SYSTEMS APPROACHES IN PUBLIC HEALTH

A Dissertation

by

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ABSTRACT

Recognition of the complexity of many public health problems has led to the search for analytic methods capable of capturing more fully than traditional study designs and statistical tests the underlying dynamic processes at work. Similarly, those with an interest in public health interventions have begun to see the limitations of standard methods in understanding the consequences of programs and policies designed to influence population-level health.

While there are a number of system science methods with potential to further public health research, there are three methods most often applied: agent-based modeling, social network analysis, and system dynamics modeling. The first discussion reviews both theoretical and practical applications of these three methods in the literature, as each has strengths and weaknesses and is better suited to studying some aspects of complex dynamic phenomena than others. Such a discussion provides practical guidance for those who wish to use these system methods in their own research. Following this, there is a discussion of different perspectives on how these methods relate to traditional behavioral research methods, and how these perspectives affect understanding of and explanation of public health problems.

Beginning with a detailed analysis of the three systems methods used in public health and following with a discussion of how different perspectives affect understanding of public health problems sets the stage for the development of a systems model of a complex

public health problem. The final section applies these lessons by developing and testing a system dynamics model of type 2 diabetes in the area known as Health Service Region 11. The model framed the problem of diabetes in this region using assumptions implicit within selecting a system dynamics model. The focus was on the effectiveness of physical activity interventions to guide decision-makers in future resource allocation and public health professionals to use appropriate methodologies for complex health problems that traditional linear approaches are unable to capture and thus unable to suggest informed routes for change. The model evaluated different “what if” scenarios of prevention and intervention strategies for reducing prevalence of (and ultimately incidence of) type 2 diabetes.

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1. INTRODUCTION

The researcher's objective is to apply methods from the newly emerging field of systems sciences to the investigation of the chronic disease problem of type 2 diabetes in South Texas in Health Service Region 11 (HSR11). This investigation begins with a review of key texts in the systems sciences literature and the application of this approach and three of its primary methods to public health. This follows with a discussion of issues pertaining to the validation of systems models. The work will conclude with the development and analysis of a systems model of type 2 diabetes in HSR11.

Recognition of the complexity of many public health problems has led in recent years to the search for analytic methods more capable of capturing the underlying dynamic processes at work than the traditional study designs and statistical tests used in public health research (e.g., surveys, cohort studies, regression analysis) (Auchincloss and Diez Roux 2008; Galea, et al. 2008; Luke and Stamatakis 2012). Similarly, those with an interest in public health interventions have begun to see the limitations of standard methods, such as randomized trials and quasi-experiments, in understanding the consequences (both intended and unintended) of programs and policies designed to influence population-level health (Hawe, et al. 2009; Sterman 2006). Finally, policy analysts turned to systems methods in an effort to add greater precision and make more realistic, attainable goals through modeling potential effects of policies on public health problems (Fitzpatrick, et al. 2012; Hirsch, et al. 2010; Jones, et al. 2006; Levy, et al. 2000; Mendez and Warner 2000; Milstein, et al. 2007).

This search for methods that move beyond a simple mechanistic cause-and-effect representation of the world has stimulated interest among public health researchers in analytic techniques developed within the evolving field of system sciences. These methods have proved successful in understanding complex adaptive phenomena in fields such as operations research, engineering, ecology, biology, and sociology (Epstein 2006; Hedstrom and Ylikoski 2010; Sterman 2000). While there are a number of system science methods that have the potential to further public health research, to date, the three methods most often applied in the field include agent-based modeling, social network analysis, and system dynamics modeling (Luke and Stamatakis 2012).

Agent-based models are especially good in addressing issues that involve heterogeneous actors and exploring phenomena thought to emerge from the interaction between such actors and their interactions with their environments (Epstein 2006; Hedstrom and Ylikoski 2010). The agents in the model can learn and adapt over the course of the simulation, and the environment can change because of the interactions of the agents. The models can test purely theoretical ideas (e.g., the role of preference in urban racial segregation; Fossett 2006) or those grounded in real-life events or situations (e.g., the food-buying preferences or exercise behaviors of individuals in a specific city; Auchincloss, et al. 2011). In each case, the goal was to identify the mechanisms through which the phenomena of interest emerged.

System dynamics models typically group actors into categories or stocks and are concerned with the flow between these conditions and the factors that influence the rate at which these flows occur (Sterman 2000; Sterman 2006). This method is especially interested in feedback loops and the unintended consequences that can arise from well-intentioned attempts to change a system (Richardson 2011; Sterman 2006). Another key concept in system dynamics modeling is that of leverage points for successful interventions. These two aspects of the approach make it especially useful in policy analysis (Homer and Hirsch 2006).

Although social network analysis can also be used to understand basic, theoretical principles of interactions between actors (e.g., Watts 2004) it primarily has been used in public health research to examine relationships within datasets pertaining to either individuals or organizations (e.g., Fowler and Christakis 2008; Valente, et al. 2010). The discussion includes key attributes of social ties such as strength and length and the types of social phenomena and collective behaviors that diffuse most effectively across these different types of network structures (Centola and Macy 2007; Granovetter 1973), as well as key constructs pertaining to social network structures such as small worlds and scale-free networks (Watts 2004).

The discussions reviews both theoretical and practical applications of these three methods in the literature, as each has strengths and weaknesses and is better suited to studying some aspects of complex dynamic phenomena than others. Such a discussion provides practical guidance for those who wish to use these system methods in their own research, especially in the areas of social epidemiology, social and behavioral health, and policy analysis. This includes a general discussion and review of the literature, and presents five general overviews. The first of these will focus on the broad area of system sciences methods and presents brief descriptions of some key introductory texts on systems methods and the intellectual roots of these approaches. The focus of these publications is on the general application of systems methods, especially in the social sciences, and not on their application within public health and its related disciplines (e.g., epidemiology, health-care policy analysis, social and behavioral health). In addition, the focus often goes beyond a discussion of the three systems methods most commonly employed in public health research, and include examinations of other systems methods such as spatial analysis, concept mapping, and cellular automata.

The next part presents a series of references that discuss the broad application of systems methods to public health research. This follows with discussions that focus on each of the three specific system sciences methods reviewed in this bibliography: agent-based models, social network analysis and system dynamics models. In each case, the review includes key introductory texts pertaining to the method as well as articles discussing application, either of the method to public health research in general or of some specific discipline within public health, such as social epidemiology, health promotion, or health-care policy.

Following this review of key texts from the systems sciences literature, there is a discussion of different perspectives on how these methods relate to traditional behavioral and epidemiological research methods, and how these perspectives affect understanding of and explanation of public health problems. This discussion specifically focuses on the problems that arise when using data from an empirical study to assess the validity of a simulation model, illustrates these problems through examination of a specific example from the public health literature, and provide alternative means of assessing model usefulness.

Although, as noted above, there is a growing enthusiasm for systems methods within public health, it is important to note that different public health researchers view these methods in fundamentally different ways. Specifically, many of their advocates within public health see them as complimenting traditional behavioral and epidemiological research methods, and as in no way an attempt to displace such methods (Kaplan 2013). Others however see them as a fundamentally different way of understanding and explaining public health problems, and as presenting a “challenge” to traditional research methods (Luke and Stamatakis 2012). Those who see the methods as complimentary often use empirical data from studies employing traditional methods and statistical analysis to validate the output of simulation models. Alfred Korzybski 1933 famously stated, “The map is not the territory.” Yet comparing model output to empirical data, as is often done in public health research, assumes traditional empirical methods and statistical techniques capture the “territory” with such accuracy that they can be of use as a yardstick against which to judge the performance and adequacy of a model.

The goal of this discussion is not to present a comprehensive review of the ways in which public health research has validated models of chronic disease, but rather to contribute to the literature on models validity and, more specifically, draw some of the key issues in this area to the attention of public health researchers. The term “validation” is highly contested within the modeling community, and is frequently confused with related terms such as “verification”, “accreditation”, or “evaluation” (Balci 1997; Grant and Swannack 2008; Kleindorfer, et al. 1998; Martis 2006; Oreskes, et al. 1994). There is also a wide range of activities that can be described under the general rubric of validation (Grant and Swannack 2008; Rykiel 1996). A review of the broader debate as to what constitutes "validation" and of the various activities that this term is used to describe is outside the scope of this dissertation. However, a discussion of the process of comparing model predictions with observations of the real-world system, a process that is often erroneously considered to be the only or primary validation criterion (Grant and Swannack 2008), makes a valuable contribution to the public health literature as such issues have received little attention in the emerging public health systems literature. This discussion introduces public health researchers to some key issues pertaining to the assessment of the validity of simulation models. In addition, it contributes to the systems literature on validation by grounding the abstract discussion of the limitations of comparing model output with empirical data in a specific example. Thus, rather than simply stating that one should or should not compare model output to data, the discussion argues that one should exercise caution in doing this and should be clear as to exactly what it is that the data can tell one about the model. The discussion also illustrates these arguments through simple graphics, making it accessible to a wide, non-technical, audience.

Beginning with a detailed analysis of the three systems methods used in public health and following with a discussion of how different perspectives affect understanding of public health problems sets the stage for the development of a systems model applying such lessons to understand the specific public health problem of type 2 diabetes in HSR11. The work is similar to that conducted by policy analysts who have used systems methods to assess the potential long-term effects of different public health initiatives on chronic disease. However, the focus of the model presented is a specific geographic area rather than on national trends and policy objectives. This approach has been less often used in public health systems studies. The group of researchers that includes Jones, et al. 2006, for example, have developed sophisticated system dynamics models to examine the effects of different types of healthcare priorities and expenditures on chronic disease prevalence (e.g., Hirsch, et al. 2010; Homer, et al. 2007; Homer, et al. 2010; Jones, et al. 2006). Such discussions examine the effects of various types of healthcare expenditures (e.g., lifestyle change programs, environmental change, health insurance, clinical management) on the projected course of chronic disease in the United States. In contrast, Mahamoud et al. 2012 describe a system dynamics model parameterized using data from the City of Toronto; this focus on a smaller geography paralleled that in the presented modeling effort.

Development of the model compared different ways of framing the problem of type 2 diabetes in HSR11 and compared conceptual differences between modeling approaches to demonstrate how different modeling frameworks affect causality and understanding of this complex health problem. Then, the analysis assessed the ways in which theoretical frameworks of modeling and of the problem affect understanding of causality of the health problem and of ways of affecting such. Such causal assumptions affect what one can learn from modeling efforts and ultimately of how to affect change in the health status of the population. Finally, through understanding the theoretical and practical implications of different frameworks on modelling complex public health problems (or the theory-practice praxis), a system dynamics model was developed and analyzed to understand the different dynamic forces contributing to development and persistence of type 2 diabetes in the specific geographic area and the potential impact of different interventions on such.

The model aggregated populations through different rates of disease progression, as well as other relevant risk factors and demographic attributes to allow for population-level analysis of potential intervention effects. By understanding the forces contributing to disease progression, the model tested the effects of different interventions for prevention and treatment of type 2 diabetes based on the effectiveness of such reported in a meta-analysis of the relevant literature. By selecting to implement the analysis through use of the system dynamics modeling framework, the model grouped actors into categories or stocks concerned with the flow between conditions and factors influencing the rate at which these flows occur. The model presented considered feedback loops and unintended consequences that may arise from well-intentioned attempts for changing a system, as well as leverage points for interventions and potential effectiveness of such.

More specifically, the model tested different ecological level for physical activity interventions to reduce obesity and, ultimately, to affect incidence and prevalence of type 2 diabetes under optimal conditions for affecting populations within the community and among primary, secondary, and tertiary levels of prevention. The model framed the problem using the assumptions implicit in selection of a system dynamics model for testing such scenarios. The focus was on the effectiveness of physical activity interventions to guide decision-makers in future resource allocation and public health professionals to use appropriate methodologies for complex health problems that traditional linear approaches are unable to capture and thus unable to suggest informed routes for change. To this end, the model assessed and evaluated different “what if” scenarios of prevention and intervention strategies for reducing prevalence of (and ultimately incidence of) type 2 diabetes.

Parameterization of the model used data pertaining to the counties comprising this region or previously aggregated regional data, as well as data from other secondary sources when county-level or regional data was unavailable. The model acts as an example of how and when systems methods are useful in guiding resource allocation decisions by applying the approach to the real-world system-of-interest of type 2 diabetes in Texas's Health Service Region 11. More importantly, the model acts as an example of how selection of a modeling approach requires the modeler to make assumptions about the world and the mechanisms that produce the phenomenon-of-interest and that there must be a purpose to modeling the system-of-interest for the model to be of value (Lorenz and Jost 2006; Meadows and Robinson 1985).

2. SYSTEMS THEORY IN PUBLIC HEALTH*

2.1 Introduction

The recognition of the complexity of many public health problems has led to the search for analytic methods capable of capturing more fully the underlying dynamic processes at work compared to traditional study designs and statistical tests. Similarly, those with an interest in public health interventions have begun to see the limitations of standard methods, such as randomized trials and quasi-experiments, in understanding the consequences (both intended and unintended) of programs and policies designed to influence population-level health. This search for methods that move beyond a simple mechanistic cause-and-effect (or risk factor–outcome) representation of the world has stimulated interest among public health researchers in analytic techniques that have been developed within the evolving field of system sciences. These methods have proved successful in understanding complex adaptive phenomena in fields such as operations research, engineering, ecology, biology, and sociology. While there are a number of system science methods that have the potential to further public health research, to date, three methods have been most often applied in the field: agent-based modeling, social network analysis, and system dynamics modeling. Each method has strengths and weaknesses, and each is better suited to studying some aspects of complex dynamic phenomena than others. Agent-based models are especially good in addressing issues that involve heterogeneous

*Reprinted with permission from Elkins, A. D., and Gorman, D. M. 2014a. Systems theory in public health. *Oxford Bibliographies: Public Health*. Edited by D. McQueen. New York: Oxford Univ. Press. [doi: 10.1093/OBO/9780199756797-0072] actors and exploring phenomena that are thought to emerge from the interaction between such actors and their interactions with their environments. The agents in the model can learn and adapt over the course of the simulation, and the environment can change as a result of the interactions of the agents. The models can be used to test purely theoretical ideas or those grounded in real-life events or situations (e.g., the occurrence of violence in a specific city). In each case the goal is to identify the mechanisms through which the phenomena of interest emerged. System dynamics models typically group actors into categories or stocks and are concerned with the flow between these conditions and the factors that influence the rate at which these flows occur. This method is especially interested in feedback loops and the unintended consequences that can occur from well-intentioned attempts to change a system. Another key concept in system dynamics modeling is that of leverage points for successful interventions. These two aspects of the approach make it especially useful in policy analysis. Although social network analysis can also be used to understand basic theoretical principles of interactions between actors (e.g., six degrees of separation, weak and strong ties) it has primarily been used in public health research to examine relationships within datasets pertaining to either individuals (e.g., the spread of smoking over time within a large cohort study containing data on connectivity) or organizations (e.g., the exchange of resources among tobacco control agencies). This article provides practical guidance for those who wish to use these system methods in their own research, especially in the areas of social epidemiology, social and behavioral health, and policy analysis.

2.2 General Overviews

Five general overviews are presented in this section. The first of these is focused on the broad area of system sciences methods. The next section presents a series of references that discuss the broad application of systems methods to public health research. This is followed by sections that focus on each of the three specific system sciences methods reviewed in this bibliography: agent-based models, social network analysis and system dynamics models. In each case, key introductory texts pertaining to the method are reviewed along with articles that discuss the application of the method either to public health research in general or to some specific discipline within public health, such as social epidemiology, health promotion, or health-care policy.

2.2.1 Systems Methods

This section presents some introductory texts on systems methods and the intellectual roots of these approaches. The focus of these publications is on the general application of systems methods, especially in the social sciences, and not on their application within public health and its related disciplines (e.g., epidemiology, health-care policy analysis, social and behavioral health). In addition, the focus of these papers often goes beyond a discussion of the three systems methods most commonly employed in public health research. While most of the papers do discuss agent-based models, social network analysis, and system dynamics models, other systems methods such as spatial analysis, concept mapping, and cellular automata are also examined. Garson 2009 provides a succinct introduction, with examples, to the three methods discussed in this bibliography as well as spatial analysis. The focus is on applications in the social sciences. A more detailed account of such applications, along with a broader discussion of systems methods, is to be found in Gilbert and Troitzsch 1999. Lansing 2003 focuses on the application of system methods in anthropology, as well as providing a detailed account of its intellectual roots in chaos theory, nonlinear dynamical systems research, and the study of the evolution of cooperation. Miller and Page 2007 and Page 2013, a web resource, provide general introductions to the ideas of complex adaptive systems and systems sciences and the methods employed in the latter. Mitchell 2011 also provides a general introduction to the theories and methods used in the study of complex adaptive systems, while Shalizi 2006 reviews a wide range of systems methods.

Garson, G. D. 2009. Computerized simulation in the social sciences: A survey and evaluation. *Simulation & Gaming* 40.2: 267–279.

This paper briefly describes and discusses four simulation methods that are increasingly being used in social science research: agent-based models, social network analysis, system dynamics models, and spatial models. Examples of the application of each method are presented along with a discussion of their strengths and limitations.

Gilbert, N., and K. G. Troitzsch. 1999. *Simulation for the social scientist*. Philadelphia: Open Univ. Press.

This book begins with a history of the use of simulation models in the social sciences and a discussion of the underlying rationale for their use. It then discusses specific models in detail, including system dynamics models, agent-based models, cellular automata, microanalytical simulations, queuing models, and multilevel simulations.

Lansing, J. S. 2003. Complex adaptive systems. *Annual Review of Anthropology* 32: 183–204.

This paper discusses the intellectual roots of the idea of complex adaptive systems. It notes that while the concerns of those who study complex adaptive systems are similar to many of the issues at the heart of anthropology, only a few anthropologists have actually used system methods in their studies. Examples of anthropological applications are then discussed.

Miller, J. H., and S. E. Page. 2007. *Complex adaptive systems: An introduction to computational models of social life.* Princeton, NJ: Princeton Univ. Press.

This book presents a comprehensive overview of the idea of complex adaptive systems and the mathematical and computational methods that have been developed to explore these. It explains key systems concepts such as emergence, self-organization, and feedback, and uses ideas and examples from an array of social and natural sciences.

Mitchell, M. 2011. *Complexity: A guided tour.* New York: Oxford Univ. Press.

This book discusses complexity both conceptually and through computer modeling methods in terms of dynamics, chaos, prediction, information, computation, evolution, and real-world applications. Methods incorporate self-reproducing computer programs, genetic algorithms, cellular automata, particle computing, computational analogy creation, and network analysis and diagramming.

***Page, S. E. 2013. Model Thinking [https://class.coursera.org/modelthinking/lecture/index]*.**

This is a free ten-week course offered through Coursera on a fairly regular basis. The course lectures are also freely available on the Coursera web page irrespective of whether one is registered. The processes covered include segregation and peer effects, tipping points, path dependence, and collective action.

Shalizi, C. R. 2006. Methods and techniques of complex systems science: An overview. In *Complex systems science in biomedicine*. Edited by T. S. Deisboeck and J. Yasha Kresh, 33–114. New York: Springer.

This chapter divides complex systems science methods into three categories captured by purpose: data analysis, model construction and evaluation, and measuring complexity. The first includes statistical learning, data mining, and time series analysis; the second includes cellular automata, agent-based models, and evaluation; the third includes information theory and complexity measurements.

2.2.2 Systems Methods in Public Health

The papers in this section have a specific focus on the application of systems sciences to public health. Finegood, et al. 2012, a bibliography, reviews more than eighty texts and web resources that apply ideas from complexity theory and systems thinking to public health research. Luke and Stamatakis 2012, a review article, provides the best available account of the current application of agent-based modeling, social network analysis, and system dynamics modeling to public health research and the potential for their use in the future. Four of the remaining six general introductions to system science methods have a more specific focus on a particular aspect of public health research: epidemiology in the case of Galea, et al. 2010, health promotion in the case of Norman 2009, health-care organization and clinical practice in the case of Plsek and Greenhalgh 2001, and health-care services in the case of Willis, et al. 2012. The edited volume de Savigny and Adam 2009 also focuses on health-care systems, but with an emphasis on financing, intervention, and evaluation. Finally, Leischow, et al. 2008 makes a compelling case for the use of system science methods in transdisciplinary research and their potential for the furtherance of team-based science in public health.

Adam, T., and D. de Savigny, eds. 2012. Special issue: Systems thinking for health systems strengthening in LM ICs: Seizing the opportunity. *Health Policy and Planning* 27.4.

This report provides an introduction to systems thinking and a discussion of its potential for strengthening health-care systems, systems applications to intervention designs and evaluations, potential challenges faced when conducting such work, and future opportunities. It emphasizes leverage points and feedback in health-care system interventions and evaluations.

Finegood, D. T., L. Johnston, P. Giabbanelli, et al. 2012. *Complexity and systems theory.* Oxford Bibliographies: Public Health. New York: Oxford Univ. Press. [obo-9780199756797-0049]

This bibliography focuses on the intersection between complexity science, systems thinking, and public health. It reviews key theoretical and methodological texts and web resources, as well as reviewing literature that incorporates systems thinking into studying individual behavior change, program planning and evaluation, and knowledge implementation, translation, and dissemination.

Galea, S., M. Riddle, and G. A. Kaplan. 2010. Causal thinking and complex system approaches in epidemiology. *International Journal of Epidemiology* 39:97–106.

This paper contrasts complex systems approaches with traditional epidemiologic methods that focus on the identification of biological and behavioral risk factors. It also discusses the reasons why systems methods have not been more widely used in epidemiologic research (beyond infectious disease epidemiology) and concludes with an example of an agent-based model of obesity.

Leischow, S. J., A. Best, W. M. Trochim, et al. 2008. Systems thinking to improve the public's health. *American Journal of Preventive Medicine* 35.2: S196–S203.

This article discusses the importance of team science and transdisciplinary research in the successful application of systems science to public health problems. Examples from the National Cancer Institute's Initiative on the Study and Implementation of

Systems pertaining to tobacco control are used to illustrate this translational and transdisciplinary approach.

Luke, D. A., and K. A. Stamatakis. 2012. Systems science methods in public health: Dynamics, networks and agents. *Annual Review of Public Health* 33: 357–376.

This review begins by presenting the need for the use of complex systems methods in public health research and contrasting these methods with traditional study designs. It then describes system dynamic modeling, social network analysis, and agent-based modeling and shows how each approach can be used to address infectious disease, tobacco control, and obesity.

Norman, C. D. 2009. Health promotion as a systems science and practice. *Journal of Evaluation in Clinical Practice* 15.5: 868–872.

This paper presents a brief summary of some of the key concepts of systems science (e.g., sensitivity to initial conditions, selforganization, social networks, and leverage points) and shows how these are central to health promotion, which it defines as the science and practice of complex adaptive systems.

Plsek, P. E., and T. Greenhalgh. 2001. The challenge of complexity in health care. *British Medical Journal* 323: 625–628.

This paper presents a brief summary of some of the key concepts of systems science and complex adaptive systems (e.g., internalized rules, nonlinearity, and self-organization) and shows how these are central to health-care organization and management and clinical practice. Three other papers that appeared in the BMJ expand upon these themes. These are introduced in this paper and referenced therein.

Willis, C. D., C. Mitton, J. Gordon, and A. Best. 2012. Systems tools for systems change. *BMJ Quality and Safety* 21.3: 250–262.

This review focuses on the application of systems science tools to the widespread transformation of large-scale health-care systems. In addition to social network analysis and system dynamics modeling, it discusses concept mapping and program budgeting and marginal analysis. The benefits and limitations of each are described, and specific examples of their use in large system transformation are provided.

