

Measuring Vulnerability to Flooding
Using Two Indices:
A Case Study of Miami-Dade County, Florida

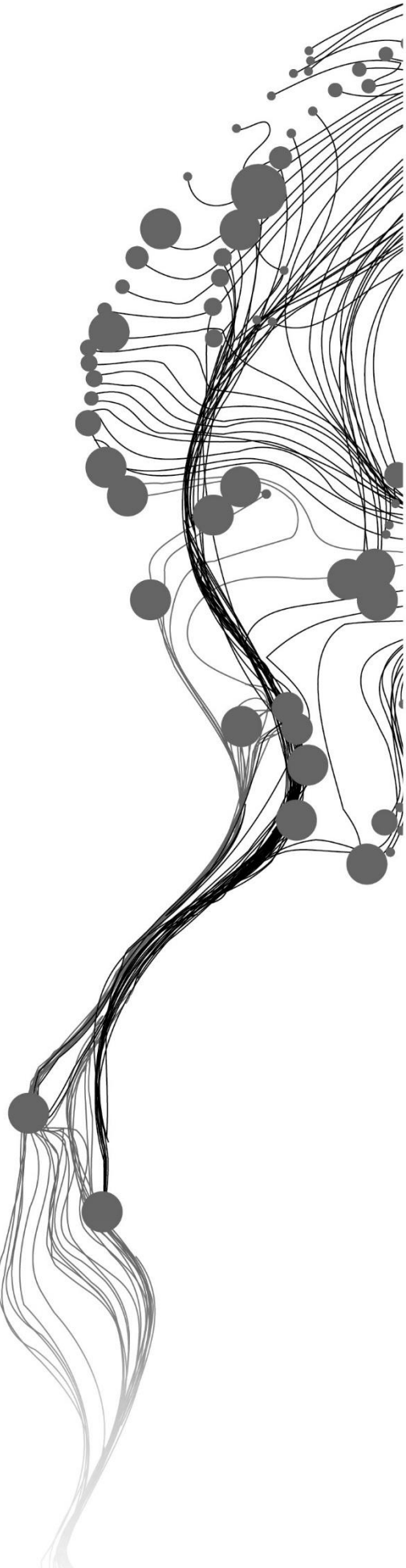
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August, 2021

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Enschede, The Netherlands, August, 2021

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.

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Abstract

This study examines flood vulnerability in Miami-Dade County on a census block group level from a social/environmental justice perspective and an economic/cost-benefit perspective using two different indices: The Hazards of Place Model and the Tax Income Protection Index. In order to help the adaptation planning process and reduce stakeholder conflict, the distribution of vulnerability in the two indices is mapped to find areas of overlap, which represent areas that multiple parties would consider worth prioritizing. The socioeconomic characteristics of census block groups in clusters of overlapping vulnerability are then examined to determine what factors drive the vulnerability of each cluster. These factors, along with the geographic, physical, and other such characteristics of two clusters of overlapping vulnerability are used as a case study to illustrate how potential interventions to address flood vulnerability vary across the County, particularly between coastal and inland areas. Finally, the distribution of clusters of overlapping vulnerability are examined alongside the boundaries of municipalities within the County to identify cities which have high concentrations of vulnerable census block groups.

The study identified 157 census block groups that were vulnerable under both the Hazards of Place Model and the Tax Income Protection Index, this is ~10% of the County total. Of these, 88 (56%) were located in inland parts of the County to the west of the Atlantic Coastal Ridge. Concentrations of these overlapping-vulnerability census block groups were significant in the City of Hialeah, which contained 43 vulnerable census block groups, and the City of Miami Beach, which contained 32. These comprise 27 and 20 percent, respectively, of the County's total number of dually vulnerable census block groups, and make up 36 percent of census block groups within each of the cities mentioned. The two case study clusters of vulnerability examined were the Hialeah Gardens and South Beach clusters, located in an inland and coastal part of the County, respectively. It was determined that the characteristics of the Hialeah Gardens cluster were better suited to non-physical adaptation projects designed to help decrease the social vulnerability and increase the resilience of the cluster's population, while the South Beach cluster was better suited for physical interventions designed to reduce flood hazard.

This study's method of using the overlap between different framework approaches to the concept of vulnerability can hopefully be used in a variety of adaptation planning situations where contrasting ideas over who or what is vulnerable and worth protecting are present, and where reaching stakeholder consensus is necessary for projects to proceed.

Acknowledgements

I would like to thank my supervisors, Dr. Diana Reckien and Prof. Richard Sliuzas, for their support throughout the thesis process. Despite the pandemic and time difference that separated us for most of the working period, they were always available to answer questions or give feedback on my choices and writing. Without them, this thesis would not have reached the point where I would be writing an acknowledgements section.

I would also like to thank my parents for always being there to help me with Excel and answer my wide assortment of questions about topics like academic writing formalities, real estate taxes, and what sorts of things I should write in my acknowledgements section. Countless minutes of googling were saved through your contributions.

Table of Contents

Abstract.....	iv
Acknowledgements.....	v
List of Figures	viii
List of Tables	ix
Key Acronyms.....	x
1. Introduction	1
1.1 Key Definitions	2
1.2 Miami’s Geographic Setting.....	3
1.3 Physical Aspects of Climate Change.....	4
1.3.1 Drivers of Climate Change Impacts on Miami-Dade County	4
1.3.2 Physical Impacts of Climate Change on Miami-Dade County	4
1.4 Miami’s Socioeconomic Setting	6
1.5 Social Impacts of Climate Change	9
1.6 Impact of Climate Change on Local Governments.....	11
1.7 Two Indices of Vulnerability.....	14
1.7.1 Hazards of Place Model.....	14
1.7.2 Tax Income Protection Index	15
1.8 Research Problem	16
1.8.1 Research Objectives.....	16
2. Methods.....	17
2.1 Data and Data Processing	17
2.2 Index Work.....	18
2.2.1 Social Vulnerability Index.....	18
2.2.2 Municipal Priority Index.....	19
2.2.3 Application of Biophysical Vulnerability Component	20
2.2.4 Combining	22
2.3 Individual Index Mapping.....	22
2.3.1 Side-By-Side Comparison Map.....	22
2.3.2 Overlap Mapping.....	23
2.3.3 Results Summary Tables and Maps	23

2.4	Potential Adaptation Measures Comparison Between Two Clusters of Vulnerability	24
2.5	Identifying Concentrations of Vulnerability.....	25
3.	Results.....	25
3.1	Social Vulnerability.....	27
3.2	Hazards of Place Model	30
3.3	Municipal Priority Index.....	33
3.4	Tax Income Protection Index	36
3.5	Comparing the Distributions of High Vulnerability.....	39
3.6	Overlap of Highly Vulnerable Areas	40
3.6.1	Barrier Islands Clusters	41
3.6.2	Mainland Clusters	41
4.	Discussion.....	43
4.1	Different Solutions	43
4.2	Concentrated Burdens	45
4.3	Potential Issues with Methodological Choices	46
4.3.1	Hispanic Population	46
4.3.2	Data Scale.....	46
4.3.3	Biophysical Vulnerability Component.....	47
4.3.4	Relevance of Vulnerability	47
4.3.5	Apartment Buildings	48
5.	Conclusion and Recommendations for Future Research.....	49
5.1	Recommendations for Future Research	50
6.	List of References.....	51
7.	Appendices.....	56
7.1	Appendix 1: Ethical Considerations, Risks, and Contingencies.....	56
7.2	Appendix 2: Variables Present in the Indices Used in this Study.....	57
7.3	Appendix 3: Table of Variables Collected for Varimax Rotation Step of Social Vulnerability Index Construction.....	58
7.4	Appendix 4: Results of Varimax Rotation Performed During Social Vulnerability Index Construction.....	59

List of Figures

Figure 1: Location of Miami-Dade County within the United States.	1
Figure 2: LIDAR elevation map of the Miami-Dade County area.....	3
Figure 3: Map of Miami-Dade County showing z-standardized per-capita income by census block group ..	8
Figure 4: Flowchart showing general methodological steps used in this study	17
Figure 5: Flowchart showing the relationship between the indices used in this study.....	18
Figure 6: Flowchart showing the steps taken to produce the SOVI, as described at length in Hazards and Vulnerability Research Institute (2016).	18
Figure 7: Example of census block group boundary trimming undertaken in this study	21
Figure 8: Example of the additive model used to combine the Social Vulnerability Index and Municipal Priority Index bin values with the elevation bin values for each census block group	22
Figure 9: Equal interval bins and choropleth gradations used in the maps for the Social Vulnerability Index, Hazards of Place Model, Municipal Priority Index, and Tax Income Protection Index sections of results.....	22
Figure 10: Reference map of the Miami-Dade County area showing neighborhoods or clusters of vulnerability mentioned in the results and discussion sections.	26
Figure 11: Distribution of census block groups within the 3 most vulnerable bins in the Social Vulnerability Index.....	27
Figure 12: Distribution of census block groups within the 6 most vulnerable bins in the Hazards of Place Model.....	30
Figure 13: Distribution of census block groups in the 3 most vulnerable bins in the Municipal Priority Index.....	33

Figure 14: Map of Miami-Dade County showing what variable drives vulnerability in the census block groups identified as high vulnerability under the Municipal Priority Index. 34

Figure 15: Distribution of census block groups in the 6 most vulnerable bins in the Tax Income Protection Index..... 36

Figure 16: Map of Miami-Dade County showing what variable drives vulnerability in census block groups identified as having high flood vulnerability under the Tax Income Protection Index..... 37

Figure 17: Distribution of CBGs that have high vulnerability under either the Hazards of Place Model or the Tax Income Protection Index 39

Figure 18: Map showing distribution of census block groups that are in one of the top 6 vulnerability bins in both the Hazards of Place Model and the Tax Income Protection Index. 40

List of Tables

Table 1: Chart summarizing the four indices discussed in this study 14

Table 2: Table showing the 6 components retained from varimax rotation for use constructing the Social Vulnerability Index 19

Table 3: Table summarizing the driving factors for high-vulnerability clusters/neighborhoods in the Social Vulnerability Index. 29

Table 4: Table summarizing the driving factors for high-vulnerability clusters/neighborhoods in the Hazards of Place Model 32

Table 5: Table summarizing the driving factors of vulnerability in clusters/neighborhoods that are highly vulnerable under both the HoPM and the TIPI..... 41

Key Acronyms

MDC: Miami-Dade County

ACR: Atlantic Coastal Ridge

SLR: Sea Level Rise

CBG: Census Block Group

SOVI: Social Vulnerability Index

HoPM: Hazards of Place Model

MPI: Municipal Priority Index

TUPI: Tax Income Protection Index

FEMA: Federal Emergency Management Agency

DFIRM(s): Digital Flood Insurance Rate Map(s)

1. Introduction

Low-lying coastal areas have long been important areas for human settlement due to their abundance of resources and access to trade, and as a result they are economically important and densely populated. In the United States¹, coastal counties create 46% of national GDP, worth \$7.9 trillion annually (NOAA, 2017) They are home to 125 million people, 40% of the country's population, and coastal populations are expected to continue growing; there is a global trend in coastward migration, and coastal population growth exceeds that of inland areas (Neumann *et al.*, 2015).

These areas are also incredibly vulnerable to climate change and sea level rise; 10% of the world's population lives in coastal areas under 10m in elevation, and two-thirds of cities with populations over 5 million are vulnerable to sea level rise (United Nations, 2015), including most of the world's megacities (Neumann *et al.*, 2015). In addition to sea level rise, climate change impacts on coastal cities will include increases in cyclone occurrence or strength, storm surge events, saltwater intrusion, and erosion, amongst others (Balica, Wright and van der Meulen, 2012). It is estimated that by 2050, the due to combined impact of the growing population and economic importance of cities and the impacts of climate change, annual flood losses in large coastal cities could exceed \$1 trillion per year (Hallegatte *et al.*, 2013), another study estimates that between 12% and 20% of global GDP could be exposed to coastal flooding due do sea level rise by 2100, assuming no flood defenses are in place (Kirezci *et al.*, 2020). As protecting all coastal areas from climate change impacts is impractical or impossible, and not all coastal areas are equally vulnerable, there is a need to identify those areas which are most vulnerable, in order to prioritize adaptation funding and projects.

Like many other coastal metropolises, Miami-Dade County (MDC) is highly exposed to climate change impacts, to the extent that it is often called the "ground zero for climate change" (Meyer, 2014; Molinaroli, Geruzoni and Suman, 2019). MDC is located in the state of Florida in the southeastern United States (See Figure 1, right), and has a population exceeding 2.7 million (U.S. Census Bureau, no date), making it the 7th most populous county in the US (U.S. Census Bureau, 2019). It is



Figure 1: Location of MDC (red) within the United States. Data from the US Census Bureau.

estimated that under NOAA's intermediate sea level rise prediction and no adaptation measures, annual flood losses for the region could surpass \$25 billion in 2050, and half a meter of sea level rise would put \$3.5 trillion in assets at risk (Treuer, Broad and Meyer, 2018).

This study seeks to map the vulnerability of MDC to climate-change driven flooding on a census block group (CBG) level, to determine what areas should be prioritized for adaptation measures. It will use two different approaches to vulnerability, one focusing on social vulnerability and the other on economic vulnerability, then look for overlap between the two. This use of two different theoretical

¹ Figures for global economic value of coastal cities/areas could not be located.

approaches to vulnerability is important because “few if any flood risk reduction programs routinely incorporate social vulnerability into such efforts, relying instead on cost–benefit analyses based on prevented property damages and not the differential socio-spatial impacts on affected communities” (Cutter *et al.*, 2013, pg. 333); however, cost-benefit and economic vulnerability are both important to local governments facing large adaptation bills. By finding areas of overlap between the two approaches to vulnerability, the results of this study could be useful for reducing stakeholder conflict and aid in adaptation planning, as well as identify potentially unexpected areas of vulnerability in the County.

1.1 Key Definitions

This study defines vulnerability as the relationship between the local population’s flood risk and resilience.

Risk is approached from a natural sciences perspective, and used here as “the probability of negative consequences” (Scheuer, Haase and Meyer, 2011). Thus, in this case study, risk represents the likelihood of flooding in any given CBG.

Resilience is defined in line with the IPCC as “The ability of a system and its component parts to anticipate, absorb, accommodate, or recover from the effects of a hazardous event in a timely and efficient manner, including through ensuring the preservation, restoration, or improvement of its essential basic structures and functions”(Lavell *et al.*, 2012). In this case study, this represents the ability of the population to deal with the economic impacts of climate-change driven flooding.

As such, vulnerability in this study is a function of how likely a CBG is to experience flooding and how well that area’s population can deal with it. This approach is taken because a lower-resilience population living in an area with low flood risk could very well be less vulnerable in reality than a higher-resilience population living in an area with high flood risk.

1.2 Miami's Geographic Setting

MDC is located in southeastern Florida, sandwiched between Biscayne Bay and the Atlantic Ocean to the east, the Florida Everglades and then Gulf of Mexico to the west, and more of the Everglades and then Florida Bay to the south. The county is generally flat and sits at a very low elevation: approximately 25% of the county lies below 1m in elevation, and the average elevation is only 1.8m (Molinaroli et al., 2019). Because of this low elevation, 94% of the County's census areas were partially or entirely within 100-year flood zones (Chakraborty *et al.*, 2014). The County sits on a limestone bedrock, which is porous by nature, this houses the shallow and unconfined Biscayne Aquifer, which supplies most of the region's drinking water. Running southwest to northeast through the region is the Atlantic Coastal Ridge (ACR), a relatively high (up to ~8m) oolite limestone formation shown in Figure 2 (right), a LIDAR map of the area. The ridge consists of two features: a narrow and generally higher prograding barrier bar to the east, and a broader and generally lower tidal bar-channel system to the west, these formed during the last interglacial period, during the Pleistocene (Usdun, 2014). The ACR divides the county into three loose topographical regions: the low-lying coastal region to the east of the ridge, the high ground on the ridge, and the low-lying inland regions to the west. The western inland regions are largely areas that were originally part of the Everglades, and were wetlands prone to seasonal flooding until drainage canals were dug in the 1930's and 40's to help prevent flooding and open the land up for development (Sealey, Burch and Binder, 2018).

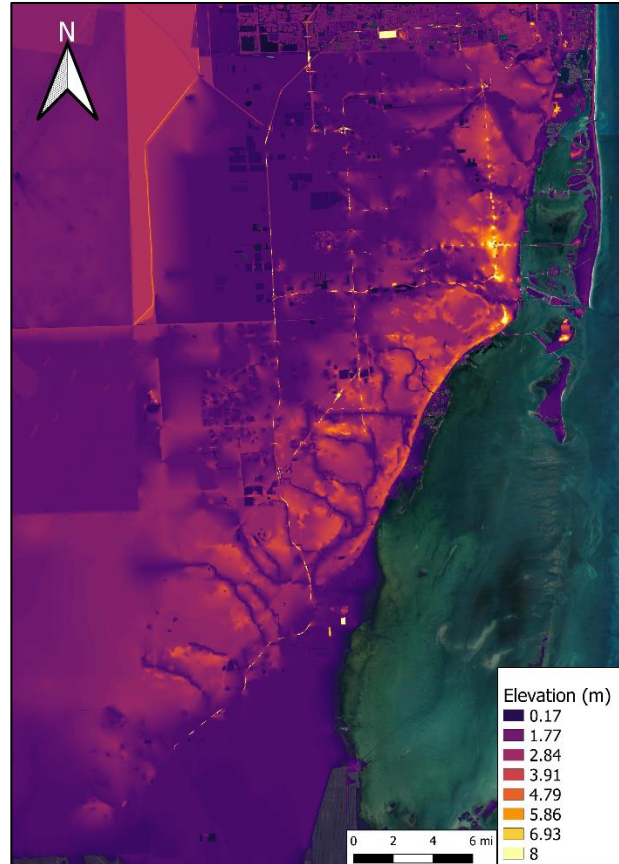


Figure 2: LIDAR elevation map of the MDC area in meters. The Atlantic Coastal Ridge is the elevation feature running SW-NE across the center of the map.

In addition to these mainland parts of MDC, there are a string of inhabited barrier islands along the coast, the outermost chain of these is, from south to north: Key Biscayne², Virginia Key, Fisher Island, and then the long island containing the municipalities of Miami Beach, Surfside, Bal Harbour, Sunny Isles Beach, and Golden Beach. There are many other inhabited islands between those just listed and the mainland, as well as Dodge Island, where the Port of Miami is located. These are a mix of natural and artificial islands, and lie only a couple feet above sea level.

Under the Köppen climate classification system, MDC has a climate split between a tropical monsoon climate in the northeastern parts of the county and a savanna climate in the rest, these have a summer rainy season and winter dry season (Kottek *et al.*, 2006). The county receives an average of 57.9 inches

² There are other barrier islands within the County to the south of Key Biscayne, at the southern entrance to Biscayne Bay, but none are presently inhabited.

(1,470mm) of rainfall annually (Escobedo *et al.*, 2010), but this can be quite variable across the county. The City of Miami receives an average of 61.9 inches (1,570 mm) of rainfall yearly, whereas nearby Miami Beach receives an average of only 51.7 inches (1,310 mm) yearly in comparison (Wikipedia Contributors, no date). Most of this rainfall comes during the rainy season, which sees afternoon thunderstorms occur almost daily.

1.3 Physical Aspects of Climate Change

1.3.1 Drivers of Climate Change Impacts on Miami-Dade County

Miami is threatened by a number of physical climate change hazards, particularly ones relating to water and flooding, the focus of this study. While there are a host of problems in this category, there are two overarching ones that drive many of the other issues: sea level rise (SLR) and increased storm intensity.

Sea level rise, driven by melting ice caps and thermal expansion, is affecting South Florida at rates greater than the global average, with local SLR rates averaging 9 ± 4 mm/year since 2006, compared to a global average of 3.2 ± 0.4 mm/year (Wdowinski *et al.*, 2016, Church and White, 2011). Local sea levels have risen 7.87 inches (20cm) since the 1930's (Molinaroli, Geruzoni and Suman, 2019), 3.9 inches (9.9cm) of which was between 2000 and 2017 alone (Southeast Florida Regional Climate Change Compact Sea Level Rise Work Group (Compact), 2019). With regards to the future, sea level rise in south Florida is projected to have increased (with regards to mean sea level in the year 2000) 10-17 inches by 2040, 21-54 inches by 2070, and 40-136 inches by 2100³ (Southeast Florida Regional Climate Change Compact Sea Level Rise Work Group (Compact), 2019). Rising sea levels eventually cause inundation, which cannot be prevented by dikes due to the porous nature of the bedrock (Treuer, Broad and Meyer, 2018), however, the host of other issues driven by and exacerbated by local SLR will create significant issues for MDC well before permanent inundation occurs, these will be discussed in the next section.

