Spatially Integrated Soc. Sciences
M.F. Goodchild + D.G. Janelle (eds). 2004.
Oxford U. Press : NY

18

Spatial Perspectives in Public Health

Anthony C. Gatrell
Janette E. Rigby

There is now a wealth of compelling evidence to suggest that location and place shape our health, our exposure to environmental features that impact upon our health, and our access to those goods and services that either promote our health or treat episodes of disease or illness that we all encounter. Moreover, the research evidence to support these claims comes from a wide range of settings across the developed and the developing worlds and at a variety of spatial scales (Gatrell 2002). Whether we are attempting to: predict the likely impact of global environmental change on vector-borne diseases such as malaria or dengue fever (Hay et al. 2000); examine the associations between radon gas emissions and the incidence of lung cancer in countries such as Sweden and the United States (Lubin and Boice 1995; Teppo 1998); or assess how proximity influences access to pre-natal (ante-natal) and other health screening services (Bentham et al. 1995; Gatrell et al. 1998) at more local scales, we cannot escape the fact that spatial context provides a backcloth against which these issues are projected.

That there are "spatial perspectives in public health" is, therefore, well established. Our purpose in this chapter is to develop that argument and to illustrate it with a small number of selected examples. Before doing so, it is appropriate to consider what is meant by "public health." It is now accepted that this covers considerable ground. It is far broader than a concern with the incidence of disease or with patterns of mortality, or with the introduction of interventions (such as sanitation schemes) to reduce the burden of disease. While these remain a concern of public health, the contemporary view is of a focus on population groups, not individuals, and on a very broad set of factors that may shape population health. These would include a focus on the social as well as the physical environment, and the broad structural determinants of health. A focus on health inequalities or "divides" features prominently in contemporary work (Shaw et al.

1999). In this way, public health is genuinely multi-disciplinary, with epidemiology, sociology, ecology, economics, psychology, law, and geography among a variety of disciplines that are needed to understand the health of the public. While the skills of biomedical scientists are required, so too are the perspectives and skills of social and environmental scientists.

One implication of this is that it is a somewhat daunting task to convey, in a short chapter, the richness of a spatial perspective on public health! Inevitably, we must be extremely selective. Our selectivity manifests itself in the following way. First, we take three broad areas of disease and consider how a spatial—and spatial analytic—perspective helps illuminate our understanding of these diseases. Here, we consider geographic research on HIV/AIDS, at a variety of spatial scales; next, we look at some research on breast cancer, examining some of the analytic methods that geographers and epidemiologists have brought to bear; last, we review some research into skin disease, showing what progress has been made in understanding links to environment. In the second main section we turn our attention to the social patterning of health, explaining how a spatial perspective sheds light on our understanding of health inequalities. We do so in two broad sections: one that considers inequalities at a regional scale; and a second section that illustrates more local spatial variation in access to those features of the built landscape that impact on health.

Understanding Disease Distributions

HIV/AIDS

As Meade and Earickson (2000, 286) observe, among the "plethora of emergent and reemergent infections . . . the diffusion of no other agent in recent time has had nearly the profound impact on people and their societies as has human immunodeficiency virus (HIV) and the acquired immunodeficiency syndrome (AIDS) it causes." As of December 2000, there were an estimated global total of 36.1 million persons living with HIV/AIDS (WHO 2000). But this is geographically differentiated, with by far the most (25.3 million) in sub-Saharan Africa, a smaller proportion (5.8 million) in south and Southeast Asia, and relatively small (in global terms) numbers in North America (920,000) and western Europe (540,000). What contribution can a spatial perspective make to our understanding of the spread and patterning of HIV and AIDS?

As both Gould (1993) and Meade and Earickson (2000) observe, getting epidemiologists to take space seriously in HIV/AIDS modeling has taken many years. "Health professionals of all kinds, and most of the public, perceive an epidemic spreading through a population over time, but they do not envision the process as happening over space or having geographic consequences" (Meade and Earickson 2000, 289–290). In an endeavor to convince skeptics of the value of a geographic approach, Gould produced a sequence of maps of disease spread across the United States, demonstrating evidence of both hierarchical diffusion (spread from the major cities to smaller cities and city-regions) and subsequent local, "contagious" diffusion (Gould and Wallace 1994).

Before his untimely death, Gould was at the forefront of attempts to understand the spatial structure of HIV spread at different spatial scales. For the United States as a whole, he took 102 of the largest cities and constructed a matrix of air passenger flows; this was converted into a matrix of contact probabilities, a transition matrix that inevitably shows high probabilities of interaction between major centers. Taking the number of AIDS cases in 1986 as a state vector, we may multiply this by the transition matrix to yield a likely distribution of cases in 1998; successive multiplication of projected state vectors by the transition matrix yields year-on-year predictions of the distribution of cases. Results show a close correspondence between the observed number of cases and those predicted by this Markov chain model. In other work, at the city-region scale, he applied the same ideas to the distribution of HIV infection over 24 boroughs and counties of New York City (Gould and Wallace 1994). Here, the transition matrix is obtained from data on flows of commuters, a justification being that there is a close correspondence between AIDS rates and the percentage of the workforce commuting from counties to Manhattan. A property of Markov chains is the eventual convergence to an equilibrium (fixed point vector), which here shows that 61 percent of cases are likely to be concentrated in Manhattan and much lower proportions elsewhere. Gould and Wallace (1994, 110) argue that "the daily commuting pattern is a spatial scavenger, sucking the HIV into the center, where it may multiply rapidly, only to be redistributed over the entire region by the very process that concentrated it."

