Chapter 1

Introduction: Spatial Analysis and Health

Eric Delmelle and Pavlos Kanaroglou - 2015

Medical Geography or Spatial Epidemiology is concerned with two fundamental questions: (1) where and when do diseases tend to occur? and (2) why do such patterns exist? The field has experienced substantial growth over the last decade with the widespread recognition that the concept of "place" plays a significant role in our understanding of individual health (Kwan 2012) while advances in geographical modeling techniques have made it easier to conduct spatial analysis at different granularities, both spatially and temporally (Cromley and McLafferty 2011). Several journals (for example *Health and Place*, *Spatial and Spatio-Temporal Epidemiology*, *International Journal of Health Geographics*, *Geospatial Health* and *Environmental Health*) have a long tradition to publishing research on topics in Spatial Epidemiology.

This introductory chapter reviews some contemporary themes and techniques in medical geography. Specifically, we discuss the nature of epidemiological data and review the best approaches to geocode and map information while maintaining a certain level of privacy. Analytical and visualization methods can inform public health decision makers of the reoccurrence of a disease at a certain place and time. Clustering techniques, for instance, can inform on whether diseases tend to concentrate around specific locations. We examine the role of the environment in explaining spatial variations of disease rates. Next, we address the importance of accessibility models, travel estimation and the optimal location of health centers to reduce spatial inequalities when accessing health services. We also review the increasing contributions of volunteered geographic information and social networks, helping to raise public awareness of the risk posed by certain diseases, especially vector-borne diseases following a disaster. The concepts of scale and uncertainty are discussed throughout as they are known to affect the suitability of certain methods and consequently impact the stability of the results. Some of the concepts set forth are illustrated with a data set of a 2010 dengue fever outbreak in Cali, Columbia. We conclude this chapter by discussing the layout and contributions of this volume to Spatial Epidemiology.

Mapping Epidemiological Data

Medical geography studies the relationship between place and health; specifically it evaluates how the physical and social environments shape the health and well-being of different individuals (Cromley and McLafferty 2011). Geographical Information Systems (GIS) and spatial analysis provide unique tools to determine where and when a particular disease has occurred and could resurface in the future. Accurate spatial (and temporal) data is thus critical to identifying such patterns.

Epidemiological data comes at different scales (disaggregated or aggregated data) and different levels of accuracy. Addresses can be transformed into geographic coordinates by means of geocoding (Goldberg, Wilson, and Knoblock 2007), but the process may be sensitive to the completeness of the addresses and the quality of the underlying network (Zandbergen 2009; Jacquez 2012). Scatter maps are used to display geocoded, disaggregated data; for example, in Figure 1(a), each dot is an occurrence of a reported dengue fever[1] case in Cali, an urban area of Colombia, during an outbreak in 2010 (Delmelle, Casas, et al. 2013). Besides cartographic outputs, GIS can link spatially-explicit data to environmental and census data using one of the available spatial join algorithms. This approach facilitates our understanding on the role that the physical and social environment may play on health and well-being.

Due to *privacy* concerns, epidemiological data may be geomasked[2], or be *aggregated* at a certain level of census geography, for instance at the county or postal and zip code level. Figure 1(c) uses a proportional symbology to map the variation of dengue cases per neighborhood, suggesting an uneven pattern. Other techniques, such as choropleth mapping, are widely used to display disease rates across an area. Figure 1(e) suggests that dengue fever rates are not randomly distributed, possibly owing to population density, shown in Figure 1(d).

A concept that has received significant attention in medical geography is the level of *spatial scale* at which the analysis is conducted (Diez Roux 2001). As pointed out by Root (2012), “the impact of neighborhoods on health is uniquely geographic”. Spatially aggregating data, however, give rise to the Modifiable Areal Unit Problem (MAUP). This is because the basic assumption of any aggregation scheme is that there is uniformity within but sharp contrast among the defined geo-statistical areas (Cromley and McLafferty 2011). Using different boundaries an analysis may lead to significantly different results. It has thus become clear that it is increasingly important to conduct analysis at several granularities of scale.

