Some Contributions of Integrated Assessment Models of Global Climate Change

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"...all models are wrong, but some are useful."
—G. E. P. Box and N. R. Draper (1987)

Introduction

It is now clear that human-induced climate change is caused by (1) oil, gas, coal, and biofuel combustion in utility and industrial boilers and land, sea, and air transportation systems that produce emissions of carbon dioxide (CO_2) and other radiatively active gases to the atmosphere; and (2) land use and land use change activities that release CO_2, methane, and/or nitrous oxide to the atmosphere (IPCC 2013). Emissions of these substances lead to net increases in the accumulations of these gases in the atmosphere (i.e., above those that occur naturally). Because these gases allow more of the heat from the sun's radiation through to the earth's surface than from the earth's surface back out to deep space, they are generally referred to as greenhouse gases (GHGs).

Assessments of the effects of climate change on people and their property, wildlife, and ecosystems indicate that these effects can be significant (IPCC 2014a). This has led to the consideration of three main approaches for ameliorating the impacts of climate change: (1) mitigation of GHG emissions, (2) adaptation to any climate changes that might occur, and (3) geoengineering to influence the amount of solar energy reaching the earth's surface and/or to influence the chemistry of the oceans. Because the relationships within and between the various biogeochemical and socioeconomic components of the earth system can be quite complex, a number of quantitative models have been developed to study earth systemwide climate changes and the effect of various types of public policies on projections of future climate change. These models have become known as "integrated assessment of climate change" or simply integrated assessment models (IAMs).[1]

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[1]Although the focus here is on the application of these modeling frameworks to climate change policy and science program management, these same models have also been used to study related issues including air

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The objective of these models is to project alternative future climates with and without various types of climate change policies in place in order to give policymakers at all levels of government and industry an idea of the stakes involved in deciding whether or not to implement various policies.

The literature on IAMs is now vast and continues to grow rapidly. However, this literature is spread across many disciplines, with publications appearing in a wide range of journals, including those that focus on earth sciences, biological sciences, environmental engineering, economics, sociology, technological change, and other related fields. This has led to some confusion about what IAMs are, what they have been developed to do, and what impacts they have already had on decision making and people's thinking about climate change problems and solutions (cf., Pindyck 2013).

This article, which is part of a symposium on the use of IAMs for climate policy,[2] examines the use of IAMs of global climate change for policy analysis and research management. The objectives are to (1) explain the models, (2) describe how they have been used, (3) assess the contributions they have made, (4) identify the key challenges that remain in developing and using them, and (5) suggest areas for improvement. Like all quantitative models used in policy analysis, these models have strengths and weaknesses. Although the highly complex and very uncertain nature of both the climate change problem and potential policy responses to it present model builders with many formidable challenges, I believe these models have already proven quite useful in assessing the magnitude of the climate change problem and the efficacy of potential solutions.

For the purposes of this article, I define an IAM of global climate change to be any model that covers the whole world and, at a minimum, includes some key elements of the climate change mitigation and climate impacts systems at some level of aggregation. Climate change studies that focus on regional and national decision making (see, e.g., Knopf et al. 2013; Fawcett, Clarke, Weyant 2014; Kraucunas et al. 2015) do not systematically cover the whole earth system and thus are not included here. In addition, there is now an extensive and rapidly growing literature on the use of benefit–cost analysis (BCA) to support climate change adaptation decision making on a regional scale (Li, Mullan, and Helgeson 2015), which is not included here due to space limitations.

The article is organized as follows. In the next section I present an overview of the two major types of global IAMs that have been used to study climate change. Then I describe applications of each model type. This is followed by a discussion of the major research challenges concerning the use of these models, highlighting areas where they can be improved. The final section presents conclusions and recommendations for further development and use of IAMs to study climate change.

An Overview of IAMs

All IAMs include the economic and natural processes that produce GHG emissions. Those emissions are used to drive a representation of the global carbon cycle and the chemical

quality, water scarcity, and food security. However, a discussion of direct applications in those areas is beyond the scope of this article.

[2]The other articles in the symposium are Metcalf and Stock (2017), which introduces the symposium and examines the role of IAMs in estimating the social cost of carbon for use in U.S. regulatory analyses, and Pindyck (2017), which examines the uncertainty that characterizes IAMs and proposes an alternative to an IAM-based social cost of carbon.

composition of the atmosphere, which is then used to drive changes in climate and sea level. The models then project how those changes impact natural systems on earth, some of which are managed by and valuable to humans. However, IAMs differ tremendously in their level of detail and the complexity and interconnections they consider. For example, some models represent the whole earth system with a small number of fairly simple equations (e.g., Nordhaus 2014), while others include thousands of equations drawn from physics, chemistry, biology, and economics (e.g., Reilly 2012b). Approximately twenty global scale IAMs have been developed (see the list of references for this article). However, there are two basic types: detailed process (DP) IAMs and benefit–cost (BC) IAMs. Both types of IAMs have been applied to climate change mitigation policy questions for several decades.[3] Although both types of IAMs include projections of GHG emissions and the costs of various ways to mitigate them (e.g., energy conservation, changes in production processes, fuel switching), they handle climate change impacts differently. DP IAMs are more disaggregated and seek to provide projections of climate change impacts at detailed regional and sectoral levels, with some using economic valuation and others using projections of physical impacts such as reductions in crop growth, land inundated by sea level rise, and additional deaths from heat stress.

In contrast, BC IAMs provide a more aggregated representation of climate change mitigation costs and aggregate impacts by sector and region into a single economic metric.[4] The main motivation for developing BC IAMs has been to use them to implement BCA to identify "optimal" climate policies, but they have also been used to calculate the costs and benefits associated with polices for which marginal costs and marginal benefits are not equal.

