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ARTICLE

Toward an analytic framework for the spatial epidemiology of compassion

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Abstract: The epidemiology of compassion seeks to better understand factors related to the experiences (giving, sharing, and receiving) of compassion. Here, we summarize existing analytic tools from different disciplines allowing analysts to explore local and neighborhood features as a context for better understanding a "geography" of compassion. We provide a brief review of the concepts defining compassion, how these concepts might be measured at local levels of geography, how epidemiology provides a framework for estimating associations between these measures and other local features, and how spatial statistical models adjust for spatial correlations and provide measures of uncertainty associated with estimated associations. We next outline how these tools, taken together, can enable empirical studies of local compassion. We discuss what sorts of epidemiologic questions can be answered, and what compromises analysts will make along the way based on choices of data and analytic methods. We seek to provide a broad framework for such analyses and outline examples illustrating the types of data available and what questions could be answered from each. This framework provides a setting for more detailed creation, description, estimation, and navigation of compassion "landscapes" from the perspectives of giving, sharing, and receiving compassion.

Keywords: spatial statistics, geography, geographic information systems, epidemiology

1. Introduction

Most definitions of compassion involve the recognition of suffering in others coupled with a motivation to act to reduce this suffering (Strauss et al. 2016, Mascaro et al. 2020). To date, most empirical studies of compassion (quantitative or qualitative) focus on individual-level assessments of the recognition of suffering and motivation to act, often measured via validated survey instruments. Mascaro et al. (2020) provide a valuable overview of modes of measurement of individual compassion and Vieten et al. (2024) present a scoping review of over 300 such individual-level measures appearing in the literature. Such studies measure and monitor levels of suffering or need, recognition of that suffering or need, and responsive action over time within sets of individuals, often within a particular setting, e.g., a health care system, a school, or a business (Trzeciak et al. 2017, Trzeciak and Mazzarelli 2019, Vieten et al. 2024).

While most empirical measures of experiences of compassion occur at the individual level, Addiss et al. (2022) highlight and review empirical studies of compassion conducted at the population level, providing an epidemiologic perspective of compassion, i.e., allowing development and evaluation of population-level interventions working toward understanding policies and drivers to develop more compassionate neighborhoods, regions, and nations to

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contribute to a more compassionate world. While the field of epidemiology traditionally focuses on negative health-related outcomes (e.g., disease or other adverse health events), there is a growing recognition that the analytic tools of epidemiology, especially the estimation and evaluation of risks and rates, can provide insight into correlates to and, perhaps, drivers of increased probabilities of positive outcomes, i.e., "positive epidemiology" (VanderWeele et al. 2020) of resilience, flourishing (Schotanus-Dijkstra et al., 2016), and compassion.

Traditional introductions to epidemiology refer to the importance of person, place, and time. To date, discussions of an epidemiology of compassion mostly focus on the features of person and time. The literature contains only a few examples that consider place when measuring features of compassion and/or exploring factors associated with locally increased or decreased compassion. Recently, D'Ear et al. (2024) compared feelings of compassion relating to the experience of serious illness or death, measured in individuals residing in two neighborhoods in Flanders, Belgium. They not only observed different levels of compassion between different neighborhoods but also observed higher levels of compassion between neighbors who reside closer together than those living farther apart.

Building on the population-level perspective reviewed in Addiss et al. (2022), the local variations of compassion reported in D'Ear et al. (2024), and a history of place-based analysis in the fields of geography, epidemiology, and spatial statistics, we frame a general analytic set of tools and strategy to estimate, reveal, map, and explore local levels of compassion. This conceptual analytic framework is anchored in three motivating spatial questions of interest deriving from the definition of compassion, namely:

- Where are individuals suffering?
- What actions are available to alleviate suffering and where?
- What local features are associated with local suffering and local response?

In the sections below, we briefly review analytic concepts and tools from the fields of geography, epidemiology, and spatial statistics that, separately, provide spatial perspectives and partial answers to the three motivating questions, and, together, consolidate these into an analytic toolbox for the spatial epidemiology of compassion by addressing components of the questions above. The framework offers many directions for spatial analysis and we illustrate several examples of the types of data available and types of answerable questions provided by the tools. We then discuss remaining challenges and many opportunities for future work to apply, expand, refine the elements of the general analytic strategy described below.

2. Interdisciplinary concepts and tools for spatial analysis

Our proposed framework draws from analytic concepts and tools from three different disciplines: geography, epidemiology, and spatial statistics. We briefly outline the extent to which analytic approaches within each discipline relate to our three motivating questions. In each summary, we identify the key tools and the analytic abilities they provide that we include in our analytic framework.

2.1 Geographic concepts and tools

The field of geography is motivated by thinking spatially, i.e., noting how insights and conclusions vary by location. In practice, observations of where something occurs can often provide key insights into what occurred, predictions of what is likely to occur, or what local factors drive why it occurred (Goodchild 2010). As a result, spatial analyses from the perspective of geography often rely on multiple data sets from multiple sources, linked via the spatial location of observation and reporting. More specifically, geographic information systems (GISs) allow analysts to *link and layer maps of different data sets containing measures for the same administrative areas* (e.g., numbers of health events from a health department and sociodemographic summaries from a census, each reported for the same small areas), and to *summarize information from one data set based on locations in another* (e.g., how many cases of disease occur within 1, 5, 10 miles from clinic locations?). Linking and summarizing data across data sets and *mapping patterns via custom cartography* allow a broad set of tools for spatial analysis via GIS (Goodchild and Haining 2004, Mitchell 2013, 2025, Mitchell and Scott Griffin 2021, Brundsdon and Comber 2025). Effective mapping of data-based statistical estimates is both a science and an art drawing from principles of data visualization (Tufte 1990, 1997, 2001, 2006), statistical graphics (Wilkinson, 2005), and cartography (Monmonmier 1996, MacEachren 1995, Field 2018, 2021, Slocum et al. 2023). Maps of such linked data have a long history of providing geographic perspectives in epidemiology and public health (Brody et al. 2000, Johnson 2006, Koch 2011, Waller 2017, Koch 2017) and allowing communication of results to health officials, policy makers, and to the general public.

In summary, our analytic framework includes three primary tools from geography, providing the ability to:

- *Link and layer maps of different data sets containing measures for the same administrative areas*,
- *Summarize information from one data set based on locations in another*, and
- *Map patterns via custom cartography*

2.2 Epidemiologic concepts and tools

The field of epidemiology involves measuring health outcomes and potential associated factors within populations to *identify how the risk of an outcome changes under different exposures to social and environmental variables*, typically based on observational (i.e., non-experimental) data. The health, sociodemographic, and population data sets linked by geographic tools provide the local ingredients for epidemiologic estimates of local risks. The concept of *risk* typically represents a probability of the outcome occurring in a group or individual exposed to specific levels of the risk factors under consideration over a defined time period. Such *risks are often estimated by epidemiologic rates denoting the number of events occurring within individuals with the same set of exposures divided by the person-time at risk*. The field of epidemiology has a rich toolbox ranging from simple summary proportions observed in population subsets to *estimated associations between risk factors and observed epidemiologic rates involving adjustments for potential confounding variables*. Under the proper assumptions, such analyses can be extended to advanced methods of causal analysis (Hernàn and Robins 2020) linking risk factors and outcomes, the development of methods for spatial causal analysis remains a challenging and very active field of methodologic research.

To recap, our analytic framework includes three primary tools from epidemiology, providing the ability to:

- *Identify how the risk of an outcome changes under different exposures to social and environmental variables*,
- *Estimate epidemiologic rates denoting the number of events occurring within individuals with the same set of exposures divided by the person-time at risk*, and
- *Estimate associations between risk factors and observed epidemiologic rates while adjusting for potential confounding variables*

2.3 Spatial statistical concepts and tools

The field of spatial statistics applied to epidemiologic data is both broad and deep (Waller and Gotway 2004, Lawson 2006, 2018, Lawson et al., 2016, Moraga 2019, Diggle and Giorgi 2019), adding adjustments to standard statistical models (typically regression models) to *incorporate spatial correlation between residual (error) terms in epidemiologic estimates of local risks, while adjusting for associations with local covariate values*. Tobler's First Law of Geography posits that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). The specification that nearby observations are more related than those taken far apart suggests a need to adjust standard analytic methods to allow for levels of correlation in residual error that fade with increasing distance between observations, similar to the manner in which longitudinal studies adjust for correlations that fade with increasing time between observations. D'Ear et al.'s (2024) analysis of compassion in Belgium neighborhoods mentioned above provides an empirical example of the presence of spatial correlation in local studies of compassion.

