How Resilience Changes with Spatial Extent and Scale: A Case Study of Sea Level Rise in Coastal Mississippi, Alabama, and Florida

by

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Abstract

Resilience is a term used in natural hazards and disasters research to describe a community's ability to recover after a damaging hazard event occurs. It is within this context that resilience is often measured using composite indicators (or indices), and perhaps the composite index most commonly applied for measuring resilience is the Baseline Resilience Index for Communities (or BRIC). Although applied to compare the relative resilience of one place to another, few studies have utilized resilience indicators to understand how changes in the spatial extent of a hazard and the scale at which resilience is measured affect the results within a given study area. The purpose of this study was to address this research gap by using the BRIC composite index to analyze changes in the measured resilience of populations along the Mississippi, Alabama, and Florida coasts resulting from increased Sea-Level Rise (SLR). To address the issue of scale, the BRIC scores from different spatial extents of SLR were calculated and analyzed at the U.S. Census tract and block group levels of geography. An Analysis of Variance (ANOVA) was performed to statistically conclude if there were any differences between sea level rise scenarios, which were followed by a Post-hoc test and Principal Component Analysis to understand how different the observations were within the study area, and why the differences were observed.

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1.0 Introduction

Resilience is "an ability to recover from or adjust easily to misfortune or change," according to the Merriam-Webster Dictionary, which holds true in academic research on the topic, even though the definition has slight alterations. In the field of ecology, resilience is the idea that ecological systems absorb change (or adapt) to maintain their relationships (Matthews et al 2014; Holling 1973). Engineering focuses on buildings and infrastructure and the ability of this infrastructure to be restored to a previous state of functionality if exposed to stress or damage (Matthews et al 2014; Cutter, Burton, Emrich 2010). From a natural hazards and disasters research perspective, resilience has morphed from Timmerman's (1981) definition of a system's ability to absorb and recover from damaging natural hazard events to "the ability to survive and cope with a disaster with minimum impacts and damage" (Burton 2015). All of these definitions are very similar to the dictionary definition since they all focus on ability to recover from some sort of perturbation. The definitions from different scientific fields differ in terms of focus, such as on ecological systems, a community within a city, or individual buildings, and how recovery from damaging natural hazard events and disasters take place within such systems.

In order to gauge how resilient populations are to natural hazards and disasters, indicators are typically used to create what is referred to as a composite index, of which there are currently 27 composite indices of resilience and social vulnerability which is an overlapping concept (Bakkensen 2017). An indicator is a measure (either quantitative or qualitative) derived from observed facts that communicate the reality of a complex situation (Cutter, Burton, and Emrich 2010). From a natural hazards and disaster resilience perspective, indicators measure different preexisting characteristics within populations that show how resilient they might be. For example, a high percent of population non-elderly within a community could mean that populations at risk from an adverse hazard impact consist mainly of younger residents that could have an easier time evacuating since they may have less mobility constraints. There are many indicators that are used as proxy measures to determine a community's resilience, and when the indicators are combined to quantitatively measure and map resilience, a composite index of resilience (also known as composite indicator) is formed. One of the most cited composite indices for measuring the resilience of communities to natural hazards and disasters is the Baseline Resilience Index for Communities (BRIC) by Cutter, Burton, and Emrich (2010) (Bakkensen 2017). When calculated, the BRIC results in a final numeric score that considers data collected and compiled within six thematic areas of resilience: social, economic, institutional, infrastructure, community capital, and environmental (Cutter, Burton, Emrich 2010).

Although utilized in a number of studies to measure resilience, few analyses have used indices such as the BRIC to understand how changes in the scale of analysis affects the measured resilience of a given study area. In other words, the results of the resilience index have not been adequately tested from one scale to the next (Burton 2015) to better understand how the representation of the resilience of populations within a study area changes from one scale to the next. The BRIC was designed to be used at different spatial resolutions, yet changes in the measured resilience of populations from one scale to the next, and how these changes could lead to different and contradictory results in a study area, is relatively unknown. The Modifiable Areal Unit Problem (MAUP) would be the most likely cause for differing results as scale changes due to aggregation (Dark and Bram 2007). As the scale gets larger, e.g. from U.S. Census Block Groups to Census Tracts, details are lost to generalization.

An additional area of opportunity pertaining to the use of composite indicators for resilience measurement is to better understand how the measured resilience of populations might change as the spatial extent of a hazard within a particular study area changes. A community's increased coastal flood risk due to Sea Level Rise (SLR) provides just one poignant example of how potential changes in hazard extent could affect differing parts of the population as more inhabited land area will be at risk of inundation given increasing sea levels. Methods applied to understand the effects of the spatial extent of a hazard on resilience can be useful to help emergency managers within a hazard zone to better understand how populations might respond to and recover from a damaging event considering different hazard extents (e.g. localized impacts to widespread damage). The latter is particularly important when considering the effects of climate change on a given coastal hazard such as a tropical cyclones, floods, and coastal erosion.

1.1 Objectives

Given the areas of opportunity outlined above, the main goal of this research is to propose a series of methods to examine how the measured disaster resilience of populations at particular places changes with respect to variations in scale of analysis and the spatial extent of a hazard zone. In other words, this research is intended to provide a series of methods to better understand how characteristics that affect the resilience within communities can change when considering the spatial extent of potential hazard impacts and the scale of analysis for which the resilience concept is measured. To address changes in a hazard's spatial extent and scale, different Sea Level Rise (SLR) scenarios were utilized since higher sea levels may result in larger spatial extents of populations being exposed to damaging storm surge and flooding. Since losses from natural hazards (and the ability to recover from them) vary geographically, and over time, as well as among different social groups, it is expected that the resilience of populations exposed to these climate-related hazards will also vary over time and space (Cutter et al. 2008; Burton 2015). The second key aspect of this research is to better understand how changes in the characteristics that affect the resilience of populations are likely to vary in different parts of the Southeastern United States under different SLR scenarios. Using coastal areas within the Southeastern United States as a case study, four research questions form the basis of this work:

1) Is there any difference in the measured resilience of coastal populations given projected changes in Sea Level Rise?

2) If there is a difference in the resilience of populations due to changes in the spatial extent of a SLR hazard zone, to what extent does the overall resilience of populations diverge?

3) Given the possibility that changes in the resilience of populations are likely to occur from one SLR zone to the next, what characteristics are most pronounced as driving the resilience of populations?

4) How do the answers to the previous three questions change with location and scale?

Research to answer these questions was applied to two study areas along the Mississippi/Alabama Gulf Coast and in coastal Southern Florida. The reason for such a comparison is that there are vastly different groups of people that live along the U.S. coastlines that would be impacted by SLR. For example, coastal Mississippi has an average median household income of $44,289 while the southern tip of Florida has a median household income of $59,307 (United States Census 2014-2017). Additionally, Florida is a popular retirement destination causing the average age to be higher than that of the national average due to increased elderly populations. Such a higher average age is not expected to be observed in Mississippi, which would be another difference that would impact resilience in the two locations. Another expected difference is a higher percentage of African American population in Mississippi than Florida, where a more Hispanic population is expected due to immigration from countries such as Cuba

(United States Census 2014-2017). Researchers have shown that race plays a role in resilience because not all races have an equal capacity to prepare for, respond to, and recover from natural hazard impacts (Cutter, Mitchell, and Scott 2010; Cutter 2009). If a group of people is marginalized and put at a disadvantage prior to a hazard impact or the recovery process, it will take them longer to recover than other populations without the same disadvantage. Since resilience looks at the ability to bounce back, if a population takes longer to recover that would indicate that they could have a lower resilience.

2.0 Review of the literature:

There are two major components of this thesis. The first is a modeled accounting of potential changes in seal level rise (SLR) for the Mississippi/Alabama Gulf Coast and the Florida coast. The second is the use of the BRIC for measuring the resilience of populations exposed to flooding from potential SLR. As such, literatures pertaining the modelling of SLR, theoretical frameworks of resilience, and quantified metrics of resilience were reviewed to justify the modelling components used in this thesis.

2.1 The modelling of SLR:

According to Rahmstorf (2012) and Doyle, Chivoiu, and Enwright (2015), there are three approaches to sea level rise modelling: a) accounting for thermal expansion, b) measuring changing ocean floor depth, and c) adding water mass to inundation area (bathtub). Thermal expansion bases predictions of SLR on how warm and cold sea water displace surrounding sea water differently. Warm water displaces more water than cold water does, and as the atmosphere heats up due to a warming climate the water will warm up and increase in volume. The method of changing the depth of the ocean floor provides the second approach and is based on the idea that the earth's crust and oceans are always moving. As such, this approach is arguably better for long term predictions due to how slowly the Earth's crust moves. The final approach is the "bathtub" (or "modified bathtub") approach. The idea behind this approach is that ice cap and glacial meltwater will return the ocean, cause increased water displacement, and raise sea levels.

The modified bathtub approach for SLR modelling is the most commonly applied method within a GIS since the SLR outputs are amenable to coupling with other GIS data such as land-use/land-cover data, U.S. Census polygons, and city boundaries (Doyle, Chivoiu, and Enwright

2015). The USGS Sea-Level Rise Animation (Usery, Choi, and Finn 2009) provides an example of the modified bathtub approach. This Sea-Level Rise Animation model points out low-lying areas that are at risk of flooding from sea-level rise using compiled elevation, land cover, and population data. To simulate SLR, current sea level elevations are increased by one-meter increments. If the land elevation in a given area is less than or equal to the increased sea level elevation, it simulated as inundated and input into the model as a conditional overlay. The conditional overlays are applied to test if the land elevation in the SLR area is less than or equal to the sea level presented, and if the elevation meets the requirement for inundation, the value of the population in the respective inundation zone is input into the mapping framework. This methodology, however, only accounts for elevations using an elevation model which leaves out factors such as tidal influxes, hydroconnectivity, or shoreline dynamics that that could drastically impact the results of the simulations (Doyle, Chivoiu, and Enwright 2015).

Surging Seas is an additional model using the bathtub approach, and this framework takes tide and hydroconnectivity into account (Climate Central 2020). To create this model, global temperatures changes are calculated, a global sea level rise model is used, and data from 55 tide gauges in the United States are utilized. The results of the global temperature changes can be input into the global SLR model to see what sea level rise could be globally. The tide gauges are used to interpolate what the mean maximum sea level is for the United States to use as the base for sea level rise prediction in the United States (Tebaldi, Strauss, and Zervas 2012).

The NOAA Digital Coast Sea-Level Viewer uses the "modified bathtub" approach (NOAA 2010). Here, NOAA uses tidal gauge outputs and VDatum to create their SLR forecasts (Doyle, Chivoiu, and Enwright 2015). VDatum is a tool that takes a grid of points that have a value of zero and puts them in the chosen tidal datum (NOAA 2017a). A tidal datum is a baseline elevation derived from water level measurements (Scherer et al. 2001). The Florida tides differ from the east to west coast due to each coast having a different amphidromic points (Brown et al 1989). An amphidromic point is a point of origin of tides for a specific area (Hicks 2006). At the amphidromic point, there is no tide that occurs and the tides radiate out in a circular fashion from that point. Florida's west coast has tides that originate in the Gulf of Mexico near the Yucatan Peninsula, while the east coast has an amphidromic point in the Atlantic Ocean (Brown et al. 1989). Having two different amphidromic points on Florida causes the east and west coast to have different tides. To compensate for this, Florida's SLR was calculated separately for each coast.

Another important point to consider is that NOAA based their SLR calculations on mean higher high water (MHHW) data (NOAA 2017a). Tide levels at any particular location (i.e., water level at the coast) vary throughout the day due to the gravitational pull of the sun and the moon on the oceans. This gravitational pull is greatest when the sun and moon align with the earth (i.e., full moon and new moon) resulting in the greatest variations between high-tide and low-tide during a monthly lunar cycle, which is known as a spring tide (Pethick 1984). High-tide levels during spring tides vary throughout the year, with the highest high-tide data used to compute the MHHW elevation at the location where the tidal data were collected. By using MHHW as the base line, all areas that could possibly be inundated are accounted for in the NOAA model since the baseline is the highest sea level that the area experiences normally. By using the spring high tide average as a base line, all areas that could possibly be inundated are accounted for in the NOAA model since the baseline is the highest sea level that the area experiences normally. One point that sets NOAA's Sea-Level Viewer apart is that it takes hydroconnectivity into account, including unconnected areas over one acre (43,560 square feet) (NOAA 2017a) (NOAA 2017b). This means that when an area is connected to the ocean and below a specified elevation it is considered inundated, but also if flooding happens inland that is not connected to the ocean, as long as it is more than an acre (43,560 square feet). The NOAA model addresses MHHW, different amphidromic points, and hydroconnectivity which deemed it more robust than other available models, and was thereby chosen for the SLR portions of this thesis.

2.2 Theoretical frameworks of resilience:

The disaster resilience concept provides the means to better understand how social characteristics of risk from SLR may change considering space and scale. It is within this context that there are multiple theoretical frameworks and models that can be utilized to explain resilience. The major ones include the Risk-Hazard model (e.g., Hewitt 1983), the Pressure and Release Model (PAR) (Blaikie et al. 1994), the Hazards of Place model (HoP) (Cutter 1996), and the Disaster Resilience of Place Model (DROP) (Cutter et al. 2008). These conceptual models help to guide the indicators that are chosen to measure disaster resilience and the application of metrics to answer different types of research questions within a given study area. The Risk-Hazard model and PAR are technically models used to explain social vulnerability, but are included in this research because social vulnerability and resilience share many connections (Cutter et al. 2008). For this reason, social vulnerability models are considered useful and meaningful tools to help guide resilience measurement.

The Risk-Hazard theoretical model is perhaps the most basic of the social vulnerability-related frameworks and states that risk is a function of hazards and vulnerability (Burton et al 2018). With this model, the focus is on the hazard and physical exposure of infrastructure, as opposed to social characteristics that increase or decrease vulnerability or resilience to hazard events (Burton et al 2018; Turner 2003). The skewed focus towards physical and environmental variables means that solutions to reduce natural hazard risk typically leaned toward physical changes to the constructed environment, such as constructing dams and levees (Burton et al 2018). Gilbert White, Ian Burton, and Robert Kates (White 1986) noticed this disconnect and began examining how humans prepared for and responded to hazard events, rather than taking a technocratic approach to reduce risk. Some human-environmental solutions were suggested, such as building codes to create buildings more equipped for hazards such floods, and attempted to understand the complex relationship between humans and their environment, but there were still flaws (White 1945). The Risk-Hazard model still did not address the impact humans had on the vulnerability or resilience of a community from hazards. Humans, and the systems they use, can make the impacts of the hazard more extreme, or lessen them (Turner 2003). The next model aimed to resolve these issues.

The Pressure and Release Model (PAR) (Blakie et al. 1994) is perhaps the most cited social vulnerability framework. The PAR posits that risk is a function of hazards multiplied by vulnerability, but hazards and vulnerability are considered opposing forces (Blakie et al 1994). The idea behind the term "pressure and release" is that risk can be thought of as a ball being pushed on at each end by these two opposing forces, and the pressure is created by the amount of vulnerability to hazards within a population (Blakie et al 1994). If vulnerability is higher, then the pressure on risk will be higher and the amount of pressure needed from the hazard to break the ball is lower. The release aspect is that if vulnerability is lower, the pressure on risk will be lower. Vulnerability in the PAR model is shown at different levels, or severity, and how the different aspects of vulnerability can stack on one another, as seen in Figure 1. The different components of vulnerability listed in Figure 1 also show a focus on more social, or societal, variables, as opposed to physical. While the PAR model is more realistic in some aspects, it does still have flaws. Physical attributes are not considered by the PAR model, and the model does not take the cyclical cycle of these events into account (Turner 2003). Moreover, many components of the model, such as political ideologies, do not lend well to the development of composite indicators such as the ones used for the BRIC.

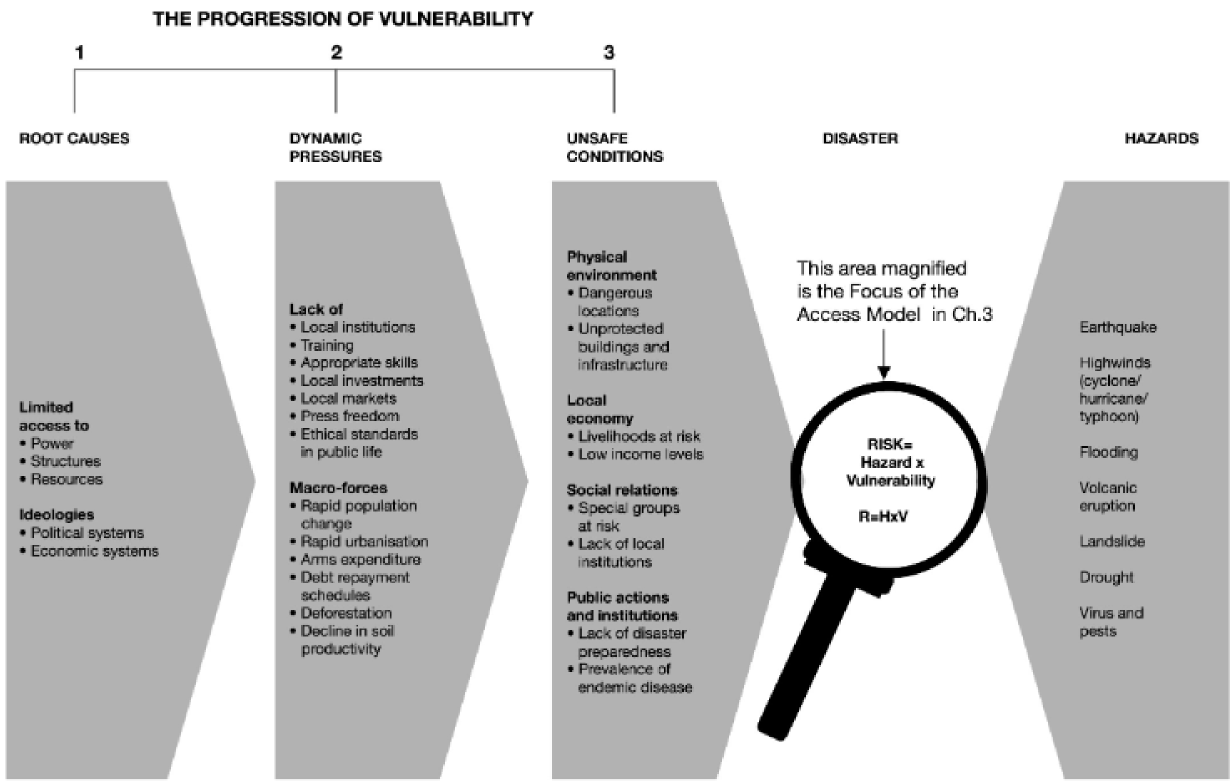

Figure 1: The PAR model from Blakie et al 1994. The pressure of vulnerability is seen on the left, and pressure from hazards on the right.

The Hazards of Place model (HoP) (Cutter 1996) takes the physical and social variables, and combines them at a specific geographic location. The HoP model was developed to demonstrate the cyclical nature of hazardous events (Figure 2). Here, risk and mitigation lead into potential hazard, which then branches off into geographic context and social fabric. The social fabric of a place leads to the social vulnerability of populations that inhabit that place. Variables applied within the social vulnerability portion of the HoP framework could include measurements of how prepared a community is, training for hazard events, population numbers, building code applications or building age, population age, or race. Geographic context leads to biophysical vulnerability, which would be similar to the Risk-Hazard model as it is a measure of hazard severity. The biophysical and social vulnerability portions are combined into respective sub-indicators and these are finally combined to give a place vulnerability, which circles back around to risk and mitigation as these affect the total vulnerability of a place. The geographic aspect within this model is important because vulnerability changes based on location. Florida is more vulnerable to hurricanes than Oklahoma due to its geographic location, for instance. Within Florida there is still variability, however. Some areas might me more prone to flooding due to soil types, or having an urban area with a large number of impervious surfaces, for example. The HoP model incorporates more to make the model more accurately represent the real world, but the model is still not without shortcomings. For instance, the model does not have a temporal or building exposure components (Cutter et al 2008).

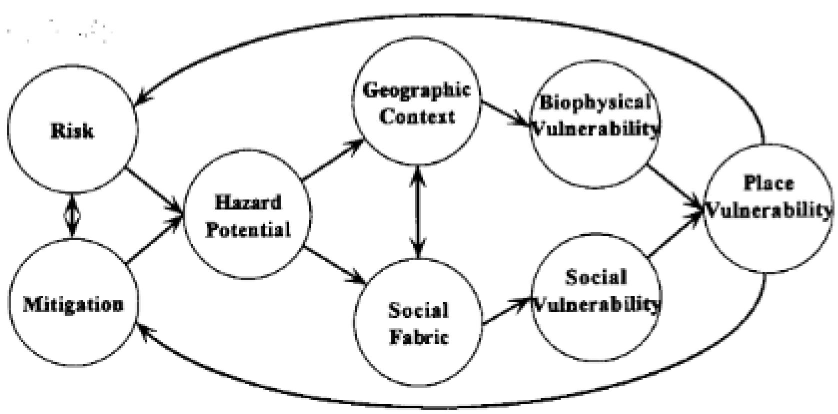

Figure 2: The HoP model from Cutter 1996.

All the models up to this point have dealt with vulnerability from a social perspective. They are the predecessors to conceptual models developed explicitly to better understand resilience. Resilience is not to be confused with vulnerability, however. Resilience focuses on the ability to recover, while vulnerability is potential for harm (Cutter et al 2008). Vulnerability is a characteristic that represents a snapshot in time, or at one specific moment in time regarding how much potential for harm there is if a hazard were to occur. The resilience of populations is linked to processes that facilitate change over time, or how much a system will recover and how quickly. The literature shows different opinions on how resilience and vulnerability are related to one another. Some view resilience as a component of vulnerability, others see vulnerability as a component of resilience, while some see the two as separate entities that have some overlap (Cutter et al 2008). The next model views the two as separate concepts with overlap.

The Disaster Resilience of Place (DROP) model (Cutter et al. 2008) focuses on resilience and incorporates a temporal aspect. The model (Figure 3) begins with baseline, or antecedent, conditions. There is inherent vulnerability and resilience in any community, but there are also social systems, built environment, and natural systems at play that contribute to how vulnerable and resilience the community is. The hazard, or event, is added to these conditions which results in immediate effects based on the antecedent conditions and hazard's severity. Coping responses, evacuation or shelters for example, will be affected by the antecedent conditions within a community and the hazard based on if the coping responses within a community are present. These three aspects combined (antecedent conditions, hazard, and coping responses) create an absorptive capacity, which indicates how much a community can withstand, or absorb, the damage from a hazard impact. If the absorptive capacity of a community is not exceeded, then there will be a high degree of recovery potential within that community. If the absorptive capacity of a community is exceeded, the recovery depends on the community's adaptive resilience. If the community exhibits adaptive resilience, then the community will still experience high recovery, but if the community does not, it will experience a low recovery rate. The degree of recovery of a community is also directly related to mitigation and preparedness that leads back to antecedent conditions, which represents if a community changes after a hazardous event to better prepare for another event. Cutter mentions that the next step is to measure the inherent resilience mentioned in the model, which was accomplished with the creation of the Baseline Resilience Indicators for Communities (BRIC) (Cutter et al. 2008) that forms the basis for the quantitative indicators development for this thesis.

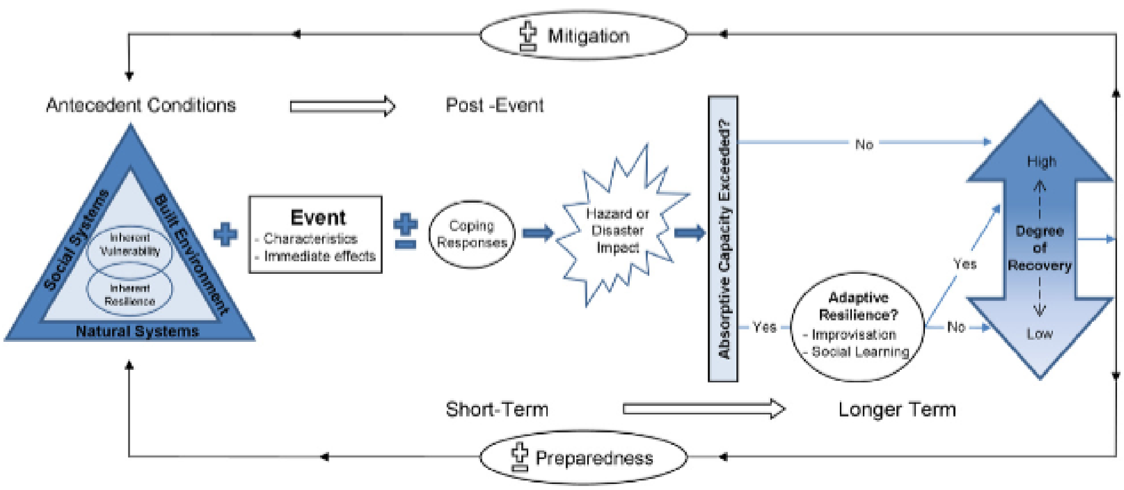

Figure 3: The DROP model from Cutter et al 2008

2.3 Indicators for measuring disaster resilience:

All of the indices follow the same general steps, which mimic what is depicted in the Nardo et al (2008) "Handbook for Composite Indicators Development." Selecting variables, normalizing the data, and aggregating the data are steps that were taken to develop current resilience indicator frameworks. Some resilience indices also included theoretical framework development and multivariate analysis as well. One of the most well cited resilience indices is the Community Disaster Resilience Index (CDRI). The CDRI (Peacock et al. 2010) that is based off the researchers Community Disaster Resilience Framework (CDRF), consists of four disaster phases and four capitals. The disaster phases break down into hazard mitigation (actions prior to the event), disaster preparedness (per-impact actions to provide resources), disaster response (executing evacuations, and plans), and disaster recovery (post-impact actions to rebuild). The other portion of the index is the capitals: social, economic, physical, and human; the variables for the index were picked from these four capitals. Social capital is meant to examine how interconnected, and trusting, a community is, which were extracted with variables such as participation is voluntary organizations, involvement in social groups, and religious participation for examples. Economic capital is designed to analyze the financial ability of a population through income, employment, and property value. Physical capital is the built environment measured by looking at components such as construction, environment, and land use planning. All of the 120 variables that were collected for this index were matched to their respective capital, as well as the disaster phases that they applied to. If a variable applied to multiple phases, then the variable was repeated. A Cronbach's alpha analysis was conducted to increase internal consistency, which reduced the 120 variables to 75. To calculate the final scores, the variables are turned into comparable forms, for example percentages, before being transformed into z-scores. An average value is calculated for each capital, regardless of disaster phase, and the capitals scores averaged together form the final CDRI scores (Figure 4). Since the variables are categorized by phase as well, the process can be done to calculate a score for each phase. After calculating z-scores, the steps are the same, but done for the phase instead of the capitals (Peacock et al 2010). One issue is that z-scores attempt to make the data fit a normal distribution. Making the data fit a normal distribution can be helpful, but with demographic data, for example, this is not ideal. Demographic data is not normal, and by forcing the data to be normal in something like an index the outcome of the normalization can be deceiving. Another issue with z-scores is outliers having a greater impact on the operation they are used in. Unfortunately, outliers are always an issue in data, but there are other methods to normalizing data that can have a more desirable outcome (Nardo et al. 2008).