The DP IAMs provide more information than the BC IAMs on the physical impacts and economic costs of climate change and the benefits of GHG emissions mitigation. This has two important implications for the BC models. First, similar to the aggregation and calibration required on the mitigation side of the BC IAMs, the more complex DP IAMs can also provide projections of the economic costs net of endogenous adaptation to climate change for key sectors (e.g., agriculture) by region. These estimates can then be aggregated for use in the BC IAMs. Since most climate impacts take place at the watershed, agricultural growing region, ecological zone, city, or similar level, this additional degree of geographical disaggregation is essential for improving the validity of the damage functions used in the aggregate BC IAMs. Second, the additional information on both the physical and economic impacts of climate change may be vitally important to decision makers in some regions and sectors.[5]

Concepts and insights from the more complex DP IAMs can be used to calibrate the simple aggregate BC IAMs and to identify where they might be improved. Concepts and results from the DP IAMs can be important to the BC-oriented models because the cost of GHG emissions mitigation functions in the aggregate BC IAMs are often calibrated to results from the more disaggregated DP IAMs, which consider much more energy sector and land use detail (including things like explicit agricultural and forestry activities, as well as changes in unmanaged ecosystems). In fact, these more detailed models have frequently been used to examine the "cost-effectiveness" of alternative policies for meeting various climate targets, such as limits on

[3]For early examples of these models, see Nordhaus (1989, 1991, 1994b), Rotmans (1990), Manne and Richels (1992); Edmonds et al. (1994); Edmonds, Wise, and MacCracken (1994), and Weyant et al. (1996).
[4]These aggregate impacts functions are sometimes calibrated to detailed sectoral climate impact projections by region.
[5]This issue is discussed in more detail later.

carbon concentrations or a maximum permissible global mean temperature increase at the lowest possible societal cost.

In the next two sections I discuss applications of the more disaggregated DP IAMs and the more aggregated BC IAMs, respectively.

Applications of Disaggregated DP IAMs

By about 1990, the early disaggregated DP IAMs were developed by adding a reduced form carbon cycle, atmosphere, ocean, and other components to existing global energy, economic, atmosphere, and ecosystems models (e.g., Edmonds et al. 1994; Edmonds, Wise, and MacCracken 1994; Rotmans 1990). Over the years, research teams have been able to incorporate sectors that are both impacted by and integral to the operation of the earth system as a whole (e.g., land use and water), which have remained high priority objectives for most teams. As described next, DP IAMs have been used in three main types of climate system and policy analysis: mitigation analysis, climate impacts analysis, and integrated mitigation and impact analysis.

Use of DP IAMs in Mitigation Analysis

There is a long history of using DP IAMs to study the energy–economy impacts of climate change mitigation policies, including about a dozen intermodel comparison studies. The current state of the art, including the results of the intermodel comparison studies, is captured nicely in "Assessing Transformation Pathways" (Clarke et al. 2014), chapter 6 of the Intergovernmental Panel on Climate Change (IPCC, 2014b) fifth assessment report, which summarizes and contrasts some 1000 scenarios produced by these models.[6] Based on the results from these models, which include many climate policy and technology assumption sensitivity analyses, the chapter demonstrates both the advantages of efficient policies and the availability of a wide range of low GHG–emitting technologies to achieve stringent climate policies favored by many nations, such as an increase in global mean temperature of no more than 2°C relative to preindustrial times, a concentration of GHGs in the atmosphere of no more than 450 parts per million (ppm) CO_2 equivalent, or reducing emissions by 80% relative to 1990 levels by 2050. In addition to focusing on technology and more realistic policy architectures than were available at the time of the fourth assessment report, this chapter reinforces several basic conclusions from previous assessments, which are summarized by Weyant (2008): (1) projections of mitigation costs are very uncertain; (2) mitigation cost projections are very sensitive to the specific assumptions made about how policies are formulated and implemented; (3) despite the uncertainties, we can put rough bounds on the range of plausible mitigation cost estimates; and (4) there are a number of general principles we can apply to the design of climate policies to help make mitigation costs lower rather than higher. I discuss each of these conclusions in more detail next.

[6]This chapter focuses on studies produced since the fourth assessment report, including Bosetti and Frankel (2012), Calvin et al. (2012), Krey et al. (2014), Kriegler et al. (2013a, 2013b, 2014a, 2014b), and Riahi et al. (2015).

Uncertainty of mitigation cost projections

Given the huge range of mitigation cost projections in the literature (Weyant 1999, 2004; de la Chesnaye and Weyant 2006; Edenhofer et al. 2006; Clarke et al. 2009; Bosetti and Frankel 2012; Kriegler et al. 2013a, 2013b, 2014a, 2014b; Krey et al. 2014), it is clear that these projections are inherently uncertain. Moreover, since most of these projections are model based, and the model parameters are sometimes held within unrealistically narrow ranges, much of the literature consists of mean projections from a number of different models with no, or at best only partial, uncertainty analyses included. This level of uncertainty in mitigation cost projections is not very surprising. The future of the world economy and the world energy system must be projected over many decades using many assumptions about productivity growth, fuel prices, technology diffusion, the development of new technologies, and the interest/discount rate used in making intertemporal investment decisions. In addition to these projections about basic energy–economic conditions, projections about future government energy–environment policies around the world must be made.

