Vulnerable Populations to Climate Change in New Jersey

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ABSTRACT

The purpose of this paper is to identify the characteristics of vulnerable populations to climate change in New Jersey, determine where concentrations of these vulnerable groups are located in the state, and assess the relationship between these groups and environmental hazards associated with climate change. There are many methods and definitional approaches to assessing vulnerability. This study more narrowly focuses on social vulnerability, which examines "the susceptibility of social groups to potential losses from hazard events or society's resistance and resilience to hazards" (Blaikie et al., 1994 and Hewitt,1997 as cited in Cutter et al., 2000, p.716). The Social Vulnerability Index 2006-10 (SoVI) (Hazards & Vulnerability Research Institute, 2013) method was employed in the assessment to identify characteristics of socially vulnerable groups to environmental hazards in New Jersey. Geographic Information Systems (GIS) were then used to identify concentrations of these groups within the state and preform environmental overlays of current and projected hazards related to climate change, specifically flooding and sea-level rise. The results of the SoVI analysis explain nearly 70% of the variance in the social vulnerability data, with three significant factors driving the majority of this variance. These significant factors can be categorized as Family Structure, Race and Socioeconomic Status; Linguistic Isolation, Ethnicity and Population Density; and Age. Given the scale and resources of the study, some diversions from the SoVI method were taken and are explained further throughout the report.

INTRODUCTION

The purpose of this paper is not to provide a review of the vulnerability literature, which is vast (see Eakin & Luers, 2006; Adger, 2006; Füssel & Klein, 2006; Birkmann, 2007; Cutter et. al., 2009; IPCC, 2012), but rather, to identify characteristics of vulnerable populations that are specific to New Jersey and how these groups might experience current and projected environmental hazards. However, a brief discussion regarding the conceptual approach taken in this study in regards to vulnerability is warranted.

Although there are many definitions of vulnerability, it has broadly been defined as the potential for loss (Cutter, 1996; Cutter et al., 2000). Expanding on this definition, the Intergovernmental Panel on Climate Change (IPCC) has defined vulnerability as the "degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity" (IPCC, 2007, p.6). Areas of social vulnerability research have also focused on the influential factors, both extrinsic and intrinsic, which contribute to the differential experience and recovery from hazard events. Intrinsic factors exist naturally within a person, such as age, race/ethnicity, gender, physical ability. Extrinsic factors occur outside of these internal factors, but contribute to overall vulnerability such as, access to financial resources, knowledge and information, geographic location, and occupation (Eakin & Luers, 2006; Shonkoff et al., 2011; California Emergency Management Agency [Cal EMA] and California Natural Resources Agency [CNRA], 2012). This approach recognizes that there are underlying social conditions that affect how individuals, which are equally affected by an event, can respond and recover differently (Blaikie et al., 1994 as cited in The Heinz Center, 2002; Cutter et al., 2000; Herberger, 2009).

The SoVI was used in this analysis given its ability to take into account social and demographic factors identified in the literature as increasing the likelihood of vulnerability to environmental hazard events (Cutter et al., 2003; Sarewitz et al., 2003). Researchers, organizations and federal agencies have applied the SoVI methodology to better understand social vulnerability in the United States (Cutter, 2008; Oxfam, 2009; Dunning & Durden, 2011; Cooley et al., 2012; Martinich et al., 2013; Nutters, 2013). The SoVI method through the use of principal components analysis is able to take demographic and social input variables and form multiple variable characteristics of vulnerable groups by identifying variables that are highly correlated to each other. This method coincides with vulnerability research, which has observed that groups often display overlapping characteristics of vulnerability (Cal EMA and CNRA, 2012). The purpose of this analysis is to find out what groupings or overlaps occur and where these populations are located within the state. However, this method should not be mistaken for a predicative model of vulnerability outcomes.

Given the complexities of climate, it is difficult to attribute the causation of an extreme weather event to climate change (Solomon et al., 2007; O'Brien et al., 2008). However, impacts from climate change expected in New Jersey include, rising sea levels and an increased magnitude of storm surge, increased temperatures, and a likely continuance of the trend towards increased occurrences of heavy precipitation events (Broccoli et al., 2013). The indirect effects of these impacts extend well beyond those listed here, with those who are already socially vulnerable at highest risk.

Common themes displayed in groups identified as having heightened social vulnerability include a lack of access to resources and information, social isolation, and mental or physical dependence. Specific attributes influencing vulnerability include low socioeconomic status, racial and ethnic categories, linguistic isolation, low educational attainment, gender (female), age (the very young and very old), compromised health and cognitive constraints, family structure (single parents and/or high number of dependents), housing tenure (renters) and occupation (service sector) (Morrow, 1999; Tierney et al., 2001; The Heinz Center 2002; Cutter et al, 2003; Newcomb College Center for Research on Women, 2008; Cutter & Finch, 2008; Balbus & Malina, 2009; Morello-Frosch et al., 2009; Gamble et al., 2013).

DISCUSSION OF GOALS

The purpose of this report is to identify vulnerable populations to climate change, which are specific to New Jersey. In doing so, the report aims to identify the characteristics of these groups and where concentrations of these populations are located in the state. To demonstrate the potential impacts to these communities from environmental hazards related to climate change, flooding and future sea-level rise is examined. Lastly, programs aimed at enabling communities to assess their own vulnerabilities will be discussed.

DESCRIPTION OF DATA

The data collected for this analysis were derived primarily from the 2010 Census and 2006-2010 American Community Survey. An initial set of 30 variables were collected for 2,010 census tracts in New Jersey. A census tract is a geographic unit of measurement used for the presentation of statistical data. Census tracts contain between 1,200 – 8,000 people and are contiguous in area, often following neighborhood boundaries within a municipality. However, census tracts can cross municipal boundaries, but are almost always contained within the boundaries of a county. A smaller unit of measurement is the Census Block Group, which subdivides the census tract and consists of 600-3,000 people. Census block groups consist of clusters of Census Blocks, the finest unit of measurement within the hierarchy of Census geographic entities (United States Census Bureau, 2010 & 2012). The variables used for the analysis were normalized using percentages, median values, per capita values or density functions.

Limitations of data

The reliance on publically available data in this analysis is both an asset and hindrance to a wider application of the method. The challenge with relying on publically available data is that the scale and type of data available varies by each variable. For instance, public health data and variables related to income are not available at very fine scales, such as block group or block level. However, when measuring social vulnerability and demographics, the finest scale data possible is what is most desirable. The reason for this is that a "smoothing" effect can occur, where pockets of high concentrations of a variable can disappear as data is aggregated when moving to larger scales of measurement (Cooley et al., 2012). However, it is largely due to a reliance on publically available data that enabled this analysis, as resources were not available for the creation of data.

In addition, many of the variables rely on estimates provided by the American Community Survey (ACS). The United States Census Bureau generates estimates for the ACS based on a survey of a sample of the population, which differs from the Decennial Census, which provides raw counts. The accuracy of ACS estimates generally decreases with increasing granularity of the scale of the data used.

It should also be noted that the variables used in the analysis serve as proxy measures and are not predictive of vulnerability outcomes. One area lacking in this application of the SoVI methodology is a focus on public health. Two measures within the original SoVI methodology aim to serve as indicators of public health (hospitals per capita and percent of population without health insurance). However, these data were not publically available for New Jersey at the census tract level and therefore, not included in this analysis. It would have been useful, for example, to have the proportion of people who are disabled as a variable. But this is not available at this scale, nor do the census files tell us how many people have disabilities, mobility limitations and other measures that make them more susceptible to hazard events.

In order to conduct the analysis, normalization of all variables at a uniform scale of measurement was necessary. As noted earlier, a "smoothing" effect can occur when using larger scaled data. However, the distortion caused by smoothing is less of a problem with census tract data than it is with municipality and county scale data. In addition to these limitations, the distribution of data when using GIS is assumed to be even across an enumeration unit (for example, census tract). In reality, the distribution of the population could differ greatly and the data should not be mistaken for point values. The results of this analysis should be considered with an understanding of these limitations.

EXPLANATION OF METHOD

The methodology employed for the analysis followed the approach taken in the Social Vulnerability Index 2006-2010 (SoVI) developed by Dr. Susan Cutter of the Hazards & Vulnerability Research Institute at the University of South Carolina. However, some divergence from this method was taken and is explained in greater detail below. The SoVI uses proxy variables that the research literature has suggested contribute to a system or individual's ability to prepare for, respond to, and recover from hazards. The SoVI consists of 30 normalized variables taken primarily from data provided in the 2010 Decennial Census and the 2006-2010 American Community Survey. A principal components analysis is applied to the dataset to reduce the initial set of variables to a smaller set of key factors, which explain a majority of the variance in the data. These key factors contain correlated variables from the initial dataset (Hazards & Vulnerability Research Institute, 2013). Principal components analysis uses matrix algebra to create a set of multivariable components that mathematically incorporate multiple variables into few components. For example, we know that high income, a college education, white collar employment, and a valuable home are individual indicators of high socioeconomic status. Principal components analysis will create a socioeconomic status component and generate a socioeconomic status factor score using a regression equation for every census tract. The average value of the factor scores for every component is 0.0, which means that every factor score for every census tract is comparable. Hence, a 1.1 factor score for census tract 16 means a high socioeconomic status whereas a -1.1 means low socioeconomic status.

In order to display the relationship between the individual census tracts and the key factors, factor scores are generated for each enumeration unit for each multivariable factor. These scores are a measure for how strongly the individual tract displays the characteristics of each key factor. A final index is then created by summing the factor scores for each enumeration unit. A step-by-step guide to the method for the SoVI 32 indicator model, the SoVI Recipe, is included in Figure 1 of the Appendix (Hazards & Vulnerability Research Institute, 2011).

Benefits

The benefit of using the SoVI is that it provides a recreatable and objective method for quantifying and spatially displaying vulnerability. Using publically available data, normalized variables are collected at a uniform enumeration unit. For this analysis, data was collected at the census tract level for the state, given the lack of availability of some data at finer scales. Please note, as above, that census tracts are surrogates for neighborhoods with 1,200-8,000 people. Census block groups are areas of 600-3,000 that comprise census tracts.

Limitations

As with any methodology, there are limitations inherit to the approach. Of particular note with the SoVI, is the use of normalized variables (Hazards & Vulnerability Research Institute, 2011). In order to conduct a comparison across variables, normalizing the variables is necessary. Normalized variables are good for displaying concentrations, but these results must be interpreted carefully and should not be confused with a measurement of raw size. An illustrative example of this concept can be understood by comparing two census tracts with differing population sizes. Census tract one displays 10% of the measured variable and is home to a total population of 1,000 persons. Census tract two displays 10% of the same variable and has a total population with 8,000 persons. In a comparison, these two census tracts would appear to be similar given that they both display 10% of the measured variable; however, the total amount of persons that these two percentages represent is drastically different – 100 and 800 persons respectively.

It should also be noted that the variables represented in the index are weighted on indicators of socioeconomic status and race. Although these characteristics have been identified throughout the literature as contributing to social vulnerability, other factors of vulnerability, such as age are not equally reflected in the overall measurement. In addition, the method displays current vulnerability and does not account for a temporal analysis that is, change in vulnerability. This information would be helpful in understanding where a community is headed (more or less vulnerable) and how to address the underlying drivers of vulnerability.

Divergence from SoVI methodology

As mentioned above, some divergence from the method was taken due to the scale of the study. Out of the original 30 variables described in the SoVI 2006-2010, two variables (hospitals per capita and percent of population without health insurance) were not included because the data were not publically available at the census tract level. The analysis was first run with 30 variables, 28 variables from the SoVI (excluding hospitals per capita and percent of population without health insurance) and two additional variables, total population and percent children living in single parent family households. After examining the results of the analysis, three variables (total population, percent of households earning greater than $200,000 annually and percent non-urban population) were “clipped” or excluded from the analysis, as they did not significantly add to the variance in the data. A final list of the 27 variables included in the analysis can be found in Table 1 of the Appendix.

Census tracts displaying no data for a given variable were left as null values. These null values are a reflection of either zero population or missing data within the tract and the population is too small for the Census Bureau to generate an estimate. Unfortunately, if a census tract is missing any one of the variables the tract is dropped entirely from the analysis. One approach that has been taken to solve this problem is to replace null values with averages, but given the scale of the study this was deemed inappropriate because too much data that are not actual data would have to be inserted for these census tracts. A total of 215 out of 2010 census tracts were dropped from the analysis because of null values.

The most notable divergence from the method is that an overall social vulnerability index was not created because the key results are clustered in a relatively few factors. By displaying each factor set separately the reader is able to consider each vulnerability cluster rather than to consider all of them as a single number that could be misleading. Rather, each of the key factors was mapped separately to highlight correlated variables or characteristics of vulnerable groups. Summing the key factors to create an index score gives equal weight to each factor and areas displaying fewer of the key factors appear less vulnerable. Given the uniqueness of some of the variables, such as measures for the elderly population, these areas would incorrectly appear as less vulnerable in a summed index.

RESULTS

After completing the principal components analysis, nearly 70% of the variance in the data could be attributed to five factors, of which three were deemed to be significant. The three significant factors have been classified as 1) Family Structure, Race and Socioeconomic Status; 2) Linguistic Isolation, Ethnicity and Population Density; and 3) Age. A chart displaying the results of the analysis, with percent of variance explained for each factor can be found in Table 2 of the Appendix. Factor scores were generated by census tract and mapped, with the data categorized by quintiles. Unique variables, specifically, percent of population living in nursing and skilled-nursing facilities and percent mobile homes were mapped separately. These variables were mapped separately because they are highly associated with vulnerability and not strongly correlated with any of the other variables in the analysis, which can lead to this data being hidden in the results. The top 20% of factor scores within each key factor were then taken to display the impact of an environmental hazard, in this case flooding and sea level rise, on vulnerable groups. The results of this analysis are included below and captured in Figures 2-28.

Characteristics and Location of Vulnerable Groups in New Jersey

Within the vulnerable groups identified, those strongly displaying characteristics of factor 1; or the top 20% of census tracts whose populations were characterized by family structure (single parent, female-headed), race (black), socioeconomic status (low) and poverty, were concentrated within the state's major cities, such as Newark, Camden, Trenton, Jersey City, and portions of the more rural south in Cumberland, Gloucester, Salem, Camden, Atlantic and Burlington counties. These concentrations can be seen in greater detail in Figure 2.

Groups strongly identifying with factor 2; or the top 20% of census tracts characterized by linguistic isolation (limited English proficiency), Hispanic ethnicity and high population density populations were clustered primarily in portions of Hudson, Bergen, Essex, Passaic, Union and Middlesex counties. Concentrations of these census tracts can be seen in greater detail in Figure 3.

The top 20% of census tracts with high concentrations of seniors, or factor 3, were primarily located along the New Jersey coastline and outside of the state's major cities. As seen in Figure 4, this group is typically located in areas without high concentrations of factor 1 or 2. For example, urban areas with high concentrations of factor 1 or 2, such as the cities of Trenton, Newark, or Elizabeth have no or relatively few census tracts with high concentrations of factor 3. In addition, coastal communities, primarily in Monmouth and Ocean counties, which have high concentrations of factor 3, have very low concentrations of factors 1 or 2.

Outside of the three primary factors, the percentage of the nursing home population and point locations for nursing home facilities were also mapped. Given the relatively small nursing home population within the state, the top 20% of census tracts were those that displayed any percentage of nursing home population greater than zero and are displayed in Figure 5. These top 20% of census tracts can be seen in every county of the state and are displayed in shades of red, increasing in darkness as the percentage of the nursing home population increases. The highest total number of these top 20% of census tracts are found in Essex, Bergen, Monmouth, Ocean, Middlesex and Union counties, however, these counties also have a relatively high number of overall census tracts within the county. Whereas the largest proportion of the top 20% of census tracts to total tracts within a county were found in Warren, Salem, Hunterdon, Mercer, Ocean, Somerset, Union, Cape May and Morris counties.

Figure 5 helps to display the issue with using percentage of the population versus metrics that account for raw size. As can be seen from the map, there are census tracts in Bergen, Hudson, Essex and Passaic counties that have no or relatively low percentages of the population residing in nursing homes, but a high number of the state's nursing home facilities. The reasoning for this is because these counties have a much larger total population size, so the percent of the population that does reside in nursing homes is much smaller in comparison to other regions of the state with smaller population size.

Lastly, the percentage of mobile homeownership was also mapped separately as it was not highly correlated to the other variables in the analysis, but strongly related to social vulnerability. The top 20% of mobile homeownership census tracts are displayed in Figure 6, darkening in shades of red as the percentage of mobile homeownership increases in the census tract. Similar to the nursing home population, the percentage of the population that is a mobile homeowner is relatively small, and any percentage of mobile home ownership within the census tract greater than zero fell within the top 20 percent of all census tracts in the state. The largest concentrations of mobile home ownership fell within the southern portion of the state in Ocean, Burlington, Gloucester, Salem, Cumberland, Cape May and Atlantic counties.

Summary of High Social Vulnerability Areas in New Jersey

Tables 3 and 4 and Figure 7 summarize the results of these analyses. These figures display the concentration of the top 20% of all vulnerability factors or unique vulnerability variables across the state. Figure 7 displays the spatial distribution of the data represented in Table 3. In summary, a high proportion of high social vulnerability census tracts are collectively located in urban areas, the rural south, and in coastal areas that are frequently impacted from storm events.

