ANNUAL REVIEWS

Annual Review of Resource Economics

The Evolution of Integrated Assessment: Developing the Next Generation of Use-Inspired Integrated Assessment Tools

Karen Fisher-Vanden[1] and John Weyant[2]

[1]Department of Agricultural Economics, Sociology, and Education, Pennsylvania State University, University Park, Pennsylvania 16802, USA; email: Kaf26@psu.edu

[2]Department of Management Science and Engineering, Stanford University, Stanford, California 94305, USA; email: Weyant@stanford.edu

Annu. Rev. Resour. Econ. 2020. 12:471–87

First published as a Review in Advance on July 7, 2020

The *Annual Review of Resource Economics* is online at resource.annualreviews.org

https://doi.org/10.1146/annurev-resource-110119-030314

JEL code: Q0

Keywords

integrated assessment, climate change

Abstract

In this review, we attempt to describe the evolution of integrated assessment modeling research since the pioneering work of William Nordhaus in 1994, highlighting a number of challenges and suggestions for moving the field forward. The field has evolved from global aggregate models focused on cost-benefit analysis to detailed process models used to generate emissions scenarios and to coupled model frameworks for impact analyses. The increased demand for higher sectoral, temporal, and spatial resolution to conduct impact analyses has led to a number of challenges both computationally and conceptually. Overcoming these challenges and moving the field forward will require not only greater efforts in model coupling software and translational tools, the incorporation of empirical findings into integrated assessment models, and intermethod comparisons but also the expansion and better coordination of multidisciplinary researchers in this field through better training of the next generation of integrated assessment scholars and expanding the community of practice.

1. INTRODUCTION

The pioneering work in integrated assessment (IA) of climate change, led by William Nordhaus (e.g., Nordhaus 1994), who was awarded the 2018 Nobel Memorial Prize in Economic Sciences for this work, was motivated by the need to develop cost-benefit tools for global mitigation policy analysis. As a result, integrated assessment models (IAMs) were global, had coarse spatial and sectoral resolution, and included feedbacks between the human and earth systems.[1] With the lack of serious mitigation efforts to address climate change and the exit of the United States from the Paris Agreement in 2017, national attention has moved away from mitigation policy assessment to improving our understanding of impacts. The usefulness of IA tools and interconnected systems thinking associated with these tools quickly became apparent to the impact, adaptation, and vulnerability (IAV) community and an array of funding agencies concerned about climate change impacts.

However, the usefulness of these tools for impact analysis is limited without improvements to account for finer spatial scale and process detail, features that were unnecessary in the earlier IAM mitigation policy work. Addressing these limitations was the focus of a US federal interagency working group workshop in 2016 held under the auspices of US Global Change Research Program (Moss et al. 2016). The workshop also emphasized the shift to "use case" framing as opposed to directly serving the needs of more narrow region and sector specific practitioners. In other words, rather than developing tools to address impacts in a certain specific sector and region, the focus has shifted to developing generalizable frameworks for specific types of problems.

Owing to the high computational demands and data-intensive work required to estimate climate change impacts, past impact studies were usually sector specific and regionally focused [e.g., Houser et al. 2015, EPA 2017, Ciscar et al. 2014; Climate Impact Lab (**http://www.impactlab.org**)]. As a result, important interactions across impacts, sectors, and regions were missed. For instance, the spatial heterogeneity of where water shortages are occurring and the competing demands for water across sectors and regions can exacerbate impacts on an individual sector and would be missed in a study that focuses on a single sector and location.

Impact studies typically fall into two categories, statistical studies and process model studies, with most studies focused on the agricultural sector (for a comparison of methods used for agricultural impact analyses, see Ciscar et al. 2018). Calvin & Fisher-Vanden (2017) show that accounting for feedbacks by incorporating statistical emulators of climate change impacts on agricultural yields into an IAM can result in yield impacts that are 20–40% higher than the yield impacts generated by process-based or statistical crop models alone.

The growing recognition that these feedbacks are important for impact analysis and the accelerated improvements in data, algorithms, and computational power that have limited climate impacts work in the past have led to the emergence of a new field that is focused on the development of tools for integrated impacts analysis. The US Department of Energy's Office of Science, for example, has coined this emerging field multisector dynamics (MSD), which they define as follows:

> Multisector dynamics seeks to advance scientific understanding of the complex interactions, interdependencies, and coevolutionary pathways of human and natural systems, including interdependencies among sectors and infrastructures. This includes advancing relevant socio-economic, risk analysis, and

[1]Highly aggregated physical process-oriented IAMs have been developed since the early 1990s as well (cf. Rotmans 1990). These models produced projections of the physical impacts of climate change at a highly aggregated level, but unlike the Nordhaus (1994) contributions, they did not attempt to value these impacts with economic metrics. Both classes of early IAMs helped significantly shape the debate about desirable global greenhouse gas (GHG) emissions pathways but were difficult for stakeholders to use in developing specific policies and measures that they could or should implement in the short run in their individual jurisdictions.

complex decision theory methods to lead insights into earth system science, while emphasizing the development of interoperable data, modeling, and analysis tools for integration within flexible modeling frameworks. (US DOE 2020)

In contrast, the Integrated Assessment Society defines IA as follows:

> Integrated assessment (IA) can be defined as the scientific "meta-discipline" that integrates knowledge about a problem domain and makes it available for societal learning and decision making processes. Public policy issues involving long-range and long-term environmental management are where the roots of integrated assessment can be found. However, today, IA is used to frame, study and solve issues at other scales. IA has been developed for acid rain, climate change, land degradation, water and air quality management, forest and fisheries management and public health. The field of Integrated Assessment engages stakeholders and scientists, often drawing these from many disciplines. (**https://www.tias-web.info/integrated-assessment/**)

In general, the emphasis on descriptive rather than prescriptive work can be a useful way to distinguish MSD from IA, although both can utilize similar tools. In addition, IA typically utilizes single, large, global models, while MSD emphasizes the coupling of process models.

In this review, we trace how the definition of IA modeling has changed over time (Section 2) and provide a short history of its evolution (Section 3). This is followed by a description of a new generation of IA tools focused on IAV (Section 4) and a discussion of the challenges faced by these new models (Section 5). Lastly, we present some ways forward, including the innovations needed to develop the next generation of use-inspired IA tools.

