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Three Method Tsunami Vulnerability Analysis of the United States East Coast

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THREE METHOD TSUNAMI VULNERABILITY

ANALYSIS OF THE UNITED STATES

EAST COAST

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ABSTRACT

The East Coast of the United States could be susceptible to tsunamis or even mega tsunamis. With this in mind it becomes essential to answer the question: Where is vulnerability to a tsunami greatest along the East Coast of the United States? To answer this question the following parameters have been set. First, the study will include county level subdivisions along the USEC that have coasts along the Atlantic Ocean. The possible source regions of a tsunami or mega tsunami are also noted. This analysis includes both social and physical factors with nine and five of them considered respectively. Three separate methods were created with these datasets to see the variance of the analysis based on changes in methods. The results show how impactful cities are in determining vulnerability due to the concentration of different peoples. There is much that can be gleaned by taking a deeper look into these analyses, especially when comparing which methodologies are most effective and for what situations they are useful for. This study highlights the need for additional research into the topic and more importantly increased awareness of policy makers towards preparing for these disasters.

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INTRODUCTION

Tsunamis are one of the most devastating natural hazards. Due to their unpredictability, large destructive potential, and the propensity of humans to build along coasts, tsunamis will continue to threaten people across the globe. This includes areas that have never experienced nor feared tsunamis. The East coast of the United States is one such area as there are no documented tsunamis to have occurred there in recorded history, which has led the population of the coast to not perceive them as a threat. While the risk may be low, it is not zero and for this reason the threat should be accounted for. As such, a framework for locating areas that have the highest vulnerability to a potential mega tsunami along the coast warranted for the area.

The question raised in this thesis is: Where is vulnerability to a tsunami greatest along the east coast of the United States? A vulnerability analysis of the east coast will help identify where more resources would need to be allocated in order to provide the best relief efforts in case of a mega tsunami. County level subdivisions are useful in this regard as they are large enough to be individually important while still being small enough to show the variance of vulnerability along the coast. The findings of this study show the dominance of cities when assessing vulnerability due to them not only being densely populated, but also being built on generally flatter areas that would allow tsunami run-up to be higher. Due to the nature of hydrological disasters and coastlines, this vulnerability map will also be useful in case of hurricanes and other water-related disasters. Studies of this kind provide information to decision makers to take seriously the threat and to create mitigation and evacuation plans.

In order to create an acceptable vulnerability analysis there are pieces of information that must be understood. The study area and the counties included must be made known. Tsunamis and mega tsunamis need to be understood as disasters in both how they are caused and the kind of destruction they leave in their wake. Why vulnerability is important and what it means is of paramount importance in order to grasp the findings of the analysis. The obtainment of data and the rationale behind why all the data were used helps when interpreting results. Three methods are used in order to find the vulnerability of each county and to document variance across the methods. This study gives credence to the fact that cities are almost exclusively the most vulnerable areas to disaster for a variety of reasons. It also shows that the more physically vulnerable areas may become increasingly vulnerable depending on the movement of people.

Study Area

The study area includes 129 counties and cities along the United States East Coast (USEC; Figure 1). The counties included in the study are only those with a direct coastline with the Atlantic Ocean and smaller bodies of water connected directly to it (e.g., Chesapeake Bay and Albemarle Sound). These counties are part of 14 separate states which include: Connecticut, Delaware, Florida, Georgia, Maine, Maryland, Massachusetts, North Carolina, New Hampshire, New Jersey, New York, Rhode Island, South Carolina, and Virginia. Some cities and counties that are near but not in contact with the coast are not included in this study. This includes cities such as Washington DC and Philadelphia, PA. Due to them being near the mouth of the Potomac and Delaware rivers respectively they are often considered coastal cities. But for the purposes of this study, they are not included as they have no direct coastline with the ocean or its features.

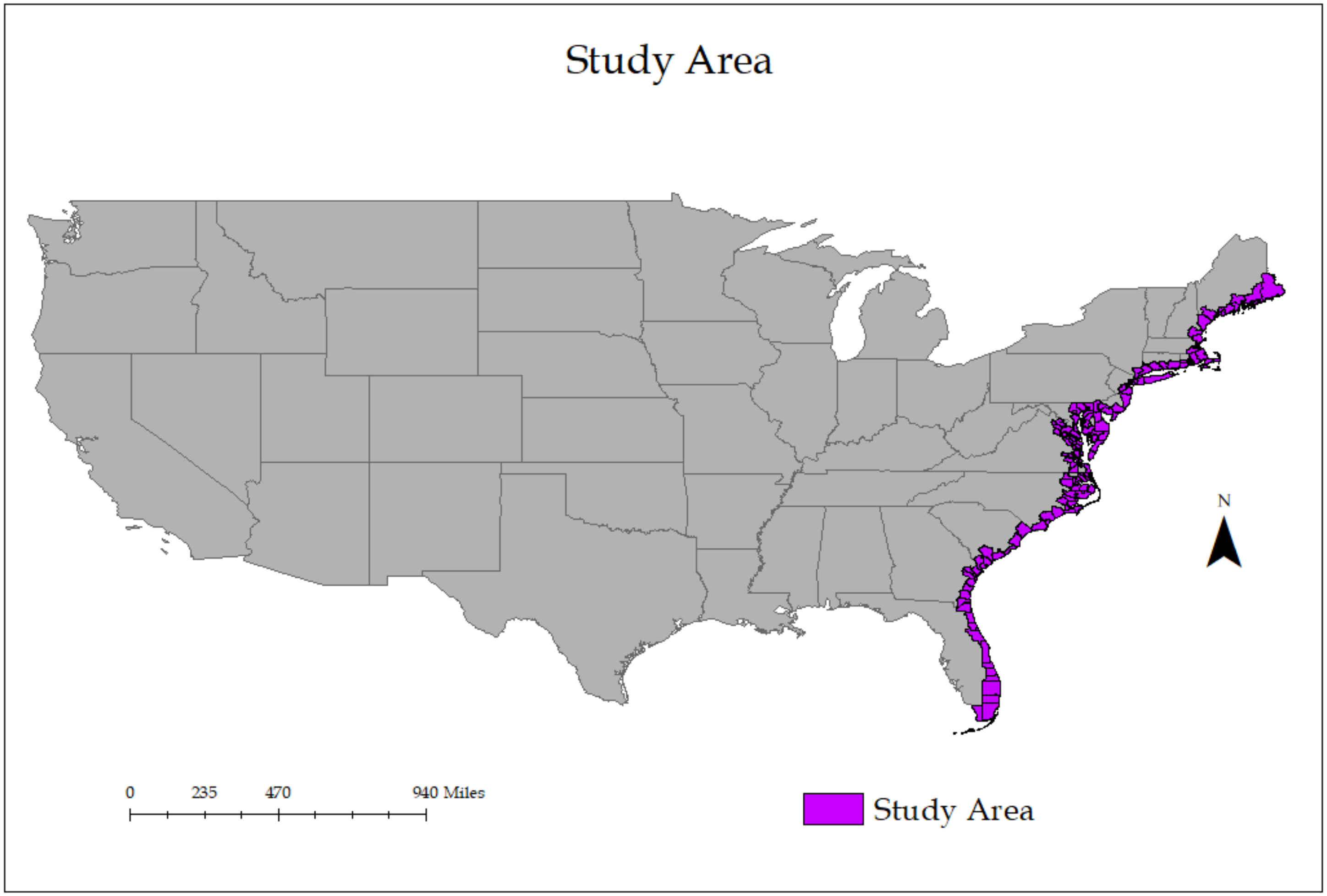

Figure 1: Map of the contiguous United States with the United States East Coast counties that are used in this study.

BACKGROUND AND LITERATURE REVIEW

What is a tsunami?

Tsunamis are a series of waves caused by submarine displacement of water, usually by earthquakes (Prothero, 2011). They vary in size and destructive capacity based on a multitude of factors. The most basic factor to consider when it comes to tsunami size and intensity is the cause of the tsunami (Prothero, 2011). The simplest terms to describe earthquake-generated tsunamis is that a sudden release of energy between two of earth's plates causes an earthquake which in turn will have an influence on the water in which it occurs. The sudden shifting of the plates displaces water that moves at incredible speeds away from the epicenter. Due to momentum the tsunami can travel for thousands of miles across the open ocean; interestingly tsunamis in the open ocean are often nearly undetectable as they tend to be small waves in open water. However, as they near land, the water begins to be forced up due to the sea floor rising which can cause the giant waves that tsunamis are best known for. Bathymetry and coastline configuration can have drastic effects on what these tsunamis look like when they reach the shore (Bletery et al., 2015). Perhaps the most infamous sign of an encroaching tsunami, outside of the earthquake that causes it, is the receding of water from the shore immediately before it hits (Röbke & Vött, 2017). Beaches can be completely cleared of water exposing the sea floor for thousands of feet. This of course is just a portent of the coming disaster. These disasters have been prevalent for humans throughout recorded history. Particularly because of their close relationship to earthquakes, tsunamis have been documented for thousands of years. Two of the most recent and most devastating natural disasters were tsunamis: 2004 Indonesian Tsunami and 2011 Fukushima tsunami. The first killed nearly a quarter of a million people while the latter is one of the costliest disasters in the history of mankind (Röbke & Vött, 2017). These earthquake-induced tsunamis have a massive range due to the number of faults between oceanic and continental plates which along with how unpredictable they are makes them a particularly dangerous hazard.

Mega tsunamis

While most tsunamis are caused by submarine earthquakes, there are examples of what are known as mega tsunamis which are caused by the sudden intrusion of material into a body of water (Goff et al., 2014). They are called mega tsunamis because of having such a large amount of mass fall into water. It is like throwing a rock into a pond: While the ripples will travel throughout the pond, they will be largest right at the entry point. The same phenomenon occurs with mega tsunamis but on a massive scale. There are two main ways that a mega tsunami can be created. The more common type is created by landslides where the earth falls into the sea usually due to volcanic eruptions. A famous example of this is the 1958 Lituya Bay mega tsunami where the wave reached over 1000 feet high from the landslide (Fritz et al., 2009). Another example is the mega tsunami that was cause when Krakatoa erupted in 1883 and caused a mega tsunami that devastated the surrounding area (Gray & Monaghan, 2003). The less common creation method is from extraterrestrial objects such as meteors or asteroids. The incredible speed at which they impact the earth releases so much energy that theoretically the mega tsunami created from it could reach miles high (Daukantas, 1998). The focus of this research is landslide created mega tsunamis, but it is worth noting how devastating an impact mega tsunami could be. As noted, the height of the water is much higher at the epicenter of these events but that is not to say that they do not travel through open water. While the heights of the tsunamis will not be hundreds of feet high in the far field, or area that is far away from the point of generation, they can still be larger than many earthquake-induced tsunamis.

Why the USEC is at risk

Multiple different possible tsunamis could affect the East Coast from the Atlantic (Grilli et al., 2014). These scenarios are not the only possible tsunami generation areas, but they are the most prevalent due to their higher risk or larger size. The first two are from tectonically active zone: The Puerto Rico trench and the Azores-Gibraltar Transform Faut (AGFZ). The Puerto Rico fault line is seismically active and has had magnitude 6+ earthquakes consistently in recent years (Grilli et al., 2014). Studies modelling possible inundation of the East Coast model a magnitude nine which could cause a large tsunami (Grilli et al., 2014). Due to the location of the fault, it would likely impact the south but is not the focus of this study. The AGFZ which caused the 1755 Lisbon tsunami (Barkan et al., 2009) is also a possible area for a tsunami to be created if a large enough earthquake were to occur there. It could wreak havoc on the USEC but is by no means a worst-case scenario for the region. Another widely discussed generation point would be along the continental shelf if a large submarine landslide were to occur (ten Brink et al., 2009). It is believed that a submarine landslide equal to a 7.0 magnitude earthquake is quite rare but possible in the region (Grilli et al., 2014). Due to proximity this could prove devastating even though the tsunami itself would be relatively small compared to others that could impact the coast. The final widely studied and likely largest albeit most unlikely of the scenarios is a mega tsunami generated by a complete flank collapse of Cumbre Vieja volcano in the Canary Islands (Tehranirad et al., 2015). While the size of the collapse could vary wildly with the most likely being 80 km3 and the largest being as high as 450 km3 it could devastate either way. The worst-case scenario in this case is likely the largest tsunami the USEC could experience. Despite the distance between the generation point and the USEC, the massive movement of material into the ocean could create a mega tsunami of incredible scale (Paris et al., 2018). The Canary Islands themselves would likely be completely devastated with parts of North Africa also having little time to evacuate. The USEC would have between five and ten hours to evacuate after the initial landslide. This is assuming that the landslide is effectively and immediately reported as it happens and that the authorities of the area understand the risk that it poses. With that being said the USEC has a large population and massive economy that would immediately be at risk should one of these events occur.

What is vulnerability?

Understanding the East Coast's susceptibility to tsunamis can help define the vulnerability of the area. Vulnerability in the case of disaster can be defined as the ability of people/environment to resist and recover from a disaster. How susceptible an area is to a disaster is not simply a function of how likely an event is to occur in this area, but also how well the people and environment can handle the event when it occurs. That is the main way it differs from risk as risk is in its simplest form represents the likelihood of an event (Smith, 2013). Of course, vulnerability is not static across all disaster or events as each one can have different variables that make an area more or less vulnerable to the event. In the case of tsunamis, the configuration of the coastline can impact how the water will run up while coastline configuration will have little impact on a hurricane's winds it is important in its impacts on storm surge. The USEC is vulnerable in this case based on previously mentioned attributes: population, wealth, and coastline. The counties along the Coast have a population of over 41 million people (Bureau, 2021). This large number in of itself speaks to the incredible vulnerability of the area. While a tsunami would not inundate an entire county, it is still worth noting how many people are very close to the coast on the Eastern Seaboard. Wealth or the economy of the region also would prove to be a main area of concern in the case of a mega tsunami. The area is home to some of the largest and wealthiest cities in the US with New York City alone having a GDP roughly the size of Canada. This could in some case make it easier for many residents to evacuate but when there is that amount of material goods then there is that much more to lose. As such there are more than human lives at risk when it comes to disasters. Tsunamis are heavily influenced by the land that they reach. Depending on the bathymetry of the coast a tsunami could be taller and faster when it reaches a coast which will impact how far inland it might make it before waters recede (Bletery et al., 2015). If there are large rivers, then they will also make it easier for a tsunami to intrude further inland. This is to say that the USEC has many factors that make it vulnerable to a tsunami based on its population, economy, and coast. Interestingly, what might make the areas the most vulnerable is actually the fact that a tsunami has not happened there in recorded history and as such the people do not understand the threat that they could pose to them. While that is more difficult to quantify, increasing public awareness on the subject will help to alleviate the impacts of such an event.

Tsunami vulnerability studies

Vulnerability is a well-known concept and as such there has been no shortage of vulnerability analyses done for tsunamis and other coastal hazards (Barkan et al., 2009; Bletery et al., 2015; Cutter et al., 2003; Febrina et al., 2020; GOTO & NAKASU, 2018; Grilli et al., 2014; Grilli et al., 2017; Ismail et al., 2012; Murthy et al., 2011; Najihah et al., 2014; Papathoma et al., 2003; Römer et al., 2012; Szlafsztein & Sterr, 2007; ten Brink et al., 2009). Tsunami vulnerability according to guidelines set by UNESCO-IOC include social, physical, environmental, and economic impacts as the main aspects of tsunami vulnerability (UNESCO 2009).

Studies of physical vulnerability

Physical vulnerability studies tend to focus on two main areas: modeling and remote sensing/ GIS. Modelling of Tsunami generation and propagation has been done in many parts of the world (Grilli et al., 2014; Grilli et al., 2017; Murthy et al., 2011). These forms of modelling are useful for seeing where run-up could possibly be the highest, but it is not always possible for them to take in some of the aspects that are important to vulnerability such as social impacts. Remote sensing/ GIS based physical vulnerability tends to focus on other aspects due to the nature of the analysis (Ismail et al., 2012; Najihah et al., 2014; Römer et al., 2012). These studies include more human aspects and at times economic and environmental as well because they are not only modelling the possible run-ups of tsunamis but instead how vulnerable an area is based on their own preconceived tsunami extremes.

Studies of social vulnerability

Social vulnerability studies often include physical vulnerability as well. However, human vulnerability also plays a greater role in mitigation as understanding populations that are vulnerable allows for more focused efforts on population characteristics (Cutter et al., 2003; GOTO & NAKASU, 2018). Social vulnerability studies also tend to be more multidisciplinary in that they are not only applicable for tsunamis but for other coastal hazards as well.

Environmental and economic vulnerability

Environmental and economic impacts are also important aspects of vulnerability as seen in the work done by Papathoma et al. (2003), who consider various aspects of buildings and how vulnerable they may be. These two aspects are not the focus of my study, but some economic data will be used to assess vulnerability. This is due to the large study area that does not allow for assessment of small areas at a micro or local scale regarding economics. This fact is generally why studies focusing on these aspects are of smaller scales as they can be better quantified at these scales.

Differing scales of tsunami vulnerability

One point of interest where vulnerability is concerned is the problem of scale regarding each aspect. Many tsunami vulnerability analyses rely heavily on building vulnerability at a micro scale for vulnerability (Omira et al., 2009; Papathoma & Dominey-Howes, 2003). This is a great way to see the vulnerability of the built environment but is of little help at the larger scale of my study. Most tsunami vulnerability analyses of large scales fall into the modelling of tsunami generation, propagation, and run up mentioned above. Other large-scale vulnerabilities are almost entirely focused on physical aspects of the area and how that impacts vulnerability. There is some limited focus on human vulnerability at large scales but usually in conjunction with the physical vulnerability. This is the focus of my research as the physical and human vulnerabilities are often the two most important factors of an area's vulnerability to a tsunami and as such more important for large scale analyses. In this regard the framework will be heavily based on Szlafsztein and Sterr's coastal vulnerability index or CVI (Szlafsztein & Sterr, 2007). This study used a state in Brazil and brought together different aspects of vulnerability into a single framework where they were weighted accordingly, and each region of the state was given values based on this index. The variables used are mostly social and physical with some income related economic issues also being used. It is of a large scale and the framework used for my study is inspired by the framework of the CVI.

DATA

Data collection and use

Data for both social and physical variables were obtained by different open-source providers. Site links are included in the appendices, so the data are readily available. Physical data were obtained from NALCMS for land cover data, GEBCO for bathymetric data, USGS for elevation, US Census for county boundaries and coastline, and NOAA for shoreline data. Social variables were obtained from the 2010 United States Census. Metadata for each data source is provided in the appendix.

Land Cover Source Data

NALCMS land cover data are derived from Rapideye and Landsat imagery in a joint effort from multiple agencies in North America. The file used for this study is the 2015 30m resolution dataset which includes the entirety of North America. There are 19 defined classes in these data derived from the Land Cover Classification System (LCCS). Agencies involved in the creation of these data are: "Canada Centre for Mapping and Earth Observation (CCMEO), the United States Geological Survey (USGS), and three Mexican organizations: the National Institute of Statistics and Geography (Instituto Nacional de Estadística y Geografía—INEGI), the National Commission for the Knowledge and Use of Biodiversity (Comisión Nacional para el Conocimiento y Uso de la Biodiversidad—Conabio), and the National Forestry Commission (Comisión Nacional Forestal—Conafor)" (NALCMS).

Bathymetry Source Data

Bathymetric contour lines created by OpenDEM using the GEBCO grids are one of the other physical data sources used in this study as well. In this case the GEBCO grid from 2021 was used but only the bathymetry grid. These data are in 15 arc second intervals and covers the bathymetry of the entire planet. The contours are split into 32 separate parts based on depth of the seafloor. The depths of interest for this study are limited to the 50 m contour but contours are also available for a variety of other depths. OpenDEM is an open-source site with different data layers available for download including but not limited to GEBCO products. The format of the data was a polyline shapefile.

Elevation Source Data

For elevation data the national map site from USGS was used. Elevation data are of 1/3 arc second resolution or 10 m resolution. This level of resolution creates large files for such an extensive area but is still not too large to be of use. Each grid used is of 1x1 degree in size so approximately 66 separate files were downloaded from the USGS elevation DEM. Each one of these was downloaded in GEOTIFF format.

County Layer Source Data

County boundaries and coastlines were obtained from the United States census site. The counties downloaded were from the 2010 layer to maintain consistency with the other census data used. These county level boundaries are 1: 500,000 resolution and were used to delineate different counties. They were mainly used as a standard attribute table to store data found from other analyses for the final analysis. As well as this they were used to find the standard length of the coastline for each county. It is notable that Maryland and Virginia both include cities as being their own counties so eight of the entities in this study are treated as counties despite being labeled as cities. They serve the same function as a sub state entity and as such are considered equal to counties. The cities in question are Baltimore, MD (there is also a Baltimore County in Maryland that is its own county. Both are used in this study.), Hampton, VA, Newport News, VA, Norfolk, VA, Poquoson, VA, Portsmouth, VA, Suffolk, VA, and Virginia Beach, VA. Refer to figure 2 to view these cities. This file was downloaded as a polygon shapefile layer.

Shoreline Source Data

Shoreline data is courtesy of NOAA National Ocean Service in the form of the medium resolution shoreline layer. Average scale of the layer is 1: 70,000 but according to NOAA it is said to differ based on the area that one is in. These data show the mean high tide mark for the entire shore. The shoreline differs from the coastline mentioned previously in that this is not a simple straight-line measurement but includes the smaller details that are lost in coastlines such as estuaries and other smaller features on or near the coast. The layer is derived from NOAA nautical charts and is downloaded in the form of polyline shapefile.

Social Source Data

Finally, all social data was retrieved from the United States Census of 2010. 2010 census data were used as when the data were downloaded there was still some unreleased data and as such it was decided to use 2010 data as it is still applicable to the region. While the entire spreadsheet was downloaded, nine variables were used in the analyses and for 129 counties along the coast. The variables in question are county level and are as follows: total population, population density, percentage of population with a high school diploma or higher, percentage of population below poverty, percentage of population over 65 years of age, percentage of households that own their own vehicle, percentage of the population that speak English as a second language, Percent of the population that is white, and percent of the population that is female. The data was downloaded in the form of an excel spreadsheet and imported into the attribute table of the county layer for us in ArcGIS.

Problems with Large Scale Studies

One of the main issues with a study such as this is that of scale. Due to the large study area a variety of decisions had to be made. First counties were decided on as they are large enough to be individually recognizable but also small enough to have variance even within the same state. Second, 10 m elevation DEM’s were used due to easy accessibility without being excessively large files. In this regard lesser resolution is effective at conveying larger county subdivisions as the miniscule variance over small areas is not as important. Land cover is similar to elevation, but the 30 m resolution was decided to be satisfactory for the purposes of this study.

Software Used in this Study

ArcMap 10.8.1 was the software used to store and create layers as well as carry out analyses for this study. This software was chosen as it is the GIS software that I am most familiar with and has all the tools and functions required.

Geodatabase Creation and Management

A master geodatabase was used to store downloaded data and new layers created during analyses. A feature dataset was also added for all shapefiles used. The projection of the Geodatabase and thus all data used for analysis was NAD 83 due to it being a standard projection and being recognizable. All layers shown in this study are within this master geodatabase to keep everything in order and easily accessible.

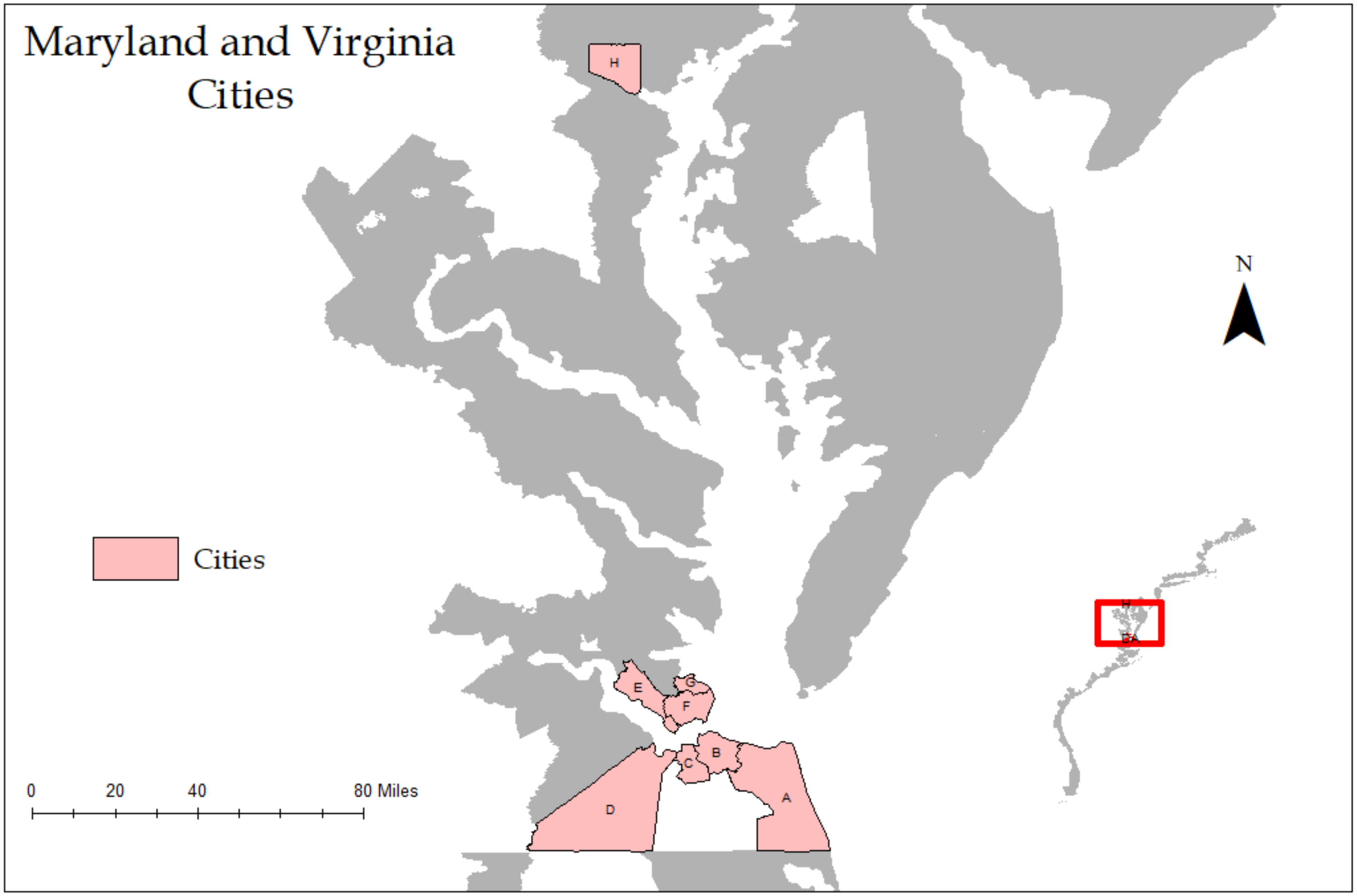

Figure 2: Map of City level subdivisions that were included as counties for this study. Cities are as follows: A- Virginia Beach, VA, B- Norfolk, VA, C- Portsmouth, VA, D- Suffolk, VA, E- Newport News, VA, F- Hampton, VA, G- Poquoson, VA, and H- Baltimore, MD.

METHODS

Due to the nature of finding vulnerabilities of entire counties each variable had to be made into a single number for each county. This was done in a variety of ways but leads to the loss of some individual features due to the relatively large size of counties which is acceptable for the purposes of this study. Smaller scale studies in areas such as cities or even within singular counties can look at the difference in the smaller areas. Szlafsztein's study used a similar method in their study of Para state in Brazil (Szlafsztein & Sterr, 2007).

Physical Variables

Elevation Rationale

Elevation is among the most prevalent variables in any study regarding vulnerability to tsunamis (Febrina et al., 2020; Murthy et al., 2011). However, the scale of this study made the use of elevation different than many other studies done over tsunami vulnerability. This was done by taking the percentage of each county that is at or below 5m above sea level, with that being the benchmark for modeled tsunamis along the USEC (Paris et al., 2018). As such it provides a useful number to give to each county to assess their individual vulnerabilities to tsunamis based on elevation.

