LETTERS OF MAP CHANGE ON FLOOD INSURANCE RATE MAPS IN THE UNITED STATES NATIONAL FLOOD INSURANCE PROGRAM

by

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DISSERTATION ABSTRACT

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Title: Letters of Map Change on Flood Insurance Rate Maps in the United States National Flood Insurance Program

In the United States of America, flooding has been the costliest environmental hazard in recent decades (NOAA National Centers for Environmental Information, 2018) and is projected to increase in many areas in the near future due to impacts of climate change on sea level rise and hydrology (Wing et al., 2018; Ghanbari et al., 2021). At the same time, the National Flood Insurance Program flood maps depicting hazard are in many places being adjusted to move buildings from higher hazard to lower hazard flood zones via initiation by the people living in these places (Dedman, 2014; Pralle, 2019).

This dissertation studies how, why, where, and who benefits from different types of these adjustments, collectively called Letters of Map Change, on Flood Insurance Rate Maps produced for the United States National Flood Insurance Program. To answer these questions, I first conduct a literature review and interviews to understand the how and why of Letters of Map Change. I then examine where buildings are altered by Letters of Map Change at county to individual property scales using Geographic Information Systems software. I finally combine these observations with United States Census Bureau American Community Survey data and tax lots in the state of Florida to assess who acquires and benefits from Letters of Map Change.

Results find that the desire to reduce insurance premiums, FIRM flood zone data quality, and socio-economic wealth determine where Letters of Map Change occur. Places with lower elevation accuracy and precision often have higher rates of inadvertent inclusions, while places with higher precision and accuracy maps often use physical alterations like raising the elevation of their property to obtain a map change. Higher indicators of wealth often correlate with increased Letters of Map Change success, but use is less frequent among the wealthiest people. The least wealthy are the least frequent to obtain Letters of Map Change, indicating public policies could be implemented so FEMA can use funds to identify where communities or individuals should get financial aid to pursue Letters of Map Change.

This dissertation includes previously published co-authored material.

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TABLE OF CONTENTS

Chapter | Page

Chapter Page

LIST OF FIGURES

LIST OF TABLES

Table Page

Table Page

Table Page

CHAPTER I

INTRODUCTION

Introduction

There is a large and ever-growing literature about how climate change is already impacting and will continue to alter and affect flood hazard around the world (Hirabayashi et al., 2013; Kundzewicz et al., 2014; Arnell and Gosling, 2016; Winsemius et al., 2016; Alfieri et al., 2017; Gudmundsson et al., 2021). Just in North America and the United States, there are many studies showing how flooding from sea level rise, more intense rainfall, tropical storms, or rain-on-snow events has already been impacted or is projected to change in coming years and decades (Musselman et al., 2018; Wing et al., 2018; Marsooli et al., 2019; Bates et al., 2021; Ghanbari et al., 2021). This abundance of research is partly due to the variety of methods that have been devised to create predictions of flood hazard. For example, flood frequency analysis, regionalized regression equations, and rainfall-runoff models are a few of the main ways technical experts such as hydrologists and engineers predict flooding (Wing et al., 2017; Jafarzadegan et al., 2018; Woznicki et al., 2019; Brunner et al., 2021). Other literatures on flood hazard focus on the human dimensions and systems of flood risk. For example, much work has been done on the social ways people are more or less “vulnerable” or “at risk” to the impacts caused by physical flood damages and destruction of their livelihoods (Cutter et al., 2003; Wisner et al., 2004; Rufat et al., 2015; Wisner, 2016; Elliott, 2019; Jacobs, 2019), and mechanisms such as insurance, mitigation, direct aid, and buyouts have been studied to gain insights how these instruments have performed in practice and who they aid or leave unaided (Holladay and Schwartz, 2010; Bin et al., 2017; Pravin, 2018; Domingue and Emrich, 2019; Loughran and Elliott, 2021).

The goal of my dissertation is to provide insights at the nexus of research topics mentioned in the previous paragraph by studying one of the primary institutions in the United States that manages flood damages to built infrastructure: flood insurance as implemented via the United States National Flood Insurance Program (NFIP). More precisely, I analyze Letters of Map Change on Flood Insurance Rate Maps (FIRMs). A FIRM is a map showing various zones of greater or lesser flood hazard. Areas on FIRMs that are predicted to have one percent or greater chance of flooding annually are called Special Flood Hazard Areas (SFHAs).

Letters of Map Change either add or remove buildings from SFHAs on FIRMs. This is important because NFIP uses flood zones like those in the SFHA on FIRMs to price insurance premiums for individual buildings, and premium payments for insurance on a building mapped into a SFHA can be hundreds or thousands of dollars per year higher than for a property outside the SFHA (FEMA, 2018a). The Federal Emergency Management Agency (FEMA) initiates the production of new FIRMs. These new FIRMs are created for individual counties to replace older maps and keep flood hazard up to date, and new FIRMs are created through the combined work of FEMA representatives, technical experts hired by FEMA, and local community members or representatives. Letters of Map Change are based on updating or collecting new scientific data to improve the accuracy or precision of flood hazard on FIRMs, but they are initiated and sought by what I call “propertied interests”, which could be elected community representatives, property developers, or property owners.

The term “Letters of Map Change” is a catch-all that incorporates several types of map alterations, which can be sub-divided into two main categories called “MT-1s” and “MT-2s” by FEMA (FEMA, 2018b, 2021a). Colloquially, “MT-1s” are referred to as Letters of Map Amendment (LOMAs) and “MT-2s” are referred to as Letters of Map Revision (LOMRs), although these terms Letter of Map Amendment and Letter of Map Revision also can have more specific meanings. The differences between LOMRs and LOMAs, as well as specific meanings, will be discussed in detail in chapter two.

The questions investigated by this dissertation arise out of a desire to investigate a seeming contradiction related to the NFIP. On the one hand, scientific literature continues to amass evidence of many places set to experience increasing flood hazard in the near future (Wing et al., 2018; Ghanbari et al., 2021). Based on these scientific understandings, a reasonable expectation would be that SFHAs on FIRMs should also be increasing over time. But on the other hand, preliminary and anecdotal evidence examining Letters of Map Change to FIRMs over the past several years suggests many buildings are being re-mapped out of SFHAs into lower hazard flood zones (Dedman, 2014; Pralle, 2019). Although I do not investigate predictions of future flood hazard due to climate change in this dissertation, I do investigate changes to the SFHA due to Letters of Map Change. The following questions guide my dissertation:

- Why and how are buildings being changed from being inside SFHAs to lower hazard flood zones?
- Where are more or fewer buildings being changed from inside SFHAs to lower hazard flood zones?

- Who is benefitting (or not benefitting) from changing these buildings out of SFHAs to lower hazard flood zones?

Broader Impacts

While Letters of Map Change might seem to only influence how much money property owners pay in insurance premiums to insure their building from flooding, there are a few important collective impacts that Letters of Map Change are likely having on the National Flood Insurance Program and the United States. As I described above, scientific studies are predicting future flood hazard will often be greater than flood hazard depicted on FIRMs, which can only be based on historical observations and other empirical data. Due to this difference, FIRMs are likely underestimating flood hazard in many places. This means that future floods are more likely to inundate greater areas as floodwaters rise to higher elevations than predicted by FIRMs, in turn inundating buildings that have recently obtained Letters of Map Change and were changed out of SFHAs to lower hazard flood zones.

There are at least two important implications if Letters of Map Change are being changed to lower hazard flood zones but are soon to or are continuing to experience flooding at higher rates than their predicted risk. The first implication is that Letters of Map Change alter the risk pool and who pays for flood damages in the wake of a flood event. Because part of the premiums paid by a property owner are based actuarily based on the flood hazard, a building owner that experiences floods and is paid claims more often than is expected to be covered by the premiums the owner pays into the program means that the program will be in a deficit. In the United States, any NFIP deficit is backed by the United States Treasury, meaning that the cost of incorrect flood insurance pricing falls on all United States taxpayers. Thus, correctly matching flood hazard and insurance premium payments is a topic that should interest all people in the United States, not just people who live in SFHAs.

The second implication depends on who is obtaining Letters of Map Change. One of the only anecdotal investigations regarding Letters of Map Change was published in a series of reports by NBC News in 2014 (Dedman, 2014). The articles claimed that wealthy home owners and property developers were obtaining Letters of Map Change with more ease and frequency than lower income property residents. While the goal of this dissertation is to build on NBC's articles and provide a more thorough investigation of evidence to assess this claim, if people with greater wealth are obtaining Letters of Map Change that remove properties out of the SFHA to lower flood hazard zones more often, over time this will increase wealth inequality because people with more wealth will pay lower insurance premiums than those with less wealth for the same damage payments after flood events. However, a key assumption here is that once propertied interests have obtained a Letter of Map Change that exempts their property from being included in the SFHA they continue to purchase flood insurance coverage and make up between 20 % and 25 % of all NFIP claims that are paid to buildings outside the SFHA (Highfield et al., 2013).

Because of the potential implications of this work, I also provide and discuss public policy ideas throughout this dissertation that might be implemented to address socially regressive outcomes that are observed, such as wealthy propertied interests more frequently using Letters of Map Change compared to people and communities with less wealth. I elaborate and provide a full discussion in the conclusion chapter on how “simple” fixes, such as providing more grant money for low-income households to use for pursuing Letter of Map Change, can at the same time contribute to larger problems such as NFIP’s debt to the United States Treasury.

Literature Review

Answering the research questions stated above can also provide insights to broader literatures and knowledge. One topic my findings contribute to is the lay-expert modes of scientific knowledge production. Callon (1999) identified three primary categories defining how non-technical experts, or “lay people”, could be involved in the production of scientific knowledge: the Public Education Model (PEM), the Public Debate Model, and the Co-Production of Knowledge Model. The PEM, similar to Wynne's (1982) “deficit model” and Freire's (1994) “banking model”, is the most passive way lay people interact with scientific knowledge production. The PEM assumes a linear transfer of scientific knowledge from scientist to lay people, and any deficit of scientific knowledge not learned by lay people is attributed to a failure of communication. At the opposite end of the spectrum from the PEM, the Co-Production of Knowledge model posits that lay people become an integral part of creating scientific knowledge with scientific efforts. Some examples of this include citizen science and volunteered geographic information (Haklay, 2013) or the Co-Creation of Science (Mauser et al., 2013). The Public Debate Model sits between the PEM and Co-Production of Knowledge model because lay people can provide opinions and open debate on scientific knowledge based on their own experiences and lay knowledge (rather than only receiving knowledge as in the PEM), but they are not actively involved in creating and deciding what constitutes scientific knowledge like in the Co-Production of Knowledge model.

Relevant work related to these models also includes research that has investigated how lay people come to understand, and sometimes mistrust, the scientific knowledge produced and used by scientific advisory committees and technical experts to shape public policies via government regulatory agencies like FEMA. Shelia Jasanoff studied examples of these advisory committees and experts, which she called “the Fifth Branch”, and argued that the most successful examples allowed agencies and their advisers the ability to negotiate the boundary between science and public policies (Jasanoff, 1990). However, because scientific knowledge is socially constructed, Jasanoff also argues that the best science advisors and technical experts can hope for is a serviceable truth. In other words, where knowledge is scientifically and socially acceptable and can support reasoned public policy decision-making. My dissertation investigates how this “serviceable truth” is achieved when FIRMs are altered by Letters of Map Change, as well as how the technical experts who hold the final decision on Letters of Map Change have ways to include FEMA approved technical partners from the community in the scientific knowledge production process to ameliorate mistrust of flood hazard maps.

Much flood hazard research focusing on how lay people interact with flood hazard knowledge and maps can be categorized under the Public Education Model. For example, this research analyzes how lay people more or less understand flood hazard knowledge and maps produced by scientific experts (Bell and Tobin, 2007; Ludy and Kondolf, 2012) or shows how these experts simplify complex uncertainties and justify representations of flood hazard to be shown to lay people (Lane et al., 2011a; Landström et al., 2013; Lane et al., 2013). Another area of research has focused on how flood hazard specialists have engaged lay people in flood hazard knowledge co-production. This has taken a variety of forms, such as crowdsourcing data for calculating flood hydrology (Coz et al., 2016; Mazzoleni et al., 2017), incorporating feedback from focus groups to generate other flood hazard products (Luke et al., 2018; Minucci et al., 2020), and lay people and experts co-producing new flood hazard knowledge and management options outside of technical experts and government agencies (Landström et al., 2011; Lane et al., 2011b; Maskrey et al., 2016; Sanders et al., 2020). However, little work on flood hazard has focused on an example of a Public Debate Model and theorized its similarities and differences to the PEM and Co-Production of Knowledge model. One contribution of my dissertation is to show how the process of Letters of Map Change on FIRMs in the NFIP is an example of the Public Debate Model. For example, lay people or elected community officials often contest new Flood Insurance Rate Maps at public meetings announcing the new maps by providing their personal observations about past floods they have seen or details about their building and property that can lead to updates and changes to flood zones by FEMA's hired technical experts. I also theorize how this creates differences in opportunities for flood hazard maps to be altered by lay person input. Related to this, this body of literature largely ignores socio-economic inequalities in the lay public and how these may influence processes and abilities to access participation. This dissertation provides quantitative investigation and support to the hypothesis that socio-economic inequality is an important determinant to what flood hazard knowledge gets debated and re-produced in a Public Debate Model example system.

This work also contributes to literature on Critical Physical Geography (Lave et al., 2014, 2018a). Critical Physical Geography philosophically revolves around three core tenants (Lave et al., 2018b). First, that Earth landscapes are rarely pristine but rather have been shaped and influenced by unequal human actions based on characteristics such as race, gender, or class (McClintock, 2015; Holifield and Day, 2017; Kelley, 2018; Urban, 2018). Second, that the unequal power relations determine what research is done, how that research is conducted, and what results are emphasized or claimed (Tadaki et al., 2015; Blue and Brierley, 2016; King and Tadaki, 2018). Third, that knowledge is not apolitical and produced apart from society, but rather is a political choice because it impacts the people and places it claims to know (Dufour et al., 2017; Lane, 2017; Law, 2018). The proposed research will add to this body of literature in two related ways. First, by showing map alteration is not only about political-economic power but is also shaped by the physical processes and what people claim to know about them. Second, that how and why property residents are able to interact with predicted flood hazard and resulting social protections in turn shapes the built environment and economic valuation of hazardous spaces.

Environmental justice in relation to regulatory science and flood hazard is a third set of literature that frames this research. Environmental justice research has historically focused on uncovering situations in which particular social groups are disproportionately affected by environmental hazards (Bullard, 2000; Pellow and Brulle, 2005; Walker, 2012). For example, environmental justice research on flood hazard exposure in the United States has shown that marginalized economic neighborhoods and communities are either disproportionately exposed to NFIP-predicted flood hazard (Maantay and Maroko, 2009; Walker and Burningham, 2011), or are less exposed to NFIP predicted physical flood hazard than wealthy or powerful groups but without the amenities (e.g., beach access in coastal areas) and social protections (e.g., flood insurance or receiving federal disaster grant money) of those property residents living in hazardous places (Collins, 2010; Chakraborty et al., 2014; Collins et al., 2018). In other words, this past research embraces what Wisner (2016) terms the ‘vulnerability paradigm for environmental hazard research’ and argues that political-economic factors like unequal access to resources are the most important influence on hazard exposure becoming a disaster and creating environmental injustices (Cutter et al., 2003; Wisner et al., 2004; Ribot, 2014; Simon, 2014; Rufat et al., 2015). However, recent critical environmental justice scholarship goes further and argues that rather than ameliorating environmental injustices, the state is a primary contributor to environmental injustices by making political-economic amenities preferentially accessible to the already powerful (Pulido, 2017; Pellow, 2018). This research contributes to these literatures by investigating how NFIP, which historically has sought to reduce barriers to insurance access and sustain primarily white homeownership, is in practice exacerbating injustices because the ability to obtain a Letter of Map Change is financially or practically unavailable to poorer and non-white individuals and communities.

Explanation of the Dissertation Format

This dissertation progresses through six chapters. After providing a quick summary of each chapter in this section, chapter one concludes with a section on the key findings of the three article-based chapters (chapters three, four, and five). Chapter two delves into the workings of National Flood Insurance Program, Flood Insurance Rate Maps, and the Letter of Map Change processes to provide an understanding of how and why Letter of Map Changes occur. The answers to why and how buildings are re-mapped to lower hazard flood zones on FIRMs by Letters of Map Change are obtained by combining literature review of primary source FEMA and NFIP documents, secondary sources such as research papers and news articles, and interviews I conducted with a few land surveyors and engineers who work on the Letter of Map Change process for FIRMs.

Chapters three, four, and five are written in article format. Chapter three is titled "Letters of Map Revision on Recently Updated Flood Insurance Rate Maps". This is published, co-authored material I wrote with Sarah Pralle, a political science professor at Syracuse University. The paper was published in the peer-reviewed journal Risk, Hazards, & Crisis in Public Policy with the title "To appeal and amend: Changes to recently updated Flood Insurance Rate Maps" (Lea and Pralle, 2021). The chapter uses Flood Insurance Rate Maps and building footprints GIS data for 255 counties across the contiguous United States to examine where Letters of Map Revision occurred between 2013 and 2019. Observations of buildings added to or removed from high hazard flood zones are combined with socio-economic data at the county and census tract scales to determine statistical differences for socio-economic variables between places with LOMRs and those without.

Chapter four, "Letters of Map Amendment and Revision Based On Fill Across the Contiguous United States" examines where Letters of Map Amendment and Letters of Map Revision Based on Fill occurred in almost 2,000 counties across the United States between 2013 and 2018. Observations of occurrence or absence of these Letters of Map Change were combined with socio-economic data at the census tract scale to calculate statistical significance for socio-economic variables.

Chapter five, "Property-scale analysis of Letters of Map Amendment and Revision Based on Fill in Florida, USA" examines Letters of Map Amendment and

Letters of Map Revision Based on Fill at the individual property scale across much of Florida. Statistical tests for significance are used to assess if variables such as property value and year built are predictors of where Letters of Map Amendment and Letters of Map Revision Based on Fill occur.

The dissertation conclusions are provided in chapter six. This chapter not only reviews the primary findings from the article chapters, but also provides a discussion of the broader literatures that this research contributes to. Appendices with full descriptions of methods used for each article chapter and references cited are provided after the conclusion section.

Key Findings

A few key results found by this research are briefly presented in this section. A more detailed discussion of the implications of these results is provided in the Conclusion chapter. Details of the research, such as descriptions of research methods, data analyses, and discussions of the results are found in the three articles. Extensive details of the methods used for each chapter can also be found in the appendices.

(1) For the 255 study counties examining Letters of Map Revision, over 20,000 buildings were re-mapped from inside to outside of the Special Flood Hazard Area. Further, SFHAs were altered by Letters of Map Revision more frequently in places where median home values are higher, buildings are newer, and percentage of white populations are higher.

(2) LOMA submissions were proportionally over-represented in flood zones such as A that were created with more approximate methods, while the flood zones like AE and VE produced using more precise and accurate methods were proportionately

underrepresented. In contrast, LOMR-F submissions were proportionately higher in the AE flood zone, but lower in the A flood zone. This finding supports the hypothesis that LOMA and LOMR-F submission rates may be influenced by flood zone data quality.

(3) Property scale analysis for LOMAs in Florida revealed that for counties with lowest average single home assessed property value homes obtaining LOMAs are statistically significantly higher value, while in the counties with the highest average assessed property values homes with LOMAs were almost always statistically significantly lower in assessed property value. For LOMR-Fs, property value was almost always statistically significantly higher for properties with LOMR-Fs than those without a Letter of Map Change.

CHAPTER II

BACKGROUND ON LETTERS OF MAP CHANGE

Introduction

Before analyzing where Letters of Map Change have occurred, in this chapter I provide background on the National Flood Insurance Program (NFIP), Flood Insurance Rate Maps (FIRMs), and types of Letters of Map Change to contextualize the research chapters in this dissertation. I begin with describing the motivations of writing this chapter and the methodologies used. The chapter then covers a brief history of the NFIP and FIRMs. I next describe the various groups of people whose work produces and revises FIRMs via Letters of Map Change before I provide an overview of how FIRMs are produced and altered by Letters of Map Change. I conclude by describing some limitations and assumptions of this research, as well as the significance of this work as NFIP begins to implement Risk Rating 2.0 in October 2021. For a quick reference to commonly used acronyms related to the topics covered in this dissertation, see Table 1.

Motivation and Methodology

The goal of this chapter is to provide understanding of how and why Letters of Map Change are sought and approved. To achieve this task, I draw upon NFIP technical documents, relevant peer-reviewed research, and semi-structured interviews I conducted with technical experts who work with Letters of Map Change.

The history of NFIP, the production of FIRMs, and the processes of Letters of Map Revision and Amendment are viewed in this chapter by frames of such academic literatures as critical physical geography and science and technology studies. In other words, I start from the assumption that the maps are socially constructed representations of flood hazard that are influenced by methodologies used to collect and analyze data (e.g., Elliott, 2021b). By reviewing relevant literature and framing flood map production in this way, I seek to contextualize the patterns of observed Letters of Map Change across the United States at various spatial scales.

The semi-structured interviews (n = 3) were conducted with land surveyors and engineers who are involved with the Letter of Map Change process either as an independent contractor or that work as hired professional technical support for FIRMs. The main goal of the interviews was to supplement the technical and research documents by obtaining facts and better understanding of the regulations that set FIRM and Letter of Map Change production. However, I also include insights and opinions from these technical experts where it is relevant and adds to the existing literature. I received an exemption approval from the University of Oregon's Institutional Review Board ("Human Subjects") to conduct this research was granted because the identity of the interview subjects is obscured and poses minimal risk. The exemption IRB Protocol Number is 01172019.029.

NFIP Background

The authorization of the National Flood Insurance Program (NFIP) in 1968 by the United States Congress came about due to the confluence of multiple factors. One primary reason for the formation of NFIP was that the program was envisioned as a way to release the federal government from being the sole funder of reconstruction after large flood events (Elliott, 2021b). In the decades prior to the authorization of NFIP, the costs of flood recovery had both risen and fell largely on the federal government for a few reasons. One reason was that a series of destructive floods, some caused by hurricanes such as Hurricane Betsy in 1965, caused federal disaster aid to rise from $52 million in 1952 to $374 million in 1966 (Hinshaw, 2006). This occurred not only because property was built in the way of floods, but also because there had become an understanding by the 1960s that the federal government should provide resources for rebuilding and recovery in the wake of destructive floods (Elliott, 2021a). These flood events kept the "hot moments" of national debates about how floods should be managed, mitigated, and recovered from on the political agenda, as floods came to not only "overflow" physical river boundaries but also the established idea that the federal government should continue to provide solely provide aid and amass debt (Callon, 1998; Donaldson et al., 2013).

Another reason paying for flood damages had been taken on by the federal government at this time was because flood experts had identified how federal funding for construction of structural flood protection in flood-prone areas, such as dams and levees, had created a "levee effect" where property developed behind these flood defenses only suffered greater losses when larger floods overwhelmed the flood structures (White, 1942; Bergsma, 2016). The federal government was then often called upon by local communities to address these flood damages that were brought about because of federal funds that went to the failed flood structures.

A third reason the burden of paying for post-flood damages fell to the federal government is because private insurers in the United States at the time were not interested in insuring properties against flood hazard on their own (Knowles and Kunreuther, 2014; Elliott, 2021a, 2021b). Because floods were often concentrated in specific regions of the country, flood risk was difficult to estimate with sufficient precision, and thus flood insurance would have to be expensive and difficult to sell, insurance companies believed flood risk was uninsurable (Elliott, 2021b). The idea was that NFIP would solve these problems by creating a national risk pool whereby policyholders would “prefund” their recovery with annual premium payments that would be set based on the flood risk each policyholder faced. In this way the federal government would end up paying less following flood events across the country, but would still act as the financial backer to help cover extreme losses (Elliott, 2021b).

Another reason the authorization of NFIP became possible at this time is because advances in hydrology and atmospheric sciences in the decades preceding the formation of NFIP meant flood hazard maps could be produced from predictive models of river discharge and flow hydraulics (Collier, 2014; Elliott, 2021a). This reliance on flood maps also allowed transfer of handling flood hazard from the federal government to individual citizens, which was premised on the idea that rational citizens would take the appropriate steps to learn and mitigate their individual risk. Said another way, floods changed from unpredictable “acts of God” to events whose probability and spatial extent could be estimated, which allowed flood hazard to be individualized and economized for citizens living in flood prone areas via Flood Insurance Rate Maps (Collier, 2014).

Today, ongoing questions and debates about the solvency of NFIP and what is a fair price to pay for insurance are examples of how the moral aspects of flood insurance arrangements will continue to shape economic decisions and relationships in the future (Elliott, 2021a). Because insurance premiums are derived from flood insurance rate maps and how they are made, it follows that Letters of Map Revision and Amendment become a part of the moral decision that has been made how NFIP operates, which in turn affects the implicated actors, groups, and societies in their individual lives and shapes new discourses about NFIP and Letters of Map Change.

This brief history of the National Flood Insurance Program was intended to help provide context in which Flood Insurance Rate Maps and Letters of Map Change operate. For more extensive histories about the formation of and changes to the National Flood Insurance Program, see Collier, 2014; Knowles and Kunreuther, 2014; Bergsma, 2016; Horn and Webel, 2019; and Elliott, 2021b, 2021a.

FIRMs Background

Flood Insurance Rate Maps (FIRMs) are the tool used to depict various flood hazard zones, which in turn are used to set insurance premiums. A new FIRM is produced as part of a Flood Insurance Study, which is when FEMA employees and FEMA's hired contractors compile relevant information and conduct analyses to produce flood elevation profiles, data tables, and FIRMs (FEMA, 2020a). From the beginning of NFIP until the early 2000s, FIRMs were printed on paper. But beginning in the 1990s, features on FIRMs such as the Special Flood Hazard Area (SFHA), which are areas predicted to have one percent or greater probability of being inundated annually, were digitized and made available on Geographic Information Systems (GIS) software. FEMA's Map Modernization initiative begun in 2002 led to digitizing all existing paper maps over the mid-2000s, and since that time FEMA has only produced digital FIRMs (FEMA, 2017, 2005). Another part of FEMAs Map Modernization initiative was that digital FIRMs would be produced at the county scale; paper FIRMs had been produced at varying scales from five to eighty square miles depending on the size of the community being mapped and the detail of flood hazard data (National Research Council, 2007).

There are a variety of flood zones that have differing flood hazards associated with them that can appear on FIRMs. Special Flood Hazard Areas (SFHAs) are an aggregation of flood zones on FIRMs, with all the flood zones included having one percent or greater probability of flooding annually based on historical hydrologic observations and hydraulic modeling (FEMA, 2021b). Flood zones are determined not only by the relative level of hazard, but also by the methods and data quality available to predict flood hazard (FEMA, 2019a; Horn and Webel, 2019). This means that FIRMs are often an amalgamation of flood hazard zones with varying levels of precision. For example, small tributary streams feeding into a larger river often will be one flood zone type (such as an "A" zone) that have lower data quality and only an approximated SFHA, but the river will be another flood zone designation (for example, an "AE" zone) based on the higher data quality and precision methods used to map it. In contrast, flooding due to coastal waves and storm surges have different processes and hydraulic models to map them, so this type of flooding is designated by different flood zones ("V" type zones) than riverine flooding. Summary descriptions of the flood zones on FIRMs that are combined into a SFHA are provided in Table 2.

The difference between a building being located inside or outside SFHAs on FIRMs is an important distinction because the owners of a building within the SFHA are required to purchase insurance if the building has a federally-backed mortgage. Further, annual flood insurance premium payments for buildings inside the SFHA are usually hundreds to thousands of dollars higher than for buildings outside the SFHA (FEMA, 2018a). This is because the pricing of flood insurance premiums is based on the elevation of expected flood inundation compared to the lowest elevation of a building. See Figure 1 for an example of how the Base Flood Elevation (BFE), or the elevation to which the SFHA floodwaters are predicted to rise for the flooding source, can affect insurance premium pricing. The area covered by SFHAs on FIRMs is determined by comparing the BFE against nearby land elevations represented in a Digital Elevation Model (DEM). A building is considered inside the SFHA when the BFE is at a higher elevation than lowest adjacent grade or elevation of the building to be insured, while buildings with elevations above the BFE are mapped outside the SFHA.

As FIRMs changed from paper to digital over time, so too have the number and types of flood zones used to depict flood hazard changed over time since the authorization of NFIP. When NFIP began, the earliest FIRMs used ‘community risk zones’ which had finer rating distinctions than FIRMs today based on topography and ‘community-specific rating factors’ (American Academy of Actuaries, 2011). However, this rating scheme was simplified in 1972 and further again in 1985 in efforts to make the maps more legible to homeowners (FEMA, 2006). This meant that details that could be used to differentiate flood zone types and differences in hazard became aggregated together, as these reforms reduced the number of flood hazard zones from sixty-eight to nine (American Institutes for Research, 2005).

Part of the answer to the question why Letters of Map Change are reducing the number of buildings within the SFHA when other flood hazard maps being produced by the scientific community predict larger flood hazard zones for the same places lies in the data used to produce FIRMs. Flood frequency analyses are commonly used to produce FIRMs and assume that annual peak floods are statistically stationary and only use historical observations of flood discharge (National Research Council, 1999). Stationarity in a flood hydrology context refers to the assumption that for a time series of observed flood discharges on a given river, the values of that data set's statistical properties (e.g., variance and percentiles) remain constant when recurrence intervals for future floods are calculated. Although hydrologists have long recognized river discharge measurements exhibit non-stationarity because probability distributions and statistical properties of time series change when new measurements are added (National Research Council, 1999; Serinaldi and Kilsby, 2015), the assumption of stationarity is part of probability distributions like the log-Pearson Type III recommended by United States federal agencies to calculate recurrence intervals for input into hydraulic models (Interagency Advisory Committee on Water Data, 1982; FEMA, 2019b). In contrast, studies predicting future scenarios of flooding altered by climate change rely on incorporating non-stationarity in their hydrologic predictions (Wing et al., 2018; Armal et al., 2020; Wobus et al., 2021). Rather than trying to incorporate future predictions into FIRMs, FEMA and the United States federal government have instead chosen to implement predictions of the impact of climate change on flood hazard into a separate set of flood hazard maps that can be created for communities to help them use for land use planning (Elliott, 2021a). However, these future looking products cannot be used to enforce floodplain management and insurance premiums. In this way, FEMA has chosen to keep knowledge about future climate change separate from risk governance via NFIP, instead providing this information only to communities that demand it (Elliott, 2021c).

Because of differences in flood zone data quality, basing FIRMs on historical observations, and FIRMs becoming out of date because FEMA has consistently been underfunded to produce new and updated FIRMs across the country, there is a perception that FIRMs are incorrect, wrong, error-prone perceptions of flood hazard (Keller et al., 2017; Schwartz, 2018). However, one of my interviewees explained the difference between a FIRM being in error and being out of date and why the difference is important to understand when seeking a Letter of Map Change when they said:

> People have asked me straight up ‘how accurate are these maps?’ What? Compared to what, exactly? Compared to a flood that you know it’s probably totally different because it’s not a flood that anyone knows. It’s a different thing, it’s a purely statistical event…I had a long conversation with an individual that was trying to get a letter of map amendment and he was saying the map was straight out wrong. And I can agree that it’s wrong, but it’s also not an error. I mean, the maps were based on the best available data at the time they were done. And a new study today would produce a different map, but that doesn’t mean the old one is wrong. It just means it’s out of date. And I really feel like the accuracy is more indicative of your understanding of what the map is based on than a comparison with an actual flood or anything like that. Perception of accuracy speaks to the understanding of the product. And I find myself working with communities or homeowners that are certain the mapping is wrong and give a whole array of reasons why it’s wrong. So, it’s helping them articulate their argument to something that could produce a [letter of map] change.

The statement from this technical expert provides the context that multiple FIRMs based on different data and parameters, as well as other flood hazard map products that incorporate climate change, can all be considered “correct” based on the assumptions and parameters defined (Weinkle and Pielke, 2017; Elliott, 2021a).

This dissertation distinguishes three phases of FIRM production and revision, as well as two groups of actors who can produce new FIRMs or initiate SFHA alterations on FIRMs. The three map stages are: (1) production of a new FIRM, (2) revising a preliminary FIRM, and (3) Letters of Map Revision and Letters of Map Amendment on regulatory FIRMs. Each of these stages is explained in greater detail in later sections of this chapter. The two groups of actors I distinguish are: (1) the United States Congress and FEMA Employees, versus (2) “propertied interests”, which can include elected community representatives, property developers, or individual property owners. I also use the term “property residents” interchangeably with property owners. The difference between these groups lies in the types of FIRM changes they initiate. The United States Congress and FEMA initiate the production of new FIRMs as part of Flood Insurance Studies to keep flood hazard up to date. Propertied interests pursue Letters of Map Change for the financial benefit of being changed to a lower hazard flood zone with corresponding lower insurance premiums. However, the work conducted to produce new FIRMs and amend or revise existing FIRMs is conducted and reviewed by FEMA’s hired contractors or cooperating technical partners.

FEMA’s Professional Technical Support and Cooperating Technical Partners

Although FEMA is the federal government agency that oversees and operates the NFIP, due to its structure and funding FEMA does not have sufficient employees and funds to conduct new mapping or LOMRs and LOMAs itself. Rather, FEMA puts out contracting bids and hires engineering firms who have the personnel with expertise to produce FIRMs to or above minimum standards set and overseen by FEMA.

The United States is subdivided into ten FEMA regions, and each region puts out its own bids and obtains its own contract with an engineering firm. There are only a few companies that FEMA has contracted with in recent years. At present, only three companies or combined groups of companies have between them the engineering contract for the ten FEMA regions (FEMA, 2021c). For example, STAR-II (an acronym for the Strategic Alliance for Risk Reduction) is a joint venture between three engineering firms (Atkins Global, Stantec, and Dewberry) and presently is contracted for five of the ten FEMA regions (STARR II, 2021). CDM Smith and AECOM are the other two engineering companies that between them are contracted for the remaining five regions. Companies are contracted by a FEMA region for 5-year periods to help with or solely perform engineering projects such as creating new FIRMs using hydrologic and hydraulic modeling and revising FIRMs via Letters of Map Revision (GAO, 2010). Letters of Map Amendment may also be conducted by the same companies contracted to perform the engineering work, but sometimes are overseen by a separate subcontractor.

The contracted companies are called "professional technical support" by FEMA. This means that in addition to their engineering contract to produce new FIRMs and help review LOMRs and LOMAs, the hired contractors provide technical support to cooperating technical partners (see next paragraph) when needed and interact with local contacts if there is something specific to a site being mapped that needs to be resolved. One interviewee told me that much of the work performed by these companies is done by employees who are located across the United States in various offices, but that these companies also have regional offices located in the FEMA regions they work with. The same interviewee further explained that employees at these regional offices often will have more familiarity with the region and have contacts in various state and local agencies who can help provide local perspectives on mapping flood hazard. The regional offices also have more direct connections with the corresponding FEMA regional offices so that the contractors can communicate with FEMA regional representatives as how best to complete mapping projects per FEMA's guidelines.

The professional technical support for each region primarily work on FEMA initiated flood insurance studies, but they are not necessarily the only group working to produce or update FIRMs. "Cooperating technical partners" is the phrase FEMA uses to denote other groups who can also be hired to help with the mapping process (FEMA, 2021d). In contrast to the FEMA hired professional technical support, cooperating technical partners can be people from local, state, or regional agencies, as well as universities and tribes, that have at least minimal knowledge and technology to support the data collection and flood hazard mapping process (GAO, 2010). An interviewee noted that ideally, cooperating technical partners are included to produce FIRMs whenever possible because these members are more representative of local communities and community members can feel like they have greater ownership or understanding of the maps. In contrast, the same interviewee noted that community members can feel that the “professional technical support” is FEMA “putting the FIRMs on the community”, which can lead to resentment and potentially greater impetus to try and alter the FIRMs.

Process of Creating a New FIRM

There are two ways new FIRMs can be produced. The first and most common way is by a FEMA initiated Flood Insurance Study. Flood studies initiated by FEMA are funded via an approved budget by the United States Congress. Each year, FEMA chooses communities in which it will take steps to produce a new FIRM based on the available funding, with priority going to places where recent development has been greatest or where FIRMs are otherwise determined to be most outdated compared to present flood hazard. FEMA regional employees then work with community representatives and FEMA’s mapping partners to obtain topographic, hydrologic, infrastructure, land use, and other relevant data sets that FEMA’s mapping partners will use to produce a new FIRM. The second way a new FIRM can be created is by a community-initiated update. In this instance, a community or municipality decides on its own it would like to update its FIRMs. Because these studies are not proposed and initiated by FEMA, the community must produce its own funds and hire its own cooperating technical partners to produce the new FIRMs.

