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

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## ABSTRACT

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 paper 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 paper examines how framing of type 2 diabetes in the Lower Rio Grande Valley (LRGV) affects which systems modeling method selects to understand the problem and to help guide policy-makers to ameliorate it. 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. The paper 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 LRGV. 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 LGRV 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 our understanding of social systems and public health problems.

Keywords: *complexity, public health, chronic disease, system dynamics, agent-based models*

*"So much of our well-intentioned hard work in public health appears to yield disappointing results"*
(McKinley and Marceau, 1999)

## 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 paper 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 paper examines how framing of type 2 diabetes in the Lower Rio Grande Valley (LRGV) affects which systems modeling method selects to understand the problem and to help guide policy-makers to ameliorate it.

### 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 incomes, 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, 2010).

*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 1). Two recent reports from the Missouri Department of Health and Senior Services (MDHSS; 2014a; 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).

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).

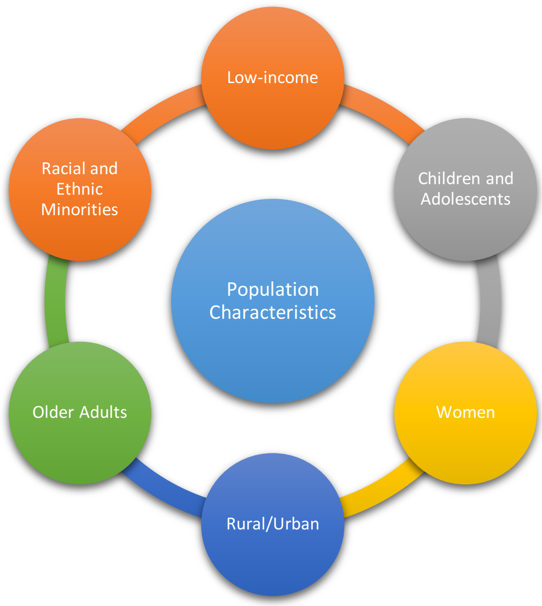


**Figure 1. Populations at High-Risk for Diabetes**

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).

## 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 are typically 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 largely determined 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 (such as 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).

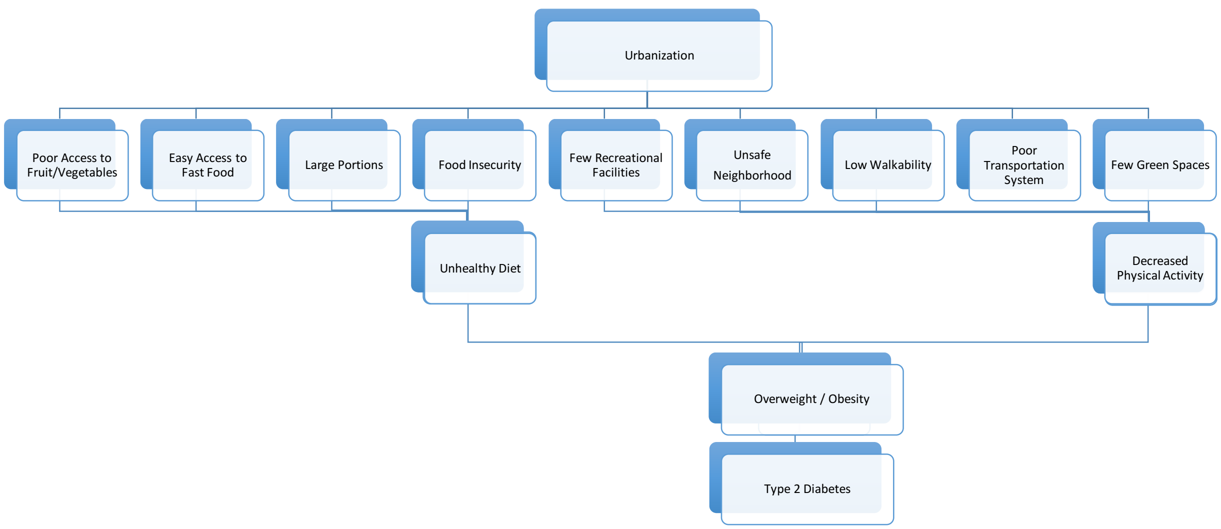


**Figure 2. Examples of Web of Causation for Two Diabetes Risk Factor Sets**

Figure 2 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 2. 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.

## 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).

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.

### 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).

### 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 will this affect 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; 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.

## 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 frequently used in testing technology or equipment to identify weaknesses that can be corrected before they are fully implemented. However, such models and tests are rarely used 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, as they are instinctively used for decision-making as people rely on mental images to understand the world around them where concepts and relationships are used 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).