2. WHAT IS INTEGRATED ASSESSMENT MODELING?

In this review, we are focused on climate change IA, although IA has been used to describe integrated work in many contexts, e.g., acid rain (Alcamo et al. 1990) and air quality (Muller & Mendelsohn 2007). Since the term integrated assessment modeling in the climate change context was used to describe the pioneering work of Nordhaus (Nordhaus 1994), there have been a number of articles written over the years attempting to define what IA modeling actually is. Some of the early attempts to define IA include Weyant et al. (1996, p. 371), who described IAMs as computational tools that "link an array of component models based on mathematical representations of information from the various contributing disciplines," Parson & Fisher-Vanden (1997, p. 589), who defined IAMs as tools that "seek to combine knowledge from multiple disciplines in formal integrated representations; inform policy-making, structure knowledge, and prioritize key uncertainties; and advance knowledge of broad system linkages and feedbacks, particularly between socioeconomic and biophysical processes." The focus of IA has expanded over time to reflect a new emphasis on interactions across scales—spatial, temporal and sectoral. Expanding the definition of IA to incorporate this new focus, IAMs are tools that capture the complex interactions and interdependencies across the natural and human systems and across spatial and temporal scales for a wide range of uses, including improving the science of fine-scale impact analysis, multi-stakeholder policy making, and the development of adaptation strategies.

Diagrams depicting the cross-system interactions, typically referred to as wiring diagrams, have also evolved as the complexity of the interactions represented in IAMs has grown over time. **Figure 1**, from the 1995 Intergovernmental Panel on Climate Change (IPCC) Second Assessment Report (Weyant et al. 1996), shows the original end-to-end wiring diagram used to characterize IAMs in the early years, while **Figure 2**, from the recent 2018 US Fourth National Assessment Report (Clarke et al. 2018), shows a much more complex web of interactions.

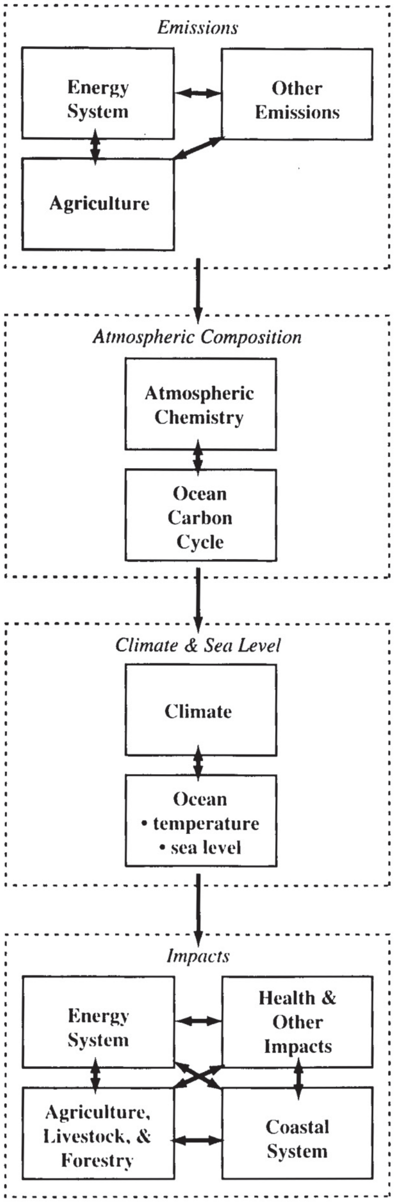

Figure 1

The end-to-end characterization of integrated assessment models (IAMs). Reproduced from Weyant et al. (1996).

Changes in what defines IA have reflected the evolution in the use of IA over time. Early IA work was primarily done to inform international climate negotiations. The DICE (Dynamic Integrated Climate and Economy) model developed by Nordhaus (e.g., Nordhaus 1994) is a stylized model developed to determine the optimal climate mitigation policy trading off abatement costs and climate change damages. These types of IAM have been referred to as benefit-cost IA models

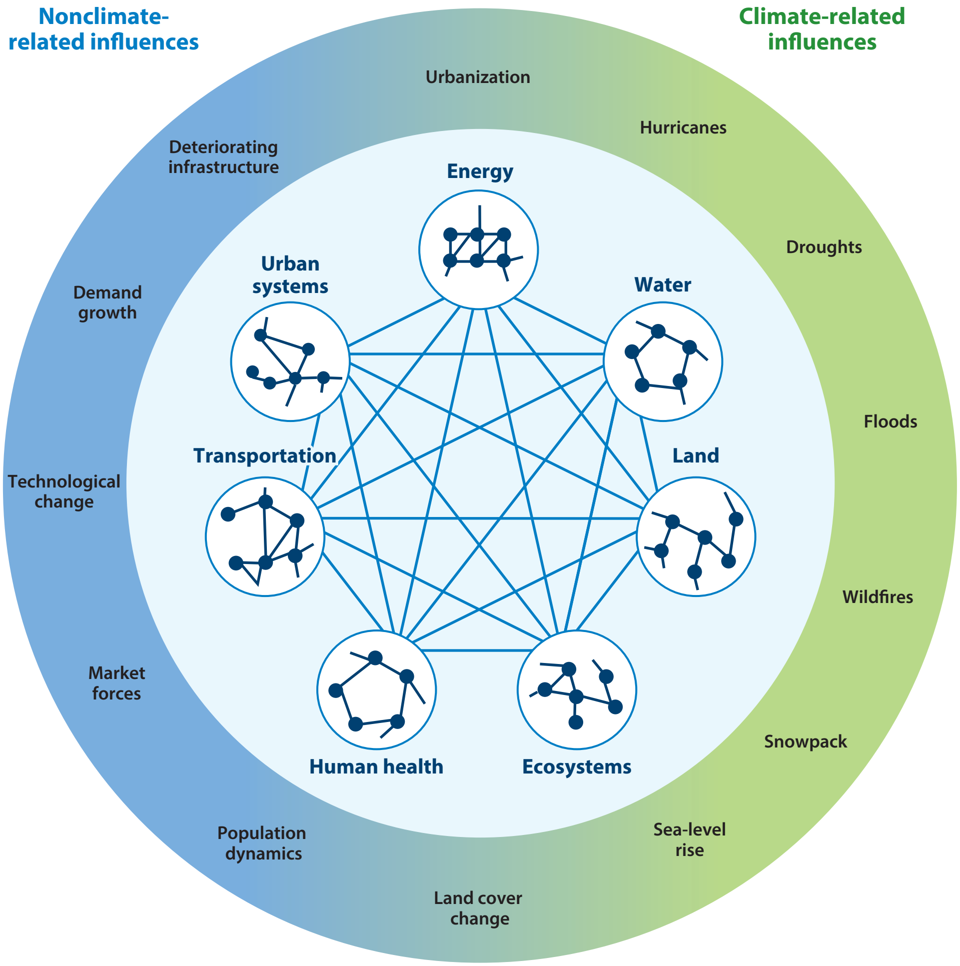

Figure 2

Complex sectoral interactions. Adapted with permission from Clarke et al. (2018).

