APPENDIX

to the

DRAFT Workshop Report:

Improving the Assessment and Valuation of Climate Change Impacts for Policy and Regulatory Analysis – Part 1

Modeling Climate Change Impacts and Associated Economic Damages

January 2011

Workshop Sponsored by:

U.S. Environmental Protection Agency

U.S. Department of Energy

Workshop Report Prepared by:

ICF International

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Workshop Agenda with Charge Questions

Participant List

Extended Abstracts

Improving the Assessment and Valuation of
Climate Change Impacts for Policy
and Regulatory Analysis

Sponsored by

EPA United States
Environmental
Protection Agency

U.S. DEPARTMENT OF
ENERGY

November 18-19, 2010   Omni Shoreham Hotel, Washington, DC

Workshop Agenda with Charge Questions

MODELING CLIMATE CHANGE IMPACTS AND ASSOCIATED ECONOMIC DAMAGES

Charge Questions: The following charge questions (appearing in boxes) were given to each of the workshop speakers. Each speaker was asked to write a short abstract (approximately 3-5 pages) and organize their presentations around these questions, though they also were encouraged to think more broadly and to consider other ideas as they see fit. The purpose of the papers and presentations was to briefly summarize the current state of the art in each area and to set the scene for a productive discussion at the workshop, not necessarily to provide complete answers to all charge questions.

November 18, 2010

Workshop Introduction

8:30 – 8:35   ***Welcome and Introductions***
               Elizabeth Kopits, U.S. Environmental Protection Agency

8:35 – 9:00   ***Opening Remarks***
               Bob Perciasepe, Deputy Administrator, U.S. Environmental Protection
                       Agency
               Steve Koonin, Under Secretary for Science, U.S. Department of Energy

9:00 – 9:25   ***Progress Toward a Social Cost of Carbon***
               Michael Greenstone, Massachusetts Institute of Technology

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Session 1: Overview of Existing Integrated Assessment Models
Moderator: Stephanie Waldhoff, U.S. Environmental Protection Agency

> Charge: Describe
>   (1) the history of climate-economic integrated assessment modeling,
>   (2) the major reduced-form and higher-complexity IAMs currently in use,
>   (3) the main strengths and weaknesses of each model,
>   (4) current areas of active research, and
>   (5) how these areas of active research might inform policy and regulatory analysis.

9:25 – 9:50   ***Overview of Integrated Assessment Models***
               Jae Edmonds, Pacific Northwest National Laboratory

Models Used for the Development of Current USG SCC Values

Charge for all model presenters: Describe the current state of your model and any recent, planned, or potential modifications. Specifically:

(1) Describe the basic structure of your model. What are key exogenous and endogenous variables?
(2) Discuss the physical impacts included in your model and how the corresponding market and non-market economic damages are calculated. What major impacts and damage categories are not included (e.g., ocean acidification and associated damages)? To what extent does the model incorporate the physical cycles for non-CO2 GHGs?
(3) What assumptions does your model make about adaptation?
(4) What assumptions does your model make about climate system "tipping points," catastrophic impacts and the corresponding economic damages?
(5) How does your model incorporate uncertainty in physical parameters such as climate sensitivity and economic parameters such as the discount rate?

9:50–10:15 **DICE**
Steve Newbold, U.S. Environmental Protection Agency

10:15–10:40 **PAGE**
Christopher Hope, University of Cambridge

10:40–10:55 **Break**

10:55–11:20 **FUND**
David Anthoff, University of California, Berkeley

Representation of Climate Impacts in other Integrated Assessment Models

Charge for all model presenters: Describe the current state of your model and any recent, planned, or potential modifications. Specifically:

(1) Describe the basic structure of your model. What are key exogenous and endogenous variables?
(2) Discuss the physical impacts included in your model and how the corresponding market and non-market economic damages are calculated. What major impacts and damage categories are not included (e.g., ocean acidification and associated damages)? To what extent does the model incorporate the physical cycles for non-CO2 GHGs?
(3) What assumptions does your model make about adaptation?
(4) What assumptions does your model make about climate system "tipping points," catastrophic impacts and the corresponding economic damages?
(5) How does your model incorporate uncertainty in physical parameters such as climate sensitivity and economic parameters such as the discount rate?

11:20–11:45 **GCAM** (JGCRI – UMD/PNNL) *and Development of iESM*
(PNNL/LBNL/ORNL)
Leon Clarke, Pacific Northwest National Laboratory

11:45–12:10 **IGSM** (MIT)
John Reilly, Massachusetts Institute of Technology

12:10–12:40 **Discussion**

12:40 – 1:40 *Lunch*

Session 2: Near-Term DOE and EPA Efforts
Moderator: Ann Wolverton, U.S. Environmental Protection Agency

1:40 – 2:00 **Proposed Impacts Knowledge Platform**
Bob Kopp, U.S. Department of Energy
Nisha Krishnan, Resources for the Future

2:00 – 2:20 **Proposed Generalized Modeling Framework**
Alex Marten, U.S. Environmental Protection Agency

2:20 – 2:40 **Discussion**

Session 3A: Critical Modeling Issues in Assessment and Valuation of Climate Change Impacts
Moderator: Ann Wolverton, U.S. Environmental Protection Agency

2:40 – 3:10 **Sectoral and Regional Disaggregation and Interactions**
Ian Sue Wing, Boston University

Charge: Review the sectoral and regional representation of economic damages in integrated assessment models. Specifically, discuss:
   (1) how damages in one category and one region may affect other categories and regions,
   (2) the relative magnitude/importance of these interactions,
   (3) how these relationships might be represented in an IAM, and
   (4) gaps in the way existing IAMs represent these relationships and major challenges in improving these representations.

3:10–3:20 *Break*

3:20–3:50   *Adaptation and Technological Change*
             Ian Sue Wing, Boston University on behalf of Karen Fisher-Vanden,
             Pennsylvania State University

Charge: Drawing from the recent literature, discuss how adaptation may influence the net social costs of climate change (adaptation costs plus residual climate damages). Specifically, discuss:

    (1) relevant studies on the observed or potential effectiveness of adaptive measures, and on private behaviors and public projects regarding adaptation;
    (2) relevant studies on how to forecast adaptive capacity;
    (3) how adaptation and technical change could be represented in an IAM (for at least one illustrative sector);
    (4) whether the information required to calibrate such a model is currently available, and, if not, what new research is needed; and
    (5) how well or poorly existing IAMs incorporate the existing body of evidence on adaptation.

3:50–4:20   *Multi-century Scenario Development and Socio-Economic Uncertainty*
             Brian O'Neill, National Center for Atmospheric Research

Charge: Discuss the methods and difficulties associated with forecasting a baseline scenario for greenhouse gas emissions and socio-economic variables (e.g., population and GDP), including the particular challenges in extending these scenarios for multiple centuries. Specifically, discuss:

    (1) relevant studies on long-term demographic and economic scenarios and the assumptions used to develop these scenarios;
    (2) relevant studies on the evolution of energy systems and the assumptions used to develop these scenarios;
    (3) the range of plausible future scenarios extending to at least 2300, including the range incorporated into major IAMs; and
    (4) what are the main challenges in representing such multi-century forecasts in an IAM.

4:20–5:00   **Discussion**

Day 2 Introduction

8:30–8:40   ***Welcome; Recap of Day 1; Overview of Day 2***
Elizabeth Kopits, U.S. Environmental Protection Agency

<u>*Session 3B*</u>*: Critical Modeling Issues in Assessment and Valuation of Climate Change Impacts (cont.)*
Moderator: Bob Kopp, U.S. Department of Energy

8:40–9:10   ***Incorporation of Climate System Uncertainty into IAMs***
Gerard Roe, University of Washington

Charge: Discuss:
   (1) the major sources of climate system uncertainty that could be represented in reduced-form integrated assessment models (such as DICE, PAGE, and FUND),
   (2) the difficulties/issues with representing the uncertainty surrounding these parameters in IAMs, and
   (3) relevant studies that estimate probability density functions for these parameters.

9:10–9:40   ***Extrapolation of Damage Estimates to High Temperatures: Damage Function Shapes***
Marty Weitzman, Harvard University

Charge: Discuss:
   (1) how damage functions behave at high temperatures in the principal reduced-form IAMs, including DICE, PAGE, and FUND;
   (2) the reasoning underlying the selection of these functional forms and alternative formulations that have been proposed in the literature;
   (3) the relative strengths of these various functional forms in terms of extrapolating damage estimates to high temperatures; and
   (4) the difficulties/issues with incorporating uncertainty regarding such "out of sample forecasts."

9:40–10:10   ***Earth System Tipping Points***
Tim Lenton, University of East Anglia

Charge: Discuss:
   (1) evidence on potential Earth system tipping points, including the most recent estimates of these tipping points based on modeling studies, paleoclimatic data, expert elicitation, and other relevant sources; and
   (2) available estimates of their probabilities under different scenarios.

10:10–10:30 *Break*

10:30–11:00 ***Potential Economic Catastrophes***
Michael Toman, World Bank

Charge: Discuss:
(1) the literature on the potential economic damages associated with catastrophic climate impacts, potentially related to Earth system tipping points;
(2) how these damages might be incorporated into reduced-form and/or higher-complexity IAMs; and
(3) the key challenges associated with translating information on the likelihood and physical consequences of particular tipping points into economic damages.

11:00–11:30 ***Nonmarket Impacts***
Michael Hanemann, University of California, Berkeley

Charge: Discuss:
(1) recent studies of potential non-market impacts of climate change;
(2) how the value of such impacts are currently represented in IAMs;
(3) how such non-market impacts could be better represented in IAMs, possibly including but not necessarily limited to alternative damage functional forms and multivariate utility functions; and
(4) key challenges of quantifying and incorporating non-market impacts into IAMs.

11:30–12:30 **Discussion**

12:30–1:30 *Lunch*

Session 4: Implications for Climate Policy Analysis and Design
Moderator: Charles Griffiths, U.S. Environmental Protection Agency

1:30–2:00 ***Implications for Design and Benefit-Cost Analysis of Emission Reduction Policies***
Ray Kopp, Resources for the Future

Charge: How can improved IAMs, as discussed in Sessions 1-3, aid in the design and evaluation of domestic emission reduction policies such as cap-and-trade or carbon taxes, and inform negotiations of international climate agreements?

2:00–2:30 ***Implications for Addressing Equity and Natural Capital Impacts***

Geoff Heal, Columbia University

Charge: How can improved IAMs, as discussed in Sessions 1-3, help policy analysts address intra-generational equity concerns, account for impacts on natural capital and ecosystem services, and better represent the substitutability between ecosystem services and market goods?

2:30–3:00   ***Implications for Choice of Policy Targets for Cost-Effectiveness Analysis***
Nat Keohane, Environmental Defense Fund

Charge: How can improved IAMs, as discussed in Sessions 1-3, help inform a cost-effectiveness analysis of various policy actions that reduce CO2 emissions? For example, how could these models help in choosing a temperature or carbon concentration target for national policies or international agreements? Are there other environmental endpoints that should be considered in cost-effectiveness analysis of climate policies (e.g., targets associated with ocean acidification)?

3:00–3:10   ***Break***

3:10–3:40   ***Implications for Managing Climate Risks***
Roger Cooke, Resources for the Future

Charge: How could improved IAMs, along the lines discussed in Sessions 1-3, help inform a risk management analysis of various policy actions that reduce CO2 emissions? For example, how could these models aid in the design of adaptation policies to manage increased climate and weather related risks, such as increased flood frequencies and storm damages?

3:40–4:15   **Discussion**

Session 5: Workshop Wrap-up

4:15–4:30   ***Summary Comments by U.S. Department of Energy***
Rick Duke, Deputy Assistant Secretary for Climate Policy

4:30–4:45   ***Summary Comments by U.S. Environmental Protection Agency***
Al McGartland, Director of the National Center for Environmental Economics

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Extended Abstracts

(click on title to go to abstract)

Estimating the Social Cost of Carbon for the United States Government

Michael Greenstone
3M Professor of Environmental Economics
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November 2010

The climate is a key ingredient in the earth's complex system that sustains human life and well being. According to the United Nation's Intergovernmental Panel on Climate Change (IPCC), the emissions of greenhouse gases (GHG) due to human activity, large the combustion of fossil fuels like coal, is "very likely" altering the earth's climate, most notably by increasing temperatures, precipitation levels and weather variability. Without coordinated policy around the globe, state of the art climate models predict that the mean temperature in the United States will increase by about 10.7° F by the end of the century (Deschenes and Greenstone 2010). Further, the distribution of daily temperatures is projected to increase in ways that pose serious challenges to well being; for example, the number of days per year where the typical American will experience a mean (average of the minimum and maximum) temperature that exceeds 90° F is projected to increase from the current 1.3 days to a 32.2 days (ibid). The especially troubling statistic is that the hottest days pose the greatest threat to human well being.

It appeared that the United States and possibly the major emitters were poised to come together to confront climate change by adopting a coordinated set of policies that could have included linked cap and trade systems. However, the failure of the United States Government to institute such a system and the non-binding commitments from the Copenhagen Accord seem to have placed the all at once solution to climate change out of reach for at least several years.

Instead, the United States and many other countries are likely to pursue a series of smaller policies all of which aim to reduce GHG emissions but individually have a marginal impact on atmospheric concentrations. These policies will appear in a wide variety of domains, ranging from subsidies for the installation of low carbon energy sources to regulations requiring energy efficiency standards in buildings, motor vehicles, and even vending machines to rebates for home insulation materials. Although many of these policies have other goals, their primary motivation is to reduce GHG emissions. However, these policies reduce GHG emissions at different rates and different costs.

In the presence of this heterogeneity and nearly limitless set of policies that reduce GHG emissions, how is government to set out a rational climate policy? The key step is to determine the monetized damages associated with an incremental increase in carbon emissions, which is referred to as the social cost of carbon (SCC).[1] It is intended to include (but is not limited to) changes in net agricultural productivity,

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[1] Under Executive Order 12866, agencies in the Executive branch of the U.S. Federal government are required, to the extent permitted by law, "to assess both the costs and the benefits of the intended regulation and, recognizing that some costs and benefits are difficult to quantify, propose or adopt a regulation only upon a reasoned determination that the benefits of the intended regulation justify its costs."

human health, property damages from increased flood risk, and the value of ecosystem services.[2] Monetized estimates of the economic damages associated with carbon dioxide emissions allows the social benefits of regulatory actions that are expected to reduce these emissions to be incorporated into cost-benefit analyses.[3] Indeed as the Environmental Protection Agency begins to regulate greenhouse gases under the Clean Air Act, the SCC can help to identify the regulations where the net benefits are positive.

The United States Government (USG) recently selected four SCC estimates for use in regulatory analyses and has been using them regularly since their release. For 2010, the central value is $21 per ton of CO2 equivalent emissions.[4] The USG also announced that it would conduct sensitivity analyses at $5, $35, and $65. The $21, $5, and $35 values are associated with discount rates of 3%, 2.5%, and 5%, reflecting that much of the damages from climate change are in the future. The $65 value aims to represent the higher-than-expected impacts from temperature change further out in the tails of the SCC distribution. In particular, it is the SCC value for the 95th percentile at a 3 percent discount rate. These SCC estimates also grow over time based on rates endogenously determined within each model. For instance, the central value increases to $24 per ton of CO_2 in 2015 and $26 per ton of CO_2 in 2020.

I was involved in the interagency process that selected these values for the SCC and this talk summarizes these efforts.[5] The process was initiated in 2009 and completed in February 2010. It aimed to develop a defensible, transparent, and economically rigorous way to value reductions in carbon dioxide emissions that result from actions across the Federal government. Specifically, the goal was to develop a range of SCC values in a way that used a defensible set of input assumptions, was grounded in the existing literature, and allowed key uncertainties and model differences to transparently and consistently inform the range of SCC estimates used in the rulemaking process.

The intent of this lecture is to explain the central role of the social cost of carbon in climate policy, to summarize the methodology and process used by the interagency working group to develop values, and to identify key gaps so that researchers can fill these gaps. Indeed, the interagency working group explicitly aimed the current set of SCC estimates to be updated as scientific and economic understanding advances.

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[2] All values of the SCC are presented as the cost per metric ton of CO_2 emissions.

[3] Most regulatory actions are expected to have small, or "marginal," impacts on cumulative global emissions, making the use of SCC an appropriate measure.

[4] All dollar values are expressed in 2007 dollars.

[5] This process was convened by the Council of Economic Advisers and the Office of Management and Budget, with regular input from other offices within the Executive Office of the President, including the Council on Environmental Quality, National Economic Council, Office of Energy and Climate Change, and Office of Science and Technology Policy. Agencies that actively participated included the Environmental Protection Agency, and the Departments of Agriculture, Commerce, Energy, Transportation, and Treasury.

Summary of the DICE model

Stephen C. Newbold
U.S. EPA, National Center for Environmental Economics[1]

This report gives a brief summary of the DICE (Dynamic Integrated Climate-Economy) model, developed by William Nordhaus, which "integrate[s] in an end-to-end fashion the economics, carbon cycle, climate science, and impacts in a highly aggregated model that allow[s] a weighing of the costs and benefits of taking steps to slow greenhouse warming" (Nordhaus and Boyer 2000 p 5). Section 1 of this report recounts the major milestones in the development of DICE and its regionally disaggregated companion model, RICE. This section also serves as a convenient reference for more detailed expositions of the model and applications in the primary literature. Section 2 describes the basic structure of the most recently published version of DICE, and Section 3 describes some key aspects of the model calibration. Section 4 gives additional details on the climate damage function in DICE, and Section 5 gives a brief description of the most recently published version of the RICE model.

Historical development

The DICE integrated assessment model has been developed in a series of reports, peer reviewed articles, and books by William Nordhaus and colleagues over the course of more than thirty years. The earliest precursor to DICE was a linear programming model of energy supply and demand with additional constraints imposed to represent limits on the peak concentration of carbon dioxide in the atmosphere (Nordhaus 1977a,b).[2] The model was dynamic, in that it represented the time paths of the supply of energy from various fuels and the demand for energy in different sectors of the economy and the associated emissions and atmospheric concentrations of carbon dioxide. However, it included no representation of the economic impacts or damages from temperature or other climate changes. Later, Nordhaus (1991) developed a long-run steady-state model of the global economy that included estimates of both the costs of abating carbon dioxide emissions and the long term future climate impacts from climate change. This allowed for a balancing of the benefits and costs of carbon dioxide emissions to help determine the optimal level of near term controls. The analysis centered on the global average surface temperature, which was "…chosen because it is a useful index (in the nature of a sufficient statistic) of climate change that tends to be associated with most other important changes rather than because it is the most important factor in determining impacts" (Nordhaus 1991 p 930). The

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[1] Prepared for the EPA/DOE workshop, Improving the Assessment and Valuation of Climate Change Impacts for Policy and Regulatory Analysis, Washington DC, November 18-19, 2010. Please note that the views expressed in this paper are those of the author and do not necessarily represent those of the U.S. Environmental Protection Agency. No Agency endorsement should be inferred. Author's email: newbold.steve@epa.gov.

[2] While it has not been the focus of the DICE model, it should be emphasized that this type of cost-effectiveness framework is still useful. For example, if policy makers decide upon a 2 degree target, then the appropriate social cost of carbon to use is the shadow price associated with that path (Nordhaus, personal communication).

categories of climate damages that were represented in the model were associated with market sectors that accounted for roughly 13% of GDP in the United States.[3]

The DICE model was first presented in its modern form by Nordhaus (1992a,b), who described the new, fully dynamic Ramsey-type optimal growth structure of the model and the optimal time path of emission reductions and associated carbon taxes that emerged from it. The full derivation and extended description of the DICE model and a wider range of applications were presented in a book by Nordhaus (1994a). The next major advance involved disaggregating the model into ten different groups of nations to produce the RICE (Regional DICE) model, which allowed the authors to examine national-level climate policies and different strategies for international cooperation (Nordhaus and Yang 1996). An update and extended description of both RICE (now with eight regions) and DICE appeared in the book by Nordhaus and Boyer (2000). The next major update of DICE, modified to include a backstop technology that can replace all fossil fuels and whose price was projected to decline slowly over time, appeared in another book by Nordhaus (2008). Finally, Nordhaus (2010) described the most recent version of the RICE model, which adds an explicit representation of damages due to sea level rise.

In addition to the studies by Nordhaus and colleagues mentioned above, DICE has been adapted by other researchers to examine a wide range of issues related to the economics of climate change. A comprehensive review is well beyond the scope of this summary, so only a few examples are mentioned here. Pizer (1999) used DICE to compare carbon tax and a cap-and- trade-style policies under uncertainty. Popp (2005) modified DICE to include endogenous technical change. Baker *et al.* (2006) used DICE to examine the effects of technology research and development on global abatement costs. Hoel and Sterner (2007) modified the utility function in DICE to include a form of non-market environmental consumption that is an imperfect substitute for market consumption, and Yang (2008) used RICE in a cooperative game theory framework to examine strategies for international negotiations of greenhouse gas mitigation policies and targets.

Basic model structure

DICE2007 is a modified Ramsey-style optimal economic growth model, where an additional form of "unnatural capital"—the atmospheric concentration of CO_2—has a negative effect on economic output through its influence on the global average surface temperature. Global economic output is represented by a Cobb-Douglas production function using physical capital and labor as inputs. Labor is assumed to be proportional to the total global population, which grows exogenously over time. Total factor productivity also increases exogenously over time. The carbon dioxide intensity of economic production and the cost of reducing carbon dioxide emissions decrease exogenously over time. In each period a fraction of output is lost according to a Hicks-neutral climate change damage function. The output in each period is then divided between consumption, investment in the physical capital stock (savings), and expenditures on emissions reductions (akin to investment in the natural capital stock). DICE solves for the optimal path of savings and emissions reductions over a multi-century planning horizon, where the

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[3] It should be emphasized that while this model and all subsequent versions of DICE necessarily make assumptions about climate and economic conditions in the far future, the important question is the extent to which current policies are robust to changes in assumptions about future variables (Nordhaus, personal communication).

objective to be maximized is the discounted sum of all future utilities from consumption. Total utility in each period is the product of the number of individuals alive and the utility of a representative individual with average income in that period. The period utility function is of the standard constant relative risk aversion (CRRA) form, and utilities in future periods are discounted at a fixed pure rate of time preference.

Calibration

The climate model in DICE2007 tracks the stocks and flows of carbon in three aggregate compartments of the earth system: the lower atmosphere, the shallow ocean, and the deep ocean. The transfer coefficients linking the flows among the compartments were "calibrated to fit the estimates from general circulation models and impulse-response experiments, particularly matching the forcing and temperature profiles in the MAGICC model" (Nordhaus 2008 p 54). The climate sensitivity parameter—the equilibrium change in global average surface temperature after a sustained doubling of atmospheric carbon dioxide concentration— was set to 3 degrees Celsius, which is near the middle of the range cited by the IPCC. The projected temperature change under the baseline scenario (with no climate controls for the first 250 years) is an increase in global average surface temperature of 3.2 degrees Celsius around year 2100 with a peak of around 6.5 degrees Celsius around year 2500.