2.2.3 Agent-Based Models

The most accessible introduction to agent-based modeling is Gilbert 2008, a short primer. A more technical introduction to the methodology, which involves actual training in model building using the NetLogo platform, is provided in Railsback and Grimm 2012. Epstein 2006 provides an excellent overview of the application of agent-based models to a wide array of research questions in which the phenomenon of emergence is of central importance. Auchincloss and Diez Roux 2008; Galea, et al. 2008; and Israel and Wolf-Branigin 2011 provide introductions to agent-based models that are more specifically focused on their potential applications in epidemiology and social service evaluation research. Finally, Grimm, et al. 2006 presents a protocol that researchers should use in reporting the results of simulations based on agent-based models, while Berk 2008 describes criteria that can be used in assessing the quality and validity of agent-based research.

Auchincloss, A. H., and A. V. Diez Roux. 2008. A new tool for epidemiology: The usefulness of dynamic-agent models in understanding place effects on health. *American Journal of Epidemiology* 168.1: 1–8.

This paper discusses the limitations of traditional epidemiologic study designs and regression models in assessing the effects of place on health. Agent-based models are presented as a way of overcoming these problems, and a model of the spatial patterning of physical activity is described. The challenges of developing agent-based models and their validation are then discussed.

Berk, R. 2008. How you can tell if the simulations in computational criminology are any good. *Journal of Experimental Criminology* 4: 289–308.

This paper begins with a brief discussion of assessing the theoretical (qualitative) credibility of agent-based models and then presents six detailed steps to be used in data-based (quantitative) assessment of models. The steps, which are applicable beyond criminological models, include specification of model inputs and parameters, the collection of data, and analyzing model output.

Epstein, J. M. 2006. *Generative social science: Studies in agent-based computational modeling*. Princeton, NJ: Princeton Univ. Press.

This book collects thirteen of Joshua Epstein's papers describing work he has conducted using agent-based models. It begins with an account of the place of agent-based modeling within generative social science and then describes a number of applications including population growth and decline, social norms, civil unrest, and smallpox bioterrorism.

Galea, S., C. Hall, and G. A. Kaplan. 2008. Social epidemiology and complex system dynamic modeling as applied to health behavior and drug use research. *International Journal of Drug Policy* 20.3: 209–216.

This paper discusses the limitations of traditional epidemiologic methods in addressing health issues of concern to social epidemiologists and the potential of complex systems analytic approaches in advancing understanding of health behavior. It uses an agent-based model of drug use behavior to illustrate the utility of such approaches in social epidemiology.

Gilbert, N. 2008. *Agent-based models.* Thousand Oaks, CA: SAGE.

This book presents a very succinct and nontechnical account of agent-based modeling. It describes the underlying rationale for the approach, the basic components and features of agent-based models, and their use in social science research. It also introduces and compares various agent-based programs such as NetLogo and Repast.

Grimm, V., U. Berger, F. Bastiansen, et al. 2006. A standard protocol for describing individual-based and agent-based models. *Ecological Modeling* 198: 115–126.

Noting the fundamental importance of reproducing observations in science, this paper describes a standard protocol to be used in the reporting of individual- and agent-based models so as to facilitate them being understood and replicated by others. The protocol has seven elements that are grouped into three categories: overview, design concepts, and details.

Israel, N., and M. Wolf-Branigin. 2011. Nonlinearity in social service evaluation: A primer on agent-based modeling. *Social Work Research* 35.1: 20–24.

This paper describes how social service research may benefit from using agent-based models in evaluating services through applying complexity theory to model nonlinear behaviors of people and of organizations. It discusses modeling concepts used in evaluation related to agents, interconnectedness, patterns, contextual change or co-evolution, behavioral ranges, and unpredictable behavior shifts.

Railsback, S. F., and V. Grimm. 2012. *Agent-based and individual-based modeling: A practical introduction.* Princeton, NJ: Princeton Univ. Press.

This textbook is for introductory social science and biology graduate classes (and independent study) in agent-based modeling. Using the software program NetLogo, it provides step-by-step training in model building, starting with fundamental design concepts (e.g., emergences, adaptation, interaction), then moving to theory development, parameterization, and calibration, and ending with model validation and analysis.

2.2.4 Social Network Models

A very brief introduction to social network analysis is presented in Borgatti, et al. 2009, with an emphasis on the type of problems that social scientists have addressed using this method. A concise introduction to the analytic methods of social network analysis is provided in Knoke and Yang 2008, and a more in-depth treatment of these can be found in Wasserman and Faust 1994. Reviews of the extant research literature on the application of social network analysis to public health problems are presented in Luke and Harris 2007 and Smith and Christakis 2008. Valente 2010 also reviews a number of key public health studies that have utilized social network analysis, as well as discussing data sources, data collection techniques and analytical tools. Hawe, et al. 2004 provides a glossary of terms used in social network analysis, while Christakis and Fowler 2009 focuses on the methods used to represent social network structure in epidemiological research.

Borgatti, S. P., A. Mehra, D. J. Brass, and G. Labianca. 2009. Network analysis in the social sciences. *Science Magazine* 323: 892–895.

This paper reviews social network analysis through a social science perspective, emphasizing historical context, basic assumptions, goals, and explanatory mechanisms. Social scientists' use of this approach focuses on individuals embedded in networks of social interactions and relationships, on answering the social order problem, and phenomena related to how autonomous individuals combine to create stable, functioning societies.

Christakis, N. A., and J. H. Fowler. 2009. Social network visualization in epidemiology. *Norsk Epidemiology* 19.1: 5–16.

This paper describes the fundamental attributes of social networks (e.g., nodes and edges), their basic topologies (e.g., small world, random graph, lattice), and the techniques used to represent them visually and to statistically analyze their properties. These aspects of social network analysis are illustrated using examples from the Framingham Heart Study and analysis of online networks.

Hawe, P., C. Webster, and A. Shiell. 2004. A glossary of terms for navigating the field of social network analysis. *Journal of Epidemiological and Community Health* 58: 971–975.

This paper provides a glossary of social network analysis terminology. It emphasizes the need for network analysis to be tailored to context and to utilize varying methods to help elucidate understanding across research fields. It discusses network constructs (e.g., structure, actors, ties, and modes) and measurement techniques (e.g., centrality, reachability, and density).

Knoke, D., and S. Yang. 2008. *Social network analysis.* 2nd ed. Thousand Oaks, CA: SAGE.

This introductory text discusses the basic principles and components of social network analysis, procedures used in data collection, and both basic and advanced methods for analyzing network structure and attributes.

Luke, D. A., and J. K. Harris. 2007. Social network analysis in public health: History, methods, and applications. *Annual Review of Public Health* 28: 69–93.

This paper discusses how network analysis helps one understand the structural and relational aspects of health through the discussion of history and development of network analysis and four network paradigm features. Network analysis is a structural approach focusing upon linkage patterns between actors, is grounded empirically, uses mathematical and computational models, and is graphical.

Smith, K. P., and N. A. Christakis. 2008. Social networks and health. *Annual Review of Sociology* 34: 405–429.

This paper discusses the impact of social networks on health via a literature review, distinguishes between social support and social network, reviews network influences on health from two types of analyses, provides future directions for social network research, and identifies policy implications. Analyses types include egocentric networks and sociocentric networks.

Valente, T. W. 2010. Social networks and health: Models, methods, and applications. New York: Oxford Univ. Press.

This book begins with a discussion of the history of social network analysis, types of network data, and data collection methods. It then examines how network analysts measure network qualities such as centrality, position, and density. It concludes with a discussion of specific applications, including diffusion of innovations and ways of intervening in networks.

Wasserman, S., and K. Faust. 1994. *Social network analysis: Methods and applications.* New York: Cambridge Univ. Press.

This is the most comprehensive text available on social network analysis. Its six sections cover types of network perspectives and data, mathematical representations, structural and locational properties, methods for assessing roles and positions, properties of dyads and triads, and statistical methods used in network analysis.

2.2.5 System Dynamics Models

The field of system dynamics developed out of the work of Jay W. Forrester and his colleagues in the area of organization and management studies. A very accessible account of this intellectual history, which also contains a clear account of the key constructs of system dynamics models, is presented in Forrester 2007. Sterman 2000 is the most detailed and extensive text on system dynamics modeling available, with application and relevance far beyond business and organization studies. While it contains some mathematical formulae, it is easily accessible to a nontechnical audience and is an indispensable resource in this field of research. The book comes with a CD that contains system software and models. The underlying principles of system dynamics modeling, which are discussed in detail at the beginning of Sterman 2000, are reframed and expanded upon for a public health audience in Sterman 2006. The potential application of system dynamics models to public health research is also the focus of Homer and Hirsch 2006. One issue that frequently arises in the field of systems research is how one judges the quality of models. Rahmandad and Sterman 2012 and Groesser and Schwaninger 2012 focus on different aspects of this problem, the former setting out guidelines for the reporting of simulation models in the scientific literature and the latter describing procedures through which model validity might be assessed. Finally, for those interested in exploring the association between system dynamics as a theory (with its emphasis on circular causality and feedback) and key theoretical traditions within the social sciences, Richardson 1991 is an essential read.

Forrester, J. W. 2007. System dynamics—a personal view of the first fifty years. *System Dynamics Review* 23.2–3: 345–358.

This paper contains a historical account of the development of system dynamics modeling by its founder. Forrester describes the process through which the field was initiated and some of the key projects in which he has been involved. He also comments on the current state of the field.

Groesser, S. N., and M. Schwaninger. 2012. Contributions to model validation: Hierarchy, process, and cessation. *System Dynamics Review* 28.2: 157–181.

This paper discusses validation of system dynamics models through a complexity hierarchy of tests, an integrative validation process, and a heuristic approach to ceasing formal validity testing. The validation cessation threshold demarcates validation activity cessation based upon target group experience, relative importance, costs, potential degree, model size, target group expectations, data intensity and availability, and expertise.

Homer, J. B., and G. B. Hirsch. 2006. System dynamics modeling for public health: Background and opportunities. *American Journal of Public Health* 3: 452–458.

This paper discusses the potential application of system dynamics models to public health issues, with an emphasis on chronic disease prevention. This is illustrated by a model that examines the effects of upstream prevention of disease onset with downstream prevention of disease complications on disease incidence, prevalence, and related deaths.

Rahmandad, H., and J. D. Sterman. 2012. Reporting guidelines for simulation-based research in social sciences. *System Dynamics Review* 28.4: 396–411.

This paper describes specific guidelines for the reporting of results from simulation-based system dynamics research. The guidelines, which are divided into minimal and preferred requirements, focus on model visualization and the reporting of models, simulation experiments, and optimization experiments. An illustrative model is presented as an example of how to use the reporting guidelines.

Richardson, G. P. 1991. Feedback thought in social science and systems theory. Waltham, MA: Pegasus.

Feedback is one of the key concepts used in system dynamics models. This book describes the evolution of the idea of feedback loops in the social sciences in terms of two threads: cybernetics and servomechanisms. System dynamics is a core discipline within the latter thread.

Sterman, J. D. 2000. *Business dynamics: Systems thinking and modeling for a complex world.* Boston: McGraw Hill.

This is the most comprehensive text available on system dynamics models. A wide range of examples are discussed in detail, including models of epidemics and innovation diffusion. The book is designed to be accessible to those with little mathematical training; the models are explained primarily through detailed stock and flow diagrams.

Sterman, J. D. 2006. Learning from evidence in a complex world. *American Journal of Public Health* 96.3: 505–514.

This paper discusses the challenges faced by public health researchers and policymakers in dealing with phenomena that are inherently complex and dynamic and the problems, such as implementation failure, that these can create. It suggests ways in which system dynamics thinking and modeling can improve both public health science and practice.

2.3 Underlying Theoretical Constructs

While the focus of the present article is on the application of systems methods to the understanding of public health problems, this section reviews some key texts that describe in a manner that is accessible to a wide audience the fundamental theoretical constructs underlying agent-based modeling, social network analysis, and system dynamics modeling. Each paper also contains numerous references that include more in-depth and technical discussion of these theoretical constructs. Granovetter 1973 and Centola and Macy 2007 discuss key attributes of social ties such as strength (i.e., strong and weak) and length (i.e., whether they form bridges within or across social networks) and the types of social phenomena and collective behaviors that diffuse most effectively across these different types of network structures. Watts 2004 also discusses key constructs pertaining to social network structures such as small worlds and scale-free networks. Two fundamental ideas that underlay the development of agent-based modeling are emergence and mechanisms. The two are related in that agent-based models strive to identify the underlying social mechanisms (e.g., preference or grievance) that explain the emergence of specific social phenomena (e.g., racial segregation or civil unrest). The idea of emergence is discussed in Cederman 2005 and the concept of causal mechanisms in Hedstrom and Ylikoski 2010; each paper discusses the theoretical roots of the idea within the field of sociology. The key theoretical constructs used in system dynamics modeling are stocks, flows, intermediate variables, delays, and feedback loops. These are described in detail in Groesser and Schaffernicht 2012, a paper that uses system dynamics to explicate the conceptual structure of mental models of dynamic systems. Wolstenholme 1992 describes a step-by-step approach to developing system dynamics models that also contains very good descriptions of the model components and how they relate to one another. Finally, Richardson 2011 presents a very thorough account of the central role played by feedback mechanisms in system dynamics models.

Cederman, L. E. 2005. Computational models of social forms: Advancing generative process theory. *American Journal of Sociology* 110.4: 864-893.

Agent-based models are especially useful for examining the emergence of social phenomena from the interactions of individual agents over time. This paper examines this generative approach to social theory development, explores its epistemological roots, and contrasts it with traditional approaches to theory development focused on the identification of laws and regularities.

Centola, D., and M. Macy. 2007. Complex contagions and the weakness of long ties. *American Journal of Sociology* 113.3: 702–734.

This paper challenges the idea that social phenomena inevitably diffuse more effectively through weak ties. Specifically, it contends that adoption of those forms of collective behavior that are risky, controversial, or costly usually requires reinforcement through multiple contacts within networks composed of strong ties.

Granovetter, M. S. 1973. The strength of weak ties. *American Journal of Sociology* 78.6: 1360–1380.

Prior to the publication of this paper social network models tended to focus on strong ties between individuals. Granovetter's paper made the case for the importance of weak ties in the transmission of social phenomena such as trust both within and across social networks.

Groesser, S. N., and M. Schaffernicht. 2012. Mental models of dynamic systems: Taking stock and looking ahead. *System Dynamics Review* 28.1: 46–68.

This paper discusses mental models of dynamic systems (MMDS) through a review of the literature and comparison of conceptual structures used in measurement, aiming to extend the conceptual structure and enhance these models. It reviews and contrasts MMDS concepts, reviews MMDS research and develops a preliminary conceptual template, and introduces dynamic systems theory.

Hedstrom, P., and P. Ylikoski. 2010. Causal mechanisms in the social sciences. *Annual Review of Sociology* 36:49–67.

Agent-based models are especially useful in the development of mechanism-based explanations of phenomenon. This article describes the theoretical and philosophical underpinnings of the mechanism-based approach, its application in the social sciences, and the role of agent-based simulations in formulating and testing mechanistic social theories.

Richardson, G. P. 2011. Reflections on the foundations of system dynamics. *System Dynamics Review* 27.3: 219–243.

This paper begins with a review of Jay W. Forrester's writing that established the field of system dynamics. It goes on to assert that endogeneity is the distinguishing feature of the system dynamics approach, and illustrates this through discussion of specific models and simulations pertaining to climate change, flood damage, and terrorism.

Watts, D. J. 2004. The "new" science of networks. *Annual Review of Sociology* 30: 243–270.

This paper reviews developments in the field of social network analysis pertaining to network structures (e.g., small worlds and scale-free networks) and the empirical analysis of these structures. It discusses specific applications relevant to public health including the spread of infectious disease and the idea of social contagion.

Wolstenholme, E. F. 1992. The definition and application of a stepwise approach to model conceptualisation and analysis. *European Journal of Operational Research* 59: 123–136.

This paper distinguishes between the feedback loop approach and the modular approach to system dynamics model construction. It explains how system behavior, conceptualization and analysis, feedback, boundaries, and delays affect structure diagramming, with predominant focus upon the modular approach giving

consideration to process structures, delays, boundaries, and information structure and strategy.

2.4 Comparison and Combinations of Methods

Each of the system science methods discussed in this bibliography has strengths and weaknesses and is better suited to addressing some public health issues than others. A direct comparison of methods that reports the results of specific simulation experiments helps highlight these strengths and weaknesses and the suitability of the method for answering specific research questions. To date, most papers that report a direct comparison of the results of simulations based on the different approaches have focused on agent-based models and system dynamics models. Seven of the eight papers reviewed in this section involve such a comparison, and four focus on the spread of infectious disease, as this is an area in which both models have seen fairly widespread application. Bobashev, et al. 2007; Macal 2010; Rahmandad and Sterman 2008; and Epstein, et al. 2008 all apply agent-based models and system dynamics models to the diffusion of infectious disease, with the latter also examining the dynamics of the spread of fear of the disease. Rahmandad and Sterman 2008 also builds different social network structures into the agent-based model. Swinerd and McNaught 2012 discusses three types of hybrid models based on agent-based and system dynamics models and presents specific examples from the published literature of models that fall within each of the three types. Two of the papers in this section also include a third systems method in the comparison. In addition to agent-based and system dynamics models, Borshchev and Filippov 2004 examines a discrete events model, which is defined as a model based on the concepts of entities, resources, and block charts describing entity flow and resource sharing. Palmius and Persson-Slumpi 2010 compares a cellular automata model, an agent-based model, and a system dynamics model of movement of people through a coffee shop and assesses the validity of each in terms of descriptive realism and ease of enrichment and fertility. Only El-Sayed, et al. 2012 involves a comparison of social network analysis with one of the other two system sciences methods, namely agent-based modeling.

Bobashev, G. V., J. M. Epstein, D. M. Goedecke, and F. Yu. 2007. A hybrid epidemic model: Combining the advantages of agent- based and equation-based approaches. In *Proceedings of the Winter Simulation Conference, 9–12 December 2007, Washington, DC.* Edited by S. G. Henderson, N. Niller, M.H. Hsieh, J. Shortle, J. D. Tew, and R. R. Barton, 1532–1537. New York: Association for Computing Machinery.

This paper describes a hybrid simulation model that takes advantage of the strengths of the agent-based approach to understand the dynamics of the initiation of an epidemic process when uncertainty is high and the strengths of the equation-based approach to more efficiently understand an ongoing epidemic when uncertainty is low.

Borshchev, A., and A. Filippov. 2004. *From system dynamics and discrete event to practical agent based modeling: Reasons, techniques, tools[http://www.informs-sim.org/wsc07papers/186.pdf]*. In *Proceedings of the 22nd International Conference of the System Dynamics Society, 25–29 July 2004, Oxford, England*. Edited by M. Kennedy, G. W. Winch, R. S. Langer, J. I. Rowe, and J. M. Yanni. Albany, NY: Systems Dynamics Society.

This paper compares system dynamics models and agent-based models through an examination of their application to a number of specific research issues (e.g., alcohol use dynamics). It highlights the advantages of agent-based models, but acknowledges that the nature of the problem being addressed should guide which modeling approach to employ.

El-Sayed, A., P. Scarborough, L. Seemann, and S. Galea. 2012. *Social network analysis and agent-based modeling in social epidemiology [http://www.epi-perspectives.com/content/9/1/1]*. *Epidemiologic Perspectives and Innovations* 9: 1.

This paper examines current and potential applications of social network analysis and agent-based modeling in social epidemiology. It highlights the problems faced by the field that each method has the potential to address in ways that are superior to traditional epidemiological methods. It also discusses the limitations of each method.

Epstein, J. M., J. Parker, D. Cummings, and R. A. Hammond. 2008. *Coupled dynamics of fear and disease: Mathematical and computational explorations [http://www.plosone.org/article/info%3Adoi%2F10.1371%2Fjournal.pone.0003955]*. *PLoS ONE* 3.12: e3955.

This paper describes the use of both a system dynamics model and an agent-based model to understand the spread of two contagious processes: infectious disease and fear of disease. The first model presented is an SIR differential equation model in which fear can spread independent of disease. An agent-based model, which includes spatial flight, is then presented.

Macal, C. M. 2010. To agent-based simulation from system dynamics. In *Proceedings of the 2010 Winter Simulation Conference, 5–8 December 2010, Baltimore, M D*. Edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 371–382. Piscataway, NJ: IEEE.

This paper compares two agent-based simulations with a system dynamics model of the Kermack-McKendrick SIR model of infectious disease epidemics. One version of the agent model is similar to the system dynamics model in that agent types are defined as classes corresponding to the three disease states (SIR) while the other uses a stochastic process to model transition between states.

Palmius, J., and T. Persson-Slumpi. 2010. A comparison of three approaches to model human behavior. In *AIP conference proceedings: Ninth International Conference on Computing Anticipatory Systems, 3–8 August 2009, Liege, Belgium*. Vol. 1303. Edited by D. M. Dubois, 354–362. Melville, NY: American Institute of Physics.

This paper compares three simulation approaches (cellular automata, system dynamics, and agent-based modeling) using three different software packages (Stella, CaFun, and SesAM) by simulating behavior in a coffee room. Models vary in terms of insight generating capacity, focus, spatiality, world view, and view of the individual, as well as descriptive realism, enrichment ease, and fertility.

Rahmandad, H., and J. Sterman. 2008. Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. *Management Science* 54.5: 998–1014.

This paper compares the output of a system dynamics model of contagious disease diffusion with agent-based models that vary in terms of agent heterogeneity and network structure (fully connected, random, scale-free, small world and ring lattice). The results are assessed for sensitivity to population size, the basic reproductive number, disease natural history, and model boundary.

Swinerd, C., and K. R. McNaught. 2012. Design classes for hybrid simulations involving agent-based and system dynamics models. *Simulation Modeling Practice and Theory* 25: 118–133.

This paper discusses three types of hybrid agent-based system dynamics simulations (interacted, integrated, and sequential hybrid designs) to gain understanding of these combinations and because they might offer potentially useful approaches to modeling complex adaptive systems. Choosing the most appropriate design involves consideration of system scale, unit and time management, and degrees and representation of agency.

2.5 Platforms and Software Packages

There are a wide variety of platforms available for agent-based modeling, social network analysis, and system dynamics modeling. The following two sections provide resources for those wishing to familiarize themselves with these platforms and software packages and to make comparisons between them. They also provide a set of references to specific platforms and software packages, some of which are commercially available and others of which are open-access.

2.5.1 Reviews of Platforms and Software

A comprehensive review and discussion of the software used in social network analysis can be found in Huisman and van Duijn 2005, while Nikolai and Madey 2009 presents a similar review of available agent-based modeling platforms. A more detailed, but nontechnical, review of five of the most popular agent-based software packages is found in

Railsback, et al. 2006. Online introductions to a number of software programs used by system dynamics researchers are provided by Forrester Consulting and SD Mega Link List. Forrester Consulting: System Dynamics Resources. This weblink provides a list of system dynamics resources published by Forrester Consulting. It includes resources of the System Dynamics Society, academic centers and education projects, simulation software, training, organizations, companies, and people, as well as links to other sources.

Huisman, M., and M. A. J. van Duijn. 2005. Software for social network analysis. In *Models and methods in social network analysis*. Edited by P. J. Carrington, J. Scott, and S. Wasserman, 270–316. Cambridge, UK: Cambridge Univ. Press.

This paper begins with a brief overview of twenty-three programs used in social network analysis. It then presents a detailed review of six of these programs that are either well-known or have features that warrant discussion. It finishes with a review of nine programs that can be used for more specialized network analysis.

Nikolai, C., and G. Madey. 2009. *Tools of the trade: A survey of various agent based modeling platforms[http://jasss.soc.surrey.ac.uk/12/2/2.html]*. *Journal of Artificial Societies and Social Simulation* 12.2.

This paper reviews more than fifty agent-based modeling platforms in terms of the following five features: programming language, type of license governing use, type of operating system, primary domain for which the platform was designed, and amount of support available to the platform user.