because they capture not only the effects of changes in climate on the economy but also the feedback of socioeconomic activity on the climate through emissions. These differ from more detailed process-based models that were also used to inform climate policy through the generation of alternative emissions scenarios. A handful of these models also estimated physical climate impacts at a more disaggregated level without generally assigning economic values to them, recognizing that (*a*) there were neither the data nor the understanding required to value those impacts at the appropriate finer scales and (*b*) the aggregate damage assessments were generally not meaningful to decision makers; that is, for decision makers in a particular sector or region (including model regions that aggregate many whole countries together) they found it difficult to use modeling results that do not include specific information about their region or country.[2] Moreover, without this information these decision makers had reason to question whether the aggregations were done in a fair and reasonable manner. Unlike the benefit-cost models that were global in scope,

[2]For an interesting perspective on this, see Dasgupta (1997).

were coarse in spatial, temporal, and sectoral scale, and included reduced form representations of the biophysical and economic processes, these models (referred to as detailed process models in Weyant 2017) have more detailed representations of the underlying socioeconomic processes generating GHG emissions. However, these models generally focused on the physical impacts of changes in climate without assessing market impacts or imputing additional nonmarket global welfare losses on attributable to those physical system changes (IPCC 2001, 2007, 2014).[3]

These models took different paths as uses changed over time. In the United States, with the shift in focus away from mitigation policy analysis to climate change impact analysis, benefit-cost models have been used to estimate the social cost of carbon, a measure of the economic cost from a unit change in emissions (e.g., ton of carbon). The US Interagency Working Group on Social Cost of Carbon developed estimates of the social cost of carbon using output from three stylized aggregate benefit-cost IAMs: DICE, PAGE (Policy Analysis of the Greenhouse Effect) (Hope 2006), and FUND (Climate Framework for Uncertainty, Negotiation, and Distribution) (Tol 2002). The social cost of carbon estimates from these models varies significantly depending on whether extreme events or adaptation are considered. Assumptions about damages in these models were the subject of a key criticism made by Pindyck in his critique of IAMs, where he concludes that IAMs "have crucial flaws that make them close to useless as tools for policy analysis" (Pindyck 2013, p. 860; 2017, p. 100).

In addition to missing the contributions of the benefit-cost IAMs described earlier, Pindyck's critique also highlights an ongoing problem that has plagued the broader IAM community for many years; i.e., many wrongly assume that IAM refers only to these three stylized aggregate IAMs used in the social cost of carbon analyses that are designed to find global emissions trajectories that balance marginal costs and benefits. This oversight ignores the growing number of models and modeling frameworks that have been developed to address many of the issues that Pindyck raises. The detailed process IAMs discussed above capture the detailed underlying socioeconomic and technological processes that are one source of Pindyck's complaints regarding arbitrary model inputs without theoretical basis. However, as discussed above, these detailed process IAMs typically lack economic interactions and feedbacks to the climate system that would allow for the incorporation of climate damages into the socioeconomic system. This problem has been exacerbated by the use of the term climate economics to only describe economic research and modeling done at the level of the three aggregate benefit-cost models (e.g., Burke et al. 2016a,b), which ignores recent breakthroughs in economics research to couple socioeconomic concepts and modeling with earth systems concepts and modeling elements (cf. Diffenbaugh et al. 2012, Reilly et al. 2012, Hejazi et al. 2014, Grogan et al. 2015, Kraucunas et al. 2015, Zaveri et al. 2016; for a representative recent set of publications on this subject see US DOE 2020). This recent work, again, addresses a significant number, but not all, of the criticisms in the Pindyck critique.

At the same time, it is sometimes alleged that these detailed process IAMs were initially designed to look only at GHG mitigation policies (Schellnhuber et al. 2014), but such assertions fundamentally misunderstand their origin. As is reported in Weyant et al. (1996) and Parson & Fisher-Vanden (1997), this has clearly not been the case since the early 1990s. It is true that the period from the early 1990s to about 2010 saw more mitigation-focused analyses, also sometimes referred to as cost-effectiveness analyses (i.e., analyses focused on minimizing the costs to achieve specific GHG emissions targets or GHG concentration targets). It is demonstrably not true, however, that the detailed process IAM groups working on assessing climate change impacts in 1995

[3] See Weyant (2017) for a comprehensive description of these different model types and how they have been used.

did not already have important insights to offer and have continued to develop those capabilities over the last 25 years.

Another unfortunate consequence of Pindyck's IAM critique is that it precludes appreciating some important current and possible future synergies between benefit-cost IAMs and detailed process IAMs. research. First, the aggregate GHG mitigation cost curves embedded in the benefit-cost IAMs are generally calibrated (formally or informally) to the mitigation results from the detailed process IAMs. Second, the aggregate global damage functions in the benefit-cost IAMs are constructed by combining individual region and sector damage functions. This might lead to a useful aggregate approximation of global damages if the combined physical and socioeconomic system was in equilibrium and changes were small enough to safely ignore the interactions and feedbacks between sectors and regions that the detailed process IAM research has shown can be critically important. Such information from detailed process IAMs could ultimately be used to refine damage functions in the benefit-cost IAMs. Finally, sensitivity analyses using benefit-cost IAMs could be used to identify high-priority areas for further detailed process IAM research and provide boundary conditions for more complex regional and sectoral studies.

3. THE EVOLVING AND WIDENING USE OF INTEGRATED ASSESSMENT TOOLS

Over the last five to ten years or so there has been a marked shift in the types of questions that IAMs are being employed to answer: from providing information on long-run trends in energy and land systems under alternative socioeconomic and policy scenarios to information on shorter-run alternative socioeconomic futures for evaluating actionable policy and regulatory options. IAMs continue to play an important role in analyzing longer-run objectives such as identifying emissions trajectories that are consistent with limiting increases in global mean temperature. However, over the last decade there has been a tremendous increase in the demand for shorter-run analyses, e.g., analyses that are more directly useful to those making decisions on mitigation and adaptation policy. This shift has been motivated by an increase in both concern about climate change impacts in the short run and in the level of detail that the models can consider due to improvements in data availability, fine-scale systems understanding, and computational capabilities.

Prior to about 2006, most IAM research was focused on long-run analyses that sought to project long-run steady state transitions of the coupled human–earth system over a 50- to 100-year time frame. Such assessments were usually based on results from individual models, groups of models, or model components. Although these analyses had fairly coarse temporal and spatial resolutions (e.g., 5- or 10-year time steps and a limited number of aggregated world regions), these models provided many useful insights into the range of long-run futures that can be expected under alternative policy regimes. These models were able to provide shorter-term results for highly aggregated regions, but those results were often inconsistent with actual emerging trends and not at a scale that was meaningful for many users.

Despite increasingly urgent calls for action to address climate change in successive assessments by the IPCC (2001, 2007), up until the mid- to late 2000s, developing countries generally viewed climate change as primarily a developed country problem and therefore expressed little interest in mitigation studies. The lack of developing country interest in impact studies was partly driven by the belief that moving forward with strategies to adapt to these changes would be giving up on the argument that developed nations should be compensating developing countries for these damages.