Familiar epidemiologic analytic tools for counts and rates such as logistic or Poisson regression typically require independent observations for accurate estimation of associations between risk factors and outcomes. However, the field of spatial statistics offers methods that adjust for spatial correlation in residuals and improve the accuracy of local estimates of epidemiologic rates, often through the inclusion of a spatially-correlated random intercept to traditional logistic or Poisson regression (see Waller and Gotway 2004, chapter 9, Lawson 2019, for details and many examples).

The inclusion of such spatially-correlated random intercepts addresses a second challenge in spatial epidemiology, i.e., the inherent tension between local statistical precision (seeking low variance rate estimates by dividing the overall study area into only a few small areas, each with large local sample size) and geographic precision (a detailed map comprised of estimated rates from many small areas, each with small sample sizes). In a fixed map of neighborhoods covering a fixed period of time, aggregating neighborhoods to make sure each aggregation meets a sample size requirement can reduce the variance of estimated rates for the aggregated areas, but such a strategy is in direct tension with the desire to define epidemiologic rates from many small neighborhoods covering the study area so that the overall map is rich in local detail. To compromise, generalized linear mixed models incorporating spatially correlated random intercepts (e.g., extensions to logistic and Poisson regression) allow *each local estimate to "borrow" information from nearby neighbors,* effectively increasing the local sample size (and reducing the local variance of the estimated rate, improving statistical precision) while maintaining the original neighborhood boundaries (maintaining geographic precision). This analytic strategy creates a local estimate of a neighborhood's rate as a weighted average between the estimate using data from that neighborhood alone and the rate estimate from each of its neighbors. Such "small area estimation" and "disease mapping" models have application in a very wide range of spatial epidemiologic studies (Waller and Gotway 2004, Lawson 2016, Moraga 2019) and are typically implemented in a hierarchical Bayesian framework providing posterior estimates of each neighborhood's epidemiologic rate along with credible intervals to show the statistical precision associated with each local estimate. The framework allows analysts to include local covariates within logistic or Poisson models, providing estimated changes in the log odds of the outcome for changes in covariate values. The family of models can be extended further to reflect additional complexities such as allowing spatial patterns in outcome rates to change over time (Waller et al. 1997, Waller and Carlin 2010, Hepler et al. 2021, 2023) or allowing associations with covariates to vary across geographic locations (Fotheringham et al. 2003, Waller et al. 2007, Wheeler and Waller 2009).

Taken together, our initial analytic framework for a spatial epidemiology of compassion includes two primary tools from spatial statistics, namely the ability to:

- *Incorporate spatial correlation between residual (error) terms in epidemiologic estimates of local risks, while adjusting for associations with local covariate values,* and
- *Allow each local rate estimate to "borrow" information from nearby neighborhoods to reduce the local variance of the estimated rate while maintaining the original neighborhood boundaries*.

3. A general analytic framework for a spatial epidemiology of compassion

Waller (2009, 2024) described spatial analysis of epidemiologic data as a cycle including four steps:

1. Define the *motivating questions*, i.e., the questions one wants to answer,
2. Consider the *ideal data* that would allow one to completely answer the motivating questions,
3. Define the *available data and methods*, almost always a compromise from the ideal data in step 2, and
4. Answer the questions one can answer with the available data and analytic tools, i.e., the *answerable questions given the available data and methods*.

A critical component of any spatial analysis is a thoughtful comparison of the questions one can answer (step 4) with the questions one wants to answer (step 1). This comparison frames results, identifies limitations, and outlines the next cycle of analyses (what additional data and/or methods would allow one to get closer to answering the questions of interest?, what additional data and/or methods can be accessed?, what answers do they provide?).

Our proposed analytic framework for a spatial epidemiology of compassion focuses on the transitions between the steps of this spatial analysis cycle, illustrated in Figure 1. First, we move from concepts to data (ideal and available), from data to analysis, from analysis to answerable conclusions by applying spatial analytic methods from the three disciplines above to the data at hand. Our framework for spatial epidemiology of compassion involves an additional step not articulated in the spatial analytic cycle, i.e., the need to move from conclusions to available actions to alleviate suffering, a key component of compassion and a key component of assessing how closely our answerable questions mirror our motivating questions.

We intend the analytic framework to serve as a general roadmap for linking local observations of suffering with local opportunities for action. We note that any single analysis of the spatial epidemiology of compassion will involve compromises between the data the analyst would like to have and the data available as well as between the motivating questions and the questions answerable in any fixed set of observations. We also note that any single study of compassion will only be able focus on specific elements of suffering and specific available local actions, often limited by the available data. To keep our focus on a general analytic framework, we provide different illustrative examples of components of our framework for different types of data sets within our descriptions of each step in the process, rather than a detailed development of a specific application based on a single data set limited to specific measures and measurements of suffering and actions.

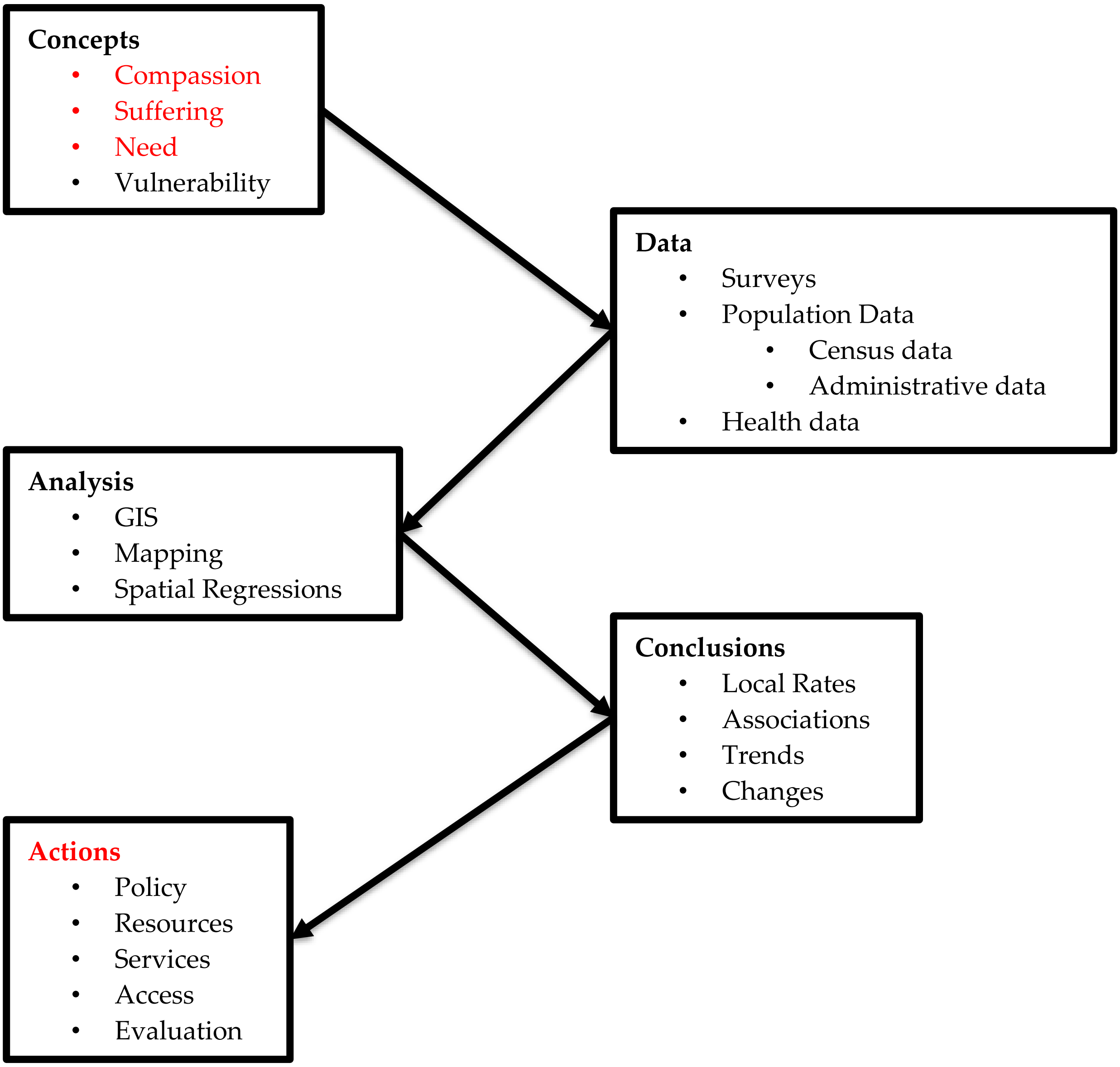


Figure 1. A conceptual analytic framework for small area spatial epidemiology of compassion.

3.1 Concepts to data

We first move from our motivating questions to the data we want and the data we can obtain. From the development above, recall the motivating questions for spatial epidemiology are:

- Where are individuals suffering?
- What actions are available to alleviate suffering and where?
- What local features are associated with local suffering and local response?