Land Cover Rationale

Land cover is one of the other most used physical variables in tsunami vulnerability analyses (Dominey-Howes & Papathoma, 2006; Papathoma et al., 2003; Kaiser et al., 2013). This is because what is on the land will have an impact on how much destruction a tsunami will cause and thus that areas vulnerability (Kaiser et al., 2013). In other studies, as well as this one, urban areas are given the highest values followed by open field such as crops and plain and then water and forests are the least vulnerable (Papathoma et al., 2003). Each cover dissipates wave energy in different ways. Urban areas have the most people and property to be lost, for these reasons urban land cover is given the greatest value.

Bathymetry Rationale

Bathymetry is among the most important factors regarding tsunami propagation (Matsuyama et al., 1999; Riquelme et al., 2015; Siva & Behera, 2016). As this is not a numerical model, far field bathymetry is not accounted for. However, the effect that continental shelves have on tsunamis has been studied and provides the basis for the valuation of bathymetry in this study. Siva and Behera's study measured the effect of the continental shelf on tsunami propagation and finds that the further the continental shelf is from the coast the higher the tsunami can build up for when it reaches the coast (Siva & Behera, 2016). In the case of this study the 50m shelf is used as that was found to have the greatest impact on tsunami propagation.

Coastline Length Rationale

The length of each individual county's coastline is important when discussing their vulnerability. Szlafsztein used the generalized length of each subdivision's coastline length in their study as well (Szlafsztein & Sterr, 2007). This is useful as the longer the coast upon which the tsunami makes landfall the larger the area of each coast can be affected by said tsunami and focused on each part of the coast.

Coastline Complexity Rationale

Coastline complexity is a complex variable which is discussed in Szlafsztein's study (Szlafsztein & Sterr, 2007). The premise of this variable is that the difference in coastline and shoreline length can impact the runup of a tsunami. Essentially the longer the shoreline is when compared the coastline the more area that can help dissipate the waves energy. If the coast is a straight line than the waves will simply run up with their energy being transferred directly into the coast. However, the more features that are found on the coast the more potential for energy transfer and thus dissipation of waves and less runup. this was calculated by dividing the shoreline length by the coastline length and the larger the number the less vulnerable that county would be.

Social Variables

Social variables were highly inspired by Cutter's work on SoVI (Cutter et al., 2003). As mentioned in the literature review this piece weighed social variables and found which ones had the most impact on an area's vulnerability to disasters. While the study is not focused on tsunamis specifically, many of the variables in the study are applicable to tsunamis. For this reason, only certain variables were used for this study and the rationale for each are generally like Cutter's work.

Total Population Rationale

The population of each county is perhaps the most logical variable to be used for a variability analysis and was given the highest weight in Szlafsztein's CVI study (Szlafsztein & Sterr, 2007). This is a logical conclusion as vulnerability is highly characterized by exposure and regarding social or human vulnerability there the more people in an area the more exposure there will be. This is true no matter the disaster as more people will cause more problems during disasters Total population is essential for understanding social vulnerability especially for subdivisions as large as counties.

Population Density Rationale

Population density is another variable that was heavily featured in the CVI study and other studies like it (Szlafsztein & Sterr, 2007; Weichselgartner, 2001; Zhang et al., 2013). Population density is important as the more concentrated people are, the more difficulty there will be during disaster. This is simply because traffic and overcrowding put increased stress on infrastructure and governments (Zhang et al., 2013). Therefore, cities are more vulnerable than other areas or counties that are less urban. Population density is an important factor to consider in case of vulnerability to disaster.

Income Rationale

The population that is below the poverty line is tends to be among the most vulnerable demographics to disaster (Cutter et al., 2003; Fothergill & Peek, 2004; Hallegatte et al., 2020). In the case of county level analyses, the stat is the percentage of population that is below this income level. Lower income levels increase vulnerability in two main ways: worse housing and increased difficulty recovering from disasters. Poorer housing is a function of being unable to afford better built homes. As mentioned in Cutter's study income is a consistent indicator of vulnerability (Cutter et al., 2003).

Age Rationale

It comes as no surprise that elderly population plays an important role in a community's vulnerability to disasters (Cutter et al., 2003; Meyer, 2016; Williams & Webb, 2020). Once again, the percentage of the county's population that is 65 or older is the statistic used for this variable. Elderly populations both have a harder time at escaping and a harder time at recovering from disasters such a tsunami. This is due to them likely having a fixed income due to retirement and so they will have a harder time replacing what is lost. Most importantly though, is that the elderly is harder to evacuate due to their circumstances. Particularly those that live alone will have a harder time escaping an incoming tsunami or the stress may be too much for their bodies to endure.

Vehicle Ownership Rationale

Transportation is paramount in case of the need for evacuation (Masozera et al., 2007; Morrow, 1999). While some of this could be alleviated by coordinated use of public transportation, it's unlikely that a satisfactory plan is in place for such an event particularly over an area as large as the USEC which in conjunction with the poor public transit in most of the United States makes for an important aspect of vulnerability (Anderson, 2013). For this reason, the percentage of households in each county that own their own vehicles was used as a variable for this study. The reason vehicle ownership was used is that the fewer people that own their own vehicles, the more people in each county that will turn to public transport or their local/ county government which will inevitably put more strain onto an already stressful situation.

Race Rationale

Race is nuanced beyond the scope of this study but is still a necessary factor in disaster vulnerability (Cutter et al., 2003; Flanagan et al., 2011; Fothergill et al., 1999). This is because different races will react to disasters differently and recover from disaster differently as well (Cutter et al., 2003). In the case of the USEC it is no secret that minorities are disproportionately represented in low income or inner-city neighborhoods (Fothergill et al., 1999). The point being that the percent of each counties population that is white was used for this study as vulnerability studies tend to agree that minorities are more vulnerable due to a plethora of factors (Flanagan et al., 2011).

Gender Rationale

Gender is another complex variable where vulnerability is concerned but is generally seen as females being more vulnerable than men (Ashraf & Azad, 2015; Cutter et al., 2003; Enarson, 1998; Rahman, 2013). For this reason, the percentage of females was used as the higher number of females in a community the more vulnerable they tend to be. This is for a variety of reasons, but it includes the lower average wages of women and the differences in their family care responsibilities as opposed to men (Ashraf & Azad, 2015).

Education Rationale

Education attainment is often a telling variable of the prosperity and vulnerability of different communities (Cutter et al., 2003; Frankenberg et al., 2013; Muttarak & Lutz, 2014). This is because lower educated people will generally know less about the risks of these disaster and less likely to heed the warnings of incoming disasters (Frankenberg et al., 2013). In the case of this study the percentage of high school graduate in the population was used as it has been found that less educated people tend to show more vulnerability toward disaster (Cutter et al., 2003).

Language Rationale

Language is a good gauge of overall community vulnerability for a few different reasons (Szlafsztein & Sterr, 2007; Teo et al., 2019; Xiang et al., 2021). First and foremost, if someone does not speak English or it is not their native language than they are less likely to comprehend warning that are given before an event and if they do it will take them longer than a native speaker to do so. Another reason is that many nonnative English speakers are foreign born and so are in a position as they are still being acclimated to American culture as well which would make it even more difficult to not only get out of harm's way but possibly more specifically recover from these disasters (Xiang et al., 2021).

Data Preparation

While the creation of the geodatabase gave a common projection and storage place for different layers, they still had to be changed for each variable to fit into a one number format used in the final analyses. The physical variables are the ones that required the most work as they were not in any type of format like what was needed for the final analyses. There were multiple steps that had to be included for each one to get them in the desired format. There was less that had to be done for the social variables as they were already in one number format for each county.

Social Variable Preparation

Social variables can all be included together as the procedure to get them into the ArcMap software was the same for all nine of the variables. Since they were downloaded as an excel spreadsheet all that needed to be done was to add them into the attribute table of the county layer that was being used. This was easily done by adding new float type fields into the attribute table of the layer and simply copying and pasting each variable over from the spreadsheet. They were sorted in alphabetical order to ensure that the correct numbers were put with correct counties but that was all that was necessary for the social variables for data preparation.

Elevation Preparation

Due to the nature of the DEM's that were downloaded to serve as the elevation variable, it was a multistep process to get them into the one number format necessary for this study. Firstly, all the 60+ DEM's had to be mosaiced together to have one file to use for the counties. This was then clipped to the county shapefile so that any excess area covered by the DEM was removed and only the counties were covered. Next a query was done to select all values that were under five meters and create a new layer with them. This layer was converted into a polygon layer individually for each county to only include the 5-meter land above sea level and below for one county. The total area of this layer was then compared to the area of the counties to determine the percentage of each county that was at or below five meters above sea level. This percentage was the value used for the elevation variable.

Land Cover Preparation

Land cover was also in a format that made it difficult to include in a one number format. This was less complicated than the elevation variable due to the nature of valuing land cover.

The land cover layer used included the entire contiguous United States which was then clipped to the 5m elevation layer. Land covers were given similar values to Papathoma's study: 1- forests, 2- wetlands and water, 3- shrubland and barren land, 4- grassland, 5- crops, and 10- Urban areas (Papathoma et al., 2003). It should be noted that 1 is the value given to the areas of least vulnerability and 10 for the highest. These reclassified values were then reduced to one number by using the zonal statistics function which was used to average the value of each county based on the number cells for each value. Urban was given a much higher value so it would have more bearing on the final average and as such the counties with highest levels of urbanism should be the most vulnerable due to the presence of people and economic activity (Papathoma et al., 2003).

Bathymetry Preparation

Bathymetry is usually done with numerical modeling, but this was not applicable to this study. Siva's study on the effects of the continental shelf on tsunami run-up was important in this regard as it gave the best alternative to a numerical model (Siva & Behera, 2016). With the 50-meter shelf being used as a contour line it was possible to do a simple proximity analysis that gave the distance from the 50-meter shelf contour to each county. This gave one number for each which made it so the higher the distance the larger the value those counties would be given. These distance values were added to the attribute table of the county file after this analysis.

Coastline Length Preparation

Coastline length was the least difficult to make into a one number format. This was done by converting the county polygon layer into a polyline layer and then only selecting the coast to create its own coastline layer. The intersect function was then used against the original county shapefile which gave the length of each segment for each county. This immediately gave the length of the coastline for each county. The measurement of the coastline length was then added to the attribute table.

Coastline Complexity Preparation

Coastline complexity was found using a similar method to the coastline length but this time using the much more detailed shoreline layer. As seen in figure 3 the shoreline layer includes coastline features which were selected in the same way that the coastline itself was. When the shoreline layer was created from this selection, the intersect function was once again used to get the total shoreline length for each county. With this number it was possible to divide the shoreline length by the coastline length to get complexity. The higher this number the longer the shoreline when compared to the coastline and the less vulnerable these counties would be.

Pre-Analysis Procedures

With all the data in the correct format the analyses could then be done. The steps for all three methods were the same for the beginning of each analysis. This entailed the reclassification of each layer on a scale of 1 to 10. Each variable that was added to the attribute table of the counties layer was converted into a raster layer to reclassify. This included every variable used except for the land cover layer as it was already in raster format and as such did not need to be included in the attribute table of the layer. After all raster layers were created, they were reclassified based on what the layer required. For every percentage layer aside from education and language the higher the percentage the higher the reclassified value. These include elevation, age, poverty, vehicle ownership, gender, language, and race. Due to education including those that had graduated high school these values were reversed, as the lower the percentage the higher the vulnerability. For each of the variables that were totals aside from coastline complexity, the higher the number the larger the values given to it. This includes bathymetry, coastline length, total population, and population density. Coastline complexity is switched as the higher the complexity of the coast the less vulnerable that county will be considered. That is what was done to every layer before the three different methodologies were utilized. Figures 4-17 show the reclassified view of each variable across the entirety of the USEC.

Additive vs Multiplicative approach

Both an additive and multiplicative approach were attempted to see if it would be worthwhile to use one over the other. These approaches are done while using the map algebra tool and as their names suggest allowing the variables to either be added or multiplied. After testing them both it was found that there were limited differences between the 2. For this reason, multiplicative analyses were omitted from this study as they provided little additional information regarding vulnerability.

Totaling Methodology

The first method utilized for the analysis was the totaling analysis. This analysis was done by simply taking all the reclassified layers and adding them together to get a final score. This was done separately with both social and physical before they were added together to get the final total vulnerability score. After they were added together, they were then divided into terciles to have a low, medium, and high vulnerability for each county. This is the simplest methodology and does not assume that physical and social variables are equal since there are nine social variables compared to only five physical variables. This makes this method tend to lean further towards the social side than physical.

Averaging Methodology

The averaging methodology differs from the totaling method in that it considers the number of variables included for social and physical vulnerability. This was done in the same way as the totaling methodology but instead of only adding the variables together they were then divided by the total amount of variables for that part of vulnerability. For the physical variables this meant adding all five variables together and then dividing by five to get the average physical vulnerability of each county. The same was done for the social variables but instead they were divided by 9. After the average of both social and physical vulnerabilities were found they were then added together to get the average vulnerability of each county. Similarly, to the totaling method these were then divided into terciles to obtain a low, medium, and high vulnerability. This methodology assumes social and physical factors account for vulnerability the same amount.

Color Cube Methodology

The final method used is called the color cube method due to the nature of the legend used for the maps created by it. This is a bivariate method in that physical and social variables were divided into terciles separately. As such there ends up being a low, medium, and high physical as well as low, medium, and high social vulnerability. This makes it so instead of only having three possible values there are instead nine possible combinations in this method which allows for a more nuanced look at the counties to see whether social or physical vulnerability has a higher impact on a county’s overall vulnerability.

Variables Table

Name	Description	Sources
Elevation	Percent of county below five meters above sea level	(Febrina et al., 2020), (Murthy et al., 2011), (Szlafsztein & Sterr, 2007)
Land Cover	Weighted values given based on their vulnerabilities to tsunamis	(Dominey-Howes & Papathoma, 2006), (Papathoma et al., 2003), (Kaiser et al., 2013)
Bathymetry	Distance from the 50-meter continental shelf	(Matsuyama et al., 1999), (Riquelme et al., 2015), (Siva & Behera, 2016)
Coastline Length	Straight line distance of the coastline of each county	(Chang et al., 2018), (Szlafsztein & Sterr, 2007)

Table 1: Table with descriptions of each variable and sources that support them.

Variables Table

Coastline Complexity	Difference in shoreline distance/ coastline distance	(Bush et al., 1999), (Sinaga et al., 2011), (Szlafsztein & Sterr, 2007)
Total Population	Total population of each county	(Szlafsztein & Sterr, 2007), (Zhou et al., 2014)
Population Density	People per square mile of each county	(Szlafsztein & Sterr, 2007), (Weichselgartner, 2001), (Zhang et al., 2013)
Income	Percent of each county's population below the poverty line	(Cutter et al., 2003), (Fothergill & Peek, 2004), (Hallegatte et al., 2020)

Table 1: Table with descriptions of each variable and sources that support them.

Variables Table

Age	Percentage of each county's population above 65 years of age	(Cutter et al., 2003), (Meyer, 2016), (Williams & Webb, 2020)
Vehicle Ownership	Percentage of households that own at least one personal vehicle	(Masozera et al., 2007), (Morrow, 1999)
Race	Percentage of people in each county that are white	(Cutter et al., 2003), (Flanagan et al., 2011), (Fothergill et al., 1999),
Gender	Percentage of people in each county that are female	(Ashraf & Azad, 2015), (Cutter et al., 2003), (Enarson, 1998), (Rahman, 2013)

Table 1: Table with descriptions of each variable and sources that support them.

Variables Table

Education	Percentage of people in each county that have at least a high school diploma	(Cutter et al., 2003), (Frankenberg et al., 2013), (Muttarak & Lutz, 2014)
Language	Percentage of people in each county that speak English as a second language	(Szlafsztein & Sterr, 2007), (Teo et al., 2019), (Xiang et al., 2021)

Table 1: Table with descriptions of each variable and sources that support them.

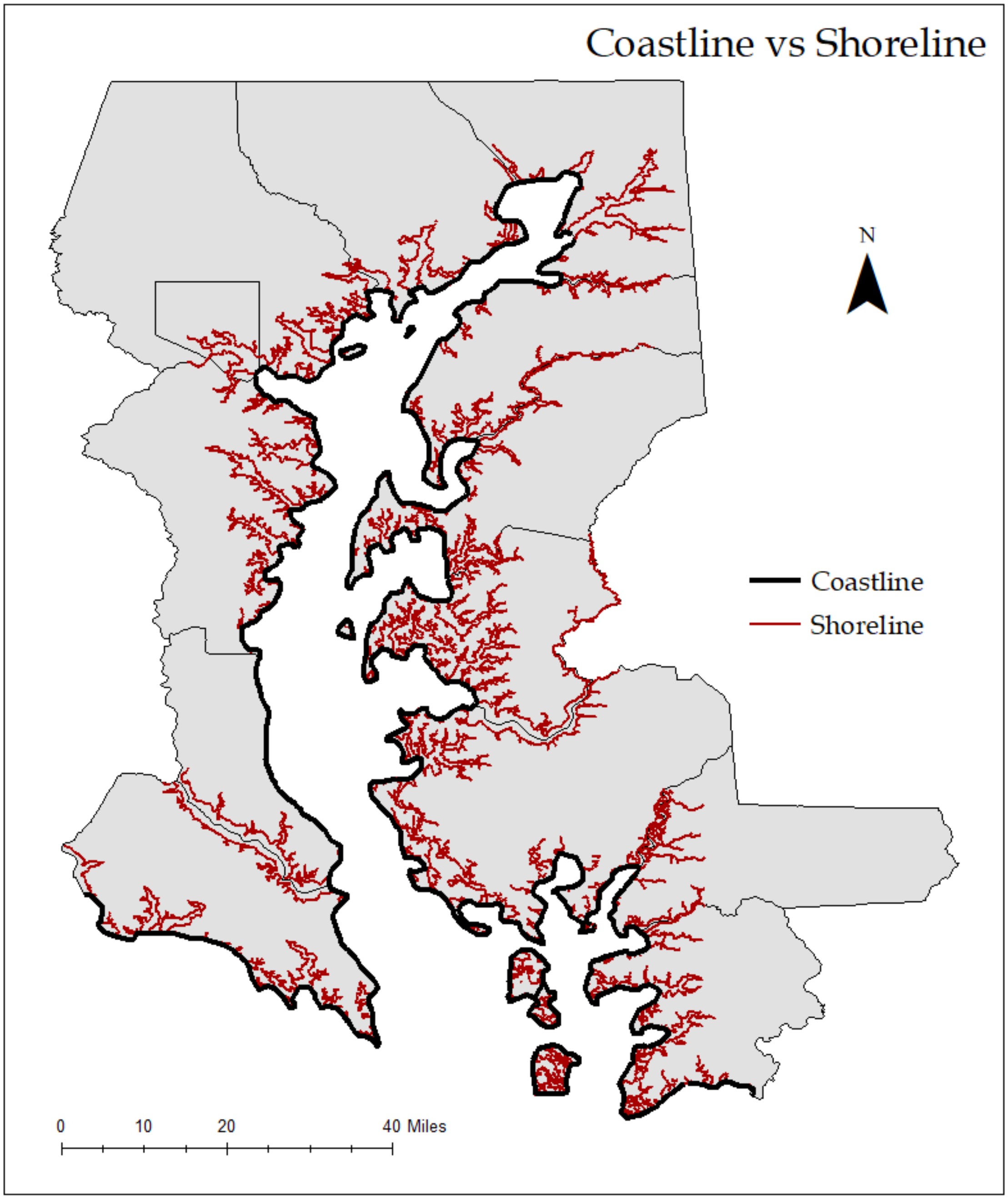

Figure 3: Map of Chesapeake Bay showcasing the difference between coastline and shoreline.

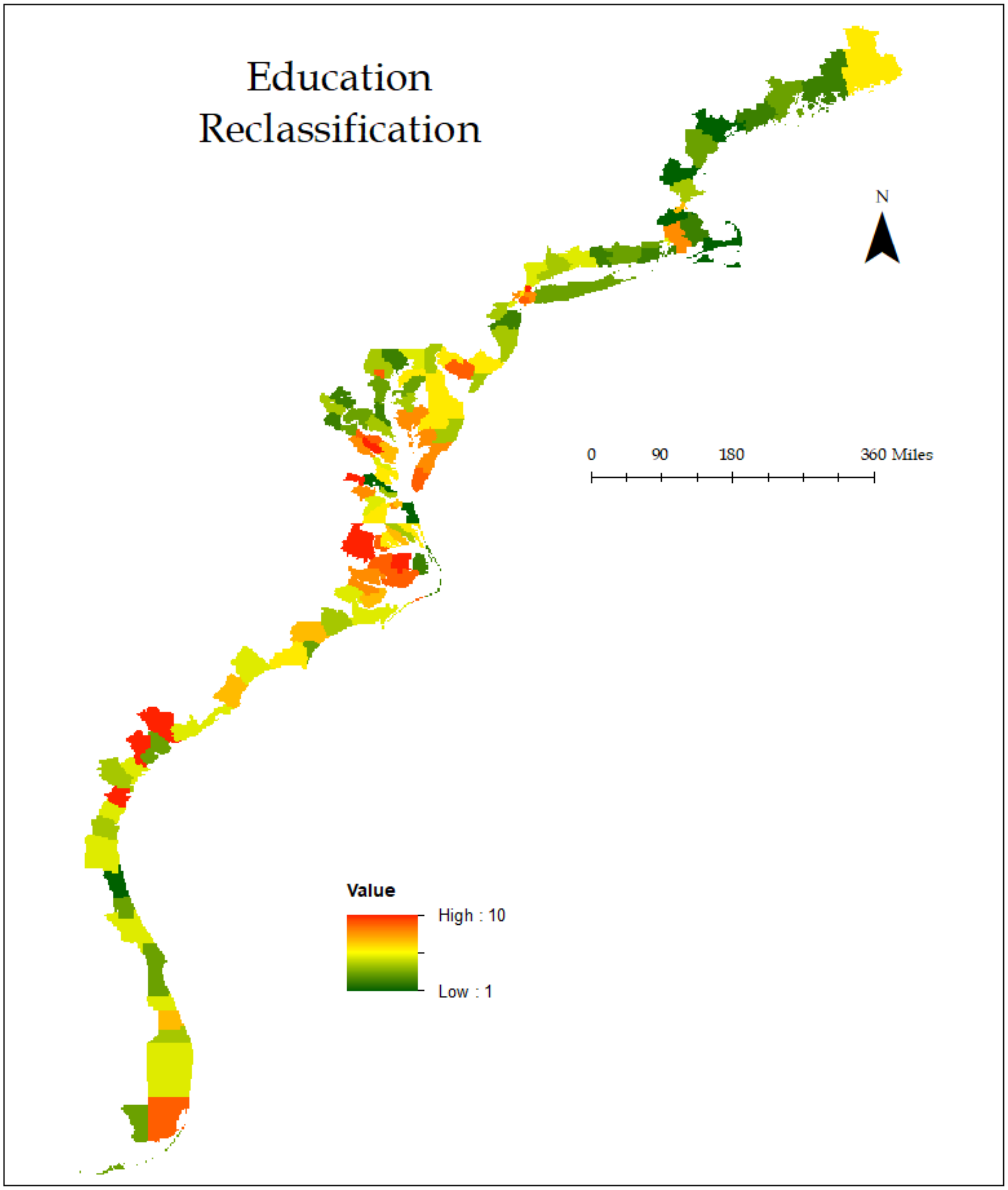

Figure 4: Reclassified layer of each counties percentage of population that are high school graduates.

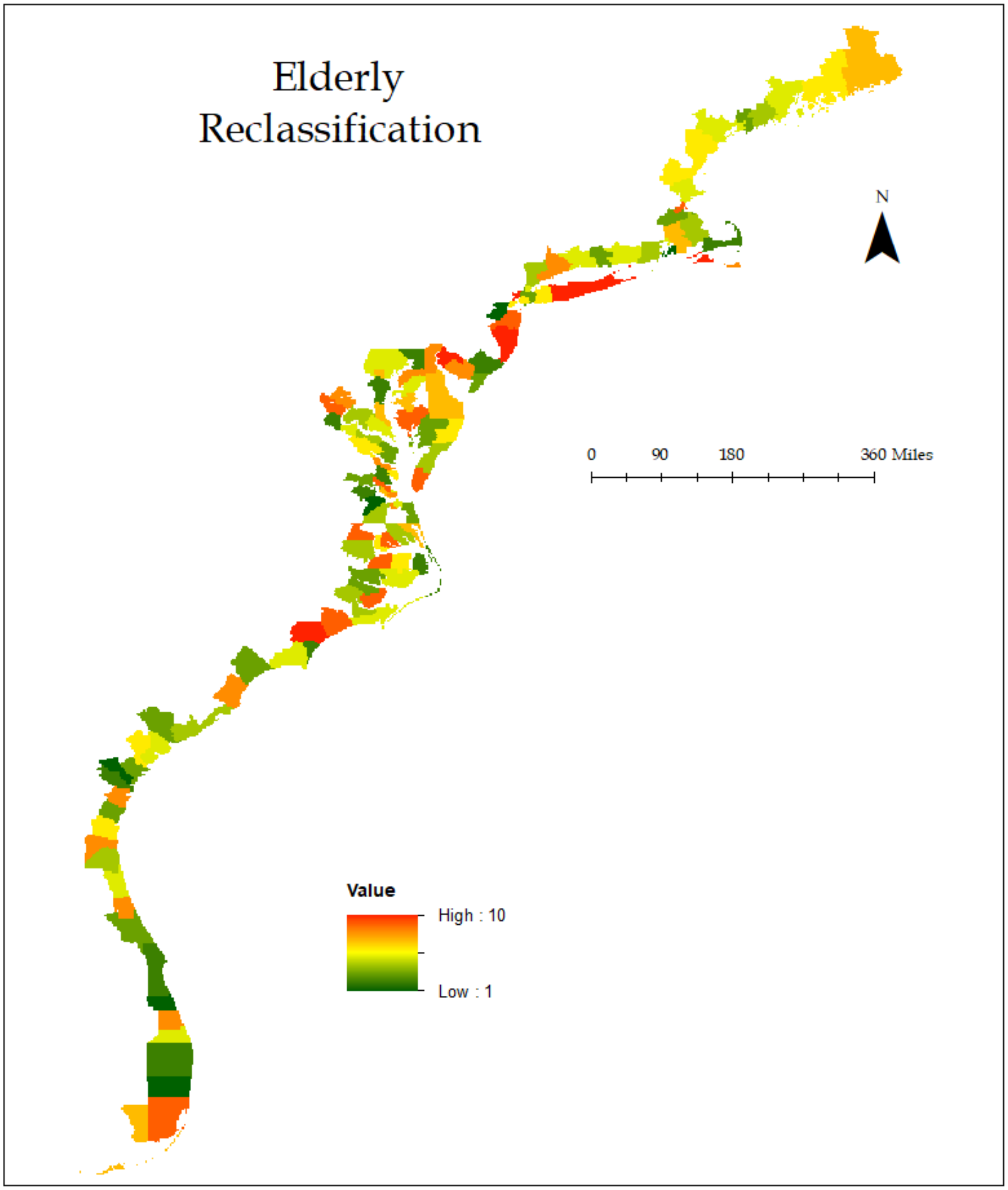

Figure 5: Reclassified layer of each counties percentage of population aged 65 and older.