In both FEMA initiated Flood Insurance Studies and community-initiated studies, the work of acquiring and validating data and creating new FIRMs is done by mapping partners, while the work is overseen and checked by FEMA regional staff. A depiction of the new flood study and FIRM adoption timeline, which includes preliminary FIRM creation as well as the comment and appeal period (described in the next section) is shown in Figure 2. The FEMA regional staff oversees that FIRMs are being produced according to the standards for flood risk analysis and mapping and that mapping partners are following the guidance documents for flood risk mapping, assessment and planning. These documents provide the basis of standards that must be met to insure a minimum quality of FIRMs as well as effective and efficient practices (FEMA, 2021e, 2021f). For example, in regards to hydrologic and hydraulic models, there are a list of models maintained by FEMA that meet minimum standards to be used to produce flood zones on FIRMs (FEMA, 2021b, 2021g). The model used to produce any flood zone on a FIRM depends on what data is available and what the mapping partners decide is most appropriate based on knowledge and characteristics of the water body being mapped. An interviewee noted that mapping partners can use models that are not on this list, but they have justify to FEMA why they are using the model and be able have FEMA approve why its use is as good or better than models on the list.

The mapping partners who perform the technical work to produce a new FIRM for a FEMA initiated flood study include some combination of the regional professional technical support, any cooperating technical partners, and potentially members from other federal agencies (e.g., Army Corps of Engineers where their levees are involved). FEMA tries to involve cooperating technical partners in the map production process whenever possible and have grants communities can apply for to obtain funds to pay the cooperating technical partners for their work. However, some communities will not have available money or people available with the skills necessary to create a cooperating technical partnership. In these places, the professional technical support teams then become the primary or only ones doing the work due to their large staff capacities to work on these projects. In contrast, communities and places with larger populations more likely have tax bases to draw from and expertise in their populations to form cooperating technical partners and share/do more of the work themselves and initiate map updates if they are trying to be hazard averse.

One potential implication of this difference in having cooperating technical partners involved and/or more money to perform additional or more detailed analyses is that it can change the SFHA. For example, one interviewee noted how more approximate and simplified methods such as one-dimensional flow modeling often produce a higher base flood elevation and larger Special Flood Hazard Area than higher precision methods like two-dimensional models. Similarly, the same interviewee also noted how communities often desire detailed bathymetric data to create more detailed and precise SFHA extents. Communities funded only by FEMA allocated budgets will not be able to improve the accuracy and precision of these models used to create the maps unless it can be done within the allocated budget, while communities funding their own mapping will be able to seek a higher level of accuracy and precision if they have the funding.

Although community representatives have been portrayed by past literature as solely seeking to reduce flood zones on FIRMs, this is not always true. One interviewee described how in the production or revision of some FIRMs, community officials have sought to increase the size of SFHA because they believe based on observed floods that the flood hazard is greater than what is shown by the present or more recent SFHA. In these cases, there should be an observed increase in the SFHA due to a LOMR if these community officials have the money and personnel to conduct a map update and if their hunch the SFHA should increase is matched by the updated data and flood modeling. However, individual residents could still seek individual exemptions for the buildings on their properties via LOMAs.

Preliminary FIRM Appeals and Comments

The flood map produced by FEMA's mapping partners from the process described in the last section is called a preliminary FIRM because when it first is released to the public outside of the mapping partners the FIRM is still a proposal and is not yet being used to determine insurance premiums and local floodplain regulations. The preliminary FIRM is released as part of the full Flood Insurance Study to the public at a community meeting so property residents can view the preliminary FIRMs and ask FEMA representatives questions about how the preliminary FIRM would change flood hazard for their building or property. If community representatives disagree with an aspect of how the mapping was done and believe the map would be more accurate with a correction, there is a minimum ninety-day appeal period after the meeting during which they can submit an appeal or a comment. An appeal is a more significant challenge to a preliminary FIRM and uses alternative hydrologic and/or hydraulic models to produce a new version of the preliminary FIRM, while a comment is a relatively minor adjustment based on the elevation of a building compared to the predicted height of flood waters. Community members or representatives generally hire independent technical experts (engineers and/or land surveyors) to perform this work, and if FEMA agrees the revisions on the alternative FIRM are valid, the FIRMs are updated and re-released as revised preliminary FIRMs.

If community members and FEMA regional representatives cannot come to an agreement that the new FIRMs are scientifically and technically correct, communities can challenge the study conducted by FEMA's hired contractors by hiring technical experts to conduct a separate study that is submitted to the Scientific Resolution Panel (National Institute of Building Sciences, 2019). These Scientific Resolution Panels are independent panels of experts organized and managed by the National Institute of Building Sciences in contract with FEMA. For each case submitted, an individual panel composed of five members with technical expertise in FIRM and Flood Insurance Studies methods is chosen to review the conflicting flood hazard data submitted by FEMA and the community and to determine which study is technically and scientifically more accurate. The community gets to choose three of the members and FEMA chooses the other two. The panel writes a decision that denies or accepts the flood elevation data submitted by the community, although the decision of the panel only serves as a recommendation to the FEMA Administrator whose task it is to resolve the conflict and chose which data will inform the new regulatory FIRM.

After all comments and appeals have been resolved, FEMA issues a letter of final determination. This letter sets a date, at least six or more months in the future, when the preliminary FIRM becomes regulatory and supersedes any prior FIRM. This provides the community time to adopt or amend its floodplain management to the new FIRM. For more information on the preliminary FIRM production and appeals process, see GAO, 2010; FEMA, 2019c; and Wilson and Kousky, 2019.

Letters of Map Revision and Amendment

After the FIRM becomes regulatory and is being used to set insurance premiums and land use regulations, the map can still undergo the same appeal and comment process. The primary difference is that alterations to the FIRM are now sorted into two broad categories which, up to this point, I have called Letters of Map Revision and Letters of Map Amendment. However, to clarify the differences and describe the sub-types of these broader categories, at this point I will change to use FEMA's terminology that what I have called "Letters of Map Revision" are actually "MT-2s" and "Letters of Map Amendment" are called "MT-1s".

The difference between "MT-2s" and "MT-1s" is based on the type of alteration proposed to the map and the scale of properties the change would affect. The "MT-2s", which also are just called Letters of Map Revision (LOMRs), occur when different hydrologic or hydraulic methods are used to produce alternative FIRMs that affect multiple properties and structures. For example, MT-2s are issued when the flood hydraulics in an area are altered by the construction of a new culvert or bridge, or when a property developer regrades an area where a new neighborhood or other new buildings will be built. Because MT-2s require the creation and review of a lot of new technical data and cover multiple properties, one interviewee noted they almost always are initiated and funded by a community, county, neighborhood association, or property developer rather than an individual property resident (also see FEMA, 2018b). Often property developers that are proposing a MT-2 where new properties will be built are required by the municipality or county in which they will be building to receive a conditional MT-2 from FEMA. Conditional MT-1s or MT-2s are submitted before a structure is built and will change the SFHA as it says so long as the topographic, elevation, hydrology, and/or hydraulic alterations via the construction process are conducted and verified when construction is complete the way the developer proposes the construction and alterations to be done. Conditional letters acronyms add a "C" to the beginning of the relevant term; for example, "CLOMA" for Conditional Letter of Map Amendment or "CLOMR" for Conditional Letter of Map Revision.

In contrast, "MT-1s" focus on providing data to show that a building presently depicted inside the SFHA should actually be outside the SFHA. The MT-1s can also be submitted for multiple adjacent buildings, although these are uncommon and I discuss MT-1s in this section with the assumption of altering a single building. There are several different "MT-1s" that can be issued. One factor that determines the specific type of MT-1 is if the building elevation is altered or information about the elevation is updated. A building can be shown to be outside the SFHA if a higher precision and/or accuracy method like land surveying is used to determine an updated elevation that is above the Base Flood Elevation (BFE), or by physically altering the lowest elevation of a building to be above the BFE. The first method, where a building is shown to have been inadvertently included in the SFHA due to topographic resolution of the data used to depict the original SFHA, is how a Letter of Map Amendment (LOMA) is obtained. FEMA allows property residents the ability to submit a request to review more precise and accurate elevation data that has been collected by licensed engineers or land surveyors because high precision and accuracy topographic data is often too costly and computationally intensive to use across the wide areas depicted on FIRMs. The second method of physically raising a building so that it resides above the Base Flood Elevation can lead to the issuing of a Letter of Map Revision based on Fill (LOMR-F). The lowest elevation of buildings can be raised using fill dirt or pylons. Both LOMAs and LOMR-Fs are audited by FEMA technical staff to determine if the submitted data meet minimum standards. Letters of Map Amendment are less stringent than LOMR-Fs, as they only require approval by a certified land surveyor because they are based on updated elevations using land surveys. In contrast, LOMR-Fs need to be approved by both a land surveyor and engineer because in addition to a land surveyor determining the building has been raised above the BFE, the engineer needs to certify that the materials used for fill are compacted enough to resist erosion related to flooding and that any fill will not significantly alter flow of water and displace flood waters onto other structures in or near the SFHA. If FEMA approves, the LOMA or LOMR-F go into effect. But if the appropriate data is not provided, or the lowest elevation of the building as shown by the LOMA or LOMR-F is still below the BFE, the LOMA or LOMR-F will be denied.

There are a few other MT-1 designations that re-map or show individual buildings outside of the SFHA. Letters of Map Amendment Out as Shown (LOMA-OAS) are validation letters that a building has its lowest elevation exceeding a nearby BFE. Out As Shown LOMAs are most frequently sought by property residents when a mortgage lender will not provide a mortgage to a property buyer (or a mortgage at a reduced rate compared to a property within the SFHA) unless the property has been verified by FEMA as being outside of the SFHA. An evaluation of a FIRM by FEMA for a property that appears outside the SFHA based on map interpretation, without any re-measurement of elevation, leads to this type of map amendment being issued. Other types of map amendment are specific versions based on the flood zone type in which the building resides. For example, a Letter of Map Revision for a Floodway (LOMR-FW) is an exemption for a building within the floodway of a river. A floodway refers to "the channel of a river or other watercourse and the adjacent land areas that must be reserved in order to discharge the base flood without cumulatively increasing the water surface elevation more than a designated height" (FEMA, 2020b). This requires more detailed review to make sure a LOMR-FW is not altering flood flows so they will inundate other buildings. A Letter of Map Revision for a Velocity Zone (LOMR-VZ) is a letter of map revision for a VE zone, which also requires more stringent review than just elevation to validate the building should indeed be outside the SFHA (FEMA, 2020c).

All MT-1s and MT-2s can also be denied by FEMA if they do not meet minimum qualifications, such as when the lowest floor or adjacent grade for a building is lower elevation than the BFE. The MT-1 and MT-2 applications can also be denied because they are incomplete and do not provide the necessary information for FEMA's contractors to make a decision to approve the MT-1. However, multiple interviewees said that often FEMA and its contractors will try to communicate and work with propertied interests to let them know what is missing so the submission can be reviewed with full information and data available before a definitive decision is made.

If an MT-1 or MT-2 is denied, applications can be submitted again for the same building or proposed construction project if the applicant states what has changed in the new application that will now show the location will be exempt from the SFHA. While ideally this should be done by raising the elevation of the structure or redesigning the development, this can also take place by altering the analysis that informs the SFHA. One interviewee described how the latter occurs and their disagreement with the process in the following statement:

> Yes, [if a Letter of Map Change is denied] you can put in a new application, but you need to explain what is different and why it is. That you're not…What gets me really upset is when…I hate when I encounter these kinds of things, like in design boards or planning board meeting where there has been a calculation for a proposed project for where the water surface will be for the base flood elevation, and then they, the community says 'well, it needs to be, you know, the floor elevations are going to need to be higher so they are not going to be affected by the BFE', and then instead of redesigning the development, they tweak the analysis. So, it's one of those things where the way that the analytical tools like HEC-RAS and all that work, if you put, change one number in one place by just a little bit, it can in some cases change the outcome pretty dramatically to their benefit. So, I think they can play the numbers game.

Another interviewee also confirmed that despite the idea that engineers should seek to be 'impartial', they might select models or parameters that favor a certain result in the depiction of SFHA extent:

> There is absolutely a range in, you know, assumptions and parameters you can use, and you have to sort of rely on people being somewhat impartial and not pushing the result one way or the other. And, you know, that's part of being a professional engineer…it's almost like the doctor's Hippocratic oath, or whatever it is. You promise to use your powers for good and not evil. You know, so you can't push an answer, you can't force the answer that you want, but I do see times where I feel like people are selecting parameters that are encouraging, that are pushing the result in the direction that they want… But if it's within the realm of what is acceptable and meets guides and specs then … you can get situations where you get an answer that is different from the way you would have done it, but it's not inaccurate.

The take-away from these two quotes above is that so long as the models and parameters can be justified, they can be seen as within the range of being "correct" and be accepted by FEMA as defining the location of the SFHA.

While reducing the price of insurance premiums is one of the primary reasons that propertied interests pursue MT-1s and MT-2s, there are costs that propertied interests will have to pay to obtain a MT-1 and MT-2. The costs for MT-1s and MT-2s can be divided into two categories. The first category is for administrative fees that pay for the MT-1 or MT-2 to be reviewed by FEMA and its contractors. To summarize, MT-1 fees run in the several hundreds of dollars, while MT-2 fees are several thousands of dollars (FEMA, 2021h). However, there are certain exemptions that do not have administrative fees. For example, LOMAs are reviewed for free, as are LOMRs based only on submission of more detailed data. The second category of costs is related to data acquisition and any alterations that are made to topography and elevation. For LOMAs, the primary cost would be for hiring a certified land surveyor to conduct the elevation measurements for a building. However, multiple interviewees described how this cost would vary depending on a number of factors. For example, one interviewee described how if the building to be surveyed is located in an A zone, which do not have determined Base Flood Elevations, an engineer will also have to be hired in addition to the land surveyor to help determine a BFE for the SFHA boundaries nearest to the building. The same interviewee also noted how the cost of the survey can also depend on if a survey benchmark is nearby that the surveyor can survey from and the number of measurements that need to be made. Another interviewee also described how insurance premiums can be more finely tuned if a survey is used to determine finished floor elevations and elevations where utilities are, but this increases the cost of the survey. For a LOMR-F, there would be the cost of both raising the property using fill, then surveying the elevation of the property. While interviewees were hesitant to give any precise examples of what these procedures cost because of the variables I note above, one of them told me “it could be hundreds of dollars, it could easily be thousands of dollars to get the survey depending on where you are located.” I created a table (see Table 3) that contains both the administrative fees and estimated data collection and landscape alteration costs into a single place to help visualize the costs for different types of Letters of Map Change.

While land surveyors and engineers are unable to know if there are potential propertied interests who would like to pursue a MT-1 or MT-2 but do not have the funds to do so, one of the interviewees did agree these people or groups likely exist even though the propertied interest would never contact them because they lacked the funds. However, the same interviewee also noted that cases can happen where a SFHA is not updated by an MT-2 like it should be, which can affect people living in the SFHA when they seek an MT-1 for their individual building. The interviewee described to me an example where a property developer had built a new subdivision that required a MT-2 because of how it would affect the hydrology and hydraulics of the SFHA. This was in a rural community that did not have much funds and staff that knew how to submit the MT-2 to FEMA, so the FIRM and SFHA were not updated to show the subdivision outside the SFHA when the homes began to be built and be sold. A new homeowner contacted the interviewee about a LOMA, but they determined that the MT-2 had never been submitted and thus that it should not be the individual property owner’s responsibility to perform the work of a new MT-1 that would cost at least thousands of dollars.

Limitations and Assumptions

I conclude these sections on the production of new FIRMs and how FIRMs are revised by Letters of Map Change by noting a limitation and assumption of this research.

As I noted in chapter one, my dissertation focuses on resolving a seeming contradiction between predictions of increasing flood hazard and observations of reductions of flood hazard across the United States on FIRMs due to LOMRs and LOMAs. However, one potentially important limitation is that I do not have Geographic Information Systems data for older FIRMs that were replaced by the present FIRMs I study in this dissertation. For example, while I might observe for an individual county that fifty buildings were changed from inside to outside of the SFHA due to LOMRs and LOMAs, it is possible that hundreds of buildings could have been added to the SFHA from the previous (now outdated) FIRM and the present one being used to set insurance premiums. The assumption I make is that LOMRs and LOMAs are adding buildings to or removing buildings from the SFHA on approximately the same level of magnitude that buildings are being added or removed from the SFHA when a new FIRM produced by FEMA and its mapping partners replaces an older FIRM. Although I was not able to examine this assumption across a wide sample of the United States given the data I was able to acquire from FEMA and other sources available to me, I hope to show in this dissertation that Letters of Map Amendment and Revision do impact who is depicted to be at greater or lesser flood hazard differently across the United States.

Risk Rating 2.0

As I prepare to finish and defend this dissertation in fall 2021, on October 1, 2021, FEMA is beginning to roll out a new risk rating and pricing methodology for the NFIP called Risk Rating 2.0. As FEMA states on their website, “the [Risk Rating 2.0] methodology leverages industry best practices and cutting-edge technology to enable FEMA to deliver rates that are actuarially sound, equitable, easier to understand and better reflect a property’s flood risk” (FEMA, 2021i). While this new rating system is sure to change insurance premiums and reinvigorate debates about the moral economic aspects of the National Flood Insurance Program, this new methodology does not disregard FIRMs. Indeed, the FIRMs are still part of the data that helps develop insurance premiums for Risk Rating 2.0, and the maps will still be used for determining mandatory purchase requirements and floodplain management building requirements (FEMA, 2021i). Said another way, understanding how FIRMs are produced, how they can be altered by LOMRs and LOMAs, where these changes occur, and who the changes affect will still be important with the implementation of Risk Rating 2.0 because Letters of Map Change will continue be an ongoing feature for FIRMs regardless how flood hazard mapping and pricing changes in the future.

Figure 1. Building above the Base Flood Elevation can save you money over time. Graphic from FEMA, 2018a (Public Domain).

Figure 2. Flood Study and Adoption Timeline. Graphic from FEMA, 2019c (Public Domain).

Table 1. Commonly used acronyms and their meanings

Acronym	**Meaning**
NFIP	National Flood Insurance Program
FEMA	Federal Emergency Management Agency
FIRM	Flood Insurance Rate Map
SFHA	Special Flood Hazard Area
LOMA	Letter of Map Amendment
LOMR	Letter of Map Revision
BFE	Base Flood Elevation

Table 2. Summary of SFHA flood zones on FIRMs. Adapted from (Horn and Webel, 2019).

Flood Zone Symbol	Description
A	Area of 1% or greater yearly flood hazard without surface elevations measured
AE	Area of 1% or greater yearly flood hazard with surface elevations measured
AO, AH	Area of 1% or greater yearly flood hazard having shallow water depths (AO) or unpredictable flow paths (AH)
A99	Area of 1% or greater yearly flood hazard with protection such as dikes, dams, and levees
V, VE, VO	Area of 1% or greater yearly flood hazard that are inundated by tidal floods

Table 3. Administrative fees and estimated data collection and construction costs for LOMAs and LOMRs. Administrative fees adapted from FEMA, 2021g. Data collection and construction costs estimated from conversations with interviewees. LOMAs and LOMR-Fs occur for one or up to several adjoining properties, while LOMRs can span in size between several properties up to covering much of a municipality. Note: The reported administrative fees are for online submission. If the submission is made by mailing paper forms, there is an additional $100 for LOMAs and $250 for LOMRs.

Request	**Administrative Fee***	**Data Collection and Construction Costs**
Single-Lot/Structure or Multiple-Lot/Structure LOMA	Free	Hundreds – thousands of dollars
Single-Lot/Single-Structure CLOMA and CLOMR-F	$600	Hundreds – thousands of dollars
Single-Lot/Single-Structure LOMR-F	$525	Hundreds – thousands of dollars
Multiple-Lot/Multiple-Structure CLOMA	$800	Hundreds – thousands of dollars
Multiple-Lot/Multiple-Structure CLOMR-F and LOMR-F	$900	Hundreds - ten thousands of dollars
LOMR Based Solely on Submission of More Detailed Data	Free	Thousands – ten thousands of dollars
CLOMR Based on New Hydrology, Bridge, Culvert, Channel or Combination Thereof	$6,750	Thousands – ten thousands of dollars
CLOMR Based on Levee, Berm or Other Structural Measures	$7,250 (plus $60/hr)	Thousands – ten thousands of dollars
LOMR Based on Bridge, Culvert, Channel, Hydrology, or Combination Thereof	$8,250	Thousands – ten thousands of dollars
LOMR Based on Levee, Berm or Other Structural Measures	$9,250 (plus $60/hr)	Thousands – ten thousands of dollars

CHAPTER III

LETTERS OF MAP REVISION ON RECENTLY UPDATED FLOOD INSURANCE RATE MAPS

This chapter includes a previously published article with co-author Sarah Pralle. The article is available online at: https://onlinelibrary.wiley.com/doi/full/10.1002/rhc3.12222

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Introduction

In the United States of America, flooding has been the most common and costliest environmental hazard over the past few decades (NOAA National Centers for Environmental Information, 2018). Various local to federal scale public policies and built infrastructures have been implemented to mitigate flooding before it happens or help with rebuilding after a flood event, but the United States National Flood Insurance Program (NFIP) has been one of the primary ways the country manages flood hazard. The NFIP is operated by the Federal Emergency Management Agency (FEMA), which partners with local governments and hired contractors to produce maps of flood hazard that in turn set flood insurance premiums. These maps, called Flood Insurance Rate Maps (FIRMs), are most often of interest due to the Special Flood Hazard Areas (SFHAs) they delineate. This is because SFHAs indicate areas of one percent or greater annual chance of inundation and are the primary designation of flood hazard used to enforce flood insurance purchase requirements, set local floodplain management regulations, and set insurance premiums.

There is a substantial literature that has studied various facets of the NFIP, only a few of which include public policy reforms and affordability (Kousky and Kunreuther, 2014; Nance, 2015; Shively, 2017; Strother, 2018), the distributional effects of NFIP payments (Holladay and Schwartz, 2010; Bin et al., 2012; McGuire et al., 2015; Ben-Shahar and Logue, 2016; Bin et al., 2017), and the uptake rates of flood insurance policies (Kousky et al., 2018). Among research specific to FIRMs, themes have included the exposure, vulnerability, and environmental justice of flood hazard depicted on FIRMs (Maantay and Maroko, 2009; Collins, 2010; Chakraborty et al., 2014; Montgomery and Chakraborty, 2015; Qiang et al., 2017; Collins et al., 2018; Frazier et al., 2020) and the impact on housing prices of being located in the SFHA (Bin and Landry, 2013; Shr and Zipp, 2019). FIRMs have also been criticized for a number of shortcomings, such as failing to incorporate predictions of how climate change will alter flood hydrology and underrepresenting the number of properties at risk of inundation from large and/or frequent flood events (Wing et al., 2017, 2018; Pralle, 2019). However, while the comparison of FIRMs to other flood predictions in past research has portrayed FIRMs as static maps, flood zones on FIRMs are frequently adjusted to add or remove properties and structures based on more detailed data becoming available, a different flood model being used, or development occurring that alters local hydraulics (FEMA, 2021b, 2019a).

This raises an important question: are there any discernable trends or patterns in alterations to SFHAs on FIRMs? The aggregated net changes across many FIRMs could provide insight into why SFHAs on FIRMs might be changing. For example, if SFHAs are increasing in size to incorporate higher flood hazard that recent research (Wing et al., 2018, 2017) has argued they are lacking, we would expect to see a subsequent increase in the number of buildings in SFHAs across many FIRMs. In contrast, previous news articles (Dedman, 2014) and research (Pralle, 2019) have suggested certain elected officials and their constituents seek to shrink (or prevent an increase in) SFHA size to reduce flood insurance premiums and requirements to pay. If this is the dominant alteration occurring on FIRMs, then we would expect to observe a net decrease in SFHA size and the number of buildings in SFHAs across many FIRMs. A third possibility is that SFHA adjustments on FIRMs are balancing increases and decreases and in aggregate sum to approximately zero. This observation could occur either because map adjustments result from fixing random errors or because preliminary expansions of the SFHA were reduced once FIRMs became regulatory.

Several works have studied how FIRMs are updated and altered over time. Wilson and Kousky (2019) examined how long it took for recent FIRMs across the United States to become regulatory after their preliminary release, and also investigated relationships between FIRMs that were revised during this process and socio-economic indicators. Pralle (2019) combined interviews with floodplain specialists and a case study in Syracuse, New York to examine how local government representatives, politicians, or community members have used their influence and/or their money to challenge and revise new FIRMs before they became regulatory. Koslov (2019) delved into the production process of FIRMs and how it related to the recovery process on Staten Island after Hurricane Sandy, showing how the type of flood zones properties were mapped into and the methods used to produce flood zone extents both limited the ability of residents to obtain buyouts and prompted action that resulted in map revisions. Similarly, in examining how SFHAs on recently updated FIRMs were reshaped in New York City, (Elliott, 2019, 2021a) argued that communities mobilize to fight the accuracy of flood maps because of the multitude of values (economic, livelihood, and so on) that are put at risk by an increase in flood hazard on updated FIRMs and the corresponding costs. However, no work as of yet has examined the magnitude of areal changes to SFHAs on FIRMs before and after they are regulatory, tried to quantify how many structures have been moved in or out of SFHAs over time, or analyzed how these changes might relate to socio-economic indicators.

This paper fills these identified gaps in the literature by examining changes to SFHAs and the buildings within them for FIRMs updated between 2013 to 2017. Using GIS FIRM layers and building footprints, we quantify the number of buildings moved in to or out of the SFHA at census tract and county scales. Building changes in to or out of the SFHA are then statistically tested between inland and coastal flood zone types and with socio-economic indicators. Our results for our 255 sample counties show that over 20,000 buildings have been removed from the SFHA between when the FIRMs were preliminarily released and their present (as of August 2019) FIRM iteration. We also find statistically significant variables at both the census tract and county scales of analysis by differentiating between all study locations and only those that had net change, coastal versus inland flood zones, and socio-economic indicators, which raise further questions of equity for FIRM revisions and amendments.

Background on Flood Insurance Rate Maps

As part of the National Insurance Reform Act of 1994, the United States Congress mandated that the Federal Emergency Management Agency (FEMA) update FIRMs every five years for the over twenty-two thousand participating jurisdictions. But funding levels since then to update maps have generally been inadequate to meet this goal, even despite the Biggert-Waters Flood Insurance Reform Act of 2012 which renewed the mandate for FEMA to develop strategies to keep its maps updated. The limited funding has meant relatively few FIRMs are updated in a timely manner and that many FIRMs are more than five years old (Department of Homeland Security, 2017; Eby and Ensor, 2019). Old maps are problematic because they increase the likelihood of a mismatch between flood hazard and premiums paid, which in turn can impact program solvency and make it impossible to establish relevant floodplain development rules, building codes, and plan for how climate change might alter flooding (Thomas and Leichenko, 2011; Knowles and Kunreuther, 2014; Adams-Schoen and Thomas, 2015). While the challenge of choosing where maps should be updated given limited funding is an important policy topic, it is beyond the scope of this paper. Instead, we focus on those FIRMs that have been recently updated by FEMA.

The special Flood Hazard Area on FIRMs contains multiple flood zones determined by methodology and flooding type, but often these are aggregated into two zone types. The A zone types delineate 1 percent or greater annual chance of flooding for inland sources of flooding, while V zones are 1 percent or greater annual chance of flooding for coastal areas with wave action and storm surge. This study, like others before it (Montgomery and Chakraborty, 2015; Wilson and Kousky, 2019), differentiates between inland and coastal flood zones when comparing SFHA changes to socio-economic characteristics.

Before describing the process of FIRM production, adoption, and revision in the next section, we want to make a distinction that has not often been made clear in prior research analyzing FIRMs. Past research examining these processes (Pralle, 2019; Wilson and Kousky, 2019) has examined how FEMA first initiates the production of updating or producing a new FIRM and has described how the “community” can appeal to FEMA to generate revised flood zones on FIRMs. In these instances, “community” has meant the individuals employed or elected by the jurisdictions (city, municipality, county, or state) that are working with FEMA contractors to produce the revised FIRMs. However, these are not the only people who can initiate a request to alter the flood zones on FIRMs, as individuals with property residing in flood zones can also go through a formal process to challenge their inclusion in a flood zone. Thus, in this paper we differentiate between what we call “community representatives” and “property residents”. While both groups generally have the same economic interest in removing properties from the SFHA to reduce insurance premiums, there is a difference between the scale at which they operate, the means about how they seek to change the FIRMs, and thus the potential for their outcome to be successful (Dedman, 2014; Pralle, 2019). Although our research does not have the means to separate the actors who are initiating the FIRM changes we analyze, making this distinction is important for improving understanding of how the observed changes to FIRMs over time are related to the actors responsible for initiating and enacting those flood zone revisions.

FIRM Production, Adoption, and Revision Process

Funds are authorized each year by the United States Congress to update maps where FEMA decides they are out of date because of age or population growth and urban development. The chosen counties then work with FEMA over approximately the next two years to gather available topographic, hydrologic, infrastructure, land use, and other relevant data sets that contracted engineers, hydrologists, and other technical experts use to produce a new map depicting flood hazard (National Academies Press, 2009). The map resulting from these steps is called the preliminary FIRM. The preliminary FIRM for a county is released to the public at a community open house meeting, but is not yet regulatory (i.e., has not yet replaced the older map to set insurance premiums) because there is a minimum ninety-day appeal period after the meeting during which community representatives and property residents can request changes to the preliminary maps. During this period if an individual residing in the community or community officials working with FEMA determine there are scientific and technical concerns with the preliminary FIRM, they can hire independent technical experts to document why the preliminary map is incorrect and re-conduct the analyses using alternative hydrologic and/or hydraulic models to produce revised FIRMs (FEMA, 2021b). The submission of these documents to FEMA are formally called appeals and comments (FEMA, 2019a), and if FEMA agrees the revisions are valid the new revised preliminary FIRMs are issued. This process sometimes requires independent parties to review and rule on appeals if a community and FEMA continue to disagree, but once all scientific and technical community-level concerns have been resolved FEMA issues a letter of final determination. This letter sets a date, at least six or more months in the future so the community has time to update its floodplain management regulations to reflect the new map, upon when the preliminary FIRM becomes effective to set insurance premiums and supersede any older map. See Wilson and Kousky (2019) for more detail on the process of producing and adopting preliminary maps.

Upon issue of a letter of final determination, the preliminary map becomes what we define as an 'initial regulatory' FIRM. Past research (Pralle, 2019; Wilson and Kousky, 2019) has only focused on the preliminary map process and how community representatives working with FEMA seek to change FIRMs before they become regulatory, but once a FIRM becomes regulatory a similar appeal and comment process to change the SFHA can still occur. Now this process is called a Letter of Map Amendment or Revision and can take place at any time (FEMA, 2019d). The difference between LOMAs and LOMRs is related to scale and initiator. LOMAs are initiated by individual property residents who seek to remove their property from the SFHA using precisely measured elevations to show their building or property is above the Base Flood Elevation, the elevation to which flood waters delineated by the SFHA are predicted to rise. LOMRs often change the SFHA for many properties and are implemented due to new stormwater infrastructure, drainage basins, re-grading, or the use of new flood models that change projections of flood hydrology and hydraulics. There are also Letters of Map Revision based on fill that raise single or multiple properties above the Base Flood Elevation. Letters of Map Amendment and Revision approved by FEMA alter the regulatory FIRM and its SFHA. Because changes to SFHAs can occur on both preliminary and regulatory FIRMs, in our analyses we differentiate between what we call the preliminary, initial regulatory, and present FIRMs.

Although the approval process for appeals and comments versus Letters of Map Amendment and Revision are essentially the same scientific process, one reason we differentiate between them is due to the possibility of different social processes acting to alter the FIRMs during these periods. For example, if preliminary FIRMs are issued that include more properties in the SFHA than past maps, property residents might try to file an appeal that reduces the extent of the SFHA and properties within it. However, once the FIRM becomes regulatory, if community officials now believe the SFHA extent is too small and not accurately depicting flood hazard, they might submit a separate revision to increase the size of the SFHA to include more properties. Another reason to differentiate changes to SFHAs between preliminary and regulatory maps is because impetus to alter the SFHAs might be different at these map stages. For example, property residents may not understand their payment obligations or may fail to appreciate the financial burden of flood insurance if their property is included in the preliminary map's SFHA because they do not yet have to pay. However, once they are paying SFHA premium rates when a FIRM becomes regulatory, they may try to change their flood designation out of the SFHA to lower their flood insurance payments. Finally, because there is a time limit on appeals and comments during the preliminary map period, some property residents might not have the time to be able to put together the needed documents and data during this time.

Methodology

To examine how SFHAs on FIRMs that became regulatory between 2013 and 2017 changed between their preliminary, initial regulatory, and present iterations, we requested and received preliminary and initial regulatory FIRMs from FEMA's Engineering Library for FIRMs that reached the initial regulatory stage between 2013 and 2017. This date range was chosen because: 1) we wanted to examine recently released FIRMs that should be more accurate to present flood hazard than older maps, and 2) earlier preliminary and initial regulatory FIRMs are not held at FEMA's Engineering library but rather are held at the local county or community level, which would make data acquisition too difficult to complete for a large number of counties. Of the counties we received data for from FEMA, 255 counties within the contiguous United States were determined to have matching preliminary and initial regulatory maps that became regulatory between the beginning of 2013 and end of 2017. We also analyzed FIRM changes at the census tract scale. The 255 study counties were sub-divided into their respective 6,858 study census tracts. Figure 1 shows locations of the study counties. The present FIRMs (as of August 2019) for these counties were downloaded from FEMA's National Flood Hazard Layer. We recognize a possible limitation in this analysis is that the analyzed FIRMs have been regulatory for different lengths of time, which could potentially impact the magnitude of flood zone revision that has taken place. However, because maps are updated asynchronously this is inherent to the data, and the maps are relatively of the same age and rely on the same methods that were available to make them.

Because it is not change in the SFHA itself that is important to understand but rather change in the number of structures in the SFHA, building footprints for each state were acquired from Microsoft's open access computer generated building footprints for the United States (Microsoft, 2018). The building footprint layers were then overlaid with preliminary, initial regulatory, and present FIRMs in ArcGIS to calculate the number of buildings in the SFHA for each map iteration at both census tract and county scales. Net change and the number of buildings added to and removed from the SFHA between both the preliminary and initial regulatory and initial regulatory and present FIRMs were then quantified using R.

These census tract and county scale building net change calculations were the dependent variable in this study. The dependent variable was combined with the independent sociodemographic variables at their matching county and census tract scales, which were acquired from the American Community Survey (ACS) 2013 to 2017 five-year estimates. Analysis of these variables provided us the ability to assess if there was social inequity between places where buildings were added to or removed from SFHAs and where they are not. We used the following variables from ACS: number of households, median income, percent of people 25 years and older with a bachelor's degree or higher, percent of people below poverty, percent of people renting a residence, percent of homeowners with a mortgage, percent of non-white residents, per capita income, median year of building construction, median home value, percent of residences without home internet, and percent of residences that were single family housing units. These variables are proxies for community wealth and knowledge of hazard, which past research suggests influence the potential for community members to alter flood maps (Pralle, 2019; Wilson and Kousky, 2019). We theorize that places with more people, higher indicators of wealth, and potentially greater ability to understand hazard will more likely have changes to their SFHAs.

Counties and census tracts were assigned a coastal dummy variable of "1" if their SFHA flood zones contained coastal flooding zones ("V" zones), which allowed us to analyze differences in the relationship of flood map revisions between coastal and inland census tracts and counties. We found using Kolmogorov-Smirnov tests that the number of buildings in each map iteration and the net change in the number of buildings between the map iterations rejected the null hypothesis of a normal distribution. Due to this finding, our analyses employed Wilcoxon–Mann–Whitney tests and binary logistic regressions.

Recognizing that the American Community Survey 2013 to 2017 five-year estimates are samples from communities and thus have margins of error surrounding the reported sociodemographic variable, we used uncertainty analyses to analyze all FIRMs versus change FIRMs for binary logistic regressions. Specifically, at both the census tract and county scales, the 95% margin of error was used to define the range of values from which a random value was picked and statistically tested 10,000 times. The resulting p values reported in Tables 4 through 7 are the 95^{th} percentile of the 10,000 random samples. In other words, a sociodemographic variable had to be statistically significant ($p < 0.05$) 9,500 or more times out of the 10,000 random samples. Along with p values, we also report for each variable the percentage of the 10,000 random samples that were statistically significant.