The ideal data for the study of the epidemiology of compassion for small, administrative areas consists of an empirical summary of compassion within each small area, defined by our motivating questions:

- The number and proportion of individuals suffering in each small area,
- The available actions to alleviate suffering within each small area, and
- Measurements of all relevant local features associated with local suffering and the ability to effectively respond.

While simple to state, in practice such data would be very difficult to obtain, so we next consider what sorts of data are available. Small area population-level spatial epidemiology analyses could focus on local population measures of risks of particular types of suffering (e.g., adverse health outcomes, or food insecurity) or perhaps local measures of need (e.g., a local measure of poverty or level of access to healthy food), or, more broadly, to local measures of multiple social determinants of need as precursors to or predictors of local suffering. We note that a local measure of *need* based on regional or national norms (e.g., poverty or food access) may not directly conform to local levels of *suffering*, a compromise between the concepts we would like to measure (suffering) to the concepts that were measured in the available data (aspects of need).

In the absence of direct observation of each individual, we can first map observed elements often associated with suffering, e.g., local lack of resources and opportunities measured by summaries such as income and educational attainment. Maps of local levels of poverty date at least to Charles Booth's famous maps of London in the late 1800s (Booth 1889, 1902) which place residents of each building into one of several socioeconomic categories. The maps effectively visualized patterns of wealth and poverty at both broad scales across the city and fine scales within each block. The classifications used carried both economic interpretations ("very poor", "wealthy") and societal interpretations ("loafers and semi-criminals", "upper middle class") but Kimball (2006) notes that Booth's visualization revealed poverty as an issue focused in specific areas of London, hence as a potentially locally treatable problem thereby encouraging local policy responses to meet the challenges involved.

The routine collection of income and education information in the official statistics of the United States and other countries allows GIS-based modern versions of Booth's map, but at the small area level rather than the household level to preserve individual privacy. Koch (2017) provides a fascinating case study of mapping different measures of poverty across small administrative regions to explore what insights are available in what ways, noting that no single approach fully captures the goal of uniquely identifying the underlying pattern, rather each map reveals different pieces of the picture, and insights into different opportunities for response.

While maps of the percent of residents of each census tract who report incomes below the federal poverty level only provide a starting point, maps of related variables often associated with challenging social settings can provide additional local insight (e.g., percent not completing high school). Many applications seek to create *indices* summarizing collections of measured variables to provide maps of a broader set of social determinants of health in the framework of neighborhood epidemiology (Duncan and Kawachi, 2018).

As an example of small area index-based data, the U.S. Centers for Disease Control uses sets of related responses to U.S. Census surveys to define a set of "Social Vulnerability Indices" (SVIs, Flanagan et al. 2011) and provides the data and an interactive mapping tool (https://www.atsdr.cdc.gov/place-health/php/svi/svi-interactive-map.html) for each of four SVI "themes". Figure 2 maps the overall SVI for counties surrounding the city of Atlanta in the state of Georgia, in the southeastern USA. Zooming in to the metro Atlanta area in Figure 3, we see further geographic detail in the overall SVI revealed in a census tract map (subdivisions of counties).

Figures 4a and 4b show the four SVI themes at the census tract level (mapped in different colors):

- Socioeconomic Status (green)
- Racial and Ethnic Minority Status (purple)
- Household Characteristics (orange)
- Housing Type and Transportation (blue)

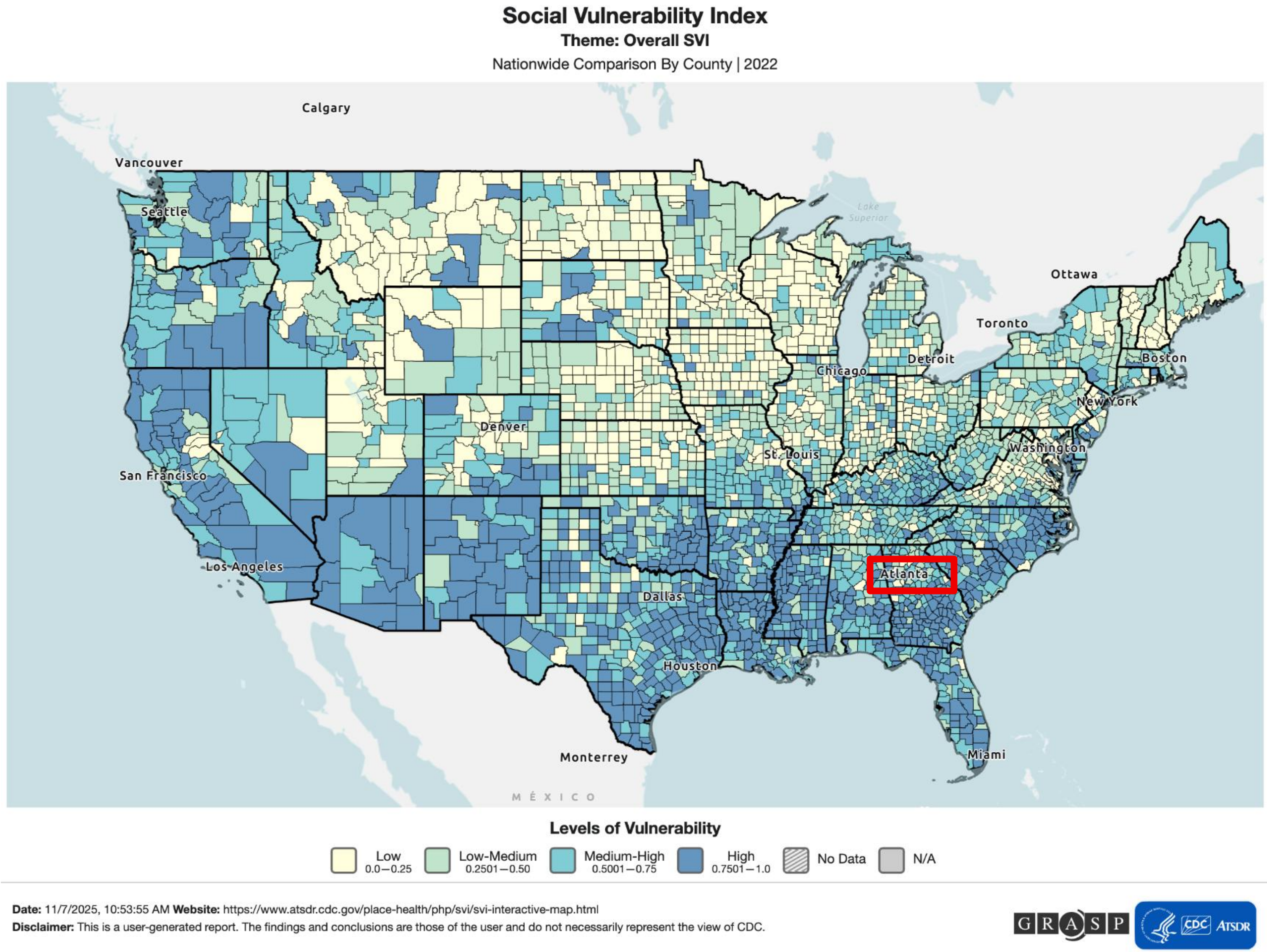


Figure 2a. County level maps of the overall Social Vulnerability Index for 2022 at the county level for the coterminous United States and reported by the U.S. Centers for Disease Control and Prevention. Detail for the red rectangle appears in Figure 2b for the area surrounding the city of Atlanta, Georgia, USA.

