A Typology for Characterizing Human Action in MultiSector Dynamics Models

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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 towards 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 towards some human end. We trace the salient features of modeled representations of human systems by organizing the typology around three key questions: 1) Who are the actors in MSD systems? 2) What are their actions? 3) 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.

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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.

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 towards 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 towards some human end. We trace the salient features of modeled representations of human systems by organizing the typology around three key questions: 1) Who are the actors in MSD systems? 2) What are their actions? 3) 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 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 et al., 2013) and critical infrastructure (Rinaldi et al., 2001). For example, insufficient cross-sector planning between the electricity and fire protection sectors has resulted in exacerbated fire risk across the Western United States (Mitchell, 2013; Syphard and Keeley, 2015). Considering longer time scales, 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). 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 (Harou, 2009; Reed, et. al., 2013; Brown et al., 2015), global change scientists examining energy-water-land futures amidst climate and socioeconomic change (Nordhaus, 1994; Fisher-Vanden and Weyant, 2020; Wilson et al., 2021), and ecologists interested in the resilience of social-ecological systems (Gunderson, 2002; Walker, 2004; Folke 2006; Biggs 2015).

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 (Liu et al., 2007; Bai et al., 2016, Beckage et al., 2018; Elsawah et al., 2020; 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 (Zhou et al. 2018, Romero-Lankao et al 2018). For instance, poor communities in Buenos Aires engage in short-term responses to floods such as moving belongings to the second floor, while local authorities have subsidized elevated houses, a longer term action aimed at helping poor families withstand storm-surges. However, these houses are very small with children often occupying the first floor due to lack of adequate space, thereby 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 towards increased reliance on imported sources from outside the state and country (Romero-Lankao 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 et al., 2018b). 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 (Mongruel, 2011; Johnson, 2016).

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 versus 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, 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; Walker et al, 2003; Marchau, 2019; Moallemi et al, 2020). *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; Walker, 2003; Lempert et. al., 2006) 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, 1993; Saltelli, 2020) who must contend with the multifarious and wicked nature (Rittel and Webber, 1973; Reed and Kasprzyk, 2009) 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 dialogue 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 illustrative existing modeling approaches for multisector analysis. While not intended as an exhaustive review, the inventory is meant to capture a variety of existing modeling approaches with an eye towards 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 time scales, 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 (Zagona, 2001; Sieber, 2006; Georgilakis, 2015) 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.

Secondly, 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: 1) consumers that are utility maximizing users of resources, 2) firms that are profit maximizing suppliers of a resource or service and, 3) 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 (Nordhaus, 1994; Fisher-Vanden and Weyant, 2020; Wilson et al., 2021), water systems analysis framed as cost-based optimization problems (Harou et al., 2009; Giuliani et al., 2021), agricultural models that assume farmer profit maximization (Howitt, 1995; Berger, 2001), 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, 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 and 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 Categories of Models

In the following, we describe key categories of models 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 categories 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 categories here for purposes of discussion.

2.5.1 Integrated Assessment Models

Climate change IAMs were developed as tools to project energy and land use emissions of greenhouse gases, initially as inputs to climate models (Edmonds and Reilly, 1983; Nordhaus, 1994; Fisher-Vanden and Weyant, 2020; 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. Trutnevyte et al., 2019; De Cian et al., 2020, Jafino et al., 2021).

