Earth's Future

RESEARCH ARTICLE
10.1029/2021EF002641

Special Section:
Modeling MultiSector Dynamics to Inform Adaptive Pathways

Key Points:
- Human action is an important determinant of multisector system behavior
- Human systems representations in multisector models are often oversimplified or fragmented
- We propose a new human systems modeling typology to synthesize insights and chart opportunities for research in multisector dynamics

Supporting Information:
Supporting Information may be found in the online version of this article.

Correspondence to:
J. Yoon,
jim.yoon@pnnl.gov

Citation:
Yoon, J., Romero-Lankao, P., Yang, Y. C. E., Klassert, C., Urban, N., Kaiser, K., et al. (2022). A typology for characterizing human action in multisector dynamics models. *Earth's Future*, *10*, e2021EF002641. https://doi.org/10.1029/2021EF002641

Received 29 DEC 2021
Accepted 22 JUN 2022

A Typology for Characterizing Human Action in MultiSector Dynamics Models

Jim Yoon[1], Patricia Romero-Lankao[2], Y. C. Ethan Yang[3], Christian Klassert[4], Nathan Urban[5], Kendra Kaiser[6], Klaus Keller[7], Brinda Yarlagadda[8], Nathalie Voisin[1], Patrick M. Reed[9], and Richard Moss[1]

[1]Pacific Northwest National Laboratory, Seattle, WA, USA, [2]National Renewable Energy Laboratory, Golden, CO, USA, [3]Lehigh University, Bethlehem, PA, USA, [4]Helmholtz Centre for Environmental Research—UFZ, Leipzig, Germany, [5]Brookhaven National Laboratory, Upton, NY, USA, [6]Boise State University, Boise, ID, USA, [7]Penn State and Dartmouth College, Hanover, NH, USA, [8]University of Maryland, College Park, MD, USA, [9]Cornell University, Ithaca, NY, USA

Abstract The role of individual and collective human action is increasingly recognized as a prominent and arguably paramount determinant in shaping the behavior, trajectory, and vulnerability of multisector systems. This human influence operates at multiple scales: from short-term (hourly to daily) to long-term (annually to centennial) timescales, and from the local to the global, pushing systems toward either desirable or undesirable outcomes. However, the effort to represent human systems in multisector models has been fragmented across philosophical, methodological, and disciplinary lines. To cohere insights across diverse modeling approaches, we present a new typology for classifying how human actors are represented in the broad suite of coupled human-natural system models that are applied in MultiSector Dynamics (MSD) research. The typology conceptualizes a "sector" as a system-of-systems that includes a diverse group of human actors, defined across individual to collective social levels, involved in governing, provisioning, and utilizing products, goods, or services toward some human end. We trace the salient features of modeled representations of human systems by organizing the typology around two key questions: (a) Who are the actors in MSD systems and what are their actions? (b) How and for what purpose are these actors and actions operationalized in a computational model? We use this typology to critically examine existing models and chart the frontier of human systems modeling for MSD research.

1. Introduction—Modeling the Complexity of MultiSector Dynamics

In modern society, sectors delivering services critical to economic productivity, environmental protection, and human wellbeing are inextricably linked through a network of interdependencies. The societal importance of cross-sectoral interactions is made especially apparent during periods of failure, manifested either abruptly or gradually, which can result in major economic loss, disrupted communities, environmental impact, and human casualties (Helbing, 2013). During Hurricanes Katrina and Sandy, for example, sudden failures in flood protection, energy and food provision, and communications cascaded into an impairment of critical services including healthcare provision, ultimately leading to the loss of human life (Franco et al., 2006; Romero-Lankao, Bruns, & Wiegleb, 2018; Romero-Lankao, Burch, et al., 2018). In 2021, Winter Storm Uri caused a major cold snap in Texas (Doss-Gollin et al., 2021) that impaired energy infrastructure, leaving over 4.5 million individuals in the state without power, with cascading impacts on drinking water and medical treatment services (Busby et al., 2021). Cross-sectoral failures also emerge more insidiously and at larger scales, as with the recent, slow-building impairment of the marine transportation sector due to COVID-19 (March et al., 2021), yielding detrimental impacts on all downstream sectors dependent on the global supply chain (Notteboom et al., 2021).

While adequate provision of services *between* sectors often underpins the final provision of any sector-specific service for society, efforts to evaluate sectoral risk exhibit "single-sector myopia," or the tendency to assess a single sector independently from that of all others. In such analysis, the adequate provision of services from external sectors is often presumed, a reliable boundary input to a single sector of interest with potential interdependencies between sectors ignored. Advocates of a cross-sectoral approach have argued that myopic focus on individual sectors can lead to pronounced misdiagnosis of risk given the interconnectedness of modern systems (Helbing, 2013) and critical infrastructure (Rinaldi et al., 2001). For example, insufficient cross-sector planning between the electricity and land management (e.g., forest management) sectors has resulted in exacerbated fire risk across the Western United States (Mitchell et al., 2014; Syphard & Keeley, 2015). Considering longer timescales, myopic focus on renewable bioenergy production for the purposes of greenhouse gas reduction ignores potential impacts on the water supply sector (Gerbens-Leenes et al., 2009; Hejazi et al., 2015).

To address interdependencies between sectors, multisector dynamics (MSD) frames the study of interacting sectors as that of a "systems of systems," acknowledging that the vulnerability, risk, and resilience of any given sector is nearly always intertwined with that of many others (Haimes, 2018; Reed et al., 2022). Such a view of sectors and their interactions calls for a complex adaptive systems approach for the understanding of cross-sectoral interactions and the role of humans therein (Moss et al., 2016). Computational modeling has emerged as an essential tool for capturing complexity, supporting quantitative analyses of interacting components of multisector systems, with dynamic representation of human components heralded as the next frontier of MSD research (Moss et al., 2016). Given the significance of human action in shaping multisector system risk, vulnerability, and evolution, several scientific communities have focused on representing human systems in multisector models including engineers working on infrastructure system planning (Brown et al., 2015; Harou et al., 2009; Reed et al., 2013), global change scientists examining energy-water-land futures amidst climate and socioeconomic change (Fisher-Vanden & Weyant, 2020; Nordhaus, 1994; Wilson et al., 2021), and ecologists interested in the resilience of social-ecological systems (Biggs et al., 2015; Folke, 2006; Gunderson and Holling, 2002; Walker et al., 2004). However, efforts to represent human action in multisector models remain fragmented across disciplinary lines and research communities. A shared framework for describing and comparing human systems modeling approaches across communities is essential to promote coherence and enhance progress on human systems modeling efforts for MSD research.

In the following, we characterize general trends in human systems modeling for multisector research, inventory existing approaches, and propose a common typology for characterizing, diagnosing, and designing such representation in both existing and new models. Section 2 describes general trends in human systems modeling and an inventory of existing approaches. Section 3 presents the new human systems modeling typology. Discussion and conclusions are provided in Section 4.

2. The State of Human Systems Modeling for Multisector Research

2.1. Human Action as Paramount Driver of System Behavior

The role of individual and collective human action is a prominent and arguably paramount determinant of interacting human-natural system behavior, trajectory, and risk (Bai et al., 2016; Beckage et al., 2018; Elsawah et al., 2020; Liu et al., 2007; Simpson et al., 2021). This human influence operates at both short-term (hourly to daily) to long-term (annually to centennially) timescales, and can both mitigate and exacerbate risk and vulnerability (Romero-Lankao & Norton, 2018; Zhou et al., 2018). For instance, local authorities have subsidized elevated houses for poor communities in Buenos Aires, a longer term action aimed at helping poor families withstand storm-surges. However, these houses are very small with children often still occupying the ground level of the home (where the first floor was originally located) due to lack of adequate space, thereby causing families to revert to short-term responses to floods such as moving belongings to higher levels and exacerbating vulnerability for the poor.

In the context of sudden catastrophes, Helbing (2013) argues that global-scale systemic failures are largely due to the networked risks that humans themselves have created through the development of interconnected systems, often unintentionally or unforeseen (Rinaldi et al., 2001). For example, the disruption of New York's food supply during Hurricane Sandy was in part due to human-initiated reforms in the 1980s, during which New York restructured its food storage and distribution systems shifting toward increased reliance on imported sources from outside the state and country (Romero-Lankao11, Burch, et al., 2018). In view of the paramount role of human action in multisector systems, new paradigms for risk evaluation have emerged to account for human response as a key determinant in defining overall system risk (Simpson et al., 2021).

In multisector systems, human actions also operate at multiple social levels. Individual social units (e.g., individual persons, households, businesses, etc.) make frequent "micro-decisions" such as where and how to commute, whether to irrigate a field, how long to run an air conditioning unit, to evacuate during a flood or fire, and so forth. These micro-decisions coalesce into wider sectoral utilization patterns and operational responses, manifesting as traffic patterns across a transportation network, water flows in a piped water supply network, occupancy rates of hospitals, or loads in an electrical grid. Beyond actions directly related to consumption and production of sectoral goods and services, human actions also interface with multisector systems in less direct, though equally influential ways. Individuals adopt new practices and technologies, decide where to settle, share information, advocate for causes, vote in elections, and choose service providers. While the impact of such actions on multisector systems is perhaps less immediate than those directly pertaining to production and consumption, they nonetheless strongly shape the long-term evolution of multisector systems.

One category of these indirect human actions that particularly contributes to the complexity of multisector systems is the emergence of human institutions that structure human interactions (Bai et al., 2016; Romero-Lankao, Burch, et al., 2018). Following Voigt (2013), which attempts to reconcile earlier descriptions by North (1990) and Ostrom (1986), institutions can be defined as "commonly known rules used to structure recurrent interaction situations that are endowed with a sanctioning mechanism," where the sanctioning mechanisms can range from the self-enforcement of conventions to group or government enforcement. Scott (2013) further describes institutions as "social structures that have attained a high degree of resilience," distinguishing between cultural-cognitive, normative, and regulative institutions. Under such a conceptualization, individual and collective values, opinions, and actions intertwine and amalgamate to shape and be shaped by the broader institutional landscape, including the formal governing laws and rules of society as well as the informal norms and values that influence social interactions and practices (Johnson, 2016; Mongruel et al., 2011).

These institutions commonly (and imperfectly) function to constrain individual human action in the service of broader societal objectives such as justice, environmental protection, and economic productivity, further evolving to meet individual and collective needs in a perpetual, contested cycle of change. Based on this view, the institutional arrangements that define the "rules of the game" (North, 1990) in multisector systems via regulations (e.g., zoning restrictions), market types (e.g., free market vs. nationalized), legal rulings (e.g., species protection), and norms (e.g., informal cooperation between community members) are themselves dynamic properties of the system that are malleable in the face of environmental, socioeconomic, cultural, and political change and that, therefore, would ideally be captured in dynamic representations of human systems within multisector models.

2.2. The Fragmentation of Human Systems Modeling Efforts

While many engineering, economic, ecological, and social science communities have recognized the salience of human action in driving interacting human-natural system outcomes and have embraced computational modeling as a useful means to represent human systems, others have contested the viability of translating theories and concepts from the social sciences into computational models of human behavior. At the philosophical level, varying views on the relationship between science and the nature of reality have fractured research efforts, with physical science communities largely embracing a positivist framing of reality and its relationship to the scientific enterprise (Geels et al., 2016), while some social science communities have advocated alternative philosophies (e.g., post-positivism, constructivism, and relativism) that arguably preclude the integration of social science insights into modeling frameworks (Castree et al., 2014). Faced with such fundamental differences, some researchers have argued that the creation of common modeling frameworks to bridge approaches and perspectives is possible and useful (Geels et al., 2016; Trutnevyte et al., 2019), while others have suggested that modeling efforts and social sciences are incommensurable and should be applied in an independent and pluralist manner due to the philosophical, methodological, and normative diversity across disciplines (Castree et al., 2014).

Among researchers embracing computational modeling as a fundamental and useful tool for multisector research, major differences have nonetheless emerged between modeling communities adopting divergent approaches to representing human systems, ranging from agent-based to computable general equilibrium to system dynamics models, to name only a few. Each of these modeling approaches adopts a unique structural conception of human systems, such as those that represent human action in the form of an abstracted, centralized decision maker versus those focusing on the distributed actions of heterogeneous actors. Divergence on underlying theories of human behavior have been equally stark, reflecting the wide range of social science theories that exist for describing or modeling human behavior, many of which are inconsistent or competing (Watts, 2017). Modeling efforts examining these inconsistencies, such as those comparing rational versus bounded-rational theories of human behavior, indicate that the choice of underlying behavioral theory strongly drives model outcomes (de Koning et al., 2017). These differences have fractured the broader human systems modeling enterprise and the community's ability to draw coherent insight across diverse modeling efforts.

2.3. Exploratory Modeling Approach and Common Typology

In the face of this philosophical and methodological diversity, a pluralistic and exploratory modeling approach offers a promising path forward for the treatment of human action in multisector models (Bankes, 1993; Marchau et al., 2019; Moallemi et al., 2020; Walker et al., 2003). *Exploratory* modeling is distinguished from *consolidative* modeling (see Bankes, 1993). In the latter, a model is typically viewed as an integration of data, theory, and process-understanding that attempts a consolidative representation of a knowable reality. From this vantage point, models are only limited for want of better data and improved representation of the underlying processes that drive system outcomes. In contrast, an exploratory modeling approach focuses on inherent epistemic limitations, for example, due to underlying deep uncertainties (Lempert, 2002; Lempert et al., 2006; Walker et al., 2003) that are assumed to severely limit the ability to model the system in consolidative fashion. Exploratory modelers accordingly view a modeling experiment as a *single* plausible conception of reality among the *many*, commonly deploying large ensembles of models that vary parametrically, theoretically, and structurally to explore, rather than predict, a wide range of potential system responses and futures.