Table 3 displays the range of social vulnerability (with a maximum score of five, with three vulnerability factors and two unique variables) that could be attributed to each census tract, from no data to three or more vulnerability factors or unique vulnerability variables. The table summarizes the number of tracts in the state that fall within each category. For example, starting in the first column, zero vulnerability factors or unique vulnerability variables are expressed in 625 or 31% of census tracts within the state. A total of 36 percent of all census tracts within the state have at least one vulnerability factor or unique vulnerability variable. The last column in the chart provides the cumulative number of census tracts that fall within each category and all categories that precede it.

Table 3: Census Tracts with High Social Vulnerability in New Jersey

Census Tracts with High Social Vulnerability*			
Number of Vulnerability Factors or Unique Vulnerability Variables	Number of Census Tracts	Percentage of Census Tracts	Cumulative Number of Census Tracts
No Data**	215	11%	215
0	625	31%	840
1	726	36%	1566
2	340	17%	1906
3+	104	5%	2010

*High vulnerability is expressed by tracts that fall within the top 20% of a single significant factor or unique variable. The significant factors are 1) Family Structure, Race and Socioeconomic Status; 2) Linguistic Isolation, Ethnicity and Population Density; and 3) Age. The two unique variables that were included in the analysis are Percent of Population Living in Nursing and Skilled-nursing Facilities and Percent Mobile Home Ownership.

**If a tract had no data for any one of the three significant factors or two of the unique variables, the entire tract was excluded from the analysis. This does not imply that these tracts are not vulnerable, only that they lack sufficient data for this assessment.

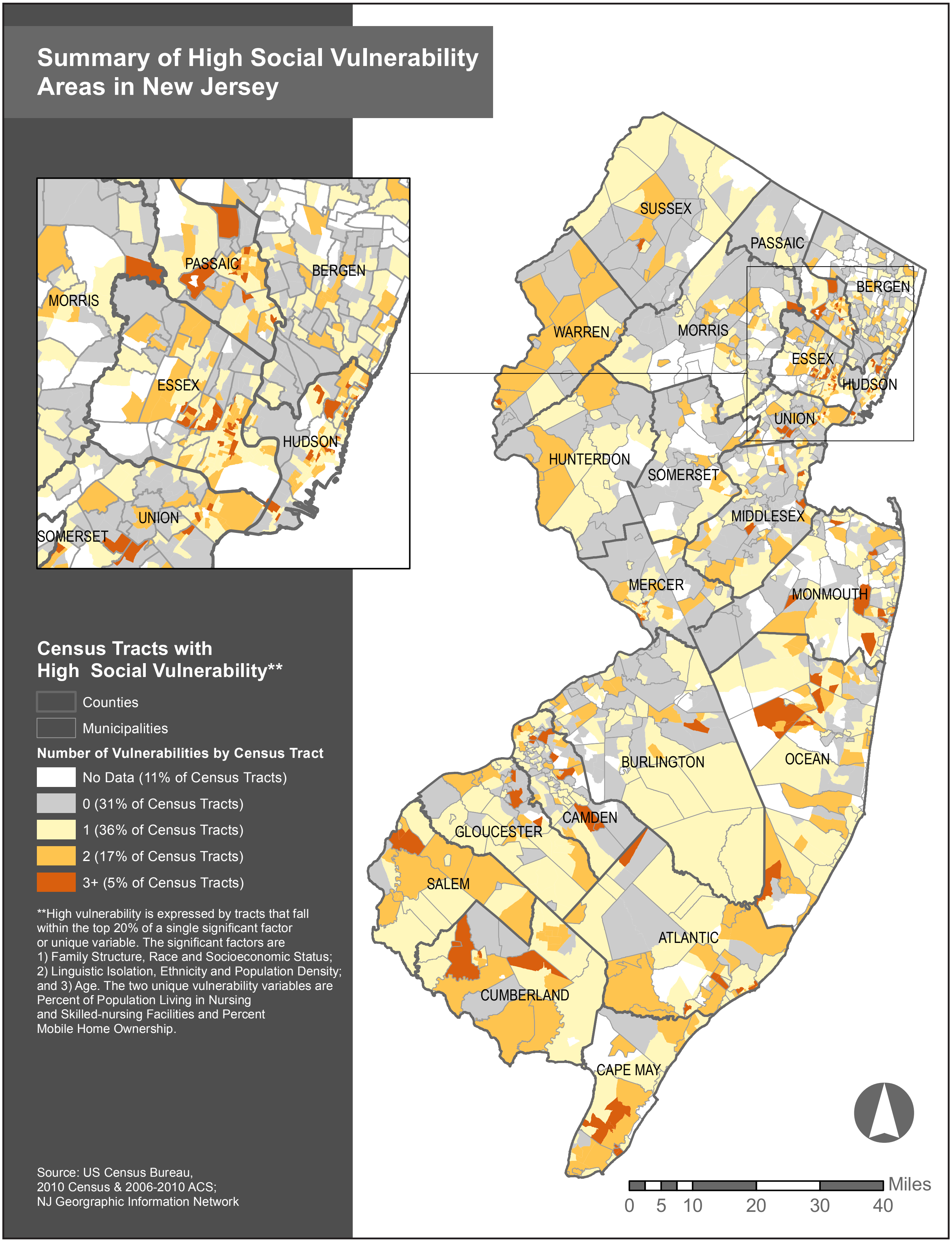
Table 4 displays the concentration of social vulnerability within the state by county. The table summarizes the number of census tracts that display two or more vulnerability factors or unique vulnerability variables by county and provides the percentage that these tracts represent within each county. For example, Essex County has 60 census tracts that display two or more vulnerability factors or unique vulnerability variables, which represents 29% of all of the census tracts within Essex County. Finally, the chart provides the total number of census tracts within the state that display two or more vulnerability factors or unique variables (444) and the percentage that these tracts represent within all tracts in the state (22%).

Table 4: Summary of High Social Vulnerability within New Jersey Counties

County Summary of High Social Vulnerability*			
Counties	Census Tracts with 2 or more Vulnerability Factors or Unique Vulnerability Variables	Total Census Tracts in County	Percent Highly Vulnerable Census Tracts
Atlantic	25	70	36%
Bergen	24	179	13%
Burlington	13	114	11%
Camden	29	127	23%
Cape May	13	33	39%
Cumberland	16	35	46%
Essex	60	210	29%
Gloucester	12	63	19%
Hudson	46	166	28%
Hunterdon	3	26	12%
Mercer	19	77	25%
Middlesex	20	175	11%
Monmouth	23	144	16%
Morris	14	100	14%
Ocean	32	126	25%
Passaic	30	100	30%
Salem	12	25	48%
Somerset	7	68	10%
Sussex	4	41	10%
Union	32	108	30%
Warren	10	23	43%
Total Census Tracts in New Jersey	**444**	**2010**	**22%**

*High vulnerability is expressed by tracts that fall within the top 20% of a single significant factor or unique variable. The significant factors are 1) Family Structure, Race and Socioeconomic Status; 2) Linguistic Isolation, Ethnicity and Population Density; and 3) Age. The two unique variables that were included in the analysis are Percent of Population Living in Nursing and Skilled-nursing Facilities and Percent Mobile Home Ownership.

Figure 7. Summary of High Social Vulnerability Areas in New Jersey



Superstorm Sandy Impacts

The top 20% of each of the vulnerable factors and unique vulnerability variables described above were examined in relation to the storm surge extents of Superstorm Sandy, which hit New Jersey on October 25, 2012. As illustrated by Figures 8-12, all of the vulnerable groups were impacted by the storm. This is especially true for concentrations of low-income African-American populations in Union, Essex, Cumberland, and Atlantic counties; linguistically isolated Hispanic populations in Union, Essex, Bergen and Hudson counties; senior and nursing home populations along the coast; and mobile homeowners in Ocean, Burlington, Atlantic, Cape May and Cumberland counties. In the following paragraphs we estimate how many people live in the most highly vulnerable areas. These estimates should not be taken at face value because not every resident was in the impacted area and the data do not match who was present in the areas during the event.

Out of the top 20% of census tracts identifying as factor 1, or characterized by family structure (single parent, female-headed), race (black), socioeconomic status (low) and poverty, 118 of these census tracts were impacted by Superstorm Sandy. Assuming that all persons were affected in a tract that was impacted by the surge (touches the census tract), these tracts account for 425,686 persons with an average population density of 8,106 persons per square mile.

For factor 2, the top 20% of census tracts characterized by linguistic isolation (limited English proficiency), Hispanic ethnicity and high population density populations, 147 census tracts were impacted by Superstorm Sandy's storm surge extents. Again, assuming all persons were affected in the census tract that was impacted, these tracts account for 575,047 persons with an average population density of 19,684 persons per square mile.

Factor 3, the top 20% of census tracts with high concentrations of seniors, 161 census tracts were impacted by Superstorm Sandy's surge extents. Assuming all persons were impacted within these tracts, the total population within these tracts is 563,021 persons, with an average population density of 5,051 persons per square mile.

Out of the top 20% of census tracts with high concentrations of nursing home residents, 95 census tracts were impacted by Superstorm Sandy's surge extents. These census tracts represent a total of 442,423 people of which 13,099 are in the nursing home population, or about 2.9%. These census tracts have an average population density of 909 persons per square mile.

Out of the top 20% of census tracts with high concentrations of mobile home ownership, 143 census tracts were impacted by Superstorm Sandy's surge extents. Within these census tracts, the average percentage of mobile home ownership is 4.4 percent.

Flooding

Similar to Superstorm Sandy, the impacts of flooding on socially vulnerable groups in New Jersey could be widespread. The best available data from the Federal Emergency Management Agency (FEMA) was used to display these impacts. Currently, FEMA is in the process of updating the flood maps for the entire state of New Jersey, but at the time of this report a complete map for the state did not exist. Where new data existed; for example, in the form of working or advisory maps along the coastline of coastal counties, this data was used.[1] Otherwise, the older but still current maps for inland portions of coastal counties and other non-coastal counties were used.

1 At the time of compiling the data layers, preliminary work maps were available for coastal portions of Atlantic, Cumberland, Essex, Hudson, Middlesex, Monmouth, Ocean, and Salem counties. Advisory maps were available for coastal portions of Bergen, Burlington, Cape May and Union counties.

The results of the flooding analysis were as follows, and are captured in Figures 13-18 in the Appendix:

- Concentrations of factor 1, or the top 20% of census tracts highly characterized by family structure (single parent, female-headed), race (black), socioeconomic status (low) and poverty, coincide with floodprone land in Union, Camden, areas of likely flooding coincide with high concentrations of vulnerable populations in portions of Union, Ocean, Camden, Salem, Cumberland, Cape May and Atlantic Counties.

- Areas of likely flooding coincide with concentrations of factor 2, the top 20% of census tracts characterized by linguistic isolation (limited English proficiency), Hispanic ethnicity and high population density populations, primarily in Union, Essex, Hudson and Bergen counties.

- Among the vulnerable groups impacted by flooding the impacts to seniors, or factor 3, appear significant. High concentrations of senior populations coincide with floodprone lands along almost the entirety of the New Jersey coastline, including Hudson, Bergen, Essex, Monmouth, Ocean, Atlantic, Cape May, Cumberland, Salem, and Gloucester counties.

- Nearly all New Jersey counties, with the exception of Burlington and Mercer counties, have high concentrations of nursing home populations and/or nursing home facilities that lie either directly in or in close proximity to floodprone lands.

- Lastly, concentrations of mobile homeowners coincide with floodprone lands in Monmouth, Ocean, Burlington, Gloucester, Salem, Cumberland, Cape May and Atlantic counties.

Sea Level Rise

Global sea level rise data developed by the National Oceanic and Atmospheric Administration for the National Climate Assessment was attained to model the potential impact of sea level rise on vulnerable populations in New Jersey. These estimates are based on global models and do not account for land subsidence or New Jersey specific tide gauge data. Nonetheless, these estimates provide a good starting point for assessing where vulnerable groups could be exposed to rising sea levels.

Projected sea level rise by year 2050 and year 2100 are provided for each of the vulnerable groups and are included in Figures 19-28 of the Appendix. Within each projection year, four possible scenarios of sea level rise are presented, with two intermediate scenarios. These scenarios each take into account differing assumptions and data. The “Lowest Scenario” is a linear model of observed rates of global sea level rise based on historical tide gauge records since 1900. The “Intermediate Low Scenario” projection primarily takes into account the impacts of ocean warming. The “Intermediate High Scenario” is based on the high end average of global scientific projections of sea level rise. The “Highest Scenario” is calculated taking into consideration global ocean warming and maximum glacier and ice sheet lost by each projection year (2050, 2100) (Parris et al., 2012). When analyzing which scenario to use, it is recommend that the Highest Scenario be used where there is very little room for risk.

For all of the projections, the counties that will be most directly impacted by rising sea levels are situated along New Jersey’s eastern coastline. Among these counties, the slightest level of sea level rise results in dramatic impacts. For example, the Lowest Scenario of projected sea level rise for year 2050, an increase of only .3 feet would put areas of Hudson, Bergen, Essex, Union, Middlesex, Monmouth, Ocean, Burlington, Atlantic and Cape May counties under water. All of the vulnerable groups discussed throughout this analysis have the potential to be greatly impacted by only the smallest increase in sea level rise.

DISCUSSION

The results of this analysis help to describe the characteristics and spatial distribution of vulnerable populations to environmental hazards in New Jersey. Although the impacts of climate change are broader than storm events, the maps included in this analysis demonstrate the potential impact of extreme events on the most vulnerable populations in the state. This report will hopefully inform discussions around the characteristics of vulnerable populations in the state, and demonstrate the need for locally based assessments.

Local leaders, decision makers and stakeholders have a great understanding of the composition of their communities, likely at a finer level than what can be seen through census tract statistics. This local level knowledge is vital in determining solutions to address particular vulnerabilities within the community. In addition, access to more publically available data at finer scales of resolution would be helpful for local decision makers and stakeholders in assessing and preparing vulnerable populations for the impacts of a changing climate.

Some measures have been taken within the state to incorporate a more holistic assessment of vulnerability at the community level. The New Jersey Department of Environmental Protection (NJDEP), Office of Coastal Management (CMP) began development of a tool to allow incorporation of built environment, natural environment and social vulnerability measures into local vulnerability assessments (NJDEP, 2011). The Office of Coastal Management has also developed an evaluation tool, Getting to Resilience, to assist communities in understanding linkages between local planning actions and opportunities for mitigation and adaptation with the goal of reducing vulnerability and increasing community resiliency. Although targeted towards coastal communities, the tool guides users through collecting data and using GIS to compile a vulnerability assessment for an area. As a result of further enhancement of these tools by the Jacques Cousteau National Estuarine Research Reserve and the Rutgers University Center for Remote Sensing and Spatial Analysis (CRSSA), both NJ Flood Mapper and Getting to Resilience are now available online and sponsored in conjunction with other partners, such as Sustainable New Jersey and the Barnegat Bay Partnership.[2] The enhanced tools allow users to visualize impacts of flooding and potential sea level rise on their communities to contribute to their identification of risk and vulnerabilities. Further enhancement of the tools is now underway with additional partners including the National Oceanic and Atmospheric Administration (NOAA), the New Jersey Recovery Fund, the Rutgers University Edward J. Bloustein School of Planning and Public Policy and the non-profit New Jersey Future. These efforts will more systematically tie NJ Floodmapper to Getting to Resilience, incorporate the outcomes of this social vulnerability mapping into the tools along with integration of other key economic, environmental, and infrastructure-related datasets, and to apply these tools to inform local vulnerability assessments as part of post-Sandy recovery efforts.

2 Getting to Resilience: A Community Planning Evaluation Tool. Last accessed February 22, 2014 from http://www.prepareyourcommunitynj.org/.

APPENDIX

Figure 1. The SoVI Recipe, Hazards and Vulnerability Research Institute

January 2011

The SoVI Recipe

1. Collect the input variables. SoVI variables are derived primarily from the US Census Bureau using the Census Data Engine with some ancillary data from the Geographic Names Information System (GNIS). Alternate data sources may include City and County Databook or individual county offices.

2. Normalize all variables as either percentages, per capita values, or density functions (i.e. 'per square mile').

3. Verify accuracy of the dataset using descriptive statistics (i.e. min/max, mean, standard deviation). Missing values can be replaced by substituting the variable's mean value for each enumeration unit. The statistical procedure will not run properly with missing values. Census units with population values of zero should be omitted.

4. Standardize the input variables using z-score standardization: $z = \frac{\chi - \mu}{\sigma}$. This generates variables with a mean of 0 and standard deviation of 1.

5. Perform the principal components analysis (PCA) using a varimax rotation and Kaiser criterion for component selection. This rotation reduces the tendency for a variable to load highly on more than one factor. Next, set parameters for the extraction of factors. This can be aided by the examination of a scree plot for significant drops in Eigenvalue as the number of components included in the analysis increases. While some disjoints in the scree are anticipated (such as those that occur between the first few components) subsequent decreases in Eigenvalue indicate appropriate thresholds for factor extraction.

6. Examine the resulting factors. Determine the broad representation and influence on (i.e. increase or decrease) social vulnerability for each factor by scrutinizing the factor loadings (i.e. correlation between the individual variable and the entire factor) for each variable in each factor.

7. Factors are named via the choosing of variables with significant factor loadings (or correlation coefficients)--usually greater than .500 or less that -.500. Next, a directional adjustment (or cardinality) is applied to an entire factor to ensure that the signs of the subsequent defining variables are appropriately describing the tendency of the phenomena to increase or decrease vulnerability.

Factor 1 below is an indicator of class and poverty. As shown in the table, the dominant factors that theoretically **increase** vulnerability (people over age 25 w/o a diploma, percent in poverty) have a significant **positive** factor loading. Conversely, the other 2 dominant factors, while still being indicators of socioeconomic status (percent employment and per capita income), theoretically **decrease** vulnerability, and exhibit a **negative** factor loading. Thus, the cardinality of this factor remains positive (+) as the signs on the factor loadings for the individual variables is consistent with their tendency on social vulnerability.