The key economic growth and preference parameters of DICE2007 are calibrated as follows. The global population is projected to grow exogenously from around 6.5 billion in 2005 to 8.6 billion around 2200. Total factor productivity growth and the discount rate parameters were calibrated to match market returns in the early periods of the model: specifically, "We have chosen a time discount rate of 1½ percent per year along with a consumption elasticity of 2. With this pair of assumptions, the real return on capital averages around 5½ percent per year for the first half century of the projections, and this is our estimate of the rate of return on capital" (Nordhaus 2008 p 61).

The abatement cost function is specified such that the marginal abatement cost, measured as a fraction of output, increases roughly with the square of the fraction of emissions abated. The backstop price—the marginal cost of eliminating the last unit of emissions in each period—is $1,170 per metric ton of carbon in the first period and falls exponentially at a rate of 5% per decade to a long run value of $585 per metric ton of carbon. The climate damage function is specified such that for small temperature changes the fraction of output lost in each period increases with the square of the increase in temperature above the preindustrial average temperature.[4] The coefficient of the damage function is calibrated so that roughly 1.7% of global economic output is lost when the average global surface temperature is elevated by 2.5 degrees Celsius above the preindustrial average.

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[4] The DICE2007 damage function has an "S-shape," so for very large temperature changes the fraction of output lost increases with temperature at a decreasing rate and asymptotes to one. However, it should be emphasized that the damage function is calibrated to damages in the range of 2 to 4 degrees Celsius. The extent of non-linearity beyond this range is unknown, so extrapolations beyond this point should not be considered reliable (Nordhaus, personal communication).

Damages

The globally aggregated climate damage function in DICE has been calibrated to match the sum of climate damages in all regions represented in the RICE model. The potential damages from climate change are divided into seven categories: agriculture, sea level rise, other market sectors, human health, nonmarket amenity impacts, human settlements and ecosystems, and catastrophes. A full recounting of the derivation of the damage functions in all categories is beyond the scope of this short summary, but to the give the reader a flavor for what is involved this section reviews three categories of damages: agriculture, heath, and catastrophes. This discussion draws heavily on Chapter 4 of Nordhaus and Boyer (2000), so the reader is referred there for more information.

Agriculture can serve as an illustrative example of some of the other categories not covered here. The basic strategy for calibrating the damage functions is to draw on estimates from previous studies of the potential economic losses in each category at a benchmark level of warming of 2.5 degrees Celsius, extrapolating across regions as necessary to cover data gaps in the literature. Some extrapolations were made using income elasticities for each impact category. As the authors explain, "United States agriculture can serve here as an example. Our estimate is that [the fraction of the value of agricultural output lost at 2.5 degrees Celsius] is 0.065 percent [based on Darwin et al. 1995]... The income elasticity of the impact index is estimated to be -0.1, based on the declining share of agriculture in output as per capita output rises" (Nordhaus and Boyer 2000 p 74-75).

The human health impacts of climate change were based on the effects of pollution and a broad group of climate-related tropical diseases including malaria and dengue fever. The increased mortality from warming in the summer and decreased mortality from warming in the winter were assumed to roughly offset and so were not included. The specification of the human health damage function involved "a regression of the logarithm of climate related [years of life lost] on mean regional temperature estimated form the data presented in Murray and Lopez [1996]" with judgmental adjustments "to approximate the difference among subregions that is climate related," and each year of life lost was valued at two years of per capita income (Nordhaus and Boyer 2000 p 80-82).

The damages from potential catastrophic impacts were estimated using results from a previous survey of climate experts by Nordhaus (1994b). The experts were asked for their best professional judgment of the likelihood of a catastrophe—specified as a 25 percent loss of global income indefinitely—if the global average surface temperature increased by 3 and by 6 degrees Celsius within 100 years. The averages of the survey responses were adjusted upward somewhat based on "[d]evelopments since the survey [that] have heightened concerns about the risks associated with major geophysical changes, particularly those associated with potential changes in thermohaline circulation" (Nordhaus and Boyer 2000 p 87). The probability of a 30 percent loss of global income indefinitely was assumed to be 1.2 and 6.8 percent with 2.5 and 6 degrees Celsius of warming, respectively. The percent of income lost was assumed to vary by region, and a coefficient of relative risk aversion equal to 4 was used to calculate the willingness to pay to avoid these risks in each region. The resulting "range of estimates of WTP lies between 0.45 and 1.9 percent of income for a 2.5_oC warming and between 2.5 and 10.8 percent of income for a 6_oC warming. It is assumed that this WTP has an income elasticity of 0.1" (Nordhaus and Boyer 2000 p 89).

Damages in the remaining categories were estimated in a similar vein, using a combination of empirical estimates from previous climate impact studies and professional judgments when needed to close the sometimes wide gaps in the literature. The table below shows the resulting global estimates of damages in each category in the 1999 version of RICE.

Damages as a percent of global output at 2.5_oC of warming

	Output weighted	Population weighted
Agriculture	0.13	0.17
Sea level rise	0.32	0.12
Other market sectors	0.05	0.23
Health	0.10	0.56
Non-market amenities	-0.29	-0.03
Human settlements and ecosystems	0.17	0.10
Catastrophes	1.02	1.05
Total	1.50	1.88

(Nordhaus and Boyer 2000 p 91)

With damages in all categories estimated, the DICE damage function was then calibrated "so that the optimal carbon tax and emissions control rates in DICE-99 matched the projections of these variables in the optimal run of RICE-99" (Nordhaus and Boyer 2000 p 104).

Recent developments

Nordhaus (2010) presented results from an updated version of the RICE model. A major extension is a new sea level rise damage function, now explicitly modeled by region as a function of the global average sea level rise rather than rolled up in the aggregate damage function. "The RICE-2010 model provides a revised set of damage estimates based on a recent review of the literature [Toll 2009, IPCC 2007]. Damages are a function of temperature, SLR, and CO_2 concentrations and are region-specific. To give an idea of the estimated damages in the uncontrolled (baseline) case, those damages in 2095 are… 2.8% of global output, for a global temperature increase of 3.4_oC above 1900 levels" (Nordhaus 2010 p 3). Other parameter updates include climate sensitivity, now set to 3.2 degrees Celsius, the elasticity of the marginal utility of income, now set to -1.5, and parameters that control economic growth rates, which are re-calibrated such that world per capita consumption grows by an average rate of 2.2% per year for the first 50 years.

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The PAGE09 model: Estimating climate impacts and the social cost of CO2

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Introduction

PAGE09 is a new version of the PAGE integrated assessment model that values the impacts of climate change and the costs of policies to abate and adapt to it. The model helps policy makers explore the costs and benefits of action and inaction, and can easily be used to calculate the social cost of CO2 (SCCO2) both today and in the future.

PAGE09 is an updated version of the PAGE2002 integrated assessment model. PAGE2002 was used to value the impacts and calculate the social cost of CO2 in the Stern review (Stern, 2007), the Asian Development Bank's review of climate change in Southeast Asia (ADB, 2009), and the EPA's Regulatory impact Analysis (EPA, 2010), and to value the impacts and costs in the Eliasch review of deforestation (Eliasch, 2008). The PAGE2002 model is described fully in Hope, 2006, Hope, 2008a and Hope, 2008b.

The update to PAGE09 been made to take account of the latest scientific and economic information, primarily in the 4th Assessment Report of the IPCC (IPCC, 2007). This short paper outlines the updated treatment of the science and impacts in the latest default version of the model, PAGE09 v1.7.

PAGE09 uses simple equations to simulate the results from more complex specialised scientific and economic models. It does this while accounting for the profound uncertainty that exists around climate change. Calculations are made for eight world regions, ten time periods to the year 2200, for four impact sectors (sea level, economic, non-economic and discontinuities) which cover all impacts, with the exception of socially contingent impacts such as massive forced migration and the threat of war, for which there are currently no economic estimates.

The treatment of uncertainty is at the heart of the model. In the calculation of the SCCO2, 45 inputs are specified as independent probability distributions; these typically take a triangular form, defined by a minimum, mode (most likely) and maximum value. The model is usually run 10000 times to build up full probability distributions of the scientific and economic results, such as the global mean temperature, the net present value of impacts and the SC CO2.

The full set of model equations and default inputs to the model are contained in a technical report available from the author. Initial results from the model are presented in a companion paper, 'The Social Cost of CO2 from the PAGE09 model'.

The changes made to PAGE2002 to create PAGE09 are outlined below under the following headings: Science, Impacts and Adaptation.

Science

Inclusion of Nitrous Oxide

The number of gases whose emissions, concentrations and forcing are explicitly modelled is increased from 3 in PAGE2002 to 4 in PAGE09. The forcing from N2O takes the same form as for

CH4, based on the square root of the concentration. The excess forcing from gases not explicitly modelled is now allowed to vary by policy.

Inclusion of transient climate response

In PAGE2002, the climate sensitivity is input directly as an uncertain parameter. The climate sensitivity in PAGE09 is derived from two inputs, the transient climate response (TCR), defined as the temperature rise after 70 years, corresponding to the doubling-time of CO_2 concentration, with CO_2 concentration rising at 1% per year, and the feedback response time (FRT) of the Earth to a change in radiative forcing (Andrews and Allen, 2008). Default triangular distributions for TCR and FRT in PAGE09 give a climate sensitivity distribution with a mean of 3 degC, and a long right tail, consistent with the latest estimates from IPCC, 2007.

Feedback from temperature to the carbon cycle

The standard PAGE2002 model contains an estimate of the extra natural emissions of CO_2 that will occur as the temperature rises (an approximation for a decrease in absorption in the ocean and possibly a loss of soil carbon (Hope, 2006)). Recent model comparison exercises have shown that the form of the feedback in PAGE2002 works well for business as usual emissions, but overestimates concentrations in low emission scenarios (van Vuuren et al, 2009).

In PAGE09, the carbon cycle feedback (CCF) is introduced as a linear feedback from global mean temperature to a percentage gain in the excess concentration of CO_2, to simulate the decrease in CO_2 absorption on land and in the ocean as temperature rises (Friedlingstein et al, 2006). PAGE09 is much better than PAGE2002 at simulating the carbon cycle feedback results for low emission scenarios in Friedlingstein et al, 2006, van Vuuren et al, 2009.

Land temperature patterns by latitude

In PAGE2002, regional temperatures vary from the global mean temperature only because of regional sulphate forcing. However, geographical patterns of projected warming show greatest temperature increases over land (IPCC, 2007, ch10, p749), and a variation with latitude, with regions near the poles warming more than those near the equator (IPCC, 2007, ch10, figure 10.8 and supplementary material).

In PAGE09 the regional temperature is adjusted by a factor related to the effective latitude of the region, and one related to the land-based nature of the regions. The adjustment is calculated for each region using an uncertain parameter of the order of 1 degC representing the temperature increase difference between equator and pole, and the effective absolute latitude of the region, and an uncertain constant of the order of 1.4 representing the ratio between mean land and ocean temperature increases.

Explicit incorporation of sea level rise

In PAGE2002, sea level rise is only included implicitly, assumed to be linearly related to global mean temperature. This neglects the different time constant of the sea level response, which is longer than the surface air temperature response (IPPC, 2007, p823).

In PAGE09, sea level is modelled explicitly as a lagged linear function of global mean temperature (Grinsted et al, 2009). The IPCC has a sea level rise projection in 2100 of 0.4 – 0.7 m from pre-

industrial times (IPCC , 2007, p409). A characteristic response time of between 500 and 1500 years in PAGE09 gives sea level rises compatible with these IPCC results.

Impacts

Impacts as a proportion of GDP

In PAGE2002, economic and non-economic impacts before adaptation are a polynomial function of the difference between the regional temperature and the tolerable temperature level, with regional weights representing the difference between more and less vulnerable regions. These impacts are then equity weighted, discounted at the consumption rate of interest and summed over the period from now until 2200. There are several issues with this representation, including the lack of an explicit link from GDP per capita to the regional weights, and the possibility that impacts could exceed 100% of GDP with unfavourable parameter combinations.

In PAGE09, extra flexibility is introduced by allowing the possibility of initial benefits from small increases in regional temperature (Tol, 2002), by linking impacts explicitly to GDP per capita and by letting the impacts drop below their polynomial on a logistic path once they exceed a certain proportion of remaining GDP to reflect a saturation in the vulnerability of economic and non-economic activities to climate change, and ensure they do not exceed 100% of GDP.
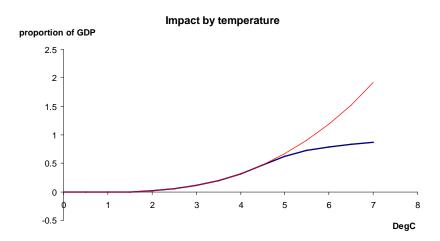
Figure 1

Figure 1 shows such an impact function, with initial benefits (IBEN) of 1% of GDP per degree, with impacts (W) of 4% of GDP at a calibration temperature (TCAL) of 2.5 degC, with a polynomial power (POW) of 3, and an exponent with income (IPOW) of -0.5. The impact function has a saturation(ISAT) starting at 50% of GDP, which keeps the impacts (blue line) below 100% of GDP even for the high temperatures shown. The red line shows what the impacts would be if they continued to follow the polynomial form without saturation.

Discontinuity impacts

As in PAGE2002, the risk of a large-scale discontinuity, such as the Greenland ice sheet melting, is explicitly modelled. In PAGE09 the losses associated with a discontinuity do not all occur immediately, but instead develop with a characteristic lifetime after the discontinuity is triggered (Lenton et al, 2008).

Equity weighting of impacts

In PAGE2002, impacts are equity weighted in a rather ad-hoc way, with the change in consumption increased in poor regions and decreased in rich ones.

PAGE09 uses the equity weighting scheme proposed by Anthoff et al (2009) which converts changes in consumption to utility, and amounts to multiplying the changes in consumption by

$$EQ(r,t) = (G(fr,0)/G(r,t))\text{^ } EMUC$$

where G(r,t) is the GDP per capita in a region and year, G(fr,0) is today's GDP per capita in some focus region (which could be the world as a whole, but in PAGE09 is normally the EU), and EMUC is the negative of the elasticity of the marginal utility of consumption. This equity weighted damage is then discounted at the utility rate of interest, which is the PTP rate.

Adaptation

The speed and amount of adaptation is modelled as a policy decision in PAGE. This allows the costs and benefits of different adaptation decisions to be investigated. In PAGE2002, adaptation can increase the natural tolerable level of temperature change, and can also reduce any climate change impacts that still occur.

In PAGE09, there is assumed to be no natural tolerable temperature change, and adaptation policy is specified by seven inputs for each impact sector. The tolerable temperature is represented by the plateau, the start date of the adaptation policy and the number of years it takes to have full effect. The reduction in impacts is represented by the eventual percentage reduction, the start date, the number of years it takes to have full effect and the maximum sea level or temperature rise for which adaptation can be bought; beyond this, impact adaptation is ineffective. Both types of adaptation policy are assumed to take effect linearly with time. An adaptation policy in PAGE09 is thus defined by 7 inputs for 3 sectors for 8 regions, giving 168 inputs in all. This is a simplification compared to the 480 inputs in PAGE2002.

The green line in figure 2 shows an illustrative tolerable temperature profile over time in an impact sector that results from an adaptation policy that gives a tolerable temperature of 2 degC, starting in
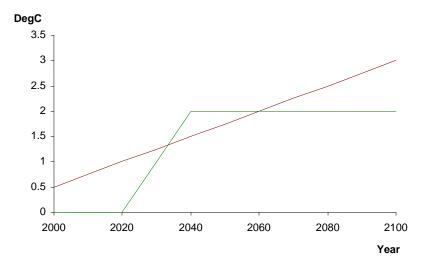
Figure 2: Temperature and tolerable temperature by date (illustrative)

2020 and taking 20 years to implement fully. If the temperature rise is shown by the red line, there will be 0.5 degC of impacts in 2000, increasing to 1 deg C by 2020, then reducing to 0 from 2030 to 2060. After 2060 the impacts start again, reaching 1 deg C by 2100.

Acknowledgement

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FUND – Climate Framework for Uncertainty, Negotiation and Distribution

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FUND (the Climate Framework for Uncertainty, Negotiation and Distribution) is an integrated assessment model linking projections of populations, economic activity and emissions to simple greenhouse gas cycle, climate and sea-level rise models, and to a model predicting and monetizing welfare impacts. Climate change welfare impacts are monetized in 1995 dollars and are modelled over 16 regions. Modelled welfare impacts include agriculture, forestry, sea level rise, cardiovascular and respiratory disorders influenced by cold and heat stress, malaria, dengue fever, schistosomiasis, diarrhoea, energy consumption from heating and cooling, water resources, unmanaged ecosystems and tropical and extratropical storms (Link and Tol, 2004). The source code, data, and a technical description of the model can be found at http://www.fund-model.org.

Essentially, *FUND* consists of a set of exogenous scenarios and endogenous perturbations. The model distinguishes 16 major regions of the world, viz. the United States of America, Canada, Western Europe, Japan and South Korea, Australia and New Zealand, Central and Eastern Europe, the former Soviet Union, the Middle East, Central America, South America, South Asia, Southeast Asia, China, North Africa, Sub-Saharan Africa, and Small Island States. Version 3.6, the latest version, runs to the year 3000 in time steps of one year.

The period of 1950-1990 is used for the calibration of the model, which is based on the *IMAGE* 100-year database (Batjes and Goldewijk, 1994). The period 1990-2000 is based on observations (http://earthtrends.wri.org). The 2000-2010 period is interpolated from the immediate past. The climate scenarios for the period 2010-2100 are based on the EMF14 Standardized Scenario, which lies somewhere in between IS92a and IS92f (Leggett *et al.*, 1992). The period 2100-3000 is extrapolated.

The scenarios are defined by varied rates of population growth, economic growth, autonomous energy efficiency improvements, and decarbonization of energy use (autonomous carbon efficiency improvements), as well as by emissions of carbon dioxide from land use change, methane emissions, and nitrous oxide emissions. FUND 3.5 introduced a dynamic biosphere feedback component that perturbates carbon dioxide emissions based on temperature changes.

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Emission reduction of carbon dioxide, methane and nitrous oxide is specified as in Tol (2006). Simple cost curves are used for the economic impact of abatement, with limited scope for endogenous technological progress and interregional spillovers (Tol, 2005).

The scenarios of economic growth are perturbed by the effects of climatic change. Climate-induced migration between the regions of the world causes the population sizes to change. Immigrants are assumed to assimilate immediately and completely with the respective host population.

The tangible welfare impacts are dead-weight losses to the economy. Consumption and investment are reduced without changing the savings rate. As a result, climate change reduces long-term economic growth, although consumption is particularly affected in the short-term. Economic growth is also reduced by carbon dioxide abatement measures. The energy intensity of the economy and the carbon intensity of the energy supply autonomously decrease over time. This process can be accelerated by abatement policies.

The endogenous parts of *FUND* consist of the atmospheric concentrations of carbon dioxide, methane and nitrous oxide, the global mean temperature, the effect of carbon dioxide emission reductions on the economy and on emissions, and the effect of the damages on the economy caused by climate change. Methane and nitrous oxide are taken up in the atmosphere, and then geometrically depleted. The atmospheric concentration of carbon dioxide, measured in parts per million by volume, is represented by the five-box model of Maier-Reimer and Hasselmann (1987). Its parameters are taken from Hammitt *et al*. (1992).

The radiative forcing of carbon dioxide, methane, nitrous oxide and sulphur aerosols is determined based on Shine *et al*. (1990). The global mean temperature, T, is governed by a geometric build-up to its equilibrium (determined by the radiative forcing, RF), with a half-life of 50 years. In the base case, the global mean temperature rises in equilibrium by 3.0°C for a doubling of carbon dioxide equivalents. Regional temperature is derived by multiplying the global mean temperature by a fixed factor, which corresponds to the spatial climate change pattern averaged over 14 GCMs (Mendelsohn *et al.*, 2000). The global mean sea level is also geometric, with its equilibrium level determined by the temperature and a half-life of 50 years. Both temperature and sea level are calibrated to correspond to the best guess temperature and sea level for the IS92a scenario of Kattenberg *et al.* (1996).

The climate welfare impact module, based on Tol (2002a; Tol, 2002b) includes the following categories: agriculture, forestry, sea level rise, cardiovascular and respiratory disorders influenced by cold and heat stress, malaria, dengue fever, schistosomiasis, diarrhoea, energy consumption from heating and cooling, water resources, unmanaged ecosystems and tropical and extratropical storms. Climate change related damages are triggered by either the rate of temperature change (benchmarked at 0.04°C/yr) or the level of temperature change (benchmarked at 1.0°C). Damages from the rate of temperature change slowly fade, reflecting adaptation (cf. Tol, 2002b).

In the model individuals can die prematurely due to temperature stress or vector-borne diseases, or they can migrate because of sea level rise. Like all welfare impacts of climate change, these effects

are monetized. The value of a statistical life is set to be 200 times the annual per capita income.[2] The resulting value of a statistical life lies in the middle of the observed range of values in the literature (cf. Cline, 1992). The value of emigration is set to be three times the per capita income (Tol, 1995; Tol, 1996), the value of immigration is 40 per cent of the per capita income in the host region (Cline, 1992). Losses of dryland and wetlands due to sea level rise are modelled explicitly. The monetary value of a loss of one square kilometre of dryland was on average $4 million in OECD countries in 1990 (cf. Fankhauser, 1994). Dryland value is assumed to be proportional to GDP per square kilometre. Wetland losses are according to estimates from Brander et al. (2006). Coastal protection is based on cost-benefit analysis, including the value of additional wetland lost due to the construction of dikes and subsequent coastal squeeze.

Other welfare impact categories, such as agriculture, forestry, hurricanes, energy, water, and ecosystems, are directly expressed in monetary values without an intermediate layer of impacts measured in their 'natural' units (cf. Tol, 2002a). Modelled effects of climate change on energy consumption, agriculture, and cardiovascular and respiratory diseases explicitly recognize that there is a climatic optimum, which is determined by a variety of factors, including plant physiology and the behaviour of farmers. Impacts are positive or negative depending on whether the actual climate conditions are moving closer to or away from that optimum climate. Impacts are larger if the initial climate conditions are further away from the optimum climate. The optimum climate is of importance with regard to the potential impacts. The actual impacts lag behind the potential impacts, depending on the speed of adaptation. The impacts of not being fully adapted to new climate conditions are always negative (cf. Tol, 2002b).

The welfare impacts of climate change on coastal zones, forestry, hurricanes, unmanaged ecosystems, water resources, diarrhoea, malaria, dengue fever, and schistosomiasis are modelled as simple power functions. Impacts are either negative or positive, and they do not change sign (cf. Tol, 2002b).

Vulnerability to climate change changes with population growth, economic growth, and technological progress. Some systems are expected to become more vulnerable, such as water resources (with population growth) and heat-related disorders (with urbanization), or more valuable, such as ecosystems and health (with higher per capita incomes). Other systems are projected to become less vulnerable, such as energy consumption (with technological progress), agriculture (with economic growth) and vector- and water-borne diseases (with improved health care) (cf. Tol, 2002b).