Sensitivity of projections to model assumptions about policy implementation

This leads to the second major conclusion regarding mitigation cost projections for achieving a particular climate policy objective: that they are very sensitive to the assumptions made about the specific policies used to achieve the emissions reductions and how those policies are implemented. Clearly, assumptions about the possible range of policy instruments and how well they might be implemented can lead to large differences (probably as large as an order of magnitude in either direction) in mitigation cost projections. This policy dependence means that analysts cannot make very precise mitigation cost projections without knowing the details of the policy regime that will be used to achieve the mitigation target. Nevertheless, these cost projections can help policymakers understand the trade-offs involved in selecting specific elements of any policy regime. For example, projections can be used to examine the cost implications of different assumptions concerning the availability of low GHG energy technologies (Kriegler et al. 2014b) and the implications of different assumptions about the degree and timing of international cooperation in achieving global climate policy objectives (e.g., Riahi et al. 2015). In addition, comparisons of the costs of regulatory versus market approaches to GHG mitigation at the country and regional level have emerged (see Knopf et al. 2013; Fawcett, Clarke, and Weyant 2014).

Ability to place bounds on estimated costs

Third, despite all the complexities and uncertainties involved, we can still place some rough bounds on mitigation costs. More specifically, under wide ranges of assumptions about the future of the world economy and possible policy architectures, we can conclude that stabilization of GHG concentrations in the atmosphere during this century at 550 ppm will likely cost somewhere between 0.1 percent and 10 percent of gross world product (GWP) per year (e.g., Weyant 1999, 2004; de la Chesnaye and Weyant 2006; Edenhofer et al. 2006; Clarke et al. 2014). This range of two orders of magnitude can probably be cut in half if the basic elements of the policy regime to be used to stabilize GHG concentrations are specified.[7] These bounds can help policymakers put

[7]Although the scenario results of the last 5 years or so (Clarke et al. 2014) show a narrower range of cost projections, in part because the cost of non-fossil-fuel-based alternative energy sources has come down, it is critically important to recognize that these results indicate ranges of published results and the studies that

climate change in perspective relative to other big societal issues such as national security, health, education, and welfare. In addition, this range of cost estimates, and its dependence on the policies assumed, provides a sense of how valuable economically efficient policies can be.

Policy design principles for lowering mitigation costs

Finally, and perhaps most importantly, several generations of mitigation cost studies have allowed us to identify and analyze a number of general principles for improving the economic efficiency of mitigation policies. The most general principle that has emerged is that broadly targeted, flexible policies lead to lower costs than narrowly focused, inflexible ones (e.g., Weyant 2008). This suggests that allowing flexibility in what, where, when, and how GHG emissions reductions are to be achieved results in lower mitigation costs across all economic assumptions and all models. For example, flexibility in where emissions reductions take place can be facilitated by allowing trading of GHG emission rights across individuals, regions, sectors, and countries. Flexibility in when emissions reductions are taken can be facilitated by allowing borrowing and banking of GHG emission rights over time. Flexibility in how emissions reductions may be achieved can be promoted by including research and development (R&D) incentives, information programs, and carefully chosen efficiency standards, along with traditional market-based mechanisms like a carbon tax or a cap and trade program. One strong conclusion from this recent work is that delays in implementing mitigation actions can cause increases in the total discounted cost of meeting a particular global GHG concentration or temperature target as emissions from new noncontrolled sources become harder and harder to offset, even if future low GHG–emitting technologies become more efficient over time (Riahi et al. 2015). Finally, allowing appropriately weighted emissions reductions in all GHGs and the use of biologic sinks (like growing more trees or simply slowing deforestation) can reduce the overall cost of achieving any climate outcome, such as a particular GHG concentration, radiative forcing, or temperature target. Clarke et al. (2014) summarize the most recent work in this area by considering the implications (across a number of recent model intercomparison projects) of key technology availabilities and alternative assumptions about when and who participates in a global GHG mitigation regime.[8]

Use of DP IAMs for Climate Impact Analysis

Although the use of DP IAMs for both GHG mitigation and climate change impact analyses has a long history (cf., Weyant et al. 1996), the use of DP IAMs for climate impacts analysis has thus far been much less systematic, with research teams focusing on impacts in sectors they are most interested in and/or able to study. Thus, for example, there have been DP IAM analyses of climate change impacts on agriculture (Boehlert and Strzepek 2013; Tai, Val Martin, and Heald 2014), water (Blanc et al. 2014; Schlosser et al. 2014; Strzepek et al. 2010), biodiversity (Meller, van Vuuren, and Cabeza 2013), coastal zone damages from sea level rise (Diaz 2016), and across multiple impact sectors (Reilly 2012b; Stehfest et al. 2014). In order to enable IAMs to be used

include them were carried out for many different purposes and thus do not reflect the full range of uncertainties over model inputs or parameters.

[8]It is important to note that even in highly disaggregated DP IAM analyses of mitigation policies, the models often do not consider options that might be important to decision makers, such as policies to stimulate energy R&D or to compensate workers for dislocations resulting from the implementation of the policies.

for more systematic assessments and comparisons of impact projections from around the world, a new effort is under way to create coordinated global scenarios for individual impact assessments and mitigation assessments (Moss et al. 2010; O'Neill et al. 2014; Riahi et al. 2016).[9]

Use of DP IAMS for Integrated Mitigation and Impacts Analysis

The third and most advanced category of applications of disaggregated DP IAMs is integrated mitigation and impact analysis, reflecting the fact that the way large-scale GHG mitigation or adaptation is implemented can change the climate, and changes in climate can change the efficacy of mitigation and adaptation strategies. Studies that consider these kinds of physical and economic interactions between impact sectors and feedbacks from them to the climate system are not possible with the more aggregated BC IAMs. However, a number of these interactions and feedbacks have been addressed with DP IAMs, including the interaction between climate and air pollution polices (Reilly et al. 2007; Chuwah et al. 2013; Nam et al. 2016), the increased competition for water between agriculture and power plant cooling that would occur in a hotter and dryer climate, and the impacts on water and land (and the resulting land emissions) of global policies that rely on massive increases in biofuels (Reilly and Paltsev 2009; Reilly et al. 2012a; Daioglu et al. 2014; Rose et al. 2014a). Additional examples of analyzing mitigation and adaptation policies simultaneously include Hinkel et al. (2013); Calvin et al. (2014); Herrero, Havlik, and Obersteiner (2013); Ermolieva et al. (2014); and Mosnier et al. (2014).