By 2007, as the impacts of climate change became more visible and developing countries were increasingly being asked to accept payments from developed countries to reduce emissions on their behalf, developing countries (as defined by the member nations of the World Bank) reversed direction and requested that the major annual report of the World Bank (2010) be focused exclusively on opportunities for climate change mitigation and adaptation in their countries. This significantly increased the focus of analyses on the shorter-term impacts of climate change on human activities, especially those likely to be experienced by vulnerable populations in low-income countries.

The IPCC's Fifth Assessment Report (IPCC 2014) continued to stress the increasing risk to human systems caused by weather extremes and concluded that climate change was increasingly exacerbating the physical and economic impacts in the most vulnerable regions and sectors. At the same time, the most important objective of planners in these same countries was to promote sustainable economic growth and prosperity. The end of 2015 marked a turning point in this progression with the adoption of 17 specific 2030 Sustainable Development Goals at the UN Sustainable Development Summit in New York in September 2015 (**https://www.un.org/millenniumgoals**). Subsequently, the agreement at the December 2015 annual climate negotiation meeting in Paris (UNFCCC 2015) set a long-term target for the increase in global mean temperature to no more than 2°C relative to preindustrial levels, and for each country to make a voluntary nationally determined contribution (NDC) to reduce GHG emissions by 2025. This NDC requirement dramatically increased the level of interest in shorter-term climate change and mitigation projections.

The Paris Accord also required countries to report actual emissions periodically through a process known as pledge and review. This allows progress toward pledges to be monitored and commitments to be added if the total emissions reduction target looks like it will not be met. These requirements increased the demand for modeling assessments of country-specific mitigation policies. In addition, there has been a related parallel increase in demands on the IA community to provide concomitant information on the nonclimate change–related metrics highlighted in the UN Sustainable Development Goals, especially those related to air quality, water availability and quality, food security, and income distribution.

This change in emphasis has created challenges for both benefit-cost and detailed process IAMs. For the more highly aggregated benefit-cost IAMs, it has led to requests for higher-resolution damage functions and mitigation cost curves. Similarly, for the detailed process IAMs it has resulted in a desire to not only produce more highly resolved information but also to develop highly resolved information on interactions and feedbacks between sectors (e.g., energy, water, land, agriculture). Requests for this type of information have occurred for three reasons: (*a*) impact and adaptation managers in individual sectors have observed that their biggest challenges are frequently related to simultaneous changes in multiple sectors; (*b*) trade (especially in food and water) either eases or exacerbates the multisector challenges these managers face; and (*c*) important linkages between mitigation and adaptation strategies exist that require modeling approaches that capture these interactions.

This trend toward desiring increasingly more detailed information from IAs pushes the emphasis in model development toward including even more detail in detailed process IAMs and leads to a realignment of the relative roles of the benefit-cost and detailed process model types. The detailed process IAMs have been asked to either provide more detailed and integrated information directly by including critical physical and economic processes at more detailed and integrated levels, or to help the IAV community understand and evaluate these linkages through the development of new IAM-oriented MSD modeling tools (e.g., US DOE 2020). Despite these trends, the original benefit-cost and detailed process IAMs will continue to play important roles in assessing progress toward long-term climate change objectives through the adoption of specific short-run policies and measures and providing boundary conditions for specific region- and sector-focused studies.

4. THE NEXT GENERATION OF INTEGRATED ASSESSMENT TOOLS: IMPACT, ADAPTATION, AND VULNERABILITY INTEGRATED ASSESSMENT MODELS

The trends described in the previous section have given rise to a new category of IAMs, which we refer to as IAV IAMs. Unlike the benefit-cost and detailed process IAMs that typically consist of a single model with reduced-form representations of socioeconomic and biophysical processes included, IAV IAMs are better described as frameworks of coupled detailed system models. The need for IAV–IA modeling frameworks has been highlighted in several recent reports and articles (e.g., Moss et al. 2016, Kling et al. 2017). The detailed structural relationships, uncertainty, and underlying data missing in the damage functions of the benefit-cost IAMs used in the social cost of carbon studies that were the target of Pindyck's critique can be largely found in the growing number of statistical and process model studies that focus on one component of the integrated system. Until recently, these component models operated independently, without feedbacks to each other. IAV IAMs are designed with the explicit objective to connect these component parts.

The wiring diagram in **Figure 3** is one example of how energy-water-land interactions can be captured in a coupled system of component models. In integrated impacts analysis, the focus is on the center box and how to capture the interlinkages across the energy-water-land physical systems, taking into account fine-scale climate information from the earth system models and feedbacks from socioeconomic sectors. Connecting these physical systems models with a socioeconomic model captures not only important human responses to sectoral impacts but also sectoral interlinkages through the passing through of prices and demand. For example, climate change impacts on the power sector will increase electricity prices, which will affect the cost of production in other sectors and demand for goods. The socioeconomic model can be thought of as the coordinator of information passing across these physical systems models to capture important sectoral interlinkages. Creating this modeling framework requires establishing linkages between the different component models, as represented by the arrows in **Figure 3**.

There are different approaches to capturing the interlinkages between the various components of the framework described in **Figure 3**. Determining which approach is most appropriate depends on how well it enables the user to address the questions of most interest in the use-inspired application considered. On one end of the spectrum, an assessment that will be used, for instance, to inform policy at the national or international level requires an approach that is concerned with the aggregation of effects across spatial and sectoral scales. On the other end of the spectrum, an assessment that will be used for fine-scale decision making requires an approach that provides spatial and sectoral detail while also capturing interactions across sectors and regions. In between, there is a continuum of uses that require a hybrid approach. Analysis of any of these use cases requires some type of coupling (hard or soft) of process models with earth systems and socioeconomic models; however, the key difference between approaches is where the emphasis lies. In the aggregate assessment case, the socioeconomic model is the focus of analysis with information from process and earth systems models incorporated through direct links to process models or the incorporation of process/statistical emulators into the socioeconomic model. In the case of fine-scale assessments, the focus of analysis is on the process models with downscaled inputs from the earth system model, where the socioeconomic model is used to tie together process models to capture interactions across sectors and regions and to provide changes in economy-wide variables that are inputs into the process models.