In the Monte Carlo analyses, most model parameters (including parameters for the physical components as well as the economic valuation components) are varied. The probability density functions are mostly based on expert guesses, but where possible "objective" estimates were used. Parameters are assumed to vary independently of one another, except when there are calibration or accounting constraints. "Preference parameters" like the discount rate or the parameter of risk aversion are not varied in the Monte Carlo analysis. Details of the Monte Carlo analysis can be found on *FUND*'s website at http://www.fund-model.org.

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[2] Note that this implies that the monetary value of health risk is effectively discounted with the pure rate of time preference rather than with the consumption rate of discount (Horowitz, 2002). It also implies that, after equity weighing, the value of a statistical life is equal across the world (Fankhauser *et al.*, 1997).

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Climate Damages in the MIT IGSM

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Integrated assessment models (IAMs) have proven useful for analysis of climate change because they represent the entire inhabited earth system, albeit typically with simplified model components that are reduced form or more highly aggregated than for example, high resolution coupled atmosphere-ocean-land general circulation models. The MIT Integrated Global System Model has been developed to retain the flexibility to assemble earth system models of variable resolution and complexity, however, even at its simplest it remains considerably more complex than most other IAMs. In its simplest formulation it retains a full coupled general circulation model of the ocean and atmosphere. Solved recursively, it solution time for a 100-year integration on a single node of computer cluster is on the order of 24-36 hours, compared with seconds or minutes for other IAMs. In that form it is not numerical feasible to solve the whole system as a fully dynamic optimizing model to find an optimal cost-benefit solution as with the DICE, PAGE, or FUND models. Indeed, inclusion of climate damages is still a work in progress in the MIT IGSM. The slow progress relative to other efforts stems from a commitment to represent explicitly the physical impacts of climate ad environmental change on activities (e.g. crop yields, water availability, coastal, inundation, ecosystem processes and functioning, health outcomes, etc.) and represent market response to these outcomes and value that response consistent with projections of resource prices as they are projected to change in the future with economic growth and under different policies to mitigate greenhouse gas emissions. This is in contrast to most of the optimizing models where climate damages are estimated as a reduced form relationship in dollars of economic loss as a function of mean global temperature change as a sufficient indicator of many dimensions of climate change, and where the damage function is itself completely independent and separable from the economy as it affects energy use and greenhouse gas emissions. The MIT IGSM is not designed to run well if the purpose is to estimate a net present value social cost of carbon. The IGSM is best seen as complementary to such efforts, and probably the focus on uncertainty in future climate outcomes is one of the areas where it can make the most contribution t the social cost of carbon discussion.

Computationally efficient versions of the IGSM have been assembled for simulating large ensembles to study uncertainty (Sokolov et al., 2009; Webster et al., 2009). Less complete but more highly-resolved model components can be combined where research demands them, such as in the study of the climate effect of aerosols (Wang, 2009; Wang et al., 2009a,b), changes in atmospheric composition and human health (Selin et al., 2009a) or agricultural impacts and land use change (Reilly, et al. 2007; Felzer et al., 2005; Melillo et al., 2009). The IGSM framework encompasses the following components:

- global economic activity resolved for large countries and regions that projects changes in human activities as they effect the earth system including emissions of pollutants and radiatively active substances and changes in land use and land cover;

- earth system modules linked to the macroeconomy that address effects of climate and environmental change on human activity, adaptation, and their consequences for the macroeconomy (this includes modules that represent water use and land use at

disaggregated spatial scales, energy and coastal infrastructure again at disaggregate spatial scales, and demography, urbanization, urban air chemistry, and epidemiological relationships that relate environmental change to human health);

- the natural and managed land system including vegetation, hydrology, and biogeochemistry as affected by human activity, environmental change and feedbacks on climate and atmospheric composition;

- the circulation and biogeochemistry of the ocean including its interactions with the atmosphere, and representations of physical and biological oceanic responses to climate change; and

- the circulation and chemistry of the atmosphere including its role in radiative forcing, and interactions with the land and ocean that determine climate change.

The suite of models that have been employed in this framework and their capabilities are briefly described below.

Human Drivers and Analysis of Impacts

Human activities as they contribute to environmental change or are affected by it are represented in multi-region, multi-sector models of the economy that solves for the prices and quantities of interacting domestic and international markets for energy and non-energy goods as well as for equilibrium in factor markets. The MIT Emissions Predictions and Policy Analysis (EPPA) model (Paltsev et al., 2005) covers the world economy. It is built on the GTAP dataset (maintained at Purdue University) of the world economic activity augmented by data on the emissions of greenhouse gases, aerosols and other relevant species, and details of selected economic sectors. The GTAP database allows flexibility to represent the world economy with greater country or sector detail (the data set has 112 countries/regions and 57 economic sectors) that we aggregate further for numerical efficiency. The model projects economic variables (GDP, energy use, sectoral output, consumption, etc.) and emissions of greenhouse gases (CO_2, CH_4, N_2O, HFCs, PFCs and SF_6) and other air pollutants (CO, VOC, NO_x, SO_2, NH_3, black carbon, and organic carbon) from combustion of carbon-based fuels, industrial processes, waste handling, and agricultural activities.

The model has been augmented with supplemental physical accounts to link it with the earth system components of the IGSM framework. To explore land use and environmental consequences, the EPPA model (Gurgel, et al., 2007; Antoine, et al.,2008) is coupled with the Terrestrial Ecosystem Model (Melillo et al., 2009). The linkage allows us to examine the ability of terrestrial ecosystems to supply biofuels to meet growing demand for low-emissions energy sources along with the growing demand for food, and to assess direct and indirect emissions from an expanded cellulosic bioenergy program. The approach generates worldwide land-use scenarios at a spatial resolution of 0.5º latitude by 0.5º longitude that varies with climate change. To analyze the economic impacts of air pollution, the EPPA model is extended to include pollution-generated health costs, which reduce the resources available to the rest of the economy (Nam et al., 2009; Selin et al., 2009a). The model captures the amount of labor and leisure lost and additional medical services required due to acute and chronic exposure to pollutants. The GTAP database allows considerable flexibility to represent the world economy with greater country or sector detail (the underlying data has 112 countries/regions and 57 economic sectors). To assess distributional and regional impacts of carbon

policy in the US, we use a model that is based on a state-level database and resolves large U.S. states and multi-state regions and households of several income classes. The U.S. Regional Energy Policy (USREP) model (Rausch et al., 2009; 2010) is nearly identical in structure to the EPPA model, except that it models states and multi-state regions in the US instead of countries and multi-country regions. The main difference from the EPPA model is the foreign sector that is represented as export supply and import demand functions rather than a full representation of foreign economies. This sacrifice of global coverage allows explicit modeling of distributional details of climate legislation and linking the USEP model to very detailed electricity dispatch models. Efforts, under separate funding, to integrate the USREP database into the GTAP base to provide a complete representation of trade are underway. Physical impacts of environmental change have been included in the model as a feedback by identifying factors (land productivity as it affects crops, livestock and forests) or sectors affected by climate or by introducing additional household production sectors (household health services that uses leisure and medical services). Thus, the approach is to work with underlying input-output and Social Accounting Matrix (SAM) that is the basis for the economic model (Matus, et al., 2008). This provides a framework for potentially linking other impacts such as coastal (Franck et al., 2010a,b, 2010; Sugiyama, et al., 2008), agriculture (Reilly et al., 2007), health (Selin, et al., 2009; Nam et al., 2010), or water (Strzepek et al., 2010) impacts.

Hydrology and Water Management

Research on components representing water management are aimed at linking hydrological changes projected by the atmospheric component of the IGSM to impacts of those changes on water availability and use for irrigation, energy, industry and households, and in-stream ecological services. These demands are driven by macroeconomic changes and changes in water supply and will in turn affect the economy as represented in the EPPA and the USREP models. Techniques have been developed to take IGSM 2-D GCM outputs and use results from the IPCC AR-4 3-D GCMs to provide IGSM-generated 3-D climates to the hydrology component of the IGSM-Land Surface Model (NCAR Community Land Model, CLM) to project runoff. Tests have been conducted for the US, where adequate data are available, to determine the spatial resolution needed to provide reliable estimates of runoff using CLM. A Water Resources System (WRS) model has been adapted from and further developed in collaboration with the International Food Policy Research Institute (IFPRI) to represent river reaches and natural and management components that affect stream-flow. The major natural components are wetlands, unmanaged lakes, groundwater aquifers and flood plains. The major managed components are reservoirs and managed lakes, and water diversions for irrigation, cooling in thermal power plants, and industrial and household needs. Constraints on use to preserve in-stream ecological water requirements can be imposed.

A series of models were adapted and developed to represent water use. These include a crop growth model (CLICROP) developed to be able to run at 2° latitude-longitude grid resolution while retaining the accuracy of a 0.5° resolution, thereby improving numerical efficiency of the modeling system (Strzepek et al., 2010a). A model of Municipal and Industrial water demand driven by per capita GDP was developed jointly with the University of Edinbough (Hughes et al., 2010; Strzepek et al., 2010a). To investigate changes in thermal electric cooling water demands, a geospatial methodology based on energy generation and geo-hydroclimatic variables has been developed (Strzepek et al., 2010b). An assessment of environmental flow requirements to assure aquatic ecosystem viability has been undertaken and an approach for using the IGSM was selected (Strzepek

& Boehlert, 2010; Strzepek et al., 2010a). These developments provide the foundation for completing linkages of the WRS with other IGSM components.

Atmospheric Dynamics and Physics

Research utilizing the IGSM framework has typically included a 2-D atmospheric (zonally-averaged statistical dynamical) component based on the Goddard Institute for Space Studies (GISS) GCM. The IGSM version 2.2 couples this atmosphere with a 2D ocean model (latitude, longitude) with treatment of heat and carbon flows into the deep ocean (Sokolov et al, 2005). The IGSM version 2.3 (where 2.3 indicates the 2-D atmosphere/full 3-D ocean GCM configuration) (Sokolov et al., 2005; Dutkiewicz et al., 2005) is a fully-coupled Earth system model that allows simulation of critical feedbacks among its various components, including the atmosphere, ocean, land, urban processes and human activities. A limitation of the IGSM2.3 is the above 2-D (zonally averaged) atmosphere model that does not permit direct regional climate studies. For investigations requiring 3-D atmospheric capabilities, the National Center for Atmospheric Research (NCAR) Community Atmosphere Model version 3 (CAM3) (Collins et al., 2006) has been used with offline coupling.

The IGSM2.3 provides an efficient tool for generating probabilistic distributions of sea surface temperature (SST) and sea ice cover (SIC) changes for the 21st century under varying emissions scenarios, climate sensitivities, aerosol forcing and ocean heat uptake rates. Even though the atmospheric component of the IGSM2.3 is zonally-averaged, it provides heat and fresh-water fluxes separately over the open ocean and over sea ice, as well as their derivatives with respect to surface temperature. This resolution allows the total heat and fresh-water fluxes for the IGSM2.3 oceanic component to vary by longitude as a function of SST so that, for example, warmer ocean locations undergo greater evaporation and receive less downward heat flux.

In offline coupling between the IGSM2.3 and CAM3, the 3-D atmosphere is driven by the IGSM2.3 SST anomalies with a climatological annual cycle taken from an observed dataset (Hurrell et al., 2008), instead of the full IGSM2.3 SSTs, to provide a better SST annual cycle, and more realistic regional feedbacks between the ocean and atmospheric components. This approach yields a consistent regional distribution and climate change over the 20th century as compared to observational datasets, and can then be used for simulations of the 21st century.

Urban and Global Atmospheric Chemistry and Aerosols

The model of atmospheric chemistry includes an analysis of all the major climate-relevant reactive gases and aerosols at urban scales coupled to a model of the chemistry of species exported from urban/regional areas (plus the emissions from non-urban areas) at global scale. For calculation of the atmospheric composition in non-urban areas, the atmospheric dynamics and physics model is linked to a detailed 2-D zonal-mean model of atmospheric chemistry. The atmospheric chemical reactions are thus simulated in two separate modules: one for the sub-grid-scale urban chemistry and one for the 2-D model grid. In addition, offline studies also utilize the 3-D capabilities of the CAM3 as noted above, as well as the global Model of Atmospheric Transport and Chemistry (MATCH; *Rasch et al.,* 1997), and the GEOS-Chem global transport model (http://geos-chem.org/).

Global Atmospheric Chemistry: Modeling of atmospheric composition at global scale is by the above 2-D zonal-mean model with the continuity equations for trace constituents solved in mass conservative or flux form (Wang et al., 1998). The model includes 33 chemical species including black carbon aerosol, and organic carbon aerosol, and considers convergences due to transport,

convection, atmospheric chemical reactions, and local production/loss due to surface emission/deposition. The scavenging of carbonaceous and sulfate aerosol species by precipitation is included using a method based on a detailed 3-D climate-aerosol-chemistry model (Wang, 2004) that has been developed in collaboration with NCAR. The interactive aerosol-climate model is used offline to model distributions of key chemical species, such as those utilized in the development of the urban air chemistry model.

Urban Air Chemistry: A reduced-form urban chemical model that can be nested within coarser-scale models has been developed and implemented to better represent the sub-gridscale urban chemical processes that influence air chemistry and climate (Cohen & Prinn, 2009). This is critical both for accurate representation of future climate trends and for our increasing focus on impacts, especially to human health and down-wind ecosystems. The MIT Urban Chemical Metamodel (UrbanM) is an update of our Mayer et al. (2000) model, and applies a third-order polynomial fit to the CAMx regional air quality model (ENVIRON, 2008) for 41 trace gases and aerosols for a 100 km x 100 km urban area. While a component of the IGSM, the urban modular UrbanM is also designed to facilitate inclusion in a number of other global atmospheric models. It has recently been embedded in the MIT interactive climate-aerosol simulation based on CAM3 in order to assess its influence on the concentration and distribution of aerosols in Asia (Cohen et al., 2009). Work is underway to further test the sensitivity of the probabilistic uncertainty results with the IGSM2.2/2.3 to this improved representation of urban chemistry. The UrbanM is presently being benchmarked in a case study of the Northeast U.S., and embedded in a global 3-D chemistry-climate model including a detailed chemical mechanism (NCAR CAM-Chem).

Chemistry-Climate-Aerosol Component: A 3-D interactive aerosol-climate model has been developed at MIT in collaboration with NCAR based on the finite volume version of the Community Climate ystem Model (CCSM3; Collins et al., 2006). Focused on analysis of aerosols, this companion sub-model is not yet integrated into the IGSM but serves as a step toward overcoming the limitations for analysis of regional issue using the IGSM 2-D atmosphere configuration. The modeled aerosols include three types of sulfate, two external mixtures of black carbon (BC), one type of organic carbon, and one mixed state (comprised primarily of sulfate and other compounds coated on BC); each aerosol type has a prognostic size distribution (Kim et al., 2008). The model incorporates such processes as aerosol nucleation, diffusive growth, coagulation, nucleation and impaction scavenging, dry deposition, and wet removal. It has been used to investigate the global aerosol solar absorption rates (Wang et al., 2009a) and the impact of absorbing aerosols on the Indian summer monsoon (Wang et al., 2009b). The UrbanM has recently been introduced into this model to study the roles of urban processing in global aerosol microphysics nd chemistry and to compute the abundance and radiative forcing of anthropogenic aerosols (Cohen et al., 2010). This effort also serves as the first step toward introducing the full UrbanM into the 3-D aerosol-chemistry-climate framework.

Ocean Component

The IGSM framework retains the capability to represent ocean physics and biogeochemistry in several different ways depending onthe question to be addressed. It can utilize either the 2-D (latitude-longitude) mixed-layer anomaly-diffusing ocean model or the fully 3-D ocean general circulation model (GCM). The IGSM with the 2-D ocean is more computationally efficient and more flexible for studies of uncertainty in climate response. In applications that need to account for

atmosphere-ocean circulation interactions, or for more detailed studies involving ocean biogeochemistry, the diffusive ocean model is replaced by the fully 3D ocean GCM component.

2-D Ocean Model: The IGSM2.2 has a mixed-layer anomaly-diffusing ocean model with a horizontal resolution of 4º in latitude and 5º in longitude. Mixed-layer depth is prescribed based on observations as a function of time and location. Vertical diffusion of anomalies into the deep ocean utilizes a diffusion coefficient that varies zonally as well as meridionaly. The model includes specified vertically-integrated horizontal heat transport by the deep oceans, and allows zonal as well as meridional transport. A thermodynamic ice module has two layers and computes the percentage of area covered by ice and ice thickness, and a diffusive ocean carbon module is included (Sokolov et al, 2005; Holian et al., 2001; Follows et al. 2006).

3-D Ocean General Circulation Model: The IGSM2.3 ocean component is based on a state-of-the-art 3D MIT ocean GCM (Marshall et al., 1997). Embedded in the ocean model is a thermodynamic sea-ice module (Dutkiewicz et al., 2005). The 3D ocean component is currently configured in either a coarse resolution (4° by 4° horizontal, 15 layers in the vertical) or higher resolution (2° by 2.5°, 23 layers; or alternate configuration with higher resolution in the topics) depending on the focus of study and the computational resources available. The efficiency of ocean heat uptake can be varied (e.g., Dalan et al. 2005) and the coupling of heat, moisture, and momentum can be modified for process studies (e.g., Klima 2008). In addition, a biogeochemical component with explicit representation of the cycling of carbon, phosphorus and alkalinity can be incorporated. Export of organic and particulate inorganic carbon from surface waters is parameterized and biological productivity is modelle as a function of available nutrients and light (Dutkiewicz et al., 2005). Air-sea exchange of CO_2 allows feedback between the ocean and atmosphere components. An additional module with explicit representation of the marine ecosystem (Follows et al., 2007) has been introduced in an "offline" (i.e. without full feedbacks to the full IGSM) configuration (see further discussion in Section 4.2.3).

Land and Vegetation Processes

The Global Land System (GLS, Schlosser et al., 2007) of the IGSM links biogeophysical, ecological, and biogeochemical components: (1) the NCAR Community Land Model (CLM), which calculates the global, terrestrial water and energy balances; (2) the Terrestrial Ecosystems Model (TEM) of the Marine Biological Laboratory, which simulates carbon (CO_2) fluxes and the storage of carbon and nitrogen in vegetation and soils including net primary production and carbon sequestratio or loss; and (3) the Natural Emissions Model (NEM), which simulates fluxes of CH_4 and N_2O, and is now embedded within TEM. A recent augmentation to the GLS enables a more explicit treatment of agricultural processes and a treatment of the managed waer systems (Strzepek et al., 2010a). The linkage between econometrically based decisions regarding land use (from EPPA) and plant productivity from TEM has been enhanced (Cai et al., 2010). And the treatment of migration of plant species to include meteorological constraints (i.e. winds) to seed dispersal has been enhanced (Lee et al., 2009, 2010a,b). The representation of natural and vegetation processes also includes a diagnosis of the expansion of lakes and changes of methne emissions from thermokarst lake expansion/degradation (Gao et al., 2010; Schlosser et al., 2010). In addition, continuing updates to CLM and TEM are also incorporated into the GLS framework. In all these applications, the GLS is operating under a range of spatial resolutions (from zonal to gridded as low as 0.5º), and is configured in its structural detail to accommodate various levels of process-oriented research both

in a coupled framework within the IGSM as well as in standalone studies (i.e. with prescribed atmospheric forcing).

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Modeling the Impacts of Climate Change: Elements of a Research Agenda

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Introduction: What is an IAM?

As illustrated in Figure 1, an integrated assessment model (IAM) of climate change is typically constructed from three interlinked sub-models, an economic model (1), a climate model (2) and an impacts model (3). It is logical to begin with the economic sub-model, which is responsible for generating time-paths of global emissions of greenhouse gases (GHGs—principally carbon dioxide, CO_2) (a). These serve as inputs to the climate submodel, which uses them to project changes in the magnitude of meteorological variables such as temperature, precipitation or sea level rise (b). Finally, the changes in climate parameters are translated into projections of global- or regional-scale economic losses by an impacts sub-model, whose primary role is to capture the feedback effect of dangerous near-term anthropogenic interference with the climate on economic activity over the longterm future (c).

Innovation is a key modulator of the clockwise circulation of the feedback loop in the figure. Improvements in the productivity of labor induce more rapid growth and increase the demand for fossil energy resources, which has a first-order amplifying effect on emissions (A). Energy- or emissions-saving technological progress tends to depress the emission intensity of the economy, slowing the rate of increase in fossil fuel use; conversely, productivity improvements in energy resource extraction lower the price of fossil fuels and induce substitution toward them, increasing emissions (B). Lastly, we can imagine that there may be innovations that boost the effectiveness of defensive expenditures undertaken in response to the threat of climate damages, or investments in creating new knowledge that enables humankind to mitigate some climate damages (C). This last category is the most speculative, as impacts will manifest themselves several decades in the future, when the state of technology is likely to be quite different from today.
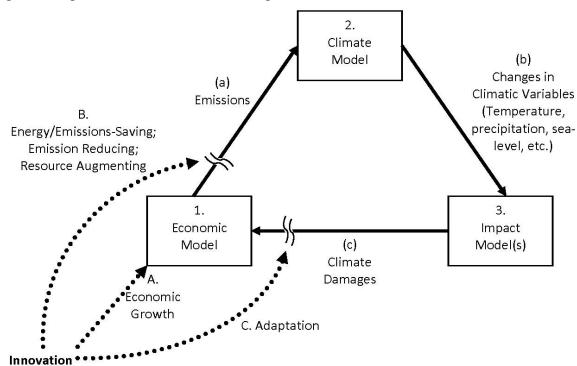
Figure 1: Integrated Assessment of Climate Change and the Effects of Innovation

Land of Cockaigne: An IAM with Regional, Sectoral and Climate Impact Detail

Imagine that there were relatively few constraints to either our computational resources or our ability to foresee the impacts of climate change. In such a world, what would an IAM look like? We could then specify a RICE- or AD-WITCH-type IAM that resolved (a) the detailed sectoral structure of production in various regions, (b) the effects of climate impacts on the productivity of those sectors, (c) the manner in which different impact endpoints combined to generate the resultant productivity effects, and (d) the response of the full range of impacts to changes in climatic variables at regional scale.