Applications of Simple Aggregate BC IAMs

There have been three main applications of BC IAMs. First, BC IAMs have been used for several decades to compute the optimal trajectory of global GHG emissions, and the corresponding prices to charge for those emissions (cf., Weyant 2015). Such optimal policies equate the marginal (discounted) benefits (in terms of climate damages avoided) with the marginal (discounted) costs (in term of mitigation effort required) of the climate change policy. Second, aggregate BC IAMs have been used to evaluate the costs (and benefits) of pursuing nonoptimal climate policies (i.e., climate targets, such as emissions, concentration, or temperature targets) rather than optimal policies. Because the aggregate mitigation components of these systems are calibrated to the more disaggregated DP IAMs, many of the basic conclusions concerning DP IAMs also hold for BC IAMs. However, in the case of BC IAMs, rough economic valuations of changes in climate damages are included and can be traded off against the costs. Third, BC IAMs have been used, especially in current U.S. climate policy deliberations, to compute the social cost of carbon (SCC), which is defined as the incremental damage caused by one more ton of carbon emissions. I discuss these three types of applications of BC IAMs in more detail next.

[9]Although the frameworks suggested in Moss et al. (2010), O'Neill et al. (2014), and Schellnhuber, Frieler, and Kabat (2014) provide excellent tools for coordinating the efforts of the earth sciences community and for benchmarking intermodel comparisons within and among them, they are not, in themselves, IAMs as defined in this article.

BC IAMs and "Optimal" Climate Polices

Optimal climate policies are those that balance the marginal cost of the last ton of emission reductions against the marginal damages resulting from the last ton emitted — such policies maximize welfare because they minimize the total cost of climate mitigation plus the remaining damages that are incurred. One way to achieve this optimal policy outcome is to impose a carbon tax that is equal to the optimal marginal mitigation cost/climate damages, which is referred to as an optimal emissions tax. Recent projections of the optimal cost of carbon from the three most widely used aggregate BC IAMs — Dynamic Integrated Climate-Economy (DICE; Nordhaus 2014), Framework for Uncertainty, Negotiation, and Distribution (FUND; Anthoff and Tol 2013), and Policy Analysis of the Greenhouse Effect (PAGE; Hope 2011) — provide mean estimates of the optimal cost of carbon that range from $10 per ton for the FUND model to $18 per ton for the DICE model to $71 per ton for the PAGE model. The differences in estimates are due primarily to differences in the models' climate damage functions, especially their treatment of the potential for catastrophic outcomes like the melting of the Greenland ice sheet or the release of trapped methane gas from thawing permafrost. The FUND estimate is lower because, unlike DICE and FUND, it does not account for such possibilities. Moreover, the potential for catastrophic outcomes (based on a survey in DICE) accounts for roughly 70 percent of global damages at 2.5 °C (Wolverton et al. 2012). Another key driver of the lower damage projections from FUND are its assumptions about the ability of those impacted by climate change to adapt to those changes (e.g., farmers can change crops, adjust planting schedules, incorporate irrigation, or apply fertilizer). PAGE also reports that the standard deviation of the optimal carbon tax is $266 per ton if all 100,000 runs in their simulations are included, but only $56 per ton if the highest 1% of the optimal results are eliminated— which highlights the significance of the "thick tail" (i.e., a probability distribution of the magnitude of climate damages that goes to zero very slowly at high damage levels) in their probability distribution over damage outcomes. This means that the optimal carbon policies can depend strongly on the modeling team's world view concerning what impacts and what range of climate outcomes to consider, and what types of adjustments those impacted are assumed to make.

Thus model choice can lead to a large range in the projections of the optimal carbon tax, and the plausible ranges of key input assumptions (many of which are discussed in more detail later) can lead to a similarly large spread in the range of projections from a single model. In fact, the combination of model choice (i.e., structure) and model input uncertainties can cause the projected optimal carbon tax to vary by one to two orders of magnitude (Rose et al. 2014b). Despite these uncertainties, however, the application of BC IAMs to climate change policy has provided numerous insights. In particular, BC IAMs have helped identify the most important drivers of the projected costs and benefits of climate policy, which has improved our ability to quantify uncertainties about model outputs of interest. Perhaps the most important contribution of these models is their ability to highlight the critical issues (such as discounting, risk, and damages) that arise in making projections of the costs and benefits of climate policies and to incorporate new scientific findings into the projections of costs and benefits in a timely and orderly fashion (e.g., Nordhaus 2013).

BC IAMs and Non-Optimal Climate Policies

The three main aggregate BC IAMs have also periodically been used to produce results for nonoptimal climate policies. For example, Nordhaus (2007) considered a number of alternative policy scenarios to an "optimal" scenario in which marginal costs equal marginal benefits, and projected that for policies that are moderately more stringent than the optimal one (e.g., limits of two times the GHG concentration or an increase of 2.5°C relative to preindustrial levels), the abatement cost was between 0.1 and 0.25 percent of income (on a present value basis). These are much lower costs than for some of the more ambitious emissions abatement programs that have been proposed (e.g., a maximum temperature increase of 2°C). Under those programs, abatement costs amount to around 1.5 percent of income.[10] Thus the cost of these nonoptimal policies exceeds the cost of the optimal policy by more than 1 percentage point of global income while reducing aggregate climate damages by only about .3 percentage points of global income.

