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The power of bridging decision scales: Model coupling for advanced climate policy analysis

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Climate policy faces increasingly complex challenges that span multiple human decision scales in nature–society systems. Contemporary climate policy models, while valuable and increasingly versatile in handling spatial and temporal scales, struggle to capture interacting multiscale decisions on the socioeconomic side. This perspective draws attention to the power of coupling among different modeling families, taking integrated assessment models (IAM), computable general equilibrium models (CGE), and agent-based models (ABM) as examples. Recent computational advances, maturity of models, availability of data, and interdisciplinary expertise make model coupling an increasingly feasible, effective, and useful tool for climate policy analysis. We examine the unique contributions of each modeling approach, highlight synergies from uniting their strengths, and discuss alternatives to and conditions for coupling. In addressing methodological challenges, we present examples of effective coupling of IAM–ABM–CGE, emphasizing the importance of maintaining model integrity while enhancing policy relevance. By bridging human decision scales and leveraging complementary strengths, coupled models can provide nuanced insights into climate–economy interactions, ultimately supporting effective and equitable—not just efficient and optimal—climate policies.

IAM CGE ABM | behavior | mitigation | adaptation | finance

Losses and damages from climate change intensify, while the implementation of climate mitigation goals repeatedly falls short of its targets. This leads to new challenges for climate policy* (Box 1) that must increasingly consider various decision-makers whose beliefs, preferences, and actions create externalities and facilitate or hinder policy implementation at different scales in society. For example, changes in individual behavior and social norms are critical to the acceptability of ambitious global mitigation goals and their implementation at the national level. Changing individual choices drive shifts in consumption patterns, cascading through markets and financial systems at the macro level. The resulting economic impacts influence the capacities of nations and individuals to fund climate policy and shape inequalities, creating feedback loops between micro, meso, and macro decision scales.

Neglecting links between decision scales—i.e., different levels in socioeconomic systems at which individuals, businesses, communities, cities, regions, sectors, nations, and international groups make decisions that shape socioeconomic and environmental outcomes—hinders effective climate policies. The choice of a decision scale in nature–society models is contested, demanding improved representations of human behavior and social institutions (1, 2), especially in climate policy models (3–6). In essence, this concerns the fundamental aggregation problem in social sciences aspiring to understand the interplay between micro behaviors and macro outcomes. Solutions range from a representative agent in economics to the "Coleman boat" in sociology (7, 8). Each micro, meso, and macro decision scale might accommodate alternative theoretical and empirical foundations of decision processes. Notably, the same decision scale often spans a variety of spatial and temporal scales, adding the third dimension to the conventional discussion on scaling in nature–society systems (9, 10). For instance, a government action leading to short-term effects for a specific neighborhood or defining global climate until 2100 might rely on the same decision processes that balance costs and benefits, affordability, and acceptability.

Despite this recognition, our understanding of cross-scale interactions between climate and society remains limited due

*Unless specified differently, "climate policy" throughout the article means both climate change mitigation (i.e., reduction of CO_2 emissions) and adaptation (i.e., reduction of current or future adverse effects from climate-induced hazards).

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to analyses focusing on single decision scales while downplaying others. Among diverse models of nature–society systems (11), three modeling families stand out in the domain of climate policy analysis: Integrated assessment models (IAM), computable general equilibrium models (CGE), and agent-based models (ABM). Each approach has been designed to address distinct questions, thereby featuring unique strengths (Figs. 1–3) and limitations (*SI Appendix*, Table S1). IAM study systemic global climate–economy interactions focusing on land use and energy sector decisions, while CGE assess cascading effects across multiple sectors and regions. Both top–down models assume "social planners" and representative rational optimizers at their respective decision scales. ABM excel in capturing social institutions and heterogeneous human behavior, enhancing distributional analysis. Yet, high computational costs and context-specific calibration of empirical ABM constrain these bottom–up models to urban, regional, or country geographies. Coupling of IAM, CGE, and ABM can leverage their complementary strengths, offering a new path to gain insights into multiple interacting decision scales unattainable by any single model.

Various communities offer examples of coupling models of nature–society systems (12, 13) Coupling intensity determines how feedback between systems can be investigated—ranging from soft/loose (separate software components with infrequent, one-way exchange) to hard/tight (software wrappers linking two codes, with bidirectional exchange and interdependent outputs) (14, 15). Earth scientists pioneered the coupling of natural processes of water, land, or air models, originally designed for different spatiotemporal scales (13, 16). Food security research demonstrates several coupling examples: biophysical crop models with farm management models and regional/global economic models (17); global food trade CGE with ABM and system dynamics models to trace distant land-use changes via telecoupling (18); and IAM with spatial ABM to study continental-scale food production under climate scenarios (19). However, while linking biophysical, earth system, and land-use models is increasingly common, coupling socioeconomic models operating at different human decision scales, let alone their application to climate policy analysis, is rare.

Harnessing such multiscale insights helps to address open policy questions (Box 1). This perspective suggests that coupling existing modeling approaches—exemplified but not limited to IAM, CGE, and ABM—is an increasingly feasible, effective, and useful tool to address emerging climate policy challenges involving multiple actors across different decision scales in nature–society systems. We provide state-of-the-art examples of coupling different families of socioeconomic models for advanced climate policy analysis and discuss when it is worthwhile. Amid methodological challenges, coupling socioeconomic models across decision scales empowers climate policy analysis and opens new possibilities for exploring complex phenomena that were previously impossible to quantify. We conclude by outlining how the frontiers of such coupled efforts can be further advanced.