Increased storm intensity, the other chief driver, includes both hurricanes and non-cyclone storm events. While the impact of climate change on the frequency of Atlantic hurricanes is still greatly debated, there are numerous studies linking warming and increased hurricane strength. Examining recent warming, Holland and Bruyère found that the proportion of hurricanes reaching categories 4 and 5 on the Saffir-Simpson scale increased by ~25-30% per °C of warming, with a corresponding decrease in the proportion of hurricanes in categories 1 and 2 (Holland and Bruyère, 2014). With regards to future change, Bender *et al.* predicts almost a 100% increase in the frequency of category 4 and 5 storms by the end of the century (Bender *et al.*, 2010). With regards to non-cyclone storm events, climate change has increased the amount of precipitation from heavy storms by 27% since 1958, a trend which is expected to continue as climate change intensifies (EPA, 2016).

1.3.2 Physical Impacts of Climate Change on Miami-Dade County

1.3.2.1 *Rising Water*

Rising sea levels are already directly impacting low-lying coastal areas, particularly on Miami Beach, where tidal flooding from so-called "king tides" has increased 400% since 2006 (Wdoniski *et al.*, 2016) This flooding is caused by astronomically-driven extra-high tides, and is both predictable and relatively

³ In metric units, this is 25.4 - 43.18 cm by 2040, 53.34 - 137.16 cm by 2070, and 101.6 - 345.44cm by 2100

minor, it is often referred to as “nuisance flooding.” However, there are concerns about the potential spread of contaminants, particularly from sewage, as well as damage to vehicles from the salt water. The problem is exacerbated by the region’s gravity-driven storm drain system, which in this case is serving to funnel water from extra-high tides back into the city (Kolbert, 2015). A recent study led by NASA’s Sea Level Change Science Team also indicates that the Moon’s orbital wobble cycle will amplify tides in the 2030s, increasing both the height and frequency of tidal flooding; some areas could experience flooding every day or two for periods of a month or longer (Rasmussen, 2021). While the flooding may be “nuisance”, adaptation measures are costly, the City of Miami Beach has budgeted \$500 million to install 58 pumps to help drain floodwater and prevent it from flowing back up the storm drain system (Flechas, 2014).

In addition, higher sea levels are linked with a higher groundwater table, which will affect inland areas across the county, particularly the western areas that used to be wetlands. As the region’s drainage system (both storm drains and canals) is gravity driven, it is estimated that with another 6-inch rise in sea levels, the region could lose half of its drainage capacity (Kolbert, 2015). A study published in 2017 indicates that this problem may be exacerbated in the future by local water management practices. In order to help combat saltwater intrusion into the Biscayne Aquifer, locks and flood control barriers on the region’s drainage canal network are managed in such a way that the water table is kept high. As sea levels rise, the water table will also need to be elevated to maintain its protective function; this makes it more likely that heavy rainfall will cause the water table to reach the surface and cause flooding (Czajkowski *et al.*, 2018).

This elevated groundwater table will also pose problems for sewage management, increasing the likelihood of groundwater contamination. There are approximately 105,000 septic systems in the region, which require a minimum of 2 feet (but preferably closer to 4 feet) of unsaturated ground beneath their discharge field in order for wastewater to be properly filtered. Rising groundwater levels mean that many such systems will cease to function properly periodically and then permanently; it is currently estimated that 56% of parcels with a septic system are currently periodically compromised, increasing to 64% within 25 years⁴. (Miami-Dade County of Regulatory and Economic Resources, Miami-Dade County Water and Sewer Department and Florida Department of Health in Miami-Dade County, 2018). Such contamination of the aquifer would be disastrous for the region, as it is the primary source of drinking water for the region, and once contaminated, it would be nigh impossible to clean.

Sea level rise and an elevated water table will also serve to exacerbate the flooding impacts of hurricanes on the region: sea level rise leaves coastal areas more vulnerable to storm surge events, while the elevated water table will increase flooding from the heavy rains that these storms bring. In addition, stronger hurricanes with heavier winds mean increased general damage across the region to infrastructure and property, increasing their economic impact on the area.

1.3.2.2 Increased Precipitation

The increased precipitation from heavy storms mentioned above is already causing flooding in parts of the county, Miami Beach has seen a 33% increase in pluvial flood events since 2006 (Wdoniski *et al.*, 2016), and some inland areas are already flooding from heavy precipitation events as well (Sealey, Burch and Binder, 2018; Lora and Leibowitz, 2020; Rivero, 2020; Harris, 2021)

⁴ 58,349 parcels currently compromised increasing to 67,234.

Due to the coupled nature of the region's stormwater and sewer system, heavy rainfall can overwhelm the ability of treatment plants to hold wastewater, causing them to release untreated sewage into the ocean, posing health risks and potentially impacting the tourism industry of the region. Additionally, heavy rains have caused backups and breaks in sewer lines, resulting in wastewater spills in inland regions as well, posing further health risks.

Heavier rainfall also poses a threat to the aquifer and drinking water supplies; heavier rainfall and flooding could leach chemicals from toxic sites (called Superfund Sites) into the aquifer, there are a dozen such sites across the County (Flavelle, 2018).

1.4 Miami's Socioeconomic Setting

MDC is made up of 34 incorporated municipalities as well as many unincorporated neighborhoods (Miami-Dade County, 2020a). Municipalities are responsible for most government functions in their territories, including services such as fire and police departments, waste collection, planning and zoning, and road construction and maintenance (Miami Dade County, 2021). Responsibility for services which are often trans-boundary by nature, such as water and sewer, is largely shared between municipalities and the County, although the extent varies by municipality. For unincorporated areas, the County provides both municipal-level and county-level services; the county can also take over elements of municipal services should their standards fall below a minimum set by the County (Miami-Dade County, 2015).

Responsibility for adaptation projects is spread across multiple levels of government. Municipalities are responsible for most projects within their jurisdiction, though for trans-boundary issues (such as sewers or waterways), the responsibility lies with the managing authority. Additionally, some projects may come from a national level, such as the Army Corps of Engineers' proposed seawalls and flood gates that aim to help protect mainland MDC from storm surge events (US Army Corps of Engineers, 2020). The picture is more complicated from a funding perspective. Municipalities can fund adaptation projects through bonds or raising fees, but can also receive funds from higher levels of government (Adaptation Clearinghouse, 2016), the same is true for the County, who also might acquire funds from municipalities within its borders. Federal projects can be federally funded, but cost sharing with local governments is also possible, the County would be responsible for funding 35% of the aforementioned Army Corps project's construction cost, as well as all maintenance costs for 50 years (US Army Corps of Engineers, 2020).

The County's population is almost entirely comprised of three ethnic groups: non-white Hispanic (43%), White (32%), and Black (20%) (Collins, Grineski, & Chakraborty, 2018)⁵, although these groups can be sub-divided into a great number of nationalities. Much of the population is made up of immigrants from the Caribbean, Central America, and South America, and their descendants. These groups are typically considered both minorities and socially vulnerable groups in existing literature, due to reasons such as language or cultural barriers, lower educational attainment, and socioeconomic reasons (Cutter, Boruff and Shirley, 2003).

⁵ If both white and non-white Hispanic are counted together as a singular Hispanic category, Miami's population is about 70% Hispanic (U.S. Census Bureau, no date).

However, Hispanics are not a minority in MDC, and Spanish is very widely spoken and is an option for government functions, and there is also a substantial Hispanic upper class and strong presence in local government. Therefore, some drivers of social vulnerability like language barriers and social exclusion are not applicable, and the vulnerability status of Hispanics in this study should be approached with caution.

Social barriers notwithstanding, what would classify large parts of MDC's population as (traditionally) socially vulnerable would be the region's low average wages. The region is characterized by an abundance of low-paying jobs, which also have lower average wages than similar jobs in other parts of the country. 47.8% of the area's labor pool falls into the poorly-paid service class, which also only has a median wage of only \$26,532, compared to a national service-class median of \$27,130 (Florida and Pedigo, 2019). The next labor category up, the working or blue collar class, makes up 18.3% of the region's workforce, and has a median income of \$28,854, compared to a national median of \$34,750; Miami has the lowest-paid working class of all large US metros (Florida and Pedigo, 2019). Overall, the Miami metro area has the 3rd lowest median income of large US metros, with a median income of \$31,702 per year, nearly \$5,000 lower than the national median of \$36,693 per year (Florida and Pedigo, 2019). Median household income for the region is only \$51,347 (U.S. Census Bureau, no date), compared to a national median of \$68,703 (SEMEGA *et al.*, 2020).

The low wages discussed above are not spread evenly across the County and its population, the Miami metro area is the second most unequal in the United States, with a GINI coefficient of 0.508 (Florida & Pedigo, 2019). This inequality is partly the result of the area's large immigrant population, there is a documented economic gap between immigrants and the established residents of an area (Smith and Fernandez, 2017). Compounding this issue is the fact that many immigrants to MDC are refugees, fleeing from violence and political turmoil in Central and South America. Indeed, compared to the region's average poverty rate of 14.3% and a White poverty rate of 9.2%, Hispanics have a poverty rate of 17.8% (Florida and Pedigo, 2019). However, the large migrant population is not the only driver of inequality in the region, as poverty is most significantly concentrated on Black residents, who have a 23.8% poverty rate, and have resided in the area essentially since the city's founding. Black poverty in MDC is similar to that found in many US metros, originating from discriminatory laws and segregation of neighborhoods, combined with chronic poverty and the resulting cycle of 'poor life outcomes' (Florida and Pedigo, 2019; Ariza, 2020).

The County's low wages and poverty increases the flood vulnerability of the region, a substantial portion of the population will likely have trouble coping with the costs of dealing with climate change impacts, such as "increased costs of insurance, property taxes, special assessments, property repairs, transportation and consumer goods, as well as a loss in overall productivity (e.g. sitting in traffic in water-clogged streets)" (Keenan, Hill, & Gumber, 2018, pg. 3), these costs and impacts are further discussed in the Social Impacts of Climate Change section (Section 1.5). However, the presence of poverty alone does not determine the flood vulnerability of a region, it is necessary also to examine the spatial distribution of that poverty and how it relates to the geographic setting of the region, particularly elevation.

The subtropical climate and coastal location are two of the main draws for the region, and as a result, wealth tended to congregate on the mainland coast and barrier islands as the region developed, as these areas have the greatest amenity value, despite their high flood risk. Meanwhile, socially vulnerable elements of society, particularly Hispanics and Blacks, were relegated to inland parts of the county, many of which have similar flood risk to the coast, but not the desirable coastal location (Collins, Grineski and Chakraborty, 2018). This is particularly evident in the northern part of Figure 3 (left), a map of relative per capita income across the study area.

This may describe the general regional pattern, however, there are exceptions to both halves of the equation, driven by historical and recent trends in settlement and investment. For example, political uncertainty and turmoil in various South American countries has led to immigration and investment in Miami by wealthier members of those societies, who see the United States as a safer and more stable investment than their home countries. This has led to a new wave of development in some of the areas along the very western edges of the county and past the 'original' inland areas where the socially vulnerable ended up (Florida and Pedigo, 2019). One example would be the city of Doral, which has grown significantly in recent years due to the political situation in Venezuela. The picture is somewhat muddled in the southern third or so of the County, which comprises largely of agricultural areas. Here there is no coastal amenity due to a large mangrove preserve running along the coast, and the inland areas have poor farm laborers, wealthy farm owners, and large mansions and developments taking advantage of zoning laws.

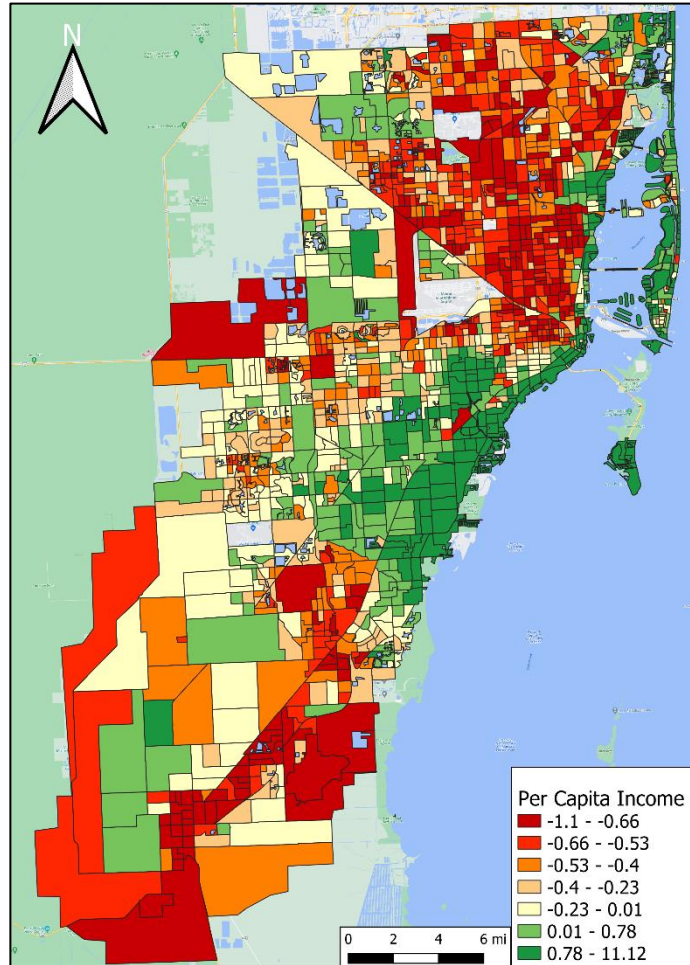


Figure 3: Map of Miami-Dade County showing relative per-capita income. Values have been z-score standardized, so the mean value is 0 and the standard deviation is 1. Values are divided into 7 quantile categories.

In addition, while the inland tendency for socially vulnerable groups mostly holds true, not all inland areas have high flood risk. For example, the socially vulnerable and largely Hispanic or Black neighborhoods, such as Little Havana, Allapattah, Liberty Square, Brownsville, and Little Haiti, are located on parts of the ACR to the west and to the north of Downtown, on high ground which FEMA's DFIRMs refer to as 'Minimal Flood Hazard'.

1.5 Social Impacts of Climate Change

One major social impact of climate change and its physical impacts is climate gentrification, described in Keenan, Hill and Gumber (2018) to have three different possible 'pathways', the first of which they have identified as already happening in MDC. This is the 'Superior Investment Pathway', where properties with superior locational and environmental attributes are substituted for or selected preferentially over those with inferior properties, a "behavior of moving financial capital to a geography that offers superior risk-adjusted returns for accommodating real estate and infrastructure" (Keenan, Hill and Gumber, 2018, pg.2) In the case of Miami, this consists of moving out of flood-prone areas onto the higher ground of the ACR, which is becoming more desirable as flood risk begins to increasingly compete for dominance with the amenity value of coastal living.

This process is already happening to some extent, Keenan, Hill and Gumber (2018) have found that homes with higher elevation have greater rates of appreciation than lower elevation properties, and that nuisance flooding is also having an impact on home appreciation rates (Keenan, Hill and Gumber, 2018) The study also found that the decrease in appreciation rate for areas with nuisance flooding accelerated around the year 2000, coinciding with observations of increased flooding in the county (Keenan, Hill and Gumber, 2018).

Due to this increased preference for higher-elevation ground, the resultant higher appreciation rates in said ground, and the fact that most of the ACR north of Downtown is presently populated by socially vulnerable groups, it is probable that redevelopment into high-end commercial and residential areas will displace the communities previously living there, who will be unable to afford the increasing rents of a gentrifying neighborhood. Such redevelopment attempts are already underway, such as the Magic City Innovation District, a massive development project planned in the predominantly Afro-Caribbean neighborhood of Little Haiti, an area where the median household income is only \$39,000 and the majority of tenants in the area are cost-burdened renters, who spend more than 1/3 of their annual income on housing (Ariza, 2020). Developers are also targeting Allapattah, a primarily Hispanic neighborhood northeast of Downtown, where multi-million dollar developments are taking place in a neighborhood where 77% of tenants are renters and average income is only \$22,600 (Sisson, 2020). However, it should be noted that while these developments are on higher ground and in socially vulnerable neighborhoods, it is not entirely clear whether they are entirely driven by climate fears and thus constitute climate gentrification, or if they are just 'regular' gentrification taking advantage of cheap land and the development of other nearby neighborhoods; climate change impacts are still beyond the normal development horizon for investors and thus may not play a factor at all in locating projects (Sisson, 2020). Regardless of motivation, however, the gentrification of neighborhoods on the ACR will still displace poor residents into lower areas with higher flood risk, so the social impact is still essentially the same in the end.

The second pathway to climate gentrification identified by Keenan, Hill and Gumber (2018) is termed the 'Resilience Investment Pathway'; this pathway is closely related to the 'Superior Investment Pathway', and takes place when public investments in resilience increase the value/performance of assets/property by reducing risk. If the investment is protecting a socially vulnerable areas, the increased rents or taxes needed to pay for the project or associated with higher-value property have the potential to displace residents from the region, this pathway is associated with the concept of 'green gentrification' (Keenan, Hill and Gumber, 2018).

The third of Keenan, Hill and Gumber's pathways to climate gentrification is termed the 'Cost-Burden Pathway', and occurs when the continuously increasing costs of dealing with climate change impacts force people to leave an area, starting with the most vulnerable elements of society and working upwards until only the most wealthy elements of society can afford to live comfortably⁶ in flood-prone areas. One major cost that is already rising is homeowners' insurance, which has increased in cost by 32.5% on average since 2016, compared to a national average increase of 10.9% (Hurst, 2021). On top of this, rates are going up again this year, often by 10% or more, this is blamed on lingering damage and claims from Hurricanes Irma in 2017 and Michael in 2018, rising costs of reinsurance, although also to a spate of largely frivolous or unscrupulous lawsuits⁷ (Salisbury, 2021), rates will only continue to increase as stronger hurricanes become more numerous (Bender *et al.*, 2010; Holland and Bruyère, 2014).

Flood insurance rates, almost entirely through the NFIP, are also generally increasing. This was driven by the bankruptcy of the program, which was in turn driven by the failure of purpose of the NFIP. "Government-subsidized insurance, through the National Flood Insurance Program, was originally intended to reduce flood zone development and risk. It has instead encouraged risky development while providing a subsidy to coastal and floodplain developers, repetitive loss property owners, and the private insurance industry" (Bagstad, Stapleton and D'Agostino, 2007, pg. 286). As a result, socially privileged groups tend to have easier access to resources to compensate for their coastal flood risk, and the cost of coastal flood protection is often borne by the public, while socially vulnerable groups inland struggle to access protective resources (Collins, Grineski and Chakraborty, 2018).

The failure of the NFIP was due to many reasons, including poor flood-risk mapping (and failure to update), massive payouts from disasters like Hurricane Katrina, properties already covered by the NFIP getting 'grandfathered-in' statues with policy changes, and a general inability to raise rates in a way that would keep the program financially stable (Bagstad, Stapleton and D'Agostino, 2007). To help rectify this situation, changes made by the Biggert-Waters Act of 2012 required the NFIP needs to update floodplain maps more frequently and "move towards charging premiums that realistically reflect calculated flood risk" (Knowles and Kunreuther, 2014, pg. 329) Such changes are reflected by the new Risk Rating 2.0 program being implemented by FEMA on October 1st 2021 or April 1st 2022; designed based on the

⁶ There may also be those who cannot afford to leave, and remain trapped in poverty there.

⁷ There seem to be a number of issues with Florida law that cause this, such as legal fee structures encouraging lawyers to take on almost any case. Another revolves around 'assignment of benefits', where a third party can stand in for an insured person when seeking payment from an insurance company. This has led to contractors (particularly roofing ones) going door to door offering to inspect and perform repairs or replacement at no cost (or even offering financial incentive) to the homeowner, then overcharging the insurance company and then filing a lawsuit if need be (Quesada, 2021, Salisbury, 2021)

assessment that many low-risk areas are overpaying for their policies while high-risk areas are dramatically underpaying (FEMA, 2021).