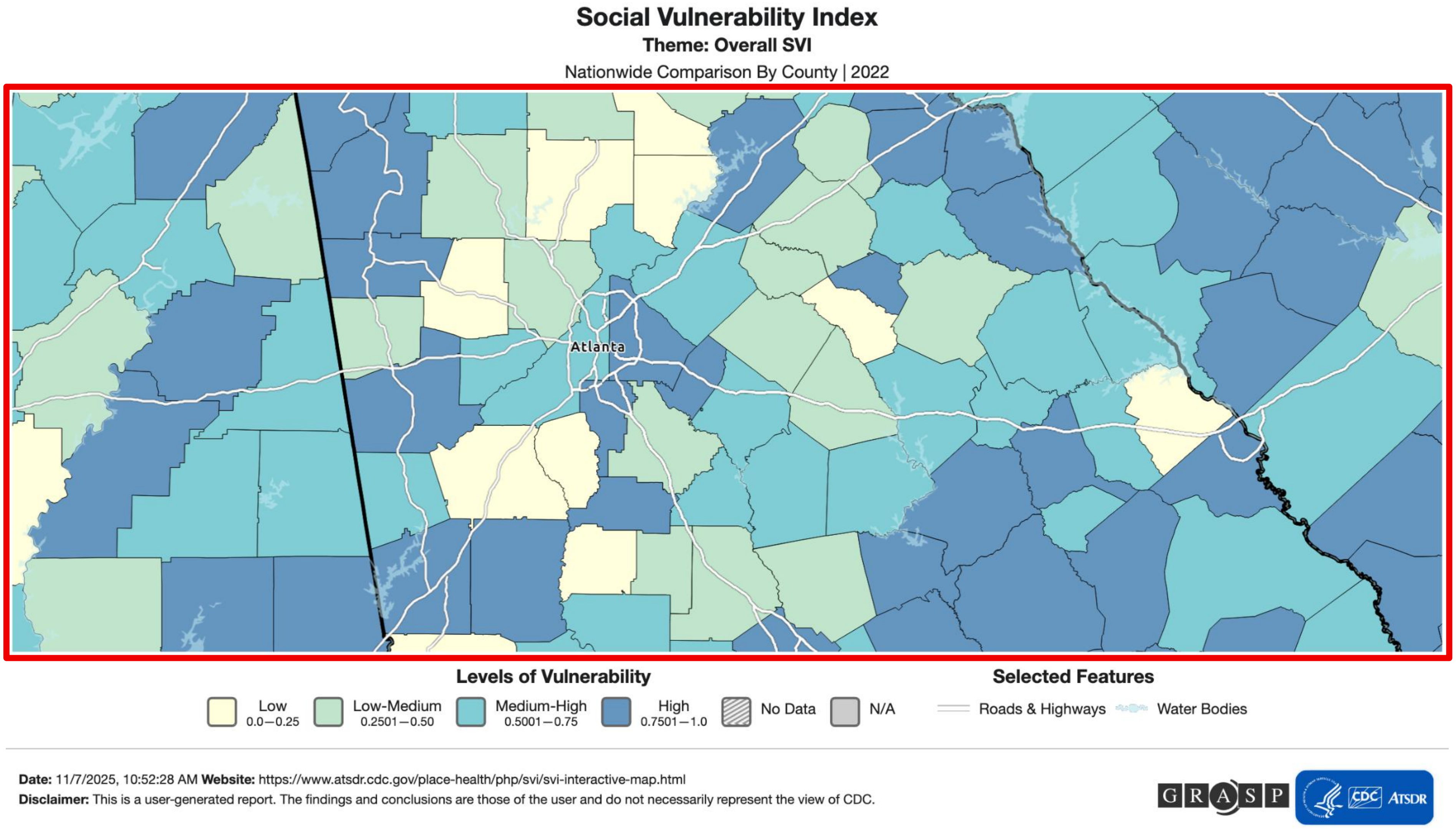


Figure 2b. County level maps of the overall Social Vulnerability Index for 2022 at the county level for the area surrounding the city of Atlanta, Georgia, USA (corresponding to the red rectangle in Figure 2a) as reported by the U.S. Centers for Disease Control and Prevention (see text).

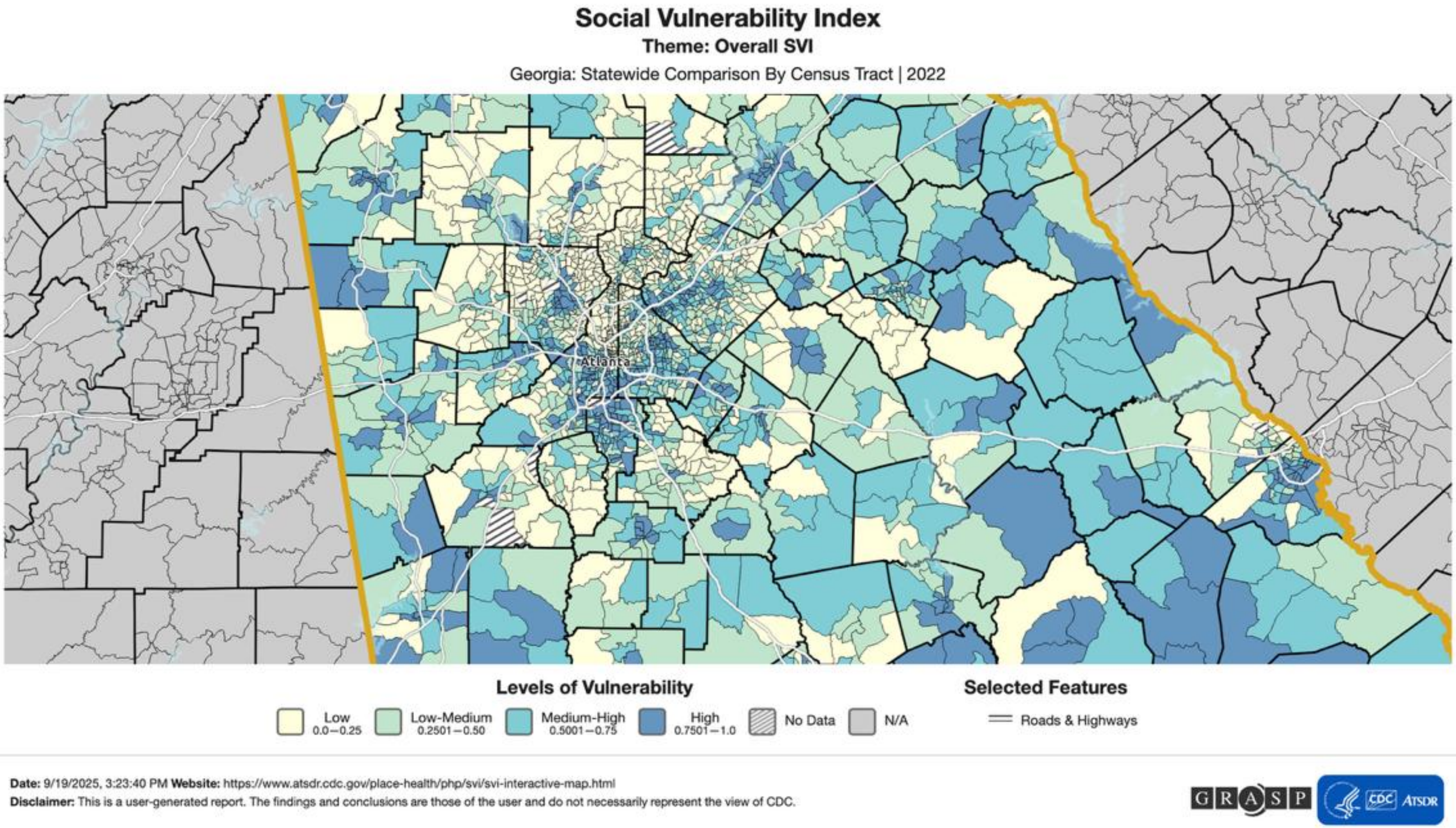


Figure 3. Maps of the overall social vulnerability by census tract for 2022 in the area surrounding the city of Atlanta, Georgia, USA calculated and reported by the U.S. Centers for Disease Control and Prevention (see text).