But Gould also argued that we need to map disease distributions, and the spread of disease, in new kinds of epidemiological spaces. One technique for doing so is multidimensional scaling (MDS). Here, conventionally we take a lower triangular matrix of "dissimilarities" between a set of objects; these might be a set of towns or cities, between which are estimated travel times. MDS seeks a new space of minimum dimensionality in which the objects are located so as to best fit the original dissimilarities; typically, so that the distances in the new space preserve, so far as is possible, the rank order of the original dissimilarities. A monotonic regression of distance on dissimilarity produces a residual sum-of-squares statistic, known as "stress." This will always be lower in a space of higher dimensionality, but usually we seek a low stress solution in two dimensions. How is this useful in HIV/AIDS research? Gould proposes that, instead of taking dissimilarities as input to the scaling procedure, we use predicted spatial interaction as a measure of the "similarity" between pairs of places. If we do so, a conventional geographical space (e.g., Ohio: Figure 18.1a) is transformed into a new "disease space" in which large cities are located close together, and the smaller population centers are dispersed (Figure 18.1b). We can use this new space in order to show that HIV infection spreads "contagiously" away from the origin.

Breast Cancer

As a disease with high (and increasing) incidence in many developed countries, breast cancer has seen considerable research investment in all aspects of disease studies. These include causation (using biomedical, environmental, and behavioral approaches), survival analysis, and access to treatment, in addition to sensitive psychosocial studies on the effects of the disease on patients and carers. Spatial perspectives impinge on many of these studies. As well as issues of spatial scale and the nature of the basic spatial units used for data collection and referencing, we have to deal with the often-complex interaction between disease latency (the time elapsing between when a

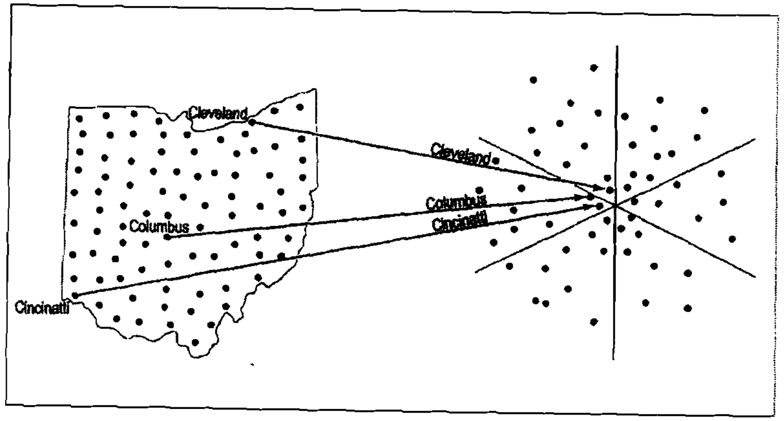

Figure 18.1. AIDS in Ohio in (a) geographic and (b) interaction space. Reprinted from Gould (1993) with permission from Blackwell Publishers Ltd.

disease is initiated and when it is diagnosed) and migration; this too is a fundamentally spatial issue.

In addition to looking at variations in disease rates represented simply in tabular form, more information can often be gained by examining *where* these rates vary, and where high and low rates occur in relation to others. Disease rates can be mapped at a variety of scales in a search for spatial patterns (Cliff and Haggett 1988). The last ten years have seen exciting developments in geographic visualization, made possible by improved computing power and functionality. For example, quite detailed data on geographic variation in breast cancer at the county scale, for both white and black females, is available in the U.S. Atlas of Cancer Mortality (Devesa et al. 1999; also online at http://cancer.gov/atlasplus/new.html). However, at more detailed spatial scales the numbers of cases may be relatively small, particularly in sparsely populated rural areas, where extremely high apparent risks can emerge from small numbers of cases. As a consequence, empirical Bayes estimates, which adjust the relative risks according to our confidence in their reliability, are increasingly used in such mapping (see Gatrell 2002 for further details and Langford 1994 for an implementation method; Clayton and Bernardinelli (1992); Rigby and Gatrell (2000) for application to breast cancer rates).

Disease mapping of breast cancer incidence at a variety of spatial scales in part of northern England was undertaken by Rigby and Gatrell (2000). An initial examination of rates over quite sizeable administrative areas (whose populations numbered a few thousands) revealed little by way of spatial patterning, and this was confirmed by a low spatial autocorrelation (Moran) coefficient. However, spatial autocorrelation generates a single measure for the entire map, and to explore whether there might be some more local processes operating, methods for detecting local association (G statistics) were used (Anselin 1995; Getis and Ord 1999). These can identify whether there are any areas whose rates are closely aligned to those in adjacent areas. This technique identified a small group of neighboring rural areas in one part of the study region, all with low incidence rates of breast cancer (Figure 18.2).