We argue that the exploratory approach is especially appropriate for contending with the complexity of multisector systems and the actions of humans therein, in which the epistemic and aleatoric uncertainties of the system and the volitional nature of human behavior can considerably confound attempts at consolidative analysis. An exploratory modeling approach creates a bridge between computational modeling and social science fields that diverge from the traditional positivist physical science orientation; a model is no longer viewed as the single authoritative representation of reality, but rather one plausible conception of reality subject to the knowledge limitations, values, and biases of the modeler (Funtowicz & Ravetz, 1993; Saltelli et al., 2020) who must contend with the multifarious and wicked nature (Reed & Kasprzyk, 2009; Rittel & Webber, 1973) of the social and environmental reality to be explored.

Under an exploratory modeling approach, a shared framework for describing and comparing models is essential to cohere insights across diverse modeling efforts. Such a framework can allow the broad multisector community engaged in human systems modeling to describe models using common terminology and to promote constructive dialog around questions such as: How are groups and categories of human actors conceived in models? How are they defined across spatial and social scales? What are the represented actions and across what temporal and spatial scales are they considered? How does the actor/action conceptualization influence the types of science and analytical questions that can be addressed? What are the theoretical and empirical bases of assumed actor behavior? How do these models embed the values and biases of the modelers and what does this entail for interpretation of model results?

2.4. General Trends in Human Systems Modeling Research

In the following section, we review general trends in human systems modeling research and inventory existing modeling approaches for multisector analysis that are illustrative. While not intended as an exhaustive review, the inventory is meant to capture a variety of existing modeling approaches with an eye toward the development of a modeling typology that can accommodate a diversity of modeling paradigms. Some prominent modeling communities relevant to multisector research focusing on representing human systems include integrated assessment, social-ecological systems, agent-based, bioeconomic, and engineering planning modelers. A high-level distinction that can be drawn between modeling efforts is between those that offer a stylized representation of a system, attempting to generate insight from a prototypical analysis that can be extrapolated to other systems sharing similar characteristics, versus those that offer a place or case-specific representation of a modeled system, typically attempting to address a specific scientific or analytic question that is often guided by stakeholder interests.

The various modeling approaches are deployed over a wide range of spatial scales from the highly local (e.g., individual communities, towns, watersheds, jurisdictions, etc.) to regional and global contexts (e.g., countries, agro-ecological zones, etc.). Likewise, there are applications across an equally wide range of timescales, ranging from the short-term (e.g., daily to monthly) to the long-term (e.g., annual to centennial). As such, multisector models vary widely as to the system features and processes that are included, and the detail and fidelity to which they are represented. For example, global-scale integrated assessment models (IAMs) represent large-scale features of the global economy and typically exclude detailed representation of local-scale infrastructure and institutions given computational demands and data limitations (Gambhir et al., 2019). In contrast, local water and energy systems models typically aim to resolve resource flows, physical infrastructure, and local institutions to a high degree of fidelity, while physical and socioeconomic conditions outside the domain of interest are treated as exogenously imposed boundary conditions (Yoon et al., 2021).

Three pertinent trends are noted in the representation of human systems in multisector models. The first is that many of the preferred modeling approaches have emerged out of the engineering and physical science communities, and as such are designed around representing physical system processes. For example, water and energy engineering planning models (Georgilakis & Hatziargyriou, 2015; Sieber, 2006; Zagona et al., 2001) largely focus on simulating the availability, movement, and depletion of the physical water or energy resources and/or the infrastructure involved in processing, treatment, and transmission of that resource for human use. In contrast, the human component of these models is handled far more simplistically, with human actors commonly represented in the form of exogenously imposed resource "demands," which the models then attempt to satisfy through the aforementioned physical mechanisms.

Second, to the extent that models endogenize human action, they lean on the assumption that human behavior reasonably approximates rationality, even if in some formulations rationality is bounded by lack of information or by cognitive processes or values that could violate assumptions of rational behavior (Simon, 1957). Approaches that adopt neoclassical economic methods typically assume rational economic actors operating at several layers of society: (a) consumers that are utility maximizing users of resources, (b) firms that are profit maximizing suppliers of a resource or service and, (c) markets that are economically efficient in brokering transactions. Prominent examples include IAMs simulating regional-to-global scale land, energy, and water use patterns as the outcome of a global market process (Fisher-Vanden & Weyant, 2020; Nordhaus, 1994; Wilson et al., 2021), water systems analysis framed as cost-based optimization problems (Giuliani et al., 2021; Harou et al., 2009), agricultural models that assume farmer profit maximization (Berger, 2001; Howitt, 1995), urban development models that deploy housing actors maximizing utility for a housing good under budget constraints (Filatova et al., 2009), and energy system models that assume a central planner attempting to minimize cost (Oikonomou et al., 2022).

A third trend, which largely emerges from the first two, is that conventional modeling approaches have omitted the role of different levels of agency and power to drive and respond to environmental change, minimizing individual and collective potential for inventiveness, technology, vision, and power in moving multisectoral systems to different, though not always desirable states. Such approaches omit key questions around social and spatial equity by failing to ask for whom, when, and where mitigation and adaptation will be promoted (Romero-Lankao & Gnatz, 2016). Under the rational actor paradigm for example, social collective behavior emerges from individuals or organizations maximizing utility functions, while the influence of structural factors that constrain individual behavior such as cultural values and inequality in access to goods, services, and assets (e.g., housing) are often omitted, leading to potential biases in the representation of causal mechanisms (Bonabeau, 2002).

2.5. Communities of Modeling

In the following, we describe key modeling communities that are pertinent to multisector research. We note here that the categories are organized around loose communities of modelers focused on shared domains or topics of interest rather than strict methodological distinctions between approaches to modeling human systems. As such, the modeling communities regularly overlap (e.g., agent-based modeling techniques have been used in social-ecological systems and engineering decision support analysis, social network models commonly overlap with agent-based modeling approaches, etc.), though we present them as distinct communities here for purposes of discussion.

2.5.1. Integrated Assessment Modeling

Climate change IAMs were developed as tools to project energy and land use emissions of greenhouse gases, initially as inputs to climate models (Edmonds & Reilly, 1983; Fisher-Vanden & Weyant, 2020; Nordhaus, 1994; Wilson et al., 2021). Subsequently they have evolved to incorporate detailed representation of emissions and impacts in sectors such as energy, industry, transportation, agriculture, and water resources and have been used as inputs to national and international climate change policymaking. In contrast to detailed, sector-specific models, IAMs focus broadly on the linkages between energy, economic, land, water, and climate systems across regions globally. Due to the need to represent the allocation of natural and human resources across different sectors, activities, and regions, IAMs represent the economic behavior of characteristic agents (producers, consumers, government institutions, etc.). In the aggregate, these agents behave rationally and demand or supply goods and services as a function of their prices.

These models typically do not endogenously represent key processes in human systems such as population growth, changes in values and institutions, or innovation in technology. Instead they rely upon exogenous scenarios such as the Shared Socio-economic Pathways (SSPs). These socioeconomic scenarios represent diverse socioeconomic futures, including institutions and human values, which might pose different levels of emissions intensity and associated difficulty in mitigating and adapting to climate change (O'Neill et al., 2010, 2014). Kriegler et al. (2015) and Riahi et al. (2015) use exogenous scenarios to model imperfect implementations of policies (e.g., regionally fragmented delays), thereby moving away from rational decision-making. Recently, there have been calls for, and visions of, advances for IAMs in representing heterogeneous actors and decision making, especially through greater engagement with the social sciences (e.g., De Cian et al., 2020; Jafino et al., 2021; Trutnevyte et al., 2019).

2.5.2. Agent-Based Modeling

Originating from the artificial intelligence community, an agent-based model (ABM) is a distributed, bottom-up simulation approach for understanding human impacts on system functioning. An "agent" in an ABM describes a programmed object that interacts with other agents and one or more systems of interest (e.g., virtual environments such as process-based hydrologic models, power grid models, or markets). Agents are autonomous (i.e., they have control over their actions), have different and potentially conflicting goals, and make decisions according to behavioral rules, with their actions and interactions shaped by and affecting their common virtual environment(s) (Dooley & Corman, 2002; Sycara, 1998). ABMs have been used for the study of several topics relevant to multisector research including land use change (Evans & Kelley, 2004; Groeneveld et al., 2017; Izquierdo et al., 2003; Liu et al., 2006; Parker & Filatova, 2008; Waddell, 2002), agricultural systems (Berger, 2001; Schreinemachers & Berger, 2011; Schreinemachers et al., 2009), electricity production and markets (Atkins et al., 2004; Chappin & Dijkema, 2007; Chassin et al., 2014; Miksis, 2010), the food-water nexus (Magliocca, 2020), water resources management (Al-Amin et al., 2018; Berglund, 2015; Ng et al., 2011; Yang et al., 2009; Yoon et al., 2021), and transportation (Bazzan & Klügl, 2014; Colon et al., 2021; Hajinasab et al., 2015; Jin & Jie, 2012; Sinha-Ray et al., 2003). While ABMs can accommodate any number of underlying behavior theories, some commonly used theories to quantify agent behavioral rules include expected utility theory (Herstein & Milnor, 1953), the theory of planned behavior (Ajzen, 1991), prospect theory (Kahneman & Tversky, 2013), and the theory of satisficing (Simon, 1972).

However, ABMs can be opaque in their assumptions (Heppenstall & Crooks, 2019) and challenging to calibrate and diagnose given their complexity (Srikrishnan & Keller, 2021). Crooks et al. (2008) further demonstrate that results derived from ABMs can be relatively arbitrary depending on the model, its components, and the underlying theories that inform it. The use of ABMs also potentially introduces a bias toward methodological individualism (e.g., neoclassic-economics, game theories, rational choice theories) in representing social behavior, practices, and structures (O'Sullivan & Haklay, 2000). While ABMs have the potential to represent bounded rationality and institutional complexity, the majority of models still use traditional rationality assumptions (Groeneveld et al., 2017), with far fewer examples of models capturing bounded rationality (de Koning and Filatova, 2020; Manson & Evans, 2007) and institutions (Srinivasan et al., 2010; Yoon et al., 2021).

2.5.3. Social Network Modeling

Social network modeling is another approach that inherently integrates the viewpoint of the individual with that of the collective to describe and understand human behavior (Kluger et al., 2020; Sayles et al., 2019; Will et al., 2020). Relationships are paramount in the social network modeling approach. Networks consist of a set of nodes, typically representing some unit of social organization, whether an individual or a collective such as an organization or community. Ties represent the links between nodes and take the form of friendship, information-sharing, kinship, and other types of relationship. Networks can be used to define or constrain which social entities in a model can interact with which other entities and how information flows between actors (Watts et al., 2019). A given network structure could be imposed exogenously on the social entities in a model (whether individuals or collectives) and the structure of this network might take an idealized form that represents real-world human social networks in certain ways (Sayles & Baggio, 2017), or might be explicitly parameterized using data from a real world network (Matous & Todo, 2015). Alternatively, network formation and structure can be endogenous to the model, whereby individuals or collectives make choices about how to affiliate as a function of various model states, attributes, or processes (Taschereau-Dumouchel, 2020). Networks can further be multi-level (whereby individuals are connected to other individuals but also aggregated into collectives that are also connected to each other) or multiplex, in which case the nodes are connected by more than one type of relationship (Locatelli et al., 2020). We finally note that social networks may also offer a means to model informal institutions such as norms through the shared values, beliefs, preferences between connected actors.

2.5.4. Social-Ecological Systems Modeling

Socio-ecological systems (SES) are a broad category of dynamic systems that have been used to study the interactions between humans and the environment, largely in the field of natural resource management and more recently in the field of urban systems. Conceptual frameworks used to describe SESs have been formalized (McGinnis & Ostrom, 2014; Partelow, 2018) and applied in several case studies. Simulation modeling of SESs was prominent in the early development of the concept of resilience (Holling, 1973), and is still used in research on understanding multiple stable states in ecosystems and regime shifts (Biggs et al., 2009; Hughes et al., 2017; Scheffer et al., 2009; Voisin et al., 2019). SES modeling draws upon several existing modeling traditions from related fields, for example, systems dynamics and agent-based modeling (Kelly et al., 2013), and thus incorporates a variety of representations of human behavior (Schlüter et al., 2017). Some SES research has focused on in-depth, contextual case studies (Schlüter et al., 2019), while other sub-fields, such as those following the tradition of dynamical systems modeling, offer highly stylized representations of prototypical systems. In doing so, these models elucidate general insights on concepts important in understanding social organization, such as cooperation, self-governance, power asymmetries, and equity (e.g., Molla et al., 2021; Muneepeerakul & Anderies, 2017). Notably for multisector research, calls have been made to link analysis of local SESs with the global system in a multi-scale, multi-level fashion (Anderies et al., 2013).

2.5.5. Engineering Decision Support Modeling

Engineering decision support models encompass a broad class of models that are used for the design, planning, and operations of physical infrastructure systems including water supply (e.g., Giuliani et al., 2021; Herman et al., 2020), energy (e.g., Oikonomou et al., 2022), and transportation (e.g., Shepherd, 2014) systems. These models vary widely in terms of formulation, and usually deploy some combination of systems dynamics, optimization, and physics-based modeling to represent the key features of an infrastructure system. Often, engineering decision support models are designed around a physical node-link network, with the nodes in models representing sources and demands for a resource, and links between nodes representing connections that are enabled by the infrastructure system of concern (e.g., a water pipeline, electric transmission line, or road). In most engineering decision support models, human resource demands are exogenously defined based upon the population characteristics of the location under consideration. Some engineering models institute a more dynamic, endogenous representation of demand, such as through willingness to pay curves in which demand responds to changes in prices (Harou et al., 2009; Loucks and Van Beek, 2017). Human management of the infrastructure systems are typically treated in prescriptive fashion, assuming some centralized manager of the system attempting to optimize a particular metric (e.g., minimize costs or supply-demand deficits). Agent-based approaches have also been adopted for engineering decision support models, for example, to simulate the mobility of travelers in a transportation network (Martinez & Viegas, 2017).