While FEMA claims that this will result in 23% of policyholders will see their premiums decrease and a further 66% will only increase between \$0 and \$10 per month (FEMA, 2021), this is on a national level; and Florida media is widely reporting that rates could triple for as many as 1 million NFIP-insured properties in Florida (out of 1.7 million) (Haughey, 2021), based on a report by the First Street Foundation (Amodeo *et al.*, 2021). Given that climate change impacts will only increase flood risk in MDC, it would follow that flood insurance rates will continue to increase as well.

For the ‘Superior Investment’ and ‘Cost-Burden’ pathways in particular, it should be noted that the migration out of biophysically vulnerable areas can occur on a number of scales. Even movement entirely within the MDC study area can cross municipal boundaries; for example, migration from Miami Beach onto the ACR entails moving from the City of Miami Beach into the City of Miami. Given that a number of municipalities, particularly those on the barrier islands and in the western part of the county, lie entirely or almost entirely in flood-prone areas, climate gentrification could significantly alter the populations and property values of entire municipalities. In addition to these local-scale changes, state-scale climate gentrification and migration is anticipated, with people leaving the region as a whole for less biophysically vulnerable areas such as central Florida, reducing the population and tax base of MDC (Keenan, Hill and Gumber, 2018). The impacts of flooding, climate gentrification, and migration on property values, local government, and budgets will be discussed in the next section, as they are critical for understanding how local governments might respond to climate change.

1.6 Impact of Climate Change on Local Governments

The impact of climate change-driven flooding on local governments will stem primarily from their budgetary reliance on property taxes, which make up 37% of the County (Miami-Dade County, 2020b) and about 50% of local municipal budgets⁸. Property taxes are assessed as a percentage of property value, so any climate change impacts that affect property value will similarly affect county and municipal revenue. Since flooding and market preference decreases the appreciation rates of low-lying properties, the *growth* of income from those property taxes, and thus municipal income in general, is also expected to decrease into the future⁹. Meanwhile, as climate change impacts get progressively worse into the future, the need/demand for adaptation projects is expected to continuously increase, as more areas become exposed and existing projects need upgrading to keep pace with continuing change. As such, the financial burden of adaptation projects will also increase, making it increasingly difficult for municipalities to fund these adaptation projects. This trend constitutes a positive feedback loop, where worsening flooding and the inability to adequately fund adaptation projects will continue to decrease property value and tax revenue, further hampering the ability to fund adaptation measures (Meyer, 2014).

To put numbers on the impacts of flooding on property value, McAlpine and Porter (2018) examined real-estate transactions between 2005 and 2016 in MDC, and found that appreciation in properties

⁸ Budgets checked were those for: Miami Springs, City of Miami, South Miami, West Miami, Opa-Locka, Miami Beach, Hialeah, and Coral Gables.

⁹ Properties generally appreciate in value over time, and therefore the tax revenue they provide would likewise increase. Flooding decreases the rate of appreciation and thus decreases the rate of increase in revenue.

projected to be inundated by tidal flooding by the year 2032 has decreased \$3.08 per year per square foot of living area, while appreciation for properties near roads that are projected to be tidally flooded by 2032 has decreased \$3.71 per year per square foot of living area (McAlpine and Porter, 2018). This added up to over \$456 million in lost value¹⁰ between 2005 and 2016, and the rates of loss are likely to increase as sea level rise predictions continue to worsen and as the public becomes more and more informed (McAlpine and Porter, 2018). Additionally, while this study only dealt with tidal flooding in coastal areas, once climate change really kicks off pluvial flooding in inland areas, the amount of property exposed to flooding will rise substantially, creating further value loss. Unless a way is found to halt or reverse climate change, a point will be reached where property values will begin to decline, as people or banks¹¹ are unwilling to accept the risk of investing in properties in flood-prone regions. Once property values begin to depreciate, municipal income will begin to properly decline, more and more severely handicapping the adaptive capacity of local governments, even as the need for such capacity becomes greater and greater (Shi and Varuzzo, 2020).

Further compounding the issue of declining municipal income is the fact that local governments are also responsible for public infrastructure in their territory. As rising sea levels and other climate change impacts increase, so too will the costs to maintain, repair, or even relocate infrastructure, placing a further drain on government budgets (Chung, 2020) The Southeast Florida Regional Climate Change Compact Inundation Mapping and Vulnerability Assessment Work Group (2012) estimates that across the County, 72 miles of roads could be inundated by 1 foot of sea level rise, 257 miles by 2 feet of sea level rise, and 556 miles by 3 feet of sea level rise, these are 0.08%, 3%, and 6% of total road area, respectively. This inundation is expected to occur within a lifetime, sea level rise projections for south Florida estimate a minimum of 1 foot of sea level rise by 2040, and between almost 2 feet and 4.5 feet by 2070 (Southeast Florida Regional Climate Change Compact Sea Level Rise Work Group (Compact), 2019). Additionally, these estimates only account for permanent inundation, and do not reflect on roads that are flooded semi-regularly by king tides or heavy rainfall. While it is difficult to estimate a cost-per-distance of road elevation, some figures from the nearby Florida Keys give a good indication of the high price tag. Raising less than 3 miles of road to withstand 2025 predicted king tide flooding could cost \$75 million, with elevating for 2045 costing \$128 million and \$181 million for 2060 (Harris, 2019). While they Florida Keys are even lower than Miami-Dade and thus require additional elevation, and assuming substantial cost reductions per unit of distance with larger projects, the price tag is still enormous, especially given the length of roads needing elevation in the County.

In addition to flooded roads, the region's sewer system will need to be overhauled, this was touched upon in the Physical Impacts of Climate Change on Miami-Dade County section (Section 1.3.2) with regards to septic systems at risk and with regards to the coupled sewer system. These upgrades will cost a substantial amount, a 2016 assessment by the MDC Water and Sewer Department estimated the cost of connecting all residential septic systems (83,000) and making the infrastructure improvements necessary to handle the increased load to be \$3.3 billion, this still leaves out another 25,000 commercial and industrial systems (Miami-Dade County of Regulatory and Economic Resources, Miami-Dade County Water and Sewer Department and Florida Department of Health in Miami-Dade County, 2018). These estimates cover extending and improving infrastructure, but do not cover the cost of hooking up

¹⁰ Since this due to decreases in appreciation rate (which is still positive), this figure is lost projected value, rather than actual value lost if the properties had been depreciating.

¹¹ Banks are involved through home mortgages or loans to developers for large projects.

individual homes to the system, an estimated \$15,000 to \$50,000 cost that is borne by the homeowner (Ariza, 2020); this would pose a significant burden to many low and middle-class homeowners, and represents another cost of climate change adaptation that might further push the 'Cost-Burden Pathway' of climate gentrification in the region.

In addition to sewer overhaul, it was mentioned previously that due to the gravity-driven nature of the County's canal network, a 6-inch rise in sea levels is estimated to eliminate half of the region's drainage capacity (Kolbert, 2015). Updating this system to keep pace with climate change is expected to cost around \$7 billion (Ariza, 2020).

Another potential adaptation cost to local governments comes from home buyout programs, where properties in hazardous areas are bought and demolished, to help reduce the exposure of an area. While voluntary programs have been around for a while (MDC is in the process of implementing one for properties damaged by Hurricane Irma), it is a possibility that governments will be required to buy properties that they cannot protect or ensure access too¹². While this is still a legal grey area (Sinclair, 2020), such a requirement could create a massive financial obligation in the future.

The important takeaway is that adaptation projects for the region are significant, a cost that will only grow as climate change intensifies, and a cost that will become progressively harder for local governments to afford. In order to help manage budgets and fund adaptation and infrastructure projects/repairs, it will be necessary to impose new fees or taxes, raise existing ones, or cut services (Shi and Varuzzo, 2020). Difficulty in raising funds has also been increased by the fact that climate risk has begun to influence credit rating and bond pricing, which will make it more difficult for local governments to fund infrastructure projects through municipal bonds, previously the traditional way to fund such projects (Chung, 2020). In extreme cases, municipalities may even 'abandon' areas that are too costly to maintain or protect, halting services to these areas and absolving themselves of the responsibility and burden; these possibilities are already being investigated in the Florida Keys, a low lying island chain to the south of MDC (Sinclair, 2020). Such fiscal policies would make the area less desirable and/or more expensive to live in, this is the 'Cost-Burden Pathway' to climate gentrification described in (Keenan, Hill and Gumber (2018).

Concerns over future costs and budgetary issues like those described here could influence the decision-making process when it comes to determining which neighborhoods get adaptation projects and which do not. If governments are not (or know they will not be) able to protect the entirety of their territory or population, it is plausible that they might focus spending on trying to get as much 'bang for their buck', choosing to protect areas with high population density or valuable property, rather than on the most socially vulnerable elements of society. For example, the Miami-Dade Back Bay Coastal Storm Risk Management Feasibility Study, which was performed by the US Army Corps of Engineers to assess the feasibility of sea walls and flood gates to protect the region from storm surges states clearly on its 'Frequently Asked Questions' page that the purpose of the project is "(...) specifically to reduce the economic damage, as well as risk to life and safety" (US Army Corps of Engineers, no date). Such an approach would aim to protect as much future taxable value and income as possible, and thus help ensure that municipalities themselves have income in the future, enabling them to function and continue to resist climate change for as long as possible.

¹² i.e. elevating a road to prevent it from becoming inundated.

The dichotomy between this financial approach and a more traditional social justice approach to defining vulnerability, and the spatial patterns that result, are what define the research problem that this study seeks to address. To accomplish this, this study will examine the vulnerability of MDC on a CBG level, comparing between two different indices, one with a social approach to vulnerability and one with an economic approach to vulnerability, these are the Hazards of Place Model and the Tax Income Protection Index. It will then compare the spatial patterns of vulnerability produced, and look for areas of overlap between the two that ‘justify’ adaptation projects from multiple perspectives. The two indices are described below.

1.7 Two Indices of Vulnerability

This study makes use of two main indices, these are the Hazards of Place Model (HoPM), as presented in Cutter, Mitchell and Scott (2000), and the Tax Income Protection Index (TIPI), which correspond to a social justice approach to vulnerability and an economic approach to vulnerability, respectively. Each of these indices includes population characteristics and biophysical vulnerability; however, to the methodology and results will first construct and examine each of these without their biophysical vulnerability component, these comprise the Social Vulnerability Index (SOVI) (see Cutter, Boruff and Shirley, 2003) and Municipal Priority Index (MPI). Table 1 (below) summarizes the two different theoretical approaches to vulnerability used in this study, and the names of the indices that result at various stages of construction.

	Social/Environmental Justice Approach to Vulnerability	Economic Approach to Vulnerability
Does not include biophysical vulnerability	Social Vulnerability Index: Uses socioeconomic variables to determine ability of population to cope with and recover from flooding.	Municipal Priority Index: Uses home value and population density to identify what areas might give governments the best “bang for their buck” when protected from flooding.
Includes biophysical vulnerability	Hazards of Place Model: Social Vulnerability index + biophysical vulnerability component.	Tax Income Protection Index: Municipal Priority Index plus biophysical vulnerability component.

Table 1: Chart summarizing the four indices discussed in this analysis. It is the distributions of the bottom two that this study principally seeks to examine.

1.7.1 Hazards of Place Model

The first index used in this study is the HoPM, which is based off (and incorporates) the earlier SOVI, which uses 28 different socioeconomic indicators to investigate how natural disasters differently affect various social groups within a population, and their differing abilities to respond to and recover from disaster (Cutter, 1996; Cutter, Boruff and Shirley, 2003). The SoVI and other indices based off its principles approach vulnerability from an environmental justice point of view, where measures to reduce flood risk should focus on the marginalized elements of society that are least able to fend for themselves (Chakraborty *et al.*, 2020).

The HoPM builds onto the Social Vulnerability Index by incorporating biophysical vulnerability, which is the geographic context of hazard potential, and more specifically describes the “proximity to hazard

sources and events” (Cutter, Mitchell and Scott, 2000, pg. 717). Since this study is focused only on flooding, biophysical vulnerability in this instance equates to/is replaced by flood vulnerability.

The addition of this biophysical vulnerability component to in the HoPM helps account the fact that a socially vulnerable population living in a less hazardous area could be less vulnerable overall than a less socially vulnerable population living in a more hazardous area. This is an important consideration when studying Miami, due to the previously described concentration of wealth on the coasts due to amenity value.

1.7.2 Tax Income Protection Index

The TIPI takes a more utilitarian approach to determining what areas should be prioritized for adaptation projects. This index is based off the idea that the high and continuously rising cost of adaptation projects makes it likely that municipalities will be unable to afford to protect themselves entirely from the impacts of climate change as impacts become more and more widespread. As previously described, these impacts will affect property values and municipal revenue in a positive feedback loop that will eventually cripple local governments (Meyer, 2014). As such, rather than approaching vulnerability from an environmental justice perspective, local governments might instead approach vulnerability from a cost-benefit or economic perspective, using what funds they have to protect as many people or as much valuable property as possible, in order to preserve as much of their tax income stream for as long as possible and giving them, in essence, the best return on their investment. This would potentially allow them to continue to exist and fund adaptation projects for a longer period of time than they would have otherwise, and also protect a larger percentage of their population. This index currently uses only 2 variables: median home value and population density. Both of these variables are weighted equally, this follows the lead of the SOVI, as it is unknown whether property value or population density would be prioritized individually. As an additional note, having an equal number of variables that ‘represent’ predominately property value or population density is necessary to keep index from favoring one side or the other, due to the additive model used.

Like the HoPM, the TIPI includes a biophysical vulnerability indicator, since densely populated or high-value areas with low flood hazard would not necessarily need to be protected before less densely populated or less valuable areas that are higher-hazard. Also like the HoPM, the TIPI can be examined without the vulnerability component, this is that MPI. To simplify the process and comparisons between the indices, the biophysical vulnerability component for the TIPI is the same as for the HoPM, this is discussed more in the Methods chapter, in Section 2.2.3.

1.8 Research Problem

With the need to prepare low-lying coastal areas for the impacts of climate change, various vulnerability analyses have been used as risk-management tools to assist in adaptation and mitigation planning, allowing governments to “anticipate future ‘hot spots’ of adverse effects” (Preston, Yuen, & Westaway, 2011). However, there are a wide variety of methodologies available, covering a broad spectrum of definitions for vulnerability, and focusing on different drivers and indicators. As such, different analyses can give very different results, depending on what definition and approach they take to vulnerability.

As a result of this complexity, identifying what areas should receive adaptation projects can be a difficult process, since parties with different definitions of vulnerability will want to prioritize different areas that they see as most vulnerable. Identifying CBGs that are highly vulnerable to flooding from both a social justice and an economic perspective can help reduce stakeholder conflict in this situation, since they represent areas that protagonists of both views can agree are highly vulnerable.

1.8.1 Research Objectives

The overall aim of this study is to compare and examine the distribution of high flood vulnerability census block groups in Miami-Dade County from a social/environmental justice perspective and an economic/cost-benefit perspective, in order to aid in the climate change adaptation project planning process. This aim will be addressed via 4 research objectives:

The first research objective is: Locate census block groups that are highly vulnerable to flood vulnerability under both the Hazards of Place Model and Tax Income Protection Index.

The second research objective is: Identify the principal driving variables of vulnerability in clusters of high vulnerability across the County.

The third research objective is: Examine how adaptation measures might differ between clusters of high flood vulnerability, based off their geographic and socioeconomic characteristics.

The fourth research objective is: Identify municipalities which have high flood adaptation burdens due to concentrations of vulnerability under both the HoPM and TIPI.

2. Methods

This section covers the steps taken to construct the HoPM and TIPI compared in this study, and the maps that were created for analysis. It starts with the collection and processing of the data that are used in both indices, then follows with the creation of each index's biophysical vulnerability-less version (the SOVI and MPI), and the subsequent application of the biophysical vulnerability element to both to produce the HoPM and TIPI. The mapping sections cover the creation of the maps for examining the distribution of high flood vulnerability in individual indices before and after the application of biophysical vulnerability, a side-by-side comparison map between the HoPM and TIPI to allow for easier visual comparison of their differing distributions, and the map showing just the overlap of CBGs with high flood vulnerability. These steps are summarized in Figure 4 (below).

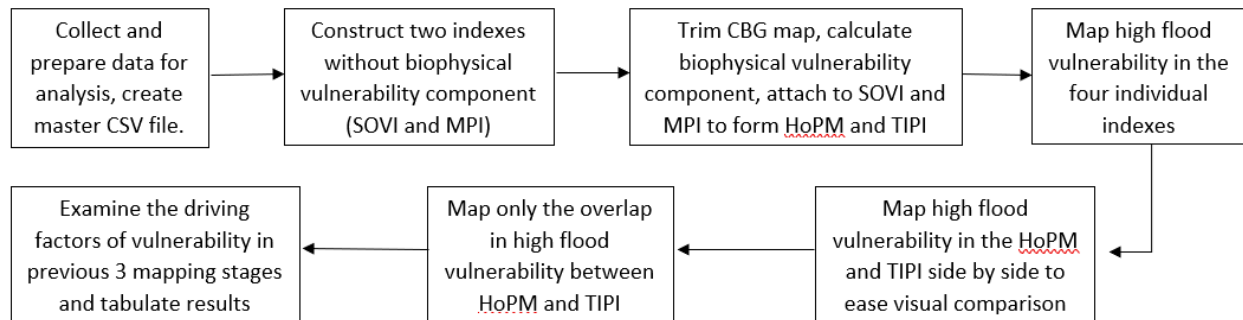


Figure 4: Flowchart showing the general methodological steps taken in this analysis.

2.1 Data and Data Processing

All data collected was done following ITC's ethics guidelines and Covid-19 risks and contingencies, this is outlined in Appendix 1.

Data collection started with socioeconomic data for MDC at the CBG level, which was needed to construct both indices used in this study. All demographic and economic data came from the 2014-2018 American Community Survey, although the downloads came from two different sources. The primary source was a shapefile of the 2015 CBGs in Florida, with a selection of attached attributes, which, in addition to socioeconomic information, included attributes such as total population and total land area for each CBG. From this, the data for just MDC was exported as a separate shapefile to make processing easier; the attribute table for this new shapefile was then exported to Excel for further processing.

The remaining variables needed for the SOVI analysis that were not present or calculable from this state CBG dataset were downloaded as parts of larger tables directly from the U.S. Census Bureau's data explorer¹³. These were joined using the GeoID attribute to form one table with all collected data, where any additional variables that required calculating from existing data were created. From this, only the variables needed for creating the two indices (excluding their biophysical component) were extracted to a new file, where any CBGs without any population were removed. This file formed the basis for the index work described in Section 2.2.

¹³ Three SOVI variables could not be found at the spatial level used in this study, these are: Percent Employment in Extractive Industries, Nursing Home Residents Per Capita, and Percent Households Receiving Social Security Benefits.

The data for adding the biophysical component to the indices consisted of a DEM of MDC obtained from the United States Geological Survey’s (USGS) 3DEP products, with 1/3 arc-second (~10m) resolution.

2.2 Index Work

Once all data collection and processing were complete, the actual analysis could begin. This started with the use of the demographic data to construct the SOVI and TIPI, a table listing the variables used in each of the indices used in this section is shown in Appendix 2. A biophysical vulnerability measure was then created and applied to both indices, this resulted in the completed hazards of place and comparison models. A flowchart summarizing the stages and indices used is shown below in Figure 5.

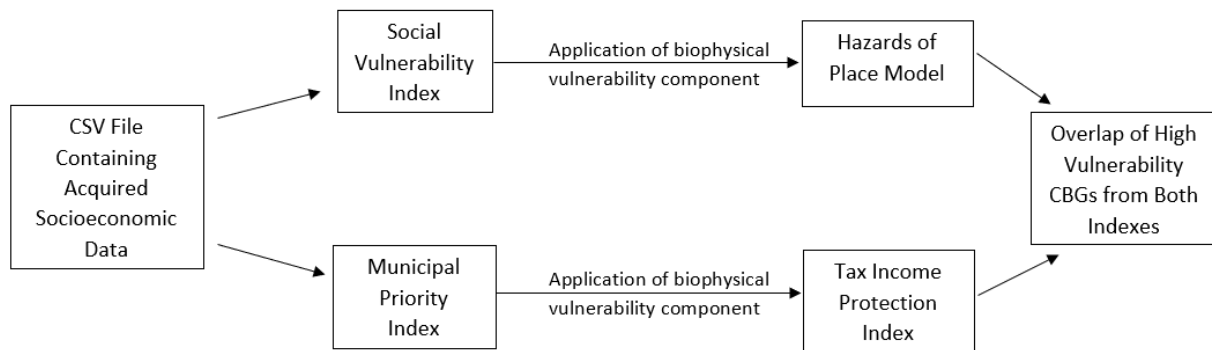


Figure 5: Flowchart showing the relationship between the indices used in this study.