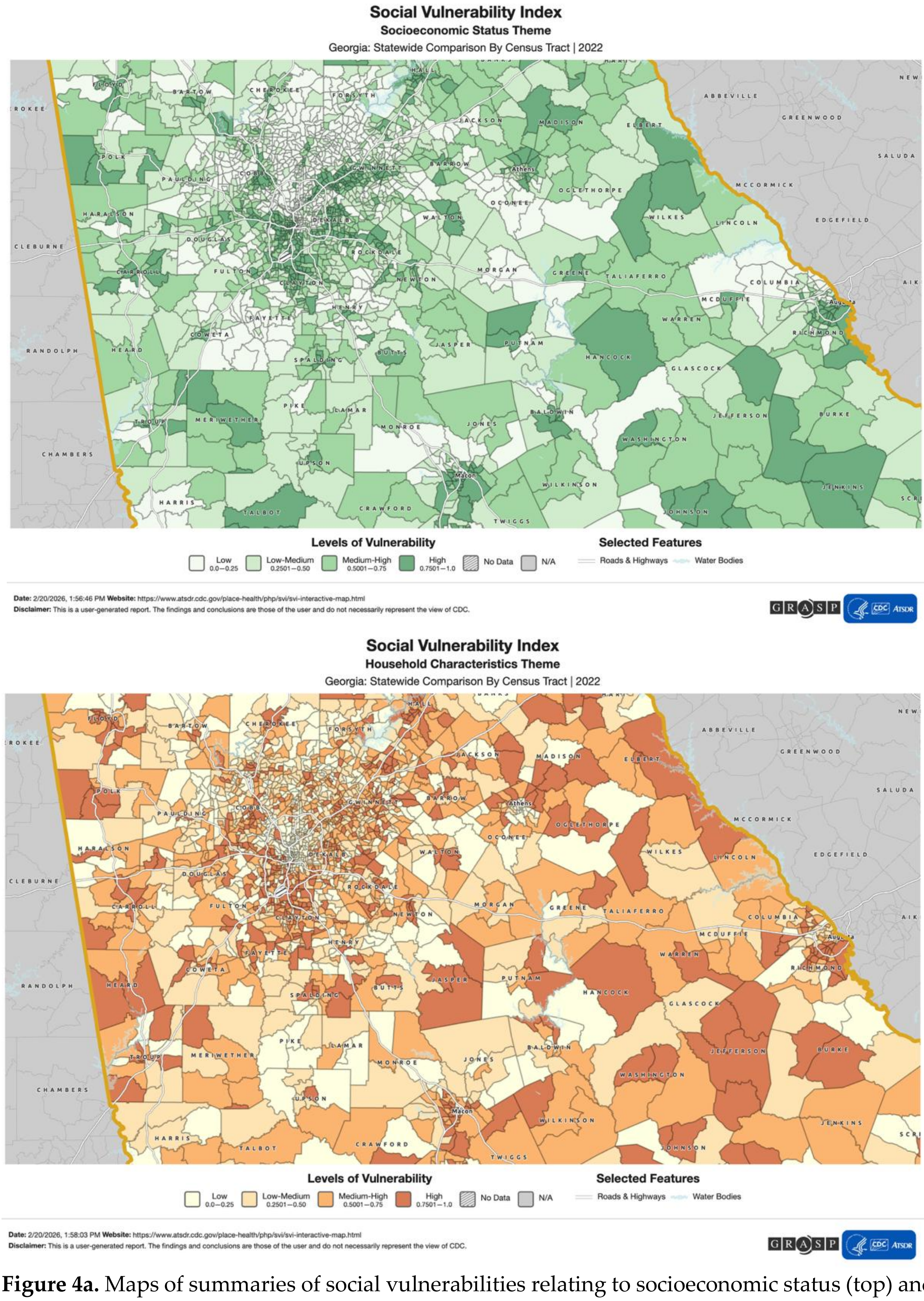
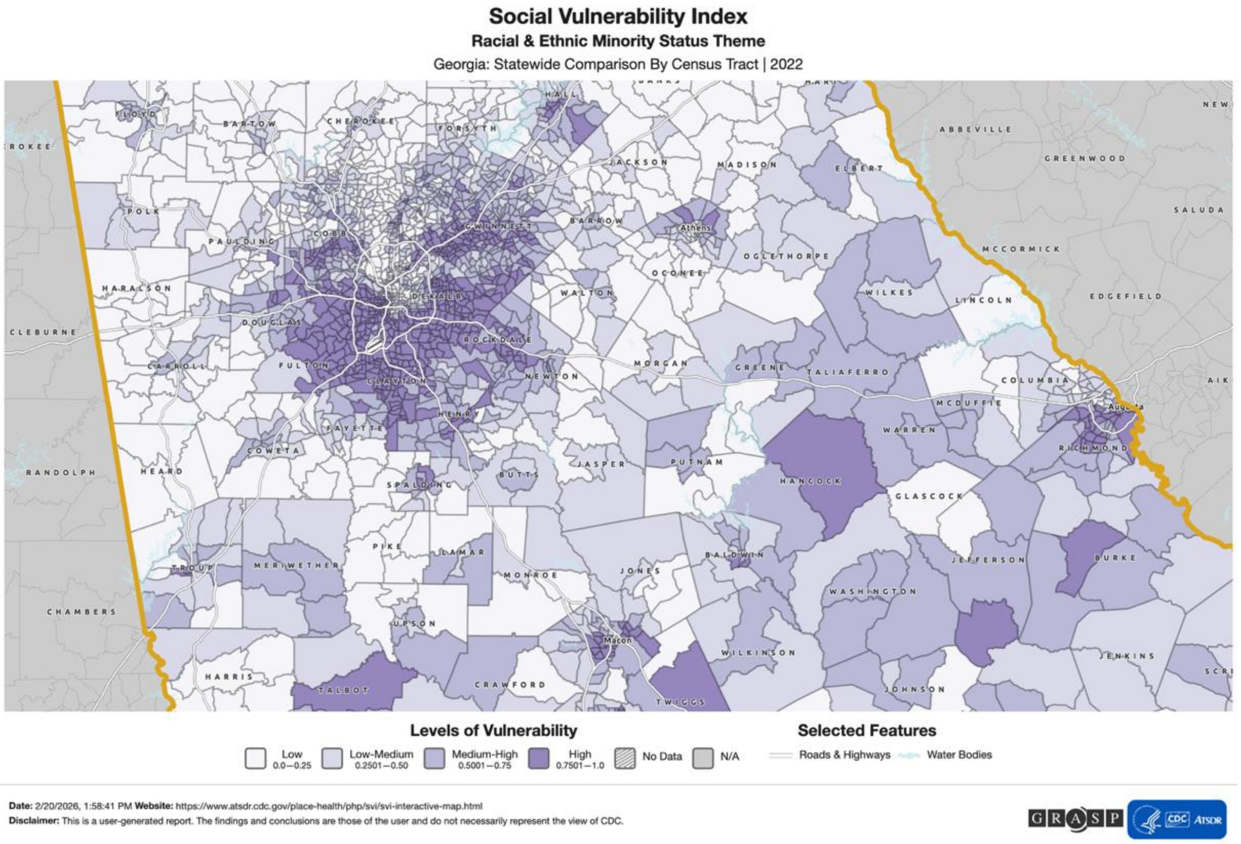


Figure 4a. Maps of summaries of social vulnerabilities relating to socioeconomic status (top) and relating to household characteristics (bottom) calculated by census tract for 2022 in the area surrounding the city of Atlanta, Georgia, USA and reported by the U.S. Centers for Disease Control and Prevention (see text).



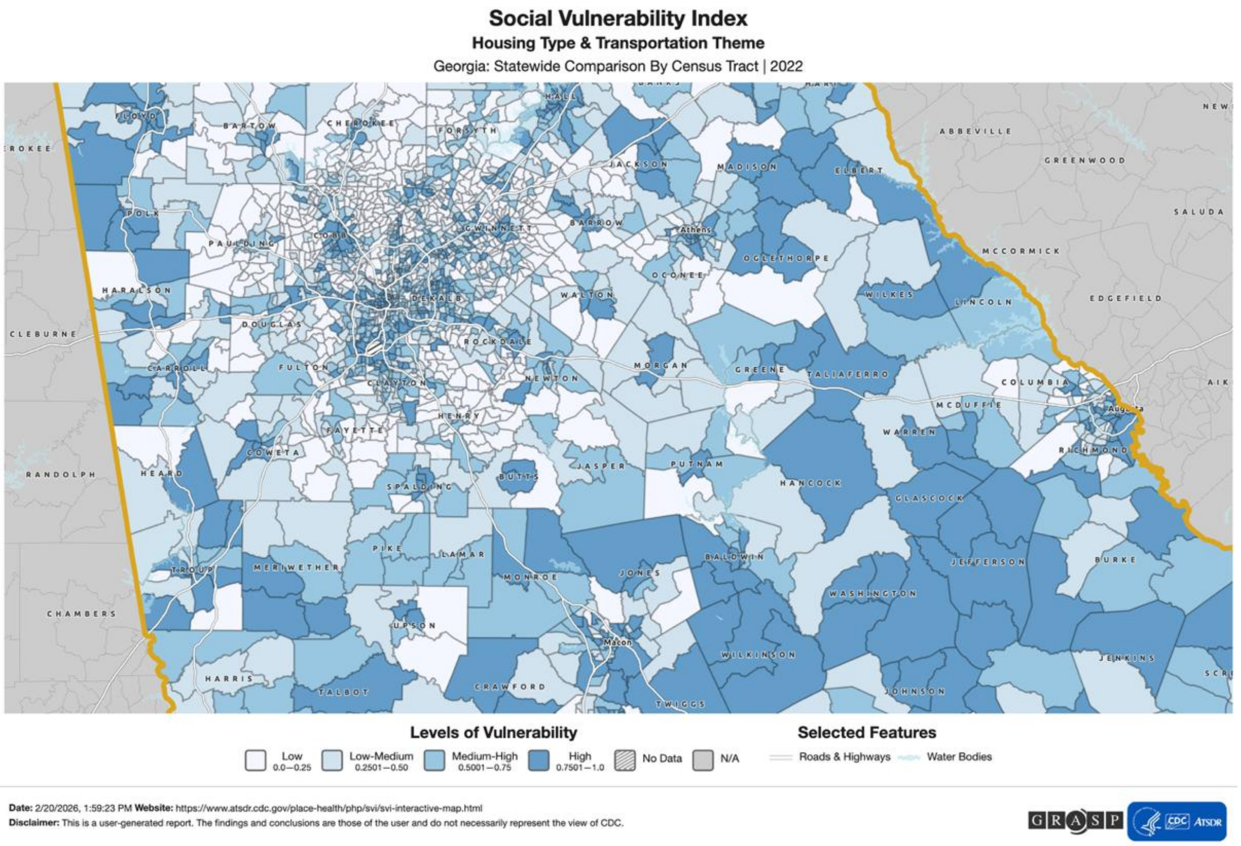


Figure 4b. Maps of summaries of social vulnerabilities relating to racial and ethnic minority status (top) and relating to housing type and transportation (bottom) calculated by census tract for 2022 in the area surrounding the city of Atlanta, Georgia, USA and reported by the U.S. Centers for Disease Control and Prevention (see text).