There are situations where individual, address-based, data can be used for spatial analyses; here we draw upon the literature on spatial point pattern analysis, rather than on methods for handling area data. There are a number of possible approaches, including that developed by Openshaw (1990), an innovative approach to exploring whether cases of a disease were clustered or not. The approach was based on investigating the probability of whether the observed number of cancer cases within a circle of radius r, centered on a point (x,y) could have occurred by chance. The study area was overlain with a lattice structure, and the intersections of the lattice points used as the (x,y) points. Hence, circles were constructed, and the number of cases in each could be determined. Where a circle was considered *significant*, it was drawn on a map. The whole process was automated, so that repeated runs could be made using circles of varying radii. A recent version, GAM/K, is available over the Web, whereby users can experiment with a sample dataset, or enter their own data and receive cluster results by return (Openshaw and Turton, www.ccg.leeds.ac.uk/smart/intro.html). In an application to the data referred to earlier, GAM/K identified several significant clusters of high rates across the study region.

This procedure has been developed in new ways by Kulldorff, who has proposed a "spatial scan statistic" that searches for clusters of disease cases. He has applied this method in a variety of contexts, including breast cancer mortality at county level in the northeastern United States. His approach was to impose circular windows on the region, centered on county geographical centroids, and then vary the radius so that different groupings of neighborhood counties were captured. His results (Kulldorff et al. 1997) indicated that the most likely cluster of breast cancer mortality was in the New York City/ Philadelphia metropolitan area, with a strong subcluster on Long Island, which was an existing concern to health professionals. Kulldorff has also facilitated availability to his spatial scan software via the web (SaTScan at www.nci.nih.gov).

Breast cancer on Long Island was also the subject of a study by Timander and McLafferty (1998). Here, point data were derived from the residential addresses of women who responded to a survey of breast cancer incidence. A clustering technique based on that developed by Besag and Newell (1991) was used to identify significant clusters of disease incidence. Whereas Openshaw's approach uses circular windows moved across the entire study area, Timander and McLafferty searched for clusters in the neighborhood of known cases by centering their circles on each case. The resultant significant circles were all in the same geographical area, possibly suggesting a link with an environmental exposure. Following the approach of Kingham et al. (1995), data from the survey relating to established risk factors for breast cancer were used to run a logistic regression, which explained 30 percent of the disease incidence. The clustering process was then repeated using the residuals from the regression. This yielded no significant findings; hence an environmental link could not be pursued.

A fundamental issue in all spatial epidemiology, of which these studies are representative, is the need to consider migration. People move house quite frequently. If we are investigating a disease that may have commenced some ten years or more earlier, then it is inappropriate to research the current place of residence. More imaginative approaches are needed (Sabel et al. 2000).

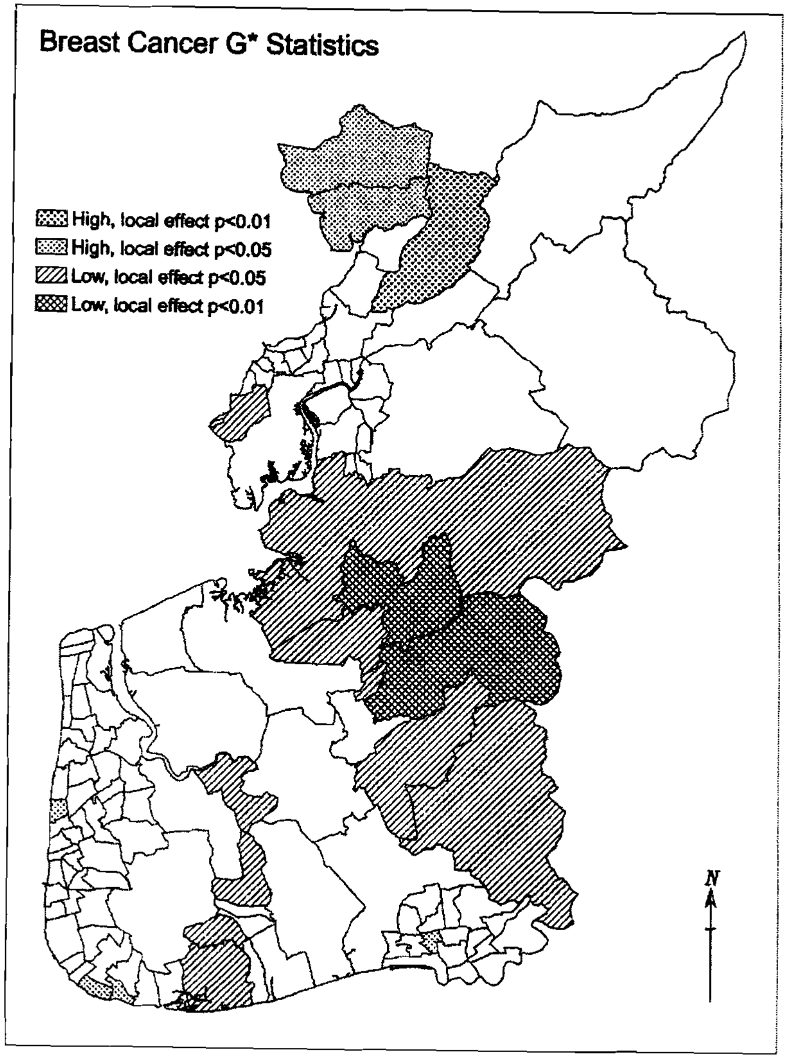

Figure 18.2. G^* statistics for breast cancer (Rigby and Gatrell, 2000).