3. A Typology for Representing Human Action in MSD Models

Here, we present a new typology for representing human action in multisector systems that is designed to handle a wide range of modeling approaches toward representing human systems such as those covered in Section 2. We adopt an operational definition of a "sector" which allows us to specify and differentiate categories of actors based upon the role(s) that they play within and among sectors. Specifically, we define a sector as a system-of-systems that consists of a diverse group of human actors, defined across individual to collective social levels, involved in the governing, provisioning, and utilizing of products, goods, or services toward some human ends. These goods and services are defined broadly, ranging from traditional physical goods such as energy, water, and food to other less tangible services such as healthcare, media and communications, and environmental amenities.

In attempting to trace the salient features of human systems within broader multisector systems, we break the typology into two key components, prefaced by a consideration of model participants and human values. Each of the two typology components corresponds to a basic question: (a) Who are the actors in multisector systems and what are their actions? (b) How are these actors and actions operationalized in a computational model?

We note that the typology components can generally be used in two forms. The first form is to identify the salient actors, actions, and interactions as they are perceived by model developers and users to exist in the real world and would therefore ideally be incorporated in a computational model. The second form is to identify the subset and abstractions of these actors, actions, and interactions that are actually incorporated in a model, serving as a means to clarify the nature of model abstractions relative to the "real world" conceptualization, compare these abstractions across models, and identify strengths and weaknesses across approaches given modeled outcomes of interest. The sub-sections to follow describe the typology components in further detail.

3.1. Preface: Model Participants and Human Values

We suggest that any assessment of human system representation in a multisector model begin with a critical reflection on the role human values play in the modeling process. Reflecting on the role human values play in a modeling endeavor can clarify the relationship between model developer, model user, and modeled actor, and identify potential biases that are inherent to the modeling process. Humans generally interface with models from three distinct vantages, (a) humans as users of the models, (b) humans as creators of models, and (c) humans as actors represented in the models. In each of these modes of interface, human values strongly shape the modeling effort (see, e.g., Keller et al., 2021; Mayer et al., 2017; Tuana, 2017, 2020; Vezér et al., 2017).

In the first mode, the values of the decision-makers or users of the models can drive the choice of objectives and influence the behaviors and the system dynamics that are represented. As a simple example, consider a modeling analysis on whether or not to elevate a house to manage flood risks (Xian et al., 2017; Zarekarizi et al., 2020). A decision-maker considering the "classic" value of economic efficiency represented by the objective to minimize the expected discounted total costs may choose a different strategy than one who additionally considers the value of robustness in the face of deep uncertainty (Ellsberg, 1961). Human values also enter the modeling process via the interpretation of model results by analysts and the communications of these modeling results to interested stakeholders, including decision makers and the general public. Given the complexity of multisector models, modelers and analysts need to translate model findings into forms of information that can be readily understood by such stakeholders including a distillation of the uncertainty of the findings (Dilling & Lemos, 2011), a translation which is subject to the values of the modeler. More broadly, values play a crucial role in analyzing questions such as: (a) How to navigate the trade-offs and synergies between objectives such as efficiency, equity, reliability, robustness, and sustainability? (b) What to sustain? (c) What is an acceptable (e.g., procedurally fair) process? (d) What are acceptable (e.g., distributionally fair) outcomes? (e) What are robust strategies given potential future changes in the stakeholders' and decision-makers' values? (f) For whom, where, and when should these synergies be pursued?

In the second mode as creators of the models, the values of the analysts can drive the design of the analytical framework and the results. For example, analysts may choose a simpler model to enable a more careful uncertainty analysis (typically at the cost of decreased model realism) (Helgeson et al., 2021) or they may choose to limit the number of considered objectives in a decision-analysis (Vezér et al., 2018). More broadly, values are important for the design of MSD research to address questions such as: (a) What processes, actions, and drivers to include? (b) Which uncertainties to consider? (c) How to navigate the trade-off between increasing model complexity and improving the representation of uncertainties? (d) Which decision-making objectives to consider, and for whom, when, and where?

In the third mode, the values of the modeled actors enter the MSD modeling enterprise in the form of assumptions regarding human behavior that potentially drive the dynamics and outcomes of the models themselves. For example, a modeled household in an ABM might be treated as a rational entity attempting to maximize expected long-term utility or as a family-caring entity with short term responses such as providing shelter for family members that constrain more effective long-term response to flood hazards. Each of these formulations assume a unique set of underlying values driving the modeled actors' behavior and action, with potentially significant impact on the conclusions that are drawn from the modeling analyses (de Koning et al., 2017).

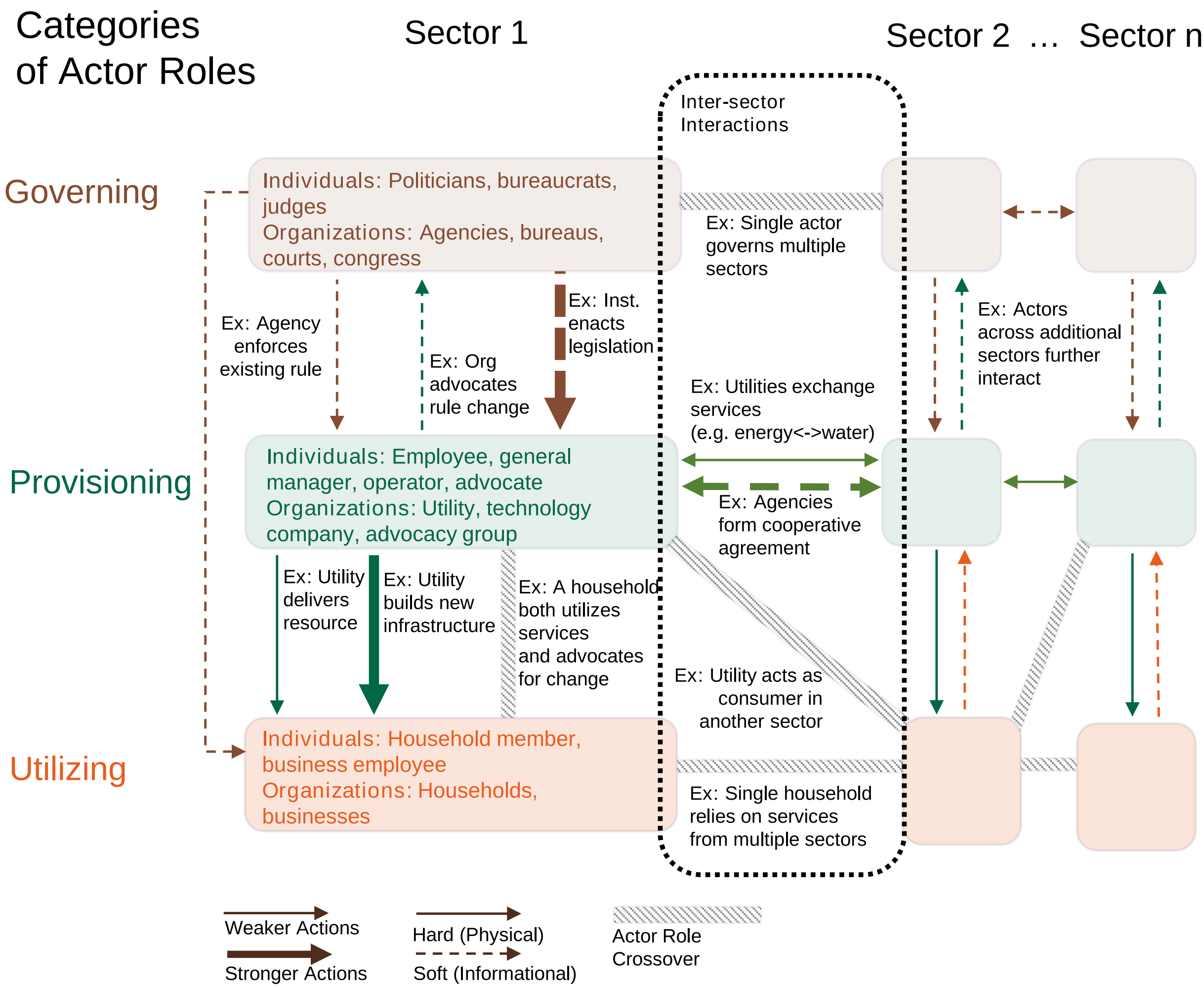

Figure 1. A general conceptualization of actors in multisector systems. We conceive of three categories of actors defined across categories of actor roles: (a) governing actors, (b) provisioning actors, and (c) utilizing actors. Within the categories, the typology can be applied flexibly at the individual or organizational level, as well as across other actor distinctions such as formal versus informal, niche versus regime, and so forth. Cross-sector relationships are conceptualized through cross-sector interactions and cross-sector actor role crossovers. Cross-sector interactions (lines with arrows between actor categories) involve a direct exchange of information or services between different sectors. Actor role crossovers (hashed connectors between actor categories) entail an actor that simultaneously appears in multiple sectors, playing a unique role in each. For example, a farmer could simultaneously be defined as a producer in the agricultural sector and a consumer in the water sector. For interaction types, we differentiate between hard (solid arrows) and soft (dashed arrows) interactions, the former entailing those interactions resulting in some direct change in the physical or built environment and the latter involving an exchange of information rather than a physical exchange or modification. The strength of an interaction is illustrated through the thickness of the line between two actors. Here, we specifically define strength as the level to which an action has the potential to influence or steer subsequent actions.

A consideration of the relation between model creator, model user, and modeled actor and how human values influence the modeling process across these three modes of human-model interface is a crucial component of representing human systems in a multisector model.

3.2. Typology Component #1—Who Are the Actors and What Are Their Actions?

The first component of the typology addresses the question: Who are the actors in multisector systems and what are their actions? As mentioned above, we adopt an operational definition of a "sector" which allows us to specify and differentiate categories of actors based upon the role(s) that they play within and among sectors. Specifically, actors are defined across three categories of roles: (a) governing actors, (b) provisioning actors, and (c) utilizing actors. The actor groups are identified along the vertical axis in Figure 1, with each actor role category extending across any number of sectors included in a model.

Actors involved in the role of governing define the institutions through which other sector actors are legislated, financed, regulated, monitored, insured, subsidized, compensated, penalized, and so forth. The governing actors define the institutional environment for a sector, the so called "rules of the game" (North, 1990). For example, a legislative body that establishes carbon emission limits that other sectoral actors are required to comply with, plays the role of a governing actor. The second category of actors entails those involved in the actual provisioning of a sectoral product, good, or service. The provisioning category include those actors responsible for the delivery of a service (e.g., an energy utility providing electrical service for a city), but also extend to those actors that indirectly participate in provisioning through attempting to influence the form of the service, technological means of production and delivery, and so on. Examples of the latter include companies that develop new technologies (e.g., solar panels) that are potentially adopted by direct service providers, civil society organizations advocating and imposing pressure on a utility to implement a specific type of infrastructure, and financial brokers coordinating exchanges of a service on the market. Finally, we have those actors involved in utilizing, the act of receiving the product, good, or service that is made available by provisioning actors and applying it for some human end use, whether that be direct consumption to sustain livelihood (such as in the physical consumption of water) or used as an input into some other human activity. Within each of the actor role categories (governing, provisioning, utilizing), we can further specify actors at varying levels of social aggregation (i.e., actors can be individuals or organizations).

The categorization of actors based upon differentiated sectoral role(s) allows for the identification of interactions between actors, visualized via the lines that connect actor groups in Figure 1. Interactions can occur between actors within a sector (intra-sector interactions) as well as between actors across sectors (inter-sector interactions). The typology highlights two prominent forms of inter-sector interactions. The first involves an exchange of service, product, or information between actors across sectors. Such an interaction typically operates between actors at the provisioning level, such as an energy utility relying on water deliveries from a water utility for power plant cooling, while the water utility relies on energy delivery from the energy utility for powering water production, treatment, and distribution operations. The second form of inter-sector interaction entails an actor role crossover, indicated by wide hashed connectors between actors in Figure 1. We specifically define an actor role crossover as a situation in which an actor simultaneously appears in multiple sectors and/or across actor role categories, playing a unique role in each.

The actor role crossover is a central feature of our conceptualization of actors in multisector systems, operationalizing the notion of actors that can "wear multiple hats" and take on different roles, depending upon the specific sectoral vantage from which that actor is viewed. Consider again an energy utility, which is perhaps most commonly viewed as a provisioning actor of energy services. However, singularly defining an energy utility as such adopts a myopic view of the actor, neglecting other secondary roles that the energy utility plays from the vantage of other sectoral actors (e.g., a utilizing actor in the water sector). Actor role crossovers in multi-sector systems take on many additional forms. Governing actors commonly have jurisdiction over multiple sectors, so can be viewed as governing actors from the vantage of multiple sectors. Take for instance a federal environmental agency that possesses regulatory authority over multiple sectors and coordinates their regulations based upon the joint environmental impact of activities across these sectors.