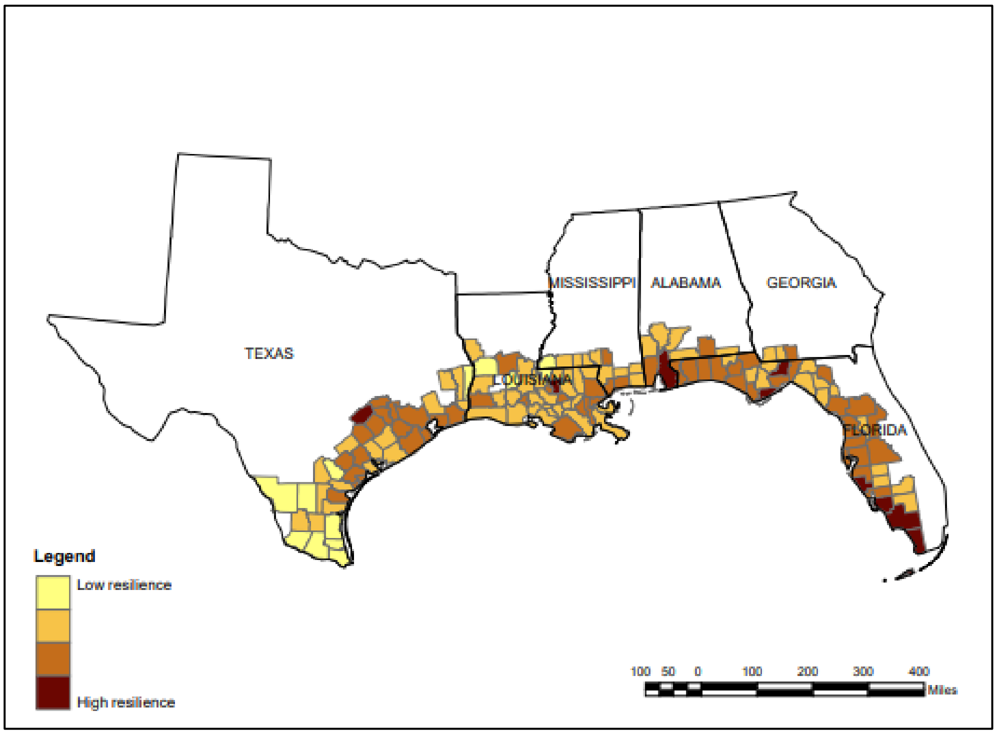

Figure 4: Final CDRI scores from Peacock et al. 2010

Another resilience index is the Resilience Capacity Index (RCI) created by Kathryn Fosters (2012). The RCI was originally designed for metro areas, as opposed to larger areas like the CDRI. The 10 variables for the index are divided into three categories: regional economic capacity, sociodemographic capacity, and community connection capacity. Regional economic capacity deals with income and employment of the metro area by measuring economic diversity, median household income, and income distribution with the Gini coefficient. Sociodemographic capacity targets the demographic characteristics such as education, age, and disabilities. Finally, the community connection capacity looks at how familiar the residents are with the community and area. To calculate RCI, the variables must be made into comparable forms, transformed into z-scores, and then all the variables are averaged. There are multiple reasons this index was not selected for this study. First, it is designed for metro areas, which are not the scale of this study. Second, there are very few variables, which would make it difficult to get a well-rounded understanding of what is going on. This is especially true when the study will be at a larger scale that will have more data available than at the metro level.

The BRIC (Figure 5) measures baseline resilience with six subcomponents, and is based on the DROP model (Cutter, Burton, Emrich 2010). The six subcomponents are: social, economic, institutional, infrastructural, community, and environmental, and each subcomponent has multiple indicators, or variables within it. The social subcomponent contains indicators dealing with age, language, and education level to capture the social capacity of communities to withstand hazard impacts. The Economic component contains housing capital, income, and employment as some examples to measure economic and livelihood stability within communities. Institutional looks at mitigation and planning from a government stand point to see how prepared the community is. Infrastructural analyzes recovery and evacuation capacity with number of police, number of vacant homes, and health care facilities, road density, and railroad miles, for example. Community capital captures residents' involvement with their community through number religious attendants, and city organizations (Burton 2015; Cutter, Burton, Emrich 2010). The Environmental component looks at what kind of protection the environment gives such as: non-erodible soils, areas not in inundation zones, and landcover, and wetland/forest reduction (Burton 2015). The process of creating BRIC consists of making the variables into a comparable form, using Min-Max rescaling, correlation analysis, averaging the subcomponent values, and adding the subcomponent scores together to get a final BRIC score. These steps provide a more robust index that avoids the z-score issues that the CDRI had. The Min-Max rescaling is also impacted by outliers, but has the benefit that it shows the spread of variables that might have a small interval. Demographic data is unlikely to see values from zero to one hundred percent, but instead values that are much closer. Min-Max rescaling is good for this reason, while z-scores would not show small intervals well (Nardo et al. 2008). The correlation analysis is done to remove variables that are highly correlated to one another. The BRIC is a robust index that implements rescaling that works well for small intervals that will most likely be witnessed in the data, which is why this index was used for this study.

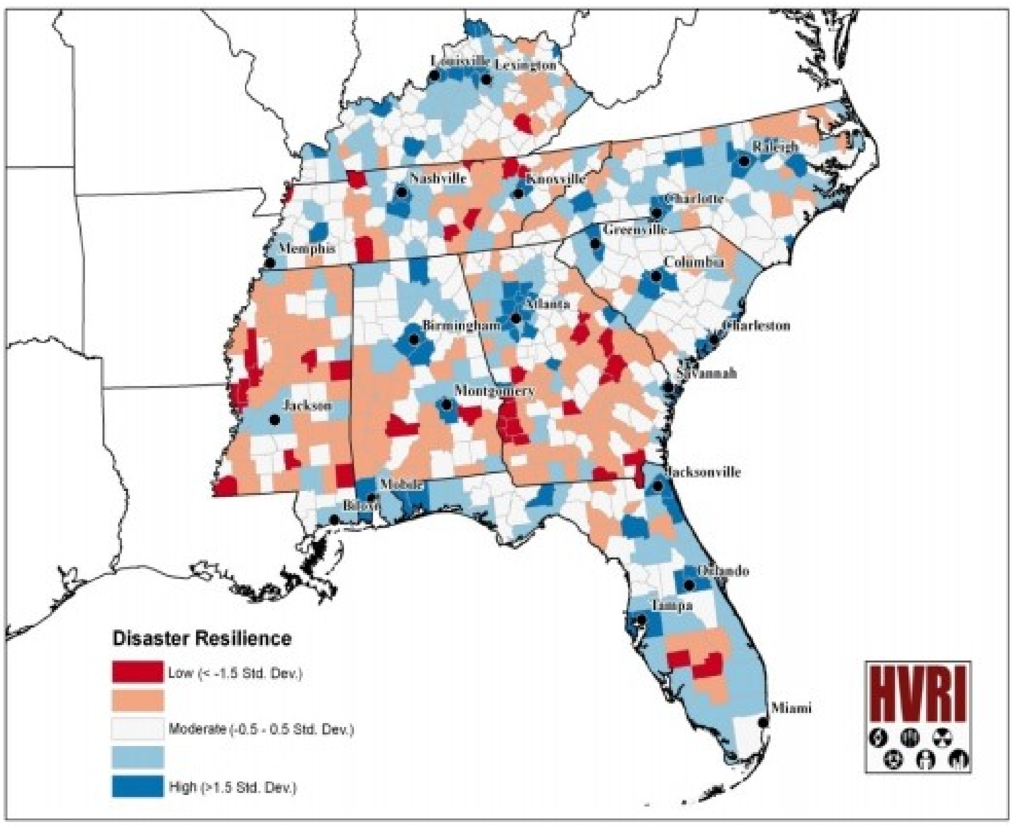

Figure 5: Final BRIC scores from Cutter, Burton, and Emrich 2010

3.0 Methods

3.1 Study Area

There were two major study areas from the southeastern United States selected for this thesis: 1) Coastal Mississippi and Alabama (MS/AL) taken together as a region, and 2) the southern tip of Florida (Figure 6). Hancock, Harrison, and Jackson Counties constitute the Mississippi study area, and Mobile and Baldwin counties make up the Alabama study area. The particular Gulf Coast counties were chosen because of their likelihood for storm surge inundation and coastal flooding based on past adverse natural hazard impacts such as the destruction from Hurricane Katrina (Burton, 2015). The counties within the MS/AL study were also being used at the time of this writing for a study funded by the NOAA MS/AL Sea Grant Consortium in which the work conducted for this thesis will contribute to. Palm Beach, Broward, Miami-Dade, and Collier County make up the Florida study area. The notion behind these two study areas is that they are likely divergent from one another in terms of characteristics that affect the resilience of populations. Coastal Mississippi has a population that is poorer along the coast, comparatively, while Florida has a multitude of large wealthy areas along its coast with higher per capita incomes (U.S. Census 2014). Miami and Palm Beach are some examples that come to mind when imagining large expensive homes along the coast.

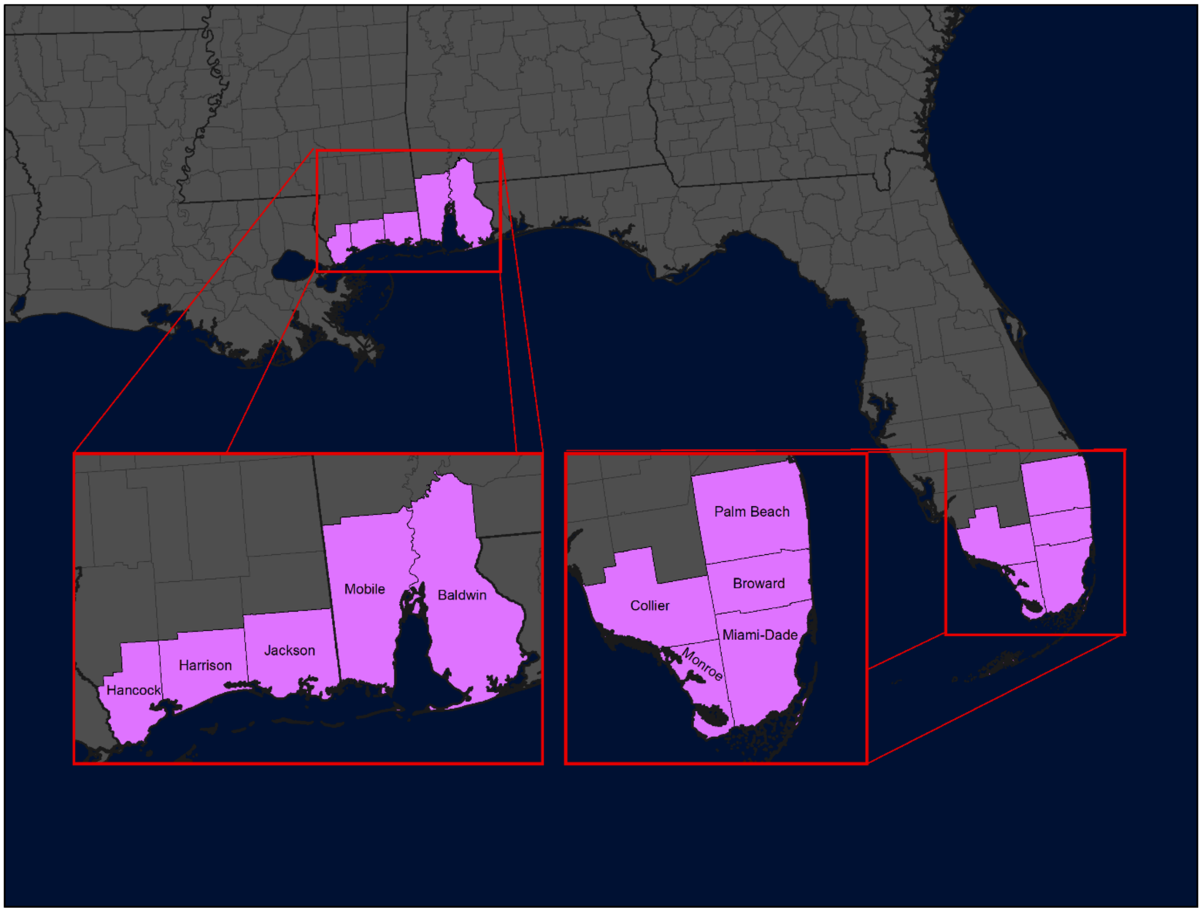

Figure 6: The study area is shown in purple.

Within the study area counties, the analysis for this thesis was conducted at both the U.S. Census Tract and Block Group levels of geography. Block groups are the smallest unit that can be used in this analysis because a multitude of data isn't available at the block level due to privacy concerns. Since blocks are so small, the census fears that releasing data at that level could be tracked back to individuals, so block groups were used to make sure all of the data would be available. Tracts were also analyzed to examine the differences between the two spatial extents.

3.2 Overview

The modelling and methodology for this thesis consisted of three major components in order to better understand how the resilience of populations may or may not change within the study area's SLR zones (Figure 7). As a starting point, the first component was used to define the different hazard scenarios that change in extent. Here, newly published NOAA SLR scenarios (Sweet et al. 2017, NOAA) that were culled from the NOAA Sea Level Rise Viewer (see section 2) was used to better understand the study area's risk of flooding under different SLR scenarios. As a subsequent step and component, a resilience composite index was constructed using the BRIC approach of Cutter et al. (2010; 2014) to analyze the resilience of the study areas under the different SLR scenarios. It's important to note that the NOAA SLR data represents a projection of SLR for the year 2100 and thereby does not represent current conditions (NOAAb 2017). The resilience data, however, was culled for the year 2014. In the absence of a robust method to forecast all of the BRIC data to 2100, the 2014 data is simply considered a baseline representing how SLR could affect the current population. It is within this context that the final component entailed the overlay of the resilience results with the SLR layers to extract the tract and block group resilience results for a difference analysis. An Analysis of Variance (ANOVA) test, Post-hoc test, and Principal Components analysis were run on the different extractions of enumeration units based on the exposure to the different hazard scenarios using the SLR layers to see if the populations are different, how different, and why they are different in terms of their final resilience scores and factors driving their resilience. The results of these tests and analyses were then compared between Mississippi, Alabama, and Florida to see if location had any impact on measured resilience outcomes. The results were also analyzed between the block group and tract scale to see if MAUP had any impact on resilience measurement. Each modelling component is discussed in detail in the subsections below.

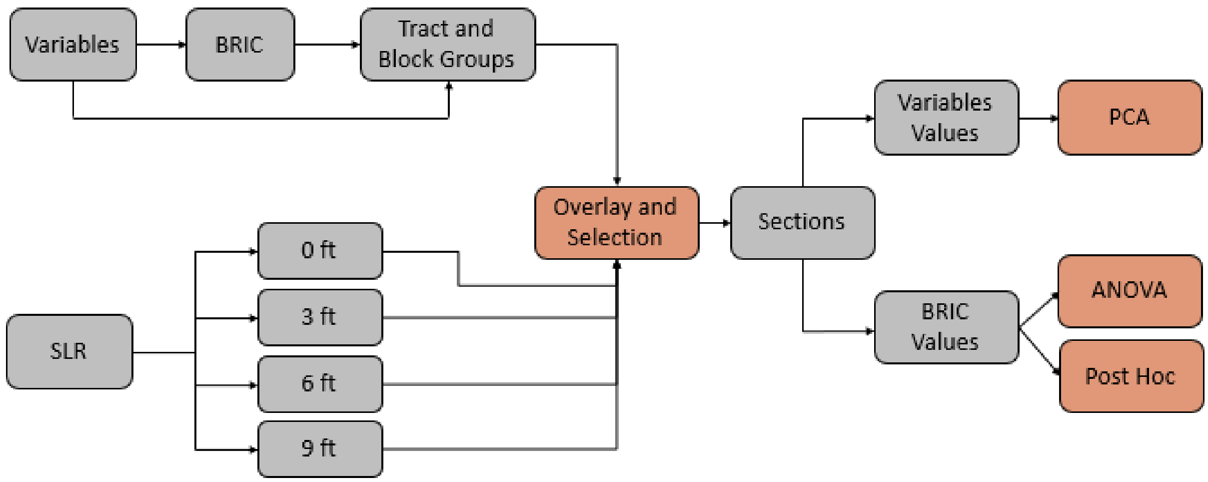

Figure 7: Process diagram for analysis

3.2.1 Sea-Level Rise (SLR)

Understanding and preparing the SLR layers was the first step. The different SLR predictions were mapped out in a raster file format created by the NOAA Office of Coastal Management. They show “potential flooding from future sea level rise” at increments of one foot starting at current mean sea level and continuing to 10 feet of sea level rise. All eleven scenarios came in a geodatabase with raster files at five-meter resolution. There are files that indicate depth, while others indicate NOAA’s confidence that the area would be flooded. In order to map confidence, NOAA had to create a hybrid method for calculating and mapping error. NOAA calculated standard scores using the root mean squared error to find the percentile rank of the error at different elevations. The equation used is:

$$Standard\ Score_{(X,Y)} = \frac{\left(Inundation_{(Water\ Surface)} - Elevation_{(X.Y)}\right)}{RMSE_{(Elevation\ Data)}}.$$

By creating these standard scores, and mapping them, different percentile ranks could be selected. The process was done using a one-tailed approach because two-tailed would have the uncertainty on the high and low side. One of those would actual be under water, so one-tailed was used. The criteria for the selection of flood inundated zones was using the 80th percentile rank, meaning that that 80% of the time the area would be flooded at the specified inundation level (Schmid, Hadley, and Waters 2014). The final files were mapped based on their percentile. For example, if a pixel was flooded nine times out of ten runs, then that pixel would be given a value of 2, meaning "wet." If the pixel was dry at least eight times out of ten, it would be given a value of 0 for "dry" (Sweet et al 2017). The value of 1 was given to pixels that did not fall into either category meaning the model could not determine with confidence flooding will occur. For the purposes of this study, the confidence files were used to determine the spatial extent of potentially inundated areas because depth is not a factor in this analysis. There were four SLR files used, which were 0, 3, 6, and 9 feet. The three feet interval offered enough change in SLR that new census units could be selected, but small enough to have multiple opportunities to see change. The SLR files overlaid on the census units for coastal Mississippi (Figure 8) provides an example of the overlay process. The southern Florida overlay map has been made available in Appendix A.

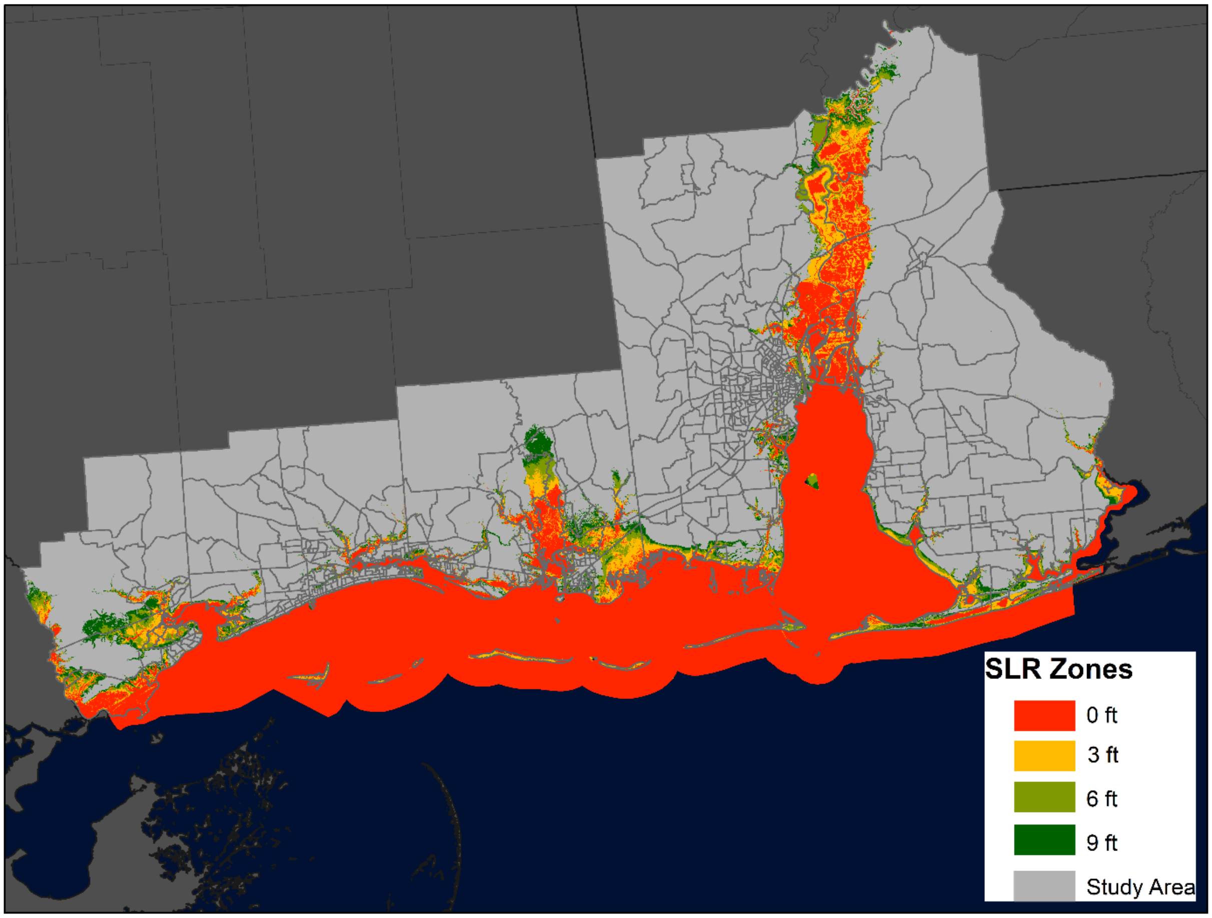

Figure 8: The SLR layers over the MS/AL Block groups. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR

3.2.2 Resilience Modeling

To analyze the resilience of the study area at both the census tract and block group level of geography, the BRIC composite index (Cutter, Burton, Emrich 2010) was used. The BRIC was chosen because it is the only resilience index that has had its input variables validated to date (see Burton 2015). The BRIC index is composed of six sub-indexes: social, economic, institutional, infrastructure, community capital, and environmental. Each of these subcomponents is made up of a number of variables (Table 1) from the set of variables from Burton 2015. Due to availability, not all of the variables from the original index could be found or calculated, which results in the final variables in the table. The Institutional subcomponent has only one variable because the other variables within this subcomponent were equally distributed across all study areas, which would not impact the final score, so they were not included. It is important to note that a correlation analysis was not conducted following the variable selection for this study. The variables used in this study were chosen from the final listed of variables from Burton 2015, which means a correlation had already been conducted to render the variables parsimonious. The raw data was collected from the U.S. Census Bureau at the block group and tract level and converted to comparable values, such as percentages and per capita indicators. The Environmental data was taken from US Geological Survey's landcover data and FEMA and transformed into percentages or land area. Once all the variables were in a comparable form, they were rescaled using a Min-Max rescaling (Cutter, Burton, Emrich 2010; Burton 2015; Cutter et al 2016). Min-Max rescaling takes all the values from one variable and gives the highest value for that variable a new value of one, while the lowest gets a new value of zero and everything in between is rescaled accordingly between zero and one. Due to the values depending on all other values within the variable, Min-Max rescaling was done separately for study areas and scale. The subcomponents received an average score between zero and one based on the variables within it. Averages were used to account for an unequal number of variables in each subcomponent. The averages from the subcomponents were then added together resulting in a final BRIC score between zero and six. Zero being the lowest resilience score and six being the highest resilience score possible.

Table 1: Variables for BRIC analysis. Direction refers to the variables effect on resilience.

