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The Utility of a System Dynamics Approach for Understanding Cumulative Health Risk from Exposure to Environmental Hazards

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Abstract

The potential of system dynamics modeling to advance our understanding of cumulative risk in the service of optimal health is discussed. The focus is on exploring system dynamics modeling as a systems science methodology that can provide a framework for examining the complexity of real-world social and environmental exposures among populations—particularly those exposed to multiple disparate sources of risk. The discussion also examines how system dynamics modeling can engage a diverse body of key stakeholders throughout the modeling process, promoting the collective assessment of assumptions and systematic gathering of critical data. Though not a panacea, system dynamics modeling provides a promising methodology to complement traditional research methods in understanding cumulative health effects from exposure to multiple environmental and social stressors.

1. INTRODUCTION

Traditional methods of assessing environmental risk have generally relied on single chemical, single route of exposure models to understand impacts on human health. These

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approaches are thus limited in assessing cumulative risk from multiple environmental stressors, or the accumulation of risk over time.¹ More contemporary approaches to understanding cumulative risk to optimal health examine risk posed by multiple stressors, including chemical, physical, biological, and psychosocial factors.^{2,3} However, these approaches are still in the early stages of development in terms of their ability to examine 1) the complex interactions of multiple sources of risk simultaneously and 2) the accumulation of these impacts over the life course.^{4,5}

Systems science, and system dynamics modeling in particular, holds much promise in expanding our capacity to understand and evaluate possible strategies to address cumulative risk to optimal health. Specifically, a systems science approach advances our ability to understand cumulative risk from a global perspective, rather than a traditional reductionist framework within which to conceptualize the problem.⁶ Building on previous research on applying system dynamics modeling to public health issues, this essay explores how system dynamics modeling can advance understanding of cumulative risk. Systems science, coupled with existing cumulative risk methods, offers a potential to bridge the gap in the conceptual and analytical framework in understanding cumulative health effects from exposure to multiple environmental and social stressors.

1.1 Background

A cumulative risk approach to environmental risk involves the analysis, characterization, and possible quantification of the combined risk to optimal health from multiple agents or stressors, including non-chemical sources of risk.^{1,3} For example, communities near large point sources of environmental stressors (such as petrochemical refineries, large chemical manufacturing complexes, or large ports associated with goods movement) or in areas with high vehicular traffic (such as major roadways) are often exposed to multiple environmental stressors that pose risks to optimal health. These potentially include chemical stressors (such as mixtures of volatile organic compounds and particulate matter), and physical stressors (such as excessive light or noise). Threats to health from these exposures are often compounded by stressors from built environments (such as incompatible pairing of residential and industrial land use and lack of amenities to facilitate active modes of transportation) and stressors from social environments (such as lack of employment opportunities, high rates of crime, or structural or institutionalized racism).^{3,7–10}

Previous research has highlighted the importance of considering environmental and social determinants of health when studying cumulative risk, particularly when working with vulnerable communities.^{3,5,11–15} There also is growing evidence that risk to optimal health from exposures to multiple environmental and social stressors accumulate over the life course.^{11,16} Several physiologic, biochemical, epigenetic, and other pathways have been demonstrated or proposed to be mechanisms for lifelong accumulation of risk through environmental exposures. These mechanisms include: dysfunction of the hypothalamic-pituitary-adrenal axis, the body's inflammatory response mechanisms, and other physiologic pathways related to allostatic load^{17–24}; mechanisms affecting telomere length regulation (cell “aging”)²⁵; and genetic methylation and other epigenetic mechanisms impacting gene expression.^{26–29}

Interactions among exposures along with subsequent physiologic responses to these multiple exposures can become complex. While it is possible that these interactions may be simply additive, often times these interactions can yield effects that are to some degree synergistic or antagonistic.³⁰ For example, studies have linked stress and stress-related chronic illnesses and biological responses with decreased cytochrome P450 activity, a major component of critical biochemical pathways that eliminate certain environmental toxins and toxicants from the body.^{31–33} This body of research suggests a potential biological mechanism wherein synergistic interactions occur between high levels of stress (likely via increased allostatic load, inflammatory responses, etc.) and decreases in the activity of biochemical pathways responsible for the elimination of environmental toxics.^{34,35} These mechanisms are further complicated by impacts from the social environment, including adverse childhood experiences, socioeconomic status, structural racism, and other social stressors and supports.^{36–38} Thus, the relationship between exposure to stressors and a reduced ability to process and eliminate environmental toxics (increasing the overall stock of risk to optimal health one may experience) may not be linear and may vary based on the status of multiple other factors that should be taken into account. However, traditional methods are limited in their ability to study such a complex system of risk.

