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Embracing Causal Complexity in Health Disparities: Metabolic Syndemics and Structural Prevention in Rural Minority Communities

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Abstract

Chronic discrimination and associated socioeconomic inequalities have shaped the health and well-being of Black Americans. As a consequence of the intersection of these factors with rural deprivation, rural Black Americans live and work in particularly pathogenic environments that generate disproportionate and interacting chronic comorbidities (syndemics) compared to their White and/or urban counterparts. Traditional prevention research has been unable to fully capture the underlying complexity of rural minority health and has generated mostly low-leverage interventions that have failed to reverse adverse metabolic outcomes among rural Black Americans. In contrast, novel research approaches—such as system dynamics modeling—that seek to understand holistic system structure and determine complex health outcomes over time provide a robust framework to develop a more accurate understanding of the key factors contributing to type 2 diabetes. This framework can then be used to establish more efficacious interventions to address disparities among minorities in rural areas. This paper advocates for a unified complex systems epistemology and methodology in advancing rural minority health disparities research. Toward this goal, we (1) provide an overview of rural Black American metabolic health research, (2) introduce a complex systems framework in rural minority health disparities research, and (3) demonstrate how community-based system dynamics modeling and simulation can help us plow new ground in rural minority health disparities research and action. We anticipate that this paper can serve as a catalyst for a long-overdue discourse on the relevance of complex systems approaches in minority health research, with practical benefits for numerous disproportionately burdened communities.

Keywords Rural minority health disparities · Complex systems · System dynamics modeling · Structural diabetes prevention

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Introduction

Rural populations in the USA have long lived in conditions of socioeconomic deprivation resulting from the confluence of economic disinvestment, unemployment, and poverty (Anderson et al. 1997). The health and well-being of Black Americans living in rural communities have been further hurt by exacerbating socioeconomic inequalities rooted in systemic discrimination (Williams and Mohammed 2009). As a result, rural Black Americans live and work in pathogenic environments that generate and perpetuate disproportionate *syndemics*, including type 2 diabetes (T2D) and other chronic conditions, compared to other demographic and geographic cohorts (Probst et al. 2011). *Syndemics* denote the presence of mutually and adversely reinforcing disease states, which are worsened over time by experienced inequities associated with socioeconomic milieux in which populations are immersed (Singer and Clair 2003).

Thus far, rural prevention research has adhered to a risk-factor epidemiology that has yielded mostly low-leverage interventions (e.g., self-management education), with underwhelming population-level results (Bolin et al. 2015). Rural minority metabolic health has been examined using conceptualizations, theories, and methodologies unable to capture either its dynamic complexity or the underlying causative role of interconnected rural deprivation and systemic discrimination. Because complex population health processes such as rural Black American metabolic syndemics are characterized by long delays between causes and effects, researchers are in a quandary to know how, where, and when to intervene, which is further exacerbated by the fact that most interventions have unintended consequences and tend to be resisted or undermined by opposing interests or limited resources (Sterman 2000). In contrast, prevention research that synergistically draws upon complex systems perspectives (Krieger 2011; Stokols et al. 2013), simulation modeling methodologies (Sterman 2000), and active community participation (Frerichs et al. 2016) has the potential to provide insights necessary to more fully explicate health disparities of rural Black Americans and lead to more effective interventions.

This paper advocates for a unified complex systems epistemology and methodology to advance rural minority health disparities research. Toward this goal, we (1) provide an overview of rural Black American metabolic health research, (2) introduce and advocate for a complex systems framework for rural minority health disparities research, and (3) outline how community-based system dynamics modeling and simulation can help us to plow new ground in prevention research and action. We also include a small system dynamics model and simulation results that represent what may emerge from an actual community-based modeling study and highlight the possibilities of computational simulation modeling for preventive measures aimed at alleviating health disparities. Using rural Black American metabolic health as a case study, we anticipate that this paper can serve as a catalyst for a long-overdue discourse on the relevance of complex systems approaches in minority health research and health equity more broadly, with practical benefits for numerous disproportionately burdened communities.

Effects of Discrimination and Rural Deprivation on Minority Health

When compared to White Americans, Black Americans are disproportionately disadvantaged with cardiovascular, metabolic, and other chronic syndemics (Beckles and Chou 2016; Williams and Mohammed 2013). The confluence of mutually reinforcing afflictions—associated with chronic exposure to structural racism, discrimination, and inequitable social, education, labor, and health policies—is linked with prolonged social trauma, stress, and early onset of chronic syndemics among Black Americans (Williams and Mohammed 2013). Inequalities in employment, income, access to public services, and educational opportunities further magnify disparities, impacting healthcare utilization and ultimately the physical health of Black Americans, when compared to White Americans (Auchincloss et al. 2008; Hayward et al. 2000; Williams and Collins 2001).

Although these exposures are ubiquitous for many Black Americans, protracted social and economic deprivation in rural areas has contributed to pronounced health disparities between rural and urban populations (Hartley 2004). The concurrent concentration of economic disinvestment, unemployment, poverty, and social disorganization in rural areas has adversely affected the health and well-being of rural populations (Bolin et al. 2015). The strain of living in inhospitable conditions for prolonged time periods has further exacerbated excess chronic disease rates among Black Americans (Williams and Collins 2001). In contrast to White Americans, Black Americans more often experience early onset of chronic morbidity, including T2D—associated with ongoing disadvantages in employment, income, and educational opportunities, as well as access to public and healthcare services (Williams and Mohammed 2009; Williams et al. 2010). Black Americans are more likely to die from T2D complications (Cowie et al. 2010) and have a 113% higher mortality rate (National Institute of Diabetes and Digestive and Kidney Diseases 2017), which is particularly pronounced in rural areas (Callaghan et al. 2017). Consequently, rural Black Americans live and work in pathogenic environments that generate and exacerbate metabolic disease burden compared to rural White American populations (Probst et al. 2011).

