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Chesapeake Coastal Community Flood Vulnerability--Prediction and Verification

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Chesapeake Coastal Community Flood Vulnerability

Prediction and Verification

A Thesis

Presented to

The Faculty of the School of Marine Science

The College of William and Mary in Virginia

In Partial Fulfillment

of the Requirements for the Degree of

Master of Science

by

Alexander D. Renaud

2016

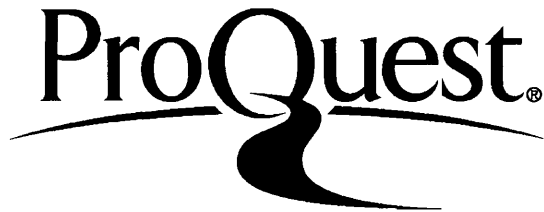
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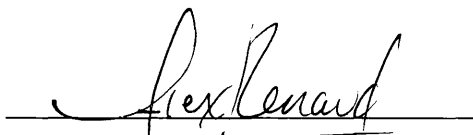
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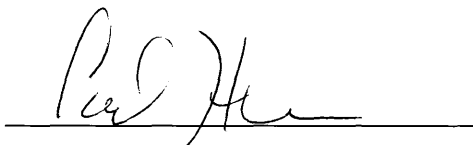
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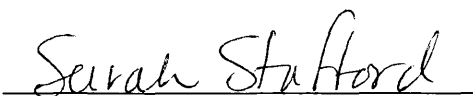
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ABSTRACT

Fast moving hurricanes and stationary nor'easters have resulted in significant flood damage in Chesapeake tidewater communities. The Chesapeake Bay region is one of America's most vulnerable regions with respect to sea-level rise, which will only increase storm surge impacts over upcoming decades. While the general trends are well documented, there is limited information relevant to specific communities' relative flood risk and response. The dearth of data is especially troublesome given the lengthy period of time generally needed for communities to plan and implement adaptive action. This study contributes to the regional understanding of flood and sea-level rise vulnerability by applying physical, social, and combined vulnerability indices to tidally influenced localities along the Chesapeake Bay. Unlike other combinations of physical and socioeconomic data, the physical vulnerability index for this study is calculated at a scale that can directly link into social vulnerability index information at local and regional levels. The research also considers the distribution of coastal natural capital (in the form of marshes and forests) alongside these indices at comparable scales.

By calculating the indices for conditions of the early 2000s, this study also tested their predictive value against Hurricane Isabel, a landmark 2003 storm that flooded areas across the region. Systematic verification "hindcasts" of past events are relatively rare for vulnerability index evaluation. By attempting to establish connections between real flooding data, socioeconomic activity, and vulnerability indices, this study questions whether theoretical vulnerability indices work as true proxies for real world conditions. The results question the true utility of these indices by showing limited relationships between vulnerability and changes in community socio-economic activity. The research also emphasizes the need for more data collection and consideration in order to better comprehensively understand coastal flood impacts and their management implications.

Chesapeake Coastal Community Flood Vulnerability
Prediction and Verification

INTRODUCTION

Fast moving hurricanes and stationary nor'easters have resulted in significant flood damage in Chesapeake Bay tidewater communities. The area is one of America's most vulnerable regions with respect to sea-level rise, which will only increase storm surge impacts over upcoming decades. While the general sea-level rise trends are clear, information relevant to specific communities' flood risk and ability to respond is quite limited. The lack of data is especially troublesome given the lengthy period of time communities need to plan and implement adaptive action. This research aims to aid coastal hazard response planning efforts by applying flood vulnerability indices to the Chesapeake Bay region. The analysis's objective is to determine how well measures of natural and socioeconomic characteristics describe and predict specific community vulnerability to storm-driven flooding. By better understanding the accuracy and reliability of community vulnerability determinants, coastal managers should be able to more effectively enhance their communities' ability to recover from coastal flood events.

The location and physical geology of the Chesapeake tidewater region largely explain why the area is so vulnerable to the impacts of storm surge and sea-level rise. Significant areas of low elevation along the Bay's shores have been experiencing rising water levels due to subsidence and ocean circulation patterns in addition to global changes (e.g. Eggleston and Pope 2013; Ezer and Corlett 2012). Physical characteristics are only part of the picture however. Differences in individual communities' human elements and natural capital characteristics are likely critical determinants of

vulnerability to coastal flood events. Consequently, it is essential to consider both natural and social aspects when analyzing coastal flood event impacts.

Over the past decade, analyses of communities' ability to weather and recover from natural disasters increasingly have considered social factors (e.g. income or age) alongside their physical characteristics (Wisner et al. 2003). A number of vulnerability indices incorporate both physical and social features of areas (e.g. Wu et al. 2002; Kleinosky et al. 2006; Martinich et al. 2011). As described by Eriksen and Kelly (2007), most of these indices are essentially snapshots of particular places at particular moments; they have not been subjected to critical analysis or verification through application to multiple flood events over time.

Communities in the Chesapeake tidewater region could benefit a great deal if flood vulnerability indices prove to be effective tools for enhancing resilience to storm-driven flooding. The region also offers a good place to test how well vulnerability indices predict flood events' impacts on specific communities. One of the problems with undertaking this kind of analysis is that the physical characteristics of the region relevant to flood vulnerability are described in ways that seldom correspond to the political units – e.g., counties and zip codes – for which socioeconomic data is compiled. In addition to applying established social vulnerability methods to the Bay area, this study develops a new physical vulnerability index at scales that better match socioeconomic data resolution. The research tests the indices' predictive power by hindcasting the impacts of Hurricane Isabel, the storm that devastated parts of the Chesapeake Tidewater region in 2003. Though it passed through the area more than a decade ago, Hurricane Isabel remains the best available test scenario for the region, having generated some of the

worst widespread flooding in over 70 years. Isabel's timing also is generally ideal because it occurred relatively soon after a decennial US Census.

In summary, this study attempts to combine multiple sources of socioeconomic and physical data with information regarding storm surge impacts to evaluate how well vulnerability indices predict community resilience to flood events. The analysis specifically studies vulnerability in the Chesapeake Bay region and tests the predictive ability of flood vulnerability indices with respect to the impact of Hurricane Isabel on Tidewater communities. This thesis details two major components:

- Chapter 1 describes the process of characterizing vulnerability across the coastal tidewater region of Maryland and Virginia by analyzing regional vulnerability distribution in terms of physical, socioeconomic, and relevant natural ecosystem factors.
- Chapter 2 investigates the impacts of coastal flooding across the area associated with Hurricane Isabel, describing the relationships between vulnerability indices, relative flooding, and changes in community socioeconomic activity.

The results demonstrate how assessed vulnerability differs across tidewater communities and identify several relative hot spots of combined vulnerability. Despite vulnerability indices' value as visualization tools, a case study of their performance suggests that their real world application falls short of predicting societal impacts of flooding. Barring analysis against different, more refined datasets, this evaluation questions the true value of their application.

BACKGROUND

Severe flooding in the coastal Chesapeake Tidewater region occurs due to a combination of tidal, storm surge, and precipitation events. Community “vulnerability,” or “the degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or stress/stressor” (Turner et al. 2003), can be characterized in a number of different ways. In addition to the risks of coastal living, the community vulnerability concept applies to a number of natural hazards, including earthquakes and tornadoes. Natural hazards impact communities differently due to unequal levels of exposure as well as the disparities in physical characteristics that shape vulnerability. At the same time demographic diversity can influence disaster impacts; two communities with the same elevation and storm surge orientation might respond in very different manners to physical damage. Natural capital – the presence of coastal ecosystems and services such as shoreline protection –also may play a role in disaster response. Coastal vulnerability assessments considering all three elements – physical vulnerability, social vulnerability, and natural capital – have become more commonly appreciated as managers plan for current and future risks.

In order to frame the study of vulnerability in this region, the following discussion provides an overview of several key elements under consideration when coastal decision-makers tackle the threats of coastal flood hazards and rising sea levels. This background begins with a discussion of the evolution of vulnerability indices as a tool for predicting

community resilience to natural disasters. The section concludes by tying vulnerability to two key related concepts, natural capital, and resilience.

Vulnerability Indices

There are a number of ways to compare coastal hazard risks across an area. Though options range from general coastal atlases to large-scale hydrodynamic models, vulnerability indices have become especially popular tools during the last two decades (North Carolina Coastal Atlas, 2014; Bush et al. 1999). In addition to providing a useful summary of intraregional risk distribution, indices can inform next steps for analyzing coastal community resilience by predicting relative vulnerability. Indices allow for a consistent analysis across a region and permit comparison of a variety of factors using consistent, quantitative measures. Researchers have attempted to create a number of hazard-related indices, including several focusing on coastal issues (Table 1).

For many years, analyses of coastal risk were specific to their study sites and lacked methods to compare relative risk. By creating indices that combine important factors contributing to physical risk, researchers began to quantify risk relationships rather than relying solely on qualitative descriptions and comparisons. As Balica and Wright (2010) point out, indices deliver information in a “relatively straight-forward way” despite multiple contributing components. Increased computing power and spatial analysis software such as GIS have contributed significantly to the rise of data-intensive vulnerability index approaches. However the utility of these indices remains limited where basic information is not readily available. Frihy et al. (2013) identified these constraints when developing a qualitative assessment of Egyptian coastal risk. They

concluded that even when using the best available data, a quantitative comparative risk approach could improve the assessment's overall value.

Literature Principal Physical Vulnerability Indicators	Gornitz et al. 1994	Clark et al. 1998	Thieler and Hammar-Klose 1999	Wu et al. 2002	Kleinovsky et al. 2006	Torreson et al. 2008	Frazier et al. 2010	McLaughlin et al. 2010	Balica et al. 2012	This Study
Elevation	Red				Red					Blue
Tidal Range	Red									Blue
Coastal slope										Blue
Fetch/Wave Energy/Characteristics	Red									Blue
Geology	Red				Red					Grey
Geomorphology	Red	Red								Grey
Storm Freq/Probability	Red									Grey
SLOSH flood model			Red	Red		Red				Grey
Distance from Shore						Red	Red			Grey
Relative SLR/Subsidence	Red							Red		Grey
Shoreline erosion/accretion	Red		Red							Grey
Storm Surge	Red							Red		Grey
Rivers Present/Discharge							Red	Red		Grey
Storm Intensity	Red			Red						Grey
FIRM Map Flood Exposure		Red								Grey
Wetland Presence					Red					Grey
Coastline Length								Red		Grey
Developed Land										Blue

Table 1 – Factors analyzed in various physical vulnerability indices from the literature. Factors used in this study's physical vulnerability index are bolded.

The number of online sea-level rise and flood viewers depicting the potential for future flood damage has significantly grown in recent years (e.g. NOAA Digital Coast 2014, Climate Central 2014). While these viewers often analyze risk purely based on elevation, new approaches to consideration of coastal hazard risk have increasingly gone beyond this singular element. In the early 1990s, Gornitz et al. (1994) and others began to refine the concepts of relative risk across wider regions through more objective consideration of factors relevant to flood risk and their spatial variation factors. These factors include geology, erosion rates, elevation, subsidence, storm probability, and tide range. The

variables are usually tailored to the particular coastal risk question at hand, such as the risk of an average storm versus that of long-term sea-level rise. Some of these risks may be more correctly characterized as longer-term influences, while other factors, such as elevation, apply to both short and long-term inundation. For the Southeast Atlantic and Gulf coasts, Gornitz et al. (1994) considered coastlines with low elevation, sediment prone to erosion, subsidence, high waves and tides, and high probability of being hit by storms as those most vulnerable to short and long-term rises in sea-level. They identified these areas by using a number of physical datasets, and proceeded to classify individual variables by binning the data and classifying the factors at risk levels ranging from 1 (Very low) up to 5 (Very high risk). The authors considered 13 variables, but categorized them into three groupings in order to better weight their relative importance when calculating their final index values.

While some researchers, e.g. Clark et al. (1998), have used secondary physical aspects such as the federal Flood Rate Insurance Maps (FIRM) of flood exposure to denote physical vulnerability aspects, most efforts have followed the Gornitz et al. (1994) approach of integrating the physical factors more directly into their analyses. The US Geological Survey considered the same ranking approach for use in rating east coast vulnerability to reduce the number of variables considered (Thieler and Hammar-Klose 1999). Balica and Wright (2010) state that limiting indicators makes sense in this context where they are intended to represent different systems rather than to identify every single individual variable in play.

In recent years, a number of studies switched away from considering individual or combined physical index factors to utilizing the National Oceanic and Atmospheric

Administration's Sea, Lake, and Overland Surges from Hurricanes (SLOSH) (NOAA NHC 2014) model to characterize the potential for damaging inundation (e.g. Frazier et al. 2010, Kleinosky et al. 2006, Wu et al. 2002). This modeling has the advantage of allowing the user to consider diverse range of flood risk that might be associated with different hurricane strengths. The use of these models results in several limitations, however, including the need for specific current climatic inputs that may not be widely available. These models also point more to damage from certain individual storms, rather than considering the vulnerability to the average coastal flood event. Despite advances in physical factor characterization and relation to risk, even the first Coastal Vulnerability Index developers acknowledged the limitations of including only the physical world in their model and noted the potential for demographic and economic factors to contribute to proper risk measures (Gornitz et al. 1994).

The concept of social vulnerability suggests that two communities with similar physical characteristics but diverse demographics may react very differently when exposed to the same disaster event. Recently, there has been increasing interest in examining variables that may alter or predict a disaster's impact on different population groups based factors including income, age, race/ethnicity, and housing tenure (Table 2). Socioeconomic factors may impact everything from the ability to evacuate to individuals' access to recovery funds. These different vulnerabilities can paint very different pictures of disaster risks across an area. Federal, state and local managers may consider this type of information when deciding how to allocate disaster resources and prioritize efforts to sustain communities before, during, and after the critical storm events.

**Literature Principal Social
Vulnerability Indicators**

	Clark et al. 1998	Wu et al. 2002	Cutter et al. 2003	Boroff et al. 2005	Kleinosky et al. 2005	Frazier et al. 2006	McLaughlin et al. 2010	Van Zandt et al. 2010	Martinich et al. 2012	Kim et al. 2013	Kim et al. 2014
Age											
Poverty											
Race											
Income											
Immigrants											
Families/Structure											
Housing Stock and Tenancy											
Gender											
Land Use											
Employees in Area/Occupations											
Unemployment/Labor force participation											
Development density											
Rural/urban dichotomy											
Infrastructure Dependence											
Disabilities											
Property Value											
Education											
Population decline											
Ethnicity											
Transience											
Single Sector Economic Dependence											
Critical Facilities											
Conservation Designation											
Roads/Railways											
Cultural Heritage											
Transportation											
Telephones											
Non-English speakers											

Table 2 – Matrix of variables considered in varying social vulnerability analyses from the literature.

Increasing appreciation for the importance of human factors inspired a number of different attempts to build vulnerability indices that combine information regarding physical and social risk. This is actually the case for several of the studies that consider multiple aspects of a community’s risks and resources (Wu et al. 2002; Kleinosky et al.

2006; Martinich et al. 2013). Unfortunately, few of these indices are particularly transferrable from one region to another. Though McLaughlin and Cooper (2010) and Balica et al. (2012) offer an interesting approach to the problem by only using scalable variables, many vulnerability indices are not comparable when the scale of events differs significantly.

Short of tremendous sources of “Big Data” collected in consistent ways across large areas, most index application necessarily focuses on vulnerability measures related specifically to the region of study. A number of studies have targeted vulnerability indices of entire nations (e.g. Brooks et al. 2005), while others continue to focus on a particular town or community (e.g. Clark et al. 1998). International comparisons may support worldwide rankings but do little to provide actionable information for coastal managers. Conversely, small scale assessments may help individual communities, but may have limited lessons that can translate to other people. Different vulnerability ranking systems even produce a variety of rankings for the same area depending on the methodology employed (Eriksen and Kelly 2007). Eriksen and Kelly (2007) suggest that the problem of comparability is not simply the result of data availability differences; in their view, differences regarding the concept of vulnerability suggest that vulnerability is never directly measurable in a truly objective manner.

Although its results also may depend on the region studied, the Social Vulnerability Index (SoVI) by Cutter et al. (2003) has become an often used common strategy for assessing socioeconomic based vulnerability within the United States using Census data and boundaries. The widespread application likely comes in part from the systematic methodology behind the index, allowing it to be easily applied to different

areas. The original index focused mostly on county-level decadal Census data, reducing 42 variables to 11 indicators serving as proxies for social vulnerability. Cutter et al. (2003) utilized the U.S. Census data to define inequalities affecting the groups' response to harm. The additive model has strengths of applying common values across the region of study.

One of the first characteristics noticeable about several indices (especially early efforts) is that they utilize ranked data rather than continuous data for certain types of variables, such as binning coastal slope angles into different categories (e.g. Gornitz et al. 1994, McLaughlin and Cooper 2010, Wu et al. 2002). These rankings should be flagged, because they may affect analyses by creating artificial thresholds within the data distribution. Balica et al. (2012) provide one solution to this by normalizing the factors between 0 and 1 relative to their own data ranges. This approach treats them as dimensionless units to allow combination with other factors yet maintains the data continuity.

Another data difference existing among some of the social vulnerability indices is that researchers make different decisions about whether to use raw numbers or percentages for population related vulnerability factors. Rygel et al. (2006) point out that Cutter's efforts with SoVI used absolute numbers, citing the rationale that more people increases vulnerability. This reasoning is potentially problematic because it can distort values based on varying population sizes – when geographic units are not perfectly standardized by population an urban community might come off as much more vulnerable than a small rural community, no matter what the relative conditions of the people within each area. Stating that both composition and raw numbers are important,

Rygel et al. (2006) therefore proceed to use both percentages and density measures. Despite the use of both percentages and densities they found no differences in using either approach for their work, suggesting that either transformation may work to move beyond individual numbers.

There have been several concerns raised about these additive component indices. Adger et al. (2004) state their concern that aggregating this kind of information into single values reduces visualization of the reasons behind vulnerability or glosses over pockets of vulnerability, especially when indices have relatively larger sub-units. Kleinosky et al. (2006) reinforce this concern that the single score creation for overall vulnerability noting that a particularly high score in one area could be obscured by low scores in others. They attempt to tease out this effect by employing Pareto rankings, i.e., grouping classes of vulnerability to some extent. The Kleinosky et al. (2006) approach also attempts to minimize issues around weighting, given that even rating indicators as equal in importance is technically still giving them a weight (Rygel et al. 2006). Pareto ranking therefore provides a possibly less biased approach to vulnerability assessment, though its application does demand evidence of clear separations within data.

There has been a fairly broad application of vulnerability indices to natural hazards, and a number of these studies target coastal elements. A focus on flooding has especially intensified as sea level rises, which will only increase the likelihood of future severe flood events. Forecasts of increasing coastal populations and either more severe or more frequent storms only reinforce this danger.

Natural Capital

While physical and socioeconomic conditions likely explain a great deal about a community's vulnerability to coastal risk, other key features ranging from grey/green infrastructure to prior storm experience may play a role as well. More researchers are now considering the important role a community's associated coastal ecosystems, or natural capital, may play during coastal storms and flooding due to their influence on hydrological processes and physical protection during these events. Coastal ecosystems are naturally adapted to the shifting environment that marks the world's shorelines. They likely have some potential to act as "bioshields" that reduce the magnitude of coastal hazard impacts, though some question the true extent of this potential (Feagin et al. 2009). The continued development of coastal areas and the costs of associated hardened protection structures has led to an increased desire to understand how society can take advantage of the benefits provided by these natural shorelines.

While environment elements such as bathymetry and fetch determine much of wave exposure conditions, research by the U.S. Army Corps of Engineers (USACE) (2013) and others has pointed to the ability of marshes, maritime forests, and other features to reduce damage to the communities around them by limiting wave action and other processes (Costanza et al. 2008, UMD IAN 2013). The USACE North Atlantic Coast Comprehensive Study (NACCS) Coastal Storm Risk Management Framework includes a focus on vulnerability, and the exposure assessment includes a population density and critical infrastructure exposure index, a social vulnerability index, and an environmental vulnerability index (USACE 2015).

Wamsley et al. (2010) examine modeled and observed data to support this notion of coastal protection by wetlands, though they suggest that the surrounding landscape and the size, speed, and direction of storms also impact this capacity. Waves may first be dampened as soon as they hit the shore, so timing of storm events may be critical to influencing the habitat a storm impacts first – e.g., whether waves first encounter seagrass or trees (Koch et al. 2009). This dampening capacity relates to the ability of vegetation to generate friction for incoming storm surges, thereby disrupting and dispersing incoming wave energy; without significant wave-setup, storm-surge can be significantly reduced (Dean and Bender 2006). Wave damage impacts may therefore connect to water levels and relative marsh size. During times when marsh vegetation stands within the entire water column, it dampens wave-energy more than periods of time when the water column extends above the vegetation’s maximum height (Augustin et al. 2009). Gedan et al. (2011) state that this wave-dampening potential exists for narrow wetlands as well as for areas with extensive marsh cover (e.g. Louisiana delta coast or the Maryland Blackwater area).

Coastal forests are another natural shoreline feature that may reduce flood damage. Though some researchers question the relative importance of other factors, one of the most famous examples of forest ecosystem flood damage reduction is the coastal protection offered by mangrove forests during the 2004 Indian Ocean Tsunami (Gedan et al. 2011). Mangrove trees both dissipated wave energy and likely blocked debris. (Cochard et al. 2008; Tanaka et al. 2007). Mangroves may not be a Chesapeake Bay feature, but forests within flood zones might have the potential to play similar roles in storm damage mitigation.

In addition to their direct flood protection potential, these coastal ecosystems may offer other indirect benefits for a coastal community. The presence of natural coastal vegetation alters the sediment below it over time, reducing erodability (Feagin et al. 2009; Gedan et al. 2011;USACE 2013). This soil stabilization may limit the potential for catastrophic shoreline retreat during both storms and longer-term periods.

Dietrich et al. (2009) suggest that marsh friction can have a significant effect on water flow during flood recession as well. Friction could therefore provide potential for reducing impacts to surrounding water quality by limiting the immediate pulse of contaminants, nutrients, or other particles that occurs after major storm events. Unlike hardened structures, natural coastal protection also might provide adequate shielding in certain locations without detracting from coastal habitat and other ecosystem services. The concept of socio-ecological resilience must be better understood in connection with coastal disasters and human development in order to sustain these benefits (Adger et al. 2005).

Resiliency

The 2012 National Research Council study, “Disaster Resilience: A National Imperative,” stressed the importance of understanding and reducing vulnerability as critical to increasing community resiliency (NRC 2012). The definition of resilience varies across a number of disciplines. While the original material science definition of resilience describes an object’s “elasticity” (Gordon 1978), in the ecological context the term describes a system’s ability to “absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and

feedbacks” (Walker et al 2004). Currently, the term often refers to the impacts to the system, individual, ecosystem, social group or even community, and its ability to recover (Norris et al. 2008). For some, the concepts of vulnerability and resilience are opposites, (e.g. Sherrieb et al. 2010), in that a vulnerable community is not a resilient community and vice versa. In the context of the Norris et al. (2008) definition above, however, resiliency may well have a strong relationship to vulnerability, but the two concepts are by no means perfect opposites. Resilient communities may have vulnerabilities, but they develop means to withstand or quickly recover from negative impacts. A resilient community therefore must be vulnerable in some sense. Otherwise, it might have no stressors to serve as an impetus to develop or exercise resilience. These forces therefore tie together to impact a community’s sustainability through times of stress, such as increased coastal flooding associated with sea-level rise.

For many coastal communities resilience may be defined as the ability of a system and its social units to anticipate hazards, accommodate the effects of hazards in a timely and efficient manner, and carry out recovery activities in ways that minimize social disruption and mitigate the effects of future flooding through preservation, restoration or improvement of its essential basic structure and functions (modified, Bruneau 2003; IPCC 2012). While defining resilience can be complicated, measuring resilience is even more challenging. The ability to systematically measure resilience to coastal storm events and associated factors such as flooding remains in its relative infancy. Measurement of resilience involves data-intensive collection of statistics pertaining to people with respect to specific locations and events. Cutter et al. (2008) set out their concept of a Disaster Resilience of Place (DROP) model, which exemplifies some of the

factors or methods that might be considered for measuring disaster resilience and sets a platform for refining their concepts of how factors contributing to inherent resilience play out during and after hazards. Their framework reflects a concept that vulnerability and resilience show extensive overlap. Cutter et al. (2008) also set out a number of potential variables as candidate indicators that may serve as proxies for social and ecological dimensions of resilience. It is important to note that these are “candidate variables” that may be collected at different scales and still must be tested in real-world applications.

More recently, some of the leading research on resilience has come from the Gulf Coast, following a suite of intensive storms in that region. One particularly innovative study by Burton et al. (2011) set out to measure recovery in real time through the use of repeat photography in Mississippi following Hurricane Katrina. The study found that measured recovery rates varied geographically, showing initial high correlation with the extent of damage from storm surge before weakening over time. Van Zandt et al. (2012) focus on recovery through housing data, particularly that of building activity following the event. They measure damage and recovery from Hurricane Ike in Galveston through intensive collection of damage assessments and house surveys directly along with building permit applications following the storm. Despite local success, these kinds of examples have not been widely replicable across different areas or time scales.

Another study focusing on Hurricane Ike conducted intensive surveys of businesses and added more remote data, such as the value of damaged property, before attempting to explain differences in these responses to Ike (Kim et al. 2014). Taken as a whole, their data also supported the notion of a drop in median housing price as a result of the storm. These studies have provided important views on specific areas. Kim et al.

(2014) demonstrate some initial ability to extend data out to county and regional levels. Overall, plenty of room remains to approach resilience measures from a larger, more regional level across state boundaries.

Given experience from multiple resilience tracking approaches, verification of vulnerability indices in the Chesapeake Bay region could go a long way towards understanding and planning for different resilience levels across the region. If strong relationships can be identified from the indices, then researchers and coastal managers will be better able to identify how elements such as past experience, infrastructure, or culture can shape flood resilience. As decision-makers consider some of these vulnerability assessments in their planning, the distinctions among them may lead to significant differences in interpretation when they focus in on a state or local level. These real world issues create adequate incentive to further explore the application of the indices to the Chesapeake Bay area, including identifying patterns in their overall score distribution and performance.

CHAPTER 1 – Chesapeake Bay Vulnerability Characterization

OVERVIEW

This study marks one of the first efforts to consider physical and social vulnerability at equivalent scales across the entire coastal Chesapeake Bay region (Figure 1.1). The development of tools to assist local, state, and regional management of resources before, during, and following coastal flood events is critical to enhancing community resilience. Unfortunately, risk and vulnerability tools have generally been unevenly applied across the country (NRC 2012). Several larger scale vulnerability analyses include the Chesapeake Bay region but are not sufficiently applicable at more local levels because they may minimize differences in local conditions by placing them in a more national context. Other recent vulnerability analyses within coastal Maryland and Virginia include targeted assessments but fail to view the Chesapeake Bay at a more holistic level (e.g. Kleinosky et al 2006). Unless a study is specifically designed for application at multi-scalar units, it is unlikely that it will be very useful for both local and large-scale applications due to the inability to translate particular data from one level to the next.

Work by the University of South Carolina Hazards and Vulnerability Research Institute (HVRI) offers one platform for developing the necessary kinds of analyses to test vulnerability index performance in the Chesapeake Bay region. The South Carolina researchers have continued developing the Cutter et al. (2003) approach to study social vulnerability. They break down the index scores for the states of Maryland and Virginia

relative to the whole nation, as well as to the states themselves. Several flood relevant viewers have included HVRI's methodology, such as Climate Central's Surging Seas tool (2014) and NOAA's SLR and Coastal Flood Viewer (2014). Some index calculations place coastal Chesapeake communities in the context of all of Virginia or Maryland (including landlocked localities) while other applications set them in the national coastwide context. Understanding the basis for the index is therefore critical to informed use of the analysis.

Much of the existing index verification work has remained at the theoretical level or has only been applied elsewhere, such as the work of Van Zandt et al. (2012) and Burton et al. (2011) on Gulf Coast impacts of Hurricane Ike and Hurricane Katrina. Their methods have shed specific light on vulnerability within their areas, but have required intensive data collection following the storms as well as specific datasets not consistently available in the Chesapeake region. These exercises are necessary to validate index approaches and therefore should be kept in mind for vulnerability assessment designs. Given that the most recent landmark storm crossing the Chesapeake Bay was Hurricane Isabel in 2003, these methods are not applicable to this region in the same manner due to the lack of adequate post-storm data collection.

To comprehensively understand coastal vulnerability, indices must analyze the social and physical dimensions at the same resolution. The development of a human scale physical vulnerability index by the Coastal Resource Management Clinic within the Center for Coastal Resources Management (CCRM) at the Virginia Institute of Marine Science (VIMS) has supported these efforts. The inclusion of physical vulnerability elements in the analysis allows comparison of the human aspects alongside it as well as

testing potential relative contribution to flood impacts. The physical vulnerability index is specifically designed to be calculated at multiple geopolitical boundary scales. The index therefore can be applied to the level at which matching socioeconomic data is available.