Skin Disease

Consider first the spatial distribution of skin cancer, of which the most serious form is malignant melanoma. This shows considerable geographic variation over a variety of scales. In Europe, for example, age-standardized incidence varies from 12.9 per

100,000 in Denmark, to only 1.9 per 100,000 in Greece. Within individual countries there is latitudinal variation (see, for example, Bulliard et al. 1994 on New Zealand). Within particular regions, such as Ontario, Canada, there is variation from district to district. Indeed, in Ontario there is evidence of regional aggregation or autocorrelation (Walter et al. 1999). For both men and women there is a significant tendency for districts with high rates to be adjacent to other high-rate districts (Moran's $I = 0.39$ for men, 0.41 for women).

Having established spatial aggregation using exploratory techniques such as autocorrelation measures merely describes a map pattern; it does not explain anything, since such a pattern can arise in a number of different ways. Indeed, a starting point in any model-based spatial analysis must surely be to examine the extent to which a range of variables "soak up" regional variation. Only if residual autocorrelation remains will it be necessary to fit a model with spatial effects, one that builds in the correlation between values in nearby zones. In the Ontario study a non-spatial regression model suggests that incidence is positively associated with employment in farming and inversely associated with income and latitude. Having established these as possible explanatory factors, a geographic analysis of residuals reveals no significant residual autocorrelation. In research within Scandinavia, similar non-spatial regression analyses have been undertaken to explain spatial variation (Aase and Bentham 1994; Bentham and Aase 1996). These reveal that estimated exposure to ultraviolet B radiation is a significant predictor of incidence, as are patterns of vacationing abroad. The authors consider what the possible impact might be of increases in UVB radiation (resulting from ozone depletion), a kind of "what if" approach that is valuable in predicting a range of possible health outcomes and in planning the demand for health services (cancer care in this context).

There is some evidence from geographical epidemiology that the hardness of water (the presence of high concentrations of calcium and magnesium salts) is a risk factor for the development of eczema in children. In a study in Nottingham, U.K. (McNally et al. 1998) researchers asked parents of children aged 4–16 years about the occurrence of "itchy skin rash" during the previous year and at any time during the child's life. Home addresses were geo-coded and assigned, using a point-in-polygon routine, to one of 33 water quality zones, for each of which mean water hardness readings were available. There is considerable spatial variation in water hardness across the city, with soft water in the north and much harder water in the south.

The proportion reporting eczema varied significantly across four categories of water hardness (Table 18.1) and logistic regression analysis confirms that the risk of eczema increases with water hardness after adjusting for other possible variables that might "confound" the relationship; these include age, sex, socio-economic status, and proximity to health centers. The interpretation of an odds ratio of 1.54 is that a child living in a hard water zone is 54 percent more likely to report eczema than one living in a soft water zone. However, this relationship holds only for younger children (under 11 years). A possible explanation is that calcium and magnesium in domestic water supplies irritate the skin.

The question then arises of what policy interventions can be introduced to mitigate the burden of disease and illness. These interventions are typically focused at the level of the individual, with exhortations to change lifestyles and behaviors: to adopt "safe sex" practices, to improve diet, or to avoid over-exposure to direct sunlight, for example. However, interventions will invariably be required that are more broadly based. For example, water parameters are open to modification, while global agreements have been reached to halt ozone depletion.

Table 18.1. Water hardness and prevalence of eczema (reported during past year) among primary schoolchildren in Nottingham, U.K.

Water Hardness Category	Number Reporting Eczema	Prevalence (%)	Odds Ratio	Confidence Interval (95%)
1	94	12.0	1.00	
2	103	14.1	1.19	0.88–1.62
3	163	14.6	1.32	1.00–1.76
4	261	17.3	1.54	1.19–1.99

Source: McNally et al. (1998, 529), with permission from Elsevier Science (*The Lancet*, 1998, vol 352, page 529).

Understanding Health Inequalities

We are all aware of considerable variations in the health status of the world's population. At their most stark, these are portrayed by figures from the annual Human Development Report (United Nations Development Programme 2001). The most recent public health indicators include life expectancy ranging from to 37 in Sierra Leone up to 80 in Japan, the infant mortality rate (per 1000 live births) ranging from 3 in Sweden, through 4–6 in many developed countries, to 132 in Malawi, and 182 in Sierra Leone. The maternal mortality ratio (per 100,000 live births) ranges from an estimate of 1 in Greece, through 8 in the United States, to 440 in Bangladesh, to 1100 in Mozambique and the Central African Republic. The largest single cause is poverty, which can manifest itself as malnutrition, absence of sanitation, and lack of access to clean drinking water and to health care. However, even in countries within the developed world there are substantial variations, again at a variety of spatial scales.

Regional Perspectives

Poverty assumes rather different guises in more affluent societies, but inequalities in health status persist at sub-national levels, demonstrating a clear need for policies to alleviate it. For example, latest estimates of male life expectancy in the United Kingdom vary from 79 in parts of southern England, to 69 in parts of urban Scotland (Office for National Statistics 2001). Figures for the United States (National Center for Health Statistics 1997) show that, for all races combined, male life expectancy varies from 75.4 in Hawaii to 68.9 in Mississippi; the figure for black males in Washington, D.C. is only 57.5 years.