Actor role crossovers are also ubiquitous on an intra-sectoral level, instances in which actors "wear multiple hats" within a single sector. For example, any individual governing or provisioning actor (e.g., a politician, utility employee, etc.) also relies on critical resources such as water, energy, and transportation for their personal physical sustenance, and thus by definition are also utilizing actors across numerous critical sectors. Subtler forms of actor role crossovers can also occur within a single sector. Consider the emergence of in-home solar and battery technology. In this case, households may primarily play the role of utilizing actors in the energy sector largely relying on an external utility for energy service, but may also play the secondary role of a provisioning actor within the same sector as they generate energy for both self-consumption and provision back to the grid. Such households may further participate in civil society organizations advocating for policy change in energy services at the provisioning or governing level (e.g., advocating for policies that promote increased compensation for net metering). Such a household can at once be viewed as a utilizing, provisioning, and governing actor in the energy sector. Considering this particular example, we reiterate that the typology is intended to identify those actor roles, interactions, and role crossovers that are deemed salient for modeling outcomes of interest. While in reality a household actor can play hundreds, if not thousands of roles across role categories and between sectors,

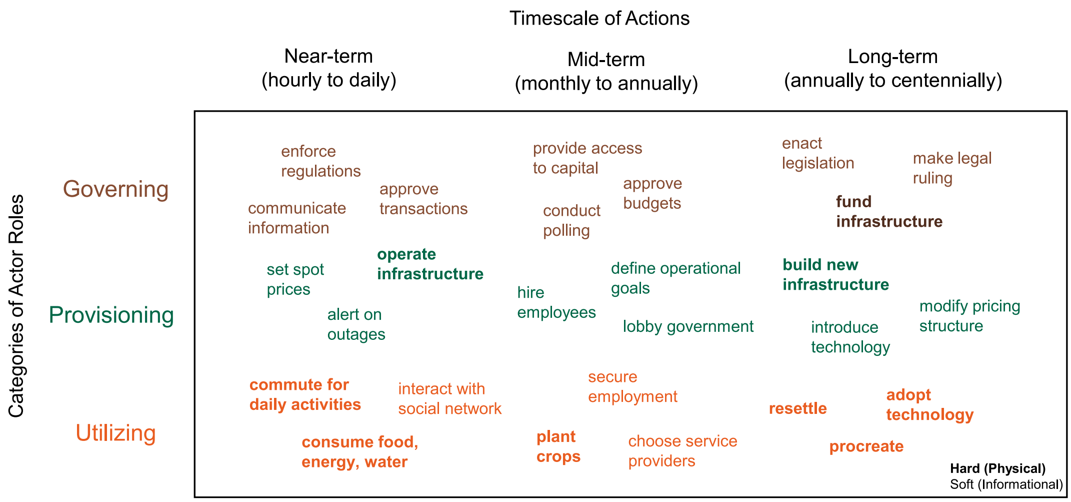

Figure 2. A canvas mapping out actions that influence multisector systems. The canvas organizes human actions across three dimensions: (a) the actor role categorizations (governing, provisioning, utilizing) set forth in the first component of the typology, (b) timescales of action ranging from hourly to centennially in multisector systems, and (c) the type of action distinguished between hard actions that result in a physical change in the environment versus soft actions which involve an exchange of information rather than a physical exchange or alteration of the environment.

modeling constructs that aim for parsimony typically only capture a few of these roles that are most relevant to the topic of inquiry.

We further note that additional dimensions of actor categorizations can also be applied within the primary governing, provisioning, and utilizing actor role categories set forth in the typology. Other potential sub-categorizations include distinguishing between formal versus informal actors such as legal versus illegal water suppliers (Klassert et al., 2015), regime and niche actors as commonly set forth in the sustainability transitions and power dynamics literature (Avelino & Wittmayer, 2016), and public versus private and profit versus non-profit actors as commonly highlighted in flood insurance research (Dubbelboer et al., 2017). Many other categorizations of actors could be conceptualized. In similar fashion to the distinction between individuals and organizations in Figure 1, the typology could be deployed examining any of these categorical distinctions between actors using them as sub-categories within the broader governing, provisioning, and utilizing categories highlighted in the general actor conceptualization.

To further specify the actions that are considered by the various actors, we conceptualize a human action "canvas" which organizes human actions across three dimensions: (a) the actor role categorizations (governing, provisioning, utilizing) set forth in Figure 1 and (b) timescales of action ranging from hourly to centennially in multisector systems, and (c) the type of action distinguished between hard actions that result in a physical change in the environment versus soft actions which involve an exchange of information rather than a physical exchange or alteration of the environment. An example canvas is presented in Figure 2 with generic actions (non-sector or domain specific) as an illustration of the concept. Following the topology of human actors (Figure 1), categories of actor roles are identified along the vertical axis of the action space.

Along the horizontal axis of the action space, actions are organized based on their timescales of action, with the timescale defined as the approximate frequency at which an action is undertaken by an associated actor. Three general timescales of action are identified: near-term (those actions undertaken by an actor at hourly to daily frequency), mid-term (those taken at monthly to annual frequency), and long-term (those taken at annual to centennial frequency). Considering these timescales of action, a utilizing actor such as a household might install sandbags, clear debris from drainage, or move their children to safe location as a near-term response to an impending flood, thus constituting a hard action located in the lower left portion of the canvas (utilizing/near-term/hard), while also contacting their neighbors to do the same (utilizing/near-term/soft.) This same household may also take the action of raising its home every 5–10 years, constituting an action located in the lower right portion of the canvas (utilizing/long-term/hard). Similar distinctions between timescales of action apply across the provisioning and governing actor role categories. A provisioning actor such as a utility might

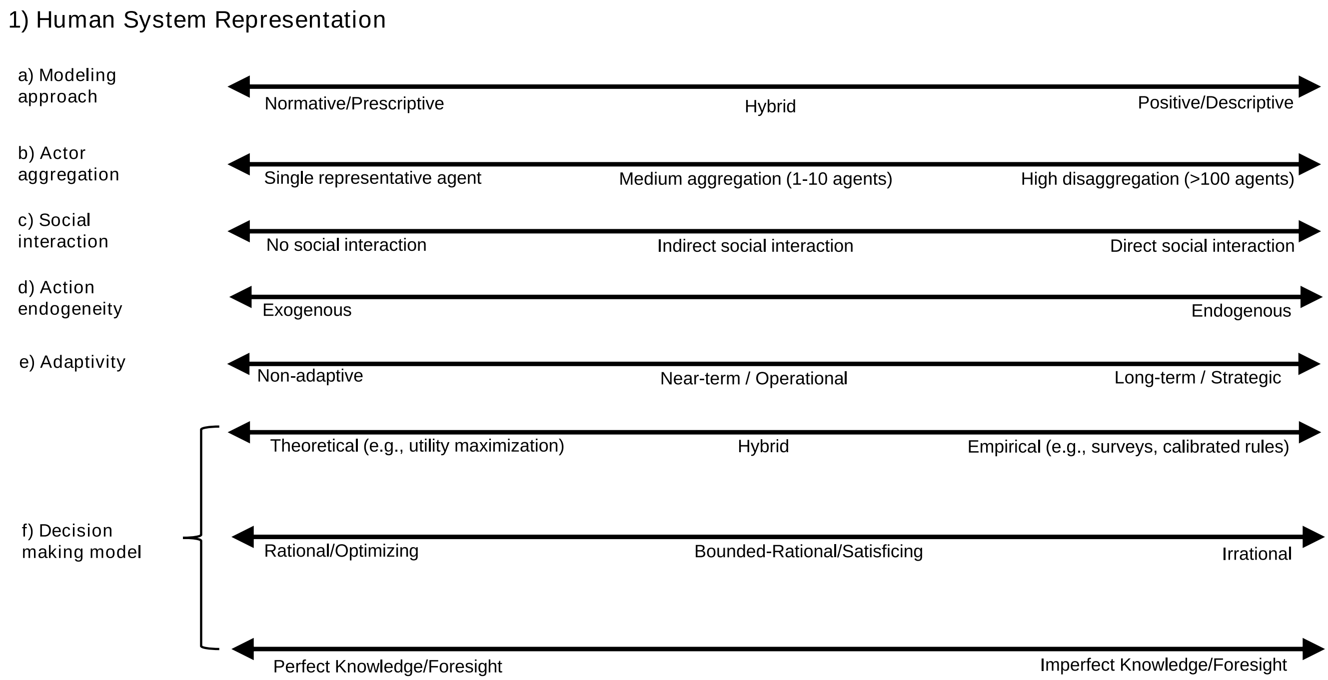

Figure 3. Axes of human system representation in multisector models. Each of the axes provide a spectrum on which to identify general differences for operationalizing human actors and actions in multisector dynamics models. In general, the axes can either be applied generally to an entire model or applied to individual actor categories within a model for higher specificity. Axis (a) indicates whether a normative/prescriptive or positive/descriptive modeling approach is applied to the actor category of interest. Axis (b) provides the level of actor aggregation for each represented actor category. Axis (c) describes the level of interaction between modeled actors, which can be applied generally across the model or to specific actor-actor relationships. Axis (d) indicates whether the action is treated exogenously or endogenously. Axis (e) indicates the level of adaptability for each actor category represented endogenously in the model (c). Short-term/operational adaptation is differentiated from long-term/strategic. The various axes in (f) describe the behavioral model applied to the actor/action, such as whether the actors are treated as rational, bounded-rational, or non-rational entities.

make daily decisions in regards to the operation of existing infrastructure (provisioning/near-term/hard), while taking action to construct new infrastructure (provisioning/long-term/hard) or overhaul customer pricing structures (provisioning/long-term/soft) far less frequently. Likewise, governing actors can enforce regulations on a daily basis (governing/near-term/soft), while typically enacting new legislation or setting a new legal precedent far less frequently (governing/long-term/soft).

We note that the conceptualization is not only useful for identifying and characterizing actions that are included in models, but just as significantly to identify those actions that are not included in models (or implicit given exogenous model assumptions). For example, while water planning models often incorporate household water demand curves (Harou et al., 2009) endogenizing near-term water use decisions, the total population and locations of these households are assumed, treating long-term household settlement actions as exogenous. We envision the canvas being utilized as part of a rigorous, transparent process for assessing the treatment of human actions in multisector models. At the onset of a modeling endeavor, a team of researchers might initiate a canvas exercise independent of a quantitative model, identifying those actions across actor role categories and over time that are assumed to significantly influence outcomes of interest. The resulting canvas of actions can subsequently be used to identify key actions to include in a model under design or compared against actions incorporated in existing models, identifying whether the represented actions are appropriately aligned with the inquiry at hand.

3.3. Typology Component #2—How Are the Actors/Actions Operationalized in a Model?

The second component of the typology addresses the question: How are the actors and actions operationalized in a model? The third component of the typology sets forth eight "axes" of model characteristics to address this final question, which are presented on Figure 3. Each of the axes provide a spectrum on which to identify general differences for operationalizing human actors and actions in MSD models. The first three axes (a–c) are applied at the level of actor groups, that is, applied to each of the actor groups that have been identified using the first component of the typology. The last five axes and sub-axes (d–f) are applied at the level of actions, that is, to each of the actions that are mapped out using the first component of the typology and included for representation in the model. Each of the axes is described in further detail below.

1(a) Modeling Approach—Differentiates the general modeling approach through which an actor is treated along a normative/prescriptive versus positive/descriptive spectrum. Under a normative/prescriptive treatment, modeled actors are idealized assuming that they have a specific set of objectives under pursuit and optimize their actions to achieve those objectives. Prescriptive approaches are often optimization-based models deployed for decision support (Harou et al., 2009; Herman et al., 2020; Oikonomou et al., 2022). On the other side of the spectrum, a positive/descriptive treatment attempts to represent an actor or actor group as they actually behave in real world systems, attempting to replicate observed behavior (de Koning and Filatova, 2020; Manson & Evans, 2007; Yoon et al., 2021). Descriptive approaches can include ABMs, econometrics, and heuristic or rule-based representations of human decision-making strategies, and may draw from sociological, behavioral, or microeconomic perspectives. Hybrid approaches are also possible, such as when computer-aided decision support is employed in real world decision making and prescriptive modeling becomes a descriptive element of how humans determine action. The modeling approach selected for any actor group is closely tied to the operationalization of their decision making model (axes 1f).

1(b) Actor Aggregation—Characterizes models based on the level of aggregation of human actors, which can range widely from a single representative decision making entity to highly disaggregated decision making via distributed model agents. For example, many IAMs aimed at addressing global-scale energy, water, and land dynamics aggregate actors at the level of countries or large regions (Fisher-Vanden & Weyant, 2020). Locale and sector-specific models in contrast might represent a single individual or household as the basic modeled unit of analysis, such as transportation ABMs that simulate individual vehicles and their passengers (Bazzan & Klügl, 2014). Actor aggregation can also be applied to provisioning and governing actors. For example, management of a system might be abstracted into a single centralized authority as in the case of many hydroeconomic models (Harou et al., 2009), or distributed among governing bodies that map onto real world organizations (Yoon et al., 2021).

1(c) Social Interaction—Characterizes the level of actor-actor interaction represented in the model, ranging from no interaction (e.g., node-link engineering planning models that represent human activity in the form of independent demand nodes), indirect interaction such as through shared utilization of a common pool resource (Castilla-Rho et al., 2015), or direct interaction that involves actor-actor knowledge or resource transfer. Direct interactions could be further subdivided based on the degree of social networking, which include random networks (i.e., agents interact with each other randomly), theoretically-based networks (Sayles & Baggio, 2017), and empirically derived networks (Matous & Todo, 2015). The social network topology itself can also be endogenous, with the existence and nature of connections between actors emerging over time, potentially in response to environmental factors in the model (Will et al., 2020). Social networks can also be modeled across scales (multi-level, Lomi et al., 2016), and can have multiple ties between actors (multi-plex, Locatelli et al., 2020). In addition to describing the general network topology, the axis can also be used to distinguish the nature of the social connections between actors, such as whether relationships are coordinative/cooperative versus conflictive, whether they entail an exchange of information or of a physical good, and so forth.