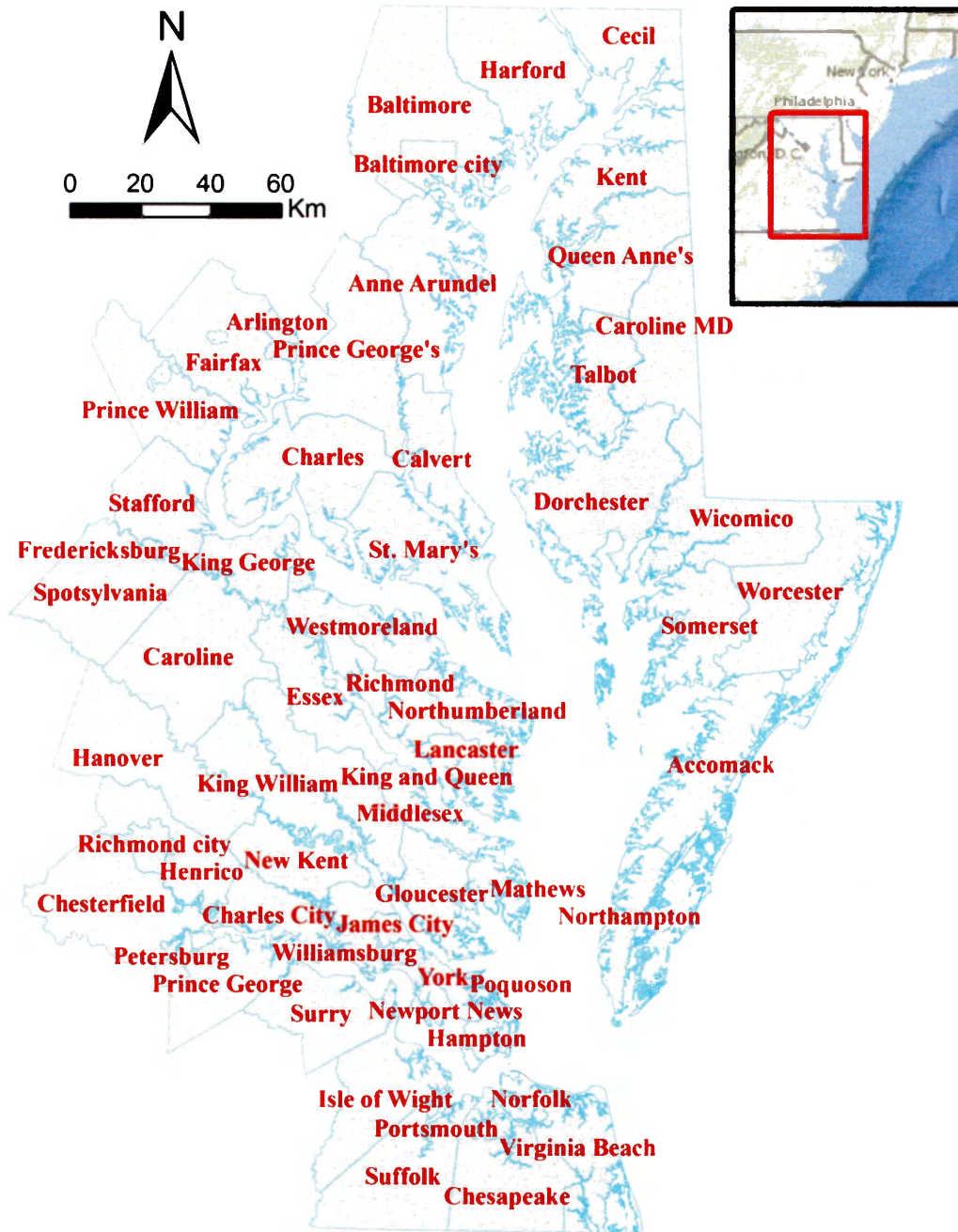


Figure 1.1 – Tidally influenced localities of Maryland and Virginia

For the social vulnerability index considerations, this study uses locality vulnerability scores calculated by the HVRI Social Vulnerability Index (SoVI) for the year 2000. The SoVI approach was also applied to the coastal Chesapeake zip codes in order to relate vulnerability scores to the verification work of Chapter 2. CCRM's own simplified social vulnerability index offers additional comparison. This study also analyzes the distribution of coastal wetlands and forests within geopolitical boundaries to identify whether natural capital distribution can enhance the prediction of flood impacts at these scales. As detailed in the Background section, coastal forests and wetlands may be able to reduce physical flood impacts.

The establishment of regional physical and social vulnerability indices and associated aspects allows for a comprehensive evaluation of flood vulnerability across the Chesapeake Bay region in the early 2000s. In addition to providing a platform to verify prediction of coastal flood impacts, constructing a physical vulnerability index at human geographic scale may help managers find better ways of incorporating wide arrays of complex information into decision-making processes. By applying a deconstructable combined vulnerability index, managers can explore what drives vulnerability across areas, focusing of either physical or socioeconomic adaptation as needed. The parallel analysis of vulnerability at two different scales reinforces isolation of significant spatial trends and supports decision-making at various levels of management. Overall, the process identifies communities that may be particularly impacted by coastal hazards that other approaches may fail to fully recognize in the relative context of tidewater Maryland and Virginia.

METHODS

The following section explains the methodologies employed in the research regarding geography and data selection, vulnerability index application and construction, and evaluation of natural capital distribution. The majority of these approaches have been developed in collaboration with the Coastal Resource Management Clinic in the Center for Coastal Resources Management (CCRM) at the Virginia Institute of Marine Science (VIMS).

Geography and Data Selection

Studying vulnerability in the context of the Chesapeake Bay region first requires defining of the exact area that constitutes the region as well as its sub-boundary levels. These decisions not only affect the context of the findings, but also impact what types of information can be analyzed.

For this study the Chesapeake Bay region is identified as the communities within Maryland and Virginia localities (counties and cities) that border the Bay or any tidally influenced portions of its tributaries (Figure 1.1). Though not all portions of each locality are floodable, this area selection allows examination of the issues at different geopolitical scales. This approach makes basic sense for considering socioeconomic factors, as developing the same area breakdowns for physical vulnerability is key to tying the two together.

Development of vulnerability indices principally considered information at the U.S. Census tract level. This approach is a natural tie to the decadal collection of data, and in recent years, more frequent surveys conducted as part of the U.S. Census Bureau's

American Community Survey. Census tracts are shaped ideally to contain populations of 4000 people, (though they may range from 1200 to 8000 in population) and thereby allow reasonable comparisons of populations. In order to further extend this analysis this research developed the equivalent vulnerability score assignments at the locality boundary level and 2000 Zip Code Tabulation Areas (ZCTAs). The locality scale allows connection of a number of state and local datasets to a census delineation of data across Maryland and Virginia. ZCTAs are physical representations of the zip codes served by the United States Postal Service; these areas are technically collections of postal routes (US Census 2015). While this translation of zip codes to ZCTAs may introduce some possible level of translation error, it is a necessary compromise that is critical to utilizing Census data at a spatial community level commonly referenced by other more frequently updated datasets.

Social Vulnerability Index Construction

This study takes several approaches to quantify the social vulnerability of coastal Virginia and Maryland localities. The principal approach utilizes data and information from the Cutter (2003) Social Vulnerability Index (SoVI) methodology created at the University of South Carolina's Hazards and Vulnerability Research Institute (HVRI). Over time the approach has evolved to respond to changing research philosophies and changing Census information (HVRI 2011). SoVI had not been widely applied at the zip code level for the year 2000 (personal communication, C. Emrich Jul 13 2015). Given the lack of preexisting application and the variability of SoVI indices depending on the

region and geographic scale utilized, this study applied the HVRI SoVI methodology (2011) with only minor modifications pertaining to available data.

Data were compiled directly from the Census as well as Social Explorer, a software product facilitating the downloading of specific demographic datasets. Twenty-seven variables were pulled or calculated to match the set that corresponds to the American Community Survey data the updated SoVI uses (Table A1.1). As with the updated official SoVI methodology, the number of hospitals and percent of population without health insurance were not available at this sub-county level. Once downloaded, the data was cleaned by removing all ZCTAs that had populations of less than 100 or significant data gaps. Following the official SoVI methodology (HVRI 2011), the data was standardized to z-scores for each variable, $z = \frac{x - \mu}{\sigma}$. A principal components analysis (PCA) was performed using JMP software, using the Kaiser criterion for selecting the components with Eigenvalues over 1; varimax rotation identified 7 factors. The factor loadings were multiplied by the variable z-scores and summed to calculate the factors. Analyzing the factor loadings for the variables for absolute values of greater than 0.500 identified the critical factors that decided whether the factor positively or negatively contributes vulnerability. The final SoVI scores then were calculated by simple summation of the seven factors.

A different process was employed at the locality scale given the existence of official SoVI county social vulnerability scores relative to hazards at the national level for the two states. The data was provided by Dr. Christopher Emrich of the University of South Carolina. The scores were calculated using the 32-variable data method for all counties in the United States. The calculations are from the same general methodology

used to calculate the zip code SoVI, though a few of the 32 variables used differ due to methodology evolution. Maryland and Virginia locality values were standardized to the region prior to analysis.

Beyond the utilization of the official SoVI scores to represent social vulnerability in the region, the CCRM Coastal Resource Management Clinic also considered a more basic social vulnerability index for comparison sake. The narrowing of social vulnerability factors allows for comparison of a simplified more easily applied index against that of the kitchen-sink method presented by South Carolina's HVRI. An index based on equally weighted, constant factors also permits cleaner deconstruction to see which social factors most contribute to overall vulnerability. This method was applied to the zip code and locality level with slight modifications. The index focuses on creating four factors pulled using GeoLytics, a demographic program analyzing US Census data over time. Each factor was standardized to a value of 1 in order to weight every component equally, with higher values contributing more to overall vulnerability. These factors were then added together and standardized to produce values between 0 and 1. Initial analysis of a wider set of Virginia variables for current distribution and past changes did not identify a clear statistical rationale for grouping variables. The clinic therefore proceeded with several core factors that appear in multiple approaches reported in the literature (e.g. Heinz Center 2002, Kleinosky et al. 2006). A number of these approaches are summarized in Table 2.

The factors consisted of:

- Income – Census average household income divided by the maximum average household income among zip codes or localities analyzed. The values then were subtracted from 1 in order to invert them, so that a higher value merited less income and therefore more vulnerability due to less resources available to respond to disaster with.
- Poverty Rate – the percentage of people below the poverty line in an area were divided by the maximum value for this characteristic across the region. The more people below the poverty line, the more people less likely to be able to fully support themselves during stable conditions let alone around a disaster.
- Age – the percentages of people over 65 and under 18 were added together for each area. These values were then divided by the maximum value in the region.

Literature has suggested older and younger people may be less able to easily evacuate in addition to other factors.

- Race/Ethnicity – the percentage of non-Caucasian people in an area was summed up and then divided by the maximum value. This indicator combined the likelihood of minorities to have less political access to government recovery funds and other resources. Greater numbers of people who do not speak English among Latino and other minority communities may also impact access to information regarding preparation, evacuation, or recovery efforts.

Physical Vulnerability Index Construction

Delineating the basic geographic boundaries in terms of community social datasets supports developing an equivalent physical index to capture multiple angles of vulnerability context. The physical vulnerability index focuses on elevation, land use,

wave exposure, and tide range, and developed land (Table 1). While the other factors are common in the literature, incorporating the developed land further focuses the study on the application at human community scales. Vulnerability calculations that did not naturally have a maximum for 1 were standardized against the highest value in the area.

Given past Chesapeake Bay storm surge experience, with greater flood potential with any stronger storm as well as future sea-level rise, the geospatial analyses targeted the vulnerabilities of those areas with elevations less than 3.05 meters (10 ft) above mean sea level as a consistent bay-wide measure of the most floodable localities or zip codes.

$$\textit{Elevation vulnerability} = \textit{ratio of area under 3.05 m}$$

To further systematically subdivide risk among the lower elevation areas, volume to surface area ratios were also calculated for areas of the communities below 3.05 meters. The calculation of this factor served somewhat as an equivalent to coastal slope, characterizing how relatively floodable the sub-3.05 m area is. Those areas with lower ratios are areas that might be at highest risk with respect to where flood waters might fully inundate. Data from the USGS National Elevation Dataset (NED) were used to generate a digital elevation model (DEM) for Virginia and Maryland. Different geoprocessing tools in ArcGIS v10.0 were applied to create a DEM for the study area corresponding to elevations between 0 and 3.05 m above sea level. Algorithms written for the ArcGIS Model Builder iterated and calculated the volume and area between those elevations in each of the corresponding zip codes/localities.

$$\textit{Lowland vulnerability} = 1 - \frac{\left(\frac{\textit{volume of geographic area below 3.05 m}}{\textit{area of geographic area below 3.05 m}} \right)}{3.05 \textit{ m}}$$

In order to analyze land cover across the region, Coastal Change Analysis Program (C-CAP) data were downloaded from the National Oceanic and Atmospheric Administration (NOAA) Coastal Services Center. For this study, 2001 C-CAP data for Virginia and Maryland sub-3.05 m elevation areas were converted and processed in ArcGIS v10.0. C-CAP land cover classifications were reclassified into 4 different land cover types: Agriculture, Developed Areas, Natural Nontidal Areas, and Wetlands. An ArcGIS spatial model was built to calculate percentage of each land use category per geographic area.

$$\textit{Development vulnerability} = \frac{\textit{sub - 3.05 m area developed land cover}}{\textit{Total area below 3.05 m}}$$

The wave exposure component was generated with the Wave Exposure Model¹ (WEMo) created by Fonseca and Malhotra (2007). The updated Version 4 estimates wave energy based on shorelines, bathymetry and wind data. Using linear wave theory and tracing of rays along fetch in along different compass directions, WEMo calculates Representative Wave Energy (RWE) in J/m, or the wave energy in one wavelength per unit wave crest width.

The model was run along the 0.5-meter contour line along the Chesapeake Bay's shorelines, with points spaced approximately every 2000 meters. The 0.5-meter contour line was selected to ensure smooth functionality given data quality in shallower water and the model performance limits. The model ran in RWE mode with the water level raised 1 meter to simulate wave conditions under storm surge scenarios. Wind data were combined for a five-year period ranging from 2010 – 2014, with WEMo analysis

¹ Available at <http://products.coastalscience.noaa.gov/wemo/>

² ESRI ArcGIS Resource Center (2012)

³ These numbers are referenced to only the places with non-zero physical vulnerability. When all zip codes

selecting for the top 5% of winds from each wind directions. The wind data placed the values in a realistic context under a mix of annual conditions, including wind fields from two substantial tropical cyclones passing through (Hurricane Irene and Hurricane Sandy) as well as the 2013 nor'easter. Three National Ocean Service buoy sites were utilized for wind data for the Bay, including wind data from York River East Rear Range Light for the lower Bay latitudes (from southern Virginia just past the state line along the western shore above the Little Wicomico River or 36°43'51.233" to 37°53'55"N), Cove Point LNG Pier for the Mid-Bay latitudes (Little Wicomico River up to the mouth of the Choptank River or 38°39'20"N, and Tolchester Beach for the Upper Bay latitudes (the Choptank mouth up through the Susquehanna or 39°36'32"N).

WEMo points were assigned to zip code/locality shorelines and the mean value was calculated for each area's shoreline. For purposes of this study, any Atlantic facing counties were assigned the maximum mean value among Chesapeake coastal counties. Zip codes with both open ocean and Bay shorelines were given the average of the maximum and the RWE value calculated for the bay shore. For any zip codes with shorter shorelines skipped by the 2000-meter point distance, values were assigned by the nearest point/nearest similar neighbor.

$$\textit{Wave Exposure vulnerability} = \textit{area mean Representative Wave Energy}$$

Local tidal range also affects coastal communities risk relationship with the water, as people build structures around the regular variations in water levels. Communities with smaller tidal ranges were considered more vulnerable to coastal flooding. That assumption concurs with other assessments in the literature such as McLaughlin and

Cooper (2010) but contrasts with Kumar et al. (2010) and others who consider higher tides representative of more coastal energy. This study argues that since tide levels are just as likely to be low as high during a flood event that much of the extra volume of water added by storm surge and other events in areas with higher tide ranges is relatively will fall within the tide range or closer to the typical high water mark. In areas with lower tide ranges the extra water volume is more likely to raise water levels above normal conditions, exposing more of coastal development to water and waves.

The mean tidal range per locality/zip code was incorporated in this index. The output of the hydrodynamic model SCHISM (Zhang and Baptista 2008) fed the tidal range calculations. This model calculates the tidal range along the Chesapeake Bay, using the 2D depth-averaged configuration calibrated against all tidal gauges inside and outside the Bay. The model grid consists of 1.8 million triangles (i.e. unstructured grid) and covers the entire US east coast with focus on the Chesapeake Bay. It has a variable resolution in space: ~25 km in the open ocean, ~1.5 km along the open coast, 500 m along the main channel of the Bay, 150-300 m along channels of tributaries, ~50 m near the shoreline, and ~100m on dry land. In a few select areas where the model does not continue all the way up certain tributaries to their tidal extent, values were extended from the furthest extent alongside any available water level data.

$$Tide\ vuln = 1 - \frac{Great\ diurnal\ tide\ range}{Greatest\ tide\ range\ in\ region}$$

The above physical data provide important basic characteristics defining a coastal area's physical nature relevant to coastal flooding. While other variables, such as the region's geology, largely explain why the Chesapeake Bay is one of the most physically

vulnerable areas to coastal flooding and future sea-level rise, this work focused on other physical characteristics to identify vulnerabilities among communities within the coastal plain. Much of the analysis was designed to focus on shorelines within the Chesapeake Bay, rather than the more dynamic nature of the open Atlantic coast, where high wave energy, beaches, and barrier islands lead to much more variable shoreline conditions; therefore assigned values may be more conservative there.

The indices' score distributions were analyzed for sensitivity to the different individual factors as well, including population density, state, and side of the Chesapeake Bay. Beyond mapping the indices, their spatial distribution was explored using a Hot Spot Analysis in ArcGIS. The analysis calculates a Getis-Ord G_i^* statistic based on the clustering of the vulnerability scores, designating areas as “Hot Spots” when a vulnerable zip code is surrounded by other higher values as well and the sum of their local values is significantly different than what is expected under assumptions of normal distribution. Hot spots are identified at the 90, 95, and 99% confidence levels.

The Getis-Ord local statistic is given as

$$G_i^* = \frac{\sum_{j=1}^n w_{i,j} x_j - \bar{X} \sum_{j=1}^n w_{i,j}}{S \sqrt{\frac{n \sum_{j=1}^n w_{i,j}^2 - \left(\sum_{j=1}^n w_{i,j}\right)^2}{n-1}}} \quad (1)$$

where x_j is the attribute value for feature j , $w_{i,j}$ is the spatial weight between feature i and j , n is equal to the total number of features and

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n} \quad (2)$$

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{X})^2} \quad (3)$$

The G_i^* statistic is a z-score so no further calculations are required

²ESRI ArcGIS Resource Center (2012)

Coastal Natural Capital

The quantification of coastal ecosystems, referred to as coastal “natural capital” given the potential to provide services, also utilizes 2001 land-cover data from Coastal Change Analysis Program (C-CAP) data from NOAA’s Coastal Services Center for Virginia and Maryland. Forests in the area under 3.05 meters were reclassified as “Deciduous,” “Evergreen,” and “Mixed Forest” as “Forest” while subclasses of “Estuarine” and “Palustrine” wetland land cover were consolidated into “Wetland” for analysis. An ArcGIS spatial model was built to calculate percentage of each land use category per sub-3.05 m area within each geographic area. Forest and wetlands were analyzed individually and then summed to create a single natural capital factor within zip codes and localities.

RESULTS

This section provides a synopsis of the distribution of physical, social, and combined vulnerability across the Chesapeake Bay region at zip code and locality scales. The results consider the overall trends associated with different population densities and sub-regions as well as the natural capital present.

Physical Vulnerability – Zip Code Scale

Figure 1.2 shows that the zip codes that were most vulnerable in the early 2000s include Ocean City and Chincoteague, Dorchester County, MD, and Poquoson, VA (the latter two areas including the two most vulnerable zip codes inside the mouth of the Chesapeake Bay). As expected, zip codes separated from the coastline and major tributaries show little to no vulnerability. A hot spot analysis of the score distribution illustrates that the highest of these scores appear as larger clusters of vulnerability that

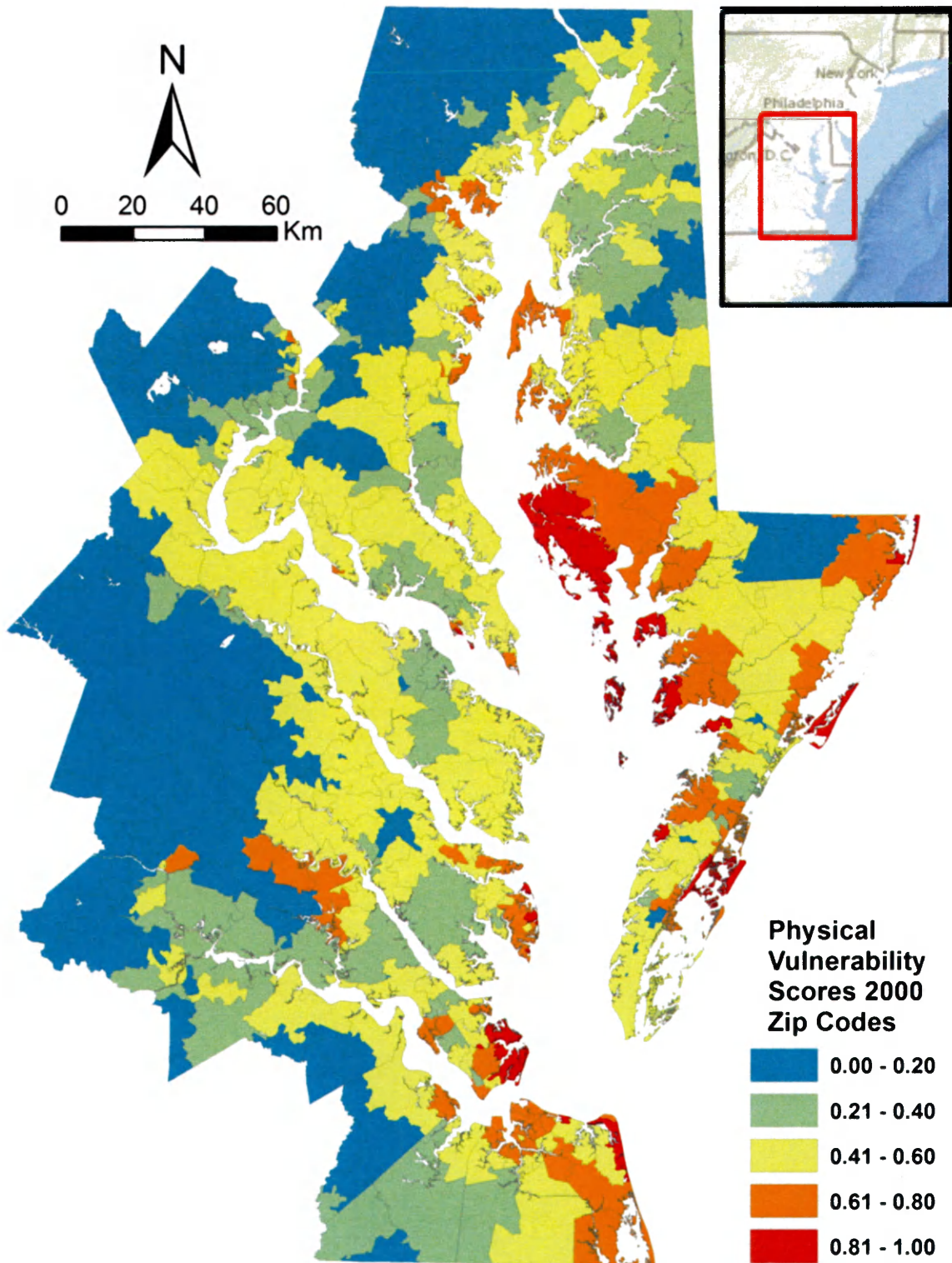


Figure 1.2 – Physical vulnerability index calculated at the scale of Zip Code Tabulated Area (ZCTA). Calculations based off of area below 10 feet, volume of that area, development in that area, tidal range, and wave exposure. Assateague Island (grey) not analyzed in boundaries as a zip code, being a zip code with no addresses.

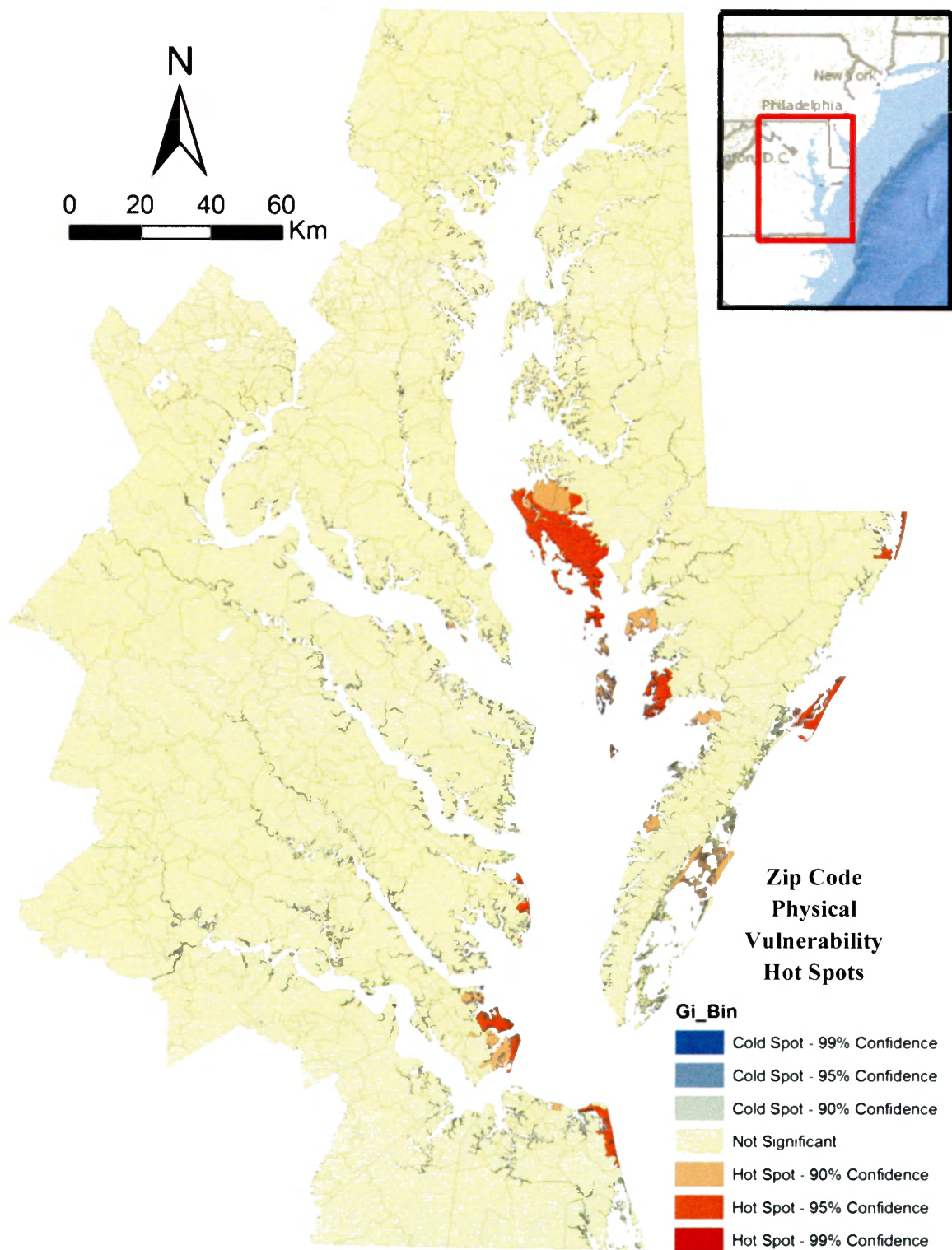


Figure 1.3 – Hot spot analysis of physical vulnerability index scores at zip code scale. Getis-Ord G_i^* statistic based on the clustering of the vulnerability scores. Areas are designated as “Hot Spots” when a vulnerable zip code is surrounded by other higher values as well and the sum of their local values is significantly different than what is expected under assumptions of normal distribution. Of note, Assateague (grey) was not included in analysis as it was not a formal zip code with addresses.

significantly differ from the overall population, especially the Peninsula's Poquoson and Hampton, Dorchester County, Virginia Beach and the developed Atlantic barrier island communities (Figure 1.2).

The final physical vulnerability scores are fairly normally distributed when the zero scores are removed (which mainly are landlocked). A sensitivity analysis suggests that removing the volume/area factor from the index has the greatest effect on the index, shifting values by an average of 25.6% when excluded (Table A1.2). Meanwhile, the index was least sensitive to the percentage of developed land under 3.05 m, which shifts values by an average of -5.4% when removed.

Social Vulnerability – Zip Code Scale

The official SoVI methodology identifies several areas of higher vulnerability scores in sectors of the northern Virginia Eastern Shore and the Washington, D.C. suburbs, as well as areas just west of the Chickahominy River, the tip of the Northern Neck, Norfolk, and Baltimore (Figure 1.4). The lower vulnerability scores appear scattered around the Bay with the exception of the southern Eastern shore. Hot spot analyses support these findings, identifying these same areas as statistically different from the overall distribution of vulnerability across the region (Figure 1.5).

The SoVI scores for the region were calculated by reducing the full complement of input variables down to seven factors made up of the different groupings of variables illustrated in Table A1.3. A sensitivity analysis of the final SoVI scores based on the factors suggests that Factor 6, which is the factor associated most with the percentage of women in the population, drives the score distribution. Interestingly, this was not the

factor with one of the higher eigenvalues from the Principal Component Analysis. This SoVI iteration was least sensitive to the factor aligned with the percent of the population who speak English as a second language, and who identify as Latinos, and who identify as Asians.

The simplified Chesapeake vulnerability index developed at CCRM shows relatively more communities are identified with higher vulnerability scores (Figure B1.1). A one-to-one analysis of this index version against the official SoVI methodology produces a statistically significant linear regression with an adjusted R^2 value of 0.44 and the SoVI scores being just under two-thirds the value of CCRM-calculated social vulnerability for the region (Figure B1.2). Hot spot analysis identifies communities such as Norfolk, Virginia Eastern Shore communities, Richmond, Baltimore, and Maryland suburbs of D.C. as regions of significant vulnerability at 90% confidence levels or higher (Figure B1.3). A sensitivity analysis suggests that the simplified index factors are somewhat similar at this level in importance, being most driven by the income indicator, which drops values an average of 20.9%, with the age indicator dropping values by 15.5%.