Railsback, S. F., S. L. Lytinen, and S. K. Jackson. 2006. Agent-based simulation platforms: Review and development recommendations. *Simulation* 82:609–623.

This paper reviews and compares five widely used agent-based model platforms: MASON, NetLogo, Repast, Java Swarm and Objective-C Swarm. The review is aimed at those who, while not expert in software development, wish to use agent-based models in their research.

***SD Mega Link List[http://wwwu.uni-klu.ac.at/gossimit/linklist.php?uk=3]*.**

This weblink by G. Ossimitz provides a list of system dynamics and systems thinking simulation tools, as well as short summaries of each. Berkeley Madonna, Decision Support Associates, Dynasys, Extend, Heraklit, MindMapper, Modeling with Molecules, MyStrategy, Powersim, SDML, SimApp, SIMGUA, Stella, T21, Vensim, Ventana Systems, Inc., and What If? are included.

2.5.2 Widely Used Platforms and Software

This section highlights some of the platforms and software packages that are most commonly used by researchers who are applying agent-based modeling, social network analysis, and system dynamics modeling to public health problems. NetLogo, RePast and Swarm are widely used platforms for agent-based modeling. Payjek and UCINET are two of the most popular software packages used in social network analysis. In the field of system dynamics modeling, Stella and Vensim are among the most popular programs. Finally, Enthought Python Distribution is a specialist programming language that allows for the creation of agent-based, social network, and system dynamics simulations.

***Enthought Python Distribution[http://www.enthought.com/products/epd.php]*.**

This package (distributed by Enthought, Inc.) contains a series of useful tools for scientific computing using the Python dynamic programming language, allowing for an array of simulations, including agent-based models, system dynamics models, and social network analysis. It was intended for audiences with programming experience, though is considered a basic programming language to learn.

***NetLogo[http://ccl.northwestern.edu/netlogo/]*.**

This program was developed at Northwestern University's Center for Connected Learning and Computer-Based Modeling to explore emergent phenomena via agents in a programmed model environment. It was intended for audiences without programming experience and for children in education and comes with a variety of sample models, including system dynamics models.

***Payjek[http://vlado.fmf.uni-lj.si/pub/networks/pajek/]*.**

This package was developed by Vladimir Batagelj and Andrej Mrvar at the University of Ljubljana to analyze and visualize large networks, including single node, bipartite, and exploratory networks, on Windows computers. It was intended for researchers and includes published network analysis algorithms (e.g., network diameter, cluster coefficient, and network density).

***RePast[http://repast.sourceforge.net/]*.**

This package was developed by individuals at the University of Chicago for agent-based modeling and simulations with options for a variety of agents, adaptive features, as well as social network, geographic information systems, and system dynamics built-ins. This package is intended for users with programming experience but supports a variety of languages and is completely object-oriented.

***Stella[http://www.iseesystems.com/softwares/Education/StellaSoftware.aspx]*.**

This program was developed by ISEE Systems Inc. to foster understanding of complex systems for educators and researchers using box mapping and modeling that allows for creation and focus on hierarchical models. It enables simulation and analysis of stock and flow diagrams and causal loop diagrams with built-in mathematical, statistical, and logical operations.

***Swarm[http://savannah.nongnu.org/projects/swarm]*.**

This software or library of object-oriented classes was developed by the Santa Fe Institute as a tool for multi-agent models of complex systems, wherein users must write the software, but can utilize the Swarm conceptual framework and libraries to implement ABMs. It was intended for audiences with experience in Objective-C or Java programming.

***UCINET[https://sites.google.com/site/ucinetsoftware/home]*.**

This program (distributed through Analytic Technologies) was developed by Lin Freeman, Martin Everett, and Steve Borgatti and is used to analyze and display network visualizations. It was intended primarily for researchers, offers flexibility in importing data from varying formats, and can support analysis of up to 2 million nodes.

***Vensim[http://vensim.com/]*.**

This program was developed by Ventana Systems, Inc., for developing and analyzing system dynamic models, and allows for instant data output and model optimization using refined calibration methods. Stock and flow diagrams and causal loop diagrams can communicate with external data sets (e.g., an Excel file) for powerful data analysis.

2.6 Journals

Most public health research that uses systems methods is published in medical and public health journals or subject-specific journals such as those focused on alcohol and drug use or policy and operations research. Of the public health journals, the American Journal of Public Health has been most active in the promotion of systems methods and has recently produced two thematic issues. The major journals that focus on the three specific systems methods discussed in this article have not been a primary outlet source for publications that focus on the application of such methods to public health problems. However, this is beginning to change as these methods become more widely used in public health, and these specialist journals are obviously key resources for those wishing to build upon their knowledge of social network analysis, agent-based modeling, and system dynamics modeling.

2.6.1 Thematic Issues of Journals

Two recent issues of the American Journal of Public Health have been devoted entirely to systems theories and methods and their application in public health research. The first of these is McLeroy, et al. 2006, which contains editorials and papers that focus on the use of systems science theory and methods by researchers addressing a range of public health issues. Of the three methods discussed in the present article, system dynamics models are the most frequency used and discussed in the papers that appear in this special issue. The second special issue, Mendez 2010, contains editorials and papers that focus specifically on the issue of tobacco control. A number of the papers included use system dynamics models or social network analysis. The importance of the National Cancer Institute (NCI) Initiative on the Study and Implementation of Systems in stimulating interest in the application of systems methods in the area of tobacco control is also highlighted in a number of the papers included in this special issue. The special issue of Health Policy and Planning Adam and de Savigny 2012 is focused on the potential for the application of systems thinking and methods for understanding health systems in low- and middle-income countries. Among the papers included are an overview of systems concepts, a review of the extent to which evaluations of interventions in the area have been informed by a systems perspective, and two case studies of specific interventions in Ghana (one focused on an additional duty hours allowance policy and one focused on a voucher system for malaria prevention).

Adam, T., and D. de Savigny, eds. 2012. Special issue: Systems thinking for health systems strengthening in LM ICs: Seizing the opportunity. *Health Policy and Planning* 27.4.

The focus of this supplement is on the application of systems thinking to policy interventions and their evaluation in low- and middleincome countries. The volume includes general conceptual papers, methodological papers, and detailed case studies of evaluations of interventions intended to strengthen health-care delivery systems.

McLeroy, K., S. J. Leischow, and B. Milstein, eds. 2006. Special issue: Thinking of systems. *American Journal of Public Health* 96.3.

Contains articles describing the application of a variety of systems methods (including system dynamics models, Markov models, multi-scale analysis, and concept mapping) to a range of public health issues (including tobacco control, healthcare delivery and chronic disease). It also contains editorials and conceptual pieces discussing the benefits derived from the application of systems thinking to complex health issues.

Mendez, D., ed. 2010. Special issue: A systems approach to a complex problem. *American Journal of Public Health* 100.7.

Contains articles describing the application of a variety of systems methods to tobacco control. In addition to editorials summarizing the contributions of systems science to tobacco control research, papers are included that describe applications to specific policy initiatives such as online smoking cessation and national smoking prevention networks.

2.6.2 Major Systems Research Journals

Most applications of system sciences methods to public health issues are published in public health, medical, or social science journals. However, specialist system sciences journals have begun to publish public health research. This section presents details of some of the major journals in this field that have a focus that is likely to be of interest to public health researchers. *Computational and Mathematical Organizational Theory, Simulation in Healthcare,* and *Systems Research and Behavioral Science* all publish articles that report on the application of systems methods to organizations, health-care services, and human behavior. The *Journal of Artificial Societies and Social Simulation* and the *Journal of Social Structure* are both open-access general systems journals, and each publishes research that will be of interest to public health investigators concerned with issues pertaining to social structure and health behavior. Finally, as their titles indicate, the *System Dynamics Review* and *Social Networks* are both specialized journals focused on one specific systems science method.

***Computational and Mathematical Organizational Theory**

[http://www.springer.com/business%2B%26%2Bmanagement/business%2Bfor%2Bprofessionals/journal/10588]*.

Computational and Mathematical Organizational Theory publishes interdisciplinary theoretical and applied research articles that focus on questions pertaining to computational methods and models, organizations, and society. It is published quarterly and is especially interested in papers that focus on new theoretical developments and modeling techniques that can be used to explain and predict the behavior of complex adaptive systems.

***Journal of Artificial Societies and Social Simulation* [http://jasss.soc.surrey.ac.uk/JASSS.html]*.**

First published in 1998, the Journal of Artificial Societies and Social Simulation is an interdisciplinary journal devoted to the exploration of social process through the application of computer simulations. It is published quarterly and is freely available online.

***Journal of Social Structure*[http://www.cmu.edu/joss/content/articles/volindex.html]*.**

The Journal of Social Structure is an interdisciplinary electronic journal of the International Network for Social Network Analysis. It publishes theoretical, methodological, and empirical articles focused on the effects of social structure (defined as linkages between social entities) on the behavior and lives of animals, humans, groups, and organizations. The articles it publishes can be freely accessed online.

Simulation in Healthcare

[http://journals.lww.com/simulationinhealthcare/pages/default.aspx]*.

Simulation in Healthcare is the journal of the Society for Simulation in Healthcare and was first published in 2006. It has a multidisciplinary orientation and publishes basic, clinical, and translational research that applies simulation technology to a wide range of health-care issues including epidemiological models of disease, education and training, and molecular and pharmacological modeling.

******Social Networks*****[http://www.journals.elsevier.com/social-networks/]*.**

Social Networks is an interdisciplinary journal that publishes empirical and theoretical papers focused on the understanding of social relations through the application of social network ideas and methods. It is published quarterly and includes papers that use a wide range of systems science methods, from individual case studies through formal mathematical modeling.

******System Dynamics Review*****[http://onlinelibrary.wiley.com/journal/10.1002/(ISSN)1099-1727]*.**

First published in 1985, System Dynamics Review is the journal of the System Dynamics Society. It is published quarterly and includes papers from researchers in the natural and social sciences, as well as engineering and policy analysis, focused on the application of system dynamics methods to social, managerial, technical, and environmental problems.

Systems Research and Behavioral Science

[http://www.wiley.com/WileyCDA/WileyTitle/productCd-SRBS.html]*.

Systems Research and Behavioral Science is the official journal of the International Federation for Systems Research. It has an interdisciplinary focus and publishes theoretical and empirical articles that apply systems approaches to a wide range of issues including organizational and societal structures, business and management processes, scientific ideas, and norms and values. It is published six times a year.

2.7 Applications to Public Health Problems

The following sections focus on the application of systems science methods to ten specific areas of public health theory and research: alcohol use and misuse, chronic disease, community interventions, drug use and misuse, health-care services, health disparities, mental health, obesity, tobacco use, and violence. Where possible, each of the three system science methods is represented in each of the sections; that is, an attempt is made to include at least one paper using agent-based modeling or social network analysis or system dynamics models. However, this is not always possible because not all methods have been applied to each of these public health areas and some methods clearly lend themselves better to some research questions than others. For the most, the papers included describe the results of a simulation or empirical study that applied a systems methodology to a specific research question. However, in instances where a reasonable body of literature is available review articles are included. It should also be noted that the distinction between categories is not rigid and that a number of papers could appear in more than one category. For example, alcohol dependence, drug dependence, and obesity are all chronic relapsing conditions, so a number of papers that deal with these conditions could have been cited under the chronic disease category. Similarly, a number of the papers that focus on a specific health condition, such as alcohol or drug misuse, use systems methods to estimate the effects of different types of policies; thus, these might have been included under the health-care services category as well as under the category describing the health condition.

2.7.1 Alcohol Use and Misuse

Alcohol use has a number of features that make the study of it amenable to the application of system sciences methods. First, it is an adaptive behavior that is influenced by social context and the environment. Second, it is a behavior that often takes place in social settings and hence whether one drinks, and how much one drinks, is influenced by the drinking of those with whom one interacts. Third, there is a long tradition in alcohol studies of classifying drinkers into types and examining how individuals move from one drinking state (e.g., moderate drinking) to another (e.g., heavy drinking). Such movement and the effect of social context on this are studied in the system dynamics model described in Mubayi, et al. 2010. Like the model developed in Scribner, et al. 2009, this was parameterized using data on college drinkers and is composed of different drinking compartments. Scribner, et al. 2009 also uses its model to test two basic types of control measures. This work is further developed in Fitzpatrick, et al. 2012 and Rasul, et al. 2011 by using the model to estimate the effects of two very specific policies that have been proposed regarding college drinking. Gorman, et al. 2006 also uses types of drinkers in its very basic agent-based model of drinking behavior. A more sophisticated, theoretically grounded agent-based model is presented in Fitzpatrick and Martinez 2012. Here both the agents (drinkers) and environment (bars) display adaptive behavior. Braun, et al. 2006 is also theoretically grounded, applying small-world network ideas to the spread of alcohol dependence. Finally, the social network analysis presented in Rosenquist, et al. 2010 is one of a number of studies that have resulted from the application of social network analysis to the various cohorts of the Framingham Heart Study.

Braun, R. J., R. A. Wilson, J. A. Pelesko, and J. R. Buchanan. 2006. Application of small-world network theory in alcohol epidemiology. *Journal of Studies on Alcohol* 67: 591–599.

This paper describes the development of a mathematical network model that uses different forms of connectivity to study the spread of alcohol dependence. The results show that diffusion is influenced by the path length between, and clustering of, network nodes, as well as by initial conditions and susceptibility to alcohol problems.

Fitzpatrick, B. G., and J. Martinez. 2012. *Agent-based modeling of ecological niche theory and assortative drinking[http://jasss.soc.surrey.ac.uk/15/2/4.html]*. *Journal of Artificial Societies and Social Simulation* 15.2: 4.

This paper presents an agent-based model designed to examine the assortment of drinkers into different types of bars based on individual, spatial, and social network characteristics. The simulation allows bars to compete for customers and use

different strategies (e.g., copy the attributes of the most successful competitor) to attract more drinkers.

Fitzpatrick, B. G., R. Scribner, A. S. Ackleh, et al. 2012. Forecasting the effect of the Amethyst Initiative on college drinking. *Alcoholism: Clinical and Experimental Research* 36.9: 1608–1613.

This paper uses a systems model of college drinking to estimate the effects of reducing the minimum legal drinking age (MLDA) on heavy episodic drinking (HED). The simulations suggest that corrections of misperceptions of social norms about drinking would be offset by increasing the social availability of alcohol, and therefore lowering the MLDA would not reduce HED.

Gorman, D. M., J. Mezic, I. Mezic, and P. G. Gruenewald. 2006. Agent-based modeling of drinking behavior: A preliminary model and potential applications to theory and practice. *American Journal of Public Health* 96: 2055–2060.

This paper presents a very simple agent-based model of the social influences affecting drinking behavior developed on a onedimensional lattice. Three types of agents are included in the simulation (nondrinkers, current drinkers, and former drinkers) and in the final version a “bar” is added to the simulated environment.

Mubayi, A., P. Greenwood, X. Wang, et al. 2010. Types of drinkers and drinking settings: An application of a mathematical model. *Addiction* 106: 749–758.

This paper describes a system dynamics model (parameterized using US college drinking data) that explores the effects of high- and low-risk drinking environments and residence-time in these environments on the transition from light to moderate drinking and moderate to heavy drinking.

Rasul, J. W., R. G. Rommel, G. M. Jacquez, et al. 2011. Heavy episodic drinking on college campuses: Does changing the legal drinking age make a difference? *Journal of Studies on Alcohol and Drugs* 72: 15–23.

This study extends the Scribner, et al. 2009 model to include underage and legal drinking age groups to estimate the effects on drinking on college campuses of lowering the legal drinking age. The simulation shows the policy would only be effective in the unlikely combination of very high alcohol availability and very low enforcement of policies.

Rosenquist, J. N., J. Murabito, J. H. Fowler, and N. A. Christakis. 2010. The spread of alcohol consumption behavior in a large social network. *Annals of Internal Medicine* 152: 426–433.

This paper uses data from the Framingham Heart Study to examine the spread of alcohol use within social networks. Clusters of both heavy drinkers and abstainers were found and social influence operated up to three degrees of separation. Female

contacts were significantly more likely to influence the spread of heavy drinking than male contacts.

Scribner, R., A. S. Ackleh, B. G. Fitzpatrick, et al. 2009. A systems approach to college drinking: Development of a deterministic model for testing alcohol control policies. *Journal of Studies on Alcohol and Drugs* 70: 805–821.

This paper describes a system dynamics model of college drinking comprising five compartments (abstainer through problem drinker) and four processes governing transitions (alcohol availability, social norms, social interactions, and individual risk). Model output is compared to data from a college drinking survey, and the model is used to assess the effects of two interventions.

2.7.2 Chronic Disease

All of the papers included in this section employ system dynamics modeling and all examine the contribution of different types of policy options to reducing various types of chronic disease. Five of the six studies reviewed were conducted by a group of investigators (comprising, among others, Jones, Hirsh, Homer, and Milstein) who have developed very sophisticated system dynamics models to examine the effects of different types of health-care priorities and expenditures on chronic disease prevalence. Hirsch, et al. 2010 and Homer, et al. 2010 focus on cardiovascular disease, while Jones, et al. 2006 and Milstein, et al. 2007 focus on diabetes. The final paper in this subgroup, Homer, et al. 2007, is focused on chronic disease in general; this contains the most detailed account of the building of these models. Each of these papers, with the exception of Milstein, et al. 2007, examines the effects of various types of health-care expenditures (e.g., lifestyle change programs, environmental change, health insurance, clinical management) on the projected course of chronic disease in the United States. Milstein, et al. 2007 is more specifically concerned with the feasibility of the goals for diabetes reduction set by the US Department of Health and Human Services. Mahamoud, et al. 2013 describes a system dynamics model parameterized using data from the city of Toronto. This paper moves beyond examining specific social policies to assessing the effects of socio-structural factors such as income and social cohesion.

Hirsch, G., J. B. Homer, E. Evans, and A. Zielinski. 2010. A system dynamics model for planning cardiovascular disease interventions. *American Journal of Public Health* 100.4: 616–622.

This paper describes a system dynamics model developed to examine the prevalence of cardiovascular disease in El Paso County, Colorado, over a forty-year period. A "status quo" model in which inputs remained unchanged and a model in which all risk factors were eliminated were compared to models that included different lifestyle, environmental, and medical interventions.

Homer, J., G. Hirsch, and B. Milstein. 2007. Chronic illness in a complex health economy: The perils and promises of downstream and upstream reforms. *System Dynamics Review* 23.2–3: 313–343.

This paper describes a system dynamics model of chronic disease for the United States from 1960 to 2010. The output of a baseline model is compared to those from

simulations in which “downstream” influences (pertaining to payers, providers, and investors) and “upstream” influences (pertaining to population-level health measures and risk management) are manipulated.

Homer, J., B. Milstein, K. Wile, et al. 2010. *Simulating and evaluating local interventions to improve cardiovascular health [http://www.cdc.gov/pcd/issues/2010/jan/08_0231.htm]*. Preventing Chronic Disease 7.1: A18.

This paper describes a system dynamics model developed to estimate trends in first-time cardiovascular events, deaths, and related costs from 2004 to 2040. A model that leaves all inputs unchanged is compared with one that reduces all risk factors to zero and four that include combinations of medical, environmental, and lifestyle interventions.

Jones, A. P., J. B. Homer, D. L. Murphy, J. D. K. Essien, B. Milstein, and D. A. Seville. 2006. *Understanding diabetes population dynamics through simulation modeling and experimentation [http://www.cdc.gov/pcd/issues/2007/jul/06_0070.htm]*. *American Journal of Public Health* 96.3: 488–494.

This paper describes system dynamics models of the history and the future of diabetes in terms of morbidity, mortality, and costs. The models examine the effects of three possible single-policy intervention scenarios (enhancing clinical management of diabetes, increasing management of prediabetes, and reducing obesity prevalence) upon total diabetes prevalence and per capita deaths from complications.

Mahamoud, A., B. Roche, and J. Homer. 2013. *Modelling the social determinants of health and simulating short-term and long-term intervention impacts for the city of Toronto, Canada. *Social Science and Medicine* 93: 247–255. [doi: 10.1016/j.socscimed.2012.06.036]

This paper describes the development of a system dynamics model of the city of Toronto that focuses on social determinants of disability and chronic illness. A number of alternative scenarios are examined, and these show that income is the most influential social determinant of health status, followed by social cohesion.

Milstein, B., A. Jones, J. B. Homer, D. Murphy, J. Essien, and D. Seville. 2007. *Charting plausible futures for diabetes prevalence in the United States: A role for system dynamics simulation modeling [http://www.cdc.gov/pcd/issues/2007/jul/06_0070.htm]*. *Preventing Chronic Disease* 4.3.

This study used the system dynamics model developed in Jones, et al. 2006 to examine the feasibility of the Healthy People 2010 (HP 2010) diabetes prevalence objective. The model showed the objective was unattainable and that the achievement of other HP 2010 objectives (e.g., increased detection rates) could increase prevalence.

2.7.3 Community Interventions

Each of the three system methods has been used to assess the mechanisms through which community-based organizations and agencies build capacity and facilitate communication between one another. The papers by Valente and colleagues each use social network analysis to assess the types of network structures that facilitate the dissemination of information and the development of collaborative relationships between organizations. Specifically, Valente, et al. 2007 examines the spread of evidence-based practices among a large network of drug prevention programs, while Valente, et al. 2010 focuses on capacity building around the issue of cancer prevention among universities and community-based organizations. Fredericks, et al. 2008 and Homer, et al. 2004 employ system dynamics models to examine community-based services for the developmentally disadvantaged and those with chronic disease, respectively. Finally, the agent-based model developed in Wang and Hu 2012 is grounded in a specific theoretical framework (as such models frequently are) and focused on the emergence of collective efficacy.

Fredericks, K. A., M. Deegan, and J. G. Carman. 2008. Using system dynamics as an evaluation tool: Experience from a demonstration program. *American Journal of Evaluation* 29.3: 251–267.

This paper discusses how systems mapping approaches may aid understanding of relationships, impacts, and consequences of program processes, as applied to a developmental disabilities demonstration program. While the program sought to provide individualized services, and more flexible agency funding and processes, results were often counter-productive. Systems mapping enabled understanding of problems in goal attainment.

Homer, J., G. Hirsch, M. Minniti, and M. Pierson. 2004. Models for collaboration: How system dynamics helped a community organize cost-effective care for chronic illness. *System Dynamics Review* 20.3: 199–222.

This paper uses system dynamics models of diabetes and heart failure in resource planning, expectation setting, and impact evaluation of a chronic care program in Whatcom County, Washington, over twenty years. It discusses the magnitude of chronic illness, the care program, the simulation role and framework, and various applications of the model.

Valente, T. W., C. P. Chou, and M. A. Pentz. 2007. Community coalitions as a system: Effects of network change on adoption of evidence-based substance abuse prevention. *American Journal of Public Health* 97.5: 880–886.

This paper discusses how network analysis can aid community coalition programs in public health, including drug abuse prevention, by measuring social capital through network indexes of density and centralization and building upon diffusion of innovation studies. The analysis evaluated dissemination of evidenced-based drug prevention programs in twenty-four cities over twenty-five years.

Valente, T. W., K. Fujimoto, P. Palmer, and T. Tanjasiri. 2010. A network assessment of community-based participatory research: Linking communities and universities to reduce cancer disparities. *American Journal of Public Health* 100.7: 1319–1325.

This paper presents the results of a network analysis of connections between eleven community-based organizations (CBOs) and five universities following their involvement in an intervention designed to increase collaboration in the development of prevention activities focused on reducing cancer disparities among Pacific Islanders in Southern California.

Wang, M., and X. Hu. 2012. Agent-based modeling and simulation of community collective efficacy. *Computational and Mathematical Organizational Theory* 18: 463–487.

