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Economic Damages from Climate Change: A Review of Modeling Approaches

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1 Introduction

Environmental scientists have been developing models and projections of climate change since, at least, the establishment of the Intergovernmental Panel on Climate Change (IPCC) in 1988. To represent the interactions of numerous natural systems, the scientific community relies on integrated assessment models (IAMs), which typically contain processes for carbon emissions, greenhouse gas concentrations, temperature increases, physical changes and social systems. Because the climate modelling community has, appropriately, focused on accurate representation of the Earth's physical systems, the socio-economic linkages to climate change in IAMs tend to be simplistic. Therefore, economists are attempting to strengthen these linkages through the extension of IAMs, gearing them toward the measure of the social cost of carbon (SCC).

The social cost of carbon approach seeks to monetize the negative externalities of climate change as the marginal social cost of an extra tonne of CO_2-equivalents in the atmosphere. This social price is operationalized as a society's aggregate *willingness to pay* to avoid the impacts of climate change (see Fankhauser, Tol, & Pearce, 1997). In other words, SCC is equal to the welfare society gains from the environmental improvement due to a one tonne reduction in CO_2 emissions. However, measurement of SCC is typically done through the lens of the *willingness to accept* climate change (Tol, 2009).[1] That is, how much would you (society) have to be paid in order to make up for the damages of climate change. Estimating these damages requires the comparison of societal welfare along different output and environmental trajectories. It is for wont of the latter that economists have turned to environmental IAMs to buttress projections of socio-economic outcomes.

This report elucidates one aspect of economic IAMs: the damage function. Damage functions map environmental changes (primarily mean temperature increases) to economic impacts. This crucial step in the determination of SCC appears in very

[1]This raises an important conceptual difficulty: willingness to pay is a marginal benefit and willingness to accept is a marginal cost. These two items equal only at the optimum. If society proceeds along a suboptimal path then the SCC value is ambiguous (Foley, Rezai, & Taylor, 2013). See section 6.3 for a further discussion.

different form in the leading economic IAMs. Through sections 3, 4, and 5 we review, in turn, the damage functions of the Dynamic Integrated Model of Climate and the Economy (DICE), the Framework for Uncertainty, Negotiation and Distribution (FUND) and the Policy Analysis of the Greenhouse Effect (PAGE). Section 6 discusses some empirical, programmatic and conceptual limitations of these three IAMs. Section 7 concludes. We begin, however, by providing a brief elaboration on integrated assessment modelling practices used by the IPCC. Readers familiar with IAMs and the IPCC's recent work may wish to skip this review.

2 Integrated Assessment Models

2.1 IPCC: Modelling with Representative Concentration Pathways

A key feature of the Intergovernmental Panel on Climate Change's (IPCC) Assessment Reports is to provide benchmark scenarios of emissions and climatic change for researchers. The *Fifth Assessment Report* (AR5) implements a new method for climate projections called Representative Concentration Pathways (RCPs) (see IPCC Working Group I, 2013). Earlier assessment reports used the IPCC scenarios (known as IS92) in the first and second assessment reports released in 1990 and 1995. In the third and fourth IPCC assessment reports (2000 and 2007) emission scenarios (SRES), summarized in *Special Report on Emission Scenarios* (IPCC Working Group III, 2000), were use to model climate change projections. RCPs differ from these earlier vintage in terms of proach and type of output.

RCPs produce estimates of global mean temperature changes and attendant impacts on human and ecological systems based on an assumed level of radiative forcing in 2100. This is in contrast to projecting a probability distribution of global mean temperature from a set of initial emissions assumptions. Indeed, RCPs are not projections in a statistical sense, they are deterministic scenarios. A RCP, therefore, does not contain a measure of variance for its projection of global temperature change. Similarly, one cannot directly compare the relative accuracy (i.e., standard error) of different RCPs. Instead, the four RCPs chosen for the AR5 are "representative" of projections used in the climate modelling literature.