1(d) Endogeneity—Indicates whether the action under consideration is treated exogenously or endogenously in the model. In an exogenous case, the action is represented in the model but is imposed by the modeler externally. In other words, an exogenously imposed model action is one that is undertaken by a modeled actor regardless of the dynamic states simulated by the model, as is often the case in engineering planning models that impose human demands on the system. In contrast, endogenous actions are those in which a modeled actor takes an action in dynamic response to the modeled state of the system. In such an instance, a behavioral model is assumed to drive an actor's decision/action, with the behavioral model a function of modeled states of the system (Balbi et al., 2013; Rai & Henry, 2016; Tsekeris & Vogiatzoglou, 2011). We further note here that actions are often linked in models, with endogenous actions ultimately traced upstream to an exogenous assumption. For example, adoption of household technologies may be identified as an endogenous action in a model, though further inspection of a model might reveal that the behavioral model underlying this adoption is a simple table that relates exogenously imposed income classes with assumed household technologies. While the endogeneity axis provides a first-order indication of which actions are treated in dynamic fashion in a model, further interrogation of an action based on the underlying behavioral model can be made using the various sub-axes in 1(f).

1(e) Adaptivity—Differentiates models based on the adaptive capacity that actors are endowed with, ranging from no adaptation to strategic adaptation. Two modes of adaptation, operational and strategic, are further distinguished, with the former involving "fine-tuning" of a fixed rule, strategy, or optimization while the latter involves the potential for structural change in the agent's behavior. An example of the former might entail an actor that is assumed to maximize some objective function that is dependent on modeled states of the model but with a structural form that remains fixed over time, as is commonly the case in optimization-based models. In such an instance, the actor's goal (e.g., maximize profits) does not change over time, though the specific action that the actor takes in any model time period might change in pursuit of that goal in response to system states. The latter might involve alteration of the drivers influencing actor behavior such as the influence of their social network (Mungovan et al., 2011) or change in actor risk profile. Actors that exhibit strategic adaptation are those that can fundamentally reshape their strategies as they learn about the system over time or alter their goals in response to system perturbations. For example, an actor might be modeled with the capacity to switch from a utility maximization to a risk avoidance behavioral model in response to a damaging event. The axes can further be used to indicate whether actors are state-aware, the degree of this awareness, and their associated ability to learn about and adapt to the system over time such as through the selective and dynamic use of state information through reinforcement learning (Bertoni et al., 2020; Hung & Yang, 2021).

1(f) Decision Making Model: Empiricism—Distinguishes whether the behavioral model of the actor is rooted in the theory of a specific discipline (e.g., economic utility maximization) or developed in an empirical fashion relying on real-world information (observed data, surveys, etc., Janssen & Ostrom, 2006). Considering housing sector models for example, household actors seeking a housing good may be treated using traditional expected utility theory (Parker & Filatova, 2008) or operationalized based on direct survey results (Brown & Robinson, 2006). The two might also be applied in hybrid fashion, with surveys and data used to parameterize a specific theoretical approach (e.g., de Koning and Filatova, 2020).

Rationality—Defines the extent to which actors are rational (e.g., optimizing a specific objective, Chappin & Dijkema, 2007) or act in accordance to bounded rationality (Malawska & Topping, 2016), or other social science theories of human behavior that incorporate heterogeneous preferences, social influences, and risk aversion (Brown & Robinson, 2006; Kaiser et al., 2020; Xianyu, 2010). Some modeling experiments have been intentionally designed to compare contending theories of human behavior across the rationality spectrum (de Koning et al., 2017).

Knowledge—Defines the knowledge endowment of actors, ranging from perfect knowledge and foresight of environmental/socioeconomic conditions and of other agent actions, to limited knowledge and foresight. For example, IAMs often assume actors that have complete information of future conditions across the model time horizon though some have attempted alternative formulations (Wilkerson et al., 2015). The level of actor foresight is a prominent consideration in water reservoir operations models, with actors endowed with no foresight, limited foresight, or perfect foresight of future inflows into the reservoir of concern (Turner et al., 2020). Accounting for incomplete information of actors is increasingly common in game theory (Shafie-Khah & Catalão, 2015) and fuzzy logic (Baloglu & Demir, 2018) modeling applications.

3.4. Applying the Typology

Lastly, we describe how to apply the typology in practice (a full example applying the typology to an existing multisector model, the Jordan Water Model, is included in the Supporting Information S1). The typology can either be applied to a model in its entirety or to specific human actor categories represented in models, in large part influenced by the type of model under consideration. For example, the typology might be applied to a model as a whole if the human system representation is generally consistent across actor categories (e.g., global macroeconomy models typically fall in this category). For models that contain multiple actor categories (e.g., households, farmers, governing authorities, etc.) such as multisector ABMs, the typology may need to be applied to each actor category separately, as the treatment of each could differ in the model implementation (e.g., farmers may be represented as bounded-rational, risk averse firms while governing authorities are modeled as welfare maximizers). Additionally, only specific components of the typology may be pertinent depending on the details

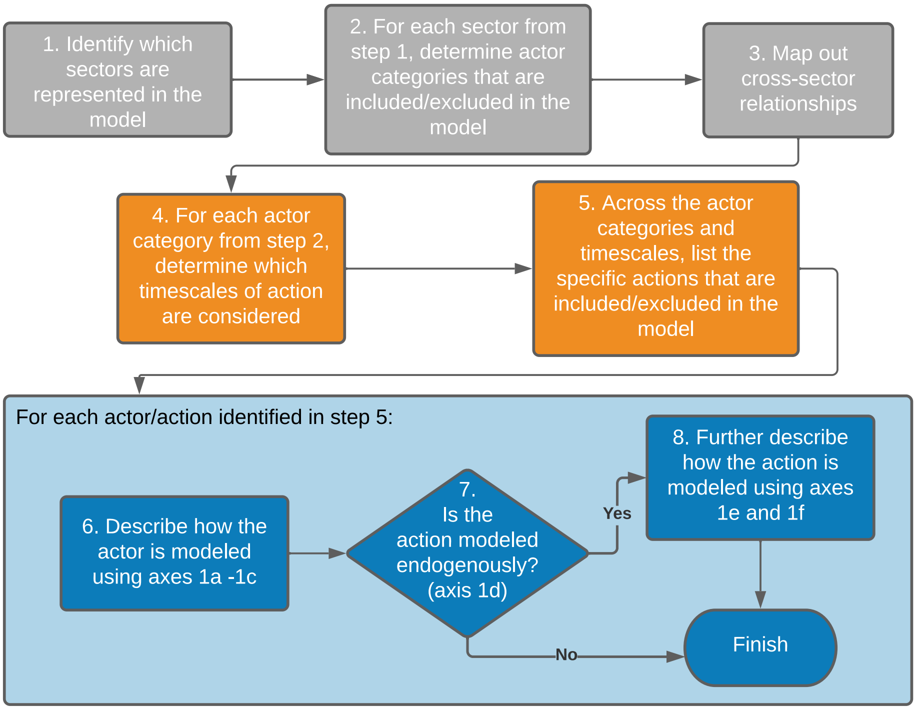

Figure 4. Workflow for applying the human systems typology components to a multisector system model. The actor topology is first applied to all actors across sectors represented in the model (steps 1–3). Action canvases are subsequently developed for each actor category identified in step 2 (steps 4–5). Finally, the axes of human system representation are applied for each action identified in step 5 (steps 6–8).

of the model. Figure 4 lays out a general workflow for applying the typology to a specific multisector model, segmented across the two typology components.

The workflow is generalizable across the diverse examples of models relevant to multisector research described earlier. For models with high levels of actor aggregation such as IAMs, only a few relevant actor categories might be identified in step 2, such as an abstracted governing actor(s) that brokers trades through global commodity market alongside provisioning/utilizing actor(s) representing national-scale resource supply and consumption behavior. When applied to models with highly distributed actor representation, such as an ABM of a multisector system, a multitude of actor categories might be identified across role categories including national governments, regulatory authorities, utility providers, informal suppliers, households, famers, and so on. For each of the actor categories identified across modeling examples, the workflow can subsequently be used (step 4–8) to identify the actions associated with each of the actor categories and how those actions are represented in the model.

4. Discussion and Conclusions

Considering the central role of humans in modern sectoral systems, the adequate representation of human action in multisector models is essential for capturing co-evolutionary human-natural dynamics in the face of short-term shocks and long-term change. However, multisector modeling efforts have typically adopted simplistic and divergent representations of human systems, thus limiting the ability to draw deep and coherent insight across diverse modeling efforts with inconsistent treatment of human actors. We advocate for a pluralistic, exploratory modeling approach for dealing with the complexity of multisector systems, the divergent structural conceptualizations of human systems therein, and the multiple contending theories on the volitional nature of human behavior. The embrace of such an exploratory approach nonetheless calls for a common framework for describing the representation of human systems in multisector models, providing researchers a shared language for comparing models and promoting the cohesion of insights across diverse modeling efforts.

Toward this end, we present a new typology for representing human action in multisector models to serve as one such framework. The typology allows a model creator, user, or stakeholder to interrogate an existing model or design a new model using two simple questions as guideposts: (a) Who are the actors in MSD systems and what are their actions? and (b) How and for what purpose are these actors and actions operationalized in a computational model? The typology is intended as a tool for both the *diagnosis* and *design* of human systems in multisector models. In the diagnostic form, the typology can be used to assess the representation of human actors in existing models, particularly serving as a mechanism to identify differences in representation between models and critically assesses whether the mode of human system representation is appropriate for the science or analytic questions at hand.

In design form, the typology can be used to guide the development of new models that are fit for purpose in addressing science and analytic questions of interest. In this regard, we suggest four promising arenas of MSD research for which the typology can support the design of coordinated modeling experiments: (a) applying uncertainty quantification to the representation human systems, (b) utilizing artificial intelligence and machine learning for the representation of human systems, (c) designing models that adequately address decision-relevant issues such as equality, equity, and justice in multisector systems (where we define equality as equal access to multisector services and equity as equal outcomes in the actual delivery and utilization of those services), and (d) synthesizing and integrating insights across diverse modeling approaches.

In the first arena, uncertainty, the typology can be used to design ensemble-based, multi-model experiments that explore divergent structural conceptualizations of human systems as well as the underlying behavioral models and their parameterizations used to represent human actions. For example, the decision making model axes could be used to identify behavioral models of human decision making that intentionally diverge in regards to the underlying theory of human behavior (e.g., rational vs. non-rational, all-knowing vs. myopic, etc.) and their structural representation of actor categories and aggregation (e.g., a bioeconomic model that assumes centralized decision making vs. an ABM with distributed, heterogeneous actors). The various representations would be strategically and intentionally deployed to evaluate the sensitivity of a specific outcome of interest (e.g., flood risk and vulnerability in a coastal zone) to the model representation.

The increasing prevalence of artificial intelligence and machine learning (AI/ML) methods in MSD models presents a second arena of research that can be supported and organized by the typology. For example, AI/ML techniques can be used in both descriptive and prescriptive forms (axis 1a), either to mimic human actors as they behave in the real world based on observed data or to simulate actors as they might ideally behave given a specific goal as they respond to their environment and adapt to change over time. In the former descriptive mode, AI/ML methods could be deployed alongside big social data (Lazer et al., 2009), for the realistic representation of human actors in multisector systems such as mimicking mobility patterns through a city (Moro et al., 2021) or to infer real-world management practices (Ekblad & Herman, 2021). In prescriptive form, modeled actors could be simulated using AI/ML techniques as state-aware agents that selectively and dynamically react to system states via reinforcement learning (e.g., see model free policy approximation methods in Powell, 2019; Bertsekas, 2019; and food-energy-water examples in Giuliani et al., 2021; Zaniolo et al., 2021; Cohen & Herman, 2021). In each of these endeavors, the typology can be used to properly orient and communicate the relationship between AI/ML methods and the modeled representation of human systems.

In the third arena, the typology can be used to align the representation of human systems in multisector models with the science or analytic question at hand, promoting decision-relevant science, a core tenet of MSD research. For example, the typology could be utilized to assess a model's ability to provide insight into the equality, equity, and justice implications of change in multisector systems. Such assessment might include the consideration of aggregation choices (Figure 3, axis b) on a model's ability to simulate distributive impacts and outcomes (Fletcher et al., 2022; Jafino et al., 2021). Models can further be assessed based on which actor categories and sub-categories are presented in a model (Figure 1), evaluating a model's ability to capture the distributive impacts of multisector system change, including both impacts on access to multisector services (equality) and outcomes in utilization of those services (equity) across socioeconomic groups (see the Supporting Information S1 for the typology applied to the Jordan Water Model, for instance). More generally, the typology can be used to guide model developers and users through a set of questions such as: (a) which actor categories are most salient for adequately capturing transition dynamics in multisector systems (e.g., are general actor categories of provisioners and utilizers adequate or are sub-categories that represent actor power differentials crucial)? (b) what particular model structures and aggregations enable or preclude effective equity analysis? and (c) how are the various modes in which values are entering the model analysis supporting or hindering an equitable analysis?

Finally, the typology can be used to integrate and synthesize diverse modeling approaches, identifying the advantages and disadvantages of each approach and points of connection between them. For example, a large scale IAM and a sector-specific engineering planning model might be deployed in synergistic fashion, with the IAM used to simulate global economic activity and feeding physical and socioeconomic boundary conditions into the sector-specific engineering model, which in turn sends local constraints back to the IAM in two-way iterative fashion (e.g., Basheer et al., 2021). Apart from direct coupling, the typology can be used to design independent but coordinated modeling experiments. A stylized and aggregated model of a system might initially be deployed to widely explore system sensitivities and uncertainties using deep uncertainty methods in a computationally tractable fashion, in turn guiding the actor categories, processes, and relationships that are included in a more detailed ABM of the system. In each of these cases, the typology can be used to distinguish models and identify points of potential integration or synergism between efforts.

