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A GIS Based Comparison of Three Social Vulnerability Indices Using Health and Exposure Data

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Abstract

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Social vulnerability indices have been used to characterize community level risk to hazards but little research has been conducted to explore the utility of using such indices in public health practice. Additionally there is no consensus regarding the best methodology for producing social vulnerability indices. This study compared three social vulnerability indices produced using three distinct structural designs and the same set of indicators to help explain the impact structural design has during the production of social vulnerability indices. This research was guided by the following research questions (operationalized as testable null hypothesis):

1. *Social vulnerability indices produced by the deductive, hierarchical and inductive methods will yield the same spatial distributions of social vulnerability at the county level for each state (New Jersey and Florida).*

2. *ED visit rates are not spatially correlated with measures of social vulnerability or exposure to air pollution at the county level for each state (New Jersey and Florida).*

The 32 Variable SoVI from 2000 was extracted from the Hazard and Vulnerability Research Institute, located on the University of South Carolina's website[1]. Rather than perform our own factor analysis, we chose to use this social vulnerability index as our inductive index. Using the same set of variables, we developed two comparison indices (the deductive and hierarchical indices). Spatial and statistical analysis was employed to compare indices both with each other and with health and exposure data. Results confirmed that indices produced by the three different structural designs produced different spatial distributions of vulnerability at the county level with the hierarchical and deductive indices being most similar. Additionally results suggested evidence of spatial correlation between social vulnerability and asthma ED visit rates in both Florida and New Jersey although the spatial relatedness was different in each state. Results did not suggest a relationship between ED visit rates and exposure to PM 2.5.

This study suggests that social vulnerability indices could be useful in the field of public health, but more research into optimal construction and implementation should be employed to ensure correct interpretation, use and applicability.

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By

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Introduction

Vulnerability research has emerged in multiple disciplines as a way to characterize community resilience in the face of hazards. By taking into account the system level variables that contribute to vulnerability and the differential experience of risk, social vulnerability research strives to turn complex institutionalized relationships into quantifiable metrics. This paper explores the utility of using social vulnerability research and indices as a way to direct applied public health interventions related to environmental exposures and specific health outcomes.

Vulnerability

The term vulnerability is used differently by practitioners in different disciplines and has come to be associated with multiple meanings and concepts[2,3]. For our purposes vulnerability is defined as "the likelihood of sustaining losses from some actual (or potential) hazard event, as well as the ability to recover from those losses"[4] or more simply as the potential for loss[5]. Social vulnerability specifically refers to dimensions of vulnerability related to social and demographic factors of geographic regions such as socio-economic status, ethnicity, race, age and occupation. Universally, "vulnerability is the result of processes in which humans actively engage and which they can almost always prevent"[2]. Social vulnerability is the product of both inequalities of place (i.e. urbanization, economic vitality) and inequalities of social conditions (i.e. race, gender, income) which together contribute to a community's susceptibility to harm and ability to respond to hazards[5]. In application, social vulnerability helps to explain the differential ability of communities to respond to and recover from hazards[6]. In this way, the concept of vulnerability is directly tied to that of risk; with risk being defined as unknown or known events likely to cause harm (to goods, services, infrastructure or health)[3].

Social Vulnerability Indices

Research into social vulnerability indices has emerged as a way of quantifying the "social dimensions of natural hazards vulnerability" therefore providing a measure of a geographic region's relative risk in the face of natural hazards [7]. Social vulnerability indices strive to quantify disparities and inequalities at the regional level through the creation of scores. There are two main categories of vulnerability indices: *Hazard specific indices* and *Composite indices*. Hazard specific indices have a specific purpose related to a singular hazard; for example identifying populations most vulnerable to climate change, flooding or heat waves. In contrast, composite indices are designed to encompass relative risk to a variety of hazard scenarios across time and space[8].

Social vulnerability indices are traditionally used in the field of disaster risk reduction, consequently much of the recent research into social vulnerability has focused on the role that vulnerability plays in "exacerbating or ameliorating the effects of disasters"[9]. But limiting research to disaster risk reduction fails to address the broader applicability of these indices to public health practice. Research into the public health applicability of social vulnerability indices could prove useful in a variety of contexts.

From a public health perspective, social vulnerability indices could be applied to explore regions at risk for specific health outcomes, excess exposure to environmental hazards, or issues of environmental injustice[10]. The ability to effectively identify vulnerable populations through social vulnerability mapping might improve public health interventions and decrease the impact of environmental hazards on the populations most vulnerable to negative health outcomes. Specifically, social vulnerability indices could serve as a framework to prioritize strategies that mitigate exposure to environmental hazards[8]. Before adoption of social vulnerability indices in public health practice their ability to characterize risk should be thoroughly researched, specifically in the context of nuances between indices produced with different structural designs, indicators and weighting schemes.

In theory, composite indices would be particularly useful, given their multi-hazard applicability. "Developing a composite index of vulnerability that reduces all variables to one number, that is comparable across time and space, and that is widely accepted by users and practitioners alike – is the "holy grail" of vulnerability assessment"[8]. Unfortunately, many of the factors that contribute to social vulnerability are complex in nature and often difficult to observe or quantify making it challenging to encompass the many different components of vulnerability into a single metric[2,11]. In practice, composite indices can also diminish the importance of individual factors of vulnerability and fail to indicate the actual structural causes of vulnerability[8]. Despite limitations, multiple composite social vulnerability indices have been developed. Currently there is currently no consensus regarding the ideal methodology for the production of social vulnerability indices[7].

Composite indices are typically constructed using one of three main structural methodologies, including the 1) Deductive, 2) Hierarchical and, 3) Inductive designs[7] (See Figure 1). The Deductive index is the most simplistic and is typically an additive index of 7 or fewer variables utilizing basic weighting[7]. The Hierarchical index is more complex, and uses between 10 and 20 indicators, which are combined into sub-indices; these sub-indices are weighted and aggregated to create the final index[7]. Finally there is the Inductive design which takes a large set of potential indicators and uses principal component analysis to identify those indicators which are most influential and important when explaining social vulnerability[7]. These indicators are then aggregated and normalized to create the index. The three different structural designs vary in complexity, but the question remains as to whether or not increases in complexity equate to better measures of vulnerability. Typically, a given researcher does not employ all three designs; consequently little research has been conducted into comparing social vulnerability indices produced from the same selection of indicators but through different processes of index construction. Consequently, this project compares three indices produced using three distinct structural designs and the same selection of variables to try to elucidate the impact structural design has during the production of social vulnerability indices.

Air Pollution and Asthma

To compare our social vulnerability indices against health and exposure data we utilized air pollution (PM 2.5) and emergency asthma visit rates (ED rates) as our comparison. Significant research has been conducted to help explain and quantify the relationship between exposure to air pollution and respiratory distress. A recent time series analysis on hospital admission data and air pollution showed associations between respiratory ED visits and exposure to ozone or PM2.5 [12]. A second time-series analysis conducted on over 400,000 ED visits suggested significant relationships between elevated ozone and increases in respiratory and asthma visits as well as between PM2.5 exposure and asthma (with an increase of effect during warmer months[13]. Research into the relationships between exposure to air pollution and asthma suggests a clear exposure disease relationship with a relatively small magnitude of effect.

Study Purpose and Aims

For social vulnerability indices to be useful from a broad public health perspective they need to be 1) accurate, 2) easy to understand, and 3) simple to use. The purpose of this thesis is to identify whether composite social vulnerability indices could be useful for identifying socially vulnerable populations for the purpose of directing applied public health interventions. Specifically, we will address the following research questions, which have been operationalized as testable null hypotheses:

1. *Social vulnerability indices produced by the deductive, hierarchical and inductive methods will yield the same spatial distributions of social vulnerability at the county level for each state (New Jersey and Florida).*
2. *ED visit rates are not spatially correlated with measures of social vulnerability or exposure to air pollution at the county level for each state (New Jersey and Florida).*

The above research questions will be explored through the following research objectives:

1. Determine if different structural designs yield the same spatial distribution of vulnerability.
2. Identify if rates of ED visits are spatially correlated with social vulnerability OR exposure to PM 2.5.
3. Identify if rates of ED visits are spatially correlated with social vulnerability AND exposure to PM 2.5.

Methods

Study Area

The study area is comprised of the states of New Jersey and Florida. New Jersey is located in the Northeastern United States and is characterized by small counties, high population and a diverse ecology. Florida is located in the Southeastern United States and is also characterized by small counties, diverse ecology and a relatively high population density. Choosing states with small counties was important, given that the smaller the spatial scale, the more likely social vulnerability score will reflect true vulnerability. As spatial scale increases, so does the diversity of people and environments within a given spatial unit. Florida and New Jersey were also ideal comparison groups because these two states differ in climate, population demographics and ecology. This variability is conducive to comparing indices across space.

Data and Measurements

Social Explorer was used to extract United States Census Data (year 2000) thought to characterize social vulnerability[1,14]; additional variables were downloaded from the 2000 Area Resource File[15] (Table 1). All variables used in this study were modeled after Cutter's 32 variable 2003 social vulnerability index[1]. Nursing home patient data was unavailable; as a proxy we used the number of nursing home beds multiplied by the rate of nursing home admissions (from the National Nursing Home Survey of 2004) to get an estimate of nursing home patients at the county level in 2000[16]. These data were used to develop the hierarchical and deductive vulnerability indices following an approach adapted from Cutter (2003) and Tate (2012)[5,7]. Shapefiles for each state were obtained from the US Census website, for TIGER products[17]. ED visit rates were obtained for New Jersey and Florida at the county level from the CDC's National Environmental Public Health Tracking Network (Tracking Network) website[18]. ED visit rates for asthma included data obtained between 2005 and 2011 averaged by county (per 10,000 population). ED visits were identified as emergency department visits during a calendar year with asthma as the primary diagnosis derived from State emergency department data. Air Pollution data included 24-hr average PM2.5 for 2006 (mapped and modeled) which was also obtained from the CDC's Tracking Network website[18]. PM 2.5 values were represented in micrograms per cubic meter.

Inductive Index

The 32 Variable SoVI from 2000 was extracted from the Hazard and Vulnerability Research Institute, located on the University of South Carolina's website[1]. Rather than perform our own factor analysis, we chose to use this social vulnerability index as our inductive index. The inductive index data was mapped using ArcGIS and GeoDa. Relative vulnerability scores were displayed in quintiles and tertiles. The same pool of variables used to develop Cutter's 32 variable SoVI was used to create the hierarchical and deductive indices to help limit modeler subjectivity[1].

Deductive Index

A deductive index was developed, using the same 32 indicators as the SoVI. Variables were obtained at the county level. Each indicator was normalized by population, or area (with the exception of per-capita income which was not normalized) and directionality was applied to variables likely to decrease vulnerability (by multiplying variables by -1). Variables were standardized using Z-score standardization: $z - score = (X - mean) \div stdev$, and multiplied by a weighting factor. Equal weighting was used and derived from the following equation: $\left(\frac{1}{n}\right) * 100$. Weighted values for each indicator were then added together at the county level resulting in an initial social vulnerability score.

$$Deductive\ SVI = \sum ((V1 * W1) + (V2 * W2) + \cdots (V32 * W32))$$

Where:

$V = Variable$

$W = Weight\ (= 3.125)$

N = Number of Variables (= 32)

Positive values imply higher vulnerability, while negative values indicate lower vulnerability. The deductive index was mapped using ArcGIS and GeoDa at the county level. Relative vulnerability scores were displayed in quintiles and tertiles.

Hierarchical Index

A hierarchical index was developed using the same variables included in the deductive index explained above but employing equal weighting at the sub index level rather than at the variable level. The index was produced manually using excel. Variables were normalized by population and directionality was applied to variables likely to decrease vulnerability (by multiplying variables by -1). Indicator variables were separated into three sub-indices representing different dimensions of vulnerability (socioeconomic status, differential access & special needs and general demographics). Component variables were standardized using Z-score standardization (see above for equation).

After standardization, variables were summed at the sub-index level and weighted using an equal weighting scheme. Equal weighting was used and derived from the following equation: $\left(\frac{1}{n}\right) * 100$ where n represents the number of sub-indices (3). County values were divided by the total number of indicators in each sub-index, creating a score for each county at the sub-index level. The sub-index level totals were combined and divided by the total number of sub-indices producing a hierarchical index score.

$$Hierarchical\ SVI = \sum((I1 * W) + (I2 * W) + (I3 * W))$$

Where:

Sub-indices are defined as I1, I2 I3:

$$I1 = \sum((V1 + V2 + \ldots.V9)/9)$$

$$I2 = \sum((V10 + V11 + \ldots.V18)/9)$$

$$I3 = \sum((V19 + V20 + \ldots V32)/14)$$

V=$Variable$

$W = Weight\ (= 33.333333333)$

Positive values imply higher vulnerability, while negative values indicate lower vulnerability. The final scores included in the hierarchical index were mapped using ArcGIS and GeoDa. Relative vulnerability scores were displayed in quintiles and tertiles.

Data Analysis

Initial exploratory analysis was conducted spatially and statistically. Data were complied in Excel and exported to ArcGIS 10.1 and SAS 9.3 for analysis. Indexes were compared by State. Each index was mapped to display relative vulnerability scores (in quintiles and tertiles). PM 2.5 and ED visits were also mapped at the county level and displayed in tertiles to show spatial distributions of high, medium and low values.

To determine whether or not different structural designs yield the same spatial distributions of vulnerability we used Getis test (G(i)) to compare statistically significant clusters in each of the different social vulnerability indices. To conduct our G(i) test we used queen contiguity of nearest neighbors using Euclidian distance. Setting a defined distance was not appropriate in this instance. GeoDa was used to estimate the spatial clustering. Spearman's correlation was used to quantify the association between indices at the county level. The inductive, deductive and hierarchical indices were compared in pairs for both spatial and statistical comparisons. ArcGIS was used to display information visually.

To identify if rates of ED visits are spatially correlated with social vulnerability OR exposure to PM 2.5 we used Local Bivariate Moran's I (Bivariate LISA). Bivariate LISA tests whether a value in a given location (X1i) is more similar to that of the average of its neighbors (X2j) than would be the case under spatial randomness. Bivariate LISA compares one 'layer' spatially to another 'layer' (i.e. values of counties in X1i are compared to neighboring counties in X2j) to help us to identify if a variable in layer 1 is significantly different from the mean given the value of their neighbors (in layer 2). For both states, each index and PM 2.5 values were compared with ED Rates to identify multivariate clustering and autocorrelation to assess whether or not there was a systematic relationship (i.e. more than random chance) between ED Visit Rates and our other variables of interest. GeoDa was used to compare spatial autocorrelation at the global and local level and ArcGIS and GeoDa were used to display information visually. Variables were graphically related in SAS to show how ED rates vary as a function of PM 2.5 exposure and how ED rates vary as a function of social vulnerability (by index). This was repeated for both states.

To identify if rates of ED visit rates were spatially correlated with social vulnerability AND exposure to PM 2.5 we compared means values for each social vulnerability index, with ED visit rates and PM 2.5 exposure. First, all data were visualized in tertiles to identify relative low, medium and high values. Social vulnerability values were compared with PM 2.5 exposures and ED visit rates were mapped. Conditional choropleth maps were used illustrate the multivariate relationship between our three variables of interest. This process was repeated for all three indices and each State. ArcGIS was used to produce the visuals.

Finally, simple Poisson regression was used to make a model of ED counts as a function of social vulnerability and exposure to PM 2.5. Z-Score standardization was used on each of the social vulnerability indices to ensure the highest level of comparability. Regression was repeated for each state three times; one iteration for each social vulnerability index. This model was used to identify whether the multivariate pattern displayed through conditional choropleth mapping was due to chance or if it was statistically significant. The equation for Poisson regression was:

$$\ln[E\ (Y/\ell)] = B_0 + B_1 X_1 + B_2 X_2$$

Where:

Y = Poisson (number of cases)

ℓ = Population

B_0 = Intercept

$B_1\ X_1$ = Beta 1 * Social Vulnerability Index Score (Inductive, Deductive of Hierarchical)

$B_2\ X_2$ = Beta 2* PM 2.5 Exposure

Results of Poisson regression were compared at the model level by state.

Results

Tables 2 and 3 display social vulnerability scores for each structural design (deductive, hierarchical and inductive) at the county level. Visual comparisons of the different indices suggest each index produces a different spatial pattern of vulnerability for both New Jersey and Florida when data is displayed in quintiles (see Maps 1 and 15). These differential spatial patterns remained consistent when data was displayed in tertiles (Maps 4-6 and 18-20). It is important to note that the three different indices are not comparable in terms of absolute value. The different indices were not scaled to maintain consistency with Cutter et al.'s methodology (2003)[5]. Although the absolute values vary by index, the relative vulnerability explained visually correlates with limited county-level variation.

Map 2 shows the distribution of PM 2.5 at the county level in NJ, displayed in tertiles to reflect low, medium and high values. In New Jersey, PM 2.5 values ranged from 10 mg per cubic meter to 14 mg per cubic meter. Map 16 shows the distribution of PM 2.5 at the county level in FL also displayed in tertiles. In Florida, PM 2.5 values ranged from 5mg per cubic meter to 12mg per cubic meter. Maps 3 and17 show ED visit rates per 10,000 displayed in tertiles (representing low, medium and high rates of admission) for NJ and FL respectively. Rates differ by state with NJ rates for admission ranging from 27.44 to 155.43 visits per 10,000 and FL rates for admission ranging from 25.13 to 86.74 visits per 10,000. General comparisons of the different indices and variables (*PM 2.5, ED Rates and ED Counts*) included in this study can be found in Tables 4 and 5.

Aim 1: *Determine if different structural designs yield the same spatial distribution of vulnerability.*

Results of Getis, G(i), Cluster Analysis vary by state. When applied in New Jersey, results show two distinct clusters in all three indices, yet the counties included in the two clusters vary by index (see Map 7). The three indices consistently identify the cluster in Northern NJ as a "cold spot", or a cluster of low values, and the cluster in Southern NJ as a "hot spot", or a cluster of high values. The clusters identified in the deductive and hierarchical indices are most similar in size. When applied in Florida, the results of the Getis Cluster Analysis are much more disparate. The "hot spots" and "cold spots" observed in the three indices vary by index construction, with the deductive and hierarchical indexes producing the most similar distribution of clusters (see Map 21). This was supported statistically with Spearman's correlation comparison of the clusters (see Table 7). It is important to note that Getis cluster analysis can only provide information on the similarities between indices at the cluster level.

The results of the cluster analysis applied in both NJ and FL imply that generally the three different social vulnerability indices produce different spatial distributions of vulnerability with the deductive and hierarchical indices producing the most similar results. This was further supported through comparison of Spearman's correlation coefficients (see Table 6) at the indicator level. For both NJ and FL, the hierarchical and deductive indices were highly correlated at a 99% confidence level (.9831 and .9877 respectively) indicating relative "sameness". In NJ, the inductive index was also highly correlated with the deductive and hierarchal indices at the 99% confidence level (.8533 and .8169). In contrast the inductive index was not significantly correlated with the deductive index at a 95% confidence level (.2102) nor was the inductive strongly correlated with the hierarchical index at the 95% confidence level (.2395). The above suggests that although general spatial distributions of vulnerability vary by index, the degree with which they are similar (or different) varies when employed in different geographic locations (i.e. their relative difference is a product of not only the index used but also the state in which the index is being used to describe).

Aim 2: *Identify if rates of ED visits are spatially correlated with social vulnerability OR exposure to PM 2.5.*

ED rates were compared to PM 2.5 exposure for both NJ and FL using Bivariate LISA. For NJ, there were eight counties with significant evidence of local spatial dispersion between ED rates compared and PM 2.5 exposures (Map 8) Moran's I value = -0.0224. Comparison between the deductive index and ED rates show significant evidence of local spatial autocorrelation in six counties (Map 9), Moran's I value = .1096. Potential clusters were primarily high-high and low-low relationships. Not surprisingly, comparison between the hierarchical index and ED rates show significant evidence of spatial autocorrelation in the same six counties (Map 10) Moran's I value = .1040. Bivariate comparison of ED rates and the inductive index suggest slight spatial autocorrelation (Map 11), Moran's I= .1008. There were 10 counties identified as potential clusters with the location of spatial clusters differing from those identified by the hierarchical and deductive comparisons. These values were all significant at the 95% confidence level but were not indicative of strong spatial autocorrelation.

Results were different for Florida. In FL, there were only 4 counties (out of 67) with significant evidence of local spatial autocorrelation between ED rates and PM 2.5 exposure (Map 22) Moran's I value = .0151. There were no high-high or high-low correlations. When the deductive measure of social vulnerability was compared with ED rates, the results suggested a negative spatial autocorrelation (dispersion), Moran's I = -.0809 with 11 counties showing potential clusters throughout Florida (Map 23). There were no low-low spatial clusters identified. As expected the bivariate comparison of ED rate with the hierarchical index produced similar results, Morans I = -.0707 (Map 24), with potential clusters dispersed similarly across the state. The bivariate comparison of ED rates with the inductive (SoVI) measure of social vulnerability produced similar results, Moran's I= -.0764 (Map 25). It is interesting to note that although the inductive performed similarly, the counties showing statistically significant spatial autocorrelation were displayed in a distinct pattern from that of the deductive and hierarchical indices. For both NJ and FL, all bivariate LISA results were significant at the 95% confidence level.

To further explore these relationships the ED rates were plotted graphically against PM 2.5 exposure and the three different measures of social vulnerability for both FL and NJ. Results suggest similar interpretation with the relationship between the variables varying by state (Graphs 1-8). The Florida plots show no relationship between the different indices of social vulnerability on ED rates. The NJ plots suggest there might be a slight linear relationship between social vulnerability indices and ED visit rates. In both NJ and FL there does not appear to be a significant linear relationship between exposure to PM 2.5 and ED visit rates as displayed graphically.

The results of the above analysis suggest that rates of ED visits are positively spatially correlated with social vulnerability in New Jersey. The results of the above analysis suggest that rates of ED visits are negatively spatially autocorrelated with social vulnerability in Florida. In New Jersey, spatial autocorrelation suggests potential clustering (neighboring values between layers are similar). In contrast, In Florida, spatial autocorrelation suggests dispersal (neighboring values between layers are dissimilar). In both cases, results of Moran's I suggest that rates are spatially dependent on social vulnerability but the relationship is different in each state. Spatial correlation estimates are stronger for NJ than for FL. Additionally, in both states, results suggest that ED visit rates are not spatially correlated with exposure to PM 2.5 (Moran's I values are extremely close to 0).

Aim 3: *Identify if rates of ED visits are spatially correlated with social vulnerability* ***AND*** *exposure to PM 2.5.*

Conditional choropleth maps were used to visually explain the spatial multivariate relationship between exposure to PM2.5 and social vulnerability on ED Rates. A distinct conditional choropleth map was produced for each index in each state. Results varied by state and index.