Figure 2: Comparison of RCP and earlier Model Generations

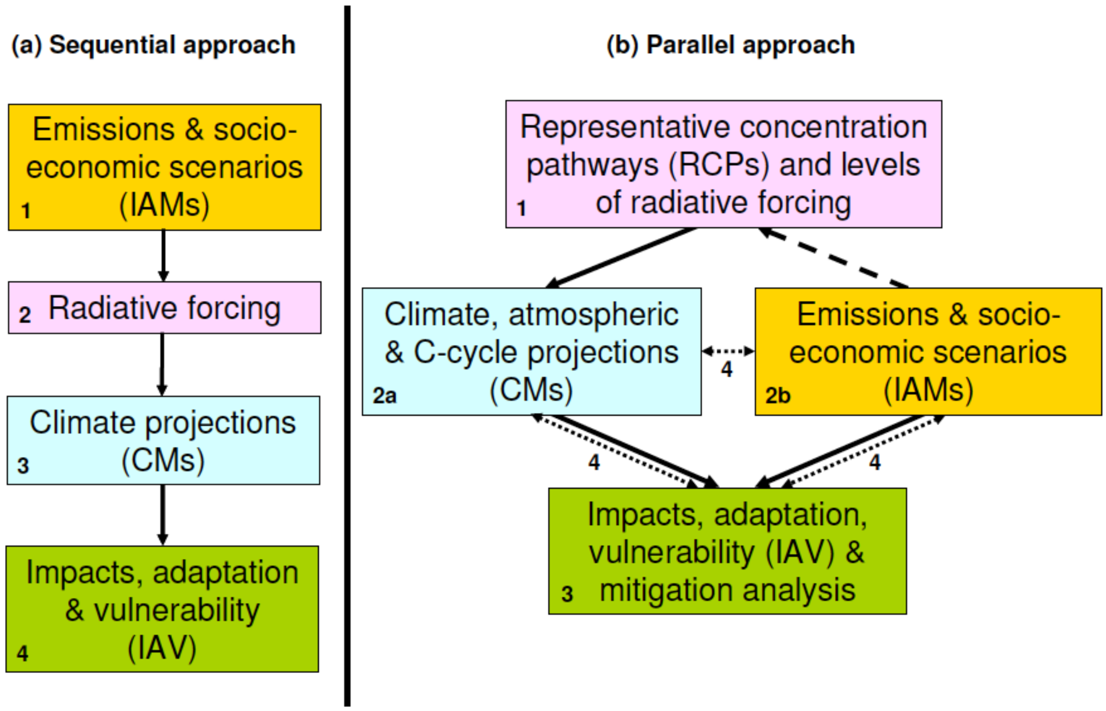


Figure 1. Approaches to the development of global scenarios: (a) previous *sequential* approach; (b) proposed *parallel* approach. Numbers indicate analytical steps (2a and 2b proceed concurrently). Arrows indicate transfers of information (solid), selection of RCPs (dashed), and integration of information and feedbacks (dotted).

Source: Moss et al., 2008, p. iv

In terms of approach, previous IPCC climate projections were built a sequentially. RCPs are developed according to a 'parallel approach' that links climate and environmental projections with integrated assessment models, or IAMs (see Figure 2). IAMs are complex algorithms linking the interactions carbon emissions, the physical environment and socio-economic systems (see Figure 3 for two schematic examples). In earlier assessment reports the IAMs used for climate projections were developed in relative isolation from the climate modelling community (Moss et al., 2008). The parallel development structure ensures that RCPs use a consistent approach that allows the Integrated Assessment Model (IAM) and Climate Model (CM) communities to each run experiments and feed information back and forth.

The IPCC chose four RCPs the *Fifth Assessment Report*. The RCPs are specified according to their assumed level of radiative forcing (in W/m^2) in the year 2100. Each pathway starts from the common base year 2000. The four RCPs are summarized in Table 1.

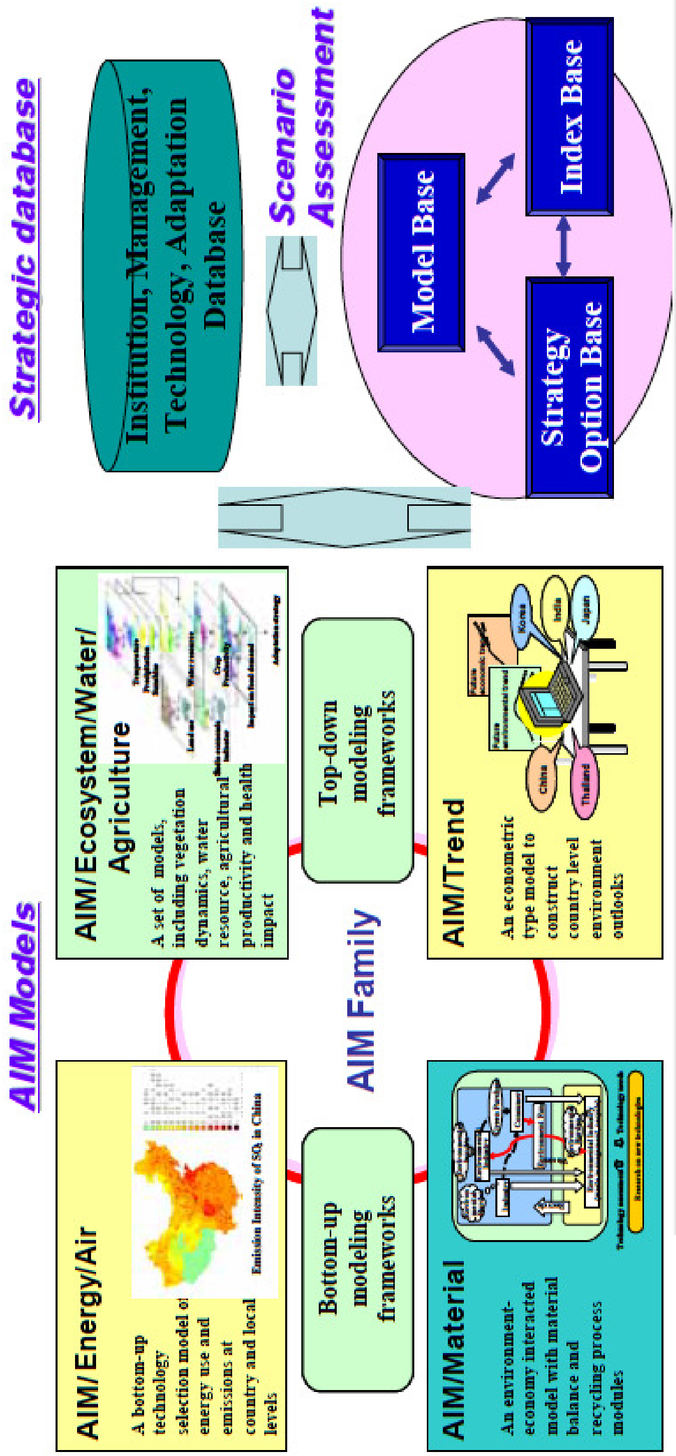
Table 1: Representative Concentration Pathways used in AR5