Subcomponent	Variable Name	Variable	Direction
Environmental	**PNF100/500**	% land area not in 100/500-year flood	(+)
	PerFor	% forested land cover	(+)
	PerNH	% land area not hydric soils	(+)
	PerNFSS	% land area in not flood and storm surge inundation zones	(+)
	LAW	Land area of protective resources (wetlands, swamps, marsh, mangroves, sand dunes, and natural barriers) (Wetland Used)	(+)
	LANWD	Land area with no wetland decline	(+)
	LANFRD	Land area with no forest and rangeland decline	(+)
	LADOS	Land area of developed open space (public parks, urban gardens, lawns, etc.)	(+)
	LACul	Area of arable cultivated land	(+)
	RivMiles	Number of river miles	(-)
	PerUrban	% land area urban (general)	(-)
Social	**PNE**	% non-elderly	(+)
	PWV	% with vehicle	(+)
	PT	% with telephone	(+)
	PNESL	% non-ESL	(+)
	PWOD	% pop without disabilities	(+)
	PNM	% non-minorities	(+)

	PPHHD2	Percent population with high school diploma	(+)
	PopOut15KM	% population not living in coastal areas (within 15 Km of the coast)	(+)
	RE	Racial Equity (ratio % white to % nonwhite population)	(-)
	EE	Educational equality (ratio % college degree to % no high school diploma)	(-)
	PerHIU	% high intensity urban form (high intensity urban)	(+)
Economic	**PHO**	% homeownership	(+)
	PE	% employed	(+)
	PNEPI	% not employed in primary industries	(+)
	PFLFP	% female labor force participation	(+)
	PerCap	Per capita household income	(+)
	HE	Ratio of % white owner-occupied housing to % nonwhite owner-occupied housing	(-)
Institutional	**CRS**	% population in county participating in community rating system for flood	(+)
Infrastructure	**PNMH**	% no mobile homes	(+)
	PVRU	% vacant rental units	(+)
	RoadMiles	Principal arterial miles	(+)
	RailMiles	Rail miles	(+)
	PBB79	% structures not built before 1970; after 1990	(+)
	HHDams	High hazard dams per sq. mile	(-)
Community Capacity	**PBSRS**	% born in state and residing in state	(+)

	PEPO	% employed in professional occupations	(+)
	PNIM	% population not international migrants	(+)

3.2.3 Overlay Analysis to Delineate Drivers of Resilience

The previous steps provided two datasets, different sea level rise scenarios and composite indices of resilience for the study areas. The final steps in this methodology provide the comparative analysis that was conducted using this data. The comparative analysis was used to answer each of the research questions. Here, the final resilience scores and the SLR layers were overlaid for a selection process that entailed selecting the census units that intersected each of the different SLR zones. Each of these selections was coded within GIS so that they distinctly represented the SLR zone that they were culled from. In other words, census units intersecting each of the four SLR scenarios (0ft, 3ft, 6ft, 9ft) were selected, and each census unit was coded to match it's respective SLR zone (i.e., 0, 3, 6, 9). All census units intersecting an SLR zone were selected, but not if they were in the last selection. For example, the block groups that intersect 0ft zone were selected, but when 3 ft of SLR was overlaid those same bock groups were not selected even though they still technically intersect the layer. The selection was done in this fashion to get a better idea of how resilience changes as SLR increases without double counting selected census units. If all intersecting units from each scenario were included, an average of all the census units would be analyzed as opposed to the different sample groups as the spatial extent moves inland and outward. An example of what units in MS and AL were selected for each SLR layer can be seen in Figures 9. The southern Florida overlay can be viewed from Appendix A.

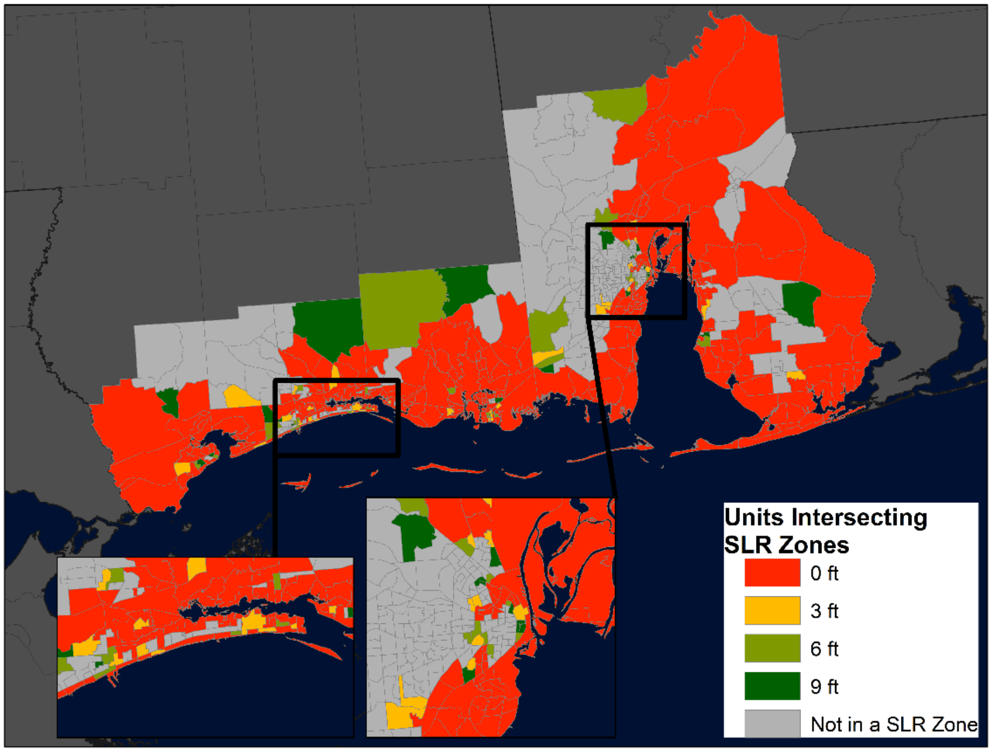

Figure 9: The MS/AL Block groups colored based on which SLR layer they intersected. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR

With the BRIC data selected and corresponding census units census coded to match the respective levels of SLR the units intersect, a series of statistical analyses were conducted to better understand the drivers of resilience within each zone and how, and to what extent, they differ. As a first step, a Principal Component Analysis (PCA) was conducted to see what variables are distinguished by the PCA as being potential drivers of the resilience of populations in the study area. A Principal Components is a data reduction technique that can be utilized to highlight which variables best describe the phenomenon being measured (Cutter, Boruff, and Shirley 2003). A PCA aims at reducing a large number of variables to a small set that still contains most of the information in the original data. The reduced dataset consists of a number of non-correlated factors that are the linear combinations of the input variables, each variable having a corresponding factor score that shows the strength of the association between each variable and its respective factor. These major phenomena that the PCA captures are the driving factors of resilience for that dataset.

3.2.4 Difference of Means Testing

The PCA provides a means to better understand the characteristics that are driving the resilience within each of the selected hazard zones and across scales. To distinguish whether the drivers of resilience are different within each zone and across scales, an Analysis of Variance (ANOVA) was utilized. Once the selection process was accomplished, an ANOVA was done to determine if the SLR zones were statistically different. An ANOVA is a difference of means test for three or more samples, which is similar to a T-Test, but a T-Test can only compare the means of two samples. The ANOVA was conducted on the study areas and scales separately as not to bias the results. What this means is that the ANOVA was conducted four times: 1) MS/AL tracts, 2) Florida tracts, 3) MS/AL block groups, and 4) Florida block groups. The reason the ANOVA had to be conducted four separate times was due to the fact that Florida and MS/AL are different areas of the US with different social and economic characteristics therefore they are comprised of different BRIC scores. Combining the BRIC score of the 0 ft SLR zone from MS/AL and Florida to calculate a mean for 0 ft SLR would be similar to combining personal income and household income to calculate a mean income. Personal and household income are calculated differently, so it is inaccurate to combine them. This principal is why the study areas and scales cannot be combined. Florida and MS/AL are two different areas with different variables, so they cannot be added together in order to preserve accuracy. The results of the ANVOA would show if the BRIC scores between the SLR zones were statistically different, which would imply that resilience changes as SLR increases.

Followed by the ANOVA, Tukey's Post-hoc test was performed on the four different ANOVA results. Tukey's Test is perhaps the most popular (Rogerson 2001), and compares the different sample means to determine how different the groups are. The procedure is similar to the ANOVA, however Tukey's Test determines how different the samples are. The results show how much difference there is between each SLR zone, and would help explain how resilience was changing as SLR increased.

4.0 Results and Discussion

4.1 Study Area Disaster Resilience

Figures 10 and 11 are the mapped BRIC scores for the study areas. The maps are symbolized using a manual classification with five classes that divide the range of resilience values into equally sized subranges from low resilience symbolized in red to high resilience symbolized in green. For both the MS/AL and Florida study areas, the mean BRIC scores were around 2.8, resulting in the 2.50 – 2.99 class being in the middle to represent the mean. The break points were picked for ease of reading and had to work across all the scales ad study areas. There are some general patterns to point out on the coasts. First, the MS/AL Gulf Coast has generally high BRIC scores comparatively, with the exception of Mobile, AL (Figure 10). There is a distinct area where resilience scores are below 2.5 that coincides with the Mobile area, and there is no block group outside of Mobile that has a score below 2.5. In contrast, the Florida study area has a relatively low resilience as a whole when the Florida indicators are aggregated (Figure 11). There are pockets of low resilience in Palm Beach and Miami, while Kendall, FL. has a higher resilience. The MS/AL study area does not have large block groups in the lowest category, while Florida does. Additionally, MS/AL does have large block groups in the highest category, while Florida only has a few small block groups in the same category. Something they have in common is that the clustering of BRIC scores in taking place in the urban areas.

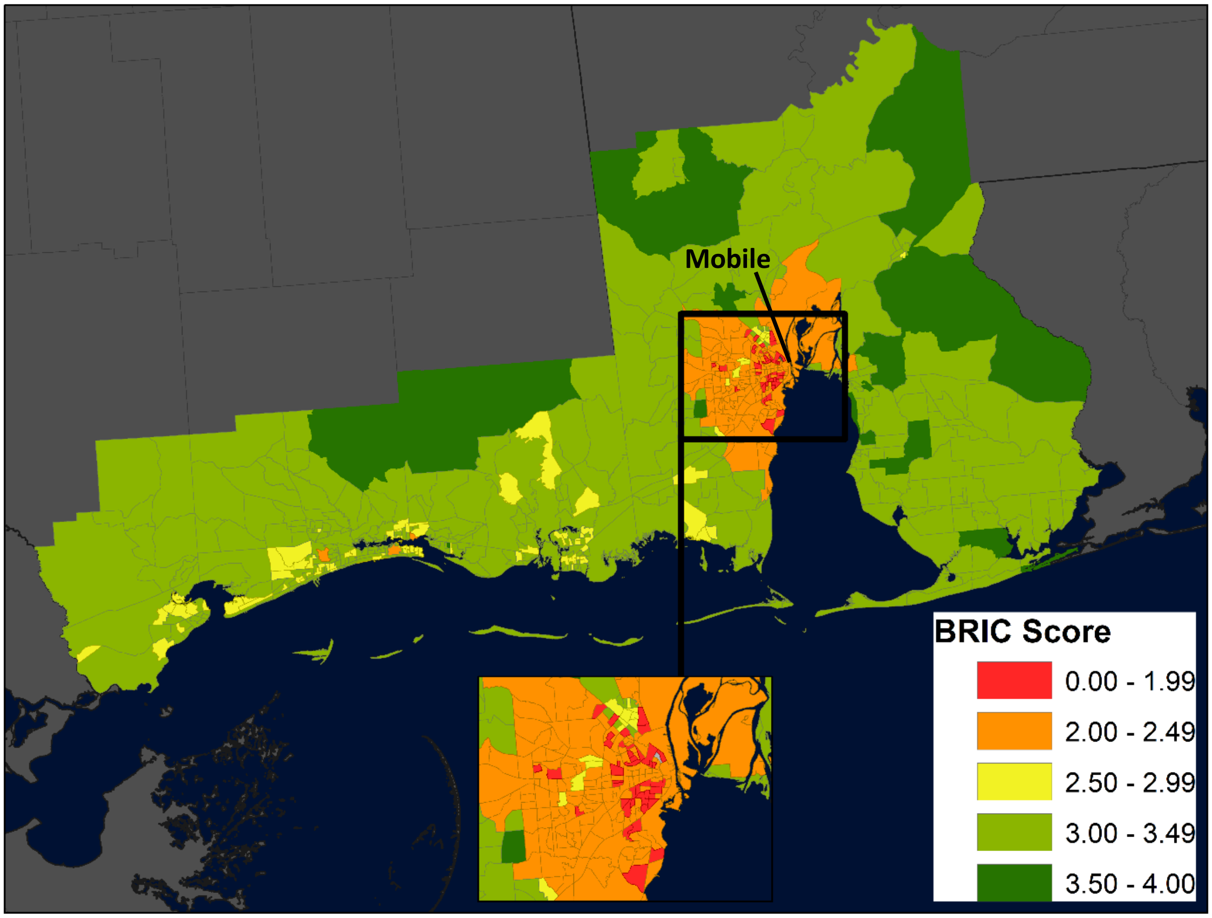

Figure 10: MS/AL block groups BRIC scores

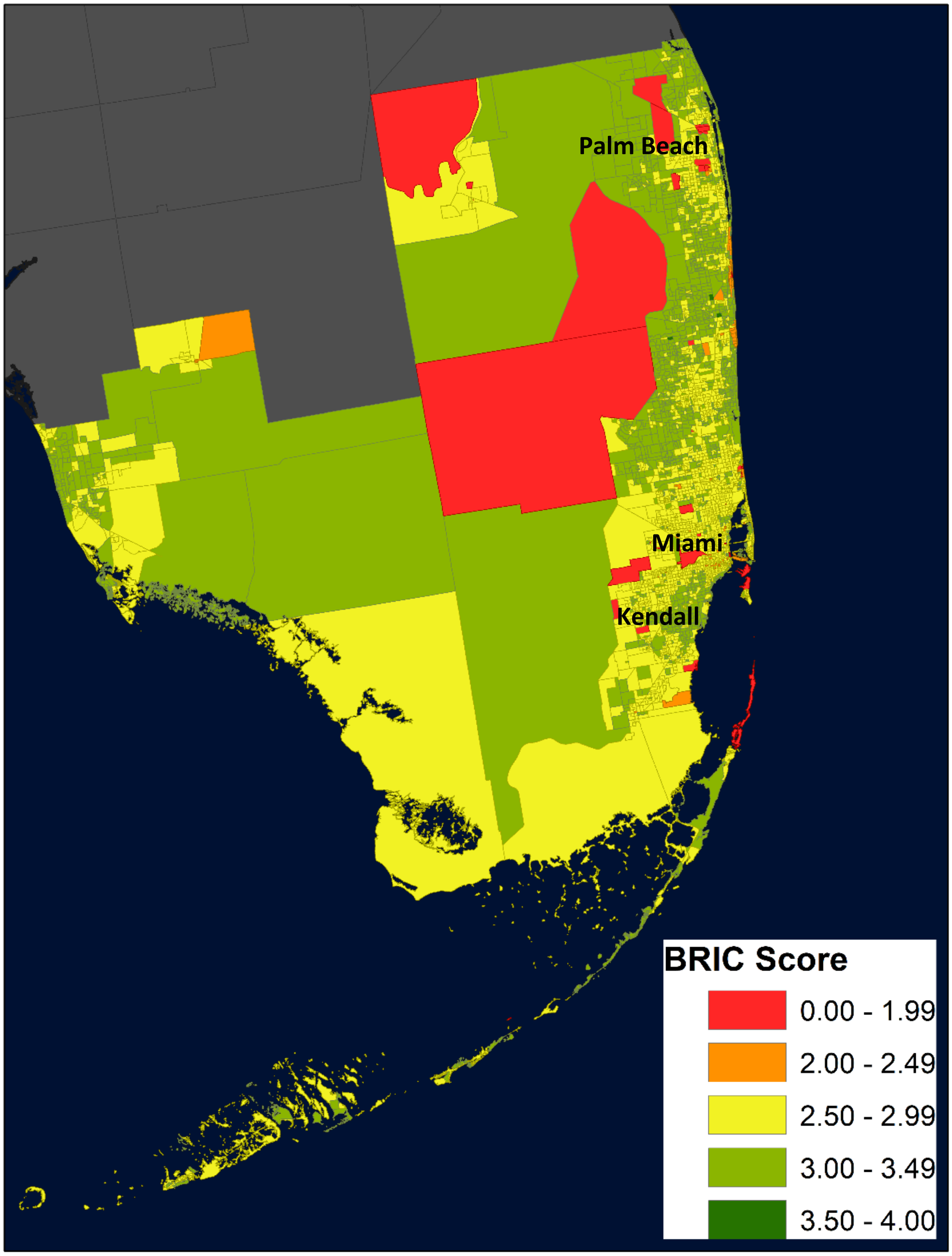

Figure 11: Florida block groups BRIC scores

4.2 Drivers of Disaster Resilience

The maps in Section 4.1 demonstrate a comparative assessment of resilience of the MS, AL, and FL coastal areas spatially. This mapping does not yield insight into what characteristics within communities are driving the differential resilience across space as seen in the figures, though. In order to better understand what is driving the resilience of populations within the study area, a PCA was conducted first at the tract level of geography for the MS/AL and Florida study areas respectively, then at the block group level. As outlined in Section 3.2.3, a PCA was conducted for the two study areas at the different scales of analysis to see how location and scale impact the drivers of resilience.

4.2.1 PCA Results: MS/AL Census Tract Level

The MS/AL tracts resulted in a total of 12 factors that explained 77.207% of the variance in the data (Table 2), but only the first 5 factors are discussed in detail below since these were deemed the most significant. Determining the significance of each factor was accomplished using scree plots (e.g., Figure 12) which demonstrates how impactful each factor is. According to a Scree plot, the elbow of the graph where it appears to level off is found and factors, or components, to the left of this point should be retained as significant.

Table 2: MS/AL tracts factors variance explained

Factor	% of Variance	Cumulative %
1	18.57	18.57
2	13.99	32.56
3	8.93	41.49
4	6.84	48.33
5	5.92	54.25
6	4.30	58.54
7	3.79	62.33
8	3.44	65.77

9	3.19	68.96
10	2.97	71.93
11	2.66	74.59
12	2.62	77.21

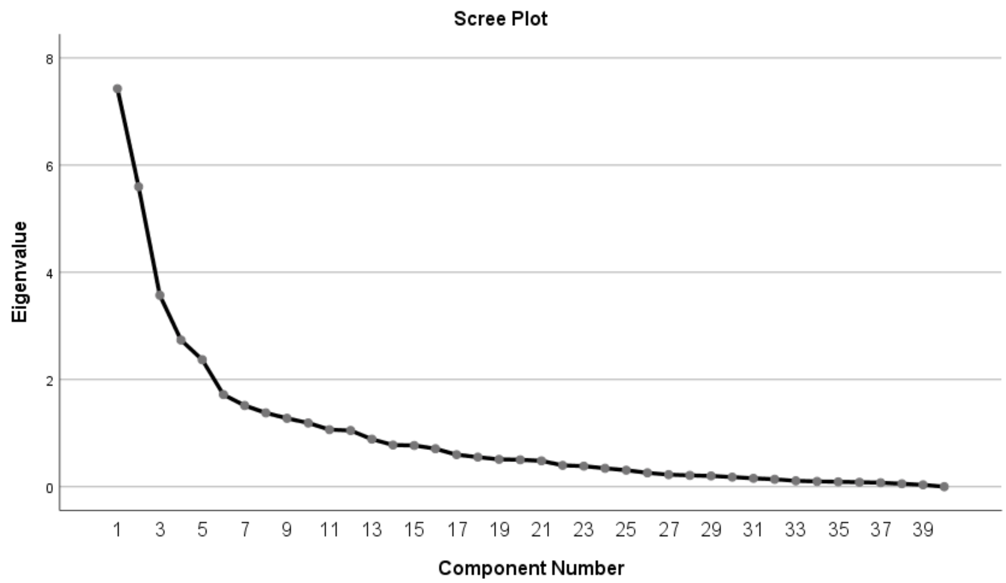

Figure 12: MS/AL tracts Scree Plot

The first factor, which is the biggest driver in terms of variance explained (% of variance = 18.57), could be described as environmental. Variables loading high within this first factor include the prevalence of high hydric soils, no wetland decline, no forest rangeland decline, high road miles, high developed open space, high river miles, high cultivated area, and high wetland area (Table 3). No wetland decline, no forest rangeland decline, and high wetland area are characteristics that are protective to an area experiencing a hazard (Burton 2015). The second factor (% variance explained = 13.99) consists of high loadings on people not born in that state, per capita income, and Caucasians. A factor with these variables is most likely explaining middle class to wealthy Caucasians that have moved to the southern Gulf Coast. Here, income plays a factor where higher levels of income provide the ability for communities to absorb losses and to become more resilient (Cutter, Boruff, and Shirley 2003). The third factor (% variance explained

= 8.93) contains high loadings on variables that pertain to female participation in the labor force, high employment, high employment not in the primary industry, and low population with disability. All of these variables communicate employment or ability to work, so the third factor is employment. High employment characteristics are a sign of stability of livelihoods, which in turn show an increase in resilience (Cutter, Burton, Emrich 2010). The fourth factor (% variance explained = 6.84) consists of high loading from low mobile homes, high population with vehicles, high population with telephone access, and high amount of high school diplomas. This factor could be described as education and accessibility. Education would be part of the factor due to the high rate of high school diplomas, while vehicle and phone access helps people communicate and move around. The ability to communicate and use transportation give people accessibility to evacuate and gain information, which would contribute to an increase in resilience. For these reasons, this factor represents educations and accessibility. The fifth factor (% variance explained = 5.92) is focused on flooding because there is high loading both variables that show areas not in the 100- and 500-year flood plain. Areas that do not have a high risk of flooding in turn have increased resilience (Burton 2015). To recap the factors are environmental, new Caucasian residents, employment, education/accessibility, and flooding.

Table 3: MS/AL tract factor break down

	1	2	3	4	5	6	7	8	9	10	11	12
PerNH	-0.456											
LANWD	0.642											
LANFRD	0.708											
RoadMiles	0.741											
LADOS	0.804											
RivMiles	0.912											
LACul	0.931											
LAW	0.932											

PBSRS		-0.718										
CRST14_1		0.439										
PerCap		0.667										
RE		0.67										
PNM		0.822										
PFLFP			0.504									
PWODHH			0.587									
PE			0.769									
PNEPI			0.895									
PWOD			0.914									
PNMH				0.606								
PWV				0.669								
PT				0.689								
PPHSD2				0.81								
PerNF100					0.913							
PerNF500					0.922							
PNESL						0.912						
PNIM						0.926						
PHO							-0.513					
PerHIU							0.407					
PVRU							0.546					
EE							0.703					
RailMiles								0.425				
PerFor								0.523				
PopOut15KM								0.8				
PNE									-0.529			
PEPO									0.754			
HE										0.652		
PerUrban										0.851		
PBB79											0.532	
PerNFSS											0.807	
HHDamSqMi												0.888

4.2.2 PCA Results: Florida Census Tract Level

The PCA conducted considering the Florida census tracts had a total of 11 factors with 73.756% of variance explained by 11 factors (Table 4). According to the Scree Plot (Figure 13), the most impactful factors are the first four, but the first seven factors will be discussed here. The reason for discussing seven factors is that the first four explain less than 50% of the variance. The next logical point in the Scree Plot is the next peak, which is the first seven factors that end up explaining 62.451% of the variance.

Table 4: Florida tracts factors variance explained

Factor	% of Variance	Cumulative %
1	20.471	20.471
2	13.428	33.900
3	10.059	43.959
4	5.905	49.864
5	4.747	54.611
6	4.029	58.640
7	3.812	62.451
8	3.105	65.557
9	2.915	68.472
10	2.742	71.214
11	2.541	73.756

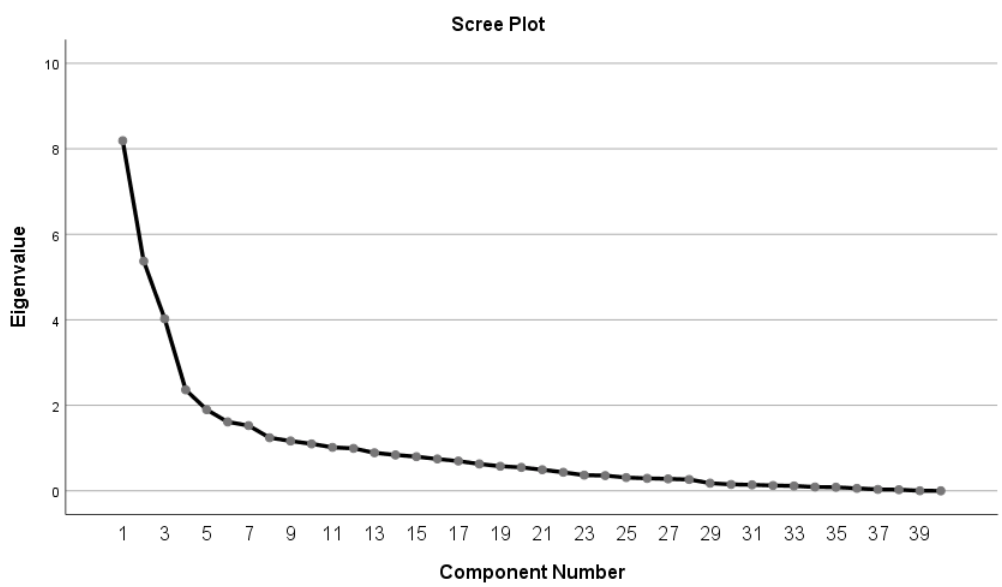

Figure 13: Florida tracts factors Scree Plot

The first factor (% variance explained = 20.471) for the Florida tracts consists the variables loading highly that include percent non-elderly, percent female labor force, percent population with high school diploma, percent no mobile homes, percent population with vehicle, percent with telephone access, percent not employed in primary industry, percent employed, and percent without disability. All of these variables have a positive correlation, which means as these values go up so does the potential resilience of populations. The variables also seem to be describing working middle class communities. The percent non-elderly variable indicates that it is a younger population. Many of the variables are related to employment, but they track toward middle class. The population in question does not work in the primary industry according to the variables which leaves the secondary, tertiary, and quaternary sectors. The Quaternary sector consists of jobs that are research based, or that require upper level education. The variable for high school diploma has a high loading in this factor, but income is not. This indicates the phenomenon that this factor is describing is educated populations, but without high income. Jobs that could require education and have low income would be secondary and tertiary jobs. Secondary and tertiary jobs are both job sectors that the middle class will hold. Therefore, since income is not present and two out of the three types of jobs left are middle class jobs, this is most likely a middle-class population. In addition, there is high loadings for employment overall and high female participation. These variables indicate that, in general, this population is working. The population also owns vehicles, which is one of the costlier items an individual can have, indicating there is some level of wealth. Therefore, this population is working and educated, and most likely middle class. Education can increase resilience, as well as employment (Cutter, Burton, Emrich). The second factor (% variance explained = 13.428) consists of high loadings on road miles, river miles, cultivated land area, no wetland decline, and wetland area. These are mostly environmental variables, but they indicate areas that are not inhabited and have not been recently. These areas have high amounts of wetland area, and they have not declined, according to the variables, which means they have been wetlands for some time. The high number of river miles makes sense with a wetland area, but there is also a high loading on the road miles indicator. The high amount of wetland is not necessary one large area. The wetlands could possibly be spread out in smaller pockets, and have population surrounding or near, which would increase roads. There is also high cultivated land though, which could indicate farming and increase road miles as well. The best name for this factor would be environmental. Wetland areas serve as a protective barrier, thereby increasing resilience.

