------------------
                         |               Robust
            ln_rtotalloss |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------------+---------------------------------------------------------------
Main                      |
               ln_rhmgp_l3 |   -.033715   .0368473    -0.91   0.360    -.1059345    .0385044
                  avprecip |   .1170633   .0121615     9.63   0.000     .0932271    .1408995
              fldareaprcnt |   .0109979   .0095449     1.15   0.249    -.0077097    .0297056
              ccaplowprcnt |   .3278183   .0901929     3.63   0.000     .1510435     .504593
             ccaphighprcnt |   -.518563   .4234588    -1.22   0.221    -1.348527    .3114009
   ccapwetlandchangeprcnt |  -.2367757    .310822    -0.76   0.446    -.8459757    .3724243
           housingunits1k |   .0049097   .0025369     1.94   0.053    -.0000624    .0098819
           medianincome1k |   .0140121   .0145517     0.96   0.336    -.0145087    .0425328
              stormevents |   .1458583   .0427805     3.41   0.001       .06201    .2297065
              disasevents |   2.669126   .1387046    19.24   0.000      2.39727    2.940982
                shoreline |   1.124249   .3746924     3.00   0.003     .3898655    1.858633
                 ALbinary |  -3.146982   .6235052    -5.05   0.000     -4.36903   -1.924935
                 FLbinary |  -3.227702   .4868687    -6.63   0.000    -4.181947   -2.273457
                 GAbinary |  -2.536007   .9919176    -2.56   0.011    -4.480129   -.5918837
                 LAbinary |  -1.982302   .6755201    -2.93   0.003    -3.306297   -.6583071
                 MSbinary |  -1.849405   .8943605    -2.07   0.039    -3.602319   -.0964901
        mitprojecttime_l3 |   .0826593   .0683177     1.21   0.226     -.051241    .2165596
                    _cons |  -.3013076   .8554602    -0.35   0.725    -1.977979    1.375364
--------------------------+---------------------------------------------------------------
Spatial                   |
                   lambda |    .514044   .0178341    28.82   0.000     .4790897    .5489982
--------------------------+---------------------------------------------------------------
Variance                  |
                   ln_phi |  -1.838373   .2075347    -8.86   0.000    -2.245134   -1.431612
                 sigma2_e |   12.39883   .5322229    23.30   0.000     11.35569    13.44197
------------------------------------------------------------------------------------------
```

Figure B.11 HMGP Four-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7235.0195
Iteration 1:   Log-pseudolikelihood = -7006.0606
Iteration 2:   Log-pseudolikelihood = -6982.1557
Iteration 3:   Log-pseudolikelihood =   -6981.84
Iteration 4:   Log-pseudolikelihood = -6981.8398

SEM with random-effects                          Number of obs =       2538

Group variable: fips                           Number of groups =        141
Time variable: dateActual                          Panel length =         18

R-sq:    within  = 0.4102
         between = 0.6900
         overall = 0.4802

Log-pseudolikelihood = -6981.8398
                                     (Std. Err. adjusted for 141 clusters in fips)

-----------------------------------------------------------------------------------
                         |               Robust
            ln_rtotalloss |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------------+---------------------------------------------------------
Main                     |
              ln_rhmgp_l4 |   .0678351   .0387518     1.75   0.080     -.008117    .1437872
                 avprecip |   .1182277    .012054     9.81   0.000     .0946023    .1418532
             fldareaprcnt |   .0116207   .0096032     1.21   0.226    -.0072012    .0304426
             ccaplowprcnt |    .326555   .0891543     3.66   0.000     .1518159    .5012942
            ccaphighprcnt |  -.5075797   .4159275    -1.22   0.222    -1.322783    .3076232
 ccapwetlandchangeprcnt   |  -.2182427   .3100839    -0.70   0.482     -.825996    .3895106
          housingunits1k  |   .0048032    .002494     1.93   0.054    -.0000849    .0096912
          medianincome1k  |   .0119993   .0146825     0.82   0.414    -.0167779    .0407764
             stormevents  |   .1455546   .0429182     3.39   0.001     .0614365    .2296728
             disasevents  |   2.676678   .1393696    19.21   0.000     2.403519    2.949838
               shoreline  |   1.092122   .3712396     2.94   0.003      .364506    1.819739
                ALbinary  |     -3.371   .6019674    -5.60   0.000    -4.550835   -2.191166
                FLbinary  |  -3.327034   .4906008    -6.78   0.000    -4.288594   -2.365474
                GAbinary  |  -2.626817   1.006373    -2.61   0.009    -4.599272   -.6543617
                LAbinary  |  -2.034862    .680004    -2.99   0.003    -3.367645   -.7020786
                MSbinary  |  -2.034088   .8823911    -2.31   0.021    -3.763543   -.3046332
      mitprojecttime_l4   |  -.0730315   .0749163    -0.97   0.330    -.2198648    .0738018
                   _cons  |    -.34115   .8583522    -0.40   0.691    -2.023489    1.341189
-------------------------+---------------------------------------------------------
Spatial                  |
                  lambda  |   .5161941   .0175557    29.40   0.000     .4817855    .5506026
-------------------------+---------------------------------------------------------
Variance                 |
                  ln_phi  |  -1.859969    .211476    -8.80   0.000    -2.274454   -1.445484
                sigma2_e  |   12.38487   .5293391    23.40   0.000     11.34739    13.42236
-----------------------------------------------------------------------------------
```