2.2.1 Social Vulnerability Index

The social vulnerability index was constructed following the ‘SOVI Recipe’ laid out on the Hazards and Vulnerability Research Institute website (Hazards & Vulnerability Research Institute, 2016), and is summarized in Figure 6 (right).

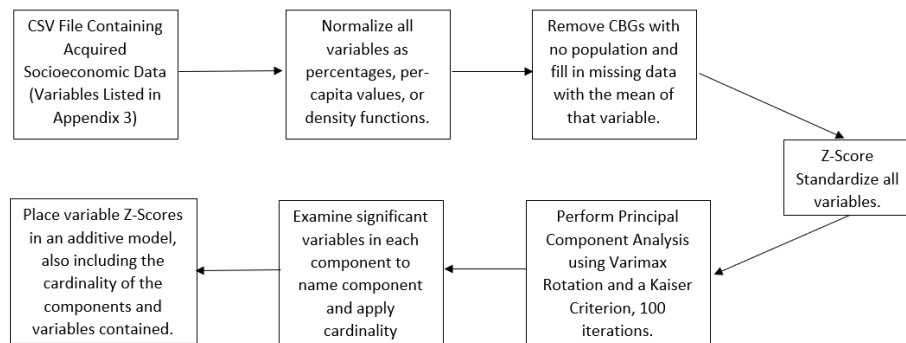


Figure 6: Flowchart showing the steps taken to produce the SOVI, as described at length in Hazards and Vulnerability Research Institute (2016).

Once the required variables, shown in Appendix 3 were collected in a single Excel spreadsheet, all variables were normalized into either percentages, per-capita values, or density functions; this allows for direct comparison between CBGs which all have different sized populations (Hazards & Vulnerability Research Institute, 2016).

Missing values in the data were replaced with the mean value for that variable¹⁴, as the procedure cannot run with missing values. Z-score standardization was then applied, creating new variables with a mean of 0 and a standard deviation of 1. These standardized variables were used as the inputs for a varimax rotation of 100 iterations with the Kaiser Criterion; this was performed in SPSS 27 (IBM Corporation, 2020). The results of this, shown in Appendix 4, gave 7 components with eigenvalues greater than 1. The author chose to remove the last of these, as no individual loading within the component exceeded a weighting value of ± 0.7 . Together, the 6 remaining components explained 63.8% of variance, these are shown in Table 2 (above).

Component	Cardinality	Name	% Variance	Dominant Variables	Component Loading
1	+	Poverty	20.457	PCT_Poverty	0.737
				PCT_200k	-0.643
				Per_Capita_Income	-0.628
				PCT_Low_Edu	0.711
				PCT_Renter	0.744
				Med_Rent	-0.659
2	+	Race	10.069	PCT_No_Vehic	0.724
				PCT_BLACK	0.809
3	-	Population	9.836	PCT_HISP	-0.902
				Pop_Per_Hse_Unit	-0.91
4	+	Special Needs	8.309	PCT_Vacant	0.789
				PCT_Young_And_Old	0.823
5	+	Family	7.837	Med_Age	0.795
				Pct_2_Parent	-0.833
6	+	Female	7.367	Pct_Fem_Head	0.848
				Pct_Fem	0.748
				Pct_Fem_Lab	0.797

Table 2: Table showing the 6 components retained for use constructing the SOVI analysis. For each component, the cardinality, percentage of variance explained, and dominant variables are shown, along with the component loading of said variables.

The key variables from each component were then extracted, these generally had a component loading exceeding ± 0.7 but not always, the lowest value taken was -0.628. Based on the positive or negative loading of the key variables in each component, the component as a whole was then assigned a cardinality to reflect its impact on social vulnerability, such that the cardinality of the component multiplied by the cardinality of each individual variable would reflect the impact of that variable on social vulnerability.

These factor cardinalities were then used with the standardized input variables in an unweighted additive equation to calculate the social vulnerability value of each CBG. These scores were then joined to the main working excel file that had the geoinformation and input variables, the ‘master working file.’

2.2.2 Municipal Priority Index

The MPI was constructed from the same demographic data file as was used in the SOVI analysis. Since it is designed to represent a more utilitarian approach to vulnerability, where governments would try to protect as many people or as much taxable value as possible, this index is based on population density and property value. Similarly to the SOVI index, the data was normalized and z-score standardized.

¹⁴ In addition to replacing blank values with the mean for the variable, this was done for two CBGs that were extreme outliers in the People Per Housing Unit variable. These two CBGs theoretically had 672 and 85 people per housing unit. The first CBG covers the University of Miami campus, and it is likely that this incredibly high value (the mean for the variable is 2.8) is due to entire dorm tower blocks being counted as a single housing unit. The second CBG covered parts of downtown Miami, including a federal prison. It is likely that this similarly increases the people per housing unit average for the CBG. In order to compensate for these outliers, particularly for standard deviation calculations, their values were replaced with the mean for the variable, excluding the outlier values from the mean calculations.

Because there are only two variables, there was no need to perform varimax rotation, and the two variables were placed in an additive unweighted equation to produce the TIPI value. This was also joined on to the master working file.

2.2.3 Application of Biophysical Vulnerability Component

Biophysical (flood) vulnerability was calculated using the elevation raster of MDC. Mean CBG elevation was chosen for the biophysical vulnerability index for several reasons. This study is only examining vulnerability to flooding, so only factors influencing that needed to be considered. In the case of Miami, this essentially narrowed the choices down to elevation and Digital Flood Insurance Rate Maps (DFIRMs), which are produced by FEMA and show the various flood zones in the area. However, using DFIRMs to try and determine biophysical vulnerability presents several issues. There are only three incident occurrence rate-based categories¹⁵: 100-year flood zones, 500-year flood zones, and not a flood zone. This, along with the fact that much of MDC falls into the 100-year flood zone, makes it difficult to use DFIRMs to compare flood risk between CBGs, since so much of MDC falls into so few categories, and there are no finer distinctions. Visual examination also shows that DFIRMs closely follow minor elevation changes, so using elevation to determine biophysical vulnerability to flooding also functions somewhat as a proxy for the DFIRMs. Additionally, an informal discussion with County officials during the research proposal phase gave several other reasons for using elevation. One such reason was that because DFIRMs are used for insurance purposes, there is the potential for outside influence on where boundaries are drawn. They also added that the DFIRMs for MDC are currently in the process of being revised, and suggested that elevation would better serve the purposes of the study.

2.2.3.1 Map Trimming

The 2015 Florida CBG map downloaded in the previous section was inadequate for constructing the biophysical vulnerability component used in the HoPM and TIPI. This was because many CBG polygons included uninhabited areas with a significantly (generally lower) different elevation from the inhabited areas. For example, many coastal CBG polygon boundaries included parts of Biscayne Bay, The Intracoastal Waterway, dense canal networks, or mangrove forests; while inland CBGs could feature lakes, canals, or marshland. As this study is basing biophysical vulnerability on the average elevation of CBGs, and since it is concerned only about the vulnerability of population rather than areas, including uninhabited areas with zero or basically zero elevation would act to reduce the average elevation of a CBG (and therefore increase its vulnerability score), despite these areas having no impact on the actual biophysical vulnerability of the area's population. This effect would be enhanced by the fact that some of these uninhabited areas could comprise large percentages of a CBG polygon's original area, as well as and the general flatness of Miami's topography and the resulting importance of even minor differences in elevation.

In order to rectify this problem, a shapefile of Miami-Dade County's 2010 census block groups was downloaded from the County's open data hub (Miami-Dade County, 2017). This particular file was

¹⁵ There are technically more categories, as each consists of a source/type of flooding and a frequency of occurrence, such as coastal/1% chance or inland/1% chance. However, this study is only concerned with frequency of occurrence, of which there are only three classes that the various categories fall into.

chosen for processing specifically because it had no census data attached for me to worry about during data processing¹⁶. Map editing was done in QGIS 3.10 (QGIS Association, 2021), with the shapefile layer set to reduced opacity and Google Maps as a basemap. The vertex editor tool was used to manually edit the boundaries of CBGs in order to remove unwanted areas of the kinds described above. Figure 7 (right) shows a typical example of the results of this, where an area that was formerly entirely within various CBGs has been cleaned up.

This process was simple along the eastern coastal areas, but significantly more complicated along the southern and western borders of the county, which are largely comprised of wetlands, agricultural regions, or limestone quarries and pools used in the cement manufacturing industry. In these regions, the boundary between urban and rural, inhabited and uninhabited was much more difficult to define, work was essentially best-guess, and encompassed areas where roads were present and tried to exclude wetlands in particular. Since the differences in elevation in this part of the county are significantly less than the differences on the coast, this inland boundary did not need to be nearly as precise as on the seaward side of the County.

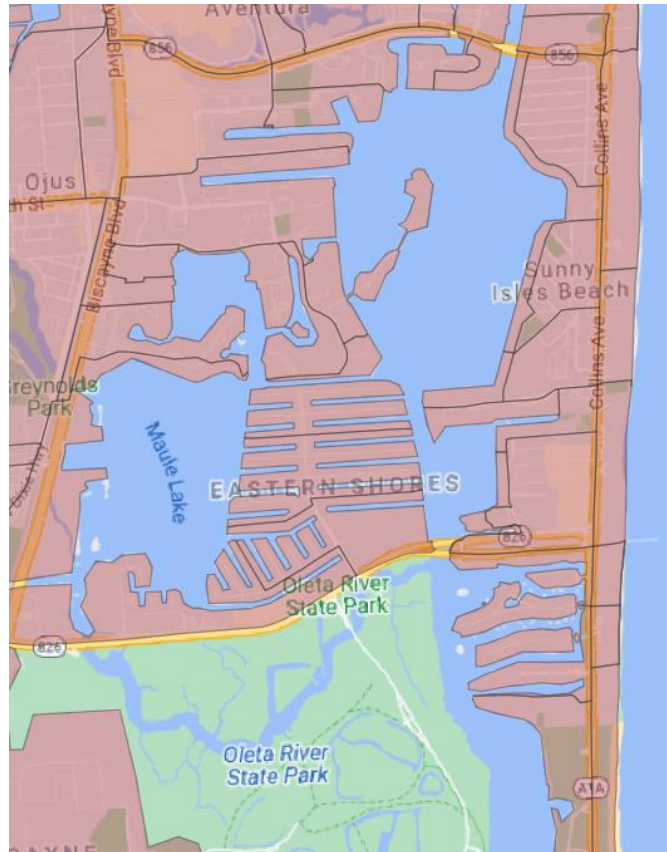


Figure 7: An example section of MDC where substantial boundary editing was required. Previously this entire section would have fallen into various CBGs, excluding the open ocean at the far right of the image.

2.2.3.2 Calculating Biophysical Vulnerability

To get the mean elevation of each CBG, the elevation raster of MDC was first clipped, using the CBG boundaries created in the previous section as the mask layer¹⁷.

The zonal statistics function of QGIS was then used to obtain the mean elevation of each CBG polygon, which was then Z-score standardized to create a more practical scale to work with. These data were then joined onto the master working file.

¹⁶ In hindsight, using a separate shapefile for editing was not necessary since I could have simply duplicated the other CBG shapefile (with attached census data) and edited one of them. It was done the way it was mostly for peace of mind at the time, but may have introduced small errors if CBG boundaries changed from 2010 to 2015.

¹⁷ Technically the clipping was done with a 0-radius buffer of the edited CBG map, this was due to geometry errors created during the map editing process that interfered with the clipping. Additionally, since the CBG average elevation calculations run based on the polygon boundaries, this whole clipping process ended up being entirely unnecessary in the end. The more you know...

2.2.4 Combining

In order to combine the SOVI and MPI each with biophysical vulnerability index, each of the three was divided via quantiles into 9 bins of 175 CBG's each. CBG's in each bin were then assigned a value between 1 and 9, based on its index score. Due to the inverse relationship between elevation and vulnerability, bin values were reversed for biophysical vulnerability, with higher elevations receiving lower values and lower elevations receiving higher values. The SOVI and MPI were then each placed in an additive model with the biophysical vulnerability index, as shown in Figure 8 (below). This step produced the Hazards of Place Model from the combination of the SOVI and biophysical vulnerability and the TIPI from the combination of the MPI and biophysical vulnerability. The distribution of these two resulting indices is what this study seeks to examine. The resulting bin values were added into the master working Excel file.

SOVI	High	9	10	11	12	13	14	15	16	17	18
	8	9	10	11	12	13	14	15	16	17	18
	7	8	9	10	11	12	13	14	15	16	17
	6	7	8	9	10	11	12	13	14	15	16
	5	6	7	8	9	10	11	12	13	14	15
	4	5	6	7	8	9	10	11	12	13	14
	3	4	5	6	7	8	9	10	11	12	13
	2	3	4	5	6	7	8	9	10	11	12
	Low	1	2	3	4	5	6	7	8	9	10
		1	2	3	4	5	6	7	8	9	
		Elevation									
		← High				Low →					

Figure 8: An example of the additive model used to combine the SOVI and MPI bin values with the elevation bin values for each CBG.

2.3 Individual Index Mapping

Once the two end-product indices (HoMP and TIPI) were completed, their Excel files were imported to QGIS and joined to a shapefile of the refined MDC CBGs. A choropleth map was then created for each index, using an equal interval classification with 8 classes. In order to ease comparison between the two indices, it was decided to only examine the three most vulnerable bins from each index, as such, the rest of the choropleth gradations were changed to white, as shown in Figure 9 (right).

SOVI	High	9	10	11	12	13	14	15	16	17	18
	8	9	10	11	12	13	14	15	16	17	18
	7	8	9	10	11	12	13	14	15	16	17
	6	7	8	9	10	11	12	13	14	15	16
	5	6	7	8	9	10	11	12	13	14	15
	4	5	6	7	8	9	10	11	12	13	14
	3	4	5	6	7	8	9	10	11	12	13
	2	3	4	5	6	7	8	9	10	11	12
	Low	1	2	3	4	5	6	7	8	9	10
		1	2	3	4	5	6	7	8	9	
		Elevation									
		← High				Low →					

Figure 9: Equal interval bins and choropleth gradations used in the maps for the SOVI, HoPM, MPI, and TIPI sections of results.

2.3.1 Side-By-Side Comparison Map

In order to allow for convenient side-by-side comparison of the distribution of high-vulnerability census block groups between the two indices, a map showing CBGs that were classified as highly vulnerable in either index was created. This was done in Excel using the same data sheet containing (at least) the GEOID, HOPM index value, and TIPI value. A new column/attribute was then created, containing the

nested if-and equation shown in Equation 1 (below), where W2 is the first cell in the column containing the HOPM values, and AA2 is the first cell in the column containing the TIPI values.

$$=IF(AND(W2>12.5,AA2<12.5),1,IF(AND(W2<12.5,AA2>12.5),2,IF(AND(W2>12.5,AA2>12.5),3,4)))$$

For each CBG, this statement checks which index classifies that CBG as highly vulnerable and returns a designated number to allow for categorical mapping of high-vulnerability areas from each index on the same map. The equation outputs a 1 if a CBG high-vulnerability in the HOPM only, a 2 if a CBG is high-vulnerability in the TIPI only, and 3 if a CBG is vulnerable in both indices, and a 4 if a CBG is vulnerable in neither index. The attribute table with this new column was then imported to QGIS, joined to the trimmed CBG boundary data, and exported as a new shapefile. This was then mapped categorically, with a different color applied to each category: blue for the HopM, yellow for the TIPI, green for overlap, and white for neither.

2.3.2 Overlap Mapping

In order to map just the census block groups that fell into the high-vulnerability categories in both indices, an if-and statement was used to create a true/false attribute which would identify CBG's that fell into the top three most vulnerable bins in both indices. This was then imported to QGIS, attached to the same trimmed CBG boundary data used throughout. A categorical coloring system was then applied to the true/false attribute, with true (i.e. high vulnerability on both indices) colored red and false (i.e. not high on both indices) colored white.¹⁸

2.3.3 Results Summary Tables and Maps

When describing the patterns of high vulnerability, the results examine the factors driving vulnerability in each cluster. This was done in QGIS by selecting all the CBGs in a cluster and examining the attribute table for 'selected features.' The threshold for a variable to be a driving factor was that it more extreme than or equal to ± 0.5 standard deviations (remember that all data was z-score standardized) in the direction increasing social vulnerability, based on the cardinality of each component¹⁹. To be considered a driving factor for the cluster, variables needed to exceed the threshold in at least 75% of CBGs in that cluster; variables could also be marked as a driver for some CBGs in the cluster if they exceeded the threshold value in at least 50% of the cluster's CBGs.

These were tabulated to summarize results in the SOVI, HoPM, and Overlap sections of the Results chapter (Section 3.0). For these tables, the vertical axis lists clusters or neighborhoods²⁰, while the

¹⁸ The reason this was done from scratch off the base attribute table rather than selecting the appropriate response from the if-then statement used in the Comparison Mapping section and mapping that separately is that the overlap mapping was done before the idea of the comparison map was conceived, and the methods are aligned to match the order that results appear in, rather than the order in which they were performed.

¹⁹ For example, the threshold for the Poverty variable would be $\geq +0.5$, since higher rates of poverty correspond with increased vulnerability. For the Per Capita Income variable, however, the threshold was ≤ -0.5 , since lower per capita income corresponds with increased vulnerability.

²⁰ For the SOVI and HoPM distributions, there were large areas of continuous high-vulnerability CBGs that span multiple neighborhoods and municipalities, mainly to the north of Downtown. Since these neighborhoods have different characteristics from each other, these were treated as separate areas rather than as one massive cluster.

horizontal axis is all the SOVI variables. Cells were marked green for variables that were a driving factor across the listed region and marked orange if they were a driver for only some CBGs in the region.

These results tabulation charts were not done for the MPI or TIPI results sections, as their vulnerability scores/status is based only off of property value and population density, rather than the various SOVI variables. Additionally, many clusters would be a mixture of the two drivers, due construction patterns common in MDC, where apartments or condominiums line large roads, while detached-home residential covers the smaller streets between. As such, high population density and high property value can neighbor each other, leading to clusters driven by both variables examined in the MPI and TIPI. With only 2 variables and the potential for overlap between the two, a different approach was used for displaying the distribution of the variables driving vulnerability across the County under the MPI and TIPI.

For these two indexes, maps of the County as the CBG level were created, using a categorized color theme to display which variables drove vulnerability in each CBG; this makes it easy to identify drivers dominant in any cluster but also to distinguish any variation in driver within individual clusters. These maps were created by selecting just the highlighted vulnerability bins from the two indices' maps and exporting them each into Excel, where a new attribute called 'Categorized' was added. This column contained an altered version of Equation 1, which had the columns modified to the relevant ones for the table: column L is z-standardized population density and column N is z-standardized median home value. The threshold value was also set to 0, which is the mean of z-standardized data, thus, the equation is measuring which of the two variables is above average for any given CBG. It returns a value of 1 if only the population density z-score is above 0, a value of 2 if only median home value has a z-score greater than 0, a 3 if both variables do, and a 4 if neither do. A threshold value of 0 rather than 0.5 standard deviations, as was done for the SOVI, HoPM, and Overlap sections, was chosen after examining the data; z-standardized values were much lower in these two variables than in the ones used in the other indices. Additionally, variables tended to fall on opposing sides of 0, so using this as a threshold value effectively divided most of the data. The equation used, Equation 2, is shown below.

$$=IF(AND(L2>0,N2<0),1,IF(AND(L2<0,N2>0),2,IF(AND(L2>0,N2>0),3,4)))$$

Once the driving variable category results were generated, the CSV files were imported to QGIS and joined to the blank template CBG map of MDC. They were then categorically mapped, with population density as a driver in yellow, median home value as a driver in blue, both as drivers in green, and neither as a driver in pink. Since the equation was only applied to CBGs previously identified as high vulnerability under the two indices, remaining CBGs were filled in white. These maps allow for the examination of the spatial distribution of the two variables across the county more effectively than trying to identify clusters and their characteristics, since the maps can show patterns down to the CBG level rather than the cluster level.