Let us write down such a model, and exploit its structure to assess the implications for the social cost of carbon. Define the following nomenclature:

Set indexes:

$t = \{0,...,T\}$ Time periods

$l = \{0,...,L\}$ World regions

$j = \{0,...,N\}$ Industry sectors

$m = \{0,...,M\}$ Meteorological characteristics

$f = \{0,...,F\}$ Climate impact endpoints

Control variables:

$q^{E}_{j,l,t}$ Sectoral energy input

$q^{K}_{j,l,t}$ Sectoral capital input

$Q^{C}_{l,t}$ Aggregate consumption

$Q^I_{l,t}$	Aggregate jelly capital investment
$a^f_{j,l,t}$	Region-, sector- and impact-specific averting expenditure
$v^f_{j,l,t}$	Region-, sector- and impact-specific adaptation investment

Economic state variables:

W	Welfare (model objective)
$q^Y_{j,l,t}$	Net sectoral product
$Q^Y_{l,t}$	Aggregate net regional product
$Q^E_{l,t}$	Aggregate regional energy use
P^E_t	Global marginal energy resource extraction cost
$Q^K_{l,t}$	Stock of aggregate jelly capital
$x^f_{j,l,t}$	Stock of region-, sector- and impact-specific adaptation capital

Environmental state variables:

G_t	Global stock of atmospheric GHGs
$M^m_{l,t}$	Region-specific meteorological variables
$z^f_{j,l,t}$	Region-, sector-, and impact-specific endpoint indexes
$\Lambda_{j,l,t}$	Region- and sector-specific damage induced productivity losses

Functional relationships:

Ξ	Global intertemporal welfare
U_l	Regional intratemporal utility
Φ_l	Regional aggregate production functions
$\Psi_{j,l}$	Sectoral production functions
Θ	Global energy supply function
ε	Global atmospheric GHG accumulation
Y^m_l	Regional climate response functions
$\varsigma^I_{l,t}$	Regional and sectoral climate impacts functions
$\lambda_{j,l}$	Regional and sectoral damage functions

1. Economic Sub-Model

Objective:

$$\max_{Q^C_{\ell,t}, q^E_{j,\ell,t}, q^K_{j,\ell,t}} \mathcal{W} = \sum_{t=0}^{T} \beta^t \Xi \left[U_1\left[Q^C_{1,t}\right], \ldots, U_{\mathscr{L}}\left[Q^C_{\mathscr{L},t}\right] \right] \qquad (1a)$$

Aggregate net regional product:

$$Q^Y_{\ell,t} = \Phi_\ell \left[q^Y_{1,\ell,t}, \ldots, q^Y_{\mathscr{N},\ell,t} \right]$$

Sectoral net regional product = Climate loss factor × Sectoral gross regional product, produced from energy and capital:

$$q^Y_{j,\ell,t} = \Lambda_{j,\ell,t} \cdot \psi_{j,\ell}\left[q^E_{j,\ell,t}, q^K_{j,\ell,t}\right]$$

(1c)

Intraregional and intratemporal market clearance for energy:

$$\sum_{j=1}^{\mathcal{N}} q^E_{j,\ell,t} = Q^E_{\ell,t}$$

(1d)

Intraregional and intratemporal market clearance for jelly capital:

$$\sum_{j=1}^{\mathcal{N}} q^K_{j,\ell,t} = Q^K_{\ell,t}$$

(1e)

Aggregate regional absorption constraint:

$$Q^C_{\ell,t} = Q^Y_{\ell,t} - Q^I_{\ell,t} - P^E_t Q^E_{\ell,t} - \sum_{f=1}^{\mathcal{F}}\sum_{j=1}^{\mathcal{N}}\left(a^f_{j,\ell,t} + v^f_{j,\ell,t}\right)$$

(1f)

Global energy trade and marginal resource extraction cost:

$$P^E_t = \Theta\left[\sum_{\ell=1}^{\mathcal{L}}\sum_{s=0}^{t} Q^E_{\ell,s}\right]$$

(1g)

Regional jelly capital accumulation:

$$Q^K_{\ell,t+1} = Q^I_{\ell,t} + (1 - \vartheta^K)Q^K_{\ell,t}$$

(1h)

Accumulation of impact-, sector- and region-specific adaptation capital:

$$x^f_{j,\ell,t+1} = v^f_{j,\ell,t} + (1 - \vartheta^f)x^f_{j,\ell,t}$$

(1i)

2. Climate Sub-Model

Global atmospheric GHG accumulation:

$$G_{t+1} = \mathcal{E}\left[\sum_{\ell} Q^E_{\ell,t}, G_t\right]$$

(2a)

Regional meteorological effects of global atmospheric GHG concentration:

$$M^m_{\ell,t} = \Upsilon^m_\ell\left[G_t\right]$$

(2b)

3. Impacts Sub-Model

Physical climate impacts by type, sector and region:

$$z^f_{j,\ell,t} = \zeta^f_{j,\ell}\left[M^1_{1,0},\ldots,M^{\mathcal{M}}_{1,0};\ldots;M^1_{\mathcal{L},t},\ldots,M^{\mathcal{M}}_{\mathcal{L},t}\right]$$

(3a)

Climate damages:

$$\Lambda_{j,\ell,t} = \lambda_{j,\ell}\left[z^1_{j,\ell,t},\ldots,z^{\mathcal{F}}_{j,\ell,t};a^1_{j,\ell,t},\ldots,a^{\mathcal{F}}_{j,\ell,t};x^1_{j,\ell,t},\ldots,x^{\mathcal{F}}_{j,\ell,t}\right]$$

(3b)

From the point of view of period t^*, the condition for optimal extraction of carbon-energy is:

$$\underbrace{\frac{\partial \mathscr{W}}{\partial Q^E_{\ell^*,t^*}} \bigg/ \frac{\partial \mathscr{W}}{\partial Q^C_{\ell^*,t^*}} = \sum_{j=1}^{\mathscr{N}} \left(\frac{\partial \phi_{\ell^*}}{\partial q^Y_{j,\ell^*,t^*}} \frac{\partial \psi_{j,\ell^*}}{\partial q^E_{j,\ell^*,t^*}} \frac{\partial q^E_{j,\ell^*,t^*}}{\partial Q^E_{\ell^*,t^*}} \right)}_{\text{I. Current marginal benefit}} - \underbrace{P^E_{t^*}}_{\substack{\text{II. Current marginal} \\ \text{extraction cost}}}$$

$$\underbrace{- \sum_{t=t^*}^{T} \beta^{t-t^*} \sum_{\ell=1}^{\mathscr{L}} \left(\frac{\partial \Xi}{\partial U_\ell} \frac{\partial U_\ell}{\partial Q^C_{\ell,t}} \frac{\partial \Theta}{\partial Q^E_{\ell^*,t^*}} Q^E_{\ell,t} \right) \bigg/ \left(\frac{\partial \Xi}{\partial U_{\ell^*}} \frac{\partial U_{\ell^*}}{\partial Q^C_{\ell^*,t^*}} \right)}_{\text{III. Resource stock effect of contemporaneous energy use}}$$

$$\underbrace{+ \sum_{t=t^*+1}^{T} \beta^{t-t^*} \frac{\partial \mathcal{E}}{\partial Q^E_{\ell^*,t^*}} \bigg/ \left(\frac{\partial \Xi}{\partial U_{\ell^*}} \frac{\partial U_{\ell^*}}{\partial Q^C_{\ell^*,t^*}} \right) \times \sum_{\ell=1}^{\mathscr{L}} \left\langle \frac{\partial \Xi}{\partial U_\ell} \frac{\partial U_\ell}{\partial Q^C_{\ell,t}} \sum_{j=1}^{\mathscr{N}} \left\{ \frac{\partial \phi_\ell}{\partial q^Y_{j,\ell,t}} \psi_{j,\ell,t} \sum_{f=1}^{\mathscr{F}} \left[\frac{\partial \lambda_{j,\ell}}{\partial z^f_{j,\ell,t}} \sum_{m=1}^{\mathscr{M}} \left(\frac{\partial \varsigma^f_{j,\ell}}{\partial M^m_{\ell,t}} \frac{\partial Y^m_\ell}{\partial G_t} \right) \right] \right\} \right\rangle}_{\text{IV. Present value of future marginal climate damage (N.B. } \partial q^Y/\partial \Lambda < 0 \text{ in general)}}$$

$$= 0 \tag{4}$$

The "social cost of carbon" in this expression is given by the combination of terms (II) + (III) - (IV). Our interest is in (IV), the marginal external cost of carbon-energy consumption, which, because it emanates from a globally well-mixed pollutant, is independent of the location in which the energy is consumed.

It is now clear to see how fundamental gaps in our understanding the render the "land of cockaigne" unattainable. The difficulty in computing the social cost of carbon stems from the terms in curly braces. Carbon-cycle modeling is sufficiently advanced to enable us to predict with a fair degree of confidence the effect of the marginal ton of carbon on the time-path of future atmospheric GHGs ($\partial \varepsilon / \partial Q^E$). Likewise, the IPCC AR4 notes global climate models' substantially improved ability to capture the future trajectory of consequent changes in temperature, precipitation, ice/snow cover and sea levels at regional scales ($\partial Y^m_l / \partial G$). But the weak links in the causal chain between climate change and economic damages continue to be the cardinality and magnitude of the vectors of physical impact endpoints as a function of climatic variables in each region out into the future ($\partial \varsigma^f_{j,l} / \partial M^m_l$), and—to a lesser extent—the manner in which these endpoints translate into

shocks to the productivity of economic sectors ($\partial \lambda_{j,l} / \partial z^f_{j,l}$).

A Critical Review of the State of Modeling Practice

To put the key issues in sharp relief, it is useful to consider how implementing the disaggregated IAM might improve upon the current state of integrated assessment practice. RICE-type IAMs represent the productivity losses incurred by climate change impacts through variants of Nordhaus' aggregate damage function, which specifies the reduction in gross regional product as a function of global mean temperature. This approach effectively collapses M^m_l to a scalar quantity in each time period. Moreover, as reviewed by NRC (2010), it then benchmarks the magnitude of various impacts and the associated economic losses for a reference level of global mean temperature change, before making
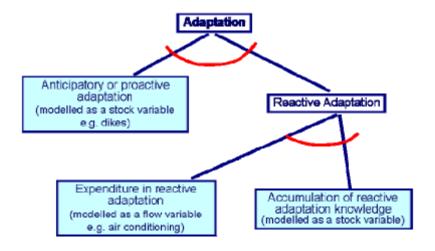
assumptions about how these costs are likely to scale with income, and finally expressing damage as a temperature-dependent fraction of regions' gross output. Therefore, the details of climatic variables' influence on impact endpoints in (3a), and of the latter's effects on economic sectors in (3b), only affect the calibration of the damage function. From that point on they are entirely subsumed within the function's elasticity with respect to global temperature change, and, in RICE-2010, sea level rise. The damage function therefore collapses (3a) into (3b), dealing only with changes in aggregate global climatic variables, skipping over impacts as state variables and implicitly aggregating over sectors to express damages purely on an aggregate regional basis.

A similar situation obtains with adaptation. A case in point is the AD-WITCH model, a variant of Nordhaus' RICE simulation which modifies the damage function by introducing stock and flow adaptation expenditures which attenuate aggregate regional productivity losses due to climate change. Formally, using eQY to denote gross regional product, net regional product is given by

$$Q^Y_{\ell,t} = \frac{1 + ADAPT_{\ell,t}}{1 + ADAPT_{\ell,t} + CCD_{\ell,t}} \tilde{Q}^Y_{\ell,t} \qquad (5)$$

where CCD is the regional climate damage function and ADAPT is an index of adaptation's effectiveness. The variable ADAPT is the output of a nested constant elasticity of substitution (CES) production function which combines inputs of contemporaneous averting expenditures with adaptation capital and adaptation knowledge according to Figure 2. The key consequence is that adaptation is able to directly influence the dynamic path of the economy, instead of being implicit in the curvature of the damage function, as with the RICE model. However, eq. (5)'s assumption that the effects of ADAPT and CCD are multiplicative seems very strong in light of the fact that the damage function already explicitly incorporates the influence of adaptation through the studies on which it is benchmarked—but only at the calibration point, not over the full range of its curvature. A prime example is Nordhaus and Boyer's (2000) use of Yohe and Schlesinger's (1998) results on the impact of sea level rise, which optimally balance the costs of abandonment and coastal defenses. The implication is that because defensive expenditures are likely to be closely associated with the magnitudes of climate impacts of various kinds within individual sectors, one should not think of aggregate adaptation expenditure as independent of future changes in the sectoral composition of output.

Figure 2: The AD-WITCH Adaptation Production Function (Bosello, Carraro and De Cian, 2010)

By dispensing with the aggregate damage function, our land of cockaigne IAM explicitly captures the dynamic evolution of impact endpoints' response to changes in climatic variables, the magnitude and intersectoral distribution of the follow-on productivity effects, and the optimal intersectoral adjustments these induce, all at regional scales. An adaptation response may therefore be modeled more precisely as averting expenditure that mitigates the sectoral and regional productivity loss associated with a particular category of climate impact. In other words, stock and flow adaptation reduces the impact elasticity of sectoral productivity shocks. Of course, the problem that besets this approach is that, except for a very few combinations of impacts, sectors and regions, the relevant elasticities are unknown.

But the good news is that this is one area in which research is proceeding apace. There are a growing number of CGE modeling studies of climate impacts (e.g., ICES) which elucidate the magnitude of both sectoral and regional damages and producers' and consumers' adjustment responses. The focus of such studies is typically a single impact category (say, f*), whose initial economic effects are computed using natural science or engineering modeling or statistical analyses. The results are often expressed as a vector of shocks to exposed sectors and regions, which are then imposed as exogenous productivity declines on the CGE models' cost functions. In the context of the IAM in section 2, this procedure is equivalent to first specifying an exogenous ex-ante effect of a particular impact $\partial \lambda_{j,l} / \partial z_{j,l}^{f*}$, before using the CGE model to compute the ex-post web of intersectoral adjustments and the consequences for sectoral output, and regions' aggregate net product and welfare:

$$\frac{\partial U_\ell}{\partial Q_{\ell,t}^C} \sum_{j=1}^{\mathcal{N}} \left(\frac{\partial \phi_\ell}{\partial q_{j,\ell,t}^Y} \psi_{j,\ell,t} \frac{\overline{\partial \lambda_{j,\ell}}}{\partial z_{j,\ell}^{f*}} \right).$$

This line of inquiry has the potential to yield two critical insights. The first is quantification of the elasticity of the economy's response to variations in the magnitude and interregional/ intersectoral distribution of particular types of impact, which has been the type of investigation pursued thus far. But second—and arguably more important—is comparative analysis of economic responses *across* different impact categories for the purpose of establishing their relative overall economic effect, conditional on our limited knowledge of their relative likelihood of occurrence, and intensity. The results could at the very least guide the allocation of effort in investigating the thorny question of how different impacts are likely to respond to climatic forcings at the regional scale, $\partial \varsigma_{j,l}^f / \partial M_l^m$.

Adaptation and Technological Change

Karen Fisher-Vanden
Elisa Lanzi
David Popp
Ian Sue Wing
 Mort Webster

The purpose of this talk is to provide a brief summary of the state of the science on the influences of adaptation on the social cost of climate change. Specifically, the charge was to discuss (not necessarily in this order):

(1) *relevant studies on the observed or potential effectiveness of adaptive measures, and on private behaviors and public projects regarding adaptation;*

(2) *relevant studies on how to forecast adaptive capacity;*

(3) *how adaptation and technical change could be represented in an IAM (for at least one illustrative sector);*

(4) *whether the information required to calibrate such a model is currently available, and, if not, what new research is needed; and*

(5) *how well or poorly existing IAMs incorporate the existing body of evidence on adaptation.*

A tall order, but important to get our arms around since estimates of the net impact of climate change could be significantly higher if adaptation is not taken into account.[1]

As elaborated below, a number of general insights have resulted from our brief foray into this topic that have implications for the development of a future research program in this area. First, modeling adaptation is inherently difficult given the nature of the adaptation process, requiring advancements in modeling techniques. Second, although there has been good empirical work done on impacts and adaptation costs, the coverage is limited requiring heroic efforts to translate the results into model parameters. More work is needed to bridge the gap between models and empirical studies. Lastly, adaptation-related technological change is generally lacking in current models but could significant lower adaptation cost estimates. This stems from a general lack of understanding of the process related to this type of technological change. More empirical work is needed in this area.

What is unique about the adaptation process that justifies the need to add features to existing integrated assessment models (IAMs)? First, adaptation is in response to current or anticipated impacts and comes in different forms: (a) reactive (e.g., changes in heating/cooling expenditures; treatment of disease; shifts in production); and (b) proactive (e.g., infrastructure construction (e.g., seawalls); early warning systems; water supply protection investments. In some IAMs adaptation

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[1] For the U.S., Mendelsohn et al. (1994) estimates that the net impact of climate change on the farming sector will be 70% less if adaptation is included while Yohe et al. (1996) estimates that the net impact on coasts will be approximately 90% less (Mendelsohn (2000)).

would occur endogenously in reaction to changes in prices due to climate impacts—e.g., more power plants built to deal with increases in demand for air conditioning; shifts in production in reaction to higher prices of factors negatively impacted by climate change. However, many adaptation activities that would occur in reality, such as investment in flood protection, would not occur in a simulated model unless there is explicit representation of climate damages to induce reactive expenditures and proactive investments.

Second, unlike mitigation investments where investments today result in reductions today, proactive adaptation investments are made today to provide protection against possible future impacts. Thus, adaptation investment decisions are inherently intertemporal and therefore 2

models need to include intertemporal decision making for proactive adaptation investments, in order to trade off future damages and current adaptation investment expenditures. Not only are we making intertemporal adaptation decisions, we are specifically making proactive adaptation investments under uncertainty. Whether we invest and how much to invest all depends on our expectations regarding future impacts and how we value the future. Therefore, we need a model that allows for intertemporal decision-making under uncertainty.

Climate damages and adaptation strategies are locally- or regionally-based. Therefore, ideally the model will include regional detail or will apply a method to aggregate up to a more coarse regional representation. Climate damages and adaptation expenditures are also sector specific—e.g., certain sectors will be impacted more than others and adaptation expenditures will be directed at specific sectors (e.g., electric power, construction). Thus, a model with sectoral detail or a way to aggregate these sector-specific impacts and expenditures is desirable.

The demand for adaptation solutions will induce adaptation-related technological change. Do inducements for adaptation-related technological change differ markedly from mitigation-related technological change, requiring a different modeling approach? To the extent that adaptation activities may be region or sector specific, markets for new adaptation techniques will be smaller than for new mitigation techniques, making private sector R&D investments less attractive. Given this, as well as the case that adaptation investments are largely public infrastructure investments, distinguishing between public R&D and private R&D may be important. Note that this is more than a question of simply basic versus applied science, but driven by the nature of demand for the final product, much in the same way that the government finances most R&D for national defense. Thus, the model needs to be capable of distinguishing between private and public investments and include mechanisms of public revenue raising to fund these projects.

To summarize, to be able to capture adaptation strategies, an ideal IAM would include the following features:

- Explicit modeling of climate damages/impacts

- Intertemporal decision making under uncertainty

- Endogenous technological change

- Regional and sectoral detail for impacts and adaptation strategies

- Connection with empirical work on impacts and adaptation

Is it feasible or even desirable to have all of these features represented in a single model, since transparency is lost as more features are added? It is important to measure the trade-offs:

- How much of this needs to be specifically represented in the model and how could be represented outside of the model

- To cite Jake Jacoby: —different horses for different courses.‖ Do we need a suite of models each designed to capture a subset of these features?

- How important is each of these features to the social cost of climate change? Sensitivity analysis could be useful here to assess whether we even need to worry about including certain features.

To answer these questions, it is useful to first survey what features currently exist in IAMs. A number of modeling approaches have been taken to capture impacts and adaptation. Computable general equilibrium (CGE) models have the advantage of providing sectoral and regional detail and capturing the indirect effects of impacts and adaptation. Thus, given its structure, CGE models can more easily accommodate regional and sectoral-specific damage functions. Most CGE models, however, do not include the type of intertemporal decision making required to model proactive adaptation investment decisions, given the computational demands required by a model with detailed regions and sectors. However, there have been a number of CGE models that have been used to estimate the cost of climate change impacts; for example,

- DART (Deke et al, 2001)—to study the cost of coastal protection

- FARM (Darwin and Tol, 2001; Darwin et al, 1995)—includes detailed land types to study the effects of sea level rise and impacts of climate change on agriculture.

- GTAP-E/GTAP-EF (Bosello et al, 2006; Bigano et al, 2008; Rosen, 2003)—has been used to study induced demand for coastal protection; effects of rising temperatures on energy demand (Bosello et al, 2007); health effects of climate change (Bosello et al, 2006); effects of climate change on tourism. Focuses on one impact at a time.

- Hamburg Tourism Model (HTM) (Berittella et al, 2006; Bigano et al, 2008)—used to study the effect of climate change on tourism.

- ICES (Eboli et al, 2010)—models multiple impacts simultaneously: impacts on agriculture, energy demand, human health, tourism, and sea level rise.

Another set of models used to study climate change impacts and adaptation fall under the category of optimal growth models. These models include intertemporal optimization but typically lack sectoral and regional detail given the computational demands this would require. These include:

- DICE/RICE (Nordhaus, 1994; Nordhaus and Yang, 1996; Nordhaus and Boyer, 2000)—DICE comprises one region, one aggregate economy, and one damage function aggregating many impacts. RICE comprises 13 regions, each with its own production function and damage function.

- AD-DICE/AD-RICE (de Bruin et al, 2009)—DICE/RICE model with adaptation. Adaptation investment added as a decision variable which lowers damages and faces an adaptation cost curve. Residual damages are separated from protection costs in the damage function.

There are also a number of simulation models that have been developed to study the effects of climate change impacts. The major difference from CGE and optimal growth models is that simulation models do not optimize an objective function, such as intertemporal utility. Instead, these models represent a number of interconnected relationships that allow for studying the propagation of perturbations to the system. Two widely used simulation models are:

- PAGE (Plambeck and Hope, 1997; Hope, 2006)—PAGE comprises eight regions each with its own damage functions for two impact sectors (economic and non-economic). The authors use information on impacts from IPCC (2001) to generate model parameter values related to impacts. In addition, PAGE stochastically models catastrophic events where the probability of an event increases when temperature exceeds a certain threshold. Simple adaptation is included in the model which reduces damages. Assumes developed countries can reduce up to 90% of economic impacts while developing can reduce up to 50%. All regions can reduce up to 25% of non-economic impacts.

- FUND (Tol et al, 1995; Tol, 1995)—referred to as a —policy optimization‖ model. Exogenous variables include population (from the World Bank), GDP per capita (from EMF 14), and energy use. Endogenous variables include atmospheric concentrations, radiative forcing, climate impacts (species loss, agriculture, coastal protection, life loss, tropical cyclones, immigration, emigration, wetland, dryland), emission reductions (energy or carbon efficiency improvements, forestry measures, lower economic output), ancillary benefits (e.g., improved air quality), and afforestation. The model comprises 9 regions with game theoretics and eight market and non-market sectors, each with its own calibrated damage function. Adaptation is modeled explicitly in the agricultural and coastal sectors, and implicitly in other sectors such as energy and human health where the wealthy are assumed to be less vulnerable to the impacts of climate change. No optimization in the base case— just simulation. In the optimization case, the model is choosing the optimal level of emissions reductions by trading off costs and benefits of reductions.

Another class of models involves hybrid combinations of the above model types. For example,

- Bosello and Zhang (2006) couple an optimal growth model with the GTAP-E model of Burniaux and Truong (2002) to study the effects of climate change on agriculture

- Bosello et al (2010) couple the ICES CGE model with an optimal growth model (AD-WITCH) to study adaptation to climate change impacts.