Recent work in the United Kingdom (Shaw et al. 1999) has used geographic visualization to reveal the nature and spatial extent of health inequalities. This work was based on the calculation of premature mortality (deaths under 65 years of age, standardized according to the related age and sex structures) and supported by a wide range of other social indicators. The units of analysis were electoral constituencies, and the report compared the 15 constituencies with the highest rates of premature mortality with 13 "best health" constituencies. The 15 "worst health" constituencies could clearly be seen to have poorer levels of employment, education qualifications, child health, and average household income. Displaying the data on maps (see Figure 18.3), 12 of the 13 "best health" constituencies, and only one of the "worst health" constituencies, were situated in the affluent south of Britain.

A major consideration within the health inequalities debate is that of equity of access to health care. In countries where there is no substantive public health care system, income will be the primary determinant of access. Here, the term "health care" may be the most basic provision of a hospital, or the proximity of a family doctor or other health professional, but it also incorporates access to preventive services such as immunization and screening, contraception and maternity services, and palliative care throughout a terminal illness.

The development of geographical information systems has supported increasingly sophisticated and robust modeling of access to health care. A fundamental issue is how we quantify the distance between a "demand point" (usually a person's home) and a "supply point," for example, a doctor's surgery. Early work simply used the straight-line distance between the two points. These calculations were often inaccurate reflections of the travel involved, for example, artificially shortening a journey that might involve a tortuous route around a river estuary. Conversely, a journey that allowed fast travel on a multi-lane highway might prove more efficient than a model for the Euclidean plane suggested. Road networks can be easily represented within a GIS, and estimates of travel times between points generated by applying different speeds to the different classes of roads encountered along the route. Jones and Bentham (1995) were concerned that a policy of centralizing emergency health services might not be the best approach for a large rural area. Taking a database of the locations and outcomes (fatalities or otherwise) of road traffic accidents, they used the road network within a GIS to simulate the route of an ambulance from the nearest ambulance station to each geo-coded accident, and then the route from the scene of the accident to the nearest hospital accident and emergency department. This allowed them to assess the distance traveled by the ambulance in connection with the outcome of the accident, and they found that the relationship between access time and health outcome was not significant. If the road networks are not explicitly classified (for example motorway, dual carriageway, minor road), measures of sinuosity (bendiness) can be calculated, which indicate that the speed of vehicles will be restricted (Lauder et al. 2001). Such work has an important role in the allocation of funding for health resources where the costs of healthcare provision to populations in remote areas are a concern.

Local Perspectives

We want here to consider three examples of work where a spatial perspective can inform our understanding of local variation in health outcomes. Consider first research in

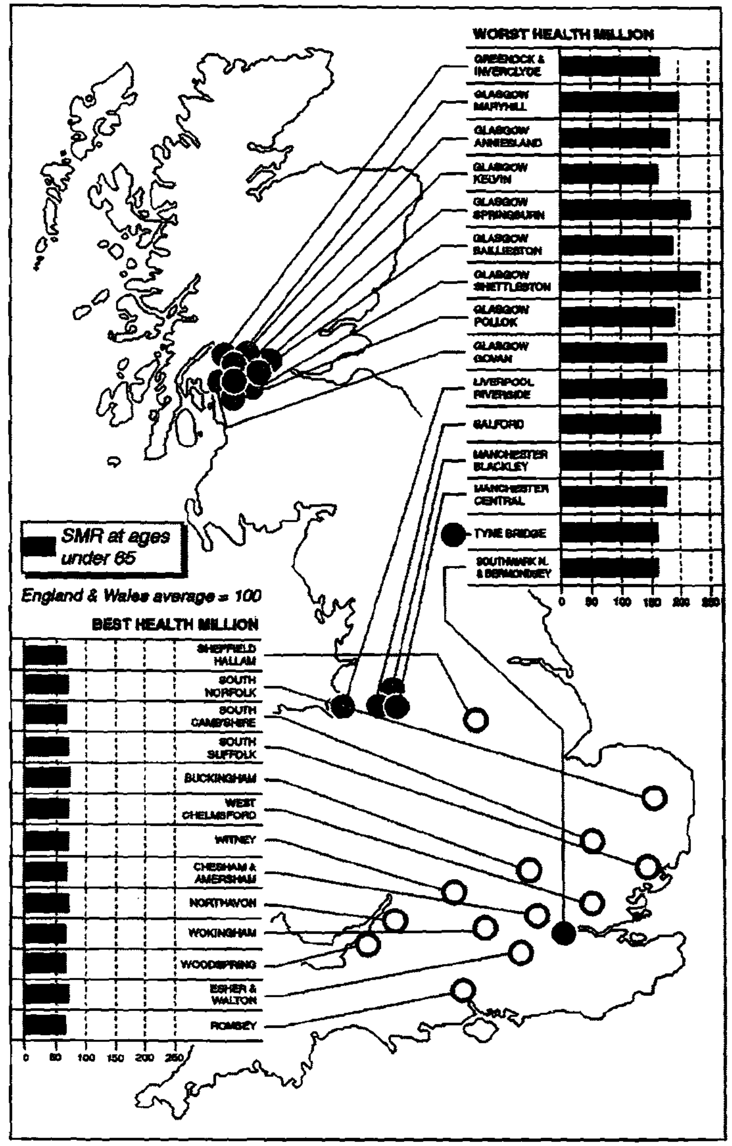

Figure 18.3. Map of mortality in U.K. constituencies. Reprinted from Shaw et al. (1999) with permission from The Policy Press, University of Bristol.