2.4 Potential Adaptation Measures Comparison Between Two Clusters of Vulnerability

In order to address the third research objective, a comparison was made between two case study clusters of high flood vulnerability. These consisted of the South Beach and Hialeah Gardens clusters, both these clusters were highly vulnerable under both the HoPM and TIPI. The comparison between the two was more discussive than technical, and covered factors such as the differences in geographic

location, the sizes of the clusters, the kinds of structures in each the different socioeconomic drivers of vulnerability (as described in Methods Section 2.3.3), and other pieces of information picked up while doing research. These factors are used to investigate how flood adaptation measures might differ between these two clusters of high flood vulnerability, to illustrate the kinds of differences that might be found across the County and the impacts they will have on planning adaptation measures.

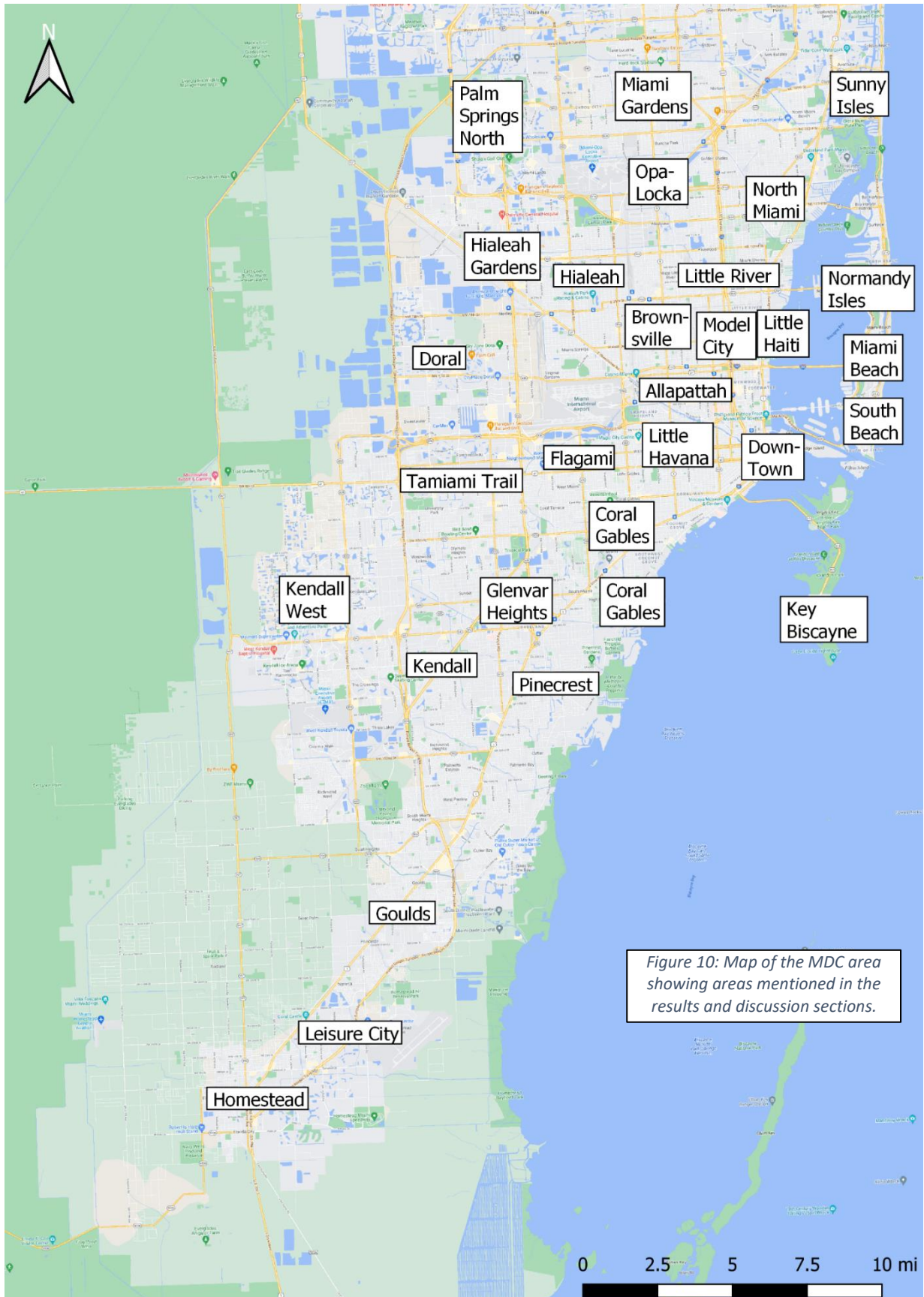
2.5 Identifying Concentrations of Vulnerability

Concentrations of vulnerability were initially identified visually by examining the map of vulnerability overlap between the HoPM and TIPI. A shapefile of municipal boundaries within MDC was then downloaded from MDC's open data hub (Miami-Dade County, 2017) and added to the QGIS project. These boundaries were used to count both the number of high flood vulnerability CBGs that overlap between the HoPM and TIPI and the number of CBGs within the municipality. This information was then used to calculate the percentage of the total number of vulnerable CBGs from overlap between the two indices present in the identified municipalities, as well as what percentage of CBGs in each municipality fell into this overlapping vulnerability category.

3. Results

In order to better examine the distribution of vulnerability across the county according to each of the two indices, the results will cover each of the two theoretical approaches to vulnerability used in this study (social justice and economic) in turn, covering first the distribution of areas with high flood vulnerability in the index without the application of the biophysical vulnerability component and subsequently in the index including it. Each results section will describe the distribution and clusters of high flood vulnerability CBGs under a particular index, and comment on the principal variables driving that vulnerability, when applicable.

Figure 10 (below) is a map of MDC, labeling areas that are mentioned throughout the Results and Discussion chapters. It itself is not part of the results but has been inserted for reference, as the other maps in the results section were too cluttered when labeled individually, and there are no maps present when discussing clusters of vulnerability in the discussion section.



3.1 Social Vulnerability

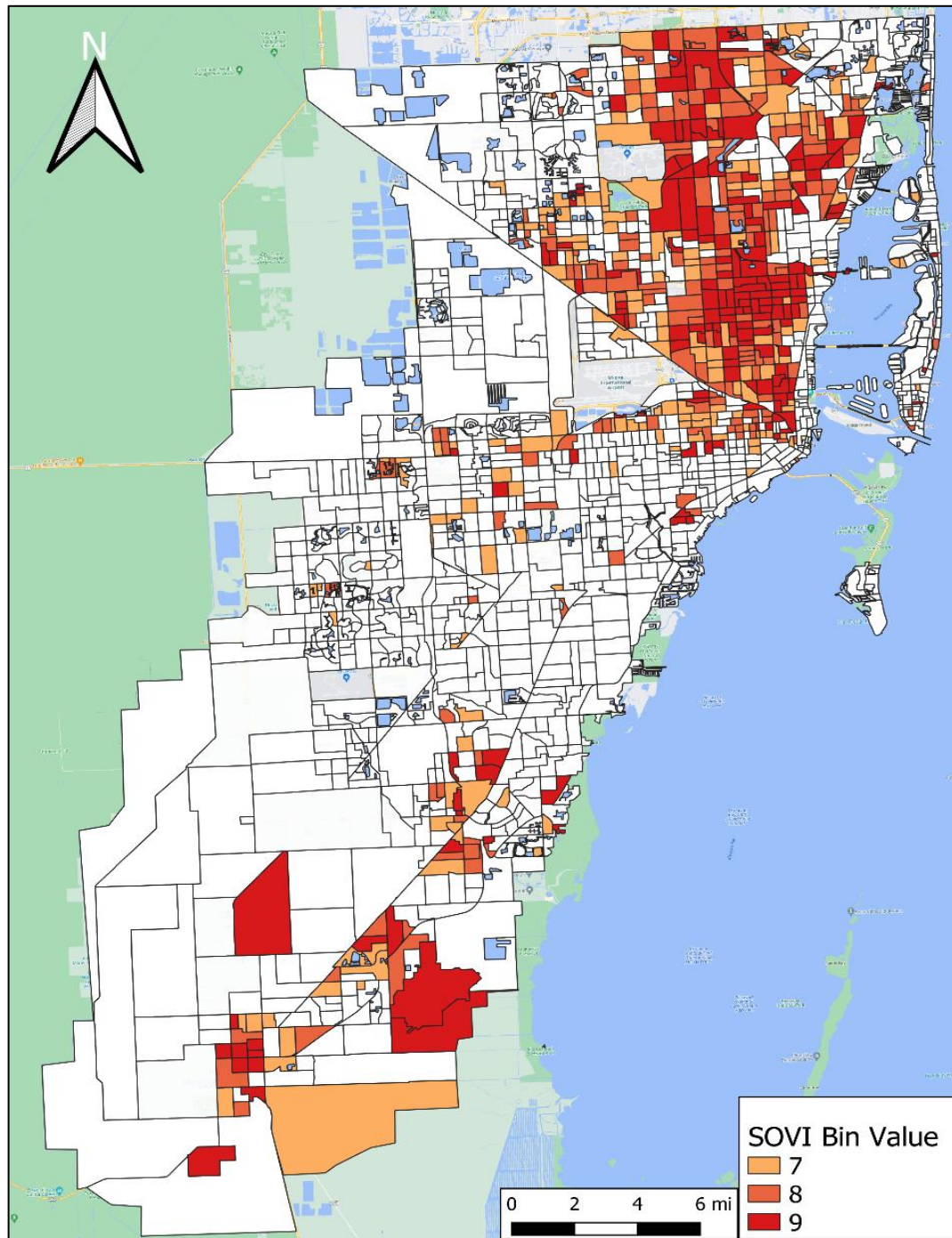


Figure 11: Distribution of the 3 most vulnerable bins in the Social Vulnerability Index. The 3 most vulnerable SOVI bins contain a total of 526 CBGs, with 176 in the most vulnerable bin, 175 in the second-most vulnerable bin, and a further 175 in the third-most vulnerable bin. These even divisions are a result of the equal-interval divisions of the data when binning the data, and the three bins/526 CBGs represent one-third of the data.

Figure 11 (above), a map of the distribution of the 3 most vulnerable SOVI bins across MDC, shows that the largest concentration of highly socially vulnerable areas is located to the north and northeast of Downtown. The northward section of this main concentration is predominantly Black neighborhoods, such as Model City (more commonly known as Liberty City), Brownsville, Little Haiti, Opa-Locka, North Miami, and Miami Gardens. These areas tend to have above average rates poverty rates, below-average per

capita income and people earning over \$200,000 annually²¹, low educational attainment, low median rent, and many single parent and female-headed households. Additionally, some CBGs in these clusters have low vehicle access, high percentages of renters, a large female labor force, and a high population-per-housing-unit rate.

Heading northeast from Downtown, the makeup of the high-SOVI CBG's is somewhat different. These areas, focused on the Little Havana, East Little Havana, Allapattah, Hialeah, and Hialeah Gardens neighborhoods, are largely Hispanic, they are also characterized by below average per capita income and few rich residents, and high poverty rates to a lesser extent. They also have high percentages of renters and low median rent. Some of the neighborhoods are also partly characterized by large elderly populations²² and many single parent and female-headed households.

Vulnerability drivers in the Tamiami Trail cluster is much less unified, the only two variables present across the cluster are a largely Hispanic population and few rich residents. The rest of the vulnerability comes from a variety of variables only characterizing some of the CBGs in the cluster; these are educational attainment, a high percentage of renters, low median rent, a large elderly population, and many single parent and female headed households.

Heading south, the Goulds cluster has no variables exceeding threshold values across the entire cluster, all driving attributes are present in only some of the cluster's CBGs. These attributes are: high percentage Black residents, below average per capita income, few rich residents, low median rent, many single parent and female headed households, a high female population, and a large female labor force.

²¹ This variable will henceforth be referred to as "few rich residents".

²² There are two variables that can reflect this. One is 'population under 5 or over 65 years of age', the other is median age. When both variables are significantly present, it is assumed that this is due to a large elderly population, whereas a large 'population under 5 or over 65 years of age' combined with a low median age would be taken to mean a large infant/child population. If only one variable is present, it will be listed individually.

In the far south of the County, the Leisure City and Homestead clusters are defined by high poverty rates, low per-capita income, few rich people, low educational attainment, high percentages of renters and low median rent, and many single parent households. Some CBGs in the two clusters are also characterized by many female-headed households, high people-per-housing-unit ratios, and low vehicle access. Table 3 (right) summarizes the results for each high social vulnerability cluster discussed in this section.

Neighborhood	Attribute	High % Hispanic	High %	High Poverty Rate	Below-Average Per-Capita Income	Low Percent Earning Over 200K	Low Educational Attainment	Low Vehicle Access	High % Renters	Low Median Rent	High Median Age	Percent Young and Old	Low 2-Parent Households	Many Female-Headed Households	High Female Population	High Female Labor Force	High Vacancies	High People-per Housing Unit
Little Havana																		
East Little Havana																		
Allapattah																		
Hialeah																		
Hialeah Gardens																		
Barrier Islands																		
Tamiami Trail																		
Homestead																		
Leisure City																		
Goulds																		
Model City																		
Brownsville																		
Little Haiti																		
Opa-Locka																		
North Miami																		
Miami Gardens																		

Table 3: Table summarizing the driving factors for high-vulnerability clusters/neighborhoods in the SOVI. Green cells represent driving factors across an entire location, while orange cells denote driving factors in only some of the CBGs in a cluster. For details on the thresholds for driving factors, please see the Results Summary Tables section of the Methods chapter.

3.2 Hazards of Place Model

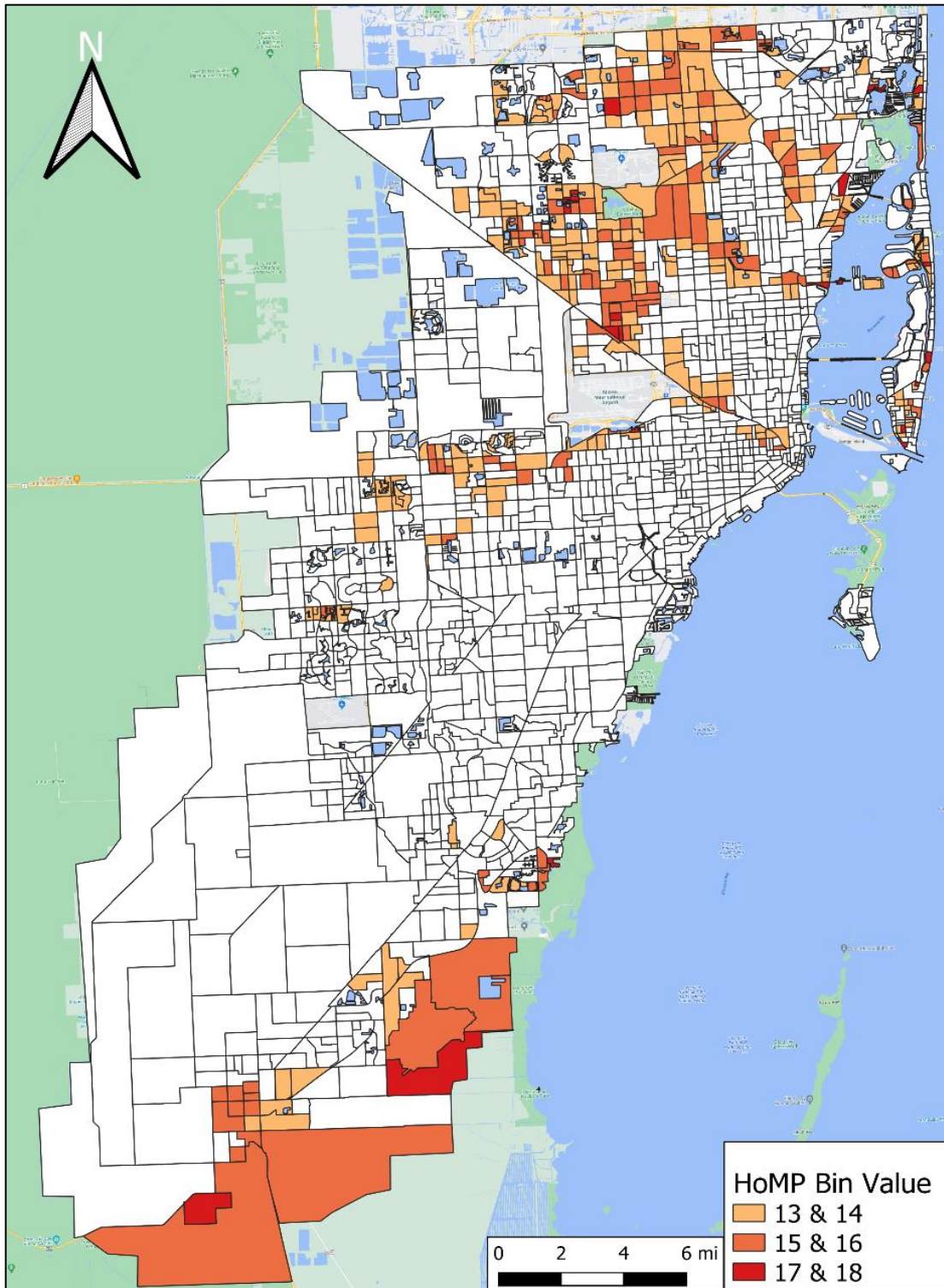


Figure 12: Distribution of high-vulnerability CBGs in the Hazards of Place Model. These 3 most vulnerable HoPM bins contain a total of 368 CBG's, with 21 in the most vulnerable bin, 117 in the second-most vulnerable bin, and 230 in the third-most

The HoPM, formed through the application of the biophysical vulnerability (elevation) data to the SOVI, causes a fairly significant shift in the distribution of high-vulnerability CBGs particularly in the regions north and northwest of Downtown (as shown in Figure 12, above) when compared to the distribution found in the SOVI (see Figure 11, above).

Many of the high-SOVI CBG's around and to the north of Downtown, such as Little Havana, Brownsville, Model City, and Little Haiti, are not classified as high vulnerability under the HoPM. This is because of their location on the high ground of the ACR, and the resulting low flood vulnerability. Some of the areas north of Downtown that remain classed as high vulnerability after the application of the biophysical vulnerability component, such as parts of Allapattah, Little River (previously included in the Little Haiti cluster), and North Miami, consist of CBGs that lie in the low areas where channels ran through the ACR when it was still a barrier bar and tidal channel system during the Pleistocene.

These decreases in high vulnerability CBGs north of Downtown are matched by a small increase in the areas to the northwest of Downtown. Clusters of high vulnerability in the SOVI index that were located to the west of the ACR, such as Opa-Locka, Miami Gardens, Hialeah, and Hialeah Gardens remain classed as high vulnerability under the HoPM, and have picked up some additional CBGs, particularly on their western edges.

These changes in area changed the vulnerability drivers of these cluster some. Opa-Locka saw a decrease in the predominance of Black ethnicity, an increase in below average per capita income, and saw a high population-per-housing-unit drop from being a driver in some parts of the cluster to not a driver. Miami Gardens saw poverty rate become a driver in some CBGs within the cluster, as did a high female population; meanwhile, the few rich residents variable decreased from being a driver across the cluster to only some CBGs within it, as did the female labor force variable. Hialeah saw below average per capita income drop from being a driver across the cluster to only some parts and a similar drop for the median rent variable. Finally, Hialeah Gardens saw a high poverty rate drop from being a driver in some of the cluster to not a driver, a drop in the low educational attainment variable from across the cluster to only some of it, the disappearance of the low vehicle access, low median rent, high median age, few 2-parent households, and high female population variables, from some of the cluster to none; it also gained the high people-per-housing-unit variable in some CBGs within the cluster.

The cluster along Tamiami Trail got larger and a more concentrated, increasing from 33 to 47 CBGs. It lost some of the outlying CBGs that were scattered to the south and east of the cluster, as well as some on the eastern edge of the cluster (which is the western edge of the ACR), in return picking up new CBGs closer to the core area of the cluster. It saw the few rich residents variable decrease from a driver across the cluster to only some CBGs within it, dropped the low median rent and few 2-parent households variables (from some CBGs to not a driver), and picked up a high female population as a driver in some of its CBGs.

The Goulds cluster shifted east, losing CBGs located on the ACR and adding some further to the east. The cluster saw a decrease in the presence of Black residents and low per capita income, and increases in the absence of rich residents (from some to most of the cluster), the addition of a high percentage of renters across the cluster, and the addition of a high percentage of residents under 5 or over 65 for some CBGs in the cluster.

