Chapter 4

Decision Support for Public Health

Lead Author: Gregory E. Glass

1. Introduction

Public health is an approach to protect and improve the health of community members by preventive medicine, health education, control of communicable diseases, application of sanitary measures, and monitoring of environmental hazards (http://www.answers.com/topic/public-health?cat=health). This overall task is achieved by assessing and monitoring populations at risk to identify health problems and establishing priorities, to formulate policies to solve identified problems and to ensure populations have access to appropriate care, including health promotion, disease prevention, and evaluation of care. During the past century, the notable public health achievements as identified by the US Centers for Disease Control and Prevention (CDC) include vaccinations and treatments against infectious diseases, injury prevention strategies, reduced occupational exposures to toxins, improved food and water safety, decreases in childhood and maternal mortality, and safer water sources. Thus, many of the key issues related to public health are incorporated in previous chapters in this report, though they may not be characterized as public health. Regardless, public health may represent a key factor in problem solving under climate change situations. Many of the anticipated public health consequences of climate change are due to the influences of temperature and precipitation patterns, as well as land cover with consequences for the affected human communities. For example, changes in the availability of food resources and the quality of drinking water are anticipated to directly affect nutritional status, the spread of communicable infectious agents, and the impacts of poor air quality on vulnerable populations and in extreme situations the creation of "environmental refugees" (Huntingford *et al.,* 2007).

Because public health is an important outcome component of decision support tools (DST) involving air quality, water management, energy management and agricultural efficiency issues, it was decided to focus on a unique public health aspect of DST/DSS by examining infectious disease systems. Infectious diseases remain a significant burden to populations both globally, as well as within the US. Some of these, such as syphilis and measles involve a relatively simple dynamic of the human host population and the parasite—be it a virus, bacterium, or other micro-organism. These diseases, therefore, tend to be influenced by social behavior and the ability to provide resources and of health education to significantly alter human behavior. However, other disease systems include additional species for their successful transmission—either wildlife species that maintain the micro-organism (zoonoses) or there are insect or arthropod vectors that serve to transmit the parasites either among people or from the wildlife to people (vector-borne diseases).

Some of the most significant diseases globally are vector-borne or zoonotic diseases. Examples include malaria and dengue. In addition, many newly recognized (i.e., emerging) diseases either are zoonoses, such as SARS, or appear to have been derived from zoonoses that became established in human populations (e.g., HIV). Changes in rates of contact between component populations of these disease systems alter the rates of infectious disease (Glass 2007). Many of these changes come about through activities involving the movement of human populations into areas where these pathogen systems normally occur or they can occur because people introduce materials with infectious agents into areas where they were not known previously (Gubler et al. 2001). The introduction of West Nile virus from its endemic area in Africa, the Middle East, and Eastern Europe into North America and its subsequent spread across the continent is a recent example. The impacts of the virus on wildlife, human, and agricultural production are an excellent example of the economic consequence of such emergent disease systems.

More recently, attention has focused on the potential impact that climate change could have on infectious disease systems, especially those with vector or zoonotic components (e.g., Gubler *et al.,* 2001). Alterations in climate could impact the abundances or interactions of vector and reservoir populations, or the way in which human populations interact with them (Gubler, 2004). In addition, there is speculation that climate change will alter the locations where disease systems are established, shifting the human population that is at risk from these infectious diseases (e.g., Brownstein *et al.,* 2005a; Fox, 2007)