2.5.2 Agent-Based Models

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) (Sycara, 1998; Dooley and Corman, 2002). ABMs have been used for the study of several topics relevant to multisector research including land use change (Izquierdo et al., 2003; Waddell, 2002; Evans and Kelley, 2004; Liu et al., 2006; Parker and Filatova, 2008; Groeneveld et al., 2017), agricultural systems (Berger, 2001; Schreinemachers et al., 2009; Schreinemachers and Berger, 2011), electricity production and markets (Atkins et al., 2004; Chappin and Dijkema, 2007; Miksis, 2010; Chassin et al., 2014), the food-water nexus (Magliocca, 2020), water resources management (Yang et al., 2009; Ng et al., 2011; Berglund, 2015; Al-Amin et al., 2018; Yoon et al., 2021), and transportation (Sinha-Ray et al., 2003; Jin and Jie, 2012; Bazzan and Klugl, 2014; Hajinasab et al., 2015; Colon et al., 2021). While ABMs can accommodate any number of underlying behavior theories, some commonly used theories to quantify agent behavioral rules include expected utility theory (Herstein and 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 et al. 2019) and challenging to calibrate and diagnose given their complexity (Srikrishnan and Keller, 2021). Crooks, Castle, and Batty (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 towards methodological individualism (e.g., neoclassic-economics, game theories, rational choice theories) in representing social behavior, practices, and structures (O'Sullivan and 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 (Manson and Evans, 2007; de Koning and Filatova, 2020) 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 (Will et al., 2020, Sayles et al., 2019, Kluger 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 and Baggio, 2017), or might be explicitly parameterized using data from a real world network (Matous and 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 Models

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 and 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, Scheffer et al., 2009, Hughes et al., 2017, Voisin et al. 2019). SES modeling draws upon several existing modeling traditions from related fields, e.g. systems dynamics and agent-based modeling (Kelly et al., 2013), and thus incorporates a variety of representations of human behavior (Schluter et al., 2017). Some SES research has focused on in-depth, contextual case studies (Schluter 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. Muneepeerakul et al., 2017; Molla et al., 2021). 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 Models

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., Herman et al., 2020; Giuliani et al., 2021), energy (e.g., Oikonomou, 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, 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 towards 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 towards 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 three key components, prefaced by a consideration of model participants and human values. Each of the three typology components corresponds to a basic question: 1) Who are the actors in multisector systems? 2) What are their actions? 3) 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, 1) humans as users of the models, 2) humans as creators of models, and 3) humans as actors represented in the models. In each of these modes of interface, human values strongly shape the modeling effort (see, for example, Mayer et al, 2017; Vezer et al, 2017; Tuana, 2017; Tuana 2020, and Keller et al, 2021).

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, 2021). 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). More broadly, values play a crucial role in analyzing questions such as: (i) How to navigate the trade-offs and synergies between objectives such as efficiency, equity, reliability, robustness, and sustainability? (ii) What to sustain? (iii) What is an acceptable (e.g., procedurally fair) process? (iv) What are acceptable (e.g., distributionally fair) outcomes? (v) What are robust strategies given potential future changes in the stakeholders' and decision-makers' values? (vi) 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: (i) What processes, actions, and drivers to include? (ii) Which uncertainties to consider? (iii) How to navigate the trade-off between increasing model complexity and improving the representation of uncertainties? (iv) 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 agent-based model 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).

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?

The first component of the typology addresses the question: Who are the actors in multisector systems? 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: 1) governing actors, 2) provisioning actors, and 3) utilizing actors. The actor groups are identified along the vertical axis in Fig. 1, with each actor role category extending across any number of sectors included in a model.