Rationale for Complex Systems Perspectives in Rural Minority Health Research

Accumulating evidence underscores the synergistic role of systemic discrimination and rural deprivation in the deterioration of rural Black Americans' metabolic health over time. Consequently, current theoretical, conceptual, and methodological approaches, which underpin rural minority health research, are not sufficient to fully explicate and guide action to ameliorate these persistent health disparities. Therefore, we advocate for the introduction and acceptance of a unified complex systems epistemology and methodology for rural minority health research in general, and for rural Black American metabolic health research in particular.

The epistemology that currently defines rural minority health research is marked by theoretical and conceptual perspectives that are grounded in linear, static, siloed, and narrowly bounded thinking and assumptions regarding causality that are incommensurate with syndemics (Sterman 2012). Instead, rural minority health should be framed within epistemological perspectives that emphasize dynamic complexity and stress the nonlinearity, interdependence, and interactions among an array of heterogeneous, evolving, and adapting elements in the system, operating across broad spatiotemporal scales. These systemic forces that shape rural minority health outcomes exhibit emergent properties (Miller and Page 2009) and render rural minority health problems irreducible. In response to the inherent limitations of current rural minority health epistemology, we advocate for a complex systems epistemology that conceptualizes rural minority health as a "complex adaptive system" (Miller and Page 2009). This epistemology is transdisciplinary and synergistically integrates theoretical perspectives that satisfy the systemic complexity of rural minority health. These theoretical perspectives include (a) ecosocial theory (Krieger 2001), (b) syndemic theory (Singer and Clair 2003), (c) social ecology (Stokols et al. 2013), and (d) complex systems theory (Miller and Page 2009).

Studying these interconnected domains as a complex adaptive system reframes our understanding of how these factors induce disproportionate metabolic risks among rural Black Americans; however, to meaningfully investigate such systems, appropriate methodologies must be employed. The methodological approaches that have defined rural minority health research are grounded in reductionism and linear causality and prioritize internal validity by employing various forms of experimental designs (Glass and McAtee 2006). The inability of these approaches to capture macrostructural domains, contextual effects, or ecological effects that unfold across varying spatial and temporal boundaries makes them unsuitable for investigating complex adaptive systems (Luke and Stamatakis 2012). Additionally, their emphasis on internal validity through experimental control inhibits the ability of these designs to incorporate characteristics of dynamic complexity, such as interdependence and nonlinearity (Hughes et al. 2015). These analytical approaches, which commonly employ statistical modeling techniques, are unable to capture most characteristics of dynamic complexity (El-Sayed et al. 2012; Luke and Stamatakis 2012).

Complex systems epistemological perspectives have helped spur the development of a distinct "toolbox" of methodological and analytical techniques that can efficiently delineate complex adaptive systems. These techniques, collectively referred to as *computational modeling and simulation*, are able to capture characteristics of dynamic complexity that elude reductionist methodologies, including, but not limited to, interdependencies, interrelationships, nonlinearities, and emergent properties (El-Sayed et al. 2012). For example, *computational simulation models* can include hypothesized causal factors across the life course and over time within different communities, as well as their interrelationships, feedbacks, and interactions (Sterman 2012). Hence, computational simulation models provide means for assessing, organizing, and synthesizing research across multiple systems (e.g., metabolic risk distribution) and approaches (e.g., data obtained using different methodologies). The advantages of such epistemological and methodological frameworks can further our understanding of and efforts to ameliorate disparities in rural Black Americans' metabolic health. As the name implies, these approaches offer the distinct advantage of *simulation*, which are computer-based (in silico) platforms that allow for various counterfactual scenarios to be tested virtually and outside the pragmatic and ethical constraints of experimental designs (in vivo experimentation) (El-Sayed et al. 2012; B. Marshall and Galea 2015; Osgood 2014). For rural minority health research, this means that a variety of experimental conditions or intervention configurations can be tested, in a matter of seconds, across long-time horizons within the same simulation model (Hammond 2009; Homer et al. 2014; Sterman 2000).

A multitude of computational modeling and simulation methodologies have been utilized to study complex adaptive systems in obesity, chronic disease, healthcare, and other health-related domains (Abdel-Hamid 2003; Homer et al. 2014). However, the choice of a specific computational modeling and simulation methodology is not mutually exclusive, as different approaches can be combined in the form of hybrid models (Osgood 2014). Hybrid models combine the advantages of their constituent approaches, which suggests their immense, albeit largely untapped, potential for studying complex adaptive systems (Osgood 2014).

The Potential of System Dynamics Modeling in Rural Minority Health Research

Although underutilized in rural minority health research, there has been an increase in system dynamics modeling (SDM) applications for chronic disease prevention (Hirsch et al. 2015). We have selected SDM to demonstrate the potential of computational simulation modeling in rural minority metabolic health, as it is especially useful for pursuing an *aggregate* understanding of the underlying causal complexity of chronic metabolic syndemics. In general, SDM is considered to be a "top-down" computational modeling and simulation approach; other approaches, such as agent-based modeling, are more commonly used to explore research questions from the "bottom-up" (Epstein 2006).

SDM can help us map and model diverse forces of change over long-time horizons so that we can understand the influences that most substantially determine outcomes over time within a complex adaptive system (Sterman 2000). Instead of testing isolated relationships between hypothesized factors and outcomes, while controlling for confounding variables (as with traditional statistical analyses), SDM seeks to build confidence in hypotheses and theories explaining how system structure (or "mechanisms," in the form of dynamic causal linkages) interacts to influence outcomes (Marshall and Galea 2015; Osgood 2014). To accomplish this, SDM begins by formulating explicit, holistic hypotheses about the key causal linkages and feedback loops underlying metabolic syndemic trends in the form of qualitative diagrams, and then quantified (mathematical) simulation models that are tested and iterated. Each model variant represents a unified hypothesis about how the broad causal web of potentially important factors generates trends in key outcomes over time (Sterman 2000).

