POLICY ANALYSIS

Challenges of Designing and Implementing High Consequence Infectious Disease Response

Joan M. King, PhD; Chetan Tiwari, PhD; Armin R. Mikler; Martin O'Neill II, PhD

ABSTRACT

Ebola is a high consequence infectious disease—a disease with the potential to cause outbreaks, epidemics, or pandemics with deadly possibilities, highly infectious, pathogenic, and virulent. Ebola's first reported cases in the United States in September 2014 led to the development of preparedness capabilities for the mitigation of possible rapid outbreaks, with the Centers for Disease Control and Prevention (CDC) providing guidelines to assist public health officials in infectious disease response planning. These guidelines include broad goals for state and local agencies and detailed information concerning the types of resources needed at health care facilities. However, the spatial configuration of populations and existing health care facilities is neglected. An incomplete understanding of the demand landscape may result in an inefficient and inequitable allocation of resources to populations. Hence, this paper examines challenges in implementing CDC's guidance for Ebola preparedness and mitigation in the context of geospatial allocation of health resources and discusses possible strategies for addressing such challenges. (*Disaster Med Public Health Preparedness*. 2018;12:563-566)

Key Words: response planning, high consequence infectious disease, geographic mapping, disease outbreaks, policy making

In the United States, recent concerns regarding high consequence infectious diseases (HCIDs), such as Ebola, have lead to the need for developing appropriate preparedness and mitigation strategies. Using Ebola as a case study, we examine initial efforts to develop such strategies and identify critical gaps that may hinder their effective implementation. Centers for Disease Control and Prevention's (CDC) planning and readiness guidelines for Ebola aim to support the identification of "preparedness and operational gaps relative to Ebola" and of the resources needed to "assist state and local jurisdictions in closing (those) self-identified gaps."[1] Although CDC guidelines provide detailed information on types of resources that are needed to address HCID outbreaks, strategies for quantifying needs at participating health care facilities remain unclear. This poses a challenge, given the uneven landscape of population distribution across the United States, their varying demographic and socio-economic characteristics, and the uneven distribution of health care facilities.

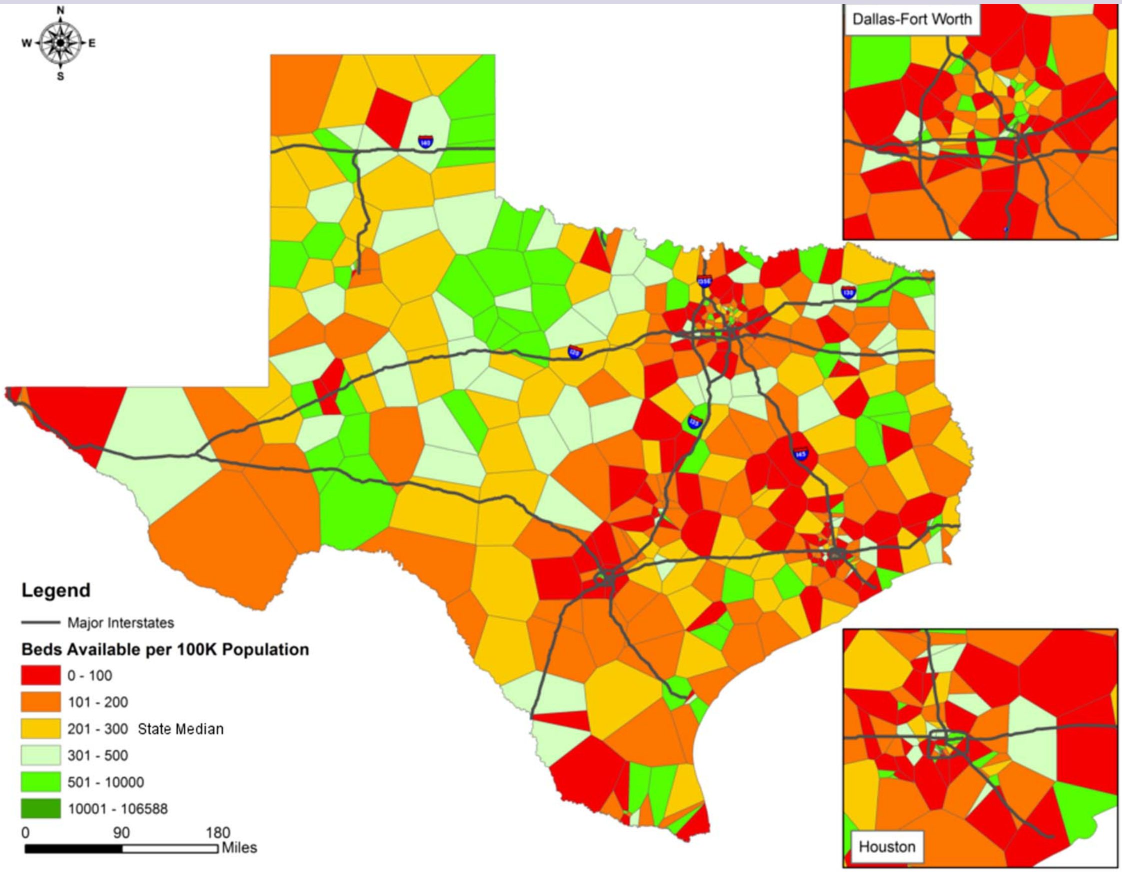
Previous research has developed methods for assessing inadequate access to health care[2] and optimizing the locations of new facilities to meet demand. Yet preparing existing health care infrastructure for mitigating a dynamic HCID outbreak presents several new challenges. First, methods to quantify the types and numbers of disease-specific resources needed at national, regional, and local hospitals must be developed. Second, as evidenced by the recent Ebola outbreak in West Africa, the characteristics of the populations exposed to the virus are an important factor in determining rate of spread amongst a population and its geographic distribution.[3] Third, fluctuations in demand that result from uncertainties in how the disease spreads can alter resource needs among existing health care facilities. Finally, any data-driven approach for managing the assessment, quantification, and distribution of HCID resources requires the development of computational methods for data integration, analysis, visualization, and reporting.