In New Jersey, the first conditional choropleth map displayed the spatial distribution of social vulnerability produced by the deductive index (Map 12). This map provides visual evidence of a relationship between social vulnerability, PM 2.5 and ED visit rates. The following observations are of particular importance. No counties with high ED rates were identified in counties with low social vulnerability (only low and medium ED rates). Additionally most counties with high ED rates were identified in counties with high social vulnerability. Specifically, five counties with ED visits in the highest tertile were identified in the segment represented by high vulnerability and medium exposure to air pollution. Only two additional counties with high ED rates were identified and they were both located in the medium tertile of social vulnerability with medium and high exposure to air pollution respectively. Furthermore, all of the counties with the lowest ED visit rates were identified in counties with low or medium social vulnerability and low or medium exposure to air pollution.

Map 13 displays the social vulnerability distribution created from the hierarchical index applied in NJ. Not surprisingly, results mimic that of the deductive index with one notable exception, Mercer County. Mercer County has a high rate of ED visits, and was identified in the medium vulnerability range in the deductive index. In contrast, the hierarchical index identified Mercer County as low vulnerability.

The NJ inductive (SoVI) conditional choropleth visually displayed a relationship between social vulnerability, PM 25 exposure and ED visit rates, although there was a lot of variability in the middle range of exposures (Map 14). The SoVI identified all of the counties with the lowest ED visit rates in the low and medium social vulnerability categories and all the counties with the highest ED rates in the medium and high social vulnerability categories. The mini-map representing medium social vulnerability and medium exposure to air pollution displayed counties with low, medium and high ED visit rates. Furthermore the middle range of ED visit rates follow no distinct pattern but this could be the product of ED visits that are not related to PM 2.5 exposure or the small measure of effect between exposure to PM 2.5 and ED visit rates.

Comparison of the Florida maps was more complex given the higher number of counties to compare. It was much more difficult to ascertain visually whether there was a significant relationship or whether the maps produced were representing "noise". When looking exclusively at the counties in Florida with the highest rates of ED visits, the deductive index performed marginally (Map 27). It identified the fewest counties with high ED visit rates in the counties with the lowest vulnerability. It also identified the most counties with high ED rates in the counties that have the highest vulnerability. There did not appear to be a relationship between PM 2.5 exposure and ED rates implying that the multivariate relationship between social vulnerability and PM 2.5 exposure was more dependent on social vulnerability then PM 2.5 exposure. The hierarchical index performed similarly with minimal differences (Map 28).

When the inductive (SoVI) index was compared to ED visit rates and PM 2.5 exposures, patterns are increasingly difficult to identify (Map 29). Counties with high, low and medium ED visit rates were identified in every single mini-map making a visual interpretation of the conditional choropleth map difficult. When only counties with high ED rates were considered, 5 were located in counties with low social vulnerability, 8 were located in counties with medium social vulnerability and 9 were located in counties with high social vulnerability suggesting a linear relationship. In contrast, when high PM 2.5 is compared with counties with high ED rates; 10 counties with high rates were located in counties with low PM 2.5 exposure, 5 were located in counties with medium PM 2.5 exposure, and 6 were located in counties with high PM 2.5 exposure, suggesting no linear relationship.

To investigate the statistical significance of the multivariate relationships visualized through conditional choropleth mapping (i.e. trends in horizontal or vertical panels) Poisson regression was used. Results of Poisson regression were displayed visually in tables 8 and 9. In both NJ and FL the relationship between social vulnerability and ED rates was statistically significant when the deductive and hierarchical indices were used. For both states the inductive (SoVI) index was not significant.

Additionally, in all models, the relationship between ED visits and PM 2.5 was not statistically significant at the alpha=0.05 level. Overall the deductive and hierarchical indices were better at predicting ED rates than the inductive index. Additionally, all three social vulnerability indices performed better in NJ than in FL (compared to ED visits).

In NJ, ED visit rates appeared spatially correlated with social vulnerability in the presence of air pollution, although the relationship with air pollution does not appear to be significant alone. ED visit rates vary slightly by index, but the relationship also changes as a product of PM 2.5 level as explained earlier. The relationship between SV indices and exposure seems strongest at the extremes. For both NJ and FL Medium ED rates were captured at all levels of social vulnerability. Results displayed on the conditional choropleth maps were further supported through statistical analysis and the results of Poisson regression explained above. These results suggest that the visual relationships displayed in the choropleth maps were statistically significant but also that the measure of effect of social vulnerability indices was small and significant and that the measure of effect of PM 2.5 was small and insignificant (at the 95% confidence level).

In FL, ED visit rates appeared slightly spatially correlated with social vulnerability in the presence of air pollution, although the relationship with air pollution did not appear to significant alone. The multivariate relationship between SV indices and exposure was difficult to discern visually. The high number of counties and the fact that low, medium and high ED visit rates were found consistently across the index made the relationship difficult to interpret. This is further supported through statistical analysis and the results of Poisson regression (stated above), which suggest that the visual relationships displayed in the choropleth maps was statistically significant but also that the measure of effect of social vulnerability indices was small and significant (except for the inductive SoVI) and that the measure of effect of PM 2.5 was small and insignificant (at the 95% confidence level).

Hypothesis One: *Social vulnerability indices produced by the deductive, hierarchical and inductive methods will yield the same spatial distributions of social vulnerability at the county level for each state (New Jersey and Florida).*

Results of our study suggest that we must reject our first null hypothesis. Social vulnerability indices produced by the deductive, hierarchical and inductive methods did not yield the same spatial distributions of social vulnerability at the county level in both Florida and New Jersey. The hierarchical and deductive indices were extremely similar, which is not surprising given the similarities of their construction, but interestingly, their degree of similarity varied as a result of the state in which they were employed. These results suggest that structural design is an important aspect of index development and that choice of design will have an effect on the dimensions of vulnerability explained by a given social vulnerability index. Future research should be developed toward exploring the impact of structural design more thoroughly and comparing additional states.

Hypothesis Two: *ED visit rates are not spatially correlated with measures of social vulnerability or exposure to air pollution at the county level for each state (New Jersey and Florida).*

The results of our study suggest that we must reject the null hypothesis. Results suggest evidence of spatial correlation between social vulnerability and ED visit rates in both Florida and New Jersey although the spatial relatedness was different in each state. There does not appear to be a significant relationship between ED visit rates and exposure to air pollution. These results are supported by the differential patterns of vulnerability displayed by the three different conditional choropleth maps for each state and the statistical significance of these relationships (i.e. results of Poisson regression). This was further supported by the Moran's I results displayed earlier. There was not only distinct variability within one state but also between NJ and FL. Future research should devote time towards looking at state specific vulnerability to identify if composite indices are appropriate for public health research.

Discussion

The results described above suggest very different relationships between social vulnerability and exposure to air pollution as a function of State. Using two States with geographic difference was intended to expose whether or not results produced by social vulnerability indices were replicable across space. The results displayed above suggest that the location where social vulnerability indices are being applied impacts the index's ability to characterize social vulnerability. This suggests that the factors that influence social vulnerability could vary at the State level. Further research should be conducted to identify whether the differences between FL and NJ were merely an anomaly or if there are systematic population-level differences in characteristics that might impact the ability of composite-level indices to accurately portray social vulnerability.

In this particular study, there was some variability in results of Bivariate LISA compared to Poisson regression. This is likely due to the different nature of the tests and what they are measuring. Moran's I calculations assume populations at risk are evenly distributed in a study area. It is possible, that the variation at the county level between ED rates impacted the results of our Moran's I calculations. Additionally, Moran's I is dependent on the weight matrix specified. For our purposes, we used a Queen Contiguity of 1. Results might vary if a different spatial weight matrix were employed. Future analysis should include an assessment of the above concerns coupled with the use of Monte Carlo analysis to substantiate results. Additional discrepancies include the significance of the inductive measures of vulnerability. Results of Bivariate LISA suggests that the inductive index of social vulnerability is spatially autocorrelated to ED visit rates in NJ, and negatively spatially autocorrelated to ED visit rates in FL. In contrast, results of Poisson regression suggest that the inductive index does not significantly explain the variability in ED rates. It is important to note that Poisson regression fails to include a spatial component, while Bivariate LISA is comparing nearest neighbors between two spatial layers. These two tests are comparable but different. Given that the Moran's I values were not very strong, and that visual interpretation shows significant variability among the spatial distribution of the inductive index, it is not surprising that the inductive index was found not significant during regression analysis.

The results of this study also prove informative regarding the differences in index construction. The inductive SoVI consistently produced different measures of vulnerability then those produced by the deductive and hierarchical structural designs. The differences between the deductive and hierarchical indices were more subtle. This suggests that when using the same variables and equal weighting, choosing whether or not to use the deductive or hierarchical index depends on whether a researcher prefers to weigh all variables equally or weigh the underlying latent constructs equally. The difference between these two structural designs is likely to be greater when there are more variations in the size of the sub-indices of the hierarchical index (consequently adding an addition weight by design). Further research is still necessary to determine whether or not one structural design performs consistently better then another structural design.

Although all three NJ conditional choropleth maps suggested a relationship between social vulnerability and ED rates, the relationship between PM 2.5 exposure and ED rates was less clear. Prior research suggestions there is a relationship between PM 2.5 exposure and asthma ED visits[12,13]. This project failed to identify evidentiary support statistically or spatially of a relationship between exposure to air pollution and ED visits in NJ or FL. This is not surprising given the small measure of effect between exposure to PM 2.5 and asthma. Although there was little evidence of a relationship between high exposure to air pollution and high ED visit rates in the series of conditional choropleth maps, that doesn't mean that a high-high relationships doesn't exist. Using a different scale or cut-off points might show a different relationship.

Much of the results of our condition choropleth mapping were dependent on sectioning the data into tertiles to identify low, medium and high values. These cut-points were somewhat arbitrary. Future research should explore the impact of using different cut-points of vulnerability and how adjusting cut-off values can impact the multivariate relationships. As an additional concern, using tertiles to display PM 2.5 might not have been the best decision given the unequal distribution of values by county (leading to unequal thirds). In the future it might be better to utilizing a geographic mean or EPA cutoffs for exposure values.

Limitations

This study methodology involved significant limitations. Using Cutters SoVI as our inductive index was a decision that ultimately made comparison of the different indices challenging. To limit modeler subjectively we attempted to use the same census data and variables that were used to produce the SoVI. Some variables required additional manipulation of data to replicate. Each decision made increased the variability between the variables used in the original SoVI and the two indices developed for this study. Consequently, the ability of this study to accurately compare the impact of structural design on index results is limited. Further research is necessary to identify the true nature of variability between indices (whether it is a function of indicator selection, modeler subjectivity or structural form). Despite limitations, this study allowed for a unique exploration of social vulnerability indices compared to environmental exposure data and health outcomes. It should be noted that the purpose of this study was not to identify which social vulnerability index is "best" but rather to explore the differences and similarities between their ability to characterize vulnerability.

Additional limitations of this study were related to the actual data. Although the census data used was derived from the 2000 census, the health and exposure data were derived from more recent years (2005 to 2011). Matching census, exposure, and outcome data by year might improve the ability of the social vulnerability indices to accurately portray relative risk measures. But practically, updating these indices with new data every year would likely be a costly and time-consuming process. Therefore using data that isn't directly corresponding to our social vulnerability index proves informative about the ability of these indices to characterize risk across time. Future research should include time-series analysis of the relationships between social vulnerability indices and their long-term ability to accurately characterize vulnerability given the spatial distribution of social vulnerability is unlikely to change dramatically from one year to the next.

The ability to accurate estimate the weight or potential influence of a single variable is a complex process that is subject to uncertainty. We decided to use equal weighting to try to limit sources of bias. Equal weighting presumes "no a-priori assumptions about the relative importance" of component variables[19]. It is important to note that choosing to use equal weighing is still a choice that will ultimately impact results. Many social vulnerability indices use equal weighting, but the use of equal weighting assumes all dimensions of vulnerability are equally important to the experience of risk. In truth, it is likely that some indicators have a greater impact on vulnerability then others. For example, it is unlikely that being employed by the extractive industry contributes to vulnerability as much as income disparity and yet in this case, we are assuming they contribute equally (see Table 1 for a full list of included indicators). Additionally, the hierarchical index is particularly sensitive to sub-index construction and weighting. Our hierarchical index used equal weighting at the sub-index level, but sub-indices did not include an equal variable numbers. Consequently, the sub-indices with more variables have a higher implicit contribution to the overall index. Future studies could limit this by using sub-indices with equal numbers of variables (an impossibility for this study).

The addition of weighting factors might impact a given social vulnerability indices ability to characterize differential vulnerability (for better or worse). To correctly employ weighting it is important to look to past research regarding the impact of variables on vulnerability (or sub-indices) and their potential ability to drive vulnerability. That being said, quantifying the impact of variables on social vulnerability is a challenge in and of itself and even a consensus among experts is likely to still have a degree of uncertainty attached. Future research should focus on analyzing individual components of vulnerability systematically. This will likely be challenging given the difficulties of assigning standard value to components of vulnerability. So often, the human experience is more than the sum of its parts, systematically deconstructing the components of vulnerability might actually lead to an oversimplification of vulnerability. Additionally there is the issue of data availability. It is quite likely that the variables that are the greatest contributors of social vulnerability are not currently measured or available. Trying to create these indices within a framework of what is known and available requires a variety of assumptions which ultimately might impact their applicability in public health practice.

In addition to the conceptual limitations of this study, measurement error is a concern. The data used to develop the social vulnerability indices was derived primarily from the 2000 US Census. These data included significant missed subjects and undercounts[14]. Those individuals most likely to be missed are also those most likely to be vulnerable populations (i.e. illegal immigrants, non-English speakers, homeless), etc. These missing data are particularly relevant because they represent the populations most at risk. Increasing the efficacy of data collection at the census level would prove useful to future iterations of social vulnerability indices.

Of additional consideration are limitations in study design. To ensure consistency and comparability regarding structural differences between indices we used the same number of variables in our deductive comparisons as were used to prequel factor analysis in the SoVI. In practice, deductive indices typically use few variables. Our deductive indices were therefore, limited in their ability to accurately capture the true appeal of the deductive index, which is ease of construction. Rather they served as a measure of relative difference.

Given that vulnerability is closely tied to place, using the smallest spatial unit possible to calculate vulnerability would likely increase the effectiveness of such indices. Given limited time and availability of data we used county level data. Counties can vary significantly in a variety of ways that contribute to disproportionate experience of risk (i.e. geographically, socio-economically, ecologically etc.). This spatial heterogeneity will appear different at various spatial scales. Consequently, exploring vulnerability at the county level likely misses the more complex dimensions of vulnerability. Future research should focus on narrowing the spatial scale to identify whether or not SV indices are more effective at characterizing risk at smaller spatial scales such as the census tract.

Finally, human error is always a concern and this study is no exception. It is likely there was some degree of human error implicit in this study. The deductive and hierarchical indices used in this study were produced manually in excel. It is likely, given the extensive amount of data used to produce these indices that there were mistakes that could have impacted results.

Conclusion and Recommendations

Social vulnerability indices strive to categorize vulnerability as a social condition and a measure of resilience in the face of hazards[2]. Social vulnerability indices have the potential to be employed as useful tools in the field of public health, but more research into the development of such indices is necessary to establish a set of best practices for index construction. This study looked specifically at the impact of structural design on index results and found that dimensions of vulnerability vary with structural design. Indices produced by the three different structural designs produced different spatial distributions of vulnerability at the county level. Additionally this study found evidence of spatial correlation between social vulnerability and ED visit rates in both Florida and New Jersey although the spatial relatedness was different in each state. These initial findings suggest that social vulnerability could be a useful public health tool if employed correctly, but to utilize effectively, further research is necessary.

The process of making social vulnerability indices requires numerous judgment calls at multiple levels beyond that of structural design. The decisions made by the researcher ultimately determine the efficacy of each index. Choosing variables, the weighting scheme, structural design as well as the method of aggregation all have complex impacts on the final indexes. Standardization of these methodologies to find the most accurate way of producing such indices would prove useful in driving future research of social vulnerability indices.

These questions into the impact of methodology on social vulnerability results bring to attention more specific concerns such as whether or not composite indices are appropriate for environmental health applications. Although composite indices represent the ultimate goal due to their broad applicability they might not be appropriate for public health practice. Specifically, in environmental health, where disease/exposure relationships often have small measures of effect, it might be beneficial to development hazard specific indices. Although the production of hazard specific indices requires more time and research, they will likely characterize differential risk to specific hazards more accurately. More research is necessary to compare composite social vulnerability indices with actual health and exposure data to fully understand their applicability within the field of public health.

Not only should the applicability of social vulnerability indices in public health practice be explored from an exposure disease relationship standpoint, but also from a holistic perspective. Do these indices provide useful information? How will public audiences and the general population use the information provided by these indices? The variety of assumptions required in the construction of such indices, requires a degree of sophistication to interpret accurately. It also requires a general understanding of the concepts of risk and vulnerability. These are fairly complex concepts that might not be easily understood by all audiences. In fact it is likely that social vulnerability information could be completely misinterpreted. Therefore before implementing in public platforms (such as the internet), research should also be conducted on the best way to share vulnerability information to ensure appropriate knowledge translation.

In conclusion, it is likely that social vulnerability indices could be useful public health tools but more research should be conducted before implementation to ensure correct interpretation, use and applicability.

Tables and Figures

Figures

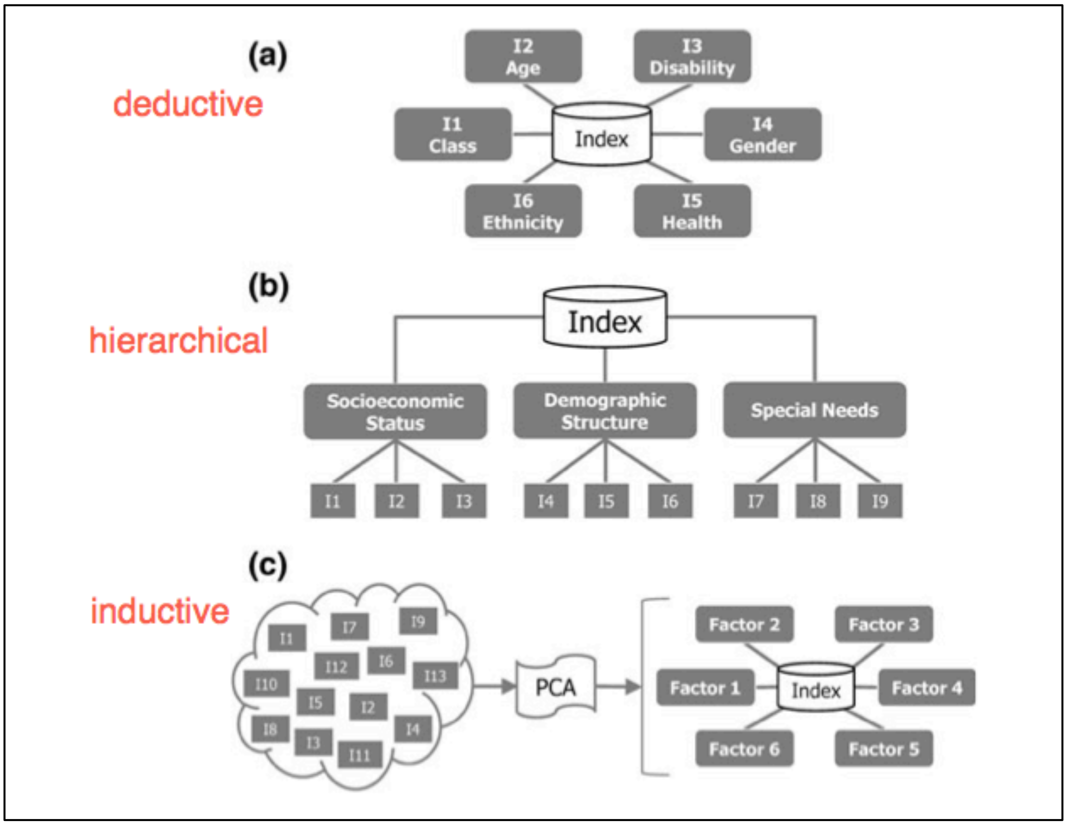


Figure 1: Index Creation: Structural Designs[7]

Tables and Graphs

Table 1: Indicators and Corresponding Dimensions of Vulnerability **Indicator**	**Dimension of Vulnerability** ***(for hierarchical index)***	**Effect on Vulnerability** ***(as values increase)***
% With Less Than 12 Grade Education	Differential Access & Special Needs	Increases
Per-Capita Income	Socio-Economic Status	Decreases
% Poverty	Socio-Economic Status	Increases
% Mobile Homes	Socio-Economic Status	Increases
Mean Housing Value	Socio-Economic Status	Decreases
% Earning > $100,000 / year	Socio-Economic Status	Decreases
Mean Contract Rent	Socio-Economic Status	Decreases
% Black	General Demographics	Increases
% Hispanic	General Demographics	Increases
% Native American	General Demographics	Increases
% Asian	General Demographics	Increases
% Female Headed Household	General Demographics	Increases
% Female	General Demographics	Increases
People Per Unit	Differential Access & Special Needs	Increases
% Kids	General Demographics	Increases
% Over 64	General Demographics	Increases
Median Age	General Demographics	Increases
% Renters	Socio-Economic Status	Increases
Housing Density	Socio-Economic Status	Increases
% Urban Population	Differential Access & Special Needs	Increases
% Population on Rural Farms	Differential Access & Special Needs	Increases
% Nursing Home Residents	Differential Access & Special Needs	Increases
% Foreign Born Recent Migrants	General Demographics	Increases
% Social Security Beneficiaries (individuals)	Differential Access & Special Needs	Increases
% in Civilian Workforce	Socio-Economic Status	Decreases
% Civilian Unemployment	Socio-Economic Status	Increases
% Female Participation in Labor Force	Socio-Economic Status	Decreases
Number of Physicians per Capita	Differential Access & Special Needs	Decreases
Number of Hospitals Per Capita	Differential Access & Special Needs	Decreases
% Employed in Transportation & Public Utilities	Socio-Economic Status	Increases
% Employed in Extractive Industry	Socio-Economic Status	Increases
% Employed in Service Industry	Socio-Economic Status	Increases

Table 1: 32 Indicators and Corresponding Dimensions of Vulnerability Explained

Table 2: Social Vulnerability Scores by Index (New Jersey)			
	Vulnerability Score		
New Jersey	*Inductive*	*Deductive*	*Hierarchical*
Atlantic County	1.87	1.00	9.04
Bergen County	-8.39	-1.50	-14.78
Burlington Count	-3.71	-1.07	-11.99
Camden County	-0.84	-0.06	-1.94
Cape May County	1.98	2.48	27.07
Cumberland Count	2.30	1.62	13.45
Essex County	-1.53	0.69	6.02
Gloucester Count	-2.26	-0.59	-8.34
Hudson County	-3.74	0.66	2.42
Hunterdon County	-10.04	-3.96	-42.85
Mercer County	-2.92	-0.85	-9.35
Middlesex County	-6.14	-1.21	-13.46
Monmouth County	-6.80	-0.69	-6.18
Morris County	-9.36	-2.28	-21.84
Ocean County	-1.32	3.68	43.11
Passaic County	-1.29	1.01	10.54
Salem County	-1.95	3.20	35.48
Somerset County	-9.46	-1.80	-15.62
Sussex County	-5.87	-0.86	-8.04
Union County	-5.08	0.24	2.90
Warren County	-3.40	-0.57	-8.64