Representing these connections in an IAV IAM can take a variety of forms, such as soft or hard coupling component models together or embedding emulators of more complex process and earth systems models into socioeconomic models. Given computational and data limitations, there is an

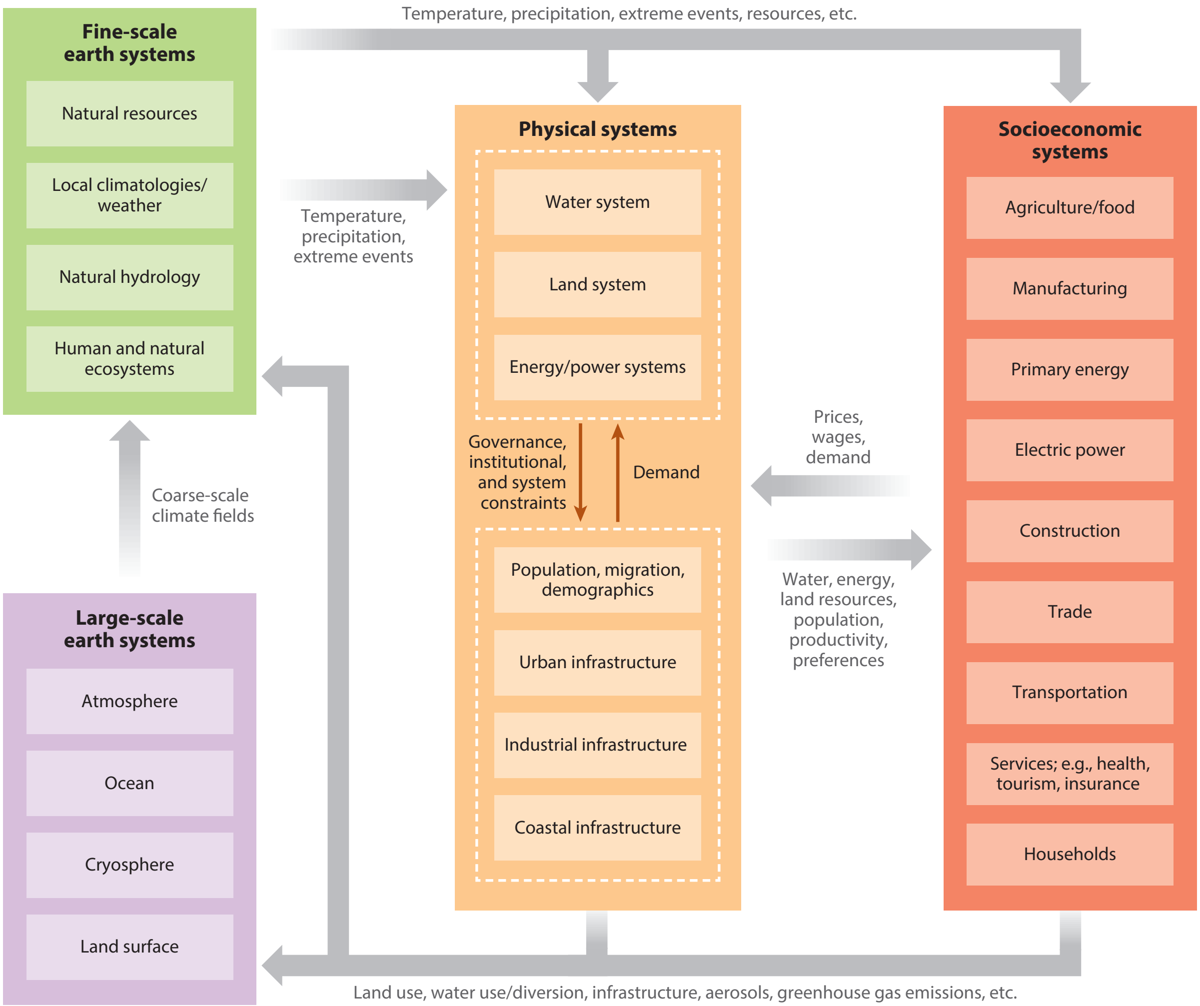

Figure 3

Components of an integrated system within an integrated assessment framework. Thanks to Robert Nicholas (Pennsylvania State University) and Robert Vallario (US DOE) for their input in creating this figure.

inherent trade-off between how closely coupled the component models are and the regional and sectoral detail provided in each. For instance, the global and comprehensive coverage required of IAMs in the past for mitigation work necessitates the construction of process and earth system model emulators that can be embedded in a coarse-scale global socioeconomic model. The new emphasis on fine-scale IAV analyses, on the other hand, necessitates preserving process and spatial detail in the component models where information is passed from one model to another through soft or hard coupling.

There have been numerous efforts to connect certain components of the integrated system shown in **Figure 3**. However, few if any capture the fully integrated system, although current efforts are underway to do this; for example, a small but growing group of community-building efforts is focused on multiregional, multisectoral dynamics that are not directly motivated by climate change concerns, but more narrowly on extreme weather events and their joint impacts integrating energy, water, land use, and agricultural systems. A significant programmatic effort in that domain has been sponsored over the last five years by the MultiSector Dynamics program within the Office of Biological and Environmental Research in the Department of Energy's Office of Science (US DOE 2020). This program has sponsored four interdisciplinary, multi-institution, US-focused projects: The Integrated Multisector Multiscale Modeling (**http://im3.pnnl.gov**) project led by Pacific Northwest National Laboratory, the Program on Coupled Human and Earth Systems (**https://www.pches.psu.edu**) at Pennsylvania State University and Stanford University, the Integrating Human and Earth Dynamics project led by the Joint Global Change Research Institute (**http://globalchange.umd.edu**), and the MSD program led by the Joint Program on the Science and Policy of Global Change at MIT (**https://globalchange.mit.edu/research/research-projects/an-integrated-framework-for-modeling-multi-system-dynamics**).

In Europe, as the major multi-institution IAM projects are now including consideration of both climate and sustainable development objectives (**https://www.cd-links.org/**; **https://cordis.europa.eu/project/id/821124**), MSD is being considered for some regions and sectors within the more highly aggregated global-scale IAMs with some downscaling.

5. CHALLENGES

Developing this next generation of IA tools does not come without challenges. We have identified three thorny areas that will require concerted efforts to overcome: (*a*) challenges related to differences in spatial, temporal, and sectoral scale between component models; (*b*) trade-offs related to model coverage and model complexity; and (*c*) representing uncertainty in the interconnected model and model diagnostics. We discuss each in turn below.

5.1. The Aggregation/Disaggregation Challenge

A major challenge in developing the next generation of IA tools is reconciling differences in spatial, temporal, and sectoral resolution across component models. Physical earth systems processes take place at spatial scales that vary over a dozen orders of magnitude from global to atomic, while socioeconomic decision-making processes range from the individual to the aggregate global scale, with many decisions taking place at different political, institutional, and social levels of aggregation in between these two extremes.

The lack of observational data often limits how well we understand and can model important relationships. For example, a critical element in every climate model is cloud dynamics. Attempts are made to understand and project cloud formation—given that water moisture in the atmosphere is in itself a major GHG—which involves physical processes that take place at spatial scales measured in meters and time intervals measured in seconds. Moreover, the presence of common air pollution particles can significantly affect the cloud formation process, making them higher or lower, thicker or thinner, and darker or lighter.