Factor 2 is an indicator vulnerable age groups (i.e. the old and the young). As you can see, both the old and the young, as well as their proxies embody the dominant factors. In examining the variables' factor scores, we see that they exhibit both positive and negative factor loadings, but since all of the variables (i.e. kids under 5, elderly over 65, median age, and social security beneficiaries) have tendency to

increase vulnerability, we apply an absolute value to Factor 2 to dissolve the negative sign on the factors that increase vulnerability, and maintain the cardinality of the variables with non-negative loadings.

Alternatively, some factors may exhibit significant **positive** factor loadings on variables that theoretically **decrease** vulnerability. Factor 4 below is one such example, with positive loadings on mean rent, mean house value and percent rich. To adjust the sign of this factor so that those variables appropriately represent their tendency to decrease social vulnerability, a negative cardinality is applied, and the factor is multiplied by -1.

8. Save the component scores as a separate file.

9. Place all the components with their directional (+, -, ll) adjustments into an additive model and sum to generate the overall SoVI score for the place.

10. Map SoVI scores using an objective classification (i.e. quantiles or standard deviations) with 3 or 5 divergent classes so illustrate area of high, medium, and low social vulnerability.

The following is an example of the 2000 County SoVI illustrating the factors loadings, naming of the factor, and the sign adjustment (cardinality), as well as the additive formula for the SoVI score. The SoVI score is computed for each enumeration unit (e.g. county, census tract, block group, etc.).

Sign Adjustment	Factor	Name	Dominant Variables	Factor Loading
+	1	Class and Poverty	QED12LESS	0.873
			QPOVTY	0.867
			QCVLBR	-0.807
			PERCAP	-0.776
ll	2	Age	MEDAGE	-0.891
			QKIDS	0.836
			PPUNIT	0.829
			QSSBEN	-0.828
			QPOP65O	-0.780
+	3	Rural, Special Needs	QRFRM	0.795
			QAGRI	0.690
			HOSPPC	0.654
			NRRESPC	0.520
-	4	Wealth	HODENT	0.682
			QASIAN	0.660
			MEANS_HSEVAL	0.579
			QRICH	0.514
			MC_RENT	0.507
+	5	Race and Gender	QFEMLBR	0.773
			QBLACK	0.703
			QFHH	0.556
			QSPANISH	-0.555
+	6	Female	QFEMALE	0.849
+	7	Service Workers	QSERV	0.782
+	8	Ethnicity and Unemployment	QINDIAN	0.861
			QCVLUN	0.540
+	9	Migrants	QTRAN	-0.837
			MIGRA	0.502

SoVI Score = Factor 1 + l(Factor 2)l + Factor 3 - Factor 4 + Factor 5 + Factor 6 + Factor 7 + Factor 8 + Factor 9

Table 1. Final Variables

This table displays the final variables used in the principal component analysis and the resulting extraction values, which measure the communality between an individual variable to all other variables.

Final Variables	Communalities*
Percent Asian	0.702
Percent Black	0.770
Percent Hispanic	0.790
Percent Native American	0.534
Percent of Population Under 5 Years or 65 and Over	0.856
Percent of Children Living in Married Couple Families	0.902
Percent of Children Living in Single Parent Family Households	0.888
Median Age	0.890
Percent of Households Receiving Social Security	0.808
Percent Poverty	0.741
Per Capita Income	0.772
Percent Speaking English as a Second Language with Limited English Proficiency	0.840
Percent Female Population	0.630
Percent Female Headed Households	0.877
Percent of Population Living in Nursing or Skilled-nursing Facilities	0.105
Percent of Population with Less than 12th Grade Education	0.578
Percent Civilian Unemployment	0.544
Population per Square Mile	0.668
People per Unit	0.533
Percent Renters	0.865
Median House Value	0.658
Median Gross Rent	0.392
Percent of Mobile Homes	0.572
Percent Employment in Extractive Industries	0.652
Percent Employment in Service Industry	0.600
Percent Female Participation in Labor Force	0.574
Percent of Housing Units with No Car	0.820

*Communalities are measures of the variance of a single variable shared with the extracted factors. Numbers range from 0.0 to 1.0. The higher the number the more variance is part of the extracted principal components.

Table 2. Results of the Principal Components Analysis with Factors and Percent Variance Explained

Factor	Cardinality	Name	% Variance Explained	Dominant Variables	Component Loading**
1	+	Family Structure (Single Working Mothers), Race (Black), Socioeconomic Status (Low)	36.071	Percent Children Living in Single Parent Households	0.895
				Percent Female Headed Households	0.870
				Percent Black	0.824
				Percent Civilian Unemployment	0.734
				Percent Poverty	0.727
				Percent Employment in Service Industry	0.663
				Percent Housing Units with No Car	0.606
				Percent Population with Less Than 12th Grade Education	0.599
				Percent Renters	0.576
				Percent Female Participation in Labor Force	0.521
				Percent Native American	0.469
				Median Gross Rent	-0.524
				Median House Value	-0.639
				Per Capita Income	-0.714
				Percent Children Living in Married Couple Families	-0.905
2	+	Linguistic Isolation, Ethnicity (Hispanic), Population Density (High)	14.680	Percent Speaking English as a Second Language with Limited English Proficiency	0.889
				Percent Hispanic	0.810
				Population per Square Mile	0.722
				Percent Renters	0.684
				Percent Housing Units with No Car	0.655
				Percent Native American	0.458
				Percent Poverty	0.449
				Percent Female Participation in Labor Force	-0.438
3	+	Age (Seniors)	7.525	Percent Population Under 5 Years or 65 and Over	0.917
				Percent of Households Receiving Social Security	0.843
				Median Age	0.792
				Percent Female Population	0.509
				Population per Square Mile	-0.659
4	+	*Extractive Industry Employment	6.643	Percent Employment in Extractive Industries	0.781
				Percent Asian	-0.659
5	+	*Mobile Home Ownership	3.831	Percent Mobile Homes	0.738
				Median House Value	-0.473
		Cumulative Variance Explained	**68.749**		

*Cardinality was adjusted

**These are correlations between the original variables and the created component. The higher the loading, the stronger they identify with the component. For example, percent children living in single parent households had a loading of 0.895 with the family structure component, one of the strongest. All scores of ≥ 0.4 are shown in the table.

Figure 2. Socially Vulnerable Groups in New Jersey: Factor 1

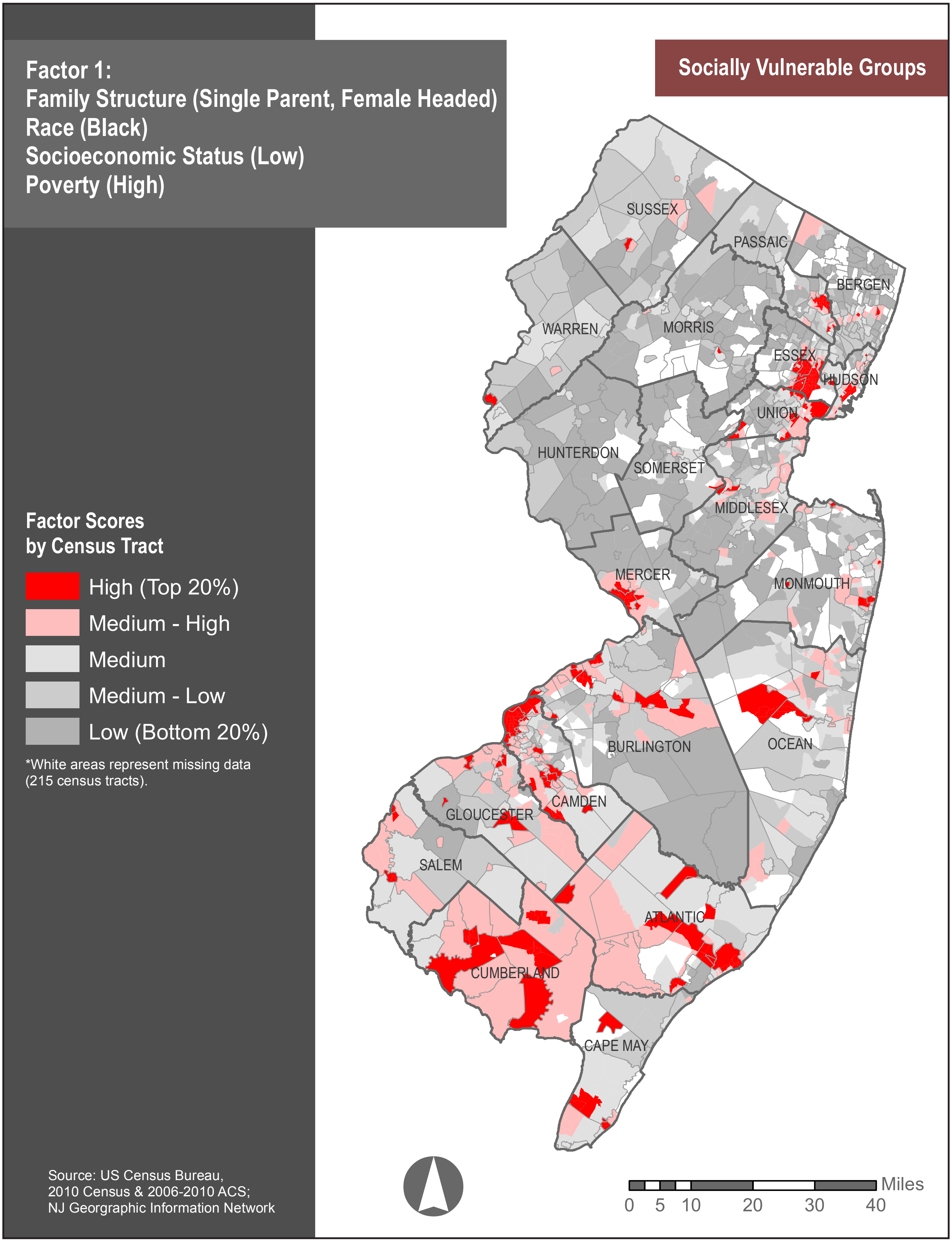


Figure 3: Socially Vulnerable Groups in New Jersey: Factor 2

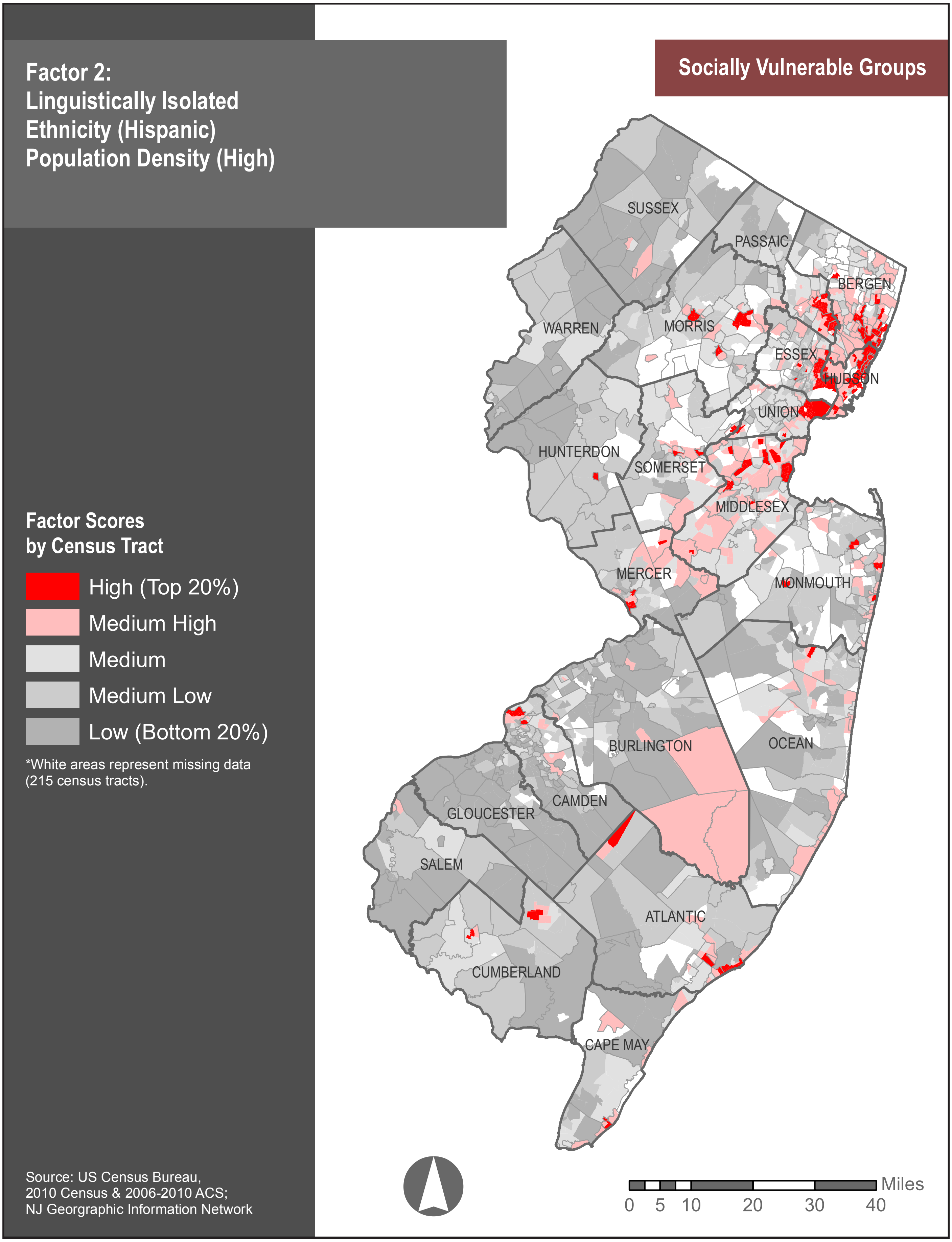


Figure 4: Socially Vulnerable Groups in New Jersey: Factor 3

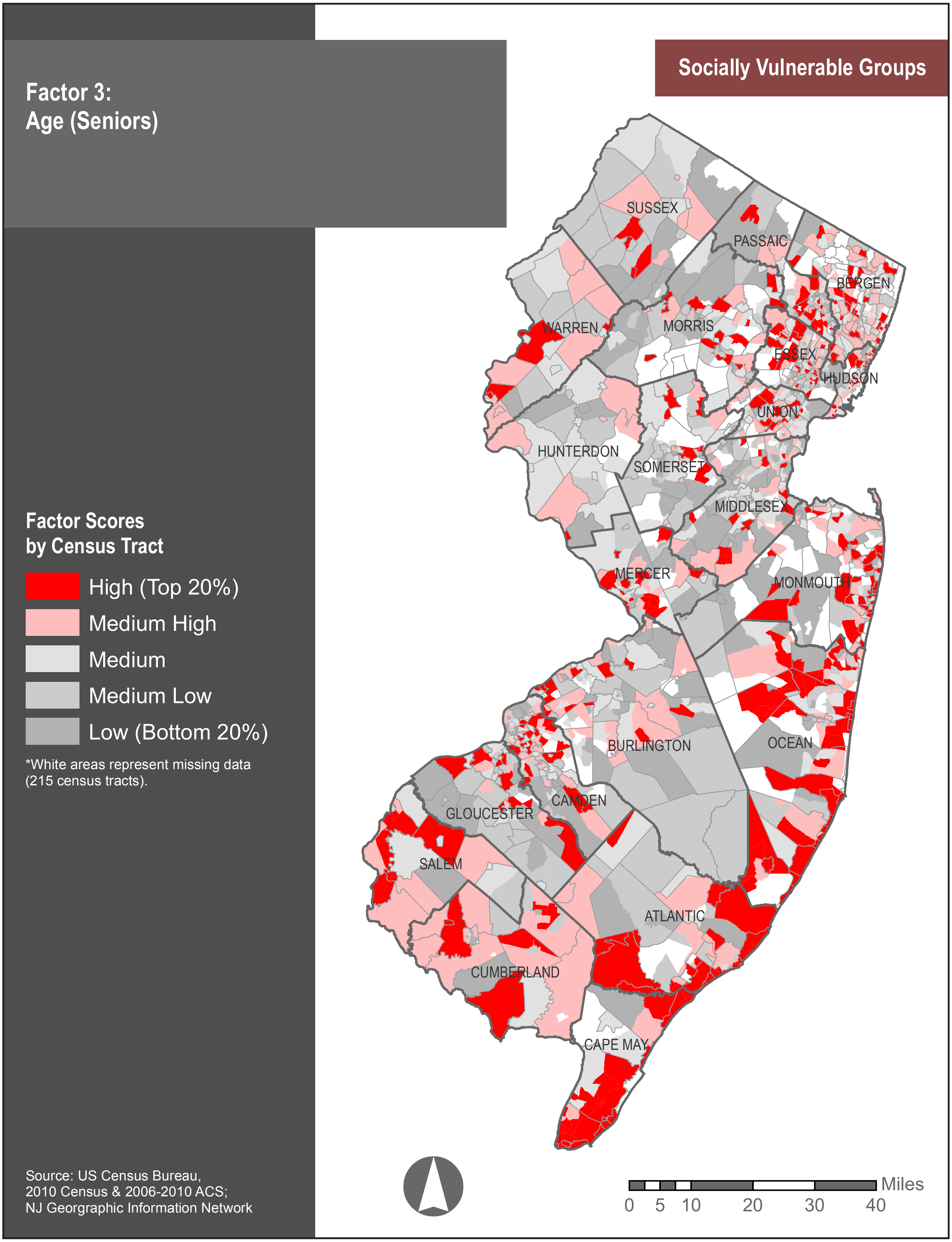


Figure 5: Socially Vulnerable Groups in New Jersey: Percent Nursing Home Population and Skilled-nursing Facilities