Each map relates to different dimensions of social vulnerability, i.e., different aspects of social and economic need and the risk of associated potential suffering. Each of the four maps reveals different summaries of potential need and local associated risks of suffering. We see both similarities and differences between the maps. The SVI Theme: Socioeconomic Status (Figure 4a, green) reveals differences between central and suburban tracks in Atlanta as well as differences between different rural areas of the state. The SVI Theme: Racial and Ethnic Minorities (Figure 4b, purple) illustrates more concentration into areas of higher proportions of similar racial and ethnic profiles, historical echoes of past housing practices and redlining, however spatial concentration is more diffuse in maps of the other three SVI Themes (Figures 4a and 4b) and the Overall SVI (Figure 3) due to the complex ecology of social and economic interactions across this geographic region.

3.2 Data to analysis

Summarizing our conceptual and analytic tools from above, collectively, our analytic toolset consists of the abilities listed in Table 1.

Table 1. Collective list of the abilities within the analytic framework for analyses of the spatial epidemiology of compassion provided by analytic tools from the disciplines of geography, epidemiology, and spatial statistics.

Discipline	Analytic tools providing ability to…
Geography	*Link and layer maps of different data sets containing measures for the same administrative areas.*
Geography	*Summarize information from one data set based on locations in another.*
Geography	*Map patterns via custom cartography.*
Epidemiology	*Identify how the risk of an outcome changes under different exposures to social and environmental variables.*
Epidemiology	*Estimate epidemiologic rates denoting the number of events occurring within individuals with the same set of exposures divided by the person-time at risk.*
Epidemiology	*Estimate associations between risk factors and observed epidemiologic rates while adjusting for potential confounding variables.*
Spatial Statistics	*Incorporate spatial correlation between residual (error) terms in epidemiologic estimates of local risks, while adjusting for associations with local covariate values.*
Spatial Statistics	*Allow each local rate estimate to "borrow" information from nearby neighborhoods to reduce the local variance of the estimated rate while maintaining the original neighborhood boundaries.*

When coupled with available data, these tools define the answerable questions, given the data to which we have access. As an example, the SVI examples in Figures 2-4 illustrate how the geographic tools of data layering and mapping provide some insight into patterns of and potential types of local need and suffering. Moving from Figure 2 to Figures 3 and 4, we see different details of pattern between county-level and tract-level summaries. Figures 4a and 4b illustrates how different SVI Themes reveal different patterns, that is, different types of need display different geographic patterns across metro Atlanta, revealing that no single map or single analysis can provide the full answer to our motivating questions but, instead, each provides insight into different components of local need and potential suffering.

The epidemiologic and spatial statistical tools above, if applied to small area epidemiologic rates, seek to answer questions such as "What proportion of a small area's population is suffering and what local covariates are associated with higher rates?" Epidemiologic regressions with spatial correlation (linking the epidemiologic tools and spatial statistical tools from the table able), can both stabilize local small area rate estimates (through the borrowing of information from neighboring small areas) and provide estimates of associations between local epidemiologic rates of need or potential suffering and local covariates.

In the compassion setting, the local proportion of a population that is suffering can be of interest, but our motivating questions extend further and include exploration of what and where actions are available to alleviate local suffering and what covariates might be associated with their ability to do so. That is, our goal is not solely to treat the epidemiologic rate as an outcome variable and identify covariates associated with this outcome. The motivating questions suggest that a spatial epidemiology of compassion also explores questions such as "Is the presence of nearby services associated with lower rates of suffering?" Or "Is the presence of nearby services associated with reductions in local rates of suffering over time?"

3.3 Analysis to conclusions

Transitioning from the standard questions answered in the spatial epidemiology of disease to the questions of interest in the spatial epidemiology of compassion requires definition of what measures of suffering (or need or vulnerability) are of interest, which services are being researched and how are these measured. Thankfully, many individuals and organizations already respond to local need and suffering based on lived or reported experiences. The analytic tools from geography can provide maps of service locations and can link service locations to surrounding estimates of need or suffering. As an example, Figure 5 illustrates an example from the state of Ohio of an interactive "Compassion Map" of faith-based services to highlight locations of services (Figure 5). Those seeking information for facilities can search via the map to identify what services are available where. Service providers can use the map to add the location of and information regarding their services. A similar example for navigating patient-client and family housing options for long-term care is outlined by Owens et al. (2025) and implemented online by the University of Maryland, Baltimore's Healthcare Housing Navigator (https://www.umaryland.edu/navigator/). While neither the Ohio Compassion map nor the Healthcare Housing Navigator examples include measures of local need, linking the map to, e.g., local SVI measures, can allow exploration of how service provision locations correspond to higher or lower levels of need (as measured by the SVI). Geography and GIS tools can further summarize travel distance and time between facilities and centroids of each small area, providing further opportunities to include access-based covariates into the spatial epidemiologic regression models. We note that these applications of such online mapping tools (a type of interactive spatial analysis) are not solely based on statistical estimates or local rates, but rather on linking a user to information. In many settings, such interactive spatial analysis will serve the compassion goal of linking services to suffering more directly than would the statistical estimates themselves. That is, the tools provide action-oriented means for users (either those in need or those seeking to support services providing relief) to enable local compassion above and beyond statistical summaries of local epidemiologic rates.