Box 1.

Contemporary climate policy challenges demanding multiscale decision analysis:

- Accounting for opinion dynamics, acceptability, lobbying, and political processes in assessing the feasibility and timing of climate policies;
- Identifying (uneven) distributional effects of climate impacts and of climate policies across different geographical regions, government levels, economic sectors, businesses, farmers, or households to enable climate justice and equity analysis;
- Understanding drivers and barriers, socioeconomic tipping points, and speed of low-carbon technology innovation and adoption by households, firms, sectors, regions, and nations;
- Eliciting adaptation constraints (economic, sociocultural, awareness, political barriers) for different actors to quantify adaptation limits, lagged adaptation and levers for socioeconomic tipping;
- Accounting for externalities and entrenched interests that resist climate policy interventions and create moral hazard and lock-ins, hindering transitions to alternative development pathways;
- Quantifying (cascading, systemic) climate transition and physical risks[†] for economic/financial systems;
- Assessing macro effects of behavioral change (interventions);
- Evaluating cost-effectiveness of policies involving public and private climate actions;
- Identifying synergies, trade-offs, and crowding-out effects between climate policies;
- Investigating if, how, and when climate impacts and mitigation/adaptation pathways could impose long-term effects on economic growth, collateral fiscal damages, and creditworthiness.

Decision Scales Commonly Represented in Models for Climate Policy Analysis

Among various nature–society models, we focus on those prevalent in climate policy analysis. Importantly, IAM, CGE, and ABM represent distinct research communities with complementary strengths—correspondingly capturing global dynamics, cross-sector cascading effects, and sociobehavioral complexity—spanning multiple decision scales (Figs. 1–3 and *SI Appendix*, Table S1). Each climate policy model puts a spotlight on whose decisions to capture and how to simulate processes regarding human decisions to deliver some form of high-order phenomena as an outcome. While these families share some elements (*SI Appendix*, Fig. S1), each employs distinct spatial and temporal scales as well as theoretical foundations about human behavior and institutions that must be carefully aligned when coupling (*SI Appendix*, *SI.C*). We elaborate on the justification of our choice of models, their assumptions, strengths, and limitations in *SI Appendix*, *SI.A*, offering a brief overview here.

IAM range from process-based (i.e., system dynamics) to optimization models (i.e., partial- or simplified general-equilibrium) (*SI Appendix*, *SI.A* and *SI.D*). They represent interlinked global climate, economy, and energy systems (Fig. 1)

[†]As emerging terms in climate policy, transition and physical climate risks refer to the economic and financial losses imposed by, correspondingly, a transition to low-carbon economy (e.g. loss of value of fossil fuel assets) and damages from climate-indiced hazards (e.g. direct destruction of infrastructure and indirect loses via value adjustments).