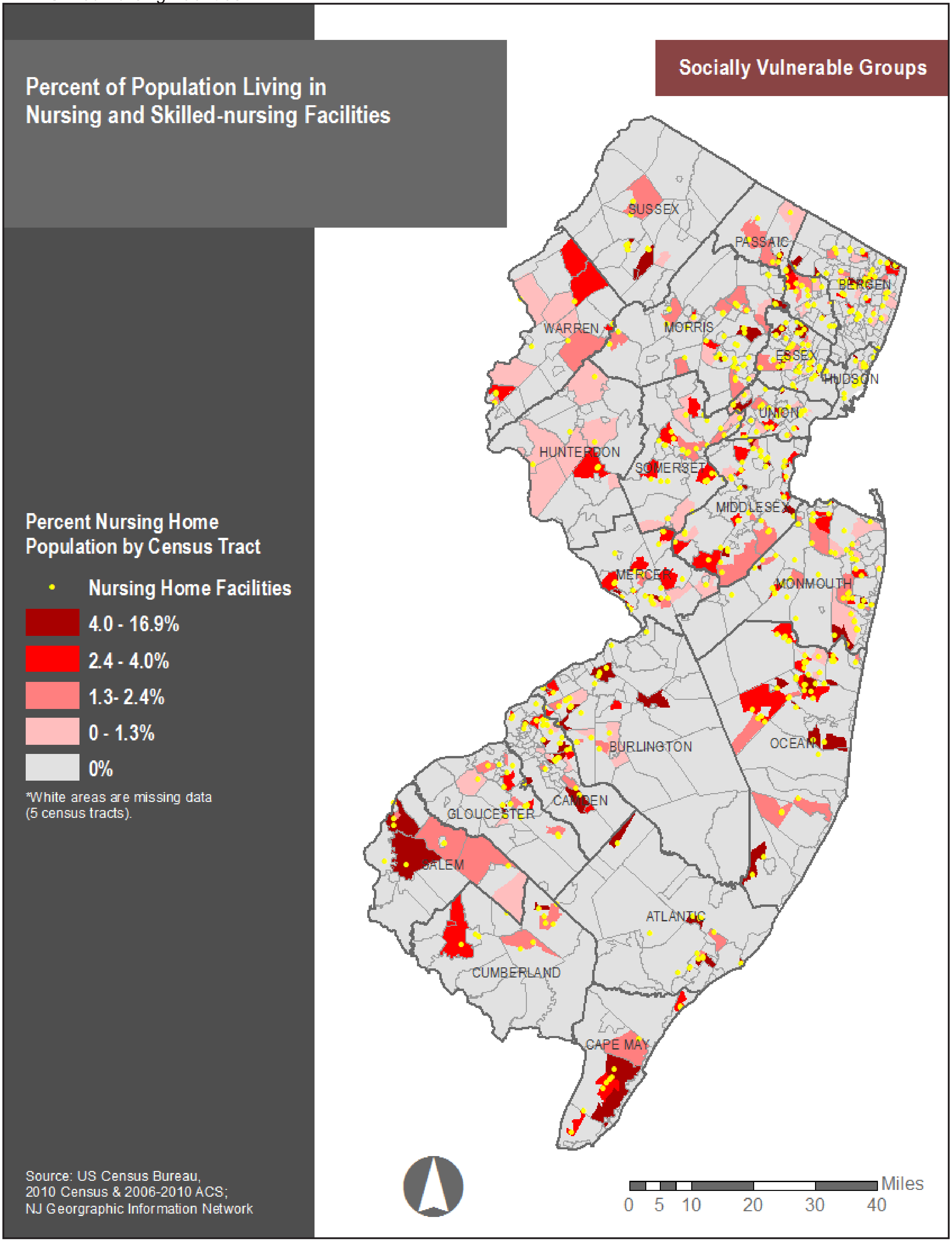


Figure 6: Socially Vulnerable Groups in New Jersey: Percent Mobile Home Population

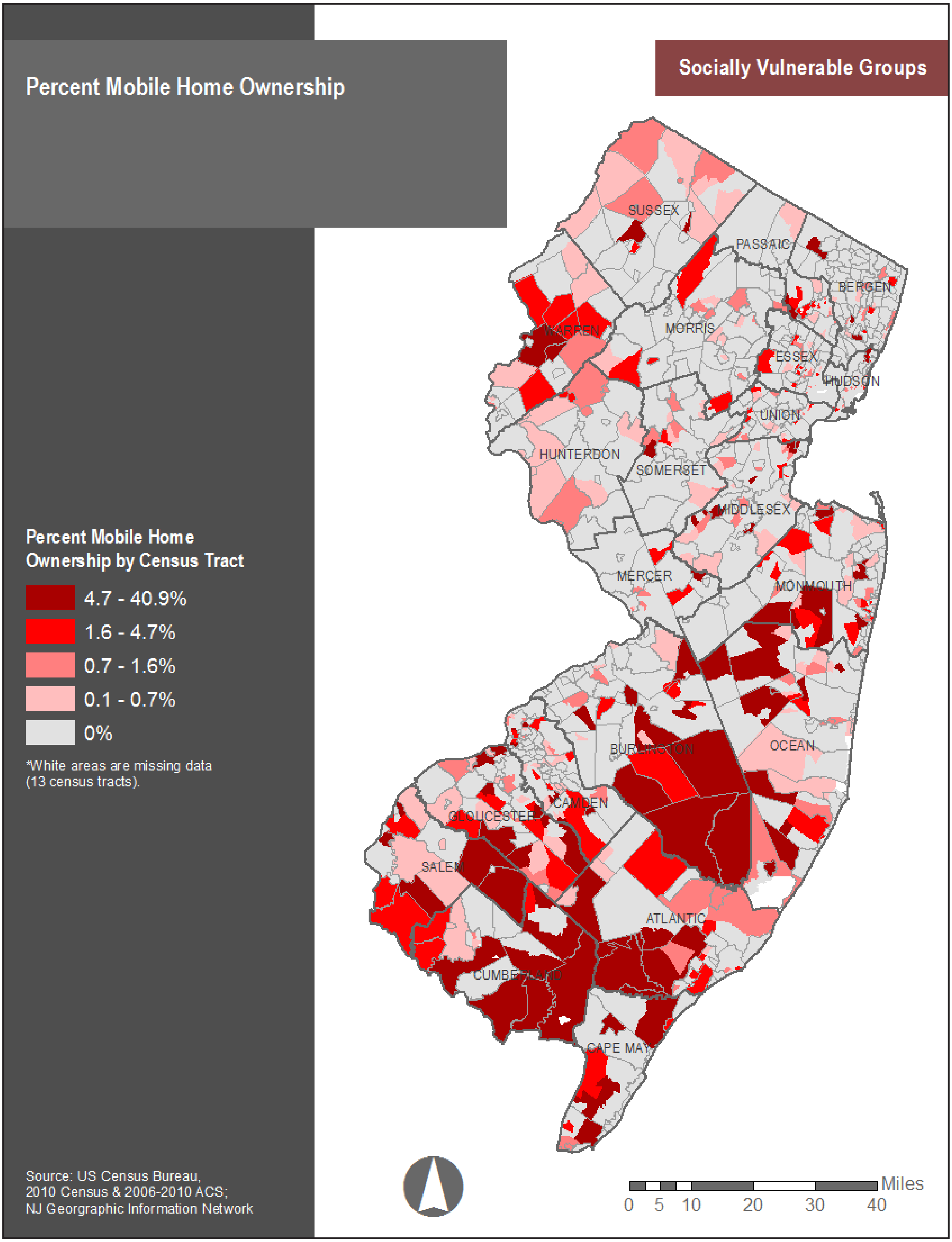


Figure 8: Superstorm Sandy and Social Vulnerability Factor 1

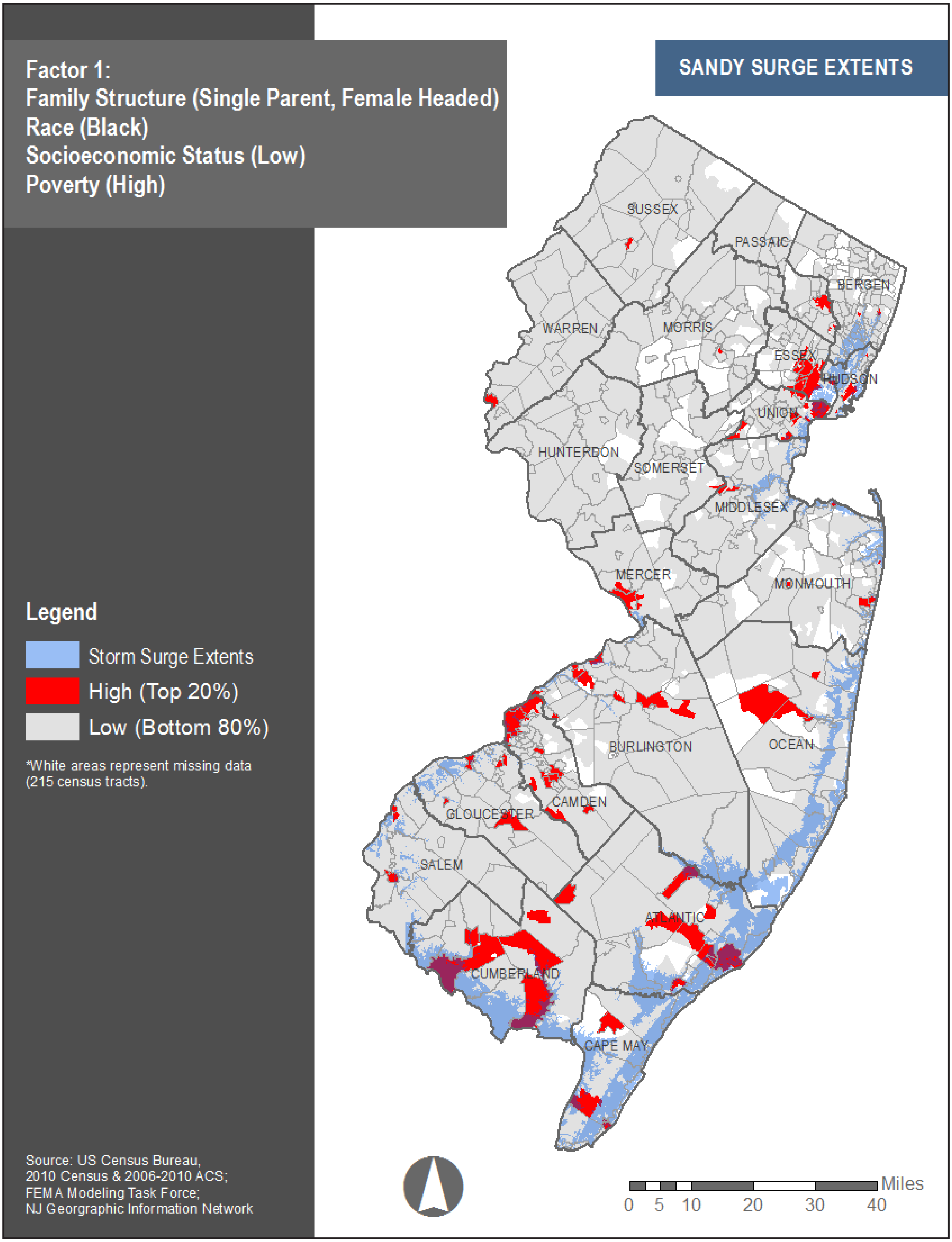


Figure 9: Superstorm Sandy and Social Vulnerability Factor 2

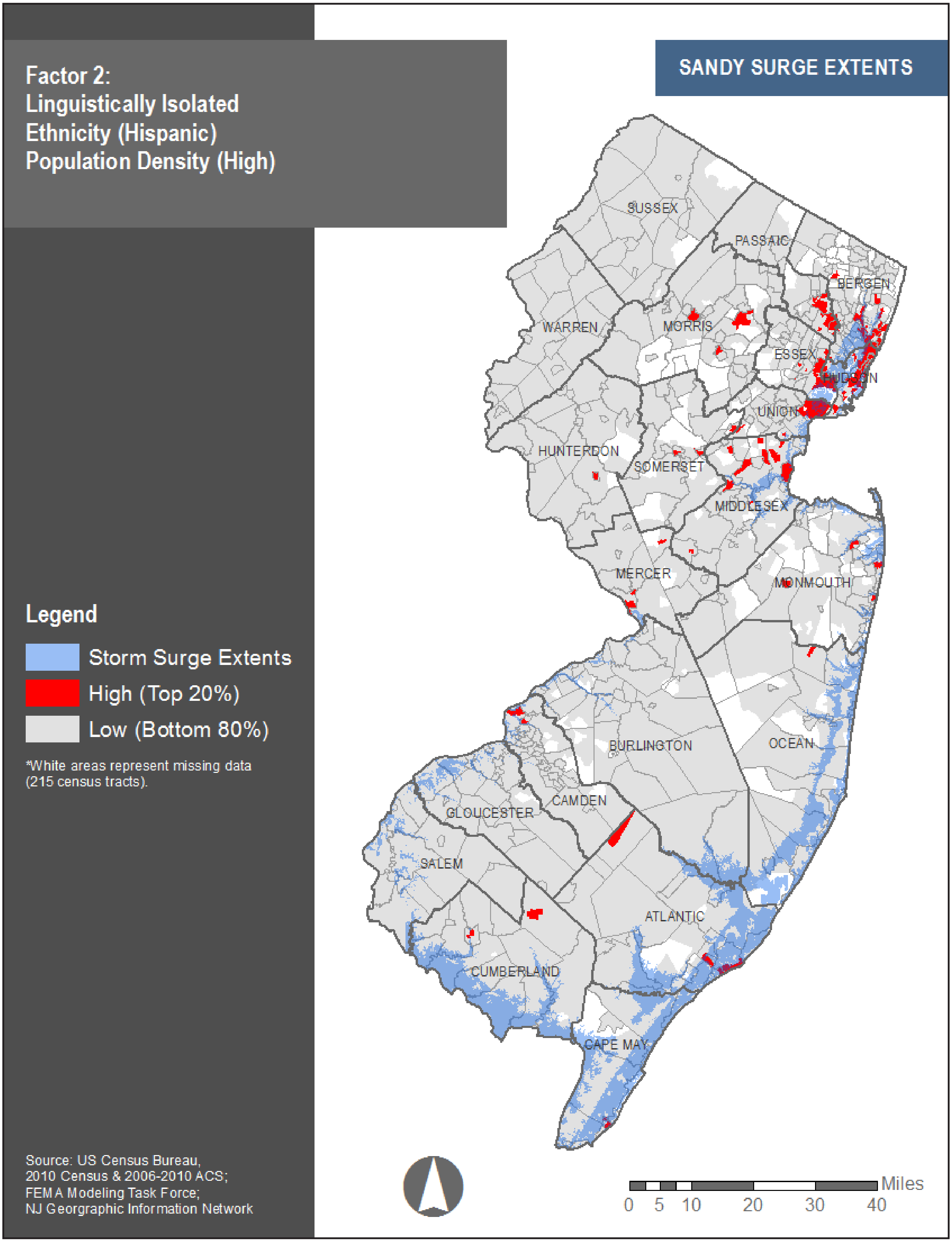


Figure 10: Superstorm Sandy and Social Vulnerability Factor 3

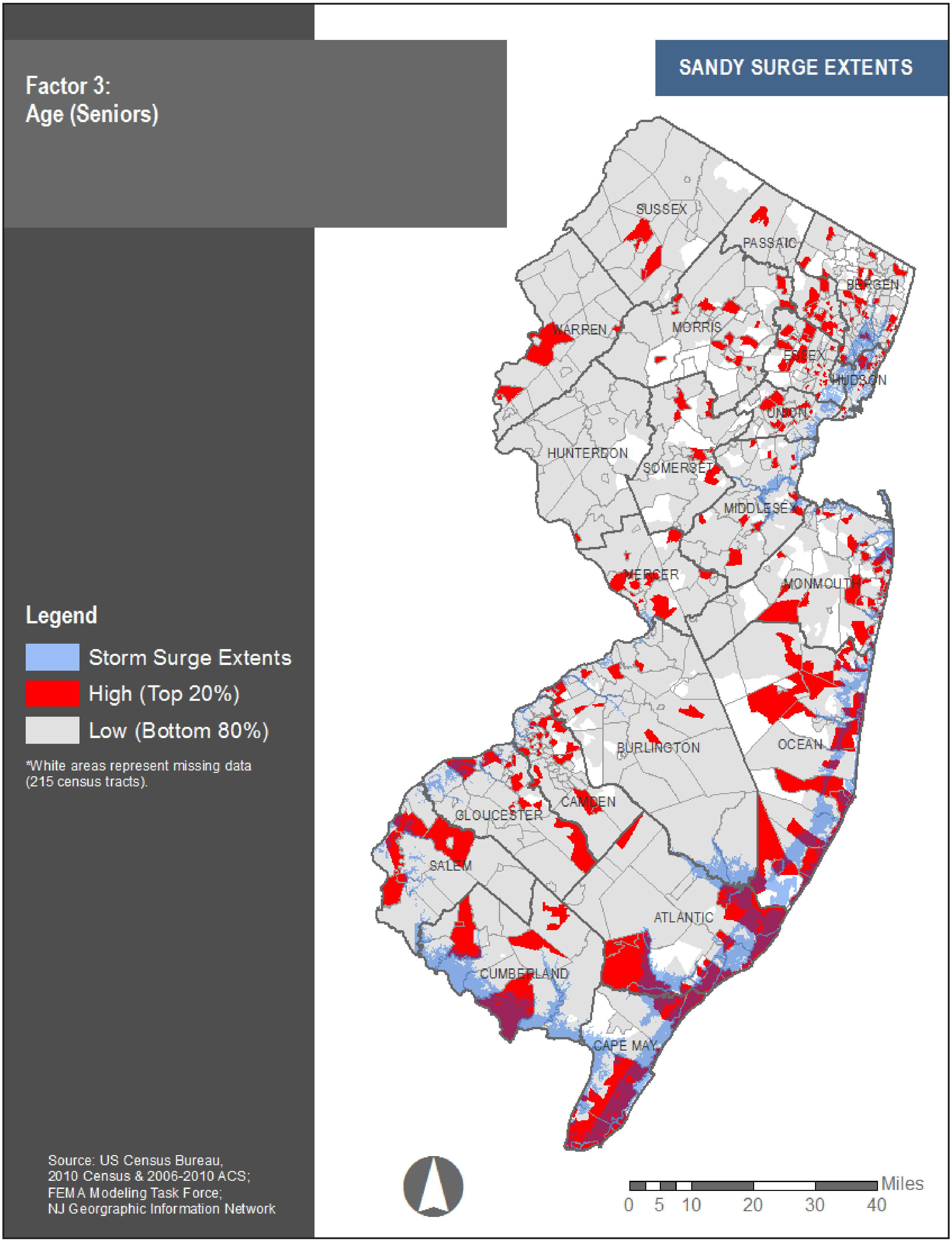


Figure 11: Superstorm Sandy and Percent of Nursing Home Population and Skilled-nursing Facilities