Name	Concentration	Team & Model	Notes
RCP2.6	490 CO_2-eq (at peak)	IMAGE model team led by Detlef van Vuuren.	This pathway involves emissions mitigation and a low forcing scenario. It is also known as RCP3PD since radiative forcing *peaks* at 3 W/m^2 and then *declines* to 2.6 W/m^2 in 2100.
RCP4.5	850 CO_2-eq	MiniCAM model team led by Allison Thompson.	This is the lower of the two mid-range pathways in which radiative forcing stabilizes by 2100.
RCP6	650 CO_2-eq	AIM model team led by Toshihiko Masui.	This is the higher of the two mid-range pathways in which radiative forcing stabilizes by 2100.
RCP8.5	1370 CO_2-eq	MESSAGE model team led by Keywan Riahi.	This extreme pathway reaches a radiative forcing level of 8.5 W/m^2 by 2100, but without stabilization. Hence the global mean temperature will continue to increase into the 22nd-century.

Source: van Vuuren et al. (2011)

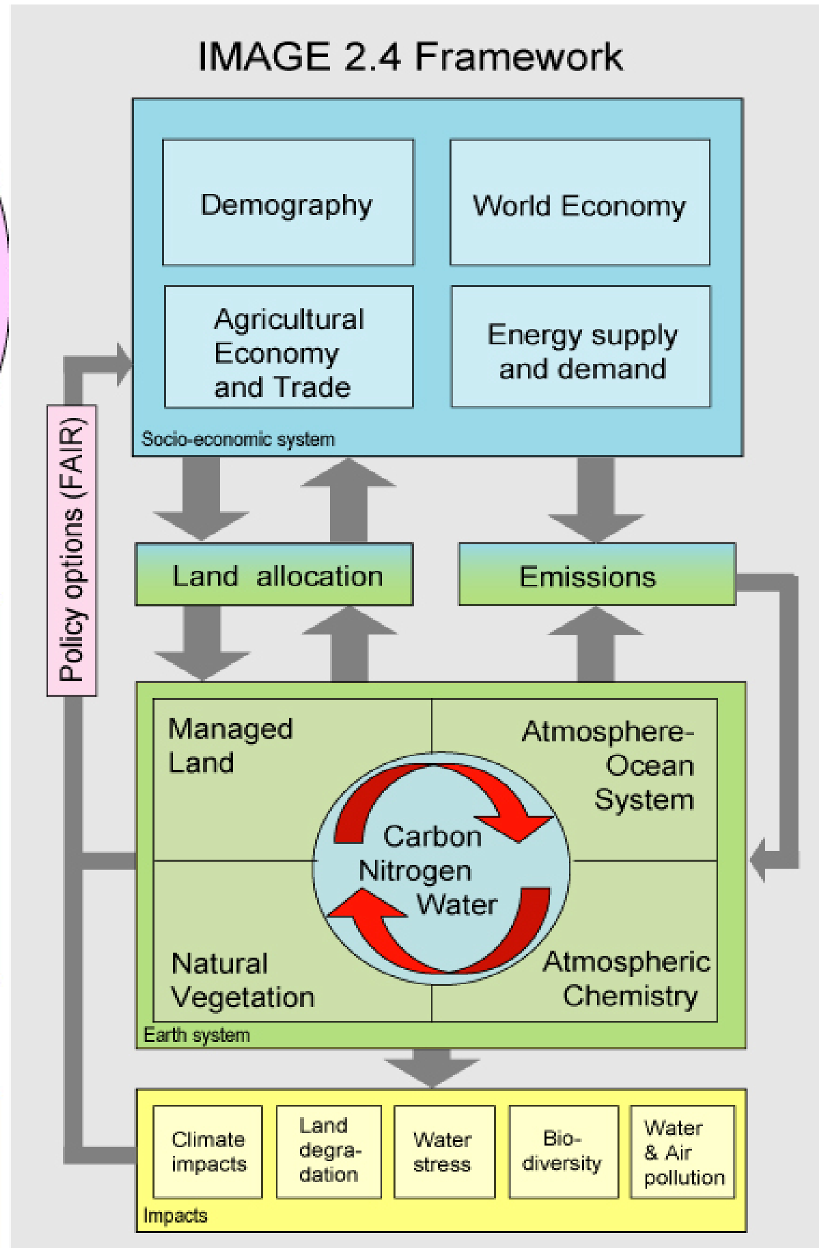
Figure 3: Diagramatic Examples of RCP Integrated Assessment Models