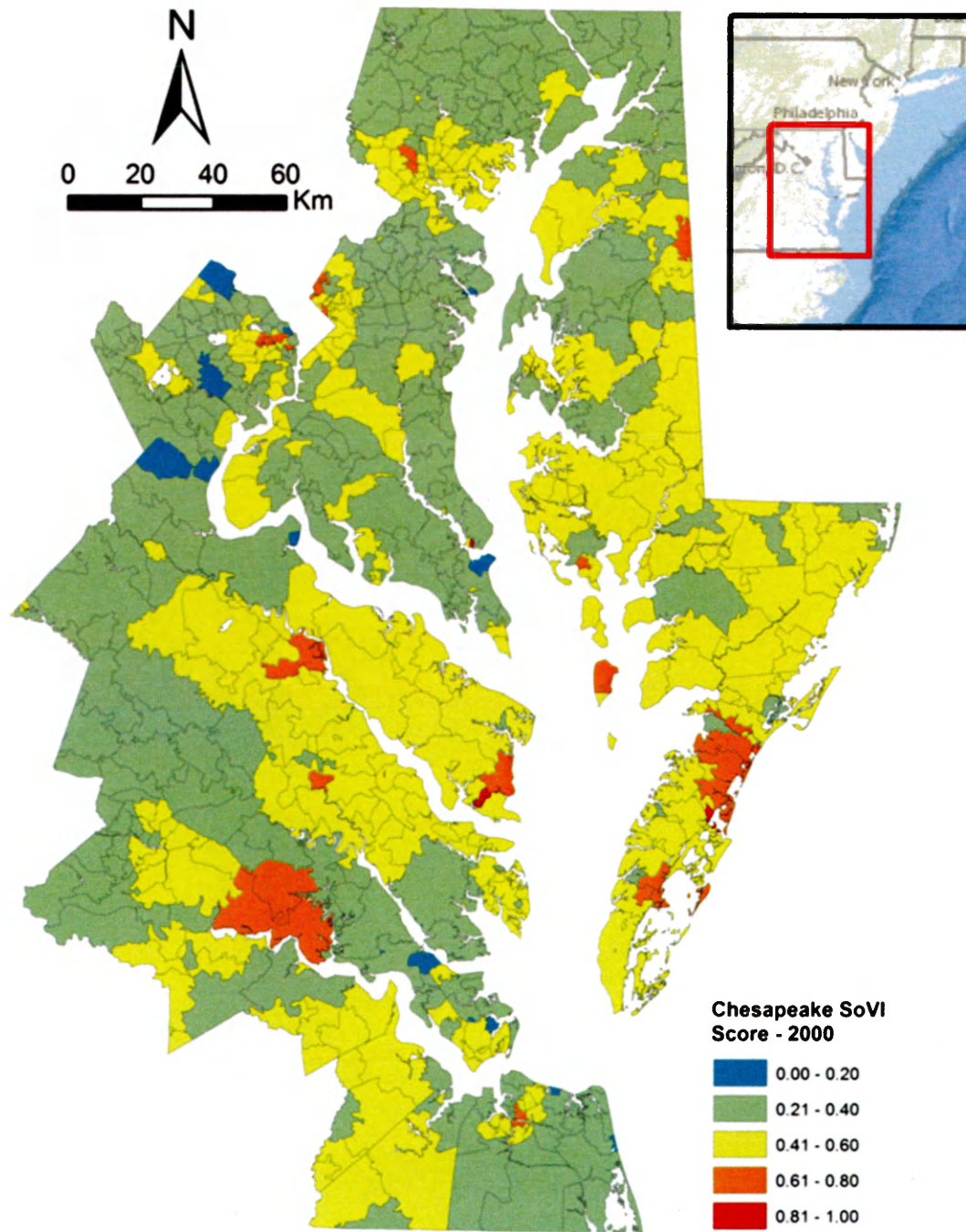


Figure 1.4 – Standardized values for the official SoVI index calculated for the tidal Chesapeake Bay region of Maryland and Virginia. Method employed from HVRI (2011) using data from the 2000 US Census. Only official zip codes were included (i.e. no areas with no addresses such as Assateague Island).

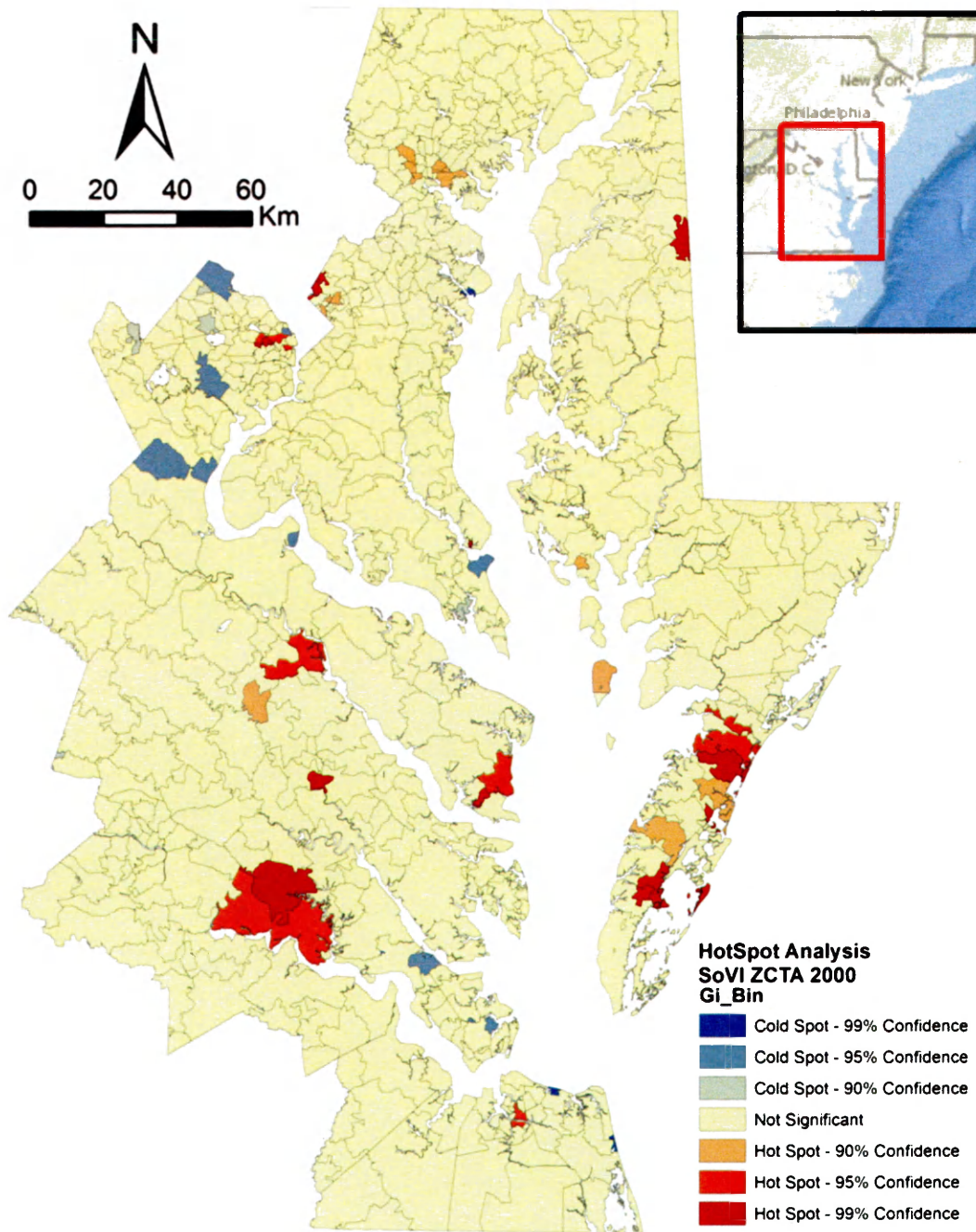


Figure 1.5 – Hot spot analysis of standardized SoVI scores at zip code scale for 2000.

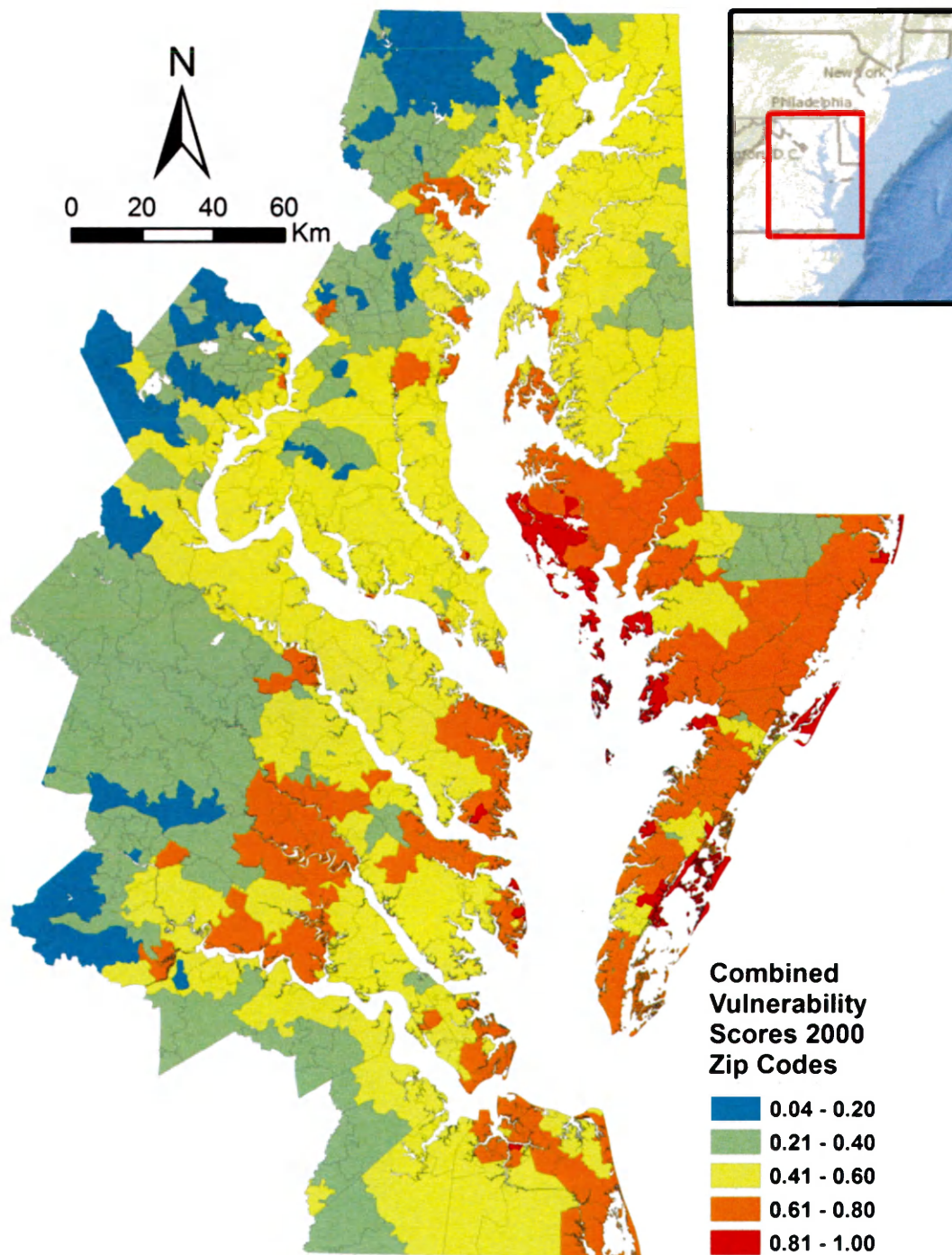


Figure 1.6 – Combined Vulnerability index at the zip code scale, weighting physical and social vulnerability equally for the year 2000. Note, Assateague (grey) is not a formal zip code and therefore was not included.

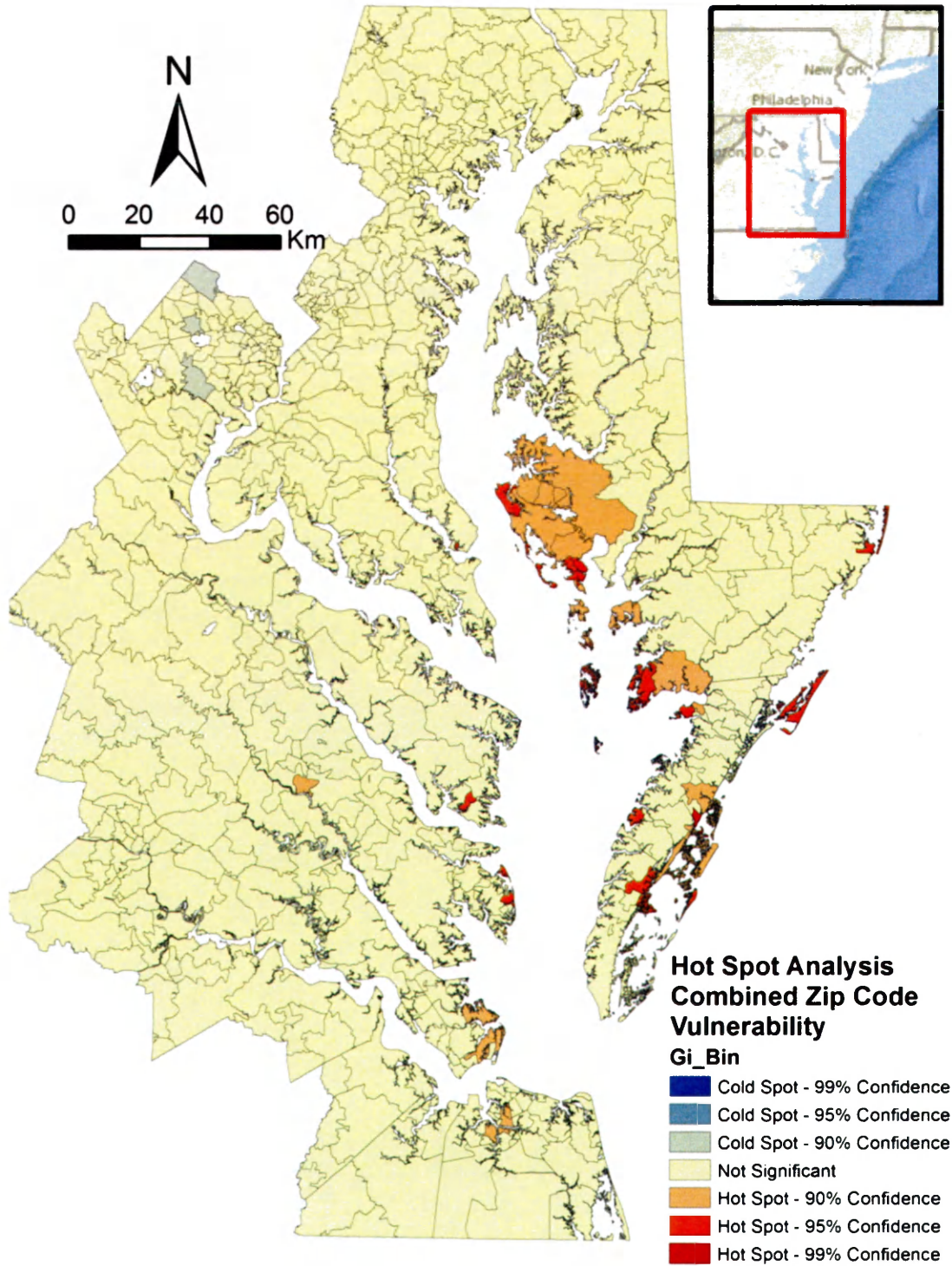


Figure 1.7 – Hot spot analysis of combined vulnerability index (physical and social equally weighted) at the zip code scale for the year 2000.

Combined Vulnerability - Zip Code Scale

When the physical and social indices are considered together as equal contributors to vulnerability, the mean score of areas with any score of physical vulnerability above zero increases to 0.56, greater than both the relative physical (0.48) and SoVI (0.41) scores. The sensitivity analysis suggests that without the physical index contribution these scores drop by 23.9% while they only drop by 16.3% when the social index component is removed.³ Figure 1.6 shows the distribution of vulnerability across the region; the higher two vulnerability categories do spread to additional areas such as more high vulnerability scores in Virginia's Northern Neck and around the York River's sources, however otherwise continue to cover many of the areas that are physically at risk. When this spatial score distribution is analyzed for significance above 90% confidence levels, significant clusters of highly vulnerable communities include a number of Eastern Shore communities from Dorchester County, MD southward, as well as Norfolk, Poquoson, and Hampton (Figure 1.7).

Locality Level Physical Vulnerability

Similar to the zip code scale, locality physical vulnerability once again concentrates towards the south and east, with the city of Baltimore as the lone Maryland locality north or west of Dorchester County in the upper two vulnerability categories for the early 2000s (Figures 1.8 and 1.9). Surry County is a location that does appear more vulnerable on the map than at the zip code scale, though this is an example where map visualization

³ These numbers are referenced to only the places with non-zero physical vulnerability. When all zip codes are considered, the SoVI element obviously outweighs the physical as all zip codes have people and hence some likely measure of social vulnerability while many zip codes lack any measure of physical vulnerability by being at higher elevations. At that level dropping the social index, drops scores by an average of 46.4% while excluding the physical index actually brings values up by 4.8%.

may exaggerate the shift across the categories. In this case Surry is in the second highest category by a relative score value less than 0.01.

The physical vulnerability index sensitivity at the locality level is similar to the zip code scale – less sensitive to percentage of the sub-3.05 m area that was developed, with an average percent drop by 1.9% (Table A1.5). Unlike at the zip code scale however, the greatest sensitivity is to the percent area below 3.05 m with the score increasing by an average of 23.7% rather than the volume/area of this sub-3.05 m region. The volume/area factor was not far below that, dropping values on average by 19.1%.

Locality Level Social Vulnerability

At the locality level, the nationwide county social vulnerability index scores from the 2000 SoVI method indicate that only Williamsburg and Petersburg, VA identify as being most vulnerable relative to the region (Figure 1.10). The two cities also identify as the only two hot spots, though hot spot analyses likely may be somewhat less effective given the low number of counties (61), which is only double the minimum suggested value of 30. A hot spot analysis confirms the significance of the lower vulnerability “Cold Spots” of Arlington and Fairfax (Figure B1.4). Data sources did not provide the breakdown of the sub-score factors, thus preventing sensitivity analysis of the score distribution drivers.

The comparative simplified social vulnerability index maintains Petersburg, at the top of social vulnerability while pushing the cities of Baltimore, Richmond, Norfolk, Portsmouth, and the southern three Eastern Shore counties into the top tier of vulnerability (Figure B1.5). It produces a vulnerability distribution where no localities

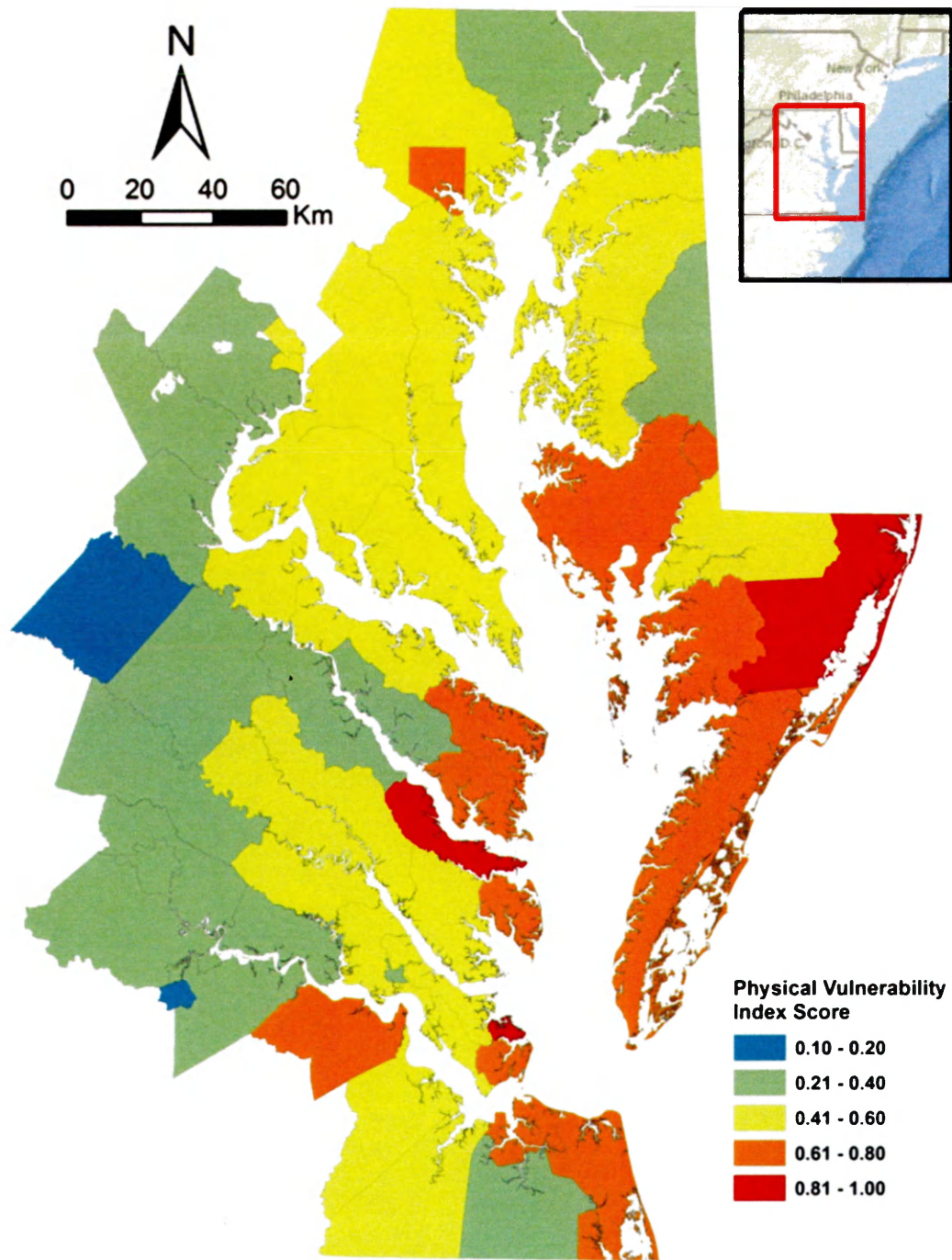


Figure 1.8 – Locality physical vulnerability index for the coastal Chesapeake Bay region based on elevation, wave energy, tidal range and development.

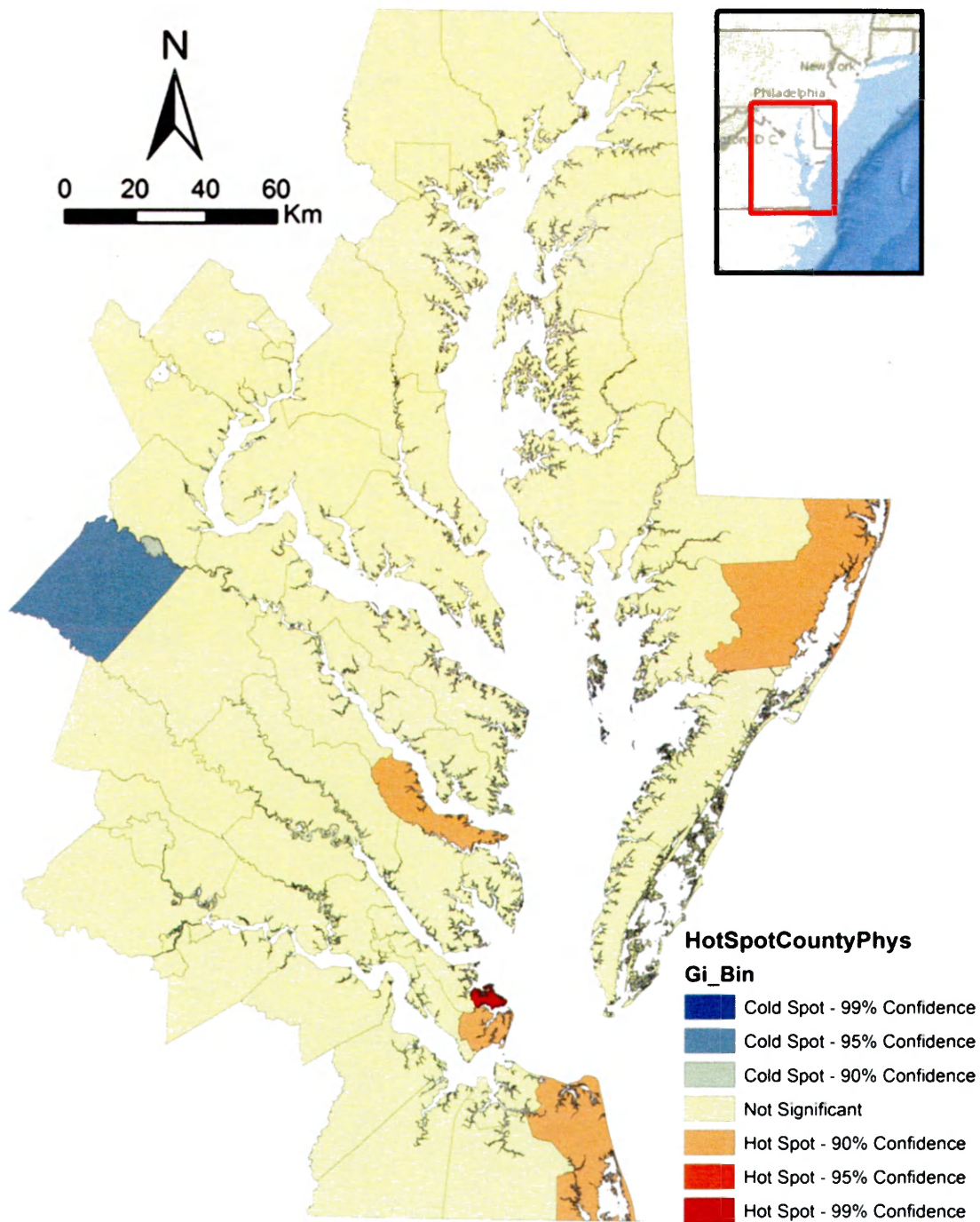


Figure 1.9 – Hot spot analysis of locality physical vulnerability index for the coastal Chesapeake Bay region.

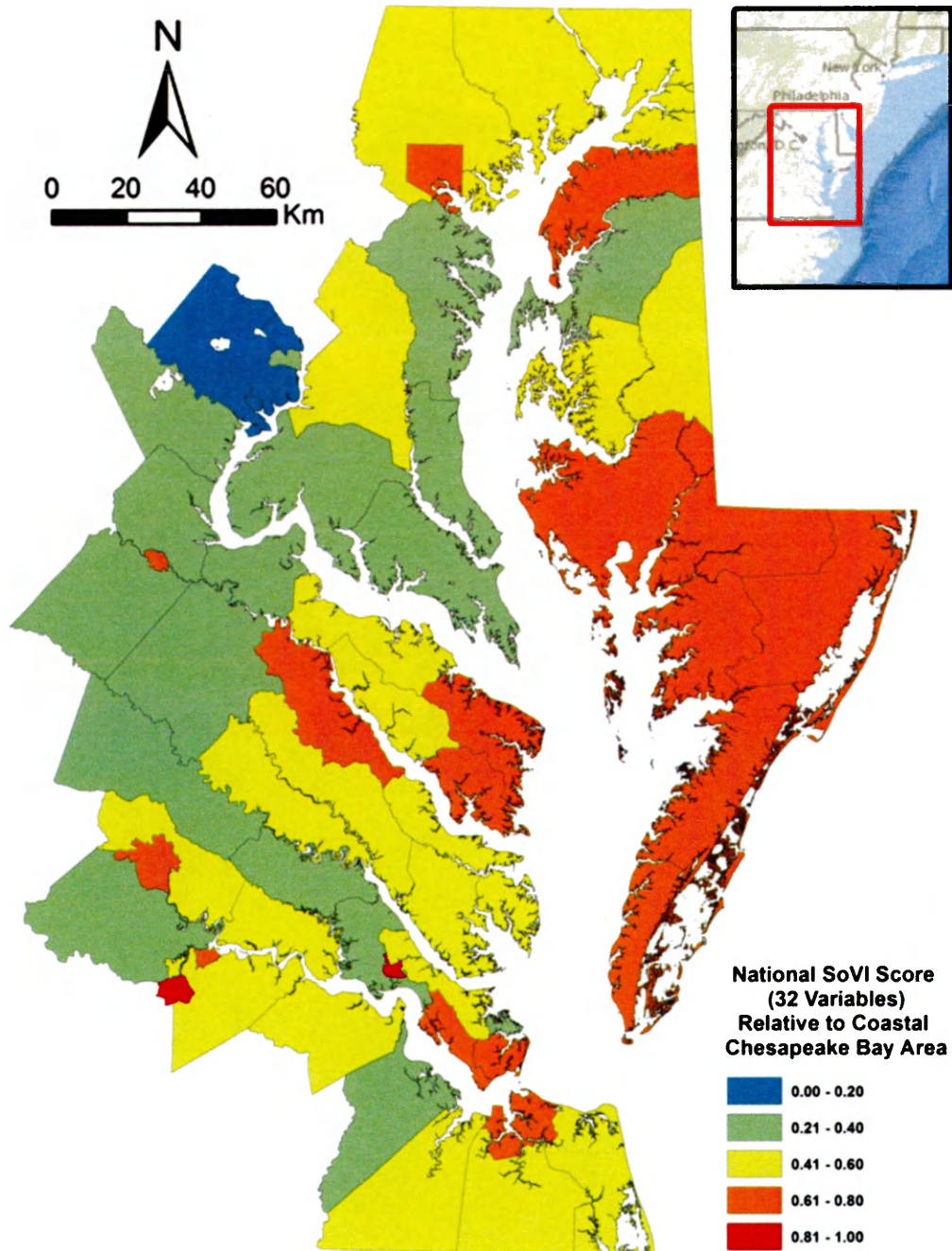


Figure 1.10 – Official national 2000 SoVI scores standardized to 0 to 1 for the Chesapeake Bay region.

appear in the lower two tiers of relative vulnerability. The simplified vulnerability index is most driven by the relative number of people over 65 or under 18 (an average drop in social vulnerability score of 19.4% without this age variable) and least affected by income, which drops the score by 2.9% (Table A1.6). The two different views of social vulnerability at this level are exceptionally similar (Figure B1.7), with a linear regression of the two sets of scores producing a line approaching an average 1:1 ratio and an adjusted R^2 value of 0.60. This value (similar to the zip code scale value of 0.64) hints at why the four factors used in the simplified version are the most commonly included among differing views of social vulnerability calculations.