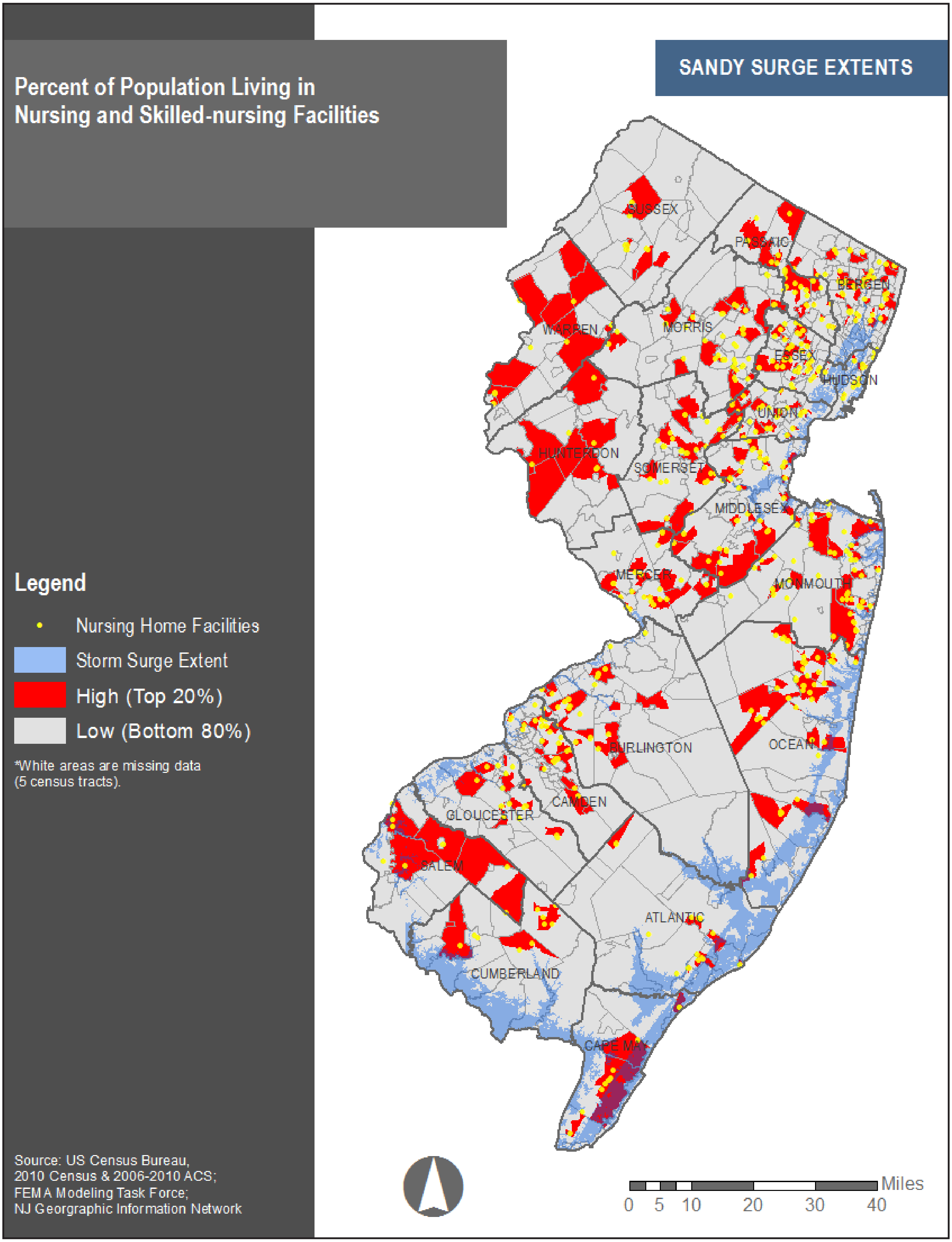


Figure 12: Superstorm Sandy and Percent Mobile Home Population

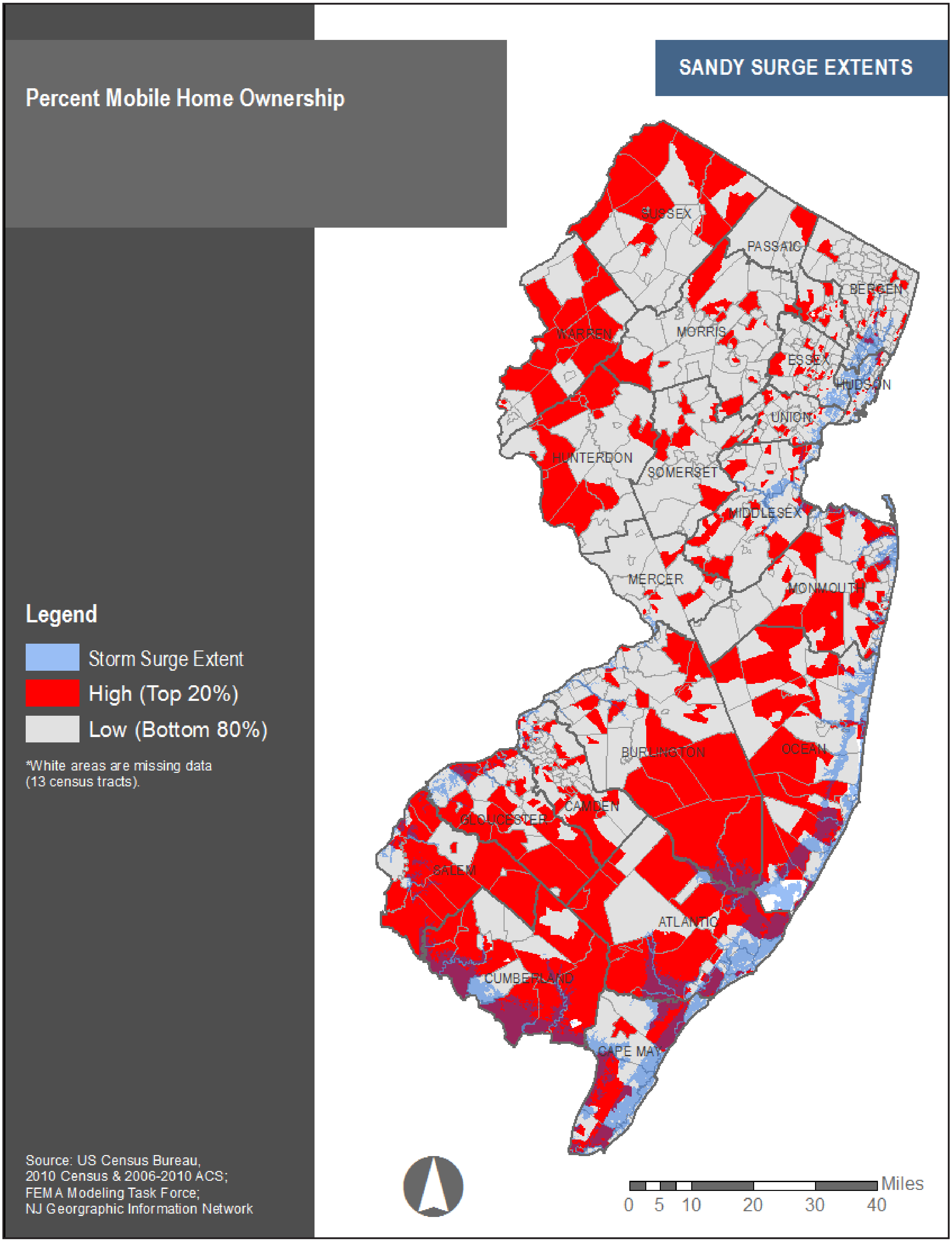


Figure 13: Floodprone Land in New Jersey

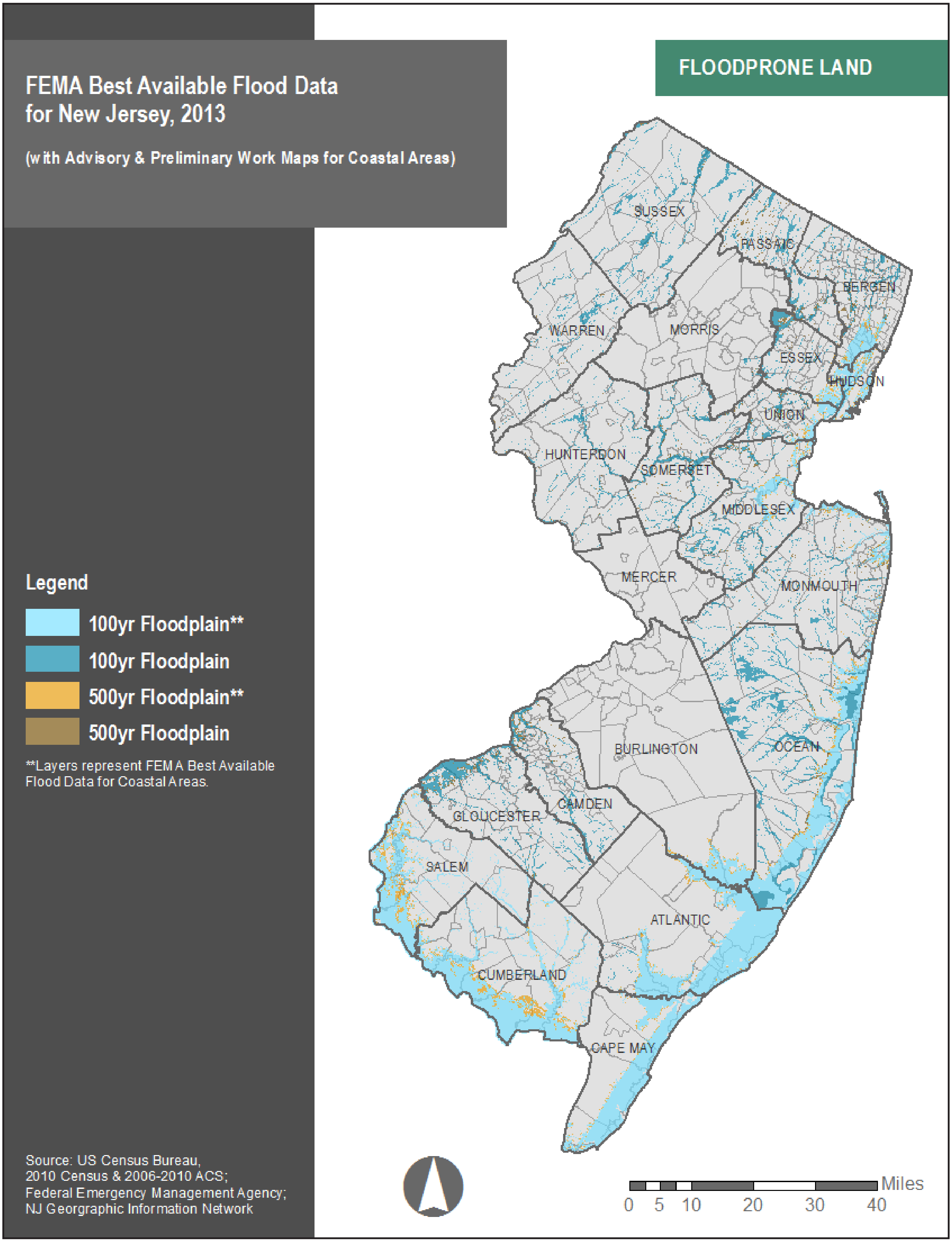


Figure 14: Floodprone Land and Factor 1

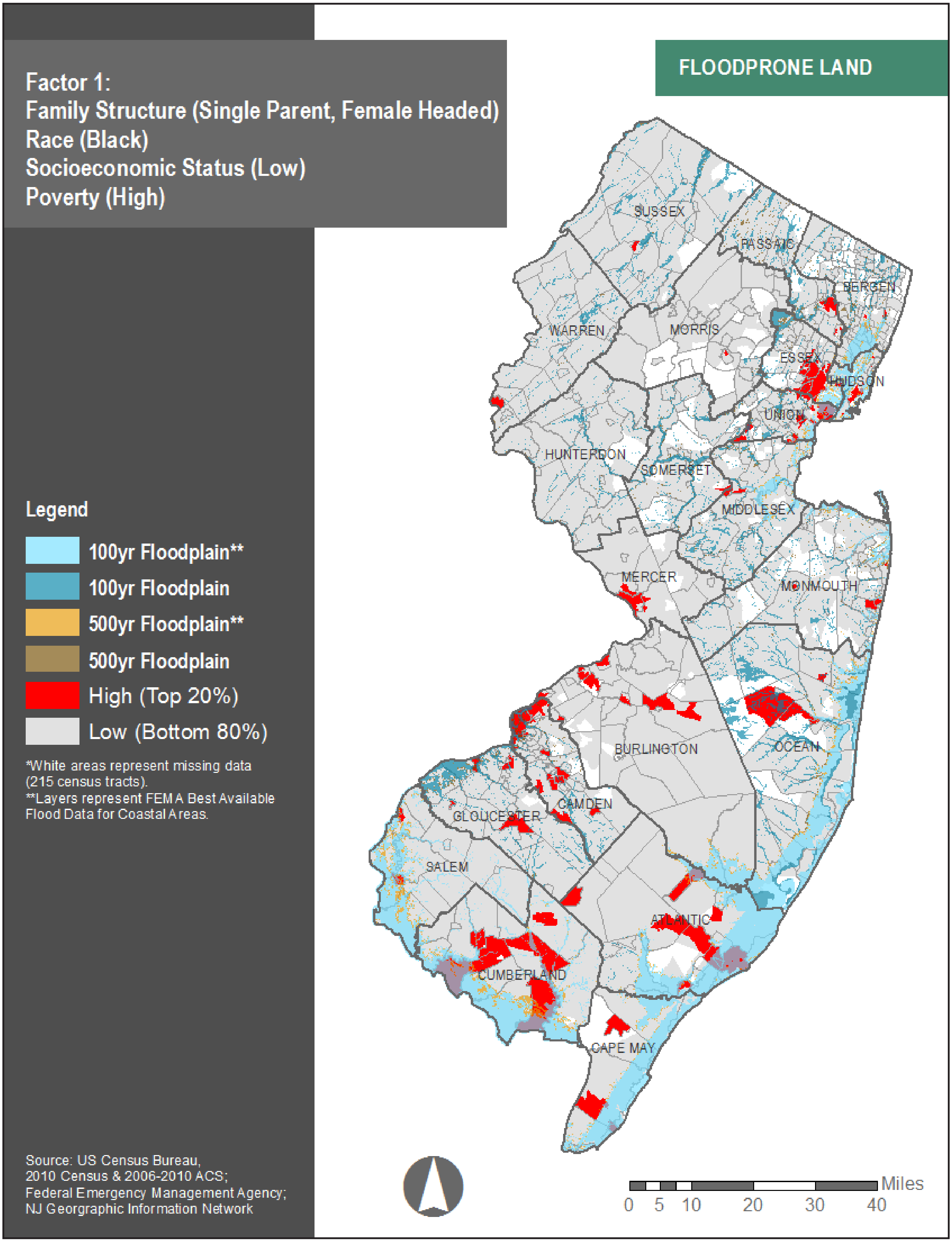


Figure 15: Floodprone Land and Factor 2

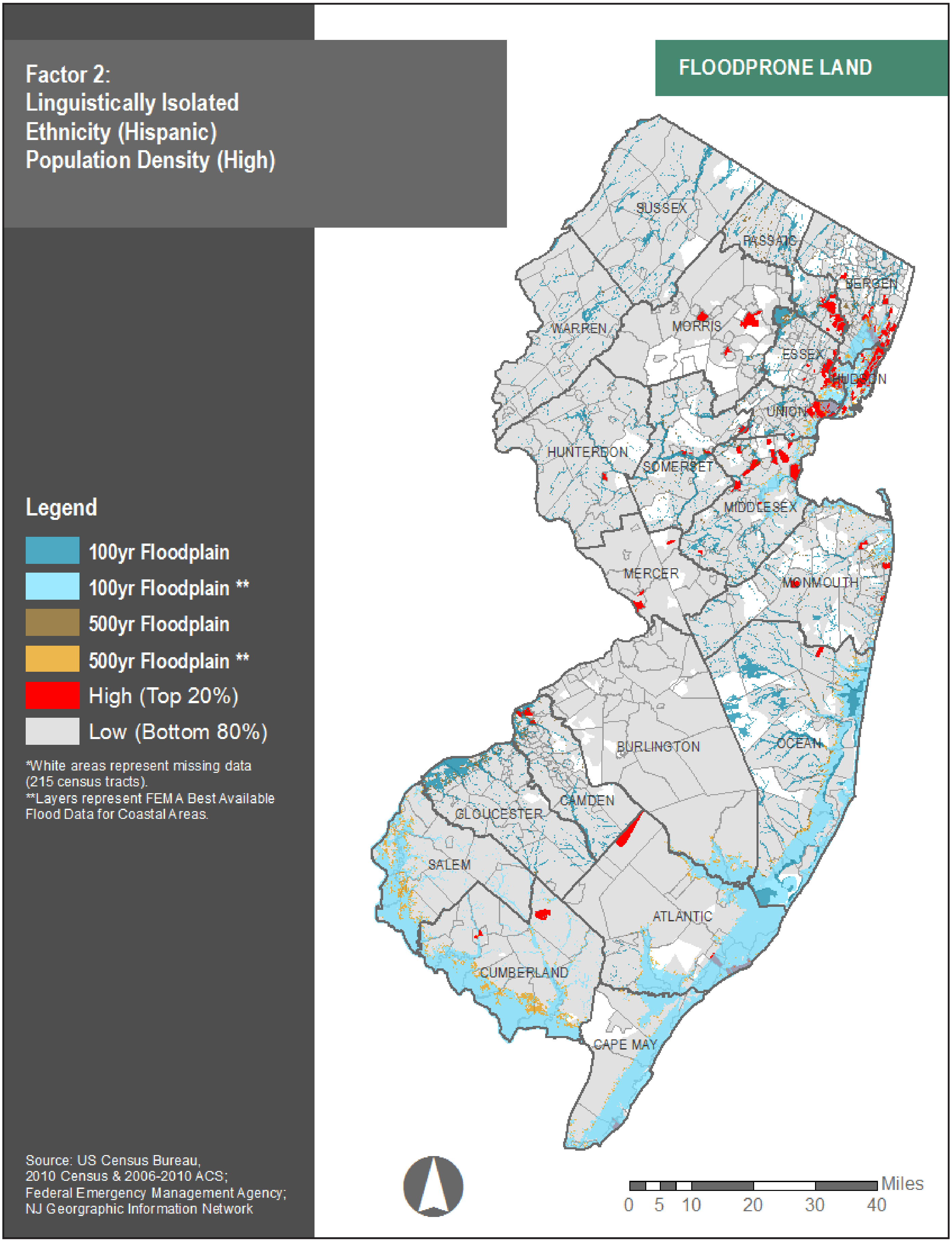


Figure 16: Floodprone Land and Factor 3

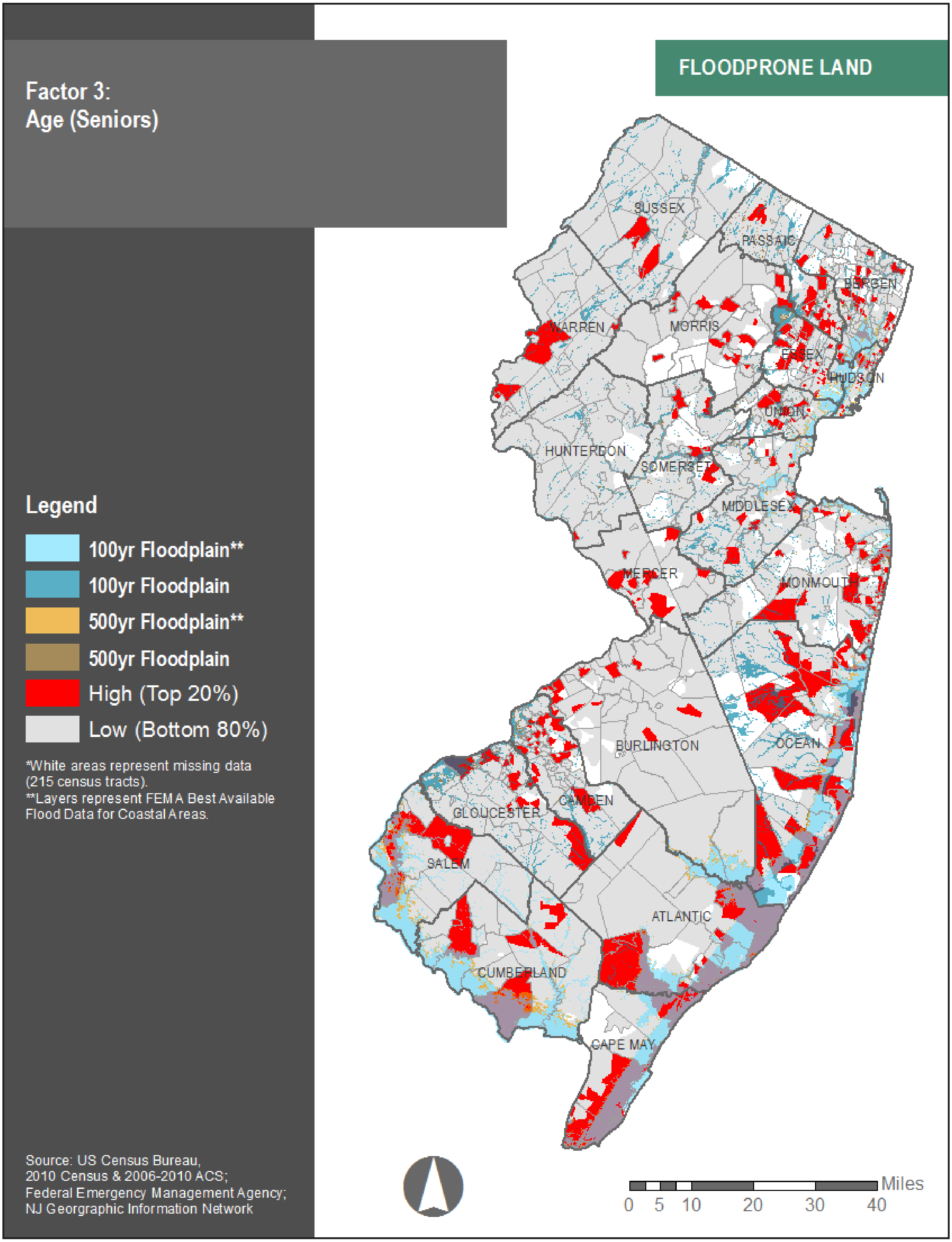


Figure 17: Floodprone Land and Percent Nursing Home Population and Skilled-nursing Facilities