Glasgow, Scotland, that has sought to explain intra-urban variation in a variety of health outcomes, including self-reported health and mental health in particular (Macintyre et al. 1993; Sooman and Macintyre 1995). Four localities within the city are studied, two in the relatively affluent northwest and two in the more deprived southwest. Broadly speaking, health is better in the two northwest localities (Table 18.2). The explanation lies, in part, in differences in the local social environment, including both the extent to which there is poor infrastructure and a variety of reported social problems. While in the northwest there is good access to local services and facilities, such as public transport, health services, and retail outlets, in the southwest these are more sparsely provided. A genuine "mapping" of public health therefore needs to document the availability of those "goods" that may impact on population health.

At the other extreme, we need to focus on proximity to environmental "bads" as well as access to health-promoting services. Here, the research effort has been driven by those working in North America, under the heading of "environmental justice." This imperative is that people have equitable access to environmental resources and that the burden of environmental costs should be shared in a reasonably equitable way. This, quite manifestly, does not happen, with political power (held differentially by local groups and institutions) and externality effects conspiring to ensure that the spatial distribution of pollution, for example, is socially patterned. Jerrett et al. (2001) have shown how to use spatial analytic methods to assess the nature of the problem. They take monitored data on particulate air pollution from 23 monitoring stations in Hamilton, Ontario. From the measurements they construct a spatially continuous surface of pollution using the geostatistical technique of kriging (see Bailey and Gatrell 1995,

Table 18.2. Local social environment and health outcomes in Glasgow, Scotland.

Area Indicator	West End (NW)	Garscadden (NW)	Mosspark (SW)	Pollok (SW)
Access to services				
Pharmacy†	97.9	96.0	87.2	92.0
Post office†	98.4	97.7	89.4	96.4
Grocery store†	99.5	99.4	97.9	98.5
Reported problems				
Discarded needles††	4.3	8.5	10.8	18.0
Poor public transport††	13.4	16.7	20.5	18.8
Assaults and muggings††	28.2	34.5	47.9	56.1
Health outcomes				
Health for age†††	35.1	22.6	29.8	13.2
HADS anxiety††††	16.5	17.7	29.8	25.6

†percentages of respondents reporting amenities within half a mile

††percentage of respondents reporting selected problems

†††percentage of respondents reporting health as excellent

††††percentage of respondents reporting anxiety

Source: Sooman and Macintyre (1995), with permission from Elsevier Science (*Health and Place*, vol. 1, 1995, pages 15–26).

for an introduction). The pollution surface is overlain on census tracts, and regression analyses conducted to determine the relationship between pollution levels and socio-economic variables such as dwelling value, household income, and unemployment. All the latter exert a significant influence on pollution exposure, though analysis of residuals shows evidence of autocorrelation, and a spatially autoregressive model is required to remove this. The conclusion is that poorer groups are significantly more exposed to pollution than higher status populations (Figure 18.4). Research such as this has led other authors (Falit-Baiamonte and Osleeb 2000) to consider a new form of location model, one that determines a configuration of noxious facilities such that the burdens associated with hazardous plants are shared as equitably as possible among sub-regions.

As noted earlier, there is now a rich vein of work emerging that demonstrates an association between mortality or morbidity and the distribution of resources (usually income) within a study region. Unequal shares of income seem to contribute to population ill health. In a local British context, Ben-Shlomo and his colleagues (1996) demonstrated that mortality was associated with variability in socio-economic status. Those local authorities in which there was high variation in deprivation (a mix of deprived and affluent small areas) had poorer health than those that were more homogeneous, once overall levels of deprivation had been controlled for. Gatrell (1997) and Boyle and colleagues (1999) have sought to introduce an explicit spatial dimension to this research. They argue, and then demonstrate, that we may look at variability (heterogeneity) not solely within a single administrative area, but also among contiguous areas. They show that morbidity is associated with variations in deprivation within small areas and their neighbors. From the perspective of an individual, one's health is shaped to some extent by income, but it is also shaped by whether one is surrounded by generally better-off, or generally worse-off neighbors.

This overtly spatial context has yet to be fully exploited by public health researchers seeking to understand health inequalities. However, there is a substantial body of research now on the impact of "context" on health. By this is meant the effect of neighborhood or local social characteristics on health. It is argued that to understand health outcomes at the individual level one needs not solely "compositional" variables (on smoking behavior, for example) but also contextual influences that are "supra-individual." For example, if seeking to predict the incidence of childhood asthma, one could hypothesize that this is shaped in part by household-level factors (dampness in the home, prevalence of smokers in the household), but also by factors operating at another level (such as the number of vehicles traveling along the road outside, or the average level of outside air pollution in the neighborhood).

The existence of health determinants at different "levels" (individual, household, neighborhood) has led to the now quite extensive use of multi-level modeling to take account of these wider spatial contexts. For example, O'Campo and her colleagues (1997) explain geographic variation in low birth weight both in terms of individual-level determinants (such as late initiation of pre-natal care) and neighborhood-level influences (such as levels of crime). The evidence from this and many similar studies is that "area-level" variables contribute some explanatory power over and above factors operating at the individual level.