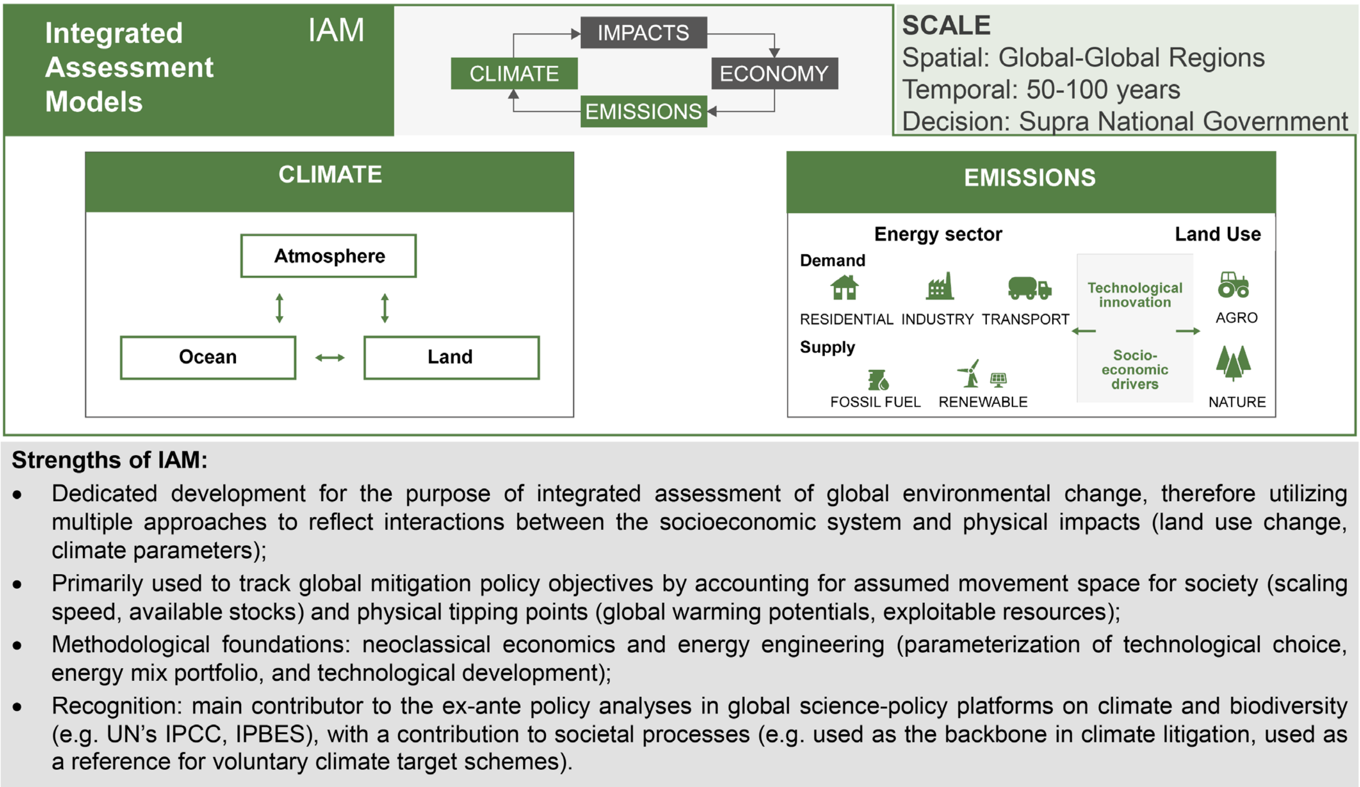

Fig. 1. Key components and strengths of IAM. While they model all four components—Climate, Impacts, Economy, and Emissions—they excel in advanced modeling of Climate and Emissions. See the extended list of IAM conceptual assumptions, data needs, strengths, and weaknesses in *SI Appendix*, Table S1.

to analyze emissions pathways and their cost-effectiveness (*SI Appendix*, Table S1). All IAM focus on aggregate "social planners" (i.e., global, supranational, national) assumed to be representative rational agents who either search for an optimal solution or find an energy mix to satisfy global emissions targets. IAM are a vital foundation for global assessment reports and annual climate negotiations but are criticized for shortcomings (*SI Appendix*, Table S1).

CGE quantify indirect macroeconomic effects cascading across economic sectors, countries, and subnational regions

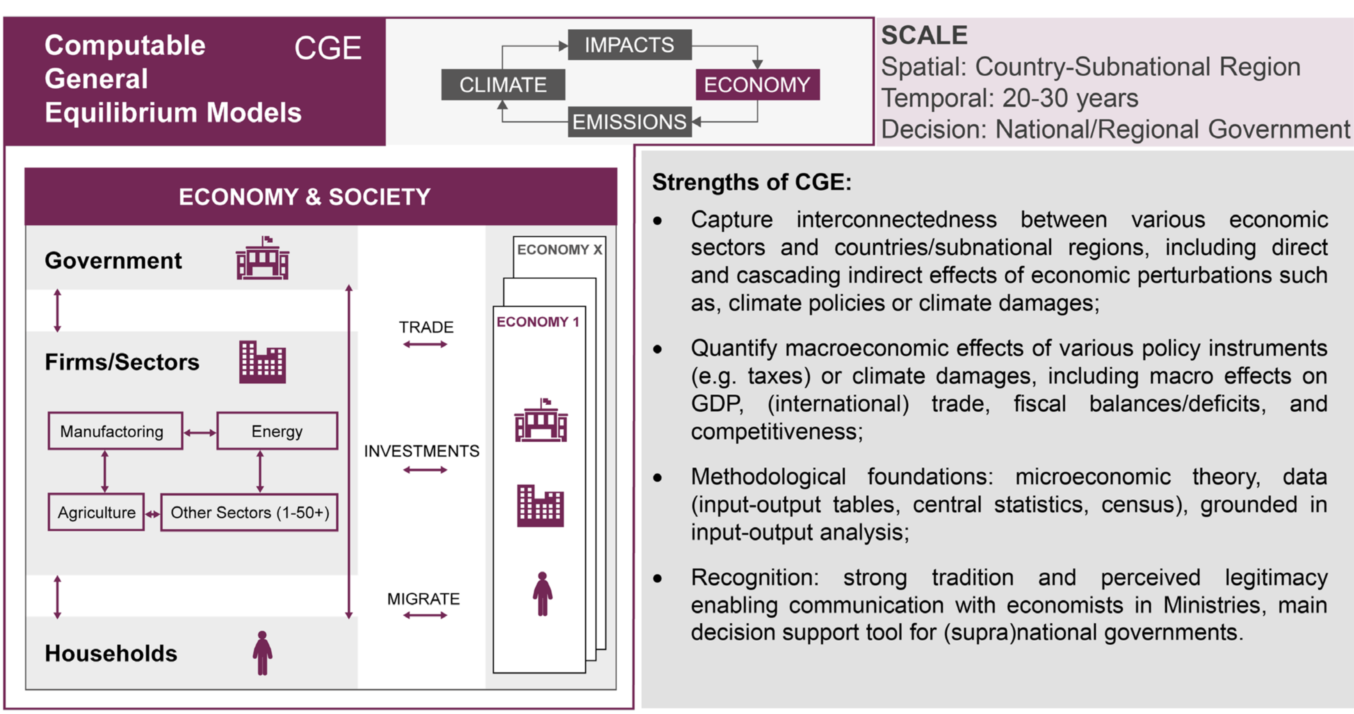

Fig. 2. Key components and strengths of CGE. Climate CGE typically model either Climate–Impacts–Economy link or Economy–Emissions–Climate link, eventually covering all four components. They excel in advanced modeling of Economy and Society. See the extended list of CGE conceptual assumptions, data needs, strengths, and weaknesses in *SI Appendix*, Table S1.