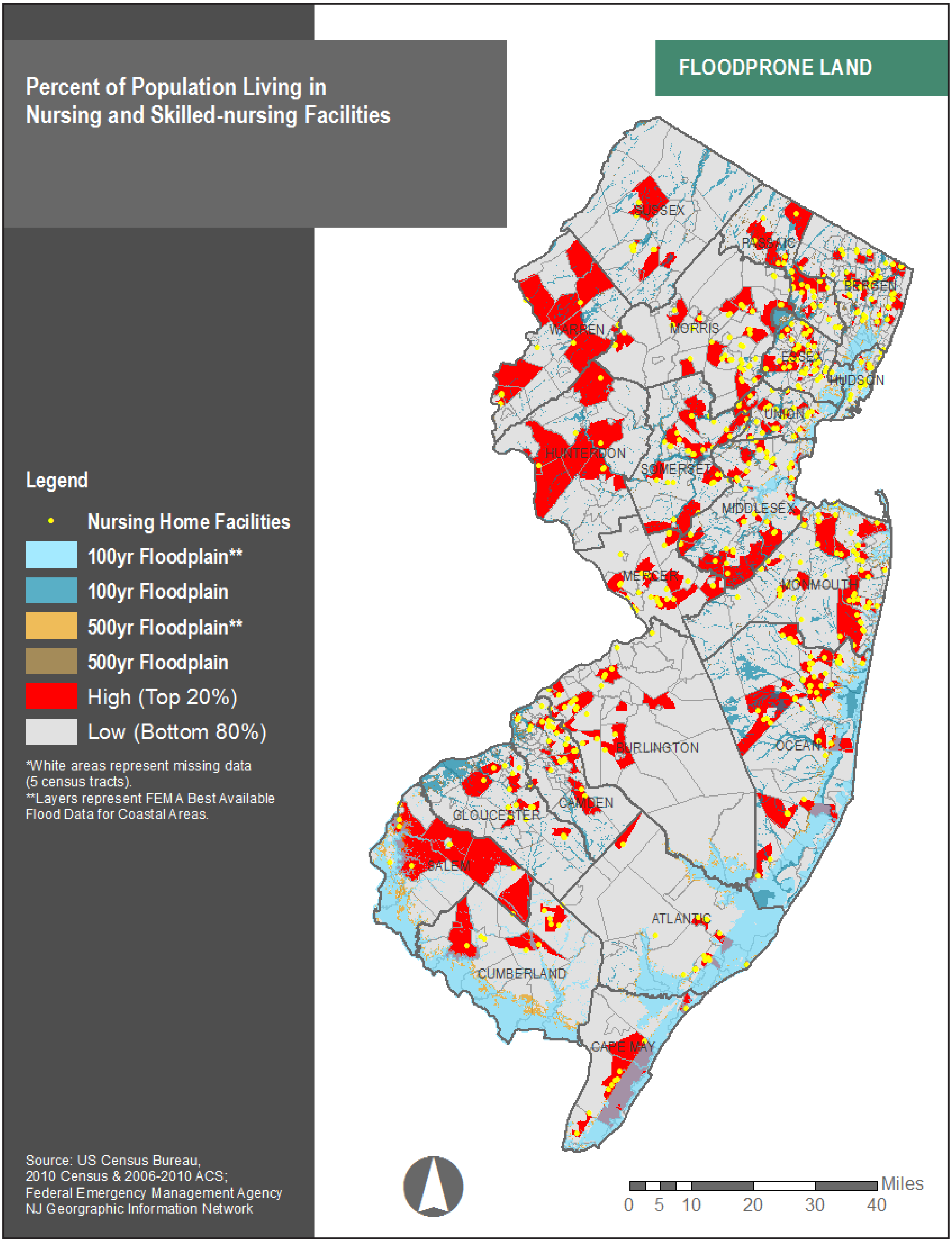


Figure 18: Floodprone Land and Percent Mobile Home Population

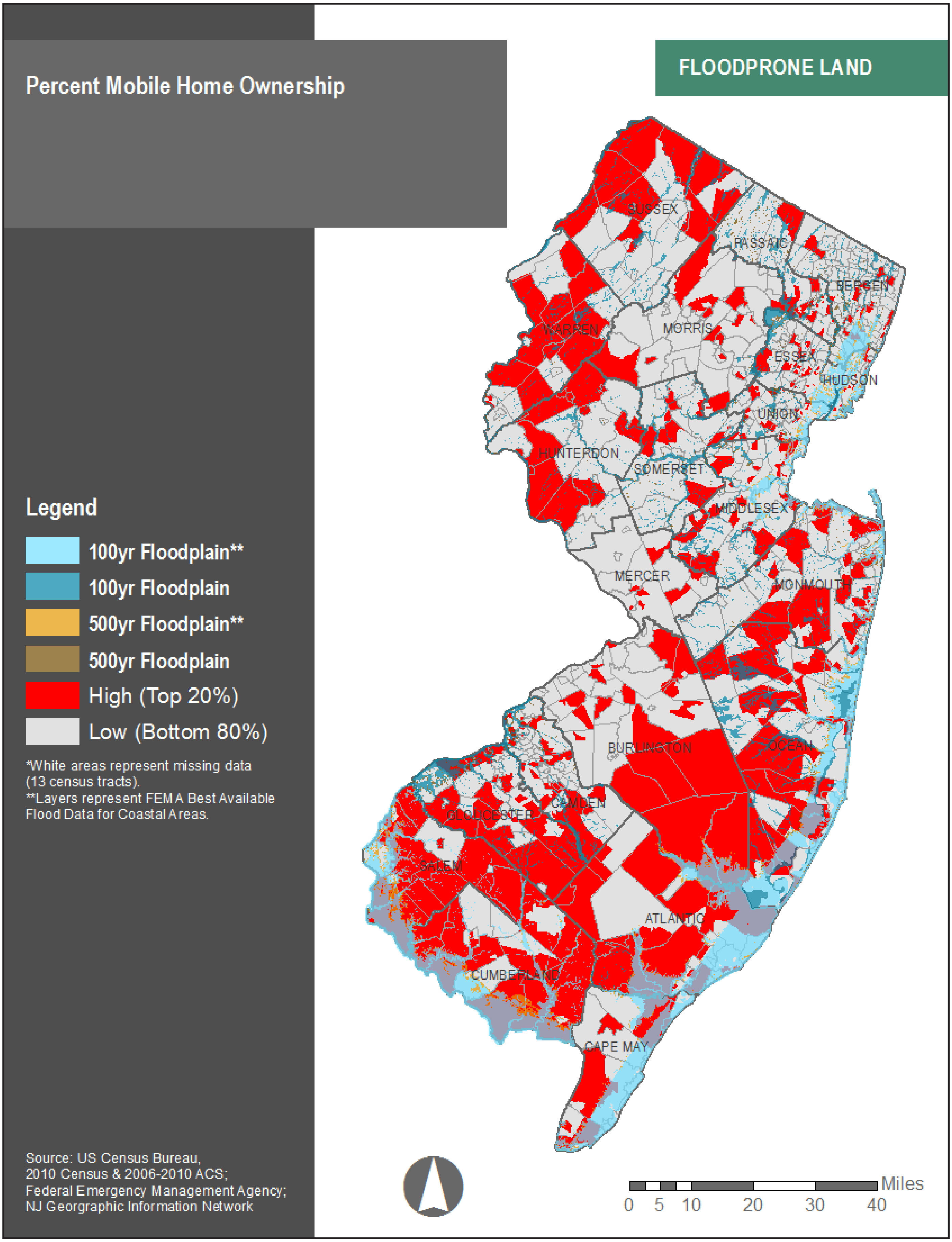


Figure 19: NOAA Sea-Level Rise Projections for 2050 and Factor 1

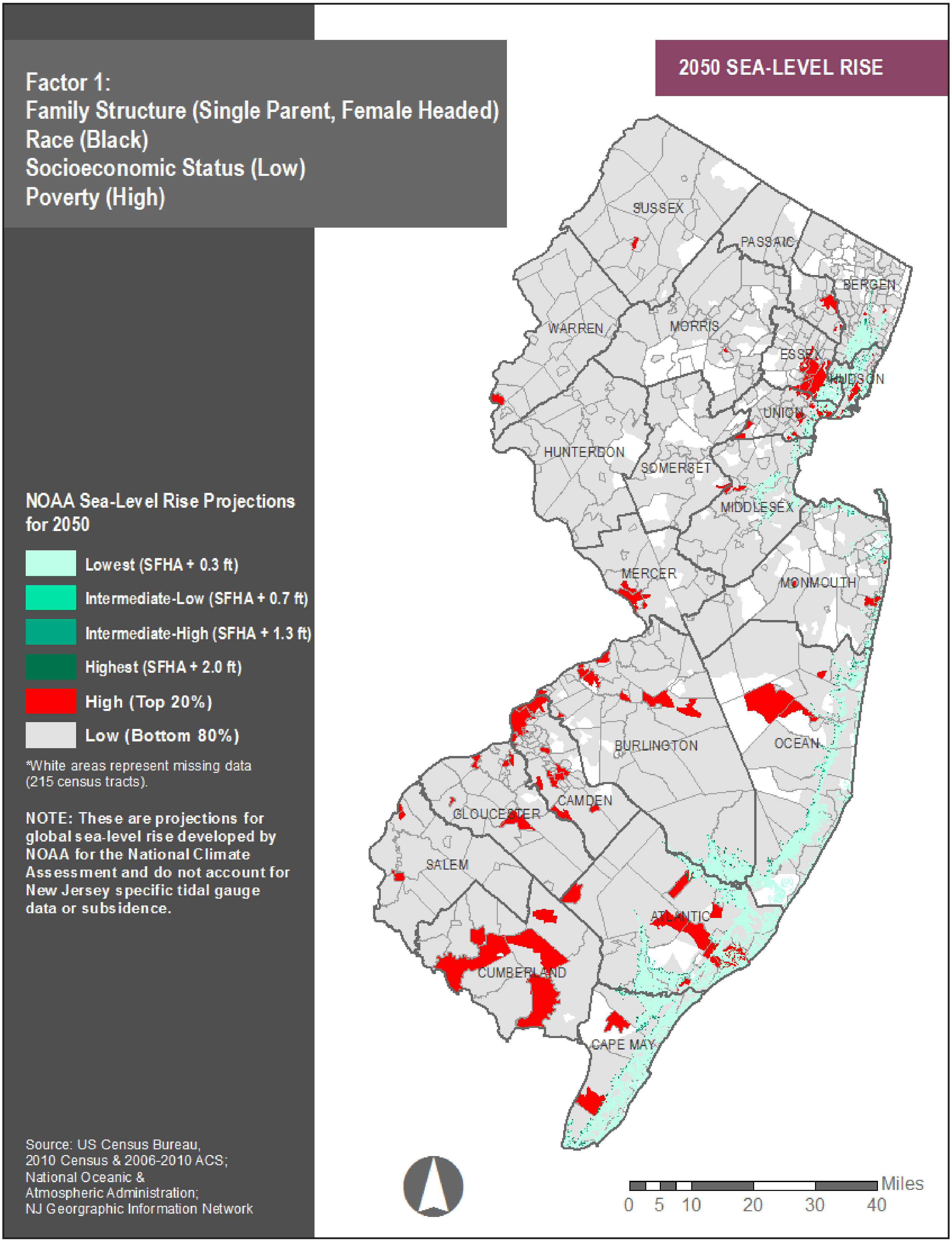


Figure 20: NOAA Sea-Level Rise Projections for 2100 and Factor 1

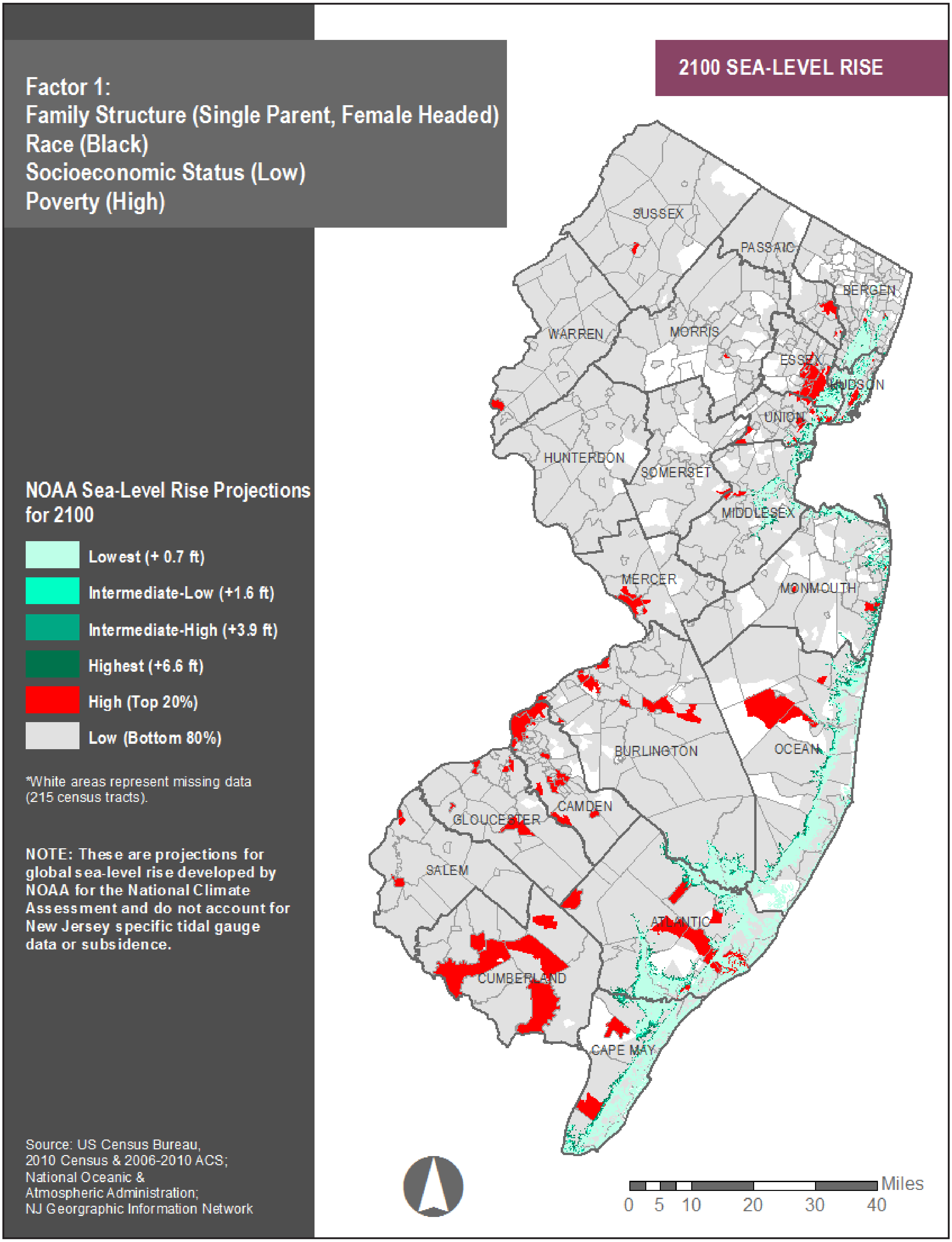


Figure 21: NOAA Sea-Level Rise Projections for 2050 and Factor 2

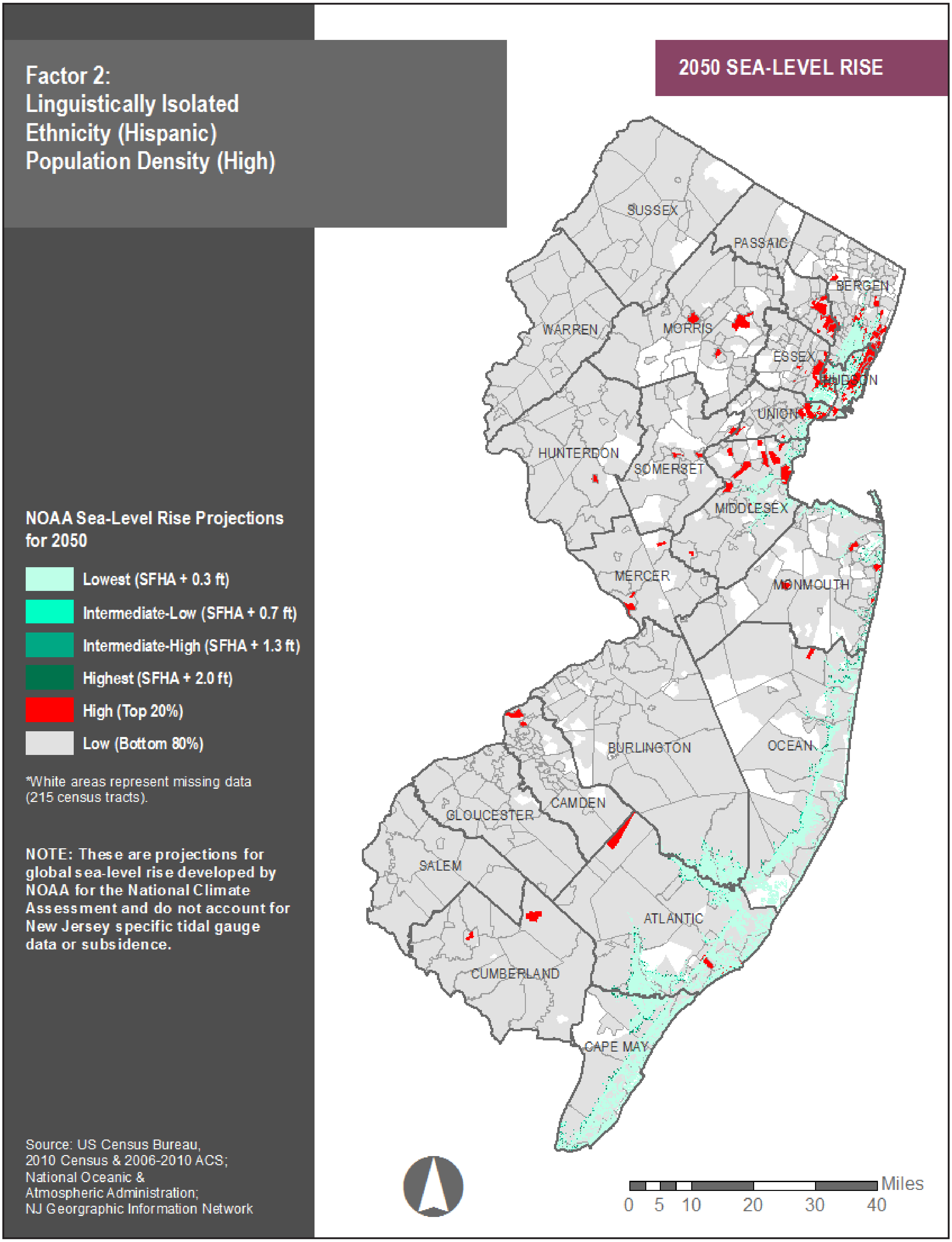


