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Review

Climate change and opinion dynamics models: Linking individual, social, and institutional level changes

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Opinion dynamics models are increasingly used to understand changes in opinions, behaviors, and policy in the context of climate change. We review recent research that demonstrates how these models enable the linkages between individual, social, institutional, and biophysical factors to explain when and how social change emerges over time and what its impact might be on emissions and the climate system. We focus on applications of opinion dynamics models to climate change and describe how factors interact in those models to create feedback loops that reinforce or dampen change. We demonstrate how these models reveal the dynamics of consensus or polarization in climate opinions, the evolution of sustainability technologies and policies, and when and how interventions or negotiations related to climate change are likely to succeed or fail.

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Introduction

Greenhouse gas emissions, global temperatures, biodiversity loss, and other indicators of climate change continue to rise. Despite the urgent need for coordinated climate action and recent advances in climate science and technological solutions, current efforts to address climate change are insufficient. The politicization of climate change and polarization in public opinion about climate change have played a key role in delaying coordinated action in the United States and beyond [1,2]. For example, public opinion impacts how salient addressing climate change is to local policy makers [3] or can lead to varying support for specific climate policies depending on the details of their design [2].

Public opinion dynamics are complex social processes that depend on people's beliefs and personal experiences, as well as peer influence, social norms, political views, and media messaging to name a few [4,5]. To examine the individual and interactive impacts of these factors on public opinion about climate change and related sustainability technologies, climate modelers have increasingly sought to enhance the representation of human opinions, behaviors, and social dynamics within natural and ecological system models [6–8].

We argue that opinion dynamics models (ODMs) offer an opportunity for teams of behavioral scientists and modelers to examine how societal and biophysical processes interact in the context of climate change. An ODM is a framework used to study how and when individuals' opinions evolve and spread within a group over time [9–11]. ODMs often simulate interactions among individuals who hold differing opinions [10]. Climate ODMs enable researchers to bridge across different societal levels [12] by treating individuals as situated and coevolving with broader contexts, including groups or social structures, institutional environments, and the biophysical Earth system [13]. Through these integrations, ODMs reveal the dynamics of consensus, polarization, and societal transitions around climate change in various contexts. These insights can explain the evolution of related technologies and policies [14–16] or when and how interventions or negotiations related to climate change are likely to succeed or fail

[17–19]. Additionally, coupling ODMs with climate system models enhances climate change predictions, clarifies the source of uncertainty in different trajectories, and identifies potential measures to overcome mitigation barriers [4,20–22]. Climate ODMs offer insights about why this might differ across contexts, why polarization appears increasingly entrenched, and the role of social dynamics, institutions, and climate change itself in such processes [23–28].

We briefly introduce ODMs followed by a review of the most recent applications to climate change. We identify individual, social, and institutional-level factors that have been tested in these models, discuss the role of reinforcing and dampening feedbacks in systemic change, and conclude with existing gaps and future directions that we expect will enrich both the behavioral science of climate change as well as the science of coupled human–climate systems.

Opinion dynamics models and climate research

ODMs have been used across disciplines, including physics, mathematics, computer science, political science, economics, psychology, and public policy [9]. ODMs can be developed using various methodological approaches, including mathematical functions [4,10,14,20,26], agent-based modeling [15,27,29,30], network approaches [31], game-theory approach [25], and data-driven modeling [32]. For example, system dynamics models provide an integrative, mathematical framework to model interactions and feedbacks among various processes influenced by multiple factors and can link microlevel processes to macrolevel phenomena [11,33]. In agent-based modeling, a finite number of connected actors, each with a discrete or continuous opinion, adjust their views based on new information and interactions, following simple mathematical rules. [34]. In this sense, actors are modeled as embedded in social spheres.

While the earliest ODMs were used to understand the conditions leading to opinion consensus, more recently, they explore diverging or polarizing public opinion [35,36] by varying the features of actors and their interactions or affiliations (see Table 1 for glossary of terms), including actors with strong opinions (e.g. stubbornness or self-persistence) [37,38], homophily in social interactions [39], and biased assimilation of new information [40,41] to understand how and why polarization has increased and what measures might achieve consensus. ODMs also examine how factors in the information environment, such as misinformation [42], opinion inoculation measures [43], algorithm filters [44], and communication frictions [45] contribute to misperceptions or biases.