Visualizing Disease Patterns and Clustering Techniques

Clustering techniques help identify whether disease events are randomly distributed and if not, where clusters may be located. Delimiting the extent of those clusters is important for the determination of areas potentially at risk. In this context, the contributions of Exploratory Spatial Data Analysis (ESDA), including kernel density estimation (KDE), are well documented in the literature (Delmelle et al. 2011; Delmelle 2009; Cromley and McLafferty 2011; Kulldorff 1997). Eisen and Eisen (2011) and Vazquez-Prokopec et al. (2009) underline the importance of GIS and ESDA to monitor vector-borne diseases, where prompt space-time monitoring techniques are

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[1] Dengue fever is a vector-borne disease transmitted from one individual to another by the the *Aedes Aegypti* mosquito (Gubler 1998).

[2] Geomasking is a process which explicitly introduces a small perturbation in the spatial coordinates of the events when those are presented in the form of a map (Kwan, Casas, and Schmitz 2004).

critical for timely detection and mitigation purposes. Spatial analytical methods can generate disease distribution maps revealing significant information in terms of direction, intensity of a disease, as well as its likelihood to spread to inhospitable areas.

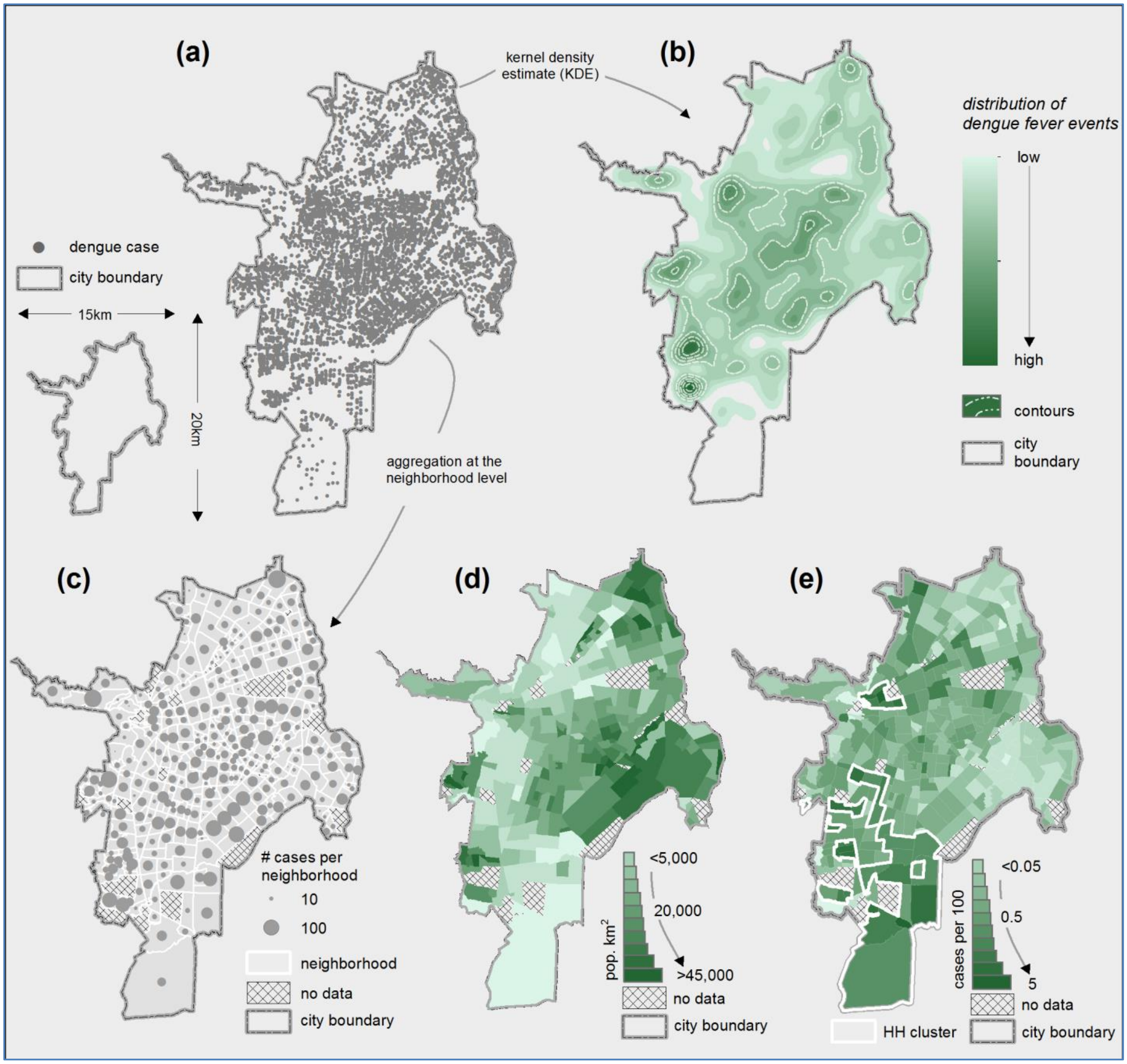

Figure 1. Dengue fever cases for the city of Colombia, 2010 (geocoded at the street intersection level), in (a). Kernel density estimation in (b), aggregated dengue cases per neighborhood in (c), population density in (d) and dengue fever rates in (e).