Because system dynamics models exist in silico, they infer advantages to researchers and policymakers, including the aforementioned ability to test multiple hypotheses and intervention scenarios through model simulation (Sterman 2012). Models that are not consistent with the available data are rejected, while consistent models are carried forward for further testing. In this way, system dynamics (SD) models represent our best understanding of complex phenomena. In the presence of uncertainty, multiple plausible models can be used to test the robustness of comparative impact estimates for competing interventions (Tian et al. 2015). An additional benefit of SDM is that it is especially amenable to participatory approaches, as it typically integrates community insights in a *group model building* (GMB) process and can be used to communicate system behavior to key stakeholders to increase consensus and buy in (Frerichs et al. 2016; Hassmiller Lich et al. 2014). Within the SDM framework, the explanation of change in outcomes over time (or *system behavior*) is explained by changes in causal factors *inside* the model's boundaries—referred to as an *endogenous* point of view (Sterman 2000). The model boundary of what is included is expanded to ensure key changes over time and can be explained mechanistically. After key causal linkages and feedback loops are uncovered using *causal loop diagrams*, system behavior is schematically captured and simulated using *stocks*, which represent the accumulation of system elements (analogous to prevalence); *flows*, which represent rates at which quantities are added to or subtracted from stocks over time (analogous to incidence); and *auxiliary variables*, which represent factors exhibiting direct, indirect, and often circular influence (*feedbacks*) over time (Sterman 2000). During model simulation, quantitative SDM is able to track stock accumulations, which are influenced by flows, feedbacks, and time delays. While an in-depth discussion of engineering a fully functional SD model is beyond the scope of this paper, detailed accounts of these approaches in population health are readily available (Hassmiller Lich et al. 2014).

Explanatory Power of System Dynamics Modeling: Circular Causality in Feedback Loops

When viewed as a complex adaptive system, the metabolic syndemics of rural Black Americans are shaped by circular causality over time, which is modeled in SDM by *feedback loops* in which the influence of an initial factor ripples through cascading factors across context, space, and time, both influencing and being influenced by these and various other factors (Sterman 2000). In contrast to traditional research conceptualizations, these factors influence one another in bidirectional and dynamic ways (Sterman 2000). Ultimately, feedback loops, and the interactions and interdependencies they represent, result in adaptation, self-organization, and the generation of counterintuitive and often unintended outcomes (e.g., uncontrolled disease states or interventions that worsen the condition) (Hammond 2009; Sterman 2006).

Graphically, feedback loops are documented through variables connected by arrows, with annotations about polarities and time delays. Polarities indicate whether the factor at the tail of the arrow—increased or decreased—influences the factor at the head of the arrow in the same (+) or opposite (−) direction. Time delays (i.e., lag time between risk exposure and disease onset) are indicated by double hash marks on the arrow body. To form a feedback loop, a path originating at any factor must move from arrow to arrow and return to the original factor. Feedback loops can either reinforce or oppose change, with reinforcing loops driving exponential growth or decay and balancing loops bringing the system toward an equilibrium (which may or may not be at a desirable level) (Sterman 2000). Research repeatedly finds that, in the presence of complexity, outcomes (such as metabolic syndemics) are largely defined by the sum and organization of underlying feedback loops (Sterman 2000). While single cause-and-effect relationships can be impactful, feedback loops tend to be more impactful because they are amplified over time. Systems analysis seeks to identify the key "dominant" feedback loops within a system that can change over time within a given context and be quite different across contexts (Sterman 2000). Because they persist over time and can drive or block efforts to change a system, understanding feedback loops is essential to avoid the "black box" association-based evidence that often underpins interventions based in linear cause-and-effect thinking. Feedback loops offer more impactful targets for intervention, particularly dominant loops identified in a given instance of a system (context at a certain point in time) (Sterman 2000).

To demonstrate the syndemic causative influence of discrimination and rural deprivation on rural Black Americans' metabolic health, Fig. 1 presents a *causal loop diagram* (CLD), which demonstrates an illustrative feedback structure in the form of feedback loops using SD notation. The diagram integrates two reinforcing feedback loops, whose linear connections are indicated in the literature, and which we hypothesize to be principal drivers of metabolic syndemics in rural Black American communities over time. *Reinforcing loop R1* illustrates the causal power of *racial discrimination*: compromised metabolic health deteriorates workforce productivity among rural Black Americans (e.g., increasing sick days), which in turn diminishes employment opportunities (e.g., employers relocating to more profitable areas), perpetuating de facto segregation and socioeconomic inequalities in rural Black American communities (e.g., poor-quality primary schools) over time (Lantz et al. 2001; National Research Council 2005). This leads to reduced socioeconomic status (e.g., due to lower-paying jobs), triggering deleterious effects on Black American community health over time (e.g., reduced community-wide purchasing power, more limitations on access to health-supportive resources as retailers leave the community) (Phillips and McLeroy 2004; Probst et al. 2004; Robert 1998). This feedback loop is a "vicious cycle" that perpetuates the detrimental effects of racial discrimination on rural Black American metabolic health.

Reinforcing loop R2 demonstrates the interacting causal power of *rural deprivation*: reduced workforce productivity decreases the desirability of doing business in rural Black American communities for employers. This in turn leads to fewer employment opportunities and more lost wages, more limited rural community resources (e.g., lower local tax revenues), and fewer community health resources (e.g., underfunded clinics)—the accumulation of which can adversely impact rural Black American community metabolic health over time (e.g., reduced access to healthcare) (Alavinia et al. 2009; Auchincloss et al. 2008; Hartley 2004; Lutz et al. 2011; Phillips and McLeroy 2004). This feedback loop represents yet another "vicious cycle," which together with the *racial discrimination* reinforcing loop perpetuates the adverse metabolic health consequences of interdependent structural racism and area deprivation in rural Black American communities. Both cycles can be expected to continue in the direction of their momentum until external force(s) (e.g., increases in rural resources) disrupt them. Combined, these causal sequences of multilevel factors drive metabolic health of rural minority populations, exemplifying the syndemic nature of discrimination and rural deprivation.