## 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).

## FRAMING AND MODELING TYPE 2 DIABETES IN THE LGRV

According to Larme and Pugh (2001), diabetes prevalence in the LGRV region is as high as 21%. Brown et al. (2002) noted that the Mexican American population predominantly comprising the LGRV population has the highest diabetes-related death rates in Texas and in certain areas of this region as many as 50% of the Hispanic population aged over 35 years have type 2 diabetes. Furthermore, 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.

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 the LRGV 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 diagnosis, disease progression, and death rates. For example, Figure 3 is a conceptual SDM that would allow one to test how an income-based eligibility criterion influences resource allocation to determine access to resources for diabetes care and management within the community. More specifically, this conceptual model would test what happens to the health status of the population if eligibility criteria allowed more people access to more resources for care.

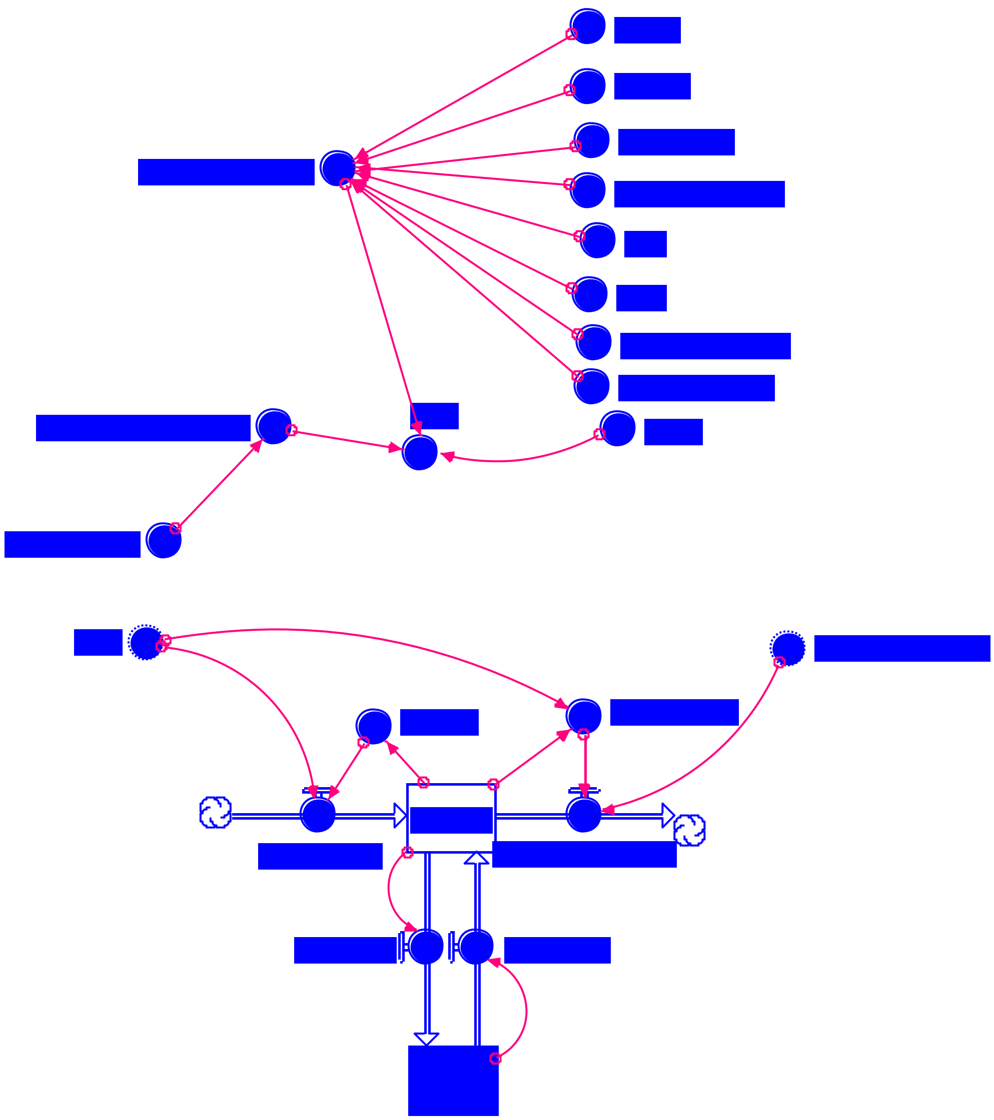

**Figure 3. Conceptual System Dynamics Model of Resource Allocation**

If the purpose of the model is to guide policy decisions pertaining to the distribution of resources, then one could test intervention related to prevention and treatment of type 2 diabetes both at a population level and among vulnerable subgroup (such as those described in Figure 1) based on their effectiveness and/or cost. Thus, a modeler seeking to find the most effective intervention to reduce type 2 diabetes within the LRGV would find value in a model that could test the effectiveness of different interventions. A modeler concerned primarily with the cost of reducing type 2 diabetes in the community could find value in a model testing the costs of different interventions given the timeframe within which costs are most important (e.g., short-term or long-term) so as to allocate resources to the intervention reflecting the best cost-savings appropriate to the timeframe.