BC IAMs and the SCC

The third application of the BC IAMs has been to estimate the SCC. Estimates of the SCC by the U.S. Interagency Working Group (IWG) on Social Cost of Carbon have been used for energy efficiency and carbon emissions rulemaking by the U.S. government (see Greenstone, Kopits, and Wolverton 2013). The IWG used the damage function modules of the three BC IAMs mentioned in the last section to obtain a range of projections of the SCC.[11] As discussed in Rose et al. (2014b), the IWG SCC reports (IWG 2010, 2013) include a wide range of SCC estimates, with the estimates again varying substantially across models and input assumptions. Rose et al. (2014b) find a pattern of results that is similar to the optimal carbon tax projections discussed in the last section (i.e., PAGE produces the highest average SCC estimates but considers more uncertainty regarding climate damages than the other models, while FUND produces the lowest average SCC estimates). For all the models used in the IWG SCC reports, SCC averages and extremes decline with higher discount rates because of the greater discounting of the models' estimates of positive annual damages over the next three centuries. The challenges discussed in the next section provide additional sources of uncertainty to consider when interpreting and assessing these SCC projections.

Major Challenges for Integrated Assessment Modeling

IAMs that have been used to study climate change policies and guide the setting of earth systems research priorities have been constructively criticized (e.g., Ackerman and Stanton 2010, 2012; Pindyck 2013, 2017; Stern 2013). The critiques have generally focused on model design choices that are limited by data and/or understanding of key relationships in the physical and socioeconomic world relevant to assessing the impacts of climate change and emissions mitigation policies. Thus these critiques serve as both limitations on the current models and challenges for improving them. In this section I summarize what the modelers, their critics, and experts in relevant disciplines say are some of the biggest challenges for improving the design and use of

[10]The *Stern Review* (Stern 2007) estimates the present value of abatement costs to be 1 percent of income.
[11]See Johnson and Hope (2012), Tol (2008, 2009), and Nordhaus (2014) for more on these projections of the SCC.

IAMS. These challenges include (1) what to count and how to count it; (2) the inclusion of extreme and discontinuous outcomes; (3) the treatment of regional, national, and international equity; (4) the treatment of intertemporal discounting and intergenerational equity; (5) projections of baseline drivers; (6) capturing interactions between impact sectors and feedbacks to the climate system; and (7) dealing with uncertainty and risk.

What to Count and How to Count It

The most fundamental challenge for the design of IAMs of global climate change is deciding which policy-relevant emissions mitigation options and climate change impacts to include and how to measure them. These considerations range from how many different impacts (aggregate costs and benefits, poverty reduction, population at risk of starvation, etc.) to consider, to whether to measure them in physical units or monetary equivalents, to whether to be more concerned about mean or possible extreme outcomes. These choices pose challenges for both DP IAMs and BC IAMs, but in somewhat different ways. For example, DP IAMs are able to put economic values on some inputs and leave others in physical impact terms, while BC IAMs can be so highly aggregated in terms of economic costs and benefits that it is not even clear which impacts have been included and whether interactions between those impacts are being considered.

The choices made about which climate change impacts to include and at what level of aggregation clearly depend on what types of decisions (e.g., public policies versus private investments) and whose interests (e.g., power plant owners, farmers, automobile drivers, residents of coastal zones) are being considered. For example, a policymaker in a low income country might be more interested in alleviating energy poverty by improving energy access and/or reducing poor air quality than in reducing climate change impacts per se, while a decision maker in a high income country might be more interested in trading off the reductions in economic output that result from reducing emissions against the losses from increases in the projected losses from extreme weather events in both poor and rich coastal regions. IAMs can help quantify these trade-offs in both monetary and physical terms, but the production and interpretation of the results necessarily requires a number of important value judgments concerning whose preferences to count and how to weigh them against one another (cf., Sussman, Weaver, and Grambsch 2015).

Inclusion of Extreme and Discontinuous Outcomes

One of the most troubling concerns about climate change is the potential for abrupt, irreversible, or catastrophic climate changes or climate change impacts (see National Research Council 2002; Lenton et al. 2008; Ackerman and Stanton (2010); IPCC 2013, 2014a). Projections of the economic costs of such extreme events are directly included in the PAGE model and captured conceptually in the damage estimates in the DICE-2013R model. However, these two models do not explicitly address tipping point concerns, primarily because tipping points have not been reliably identified. It is important to emphasize that other than expert opinion, there is not yet much basis for determining the size, timing, or probability of such tipping points or the economic damages that would result from them. Although this lack of empirical evidence is inescapable, these discontinuities may result in some of the most serious climate change impacts.

To date, the use of expert elicitations to characterize the functional form and uncertainty of these tipping points has been rare. Early expert elicitations on the probability of extreme climate outcomes (Morgan and Keith 1995) and impacts (Nordhaus 1994a) have been extremely valuable. However, these assessments have not addressed the issue of the "independence" of experts. It can easily be the case that experts are not independent if many of them have received identical training, use the same approaches to modeling and analysis, and maybe even have the same mentors. The issue of independence can be addressed by "combining expert opinions" (Morris 1977, 1983; Clemen and Winkler 1986), which, although difficult to accomplish, is almost certainly necessary.