Through enabling the critical examination and design of models, the typology provides a framework through which to cohere human systems modeling efforts and strategically coordinate the enhancement of human systems representation in advanced, coupled human-natural-engineered models. Orienting diverse multisector modeling approaches using the typology can provide a roadmap for human systems modeling in MSD, charting new frontiers of complex human-Earth systems research that judiciously, coherently, and equitably represent human actors in multisector models.

Data Availability Statement

No new data was generated for this effort.

Acknowledgments
This research was co-supported by the U.S. Department of Energy, Office of Science, as part of research in Multi-Sector Dynamics, Earth and Environmental System Modeling Program and the Penn State Center for Climate Risk Management.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-t

Al-Amin, S., Berglund, E. Z., Mahinthakumar, G., & Larson, K. L. (2018). Assessing the effects of water restrictions on socio-hydrologic resilience for shared groundwater systems. *Journal of Hydrology*, *566*, 872–885. https://doi.org/10.1016/j.jhydrol.2018.08.045

Anderies, J. M., Folke, C., Walker, B., & Ostrom, E. (2013). Aligning key concepts for global change policy: Robustness, resilience, and sustainability. *Ecology and Society*, *18*(2), art8. https://doi.org/10.5751/es-05178-180208

Atkins, K., Barrett, C., Homan, C., Marathe, A., Marathe, M., & Thite, S. (2004). Marketecture: A simulation-based framework for studying experimental deregulated power markets.

Avelino, F., & Wittmayer, J. M. (2016). Shifting power relations in sustainability transitions: A multi-actor perspective. *Journal of Environmental Policy and Planning*, *18*(5), 628–649. https://doi.org/10.1080/1523908x.2015.1112259

Bai, X., Van Der Leeuw, S., O'Brien, K., Berkhout, F., Biermann, F., Brondizio, E. S., et al. (2016). Plausible and desirable futures in the Anthropocene: A new research agenda. *Global Environmental Change*, *39*, 351–362. https://doi.org/10.1016/j.gloenvcha.2015.09.017

Balbi, S., Bhandari, S., Gain, A. K., & Giupponi, C. (2013). Multi-agent agro-economic simulation of irrigation water demand with climate services for climate change adaptation. *Italian Journal of Agronomy*, *8*(3), e23. https://doi.org/10.4081/ija.2013.e23

Baloglu, U. B., & Demir, Y. (2018). An agent-based Pythagorean fuzzy approach for demand analysis with incomplete information. *International Journal of Intelligent Systems*, *33*(5), 983–997. https://doi.org/10.1002/int.21908

Bankes, S. (1993). Exploratory modeling for policy analysis. *Operations Research*, *41*(3), 435–449. https://doi.org/10.1287/opre.41.3.435

Basheer, M., Nechifor, V., Calzadilla, A., Siddig, K., Etichia, M., Whittington, D., et al. (2021). Collaborative management of the Grand Ethiopian Renaissance Dam increases economic benefits and resilience. *Nature Communications*, *12*(1), 1–12. https://doi.org/10.1038/s41467-021-25877-w

Bazzan, A. L., & Klügl, F. (2014). A review on agent-based technology for traffic and transportation. *The Knowledge Engineering Review*, *29*(3), 375–403. https://doi.org/10.1017/s0269888913000118

Beckage, B., Gross, L. J., Lacasse, K., Carr, E., Metcalf, S. S., Winter, J. M., et al. (2018). Linking models of human behaviour and climate alters projected climate change. *Nature Climate Change*, *8*(1), 79–84. https://doi.org/10.1038/s41558-017-0031-7

Berger, T. (2001). Agent-based spatial models applied to agriculture: A simulation tool for technology diffusion, resource use changes and policy analysis. *Agricultural Economics*, *25*(2), 245–260. https://doi.org/10.1111/j.1574-0862.2001.tb00205.x

Berglund, E. Z. (2015). Using agent-based modeling for water resources planning and management. *Journal of Water Resources Planning and Management*, *141*(11), 04015025. https://doi.org/10.1061/(asce)wr.1943-5452.0000544

Bertoni, F., Giuliani, M., & Castelletti, A. (2020). Integrated design of dam size and operations via reinforcement learning. *Journal of Water Resources Planning and Management*, *146*(4), 04020010. https://doi.org/10.1061/(asce)wr.1943-5452.0001182

Bertsekas, D. (2019). *Reinforcement learning and optimal control*. Athena Scientific.

Biggs, R., Carpenter, S. R., & Brock, W. A. (2009). Turning back from the brink: Detecting an impending regime shift in time to avert it. *Proceedings of the National Academy of Sciences*, *106*(3), 826–831. https://doi.org/10.1073/pnas.0811729106

Biggs, R., Schlüter, M., & Schoon, M. L. (Eds.). (2015). *Principles for building resilience: Sustaining ecosystem services in social-ecological systems*.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, *99*(suppl 3), 7280–7287. https://doi.org/10.1073/pnas.082080899

Brown, C. M., Lund, J. R., Cai, X., Reed, P. M., Zagona, E. A., Ostfeld, A., et al. (2015). The future of water resources systems analysis: Toward a scientific framework for sustainable water management. *Water Resources Research*, *51*(8), 6110–6124. https://doi.org/10.1002/2015wr017114

Brown, D. G., & Robinson, D. T. (2006). Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. *Ecology and Society*, *11*(1), art46. https://doi.org/10.5751/es-01749-110146

Busby, J. W., Baker, K., Bazilian, M. D., Gilbert, A. Q., Grubert, E., Rai, V., et al. (2021). Cascading risks: Understanding the 2021 winter blackout in Texas. *Energy Research & Social Science*, *77*, 102106. https://doi.org/10.1016/j.erss.2021.102106

Castilla-Rho, J. C., Mariethoz, G., Rojas, R., Andersen, M. S., & Kelly, B. F. (2015). An agent-based platform for simulating complex human–aquifer interactions in managed groundwater systems. *Environmental Modelling & Software*, *73*, 305–323. https://doi.org/10.1016/j.envsoft.2015.08.018

Castree, N., Adams, W. M., Barry, J., Brockington, D., Büscher, B., Corbera, E., et al. (2014). Changing the intellectual climate. *Nature Climate Change*, *4*(9), 763–768. https://doi.org/10.1038/nclimate2339

Chappin, E. J., & Dijkema, G. P. (2007). An agent based model of the system of electricity production systems: Exploring the impact of CO_2 emission-trading. In *2007 IEEE international conference on System of Systems Engineering* (pp. 1–5). IEEE.

Chassin, D. P., Fuller, J. C., & Djilali, N. (2014). GridLAB-D: An agent-based simulation framework for smart grids. *Journal of Applied Mathematics*, *3*, 1–12. https://doi.org/10.1155/2014/492320

Cohen, J. S., & Herman, J. D. (2021). Dynamic adaptation of water resources systems under uncertainty by learning policy structure and indicators. *Water Resources Research*, *57*(11), e2021WR030433. https://doi.org/10.1029/2021wr030433

Colon, C., Hallegatte, S., & Rozenberg, J. (2021). Criticality analysis of a country's transport network via an agent-based supply chain model. *Nature Sustainability*, *4*(3), 209–215. https://doi.org/10.1038/s41893-020-00649-4

Crooks, A., Castle, C., & Batty, M. (2008). Key challenges in agent-based modelling for geo-spatial simulation. *Computers, Environment and Urban Systems*, *32*(6), 417–430. https://doi.org/10.1016/j.compenvurbsys.2008.09.004

de Koning, K., & Filatova, T. (2020). Repetitive floods intensify outmigration and climate gentrification in coastal cities. *Environmental Research Letters*, *15*(3), 034008. https://doi.org/10.1088/1748-9326/ab6668

de Koning, K., Filatova, T., & Bin, O. (2017). Bridging the gap between revealed and stated preferences in flood-prone housing markets. *Ecological Economics*, *136*, 1–13. https://doi.org/10.1016/j.ecolecon.2017.01.022

De Cian, E., Dasgupta, S., Hof, A. F., van Sluisveld, M. A., Köhler, J., Pfluger, B., & van Vuuren, D. P. (2020). Actors, decision-making, and institutions in quantitative system modelling. *Technological Forecasting and Social Change*, *151*, 119480. https://doi.org/10.1016/j.techfore.2018.10.004

Dilling, L., & Lemos, M. C. (2011). Creating useable science: Opportunities and constraints for climate knowledge use and their implications for science policy. *Global Environmental Change*, *21*(2), 680–689. https://doi.org/10.1016/j.gloenvcha.2010.11.006

Dooley, K., & Corman, S. (2002). Agent-based, genetic, and emergent computational models of complex systems. In *Encyclopedia of Life Support Systems*.

Doss-Gollin, J., Farnham, D. J., Lall, U., & Modi, V. (2021). How unprecedented was the February 2021 Texas cold snap? *Environmental Research Letters*, *16*(6), 064056. https://doi.org/10.1088/1748-9326/ac0278

Dubbelboer, J., Nikolic, I., Jenkins, K., & Hall, J. (2017). An agent-based model of flood risk and insurance. *The Journal of Artificial Societies and Social Simulation*, *20*(1), 6. https://doi.org/10.18564/jasss.3135

Edmonds, J., & Reilly, J. (1983). A long-term global energy-economic model of carbon dioxide release from fossil fuel use. *Energy Economics*, *5*(2), 74–88. https://doi.org/10.1016/0140-9883(83)90014-2

Ekblad, L., & Herman, J. D. (2021). Toward data-driven generation and evaluation of model structure for integrated representations of human behavior in water resources systems. *Water Resources Research*, *57*(2), e2020WR028148. https://doi.org/10.1029/2020wr028148

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *Quarterly Journal of Economics*, *75*(4), 643–669. https://doi.org/10.2307/1884324

Elsawah, S., Filatova, T., Jakeman, A. J., Kettner, A. J., Zellner, M. L., Athanasiadis, I. N., et al. (2020). Eight grand challenges in socio-environmental systems modeling. *Socio-Environmental Systems Modelling*, *2*, 16226. https://doi.org/10.18174/sesmo.2020a16226

Evans, T. P., & Kelley, H. (2004). Multi-scale analysis of a household level agent-based model of landcover change. *Journal of Environmental Management*, *72*(1–2), 57–72. https://doi.org/10.1016/j.jenvman.2004.02.008

Filatova, T., Parker, D., & Van der Veen, A. (2009). Agent-based urban land markets: Agent's pricing behavior, land prices and urban land use change. *The Journal of Artificial Societies and Social Simulation*, *12*(1), 3.

Fisher-Vanden, K., & Weyant, J. (2020). The evolution of integrated assessment: Developing the next generation of use-inspired integrated assessment tools. *Annual Review of Resource Economics*, *12*(1), 471–487. https://doi.org/10.1146/annurev-resource-110119-030314

Fletcher, S., Hadjimichael, A., Quinn, J., Osman, K., Giuliani, M., Gold, D., et al. (2022). Equity in water resources planning: A path forward for decision support modelers. *Journal of Water Resources Planning and Management*, *148*(7), 02522005. https://doi.org/10.1061/(asce)wr.1943-5452.0001573

Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. *Global Environmental Change*, *16*(3), 253–267. https://doi.org/10.1016/j.gloenvcha.2006.04.002

Franco, C., Toner, E., Waldhorn, R., Maldin, B., O'Toole, T., & Inglesby, T. V. (2006). Systemic collapse: Medical care in the aftermath of hurricane Katrina. *Biosecurity and Bioterrorism: Biodefense Strategy, Practice, and Science*, *4*(2), 135–146. https://doi.org/10.1089/bsp.2006.4.135

Funtowicz, S. O., & Ravetz, J. R. (1993). Science for the post-normal age. *Futures*, *25*(7), 739–755. https://doi.org/10.1016/0016-3287(93)90022-l

Gambhir, A., Butnar, I., Li, P. H., Smith, P., & Strachan, N. (2019). A review of criticisms of integrated assessment models and proposed approaches to address these, through the lens of BECCS. *Energies*, *12*(9), 1747. https://doi.org/10.3390/en12091747

Geels, F. W., Berkhout, F., & Van Vuuren, D. P. (2016). Bridging analytical approaches for low-carbon transitions. *Nature Climate Change*, *6*(6), 576–583. https://doi.org/10.1038/nclimate2980

Georgilakis, P. S., & Hatziargyriou, N. D. (2015). A review of power distribution planning in the modern power systems era: Models, methods and future research. *Electric Power Systems Research*, *121*, 89–100. https://doi.org/10.1016/j.epsr.2014.12.010

Gerbens-Leenes, W., Hoekstra, A. Y., & van der Meer, T. H. (2009). The water footprint of bioenergy. *Proceedings of the National Academy of Sciences*, *106*(25), 10219–10223. https://doi.org/10.1073/pnas.0812619106

Giuliani, M., Lamontagne, J. R., Reed, P. M., & Castelletti, A. (2021). A state-of-the-art review of optimal reservoir control for managing conflicting demands in a changing world. *Water Resources Research*, *57*(12), e2021WR029927. https://doi.org/10.1029/2021wr029927

Groeneveld, J., Müller, B., Buchmann, C. M., Dressler, G., Guo, C., Hase, N., et al. (2017). Theoretical foundations of human decision-making in agent-based land use models—A review. *Environmental Modelling & Software*, *87*, 39–48. https://doi.org/10.1016/j.envsoft.2016.10.008

Gunderson, L. H., & Holling, C. S. (Eds.) (2002). *Panarchy: Understanding transformations in human and natural systems*. Island press.