Combined Locality Level Vulnerability

When the physical vulnerability and 2000 relative SoVI scores are combined with equal weighting, the top tier of vulnerability concentrates primarily on the main stem of the Bay, identifying Baltimore as the only locality north of Dorchester to fall into this top tier of vulnerability (Figures 1.11 and 1.12). Spotsylvania and Fairfax counties appear as the least vulnerable overall. The combined index is relatively similarly sensitive to the physical and social vulnerability elements, dropping an average of 26.2% and 23.1% with the respective exclusion of either.

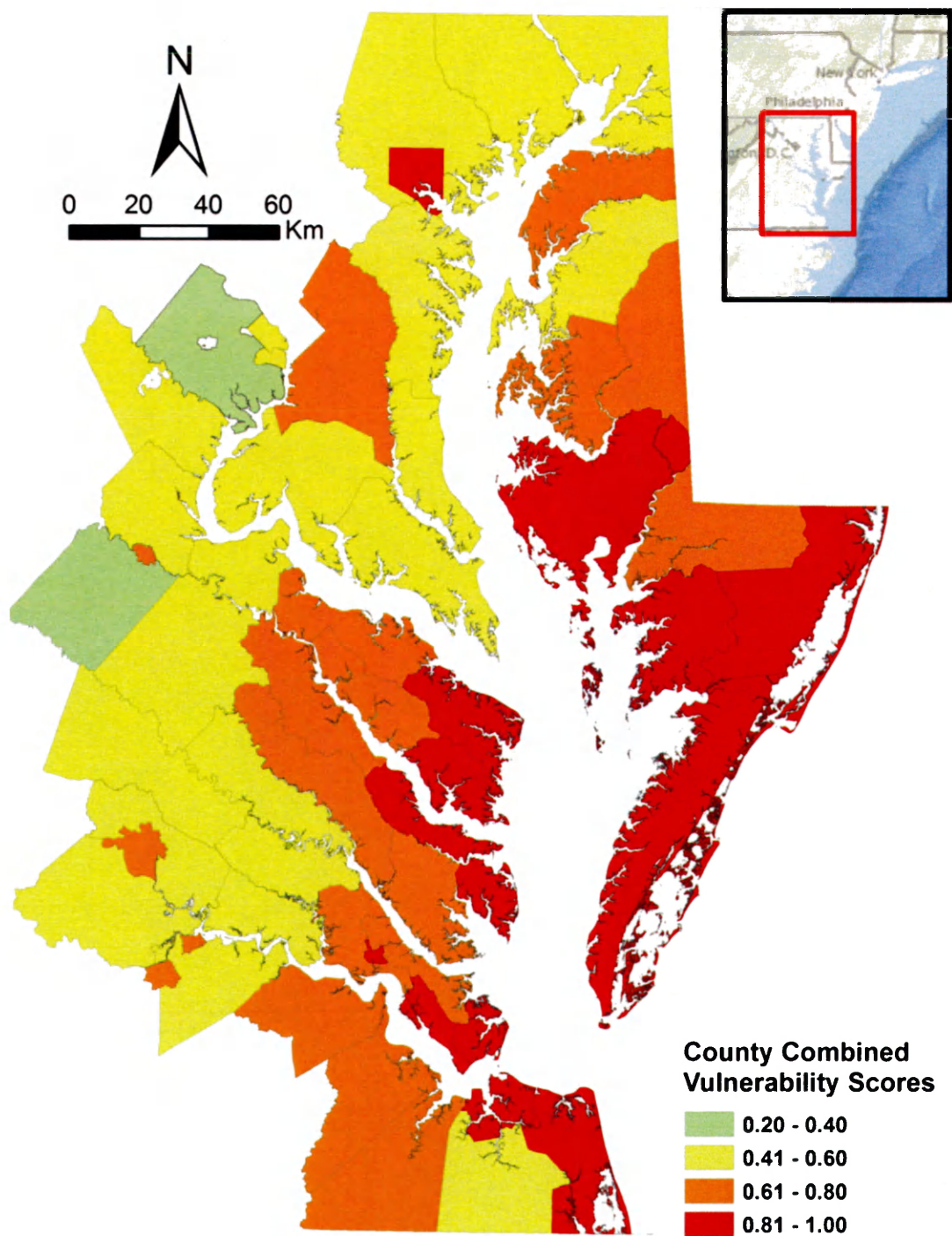


Figure 1.11 – Locality scale combined vulnerability index for 2000 for the Chesapeake Bay region.

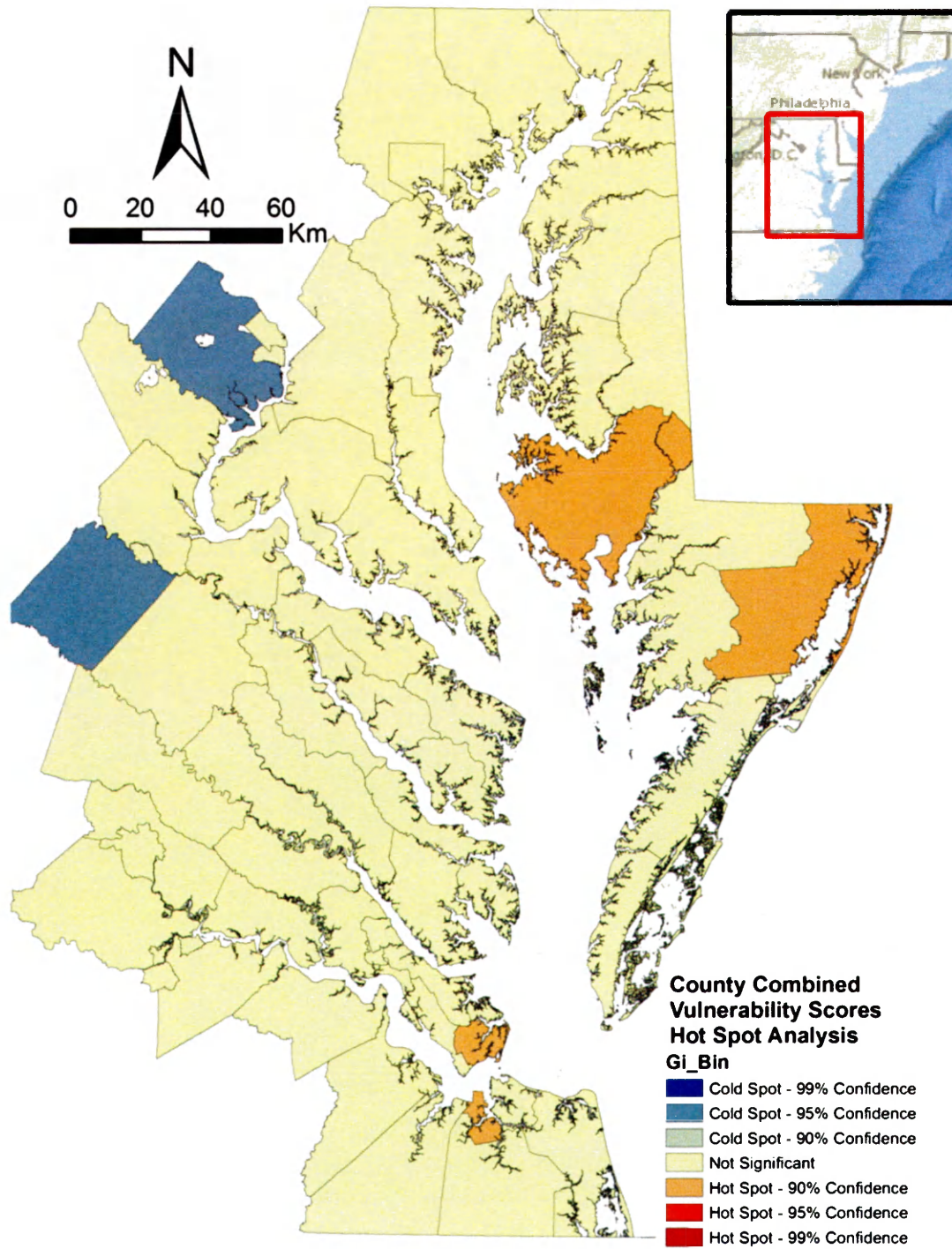


Figure 1.12 – Hot spot analysis of locality scale combined vulnerability index for the year 2000.

Index Trends and Relative Distribution

The above analysis identifies specific areas of significant vulnerability. The work also establishes that physical indices at both scales are least driven by the percent of developed land below 3.05 meters. The comparison of various renditions of Chesapeake Bay region coastal vulnerability indices for the early 2000s allows for recognition of broader regional patterns. These patterns are especially isolatable for the zip code scale indices, where the higher number of geographies allows for more statistical power than the lower number of areas at the locality level allows when sub-divided. Only non-zero vulnerability areas were included in this analysis in order to keep the analysis within the context of those areas actually faced with coastal flooding. The locality SoVI scores were not specifically developed for the region and thus are not the perfect equivalent of the zip code vulnerability calculations. This element translates to combined vulnerability analysis as well.

Scores on the Eastern Shore repeatedly appear high relative to the rest of the region.⁴ An ANOVA of the Eastern shore Zip codes suggests a significant difference at the 0.05 confidence level between those and zip codes west of the Chesapeake Bay for both social and physical vulnerability index scores. Figures 1.13 and 1.14 illustrate the differences in different score distributions across different breakdowns of the region. This bay shore vulnerability distribution applies to the comparative CCRM basic social vulnerability index as well (0.55 vs. 0.51, $p < 0.001$).

⁴ The Eastern Shore being defined as the areas on the Delmarva peninsula below the Delaware-Chesapeake Canal (one ZCTA does span both sides, but is principally on the southern side). At the county level, Cecil County, MD spans both sides of the canal and therefore not included as the Eastern side of the Chesapeake Bay definition.

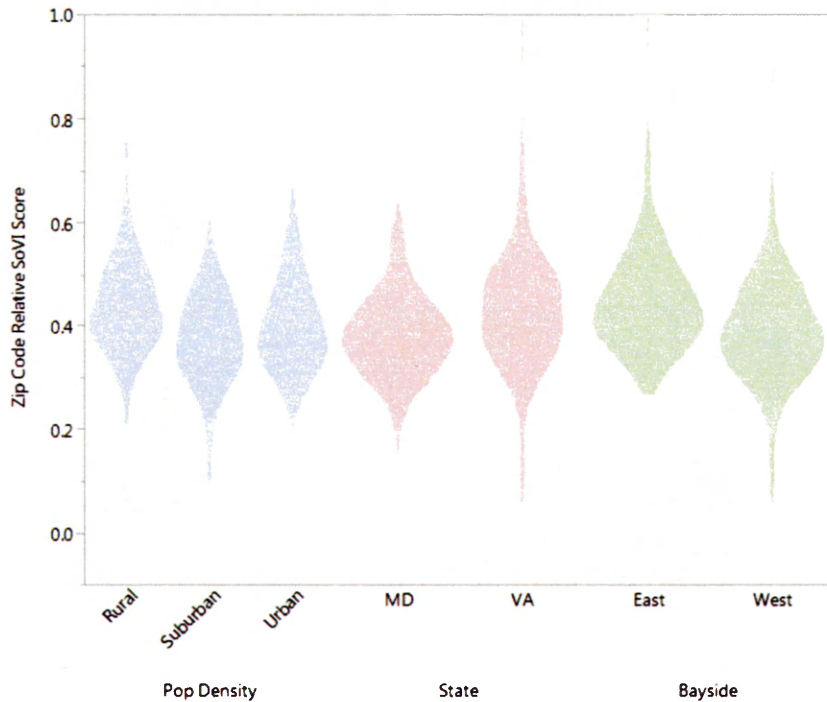


Figure 1.13 – Distributions of relative SoVI 2000 scores at zip code scale. Rural, Suburban, and Urban zip codes as defined by breaks at 1000 and 100 persons per square mile. Significant differences amongst mean vulnerability values of 0.44, 0.38 and 0.40. Differences in state significant at $p < 0.001$, mean value of 0.38 and 0.43. East vs West shores of the Bay significant at $p < 0.001$, mean value of 0.50 vs 0.39.

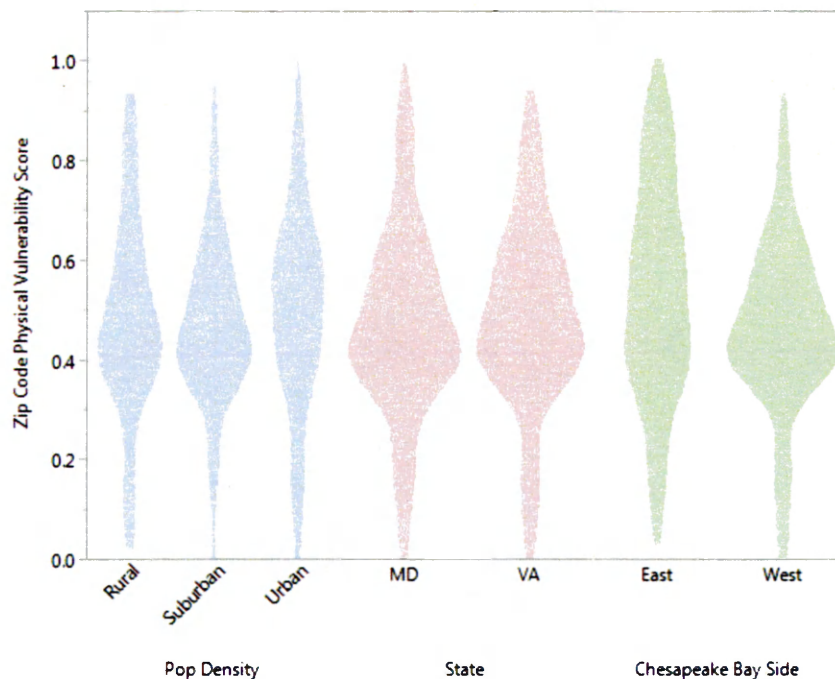


Figure 1.14 – Distributions of non-zero physical vulnerability at the zip code level between population density, states and side of the Chesapeake. Side of Bay means East – 0.53, West -0.46 with ANOVA $p < 0.001$. States not sign different ($p > 0.445$). Population density levels not significantly different ($p > 0.528$).

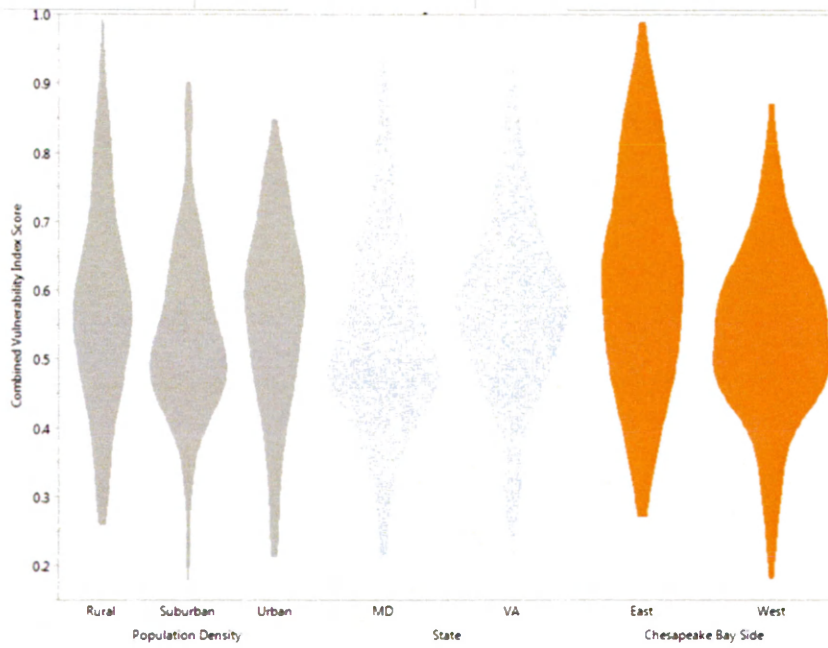


Figure 1.15 – Distributions of combined vulnerability at the zip code level between population density, states and side of the Chesapeake. Eastern shore mean value of 0.62 significantly higher than Western shore 0.54 ($p < 0.001$). Mean Virginia score of 0.58 higher than Maryland score of 0.54 at significant level ($p < 0.004$). For population density, urban and rural were both significantly higher than suburban areas ($p < 0.02$).

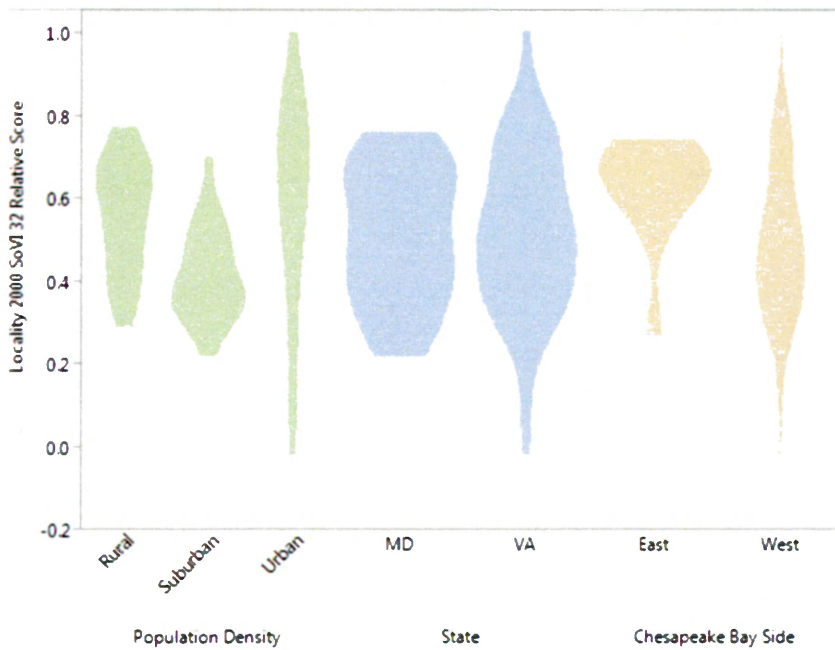


Figure 1.16 – Locality level 2000 SoVI relative score distribution. Eastern shore localities' median value of 0.69 significantly higher than Western shore median of 0.64 ($p = 0.033$). MD and VA not significantly different. Suburban locality median score of 0.38 significantly different from rural 0.57 and urban 0.66 ($p = 0.002$ and 0.013)

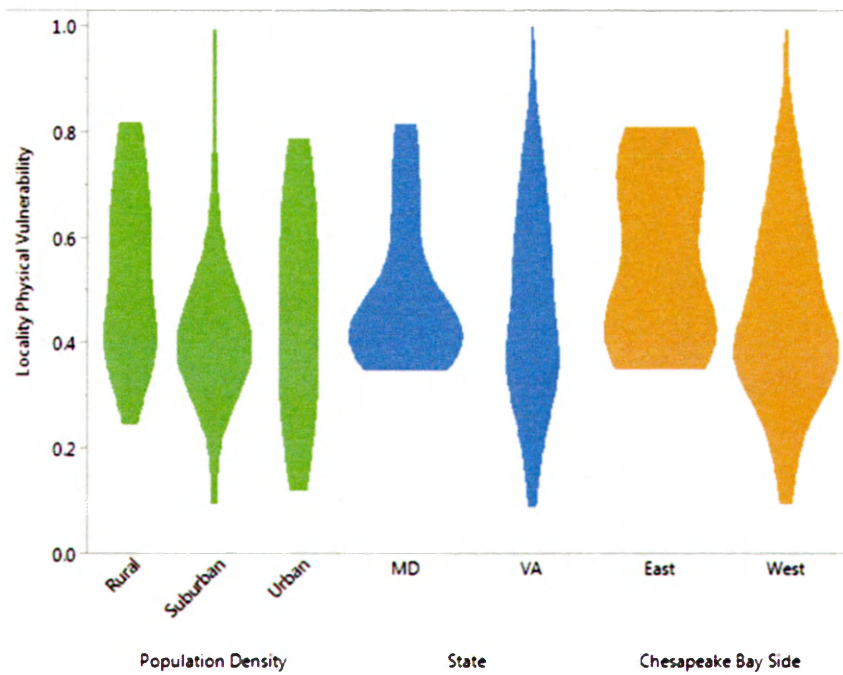


Figure 1.17 – Distribution of physical vulnerability at the locality level. As a whole all comparisons show no overall significantly different distribution. Rural localities show higher values than suburban localities, which were shared an average score to urban localities. Suburban median of 0.45 was significantly different than rural localities median value of 0.51.

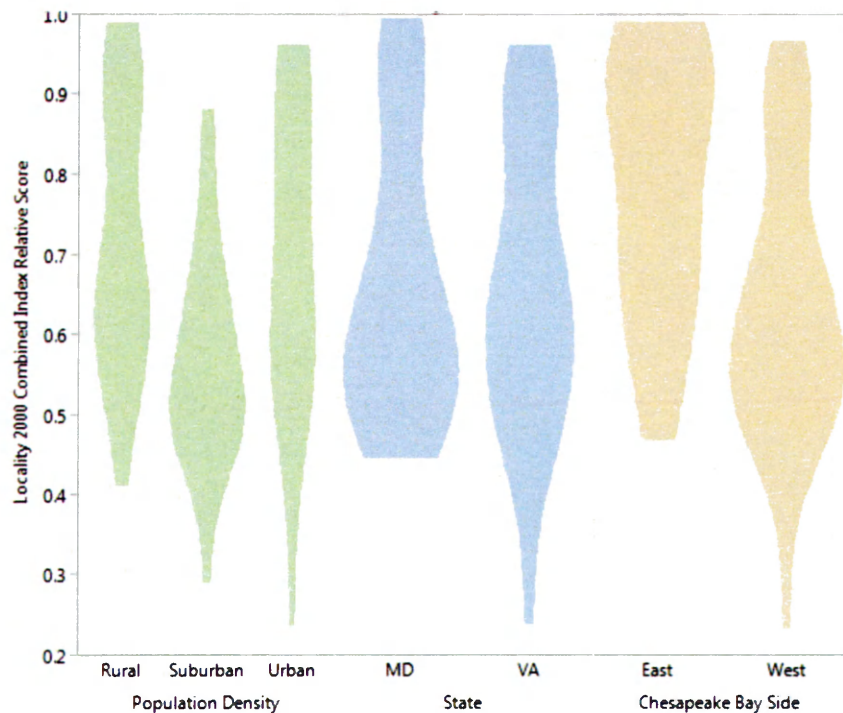


Figure 1.18 – Locality combined vulnerability trends by population density, state, and bay side. The Eastern Shore median value of 0.82 is significantly higher than the Western shore value of 0.6 ($p=0.014$). Suburban median score of 0.44 proved significantly lower than rural (0.52) and urban (0.55) ($p=0.013$ and 0.072).

The significant difference was greatest for combined vulnerability scores, with the mean Eastern Shore vulnerability falling 0.08 above that of the average Western shore score (Figure 1.15). At the locality level, Eastern Shore mean and median scores also tallied above those of the Western shore in each case (including the CCRM social vulnerability version), though this difference only appeared significant at the 0.05 level for the combined vulnerability score (Figures 1.16 – 1.18). Note that only 10 of the 61 counties analyzed are on the Eastern shore, and therefore provide a somewhat less than ideal comparative sample sizes.

Between the two states, the vulnerable coastal regions of Maryland and Virginia do not show any significant difference in physical vulnerability at either the zip code or locality scales (Figures 1.14 and 1.17). Once social vulnerability is incorporated at the zip code level, Virginia does show up as significantly more vulnerable overall than Maryland. Incorporating social vulnerability also differentiates the two populations in the combined zip code vulnerability sets. The differences in mean vulnerability values are 0.05 and 0.04 respectively, with the disparities driven by Virginia's mean higher social vulnerability (Figures 1.13 and 1.15). At the locality scale, social vulnerability did not differ significantly between the two and therefore did not lead to significance at the combined vulnerability difference either (Figures 1.16 & 1.18).

When considered for equal application across different levels of population density, the zip level SoVI showed a statistically significant higher vulnerability than both the urban and suburban zip codes (Figure 1.13). This difference was not seen in the physical vulnerable context, but the difference between rural and suburban zip codes remains for combined vulnerability, with rural areas having the highest mean scores and

suburban areas with the lowest (though urban and rural communities no longer show up as unique from each other) (Figure 1.14 and 1.15).

At the locality level, rural, suburban, and urban communities all differ significantly from each other in terms of social vulnerability with suburban areas once more showing the lowest mean vulnerability and urban areas slightly edging out rural ones for the highest. This distribution may be influenced by the 2000 SoVI version calculations used for locality scores that include certain population density levels themselves as factors leading to vulnerability calculations (Figure 1.16). Physical vulnerability calculation once again suggests a lack of significant difference when comparing all three populations (Figure 1.17). When adding physical and social vulnerability together, suburban communities have statistically significantly lower vulnerability values than either urban or rural communities (Figure 1.18).

Overall, the various indices provide a systematic approach to considering vulnerability across the Chesapeake region. The Eastern Shore consistently appears as more vulnerable across different index versions while the sociodemographic characteristics of suburban zip codes consistently place them in the lower end of vulnerability when considered alongside physical vulnerability elements. Other than the Eastern Shore, the physical vulnerability index appears rather consistent across different geographic subdivisions and scales.

Natural Capital

While no statistical hot spots exist when forests and wetlands are considered together as natural capital, there generally is a high distribution of these ecosystems across much of

the region's sub-3.05 m areas (Figure 1.19). Many of these areas appear up the tributaries rather than along the main stem of the Bay. As expected, key urban areas such as Hampton Roads, which appears as highly vulnerable across the different indices, have little relative natural capital.

When forests and wetlands are considered individually the distribution changes somewhat allowing for identification of significant hot spots (Figures B1.8 and B1.9). For wetlands alone, hot spots appear at the headwaters of the Patuxent River, the York River, south side of the James River, and the Eastern Shore (Figure B1.10). For forests, the hot spot areas are slightly more scattered, but generally appear slightly further up the tributaries (Figure B1.11). Whereas the distribution of highest values for wetland distribution includes highly vulnerable areas of the Eastern Shore, much of the distribution of relatively high percentage forest areas falls further up the Bay's tributaries in less physically vulnerable areas.

When considered as pure raw area numbers (rather than percentages), western Dorchester County and the mid-Eastern shore, Gloucester County, Mathews, the Dismal Swamp area, and west of the Chickahominy river, and the Aberdeen Proving Grounds area are the main hot spots of natural capital on the Bay (Figure B1.12). These areas than include several larger zip codes and have greater areas below 3.05 m. Variability in absolute size should also be kept in mind when interpreting natural capital distribution in percentage terms.

At the locality level, results are similar, with combined natural capital percent land also peaking further up the tributaries rather than on the main stem of the Bay. A hot spot analysis of that distribution identifies no significant hot spots, only showing

significant cold spots in the central Hampton Roads area, Baltimore, and Arlington and Alexandria. The raw area numbers do recognize Dorchester, Somerset, Accomack counties, and Virginia Beach as hot spots once again.