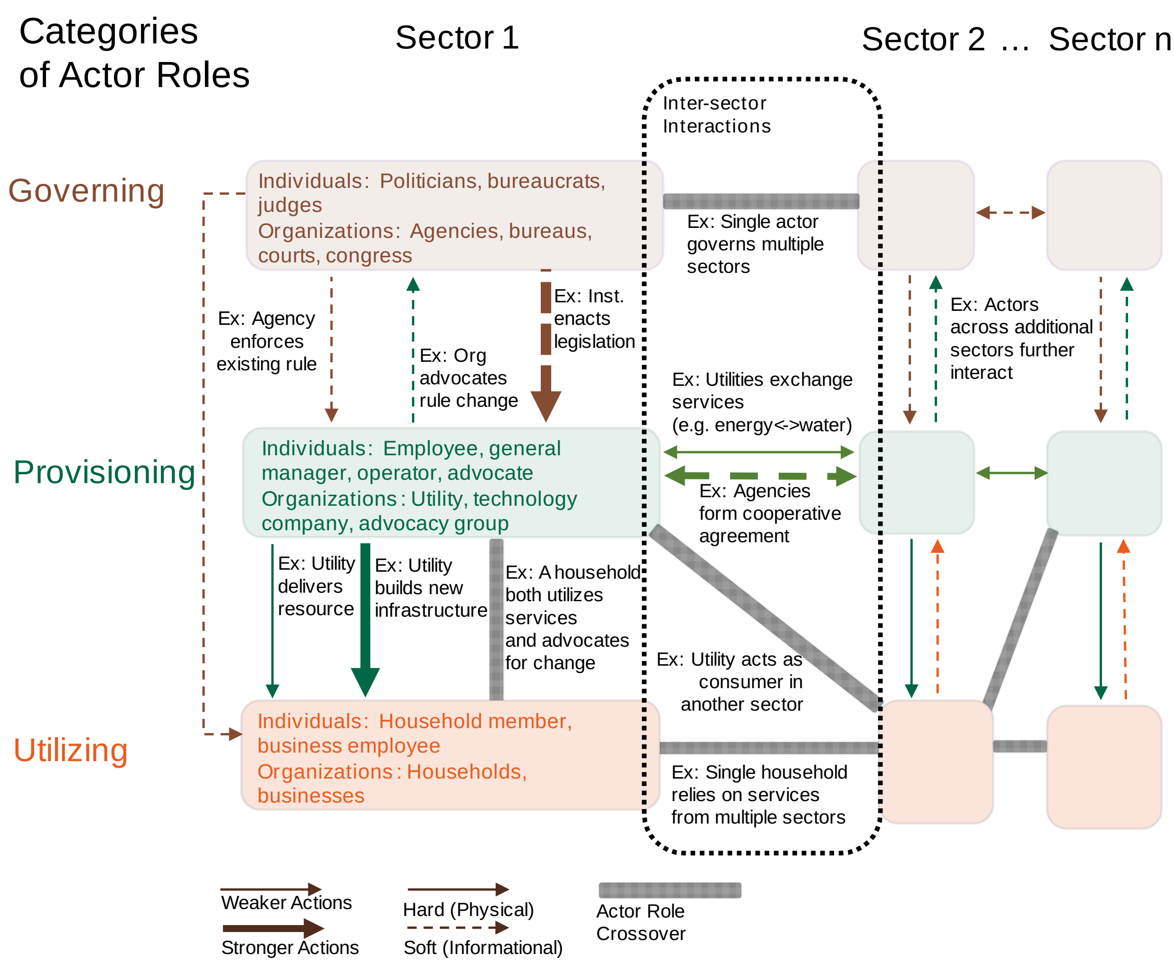

Figure 1 - A general conceptualization of actors in multisector systems. We conceive of three categories of actors defined across categories of actor roles: 1) governing actors, 2) provisioning actors, and 3) utilizing actors. Cross-sector relationships are conceptualized through cross-sector interactions 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.

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

Before proceeding to the second typology component, we 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. For example, sustainability transitions research commonly frames actor relations in terms of power dynamics between regime and niche actors (Avelino and Wittmayer, 2016). Many other categorizations of actors could be conceptualized: public versus private, formal versus informal, profit versus non-profit. While the typology does not explicitly focus on these sub-categorizations, we suggest that they can be accommodated as sub-categorizations within the primary actor role categories.

3.3 Typology Component #2 – What are their actions?

The second component of the typology addresses the question: What are the actions considered? While the actor topology from the first component already touches upon this question in the form of interactions between actor groups (each of which arises out of an action), the second component hones in on it through the conceptualization of a human action "canvas" which organizes human actions across 3 dimensions: 1) the actor role categorizations (governing, provisioning, utilizing) set forth in the first component, 2) timescales of action ranging from hourly to centennially in multisector systems, and 3) 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 Fig. 2 with generic actions (non-sector or domain specific) as an illustration of the concept. Following the topology of human actors (Fig. 1), categories of actor roles are identified along the vertical axis of the action space.