Haimes, Y. Y. (2018). *Modeling and managing interdependent complex systems of systems*. John Wiley & Sons.
Hajinasab, B., Davidsson, P., Persson, J. A., & Holmgren, J. (2015). Towards an agent-based model of passenger transportation. In *International Workshop on Multi-Agent Systems and Agent-Based Simulation* (pp. 132–145). Springer.
Harou, J. J., Pulido-Velazquez, M., Rosenberg, D. E., Medellín-Azuara, J., Lund, J. R., & Howitt, R. E. (2009). Hydro-economic models: Concepts, design, applications, and future prospects. *Journal of Hydrology*, *375*(3–4), 627–643. https://doi.org/10.1016/j.jhydrol.2009.06.037
Hejazi, M. I., Voisin, N., Liu, L., Bramer, L. M., Fortin, D. C., Hathaway, J. E., et al. (2015). 21st century United States emissions mitigation could increase water stress more than the climate change it is mitigating. *Proceedings of the National Academy of Sciences*, *112*(34), 10635–10640. https://doi.org/10.1073/pnas.1421675112
Helbing, D. (2013). Globally networked risks and how to respond. *Nature*, *497*(7447), 51–59. https://doi.org/10.1038/nature12047
Helgeson, C., Srikrishnan, V., Keller, K., & Tuana, N. (2021). Why simpler computer simulation models can be epistemically better for informing decisions. *Philosophy of Science*, *88*(2), 213–233. https://doi.org/10.1086/711501
Heppenstall, A., & Crooks, A. (2019). Guest editorial for spatial agent-based models: Current practices and future trends. *GeoInformatica*, *23*(2), 163–167. https://doi.org/10.1007/s10707-019-00349-y
Herman, J. D., Quinn, J. D., Steinschneider, S., Giuliani, M., & Fletcher, S. (2020). Climate adaptation as a control problem: Review and perspectives on dynamic water resources planning under uncertainty. *Water Resources Research*, *56*(2), e24389. https://doi.org/10.1029/2019wr025502
Herstein, I. N., & Milnor, J. (1953). An axiomatic approach to measurable utility. *Econometrica, Journal of the Econometric Society*, *21*(2), 291–297. https://doi.org/10.2307/1905540
Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, *4*(1), 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245
Howitt, R. E. (1995). Positive mathematical programming. *American Journal of Agricultural Economics*, *77*(2), 329–342. https://doi.org/10.2307/1243543
Hughes, T. P., Barnes, M. L., Bellwood, D. R., Cinner, J. E., Cumming, G. S., Jackson, J. B., et al. (2017). Coral reefs in the Anthropocene. *Nature*, *546*(7656), 82–90. https://doi.org/10.1038/nature22901
Hung, F., & Yang, Y. E. (2021). Assessing adaptive irrigation impacts on water scarcity in nonstationary environments—A multi-agent reinforcement learning approach. *Water Resources Research*, *57*(9), e2020WR029262. https://doi.org/10.1029/2020wr029262
Izquierdo, L. R., Gotts, N. M., & Polhill, J. G. (2003). FEARLUS-W: An agent-based model of river basin land use and water management. In *Framing land use dynamics: Integrating knowledge on spatial dynamics in socio-economic and environmental systems for spatial planning in western urbanized countries, university, The Netherlands*.
Jafino, B. A., Kwakkel, J. H., & Taebi, B. (2021). Enabling assessment of distributive justice through models for climate change planning: A review of recent advances and a research agenda. *Wiley Interdisciplinary Reviews: Climate Change*, *546*, e721.
Janssen, M. A., & Ostrom, E. (2006). Empirically based, agent-based models. *Ecology and Society*, *11*(2), art37. https://doi.org/10.5751/es-01861-110237
Jin, X., & Jie, L. (2012). A study of multi-agent based model for urban intelligent transport systems. *International Journal of Advancements in Computing Technology*, *4*(6), 126–134. https://doi.org/10.4156/ijact.vol4.issue6.15
Johnson, T. (2016). Cooperation, co-optation, competition, conflict: International bureaucracies and non-governmental organizations in an interdependent world. *Review of International Political Economy*, *23*(5), 737–767. https://doi.org/10.1080/09692290.2016.1217902
Kahneman, D., & Tversky, A. (2013). Prospect theory: An analysis of decision under risk. In *Handbook of the Fundamentals of Financial Decision Making: Part I* (pp. 99–127).
Kaiser, K. E., Flores, A. N., & Hillis, V. (2020). Identifying emergent agent types and effective practices for portability, scalability, and intercomparison in water resource agent-based models. *Environmental Modelling & Software*, *127*, 104671. https://doi.org/10.1016/j.envsoft.2020.104671
Keller, K., Helgeson, C., & Srikrishnan, V. (2021). Climate risk management. *Annual Review of Earth and Planetary Sciences*, *49*(1), 95–116. https://doi.org/10.1146/annurev-earth-080320-055847
Kelly, R. A., Jakeman, A. J., Barreteau, O., Borsuk, M. E., El Sawah, S., Hamilton, S. H., et al. (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
Klassert, C., Sigel, K., Gawel, E., & Klauer, B. (2015). Modeling residential water consumption in Amman: The role of intermittency, storage, and pricing for piped and tanker water. *Water*, *7*(7), 3643–3670. https://doi.org/10.3390/w7073643
Kluger, L. C., Gorris, P., Kochalski, S., Mueller, M. S., & Romagnoni, G. (2020). Studying human–nature relationships through a network lens: A systematic review. *People and Nature*, *2*(4), 1100–1116. https://doi.org/10.1002/pan3.10136
Kriegler, E., Riahi, K., Bauer, N., Schwanitz, V. J., Petermann, N., Bosetti, V., et al. (2015). Making or breaking climate targets: The AMPERE study on staged accession scenarios for climate policy. *Technological Forecasting and Social Change*, *90*, 24–44. https://doi.org/10.1016/j.techfore.2013.09.021
Lazer, D., Pentland, A. S., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., et al. (2009). Life in the network: The coming age of computational social science. *Science*, *323*(5915), 721–723. https://doi.org/10.1126/science.1167742
Lempert, R. J. (2002). A new decision sciences for complex systems. *Proceedings of the National Academy of Sciences*, *99*(suppl 3), 7309–7313. https://doi.org/10.1073/pnas.082081699
Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006). A general, analytic method for generating robust strategies and narrative scenarios. *Management Science*, *52*(4), 514–528. https://doi.org/10.1287/mnsc.1050.0472
Liu, J., Dietz, T., Carpenter, S. R., Alberti, M., Folke, C., Moran, E., et al. (2007). Complexity of coupled human and natural systems. *Science*, *317*(5844), 1513–1516. https://doi.org/10.1126/science.1144004
Liu, X., Li, X., & Anthony, G. O. Y. (2006). Multi-agent systems for simulating spatial decision behaviors and land-use dynamics. *Science in China Series D: Earth Sciences*, *49*(11), 1184–1194. https://doi.org/10.1007/s11430-006-1184-9
Locatelli, B., Pramova, E., Di Gregorio, M., Brockhaus, M., Chávez, D. A., Tubbeh, R., et al. (2020). Climate change policy networks: Connecting adaptation and mitigation in multiplex networks in Peru. *Climate Policy*, *20*(3), 354–372. https://doi.org/10.1080/14693062.2020.1730153
Lomi, A., Robins, G., & Tranmer, M. (2016). Introduction to multilevel social networks. *Social Networks*, *100*(44), 266–268. https://doi.org/10.1016/j.socnet.2015.10.006
Loucks, D. P., & Van Beek, E. (2017). *Water resource systems planning and management: An introduction to methods, models, and applications*. Springer.
Magliocca, N. R. (2020). Agent-based modeling for integrating human behavior into the food–energy–water nexus. *Land*, *9*(12), 519. https://doi.org/10.3390/land9120519
Malawska, A., & Topping, C. J. (2016). Evaluating the role of behavioral factors and practical constraints in the performance of an agent-based model of farmer decision making. *Agricultural Systems*, *143*, 136–146. https://doi.org/10.1016/j.agsy.2015.12.014

Manson, S. M., & Evans, T. (2007). Agent-based modeling of deforestation in southern Yucatan, Mexico, and reforestation in the Midwest United States. *Proceedings of the National Academy of Sciences*, *104*(52), 20678–20683. https://doi.org/10.1073/pnas.0705802104
March, D., Metcalfe, K., Tintoré, J., & Godley, B. J. (2021). Tracking the global reduction of marine traffic during the COVID-19 pandemic. *Nature Communications*, *12*(1), 1–12. https://doi.org/10.1038/s41467-021-22423-6
Marchau, V. A., Walker, W. E., Bloemen, P. J., & Popper, S. W. (2019). *Decision making under deep uncertainty: From theory to practice* (p. 405). Springer Nature.
Martinez, L. M., & Viegas, J. M. (2017). Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. *International Journal of Transportation Science and Technology*, *6*(1), 13–27. https://doi.org/10.1016/j.ijtst.2017.05.005
Matous, P., & Todo, Y. (2015). Exploring dynamic mechanisms of learning networks for resource conservation. *Ecology and Society*, *20*(2), art36. https://doi.org/10.5751/es-07602-200236
Mayer, L. A., Loa, K., Cwik, B., Tuana, N., Keller, K., Gonnerman, C., et al. (2017). Understanding scientists' computational modeling decisions about climate risk management strategies using values-informed mental models. *Global Environmental Change*, *42*, 107–116. https://doi.org/10.1016/j.gloenvcha.2016.12.007
McGinnis, M. D., & Ostrom, E. (2014). Social-ecological system framework: Initial changes and continuing challenges. *Ecology and Society*, *19*(2), art30. https://doi.org/10.5751/es-06387-190230
Miksis, N. K. (2010). Electric power market modeling with multi-agent reinforcement learning.
Mitchell, R. J., Liu, Y., O'Brien, J. J., Elliott, K. J., Starr, G., Miniat, C. F., & Hiers, J. K. (2014). Future climate and fire interactions in the southeastern region of the United States. *Forest Ecology and Management*, *327*, 316–326. https://doi.org/10.1016/j.foreco.2013.12.003
Moallemi, E. A., Kwakkel, J., de Haan, F. J., & Bryan, B. A. (2020). Exploratory modeling for analyzing coupled human-natural systems under uncertainty. *Global Environmental Change*, *65*, 102186. https://doi.org/10.1016/j.gloenvcha.2020.102186
Molla, N., DeIonno, J., & Herman, J. (2021). Dynamics of resilience–equity interactions in resource-based communities. *Communications Earth & Environment*, *2*(1), 1–8. https://doi.org/10.1038/s43247-021-00093-y
Mongruel, R., Prou, J., Ballé-Béganton, J., Lample, M., Vanhoutte-Brunier, A., Réthoret, H., et al. (2011). Modeling soft institutional change and the improvement of freshwater governance in the coastal zone. *Ecology and Society*, *16*(4), art15. https://doi.org/10.5751/es-04294-160415
Moro, E., Calacci, D., Dong, X., & Pentland, A. (2021). Mobility patterns are associated with experienced income segregation in large US cities. *Nature Communications*, *12*(1), 1–10. https://doi.org/10.1038/s41467-021-24899-8
Moss, R. H., Fisher-Vanden, K., Delgado, A., Backhaus, S., Barrett, C. L., Bhaduri, B., et al. (2016). Understanding dynamics and resilience in complex interdependent systems, prospects for a multi-model framework and community of practice. In *Workshop Report, US Global Change Research Program Interagency Group on Integrative Modeling*.
Muneepeerakul, R., & Anderies, J. M. (2017). Strategic behaviors and governance challenges in social-ecological systems. *Earth's Future*, *5*(8), 865–876. https://doi.org/10.1002/2017ef000562
Mungovan, D., Howley, E., & Duggan, J. (2011). The influence of random interactions and decision heuristics on norm evolution in social networks. *Computational & Mathematical Organization Theory*, *17*(2), 152–178. https://doi.org/10.1007/s10588-011-9085-7
Ng, T. L., Eheart, J. W., Cai, X., & Braden, J. B. (2011). An agent-based model of farmer decision-making and water quality impacts at the watershed scale under markets for carbon allowances and a second-generation biofuel crop. *Water Resources Research*, *47*(9). https://doi.org/10.1029/2011wr010399
Nordhaus, W. D. (1994). *Managing the global commons: The economics of climate change* (Vol. 31). MIT Press.
North, D. (1990). *Institutions, institutional change and economic performance (political economy of institutions and decisions)*. Cambridge University Press. https://doi.org/10.1017/CBO9780511808678
Notteboom, T., Pallis, T., & Rodrigue, J. P. (2021). Disruptions and resilience in global container shipping and ports: The COVID-19 pandemic versus the 2008–2009 financial crisis. *Maritime Economics & Logistics*, *23*(2), 179–210. https://doi.org/10.1057/s41278-020-00180-5
O'Neill, B. C., Dalton, M., Fuchs, R., Jiang, L., Pachauri, S., & Zigova, K. (2010). Global demographic trends and future carbon emissions. *Proceedings of the National Academy of Sciences*, *107*(41), 17521–17526. https://doi.org/10.1073/pnas.1004581107
O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., et al. (2014). A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Climatic Change*, *122*(3), 387–400. https://doi.org/10.1007/s10584-013-0905-2
O'Sullivan, D., & Haklay, M. (2000). Agent-based models and individualism: Is the world agent-based? *Environment and Planning A*, *32*(8), 1409–1425. https://doi.org/10.1068/a32140
Oikonomou, K., Tarroja, B., Kern, J., & Voisin, N. (2022). Core process representation in power system operational models: Gaps, challenges, and opportunities for multisector dynamics research. *Energy*, *238*, 122049. https://doi.org/10.1016/j.energy.2021.122049
Ostrom, E. (1986). An agenda for the study of institutions. *Public Choice*, *48*(1), 3–25. https://doi.org/10.1007/bf00239556
Parker, D. C., & Filatova, T. (2008). A conceptual design for a bilateral agent-based land market with heterogeneous economic agents. *Computers, Environment and Urban Systems*, *32*(6), 454–463. https://doi.org/10.1016/j.compenvurbsys.2008.09.012
Partelow, S. (2018). A review of the social-ecological systems framework. *Ecology and Society*, *23*(4), art36. https://doi.org/10.5751/es-10594-230436
Powell, W. B. (2019). A unified framework for stochastic optimization. *European Journal of Operational Research*, *275*(3), 795–821. https://doi.org/10.1016/j.ejor.2018.07.014
Rai, V., & Henry, A. D. (2016). Agent-based modelling of consumer energy choices. *Nature Climate Change*, *6*(6), 556–562. https://doi.org/10.1038/nclimate2967
Reed, P. M., Hadjimichael, A., Moss, R. H., Brelsford, C., Burleyson, C. D., Cohen, S., et al. (2022). Multisector dynamics: Advancing the science of complex adaptive human-earth systems. *Earth's Future*, *10*(3), e2021EF002621. https://doi.org/10.1029/2021ef002621
Reed, P. M., Hadka, D., Herman, J. D., Kasprzyk, J. R., & Kollat, J. B. (2013). Evolutionary multiobjective optimization in water resources: The past, present, and future. *Advances in Water Resources*, *51*, 438–456. https://doi.org/10.1016/j.advwatres.2012.01.005
Reed, P. M., & Kasprzyk, J. (2009). Water resources management: The myth, the wicked, and the future. *Journal of Water Resources Planning and Management*, *135*(6), 411–413. https://doi.org/10.1061/(asce)wr.1943-5452.0000047
Riahi, K., Kriegler, E., Johnson, N., Bertram, C., Den Elzen, M., Eom, J., et al. (2015). Locked into Copenhagen pledges—Implications of short-term emission targets for the cost and feasibility of long-term climate goals. *Technological Forecasting and Social Change*, *90*, 8–23. https://doi.org/10.1016/j.techfore.2013.09.016
Rinaldi, S. M., Peerenboom, J. P., & Kelly, T. K. (2001). Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control Systems Magazine*, *21*(6), 11–25.
Rittel, H. W., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences*, *4*(2), 155–169. https://doi.org/10.1007/bf01405730