How Complex Systems Perspectives Can Advance Prevention Research

In response to deteriorating health among disadvantaged populations (e.g, increases in T2D prevalence among rural Black Americans), prevention programs and interventions have been predominantly low-leverage (e.g., behavioral interventions to improve dietary intake), overlooking the underlying and interconnected sociostructural mechanisms that have generated excess metabolic syndemic afflictions over time (Mendenhall et al. 2017). The current epistemological and methodological perspectives within rural minority health research, which have

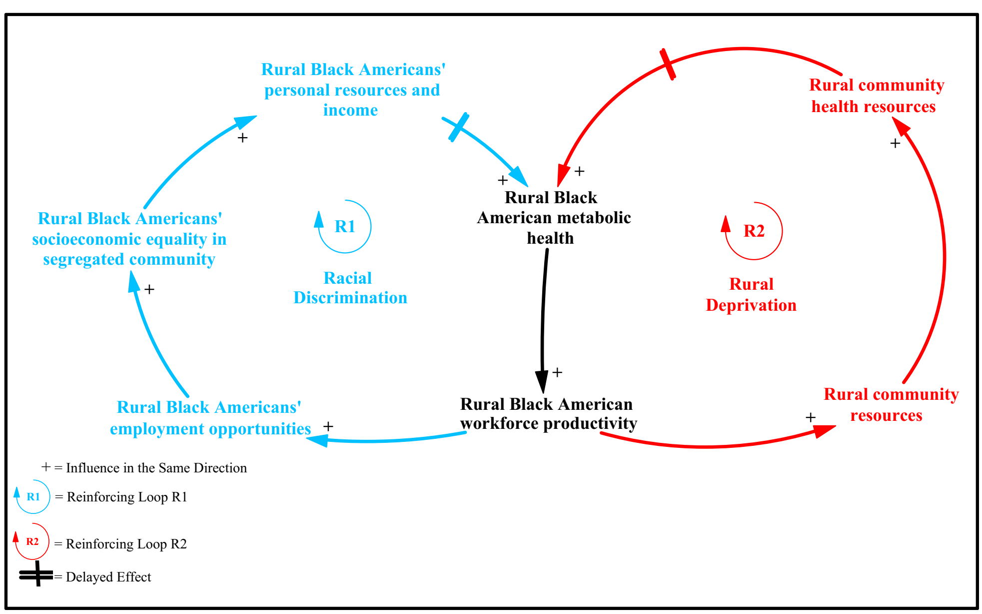

Fig. 1 Illustrative feedback structure of "racial discrimination" and "rural deprivation" as key causal forces of Black American health disparities in rural areas

overlooked the dynamic complexity of the complex adaptive system that generates the metabolic syndemic among rural Black Americans, have guided these disappointing prevention efforts. This phenomenon may be also described by the concept of "policy resistance," which is seen in many intervention contexts, where attempts to make a change for the better are ineffective, have unanticipated, or have even exacerbatory side effects (Sterman 2012). In other words, the complex adaptive system that shapes rural Black American metabolic health resists the effects of preventive efforts and generates a discouraging illusion of intractability that stems from the incompatibility of a reductionist paradigm with efforts to understand the dynamically complex problems (Marshall and Galea 2015; Sterman 2006). Further, preventive efforts guided by reductionist perspectives have led to interventions that address symptoms of metabolic health disparities, rather than their root causes, thereby diminishing the impacts of these well-intended preventive efforts (Sterman 2006).

It is our contention that infusing rural minority health research (including rural Black Americans' metabolic health) with a unified complex systems epistemology and methodology will ultimately lead to more effective preventive actions. Complex systems theoretical perspectives, and especially the conceptualization of such persistent problems as complex adaptive systems, can transform our understanding of how such disparities develop and why they persist over time, and how key causal factors are interrelated and interdependent. Guided by these innovative ways of thinking, utilizing computational modeling and simulation approaches can be brought to bear to explore (in silico) a boundless array of preventive actions across long time frames to identify high-leverage structural interventions (El-Sayed et al. 2012; Sterman 2006, 2012). In other words, computational simulation models, grounded in theoretical perspectives that better capture the underlying causative structure of disparities, can serve as powerful decision-making tools for informing preventive actions.

System Dynamics Modeling in Health Disparities Prevention: an Applied Example

The goals of a full-fledged SDM effort to address rural Black American metabolic health disparities would be the following: (a) the identification of the dominant feedback loops that drive these syndemics and (b) developing strategic plans by engaging community stakeholders in model-based learning that will most optimally target these loops (Sterman 2012). Below, we provide an example of how SD GMB can be used to improve rural Black Americans' metabolic health.

SD GMB would involve a group of stakeholders and subject-matter experts, who are guided by SD experts and facilitators, comprising a group of about 20 individuals, across two principal stages. In the first stage, stakeholders and subject-matter experts would work collaboratively to reach consensus on the structural causal factors and their relationships (e.g., mediators, moderators, consequences of change, and feedback loops) that lead to poor metabolic health among rural Black Americans. This would include (a) creating a *model boundary chart*, where factors believed to be relevant to metabolic health are identified and then classified into three categories: (1) endogenous (included in subsequent SD GMB steps as variables whose change over time is explained within the model), (2) exogenous (included in subsequent SD GMB steps as inputs, whose values affect endogenous variables but in whom change is not explained within the model), and (3) excluded (elicited and considered, but determined to be excluded from current SD GMB steps); (b) generating *behavior-over-time graphs* (BOTGs) that approximate trends in endogenous variables over time and indicating the causes of such trends (potentially including other co-occurring trends); and (c) using the model boundary chart and BOTGs to generate a *causal loop diagram* (see Fig. 1), which would be the first comprehensive map of the key structural forces that influence rural Black Americans' metabolic health over time (Sterman 2000). Next, the research team would then construct a qualitative SD model by integrating the outcomes of the SD GMB session (model boundary chart, BOTG, and CLD with stocks and flows), which will constitute the first complete comprehensive theoretical explanation of rural Black Americans' metabolic health over time.