The ESDA techniques are used traditionally to identify spatial and more recently spatio-temporal patterns. The statistical significance of identified clusters is tested by Monte-Carlo simulations. Kulldorff et al. (1998) and Levine (2006) have developed spatial analytical tools (SatScan and CrimeStat, respectively) to detect clusters of point events and then to conduct simulations for the evaluation of the statistical significance of those clusters. Such tools are now incorporated into commercial GIS packages and are available to the common GIS user (Fischer and Getis 2009). An example of an ESDA technique is the Kernel Density Estimation, illustrated in Figure 1(b) for monitoring hot spots of dengue fever. In essence, the map shows areas with greater expectation of dengue fever occurrences. Contours reinforce the extent of such hot spots.

Space-time clustering techniques are still in their development phase, partly due to their computational challenges (Jacquez, Greiling, and Kaufmann 2005; Robertson et al. 2010). Research on space-time clustering tests has focused mainly on uncertainty, which is introduced through biased or incomplete data, perhaps because of incorrect addresses or inaccurate reported diagnosis (Lam 2012, Malizia 2012). Within the limits imposed by computational requirements, much recent research attempts to remedy weaknesses in visualization techniques (Delmelle et al. 2014a).

Nearby observations may exhibit similarity (Tobler 1970). *Spatial autocorrelation*, estimated by a global Moran's I statistic (Moran 1950), measures whether nearby data (generally aggregated) are dependent on one another, while its local statistic counterpart (Anselin 1995) informs on where those clusters of similar observations tend to occur. For the neighborhood data, for example, shown in Figure 1(e), the estimated Moran's I value is 0.14, indicating a weak autocorrelation. The Moran's I statistic can be extended in time to detect space-time autocorrelation (Goovaerts and Jacquez 2005).

Environment and Health

Geographers, statisticians and public health experts have not only focused on the detection of spatial clusters of diseases, but also on the evaluation of the association of natural factors and the built environment with health and individual wellbeing. The hypothesis here is that geographic behaviors and outcomes of health (that is, *health disparities*) cannot only be explained by *individual* factors; *neighborhood factors* are likely to play a contributing role (Diez Roux 2001; Krieger et al. 2003). For instance, individuals living in rural regions will experience geographic barriers in traveling to health services, given that the numbers of facilities that can be reached within a certain time budget is much smaller than in urban areas. Women living in poor areas may find it particularly difficult to access mammography facilities when they do not have a vehicle and must rely on public transportation (Peipins et al. 2011). Children walking to schools or living in an environment where parks and playgrounds are readily accessible may be prone to be more active than others (Cooper et al. 2010). Clusters of violence in urban neighborhoods may be related to alcohol outlets (Grubesic and Pridemore 2011). These examples illustrate the breadth of pathways through which environmental factors give rise to *health disparities* over space.

Other non-neighborhood factors may play an important role in shaping our understanding of the potential for outbreaks of certain diseases. As suggested by Comrie (2007), climatic variation and weather-related factors is likely to create particularly suitable conditions for certain vectors to thrive and potentially increase the geographical extent of vector-borne diseases.

Spatial regression and multi-level modeling are examples of some of the key methods that were developed for the evaluation of the impact of neighborhoods on health (Cromley and McLafferty 2011). Variation in the dependent variable (disease rate, accessibility) can be explained by a set of individual characteristics (age, gender, income and education for instance), environmental factors (neighborhood characteristics) and spatial terms accounting for the presence of spatial autocorrelation. Geographically Weighted Regression quantifies the spatial importance of each explanatory variable on the dependent variable (Fotheringham, Brunsdon, and Charlton 2003).