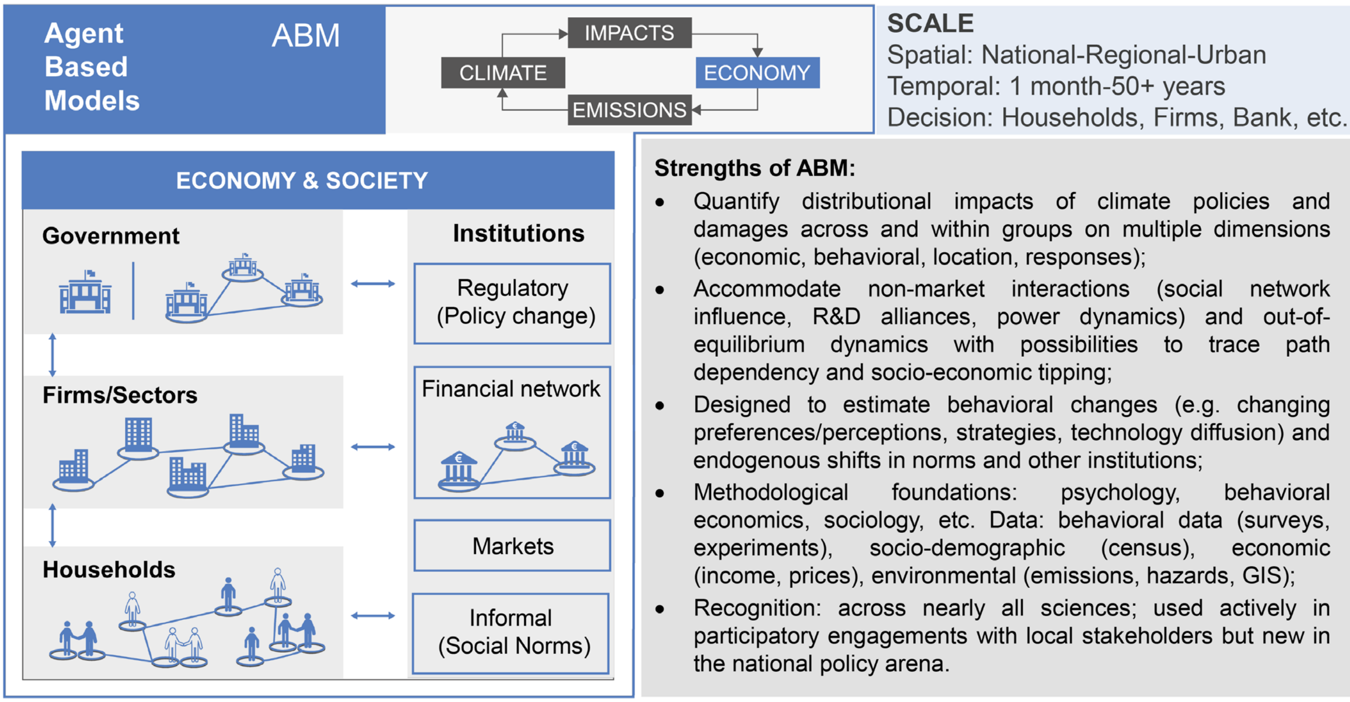

Fig. 3. Key components and strengths of ABM. Climate ABM typically model either Climate–Impacts–Economy link or Economy–Emissions–Climate link, eventually covering all four components. They excel in advanced modeling of Economy and Society. See the extended list of ABM conceptual assumptions, data needs, strengths, and weaknesses in *SI Appendix*, Table S1.

via interconnected markets and trade networks (Fig. 2). This family embraces econometrics and optimization principles, connecting with partial-equilibrium models (*SI Appendix*, Fig. S1 and *SI.D*). Unlike IAM emphasizing energy sector and supranational regions (e.g. EU), CGE simplify the "climate" link to enable detailed intersectoral dynamics across 60+ sectors and regions (e.g., 271 regions in Europe). Their decision scale focuses on the "market responses" of representative (groups of) firms, households, and governments to policy/environmental shocks, grounded in microeconomic theory (*SI Appendix*, *SI.A*). As mainstream economic assessment tools, CGE offer multiple opportunities for climate policy analysis despite shortcomings (*SI Appendix*, Table S1).

Complementary to the top–down IAM and CGE, ABM are bottom–up models that simulate behavioral rules of many heterogeneous agents from governments to individuals (*SI Appendix*, *SI.C* and *SI.D*). ABM embrace a mix of models, from stylized, e.g. grounded in Game Theory, to empirical simulations employing data-driven rules, statistical, and network analysis. Their common purpose is to explore the implications of realistic human behavior by quantifying cumulative impacts of behavioral biases, social interactions, learning, and heterogeneity (Fig. 3). The theoretical assumptions for decision scales ABM draw from psychology, sociology, (behavioral) economics, geography, and policy studies. These models provide insights into distributional impacts, technology or norm diffusion, and socioeconomic tipping, amid methodological challenges (*SI Appendix*, Table S1).