The research team would then use the qualitative SD model to formulate a quantitative SD model. Quantitative SD models consist of nonlinear, first-order differential equations that are rigorously tested and refined to ensure the robustness of conclusions about interventions (Ford 2010; Luke and Stamatakis 2012; Sterman 2000). Creating a quantitative SD model includes (a) *model parameterization*, where numeric values are assigned to factors and their relationships; (b) *model calibration*, where the SD model is tested to determine whether the model generates simulation results that align with time-series historic data, and making appropriate adjustments to model parameters; (c) *model testing*, involving rigorous review and analyses to verify the model is error free and implemented as intended and to establish model validity and reliability, vital to ensuring confidence and trustworthiness in the model and its outputs during subsequent learning lab simulation experiments; and (d) *sensitivity and uncertainty analysis*, involving the running of various simulation scenarios to evaluate the impacts of uncertain parameters on model conclusions/insights (e.g., by conducting Monte Carlo-style analyses that vary uncertain model parameters across a wide range to determine their impacts on simulation results to determine the impact of uncertainty on intervention recommendations or simulated outcomes) (Ford 2010; Kelly et al. 2013; Sterman 2000).

Once the quantitative SD model has been thoroughly tested, SD GMB stakeholders would reconvene to engage in a participatory learning lab (Marshall et al. 2015). Guided by the research team, stakeholders would lead a series of simulation experiments to identify structural policy-grounded factors as optimal leverage points to improve rural Black American metabolic health. The power of computer-based simulation modeling for testing counterfactuals permits the comparative testing of a wide array of potential interventions, both individually and in combination, across a long-time horizon (Ford 2010). These sessions have potential to shift the "mental models" of stakeholders and reduce narrow and siloed thinking by demonstrating the interrelated impacts of policies across long time periods. At the conclusion of the learning lab, the research team would again conduct sensitivity and uncertainty analyses to assess the robustness of the intervention configurations identified by stakeholders (Tian et al. 2015).

To illustrate how SDM can provide insights into rural Black American metabolic health, we have created an illustrative concept model (Fig. 2*)* focusing on and quantifying the *rural deprivation* feedback loop depicted in the causal loop diagram in Fig. 1. An interactive version of this concept model is included as Supplement 1 (interested readers can download the required software from http://vensim.com/free-download/). This SD model is not based on an actual case study; rather, it has been developed to demonstrate the importance of capturing feedback loops and inertial factors (i.e., stocks) and their pace of change, as well as the potential of SDM for identifying "high-leverage" interventions in rural minority health disparities. Figure 2 consists of 10 equations and seven parameters and includes a simple stock-and-flow structure, with its underlying mathematical representation in the form of ordinary differential equations as illustrated here for the number of rural Black Americans with T2D: Rural BA with type 2 diabetes(t) = $\int_{t-}$ [onset(s) − deaths(s)]ds + Rural BA with type 2 diabetes(t_0).

A full description of the model formulae and parameters can be found in Supplement 2, which are documented per conventional SDM reporting guidelines. We simulated this simple model over 20 years under three scenarios: (1) baseline condition, (2) 50% decline in rural resources for a limited period of time, and (3) increase in rural resources for a limited period of time, which represents a potential intervention scenario that stakeholders and subject-matter experts might suggest in a learning lab session. For the three scenarios, the model begins in an equilibrium in which there are 1000 Black Americans in a rural community, 200 of whom have T2D, and births and deaths are set equal to four per year.

The simulation results for the three scenarios considered are presented in Figure 3, with changes in rural resources (a), and an exogenous variable) creating changes over time in *rural Black Americans with T2D* (b), *rural Black Americans without T2D* (c), and *productivity* (d). The last three variables (b–d) are endogenous, and projected trends are illustrated corresponding to the specified changes in variable a. As expected, when compared to scenario 1 (baseline condition), scenario 2 (50% decline in rural resources between years 2–7) results in a reduction in rural

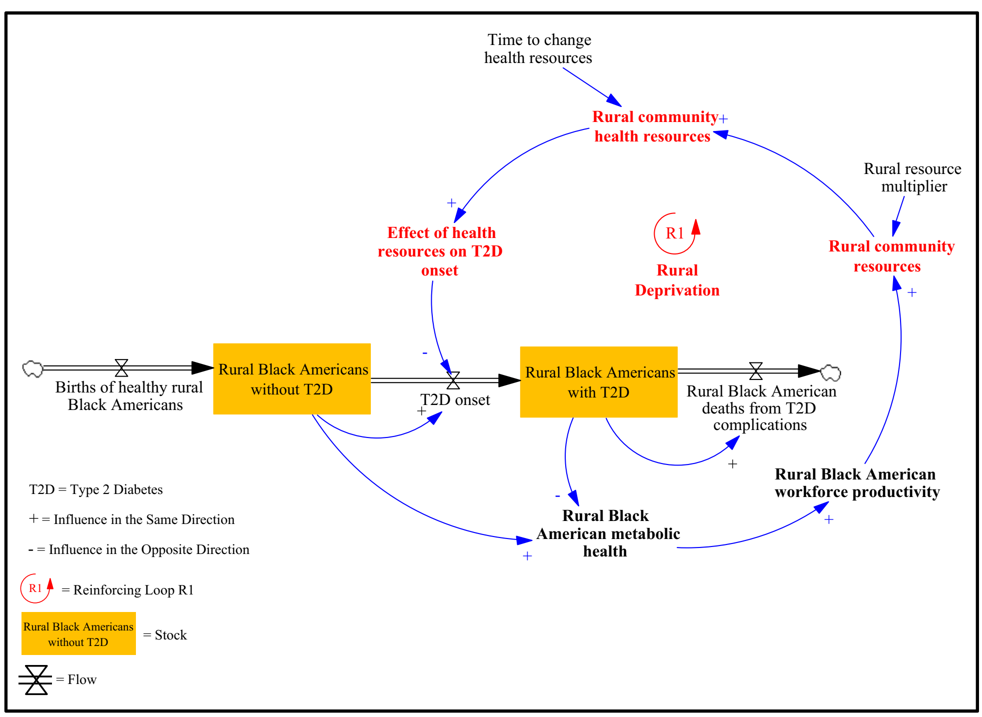

Fig. 2 Concept model of rural deprivation and its impact on rural Black American metabolic health