What defines a neighborhood and the concept of scale will affect which methodology is used and ultimately the results. Krieger et al. (2003) underline that the geographic scale of secondary data, such as socio-economic characteristics, may determine the level of aggregation at which a study is conducted. Evaluating the effect of different artificial boundaries is thus necessary by repeating those analyses at different scales. Using only the local scale of a neighborhood may not account for the entire activity space of an individual (Cummins 2007). GPS and GIS technologies appear to be particularly useful in mapping the daily activity of individuals and determining the extent of an individual's neighborhood (Kwan 2004). Also, in studies of exposure analysis it is important to take account of the residential history of subjects under study, although relevant data are not always available (Root 2012).

Health Care Provisions and Accessibility

Accessibility is a critical element of any health care system. In an ideal system, every member of a community should have similar access to health care professionals; however, a perfect match between supply and demand is not possible, leading to spatial inequalities (Cromley and McLafferty 2011; Parker and Campbell 1998). In rural areas, for instance, access to care is constrained due to longer travel distances and scarcity of providers.

A critical objective of a health care system is to guarantee a minimum level of geographic access to primary care services. Accessibility below that level can make the difference between life and death or between a controlled outbreak and an epidemic (Higgs 2004). *Travel impedance* is thus a contributing factor in the utilization of health care services (Lovett et al. 2002; Delamater et al. 2012). Impedance can be evaluated with different metrics such as travel distance (Euclidean or network), or travel time. The latter may be a more precise measure since it accounts for en-route conditions (Cromley and McLafferty 2011). Delmelle, Cassell, et al. (2013) propose a GIS-based methodology to estimate travel impedance for children with birth defects, suggesting that children living in urban areas have a much lower travel burden than children in rural areas. Having to rely on public transportation, urban residents of low-income areas may be at a disadvantage. Several internet-based providers (Open Street Map, GoogleMaps) can estimate travel impedance; however, when using those providers, careful attention must be paid to confidentiality issues, the accuracy of the travel estimates themselves and the restriction in the number of queries that can be submitted to those providers.

One way of visualizing health care accessibility is by means of KDE, as discussed in previous sections of this introduction. In this case, one can estimate the density of service providers over space, revealing differences in access (Lewis and Longley 2012; Casas, Delmelle, and Varela 2010). Another popular approach is the *two-step floating catchment area* (Luo and Wang 2003) which evaluates the availability of health services in regards to population need. Methods based on gravity models can capture the interaction of an individual with a health facility, using several of its characteristics, including size and quality of service. Nevertheless, these aforementioned approaches remain theoretical in nature. Although more difficult to obtain due to confidentiality concerns, *revealed accessibility* provides actual information on the utilization of health services, allowing the identification of facilities that are underutilized or overutilized while delimiting the catchment area of any facility. It is therefore desirable for researchers to obtain information on the utilization of health services at a disaggregated level.

Disparities in geographical accessibility can be reduced by selecting the *optimal location and capacity* for new health centers or when existing facilities are to be upgraded or their size calibrated (Wang 2012). Operations Research and Location-Allocation Modeling are proven techniques that effectively answer questions as to where new facilities should be opened and of what capacity in order to maximize coverage and minimize travel. More behavioral research is needed coupled with simulation modeling regarding the utilization of health care services following a change in the structure of a network of facilities.

Volunteered Geographic Information

Boulos et al. (2011) discuss the increasing interest among health researchers to disseminate analytical functionality over the internet, partly due to the massive epidemiological datasets that are becoming available through social networks, such as twitter (Freifeld et al. (2010); Chunara, Andrews, and Brownstein (2012)). However, the development of analytical methods over the web are computationally challenging; for instance commonly used spatial analytical functions, such as the KDE, are time consuming as web-based GIS services (Dominkovic et al. 2012; Delmelle et al. 2014b). Adding the dimension of time, for the development for example of space-time clustering techniques, presents serious research challenges.

Participation of *volunteers* in mapping health information has the inherent potential to foster community involvement, ultimately improving the well-being of individuals (Skinner and Power 2011). This is critical especially for developing countries where there are limited financial resources and GIS expertise (Fisher and Myers 2011; Kienberger et al. 2013). Following the Haiti earthquake (Zook et al. 2010), for example, volunteers over the internet helped to create a geospatial database that proved to be very useful for the allocation of resources to places of higher need.