Table 2: Social Vulnerability Scores by Index for New Jersey

Table 3: Social Vulnerability Scores by Index (Florida)							
	Vulnerability Score				Vulnerability Score		
Florida	*Inductive*	*Deductive*	*Hierarchical*	***Florida***	*Inductive*	*Deductive*	*Hierarchical*
Alachua County	4.22	-1.46	-16.31	Lee County	0.49	-0.32	-2.00
Baker County	-1.93	0.40	3.54	Leon County	3.07	-1.53	-15.42
Bay County	0.79	-0.13	-1.59	Levy County	0.65	0.94	8.09
Bradford County	-1.84	0.26	1.14	Liberty County	-3.81	0.32	0.88
Brevard County	0.31	-0.66	-5.78	Madison County	2.52	0.94	9.25
Broward County	-1.93	-0.56	-3.19	Manatee County	0.94	-0.33	-2.02
Calhoun County	0.18	1.22	11.00	Marion County	2.01	0.43	4.69
Charlotte County	4.50	0.17	3.00	Martin County	-1.16	-1.04	-8.76
Citrus County	3.36	0.77	7.71	Miami-Dade Count	-0.20	0.85	10.95
Clay County	-2.60	-0.92	-7.66	Monroe County	-4.20	-1.54	-15.34
Collier County	-2.82	-0.85	-5.94	Nassau County	-4.77	-0.79	-7.26
Columbia County	-0.09	0.42	3.17	Okaloosa County	-0.09	-0.47	-4.65
DeSoto County	-2.64	1.15	12.23	Okeechobee Count	-2.70	0.86	8.30
Dixie County	0.56	1.10	8.57	Orange County	-0.06	-0.44	-2.66
Duval County	-0.23	-0.46	-3.61	Osceola County	0.57	0.43	5.70
Escambia County	1.42	0.04	-0.15	Palm Beach Count	-1.50	-0.91	-6.60
Flagler County	1.83	-0.21	-0.10	Pasco County	2.15	0.28	3.46
Franklin County	1.24	0.27	2.15	Pinellas County	1.21	-0.14	-0.95
Gadsden County	3.05	0.89	9.07	Polk County	-0.48	0.47	5.05
Gilchrist County	-1.17	0.22	1.53	Putnam County	0.32	1.00	9.36
Glades County	-2.68	1.57	16.07	St. Johns County	-3.81	-2.11	-19.34
Gulf County	0.94	0.45	3.18	St. Lucie County	1.04	0.29	3.85
Hamilton County	-0.01	1.45	11.36	Santa Rosa Count	-1.92	-0.70	-6.66
Hardee County	-0.07	1.67	17.00	Sarasota County	2.43	-0.80	-6.33
Hendry County	-1.33	1.42	15.56	Seminole County	-2.42	-1.63	-13.67
Hernando County	2.38	0.67	7.05	Sumter County	0.09	1.03	9.64
Highlands County	3.69	1.13	12.44	Suwannee County	1.14	1.23	11.68
Hillsborough Cou	-0.61	-0.60	-4.63	Taylor County	0.61	0.66	5.61
Holmes County	0.25	0.79	6.40	Union County	-2.12	-0.65	-9.64
Indian River Cou	1.61	-0.50	-3.56	Volusia County	2.05	-0.18	-1.57
Jackson County	1.60	0.32	2.59	Wakulla County	-2.66	-0.66	-6.63
Jefferson County	0.29	0.07	1.45	Walton County	0.79	-0.04	-0.86
Lafayette County	-1.77	-0.45	-4.64	Washington Count	1.01	0.71	6.95
Lake County	0.85	0.10	2.03				

Table 3: Social Vulnerability Scores by Index for Florida

Table 4: Exploratory Analysis of Variables and Indicies (New Jersey)					
Model	Mean	Median	Standard Deviation	Min	Max
Deductive	-0.04	-0.57	1.83	-3.96	3.68
Standardized Deductive	*0*	*-0.3*	*1.02*	-2.18	2.07
Hierarchical	-0.62	-6.18	19.63	-42.85	43.11
Standardized Hierarchical	*0*	*-0.29*	*1.04*	-2.24	2.31
Inductive (SoVI)	-3.71	-3.4	3.73	-10.04	2.3
Standardized Inductive (SoVI)	*0*	*0.08*	*1*	-1.7	1.61
Variable	Mean	Median	Standard Deviation	Min	Max
PM 2.5 (*micrograms per cubic meter)*	11.33	11	1.2	10	14
ED Rates	75.15	66.33	30.09	27.44	155.43
ED Counts	3159.73	2676.43	2675	322.14	12171
Population	400683.33	423392	245685.17	64285	884118

Table 4: Exploratory Analysis of Variables and Indices (New Jersey)

Table 5: Exploratory Analysis of Variables and Indicies (Florida)					
Model	Mean	Median	Standard Deviation	Min	Max
Deductive	0.09	0.22	0.86	-2.11	1.67
Standardized Deductive	*0*	*0.15*	*1*	-2.56	1.84
Hierarchical	1.11	1.53	8.18	-19.34	17
Standardized Hierarchical	*0*	*0.05*	*1*	-2.5	1.94
Inductive (SoVI)	0.04	0.29	2.07	-4.77	4.5
Standardized Inductive (SoVI)	*0*	*0.12*	*1*	-2.32	2.15
Variable	Mean	Median	Standard Deviation	Min	Max
PM 2.5 (*micrograms per cubic meter)*	9.6	10	1.46	5	12
ED Rates	54.1	54.95	14.89	25.14	86.74
ED Counts	1518.08	495.29	2698.49	27	14969,14
Population	238542.96	87366	396521.09	7021	2253362

Table 5: Exploratory Analysis of Variables and Indices (Florida)

Table 6: Spearman's Correlation Coefficients (Index Comparison)			
New Jersey	*Inductive*	*Deductive*	*Hierarchical*
Inductive	1		
Deductive	0.8533**	1	
Hierarchical	0.8169**	0.9831**	1
Florida	*Inductive*	*Deductive*	*Hierarchical*
Inductive	1		
Deductive	0.2102	1	
Hierarchical	0.2395*	0.9877**	1
** significant at 95% confidence level*			
*** significant at 99% confidence level*			

Table 6: Spearman's Correlation Coefficients to Compare Indices (for both New Jersey and Florida)

Table 7: Spearman's Correlation Coefficients (Index Comparison) (Getis Cluster)			
New Jersey	*Inductive*	*Deductive*	*Hierarchical*
Inductive	1		
Deductive	.8092**	1	
Hierarchical	.6748*	.8207**	1
Florida	*Inductive*	*Deductive*	*Hierarchical*
Inductive	1		
Deductive	0.1015	1	
Hierarchical	.3572*	.6956**	1
** significant at 95% confidence level*			
*** significant at 99% confidence level*			

Table 7: Spearman's Correlation Coefficients to Compare Significant Clusters (for both New Jersey and Florida)

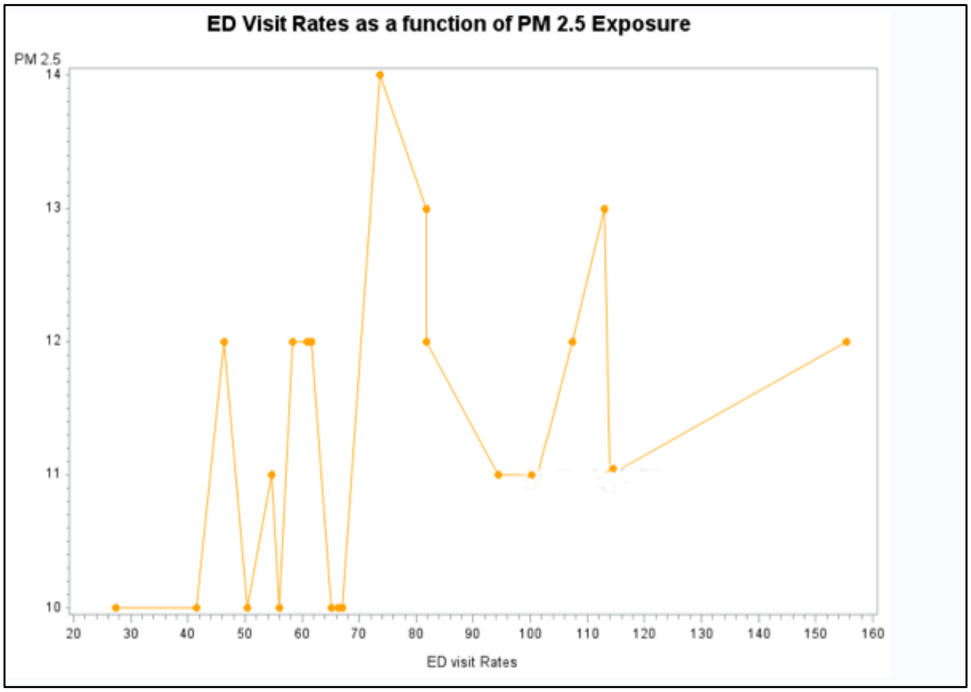
Table 8: Poisson Model Comparison (New Jersey)		Wald				
Model		Std. Error	95% Confidence Limits		Chi-Square	P-Value
Model 1: PM 2.5 + Deductive						
Intercept	-6.12	0.77	-7.65	-4.61	62.59	<.0001
Deductive	0.23	0.09	0.05	0.41	6.39	0.0115
PM 2.5	0.11	0.07	-0.02	0.24	2.82	0.0933
Model 2: PM 2.5+ Hierarchical						
Intercept	-6.23	0.8	-7.82	-4.67	60.54	<.0001
Hierarchical	0.21	0.09	0.02	0.39	5.1	0.024
PM 2.5	0.12	0.07	-0.01	0.25	3.13	0.0771
Model 3: PM 2.5 + Inductive (SoVI)						
Intercept	-5.44	0.61	-6.64	-4.23	78.23	<.0001
Inductive (SoVI)	0.09	0.02	0.05	0.13	23.48	<.0001
PM 2.5	0.08	0.05	-0.02	0.18	2.45	0.1174

Table 8: Poisson Model Comparison (New Jersey)

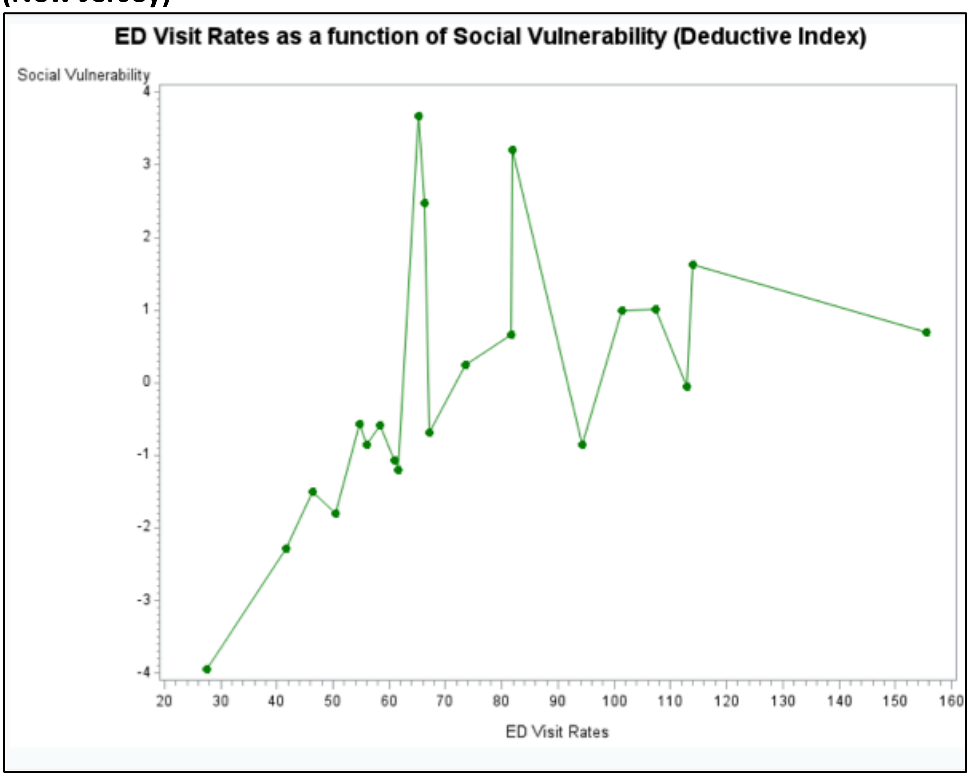
Table 9: Poisson Model Comparison (Florida)		Wald				
Model		Std. Error	95% Confidence Limits		Chi-Square	P-Value
Model 1: PM 2.5 + Deductive						
Intercept	-5.15	0.23	-5.61	-4.70	500.32	<.0001
Deductive	0.09	0.03	0.03	0.16	7.96	0.0048
PM 2.5	0.01	0.03	-0.04	0.06	0.31	0.577
Model 2: PM 2.5+ Hierarchical						
Intercept	-5.21	0.23	-5.65	-4.77	530.24	<.0001
Hierarchical	0.09	0.03	0.03	0.15	8.42	0.0037
PM 2.5	0.02	0.02	-0.03	0.07	0.58	0.4458
Model 3: PM 2.5 + Inductive (SoVI)						
Intercept	-5.37	0.25	-5.85	-4.89	479.79	<.0001
Inductive (SoVI)	-0.03	0.04	-0.10	0.05	0.59	0.4413
PM 2.5	0.03	0.03	-0.02	0.09	1.68	0.1956

Table 9: Poisson Model Comparison (Florida)

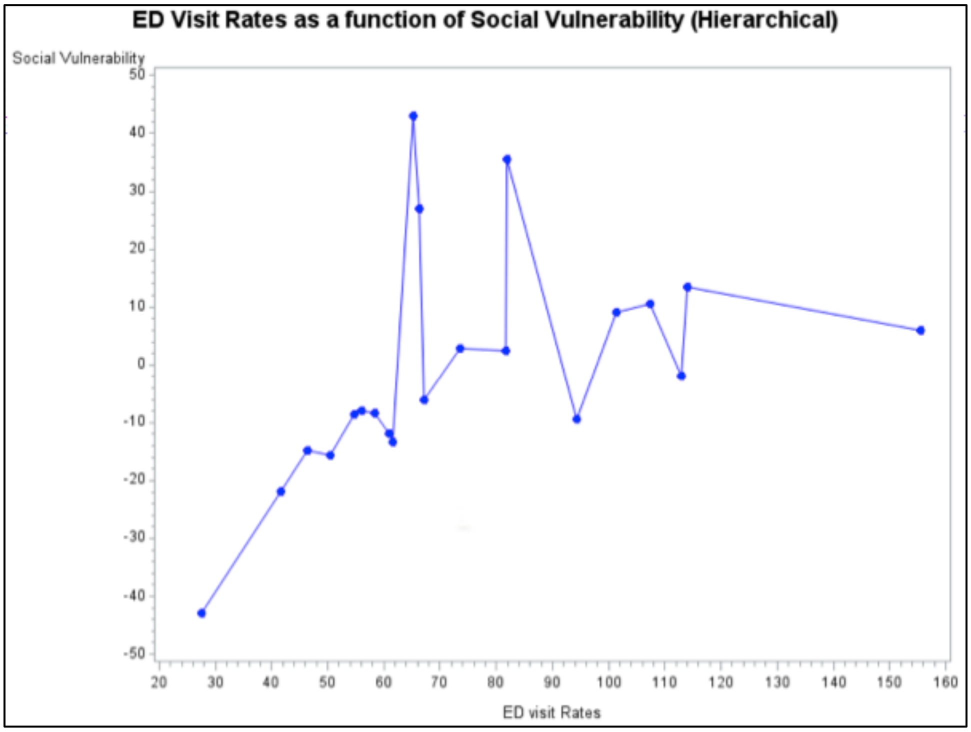
Graph 1: ED Visit Rates Compared to PM 2.5 Exposure (New Jersey)



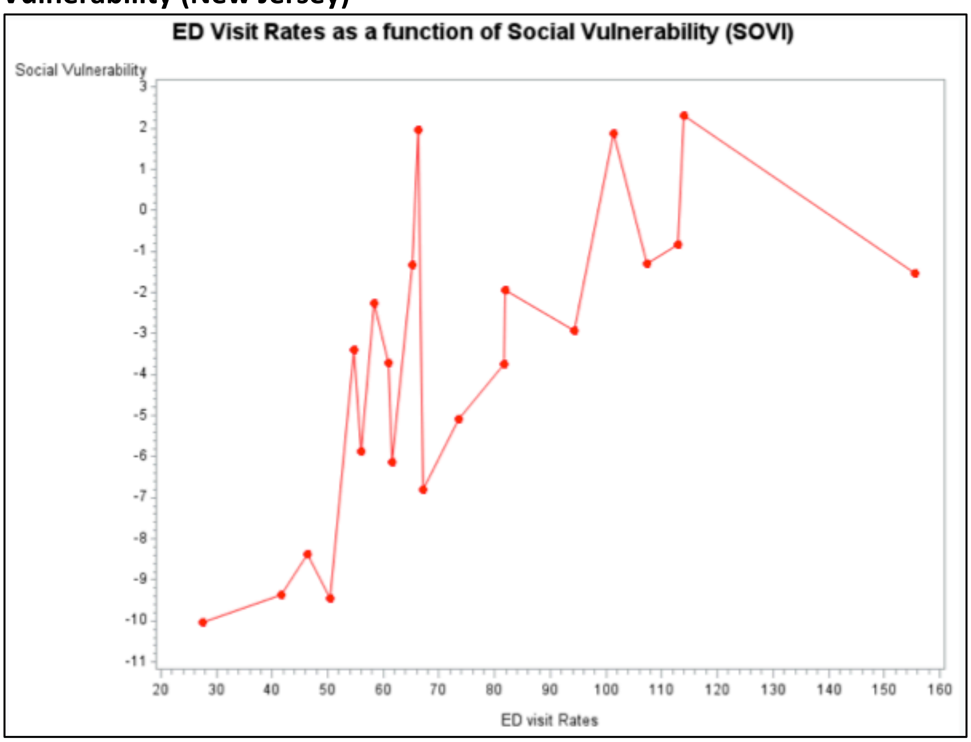
Graph 2: ED Visit Rates Compared to the Deductive Measure of Social Vulnerability (New Jersey)



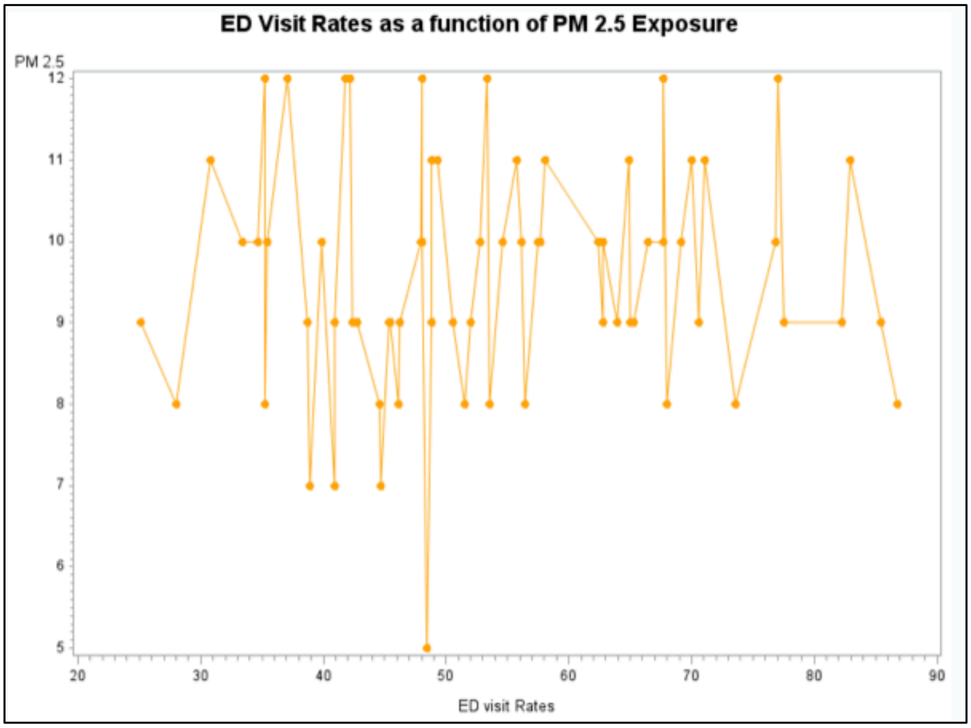
Graph 3: ED Visit Rates Compared to the Hierarchical Measure of Social Vulnerability (New Jersey)



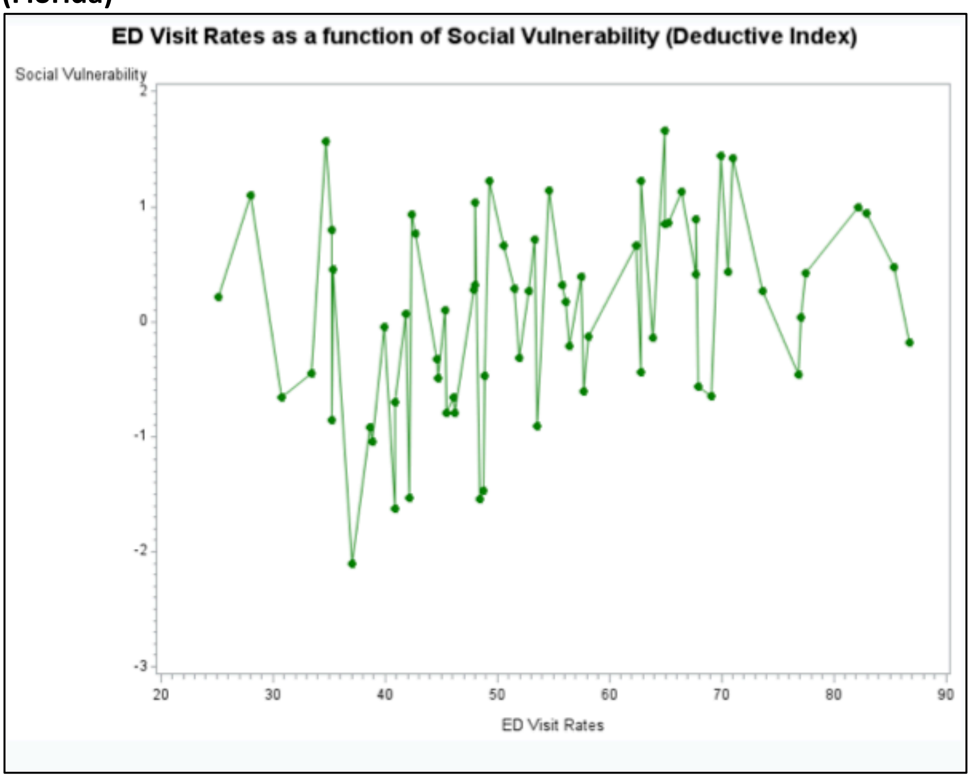
Graph 4: ED Visit Rates Compared to the Inductive (SoVI) Measure of Social Vulnerability (New Jersey)