Unlike many of the other applications in this report where Earth observations and modeling are of growing importance, the use of Earth observations by the public health community has been sporadic and incomplete. Although early demonstrations showed their utility for identifying locations and times that vector-borne diseases were likely to occur (e.g., Linthicum *et al.,* 1987; Beck *et al.,*1997), growth of their application has been comparatively slow. Details of the barriers to implementation include the need to "scavenge" data from Earth observation platforms, as none of these are designed for monitoring disease risk. This is not an insurmountable problem and in fact, only few applications for Earth observations have dedicated sensors. However, disease monitoring requires a long history of recorded data to provide information concerning the changes in population distribution and the environmental conditions associated with outbreaks of disease. Detailed spectral and spatial data need to be of sufficient resolution and the frequency of observations must be high enough to enable identification of changing conditions (Glass 2007). As a consequence, many DSTs undergoing development have substantial integration of Earth observations but lack an end-to-end public health outcome, particularly when focusing on infectious diseases. Therefore, the Decision Support System to Prevent Lyme Disease (DDSPL) supported by the CDC and Yale University was selected to demonstrate the potential utility of these systems within the context of climate change science. Lyme disease is a vector-borne, zoonotic bacterial disease. In the US it is caused by the spirochete, *Borrelia burgdorferi,* and it is the most common vector-borne disease with tens of thousands of reported cases annually (Piesman and Gern 2004). Most human cases occur in the Eastern and upper Mid-West portions of the US, although there is a secondary focus along the West Coast of the country. In the primary focus, the black-legged tick (or deer tick), of the genus *Ixodes,* is most often found infected with *B. burgdorferi*.

2. Description of DDSPL

The diverse ways in which Lyme disease presents itself in different people has made it a public health challenge to ensure that proper priorities are established, to formulate policies to solve the problem, and to ensure that populations have access to appropriate care. The CDC uses DDSPL to address questions related to the likely distribution of Lyme disease east of the 100th meridian, where most cases occur (Brownstein *et al.,* 2003). This is done by identifying the likely geographic distribution of the primary tick vector (the black-legged) tick in this region. DDSPL uses field reports of the known distribution of collected tick vectors, as well as sites with repeated sampling without ticks as the outcome space. DDSPL uses satellite data, and derived products such as land cover characteristics, and census boundary files and meteorological data files to identify the best statistical predictor of the presence of black-legged ticks within the region. Land cover is derived from multi-date Landsat TM imagery and 10-m panchromatic imagery.

DDSPL combines the satellite and climate data with the field survey data of *Ixodes* ticks sampled at locally sampled sites throughout the region (Brownstein *et al.,* 2003) or from rates of reported cases of Lyme disease (Brownstein *et al.,*2005b) in spatially explicit statistical models to generate assessment products of the distribution of the tick vector or human disease risk, respectively. These models are validated by field surveys in additional areas and the sensitivity and specificity of the results determined (figure 1). Thus, the DDSPL is primarily a DST for prioritizing the likely geographic extent of the primary vector of Lyme disease in this region (figures 1 and 2). It currently stops short of characterizing the risk of disease in the human population but is intended to delimit the area within which Lyme disease (and other diseases caused by additional pathogens carried by the ticks) might occur (Figure 2). Researchers at Yale University are responsible for developing and validating appropriate analytical methods to develop interpretations that can deal with many of the challenges of spatially structured data, as well as the acquisition of Earth science data that are used for model DDSPL predictions. The distinction between the presence/abundance of the tick vector and actual human risk relies on the effects of human population abundance and behavioral heterogeneity (e.g., work or recreational activity) that can alter the contact rate between the tick vector and susceptible humans. However, such detailed human studies (especially behavioral heterogeneity) are typically not available (Malouin *et al.,* 2003). In Brownstein *et al.* (2005b) analysis, they found that although the entomological risk (the abundance of infected ticks) increased with landscape fragmentation, the human incidence of Lyme disease decreased, thus indicating there is a complex relationship between the landscape, the population of ticks, and the human response resulting in the health outcome.