STRATEGIES FOR DESIGNING PREPAREDNESS PLANS FOR HCIDS

CDC guidelines suggest sharing of resources stratified by 3 levels of assessment and care: frontline health care facilities, Ebola assessment hospitals, and Ebola treatment centers.[1] Estimating how to distribute limited resources among facilities while ensuring adequate population coverage presents a spatial optimization problem that must consider the locations of where and how people are likely to access treatment. We show that the patterns of health care access and utilization are likely to vary across rural and urban areas and present a tradeoff between geographic access and availability. Areas with increased access are shown to actually have less acute care beds per population than areas with fewer facilities, because

FIGURE 1

Hospital acute care bed density. Beds available per 100k population. This shows areas in which beds available for acute care are limited in an influx of patients, such as an outbreak.



the population demands are higher in such urban areas (Figure 1).

Rural-urban disparity in access to and utilization of medical care is a commonly explored problem.[4] Identifying gaps in residents' access to care without the stress of an Ebola outbreak can help providers be better prepared. For instance, rural residents are characteristically older and poorer—attributes that may affect health care access and utilization.[4,5] They tend to have a usual place of health care, which makes a resident more likely to seek care when ill compared with urban dwellers.[6] However, they may also have to travel longer distances for care,[4,5] resulting in greater geographic access disparities compared with urban areas.[6] However, due to the lack of a robust, publically available baseline data set on how populations access health care resources, it is difficult to identify which hospitals have disparities or need resources to treat an influx of Ebola cases. Further, while CDC guidelines provide guidance on the types of resources that are needed to ensure adequate preparedness at each hospital, the number of resources needed to handle all possible Ebola patients in a given geographic region remains unknown. Understanding this, the CDC recommends that government stockpiles of Ebola-related health resources, such as personal protective equipment, be distributed within health service region.[7] We argue that the subsequent distribution of such resources to hospitals within health service regions must be guided by population demand for services—which tends to be uneven across geographic space.

It is assumed that people will use their closest health service, based on the Dartmouth Hospital Referral Regions.[8] To approximate such service regions, Voronoi partitions are constructed around each hospital in Texas (Figure 1). For each facility, a ratio of the number of acute care beds to the total population was used as a measure for available resources. These include intensive care units but not pediatric beds, which are subject to a separate CDC plan. As noted in the inset maps (Figure 1), the smaller Voronoi-based service regions in the 2 major metropolitan areas in Texas suggest better spatial access to available health care facilities. However, those areas also show significant local variations in the number of acute care beds that are available to the population. Existing disparities in access due to transportation,

https://doi.org/10.1017/dmp.2017.128 Published online by Cambridge University Press

education, and income further complicate the assessment of resources required at the various clinics.[5]