- AD-WITCH (Bosello et al, 2010)—an optimal growth model with detailed bottom-up representation of the energy sector. Comprises 12 regions where the following seven control variables exist for each region: investment in physical capital, investment in R&D, investment in energy technologies, consumption of fossil fuels, investment in proactive adaptation, investment in adaptation knowledge; and reactive adaptation expenditure. These alternative uses of regional income compete with each other.

To parameterize these models, most modeling teams look to empirical studies of impacts and adaptation and are faced with similar frustrations. First, as elaborated in Agrawala and Fankhauser (2008), the empirical work in the area of adaptation is severely lacking. The authors find that although information exists on adaptation costs at the sector level, certain sectors (e.g., coastal zones and agriculture) are studied more heavily than others. Second, most empirical studies are not done with modeling applications in mind. Most modelers find themselves forced to devise methods to scale up from the regional and sectoral results generated by empirical studies.

There have been a few recent studies that have attempted to summarize the empirical work on adaptation costs; e.g.,

- Agrawala and Fankhauser (2008)—provides a critical analysis of empirical work on adaptation costs. Tables summarize empirical sectoral studies on adaptation costs. Sectors include coastal zones, agriculture, water resources, energy demand, infrastructure, tourism and public health.

- World Bank (2010)—report from The Economics of Adaptation to Climate Change (EACC) study. Seven sector-specific studies: infrastructure, coastal zones, water supply and flood protection, agriculture, fisheries, human health, extreme weather events. Provides detailed estimates of adaptation costs; some generated using dose response functions with engineering estimates and some generated from sector-specific models.

- UNFCCC (2007)—regional studies (Africa, Asia, Latin America, and small island developing States) on vulnerability; current adaptation plans/strategies; future adaptation plans/strategies. Most information from national communications to the UNFCCC, regional workshops, and expert meetings.

A few modeling teams have made serious attempts to integrate existing empirical work on adaptation into their model; for example,

- AD-DICE/AD-RICE: starts with damage functions of Nordhaus and Boyer (2000) and uses empirical studies to separate residual damages from adaptation costs. Various studies on adaptation measures for certain sectors (i.e., agriculture and health) and estimates of adaptation costs from existing studies are used. Also, other model results—e.g., results from FUND—are used to estimate adaptation costs in response to sea level rise. Empirical studies to separate residual damages from adaptation costs are not available for many of the sectors—i.e., other vulnerable markets; non-market time use; catastrophic risks; settlements—so assumptions were made in order to separate the damage costs. However, these sectoral estimates are ultimately aggregated up to one damage cost number and one adaptation cost number to fit with the one sector structure of the model.

- AD-WITCH: Uses empirical information from the construction of damage functions in Nordhaus and Boyer (2000), the studies in Agrawala and Fankhauser (2008); and UNFCCC (2007) to separate residual damages from adaptation costs. Similar to AD-DICE, using these empirical studies to separate the damage estimates in Nordhaus and Boyer (2000) into residual damages and adaptation costs.

Comparing this brief survey of existing work in this area with the list of required modeling features needed to model adaptation, a couple of key research voids stand out. First, none of these models include decision making under uncertainty, and for good reason. It is difficult to do. Optimal growth models like DICE with intertemporal decision making are deterministic and fully forward-looking. Past approaches to modify such a model to be stochastic usually entail the following steps:

1) Create multiple States of the World (SOWs), each with different parameter assumptions and different probabilities of occurrence;

2) Index all variables and equations in the model by SOW;

3) Add constraints to the decision variables so that for all time periods before information is revealed, decisions must be equal across SOWs.

The problem with this approach is that it rapidly becomes a very large constrained nonlinear programming problem, and often the model will not converge to a solution for more than a trivial number of SOWs. The general problem of decision making under uncertainty is a stochastic dynamic programming problem that requires the exploration of a large number of samples of outcomes in every time period. The challenge is to fully explore the sample space while keeping the model computationally tractable. Promising on-going research by Mort Webster and his team at MIT could offer an alternative approach to modeling decision making under uncertainty. Webster's NSF-funded project team is currently developing a formulation based a new approach called Approximate Dynamic Programming, introduced by Powell (2007) and others. This approach implements dynamic programming models by iteratively sampling the state space using Monte Carlo techniques, approximating the value function from those samples, and using approximate value functions to solve for an approximate optimal policy, then repeating. This approach has been used successfully in other contexts for very large state spaces. Mort Webster's team is currently developing an ADP version of the ENTICE-BR model to study R&D decision making under uncertainty.

Second, adaptation-related technological change is largely absent in current models. Most models are calibrated using existing knowledge of adaptation strategies and costs with no allowance for improvements in these strategies and technologies. AD-WITCH (Bosello et al, 2009) does attempt to account for this by including investment in adaptation knowledge as a decision variable that competes with other types of investment. Investments in adaptation knowledge accumulate as a stock which reduces the negative impact of climate change on gross output. However, the lack of empirical studies on adaptation-related technological change limits the modelers' ability to calibrate their model based on empirical knowledge. In the case of AD-WITCH, adaptation knowledge investments only relate to R&D expenditures in the health care sector where empirical data exist. This suggests that more empirical research in this area is desperately needed.

Third, differences in adaptive capacity or differences in the ability of regions to adapt to climate change are also important to capture in model analyses given the implications for distributional effects but are typically not represented in existing models. The FUND model implicitly captures adaptive capacity in the energy and health sectors by assuming wealthier nations are less vulnerable to climate impacts. However, it seems that only one model, AD-WITCH, attempts to explicitly capture adaptive capacity through the inclusion of investments in adaptation knowledge as a decision variable. Not only does this variable capture R&D investments in adaptation-related

technologies as discussed in the previous paragraph, it also captures expenditures to improve the region's ability to adapt to climate change. Issues arise, however, when the model is calibrated since the modelers were only able to identify one source of qualitative information on adaptive capacity (i.e., the UNFCCC (2007) report discussed above) which only covers four aggregate regions (Africa, Asia, small island developing States, and Latin America). Assumptions were then made to translate this information to the regional representation and model parameters in AD-WITCH.

Lastly, another area where empirical work to inform models is lacking is in the dynamics of recovery from climate change impacts. Most models represent climate damages as a reduction in economic output which is assumed to recover over time. Empirical work on thresholds and time to recover including factors that influence these variables could help inform models on the type of dynamics that should be captured in impact and adaptation analyses. Also, better techniques to translate results from empirical studies to models are needed since the sectoral and regional detail of empirical studies does not typically align with the sectoral and regional detail in models. In general, to address the disconnect between empirical studies and modeling needs, we as a research community need to devise better ways to facilitate communication between empirical researchers and modelers.

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Knowability and no ability in climate projections

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Introduction

The purpose of this note is to provide a referenced summary of the present scientific understanding about future climate change, tailored towards the kind of global climate factors that are captured in Integrated Assessment Models (IAMs). In outline, it is organized as follows:

i) *Equilibrium climate sensitivity* is the long-term response of global temperature to a doubling of atmospheric CO_2. I review the causes of our current uncertainty, and the prospects for reducing it.

ii) Two other measures of climate change are arguably more important in this context. First the *climate commitment* is a measure of the climate change we already face because of emissions that have already occurred.

iii) The very long timescales associated with attaining equilibrium, especially at the high end of possible climate sensitivity, mean that the *transient climate response* is of greater relevance for climate projections over the next several centuries.

iv) Due to the inherent uncertainties in the climate system, a *flexible emissions strategy* is far more effective in avoiding a given level of global temperature change, than a strategy aims to stabilize CO_2 at a particular level.

v) Many important climate impacts are fundamentally regional in nature. Among climate models, regional climate projections correlate only partially with global climate projections.

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Climate sensitivity

Climate sensitivity (here given the symbol T_{2x}, and sometimes called the equilibrium climate sensitivity) is the long-term change of annual-mean, globalmean, near-surface air temperature in response to a doubling of carbon dioxide above preindustrial values. It has long been a metric by which to compare different estimates of the climate response to greenhouse gas forcing (e.g., Charney, 1979). There is a vast literature that has researched climate sensitivity from every possible angle, ranging from state-of-the-art satellite observations of Earth's energy budget, to geological studies covering hundreds of millions of years. A fine review of where things stand can be found in Knutti and Hegerl (2008).

Figure 1 shows a variety of probability distributions (pdfs) of climate sensitivity. A prominent feature of such estimates is that they all exhibit considerable skewness. In other words, while the lower bound is confidently known, the upper bound is much more poorly constrained. There is a small but nontrivial possibility (about 25 %) that the climate sensitivity could exceed 4.5 $_o$C. One concern that has been raised is that the current generation of IPCC climate models (from the fourth assessment, or AR4) does not span the range of climate sensitivity that is allowable by observations (the blue

histogram in figure 1 clusters too narrowly around the modes of the other pdfs). The reason for this appears to be that the IPCC climate models do not sample the full range of possible aerosol forcing (Armor and Roe, 2010). This should not be surprising since they are designed to represent the "best" estimate of climate (something akin to the mode of the distribution). However, since these computer models are the only tools available for modeling regional climates, it should perhaps be a concern that they are under sampling the range of possible futures. I next outline briefly how estimates are made from observations and models. The purpose of doing so is to straightforwardly demonstrate the important sources of uncertainty.

Figure 1. Various estimates of climate sensitivity. In order of the legend: i) from multi-thousand ensembles from one climate model (Stainforth et al., 2005), ii) from feedbacks with climate models (Roe and Baker, 2007), iii) from modern observations (Armour and Roe, 2010), iv) from glacial climates (Hansen et al., 1984), v) A histogram of T_{2x} from 19 main IPCC AR4 models (IPCC, 2007).

Estimates of climate sensitivity from observations.
A linear approximation of the Earth's energy budget is:

$$R = H + \lambda^{-1}T, \tag{1}$$

where R is the radiative forcing (units W m^{-2}), H is the heat going into the world's oceans and being stored there, and $\lambda^{-1}T$ is the climate response in terms of the global-mean, annual-mean, near-surface air temperature T, and the climate sensitivity parameter, λ. (e.g., Roe, 2009, Armour and Roe, 2010, and many others). For silly historical reasons the terminology here can be confusing. λ is a more fundamental measure of climate system than T_{2x}, since it does not depend on any particular forcing. λ and T_{2x} are related in the following way. Let R_{2x} be the radiative forcing due to a doubling of CO_2 over pre-industrial values (≈ 4 W m-2). In the long-term equilibrium, ocean heat uptake goes to zero, and so the climate sensitivity is just:

$$T_{2x} = \lambda R_{2x} \tag{2}$$

The point of this algebra is to make it clear that the goal of estimating climate sensitivity from observations is the goal of estimating λ from Equation (1):

$$\lambda = \frac{T}{R - H} \tag{3}$$

We have observations of T, R, and H, whose probability distributions are shown in figure 2. Hereafter we refer to R-H as the climate forcing, since it is the net energy imbalance that the atmosphere must deal with. H and T are actually quite well constrained, as is the radiative forcing associated with CO_2 and other greenhouse gases. As is clear from figure, the major source of uncertainty is R and, in particular, the component of R that is due to aerosols (small airborne particulates that can be either liquid or solid).

The reason that aerosol forcing is hard to constrain is that 1) the spatial pattern and lifetime is extremely complicated to observe (they are primarily in the Northern Hemisphere and downwind of major industrial economies); 2) some aerosols have a cooling effect, some have a warming effect; 3) aerosols alter the thickness, lifetime, and height of clouds – a powerful indirect effect that is hard to measure and attribute properly. The community is confident, however, that the net aerosol effect is almost certainly negative. More information about aerosol uncertainties can be found in Menon (2004).

Thus, from Eqs. 2 and 3, the probability distribution of climate sensitivity comes from combining a relatively narrow distribution (the well-known temperature

Figure 2: Probability distributions of the terms in the Earth's energy budget, based on IPCC 2007, and updated for newer ocean heat uptake observations. See Armour and Roe, 2010 for details. Total climate forcing is equal to R-H in Eq. 3. Also shown is the total forcing excluding aerosols, which is the climate forcing experienced by the Earth, if all anthropogenic emissions ceased immediately.

change) in the numerator with a relatively broad distribution (the much less wellknown climate forcing (i.e., R-H)) in the denominator of Eq. 3. It is this combination that produces the skewed distribution seen in figures 1 and 3c. The graphs in figure 3 are the fundamental reason why we can say with great confidence that it is very likely that observed forcing has not been large enough to imply a climate sensitivity of less than about 1.5 oC. On the other hand, uncertainties in observed forcing also mean that we cannot confidently rule out the disconcerting possibility that the modern warming has occurred with small climate forcing, which would imply very high climate sensitivity. Note that the curves in figure 1 and 3 are consistent with the probabilities given in the 2007 IPCC report.
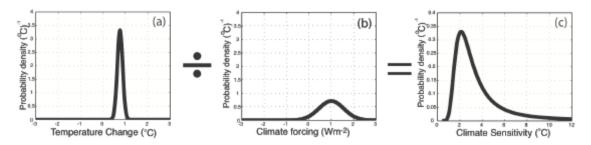

Figure 3: The calculation of climate sensitivity from observations involves combing a relatively narrow probability distribution of T (panel a) in the numerator, with a relatively broad distribution of F= H-R (panel b) in the denominator of Eq. (3). This leads to the skewed distribution of climate sensitivity (panel c). Note the pdfs must be combined properly - it is not just a simple division - but the point is hopefully clear.

Estimates of climate sensitivity from models.
Climate sensitivity also can be estimated from climate models. Figure 1 shows three such efforts. The first is the spread of T_{2x} among the main IPCC AR4 models. One issue is that the mainstream IPCC AR4 climate models are not designed to explore the edges of the probability distribution, but

instead are designed with the most likely combination of model parameters, and parameters are 'tuned' to reproduce observed climate history. Clear evidence of that tuning comes from the correlation of climate sensitivity and imposed aerosol forcing in the models in such a direction that twentieth century observations tend to be reproduced (Kiehl, 2007, Knutti, 2008). Such tuning is not problematic if models are interpreted as reflecting combinations of climate sensitivity and aerosol forcing that are consistent with observed constraints (Knutti, 2008). However AR4 models do not fully span the range of aerosol forcing allowed by observations (Kiehl, 2007; IPCC, 2007). This is the likely reason that the AR4 models under sample of the full range of possible climate sensitivity, as seen in figure 1.

Climate sensitivity can also be estimated by using thousands of integrations of the same climate model with the parameters varied by reasonable amounts, a strategy pursued by the climateprediction.net effort (figure 1, e.g., Stainforth et al., 2005). This work also found a skewed pdf of T2x. Roe and Baker (2007) explain this in terms of a classic feedback analysis, summarized in figure 4. The relationship between feedbacks and response also produces a skewed distribution because of the way that positive feedbacks have a compounding effect on each other (e.g., Roe, 2009). The range of feedbacks as diagnosed within the AR4 models produces a pdf of climate sensitivity that is quite consistent with the pdf estimated from observations (figure 1). This should be expected since it is observations that ultimately provide constraints on the models.
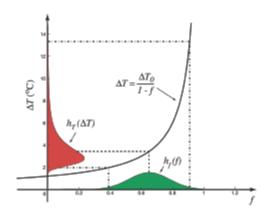

Figure 4: Model feedbacks and climate sensitivity. The black curve shows the mapping between climate feedbacks (x-axis, green curve), and climate response (y-axis, red curve). See Roe and Baker, 2007 for details.

Prospects for improved estimates of climate sensitivity.

Can a narrower range of climate sensitivity be expected soon? One can ask: how might more accurate observations or better climate models change the estimate of T_{2x}?

Reducing uncertainty in either forcing or feedbacks would produce a narrower range. However it is the nature of these skewed distributions that the mode of T_{2x} moves to higher values as the range of forcing or feedbacks is narrowed, leaving the cumulative probability of $T_{2x} > 4.5°C$ stubbornly persistent (Allen et al., 2007; Roe and Baker, 2007; Baker et al., 2010).

It should also be made clear that there are formidable scientific challenges in reducing uncertainty in climate model feedbacks, or in observing the aerosol forcing better. Progress will occur, but it is likely that it will be incremental. Another line of attack is to try to combine multiple estimates of climate sensitivity in a Bayesian approach that might, in principal, significantly slim the fat tail of T_{2x} (e.g., Annan and Hargreaves, 2006). However, as with all Bayesian estimates, the value of the analysis is critically sensitive to 1) the independence of different observations; and 2) structural uncertainties within and among very complex models (e.g., Henriksson et al., 2010; Knutti et al., 2010). An objective assessment of these factors has proven elusive, rendering the information obtained by the exercise hard to interpret, and there is an acute risk that it produces overconfident estimates.

Overall it is probably prudent to anticipate that there will not be dramatic reductions in uncertainty about the upper bound on climate sensitivity (Knutti and Hegerl, 2008). On the timescale of several decades, Nature herself will slowly reveal more of the answer. We will learn about the transient climate response (see below) more quickly than the equilibrium climate sensitivity. Those interested in understanding the above arguments in greater depth would do well to read the work of Prof. Reto Knutti (at ETH in Switzerland) and his collaborators. His research is of extremely high caliber, and quite accessible for a non-specialist.

The climate commitment.

What if all human influence on climate ceased overnight? Such a scenario— called the *climate commitment*—informs us of the climate change we already face due only to past greenhouse gas emissions. Framing the question this way has proven to be useful in providing a conceptual lower bound on future climate warming.

Early definitions of the climate commitment simply fixed CO_2 concentrations at current levels (e.g., Wigley, 2005; Meehl et al., 2005), but maintaining current levels actually requires continued emissions. Lately the focus has been more appropriately on the consequences of establishing zero emissions (e.g., Solomon et al., 2009). Two important, though sometimes overlooked points should be made. Firstly the geological carbon cycle means that, although much of the anthropogenic CO2 ultimately gets absorbed by the ocean, some fraction — about 25 to 40% — remains in the atmosphere for hundreds of thousands of years (e.g., Archer et al., 2009). Secondly aerosols, have a short lifetime in the atmosphere (days to weeks). Thus when human influence ceases, aerosols are rapidly washed out of the atmosphere and the effect of this is to unmask additional warming due to
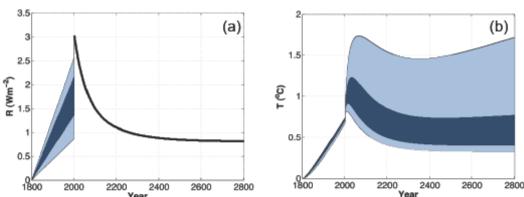

Figure 5: Idealized representation of the climate commitment following a cessation of all human influence on climate. Based on Armour and Roe, 2010. Panel (a) shows a simple view of how uncertainty in forcing has grown since 1800, as allowed by IPCC 2007 observed uncertainties. After emission cease (here at yr 2000) the uncertain aerosols quickly vanish, there is a jump in forcing due to sudden unmasking of the (relatively well-known) radiative forcing due to CO_2 and other greenhouse gases, which then declines slowly over time (black line). Panel (b) shows the temperature over this period, from a simple climate model. For each possible trajectory of past climate forcing history, a different value of climate sensitivity is implied, in order that the accurately known past warming is reproduced (low past forcing requires high climate sensitivity, and vice versa). The light blue curve shows the 90% confidence range, as permitted by uncertainties in observations, which ultimately grows to be 0.3 to 6°C at equilibrium. The dark blue curve is the 'likely' IPCC range (68%). It is this range that is spanned by the main IPCC AR4 models because they under sample the allowed range of past forcing. Note that these calculations here only include uncertainties due to aerosols. The spread would be larger if uncertainties in GHG and ocean heat uptake were included. Nonetheless the graph highlights that uncertainty in future temperatures is a result of uncertainty in past forcing.

the much more slowly declining CO2 (illustrated in figure 2 and 5).

Figure 5 shows an idealized calculation of the climate commitment from Armour and Roe (2010), which contains more details. The purpose of showing this is to highlight that our uncertainty about future temperature comes primarily from our uncertainty about past forcing. After ceasing all emissions, the degree and trajectory of future warming depends on the state of the current climate forcing. We face the disconcerting possibility that our ultimate climate commitment already exceeds 2 °C, because of our current inability to rule out that past warming occurred with relatively little climate forcing. In other words, the lower flank of the pdf of the past climate forcing distribution (figure 5a) controls the upper flank of the pdf of the future temperature response (figure 5b).

Climate forcing and climate sensitivity are not independent.

Perhaps the most important point to emphasize for the application to integrated assessment models (IAMs) is that climate sensitivity and climate forcing are not independent of each other. For any projections made of the future, a starting point for the current climate forcing must be assumed. We are currently quite uncertain about what that starting point is. If aerosol forcing is strongly negative, there is a strong implication that climate sensitivity is high. If aerosol forcing is weak, climate sensitivity must be low. Uncertainties in climate forcing and climate sensitivity must not be assumed to be independent.

The transient climate response.

Equilibrium climate sensitivity relates to a hypothetical distant future climate after the system has equilibrated to a stipulated forcing. The transient climate response over the course of a few centuries may be a more directly useful property of the climate system. A formal definition of the transient climate sensitivity has been proposed as the global-average surface air temperature, averaged over the 20-year period centered on the time of CO_2 doubling in a 1% yr^{-1} increase experiment, which occurs roughly at 2070. While this metric may be more relevant for the future, a negative trade-off is that its exact value depends on this artificially defined trajectory of emissions.

For reasons discussed below, the transient climate response is much better constrained than climate sensitivity. In the words of the IPCC, it is very likely (> 9- in-10) to be greater than 1°C and very unlikely (< 1-in-10) to be greater than 3 °C. Thus the community is much more confident about the evolution of the climate over the coming century than it is about the ultimate warming.

The immensely long timescales of high sensitivity climates.

A key factor in the long-term evolution of the climate is the diffusive nature of the ocean heat storage (figure 6b). In order to reach equilibrium the ocean abyss must also warm, and because of the relatively sluggish circulation of the deep ocean, the upper layers must be warmed before the lower layers, and the more the temperature change must be, the longer diffusion takes to work. A simple scaling analysis (e.g., Hansen et al., 1985) shows that:

$$\text{Climate adjustment time } \alpha \text{ (climate sensitivity)}^2$$

Thus if it takes 50 yrs to equilibrate with a climate sensitivity of 1.5 °C, it would take 100 times longer, or 5,000 yrs to equilibrate if the climate sensitivity is 15 °C. Although Nature is of course more complicated than this, the basic picture is reproduced in models with an (albeit simplified)

ocean circulation. Figure 6a shows one such calculation from Baker and Roe (2009), though there are others (in particular see Held et al., 2010).

If IAMs are to be used to project out more than a few decades, it is critical that they represent this physics correctly. A single adjustment time for climate, or a deep ocean that is represented as a uniform block, cannot represent this behavior.