1.2 Objectives

Considering this body of research, we argue that a systems science approach will add to environmental health researchers' ability to examine the accumulation of risk to optimal health from multiple exposures. A systems science approach provides methodologies to examine these issues through a global lens, which can complement the more reductionist approaches currently available. Specifically, we propose system dynamics modeling as a potentially valuable tool to incorporate a systems perspective into the study of cumulative risk. The next section introduces system dynamics modeling in the context of studying cumulative risk. We provide examples of how its key features as an analytical and communication tool can contribute to the research of cumulative risk. We conclude our essay with a discussion of the potential limitations of the method and ways to ensure rigor in the modeling process and its outcomes.

2. SYSTEM DYNAMICS MODELING: A SYSTEMS SCIENCE METHODOLOGY

Systems science includes a diverse set of methodologies. No single method is universally better than another, and the choice of methodology is dependent on the research question at hand.³⁹ One specific methodology that shows promise in assessing cumulative risk through a systems lens is system dynamics modeling. Classic examples applying system dynamics to environmental health-related problems include Jay Forrester's *Urban Dynamics*, which examined factors related to urban growth, and Donella Meadows and colleagues' *Limits to Growth*, which examined broader trends in economics, population growth, pollution, and resource management.^{40,41} Other examples include the use of system dynamics models to inform policy decisions on a variety of environmental health topics.^{42–45}

For public health audiences, a brief introduction to system dynamics in public health and healthcare contexts is available in Sterman⁴⁶ and Homer and Hirsch⁴⁷. More detailed description of the methodology is available in Forrester⁴⁸ and Sterman⁴⁹. Fundamentally, system dynamics models are mathematical representations of 1) inter-relationships between various system parts, 2) feedback loops or circular causality among the inter-related system parts, and 3) delays in accumulation of information, materials, and other state variables (e.g., risk) within the system. Key stakeholder inputs and empirical data are used to inform the model structure and value of model parameters. When simulated, the structure of the modeled system generates various system behaviors. By modifying the model structure or adjusting the model parameters, one can see the effect of different policies on the system behaviors. The next sections highlight key features of system dynamics models, including the model building process, and how they are of potential utility for enhancing our capacity to understand cumulative risk in environmental health research and practice.

2.1 Accumulations: Stocks and Flows

The concept of stocks and flows in system dynamics can be beneficial in studying cumulative risk. A stock is an accumulation of material, information, or other resource over time, and the quantity of the stock reflects the net changes in its inflows and outflows. In that sense, cumulative risk can be conceptualized as a stock that accumulates over the life course, and it thus reflects the net changes in risk over time. Risk due to environmental stressors would flow into the stock, while factors related to increased resilience or risk mitigation result in risk outflows. Further, the stock and flow model of accumulation of risk can be split out across key life stages (e.g., in utero, early life, adolescence, early adulthood, middle adulthood, later adulthood). The flow of risk migrates overtime. Using the modelling process, the amount of risk added to the stock at each stage of life (increased exposures), as well as risk leaving the stock (e.g., increased resiliency) can be modelled. The rate at which risk is entering or leaving the stocks at various life stages can be determined by inputs from variables and feedback loops based on inputs from variables within the system.

As shown in Figure 1, stocks are represented with rectangular boxes. The flow rates are illustrated with double-lined arrows indicating pipelines with valves. The cloud symbols in system dynamics modelling language represent the source of inflow or the depository for the outflow, and implies the conceptual boundary of the model. The stock of cumulative risk will increase if more risk is added than mitigated. Cumulative risk will decrease if more risk is mitigated than added. Cumulative risk will remain unchanged if the risk added is comparable to the risk mitigated. In order to better understand and manage the net accumulation of risk, it is helpful to decouple the factors that add to the stock level of risk (such as environmental stressors) from the factors that mitigate the stock level of risk (such as resilience). Further, we can expand the accumulation of risk across different stages of the life course (see figure 2). This can aid in understanding the systemic processes by which risk accumulates, allow researchers to simulate interventions that target different components within the system, in order to observe how the intervention may alter cumulative risk over time.