In contrast, by selecting an agent-based model, the modeler is making the assumption that 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 2. 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 4 presents a preliminary ABM of access to restaurants in the LRGV.

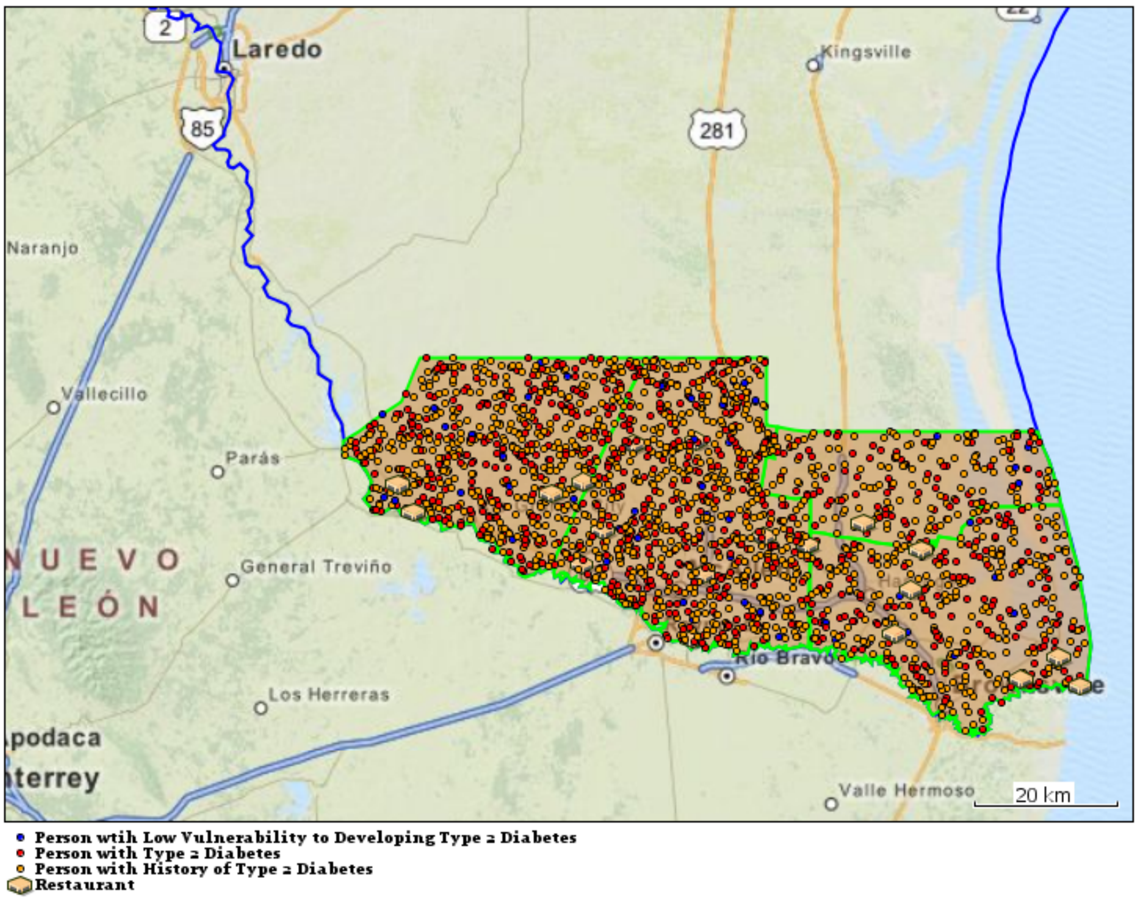


**Figure 4. Conceptual Agent-based Model Testing the Influence of Restaurants on Type 2 Diabetes among Different Populations in the LGRV**

## CONCLUSION

Selecting a modeling approach requires the modeler to make assumptions about the world and the mechanisms that produce the phenomenon-of-interest. In addition, 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). 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 the LRGV, 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 entails 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. Policies can be 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 an economically disadvantaged, high-risk population such as that of the LRGV 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 two modeling approaches discussed above recognize that this is unreasonable when individuals lack the resources to eat in a healthy manner and engage in physical activity and when the environments in which they live are not conducive to engaging in either behavior.

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