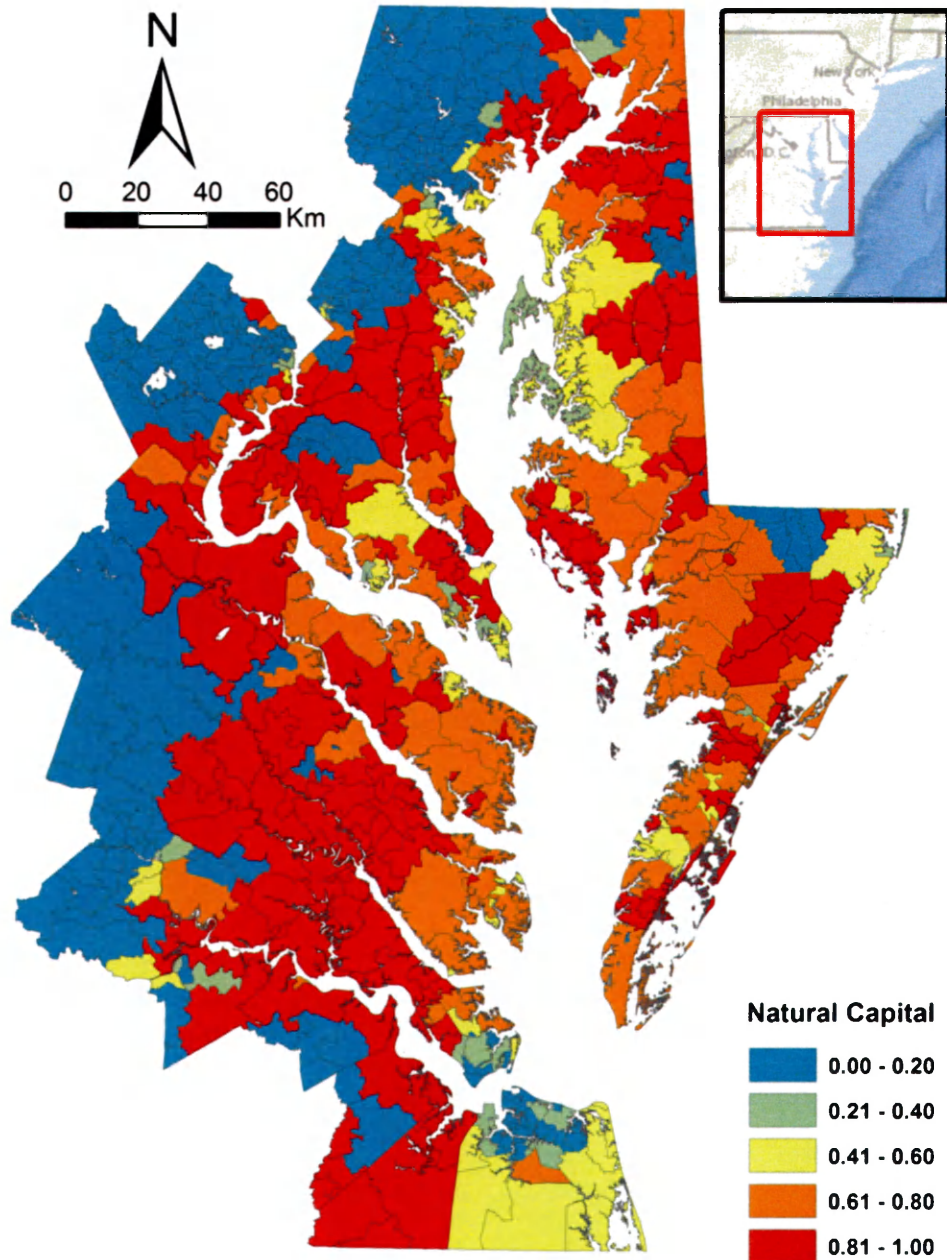


Figure 1.19 – Standardized natural Capital consisting of land cover percentages of both marsh/wetlands and forests within sub-3.05 meter zone based on 2001 C-CAP data. Assateague island (grey) was not included due to not being a formal zip code.

DISCUSSION

This study successfully calculates vulnerability for the Chesapeake Bay region in the early 2000s from different angles at both the zip code and locality scales. While analyzing one version of vulnerability index alone provides value, considering them together provides additional insights about their consistency and allows for targeting of potential problem areas. The development of the physical vulnerability index at human community scales is critical to this effort. The physical index keeps coastal policy and management in mind by providing actionable information that can target vulnerable areas at scales that match community boundaries.

Consistent Physical Vulnerability

From the physical perspective (Figures 1.3 and 1.8), the fact that similar areas fall into the top two vulnerability categories at both zip code and locality scales strengthens the message that these locations might be areas of concern irrespective of their demographics – especially for the significant hot spots of Poquoson, Hampton, Virginia Beach and Ocean City. This physical vulnerability index’s consistency at different demographic boundary levels supports the potential for establishing physical indices at human scales. The development should reduce the number of mismatch issues that arise when vulnerability issues are addressed using social and physical data from different resolutions.

There are some discrepancies in regional score distribution between scales, but these are only to be expected when aggregate data use likely blurs differences and extremes within sub-regions, as flagged by Fekete (2012). The main area where the

difference does merit concern is a selection of Eastern Shore small coastal communities. Cross's (2014) work warns about the risk that small communities face following natural disasters. Potential population loss may be particularly likely there as residents choose between waiting significant amounts of time for home repair following a disaster, or simply getting a different home in a new community. Although the physical index does calculate the Eastern Shore region as more highly vulnerable at both scales, managers should be wary of the likelihood of larger scale assessments of coastal risk to underrepresent physical vulnerability in small communities. These types of issues underscore the need to connect physical vulnerability to social vulnerability at the same scale.

From a management perspective, the physical index development process produces a product that may be easily communicated within vulnerability discussions. The index approach by no means replaces technical high detail index approaches equivalent to Gornitz and White (1992) or models of street-level flooding by specific hurricanes or other events (e.g. Wang et al. 2014). Just as street signs and addresses made it easier for people to find places, assignment of physical vulnerability at zip code or locality scales creates a better starting point for vulnerability discussions. This index allows this broad application while still permitting drilling down when smaller-scale local discussions are required.

Social Vulnerability Variability

In contrast to the physical vulnerability index utilized here, the various versions of the social vulnerability index are harder to compare. The different methodologies behind them make them less compatible – one, applying the widely accepted Hazards and

Vulnerability Institute (HVRI) SoVI recipe (2011) to the coastal Chesapeake region, one built for comparison using four top social vulnerability factors, and one at the locality scale using values utilized by Cutter (2003) and HVRI at the national scale for 2000. The fact that the SoVI scores and simplistic Chesapeake social vulnerability method moderately correlate (adj. $R^2 = 0.44$ for zip code scale and 0.6 for the locality scale) suggest a reasonable level of statistical similarity even if the maps do not perfectly visually line up. The designation of only two localities into the highest vulnerability class and as hot spots does raise some concerns about the utility of using national scale scores for standardized regional analysis in the Chesapeake Bay region.

Even though the zip code and locality SoVI scores were derived using different geographic contexts, both score distributions identify the Eastern Shore as more socially vulnerable. This result is consistent with the pattern produced by the physical vulnerability indices. Though application of these Cutter-based SoVI scores face several criticisms (See Background), in this instance the alternative CCRM basic social vulnerability index supports these distributions. The agreement by the indices strengthens the case for paying special attention to the flood threat to the Eastern Shore.

The application of the SoVI index also addresses concerns regarding its equal application to different community densities (Kleinosky et al. 2006). The initial inclusion of census factors such as percent urban population in the original SoVI 2000 application makes this analysis especially relevant (HVRI 2013). Though mean values are similar, one could claim to see this effect at the locality scale SoVI (calculated with the initial approach), where urban values make up the top tier of the vulnerability score distribution (the only 2 localities above 0.8 are two city localities). This study cannot say whether this

difference is due to the scale difference or updated SoVI methodology. The issue appears to have been reduced for the 2000 SoVI developed specifically for the coastal Chesapeake Bay zip codes, where rural areas come across as most socially vulnerable. In both applications, the suburban zip codes score as less vulnerable areas, meeting the Cutter et al. (2003) intent that these areas with populations that are typically more homogenous, wealthy, and better educated, and therefore are better suited to handle natural hazards.

The index application shows that clusters of social vulnerability do theoretically exist in vulnerable coastal areas where it may interact with flooding. This distribution supports the need for coastal managers to be aware that systemic vulnerability threatens particular local areas. Given the fact that social vulnerability remains an element that can only be measured in proxies (Tate 2012), this application merely represents an approximate potential understanding of the world.

Combined Vulnerability Reinforcement

Given the distribution of scores within the physical vulnerability index and the SoVI scores for the area last decade, it is not surprising that the combined index highlights parts of the Eastern Shore and Hampton Roads as particularly vulnerable. While equally weighting the physical and social factors is technically a form of subjective weighting, this construction creates a structure which is more easily broken apart when needed. Martinich et al. (2013) state the need to separate social and climate vulnerability in order to study which leads to which down the road. Deconstruction may allow analysis of how social and physical factors might interact over longer periods of time with increased future risks posed by sea-level rise.

The combined index results counter arguments that depict the region's city centers as the only areas of extreme coastal flood risk. This kind of analysis targets a much wider array of vulnerable communities for policy-makers and managers to address with preparation, recovery, and adaptation plans. Once more, the suburban areas stand out as communities that are likely to be better off when faced by flood events. At the zip code scale, one may claim that Virginia tidewater communities are possibly more vulnerable on average than Maryland's communities given the slightly (though statistically significant) higher distribution in overall scores.

Potential Natural Capital Distribution Impact

The fact that the physical vulnerability index considers developed land as increasing vulnerability generally means that the distribution of marsh and forest as a percentage of the sub-3.05 meter zone appears in areas with lower physical vulnerability scores. While shrub, agriculture, and other land covers may play a role here, this relationship means that the physical vulnerability index may already capture the benefits of natural capital – by considering the development factor as natural capital's inverse value. From a regional standpoint this distribution illustrates that simple preservation of existing natural capital may not be extremely effective towards lowering coastal vulnerability in the areas that physically need it the most. Instead, this spatial reality may promote a stance for more aggressive rehabilitation and expansion of natural capital (such as installing living shorelines and other green infrastructure) along many of the more vulnerable areas in order to establish benefits of natural capital in these areas.

While attempts at restoring and expanding natural resources might not upgrade ecosystem protection benefits to the level of those provided by larger natural capital

zones such as the Blackwater Marsh area in Dorchester County, MD or Gloucester County's marshes, they still may have selected positive effects. Gedan et al. (2011) claim wave-dampening potential for even narrow marshes. Bilkovic and Roggero (2008) point to the ability of living shorelines and alternative approaches to enhance local conditions and contribute to cumulative coastal ecological benefits. Given potential cost savings over typical shoreline management alongside these natural capital benefits (Manis et al. 2015), living shorelines and equivalent efforts may further support strategic handling of flood vulnerability at present and future levels.

Besides a few large natural areas along the main stem of the Bay on the central Eastern Shore, many of the hot spots of sub-3.05 floodable areas with high percentage forest or marsh resources appear further up the Bay's tributaries. This distribution suggests that many of the areas with high percentage natural capital land cover are up small tributaries. They likely do not provide the same suite of services as coastal ecosystems further downstream due to the lack of larger waves forming there. While other ecosystem benefits to these upstream communities and the Chesapeake at large no doubt still fully function, the lack of specific protection benefits such as wave dampening may change their valuation with regard to coastal flooding. Future efforts taking natural capital into account for flood vulnerability therefore might consider noting appropriate zones where natural capital could have the most leverage.

Further Management Implications

The parallel windows on coastal vulnerability in Maryland and Virginia build a platform to consider multiple complex angles of coastal management. The general index transferability between different scales not only allows flexibility, but also facilitates

exploration of policy and management issues from both top down and bottom up directions. Beyond the insights provided by the co-application of these scales, the question remains of how these indices directly tie to manageable, actionable information. From the physical index perspective, the individual aspects of elevation or wave exposure are not necessarily easily changeable in themselves, but they can still be addressed. By breaking the index factors out, a local coastal manager might consider pushing for rezoning certain floodable areas against investing in wave reduction strategies.

Though simplistic, the combination of the physical and social vulnerability indices (along with the natural capital consideration at the same level) allows analysis about whether strategizing adaptation around physical risk reduction or your community's demographics is likely going to deliver more results. This information may support a number of different management options. For example, a community or locality having recently enrolled in a program such as FEMA's Community Rating System might decide what category should be prioritized to see the most actual risk reduction in addition to discounting residents' flood insurance rates. By identifying vulnerable communities, the index may also support requests for more detailed sub-community vulnerability analyses, thereby serving as the equivalent of the first level of the tiered approach to coastal resilience quantification considered by the U.S. Army Corps of Engineers (Rosati et al. 2015).

Social vulnerability likely is more politically difficult to manage than physical vulnerability. The HVRI SoVI does not make it easy to backtrack from index scores to specific manageable factors. For those managers who are able to obtain all the information necessary to deconstruct the principle component analysis (PCA), the end

result of vulnerability proxies still limits action (Tate 2012). Many paths forward may remain unclear short of eliminating poverty, better educating all residents, or other significant goals beyond a coastal manager's control.

Social vulnerability information also can be interpreted both ways, limiting our ability to identify a factor's vulnerability as positive or negative. In the case of people's past flood experience, some individuals may act more wisely the next time, while others consider the past impacts as the damage ceiling for the present as well (Fekete 2012). The fact that the official SoVI has been designed without any specific hazard in mind does not facilitate this management task. A simplistic version such as the CCRM comparative model certainly can provide some measure of similar vulnerability calculations. Even then, the constraints of available data highlighted by King (2001) continually challenge analysis of social vulnerability constructs.

These types of studies allow for evaluating the concepts behind social vulnerability. The same approach to the physical index at zip code, U.S. Census tract, or other levels can also be combined with socioeconomic information that targets flood issues. For example, CCRM has combined physical vulnerability with the percentages of people with disabilities, poverty status, age dependencies, and people with no cars to target flood evacuation issues in Hampton Roads (unpublished). Managers there could consider what policy options can help eliminate the identified evacuation problem hot spots. By approaching these types of case studies from the same systemic approach and enhancing efforts to verify them, vulnerability indices can potentially transition from academic exercises to practical coastal community applications.

CONCLUSIONS

As one of the first efforts to consider physical and social vulnerability at equivalent scales across the entire coastal Chesapeake Bay region, this study establishes a framework for the development of resource management tools pertaining to coastal flood risk. In addition to applying known social vulnerability indices, this work offers one of the few developments of a physical vulnerability index specifically designed to directly connect to socioeconomic information. The general approach of parallel scales supports equal consideration of different variables on the same map within the same geographic and community contexts. The analytical tool developed for this project can study a wide array of implications involved with management of differing aspects of coastal vulnerability, from evacuation schemes to forecasting where future flood-related problems might be likely to occur.

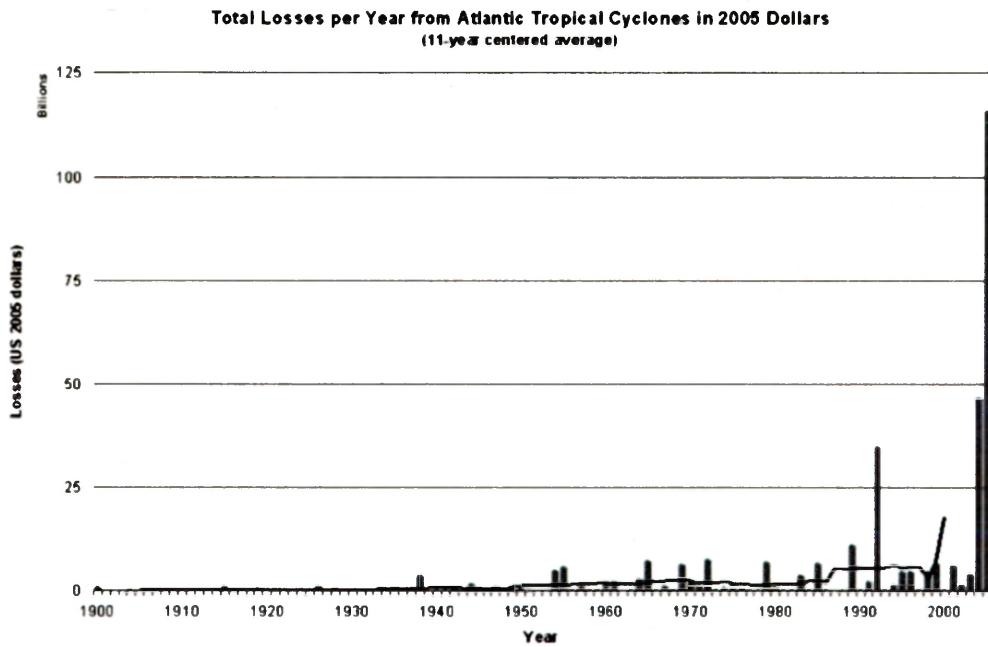
Short of further validation work, however, these vulnerability indices remain rather theoretical. Therefore, successful index application must provide a strong platform for testing their performance against real world events at a regional scale. The use of physical vulnerability and natural capital at the zip code and locality boundaries ensures that vulnerability considering both aspects can be understood together before tying the analysis to socioeconomic information available at these scales. Comprehensive community connections should advance the science of vulnerability and resilience by supporting evaluation of index performance against different flood scenarios.

CHAPTER 2 – Coastal Flood Impact Detection

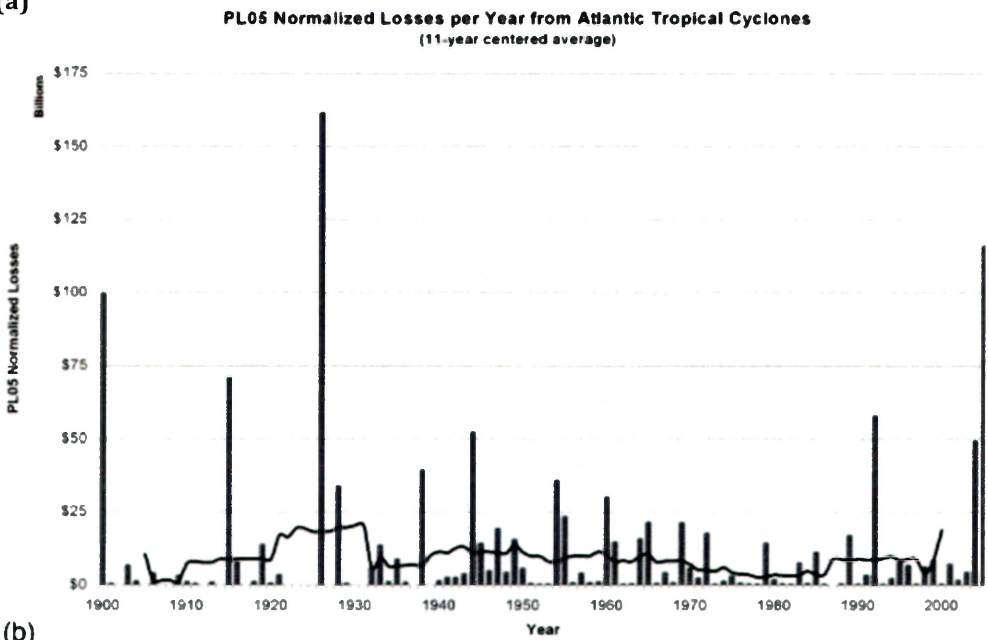
OVERVIEW

Sea-level rise will increase the risks for coastal communities, but these threats from rising seas are by no means new. Atlantic tropical cyclone damage measures in the billions of dollars over the past century (Pielke et al. 2008). While general damage records suggest an increasing trend in the magnitude storm impacts, Pielke et al.'s (2008) normalization of damages by population and coastal development clearly illustrates that there is a significant human element to the severity of these disasters (Figure 2.1). While high wind speeds cause critical damage during events, storm surge and coastal flooding often bring the greatest devastation (NOAA NHC 2014b). In addition to physical vulnerability to flood damage, social vulnerability has become increasingly accepted as an important aspect of immediate and long-term impacts of coastal flooding (Wisner et al. 2003).

Despite recognition of the importance of physical and social storm vulnerability assessment, few real world validation efforts have been made. Consequently, we still know relatively little about the robustness of vulnerability indices (Tate 2012). In order to understand what factors most contribute to a community's vulnerability to coastal flooding, it is possible to test the performance and accuracy of vulnerability indices by applying them to past coastal flood events. In the Chesapeake Bay region, Hurricane Isabel's widespread flooding provides a good platform for a natural regional experiment.



(a)



(b)

Figure 2.1 – From Pielke et al. (2008) **a)** total losses from Atlantic tropical cyclones in 2005 dollars **b)** normalizing the data for base-year economic damage with inflation, wealth and population.

Though not specifically described as “social vulnerability” factors at the time, officials did identify related concerns in some areas, such as the difficulty of communicating information to various ethnic communities regarding storm preparation and recovery (USACE and FEMA 2005). This communication issue illustrates the need for the kind of data that might support community adaptation to coastal hazards. This study seeks this kind of information by approaching the task from a new angle. The analysis compares vulnerability conditions prior to the storm to changes in coastal community well-being after the storm.

Analysis of local socioeconomic data allows for the exploration of how different Chesapeake communities respond to severe flood events. The natural assumption that more extensive flooding (and associated damage) leads to greater disruption in the local economy should show up in the socioeconomic record in various forms, such as the unemployment rate increase seen in areas affected by the 1993 Midwest floods (Xiao and Feser 2014). This study on Chesapeake Bay flood impacts compares changes in factors ranging from business patterns to changes in average income observed during the Hurricane Isabel period. This research assesses whether the signals can be observed consistently across Chesapeake Bay urban, suburban, and rural areas rather than focusing only on specific sub-regions such as Kleinosky et al. (2007).

Flood impact signals are identified by tying the actual flood statistics to common measures of socioeconomic performance at the community level. This process differs from a number of existing attempts to verify indices (e.g. Burton et al. 2011; Kim et al. 2014) because it evaluates the performance of the indices with existing socioeconomic data rather than actively surveying recovery. In doing so, this research attempts to

develop an exportable approach that could be applied even when available resources limit immediate detailed study of an area following a flood event. Evaluation at a regional level matches state and local boundary lines that may be more relevant to distribution of resources and aid. This examination then considers the specific flood impacts against vulnerability indices (social, physical, and combined) and relative natural capital to explore the rationale behind any patterns in coastal flood impacts on community economies.

METHODS

Identification of Flood Impacted Communities

To study flood impacts across the entire Chesapeake region, the ideal study requires a major storm that caused flooding across the whole region rather than isolated pockets. For the Chesapeake Bay region, this storm exists in the form of Hurricane Isabel. At the regional scale, the storm marked the highest water levels since the Chesapeake-Potomac Hurricane of 1933 (Figure 2.2). In the southern bay (around Hampton roads), storm surges of over 5-6 feet occurred, while water rose 3-5 feet in the central Chesapeake Bay, and 6-8 feet in the upper Bay (Annapolis and north) (Beven and Cobb 2004). Once it made landfall as a Category 2 storm near Drum Inlet, North Carolina, Hurricane Isabel then weakened to a tropical storm over the Chesapeake region (Beven and Cobb 2004). As of 2011, Hurricane Isabel's damage estimate was updated to \$5.370 billion for the total storm with estimates of insured property damage in Virginia and Maryland at \$925 and \$410 million respectively, illustrating the widespread impact (Beven and Cobb 2004).

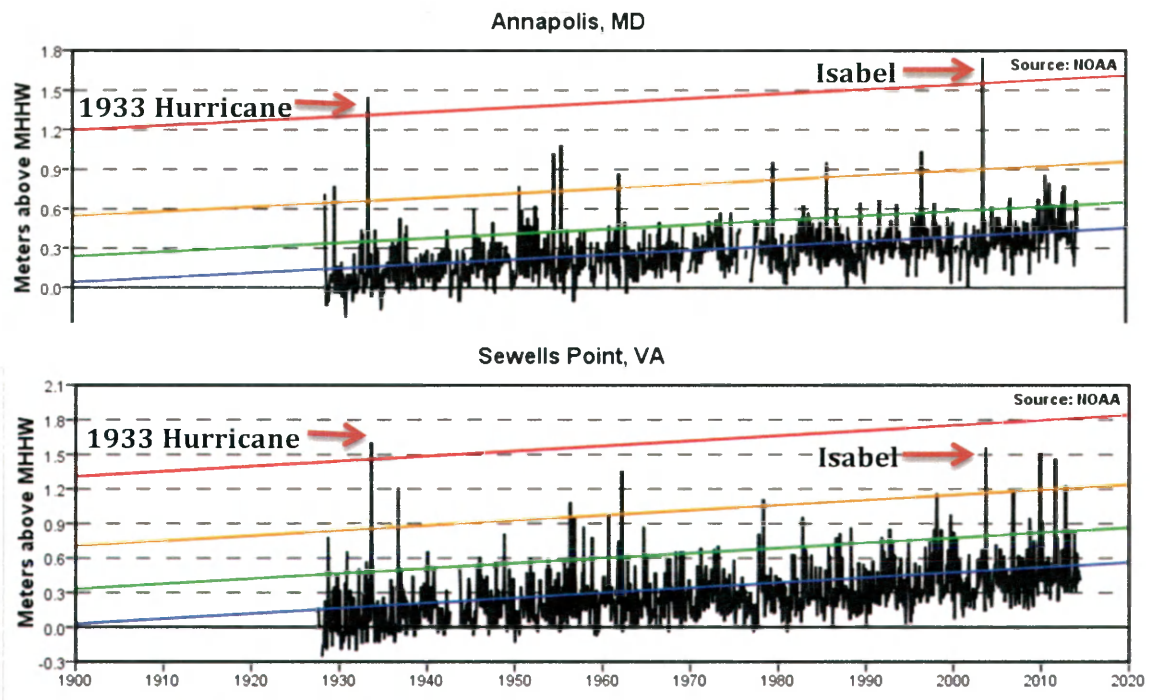


Figure 2.2 – From NOAA Tides & Currents (2014). Extreme water levels at Annapolis and Norfolk (Sewells Point). Note the 2003 spike of Hurricane Isabel’s storm surge relative to the past decade and time series as a whole. Referenced to Mean Higher High Water.

Teasing out damage caused specifically by flooding can be complicated for multiple reasons, including incomplete datasets, privacy issues, and the difficulty of differentiating wind from water damage. Even for substantial efforts such as the Spatial Hazard Events and Losses Database for the United States (SHELDUS), data falls short for certain counties and events (HVRI 2015). Given poor flood damage detail for Hurricane Isabel, this study treated a community’s maximum flood extent as an approximation for potential flood induced damage. This approach allows for a comparable standard indicator of potential damage that can be extended across the region despite the lack of true damage data; the method is not altogether different than a verification attempt by Finch et al. (2010) using flood depth in New Orleans (where most areas were flooded at this city scale). While this analysis likely involves certain

limitations, it generates less area size bias than simply using raw flood area numbers, with the relative percent of an area that flooded generally matching the equivalent trend in raw area flooded (Figures 2.3 & B2.1).

Calculating the flood percentage of New Jersey zip codes during Hurricane Sandy, a storm with higher quality impact data and accessibility, offers a useful comparison. Zip code boundaries were taken from 2012 US Census data, the state coastline from the New Jersey Department of Environmental Protection (2009), and flood data was obtained from the FEMA Modeling Task Force on Hurricane Sandy Impact Analysis (2013). Comparison of the data with total FEMA inspected damage from Housing Assistance information reveals a positive relationship between flood percent and damage, especially when binned (Figures 2.4 and B2.2).⁵

Although tidal gauge records and other datasets show various elements of past flooding, exact mapping of the Hurricane Isabel's flood area is not possible from observation. After initial efforts to document exact flood extent via communications with the Federal Emergency Management Agency (FEMA) and associated contractors using U.S. Geological Survey (USGS) high water marks, modeling the flooding remained a better option to best standardize flood impacts across Maryland and Virginia. The study incorporates a hindcast of Hurricane Isabel by Zhang and Baptista's (2008) finite-element SCHISM (Semi-implicit Cross-scale Hydroscience Integrated System Model) for cross-scale ocean circulation. Compared to reports in various Virginia regional hazard mitigation plans and other sources, the model appears to consistently highlight affected regions, particularly within the Virginia area.

⁵ OpenFEMA Housing Assistance dataset at <http://www.fema.gov/openfema-dataset-housing-assistance-data-owners-v1> targeting disaster 4086

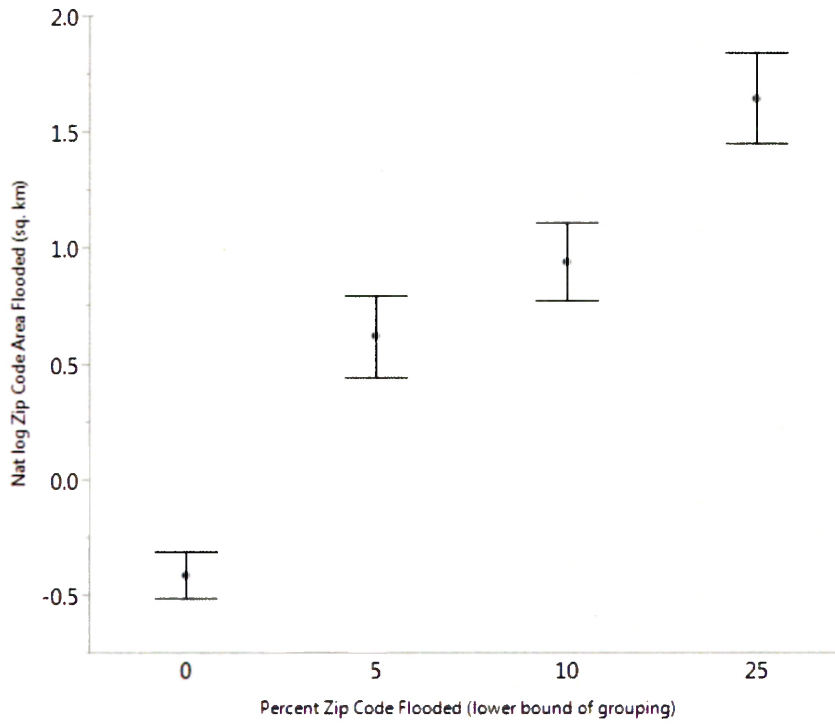


Figure 2.3 – Zip code flood area in terms of binned flood percent (x-axis marked by lower partition of flood bin grouping) against raw area flooded.