Conceptually, Figure 1 represents the accumulation of exposures to risk in a child and the resultant increase in the child's allostatic load, similar to what has been described elsewhere.¹¹ The stock of cumulative risk generates allostatic load, and this causal relationship is represented by an arrow with a positive sign. Such a conceptual model can be used to infer the effect of two inter-related stocks accumulating at a different rate. Stocks represent delays in the system because the accumulation of a stock is a result of the rate of the outflow lagging behind the rate of the input.⁴⁹ Stressors that generate cumulative risk may not have immediate effect on the allostatic load (particularly if the stressors are infrequent and one's coping or resiliency is able to counter the impact of the stressor before any negative physiological effects occur). However, as these stressors build cumulative risk over time, eventually the accumulation of risk will trigger an increase inflow of allostatic load. This is consistent with the theory that chronic stressors have more harmful effect on the allostatic load than short-term stressors. In a system dynamics simulation model, it is possible to mathematically define the specific trigger mechanism.⁴⁹

2.2 Multiple Causality and Feedback Loops

Traditional approaches to understanding risk tend to focus more on single agent, single route of exposure, and single outcome approaches. This approach yields critical information about individual component of the overall cumulative risk system but is limited in its ability to model more global aspects of this system. System dynamics modeling can complement this approach by accounting for multiple interacting stressors and their impact on health in a dynamic sense. For example, in a low-income community, management of total cumulative risk can be difficult because factors leading to accumulations of risk may interact or be part of multiple feedback loops. These feedback loops can amplify or moderate the risk accumulation over time. Figure 3 illustrates how a hypothetical system's complexity is increased by multiple reinforcing loops (R) impacting the rate at which risk is generated, while also being moderated through a balancing loop (B).

In Figure 3, expansion of industry potentially increases toxic air emissions in the surrounding community, which is one source of risk. The toxic air emissions can depress surrounding property values, as represented by a negative (or inverse) causal relationship. The property value is positively related to non-industry related commercial and residential activities in the area. This implies that with a lower property value, there will be less non-industry related business activities, leading to less employment. With fewer jobs (outside of industry-related employment) and less investment in the area overall, unemployment and poverty rates would rise, creating additional sources of risk. This in turn makes property cheaper for industry to purchase, allowing it to continue to expand, leading to continual worsening of cumulative risk.

Industry expansion is in part held in check within this example system by a balancing loop (B). In this balancing loop, as industry expands, toxic air increases. As toxic air increases, barriers to further air emissions through policies can emerge (for example, the restriction of emissions through stricter air permitting policy). As barriers due to increased air permitting restrictions increase, this negatively impacts industry expansion, reducing toxic air within the system. Later in the modeling stage, these causal relationships can be mathematically

defined, real or hypothesized numbers and estimates can be loaded into the model, and the overall impact of multiple feedback loops on the cumulative risks can be studied.⁴⁹

In another example, Figure 4 demonstrates how multiple reinforcing loops (R) create vicious cycles that can prevent the community from alleviating the accumulation of risk.

Specifically, a continued rise in unemployment and poverty rates in an area may cause residents in need of money to turn to illegal activities. This increase in crime leads to increased reporting and perception of crime, which leads to decreased property values and commercial activities. It also leads to an increase in incarceration among residents in this community, which decreases the likelihood of finding employment upon reentry to the community, further increasing the poverty rate.⁵⁰ This lack of employment and income negatively impact the resiliency and sustainability of the community in terms of its ability to mitigate the impacts of accumulated risk. As a next step, this conceptual model could then be further operationaled by mathematically defining the causal relationships using real or estimated data, and show the extent of overall impact on the cumulative risks.⁴⁹

2.3 Model Building and Schematic Representation

Sexton and Linder called for a schematic representation that can depict “postulated connection among independent variables and between independent and dependent variables (pg. S86).”⁵ Such a schematic representation can make assumptions explicit, serve as a communication tool to clarify concepts, and identify intervention strategies. The system structure depicted in system dynamics modeling language (i.e., causal relationships, feedback loops, stocks and flows) is a hypothesis for explaining a system behavior of interest, and therefore is called a dynamic hypothesis. A dynamic hypothesis reveals the mental models of the system perceived by those building the model.^{51,52} The process clarifies assumptions made about various causal relationships, what is included and excluded within the system boundary, and how one defines different variables.

For example, in Figure 2, there is an assumption that higher property value would lower the industry expansion but increase non-industrial business activities. In this case, the modelers must clarify how the business activities are defined and how these differ from industry-related expansion. Black calls this communication role of schematic representation in system dynamics as a “boundary object,” and it helps to ensure that everyone involved in the modeling project conceptually understands the relationships among the different components of the risk system in an aligned manner.⁵³ Thus, the process and language of building a system dynamics model structure can serve as a vehicle for ensuring that all stakeholders are communicating through a common language that makes assumptions about and relationships within the system transparent for all to discuss, debate, and reconcile.