Results

Table 1 shows summary statistics of the study sample at the county scale. One consistent result is that all the variables have right-skewed distributions with maximum value outliers and large standard deviations. The county median size was 1479.5 square kilometers, but there were a few large, low population counties. The median number of buildings for the counties was 31,309, with a standard deviation of 58,539 and a maximum of 445,568 buildings. The median size covered by the Special Flood Hazard Area for a county was 145.6 square kilometers, and the median number of buildings in the SFHA for preliminary maps was 1,358. Although the median percentage of county area covered by the SFHA was about 11%, the median number of buildings in the SFHA was only 4.4%. This suggests that for many of the study counties, until high percentages of a county are covered by the SFHA the matching percent of buildings in the SFHA were usually lower. While the numbers for the census tracts were smaller, they followed the same trends seen at the county scale (Table 2). Kolmogorov-Smirnov tests for all variables at both the county and census tract scales were statistically significant ($p < 0.001$), leading to a rejection of the null hypothesis of normal distributions and use of non-parametric statistical tests in our further analyses.

Sums of the Special Flood Hazard Area and the number of buildings in the Special Flood Hazard Area for all study counties in the Preliminary, Initial Regulatory, and Present FIRM iterations are shown in Table 3. Net change for the SFHA and buildings in the SFHA is also shown in Table 3. Both areal extent of the SFHA and buildings in the SFHA decline between preliminary and initial regulatory FIRMs, as well as between the initial regulatory and present FIRMs. While 3,182 buildings and 2,298 buildings were added to the SFHA between preliminary and initial regulatory FIRMs and initial regulatory to present FIRMs, respectively, 13,005 buildings were removed between preliminary and initial regulatory FIRMs and 14,281 buildings were removed between initial regulatory to present FIRMs. From the preliminary maps to present, the net reduction for the study area was 107.2 square kilometers and 21,806 buildings.

Figure 2 shows the distribution of building changes in the SFHA between the preliminary and initial regulatory as well as initial regulatory and present FIRMs at the county scale. The histogram shows only counties that had a non-zero value (i.e., building change into or out of the SFHA), with positive values indicating the number of buildings in the SFHA increased and negative values indicating the number of buildings in the

SFHA decreased. Out of the 255 counties in our study sample, 101 counties had map revisions that changed buildings in the SFHA between preliminary and initial regulatory FIRMs, while 115 counties had buildings in the SFHA change between the initial regulatory and present FIRMs. Fifty counties had at least one building change in to or out of the SFHA between both preliminary and initial regulatory and initial regulatory and present FIRMs. Thus, about 40% of FIRMs were revised between their preliminary release and becoming initially regulatory, 45% of counties have had revisions between their initial regulatory and present FIRMs, and 19.6% had buildings change in the SFHA between preliminary to initial regulatory and initial regulatory to present. In total, 166 counties had at least one building change in to or out of the SFHA between the preliminary and present FIRMs, meaning 65% of our study counties experienced some change between its preliminary and present FIRM.

Multiple statistically significant differences in the means of American Community Survey sociodemographic variables were found at the census tract and county scales when the 6,858 census tracts and 255 counties were compared to only census tracts and counties that had SFHA buildings change between the preliminary to initial regulatory and initial regulatory to present FIRMs using Wilcoxon-Mann-Whitney tests. The p-values reported for the Wilcoxon-Mann-Whitney test results and binary logistic regressions below are the 95th percentile p values of all p values out of 10,000 random samples defined by the margins of error. Table 4 shows the results at the census tract scale, while Table 5 shows county scale results. Percent Homeowners with Mortgage ($z = -2.258$, $p < 0.05$), Percent Non-White ($z = -7.580$, $p < 0.001$), and Percent Single Family Housing ($z = -2.442$, $p < 0.05$) had a statistically significant lower mean value for census tracts where buildings moved into or out of the SFHA between preliminary and initial regulatory FIRMs compared to all census tracts in our sample, while Per Capita Income ($z = -2.282$, $p < 0.05$) and Median Year Construction ($z = -2.932$, $p < 0.01$) had statistically significant higher mean values in census tracts where buildings changed in or out of the SFHA between preliminary and initial regulatory FIRMs when compared to all census tracts. For initial regulatory to present FIRMs, census tracts where buildings changed into or out of the SFHA had significantly higher mean values for the Number of Households ($z = -3.924$, $p < 0.001$), Median Year Construction ($z = -7.629$, $p < 0.001$), and Median Home Value ($z = -2.670$, $p < 0.01$) when compared to all census tracts. Percent No Home Internet ($z = -3.267$, $p < 0.01$) had a statistically significant lower mean for census tracts where buildings changed in or out of the SFHA between initial regulatory and present FIRMs when compared to all census tracts, meaning census tracts where buildings changed into or out the SFHA had an average percent of more households with home internet than the mean percentage of all census tracts in our study sample.

Binary logistic regressions were used to test whether the independent variables from the ACS were predictive of FIRMs having buildings move in to or out of the SFHA (results in Table 6 and Table 7). At the census tract scale, we find that census tracts with coastal flood zones (“V” zones) are twice as likely to have buildings change between preliminary and initial regulatory FIRMs than census tracts without these flood zones. Similarly, census tracts with coastal flood zones are 1.3 times more likely to have buildings change in or out of the SFHA between the initial regulatory and present FIRMs, although the presence of coastal flood zones for these changes was just above the threshold of significance ($p = 0.06$). Similar to the Wilcoxon-Mann-Whitney tests, Percent Non-White ($p < 0.001$), Median Year Construction ($p < 0.05$), and Per Capita Income ($p < 0.05$) were significant predictors of census tracts with buildings that changed into or out of the SFHA between the preliminary and initial regulatory FIRMs, while the Number of Households, Median Year Construction, Median Home Value, Percent No Home Internet, and Median Income were all significant predictors for net building change in and out of the SFHA between initial regulatory and present FIRMs.

Discussion and Conclusion

By quantifying the buildings added to and removed from Special Flood Hazard Areas (SFHAs) on recently updated Flood Insurance Rate Maps (FIRMs) from their preliminary release to present (as of August 2019), we find that the majority of change has been building removals (i.e., a decrease in mapped flood hazard) from SFHAs. This finding is in line with recent research that suggests SFHAs on FIRMs are under depicting flood hazard in many places across the United States (Wing et al., 2017, 2018). If Wing et al.'s predictions of flood hazard are correct and flood risk across the United States is generally increasing because of development, climate change, and other factors, we would not expect to see so many buildings removed from SFHAs. Of the changes we observed, we found a number of statistically significant American Community Survey variables related to buildings changing into or out of SFHAs. At both the census tract and county scales, places with more households had more likelihood to have buildings change. At the census tract scale, the number of homeowners with mortgages was lower where changes occur (i.e., more homeowners own their homes outright) and Per Capita Income and Median Home Value was higher where building changes occur. These findings support previous hypotheses and findings that larger, affluent communities have greater resources to lodge formal appeals or revisions (Dedman, 2014; Pralle, 2019).

More buildings changed in or out of the SFHA in places with newer buildings and in coastal (“V”) flood zones. The median year of building construction was statistically significant between both preliminary to initial regulatory FIRMs and initial regulatory to present FIRMs at the census tract scale using the Wilcoxon-Mann-Whitney test. Median year of construction was also a statistically significant predictor variable at both the census tract and county scales for binary logistic regression. One reason for this could be that property developers building new structures in SFHAs seek to revise SFHAs or use fill to raise new buildings above the base flood elevation. Similar to Wilson and Kousky’s (2019) observation that coastal counties are 2.3 times more likely to have preliminary to initial regulatory building changes into or out of the SFHA, we found that coastal census tracts are two times as likely to have a building change in or out of the SFHA between preliminary and initial regulatory FIRMs than inland census tracts. While we do not observe this at the county scale, which may be due to differences in how we defined coastal census tracts and counties, we agree with Wilson and Kousky's (2019) hypotheses that the greater likelihood of change in coastal census tracts could be due either to the physical hydrologic and hydraulic mapping methods used in coastal areas or to the politics of hazards where amenity and land values are often higher in coastal areas than inland.

One strength of this study was our ability to analyze census tracts and thus provide insight where county level analysis might be too coarse. For example, the statistically significant difference at the census tract scale of percent non-white population in the Wilcoxon-Mann-Whitney test and binary logistic regression for preliminary to initial regulatory building changes shows that changes are happening more often where the population is more proportionately white, but this statistical significance is not observed at the county scale for the same variable with the same tests. While we cannot determine the cause of these differences between our data, Pralle (2019) provides one potential explanation based on their observations in Syracuse, New York. Census tracts or neighborhoods with more non-white people have been historically dispossessed in the United States and thus have fewer financial and political resources to change maps via flood hazard knowledge, to construct flood defenses, or to otherwise change the river hydraulics in ways to mitigate flood hazard. Regardless of the reasons for the building changes, our finding indicates that for some variables like percent non-white population, the county level data is likely obscuring finer-level insights. We still chose to perform county scale analyses because preliminary FIRMs are usually updated at the county scale, and to have comparable results to previous studies like Wilson and Kousky (2019) whose results were at the county scale. But we believe the census tract data is more insightful because of the variation in socioeconomic data that is obscured when aggregated to the county scale. However, the Wilcoxon-Mann-Whitney test and binary logistic regression tests at the census tract and county scales are still limiting because they can only discern relative difference between places and cannot analyze change for individual properties. Future research could investigate SFHA changes at the individual property scale where GIS data is available to determine if there are relationships between map adjustments and attributes like property value or year the structure was built. Future work could also plot the locations of Letters of Map Amendment requested by property residents to remove individual buildings from the SFHA to better help differentiate SFHA alterations by "property residents" from "community representatives".

There are multiple explanations for the over 20,000 SFHA building removals identified in this study. One possible reason is that FEMA frequently overestimates flood hazard in preliminary maps that is later rectified by revisions. While this might be true for individual counties or census tracts, overestimation of flood hazard seems unlikely across many counties because other flood studies of recent years argue that FEMA maps are more often under predicting hazard (Wing et al., 2017, 2018). Given that a significant percentage (20% or higher) of NFIP claims are paid to properties outside the SFHA (Highfield et al., 2013), FIRMs appear to err on the side of excluding high risk properties rather than including low risk structures. It seems unlikely, then, that FIRMs are systematically overestimating flood hazard across the 255 counties studied.

Another reason that buildings could be removed from SFHAs is because flood hazard mitigation is reducing high flood hazard zones. For example, a community might construct a levee or other flood protection and obtain a Letter of Map Revision that removes properties from the SFHA. It seems likely that this has occurred in some individual census tracts and counties, but it is unlikely happening in all of the counties analyzed in this study. While beyond the scope of this study, this question could be investigated further by identifying how many counties in this study participate in FEMA's Community Rating System (CRS). The CRS program incentivizes flood hazard reduction with insurance premium reductions (Brody et al., 2009; Highfield and Brody, 2013, 2017), and buildings might have been removed from the SFHA because of flood mitigation programs implemented between 2013 to present.

A third possible reason for our observations of a net loss of buildings in SFHAs on FIRMs is that community representatives and property residents seek to hire independent technical experts who use FEMA approved hydrology and hydraulic models to produce new FIRMs whose SFHA extent include fewer buildings. This seems to us a likely reason for many of the building removals we have documented. One reason is because this dynamic has been observed in previous research (Soden et al., 2017; Pralle, 2019). Another reason is because the two options noted above seem unlikely across many counties because such changes are local in nature, while changing flood models or hydrology is systemic to how FIRMs are generated and revised. However, because there are multiple reasons why flood zones might change and we cannot discern those differences in this paper, this is a topic for continuing research. Our data also cannot speak to whether there are biases in the building additions or removals due to political reasons (Wilson and Kousky, 2019), but if changes are occurring outside the basis of scientific depictions of flood hazard, that merits more investigation. Finally, it should be reiterated that our results examine how new FIRMs have been altered since their preliminary stage, but we do not examine how the SFHA extents of preliminary FIRMs differ from the older FIRMs they are proposed to replace. Future research should investigate these changes as well to better understand how FIRMs change over time.

One policy implication from this work is that greater federal funding for FEMA flood studies that produce and revise preliminary maps should be directed to communities where the American Community Survey variables we analyzed (or other equivalent socioeconomic metrics) fall below certain thresholds. Similarly, a voucher system could be developed for property resident-initiated building removals whereby property residents who can show they have financial need can qualify to have costs associated with data collection or Letter of Map Amendment or Revision submission waived. By developing and implementing these changes, FEMA could address not only flood hazard but also affordability and social equity for insurance policies (Elliott, 2019).

As flooding continues to occur, maintaining accurate Flood Insurance Rate Maps and risk-based pricing will continue to be an important task for the National Flood Insurance Program. Balancing flood hazard with equity and fairness in preparation, exposure, and recovery are now important conversations for NFIP as the risks and costs of floods increase in the USA (Nance, 2015; Elliott, 2019; Pralle, 2019; Frazier et al., 2020; Smiley, 2020; Elliott, 2021a). Continuing work that investigates and understands why Flood Insurance Rate Maps flood zones are altered and by whom will be an important contribution that informs these broader conversations in the National Flood Insurance Program.

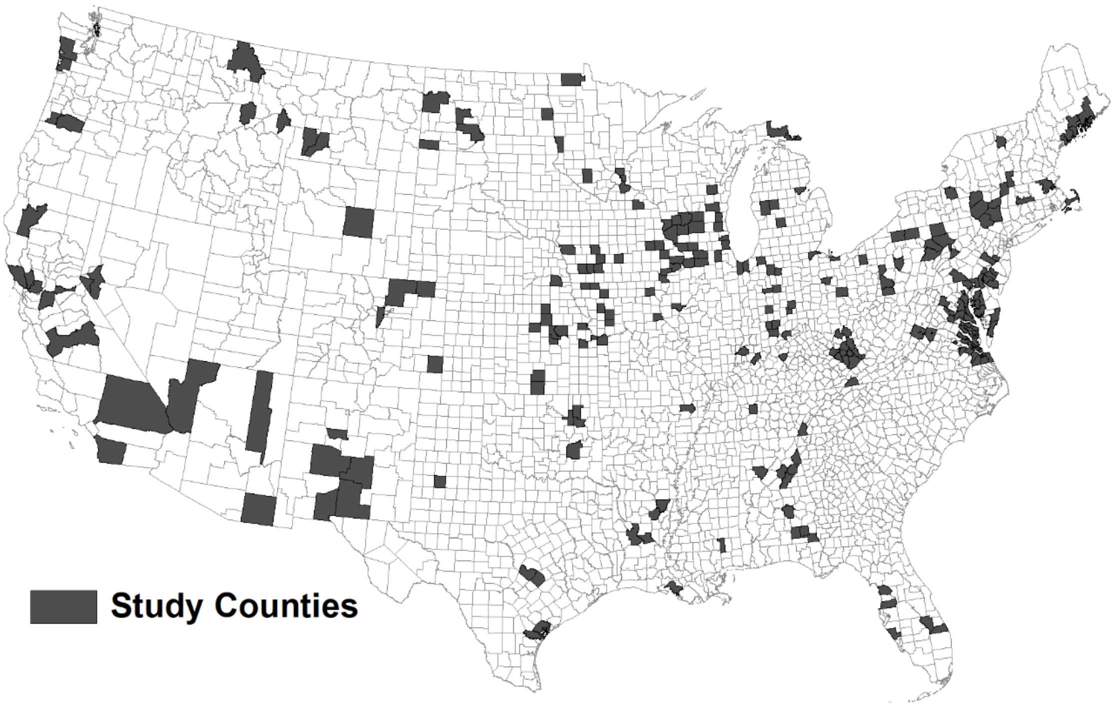

Figure 1. The 255 study sample counties.

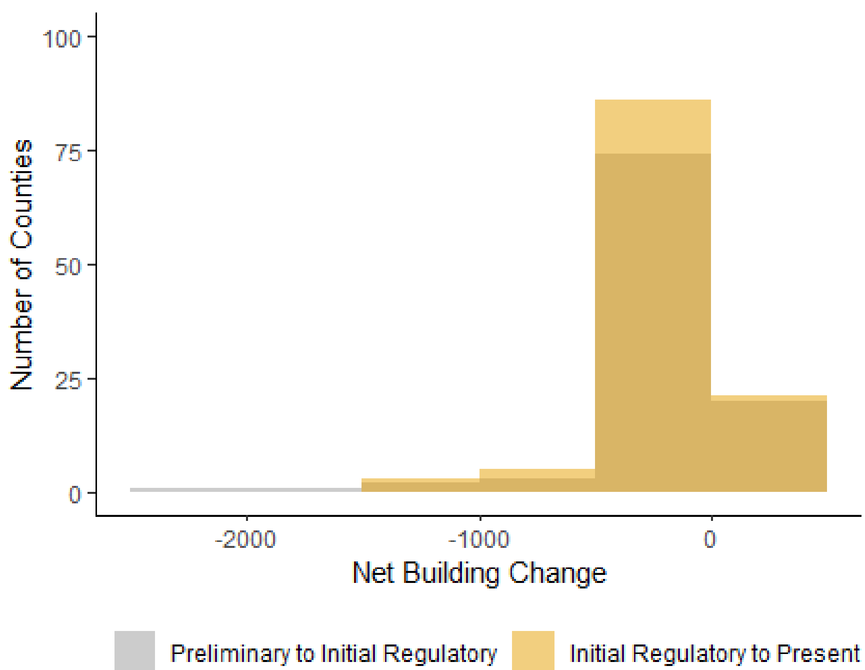

Figure 2. Net Building Change Histogram at County Scale.

Table 1. County FIRM Summary Statistics

	Minimum	**25th Percentile**	**Median**	**Mean**	**75th Percentile**	**Maximum**	**Standard Deviation**
Area (sq. km)	18.926	1,048.828	1,479.516	2,488.598	2,209.775	44,009.221	4,243.727
Number of Buildings	4,821	16,264	31,309	49,802.31	54,135	445,568	58,539
SFHA (sq. km)	2.208	82.063	145.628	231.712	292.609	1,758.231	253.876
Buildings in SFHA	32	686	1,358	2,840.271	3,146	47,372	4,619
% SFHA	0.122	6.283	11.363	13.796	16.764	83.214	11.488
% of buildings in SFHA	0.343	2.273	4.433	6.799	7.994	80.678	7.695
Pr-In Net Buildings Change	-2,252	-2.5	0	-38.522	0	324	211.006
In-Re Net Buildings Change	-1,329	-6.5	0	-46.992	0	61	174.714

Note: Pr-In refers to Preliminary to Initial Regulatory, and In-Re refers to Initial Regulatory to Present.

Table 2. Census Tract FIRM Summary Statistics

	Minimum	**25th Percentile**	**Median**	**Mean**	**75th Percentile**	**Maximum**	**Standard Deviation**
Area (sq. km)	0.065	2.842	8.018	92.533	42.663	18,013	503.137
Number of Buildings	26	1,119.25	1,654.5	1,851.792	2,383	14,611	1,056.258
SFHA (sq. km)	0	0.229	0.931	8.616	4.650	623.509	31.128
Buildings in SFHA	0	8	30	105.609	104	3,295	211.364
% SFHA	0	4.376	9.281	14.795	19.199	100	15.731
% of buildings in SFHA	0	0.585	1.919	6.238	5.907	100	12.336
Pr-In Net Buildings Change	-1,084	0	0	-1.432	0	327	21.836
In-Re Net Buildings Change	-1,288	0	0	-1.747	0	61	22.707

Note: Pr-In refers to Preliminary to Initial Regulatory, and In-Re refers to Initial Regulatory to Present.

Table 3. Summary of SFHA and building changes for study sample FIRMs

	Preliminary	**Initial Regulatory**	**Present**	**Pr-In Net**	**In-Re Net**	**Pr-Re Net**
SFHA (sq. km)	59,086.66	59,037.35	58,979.43	-49.31	-57.92	-107.23
Buildings in SFHA	724,269	714,446	702,463	-9,823	-11,983	-21,806

Note: Pr-In refers to Preliminary to Initial Regulatory, and In-Re refers to Initial Regulatory to Present.

Table 4. Comparison of All Census Tracts with Change Census Tracts

	All (n = 6858)	**Pr-In Change (n = 547)**	**Significance**	**All (n = 6858)**	**In-Re Change (n = 737)**	**Significance**
	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%)	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%)
Number of Households	1,694.0 (749.6)	1,749.8 (867.3)	0.181 (0.02%)	1,693.1 (752.3)	1,846.2 (939.9)	0.000 *** (100%)
Median Income	65,738.9 (30,960.1)	65,361.5 (29,203)	0.940 (0%)	65,728.9 (31,030.5)	65,991.7 (30,825.0)	0.981 (0%)
% Bachelor's Degree or higher	30.423 (18.526)	30.606 (17.765)	0.533 (0%)	30.411 (18.577)	30.711 (18.305)	0.563 (0%)
% Below Poverty	13.650 (11.882)	12.368 (9.519)	0.485 (0%)	13.646 (11.834)	13.129 (10.649)	0.980 (0%)
% Renter	32.848 (21.547)	31.504 (20.631)	0.224 (11.58%)	32.855 (21.404)	32.274 (19.867)	0.985 (0%)
% Homeowner with Mortgage	64.307 (17.044)	62.780 (17.500)	0.023 * (98.78%)	64.393 (17.078)	64.082 (17.802)	0.827 (8.85%)
% Non-White	22.525 (23.416)	16.031 (20.739)	0.000 *** (100%)	22.588 (23.389)	21.259 (20.765)	0.974 (0%)
Per Capita Income	32,467.4 (14,714.5)	34,490.8 (16,842)	0.022 * (99.74%)	32,449.9 (14,737.9)	32,514.9 (14,132.8)	0.865 (0%)
Median Year Construction	1,975.0 (14.666)	1,977.1 (14.259)	0.003 ** (100%)	1,975.0 (14.671)	1,979.6 (14.670)	0.000 *** (100%)
Median Home Value	237,623 (169,368)	241,256 (163,230)	0.414 (0%)	237,734 (167,563)	258,902 (190,733)	0.007 ** (100%)
% No Home Internet	20.679 (12.446)	20.113 (10.706)	0.945 (0.01%)	20.640 (12.326)	19.067 (11.681)	0.001 ** (100%)
% Single Family Housing	73.430 (21.250)	69.934 (24.782)	0.014 * (99.99%)	73.438 (21.217)	73.772 (20.359)	0.971 (0%)

Note: Pr-In refers to Preliminary to Initial Regulatory, and In-Re refers to Initial Regulatory to Present. Statistical significance of Wilcoxon-Mann-Whitney tests indicated by *p < 0.05, **p <0.01, and ***p < 0.001.

Table 5. Comparison of All Counties with Change Counties

	All (n = 255)	**Pr-In Change (n = 101)**	**Significance**	**All (n = 255)**	**In-Re Change (n = 115)**	**Significance**
	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%)	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%)
Number of Households	62,257.3 (110,984.5)	77,223.9 (113,815.8)	0.042 * (100%)	62,288 (111,087.7)	102,671.8 (146,070.1)	0.000 *** (100%)
Median Income	55,581.7 (14,782.4)	55,923.9 (14,825.5)	0.791 (0%)	55,822.5 (14,631.5)	58,771.1 (16,050.5)	0.086 (36.95%)
% Bachelor's Degree or higher	25.069 (10.097)	25.946 (10.695)	0.508 (0%)	24.984 (10.195)	28.790 (10.725)	0.000 *** (100%)
% Below Poverty	14.094 (5.655)	14.016 (5.382)	0.972 (0%)	14.046 (5.727)	13.801 (5.843)	0.689 (0%)
% Renter	29.725 (8.905)	29.784 (8.902)	0.960 (0%)	29.700 (8.759)	31.559 (8.348)	0.036 * (98.96%)
% Homeowner with Mortgage	58.436 (11.562)	58.683 (10.921)	0.976 (0%)	58.652 (11.421)	62.003 (10.063)	0.008 ** (100%)
% Non-White	16.830 (14.993)	15.991 (15.272)	0.662 (0%)	16.870 (14.903)	19.186 (14.115)	0.034 * (100%)
Per Capita Income	28,810.8 (6,497.4)	29,333.4 (6,887.6)	0.646 (0%)	28,878.2 (6,425.8)	30,358.2 (6,903.9)	0.060 (84.17%)
Median Year Construction	1,974.2 (11.0)	1,974.3 (10.8)	0.909 (0%)	1,974.3 (11.1)	1,977.0 (9.3)	0.056 (86.42%)
Median Home Value	179,089.1 (98,999.7)	187,086.8 (106,804.3)	0.554 (0%)	179,131.2 (98,020.2)	208,137.8 (109,336.4)	0.003 ** (100%)
% No Home Internet	24.382 (7.624)	23.682 (7.528)	0.374 (0%)	24.380 (7.493)	21.690 (7.374)	0.000 *** (100%)
% Single Family Housing	75.549 (9.177)	74.257 (9.197)	0.219 (0.53%)	75.627 (9.233)	74.104 (7.192)	0.043 * (97.68%)

Note: Pr-In refers to Preliminary to Initial Regulatory, and In-Re refers to Initial Regulatory to Present. Statistical significance of Wilcoxon-Mann-Whitney tests indicated by $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Table 6. Binary Logistic Regression Model Results at Census Tract Scale

	Pr-In			In-Re		
	Coefficient (Std. Err.)	**Lower and Upper 95% Conf. Int.**	***p* (%)**	**Coefficient (Std. Err.)**	**Lower and Upper 95% Conf. Int.**	***p* (%)**
Coastal	0.662 (0.151)	0.358 0.954	0.000 *** (100%)	0.267 (0.142)	-0.018 0.541	0.060 (85.03%)
Number of Households	0.000 (0.000)	-0.000 0.000	0.201 (3.04%)	0.000 (0.000)	0.000 0.000	0.011 * (100%)
Median Income	0.000 (0.000)	-0.000 0.000	0.720 (17.25%)	-0.000 (0.000)	-0.000 -0.000	0.005 ** (99.78%)
% Bachelor's Degree or higher	-0.003 (0.004)	-0.013 0.006	0.500 (14.07%)	-0.000 (0.004)	-0.009 0.007	0.833 (2.61%)
% Below Poverty	-0.001 (0.006)	-0.015 0.011	0.829 (6.34%)	0.000 (0.005)	-0.010 0.011	0.944 (2.19%)
% Renter	-0.000 (0.004)	-0.009 0.007	0.814 (6.14%)	0.000 (0.003)	-0.006 0.007	0.962 (0.31%)
% Homeowner with Mortgage	-0.002 (0.003)	-0.009 0.004	0.504 (44.65%)	-0.007 (0.002)	-0.013 -0.001	0.009 ** (99.3%)
% Non-White	-0.012 (0.003)	-0.019 -0.006	0.000 *** (100%)	-0.000 (0.002)	-0.004 0.004	0.974 (0%)
Per Capita Income	0.000 (0.000)	0.000 0.000	0.015 * (99.11%)	-0.000 (0.000)	-0.000 0.000	0.608 (23.26%)
Median Year Construction	0.008 (0.003)	0.000 0.015	0.040 * (97.64%)	0.026 (0.003)	0.019 0.033	0.000 *** (100%)
Median Home Value	-0.000 (0.000)	-0.000 0.000	0.171 (47.37%)	0.000 (0.000)	0.000 0.000	0.000 *** (100%)
% No Home Internet	-0.000 (0.006)	-0.012 0.012	0.970 (0.13%)	-0.019 (0.005)	-0.029 -0.008	0.000 *** (100%)
% Single Family Housing	-0.005 (0.003)	-0.012 0.001	0.144 (68.77%)	0.002 (0.003)	-0.003 0.009	0.356 (25.29%)
Intercept	-17.049 (7.891)	-32.605 -1.664	0.030 * (99.07%)	-53.014 (6.843)	-66.508 -39.677	0.000 *** (100%)

Note: Pr-In refers to Preliminary to Initial Regulatory, and In-Re refers to Initial Regulatory to Present. Statistical significance of logit model indicated by *p < 0.05, **p <0.01, and ***p < 0.001.

Table 7. Binary Logistic Regression Model Results at County Scale

	Pr-In			In-Re		
	Coefficient (Std. Err.)	**Lower and Upper 95% Conf. Int.**	***p* (%)**	**Coefficient (Std. Err.)**	**Lower and Upper 95% Conf. Int.**	***p* (%)**
Coastal	-0.003 (0.395)	-0.784 0.773	0.993 (0%)	-0.621 (0.452)	-1.534 0.248	0.169 (0.75%)
Number of Households	0.000 (0.000)	-0.000 0.000	0.582 (0%)	0.000 (0.000)	0.000 0.000	0.003 ** (100%)
Median Income	-0.000 (0.000)	-0.000 0.000	0.913 (0.16%)	-0.000 (0.000)	-0.000 0.000	0.186 (54.87%)
% Bachelor's Degree or higher	-0.001 (0.029)	-0.059 0.055	0.946 (0%)	0.009 (0.032)	-0.053 0.073	0.771 (0.06%)
% Below Poverty	-0.002 (0.053)	-0.106 0.102	0.968 (0.1%)	0.002 (0.057)	-0.112 0.116	0.966 (0.13%)
% Renter	0.001 (0.029)	-0.056 0.060	0.949 (0.02%)	0.004 (0.032)	-0.060 0.068	0.887 (0.18%)
% Homeowner with Mortgage	0.000 (0.021)	-0.041 0.043	0.968 (0.04%)	0.001 (0.026)	-0.049 0.054	0.947 (0.12%)
% Non-White	-0.003 (0.015)	-0.034 0.026	0.804 (0%)	0.001 (0.018)	-0.033 0.037	0.922 (0%)
Per Capita Income	0.000 (0.000)	-0.000 0.000	0.912 (1.25%)	0.000 (0.000)	-0.000 0.000	0.959 (0.21%)
Median Year Construction	-0.004 (0.015)	-0.034 0.025	0.749 (0%)	0.059 (0.019)	0.022 0.099	0.002 ** (100%)
Median Home Value	-0.000 (0.000)	-0.000 0.000	0.981 (0%)	0.000 (0.000)	-0.000 0.000	0.926 (0%)
% No Home Internet	0.001 (0.034)	-0.065 0.068	0.955 (0.01%)	-0.024 (0.038)	-0.101 0.049	0.520 (5.78%)
% Single Family Housing	-0.038 (0.024)	-0.087 0.009	0.122 (63.71%)	-0.000 (0.030)	-0.060 0.059	0.981 (0%)
Intercept	12.326 (31.194)	-48.962 73.800	0.692 (0%)	-111.644 (38.585)	-189.561 -37.539	0.003 ** (100%)

Note: Pr-In refers to Preliminary to Initial Regulatory, and In-Re refers to Initial Regulatory to Present. Statistical significance of logit model indicated by *p < 0.05, **p <0.01, and ***p < 0.001.

Bridge: Chapter III: Letters of Map Revision on Recently Updated Flood Insurance Rate Maps and Chapter IV: Letters of Map Amendment and Revision Based on Fill Across the Contiguous United States

Chapters III and IV are similar in many ways. They both use statistical methods such as Wilcoxon-Mann-Whitney tests to determine if there are significant differences for socio-economic variables between counties or census tracts with map change versus those without map changes. Chapter III focuses on map changes by Letters of Map Revision, which alter Flood Insurance Rate Maps because of approved changes to hydrology and hydraulic models. Chapter IV instead focuses on Letters of Map Amendment and Letters of Map Revision Based on Fill, which are due to raising the elevation of a building or more precise topographic measurements.

CHAPTER IV

LETTERS OF MAP AMENDMENT AND REVISION BASED ON FILL ACROSS THE CONTIGUOUS UNITED STATES

Introduction

Predicting flood hazard is an essential part of flood preparation, management, and mitigation. Scholars from a wide variety of fields have provided important contributions to the many ways that inform predictions of flood hazard. Some of these contributions include improving understandings of how hydrology and hydraulics inform mapped representations of flood hazard (Md Ali et al., 2015; Saksena and Merwade, 2015; Fereshtehpour and Karamouz, 2018; Muthusamy et al., 2021), how flood maps are social constructions of the data provided (Lane, 2014; Haughton and White, 2018; Elliott, 2021a), and how who is included in decision making determines decisions about flood hazard and mapping (Landström et al., 2011; Lane et al., 2011b; Lane, 2014).

While these contributions have advanced understandings of depicting flood hazard, studies that investigate alterations to flood hazard maps over time have largely been divided along physical or human geography (and related discipline) lines. For example, research on physical flood modeling mainly focuses on developing new models and debating the advantages of certain hydrologic and hydraulic methods over others (Wing et al., 2017; Jafarzadegan et al., 2018; Woznicki et al., 2019). This work is then often combined with various socio-economic metrics to determine vulnerability or resilience (Wing et al., 2018; Qiang, 2019). While these methods are beneficial to understanding potential relationships between physical and social processes, they usually obscure or minimize the social construction process and who has power to decide and on what grounds decisions are made. In contrast, studies on power and social construction of flood mapping make findings sound as though changes always end up being due to money and power, with the physical environment taking backseat, if it is considered at all (Wilson and Kousky, 2019; Pralle, 2019; Lea and Pralle, 2021). While there has been recent research that has begun to investigate biophysical and human geographic aspects of flood map alteration together (Elliott, 2021a; Frazier et al., 2020), more work is needed in this area.

The goal of this paper is to theorize and examine the physical, social, and technological aspects that affect flood map production for a system that affects how millions of people interact with flood hazard. This will be achieved by investigating and quantifying Letters of Map Amendment to Flood Insurance Rate Maps in the United States National Flood Insurance Program. Letters of Map Amendment alter what buildings reside within what FIRMs designate Special Flood Hazard Areas (SFHAs), or zones with one percent or greater probability inundation based on hydraulic predictions of historic hydrologic data and elevation models. While FIRMs are created by contracted technical experts such as engineers, people living in or who own a building within SFHAs can submit Letters of Map Amendment to have their building changed to outside the SFHA if they can obtain more precise and accurate elevation data to show the property is above the Base Flood Elevation, or the elevation to which the flood waters of the SFHA are predicted to rise. Evaluating where LOMAs occur, the socio-economic characteristics of places with occurrence or absence, who is involved in the LOMA process, and how the process works will collectively provide greater insight into this specific system as well as more general knowledge about the interaction between the physical, social, and technological factors affecting flood mapping.

This paper advances through the following sections. In the section titled “NFIP Background” I provide contextual information on the National Flood Insurance Program before I theorize the physical processes and human characteristics that should increase or decrease flood map alterations over time in the section named “Hypothesizing where LOMAs and LOMR-Fs occur on FIRMs”. I then describe the methodologies I used in the “Methods” section before presenting my findings in the “Results” section. The “Discussion and Conclusion” section provides my interpretations and summary of the results in broader context to this study.

NFIP Background

The United States National Flood Insurance Program (NFIP) is operated by the Federal Emergency Management Agency (FEMA). FEMA oversees the production of Flood Insurance Rate Maps (FIRMs), which depict areas of varying flood hazard and are created and updated per United States county. The extent of Special Flood Hazard Areas (SFHAs) on FIRMs, which are areas predicted to have one percent or greater probability of being inundated annually, is determined by comparing the elevation which the SFHA floodwaters are predicted to rise to (called the Base Flood Elevation) against elevations of locations represented in a Digital Elevation Model. To determine if a building intersects and is considered within the SFHA, the Base Flood Elevation (BFE) is compared to the lowest adjacent grade or elevation of the building to be insured. Buildings whose lowest level is below the BFE are mapped inside the SFHA, while buildings with elevations above the BFE are mapped outside the SFHA.

One difficulty NFIP faces is that flood insurance is priced and sold based on the flood hazard for an individual property, but producing flood hazard maps across the United States at such fine detail is rarely considered economical. Because of this, FEMA's hired contractors who produce FIRMs most frequently use DEMs derived from topographic maps (such as those as part of the National Elevation Dataset, or NED) or LiDAR to cost-effectively map flood hazard across the United States. These elevation datasets have a larger range of uncertainty compared to more accurate and precise methods that could also be used, such as land surveying. For example, studies have shown older USGS NED maps have 2-20 meters of vertical uncertainty (Li and Wong, 2010) and LiDAR to have a smaller uncertainty anywhere from 0.05 meters up to 1.5 meters (Aguilar et al., 2010). Both of these ranges of uncertainty could be important for determining if a building is inside or outside a SFHA because BFEs and building elevations on FIRMs are determined by increments of 0.1 feet.