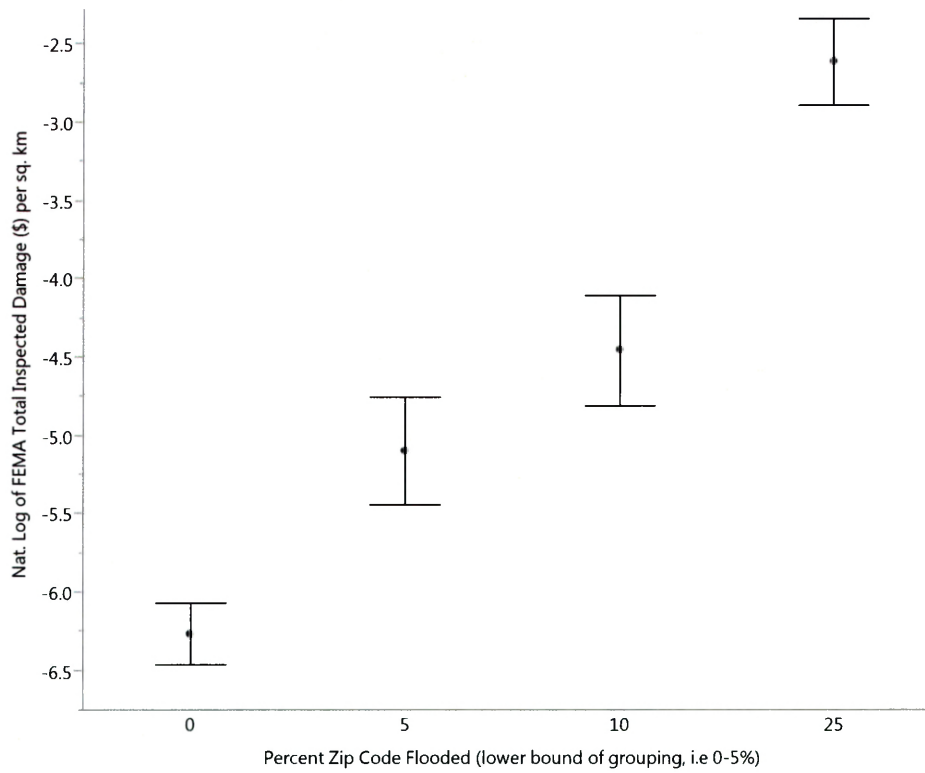


Figure 2.4 – Hurricane Sandy zip code FEMA inspection damage by binned percent zip code flooded.

The SCHISM model output the data as an .XML file which was converted in ArcGIS to a TIN file which then could be translated into raster file and projected in the proper coverage layer. A series of processes was run via an ArcGIS model to calculate the raw amount of land flooded within each geographic area as well as the percentage of flood area within each area. These calculations were performed for each locality and zip code tabulation area (ZCTA) level.

Socioeconomic Flood Impact Data Collection

In order to compare change in socioeconomic conditions, the analysis considered a variety of different approaches to measure change in coastal communities affected by storm surge events. Ultimately, the evaluation involved initial compilation of datasets that were available in the majority of communities across Virginia and Maryland. While a wide range of data showed promise, several datasets had significant gaps across the Chesapeake Bay region or were not consistently available. For example, the Zillow Home Value Index (ZHVI) provides an excellent record of housing values over time back through 1996 at a variety of geographical boundary levels, yet fails to include these for significant areas of Virginia such as the Eastern Shore and Northern Neck (Zillow 2015). In other cases, data were not always available on an every year basis, but still provided reasonable time windows around Hurricane Isabel. The final data selection includes groups of variables that provide better resolution at the spatial level due to their availability at the zip code level while others provide better temporal resolution but only are available at the locality level.

All datasets were transformed to the equivalent of a per capita or mean value from their aggregate values in order to minimize potential effects of different community area and population size on the analysis. The following datasets showed initial potential for consideration as vulnerability indicators:

- Zip Code Data
 - Internal Revenue Service individual income tax data⁶ (2001 & 2004)
 - Mean household annual adjusted gross taxable income (AGI)
 - Mean household annual taxable salaries & wages
 - Business pattern data⁷ (available annually 1994 - present)
 - Mean annual payroll per establishment (2002, 2003, 2004) – all forms of compensation, such as wages, salaries, commissions and bonuses before taxes are removed. Establishment defined according to the North American Classification System as a physical site where service or industry operations take place
 - Mean first quarter payroll per establishment (2003, 2004) – payroll for the January – March period

⁶ <http://www.irs.gov/uac/SOI-Tax-Stats-Individual-Income-Tax-Statistics-ZIP-Code-Data>

⁷ <http://www.census.gov/econ/census/data/geo.html> &
https://www.census.gov/econ/cbp/download/04_data/

- Locality Level
 - Monthly taxable sales (2000 through 2006) – the revenue sales tax is collected from, obtained from personal communications with the Virginia Department of Taxation and the Comptroller of Maryland (2014)
 - Annual average unemployment data (2002, 2004) – collected from the Bureau of Labor statistics⁸
 - New private residential building permits (calculated per square kilometer for each locality) (2002 & 2004) – US Census⁹
 - School district enrollment data (2002 and 2004) – from Maryland and Virginia State Departments of Education archive data
 - Virginia Composite Index¹⁰ (2000-2002 and 2002-2004) - Estimate of school district ability to pay for their operation based on value of real property, real sales and taxable sales, population and school average daily membership; computed every 2-year period

Once collected, these socioeconomic datasets were matched to coastal localities and zip code tabulated areas. Those geographies with populations below 100 or missing data were removed from further analysis.

Community Flood Impact Detection

Each socioeconomic dataset was tied to flood percent values for their corresponding zip codes or localities in order to inform better estimates of potential thresholds within the

⁸ <http://www.bls.gov/lau/#cntyaa>

⁹ <http://censtats.census.gov/bldg/bldgprmt.shtml>

¹⁰ http://www.doe.virginia.gov/school_finance/budget/compositeindex_local_abilitypay/

flood data. After initial data exploration, common thresholds were set across data at flood percentage breaks of 5, 10, and 25 for zip code levels, creating four bins. These were chosen as standard levels that provided relatively even zip code counts for maintaining relatively equal counts. The standard set of flood groupings allowed analysis across several subsets of the data (subsets including “only western shore VA zip codes”, “only sub-30 km² zip codes”, “only flooded zip codes”). At the locality level, break values of 1, 3, and 10 percent were first applied to flood impact detection.

The standard process was followed with more specific threshold detection accomplished by exploring the data with “Partition Models” in JMP software, which recursively splits the flood percent data according to possible groupings or splits evident within the socioeconomic data. For zip codes this method was only applied to the geographies that at least had some flooding to avoid complicating analysis with the large number of landlocked non-floodable areas. Two top thresholds were kept from the partition analysis at the zip code level. Additional breaks within the same 10% bracket (i.e. 0-10, 10-20, . . .) were ignored to prevent significant skewing of data distribution and variance. At the locality level, only the top partition (as long as it was not within 5 data points of the top or bottom flood percentage) was used to create two flood bin groups for each variable. Once calculated, the top splits were used to inform larger groupings of the impact data for the next tier of analysis. By running the analysis on each grouping, different potential thresholds were identified for each variable.

Transforming data to natural log values improved parametric statistical testing and ensured that the differences being analyzed between these values were relative to the values themselves, minimizing the effect of differently populated or sized communities.

A Before-After-Control-Impact (BACI) type test was applied to the majority of variables. The analysis was conducted in JMP with a “Matched Pairs” analysis in order to analyze the mean difference before and after Hurricane Isabel flooding; the Across Groups tests F-test is equivalent to the results of a repeated measures analysis that may also be calculated via a multivariate analysis of variance model.

Beyond the standard BACI design, the timing of monthly taxable sales data also allowed for time-series analysis of each locality. Monthly taxable sales were analyzed for a period from January 2001 through December 2006 with Minitab’s software, using their time series decomposition analysis to account for both overall trend and monthly seasonality. These years generally marked a period of economic growth. The end product of this was the production of a fit model for the overall period, generating residuals for the model. The decomposition smooths data using a moving average, generating median values for the seven years to create seasonal indices to adjust the data to the trend line with least squares regression. Generating this kind of model rather than a more complex autoregressive integrated moving average model (ARIMA) produces corresponding residuals in a consistently repeatable manner.

The impact of Hurricane Isabel flooding was assumed to be greatest where the actual taxable sales most differed from the fit model in the months following the storm. The final analyses tested for differences in average residuals 6 months before and after the storm, 3 months before and after, and the individual month following the storm (October). Figure 2.5 illustrates the creation of the modeled time series against the actual values for Gloucester County, VA. The Gloucester County analysis also provides an

example where the deviation of the model from the actual data (i.e. the residual) was at its greatest value for the entire time series for the October immediately following Hurricane Isabel. Calculating the same residual ranking for all localities suggested that some form of residual analysis across the region showed some potential when considered against flooding by Hurricane Isabel (Figure B2.3).

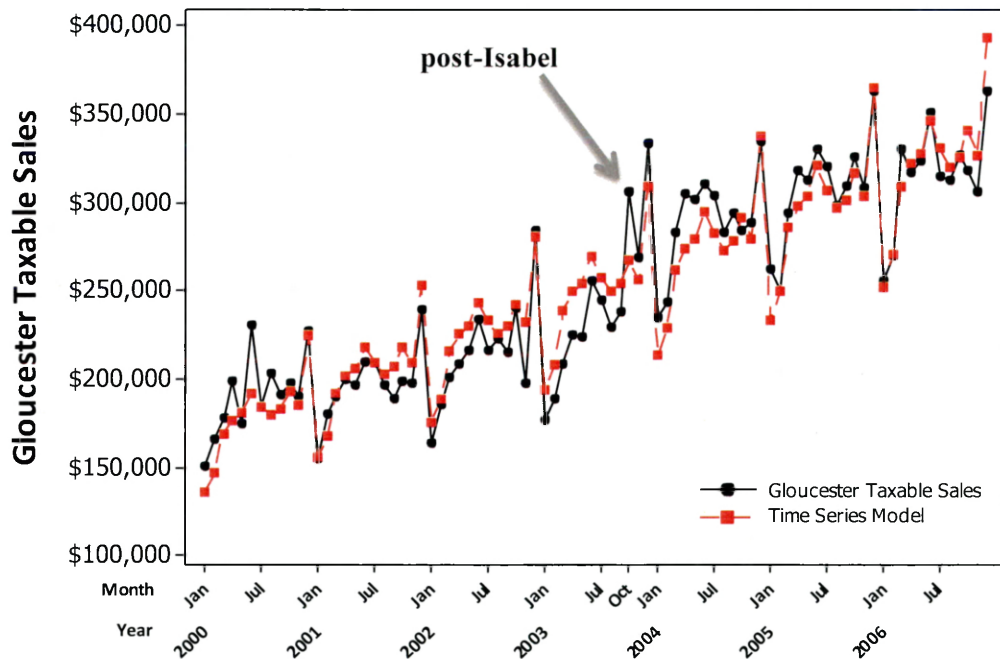


Figure 2.5 – Time series analysis of taxable sales in Gloucester County, VA. Arrow points out first full month following Hurricane Isabel.

Vulnerability Index Verification

Those socioeconomic datasets that showed significant difference in response across Hurricane Isabel flood groupings were selected as the datasets to test various vulnerability indices against. Repeated measures MANOVA calculated whether there were any statistically significant interactions between the percent flooding of zip codes (or localities) and their vulnerability index rankings in the context of socioeconomic change. Flooding percent was maintained at the bin levels from the Hurricane Isabel

impact detection, while physical vulnerability and social vulnerability index values were reduced to categories based on breaks at 0.2, 0.4, 0.6, and 0.8 (i.e. creating ordinal vulnerability categories of 1-5). The indices were assessed separately before being tested in their combined index format. Potential natural capital correlations (in the form of the relative percent forest and marsh within the zip code) were analyzed as well. The overall approach also identifies any interactions between vulnerability values and time exclusive of flooding impacts.

RESULTS

The approach successfully hindcasted the flooding from Hurricane Isabel and connected the flooding to socioeconomic changes. However, vulnerability index scores showed limited ability to predict the impacts of flooding extent on changes in coastal community socioeconomic activity.

Hurricane Isabel Flood Distribution

Small zip code tabulated areas (ZCTAs) in Gloucester and Mathews counties were home to the highest percent flooded zip code areas during Hurricane Isabel. The overall flood map generally matches the storm surge areas described by Beven and Cobb 2004, although it does not perfectly match corresponding concepts of conditions in the upper Bay (Figures 2.6 and 2.7). The relative area below 3.05 meters is lower towards the top of the Bay, suggesting that equivalent storm surge may not flood the upper Bay areas as much as it impacts areas further down the main stem. Hot spot analysis identifies the southern portion of the Maryland Eastern Shore, the ocean side of the Virginia Eastern

shore, the Virginia Peninsula area, and Mobjack Bay as hot spot region clusters at 90% confidence interval levels (Figure B2.4). At the locality level the higher flooding mirrored the clusters of zip code flood percent values (Figure B2.5), with hot spot analysis pointing out Hampton, Poquoson, and Northampton as the three centers of significant flooding above the 95% confidence interval (Figure B2.6).

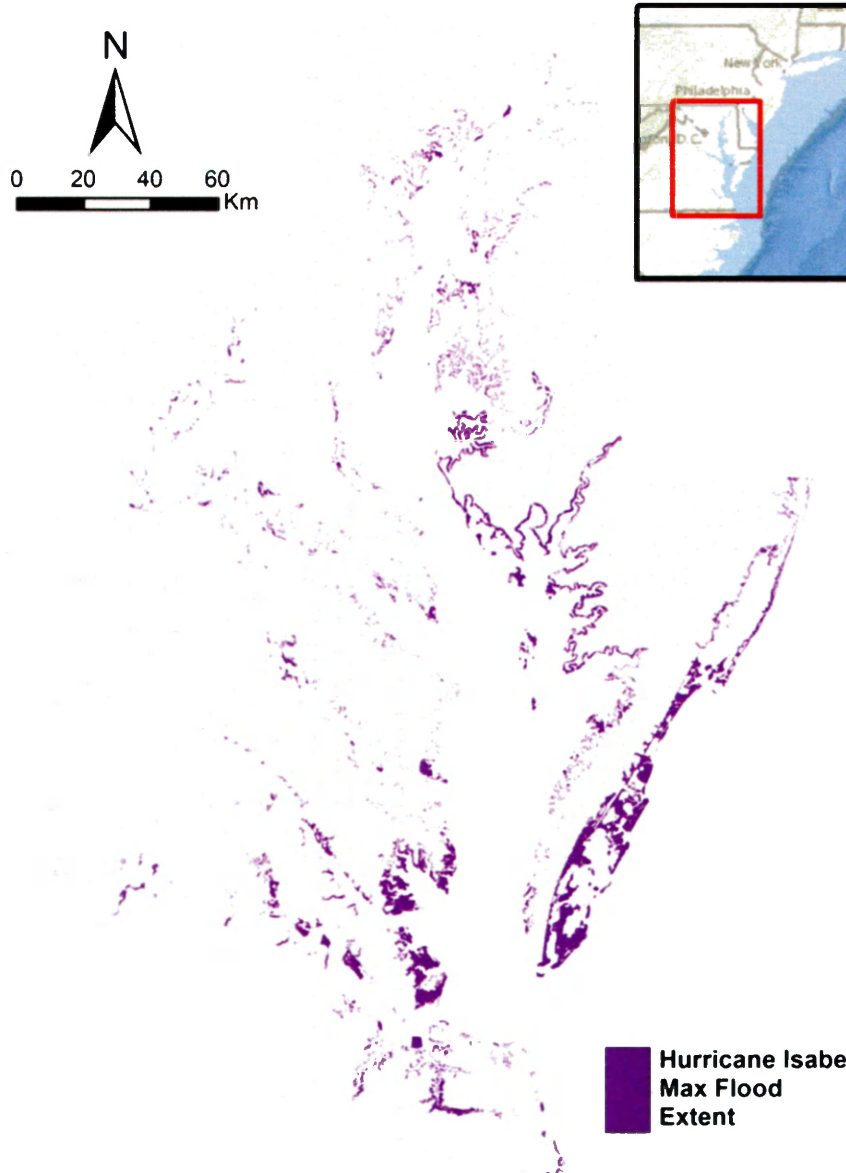


Figure 2.6 – Maximum flood extent of Hurricane Isabel (September 2003) as modeled by SCHISM/SELFE

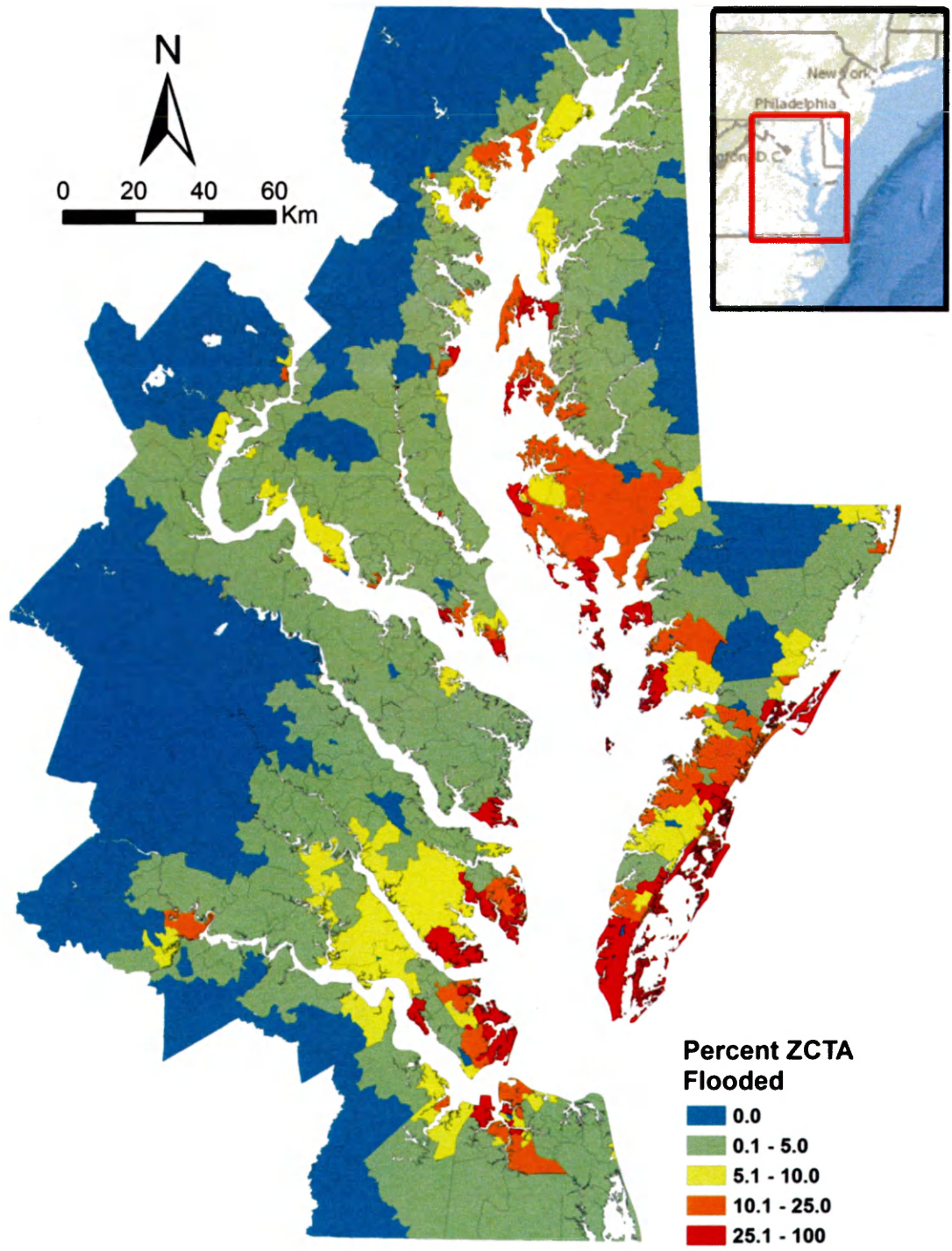


Figure 2.7 – Percent of zip code tabulated area (ZCTA) flooded by Hurricane Isabel. Note Assateague Island (grey) not included as it was not an actual zip code boundary due to no addresses.

Hurricane Isabel Flood Impact Detection – Zip Code Level

Detecting the impacts of Hurricane Isabel within a variety of data variables produced a mixed outcome. As illustrated by Tables A2.3 - A2.5, several variables did reflect significant disparities in change before and after Hurricane Isabel based on how much they flooded. The relationships were especially significant for the datasets that used variable-specific thresholds for grouping zip codes by relative amount of flooding. The significance was especially evident when extreme outliers¹¹ were included (e.g. Figure B2.7), though mostly remained true for cases even when they were removed.

The anticipated results assumed that the least flooded zip codes would see the greatest increase in socioeconomic activity while the most flooded zip codes would see the least increase in socioeconomic activity, with mid-level flooded areas falling somewhere in between (e.g. Figure B2.8a). Alternatively, one might have predicted that only the most flooded zip codes should show a difference in variable change before and after the flooding, based on the idea that there may be a certain threshold of flooding required to affect the economy negatively at a community-wide scale (e.g. Figure B2.8b). Despite the statistical significance of relationships between flooding and changes in socioeconomic activity (Figures 2.8, 2.9, & B2.9 – B2.12), the relationships did not match the expected overall trends and distributions.

¹¹ Besides those already removed for sub-100 person populations and other data inconsistencies

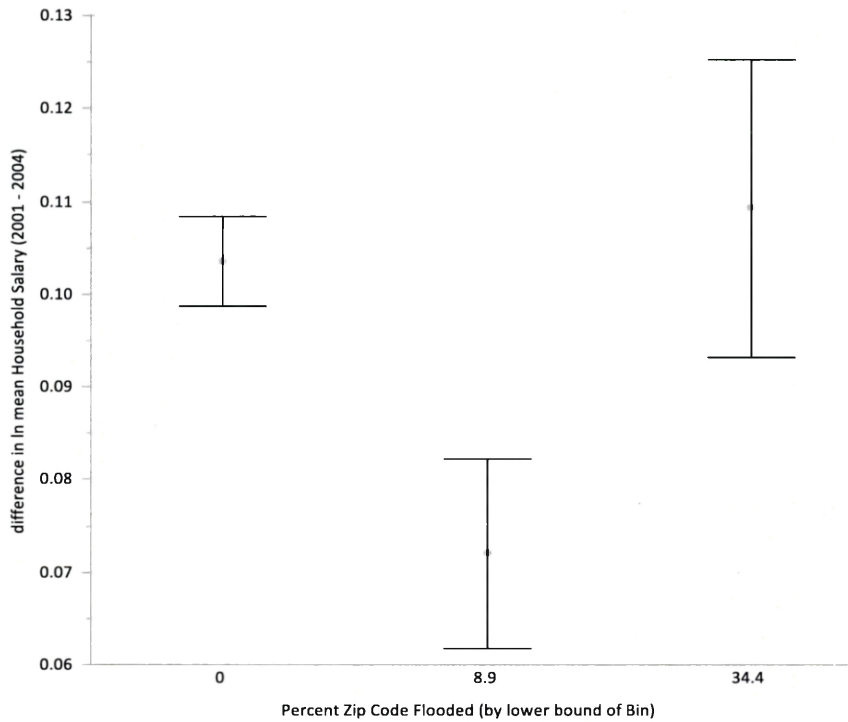


Figure 2.8 – Change in zip code mean household salary between 2001 and 2004 by grouped household salary-specific flood percentage bins (determined by partition analysis) among flooded Chesapeake zip codes with 2 extreme outliers removed. Standard error bars. Significantly different overall in ANOVA, at $p=0.006$.

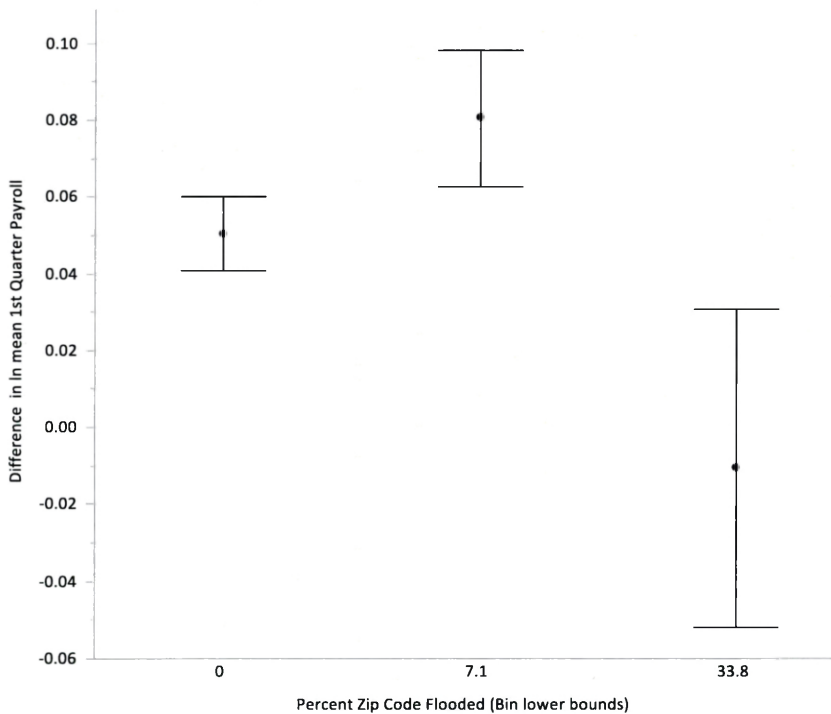


Figure 2.9 – Change in zip code mean establishment first quarter payroll between March 2002 and March 2004 by grouped payroll-specific flood percentage bins (determined by partition analysis) among flooded Chesapeake zip codes with 2 extreme outliers removed. Standard error bars. Significantly different overall with ANOVA, $p=0.020$.

First quarter payroll is the variable at the zip code level that provides the narrowest window around the flooding from Hurricane Isabel (six months on either side), which possibly explains why it is the variable that meets expectations most closely. While the most flooded zip codes did see the least increase in first quarter payroll and annual payroll (Figures B2.9 and B2.10), the middle flood groupings in both cases saw more growth than the least flooded zip codes. Even with the analysis of adjusted gross income (AGI), the middle flood group deviated from the least flooded groups by an even greater extent than the most flooded zip codes (Figure B2.11).

While these distributions with unexpected changes in mid-level flooded zip codes do not support a consistent trend, the variation may well support some aspects of differences in vulnerability and/or economic response among those areas impacted by the flooding. In addition to differing rates of change in variables in relation to Hurricane Isabel flooding, some of the areas that flooded the most also have generally lower values even before Hurricane Isabel passed through. As seen in Figure B2.13, in a number of cases these differences were not just partial-trends (such as Figure B2.14), but statistically significantly different as well. The BACI analysis already accounts for any distortion of results by these different starting values by transforming them through their natural logs before analyzing differences through time. The analyzed socioeconomic variables that showed significant differences among flood groups therefore still provide adequate platforms for testing vulnerability indices against.

Vulnerability Index Verification – Zip Code Scale

As Figure 2.10 illustrates, ideal vulnerability verification results would isolate statistically significant interactions between the indices, flooding, and change in socioeconomic activity. In this idealized scenario, vulnerability scores would negatively correlate with socioeconomic change in the most flooded zip codes while showing less strong or zero correlation with socioeconomic change in the least flooded zip-codes. The example would match the idea that a threshold of flooding is necessary to observe diverse socioeconomic impacts based on differing vulnerability. Otherwise, if the socioeconomic calibration variables were fine enough to show any small difference in response even in the case of minor floods, vulnerability indices might predict significantly different responses at any level of flooding. Given the temporal and spatial limitations and coarse nature of the aggregate data, the latter is unlikely. Failure of the various indices to correlate with changes in the socioeconomic test variables does apply here as well.

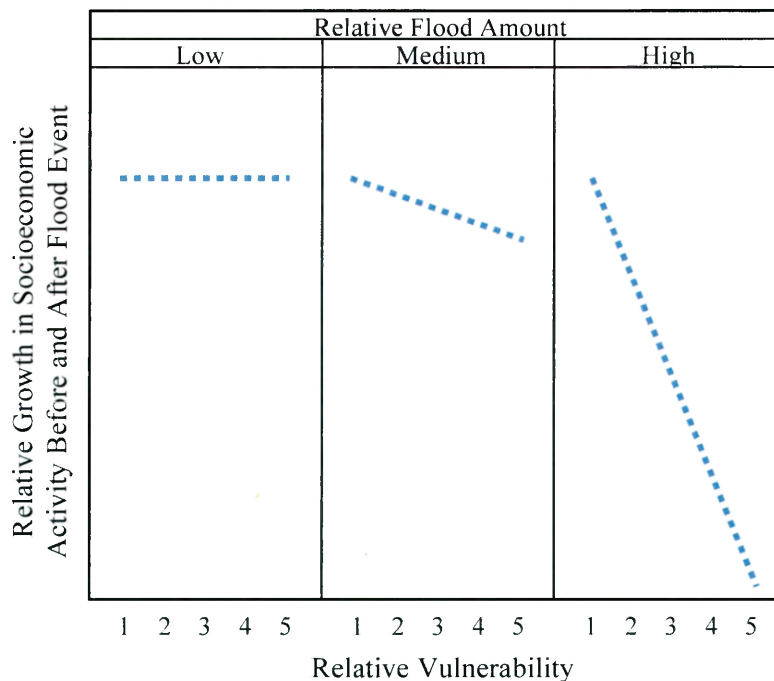


Figure 2.10 – Idealized theoretical results of vulnerability index verification, significant interactions between the indices, flooding and change in socioeconomic activity. The most flooded zip codes show decreasing increase in socioeconomic activity around a severe flood event, decreasing with vulnerability. The least flooded zip codes see higher growth, with little or no pattern among differently vulnerable areas.