This paper uses complexity science and the theory of planned behavior to generate agent-based models to study collective efficacy formation of a community. Simulations include modifying an event model for generating community events and a community model with personal resources, behavioral intentions, and perceived behavior controls.

2.7.4 Drug Use and Misuse

Both system dynamics and agent-based models have been used to assess the effects of different types of policies on different forms of drug use. The special edition of *Bulletin on Narcotics* (United Nations International Drug Control Programme 2001) contains a number of examples of the application of the former method to illicit drug control policy and examines the benefits derived from the application of this approach. Caulkins, et al. 2007 and Winkler, et al. 2003 each use models composed of stocks of different types of drug users to assess the effects of various forms of drug control policy (such as prevention, harm reduction, and treatment) on the escalation of drug use within a population. Like the system dynamics model of Caulkins, et al. 2007, Dray, et al. 2008, an agentbased model, is focused on Australian drug policy, but in this case the emphasis is on criminal justice interventions and not treatment and prevention. This model is based on a specific geographic location (Melbourne), as is the agent-based model described in Hoffer, et al. 2009. The latter examines open-air drug markets in the city of Denver, Colorado. Perez, et al. 2012 describes the development of an agent-based model named *SimAmph*, the purpose of which is to examine a broad range of drug control policies in Australia. Dray, et al. 2011 and Moore, et al. 2009 describe the results of the application of this simulation model to examine the effects of specific forms of drug policy on specific health outcomes.

Caulkins, J. P., P. Dietze, and A. Ritter. 2007. Dynamic compartmental model of trends in Australian drug use. *Healthcare Management Science* 10: 151–162.

This study develops a five-part compartment model composed of different types of drug users (e.g., cannabis only, regular injection drug users) to examine trends in illicit drug use in Australia through 2050. The model output is compared to survey data and used to estimate the effects of three interventions (primary prevention, harm reduction, and controlling supply).

Dray, A., L. Mazerolle, P. Perez, and A. Ritter. 2008. Policing Australia's "heroin drought": Using an agent-based model to simulate alternative outcomes. *Journal of Experimental Criminology* 4: 267–287.

This study describes an agent-based model designed to assess the impact of three types of policing (random patrols, hot-spot crackdowns, problem solving) on problems associated with heroin use, including number of users and number of users in treatment. The model comprises a variety of agents (e.g., users, dealers, outreach workers) and is based on data from Melbourne, Australia.

Dray, A., P. Perez, D. Moore, et al. 2011. Are drug detection dogs and mass media campaigns likely to be effective policy responses to psychostimulant use and related harm? Results from an agent-based simulation model. *International Journal of Drug Policy* 23.2: 148–153. [doi: 10.1016/j.drugpo.2011.05.018]

This paper describes a project that used SimAmph (Perez, et al. 2012) to assess the impact of two drug prevention policies on drug use and related harms. The simulations showed that mass media campaigns were ineffective among regular and hard-core drug users but did reduce escalation of use and health problems among novice and occasional users.

Hoffer, L. D., G. Bobashev, and R. J. Morris. 2009. Researching a local heroin market as a complex adaptive system. ***American Journal of Community Psychology*** **44: 273–286.**

This paper is premised on the idea that illicit drug markets are a form of self-organizing complex adaptive system and describes a study that used ethnographic data to develop an agent-based model of an open-air heroin market in Denver, Colorado. The agents are customers, brokers, sellers, private dealers, police officers, and homeless individuals.

Moore, D., A. Dray, R. Green, et al. 2009. Extending drug ethno-epidemiology using agent-based modeling. ***Addiction*** **104: 1991–1997.**

This paper describes a project that used SimAmph (Perez, et al. 2012) to integrate epidemiologic and ethnographic recreational drug use data from three Australian cities. The model, composed of various types of agents (e.g., regular and hard-core users), is illustrated using the example of adverse effects resulting from the introduction of adulterated pills into the ecstasy market.

Perez, P., A. Dray, D. Moore, et al. 2012. SimAmph: An agent-based simulation model for exploring the use of psychostimulants and related harm amongst young Australians. ***International Journal of Drug Policy*** **23.1: 62–71.**

This paper describes the development of an agent-based model (SimAmph) of psychostimulant use among Australian youth. The model enables agents to move through five stages of drug use (novice, occasional user, regular user, hard-core user, marginal user) according to dynamic changes in the settings in which they acquire drugs, peer influences, and the experience of health problems.

United Nations International Drug Control Programme. 2001. Special issue: Dynamic drug policy: Understanding and controlling drug epidemics. *Bulletin on Narcotics* 53.1–2.

This special edition contains ten papers that use a dynamic systems framework to understand drug epidemics and policy. The papers make a strong case for considering drug epidemics as inherently dynamic and characterized by nonlinearity and positive and negative feedback. A number of the papers also contain applications of mathematical models to specific drug epidemics.

Winkler, D., J. P. Caulkins, D. A. Behrens, and G. Tragler. 2003. Estimating the relative efficiency of various forms of prevention at different stages of a drug epidemic. *Socio-Economic Planning Sciences* 38: 43–57.

This paper uses a compartment model composed of light and heavy drug users to estimate the effects of different types of prevention and treatment on the course of a drug epidemic. Key mechanisms in the model are contagion (a positive feedback loop) and observation of the adverse effects of use (a negative feedback loop).

2.7.5 Health-care Services

Given its origins in operations research and management studies, it is not surprising that system dynamics modeling has been widely applied in the area of health-care service research. Seven of the eight papers contained in this section use this approach. Brailsford, et al. 2004; Elf, et al. 2007; Lane and Husemann 2008; Thompson, et al. 2012; and Vanderby and Carter 2010 are examples of the application of system dynamics models to specific area of health-care service delivery in the United States, Europe, and Asia. Brailsford, et al. 2004 presents a conceptual map followed by a quantitative system dynamics model of the emergency health-care system for the City of Nottingham, England. Elf, et al. 2007 presents a purely conceptual model in the form of a causal feedback loop diagram detailing the structure of the care planning process with a view to using this to improve quality of care and patient outcomes. Lane and Husemann 2008 models acute patient flows using system dynamics mapping of interview and hospital site visit data. Thompson, et al. 2012 estimates the proportion of those with age-related dementia in Singapore by creating a system dynamics model to simulate different stages of dementia and a model incorporating trend data on fertility rates to estimate future living arrangements for this population. Vanderby and Carter 2010 examines the applicability of system dynamics modeling to hospital patient flow from a strategic planning orientation by creating a model analyzed by validation and scenario tests. Milstein, et al. 2010 has a broader focus on a wide array of potential health-care reform strategies in the United States. Cooper, et al. 2007 describes how the modeling techniques of decision trees, Markov processes, and discrete event simulations (DES) are useful in economic evaluations and illustrate differences and similarities of the approaches through coronary heart disease examples. Finally, Cunningham, et al. 2012 presents a systematic review of articles that have used social network analysis as a tool for understanding health-care quality and safety.

Brailsford, S. C., V. A. Lattimer, P. Tarnaras, and J. C. Turnbull. 2004. Emergency and on-demand health care: Modelling a large complex system. *Journal of the Operational Research Society* 55: 34–42.

This paper discusses the process of system dynamics modeling to understand emergency and on-demand health-care systems in Nottingham, England. The process involved interviewing to construct a conceptual map, which was used in development of a stock-flow model simulating patient flows to identify system bottlenecks under different scenario tests.

Cooper, K., S. C. Brailsford, and R. Davies. 2007. Choice of modelling technique for evaluating health care interventions. *Journal of the Operational Research Society* 58.2: 168–176.

This paper discusses how health-care intervention evaluation may benefit from economic evaluation modelling techniques and their applicability to different interventions. It asserts that choice of technique depends upon intervention approach, as well as technique acceptance, model error, model appropriateness, dimensionality, model development ease, and speed.

Cunningham, F. C., G. Ranmuthugula, J. Plum, A. Georgiou, J. I. Westbrook, and J. Braithwaite. 2012. Health professional networks as a vector for improving healthcare quality and safety: A systematic review. *BMJ Quality and Safety* 21.3: 239–249.

This paper presents a systematic review of twenty-six studies that employed different forms of social network analysis to examine quality of care and patient safety. The types of network structures and functions assessed in these studies include centrality, density, homophily, stability, and reciprocity.

Elf, M., M. Poutilova, and K. Öhrn. 2007. A dynamic conceptual model of care planning. *Scandinavian Journal of Caring Sciences* 21: 530–538.

This paper describes an exploratory conceptual model of care planning processes to identify key variables and their relationships to the care planning process and to construct a conceptual model by building upon system dynamics techniques. It discusses the approach philosophy and model building processes and presents a conceptual causal feedback loop diagram.

Lane, D. C., and E. Husemann. 2008. System dynamics mapping of acute patient flows. *Journal of the Operational Research Society* 59: 213–224.

This paper uses a hybrid of systems mapping and system dynamics modeling to improve acute patient flow within the United Kingdom's National Health Service (NHS). Staff workshops and reports to authorities used stock/flow diagrams of management patterns and whole-system patient blockages and altering resource and treatment pathways levels to communicate how system dynamics ideas may improve patient management processes.

Milstein, B., J. Homer, and G. Hirsch. 2010. Analyzing national health reform strategies with a dynamic simulation model. *American Journal of Public Health* 100.5: 811–819.

This paper describes a system dynamics model developed to examine the effects of different types of health-care reform policies on morbidity, mortality, health disparities, and costs in the United States over a twenty-five-year period. The interventions assessed include increased insurance coverage, increased primary care capacity, reductions in reimbursement rates, improved health promotion, and ensuring safer and healthier environments.

Thompson, J. P., C. M. Riley, R. L. Eberlein, and D. B. Matchar. 2012. Future living arrangements of Singaporeans with age-related dementia. *International Psychogeriatrics* 24.10: 1592–1599.

This paper uses system dynamics modeling to estimate prevalence of Singaporeans with dementia. It simulates population by age cohort, then expands to include flow of elderly individuals with a constant dementia incidence, projected cohort size to estimate family sizes, and estimated population of those with mild, moderate, or severe dementia living with family.

Vanderby, S., and M. W. Carter. 2010. An evaluation of the applicability of system dynamics to patient flow modelling. *Journal of the Operational Research Society* 61: 1572–1581.

This paper aims to determine if system dynamics modeling is applicable for understanding the general trends and causes of variations among patient cohorts in a hospital setting. The model imposes delays on patients throughout the patient flow process where delay durations are based on the state of the dynamic system.

2.7.6 Health Disparities

Neighborhood residential segregation was one of the early social phenomena studied using agent-based models. It is the idea that this is an emergent phenomenon that attracted such interest. Fossett 2006 describes this work in detail and presents agent-based models of neighborhood segregation that are built on the mechanisms of preference and social distance. Auchincloss, et al. 2011 and Yang, et al. 2011 use agent-based modeling to examine the influence of such neighborhood segregation on health-related behaviors. The former is an abstract model focused on the effects of neighborhood segregation on diet and the latter is a model built on the city of Ann Arbor, Michigan, that examines adult walking patterns. Widener, et al. 2013 also uses agent-based models to assess the effects of neighborhood inequality on diet. This model, like that of Yang, et al. 2011, is geographically grounded in an actual city (Buffalo, New York). This city is also the setting for Metcalf and Widener 2011 and its system dynamics model of the development of sustainable agriculture in poor neighborhoods. Finally, Diez Roux 2011 presents six system dynamics models that focus on various dimensions of the association between socioeconomic disparities and adverse health outcomes.

Auchincloss, A. H., R. L. Riolo, D. G. Brown, J. Cook, and A. V. Diez Roux. 2011. An agent-based model of income inequalities in diet in the context of residential segregation. *American Journal of Preventive Medicine* 40.3: 303–311.

This paper describes an agent-based model that examined the influence of food preference, price, residential economic segregation, and segregation of food stores on diet. The model showed that shifting the preference of low-income households to healthy foods could not, in itself, reduce segregation of healthy food resources or income differentials in diet.

Diez Roux, A. V. 2011. Complex systems thinking and current impasses in health disparities research. *American Journal of Public Health* 101: 1627–1634.

This paper discusses the types of population health problems that are best suited to analysis using complex systems methods. It then presents six system dynamics models focused on specific questions pertaining to issues such as gene-environment interactions and trans-generational transmission of early life experiences that remain unanswered in the field of health disparities research.

Fossett, M. 2006. Ethnic preferences, social distance dynamics, and residential segregation: Theoretical explorations using simulation analysis. *Journal of Mathematical Sociology* 30: 185–274.

This paper describes the development of an agent-based model of the underlying dynamics of neighborhood residential segregation. The models are built on two competing theoretical frameworks, one sociological (social distance theory) and one economic (individual preference theory).

Metcalf, S. S., and J. J. Widener. 2011. Growing Buffalo's capacity for local food: A systems framework for sustainable agriculture. *Applied Geography* 31:1241–1251.

This paper describes the development of a system dynamics model of sustainable agriculture as a food source in Buffalo, New York. The model is grounded in ideas about the human right to labor the land and have access to healthy and fresh foods, and the challenges to these rights that occur within impoverished and disenfranchised urban neighborhoods.

Widener, M. J., S. S. Metcalf, and Y. Bar-Yam. 2013. Agent-based modeling of policies to improve urban food access for low- income populations. *Applied Geography* 40: 1–10.

This paper describes a spatially explicit agent-based model of low-income families' consumption of fresh fruit and vegetables in Buffalo, New York. The effects of four policy scenarios (introduction of farmers' markets, increased shopping frequency,

increasing the percentage of convenience stores that sell healthy food, implementation of mobile markets) are examined in the simulations.

Yang, Y., A. V. Diez Roux, A. H. Auchincloss, D. A. Rodriguez, and D. G. Brown. 2011. A spatial agent-based model for the simulation of adults' daily walking within a city. *American Journal of Preventive Medicine* 40.3: 353–361.

This paper describes an agent-based model that simulates adult walking for purposes such as work, shopping, and leisure within a landscape based on Ann Arbor, Michigan. The agents have properties such as age, gender, socioeconomic status, and attitudes to walking, and the environment varies in terms of safety and aesthetics.

2.7.7 Mental Health

The application of system science methods to mental health problems is fairly novel, although clearly some of the papers under the alcohol and drug categories could be included under the umbrella of "mental health." These methods have been used primarily in relation to disorders seen to spread, at least in part, through social interactions. The system dynamics model of Gonzalez, et al. 2003, for example, conceives of bulimia as influenced by peer pressure. Meisel, et al. 2013 applies social network analysis to a small group of pathological gamblers and compares their network structures and contacts to those of non-pathological gamblers. Fowler and Christakis 2008 and Rosenquist, et al. 2011 examine much larger social networks using data from the Framingham Heart Study cohorts. The latter examines the spread of depression through the networks over time, while the former examines the spread of “positive emotions.”

Fowler, J. H., and N. A. Christakis. 2008a. Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the Framingham Heart Study. ***British Medical Journal*** **337: a2338.**

This paper uses data from the Framingham Heart Study offspring cohort to examine the spread of happiness (positive emotions) within social networks from 1983 to 2003. Clusters of happy and unhappy people were identified that were significantly greater than expected by chance, and the spread of happiness diffused up to three degrees of separation.

Gonzalez, B., E. Huerta-Sánchez, A. Ortiz-Nieves, T. Vásquez-Alvarez, and C. Kribs-Zaleta. 2003. Am I too fat? Bulimia as an epidemic. ***Journal of Mathematical Psychology*** **47: 515–526.**

This paper examines the role of college-peer pressure on anorexia-free bulimia dynamics through a model of bulimia progression and treatments. The theoretical model resembles an infectious disease model through the incidence rate and treatment rate on the influence of peer pressure, where a series of proofs test the model propositions.

Meisel, M. K., A. D. Clifton, J. MacKillop, J. D. Miller, W. K. Campbell, and A. S. Goodie. 2013. Egocentric social network analysis of pathological gambling. *Addiction* 108.3: 584–591.

This paper presents the results of a study that examined the social networks of eighteen pathological gamblers and twenty-two nonpathological gamblers. The networks of the former contained more gamblers, smokers, and drinkers, but no structural differences in the networks of the two groups were observed.

Rosenquist, J. N., J. H. Fowler, and N. A. Christakis. 2011. Social network determinants of depression. *Molecular Psychiatry* 16: 273–281.

This paper uses data from the Framingham Heart Study to examine the spread of depression within social network. Depression was found to travel along network ties up to three degrees of separation. Network size, position within the network, and the gender of the depressed friend each influenced the diffusion of depression.

2.7.8 Obesity

System dynamics models and agent-based models have not been extensively used to study obesity, although Hammond 2009 describes the potential for the application of the latter method. In contrast, social network analysis has been applied quite extensively to the study of obesity. This is because it is easy to conceive of this as a health outcome that is influenced by behaviors (such as exercising and eating) that are affected by family, friends, and acquaintances. Cunningham, et al. 2012 presents a systematic review of studies that examine the influence of friends on body weight. Christakis and Fowler 2007 studies the spread of obesity among subjects from the Framingham Heart Study in probably the most widely cited social network analysis published to date. Critiques of the analyses and their interpretation are presented in Lyons 2011 and Cohen-Cole and Fletcher 2008a. The former also contains an interesting account of the difficulties encountered in getting a critical analysis of a highly cited paper published. Cohen-Cole and Fletcher 2008b extends the authors' critique of the Framingham social network studies through an analysis that purports to show that the methods used in these can produce network effects even with quite implausible health outcomes. Fowler and Christakis 2008 is a detailed response to the earliest of the critiques of Cohen-Cole and Fletcher. Finally, Gesell, et al. 2012 uses social network analysis to examine network structures that emerge from the involvement of families in an intervention program as opposed to the networks through which obesity spreads.

Christakis, N. A., and J. H. Fowler. 2007. The spread of obesity in a large social network over 32 years. *New England Journal of Medicine* 357.4: 370–379.

This paper uses data from the Framingham Heart Study offspring cohort to examine the spread of obesity within social networks between 1971 and 2003. The results show that risk of obesity was significantly elevated up to three degrees of separation between an obese individual and those who were part of his/her social network.

Cohen-Cole, E., and J. M. Fletcher. 2008a. Is obesity contagious? Social networks vs. environmental factors in the obesity epidemic. *Journal of Health Economics* 27: 1382–1387.

This paper tests the Christakis and Fowler 2007 social network model of obesity using the Add Health dataset and reports similar results for the spread of obesity among same-sex friends. However, it finds that the effect is no longer statistically significant once additional environmental controls and friendship selection are taken into account in the analysis.

Cohen-Cole, E., and J. M. Fletcher. 2008b. Detecting implausible social network effects in acne, height, and headaches: Longitudinal analysis. *British Medical Journal* 337: a2533.

This paper contends that the statistical methods used by Christakis and Fowler to identify the spread of health-related behaviors through social networks are fundamentally flawed and can produce "network effects" where none exist. The authors demonstrate this by applying these methods to three health outcomes that are unlikely to be subject to network influence.

Cunningham, S. A., E. Vaquera, C. C. Maturo, and K. M. Venkat Narayan. 2012. Is there evidence that friends influence body weight? A systematic review of empirical research. *Social Science and Medicine* 75: 1175–1183.

This paper presents the findings of a systematic review of studies that have examined the influence of friends on body weight. Sixteen studies met the inclusion criteria of the review, which also sought to identify the mechanisms through which influence occurred. Most study designs were unable to identify such mechanisms.

Fowler, J. H., and N. A. Christakis. 2008b. Estimating peer effects on health in social networks: A response to Cohen-Cole and Fletcher; Trogdon, Nonnemaker, Pais. *Journal of Health Economics* 27: 1400–1405.

The authors address Cohen-Cole and Fletcher 2008a, critique of their study of the spread of obesity in subjects from the Framingham Heart Study (FHS; Christakis and Fowler 2007). They also present their own analysis of the Add Health dataset used by Cohen-Cole and Fletcher, as well as additional analysis of the FHS data.

Gesell, S. B., K. D. Bess, and S. L. Barkin. 2012. *Understanding the social networks that form within the context of an obesity prevention intervention [http://www.hindawi.com/journals/jobes/2012/749832/cta/]*. *Journal of Obesity* Article ID 749832, 10 pages.

This paper presents findings from a study that examined changes in social network structure that occurred during participation in a culturally oriented obesity prevention program targeted at poor Latino families. New and more varied network structures were observed at follow-up in the intervention group compared to the control group.

Hammond, R. A. 2009. *Complex systems modeling for obesity research [http://www.cdc.gov/pcd/issues/2009/jul/09_0017.htm]*. *Preventing Chronic Disease* 6.3.

This paper discusses those aspects of the obesity epidemic, such as the multiplicity of levels of analysis involved, that make it a challenge to study and control but that also characterize it as a complex adaptive system. It describes a number of modeling techniques that have application to obesity research, with most emphasis on agent-based modeling.

Lyons, R. 2011. The spread of evidence-poor medicine via flawed social network analysis. *Statistics, Politics, and Policy* 2.1, Article 2.

This paper presents a critique of the statistical methods used by Christakis and Fowler in their series of studies of the effects of social networks on various health outcomes. It illustrates these problems through a detailed examination of their analysis of obesity. It concludes that there is no evidence to support the hypothesis that obesity is contagious.

2.7.9 Tobacco Use

Two of the three system sciences methods discussed in this article are represented by the texts that appear in this section, the exception being agent-based modeling. Four of the eight texts employed social network analysis. Christakis and Fowler 2008 is another from the authors' series of analyses of data from the Framingham Heart Study. Harris, et al. 2008; Leischow, et al. 2012; and Luke, et al. 2010 focus not on individuals but on the structure and functions of associations that exist among different types of tobacco control agencies and organizations. The three articles that employ system dynamics modeling each examine the effects of tobacco control policies on smoking behavior. Levy, et al. 2000 examines the effects of policies targeted at youth in the United States, while Mendez and Warner 2000 explores the prospects for success of the smoking prevalence goals set forth by the US Department of Health and Human Services. Tobias, et al. 2010 also uses system dynamics modeling to examine national tobacco control policies, in this case those of the New Zealand government. Finally, the National Cancer Institute's Initiative on the Study and Implementation of Systems, and the social network and system dynamics projects that resulted from it, are described in detail in the monograph National Cancer Institute 2007.

Christakis, N. A., and J. H. Fowler. 2008. The collective dynamics of smoking in a large social network over 32 years. ***New England Journal of Medicine*** **358.21: 2249–2258.**

This paper uses data from the Framingham Heart Study offspring cohort to examine the spread of smoking within social networks between 1971 and 2003. The analysis identified the emergence of distinct clusters of smokers and non-smokers over time and found that influence within these extended up to three degrees of separation.

Harris, J. K., D. A. Luke, R. C. Burke, and N. B. Mueller. 2008. Seeing the forest and the trees: Using network analysis to develop an organizational blueprint of state tobacco control systems. *Social Science and Medicine* 6: 1669–1678.

This paper presents the results of a study that used social network analysis to examine the inter-organizational structure (specifically, density and centrality) of tobacco control programs from eight states containing different types of agencies (e.g., state agencies, coalitions). Network visualization and statistical analysis revealed common organizational structures across the states.

Leischow, S. J., K. Provan, J. Beagles, et al. 2012. Mapping tobacco quitlines in North America: Signaling pathways to improve treatment. *American Journal of Public Health* 102.11: 2123–2128.

This paper describes the results of a study that examined network relationships among 63 tobacco quitlines in the United States and Canada, as well as funders and the central coordinating organization. The analysis shows that the quitlines have developed into an interconnected network and that the coordinating organization is central to this structure.

Levy, D. T., M. Cummings, and A. Hyland. 2000. A simulation of the effects of youth initiation policies on overall cigarette use. *American Journal of Public Health* 90.8: 1311–1313.

This paper describes a system dynamics model comprising never-smokers, current smokers, and ex-smokers (differentiated by age, sex, and race/ethnicity) used to

examine the effects on prevalence of policies to reduce youth smoking initiation. The model predicted these would have limited short-term effects and that policies to improve cessation rates are also necessary.