Figure 22: NOAA Sea-Level Rise Projections for 2100 and Factor 2

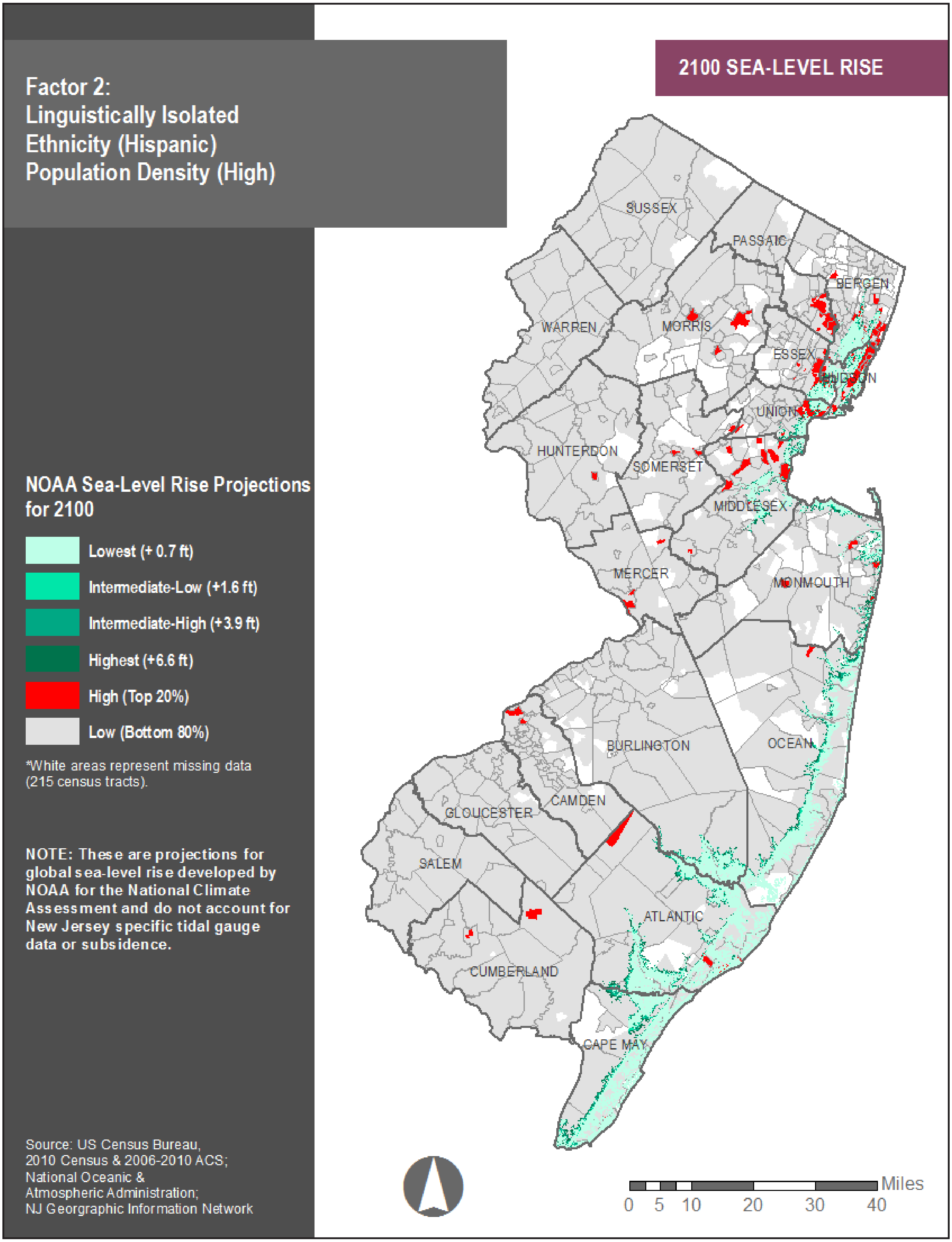


Figure 23: NOAA Sea-Level Rise Projections for 2050 and Factor 3

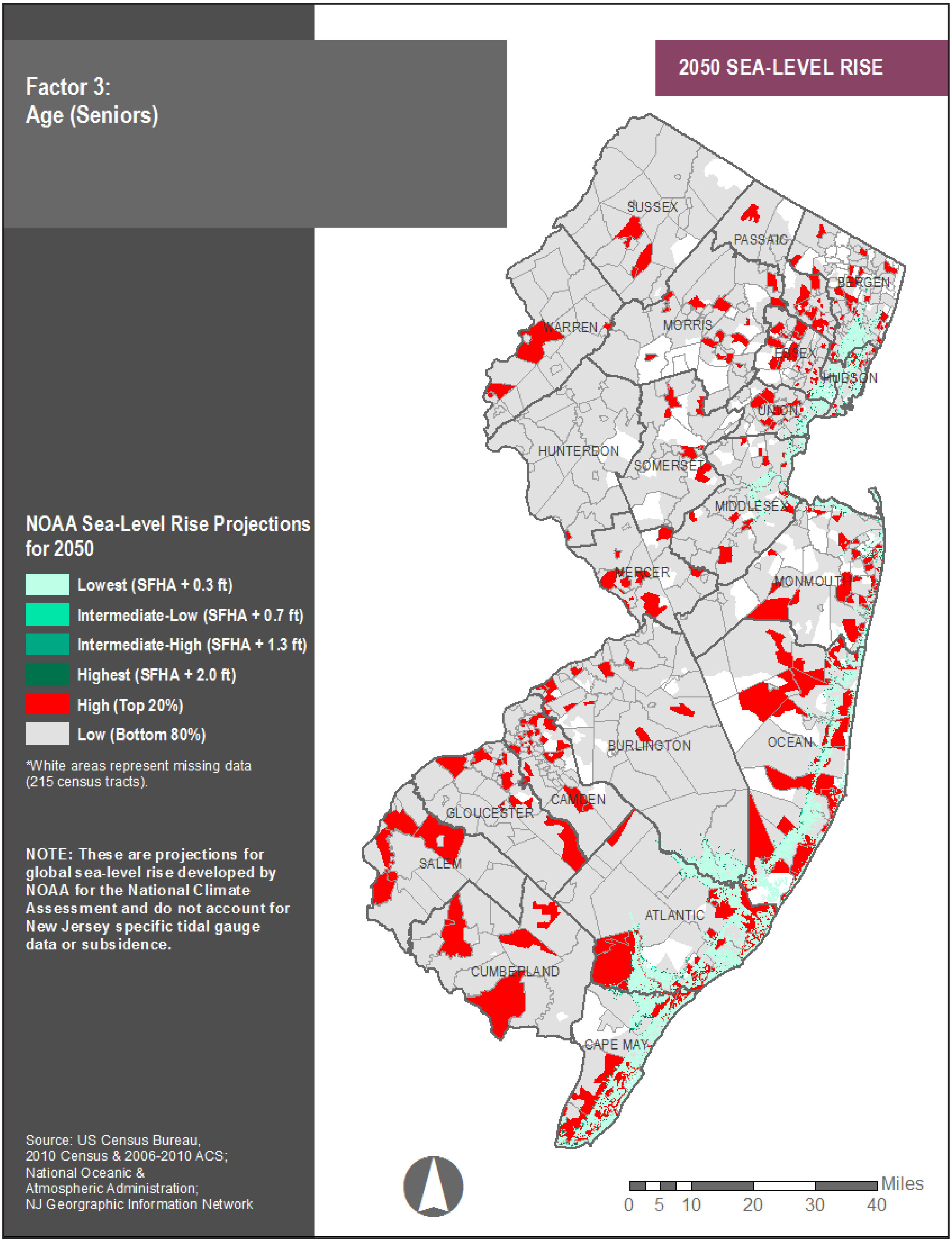


Figure 24: NOAA Sea-Level Rise Projections for 2100 and Factor 3

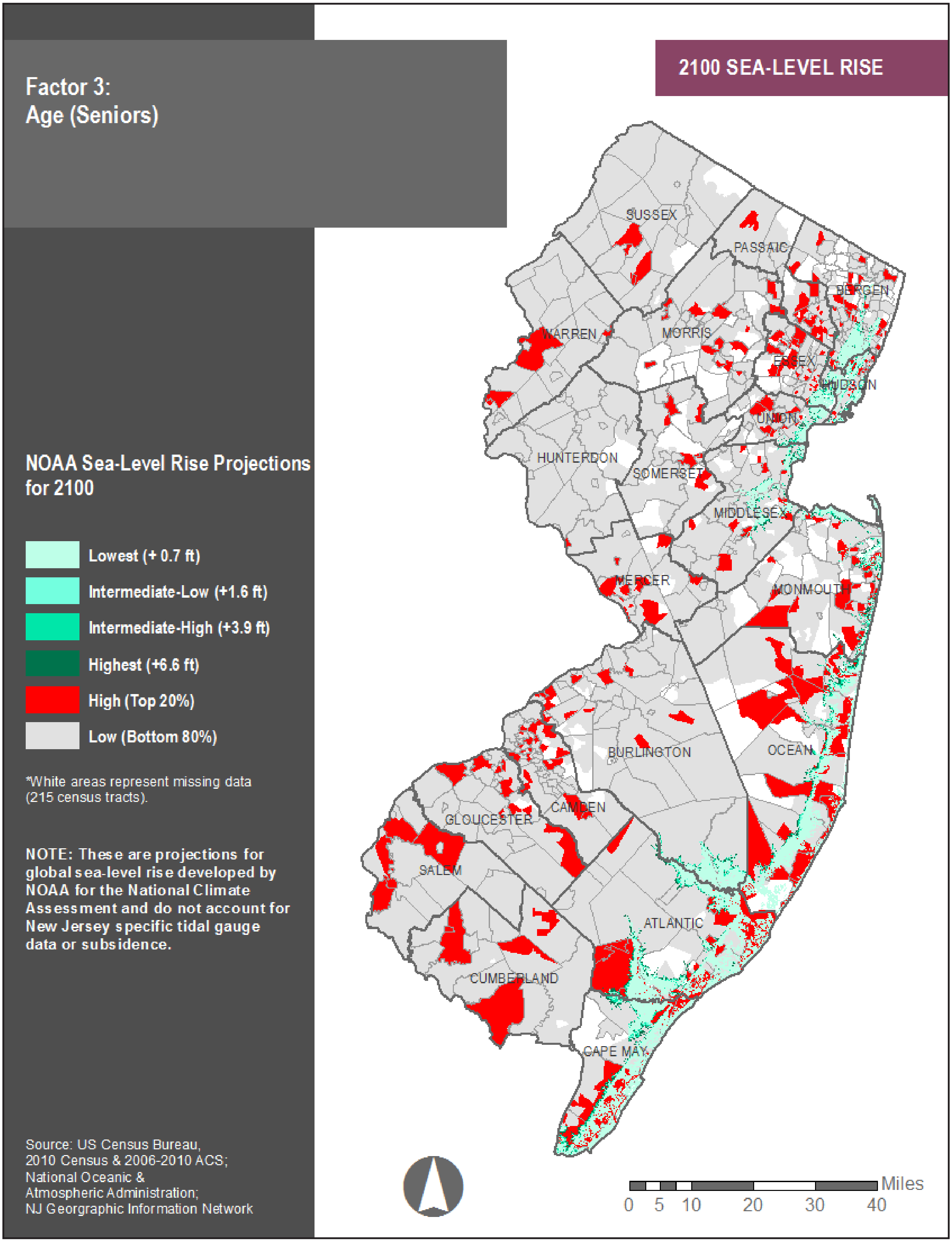


Figure 25: NOAA Sea-Level Rise Projections for 2050 and Percent Nursing Home Population and Skilled-nursing Facilitiesnursing Facilities