Vulnerability Index	Significant Variable	Dataset	Index Performance	Data Relationships/Trends
<i>Theoretical</i>				
Any	Any	Any	Strong	Strong negative correlation between vulnerability and socioeconomic change for most flooded zip codes. Trend signal decreases with less flooding.
<i>Zip Code Scale</i>				
Social	1 st Quarter Payroll	Flooded Zip Codes	Weak	Limited score distribution amongst most flooded zip codes, but positive correlation; no trend for mid-level flooding; slight partial negative trend at low level flooding.
Social	Household Salary	Flooded Zip Codes	Weak	Limited score distribution amongst most flooded with limited separation of means. Mid-level flood shows somewhat positive trend. Low-level flood shows little to slight negative trend.
Physical	Household Adj. Gross Income (AGI)	Flooded Zip Codes	Weak	No clear trend for most flooded zip codes. Slight positive trend for mid-level. Limited for low flooded.
Physical	Annual Payroll	Small Zip codes	Weak/Moderate	No clear trend for the most flooded zip codes. Negative trend for second most flooded. Limited trends for least flooded.
Physical	Household Salary	Flooded Zip Codes	Moderate/Strong	Clear separation amongst means in negative correlation for most flooded; slight neg. trend for mid-level flooded; no clear trend for least flooded. <u>Most flooded still rather high in growth.</u>
Combined	1 st Quarter Payroll	Flooded Zip Codes	Weak	Limited/slight positive trend for most flooded. No significant trends at lower flood levels.
Combined	Household AGI	Flooded Zip Codes	Weak	Through most flooded, most vulnerable is close to the lowest growth, no trend for most flooded or the least flooded. Slight positive trend for the mid-level of flooding.
Combined	Household AGI	Small Zip Codes	Weak/Moderate	The most vulnerable of the most flooded areas reflects the least growth across the spectrum, giving some potential for a negative trend or threshold. Upper-mid level shows limited to slightly positive trend. Lower mid-level partially negative trend. Low flooding shows general lack of trend.
Combined	Annual Payroll	Small Zip Codes	Weak	The most flooded areas see increase in growth with vulnerability, flagging this operation despite negative correlations for mid-level flood areas and no trend for the least flooded.
<i>Locality Scale</i>				
Social	1-month Taxable Sales Residual	All Localities	Weak/Moderate	Less flooded localities show limited trend towards less difference from expected values following storm. More flooded localities lack full vulnerability score distribution but have possible trend towards less similar to expected following flood.

Table 2.1 – Summary of vulnerability index verification interpretation for results with statistically significant interactions among flooding, vulnerability, and relative change in socioeconomic activity. Index performance is marked on a scale of very weak to very strong.

Despite the fact that statistical analysis identified a number of significant interactions between flooding, vulnerability index scores, and changes in socioeconomic activity, these interactions did not necessarily support solid performance of the vulnerability indices to predict response to flood impacts. Data visualization provides insight on the relevance of the interaction's statistical significance through the following interpretations. Table 2.1 summarizes the analyses of index performance explained in more detail in the following sections. As the table shows, index performance can generally be described as weak.

Social Vulnerability

The social vulnerability index application showed limited ability to predict socioeconomic activity reflecting Hurricane Isabel's flood impacts. Of the five cases demonstrating significant relationships between flooding and socioeconomic change before and after Isabel, only differences in mean household salary and first quarter payroll significantly interacted with zip code flooding and relative social vulnerability (Table A2.8). These two sets of results showed no clear separation or mostly trended in the wrong direction relative to expectations (Figures 2.11 and B2.15). Performance analysis may be somewhat limited, as under 4% of the zip codes that were flooded had social vulnerability scores in the two highest categories. This score distribution constraint is likely due to relative socioeconomic status of coastal Chesapeake communities and the application of the official Social Vulnerability Index (SoVI) to the region. SoVI application calculates relatively few zip codes as the highest scores when transformed to a relative scale, creating some flags that Fekete (2010) warns of. Overall there seems to

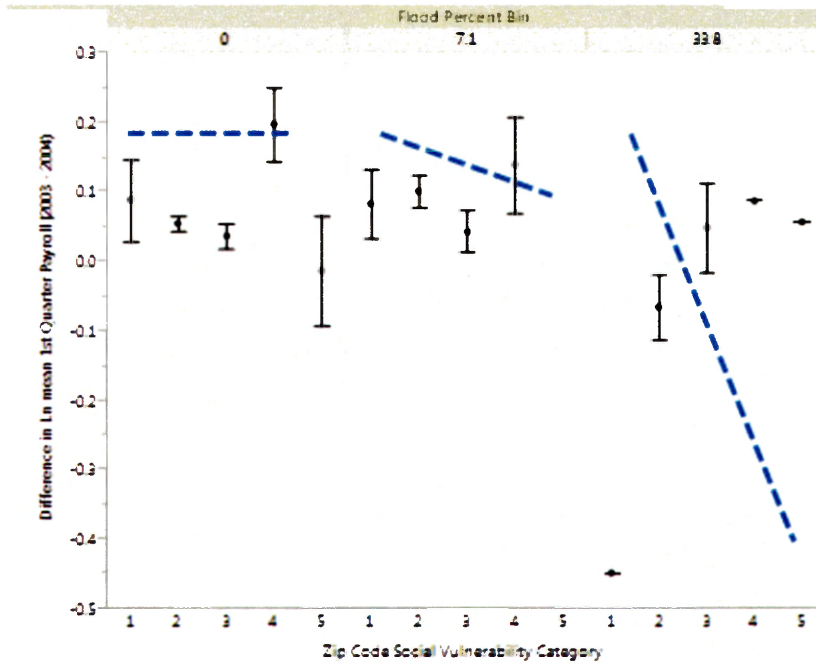


Figure 2.11 – Significant interaction between social vulnerability score (binned into 5 score categories corresponding to 0 - 0.2, 0.2-0.4 . . .), flooding and change in mean first quarter payroll between 2003 and 2004 by grouped salary-specific flood percentage bins among flooded Chesapeake zip codes, $p=0.005$. Top x-axis labels are lower partitions of groupings. Standard error bars. 2 extreme outliers removed. Expected trends overlaid as dashed lines.

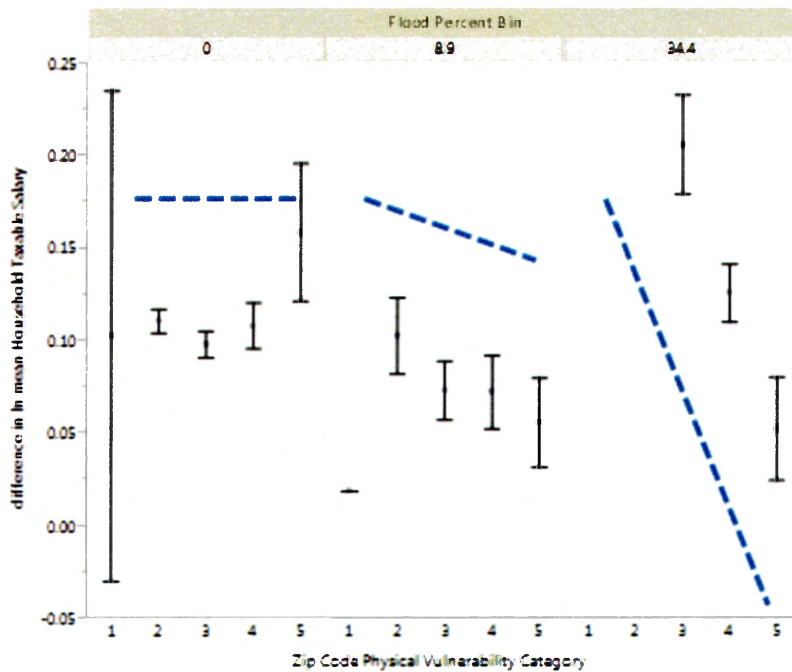


Figure 2.12 – Significant interaction ($p=0.04$) between physical vulnerability score (binned into 5 score categories corresponding to 0 - 0.2, 0.2-0.4 . . .), flooding, and change in mean household salary between 2001 and 2004 by grouped salary-specific flood percentage bins (axis labels are lower partitions of groupings) among flooded Chesapeake zip codes with 2 extreme outliers removed. Standard error bars. Expected trends overlaid as dashed lines.

be no support for any strong relationship between social vulnerability and socioeconomic performance in these zip codes.

Physical Vulnerability

Of the five datasets showing a significant relationship between Hurricane Isabel flood levels and socioeconomic variables, the physical vulnerability index significantly interacted with the relative flood levels for three of them: mean household taxable salary, household adjusted gross income (AGI) and annual payroll (Table A2.7). AGI generally failed to support isolation of projected trends in socioeconomic response (Figures B2.16). Change in mean annual payroll for smaller zip codes shows a hint of the expected results, with those zip codes flooding between 10% and 25% illustrating a non-significant trend towards less growth among higher physically vulnerable areas (Figure B2.17). This trend remains somewhat limited and within the standard error, however, and would require further explanation of why the relationship does not extend to the most flooded zip codes.

Only the interaction between taxable household salary (Figure 2.12) generally supports the expected hypothesis of the interactions between vulnerability and socioeconomic impact, illustrating a clear separation in differences before and after Isabel between those zip codes with vulnerabilities of 3, 4, and 5 in those zip codes that flooded by 34.4% or more. There appears to be a less strong (and not significant) trend in those zip codes flooding between 8.9% and 34.4% as well. Those areas with vulnerability scores of 0.8 or above (i.e. score category 5) especially see mean values below the overall average change in household taxable salary across this period. Despite a split of 2001 to 2004 around Hurricane Isabel, mean household salary therefore does suggest that the

physical vulnerability index has the potential to predict some flooding impacts at a zip code scale. The fact that the variable did not capture differences across all data-subsets does raise some questions though.

Combined Vulnerability

The combined vulnerability index (weighting physical and social vulnerability equally) also showed limited potential for predicting socioeconomic change in zip codes affected by Hurricane Isabel. The change in AGI in the most vulnerable of the most flooded small zip codes does show some separation in growth from the rest of zip codes. However, the limited number of points trending in that direction, as well as an opposite trend in the second most flooded areas, suggests that the support is not very strong (Figure 2.13).

Overall, the indices generally fail to support hypothesized results when analyzing the significance for first quarter payroll, household AGI, and mean annual payroll (Figures 2.13, B2.18 – B2.20). The point should be made that sub-datasets containing only flooded zip codes excluded all areas labeled as category 1 combined vulnerability (i.e., score less than 0.2 on 0-1 scale), because none of those areas were flooded. While different weighting of various combinations of physical and social vulnerability could be explored in the future, overall results do not appear consistent enough to provide significant support for the application of the basic combined vulnerability index.

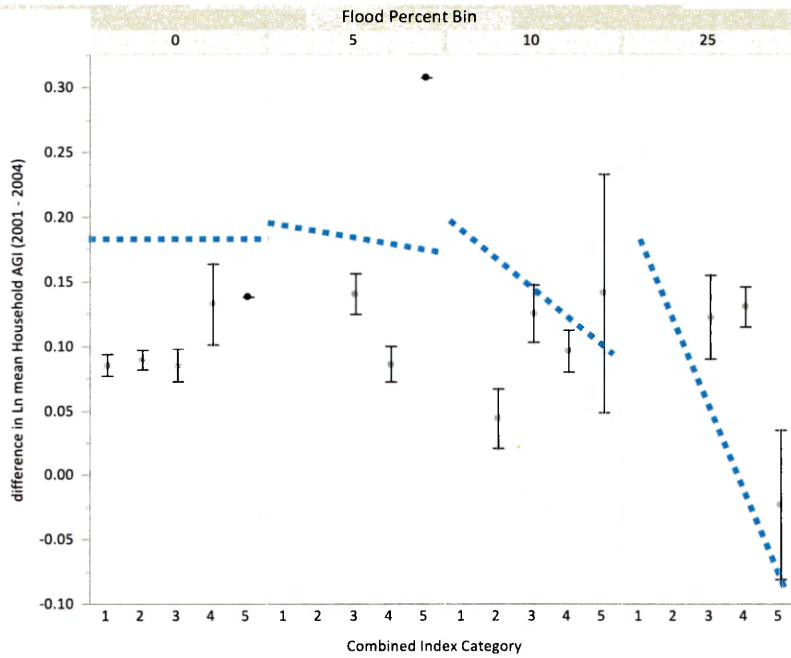


Figure 2.13 – Significant interaction between combined vulnerability score (binned into 5 score categories corresponding to 0 - 0.2, 0.2-0.4 . . .), flooding, and change in mean household adjusted gross income (AGI) between 2001 and 2004 by common flood percentage bins among small sub-30 km² Chesapeake zip codes, p=0.011. Top x-axis labels are lower partitions of groupings. Standard error bars. 11 extreme outliers removed. Expected trends overlaid as dashed lines.

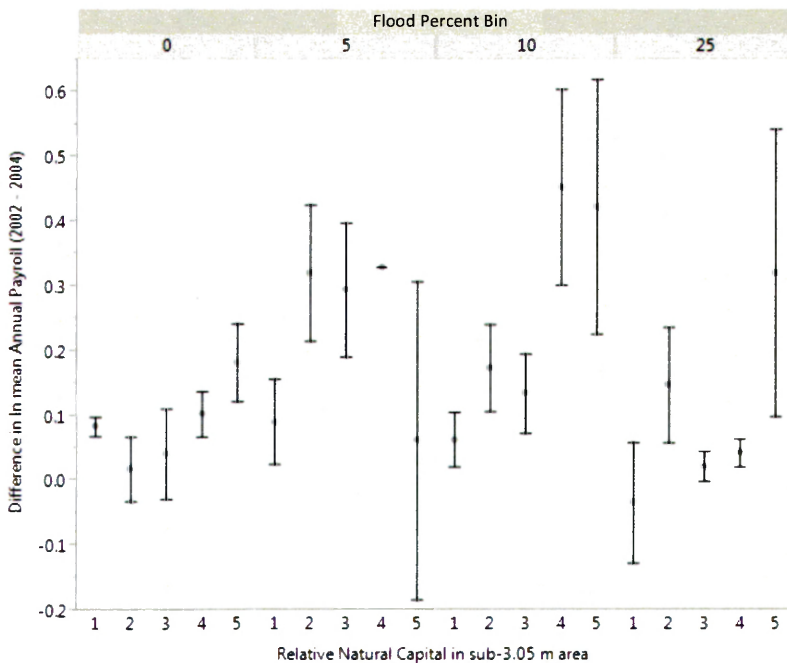


Figure 2.14 – Significant interaction between relative natural capital binned into 5 score categories corresponding to 0 - 0.2, 0.2-0.4 . . .), flooding, and change in mean annual payroll by common grouped flood percentage bins among small sub-30 sq.km Chesapeake zip codes, p=0.016. Standard error bars. 3 extreme outliers removed. Top x-axis labels are lower partitions of groupings.

Natural Capital

The amount of relative natural capital (in terms of forest and marsh) within the floodable area of a zip code did show some significant interaction with Hurricane Isabel flooding when considered alone ¹²(Table A2.8). Among the smaller zip code data subset, evidence generally points towards greater growth in annual payroll for areas with higher percent natural capital (Figure 2.14). The relationship between natural capital and annual payroll change outside the context of flooding does seem to show some trend (though not significant). The existence of this trend raises a question of how intensely the flooding is key to the interaction (Figure B2.21). These same trends do not carry over to household AGI and household taxable salary in quite the same way (Figures B2.22 and B2.23). Though not fully integrated into an index at this point, the relationships may suggest some different behavior based on the land cover of floodable areas during this period in time.

Hurricane Isabel Flood Impact Detection – Locality Level

Flood impact analysis at the locality level generally matched expectations of the individual variables. For example, more flooded localities experienced greater construction costs, less of a drop in unemployment, and in Virginia, less ability to pay for residents' public education after Hurricane Isabel relative to before (Figures 2.15, B2.24 and B2.25). Seven of sixteen datasets – nearly half of those tested – showed significance, with four of seven doing so when using a variable-specific flood group partition (Table A2.10 – A2.11).

¹² Natural capital was originally intended to be combined with the combined vulnerability index to improve indices, but given the limited performance this analysis was not conducted

Beyond the other variables considered at individual points before and after the storm, time-series mean absolute residuals suggest that there was more atypical economic activity following Isabel relative to the months before the storm. These locality-scale findings consistently show the same story that greater flood damage may show greater differences in economic activity relative to normal (Figure 2.16). In addition to the flood impact detection results, analysis showed that those localities that flooded were somewhat less well-off socioeconomically even before the storm passed through, though not in at a statistically significant level (Figure B2.28). These trends were not always as marked as they were in the zip code analysis, but should be noted.

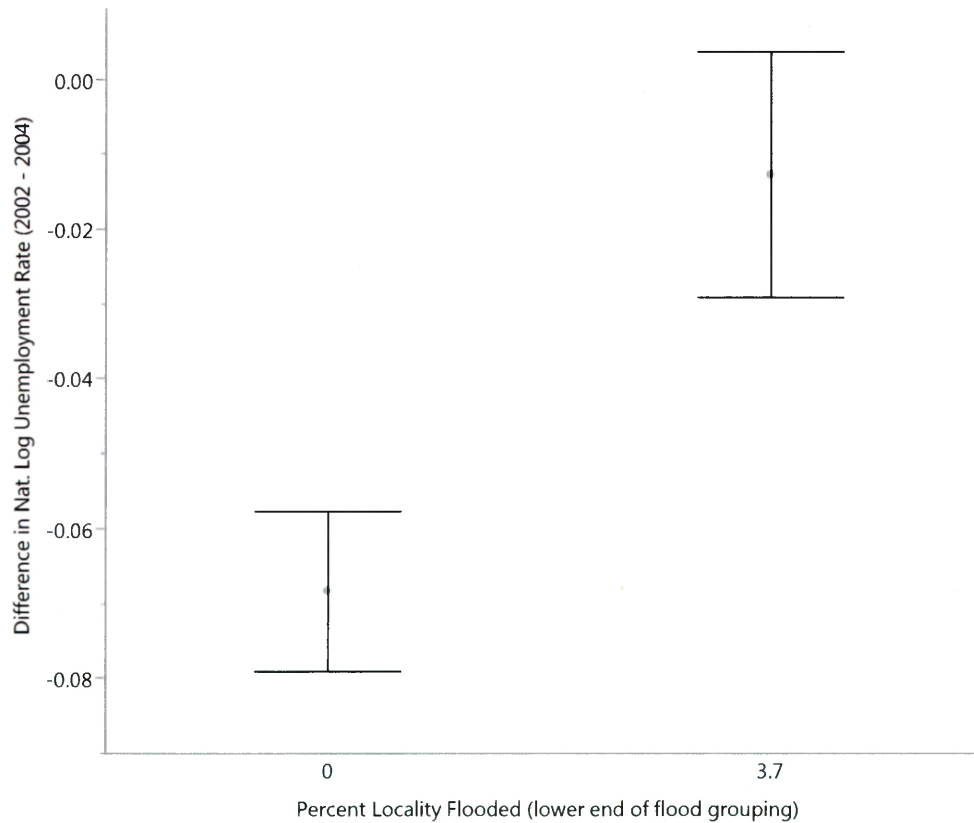


Figure 2.15 – Change in unemployment rate before and after Hurricane Isabel by taxable sales-specific flood percentage bins among coastal Chesapeake localities. 1 extreme outlier removed. Significant ANOVA, $p=0.007$. Standard error bars.

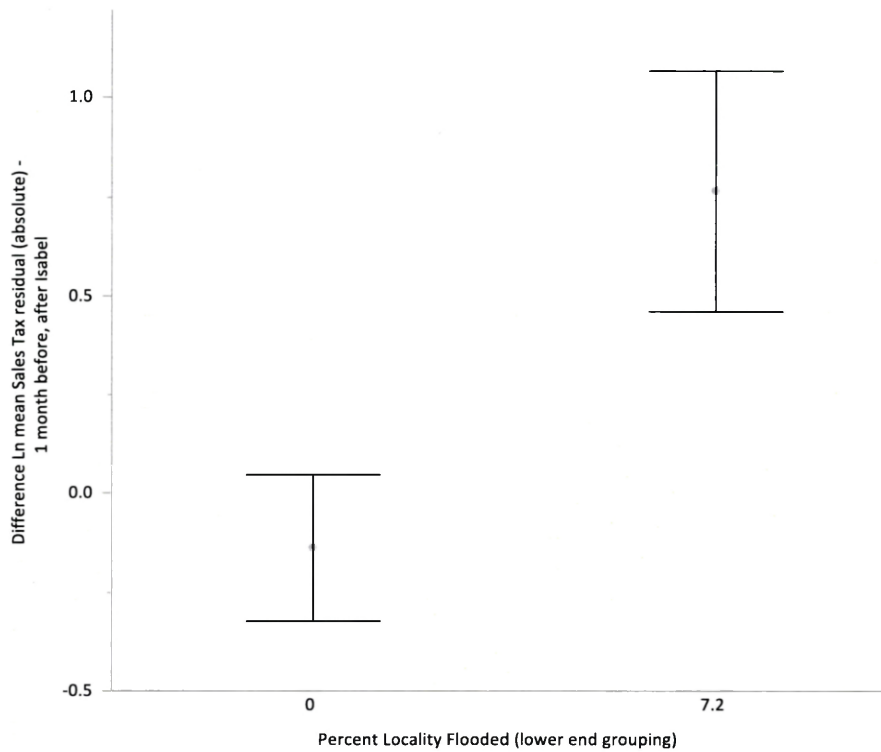


Figure 2.16 – Change in 1-month mean absolute residuals of taxable sales time series model before and after Hurricane Isabel by taxable sales-specific flood percentage bins among coastal Chesapeake localities. 5 extreme outliers removed. Significant ANOVA, $p=0.016$. Standard error bars.

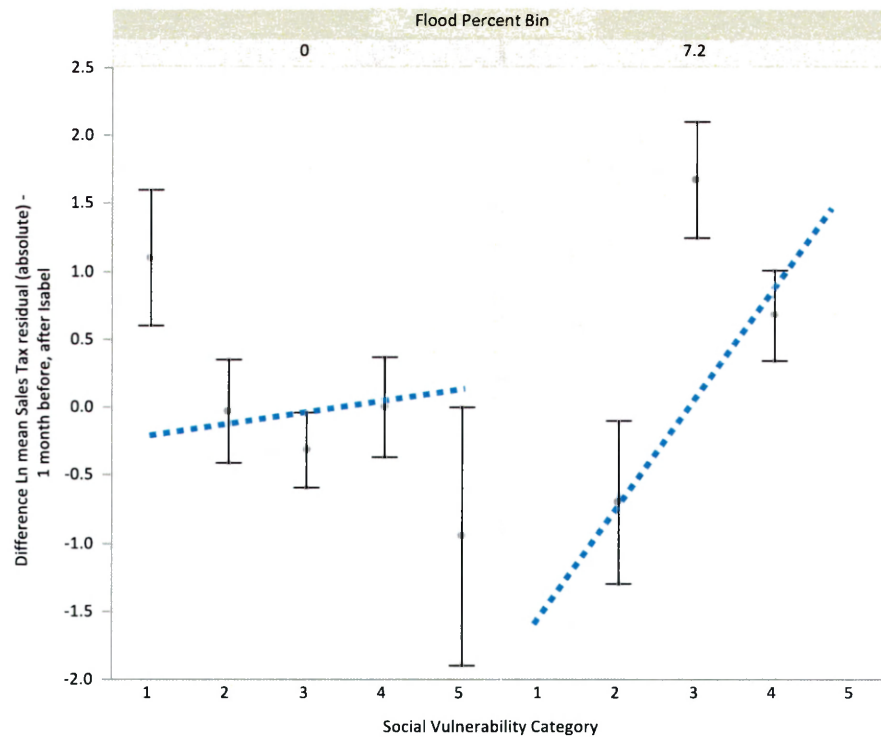


Figure 2.17 – Significant interaction between social vulnerability and change in 1-month mean absolute residuals of taxable sales time series model before and after Hurricane Isabel among taxable sales-specific flood bins, $p=0.048$. Top x-axis labels are lower partitions of groupings. Standard error bars. 8 extreme outliers removed. Expected trends overlaid as dashed lines.

Vulnerability Index Verification – Locality Scale

Despite a number of potential signals for Hurricane Isabel flood impacts, only the social vulnerability index significantly interacted with flood levels and socioeconomic activity change before and after Hurricane Isabel (Table A2.12). Among less flooded localities, more vulnerable areas met sales expectations more closely in the month following Hurricane Isabel than the month before (Figure 2.17). For more flooded localities, the three social vulnerability score ranges represented showed as significantly different, but did not produce a clear trend. While the least socially vulnerable localities met expected taxable sales more closely after the flooding, the mid-vulnerable areas departed more from expected than the more socially vulnerable localities following flooding. These differences in trends between the two flood-levels may identify some potential difference in post-storm recovery associated with social vulnerability above a threshold. At the same time the combination of a lack of a clear trend and the narrow social vulnerability score distribution among the more flooded zip codes limits any strong conclusions.

Beyond the interaction with flood level, the physical and social vulnerability indices appeared to correlate directly with differences in unemployment rates and expected 3-month taxable sales before and after Hurricane Isabel. Visualizing the interaction between taxable sales model residuals and physical vulnerability appears to show no meaningful trend (Figure B2.29). While the zip codes with mid-level social vulnerability scores are all equal to each other in terms of unemployment rate change, both ends of the relative social vulnerability index scores (categories 1 and 5) do significantly differ (Figure B2.30).

Overall, locality level factors did not appear to reveal great potential for vulnerability index effectiveness despite significant differences at the flood level and value changes alone.

DISCUSSION

This study shows that several applications of vulnerability indices to the Chesapeake Bay region do not strongly predict socioeconomic responses of coastal communities to flooding. In addition to their own limitations, the performance of the indices may have been impacted by the strength of Hurricane Isabel, the insulation of the regional economy, and the silver linings of disaster relief. Ultimately, the available indicators of changes in socioeconomic activity may also not be fully compatible with representing true impacts of coastal flooding.

Lack of Strong Support

Overall, this research illustrates that most observations do not support isolation of relationships among factors and significant interactions with flooding; they do not translate into strong support of a positive relationship between physical, social, or combined index values and socioeconomic change. The existence of only one potential relationship between the vulnerability indices and impacts of the region's greatest storm-surge event in 70 years raises questions about the applicability of current indices to real world coastal flood events.

The strongest verification variable, the household taxable salary of flooded zip codes, shows that there is some potential for the predictive use of the physical

vulnerability, but there are several caveats. Taxable salary did not show significant relationships with flooding and vulnerability across other subsets of zip-codes (e.g. solely west-shore VA or small zip codes). An ideal verification would perform across multiple subsets of the data.

The social vulnerability index application essentially falls short across all factors. Cutter's SoVI approach (HVRI 2013) does not demonstrate any meaningful significant interactions with flooding across the board, even though it has been incorporated into a number of areas and products, including NOAA's Sea Level Rise Viewer (2014) and Climate Central's Surging Sea's module (2015). Despite the notion that people who have experienced one disaster are better adapted to respond to other disasters (Newman et al. 2014), the application of a social vulnerability index targeted to all disasters might not have been tailored enough to the specific impacts associated with flooding in the Chesapeake region. Tate (2012) highlights the issue that social vulnerability cannot be directly observed. Therefore researchers are only left with various proxies to construct and measure them, which are more likely impacted by subjectivity and biases in world-view.

This research suggests that the ability of current vulnerability indices to predict real world impacts of storm events is limited. The following sections explore reasons for short-comings of index application in the context of Hurricane Isabel in order to highlight options to improve vulnerability assessment for future applications to coastal management.

Storm Impact Levels

Although Hurricane Isabel was unparalleled in terms of recent Chesapeake Bay area-wide flooding, the damage it caused may not have been widespread enough to allow the indices to predict different community impacts accurately. There simply may be too many other factors at work for widespread application of current vulnerability indices below calamity level.

It is possible that only the highest flooded areas may have been truly impacted economically at a level that could be systematically detected. Given their limited number, these especially affected areas may have appeared as outliers that were unable to drive overall trends. The fact that only the most flooded zip codes clearly saw taxable salary change significantly differently relative to physical vulnerability (Figure 2.12) could suggest that a certain threshold of flooding or damage must be crossed for the indices to apply. Hurricane Isabel may not have flooded enough areas sufficiently to see the patterns across the board within different socioeconomic activity measures. If so, deeper investigation of flood impacts in these outlier communities across several different storms may be necessary to statistically support the potential for vulnerability indices to predict socioeconomic impacts.

On the other hand, the Virginia Department of Emergency Management totals state damages (non-economic) at \$1.9 billion seem to suggest otherwise, with 1,400 businesses damaged (77 destroyed), 9,027 homes damaged (1,124 destroyed), and 100 localities declared major disaster areas (VDEM 2015). Though data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) does not adequately drill down to individual localities or zip codes, some regional assessments do

so. For example, the Hampton Roads area claims that nearly 6% of Hampton Roads real property was damaged as a result of Isabel (HRPDC 2006). The housing damage value may not necessarily have translated into real economic processes. Social vulnerability verification limits here may be representative of the differing levels of success in other similar efforts to evaluate vulnerability index performance (Tate 2012).

In some cases, social vulnerability differences appear greatest between the areas that flooded least and those that flooded moderately during Hurricane Isabel (e.g. Figure B2.12), rather than those that flooded the most. In these examples, the mid-range of percent flooded zip codes actually grew at greater rates than the least flooded areas. While the variables involved in these trends were included under the assumption that differing vulnerability could explain the unexpected results, the limited amount of significant correlation and interaction may suggest that these differences were actually due to noise or other factors not readily identifiable. These trends may merit more extensive examination in future studies to confirm their true drivers.

Though saturated soils and other conditions could have altered patterns of wind damage and power loss, the inland track of Hurricane Isabel's center does not likely predict different damage patterns. Some of the greatest wind gusts likely occurred towards the mouth of the Bay where flooding was widespread as well (Figure B2.31). The record wet summer leading up to Hurricane Isabel that resulted in a record high-water table and saturated soil across the region (e.g. Figure 2.18; USGS 2003) meant that sub-tropical winds could knock out trees and power more easily than the average storm, affecting more areas than expected. Damage therefore may have deviated from a distribution of flood-

dominated distribution to such an extent it eliminated flooding's role as the usual worst offender for storm damage.