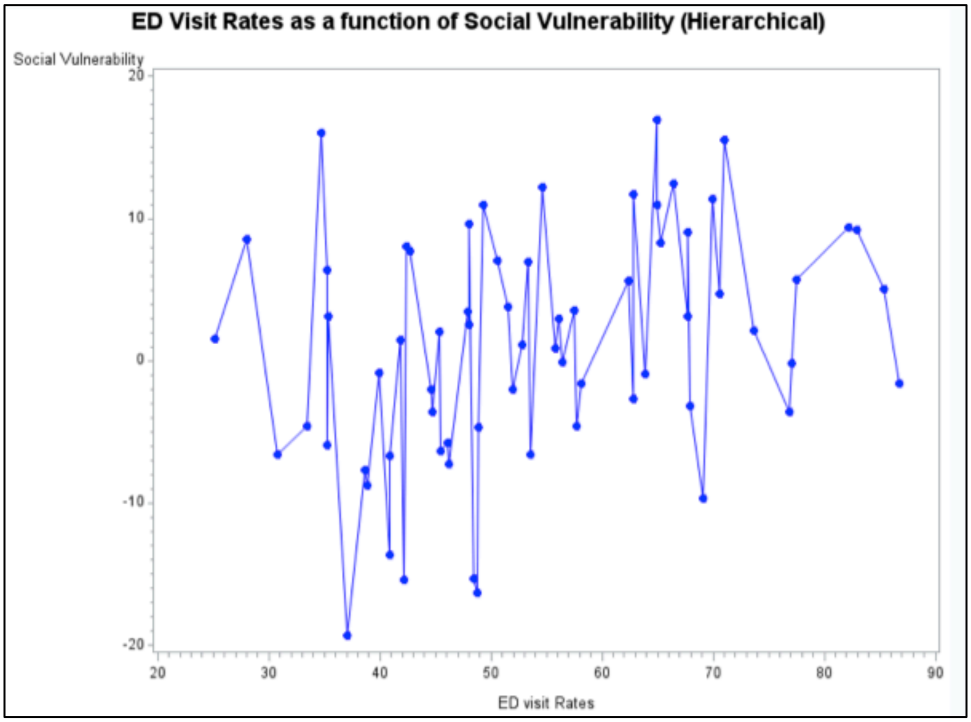
Graph 5: ED Visit Rates Compared to PM 2.5 Exposure (Florida)



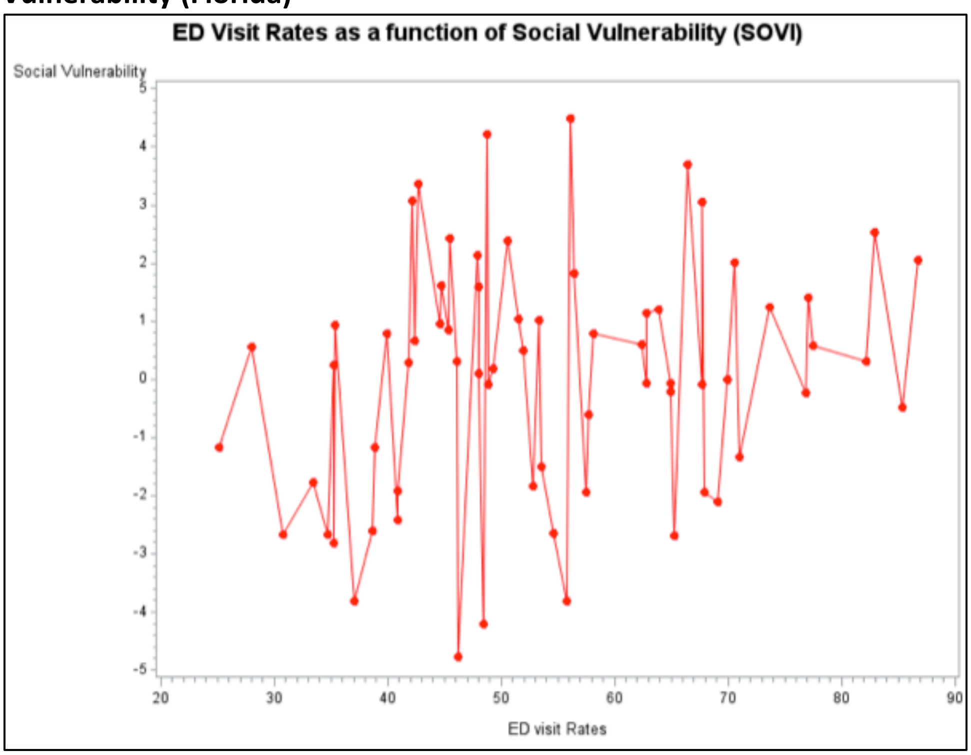
Graph 6: ED Visit Rates Compared to the Deductive Measure of Social Vulnerability (Florida)



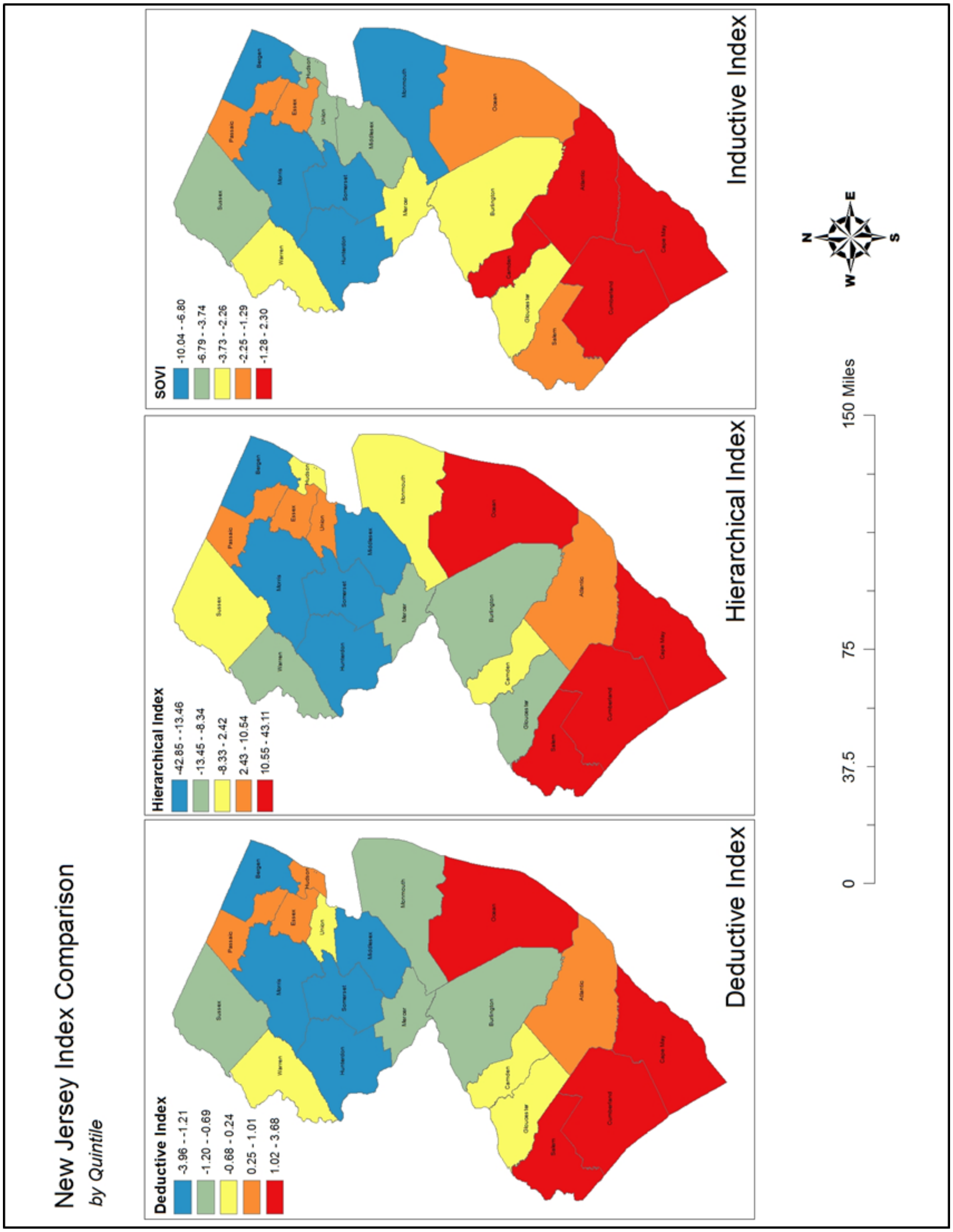
Graph 7: ED Visit Rates Compared to the Hierarchical Measure of Social Vulnerability (Florida)



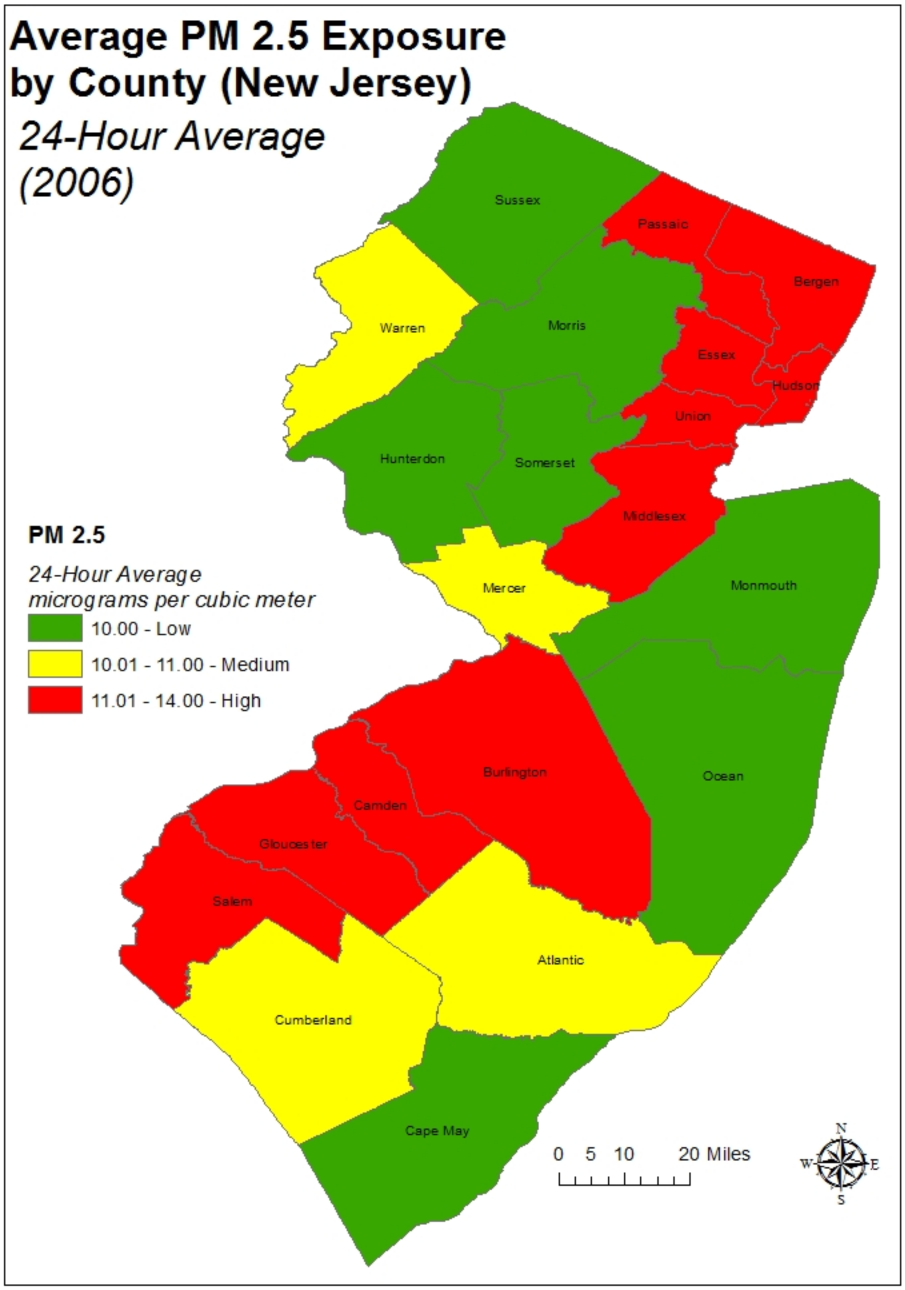
Graph 8: ED Visit Rates Compared to the Inductive (SoVI) Measure of Social Vulnerability (Florida)



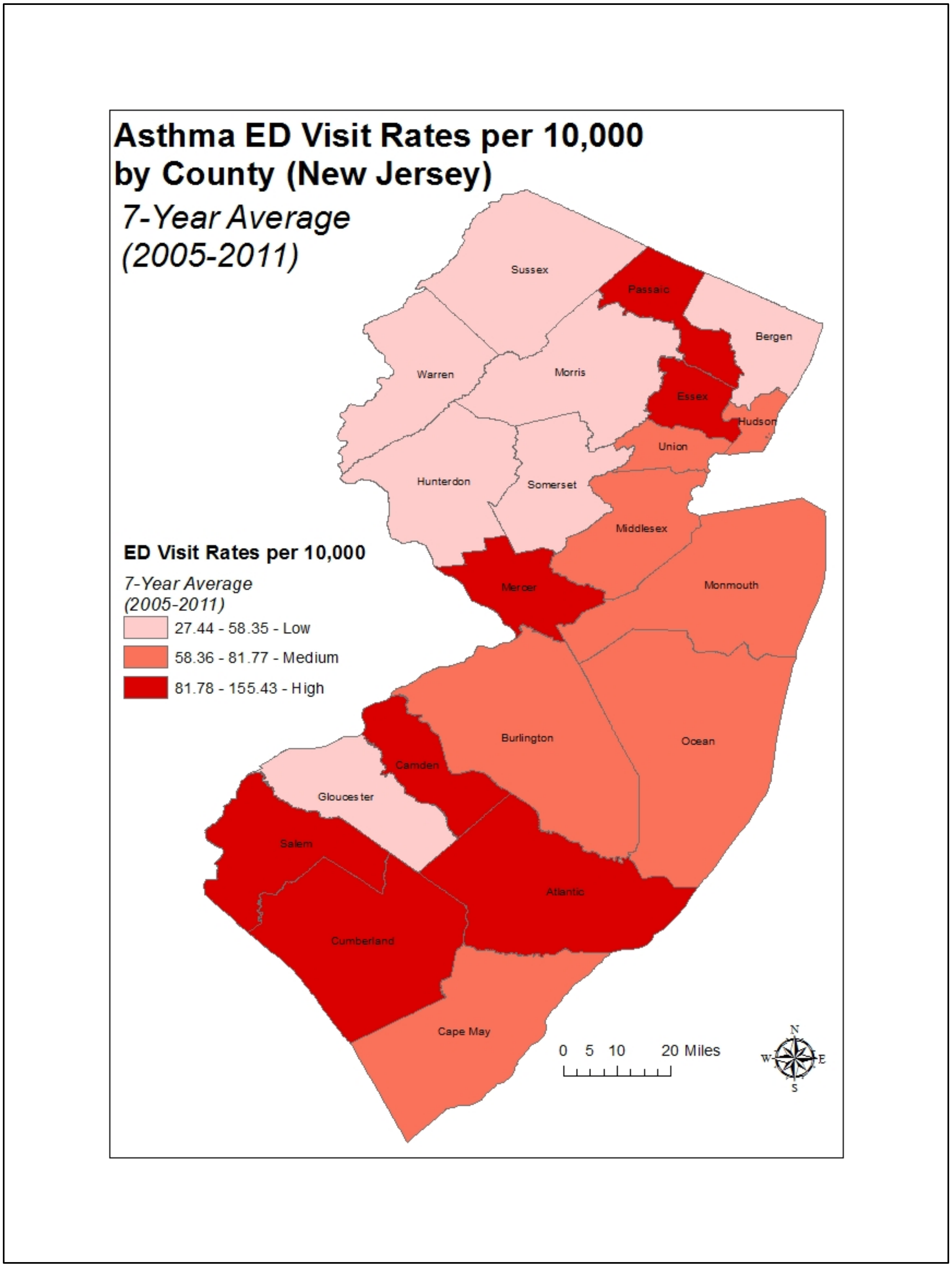
New Jersey Maps



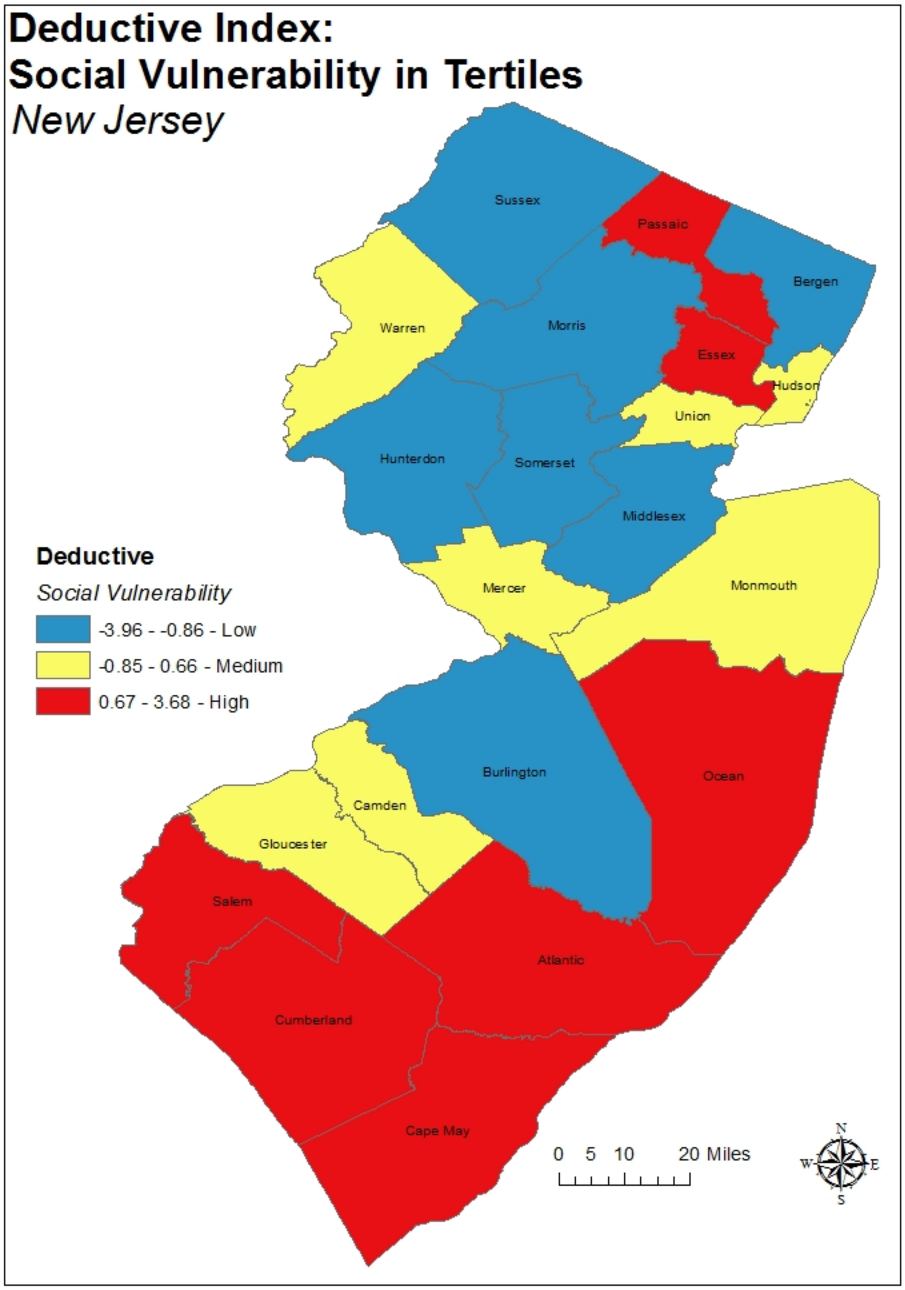
Map 1: The Deductive, Hierarchical and Inductive Measures of Social Vulnerability (for New Jersey) Displayed in Quintiles



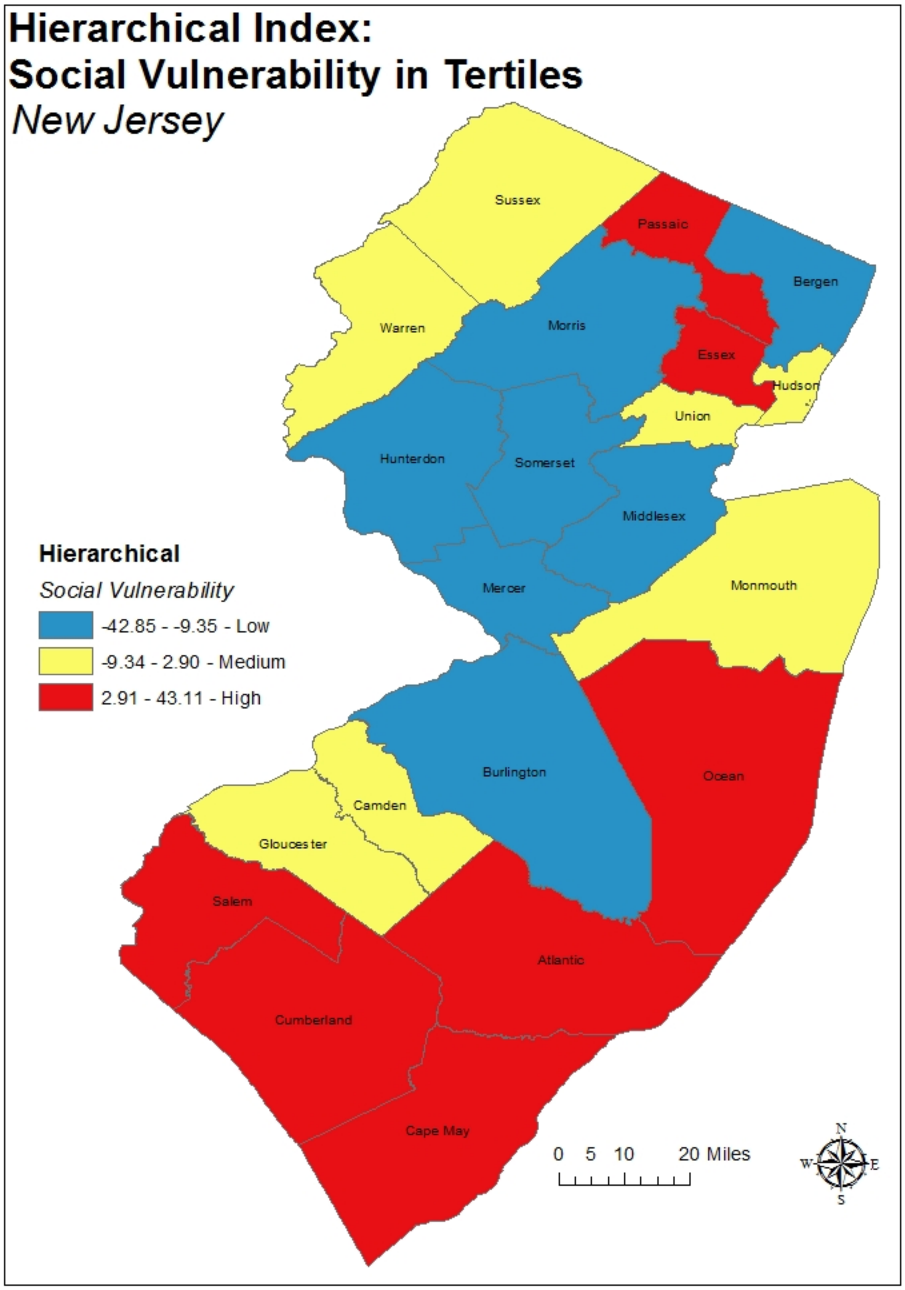
Map 2: Average PM 2.5 Exposure for New Jersey displayed in Tertiles