The clusters in Homestead and Leisure city also both shifted off the ACR, dropping CBGs located on the Ridge and picking up new ones located in the low ground to the east of the Ridge. This shift changed the vulnerability drivers of the two clusters slightly, some CBGs in both clusters are now also characterized by high percentages of Black residents and a high female labor force, and there have been decreases in the presence of high percentages of renters and low median rent. The presence of single-parent households also decreased in Homestead from across the whole cluster to only some of it, and Leisure City saw added a high female population percentage as a driver to some of its CBGs.

The barrier islands smattering from the SOVI index has grown into 3 distinct clusters in the HoPM, which are (from south to north) South Beach, Normandy Isles, and Sunny Isles. The South Beach cluster is defined by low vehicle access and high vacancies across the cluster, and few rich residents and a high percentage of renters in some of the cluster’s CBGs. Normandy Isles is defined by a high percentage of renters across the cluster, and few rich residents, low vehicle access, and many single parent and female-headed households in some of the cluster’s CBGs. Sunny Isles is characterized by a large elderly population and high vacancies across the cluster, with some CBGs having few rich residents, a high female population, and large female labor force.

Table 4 (right) summarizes the driving factors for clusters with high flood vulnerability under the HoPM, as described in this section.

Attribute Neighborhood	High % Hispanic	High % Black	High Poverty Rate	Below-Average Per-Capita Income	Low Percent Earning Over 200K	Low Educational Attainment	Low Vehicle Access	High % Renters	Low Median Rent	High Median Age	Percent Young and Old	Low 2-Parent Households	Many Female-Headed Households	High Female Population	High Female Labor Force	High Vacancies	High People-per-Housing
Allapattah																	
East Little Havana																	
Goulds																	
Hialeah Gardens																	
Hialeah																	
Homestead																	
Leisure City																	
Miami Gardens																	
North Miami																	
Opa-Locka																	
Tamiami Trail																	
South Beach																	
Normandy Isles																	
Little River																	
Sunny Isles																	

Table 4: Table summarizing the driving factors for high-vulnerability clusters/neighborhoods in the SOVI. Green cells represent driving factors across an entire location, while orange cells denote driving factors in only some of the CBGs in a cluster. For details on the thresholds for driving factors, please see the Results Summary Tables section of the Methods chapter.

3.3 Municipal Priority Index

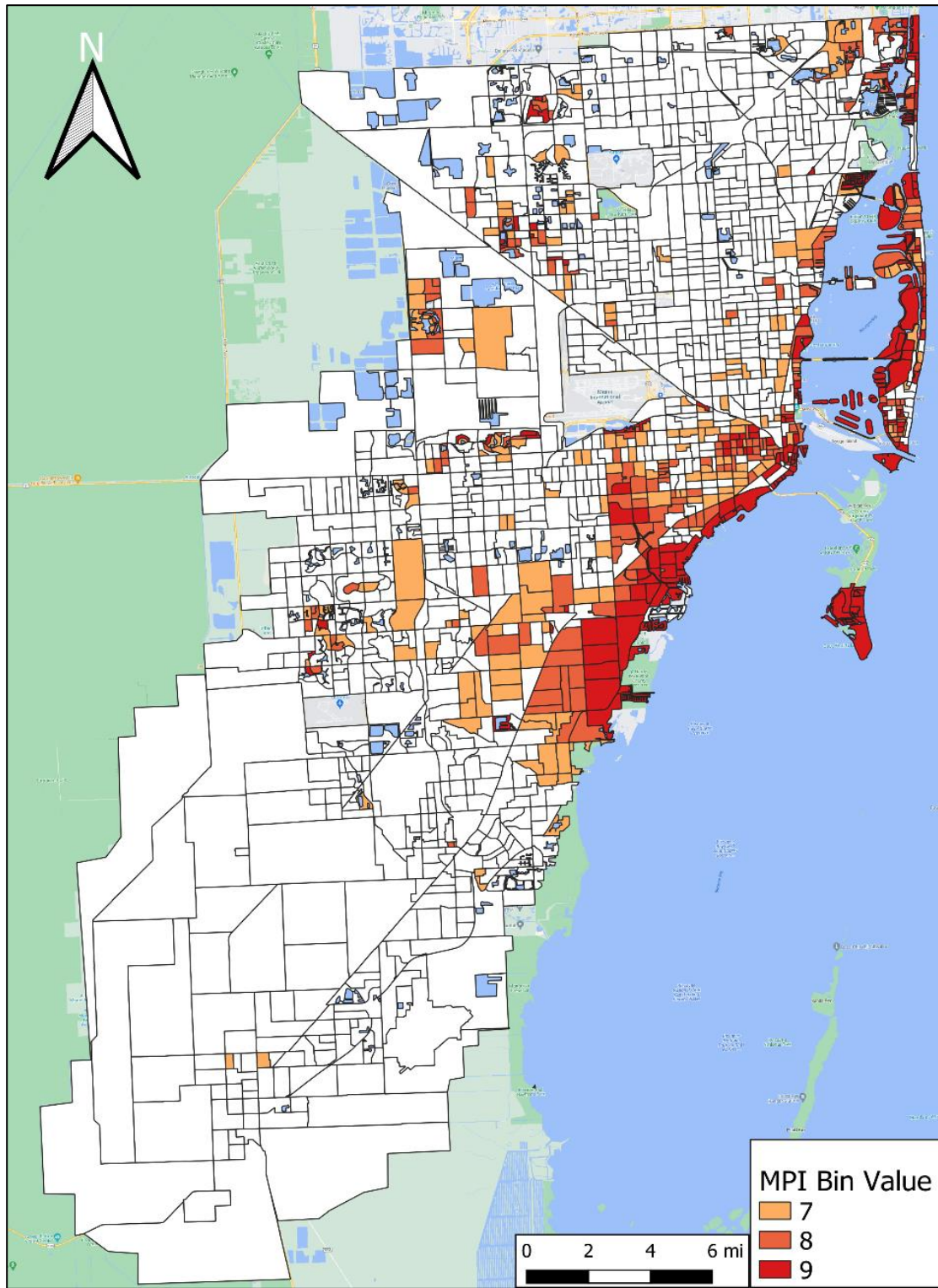


Figure 13: Distribution of the 3 most vulnerable bins in the Municipal Priority Index. The 3 most vulnerable MPI bins contain a total of 526 CBGs, with 176 in the most vulnerable bin, 175 in the second-most vulnerable bin, and a further 175 in the third-most vulnerable bin. These even divisions are a result of the equal-interval divisions of the data when binning the data, and the three bins/526 CBGs represent one-third of the data.

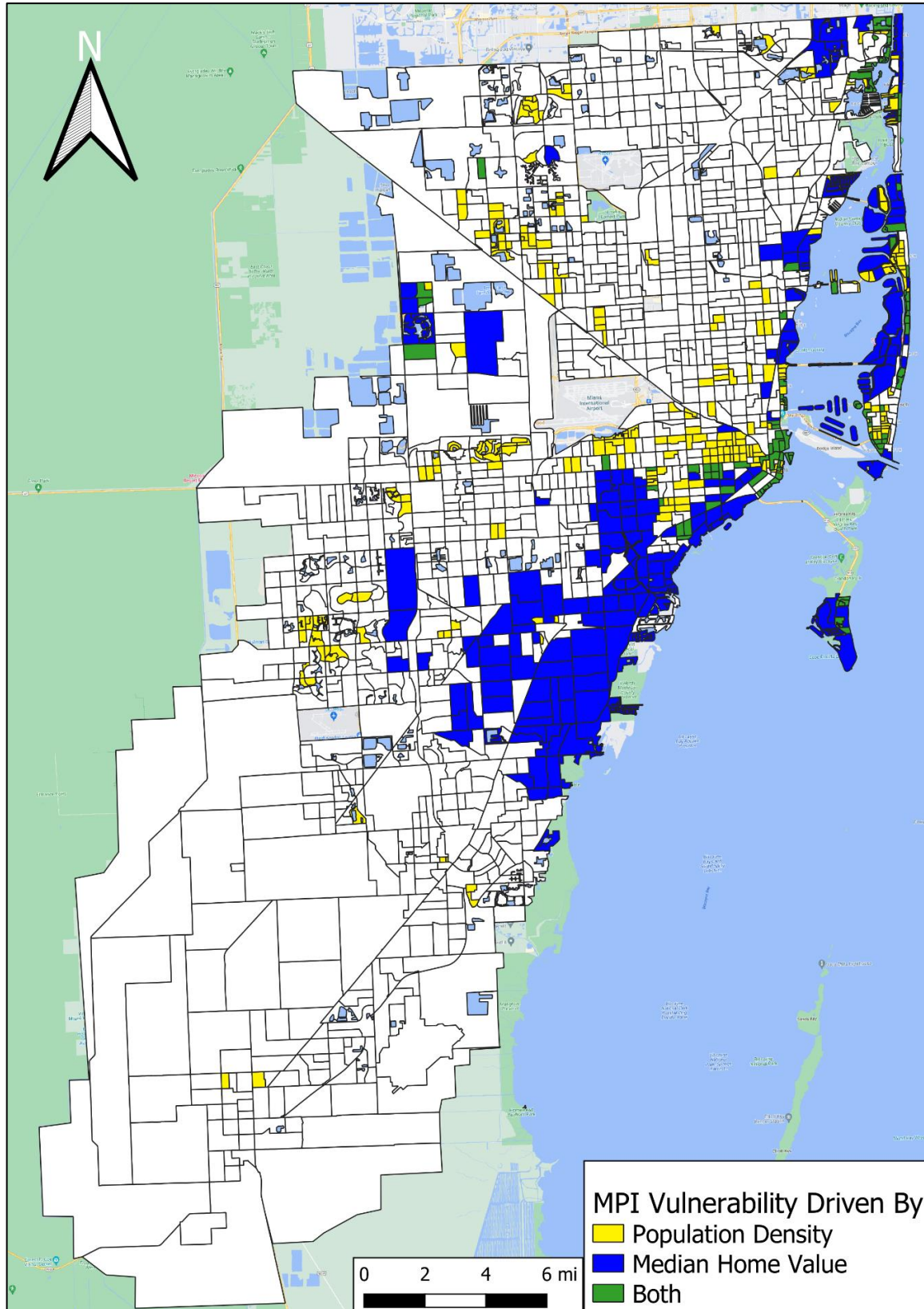


Figure 14: Map of MDC showing what variable drives vulnerability in the CBGs identified as high vulnerability under the MPI.

Figure 13 (above) shows the distribution of the 3 highest vulnerability bins in the MPI, which measures vulnerability based off population density and property value. Many of the vulnerable areas are concentrated along the coastal strip and barrier islands, although there are scattered vulnerable CBGs throughout the inland areas of the County. Particular concentrations of vulnerability are the barrier islands, around Downtown and East Little Havana, and then down the coast through Coral Gables, Pinecrest, and Kendall; vulnerability in these clusters (excluding the barrier islands ones) extend relatively far inland (~4 miles). Looking at Figure 14 (above), which shows the variables driving vulnerability across the CBGs, some of the clusters are relatively homogenous, while others are driven by both variables.

The barrier islands are quite mixed: South Beach and the easternmost strips of Miami Beach and Normandy Isles are driven by population density or both population density and home value, these areas are mostly condominiums. On the western side of these areas are detached-home residential neighborhoods, which are driven by just median home value, as is the majority of Surfside further north. At the very northern end of the barrier islands in the County, Sunny Isles has areas that are driven by either variable individually, but also areas driven by a mixture. Key Biscayne is less of a mixture; some parts (which are covered in condominiums) are driven by both variables, while the rest of the island is driven by just property value.

Moving to the mainland, there is a large cluster of median home value-driven vulnerability to the southwest of Downtown, this consists of mostly detached single-family homes in the municipalities/neighborhoods of Coral Gables, Pinecrest, and parts of Kendall, these are some of the more affluent suburban areas in the County and, as such, command high property values even in more inland areas away from ocean access.

To the north of this cluster is a spread of population density driven vulnerable CBGs, from east to west these are: East Little Havana, Little Havana, Flagami, and then the Tamiami Trail cluster. These are mostly areas of apartment buildings along a major transit corridor²³. Hialeah, Hialeah Gardens, and Palm Springs North also have small clusters driven by population density.

Doral is a mixed cluster, with some CBGs driven by each individual variable and some driven by both.

Downtown is a cluster of overlap, driven by both home value and population density. This is a result of the many condominiums/apartments in the area, and the high price they command due to their prime location. As a general trend, clusters of overlap seem to represent condominiums, since they present both a high population density and a high home value, this is reinforced by the fact that they are most frequently found in desirable coastal locations and/or urban cores. Clusters of high population density alone are more representative of apartments in working class areas, based off their locations along transit corridors and in neighborhoods identified as high vulnerability in the SOVI or HoPM analyses.

²³ Tamiami Trail runs from Downtown in the east all the way out of the study area to the west. When referring to it as a cluster, however, only the area labeled as such in Figure 10 is meant.

3.4 Tax Income Protection Index

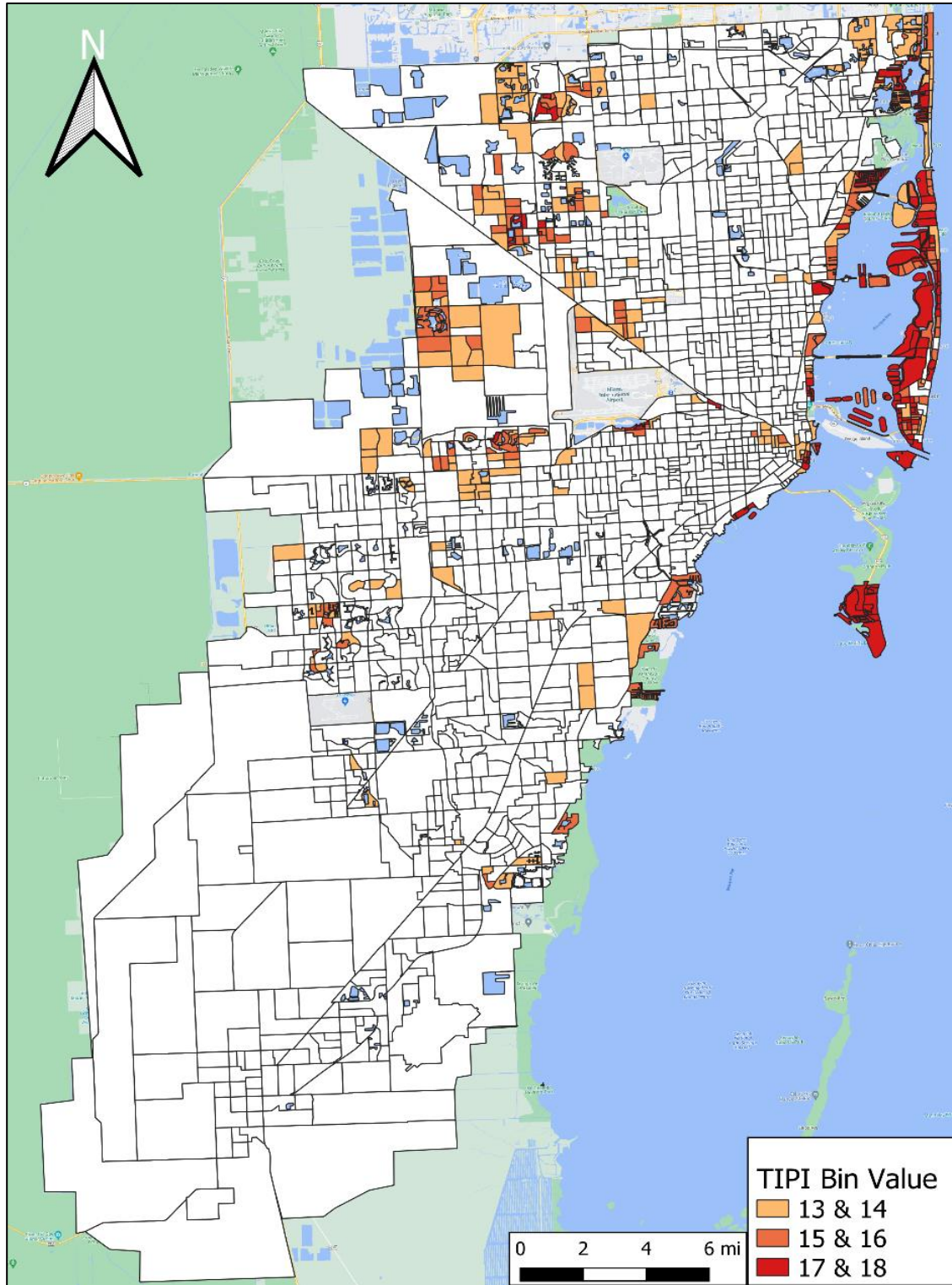


Figure 15: Distribution of high-vulnerability CBGs in the Tax Income Protection Index. There are 395 CBG's in these 3 most vulnerable bins, with 123 in the most vulnerable bin, 114 in the second-most vulnerable bin, and 158 in the third-most.

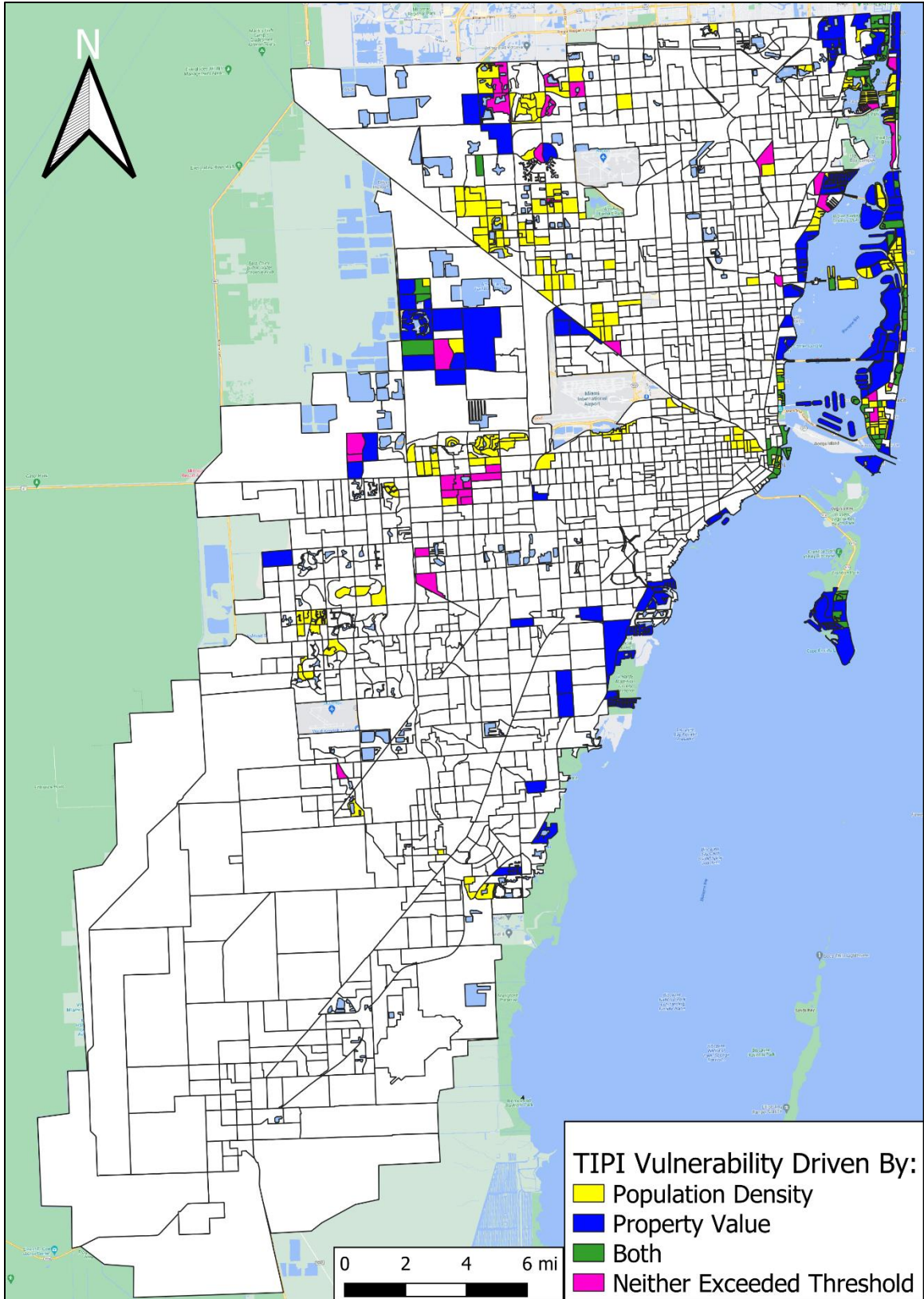


Figure 16: Map of MDC showing what variable drives vulnerability in CBGs identified as having high flood vulnerability under the TIPI.