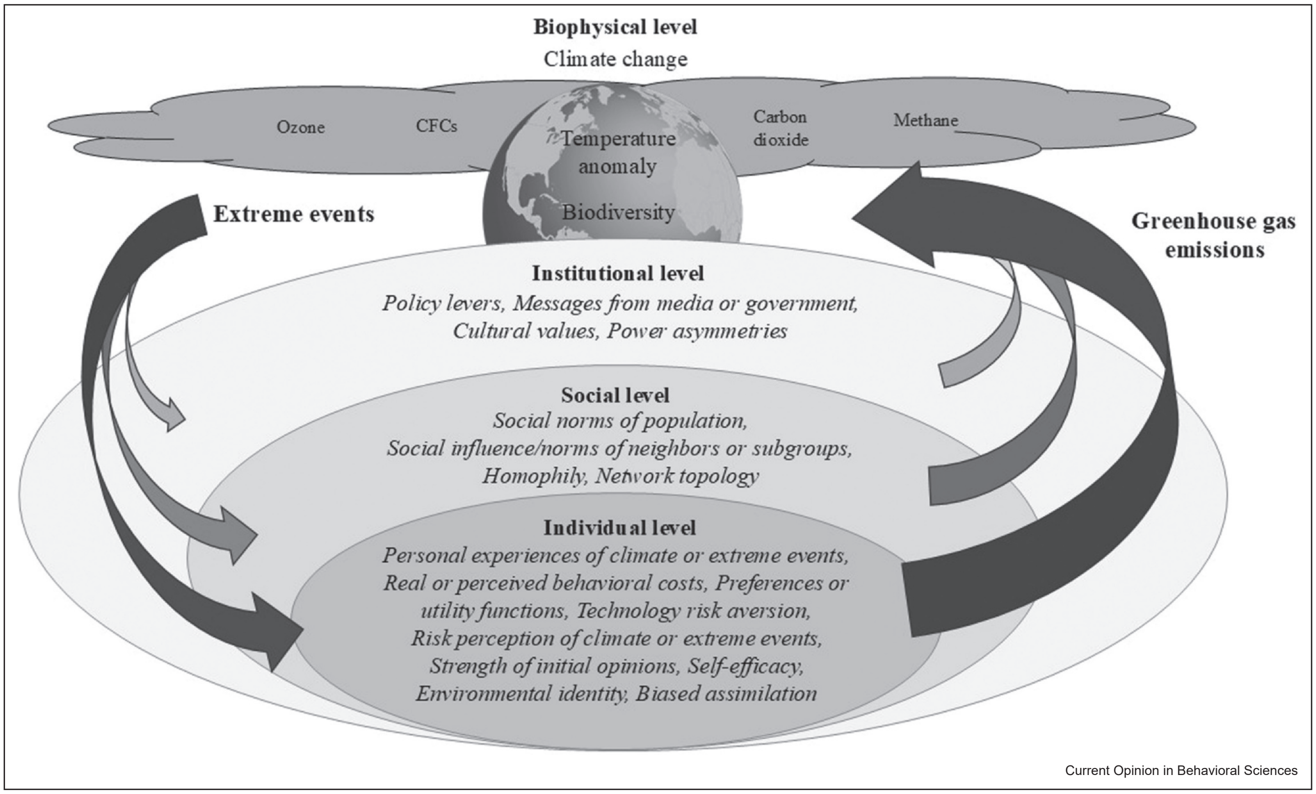
ODMs are being increasingly applied to the issue of climate change [6,46]. These models aim to understand how individual, social, institutional, and biophysical factors interact (Figure 1) to shape the distribution of climate opinions and policy support [23,47,48] or emissions-relevant behaviors [4,20], including the adoption of specific technologies such as electric vehicles or residential solar [16,32,49] or moving away from emissions-intensive behaviors, such as meat consumption [21]. Other models examine how opinion dynamics interact with institutional-level measures to shape outcomes such as climate policy implementation [4,14,15], development of sustainable infrastructure [30], or climate negotiations [17].

Table 1

Glossary of definitions

Concepts	Definitions
Stubborn or self-persistent actors	An actor's strong adherence to the initial opinion so that they are less likely to change their opinions.
Homophily	A strong preference to interact only with people with similar opinions or a similar social identity.
Biased assimilation and confirmation bias	The tendency to seek out information or interpret information in a way that supports your initial opinions.
Opinion inoculation	A group of actors who try to act as a barrier to the spread of disinformation.
Social influence	Changes in an individual's thoughts, feelings, attitudes, or behaviors that result from interaction with another individual or a group.
Social norms	A shared standard of the most common or acceptable behavior within a group or community. Based on what people believe to be normal, typical, or appropriate.
Utility function	Used to predict how an actor will behave based on a mathematical representation of their preferences. Determines which action will maximize the actor's welfare or satisfaction.
Self-efficacy	A person's belief in their ability to perform the actions needed to achieve a specific goal.
Network topology	The arrangement of the elements, including the number of actors and connection features between actors, in a social network.
Theory of planned behavior	A psychological model proposing that behavior is determined by behavioral intentions, which are shaped by an actor's attitude about a behavior, subjective norms about the behavior, and perceived behavioral control.
Protection-motivation theory	A psychological framework that explains how people react to perceived threats and are motivated to protect themselves.