The demand for services may exhibit a dynamic, evolving behavior, as Ebola is known to spread differently in populations with different demographic and socio-economic characteristics.[3,9] Potentially rapid increases in demand for services can place a significant strain on the availability of existing resources, thereby resulting in a breakdown of the mitigation effort. Estimating the dynamic behavior of Ebola through the construction of mathematical models based on prior outbreaks would be one manner response plans could be evaluated. Such models incorporate local and regional population characteristics along with disease-specific parameters to simulate the dynamics of the disease as it spreads with varying levels of intensity across a given population.[10-12] One approach to estimate the dynamic behavior of Ebola is through the construction of mathematical models based on prior outbreaks.[10,13-16] Such models incorporate local and regional population characteristics along with disease-specific parameters to simulate the dynamics of the disease as it spreads with varying levels of intensity across a given population.

The SEIR (Susceptible, Exposed, Infected, Removed) model can be used to simulate the spread of a disease among a given population with counts that are determined using US Census data along with other disease parameters obtained from published CDC reports.[13-16] In the SEIR model, individuals can either be susceptible to the disease (S), exposed, meaning the person has made contact with an infected individual but is yet asymptomatic (E), infected (I), or, eventually, considered recovered or removed (R). The total population at time t is to be denoted by N where

$$N(t) = S(t) + E(t) + I(t) + R(t).$$

The equations driving the SEIR model are as follows:

$$\mathrm{d}S/\mathrm{d}t = -\beta SIN$$

$$\mathrm{d}E/\mathrm{d}t = \beta SIN - \delta E$$

$$\mathrm{d}I/\mathrm{d}t = \delta E - \gamma I$$

$$\mathrm{d}R/\mathrm{d}t = \gamma I$$

The rate of incubation β, latent period δ, and infectious period γ are used to estimate the number of Ebola cases in a population with a given set of characteristics. The estimation of appropriate values for these parameters can be challenging given the lack of data that is currently available for Ebola and uncertainties in how different strains of the disease may spread differently among populations. Further, uncertainties in how the onset of the disease is determined and its incubation period (ie, the time between exposure and visible symptoms of Ebola) can lead to large variances in the simulation results. Currently, the World Health Organization estimates the incubation period for Ebola to be between 2 and 21 days.[17] However, recent mathematical models based on recent outbreaks use an average of 7-12.7 days.[14] The latent period (ie, the period during which no symptoms are evident) is essential to planning mitigation efforts as it provides information on how long a potentially exposed individual must be kept under observation for Ebola symptoms. In several models, this period is usually assumed to be between 10 and 21 days. Previous studies have determined the infectious period to be between 6.5 and 21 days.[13-17] Uncertainties in the parameters used in the SEIR model require the development of computational tools that allow end-users to easily manipulate these simulation parameters and measure their impacts on how the disease spreads through a population. The results of such simulation models can also be used to develop strategies to proportionally re-allocate existing resources from one area to another or to develop plans for offloading patient demand from one geographic region to another.

CONCLUSIONS

CDC guidelines provide critical information on the types of resources needed to address Ebola or other HCID outbreaks. However, without an emphasis on understanding the spatial configuration of population demand, existing health care facilities, and patterns of health care access, the implementation of current CDC guidelines are likely to be ineffective. Furthermore, public health planning agencies must recognize the dynamically changing landscape of demand and how it relates to existing health care infrastructure. Complex trade-offs exist between how rural and urban hospitals need to prepare for outbreaks and how hospitals need to account for surges in demand. The lack of baseline regional Ebola data can be addressed by using simulation models to estimate the demand for health care resources.[11] The need to integrate data with complex mathematical and simulation models requires the development of computational tools that can present decision-makers with data driven and spatially-targeted intervention strategies. The REsponse PLan ANalyzer (RE-PLAN)[18,19] is a spatially-explicit framework that provides the computational infrastructure needed to develop such systems.[20,21] It is designed to store, manage, and analyze large amounts of disparate data and execute computational models through a point-and-click interface. RE-PLAN allows decision-makers to evaluate population structures across space and develops response strategies for bioemergency preparedness under constraints that can be expressed by users of the system. Similar tools to integrate regional data on health care infrastructure and rapidly analyze population demand for services need to be developed.[9]

About the Authors

Center for Computational Epidemiology and Response Analysis (CeCERA), University of North Texas, Denton, Texas.

Correspondence and reprint requests to Joan M. King, Center for Computational Epidemiology and Response Analysis (CeCERA), University of North Texas, Denton, TX 76201 (e-mail: JoanKing@my.unt.edu).