The extremely high temperatures found in the fat tail of climate sensitivity cannot be reached for many centuries for very robust physical reasons. Failure to incorporate this fact will lead to a strong distortion of the evolution of possible climate states, and of the subsequent IAM analyses based on them.
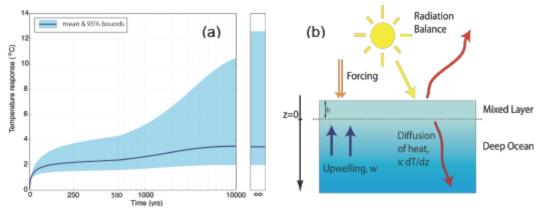

Figure 6: (a) The evolution of possible climate trajectories in response to an instantaneous doubling of CO_2 given the existing uncertainty in climate sensitivity. From Baker and Roe, 2009. Note the change to a logarithmic x-axis after 500 years. Low climate sensitivity is associated with rapid adjustment times (decades to a century). High climate sensitivity has extremely long adjustment times – thousand of years. This results from the fundamentally diffusive nature of the ocean heat uptake, illustrated schematically in panel (b). Such behavior is also reproduced in more complete physical models. See Held et al. (2010), for example.

CO₂ stabilization targets are a mistake.

A prominent part of the conversation about action on climate change has centered on what the right level of CO_2 should be in the atmosphere (e.g., Solomon et al., 2010). Some advocate for 350 ppmv (e.g., Hansen et al. 2008), though we are already past 380 ppmv and climbing, others contemplate the consequences of 450 ppmv (e.g., Hansen, et al., 2007), still others 550 ppmv (Pacala and Soccolov, 2004; Stern, 2007).

However decreeing and setting in stone a particular target for CO_2 is fundamentally the wrong approach, and a vastly inefficient way to avoid a particular climate scenario. This point was made very elegantly and powerfully in a study by Allen and Frame (2007), reproduced in figure 7. Panel a) shows a scenario of what could happen if we decided today to stabilize CO_2 at 450 ppmv by 2100,
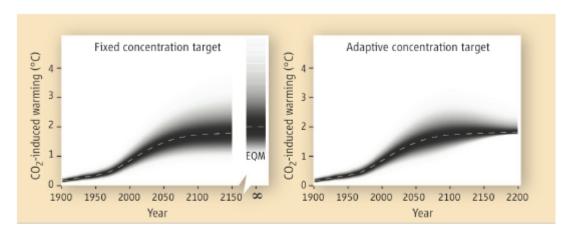

Figure 7: reproduced from Allen and Frame (2007). Carbon dioxide–induced warming under two scenarios simulated by an ensemble of simple climate models. (Left) CO_2 levels are stabilized in 2100 at 450 ppm; (right) the stabilization target is recomputed in 2050. Shading denotes the likelihood of a particular simulation based on goodness-of-fit to observations of recent surface and subsurface-ocean temperature trends. The darker the shading, the likelier the outcome.

and then waited for the climate to evolve. Our current best guess is that would lead to an equilibrium temperature change of 2 °C, taking us to the edge of what some have called dangerous climate change. However because of our current uncertainty in climate sensitivity, the envelope of possible climate states is quite broad by 2150. In other words, our hypothetical choice that we made today still leaves us exposed to a quite broad envelope of risk. Note, though, that figure 7a is consistent with figure 6 – temperatures in the fat tail of high climate sensitivity are still very, very far from equilibrium at 2150.

Panel b) of figure 7 considers an alternative strategy in which we still act according to our best guess today, but re-compute a new concentration target at 2050, based on the fact that 40 years have elapsed and Nature has given us more information about what trajectory we are on. Figure 7b makes it clear that this adaptive strategy is vastly more effective in achieving a desired climate target (in this case a global temperature change of 2 °C). Because the link between CO_2 levels and global temperature is uncertain, and because it is prudent to anticipate only incremental advances in our understanding, it is common sense to pursue a strategy that has built-in flexibility rather than declaring a fixed concentration.

How well do global projections correspond to regional projections?
Many of the most important climate impacts – changes in hydrology, storminess, heat waves, snowpack, etc. – are fundamentally regional in nature. How reliable is global climate change as a predictor of regional climate change? Since this is a question about the future, we are forced to use climate models. Figure 8 analyzes how well global climate sensitivity correlates with local climate change (in this case annual mean temperature and precipitation change in 2100), comparing among eighteen different IPCC models (IPCC, 2007).

It takes a correlation of $r \sim 0.75$ before half of the variance (i.e., r^2) of the local climate change is attributable to the global climate change. Only a very few patches of the planet achieve even this level of correlation in annual temperature (Figure 8a) and nowhere reaches this measure in annual precipitation (Figure 8b). This highlights that the connection between regional and global climate change is not that strong. This result should not be surprising: though models may all agree on the *sign* of the climate change in a given region, there is a great deal of scatter and individual model vagaries in projecting the *magnitude* of the climate change. Research into the limits of regional predictability is only just beginning. A useful starting point is Hawkins and Sutton (2009).
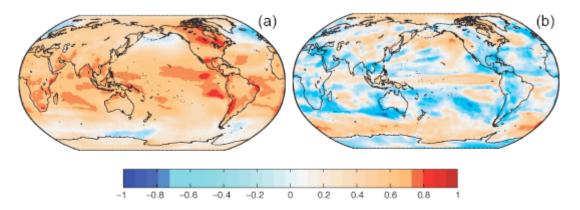

Figure 8: a) correlation among 17 IPCC climate models of their global equilibrium climate sensitivity and their local annual-mean temperature change in 2100,; b) same as a), but for annual-mean precipitation. Calculation made by N. Feldl from IPCC archived model output based on the A1B emissions scenario, and similar plots for other variables are at http://earthweb.ess.washington.edu/roe/GerardWeb/Publications.html.

Summary.

1) The most important point to drive home is that uncertainty is not ignorance. The planet has warmed in the recent past, and will continue to warm for the foreseeable future. That this is a result of our actions is beyond rational dispute. The overwhelming preponderance of the IPCC 2007 report is extremely reliable, and reflects an objective characterization of the best current understanding about climate. All of the following points are consistent with (and in many cases drawn from) that report.

2) A traditional measure of the planet's response, equilibrium climate sensitivity is uncertain, primarily because of uncertainty in the radiative forcing due to aerosols. This precludes us from calibrating our models of climate with greater accuracy.

3) However a focus on climate sensitivity may be misplaced because of the tremendously long timescales associated with reaching equilibrium – thousands of years in the case of the fat tail of high climate sensitivity.

4) If all human influence were to cease today, the rapid loss of anthropogenic aerosols from the climate would unmask CO_2 warming, and the planet's temperature would increase as a result. The degree of warming is quite uncertain.

5) For related reasons, a strategy that aims to stabilize concentration of greenhouse gasses at a particular level is a mistake, because the degree of warming is still unpredictable. A strategy that aims for a flexible emissions will be much more effective at preventing a particular level of warming.

6) IAMs have to make choices about how to represent climate forcing associated with human activity. We are quite uncertain about what this level is right now. It is crucial to appreciate that uncertainty in climate sensitivity and uncertainty in climate forcing cannot be treated as independent.

7) Many climate damages both to humans and to the biosphere result from regional climate factors. Unfortunately, there is relatively little agreement among climate models about how global climate changes relate to local climate changes, and this is especially true in some of the most vulnerable subtropical regions. Thus the meaning of analyses that use only global temperature changes to assign climate damages is unclear.

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Notes for EPA & DOE discussion meeting

Martin L. Weitzman
November, 2010

First thoughts on "'thinking about' high-temperature damages from potential catastrophes in climate change."

'Thinking about' is the right phrase. This is a notoriously intractable area even to conceptualize, much less to model or to quantify. Don't expect miracles or breakthroughs here — too many "unknown unknowns" with seemingly non-negligible probabilities to feel comfortable with.

What is the nature of the beast?

The economics of climate change consists of a very long chain of tenuous inferences fraught with big uncertainties in every link: beginning with unknown base-case GHG emissions; then compounded by big uncertainties about how available policies and policy levers will transfer into actual GHG emissions; compounded by big uncertainties about how GHG flow emissions accumulate via the carbon cycle into GHG stock concentrations; compounded by big uncertainties about how and when GHG stock concentrations translate into global average temperature changes; compounded by big uncertainties about how global average temperature changes decompose into regional climate changes; compounded by big uncertainties about how adaptations to, and mitigations of, regional climate-change damages are translated into regional utility changes via a regional "damages function"; compounded by big uncertainties about how future regional utility changes are aggregated into a worldwide utility function and what should be its overall degree of risk aversion; compounded by big uncertainties about what discount rate should be used to convert everything into expected-present-discounted values. The result of this lengthy cascading of big uncertainties is a reduced form of truly enormous uncertainty about an integrated assessment problem whose structure wants badly be transparently understood and stress tested for catastrophic outcomes.

Let welfare W stand for expected present discounted utility, whose theoretical upper bound is B. Let $D \equiv B-W$ be expected present discounted disutility. Here D stands for what might be called the "diswelfare" of climate change. Unless otherwise noted, my default meaning of the term "fat tail" (or "thin tail") will concern the upper tail of the PDF of lnD, resulting from whatever combination of probabilistic temperature changes, temperature-sensitive damages, discounting, and so forth, by which this comes about. Empirically, it is not the fatness of the tail of temperature PDFs *alone* or the reactivity of the damages function to high temperatures *alone*, or any other factor *alone*, that counts, but the *combination* of all such factors. Probability of welfare-loss catastrophe declines in impact size, but key question here is: *how fast* a decline relative to size of catastrophe? When we turn to theory, it seems to highlight that the core "tail fattening" mechanism is an inherent inability to learn about extreme events from limited data.

What do rough calculations show about this beast?

I have played with some extremely rough numerical examples. GHG concentration implies a PDF of temperature responses implies a PDF of damages (given a "damages function"). In order to get tail fatness to matter for willingness to pay to avoid climate change requires a *much* more reactive damages function than the usual quadratic. Usual quadratic damages function loses 26% of output for a 12dC temperature change. At 2% annual growth rate, 12dC change 200 years from now implies that welfare-equivalent consumption then will still be *37 times higher than today*. If you use the standard quadratic damages function, you cannot get much damage from extreme temperatures. If make a reactive damages function, such that, say, 12dC temperature increase causes welfare-equivalent consumption to shrink to, say, 5% of today's level, then get very high WTP to reduce GHG target levels. Model is terrified of flirting with high CO2-e levels, especially above 700 ppm. Incredible dependence on degree of risk aversion (2, 3, or 4?), fatness of tail PDFs (climate sensitivity PDF: normal, lognormal, Pareto?), and so forth. My own tentative summary conclusion: tail of extreme climate change welfare-loss possibilities is much too fat for comfort when combined with reactive damages at high temperatures. It looks like this could influence such things as social cost of carbon.

Is there anything constructive to take away from this gloomy beast?

My tentative answer: a qualified maybe. Some possible rough ideas follow.

1. Keep a sense of balance. A small but fat-tailed probability of disastrous damages is not a realization of a disaster. Highly likely outcome is a future sense that we dodged a bullet (like Cuban missile crisis?). Yet when all is said and done, catastrophic climate change looks to me like a very serious issue.

2. Try standard CBA or IAM exercises in good faith. *But*, be prepared – when dealing with extremes – that answers might depend non-robustly upon seemingly-obscure assumptions about tail fatness, about how the extreme damages are specified (functional forms, parameter values, etc.), assumptions about rates of pure time preference, degrees of risk aversion, Bayesian learning, CO2 stock inertia, CH4 releases from clathrates, mid-course correction possibilities, etc. Some crude calculations seem to indicate great welfare sensitivity to seemingly-obscure factors such as the above, most of which are difficult to know with any degree of precision. Do CBAs and IAMs, study answers, but maybe don't try to deny the undeniable if these answers are sensitive to tail assumptions in a highly nonlinear welfare response to extreme uncertainty.

3. Should we admit to the public that climate change CBA looks more iffy and less robust than, say, CBA of SO2 abatement, or would this be self defeating?

4. Maybe there should be relatively more research emphasis on understanding extreme tail behavior of climate-change welfare disasters. Alas, this is very easy to say but very difficult to enact. How do we learn the fatness of PDF tails from limited observations or experience?

5. A need to compare how fat are tails of climate-change welfare loss with how fat are tails of any proposed solutions, such as nuclear power, below-ground carbon sequestration, etc.

6. Suppose that a lot of expected present discounted disutility is in the bad fat tail of the welfare-loss PDF. Realistically, how can we limit some of the most horrific losses in worst-case scenarios? Can we filter-learn fast enough to offset residence time of atmospheric CO_2 stocks by altering GHG emission flows in time to work? Is tail fatness an argument for developing an emergency-standby backstop role for fast geoengineering? Any other backstop options?   Take-home lesson here: hope for the best and prepare for the worst. At least we should be prepared, beforehand, for dealing with ugly scenarios, even if they are low-probability events. Should the discussion about emergency preparedness begin now?

Earth System Tipping Points

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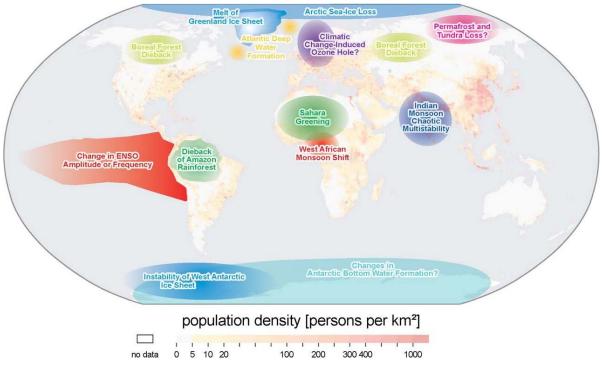
Definitions

A **tipping point** is a critical threshold at which the future state of a system can be qualitatively altered by a small change in forcing[1]. A **tipping element** is a part of the Earth system (at least sub-continental in scale) that has a tipping point[1]. Policy-relevant tipping elements are those that could be forced past a tipping point this century by human activities. **Abrupt climate change** is the subset of tipping point change which occurs faster than its cause[2]. Tipping point change also includes transitions that are slower than their cause (in both cases the rate is determined by the system itself). In either case the change in state may be reversible or irreversible. **Reversible** means that when the forcing is returned below the tipping point the system recovers its original state (either abruptly or gradually). **Irreversible** means that it does not (it takes a larger change in forcing to recover). Reversibility in principle does not mean that changes will be reversible in practice.

Tipping elements in the Earth's climate system

Previous work[1] identified a shortlist of nine potential policy-relevant tipping elements in the climate system that could pass a tipping point this century and undergo a transition this millennium under projected climate change. These are shown with some other candidates in Figure 1.

Figure 1: Map of potential policy-relevant tipping elements in the Earth's climate system overlain on population density. Question marks indicate systems whose status as tipping elements is particularly uncertain.

We should be most concerned about those tipping points that are nearest (least avoidable) and those that have the largest negative impacts. Generally, the more rapid and less reversible a transition is, the greater its impacts. Additionally, any positive feedback to global climate change may increase concern, as can interactions whereby tipping one element encourages tipping another. The proximity of some tipping points has been assessed through expert elicitation[1,3]. Proximity, rate and reversibility have been also assessed through literature review[1], but there is a need for more detailed consideration of impacts[4]. The following are some of the most concerning tipping elements:

The **Greenland ice sheet** (GIS) may be nearing a tipping point where it is committed to shrink[1,3]. Striking amplification of seasonal melt was observed in summer 2007 associated with record Arctic sea-ice loss[5]. Once underway the transition to a smaller ice cap will have low reversibility, although it is likely to take several centuries (and is therefore not abrupt). The impacts via sea level rise will ultimately be large and global, but will depend on the rate of ice sheet shrinkage. Latest work suggests there may be several stable states for ice volume, with the first transition involving retreat of the ice sheet onto land and around 1.5 m of sea level rise[6].

The **West Antarctic ice sheet** (WAIS) is currently assessed to be further from a tipping point than the GIS, but this is more uncertain[1,3]. Recent work has shown that multiple stable states can exist for the grounding line of the WAIS, and that it has collapsed repeatedly in the past. It has the potential for more rapid change and hence greater impacts than the GIS.

The **Amazon rainforest** experienced widespread drought in 2005 turning the region from a sink to a source (0.6-0.8 PgC yr^{-1}) of carbon[7]. If anthropogenic-forced[8] lengthening of the dry season continues, and droughts increase in frequency or severity[9], the rainforest could reach a tipping point resulting in dieback of up to ~80% of the rainforest[10-13], and its replacement by savannah. This could take a few decades, would have low reversibility, large regional impacts, and knock-on effects far away. Widespread dieback is expected in a >4 °C warmer world[3], and it could be committed to at a lower global temperature, long before it begins to be observed[14].

The **Sahel and West African Monsoon** (WAM) have experienced rapid but reversible changes in the past, including devastating drought from the late 1960s through the 1980s. Forecast future weakening of the Atlantic thermohaline circulation contributing to 'Atlantic Niño' conditions, including strong warming in the Gulf of Guinea[15], could disrupt the seasonal onset of the WAM16 and its later 'jump' northwards[17] into the Sahel. Whilst this might be expected to dry the Sahel, current global models give conflicting results. In one, if the WAM circulation collapses, this leads to wetting of parts of the Sahel as moist air is drawn in from the Atlantic to the West[15,18], greening the region in what would be a rare example of a positive tipping point.
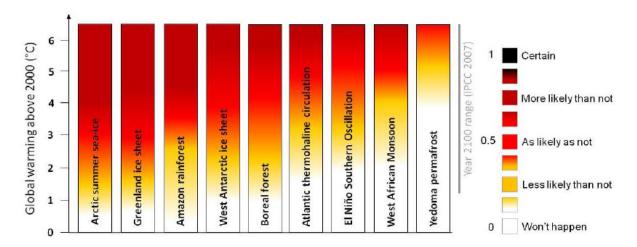
The **Indian Summer Monsoon** (ISM) is probably already being disrupted[19,20] by an atmospheric brown cloud (ABC) haze that sits over the sub-continent and, to a lesser degree, the Indian Ocean. The ABC haze is comprised of a mixture of soot, which absorbs sunlight, and some reflecting sulfate. It causes heating of the atmosphere rather than the land surface, weakening the seasonal establishment of a

land-ocean temperature gradient which is critical in triggering monsoon onset[19]. Conversely, greenhouse gas forcing is acting to strengthen the monsoon as it warms the northern land masses faster than the ocean to the south. In some future projections, ABC forcing could double the drought frequency within a decade[19] with large impacts, although it should be highly reversible.

Estimation of likelihood under different scenarios

If we pass climate tipping points due to human activities (which in IPCC language are called "large scale discontinuities"[21]), then this would qualify as dangerous anthropogenic interference (DAI) in the climate system. Relating actual regional tipping points to e.g. global mean temperature change is always indirect, often difficult and sometimes not meaningful. Recent efforts suggest that 1 °C global warming (above 1980-1999) could be dangerous as there are "moderately significant"[21] risks of large scale discontinuities, and Arctic sea-ice and possibly the Greenland ice sheet would be threatened[1,22]. 3 °C is clearly dangerous as risks of large scale discontinuities are "substantial or severe"[21], and several tipping elements could be threatened[1]. Under a 2-4 °C committed warming, expert elicitation[3] gives a >16% probability of crossing at least 1 of 5 tipping points, which rises to >56% for a >4 °C committed warming. Considering a longer list of 9 potential tipping elements, Figure 2 summarizes recent information on the likelihood of tipping them under the IPCC range of projected global warming this century.

Figure 2: Burning embers diagram for the likelihood of tipping different elements under different degrees of global warming[23] – updated, based on expert elicitation results[3] and recent literature.

Early warning prospects

An alternative approach to assessing the likelihood of tipping different elements is to try and directly extract some information on their present stability (or otherwise). Recent progress has been made in identifying and testing generic potential early warning indicators of an approaching tipping point[1,24-27]. Slowing down in response to perturbation is a nearly universal property of systems approaching various types of tipping point[25,27]. This has been successfully detected in past climate records approaching different transitions[24,25], and in model experiments[24-26]. Other early warning indicators that have been explored for ecological tipping points[28], include increasing variance[28], skewed responses[28,29] and their spatial equivalents[30]. These are beginning to be applied to anticipating climate tipping points. For

climate sub-systems subject to a high degree of short timescale variability ('noise'), flickering between states may occur prior to a more permanent transition[31]. For such cases, we have recently developed a method of deducing the number of states (or 'modes') being sampled by a system, their relative stability (or otherwise), and changes in these properties over time[32].

Applying these methods to observational and reconstructed climate indices leading up to the present, we find that the Atlantic Multi-decadal Oscillation (AMO) index, which is believed to reflect fluctuations in the underlying strength of the thermohaline circulation, is showing signs of slowing down (i.e. decreasing stability) and of the appearance of a second state (or mode of behavior). On interrogating the underlying sea surface temperature data (used to construct the index), we find that recent significant changes are localized in the northernmost North Atlantic, and are investigating the possible relationship with changes in Arctic sea-ice cover. Meanwhile, some other climate indices, e.g. the Pacific Decadal Oscillation (PDO) show signs of increasing stability.

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Catastrophic Climate Change

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Introduction

The question of how to assess prospects of climate change catastrophes has been the focus of a great deal of recent research and debate. An example of the classic conundrum of low probability – high consequences events, a climate change catastrophe is a highly unlikely event, but if it did occur it would severely affect well-being across the world – though it would affect poor countries much more seriously than richer countries.[1] The larger geographical scale of climate change catastrophes distinguishes them from more localized extreme events. The consequences of catastrophes also are in varying degrees very costly, if not possible, to reverse.

Examples of global catastrophes include very large and relatively rapid increases in sea level from faster melting and collapse of ice sheets, slower changes in ocean currents that have insidious effects on weather patterns, and large scale destruction of forests and other ecosystems. fairly rapid loss of global forest cover. Unlike sudden disasters such as earthquakes, the onset of these events is measured in multiple decades or centuries; but once they occur it is impossible to reverse the impacts. Other permanent effects of climate change are anticipated to be increases in the frequency and severities of droughts, floods, and hurricanes, leading to corresponding destruction of crops, water supplies, and coastal infrastructure. While each of these individual events is a more localized disaster, the cumulative effect could be a global catastrophe created by the —cascading consequences‖ of more localized disasters occurring in relatively quick succession, each amplifying the effects of others.[2]

A key step in evaluating risks of climate change catastrophes is to assess not only the impacts on the physical climate system, but also the consequences in terms of human impacts. The most immediate implication is that while a physical —tipping point‖ may be reached at some unknown future date T^0, the human impacts will evolve more slowly, reaching an intensity viewed as catastrophic only at some date $T^1 > T^0$. This distinguishes climate change from, for example, the risk of catastrophe posed by a gigantic volcanic eruption, or nuclear war. While a gradual onset of impacts will not prevent a catastrophe if reversal is not possible, it can provide a window of time for major action to avert or adapt to the threat – if signals of the changes are detectable. More fundamentally, the assessment of what constitutes catastrophic human impacts involves not just climate change and earth system science, but

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[1] In terms of absolute numbers, losses are likely to be larger in richer nations. As a percentage of GDP, however, less developed countries are likely to face higher damages since most are more dependent on agriculture and less likely to have the resources to adopt measures that could reduce damages.