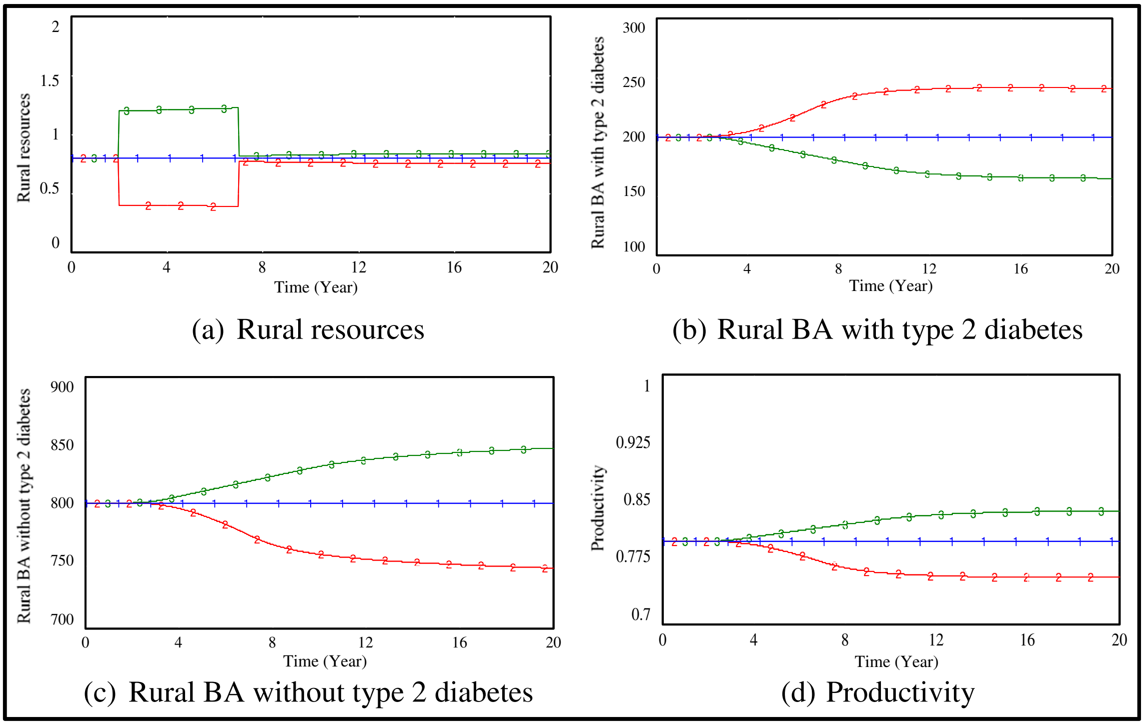

Fig. 3 Simulation results from concept model, for three scenarios over 20 years. Line 1 represents scenario 1 (baseline), line 2 represents scenario 2 (decline in rural resources for a limited time), and line 3 represents an intervention scenario (increase in rural resources for a limited time). **a** Rural resources. **b** Rural BA with type 2 diabetes. **c** Rural BA without type 2 diabetes. **d** Productivity

resources, deteriorates the metabolic health of rural Black Americans, and, due to the reduced number of metabolically healthy individuals in the rural Black American population, lowers the productivity of the community workforce. Perhaps surprisingly, despite the restoration of rural resources after year 7 in scenario 2, the prevalence of rural Black American T2D continues to rise because the community has become trapped in a vicious cycle of rural deprivation and cannot improve its workforce productivity. As demonstrated in scenario 3 (50% increase in rural resources between years 2–7), the direction of the underlying feedback loop reverses to become a virtuous cycle—with improvements in both metabolic health of rural Black Americans and productivity of the community workforce lasting beyond the end of the surge in community resources—illustrating the power of SDM for identifying high-leverage interventions. Also, it is worth noting that the pace at which rural resources change affects T2D prevalence. For example, in scenario 2, the pace of change in rural resources is 3 years; however, if rural resources change more rapidly (e.g., 1 year), T2D prevalence would be higher because rural resources diminish faster, increasing the T2D onset rate.

SD model building is typically an iterative process aimed at strengthening confidence in SD models over time. Although a full-fledged SD model can be a powerful decision-making tool for preventive efforts, it is quite common for a SDM project to lead to further modeling endeavors that expand, improve, or adapt the SD model based on new research questions or different contexts or populations. Further, SDM can provide guidance that would be valuable for conventional research endeavors; for example, gaps in empirical data or knowledge can be revealed through the construction of CLDs and the SD model testing and validation process.

The Limitations of System Dynamics Modeling

While uniquely powerful for exploring dynamic complexity and identifying high-leverage policy interventions, SDM has several limitations that should be noted. First, as is the case with all models, SD models are built for a specific purpose or problem and are not intended to universally explain all categories of complex phenomena (Hughes et al. 2015). This is related to the second limitation, which concerns the level of detail in an SD model, in that models that are overly complex can be unwieldy to test and understand. On the other hand, overly simple models can neglect important parameters that are vital to simulating, or matching (with a mechanistic explanation in the form of the model) system behaviors (Hughes et al. 2015; Kelly et al. 2013). Given that large SD modeling projects are more time- and labor-intensive, compared to traditional prevention research approaches, and that developing an SD model is an iterative process that may span months or even years, achieving optimal model parsimony is essential (Hassmiller Lich et al. 2013; Hughes et al. 2015). This is true of any dynamic simulation modeling approach (e.g., ABM), as overly simplistic models may be incomplete and leave out key influences, while overly large or complex models become laborious or even impossible to comprehensively test and validate (El-Sayed et al. 2012).