More concretely, Klopogge and van der Sluijs presented four projects that integrated (to various degrees) stakeholder involvement into an assessment of accumulating risk associated with climate change, as well as potential solutions for managing this risk.⁵⁴ They noted that critical barriers with incorporating stakeholder input were that the stakeholders’ perspectives and knowledge were 1) not allowed to be integrated into the overall research process from the beginning, 2) not adequately interpreted, or 3) not accurately incorporated into the research process by the research team after this information was collected and interpreted.

Also, researcher knowledge, perspectives, and underlying assumptions and values may not match those of other stakeholders. The authors note that these barriers could be attributable to system boundaries being established prior to engaging the stakeholders, or to having inflexible boundary definitions once stakeholders become engaged. The schematic representations in system dynamics allows all stakeholders to jointly “construct shared understanding among people with differing domain expertise.”⁵³ This process also increases transparency among all stakeholders about the variables being considered, as well as the relationships among them.

2.4 Data Collection, Model Calibration, and Model Validation

Researchers call for systematic collection and interpretation of data to study cumulative risk.^{2,5} One first step to achieving this goal is to identify indicators and measures of various stressors and to collect longitudinal data from high-priority target populations. System dynamics modeling can help researchers focus their efforts on identifying critical sets of data that may be missing, as well as where to make strategic investments in data collection. By building and examining a preliminary model, one can create an inventory of data that will be needed to populate the model, identify sources (or potential sources) of data that already exist, and develop a list of data elements needed to be collected in moving forward if and when resources become available. Using Figure 3 as an example, modelers have identified data needs for the variables relating to poverty, expansion of industry, toxic air, property values, business activities, jobs, and permitting. Each of these variables would need to be operationalized based, in part, on what data sources were available. Limitations on what type of data are available may create assumptions within the model that would need to be acknowledged.

For this example, much of the required data are available through census (e.g., poverty, jobs, business activities), EPA (e.g., toxic air), or other Federal public databases in the United States, as well as local databases (e.g., local tax districts for expansion or property values). If data sources are not readily available, data collection may be necessary, if feasible. When data collection is not feasible, the model must rely on estimates and expert judgment. Jay Forrester, the founder of system dynamics, emphasized that most important data for understanding complex systems come from “mental databases.” This idea acknowledges that not all things in the world are measured, including many of the things that we know to be important. Leaving out these unmeasured factors creates more bias in the model than would incorporating the best estimates.⁵⁵ This has led to the system dynamics field embracing diverse information sources and data in different formats, and, therefore, not limiting itself to hard, quantitative data.

Qualitative information, expert judgments, and estimations with face validity all serve as important data sources, as long as they contribute to the purpose and accuracy of the model. There are techniques, such as sensitivity analysis, for accommodating gaps in the information used for system dynamics modeling, such as when data regarding variables or relationship among variables are not available.⁴⁷ More recently, Hosseinichimeh et al. developed a set of techniques for estimating parameter values and identifying data sources

with a group of subject matter experts and stakeholders participating in the group model building process.⁵⁶

After the conceptualization phase of generating qualitative diagrams, variables and their causal relationships are operationalized as a set of differential and algebraic equations. At this point, empirical data can be incorporated into the model, which allows the model to simulate changes in parameters across time. The technical details of formulating equations are available in various system dynamics references.⁴⁹ The results of these simulations are then evaluated for their ability to accurately replicate the behaviors of the system of interest. This process often leads to further modification of parameter values, coefficients, and relationships among model parameters to improve the model's accuracy and utility.

Cumulative risk studies frequently utilize iterative processes.² This is a key advantage of using system dynamics modeling, as the iterative model building and simulation process often leads to the identification of critical flaws in the mental models of or information gaps within the system. While the model is being formulated, it is repeatedly tested and modified. Some of the typical testing practices include: extreme condition testing – does the model behave reasonably with extreme input values?; behavior reproduction – can the model replicate observed data and trends?; and checking for violation of physical laws.⁴⁹ Other important criteria include assessing whether the model is useful for revealing the limitations of our own assumptions and mental models, and in this fashion contributes to our learning and decision making.⁴⁸ Following Forrester's perspective, the system dynamics field recognizes that all models are simplified representations of a real system; therefore, while the models must strive to avoid biases, one must always be aware of the limitations of models.