(a) Asia-Pacific Environmental Innovation Strategy Project



Source: APEIS-IEA Technical Summary

(b) Integrated Model to Assess the Global Environment



Source: IMAGE website

2.2 The Social Cost of Carbon

Most IAMs, including those used to generate the RCPs, model economic responses and damages as shifting energy profiles and physical impacts, meaning the use of even simplistic economic models is often lacking. Although each IAM may add its own economic complexities,[2] they are not designed for economic assessments (Nordhaus & Sztorc, 2013, p. 23). Indeed RCPs are designed to capture the direct, indirect and feedback effects of carbon emissions on the physical environment. Of course, it is often easier for policymakers to work with a single numerical estimate of impacts, which has generated a demand for measuring climate change damages in terms of dollars or lost GDP. Since RCPs are in no way designed to produce monetary estimates, economists have stepped into the modeling fray. The three economic IAMs reviewed in this report are designed to yield such an impact estimate via the social cost of carbon (SCC).

The three models reviewed here – DICE, FUND and PAGE – are chosen because they are, academically and politically, the most prominent IAMs that calculate the economic cost of climate change. The models offer more economic detail than environmental IAMs, but are still much more rudimentary than typical macroeconomic models. According to the US Interagency Working Group on Social Cost of Carbon (2010, p.5-6):

> These models are useful because they combine climate processes, economic growth, and feedbacks between the climate and the global economy into a single modeling framework. At the same time, they gain this advantage at the expense of a more detailed representation of the underlying climate and economic systems. DICE, PAGE and FUND all take stylized, reduced-form approaches [...] Other IAMs may better reflect the complexity of the science in their modeling frameworks but do not link physical impacts to economic damages [...] Underlying the three IAMs selected for this exercise are a number of

[2]Examples include: demand responses in the MACRO algorithm of MESSAGE; the cost in terms of GDP of adaptation in IMAGE, and; the costs of environmental and water systems investment in AIM.

> simplifying assumptions and judgements reflecting the various modelers' best attempts to synthesize the available scientific and economic research characterizing these relationships.

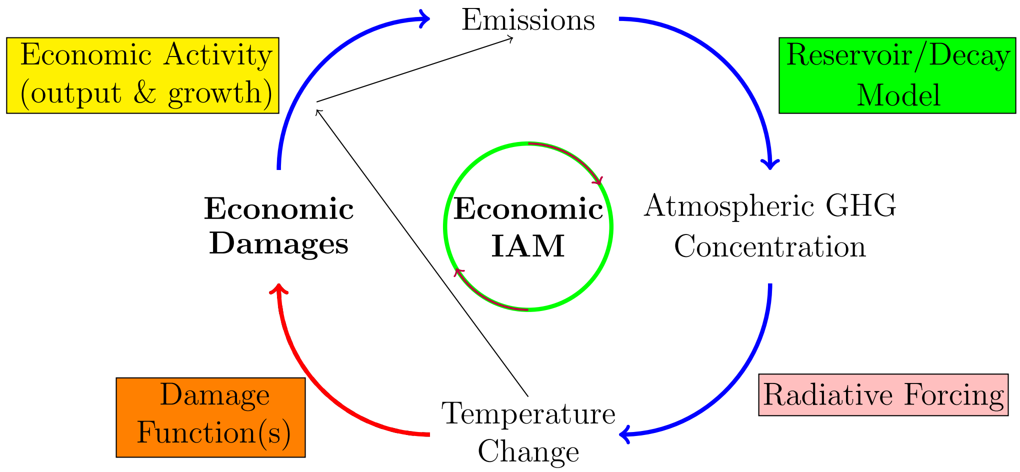
Hence, although these IAMs are considered to be on the cutting edge of economic climate modelling, they still impose a great deal of simplification in their environmental and economic aspects. Furthermore, as shown below, the extent of simplification varies widely across these models.

Economically, the uniting feature of the FUND, DICE and PAGE models is that they are each built on the principle of measuring climate change as a negative externality (i.e., the social cost of carbon). SCC is defined as the marginal impact of emissions above pre-industrial levels ($\approx$ 250-300ppm CO_2). Beyond this common conceptual basis, the calculation of SCC varies greatly between the models (and even between different vintages of the same model). Indeed, even the baseline against which different carbon concentration paths are compared is quite different in each model.[3] A detailed comparison of the models' final social cost estimates is beyond the scope of this report. Rather, sections 3 through 5 elucidate the functional forms of each model's mapping of climatic variables into economic impacts (damages or benefits, as the case may be).

Conversely, the environmental aspects of these three IAMs are far less diverse. This is because the economists' have built their models on top of the extant environmental IAMs, similar to those used to generate RCPs. Therefore, the economic IAMs share a basic modelling structure (Figure 4). The models connect emissions to atmospheric greenhouse gas concentrations by a carbon reservoir or decay model; concentrations are, in turn, translated into global (and regional) mean temperature changes via an equation for radiative forcing. These two modelling steps come entirely from the climatic and environmental literature. Environmental IAMs then link these changes to physical and biological impacts which have some (weak) connection to the economies' emissions trajectories, as represented by the thin arrows in Fig.

[3]The FUND model, for example, simulates carbon 'pulses' in each year and sums their total net (positive or negative) effect (Ackerman & Munitz, 2012a). The DICE model projects costs on a rolling basis starting from some initial conditions, and compares economic values against the continuation of 2010 global policies at the baseline (Nordhaus & Sztorc, 2013).