The focus of each modeling family on a specific decision scale limits their ability to answer questions that span multiple decision scales (Box 1). Yet, climate policy analysis increasingly requires joint consideration of behavioral change, agents' heterogeneity, economic and policy feedback loops, cascading and rebounding market effects, and uncertainties necessitating the combination of these complementary approaches. Below, we present several state-of-the-art examples of these developments, focusing on mutual benefits from IAM, CGE, and ABM coupling.

Multiscale Phenomena in Socioeconomic Models for Climate Policy

Examples of Coupling IAM, CGE, and ABM. Today, several coinciding factors create momentum for useful, effective, and feasible coupling of IAM, CGE, and ABM for climate policy analysis.

Example 1: Coupled IAM-ABM to study the financial implications of mitigation policies (Fig. 4*A* and *SI Appendix*, *SI.C1*). Central banks and financial regulators increasingly focus on the financial implications of climate transition risks (20). Traditional IAM and CGE can describe structural transition pathways across economic sectors under climate scenarios but run at temporal scales that are too coarse for financial stability analysis (21). By contrast, ABMs excel at capturing short-term dynamics in financial networks (22, 23). However, they often lack connections to global decarbonization trajectories (24). A soft, one-way coupling approach (25) effectively connects an IAM that simulates global, long-term low-carbon transitions and associated carbon price policies (26) with an ABM capturing detailed financial interactions among heterogeneous households, firms, banks, and policymakers (27, 28). Specifically, global macrolevel mitigation scenarios from IAM inform the ABM, which then quantifies macroeconomic and financial risks—like unemployment, inflation, financial fragility, and public debt—related to those scenarios. This coupling allows policymakers to better assess financial

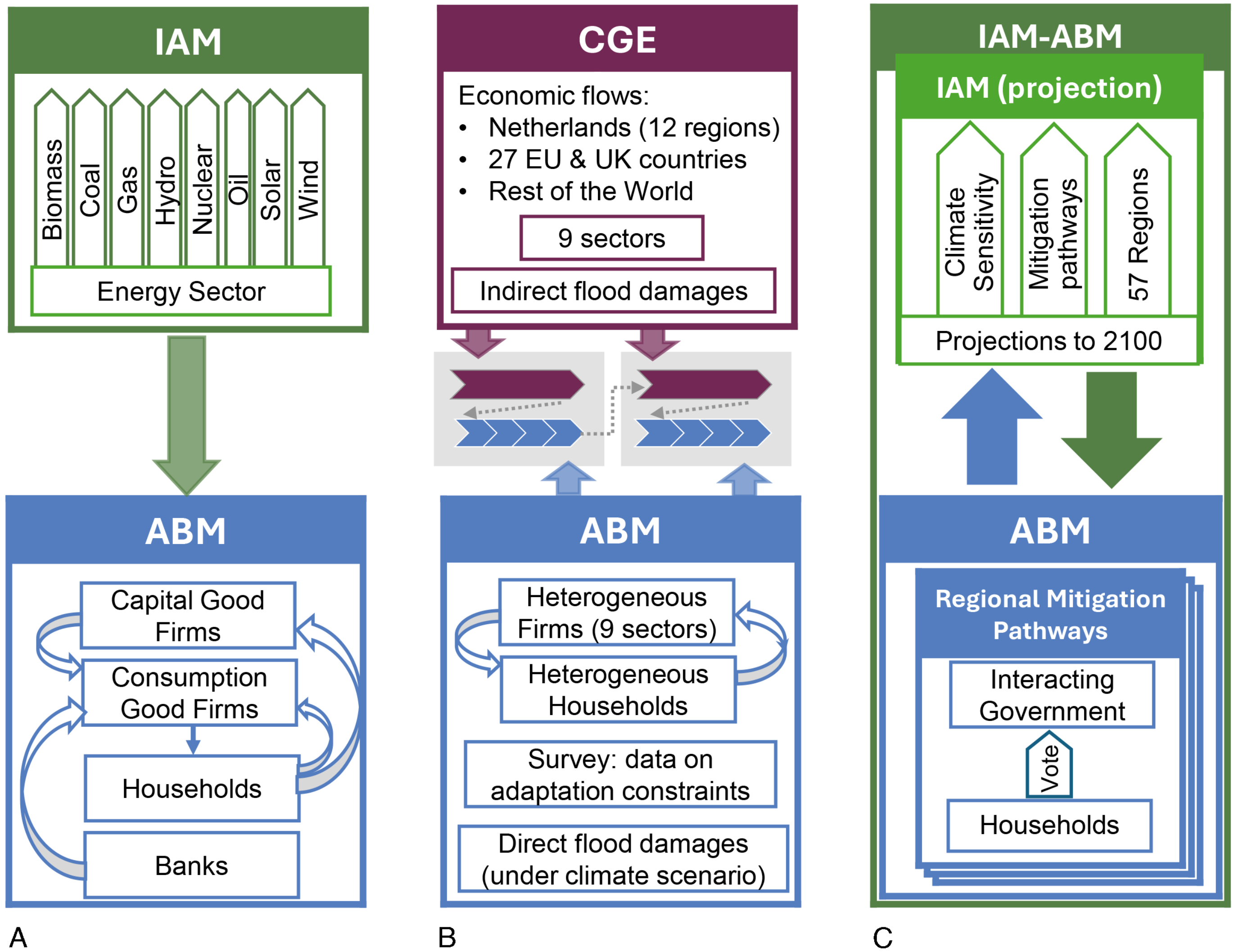

Fig. 4. Coupling different families of models for multiscale climate policies. (*A*) illustrates the coupling of Integrated Assessment and Agent-Based models to study the financial implications of mitigation policies; (*B*) illustrates the coupling of Computable General Equilibrium and Agent-Based models to assess macroeconomic effects of household adaptation behavior. (*C*) illustrates the coupling of Integrated Assessment and Agent-Based models to study the impact of voters and international negotiations on net-zero pledges.

feasibility and manage climate transition risks across actors and short, medium, and long-term scales.