3. Potential Future Use and Limits

Future use of DDSPL depends to a great extent on public health policy decisions exterior to the DST. The perspective of the role that Lyme disease prevention rather than treatment of diseased individuals will play is a key aspect of the importance that DDSPL will experience. For example, studies have shown that even in Lyme disease endemic regions, risk communication often fails to reduce the likelihood of infection (Malouin, *et al.,* 2003). In principle, policy makers may decide that it is more cost effective to provide improved treatment modalities rather than investing in educational programs that fail to reduce disease burden. Alternatively, the development of vaccines is time consuming, costly, and may have additional risks of unacceptable side effects that affect the likelihood that this would be a policy choice. Thus, depending on policy decisions and the effects of alternative interventions, the DDSPL might be used to forecast risk areas for educational interventions, to inform health care providers in making diagnoses, or to plan mass vaccination campaigns.

Currently, the removal of the licensed Lyme disease vaccine from the general public has eliminated this as a strategy to reduce the disease burden. The apparent lack of impact of targeted education also makes this a less likely strategy. Thus, the extent to which treatment modalities rather than prevention of infection will drive the public health response in the near future will play a major role in the use of DDSPL. However, even if the decision is made to focus on treatment of potentially infected individuals, DDSPL may still be useful by identifying regions where disease risk may be low, helping health care workers to focus clinical diagnoses on alternate causes.

Presuming that the DST continues to be used, the need for alternative/improved Earth science data to clarify environmental data for DDSPL such as land cover, temperature, and moisture regimes is currently uncertain. The present system reports a sensitivity of 88 percent and specificity of 89 percent—generally considered a highly satisfactory result. Sensitivity and specificity are considered the two primary measures of a method's validity in public health analyses. Sensitivity in the DDSPL model refers the to expected proportion of times (88 percent) that ticks would be found when field surveys were conducted at sites that the DDSPL predicted they should occur. Specificity refers to the proportion of times (89 percent) that a survey would not be able to find times at sites where the DDSPL excluded them from occurring. These two measures provide an estimate of the "confidence" the user can have in the DST prediction (Selvin 1991). These analyses extended geographically from the East Coast to the 100th meridian and were validated by field sampling for the presence of *Ixodes* ticks at sites throughout the region.

Typically, patterns of weather regimes appear to have a greater impact on distribution than more detailed information on land cover patterns. However, some studies indicate that fragmentation of forest cover and landscape distribution at fairly fine spatial resolution can substantially alter patterns of human disease risk (Brownstein *et al.,* 2005b). These results also suggest that human incidence of disease may, in some areas of high transmission, be decoupled from the model constructed for vector abundance, reemphasizing the distinction between a key component (the vector) and actual human risk. When coupled with the stated accuracy of the DDSPL in identifying vector distribution, this would suggest that future efforts will probably require an additional model structure that includes sociological/behavioral factors of the human population that puts it at varying degrees of risk. An additional limit of the DDSPL is that it does not explicitly incorporate human health outcomes in its analyses. In part, this reflects a public health infrastructure issue that limits detailed information on the distribution of human disease to (typically) local and state health agencies. For example, confidentiality of health records, including detailed locational data, such as home addresses, are often shielded in the absence of explicit permission. This makes establishing the relationship between monitored environmental conditions and human health outcomes difficult. One solution is to aggregate data to some jurisdictional level. However, this produces the well know "ecological fallacy" in establishing relationships between environmental factors and health outcomes (Selvin 1991). With appropriate planning or the movement of the technology into local public health agencies, these challenges could be overcome. Some localized data (e.g., Brownstein *et al.,* 2005b) of human health outcomes have been used to evaluate the utility of DDSPL and indicate that there is good potential for the DSS to provide important information on local risk factors.

4. Uncertainty

Uncertainty in decision making from DDSPL is based on the results of statistical analyses in which standard statistical models with spatially explicit components, such as autologistic intercepts of logistic models, are used to account for spatial autocorrelation in outcomes. The statistical analyses are well-supported theoretically. Typical calibration approaches involve model construction followed by in-field validation. Accuracy of classification is then assessed in a sensitivity-specificity paradigm.