The TIPI, formed by adding the biophysical vulnerability (elevation) component to the MPI, drastically changes the distribution of highly vulnerable CBG's across the county, as shown in Figure 15 (above). It almost entirely removes the Coral Gables – Pinecrest – Kendall cluster from the included bins, while the number of assorted high-vulnerability CBGs in the western part of the county has increased, principally in Doral, Hialeah Gardens, Palm Springs North, and the Tamiami Trail cluster. As with the HoPM, this shift is because of the ACR, upon which the Coral Gables – Pinecrest – Kendall cluster sat, aside from a few miscellaneous CBGs to the east of the ACR or in low points within it; these remained vulnerable after the addition of the biophysical vulnerability component. While Coral Gables, Pinecrest, and Kendall had high vulnerability scores in the MPI, they had low biophysical vulnerability scores, and were thus replaced by CBGs further west, which had lower MPI vulnerability scores but higher biophysical vulnerability scores.

The increases in highly vulnerable CBGs in these western areas came from both variables; a map showing the driving variables in CBGs in the TIPI index across the County is shown in Figure 16 (above). Hialeah Gardens added more CBGs with high population densities, while Doral added more driven by high home value. Palm Springs North also added some CBGs whose vulnerability is driven by home value, but it, along with the Tamiami Trail cluster, both added several CBGs which were classified as being driven by neither variable. These CBGs, of which there are 32 across the County, have below average population density and median home value, but their scores are still high enough that, when combined with a high biophysical vulnerability, they fall within the top third of vulnerability bins under the TIPI index. Thus, the 'neither' driver is simply a result of falling below the threshold value used rather than not actually being driven by any variable.

The barrier islands and coastal strip north of Downtown remains mostly unchanged between the MPI and TIPI, as the barrier islands and flat ground to the east of the ACR are extremely low-lying, and thus have high biophysical vulnerability scores as well as high MPI scores. The area has lost a few CBGs off its western edge which were located fully on the ACR, which were replaced by other CBGs on the barrier islands. Additionally, some CBGs in the coastal strip which extend far enough inland to include parts of the ACR were downshifted out of the high-vulnerability bins, as the high ground within the CBG boundary lowered their biophysical vulnerability scores enough to make a difference; this is one issue with the spatial resolution of the data the method of using average elevation across a cell, as variation in vulnerability within CBGs cannot be captured. This will be discussed in more detail in the Data Scale section of the Potential Issues with Methodological Choices section (Section 4.3.2).

3.5 Comparing the Distributions of High Vulnerability

Figure 17 (right) shows the distribution of CBGs that have high flood vulnerability in either or both the two final indices, the HoPM and TIPI.

These results show that regardless of which index or approach to vulnerability is being used, the elevation of the ACR is enough that there are no high-elevation CBGs whose other vulnerability characteristics (either social or economic) are significant enough to warrant prioritization for flood adaptation measures over less vulnerable areas on lower ground.

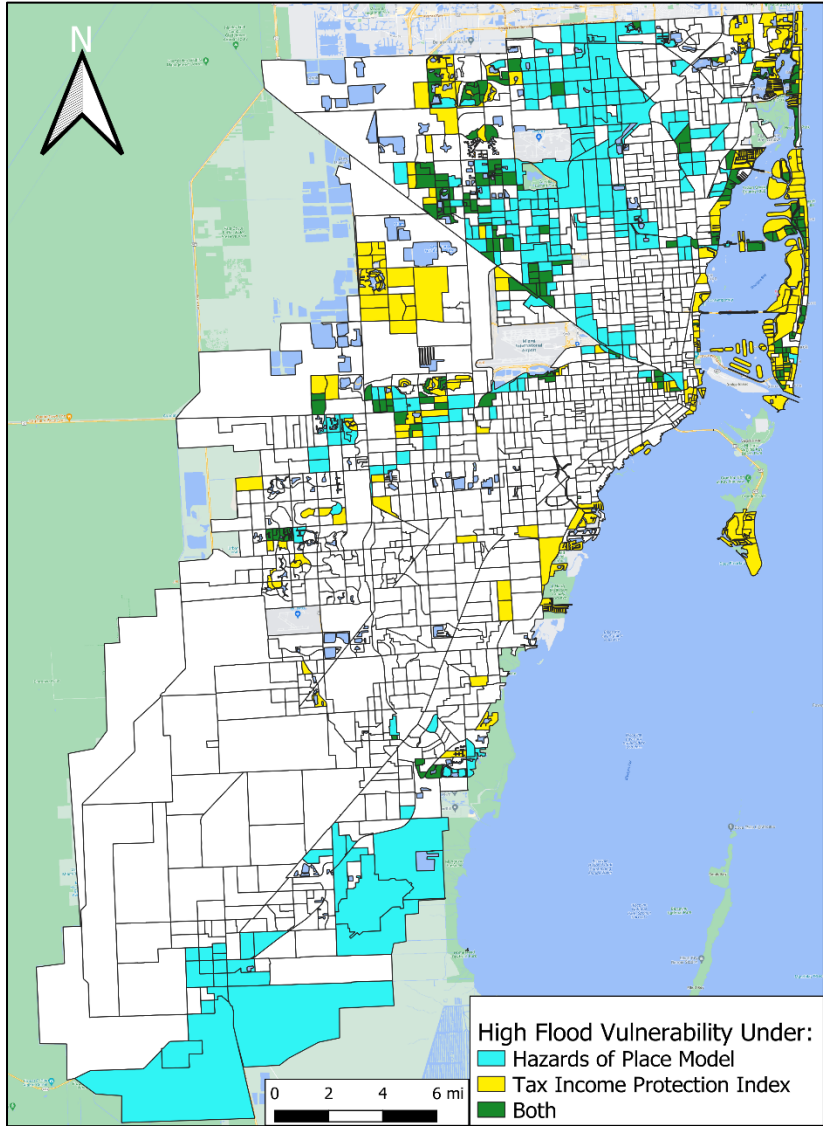


Figure 17: Distribution of CBGs that have high vulnerability under either the HoPM or the TIPI.

3.6 Overlap of Highly Vulnerable Areas

While the previous sections examined the distribution of CBGs with high vulnerability in *individual indices*, this section focuses on the distribution of CBGs with high vulnerability under *both* indices, these dually vulnerable CBGs are shown in Figure 18 (right). Finding overlap between the HoPM and TIPI is this study's first research objective, and is necessary to achieve the others.

Finding these areas of overlap is important for planning adaptation projects and reducing stakeholder conflict because the process of selecting the locations of adaptation projects determines where resources will be allocated, so it is a highly political process, with stakeholders pushing for different perspectives on vulnerability that benefit their interests. As such, it can be difficult to determine what areas should be prioritized for adaptation funding and projects.

Finding where multiple flood vulnerability indices with different perspectives on

vulnerability overlap can help select areas for projects and reach stakeholder consensus or compromise, since the selected areas will be vulnerable from multiple points of view. This analysis indicates that 157 CBGs fall into one of the top 3 vulnerability bins in both indices, this is about 10% of the County total of 1576 CBGs.

Concentrations of overlap include one running through Palm Springs North, Miami Lakes, and Hialeah-Miami Springs; a cluster along Tamiami Trail out in Fontainebleau, one in East Little Havana, three clusters along the barrier islands in Miami Beach, Normandy Isles, and Sunny Isles Beach, and numerous

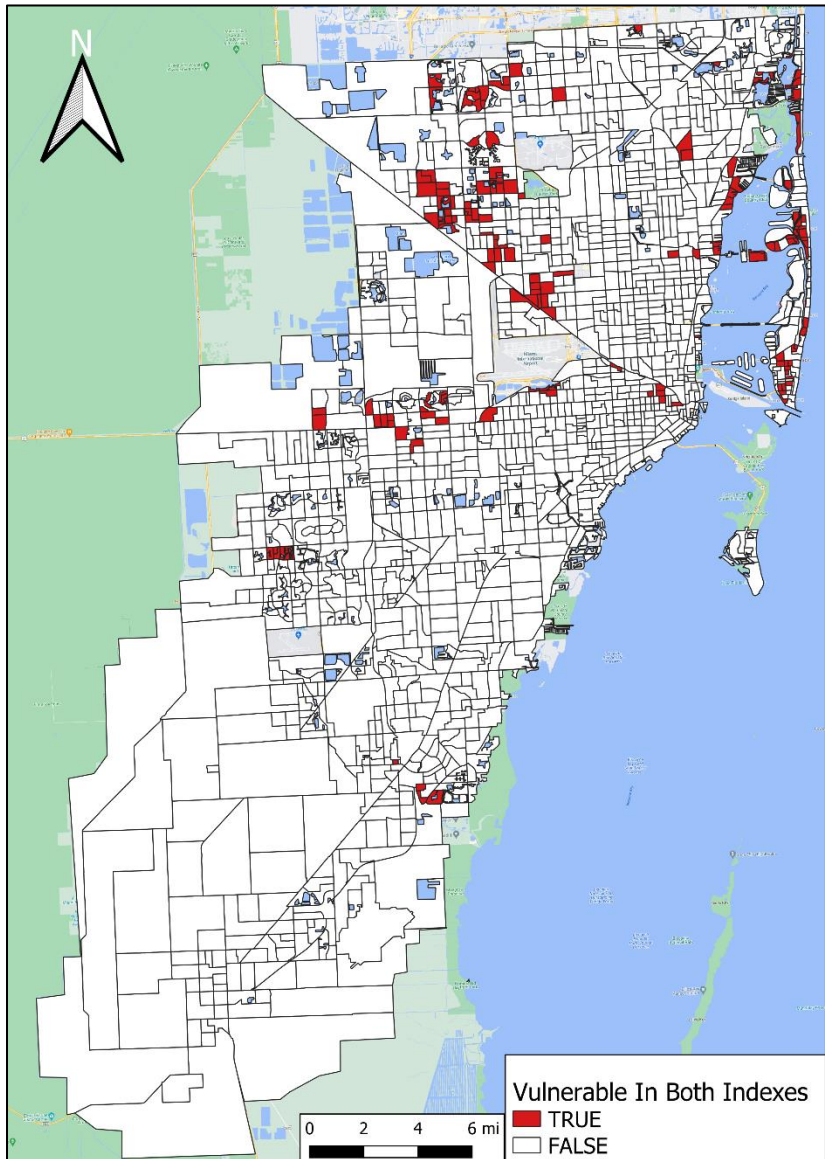


Figure 18: Map showing distribution of CBGs that are in one of the top 6 vulnerability bins in both the HoPM and TIPI.

other smaller clusters. The drivers behind the high vulnerability in each of these will be discussed below, and are summarized in Table 5 (right).

3.6.1 Barrier Islands Clusters

Looking at variables from the HoPM, the South Beach cluster is defined by low vehicle access and high vacancies, some CBGs in the cluster also have few rich residents, a high percentage of renters, low median rent, and many single parent and female-headed households. From the TIPI index, some CBGs in the cluster also have a high population density.

The Normandy Isles cluster is defined by a high percentage of renters, some CBGs in the cluster also have high vacancies, low vehicle access, few rich residents, and many single parent and female-headed households. From the TIPI index, the cluster also has high population density across the cluster.

Sunny Isles is defined by a large elderly population and high vacancies, some CBGs also have few rich residents, a large female population, and large female labor force. From the TIPI index, some CBGs in the cluster have high population densities.

3.6.2 Mainland Clusters

The Tamiami Trail cluster is characterized across the cluster only by a large Hispanic population, with the rest of the vulnerability being driven by few rich residents, low educational attainment, a high percentage of renters, many residents under 5 or over 65 years of age, or a large female population, these variables are present in some of the cluster's CBGs. From the TIPI index, some of the CBGs in the cluster were also defined by a high population density.

The small cluster in East Little Havana is characterized across the cluster by quite a few variables; these are: a largely Hispanic population, a high poverty rate, low per-capita income, few rich residents, low educational attainment, low vehicle access, a high percentage of renters, and low median rent; some CBGs in the cluster also have a high percentage of single parent and female-headed households. From the TIPI index, the cluster is also defined by high population density.

The Hialeah cluster is characterized by a large Hispanic population, below average per capita income, and low educational attainment, some CBGs in the cluster also have a high poverty rate, few rich residents, low vehicle access, high percentages of renters and low median rents, a large elderly population, and many single parents and female-headed households.

Hialeah Gardens differs somewhat; it is characterized across the cluster by a Hispanic population, below average per capita income, and few rich

Attribute Neighborhood	High % Hispanic	High % Black	High Poverty Rate	Below-Average Per-Capita Income	Low Percent Earning Over 20K	Low Educational Attainment	Low Vehicle Access	High % Renters	Low Median Rent	High Median Age	Percent Young and Old	Low 2-Parent Households	Many Female-Headed Households	High Female Population	High Female Labor Force	High Vacancies	High People-per-Housing
East Little Havana	Green		Green	Green	Green	Green	Green	Green	Green								
Hialeah Gardens	Green			Green													
Hialeah	Green			Green													
Palm Springs North	Green			Green													
Tamiami Trail North Miami	Green			Green													
South Beach							Green										
Normandy Isles								Green									
Sunny Isles										Green							

Table 5: Table summarizing the driving factors of vulnerability in clusters that are highly vulnerable under both the HoPM and the TIPI. Green cells represent driving factors across an entire location, while orange cells denote driving factors in only some of the CBGs in a cluster. For details on the thresholds for driving factors, please see the Results Summary Tables section of the Methods chapter.

residents. Variables driving vulnerability in some clusters consist of low educational attainment, a high percentage of renters, and a high people-per-housing-unit ratio. From the TIPI index, some CBGs in the cluster also have a high population density.

Palm Springs North has no defining variables present across the cluster, vulnerability is driven by a mixture of variables present in only some of the CBGs, these are: Hispanic population, below average per capita income, few rich residents, a high percentage of renters, low median rent, many female-headed households, and a large female population. From the TIPI index, Palm Springs North has a high population density in some CBG's.

North Miami also has no cluster-defining variables. Vulnerability in the cluster is driven by a mixture of a large Black population, a high poverty rate, few rich residents, a high percentage of renters, a large female population, and a large female labor force; these variables are present in some of the cluster's CBGs.

4. Discussion

The distribution of overlap between the HoPM and TIPI is significant because it shows that high flood vulnerability is not confined to immediately coastal areas, but also extends to substantial inland areas as well; 56% of the highly vulnerable CBGs (88/157) were located to the west of the ACR. This is important because the differences in the geographic and socioeconomic characteristics of highly vulnerable areas, particularly between clusters on the barrier islands or coastal side of the ACR and those on the inland side, mean that different solutions for reducing flood vulnerability will need to be found each area. Additionally, the tendency for vulnerability to cluster, on both sides of the ACR, also means that the burden of adaptation is not spread evenly across the County, but rather, falls heavily on certain municipalities. The differences in cluster characteristics and solutions and the concentrated burdens of adaptation will form the core of this discussion, followed by discussion about potential methodological issues and other points about the analysis and results.

4.1 Different Solutions

The differences in socioeconomic and geographic characteristics between different cluster of vulnerability, as well as characteristics such as the kinds of structures in a region, distance from the ocean, and neighboring adaptation measures, all make a difference when it comes to determining what kinds of adaptation measures are most appropriate for dealing with high flood vulnerability. Given that flood vulnerability in this study is the combination of both socioeconomic and biophysical factors, efforts to reduce vulnerability can approach the problem along either or both axes. This is important because depending on the area, reducing vulnerability via one axis may be far more difficult, costly, of time-consuming that tackling the problem via the other. To better show how the different neighborhood characteristics described in the previous paragraph and different axes approaches to addressing flood vulnerability interact to produce different solutions across MDC, two clusters of overlapping vulnerability will be examined below.

The first example is the South Beach cluster, located on the barrier islands. The cluster consists mostly of a mixture of high-rise apartments/condominiums and lower apartments, covering well under 1 square mile in several small sub-clusters. Its geographic characteristics make cluster is a good candidate for physical adaptation projects designed to reduce the biophysical component of flood vulnerability: it is small in area and close to the ocean. This makes physical interventions such as elevating roads, increasing stormwater drainage capacity, and installing pumps to drain stormwater faster and deal with tidal flooding feasible solutions for this cluster. The small size of the cluster would help keep costs down, and the coastal location means water can be directly returned to the ocean without the need for lengthy down-stream improvements in storm drainpipes. Indeed, this is what the City of Miami Beach has done, spending \$500 million on re-designing its stormwater system, installing pumps, and elevating certain roads (City of Miami Beach, 2020a, 2020b).

An example in the opposite direction would be the Hialeah Gardens cluster, located in an inland part of the County west of the ACR. The cluster consists of mostly detached homes in 3 sub-clusters, spread out over roughly 3.5 square miles, with other neighborhoods surrounding it. These attributes make physical interventions to reduce biophysical vulnerability in this area difficult: the western location makes improving the ability and capacity of storm drains in the area difficult and time-consuming due to the

need for downstream improvements first to handle the increased discharge²⁴, and elevating roadways without storm-drain capacity would just cause water to pond on peoples' properties. The large number of structures in the cluster would make elevating them all more difficult, and this might also just displace stormwater into surrounding neighborhoods, causing flooding there instead. Bioswales could be a viable solution, but with the water table so close to the surface and the frequent rains of the summer months, they could potentially hold standing water which would be a breeding ground for mosquitoes, which poses another issue²⁵. As such, it might be desirable to focus on reducing the social vulnerability of the area instead (or as a first step), targeting factors such as below average per capita income, low educational attainment, and the large presence of renters through economic incentives to create better jobs in the region, vocational training in in-demand technical skills, or increased funding to the area's public schools.

In this manner, vulnerability might be reduced by increasing the resilience of the local population to flooding, rather than reducing the flooding itself. While such measures might not work in the long run as flooding continues to worsen with climate change, they could at least act as a stopgap, providing time for more permanent flood-reducing interventions to be introduced. Focusing on decreasing social vulnerability by improving access to resources and income would have other benefits as well, such as decreasing vulnerability to hazards other than flooding, such as high winds from hurricanes. Other methods of reducing social vulnerability, such as improving educational attainment, provide transferable skills that would help residents if migration out of the area became required, and could also simultaneously help the neighborhoods around the cluster of high flood vulnerability overlap, which could still be highly vulnerable under just one of the two indices used in this study. For example, increasing funding and improving the quality of education at a local high school would help all the neighborhoods in its catchment, while increasing the capacity of storm drains in a neighborhood would only help the targeted neighborhood.

While this case study only examines 2 clusters of high flood vulnerability in the County, it illustrates how adaptation measures will need to focus on the different characteristics of individual high flood vulnerability neighborhoods, rather than trying to apply a broad solution across the County as a whole. Additionally, many of the characteristics that determine whether an area is better suited to physical or non-physical adaptation project are somewhat separate from the variables that drive vulnerability in the cluster; the geographic context of an area with regards to its location and neighboring areas, larger-scale adaptation projects, and the kinds and quantity of structures in the neighborhood are all factors that must be determined independently of the data used in the indices found in this study. Due to the vast population, socioeconomic, geographic, and contextual differences between locations, identifying suitable adaptation measures for areas is fairly case-by-case process, as the complexity does not readily permit a standardized process.

²⁴ Discussed further in the Relevance of Vulnerability section of the Potential Issues with Methodological Choices section (section 4.3.3).

²⁵ In addition to the nuisance cause by mosquitoes, the ones in South Florida are also a vector for diseases, most recently Zika in 2016.