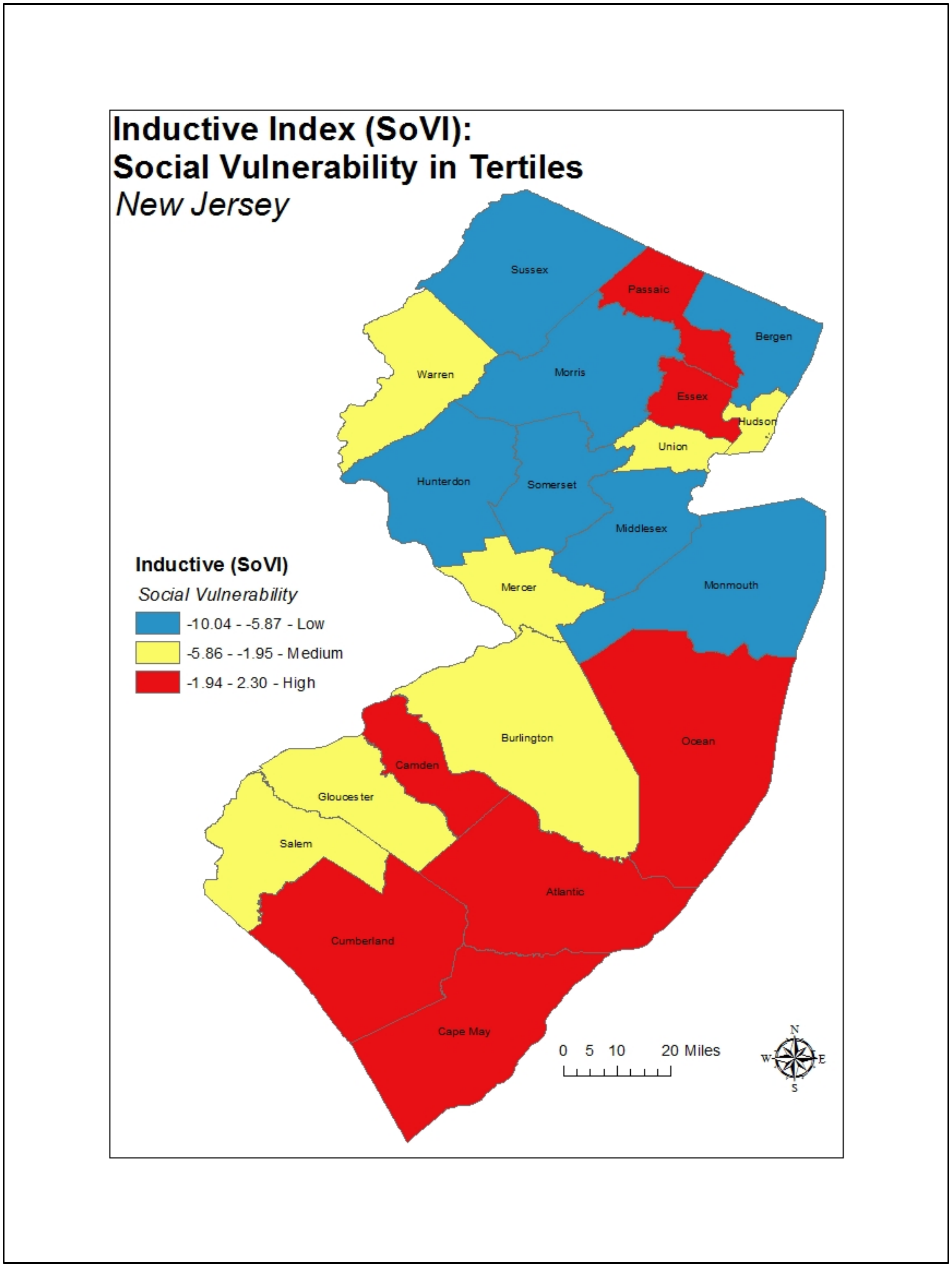
Map 3: Asthma Emergency Department Visit Rates per 10,000 by County for New Jersey



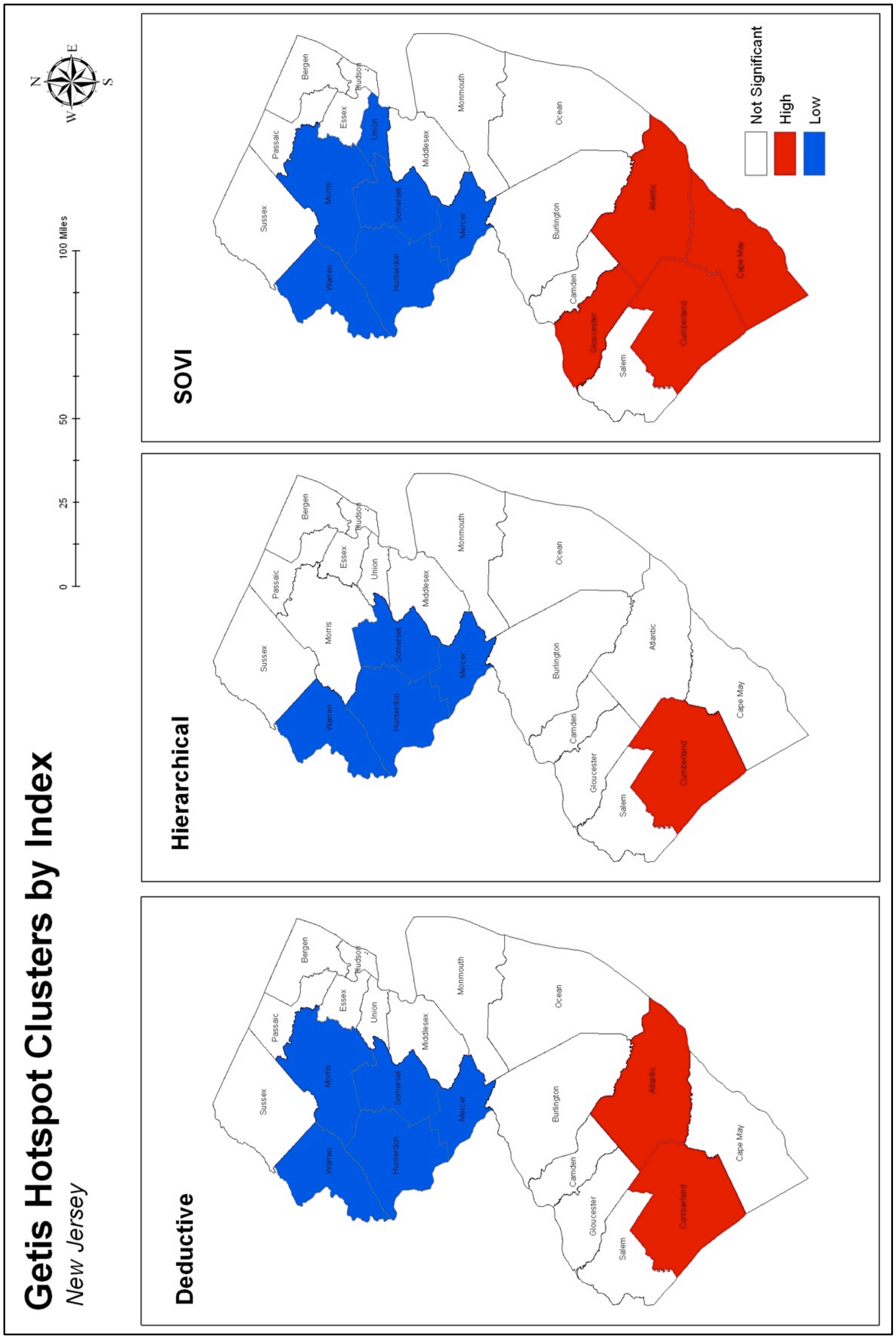
Map 4: The Deductive Index of Social Vulnerability Displayed in Tertiles for New Jersey



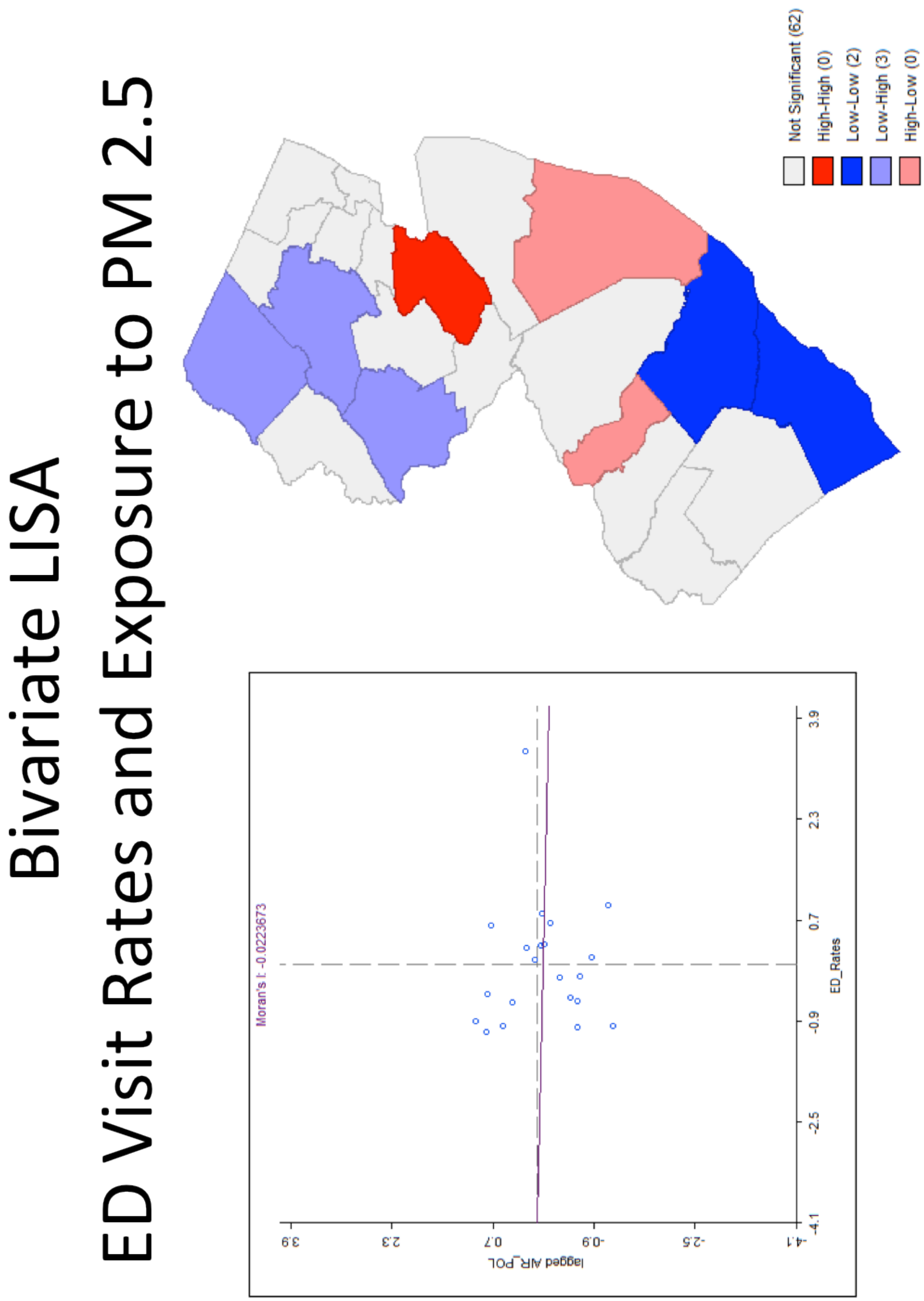
Map 5: The Hierarchical Index of Social Vulnerability Displayed in Tertiles for New Jersey



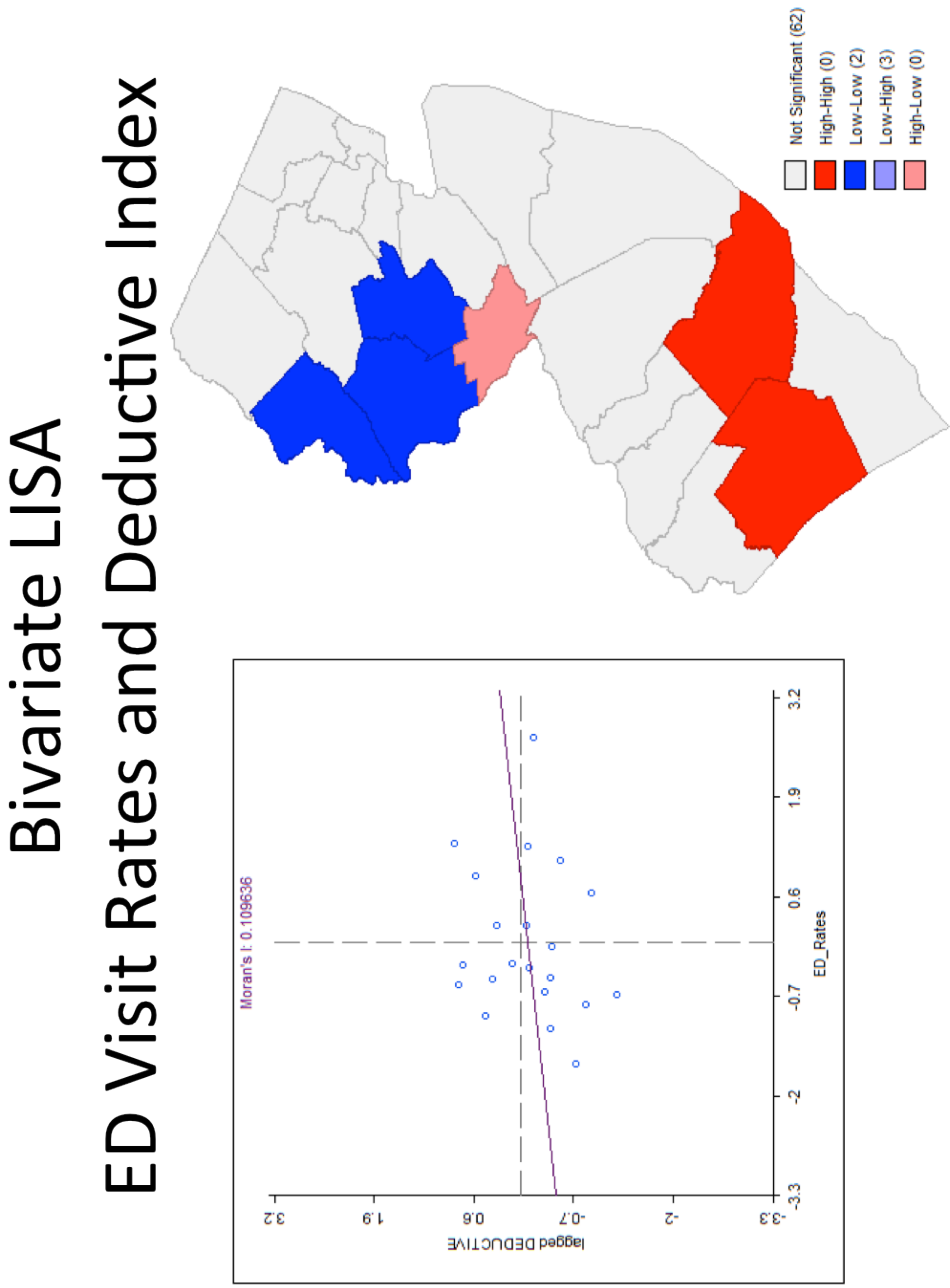
Map 6: The Inductive Index of Social Vulnerability Displayed in Tertiles for New Jersey



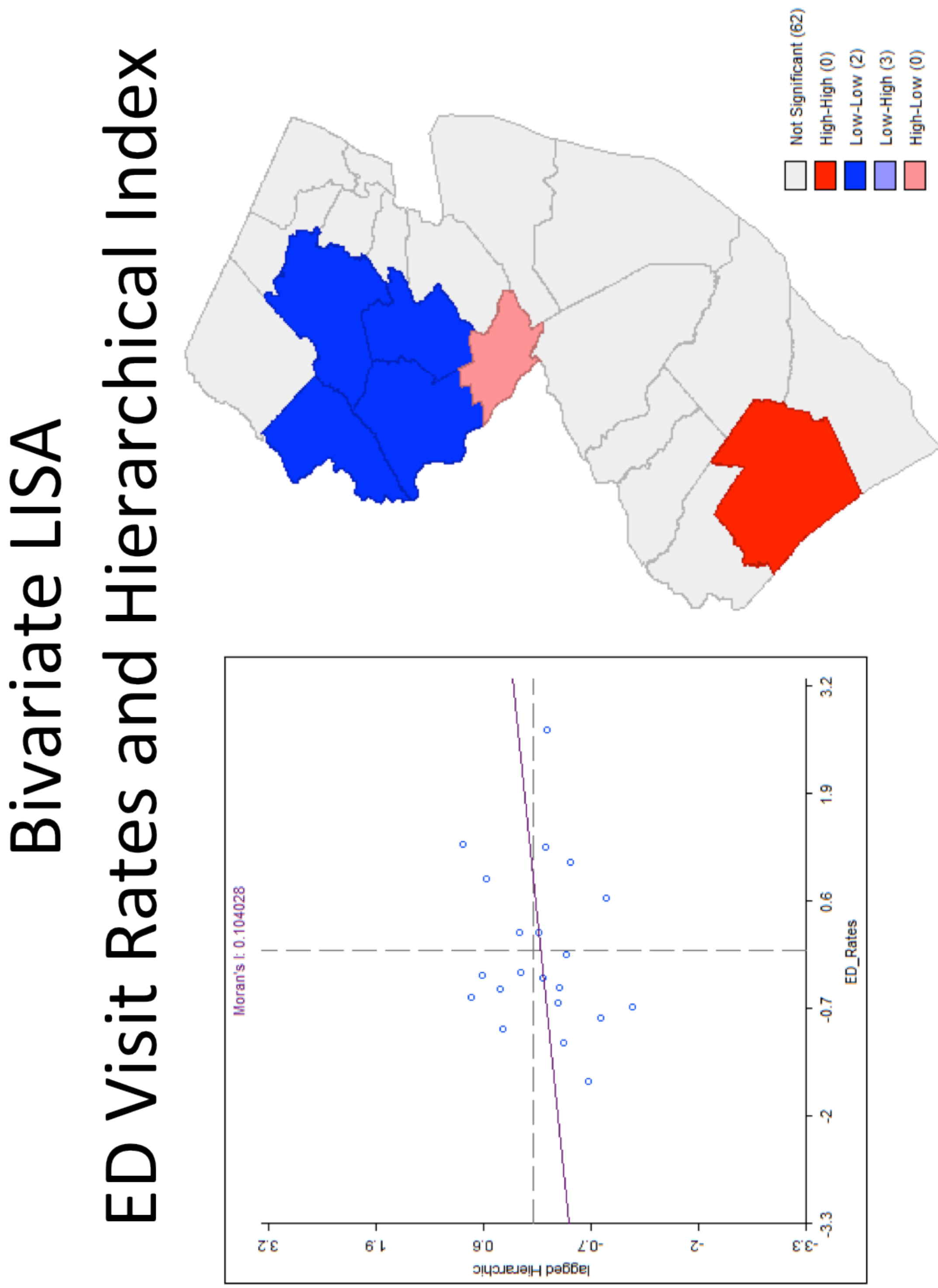
Map 7: Significant Getis Clusters for the Deductive, Hierarchical and Inductive measures of Social Vulnerability in New Jersey



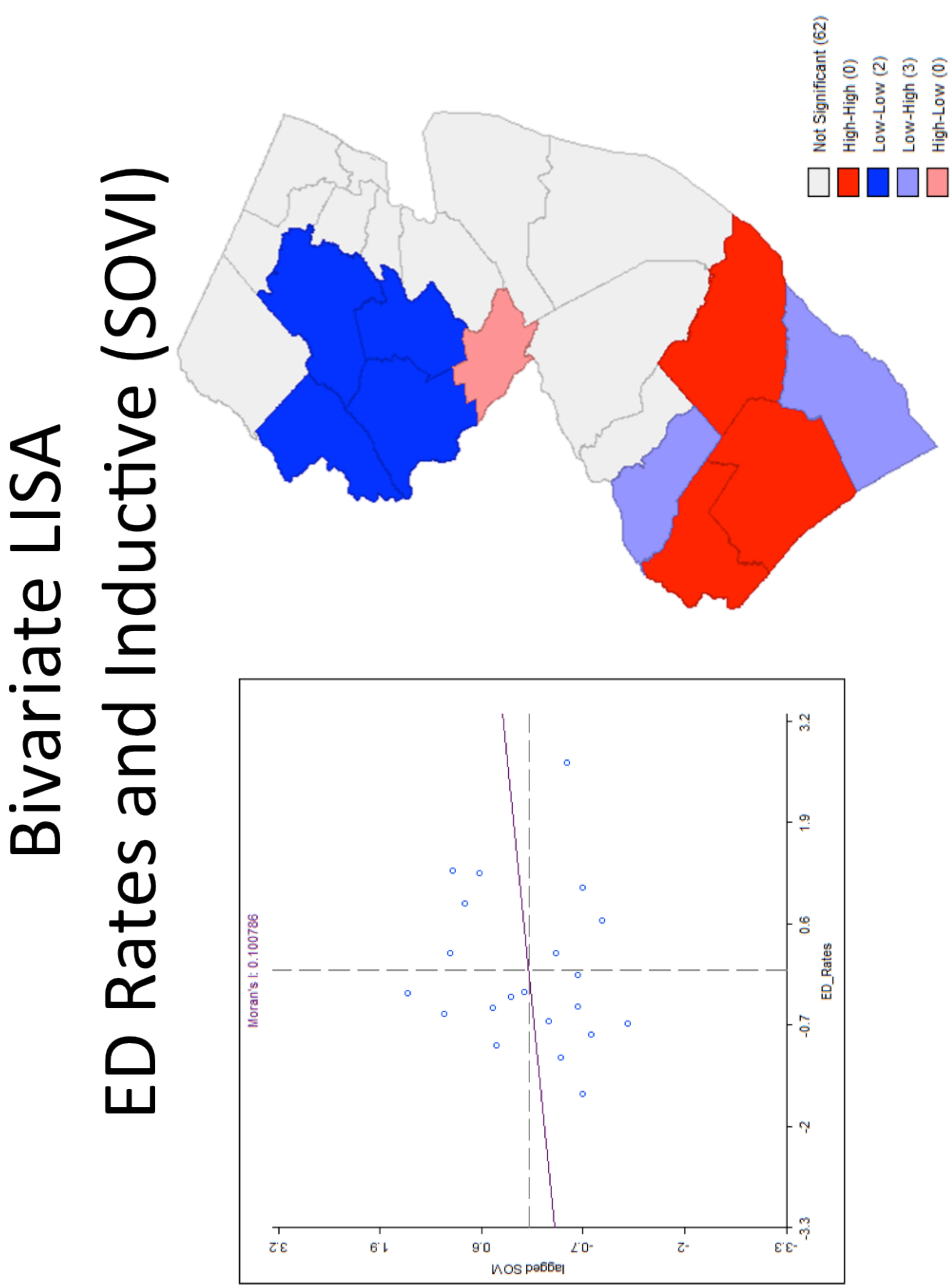
Map 8: Bivariate LISA results comparing PM 2.5 to Asthma Emergency Department Visit Rates in New Jersey