Figure 4: Economic Damages as the Social Cost of Carbon in IAMs



4. The economic IAMs discussed throughout build on this environmental structure by introducing a sub-model of economic damages which are then translated into economic activity and, hence, emissions trajectories.

Exactly how global and regional temperature changes[4] are translated into economic impacts is the focus the subsequent three sections. We first review the most recently revised model: William Nordhaus's the Dynamic Integrated Model of Climate and the Economy (DICE 2013R).[5] DICE uses the most simplistic damage function of the three IAMs reviewed here because, interestingly, Nordhaus is purposefully reducing the model's complexity. We provide some comparison to the earlier versions, DICE 2010 and DICE-99. More surprising is that DICE is the only model with endogenously determined economic activity. The other two models reviewed are, respectively, the Framework for Uncertainty, Negotiation and Distribution (FUND) and the Policy Analysis of the Greenhouse Effect (PAGE), both of which have more complex damage functions but exogenously determined growth paths. Because FUND is a highly complex model, we detail only the most impactful

[4] CO_2 concentrations directly impact the economy in some of FUND's sectors, see sec. 4.

[5] The regional version, Regional Integrated Model of Climate and the Economy (RICE 2013), is a simply disaggregated version of DICE 2013R and therefore does not add to the understanding of Nordhaus's approach to modelling damages.

damage functions. Finally, PAGE is reviewed as something of a third way between the approaches of DICE and FUND.

3 DICE: Dynamic Integrated Model of Climate and the Economy

William Nordhaus's Dynamic Integrated model of Climate and the Economy (DICE) – and its regional variant (RICE)[6] – is the longest-running and, perhaps, best known model of the social cost of carbon. The model has undergone several major revisions in recent years. In particular, the functional form of damages has become progressively less complex in recent versions. The most recent version, DICE 2013R, has a single-equation representation of damages. We begin with a thorough review of DICE 2013R in section 3.1, and then compare its damage function to the more complicated vintages DICE 2010 and DICE-99 in sections 3.2 and 3.3, respectively.

3.1 DICE 2013R

The economy in all versions of DICE is a discrete-time Ramsey-type dynamic optimization framework built on a global level. The model reviewed here, DICE 2013R, is the latest version available. There are major changes from the previous version DICE 2010, which is discussed below in section 3.2. In DICE 2013R, Nordhaus has taken a step back and reduced the complexity of the damage function (and of the model overall). The major departures from earlier versions are:

(i) Carbon extraction costs are now nil. Hence, there is no need to estimate the Hôtelling extraction costs;

(ii) Rather than earlier vintages' baseline of no policy action against climate change, the baseline scenario is now unchanged policies from 2010, and;

[6] The regions in RICE are the US, EU, Japan, Eastern Europe & FSU, China, India, Middle East, SSA, Latin America, other HICs, other LICs.

(iii) The damage function is now a single, reduced-form equation.[7] The 2013 damage function is based on the thorough yet admittedly incomplete survey of the literature in Tol (2009) . To account for non-quantified impacts (e.g. extreme storms) Nordhaus adds an "ad hoc" 25% increase to the estimated level of damages.

In keeping with earlier vintages, CO_2 is the only endogenous GHG in the production process. The emissions-to-CO_2 atmospheric concentration model is a 3-reservoir carbon cycle. Equivalents (e.g. CH_4, SO_2, and CFCs) are treated as exogenous. There is assumed to be a "backstop technology" (i.e., a pure, renewable energy source) that eventually becomes globally available and competitively priced relative to fossil fuels. The discrete time steps in the DICE and RICE models are decades, i.e. $\Delta t = 10$ years. Therefore, the model has only 10 iterations before reaching the year 2100. Nordhaus's equations are parameterized to reflect these large temporal steps. On the economic side, damages, although now more simple, continue to be modelled as 'negative capital' that reduces net output. Like the other models reviewed here, there is no direct impact on agents' utility – all damages are effectuated through output reductions. Finally, DICE is run as a deterministic optimal control problem.[8] Use of an optimizing representative agent distinguishes DICE from the FUND and PAGE models that generate scenarios from repeated random sampling from predefined distributions (i.e., without any optimization criteria).

The economy in the DICE 2013R model has the standard intertemporal optimization structure with CES utility

$$\max_{c,\mu} \sum_{t=1}^{T} (1+\rho)^{-t} \cdot L(t) \cdot \frac{c(t)^{1-\eta}}{1-\eta} \tag{1}$$

[7]This is down from 7 sectoral damage estimated in versions up to the DICE 2007. The DICE 2013R manual states "further work indicated those [sector-specific damage] estimates were increasingly outdated and unreliable." (Nordhaus & Sztorc, 2013, p. 11)

[8]The DICE model is written in General Algebraic Modeling System (GAMS) and in Excel. However, as of this writing, the Excel version of DICE 2013R is not accessible on the DICE website, although it says that it should be.