However, little attention is paid in the current model to assessing uncertainty in the environmental data obtained from remotely sensed (or even *in situ*) monitors of the environment. For example, most of the derivative data, such as land cover, may change with population growth and development. In addition, the use of average environmental conditions provide an approximate characterization of local edaphic conditions that may affect the abundance of the the tick vectors.

Whether these are the primary sources of "error" in the sensitivity and specificity results (although these are considered excellent results) of the DDSPL is not addressed and is an area the public health applications need to consider in future applications. Alternatively, there are biological reasons for the errors in the model, including the interaction of climatic factors and tick activity that may be responsible for sites predicted to have ticks that were not found to have them. To resolve some of the biological/environmental issues, validation is ongoing.

There also are a number of public health issues that affect the certainty of the DDSPL (and any DST) that are extrinsic to the system or tool. Accuracy in clinical diagnoses (both false positives and negatives), as well as reporting accuracy can affect the evaluation of the tool's utility. Currently, this is an issue of serious contention and forms part of the rationale for focusing on accurately identifying the distribution of the primary tick vector, as an integral step in delimiting the distribution of the disease and evaluating needs for the community.

5. Global Change Information and DDSPL

The relationship between climate and public health outcomes is complex. It is affected both by the direction and strength of the relationship between climatic variability and the component populations that make up a disease system, as well as the human response to changes in disease risk (Gubler 2004).

The DDSPL is one of the few public health DSTs that has explicitly evaluated the potential impact of climate change scenarios on this infectious disease system. Assuming that evolutionary responses of the black-legged tick, *B. burgdoferi* and the reservoir zoonotic species remains little changed under rapid climate change, Brownstein *et al.,* (2005a) evaluated anticipated changes in the distribution and extent of disease risk.

This analysis used the basic climate-land cover suitability model developed for DDSPL and selected the Canadian Global Coupled Model (CGCM1) under two historically forced integrations. The first with a 1 percent per year increase in greenhouse gas emissions and the second with greenhouse gas and sulfate aerosol changes, resulted in a 4.9 and 3.8° Celsius increase in global mean temperature by the year 2080. Near (2020), mid (2050) and farpoint (2080) outcomes were evaluated (Figure 3). The choice of CGCM1 was based on the Intergovernmental Panel on Climate Change criteria for vintage, resolution, and validity (Brownstein *et al.,* 2005a).

Extrapolation of the analyses suggest that the tick vector will experience a significant range expansion into Canada but will also experience a likely loss of habitat range in the current southern portion of its range (figure 3). This loss of range is thought to be due to impact of increased temperatures causing decreased survival in ticks when they are off their feeding hosts. It also is anticipated that its range will shift in the central region of North America – where it is currently absent. When coupled with the anticipated continued human movement to more southern portions of the country, the numbers of human cases are expected to show an overall small decrease.

These long-range forecasts disguise a more dynamic process with ranges initially decreasing during near and mid-term timeframes. This range reduction is later reversed in the long-term producing the overall pattern described by the authors. The impact in range distribution also produces an overall decrease in human disease risk as suitable areas move from areas of primary human concentration to areas that are anticipated to be less well populated.

Thus, DSS similar to those developed for Lyme disease have the potential for providing both near- and far-term forecasts of potential infectious disease risk that are so important for public health planning. In addition, detailed studies (e.g. Brownstein *et al.,* 2005b) provide public health agencies with important information on drivers of human risk that have been difficult to obtain by other means. As a consequence, DSS using remotely sensed data sources either in part or whole have the potential to significantly improve the health of communities.

The primary challenges for the Earth science community involve understanding the needs of the public health community for the appropriate data at the appropriate spatial, temporal, and spectral scales. This will involve understanding a historically entrenched set of methodologies for interpreting health data and establishing causal relationships between inputs (environmental data) and outputs (health outcomes). In addition, there is the challenge of performing these tasks in the presence of limited resources for a community that has little cultural understanding of both the strengths and limitations of the data derived from these sources.