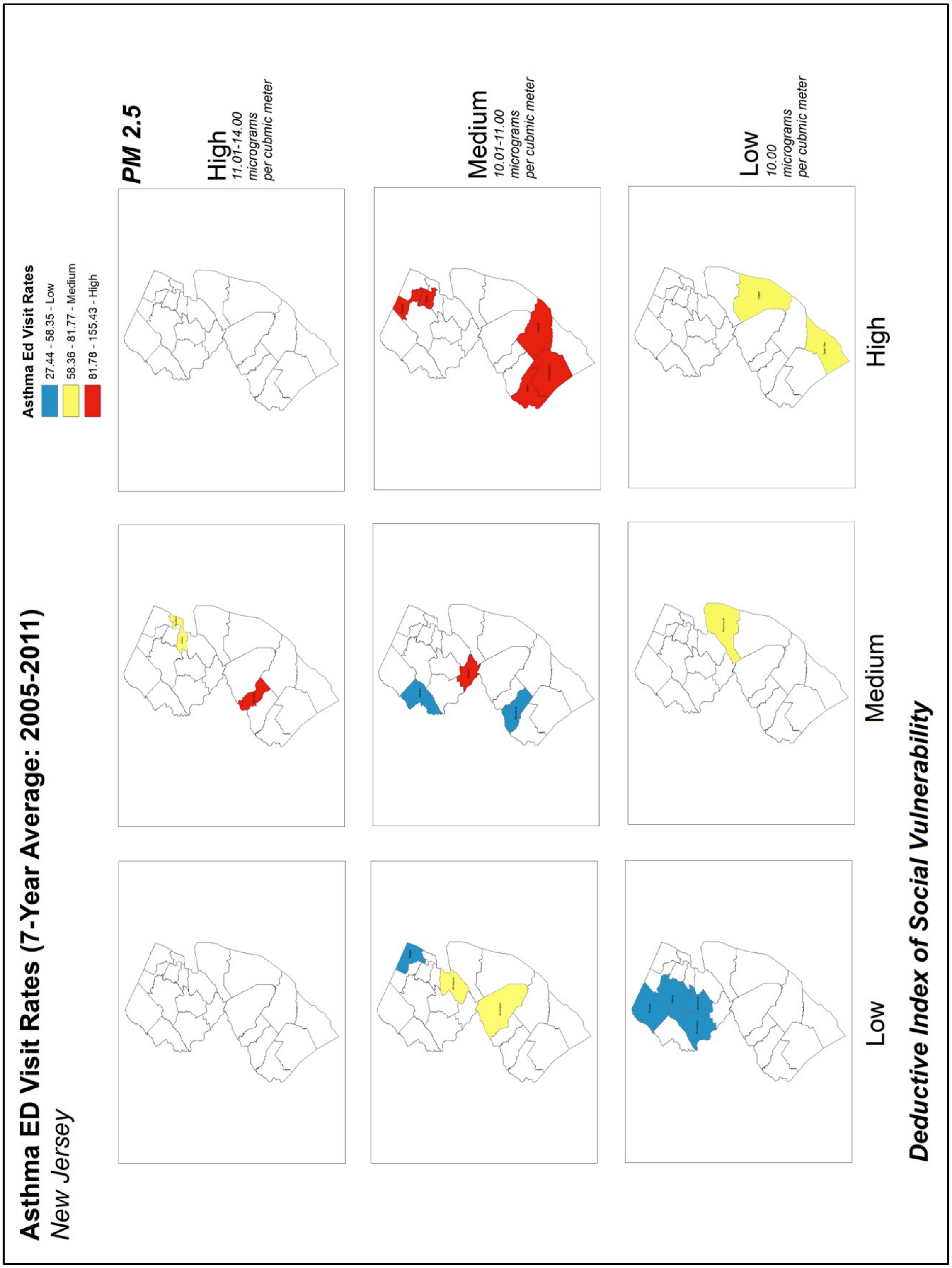
Map 9: Bivariate LISA results comparing the Deductive Measure of Social Vulnerability to Asthma Emergency Department Visit Rates in New Jersey



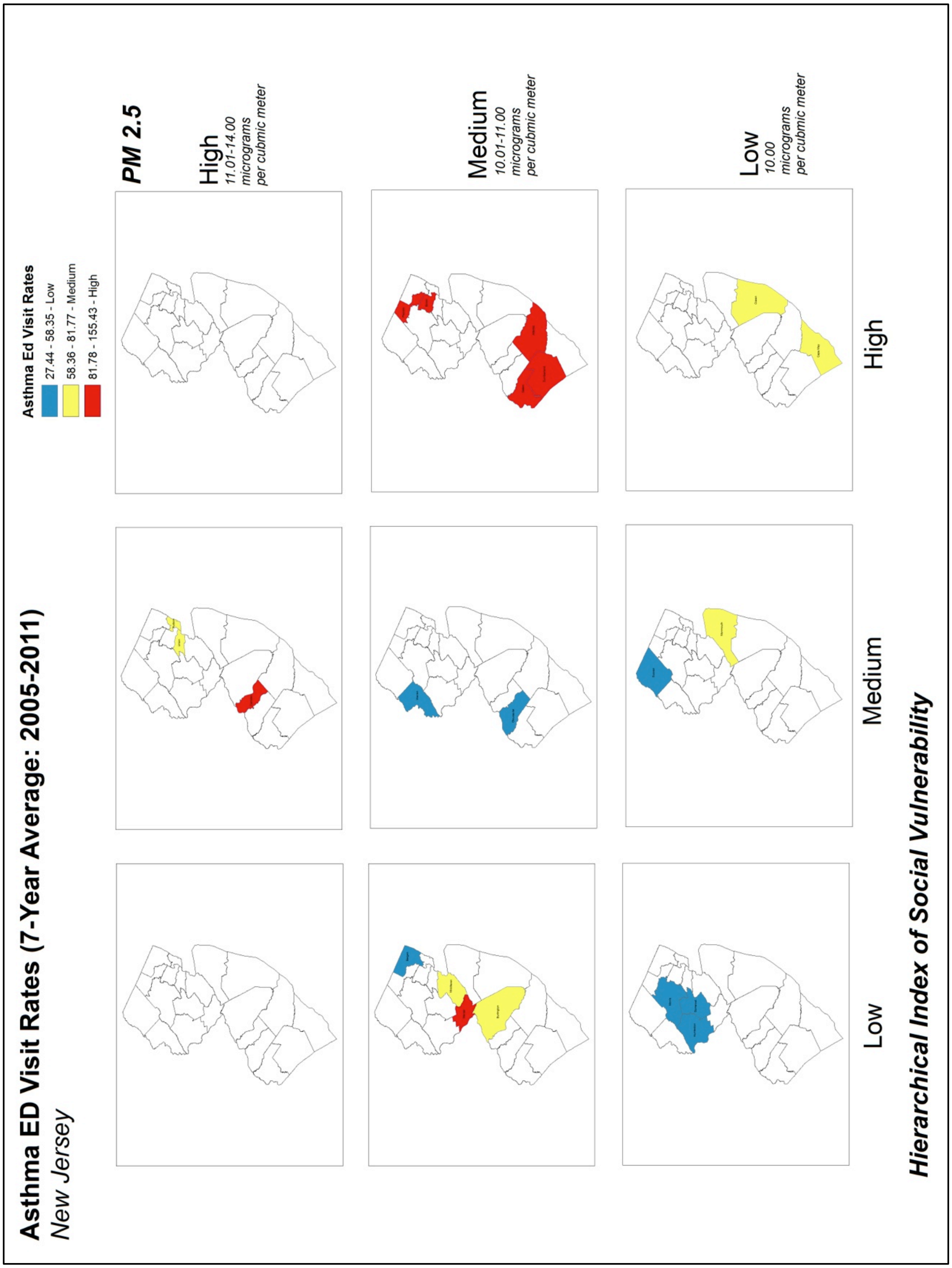
Map 10: Bivariate LISA results comparing the Hierarchical Measure of Social Vulnerability to Asthma Emergency Department Visit Rates in New Jersey



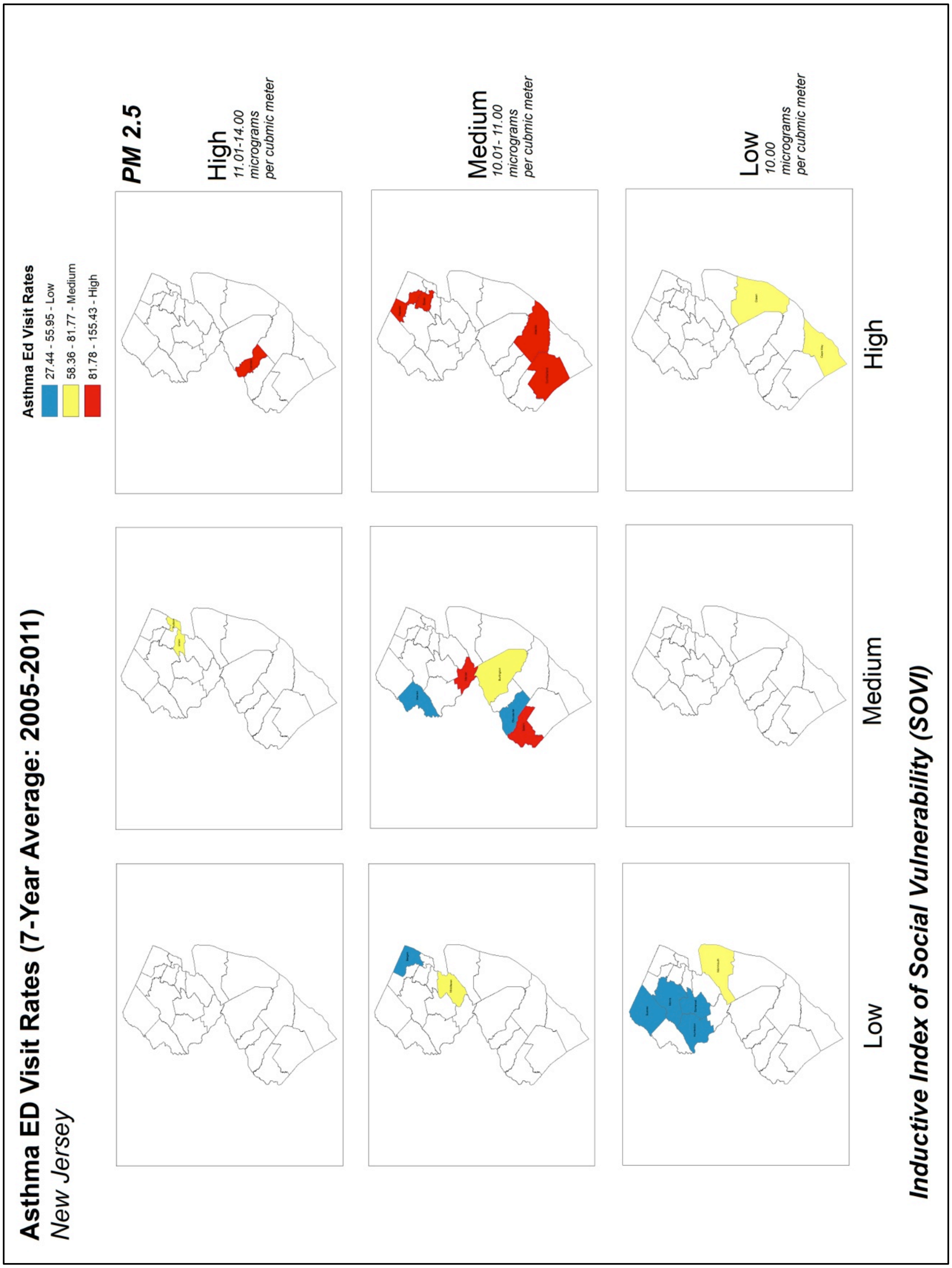
Map 11: Bivariate LISA results comparing the Inductive (SoVI) Measures of Social Vulnerability to Asthma Emergency Department Visit Rates in New Jersey



Map 12: Conditional Choropleth Map Showing Asthma Emergency Department Visit Rates compared to PM 2.5 levels and the Deductive Measure of Social Vulnerability

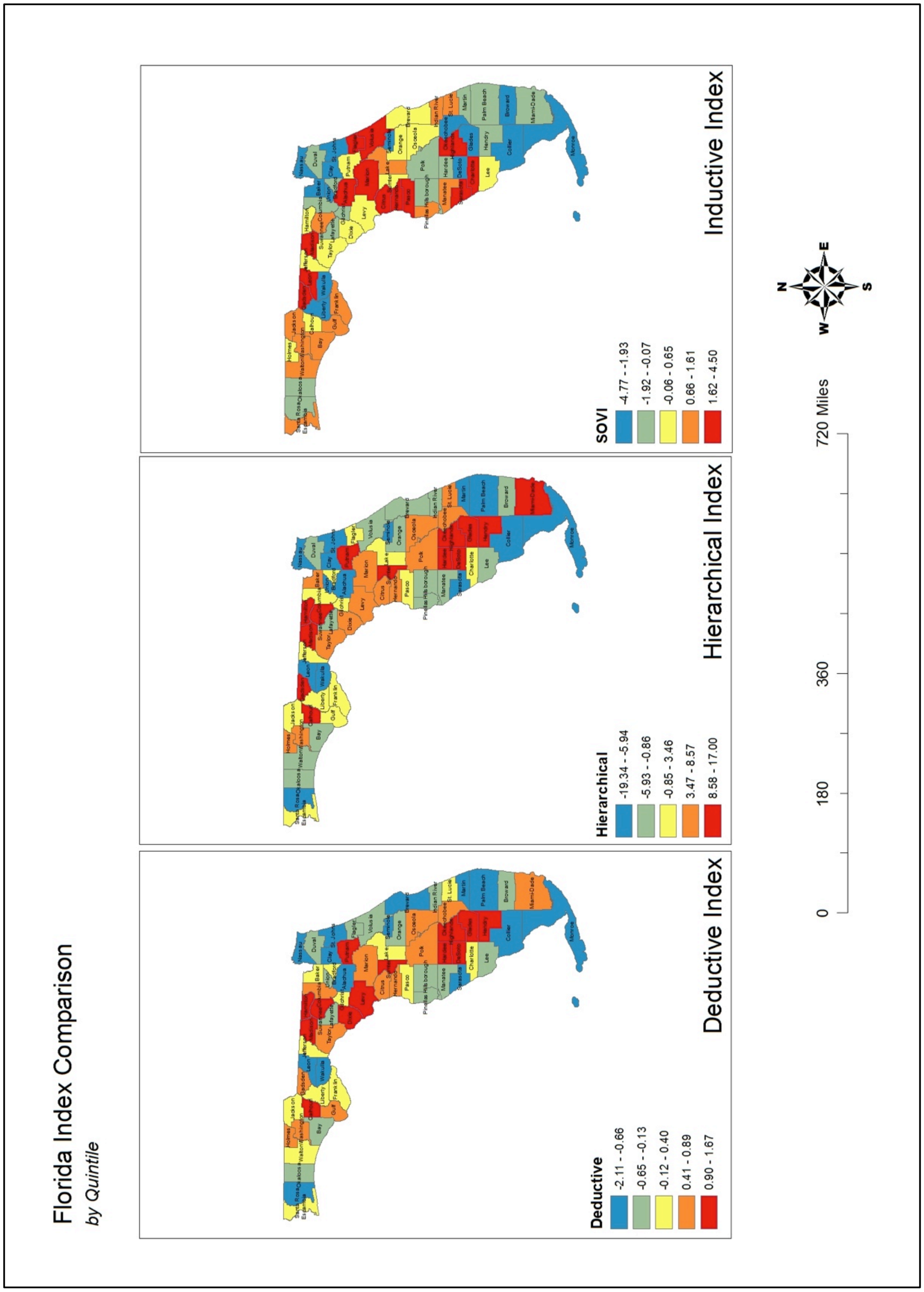


Map 13: Conditional Choropleth Map Showing Asthma Emergency Department Visit Rates compared to PM 2.5 levels and the Hierarchical Measure of Social Vulnerability

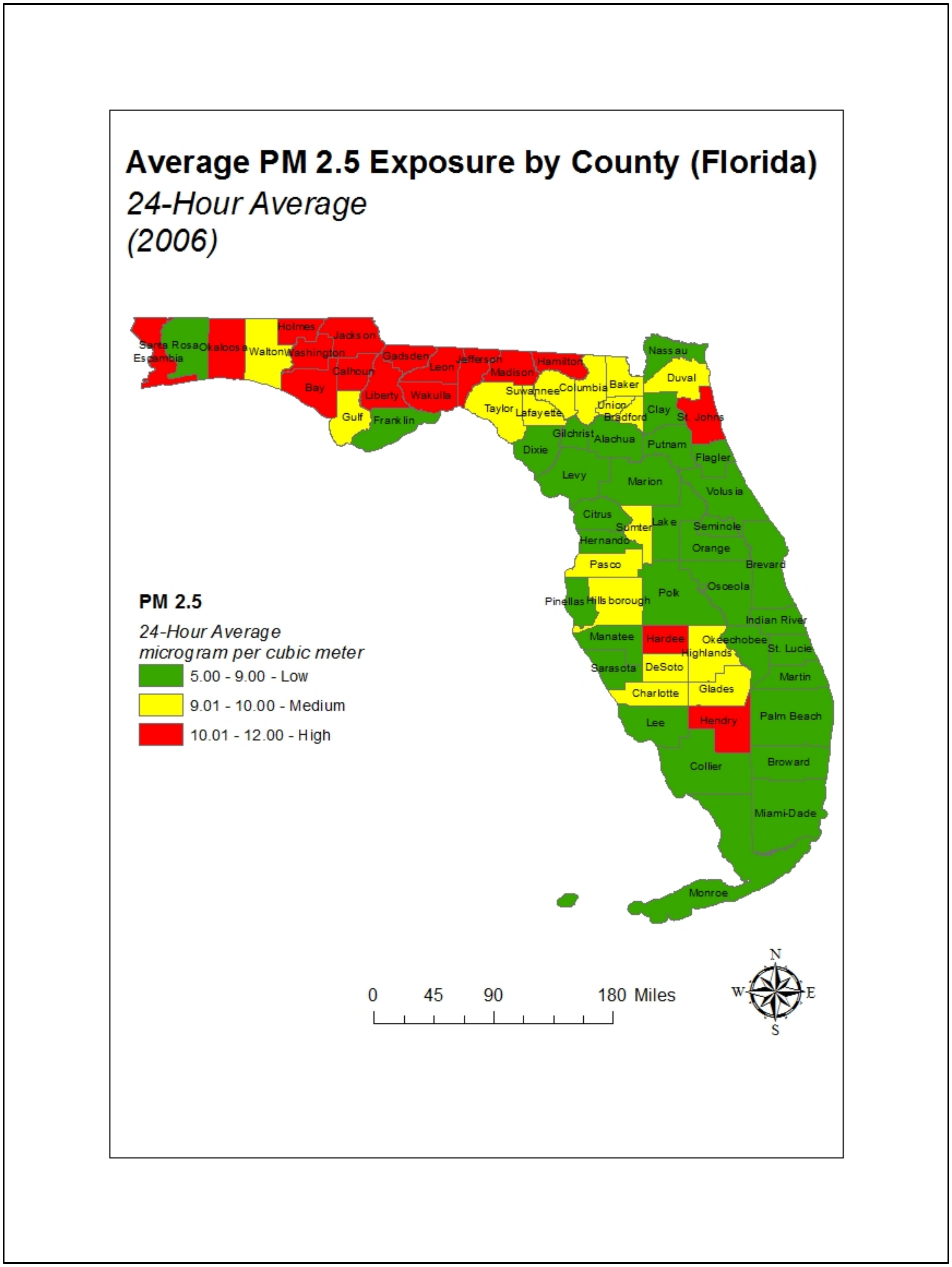


Map 14: Conditional Choropleth Map Showing Asthma Emergency Department Visit Rates compared to PM 2.5 levels and the Inductive (SoVI) Measure of Social Vulnerability