Figure B.12 HMGP Five-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood =  -7230.658
Iteration 1:   Log-pseudolikelihood = -7005.7114
Iteration 2:   Log-pseudolikelihood = -6983.0805
Iteration 3:   Log-pseudolikelihood = -6982.8275
Iteration 4:   Log-pseudolikelihood = -6982.8273

SEM with random-effects                          Number of obs =      2538

Group variable: fips                          Number of groups =       141
Time variable: dateActual                         Panel length =        18

R-sq:    within  = 0.4128
         between = 0.6810
         overall = 0.4799

Log-pseudolikelihood = -6982.8273
                                  (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
ln_rhmgp_l5	-.0460722	.0437543	-1.05	0.292	-.131829	.0396847
avprecip	.1185139	.0120359	9.85	0.000	.094924	.1421038
fldareaprcnt	.0107525	.0095644	1.12	0.261	-.0079933	.0294984
ccaplowprcnt	.3252134	.0899743	3.61	0.000	.148867	.5015598
ccaphighprcnt	-.4988956	.4246516	-1.17	0.240	-1.331197	.3334061
ccapwetlandchangeprcnt	-.2591387	.3124971	-0.83	0.407	-.8716218	.3533444
housingunits1k	.0049114	.0025668	1.91	0.056	-.0001195	.0099424
medianincome1k	.0153219	.0143976	1.06	0.287	-.0128968	.0435406
stormevents	.1465869	.0421618	3.48	0.001	.0639512	.2292226
disasevents	2.661081	.1390086	19.14	0.000	2.388629	2.933533
shoreline	1.130579	.3759561	3.01	0.003	.3937183	1.867439
ALbinary	-3.124844	.638937	-4.89	0.000	-4.377137	-1.872551
FLbinary	-3.217886	.4889693	-6.58	0.000	-4.176248	-2.259524
GAbinary	-2.527768	.9891147	-2.56	0.011	-4.466397	-.5891384
LAbinary	-1.95684	.6762116	-2.89	0.004	-3.282191	-.6314897
MSbinary	-1.83065	.8912104	-2.05	0.040	-3.57739	-.0839095
mitprojecttime_l5	.037021	.0905045	0.41	0.683	-.1403645	.2144064
_cons	-.3847612	.847487	-0.45	0.650	-2.045805	1.276283
Spatial						
lambda	.5139455	.0177731	28.92	0.000	.4791108	.5487801
Variance						
ln_phi	-1.820343	.2051976	-8.87	0.000	-2.222522	-1.418163
sigma2_e	12.38415	.5298	23.38	0.000	11.34576	13.42254

Figure B.13 FMA Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7235.3563
Iteration 1:   Log-pseudolikelihood = -7007.6958
Iteration 2:   Log-pseudolikelihood = -6983.8789
Iteration 3:   Log-pseudolikelihood = -6983.5704
Iteration 4:   Log-pseudolikelihood = -6983.5701

SEM with random-effects                         Number of obs =       2538

Group variable: fips                         Number of groups =        141
Time variable: dateActual                        Panel length =         18