Figure 1



An illustration of how a society (social system) interacts with the biophysical environment. The society is composed of individual, social, and institutional levels that influence one another. Individuals hold varying opinions, attitudes, and beliefs about climate change risks and their relationship with the natural environment. These factors influence self-efficacy and shape personal preferences or biases regarding certain emissions-relevant behaviors, policies, or technologies. At the social level, individual attributes are shaped by existing social norms within the population, interactions within affiliated groups, and social network topology. Additionally, institutional factors — such as policies, media and government messaging, culture, and power asymmetries — play significant roles in shaping both individual attributes and broader social norms. These diverse factors, embedded at different social levels, interact with one another to influence human activities, such as burning fossil fuels, deforestation, and industrial processes. These activities have increased the concentration of greenhouse gases in the atmosphere, resulting in temperature anomalies and ultimately climate change at the biophysical level. The changing biophysical environment then causes extreme events that impact not only individual experiences and perceptions but also social norms, policy, and media and governmental messages. These coincidental changes reshape structures and feedback loops across individual, social, and institutional levels.

Individual-level factors

Individual actors in ODMs vary in their psychological richness (Table 2). While some models assume rational actors who carefully weigh risks, costs, and benefits [27,49] using a utility function to identify an optimal response [14,22,24,25,31], others introduce more psychological realism by including individual differences in traits or cognitive constraints or biases [4,20,48,51]. Some models represent actors as relatively homogenous [22,26], while others include heterogenous actors that vary in their traits or strategies [17,23,24,30,32,47]. Other models test specific psychological or empirically informed theories of human decision-making such as theory of planned behavior [16,20,21] or protection-motivation theory [21,27].

Social-level factors

A frequent feature of ODMs is that individuals' opinions and decisions are heavily influenced by surrounding people or one's affiliated groups (Table 2). Individuals tend to follow the opinions or behaviors of their neighbors in a network. The network might represent geographic proximity [50], a social or political identity group [15,27,30], or the entire general public [4,20]. ODMs can also examine the effects of different social network structures — how actors are connected to other actors — on the spread of opinions or behaviors, often including homophily or a preference for interacting with similar others [4,14–16,24,25,39,47,48].

Table 2

Driving factors in climate opinion dynamics models.

Levels	Descriptions	Examples
Individual level	Perceptions of costs and benefits	• Personal experience with climate change or extreme weather [4,27,29] • Real or perceived behavioral costs [27,49] • Preferences or utility functions [14,15,22,24,25,31] • Technology risk aversion [32,49]
	Traits and cognitive processes	• Risk perceptions about climate change or environmental extreme events [18,20,21,23,27,28,48,50] • Strength of initial opinions/stubbornness [12,14,17,18,20,22,23,47,48] • Self-efficacy [20,21,27] • Environmental identity [50] • Biased assimilation/confirmation bias[4,20,48]
Social level	Social influence and norms	• Social norms of the population [4,6,17,19,22,23,29,49,51] - *Election results* [14] • Social influence or norms of neighbors or a subgroup of the population [16,18,24–27,30,31,48,50] • Homophily by subgroups - *Shared opinion* [4,39,48] - *Economic status:* rich vs poor [15,16,24,25] - *Political affiliation*: right vs left political party [14,15] - *Social identity* [47] • Network topology[23,24,47,50]
Institutional level	Formal institutions	• Policy levers [4,16,19,26,30,32,49,51] • Messages from media or government [23,27,50]
	Less formal institutions	• Cultural values [32] • Power asymmetries: - *Leaders* vs *rest* [18] - *Opinion leaders* vs *followers* [52,53] - *More* vs *less powerful nations* [17]
Biophysical level		• Extreme events or changing climate [4,18,20–22,25,26,28,29]

Table 2: Illustrative list of prominent factors frequently included in climate ODMs at each of the societal levels. Many of these factors influence climate opinion dynamics but also update and change in response to shifting climate opinions among actors in the model.