A further challenge for the use of IAMs that has not yet been fully resolved is the potential for highly skewed distributions (i.e., fat tails) of uncertain variables, an issue raised by Weitzman (2009) and discussed extensively in the literature (cf., Weitzman 2013). A simplified way to state Weitzman's argument is that the combination of fat tails and strong risk aversion may lead to large losses in expected welfare. If this is the case, then the true BC IAM damage projections could become unbounded or extremely large.

Another important limitation of the simple BC IAMs, and to a lesser extent the DP IAMs, is that the whole climate system is represented with a very small number of equations drawn from highly reduced-form climate models (e.g., the Model for the Assessment of Greenhouse Gas Induced Climate Change [MAGICC] in Meinshausen, Raper, and Wigley 2011). These models generally include only energy balance equations, thus excluding the conservation of momentum and mass balance equations included in a full-scale climate or earth system model (Washington and Parkinson 2005). In actual tests of temperature projections, these models have been found to match the behavior of full-scale climate models for scenarios that move gradually from one steady state to another, but not in cases where more rapid changes are considered (van Vuuren et al. 2011; Schaeffer et al. 2013; Zickfeld et al. 2013; Rose et al. 2014b).

Treatment of Regional, National, and International Equity

The application of IAMs to climate policy has generally been efficiency focused; equity considerations have rarely been addressed directly, except for occasional ex post reporting of economic impacts across various socioeconomic strata within and between nations. This is unfortunate because equity and fairness issues often dominate the political debate concerning what to do about climate change. Moreover, this shortcoming is not easily fixed after a model with an efficiency-based optimizing architecture has been run, because of the many equity trade-offs and approximations that are typically made when such models are constructed in the first place. In addition, the global or regional representative consumer formulations, in which the choices of—and impacts on—a single "average" consumer are used to represent all consumers in an economy, that are included in some BC IAMs can make it hard to assess impacts across income classes at the national or international level. Consider the plight of the approximately two billion people on earth who live in areas without functioning goods and financial markets. Since they have no markets, these people have no (measured) income and make no (measured) expenditures. Thus, if the climate changes, they absorb no (measured) impacts and would not benefit from any reductions in those impacts that result from any policy designed to reduce carbon emissions. This means that if an optimal carbon tax is computed for a market or country based on global costs and benefits, the impacts on the world's poorest people will not be included.[12]

A related challenge for applying IAMs to climate policy concerns aggregation across countries: whose damages should be considered and how should they be weighted in computing an aggregate impact metric? This raises some daunting analytic as well as deep philosophical issues. For example, should market exchange rates or purchasing power parity weights be used to value economic damages in developing countries relative to those in developed countries? This by itself can change the valuation of Chinese impacts vis-à-vis those in the United States or European Union by a factor of two or more. But the difficulty does not stop with dollar equivalent issues: weighting losses in wealthy versus poor countries is not straightforward (Adler 2012), and it is not lost on poor countries that putting less weight on their impacts because they produce less marketed economic output can lead to climate policy recommendations that are unfair to them.

Another related challenge for DP IAMs is how to include nonclimate benefits or costs, which can be a major issue in policy debates, especially in developing countries, where air pollution and energy access can often be higher priorities than climate change per se. Recent research with two major DP IAMs highlights the significance of considering this broader set of objectives (Pachauri, Van Ruijven, and Nakicenovic 2013), which are just starting to be incorporated into DP IAMs but do not yet (and maybe cannot) figure explicitly in BC IAMs.

A final practical challenge for global BC IAMs is that even if all the site-specific physical climate change impacts can be projected and valued and aggregated with impacts in other sectors and other regions at a specific point in time, all the aggregation methods would need to be revised over time. Although this could arguably be done well for small changes, it could be problematic for the types of large systematic variations that are the biggest concern as the climate changes. This is also a challenge for DP IAMs, but it is easier to include nonlinearities in these models.

Treatment of Inter-temporal Discounting and Intergenerational Equity

In addition to the issue of treating countries consistently and fairly, it is necessary to weigh costs and benefits over time, which ultimately means considering the preferences of as-yet unborn generations. Clearly, this cannot be done directly. Thus people making decisions today on behalf of those not yet alive need to make collective ethical choices about what kind of opportunities (usually characterized as a particular state of the climate system measured by global mean temperature, GHG concentration, or maximum climate damages allowable by some future date) they want to leave future inhabitants of planet Earth (Portney and Weyant 1999; Arrow et al. 2013). BC IAMs use the discount rate to trade off the benefits and costs of climate polices, while the DP IAMs typically use the discount rate to pick cost-effective mitigation technologies and to make ex post comparisons of any valued climate damages with those mitigation costs.

[12]See Adler (2012) for more on this type of critique of BCA, as well as a well-developed argument for using much more nuanced social welfare functions (SWFs) instead.

There are two conflicting views in the economics literature concerning how to think about discounting (Nordhaus 2013). The first is the prescriptive view taken by Cline (1992) and Stern (2007), which leads to the conclusion that any positive pure rate of time preference is unethical. The second is the descriptive view, advocated by Lind (1995) and Nordhaus (1994a), which assumes that investments to slow climate change must compete with investments in other areas.

To summarize, intertemporal equity is extremely important in determining the appropriate rate of implementation of policies designed to reduce carbon emissions—explicitly in the BC IAMs and implicitly in the DP IAMs. Low discount rates generally make rapid implementation of such policies much more urgent than high discount rates because damages are projected to grow steadily over time at a much more rapid rate than mitigation costs.