R-sq:    within  = 0.4111
         between = 0.6845
         overall = 0.4795

Log-pseudolikelihood = -6983.5701
                                     (Std. Err. adjusted for 141 clusters in fips)

------------------------------------------------------------------------------------
                        |               Robust
           ln_rtotalloss |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------------+----------------------------------------------------------
Main                    |
                ln_rfma |   .0195101   .1118469     0.17   0.862    -.1997058     .238726
               avprecip |   .1175948   .0120298     9.78   0.000     .0940167    .1411728
           fldareaprcnt |   .0111393   .0095293     1.17   0.242    -.0075377    .0298163
           ccaplowprcnt |   .3285794   .0898556     3.66   0.000     .1524657    .5046932
          ccaphighprcnt |  -.4958617   .4178434    -1.19   0.235     -1.31482    .3230964
ccapwetlandchangeprcnt |  -.2467581   .3100957    -0.80   0.426    -.8545345    .3610183
        housingunits1k |   .0048142   .0025226     1.91   0.056    -.0001299    .0097584
         medianincome1k |    .013783   .0144779     0.95   0.341    -.0145932    .0421592
           stormevents |   .1465174   .0418507     3.50   0.000     .0644915    .2285433
           disasevents |   2.666058    .138191    19.29   0.000     2.395209    2.936908
              shoreline |   1.128529   .3740571     3.02   0.003     .3953903    1.861667
               ALbinary |   -3.20169   .6113886    -5.24   0.000    -4.399989    -2.00339
               FLbinary |  -3.227245   .4888471    -6.60   0.000    -4.185368   -2.269122
               GAbinary |  -2.549739    .992748    -2.57   0.010    -4.495489   -.6039882
               LAbinary |  -1.983637   .6758725    -2.93   0.003    -3.308322   -.6589509
               MSbinary |  -1.893687    .887495    -2.13   0.033    -3.633145   -.1542288
        mitprojecttime |  -.2204551   .3488598    -0.63   0.527    -.9042078    .4632976
                  _cons |  -.3610644   .8591631    -0.42   0.674    -2.044993    1.322864
-------------------------+----------------------------------------------------------
Spatial                 |
                 lambda |    .514877   .0177431    29.02   0.000     .4801012    .5496527
-------------------------+----------------------------------------------------------
Variance                |
                 ln_phi |  -1.837004   .2065333    -8.89   0.000    -2.241802   -1.432206
               sigma2_e |   12.39585   .5317214    23.31   0.000      11.3537    13.43801
------------------------------------------------------------------------------------
```

Figure B.14 FMA One-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7232.8899
Iteration 1:   Log-pseudolikelihood = -7007.6771
Iteration 2:   Log-pseudolikelihood = -6983.8768
Iteration 3:   Log-pseudolikelihood = -6983.5835
Iteration 4:   Log-pseudolikelihood = -6983.5833

SEM with random-effects                          Number of obs =       2538

Group variable: fips                          Number of groups =        141
Time variable: dateActual                         Panel length =         18

R-sq:    within  = 0.4120
         between = 0.6862
         overall = 0.4806

Log-pseudolikelihood = -6983.5833
                                  (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
ln_rfma_l1	.0230263	.0548826	0.42	0.675	-.0845416	.1305943
avprecip	.1176696	.0121081	9.72	0.000	.0939381	.1414011
fldareaprcnt	.0112824	.0095865	1.18	0.239	-.0075068	.0300717
ccaplowprcnt	.324286	.0896886	3.62	0.000	.1484996	.5000723
ccaphighprcnt	-.5156544	.4245244	-1.21	0.224	-1.347707	.316398