The third factor (% variance explained = 10.059) has high loadings of people born in the state, Caucasian, racial equality, and housing equality. These factors are describing the Caucasian population that was born and raised in the area that are greater than other races and own more homes than other races, or Caucasian dominated areas. The fourth factor (% variance explained = 5.905) consists of high loadings of percent not international migrant and non-ESL. The population for this factor is people born in the U.S that speak English as their first language. Having a higher amount of native English speakers increases resilience (Cutter, Burton, and Emrich 2010). The fifth factor (% variance explained = 4.747) has high loadings of percent vacant rental unit, high intensity urban area, buildings built between 1970 and 1990, and home ownership. Vacant rental units and high intensity urban are negative which means the population is experiencing the opposite. In this case, the population would be experiencing low vacant rentals and low urban area. Low urban area increases resilience, but low vacant rentals and buildings built between 1970 and 1990 decrease resilience (Burton 2015). The other two variables, built year and home ownership, show older homes that are in fact owned. The fifth factor could be representing rural middle-class home owners because the population is not in an urban setting, the homes are owned, and older which means they homes would be cheaper. Factor six (% variance explained = 4.029) contains high loadings of population near the coast, not hydric soils, and urban. These variables could represent cities on the coast. Not hydric soils decrease risk because they are not erodible, and thereby increase resilience (Burton 2015). Factor seven consists of areas not in the 100- and 500-year flood plain and storm surge, which can be called flooding. Areas located outside of potential flooding have decreased risk resulting in increased resilience (Burton 2015).

Table 5: Florida tract factor break down

	1	2	3	4	5	6	7	8	9	10	11
PNE	0.553										
PFLFP	0.666										
PPHSD2	0.699										
PNMH	0.769										
PWV	0.862										
PWODHH	0.864										
PT	0.924										
PNEPI	0.926										
PE	0.935										
PWOD	0.944										
RoadMiles		0.595									
RivMiles		0.881									
LACul		0.979									
LANWD		0.979									
LAW		0.979									
PBSRS			-0.585								
PNM			0.564								
RE			0.741								
HE			0.769								
PNIM				0.884							
PNESL				0.912							
PVRU					-0.568						
PerHIU					-0.541						
PBB79					0.419						
PHO					0.684						
PopOut15KM						-0.46					
PerNH						0.708					
PerUrban						0.75					

PerNFSS							-0.609				
PerNF500							0.826				
PerNF100							0.873				
PEPO								0.522			
EE								0.651			
PerCap								0.719			
LADOS									0.495		
LANFRD									0.679		
PerFor									0.776		
RailMiles										0.879	
HHDamSqMi											0.375
CRST14_1											0.796

4.2.3 PCA Results: MS/AL Census Block Group Level

The MS/AL block groups had a total of 12 factors that explained 69.996% of the variance (Table 6). The Scree Plot (Figure 14) shows that the most impactful factors are the first four. However, the first eight will be analyzed for the same reason as the Florida Tract. The first eight factors explain 58.389% of the variance (Table 6).

Table 6: MS/AL block groups factors variance explained

Factor	% of Variance	Cumulative %
1	17.432	17.432
2	10.820	28.252
3	6.943	35.195
4	6.664	41.859
5	4.797	46.656
6	4.343	50.999
7	3.835	54.894
8	3.555	58.389
9	3.047	61.437
10	2.978	64.414
11	2.873	67.288
12	2.709	69.996

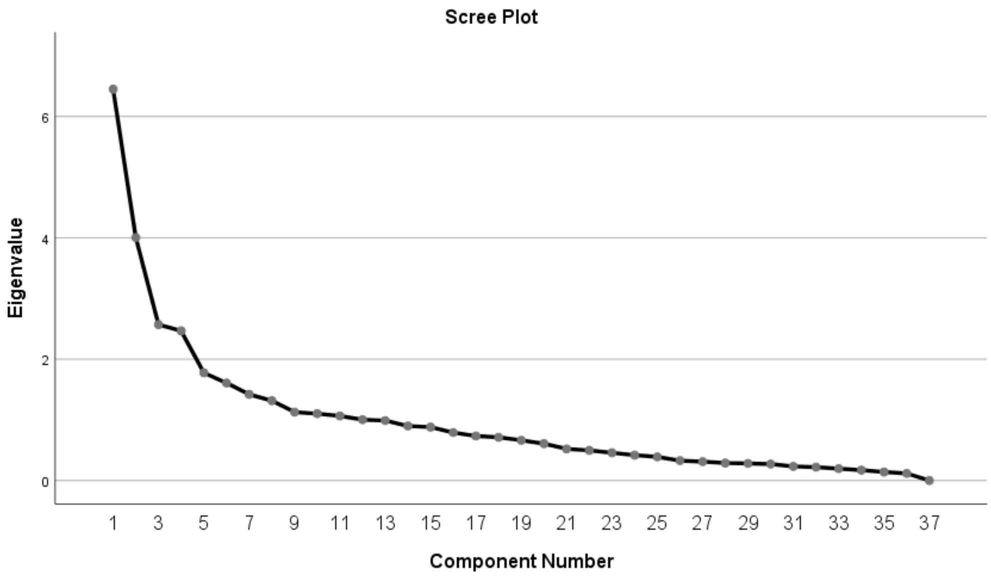

Figure 14: MS/AL block groups Scree Plot

The first factor (% variance explained = 17.432) has high loadings on environmental based variables with forest area, no forest/rangeland decline, developed open space area, cultivated land area, wetland area, river miles, but also road miles and population away from the coast. Due to the cultivated, no rangeland decline, and roads, this could be a rural area with farming that is also combined with wetland. Cultivated and rangeland indicate farming, but access is required to get to these farms, which could explain the roads. Most of the high loaded variables revolve around an environmental theme which makes the first factor here also environmental. Wetlands and forest provide barriers that in turn increase resilience, while roads allow evacuation that increases resilience (Burton 2015). The second factor (% variance explained = 10.820) has high loadings in percent employed, percent population with vehicle, percent population without disability, percent not employed in primary industry, and percent population with phone access. Three of the variables deal with employment, so a major part of this factor is working. The other two variables deal with accessibility. The second factor could represent employment and accessibility. Employment is a sign of secure livelihood, which increases resilience (Cutter, Burton, and Emrich 2010). The third factor (% variance explained = 6.943) includes high loadings of professional occupation, population with high school diploma, education equality, and per capita income. Professional occupation, high school diploma, and per capita indicate a highly educated and well-off population. The high school diploma variable indicates that the population is educated, but there is evidence that the population obtained a higher educated as well. Professional jobs are part of the quaternary job sector which requires higher education typically. These types of jobs are better paying as well, which explains the high loading per capita. For these reasons, the third factor is educated and wealthy. Education is a main driver according to this factor, and education increases resilience (Cutter, Burton, and Emrich 2010). The fourth factor (% variance explained = 6.664) involves all the flooding variables: not in 100- and 500- year flood plain and not in storm surge. Areas that are not at risk of flooding have increased resilience (Burton 2015). The fifth factor (% variance explained = 4.797) includes high loadings of high intensity urban, non-elderly, and home ownership, but high intensity urban and non-elderly are negative. These variables being negative means that this population is not in an urban area, elderly, but has home ownership. Variables that describe urban to rural living in homes owned by elderly would indicate the factor could be representing retired communities. Elderly population actually decreases resilience (Burton 2015). The sixth factor (% variance explained = 4.343) includes non-ESL speakers and non- international migrants, which means U.S. born English speakers, thereby increasing resilience (Cutter, Burton, and Emrich 2010). The seventh factor (% variance explained = 3.835) contains hydric soils, due to being negative, and no wetland decline, which means this factor is simply wetlands. Wetlands create a barrier to hazards which increases resilience (Burton 2015). The eighth and final factor (% variance explained = 3.555) contains high loadings of racial and housing equality which could represent equality. Inequality, racial and housing, can decrease resilience (Cutter, Burton, and Emrich 2010). To recap, the factors are rural farming/wetland, employment/accessibility, educated/wealthy, flooding, retired, U.S. born English speakers, wetlands, and equality.

Table 7: MS/AL block groups factor break down

	1	2	3	4	5	6	7	8	9	10	11	12
PopOut15KM	0.466											
PerFor	0.551											
RoadMiles	0.711											
LANFRD	0.74											
LADOS	0.798											
LACul	0.82											
LAW	0.82											
RivMiles	0.864											
PE		0.662										
PWV		0.679										
PWOD		0.701										
PNEPI		0.742										
PT		0.756										
PEPO			0.403									
PPHSD2			0.651									
EE			0.735									
PerCap			0.806									
PerNFSS				-0.679								
PerNF500				0.882								
PerNF100				0.908								
PerHIU					-0.626							
PNE					-0.397							
PHO					0.763							
PNESL						0.923						
PNIM						0.93						
PerNH							-0.706					
LANWD							0.71					
RE								0.779				
HE								0.811				
PNMH									-0.535			
PNM									0.587			
CRSBG14_1									0.718			
PVRU										0.529		

PBB79										0.812		
RailMiles											0.578	
PerUrban											0.682	
HHDamSqMi												0.904

4.2.4 PCA Results: Florida Census Block Group Level

Florida block groups had a total of 11 factors that explain 66.178% of the variance (Table 8). The Scree Plot (Figure 15) shows that the first six factors are the most impactful, and explain 50.253% of the variance (Table 8).

Table 8: Florida Block groups factors variance explained

Factor	% of Variance	Cumulative %
1	14.341	14.341
2	12.882	27.223
3	7.809	35.033
4	5.437	40.470
5	4.921	45.390
6	4.863	50.253
7	3.865	54.118
8	3.384	57.502
9	3.020	60.552
10	2.918	66.440
11	2.737	66.178

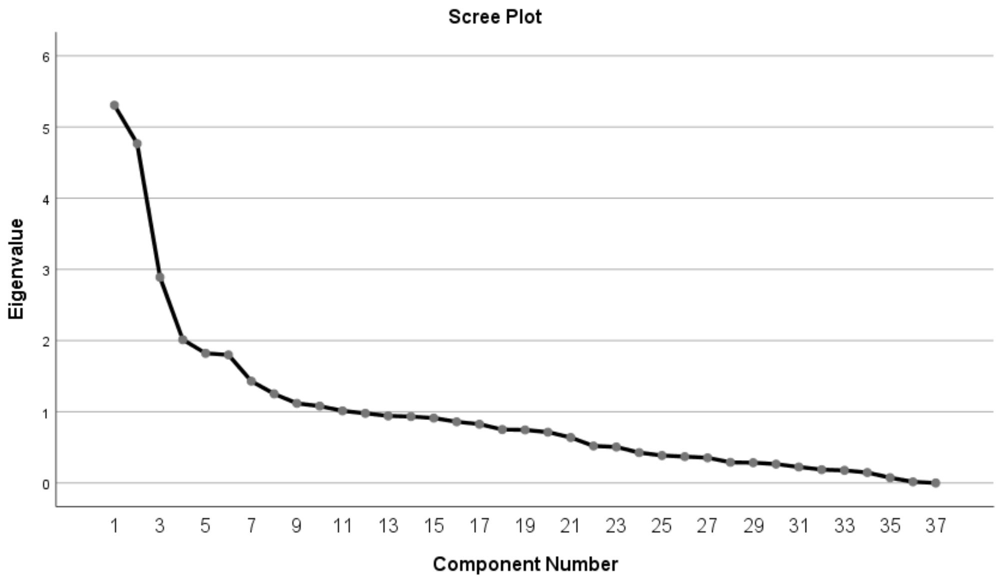

Figure 15: Florida block groups Scree Plot

The first factor (% variance explained = 14.341) is once again high loading environmental variables with river miles, no wetland decline, cultivated, and wetland. The best name for this factor would be environmental. The second factor (% variance explained = 12.882) contains high loadings on variables such as populations with at least a high school diploma, no mobile homes, populations without disability, households with vehicle, population employed, and populations not employed in the primary industry. These variables are similar to some seen in the Florida Tracts which showed a working middle class. The population is not in the primary industry, but not in professional jobs either, which means they are holding middle class jobs. Employment is two of the variables which could also indicate they are a working population. The population is educated, working, and has enough money to own a vehicle (or depends on it for work), which indicates this factor is working middle class. Without disability and vehicles make evacuation easier, employment indicates stable livelihood, and non-mobile homes can sustain more damage making all of these increase resilience (Burton 2015). The third factor (% variance explained = 7.809) has high loadings that pertain to U.S. born English speakers with the variables non international migrant and non-ESL speakers, and these characteristics increase resilience (Cutter, Burton, and Emrich 2010). The fourth factor has high loadings of low urban area, low high intensity urban area, high amounts hydric soils, populations away from the coast, and developed open space area. Hydric soil can indicate wetlands since that kind of soil is capable of holding water. Low urban, high intensity urban, and developed open space indicate a rural area since these are indicating the opposite of an urban area. The fourth factor could represent rural away from the coast. Areas away from the coast will most likely be at less risk for flooding, which will increase their resilience (Cutter, Burton, and Emrich 2010). The fifth factor (% variance explained = 4.921) contains high loadings of high elderly, housing equality, racial equality, and non-minorities. Housing/racial equality and non-minorities are showing a Caucasian dominated population, which means factor five is elderly Caucasian. Elderly will actually decrease resilience since it is harder for elderly to evacuate and bounce back after a hazard (Burton 2015). Factor six (% variance explained = 4.863) has high loadings for flooding in areas not in the 100- and 500- year flood plain and storm surge, which will increase resilience since the areas are at less risk (Burton 2015). To recap, the factors are environmental, working middle class, U.S. Born English speakers, rural area away from coast, elderly Caucasian, and flooding.

Table 9: Florida block groups factor break down

	1	2	3	4	5	6	7	8	9	10	11
RivMiles	0.873										
LANWD	0.978										
LACul	0.98										
LAW	0.98										
PPHSD2		0.654									
PNMH		0.665									
PWOD		0.739									
PWV		0.79									

PE		0.828									
PNEPI		0.845									
PNIM			0.867								
PNESL			0.929								
PerUrban				-0.8							
PerNH				-0.731							
PerHIU				-0.424							
PopOut15KM				0.497							
LADOS				0.504							
PNE					-0.574						
HE					0.553						
RE					0.609						
PNM					0.709						
PerNFSS						-0.582					
PerNF500						0.833					
PerNF100						0.882					
PVRU							-0.621				
PT							-0.609				
PHO							0.459				
RoadMiles								0.528			
RailMiles								0.816			
PBB79									-0.469		
PerCap									0.597		
EE									0.611		
LANFRD										0.593	
PerFor										0.776	
CRSBG14_1											0.393
PEPO											0.414
HHDamSqMi											0.779

4.2.5 Between Study Area and Scale PCA Comparison

Table 10 shows that all, but Florida tracts, have environmental as the first factor. This means that across both study areas and scales that the environmental characteristics explain the greatest percentage of variance when considering what variables may be the most important contributing factors to the resilience concept considering this particular study area. Conversely, all of the PCA runs with the exception of the MS/AL tract level have a variation of working and employment as one of the top two factors. Overall, this shows that location and necessarily scale is associated with what may be the most pertinent drivers of resilience within the study area. The first two factors are nearly the same across all study areas and scales, while the rest is also quite similar but in a different order. Environmental, employment, and flooding appear in every study area and scale. Variables measuring non-minorities, education, and non-foreign residents appear in three of the four study areas and scales. This further proves that the same factors could be driving resilience, but the impact of the factors changes with location and scale. The PCA demonstrated that the biggest drivers of resilience in terms of variability explained that differ according to scale are environmental and employment/working, and the remaining drivers are the same between locations and scales with a different order of impact.

Table 10: The final factor names for each scale and study area together

	Tract		**Block Group**	
	MS/AL	**FL**	**MS/AL**	**FL**
1	Environmental	Working/Educated	Environmental	Environmental
2	New Caucasian Residents	Environmental	Employment/Accessibility	Working Middle Class
3	Employment	Native Caucasian Dominant	Educated/Wealthy	U.S. Born English Speaking
4	Education/Accessibility	U.S. Born English Speaking	Flooding	Rural Area Away from Coast
5	Flooding	Rural Middle-Class Home Owners	Retired	Elderly Caucasian
6		Coastal Cities	U.S. Born English Speaking	Flooding
7		Flooding	Wetlands	
8			Equality	

4.3 Results of Statistical Analyses to Understand the Differences Between Groups

4.3.1 ANOVA

The PCA results in subsections 4.2 only go so far in that they demonstrate that the variables that explain the most variability in the resilience assessment are relatively constant across the scales chosen for this analysis. Gaining an improved understanding of how the measured resilience of populations changes with the spatial extent of the SLR hazard was the subsequent step. To accomplish this step, an ANOVA was conducted on the composite BRIC scores selected via their intersection with the four SLR zones identified for this research. This is to understand if there is any statistical difference between the overall resilience of populations within each SLR zone (0ft., 3ft., 6ft., 9ft.), and at the two different scales of analysis explored for this work. The results of the ANOVA (Table 11) show that there is no statistically significant difference in the resilience of populations considering the different SLR zones at the census block group level. The latter applies to both study regions (i.e. the Mississippi/Alabama coastal counties and the Southern Florida coast). However, there is a statistically significant difference between the two study areas at the census tract level of geography. The typical level of significance for the ANOVA and Post-hoc tests are P <= 0.05 where the null hypothesis that the samples are the same is rejected, and MS/AL tracts and Florida tracts show that the statistical significance between groups was .002 and .003 respectively (see Table 11). This shows that there is a significant difference between the resilience of populations as per the composite index within the different SLR zones at the census tract level. This significance was not demonstrated at the block group level for Florida, however. Table 11 shows levels of significance for the tract level comparison at 0.06 and 0.657 respectively.

Table 11: ANOVA Significance Results

	Tract		**Block Group**	
	MS/AL	**FL**	**MS/AL**	**FL**
Significance	0.002	0.003	0.066	0.657

The differences in statistical significance across the SLR groups that were signaled by the ANOVA have demonstrated that the MAUP is likely occurring and impacting the results of the

ANOVA. Here, a statistical bias may be resulting when the block group level census data is aggregated into tracts. The result is that the values, and any corresponding indicators derived from them, are being influenced by aggregation and the scale and shape of the aggregation unit. In this case, the aggregation of census data may have led to distinct zones distinguishable within the ANOVA, but not recognized at higher resolutions. This result demonstrates that scale matters and that a one-size-fits-all approach for measuring resilience may not be fully beneficial. It is within this context that the MS/AL study area does not experience MAUP to the same degree that the Florida study area does. The MS/AL census units still exhibited statistical significance at the tract level, and not at the block group level. This change, although to a lesser degree, still shows MAUP is at play since once again the only variable changed was scale.

Unfortunately, the ANOVA is limited because it only tests to see if groups are different or the same considering data means, so the result is global and fails to demonstrate the extent of differences between groups, if any. For this reason, Post-hoc tests were developed to see how different groups are, and which groups are different. To explore the relationship between the SLR groups and resilience further, Turkey's Post-hoc test was conducted for the Post-hoc portion of the analysis. Tukey's Post-hoc test compares the means of the different groups to show how different the groups were from each other. Surprisingly, the results indicated that there was almost no statistical significance between the groups. Table 12 demonstrates that for MS/AL tracts there is only significance between 0 ft and 9 ft of SLR of 0.025. In the previous ANOVA there was significance for the MS/AL tracts, but the ANOVA test was most likely picking up the relationship between 0 ft and 9 ft SLR. This shows that the ANOVA can be misleading since it showed promising results, which is why the ANOVA was followed by a Post-hoc test. When the relationships were analyzed more in-depth through the Post-hoc test, it becomes clear that there is little difference between the measured resilience between the 4 SLR zones unless the extremes are considered (i.e., 0ft. and 9ft.). These paradoxical results are reflected when the Florida tracts are considered as well. Florida tracts had a statistical significance in the ANOVA, but only had significance between SLR of 0 feet and 6 feet of 0.011 (Table 13). While a value of 0.011 is statistically significant, it is the same as the MS/AL tracts where only having significance between two groups might not equate to statistical difference within the entire study area at that scale.

Both Tables 14 and 15 are at the block group level and show no significance, which was expected based on the previous ANOVA. The best significance for the MS/AL study area occurred between the 0 ft and 9ft SLR Zones at both scales. Florida did not show the same relationship between scales. The best significance for Florida block groups was between 0 ft and 3 ft SLR at $P \leq 0.678$ (Table 15), while the best significance at the tract level was between 0 ft and 6 ft SLR. MS/AL study area shows that scale did not stop the same general trends from coming through in the Post-hoc tests since the same zones had the best significance for both scales, while in the Florida study area the scale change impacted the trends.

Table 12: Tukey's Test results for MS/AL tracts with significance of 0.05

	0 ft	**3 ft**	**6 ft**	**9 ft**
0 ft		0.115	0.181	0.025
3 ft	0.115		0.997	0.734
6 ft	0.181	0.997		0.878
9 ft	0.025	0.734	0.878	

Table 13: Tukey's Test results for Florida tracts with significance of 0.05

	0 ft	**3 ft**	**6 ft**	**9 ft**
0 ft		0.249	0.011	0.158
3 ft	0.249		0.695	0.685
6 ft	0.011	0.695		0.971
9 ft	0.158	0.685	0.971	

Table 14: Tukey's Test results for MS/AL block groups with significance of 0.05

	0 ft	3 ft	6 ft	9 ft
0 ft		0.470	0.578	0.133
3 ft	0.470		1.000	0.848
6 ft	0.578	1.000		0.817
9 ft	0.133	0.848	0.817	

Table 15: Tukey's Test results for Florida block groups with significance of 0.05

	0 ft	3 ft	6 ft	9 ft
0 ft		0.678	0.999	0.891
3 ft	0.678		0.844	1.000
6 ft	0.999	0.844		0.933
9 ft	0.891	1.000	0.933	

4.3.2 Moran's I

Since the ANOVA and Post-hoc tests offered inconclusive results, methods utilizing the concept of spatial autocorrelation were employed to better understand the underlying patterning of resilience within the different SLR zones. Spatial autocorrelation is based on the basic principal that data values measured at a given spatial location are dependent on the values around it. The most common example of spatial autocorrelation is clustering, where objects in the same group are more similar to each other than those in other groups. An example of this would be positive spatial autocorrelation in high-end neighborhoods. Typically, costly homes in an exclusive neighborhoods will be located in proximity to other costly homes, or clustered. It is unusual to see a large affluent home in a community consisting of predominantly mobile and modular homes, for example. The other example of autocorrelation is when values are dispersed, or repelled by one another (i.e., negative spatial autocorrelation). The same values want to be as far from one another as possible. The final possibility is random, or no spatial auto correlation. Moran's I is a spatial statistic used to measure spatial autocorrelation that analyzes the data and determines if the same values are spatially near each other (clustered), repelling each other (dispersed), or random. It is within this context that a global Moran's I was run in ArcGIS to see if the resilience of populations is clustered within the SLR zones.

Figures 16-19 demonstrate that the resilience data is clustered into very distinct geographic zones. The Moran's Index ranges from -1 to 1 with anything below 0 being dispersed, above zero clustered, and 0 being completely random. All of these results are between 0 and 1 meaning they are clustered, but the closer to 1 the Moran's Index is, the more clustered the data is. Conversely, the closer to 0 the Moran's Index the closer to random the data is. The data is still clustered because it is above 0, but it is not highly clustered. Figures 16 and 18 shows that MS/AL tracts and block groups are highly clustered with a Moran's Index of 0.87 at the tract level and 0.99 at the block group level. Since the same values are clustering together, there is little statistical variation is the different SLR zones. The reason being that when SLR increases from 0 ft to 3 ft, for example, the census units that are included in the 3 ft SLR are still of the same cluster from 0 ft. Likewise, since the data is clustered, there are multiple clusters being captured in one SLR zone, which is essentially averaging all the values. The Florida study area is similarly clustered, but not nearly as much as the MS/AL study areas. Figure 17 and 19 shows that at the Tract level there is a Moran's Index of 0.09, while at the block group level Moran's Index is 0.13. These scores are low, but still show clustering. Another noteworthy result is that Moran's Index is higher in both study areas at that census block group Level as opposed to the tract level. Higher clustering, or auto-correlation, at the block group level is once again showing that scale has a sizable impact on the results of this study and should be considered when choosing the appropriate spatial resolution for measuring resilience. Every analysis thus far has shown that the block groups between the two study areas show similar results relative to their study areas, and this occurs with the tracts as well. This Moran's Index analysis was done at the global scale, and showed BRIC Scores are spatially auto correlated for the study area as a whole. A series of Moran's I analysis were also conducted at the local level to show the relationships between clusters. Local Moran's I is a local spatial autocorrelation statistic that is based on the Moran's I statistic where each observation gives an indication of the extent of significant spatial clustering of similar values around that observation (Anselin, L 1995).