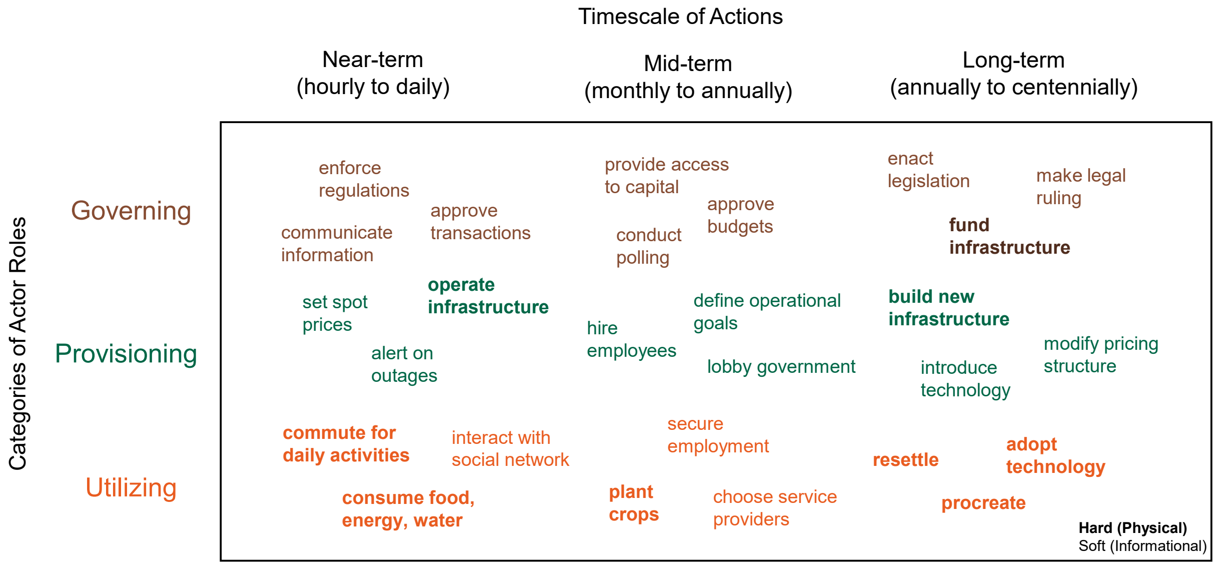

Figure 2 – A canvas mapping out actions that influence multisector systems. The canvas organizes human actions across 3 dimensions: 1) the actor role categorizations (governing, provisioning, utilizing) set forth in the first component of typology, 2) timescales of action ranging from hourly to centennially in multisector systems, and 3) 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.

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 canvass (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 canvass (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 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). 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.

3.4 Typology Component #3 – How are the actors/action operationalized in a model?

The last 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 8 "axes" of model characteristics to address this final question, which are presented on Fig. 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, i.e., 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, i.e., to each of the actions that are mapped out using the second component of the typology and included for representation in the model. Each of the axes is described in further detail below.