Institutional-level factors

ODMs also frequently specify features of the institutional context (Table 2), defining human-made constraints that influence individual-level decisions through the introduction of legislation, impacts on the monetary costs or benefits of different actions, or infrastructure development [54]. For example, a policy that introduces economic incentives for pro-climate behaviors and disincentives for emissions-intensive ones will increase the likelihood that an actor engages in pro-climate behaviors, all else being equal [4,15,22,49]. Signals from media, government actors, or an election can communicate broad norms and opinions [14,23,27,50]. Less formal institutions can also influence opinion dynamics by conferring power (e.g. through economic status, fame, and reputation) to a few actors [18] or nations [17] over others. Culturally transmitted value systems can also shape climate-related opinions and behaviors [32].

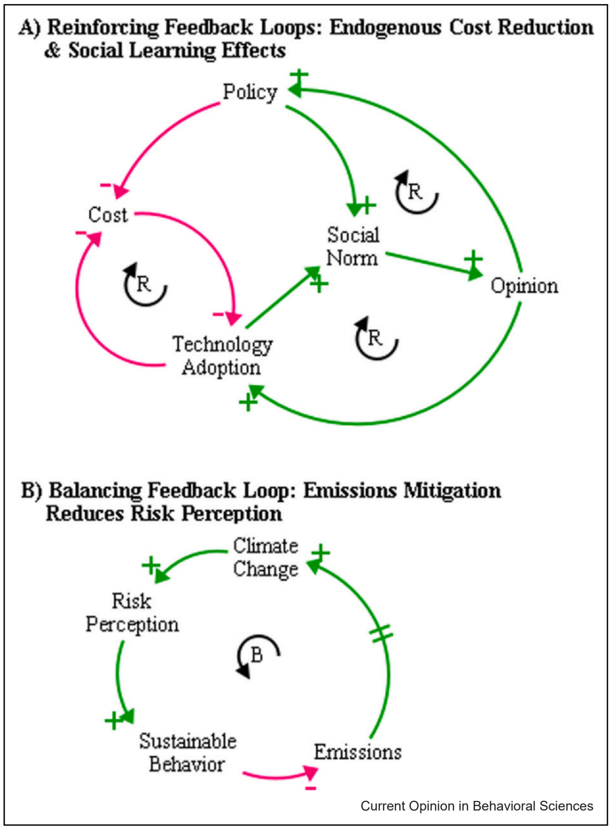
Feedback loops: processes of interdependent system change

ODMs make explicit the processes by which a system changes or adapts over time. They are often characterized by feedback loops, which can amplify or dampen the influence of perturbations to a system (Figure 2). Feedback loops occur when model components interact such that actions or decisions at one point modify subsequent actions or outcomes at other levels. Reinforcing (positive) feedback loops can accelerate change and destabilize a system — this is similar to concepts such as 'the spiral of action' [55] or 'a slippery slope' [56]. Balancing (negative) feedback loops slow change and increase the stability or resilience of a system — concepts such as 'echo chambers' [57] or a valley in an 'attractor landscape' [58] reflect balancing loops.

Reinforcing feedback loops and tipping points

Two common reinforcing feedback loops in climate ODMs are endogenous cost reduction effects and social learning effects [4,15,27,30,32,49], which can create rapidly increasing benefits to adopting a technology or behavior as more and more people adopt it. As is displayed in Figure 2a, monetary costs and associated risks often fall as more people adopt a technology, and the lowered costs lead to more adoption by a wider range of people. Greater adoption can also change the behavioral social norm, leading to more positive public opinion and imitation, both of which drive endogenous social change. These reinforcing feedback loops can be jump-started by sustainability policy measures, such as the

Figure 2



Examples of reinforcing and balancing feedback loops included in recent climate ODMs. Green arrows (+) indicate a positive or reinforcing relationship, such that an increase in the first variable leads to an increase in the second variable, similar to a positive correlation in that both variables change in the same direction. Pink arrows (-) indicate a negative or balancing relationship, where an increase in the first variable leads to a decrease in the second variable, similar to a negative correlation in that variables change in opposite directions. R indicates a reinforcing loop and B a balancing loop. Two dashed lines across an arrow indicate a delay in how long it takes for one variable to impact the next one. The relationships between the variables in Figure 2 a,b are described in the text below.

introduction of bike lanes or subsidies for electric vehicles, that reduce costs of adoption for early movers [30,49] and communicate a changing social norm [4,59,60]. When policies are endogenous [4,15,30], these dynamics can be reinforced as people's behaviors and opinions change and they, in turn, demand or accept more stringent policies.