Luke, D. A., J. K. Harris, S. Shelton, P. Allen, B. J. Carothers, and N. B. Mueller. 2010. Systems analysis of collaboration in 5 national tobacco control networks. *American Journal of Public Health* 100.7: 1290–1297.

This paper presents the results from a statistical analysis of five organizational networks funded through the Centers for Disease Control and Prevention's National Network Initiative. The analysis focused on the structural and organizational predictors of collaboration and showed that this was influenced by geographic location, agency type, perceived organizational importance, and the type of tobacco control work the agency conducted.

Mendez, D., and K. E. Warner. 2000. Smoking prevalence in 2010: Why the Healthy People goal is unattainable. *American Journal of Public Health* 90.3: 401–403.

This study uses a system dynamics model of smoking prevalence to examine the feasibility of the Healthy People 2010 (HP 2010) smoking prevalence objective of 13 percent. The model examines the effects of various changes in smoking initiation and cessation rates and shows that the HP 2010 objective is unattainable.

National Cancer Institute. 2007. *Greater than the sum: Systems thinking in tobacco control.* Tobacco Control Monograph No. 18. Bethesda, MD: U.S. Department of Health and Human Services, National Institutes of Health, National Cancer Institute. NIH Pub. No. 06-6085.

This seven-chapter monograph focuses on the complex interconnectivity between tobacco control and public health systems analysis. It emphasizes the importance of transdisciplinary research and the need for the utilization of system approaches to tobacco control organization and management, dynamics, and network analysis.

Tobias, M., R. Y. Cavana, and A. Bloomfield. 2010. Application of a system dynamics model to inform investment in smoking cessation services in New Zealand. *American Journal of Public Health* 100.7: 1274–1281.

This paper describes the development of a system dynamics model to improve long-term decision-making regarding government investment in tobacco control initiatives in New Zealand. Specifically, it compared a business-as-usual scenario with an enhanced cessation intervention scenario and found that the latter produced substantial benefits in terms of smoking prevalence, tobacco consumption, and tobacco-attributable mortality.

2.7.10 Violence

The articles in this section describe the application of systems methods to various types of violent behavior. Richardson 1987 and Epstein 2002 focus on political and civil unrest and the violence that can arise from the spread of dissatisfaction with centralized authority within a population. Each also examines the effects of attempts to repress such civil unrest. Epstein 2002 is an abstract agent-based model, whereas Richardson 1987 uses system dynamics modeling and applies this to a specific country. The other three papers included in this section also develop models of specific geographic locations, either a city or a neighborhood within a city in the United States. Groff 2007 presents an agent-based model of violent crime in Seattle, Bridgewater, et al. 2011 a system dynamics model of youth violence in Boston, and Papachristos, et al. 2012 a social network analysis of gunshot injuries in a Boston neighborhood. Each paper nicely demonstrates the strengths of the different approaches, the agent-based model being built on specific theoretical mechanisms, the system dynamics model being built through a diverse team of stakeholders, and the social network analysis being conducted using existing data that describes the association between individuals.

Bridgewater, K., S. Peterson, J. McDevitt, et al. 2011. A community-based systems learning approach to understanding youth violence in Boston. *Progress in Community Health Partnerships* 5.1: 67–75.

This paper describes a system dynamics model of youth violence in Boston that was developed through a collaboration of academics, community members, and current or former gang members. The model is used to estimate the amount of community trauma, youth violence, and gun violence over twelve years.

Epstein, J. M. 2002. Modeling civil violence: An agent-based computational approach. *Proceedings of the National Academy of Science* 99 (Suppl. 3): 7243–7250.

This paper describes an agent-based model of the emergence of civil violence. The model contains two types of agents: members of the general population and agents of the central authority (i.e., police). Violence spreads among the former as a result of changes in the perceived legitimacy of the central authority, perceived hardship, and risk aversion.

Groff, E. R. 2007. Simulation for theory testing and experimentation: An example using routine activity theory and street robbery. *Journal of Quantitative Criminology* 23: 75–103.

This paper describes an agent-based simulation of street robbery that uses a geographic information system to create an environment based on the street network structure of Seattle, Washington. The agent types (offenders, targets, guardians, and police) and their interactions with one another and their environment are grounded in routine activities theory.

Papachristos, A. V., A. A. Braga, and D. M. Hureau. 2012. Social networks and risk of gunshot injury. *Journal of Urban Health: Bulletin of the New York Academy of Medicine* 89.6: 992–1003.

The research reported in this paper used data from police records to study gunshot victimization among a network of 763 individuals from Boston's Cape Verdean community. The analysis showed that the closer an individual was in the social network to a gunshot victim, the greater the probability he/she would also be a victim.

Richardson, J. M., Jr. 1987. Violence and repression: Neglected factors in development planning. *Futures* 19.6: 651–658.

This paper discusses application of system dynamics modeling to understand political violence and repression in Argentina. It describes repression, development, and violence patterns related to economic performance and perceived satisfaction, opposition movement strength and support, repression and its propensity, and violence potential, probability, scope, intensity, and duration.

3. VALIDATING MODELS IN PUBLIC HEALTH

The application of systems method to the understanding of public health problems (e.g., alcohol and drug abuse, chronic disease, obesity, tobacco use, and violence) has grown considerably in the past decade. System methods are seen by many of their advocates within public health as complimenting traditional behavioral and epidemiological research methods, while others see them as a fundamentally different way of understanding and explaining public health problems. Those who see the methods as complimentary often use empirical data from studies employing traditional methods and statistical analysis to validate the output of simulation models. As in other fields of applied research in which modeling has become popular, this tendency to equate a model's correspondence to data with the model corresponding to reality is especially pronounced when the goal of the modeling is to inform public policy. This section discusses the problems that arise when using data from an empirical study to assess the validity of a simulation model. It illustrates these problems through an examination of a specific example from the public health literature. The example demonstrates that, rather than empirical data being superior to the model, each is better considered as simply capturing a different aspect of a real-world system. Alternative means of assessing model usefulness are also discussed.

3.1 Introduction

The application of systems methods (notably system dynamics modeling, agent-based modeling, and social network analysis) to the understanding of a wide range of public health problems has grown considerably in the past decade (Elkins and Gorman 2014;

Galea, et al. 2010; Luke and Stamatakis 2012). Much of the impetus for this has come from recognition of the complexity of many public health problems and a search for analytic methods better able to capture the underlying dynamic processes at work compared to traditional study designs and statistical approaches. The limits of traditional research designs (e.g., randomized trials and cohort studies) and the statistical analyses typically used to analyze data from such studies (e.g., regression analyses and descriptive statistics) have become especially noticeable in research on public health problems where multiple heterogeneous interacting elements produce emergent, population-level effects that involve feedback mechanisms and develop in a non-linear fashion (Diez Roux 2011; Hammond 2009; Luke and Stamatakis 2012). Such problems include alcohol abuse, drug use, violence, obesity, tobacco-use, and chronic diseases (e.g., diabetes and heart disease), all of which are conditions particularly resistant to traditional individual-level interventions (McKinley and Marceau 1999; Susser 1995). Systems methods, it is argued, can be used not only to better understand the complexity of such problems but also to identify leverage points for interventions and to assess potential effectiveness of different types of policies and programs designed to influence population-level health (Hawe, et al. 2009; Trickett, et al. 2011). Thus, as in other fields of study, the attraction of systems methods in public health resides not only in their promise to provide better understanding of natural and social phenomena but to also to provide a means of ameliorating societal problems (see Oreskes 1998). While such methods provide a means for studying and ameliorating societal problems, such benefits only come with proper application of those methods.

System methods are also viewed in different ways by public health researchers. Specifically, they are seen by many of their advocates within public health as complimenting traditional behavioral and epidemiological research methods, and as in no way an attempt to displace such methods (Kaplan 2013). Others however see them as a fundamentally different way of understanding and explaining public health problems, and as presenting a “challenge” to traditional research methods (Luke and Stamatakis 2012). Those who see the methods as complimentary often use empirical data from studies employing traditional methods and statistical analysis to validate the output of simulation models. Alfred Korzybski 1933 famously stated: “The map is not the territory”, yet this predominant approach to model validation in public health research assumes traditional empirical methods and statistical techniques capture the “territory” with such accuracy that they can be used as a yardstick against which to judge the performance and adequacy of a model.

The current section questions whether public health simulation models can, and should, be “validated” through comparison to empirical data. The next section briefly describes the underlying rationale for this approach to model validation. The following section examines some of the problems with this approach that have been raised in the broader modeling literature. This is followed by a detailed discussion of a specific example from the public health literature that illustrates these problems. The example is a system dynamics model of college drinking, developed by Scribner and colleagues, which is comprised of five compartments (abstainer through heavy episodic drinker) and three processes governing transitions (social norms, social interactions and individual risk)

(Ackleh, et al. 2009; Scribner, et al. 2009). It focuses specifically on the comparison of the model output with data from a survey of college drinking behavior, the Social Norms Marketing Research Project (SNMPR) (DeJong, et al. 2006; Scribner, et al. 2008). Following the examination of this specific example, this section concludes with a discussion of some other approaches to model evaluation that might be more useful in assessing public health systems models.

3.2 Model Validation

The rapidity of the adoption of systems methods within the field of public health has meant that some of the underlying philosophical issues regarding the use of such methods have not been explored and debated in much detail. One such issue that is particularly pronounced with those models intended to help solve social problems is the need to demonstrate that they resemble with some degree of accuracy the real-world systems to which they pertain (Oreskes 1998). The closer the resemblance, so the reasoning goes, the more justified one is in conducting virtual experiments using the simulation model and the more confidence one can have that the results of such experiments can guide interventions and policies in the real-world system. The term most commonly used to describe the assessment of a simulation model in terms of how well it resembles the real-world system to which it pertains is "validation."

We acknowledge at the outset that the term "validation" is highly contested within the modeling community, and is frequently confused with related terms such as "verification", "accreditation", or "evaluation" (Balci 1997; Grant and Swannack 2008;

Kleindorfer, et al. 1998; Martis 2006; Oreskes, et al. 1994). There is also a wide range of activities that can be described under the general rubric of validation (Grant and Swannack 2008; Rykiel 1996). A review of the broader debate as to what constitutes “validation” and of the various activities that this term is used to describe is outside the scope of this section. Instead, our focus is on the process of comparing model predictions with observations of the real-world system, a process that is often erroneously considered to be the only or primary validation criterion (Grant and Swannack 2008).

Not surprisingly given its emphasis on solving societal problems, the demand that systems models be validated in terms of their correspondence to the real-world system is prevalent in the public health research literature. In addition, as in other areas in which models are validated using such a criterion, the standard approach to assessing the model’s correspondence to reality is to compare it to the results of an empirical study. Thus, a common first step used in models that attempt to assess the effects of policies and prevention initiatives is to compare the model output to historical trends in the conditions that are the target of the intervention (e.g., Homer, et al. 2007; Jones, et al. 2006). In assessing the validity of the model, its output is usually compared to the results obtained from empirical studies of the same phenomenon. So for example, from this perspective the expectation is that a valid model of the effects of low-level environmental exposure to lead in children should generate output that resembles empirical data pertaining to lead poisoning among children who have experienced low-level exposure (see Oreskes 1998). The underlying assumption of such an approach is that: “Empirical data can help make model input assumptions as valid as possible and can be used to test the output of models and their power to explain real-world phenomena of interest" (Hammond 2009, pages 5-6, emphasis added). The more the model can reproduce the historical data, the more confidence one can have in its ability to predict future trends under conditions of different policy options (Homer 1996). This has long been a common practice within the field of modeling, and often involves a subjective assessment of the "see how well the simulated data matches the observed data test" (Rykiel 1996, 242).

3.3 Problems with Validating Open Systems

As noted above, one of the underlying assumptions of the approach to model validation that focuses on comparing model output to data is that the latter captures with some accuracy the underlying dynamics of the real world system that it is measuring. At its extreme, this would look like Figure 1, with a perfect match occurring between the empirical data and the real-world system. In the overwhelming majority of research project, however, such perfection is unattainable due to problems such as selection bias, residual confounding and measurement error, and so an exact mapping of the data onto the real-world system is unlikely. However, one can assume that the match between the two is considered to be good by those who compare empirical data to model output as a means of validating the latter. For were there not some expectation that the data resemble the real-world system with some accuracy then there would be no point in comparing the output of the simulation model to the data as a means of generating confidence in the model's ability to predict the future state of the system.

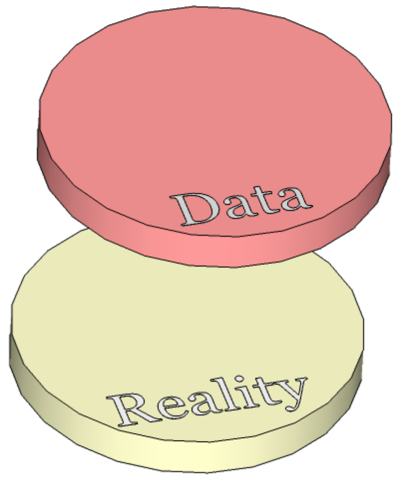

Figure 1. Ideal Empirical Data Perfectly Captures the Real-World System

At a very basic level, judging the validity of simulation models in terms of results from empirical studies that use traditional research designs to collect data that is then analyzed using standard statistical methods is somewhat paradoxical. For, as noted earlier, one of the primary reasons for use of such models is that they provide an understanding of phenomena in terms of feedback, nonlinearity, and emergent properties that cannot easily be captured using traditional research designs and statistical methods. Thus, using traditional techniques to “validate” systems methods is at odds with the idea that the latter are, to use the term employed by Luke and Stamatakis 2012, a “challenge” to the former.

Beyond this, however, there are deeper philosophical issues with the assumption that the validity of a simulation model be judged in terms of how well it resembles or corresponds to data from an observational or analytic study. The philosophical roots of the critique of using data from empirical studies to validate simulation models emerged from the constructivist and anti-foundationalist schools of systems theory which challenge, to varying degrees, the idea that there exists a single reality that can be accurately measured and against which a model can be judged (for details see Kleindorfer, et al. 1998). In recent years, Oreskes has presented a clearly articulated argument against the use of empirical research to validate models and has highlighted the marked tendency to use such an approach in applied areas of research (Oreskes 2003; Oreskes 1998; Oreskes, et al. 1994).

Oreskes' critique of the use of data from empirical studies to validate simulation models is founded upon the fundamental issue that the vast majority of such models of natural and social phenomena are open systems, that is they are inevitably incomplete or partial representations of the natural systems to which they pertain. More specifically, this openness falls within three general categories (Oreskes 2003); see also Oreskes 1998 in which this issue is discussed in terms of four similar categories called "flaws"). First, the way in which we conceptualize models is always incomplete, either because we deliberately choose to leave certain features out, or because we are unaware of all of the important features, or because we are mistaken or misguided about the nature of the problem. For example, in Scribner, et al.'s 2009 conceptual model of college drinking (which is discussed in more detail below) the three "underlying processes" identified are social norms, social interactions, and individual risk. Other factors that might affect college drinking (e.g., price of alcohol, advertising, availability of other drugs, presence of prevention and treatment services) were deliberately excluded. Such a partial representation of the real system does not make for a "bad model", but it does make for an "open" model according to Oreskes 2003.

The second way in which models are open according to Oreskes 2003 is in terms of how well the numerical variables represent the core elements of the system. All models contain constructs whose qualities can only be partially discerned and distinguished, and assigning values to these qualities will often involve significant error (see also Rykiel 1996). In the Scribner, et al. 2009 model, "the essential features related to patterns of college drinking" are represented by five drinking compartments: abstainers, light drinkers, moderate drinkers, problem drinkers and heavy episodic drinkers (Scribner, et al. 2009, 806). Each compartment is assumed to contain individuals who are similar with regard to their drinking behavior. This is a reasonable simplifying assumption, but fewer or more compartments might have been used to represent the essential features of the model (e.g., Mubayi, et al. 2011), or each drinker may have been assumed to be unique as would occur in an agent-based model (e.g., Fitzpatrick and Martinez 2012).

Finally, what Oreskes 2003 describes as openness is also evident in how well the mathematical equations used in the model to capture the processes of interest. In the Scribner, et al. 2009 model, for example, the social norm construct is operationalized as the rate at which individuals transition between drinking states (e.g., from abstainer to light drinker) and this is based on their perception that a certain level of drinking is typical among *all students on campus*. This is a perfectly reasonable assumption, but it might also be argued that such transition between drinking states is driven less by the drinking behavior of all student drinkers at a university or college than it is by the drinking behavior of one's immediate peers. Or it might be that the transition of drinkers within the same category is influenced by the context within which interactions take place (e.g., Mubayi, et al. 2011). Thus, the mathematical equations used in the model could include a quite different transition rate.

It is worth noting that these three aspects of what Oreskes 2003 calls "openness" are also evident in the empirical or observational studies with which model output is compared in the validation process. Like simulations, empirical studies are almost always based on partial theories or conceptual models, and the concepts that comprise these are frequently abstract and vague in nature (e.g., social norms, peer group) (Babbie 1995, pp. 75-76). Likewise, the data collected are frequently based on inference-laden operational measures (e.g., "peers" are those with whom an individual attends school) and are often incomplete or inaccurate (e.g., due to non-response, attrition and faulty recall of subjects). Finally, the statistical analyses employed also have built in assumptions about the nature of the data and the relations between variables (e.g., that the data are normally distributed and the relationships are linear). Thus, comparing output from a simulation model of *phenomenon X* with the results of a statistical analysis of data from an empirical study of *phenomenon X* is a comparison of two partially and imperfectly captured systems of *phenomenon X*. They are, as Rykiel observes, "two moving targets that we try to overlay one upon the other" (Rykiel 1996, 235).

Figure 2 illustrates the idea that empirical data and the model output capture different aspects of the real-world system, wherein the model not matching the data might be a function of each capturing different aspects of a real-world system instead of the data being a superior representation against which the adequacy of the model output is to be judged. Accordingly, the data may not constitute the best test of the model (Rykiel 1996). One of the implications of such a view of empirical data and simulation output is that it opens the door to the possibility that the latter may actually be a better representation of the real-world system of interest than the former for some purposes (Eck and Liu 2008; Rykiel 1996).

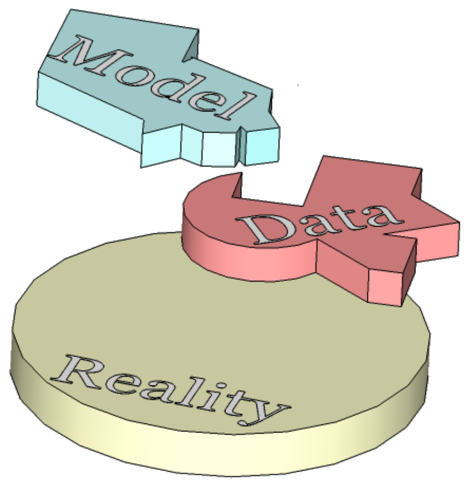

Figure 2. Model Output and Empirical Data Capture Different Aspects of the Real-World System

3.4 Example from Public Health Research

We will explore these implications in more detail through an examination of Scribner, et al.'s 2009 system dynamics model of college drinking, and specifically the use of data from the SNMRP to validate the predictions of the model" (Scribner, et al. 2009, 811). This is a good example to use to illustrate some of the issues raised by Oreskes 2003 concerning model validation as Scribner and colleagues explicitly state that they use survey data "to validate the predictions of the model" (Scribner, et al. 2009, 811). In addition, in an earlier paper they state that the "obvious value" of comparing the model output to data "is that once the model has been validated with data, it can be used to make predictions" (Ackleh, et al. 2009, 497). Thus, there is explicit acceptance of the idea that empirical data can be used as a standard against which to assess the validity of simulation models.

We should make it clear however that we are not presenting a general critique of the model presented by Scribner, et al. 2009. Indeed, we consider it an eloquent model that has yielded valuable insights into the nature of college drinking and allowed assessment of the possible effects of different policies targeted at this problem (see Fitzpatrick, et al. 2012; Rasul, et al. 2011). Rather, we are simply questioning whether there is much to gain from comparing the output of the model to the results obtained from an empirical study, and more specifically whether the data say very much about the usefulness and heuristic value of the model.

The model validation presented by Scribner, et al. 2009 involved two comparisons of the model output and the SNMRP data, one focused on the model's ability to predict the proportion of drinkers in each of the five drinking categories and one focused on the model's ability to predict the alcohol outlet density of campuses. With regard to the former, the analysis presented by Scribner, et al. 2009 focused on four of the 32 campuses included in the SNMRP, representing a range from relatively low alcohol outlet density to relatively high alcohol outlet density (defined as the number of bars per undergraduate student within three miles of the campus; Scribner, et al. 2008). Specifically, the analysis presented involved a comparison of the predictions of the model over a four-year period for each of the four campuses with the proportion in each compartment found in the SNMRP data. In nearly all of the 80 comparisons presented (5 drinking categories x 4 campuses x 4 years), the empirical data fell within the standard proportion estimator error bars generated by the model (see Figure 3 of Scribner, et al. 2009).

With regard to the density comparison, the model is said to have done a "reasonable job" in predicting outlet density for each of the four campuses (Scribner, et al. 2009, 814), specifically, as the empirical measure of density increased (from 5.25 to 32.81), so did the index generated by the model (from .01 to .77). However, there was almost no difference between the middle two campuses on the index (.23 and .24), whereas the bar-density of the two as measured by the survey was quite different (10.75 and 16.23). Extending this analysis to the entire SNMRP sample of campuses, Ackleh and colleagues found "…that all the 32 fits were quite satisfactory, with the model output within two standard deviations of the data" (Ackleh, et al. 2009, 491). They also compared the model's alcohol density index for all 32 campuses with the empirical measure of the physical availability of alcohol and obtained an R^2 of 0.2293, which increased to 0.3112 when only the 20 residential campuses were included in the analysis (Ackleh, et al. 2009).

Thus, in the case of the proportion of individuals in each drinking compartment, and to a lesser extent the bar density of the four campuses, Scribner, et al.'s 2009 system dynamics model is able to predict with some accuracy the empirical data pertaining to each campus that was collected in the SNMRP. But does this degree of correspondence validate the model? Or is the SNMRP survey simply capturing a part of the real-world college drinking system which may or may not be a good representation of this, and therefore may or may not tell one much about the value of the system dynamics model? Is it, as Oreskes 2003 would argue, an open system that cannot be used to validate the model, which is a different open system?

Concern that the SNMRP data pertaining to drinking categories might only provide a partial view of the real-world system it is intended to capture (and hence be a very limited yardstick against which to validate the model) seems reasonable when one examines these data in a little detail. This shows the response rate across the four years of the study was just 53% (n=19,838), and that the final analysis sample was further reduced to those with available data for all variables, decreasing it from 19,838 to 17,051 students (Scribner, et al. 2008, 113). Additionally, the survey questions used are open to varying interpretation by respondents. For example, one question asked, "During the past 30 days, on how many occasions did you use alcohol (beer, wine, liquor)?" and responses choices included, "never," "1-2 times," "3-5 times," "6-9 times," "10-19 times," "20-39 times," and "40 or more times" (Scribner, et al. 2008, 114). The survey question did not provide a definition of "occasions", allowing room for varying definitions (e.g., an occasion might be a party lasting a few hours or a three-day vacation). In addition, the response categories are fairly broad: one could drink 20 times during the past 30 days or 35 times during the past 30 days, but each would receive the same score. While there is nothing wrong with this *per se*, it is likely that these issues pertaining to response rate and measurement uncertainty will produce a dataset that bears more of a resemblance to the one depicted in Figure 2 than the one depicted in Figure 1. Thus, the extent to which these data validate the model and increase confidence in its ability to predict changes in the real-world system is questionable.