ccapwetlandchangeprcnt	-.2331907	.3112956	-0.75	0.454	-.8433188	.3769374
housingunits1k	.0049371	.0025364	1.95	0.052	-.0000341	.0099083
medianincome1k	.0142046	.0144829	0.98	0.327	-.0141814	.0425907
stormevents	.1460845	.0423776	3.45	0.001	.063026	.229143
disasevents	2.667493	.1375017	19.40	0.000	2.397995	2.936992
shoreline	1.100761	.3738071	2.94	0.003	.3681129	1.83341
ALbinary	-3.222026	.6138774	-5.25	0.000	-4.425203	-2.018848
FLbinary	-3.283771	.4903563	-6.70	0.000	-4.244851	-2.32269
GAbinary	-2.565993	.9926371	-2.59	0.010	-4.511526	-.6204598
LAbinary	-1.980196	.6733203	-2.94	0.003	-3.29988	-.6605128
MSbinary	-1.901411	.8881724	-2.14	0.032	-3.642197	-.1606251
mitprojecttime_l1	.0813494	.246817	0.33	0.742	-.4024031	.5651018
_cons	-.3638403	.8545672	-0.43	0.670	-2.038761	1.311081
Spatial						
lambda	.5135529	.0180667	28.43	0.000	.4781428	.5489631
Variance						
ln_phi	-1.843066	.2082263	-8.85	0.000	-2.251182	-1.43495
sigma2_e	12.40431	.5337393	23.24	0.000	11.3582	13.45042

Figure B.15 FMA Two-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7233.9768
Iteration 1:   Log-pseudolikelihood = -7007.5039
Iteration 2:   Log-pseudolikelihood = -6983.7139
Iteration 3:   Log-pseudolikelihood = -6983.4225
Iteration 4:   Log-pseudolikelihood = -6983.4223

SEM with random-effects                          Number of obs =       2538

Group variable: fips                          Number of groups =        141
Time variable: dateActual                         Panel length =         18

R-sq:     within  = 0.4120
          between = 0.6849
          overall = 0.4803

Log-pseudolikelihood = -6983.4223
                                   (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
ln_rfma_l2	-.0866352	.083999	-1.03	0.302	-.2512702	.0779998
avprecip	.1170578	.0120855	9.69	0.000	.0933707	.1407449
fldareaprcnt	.0109233	.0095645	1.14	0.253	-.0078228	.0296693
ccaplowprcnt	.3261257	.0899895	3.62	0.000	.1497495	.5025019
ccaphighprcnt	-.501044	.4217587	-1.19	0.235	-1.327676	.3255878
ccapwetlandchangeprcnt	-.2437642	.3083142	-0.79	0.429	-.8480489	.3605204
housingunits1k	.0048513	.0025362	1.91	0.056	-.0001196	.0098222
medianincome1k	.0148469	.0145048	1.02	0.306	-.0135819	.0432757
stormevents	.1460114	.0428255	3.41	0.001	.0620749	.2299478
disasevents	2.675178	.1391152	19.23	0.000	2.402518	2.947839
shoreline	1.121334	.3742255	3.00	0.003	.3878655	1.854803
ALbinary	-3.199007	.6104881	-5.24	0.000	-4.395542	-2.002473
FLbinary	-3.230466	.4915895	-6.57	0.000	-4.193963	-2.266968
GAbinary	-2.55291	.9933048	-2.57	0.010	-4.499752	-.6060686
LAbinary	-1.963597	.6761077	-2.90	0.004	-3.288744	-.6384502
MSbinary	-1.87319	.8866763	-2.11	0.035	-3.611044	-.1353363
mitprojecttime_l2	.2553213	.2456881	1.04	0.299	-.2262185	.7368611
_cons	-.2922641	.8471031	-0.35	0.730	-1.952556	1.368027
Spatial						
lambda	.5138031	.0179104	28.69	0.000	.4786993	.5489069
Variance						
ln_phi	-1.837258	.2076672	-8.85	0.000	-2.244279	-1.430238
sigma2_e	12.39887	.5322883	23.29	0.000	11.35561	13.44214

Figure B.16 FMA Three-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7231.6411
Iteration 1:   Log-pseudolikelihood = -7006.7151
Iteration 2:   Log-pseudolikelihood = -6983.3085
Iteration 3:   Log-pseudolikelihood = -6983.0344
Iteration 4:   Log-pseudolikelihood = -6983.0342

SEM with random-effects                          Number of obs =       2538

Group variable: fips                          Number of groups =        141
Time variable: dateActual                         Panel length =         18

R-sq:    within  = 0.4134
         between = 0.6869
         overall = 0.4818

Log-pseudolikelihood = -6983.0342
                                   (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