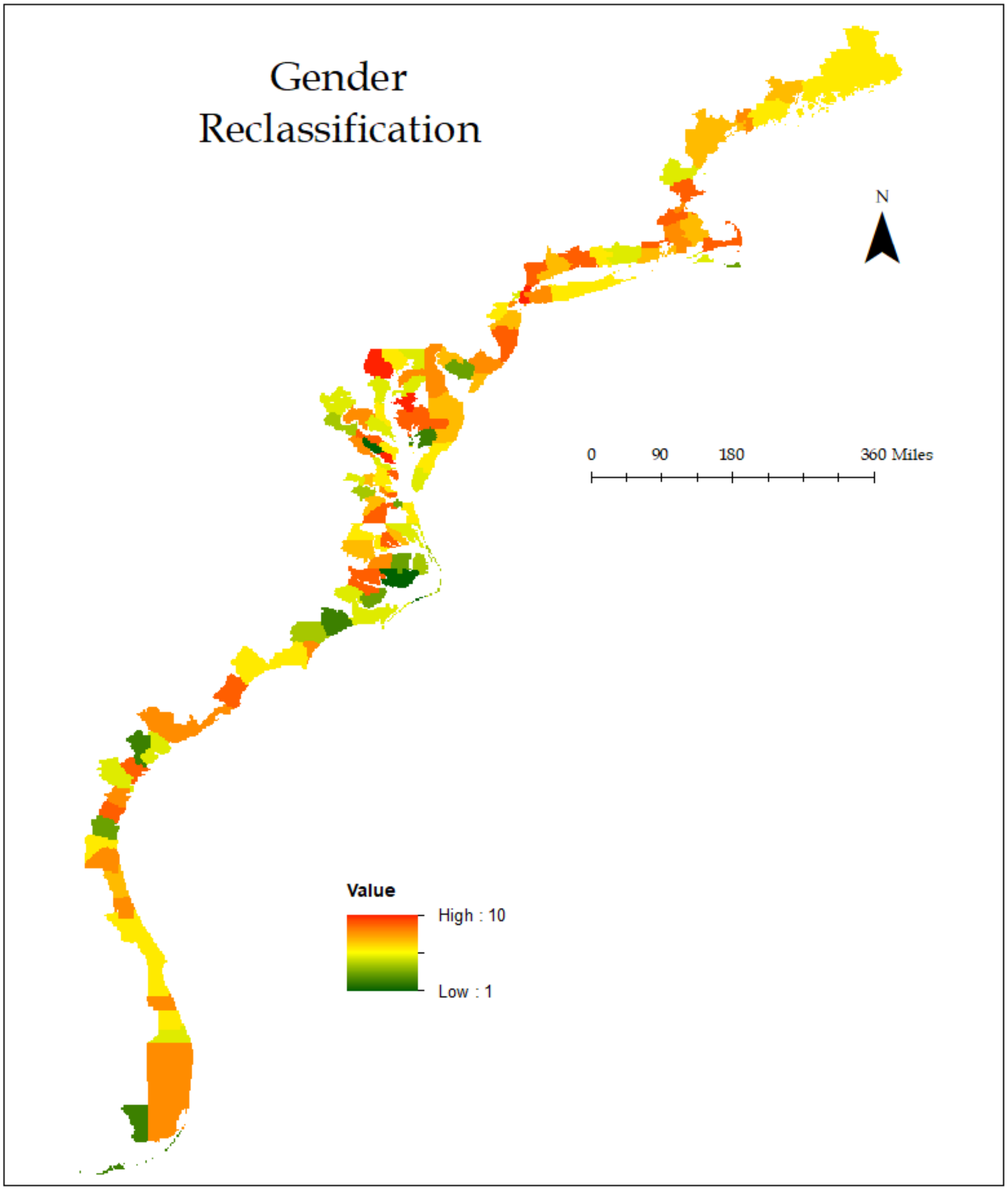

Figure 6: Reclassified layer of each counties percentage of the population that is female.

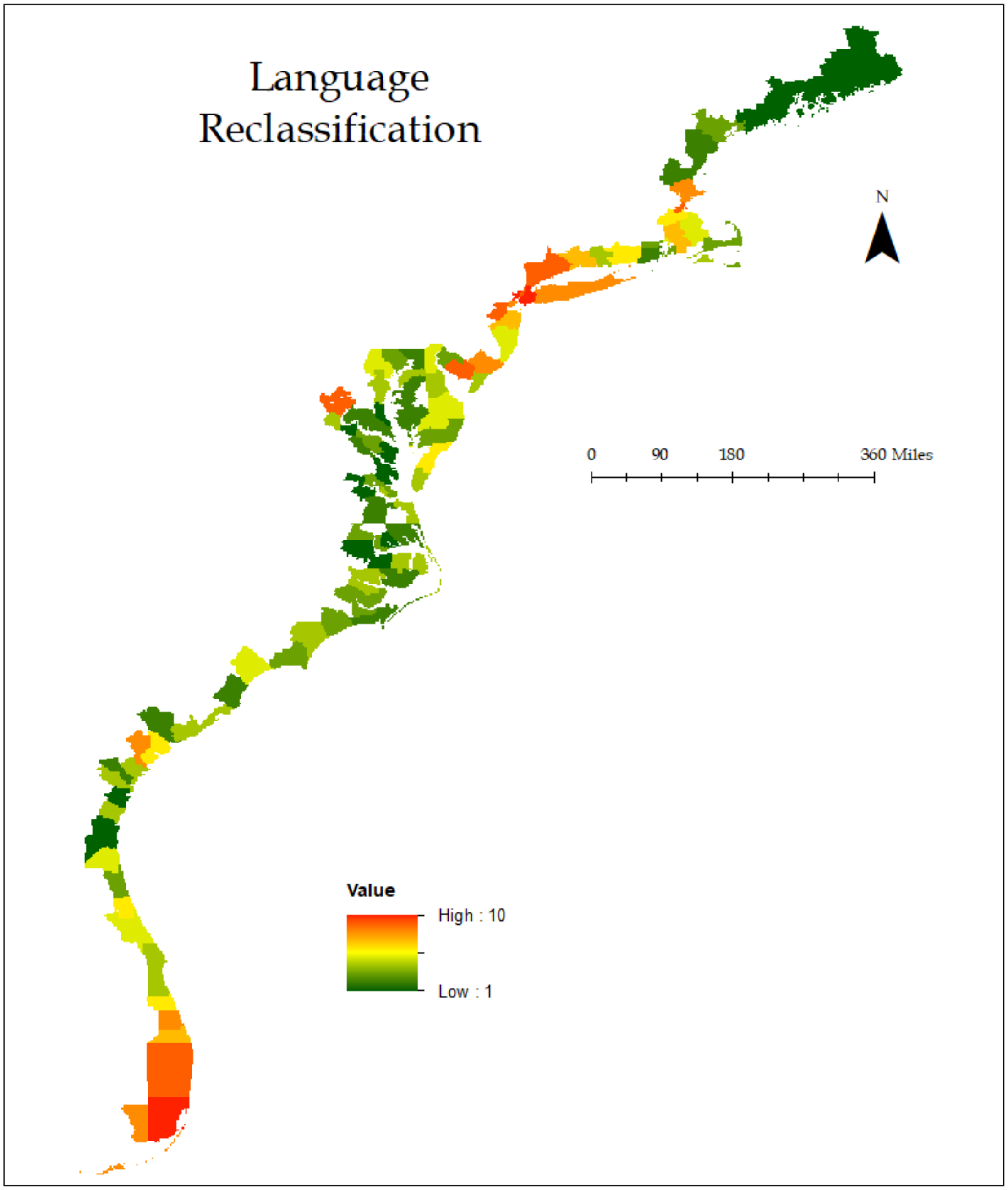

Figure 7: Reclassified layer of each counties percentage of population that speaks English as a second language.

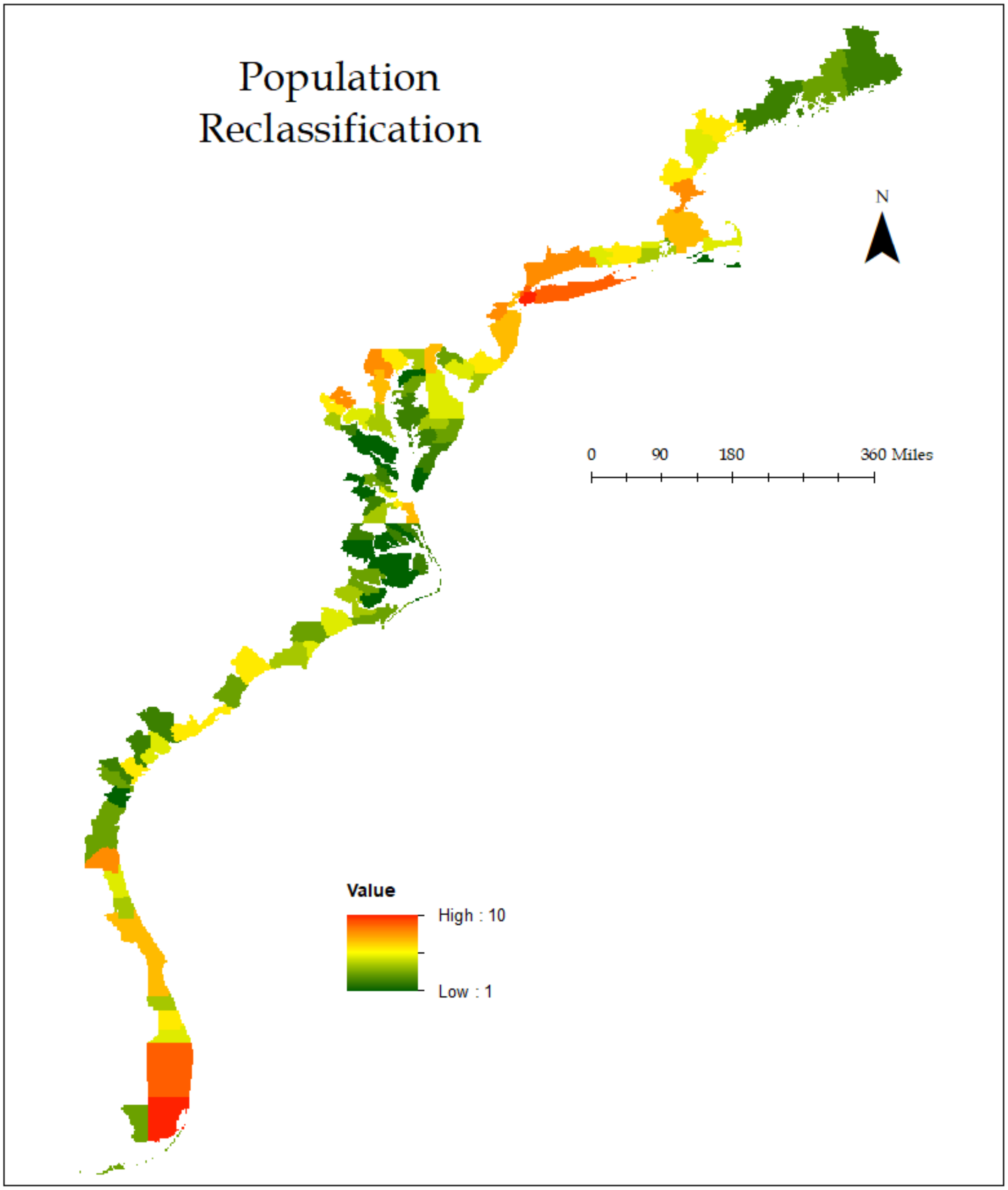

Figure 8: Reclassified layer of each counties total population.

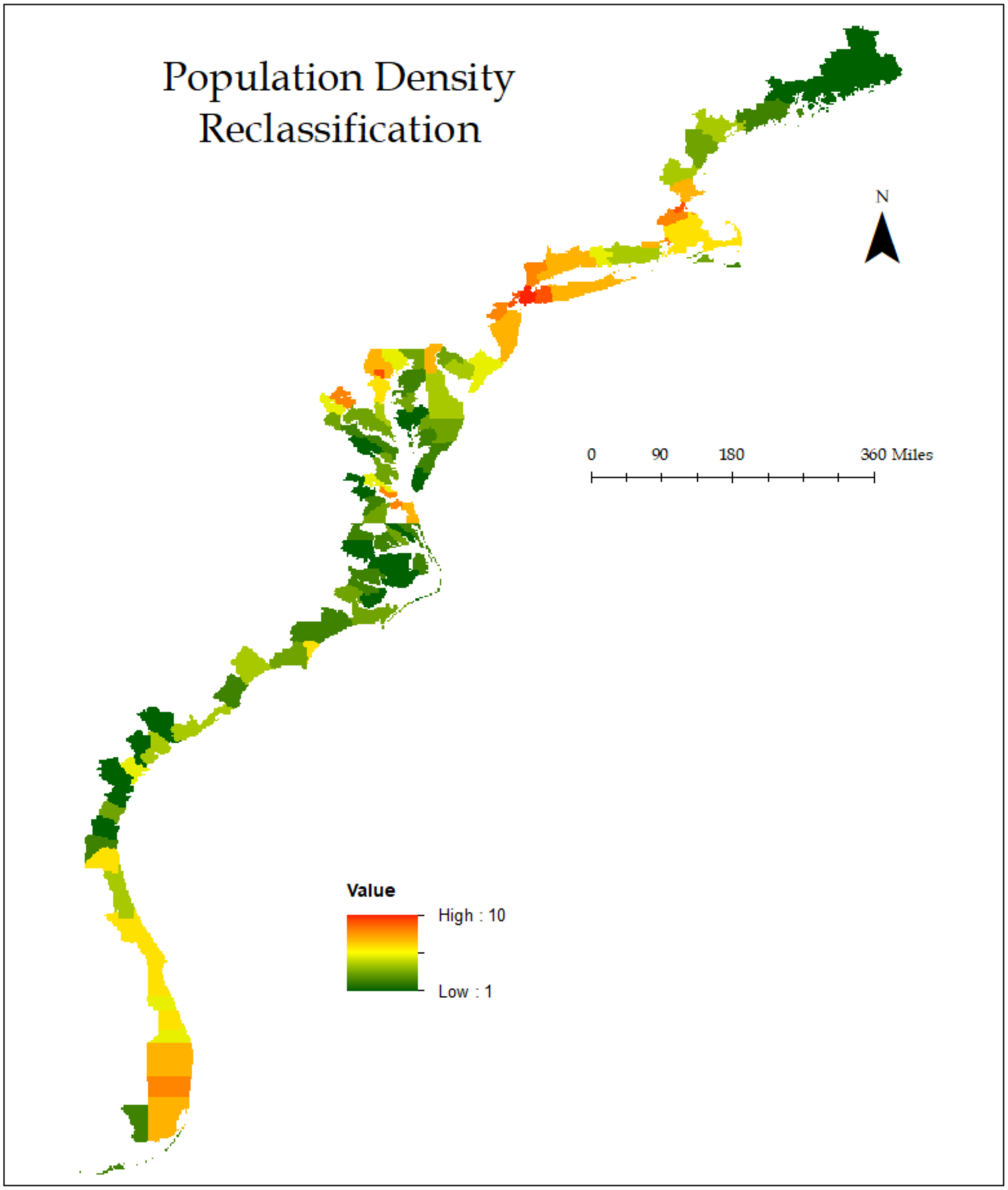

Figure 9: Reclassified layer of each counties population density.

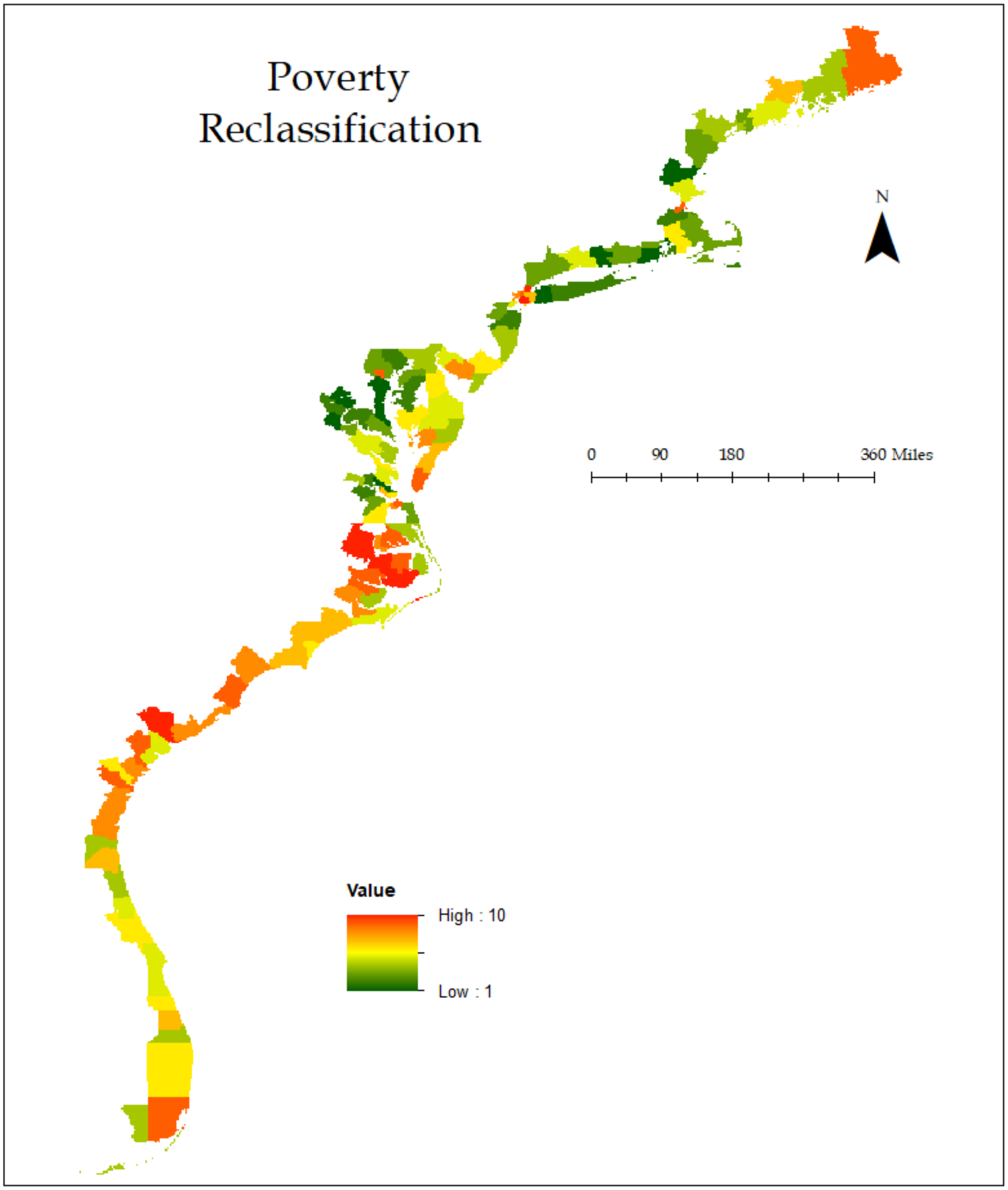

Figure 10: Reclassified layer of each counties percentage of population below the poverty line.

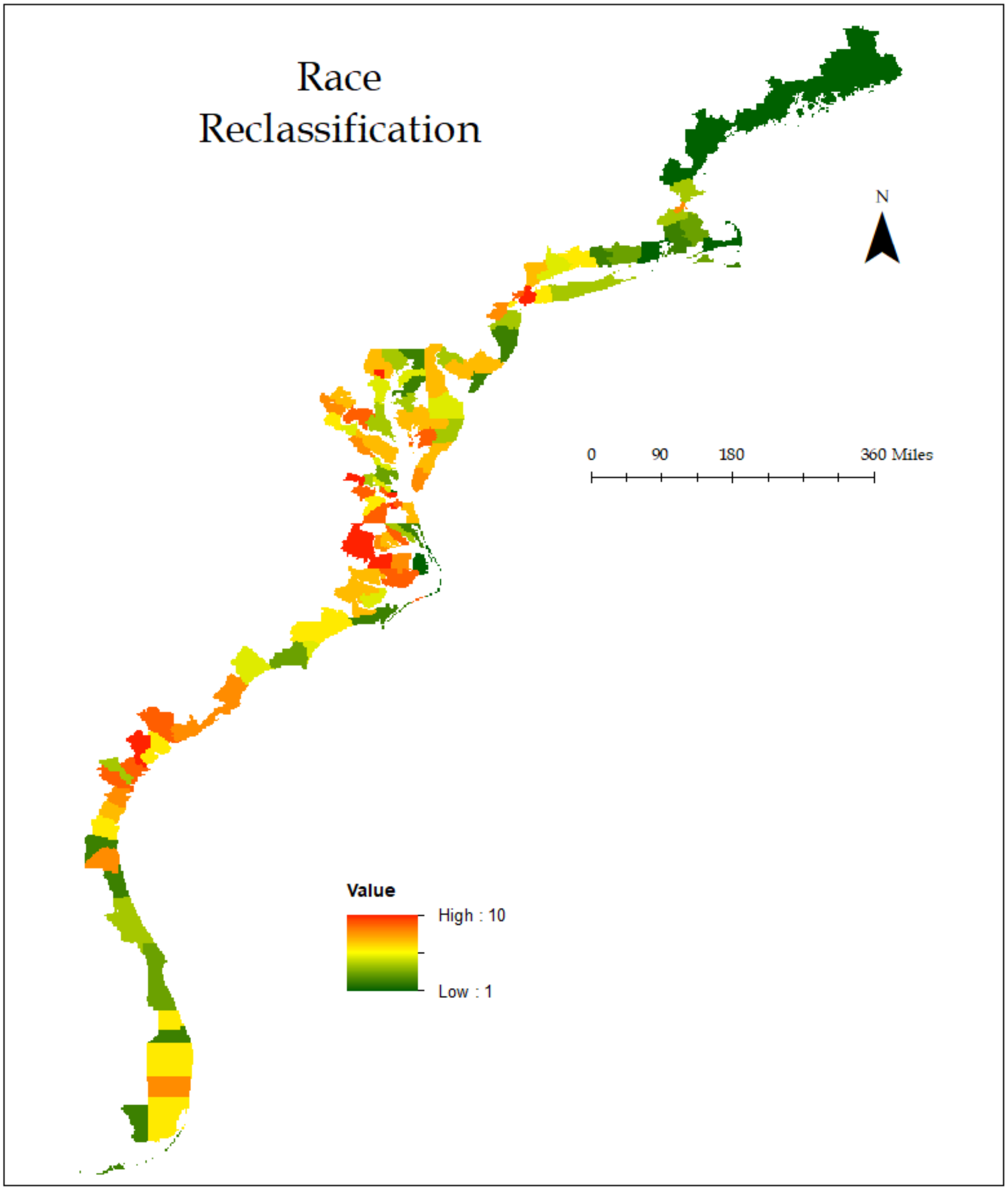

Figure 11: Reclassified layer of each counties percentage of population that is white.

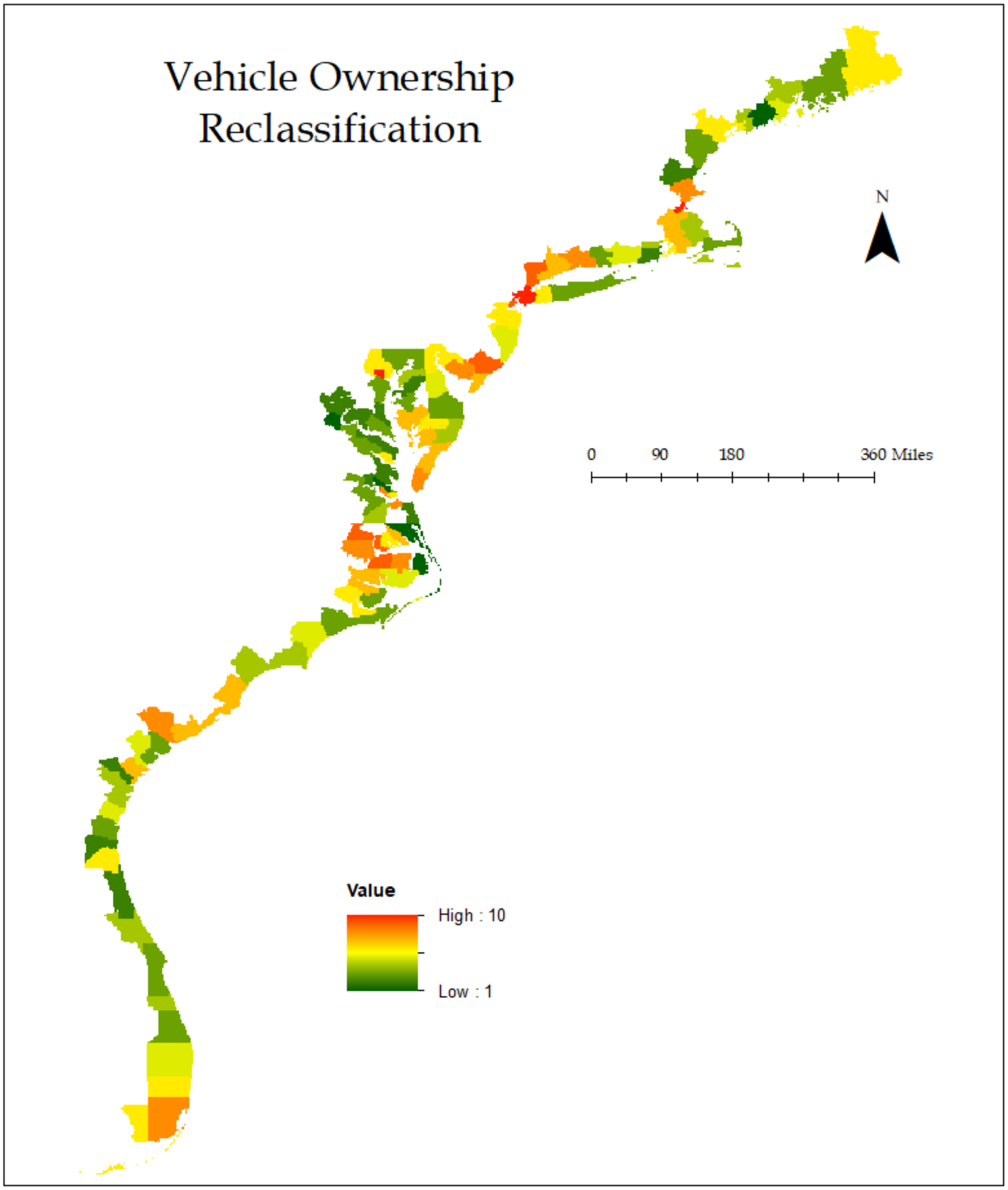

Figure 12: Reclassified layer of each counties percentage of households that own their own personal vehicle.

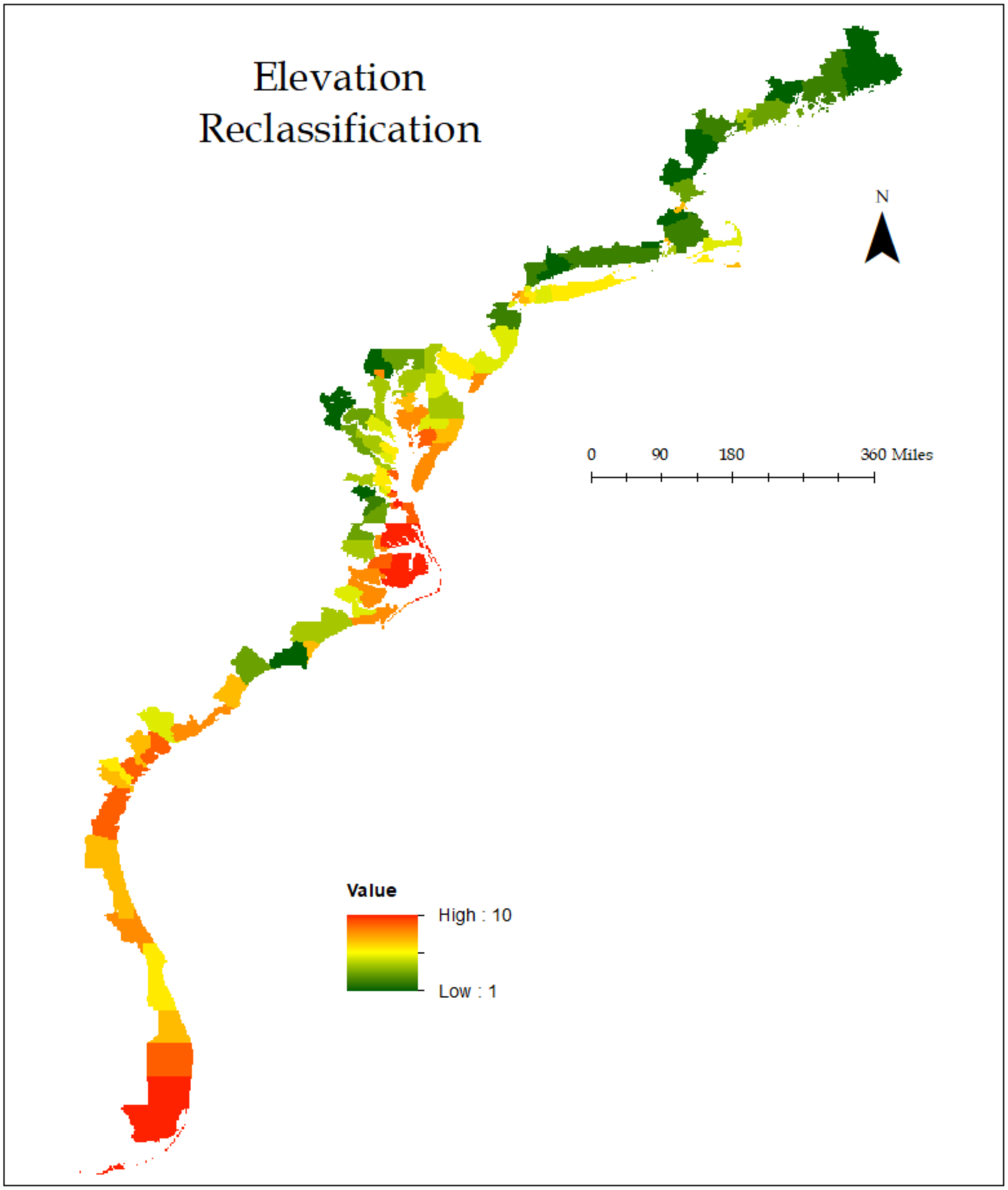

Figure 13: Reclassified Layer of each counties percentage of land that is at or below 5m above sea level.