Integrating Complex Systems Perspectives in Rural Minority Health Disparities Prevention

Our earnest hope is that the potential of integrating complex systems epistemology and methodology into ongoing and future work becomes apparent to prevention science researchers and practitioners once they consider the points we have tried to make here. In our view, complex systems approaches represent the "new frontier" for innovative research endeavors, which offer the prospect of reversing persistent health problems that impact rural minority populations and that have eluded prevention scientists and policymakers for years. However, as is usually the case with novel scientific endeavors, numerous barriers exist that should be acknowledged. For example, most formal education and training remain entrenched in conventional, reductionist, and linear perspectives. Further, academic journals, funders, and even community stakeholders are more familiar and remain comfortable with the "status quo."

Fortunately, complex systems perspectives constitute an emerging domain of research and action in the diverse fields of prevention science. As these perspectives gain acceptance, the wealth of resources that address epistemology, methodology, or both that are available to both novices and pros continues to grow, and in turn, enable interested individuals from varied backgrounds to integrate complex systems into their work. First, several excellent books are available, in particular, *Business Dynamics* (by John Sterman 2000), *Thinking in Systems: A Primer* (by Meadows 2008), and *Growing Inequality: Bridging Complex Systems, Population Health, and Health Disparities* (by Kaplan et al. 2017). Second, a multitude of training courses, both in-person and online, are available through modeling software developers, universities, and other institutions (e.g., *Nuts and Bolts of System Dynamics Models* is an excellent MOOC course offered by Coursera at https://www.coursera.org/). Third, several types of computational simulation modeling software are available free of charge (e.g., Vensim; NetLogo; AnyLogic), and these software packages include excellent tutorial and training components. Finally, the scientific literature on complex systems epistemology and methodology continues to expand and includes guidance spanning from SD GMB scripts to SD model testing and validation techniques. These and other resources provide numerous avenues for prevention scientists and practitioners to learn more about these innovative ways of thinking and conducting applied research.

Conclusions

As complex adaptive systems, metabolic syndemics of rural Black Americans exhibit characteristics that necessitate the infusion of new epistemological and methodological frameworks. The time is now to introduce a new discourse in rural minority health disparities research and embrace innovative approaches to improve the metabolic health of rural minorities and ultimately see a more productive and economically viable rural America. A comprehensive complex systems epistemological and methodological framework can foster new directions in rural minority health disparities research and bring about positive population health impacts. In particular, community-based SDM can be used as a strategic tool to mitigate T2D afflictions in rural Black American communities by improving our understanding of the underlying feedback structures, identifying dominant feedback loops, and identifying high-leverage interventions. Finally, complex systems perspectives have the potential to advance prevention research and action in general by addressing an array of complex social and population health problems, from the obesity pandemic and related comorbidities to substance abuse and associated consequences.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants performed by any of the authors.

Informed Consent For this type of study formal consent is not required.

References

Abdel-Hamid, T. K. (2003). Exercise and diet in obesity treatment: An integrative system dynamics perspective. *Medicine & Science in Sport & Exercise, 35*, 400–413.

Alavinia, S. M., Molenaar, D., & Burdorf, A. (2009). Productivity loss in the workforce: Associations with health, work demands, and individual characteristics. *American Journal of Industrial Medicine, 52*, 49–56.

Anderson, R. T., Sorlie, P., Backlund, E., Johnson, N., & Kaplan, G. A. (1997). Mortality effects of community socioeconomic status. *Epidemiology, 8*, 42–47.

Auchincloss, A. H., Roux, A. V. D., Brown, D. G., Erdmann, C. A., & Bertoni, A. G. (2008). Neighborhood resources for physical activity and healthy foods and their association with insulin resistance. *Epidemiology, 19*, 146–157.

Beckles, G. L., & Chou, C.-F. (2016). Disparities in the prevalence of diagnosed diabetes—United States, 1999–2002 and 2011–2014. *Morbidity and Mortality Weekly Report, 65*, 1265–1269.

Bolin, J. N., Bellamy, G., Ferdinand, A. O., Kash, B. A., & Helduser, J. W. (2015). *Rural Healthy People 2020*. Retrieved from College Station, TX

Callaghan, T. H., Towne, S. D., Bolin, J., & Ferdinand, A. O. (2017). Diabetes mortality in rural America: 1999:2015. Retrieved from College Station, TX

Cowie, C. C., Rust, K. F., Byrd-Holt, D. D., Gregg, E. W., Ford, E. S., Geiss, L. S., ... Fradkin, J. E. (2010). Prevalence of diabetes and high risk for diabetes using A1C criteria in the US population in 1988–2006. *Diabetes Care, 33*, 562–568.

El-Sayed, A. M., Scarborough, P., Seemann, L., & Galea, S. (2012). Social network analysis and agent-based modeling in social epidemiology. *Epidemiologic Perspectives & Innovations, 9*, 1–10.

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

Ford, A. (2010). *Modeling the environment: An introduction to system dynamics models of environmental systems*. Washington, DC: Island Press.

Frerichs, L., Hassmiller Lich, K., Dave, G., & Corbie-Smith, G. (2016). Integrating systems science and community-based participatory research to achieve health equity. *American Journal of Public Health, 106*, 215–222.

Glass, T. A., & McAtee, M. J. (2006). Behavioral science at the crossroads in public health: Extending horizons, envisioning the future. *Social Science and Medicine, 62*, 1650–1671.

Hammond, R. A. (2009). Complex systems modeling for obesity research. *Preventing Chronic Disease, 6*, 1–10.

Hartley, D. (2004). Rural health disparities, population health, and rural culture. *American Journal of Public Health, 94*, 1675–1678.

Hassmiller Lich, K., Ginexi, E. M., Osgood, N. D., & Mabry, P. L. (2013). A call to address complexity in prevention science research. *Prevention Science, 14*, 279–289.

Hassmiller Lich, K., Minyard, K., Niles, R., Dave, G., & Gillen, E. M. (2014). System dynamics and community health Methods for Community Public Health Research: Integrated and Engaged Approaches (pp. 129–170).

Hayward, M. D., Miles, T. P., Crimmins, E. M., & Yang, Y. (2000). The significance of socioeconomic status in explaining the racial gap in chronic health conditions. *American Sociological Review*, 910–930.