subject to:

$$\Lambda(t) = \theta_1(t)\underbrace{\mu(t)^{\theta_2}}_{\text{emissions reductions rate}} \tag{2}$$

$$\Omega(t) = \psi_1 T_{AT}(t) + \psi_2 T_{AT}(t)^2 \tag{3}$$

$$Q(t) = \underbrace{[1-\Lambda(t)]}_{\text{abatement}} \cdot \underbrace{[1+\Omega(t)]^{-1}}_{\text{damages}} \cdot Y(t) = [1-\Lambda(t)] \cdot \left(\frac{A(t)K(t)^{\alpha}L(t)^{1-\alpha}}{1+\Omega(t)}\right) \tag{4}$$

where $\Lambda(t)$ is the abatement effort, $\Omega(t)$ is the damage function which is a quadratic function of global mean atmospheric temperature, T_{AT}, with $\phi_1 \geq 0, \phi_2 > 0$. Equation (1) says the representative agent chooses its per consumption level, $c(t)$, at each time interval (for $t = 1, \ldots, T$) which is discounted by the fixed pure rate of time preference, ρ. The discounted per capita consumption from each period is scaled by the total population $L(t)$ at time t in accordance with the aggregate willingness to pay approach (see Tol, 2009).

As usual $Y(t)$ denotes the level of gross global output. However, the more important variable in this model is the level of output net of climatic damages and abatement costs, $Q(t)$. Although different scenarios can be run by varying the parameters, $\mu(t)$ is central to comparing abatement policies. The model can be run with $\mu(t)$ as a control variable. This produces the 'optimal path' of DICE. However, $\mu(t)$ can be fixed according to some predefined set of policies. Regardless of the role played by $\mu(t)$, it effectively determines how much current consumption the agent foregoes in favour reduced pollution.

In addition to equations (1)–(4) the model's accounting is closed via the standard relations

$$Q(t) = C(t) + I(t), \quad c(t) = \frac{C(t)}{L(t)}, \quad K(t) = I(t) - \delta_k K(t-1) \tag{5}$$

where $C(t)$ is total consumption, $I(t)$ is investment in capital, $c(t)$ is per capita consumption and δ_k is a fixed rate of capital depreciation.

Population, $L(t)$, and technology, $A(t)$, both grow exogenously according to the discrete logistic functions

$$L(t) = (1 + g_L(t))\, L(t-1) \qquad \text{where,} \qquad g_L(t) = \frac{g_L(t-1)}{1+\delta_L}$$

$$A(t) = (1 + g_A(t))\, A(t-1) \qquad \text{where,} \qquad g_A(t) = \frac{g_A(t-1)}{1+\delta_A}$$

The dynamic climate equations are in a highly reduced form. Emissions, CO_2 concentration, radiative forcing and temperature change are described by a total of 7 equations. First, emissions are the sum of industrial emissions, E_{ind}, which is driven by global output levels, and emissions from land use, E_{land}, which are treated as exogenous.

$$E(t) = E_{ind}(t) + E_{land}(t) \tag{6}$$

where

$$E_{ind}(t) = \sigma(t)\Big[1 - \mu(t)\Big] \underbrace{A(t)K(t)^{\alpha}L(t)^{1-\alpha}}_{Y(t)} \tag{7}$$

The parameter $\sigma(t)$ captures the carbon intensity of production. Although exogenous, the forward estimates are based on a logistic equation similar to technological and population growth:

$$\sigma(t) = (1 + g_\sigma(t))\, \sigma(t-1) \qquad \text{where,} \qquad g_\sigma(t) = \frac{g_\sigma(t-1)}{1+\delta_\sigma}$$

Emissions become slowly decaying CO_2 concentrations according to a 3-reservoir model of atmospheric concentrations (M_{AT}), upper ocean concentrations (M_{UP}) and deep ocean concentrations (M_{LO}),

$$\begin{pmatrix} M_{AT}(t) \\ M_{UP}(t) \\ M_{LO}(t) \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{21} & 0 \\ \phi_{12} & \phi_{22} & \phi_{31} \\ 0 & \phi_{23} & \phi_{33} \end{pmatrix} \begin{pmatrix} M_{AT}(t-1) \\ M_{UP}(t-1) \\ M_{LO}(t-1) \end{pmatrix} + \begin{pmatrix} E(t) \\ 0 \\ 0 \end{pmatrix} \tag{8}$$

Emissions feed directly into atmospheric concentrations of CO_2 which slowly degrade ($0 < \phi_{11} < 1$), but persistently feed into the oceans' holding of GHGs ($\phi_{12}, \phi_{23} > 0$) which prolongs atmospheric concentration levels ($\phi_{21} > 0$).

As emissions lead to concentrations the greenhouse effect raises the global mean temperature according to DICE's simplified radiative forcing function

$$F(t) = \lambda \log_2 \left[\frac{M_{AT}(t)}{M_{AT}(1750)} \right] + F_{exog}(t) \tag{9}$$

where non-CO_2 gases are assumed to have a net exogenous impact on radiative forcing, F_{exog}. As seen in (9), the radiative forcing level is determined with respect to pre-industrial (1750 CE) levels of CO_2 concentrations.