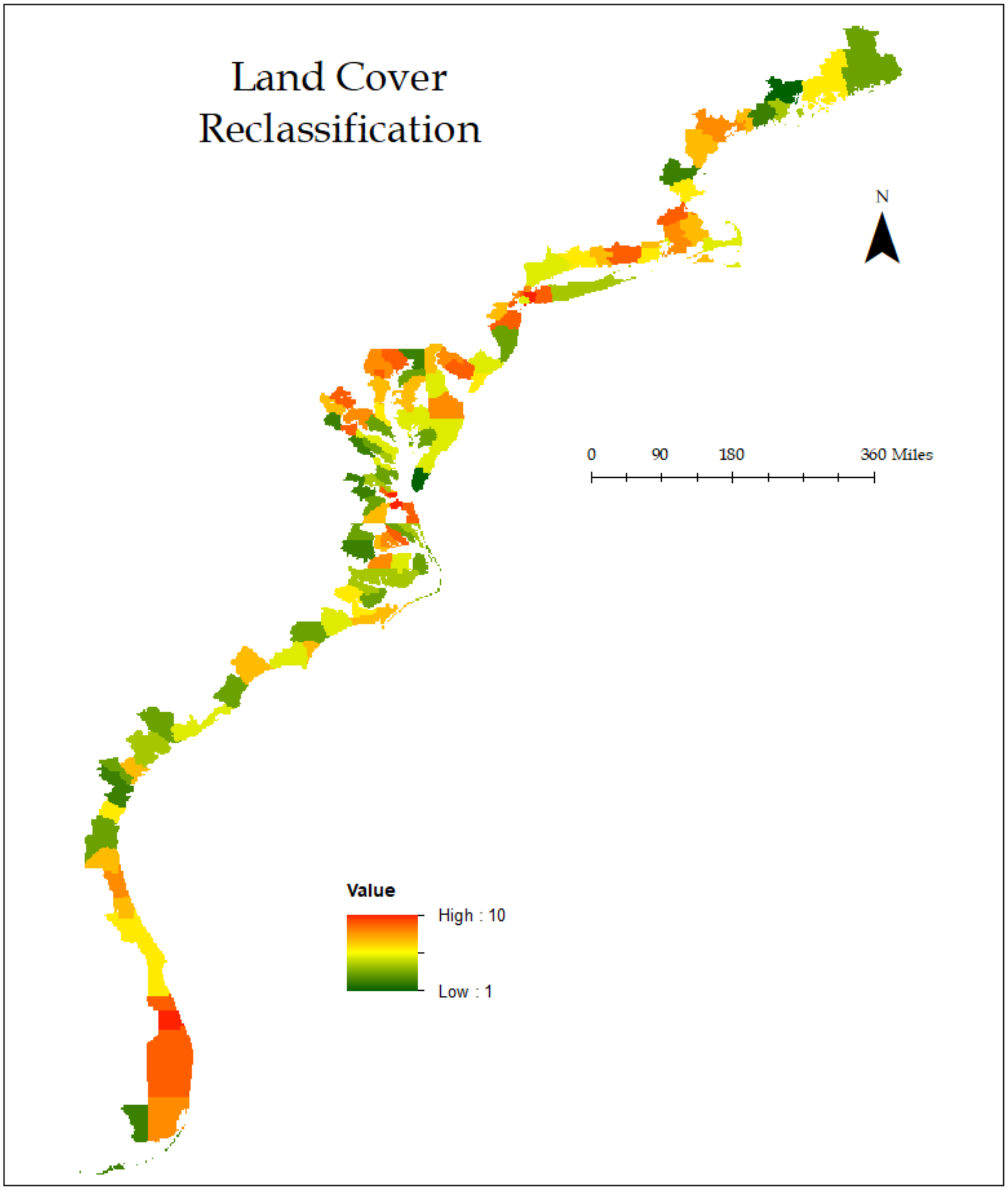

Figure 14: Reclassified layer of each counties land cover zonally averaged.

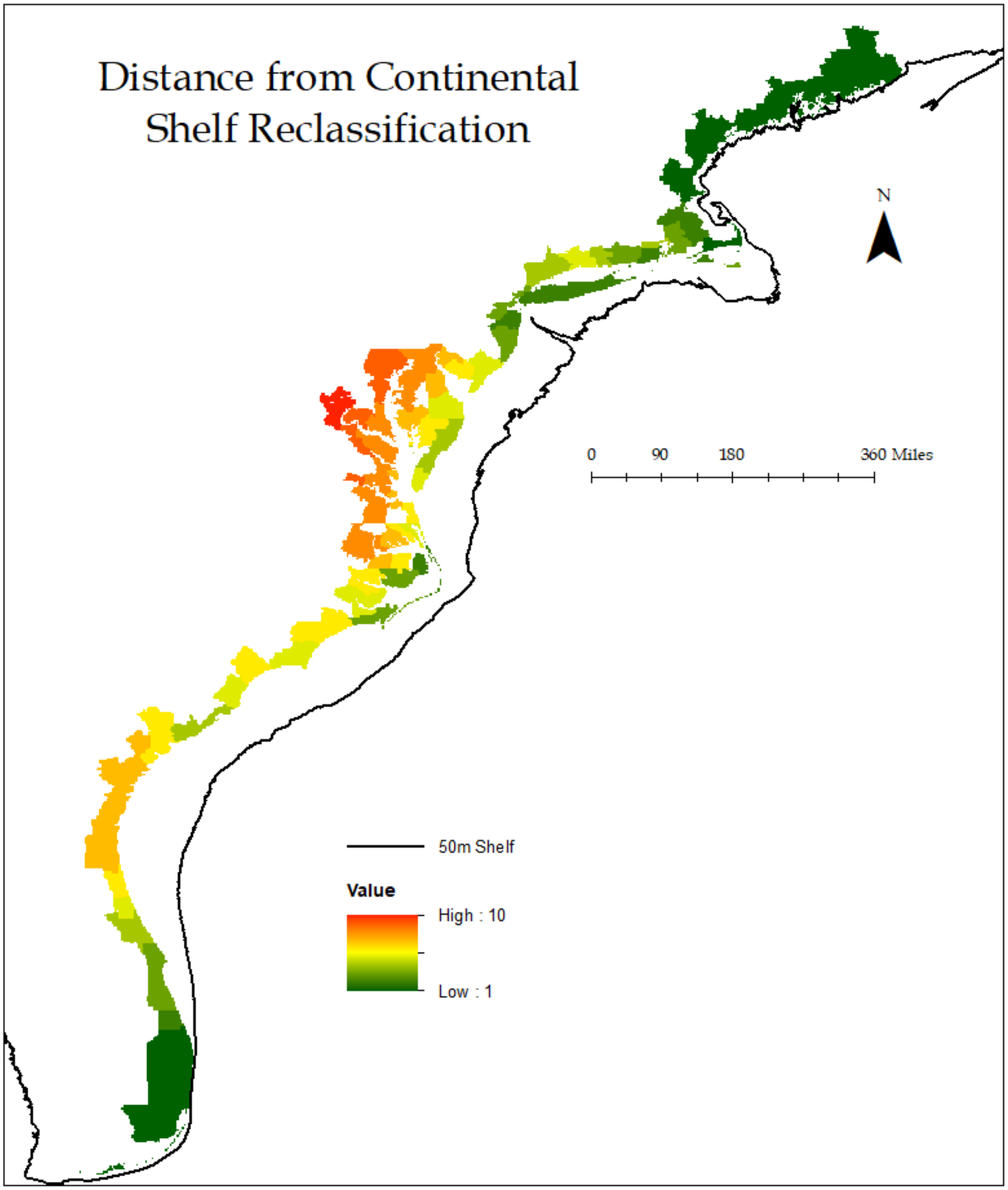

Figure 15: Reclassified layer of each counties distance from the 50m bathymetric contour.

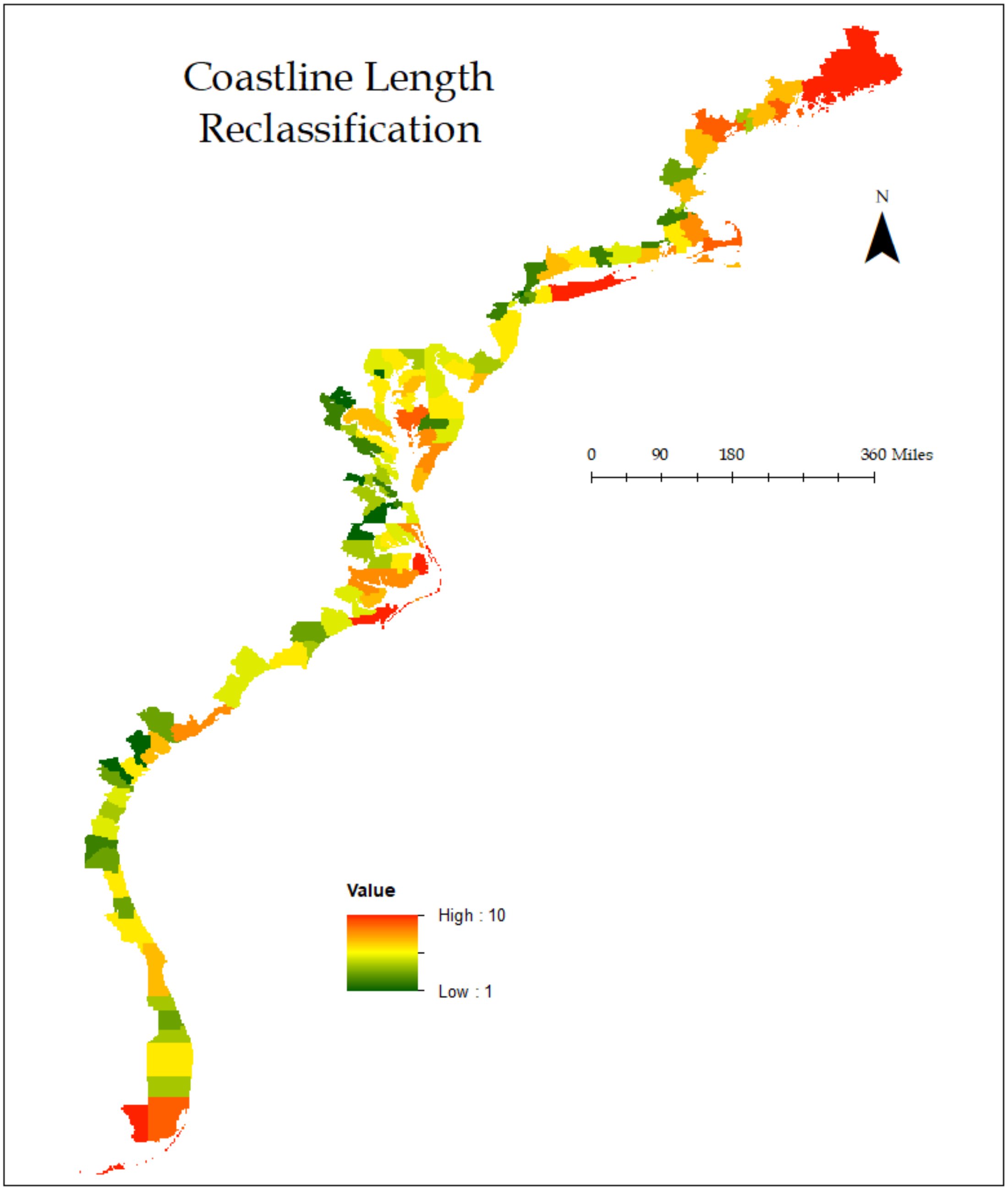

Figure 16: Reclassified layer of each counties length of coastline.

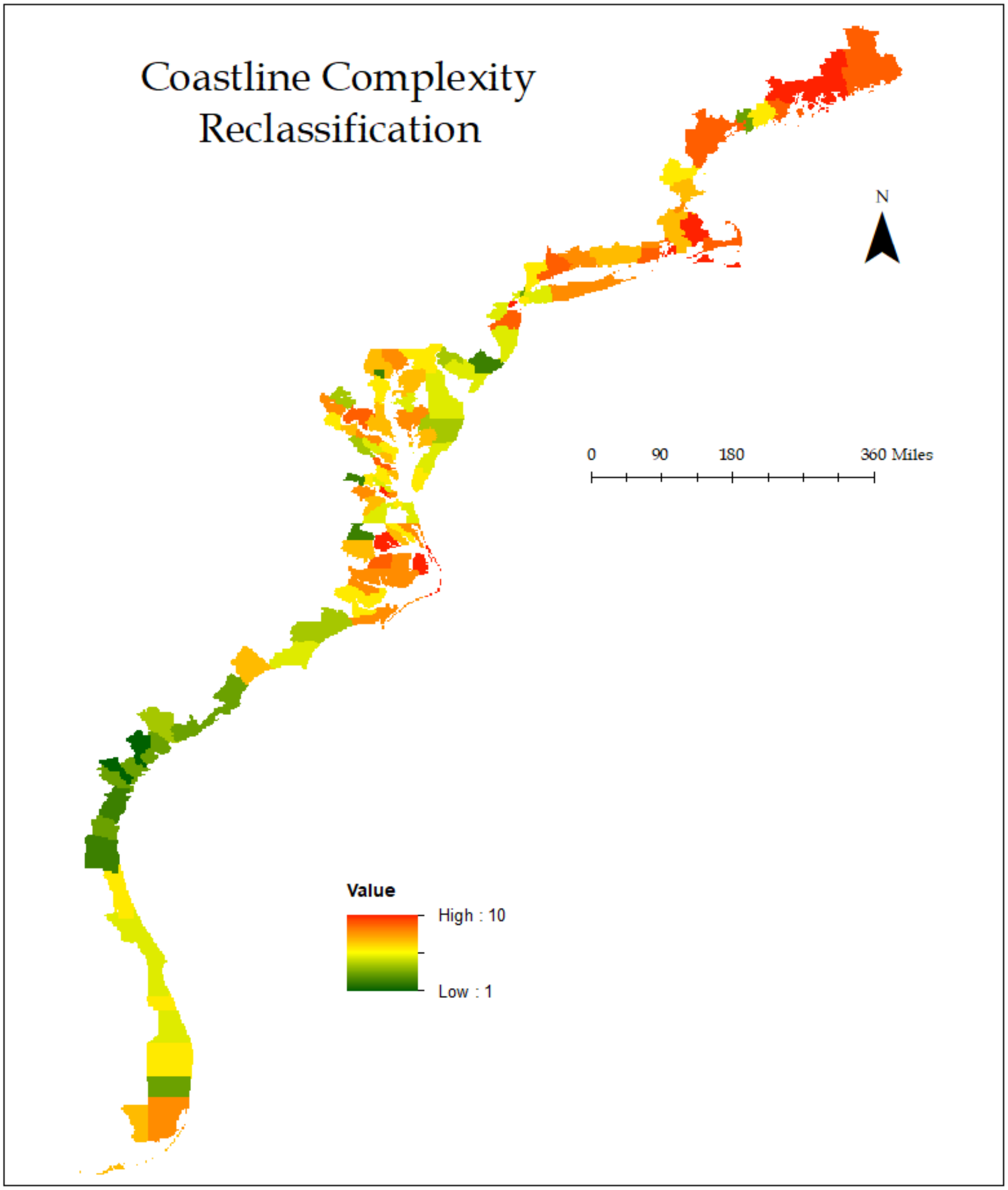

Figure 17: Reclassified layer of each counties coastline complexity.

RESULTS

The results of the three analyses will be shown in this section. The totaling method assumes that all variables are worth the same amount, but that social vulnerability is worth more due to there being more social variables. The averaging method instead assumes that both physical and social variables have equal impact on the vulnerability of an area. The color cube method is a bivariate method that splits the physical and social vulnerability into terciles individually which are then brought together in the final map.

Totaling Method Results

Totaling methodology assumes that all variables are worth the same amount, but that social vulnerability has more bearing on overall vulnerability than physical vulnerability does. The maximum possible social vulnerability score in this method is 90 while the maximum possible physical vulnerability score is 50. This means the maximum possible overall vulnerability score would be 140 using the totaling method. Figure 18 shows the physical vulnerability of the USEC using the totaling method. Perquimans county, NC has the highest total physical vulnerability with a score of 41. Rockingham county, NH has the lowest total physical vulnerability with a score of 13. Figure 19 shows the social vulnerability of the USEC using the totaling method. Kings County, NY has the highest total social vulnerability with a score of 85. Dare county, NC has the lowest total social vulnerability with a score of 22. Figure 20 shows the final vulnerability using this method after adding both the physical and social vulnerabilities together. Miami-Dade County, FL has the highest total vulnerability with a score of 112. Rockingham County, NH has the lowest total vulnerability with a score of 41. Figure 21 is the result of dividing the final vulnerability into terciles of low, medium, and high. Low values were those that were between 41-64, medium were 65-88, and high were 89-112. There are 17 counties that fall into the high category, 37 counties that fall into the low category, and 75 that fall into medium category.

Averaging Method Results

Averaging methodology assumes that physical and social vulnerability are equal regarding overall area vulnerability. Due to the nature of this method the maximum possible score for both the average physical and social vulnerabilities is 10 which means the maximum average score is 20. Figure 22 shows the physical vulnerability of the USEC using the averaging method. Perquimans County, NC has the highest average physical vulnerability score at 8. Rockingham County, NH has the lowest average physical vulnerability score at 2. Figure 23 shows the social vulnerability using the averaging method. The highest average social vulnerability is shared by Kings County and Bronx County, NY with a score of 9. The lowest average social vulnerability is shared by six counties: Camden, NC, Dare, NC, Lincoln, ME, Nantucket, MA, Sagadahoc, ME, and Queen Anne's, MD with scores of 2. Figure 24 shows the overall vulnerability after adding both the physical and social vulnerabilities together. Miami-Dade County, FL has the highest average overall vulnerability with a score of 15. The lowest average overall vulnerability is shared by three counties: Lincoln, ME, Rockingham, NH, and Sagadahoc, ME with scores of 5. Figure 25 is the result of dividing the final vulnerability into terciles of low, medium, and high. Low values were those that were between 5-8, medium were 9-11, and high were 12-15. There are 24 counties that fall into the high category, 32 in the low category, 73 in the medium category.

Color Cube Method Results

The color cube method brings the social and physical vulnerabilities together without adding them together so the nuance of what makes the county more vulnerable can be seen. This method does not use scores but instead splits both the physical and social variables into terciles before combining them. This gives nine possible combinations between social and physical variables. Figure 26 shows the Physical vulnerability split into terciles. There are 32 counties that have high physical vulnerability, 25 counties that have low physical vulnerability, and 72 counties that have medium physical vulnerability. Figure 27 shows the social vulnerability split into terciles. There are nine counties that have high social vulnerability, 65 counties that have low social vulnerability, and 55 counties that have medium social vulnerability. Figure 28 shows the different combinations that are created when the social and physical terciles are put together. It is called the color cube methodology as the color that the county falls into on the cube is the result of the combination of the two variables. H represents high vulnerability, M represents medium vulnerability, and L represents low vulnerability. These are also in a format where social vulnerability is represented by the first letter and physical vulnerability is represented by the second letter. Each combination has multiple counties included in it and the number for each combination is as follows: HH-2, HL-1, HM-6, LH-16, LL-14, LM-35, MH-14, ML-10, and MM-31.

Small Scale Maps

While maps of the entire USEC allow general trends and differences to be seen, smaller scale maps allow for a more thorough understanding of what causes the variance. As such six localized figures were created with a graphic of each method sided by side within. These will allow for a viewing and dissection of each method to see what causes the variance between them. Figure 29 is the localized view of Chesapeake Bay counties of Maryland. Figure 30 shows the counties around the Hampton Roads region of Virginia. Figure 31 includes the five Boroughs of New York City and the county of Hudson, NJ. Some of the city of Boston and its surrounding area are included in figure 32. A large portion of the coast of North Carolina is seen in figure 33. Finally, the area surrounding Miami, FL is examined in figure 34.

Chesapeake Bay

The counties of Maryland that surround the Chesapeake Bay showed variability between each method and are thus a useful area to take a closer look at. Figure 29 includes the graphics that will be discussed here. While the totaling and averaging methods are relatively unremarkable outside of the city of Baltimore, the color cube method shows a great deal of variability. This is due to the high physical vulnerability that the Bay has according to the method. Baltimore itself is not particularly physically vulnerable but as already covered, since it is a city, it has among the highest social vulnerability.

Hampton Roads

The next smaller region that will be examined is the Hampton Roads region in Virginia. Figure 30 has the graphics that include each of the methods for this area. Totaling and averaging methods are identical with the exception of Poquoson County being low vulnerability with the totaling method and medium vulnerability in the averaging method. The exceedingly high vulnerability of the counties at the entrance of this coastal feature draws the eye. This includes six city counties: Hampton, Newport News, Norfolk, Poquoson, Portsmouth, and Virginia Beach. As noted, all six of these are considered cities and it shows in the vulnerability of the area. Poquoson and Virginia Beach are both highly physically vulnerable while lacking social vulnerability. Hampton, Newport News, and Norfolk are highly socially vulnerable while being of medium social vulnerability. Finally, Portsmouth is one of only two counties in the entire study that was found to have both high social and physical vulnerability.

New York City

The New York City area comes as no surprise in terms of being highly vulnerable. As by far the largest city by population in the United States it naturally ranks among the most vulnerable areas of the country in most vulnerability studies. However, according to this study there is some variability to the counties that make up or are near the city. Figure 31 includes the graphics that showcase the vulnerability of the area. The variability cannot be seen in the totaling or averaging methods as all six counties have high vulnerability in these studies, however, the color cube method shows a slightly different amount of variability. Physical vulnerability accounts for most of the discrepancies seen between the counties as all but one of the counties has high social vulnerability. The one county that does not have high social vulnerability is Richmond County which is better known as Staten Island.

Northeast Massachusetts

The region of Northeast Massachusetts that was used includes a part of the city of Boston. Figure 32 includes the graphics that showcase the areas vulnerability. Not all of Boston is included as the only county included that can truly be considered a part of the city is Suffolk. The rest of the counties have some of the suburbs but as seen in the figure are not highly physically or socially vulnerable. Due to this Suffolk is the main county of concern in this area.

As with the other large cities included, this is highly socially vulnerable but also has medium physical vulnerability.

North Carolina

The next region selected is the Northern counties of North Carolina. This includes most counties that are in North Carolina used in this study. Figure 33 includes the graphics that show the vulnerability of the area using all three methods. What is of note is that there is variability between the totaling and averaging methods when viewing this region. This can be explained by this being one of the most physically vulnerable areas of this study and as such the totaling method that makes physical vulnerability less impactful shows this area as being less vulnerable. With the area around Albemarle Sound, which is the Northern portion of this region showing relatively high vulnerability in methods.

Southern Florida

The final region that was studied is that of Southern Florida, which was chosen due to the presence of the city of Miami in the area. Figure 34 includes the graphics of each method in the area. Miami-Dade County is one of only two counties that have both high social and physical vulnerability in this study. With that in mind as well as the fact that it is among the largest cities in the study, it is a required region to discuss.

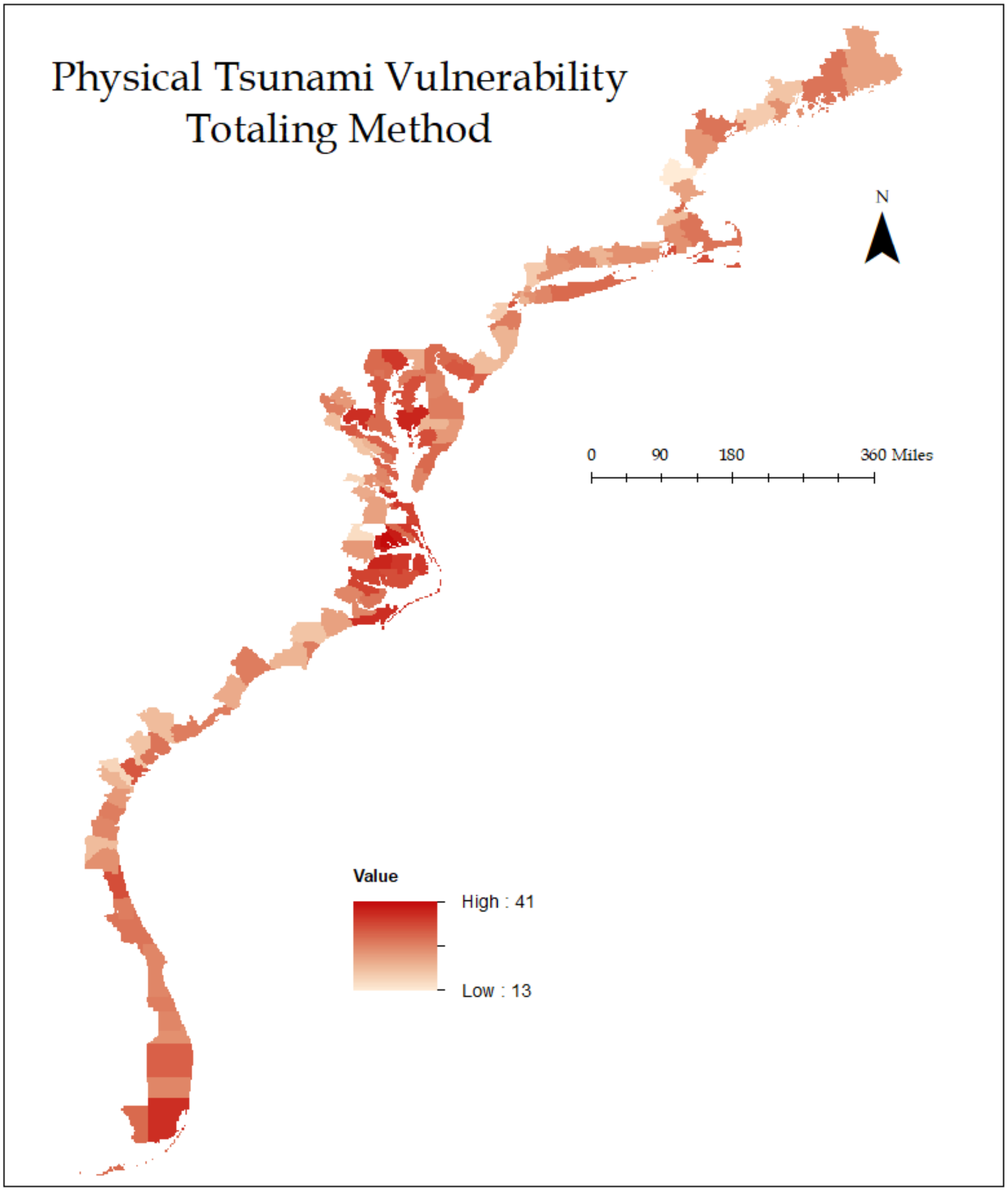

Figure 18: Physical vulnerabiliy of each county using the totaling method.