The accuracy and precision of a DEM is one of the main factors that can determine which flood zone(s) make up a SFHA. The SFHA on a FIRM is not a homogenous area, but rather is an aggregation of various flood zones that are determined by the type of flooding as well as the data quality and methods used to quantify flood hazard (Horn and Webel, 2019). For example, flood predictions near large population centers likely will rely on a more accurate and precise elevation dataset, and thus might have a different flood zone designation, than the same type of flooding source near few people and buildings that uses more approximate elevation data. Summary descriptions of the various flood zones that are aggregated to form SFHAs are provided in Table 1.

Besides FEMA authorizing the creation of a new FIRM, there are two ways FEMA recognizes that a building can be shown to be no longer inside the SFHA: (1) if a higher precision and/or accuracy method like land surveying is used to determine an updated elevation; or (2) physically altering the elevation of a building. The first way is how a Letter of Map Amendment (LOMA) is obtained. FEMA allows a property resident or owner the ability to submit a request to review more precise and accurate elevation data that has been collected by licensed engineers or land surveyors that, if approved by FEMA, will alter the SFHA designation for a building. The second method of physically raising the lowest elevation of a building so that it resides above the Base Flood Elevation describes a Letter of Map Revision based on Fill (LOMR-F). This is most often achieved using materials such as fill dirt or pylons. Both LOMAs and LOMR-Fs are audited by FEMA engineers to determine if the submitted data meet minimum standards. If FEMA approves, the LOMA or LOMR-F go into effect. But if the appropriate data is not provided, or the lowest elevation of the building as shown by the LOMA or LOMR-F is still below the BFE, the LOMA or LOMR-F will be denied.

There are a few other ways that individual buildings can also be re-mapped or shown outside of the SFHA. One of these is known as a Letter of Map Amendment Out As Shown. Sometimes a mortgage lender will not provide a mortgage to a homebuyer (or a mortgage at a reduced rate compared to a home within the SFHA) unless the property has been verified by FEMA outside of the SFHA. An evaluation of a FIRM by FEMA for a property that appears outside the SFHA based on map interpretation, without any re-measurement, leads to this type of map amendment being issued. Other types of map amendment are specific versions based on the flood zone type in which the building resides. For example, a Letter of Map Revision for a Floodway (LOMR-FW) is an exemption for a building within the floodway of a river. A floodway is part of a river channel or similar watercourse where the discharge of the BFE must be able to pass without increasing above a designated height (FEMA, 2020b). A Letter of Map Revision for a Velocity Zone (LOMR-VZ) is a letter of map revision for a VE zone, which also requires more stringent review than just elevation to validate the building should indeed be outside the SFHA. All of these types of Letters of Map Revisions and Amendments can also be denied by FEMA if they do not meet minimum qualifications. Collectively, all of these types of Letters of Map Amendment and Letters of Map Revision that affect a single building are called "MT-1s" by FEMA. In contrast, changes to flood hydraulics in an area that often affect a larger area and multiple buildings, such as constructing a new culvert or bridge, or a property developer building a new neighborhood, require a "MT-2". These "MT-2s" are also called Letters of Map Revision (LOMRs). This paper only focuses on analyzing "MT-1s" because previous work has investigated elements of "MT-2s" (Pralle, 2019; Wilson and Kousky, 2019; Lea and Pralle, 2021), while no work to my knowledge has investigated "MT-1s".

In theory, by this process some buildings should be mapped into the SFHA over time while others are mapped out. However, in reality, LOMAs only are submitted to change buildings from inside to outside the SFHA. This is because there is no difference in the insurance benefits that can be obtained from buying an insurance policy whether a building is inside or outside the SFHA, but insurance premiums are often hundreds to thousands of dollars lower per year outside versus inside the SFHA (FEMA, 2018a). Similarly, in theory the residents or owners of every building in the SFHA should at least seek a LOMA if not LOMR-F. However, there are costs associated with land survey and submitting a LOMA or LOMR-F, as well as the cost of raising a building for LOMR-Fs. Because of these costs, people with greater means and wealth might pursue MT-1s more frequently than people with less means and wealth.

Hypothesizing where LOMAs and LOMR-Fs occur on FIRMs

This section hypothesizes where LOMAs and LOMR-Fs, as well as denials for each, will occur more or less frequently. I hypothesize there are three primary factors that determine where LOMAs, LOMR-Fs, and their denials occur, as well as how many occur per a unit of study such as a census tract or county. Recognizing that LOMAs and LOMR-Fs are specific to the National Flood Insurance Program flood maps, in this section I talk about changes to hypothetical flood maps generally while using LOMAs and LOMR-Fs as examples of alterations to predicted flood area based on topographic changes.

In the hypothetical flood maps envisioned, I assume that hydrology (discharge) and the hydraulic model used (as well as parameters within that model) to create the predicted inundated area remains the same for each map. I assume as well that each predicted inundation area is initially determined using a DEM where the elevational uncertainty is 1 foot (about 0.3 meters) or greater, similar to DEMs such as those from the United States NED. Thus, changes to representations of elevation on DEMs, whether by more precise measurement or by altering the land elevation, are the only ways the extent of inundated area change.

The first factor determining the number of inadvertent inclusions (LOMAs) and increased elevations for a building that could occur per areal unit of observation is the number of buildings in the predicted inundated area (e.g., the SFHA on FIRMs). For example, in the empirical observations provided later in this paper, the areal units are United States Census Tracts. The number of buildings in the predicted inundated area sets the maximum number of combined inadvertent inclusions and elevated buildings that could be obtained, as hypothetically every building could either have been inadvertently included in the predicted inundated area or could be elevated above the elevation of predicted flooding. However, the reasons why, and thus how many, inadvertent inclusions versus raised buildings would be observed will differ based on the original DEM used.

I assume the DEM precision and accuracy will first be improved to determine the number of inadvertent inclusions before buildings are elevated. The second factor that specifically determines the number of inadvertent inclusions that could occur is what I call the false positive potential. This refers to the number of buildings that are found to have been falsely been mapped inside the original predicted inundation area with the less precise DEM elevations when more precise and accurate elevation data show the building is actually a higher elevation than the predicted floodwaters elevation. False negatives could also occur for buildings initially shown outside the inundated area that are determined to actually be inside the predicted flood area with more precise elevation data, but these are not investigated in this study because in NFIP people only seek false positives.

The buildings mapped in the flood area by both the less and more precise elevation models can only be changed to outside the flood area by raising their elevation above the flood water elevation. Assuming any building inadvertently included in the predicted flood area does not also raise the elevation of the building, the maximum number of buildings that could be raised up above the predicted flood elevation would be the difference between the number of buildings inadvertently included and the total number of buildings in the predicted flood area.

While total potential change and false positive potential set the maximum number of inadvertent inclusions and elevated buildings, a third factor hypothesized to affect inadvertent inclusions and elevated buildings in a system like NFIP where property residents can seek map change is socio-economic characteristics. This is hypothesized because data collection for LOMAs and LOMR-Fs in NFIP cost money (LOMR-F also have the cost of elevating the structure). This hypothesis is also supported by past literature that has found wealthier and socially advantaged people more often have the time and ability to persevere navigating federal disaster aid or mitigation programs (Domingue and Emrich, 2019; Loughran and Elliott, 2021). Assuming aggregated socio-economic data like median income for an area such as a census tract and that places with similar numbers of buildings in the SFHA are being compared, I hypothesize that places with higher wealth indicators like median income will have higher rates of inadvertent inclusions and elevated buildings than places with lower socio-economic wealth and status metrics.

In a public insurance program like NFIP, another factor that could affect the number of inadvertent inclusions and raised buildings are public policy changes that change the insurance pricing or otherwise affect aid or payments when a flood event occurs. For example, if pricing for insurance within the predicted flood zone were to increase, this could provide greater incentive for property residents to seek an inadvertent inclusion or raise the elevation of their building. This could also extend beyond insurance to other ways mapping might affect disaster aid.

Although this study analyzes the number of buildings in the SFHA and socio-economic characteristics in relation to MT-1s, LOMAs, LOMR-Fs, and their denials, there is not a way to reasonably obtain land survey grade elevation data for each building in the SFHA across the United States to assess false positive potential. Instead, this study uses SFHA flood zones as a proxy for elevation data quality (Table 1). I hypothesize that when comparing the percentage of buildings in each flood zone to the percentage of LOMAs and LOMR-Fs per flood zone type, LOMAs will occur proportionally more in flood zone types like A and V that use approximate methods and less in flood zones that use higher accuracy and precision methods such as AE, AO, AH, A99, and VE zones. In contrast, I hypothesize that flood zones with higher precision methods will have proportionally higher rates of LOMR-Fs and vice versa because LOMR-Fs will be used more where there is low elevation uncertainty and the only way to change from inside to outside the SFHA is by increasing the elevation of the building. The null hypothesis is that there will not be distinguishable differences between the proportion of LOMAs and LOMR-Fs in these flood zones and the percentage of buildings in the flood zones.

Methods

I included MT-1s in my initial analysis if: (1) the MT-1 was submitted between January 1, 2013 to December 31, 2018, and (2) if the MT-1 was located in a county that had a county-wide FIRM issued before January 1, 2013. I used the 2013-2018 time frame because it allowed me to compare a large number (n = 1920) of counties where MT-1s occurred during the same time period (Figure 1). Beginning earlier than 2013 would have reduced the number of study counties because fewer counties would not have yet issued a Flood Insurance county-wide study, while starting after 2013 would have reduced the study period and would not have added a large number of additional study counties.

I obtained four data sources to begin my analyses: (1) PDFs containing information about MT-1s, (2) United States census tracts, (3) FEMA Flood Insurance Rate Maps, and (4) Microsoft United States building footprints. I acquired the PDFs, which contained basic information about every MT-1 submitted to FEMA, from FEMA's Map Service Center website (FEMA, 2020d). I also downloaded the Flood Insurance Rate Map Geographic Information System (GIS) geodatabase files for each contiguous US state from FEMA's Map Service Center. The United States Census Bureau website was the repository from which I obtained the United States census tract shapefiles (United States Census Bureau, 2020), and I downloaded GIS layers containing building footprints for each state from Microsoft's open data of all 2018 United States buildings (Microsoft, 2018).

Once I downloaded the MT-1 PDFs from FEMA's Map Service Center website, I wrote and ran an R script that extracted the address, latitude, longitude, designation, date of issue, and identifying case number from the PDFs to comma delimited files for each state. When I began preliminary data analysis using the latitude and longitude values extracted from the PDFs, I determined that a significant number of these points were being located in the incorrect census tract when compared to latitude and longitude values derived from geocoding the extracted addresses. Due to this, I decided to geocode all MT-1s using a python script I wrote that called Google's Geocoding API. I then compared the geocoded latitude and longitude for each MT-1 to the latitude and longitude values extracted from the PDFs. If the PDF extracted and geocoded latitude and longitude values were located in different census tracts, I determined and corrected the difference in the geocoded data set. For full details on the steps used to extract, clean, and prepare the MT-1s for analysis, see Appendix B.

I transformed the census tracts, Flood Insurance Rate Maps, and building footprint GIS layers to the United States Albers Equal Area projected coordinate system to maintain accurate area representations. Overlaying these GIS files with the geocoded latitude and longitude locations for the MT-1s calculated the observed number of MT-1s and buildings in each flood zone type per census tract. I included a census tract in the analysis dataset if the census tract intersected the other GIS layers and met the following criteria: (1) the FIRM was released before 2013; (2) there were more than 0 buildings in the Microsoft building footprints layer; (3) the SFHA extent was greater than 0 square kilometers. I then calculated summary statistics for the data, including SFHA, the number of buildings in the SFHA, and the number of MT-1s. I also calculated the number of MT-1s by designation type to determine the more and less prevalent designation types pursued by propertied interests and issued by FEMA.

To investigate if there was a relationship between the LOMA and LOMR-F designation types and the flood zones in which they were located across the contiguous United States, the number of LOMAs and LOMR-Fs located within each flood zone type were summed for all census tracts. Other designation types were not investigated because they made up a small proportion of MT-1s or were not influenced by altering data or buildings. The percentage of all MT-1s, LOMAs, and LOMR-Fs located in each flood zone type were compared to the percentage of buildings intersecting each flood zone type to test the hypothesis that LOMAs occur in less precise and accurate flood zones while LOMR-Fs occur with greater frequency in more precise and accurately measured flood zones.

To analyze the relationship between designation types and sociodemographic variables at the census tract scale, I acquired American Community Survey (ACS) 2013 to 2017 five-year estimate data. I chose four categories to test the relationship with the ACS variables: (1) all MT-1s, (2) LOMAs, (3) LOMR-Fs, and (4) LOMA and LOMR-F denials. The number of rulings for each of these four designation types were the dependent variable(s), while the variables from the ACS were the independent variables. I chose the following ACS variables for analysis: number of households, median income, percent of people 25 years and older with a bachelor’s degree or higher, percent of people below poverty, percent of people renting a residence, percent of homeowners with a mortgage, percent of non-white residents, per capita income, median year of building construction, median home value, percent of residences without home internet, and percent of residences that were single family housing units. I chose these variables because they are proxies for individual or community wealth, knowledge of mitigating hazard, and knowledge of navigating government bureaucracy of programs like NFIP and the process of Letter of Map Revision submission, which previous research argues are important predictors where flood maps are altered (Wilson and Kousky, 2019; Lea and Pralle, 2021). I hypothesize that places with more people, higher indicators of wealth, and higher rates of formal education will more likely have changes to their SFHAs than places without MT-1s.

During data exploration, I used Kolmogorov-Smirnov tests for data normality and determined that the number of MT-1s and number of buildings per census tract rejected the null hypothesis of these data being normally distributed. Due to this finding, I employed Wilcoxon–Mann–Whitney tests and binary logistic regressions. In the logistic regressions, I also analyzed if there was a statistical difference in the occurrence of the four chosen designation categories (all MT-1s, LOMAs, LOMR-Fs, LOMA and LOMR-F denials) between census tracts with and without coastal flooding zones ("V" zones) by assigning a coastal dummy variable of "1" if a census tract had a SFHA containing "V" or "VE" flood zones.

Because the ACS five-year estimates are survey samples and contain margins of error around the reported estimate for a given variable, I used uncertainty analysis in the Wilcoxon-Mann-Whitney tests and Binary Logistic Regressions to robustly analyze the relationships between the four chosen designation categories and ACS variables. For each ACS variable and census tract, the R script I wrote and ran used the ACS estimate and 95% margin of error to define a range of possible values from which a random value was picked on the i'th iteration of 10,000 iterations. On each iteration, I combined the randomly chosen ACS variable value with its matching designation categories data for each census tract before using the Wilcoxon-Mann-Whitney tests and Binary Logistic Regressions. The result was a probability distribution of statistical significance for each ACS variable. The p values I report in Table 5 and Table 6 are the 95th percentile of the 10,000 iterations. I determined an ACS variable was statistically significant if in 9,500 or more iterations the variable was statistically significant. To help contextualize the magnitude of significance for each variable, I also included the percentage of the 10,000 random samples that were statistically significant and the z value of the test with the 95th percentile out of the 10,000 iterations in the tables.

Results

There were 44,824 census tracts in the 1,920 study counties that were analyzed. Of these, 23,094 census tracts had one or more MT-1 submissions, which was 51.5% of the total number of census tracts. Table 2 shows summary statistics at the census tract scale. The median size of a census tract was 7.82 square kilometers, but there were a small proportion of very large census tracts. The median number of buildings for the census tracts was 1,668, with a standard deviation of 1,123 and a maximum of 19,374 buildings. The median size covered by the Special Flood Hazard Area for a county was 0.83 square kilometers, while the median percentage of census tract area covered by the SFHA was 8.12 %. Similarly, the median number of buildings in the SFHA was 26, but the median percentage of buildings in the SFHA was only 1.56 %. In other words, Table 2 shows that for many census tracts, until high percentages of the census tract are covered by the SFHA, the matching percent of buildings in the SFHA were usually lower. Kolmogorov-Smirnov tests for all variables were statistically significant ($p < 0.001$), leading to a rejection of the null hypothesis of normal distributions and use of non-parametric statistical tests in later analyses.

The number of MT-1s divided into their respective designation types is displayed in Table 3. The Letters of Map Amendment (LOMA) are the most common, being almost 70% of all MT-1s submitted between 2013-2018. The LOMA denials (LOMA-DEN), LOMA Out As Shown (LOMA-OAS), and Letter of Map Revision Based on Fill (LOMR-F) categories each were close to 9% each, comprising most of the remainder of all MT-1 submissions. Adding up all denial (DEN) types, all denials together only accounted for 9.41% of submitted MT-1s. In other words, about 90.5% of all MT-1 submissions were successful.

The number and percentages of all MT-1s, LOMAs, and LOMR-Fs subdivided by flood zone type are shown in Table 4. The table also includes the number and percentage of buildings in each flood zone for comparison. When examining all MT-1s together, it can be observed that flood zones created with approximate hydrologic and/or hydraulic methods (A and V zones) have about an equal percentage (V zone) or greater percentage (A zone) of MT-1 submissions than buildings percentage, while the flood zones with more precise and accurate methods (AE, AH, AO, A99, VE) have a lower percentage of MT-1 submissions compared to their percentage of SFHA buildings. For LOMAs, the A zone has a larger percentage of LOMAs submitted (37.07%) compared to the percentage of buildings in the SFHA (21.28%), but other flood zone LOMA percentages are lower than the percentage of buildings in the SFHA. For LOMR-Fs, only the AE zone has a larger percentage of LOMR-F submissions compared to the percentage of buildings, while the other flood zones have lower LOMR-F submission percentages than the percentage of buildings in the SFHA.

Most sociodemographic variables from the American Community Survey had statistically significant differences in their means when census tracts with any MT-1 submissions were compared to census tract without a MT-1 filed during the study period. The p-values reported for the Wilcoxon-Mann-Whitney test results and binary logistic regressions in the following paragraph are the 95th percentile p values of all p values out of 10,000 random samples set by the margins of error. Table 5 shows results for the

Wilcoxon-Mann-Whitney tests at the census tract scale. For the comparison between census tracts with one or more MT-1 submission versus census tracts without a MT-1 submitted during the study period, the only variable that was not statistically significant was Percent of Homeowners with a Mortgage. The Number of Households (z = -36.9428), Median Income (z = -22.487), Percent Bachelor's Degree or higher (z = -14.949), Per Capita Income (z = -23.952), Median Year Construction (z = -21.112), Median Home Value (z = -14.481), and Percent Single Family Housing (z = -17.306) all had higher mean values for census tract with a MT-1, while Percent Below Poverty (z = -24.824), Percent Renter (z = -29.635), Percent Non-White Population (z = -37.4), and Percent No Home Internet (z = -16.075) all had lower means for census tracts with MT-1 submissions. For census tracts where there were only LOMA and LOMR-F denials (versus census tracts without a LOMA or LOMR-F denial), the Number of Households, Percent of Homeowners with a Mortgage, Percent Non-White, Per Capita Income, Median Year Construction, and Median Home Value were statistically significant.

Binary logistic regressions were used to test if independent variables from the ACS provided statistically significant predictions of MT-1 submission types occurring in a census tract. Results are shown in table 6. For all MT-1s, LOMAs, and LOMR-Fs, only LOMR-Fs had coastal flood zones as statistically significant. For census tracts with all MT-1s, the odds of a census tract with coastal flood zones ("V" type zones) having one or more MT-1s are very high (odds ratio = 1.579763e+06) compared to a census tract without a coastal flood zone type. Similarly, the odds of a LOMA occurring where "V" type zones are present are 1.2 more times likely than a census tract without a coastal flood zone, while the odds of a LOMR-F occurring where there is a "V" type zone in the census tract is 1.6 times more likely than census tracts without “V” type zones. Many variables that were statistically significant for the binary logistic regressions were the same ones that were statistically significant for the Wilcoxon-Mann-Whitney tests.

Discussion and Conclusion

By quantifying the MT-1s submitted in the attempt to change a building from inside to outside of the Special Flood Hazard Area (SFHA) on Flood Insurance Rate Maps (FIRMs) across the contiguous United States between 2013 and 2018, I found that the majority of MT-1 submissions were approved Letter of Map Amendments (LOMAs) and that approximately 90% of submitted MT-1s are approved. This is essentially the same as the 89% approval rate cited in Dedman (2014). I also discovered that LOMA submissions were proportionally over-represented in flood zones such as A and V that were created with more approximate methods, while the flood zones like AE and VE produced using more precise and accurate methods were proportionately underrepresented. This finding supports the hypothesis that LOMA submission rates may be influenced by flood zone data quality.

My results show that many socio-demographic variables have a statistically significant difference between places that had MT-1 submissions between 2013 and 2018 and places that did not. This result supports previous findings that larger and more affluent communities have greater resources to lodge appeals or revisions (Dedman, 2014; Wilson and Kousky, 2019; Lea and Pralle, 2021). However, the data also contain new insights, such as the finding that places with LOMA and LOMR-F denials had statistically significant higher per capita income and median home values than places that did not have a denial. This result provides evidence against a hypothesis that denials occur more frequently in places with lower wealth, but supports the hypothesis that personal and community wealth is an important factor in the ability to submit a LOMA or LOMR-F regardless if it ends up approved or denied. However, there are very likely 'missing' denials from this dataset that might alter these results, as some property residents who find via land survey the elevation of their structure is still below the Base Flood Elevation (BFE) likely do not submit a MT-1 they are sure will be denied.

Letters of Map Revision Based on Fill were 1.6 times more likely to appear in census tracts with a coastal flood zone than a census tract without. One potential reason for this observation would be that because almost all of the coastal zones in study were VE zones with relatively high accuracy and precision elevation data, the only way for many properties to successfully change from inside to outside SFHA would be with LOMR-F. Because coastal areas often have communities with higher affluence than places inland (Wilson and Kousky, 2019), they also more likely have the ability to pay for renovations to a structure or build a new elevated structure as part of the LOMR-F. My finding that coastal zones did not have statistically significant differences for LOMAs and MT-1 submissions, which contrasts with the importance differences between coastal and inland flooding observed by Wilson and Kousky (2019) and Lea and Pralle (2021), could also show an important difference between MT-2s and MT-1s. For MT-2s, coastal zones like VE seem to be more frequently altered because of hydrology and hydraulics, but alterations are not any more common due to inadvertent inclusions of structures based on incorrect elevation as shown in this study.

The result showing that the median year of construction for LOMR-Fs is statistically significantly much more recent than census tracts without a LOMR-F provides evidence, along with similar findings for LOMRs by Lea and Pralle (2021), that LOMRs and LOMR-Fs may often be tied to new construction. This makes sense because to place fill dirt for a building or raise it, the structure either must be built new after the fill dirt is placed or be re-built in some way so that the renovation date is considered the year built.

While many sociodemographic indicators are statistically significantly different in favor of places with LOMR-Fs having more power than those without LOMR-Fs, one seemingly contrary observation was that median home value was statistically significantly lower for places with LOMR-Fs than places without. A possible explanation is that this might be because many structures filing for LOMR-Fs are not residential properties. Although this study cannot quantify the types of land use for MT-1 submissions, I qualitatively observed that many of the LOMR-Fs seemed to occur for non-residential (e.g., commercial or industrial) types of land use when performing latitude and longitude corrections for MT-1s. So, one possibility is that residences in the same census tracts as these commercial or industrial LOMR-Fs have lower property values because they are less desirable places to live next to these land use types. Future research could investigate MT-1s at the individual property scale to gain insight into the breakdown of land use types for MT-1 submissions.

There are a few limitations or assumptions my research could not attend to. One of the limitations is that FIRMs are not static maps, and the SFHAs could have been updated between 2013 and 2018, resulting in change of SFHA extent and different SFHA and number of buildings in the SFHA than observed from the August 2019 maps used in this research. While this likely affected some counties in my study, I assume the overall effect on the results is negligible. One assumption is that the results can represent MT-1s for other time periods beyond the scope of this analysis. Because the 2013-2018 time period is arbitrary, different time periods might lead to different results. Another assumption is that the temporality of MT-1 submissions does not affect these results, but there may be an uneven temporality to the rates at which MT-1s are submitted in different places. For example, after a new map is updated, there may be a spike in MT-1 submissions within the first couple years, but then the MT-1 submissions may decrease after a few years. If my analysis observed a county FIRM after this initial period, I might miss many of the MT-1s submitted for that FIRM. Similarly, MT-1 submissions likely are much higher where new property development is occurring or might rise in the years after a flood event occurs in a community, also affecting where more MT-1 submissions are occurring. To better understand these trends, future research on MT-1s should also use a temporal analysis to understand the pattern over time of submissions.

Although the intentions of the LOMAs and LOMR-Fs seem just by allowing floodplain residents to amend maps through improving data quality, through actual implementation I found signals in my data analysis that cost and/or knowledge of access are likely inhibiting access to groups disadvantaged or dispossessed in those ways. For example, based on Z scores, the biggest statistical difference in the Wilcoxon-Mann-Whitney tests was for percent non-white population for MT-1 submissions. The average percentage of non-white population for a census tract with a MT-1 submission was 20%, while the average percentage of non-white population for census tracts without a MT-1 submission was 29%. This result, similar to a result found by Lea and Pralle (2021) for LOMRs, is not necessarily an indicator that race is being used to discriminate where MT-

1s or MT-2s are being submitted, but rather suggests that communities of color likely have fewer resources to submit MT-1s and MT-2s, even when studies show many non-white communities to be at high risk of flooding (National Academies Press, 2019; Frank, 2020).

The finding that MT-1 submission occurs more frequently where socio-economic indicators are higher supports prior work showing how various aspects of flood risk mapping can increase already existing inequalities (Maantay and Maroko, 2009; Paganini, 2019; Herreros-Cantis et al., 2020; Elliott, 2021a). The unequal ability to access MT-1 submissions reinforces environmental injustices of flood hazard mapping because property residents who can ‘facilitate’ living in hazardous places by obtaining a LOMA or LOMR-F create physical or social protections for themselves, while those who are ‘marginalized’ by NFIP’s costs have to choose between expensive insurance whose cost is too difficult to bear or going without insurance and hoping governmental aid will be provided if a flood occurs (Collins, 2010). In other words, MT-1 submissions show how the social (re)construction of FIRMs unequally determine who is removed or remains in the SFHA. Before and after a successful MT-1 submission the FIRMs are ‘correct’, but those with greater means have more ways they can attempt to change the initially provided hazard representation to their benefit.

It should also be noted that LOMAs (but also potentially LOMR-Fs) do not necessarily make these affected buildings any less exposed to hazard. Because only elevation data is being considered for a LOMA or LOMR-F, if flood hazard extent of the SFHA is also underrepresented by the hydrology or hydraulics, properties will be at higher flood risk than shown by the FIRMs. Recent studies using alternative hydrologic and hydraulic approaches argue that many FIRMs underrepresent future flood hazard (Wing et al., 2017, 2018). Indeed, if flood frequency and magnitude is increasing but data used to produce flood maps are based only on the past, more communities and individuals who are issued LOMAs or LOMRs and believe they are safe will believe they no longer need to buy insurance. This has already happened in Central, Louisiana, where the community was inundated by a flood just after a significant area of the city was issued a LOMR and many people decided to stop buying insurance (Mukerji, 2020).

As flood hazard continues to change with updates to biophysical representations and predictions of flood hazard, questions of accuracy and pricing will continue to be important conversations in the National Flood Insurance Program. Understanding inequalities in the ability of those mapped into predicted high hazard flood zones to alter their costs to benefits ratio based on underlying data quality can help guide important broader decisions the United States must make in regards to equity of flood hazard preparation and management as the risks and costs of floods increase in the USA (Nance, 2015; Elliott, 2019; Herreros-Cantis et al., 2020; Smiley, 2020; Lea and Pralle, 2021). Continuing this work that analyzes property resident-initiated alterations to Flood Insurance Rates maps will help provide understandings of who benefits and who does not from the organization of NFIP and hopefully will help to implement more equitable solutions.

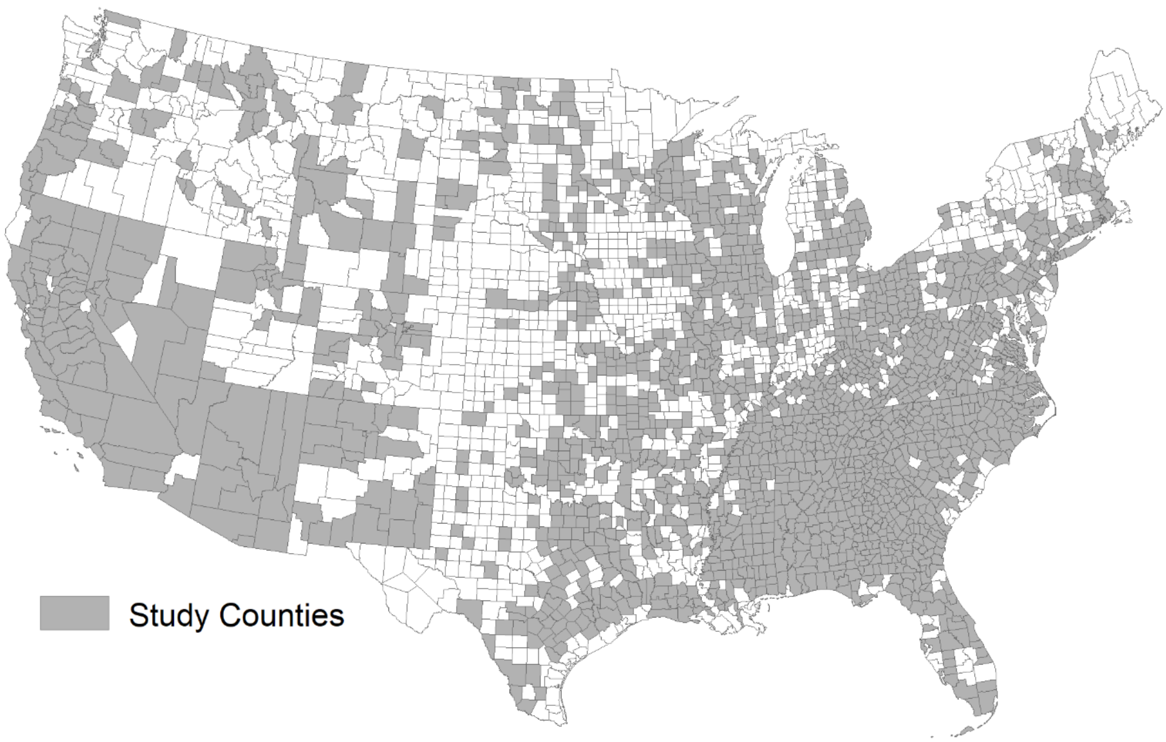

Figure 1. Map showing study counties included in this analysis (n = 1920)

Table 1. Summary of SFHA flood zones on FIRMs. Adapted from Horn and Webel, 2019.

Flood Zone Symbol	**Description**
A	Area of 1% or greater yearly flood hazard without measured elevations
AE	Area of 1% or greater yearly flood hazard with surface elevations measured
AO, AH	Area of 1% or greater yearly flood hazard having shallow water depths (AO) or unpredictable flow paths (AH)
A99	Area of 1% or greater yearly flood hazard with protection such as dikes, dams, and levees
V, VE	Area of 1% or greater yearly flood hazard that are inundated by tidal floods

Table 2. Summary statistics for census tracts in the analysis. n = 44,824

	Minimum	**25th Percentile**	**Median**	**Mean**	**75th Percentile**	**Maximum**	**Standard Deviation**
Area (sq. km)	0.064	2.78	7.82	95.16	49.22	22,504.55	469.82
Number of Buildings	1	1,105	1,668	1,877.29	2445	19,374	1,123.34
SFHA (sq. km)	9.14e-09	0.17	0.83	10.44	4.79	3503.50	49.09
Buildings in SFHA	0	5	26	104.73	92	6,022	249.64
% SFHA	4.37e-08	3.51	8.12	14.68	17.94	100	18.15
% of buildings in SFHA	0	0.350	1.56	6.51	5.08	100	14.90
MT-1 submissions	0	0	1	2.83	3	439	8.40

Table 3. Letter of Map Change Submissions between 2013 and 2018 by designation type. n = 126,887

Designation Type	**Percent (number)**
LOMA	69.77 (88,531)
LOMA-DEN	8.77 (11,130)
LOMA-OAS	8.95 (11,357)
LOMR-F	8.85 (11,239)
LOMR-F-DEN	0.63 (811)
LOMR-F-OAS	0.00 (3)
LOMR-FW	2.96 (3,760)
LOMR-FW-DEN	0.00 (7)
LOMR-FW-OAS	0.00 (1)
LOMR-VZ	0.02 (38)

Table 4. Shows the number and percentage of all submitted MT-1s, Letters of Map Amendment, and Letters of Map Revision Based on Fill submitted to in each flood zone type and the number and percentage of buildings in each flood zone. SFHA building sum = 4,694,499

Flood Zone	% MT-1s submitted (number submitted)	% LOMAs submitted (number submitted)	% LOMR-Fs submitted (number submitted)	% buildings in SFHA (number)
A	32.77 (41,578)	37.07 (32,752)	20.90 (2,340)	21.28 (999,151)
AE	60.23 (76,424)	56.08 (49,541)	70.56 (7,897)	66.60 (3,126,745)
AH	5.06 (6,421)	5.32 (4,708)	5.40 (605)	6.31 (296,505)
AO	1.68 (2,137)	1.38 (1,221)	2.81 (315)	3.37 (158,353)
A99	0.03 (41)	0.01 (6)	0.16 (19)	0.71 (33,664)
V	0.00 (2)	0.00 (0)	0.00 (0)	0.00 (77)
VE	0.21 (274)	0.12 (107)	0.13 (15)	1.70 (80,004)

Table 5, part 1. Wilcoxon-Mann-Whitney test results for MT-1 Submissions and Letters of Map Amendment. Statistical significance for Tables 5 and 6 indicated by *p < 0.05, **p <0.01, and ***p < 0.001.

	With MT-1 (n = 22,536)	Without MT-1 (n = 16,283)	Significance	With LOMA (n = 18,280)	Without LOMA (n = 4,256)	Significance
	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%) Z	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%)
Number of Households	1,875.73 (835.824)	1,603.77 (729.97)	0.000 *** (100%) -36.94	1,890.04 (842.49)	1,814.26 (811.665)	0.000 *** (100%) -5.33
Median Income	65,199.32 (30679.1)	60,453.36 (32406.5)	0.000 *** (100%) -22.48	65,554.83 (30613.0)	63,315.37 (30666.4)	0.000 *** (100%) -5.44
% Bachelor's Degree or higher	30.74 (18.27)	29.02 (19.77)	0.000 *** (100%) -14.94	30.72 (18.13)	30.81 (18.83)	0.588 (0%) -0.54
% Below Poverty	13.13 (10.50)	16.48 (13.12)	0.000 *** (100%) -24.82	12.83 (10.22)	14.28 (11.35)	0.000 *** (100%) -6.92
% Renter	30.53 (19.72)	36.89 (22.51)	0.000 *** (100%) -29.63	29.73 (19.34)	33.56 (20.72)	0.000 *** (100%) -11.26
% Homeowner with Mortgage	62.54 (16.09)	62.05 (18.87)	0.292 (58.11%) -1.05	62.63 (15.77)	62.74 (17.34)	0.376 (46.87%) -0.88
% Non-White	20.20 (20.20)	29.02 (25.15)	0.000 *** (100%) -37.40	19.23 (19.64)	23.76 (21.95)	0.000 *** (100%) -13.32
Per Capita Income	32,510.02 (15152.9)	30,214.25 (16158.9)	0.000 *** (100%) -23.95	32,728.36 (15115.9)	31,684.33 (15090.5)	0.000 *** (100%) -5.44
Median Year Construction	1976.82 (15.24)	1973.22 (17.06)	0.000 *** (100%) -21.11	1976.83 (15.03)	1976.80 (16.07)	0.590 (0%) -0.53
Median Home Value	230,689 (183585)	225,900.5 (201277)	0.000 *** (100%) -14.48	232,067.5 (183980)	225,250.5 (178478)	0.001 ** (100%) -3.10
% No Home Internet	21.04 (12.31)	23.79 (14.88)	0.000 *** (100%) -16.07	20.98 (12.15)	21.58 (13.03)	0.116 (70.74%) -1.56
% Single Family Housing	74.05 (20.01)	69.63 (23.47)	0.000 *** (100%) -17.30	74.50 (19.75)	72.00 (20.84)	0.000 *** (100%) -7.31

Table 5, part 2: Wilcoxon-Mann-Whitney test results for Letter of Map Revision Based on Fill and Census Tracts with LOMA and LOMR-F Denials. Statistical significance for Tables 5 and 6 indicated by *p < 0.05, **p <0.01, and ***p < 0.001.