Data and understanding of these processes occur at the scale at which these physical and chemical processes actually take place; however, given computational limitations, climate models must solve at a much coarser resolution than these individual processes. As a result, these processes are represented at a higher level of aggregation in climate models through parameterization—aggregating the impacts of these individual processes into variables at the level of spatial and temporal aggregation (typically 50 × 50 km grid cells and hourly time steps) required by the climate model. These aggregations lead to uncertainties about the current state of the climate system at the start of the projection period and about how well those aggregation rules will represent the underlying processes that determine, say, the formation of clouds in any scenario designed to project the future of the climate system.

In the socioeconomic domain, a simple example of the aggregation/disaggregation challenge is the usual practice of grouping large numbers of consumers or producers together and aggregating their preferences or resulting behavior to represent them with a single representative average consumer or firm. This can provide a reasonable approximation of the behavior of individuals when preferences are fairly homogeneous, but potentially a very poor one if they are not.[4] To the extent decision makers are interested in the impacts of climate change or climate change policy on groups of people with markedly different attributes (e.g., incomes), these aggregations can prohibit analysts from seeing the impacts on subgroups (e.g., very-low-income individuals)[5] that they and their clients may be particularly interested in (Merrick & Weyant 2019).

5.2. Trading Off Systems Completeness with Systems Complexity

At a conceptual level, IA tools can be used to gain insights into how a system operates, what most influences what, and what types of policy interventions would be most preferable. On the other hand, including greater detail in IAMs can provide more realism because it allows the conditions under which individuals and corporations will be making decisions to be represented more explicitly. However, if data or computational constraints limit the degree of needed geographic, temporal, or systems complexity, insights regarding the interactions and feedbacks between the modeled system and the broader system may not be possible. Additionally, it may be possible to develop new insights at the more disaggregated and operational level if the necessary detail is included in the analysis.

How an emissions trading system might be represented at varying levels of regional scale and disaggregation is an illustration of these types of trade-offs. At a conceptual level, a global-scale partial or general equilibrium model can be used to show that there will be mutual benefits from emissions trading between regions with high marginal abatement costs and regions with lower marginal abatement costs. This should logically lead to lower total costs for achieving any specific level of global emissions reduction and more emission reductions for any fixed level of global mitigation costs. It may even be possible to get a rough idea (e.g., within a factor of two or three) of the benefits of such a trading program. However, absent a globally coordinated uniform carbon tax or equivalent cap-and-trade system, it is difficult to see how these types of market instruments could be implemented at the global scale. The same type of calculation can be done at the national level or subnational level and might be easier to implement, as the institutional and legal systems will be more consistent when a more limited market in considered. To model these national or subnational trading systems, however, will require adding more economic and institutional complexity into the modeling framework, which may be difficult to represent and computationally solve.

5.3. Uncertainty and Diagnostics

A continuing challenge for modelers is how to characterize the uncertainties inherent in their results and how to provide guidance to decision makers on interpreting these uncertainties. In a post-review of the IPCC Fourth Assessment Report, the InterAcademy Council (2010) provided a particularly stark critique of the IPCC and, by extension, the entire global climate change research community on this issue. The complexities of both human-induced climate change and the

---

[4]A stark nonclimate science example of working with averages can be found in Savage (2012) where the discussion is motivated by the image of an extremely inebriated individual trying to walk down the center line of a busy freeway and is fine on average for a few minutes but most likely already dead in reality.

[5]See Dennig et al. (2015) for a promising approach for including income distribution considerations into highly aggregated economic models. To be meaningful to many decision makers, however, such methods may need to be applied to more specific populations, cutting across regions and income strata.

policies designed to address it mean that there are vast uncertainties regarding appropriate model formulations, key model inputs and parameters (e.g., baseline rates of economic growth and technological change, the lag in the rate of heat transfer from the atmosphere to the deep ocean), and important model outcomes (e.g., changes in projected regional temperatures and precipitation amounts, lengths of growing seasons, sea-level rise, and storm surge levels).

Related to the uncertainty challenge, as the IAM community has moved toward shorter-run analyses in specific regions, there is increased interest in model diagnostics. This usually starts with an interest in seeing how well a particular model would have projected what actually happened over some historical time period, commonly referred to as hind casting. Given that the world at the start of the historical time period was itself highly uncertain, this is, in fact, a poorly posed question, and there is no guarantee that a model that matches history most closely is going to be the best model to use to project the future.

Another form of diagnostics involves comparing key results from a range of models for sets of standardized scenarios. These model intercomparison exercises can help identify which model features and parameter values are most important in explaining differences in model results.[6] Instances where disparate sets of models produce similar results that are consistent with experience can give us more confidence in those results. Model intercomparisons can also be designed to investigate differences in model behavior across variations in structural or parameter assumptions outside the range of plausible values. These diagnostic scenario exercises can help isolate reasons for intermodel differences.

Most model comparisons, however, are focused on providing information and insights that are relevant to current decision making. This in turn makes characterizing all of the uncertainties relevant to that objective critically important. One would not want to assume a strong correlation of results over a small range of external driver or parameter assumptions, only to be surprised that equally plausible assumptions lead to dramatically different results.

In this way, uncertainty characterization and model diagnostics are strongly linked, implying that model building, uncertainty characterization, and model diagnostics should all be planned and executed in combination. Model development requires data and a structural understanding of the systems that are being modeled. This information is used to build the model, characterize uncertainty of the model results, and test the accuracy of the model projections relative to other models or observations of systems variables. Deciding how to use the information in a way that maximizes the usefulness of the models requires a greater reliance on either classical statistics or more modern data science methods than has been the case so far.

6. FUTURE DIRECTIONS

Continuing to build on these past successes in IA and addressing the challenges described in the previous section will require progress to be made in certain key areas: (*a*) the development of model coupling software and translational tools, (*b*) the incorporation of empirical findings into IAMs, (*c*) intermethod comparisons, (*d*) training the next generation of IA scholars, and (*e*) building a community of practice.

6.1. Coupling Software and Translational Tools

The movement toward modeling frameworks for IAV analyses that include greater physical system detail, feedbacks between component models, and finer resolution (spatial, temporal, and sectoral) has created a need for innovation in computational tools. Aggregate benefit-cost IAMs

[6]For a number of model intercomparison studies, see the Energy Modeling Forum (**http://emf.stanford.edu**).

and detailed process IAMs have not faced the computational challenges now being faced by IAV IAMs. As discussed in Section 4 and depicted in **Figure 3**, IAV IAMs require the passing of information across component models that operate at very different scales and run on different software platforms. This can lead to complicated computational challenges.