[2] This possibility appears to have received little systematic attention in reviews of climate change impacts by the IPCC and others, though it figures prominently in discourse about national security consequences of climate change.

also inherent value judgments about what magnitude and speed of consequences are deemed to be catastrophic. For example, the now-often-cited —scientific near-consensus‖ about the urgent need to hold warming to less than 2°C relative to pre-industrial times reflects more than a natural science evaluation of climate change impacts.

Climate change catastrophes pose a familiar challenge for assessing the impacts of low probability – high impact events: while exact quantification is not possible, the most extreme adverse impacts from climate change—say the worst 1% of scenarios—may account for a large portion of losses in expected value terms. This implies that focusing primarily on a trajectory of more likely anticipated climate change damages may miss an important part of the problem.[3] Yet, these consequences of an unlikely but possible climate change catastrophe need to be weighed against a variety of other risks society faces.

Further complicating the problem is that climate change catastrophes may be better characterized by ignorance than uncertainty. That is, not only do we not know the probability of a particular mega-catastrophe occurring, we do not even know many of the possible outcomes. A catastrophe from climate change could stem from a cause or have impacts that currently receive little attention.[4] Some authors have suggested that this level of ignorance, coupled with the very low probability of an event and the possibility of extremely severe impacts, hamstrings the use of rational-choice based methods for analyzing response options. This in turn requires confronting the possibility that attitudes of the broader public about such events will not align very well with the results of a more systematic evaluation of the pros and cons of different response options, raising questions about what sets of preferences and beliefs should govern policy making.

Climate Change Catastrophes

The most widely discussed large-scale impact of climate change is **global sea level rise**. The collapse of the West Antarctic Ice Sheet (WAIS) or Greenland ice sheets could lead ultimately to a sea level rise of several meters, with consequences great enough to be considered a global catastrophe in the absence of massive and costly relocation because of the number of people living near the coasts. A key uncertainty is how rapidly this change in sea level might occur. Previously it had been thought that such large changes might require much longer than a century, but some recent studies suggest that substantial change could occur in this century. Anthoff et al. (2009) report figures for world losses

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[3] For many classes of disasters and catastrophes, the most extreme small percent of the situations represent a significant proportion of the losses. We have witnessed this —fat tail‖ phenomenon recently with terrorist deaths and losses in a financial crisis. 9/11 and the 2008-09 financial meltdown caused more deaths and dollar losses respectively than all terrorist incidents and financial catastrophes in the post WWII era. With such phenomena, losses are better characterized by a power law than by a normal or even lognormal distribution. The debate about fat tails in relation to climate catastrophes has been a subject of lively recent debate among Weitzman, Pindyck, Nordhaus, and others.

[4] The history of the past 40 years is sobering with respect to the ability to identify catastrophe risks. In 1970, nuclear war would have been the leading contender for any world catastrophe, and looking forward few would have predicted the major looming threats of the current era, which would include not just climate change, but also global pandemics and terrorism.

(based on 1995 baseline conditions) that are relatively small – on the order of 0.5% of world GDP for a 5 m rise. Dasgupta et al. (2007) report figures for developing countries on the order of 6% of GDP, those these estimates do not take account of possibilities for ex ante efforts to mitigate risks. On the other hand, estimates based on historical baselines will tend to under-state the economic impacts of sea level rise by not taking account of likely future growth in the coming years in the share of GDP concentrated in coastal areas.[5]

A second important category of global catastrophe risk involves **disruptions of ocean circulation from climate change,** with potentially disastrous effects on regional weather patterns and long-term climate (Vellinga and Wood 2008). Such impacts are most commonly seen as developing over many hundreds of years. In contrast, **very large-scale ecosystem disruptions** could occur significantly sooner. Changes in ecosystems resulting from changes in temperature and rainfall incidence and increased climate variability have the potential to cause very significant loss of biodiversity—on the order of 20-30% extinction within a few decades. There is also the prospect of major changes in vegetation, in particular, irreversible conversion of forest to grassland, desertification, and acidification of the ocean (Smith, Schneider, Oppenheimer et al. 2009). Another cause for significant concern is the possibility that positive feedback effects in the climate change process itself could occur (e.g., liberation of trapped methane from ice, rapid increases in CO_2 from vegetation dieback, or increased heat absorption as glaciers retreat), causing the abovementioned changes to occur more rapidly.

There also has been significant scientific research on how climate change can effect more localized disasters, such as heat waves, flooding, droughts, and changes in hurricane frequency or intensity. Less understood is how **a number of smaller disasters** all occurring over a relatively short time period could mutually reinforce each other in such as way that the **resulting "cascade of consequences" becomes a global catastrophe**. Extreme events can have secondary consequences that generate substantial amounts of additional damages; secondary consequences in turn can trigger tertiary consequences that further amplify the adverse consequences; and so on. One example would be if increased drought from climate change in different regions successively caused a series of local food shortages to occur in close proximity, leading to political instability, a breakdown of civil order, large-scale migration for survival, and regional conflicts. Another example could be a series of local fires occurring in climate-stressed forests and grasslands overly widely dispersed areas, adding up to a large-scale destruction of resources, ecosystem services, and livelihoods over a large area.

The compounding or amplifying effects of individual adverse impacts would be the result of exceeding the resilience of a number of local socioeconomic systems in rapid succession. More frail components of socioeconomic systems, such as marginal subsistence agriculture, represent potential places of vulnerability. Cascading-event catastrophes could occur much more rapidly than the slower-onset global impacts discussed above, especially as climate change accelerates and greater negative impacts occur at local scales. It is possible that more comprehensive local monitoring of disaster risks may facilitate the

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[5] Using 1995 data, it has been estimated that around 400 million people would be impacted by a 5 m rise in sea level and that a WAIS collapse in 100 years could cause, at the peak, 350,000 forced migrations a year for a decade (Nicholls, Tol and Vafeidis 2008).

development of early warning indicators for cascading catastrophes. For example, if several years of historically unusual drought weakened agricultural systems in many vulnerable parts of the world, there would be a stronger basis for concern about cascading consequences than if agricultural failures were not occurring in such rapid succession. However, the time interval for action to avert the potential catastrophe could be short.

Traditional responses to the risk of extreme events are of limited value in mitigating risks of a mega-catastrophe. The underlying changes in the climatic system could not be reversed over any time scale relevant for decision-makers. Traditional insurance mechanisms will not function effectively for this type of event, because the risks are —systemic‖ and cannot effectively be reallocated to diversify. Moreover, significant international transfers from richer to more vulnerable poorer countries are unlikely when a catastrophe affects broad swaths of the world.

Evaluating Climate Change Catastrophe Risks

The traditional economic model for decision making under uncertainty is expected utility theory, in which decision makers maximize the utility they receive from potential outcomes weighted by the probability the outcomes will occur. In the climate change economics literature, GHG abatement policies with the expected net benefits over time are identified using dynamic Integrated Assessment Models (IAMs) that compare the anticipated costs of abatement with avoided damages from climate change over time. By and large these models are deterministic and are used for scenario-based comparisons of policies under different assumptions about climate change damages and abatement costs. However, a literature has developed in which catastrophes are treated as (usually known) large-scale rapid-onset economic damages with an uncertain date of occurrence, the probability of which increases as atmospheric GHG concentrations rise.[6]

A common finding in these studies is that while the risk of such catastrophes increases the expected economic benefits of more rapid GHG mitigation, the effect is not that significant qualitatively unless the probability of nearer-term catastrophe is quite high, the size of the catastrophe is truly astronomical, or the discount rate used to value future catastrophic impacts is quite low. The scientific information on catastrophes summarized above indicates that catastrophes are extremely unlikely in any time frame short of several decades at the very least, and that while the ultimate effects may indeed be huge, the most severe impacts will develop only gradually. Until scientific understanding of climate change catastrophes leads to stronger findings on their proximity and severity, the choice of discount rate will be the most important determinant of the cost of future catastrophes in the expected-utility framework.

The discount rate issue in turn continues to be very hotly debated, and only a very brief summary of key points is offered here. Two strands of positive analysis has argued for applying a lower discount rate to longer-term climate change costs, including catastrophes, than might be inferred from research on consumer time preference or rates of return on investment. One is that individuals may discount the future hyperbolically, so rates of discount decline and ultimately plateau at a fairly low number as one

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[6] References – Kverndokk et al, Pizer, Nordhaus. Earlier foreshadowing by Manne.

goes out into the future. The other is that when one accounts for the higher marginal utility of income for the poor facing more adverse impacts from climate change, then under reasonable assumptions the effective time discount rate after adjusting for distributional differences is reduced. In addition, if climate change has the most severe effects on longer-term economic growth when growth itself is more likely to be weak, then policies to reduce the threat of catastrophe will have a lower effective discount rate because of their contribution to reducing intertemporal economic risk.[7]

Even with these considerations, however, the resulting implied discounting of future over current returns may not be small enough for catastrophes to carry major weight in evaluating the potential impacts of climate change. Unless the discount rate is under 1%, and perhaps even close to zero, severe future consequences that will not arrive for some time and are not world-threatening may still be too —telescoped.‖ Stern and others have addressed the issue of discounting by using normative arguments to suggest a discount rate at or near zero is in fact appropriate. Two other arguments, not so dependent on normative precepts, may also add weight to the importance of catastrophe risks in evaluating climate change impacts.

Hypothesis 1: People are Not Expected Utility – Maximizers
There is a growing literature from behavioral economics and psychology which demonstrates that individuals do not consistently make decisions according to the expected utility paradigm.[8] If individuals are only boundedly rational, they have neither the time nor the capacity to fully assess the consequences of decisions. In that case, individuals adopt certain rules of thumb and mental shortcuts to make decisions. These so-called heuristics can lead to choices that depart from predictions of expected utility theory.

When thinking about possible disasters, it has been found that people tend to be over-optimistic, thinking negative outcomes are less likely to happen to them. When a risk is highly emotional, however, people can disregard probabilities altogether, treating all outcomes as equal (—probability neglect‖). Individuals also seem to place an added value on certainty, preferring to reduce a small risk to zero by more than they value reducing a larger risk by a greater amount. Errors of commission are viewed as worse than errors of omission. This can lead to a tilt to the side of inaction.

Experimental also has found that context matters, often significantly, a when making decisions. For instance, when probabilities are unknown and must be estimated, individuals have been found to assess an event as more likely when examples come to mind more easily (the —availability heuristic‖). People can disproportionately prefer to maintain the status quo in their choices, even if conditions or options change. Individuals sometimes —anchor‖ their preferences on an available piece of information, and fail to update their assessments adequately in the face of new information. Individual choices are also

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[7] [add references] Strictly speaking, the second and third arguments are not about the actual rate of time preference, but rather about how factors related to distributional impacts and risk that enter the maximand of the intertemporal utility calculation affect the implied discounting of future over current returns.

[8] This discussion is taken from Kousky et al (2009), which contains references to the relevant behavioral economics literature.

strongly affected by the way that information is presented. Thus, individuals may make different choices for the same decision if it is merely phrased differently (—framing effects‖). Choices depend upon the extent to which a risk evokes feelings of dread. Personal utility also is sensitive to individuals' perceptions of equity and fairness.

These various behavioral attributes can imply higher or lower values attached to catastrophe risks than would be implied by expected utility theory. The former would follow from dread or the evaluation of all catastrophes as roughly equal in likelihood. The latter would follow from optimism bias, or a preference for reducing small and familiar risks to zero over reducing more substantially an unfamiliar risk – of which climate change catastrophe certainly is an example. While the direction of bias has to be assessed empirically, the existence of these various —non-rational‖ attitudes raises an important but not new question for evaluating climate change catastrophe risks in setting public policy: if decision makers believe they have better information than the general public and that they are less subject to emotional biases, to what extent should their valuation of alternatives supersede those of members of the general public?

Hypothesis 2: People are Non-Egoistic Expected Utility – Maximizers

A second approach that has been taken in the literature for addressing long-term threats posed by climate change is to see individuals today, imperfect information and all, as interested in more than maximizing the discounted present value of their lifetime expected utility streams. One can broadly define this as altruistic preferences, but this label can cover several different forms of preferences.

A traditional approach to altruistic preferences is to include some measure of next-generation or other future utility in the preferences of members of the current generation. In this setting, individuals will weigh the potential costs of a climate change catastrophe in terms of its anticipated impacts on future welfare, as well as the possibly slight impact on current individuals' egoistic well-being. Consequently, individuals will derive utility in part from the —bequest they leave to the future in terms of a lowered (endogenous) risk of a climate change catastrophe. However, there are both theoretical and empirical reasons to expect individuals to discount the welfare of future generations relative to their own egoistic welfare. This takes us back to the question previously mentioned in the context of time preference, as to how powerful an influence this form of altruism might be in the current generation's assessment of risks of climate change catastrophes.[9]

A second approach is to depart from a purely utilitarian framework by supposing that individuals see themselves (or should do) as having a moral obligation to future generations. This mixing of obligations and conventional utilitarian motivations implies some degree of lexicography in individuals' preferences – or, critics of utilitarianism might say, an innate failure of the standard economic model to describe what really motivates people. In this view, if a potential future catastrophe threatens to impose a

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[9] Current individuals also could believe, as Schelling for example has suggested, that other kinds of bequests to the future would have higher value; or they could further discount bequests of a less risky climate out of concern that unless the —chain of obligation‖ is maintained, something impossible to assure, the sacrifice made today would be wasted in the future.

morally inacceptable burden on the future, people will be (or at least can be) motivated to endure potentially extra-ordinary sacrifices to reduce the threat. The expression of that moral sentiment by individuals as citizens and stewards, versus utilitarian consumers, would be found through public choice exercises like voting for tough restrictions on future GHG emissions.

This conception is both stimulating and frustrating, since it does not offer any straightforward way of assessing how economically significant is the threat of a future climate change catastrophe. Aside from uncertainty about what the triggering level of threat to the future might be, does one regard current almost universal reticence to support tough GHG restrictions as due to (correctable) moral failing? Lack of information? Lack of leadership? The result of rational leadership, because the threat of climate change is seen as less significant than other threats or because international collective action problems have not been solved?

A third possible approach that has received less attention is that individuals have preferences that include some notion of —planetary health‖ as a global public good. Rather than seek to describe concern about risks of catastrophe from climate change as deriving only from more fundamental concerns for intergenerational altruism or fairness, one could posit that individuals derive some direct benefit from having greater confidence in the ability of planetary systems to remain undisrupted, without the need to unpack the rationales in terms of future human well-being, satisfaction of moral sentiment, or a pure existence benefit. This approach allows one to sidestep some of the difficulties encountered in either the altruistic utilitarian or moral-obligations conceptions. In particular, the normative approach to setting discount rates can be embedded in a framework of preferences without having to be an ad hoc add-on.[10] However, this does not get around the huge empirical problems in assessing the value that members of the current generation might place on reducing risks of future climate change catastrophes.[11]

Catastrophe Risks and Rational Choice Approaches to Policy

While it is certainly possible to debate the capacity of expected —utility types of analyses to adequately capture the social opportunity cost of climate change catastrophe threats, it is in cases like this that a disciplined application of rational-choice based analysis more broadly defined can prove most useful. A thoughtful, systematic, and transparent weighing of benefits and costs, broadly defined, is at the heart of such an approach. The presence of —deep‖ uncertainty or ignorance about the types and likelihoods of potential catastrophes means that we must include, in addition to sensitivity analysis on these

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[10] A fundamental criticism of conventional expected-utility analysis for assessing future climate change risks is that it combines conventional time-preference considerations in assessing the opportunity cost of reducing threats with the explicitly ethical question of how much the current generation will feel willing or bound to do in protecting the future.

[11] Ideas like this arise often in literature on environmental stewardship, but I am not aware of many treatments of the idea in economic terms. One example is the paper by Kopp and Portney [ref to add], who describe a thought experiment in which individuals value —well being of the future,‖ and the willingness-to-pay for that value can be discerned through a stated preference valuation effort. While one can debate the merits of the valuation approach even in a thought experiment, the concept is very similar to what I am trying to describe here. Unfortunately, the question of how one would ascertain such valuation remains a barrier to empirical implementation of the concept.

characteristics, focused analysis of the robustness and flexibility of options in addition to the benefits and costs. With respect to what seem to be behavioral biases in the assessment of catastrophe risks by individuals, decision makers must make (and then defend) informed judgments on behalf of those they serve as to when the seeming biases reflect a high degree of economic risk aversion, or dread, and when the biases reflect other factors (framing effects, optimism bias, and the like) that can be viewed as inaccurate comprehension of the tradeoffs involved.

Posner (2005) argues that uncertainty over benefits and costs should not prevent using the basic structure of cost-benefit analysis for evaluating and comparing options, but that this should be framed in a —tolerable-windows‖ approach. This involves using a range of plausible risk estimates to help identify levels of spending on reducing risk for which benefits clearly exceed the costs, for which costs clearly exceed benefits. Policies then can be designed with the goal to remain in this window.[12] This approach does not provide or depend on —a number‖ for how to evaluate the impacts of potential future climate change catastrophes. In particular, it does not treat them as largely irrelevant economically given their low probabilities and long time frames to be realized. Instead it provides flexibility as to how different considerations about climate change catastrophes are brought into the assessment, including risk aversion and concerns about future sustainability as well as costs of risk mitigation, while insisting on transparency and a persuasive argument for how these considerations are to be addressed.

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[12] This idea is akin to value-of-information approaches. If one has some confidence in the evaluation of costs of different policies but great uncertainty about the potential benefits, one could investigate how large the potential benefits might have to be to make a case for the selection of one set of options over another in a portfolio. Similarly, if the benefits are reasonably well understood conditional on a catastrophe occurring, but there is uncertainty about the probability of a catastrophe, then one can ask how large the probability would have to be to justify a particular portfolio of actions.

Natural Capital and Intra- Generational Equity in Climate Change

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Introduction

There are two dimensions of equity that are relevant in an evaluation of the impact of climate change – inter- and intra-generational. It is the former that has been most discussed in the literature to date – all of the extensive debate about the choice of a discount rate in climate models is in effect a debate about intergenerational equity and how to model our concerns about this. And clearly this is very relevant in a climate context – emissions made today will affect generations not yet born, so that issues of intergenerational fairness are central to any discussion of climate policy. But intragenerational issues loom large too: climate change is an external cost imposed largely by rich countries on poor ones, and in addition there is evidence that in any given country it affects poor people more than rich. This dimension of climate change has not been extensively discussed.

Climate change affects our stock of natural capital – for example, the IPCC has estimated that by 2100 in the range of 30-40% of currently extant species may be driven extinct by climate-induced changes in their ecosystems. This would represent a massive transformation of the biospehere, one unprecedented in human history. Glaciers and snowfields are also likely to diminish greatly in extent, affecting water supplies to many regions. Changes like this in our natural capital could have far-reaching consequences, and these are likely to be felt more by poor than by rich countries, and more by poor than rich groups in any country (World Bank 2006). So intra-generational equity and natural capital impacts are related: the latter is likely to reinforce concerns about the former. An important question here is whether some other form of capital – human, intellectual or physical, can replace natural capital. To the extent that this is possible, it may be possible to ameliorate some of the intra-generational equity impacts of climate change. In the notes that follow, I begin to develop some of these points, making suggestions about how they might be modeled.

Equity and Discounting

As anyone who has spent even a short time on the economics of climate change must be aware, a central issue is the choice of the pure rate of time preference (PRTP), to be distinguished clearly from the consumption discount rate (CDR). The PRTP is the δ in the expression $\int_0^\infty u(c_t)e^{-\delta t}\,dt$ where c_t is aggregate consumption at time t, u is a utility function showing strictly diminishing returns to consumption and we are summing discounted utility over all remaining time.

The other discount rate concept, the CDR, is the rate of change of the present value of the marginal

utility of consumption, that is, the rate of change of $\dfrac{e^{-\delta t}\,du(c_t)}{dc_t}$. For the case of a single consumption

good - and we will turn to the case of multiple goods later - it follows from well-known arguments going back to Ramsey [1928] (see Heal [2005] for a review) that this is equal to the PRTP plus the rate of change of consumption times the elasticity of the marginal utility of consumption:

$$\rho_t = \delta + \eta\left(c_t\right)R\left(c_t\right) \tag{1}$$

where ρ_t is the consumption discount rate applied to consumption at time t, $\eta\!\left(c_t\right) = -\dfrac{cu''}{u'} > 0$ is the

elasticity of the marginal utility of consumption and $R(c_t)$ is the rate of change of consumption at time t.

(Here $u' = \dfrac{du(c)}{dc}$ and $u'' = \dfrac{d}{dc}u'$.)

What do these two discount rates mean? The PRTP δ is the rate at which we discount the welfare of future people *just because they are in the future*: it is, if you like, the rate of intergenerational discrimination. Note that there are at least two reasons why we may wish to value increments of consumption going to different people differently: one is that they live at different times, which is captured by δ, and the other is that they have different income levels, which we discuss shortly.[2] A PRTP greater than zero lets us value the utility of future people less than that of present people, *just because they live in the future rather than the present*. They are valued differently even if they have the same incomes. Doing this is making the same kind of judgment as one would make if one valued the utility of people in Asia differently from that of people in Africa, except that we are using different dimensions of the space-time continuum as the basis for differentiation.

That an increment of consumption is less important to a rich person than to a poor person has long been a staple of utilitarian arguments for income redistribution and progressive taxation (see Sen [1973]), and is almost universally accepted. This is reflected in the diminishing marginal utility of consumption, and the rate at which marginal utility falls as consumption rises is captured by $\eta(c_t)$. Equation 1 pulls together time preference and distributional judgments, or considerations based on inter- and intra-generational judgments: the rate at which the value of an increment of consumption changes over time, the CDR ρ_t, equals the PRTP δ plus the rate at which the marginal utility of consumption is falling. This latter is the rate at which consumption is increasing over time $R(c_t)$ times the elasticity of the marginal utility of consumption $\eta(c_t)$.

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[2] We could also value them differently for all manner of other reasons - differences in nationality, ethnicity, and proximity either physically or genetically. In general we don't do these things, at least explicitly, which to me makes it strange that we do explicitly discriminate by proximity in time.

Equity and Climate Change

As we have just seen, there are two dimensions of equity that are important in the context of climate change: equity between present and future generations, the aspect that has been most extensively discussed, and equity between rich and poor countries or groups, both now and in the future – inter- and intra-generational issues. This second dimension is invisible in aggregative one-good models, which is one reason why we need a many-good model to talk seriously about climate change. The discussions below will reinforce the need for some measure of disaggregation in the analysis of the economics of climate change if we are to grapple with equity issues.

The parameter η the elasticity of the marginal utility of consumption, summarizes our preference for equality: it determines how fast marginal utility falls as income rises. There are two ways in which this affects the case for action on climate change.