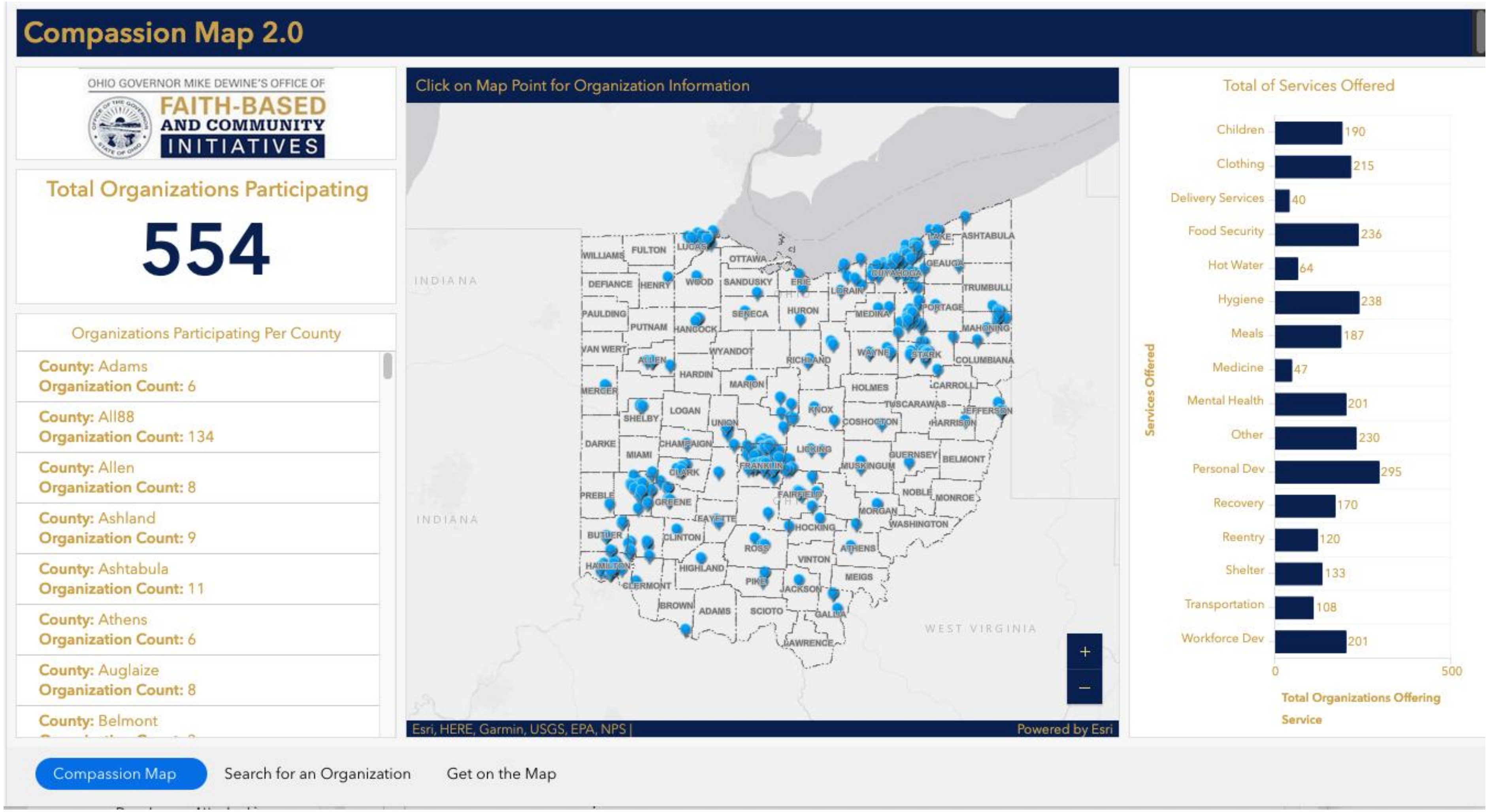


Figure 5. Example of a map of service locations provided by the state of Ohio via their interactive Compassion Map 2.0. (https://experience.arcgis.com/experience/e71bc1bd5883477f9ab5ba973ce99a31; https://governor.ohio.gov/priorities/faith-based-initiatives)

When comparing our three motivating questions to the questions answerable by such maps, we must consider the completeness and timeliness of data regarding service providers. For instance, the Ohio map focuses on faith-based services and may not include services supported by state and local governments or other local organizations outside of the faith-based community. In addition, while online maps offer the opportunity for timely updates as service providers start and end services at given locations, such live updating requires coordination between the service providers and the data stewards updating the online map and any lags in updates can hamper accurate conclusions of what services are available where.

3.4 Conclusions to action

As noted, the spatial epidemiology of compassion involves an extra step often not included in the standard spatial epidemiology toolbox, namely connecting the spatial data and estimates to services and action. The example data sets and interactive maps above allow insight into components of the spatial epidemiology of compassion and offer initial links between local estimates of perceived need and potential suffering, and we consider three additional examples illustrating how the spatial analysis abilities summarized in Table 1 offer insights into further connections between local suffering and local responses.

3.4.1 Example: Mapping food outlets, local food insecurity, and transportation access

As a first example, the Emory University Global Diabetes Research Center, recently introduced a mapping tool relating to food insecurity (https://diabetes.emory.edu/research/atlanta-food-map.html). The interactive map includes data layers providing an index of local food insecurity (a map of level of need and potential suffering) layered with locations of food access via businesses and food panties/food shelf charities (potential services to ease food insecurity). Figure 6 illustrates a screenshot where census tract areas in the Atlanta metro area are shaded by a Food Access Index (summarizing census sociodemographic variables associated with food insecurity), and information is provided for a selected census tract regarding census demographics (in the box at the upper left of the map window), and summaries of food facilities in the "Food Places" column on the left of the screenshot. Figure 7 reveals how the map updates as we zoom into the selected census tract, now revealing nearby available mass transit routes and locations of specific food outlets as dots with colors corresponding to their health ranking. As with the Ohio Compassion Map and the Maryland Housing map, the tool does not represent a single statistical analysis of risk factors relating to food insecurity, but rather an interactive opportunity to find out where food need is highest, what food sources are nearby, how healthy they are, and what mass transit routes can provide access. For many users, these are more important analytic goals for achieving local compassion for this need than a statistical estimate of association. Figures 6 and 7 represent examples of a dynamic spatial epidemiologic tool relating food access, food distribution and transportation providing insight regarding local levels of need, local locations of services, and potential transportation options, which in turn offer insight into possibilities for alleviating suffering.

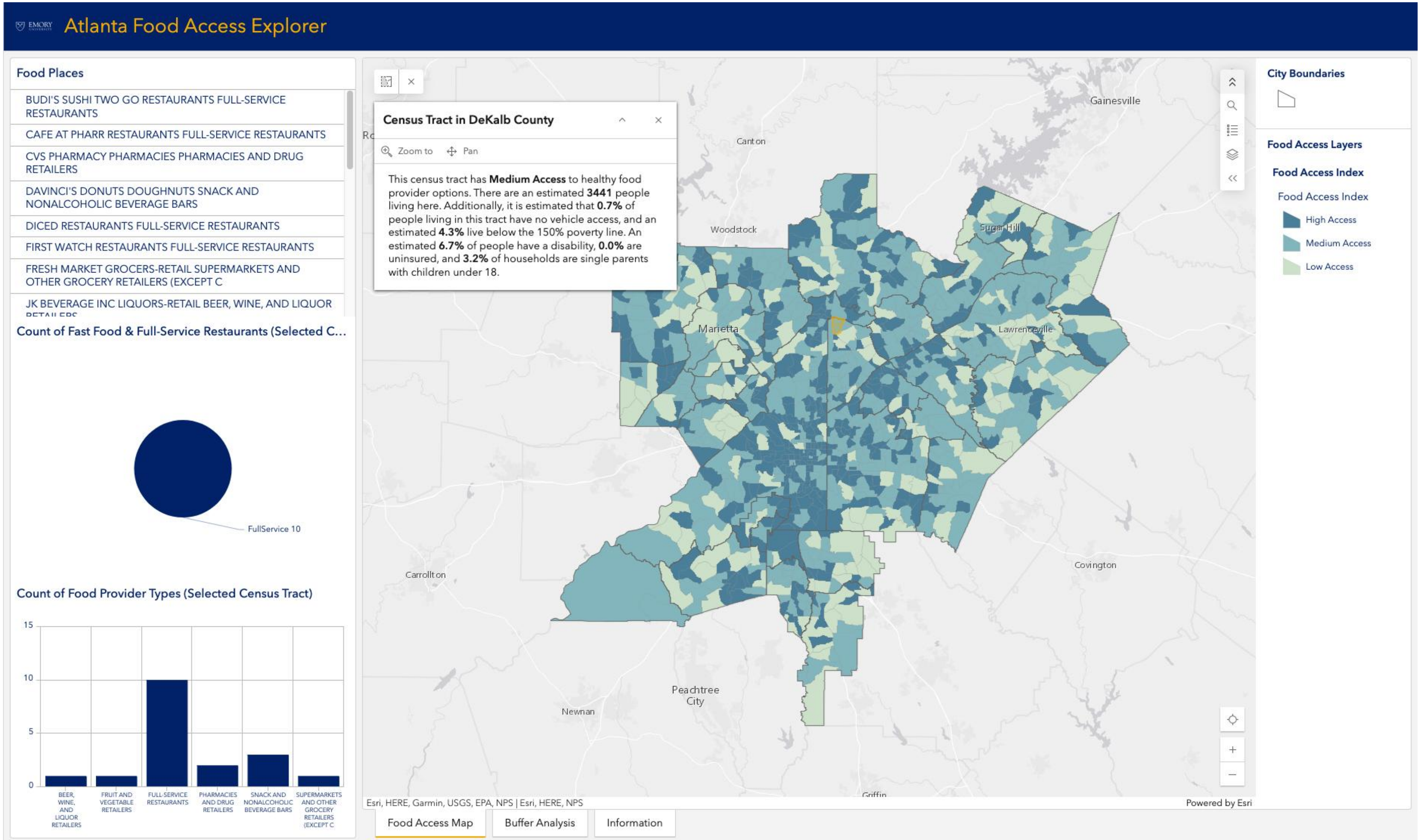


Figure 6. A screenshot of the Atlanta Food Access Explorer, an interactive tool mapping census tracts across the metro Atlanta area, shaded by a Food Access Index. The information on the left hand column summarizes access to different types of food outlets in a particular census tract in DeKalb County, Georgia, outlined in yellow with summary demographic information in the box at the upper right of the map.