Romero-Lankao, P., Bruns, A., & Wiegleb, V. (2018). From risk to WEF security in the city: The influence of interdependent infrastructural systems. *Environmental Science & Policy*, *90*, 213–222. https://doi.org/10.1016/j.envsci.2018.01.004

Romero-Lankao, P., Burch, S., Hughes, S., Auty, K., Aylett, A., Krellenberg, K., et al. (2018). Governance and policy. In C. Rosenzweig, W. Solecki, P. Romero-Lankao, S. Mehrotra, S. Dhakal, & S. Ali Ibrahim (Eds.), *Climate change and cities: Second assessment report of the urban climate change research network* (pp. 585–606). Cambridge University Press.

Romero-Lankao, P., & Gnatz, D. M. (2016). Conceptualizing urban water security in an urbanizing world. *Current Opinion in Environmental Sustainability*, *21*, 45–51. https://doi.org/10.1016/j.cosust.2016.11.002

Romero-Lankao, P., & Norton, R. (2018). Interdependencies and risk to people and critical food, energy, and water systems: 2013 flood, Boulder, Colorado, USA. *Earth's Future*, *6*(11), 1616–1629.

Saltelli, A., Benini, L., Funtowicz, S., Giampietro, M., Kaiser, M., Reinert, E., & van der Sluijs, J. P. (2020). The technique is never neutral. How methodological choices condition the generation of narratives for sustainability. *Environmental Science & Policy*, *106*, 87–98. https://doi.org/10.1016/j.envsci.2020.01.008

Sayles, J. S., & Baggio, J. A. (2017). Social–ecological network analysis of scale mismatches in estuary watershed restoration. *Proceedings of the National Academy of Sciences*, *114*(10), E1776–E1785. https://doi.org/10.1073/pnas.1604405114

Sayles, J. S., Garcia, M. M., Hamilton, M., Alexander, S. M., Baggio, J. A., Fischer, A. P., et al. (2019). Social-ecological network analysis for sustainability sciences: A systematic review and innovative research agenda for the future. *Environmental Research Letters*, *14*(9), 093003. https://doi.org/10.1088/1748-9326/ab2619

Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter, S. R., Dakos, V., et al. (2009). Early-warning signals for critical transitions. *Nature*, *461*(7260), 53–59. https://doi.org/10.1038/nature08227

Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., et al. (2017). A framework for mapping and comparing behavioural theories in models of social-ecological systems. *Ecological Economics*, *131*, 21–35. https://doi.org/10.1016/j.ecolecon.2016.08.008

Schlüter, M., Müller, B., & Frank, K. (2019). The potential of models and modeling for social-ecological systems research. *Ecology and Society*, *24*(1), art31. https://doi.org/10.5751/es-10716-240131

Schreinemachers, P., & Berger, T. (2011). An agent-based simulation model of human–environment interactions in agricultural systems. *Environmental Modelling & Software*, *26*(7), 845–859. https://doi.org/10.1016/j.envsoft.2011.02.004

Schreinemachers, P., Berger, T., Sirijinda, A., & Praneetvatakul, S. (2009). The diffusion of greenhouse agriculture in Northern Thailand: Combining econometrics and agent-based modeling. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *57*(4), 513–536. https://doi.org/10.1111/j.1744-7976.2009.01168.x

Scott, W. R. (2013). *Institutions and organizations: Ideas, interests, and identities*. Sage Publications.

Shafie-Khah, M., & Catalão, J. P. (2015). Multi-layer agent-based decision making model with incomplete information game theory to study the behavior of market participants for sustainability. In *2015 48th Hawaii International Conference on System Sciences* (pp. 856–865). IEEE.

Shepherd, S. P. (2014). A review of system dynamics models applied in transportation. *Transportmetrica B: Transport Dynamics*, *2*(2), 83–105. https://doi.org/10.1080/21680566.2014.916236

Sieber, J. (2006). WEAP water evaluation and planning system.

Simon, H. A. (1957). Models of man; social and rational.

Simon, H. A. (1972). Theories of bounded rationality. *Decision and organization*, *1*(1), 161–176.

Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., et al. (2021). A framework for complex climate change risk assessment. *One Earth*, *4*(4), 489–501. https://doi.org/10.1016/j.oneear.2021.03.005

Sinha-Ray, P., Carter, J., Field, T., Marshall, J., Polak, J., Schumacher, K., et al. (2003). Container World: Global agent-based modelling of the container transport business. In *Proceedings of 4th International Workshop on Agent-Based Simulation*.

Srikrishnan, V., & Keller, K. (2021). Small increases in agent-based model complexity can result in large increases in required calibration data. *Environmental Modelling & Software*, *138*, 104978. https://doi.org/10.1016/j.envsoft.2021.104978

Srinivasan, V., Gorelick, S. M., & Goulder, L. (2010). A hydrologic-economic modeling approach for analysis of urban water supply dynamics in Chennai, India. *Water Resources Research*, *46*(7). https://doi.org/10.1029/2009wr008693

Sycara, K. P. (1998). Multiagent systems. *AI Magazine*, *19*(2), 79.

Syphard, A. D., & Keeley, J. E. (2015). Location, timing and extent of wildfire vary by cause of ignition. *International Journal of Wildland Fire*, *24*(1), 37–47. https://doi.org/10.1071/wf14024

Taschereau-Dumouchel, M. (2020). Cascades and fluctuations in an economy with an endogenous production network.

Trutnevyte, E., Hirt, L. F., Bauer, N., Cherp, A., Hawkes, A., Edelenbosch, O. Y., et al. (2019). Societal transformations in models for energy and climate policy: The ambitious next step. *One Earth*, *1*(4), 423–433. https://doi.org/10.1016/j.oneear.2019.12.002

Tsekeris, T., & Vogiatzoglou, K. (2011). Spatial agent-based modeling of household and firm location with endogenous transport costs. *Netnomics: Economic Research and Electronic Networking*, *12*(2), 77–98. https://doi.org/10.1007/s11066-011-9060-y

Tuana, N. (2017). Understanding coupled ethical-epistemic issues relevant to climate modeling and decision support science. *Scientific Integrity and Ethics in the Geosciences*, *73*, 157–173. https://doi.org/10.1002/9781119067825.ch10

Tuana, N. (2020). Values-informed decision support: The place of philosophy. In *A guide to field philosophy* (pp. 143–159). Routledge.

Turner, S. W., Xu, W., & Voisin, N. (2020). Inferred inflow forecast horizons guiding reservoir release decisions across the United States. *Hydrology and Earth System Sciences*, *24*(3), 1275–1291. https://doi.org/10.5194/hess-24-1275-2020

Vezér, M., Bakker, A., Keller, K., & Tuana, N. (2017). Epistemic and ethical values in decision analytical models: Flood risk management in coastal Louisiana. *Climatic Change*, *147*(1–2), 1–10. https://doi.org/10.1007/s10584-017-2123-9

Vezér, M., Bakker, A., Keller, K., & Tuana, N. (2018). Epistemic and ethical trade-offs in decision analytical modelling. *Climatic Change*, *147*(1), 1–10. https://doi.org/10.1007/s10584-017-2123-9

Voigt, S. (2013). How (not) to measure institutions. *Journal of Institutional Economics*, *9*(1), 1–26. https://doi.org/10.1017/s1744137412000148

Voisin, N., Tidwell, V., Kintner-Meyer, M., & Boltz, F. (2019). Planning for sustained water-electricity resilience over the US: Persistence of current water-electricity operations and long-term transformative plans. *Water Security*, *7*, 100035. https://doi.org/10.1016/j.wasec.2019.100035

Waddell, P. (2002). UrbanSim: Modeling urban development for land use, transportation, and environmental planning. *Journal of the American Planning Association*, *68*(3), 297–314. https://doi.org/10.1080/01944360208976274

Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. (2004). Resilience, adaptability and transformability in social–ecological systems. *Ecology and Society*, *9*(2), art5. https://doi.org/10.5751/es-00650-090205

Walker, W. E., Harremoës, P., Rotmans, J., Van Der Sluijs, J. P., Van Asselt, M. B., Janssen, P., & Krayer von Krauss, M. P. (2003). Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment*, *4*(1), 5–17. https://doi.org/10.1076/iaij.4.1.5.16466

Watts, D. J. (2017). Should social science be more solution-oriented? *Nature Human Behaviour*, *1*(1), 1–5. https://doi.org/10.1038/s41562-016-0015

Watts, J., Morss, R. E., Barton, C. M., & Demuth, J. L. (2019). Conceptualizing and implementing an agent-based model of information flow and decision making during hurricane threats. *Environmental Modelling & Software*, *122*, 104524. https://doi.org/10.1016/j.envsoft.2019.104524

Wilkerson, J. T., Leibowicz, B. D., Turner, D. D., & Weyant, J. P. (2015). Comparison of integrated assessment models: Carbon price impacts on US energy. *Energy Policy*, *76*, 18–31. https://doi.org/10.1016/j.enpol.2014.10.011

Will, M., Groeneveld, J., Frank, K., & Müller, B. (2020). Combining social network analysis and agent-based modelling to explore dynamics of human interaction: A review. *Socio-Environmental Systems Modelling*, *2*, 16325. https://doi.org/10.18174/sesmo.2020a16325

Wilson, C., Guivarch, C., Kriegler, E., van Ruijven, B., van Vuuren, D. P., Krey, V., et al. (2021). Evaluating process-based integrated assessment models of climate change mitigation. *Climatic Change*, *166*(1), 1–22. https://doi.org/10.1007/s10584-021-03099-9

Xian, S., Lin, N., & Kunreuther, H. (2017). Optimal house elevation for reducing flood-related losses. *Journal of Hydrology*, *548*, 63–74. https://doi.org/10.1016/j.jhydrol.2017.02.057

Xianyu, B. (2010). Social preference, incomplete information, and the evolution of ultimatum game in the small world networks: An agent-based approach. *The Journal of Artificial Societies and Social Simulation*, *13*(2), 7. https://doi.org/10.18564/jasss.1534

Yang, Y. C. E., Cai, X., & Stipanović, D. M. (2009). A decentralized optimization algorithm for multiagent system–based watershed management. *Water Resources Research*, *45*(8), 8430. https://doi.org/10.1029/2008wr007634

Yoon, J., Klassert, C., Selby, P., Lachaut, T., Knox, S., Avisse, N., et al. (2021). A coupled human–natural system analysis of freshwater security under climate and population change. *Proceedings of the National Academy of Sciences*, *118*(14), e2020431118. https://doi.org/10.1073/pnas.2020431118

Zagona, E. A., Fulp, T. J., Shane, R., Magee, T., & Goranflo, H. M. (2001). Riverware: A generalized tool for complex reservoir system modeling 1. *JAWRA Journal of the American Water Resources Association*, *37*(4), 913–929. https://doi.org/10.1111/j.1752-1688.2001.tb05522.x

Zaniolo, M., Giuliani, M., & Castelletti, A. (2021). Policy Representation Learning for multiobjective reservoir policy design with different objective dynamics. *Water Resources Research*, *37*, e2020WR029329.

Zarekarizi, M., Srikrishnan, V., & Keller, K. (2020). Neglecting uncertainties biases house-elevation decisions to manage riverine flood risks. *Nature Communications*, *11*(1), 1–11. https://doi.org/10.1038/s41467-020-19188-9

Zhou, T., Voisin, N., & Fu, T. (2018). Non-stationary hydropower generation projections constrained by environmental and electricity grid operations over the western United States. *Environmental Research Letters*, *13*(7), 074035. https://doi.org/10.1088/1748-9326/aad19f