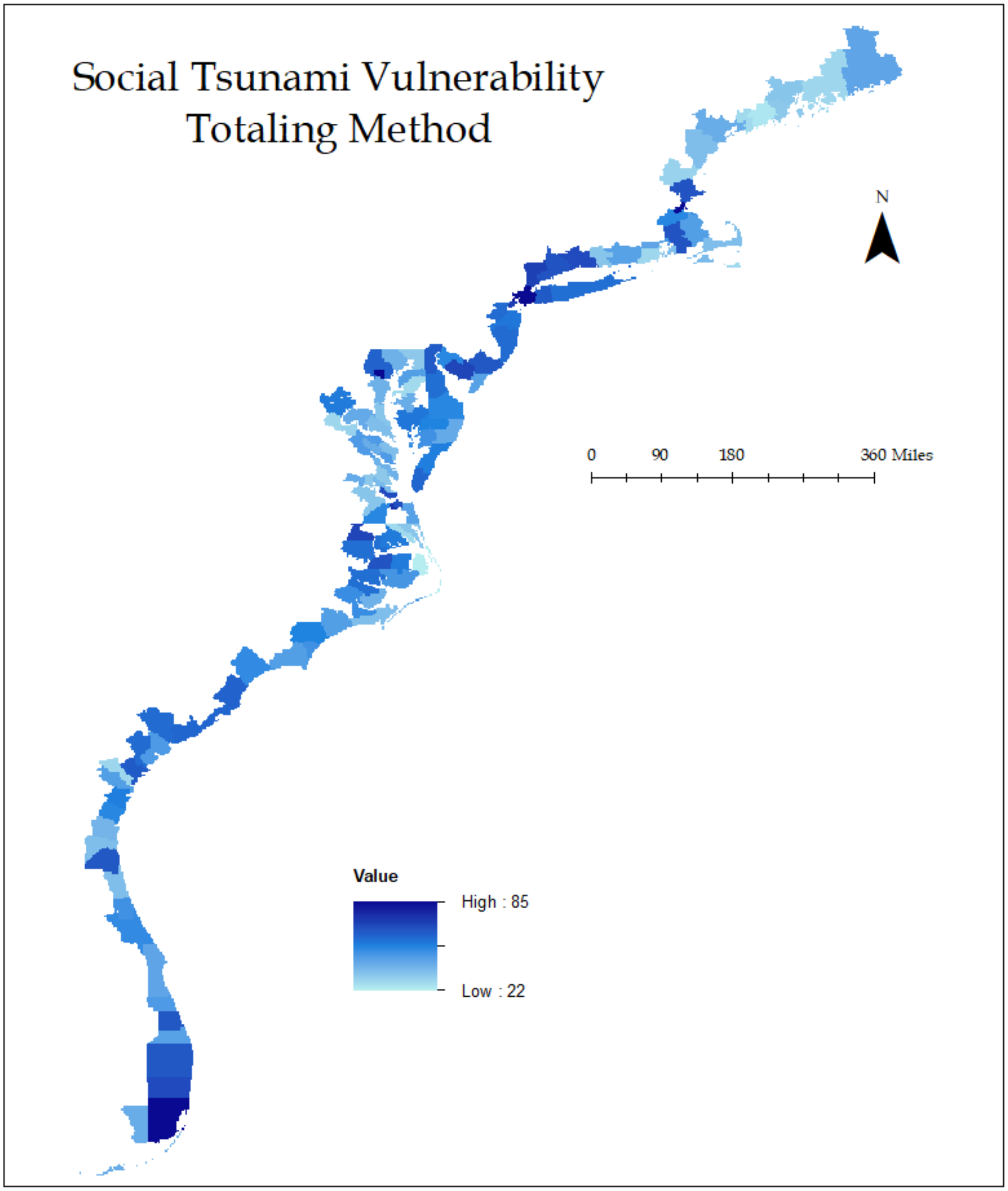

Figure 19: Social vulnerability of each county using the totaling method.

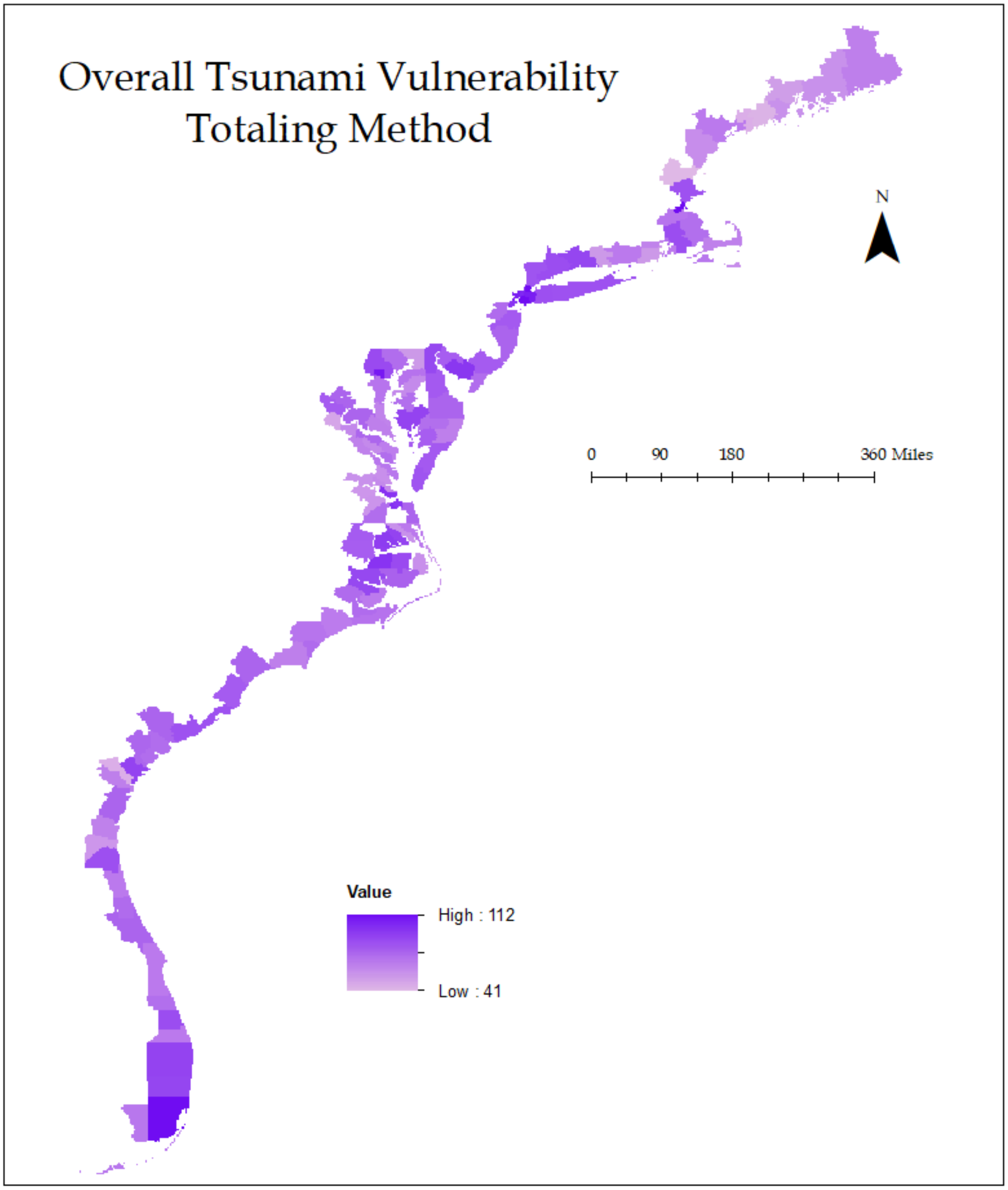

Figure 20: Final layer for the totaling method that shows the vulnerability of each county by value.

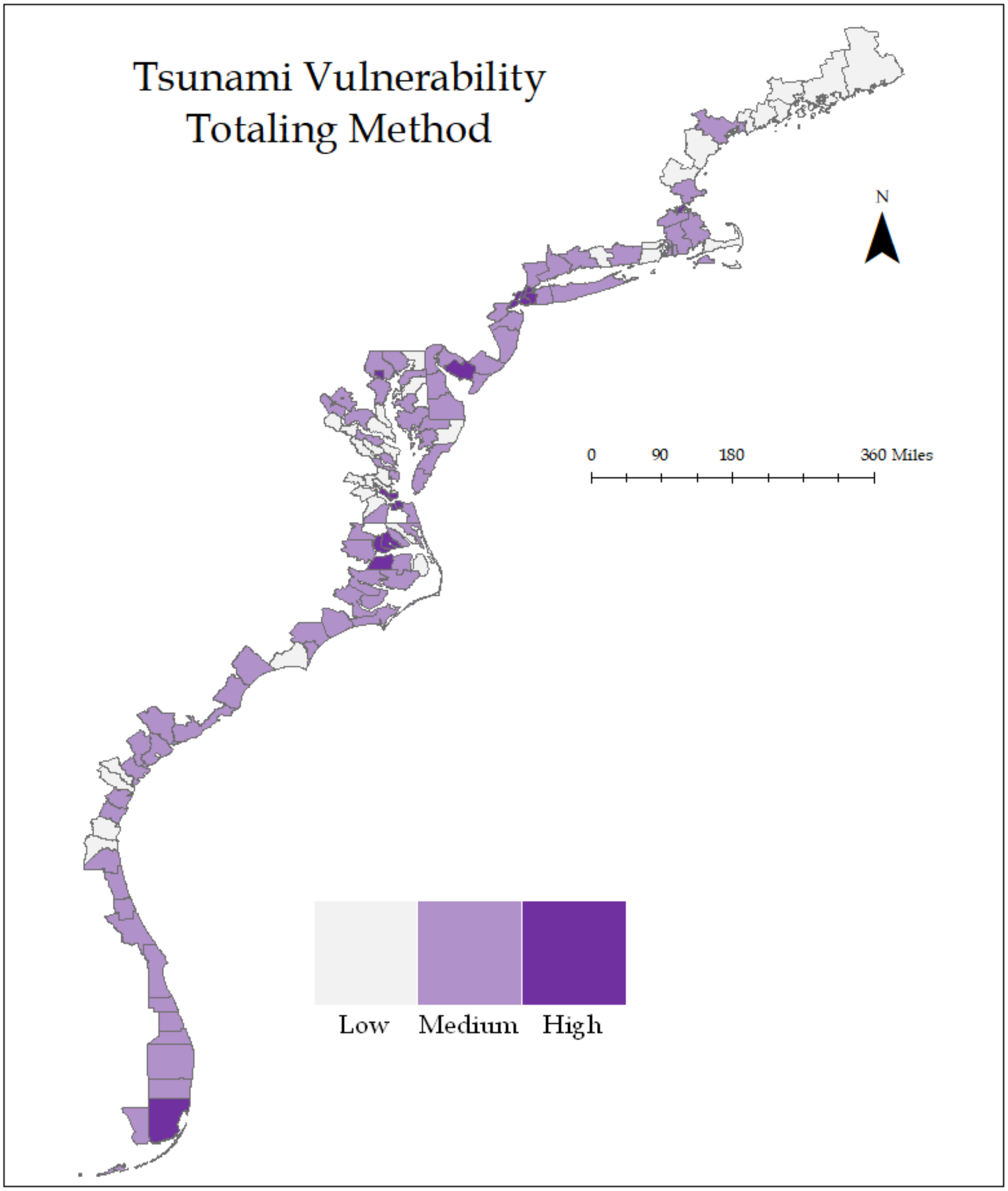

Figure 21: Final layer for the totaling method that shows the vulnerability of each county in terciles.

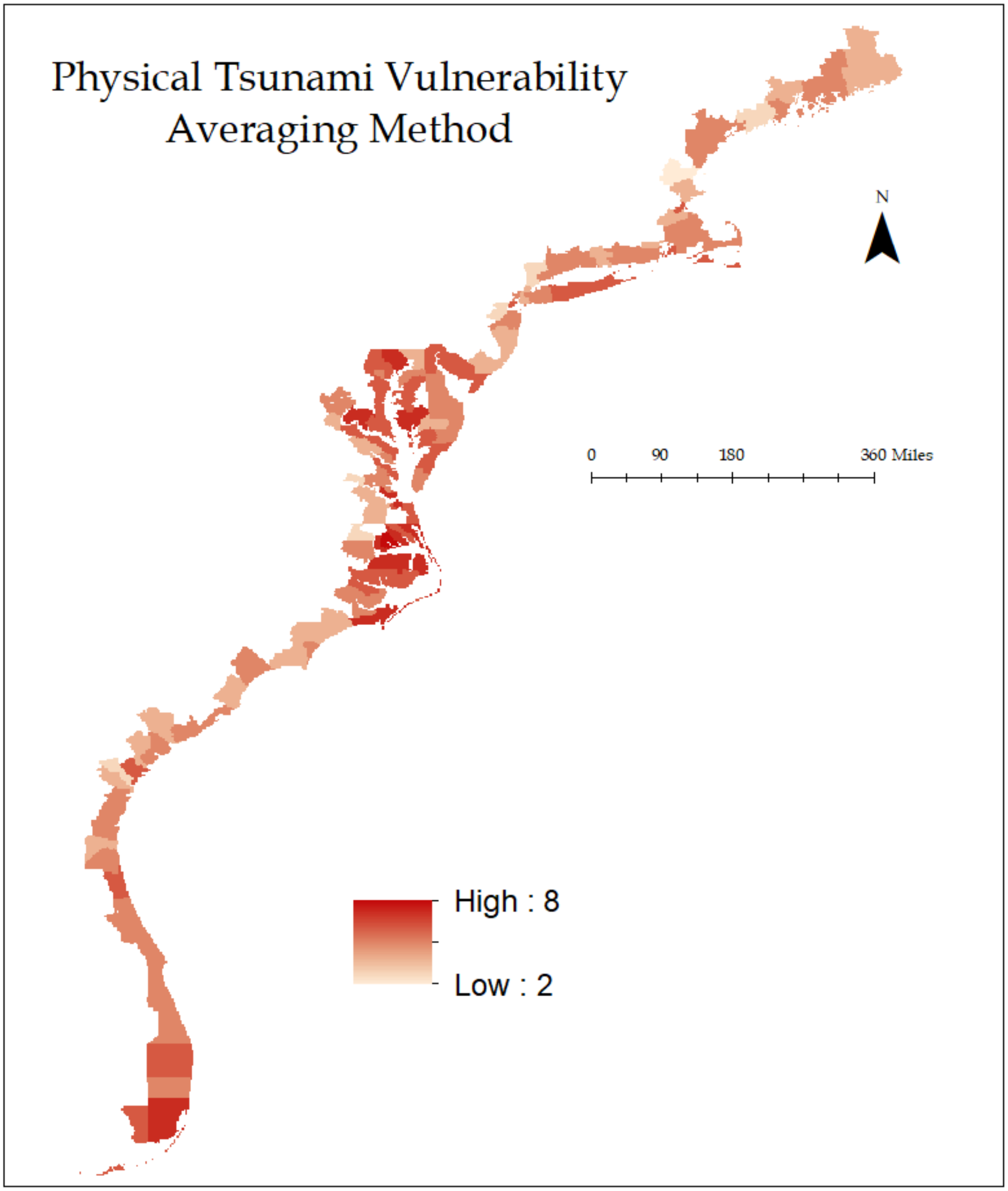

Figure 22: Physical vulnerability oof each county using the averaging method.

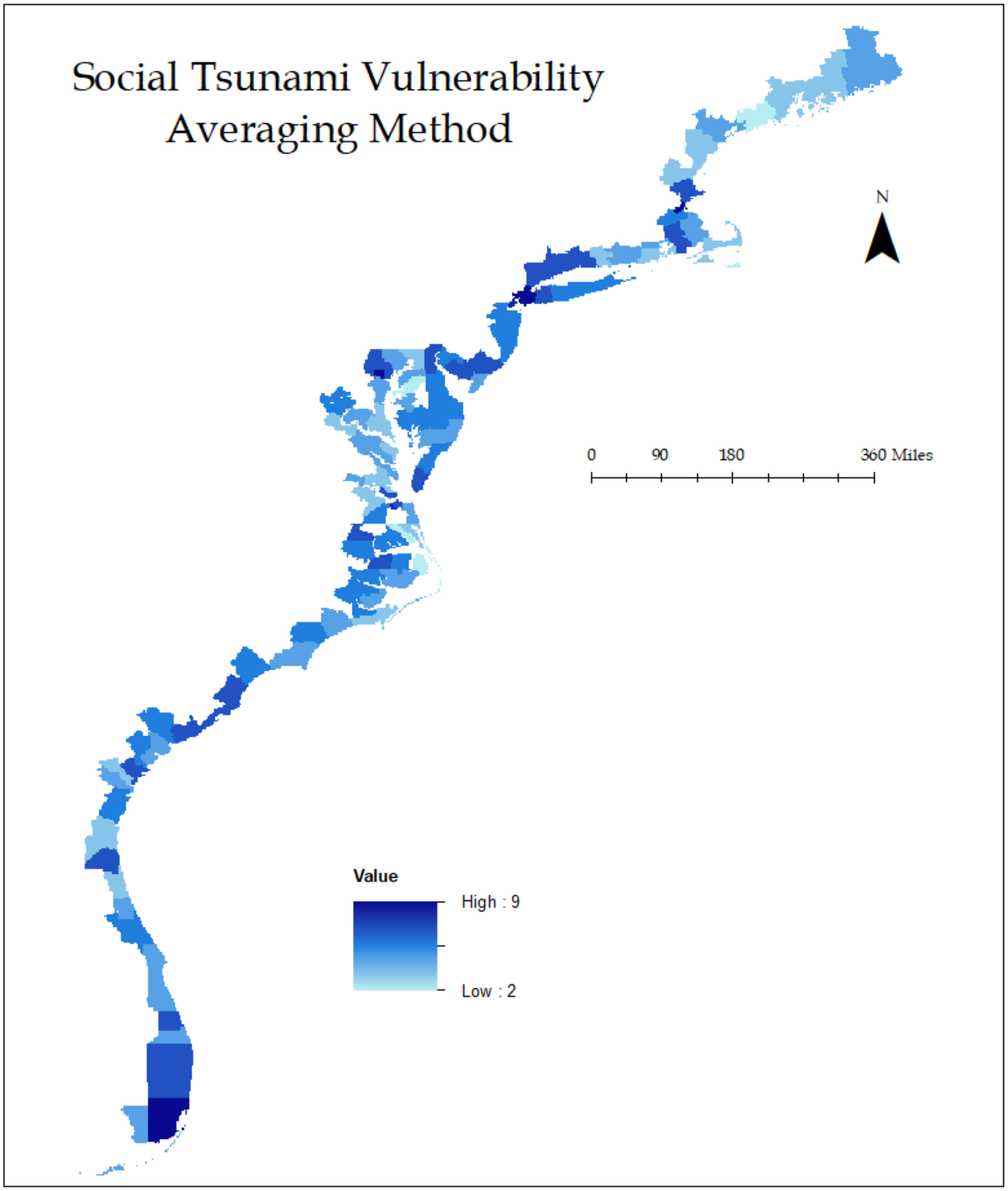

Figure 23: Social vulnerability of each county using the averaging method.

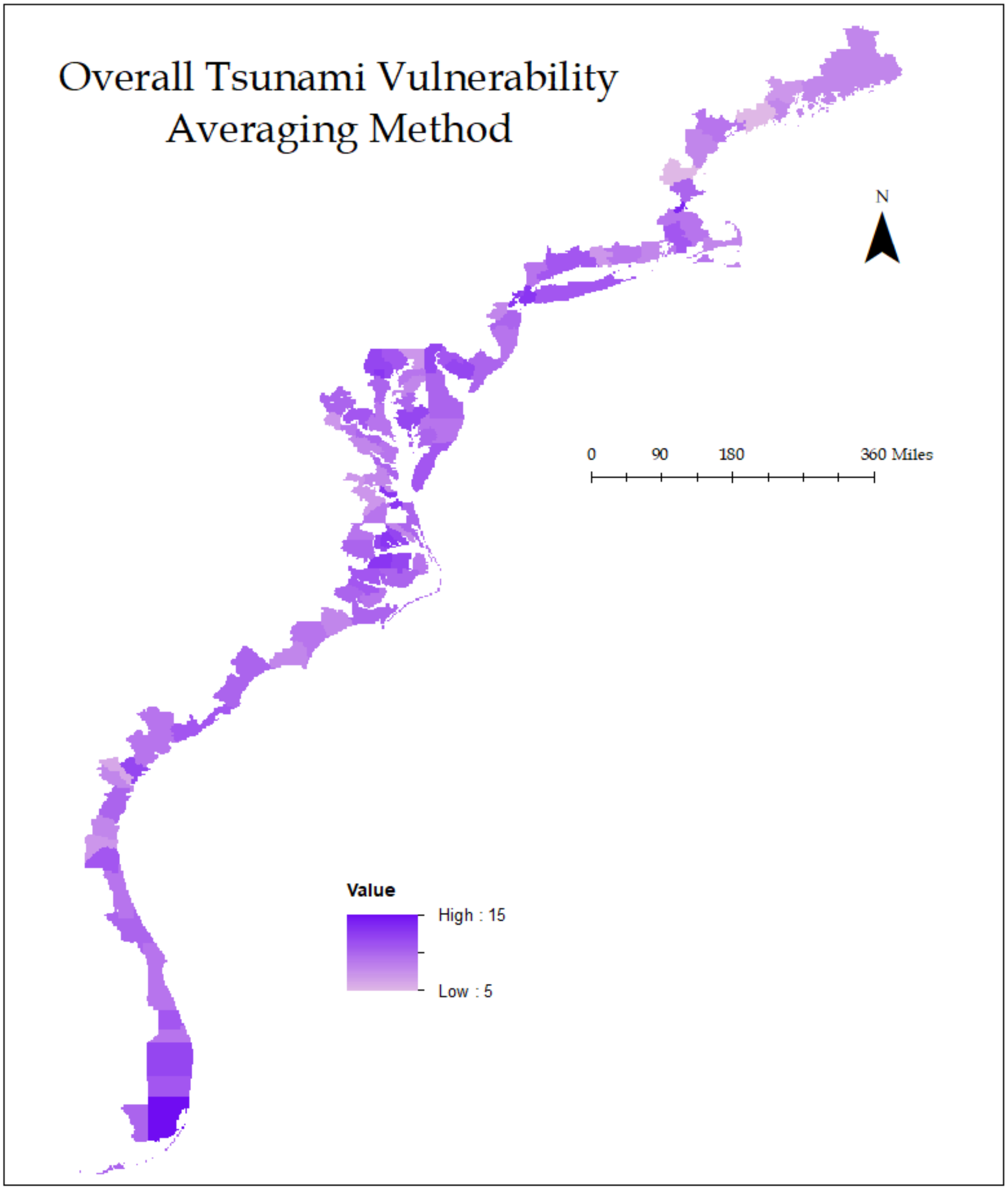

Figure 24: Final layer for the averaging method that shows the vulnerability of each county by value.

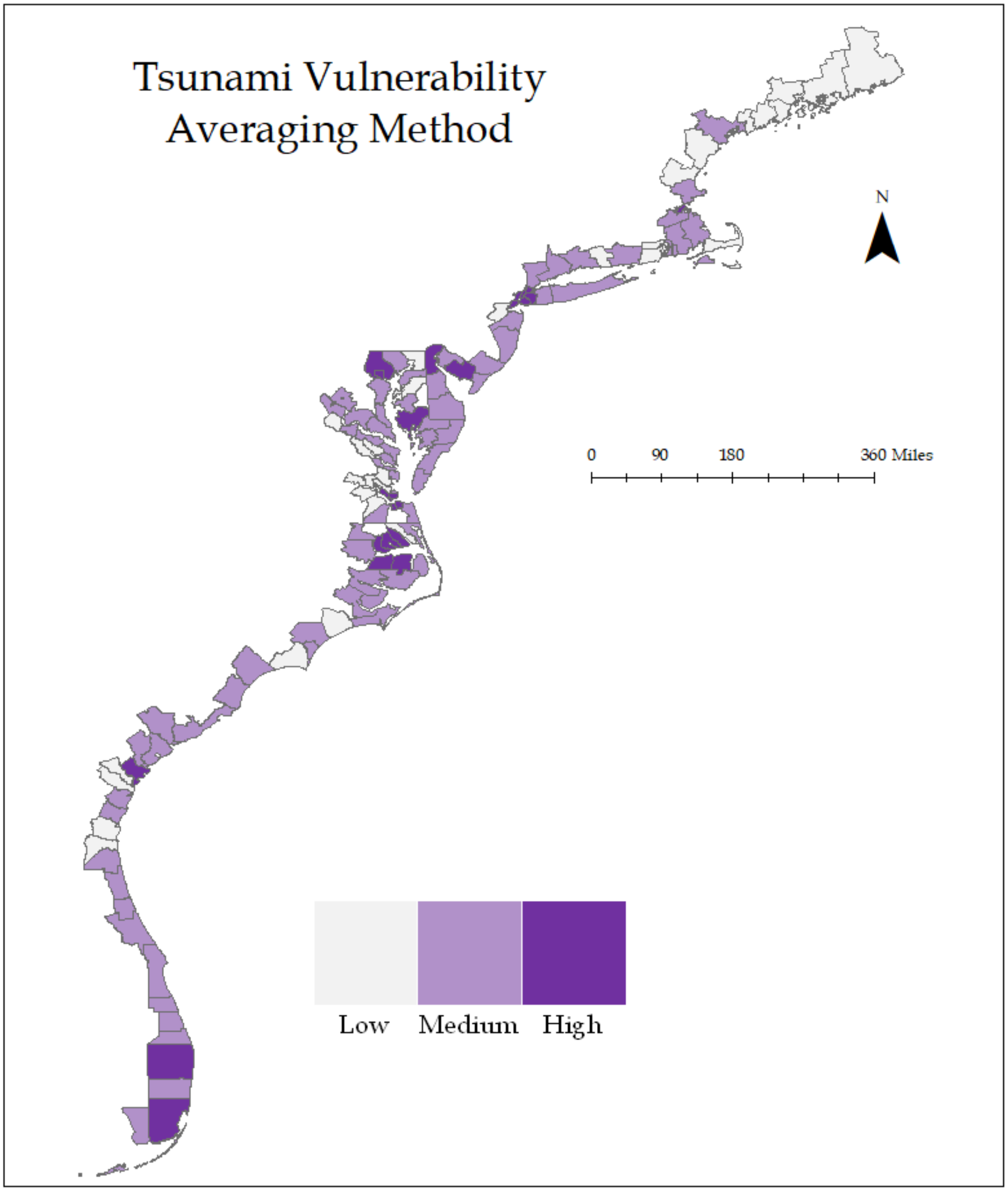

Figure 25: Final layer for the averaging method that shows the vulnerability of each county in terciles.