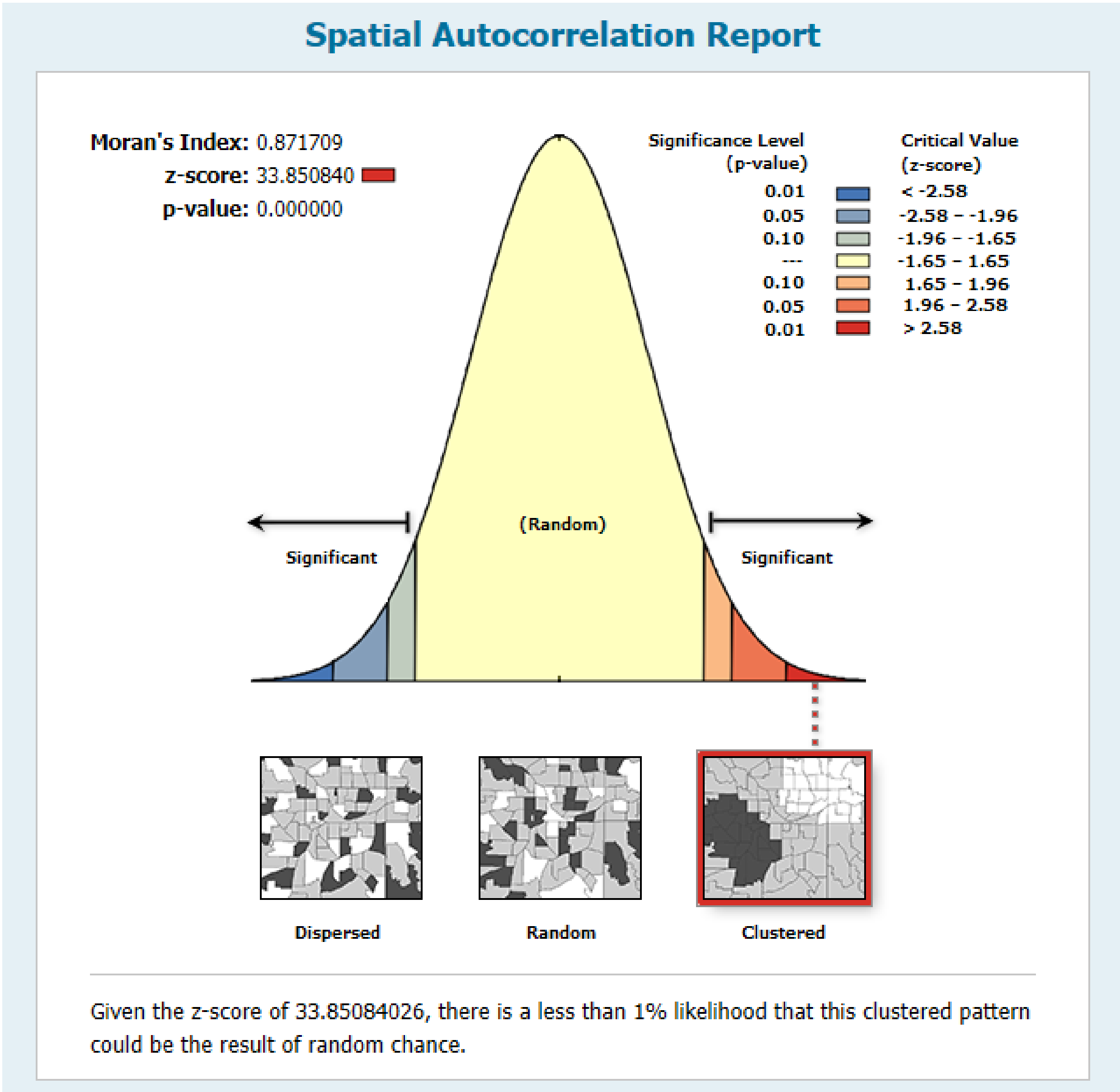

Figure 16: MS/AL tracts Global Moran's I Analysis conducted on BRIC Scores.

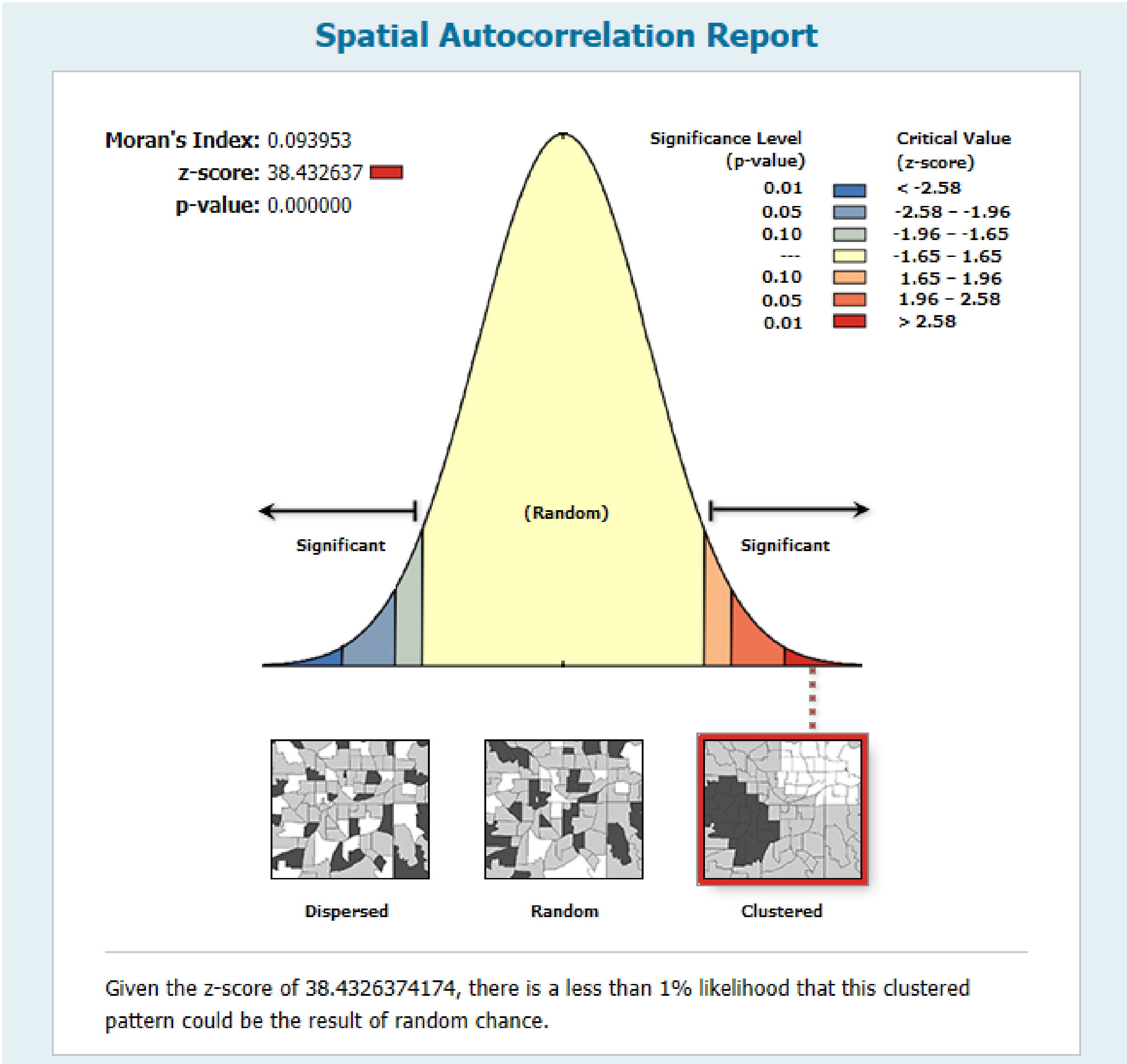

Figure 17: Florida tracts Global Moran's I Analysis conducted on BRIC Scores.

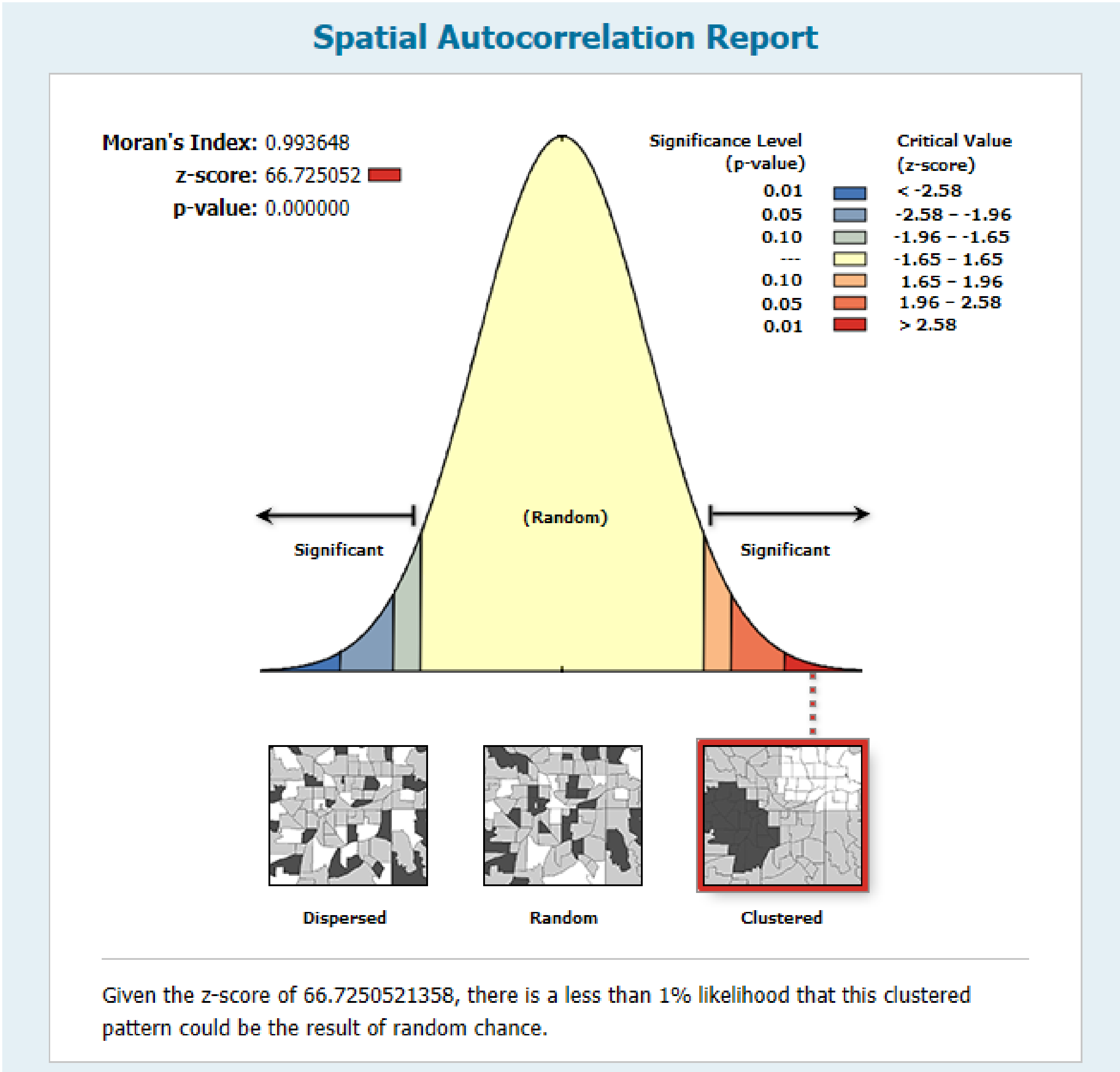

Figure 18: MS/AL block groups Global Moran's I Analysis conducted on BRIC Scores.

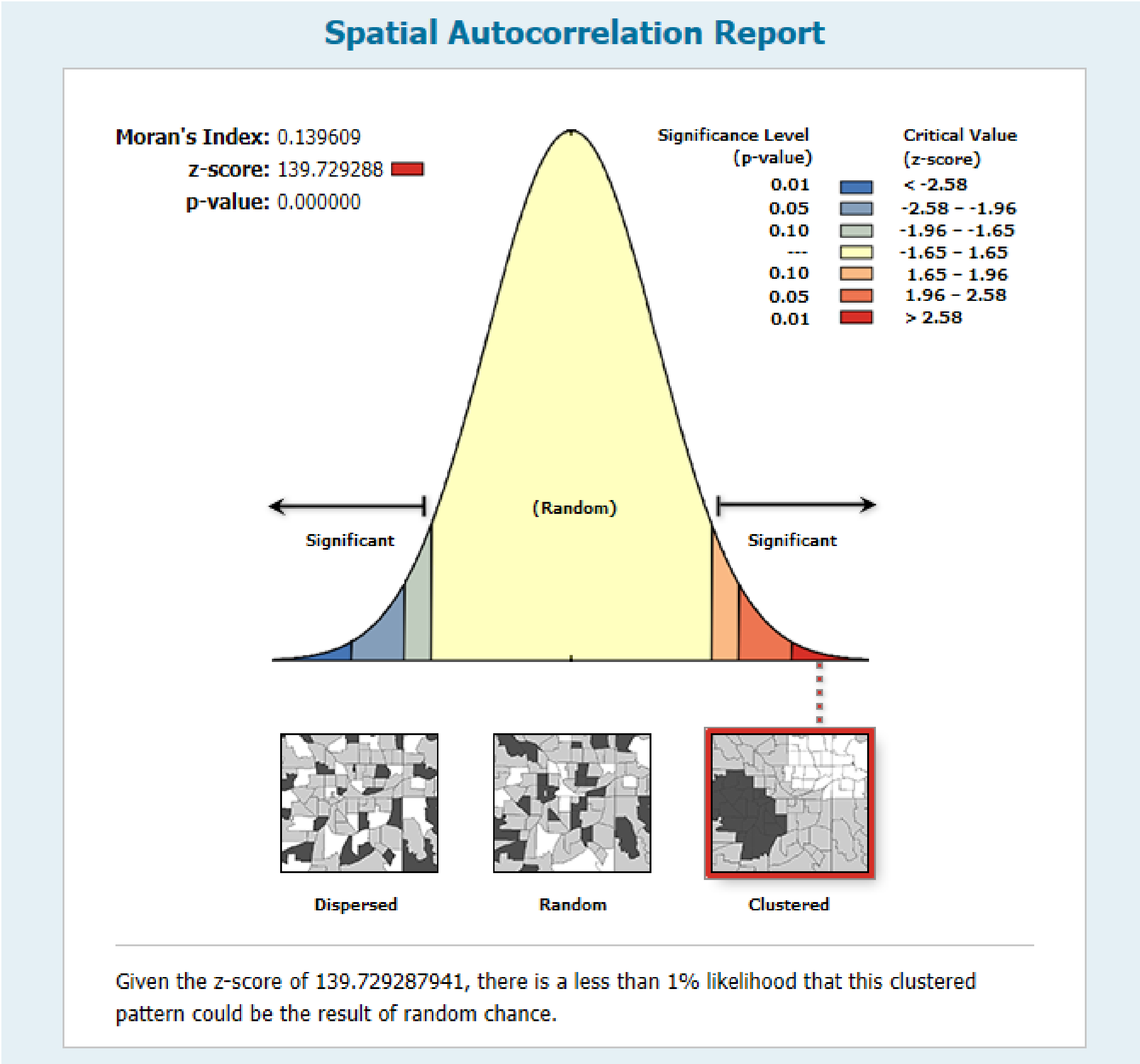

Figure 19: MS/AL block groups Global Moran's I Analysis conducted on BRIC Scores.

The results of the local Moran's I shows where census units with high and low composite scores of resilience are in relation to each other. If there are two census units next to each other with high BRIC Scores, then it will have a High-High relationship. The other possible relationships are High-Low (a high next to a low), Low-High (low next to high), Low-Low (low next to low), and not statistically significant. Figures 20 and 21 show MS/AL tracts and block groups respectively with the Moran's I results.

The area of Low-Low resilience in both Figures 20 and 21 encompass the city of Mobile. High-High resilience areas encompass Diamondhead and D'Iberville. Gulfport and portions of Biloxi seem to be in areas that don't have statistical significance. Some block groups, for example, within the greater Mobile area have High-Low block groups. This means that those block groups in the Mobile area have high resilience scores and are juxtaposed next to block groups with low resilience scores. There are also block groups in the Gulfport area that a low-high resilience relationship with Diamondhead and D'Iberville communities.

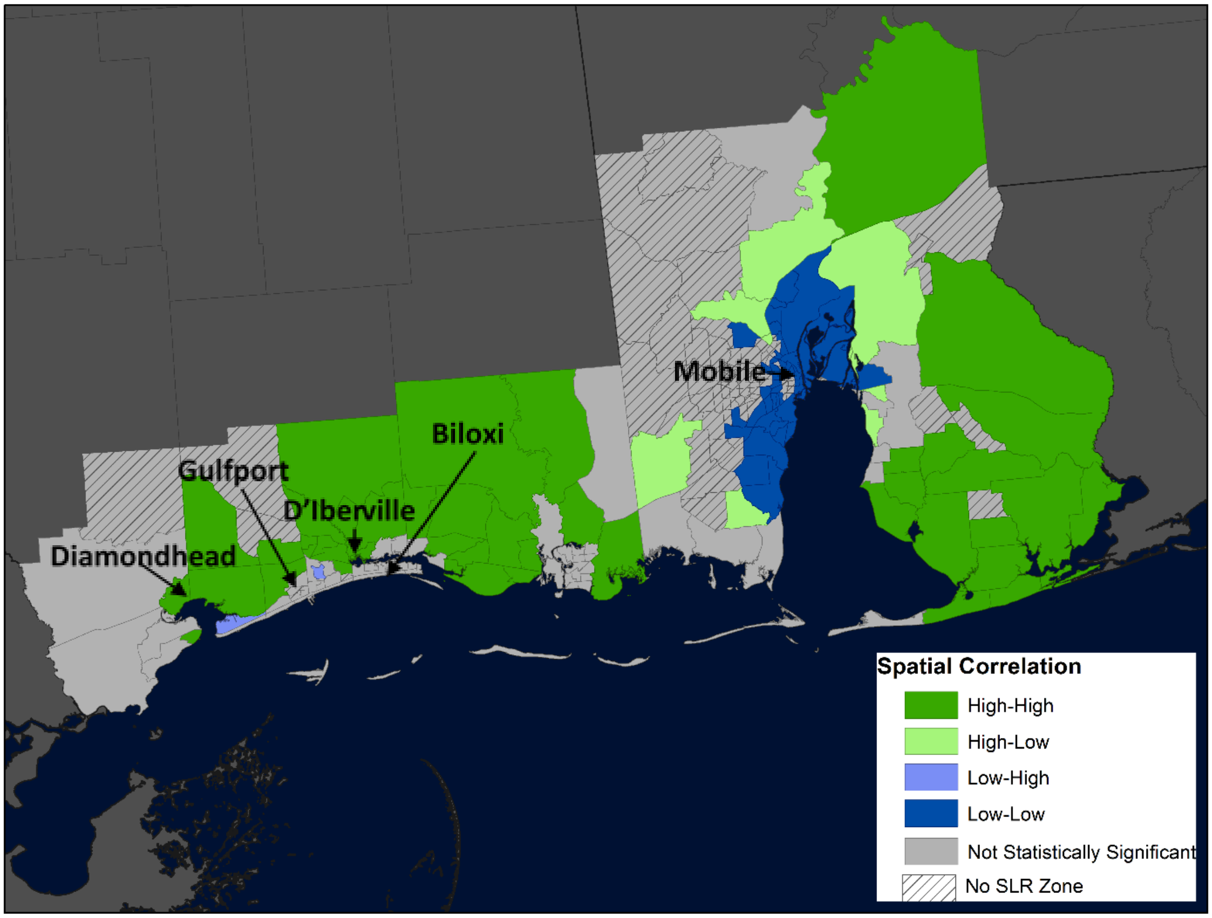

Figure 20: MS/AL tracts Moran's I Analysis. Hatched areas did not intersect any of the SLR layers. Grey were not statistically significant.

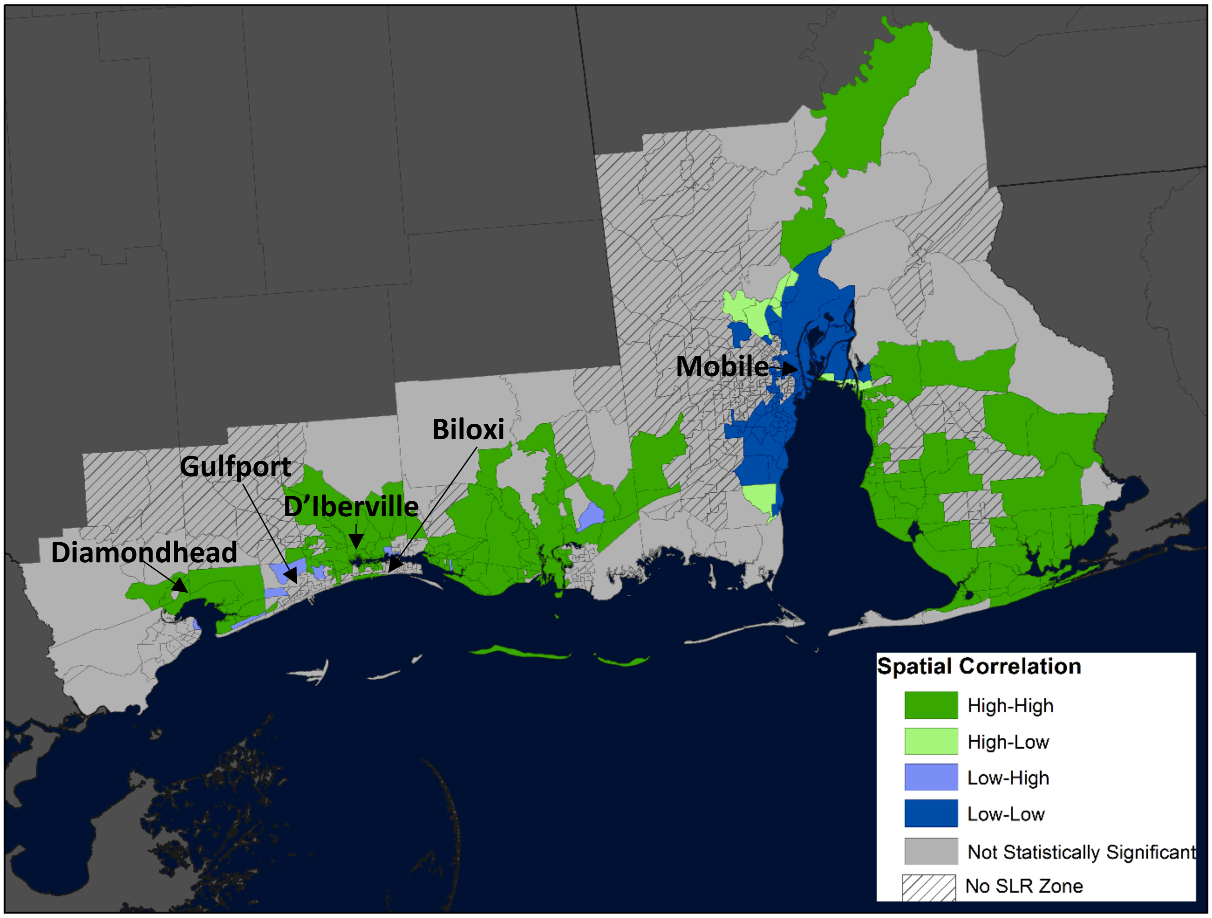

Figure 21: MS/AL block groups Moran's I Analysis. Hatched areas did not intersect any of the SLR layers. Grey were not statistically significant.

Figures 22 and 23 show all of the Florida study area, but due to the high population along the east coast it is difficult to see what is actually occurring. A majority of the Florida study area is actually very large census units that do not aid in understanding the data, so most of the Moran's I analysis for Florida will be directed at Figures 24 and 25 that are zoomed in to the populated east coast. The top portion of the study area is mostly High-High resilience with some low high scattered throughout, while the bottom portion is the opposite with Low-Low resilience and some high low scattered throughout. There is a clear division between these two sections where there is a strip of units that are not statistically significant. This divide is most likely the area between Fort Lauderdale to the north and Hollywood to the south, which is Dania Beach. Another interesting finding clearly seen in Figure 25 is a bulls-eye type of effect of clustering within block groups. Miami is an area of Low-Low resilience, but instead of the entire area being Low-Low there is a pocket of high-Low resilience which appears to be the Kendall area surrounding Zoo Miami. This makes sense because the Zoo Miami is not statistically significant because there was most likely no demographic data for this area meaning the values were null instead of zero.