ln_rfma_l3	-.0464558	.0643059	-0.72	0.470	-.1724931	.0795816
avprecip	.1161974	.0121886	9.53	0.000	.0923083	.1400866
fldareaprcnt	.0111312	.0095859	1.16	0.246	-.0076568	.0299192
ccaplowprcnt	.3223173	.0892839	3.61	0.000	.147324	.4973106
ccaphighprcnt	-.5107418	.4258084	-1.20	0.230	-1.345311	.3238273
ccapwetlandchangeprcnt	-.242443	.3063466	-0.79	0.429	-.8428713	.3579852
housingunits1k	.0049125	.0025458	1.93	0.054	-.0000772	.0099022
medianincome1k	.0157341	.014435	1.09	0.276	-.012558	.0440262
stormevents	.1475061	.0427194	3.45	0.001	.0637777	.2312346
disasevents	2.668939	.1377388	19.38	0.000	2.398976	2.938902
shoreline	1.099227	.3742176	2.94	0.003	.3657741	1.83268
ALbinary	-3.185318	.6102058	-5.22	0.000	-4.381299	-1.989336
FLbinary	-3.248595	.4872519	-6.67	0.000	-4.203591	-2.293599
GAbinary	-2.542085	.9910846	-2.56	0.010	-4.484576	-.5995953
LAbinary	-1.94144	.6735763	-2.88	0.004	-3.261625	-.6212544
MSbinary	-1.851405	.8851628	-2.09	0.036	-3.586293	-.1165182
mitprojecttime_l3	.3343934	.2064627	1.62	0.105	-.070266	.7390528
_cons	-.3466054	.8531003	-0.41	0.685	-2.018651	1.32544
Spatial						
lambda	.5119832	.0179548	28.52	0.000	.4767925	.547174
Variance						
ln_phi	-1.844388	.208421	-8.85	0.000	-2.252885	-1.43589
sigma2_e	12.40591	.5338408	23.24	0.000	11.3596	13.45222

Figure B.17 FMA Four-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7235.3545
Iteration 1:   Log-pseudolikelihood = -7008.2923
Iteration 2:   Log-pseudolikelihood = -6984.2279
Iteration 3:   Log-pseudolikelihood = -6983.9169
Iteration 4:   Log-pseudolikelihood = -6983.9167

SEM with random-effects                      Number of obs =       2538

Group variable: fips                      Number of groups =        141
Time variable: dateActual                     Panel length =         18

R-sq:    within  = 0.4113
         between = 0.6856
         overall = 0.4799

Log-pseudolikelihood = -6983.9167
                                 (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
ln_rfma_l4	.0069838	.0709117	0.10	0.922	-.1320006	.1459681
avprecip	.117713	.0121152	9.72	0.000	.0939677	.1414583
fldareaprcnt	.0112005	.0096031	1.17	0.243	-.0076212	.0300221
ccaplowprcnt	.3250026	.0888678	3.66	0.000	.1508249	.4991803
ccaphighprcnt	-.5094256	.4258741	-1.20	0.232	-1.344123	.3252724
ccapwetlandchangeprcnt	-.2388019	.3094599	-0.77	0.440	-.8453322	.3677283
housingunits1k	.0049027	.0025513	1.92	0.055	-.0000979	.0099032
medianincome1k	.01431	.014632	0.98	0.328	-.0143682	.0429881
stormevents	.1458419	.042427	3.44	0.001	.0626864	.2289973
disasevents	2.66486	.1405544	18.96	0.000	2.389379	2.940342
shoreline	1.108737	.3742856	2.96	0.003	.3751506	1.842323
ALbinary	-3.216158	.6161328	-5.22	0.000	-4.423756	-2.00856
FLbinary	-3.265607	.4926608	-6.63	0.000	-4.231205	-2.30001
GAbinary	-2.561817	.9931265	-2.58	0.010	-4.508309	-.6153249
LAbinary	-1.979843	.6776623	-2.92	0.003	-3.308037	-.6516493
MSbinary	-1.898589	.8867905	-2.14	0.032	-3.636666	-.1605115
mitprojecttime_l4	.0536668	.2432805	0.22	0.825	-.4231542	.5304879
_cons	-.3650976	.8554525	-0.43	0.670	-2.041754	1.311559
Spatial						
lambda	.5143007	.0177479	28.98	0.000	.4795156	.5490859
Variance						
ln_phi	-1.841173	.2083295	-8.84	0.000	-2.249492	-1.432855
sigma2_e	12.40362	.5324966	23.29	0.000	11.35995	13.44729

Figure B.18 FMA Five-Year Lag Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7225.9882
Iteration 1:   Log-pseudolikelihood = -7002.9806
Iteration 2:   Log-pseudolikelihood = -6980.8369
Iteration 3:   Log-pseudolikelihood = -6980.6147
Iteration 4:   Log-pseudolikelihood = -6980.6146

SEM with random-effects                          Number of obs =      2538