Projections of Baseline Drivers

As mentioned earlier, the optimal levels of GHG emissions in BC IAMs depend on the GHG emissions baseline used. Historically the main drivers of baseline GHG emissions scenarios have been projections of future population by region, economic growth and its composition by sector and region, and future fuel prices, as well as technology costs and performance. Now that many countries have adopted climate policies in one form or another, an additional challenge is projecting the effect of these policies and measures on future emissions, which would serve as a baseline from which to examine the impacts of any new targets or new policies and measures we might want to evaluate. A further major challenge for both the mitigation and impacts/adaptation analyses is projecting the impacts of technological change on costs and benefits over 50 to 100 years or more.[13]

This same baseline dependence also holds for the mitigation and climate change impacts calculated by the DP IAMs, thus making it desirable to consider a range of baselines when making assessments. Climate change impact assessments can be especially sensitive to the baseline assumed, especially in cases where "tipping points" may be reached; the closer the tipping point is to the baseline the more likely it is to be triggered.

Capturing Interactions Between Impact Sectors and Feedbacks to the Climate System

A formidable challenge for all IAMs is capturing important interactions between impacted sectors and regions, and feedbacks that can occur between the impacted sectors and atmospheric concentrations of GHGs, temperatures, and precipitation. Other than the reduction in global economic output resulting from climate change damages and climate mitigation, the BC IAMs are too aggregated to study these interactions and feedbacks. The DP IAMs have made slow, but steady, progress on these effects over the last 20 years, with great emphasis increasingly being placed on interactions among the global energy, water, land, and food systems. According to the IPCC (2014a, chap. 19), many of the most severe impacts of climate changes in specific sectors in particular regions will result from interactions between these particular regions and sectors and other regions or impact sectors. These interactions can occur at the physical level;

[13]See Clarke et al. (2014) for a review of the sensitivity of mitigation cost projections to technology assumptions. Neumann and Strzepek (2015) and Li, Mullan, and Helgeson (2014) discuss impacts and adaptation technology dependencies.

for example, climate change can cause a particular region to become hotter and dryer, thus increasing competition for limited water between agricultural, power plant cooling, and household uses (Taheripour, Hertel, and Liu 2013). These shortages can result in abrupt economic adjustments, with both food and energy becoming more expensive in the region, which could also affect other economic sectors in the region (Baldos and Hertel 2014). Trade and transfers of water, food, and energy from other regions could ameliorate impacts in regions that are experiencing shortages, but would also lead to price increases in the regions where the trade and transfers originate. A particularly pernicious result—that is already occurring in a number of places—is increases in temperature and decreases in water in key growing regions. This has led to more irrigation being fed largely by depleting groundwater resources (Grogan et al. 2015). If the groundwater aquifers in these regions approach depletion, the cost of water will increase, which will put incredible pressure on farms in regions that are already very vulnerable and poverty stricken (Zaveri et al. 2016). Although capturing these types of interactions is not yet standard in most DP IAMs (Reilly et al., 2012b), there has been a lot of research showing how these interactions would likely occur in particular regions and sectors. For example, Diffenbaugh et al. (2012) examine the effects drought and biofuel mandates can have on both grain and energy price volatility.

Dealing with Uncertainty and Risk

The complexities of both human-induced climate change and the policies designed to address it mean that there are vast uncertainties regarding 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 temperatures and precipitation amounts).[14] There are a number of ways to address all of this uncertainty, starting with sensitivity analysis on key parameters and model inputs of the type discussed earlier.[15] In addition, Monte Carlo simulations (in which input and parameter values are selected from probability distributions) can be run through the models in order to produce probability distributions over important model outputs—such as changes in temperatures and sea levels—as well as total climate change damage and mitigation costs.

Although sensitivity analyses and Monte Carlo simulations are a good place to start, two other crucial dimensions of the climate change problem should be included in any comprehensive attempt to inform climate policy decisions. First, decisions made today can be revisited and modified at any point in the future as new information on climate change damages and mitigation costs becomes available (see, e.g., Manne and Richels 1992; Ha Duong, Grubb, and Hourcade 1997; Rozenberg et al. 2010). Thus decision making about climate change is one of sequential decision making under uncertainty. This means that society can hedge against bad climate outcomes by adopting mitigation policies that are more stringent than would be suggested by expected damages and mitigation costs without going all the way to the mitigation levels suggested by the worse possible damage and mitigation cost outcomes. The second crucial dimension of climate change uncertainty that has yet to be systematically addressed by

[14]See InterAcademy Council (2010) for a particularly noteworthy critique of the IPCC and, by extension, the entire global climate change research community on this issue.
[15]Clarke et al. (2014) summarize the results of numerous intermodel comparison studies, which include sensitivity analyses of alternative model structures as well as selected model input assumptions.

researchers are assumptions about the decision makers' attitudes toward risk. Much of the application of modern decision theory targets decisions where the stakes are important, but not sufficiently important to have a major influence on the individual's overall level of wealth. Thus, since at least Raiffa (1968) and Howard (1984), researchers have used exponential utility functions with constant relative risk aversion to represent the preferences of individual decision makers because this approach tends to provide good approximations when the outcomes of decisions are not expected to have a major influence on the individual's overall level of wealth.[16] However, in the case of climate change, where the stakes can be extremely high and highly correlated with other big societal decisions, and good experts may be hard to find, special care must be exercised in interpreting model results. Current IAMs generally make one fairly homogeneous set of simplifying assumptions about risk attitudes and the implications of alternative assumptions are generally not explored in any depth,[17] which may lead to results that understate society's degree of risk aversion towards bad outcomes and lead to less emissions mitigation than would be desirable.