	With LOMR-F (n = 4,759)	Without LOMR-F (n = 17,777)	Significance	With Denial (n = 7,164)	Without Denial (n = 15,372)	Significance
	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%) Z	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%) Z
Number of Households	2,140.34 (1064.58)	1,804.33 (751.76)	0.000 *** (100%) -20.01	1,936.53 (856.12)	1,846.63 (828.90)	0.000 *** (100%) -7.89
Median Income	66,983.49 (30243.8)	64,626.4 (30720.5)	0.000 *** (100%) -6.68	65,271.47 (30345.2)	65,198.24 (30851.9)	0.459 (0.41 %) -0.73
% Bachelor's Degree or higher	32.32515 (17.66)	30.34 (18.39)	0.000 *** (100%) -8.97	30.99 (18.15)	30.63 (18.32)	0.055 (92.53%) -1.91
% Below Poverty	12.45 (10.28)	13.25 (10.50)	0.000 *** (100%) -5.20	12.96 (10.14)	13.15 (10.52)	0.901 (0.14%) -0.12
% Renter	30.41 (19.49)	30.53 (19.68)	0.984 (0%) -0.01	30.38 (19.31)	30.65 (19.92)	0.908 (0%) -0.11
% Homeowner with Mortgage	63.49 (16.00)	62.36 (16.20)	0.000 *** (100%) -4.60	62.22 (15.68)	62.77 (16.25)	0.004 ** (99.94%) -2.83
% Non-White	19.85 (19.10)	20.38 (20.49)	0.439 (24.07) -0.77	19.05 (19.10)	20.71 (20.54)	0.000 *** (100%) -4.76
Per Capita Income	32,984.66 (14643.5)	32,344.95 (15116.2)	0.000 *** (100%) -5.28	33,024.47 (15163.1)	32,363.44 (15094.9)	0.000 *** (100%) -3.82
Median Year Construction	1982.53 (15.04)	1975.317 (14.92)	0.000 *** (100%) -29.50	1975.83 (15.31)	1977.29 (15.18)	0.000 *** (100%) -7.09
Median Home Value	227,361.7 (165748)	231,908 (188754)	0.000 *** (100%) -4.27	237,499.6 (186451)	227,808.2 (182462)	0.000 *** (100%) -4.80
% No Home Internet	19.46 (12.03)	21.52 (12.42)	0.000 *** (100%) -10.87	20.88 (11.81)	21.14 (12.53)	0.764 (0.17%) -0.29
% Single Family Housing	74.23 (19.44)	73.95 (20.15)	0.962 (0%) -0.04	74.04 (19.64)	74.00 (20.19)	0.513 (0.01%) -0.65

Table 6, part 1: Binary Logistic Regression test results for MT-1 Submissions and Letters of Map Amendment.

	MT-1			LOMA		
	Coefficient (Std. Err.)	Lower and Upper 95% Conf. Int.	*p* (%) Z	Coefficient (Std. Err.)	Lower and Upper 95% Conf. Int.	*p* (%) Z
Coastal	14.264 (72.386)	11.755 41.316	0.843 (0%) 0.19	0.172 (0.239)	-0.274 0.668	0.471 (0%) 0.72
Number of Households	0.000 (0.000)	0.000 0.000	0.000 *** (100%) 29.41	0.000 (0.000)	0.000 0.000	0.000 *** (100%) 7.34
Median Income	0.000 (0.000)	0.000 0.000	0.001 ** (100%) -3.23	0.000 (0.000)	0.000 0.000	0.968 (0.2%) -0.03
% Bachelor's Degree or higher	-0.002 (0.001)	-0.004 -0.000	0.003 ** (99.98%) -2.91	-0.005 (0.001)	-0.008 -0.001	0.002 ** (100%) -3.00
% Below Poverty	-0.005 (0.001)	-0.007 -0.002	0.000 *** (100%) -4.16	-0.000 (0.002)	-0.004 0.004	0.826 (9.51%) -0.21
% Renter	-0.005 (0.000)	-0.007 -0.003	0.000 *** (100%) -6.3	-0.005 (0.001)	-0.008 -0.002	0.000 *** (100%) -3.88
% Homeowner with Mortgage	-0.000 (0.000)	-0.001 0.000	0.485 (48.41%) -0.69	-0.000 (0.001)	-0.002 0.002	0.910 (9.67%) -0.11
% Non-White	-0.012 (0.000)	-0.013 -0.011	0.000 *** (100%) -24.60	-0.007 (0.000)	-0.009 -0.005	0.000 *** (100%) -7.98
Per Capita Income	0.000 (0.000)	0.000 0.000	0.022 * (98.61) 2.28	0.000 (0.000)	0.000 0.000	0.952 (0.99%) 0.05
Median Year Construction	0.003 (0.000)	0.002 0.005	0.000 *** (100%) 5.47	-0.004 (0.001)	-0.006 -0.002	0.000 *** (100%) -3.60
Median Home Value	0.000 (0.000)	0.000 0.000	0.954 (0%) -0.05	0.000 (0.000)	0.000 0.000	0.039 * (97.33%) 2.05
% No Home Internet	-0.000 (0.001)	-0.002 0.001	0.652 (16.65%) -0.45	0.000 (0.002)	-0.004 0.004	0.970 (0.11%) 0.03
% Single Family Housing	0.002 (0.000)	0.001 0.004	0.000 *** (100%) 3.80	-0.000 (0.001)	-0.002 0.002	0.908 (0.5%) -0.11
Intercept	-7.551 (1.384)	-10.265 -4.838	0.000 *** (100%) -5.45	10.658 (2.477)	5.812 15.522	0.000 *** (100%) 4.30

Table 6, part 2: Binary Logistic Regression test results for Letter of Map Revision Based on Fill and Census Tracts with LOMA and LOMR-F Denials.

	LOMR-F			Denials		
	Coefficient (Std. Err.)	Lower and Upper 95% Conf. Int.	*p* (%) Z	Coefficient (Std. Err.)	Lower and Upper 95% Conf. Int.	*p* (%) Z
Coastal	0.466 (0.199)	0.063 0.848	0.019 * (100%) 2.33	0.448 (0.171)	0.109 0.784	0.008 ** (100%) 2.61
Number of Households	0.000 (0.000)	0.000 0.000	0.000 *** (100%) 11.77	0.000 (0.000)	0.000 0.000	0.000 *** (100%) 11.18
Median Income	0.000 (0.000)	0.000 0.000	0.968 (0.27%) 0.03	0.000 (0.000)	0.000 0.000	0.036 * (96.83%) -2.08
% Bachelor's Degree or higher	0.000 (0.001)	-0.003 0.003	0.824 (2.79%) 0.22	-0.000 (0.001)	-0.003 0.002	0.791 (3.97%) -0.26
% Below Poverty	0.000 (0.002)	-0.004 0.004	0.968 (0.19%) 0.03	0.000 (0.002)	-0.003 0.004	0.953 (1.22%) 0.05
% Renter	0.012 (0.001)	0.009 0.015	0.000 *** (100%) 7.97	-0.001 (0.001)	-0.004 0.001	0.230 (62.69%) -1.19
% Homeowner with Mortgage	-0.001 (0.001)	-0.003 0.001	0.263 (69.26%) -1.11	-0.002 0.001	-0.004 -0.000	0.012 * (99.03%) -2.49
% Non-White	-0.001 (0.001)	-0.003 0.000	0.089 (85.66%) -1.69	-0.003 (0.000)	-0.005 -0.001	0.000 *** (100%) -4.06
Per Capita Income	0.000 (0.000)	0.000 0.000	0.383 (45.66%) 0.87	0.000 (0.000)	0.000 0.000	0.814 (10.07%) 0.23
Median Year Construction	0.030 (0.001)	0.027 0.033	0.000 (100%) 22.12	-0.010 (0.001)	-0.012 -0.008	0.000 *** (100%) -9.59
Median Home Value	0.000 (0.000)	0.000 0.000	0.002 ** (100%) -3.07	0.000 (0.000)	0.000 0.000	0.000 *** (100%) 3.42
% No Home Internet	-0.002 (0.002)	-0.006 0.001	0.211 (65.56%) -1.24	-0.002 (0.001)	-0.005 0.001	0.265 (59.94%) -1.11
% Single Family Housing	0.005 (0.001)	0.002 0.008	0.000 *** (100%) 4.03	0.000 (0.001)	-0.002 0.002	0.927 (0.2%) 0.09
Intercept	-62.356 (2.728)	-67.725 -57.028	0.000 *** (100%) -22.85	19.528 (2.121)	15.371 23.686	0.000 *** (100%) 9.20

Bridge: Chapter IV: Letters of Map Amendment and Revision Based on Fill Across the Contiguous United States and Chapter V: Property-Scale Analysis of Letters of Map Amendment and Revision Based on Fill in Florida, USA

Chapter IV focuses on analyzing Letters of Map Amendment with socio-economic variables at the census tract scale across the contiguous United States. The limitation here is that there is a mismatch between the scale of analysis (census tract) and the scale of change (individual property). Chapter V investigates Letters of Map Amendment with individual property scale tax lot data in the state of Florida to understand the types of properties obtaining LOMAs and characteristics about residential single family home properties in different Florida counties.

CHAPTER V

PROPERTY-SCALE ANALYSIS OF LETTERS OF MAP AMENDMENT AND REVISION BASED ON FILL IN FLORIDA, USA

Introduction

With climate change now impacting global and regional hydrology, analyses and discussions about flood hazard and vulnerability, as well as how decisions are made regarding flood exposure and resilience, are important to investigate and critique in order to provide knowledge on how damages and inequities of flood risk might be reduced. At broader global and national scales, much important work has been done to show how climate change is altering flood hazard via rising sea levels and altered precipitation regimes (Alfieri et al., 2017; Wing et al., 2018; Marsooli et al., 2019; Bates et al., 2021; Ghanbari et al., 2021; Gudmundsson et al., 2021). Similarly, research has studied the variety of ways governmental and private groups help people prepare for, mitigate losses from, and rebuild from or seek funds to aid relocation when flood events occur, such as direct aid, mitigation, grants, loans, and insurance (Holladay and Schwartz, 2010; Bin et al., 2017; Pravin, 2018; Domingue and Emrich, 2019; Loughran and Elliott, 2021).

There has also been important work done that focuses on how individuals navigate and make decisions about how to manage flood hazard in the plurality of "values" it can put at risk, such as damage to the property and buildings they own or live in, alteration to their livelihoods, and perceptions of fairness in access to flood hazard aid or mitigation (Elliott, 2019, 2021a). Focusing on individual properties and buildings that can be exposed to floodwaters, there are three main actions the property owner or resident might take in the attempt to reduce future flood risk. The first way would be moving to a different property, whether selling the property in the present market or by a planned retreat of multiple structures or of a community (Mach et al., 2019; Siders, 2019; Pinter and Rees, 2021). The second option would be physical alteration by raising the elevation of the property and/or building so that floodwaters cannot or have less likelihood of causing damages (Zhao et al., 2016). A third potential method would be to alter any depictions of the flood hazard as it is presently known, which in turn might affect social benefits related to planning for and paying for future flood damages (Pralle, 2019; Wilson and Kousky, 2019; Lea and Pralle, 2021). For example, if by using a different flood model or elevation dataset a property is shown to have a lower flood hazard than previously depicted, the property might qualify for lower insurance premium payments.

In the United States, one of the primary ways people living in high hazard flood areas interact with preparing for and recovering from flood events is through the National Flood Insurance Program. The NFIP is overseen by the Federal Emergency Management Agency, which produces Flood Insurance Rate Maps that are used to set insurance premium rates based on flood risk. People living in high hazard flood zones shown by the FIRMs, called Special Flood Hazard Areas, have the ability to alter these SFHAs either by elevating their property (called Letters of Map Revision Based on Fill) or by showing with an updated land survey their building resides at a higher elevation than the floodwaters elevation of the SFHA (called Letters of Map Amendment).

Little work has been done to study where buildings have been elevated by Letters of Map Revision Based on Fill or property residents have sought to alter depictions of flood hazard using Letters of Map Amendment. Zhao et al. (2016) examined the relationship between elevating properties and implementing a voucher program related to flood insurance affordability in Charleston County, South Carolina, but the paper did not focus specifically on Letters of Map Revision Based on Fill. Lea and Pralle (2021), which is also chapter III of this dissertation, investigated the relationship between Letters of Map Revision and socio-economic factors for counties and their census tracts where FIRMs had recently been updated, finding that property resident changes to FIRMs altered the SFHA more often where median home values are higher, buildings are newer, and the percentage of white populations are higher. Similarly, chapter IV of this dissertation studied Letters of Map Amendment across almost 2,000 counties and found higher indicators of wealth where LOMAs occurred versus where they did not.

However, one limitation in these past studies has been the inability to perform analyses at the individual property scale. Previous studies have relied on aggregated census tract or county data to study relationships between map change and socio-economic variables. Because of this, the past research has painted a simplistic picture that wealthier places have higher LOMR/LOMA rates (Lea and Pralle, 2021), but has been unable to determine specifically who within these places are obtaining map alterations. While related recent work has investigated the individual property scale and relationships between increasing flood hazard and property values (Shr and Zipp, 2019; Hino and Burke, 2021) and inequities (Bick et al., 2021), in this paper I aim to add observations of where and who is presently seeking flood hazard mitigation by raising buildings and seeking updated data to show reduced flood hazard within the NFIP.

This study advances on the previous work because it examines a variety of counties across the state of Florida using property scale tax lot data. This paper investigates the question: what are the characteristics of homes with successful Letters of Map Amendment and Letters of Map Revision Based on Fill? I find that LOMAs and LOMR-Fs most frequently occur for homes above the median home value in counties where average home values are among the lowest ranked in Florida. In contrast, I also find that LOMAs more often occur for homes around or below the median home value in counties ranked among those with the highest average home values.

Background

Before examining where Letters of Map Amendment (LOMAs) and Letters of Map Revision Based on Fill (LOMR-Fs) have recently occurred in Florida, I first review how Flood Insurance Rate Maps (FIRMs) are produced and altered by LOMAs and LOMR-Fs. The United States Federal Emergency Management Agency (FEMA) operates the National Flood Insurance Program (NFIP), which is tasked with overseeing the production of FIRMs across the United States. Special Flood Hazard Areas (SFHA) on FIRMs are extents predicted to have one percent chance or higher of annual flooding. The contractors FEMA hires and works with to produce FIRMs rely on broad coverage Digital Elevation Models (DEMs) derived from photogrammetry or LiDAR, such as those found in the National Elevation Dataset, which together with hydraulic models are used to generate the SFHAs.

The accuracy and precision of a DEM, as well as the type of flooding (riverine versus coastal), are important factors that can determine which flood zone(s) make up a SFHA. The SFHAs on FIRMs appear homogenous when aggregated together, but they actually are made up of specific flood zone types determined by flooding source, data quality, and methods used to quantify flood hazard (Horn and Webel, 2019). For example, large population centers are likely to have more accurate and precise elevation datasets and past studies or data about flooding sources, which in turn can produce more detailed flood zones. The general types of these on FIRMs where elevations have been verified to a minimum standard are known as “AE” zones (for inland/riverine flooding sources) and “VE” zones (for coastal flooding due to storm surge and velocity waves). There are other types of flood zones for specific hazards; for example, for inland flood hazard having shallow water depths (“AO” zones) or unpredictable flow paths (“AH” zones). In contrast, flood zones with only approximated surface water elevations for the BFE are either “A” zones for inland flooding or “V” zones for coastal flood hazard.

Letters of Map Amendments exist as part of NFIP and its FIRMs because the elevation data sets used to produce flood zones like the SFHA often have some amount of uncertainty or interpolation. Property residents can use a more precise and accurate measurement method, such as land surveying, to determine if the building they want to insure resides above what is called the Base Flood Elevation (BFE). The BFE is the local elevation the SFHA flood waters are expected to rise to. If the land survey determines the building is at a higher elevation than the BFE, the property resident can submit a request for a LOMA to FEMA.

Letters of Map Revision Based on Fill allow a property resident a second way to pursue changing the flood zone designation for a building from inside to outside the SFHA. If a building is determined to be within the SFHA because its elevation is lower than the BFE, the building can be raised to a higher elevation using fill dirt or pylons. When the elevation of the raised building exceeds that of the BFE, the property resident can apply to obtain a LOMR-F for the building.

There are also other ways FEMA approves re-mapping or confirming an individual building to be outside of the SFHA. A Letter of Map Amendment Out as Shown (LOMA-OAS) is a confirmation property residents can obtain that certifies the lowest building height is above the BFE, and thus the building is outside the SFHA. One reason a property resident would seek a LOMA-OAS is because a mortgage lender might not provide a mortgage to a property buyer unless the property has been verified by FEMA to be outside of the SFHA. If FEMA, based on available data, interprets the building to be outside the SFHA, a LOMA-OAS is issued. While LOMA-OAS designations are fairly common, they are not studied in this paper because they do not change FIRMs (and thus the relationship between level of hazard and its relationship to insurance premium payments).

The remaining types of map changes are specific to the flood zone type in which the building resides. For example, a Letter of Map Revision for a Floodway (LOMR-FW) is an exemption for a building within the floodway of a watercourse. A floodway is part of a river channel or similar watercourse where the discharge of the BFE must be able to pass without increasing above a designated height (FEMA, 2020b). A Letter of Map Revision for a Velocity Zone (LOMR-VZ) removes a building from the SFHA for a coastal (VE) zone, which also requires more stringent review than just elevation to validate the building should indeed be outside the SFHA. All of these types of Letters of Map Revisions and Amendments can also be denied by FEMA if they do not meet minimum qualifications (for example, if the lowest elevation of the building is below the BFE). Because they are relatively rare, LOMR-FWs and LOMR-VZs (and their denials) are reported in this study, but are not analyzed.

Collectively, all of these types of Letters of Map Amendment and Letters of Map Revision that affect a single building are called “MT-1s” by FEMA. In contrast, changes to flood hydraulics in an area that often affect a larger area and multiple buildings, such as constructing a new culvert or bridge, or a property developer building a new neighborhood, require a “MT-2”. These “MT-2s” are also called Letters of Map Revision (LOMRs). This paper only focuses on analyzing “MT-1s” because previous work has investigated elements of “MT-2s” (Pralle, 2019; Wilson and Kousky, 2019; Lea and Pralle, 2021), while no work to my knowledge (besides chapter four in this dissertation) has investigated “MT-1s”.

One of the primary reasons people pursue trying to change their building from inside the SFHA to a lower hazard flood zone is because buildings with a federal mortgage are required to purchase NFIP flood insurance. Another common motivator to seek a Letter of Map Amendment (LOMA) or Letter of Map Revision Based on Fill (LOMR-F) is because structures outside the SFHA have lower depicted flood risk. In the actuarial rating system of NFIP, this means buildings outside the SFHA have lower insurance premiums, often by hundreds if not thousands of dollars per year (FEMA, 2018a).

Despite the allure of removing a building from the SFHA, LOMAs and LOMR-Fs have financial costs that may be inhibiting residents with less wealth and means from accessing these processes and benefits. For example, a property resident needs to hire a professional land surveyor and/or engineer to conduct a land survey and obtain a surveyed lowest elevation or grade for the building in relation to the BFE. While this cost likely varies based on the provider, location, existing data, and size of building, at minimum this task is likely to be hundreds of dollars. For LOMR-Fs there is the cost of raising the property and structure, as well as an additional administrative fee for FEMA to review the application (FEMA, 2021h). Again, this will vary based on the size of the property and building, the height (how much) the property and/or building will be elevated, but likely will run at least thousands of dollars.

These costs could further exacerbate inequality in flood risk because those with the means to do so can remove their properties and get lower premiums for the same coverage in result of flood, but if then properties inside SFHA and removed by LOMA are flooded, the money saved by the LOMA removed property resident doesn't have to be paid back, while the property residents still in the SFHA, who had to pay higher rates, have spent more money even though they were at same hazard as the removed property/properties. Another way this could exacerbate inequality is that if two properties are relatively equal (e.g., similar year built, size, and so on), buildings outside of flood hazard zones have been found to have higher property values than the equivalent properties inside the SFHAs because of the hazard price discount. Because owning a home is one of the main and only ways many people have for equity in the United States, those who can access LOMAs or LOMR-Fs could potentially increase their property values and thus wealth, increasing the wealth gap between them and property residents unable to change their flood hazard designation to outside the SFHA. While the general trend I observed in chapter IV is that LOMAs and LOMR-Fs occur less frequently in places with lower average or median wealth indicators, this study uses property scale data to investigate the relationship between LOMAs/LOMR-Fs and property scale characteristics.

Theory

This section hypothesizes where LOMAs and LOMR-Fs occur more or less frequently based on individual property-scale characteristics, such as assessed property value and effective year built. I begin from and build on the hypotheses and results from chapter IV. In chapter IV, I hypothesized there were three factors would determine where greater or lesser numbers of LOMAs and LOMR-Fs would occur. First, the number of buildings in the SFHA per areal unit of observation (e.g., census tract or county) set the maximum limit of combined LOMAs and LOMR-Fs that could occur. Second, the maximum number of buildings that could obtain a LOMA was determined by what I call "false positive potential", or where with a more precise elevation measurement using land survey a building is determined to be above the BFE and outside the SFHA. I hypothesized and found evidence in my results that flood zones could be used as a proxy for where there would be greater or lesser false positive potential. With these two physical flood mapping parameters determined, the third factor was socio-economic characteristics. Places with higher indicators of wealth had LOMAs and LOMR-Fs more often than places without LOMAs and LOMR-Fs.

The difference in this study is that instead of aggregated socio-economic characteristics like median income, I use assessed property value and the effective year built for single family homes to analyze relationships with LOMA and LOMR-F occurrence. Based on findings from the previous work that has examined LOMRs, LOMAs, and LOMR-Fs at county and census tract scales, one hypothesis for findings in this study would be a simple linear correlation that higher value homes (with home value being used as a proxy for wealth) have greater rates of LOMAs and LOMR-Fs (Wilson and Kousky, 2019; Lea and Pralle, 2021). However, I hypothesize that increasing property values will result in increases in the number of LOMAs and LOMR-Fs up to a point, but beyond this point they will decrease. I hypothesize this because NFIP flood insurance for single family homes can only hold a maximum coverage of $250,000 for damages to home and another $100,000 for contents (FEMA, 2021j). Because of this limit, high value properties (e.g., $1,000,000 or more) will only be able to cover less than a third of their home value with federal flood insurance, so they might decide to forgo it or combine it with other private insurance. These high value homes are also less likely to have a federal mortgage, so even if they reside in the SFHA they would not be required to purchase insurance. Similarly, for these high value properties, if they cannot obtain a LOMA, they might also decide a LOMR-F is not cost-effective or that paying the extra insurance costs is not a burden on expenses. To study this, I analyze the percentiles of property values per Florida county for properties with LOMAs and LOMR-Fs versus other properties located in the SFHA and the same flood zones.

The term "effective year built" refers to the year when any substantial alterations or improvements were made to the house. Because using fill to raise a home will generally necessitate changes to home structure, the year fill was put in (unless another home improvement was made even more recently) should be reflected in this value. Thus, I hypothesize that homes that used fill and obtained a successful LOMR-F designation will have newer effective year built values versus other properties in the SFHA. In contrast, there is no reason to expect that effective year built values for LOMAs should be statistically significantly different from building ages for buildings within the SFHA that did not obtain a LOMA or LOMR-F.

Methods

I used four data sources in this study: (1) MT-1 data, (2) Florida county tax lots shapefiles and geodatabase tables, (3) Florida Flood Insurance Rate Maps, and (4) Florida building footprints. The MT-1 data were initially in PDFs that I acquired from FEMA's Map Service Center website (FEMA, 2020d). I also obtained the Florida Flood Insurance Rate Map shapefile from FEMA's Map Service Center. I downloaded the Florida tax lot shapefiles and geodatabase tables per Florida county from the Florida Department of Revenue (Florida Department of Revenue, 2020). The Florida building footprints layer is an open data layer created by Microsoft that I downloaded from GitHub (Microsoft, 2018).

To extract the MT-1 data into a useable format from the PDFs, I wrote and ran an R script that extracted the address, designation type, date of issue, and identifying case number from all PDFs in Florida with a date of issue between January 1, 2013 and December 31, 2018 to a new comma delimited table. I only included counties that had a countywide Flood Insurance Rate Map issued before January 1, 2013 in my analyses so I would only compare places that had the same length of time for MT-1s to be submitted. Next, I geocoded the MT-1 addresses for the qualifying counties using a python script that accessed Google's Geocoding API. I then overlaid the resulting latitude and longitude points with the tax lots layers and confirmed addresses matched from the PDFs and the tax lots. Manual corrections were used where any discrepancies existed. For full details on my process of extraction, cleaning, and preparation for analysis of the MT-1 data, see Appendix C.

For each study county, I determined the number of properties for each of the one hundred Florida Department of Revenue land use types before aggregated these individual land use designations into broader land use categories also defined by the Florida Department of Revenue (e.g., Residential, Commercial, Industrial). I then overlaid the tax lot layers with the Florida FIRM and Florida building footprint layers to produce counts for the number of properties for each land use type and category that had a building intersecting the SFHA.

To determine the land use type, assessed property value, and effective year built for all MT-1 locations, I overlaid the tax lots and MT-1 points. I found via data exploration that LOMAs and LOMR-Fs are among the most prevalent types of MT-1s and result in a change that affects flood insurance premiums, so I selected these specific types of MT-1s for further analyses. Using exploratory data analysis, I also determined that a large majority (over 80%) of buildings in the SFHA with LOMAs and LOMR-Fs were residential single-family homes, so I selected these properties for further analyses. Because I found that the majority of LOMAs and LOMR-Fs occurred for residential single-family housing, I also obtained assessed property value and year built for all single family housing properties in each study county and determined for each property if it did or did not have a building that intersected the SFHA.

For counties that had thirty or more LOMAs and/or LOMR-Fs, I used Wilcoxon-Mann-Whitney tests to determine if there were statistically significant differences in the distributions of property values and year houses were built for properties with LOMAs and/or LOMR-Fs compared to properties in the SFHA without a MT-1. I performed these tests at the county scale to compare property values that were relatively within same market influences and thus should have similar assessed property values. I also determined the property value and effective year built percentiles for each home with a LOMA and LOMR-F by comparing its property value or year built value against all respective values for homes within the SFHA in the same county. Once I obtained these values, I aggregated them into a single distribution for all counties with thirty or more LOMAs and LOMR-Fs to observe the pattern of home values and year built values across all study counties for LOMAs and LOMR-Fs.

Because the percentiles I obtained to compare property values and effective year built values compared the LOMA or LOMR-F against all other properties in a county's SFHA, this meant that homes of very different value and exposed to different types of flooding were being compared. To try and control for this, I further determined property value percentiles by comparing the value of a LOMA or LOMR-F against only properties in the same flood zone.

Results

The designation type for all MT-1s submitted between the beginning of 2013 and the end of 2018 for the Florida study counties, as well as the designation type for all single-family homes, is displayed in Table 1. The results show that over two-thirds of all MT-1s submitted, as well as those approved for single-family homes, were Letters of Map Amendments (LOMAs). Letters of Map Revision Based on Fill (LOMR-F), Letters of Map Amendment Out-As-Shown (LOMA-OAS), and Denied Letters of Map Amendment (LOMA-DEN) compose most of the remainder of submitted MT-1s. Denials for LOMR-Fs (LOMR-F-DEN), as well as Letters of Map Revision for Floodways

(LOMR-FW) and Coastal Zones (LOMR-VZ), are relatively rare and not analyzed further in this study due to their small number of occurrences.

Table 2 shows counts and percent of land use groups for all properties across the study counties, as well as for all properties that have a building that intersects the SFHA and for properties with all MT-1s, LOMAs, or LOMR-Fs. The Number of Properties column shows that across the Florida study counties, 87% of all properties are classified as residential. Further, the number of residential properties with a building in the SFHA is proportionately even higher, as 93.7% of all buildings that intersect the SFHA are residential. The percent of MT-1 and Letters of Map Amendment for residential properties are close to or within one percent of the percentage of residential buildings in the SFHA, being 92.5 % and 93.0 %, respectively. In contrast, only 86.7% of Letter of Map Revisions Based on Fill were for residential properties, as LOMR-F percentages had approximately twice the rate of all MT-1s and Letters of Map Amendment for land use types such as commercial, industrial, and institutional.

Table 3 shows the breakdown of the number of buildings in the SFHA, as well as the number of LOMAs and LOMR-Fs, per residential land use type for all study counties in Florida. The table shows that while single-family homes make up only 53% of residential land use buildings that are within the SFHA, 83.9% of LOMAs and 80.9% of LOMR-Fs were submitted for single family housing. None of the other land use types had a LOMA percentage over 6% or a LOMR-F percentage over 9%.

Figure 1 contains four maps that depict: (A) the number of single-family homes in the SFHA, (B) the percentage of single-family homes in the SFHA (the number of single-family homes in the SFHA divided by the total number of single-family homes in the county), (C) the number of LOMAs for single-family homes, and (D) the number of LOMR-Fs for single-family homes per Florida county. The number of single-family homes generally is larger in larger population centers, such as the example of Miami-Dade county. In contrast, some of the counties with lower numbers of total buildings in the SFHA have the highest percentage of buildings mapped into the SFHA. The pattern of LOMAs and LOMR-Fs in some cases follows where the total number or percentage of homes in the SFHA are high, although there are also counties with high LOMA or LOMR-F counts that have relatively low total number of homes or percentage of homes in the SFHA.

The number of single-family homes in the SFHA per flood zone type, as well as the number of LOMAs and LOMR-Fs per flood zone type, is shown in Table 4. As was observed in chapter four of this dissertation, the percentage of buildings in the A flood zones is lower than the proportional percentage of LOMAs and LOMR-Fs in the A flood zone. Similarly, the percentage of buildings in the AE flood zone is higher than the percentage of LOMAs and LOMR-Fs for the AE zone. In contrast to chapter four of this dissertation, the AH zone has a higher proportion of LOMAs than the percentage of buildings in the AH zone, although the percentage of LOMR-Fs is lower than the percentage of buildings. There are relatively few single-family homes located in AO and VE zones, and relatively even fewer LOMAs and LOMR-Fs for the AO and VE zones.

Results of the Wilcoxon-Mann-Whitney tests that compared assessed property values and effective year built values for single-family homes with LOMAs versus homes in the SFHA but without LOMAs for each county with thirty or more LOMAs are provided in Table 5. For assessed property values, the results indicate that nineteen of the twenty-five counties had statistically significant differences in their distributions for assessed home value. However, when you compare the distributions of homes with LOMAs versus homes with a building in the SFHA, seven counties had homes where the mean assessed property value for the properties with a LOMA was statistically significantly higher than homes in the SFHA, while the other twelve counties had homes in the SFHA with a higher mean assessed property value than properties with a LOMA. For effective year built values, fifteen of the twenty-five counties had statistically significant differences. Of these statistically significant counties, all fifteen have statistically significantly younger properties (properties built more recently) with LOMAs than for all other properties in the SFHA.

Table 6 shows the Wilcoxon-Mann-Whitney test results for assessed property values and effective year built values where there were thirty or more LOMR-Fs compared to other properties without a MT-1 in the SFHA. Of the thirteen counties that met this criteria, nine of them had statistical significance for assessed property value, while all thirteen counties had statistical significance for effective year built. Seven of the nine counties had statistically significant higher mean home values for properties with LOMR-Fs than the mean home value for properties without a MT-1 in the SFHA, with the other two having statistically significantly lower mean values for properties with LOMR-Fs than properties with a building in the SFHA but without a MT-1. All thirteen counties had significance for LOMR-Fs where the effective year built was newer (built more recently) than the mean value for other SFHA properties without a MT-1.

Figure 2 shows percentile distributions of assessed property values and effective year built values for single-family homes with LOMAs and LOMR-Fs. Each individual percentile for a home with a LOMA or LOMR-F was calculated by comparing the property value or year built value against a distribution of values derived from all other single family homes in the SFHA for the county in which the LOMA or LOMR-F was located. The distribution of assessed home value percentiles for LOMAs is fairly even across most percentiles. However, more properties are contained in the lower half of the percentiles, as the median value of the distribution is 48.6. In contrast, there are a greater proportion of property values at higher percentiles for properties that obtained LOMR-Fs, as the median value of the LOMR-F assessed property value percentile distribution is 62.3. For effective year built values, the median value of the percentile distributions are 57.2 for LOMAs and 92 for LOMAs. These results indicate that buildings that obtain LOMAs are more often slightly newer (or with a renovation) than other buildings in the SFHA, while buildings that use fill are frequently among the newest buildings compared to those in the SFHA.

The property value percentile distributions for LOMAs and LOMR-Fs subdivided by A, AE, and AH flood zones are shown in Figure 3. For LOMAs, the results are mixed. The median value of the percentile distribution for homes that obtained a LOMA in an A flood zone compared to the property value of other homes in the A zone is 59.1, indicating that half of the LOMAs were obtained for homes where the property values was in about the top 40 percent compared to other homes in the same county and A flood zone. In contrast, the median value for AE flood zone was 45, meaning that more than half of the homes were in the lower 50% of property values of AE zones. For AH zones, the median was 50.6. This meant that for AH zones, about half the homes that obtained LOMAs were in the lower 50% and the other half were in the upper 50%. In contrast to

LOMAs, the median property value percentiles for homes with LOMR-Fs all were higher than 50. The median for A zone LOMR-Fs was 78.3, while the median for the AH zone LOMR-F homes was 77. The median for LOMR-Fs in the AE zone was 58.5. Thus, for all flood zone types, the majority of properties obtaining a LOMR-F were relatively higher value than others in the SFHA.

Discussion and Conclusion

Examining property scale characteristics for properties in select Florida counties that had Letters of Map Amendment (LOMAs) and Letters of Map Revision Based on Fill (LOMR-F) between 2013 and 2018, I found that the majority of LOMAs and LOMR-Fs were issued for single family homes. I also discovered that when the assessed property values for these single-family homes with LOMAs and LOMR-Fs were compared to homes remaining in the Special Flood Hazard Area (SFHA), the mean value of SFHA properties was important to predicting if LOMAs and LOMR-F mean values would have a statistically significant higher or lower value. I observed that five of the six counties with the lowest SFHA mean values had statistically significant higher LOMA values, and all seven counties with statistically significant higher LOMAs were for counties whose mean SFHA property value was in the bottom half of the twenty-five study counties. In contrast, ten of the twelve counties with the highest SFHA mean property values had statistically significant higher SFHA mean property value than the LOMA mean property value. A similar pattern emerged for LOMR-Fs, as the five counties with lowest SFHA mean values all had statistically significant higher LOMR-F mean just values. In contrast, the only two counties that had statistically significant higher SFHA mean just values compared to LOMR-F property values had the second and third highest SFHA mean property values of the thirteen counties analyzed. The main deviation from the trend for LOMR-Fs was that Collier county, which had the highest mean SFHA property value, had a statistically significant even higher LOMR-F mean value.

Places that had buildings in the SFHA with higher property values than properties with LOMAs or LOMR-Fs also had many of the highest mean property values compared to other study counties, and in these places the wealthier people at flood risk likely have ways to facilitate living in high hazard area. For example, besides NFIP insurance, they likely also have (or exclusively have) private insurance because NFIP insurance only covers up to $500,000 in damages for structure and contents. These property residents also more likely have other sources of equity that is not held in their home, which is likely the primary or only source of finance/capital with more moderate to lower value homes, which might explain why the latter are more often likely to pursue a LOMA/LOMR-F. In contrast, property residents with higher percentile property home values in the counties among the lowest average home values are most frequently accessing LOMAs and LOMR-Fs. This finding provides evidence that residents in homes with lower values (below a county median) might be not have the financial means or time to obtain a LOMA or LOMR-F.

All thirteen counties with more than 30 LOMR-Fs had statistically significant more recent effective year built mean values than the mean effective year built for other properties in the SFHA. This finding makes sense because properties have to be altered or built new to incorporate fill, and thus these properties will have recent effective build dates to that year the structure was altered or built. All fifteen of the twenty-five counties with thirty or more LOMAs that had statistically significant differences also had significantly younger properties for LOMAs than the other properties in the SFHA. Similar to LOMR-Fs, this observation can most likely be explained by the fact that when new buildings are built on property shown to be within the SFHA in Florida, they must be the same elevation or exceed the Base Flood Elevation unless a special variance from elevation requirements is granted by the municipality or state (Florida Division of Emergency Management, 2017). Thus, new home construction seems to be a significant factor to influence the age of buildings obtaining LOMAs and LOMR-Fs. Future research should investigate actual year built of homes in addition to effective year built to better analyze differences between updates for older construction versus newly constructed buildings.

The analyses of assessed property values and effective year built values in this paper are only aggregates of the individual county data, which are not analyzed further here. However, medians, standard deviations, and counts of buildings in the SFHA, LOMAs, and LOMR-Fs broken down by each flood zone for each individual county is provided in Appendix D.