Example 2: Coupled CGE-ABM to assess the macroeconomic effects of household adaptation behavior (Fig. 4*B* and *SI Appendix*, *SI.C2*). Adaptation behavior of individual households is shaped by various adaptation constraints—subjective perceptions, social norms, social networks (29, 30)—hindering its integration in traditional macroeconomic models (31). CGE, while capable of quantifying indirect effects of climate adaptation across economic sectors and regions, often simplify behavioral responses (*SI Appendix*, Table S1). ABM, conversely, provide empirically grounded representations of individual adaptation behavior influenced by social interactions (32). To leverage both strengths, a two-way, hard coupling between spatial CGE representing cross-sectoral and interregional economic flows (33, 34) and ABM simulating heterogeneous household behaviors based on survey data and social psychological principles (35, 36) has been developed. The coupling operates annually, with CGE economic variables constraining household adaptation in ABM. Cumulative household consumption and adaptation investments and experienced climate damages from ABM, then feed back to influence regional economies in CGE. This process explicitly captures how microlevel adaptation constraints propagate into macrolevel economic outcomes, revealing distributional impacts, socioeconomic tipping points, and cost-effectiveness of policy interventions (37).

Example 3: Coupled IAM-ABM to simulate the impact of voters and international negotiations on net zero pledges (Fig. 4*C* and *SI Appendix*, *SI.C3*). Climate mitigation pledges emerge from complex interactions between local voter preferences and international negotiations (38–40). IAM traditionally omit these local sociopolitical dynamics, instead assuming optimal global mitigation pathways guided by representative social planners. In contrast, ABM can capture heterogeneous voter preferences, social influences, and individual behaviors shaping public support for climate actions (4, 41–43), amid lacking the global decision scale IAM offer. To connect these decision scales, a two-way hard-linked coupling of ABM-IAM was implemented, connecting IAM, which encompasses international negotiations and economic impacts across 57 global regions, with an ABM representing local voter heterogeneity

Box 2.

Benefits of coupling socioeconomic models across decision scales:

1. Enhanced policy relevance: Connects micro-level behaviors, meso-level institutions, and macro-level dynamics for more effective climate policy.
2. Improved predictive power: Uncovers emergent cascading impacts, tipping-points, and distributional effects, hidden by single-scale approaches.
3. Strengthened methodological rigor: Combines robust macroeconomic foundations with empirically grounded behavioral realism.
4. Scientific efficiency: Reuse decades-verified modelling and interdisciplinary knowledge, avoiding duplication.
5. Policy design innovation: Enables multiscale instruments targeting behavioral, institutional, and economic barriers simultaneously.

and policy (un)acceptability (43). Household-level voter characteristics—subjective climate risk perceptions and financial constraints—in ABM influence each of the 57 regional governments' positions in global climate negotiations every 5 y. The resulting international agreements then feed back into coupled IAM–ABM, dynamically shaping regional emissions commitments over time. This coupling approach endogenizes political feasibility, explicitly modeling how sociopolitical factors shape and constrain global mitigation pathways, thus capturing potential tipping points in public support and policy implementation feasibility.

Novel Insights Enabled by Coupling IAM, CGE, and ABM. Coupling decisions of actors prominent in IAM, CGE, and ABM offers several benefits (Box 2), including tracing micro-meso-macro decision feedback at the disaggregation level relevant for each policy question. It enables our three coupling examples to deliver novel insights for climate policy.

The first coupled IAM–ABM provides in-depth and behaviorally grounded insights into the transition risks of global mitigation pathways, with particular attention to the critical role of climate financing, and the longer-term macroeconomic impacts of global emission pathways on production, unemployment, inflation, and the public debt in different global regions (*SI Appendix*, *SI.C1*). Bringing finance and monetary policy into the analysis of abatement pathways is a critical component for informing within-country decision-making and global climate negotiations by revealing the financial and monetary consequences of any given abatement pathway and assessing their feasibility.

The second coupled CGE–ABM explicitly traces how private adaptation constraints, which shape household behavior driven by psychological theory and survey data, affect sectors, and macroeconomic performance across temporal and spatial scales. Unlike traditional models with simplified damage and private adaptation decisions, it unites both behavioral heterogeneity and coherent macroeconomic dynamics. This shows how diverse adaptation constraints expose distributional vulnerabilities and enable tipping points in adaptation diffusion locally or nationally. By coupling microlevel decisions over time and across regions, it demonstrates cross-regional and cross-sectoral spillovers on GDP, employment, and welfare, informing more targeted, effective policy interventions' mixes (*SI Appendix*, *SI.C2*).