Finally, radiative forcing levels raise the atmospheric temperature T_{AT}, which interacts with the deep ocean temperature, T_{LO}, according to

$$T_{AT}(t) = T_{AT}(t-1) + \xi_1 \Big\{ F(t) - \xi_2 T_{AT}(t-1) - \xi_3 \big[T_{AT}(t-1) - T_{LO}(t-1) \big] \Big\} \tag{10}$$

$$T_{LO}(t) = T_{LO}(t-1) + \xi_4 \big[T_{AT}(t-1) - T_{LO}(t-1) \big] \tag{11}$$

Recall that it is only the level of the atmospheric temperature, T_{AT}, that drives the damage function in equation (3).

Since the DICE model is a deterministic optimal control model, scenario comparison is generated by the choice of parameters and initial conditions. In each scenario the marginal cost of carbon is calculated by the Euler optimality condition. For the

i^{th} parameterized scenario we have:

$$\text{Social Cost of Carbon}(t)_i = 1000 \cdot \left(-\frac{\partial E(t)/\partial t}{\partial C(t)/\partial t} \right) \tag{12}$$

This gives the standard value of the 'shadow price' of carbon emissions (scaled up by 1000 in Nordhaus's GAMS coding). The value in (12) gives the SCC valued under different policy scenarios. In other words, this figure tells policymakers what the price of CO_2 emissions should be set at, in \$ per tC for year t, to achieve a particular, reduced emissions trajectory (Nordhaus & Sztorc, 2013, p. 32-34).

3.2 DICE 2010

The previous version of the DICE/RICE models differed from the most recent version only in terms of baseline scenario and the damage function equations. The basic economic and climatological framework remains unchanged (see Nordhaus, 2010a, 2010b). In particular, net output $Q(t)$ is still derived as gross output, $Y(t)$, scaled down by damages and abatement costs:

$$Q_{2010}(t) = [1 - \Lambda(t)] \cdot [1 + \Omega_{2010}(t)]^{-1} \cdot Y(t) \tag{4$'$}$$

where all variables are the same as in DICE 2013R, but the damage function, Ω_{2010}, has a different structure (discussed below).

The 2010 version of DICE uses the same 3-reservoir model of carbon capture, radiative forcing and temperature change functions as well as the same functional form of industrial (endogenous) and land (exogenous) emissions as specified in equations (6) through (11) above.

An important addition in the DICE 2010 model is the explicit inclusion of Sea Level Rise, $SLR(t)$. Although omitted in DICE 2013R, SLR directly increases the calculation of the damage function Ω_{2010}. Sea level rise for DICE 2010 is specified as

$$SLR(t) = SLR(t-1) + \left[\sum_{j=1}^{5} \pi_{1,j} + \pi_{2,j} T(t-1) + \pi_{3,j} \left(T(t-1) - \bar{T}^j \right) \right] \tag{13}$$

where each π is a parameter and $\bar{T}$ is a threshold temperature, above which Arctic ice sheets begin to melt (Nordhaus, 2010b).

Equation (13) is the sum of the past accumulated level of SLR and the impact from thermal expansion, glacier melting and shrinking ice sheets. The parameters for each of these effects are calibrated for each of the world's five oceans ($j = 1, \ldots, 5$). The sum of these three oceanic drives (in the square brackets) are used to determine the decadal increase in sea levels above their height in 2000.

In the supporting documentation to his PNAS paper outlining DICE 2010, Nordhaus (2010b) defines the damage function in generic form as

$$\Omega_{2010}(t) = \frac{g\left(T(t), SLR(t), M_{AT}(t)\right)}{1 + g\left(T(t), SLR(t), M_{AT}(t)\right)} \tag{14}$$

where $T(t)$ is global/regional mean temperature over pre-inudstrial levels, $SLR(t)$ is the sea level rise above 2000 levels and $M_{AT}(t)$ is, as before, the atmospheric concentration of CO_2. Equation (14) suggests each of these variables directly increases the level of damages to the economy. Unfortunately, the supplemental documentation does not provide a more specific formulation of damages than (14).

Thankfully the damage function can be found in Excel algorithm for DICE 2010.[9] However, this function utilizes only temperature and sea level rise – both of which are quadratic. Specifically, Nordhaus's Excel spreadsheet uses:

$$\Omega_{2010}(t) = \tau_1 T(t) + \tau_2 T^2(t) + \lambda_1 SLR(t) + \lambda_2 SLR^2(t) \tag{15}$$

where the parameters $\tau_{1,2}$ and $\lambda_{1,2}$ are given.

Thus, DICE 2010 is virtually identical to the most recent Nordhaus model with the exception of an explicit modelling of sea level rises and its quadratic impact on net output in (4′).

[9] Available at http://www.econ.yale.edu/~nordhaus/homepage/RICEmodels.htm

3.3 DICE-99

The 1999 version of the DICE and RICE models, detailed in Nordhaus and Boyer (2000), differ in several important aspects from the later 2007, 2010 and 2013 versions. An important distinction is that DICE-99 and RICE-99 are not just aggregated/disaggregated versions of the same model, as is the case with later vintages (albeit with differing, empirical paramaterization for the various regions). RICE-99 employs a cap-and-trading scheme which cannot be modeled at the global (DICE) level. Secondly and, more importantly for our purposes, the DICE-99 documentation outlines damage functions for 7 sectors.[10]

As with all versions of DICE, the 1999 vintage uses a Ramsey optimization framework in which climate change is treated as a 'negative accumulated capital'. Therefore, the objective function (or, 'General Welfare') function is a discrete-time, discounted utility function (scaled for the population) as in equation (1). Also in keeping with later vintages, population and technology grow according to a logistic, exogenous equation. DICE-99 was the first to introduce the 3-reservoir model as represented in (8), and uses the same radiative forcing and temperature change equations (9)–(11).