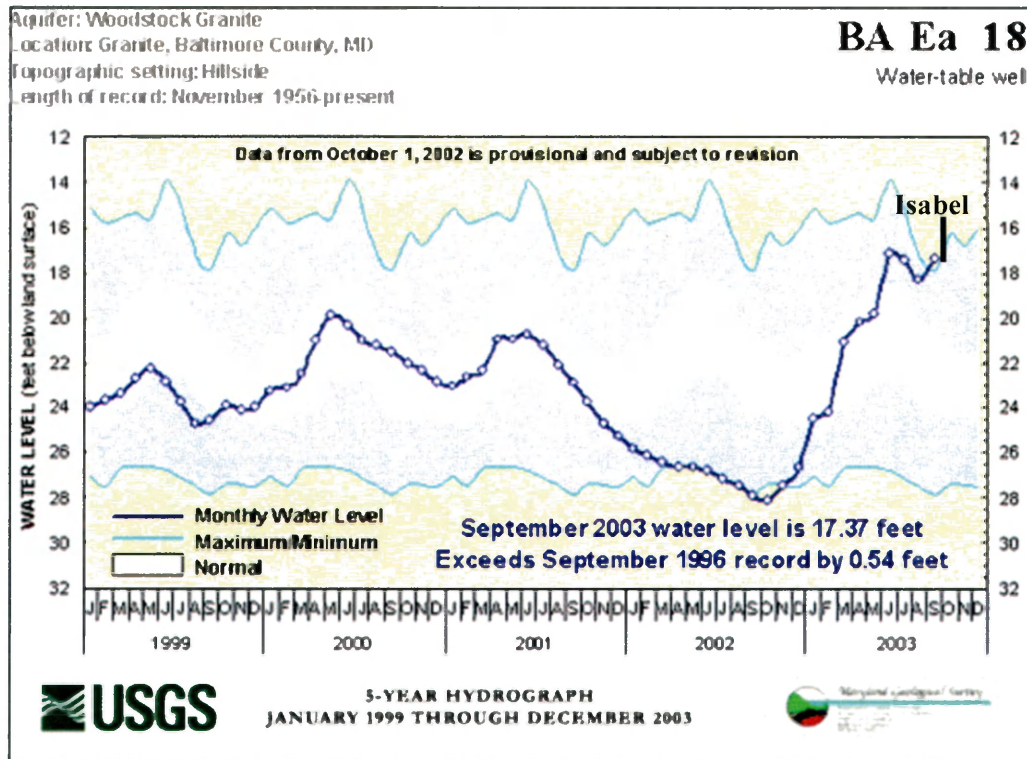


Figure 2.18 – Water table levels in Baltimore County for the 5 years leading into Hurricane Isabel. Figure from Source USGS (2003). Record high water table levels follow a year of drought.

Insulated Regional Economy

Though some dataset iterations excluded a number of zip codes around Washington, DC (such as analyzing only flooded zip codes, thereby eliminating a number of non-shoreline urban and suburban zip codes) the federal government, its dependent industries, and the spread of their workers and their salaries across the region could possibly dampen the impact of flooding in the region. A report by Quirante (2009) highlights how the Washington, DC Metro area consistently weathers recessions better than other regions

due to the federal government's presence. This kind of stability could easily influence the stability of socioeconomic activity across natural disasters as well. While most federal employees may be concentrated in the Potomac River region, the number of military personnel in the Hampton Roads area and other coastal zones may also complicate interpretations of changes in socioeconomic variables over this time.

Disaster Silver Lining

Baade et al. (2007) and others have suggested that some disruption in the form of a hurricane could actually be good for communities in an economic context. While Hallegatte and Dumas (2009) admit the potential for poverty traps in areas of intense and/or repetitive hazards, overall they see disasters as inconsequential in longer-term periods. Though disasters may affect physical capital, they may in turn support investment in labor and human capital and accelerate acceptance of new community improvements (Skidmore and Toya 2007). The locality taxable sales data utilized in this study may have shown the potential for this kind of impact in a few areas, but this interaction could have varied among different types of localities, thereby conflating results.

Albala (1993) identifies that construction sectors tend to increase following disasters, however, the economy of this type of investment might not be evenly distributed across the coastal Chesapeake region. For example, while Gloucester County, VA has a Home Depot and a Lowes that might experience increased sales prior to and following a flood event, neighboring counties that lack similar levels of equivalent commerce, such as Mathews or Middlesex, may see citizens spending most money across county lines. Consequently, the latter two counties might not show similar effects even if

they were significantly impacted. An analysis of hurricane impacts on the Hampton Roads region also claims that models such as FEMA's HAZUS model may underestimate the recovery economy following such storm events, perhaps because of a desire to avoid overestimating potential benefits when discussing costs (HRPDC 2006).

Disaster Relief

Disaster relief provided to Chesapeake tidewater communities (along with flood insurance benefits) may have been fairly effective in minimizing Hurricane Isabel's flood impacts over the longer term. Economic relief serves as a source of newly injected money and may allow affected communities to recoup losses. Virginia records show that housing assistance, other needs assistance, small business loans, and mitigation provided more than \$149 million in state recovery assistance between September 18, 2003 and April 30, 2004 (VDEM 2015). Another \$270 million went into the state economy for state agencies, local government, utilities, and transportation during this period.

Even in communities where a number of individuals were severely impacted and/or lacked flood insurance, people could have ended up as outliers who slipped through the cracks while the local economy as a whole moved along. Consequently, their losses might not show at the aggregate level. Finch et al. (2010) stated that likely due to the greater resources of the less vulnerable and public support provided to more vulnerable people, mid-level socially vulnerable groups actually saw slower recovery following Katrina in New Orleans. These kinds of patterns may further complicate identification of interactions across the much wider region addressed in this study.

Factor Compatibility

Though coastal scientists often lament the lack of updates to physical and biological datasets (e.g. physical vulnerability indices such as Gornitz et al. 1994), rapid rates of societal change now make conventional socioeconomic data the coarser element. In their own review of resilience information Knight and Link (2015) call out data input as the most critical challenge for these types of assessments. Much of the socioeconomic data available at a wide spread level surrounding Hurricane Isabel may fall short for this analysis due to temporal or spatial limitations associated with aggregate measures. At the locality level, taxable sales provide a great measure of local economic activity, but this data may not work where only certain sub-locality areas are severely impacted. On the other hand, the smaller spatial scale afforded by the zip code data may be nullified by the fact that impacts may not last more than several months.

The aggregate nature of the datasets also prevents identification of how well various wealthier or poorer areas handle flooding, with average values failing to represent reality (Fekete 2012). The composition of permanent residents of an area may also widely differ in terms of income and other characteristics prior and following an event.

Deruygina et al. (2014) illustrate just how powerful U.S. Treasury access to unconventional sub-aggregate information can be by showing how returnees to disaster areas differed from permanent disaster refugees. Adequate detection may require finer resolution at both scales.

In spite of efforts to use data from “outside the box,” the variables utilized for Hurricane Isabel impact detection and index verification may still have led into the trap and constraints associated with the data available to data mining studies (Fekete 2012;

King 2001). Though all considered factors can tie to community socioeconomic performance in some manner, some may be too indirect of a relationship to reflect the true impacts of floods or other disasters. This relationship may be especially true for social vulnerability, where the indices themselves are indirect substitutions for reality (Fekete 2009). Overall, government collected data may provide too coarse a view of community health that still remains separated from actual human activity. Given people's ability to call upon savings or credit when faced with covering unexpected damages, private financial institutions may well hold the right type and scale of personal information needed to assess flood impacts and true index performance. It is no surprise that the National Research Council report, "Disaster Resilience: A National Imperative," strongly recommends creating a national disaster impact database (NRC 2012).

Targeted surveys have even related credit scores to personal behavior such as the likelihood of relationship longevity and divorce (Dokko and Hayes 2015), and therefore might show potential for application to money spent following disaster hardship. Though background research explored the basic availability of bank account and credit or debt information with several companies, barriers regarding privacy and data compilation/storage prevented access (e.g. personal communications Solof Dec 2014; Sheehan Dec 2014). This thesis research experience suggests that various public/private research agreements must be ironed out prior to analyzing events such as Hurricane Isabel occurring in order to apply these at systematic scales.

Natural Capital Influence

Given the limited success in identifying meaningful predictive ability in the various vulnerability indices, this study did not consider natural capital's combined contribution

to their ability to predict flood impacts. The natural analyses that were conducted suggested that areas with higher natural capital (in the form of percent of sub-3.05 m area covered by marsh and forest) showed some correlation towards higher growth in mean annual payroll across this period. At first glance this could suggest some benefits to having highly vegetated flood plains. One could be tempted to conclude that having a higher-percent of your sub-3.05 area as natural capital was better than having lesser amounts during this time period.

While this study does not dig deeply enough to assign cause, the existence of the trend regardless of flood amount possibly suggests something to do with economic activity in this floodable land rather than Hurricane Isabel itself. Future studies could attempt to isolate a factor at more local levels to see what did happen in these specific locations. In Virginia, the General Assembly's passage of a Freedom of Engineering Bill in 1999 shifted septic permitting, which led to development of more structures in previously prohibited areas along the states' coastlines; in turn this development could have led to more economic growth over this period, creating a broad, but false, signal of Hurricane Isabel interaction (Saunders 2011; personal communication with L.Lawrence 2015). This study cannot tie these two events together, but merely acknowledges the potential for other large forces at work during this time period. External influences like this last one illustrate the need for caution. No matter what the combination of factors in index creation or evaluation, no system can guarantee capturing all influences (Fekete 2012).

CONCLUSIONS

This thesis aimed to move beyond the range of many extant post-disaster recovery studies by analyzing flood impacts at the same regional scale that vulnerability indices are applied in order to test their effectiveness. By attempting to verify the applicability of vulnerability indices in coastal Chesapeake Bay communities, this approach ideally allows for the development of solutions that can be directly incorporated into the management of flooding impacts associated with storm surge events and future sea-level rise. The importance of better understanding community vulnerability to natural hazards continues to grow as more people recognize the costs of not enhancing resilience to these types of events (NRC 2012). This type of study is therefore critical to contributing to our knowledge base and national well-being. Unfortunately, this research does not defend the use of vulnerability index information to predict the impact of coastal flood events on different types of communities.

While coastal researchers worry about how fast the physical and natural world is changing, human patterns operate at an entirely different dynamic level. Social vulnerability has become increasingly identified as a key element of comprehending natural hazard risk (Wisner et al. 2003), yet only recently has society begun to expand our access to the information necessary to assess social vulnerability accurately. To identify wide-reaching patterns, research requires widely available data that relates to specific geographical borders. The U.S. Census data can provide the geographically specific snapshot in time needed to create social vulnerability indices (e.g. SoVI from Cutter et al. 2003), but these data appear less able to illustrate the impacts of specific storm events needed to analyze how human behavior assumptions play out in real world situations.

Interesting individual case studies of coastal disaster recovery processes exist (e.g. Burton et al. 2011), but more effective vulnerability index assessment demands better access to data that can more systematically illustrate the status of people before and after events across the region, especially at the socioeconomic level. More out of the box application of new data streams may provide new methods to understanding the complexity of human-natural systems. Coastal flood management especially requires better information reflecting conditions that can be actively managed. Without expansion of potential data sources, our ability to systematically analyze real-world natural disasters to provide predictions useful in mitigating the impacts of future storm events will remain limited.

Although this research effort did detect some limited potential for physical index performance, overall it generally failed to identify meaningful trends in relationships between vulnerability indices and flood impacts, especially the much-applied social vulnerability indices. The social vulnerability index shortcoming remained even when social characteristics were combined with community physical conditions. While limitations can be explained away by data inconsistencies and inadequacies, as a whole these findings question the ability of these indices to predict and support planning for disaster impacts. As long as studies like this one show weak index predictive performance for landmark storm events, regional and local managers in the Chesapeake Bay region may want to think twice before throwing out other evaluation tools in favor of these vulnerability indices.

APPENDIX A – ADDITIONAL TABLES

VARIABLE	DESCRIPTION
QASIAN	Percent Asian
QBLACK	Percent Black
QHISP	Percent Hispanic
QNATAM	Percent Native American
QAGEDEPT†	Percent of Population Under 5 Years or 65 and Over
QFAM†	Percent of Children Living in Married Couple Families
MEDAGE	Median Age
QSSBEN	Percent of Households Receiving Social Security
QPOVTY	Percent Poverty
QRICH200K	Percent of Households Earning Greater Than \$200,000 Annually
PERCAP	Per Capita Income
QESL†	Percent Speaking English as a Second Language with Limited English Proficiency
QFEMALE	Percent Female
QFHH	Percent Female Headed Households
QNRRES	Percent of Population Living in Nursing and Skilled-Nursing Facilities
HOSPTPC	Hospitals Per Capita (County Level ONLY)
QNOHLTH†	Percent of Population Without Health Insurance (County Level ONLY)
QED12LES	Percent with Less Than 12 th Grade Education
QCVLUN	Percent Civilian Unemployment
PPUNIT	People Per Unit
QRENTER	Percent Renters
MDHSEVAL†	Median House Value
MDGRENT†	Median Gross Rent
QMOHO	Percent Mobile Homes
QEXTRCT	Percent Employment in Extractive Industries
QSERV	Percent Employment in Service Industry
QFEMLBR	Percent Female Participation in Labor Force
QNOAUTO†	Percent of Housing Units with No Car
QUNOCCHU	Percent Unoccupied Housing Units

Table A1.1 – Official SoVI variables from the Hazards and Vulnerability Research Institute at the University of South Carolina (HVRI 2011).

Factor Removed	No Tide Range	No Representative Wave Energy	No Developed Area	No Area Below 3.05 Feet	No Volume/Area
Mean Value Change (%)	-22.3	4.4	-5.4	20.2	-25.6

Table A1.2 – Sensitivity analysis of physical vulnerability at zip code scale, illustrating percent change in final index value when individual subcomponents are removed.

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
	qblack	qagedep	qrich	qasian	qed12les	qfemale	qnrresp
	qfam (-)	medage	percap	qhispc	qextrct		
	qpovty	qssben	med_hsva	qesl	qnoauto		
	qfhh	ppunit0 -	mdgrent				
	qcvlun	qfemlbr (-)					
		qunnocchu					
Contribution to Vulnerability	+	+	-	+	+	+	+

Table A1.3 – SoVI factor groupings. Abbreviations explained in Table A1.1. Plus and minus signs describe sign of contribution to vulnerability (or the sign of relationship to the factor).

Factor Removed	Age	Income	Poverty	Race
Mean Value Change (%)	-15.5	-20.9	18.0	18.4

Table A1.4 - Sensitivity of CCRM comparative social vulnerability index calculated at the zip code scale.

Factor Removed	Area sub-3.05 m	Volume/Area	Pct sub-10 area Developed	Tide Range	Wave Energy
Mean Value Change (%)	23.7	-19.1	-1.9	-12.9	10.2

Table A1.5 – Sensitivity of locality physical vulnerability index showing percent change in value when factor omitted.

Factor Removed	Age	Race	Income	Poverty
Mean Value Change (%)	-19.4	11.5	-2.9	7.4

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Table A1.6 – Sensitivity of locality scale CCRM comparative social vulnerability index.

Variable	Flood Percent Partition 1	Flood Percent Partition 2
Household AGI '01-'04	15.6	0.7
Household salary '01-'04	8.9	34.4
Mean 1 st Qtr Payroll '03-'04	33.8	7.1
Mean Annual Payroll '02-'03	9.3	11.6
Mean Annual Payroll '02-'04	7.1	11.6

Table A2.1 – Partitions in flood percent specific to variables used for analysis at zip code scale.

Variable – All Zip Codes	Significance of Mean Difference, p>F	
	<i>Without Extreme Outliers</i>	<i>With Outliers</i>
Household AGI '01-'04	0.119	0.318
Household salary '01-'04	0.283	0.02
Mean 1 st Qtr Payroll	0.108	0.254
Mean Annual Payroll '02-'03	0.486	0.362
Mean Annual Payroll '02-'04	0.067	0.024

Table A2.2 – All Zip Codes with common flood bin partitions. Values were transformed using their natural log before analysis. P-values of mean difference significance calculated via matched pairs analysis for before and after Hurricane Isabel with and without extreme outliers. Bolded signifies significant at 0.05 confidence level.

Variable – Flooded Only Zips	Significance of Mean Difference, p>F	
	<i>Without Extreme Outliers</i>	<i>With Outliers</i>
Household AGI '01-'04	0.078	0.571
Household salary '01-'04	0.275	0.052
Mean 1 st Qtr Payroll	0.140	0.265
Mean Annual Payroll '02-'03	0.544	0.344
Mean Annual Payroll '02-'04	0.341	0.106

Table A2.3 – Flooded Only zip codes with common flood bins. Values were transformed using their natural log before analysis. P-values of mean difference significance calculated via matched pairs analysis for before and after Hurricane Isabel with and without extreme outliers. Bolded signifies significant at 0.05 confidence level.

Variable – Just Small Zip Codes Set	Significance of Mean Difference, p>F	
	<i>Without Extreme Outliers</i>	<i>With Outliers</i>
Household AGI '01-'04	0.039	0.374
Household salary '01-'04	0.482	0.065
Mean 1 st Qtr Payroll	0.077	0.308
Mean Annual Payroll '02-'03	0.209	0.116
Mean Annual Payroll '02-'04	0.010	0.019

Table A2.4 – Just Small Zip codes (common flood splits). Values were transformed using their natural log before analysis. P-values of mean difference significance calculated via matched pairs analysis for before and after Hurricane Isabel with and without extreme outliers. Bolded signifies significant at 0.05 confidence level.

Variable – West shore VA Zips	Significance of Mean Difference, p>F	
	<i>Without Extreme Outliers</i>	<i>With Outliers</i>
Household AGI '01-'04	0.679	0.792
Household salary '01-'04	0.633	0.806
Mean 1 st Qtr Payroll	0.202	0.202
Mean Annual Payroll '02-'03	0.099	0.438
Mean Annual Payroll '02-'04	0.087	0.141

Table A2.5 – Just western shore of Virginia zip codes (common flood bins). Values were transformed using their natural log before analysis. P-values of mean difference significance calculated via matched pairs analysis for before and after Hurricane Isabel with and without extreme outliers. Bolded signifies significant at 0.05 confidence level.

Variable – Flooded Only with variable- specific flood bins	Significance of Mean Difference, p>F	
	<i>Without Extreme Outliers</i>	<i>With Outliers</i>
Ln household AGI '01-'04	0.006	<0.001
Ln household salary '01-'04	0.006	<0.001
Ln Mean 1 st Qtr Payroll	0.020	0.038
Ln Mean Annual Payroll '02-'03	0.159	0.001
Ln Mean Annual Payroll '02-'04	0.341	0.012

Table A2.6 – P-values of mean difference significance calculated via matched pairs analysis for before and after Hurricane Isabel with and without extreme outliers. Values were transformed using their natural log before analysis. Bolded text highlights significance at 0.05 confidence level.

Index		Physical Vuln		Social Vuln		Combined Vuln		Relative Natural Capital	
Common Flood Bins		<i>Interaction Significance (p>F)</i>							
Dataset	Variable	Time* *Flood *Phys	Time* Phys	Time* Flood *Soc	Time* Soc	Time* Flood* Comb	Time* Comb	Time* Flood* NatCap	Time* NatCap
Small Zip Codes	Mean Annual Payroll '02-'04	0.011	0.169	0.124	0.836	0.021	0.862	0.016	0.110
Small Zip Codes	Household AGI '01-'04	0.110	0.129	0.474	0.627	0.011	0.223	0.188	0.750

Table A2.7 – Significance of interactions using common flood groupings for zip codes with no large outliers. Values were transformed using their natural log before analysis. Interaction significance calculated using repeated measures manova. Bolded text highlights significance at 0.05 confidence level.

Index		Physical Vuln		Social Vuln		Combined Vuln		Relative Natural Capital	
Specific Flood Bins		<i>Interaction Significance (p>F)</i>							
Variable	Time* *Flood *Phys	Time* Phys	Time* Flood *Soc	Time* Soc	Time* Flood* Comb	Time* Comb	Time* Flood* NatCap	Time* NatCap	
Household AGI '01-'04	0.003	0.065	0.685	0.1	<0.001	0.517	0.048	0.552	
Household salary '01-'04	0.040	0.625	<0.001	0.183	0.517	0.686	0.012	0.950	
Mean 1 st Qtr Payroll	0.091	0.351	0.005	0.291	0.0111	0.742	0.101	0.429	

Table A2.8 – Significance of interactions of vulnerability indices using variable specific flood bins excluding extreme outliers. Values were transformed using their natural log before analysis. Excluding any zip codes that were not flooded at all. Interaction significance calculated using repeated measures manova. Bolded text highlights significance at 0.05 confidence level.

Variable	Variable-Specific Flood Percent Split	Partition R ² Value
Unemployment Rate '02-'04	3.7	0.07
Taxable Sales Abs. Residuals – 6 months pre/post	1.5	0.03
Taxable Sales Abs. Residuals – 3 months pre/post	9.3	0.18
Taxable Sales Abs. Residuals – 1 month pre/post	7.2	0.05
VA Composite Index '02-'04	1.8	0.11
School Enrollment '02-'04	1.4	0.03
Building Permit '02-'04	7.1	0.05
Construction Cost '02-'04	0.8	0.06

Table A2.9 - Partitions in flood percent specific to variables used for analysis at locality scale. Bolded text highlights significance at 0.05 confidence level.

Variable – Common Flood Bins Dataset	Significance of Mean Difference, p>F	
	<i>Without Extreme Outliers</i>	<i>With Outliers</i>
Unemployment Rate '02-'04	0.167	0.575
Taxable Sales Abs. Residuals – 6 months pre/post	0.369	0.386
Taxable Sales Abs. Residuals – 3 months pre/post	0.046	0.039
Taxable Sales Abs. Residuals – 1 month pre/post	0.220	0.066
VA Composite Index '02-'04	0.011	0.269
School Enrollment '02-'04	0.617	0.985
Building Permit '02-'04	0.229	0.166
Construction Cost '02-'04	0.029	0.110

Table A2.10 – Locality scale flood impact detection, common flood percent partitions for analysis using natural log transformed values. P-values of mean difference significance calculated via matched pairs analysis for before and after Hurricane Isabel with and without extreme outliers. Bolded signifies significant at 0.05 confidence level.

Variable – Variable-specific flood bin partitions	Significance of Mean Difference, p>F	
	<i>Without Extreme Outliers</i>	<i>With Outliers</i>
Unemployment Rate '02-'04	0.007	0.064
Taxable Sales Abs. Residuals – 6 months pre/post	0.540	0.065
Taxable Sales Abs. Residuals – 3 months pre/post	0.005	0.005
Taxable Sales Abs. Residuals – 1 month pre/post	0.016	0.024
VA Composite Index '02-'04	0.005	0.030
School Enrollment '02-'04	0.962	0.202
Building Permit '02-'04	0.111	0.319
Construction Cost '02-'04	0.646	0.168

Table A2.11 – Locality scale flood impact detection, variable-specific flood percent partitions for analysis after transformation into natural log values. P-values of mean difference significance calculated via matched pairs analysis for before and after Hurricane Isabel with and without extreme outliers. Bolded signifies significant at 0.05 confidence level.

Index		Physical Vuln.		Social Vuln.		Combined Vuln.		Rel. Natural Capital	
		<i>Interactions and Significance (p>F)</i>							
Flood Bins	Impact Variable	Time* Flood* Phys	Time* Phys	Time* Flood* Soc	Time* Soc	Time* Flood* Comb	Time* Comb	Time* Flood* NatCap	Time* Nat Cap
Common	Construction Cost '02-'04	0.833	0.806	0.435	0.522	0.483	0.696	0.670	0.644
Common	Taxable Sales Abs. Residuals – 3 months pre/post	0.053	0.005	0.828	0.691	0.687	0.876	0.502	0.631
Variable-Specific	Taxable Sales Abs. Residuals – 3 months pre/post	0.253	0.052	0.067	0.327	0.127	0.813	0.698	0.155
Variable-Specific	Taxable Sales Abs. Residuals – 1 month pre/post	0.426	0.911	0.048	0.444	0.592	0.543	0.415	0.188
Variable-Specific	Unemployment Rate '02-'04	0.778	0.868	0.845	0.003	0.973	0.547	0.436	0.415
Variable-Specific	VA Composite Index '02-'04	0.930	0.202	0.906	0.837	0.371	0.948	0.466	0.418
Common	VA Composite Index '02-'04	0.686	0.355	0.931	0.749	0.413	0.869	0.552	0.460

Table A2.12 - County scale detection of significant interactions between flood percent and vulnerability factors using variable specific flood partitions and natural log transformation of values.

APPENDIX B – ADDITIONAL FIGURES

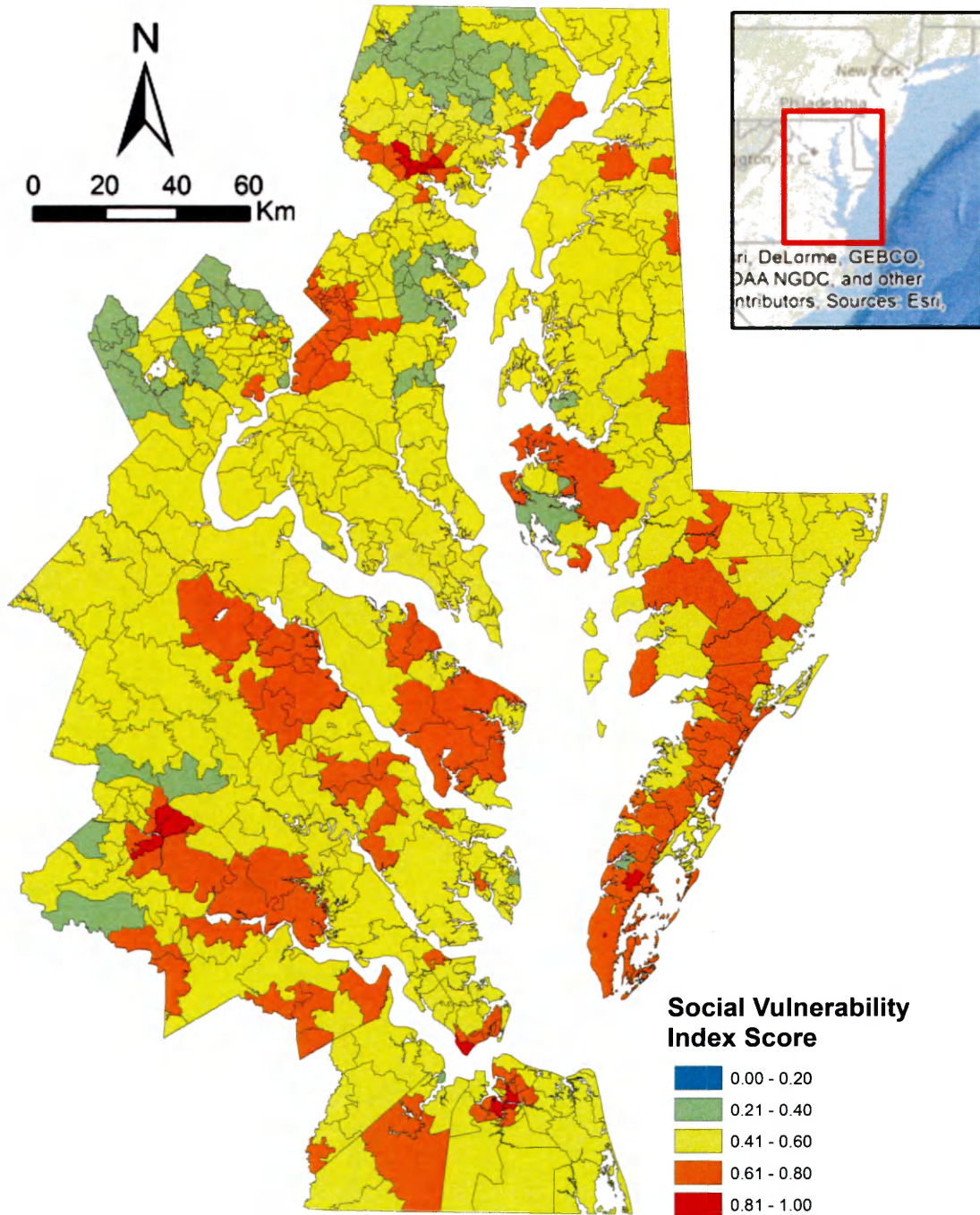


Figure B1.1 – Simplified CCRM comparative Chesapeake social vulnerability index for 2000 based off of income, race, age, and poverty.

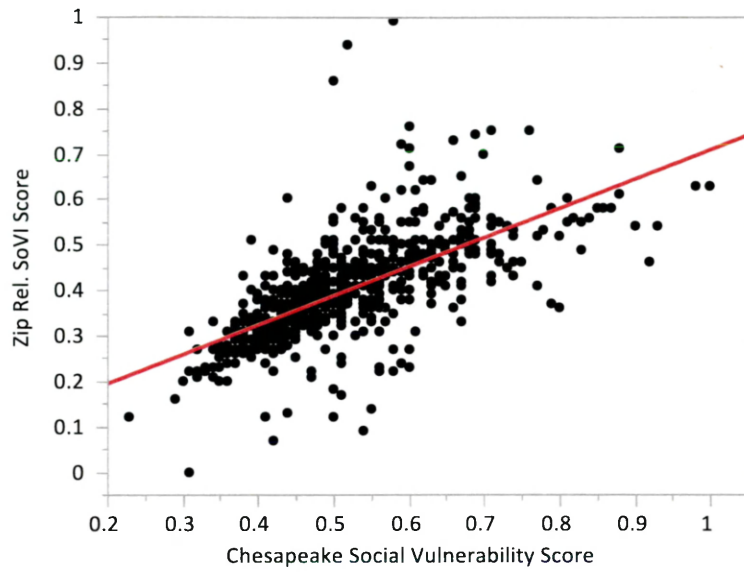


Figure B1.2 – Linear Regression of simplified four-factor Chesapeake social vulnerability index against application of official SoVI scores relative to the region. Adjusted R squared value of 0.44 with an equation of $SOVI01 = 0.07 + 0.64 * CCRMSocVuln$.