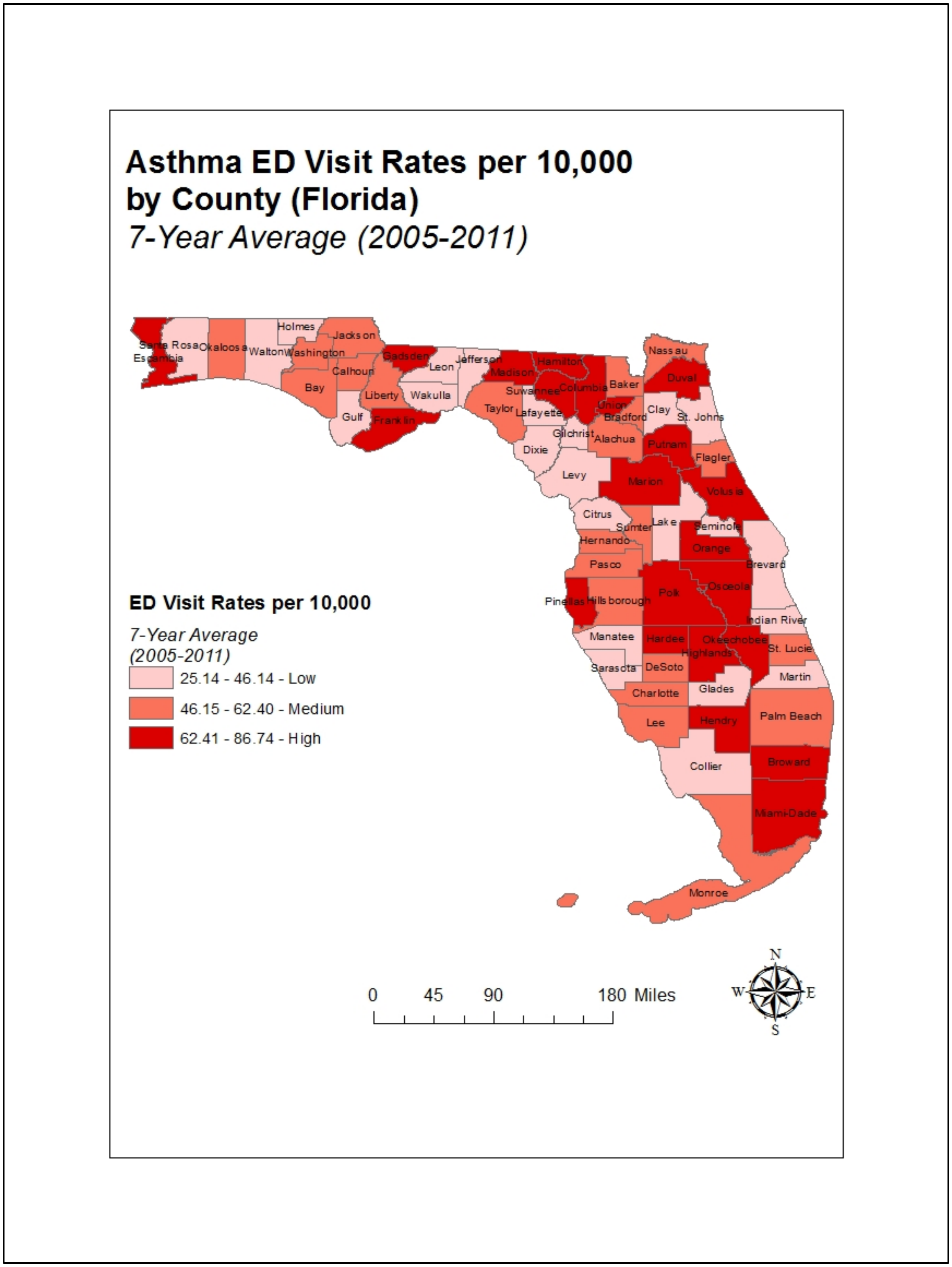
Florida Maps



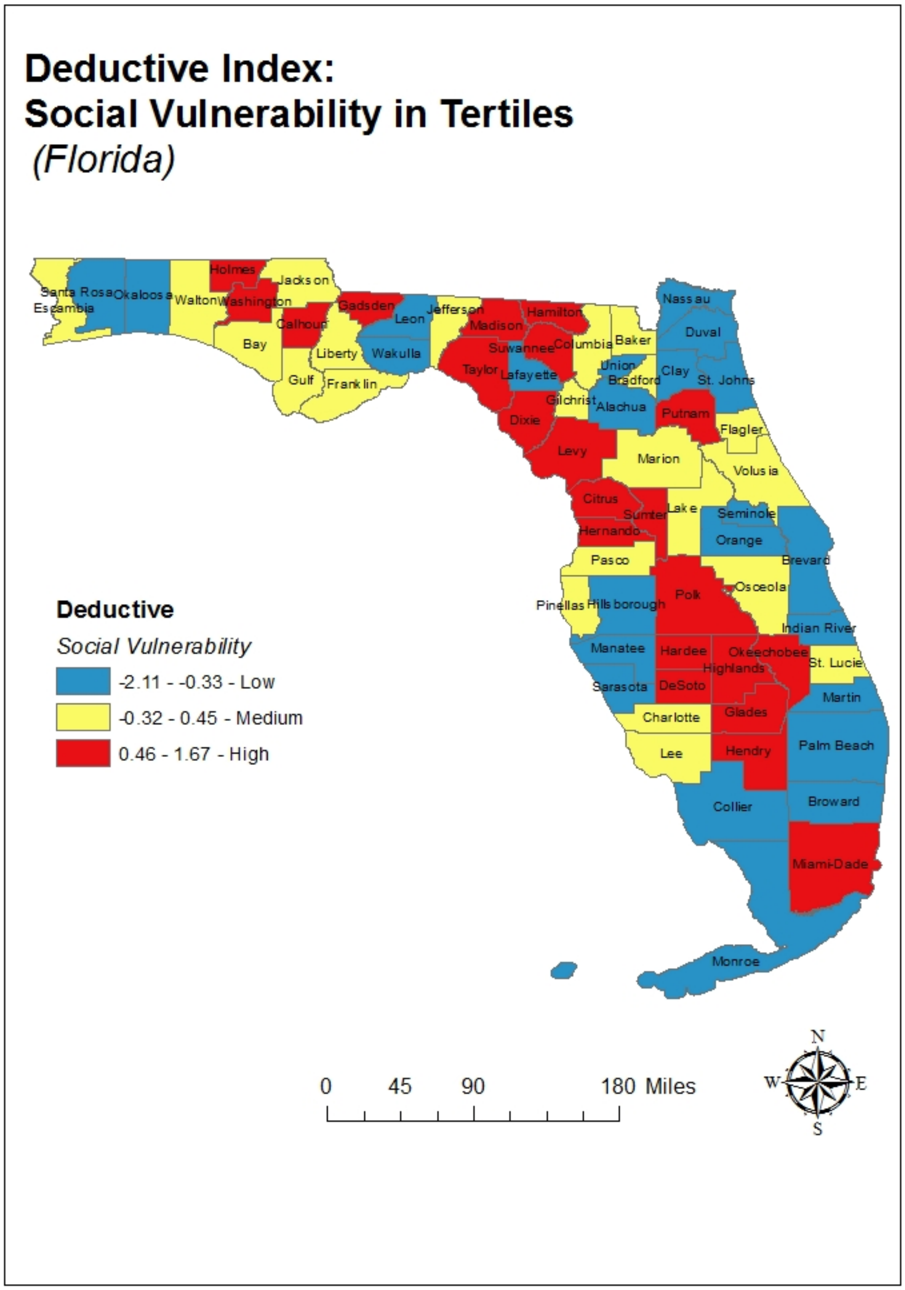
Map 15: The Deductive, Hierarchical and Inductive Measures of Social Vulnerability (for Florida) Displayed in Quintiles



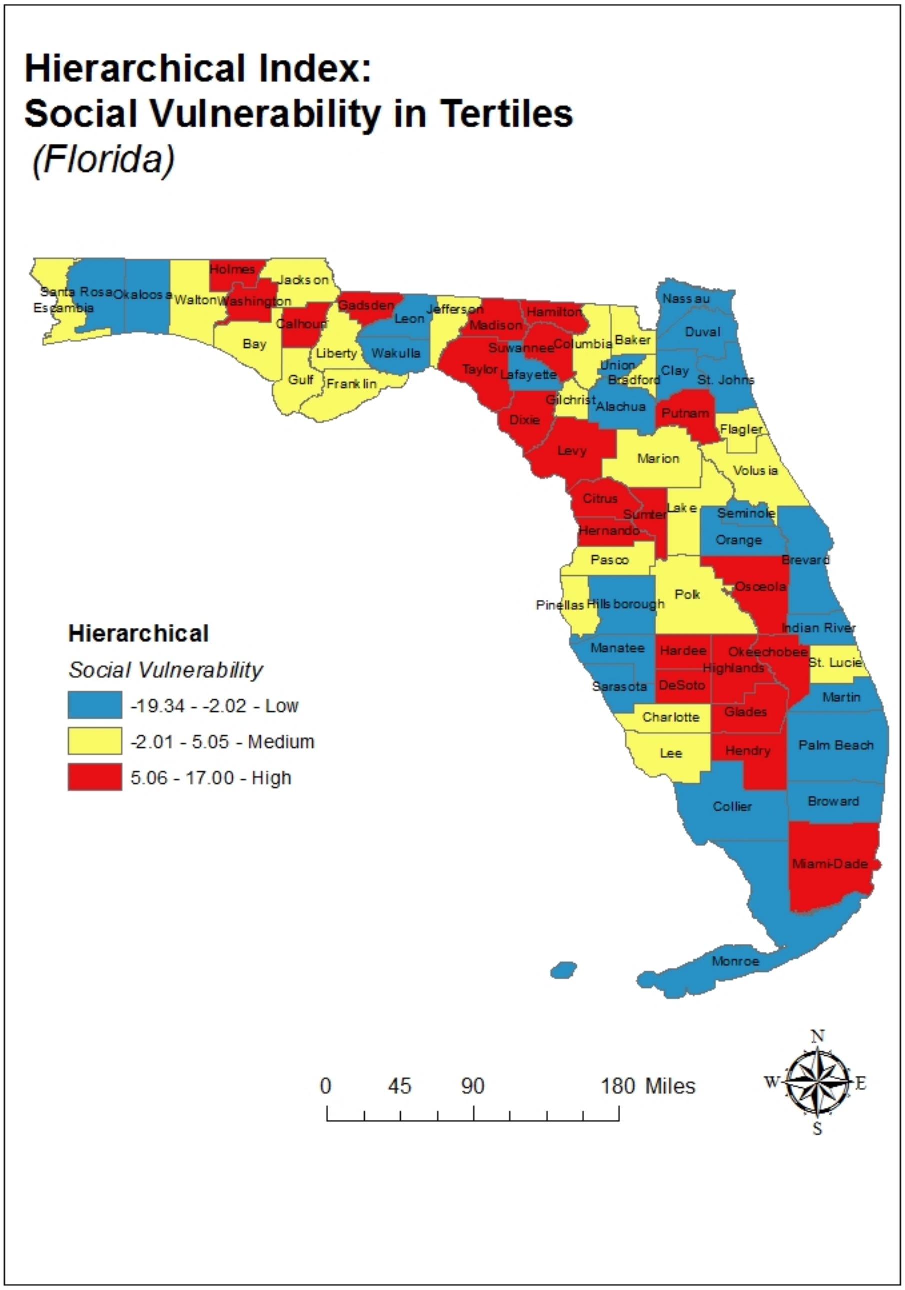
Map 16: Average PM 2.5 Exposure for Florida displayed in Tertiles



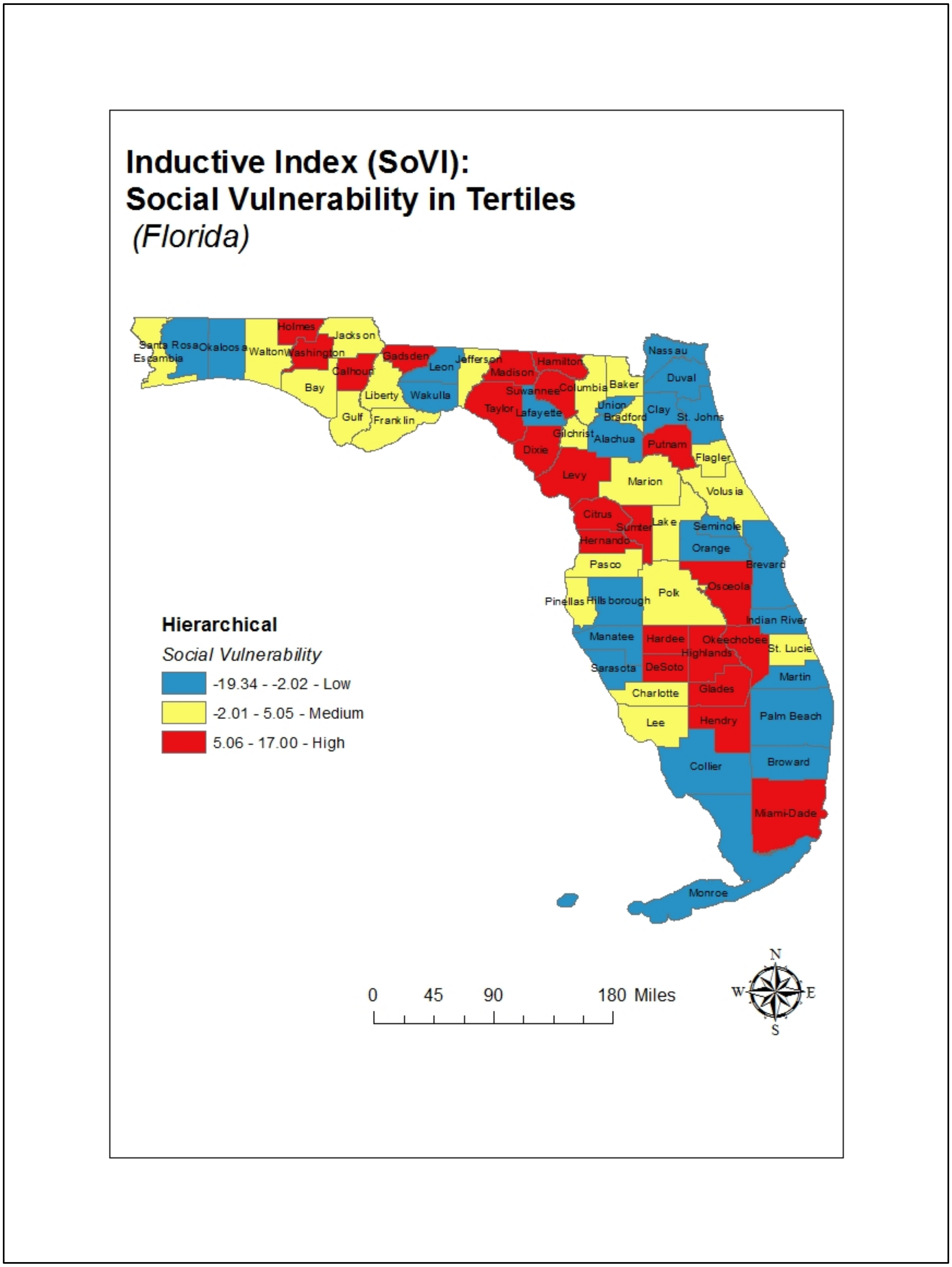
Map 17: Asthma Emergency Department Visit Rates per 10,000 by County Florida



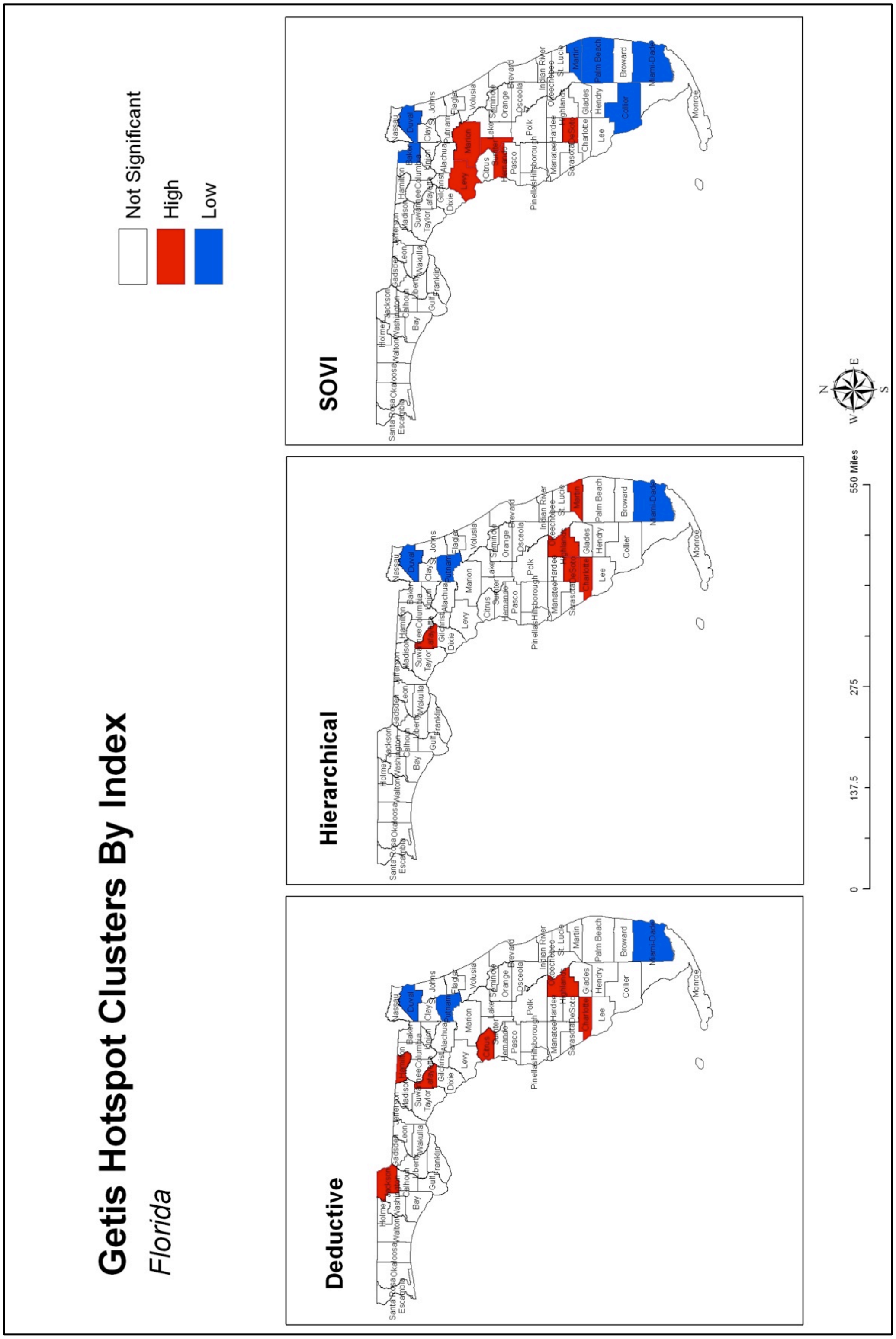
Map 18: The Deductive Index of Social Vulnerability Displayed in Tertiles for Florida



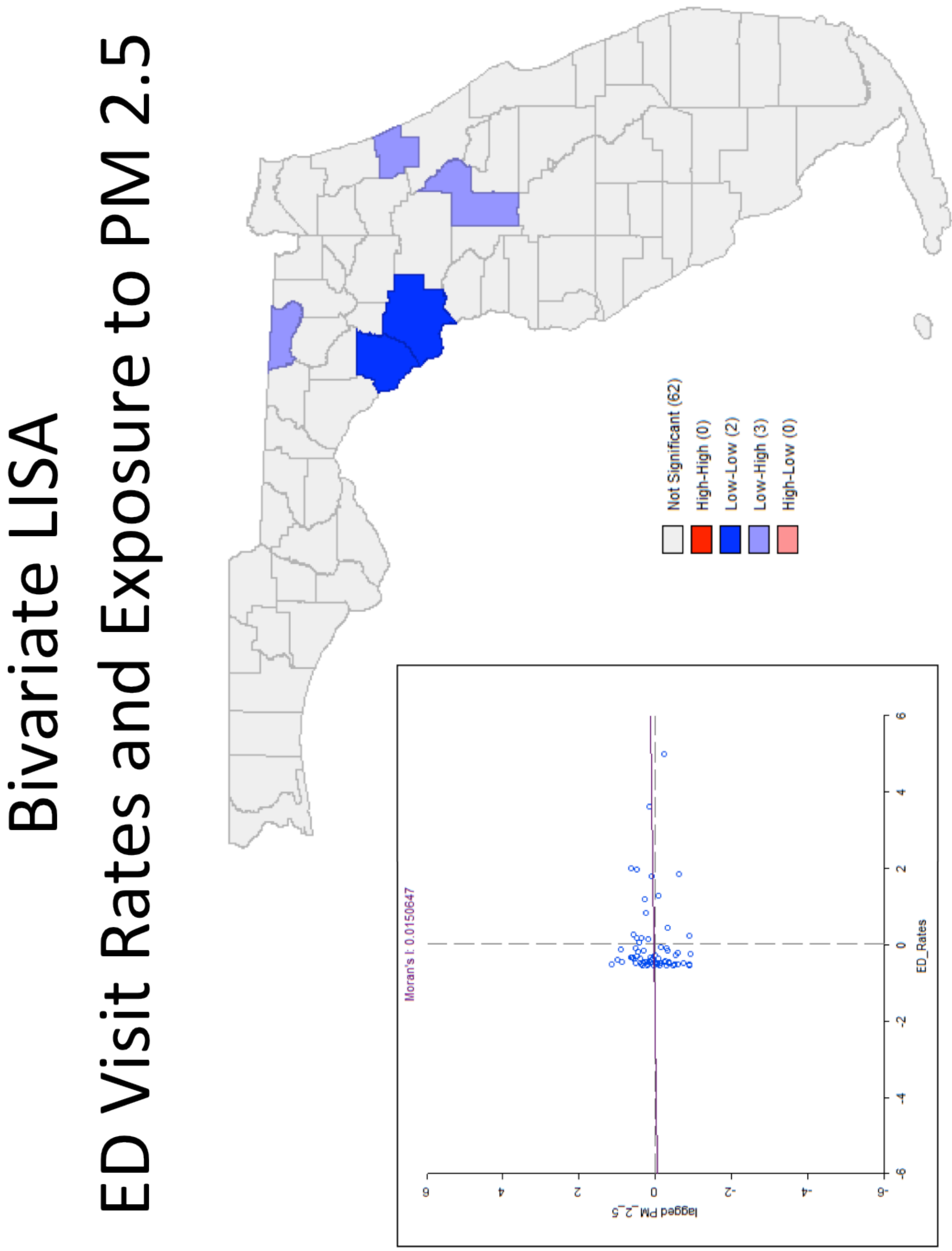
Map 19: The Hierarchical Index of Social Vulnerability Displayed in Tertiles for Florida