Reinforcing feedbacks can create a tipping point, where a small perturbation can lead to a large and sometimes rapid endogenous change that gives rise to a qualitatively different system state [6,28,59,61]. Tipping points in social behavior are sometimes modeled by a threshold — the number or proportion of others in one's network who must make a decision before a given actor does so — that captures the interdependency among actors' behaviors or opinions [62,63]. For example, in some models, the "committed minority" or "trendsetter" group of early adopters is slow to grow due to initial high costs of a technology or due to social friction of having a unique opinion, which can lead to self-silencing [19,59]. However, at a certain tipping point, the number of adopters is great enough that they have made it significantly less costly for others to adopt through impacting social learning or normative pressures, reducing costs, or returns to scale. Diffusion of adoption now accelerates since the opinion or behavior is not only viewed as more common, but also as morally correct [59]. This suggests that policy interventions aimed at making changes more visible to neighbors are likely to have a greater impact than those that simply encourage more discussions among neighbors [19,60].

Balancing feedback loops and path dependence

Balancing or dampening feedback loops are also common in climate ODMs. For example, social norms can have the reinforcing effect once enough people change, but they can also initially work to maintain the status quo [25,26,59,64]. The perception that most others do not support climate policies or adopt a technology can slow change that might otherwise occur due to increasing climate concerns or decreasing barriers to adoption [19,22,49]. This balancing feedback can persist until a behavior or opinion reaches a critical adoption threshold [19,22,49]. In the context of climate change, widespread underestimation of pro-climate opinions and behavior may thus stifle climate action [19,65].

Balancing feedback loops also exist between the human and climate systems. As is displayed in Figure 2b, adoption of sustainable behaviors will lead to emissions mitigation. This might eventually reduce extreme events along with the public's associated risk perceptions about climate change and thereby decrease their willingness to engage in further mitigation activities [4,6,20,21,25]. Since there is a delay between emissions reductions and impacts on global temperature or extreme events, the balancing effect generally occurs slowly over the course of a model run. However, reduction in risk perceptions may occur more quickly if cognitive processes such as biased assimilation alter how actors process incoming temperature or weather information [4]. Additionally, this balancing loop is often one of several loops within a climate ODM, and the reinforcing feedback loops (e.g. endogenous cost reductions, social learning) that work on a shorter timescale might overcome the effects of this balancing loop.

Path dependency refers to the long-lasting effect of early decisions or choices on subsequent ones, which can also exert a dampening effect on a system. The adoption of some technologies or early policy decisions, such as the type of energy infrastructure or transportation system built, can constrain future options [14,49]. This creates the challenge of identifying ways to overcome existing lock-ins (e.g. as in the case of fossil fuel infrastructure) while also identifying policies and pathways that lock-in 'desirable' behaviors, such as renewable energy or low-carbon transportation options.

What insights do climate opinion dynamics models provide?

Insights about opinion polarization and convergence

ODMs reveal conditions that tend to lead to polarization or extreme opinions. For example, greater homophily often increases opinion polarization [25,39,48]. Interacting with similar others and estimating social norms based on those interactions can create echo chambers leading to a false perception of consensus and reducing the likelihood that actors change opinions or behaviors in the opposite direction [4,25]. At the same time, if actors are somewhat ambiguous about their opinion when interacting with others, then a population that starts off with a heterogenous distribution of climate concern can end up with high climate concern at the population-level, even with homophily [48].

Widely shared external shocks or carefully designed policy levers can mitigate polarization and increase consensus, especially if they occur before polarization or habits are too extreme or fixed [14,26,28]. However, when the impacts of extreme climate events are asymmetric, impacting certain groups more than others, polarization can increase [25].

Once polarization exists, it can limit the influence of climate policies or messaging due to reduced effects on those with extreme opinions [23,24,26]. High polarization can also lead to oscillations in renewable energy investments and emissions as governments attempt to appease opposing factions of the population [14,26]. However, if one party is stronger than the other, that party tends to lead the changes and investments tend to shift in their direction due to technological lock-ins [14].

Insights for climate and policy outcomes

Some climate ODMs have shown that when social influence on opinion is accounted for, policy levers may not need to be as stringent to have the same emissions impact [15,24,30,46]. Weaker climate policies may take longer to make big impacts, but since they often have more public support, they may be worthwhile compared to stringent policies that can sharply alter behavior but often result in public backlash [46]. However, when social influence is weak and there is strong homophily, actors may resist and delay climate policy for longer, leading to substantial global temperature warming [4].