Structure of the Book

Previous sections in this introduction highlight that there is an established tradition of the application of existing spatial analytic methods and techniques to public health. The reverse, however, is also true. Public health issues pose new challenges for spatial analysts forcing them to innovate and develop new methodologies, thus enhancing the field of spatial analysis. The symbiotic relationship between spatial analysis and health is the subject matter of this book. The sixteen chapters included in the volume are discussing methods and techniques that are applied to substantive issues of health. In dividing the material into parts we had two choices. The first was to group the papers by type of methodology and the second by the substantive area where the methods are applied. Although both ways have their drawbacks and advantages, we selected the latter method since many researchers in the field are interested in specific areas of health and this way the book will be of better service to the research community.

We divided the material into five parts. Part 1 covers purely methodological issues in spatial analysis that have wide applicability in a variety of public health issues. The four parts that follow focus on methods as they are applied to: infectious disease (Part 2), chronic disease (Part 3), exposure (Part 4), and accessibility (Part 5). A more detailed description of the contents in the five parts follows.

Part 1: Methods

Three papers are included in this part. The chapter by Linda Beale sets the stage for subsequent chapters by discussing the benefits from using GIS in Spatial Epidemiology. She covers substantial ground by describing the uses of GIS in visualizing, exploring and modelling methods that have been developed specifically for the use and exploitation of the spatial properties of epidemiological data. One issue that Beale brings to the forefront is that for all these methods to yield fruits it is important for the data to be properly and correctly geo-referenced.

The theme of the first paper ties with the second paper by DeLuca and Kanaroglou which is set to evaluate three popular and commercially available methods of automatic geocoding. These are (1) ESRI's Online geocoding available through ArcGIS.com, (2) an online geocoding service provider, GeoCoder.ca and (3) the freely available Yahoo geocoding API. The data set used for the evaluation is residential addresses in the City of Hamilton, Canada, using the parcel fabric of the city as a baseline. Results indicate that a disturbing proportion of the geocodes can be off significantly and in some cases by as much as six kilometers. Errors introduces through geocoding may have severe implication for studies in health geography. These include exposure misclassification or erroneous assessment of accessibility.

The third paper by Paez et al. is comparing two seemingly overlapping techniques that are used to detect the concentration of events over space. These are the techniques of clustering and co-occurrence. The paper uses simulations as well as data on events of pediatric cancer from Murcia, Spain, to demonstrate the concepts. The results indicate that the two are not competing techniques but can provide complementary results for the better understanding of the process that generates the events.

Part 2: Infectious Disease

The paper by Bossak and Welford opens the theme on infectious disease by examining one of the most lethal epidemics ever that killed 30 to 50 percent of the population in certain parts of Europe within four years. This was the mid-14th century Medieval Black Death. The authors examine the spatial and temporal aspects of the disease bringing historical but also environmental and socio-economic data within a modern spatial analytical framework offering a fresh look at the epidemic.

The second paper in this part, by Delmelle et al., discusses space-time visualization methods to examine and detect infectious disease outbreaks. The method proposed in this paper is the well-known Kernel Density Estimation, a spatial technique, extended to include the temporal dimension. The proposed method is applied to Dengue Fever data from Cali, Columbia, for the year 2010.

In the third paper of part 2, Carrel discusses methods for the exploration and identification of spatial patterns in the changing genetic character of infectious disease pathogens, such as viruses, bacteria and protozoa. She claims that understanding where and when the pathogen genetic changes are taking place is crucial in preventing or containing infectious disease outbreaks. Several exploratory methods are discussed in this context, including interpolation and clustering techniques, as well as modelling such as geographically weighted regression.

Part 3: Chronic Disease

This part consists of three chapters. The first by Wheeler and Siangphoe discusses a family of models that derive from the generalized additive model, as they relate to the analysis of the spatial variation of disease risk. Several modelling approaches are compared within a simulation framework. The methods are applied to data from Los Angeles County for the investigation of the spatial variation of risks for non-Hodgkin lymphoma.

The second paper in this part by Gruebner et al., turns to examine the mental well-being in urban areas. More specifically, the focus is in urban slums. Using generalized linear regression models and spatial autocorrelation the authors analyze a cross section of survey data collected in the slums of Dhaka. The WHO-5 Well-being Index was used to assess mental well-being. The authors test the hypothesis that this metric is related to the socio-ecological environment in the slums.

In the third paper Goovaerts and Goovaerts introduce a variety of methods for the visualization and exploration through spatial analysis of a time series of health data. The techniques include 3D displays, binomial kriging, joinpoint regression and cluster analysis. The methods are applied to incidences of late-stage breast cancer diagnosis for counties in Michigan Lower Peninsula over the period 1985-2007.