This growing emphasis on model coupling has spawned a new research field focused on developing innovative methodologies and tools to translate information between models. Iterating across models to arrive at an equilibrium requires not only enhanced computational power and the ability to transfer large amounts of data, but also the translation of information across models with widely different temporal, sectoral, and spatial scales. The development of coupling software and translational tools, therefore, has become critical to doing this work, requiring computer software expertise that is not easy to come by.

6.2. Incorporating Empirical Findings into Integrated Assessment Models

As discussed earlier, impact analyses have predominantly focused on one sector and region and have therefore ignored important interactions and feedbacks across sectors and regions. Although the IA modeling community has moved toward multisector and multiregional frameworks for impact analyses, a persistent problem is that detailed sectoral and regional studies have not made their way into IAMs, yet they could be useful in the parameterization of these models. A big source of the problem is that many of these studies (e.g., econometric analyses) have not been designed with the purpose of being useful to IAMs.[7] These studies are typically too specific to a particular sector or region to be generalizable and therefore useful to IAMs. Changing this will require econometricians and modelers to work collaboratively to develop empirical results that can be easily translated into IAMs.

6.3. Intermethod Comparisons

The trade-offs associated with coupling approaches imply that something is lost when one approach is taken over another. An important part of IA work in the past has been model diagnostics and intercomparison, as described in Section 5. Historically, IA diagnostics work has focused on model comparisons where models are harmonized to tease out differences in results due to differences in model structure. With the movement to coupled models, the focus has shifted to intermethod comparisons where differences in results are explained by differences in method rather than model—e.g., statistical emulator versus process model versus IAM. This type of intermethod comparison in the context of agricultural impacts was the focus of a recent special issue of the journal *Environmental Research Letters* (Vol. 12, 2017) where comparisons were made between statistical models, process models, and IA models in their estimates of climate change impacts on agricultural yields (Ciscar et al. 2018). These types of intermethod comparisons need to be conducted on other sectors (e.g., water and electric power).

6.4. Training the Next Generation of Integrated Assessment Scholar

Historically, IAM researchers have come from an energy-engineering-economics tradition. With a greater emphasis on modeling the process detail necessary for impact analyses, IAM teams have become not only more multidisciplinary but also transdisciplinary, as this work requires researchers

[7] See the special issue of *Energy Economics* (Vol. 46, 2014) that explores this for a number of impact sectors, including health, water, urban sector, land use, and agriculture (Fisher-Vanden et al. 2014).

to have a deeper understanding of the models they are connecting to. It is no longer possible to toss model results over the transom to another model and hope to capture important interactions. It requires tighter and more precise coupling across component models to ensure that the regional and sectoral connections are correctly captured.

One of the largest shifts occurring in the IA community is the need for transdisciplinary researchers—i.e., researchers that are experts in their own field but also have a deep understanding of other fields necessary for the detailed model coupling required for IAV analysis. This is likely to be the largest challenge for moving this field forward in the future, as it requires a major commitment on the part of the researcher to become steeped in the methodology of another discipline, and academic disciplines do not typically reward—in terms of publications and promotions—transdisciplinary work. With the awarding of the 2018 Nobel Memorial Prize in Economic Sciences to William Nordhaus for his work in IA, there is optimism that more will be attracted to this type of transdisciplinary research.

6.5. Building a Community of Practice

In addition to the several important areas for future IA research identified in Section 5, progress is needed in institutional approaches designed to improve the usefulness of the IA community as a whole. These institutions seek to fill much-needed scientific gaps in the underlying global change disciplines and in the interfaces between them. In addition, progress needs to be made in developing a comprehensive scientific strategy for dealing with uncertainty, improving the communication of model results to those who could most benefit from understanding them, and improving model credibility.

One response to these modeling challenges has been to organize the relevant research communities into communities of practice to coordinate and prioritize research, exploit synergies, and avoid duplication of effort. With an increase in—and spread of—IA research and IA model intercomparison studies around the world, there became a clear need to establish such an institution for the IA community. This led to the establishment of the Integrated Assessment Modeling Consortium in 2007 (**http://www.globalchange.umd.edu/iamc/**) to coordinate this research, set research priorities, avoid duplication of effort, and interface with other research communities, as well as international organizations. The newly established MSD community, which as described earlier is more focused on descriptive impacts analyses, has taken similar steps to develop a community of practice.

7. CONCLUSION

Our review of the history of IA modeling of climate change illustrates the broad range of analytical tools that have been developed over the last 30 years. This research has involved a very large number of disciplines and research communities. Early IAMs proved quite useful in identifying trade-offs between aggregate global GHG emissions, climate change impacts, and economic growth.

Over the last two decades, as the climate has continued to change, climate-directed policies have been difficult to implement at a pace that seems appropriate, and climate change impacts are starting to become more severe. In response to this challenge, analysts and decision makers alike have sought shorter-term and more geographically explicit information that can be used in deciding on specific shorter-run policies and measures that they could productively pursue immediately in their individual jurisdictions. This has led the IAM community to either include the requisite detail in global-scale models directly or, more recently, to build modeling frameworks that bring the IA perspective down to the level at which decision makers can actually use their model results more directly in their policy deliberations.

The relative influence of the more highly aggregated and more highly resolved approaches to IA has now shifted fairly rapidly downstream as fears of a potential climate catastrophe have grown dramatically over the last five years or so. However, as the disparate communities involved in IAM research at different scales have not had much interaction up to this point, it appears they have a lot to learn from each other. In fact, these communities now need each other more than ever to develop use-inspired IAM tools.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

LITERATURE CITED

Alcamo J, Shaw R, Hordijk L, eds. 1990. *The RAINS Model of Acidification: Science and Strategies in Europe*. Dordrecht, Neth.: Kluwer

Burke M, Craxton M, Kolstad CD, Onda C, Allcott H, et al. 2016a. Opportunities for advances in climate change economics. *Science* 352(6283):292–93

Burke M, Craxton M, Kolstad CD, Onda C. 2016b. Some research challenges in the economics of climate change. *Clim. Change Econ.* 7(2):1650002

Calvin K, Fisher-Vanden K. 2017. Climate change impacts on agriculture: the role of integrated assessment models. *Environ. Res. Lett.* 12:115004

Ciscar JC, Feyen L, Soria A, Lavalle C, Raes F, et al. 2014. *Climate impacts in Europe. The JRC PESETA II Project*. JRC Sci. Policy Rep. EUR 26586EN, Eur. Comm., Luxembourg. **http://publications.jrc.ec.europa.eu/repository/handle/JRC87011**

Ciscar JC, Fisher-Vanden K, Lobell D. 2018. Synthesis and review: an inter-method comparison of climate change impacts on agriculture. *Environ. Res. Lett.* 13:070104