Models that account for heterogeneity in climate impacts, for example as a function of wealth, can lead more affected groups (e.g. the poor) to adopt mitigation efforts earlier than the rest of the population [25]. If groups that are more affected interact with those less affected, social influence can lead those less impacted (e.g. the rich) to also adopt mitigation behaviors.

Interpreting insights from complex adaptive systems

While much social science research assesses relationships between variables at a single point in time or over short time horizons, often to infer causal relationships, ODMs are complex adaptive systems that model the evolution of cross-level interactions over longer time frames. They thus reveal different relationships and patterns that are not easily discernible from common methods in the behavioral sciences such as lab experiments or surveys. For example, introducing 'leaders' with greater social influence does not automatically speed up shifts of public opinion since leaders in two opposing opinion groups can slow change as they persuasively push in different directions [18]. Similarly, when some nations are more influential than others in a climate negotiation model, the ideal negotiation strategy changes, and being an early mover who holds their climate position is not as effective as when all nations are equally influential [17].

While these models may not be ideal for isolating causal relations between two variables, they can identify feedback loops, influential factors, and key leverage points for an outcome of interest (e.g. global carbon emissions), including the role of social influence and norms [4,6,21,22,32] or the speed and stringency with which governments enact climate policy [4,15,24,26]. Indeed, these types of insights — how cross-level factors interact to bring about or stifle climate action — are one pathway toward an embedded behavioral science that links individual and institutional level inputs to understand both the system dynamics and the overall effects on outcomes at different levels.

Future directions

There are some gaps in existing models that can inform directions for future research. First, future climate models could account for individual and social heterogeneity by extending existing climate ODMs to include the evolution of social power [66] and the integration of a wider range of network topologies [37,67]. In many of the models reviewed, the climate system is an external or exogenous input to the model. Building on recent examples [4,20,22,25], efforts to endogenize climatic responses by coupling human system models to simplified climate models is an important path forward for understanding the bidirectional interactions between group dynamics, including political and other interest groups, and the changing climate. These coupled models could also elucidate the effectiveness of different policy measures in altering emissions trajectories, including the sequence and packaging of policies to increase bipartisan support and buy in. By taking a systems-of-systems approach, climate ODMs can expand to purposefully include key feedbacks between societal levels and the climate (see Figure 1) to integrate disconnected disciplinary knowledge and offer new system understandings and insights [68].

Additionally, climate ODMs could be psychologically and socially enriched through more iterative collaboration between computational modelers and behavioral scientists [6,61,69]. In particular, while many ODMs share features such as risk preferences, social influence, and/or homophily, they vary in how these concepts are operationalized, which can lead to very different model outcomes [70,71]. For example, the decision to base social norms on the population average can slow change and promote consensus [19,22], while instead utilizing local or subgroup norms can lead to polarization or echo chambers [24,25,39,47].

One guide to these decisions is empirical data. Some climate ODMs utilize public opinion data sets [4,48] or collect their own survey data [15,16] to initialize or parameterize models. However, these data do not cover all aspects of the models, and there is limited longitudinal data needed to understand changes over time. Incorporation of longitudinal, social media, or even AI-generated data could result in new, custom data sets to inform models in more nuanced ways. The methods to incorporate such data into creating credible synthetic populations have been advancing [72–74], and climate ODMs will benefit from expanding in this way. It is also important to keep in mind that model results that depart from empirical findings could indicate that a range of outcomes beyond our current experiences are possible in complex adaptive systems [69].

When data are not available, researchers may consider modeling the same concept in different, theoretically informed ways to understand how much variance in the model outcomes depends on the modeling decisions, similar to parameter sensitivity analyses [36,70]. These variations on model components or modules could be stored in an open-access code bank, available to researchers, and could undergo a process of peer review by domain experts.

Overall, climate ODMs are particularly beneficial in that they (1) account for complex, multilevel interactions relevant to climate change; (2) analyze changes in public opinion and other outcomes over long time horizons; (3) allow for comparisons in outcomes between different scenarios and social conditions; and (4) allow behavioral scientists to understand the interdependence among actors and the broader structures and systems in which they are embedded. As they develop, they will continue to offer more insights to inform climate policy, messaging and communications, and strategies for introducing new technologies that promote social change toward sustainability.

Data Availability

No data were used for the research described in the article.

Declaration of Competing Interest

There is no financial/personal interest or belief that could affect our objectivity.

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