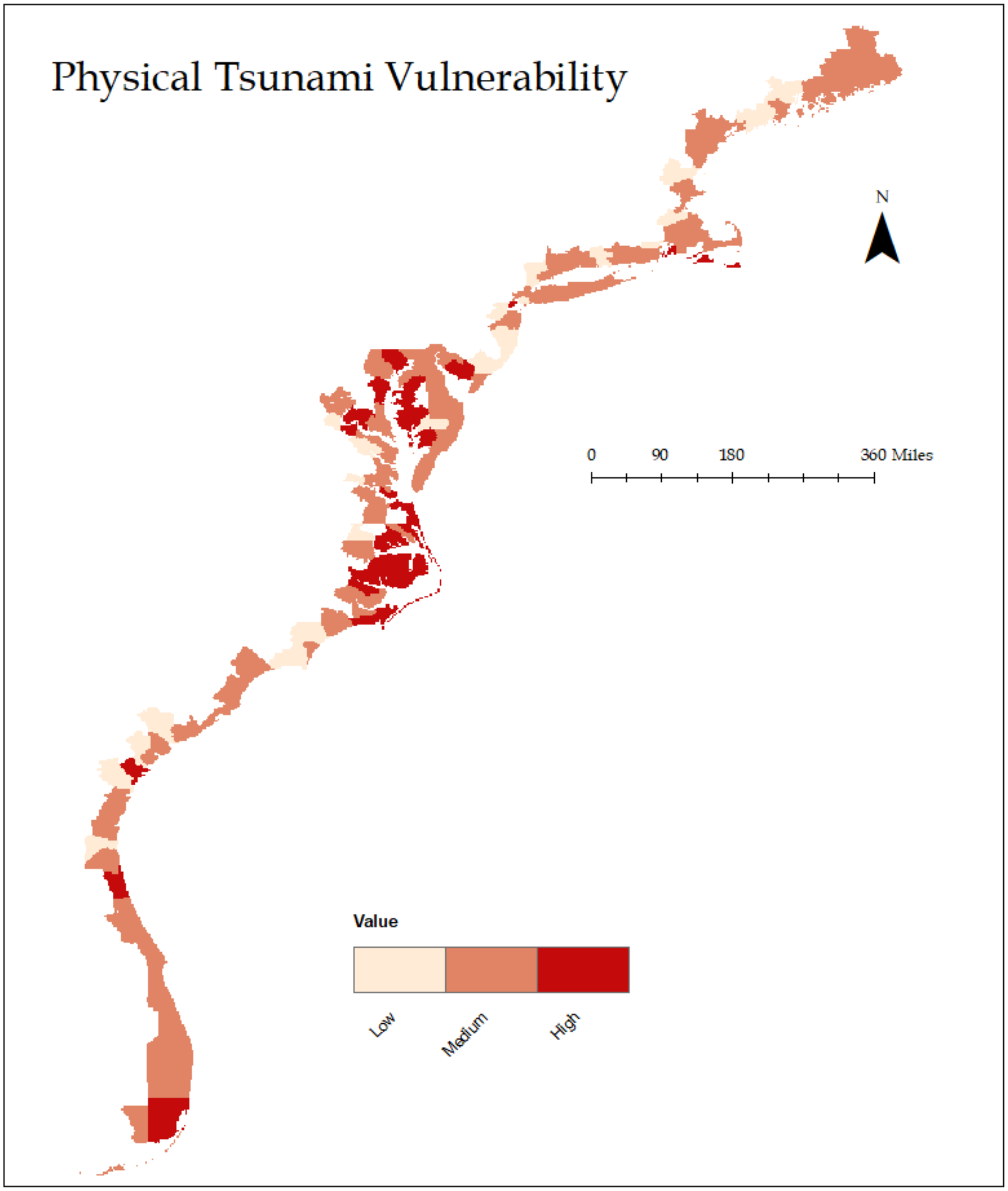

Figure 26: Phyiscal vulnerability of each county by dividing the total method into terciles. This is the layer used for the physical portion of the color cube method.

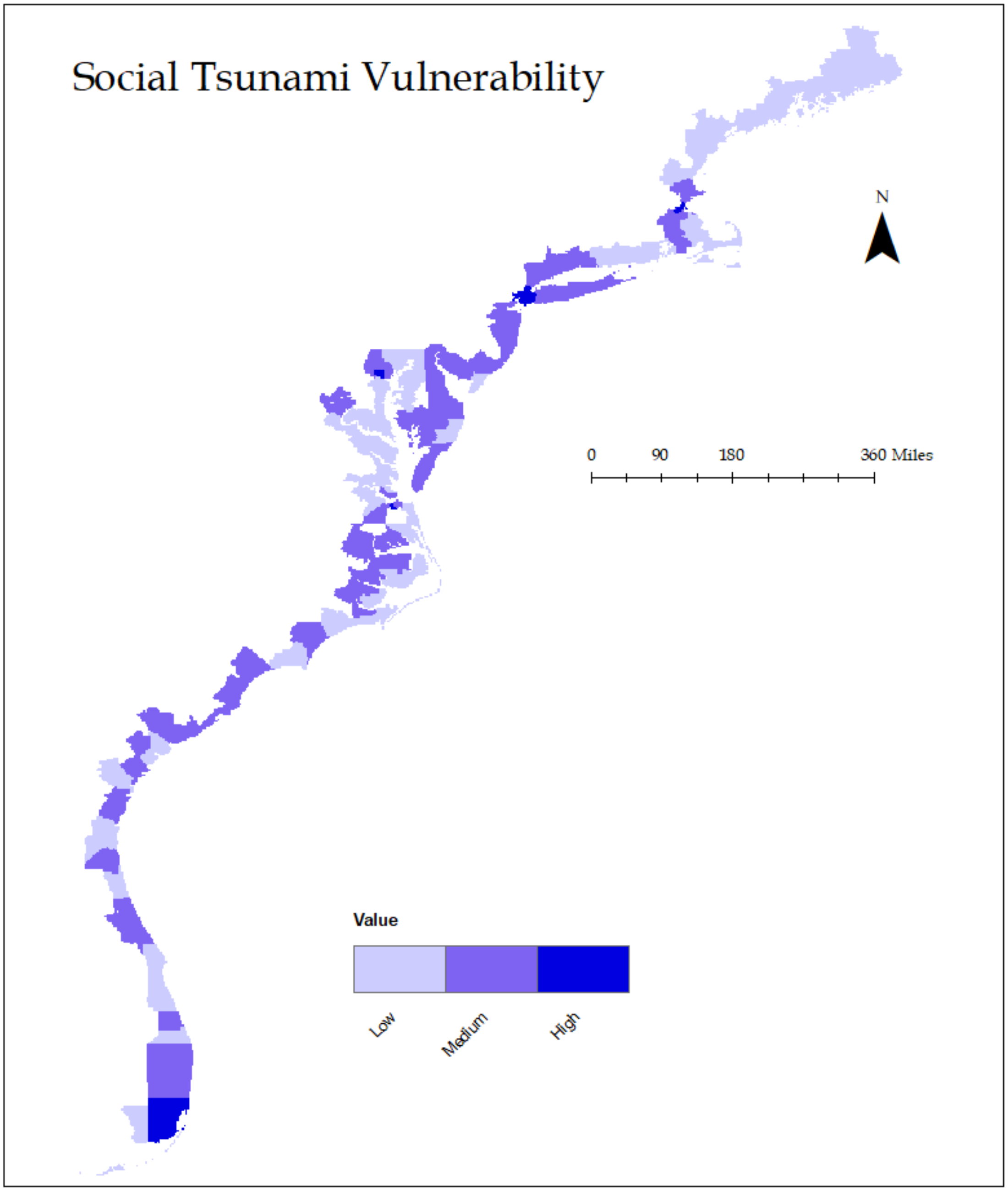

Figure 27: Social Vulnerability of each county by dividing the totaling method into terciles. This is the layer used for the social portion of the color cube method.

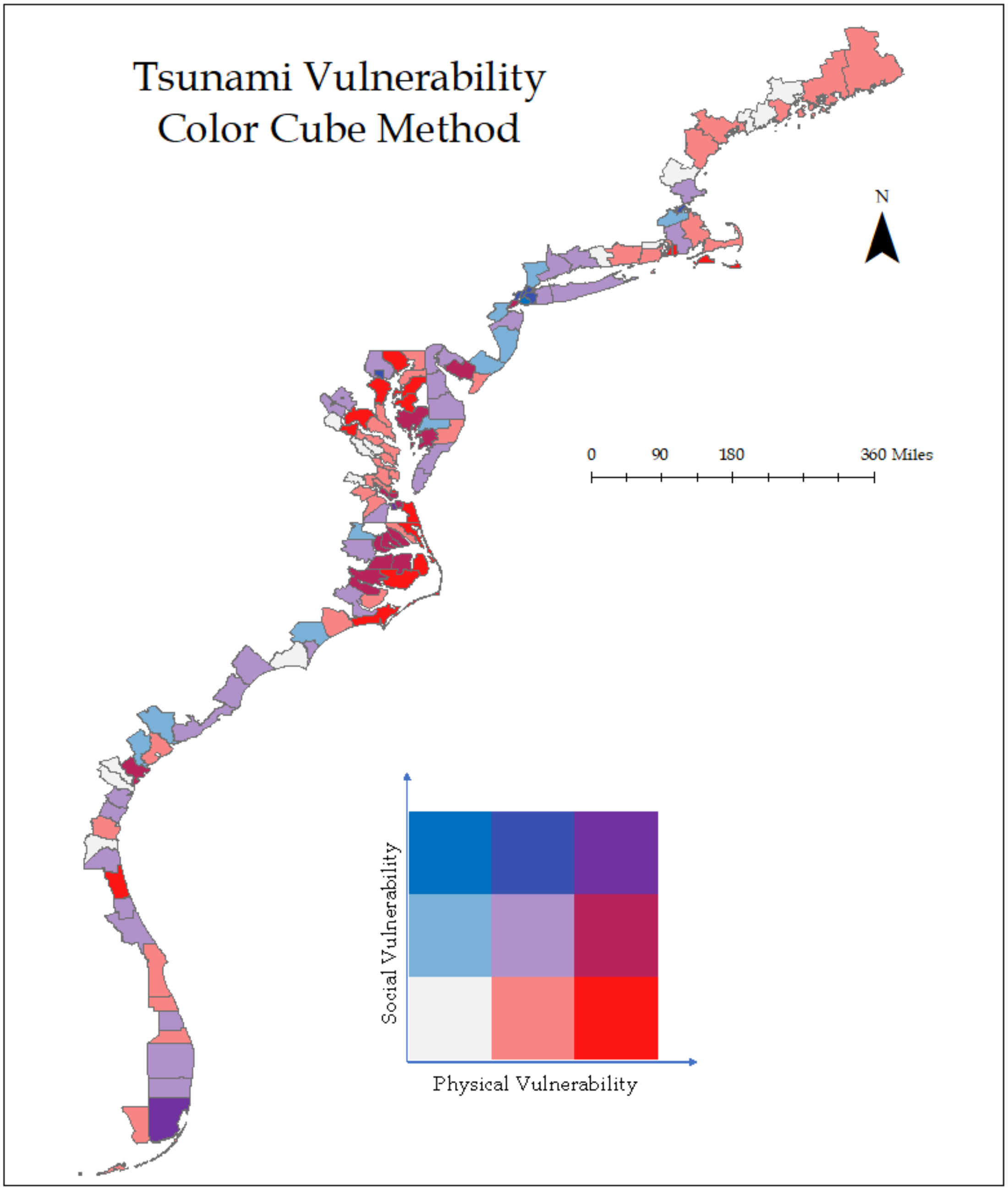

Figure 28: Vulnerability Layer created using the color cube method.

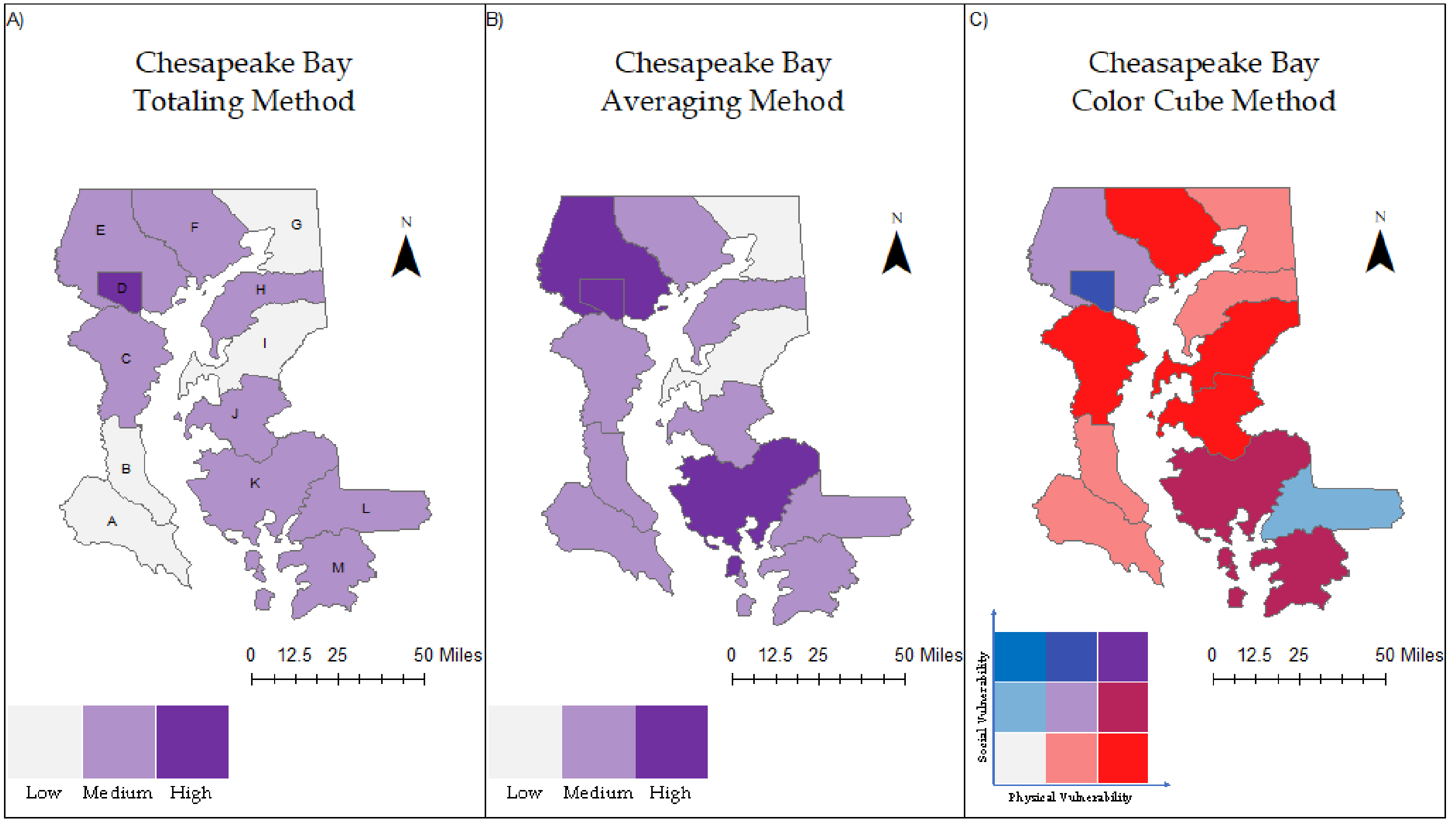

Figure 29: Localized view of Chesapeake Bay counties of Maryland. Each graphic shows the different methods used for analysis. County and city names are as follows: A- St Mary's, B- Calvert, C- Anne Arundel, D- Baltimore City, E- Baltimore, F- Harford, G- Cecil, H- Kent, I- Queen Anne's, J- Talbot, K- Dorchester, L- Wicomico, M- Somerset.

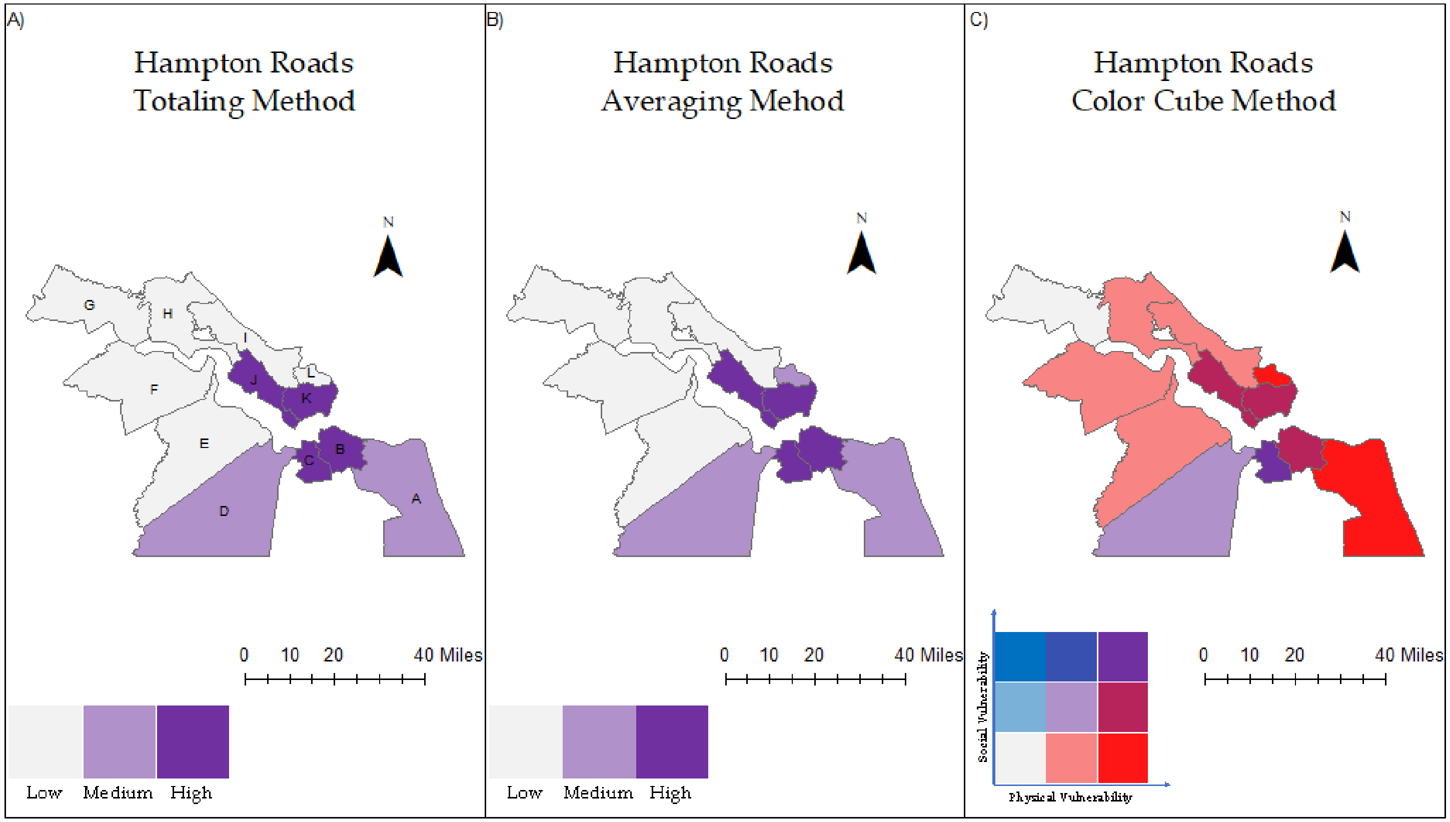

Figure 30: Localized view of Hampton Roads Region in Virginia. Each graphic shows the different methods used for the Analyses. County and City names are as follows: A- Virginia Beach, B- Norfolk, C- Portsmouth, D- Suffolk, E- Isle of Wight, F- Surry, G- Charles City, H- James City, I- York, J- Newport News, K- Hampton, L- Poquoson.

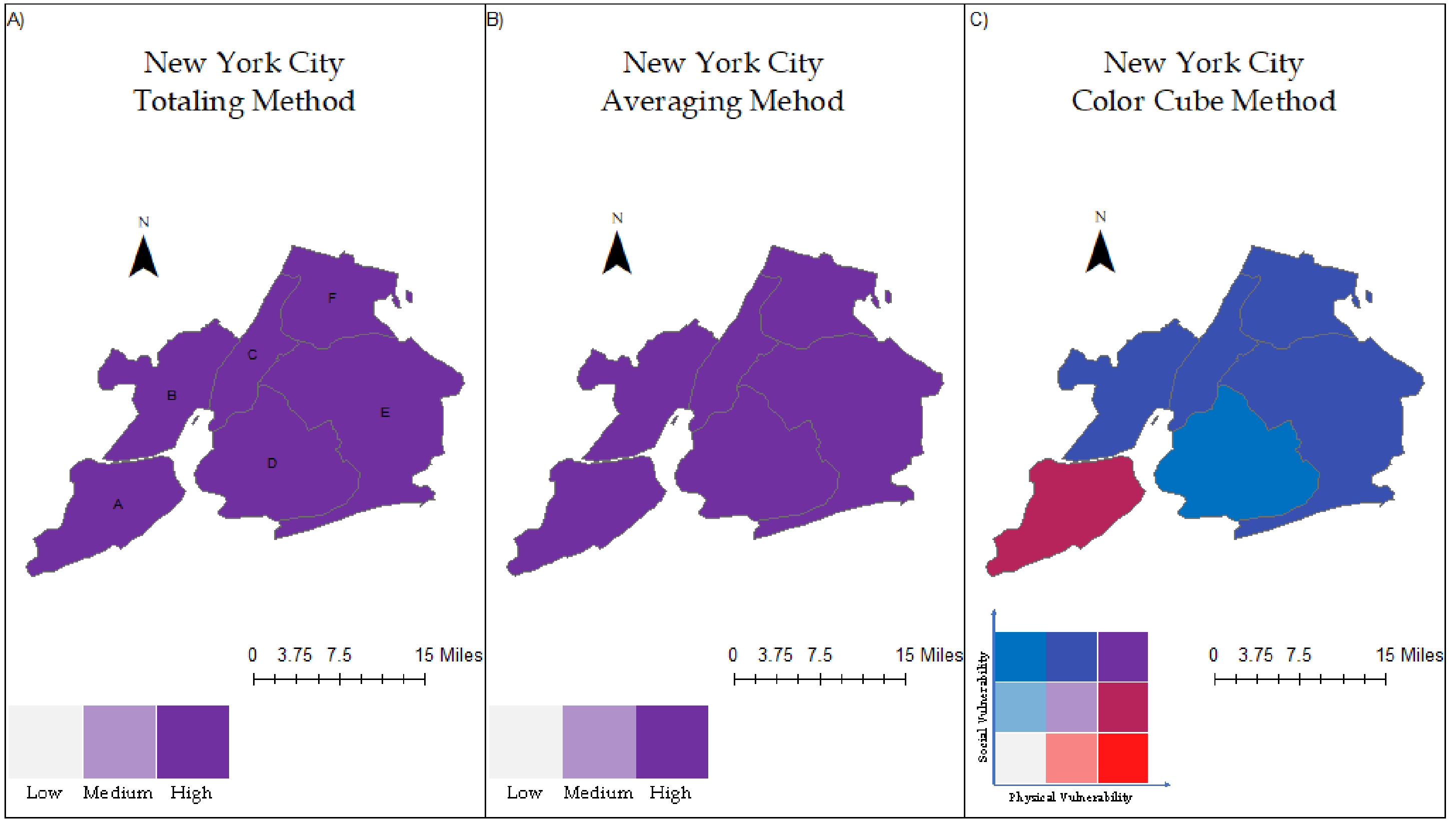

Figure 31: Localized view of New York City including Hudson County, NJ. Each graphic shows the different methods used for the analyses. County names are as follows: A- Richmond, B- Hudson, NJ, C- New York, D- Kings, E- Queens, F- Bronx.

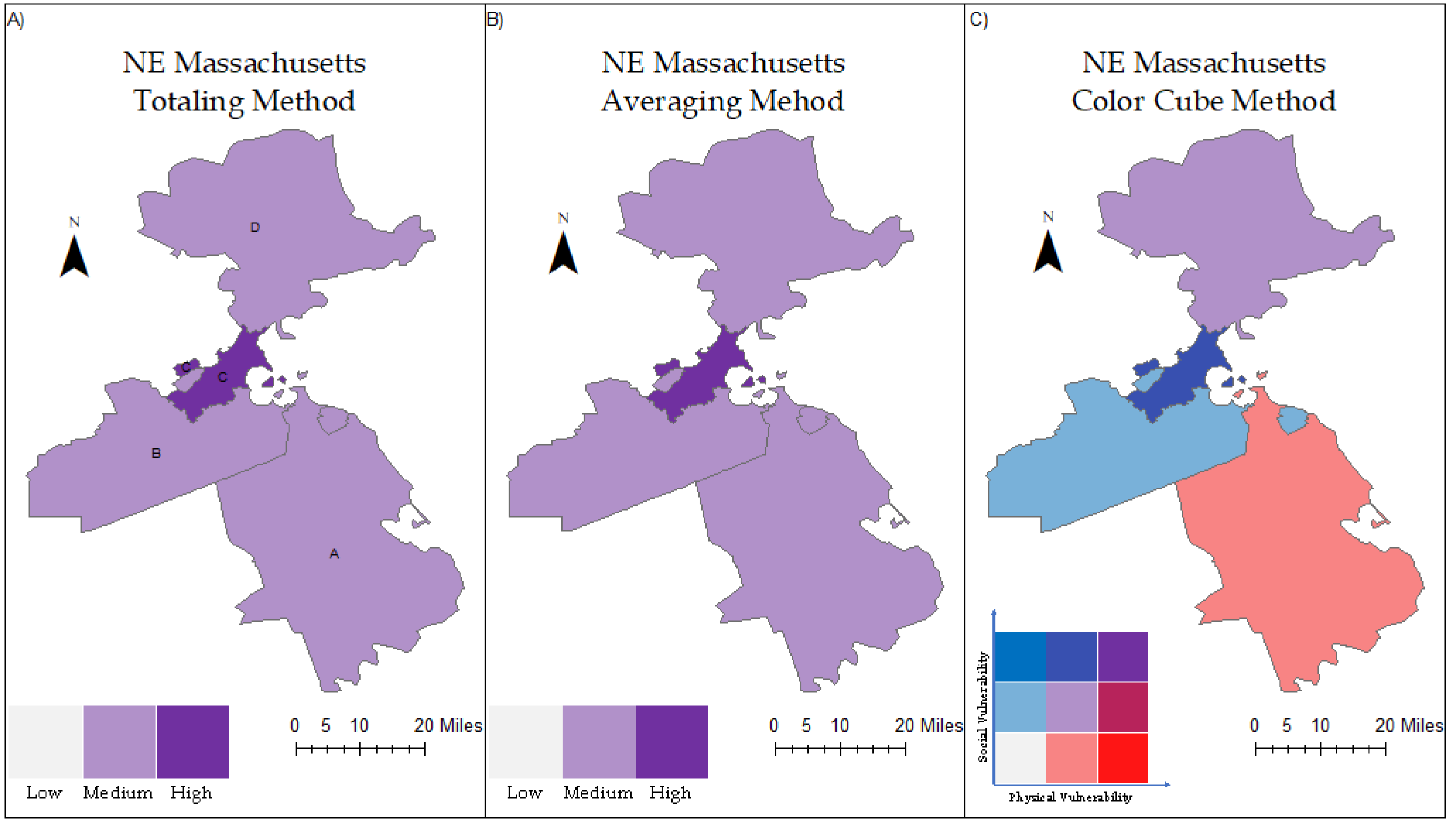

Figure 32: Localized View of Northeast Massachusetts. Each Graphic shows the different methods used for the analyses. County names are as follows: A- Plymouth, B- Norfolk, C- Suffolk, D- Essex.