Clarke L, Nichols L, Vallario R, Hejazi M, Horing J, et al. eds. 2018. Sector interactions, multiple stressors, and complex systems. In *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment*, Vol. 2, ed. DR Reidmiller, CV Avery, DR Easterling, KE Kunkel, KLM Lewis, et al., pp. 638–68. Washington, DC: US Glob. Change Res. Prog. **https://nca2018.globalchange.gov/downloads/NCA4_Ch17_Complex-Systems_Full.pdf**

Dasgupta P. 1997. *Environmental and Resource Economics in the World of the Poor*. Washington, DC: Resour. Future

Dennig F, Budolfson MB, Fleurbaey M, Siebert A, Socolow RH. 2015. Inequality, climate impacts on the future poor, and carbon prices. *PNAS* 112(52):15827–32

Diffenbaugh NS, Hertel TW, Scherer M, Verma M. 2012. Response of corn markets to climate volatility under alternative energy futures. *Nat. Clim. Change* 2:514–18

EPA (US Environ. Prot. Agency). 2017. *Multi-model framework for quantitative sectoral impacts analysis: a technical report for the fourth national climate assessment*. Rep. EPA 430-R-17-001, EPA, Washington, DC

Fisher-Vanden K, Popp D, Sue Wing I, eds. 2014. *Energy Econ*. 46

Grogan DS, Zhang F, Prusevich A, Lammers RB, Wisser SD, et al. 2015. Quantifying the link between crop production and mined groundwater irrigation in China. *Sci. Total Environ.* 511:161–75

Hejazi M, Edmonds J, Clarke L, Kyle P, Davies E, et al. 2014. Integrated assessment of water scarcity over the 21st century under multiple climate change mitigation policies. *Hydrol. Earth Syst. Sci.* 18:2859–83

Hope C. 2006. The marginal impacts of CO_2 from PAGE2002: an integrated assessment model incorporating the IPCC's five reasons for concern. *Integr. Assess.* 6(1):19–56

Houser T, Hsiang S, Kopp R, Larsen K, Delgado M, et al. 2015. *Economic Risks of Climate Change: An American Prospectus*. New York: Columbia Univ. Press

InterAcademy Council. 2010. *Climate Change Assessments. Review of the Processes and Procedures of the Intergovernmental Panel on Climate Change. Committee to Review Intergovernmental Panel on Climate Change.* Amsterdam: InterAcademy Council

IPCC (Intergov. Panel Clim. Change). 2001. *Climate Change 2001: Synthesis Report. A Contribution of Working Groups I, II, and III to the Third Assessment Report of the Intergovernmental Panel on Climate Change*, ed. RT Watson, Core Writing Team. Cambridge, UK/New York: Cambridge Univ. Press

IPCC (Intergov. Panel Clim. Change). 2007. *Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. RK Pachauri, Core Writing Team. Geneva: IPCC

IPCC (Intergov. Panel Clim. Change). 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. Core Writing Team, RK Pachauri, L Meyer. Geneva: IPCC

Kling CL, Arritt RW, Calhoun G, Keiser DA. 2017. Integrated assessment models of the food, energy, and water nexus: a review and an outline of research needs. *Annu. Rev. Resour. Econ.* 9:143–63

Kraucunas I, Clarke L, Dirks J, Hathaway J, Hejazi M, et al. 2015. Investigating the nexus of climate, energy, water, and land at decision-relevant scales: the platform for regional integrated modeling and analysis (PRIMA). *Clim. Change* 129(3–4):573–88

Merrick JH, Weyant JP. 2019. On choosing the resolution of normative models. *Eur. J. Oper. Res.* 279(2):511–23

Moss RH, Fisher-Vanden K, Delgado A, Backhaus S, Barrett CL, et al. 2016. *Understanding dynamics and resilience in complex interdependent systems: prospects for a multi-model framework and community of practice*. Rep., US Glob. Change Res. Prog., US Dep. Energy, Washington, DC

Muller NZ, Mendelsohn RO. 2007. Measuring the damages due to air pollution in the United States. *J. Environ. Econ. Manag.* 54:1–14

Nordhaus WD. 1994. *Managing the Global Commons: The Economics of Climate Change*. Cambridge, MA: MIT Press

Parson EA, Fisher-Vanden KK. 1997. Integrated assessment models of global climate change. *Annu. Rev. Energy Environ.* 22:589–628

Pindyck RS. 2013. Climate change policy: What do the models tell us? *J. Econ. Lit.* 51(3):860–72

Pindyck RS. 2017. The use and misuse of models for climate policy. *Rev. Environ. Econ. Policy* 11(1):100–14

Reilly J, Paltsev S, Strzepek K, Selin N, Y. Cai H-M, et al. 2012. Valuing climate impacts in integrated assessment models: the MIT IGSM. *Clim. Change* 117:561–73

Rotmans J. 1990. *Image: An Integrated Model to Assess the Greenhouse Effect*. Dordrecht: Kluwer

Savage SL. 2012. *The Flaw of Averages: Why We Underestimate Risk in the Face of Uncertainty*. Hoboken, NJ: Wiley

Schellnhuber HJ, Frieler K, Kabat P. 2014. Global climate impacts: a cross-sector, multi-model assessment special feature. *PNAS* 111(9):3225–97

Tol R. 2002. Estimates of the damage costs of climate change, part I: benchmark estimates. *Environ. Resour. Econ.* 22:47–73

UNFCCC (UN Framew. Conv. Clim. Change). 2015. *Paris Agreement*. UNFCCC, Bonn, Ger. **https://unfccc.int/files/meetings/paris_nov_2015/application/pdf/paris_agreement_english_.pdf**

US DOE (US Dep. Energy). 2020. *Multisector dynamics*. Off. Sci., US Dep. Energy, Washington, DC. **https://climatemodeling.science.energy.gov/program/multisector-dynamics**

Weyant JP. 2017. Some contributions of integrated assessment models of global climate change. *Rev. Environ. Econ. Policy* 11(1):115–37

Weyant JP, Davidson O, Dowlatabadi H, Edmonds J, Grubb M, et al. 1996. Integrated assessment of climate change: an overview and comparison of approaches and results. In *Climate Change 1995: Economic and Social Dimensions. Contribution of Working Group III to the Second Assessment Report of the Intergovernmental Panel on Climate Change*, ed. JP Bruce, H Lee, EF Haite, pp. 367–96. Cambridge, UK: Cambridge Univ. Press

World Bank. 2010. *World Development Report 2010: Development and Climate Change*. Washington, DC: World Bank. **https://openknowledge.worldbank.org/handle/10986/4387**

Zaveri E, Grogan DS, Fisher-Vanden K, Frolking S, Lammers RB, et al. 2016. Invisible water, visible impact: groundwater use and Indian agriculture under climate change. *Environ. Res. Lett.* 11:084005

Annual Review of Resource Economics

Volume 12, 2020

Contents

Errata

An online log of corrections to *Annual Review of Resource Economics* articles may be found at http://www.annualreviews.org/errata/resource