This work builds on a 2018 report conducted by FEMA on the affordability of flood insurance that found incomes are lower inside SFHA for many states compared to outside the SFHA, although Florida was one of the few exceptions where property values were higher inside the SFHA than outside (FEMA, 2018c). Breaking the data down to the finer county scale, this study shows the greater geographic variation where certain places have higher property values inside the SFHA than the LOMAs or LOMR-Fs being changed to outside the SFHA, while other counties follow the national trend with higher value properties obtaining LOMAs and LOMR-Fs and the lower value properties being retained in the SFHA. So, one advancement this work provides is that finer scales of analysis than states, such as the county or down to the individual scale, help us understand that location and situation are important to understanding who is obtaining LOMAs and LOMR-Fs. The blanket statement that property values are higher in the SFHA versus outside the SFHA when data are aggregated to the state of Florida obscures much of the finer scale nuance of not only who is exposed across different places in Florida, but also who is accessing LOMAs and LOMR-Fs to reduce their flood risk.

One assumption in this study is that there was not an increase in property value for the 2019 assessed property values I used due to the LOMA or LOMR-F changing the property to be outside the SFHA between 2013 and 2018. While FEMA's own work shows price reductions for many properties included in SFHAs (FEMA, 2018c) and theory suggests that properties should gain property value when changed to outside the SFHA, Shr and Zipp (2019) did not find significant increases for property values in Pennsylvania when LOMRs changed properties from inside to outside the SFHA. Another potential limitation is that this study does not have access a record of when flood events occurred and what properties they affected, which might also alter property values over time. Future research should try to address these shortcomings using hedonic valuation models (Bin and Landry, 2013; Shr and Zipp, 2019).

In October 2021, FEMA began implementing Risk Rating 2.0, which will use more data to further individualize calculations of flood hazard at the individual property scale. FEMA states on their website that "the [Risk Rating 2.0] methodology leverages industry best practices and cutting-edge technology to enable FEMA to deliver rates that are actuarily sound, equitable, easier to understand and better reflect a property's flood risk” (FEMA, 2021i). As FIRMs will still be used to help develop insurance premiums and to determine mandatory purchasing requirements for flood insurance under Risk Rating 2.0, and given FEMA’s own statement of interest in equitable flood insurance pricing as flood hazard continues to change, continuing to study where LOMAs and LOMR-Fs are occurring and who is obtaining them can factor into future analyses of flood hazard equity.

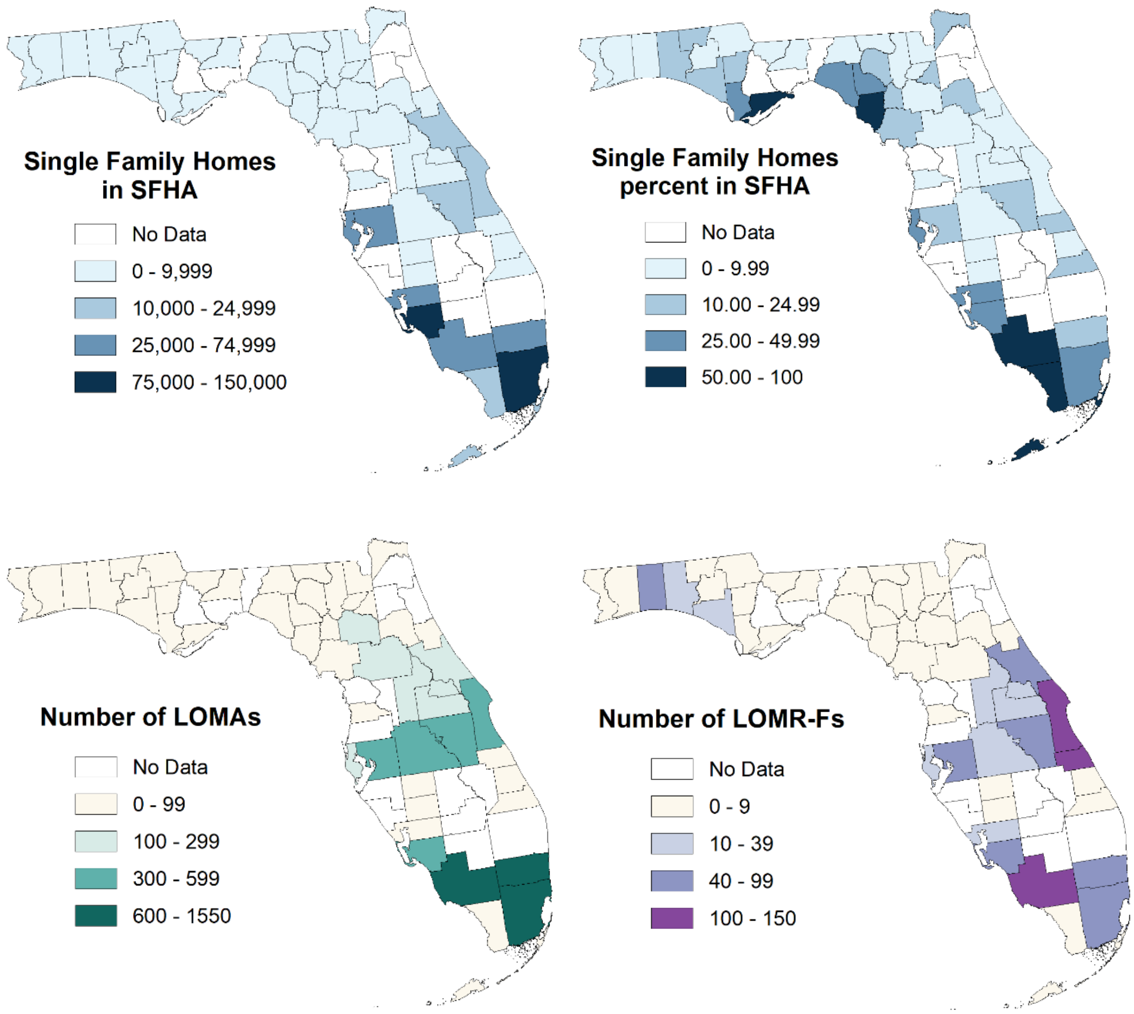

Figure 1. Map A (top left) shows the number of single-family homes located in the SFHA for each Florida county. Map B (top right) shows the percentage of single-family homes for each Florida county that are located in the SFHA. Map C (bottom left) shows the number of LOMAs obtained in each county during the study period. Map D (bottom right) shows the number of LOMR-Fs obtained in each county during the study period

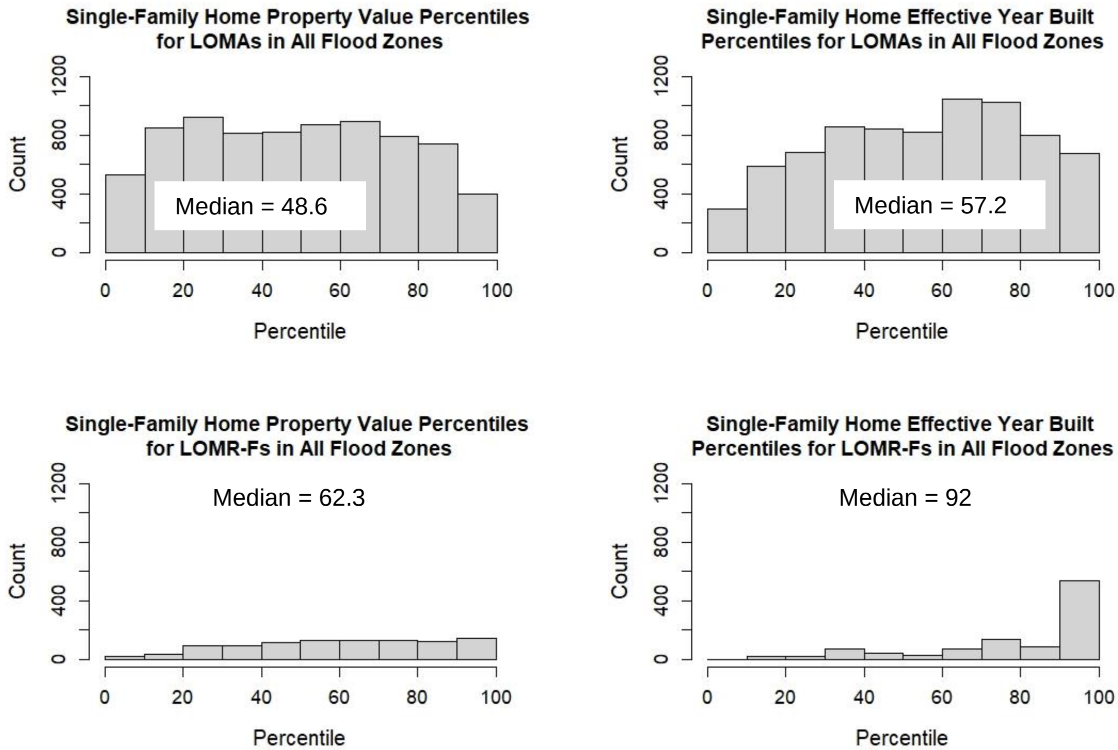

Figure 2. Histograms showing the percentiles of single-family homes that obtained a LOMA or LOMR-F for assessed property values (left top and bottom) and effective year built values (right top and bottom) as compared to assessed property values or effective year built values for properties in the SFHA within the same county where the LOMA or LOMR-F was located

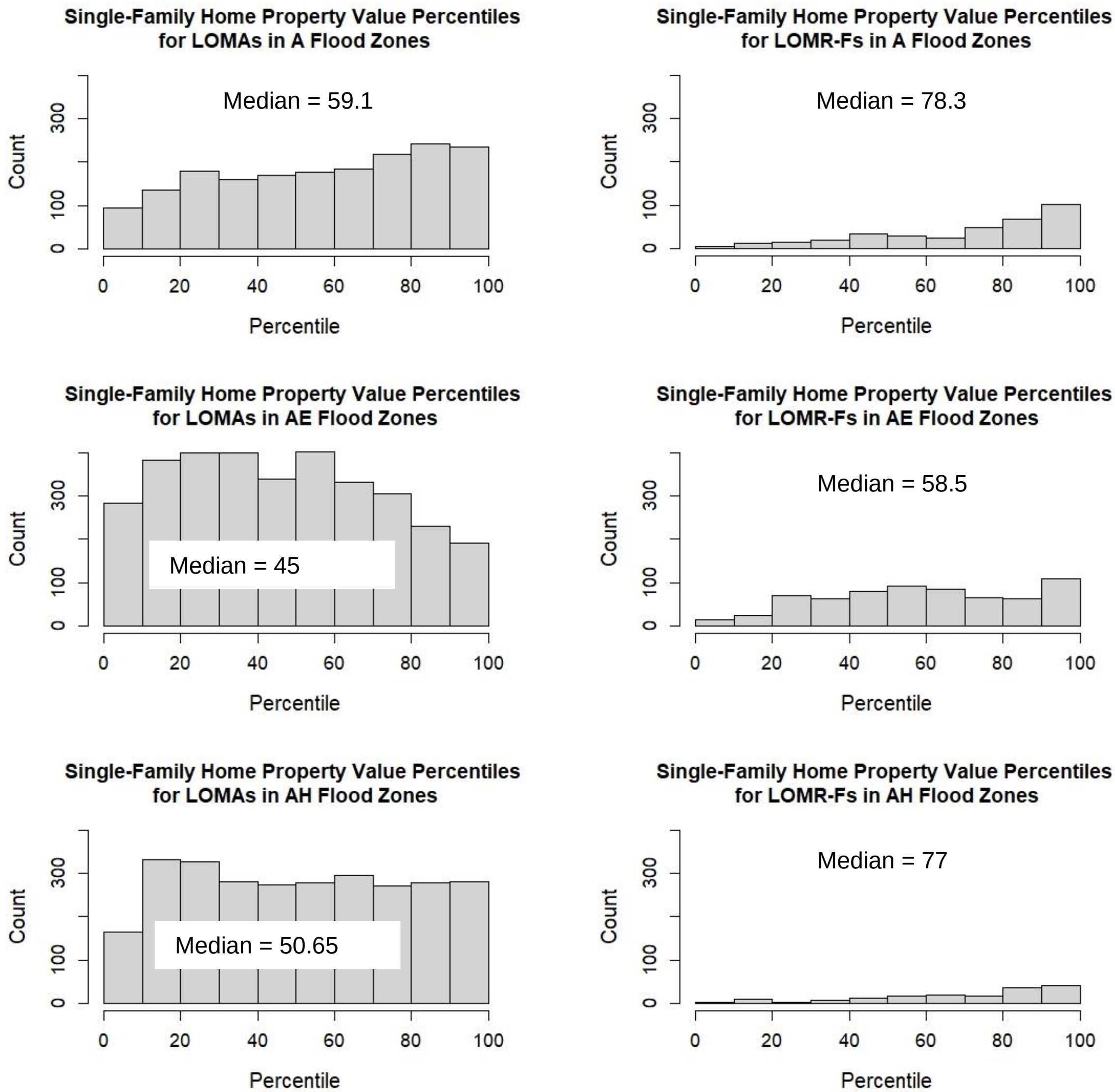

Figure 3. Histograms showing the percentiles of single-family homes that obtained a LOMA or LOMR-F for assessed property values based on flood zone. Percentiles were obtained by comparing the assessed property value for a LOMA or LOMR-F with properties in the same flood zone and county where the LOMA or LOMR-F was located

Table 1. Total number of MT-1s and number of MT-1s for single-family homes by designation type for all study counties

Designation	**Number (percent) n = 14,728**	**Number Single-Family Homes (percent) n = 11,460**
LOMA	10,058 (68.29%)	7,851 (68.50%)
LOMA-DEN	1,166 (7.91%)	932 (8.13%)
LOMA-OAS	1,670 (11.33%)	1,396 (12.18%)
LOMR-F	1,687 (11.45%)	1,185 (10.34%)
LOMR-F-DEN	77 (0.52%)	43 (0.37%)
LOMR-FW	68 (0.46%)	52 (0.45%)
LOMR-VZ	2 (0.01%)	1 (0.01%)

Table 2. Shows the number and percent of properties, buildings in the SFHA, Letter of Map Change submissions, Letters of Map Amendment, and Letters of Map Revision Based on Fill aggregated per land use group for all Florida study counties

Land Use Group	**Number of Properties (%)**	**SFHA Buildings (%)**	**LOMC (%)**	**LOMA (%)**	**LOMR-F (%)**
Residential	6,662,744 (87.663%)	1,209,312 (93.72%)	13,634 (92.57%)	9,356 (93.02%)	1,463 (86.72%)
Commercial	259,117 (3.409%)	38,208 (2.96%)	554 (3.76%)	356 (3.53%)	128 (7.587%)
Industrial	64,597 (0.849%)	13,506 (1.04%)	241 (1.63%)	148 (1.47%)	51 (3.023%)
Agricultural	203,304 (2.674%)	12,034 (0.93%)	189 (1.28%)	137 (1.36%)	12 (0.711%)
Institutional	39,219 (0.516%)	4,603 (0.35%)	68 (0.46%)	42 (0.41%)	17 (1.007%)
Governmental	206,539 (2.717%)	7,283 (0.56%)	22 (0.14%)	9 (0.08%)	9 (0.533%)
Miscellaneous	73,030 (0.960%)	3,972 (0.30%)	14 (0.09%)	6 (0.05%)	7 (0.414%)
Other	91,813 (1.208%)	1,134 (0.08%)	6 (0.04%)	4 (0.03%)	0 (0%)

Table 3: Shows the number and percent of buildings in the SFHA, as well as the number of buildings with LOMAs and LOMR-Fs, per residential land use type

Residential Land Use	**SFHA Buildings (%) n = 1,209,312**	**LOMAs (%) n = 9,356**	**LOMR-Fs (%) n = 1,463**
Vacant Residential + Commons	33,076 (2.73%)	294 (3.74%)	66 (4.51%)
Single Family	642,118 (53.09%)	7,851 (83.9%)	1,185 (80.9%)
Mobile Homes	53,463 (4.42%)	126 (1.34%)	1 (0.06%)
Multi-Family	31,632 (2.61%)	546 (5.83%)	131 (8.95%)
Condominiums	433,685 (35.86%)	525 (5.61%)	70 (4.78%)
Miscellaneous Residential	15,338 (1.26%)	14 (0.14%)	10 (0.68%)

Table 4. Shows the number of Single-Family Homes in the Special Flood Hazard Area (SFHA), as well as number of LOMAs and LOMR-Fs, located in each flood zone type for the Florida study counties. Note: SFHA Single-Family Homes numbers do not include LOMAs and LOMR-Fs

Flood Zone	**SFHA Single-Family Homes n = 648,403**	**LOMAs n = 7,851**	**LOMR-Fs n = 1,181**
A	47,595 (7.34%)	1,798 (22.90%)	353 (29.88%)
AE	418,136 (64.48%)	3,266 (41.59%)	664 (56.22%)
AH	158,395 (24.42%)	2,784 (35.46%)	163 (13.80%)
AO	750 (0.11%)	0 (0%)	1 (0.08%)
VE	23,527 (3.62%)	3 (0.03%)	0 (0%)

Table 5 (next page). Wilcoxon-Mann-Whitney tests between properties with Letters of Map Amendment (LOMAs) and properties without a Letter of Map Change in the SFHA for 2019 assessed property value and effective year built per county with thirty or more LOMAs. Statistical significance of Wilcoxon-Mann-Whitney tests indicated by *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$.

	2019 Assessed Property Value			Effective Year Built		
	LOMAs	SFHA	Significance	LOMAs	SFHA	Significance
	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (z)	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%)
Alachua	215,824 (118,778)	190,457 (130,372)	0.000*** (-4.45)	1991.9 (10.10)	1987.6 (11.50)	0.000*** (-5.45)
Bay	222,651 (129,931)	239,749 (259,280)	0.124 (-1.53)	1996.6 (18.02)	1991.7 (15.42)	0.002** (-3.08)
Bradford	175,432 (65,161)	136,812 (97,847)	0.000*** (-4.12)	1998.3 (12.88)	1981.5 (17.96)	0.000*** (-5.97)
Brevard	263,914 (150,201)	290,164 (222,428)	0.273 (-1.09)	2003.9 (6.30)	2003.4 (7.48)	0.925 (-0.09)
Broward	401,491 (265,452)	489,068 (723,847)	0.000*** (-3.77)	1979.7 (15.73)	1976.1 (17.82)	0.000*** (-8.64)
Charlotte	207,406 (91,706)	267,165 (232,179)	0.018* (-2.35)	1990.5 (13.65)	1988.4 (15.17)	0.337 (-0.95)
Collier	384,598 (466,290)	706,094 (1,518,342)	0.000*** (-14.55)	1997.9 (9.73)	1993.9 (14.70)	0.000*** (-8.06)
Escambia	193,243 (142,609)	310,501 (298,348)	0.010* (-2.56)	1998.3 (9.63)	1990.5 (16.02)	0.006** (-2.70)
Hillsborough	212,403 (115,539)	328,932 (382,873)	0.000*** (-7.22)	2002.2 (7.84)	2001.5 (10.47)	0.970 (-0.03)
Indian River	261,946 (209,266)	677,243 (1,015,797)	0.002** (-3.01)	1995.4 (10.60)	1993.4 (13.83)	0.703 (-0.38)
Lake	230,884 (124,274)	208,840 (158,796)	0.000*** (-3.96)	1995.6 (12.68)	1992.2 (17.64)	0.000*** (-3.52)
Lee	264,277 (136,690)	374,987 (493,189)	0.000*** (-3.38)	1999.4 (9.02)	1993.9 (10.50)	0.000*** (-9.48)
Marion	190,724 (128,161)	142,581 (128,117)	0.000*** (-8.16)	2006.9 (7.69)	2000.7 (9.02)	0.000*** (-9.49)
Miami-Dade	317,173 (186,864)	463,710 (1,038,927)	0.983 (-0.02)	1983.8 (17.78)	1979.7 (19.55)	0.000*** (-6.41)
Monroe	754,433 (655,847)	729,560 (804,126)	0.813 (-0.235)	2006.0 (9.44)	2000.9 (9.20)	0.000*** (-5.55)
Okaloosa	393,704 (388,349)	461,686 (446,493)	0.024* (-2.24)	2001.7 (12.45)	1989.3 (12.78)	0.000*** (-6.53)
Orange	345,475 (305,648)	405,627 (605,884)	0.011* (-2.54)	1992.9 (14.23)	1991.2 (15.19)	0.173 (-1.35)
Osceola	193,416 (95,595)	200,011 (114,752)	0.047* (-1.98)	1998.6 (9.71)	1996.7 (12.79)	0.088 (-1.70)
Pinellas	226,702 (132,684)	372,750 (369,352)	0.000*** (-9.42)	1992.7 (10.51)	1991.2 (9.95)	0.025* (-2.23)
Polk	199,914 (139,761)	173,463 (111,892)	0.000*** (-6.66)	1993.5 (14.27)	1990.2 (17.80)	0.014 (-2.45)
Putnam	191,733 (119,890)	209,081 (205,664)	0.764 (-0.29)	1992.8 (12.75)	1987.7 (14.75)	0.099 (-1.64)
Santa Rosa	420,588 (502,368)	304,840 (287,702)	0.671 (-0.42)	1995.4 (13.32)	1993.7 (13.19)	0.499 (-0.67)
Seminole	331,709 (198,284)	299,954 (200,147)	0.002** (-3.07)	1993.8 (12.45)	1990.9 (15.63)	0.092 (-1.68)
Volusia	219,633 (153,699)	212,250 (211,404)	0.000*** (-5.21)	1993.1 (11.83)	1987.0 (13.63)	0.000*** (-6.87)
Walton	392,505 (428,271)	613,470 (825,845)	0.035* (-2.09)	2004.8 (11.50)	1998.2 (10.68)	0.000*** (-3.76)

Table 6. Wilcoxon-Mann-Whitney tests between properties with Letter of Map Revision Based on Fill (LOMR-F) and properties without a Letter of Map Change in the SFHA for 2019 assessed property value and effective year built per county with thirty or more LOMR-Fs. Statistical significance of Wilcoxon-Mann-Whitney tests indicated by *p < 0.05, **p <0.01, and ***p < 0.001.

	2019 Assessed Property Value			Effective Year Built		
	LOMR-Fs	SFHA	Significance	LOMR-Fs	SFHA	Significance
	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (z)	Mean (Std. Dev.)	Mean (Std. Dev.)	*p* (%)
Bay	408,549 (328,014)	239,749 (259,280)	0.000*** (-4.62)	2011.6 (7.86)	1991.7 (15.42)	0.000*** (-8.06)
Brevard	333,801 (177,745)	290,164 (222,428)	0.000*** (-5.22)	2009.0 (5.26)	2003.4 (7.48)	0.000*** (-8.82)
Broward	423,977 (236,671)	489,068 (723,847)	0.039* (-2.05)	2003.0 (10.85)	1976.1 (17.82)	0.000*** (-10.12)
Collier	819,890 (755,887)	706,094 (1,518,342)	0.000*** (-6.00)	2011.8 (8.16)	1993.9 (14.70)	0.000*** (-14.29)
Hillsborough	268,032 (121,662)	328,932 (382,873)	0.211 (-1.24)	2014.0 (4.03)	2001.5 (10.47)	0.000*** (-12.36)
Indian River	309,704 (255,379)	677,243 (1,015,797)	0.003** (-2.93)	2003.0 (10.83)	1993.4 (13.83)	0.000*** (-8.54)
Lee	292,798 (168,690)	374,987 (493,189)	0.389 (-0.86)	2007.1 (9.17)	1993.9 (10.50)	0.000*** (-10.72)
Miami-Dade	322,835 (241,196)	463,710 (1,038,927)	0.708 (-0.37)	2000.3 (5.95)	1979.7 (19.55)	0.000*** (-8.31)
Okaloosa	1,079,671 (863,517)	461,686 (446,493)	0.000*** (-9.56)	2009.2 (8.11)	1989.3 (12.78)	0.000*** (-12.35)
Osceola	254,032 (111,565)	200,011 (114,752)	0.000*** (-5.07)	2006.3 (8.48)	1996.7 (12.79)	0.000*** (-6.87)
Pinellas	305,873 (115,278)	372,750 (369,352)	0.476 (-0.71)	2008.4 (12.11)	1991.2 (9.95)	0.000*** (-7.10)
Polk	245,087 (136,364)	173,463 (111,892)	0.000*** (-5.91)	2010.8 (7.11)	1990.2 (17.80)	0.000*** (-8.57)
Volusia	359,202 (573,653)	212,250 (211,404)	0.000*** (-6.84)	2011.9 (7.96)	1993.1 (11.83)	0.000*** (-11.95)

CHAPTER VI

CONCLUSION

Summary of Results

This dissertation examined changes initiated by property residents to Flood Insurance Rate Maps used by the United States National Flood Insurance Program. Specifically, these changes alter and almost always reduce the areal extent of the Special Flood Hazard Area, or area predicted to have one percent or greater chance of being inundated annually. These alterations to the SFHA on FIRMs can take two primary forms: (1) Letters of Map Amendments, which rely on more precise surveys and floodplain mapping to show a building has been inadvertently included in the SFHA and should be mapped outside the SFHA, or (2) Letters of Map Revision, which change SFHA extent because of updated hydrologic and/or hydraulic mapping or because a property elevated its building above the predicted floodwaters.

Chapter III mapped and quantified buildings moved in and out of the SFHA due to Letters of Map Revision for 255 counties (and their census tracts) across the United States. The results showed that the vast majority of change in SFHA designation for buildings was due to their removal rather than addition, as the net change was over 20,000 buildings removed within these counties. These changes at the census tract and county scales were also combined with United States Census Bureau American Community Survey data to assess statistical relationships between where change occurred (or not) and socio-economic variables. Results from Wilcoxon-Mann-Whitney tests and Binary Logistic Regressions found statistically significant differences that median home values are higher, buildings are newer, and percent of white populations are higher where

Letters of Map Revision occur. The results provide evidence that Letters of Map Revision occur more often where people and communities have greater socio-economic means, which raises questions of equity in access to Letters of Map Revision.

Letters of Map Amendment and Letters of Map Revision based on Fill were analyzed in chapters IV and V. Chapter IV examined LOMAs at the census tract scale for approximately 2,000 counties across the contiguous United States. The results showed that submitted Letters of Map Change (everything together) were over-represented in flood zones with less precise methods and underrepresented in flood zones with more precise and accurate methods. Where Letters of Map Amendment and Letters of Map Revision Based on Fill occurred or not was also combined with American Community Survey data to assess statistical significance for socio-economic variables. For almost every variable tested, census tracts had higher wealth and newer buildings where Letters of Map Amendment or Revision had been submitted versus where they had not. This supports findings from chapter IV that LOMAs and LOMR-Fs occur in communities with greater socio-economic means, leaving those people with lesser means unable to seek or obtain map alterations.

Chapter V used property-scale data in the state of Florida to determine what types of properties obtain Letters of Map Amendment and Letters of Map Revision Based on Fill. The results showed the majority of LOMAs and LOMR-Fs occur for residential properties and specifically single-family homes, although a wide variety of land use types take advantage of these map alterations. Single family homes were investigated further by testing if there were statistical differences in the mean assessed property values and in the year home built between properties with a LOMA or LOMR-F or without. Through my analysis I observed that counties where properties without LOMAs or LOMR-Fs had the lowest mean assessed value had statistically significantly higher mean values for properties with LOMAs, while counties where homes without LOMAs and LOMR-Fs had the highest mean values had statistically significantly lower mean values for homes with LOMAs. However, where LOMR-Fs occurred, property values were almost always higher for homes with LOMR-Fs than those without a LOMA or LOMR-F.

Implications of Results

One contribution this dissertation makes is to the topic of lay-expert modes of scientific knowledge production, specifically in regards to flood hazard knowledge production. As evidenced through this dissertation, Flood Insurance Rate Maps as part of the National Flood Insurance Program should not be viewed through the Public Education Model of experts needing to improve communication of flood hazard or lay people needing to learn more about flood hazard, but rather as a form of the Public Debate Model where lay people can challenge Special Flood Hazard Areas on flood hazard maps by hiring independent experts to collect more data or evaluate flood hazard in a different (but approved) way. Another contribution of this dissertation is to show that socio-economic differences of lay people can influence flood map production, specifically in knowledge production like that in the National Flood Insurance Program. In contrast, socio-economic differences in lay people should not matter if FIRMs were in the form of the Public Education Model, if they were only provided by technical experts to communities and could not be changed by Letters of Map Change, because in this case only experts would have control over map production. Even any debates among experts in this case should not influence methods used on communities with different socioeconomics unless somehow there was a systematic bias of mapping based on socio-economic characteristics (assuming resources to communities are equal and experts only focused on biophysical data for mapping flood hazard). For the Co-Production of Knowledge Model, socio-economic differences should also be theoretically be minimal if experts make sure they are acting the same (or at least are engaging in reflexive practices) with all lay people involved in flood map production. But in the Public Debate Model, particularly in the way NFIP is set up that the 'debate' means property resident paying to hire engineers or land surveyors to perform new scientific analyses, that socio-economic difference becomes most apparent. Because in this method of knowledge production, those with means and time, which are more likely to be people who are relatively wealthier, will get map changes incorporated that they want, while people unable to take time and money will be less informed of the process and less able to pay.

This dissertation has also sought to bring insights from Critical Environmental Justice to flood hazard research. Rebecca Elliot notes that while NFIP is often touted as a failure, it had never failed to be reauthorized and thus must have desirable qualities. For example, she cites one example that NFIP has kept flood insurance more affordable than if it were operated by private insurance (Elliott, 2021b). However, she also notes that NFIP developed out of and is designed in support of mass homeownership post World War II that has carried through to present day (Elliott, 2021a). This advantages people who own homes, who are disproportionately white and relatively affluent people (USA Facts, 2020). Insurance is also more obtainable to those with higher incomes. Zac Taylor has shown in Florida it is non-white and poor who are more housing-cost burdened and thus less likely to be able to afford flood insurance or seeking a Letter of Map Change

(Elliott, 2021a, p. 171). Thus, the issue of access often may not be knowledge, but lack of cash (Elliott, 2017). In this way, Critical Environmental Justice scholarship might describe the National Flood Insurance Program and Letters of Map Change as just another way the state may see itself as equitable and well-intentioned but is still contributing to environmental injustices by making political-economic amenities preferentially accessible to the already powerful (Pulido, 2017; Pellow, 2018). I suggest future research should investigate the relationship between Letters of Map Change and where flood damage claims are paid outside of the SFHA to further assess if Letters of Map Change are being used to exacerbate wealth inequality.

As I mentioned in earlier chapters of this dissertation, my “simple” public policy recommendation for FEMA and state agencies interested in helping low-income and non-white communities gain higher rates of Letter of Map Change submissions and approvals would be to provide grants or other forms of aid to these people and communities. While this could be done in a “passive” manner (e.g., where individuals or communities have to become aware these grants or aid exist, then apply for them), I would advocate distributing aid should be pursued in a more “active” manner (e.g., federal or state agencies use tools and contact local community groups to identify and provide aid to people who qualify) because scientific literature shows how low-income and/or non-white populations often are underserved in regards to disaster aid and mitigation (Domingue and Emrich, 2019; Loughran and Elliott, 2021). However, while grants and similar financial aid might help reduce the discrepancy of access and use of Letters of Map Change, I suggest this public policy recommendation should only be pursued if other technical changes to FIRMs, such as flood hazard on FIRMs incorporating future non-stationarity predictions of future flood scenarios due to climate change, are also implemented in tandem with my proposed financial aid.

I argue the financial aid and technical change must occur together because the proposed aid might only cause further problems for both the individuals receiving it and the NFIP and United States more broadly if implemented without technical changes to FIRMs. I see at least two potential repercussions of only implementing the proposed aid. First, if more buildings in low-income and non-white communities obtain LOMAs or LOMR-Fs and afterwards fail to continue carrying flood insurance, if future floods exceed the SFHA and inundate these properties, they will still need post-disaster aid and not be covered by flood insurance (Mukerji, 2020). A second potential implication is that even if the people whose buildings are removed from the SFHA by LOMAs or LOMR-Fs do continue to buy insurance and obtain insurance claims in the wake of larger future floods, this will exacerbate the debt owed by NFIP to the United States Treasury because people will be obtaining more in claims payments than they are paying into NFIP based on their insurance premiums. In turn, this implicates all United States taxpayers as paying for the future costs of floods. However, the other side of this argument is that incorporating climate change predictions into flood hazard that will likely show larger areas of flood hazard for these communities and people with little wealth will mean these people will less likely be able to afford to pay for flood insurance unless there is aid to help them on the basis of financial need. In the end, as Rebecca Elliott points out, people living in the United States are going to have to collectively decide these moral economic questions related to flood insurance damage payments (Elliott, 2021a).

If public policy does not change, communities and individuals still can take precautions to reduce future flood hazard while still seeking accurate and precise elevations and future flood predictions. For example, local communities can adopt land use ordinances so that properties have to have a "freeboard" (an extra one or two feet elevation above the Base Flood Elevation) for a building to be considered outside of the SFHA, which will reduce the likelihood of future flood damages or magnitude of damage. Individual home owners can also seek to raise their homes to higher elevations, as well as make sure that vital utilities and valuable personal property are stored above the lowest floor of the home. At the least, any home that obtains a LOMA or LOMR-F should continue to carry flood insurance if at all economically feasible for the homeowner, as the premiums will be cheaper than when the home was inside the SFHA and future floods could exceed the BFE and inundate parts of the house.

Finally, this research has also added to Critical Physical Geography literature related to flood hazard. One way in which this dissertation contributes to Critical Physical Geography was by making the attempt to incorporate elements of physical geography (via flood zones and Letters of Map Change) and human geography (via American Community Survey socio-economic data and Florida Tax Lots data) while also considering how FIRM knowledge production is influenced and determined by the people and technology involved. While research focused on biophysical flood hazard, the social implications of flood hazard, and the techniques and technologies used to understand and govern flood hazard will all be important to future understandings of flood hazard, my hope is that future research will continue to seek to understand flood hazard knowledge by considering these elements together.

APPENDIX A

CHAPTER III DETAILED METHODS AND JUSTIFICATIONS

Determining time and spatial scales for Chapter III analyses

Before I conducted analyses, two questions needed to be resolved:

- What counties/census tracts would be included in the analysis?
- Over what time period would my analysis cover?

To understand my decisions to these questions, I will describe background about Flood Insurance Rate Maps (FIRMs) and Letters of Map Revision (LOMRs).

Flood Insurance Rate Maps are created or updated per United States county, with counties being updated asynchronously. Said another way, FIRMs across the United States get updated at various different times. Because of this, it is impossible to study a large number of new or updated FIRMs that were all created at the same time. Thus, the approach taken in this research was to define a study time period and examine changes to FIRMs from their preliminary maps to present maps ("present" as of August 2019) for FIRMs that became regulatory between the beginning of 2013 and the end of 2017. Thus, the number of counties and census tracts in the analysis were defined by this time period.

There are four categories of data that were initially collected to conduct analyses:

1) Flood Insurance Rate Maps (shapefiles)
2) United States Census Tracts (shapefiles)
3) United States Building Footprints (geojson files)
4) American Community Survey Data (.csv files)

Below I use corresponding categories of the data listed above where I detail how each data type was acquired and initially prepared before analysis. I then describe the steps taken to analyze all the data together to answer the research question.

Flood Insurance Rate Maps (shapefiles)

To study change in the number of buildings in the Special Flood Hazard Area (SFHA) for recently mapped/updated Flood Insurance Rate Maps (FIRMs), I examined FIRMs at three points in time for each study county: (1) its preliminary map; (2) its initial regulatory map; and (3) its present (August 2019) map. While the present maps were freely available and downloaded from the Federal Emergency Management Agency's (FEMA) Map Service Center website, the preliminary and initial regulatory FIRMs had to be purchased from FEMA's Engineering Library. Sarah Pralle (an associate professor of Political Science at Syracuse University) and I inquired to obtain data for preliminary and initial regulatory FIRMs that became regulatory between 2013 and 2017. I received an external hard drive sent to me by FEMA which contained several hundred preliminary and initial regulatory FIRMs across the United States approximately during this time period. Sarah purchased these data; without her generous contribution this work would not have been possible.

I prepared the FIRMs for analysis using the following steps:

<u>1) Re-name 'S_Fld_Haz_Ar.shp' files, project, and import to geodatabase</u>

I found that in essentially all folders sent to me by FEMA that contained the flood zones polygons for a county or its equivalent, all these files had the same name: 'S_Fld_Haz_Ar.shp'. However, I also found there was also an .xml file in these same file folders, with its name being the Federal Information Processing Standard (FIPS) code of the county or equivalent.