Part 4: Exposure

Exposure analysis is the subject of three chapters in Part 4 of the book. The first paper by Adams and Kanaroglou explores a recurring theme in air quality exposure that relates to assigning outdoor exposure estimates to subjects that are calculated as long-term mean concentrations of ambient air quality from incomplete time series data sets. A method is proposed that appears to produce better estimates of long term mean concentrations. The method is evaluated through simulations and data from Paris, France.

The paper by Griffith, second in this part of the book, examines the correlation between metal concentrations found in yard soil and in dust from inside residences to blood lead levels of children less than six years of age living in those residences. Taking into account socio-demographic characteristics, the relationship is examined at various geographic scales using canonical correlation analysis. The primary data used were collected from Syracuse, New York, in the time period 1992-96.

The last paper in this part, by Jerrett et al., is adapted from a lengthy 2012 National Academy of Science report on exposure science. The paper provides an overview of the state of the art in exposure science and highlights potential future directions, especially with the emergence of new technologies for the collection of more accurate exposure data. New concepts, such as “ubiquitous”, “embedded” and “participatory” sensing, are discussed that are to have substantial relevance for exposure science in the 21st century.

Part 5: Accessibility and Health

The last part of the book consists of four papers. The first paper by Murray and Grubesic provides an overview of optimization models developed in location analysis to support strategic decisions for the siting of hospitals, clinics and health care facilities. The objective of such models is to ensure that given a spatial distribution of the population the number, size and location of facilities are sufficient to guarantee adequate accessibility to health care. The chapter serves as an introduction to the chapters that follow in this part.

The paper by Wang et al. focuses on the accessibility of cancer centers in the United States, as proposed by the National Cancer Institute. The authors use spatial optimization methods, such as integer and quadratic programming to evaluate two scenarios of improving population accessibility to the centers. The first scenario is the allocation of additional resources to existing centers and the second is the establishment of additional centers.

Lewis, in the third chapter of this part, digs deeper into the concept of accessibility to healthcare services by examining how it is conceptualized, qualified, quantified and modeled. He focuses on the spatial dimensions after first describing a holistic view of conceptualizing access. Important is the distinction he draws between an epidemiological and a spatial framework within which access is conceptualized and analyzed.

The last chapter in this part is by Coutts and Horner that examine the relationship between the accessibility of people to green space and premature mortality. The specific study employs regression analysis using death certificates for the state of Florida in the time period 2000 to 1012. Proximity to green space was estimated with the help of GIS. The developed model controls for social and demographic characteristics of subjects. The results, although exploratory, indicate that distance of place or residence from green space increases the likelihood of premature death.

Concluding Remarks

In this chapter we have discussed current and emerging research themes in Spatial Analysis as they apply to issues of public health. We then provided an overview of the contributions to those issues through the volume in hand. Although the majority of the papers in the volume are heavily methodological in nature, two are focusing on conceptual contributions. The paper by Carel proposes that the timing and location of genetic mutations of pathogens are crucial in understanding the spread of infectious disease. To test this proposition she recommends the use of well-known methods in spatial analysis, including interpolation, clustering and regression. Also, Lewis in his paper discusses the conceptualization of accessibility and he proposes several measures for it derived from spatial analysis methods.

For the rest of the papers, while all dwell on methods, one can classify them into three types. The first group of papers is dealing with spatial data and proposes ways to enhance the accuracy of georefencing or to combine different databases into a single spatial framework that allows a richer analysis of public health phenomena (Deluca and Kanaroglou, Bossak and Welford). The second group reviews methods that are suitable for specific problems of public health and examine new and innovative technologies that are expected to play a significant role in spatial epidemiology for the years to come (Jerrett et al., Murray and Grubesic). All the rest of the papers in the volume can be considered to form a third group that proposes the use of a combination of known or new spatial analysis methods to study various types of problems in public health. It is interesting that in some of the papers the application of a combination of well-established spatial analytic methods can provide insights to phenomena that are not clear with the use of a single method.

The substantive issues discussed in the volume go beyond to identifying relationships between disease and socio-demographic factors and into conceptual or institutional issues. In some instances old problems, such as the mid-14th century Medieval Black Death in Europe, are analyzed within a GIS using modern spatial analytic modeling methods (Bossak and Welford). We believe that academics as well as practitioners in the field will find the papers interesting and informative and will make use of the methodologies discussed in this book in their own research.

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