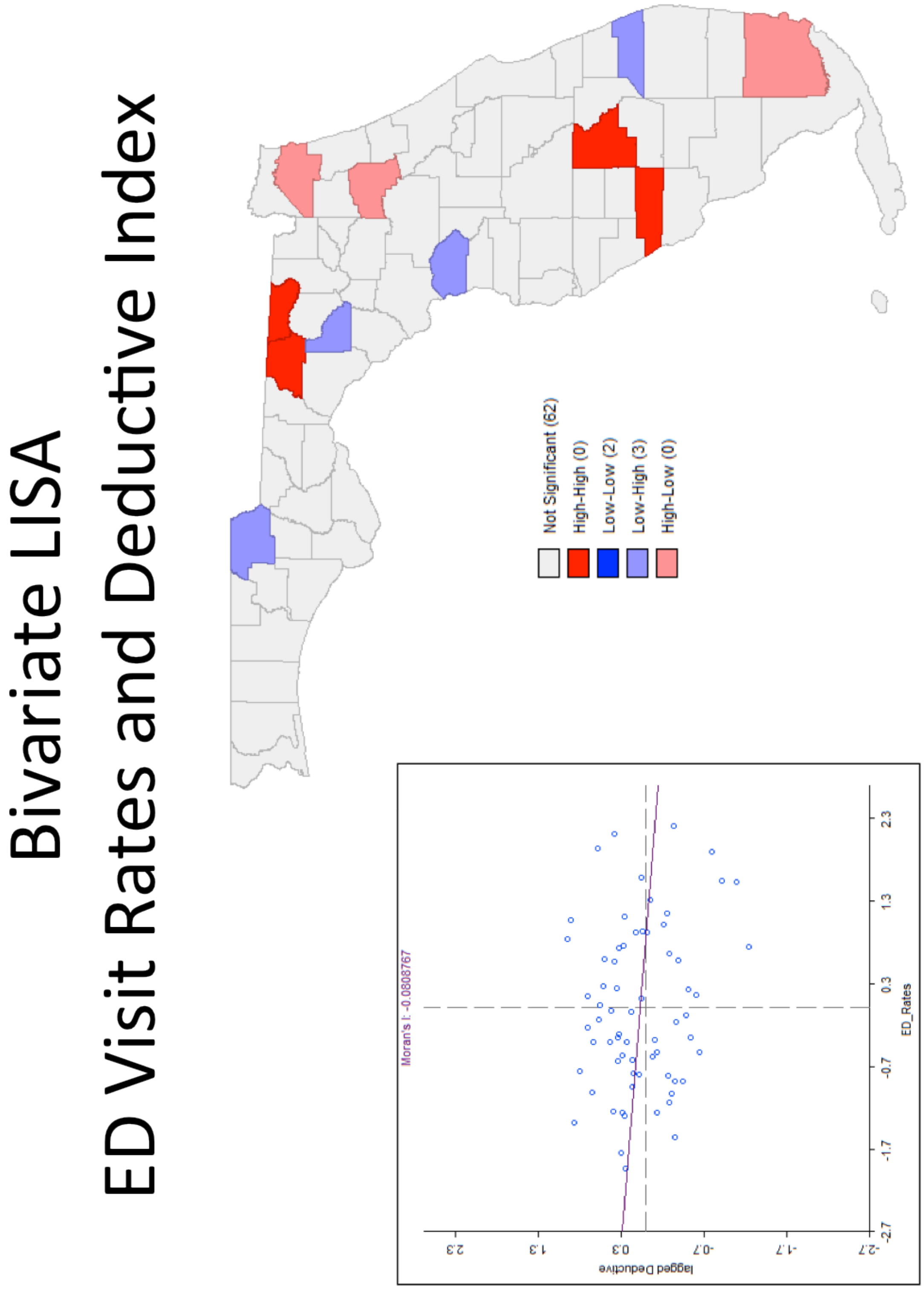
Map 20: The Inductive (SoVI) Index of Social Vulnerability Displayed in Tertiles for Florida



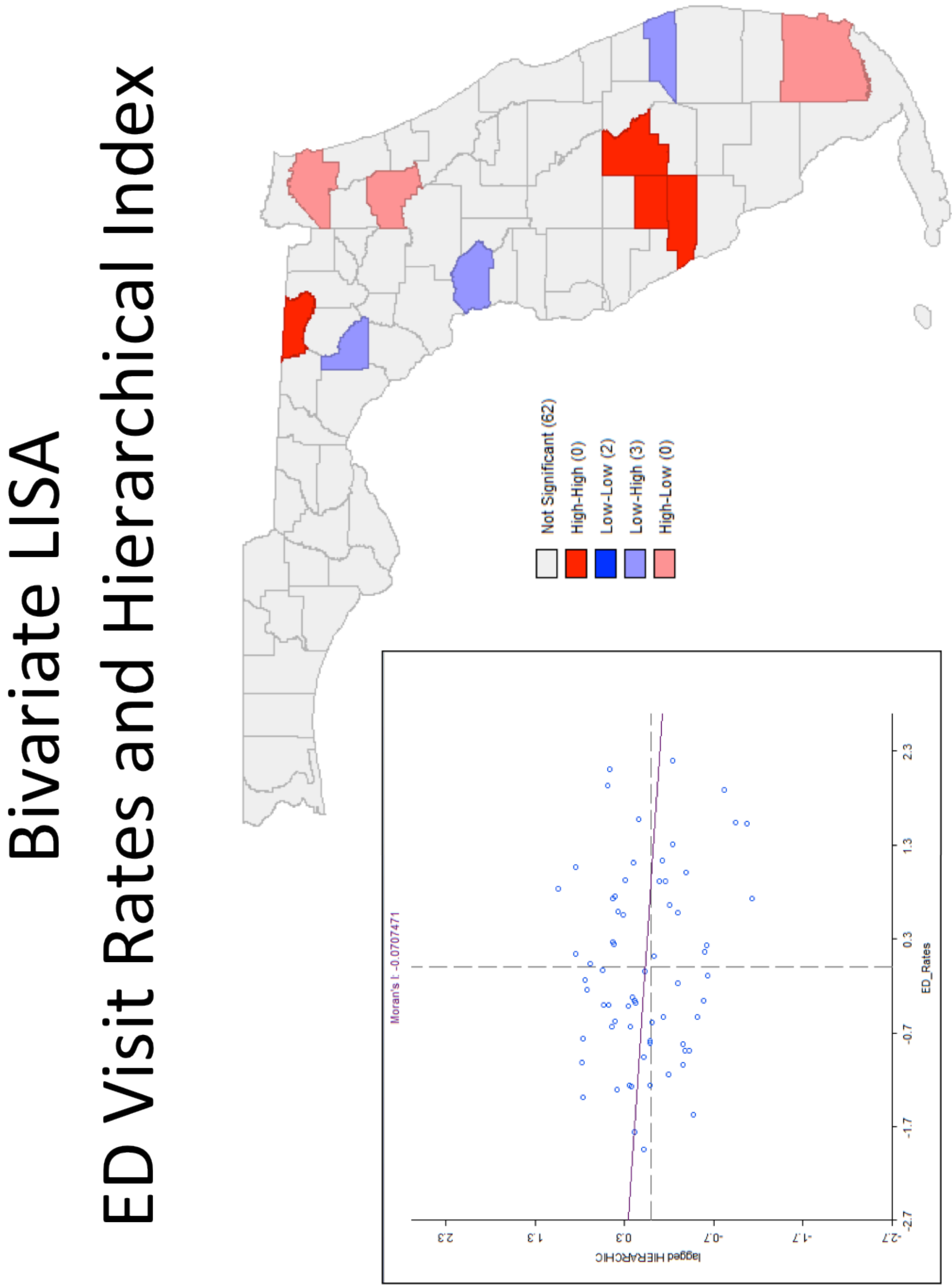
Map 21: Significant Getis Clusters for the Deductive, Hierarchical and Inductive measures of Social Vulnerability in Florida



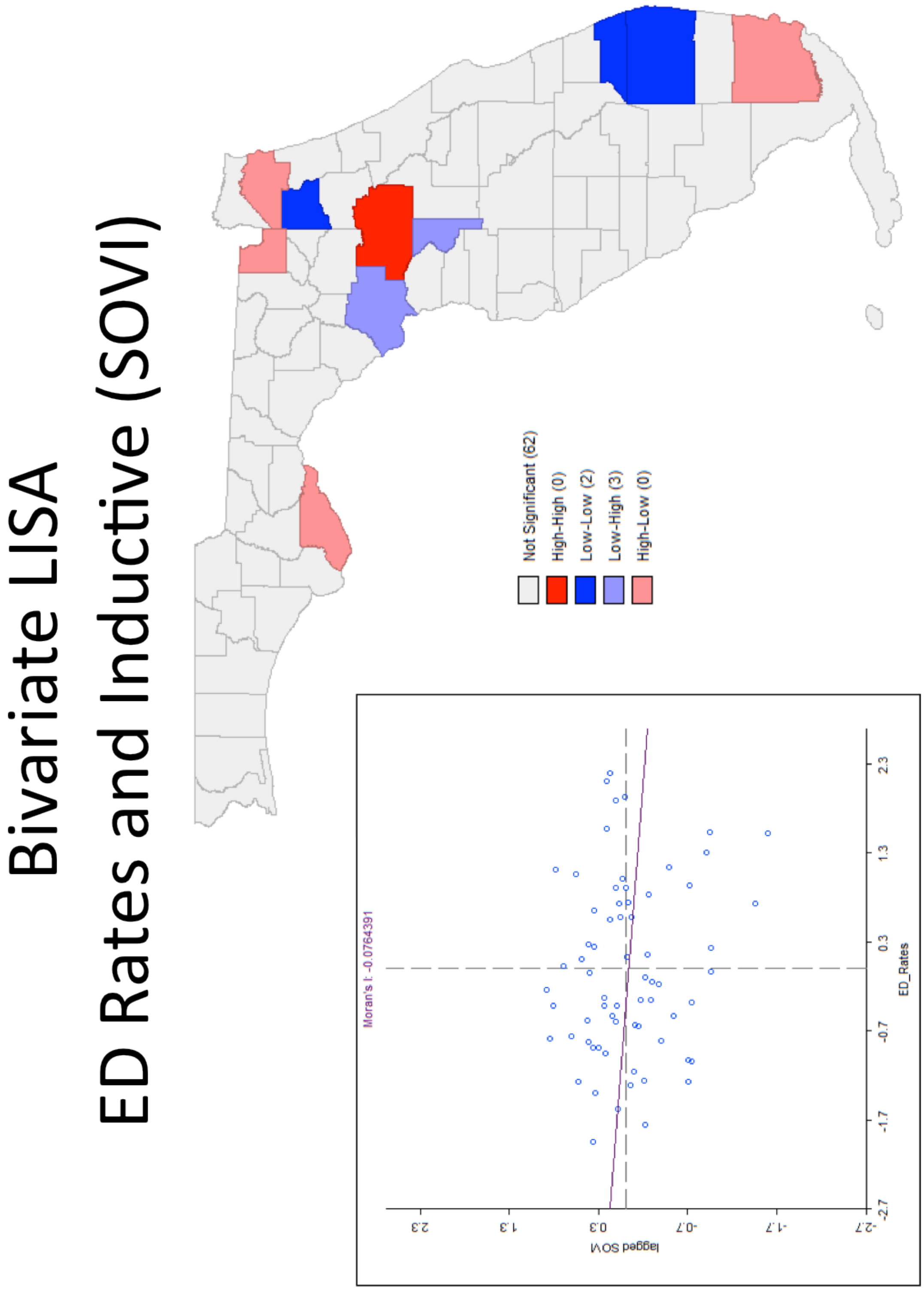
Map 22: Bivariate LISA results comparing PM 2.5 to Asthma Emergency Department Visit Rates in Florida



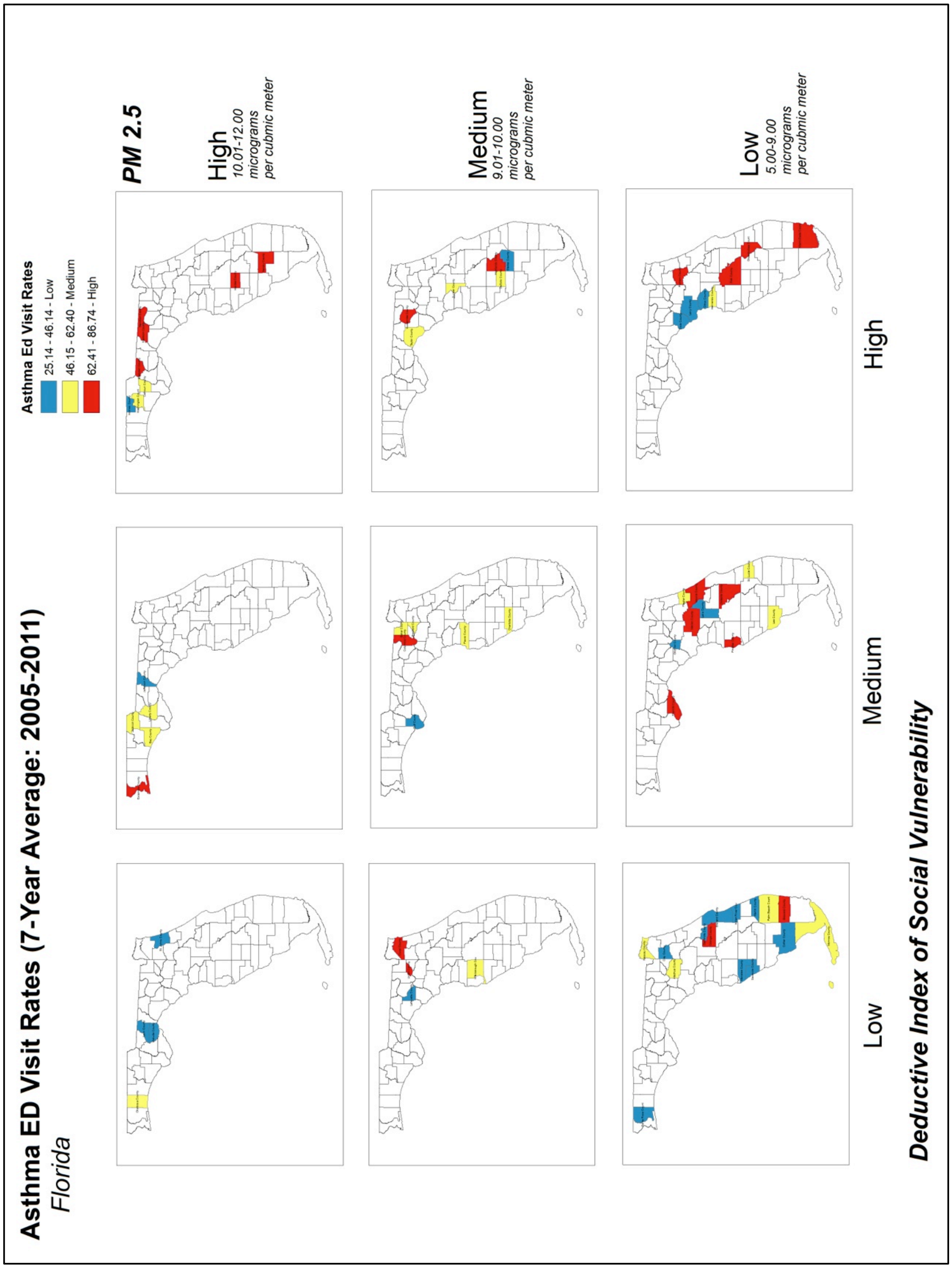
Map 23: Bivariate LISA results comparing the Deductive Measure of Social Vulnerability to Asthma Emergency Department Visit Rates in Florida



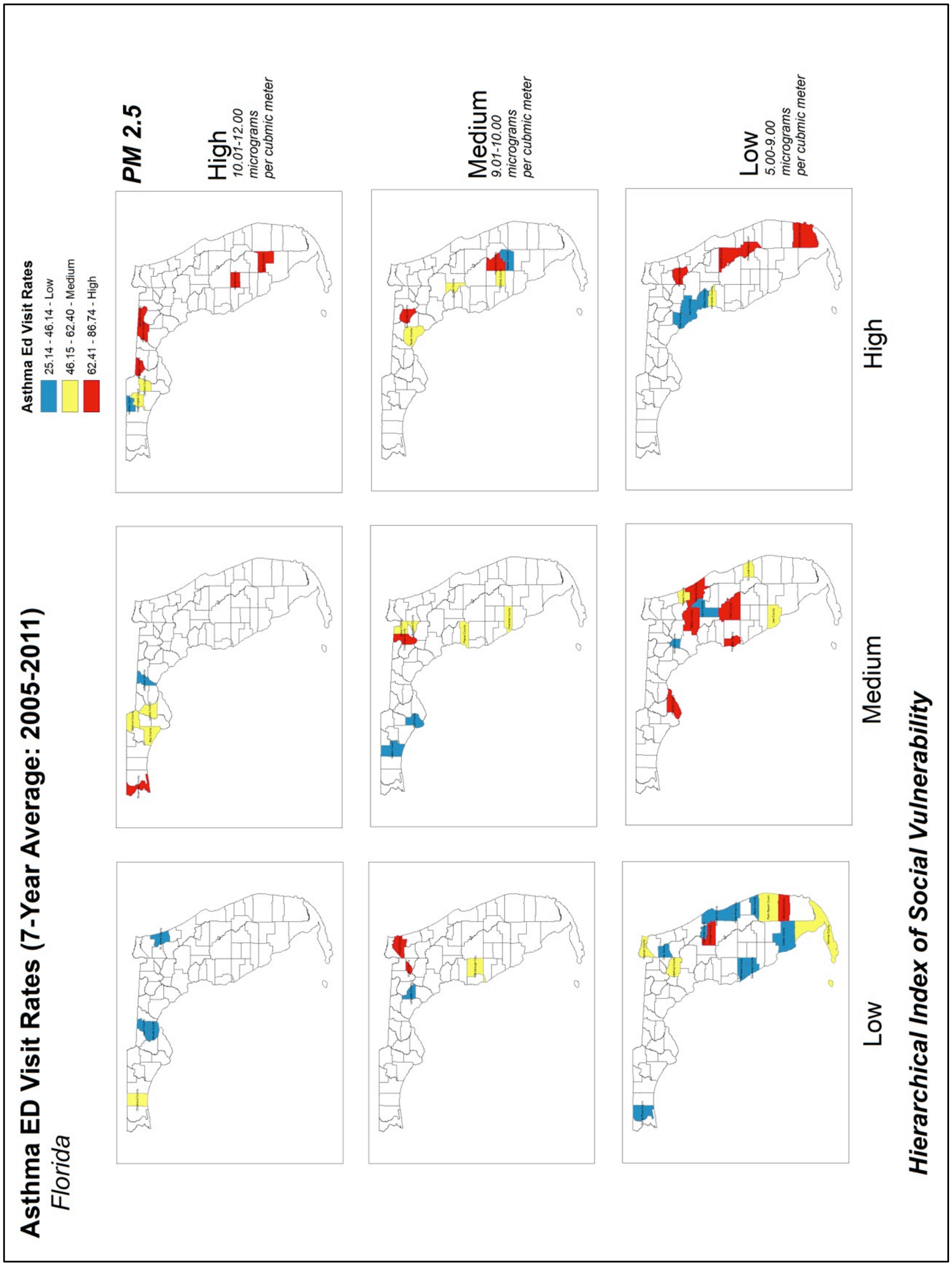
Map 24: Bivariate LISA results comparing the Hierarchical Measure of Social Vulnerability to Asthma Emergency Department Visit Rates in Florida



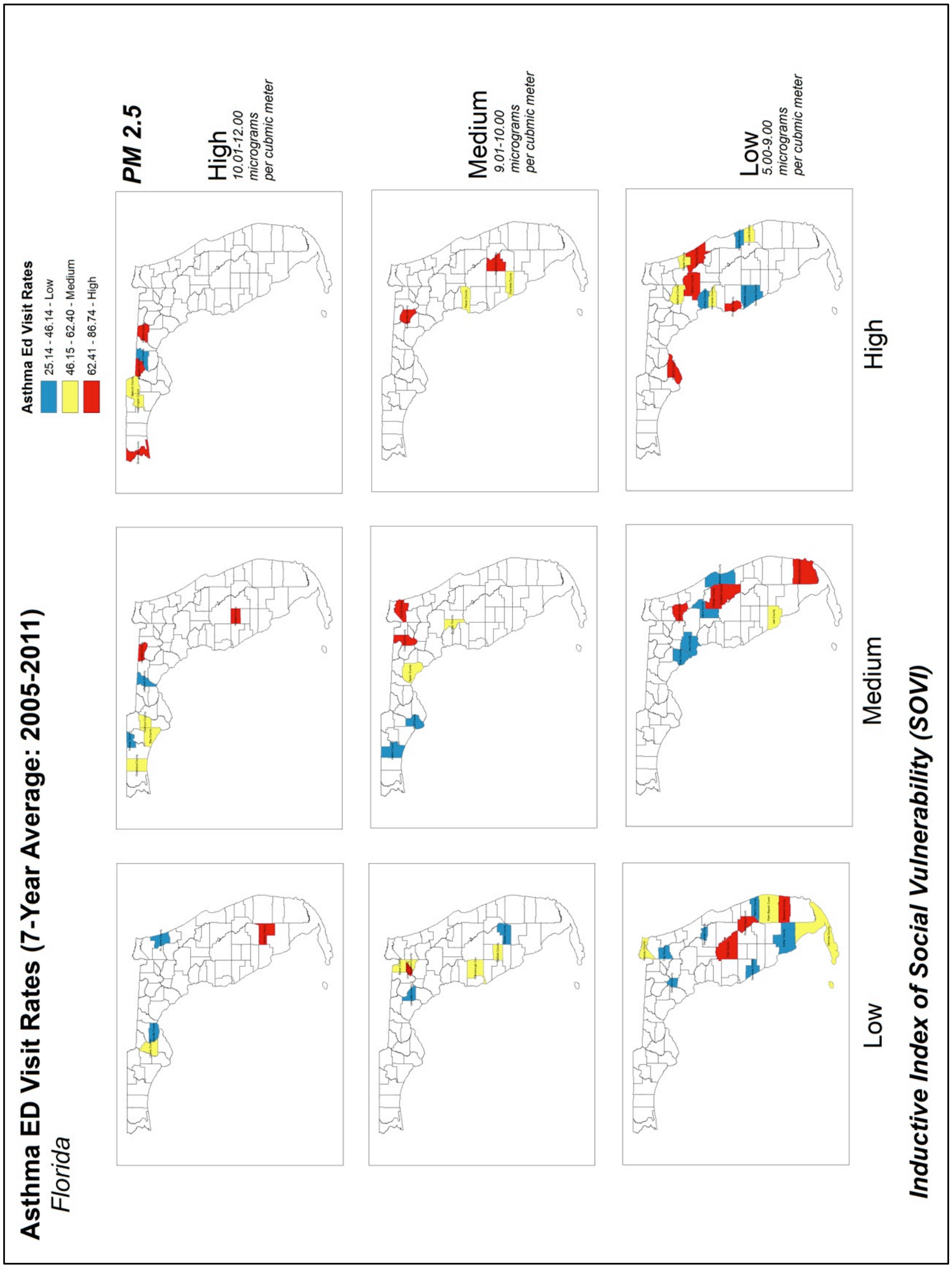
Map 25: Bivariate LISA results comparing the Inductive (SoVI) Measure of Social Vulnerability to Asthma Emergency Department Visit Rates in Florida



Map 26: Conditional Choropleth Map Showing Asthma Emergency Department Visit Rates compared to PM 2.5 levels and the Deductive Measure of Social Vulnerability



Map 27: Conditional Choropleth Map Showing Asthma Emergency Department Visit Rates compared to PM 2.5 levels and the Hierarchical Measure of Social Vulnerability



Map 28: Conditional Choropleth Map Showing Asthma Emergency Department Visit Rates compared to PM 2.5 levels and the Inductive (SoVI) Measure of Social Vulnerability

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