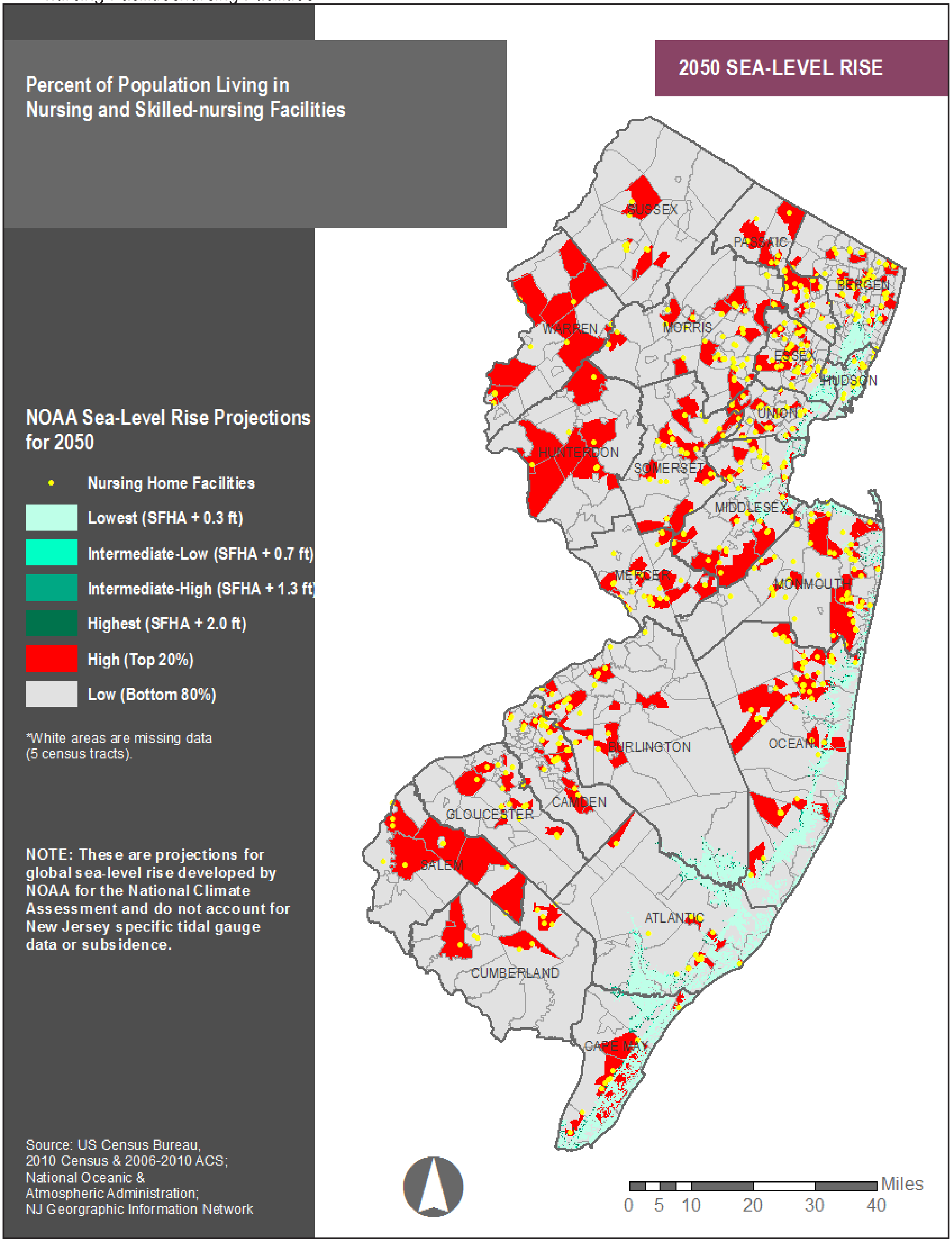


Figure 26: NOAA Sea-Level Rise Projections for 2100 and Percent Nursing Home Population and Skilled-nursing Facilities

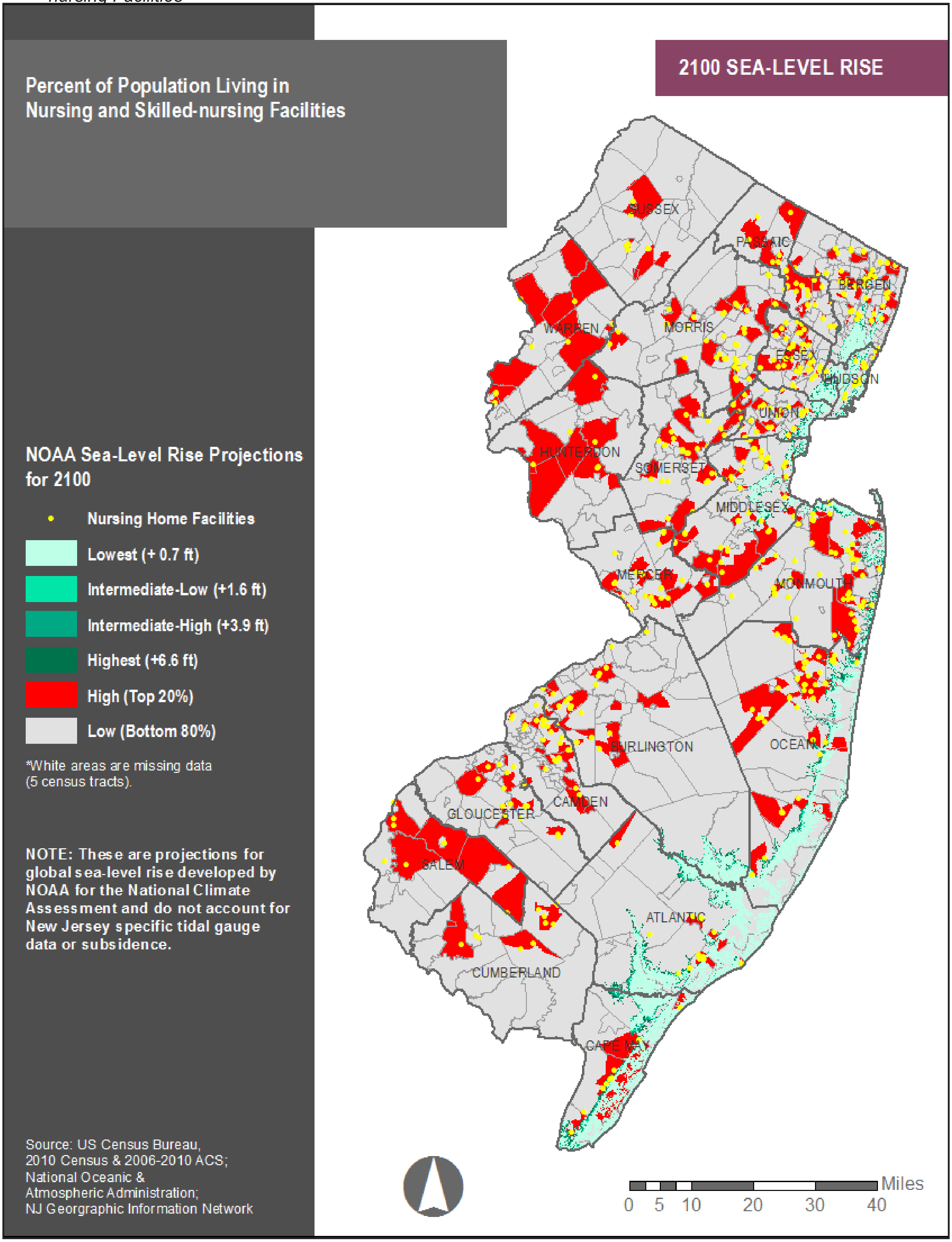


Figure 27: NOAA Sea-Level Rise Projections for 2050 and Percent Mobile Home Population

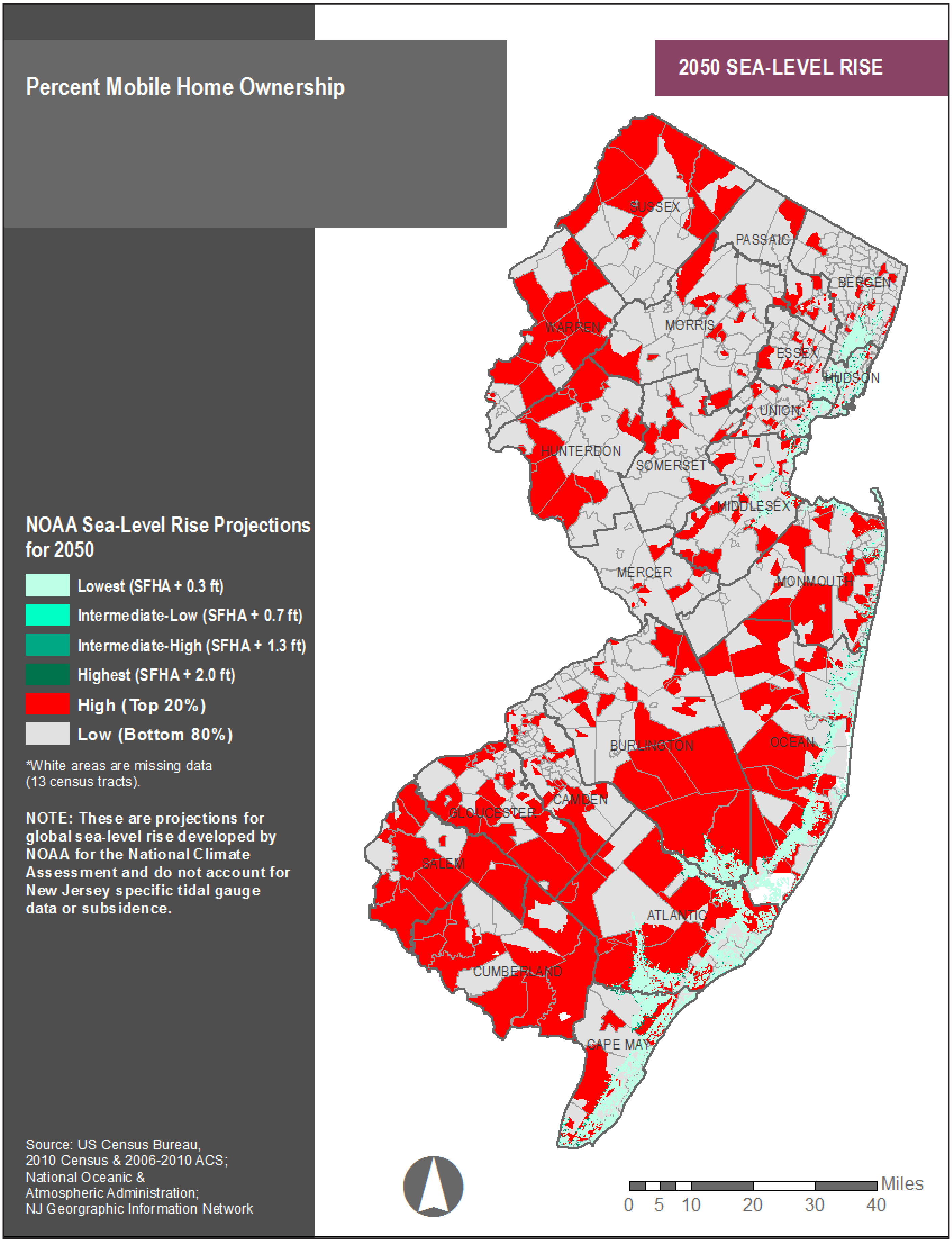
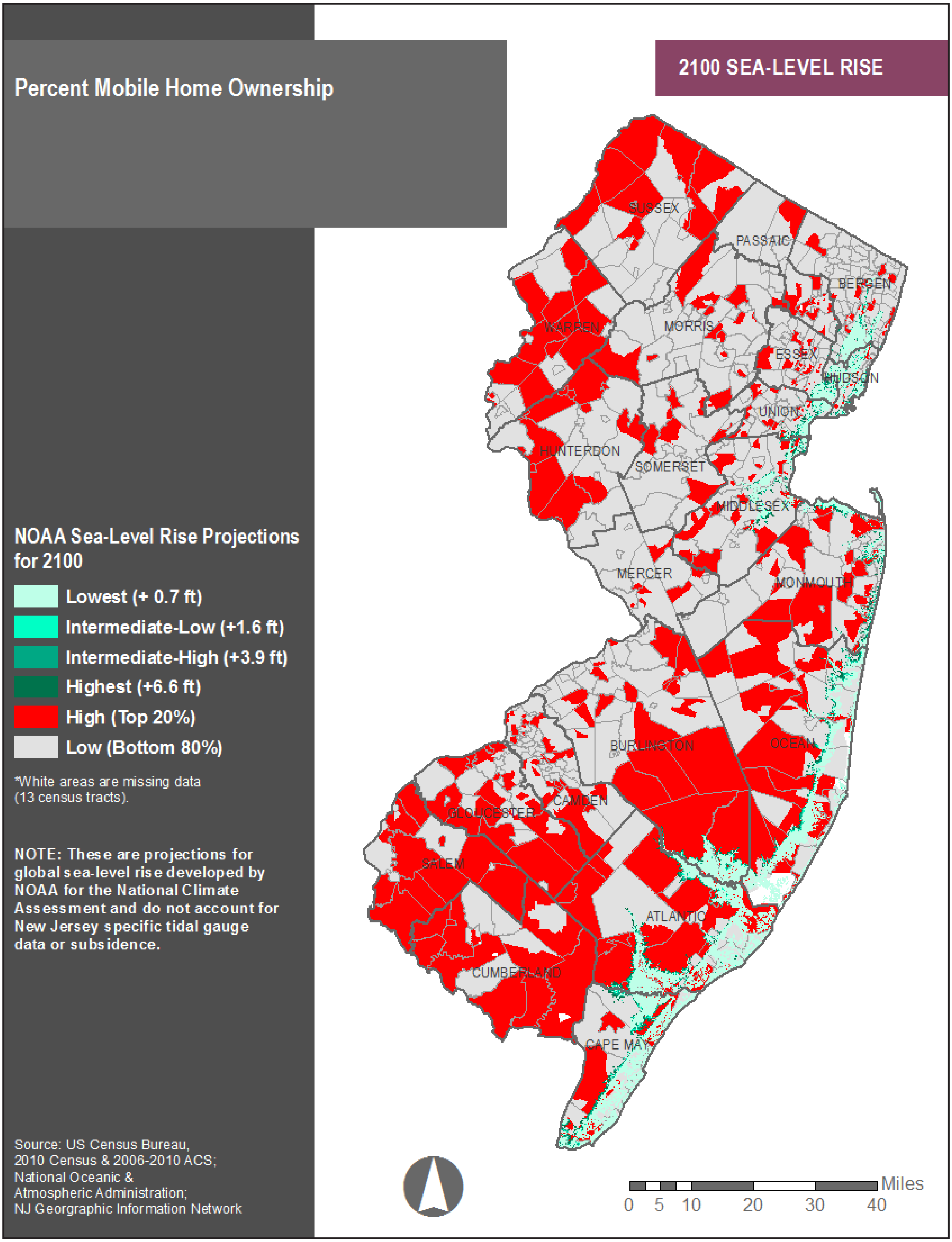


Figure 28: NOAA Sea-Level Rise Projections for 2100 and Percent Mobile Home Population



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