Group variable: fips                          Number of groups =       141
Time variable: dateActual                         Panel length =        18

R-sq:    within  = 0.4165
         between = 0.6840
         overall = 0.4834

Log-pseudolikelihood = -6980.6146
                                      (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
ln_rfma_l5	-.1768336	.0635463	-2.78	0.005	-.3013821	-.0522852
avprecip	.1171572	.0120019	9.76	0.000	.0936339	.1406804
fldareaprcnt	.0104076	.0095861	1.09	0.278	-.0083809	.0291961
ccaplowprcnt	.3207561	.0886348	3.62	0.000	.147035	.4944772
ccaphighprcnt	-.4809683	.4242368	-1.13	0.257	-1.312457	.3505206
ccapwetlandchangeprcnt	-.2962371	.3037943	-0.98	0.329	-.891663	.2991889
housingunits1k	.0047619	.0025631	1.86	0.063	-.0002617	.0097854
medianincome1k	.0175647	.0144885	1.21	0.225	-.0108322	.0459617
stormevents	.1471561	.0425493	3.46	0.001	.063761	.2305513
disasevents	2.63363	.1376695	19.13	0.000	2.363803	2.903457
shoreline	1.112292	.374448	2.97	0.003	.3783878	1.846197
ALbinary	-3.169453	.6113128	-5.18	0.000	-4.367605	-1.971302
FLbinary	-3.206049	.4905975	-6.53	0.000	-4.167603	-2.244496
GAbinary	-2.551518	.9902951	-2.58	0.010	-4.492461	-.6105752
LAbinary	-1.928374	.6750037	-2.86	0.004	-3.251357	-.6053911
MSbinary	-1.850463	.8849192	-2.09	0.037	-3.584873	-.1160532
mitprojecttime_l5	.6053513	.2168724	2.79	0.005	.1802892	1.030413
_cons	-.4228166	.850016	-0.50	0.619	-2.088817	1.243184
Spatial						
lambda	.5100014	.0177681	28.70	0.000	.4751766	.5448261
Variance						
ln_phi	-1.829949	.2069025	-8.84	0.000	-2.23547	-1.424427
sigma2_e	12.3831	.5329414	23.24	0.000	11.33855	13.42765

Figure B.19 HMGP Mitigated Properties Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7234.7676
Iteration 1:   Log-pseudolikelihood = -7006.0318
Iteration 2:   Log-pseudolikelihood = -6983.0943
Iteration 3:   Log-pseudolikelihood = -6982.8217
Iteration 4:   Log-pseudolikelihood = -6982.8215

SEM with random-effects                        Number of obs =       2538

Group variable: fips                        Number of groups =        141
Time variable: dateActual                       Panel length =         18

R-sq:     within  = 0.4101
          between = 0.6897
          overall = 0.4801

Log-pseudolikelihood = -6982.8215
                                  (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
numberOfFinalProperties	-.0013911	.0023818	-0.58	0.559	-.0060593	.0032771
avprecip	.1165548	.0121793	9.57	0.000	.0926838	.1404259
fldareaprcnt	.0111956	.0095141	1.18	0.239	-.0074517	.0298429
ccaplowprcnt	.325086	.0894012	3.64	0.000	.149863	.500309
ccaphighprcnt	-.515519	.418103	-1.23	0.218	-1.334986	.3039479
ccapwetlandchangeprcnt	-.2448906	.3092553	-0.79	0.428	-.8510199	.3612386
housingunits1k	.0048725	.0024723	1.97	0.049	.0000269	.009718
medianincome1k	.0127039	.0144834	0.88	0.380	-.015683	.0410908
stormevents	.1468951	.0427016	3.44	0.001	.0632016	.2305887
disasevents	2.668293	.1381928	19.31	0.000	2.39744	2.939145
shoreline	1.105015	.3715112	2.97	0.003	.3768668	1.833164
ALbinary	-3.219893	.6073333	-5.30	0.000	-4.410244	-2.029542
FLbinary	-3.237646	.4850624	-6.67	0.000	-4.188351	-2.286941
GAbinary	-2.543759	.9994384	-2.55	0.011	-4.502622	-.5848957
LAbinary	-2.003436	.6745883	-2.97	0.003	-3.325605	-.6812673
MSbinary	-1.889223	.8854574	-2.13	0.033	-3.624688	-.1537585
mitprojecttime	.0520036	.029994	1.73	0.083	-.0067835	.1107908
_cons	-.2566029	.8559186	-0.30	0.764	-1.934173	1.420967
Spatial						
lambda	.5159662	.0177993	28.99	0.000	.4810802	.5508522
Variance						
ln_phi	-1.860681	.2107041	-8.83	0.000	-2.273654	-1.447709
sigma2_e	12.39574	.5331456	23.25	0.000	11.35079	13.44068

Figure B.20 FMA Mitigated Properties Spatial Error Model Results