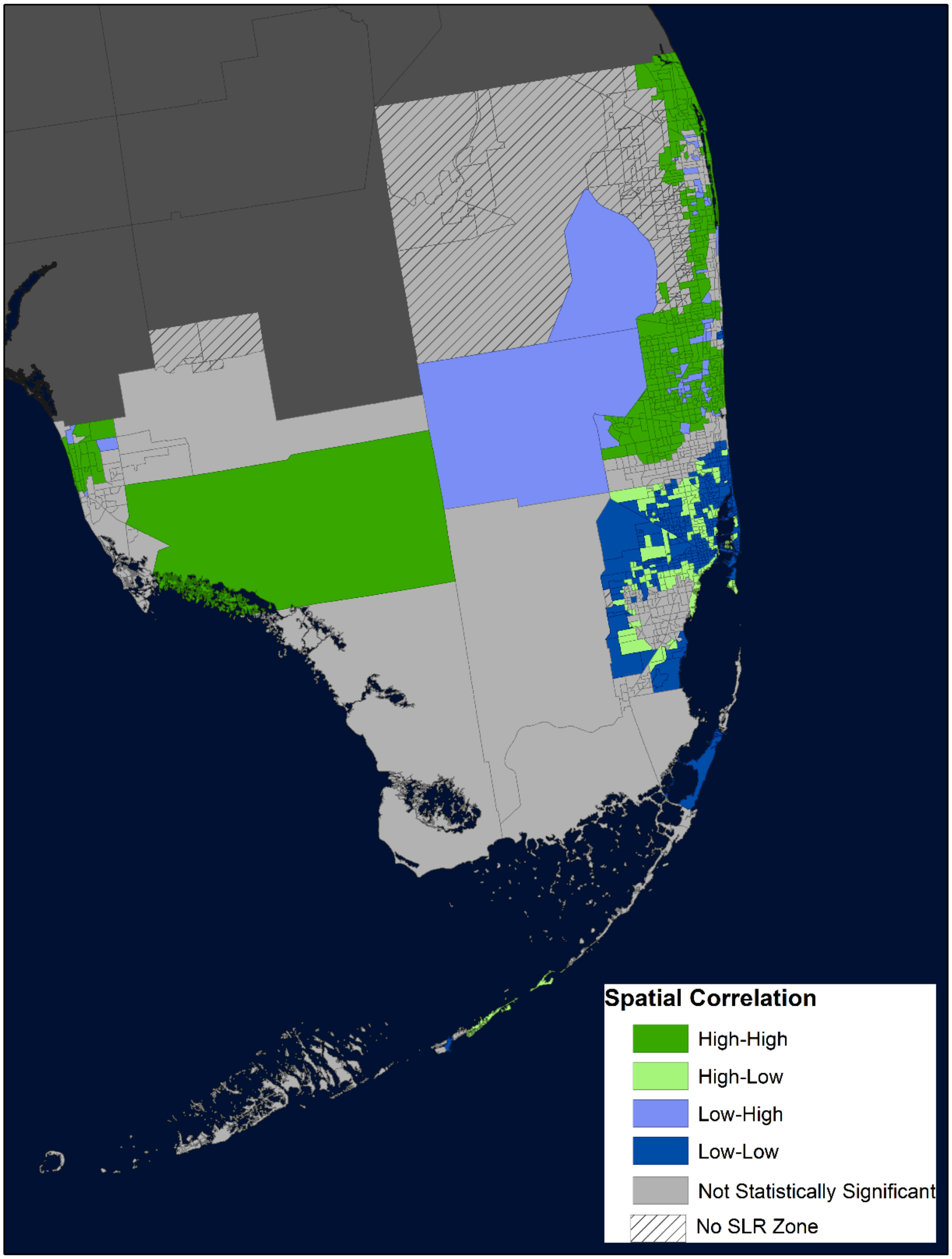

Figure 22: Florida tracts Moran's I Analysis. Hatched areas did not intersect any of the SLR layers. Grey were not statistically significant.

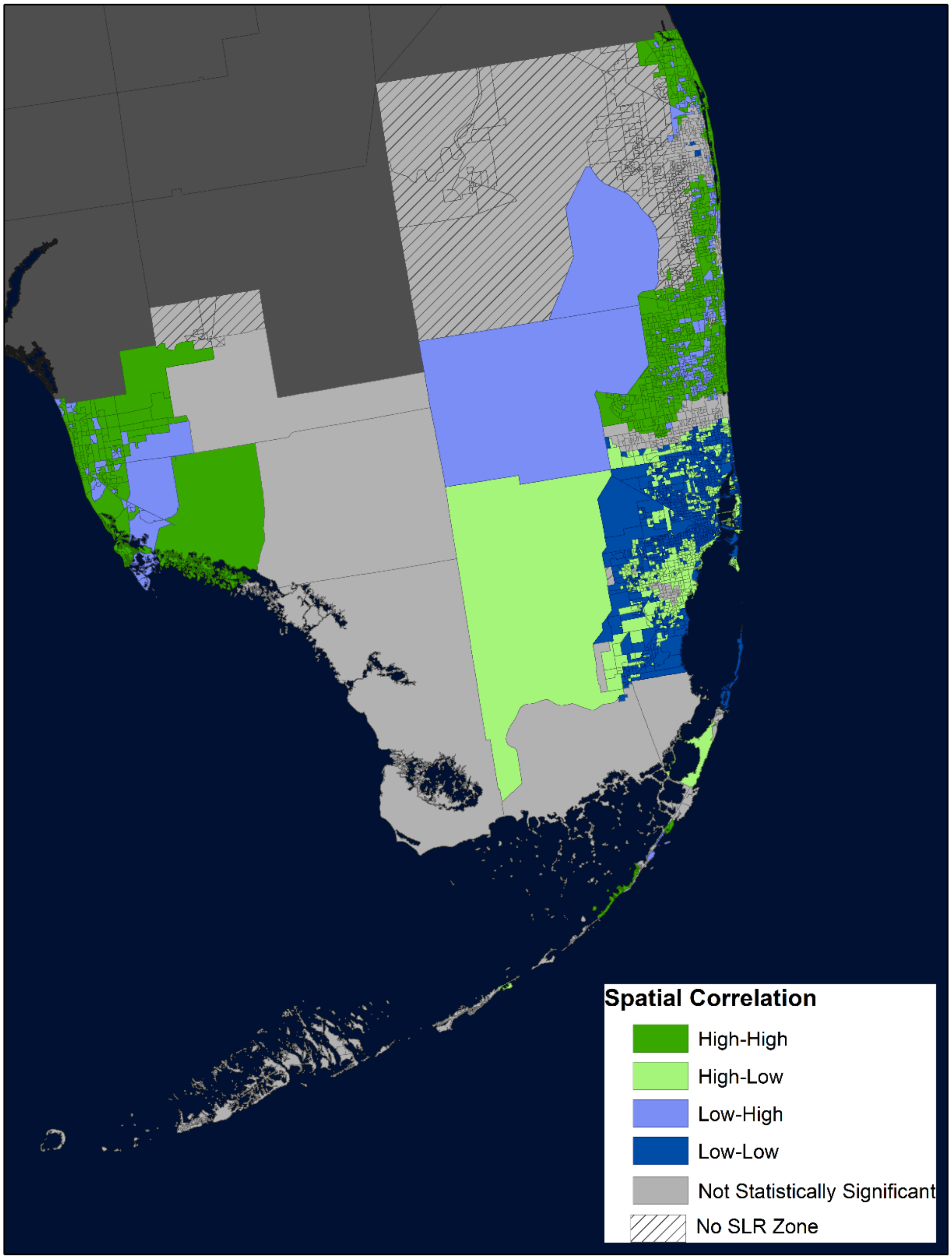

Figure 23: Florida block groups Moran's I Analysis. Hatched areas did not intersect any of the SLR layers. Grey were not statistically significant.

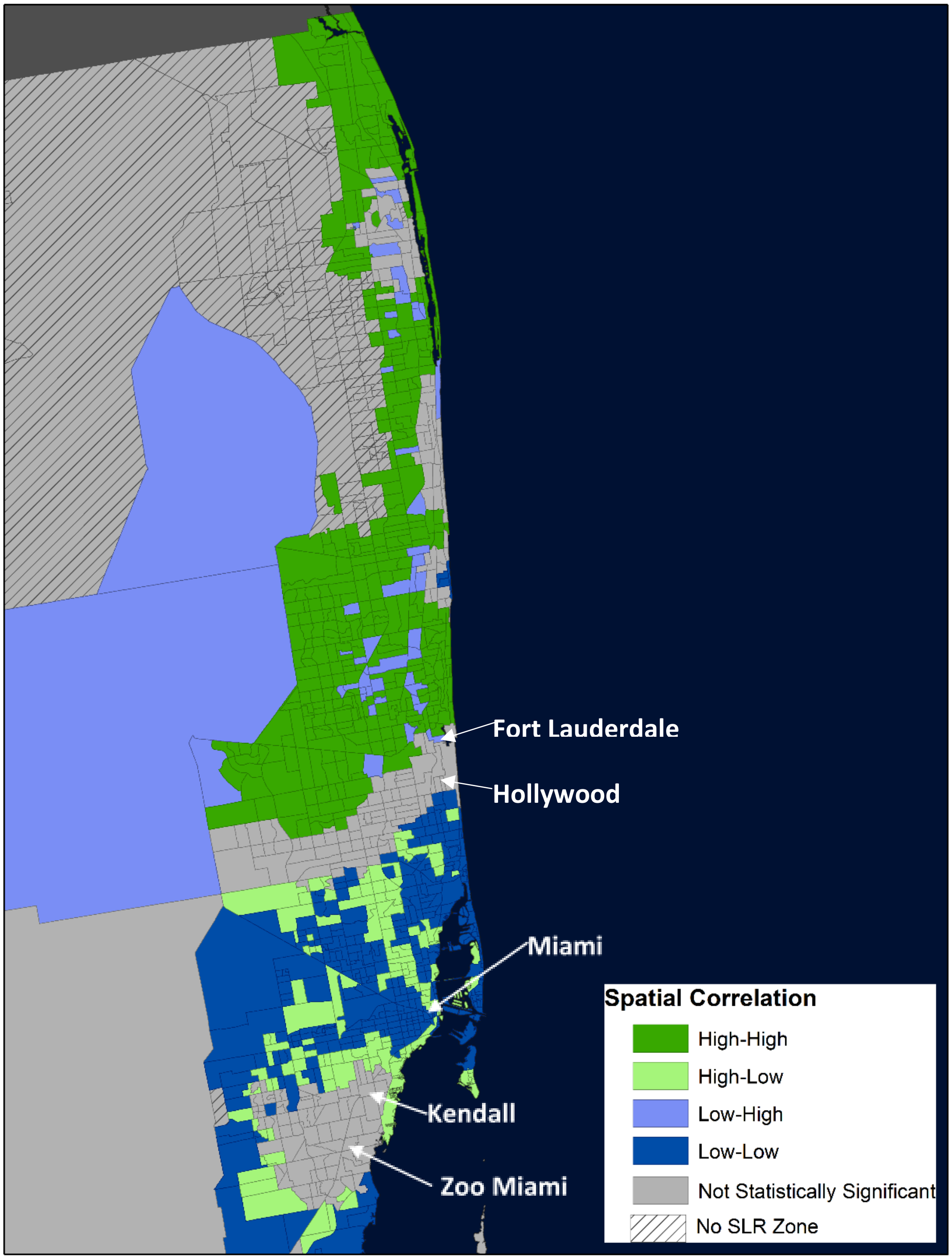

Figure 24: Florida tracts Moran's I Analysis. Zoomed into the East Coast. Hatched areas did not intersect any of the SLR layers. Grey were not statistically significant

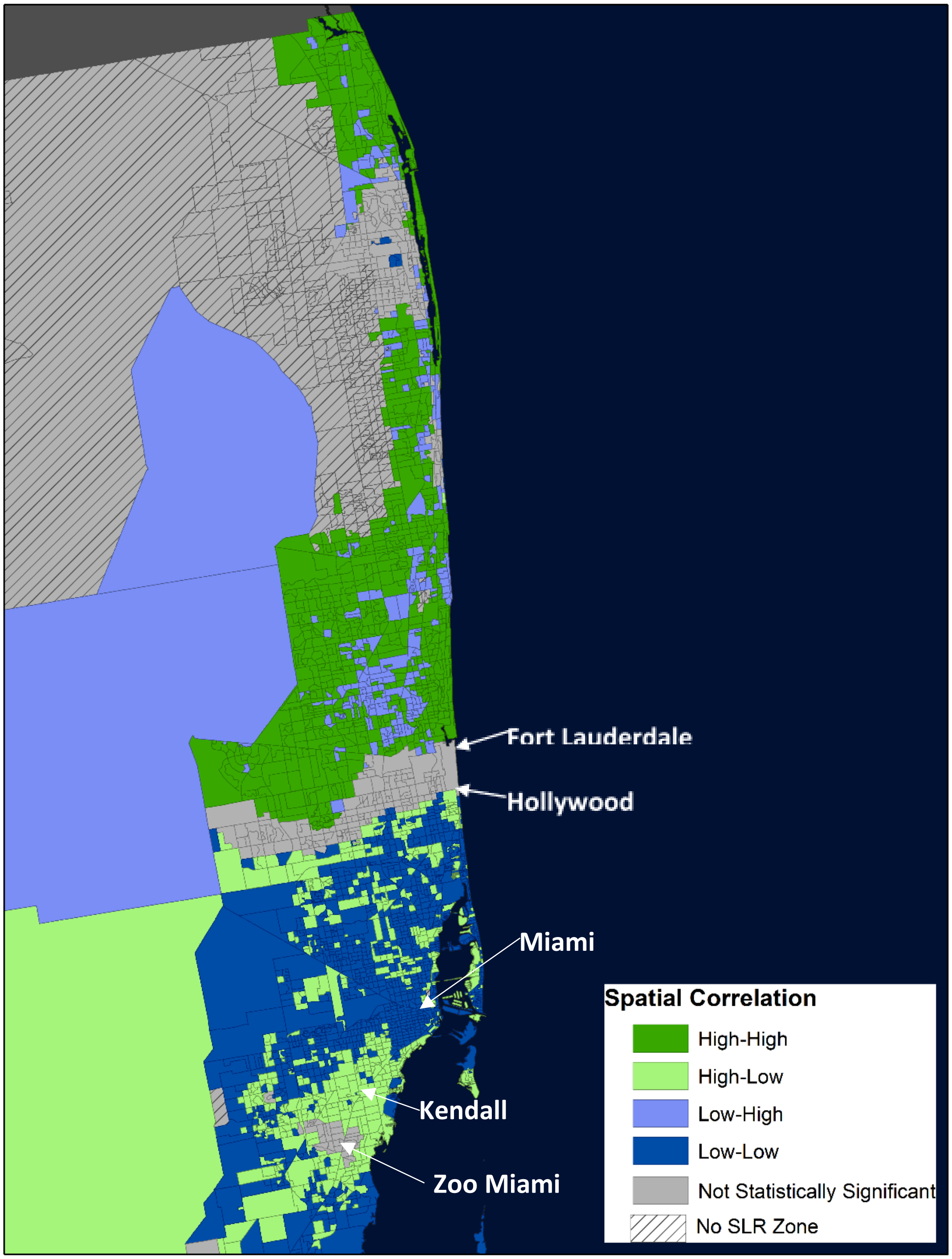

Figure 25: Florida block groups Moran's I Analysis. Zoomed into the East Coast. Hatched areas did not intersect any of the SLR layers. Grey were not statistically significant.

The local Moran's I analysis gave some insight into why the ANOVA and Post-hoc tests showed low statistical relationship results. A good example would be the Florida coast which showed inconclusive statistical results. The SLR layers would be along the entire coast, which means the High-High resilience and Low-Low resilience areas would be grouped together because they bother intersect one of the SLR layers. There is clearly a pattern with this data as seen in the Moran's I test (Figures 22 – 25), but when those clusters are aggregated the patterns cannot be discerned.

5.0 Conclusions

5.1 Overview

The results of this analysis have demonstrated that spatial units with similar resilience (considering the selected study areas along the Alabama, Florida, and Mississippi coasts) tend to cluster leading to a degree of homogeneity when considering the resilience of populations within different SLR zones. It is within this context that the relationship between resilience and spatial location is more complex than what could be ascertained by the SLR zones proposed, and the latter illustrated that the measured resilience of a given place is dependent on location and scale. The cluster patterns of similar resilience scores differed from MS/AL to Florida, but had similarities as well, such as clusters occurring in urban areas and spatial dispersion occurring in rural areas. These patterns would be intensified or depressed depending on what scale was used.

5.2 Is there any difference in the measured resilience of coastal populations given projected changes in Sea Level Rise?

In order to answer the first research question, U.S. census enumeration units (tracts and block groups) were selected based on if they intersected one of four SLR zones. The SLR zones consisted of 0 ft, 3 ft, 6 ft, and 9 ft of predicted SLR. If a census unit intersected one of the SLR zones, it was coded to reflect which zone it intersected, and could only be selected once. After the selection process was complete, an ANOVA was conducted to compare the means of all the BRIC values in each SLR zone. The results of the ANOVA demonstrated that there was no statistical difference levels of resilience at the block group level at either study area. This signifies that the ANOVA did not detect any statistical differences between the mean BRIC scores in any of the SLR zones. There was statistical significance, however, in both study areas at the census tract level. In short, there are statistically significant differences in the resilience of populations between the zones at the tract level, but not the block group level.

5.3 If there is a difference in the resilience of populations due to changes in the spatial extent of a SLR hazard zone, to what extent does the overall resilience of populations diverge?

In order to answer the second research question, a Post-hoc test was conducted, specifically Tukey's. Post-hoc tests reveal how much difference there is between multiple group means, and typically follows an ANOVA. It was deemed that there was no difference at the block group level considering the ANOVA, so the focus was at the tract level to see how much difference there was between each SLR Zone. The results illustrated that there was a significant difference between 0 ft and 9 ft SLR at the MS/AL study area, but there was no difference between any of the other zones. The same occurred when considering the Florida study area where there was only one instance of significant difference, at 0 ft and 6 ft SLR, whereas there was no difference between the rest of the zones. In short, there was minimal difference between the SLR zones at either study area at the tract level, and no differences at the block group level.

In order to find out why the results from the ANOVA and Post-hoc were occurring, a Moran's I analysis was conducted. Moran's I is a spatial statistic that determines if data, in this case composite resilience scores, has spatial autocorrelation. Spatial autocorrelation means that the data values of one point depend on the values around it, which can result in a dispersed or clustered pattern, or random if there is no spatial autocorrelation. Moran's I determined that there was spatial autocorrelation in all study areas and scales that resulted in a clustered pattern, which results in similar values being near one another. Once the Moran's I results were mapped, it was clear to see why the ANOVA and Post-hoc rendered little to no differences. In urban areas, the BRIC scores would cluster resulting in pockets of high or low resilience along the coast. The ANOVA and Post-hoc are executed by comparing means of groups, but within each SLR zone there were very high and low values due to the pockets of high and low resilience created by clustering. When there are very high and low values, the average is typically in the middle, which is what happened for every SLR Zone, resulting in little to no statistical differences. Although the answers to research question one and two show there is little to no difference, it may be because the statistical tests (ANOVA and Tukey's Post-hoc) were not designed to measure the phenomenon which is occurring: clustering.

5.4 Given the possibility that changes in the resilience of populations are likely to occur from one SLR zone to the next, what characteristics are most pronounced as driving the resilience of populations?

In order to answer the third research question, a PCA was conducted. All the variables that make up the composite BRIC scores were analyzed to see which variables explain the most variability and best describe the phenomena being measured (i.e. disaster resilience). The factors of the PCA can be considered the most significant drivers of resilience according to the PCA. The main driver of resilience, across both study areas, are environmental factors. The Environmental Component is the factor explaining the most variance for MS/AL tracts, block groups, and Florida block groups, and the second when considering the Florida tracts. For three of the four study areas and scales, the second factors revolved around the same theme of employment. Florida tracts had employment as the first factor and environmental as the second factor. This means that across all study areas and scales, the environmental and employment factors can be considered the biggest drivers of resilience. Having the same two factors that explain between 27 and 33% of all variance within the resilience scores indicates that environmental and employment are the most pronounced drivers of resilience.

5.5 How do the answers to the previous three questions change with location and scale?

An interesting portion of this study demonstrates that even though the composite resilience measurement of populations did not change with SLR, the resilience scores did change with scale. In the ANOVA and Post-hoc tests, the block group and tracts typically acted in ao parallel way within their given study area. This became most obvious following the ANOVA, where the census tracts had statistically significant results, while the block groups did not. Also, when comparing the drivers of resilience, the block groups had similar driving characteristics, while the tracts changed slightly. The statistical measures showed a distinct difference with the different scales. This distinct difference held true given the Moran's I analysis. Here, both study areas experienced increased clustering from the tract to the block group level. MS/AL had an extremely high Moran's I score at both block group and tract levels, while Florida had a relatively low Moran's Index for both scales. There were also far different levels of clustering for both. Florida showed the full range of spatial clustering types along the cost (Low-Low, High-High, Low-High, High-Low), while MS/AL only showed High-High and Low-Low. Seeing such vastly differential clustering in the study areas makes the fact that the two study areas share the same primary drivers of resilience even more interesting.

5.6 Future Study Suggestions

This study was limited to two relatively small study areas, one year, and one hazard. The restrictions were made in order to complete the study for a Master's Thesis and gain a more nuanced understanding of what resilience looks like spatially. These limitations leave many things that can be expanded on in the future. Only two study areas were focused on in this study, MS/AL and Florida. Although the results of this study showed little statistically differences, in other parts of the U.S this may not be true. There was also a total of only ten counties in between the study areas. By looking at different parts of the U.S., and comparing more study areas, more insight can be gained regarding how quantified measurements of resilience behave spatially across scales. Another future study suggestion is to look at how resilience is changing over time. This study only looked at 2014, but the variables that make up the BRIC are constantly changing. How different areas change over time, how different scales change over time, or how resilience in general changes are all avenues for future research. Finally, the variables used in the BRIC and the locations were focused on SLR, but there are many natural hazards affecting both or coasts and inland areas. Resilience in communities that experience tornados could be completely different than those at risk of hurricanes and SLR. Difference in how resilience is manifested spatially could be analyzed in different town across the U.S. that experience different hazards.

5.7 Research Contributions

The significance of this study was the development of a methodology that can be used to analyze what effects scale and hazard extent can have on measured resilience. The methodology proposed can be modified for any area that has available data. Moreover, the BRIC, which provided the resilience measurement method for this study, is amenable to being modified to fit any hazard. There were variables in the original BRIC index pertaining to earthquakes that were not used since this study, for instance. If a future study wished to analyze earthquake resilience, variables pertaining to SLR could be removed. The results of this study illustrated that scale, or MAUP, can have an impact on the results, and the methodology proposed can help illuminate such impacts.

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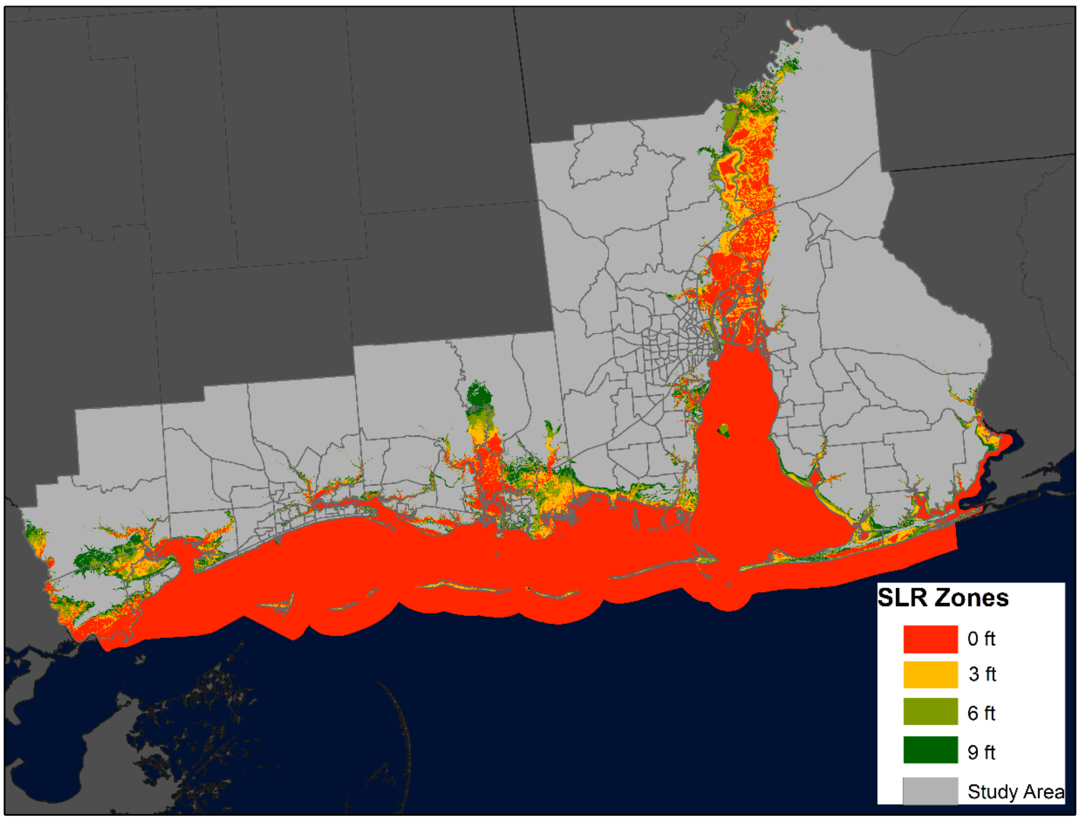
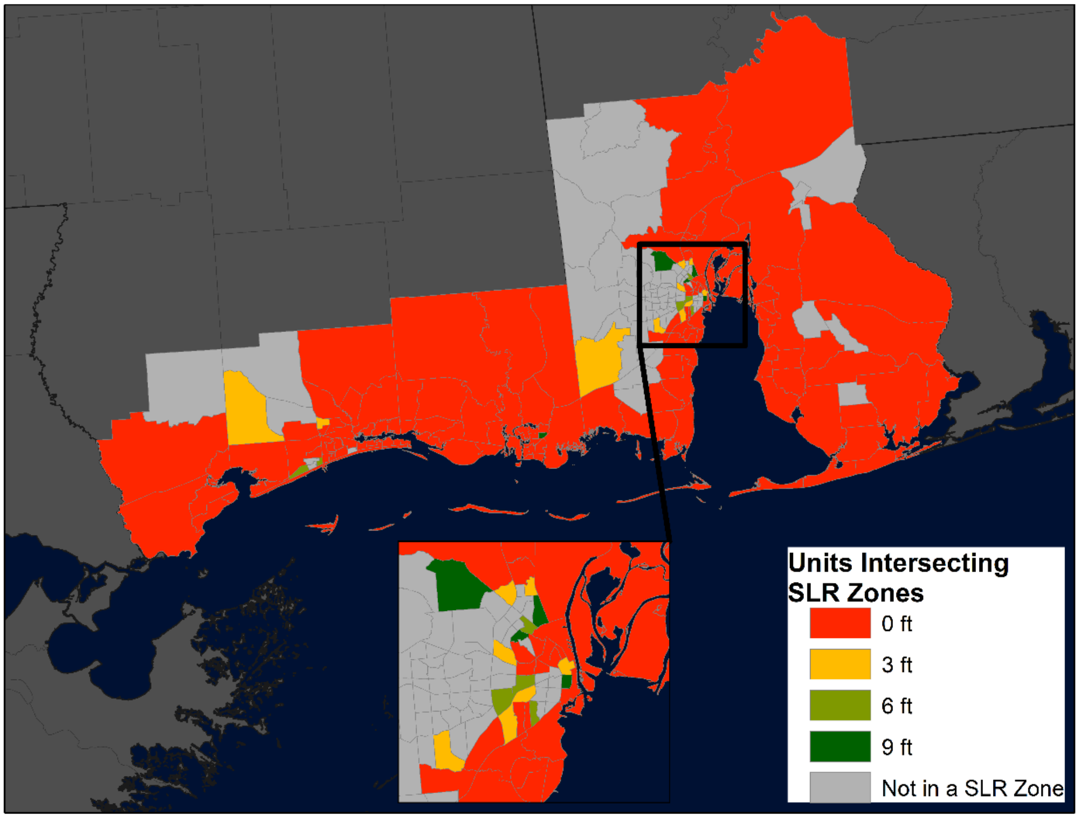
Appendix A