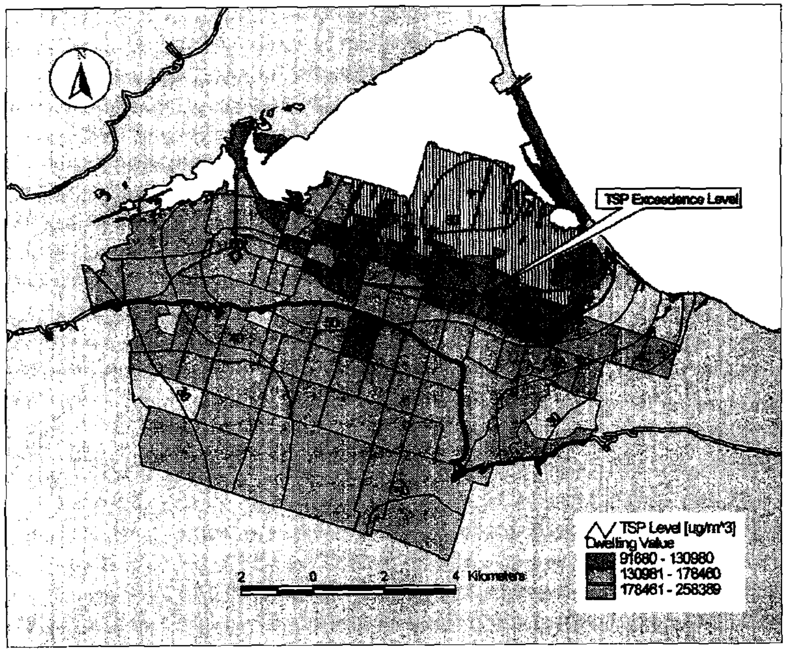

Figure 18.4. Dwelling values and total suspended particulates in Hamilton, Ontario, 1985–94. Reprinted from Jerrett et al. (2001, 966) with permission from Pion Limited, London.

Concluding Remarks

We have but scratched the surface of a growing, and rich literature on the geography of health (or "medical geography"), a literature that demonstrates quite convincingly that space and place figure prominently in epidemiology and public health. While this connection has a history stretching back into the nineteenth century and beyond, only quite recently has spatial context begun to re-emerge. In part this is due to the emergence of geo-referenced data and the technical advances offered by GIS and contemporary spatial analysis. Striking advances have been made in geographic visualization, exploratory spatial data analysis, and geographic modeling. Of course, these insights offer only a partial picture, and we must turn to other methodological perspectives—including qualitative methods—to gain a fuller understanding of ill health. We need to progress in other directions too, of which an understanding of health and disease "through the life-course" is paramount. As we have hinted here, a spatial perspective will continue to figure prominently.

References

Aase, A., and G. Bentham. 1994. The geography of malignant melanoma in the Nordic countries: The implications of stratospheric ozone depletion. *Geografiska Annaler* 76B: 129–139.

Anselin, L. 1995. Local indicators of spatial association. *Geographical Analysis* 27: 93–115.

Bailey, T.C., and A.C. Gatrell. 1995. *Interactive Spatial Data Analysis*. Harlow: Addison Wesley Longman.

Ben-Shlomo, Y., I. White, and M. Marmot. 1996. Does the variation in the socio-economic characteristics of an area affect mortality? *British Medical Journal* 312: 1013–1014.

Bentham, G., and A. Aase. 1996. Incidence of malignant melanoma of the skin in Norway, 1955–1989: Associations with solar radiation, income, and holidays abroad. *International Journal of Epidemiology* 25: 1132–1138.

Bentham, G., J. Hinton, R. Haynes, A. Lovett, and C. Bestwick. 1995. Factors affecting non-response to cervical cytology screening in Norfolk, England. *Social Science and Medicine* 40: 131–135.

Besag, J., and J. Newell. 1991. The detection of clusters in rare diseases. *Journal of the Royal Statistical Society Series A* 154: 143–155.

Boyle, P., A.C. Gatrell, and O. Duke-Williams. 1999. The effect on morbidity of variability in deprivation and population stability in England and Wales: An investigation at small-area level. *Social Science and Medicine* 49: 791–799.

Bulliard, J-L., B. Cox, and J.M. Elwood. 1994. Latitude gradients in melanoma incidence and mortality in the non-Maori population of New Zealand. *Cancer Causes and Control* 5: 234–240.

Clayton, D., and L. Bernardinelli. 1992. Bayesian methods for mapping disease risk. In P. Elliott, J. Cuzick, D. English, and R. Stern. (eds.), *Geographical and Environmental Epidemiology*. Oxford: Oxford University Press, 205–200.

Cliff, A.D., and P. Haggett. 1988. *Atlas of Disease Distributions*. Oxford: Oxford University Press.

Devesa, S.S., D.J. Grauman, W.J. Blot, G.A. Pennello, R.N. Hoover, and J.F. Fraumeni, Jr. 1999. *Atlas of Cancer Mortality in the United States 1950–94*. Washington, D.C: National Institutes of Health.

Falit-Baiamonte, A., and J.B. Osleeb. 2000. An equity model for locating environmentally hazardous facilities. *Geographical Analysis* 32: 351–368.

Gatrell, A.C. 1997. Structures of geographical and social space and their consequences for human health. *Geografiska Annaler* 79B: 141–154.

Gatrell, A.C. 2002. *Geographies of Health*. Oxford: Blackwell Publishers.