Conclusions and Recommendations for Further Development and Use of IAMs

This article has summarized some of the contributions of IAMs to the development of climate policy and the setting of research priorities on global climate change. It has also identified some of the key challenges that remain in developing and using these models. Given the challenges involved in producing IAM results and the many uncertainties underlying those results, I believe it is best to view these models as providing a good place to start in terms of basic principles and rough numbers to use in developing short-term (say through the next 5 to 10 years) policies and research priorities, but a poor place to finish in the design of specific longer-term global policies. Nevertheless, as these models become more refined and spatially explicit, their results will provide more relevant information and more reliable guidance to policy advisers and science program managers to help them make better decisions over the long time period (decades to centuries) required to effectively address the climate change problem.

To some economists working on climate change policy, however, the challenges I have discussed, as well as the complexities and uncertainties inherent in the climate problem and its possible solutions, make the IAMs described here worse than useless. In particular, Pindyck (2013, p. 870) concludes that IAMs "are of little or no value for evaluating alternative climate change policies and estimating the SCC." Although Nordhaus (2014, p. 301) agrees with many of Pindyck's individual criticisms, he reaches a different conclusion regarding the usefulness of the current generation of climate policy BC IAMs:

> Pindyck's criticism of IAMs touches both empirical and conceptual issues. Beginning with the empirical questions, he highlights (1) the social preference function, particularly the discount rate, (2) the damage function, (3) the potential

[16]The assumption of constant relative risk aversion implies that a decision on climate change can safely be analyzed without looking at the correlations between that decision and all the other decisions a decision maker has made for which the payoffs are not yet known with certainty.

[17]Lempert (2015) and Toman (2015) provide guidance on what to do when these simplifying assumptions do not hold.

> for catastrophic changes, and (4) the temperature sensitivity to greenhouse gas increases. While Pindyck's observations about the empirical weaknesses of IAMs or calculations of the SCC are worthy of careful study, the conclusion that IAMs are therefore useless fundamentally misconceives the enterprise.

Following Nordhaus (2014), I would argue that the main contribution of IAMs thus far, including aggregate BC IAMs, has been to provide conceptual frameworks for developing insights about highly complex, nonlinear, dynamic, and uncertain systems, even though these models have not yet been able to provide high precision forecasts. Even at their current stage of development, IAMs allow us to conduct "If..., then..." analyses of the impacts of different factors that are internal or external to their operation. More importantly, these models have provided important insights into many aspects of climate change policy. I review and summarize some of these insights and contributions here and then present some recommendations for further development and use of IAMs.

First, aggregate BC IAMs have improved our understanding of the importance of cost-effectiveness in designing climate policies; the value of using market-based policy instruments (like emissions taxes) versus command-and-control regulations; the value of information about new technologies and improvements in the science of climate change, GHG mitigation, and climate impacts; the importance of broad participation in mitigating carbon emissions; the potential volatility in carbon prices that can result from systems that cap emissions; and the costs of alternative approaches to reducing emissions. Perhaps the most valuable contribution of systematic models such as aggregate BC IAMs is in highlighting the importance of critical issues and uncertainties (such as discounting, risk assessment, and damages) in evaluating alternative policies and regulations, and the ability they provide to incorporate new scientific findings into the assessments in a timely and orderly fashion.

Second, projections from DP IAMs provide much more detail than BC IAMs by identifying key energy technologies and impact sectors/regions, including energy, water, land, agriculture, forestry, and ecosystem impacts in exceptionally hot and cold or wet and dry regions. In addition, DP IAMs are increasingly being used to study interactions between mitigation and impacts/adaptation by accounting for competition for water and land that could have large joint impacts on the agricultural, forestry, energy, and ecosystem sectors as well as on the global carbon cycle and the amount of solar energy that gets reflected back into deep space. Results at this level can be extremely useful to international negotiators as well as national and subnational decision makers because they represent impacts that can be directly measured, many of which have already been observed (IPCC 2014a).

With these contributions and challenges of IAMs in mind, my first recommendation concerning the further development and use of IAMs in the climate policy arena is to consider an even more comprehensive set of sensitivity analyses than has typically been included thus far—one that includes alternative treatments of concepts such as equity, attitudes toward risk, and the amount of technological optimism. In this way, numbers and policies that are robust (see Lempert 2015 for a working definition) across all these dimensions can be identified and used to find solutions that are more stable and are characterized by less uncertainty.

Second, given all the uncertainties concerning the inputs to, structures of, and parameter values included in IAMs, it is important to continue to develop decision support tools based on—and supplementary to—conventional IAMs. For example, tools could include robust planning methods that use extensive sensitivity analyses to identify decisions that lead to good outcomes over a wide range of input assumptions or decision theory–based approaches that focus on likely dependencies among model inputs and the sequential characteristics of climate policy decisions where a decision can be taken today and revised periodically based on new information.

Finally, although most of the major uncertainties confronting the models will not be resolved for decades, society cannot afford to wait to make climate policy decisions until these uncertainties are resolved and the BC or DP IAM calculations are further refined. Nevertheless, as suggested in several assessments (e.g., Lempert 2015; Toman 2015), the analysis of these decisions can be placed in a broader context that recognizes both that the risks associated with these uncertainties can be quantified and managed and that the world includes many different regional and sectoral decision makers with different perceptions of the severity of the climate change problem, different stakes in climate outcomes, different preferences, different attitudes toward equity, and different attitudes toward risk. This challenge is made ever more difficult by the interactions between climate change and other major global issues such as air and water quality, poverty, food security, national security, and human health. Welfare measured across climate mitigation and impacts/adaptation around the globe is a large challenge, but even this conception of welfare needs to be placed in a broader context. IAMs can provide very useful information, but this information needs to be carefully interpreted and integrated with other quantitative and qualitative inputs in the decision-making process. As astutely observed by one reviewer of this article: "the models can be very useful, but not usually on their own."

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