Published online: March 19, 2018.

REFERENCES

1. Centers for Disease Control and Prevention. Hospital preparedness: a tiered approach. Interim guidance for preparing frontline healthcare facilities for patients under investigation (PUIs) for Ebola virus disease (EVD). Centers for Disease Control and Prevention website http://www.cdc.gov/vhf/Ebola/healthcare-us/preparing/frontline-healthcare-facilities.html. Updated August 28, 2015.
2. Higgs G. A literature review of the use of GIS-based measures of access to health care services. *Health Serv Outcomes Res Methodol*. 2004;5(2):119-139.
3. WHO Ebola Response Team. Ebola virus disease in West Africa—The first 9 months of the epidemic and forward projections. *N Engl J Med*. 2014;371(16):1481-1495.
4. Braden J, Beauregard K. *Health status and access to care of rural and urban populations (AHCPR publications No. 94-0031). National Expenditure Survey Research Finding: 18, Agency for Healthcare Policy and Research.* Rockville, MD: Public Health Service; 1994.
5. Larson SL, Fleishman JA. Rural-urban differences in usual source of care and ambulatory service use. *Med Care*. 2003;41(7):III65-III74.
6. Goodman DC, Fisher E, Stukel TA, Chang C. The distance to community medical care and the likelihood of hospitalization: is closer always better? *Am J Public Health*. 1997;87(7):1144-1150.
7. Centers for Disease Control and Prevention. CDC Newsroom. CDC increasing supply of Ebola-specific personal protective equipment for U.S. hospitals. https://www.cdc.gov/media/releases/2014/p1107-Ebola-ppe.html. Published November 2014. Accessed September 2017.
8. The Dartmouth Atlas of Health Care. Lebanon, NH: The Dartmouth Institute for Health Policy and Clinical Practice, 2008.
9. Comber AJ, Brunsdon C, Radburn R. A spatial analysis of variations in health access: linking geography, socio-economic status and access perceptions. *Int J Health Geographics*. 2011;10(44):1-11.
10. Kadri F, Chaabane S, Tahon C. A simulation-based decision support system to prevent and predict strain situations in emergency department systems. *Simul Modell Pract Theory*. 2014;42:32-52.
11. Djanatliev A, German R. Prospective healthcare decision-making by combined system dynamics, discrete-event and agent-based simulation. 2013 Winter Simulations Conference (WSC); 2013.
12. Jimenez T, Mikler AR, Tiwari C. A novel space partitioning algorithm to improve current practices in facility placement. *IEEE Trans Syst Man Cybern A Syst Human*. 2012;42(5):1194-1205.
13. Rachah A, Torres DFM. Mathematical modelling, simulation, and optimal control of the 2014 Ebola outbreak in West Africa. *Discrete Dyn Nat Soc*. 2015;2015:1-9.
14. Legrand J, Grais RF, Boelle PY, Valleron AJ, Flahault A. Understanding the dynamics of Ebola epidemics. *Epidemiol Infect*. 2006;135(4):610-621.
15. Grigorieva E, Khailov E. Optimal intervention strategies for a SEIR control model of Ebola epidemics. *Mathematics*. 2015;3(4):961-983.
16. Do TS, Lee YS. Modeling the spread of Ebola. *Osong Public Health Res Perspect*. 2016;7(1):43-48.
17. World Health Organization. Ebola virus disease factsheet. http://www.who.int/mediacentre/factsheets/fs103/en/. Published January 2016. Accessed September 2017.
18. Schneider T, Mikler A. RE-PLAN: a computational framework for REsponse PLan ANalysis. *Int J Funct Inform Personalised Med*. 3(2):103-121.
19. O'Neill M, Mikler AR, Indrakanti S, Tiwari C, Jimenez T. RE-PLAN: an extensible software architecture to facilitate disaster response planning. *IEEE Trans Syst Man Cybernetics Systems*. 44(12):1569-1583. http://doi.org/10.1109/TSMC.2014.2332137
20. Schneider T, Mikler AR, O'Neill M. Computational tools for evaluating bioemergency contingency plans. Proceedings of the 2009 International Conference on Disaster Management; 2009.
21. De'Cock K. CDC global health strategy 2012-2015. Centers for Disease Health and Prevention; 2012. http://www.cdc.gov/globalhealth/strategy/pdf/cdc-globalhealthstrategy.pdf. Accessed May 1, 2015.