Gatrell, A.C., S. Garnett, J. Rigby, A. Maddocks, and M. Kirwan. 1998. Uptake of screening for breast cancer in South Lancashire. *Public Health* 112: 297–301.

Getis, A., and J.K. Ord. 1999. Spatial modelling of disease dispersion using a local statistic: The case of AIDS. In D.A. Griffith, C.G. Amrhein, and J.M. Huriot (eds.), *Econometric Advances in Spatial Modelling and Methodology: Essays in Honour of Jean Paelinck*. Dordrecht: Kluwer, 143–158.

Gould, P.R. 1993. *The Slow Plague*. Oxford: Blackwell.

Gould, P., and R. Wallace. 1994. Spatial structures and scientific paradoxes in the AIDS pandemic. *Geografiska Annaler* 76B: 105–116.

Hay, S.I., S.E. Randolph, and D.J. Rogers (eds.), 2000. *Remote Sensing and GIS in Epidemiology*. London: Academic Press.

Jerrett, M., R.T. Burnett, P. Kanaroglou, J. Eyles, N. Finkelstein, C. Giovis, and J.R. Brook. 2001. A GIS-environmental justice analysis of particulate air pollution in Hamilton, Canada. *Environment and Planning A* 33: 955–973.

Jones, A.P., and G. Bentham. 1995. Emergency medical service accessibility and outcome from road traffic accidents. *Public Health* 109: 169–177.

Kingham, S., A. Gatrell, and B. Rowlingson. 1995. Testing for clustering of health events within a geographical information system framework. *Environment and Planning A* 27: 809–821.

Kulldorff, M., E.J. Feuer, B.A. Miller, and L.S. Freedman. 1997. Breast cancer in northeastern United States: A geographical analysis. *American Journal of Epidemiology* 146: 161–170.

Langford, I.H. 1994. Using empirical Bayes estimates in the geographical analysis of disease risk. *Area* 22:142–149.

Lauder, C., C. Skelly, and L. Brabyn 2001. Developing and validating a road travel time network for cost path analysis. *Proceedings of SIRC 2001*. University of Otago, New Zealand, 2–5 December 2001: 225–231.

Lubin, J.H., and J.D. Boice. 1997. Lung cancer risk from residential radon: Meta-analysis of eight epidemiologic studies. *Journal of the National Cancer Institute* 89: 49–57.

Macintyre, S., S. Maciver, and A. Sooman. 1993. Area, class and health: Should we be focusing on places or people? *Journal of Social Policy* 22: 213–234.

McNally, N.J., H.C. Williams, D.R. Phillips, M. Smallman-Raynor, S. Lewis, A. Venn, and J. Britton. 1998. Atopic eczema and domestic water hardness. *The Lancet* 352: 527–531.

Meade, M.S., and R.J. Earickson. 2000. *Medical Geography*. 2nd edition. New York: Guilford Press.

National Center for Health Statistics. 1997. *US Decennial Life Tables for 1989–91*. Washington, D.C.: U.S. Government Printing Office.

O'Campo, P., X. Xue, M-C. Wang, and M. Caughy. 1997. Neighborhood risk factors for low birthweight in Baltimore: A multilevel analysis. *American Journal of Public Health* 87: 1113–1118.

Office for National Statistics. 2001. *Health Statistics Quarterly, Autumn 2001*. London: The Stationery Office.

Openshaw, S. 1990. Automating the search for cancer clusters: A review of problems, progress and opportunities. In R.W. Thomas (ed.), *Spatial Epidemiology*. London: Pion, 48–78.

Rigby, J.E., and A.C. Gatrell. 2000. Spatial patterns in breast cancer incidence in northwest Lancashire. *Area* 32: 71–78.

Sabel, C.E., A.C. Gatrell, M. Löytönen, P. Maasilta, and M. Jokelainen. 2000. Modelling exposure opportunities: Estimating relative risk for motor neurone disease in Finland. *Social Science and Medicine* 50: 1121–1137.

Shaw, M., D. Dorling, D. Gordon, and G.D. Smith. 1999. *The widening gap: Health inequalities and policy in Britain*. Bristol: The Policy Press.

Sooman, A., and S. Macintyre. 1995. Health and perceptions of the local environment in socially contrasting neighbourhoods in Glasgow. *Health and Place* 1: 15–26.

Teppo, L. 1998. Problems and possibilities in the use of cancer data by GIS: Experience in Finland. In A.C. Gatrell and M. Löytönen (ed.), *GIS and Health*. London: Taylor and Francis, 167–77.

Timander, L.M., and S. McLafferty. 1998. Breast cancer in West Islip, NY: A spatial clustering analysis with covariates. *Social Science and Medicine* 46: 1623–1635.

United Nations Development Programme. 2001. *Human Development Report 2001*. New York: Oxford University Press.

Walter, S.D., S.M. Taylor, and L.D. Marrett. 1999. An analysis of determinants of regional variation in cancer incidence: Ontario, Canada, In A. Lawson, A. Biggeri, D. Böhning, E. Lesafre, J.F. Viel, and R. Bertollini (ed.), *Disease Mapping and Risk Assessment for Public Health*. Chichester: John Wiley, 365–381.

WHO. 2000. *Report on the Global HIV/AIDS Epidemic*. Geneva: World Health Organisation.