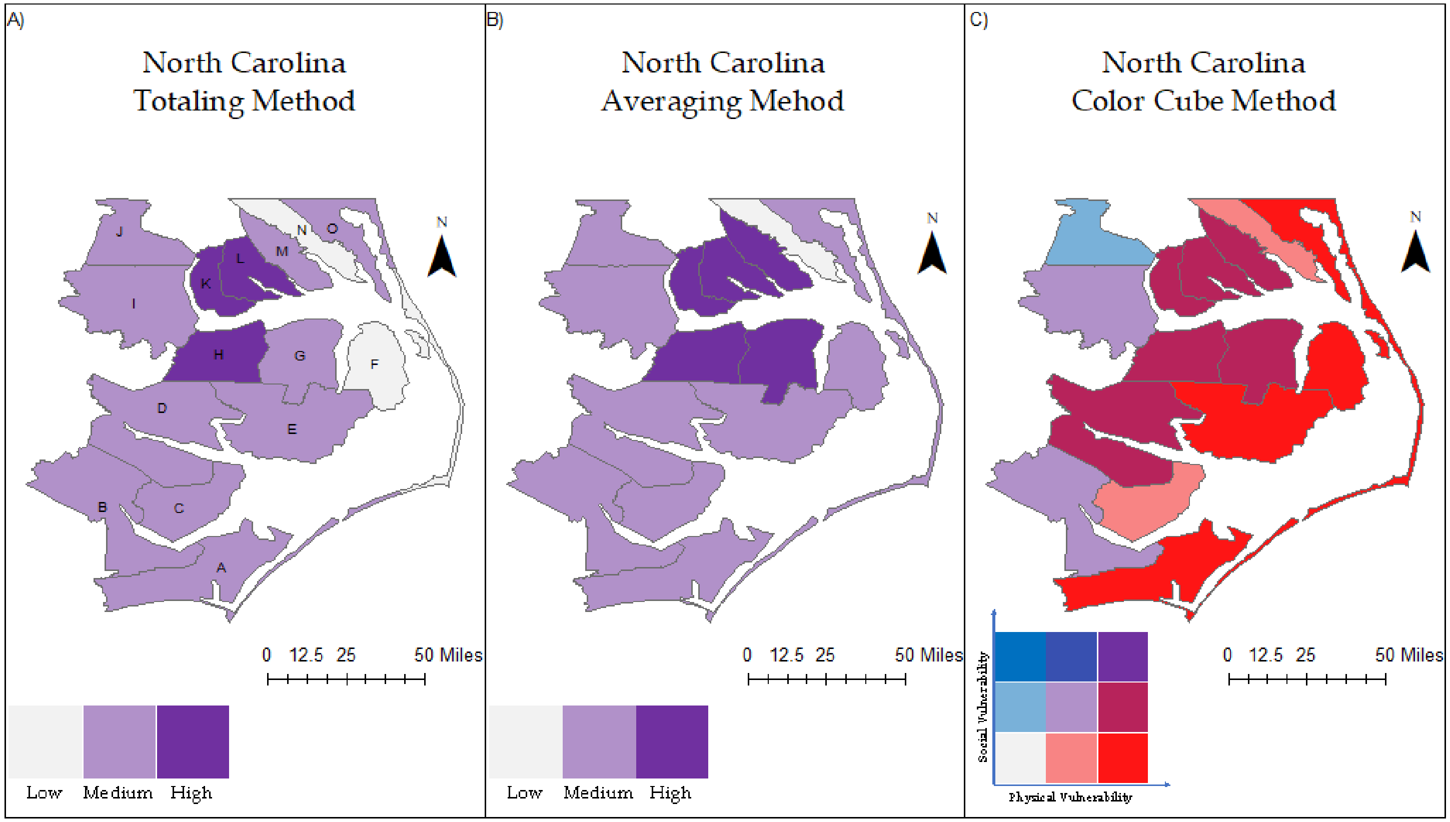

Figure 33: Localized view of North Carolina. Each graphic shows the different methods used for the analyses. County names are as follows: A- Carteret, B- Craven, C- Pamlico, D- Beaufort, E- Hyde, F- Dare, G- Tyrell, H- Washington, I- Bertie, J- Hertford, K- Chowan, L- Perquimans, M- Pasquotank, N- Camden, O- Currituck.

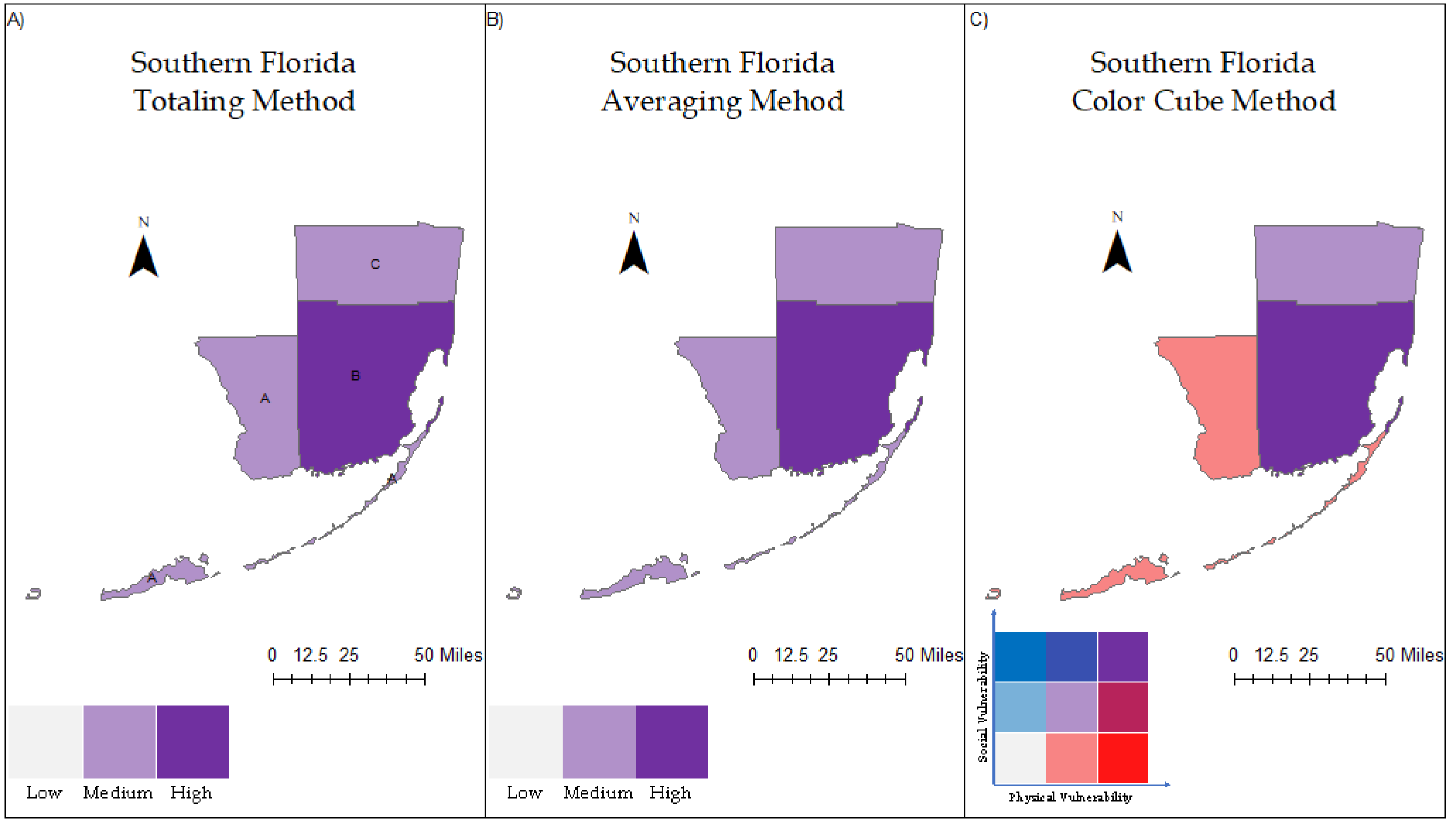

Figure 34: Localized view of South Florida. Each graphic shows the different methods used for the analyses. County names are as follows: A- Monroe, B- Miami-Dade, C- Broward

DISCUSSION

Similarities and Differences Between Methods

Similarities

The most obvious similarity between the three methods is the prevalence of cities in the high vulnerability classification. In all three methods the areas that encompass the cities of Baltimore, Boston, Miami, New York City, and the greater Hampton Roads area all have at least one county with high vulnerability. The reasons for cities showing the most vulnerability are complicated and varied but these methods follow that idea that cities tend to be the most vulnerable areas (Borden et al., 2007). Even with the averaging method they stand out due to how socially vulnerable they are. In almost every variable used for social vulnerability studies, counties with cities are at or near the top.

While cities tend to be high in most social variables the same is not true for the concentration of high physical vulnerability. Physical variables like elevation, land cover, shelf distance, coastline and shoreline differences are not as directly linked as are some of the social variables, meaning that the presence of a high value in one physical variable does not automatically lead to the presence of a high value in a different physical variable. For example, Miami-Dade County has high physical vulnerability despite a low bathymetry score. The opposite can also be found in counties with one high physical vulnerability score while the rest are low. In general, however, it is easier to see the cities in each method than it is to see the physical vulnerability driven counties as they do not cluster like socially vulnerable cities. It is also worth noting that the totaling and averaging method give the exact same vulnerability to every county within New York City. The color cube map shows that vulnerability is low outside of NYC and Boston. As the vulnerability is relatively low across the region there is less room for variance by splitting them into terciles and thus their vulnerabilities all match. Similar trends can be seen across swathes of South Carolina, Georgia, and Florida where there is little variance between methods and vulnerabilities.

The main similarities that can be gleaned across the entirety of the USEC according to these three methods are: large cities are always highly vulnerable, physical vulnerability is not as focused as social vulnerability, and social variables alone can lead to high vulnerability while physical vulnerability cannot do the same. This is likely partially due to the methods used but due to the nature of human settlement it stands to reason that this is also real-world trend.

Differences

While there are a variety of trends that can be seen across each method, there are an equal number of differences. The color cube method illustrates these differences well in that some counties that look vulnerable using this method are not vulnerable according to the other two methods. Two examples of this are Nantucket, MA and Queen Anne’s, MD. Examining these two counties shows high physical vulnerability with low social vulnerability. However, both counties are categorized as low vulnerability according to the other two methods despite the low vulnerability categorization, these counties are physically vulnerable, as shown by the color cube method. The opposite is not true as every county that has high social vulnerability in the color cube method has high overall vulnerability using the other two methods. There are only marginal differences between the totaling and averaging methods with the main being that there are seven more high vulnerability counties in the averaging method than the totaling.

What makes a place vulnerable?

The vulnerability of each area has different drivers unique to that area. For areas that show high vulnerability both socially and physically, there are commonalities between them. There are two such counties according to the Color Cube Method. These counties are Portsmouth, VA and Miami-Dade, FL. Portsmouth shows high social vulnerability in both population density and race values. To add to these, many of the other social variables are above average. Miami-Dade shows similar trends but as it is home to a larger city, tends to show higher social vulnerability. In both counties, physical vulnerability is increased by among the highest elevation values on the entire coast. The other physical variables differ in that Portsmouth has high land cover values and moderate values in the other three variables whereas Miami-Dade has low bathymetry score and above average in the other three. What these areas have in common is they are home to cities and are low lying. This is not to say that all low-lying cities have high physical vulnerability but instead that they have the greatest likelihood of including all the ingredients of the highest vulnerability areas. Miami and Portsmouth show this and are of concern as they show high vulnerabilities in both in their current state and without change to their populations or the surrounding environment.

High social vulnerability is common in cities in this study. The largest cities on the coast all have high social vulnerability: Baltimore, Boston, Miami, and New York City have the highest social vulnerability scores. This is driven primarily by high total population, low income levels, race scores showing high minority concentration, and low education attainment. The only other area that shows high social vulnerability is the city of Portsmouth. Other areas show concentrations of medium social vulnerability but generally lack the population to show among the highest social vulnerabilities.

High physical vulnerability is driven by high scores in two or more variables. While cities denote the areas of highest social vulnerability, physical vulnerability does not focus in the same ways. Physical vulnerability tends to be high in three regions: North Carolina, Hampton Roads, and Chesapeake Bay. Chesapeake Bay has high bathymetry and elevation scores, Hampton Roads has high elevation and land cover scores, and North Carolina has high elevation and coastline scores. Miami-Dade also shows high physical vulnerability. The methods of this study show low lying areas that have high scores in one other physical variable to be among the most physically vulnerable areas along the coast.

Neither social or physical vulnerabilities are static and should be monitored for changes in each region that already shows vulnerability. Cities that are less physically vulnerable today could become more so with coastal erosion or sea level rise. Physically vulnerable areas could find themselves more socially vulnerable depending on the demographic changes in the regions. Understanding these changes and their impacts on vulnerability can help to plan for the future of these areas so they are better prepared for possible disasters.

Benefits, Drawbacks, and Uses of Methods

Totaling Methodology Benefits and Drawbacks

Due to being the simplest method, the totaling method tends to have the simplest benefits. First, it shows the data in its most raw form and allows an easy view of each individual variables effect on the study. Also, before being switched into terciles it shows the greatest variance between counties due to the sheer number of possible values. This is a benefit if viewed before it is switched into tercile format. The final main benefit is simplicity.

The drawbacks of this method are linked with its benefits. While the sheer number of values lets you see the miniscule differences between counties, these minute differences are worth little in the grand scheme of things. The next possible drawback is that this method is skewed toward social vulnerability as there are four more social variables than physical variables. As such this is the method that provides the most skewed results.

Averaging Methodology Benefits and Drawbacks

The averaging method has benefits that are mostly related to its differences from the totaling method—this method treats physical and social vulnerability as equal whereas the totaling method is skewed toward social vulnerability. A main drawback of this method is that it limits the variance of vulnerability. While it has more values than the color cube method, it is harder to see what drives the variance between counties because each variable is worth so little after averaging.

Color Cube Methodology Benefits and Drawbacks

The color cube method is the most useful method. It allows for variance and for the drivers behind that variance to be seen much more easily. By not adding the physical and social vulnerabilities, it is easier to see which type of vulnerability may be driving overall vulnerability. It also allows for an understanding of how the vulnerability of these areas may change with changing demographics or landscapes in the future. This is to say that if a county has high physical vulnerability but low social vulnerability, that may be subject to change. This is because depending on the movement of humans and if a large city may start to grow there then it will become more socially vulnerable and thus its overall vulnerability would be quite high. The same could happen for a city that is highly socially vulnerable but has low physical vulnerability. If the landscape changes from phenomena such as sea level rise, the city may become more physically vulnerable while already being socially vulnerable.

The drawbacks of this method are related to the fact that both social and physical vulnerability are split into terciles limiting their variability. Only having three levels of vulnerability masks small differences between counties and thus counties that are only marginally similar in terms of overall vulnerability may be grouped together.

Uses of Each Method

The totaling method created in this study should primarily be used if the overall vulnerability of a county needs to be found. If all variables are treated equally and social vulnerability is more impactful than physical vulnerability, this method will show that. Cities will be vulnerable in all methods, so this method is likely best used to show the vulnerabilities of other areas. Non-city counties will be more useful in finding the variance of each county relative to each other, particularly with the 140 scores that are possible in this method. Despite being skewed towards large cities due to the prevalence of social vulnerability, we can see the overall variance between each county here.

The averaging method allows for physical vulnerability to haver larger impacts on each county. As such this is the most useful method for counties that are the most physically vulnerable. Physically vulnerable areas are less pronounced in the first method. This method changes that since these physically vulnerable areas are better represented. Areas such as North

Carolina are the best for this method as it will show that they are still highly vulnerable despite not having high social scores.

The color cube method is useful for planning purposes. Policy makers can use this method to better understand what their focuses should be in their respective counties. The other two methods give overall vulnerability but do not show whether physical or social variables drive vulnerability. Using a bivariate method, it is possible to see which vulnerability is low, medium, or high and plan accordingly. This can be applied to counties that are highly socially or physically vulnerable as there are different ways to alleviate these two types of vulnerability.

Limitations of this Study

This study accomplished the goal of locating what areas of the USEC are the most vulnerable to a tsunami but there are a few considerations to make. Variable selection and weighting are among the most important aspects of any vulnerability study. While the variables selected for this paper are all backed by prior research, no area can truly understand what variables are most important to their vulnerability until a disaster occurs. Since a tsunami has not occurred in this region in recorded history the true weight of each variable cannot be found. The next limitation involves numerical modeling. While modeling can help in understanding the propagation and run up of this study, this was not the goal of the research. The goal was to create a vulnerability analysis that could be done by counties individually for what suits their needs. Numerical modeling is not easily accessible and does not give actual vulnerability ratings to each county. The final major limitation was that of scale. This is because each community is unique and so are not going to experience vulnerability in the same way. Individually counties would use smaller subdivisions but by using counties it makes it possible to view which regions and more specifically counties within those regions are most vulnerable.

Future Research

As mentioned, this study is meant to be able to transition into smaller scale studies. While using counties as the subdivision worked well for this study, due to their size they cannot give an in depth look at smaller communities within them. No county has uniform distribution of the different variables used in this study and as such smaller subdivisions would give a better look into the true vulnerability of communities. With knowledge of the most vulnerable counties based on this study, it gives the opportunity to take the most vulnerable counties shown in this study and analyze them further. Further research would include using smaller social subdivisions within a single county or city to see the most vulnerable parts of the area. This could be done with either census tracts or even more preferably census blocks as these would allow the variation within an area to be seen. Future research would also allow for tweaking of the methodology and through researching the concept more it may be possible to update this study to create a timelier product. This could either reinforce the findings of this study or disprove them which are both satisfactory results and could provide a better study of the smaller areas. After this it would be preferable to work with the subdivisions whether that be state, county, or local governments to assist in preparation, mitigation, and awareness measures so these areas understand the danger of these disasters and how to withstand them should the worst happen.

CONCLUSION

There is no specific region of the USEC that is the most vulnerable. However, as discussed there are regions that stick out due to their increased vulnerability. As a rule, large cities generally dominate this section with Miami, Baltimore, New York City, and Boston being the prime examples. However, there are areas like the Hampton Roads and Albemarle Sound of North Carolina that stick out due to their high physical vulnerabilities. The important conclusion that can be drawn is that it is not as simple as being the largest city makes an area the most vulnerable. If the disaster hits harder in an area due to the physical landscape of the land, then it can have a greater impact on a smaller population. While Miami is a large city, it is overall much smaller than New York City. Despite this it stands out as one of only two counties with high physical and high social vulnerability. The other county is Portsmouth which is not home to a large city. However, any area that has high vulnerability should be noted since a disaster would likely impact them greatly either way.

According to the results of this study there are a few major areas of concern for vulnerability along the USEC. The most notable and least surprising of the results is that all large cities along the coast show high vulnerability in every method used. The areas of high physical vulnerability are less concentrated. The most highly physical vulnerable areas are centered around Chesapeake Bay, Hampton Roads, North Carolina, and Southern Florida. The large cities that also land in these highly physical vulnerable regions should garner the most attention. These cities are Miami, Hampton Roads, New York City, and Baltimore.

The methods of this study were able to differentiate between counties of low to high vulnerability. This is important as a more highly vulnerable county should take precedent over a less vulnerable county when disaster planning takes place. Giving all counties and larger areas the same amount of care would be a waste of resources if one community is better equipped to handle it in both their physical landscape and their population. The study accomplished the goal of finding the vulnerabilities of the counties of the USEC.

Tsunamis naturally cause great distress in any area where they may happen. Despite this there is limited preparation along the USEC in case of a large tsunami that could be generated by several sources. Increasing awareness of the disaster is always an effective measure to reduce vulnerability. While the population may not take the threat seriously, simply understanding that a threat is present makes one better equipped to handle it. Coastal communities understand this better than most as they are no strangers to disasters such as hurricanes or Nor'easters. What must be accomplished now is the implementation of these general plans to mitigate a possible disaster. More specifically, each county should prepare its own unique plan for these disasters. This would be possible by studying their own counties individually to find the nuance of their populations and where the most help would be needed. The goal of each decision-making body along the USEC should be to reduce the possible damage of any hypothetical disaster to their population and this study aimed to see which counties have the most work to do to accomplish this.

LITERATURE CITED

Anderson, M. (2013). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. https://doi.org/10.3386/w18757

Ashraf, M. A., and M. A. Azad. 2015. Gender issues in disaster: Understanding the relationships of vulnerability, preparedness and capacity. *Environment and Ecology Research* 3 (5):136–142.

Barkan, R., U. S. ten Brink, and J. Lin. 2009. Far field tsunami simulations of the 1755 lisbon earthquake: Implications for tsunami hazard to the U.S. East Coast and the Caribbean. *Marine Geology* 264 (1-2):109–122.

Bletery, Q., A. Sladen, B. Delouis, and L. Mattéo. 2015. Quantification of tsunami bathymetry effect on finite fault slip inversion. *Pure and Applied Geophysics* 172 (12):3655–3670.

Borden, K. A., M. C. Schmidtlein, C. T. Emrich, W. W. Piegorsch, and S. L. Cutter. 2007. Vulnerability of U.S. cities to environmental hazards. *Journal of Homeland Security and Emergency Management* 4 (2).

Bureau, U. S. C. 2021. Coastal areas. *Census.gov*. https://www.census.gov/topics/preparedness/about/coastal-areas.html (last accessed 1 November 2021).

Bush, D. M., W. J. Neal, R. S. Young, and O. H. Pilkey. 1999. Utilization of geoindicators for rapid assessment of coastal-hazard risk and mitigation. *Ocean & Coastal Management* 42 (8):647–670.

Chang, S., J. Yip, T. Conger, G. Oulahen, and M. Marteleira. 2018. Community vulnerability to coastal hazards: Developing a typology for disaster risk reduction. *Applied Geography* 91:81–88.

Cutter, S. L., B. J. Boruff, and W. L. Shirley. 2003. Social vulnerability to environmental hazards*. *Social Science Quarterly* 84 (2):242–261.

Daukantas, P. 1998. Update: Asteroids make waves. *Computers in Physics* 12 (2):114.

Enarson, E. 1998. Through women's eyes: A gendered research agenda for disaster social science. *Disasters* 22 (2):157–173.

Febrina, R., D. K. Evan, L. Afriani, R. M. Retno, Susilorini, and H. A. Fitra. 2020. The analysis of tsunami evacuation route based on Geographic Information System: A case study in the coast of Lampung Bay. *IOP Conference Series: Materials Science and Engineering* 807:012022.

Flanagan, B. E., E. W. Gregory, E. J. Hallisey, J. L. Heitgerd, and B. Lewis. 2011. A social vulnerability index for disaster management. *Journal of Homeland Security and Emergency Management* 8 (1).

Fothergill, A., and L. A. Peek. 2004. Poverty and disasters in the United States: A review of recent sociological findings. *Natural Hazards* 32 (1):89–110.

Fothergill, A., E. G. Maestas, and J. A. D. R. Darlington. 1999. Race, ethnicity and disasters in the United States: A review of the literature. *Disasters* 23 (2):156–173.

Frankenberg, E., B. Sikoki, C. Sumantri, W. Suriastini, and D. Thomas. 2013. Education, vulnerability, and resilience after a natural disaster. *Ecology and Society* 18 (2).

Fritz, H. M., F. Mohammed, and J. Yoo. 2009. Lituya Bay landslide impact generated mega-tsunami 50th anniversary. *Pure and Applied Geophysics* 166 (1-2):153–175.

Geist, E. L. 1998. Local tsunamis and earthquake source parameters. *Advances in Geophysics* :117–209.

Goff, J., J. P. Terry, C. Chagué-Goff, and K. Goto. 2014. What is a mega-tsunami? *Marine Geology* 358:12–17.

GOTO, Y., and T. NAKASU. 2018. Human vulnerability index for evaluating tsunami evacuation capability of Communities. *Journal of Japan Association for Earthquake Engineering* 18 (6).

Gray, J. P., and J. J. Monaghan. 2003. Caldera collapse and the generation of waves. *Geochemistry, Geophysics, Geosystems* 4 (2).

Grilli, S. T., C. O'Reilly, J. C. Harris, T. T. Bakhsh, B. Tehranirad, S. Banihashemi, J. T. Kirby, C. D. Baxter, T. Eggeling, G. Ma, and F. Shi. 2014. Modeling of SMF tsunami hazard along the upper US East Coast: Detailed impact around Ocean City, MD. *Natural Hazards* 76 (2):705–746.

Grilli, S., A. R. Grilli, B. Tehranirad, and J. T. Kirby. 2017. Modeling tsunami sources and their propagation in the Atlantic Ocean for coastal tsunami hazard assessments and inundation mapping along the U.S. East Coast. *Coastal Structures and Solutions to Coastal Disasters 2015*.

Hallegatte, S., A. Vogt-Schilb, J. Rozenberg, M. Bangalore, and C. Beaudet. 2020. From poverty to disaster and back: A review of the literature. *Economics of Disasters and Climate Change* 4 (1):223–247.

Ismail, H., A. K. Abd Wahab, M. F. Mohd Amin, M. Z. Mohd Yunus, F. Jaffar Sidek, and B. Esfandier J. 2012. A 3-tier tsunami vulnerability assessment technique for the north-west coast of Peninsular Malaysia. *Natural Hazards* 63 (2):549–573.

Kaiser, G., B. Burkhard, H. Römer, S. Sangkaew, R. Graterol, T. Haitook, H. Sterr, and D. Sakuna-Schwartz. 2013. Mapping tsunami impacts on land cover and related ecosystem service supply in Phang Nga, Thailand. *Natural Hazards and Earth System Sciences* 13 (12):3095–3111.

Kelletat, D., S. R. Scheffers, and A. Scheffers. 2007. Field signatures of the SE-asian mega-tsunami along the west coast of Thailand compared to Holocene Paleo-tsunami from the Atlantic Region. *Pure and Applied Geophysics* 164 (2-3):413–431.

Masozera, M., M. Bailey, and C. Kerchner. 2007. Distribution of impacts of natural disasters across income groups: A case study of new orleans. *Ecological Economics* 63 (2-3):299–306.

Matsuyama, M., J. P. Walsh, and H. Yeh. 1999. The effect of bathymetry on tsunami characteristics at Sisano Lagoon, Papua New Guinea. *Geophysical Research Letters* 26 (23):3513–3516.

Meyer, M. A. 2016. Elderly perceptions of social capital and age-related disaster vulnerability. *Disaster Medicine and Public Health Preparedness* 11 (1):48–55.

Morrow, B. H. 1999. Identifying and mapping community vulnerability. *Disasters* 23 (1):1–18.

Murthy, M. V., T. Usha, Y. Pari, and N. T. Reddy. 2011. Tsunami vulnerability assessment of Cuddalore using numerical model and GIS. *Marine Geodesy* 34 (1):16–28.

Muttarak, R., and W. Lutz. 2014. Is education a key to reducing vulnerability to natural disasters and hence unavoidable climate change? *Ecology and Society* 19 (1).

Najihah, R., D. M. Effendi, M. A. Hairunnisa, and K. Masiri. 2014. Tsunami vulnerability assessment mapping for the west coast of Peninsular Malaysia using a Geographical Information System (GIS). *IOP Conference Series: Earth and Environmental Science* 18:012047.

Omira, R., M. A. Baptista, J. M. Miranda, E. Toto, C. Catita, and J. Catalão. 2009. Tsunami vulnerability assessment of casablanca-morocco using numerical modelling and GIS Tools. *Natural Hazards* 54 (1):75–95.

Papathoma, M., D. Dominey-Howes, Y. Zong, and D. Smith. 2003. Assessing tsunami vulnerability, an example from Herakleio, Crete. *Natural Hazards and Earth System Sciences* 3 (5):377–389.

Papathoma, M., and D. Dominey-Howes. 2003. Tsunami vulnerability assessment and its implications for coastal Hazard Analysis and Disaster Management Planning, gulf of corinth, Greece. *Natural Hazards and Earth System Sciences* 3 (6):733–747.

Paris, R., R. S. Ramalho, J. Madeira, S. Ávila, S. M. May, G. Rixhon, M. Engel, H. Brückner, M. Herzog, G. Schukraft, F. J. Perez-Torrado, A. Rodriguez-Gonzalez, J. C. Carracedo, and T. Giachetti. 2018. Mega-tsunami conglomerates and flank collapses of Ocean Island volcanoes. *Marine Geology* 395:168–187.

Prothero, D. R. 2011. Chapter 2: Tsunamis, The Sea Rises Up. In *Catastrophes!: Earthquakes, tsunamis, tornadoes, and other earth-shattering disasters*. Baltimore: Johns Hopkins University Press.

Rahman, M. S. 2013. Climate change, disaster and gender vulnerability: A study on two divisions of Bangladesh. *American Journal of Human Ecology* 2 (2).

Riquelme, S., M. Fuentes, G. P. Hayes, and J. Campos. 2015. A rapid estimation of near-field tsunami runup. *Journal of Geophysical Research: Solid Earth* 120 (9):6487–6500.