The alcohol outlet data used to validate the model are much less subject to selection and reporting bias as these were obtained from the alcohol control boards in the states in which the 32 campuses were located, and which license alcohol outlets such as bars and package goods stores. Only one state was unable to provide such license data (and in this case, project staff visually recorded the outlets close to the campus) and 96% of the outlets were successfully geocoded to a street address. However, the type of uncertainty in how well numerical variables represent the core elements of a system that Oreskes 2003 observes makes for an open system was certainly present in turning these data into a measure of outlet density. In the validation exercise, this was operationalized in terms of the number of bars per undergraduate student within three miles of the campus (Scribner, et al. 2009, 814). Outlets other than bars might have been included. Indeed, off-sale outlets were included in the SNMRP dataset, but were found to be much less densely concentrated around campuses (see Table 1 of Scribner, et al. 2008). Alcohol outlet density could also have been calculated by outlets-per-roadway-mile, rather than per 1,000 students. Buffers other than 3-miles could have been used, as indeed they were in Scribner, et al. 2008. Again, there is nothing inherently wrong with the decisions made about how to represent alcohol outlet density in the statistical model of the data, but these decisions are likely to create a set of results that look more those in Figure 2 than those in Figure 1.

3.5 Conclusion

The above discussion and specific example which we examined in detail suggest that approaching model validation in terms of a comparison of model output with empirical data is an exercise fraught with difficulties. The example illustrates the issues raised by Oreskes 2003 concerning the comparison of model output to empirical data as a means of validating the former and justifying its use to make predictions about the future state of the real world system to which it pertains. If such a comparison of model output to empirical data is of limited usefulness, how then might one go about assessing the value of a simulation model? Oreskes 1998 argues that we should move away from the use of the term validation entirely and instead focus on model evaluation. The former term, she contends, implies only an affirmative result, with the model nearly always resembling the data. Evaluation, on the other hand, implies an assessment in which the criteria for model success are clearly articulated and in which a negative appraisal is as likely as a positive one. These criteria for success would involve evaluating the model in ways other than the correspondence of its output to empirical data.

These alternative ways of evaluating a model include comparing it to other models, sensitivity analysis, and extreme condition tests, and in deciding upon which of these to employ it is important to consider relations between the amount of data available and level of understanding of the system influences in the particular problem one is addressing (Grant and Swannack 2008; Rykiel 1996). Where the level of understanding and amount of data available are low then conceptual evaluation is most relevant, for example whether the model can reproduce the relationships between model components and their dynamic behavior (Rykiel 1996). Quantitative evaluation is most appropriate where both the level of understanding and availability of data are high. The tendency in much public health research has been to move to quantitative evaluation of models irrespective of the level of understanding of the system influences that affect the problem of interest and the amount of data available.

Ultimately, the value of any model resides in its ability to further our understanding of the real-world system we are studying. While one should not expect a model to be able to predict the future behavioral of a real-world system with absolute certainty, one should expect simulations results to provide new knowledge to help reduce (in some useful way) uncertainty with which to view the future of the real-world system of interest (Grant and Swannack 2008). The relative amount of knowledge gained depends largely upon the current state of the knowledge about the system of interest. This roots in the assumptions that use of the systems approach to solve the problem implies one is dealing with a system for which there are relatively few data and likely little understanding, and the less one understands about a system, the more there is to learn about it. So, for example, the model developed by Scribner, et al. 2009 was used to estimate the potential effects of lowering the legal drinking age on alcohol consumption on colleges and university campuses (Rasul, et al. 2011). The results of the simulation show that lowering the legal drinking age would only be effective in the unlikely event of a combination of very high alcohol availability and very low enforcement of polices. This demonstrates the useful of the model in understanding the system influences that drive college drinking and its ability to help us understand the potential effects of various policy options. These seem better criteria by which to evaluate the model than whether it can generate output that look like empirical data pertaining to college drinking and the availability of alcohol on college campuses.

4. THE VALUE OF THE FRAME: PAINTING COMPLEXITY USING TWO CHRONIC DISEASE MODELS

4.1 Introduction

As with all chronic diseases, it is now recognized that type 2 diabetes is a complex health issue, the etiology of which involves numerous risk factors operating at different ecological levels of analysis. However, this ecological complexity of the problem seldom manifests itself in the interventions for preventing the problem, which typically focus on changing behavior through universal health education, with the assumption of a homogeneous population. This section examines the limitations of this way of framing the problem of type 2 diabetes, particularly its failure to capture the way in which this problem emerges because of dynamic interactions between individuals and their environments and how these interactions vary in fundamental ways depending upon the context within which they occur. Specifically, the section examines how framing of type 2 diabetes in the Health Service Region 11 (HSR11) affects which systems modeling method selects to understand the problem and to help guide policy-makers to ameliorate it. HSR11 includes the following 19 counties: Aransas County, Bee, Brooks County, Cameron County, Duval County, Hidalgo County, Jim Hogg County, Jim Wells County, Kenedy County, Kleburg County, Live Oak County, McMullen County, Nueces County, Refugio County, San Patricio County, Starr County, Webb County, Willacy County, and Zapata County (DSHS: CHS 2014b).

Each systems model has a paradigm characterizing it by a set of fundamental rules and underlying concepts. That is, each method bases on assumptions of how the model should be constructed and the knowledge obtainable from such assumptions. By assuming the model should be constructed in a certain way, the modeler (whether implicitly or explicitly) frames the problem by making assumptions about the phenomenon-of-interest. Choosing to develop any model asserts that the model proscribes to paradigmatic assumptions for how it would contribute something of value) in some capacity (for a purpose), which is ultimately affected by understanding, interpretation, and application of the problem. This section describes how specific types of systems methods, those using agent-based models (ABMs) and system dynamics models (SDMs), can produce very different ways of understanding the problem of, and the leverage points for, type 2 diabetes in the HSR11. Additionally, it moves beyond simply outlining the general differences in the use and applications of ABM and SDM, to presenting models demonstrating how framing of the problem and model paradigmatic assumptions affect understanding of the problem of type 2 diabetes in the HSR11 and its potential leverage points. While the examples are specific to a health problem in a specific community, the significance of such an approach is in its generalizability to how understanding social system behavior depends upon how framing the problem and the paradigmatic assumptions of the modeling method affect understanding of social systems and public health problems.

4.2 Type 2 Diabetes is a Complex Health Issue

As with all chronic diseases, it is now recognized that type 2 diabetes is a complex health issue, the etiology of which involves numerous risk factors operating at different ecological levels of analysis (e.g., individual, interpersonal, organizational, community, and policy) (Hill, et al. 2013). Unhealthy diet, sedentary lifestyle, stress and obesity are among the key risk factors for type 2 diabetes, and these too are the result of interactions between complex processes operating at different levels of analysis (Kaldor, et al. 2015; Kelly and Ismail 2015; Schulze and Hu 2005). However, this recognition of the ecological complexity of type 2 diabetes seldom manifests itself in the interventions that emerge for preventing the problem. These interventions tend to frame the problem as one of individual responsibility and typically try to change the behavior and lifestyle of individuals through universal health education and information programs designed to improve diet and exercise (Kaldor, et al. 2015). Such interventions have, at best, small to moderate effects on diet, physical activity and weight (Bhattarai, et al. 2013; Gottmaker, et al. 2011; Orrow, et al. 2012).

Behavioral interventions infrequently address the constellation of risk factors for diabetes that vary across population subgroups and geographic locations. For example, the influence of occupational stress and childhood socioeconomic status appears to interact with gender and mental health (Kelly and Ismail 2015). Given such complexity, a universal intervention targeted at males and females and individuals from diverse socioeconomic circumstances is unlikely to have the desired effect. A second implication of the complexity of the problem is that risk factors for type 2 diabetes that operate at different levels interact with one another (Galea, et al. 2009; Roberto, et al. 2015). Therefore, intervening at one level (e.g., educating people about healthy food choices) may be pointless if the food and social environments have already shaped individuals' preferences for cheap, processed, energy-dense foods and if the food environment provides few available options for an affordable healthy diet (Gortmaker, et al. 2011).

This section examines the limitations of this way of framing the problem of type 2 diabetes, particularly its failure to capture the way in which this problem emerges from dynamic interactions between individuals and their environments and how these interactions vary in fundamental ways depending upon the context within which they occur. Specifically, the section examines how framing of type 2 diabetes in the Health Service Region 11 (HSR11) affects which systems modeling method selects to understand the problem and to help guide prevention and intervention efforts to ameliorate it.

4.2.1 Etiology and Risk Factors

According to the Texas Health Institute 2010, diabetes is a statewide epidemic. Diabetes was the third leading cause of death nationally, sixth leading cause of death in the State of Texas, and the third leading cause of death in some localities. Prevalence rates are especially high among those with low income, African Americans, Hispanics and those over 65 years of age (Office of Surveillance, Evaluation, and Research 2013, Figure 5). In terms of geographic location, prevalence rates are highest (between 12.5% and 15.3%) in the eastern and southern parts of the state (Office of Surveillance, Evaluation, and Research 2013, Figure 4). These data are even more troubling when considering that experts believe there exists considerable underreporting of the disease as a cause of death due to inconsistencies in reporting on death certificates. Estimates by the Texas Diabetes Council for 2008 suggested that 1.7 million (or one in 12 Texas adults) have been diagnosed with diabetes, 425,000 Texas adults with the disease went undiagnosed, and over one million Texas adults were prediabetic and at high risk for developing the disease within the next decade (Texas Health Institute [THI] 2010).

4.2.2 Population Subgroups

There exist marked socioeconomic, gender and race/ethnic disparities in type 2 diabetes prevalence meaning that some populations are at greater risk than are others (Figure 3). Two recent reports from the Missouri Department of Health and Senior Services (MDHSS 2014a; MDHSS 2014b) summarized the population characteristics that increase risk of type 2 diabetes, and the broad strategies best suited to address risks factors within these population subgroups, into the following groups: racial and ethnic minorities, children and adolescents, older adults, low-income, rural/urban, and women. Racial and ethnic minority population risk factors included access to health care and other resources for diabetes, language, literacy, cultural norms, and beliefs in relation to health behaviors, cultural attitudes in relation to body image, and stress, and susceptibility. Strategies to address racial/ethnic minority population considerations included improving access to health care and other resources for diabetes, addressing barriers related to language, tailoring to culture, providing cultural competency training, developing self-management skills, involving priority populations, engaging stakeholders, addressing participant needs, using established settings, and screening programs (MDHSS 2014a).

Figure 3. Populations at High-Risk for Diabetes

Children and adolescent population considerations included developmental changes, lower compliance rates, desire for independence/autonomy, peer influence, the role of family support, influence of schools on diabetes self-management, increased diagnosis of diabetes, and possible increased risk and rate of complications associated with diabetes. Strategies to address the children and adolescents included tailoring to age groups, empowering children and adolescents, capitalizing on desire for independence, addressing peer pressure, addressing social norms, and family support systems (MDHSS 2014a).

Older adult population considerations included a disproportionate disease burden, lack of access to affordable care, food preference and an inactive lifestyle, lack of education, and the aging process. Strategies to address older adult population considerations included addressing chronic diseases and medications, improving access to affordable care, providing opportunities to learn about and practice self-management, and building and maintaining social support (MDHSS 2014a).

Low-income population considerations included access to health care, health care coverage, cost of a healthy lifestyle, cost of diabetes management, and stress. Strategies to address low-income population considerations included improving access to health care, creating opportunities for more affordable prevention and health care, and addressing participant needs (MDHSS 2014a).

Rural/urban population considerations included access to health care, perception of health, provider availability, and environmental constraints. Strategies to address rural/urban population considerations included improving access to health care, promoting self-management, restructuring the environment, and transportation (MDHSS 2014a). It should be noted that while there are many risk factors common to urban and rural population (e.g., low socioeconomic status), there are others that are more pronounced in one setting than another (e.g., rural neighborhoods may have no public transportation system, while urban neighborhoods may have unsafe public transportation systems) (Hill, et al. 2013).

Population considerations for women included a history of gestational diabetes, family commitments, and racial disparities. Strategies to address female population considerations included prenatal care and social support strategies (MDHSS 2014a).

4.2.3 Type 2 Diabetes in South Texas

According to the Texas Health Institute's 2010 report *Responding to the Epidemic: Strategies for Improving Diabetes Care in Texas,* diabetes is a statewide epidemic. Diabetes was the third leading cause of death nationally, sixth leading cause of death in Texas, and up to third leading cause of death in some localities. This is more problematic when considering experts speculate this underreporting of this disease as a cause of death due to inconsistencies in reporting on death certificates. Estimates by the Texas Diabetes Council for 2008 suggested that 1.7 million or one in 12 Texas adults have been diagnosed with diabetes, 425,000 Texas adults were not diagnosed, and over one million Texas adults were pre-diabetic and at high risk for developing the disease within the next decade (THI 2010).

Reports suggest the prevalence of diabetes is keeping pace with the increasing national prevalence. For example, analysis of Texas Behavioral Risk Factor Surveillance System (BRFSS) survey found an increased rate of diabetes from 7.9 percent in 2005 to 9.3 percent in 2009. Diabetes is a major health threat to Texas and certain localities are at increased risk, including HSR11 region (THI 2010).

According to Larme and Pugh 2001, diabetes prevalence in the Lower Rio Grande Valley (LRGV), a region comprised of four counties of HSR11 (Cameron County, Hidalgo County, Starr County, and Willacy County) at the time of the study was as high as 21%. According to Brown, et al. 2002, the Mexican American population predominantly comprising the LRGV population has the highest diabetes-related death rates in Texas and certain areas of this region have populations with type 2 diabetes affecting 50% of the Hispanic population age 35 years and older. Brown, et al. 2005 assert that in communities with high diabetes-related unemployment, income reductions related to diabetes translate into decreased local spending. This, in turn, leads to layoffs and decreased expenditures. Thus, medical expenditures influence the local economy of the community externally in that most are inflows largely from outside the community, but are spent locally (Brown, et al. 2005).

In 2012, diabetes prevalence in Texas was 10.5% (95% CI: 9.8-11.5%) and 19.5% (95% CI: 15.9-23.6%) among Adults (18 years or older) in Health Service Region 11 (HSR11) in which the HSR11 is located; prediabetes prevalence was 6.2% (95%CI: 5.3-7.2%) and 5.0% (95% CI: 3.1-8.0%), respectively. The age-adjusted, annual death rate in Texas was 21.9 per 100,000 persons (95% CI: 21.3-22.5%) and in HSR11 was 30.3 per 100,000 persons (95% CI: 27.8-32.8%) (DSHS: OSER 2015).

In 2009‒2012, 37% of U.S. adults aged 20 years or older had prediabetes based upon fasting glucose or A1C levels. After adjusting for population age differences, the percentage of prediabetes was similar for non-Hispanic Whites (35%), non-Hispanic Blacks (39%), and Hispanics (38%) (CDC 2014). According to the CDC's Division of Diabetes Translation (n.d.), in Texas, 15-25% of people with prediabetes will develop diabetes within 5 years.

4.3 Framing the Problem

The way in which a problem is framed affects which systems modeling method one uses to understand the problem and to help guide policy-makers to ameliorate it. In public health research, socioecological models have been used to better understand the etiology of a wide variety of public health problems and to guide public health interventions (Richard, et al. 2011), including those pertaining to policies and environmental strategies focused on the physical activity and food environments (Sallis, et al. 2006; Story, et al. 2008). These models move away from the traditional understanding of health behavior in terms of individual knowledge, attitudes and behavior to an emphasis on the social, economic, normative, and environmental factors that shape and maintain unhealthy behaviors (Hill, et al. 2013).

In traditional prevention models, health problems typically are framed in terms of individual lifestyle, choice, and personal responsibility. The socioecological approach makes it clear that lifestyle and personal responsibility develop within different environmental contexts, and that some of these are more conducive to a healthy lifestyle and eating responsibly than others. It also makes it clear that one's choice as to what to eat and whether to exercise is determined largely by what is available in one's immediate environment and one's socioeconomic position. In short, individuals are born into and develop within food and activity environments that are shaped by the private sector, public policy and local, national and international economic forces (e.g., temporal changes in the sugar and fat content of the US food supply, food and beverage marketing, urbanization, changes in community transportation infrastructure, and developments in communication such as cell phones and the Internet). These are factors beyond the control of individuals, but factors fundamentally affecting individual norms, preferences, desires, habits and perceptions (Gortmaker, et al. 2011; Hill, et al. 2013). This is a fundamentally different way to frame the problem than the dominant approach that sees type 2 diabetes as mainly a problem that can be rectified by changing individuals through educational initiatives.

Given the intractability of diabetes to individual-level behavioral modification interventions, interest in the use of socioecological models has grown in type 2 diabetes research in recent years. A prime example of this is the recent report of the American Diabetes Association Prevention Committee (Hill, et al. 2013) which examined in detail the socio-ecological determinants of the disease using a model of levels and sectors of influence initially developed by the Institute of Medicine 2012 to explain childhood obesity. The model moves beyond identification of individual and behavioral risk factors to a focus on the various environmental settings that influence energy intake and energy expenditure, which in turn affect the one of the down-stream risk factor for type 2 diabetes which is body weight. The environments are comprised of the school environments, the healthcare and work environments, the physical activity environments, and the food and beverage environments. Hill et al. 2013 describe in detail the myriad of risk factors within each of these settings, with an emphasis on how social and environmental factors (e.g., living in an unsafe neighborhood, poor access to recreational facilities, green spaces and a healthy food supply, and greater accessibility of fast food) lead to changes in population-level food consumption and physical activity and greater risk of type 2 diabetes. They also draw attention to the fact that the risk factors within any one of these settings in a particular geographic location (e.g., an urban setting) may look different to those that operate to increase risk of type 2 diabetes in another geographic location (e.g., a rural setting).

Epidemiologists have developed a number of heuristic models to help understand the etiology of complex chronic health problems such as type 2 diabetes that involve the interaction between risk factors operating at different levels of analysis and interacting dynamically over time. One such heuristic model is the web of causation, which enables one to think about the etiology of diseases in terms of a multiple webs (or pathways), each involving multiple strands (MacMahon, et al. 1960; Schwartz and Susser 2006). As noted above, research on type 2 diabetes has identified two large webs, one entailing risk factors pertaining to excessive energy intake (food and beverage consumption) and one pertaining to insufficient energy expenditure (physical inactivity) (Hill, et al. 2013). The influence on type 2 diabetes of these risk factors is mediated through obesity and overweight status. Indeed, the interdependence between type 2 diabetes and obesity is such that the term “diabesity” has been introduced into the literature (Hill, et al. 2013).

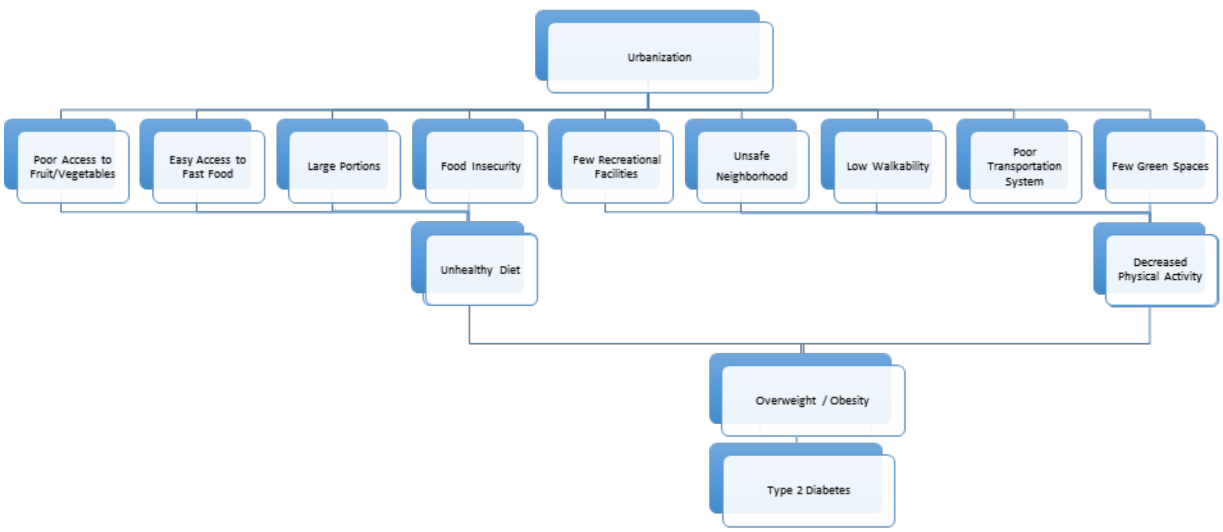

Figure 4. Example Web of Causation for Two Diabetes Risk Factor Sets

Figure 4 presents an example of two of the main webs of causation associated for diabetes in an urban setting, based on the socioecological risk factors described by Hill et al. 2013. The two pathways from an urban setting each run through body weight but each entails a different domain of risk factors, one focused on the food and beverage environment and one on the physical activity environment. It should be noted that the example does not include all of the possible strands within each of these webs. In addition to these two relatively well-established webs pertaining to type 2 diabetes, there are likely others, such as the recent stress models described by Kelly and Ismail 2015. The strands within these will likely look different to those shown in Figure 4. The primary function of the figure is to offer a heuristic device that helps one understand the multiple causal pathways associated with a chronic disease such as type 2 diabetes. However, such a device can also be used to help guide the construction of systems models and to identify possible leverage points for interventions.

4.4 Overview of Chronic Disease Systems Models

There is growing recognition that relationships between risk factors at multiple levels influencing health and disease often involve dynamic feedback and changes over time. Such nonlinear mechanisms challenge traditional statistical approaches to identifying causality (Galea, et al. 2009). In contrast, system science approaches offer holistic understanding of dynamically complex problems and provide tools for addressing such problems through use of various modelling methods, such as system dynamics models and agent-based models (Forrester 1971; Mahamoud, et al. 2013; Meadows 2008; Sterman 2006). These computational systems models take into account the causal influence at multiple levels and the interrelations among causal covariates that strain most widely used analytic methods (Elkins and Gorman 2014; Galea, et al. 2009; Luke and Stamatakis 2012).

System dynamics models (SDMs) and agent-based models (ABMs) have been used to study the effects of different social policies on chronic disease problems, as these models provide a means to test theories about reality where complex relations exist between multiple variables, feedbacks, and dependence between individuals, as well as inputs at varying levels of organization and across time. Such a method applied to chronic disease allows for the prediction of etiologic agents and effects of interventions, defining characteristics of at-risk individuals, and identifying key data missing from understanding of health and disease (Ness, et al. 2007). Each approach has strengths and weaknesses and therefore their application to understanding chronic disease, and diabetes in particular, have varied.

4.4.1 Agent-based Models of Type 2 Diabetes

Agent-based modeling provides a potentially powerful tool for understanding and constructing the mechanisms that generate macro-level social forms (Cedermann 2005; Epstein 1999; Gilbert 2008). It involves "growing" social systems and structures in a computer from the interactions of individual entities (or "agents") that use local and simple behavioral rules to move about their simulated environment and to interact with one another (Epstein and Axtell 1996). As Epstein 1999 observes, ABMs provide a computational test as to whether a specific set of local interactions (that is, a specific micro-specification) is sufficient to generate or "grow" the macrostructure of interest.

With regard to type 2 diabetes, ABMs have used to examine a number of the risk factors associated with the disease – notably diet, exercise, and weight. Of most interest to the current attempt to model the effects of prevention efforts focused on type 2 diabetes in south Texas, are those simulation projects that have built agent-based models using data pertaining to specific geographic locations (e.g., Widener, et al. 2013; Yang, et al. 2011). Orr et al. 2014, for example, developed a simulation model that represented the economic and racial distribution (black and non-Hispanic whites only) of the 100 largest metropolitan statistical areas in the USA. They used the model to examine the effects on healthy diet of improving school quality by lowering the student-to-teacher ratio in neighborhoods in which this was high. They were especially interested in the policy's impact on black-white disparity in healthy eating. The effects of the policy were examined under different levels of social norms concerning a desirable level of healthy diet and in the presence and absence of social network influences on this social norm. The simulations showed that the policy had a positive effect on the population-level racial disparity in diet, but it did not entirely eliminate it. The effect of the policy also varied under different social norm and social network conditions (e.g., the reduction in disparity was smallest when the norm was healthy).