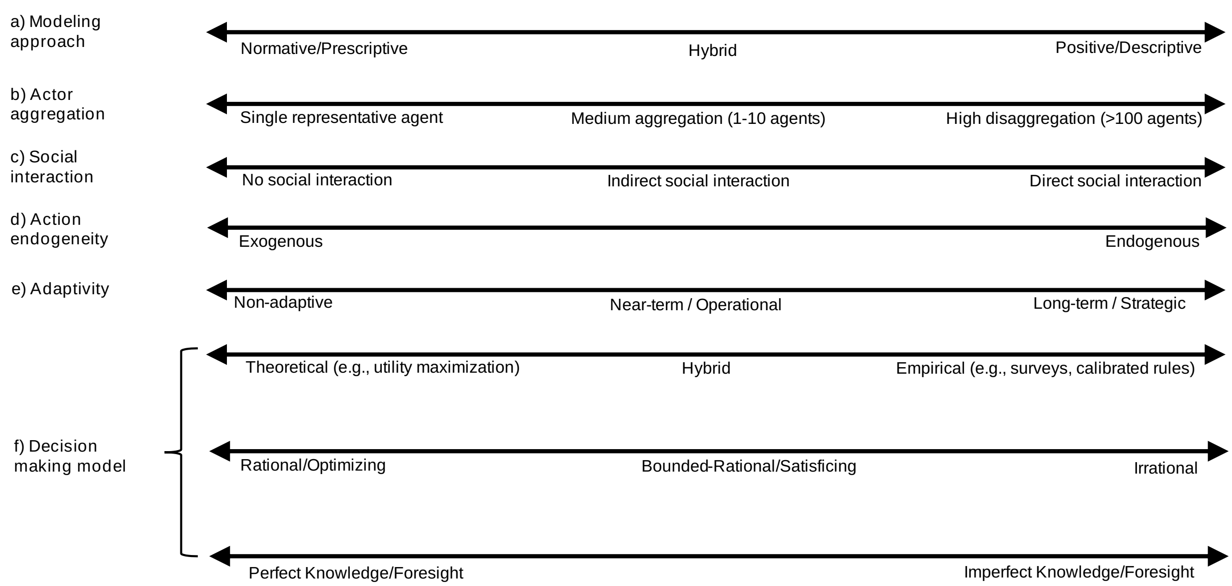

Figure 3 – Axes of human system representation in multisector models. Each of the axes provide a spectrum on which to identify general differences for operationalizing human actors and actions in MSD models. In general, the axes can either be applied generally to an entire model or applied to individual 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

1a. 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; Oikonomou, 2022; Herman et al., 2020). 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 (Manson and Evans, 2007; de Koning and Filatova, 2020; Yoon et al., 2021). Descriptive approaches can include agent-based models, 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) .

1b. 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 integrated assessment models aimed at addressing global-scale energy, water, and land dynamics aggregate actors at the level of countries or large regions (Fisher-Vanden and 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 and Klugl, 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).

1c. 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 and Baggio, 2017), and empirically derived networks (Matous and 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., 2015), 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.

1d. 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 (Tsekeris et al., 2011, Balbi et al., 2013, Rai & Henry, 2016). 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 1f.

1e. 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 functions 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 and Yang, 2021).

1f. 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 and Ostrom, 2006). Considering housing sector models for example, household actors seeking a housing good may be treated using traditional expected utility theory (Parker and Filatova, 2008) or operationalized based on direct survey results (Brown and 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 et al., 2020).

Rationality - Defines the extent to which actors are rational (e.g. optimizing a specific objective, Chappin and Dijkema 2007) or act in accordance to bounded rationality (Malawska, 2016), or other social science theories of human behavior that incorporate heterogeneous preferences, social influences, and risk aversion (Brown and Robinson, 2006, Xianyu, 2010, Kaiser et al., 2020). 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-Khan and Catalao, 2015) and fuzzy logic (Baloglu and Demir, 2017) modeling applications.

3.5 Applying the Typology

Lastly, we demonstrate applying the typology in practice. 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 of the model. Fig. 4 lays out a general workflow for applying the typology to a specific multisector model, segmented across the 3 typology components.