```
. //Spatial-error model (SEM)
. //SEM with random-effects
. xsmle $ylist $xlist, emat(W) model(sem) re vce(robust)
note: TXbinary dropped because of collinearity
Iteration 0:   Log-pseudolikelihood = -7235.0302
Iteration 1:   Log-pseudolikelihood = -7007.3187
Iteration 2:   Log-pseudolikelihood = -6983.4798
Iteration 3:   Log-pseudolikelihood = -6983.1761
Iteration 4:   Log-pseudolikelihood = -6983.1759

SEM with random-effects                          Number of obs =       2538

Group variable: fips                          Number of groups =        141
Time variable: dateActual                         Panel length =         18

R-sq:     within  = 0.4113
          between = 0.6843
          overall = 0.4796

Log-pseudolikelihood = -6983.1759
                                   (Std. Err. adjusted for 141 clusters in fips)
```

ln_rtotalloss	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Main						
numberOfFinalProperties	.0976792	.0633084	1.54	0.123	-.026403	.2217615
avprecip	.1176179	.0120373	9.77	0.000	.0940252	.1412106
fldareaprcnt	.0110632	.0095545	1.16	0.247	-.0076633	.0297896
ccaplowprcnt	.3272636	.089463	3.66	0.000	.1519193	.5026079
ccaphighprcnt	-.5048891	.4186987	-1.21	0.228	-1.325523	.3157453
ccapwetlandchangeprcnt	-.2446725	.3089441	-0.79	0.428	-.8501918	.3608468
housingunits1k	.0048674	.0025261	1.93	0.054	-.0000837	.0098185
medianincome1k	.0139611	.014464	0.97	0.334	-.0143877	.04231
stormevents	.1467078	.0420308	3.49	0.000	.0643288	.2290867
disasevents	2.666465	.1380602	19.31	0.000	2.395872	2.937058
shoreline	1.131312	.3743181	3.02	0.003	.3976618	1.864962
ALbinary	-3.203297	.6119273	-5.23	0.000	-4.402652	-2.003941
FLbinary	-3.227397	.487632	-6.62	0.000	-4.183138	-2.271656
GAbinary	-2.55056	.9938201	-2.57	0.010	-4.498412	-.6027084
LAbinary	-1.97907	.6750469	-2.93	0.003	-3.302138	-.6560026
MSbinary	-1.895367	.8868275	-2.14	0.033	-3.633517	-.1572171
mitprojecttime	-.229548	.1762615	-1.30	0.193	-.5750143	.1159183
_cons	-.3437957	.8497839	-0.40	0.686	-2.009342	1.32175
Spatial						
lambda	.5149455	.0177289	29.05	0.000	.4801975	.5496935
Variance						
ln_phi	-1.834404	.2066926	-8.88	0.000	-2.239514	-1.429294
sigma2_e	12.39045	.5315547	23.31	0.000	11.34862	13.43227