2.5 Identifying and Simulating Policy and Intervention Strategies

System dynamics model allows simulation of system behaviors under different conditions of varying degrees, sometimes with different time spans, and documents changes of all variables in the model as changes to model parameters are varied for simulation. The modelling process ensures that all changes are fully documented. Multiple iterations of simulations, each with a different modification to system parameters (e.g., inputs, rates of change, relationships among variables, etc.), are possible, leading to the potential for comparing outcomes over time across versions of modifications to the system.⁵⁷ Therefore, system dynamics models of cumulative risk would prove useful in identifying potential leverage points within a system where reducing or managing risk would be most feasible. This can be accomplished by modeling potential intervention and policy strategies and evaluating the impact of these interventions on the system. Specifically, by simulating changes in the elements of the model (such as the rates of flows within specific elements of the system, for example by modeling reductions in the amount of toxic emissions due to changes in permitting), or changes in the structure of the model itself, system dynamics models can simulate potential interventions and evaluate their effects on cumulative risk.

These simulations can estimate 1) magnitude of impact of an intervention, 2) time until impact may be observed, and 3) the cost-benefit of an intervention. Even more abstractly, the simulations can reveal limitations in the underlying assumptions of the interventions

themselves, highlighting potential weaknesses in the theoretical or conceptual frameworks guiding them. These virtual experiments, in turn, can help researchers to better estimate the behavioral trends of the system over the long term and can aid in determining which strategies have greater potential for reducing or mitigating cumulative risk.³⁹ Estimates of long term potential impacts of interventions can be critical in decision making and priority setting by non-research stakeholders, especially since cumulative risk assessment involves long-term health concerns in the population. However, as with other modeling or simulation methodology, the results from system dynamics modeling are, in the end, estimates, and have an associated degree of error.

Interventions focusing on improving environmental health often have small impacts on the long-term trends observed within those communities facing disproportionate exposures, even after large amounts of resources and effort are devoted to the problem. When examined through a system dynamics lens, this long-term lack of effectiveness is often due to structural elements and unanticipated relationships among these elements embedded within the complexity of the overall system. This includes the kinds of structural feedback loops and delays built into the systems that were discussed in the examples illustrated by Figures 3 and 4.

A more concrete example of these reinforcing and balancing feedback loops and delays looks at the issue of chronic disease prevalence with a systems perspective.⁴⁷ Feedback loops and delays enable the system to react to changes and maintain homeostasis, where homeostasis, in this example, is the pre-intervention trend in incidence and prevalence rates of chronic disease within the targeted population.⁵⁸ Examples of this phenomenon include persistent disparities in terms of morbidity, stress, behaviors associated with negative health outcomes, social determinants of health, and exposures from environmental toxics, regardless of intervention.⁴ The delay phenomenon also can be observed in the delay time between intervention (such as with early childhood development) and observed health outcomes later in life. Previous work has demonstrated the utility of studying these feedback loops in informing the development of interventions, as well as in assessment and evaluation efforts.^{59,60}

2.6 Stakeholder Engagement

Stakeholder engagement is critical when studying cumulative risk.² Stakeholders can be defined in several ways, but here we define them as those individuals or organizations that would be affected by an issue (either directly or indirectly), or could affect the outcome of a policy or decision making process regarding the issue.⁶¹ Specific examples from our previous work include local policy makers, residents and neighborhood associations, industry, local business leaders, and researchers.

Stakeholder input is essential for defining problems, obtaining relevant information, and providing insight into the cumulative risk research process, including the interpretation and evaluation of results, decisions, and their consequences. BeLue, et al., note that using system dynamics modeling offers many benefits to projects seeking to engage stakeholders, including viewing the underlying issues from a systems point of view, where participants can see how factors are interrelated and can help with identifying potential leverage points.⁶²

System dynamics modeling frequently includes a “back and forth” exchange among all stakeholders, ensuring that the method is capturing key determinants of risk, as well as producing results that most closely represent the real world. Referred to as Group Model Building, this practice engages stakeholders across the spectrum of the research process, helping the entire team to consider system structure from diverse perspectives and merge these perspectives into a coherent structure.^{63–66} Guides for best practices for running stakeholder meetings are widely available in the system dynamics community.^{56,63,64,66–68}