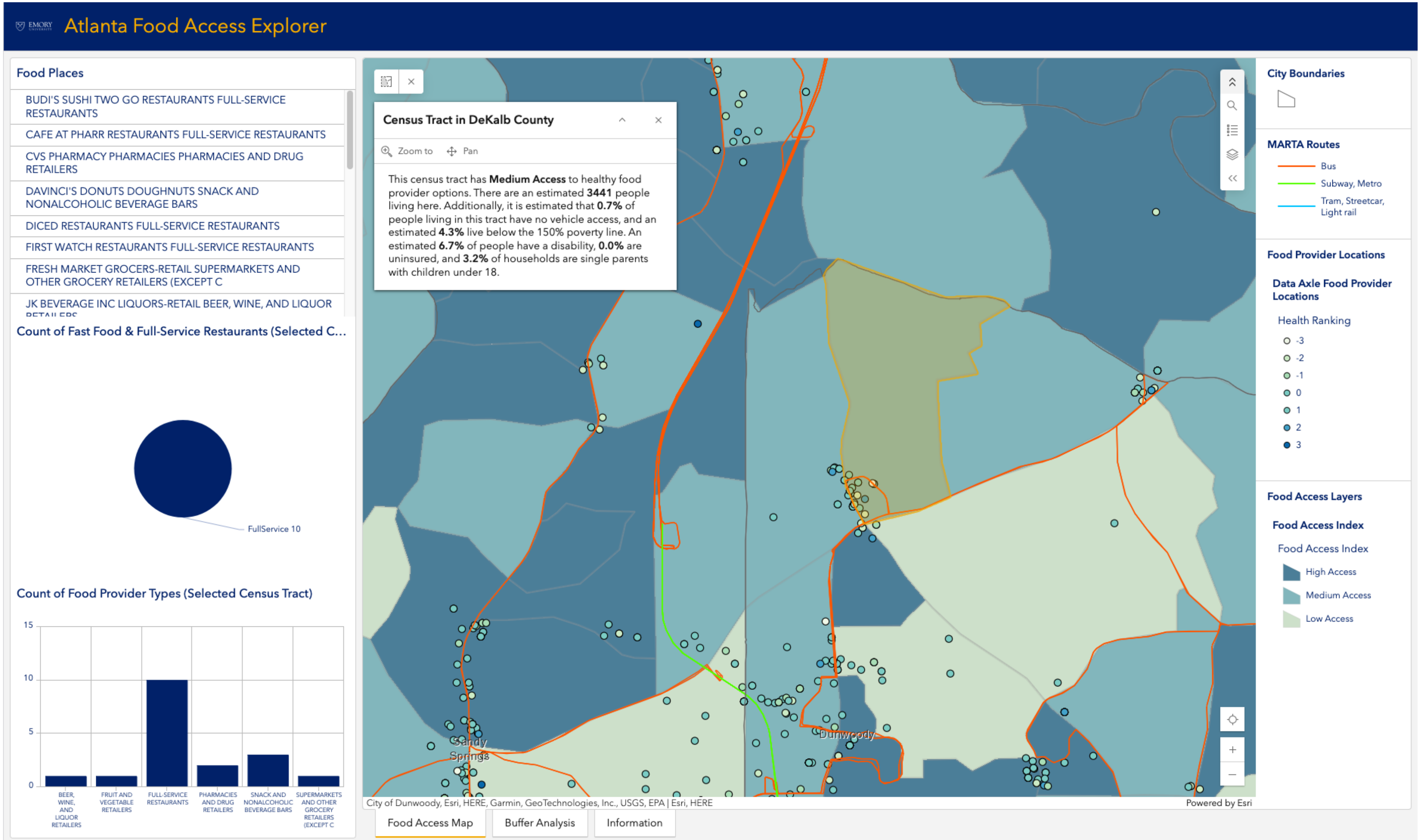


Figure 7. A second example from the Atlanta Food Access Explorer zooming in to the selected census tract illustrating individual food outlet locations visualized by a reported health ranking and illustrating mass transportation routes.

3.4.2 Example: Spatial patterns in substance use

Figures 6 and 7 provide dynamic tools for exploring local need and local responses for users seeking to find available links between the two. More traditional epidemiologic analyses also play a role in understanding patterns for different types of need and suffering in order to propose new policies/responses, or to evaluate the impact of existing policies/responses on reducing local need and suffering. The set of spatial statistical tools offers additional opportunities for estimating, monitoring, and gaining understanding local patterns of suffering, local patterns of response, and their dynamic evolution over time. Such analyses often require a close collaboration between researchers and policy makers, motivating novel solutions bridging traditional disciplinary boundaries.

Geographic and temporal patterns and trends in substance use and overdose mortality offer examples of such interdisciplinary collaborations. Local levels of suffering related to overdose mortality change over time with changing markets, distribution, and use patterns, sometimes with striking impact. Treatment patterns also change over time, often in response to new patterns of harms or to new laws. During the expansion of methamphetamine use, state laws often attempted to restrict access to precursor ingredients. While new policies initially reduced mortality, over time the distribution system shifted production from small, relatively independent developers to larger, interconnected production systems. The work of Gruenewald et al. (2013, 2021) represents a collaboration between researchers in substance use epidemiology and researchers in spatial epidemiology to map the growth and spread of methamphetamine harms across California, providing insight into potential local drivers of these patterns (changing regulations and the drug market's response to these changes). Similarly, Hepler et al. (2021, 2023) explored the changes in county-level rates of opioid mortality and the impact of (a) the introduction fentanyl to local use and (b) changes in local treatment options available by county to better understand the complex ecology of the evolving risks of opioid overdose mortality and treatment responses over time. While not directly framed as studies of compassion, these examples do estimate local patterns of harm and suffering to reveal opportunities for local action in this challenging setting.

3.4.3 Example: Optimizing local vaccine distribution

Taking the spatial statistical approaches a step further, Zhong et al. (2025) added a perspective of optimizing the spatial distribution of a service to meet multiple local goals. They examined ways to improve the geographic distribution of local sites distributing the COVID-19 vaccine when it first came available (and while it remained a limited resource) to meet three potentially competing goals: To place distribution sites: (1) where need was greatest (i.e., where local transmission was highest during a given week); (2) where racial equity in access was best achieved (i.e., avoiding racial disparities in distribution); and (3) where the greatest number of residents of a county would receive vaccinations during distribution. These three goals are each important but maximizing vaccine distribution to meet all three simultaneously required the full toolbox above.

4. Discussion

While the examples above do not represent a single, focused analysis of the spatial epidemiology of compassion, they reveal many of challenges and opportunities involved. Our conceptual framework builds from the standard definition of compassion linking suffering and capacity to alleviate suffering, to consider which local data can inform estimates of local levels of suffering, what questions analytic techniques from multiple fields can answer, and how these answerable questions compare to underlying motivating questions. We illustrate our framework via multiple examples each addressing part of the big picture, providing a context for placing different analyses along a continuum connecting local suffering, local data sets, local responses, and local evaluations of success of these responses.

The examples clearly illustrate multiple challenges in conducting comprehensive assessments of the spatial epidemiology of compassion. Identifying data appropriate to the primary questions of interest remains a key challenge and spatial analysts must document and discuss the choices they make since the data one can access often differ from the data one needs to answer the question of interest. The available data and available analytic tools define the answerable questions and any spatial epidemiologic analysis of local compassion, must evaluate how closely the questions answered mirror the questions originally asked.

The examples above also illustrate the opportunity to consider more broadly what we consider a spatial epidemiologic analysis of compassion. The interactive maps allowing users to explore patterns of suffering and need as well as patterns of available services for responding often offer a more direct connection between our analytic framework and local suffering and services than would the traditional output of a logistic or Poisson regression relating risk factors to epidemiologic rates. The examples also illustrate the great opportunity for linking disciplinary perspectives across shared interests in alleviating local suffering. Careful analyses, whether interacting with linked data to identify local services or estimating spatially correlated epidemiologic rates of levels of suffering, benefit greatly from spatial perspectives from geographers, epidemiologists, spatial statisticians, policy makers, and the general public. The maps allow for communication of results by location and serve as motivators of the next set of questions and actions available.

5. Conclusion

In summary, the field of spatial epidemiology involves the analysis of patterns across space and time using analytic tools from geography, epidemiology, and spatial statistics. When applied to compassion, the patterns discovered through these tools use available data to provide insight and evaluation of complex patterns of need and suffering, complex patterns of opportunities to respond, and complex options for ongoing monitoring of both suffering and actions to ameliorate it (Kienast 2020). The concepts, analytic tools, and analytic framework outlined above can provide a guideline for linking concepts to data, data to analyses, analyses to conclusions, and conclusions to action. While the examples above only provide some of the pieces in a complicated puzzle, they also illustrate opportunities to move toward a more holistic set of analytic tools for a broader, empirical perspective on the spatial epidemiology of compassion. Descriptive maps of correlates of need provide insight into areas of greatest potential for suffering. Similarly, descriptive maps of services provide insight into areas well-covered by options for support, and gaps in current coverage. More complex analyses identify patterns over time and opportunities for improving local coverage to better serve those needing support. Together, the examples illustrate how different sorts and sources of data can reveal different components of the spatial epidemiology of compassion. As a result, spatial analyses of local compassion benefit from multidisciplinary perspectives to better link the questions we can answer with the questions we want to answer to implement effective local support systems for meeting and alleviating suffering where and when it happens.

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