Röbke, B. R., and A. Vött. 2017. The tsunami phenomenon. *Progress in Oceanography* 159:296–322.

Römer, H., P. Willroth, G. Kaiser, A. T. Vafeidis, R. Ludwig, H. Sterr, and J. Revilla Diez. 2012. Potential of remote sensing techniques for tsunami hazard and vulnerability analysis – a case study from Phang-Nga Province, Thailand. *Natural Hazards and Earth System Sciences* 12 (6):2103–2126.

Schambach, L., S. T. Grilli, J. T. Kirby, and F. Shi. 2018. Landslide tsunami hazard along the upper US East Coast: Effects of slide deformation, bottom friction, and frequency dispersion. *Pure and Applied Geophysics* 176 (7):3059–3098.

Sinaga, T. P., A. Nugroho, Y.-W. Lee, and Y. Suh. 2011. GIS mapping of tsunami vulnerability: Case study of the jembrana regency in Bali, Indonesia. *KSCE Journal of Civil Engineering* 15 (3):537–543.

Smith, K. 2013. *Environmental hazards: Assessing risk and reducing disaster*. Abingdon: Routledge.

Szlafsztein, C., and H. Sterr. 2007. A GIS-based vulnerability assessment of coastal natural hazards, state of Pará, Brazil. *Journal of Coastal Conservation* 11 (1):53–66.

Tehranirad, B., J. C. Harris, A. R. Grilli, S. T. Grilli, S. Abadie, J. T. Kirby, and F. Shi. 2015. Far-field tsunami impact in the North Atlantic basin from large scale flank collapses of the Cumbre Vieja volcano, La Palma. *Pure and Applied Geophysics* 172 (12):3589–3616.

Teo, M., A. Goonetilleke, K. Deilami, A. Ahankoob, and M. Lawie. 2019. Engaging residents from different ethnic and language backgrounds in disaster preparedness. *International Journal of Disaster Risk Reduction* 39:101245.

ten Brink, U. S., H. J. Lee, E. L. Geist, and D. Twichell. 2009. Assessment of tsunami hazard to the U.S. East Coast using relationships between submarine landslides and earthquakes. *Marine Geology* 264 (1-2):65–73.

Unesco/Intergovernmental Oceanographic Commission. Tsunami risk assessment and mitigation for the Indian Ocean: knowing your tsunami risk-and what to do about it. Unesco, 2009.

Weichselgartner, J. 2001. Disaster mitigation: The concept of vulnerability revisited. *Disaster Prevention and Management: An International Journal* 10 (2):85–95.

Williams, B. D., and G. R. Webb. 2020. Social vulnerability and disaster: Understanding the perspectives of Practitioners. *Disasters* 45 (2):278–295.

Xiang, T., B. J. Gerber, and F. Zhang. 2021. Language access in emergency and disaster preparedness: An assessment of local government "whole community" efforts in the United States. *International Journal of Disaster Risk Reduction* 55:102072.

Zhang, N., H. Huang, B. Su, and H. Zhang. 2013. Population evacuation analysis: Considering dynamic population vulnerability distribution and disaster information dissemination. *Natural Hazards* 69 (3):1629–1646.

Zhou, Y., N. Li, W. Wu, J. Wu, and P. Shi. 2014. Local spatial and temporal factors influencing population and societal vulnerability to natural disasters. *Risk Analysis* 34 (4):614–639.

APPENDICES

Social Variable Data

Social Variables

NAME	Language	Education	Populatior	Poverty	Vehicles	Gender	Race	Elderly	PopDensit
Accomack	5.3	78.9	34066	9.7	9.1	51	68.7	13.5	564
Anne Arundel	3.6	90	527020	3.3	4.6	50.5	79.3	10.8	7090
Atlantic	11	84.7	273162	8.8	13.5	51.5	67.4	9.6	3292
Baltimore	4.7	88.8	799195	5.3	7.6	52.7	67.9	13.8	9779
Baltimore	3.7	77.4	620538	16.5	29.2	53	31.4	16.2	42154
Barnstable	2.4	94.7	217483	5	4.6	52.3	95.4	10.5	5955
Beaufort	3.7	81.5	47185	14.4	9.3	52.2	68.8	12	527
Beaufort	6.1	90.6	155550	7.4	5.1	50.4	75.4	14.1	2445
Bertie	0.3	72.3	20890	19.1	10.1	51.3	36.3	13.4	275
Brevard	3.1	90.6	540583	7.2	4.5	51	85.9	10.2	5042
Bristol	8.3	80.1	546433	8.8	9.5	51.6	91.6	16.3	6600
Bristol	4.6	86.2	50501	3.5	7.1	51.9	97.4	14.4	14442
Bronx	25.1	68.8	1365725	25.8	58.8	53.2	23.5	13.9	150726
Broward	14.8	87.1	1734139	9.1	7.1	51.5	66.1	8.7	12337
Brunswick	2.7	84.7	101994	10.2	5.7	51.1	85.7	14.1	1301
Bryan	1.3	88.4	29039	8.8	3.9	50.6	83.1	8.7	313
Calvert	1	91.9	87891	2.8	3.2	50.7	84	17.2	2004
Camden	1.1	89.1	49293	12.6	4.5	48.9	76.6	15.6	368
Camden	1.8	88.4	9719	6.5	1.2	50.4	82.9	13.2	289
Cape May	3.4	88.2	97684	6.4	9.3	51.3	91.9	11.6	3847
Carteret	1.9	87.6	65068	8.1	4.8	50.6	90.8	13.7	1017
Cecil	1.8	86.7	100139	6.3	4.6	50.4	92.3	9.4	1567
Charles	1.8	90.4	143912	3.7	3	51.6	55.8	13.3	1391
Charles City	0	74.8	7205	6.4	4.6	50.1	43.7	12	305
Charleston	3.3	87.4	342434	11.5	8.9	51.5	65.6	12.8	2350
Chatham	3.1	87.4	256428	11.6	8.6	51.9	55.3	12.3	3748
Chowan	2.6	77.4	14859	12.6	13.3	50.9	61.8	15.1	868
Colleton	1.9	75.3	38833	17.7	10.3	51.7	58.7	12.3	303
Craven	2.7	87.5	100001	11.7	8.2	50.3	71.7	13.1	1137
Cumberland	2.7	93.3	279994	6.9	7.7	51.3	94.5	14.5	2018
Cumberland	11.6	75.8	155456	12.8	11.5	48.5	67.9	18.6	2050
Currituck	1.4	84.7	23299	6.2	2.6	50.1	92.5	16.4	506
Dare	3.6	91.8	33650	6	1.5	49.4	94.6	10.3	594
Dorchester	1.9	81	32287	9.5	9.4	52.3	69.4	23.6	462
Dukes	3.2	93.5	16155	5.5	6	50.6	88.7	26.6	1064
Duval	5	87.2	854848	10.4	7.7	51.5	64.1	13.3	6438
Essex	10	88.2	735642	7.7	10.6	52	83.7	13.8	9681
Essex	1.3	80.1	10901	8.3	4.6	51.6	60	15.1	369

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NAME	Language	Education	Populatior	Poverty	Vehicles	Gender	Race	Elderly	PopDensit
Fairfax	14.9	91.9	1048554	3.4	3.7	50.6	67.6	19.6	13157
Fairfield	11.7	88.3	905342	5.6	8.5	51.4	78.5	18.2	9586
Flagler	5.8	90.2	91806	8	3.7	51.7	85.1	19.9	2559
Georgetown	2	83.4	60236	13.2	9.3	52.2	63.7	18.2	747
Gloucester	0.9	85.3	36610	7.4	3.4	50.8	88.4	9.8	1123
Glynn	3.7	86.1	77632	11.7	6.2	52.3	71	12.3	1428
Hampton	2.2	88.6	139046	9.1	7.3	51.9	45.7	18.8	15211
Hancock	0.6	91	54309	6.8	4.9	51.1	98.1	14.9	259
Harford	2.2	91	242888	4	4.8	51.1	83.7	14.4	3308
Hertford	2.8	73.5	24384	17.5	12.6	51	37	21.4	580
Horry	4.4	86.9	258267	11.6	5.2	51	80.8	11.9	2093
Hudson	25.3	80.3	622123	12.8	33.8	50.6	57.8	30.2	58857
Hyde	1.5	76.7	5721	22.5	7	41.8	57.5	14.3	70
Indian River	6.6	86.3	135518	8.9	5.5	51.6	88.5	8.3	4074
Isle of Wight	1.4	86.2	34762	5	4.8	51.2	73.7	6.8	815
James City	2.6	93.3	64386	3.9	3.8	51.4	82.3	11.6	4390
Jasper	8.7	74.9	23634	14.2	6.4	46.7	39.7	15.1	232
Kent	3.5	84.9	156918	9.3	6.5	51.8	72.1	17.3	1835
Kent	3.6	86	20018	5.1	5.5	51.8	81.6	18.8	738
Kent	2.5	89.5	167235	4.9	5.8	52	95.2	13	7467
King George	0.8	90.2	22794	5.1	4.8	49.8	80.7	14.6	633
Kings	24.1	77.8	2466782	18.8	56.5	52.9	45.1	16	179105
Knox	0.4	89.7	40111	7.9	6.6	50.8	98.7	13.8	885
Lancaster	0.6	82.3	11478	6.9	7.2	52.8	70.5	11.1	1279
Liberty	3.7	88.7	63854	15	5.9	50.6	49.9	10	410
Lincoln	0.4	92.4	34719	7.7	2.7	51	98.8	12.5	677
Martin	7.1	88.6	144322	6	4.6	50.6	89.5	13.9	3499
Mathews	0.7	84.5	9004	7.3	3.5	52.2	88.3	15.4	1151
McIntosh	0.7	75.1	13817	11.2	5.4	51.5	61.7	18.9	265
Miami-Dade	35.5	77	2445374	13.8	11.1	51.6	74.5	21	10326
Middlesex	3.3	92	164774	3	4.5	51.1	90.9	11.4	3267
Middlesex	15.6	88	798882	4.9	8.3	50.9	63.8	5.9	16009
Middlesex	1.2	87.6	10831	9.4	3.2	50.5	80.2	20.1	1019
Monmouth	7.1	91.2	628112	4.5	7.9	51.4	84.6	20.4	9065
Monroe	9.5	89.8	73065	6.9	8.1	46.9	90.7	16.6	610
Nantucket	2.5	93.4	10069	3.6	5.2	48.5	92.2	19.6	978
Nassau	0.7	86.5	71099	7.1	3.8	50.9	91.2	18.1	963
Nassau	10.4	89.7	1329083	3.4	7.2	51.7	75.3	14.8	32145
New Castle	4.8	88.4	533514	6.6	7.9	51.6	70.1	19.2	7624
New Hanover	3.2	89.5	197272	8.9	6.3	51.7	80.3	9.4	6840
New Haven	7.5	87.7	856688	7.9	10.7	51.9	77.8	13.8	10103

NAME	Language	Education	Populatior	Poverty	Vehicles	Gender	Race	Elderly	PopDensit
New London	5.4	89.8	272360	5	6.3	50.2	85.6	14.5	2780
New York	17.2	84.6	1583345	14.5	77.7	53	58.8	11.3	329856
Newport	2.2	91.1	83253	4.5	7.7	51.2	93.4	8.9	6342
Newport News	3.6	88.9	181822	10.4	10.5	51.7	53.5	17.4	14308
Norfolk	6.4	93.1	662077	4.1	9.3	52.1	84.8	11.4	11645
Norfolk	3.3	83.9	242143	13.5	11.4	48.5	50	14.2	19704
Northampton	3.4	78	12572	15.8	11.1	50.4	60.3	22.8	424
Northumberland	0.3	84.1	12419	6.1	3	51	71.4	11.5	892
Ocean	4.5	89.1	569374	6.4	6.8	52.1	92.2	26.8	8347
Onslow	2.7	88.1	169207	11	4.7	45.7	76.2	21.7	877
Palm Beach	13	86.8	1299356	8.6	6.2	51.6	76	10.4	7699
Pamlico	2.5	82.7	13072	6	4.5	48.2	78.5	21.4	402
Pasquotank	2.1	81.9	40167	13.8	8.8	51.3	59.3	13.1	1259
Pender	3.5	83.8	50256	10.6	6.5	49.8	77.2	28.6	480
Perquimans	0.3	85.3	13091	13.4	7.3	52	72.4	20.9	607
Plymouth	4.3	91.8	490784	5	5.8	51.3	88	13.1	4728
Poquoson	2.2	93.9	12099	3.7	4.3	50.7	96.6	14.4	4630
Portsmouth	1.3	81.7	96785	12.3	10	51.9	44.4	20.2	17133
Prince William	13.2	88.4	379415	3.8	3.1	50.2	62.1	22.5	3792
Queen Anne's	1.9	89.7	46945	3.8	3.3	50.3	90.2	14.2	890
Queens	28.8	80	2199169	10.6	36.3	51.7	44.6	12.1	116103
Richmond	11.4	87.5	463450	8.1	15.7	51.5	77	15.3	50654
Richmond	2.6	74.6	9328	8	4.8	43.1	66.9	15.2	450
Rockingham	1.8	93.5	294638	3	3.1	50.5	96.9	15.3	2436
Sagadahoc	0.6	91.8	35688	5.7	5.7	51.6	98.1	11.8	904
Salem	2.8	85.6	65982	7.4	8.2	51.3	82.2	24.1	1473
Somerset	2.8	80.9	26411	12.7	9.4	46.3	56.4	11.7	523
St. Johns	2.3	92.8	180624	6.2	3.9	51.3	91.3	14.1	2411
St. Lucie	9.4	83.4	269659	10.1	4.5	51	76.3	20	5250
St. Mary's	1.9	89	102086	4.7	4.7	50.1	82.6	14.6	1311
Stafford	3.7	91.5	124587	3.2	2.5	49.7	74.4	10.5	1656
Suffolk	18.2	83.1	704460	15.7	33.9	51.8	60.3	20.9	53804
Suffolk	8.9	89.4	1482548	3.8	5	50.8	84.3	24.3	8654
Suffolk	1.3	84.7	82544	8.8	5.4	52.1	54.6	12.7	1217
Surry	1.2	78.8	7039	3.8	4.6	49.7	51.8	10.2	210
Sussex	5.1	85.2	190846	8	4.3	51.2	80.8	16.9	2110
Talbot	1.9	88	37361	4.3	4.6	52.6	83.4	17.3	1398
Tyrrell	3.3	73.9	4374	15.6	10.3	47.9	60.3	14.8	90
Virginia Beach	3.8	92.5	435996	4.8	3.6	51	72.6	12.4	7997
Volusia	4.6	87.3	496053	9.4	5.7	51.1	84.8	11.2	4850

NAME	Language	Education	Populatior	Poverty	Vehicles	Gender	Race	Elderly	PopDensit
Waldo	0.3	90	38740	10.2	5.5	51.2	98.8	14.4	381
Washington	0.9	85.2	33154	14.1	7.5	50.8	94.7	17.2	107
Washington	0.9	76	13248	19.6	13.4	51.6	46.4	21.3	341
Washington	1.9	91.9	126987	3.4	3.6	51.4	95.3	13.4	2644
Westchester	12.3	87.4	939406	5.8	14.2	51.9	69.8	13.3	14723
Westmoreland	2.5	76.5	17237	7.6	3	51.9	69.5	13	765
Wicomico	4.7	84.3	96951	7.8	7.6	52.2	71.4	11.9	1727
Worcester	2.3	88.4	51133	6.2	5.8	51.4	84.5	15.4	1069
York	1.8	90.1	197457	5.6	4.5	51.3	97.7	15.5	1422
York	2.3	94.5	64846	3.2	2.1	51	80.8	20.6	3231

Physical Variable Data

Physical Variables

NAME	Shoreline	Coastline	Shoreline_Coa	Elevation	Bathymetry	Land_Cover
Accomack	887.0062	119.463	7.424943	0.7254	0.631906	2.727445
Anne Arundel	301.3885	55.23359	5.456616	0.1955	2.090091	3.177565
Atlantic	452.5115	23.25623	19.45765	0.3183	0.783008	2.727445
Baltimore	159.2952	31.72344	5.021372	0.0282	2.234245	3.506816
Baltimore	39.9747	0.94837	42.15095	0.6428	2.355061	4.399301
Barnstable	518.6525	218.2153	2.376792	0.3246	0.004215	2.727445
Beaufort	332.403	91.15067	3.646743	0.7602	0.959415	2.603944
Beaufort	1179.079	68.08381	17.31805	0.855	0.927458	2.603944
Bertie	103.4042	23.34414	4.429556	0.1905	1.538233	1.90698
Brevard	580.0706	73.71458	7.869143	0.3898	0.392031	2.961146
Bristol	196.6647	42.92777	4.581294	0.0969	0.460345	3.506816
Bristol	50.84547	20.6554	2.461607	0.512	0.636313	2.727445
Bronx	73.70763	13.28274	5.549129	0.3166	0.452742	3.506816
Broward	331.6095	24.20549	13.69977	0.9971	0.021525	4.148919
Brunswick	401.6953	49.01889	8.194705	0.0029	0.721968	2.661781
Bryan	208.826	3.317257	62.9514	0.4182	1.350696	2.409149
Calvert	138.2845	31.95984	4.326819	0.2012	1.800327	2.961146
Camden	480.387	31.94666	15.03716	0.839	1.239894	2.331003
Camden	187.6341	32.16158	5.834107	0.9623	0.939595	2.409149
Cape May	534.9579	61.90079	8.642182	0.7716	0.727936	2.961146
Carteret	767.5303	250.4083	3.065115	0.8179	0.455665	3.087816
Cecil	172.8746	28.07885	6.156757	0.1298	1.761568	1.90698
Charles	190.4979	65.95564	2.888273	0.1627	2.121821	3.536433
Charles City	136.8044	4.654552	29.39152	0.2251	1.979496	1.775548
Charleston	1564.047	97.30015	16.07446	0.7916	0.660879	2.661781
Chatham	835.2689	50.05397	16.68737	0.9205	1.142439	3.192798
Chowan	75.93913	39.80389	1.907832	0.7916	1.425267	3.081596
Colleton	249.2135	19.96255	12.48405	0.3284	0.893153	2.409149
Craven	228.1192	36.74245	6.208601	0.2891	0.77041	2.878044
Cumberland	369.9796	146.7095	2.521852	0.0692	0.026125	3.506816
Cumberland	436.1194	49.2919	8.847689	0.3492	0.93608	4.148919
Currituck	342.2881	113.0033	3.02901	0.9903	0.813394	2.53592
Dare	458.7958	280.5922	1.635099	0.9897	0.203116	2.248727
Dorchester	559.2748	142.0011	3.938525	0.7975	1.302309	2.661781
Dukes	223.3411	116.9884	1.909089	0.3537	0.207308	3.039434
Duval	421.5981	19.9857	21.09499	0.4875	1.09441	3.087816
Essex	334.8978	78.16709	4.284383	0.1681	0.030645	2.961146
Essex	125.6678	11.48488	10.94202	0.1657	1.901241	1.910636

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NAME	Shoreline	Coastline	Shoreline_Coa	Elevation	Bathymetry	Land_Cover
Fairfax	74.64483	7.472797	9.988874	0.0367	2.549612	4.375698
Fairfield	165.0014	59.05894	2.793842	0.0541	0.660708	2.727445
Flagler	115.9249	18.52662	6.257207	0.4996	0.800459	3.037187
Georgetown	548.5697	40.12347	13.67204	0.5663	0.715613	2.201854
Gloucester	194.8057	27.80189	7.006924	0.4096	1.465937	2.178783
Glynn	545.0278	26.81028	20.32906	0.9254	1.265293	2.869078
Hampton	60.30034	15.73944	3.831162	0.9137	1.362005	7.238589
Hancock	760.9103	344.8148	2.206722	0.0741	0	2.961146
Harford	137.3997	42.68142	3.219193	0.1372	2.056011	4.337218
Hertford	75.0363	2.938076	25.53926	0.1711	1.733035	2.192429
Horry	193.9745	38.12371	5.088029	0.1192	0.967138	3.192798
Hudson	87.52979	10.39015	8.424301	0.678	0.419363	3.536433
Hyde	404.3092	106.2832	3.804073	0.9995	0.339512	2.512102
Indian River	154.6667	22.92657	6.746179	0.377	0.303907	4.963938
Isle of Wight	105.5627	23.42039	4.507301	0.0973	1.571797	2.198208
James City	163.0436	24.62545	6.620939	0.2568	1.6774	2.512102
Jasper	358.0526	4.558912	78.53904	0.4464	1.196075	2.53592
Kent	275.8004	36.81543	7.491436	0.2669	1.170967	2.727445
Kent	228.3693	52.09959	4.383323	0.2396	1.694684	2.409149
Kent	54.96445	15.48707	3.549055	0.0507	0.612045	3.177565
King George	126.3193	29.41781	4.293975	0.1399	2.331511	4.519994
Kings	100.8496	15.14182	6.660336	0.4898	0.248652	2.686725
Knox	372.7881	160.2636	2.326094	0.1548	0.002621	2.603944
Lancaster	169.0188	40.98199	4.124221	0.2917	1.482644	2.504928
Liberty	339.0408	19.07757	17.7717	0.5763	1.294014	1.966585
Lincoln	359.8031	57.74094	6.231334	0.1219	0.008657	1.90698
Martin	168.9035	22.30073	7.573898	0.4613	0.085022	4.215785
Mathews	168.4207	34.28673	4.912124	0.9056	1.391175	2.366791
McIntosh	694.4106	32.70705	21.23122	0.8927	1.280906	1.897757
Miami-Dade	583.6474	165.1947	3.533088	0.9988	0.035095	3.714675
Middlesex	62.81678	15.5395	4.042395	0.0888	0.671913	3.039434
Middlesex	89.91333	12.29954	7.310303	0.1032	0.439271	3.052525
Middlesex	116.8014	39.89371	2.927814	0.2063	1.483937	2.792859
Monmouth	132.1295	51.08079	2.586677	0.1026	0.168535	4.337218
Monroe	1376.794	312.0456	4.412158	0.9999	0.067743	2.033583
Nantucket	90.2035	60.87543	1.481772	0.4973	0.397197	2.661781
Nassau	289.1361	14.78926	19.55042	0.4554	1.199401	2.430165
Nassau	365.1386	48.36244	7.550045	0.3241	0.248536	4.375698
New Castle	256.7437	38.84034	6.610234	0.2068	1.534471	3.177565
New Hanover	283.0461	29.86443	9.477701	0.4733	0.799823	3.275759
New Haven	151.5923	48.80566	3.106039	0.0656	0.741252	2.961146

NAME	Shoreline	Coastline	Shoreline_Coa	Elevation	Bathymetry	Land_Cover
New London	187.7841	39.80915	4.717108	0.0646	0.367422	4.148919
New York	87.26567	4.687237	18.61772	0.4976	0.404774	4.963938
Newport	124.7223	115.0825	1.083764	0.1808	0.447838	3.506816
Newport News	59.74461	26.03676	2.294625	0.3267	1.474633	4.777217
Norfolk	56.80062	13.98678	4.061023	0.0359	0.128392	4.756432
Norfolk	91.29242	15.31165	5.962285	0.9727	1.264509	8.114066
Northampton	560.087	81.1425	6.902511	0.7613	0.840059	1.386631
Northumberland	239.0424	42.11142	5.676426	0.3989	1.488177	2.716733
Ocean	462.5292	48.82556	9.473095	0.3235	0.28356	2.409149
Onslow	376.0021	30.72011	12.23961	0.1985	0.937973	2.716733
Palm Beach	273.6029	45.35258	6.032797	0.9085	0.015517	4.519994
Pamlico	321.2715	58.17693	5.522317	0.7887	0.814303	2.294185
Pasquotank	141.7664	31.4161	4.512539	0.998	1.088272	4.315989
Pender	175.2591	17.13713	10.22687	0.2103	1.020941	2.28858
Perquimans	81.61134	50.56097	1.614117	0.953	1.211639	3.728701
Plymouth	212.7731	109.274	1.947151	0.0996	0.121366	3.052525
Poquoson	50.99796	10.14001	5.029379	0.9994	1.380754	3.188257
Portsmouth	47.5117	6.214234	7.645624	0.8945	1.38607	7.492329
Prince William	40.34601	12.67981	3.181911	0.0249	2.675068	3.084844
Queen Anne's	275.8019	64.56448	4.271728	0.2483	1.648069	3.037187
Queens	125.0655	16.99782	7.357739	0.4043	0.235517	5.541608
Richmond	55.81461	31.17292	1.790484	0.2862	0.364244	4.215785
Richmond	101.8909	12.04479	8.459332	0.2161	1.740355	2.196949
Rockingham	120.4867	19.89589	6.055859	0.0497	0.015231	1.90698
Sagadahoc	327.1801	22.60752	14.47218	0.2152	0.023859	3.052525
Salem	410.7165	37.71549	10.88986	0.3699	1.249479	3.456465
Somerset	509.3475	104.3801	4.879739	0.8395	0.926015	2.331003
St. Johns	228.7202	42.20538	5.41922	0.4769	0.890073	3.39877
St. Lucie	169.0934	21.90297	7.720113	0.4618	0.185874	5.692583
St. Mary's	305.5407	74.32511	4.110868	0.309	1.613785	2.432412
Stafford	72.5666	12.60567	5.756661	0.0529	2.626629	1.966585
Suffolk	89.10816	24.88103	3.58137	0.4647	0.212588	4.337218
Suffolk	962.9691	307.7666	3.128894	0.3693	0.163143	2.504928
Suffolk	77.52311	8.991996	8.621346	0.1144	1.493186	3.224396
Surry	93.71229	26.54635	3.530138	0.0533	1.76117	1.591069
Sussex	351.3422	47.11356	7.457349	0.243	0.734305	3.506816
Talbot	416.4375	54.62872	7.623051	0.5794	1.563846	3.081596
Tyrrell	163.0851	47.78928	3.412588	0.9999	0.879195	2.723024
Virginia Beach	319.7183	40.51401	7.891548	0.9309	0.98738	4.718072
Volusia	435.0976	51.03251	8.525891	0.6927	0.538959	2.869078

NAME	Shoreline	Coastline	Shoreline_Coa	Elevation	Bathymetry	Land_Cover
Waldo	134.6073	62.00286	2.170986	0.0337	0.008597	0.876328
Washington	661.1027	261.3514	2.529554	0.0434	0	2.409149
Washington	72.83781	24.94287	2.920185	0.8545	1.159964	3.476635
Washington	181.4604	72.377	2.507156	0.1053	0.176952	2.961146
Westchester	87.20798	14.17214	6.153478	0.0766	0.540231	2.792859
Westmoreland	164.9426	43.92384	3.755196	0.2605	1.800607	2.725425
Wicomico	166.5325	13.72318	12.13512	0.3089	0.86144	2.783046
Worcester	389.5326	32.84088	11.86121	0.5109	0.627149	2.686725
York	173.0811	63.41317	2.729418	0.0385	0.01027	3.087816
York	111.0149	13.45645	8.24994	0.3689	1.486588	2.49083

Abbreviations

USEC- United States East Coast

NTHMP- National Tsunami Hazard Mitigation Program

NALCMS- North American Land Change Monitoring System

GEBCO- The General Bathymetric Chart of the Oceans

NOAA- National Oceanic and Atmospheric Administration

FHSU- Fort Hays State University

CN- Connecticut

DE- Delaware

FL- Florida

GA- Georgia

ME- Maine

MD- Maryland

MA- Massachusetts

NC- North Carolina

NH- New Hampshire

NJ- New Jersey

NY- New York

RI- Rhode Island

SC- South Carolina

VA- Virginia

Links to Data Sources

http://www.cec.org/north-american-environmental-atlas/land-cover-30m-2015-landsat-and-rapideye/- Land Cover data

https://www.opendem.info/download_bathymetry.html- Bathymetry data

https://apps.nationalmap.gov/downloader/#/- Elevation data

https://shoreline.noaa.gov/data/datasheets/medres.html- Shoreline data

https://www.census.gov/data/datasets.html- Census Data

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