2.7 Limitations

It is important to consider limitations of system dynamics modeling as a tool for studying cumulative risk. A system dynamics model of cumulative risk should be used to understand the interaction among various stressors and their impact, and should not focus solely on point prediction of the future system state. Forecasting is not the main purpose of system dynamics modeling. Rather, the model is a learning tool for examining opportunities for improving environmental health and quality of life with a systems perspective.⁶⁹

Just as with any other model, system dynamics models are simplifications of reality. In this sense, it is important to recognize that the model outcomes are reflections of the model structure, and biased models will generate biased results. In other words, the structure of the system represented in the model is dependent on the inputs (i.e., data, assumptions). If these inputs are of low quality (or simply incorrect) then the model’s utility may be compromised. Gaining input from multiple categories of stakeholders (for example, community representatives and advocates, regulators, researchers and other scientists) is critical to mitigating this limitation. Input from these groups should occur at all stages of the modeling process, including during model building and, particularly, during interpretation, to ensure that the model is representing the system as observed from the respective viewpoints of the various stakeholders. These groups can also help with interpreting any counterintuitive results that may come from various model runs as either incorrect, biased, or of actual utility.

The limits of a system dynamics model are strongly dependent on the model’s boundaries (e.g., which parameters and relationships are included and excluded), the availability and quality of data to be used in the model, and any biases introduced by participants supporting the construction of the model. Therefore, the modelers must strive for rigor in the modeling process by again engaging a balanced group of stakeholders, utilizing the highest quality data available, and performing various tests for model validity.^{49,63}

Further, building a system dynamics model is a challenging undertaking. There are often a number of challenges facing teams, including defining model boundaries, ensuring sufficient precision of variables and relationships within the model, operationalization of the variables and data sources used to populate the model, and setting assumptions behind the variables and relationships within the system, whether data are available or not. Beyond these operational barriers are differences in assumptions brought to the model building process, purposes of engaging in the modeling exercise, and expectations behind the modeling process itself.

Given these limitations and potential challenges, it is important to note that a system dynamics model need not be complicated to be useful. In order for a model to generate insights, the model must be built with a specific problem focus. Small, parsimonious models can prove remarkably powerful in aiding researchers, policy makers and community advocates in identifying the most effective use of limited financial, human, or social capital resources.⁷⁰

3. CONCLUSION

We see systems science, with particular focus on the methodology of system dynamics, as a way to advance the understanding of cumulative risk. With system dynamics modeling, the system of cumulative risk can be understood in such a way that the complexity of the model stems from accumulation of materials and information, feedback loops, and time delays. This allows conceptualization of dynamic interactions among different sources of risk and their combined impacts on health-related outcomes. Further, this approach can aid in discovering leverage points for future interventions and policy strategies aimed at reducing cumulative risk.

A systems approach offers many advantages to cumulative risk researchers. It allows researchers to conceptualize the problem beyond a reductionist viewpoint, thus yielding new insights into why risk accumulates in a given system. Through defining the boundary of the system being analyzed, the research team can focus on specific issues. The modeling and simulation capacity allows for interventions to be tested for potential impact on health and health-related outcomes, cost-effectiveness, and feasibility. The Group Model Building process requires engagement of and input from the entire spectrum of stakeholders, while simultaneously building trust, understanding, and capacity amongst these stakeholders.

In recent years, the methodologies of systems science have made major contributions to the advancement of environmental and public health research, including the examples presented earlier in this essay. System dynamics, in particular, may be a useful addition to the analytical and methodological toolkit used to increase our understanding of cumulative risk. Keeping in mind its limitations, system dynamics modeling has significant potential for advancing the study of cumulative risk from environmental and social hazards.

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Text Box 1:**Sample Questions from Group Model Building Exercises:**

- How is the target community defined? Who is included? Who is not included?
- How do we define the risk (or the key problem), and what is the historical trend of the risk?
- What explains this historical trend? More specifically:
 - What are the sources of risk to the health of the community's residents? What are factors that help prevent risk or help promote health in the target community?
 - What are the relationships among these sources of risk? If a specific source gets worse or better, what happens to the other variables impacted by or impacting this source?
 - What factors contribute to these sources of risk being increased or decreased in the community or in the scientific literature?
 - If a specific factor changes, what would be the expected change in cumulative risk in our community?
- What are some possible sources of data for each variable?
- What are the preferred policy or other intervention options?

Figure 1.
Conceptualizing Cumulative Risk as a Stock

Figure 2.
Risk accumulation across the life-course

Figure 3:
Examples Factors Adding to Cumulative Risk

Figure 4.
Examples of Factors Mitigating Cumulative Risk