4.4.2 System Dynamics Models of Diabetes

Unlike ABMs that emphasize the heterogeneity of actors and the importance of their interactions, the basic building blocks of system dynamics models are stocks that are accumulations of things within the system (e.g., diabetic patients) and flows that are the rates at which things transition between stocks (e.g., the rate at which prediabetics transition to diabetics). Using such models, the researcher can observe the consequences of manipulating the variables that influence flows (e.g., how does the prevalence of obesity in a population affect the prevalence of diabetes). The researcher can also manipulate these variables using data from the scientific literature pertaining to specific types of interventions (e.g., how much of a reduction in the prevalence of obesity can we anticipate from primary prevention programs and how this affects the prevalence of diabetes). This is the basis of using systems dynamic models to conduct virtual experiments. And such models have been employed by public health researchers to study a variety of chronic diseases (notably cardiovascular disease), especially the effects of population dynamics, social determinants, treatment modalities, and upstream and downstream interventions on incidence, prevalence and mortality (e.g., Hirsch, et al. 2010; Homer, et al. 2007; Homer, et al. 2010; Mahamoud, et al. 2012).

With regard to diabetes, Jones et al. 2006 developed a SDM to examine the growth of diabetes since 1980 and the future of diabetes morbidity, mortality, and costs to 2050. The model was calibrated using US Census data, health data pertaining to the US adult population and evidence from the scientific literature. The prevalence and morbidity output of three models, each employing a different policy intervention (enhancing clinical management of diabetes, increasing management of prediabetes, and reducing obesity prevalence), was compared to a baseline model that included no intervention. The analyses showed the importance of obesity in driving diabetes prevalence, the inability of management and control measures alone to control prevalence, and significant delays between primary prevention measures and improvements. Milstein et al. 2007 used the model developed by Jones et al. 2006 to examine the feasibility of the Healthy People 2010 diabetes prevalence objective, which sought a reduction from 39% in 1997 to 25% in 2010. The simulation output demonstrated that this objective was implausible and, hence, unattainable. It also showed that the achievement of other Healthy People 2010 diabetes objectives, such as increasing diagnosis and decreasing mortality, would serve to increase prevalence.

4.5 Selecting a Modeling Approach

A model, whether mental or mathematical, empirical or systems, is only as good as the assumptions upon which it is based, the formulae producing it, and how effectively it captures the real system-of-interest. Within social system modeling, recognition is increasing for the need for systems methods that capture social complexity and dynamics in order to produce effective change for deficiencies, but there has been little attention given to theoretical assumptions regarding complexity and the purpose of the system. This is particularly true in systems modeling of health problems and potential interventions, where such assumptions influence model development and interpretation (Sterman 2006).

In developing public health interventions, program developers and policy analysts frequently rely on simple unidirectional models of cause-and-effect that ignore and disregard the complexity of the phenomenon they hope to change (Hirsch, et al. 2007). Interventions built upon such models are frequently ineffective (and at times iatrogenic), but results that are unrelated to or at odds with those expected are ignored, explained away, or put down to poor model fit (Hirsch, et al. 2007). Yet programs built upon such principles are in continued use as the mental models that inform these are rarely subjected to critical tests. There are fundamental reasons why people misjudge the behavior of systems, as there are orderly processes working in creating human judgment and intuition that often lead to wrong decisions when faced with complex and highly interacting systems. Interventions that are more effective are only likely to occur through a better understanding of the social system-of-interest that the program seeks to correct (Forrester 1971).

Social and public health systems are complex and hard to understand and to change, but new laws and government programs rarely use formal simulation models to estimate the effects of these before implementation (Sterman 2006). It is possible to construct computer models of social systems that, while simplifying "real world" processes, are far more comprehensive and formal than the mental models otherwise used as the basis for governmental and programmatic action. Such computer models are used frequently in testing technology or equipment to identify weaknesses that can be corrected before they are fully implemented. However, such models and tests are used rarely in guiding programs or legislation to prevent failures in social and public health systems. While these models and tests do not guarantee against failure, but they do allow for identifying potential problems and intervention points in ways that the typical processes guiding interventions within these systems do not (Forrester 1971).

There is nothing novel about using models to represent social systems; they are used inherently in decision-making as people rely on mental images to understand the world around them where concepts and relationships might be of use in representing the real system. A mental image is a model that acts as a basis for decision-making whether by individuals or institutions. However, a mental model is fuzzy, incomplete, and dynamic as it changes with time and context of a situation; its underlying assumptions are typically not clear, and its goals may vary over time. A computer model that explicitly articulates the underlying assumptions and mechanisms of the system allows for more complexity, and avoids internal contradiction and faulty assumptions that frequently appear in mental models. Computer models are stated explicitly, wherein mathematical notation is unambiguous, language is clear, simple and precise, and concepts and relationships are clearly stated; mental models tend not to have these features (Forrester 1971).

However, it is important to recognize that a computer model is only as good as the expertise behind its formulation and how that captures the essence of the social system it presumes to represent. Building mathematical models on formulated techniques and/or according to a conceptual structure that does not capture the multiple-feedback-loops and nonlinear nature of real systems limits any model. Such models explain why there are so many failed efforts to improve social systems. As computer models can be constructed that are superior to mental models, such models should be used as the basis for social and public health programs. This would move us beyond the use of ineffective interventions based on ill-conceived mental models of social problems and facilitate the development of effective interventions and changes in system deficiencies (Forrester 1971; Sterman 2006).

In addition, simulation models provide researchers and policymakers with "low cost laboratories for learning" (Sterman 2006). One can manipulate features of these worlds in a manner that is not feasible or ethical in the real world. One can also accelerate the effects of changes in these features and observe how they affect the behavior of other parts of the system. In the real world, the effects of such changes may take years to unfold, and the mechanisms through which they affect behavior may be unobservable (Sterman 2006).

4.5.1 Choosing Between Models

When attempting to use models to intervene within social systems and health, it is important to understand what the assumptions are and the value of the method chosen for modeling that system. It is important to use systems models appropriate to the system-of-interest that consider not only the contextual factors related to individuals, the environment, and their interactions, but also to consider how the value of the model sought for producing change in such a system is influenced by the method and its assumptions that allow for interpretation of social system behavior. Not only must the model formulation capture the essence of the real-world system, the modeling technique must use a conceptual structure appropriate to understanding and changing that system in order to be useful.

Each systems model has a paradigm characterizing it by a set of fundamental assumptions and underlying concepts wherein each method is itself based on a model of how the model should be done. By assuming the model should be done a certain way, the modeler (whether explicitly or implicitly) makes assumptions about the world (Lorenz and Jost 2006; Meadows and Robinson 1985). For example, when a modeler selects a system dynamics model, he/she selects a paradigm that asserts that the system-of-interest is comprised of stocks, rates, levels and feedback loops (Meadows 1989; Sterman 2006). In contrast, in selecting an agent-based model, the modeler is assuming that there is some emergent quality to the phenomenon-of-interest and that the underlying mechanisms explaining this are due to the micro-interactions between autonomous agents over time and between agents (that have the capacity to learn and adapt) and their environments (Cederman 2005; Macy and Willer 2002). Thus, questions about policy decisions and resources can be seen as most amenable to understanding through SDMs (e.g., Jones, et al. 2006; Homer, et al. 2010), whereas questions about the effects of social interactions and the built environment might require the micro-detail of agent-based models (e.g., Auchincloss and Diez Roux 2008; Orr, et al. 2014). However, it should be noted that some systems can be modeled using either approach and that hybrid simulations involving both approaches have also been developed in some areas of public health research, notably infectious disease epidemiology (Borshchev, et al. 2007; Macal 2010; Rahmandad and Sterman 2008).

4.5.2 Framing and Modeling Type 2 Diabetes

Brown, et al. 2005 assert that, in communities with high diabetes-related unemployment, income reductions related to diabetes translate into decreased local spending, increased layoffs, and increased medical. Since these high-risk communities have a particularly high prevalence and incidence of the disease, a model capturing the extent of the health problem and the economic burden it imposes, while at the same time analyzing an array of possible intervention effects, could be crucial to reducing type 2 diabetes and informing policy decisions. Such issues might be best addressed through a system dynamics model.

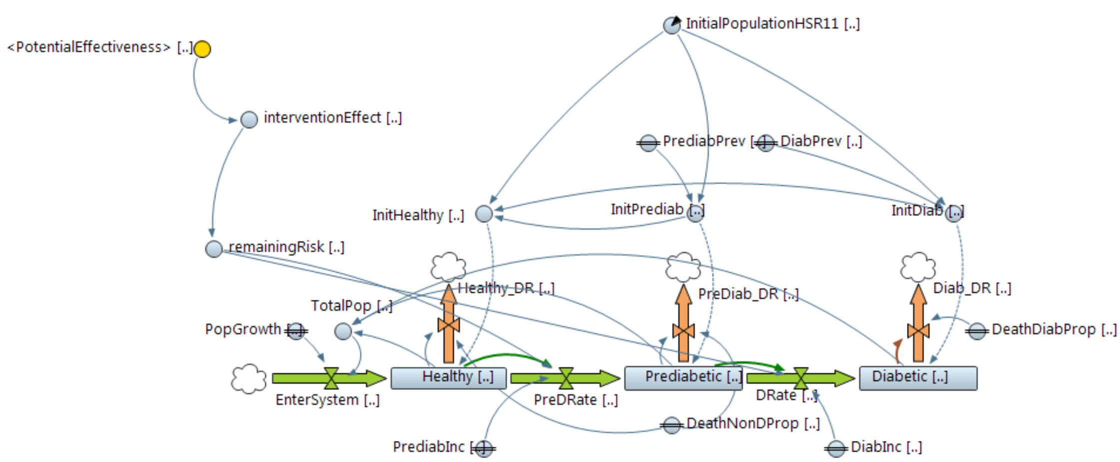

Figure 5. Conceptual SDM of Intervention Effectiveness on Diabetes Progression

As noted above, by framing type 2 diabetes as a population-level problem and selecting a system dynamics model, the modeler assumes the system-of-interest and problem within such is comprised of stocks, rates, levels, and feedback. Thus, modeling type 2 diabetes prevalence in HSR11 could assume the population is comprised of stocks of people within different vulnerability states that enter, leave, or progress through the system via mechanisms pertaining to disease progression, and death rates in the event. For example, if the purpose of the model is to test interventions on decreasing incidence to reduce overall prevalence related to prevention and treatment of type 2 diabetes both at a population level and among aggregate vulnerable subgroups (e.g., Figure 3) based on their effectiveness, then one could use a system dynamics model (e.g., Figure 5). Thus, a modeler seeking to find the most effective intervention to reduce type 2 diabetes within HSR11 could find value in a model that could test the effectiveness of different interventions to allocate resources to the intervention reflecting the most effective and appropriate to the timeframe of interest. Exploration of such a model is included later in the analysis.

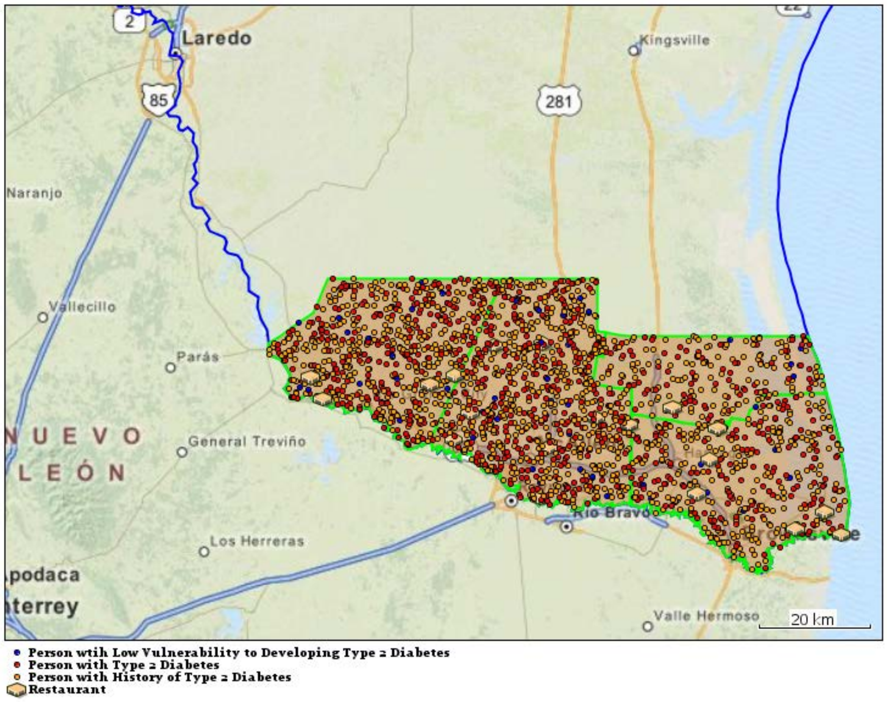

Figure 6. Conceptual ABM of Restaurant Proximity on Diabetes in the LRGV

In contrast, by selecting an agent-based model, the modeler assumes type 2 diabetes is an emergent quality produced by interactions between autonomous agents as they interact with one another and with their environment. Prior modeling efforts have shown that the main risk factors for type 2 diabetes (obesity, diet, and lack of exercise) are influenced by social interactions within networks and by the built environment (e.g., Orr, et al. 2014; Yang, et al. 2011). These are the domains of risk factors shown in Figure 4. The value of such a modeling exercise lies in its ability to guide community-based interventions pertaining to issues such as the number of fast food restaurants, the safety of public places, and the availability of green spaces (Sallis and Glanz 2009). Figure 6 presents a preliminary ABM of access to restaurants in the Lower Rio Grande Valley of Texas.

5. A SYSTEM DYNAMICS MODEL EVALUATING INTERVENTION EFFECTIVENESS ON TYPE 2 DIABETES IN SOUTH TEXAS

Diabetes is a growing health problem for which there are no quick or easy fixes and is a substantial cost burden to address; modeling such necessitates using a method capable of handling such non-linearity and one capable of capturing the multiple conflicting goals policy makers and others might have in addressing such a dynamic, complex issue. Solutions for such require focusing on the risk factors and interventions for treatment and prevention that address the issues as a system instead of just focusing on parts therein (Jones, et al. 2006).

The following model is a system dynamics model exploring the past and future burden of diabetes in terms of morbidity, mortality, and effectiveness of two common approaches to treating type 2 diabetes. Both interventions focused on reducing prevalence of type 2 diabetes through treating and preventing obesity through physical activity. The model tests the reported effectiveness of physical activity interventions for treating obesity in the specific region of South Texas known as Health Service Region 11. Major aims of this model were to:

(1) Computationally assess Health Service Region 11 data sources for diabetes population management and prevention to understand the dynamic relationships contributing to yearly incidence, prevalence, and potential complications for populations in the community over the long-term.

(2) Develop a modeling framework capturing type 2 diabetes as a public health threat in HSR11 that uses a method best suited to comparing and contrasting the

health effectiveness of public health programs that afford more comprehensive allocation of resources.

(3) Build a model to learn valuable information about this health problem in this specific context as a capacity-planning tool capable of representing various leverage points and testing different interventions for reducing prevalence of type 2 diabetes that are both effective and realistic.

This model acts as an example of how and when systems methods are useful in guiding resource allocation decisions by applying the approach to the real-world system-of-interest of type 2 diabetes in South Texas. The focus is on the effectiveness of physical activity interventions to guide decision-makers in future resource allocation and public health professionals to use appropriate methodologies for complex health problems that traditional linear approaches are unable to capture and thus unable to suggest informed routes for change.

Developing a comprehensive system-wide approach for a specific community that is considerate of intervention effectiveness in resource planning and allocation constitutes an important and novel contribution to the literature. This project is also significant due to its focus on a particularly vulnerable population in South Texas. As this community has a particularly high prevalence and incidence and is at increased risk, a model capturing the extent of the health problem and analyzing the potential effects of an array of possible intervention effects could be crucial to reducing type 2 diabetes.

5.1 Model Design and Analysis

As with all models, the model makes assumptions to simplify understanding and includes some levels of uncertainty. Parameterization of the model used data pertaining to the counties comprising this region or previously aggregated regional data, as well as data from other secondary sources when county-level or regional data was unavailable. Model parameter calibration relied upon historical data available in the specific counties comprising HSR11 aggregated to the region, but utilized state-level data when county-level data was unavailable. As much of the data ended in 2012, model initialization began in 2013 with a daily time step using Euler Differential Equation Methods, Modified Newton Algebraic Equation Methods, RK45+Newton Mixed Equation Methods, and linear interpolation with a daily time step.

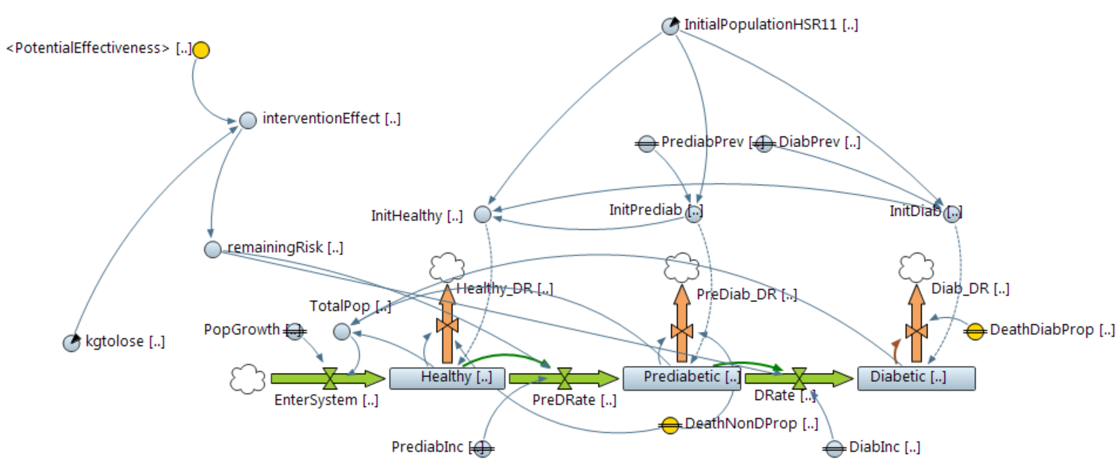

Figure 7. A System Dynamics Model of Intervention Effectiveness on Diabetes

Figure 7 presents the general causal structure of the system dynamics model of type 2 diabetes and its connections to obesity, while Figure 8 presents the general causal structure or sub-model important to capturing how obesity relates to prevention and treatment ultimately of type 2 diabetes.

Both models utilized multi-dimensional HyperArrays with two dimensions for different categories of obesity (ultimately represented by *BMIstatus*) and different types of participation (*Participation*). Participation included three categories: (1) no intervention (*No*), (2) participation in the individual behavior change intervention (*Intervention1*), and (3) participation in the creation or enhanced access to places for physical activity intervention (*Intervention2*). Effectiveness of interventions based upon a meta-analysis of physical activity interventions for reducing obesity detailed later (Wu, et al. 2011).

5.1.1 Diabetes Progression Model

Figure 7 categorizes people by health status through aggregation in one of three stocks: (1) the healthy population (*Healthy*), (2) the population with [diagnosed] prediabetes (*Prediabetic*), and (3) the population with [diagnosed] type 2 diabetes (*Diabetic*). Each stock represents the number of individuals (N) in that health status at that specific point in time in HSR11.

Healthy represents individuals that did not have diagnosed prediabetes or diabetes. This stock does not account for other health conditions, such as that the people in this stock may not actually be healthy, as some might be unhealthy for other reasons outside of prediabetes or diabetes. However, this model is specific to progression of type 2 diabetes so these other health factors are not accounted for in the present model. Initialization of *Healthy* ($Healthy_0$) was the population not diagnosed with prediabetes or diabetes at model start (*InitHealthy*).

Prediabetic represents individuals diagnosed with prediabetes. This stock does not account for other conditions the individuals might have and is specific only to individuals diagnosed with prediabetes. The initial value of the population with diagnosed prediabetes ($Prediabetic_0$) was calculated using the total initial population size for all counties in HSR11 (*InitialPopulationHSR11)* by the county-level prevalence of diabetes (*PrediabPrev*) as the initial diabetic prevalence (*InitPrediab*).

Diabetic represents individuals diagnosed with diabetes. This stock does not account for other conditions the individuals might have and is specific only to individuals diagnosed with diabetes. The initial value of the population with diagnosed diabetes ($Diabetic_0$) was equivalent to *InitDiab*, calculated through similar means but for the current prevalence of diabetes (*DiabPrev*).

Flows or movement into, throughout, and out of the system represented the movement of people per day (N/Δt) .People enter the system (*EnterSystem*) through a flow representing population growth and leave by death flows representing rates of death for that categorization. The model does not account for leaving the system in other ways than death or for people to enter the system (e.g., moving into the HSR11) in states other than *Healthy*, though it is likely people would enter the system in states.

EnterSystem represents the sum of total population multiplied by the population growth per day. People flow through the system from *Healthy* to *Prediabetic* through a flow (*PreDRate*) equivalent to the sum of the incidence rate of prediabetes (*PrediabInc*), the healthy population, and the potential effectiveness of the intervention (*PotentialEffectiveness*). People flow through the system from *Prediabetic* to *Diabetic* through a flow (*DRate*) equivalent to the sum of the incidence rate of diabetes (*DiabInc*), the healthy population, and *PotentialEffectiveness*.

People could leave the system through death flows, represented by mortality rate or the number of deaths per day scaled to the population dependent upon health status. The *Healthy* Death Rate (*Healthy_DR*) represented mortality rate data on the number of deaths not due to prediabetes or diabetes for those in the *Healthy* stock per day. The prediabetic death rate (*PreDiab _DR*) represented mortality rate data on the number of deaths due to prediabetes for those in the *Prediabetic* stock per day. The diabetic death rate (*Diab_DR*) represented the mortality rate or the number of deaths due to diabetes for those in the *Diabetic* stock per day.

Total Population (*TotalPop*) represented the population of people in HRS11 at the specified time (N) equal to the sum of the *Healthy*, *Prediabetic*, and *Diabetic* stocks at a specified point in time.*InitialPopulationHSR11* (N) was the total population within HRS11 region in the year 2012. It based on DSHS: CHS county-level frequency population data from the 2010 Series Estimates of population per year, then aggregated to the region by year (DSHS: CHS 2014a). The initial values of populations (N) for each health status based upon this number. The initially healthy population (*InitPrediab*) represented the number of people (N) in the region that had not been diagnosed with diabetes or prediabetes by initialization. The initially population with diagnosed prediabetes (*InitPrediab*) and initially diabetic population (*InitDiab*) represented the number of people in the region by initialization diagnosed with prediabetes and the number of people in the region diagnosed with diabetes, respectively.

According to the DSHS Office of Surveillance Evaluation, and Research (OSER), in 2012 in HSR11, the prevalence of diagnosed prediabetes (not during pregnancy) was 5.0% at a 95% CI[3.1-8.0] and the prevalence of diagnosed diabetes (not during pregnancy) was 19.5% at a 95% CI[15.9, 23.6] of the population aged 18 years and older (DSHS: OSER 2015). Prevalence of prediabetes for populations aged 20 years and older in the county could not be obtained or that did include pregnant women while some data in the model does not include adults 18 years to 20 years old. Since this specific data could not be obtained for prevalence for 2012, the proportion of the population in HSR11 in 2012 diagnosed with prediabetes (*PrediabPrev*) and the proportion diagnosed with diabetes (*DiabPrev*) were set to 0.05 and 0.195, respectively.