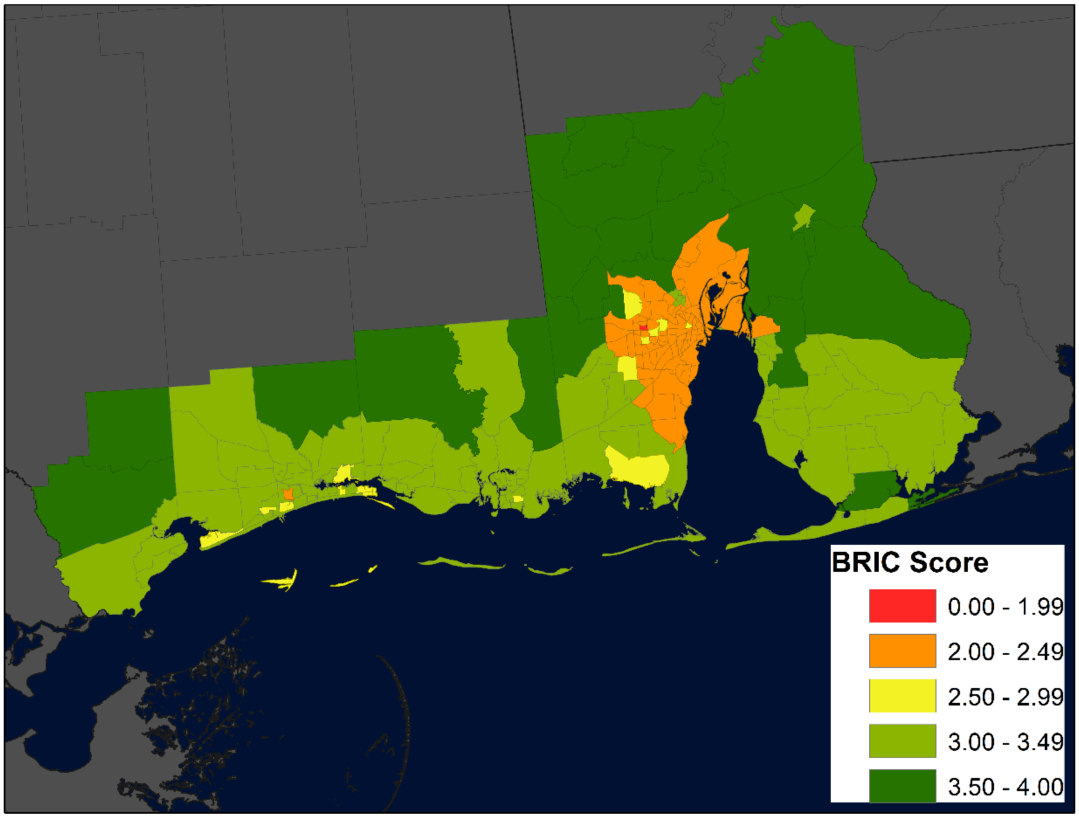
Appendix A contains the MS/AL figures regarding SLR zones, what SLR zone the census unit intersects, and census units' BRIC scores. These figures correspond to section 3.2.1 Sea-Level Rise (SLR), 3.2.3 Overlay Analysis to Delineate Drivers of Resilience, and 4.1 Study Area Disaster Resilience.



A1: The SLR layers over the MS/AL tracts. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR



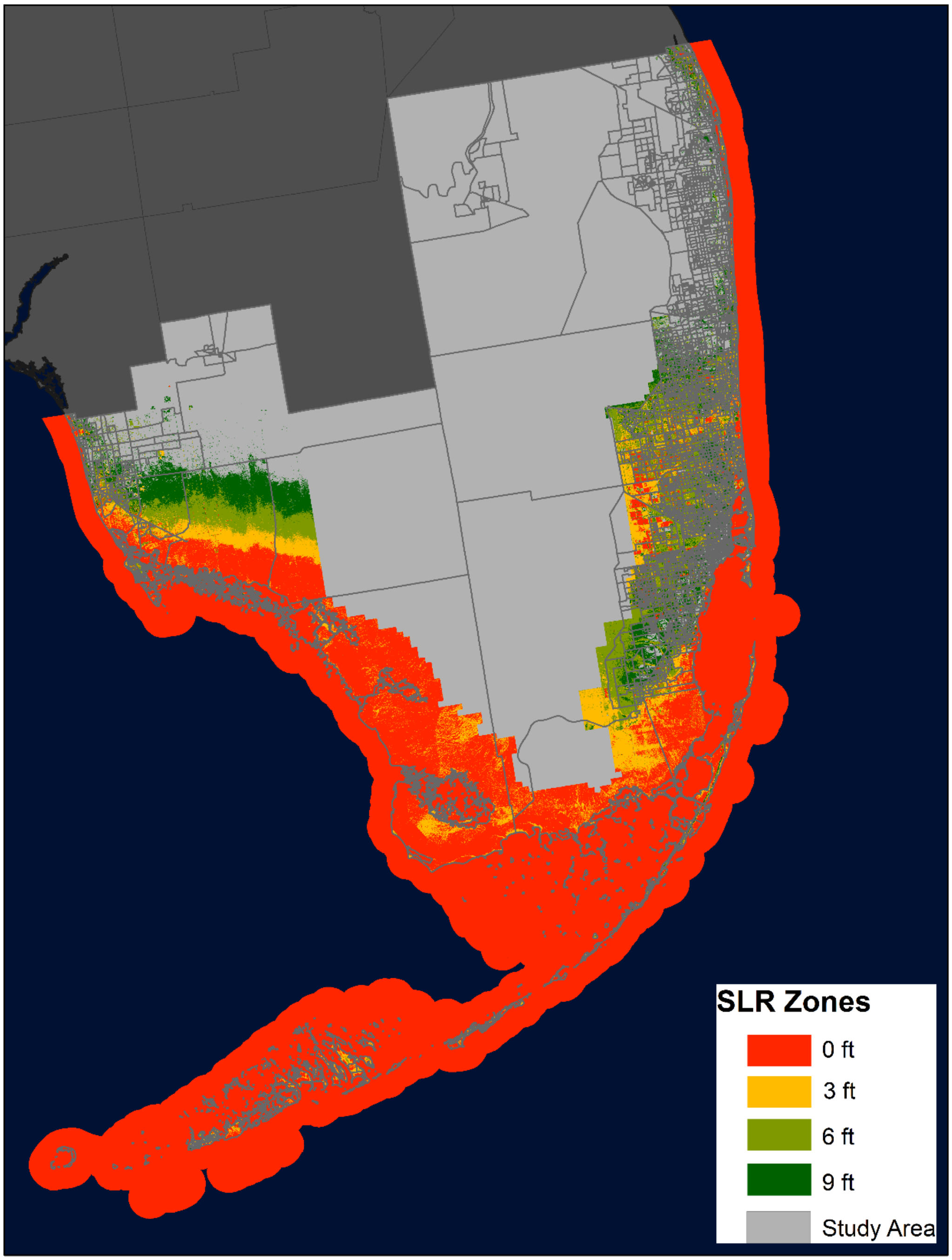
A2: The MS/AL tracts colored based on which SLR layer they intersected. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR



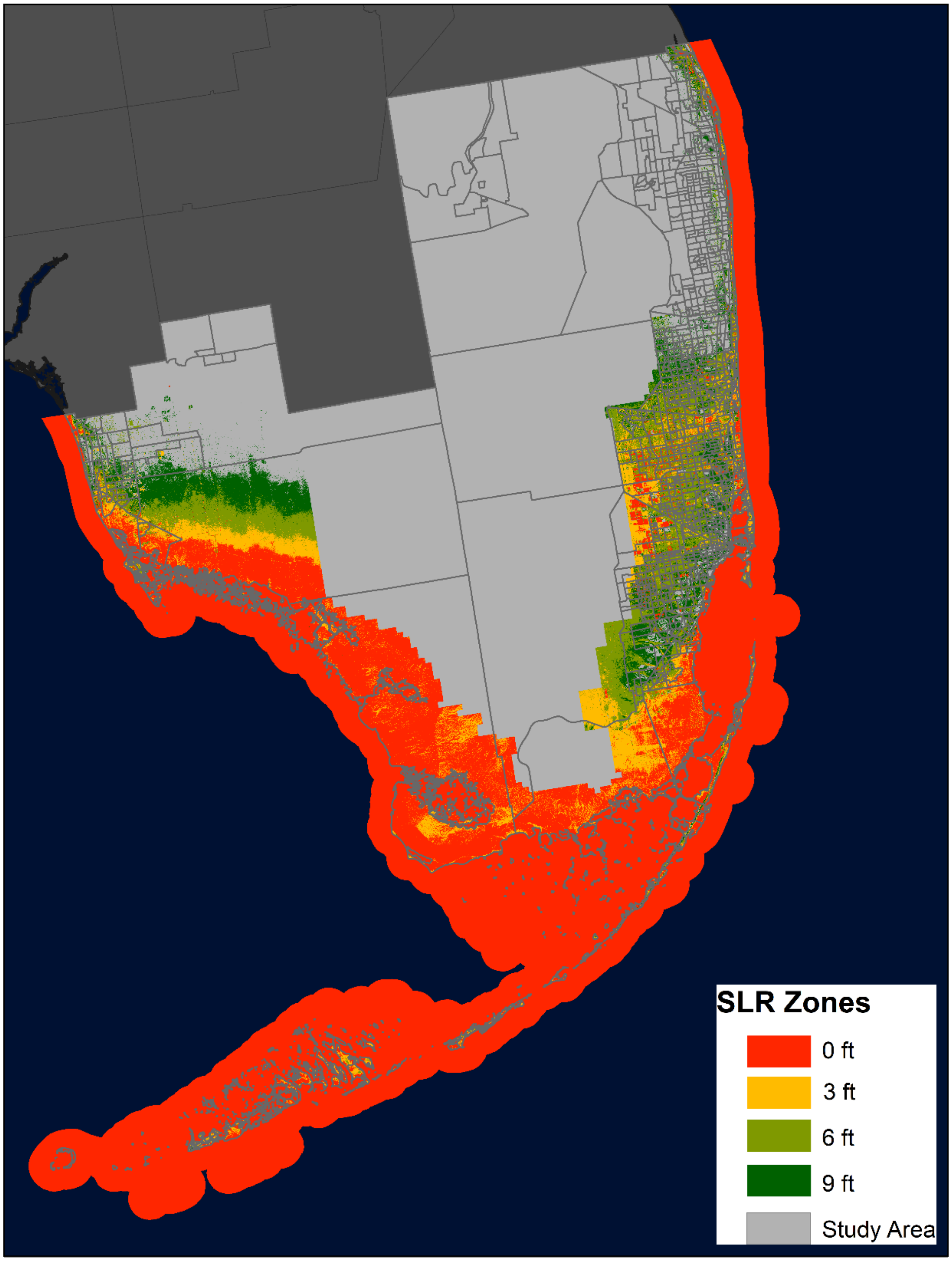
A3: MS/AL tracts BRIC Scores

Appendix B

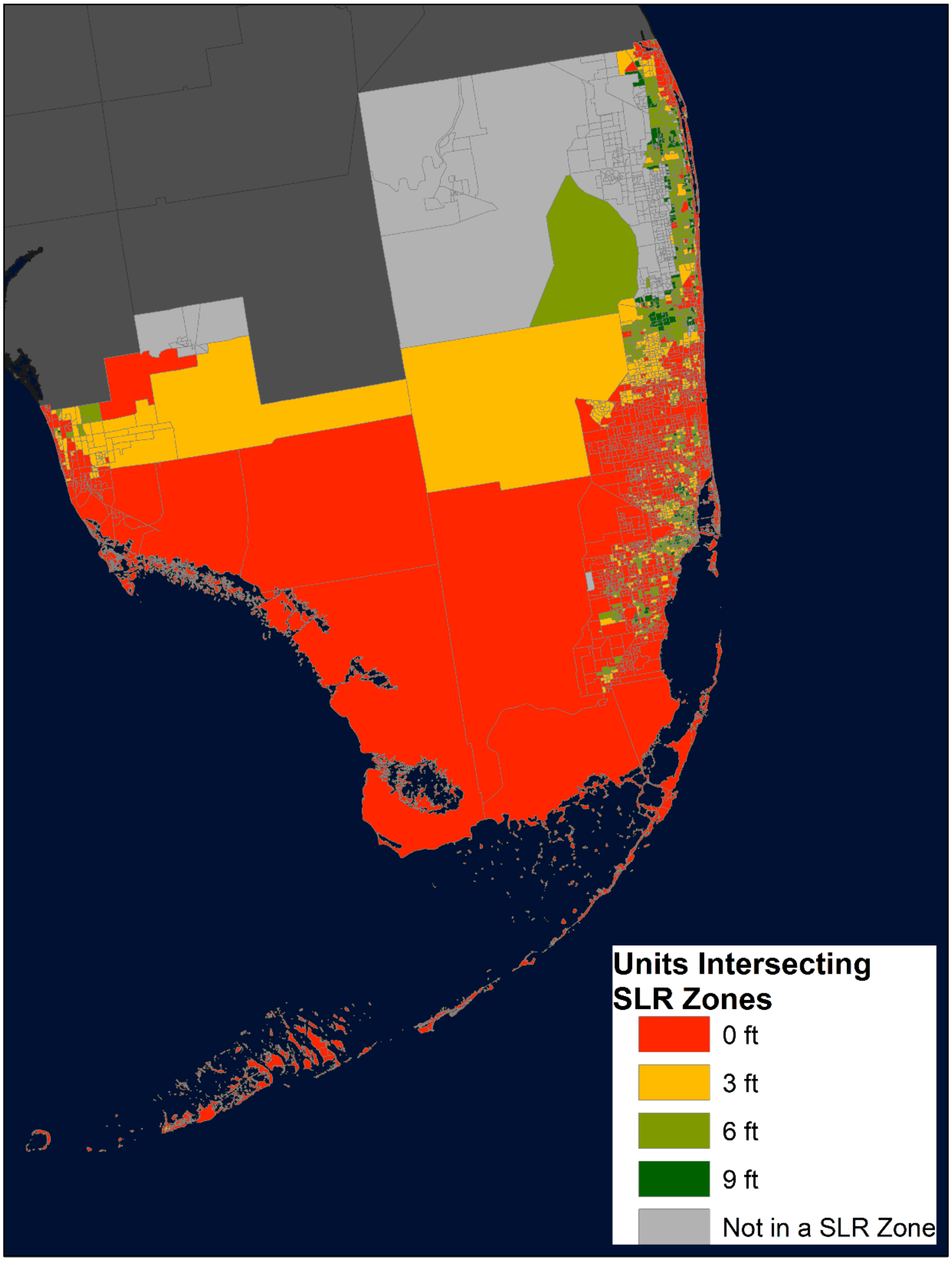
Appendix B contains the Florida figures regarding SLR zones, what SLR zone the census unit intersects, and census units' BRIC scores. These figures correspond to section 3.2.1 Sea-Level Rise (SLR), 3.2.3 Overlay Analysis to Delineate Drivers of Resilience, and 4.1 Study Area Disaster Resilience.



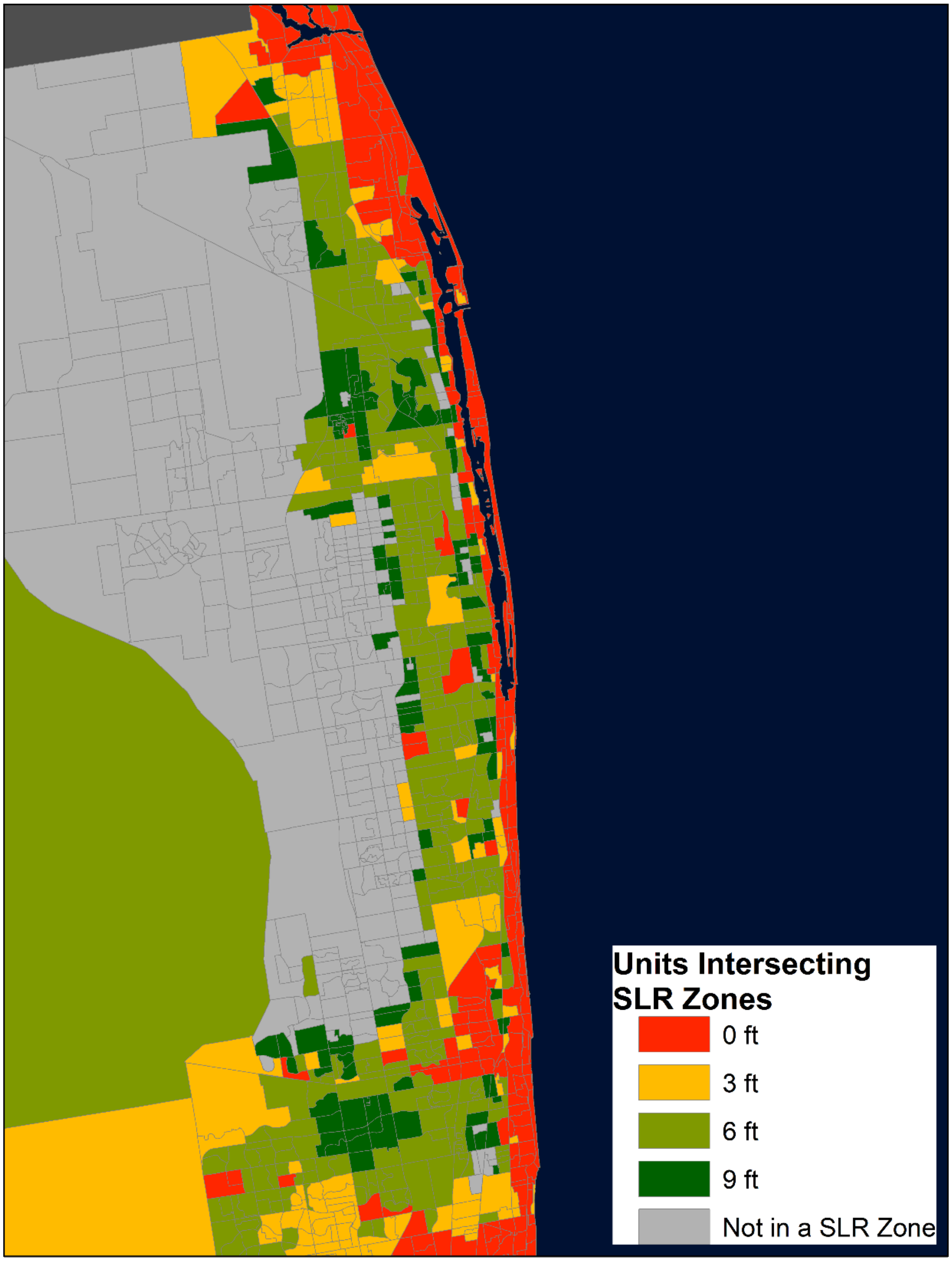
B1: The SLR layers over the Florida block groups. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR



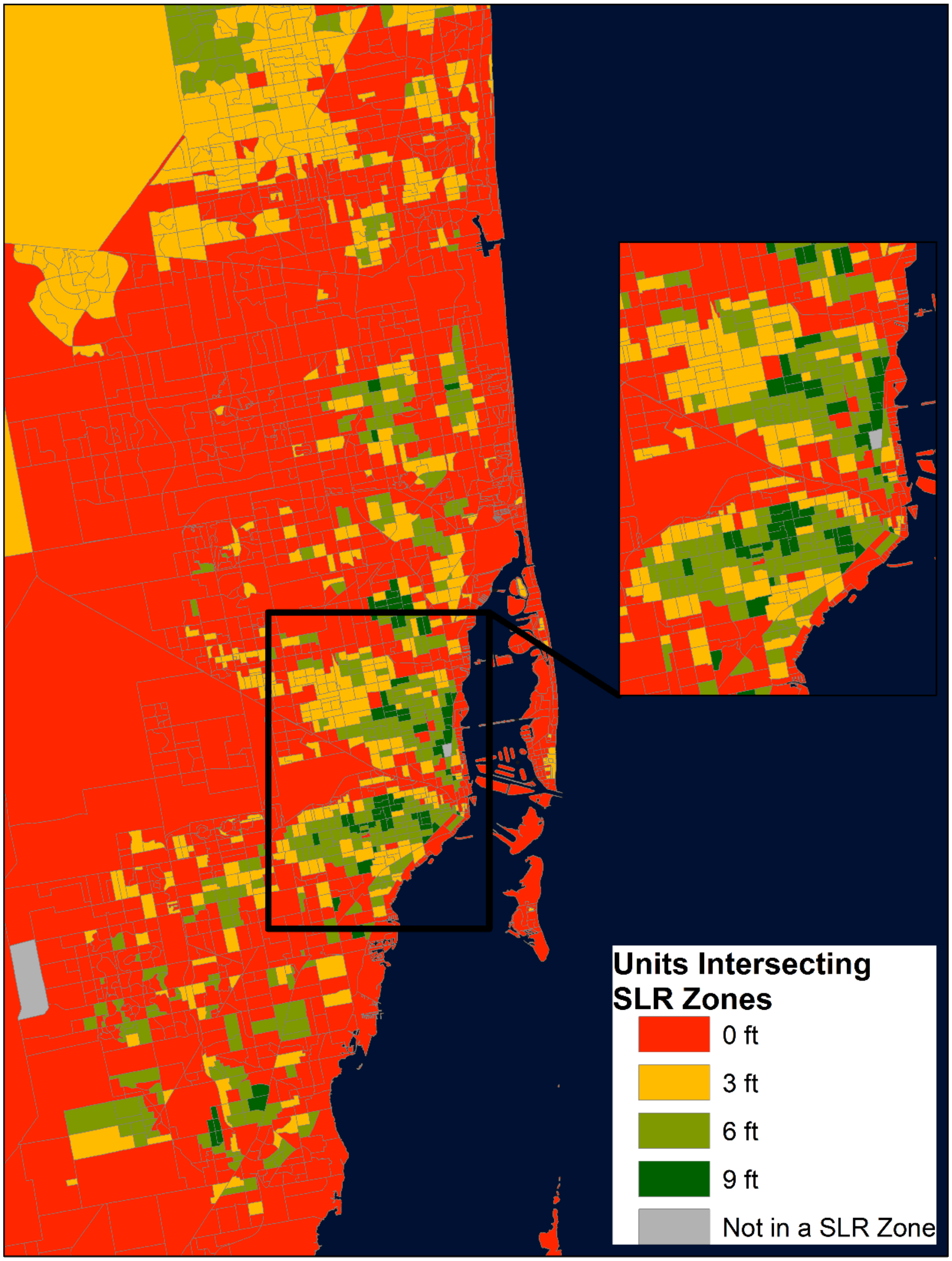
B2: The SLR layers over the Florida tracts. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR



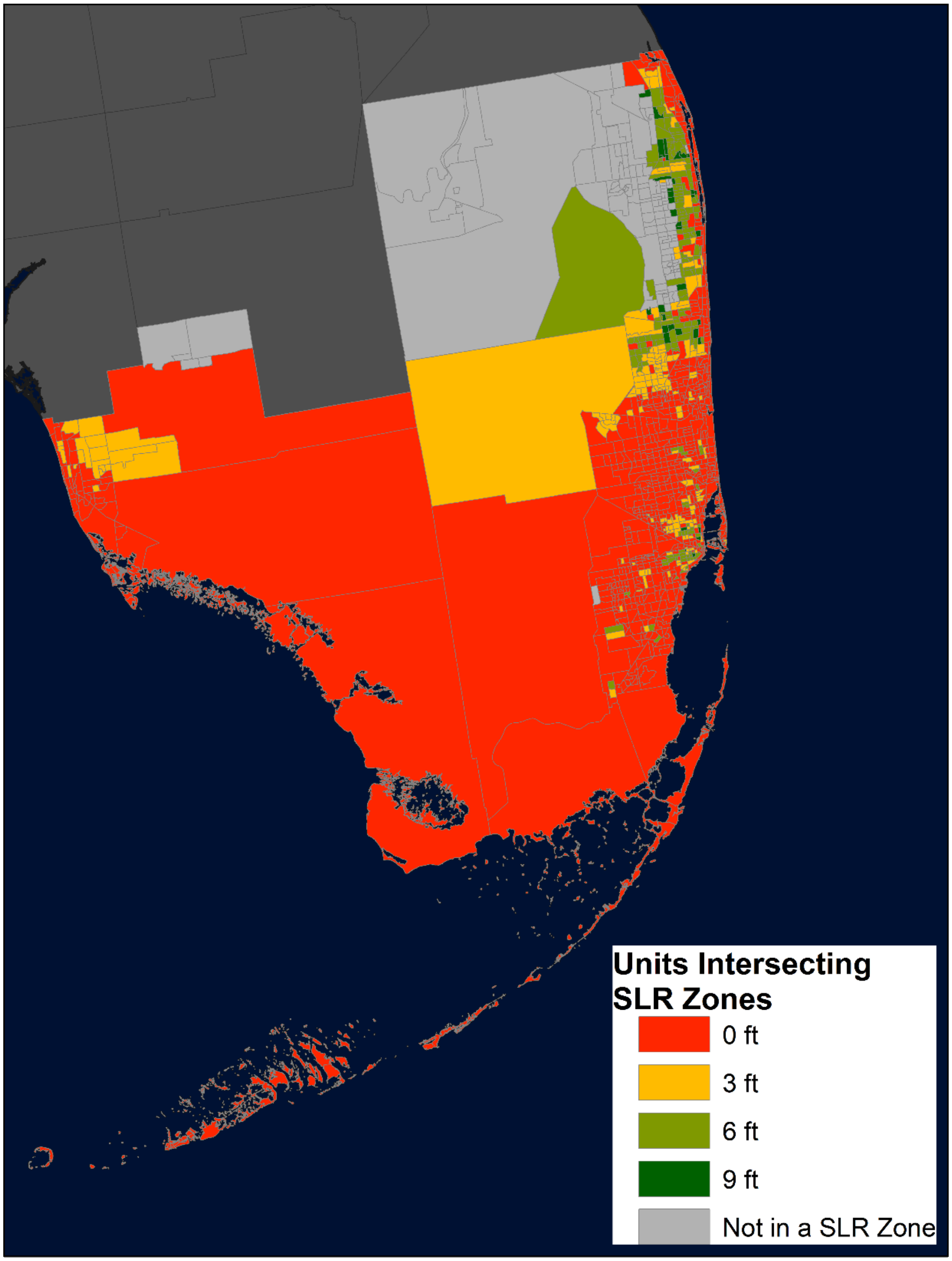
B3: The Florida block groups (zoomed out) colored based on which SLR layer they intersected.
Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR



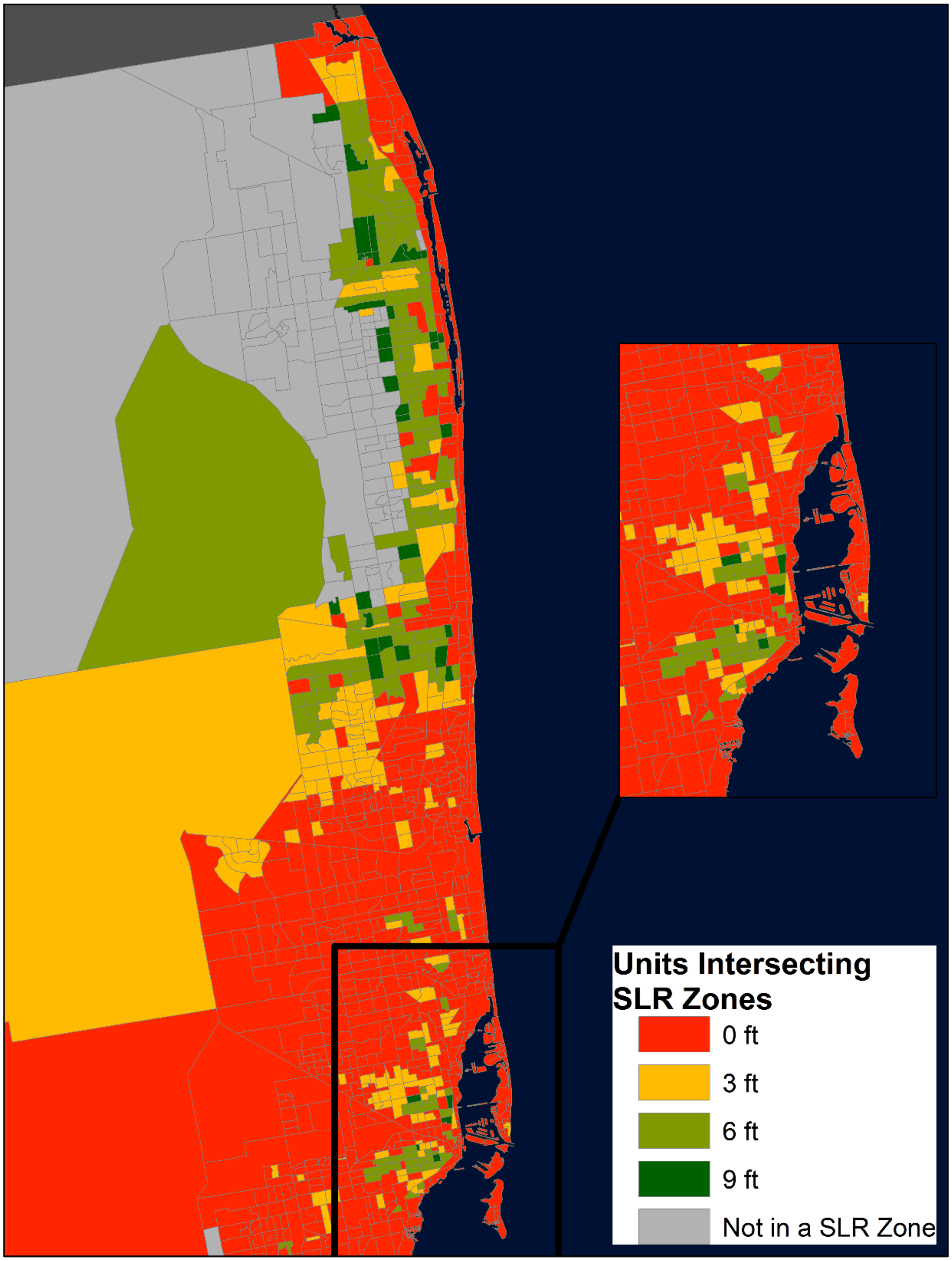
B4: The Florida block groups (Zoomed into north east) colored based on which SLR layer they intersected. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR



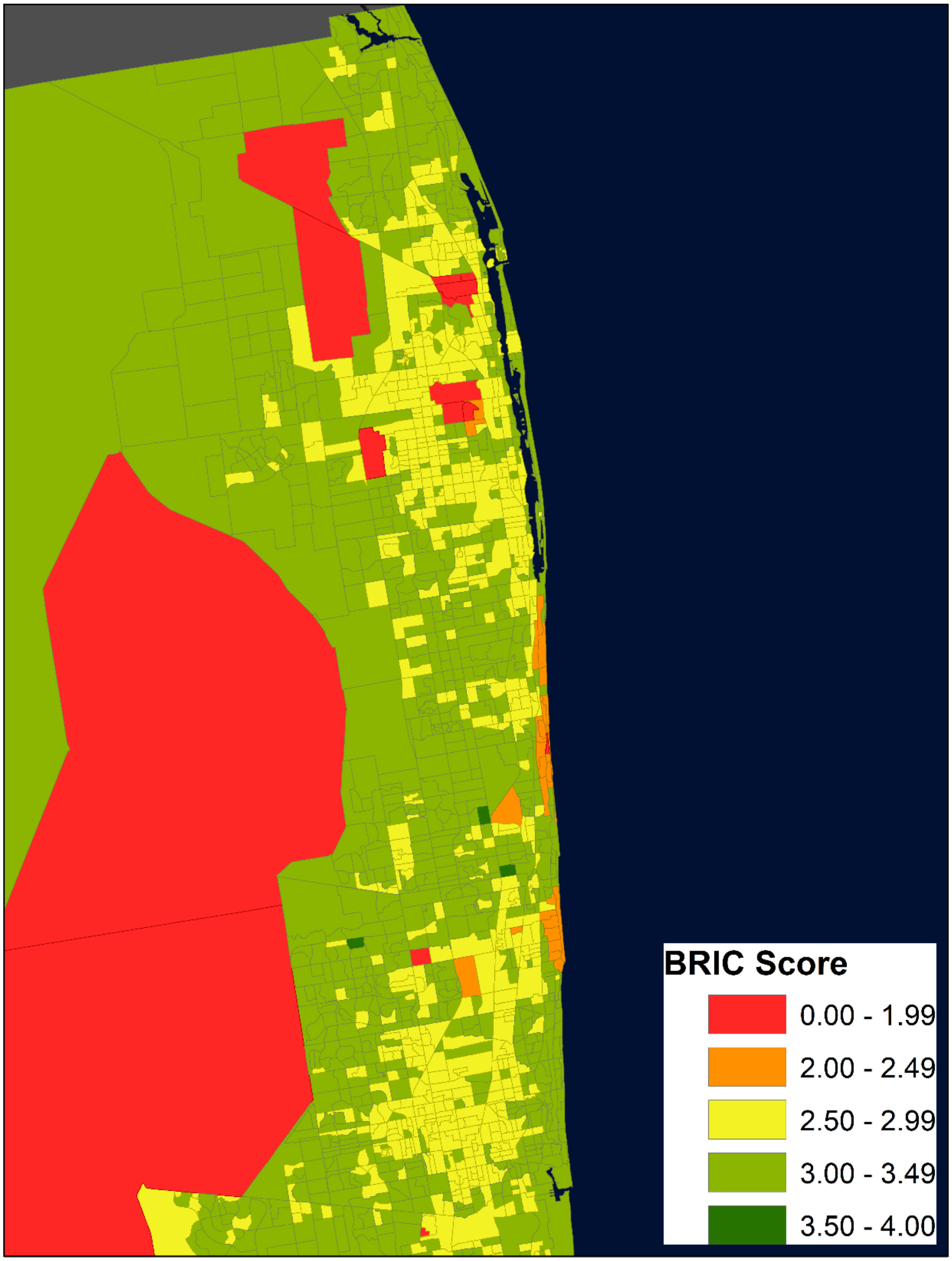
B5: The Florida block groups (zoomed into south east) colored based on which SLR layer they intersected. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR



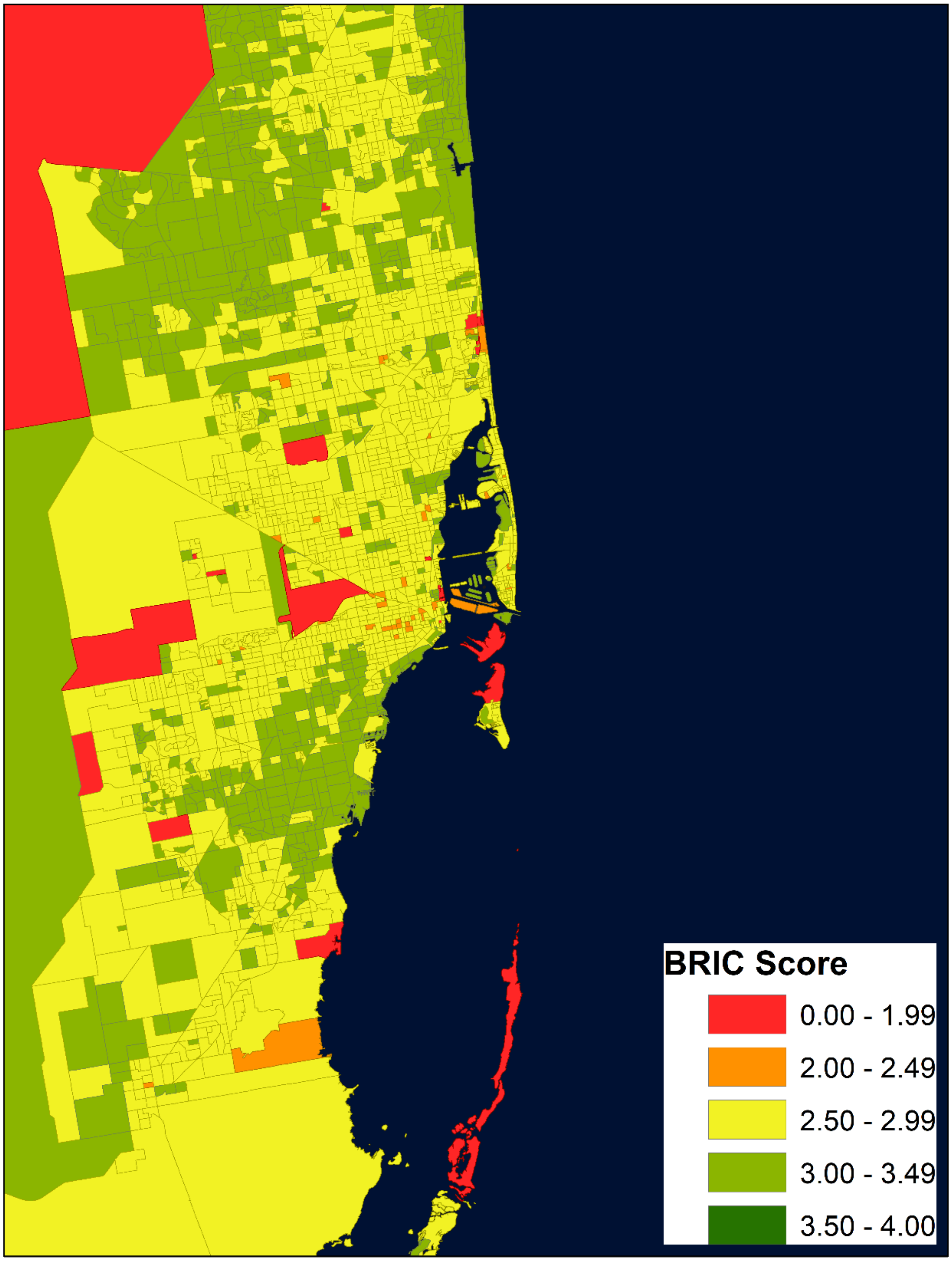
B6: The Florida tracts (zoomed out) colored based on which SLR layer they intersected. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR



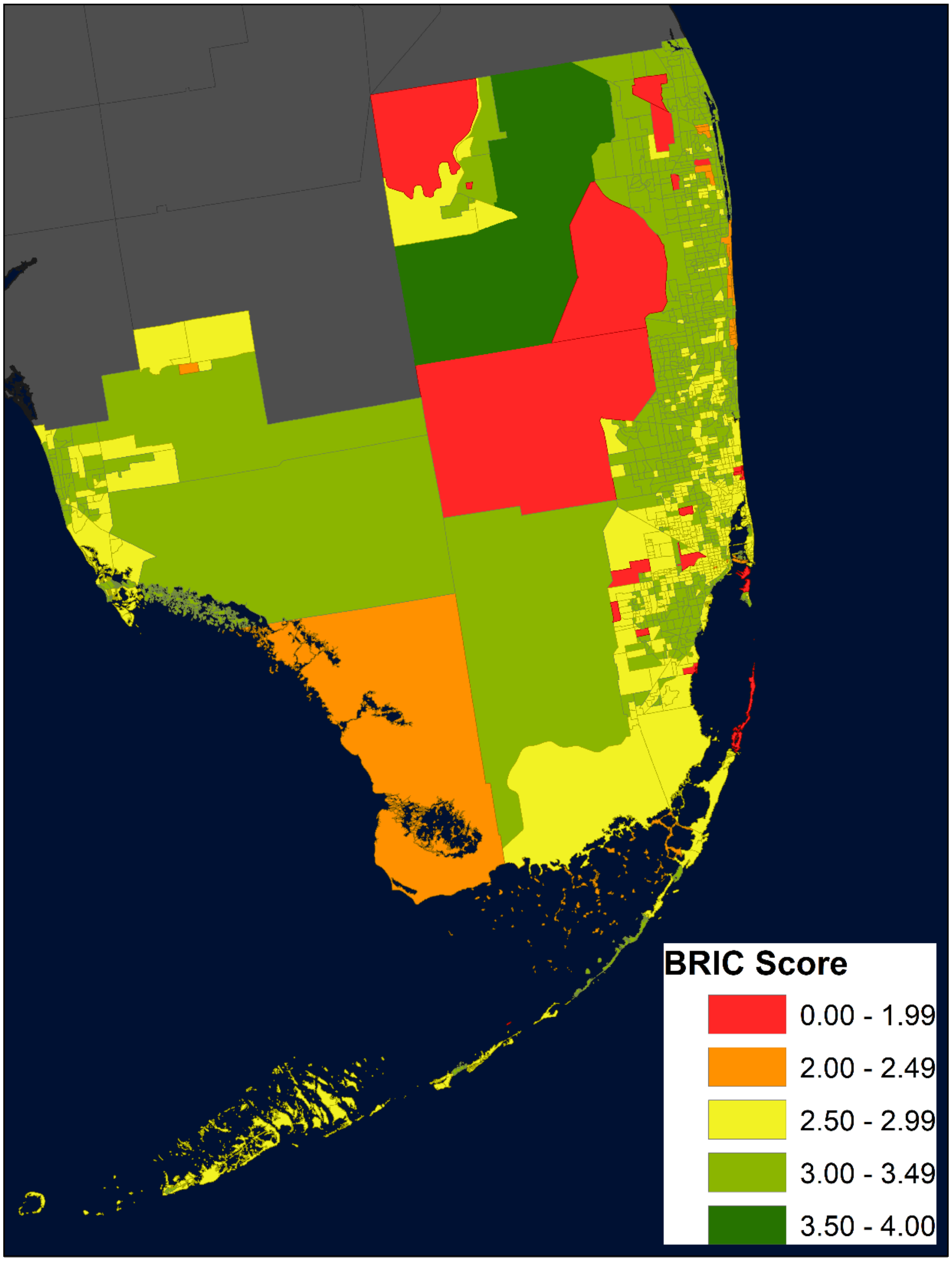
B7: The Florida tracts (zoomed into east coast) colored based on which SLR layer they intersected. Red – 0 ft SLR, Yellow – 3 ft SLR, Light Green – 6 ft SLR, Dark Green – 9 ft SLR



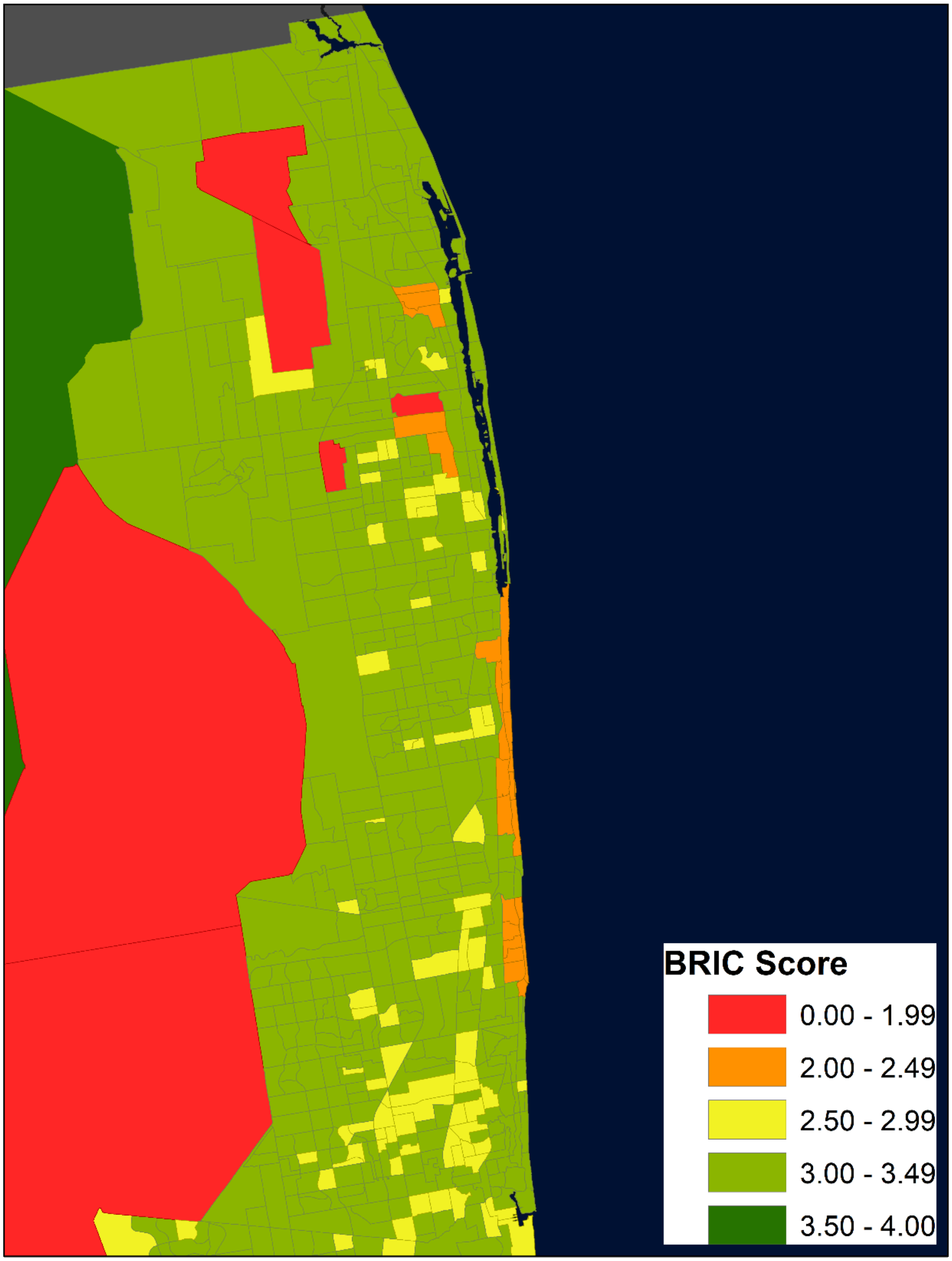
B8: Florida block groups BRIC Scores zoomed into north east



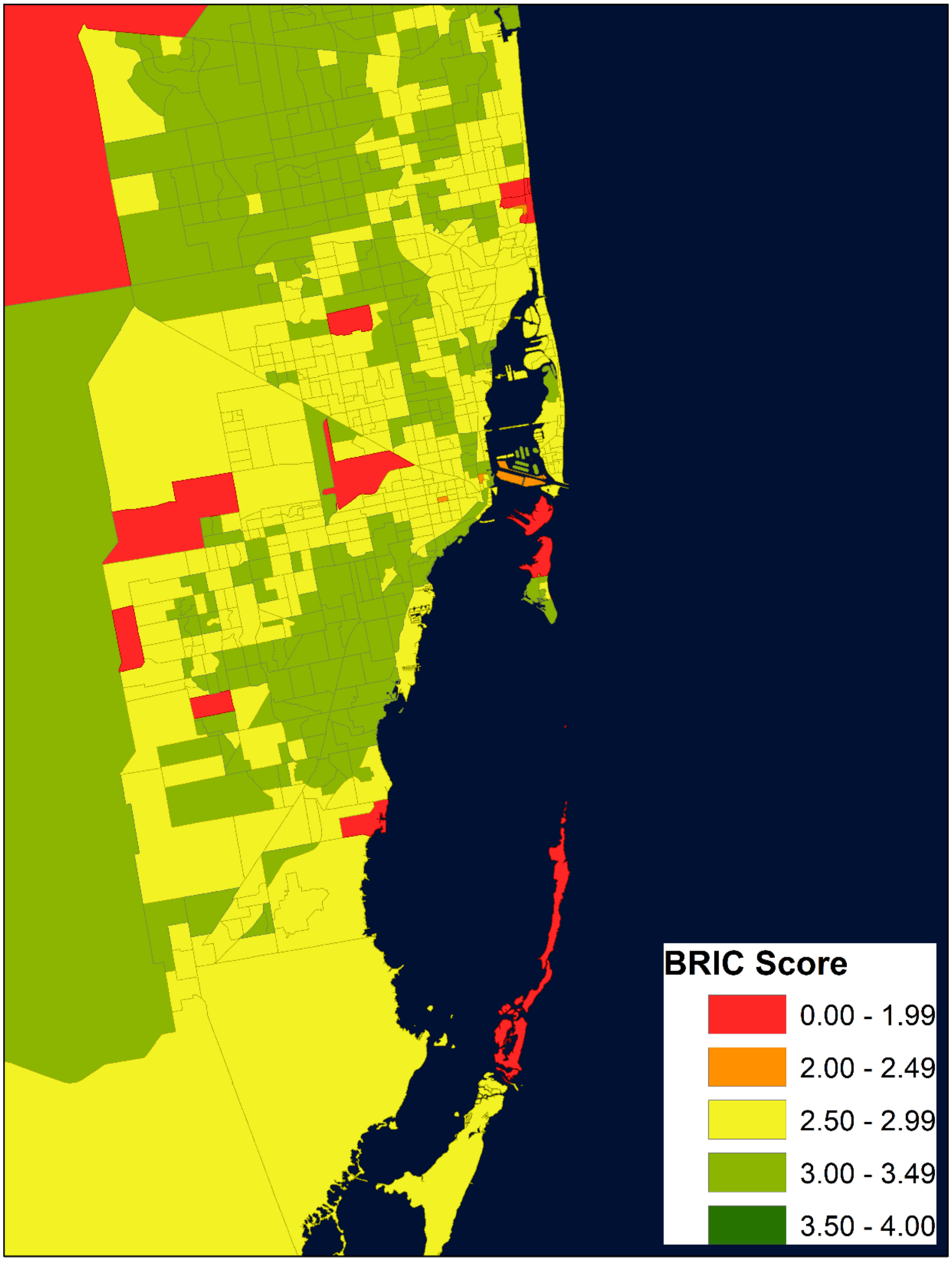
B9: Florida block groups BRIC Scores zoomed into south east



B10: Florida tracts BRIC Scores zoomed out



B11: Florida tracts BRIC Scores zoomed into north east



B12: Florida tracts BRIC Scores zoomed into south east