To get all of the 'S_Fld_Haz_Ar.shp' layers, I ran python scripts ("Pr_OrigFiles_toGdb.py" for preliminary FIRMs and "In_OrigFiles_to_Gdb.py" for initial regulatory FIRMs) that went through all folders and selected and reprojected (to USA Albers Equal Area projection) any 'S_Fld_Haz_Ar.shp' layers that also had a .xml file with a matching county FIPS code. These FIRMs shapefiles were then converted to a geodatabase (either "Prelim.gdb" for preliminary FIRMs or "Final.gdb" for initial regulatory FIRMs).

<u>2) Get data information about preliminary and initial regulatory FIRMs, use to find matches</u>

To help discern if files were different or similar and to find matching case numbers between preliminary and initial regulatory FIRMs, I wrote and ran python scripts "Pr_DataInfo.py" and "In_DataInfo.py". These files contained FIPS codes matching to publication date and FEMA case numbers. I then went through the hundreds of preliminary and initial regulatory FIRMs based on their data in these csv files to determine FIRMs that had matching case numbers for both preliminary and initial regulatory maps. Through this process I determined that there were 255 counties that had matching preliminary and initial regulatory maps and fell within the study time period and that also had not had a new round of preliminary and initial regulatory FIRMs issued more recently.

<u>3) Download matching present FIRM shapefiles from FEMA’s Map Service Center Website</u>

I downloaded state FIRMs for each of the contiguous United States from FEMA's Map Service Center Website in August 2019 to serve as the present FIRMs in the analysis. Specifically, I went to the Map Service Center Website (https://msc.fema.gov/portal/home) and selected the link "Search All Products". On the Advanced Search page (https://msc.fema.gov/portal/advanceSearch) I then searched for a county or city in each state of the contiguous United States. For each county or city there was the selection under "Effective Products" to download from the National Flood Hazard Layer a state-wide FIRM under "NFHL Data-State".

The state FIRM for each of the 48 contiguous states was downloaded in a .zip file folder. The following steps were taken to prepare the data in shapefile format for analysis.

<u>3a) Extract data from .zip files to new file folders</u>

I wrote and used the python script "PresentFIRMs_Extract_Zips.py" to systematically extract the state FIRMs from their .zip file folders and save them to new file folders.

<u>3b) Project SFHA to USA Albers and save to geodatabase</u>

I wrote and used the python script "PresentFIRM_to_Gdb.py" for the FIRMs produced in step 1, which projected each state FIRM using the USA Albers Projected Coordinate System and then imported these FIRMs into a geodatabase.

<u>4) Use Select4Analysis.py to copy selected preliminary and initial regulatory FIRMs to analysis geodatabase</u>

For all preliminary and initial regulatory files I made "Pr_In_For_Analysis.csv", which was paired with the python script "Select4Analysis.py" to copy all shapefiles in ArcGIS that were listed on the .csv file from Prelim.gdb and Final.gdb to the Analysis.gdb.

<u>5) Run RenameAnalysisFiles.py</u>

I then wrote and ran RenameAnalysisFiles.py to loop through and rename the preliminary and initial regulatory FIRM layers to match with the file format of the present FIRM layers in Analysis.gdb. The naming file format for these layers was "xx_fips", where “xx” was Pr (for preliminary), In (for initial regulatory), or Re (for present), and “fips” was the six digit fips code (either 5 digit county code + “C” denoting it was a county, or 6 digit city/municipality code.

United States Census Tracts (shapefiles)

Shapefiles for Census Tracts in each contiguous state were downloaded from the United States Census Bureau website. Specifically, I went to the web interface for TIGER/Line Shapefiles (*https://www.census.gov/cgi-bin/geo/shapefiles/index.php*), selected the year 2018, and selected "Census Tracts". Then I downloaded shapefiles for each of the 48 contiguous states as .zip file folders.

The following steps were taken to prepare the data in shapefile format for analysis.

<u>1) Extract data from .zip files to new file folder and project to USA Albers</u>

I wrote and used the python script "Tracts_Extract_Zips.py" to systematically extract the census tracts from their .zip file folders and save them to new file folders

<u>2) Project SFHA to USA Albers and save to geodatabase</u>

I wrote and used the python script "Tracts_OrigFiles_to_Gdb.py", which projected each state census tract using the USA Albers Projected Coordinate System and then imported these census tracts into the analysis geodatabase

United States Building Footprints (geojson files)

The following steps were used to prepare the building footprint layers for each contiguous US state

1) Download building footprints from GitHub

The building footprint layers are available for download from the following GitHub link:

https://github.com/microsoft/USBuildingFootprints

The buildings can be downloaded in geojson format at the state scale, so I downloaded the 48 contiguous US state files.

Note: These data were created by Microsoft and the release of the data was in July 2018, so likely the data itself in its representation of existing buildings is from late 2017 or early 2018. Thus, buildings built in 2018 might not be included. Similarly, I noticed in later steps of data analysis when viewing the data in ArcMap that buildings in Google Maps compared to the building footprints layer did not always match exactly (sometimes building in Google Maps missing from layer, sometimes structure was in layer that was not a building on Google Maps). This likely was due to methods used in data acquisition. So the number of buildings may not be perfect match to reality, but represent a close enough approximation to be used for this analysis.

2) Convert building footprints from geojson to shapefiles using custom ArcGIS toolbox and "Buildings_to_gdb.py"

I had to convert the geojson state building footprint files to shapefiles to be able to use them with my other shapefiles. There is no tool to do this in ArcGIS or similar software I had access to, and most of the state files were too big for simple file converters from geojson to shapefiles that are available on the world wide web.

After some searching, I found a custom ArcGIS toolbox for converting geojson to shapefile at link:

https://github.com/germrothdaniel/MicrosoftBuildingsToFeatureclass

However, when I tried to convert whole state layers of buildings from geojson to shapefiles, I again found that most of the full state files were too large and my computer ran out of memory (and thus failed to do the conversion) when trying to convert such big file sizes. To deal with this, I broke the geojson files into smaller pieces, using methods described below:

I used information from the following links to perform the breaking apart of geojson files

https://gis.stackexchange.com/questions/298480/converting-large-geojson-to-shapefile

https://gis.stackexchange.com/questions/16340/alternatives-to-ogr2ogr-for-loading-large-geojson-files-to-postgis/16357#16357

Specifically, the steps I took are as follows:

<u>2a) Installed Node software on computer path:</u>

C:\Users\devin\node_modules\npm\node_modules

<u>2b) Downloaded geojsplit to break geojson files into smaller pieces</u>

copy downloaded geosplit folder from github:

https://github.com/woodb/geojsplit, or *https://www.npmjs.com/package/geojsplit*

to file path:

"C:\Users\devin\node_modules\npm\node_modules"

Now full path: C:\Users\devin\node_modules\npm\node_modules\geojsplit\bin\geojsplit

I also installed optimist package by copying and running "npm i optimist" in powershell (*https://www.npmjs.com/package/optimist*)

<u>2c) Changed directory in Windows Powershell (example code below)</u>

PS C:\Users\devin> Set-Location "C:\Users\devin\Desktop\US_buildings\Alabama"

<u>2d) Used geojsplit in Windows Powershell (example code below)</u>

PS C:\Users\devin\Desktop\US_buildings\Alabama>

node --max-old-space-size=500

C:\Users\devin\node_modules\npm\node_modules\geojsplit\bin\geojsplit -a 4 -l 100000 -v -o C:\Users\devin\Desktop\US_buildings\Alabama

C:\Users\devin\Desktop\US_buildings\Alabama\Alabama.geojson

All the split files now had 100,000 buildings (or less), so then I could use the custom ArcGIS toolbox for converting geojson to shapefile at link below without running out of memory:

https://github.com/germrothdaniel/MicrosoftBuildingsToFeatureclass

Specifically, I used the "Json_to_Featureclass" custom toolbox within a python script I wrote named "Buildings_to_gdb.py" to loop through and convert all geojson partial state files to a geodatabase [NOTE: this was still computationally intensive, even though computer could handle files individually without crashing memory, this took a few days of constant 24-hr computer processing]

3) Union partial state files back into larger shapefiles

Once all the partial state files had been converted to shapefiles, I used the union tool in ArcGIS to combine partial state files into larger shapefiles. This was not done in any super systematic way, but for each state I ended up with between 1 (states with the fewest buildings) and 4 (states with the most buildings) state building shapefiles. All of these shapefiles were then imported to the geodatabase

\\NFIP_maps\Pralle_Collaboration\GIS\test.gdb

4) Add unique ID for each building polygons using “Add_BldID.py”

I then wrote a python script called “Add_BldID.py” that added a unique building id number for each building polygon in each state buildings layer. The idea was to use this so I could tell if a building polygon intersected multiple flood hazard zones in SFHA, so I could determine which one to assign it to and not duplicate its inclusion in the analysis. It also allowed to keep buildings that were added to the SFHA vs. buildings removed from the SFHA separate.

American Community Survey Data (.csv files)

The following selections for download were made for all continuous ("lower 48") states:

- S0802 - MEANS OF TRANSPORTATION TO WORK BY SELECTED CHARACTERISTICS
- S1501 - EDUCATIONAL ATTAINMENT
- S1701 - POVERTY STATUS IN THE PAST 12 MONTHS
- S1810 - DISABILITY CHARACTERISTICS
- S1901 - INCOME IN THE PAST 12 MONTHS (IN 2017 INFLATION-ADJUSTED DOLLARS)
- S1902 - MEAN INCOME IN THE PAST 12 MONTHS (IN 2017 INFLATION-ADJUSTED DOLLARS)
- S1903 - MEDIAN INCOME IN THE PAST 12 MONTHS (IN 2017 INFLATION-ADJUSTED DOLLARS)
- S2503 - FINANCIAL CHARACTERISTICS
- S2506 - FINANCIAL CHARACTERISTICS FOR HOUSING UNITS WITH A MORTGAGE

- S2507 - FINANCIAL CHARACTERISTICS FOR HOUSING UNITS WITHOUT A MORTGAGE
- B02001 (Race)
- B19301 (Per Capita Income)
- B25077 (Median Home Value)
- B25035 (Median Year Construction)
- S1601 (Language Spoken at Home)
- S2801 (Presence of Computer/Internet)
- S1101 (Households and Families)

From this data the following variables were extracted/created for analysis:

- Number of households
- Median Income
- Percent Bachelor's Degree (specifically, this is Percent of Bachelor's or higher in age 25+)
- Below Poverty Percent
- Percent Non-White
- Per Capita Income
- Percent home owners with mortgage
- Percent renters
- Median Year of Construction
- Median Home Value
- Percent single family housing
- Percent No Home Internet

I downloaded selected 2013-2017 ACS data using the following steps

1) American FactFinder website

I went to US Census Bureau American FactFinder

(*https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml*)

2) Search for desired data and download

I used Advanced Search -> Show Me All

Then I selected Geographies -> 'Census Tract 140' from "Select a geographic type" pull-down menu

Selected a State

Select 'All Census Tracts within state' and click 'Add to your selection'

Selected the datasets I wanted (see below). For example: ‘S1903 'MEDIAN INCOME IN THE PAST 12 MONTHS (IN 2017 INFLATION-ADJUSTED DOLLARS)'

The 'dataset' column for this selection "2017 ACS 5-year estimates" was selected

Click Download at bottom of page

3) Extract csv files from zip files

Once the ACS data were downloaded, I extracted them from the downloaded .zip files using "ACS_Extract_Zips.py". This created a folder for each state and stored all the csv files that were downloaded.

Analysis steps

1) Create state_codes.csv

I first created a file called state_codes.csv. This file contains two columns, the first being the state FIPS code identifier and the second containing the state name. This was used in the analysis Python files “LOMR_Buildings_per_FldZone_new” to match the building files that were named by state (example: "Florida1") and the FIRMs which used fips codes (example: "12115C").

<u>2) Calculate number of buildings per flood zone for each FIRM iteration</u>

I then ran the python script "LOMR_Buildings_per_FldZone_new.py". This script calculated the area and number of buildings per flood zone type for all census tracts covered by the study counties. The output file was "LOMC_Zones_Buildings_per_CT.csv"

<u>3) Combine “LOMC_Zones_Buildings_per_CT.csv" with matching ACS census tract data</u>

Wrote and ran “Tracts_ACS_Combine_Sample.py”, which used the census tract id codes from “LOMC_Zones_Buildings_per_CT.csv" to loop through and append the matching ACS data described in section 4. The output file was named “CensusTract_corrs_sample.csv”

<u>4) Perform analyses using "LOMR_data_exploration.R"</u>

Wrote and ran parts of "LOMR_data_exploration.R". This script used “CensusTract_corrs_sample.csv” to find building and SFHA changes between the preliminary, initial regulatory, and present FIRMs. The script also was used to create output visuals like histograms, and also ran the Wilcoxon-Mann-Whitney tests and Logistic Regressions.

APPENDIX B

CHAPTER IV DETAILED METHODS AND JUSTIFICATIONS

Determining time and spatial scales for Chapter IV analyses

Before I conducted analysis, two questions needed to be resolved:

- What counties/census tracts would be included in the analysis?
- Over what time period would my analysis cover?

To understand my decisions to these questions, I will describe background about Flood Insurance Rate Maps (FIRMs) and Letters of Map Change (Amendment?).

I decided to use only counties (and their respective census tracts) that had a county-wide Flood Insurance Study conducted prior to the beginning of my study period. Flood Insurance Rate Maps, produced as part of a Flood Insurance Study, can be updated at various scales. In some studies, a whole county is assessed and maps are generated or updated for all its potential flooding sources. In other flood insurance studies, only parts of a county (e.g., only within a municipality) are mapped. As of the beginning of my decided study period (1/1/2013), some counties had FIRMs, but didn't have a county-wide FIRM. I determined this by going through all United States counties in FEMAs Map Service Center, as each county has a record of all Flood Insurance Studies conducted. I created a file named "FIS_dates.xlsx" on which I recorded the FIPS county (or equivalent) for all counties and county equivalents in the contiguous United States, as well as the date of the county's first (earliest in time) county-wide Flood Insurance Study. I could determine which Flood Insurance Studies were county-wide because it had the county or equivalent corresponding five digit FIPS code + "CV" (e.g., "41005CV" for Clackamas County, OR), with a few digits after as well denoting the number of the document in the release and usually an ending letter that placed it in time relative to other FIS reports (e.g., if 3 county-wide releases have occurred in the past, the most recent would have a "C" at the end, the middle one a "B", the oldest an "A"; sometimes the oldest one did not have a letter, so "A" began with second oldest). Other older reports were usually maps that had been done for a specific municipality but not the whole county. The oldest FIS county-wide date was recorded for each county or equivalent on "FIS_dates.xlsx". Some counties have never had a county-wide FIS released, so an "NA" was recorded for these counties. I realize this may exclude some counties from analysis that only had partial county coverage but did not change (i.e., did not have a new flood insurance study) over the analysis timeframe (2013-2018). However, my choice was to compare fully mapped counties against each other so there would not be any difference in the analysis between partially mapped counties and fully mapped counties, which might affect the results.

The study period was decided to be 1/1/2013 to 12/21/2018. Any Letter of Map Change with its date stamp during this time period in a county that has at least one county-wide flood insurance study before 1/1/2013 was included for analysis. This time period was arbitrary and does create a couple of assumptions I described below. This time period was chosen largely based on my initial methods (which later changed and could have accommodated a longer time period, although a longer time period would have had created its own assumptions as described below). Because I had to extract the Letter of Map Change data from PDFs, I initially found that older PDFs (about 2011 or 2012 and older, although it depended by county) were simply images and did not have any embedded text that could be extracted using the R script I initially developed. Because at the time it seemed I would have to extract data from any image-based PDFs manually, placing the cutoff at 2013 seemed a logical boundary. 2018 was chosen as end of time period since I began conducting this work in 2019. Later, I would develop a method that read text from images, so in theory at that time I also could have extended my earlier in time. However, besides the additional work this would have entailed, it would have created two other problems/assumptions. First, using an earlier start date but same parameters would have meant losing some counties from the analysis, as the earlier in time the fewer counties had a county-wide flood insurance study. Second, the American Community Survey data I used in my analysis was 2013-2017 5-year average estimates, which I assumed corresponded well with my 2013-2018 Letter of Map Change data. Starting earlier would have led to inclusion of LOMC data years ahead of the ACS data to which it would be compared in regression analysis. Thus, keeping the 2013-2018 LOMC time period made sense. However, one issue that cannot be easily rectified with the data I have is that in some of the counties I analyzed they had a new flood insurance study issued during my study period. I had to make the assumption that this did not affect my analysis, although in some senses it likely did. This seems likely because when a new Flood Insurance Study is conducted, all existing Letters of Map Change that are in effect are checked to see if with the new data they are still effective. Some LOMAs, for example, will no longer be effective (i.e., their base flood elevations will be below the new SFHA base flood elevations) and they will change from ‘effective’ to ‘historic’ LOMCs. In my analysis I used both ‘effective’ and ‘historic’ LOMCs because I did not know when during the study period they might have changed. Also, there may be a temporal component to when Letters of Map Change are more/less submitted. It may be that many more LOMCs are submitted right after a new FIRM is issued, with fewer LOMCs the longer the map is in effect. However, I didn’t conduct a temporal analysis of LOMCs, so I cannot affirm this or note how it might have affected my analysis.

To answer the research question, there are six categories of data that were initially collected to conduct analyses:

1) Analysis Counties csv file (.csv file)
2) Flood Insurance Rate Maps (shapefiles)
3) United States Counties (shapefile)
4) United States Census Tracts (shapefiles)
5) United States Building Footprints (geojson files)
6) Letter of Map Amendment files (PDFs)

Below I use corresponding categories of the data listed above where I detail how each data type was acquired and initially prepared before analysis. I then describe the steps taken to analyze all the data together to answer the research question.

Analysis Counties csv file (.csv file)

As described above in the background section, I decided to only analyze LOMAs that were submitted between January 1, 2013 and December 31, 2018 for counties that had a county-wide FIRM in effect prior to January 1, 2013. Further justification for these reasons is described below in section 6 about the Letter of Map Amendment data.

<u>1) Use Map Service Center website to find earliest county-wide FIRM release</u>

I used data on FEMA's Map Service Center website to determine the first county-wide FIRM dates for each county in the United States. First, I created a file named "FIS_dates.xlsx". This file had two columns. The first column had the FIPS county or equivalent value for all counties and equivalents in the contiguous United States, which I obtained from the United States Counties and Equivalents shapefile attribute table (see section 3) and double-checked using the counties and equivalents Wikipedia pages for each of the 48 states in the contiguous United States. The second column contained the date of the county or equivalent's first (earliest in time from past to present) county-wide Flood Insurance Study, which released a "county-wide" FIRM (meaning effectively all hazardous water bodies for the county or equivalent had been mapped). This was determined for each individual county by searching it on the Map Service Center Website (*https://msc.fema.gov/portal/home*), selecting the link "Search All Products", then on the Advanced Search page (*https://msc.fema.gov/portal/advanceSearch*) searching for counties or equivalents using their name or FIPS code. For each individual county or equivalent, I looked under "Effective Products" -> "FIS Reports" and "Historic Products" -> "FIS Reports" to find the PDFs and their matching dates for all past Flood Insurance Studies that had been done for the county or equivalent. I could determine which Flood Insurance Studies were county-wide because it had the county or equivalent corresponding five digit FIPS code + "CV" (e.g., "41005CV" for Clackamas County, OR), with a few digits after as well denoting the number of the document in the release and usually an ending letter that placed it in time relative to other FIS reports (e.g., if 3 county-wide releases have occurred in the past, the most recent would have a "C" at the end, the middle one a "B", the oldest an "A"; sometimes the oldest one did not have a letter, so "A" began with second oldest). Other older reports were usually maps that had been done for a specific municipality but not the whole county. The oldest FIS county-wide date was recorded for each county or equivalent on "FIS_dates.xlsx". Some counties have never had a county-wide FIS released, so an "NA" was recorded for these counties. I chose to compare fully mapped counties against each other so there would not be any comparison in the analysis between partially mapped counties and fully mapped counties, which would have been an unequal comparison.

<u>2) subset data to get only counties with FIRMs before 2013</u>

Once a date or "NA" was acquired for all counties and equivalents in "FIS_dates.xlsx", I sorted the file by date and then copied and saved the county and equivalent FIPS codes for all counties with a pre-2013 Flood Insurance Study (1,988 total) to new file "Counties_Before_2013.csv".

"Counties_Before_2013.csv" would then be joined with the United States Counties layer to select appropriate counties for analysis.

Flood Insurance Rate Maps (shapefiles)

The FIRM layers used in this analysis were the same as whose preparation is described in the Letter of Map Revision methods appendix. See step 3 as part of the section named "Flood Insurance Rate Maps (shapefiles)" in Appendix A for how the present FIRM layers were prepared for data analysis.

Note: These were present iterations of Flood Insurance Rate Maps at the date they were downloaded, so an assumption is that the Special Flood Hazard Area extents I ended up selecting from the files and using were representative for 2013-2018 time period, even though the SFHA can change areal extent due to Letters of Map Revision.

United States Counties (shapefile)

A shapefile of all United States counties for 50 states plus territories was downloaded from the United States Census Bureau website. Specifically, I went to the web interface for TIGER/Line Shapefiles (https://www.census.gov/cgi-bin/geo/shapefiles/index.php), selected the year 2018, and selected the "counties (and equivalent)" and downloaded the shapefile in a .zip file folder.

The following steps were taken to prepare the data in shapefile format for analysis.

<u>1) Extract data from .zip files to new file folder and project to USA Albers</u>

Because it was a single file, I manually unzipped the .zip folder. I then projected the counties shapefile using the USA Albers Projected Coordinate System.

<u>2) Join with "Counties_Before_2013.csv" to produce Analysis Counties</u>

I then joined the USA Albers Projected shapefile with the "Counties_Before_2013.csv" I produced as described in section 1. The output of this join resulted in 1,988 counties and equivalents in the contiguous United States. In ArcGIS I then used Feature Class to Geodatabase to move these counties into a geodatabase, and named the layer "Analysis_Counties"

United States Census Tracts (shapefiles)

The Census Tract layers used in this analysis were the same as whose preparation is described in Appendix A. See the section named “United States Census Tracts (shapefiles)” in Appendix A for information how the census tract layers were prepared for data analysis.

United States Building Footprints (geojson files)

The building footprint layers used in this analysis were the same as whose preparation is described in Appendix A. See the section named “United States Building Footprints (geojson files)” in Appendix A for information how the building footprint layers were prepared for data analysis.

Letter of Map Amendment files (PDFs)

1) Download LOMAs from FEMA Map Service Center and unzip files using python script "LOMAs_Extract_Zips.py"

Letter of Map Amendment PDFs can be accessed by searching for the 'FIPS code' + 'c' (e.g., 12099c) or six digit FIPS code for cities at the following link:

https://msc.fema.gov/portal/advanceSearch

At the above link, for all counties/cities with a county/city-wide FIRM, under "Effective Products" and "Historic Products" you can find "LOMC", under which you find "LOMA", with the number next to them indicating all number of in effect or historically effective LOMAs. Next to these you can click "DL ALL", which opens a new window from which you can download zip file(s) containing all effective or historic LOMAs.

1a) Download zip folders containing PDFs of all effective and historic LOMAs per contiguous US County

I went through all FIPS codes in contiguous United States (so excluding D.C., Alaska, Hawaii, and other territories) and downloaded all Effective and Historic LOMAs for all counties and cities that have a county-wide or city-wide FIRM, denoted by the "C" at end of FIPS code. In the Map Service Center search, the FIPS code entered would provide the "COUNTY NAME ALL JURISDICTIONS".

1b) Extract zip folders using "LOMAs_Extract_Zips.py"

After all data was downloaded, I extracted all PDFs of LOMAs to new folders using the python script "LOMAs_Extract_Zips.py"

2) Geocode addresses to get latitude and longitude

On the LOMA PDFs there were many types of data that were of interest, such as: date the LOMA was ruled on; designation type (e.g., LOMA, LOMR-F, LOMA-DEN...); case number; latitude; longitude; address

In an earlier attempt to analyze this data, I extracted the latitude and longitude values directly from the PDFs and used these for the LOMA locations. However, I found some LOMAs when I used this method were in error either because their lat/long values were not precise enough (before 2016 lat/long had values to 3 decimal degrees; on a census tract boundary this could land the point in the wrong census tract) or were just incorrect. Due to this in I decided to geocode all the PDFs using the provided addresses, and then I would check geocoded lat/longs versus the lat/long values directly from the PDFs.

This process of geocoding and preparing the LOMA points for analysis contained many steps, which are detailed below.

2a) Run LOMAs_PDF_text_extract.R script

Once PDFs were extracted and in folders by county, I wrote and ran R script "LOMAs_PDF_text_extract" to extract data from PDFs including address lines; these were not always complete because some addresses were on multiple lines or were not found on the rows of the PDF I had the code extract text from. The outputs for each county were saved to new csv files on the file path:

\\NFIP_maps\Pralle_Collaboration\LOMAs_csvs\2013_2018_wAddress

2b) Run "Combine_LOMA_csvs2.py"

Ran python code, which combined all county csvs by state. Output csvs saved on file path: \\NFIP_maps\Pralle_Collaboration\LOMAs_csvs\2013_2018

2c) Run "LOMAs_remove_duplicates.R"

For the state csv files, ran remove duplicates code that removed duplicate LOMA rows, since there were duplicate PDFs in different county folders for same state.

2d) Download ImageMagick and Ghostscript software

After running R code extracting text from text-readable PDFs as described in step 2, there was still limitation that many addresses were not being written in output csvs. I realized that many of the LOMA PDF documents are all set up in the same orientation so that the text for addresses and other text of interest was in the same place on the PDFs. Thus, the idea was that I could convert PDFs to images and then read them as text. To do this, I first acquired the free software packages of ImageMagick and Ghostscript from the World Wide Web to be able to perform this work.

As via step 1, I had obtained Letter of Map Amendment PDF files in folders by county, but to run the next step of PDF to images I wanted to put the files into folders by state. To do this, I ran a python script named "LOMA_PDFs_to_state_folders" which looped through all the county folders (which were named by their 5 digit FIPS code) and put them in state folders (named xx_LOMAs, where xx is two digit state FIPS code) based on first two digits from county FIPS codes (which is the state identifier). I copied over all PDFs that had year designations in their name between 12- and 19-, because some of the 12- where official in 2013, and some of 19- were official in 2018.

2e) Run PDF to JPG and crop via Powershell

Once the files were copied to their state folders, via Windows Powershell I used the command line to operate through ImageMagick (and in turn Ghostscript) and do batch PDF to JPG conversion and crop the resulting images to get segments of text I wanted. Below the process is described of work I did for each state folder.

First, use Set-Location to get to directory:

PS C:\Users\devin> Set-Location "G:\NFIP_maps\Pralle_Collaboration\LOMAs_PDFs_states\xx_PDFs" where "xx" is two-digit state FIPS code

Then, for each state folder I used the following line in Powershell to convert the first page of each PDF in the folder to an image:

PS G:\NFIP_maps\Pralle_Collaboration\LOMAs_PDFs_states\xx_LOMAs> magick convert -density 175 *.pdf[0] outimg.jpg

In the line above "xx" is the state FIPS code identifier, "magick" calls the ImageMagick software, density sets dots per inch of 175, *.pdf selects all pdfs in the directory, [0] means only the first page is converted from pdf to jpg.

After the initial conversion of first page of the PDFs to JPGs, I used crop via Powershell to batch crop the full JPGs to segments with text I wanted. Originally, my plan was to obtain the following data: Case Number, Date, Designation, Street Address, Place/Community, Latitude and Longitude, what was removed (or not)

This would be done using bounding boxes where the data would be on the resulting image; on some PDFs however the data were not in this bounding box, so these were not useful. Example bounding box information is below:

To crop for Case Number:

PS G:\NFIP_maps\Pralle_Collaboration\LOMAs_PDFs_states\xx_LOMAs> magick convert -crop 229x42+1038+15 *.jpg casenum.jpg

However, because the success rate of extracting and reading text was not as high as I had hoped, and also because of the computationally expense to do many states (it could be several hours up to over a day for larger states to convert PDFs to JPGs, then up to another few hours to crop all the images), for most states I only cropped to get case number and street address. A few states I also got place/community if that was poor output from R code text extracting from PDFs (see step 2). All the others (except Removed, which was not done using the R script) had high success from R script text extract (step 2), so as described in the following steps I combined outputs from text extraction and image reading and then cleaned those outputs (see steps 7-9)

NOTE: Cropping was done computing one line at a time in Powershell, and after each run I cut and pasted the results into a different folder before running the next one so I did not try to crop already cropped images, since I was selecting all JPGs in the folder using *.jpg

* Another issue was that ImageMagick issue of used temporary disk space when performing PDF -> JPG, and for a few of the states with most PDFs I didn't have disk space to store them all for one run via Powershell. I either had to use a computer with more disk space, or break up into multiple runs on my computer. See link here for more information: https://www.imagemagick.org/discourse-server/viewtopic.php?t=15960#:~:text=ImageMagick%20requires%20temporary%20files%20when,temporary%20files%20before%20it%20exits.

2f) R code to read text from images

Once the cropped images were completed for the states above so that casenum, date, desig, address, place, latlon, and remove were all produced and moved to respective state folders, I ran an R code script named "LOMAs_image_text_extract.R" that went through the folders and used the tesseract package, an optical character recognition software, to identify the text in each image, which then was combined and produced into state csv files.

<u>2g) Combine LOMA csvs from text extract and image reading</u>

Now with outputs from PDF text extraction and image reading, each of which had some correct addresses and some not, I wanted to get just the correct addresses for both. I realized that the text extracted addresses always had correct text from PDF, but most frequently only had part of address if address was on multiple lines. In contrast, the image reading was good at getting the full address because it had all the text it could read from the image, however, sometimes (uncommon but it did happen) sometimes the image read individual letters or numbers wrong.

To deal with this, I wrote and ran "Geocode_update_addresses", which used the PDF text extracted addresses, but updated them if they were contained within the matching full address (using case number) from image reading output. If no output was written from PDF text extract, the output from the image reading output was substituted for it. Thus, this new output csv had many more complete addresses. However, some were partial or incorrect from image reading (it was frequently evident when it went wrong because it often produced special characters or words that didn't make sense in addresses), so this still required manual cleaning.

<u>2h) Manually clean files, remove those without addresses</u>

The output csv files from step 8, saved using name convention "LOMAData_xx" (xx is state FIPS code) on file path:

G:\NFIP_maps\Pralle_Collaboration\LOMAs_csvs\2013_2018_wAddress\StateFiles

I then did any cleaning that needed to be done on the addresses or other outputs.

Because some LOMAs did not have a valid address listed, I sorted the csv files by address and removed out all the LOMAs that did not have a proper street address. These were put in new "LOMAs_xx_removed" csvs on same file path.

NOTE: Some LOMAs had multiple valid addresses listed either individually (e.g., 105 Main St. and 203 Elm St.), or in aggregate (example: 212-216 W Jefferson Street). For these I just used the first/one valid address (105 Main St. and 212 W Jefferson Street from examples above), so others were not included. This was done because I needed just one point to represent the LOMA per a census tract. So it did remove the collective multi-property removal of a few LOMAs, but for my uses this was fine.

2i) Create new csv file for input to geocoding

Once addresses were cleaned, I then manually created a new csv file for each state that would be the input file for geocoding. These files were named using the convention "statename_LOMAs_input" and saved on file path:

\\NFIP_maps\Pralle_Collaboration\LOMAs_csvs\2013_2018_wAddress\InputGeocode

These csv files contained 4 columns: 1) address (street address, city/county, state), 2) case number, 3) designation, 4) date

2j) Google Geocoder using python script

I then used the python script "GoogleAPI_geocoding_addresses.py" to batch geocode the addresses in "statename_LOMAs_input" csvs. Output files, named using the convention "statename_LOMAs_output" on the file path:

\\NFIP_maps\Pralle_Collaboration\LOMAs_csvs\2013_2018_wAddress\OutputGeocode

The output files included the inputs, plus latitude, longitude, and location type.

Location type referred to precision of geocoding locations. ROOFTOP were generally the best, having direct match of address and linked to rooftop of structure or a property. RANGE_INTERPOLATION used interpolation to estimate the location of an address GEOMETRIC_CENTER and APPROXIMATE were less accurate estimates of location of an address

* NOTE: before I could run python file and use Google geocoding API, I had to:

download google maps services python code from github:

https://github.com/googlemaps/google-maps-services-python

After unzipping the master folder, I copied the downloaded 'googlemaps' folder to path C:\Python27\ArcGIS10.5\Lib\site-packages (I think this was essentially equivalent to using pip install, which I couldn't figure out how to work correctly)

I also had to set up a Google Geocoding API and billing account. Essentially, I followed equivalent steps found on the youtube video below, except my python code is slightly different and uses dictionaries instead of Pandas module and data frames.

https://www.youtube.com/watch?v=zdPW4aVha8M

<u>2k) Review geocoding output, determine missing from output and run through geocoder again or manually geocode</u>

Once the geocoding outputs were generated, I examined the "statename_LOMAs_output" files and made sure the number of LOMAs in the input files matched the number in the output. In a few states not all LOMAs were geocoded, so for those states I had to determine the missing LOMAs that were not geocoded and I manually geocoded these or ran them a second time using the "GoogleAPI_geocoding_addresses.py" script. The second input file was named by convention "statename_LOMAs_outmissing". However, this only applied for a few states, so for many states I did not have to do this step. This applied for some of the earliest states I did because I didn't at that time have a way to correct and get full addresses, so sometimes I was missing part of an address and that was why the geocoding failed.

<u>2l) Combine geocode output, missing, and removed csvs</u>

I then manually combined the LOMAs contained in the geocode output file, the LOMAs that were missing from the input to the output geocoding (see step 12, this did not always apply), and the LOMAs that were removed before geocoding because they did not have a valid address. These were saved in csvs with naming convention "statename_LOMAs_combined" on file path:

\\NFIP_maps\Pralle_Collaboration\LOMAs_csvs\2013_2018_wAddress\Combined

Then I added two new colums of data to the "statename_LOMAs_combined" files named "lat" and "long", which were the latitude and longitude values text extracted from PDFs. I acquired these (which had previously been cleaned when I thought I was going to use those text extracted lat/long values) from files with naming convention "statename_LOMAs" on file path:

\\NFIP_maps\Pralle_Collaboration\LOMAs_csvs\2013_2018

These "statename_LOMAs_combined" files were then backed up on Dropbox under path: Dropbox -> Backups -> Dissertation -> GeocodingQ1 -> Combined

<u>2m) Compare geocode combined lat/longs vs. PDF lat/longs</u>

Now that the "statename_LOMAs_combined" files contained both geocoded latitude/longitude as well as lat/long directly from PDFs, I wanted to compare the two locations and make sure that the latitude and longitude being used for each LOMA seemed correct. I assumed that latitude and longitude from geocoding was correct, but I checked the matching points against each other in two ways.

First, I visually viewed the geocoded latitude and longitude locations with state census tracts, and I corrected any points that were located outside the state. To do this, I used google's geocoder (https://developers-dot-devsite-v2-prod.appspot.com/maps/documentation/utils/geocoder) to search both points. I also used FEMA's Map Service Center website and searched the matching case number and compared the flooding source to make sure it made sense. I choose which point of the geocoded or PDF point was correct, and I updated the geocoding lat/long, if necessary. I kept using and updated the "statename_LOMAs_combined" files.

I then used the tool "Table to Geodatabase" in ArcGIS to convert the "statename_LOMAs_combined" files to geodatabase tables on file path: G:\NFIP_maps\Pralle_Collaboration\GIS\test.gdb

Then I wrote and used the script "Geocode_error_assessment_by_state.py", which used 2018 Census Tract GIS layer and plotted the points in ArcGIS and determined which points were in different census tracts (and different counties using the first five numbers of the census tract FIPS codes). The results were saved in files "Statename_Error" on file path \\NFIP_maps\\Pralle_Collaboration\\LOMA_Error_Assessment\\.