The third coupled ABM-IAM offers a novel perspective by modeling emission pathways as the endogenous result of the interaction between global climate negotiations and public support that governments across 57 regions receive from voters rather than assuming that a globally optimal mitigation target is acceptable (*SI Appendix*, *SI.C3*). By effectively endogenizing political feasibility into climate–economy modeling, it highlights the role of the mesoscale, where household behavior aggregates into regional dynamics, as a critical friction/lever point. The coupled model enables capturing path dependence and sociopolitical tipping points, improving the feasibility assessment of mitigation pathways, and evaluation of policies based on public communication and engagement interventions.

To Couple, or Not to Couple, That Is the Question. While combining the strengths of IAM, CGE, and ABM could deliver profound benefits (Box 2), it comes with scientific and methodological challenges. All five challenges (*SI Appendix*, *SI.B*) stem from the necessity to avoid treating coupled models as black boxes and instead: 1) ensure conceptual alignment [no "integronsters" (14)] and interpretability; 2) align spatial, temporal, and decision scales; 3) resolve computational issues, like software incompatibility, sensitivity, and uncertainty propagation; 4) ensure thorough calibration and validation; and 5) engage in a constructive dialog across interdisciplinary communities. Trade-offs between these challenges and benefits of coupling could help decide whether coupling is feasible, and when alternatives like "within single modeling family" extensions or reconceptualizing a new nature–society model from scratch (*SI Appendix*, Box S1) are appropriate.

The standard way to handle different decision scales is to extend a single modeling family without revising its assumptions. "Nontypical" features—behavioral change, heterogeneous agents, or macro/policy institutions—are then added incrementally in IAM, CGE, and ABM (*SI Appendix*, *SI.D*). This approach works when time or capacity is limited but is similar to adding a few brushstrokes to a finished painting: only a simplified representation of a new feature is included. Since the original model remains unchanged, its weaknesses (*SI Appendix*, *SI.A*) persist, limiting the desired analysis.

At the opposite extreme is building from scratch a comprehensive new nature–society model capable of addressing diverse climate policy questions. Full reconceptualization discards redundant assumptions and endogenizes mechanisms across multiple decision, spatial, and temporal scales. This "supermodel" idea has been attractive for decades (44) and guided first-generation IAM and system dynamics efforts, like World3 (45). However, a new supermodel requires heavy resource investment and time to gain trust among policymakers, while facing the "complexity curse" (reduced transparency due to too many interacting mechanisms). Inevitably, some features will remain excluded due to knowledge gaps or shifting policy priorities.

Coupling models, like established IAM, CGE, and ABM, offer a pragmatic middle ground, leveraging the trusted strengths of each approach while offsetting limitations (#1-2 in Box 2). Reusing validated models as components is efficient (#3-4 in Box 2) and harnesses the existing trust of policy makers with familiar models used as elements, permitting them to test what was previously unattainable (#5, Box 2) at the cost of addressing associated challenges (*SI Appendix*, *SI.B*).

Trade-offs among the three approaches remain: one can stretch a familiar model beyond its intended scope for partial insights, spend more effort to couple validated models for tailored answers, or create a resource-intensive "supermodel" for the precise alignment with policy questions. Ultimately, the choice—stretching a familiar model, coupling models from different families, or creating a new "supermodel"—depends on the resources (expertise, capacity, funding, time) available and the new features needed to address policy questions. In the meantime, successful experimental coupling is already happening, proving to be a viable complementary alternative.

Future Outlook. The progress in advancing individual models and these first promising examples suggests a path for advancing the frontiers of model coupling.

Frontier 1–Assessing multiscale policy levers. Given their methodological strengths, IAM, CGE, and ABM analyses serve different policymakers and stakeholders, each contributing unique insights. Coupling these models' strengths can help connect (supra)national and regional governments with on-the-ground implementation challenges. Having a macromodel for climate policy analysis that allows testing mixes of behavioral interventions, regulatory, market, and financial policies for steering proenvironmental choices at different decision scales will enable (participatory) codesign of policies with an understanding of human behavior, economy-wide responses, and climate feedback (on impacts, emissions). Such policy mixes could utilize knowledge of how social norms, opinions, and innovations are formed and spread to facilitate, speed up, and upscale climate grassroots action, ultimately contributing to environmental improvements. Multiscale analysis can also identify and quantify potential unintended consequences and spillover effects of climate policies (rebound effect of energy-efficient technologies, increased urbanization in hazard-prone areas following public adaptation). Relying on a single modeling approach often means overlooking crucial dynamics emerging at other scales, resulting in misguided subsidies, unforeseen inequalities, neglecting governance, spatial, and economic implications and material needs on the ground.

Frontier 2–Aligning macro trends with distributional impacts. Coupling different socioeconomic models refines the granularity of climate–economy analysis by matching overall global and national trends and climate targets with specific winners and losers across and within society, sectors, and regions. Understanding the socioeconomic consequences of climate change and policies to individual stakeholders requires both a comprehensive understanding of the overall dynamics at the macro−and mesolevels and a detailed representation of individual actors and their exposures. Model coupling can bridge micro-macro feedback loops among behavior, macroeconomics, emissions, and climate dynamics and allow multiscale policy impact assessment. This approach can align global and national climate goals with local governance, spatial and social considerations, resource requirements, adaptation limits, and financial risks—the factors that often obstruct policy implementation or increase its costs. Moreover, it allows us to track progress toward climate targets, examining the costs for various regions and sectors beyond just GDP, accounting for multidimensional well-being, equity, human behavior, and social processes critical for the implementation of climate policies. The coupling of carefully validated models at different scales enables policymakers to design targeted policies and avoid unintended consequences for stakeholders which are overlooked in models lacking heterogeneity.