As η rises, the marginal utility of consumption falls more rapidly. If consumption is growing over time, then this means that the marginal utility of future generations falls more rapidly with larger values of η and therefore we are less concerned about benefits or costs to future generations. We are less future-oriented - the consumption discount rate ρ is higher - and so place less value on stopping climate change. So via this mechanism, *a stronger preference for equality leads to a less aggressive position on the need for action on climate change*. Preferences for equality and action on climate change are negatively linked here.

There is another offsetting effect, not visible in an aggregative model. Climate change is an external effect imposed to a significant degree by rich countries on poor countries. The great majority of the greenhouse gases currently in the atmosphere were put there by the rich countries, and the biggest losers will be the poor countries - though the rich will certainly lose as well. Because of this, *a stronger preference for equality will make us more concerned to take action to reduce climate change*.

So we have an ambiguous impact of a stronger preference for equity on our attitude towards climate change. Via the mechanism captured in the formula for the consumption discount rate, equation 1, it makes us less future oriented - provided consumption is growing. (If consumption were to fall, it would make us more future oriented, and if consumption of some goods were to rise and that of others to fall, the effect would be a priori unclear.) And via our concern for the poor countries in the world today it makes us more future-oriented. Unfortunately, without exception analytical models capture only the first of these effects. They are aggregative one-sector models or models with no distributive weights and so their operation does not reflect the second mechanism mentioned above. This explains the really puzzling and counter-intuitive result that a greater preference for equality in Nordhaus's DICE model leads to less concern about climate change.

To capture fully the contradictory impacts of preferences for equality on climate change policy, we need a model that is disaggregated both by consumption goods and by consumers, allowing us to study the consumption of environmental as well as non-environmental goods and also the differential impacts of climate change on rich and poor nations.

Natural Capital and Climate Change

Return to equation (1) for the consumption discount rate. Note that if consumption were *falling* rather than *rising* over time (the latter being the universal assumption in IAMs), then the second term in the expression for ρ_t would be negative and the CDR could in principle be negative, that is the value of an increment of consumption could be rising over time rather than falling. We would not be discounting but doing the opposite, whatever that is. It is not impossible that in a world of dramatic climate change and environmental degradation, consumption might fall at some point. It is even more likely that *some aspects of consumption, or the consumption of some social groups,* would fall while other continue to rise - recognizing this requires that we treat consumption as a vector of different goods that can be affected differently by climate change. For an early recognition of this point see Fisher and Krutilla [1975], who comment that increasing scarcity of wilderness areas may drive up our valuation of them. A more detailed analysis in the context of a growth model is in Gerlagh and van der Zwaan [2002], who make the interesting point that with limited substitutability between environmental and manufactured goods and the growing scarcity of environmental goods, there is likely to be a version of Baumol's disease - an ever larger portion of income being spent on non-manufactured goods.

Let's follow this line of thought and disaggregate consumption at date t into a vector $c_t = (c_{1,t}, c_{2,t}, ..., c_{n,t})$ of n different goods. (We will mention briefly later the case in which these are the consumption levels of different countries or social groups.) Utility is increasing at a diminishing rate in all of these goods and is a concave function overall. In this case we have to change equation 1 for the consumption discount rate. Now there is a CDR for each type of consumption and we have n equations like equation 1, with a CDR for each good i equal to the PRTP plus the sum over all goods j of the elasticity of the marginal utility of consumption of good i with respect to good j times the growth rate of consumption of good j:

$$\text{(2)}$$

where $\rho_{i,t}$ is the CDR on good i at date t, $R(c_{i,t})$ is the rate of change of consumption of good i at date t, and $\eta_{ij}(c_t)$ is the elasticity of the marginal utility of good i with respect to the consumption of good j (see Heal [2005] for details: the most general framework of this type can be found in Malinvaud's classic paper [1953]). The own

$$\rho_{i,t} = \delta + \eta_{ii}\left(c_t\right)R\left(c_{i,t}\right) + \sum_{j\neq i}\eta_{ij}\left(c_t\right)R\left(c_{j,t}\right)$$

t the cross elasticities $\eta_{ij}(c_t)$, $j\neq i$, are zero if the utility fu........... ....ve either sign.
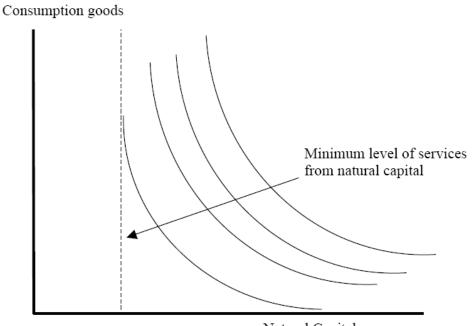
As an illustration consider the constant elasticity of substitution utility function

$$\text{(3)}$$

Here we can think of c as produced consumption and s as natural capital, an environmental stock that produces a flow of ecosystem services. (See Barbier and Heal for a discussion of this concept [2006] and the World Bank for a detailed review of the role of natural capital in the growth process [2006].) In this case the cross elasticity of the margi

$$\left[\alpha c^\sigma + (1-\alpha)s^\sigma\right]^{\frac{1}{\sigma}}$$

n depends on whether c and s are substitutes or complements. For an elasticity, ... substitutes and the cross elasticity is positive, and vice versa.

Let's test our intuitions on this. Take the case where natural capital and produced consumption are highly complementary, so that indifference curves are near to right angled and the elasticity σ is close to zero. Then the cross elasticity is negative. This means that if the stock of natural capital is rising then this reduces the consumption discount rate on the regular good. Conversely if the availability of natural capital is falling then this raises the consumption discount rate on the consumption good. These results make sense: because of the assumed complementarity, an increase in the amount of the environmental good will raise the marginal utility of the consumption good and so tend to lower the consumption discount rate, and vice versa. Of course, the own elasticity on natural capital is positive so that if the availability of this good is falling then this will tend to make its own consumption discount rate negative.

Whether produced goods and environmental services are substitutes or complements in consumption is not an issue that has been discussed in the literature, as with the few exceptions mentioned above people have worked with one-good models. There do however seem to be reasons to suppose that complementarity is the better assumption, with $\sigma < 1$. Dasgupta and Heal [1979], following Berry Heal and Salamon [1978], suggest that in production there are technological limits to the possibility of substituting produced goods for natural resources. In particular we invoke the second law of thermodynamics (Berry and Salamon are thermodynamicists) to suggest that if energy is one of the

Consumption goods

Minimum level of services
from natural capital

Natural Capital

inputs to a production process, then there is a lower bound to the isoquants on the energy axis. Similarly one can argue that certain ecosystem services or products, such as water and food, are essential to survival and cannot be replaced by produced goods. There are therefore lower bounds to indifference curves along these axes, implying if the utility function is CES that $\sigma < 1$.

The figure illustrates this idea: it shows indifference curves for a two-argument utility function, consumption of produced goods and of ecosystem services, as in equation 3 above. There is a minimum level of ecosystem services needed for survival - think of this as water, air, and basic foodstuffs, all of which are ultimately produced from natural capital. For low welfare levels there is no substitutability between these and produced goods, so that indifference curves are close to right angled. At higher welfare levels where there are abundant amounts of both goods there is more scope for substitution. Taken literally, this implies that the elasticity of substitution is not constant but depends on and increases with welfare levels. This of course is not reflected in the CES function such as 3. A function with these properties is

$$\left[\alpha c^{\sigma} + (1-\alpha)(s-\varepsilon)^{\sigma} \right]^{\frac{1}{\sigma}} \tag{4}$$

which is simply the CES function we noted before, with the zero of the ecosystem service axis transformed by $\varepsilon > 0$. Utility is not defined for $s > \varepsilon$. Relative to the transformed origin $(\varepsilon, 0)$ there is still a constant elasticity of substitution σ but relative to $(0,0)$ the elasticity is not constant. For $\sigma > 1$, every indifference curve, every welfare level, can be attained with only ε of ecosystem services, whereas with $\sigma < 1$ greater welfare levels require greater levels of ecosystem services (and of consumption goods).

These ideas can be applied to modeling equity: it is generally recognized that poor countries, or poor groups within countries, are more dependent on natural capital and its services than are richer groups (World Bank [2006]). They have less capacity to substitute alternative goods for the services of natural capital and so show more complementarity between natural capital and other goods. In terms of the figure, their indifference curves are lower and closer to being right angled. This means that they have different consumption discount rates from other groups: if the stock of natural capital is falling then they will have higher consumption discount rates on the common consumption good. In this sense they will appear to be more impatient. Of course as noted above their discount rate on natural capital will be negative, so we will have the paradox of an apparently impatient group – with respect to the consumption good – being willing to invest for low returns in natural capital.

A Sterner Perspective

It's worth looking in more detail at the Sterner and Persson development of this point [2007]. They talk about the effect of changes in relative prices rather than consumption of produced and environmental goods, but the point is the same. If we consume both produced goods and the services of the environment, as in the utility function 3, then we can expect that with climate change environmental services will become scarce relative to produced goods and therefore their price will rise relative to that of produced goods (the "environmental Baumol disease" that Gerlagh and van der Zwaan refer to [2002]). Consequently the present value of an increment of environmental services may be rising over time, and the consumption discount rate on environmental services may thus be negative, precisely the point that we were making in equation 2 above. This could be the case even with a high PRTP, which is the main point of the Sterner and Persson paper. They also present an interesting modification of Nordhaus's DICE model to incorporate this point. They replace the standard utility function, which is an

isoelastic function of aggregate consumption, by a CES function along the lines of equation 3 above, but modified to reflect a constant relative risk aversion:

$$\left[(1-\gamma)c^{1-1/\sigma} + \gamma s^{1-1/\sigma} \right]^{(1-\alpha)\sigma/(1-\sigma)} / (1-\alpha)$$

They assume that the supply of environmental services is negatively affected by temperature according to the square of temperature, and that the share of environmental goods in consumption is about 20%, use these assumptions to calibrate the modified DICE model and and then run the model with the PRTP used by Nordhaus. Their runs show that even with such a high PRTP the presence of an environmental stock that is damaged by higher temperatures radically transforms the optimal emissions path of CO and leads to a vastly more conservative policy towards climate change, with emissions both staying lower and falling faster. In fact it leads to a more aggressive reduction in greenhouse gases than recommended by the Stern Review.

Natural Capital and Production

I have emphasized so far that natural capital can affect human welfare directly, and needs to be thought of as an argument of the welfare function. Natural capital also affects a nation's production possibilities: I mentioned above changes in hydrology such as melting of glaciers and reduction in winter snowfields, both of which are already in evidence and are affecting agriculture in some regions. They will affect it further over the coming decades. This is quite separate from any impact that changes in temperature and precipitation may have on agriculture. Other changes in natural capital will probably affect agriculture – changes in species abundance and distribution, for example, can affect whether birds and insects pollinate crops.

Modeling Different Groups

I commented above that equation 2 can be given a different interpretation: instead of

$$\rho_{i,t} = \delta + \eta_{ii}\left(c_t\right)R\left(c_{i,t}\right) + \sum_{j \neq i}\eta_{ij}\left(c_t\right)R\left(c_{j,t}\right) \tag{2}$$

the subscripts i and j referring to different goods, they can be taken as referring to the amounts of a single good consumed by different groups – these could be social groups within a country or they could be different countries. I this case we have different consumption discount rates for each group's consumption, and the elasticities now indicate how the marginal valuation of consumption by one group depends on the consumption levels of others. Do we value on increment of consumption to the poor more if everyone else is very rich than if most others are also poor? Presumably the answer to this is yes, but these are issues that have not featured at all in the discussions to date.

Choosing η

The elasticity of the marginal utility of consumption plays a central role in much of our discussion. Unfortunately this variable plays two roles in our models: it expresses our distributional preferences, which is the way we have been using it here, and it also expresses our aversion to risk. Most empirical estimates of the value of η come from studies of behavior in the face of risk, but it seems clear that these two interpretations of η are really quite different, and that our aversion to risk tells us little if

anything about our preferences for income equality. Given this, we need to find a way of expressing preferences that does not conflate distributional and risk preferences. Recursive formulations such as that of Kreps and Porteus are relevant here.

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Managing Climate Risks

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Many Integrated Assessment Models (IAMs) maximize the present value of consumption, equating the marginal benefits of abatement in terms of reduced climate damages with the marginal costs of reducing emissions. Every trader, banker, and investor knows that maximizing expected gain entails a trade-off with risk. According to the theory of rational decision, preferences can always be represented as expected utility, hence from this viewpoint, any aversion to risk could be folded into the rational agent's utility function. This theory, recall, applies to rational *individuals*; groups of rational individuals do not comply the axioms of rational decision theory. The fact is that 'professional risk taking organizations' do manage risk, and not by bending the utility function of a representative consumer. Rather, they employ techniques like value at risk, and optimize expected gain under a risk constraint. Managing risk is a problem of group decision.
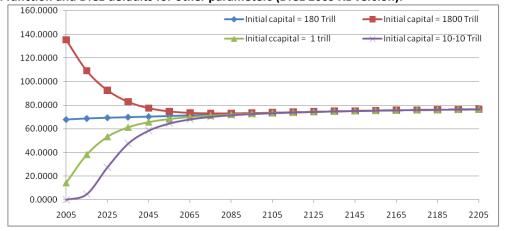
Weitzman (2009) has recently called attention to the risks of climate change, arguing that current approaches court probabilities on the order of 0.05~0.01 of consequences that would render life as we know it on the planet impossible. What is the plan to manage this "tail risk"? Risk management shifts the research question from 'how does the optimal abatement level change for different parameter values?' to 'how does our policy choice fare under the range of potential future conditions and how can we buy down the risk of catastrophic outcomes?' As such, it places the quantification of uncertainty in the foreground. Uncertainty quantification is more than a modeler putting distributions on his/her model's parameters. The antecedent question reads: 'is it the right model? What is the model uncertainty?' Failing a definitive answer to that question, *stress testing* our current models for their ability to handle tail risks, and exploring *canonical model variations* are essential steps prior to quantifying uncertainty on parameters. Gone are the days when quantification of the uncertainties was left to the modelers themselves; at the state of the art, quantification is done by *structured expert judgment* in a rigorous and transparent manner.

Stress Testing

Stress testing is preformed to check that models remain realistic and capture the relevant possibilities when their parameters are given extreme values. Many IAMs specify economic damages as a function of temperature change, and model their impact on output and utility. For example, damages at time t induced by temperature change T(t) from pre-industrial mean temperature are represented in DICE as factor that reduces economic output: $1/[1 + 0.0028388T(t)^2]$. The standard Cobb Douglas production function expresses output as a function of total factor productivity, capital stock and labor. Capital depreciates at rate 10%, and is augmented by savings (in the DICE "Base" case the savings rate is
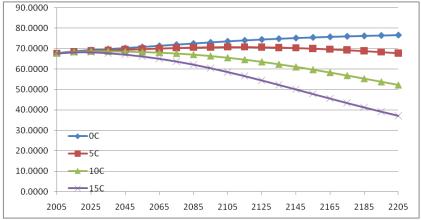
optimized with damages set equal to zero, then damages are reinstated). Temperature induced damages and abatement efforts reduce output. Setting damage and abatement equal to zero, an illustrative stress test of the Cobb Douglass model with constant population, constant total factor productivity and DICE values for other parameters is shown in Figure 1. Four output trajectories with initial capital ranging from 10 times the DICE value ($1800 Trill) to $100 ($1.6×10^{-8} for each inhabitant). The limiting capital value is independent of the starting values – with a vengeance: the four trajectories are effectively identical after 60 years. Such obviously unrealistic consequences underscore the need for circumscribing the empirical domain of application of these simple models. Put the factories and laborers on the Moon and they will produce nothing; other things are involved. Regardless whether the model adequately describes small departures from an equilibrium state, its use for long term projections inevitably entails this sort of behavior and putting uncertainty distributions on the model's parameters will not change that.

Figure 1. Output gross of abatement cost and climate damage ($trill 2000 USD) Base case, no temperature damage, no abatement, constant population, constant total factor productivity (0.0307951), initial output from production function and DICE defaults for other parameters (DICE 2009 XL version).

A second stress test examines the effect of adding temperature induced economic damages, again without abatement. With $180 Trill initial capital, we assume that temperature increases linearly, leaving other parameters as in the previous case. Figure 2 shows four economic output trajectories, corresponding to temperature increases of 0, 5, 10, and 15 degrees Celsius in 200 years.

Figure 2. **Output after damages before abatement, initial capital = 180 $trill, constant population, constant productivity, no abatement, temperature in 200 yr (linear increments)**

No scientist claims that life as we know it could exist with 10°C global warming. With a steady temperature rise leading to 10°C above pre-industrial levels in 200 years, this model predicts that output would be reduced to 68.% of its value without temperature rise. Such projections seem a bit sanguine. The essential feature is that climate induced damages hit only economic output; as a result capital can never decrease faster than its natural depreciation rate, and this rate of decrement is reached only for infinite temperature. Again, putting uncertainty on other model parameters may cloud this picture, but will not change this feature.

Canonical Model Variation

It is often noted that simple models like the above cannot explain large differences across time and geography between different economies, pointing to the fact that economic output depends on many factors not present in such simple models. To "save the phenomena" researchers have proposed enhancing the basic model with inter alia social infrastructure, government spending, human capital, knowledge accretion, predation and protection, extortion and expropriation (see Romer (2006), chapter 3). Before proliferating this model, however, it is well to reflect on its fundamental assumptions about damage, capital and output. Could different model types with comparable prime facie plausibility result in macroscopically different behavior?

We illustrate with one variation based on the following simple idea: Gross World Production (GWP[trillion USD 2005]) produces pollution in the form of greenhouse gases; pollution, if unchecked, will ultimately destroy necessary conditions for production. This simple observation suggests that Lotka Volterra type models might provide a perspective which an uncertainty analysis ought not rule out. The quantity of anthropogenic greenhouse gases in the atmosphere at year t, GHG(t) [ppm CO_2], is the amount in the previous year, less what has decayed at a rate, say, 0.0083, plus any new emissions in time period t. Assume that new emissions are a fixed fraction, say, 0.024 of GWP (Kelly and Kohlstadt 2001). Different values can be found in the literature, but these are representative. Real GWP has grown at an annual rate of 3% over the last 48 years (this includes population growth); assume that this growth is decreased by a damage function D of temperature T, and ultimately of GHG, this gives the following system:

(1)   GHG(t+1) = (1−0.0083)GHG(t) + 0.024×GWP(t).

(2)   GWP(t+1) = [1+ 0.03 − D(T(GHG(t)))]GWP(t).

If D were linear in GHG, this would be a simple Lotka Volterra type system. With *cs* as the climate sensitivity and 280 ppm the pre-industrial level of greenhouse gases, equilibrium temperature follows T(GHG(t)) = *cs*× ln(GHG(t)/280)/ln(2). Adopting Weitzman's (2010) notion of a "death temperature" of 18°C we write damages as D(GHG)(t) = $(T/18)^2$. Anthropogenic greenhouse gases increase with production; if GWP(t) were constant, they would increase to a constant 0.024×GWP/0.0083 However, as GWP increases, GHGs and temperature keep rising as well, lowering the growth rate of GWP. When   D > 0.03, GWP starts decreasing. Eventually 0.024×GWP < 0.0083, and then greenhouse gases start decreasing, reducing damages to a point where production can start growing again.   Figure 2 shows

GWP and GHG as functions of time out to 500 yrs, with all variables at their nominal values. GWP collapses. Greenhouse gases also collapse, but not to their initial level; hence the next upswing in GWP is attenuated.   A steady state is eventually reached after some 1,500 years. This is not offered as a plausible model, its role is to spotlight the fundamental modeling assumptions. Evidently, different ways of modeling the impact of climate change damages give qualitatively different predictions, and steady state values may not be relevant for current policy choices. Neither theoretical nor empirical evidence exclude the Lotka Volterra type of interaction between damages and production presented here. A credible uncertainty analysis should fold in this and other possibilities, which brings us to the next point of examining a range of future conditions for a given policy choice.
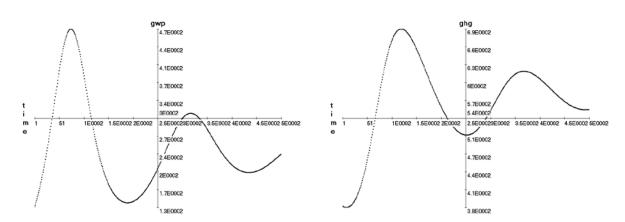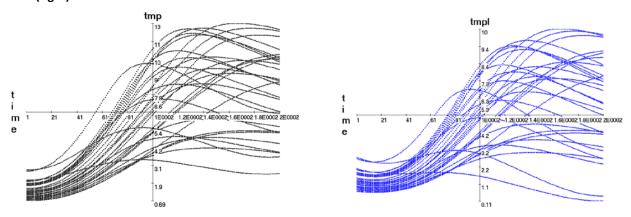
Figure 3: The impact of climate damages on GWP (left) and greenhouse gases (right)

Structured Expert Judgment for Quantifying Uncertainties

Uncertainty analysis with climate models must be informed by the broad community of climate experts - not simply the intuitions or proclivities of modelers - through a process of structured expert judgment. Experience teaches that independent experts will not necessarily buy into the models whose parameter uncertainties they are asked to quantify. Hence, experts must be queried about observable phenomena, results of thought-experiments if you will, and their uncertainty over these phenomena must be 'pulled back' onto the parameters of the model in question. This process is analogous to the process by which model parameters would be estimated from data, if there were data. The new wrinkle is that data are replaced by experts' uncertainty distributions on the results of possible, but not actual, measurements. The 'pull back' process is called probabilistic inversion, and has been developed and applied extensively in uncertainty analysis over the last two decades (see Cooke and Kelly 2010 and references therein). In general, an exact probabilistic inverse does not exist, and the degree to which a model enables a good approximation to the original distributions on observables forms an important aspect of model evaluation. Four features of the structured expert judgment approach deserve mention: (i) Experts are regarded as statistical hypotheses, and their statistical likelihood and informativeness are assessed by their performance on calibration questions from their field whose true values are known post hoc. (ii) Experts' ability to give statistically accurate and informative assessments is found to vary considerably. (iii) Experts' uncertainty assessments are combined using performance based weights. (iv) Dependence, either assessed directly by experts or induced by the probabilistic inversion operation, is a significant feature of an uncertainty analysis.

When uncertainty has been quantified in a traceable and defensible manner, an ensemble of possible futures for each policy choice may be generated. Figure 4 shows 30 Lotka Volterra temperature trajectories out to 200 years, with BAU emissions at 2.4% GWP (left) and stringent emissions at 1.5% of GWP (right); and using representative distributions for uncertain variables. Employing a value at risk management strategy, we would search for an emissions path optimizing consumption while holding the probability of exceeding a stipulated temperature threshold below a tolerable threshold.

Figure 4: Possible temperature trajectories under (left) emissions at 2.4%GWP and (right) emissions at 1.8% GWP (right)

These reflections challenge us to deploy risk management strategies on a global scale. We suggest this begin with (i) stress testing models, (ii) exploring alternative models, and (iii) quantifying uncertainty in such models via structured expert judgment. We are condemned to choose a climate policy without knowing all the relevant parameters, but we are not condemned to ignore the downside risks of our choices.

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