In the “Statename_Error” file, if PDF lat/long and geocoded lat/long were in same census tract and/or county, ‘NA’ was saved instead of the census tract/county identifiers. To remove the ‘NA’s so I could only have the mismatches between PDF and geocoded locations, I wrote and ran the script “Geocode_CT_error_corrections.py”, which created new csv files “Statename_CT_Error_Corrections” on file path

\\NFIP_maps\\Pralle_Collaboration\\LOMA_Error_Assessment\\, which only had the LOMAs with difference between PDF and geocoded lat/longs. A few of the first csvs I didn't have this step developed, so their updated info is stored in the text file "Error_Corrections_Catalog"

I used the "Statename_CT_Error_Corrections" file to determine which points were in different census tracts and counties and recorded my reasoning in the 'ErrorCorrection' column in these files. For each pair of points, I used google's geocoder (https://developers-dot-devsite-v2-prod.appspot.com/maps/documentation/utils/geocoder) to search and find locations for both points. I also used FEMA's Map Service Center website and searched the matching case number and compared the flooding source to make sure it made sense. I choose which point of the geocoded or PDF point was correct, and I updated the geocoding lat/long, if necessary. I kept using and updated the "statename_LOMAs_combined" files.

Thus, the data product I created for each state in the "statename_LOMAs_combined" generated latitude and longitude points (under the "latitide" and "longitude" columns in the file) I verified the correct latitude and longitude for all points where original geocode and PDF lat/longs were in different census tracts and/or counties.

These final "statename_LOMAs_combined" files were then backed up on Dropbox under path: Dropbox -> Backups -> Dissertation -> GeocodingQ1 -> Final_for_Analysis

<u>2n) Convert csv to geodatabase for LOMA analysis</u>

I then used the tool "Table to Geodatabase" in ArcGIS to convert the "statename_LOMAs_combined" files to geodatabase tables on file path: G:\NFIP_maps\Pralle_Collaboration\GIS\test.gdb. I deleted the same file that had been uploaded in step 13 and uploaded the corrected version after step 14. These would be the points used for analysis of LOMAs as described in the text file "LOMA_SpatialDistribution_Metadata".

Analysis Steps

1) LOMA calculations per census tract

Once all the files described in the above sections were ready in the geodatabase, I ran the python script "LOMA_Buildings_per_FldZone_new.py". This script calculated the following:

- Land area for each census tract (open water was removed from FIRMs, then intersected with census tract layer)
- Number of buildings whose centroid in each census tract (some buildings overlapped multiple census tracts, so to not double count buildings they were only counted if the centroid was in the census tract)
- Total number of submitted LOMAs per census tract (any ruling designation)
- Area in sq. km and number of buildings intersecting each flood zone (NOTE: some buildings might overlap multiple flood zone types. The code used the following hierarchy: VE, V, A99, AH, AO, AE, A, where VE is highest/first, A is lowest/last. In other words, if a building intersected multiple zones, it only was counted in the highest zone in the hierarchy)
- Number of LOMAs with each flood zone and designation combination

These results were saved in two main files per state:

- "TractData_statename.csv"
- "LOMAData_statename.csv"

Two additional files were also created, which will be described in greater detail later in this section:

- LOMAs_FldZones_Counts.csv
- LOMAs_FldZones_Outside.csv

2) Remove counties without full FIRM coverage

I found that some of the counties that claim to have a FIRM before 2013 didn't have their county FIRM GIS layer available as part of state FIRM layer or available to download as an individual county on FEMA's Map Service Center website. For these 68 counties I removed all matching census tracts from the respective TractData_statename.csvs and LOMAData_statename.csvs.

I also created a new file named "Counties_Before_2013_fullcountyFIRMs.csv" containing the remaining 1,920 counties FIPS codes. Because of missing data for these 68 counties, analysis was on remaining 1,920 counties.

3) Add LOMAs that were > 100 m from any flood zone

The next step was to add LOMAs to the respective LOMAData state files from the LOMAs_FldZones_Outside.csv. This file contained LOMAs from all states that were greater than 100 meters from any flood zone, as in LOMA_Buildings_per_FldZone_new.py script these LOMAs were not assigned to any flood zone and LOMA designation.

To assign a LOMA designation and determine the appropriate flood zone type, I wrote and ran the python script “LOMA_Outside_adds.py”. This script looped through each LOMA and used buffer in a while loop that increased its size until it intersected a flood zone to which it was assigned. The outputs from this method were saved in the file

LOMAs_FldZones_Outside_adds.csv. A small number of LOMAs (about 70) didn't find a match using the method in LOMA_Outside_adds.py (I had a 7 kilometer limit on the search), so I copied them to a new csv (LOMAs_FldZones_Outside_zeros.csv) and determined the combined flood zone and LOMA Designation manually. Once I completed the manual matching, I copied the results in LOMAs_FldZones_Outside_zeros.csv back to LOMAs_FldZones_Outside_adds.csv.

I then added a new column in LOMAs_FldZones_Outside_adds.csv with header name 'state', which contained the state name for the matching row based on the first two digits of the census tract geoid.

Once all LOMA designation and flood zone matches were set in LOMAs_FldZones_Outside_adds.csv, I created a new folder "LOMA_Outside_Adds". To this folder I copied all LOMAData_statename csvs, which were the results from the analysis steps described above. I then wrote and ran the pyton script LOMA_Outside_combine_csvs.py, which added the LOMAData results from LOMAs_FldZones_Outside_adds.csv to their respective LOMAData state csvs.

<u>4) Remove 2+ counts for LOMAs within 100 m of multiple flood zones</u>

The next step was to account for LOMAs that were counted 2+ times because they were not within any one flood zone but were within 100 meters of 2 or more flood zones. These LOMAs and how many times they were counted were saved in the file LOMAs_FldZones_Counts.csv

I first determined which of the LOMAs of the 2+ counts should be kept (ie, which flood zone it was assigned to). I wrote and ran the python script "LOMA_counts_keep.py", which for each LOMA point determined the closest flood zone, which was assumed the correct assignment, using an expanding buffer until it overlapped with a flood zone.

I then wrote and ran the python script “LOMA_counts_remove”, which calculated and saved the LOMA removals to the state csv files

<u>5) Final data cleaning and checks</u>

After this, in theory the summed number of LOMAs in each "LOMAData_statename2" csv should have been equal to the number of LOMAs in the "statename_LOMAs_combined" geodatabase tables. However, I found many of the states did not quite match. To determine which census tracts had differences, I first wrote and ran the python script "LOMA_state_tract_counts.py" to count the number of LOMAs for all census tracts in the analysis counties. I then compared the outputs (saved in "XX_LOMAs_cnt.csv" files, where XX was state abbreviation) to the number of LOMAs counted in each census tract intersection with the FIRM (this was 'CT_LOMA' column in the TractData_statename.csv files) and the summed number of LOMAs for each census tract from the LOMAData_statename.csv files to find the differences. I then either ran the python script "LOMA_Buildings_per_FldZone_new_CT.py" to calculate TractData_statename and LOMAData_statename files again and check visually in GIS that numbers made sense, or did these calculations manually to resolve the differences.

I also found there were a small number (about 30) census tracts that had a percentage > 100% of buildings in the SFHA when examining initial outputs in the R code used for analysis. I copied these census tracts to a new csv named "CTs_Over100pct_Blds_SFHA" and manually went back to make corrections that made their percent of buildings in the SFHA numbers make sense to 100% or lower (usually the number of buildings in CT or in flood zones was miscounted).

I also found there were a few census tracts that had zero buildings from the Microsoft Buildings layer. Mostly these were either extremely small "sliver" census tracts or were islands for a couple coastal states (Cali + Florida) where the buildings layer didn't have coverage. I removed these census tracts from analysis at the beginning of using the R code for data analysis.

6) Join LOMA data with ACS data

Before running the uncertainty analysis for the LOMC R code, I needed to also join the LOMC data with the matching ACS data. To do so, I ran the python script "CT_ACS_extract.py" to get ACS data for matching census tracts, which was saved to "CT_ACS_data.csv". I then manually copied the data from "CT_ACS_data.csv" to the "LOMAData_AllStates.csv" file, so the latter now contained all the LOMC data with its matching ACS selected variables. This is the file I used for analysis in R code.

7) Analyses

Final analysis steps here

APPENDIX C

CHAPTER V DETAILED METHODS AND JUSTIFICATIONS

Determining time and spatial scales for Chapter V analyses

Before I conducted analysis, two questions needed to be resolved:

- What counties/census tracts in Florida would define the analysis Tax Lots?
- Over what time period would my analysis cover?

See Appendix A and Appendix B for background regarding FIRMs and LOMAs. The analysis of LOMAs across Florida was decided to be the same temporal bounds as the analysis of LOMAs across the United States (1/1/2013-12/31/2018). Same as in the analysis of LOMAs in the contiguous United States for this time period, in Florida I only analyzed Tax Lots in counties that had a county-wide FIRM issued before 2013.

To answer the research question, there are seven categories of data that were initially collected to conduct analyses:

1) Tax Lots for Florida counties (shapefiles)
2) Attribute Tables for Tax Lots (geodatabase files)
3) Florida Flood Insurance Rate Map (shapefile)
4) Florida Counties (shapefile)
5) Florida census tracts (shapefile)
6) Florida building footprints (geojson)
7) Florida Letter of Map Amendment files (PDFs)

Below I use corresponding categories of the data listed above where I detail how each data type was acquired and initially prepared before analysis. I then describe the steps taken to analyze all the data together to answer the research question.

Tax Lots for Florida counties (shapefiles)

1) Create FL_county_fips_codes.csv that contains county names and county fips codes

Before downloading Tax Lots shapefiles, I created FL_county_codes.csv that contained two columns:

- column 1 contained the two-digit code used by Florida Department of Revenue to denote each of the 67 Florida counties
- column 2 contained the corresponding county name for each county code in column 1

2) Download Tax Lots zip files

I manually downloaded the 2019 tax lots shapefiles in .zip file folders from the Florida Department of Revenue website (*https://floridarevenue.com/property/Pages/DataPortal_RequestAssessmentRollGISData.aspx*)

3) Unzip files

I then wrote and ran python script "TaxLots_Extract_Zips.py" to loop through and extract the zipped file folders to new folders that were the name of the respective county.

4) Create new geodatabase and import Tax Lots to geodatabase

First, created a new geodatabase named FL_analyses.gdb.

Next, I wrote and executed the python script "TaxLots_to_gdb_project.py", which did two main things:

4a) "walked" through all Tax Lot files and exported shapefiles to FL_Analyses.gdb

4b) Looped through the files in FL_Analyses.gdb and re-projected them from Florida State Plane to NAD 1983 (2011) Contiguous USA Albers projection. Using data from

FL_county_fips_codes.csv, the new projected files had new names based on the following structure: "TL_" + FIPS, where 'FIPS' was the five-digit county FIPS code

Attribute Tables for Tax Lots (geodatabase files)

1) Download Tax Lots zip files

I downloaded the database files containing attribute information for FL tax lots from Florida Department of Revenue website https://floridarevenue.com/property/Pages/DataPortal_RequestAssessmentRollGISData.aspx

2) Unzip files

I then wrote a python code script "DBFs_Extract_Zips.py" to loop through and extract the zipped file folders to new folders that were the name of the respective county.

3) Create new geodatabase and import Tax Lots to geodatabase

Wrote and executed python script "DBFs_to_gdb_rename.py", which did two main things"

3a) "walked" through all Tax Lot database files and exported database files to FL_Analyses.gdb

3b) Looped through the tables in FL_Analyses.gdb and re-named them based on their matching FIPS codes from FL_county_fips_codes.csv, so the new projected files had new names based on the following structure: "DB_" + FIPS, where 'FIPS' was the five-digit county FIPS code

Florida Flood Insurance Rate Map (shapefile)

The Florida FIRM layer used in this analysis was one of the files whose preparation is described in Appendix A. See step 3 within the section named “Flood Insurance Rate

Maps (shapefiles)" in Appendix A for information how the present Florida FIRM layer was prepared for data analysis.

Florida Counties

Did I use FL counties shapefile?

Florida Census Tracts

Did I use FL census tracts shapefile?

Florida building footprints (geojson)

The Florida building layers used in this analysis were included in the preparation described in Appendix A. See the section title "United States Building Footprints (geojson files)" in Appendix A for information how the building footprint layers were prepared for data analysis.

Florida Letter of Map Amendment files (PDFs)

For the Florida analysis I started with the "Florida_LOMAs_combined" csv and geodatabase table that I created as part of the United States census tract scale analyses. See section 6 in the United States Letter of Map Amendment Methods Appendix for how the LOMAs were prepared for data analysis.

However, the files in the US analysis were only checked to be within a census tract, so not all of the geocoded LOMAs were located and matching with Tax Lot locations.

<u>1) Find (mis)matching addresses between from LOMA PDFs and Tax Lot intersections</u>

To check this, I first wrote and ran the python script "FL_LOMAs_TLs_match", which looped through each LOMA point and used the matching county census tracts layer to find the address of the polygon from that layer that it intersected. This allowed me to see for each LOMA point which locations had matching addresses and which did not. This was saved in csv file named "Florida_LOMAs_TaxLots_matching".

<u>2) Remove invalid addresses</u>

The csv file contained LOMAs that didn't have valid addresses, so I removed those and saved another csv file named "Florida_LOMAs_TaxLots_matching_NoAddressRemoved"

<u>3) Determine why address mismatch and record in "FL_LOMAs_TaxLot_errors_all.csv"</u>

I then added a column to the csv file in step 2 that allowed me to compare address number from LOMA PDF versus from Tax Lots. If number differed, I copied the row to a new file named "FL_LOMAs_TaxLot_errors_all.csv". I then went through each LOMA and tried to resolve the difference between the addresses. For essentially all LOMAs, the resolution occurred one of three ways: 1) I found the address on the Tax Lots file and updated the latitude and longitude values to intersect the Tax Lot, 2) I determined there was a reason that although the address wasn't a match the point was in the correct place, 3) or the point seemed in the correct place, but the Tax Lot data was null for the polygon. There were also a small number I could not determine why there was a mismatch.

<u>4) Update LOMA locations</u>

Once these corrections were made, I wrote and ran python code "FL_LOMAs_TLs_updates", which again used select by location to get information about property for each LOMA point it intersected for those LOMAs that had updated lat/long locations.

Then I wrote/ran "FL_LOMAs_TLs_updates2" python code that updated the "Florida_LOMAs_TaxLots_matching_NoAddressRemoved" csv by updating new lat/longs where applicable, as well as removing LOMAs that I was unable to find an equivalent match for. The new file was called "Florida_LOMAs_TaxLots_updated.csv" Then I wrote/ran "FL_LOMAs_TLs_updates3" python code that added county and census tract FIPS codes as well as flood zone and LOMA designation for each submitted LOMA. New file was called "Florida_LOMAs_TaxLots_final.csv"

(**Some flood zones have unknown values, need to update these still)

I also wanted updated latitude/longitude for LOMAs where it had been updated. This was done and saved to new csv named "Florida_LOMAs_withupdates.csv" by writing and running python script named FL_LOMAs_update_LOMAs.py.

I had some problems with errors being in the "Florida_LOMAs_TaxLots_final.csv" that I couldn't identify the source in the earlier python scripts, so I wrote and ran FL_LOMAs_Corrections.py and FL_LOMAs_Corrections2.py for LOMAs that had unknown flood zone types, which used the "Florida_LOMAs_withupdates.csv" file to match with overlapping/nearest census tract, county, and SFHA flood zone. Inputs were in "Florida_LOMAs_ToCorrect.csv" files, and outputs saved to "Florida_LOMAs_Corrected.csv" files. Results from the output files then were copied back into the "Florida_LOMAs_TaxLots_final.csv" file, which was used for analysis.

Analysis Steps

<u>1) Get property values per county for all single-family homes in and out of SFHA</u>

For LandUse_ByCounty analysis, first added 'LandUse' field to each of the analysis TL_fips layers in the geodatabase, joined geodatabase table and copied the land use data from the table to the new column in the layer. Then I wrote and ran

"FL_LandUse_PerCounty.py", which found the number of properties for each land use type per county. The output data were saved in the file Florida_LandUse_ByCounty.csv. To find the number of buildings in the SFHA for each land use type per county, I wrote and ran the script "FL_SFHA_LandUse_PerCounty.py". The number of buildings in the SFHA for each land use for each study county were saved in the file Florida_SFHABlds_LandUse_ByCounty.csv.

Wrote and ran "FL_LOMAs_SFHA_Taxlots.py", which determined single home properties in/out of SFHA (excluding those with LOMAs intersecting them) and saved their property characteristics to csv files named "Florida_TLs_SFHA" and "Florida_TLs_NotSFHA". Respectively, these files had data for each property that either had a building inside or outside (not in) the SFHA. I then separated this data into csv files by county because the single files for all this data were too big. A csv file that contained the total counts of properties per county as well as properties with a building inside or outside the SFHA were saved to the file named "TLs_CountyData_Florida.csv"

<u>2) Perform Analyses</u>

Performed statistical calculations and analyses included in Chapter 5 in the R script named “FL_LOMAs_Analyses.R”

APPENDIX D

SINGLE-FAMILY HOME ASSESSED PROPERTY VALUES TABLE BY FLOOD ZONE TYPE PER FLORIDA COUNTY

The table below shows the median value, standard deviation, and number of buildings for single-family homes in each Florida study county sorted by SFHA flood zones and divided into one of four categories: (1) outside the SFHA, (2) inside the SFHA but without a MT-1, (3) inside SFHA with a LOMA, (4) inside SFHA with a LOMR-F. An NA in a column denotes there were no LOMAs or LOMR-Fs for single family homes for the corresponding flood zone, or that there was insufficient data to calculate a standard deviation.

Flood Zone	**SFHA Median Value (Standard Deviation) n**	**LOMA Median Value (Standard Deviation) n**	**LOMR-F Median Value (Standard Deviation) n**
Alachua County (FIPS: 12001)			
Outside SFHA Median Value (SD): 151,643 (110,463) n = 46,049			
A	156,517 (138,051) n = 1504	193,334 (117,572) n = 226	305,110 (124,343) n = 6
AE	155,006 (109,394) n = 623	224,984 (124,606) n = 36	231,877 (NA) n = 1
AO	69,323 (NA) n = 1	NA	NA
Baker County (FIPS: 12003)			
Outside SFHA Median Value (SD): 126,156 (68,885) n = 3,969			
A	155,048 (58,722) n = 48	181,673 (NA) n = 1	NA
AE	115,210 (46,433) n = 44	NA	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Bay County (FIPS: 12005)			
Outside SFHA Median Value (SD): 112,064 (93,540) n = 40,483			
A	131,976 (75,222) n = 2,125	169,433 (71,021) n = 30	197,999 (95,018) n = 17
AE	161,354 (196,605) n = 5,319	247,887 (157,018) n = 33	597,281 (368,862) n = 16
AH	256,224 (NA) n = 1	NA	NA
VE	426,723 (476,389) n = 908	NA	NA
Bradford County (FIPS: 12007)			
Outside SFHA Median Value (SD): 80,057 (64,676) n = 3,902			
A	99,490 (71,870) n = 464	172,375 (67,728) n = 25	NA
AE	133,296 (126,457) n = 255	170,146 (63,194) n = 17	128,384 (NA) n = 1
Brevard County (FIPS: 12009)			
Outside SFHA Median Value (SD): 169,920 (130,173) n = 162,356			
A	230,750 (101,611) n = 7,955	217,830 (108,617) n = 203	282,690 (117,189) n = 116
AE	230,100 (259,654) n = 3,837	299,360 (178,480) n = 97	379,595 (300,515) n = 28
AH	243,430 (74,552) n = 774	223,210 (66,836) n = 9	234,650 (82,213) n = 4
AO	250,580 (196,185) n = 89	NA	707,660 (NA) n = 1
VE	800,670 (468,650) n = 511	1,362,260 (NA) n = 1	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Broward County (FIPS: 12011)			
Outside SFHA Median Value (SD): 288,950 (219,389) n = 300,964			
AE	511,805 (1,030,136) n = 14,810	365,785 (320,130) n = 504	332,180 (132,983) n = 22
AH	265,630 (285,617) n = 44,902	314,230 (214,071) n = 737	327,210 (277,718) n = 35
AO	997,885 (1,030,890) n = 146	NA	NA
VE	2,215,190 (4,487,751) n = 307	NA	NA
Calhoun County (FIPS: 12013)			
Outside SFHA Median Value (SD): 57,030 (48,638) n = 2,004			
A	88,146 (113,834) n = 34	NA	NA
AE	37,607 (41,425) n = 238	NA	NA
AH	49,092 (20,499) n = 9	NA	NA
Charlotte County (FIPS: 12015)			
Outside SFHA Median Value (SD): 158,655 (69,767) n = 34,533			
A	214,187 (71,947) n = 373	224,900 (76,642) n = 44	214,924 (41,716) n = 3
AE	212,422 (156,062) n = 30,672	137,964 (90,056) n = 53	210,326 (108,861) n = 20
VE	490,643 (707,675) n = 1,385	NA	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Collier County (FIPS: 12021)			
Outside SFHA Median Value (SD): 330,626 (443,946) n = 20,398			
A	83,569 (155,458) n = 43	NA	NA
AE	478,699 (1,568,370) n = 22,227	437,363 (538,306) n = 90	526,270 (939,826) n = 31
AH	301,662 (444,425) n = 29,462	267,407 (459,548) n = 1,456	551,078 (674,868) n = 79
VE	3,351,380 (8,395,037) n = 540	NA	NA
Columbia County (FIPS: 12023)			
Outside SFHA Median Value (SD): 107,188 (73,436) n = 10,460			
A	122,680 (83,182) n = 356	172,817 (75,282) n = 12	299,765 (26,036) n = 2
AE	124,797 (97,636) n = 277	155,218 (NA) n = 1	NA
AH	114,712 (58,229) n = 233	116,404 (123,845) n = 4	NA
De Soto County (FIPS: 12027)			
Outside SFHA Median Value (SD): 104,229 (81,466) n = 4,868			
A	150,958 (106,582) n = 161	192,486 (NA) 1	NA
AE	149,040 (120,776) n = 203	457,657 (419,300) n = 2	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Dixie County (FIPS: 12029)			
Outside SFHA Median Value (SD): 51,000 (37,094) n = 1,004			
A	50,700 (29,372) n = 97	NA	NA
AE	90,600 (74,929) n = 953	NA	NA
VE	152,600 (92,552) n = 137	NA	NA
Escambia County (FIPS: 12033)			
Outside SFHA Median Value (SD): 112,446 (96,148) n = 86,695			
A	113,215 (70,894) n = 596	117,117 (51,210) n = 15	138,948 (NA) 1
AE	207,926 (243,902) n = 3,675	175,307 (172,395) n = 16	NA
AH	100,838 (28,374) n = 63	NA	NA
AO	331,892 (277,238) n = 90	NA	NA
VE	486,653 (412,867) n = 816	NA	NA
Flagler County (FIPS: 12035)			
Outside SFHA Median Value (SD): 176,245 (120,915) n = 34,822			
A	154,883 (81,843) n = 126	157,512 (42,313) n = 5	NA
AE	294,344 (179,323) n = 2,623	284,338 (195,272) n = 17	414,898 (240,086) n = 4
AO	1,367,946 (125,251) n = 10	NA	NA
VE	574,740 (488,545) n = 135	NA	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Franklin County (FIPS: 12037)			
Outside SFHA Median Value (SD): 89,225 (107,456) n = 1,874			
A	90,868 (78,366) n = 65	138,951 (NA) n = 1	NA
AE	195,319 (147,997) n = 1,187	205,325 (68,322) n = 3	NA
AH	126,084 (58,166) n = 44	NA	NA
VE	362,252 (301,237) n = 2,172	525,992 (NA) 1	NA
Gadsden County (FIPS: 12039)			
Outside SFHA Median Value (SD): 69,475 (64,268) n = 9,205			
A	123,796 (74,858) n = 47	159,419 (98,828) n = 4	NA
AE	152,653 (153,794) n = 109	230,379 (103,116) n = 6	291,651 (NA) n = 1
Gilchrist County (FIPS: 12041)			
Outside SFHA Median Value (SD): 110,493 (60,142) n = 1,644			
A	71,938 (46,589) n = 29	77,505 (NA) n = 1	75,343 (NA) 1
AE	123,040 (96,177) n = 307	102,010 (61,176) n = 3	NA
Gulf County (FIPS: 12045)			
Outside SFHA Median Value (SD): 105,453 (109,361) n = 2,678			
A	87,363 (75,145) n = 223	167,640 (78,938) n = 10	NA
AE	118,277 (105,733) n = 1,371	229,512 (194,280) n = 10	399,756 (113,773) n = 3
AH	21,042 (3,943) n = 6	NA	NA
VE	399,886 (212,824) n = 462	NA	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Hamilton County (FIPS: 12047)			
Outside SFHA Median Value (SD): 61,155 (51,513) n = 1,555			
A	104,946 (55,226) n = 33	112,404 (NA) n = 1	NA
AE	67,682 (57,195) n = 59	NA	NA
Hardee County (FIPS: 12049)			
Outside SFHA Median Value (SD): 78,668 (56,519) n = 3,845			
A	119,777 (46,685) n = 32	134,453 (9,634) n = 2	118,088 (NA) n = 1
AE	105,444 (98,338) n = 80	101,980 (10,600) n = 2	NA
Hernando County (FIPS: 12053)			
Outside SFHA Median Value (SD): 130,557 (70,324) n = 56,103			
A	119,269 (87,672) n = 41	276,154 (18,958) n = 3	NA
AE	134,260 (88,624) n = 2,225	170,708 (47,856) n = 20	270,175 (11,711) n = 4
AH	84,708 (37,049) n = 5	NA	NA
VE	235,502 (148,935) n = 1,225	NA	NA
Hillsborough County (FIPS: 12057)			
Outside SFHA Median Value (SD): 173,775 (148,469) n = 268,777			
A	187,397 (126,941) n = 3,519	204,930 (108,274) n = 102	276,704 (96,142) n = 26
AE	216,751 (345,916) n =38,442	171,098 (118,030) n = 280	209,556 (132,256) n = 57
VE	1,287,895 (1,371,438) n = 430	NA	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Holmes County (FIPS: 12059)			
Outside SFHA Median Value (SD): 60,988 (43,336) n = 2,628			
A	66,170 (43,952) n = 174	NA	NA
AE	50,281 (51,855) n = 119	NA	NA
Indian River County (FIPS: 12061)			
Outside SFHA Median Value (SD): 171,434 (347,350) n = 38,789			
A	186,215 (124,025) n = 635	179,132 (41,968) n = 7	204,984 (106,690) n = 43
AE	284,127 (871,265) n = 6,499	205,347 (233,463) n = 24	260,394 (290,191) n = 106
AO	2,193,519 (141,125) n = 7	NA	NA
VE	1,989,943 (2,155,758) n = 302	NA	NA
Jackson County (FIPS: 12063)			
Outside SFHA Median Value (SD): 60,059 (62,347) n = 8,690			
A	67,188 (92,093) n = 107	66,107 (2,688) n = 2	NA
AE	63,491 (80,289) n = 105	NA	NA
Lafayette County (FIPS: 12067)			
Outside SFHA Median Value (SD): 73,678 (55,418) n = 595			
A	48,457 (32,743) n = 34	61,024 (NA) 1	NA
AE	131,198 (70,704) n = 181	NA	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Lake County (FIPS: 12069)			
Outside SFHA Median Value (SD): 176,868 (103,445) n = 86,656			
A	166,265 (134,267) n = 2,324	188,189 (108,207) n = 198	246,084 (99,826) n = 18
AE	186,091 (189,131) n = 1,516	261,667 (163,761) n = 54	275,859 (12,123) n = 8
Lee County (FIPS: 12071)			
Outside SFHA Median Value (SD): 166,338 (166,372) n = 122,659			
A	149,383 (81,974) n = 853	179,669 (59,820) n = 36	183,706 (57,612) n = 10
AE	247,910 (316,191) n = 72,216	234,981 (140,900) n = 277	213,178 (181,972) n = 76
AH	230,934 (225,083) n = 622	322,997 (123,545) n = 37	408,585 (64,594) n = 11
VE	857,561 (1,595,880) n = 2,991	NA	NA
Leon County (FIPS: 12073)			
Outside SFHA Median Value (SD): 160,023 (125,540) n = 60,987			
A	162,405 (169,602) n = 677	137,689 (85,489) n = 16	336,909 (170,085) n = 5
AE	95,292 (101,594) n = 1,802	198,880 (102,535) n = 10	NA
Levy County (FIPS: 12075)			
Outside SFHA Median Value (SD): 102,822 (73,046) n = 5,036			
A	126,249 (92,974) n = 154	168,253 (49,992) n = 2	NA
AE	134,350 (90,112) n = 848	131,457 (54,881) n = 4	NA
AO	147,258 (NA) n = 1	NA	NA
VE	266,062 (143,425) n = 269	NA	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Madison County (FIPS: 12079)			
Outside SFHA Median Value (SD): 56,157 (55,508) n = 2,600			
A	88,266 (87,347) n = 102	266,419 (124,365) n = 5	77,869 (NA) n = 1
AE	65,144 (42,931) n = 35	NA	NA
Marion County (FIPS: 12083)			
Outside SFHA Median Value (SD): 121,642 (91,663) n = 95,342			
A	115,586 (109,148) n = 1,911	158,660 (68,227) n = 80	860,983 (NA) n = 1
AE	112,950 (142,072) n = 2,045	173,560 (154,725) n = 108	206,503 (476,013) n = 4
Martin County (FIPS: 12085)			
Outside SFHA Median Value (SD): 249,580 (694,692) n = 39,612			
A	177,850 (26,978) n = 25	NA	NA
AE	378,750 (622,316) n = 4,854	367,120 (220,186) n = 21	383,475 (40,269) n = 2
AH	246,245 (108,966) n = 204	263,980 (75,155) n = 4	310,180 (NA) n = 1
VE	1,230,090 (3,047,243) n = 315	NA	NA
Miami-Dade County (FIPS: 12086)			
Outside SFHA Median Value (SD): 262,952 (305,731) n = 202,752			
A	256,619 (272,170) n = 32	NA	NA
AE	303,154 (1,405,609) n = 67,785	277,484 (249,468) n = 373	282,917 (379,284) n = 21
AH	268,339 (189,739) n = 81,006	287,157 (124,838) n = 531	275,956 (57,904) n = 33
VE	2,760,808 (5,356,420) n = 434	NA	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Monroe County (FIPS: 12087)			
Outside SFHA Median Value (SD): 472,592 (592,559) n = 2,067			
AE	474,728 (569,162) n = 20,481	522,831 (657,813) n = 78	259,187 (133,474) n = 2
AO	4,131,329 (3,245,877) n = 5	NA	NA
VE	956,924 (1,431,386) n = 3,404	1,232,268 (NA) n = 1	NA
Nassau County (FIPS: 12089)			
Outside SFHA Median Value (SD): 203,807 (253,828) n = 16,868			
A	168,580 (76,237) n = 530	209,633 (42,803) n = 6	271,827 (27,363) n = 2
AE	378,723 (296,171) n = 1,315	438,143 (169,200) n = 6	380,831 (93,644) n = 2
AO	339,094 (94,291) n = 21	NA	NA
VE	602,267 (508,049) n = 303	NA	NA
Okaloosa County (FIPS: 12091)			
Outside SFHA Median Value (SD): 153,202 (163,191) n = 55,560			
A	172,305 (106,724) n = 467	149,503 (116,798) n = 21	119,903 (NA) 1
AE	308,259 (369,401) n = 2,664	332,223 (435,617) n = 37	860,040 (862,108) n = 78
VE	523,050 (644,037) n = 802	NA	NA
Orange County (FIPS: 12095)			
Outside SFHA Median Value (SD): 213,304 (202,900) n = 273,803			
A	241,140 (141,463) n = 2,854	253,058 (145,826) n = 88	304,024 (71,591) n = 7
AE	221,196 (714,631) n = 6,300	279,278 (390,376) n = 97	346,772 (715,668) n = 21

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Osceola County (FIPS: 12097)			
Outside SFHA Median Value (SD): 171,000 (102,715) n = 74,148			
A	179,750 (140,509) 3,396	184,900 (96,460) n = 92	229,650 (117,753) n = 22
AE	175,400 (99,135) n = 6,747	155,950 (94,008) n = 294	212,200 (107,085) n = 48
Pinellas County (FIPS: 12103)			
Outside SFHA Median Value (SD): 178,897 (122,841) n = 173,426			
A	254,185 (149,474) n = 3,958	209,793 (146,758) n = 52	464,076 (187,788) n = 4
AE	256,003 (282,368) n = 65,220	194,935 (129,349) n = 246	278,536 (80,149) n = 30
AH	171,936 (6,994) n = 3	NA	NA
AO	323,420 (69,370) n = 4	NA	NA
VE	712,738 (963,570) n = 3,431	NA	NA
Polk County (FIPS: 12105)			
Outside SFHA Median Value (SD): 145,679 (91,602) n = 155,240			
A	140,692 (64,410) n = 3,496	154,792 (98,883) n = 297	246,423 (54,385) n = 17
AE	164,485 (145,524) n = 3,064	180,744 (181,150) n = 188	189,017 (177,093) n = 22
AH	124,701 (76,837) n = 22	NA	NA
Putnam County (FIPS: 12107)			
Outside SFHA Median Value (SD): 86,310 (117,550) n = 12,382			
A	142,740 (107,855) n = 802	148,025 (115,459) n = 26	NA
AE	203,990 (252,255) n = 1,017	254,575 (140,005) n = 4	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
St. Lucie County (FIPS: 12111)			
Outside SFHA Median Value (SD): 175,500 (81,115) n = 90,592			
A	75,500 (106,268) n = 156	381,200 (NA) 1	NA
AE	235,300 (180,218) n = 2,501	443,250 (505,227) n = 2	NA
AH	233,900 (65,681) n = 607	154,000 (35,253) n = 3	NA
AO	339,900 (35,561) n = 6	NA	NA
VE	382,900 (493,945) n = 212	NA	NA
Santa Rosa County (FIPS: 12113)			
Outside SFHA Median Value (SD): 144,255 (111,480) n = 43,403			
A	93,977 (47,664) n = 90	81,642 (28,407) n = 9	NA
AE	211,158 (198,621) n = 3,724	268,878 (537,555) n = 27	318,952 (12,852) n = 3
VE	436,702 (437,952) n = 989	NA	NA
Seminole County (FIPS: 12117)			
Outside SFHA Median Value (SD): 212,851 (132,015) n = 114,089			
A	258,684 (159,224) n = 1,810	280,153 (170,551) n = 61	637,708 (153,633) n = 6
AE	252,011 (225,544) n = 2,850	281,876 (222,545) n = 64	321,690 (181,819) n = 7
AH	201,294 (55,489) n = 167	219,756 (NA) n = 1	NA

Flood Zone	SFHA Median Value (Standard Deviation) n	LOMA Median Value (Standard Deviation) n	LOMR-F Median Value (Standard Deviation) n
Suwannee County (FIPS: 12121)			
Outside SFHA Median Value (SD): 92,696 (73,747) n = 4,491			
A	90,434 (63,666) n = 120	114,458 (31,076) n = 5	NA
AE	85,462 (75,172) n = 511	231,347 (34,074) n = 2	NA
Taylor County (FIPS: 12123)			
Outside SFHA Median Value (SD): 61,355 (50,203) n = 2,744			
A	75,780 (58,735) n = 227	110,630 (45,754) n = 8	NA
AE	91,580 (89,460) n = 811	NA	NA
AH	66,680 (62,340) n = 133	138,650 (4,157) n = 2	NA
VE	176,125 (118,082) n = 306	NA	NA
Union County (FIPS: 12125)			
Outside SFHA Median Value (SD): 76,377 (50,012) n = 1,133			
A	99,791 (37,873) n = 23	200,265 (NA) n = 1	NA
AE	87,695 (64,080) n = 13	NA	NA
Volusia County (FIPS: 12127)			
Outside SFHA Median Value (SD): 162,820 (123,679) n = 141,793			
A	130,859 (106,018) n = 4,291	186,747 (86,352) n = 70	241,190 (79,679) n = 35
AE	162,399 (199,446) n = 10,787	181,785 (175,893) n = 151	193,319 (850,504) n = 28
AH	160,718 (52,955) n = 132	NA	NA
VE	747,762 (369,159) n = 370	NA	NA

Flood Zone	**SFHA Median Value (Standard Deviation) n**	**LOMA Median Value (Standard Deviation) n**	**LOMR-F Median Value (Standard Deviation) n**
Walton County (FIPS: 12131)			
Outside SFHA Median Value (SD): 245,789 (646,131) n = 18,383			
A	228,621 (292,417) n = 354	175,752 (517,767) n = 25	676,962 (687,957) n = 7
AE	291,334 (417,579) n = 2,479	288,720 (183,360) n = 9	798,722 (577,327) n = 18
VE	665,488 (1,383,200) n = 741	NA	NA
Washington County (FIPS: 12133)			
Outside SFHA Median Value (SD): 71,894 (51,094) n = 3,899			
A	75,262 (57,067) n = 122	114,735 (57,397) n = 3	167,697 (NA) n = 1
AE	56,425 (41,952) n = 111	NA	NA

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