Hirsch, G., Homer, J., & Tomoaia-Cotisel, A. (2015). System dynamics applications to health and health care—Introduction. *System Dynamics Review, 15*, 1–4.

Homer, J., Wile, K., Yarnoff, B., Trogdon, J. G., Hirsch, G., Cooper, L., ... Orenstein, D. (2014). Using simulation to compare established and emerging interventions to reduce cardiovascular disease risk in the United States. *Preventing Chronic Disease, 11*, 1–14.

Hughes, B. P., Newstead, S., Anund, A., Shu, C. C., & Falkmer, T. (2015). A review of models relevant to road safety. *Accident Analysis and Prevention, 74*, 250–270. https://doi.org/10.1016/j.aap.2014.06.003.

Kaplan, G., Diez Roux, A. V., Simon, C. P., & Galea, S. (2017). *Growing inequality: Bridging complex systems, population health, and health disparities*. Washington, DC: Westphalia Press.

Kelly, R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., ElSawah, S., Hamilton, S. H., ... Voinov, A. A. (2013). Selecting among five common modelling approaches for integrated environmental assessment and management. *Environmental Modelling & Software, 47*, 159–181. https://doi.org/10.1016/j.envsoft.2013.05.005.

Krieger, N. (2001). Theories for social epidemiology in the 21st century: An ecosocial perspective. *International Journal of Epidemiology, 30*, 668–677.

Krieger, N. (2011). *Epidemiology and the people's health: Theory and context*. New York: Oxford University Press.

Lantz, P. M., Lynch, J. W., House, J. S., Lepkowski, J. M., Mero, R. P., Musick, M. A., & Williams, D. R. (2001). Socioeconomic disparities in health change in a longitudinal study of US adults: The role of health-risk behaviors. *Social Science and Medicine, 53*, 29–40.

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

Lutz, B., Molloy, R., & Shan, H. (2011). The housing crisis and state and local government tax revenue: Five channels. *Regional Science and Urban Economics, 41*, 306–319.

Marshall, B., & Galea, S. (2015). Formalizing the role of agent-based modeling in causal inference and epidemiology. *American Journal of Epidemiology, 181*, 92–99.

Marshall, D., Burgos-Liz, L., Ijzerman, M. J., Crown, W., Padula, W. V., Wong, P. K., et al. (2015). Selecting a dynamic simulation modeling method for health care delivery research—Part 2: Report of the ISPOR Dynamic Simulation Modeling Emerging Good Practices Task Force. *Value in Health, 18*, 147–160.

Meadows, D. H (2008). *Thinking in systems: A primer*. White River Junction, VT: Chelsea Green Publishing.

Mendenhall, E., Kohrt, B. A., Norris, S. A., Ndetei, D., & Prabhakaran, D. (2017). Non-communicable disease syndemics: Poverty, depression, and diabetes among low-income populations. *The Lancet, 389*, 951–963.

Miller, J. H., & Page, S. E. (2009). *Complex adaptive systems: An introduction to computational models of social life*. Princeton: Princeton University Press.

National Institute of Diabetes and Digestive and Kidney Diseases. (2017). Diabetes statistics. Retrieved from https://www.niddk.nih.gov/health-information/health-statistics/diabetes-statistics

National Research Council. (2005). *Quality Through Collaboration: The Future of Rural Health Care*. Washington, DC: The National Academies Press.

Osgood, N. (2014). *What tools does complex systems modeling provide for understanding population health and health disparities?* Paper presented at the Conference on Complex Systems, Health Disparities and Population Health: Building Bridges, Washington, D.C.

Phillips, C. D., & McLeroy, K. R. (2004). Health in rural America: Remembering the importance of place. *American Journal of Public Health, 94*, 1661–1663.

Probst, J. C., Moore, C. G., Glover, S. H., & Samuels, M. E. (2004). Person and place: The compounding effects of race/ethnicity and rurality on health. *American Journal of Public Health, 94*, 1695–1703.

Probst, J. C., Bellinger, J. D., Walsemann, K. M., Hardin, J., & Glover, S. H. (2011). Higher risk of death in rural Blacks and whites than urbanites is related to lower incomes, education, and healthcare coverage. *Health Affairs, 30*, 1872–1879.

Robert, S. A. (1998). Community-level socioeconomic status effects on adult health. *Journal of Health and Social Behavior*, 18–37.

Singer, M., & Clair, S. (2003). Syndemics and public health: Reconceptualizing disease in bio-social context. *Medical Anthropology Quarterly, 17*, 423–441.

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

Sterman, J. D. (2006). Learning from evidence in a complex world. *American Journal of Public Health, 96*, 505–514.

Sterman, J. D. (2012). Sustaining sustainability: Creating a systems science in a fragmented academy and polarized world. In M. P. Weinstein & R. E. Turner (Eds.), *Sustainability science: The emerging paradigm and the urban environment* (pp. 21–58). New York: Springer.

Stokols, D., Lejano, R. P., & Hipp, J. (2013). Enhancing the resilience of human-environment systems: A social ecological perspective. *Ecology and Society, 18*, 7–18.

Tian, Y., Hassmiller Lich, K., & Osgood, N. D. (2015). Coupled sensitivity analysis, calibration, and uncertainty analysis using a system dynamics model for stroke comparative effectiveness research. *Medical Decision Making, 36*, 1043–1057.

Williams, D. R., & Collins, C. (2001). Racial residential segregation: A fundamental cause of racial disparities in health. *Public Health Reports, 116*, 404.

Williams, D. R., & Mohammed, S. A. (2009). Discrimination and racial disparities in health: Evidence and needed research. *Journal of Behavioral Medicine, 32*, 20–47.

Williams, D. R., & Mohammed, S. A. (2013). Racism and health II: A needed research agenda for effective interventions. *American Behavioral Scientist, 57*, 1200–1226.

Williams, D. R., Mohammed, S. A., Leavell, J., & Collins, C. (2010). Race, socioeconomic status, and health: Complexities, ongoing challenges, and research opportunities. *Annals of the New York Academy of Sciences, 1186*, 69–101.