Frontier 3–Socioeconomic tipping and transformative climate action. Coupling IAM, CGE, and ABM provides a powerful framework for understanding socioeconomic tipping processes essential for accelerating climate actions. This enables the identification of critical tipping points where individual behavioral change ignites, reaches critical mass, and nonlinearly propagates leading to large-scale socioeconomic and environmental transformations. Current macroclimate–economy models treat technologies and behavior/preference/perception change as universally available, acceptable, and immediately adoptable solutions, provided they are economically viable. It leads to overestimating the climate policy performance. Enhancing these assessments by incorporating realistic diffusion patterns of technologies and behavioral strategies via ABM–CGE/IAM coupling opens unique opportunities to explicitly trace how network effects—trade, financial, knowledge spillovers, and social opinion dynamics—form and lead to positive tipping and accelerated climate actions. It also permits the analysis of negative cascading effects, including the emergence of (systemic) climate transition/physical risks. Recognizing (un)desired socioeconomic tipping points is essential for timely policy interventions, and coupled modeling offers tools for such anticipatory explorations.

Frontier 4–Nexus of climate mitigation and adaptation policies. Quantifying interactions between mitigation–adaptation becomes increasingly important. Yet, these policies work at and across different scales, with various processes only partially captured by individual climate–economy models. Coupled IAM, CGE, and ABM is key to investigating the mitigation–adaptation nexus, in which national- or sector-level mitigation actions can undermine local adaptive capacity or where mitigation efforts in country/region X could reduce adaptation needs in country/region Y. Modeling the mitigation-adaptation nexus will require aligning: i) ABM strengths to represent social interactions among behaviorally diverse actors, technological innovation and diffusion among heterogeneous firms, or climate risk propagation in financial networks; ii) CGE abilities to capture data-driven cross-sector and cross-regional trade-offs and spillovers; and iii) IAM power to consolidate feedback loops between socioeconomic and climate systems. Maintaining these strengths in a coupled modeling system enables the systematic investigation of cross-scale interactions critical to assessing synergies and trade-offs between mitigation and adaptation goals, quantifying transition and physical risks for various economic actors, and supporting more coordinated responses to climate change at local, national, and global scales. IAM, CGE, and ABM coupling can increase the accuracy not only of combined climate policy packages for (inter)national and local decision-makers but also general economic and social policy.

Frontier 5–Methodological advancements. Collaborative efforts across IAM, CGE, and ABM communities not only advance policy development but also expand scientific frontiers, such as improved model granularity while maintaining global coverage. In the context of pushing the methodological boundaries, AI and machine learning will also play a role. They can help accelerate computationally intensive parts of coupled models, and Large Language Models could enhance specific modeling parts, for example, by informing how complex human behaviors and social interactions can be represented (46). However, the fundamental challenges in model coupling remain primarily conceptual in nature, requiring careful conceptual alignment and interpretation of model interactions across different theoretical frameworks. Having this dialog will foster interdisciplinary collaboration and knowledge transfer, resulting in a more holistic understanding of complex socioeconomic feedback mechanisms and improved cross-validation of results at different scales. As with any other interdisciplinary work, constructive dialogs, including joint conference sessions, model intercomparison efforts focused on decision scale representation, and joint research method schools, are instrumental (*SI Appendix*, *SI.B, Challenge 5*).

Conclusions

Contemporary climate policy challenges require assessing impacts and policies across decision scales: from individual behaviors and sector-specific business strategies to regional, national, and global consequences for the economy, society, and the environment, and back from macro to micro. Coupling existing modeling approaches—exemplified but not limited to IAM, CGE, and ABM—is an increasingly feasible, effective, and useful tool to address these challenges. By leveraging their respective strengths to offset limitations, coupling these models allows for exploring novel policy and research questions regarding complex phenomena that were previously impossible to quantify. It makes the dialog between these modeling communities timely. Furthermore, recent computational advances, data availability, the maturity of models, and interdisciplinary expertise create momentum for model coupling, providing a nuanced, multidimensional understanding of climate policies. We advocate for model coupling whenever the benefits of enriched policy analysis spanning different decision scales outweigh the resource investments to manage associated complexities. While science has progressed in addressing the challenges of IAM–CGE–ABM coupling (*SI Appendix*, *SI.B*), some considerations remain. To avoid reinventing the wheel, the coupling should enable different models to deploy their respective strengths, promoting synergies of their complementarities rather than reproducing overlaps. With progress in handling challenges, the benefits of model coupling tailored to specific policy questions (rather than all-purpose generic coupling) make it an attractive alternative to within-model extensions or new modeling from scratch. While model coupling is common in the natural sciences, efforts to link socioeconomic models are only now emerging. Our article advocates for strengthening these connections to support the development of coherent, economically efficient, effective, and equitable climate strategies through improved cross-scale analysis, ultimately leading to more acceptable and implementable policies.

Data, Materials, and Software Availability. This Perspective article does not report new data. All the information is already included in the article main text and/or *SI Appendix*.

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