As county-level data for the prediabetes incidence rate could not be found, the incidence rate of prediabetes (*PrediabInc*) based upon National Center for Health Statistics annual data of the total number of people with prediabetes in Texas from 2008 to 2012 (CDC 2015c) to establish the percentage of growth per day of new cases of prediabetes among Texas residents. *PrediabInc* was set at a constant of 0.0031 new cases per day.

The incidence rate of diabetes (*DiabInc*) used 2004 to 2012 county-level diagnosed diabetes incidence data from the CDC's Behavioral Risk Factor Surveillance System (BRFSS) and from the US Census Bureau’s Population Estimates Program (CDC 2015a), aggregating the number of newly diagnosed cases in the selected counties per year and determining the proportion of new cases per day (CDC, 2015b).

The population growth per day (*PopGrowth*) represented the daily proportion of people per day in the region based upon county-level population data from 2010 Series

Estimates from 2000 to 2012 (DSHS: CHS 2014a) aggregated to the region each year, then calculating the annual percent growth rate for the region and converting it to the daily growth for the region. *PopGrowth* was set at a constant of 0.0001 people per day.

The proportion of deaths for the total population based on Texas Department of State Health Services: Center for Health Statistics's (DSHS: CHS) Texas Health Data from 2000 to 2012 using Texas Resident Death mortality data of frequency of deaths by county per year for Texas residents who die in Texas and out-of-state (DSHS: CHS 2015). The frequency of deaths per county was aggregated by year per region to determine the proportion of deaths due to all causes for the total region population.

The proportion of deaths due to diabetes based on DSHS: CHS Texas Health Data from 2000 to 2012 using frequency of deaths by county per year for Texas residents who die in Texas and out-of-state due to Diabetes Mellitus (identified by the death certificate as the single underlying cause of death). This was aggregated to the region by year to calculate the proportion of deaths per day due to the selected cause (*DeathDiabProp).*

The proportion of deaths not due to diabetes (*DeathNonDProp*) based on DSHS: CHS Texas Health Data from 2000 to 2012 (DSHS: CHS 2015) using the difference between the frequency of deaths by county per year for Texas residents due to all causes and the frequency of deaths by county per year for Texas residents due to Diabetes Mellitus. Analysis aggregated this to the region by year to calculate the proportion of deaths per day not due to the selected cause.

5.1.2 Obesity Sub-Model of Energy Balance

According to the CDC's National Center for Health Statistics 2003, the average man of 5'9" height and average woman of 5'4" height classify by weight using the weights in pounds (which was used to calculate weight in kilograms) reported in Table 1. The values for weight in pounds were converted to weight in kilograms and the minimum values for each category of man and women were used in the analysis as an average for the two sexes. Future analysis should consider separating these values due to the difference in risk and potential effect for different sexes based upon BMI status and caloric burn of the interventions and needed for a healthy weight status.

BMI Category	Male		Female	
	Min	*Max*	*Min*	*Max*
Healthy (lb)	121	163	108	144
Overweight (lb)	164	195	145	173
Obese (lb)	196		174	
Healthy (kg)	54.88	73.94	48.99	65.32
Overweight (kg)	74.39	88.45	65.77	78.47
Obese (kg)	88.90		78.93	

Table 1. Weight Classification

Figure 8 categorizes people by weight through aggregation in a stock representing weight by BMI classification or status (*BMIstate*). Each state represents the minimum weight or mass of individuals in that BMI status (kg/N) at that specific point in time in HSR11. Initialization of weight ($Weight_0$) used the average weight in kilograms of both sexes per BMI category.

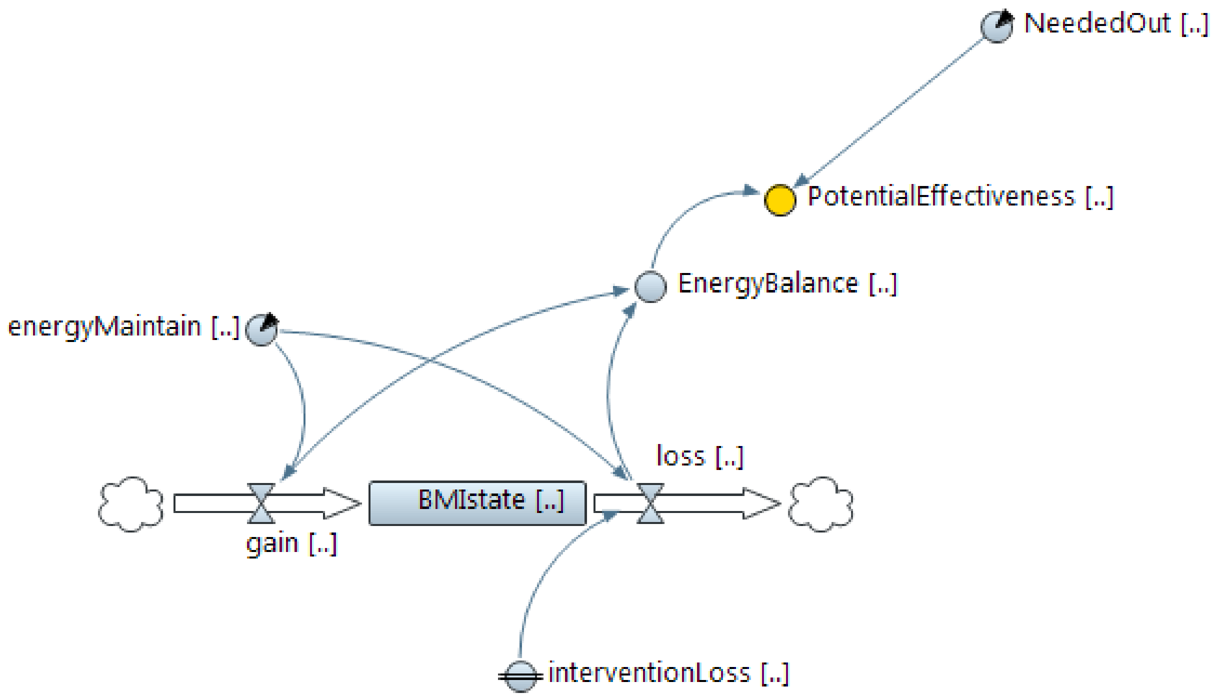

Figure 8. Obesity Sub-model of Energy Balance

Flows of energy per day into the system (*gain*) and out of the system (*loss*) represented the energy balance or difference in energy in and energy out per person per day (*EnergyBalance*) by participation status and *BMIstate*. *EnergyBalance* depended on the total energy balance or energy in and energy out needed to maintain weight (*energyMaintain*) given the BMI classification of the individuals (kg/Δt). Table 2 reports the values in kilocalories per day and in kilograms per day by sex and BMI category, as well as the average for both sexes per by BMI category.

BMI Category		Maintain Weight			
		$kcal_{in}$/day	$kcal_{out}$/day	kg_{in}/day	kg_{out}/day
Male	Healthy	1872.16	1872.16	0.2426	0.2426
	Overweight	2193.62	2193.62	0.2843	0.2843
	Obese	2432.86	2432.86	0.3153	0.3153
Female	Healthy	1597.92	1597.92	0.2071	0.2071
	Overweight	1791.06	1791.06	0.2321	0.2321
	Obese	1942.44	1942.44	0.2517	0.2517
$Average_{Healthy}$		1735.04	1735.04	0.2249	0.2249
$Average_{Overweight}$		1992.34	1992.34	0.2582	0.2582
$Average_{Obese}$		2187.65	2187.65	0.2835	0.2835

Table 2. Baseline Energy Balance for Weight Maintenance

5.1.3 Model Connectivity

The effectiveness of the intervention for the region population (*PotentialEffectiveness*) applied to the weight in kilograms an individual would have to lose to reduce risk in addition to the energy intake and expenditure for weight maintenance based on their BMI category (*NeededOut)* to establish the intervention effect given the individual BMI level. The model assumes all participants are actively involved within the intervention, which is an unrealistic assumption, but assumes that, if such an approach were to be used and everyone participated, the model generate the maximum effect such an intervention could obtain even with such an unrealistic assumption. However, if participation or retention were included, this would be an appropriate place to do so. The intervention's purported efficacy (*interventionEffect*), and the population that would, due to the nature of the intervention design, not participate in the intervention so have no chance of it having influence on disease progression for such.

The model tested two types of interventions of physical activity to reduce obesity and ultimately reduce the incidence and prevalence of type 2 diabetes. Wu, et al. 2011 performed a systematic review of physical activity interventions, wherein the authors reviews 5579 articles, identified 91 effective interventions for promoting physical activity, and calculated cost-effectiveness ratios as cost per MET-hour gained per day per individual reach and compared these to U.S. guideline-recommended levels. Intervention effectiveness was expressed as the percentage change of adequate physical activity per day or MET-hours gained per person per day divided by the 1.5 MET-hours for adults with a moderate physical activity of 3.0 METs, which the authors reported as MET-hours gained/day/person by type of intervention. Intervention types included (1) point-of-decision prompts, (2) community campaign, (3) individually adapted change (categorized for “all”, as well as “low-intensity” and “high-intensity”), (4) social support (categorized for “all”, as well as “low-intensity” and “high-intensity”), (5) school-based physical activity intervention, and (6) creation or enhanced access to places for physical activity (Wu, et al. 2011).

The model tested the reported effectiveness of MET-hours gained/day/person for the individually adapted change intervention type as a whole ($InterventionEffect_1$) and for the creation or enhanced access to places for physical activity intervention type ($InterventionEffect_2$) in achieving the guideline-recommended physical activity for adults (Wu, et al. 2011). These values were used in calculating the intervention effectiveness as a proportion of the guideline-recommended physical activity for adults and then applying it to the recommended values for weight-loss given the weight categorization. Baseline assumed no intervention, thus no intervention effect.

According to the National Institutes of Health's National Heart, Lung, and Blood Institute (NHLBI), one can safely lose 1 to 2 pounds per week, requiring a reduction in caloric intake by 500-1000 calories per day and the initial goal of weight loss therapy should be a reduction of bodyweight by approximately 10 percent from baseline (NHLBI 2010; NHLBI 1998). Guidelines were standardized to 3.0 METs per half-hour used the minimal weight of the different weight categories for males and females. Calculation of the weight needed to lose 10% of bodyweight (*NeededOut*) depended upon kilocalories needed to lose 10% of bodyweight and kilocalories needed at suggested levels of weight reduction of 1-2 lbs. per week. The model assumed that people could safely lose the maximum amount of 2 pounds per week per person, which is unlikely but again such an assumption demonstrates how effective an intervention is likely to be under ideal conditions. Kilocalories burned per day safe to burn per day was set at 2204.57 kcal or 0.13 kg per day or 15432 kcal per week or 0.91 kg per week.

The model optimistically assumes that intervention participants could lose 1000 calories per day to remain within the safe range of weight reduction or 2 pounds per week per person. The equation to calculate calories based on an analysis from Ainsworth, et al. 2011, wherein:

$$kilocalories = MET\ weight\ in\ kilograms\ duration\ in\ hours$$

Thus, to burn 1000 kcal at the recommended physical-activity guideline lines of 3.0 MET by the minimum weight of an overweight male of average height and of an overweight female of average height would require 4.48 hours and 5.07 hours respectively. To burn 1000 kcal at the recommended physical-activity guideline lines of 3.0 MET by the minimum weight of an obese male of average height and of an obese female of average height would require 3.75 hours and 4.22 hours respectively. The model used the minimal weight for the sex-specific weight categorization to calculate the calorie reduction needed to reduce weight by 10% of the bodyweight.

Calories burned per day in a sedentary lifestyle was sex-dependent. Average values came from mean values for weight and height by sex and age category of 20-74 years from NHANES 1999-2002 data (Ogden, et al. 2004). Calculation of the calories burned per day in a sedentary lifestyle relied upon the following equations using the minimum weight required for each BMI categorization by respective sex ($Calories_{BurnedM}$ and $Calories_{BurnedF}$, respectively) (Herron 2013).

$$Calories_{BurnedM} = 1.2[66 + (6.23\ weight(lbs)) + (12.7\ height(in)) – (6.8\ age(years))]$$

$$Calories_{BurnedF} = 1.2[655 + (4.35\ weight(lbs)) + (4.7\ height(in)) - (4.7\ age(years)]$$

Standardized age for both sexes was set 20 years, as that was the start of the age category and this modeling approach requires aggregation and not individuality, whereas an ABM would better capture discrepancies related to age and should be considered in future analyses. Standardizing height was similar to age, but using the average value per sex. Weight standardized to the minimal weight in pounds per sex and BMI classification.

BMI		Intervention$_1$		Intervention$_2$	
		kcal/day	kg/day	kcal/day	kg/day
Male	Healthy	13.72	0.0018	17.01	0.0022
	Overweight	18.60	0.0024	23.06	0.0030
	Obese	22.23	0.0029	27.56	0.0036
Female	Healthy	12.25	0.0016	15.19	0.0020
	Overweight	16.44	0.0021	20.39	0.0026
	Obese	19.73	0.0026	24.47	0.0032

Table 3. Intervention Effects on Energy Expenditure per Day

BMI	Intervention$_1$		Intervention$_2$	
	kcal/day	kg/day	kcal/day	kg/day
AverageHealthy	12.98	0.0017	16.10	0.0021
AverageOverweight	17.52	0.0023	21.72	0.0028
AverageObese	20.98	0.0027	26.01	0.0034

Table 4. Average Intervention Effects on Energy Expenditure per Day

Table 3 details the values obtained from the calculations for total calories burned per day and kilograms burned per day in each intervention scenario by sex, and then as the average of both sexes weighted equally per *BMIstate* (Table 4). Future studies should consider the importance of sex and other risk factors increasing risk for vulnerable populations. Figure 9 presents selected simulation output for the model using the values and calculations based upon the historical data and meta-analysis. The baseline simulation ran from the first day of January in 2013 and forecasting out five years with a daily time step, relying upon the trend analysis in projecting future rates for population growth and mortality, as well as obesity and diabetes incidence rates and prevalence. The model was able to reproduced historical data on prediabetes prevalence, as well as diagnosed diabetes, population obesity rates, and reported death rates.

5.2 Simulation Results

Figure 9 graphically demonstrates the effect of the different interventions on diabetes using stacked charts above sorted by state of diabetes progression and then categorized by participation status. Time-plot graphs illustrated states of diabetes progression and intervention effects through sorting by participation status, then by population BMI categorization.

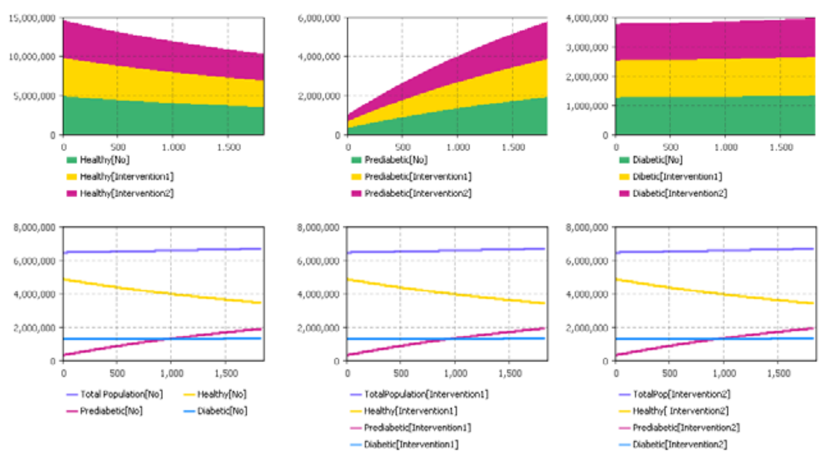

Figure 9. Simulation Results

Table 5 illustrates that, compared to the baseline scenario for obesity state, the individualized intervention had a reported effect on obesity state of 0.000% for the healthy weight population, a decrease of 0.0139% for the overweight populations, and a decrease of

0.0196% on the obese populations. The environmental adaptation intervention had a reported effect on obesity state of 0.0000% for the healthy weight population, a decrease of 0.0169% for the overweight populations, and a decrease of 0.0248% on the obese populations. Neither intervention had statistically significantly effects on obesity status within the populations.

	Healthy	Overweight	Obese
No	--	--	--
Intervention_1	0.0000	-0.0139	-0.0196
Intervention_2	0.0000	-0.0169	-0.0248

Table 5. Percent (%) Growth by Obesity State Compared to Baseline

Table 5 illustrates that, compared to the baseline scenario for obesity state, the individualized intervention had a reported effect on obesity state of 0.000% for the healthy weight population, a decrease of 0.0139% for the overweight populations, and a decrease of 0.0196% on the obese populations. The environmental adaptation intervention had a reported effect on obesity state of 0.0000% for the healthy weight population, a decrease of 0.0169% for the overweight populations, and a decrease of 0.0248% on the obese populations. Neither intervention had statistically significantly effects on obesity status within the populations.

	Healthy	Prediabetic	Diabetic
No	--	--	--
Intervention_1	0.91	-1.51	-0.14
Intervention_2	1.13	-1.86	-0.17

Table 6. Percent (%) Growth by Diabetes State Compared to Baseline

Table 6 illustrates that, compared to the baseline scenario for disease progression, the individualized intervention found an increase in healthy populations of 0.91%, decrease in pre-diabetes individuals of 1.51%, and decrease in diabetic individuals of 0.14%. Compared to the baseline scenario for disease progression, the environmental-adaptation intervention scenario found an increase in healthy populations of 1.13 %, a decrease in pre-diabetes individuals of 1.86%, and a decrease in diabetic individuals of 0.17%. Neither intervention had statistically significantly effects on diabetes status within the populations.

5.3 Conclusions

The model aggregated populations through different rates of disease progression, as well as other relevant risk factors and demographic attributes to allow for population-level analysis of potential intervention effects. By understanding the forces contributing to disease progression, the model tested the effects of different interventions for prevention and treatment of type 2 diabetes based on the effectiveness of such reported in a meta-analysis of the relevant literature. By selecting to implement the analysis through use of the system dynamics modeling framework, the model grouped actors into categories or stocks concerned with the flow between conditions and factors influencing the rate at which these flows occur. The model presented considered feedback loops and unintended consequences that may arise from well-intentioned attempts for changing a system, as well as leverage points for interventions and potential effectiveness of such.

More specifically, the model tested physical activity interventions framing the problem first through different ecological levels of affect incidence and prevalence of diabetes under optimal conditions to affect populations within the community and primary, secondary, and tertiary levels of prevention, and then applying a framework of system dynamics modelling to test such scenarios. The focus was on the effectiveness of physical activity interventions to guide decision-makers in future resource allocation and public health professionals to use appropriate methodologies for complex health problems that traditional linear approaches are unable to capture and thus unable to suggest informed routes for change. To this end, the model assessed and evaluated different “what if” scenarios of prevention and intervention strategies for reducing prevalence of (and ultimately incidence of) type 2 diabetes.

The model acts as an example of how and when systems methods are useful in guiding resource allocation decisions by applying the approach to the real-world system-of-interest of type 2 diabetes in Texas’s Health Service Region 11. More importantly, the model acts as an example of how selection of a modeling approach requires the modeler to make assumptions about the world and the mechanisms that produce the phenomenon-of-interest, and that there must be a purpose to modeling the system-of-interest for the model to be of value (Lorenz and Jost 2006; Meadows and Robinson 1985).

6. SUMMARY

Development of the model compared different ways of framing the problem of type 2 diabetes in HSR11 and compared conceptual differences between modeling approaches to demonstrate how different modeling frameworks affect causality and understanding of this complex health problem. Then, the analysis assessed the ways in which theoretical frameworks of modeling and of the problem affect understanding of causality of the health problem and of ways of affecting such. Such causal assumptions affect what one can learn from modeling efforts and ultimately of how to affect change in the health status of the population. Following this, a discussion built around understanding the theoretical and practical implications of different frameworks on modelling complex public health problems to develop two conceptual models (a system dynamics model and an agent-based model) to illustrate these important differences. Finally, development and analysis of a system dynamics model demonstrated such an approaches ability to assess the different dynamic forces contributing to development and persistence of type 2 diabetes in the specific geographic area, as well as the effectiveness of interventions framing the problem in different ways to hinder such.

While a system dynamics model or an agent-based model might each capture important aspects of a real-world system, which model is of value will depend upon the selection of an approach, since the latter reflects the modeler's (1) framing of the problem and (2) purpose in modeling the system-of-interest. In modeling type 2 diabetes in HSR11, a system dynamics model could be more valuable than an agent-based model if the purpose of the model is to make decisions about allocating resources to reduce prevalence in the population reflective of the value the modeler holds in the effectiveness and/or costs of different interventions. On the other hand, an agent-based model would be more valuable if the purpose of the model is to understand the effects of social interactions among autonomous agents and the environment on the prevalence of type 2 diabetes and to identify community-based interventions focused on social networks and the local built environment.

From a socioecological viewpoint both modeling approaches have value as they each entail framing the problem of type 2 diabetes as something other than a problem resulting from deficiencies in the knowledge, attitudes and behavior of individuals. Accordingly, each moves the discussion of solutions to the problem of type 2 diabetes away from behavioral and education-based interventions designed to “fix” individuals one-by-one. As noted above, such interventions have proven to be of limited efficacy, and it is now increasingly recognized that other approaches to prevention need to be considered (Hill, et al. 2013; Kaldor, et al. 2015). Both system dynamics and agent-based models redirect prevention efforts from an emphasis on individuals and programs to an emphasis on policies and communities. Potential policy or environmental-level interventions introduced at both a state level and a local level, and evidence suggests that they are more effective in reducing the major risk factor for diabetes, such as poor nutrition, physical inactivity obesity, than are individual-level programs (Graff, et al. 2012; McKinley and Marceau 1999; Sallis and Glantz 2009). Moreover, such approaches are especially relevant to a high-risk population such as that of HSR11, as they avoid framing the problem in a manner that “blames the victim.” The individual-level framing of diabetes that informs the dominant educational approaches to type 2 diabetes prevention essentially holds those at-risk responsible for engaging in health-promoting behaviors (Adler and Stewart 2009).

The final model aggregated populations through different rates of disease progression, as well as other relevant risk factors and demographic attributes to allow for population-level analysis of potential physical-activity intervention effects. Major aims of the model were to:

(1) Computationally assess Health Service Region 11 data sources for diabetes population management and prevention to understand the dynamic relationships contributing to yearly incidence, prevalence, and potential complications for populations in the community over the long-term.

(2) Develop a modeling framework capturing type 2 diabetes as a public health threat in HSR11 that uses a method best suited to comparing and contrasting the health effectiveness of public health programs that afford more comprehensive allocation of resources.

(3) Build a model to learn valuable information about this health problem in this specific context as a capacity-planning tool capable of representing various leverage points and testing different interventions for reducing prevalence of type 2 diabetes that are both effective and realistic.

By understanding the forces contributing to disease progression, the model tested the effects of different interventions for prevention and treatment of type 2 diabetes based on the effectiveness of such reported in a meta-analysis of the relevant literature. By selecting to implement the analysis through use of the system dynamics modeling framework, the model grouped actors into categories or stocks concerned with the flow between conditions and factors influencing the rate at which these flows occur. The model presented considered feedback loops and unintended consequences that may arise from well-intentioned attempts for changing a system, as well as leverage points for interventions and potential effectiveness of such.

The model acts as an example of how and when systems methods are useful in guiding resource allocation decisions by applying the approach to the real-world system-of-interest of type 2 diabetes in Texas's Health Service Region 11. More importantly, the model acts as an example of how selection of a modeling approach requires the modeler to make assumptions about the world and the mechanisms that produce the phenomenon-of-interest, and that there must be a purpose to modeling the system-of-interest for the model to be of value (Lorenz and Jost 2006; Meadows and Robinson 1985).

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