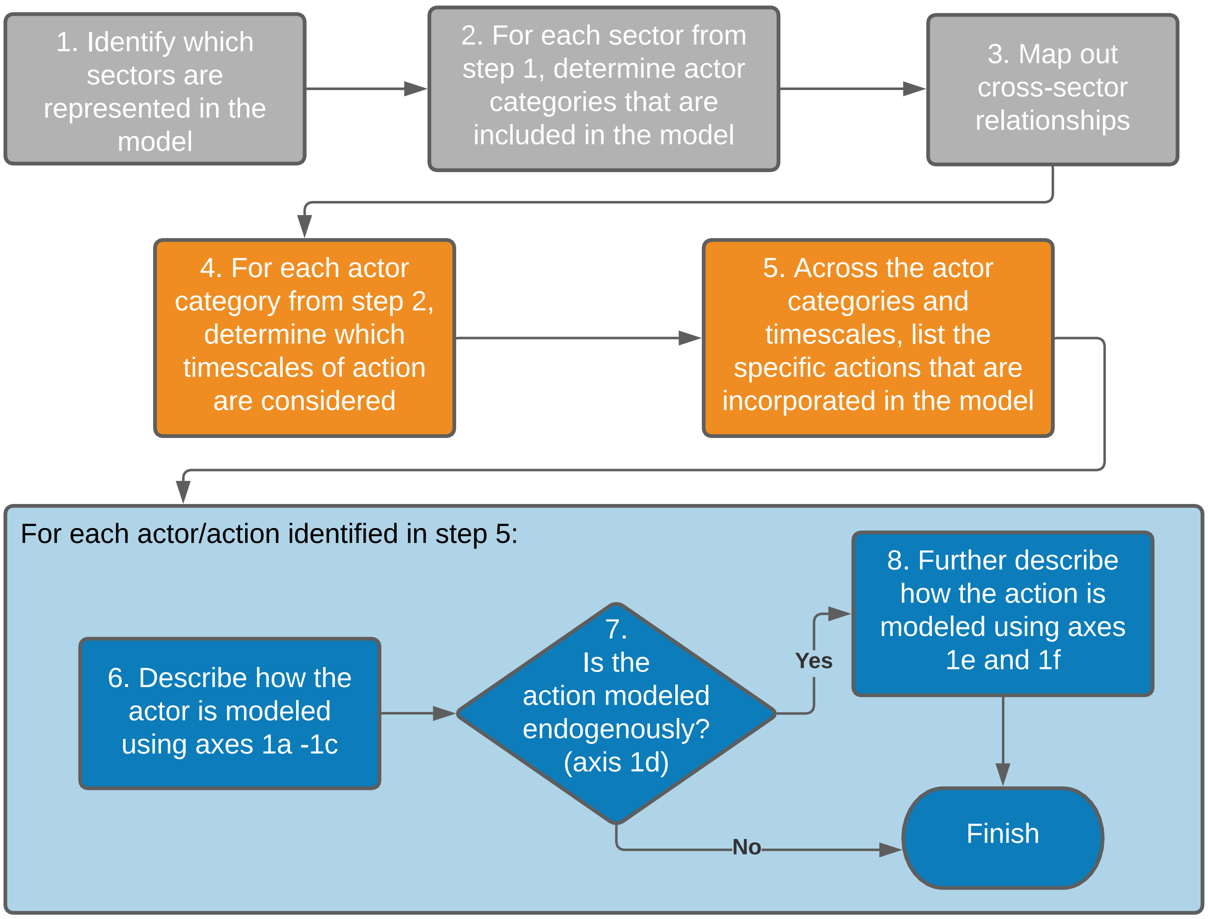

Figure 4 – Workflow for applying the human systems typology components to a multisector system model. The actor topology is first applied to all actors across sectors represented in the model (steps 1-3). Action canvases are subsequently developed for each actor category identified in step 2 (steps 4-5).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

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 agent-based model 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.

Towards 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 three simple questions as guideposts: 1) Who are the actors in MSD systems?, 2) What are their actions?, and 3) 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: 1) applying uncertainty quantification to the representation human systems, 2) utilizing artificial intelligence and machine learning for the representation of human systems, 3) designing models that adequately address decision-relevant issues such as equality, equity, and justice in multisector systems and 4) synthesizing and integrating insights across diverse modeling approaches.

In the first arena, 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 versus non-rational, all-knowing versus myopic, etc.) and their structural representation of actor categories and aggregation (e.g., a bioeconomic model that assumes centralized decision making versus an agent-based model 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, 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 and 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 and Bertsekas, 2019; and food-energy-water examples in Giuliani et al., 2021, Zaniolo et al., 2021, Cohen and 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 used to design a modeling experiment that focuses on the equity implications of energy transitions, systematically guiding model developers and users through a set of questions such as: 1) which actor categories are most salient for adequately capturing transition dynamics (e.g., are general actor categories of provisioners and utilizers adequate or are sub-categories that represent actor power differentials crucial)?, 2) what particular model structures and aggregations enable or preclude effective equity analysis? and 3) 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 agent-based model 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.

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