4.2 Concentrated Burdens

The distribution of vulnerability clusters across MDC means that certain municipalities will have much larger adaptation burdens than others. This could be especially problematic due to the link between low income, social vulnerability, and flood vulnerability, municipalities with socially vulnerable populations where low income is a driving factor would have a more difficult time funding paying for adaptation projects, due to more limited funding options. A municipality with a low-income population could have a harder time increasing taxes or utility fees due to the impact it would have on their residents, although a study by Merrill *et al.* (2018) indicated that financing projects via funding mechanisms that directly impose on those who benefit from the project was more acceptable than methods applied to a wider population base²⁶. Bonds or loans are a common way of paying, but would require some form of additional funding for repayment over time with interest, so the municipality would still need extra income (LaDuca and Kosco, 2014). State or federal grants do exist but are fairly competitive to get, especially as the impacts of climate change increase across the country as a whole (LaDuca and Kosco, 2014). Funding for such grants also may depend somewhat on politics, as certain administrations may be less likely to fund programs related to climate change than others. Large concentrations of flood vulnerability within a municipality compound this issue, as more areas needing protection will only increase the size, complexity, and cost of projects. In MDC, two municipalities particularly stand out in their concentrations of vulnerability, these are the City of Hialeah and the City of Miami Beach.

The City of Hialeah covers some 23 miles of western MDC, and is comprised of the Hialeah and Hialeah Gardens clusters of vulnerability²⁷, as described throughout the results sections. Out of the 157 CBGs with high flood vulnerability under both the HoPM and TIPI, Hialeah contains 43, 27% of the total. Hialeah contains 121 CBGs, so these high flood vulnerability ones make up 36% of CBGs within the city.

The City of Miami Beach covers 7.7 square miles of barrier islands on the eastern side of the County, and is comprised of the South Beach and Normandy Isles clusters of vulnerability (as well as the Miami Beach label on the reference map (Figure 10)), it is made up of 88 CBGs. The City of Miami Beach contains 32 CBGs that are highly vulnerable under both the HoPM and TIPI, this is 20% of the County total; these 32 comprise 36% of CBGs within the City.

For adaptation planning at the County or greater levels of government, it is important to know not just where clusters of high flood vulnerability are, but also who is responsible for addressing them, and how the size or driving variables of these clusters impact the ability of the responsible government to tackle them, as in many cases, regional adaptation is only as strong as its weakest link.

In MDC, the Cities of Hialeah and Miami Beach alone contain nearly half of the total CBGs with high flood vulnerability under both indices, and as such are likely to be more burdened than other municipalities; this means they could have a harder time dealing with adaptation projects on their own. As such, if higher levels of government such as the County, State, or Federal governments were looking

²⁶ However, it is important to note that 90% of households in this study has income above the national median, it is possible that lower-income households may favor funding via a wider population base as it would not directly impact them as much.

²⁷ Hialeah Gardens is technically a separate municipality from Hialeah, but due to what the actual municipal boundaries are like, the Hialeah Gardens cluster is actually mostly the western and northwestern parts of the municipality of Hialeah, rather than lying within Hialeah Gardens itself.

to provide aid to municipalities in the region to assist in funding adaptation projects, these municipalities would be ideal recipients, since they represent the 'weak link' in the area.

4.3 Potential Issues with Methodological Choices

4.3.1 Hispanic Population

One potential question of the methods used in this analysis, raised by the local racial/ethnic composition of Miami, is whether or not Hispanic ethnicity would constitute a driving factor for social vulnerability. The inclusion of race in social vulnerability analysis revolves around the societal barriers faced by minorities, such as language and government representation. It is arguable, however, that these barriers have been eliminated in MDC, and that Hispanic ethnicity would therefore not contribute to social vulnerability at the present day. As discussed in the 'Miami's Socioeconomic Setting' (section 1.4), MDC's population is 43% non-white Hispanic (Collins, Grineski and Chakraborty, 2018) and 70% total Hispanic (U.S. Census Bureau, no date), and, as such, hardly constitutes a minority population. An ordinance declaring English the sole/official language of local government was struck down in 1993 (Booth, 1993), and virtually all functions of daily life can be conducted entirely in Spanish. Hispanics are widely represented in local government, and all government websites and information are available in Spanish. While it would take a more thorough analysis and statistical work to determine whether or not Hispanic ethnicity²⁸ is a contributing factor to social vulnerability in MDC, the possibility that it does not in this locality is certainly worth bearing in mind.

4.3.2 Data Scale

While the census block group is the smallest scale at which data could be readily found, it is still large enough to raise some issues in the analysis, namely with the average elevation calculations used to calculate biophysical (flood) vulnerability. This is particularly true right along the coast of the mainland, where there is a narrow strip of low-lying ground followed by a sharp and substantial increase in elevation onto the ACR, but also in inland areas where there is an appreciable difference in elevation across a CBG. The result of this is that while the average elevation (and thus biophysical vulnerability bin value) of a CBG may not be particularly low, certain parts of that CBG may be, and this would not be reflected in the analysis. As such, certain vulnerable pockets of population could be missed out when planning adaptation projects. This issue could potentially be addressed to some extent by using the lowest elevation in a CBG instead of the mean, or perhaps by calculating the SOVI or MPI values/bins for each CBG and then applying them to the biophysical vulnerability component on a pixel-by-pixel basis, which would allow for flood vulnerability to be mapped on a finer resolution. However, using minimum elevation within a CBG would require very detailed trimming of data to remove uninhabited areas with low locations to avoid overestimating vulnerability in certain areas, while mapping vulnerability at the resolution of an elevation DEM would account for variations in elevation within a CBG, but not for variations in population characteristics such as population density or property value.

If, for example, the low ground in a CBG has a higher population density than the higher ground (due to apartment buildings on the low ground but houses on the high ground), the vulnerability of that CBG should be higher than stated, since the population is more focused in the more biophysically vulnerable

²⁸ Or non-white Hispanic rather than total Hispanic.

part of that CBG. However, unless using extraordinarily detailed data for a very small area, it is unlikely that population characteristic variations within individual CBGs are possible or practical to capture, especially when using large study areas such as an entire county.

4.3.3 Biophysical Vulnerability Component

The use of average CBG elevation as a biophysical vulnerability component works well with the data scale used in this study and does an adequate job at giving a relative indication of flood vulnerability, given the kinds of flooding that Miami experiences and the large amount of the County that falls within the 100-year flood plain. However, it does not take into account existing infrastructure designed to reduce flooding, most notably stormwater drainage via canals and the County's storm drain and sewer system. A flood model for the county incorporating such details and using a number of different return-period design storms and floods, particularly under the 100-year mark, would provide a more accurate depiction of flood vulnerability across the County and increase the accuracy of the results.

4.3.4 Relevance of Vulnerability

While this analysis seeks to identify the CBGs most vulnerable to climate change flood impacts under two different approaches to vulnerability that local governments might employ, it is necessary to note that there are other ways governments might choose to define vulnerability. For example protecting major infrastructure investments, such as the Port of Miami, power plants, airports, or highways, might take funding priority over residential areas, due to their economic importance to the region.

Additionally, just because a CBG has been identified as highly vulnerable from multiple viewpoints does not mean it is high priority for adaptation efforts; adaptation planning and prioritization would also include factors such as feasibility, cost, the vulnerability of neighboring areas, technical concerns, and the source of flooding, none of which are included in this analysis.

One example of this is the Flagami neighborhood, which has several high-vulnerability CBGs in both indices; it is located to the south of Miami International Airport and falls within the 'Tamiami Cluster' of vulnerability identified in this study.

Parts of the neighborhood lie in a depression which presently experience severe flooding from heavy rainstorms, which damage cars, homes, and their contents; it took a week to pump out the neighborhood after a major storm in May of 2020 (Harris, 2021). Despite these current issues and the high vulnerability of the area, in the City of Miami's stormwater master plan, this neighborhood is in the fourth group of neighborhoods awaiting projects, and it could take 5-10 years to get through just the first group. The delay is driven by technical issues: in order to use the stormwater pumps needed to move water out of the basin, the whole drainage network downstream would need improvement to increase drainage capacity (Harris, 2021). This emphasizes the point that vulnerability may be used to identify areas in need of adaptation projects, but that it is not all-deciding when it comes to prioritizing projects, particularly infrastructure-based ones.

Additionally, as mentioned in Comparing the Distributions of High Vulnerability section (Section 3.5), no area fully located on the ACR makes it into the top vulnerability bins. This is important because even though these areas, particularly the socially vulnerable ones north of Downtown, are not vulnerable to flooding, they can still be very vulnerable to secondary or tertiary impacts of climate change-driven

flooding. For example, while these neighborhoods might not themselves be vulnerable to flooding, flooding in other neighborhoods is currently/could potentially exacerbate or trigger climate gentrification in these not-flood-vulnerable neighborhoods (Keenan, Hill and Gumber, 2018; Ariza, 2020; Sisson, 2020); therefore the residents of these areas are vulnerable to the detrimental knock-on effects of flooding, even if they are not vulnerable on a primary level. Thus, it must be kept in mind that this study is only examining direct flood vulnerability, and that there are many other aspects to even just vulnerability to climate change-driven flooding that are not accounted for in this analysis.

4.3.5 Apartment Buildings

One other issue of note is the impact of apartment buildings on the results of this analysis. Since apartment buildings or condominiums have high population densities, they increase the scores of their CBGs in the TIPI. However, given their multi-story nature, their residents are not as biophysically vulnerable to flooding as residents of detached homes would be, due to their elevation within a structure, so their presence may lead to an over-estimation of flood vulnerability in the TIPI, since they do not actually represent a high density of people vulnerable to flooding.

However, the need to repair damage to the ground floor of apartment/condominium buildings and the increasing cost of insurance will still impact tenants via higher rents. Additionally, property taxes are still paid on the value of apartments and condominiums by their owners, so flooding that impacts building value will also impact municipal revenue through the processes described in Section 1.6. Depending on how flooding impacts the value of multi-story buildings, this may or may not help compensate for the over-estimation of vulnerability due to population density, as described in the previous paragraph.

Additionally, there is still impacts to tenant income via roads blocked by floodwaters, and the economic loss from one apartment building blocked by flood water is greater than the impacts from a single or even many homes. Furthermore, permanent loss of access to apartment buildings over a longer time-horizon via inundation has a more significant impact on the availability of housing, since the loss of one building/area necessitates the rehousing of a larger number of people than the loss of a single house. Thus, while apartments buildings or condominiums and their residents may be less vulnerable to direct losses and costs from flooding, they still contribute to the vulnerability of an area as a result of their population densities.

5. Conclusion and Recommendations for Future Research

This study examined flood vulnerability across Miami-Dade County (MDC) on a census block group (CBG) level using two different indices, the Hazards of Place Model (HoPM) and the Tax Income Protection Index (TIPI). These indices approached vulnerability from a social justice perspective and an economic/cost-benefit perspective, respectively, to examine how different governmental priorities might impact what areas are seen as vulnerable and where adaptation projects are placed. In order to assist in the process of choosing locations for adaptation projects and reduce stakeholder conflict, the distribution of high flood vulnerability in the two indices was then compared to identify areas of overlap between the two, as these represent areas where multiple stakeholders from different theoretical approaches to vulnerability would be more likely to agree upon as vulnerable.

This study identified 157 census block groups (CBGs) of overlap between the two indices, located in 9 principal clusters as well as numerous isolated CBGs. Of these, 88 (56%) were located in inland areas of the County west of the Atlantic Coastal Ridge (ACR). This distribution is important because the socioeconomic, geographic, and physical characteristics of these inland vulnerable areas means that adaptation projects will likely need to take different forms than projects located in coastal parts of the County. These differences were illustrated using a case study comparison between the South Beach and Hialeah Gardens clusters, which represented a coastal and an inland cluster of high flood vulnerability, respectively. Examining the characteristics of each cluster indicated that the Miami Beach cluster was well suited toward a physical intervention designed address flood vulnerability by reducing the biophysical component of vulnerability, while Hialeah might be better served by projects aiming to reduce the social vulnerability component of flood vulnerability. This was due to the South Beach cluster's small spatial extent and close proximity to the ocean, which meant that interventions such as raising roads and increasing stormwater draining capacity were relatively straightforward, while the Hialeah Gardens cluster's large spatial extent and inland location made similar physical interventions much more difficult. Instead, projects aimed at mitigating some of the drivers of social vulnerability in the cluster, such as below-average per capita income, low educational attainment, or a high percentage of renters, would help reduce flood vulnerability in the cluster by increasing the resilience of the population to flooding they experience, at least until physical interventions could be implemented.

Additionally, this study examined the distribution of high flood vulnerability CBGs in the overlap between the HoPM and TIPI with regards to municipal boundaries in the County, to identify cities which might have high adaption burdens due to concentrations of flood vulnerability within their jurisdiction. The Cities of Hialeah and Miami Beach both had large concentrations of highly vulnerable CBGs within their borders, together containing 47% of all CBGs identified as highly vulnerable under both indices; additionally, these highly vulnerable CBGs comprised 36% of the total CBGs in each of the municipalities. The high portion of these municipalities that is classed as vulnerable, and their large share of the County total, indicates that they would make good candidates for external aid for funding adaptation projects, as they arguably face more of a problem than other cities within the County.

5.1 Recommendations for Future Research

Recommendations for future research on this topic fall into two categories: methodological improvements on the present study, and the broader application of this study's methods to vulnerability research and adaptation planning.

As discussed in the Results chapter's Section 4.3, there are several methodological improvements that could be made that would improve the results of this study. Of these, the one which would most require further research would be whether or not Hispanic ethnicity constitutes a driver of social vulnerability in MDC, or in areas where Hispanics constitute a minority-majority in general. Given the widespread use of SOVI-based analyses, the ability to tune particular variables based on the specific characteristics of locations would prove useful.

The Tax Income Protection Index and its component Municipal Priority Index in this study exist in only a basic form, and would undoubtedly benefit from further development. While the simple 2-variable approach used here gets the point across, further research into what factors governments would consider drivers of vulnerability under an economic or cost-benefit framework would allow for factors other than the existing ones (population density and property value) to be incorporated into the two indices. Identifying additional variables for the existing factors would also improve the robustness of the indices.

While the specific methodology used in this study, particularly the biophysical vulnerability component, was designed with the geographic and socioeconomic context of Miami in mind, the general methodology and principles used in this study can be used elsewhere. With so many coastal urban areas threatened by climate change, it is probable that MDC is not the only one that is unlikely to be able to fund enough adaptation projects to protect the entirety of its population or area. This will raise the fundamental question of 'who or what do we protect and why?', a question this study aims to help answer.

While the specific indices used may change, the basic principle of comparing between multiple indices based on different theoretical approaches to vulnerability in order to reach common ground is one that can be readily applied to aid in planning adaptation measures and reducing stakeholder conflict.

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7. Appendices

7.1 Appendix 1: Ethical Considerations, Risks, and Contingencies

Ethical Considerations

The data sets used in this project are government-collected and publicly available, so no ethical issues concerning their use are anticipated. There is the potential for ethical concerns regarding the formative discussions with County adaptation team members or other academics, however. The discussions are meant to help get expert advice on the topic, and no personal data about any of the interviewees will be collected. Written consent to participate will be obtained prior to any discussions, and should it be desired by the ITC Ethics Committee, these discussions can be recorded and transcribed in order to comply with data transparency/storage regulations.

Risks and contingencies

Due to the Covid-19 pandemic, the methodology is designed to be low-risk, hence the use of preexisting publicly available data sets and digitally conducted discussion. One possible risk is that the most recent survey data may be from 2008-2012, and thus may not reflect the current state of affairs. Unfortunately, information from the 2020 census is not anticipated to be released until March 2021, and thus is not likely to be used in this study.

Impact on Property Values

With any study of flood vulnerability, there is the possibility that the results could impact property values. In this instance, however, the probability is minimal, for several reasons. Firstly, flood vulnerability in this analysis is not just based off of flood risk but also the characteristics of the area's population, which should be less relevant to property values than purely a flood risk assessment. Secondly, flood insurance risk is determined by FEMA's DFIRMS, which are the official determinants of flood risk, so this analysis should have no bearing on insurance rates. Finally, all data used here is publicly available, and there are also public flood risk finders present online, so it is not like the use of flood risk in this study is particularly novel.

7.2 Appendix 2: Variables Present in the Indices Used in this Study

	Social Vulnerability Index / Hazards of Place Model:	Municipal Priority Index / Tax Income Protection Index:
Variables:	<ol style="list-style-type: none"> 1. Percent of population below poverty line. 2. Percent households earning over \$200,000 annually. 3. Per Capita Income 4. Percent of population with less than a 12th grade education. 5. Percent of population renting. 6. Median Gross Rent 7. Percent housing units with no car. 8. Percent of population that is Black. 9. Percent of population that is Hispanic. 10. Population per housing unit. 11. Percent of housing units that are vacant. 12. Percent of population under 5 or over 65 years of age. 13. Median age. 14. Percent of children in a 2-parent family. 15. Percent female headed households. 16. Percent of population that is female. 17. Percent female participation in the labor force. 	<ol style="list-style-type: none"> 1. Median Home Value 2. Population Density (calculated from CBG population and land area).
Biophysical Vulnerability Component	Average Elevation of each Census Block Group.	Average Elevation of each Census Block Group.

7.3 Appendix 3: Table of Variables Collected for Varimax Rotation Step of Social Vulnerability Index Construction

Variable	Description
PCT_ASIAN	Percent Asian
PCT_BLACK	Percent Black
PCT_HISPANIC	Percent Hispanic
PCT_Native	Percent Native American
PCT_Young_And_Old	Percent Population Under 5 or Over 65 Years of Age
PCT_2_Par	Percent Children Livign in 2-Parent Families
Med_AGE	Median Age
PCT_Poverty	Percent Poverty
PCT_200k	Percent Households Earning Over \$200,000 Annually
Per_Capita_Income	Per Capita Income
PCT_Poor_English	Percent Speaking English as a Second Language with Limited English Proficiency
PCT_Fem	Percent Female
PCT_Fem_Head	Percent Female Headed Households
PCT_Low_Edu	Percent with Less than 12th Grade Education
PCT_Unemp	Percent Civilian Unemployment
Pop_Per_Hse_Unit	People Per Housing Unit
PCT_Renter	Percent Renters
MEDOOHVAL	Median Housing Value
Med_Rent	Median Gross Rent
PCT_Mobile	Percent Mobile Homes
PCT_Serv	Percent Employment in Service Industries
PCT_Fem_Lab	Percent Female Participation in Labor Force
PCT_No_Vehic	Percent of Housing Units with No Car
PCT_Vacant	Percent Unoccupied Housing Units

This list of variables input to the varimax rotation came from the Hazards & Vulnerability Research Institute (2016). There were 3 additional variables that were supposed to be included but could not be found, these are: Precent Households Receiving Social Security Benefits, Nursing Home Residents per Capita, and Percent Employment in Extractive Industries.

7.4 Appendix 4: Results of Varimax Rotation Performed During Social Vulnerability Index Construction.

	Component						
	1	2	3	4	5	6	7
PCT_BLACK	.331	.809	-.130	-.176	.147	.130	-.077
PCT_Native	-.028	.064	.123	.013	-.052	-.031	-.631
PCT_ASIAN	-.110	.023	.220	-.241	-.343	.055	.045
PCT_HISP	.107	-.902	-.245	.051	.005	.007	.017
PCT_Young_And_Old	.079	-.061	.136	.823	-.065	.139	-.024
PCT_2_Par	-.351	-.099	-.041	.163	-.833	-.141	.040
MED_AGE	-.116	-.219	.166	.795	-.079	.039	-.064
PCT_Poverty	.737	.151	.003	.015	.286	-.026	.078
Pct_200k	-.643	.160	.161	.247	-.069	-.367	.388
Per_Capita_Income	-.628	.104	.407	.279	-.061	-.322	.300
PCT_Poor_English	.597	-.604	-.233	.211	.067	-.019	-.031
PCT_Fem	-.016	.007	-.034	.229	.037	.748	.200
Pct_Fem_Head	.311	.114	.068	-.149	.848	.162	-.014
PCT_Low_Edu	.711	-.039	-.373	.166	.185	-.062	-.081
PCT_Unemp	.391	.524	-.122	-.034	.133	.054	.010
Pop_Per_Hse_Unit	-.009	.061	-.910	-.191	-.027	.032	-.023
PCT_Renter	.744	-.153	.203	-.243	.209	-.020	.086
MEDOOHVAL	-.510	.121	.201	.300	-.041	-.388	.442
Med_Rent	-.659	-.130	.244	-.171	-.179	.022	-.052
PCT_Mobile	-.008	.001	-.210	.193	.199	-.240	-.532
PCT_Serv	.606	.234	-.089	-.074	.052	.045	-.059
PCT_Fem_Lab	-.018	.132	-.082	-.005	.131	.797	-.016
PCT_No_Vehic	.724	.130	.344	.106	.170	-.106	.083
PCT_Vacant	-.172	.145	.789	.108	-.029	-.127	-.042