There are, however, crucial differences in the basic structure of DICE-99. First, while the gross production function, $Y_{99}(t)$, is Cobb-Douglas, it now has a third factor of production: carbon energy. This is operationalized as an 'energy services' input, or $ES(t)$, such that:

$$Y_{99}(t) = A(t)K(t)^{\alpha}ES(t)^{\beta}L^{1-\beta-\alpha} - c_E \cdot ES(t), \quad \text{with } 0 < \alpha + \beta < 1 \tag{16}$$

where, as before, $A(t)$ is Hicks-neutral technology, $L(t)$ is labour input and $K(t)$ is physical capital. The exponents α, β and $1-\alpha-\beta$ are the elasticities of output with respect to the three factors of production. Clearly there are constant returns to scale and diminishing returns to each factor. The deducting $c_E ES(t)$ term represents the

[10]Documentation for the DICE-99 model is still available in the *Warming the World: Economics Models of Global Warming* section of Nordhaus's homepage. The damage functions for the sectors discussed below are found in Chapter 4.

cost of carbon energy in production.

The cost of carbon, $c_E(t)$, is treated as a Pigovian tax and is set equal to the Hôtelling cost, $q(t)$, plus a markup, $\varrho(t)$,

$$c_E(t) = q(t) + \varrho(t) \tag{17}$$

Since $q(t)$ is derived from the Hôtelling rule it is determined by an optimization subroutine in DICE-99 (and why, presumably, it has been left out of later versions).

Although damages are more complex in DICE-99, the net output function takes a similar form as before, however abatement costs are not explicitly modelled in this vintage:

$$Q_{99}(t) = (1 + \Omega_{99}(t))^{-1} \cdot Y_{99}(t) \tag{18}$$

Therefore, only climate damages separate gross and net output in DICE-99. The emissions-reduction strategy is, instead, modelled as a cap-and-trade scheme at the regional level, requiring the use of RICE-99. That is, abatement efforts can only be captured by the regional version of Nordhaus and Boyer's model.

In RICE-99 carbon limits and inter-region trading are built into the model according to

$$Q_{99,i}(t) + \tau_i(t)[\Pi_i(t) - E_i(t)] = C_i(t) + I_i(t) \tag{19}$$

where i is the region's index. C_i and I_i the region's total consumption and investment. $\Pi_i(t)$ is the region's total allowance (cap) on carbon emissions for the period and $\tau_i(t)$ is the price of the permits. This may also be interpreted as the emissions tax, rather than the permit price, depending on the policy framework (Nordhaus & Boyer, 2000, chapter 2). The trading scheme model is an interesting divergence from later DICE models, but further discussion is beyond the scope of this report.

In the mathematical overview of the DICE-99 model, Nordhaus and Boyer (2000, chapter 3), as well as in the GAMS code (Nordhaus & Boyer, 2000, appendix D), appear to use only a single damage function affecting the aggregate output level represented in equations (16) and (18). This is the familiar quadratic temperature-damage equation

$$\Omega_{99}(t) = \phi_1 T(t) + \phi_2 T^2(t) \tag{20}$$

However, in Chapter 4 Nordhaus and Boyer (2000) state that they have estimated damage functions for seven sectors. These are:

1. Agriculture
2. Sea level rise
3. Other market sectors
4. Health
5. Non-market amenity impact
6. Human settlements and ecosystems
7. Catastrophes

For each sector their approach is to first estimate parametric damages assuming at 2.5°C increase in global mean temperature and to then extrapolate the damages to higher and lower levels of climate change.

Only after reviewing the empirical literature for such damages do they estimate "impact indices as functions of temperature" (Nordhaus & Boyer, 2000, chapter 4, section 4). Although Nordhaus and Boyer are careful in the calibration of the parameters, the damage functions themselves tend to be fairly simple. For the 6 sectors explicitly modelled, Nordhaus and Boyer use only 3 functional forms.[11]

The baseline damage function is in agriculture which is quadratic (quite similar to equation 20) and is specified for each i region's temperature level T_i above the temperature that would prevail without climate change T_i^0. The agricultural damage function is

$$\Omega_{ag} = \alpha_0 + \alpha_1(T_i(t) + T_i^0(t)) + \alpha_2(T_i(t) + T_i^0(t))^2 - \left[\alpha_0 + \alpha_1 T_i^0(t) + \alpha_2 + T_0^2(t)\right] \tag{21}$$

This equation is also used to estimate regional-level damages for the "other markets"

[11]Catastrophic damages follow a piecewise function in temperature that is linear for global mean temperatures from 0°to 3°above pre-industrial levels, and exponential for $T(t) > 3°$. No further details are provided.

Ω_{om}, and "non-market amenities" sectors Ω_{nm}. Therefore, the difference in damages among these three sectors comes only from parameter calibration.

The second important damage function form come from sea level rise, which is based on global mean temperature change, $T(t)$. However, unlike the SLR damages in (13) for DICE 2010, DICE-99 models sea level rise according to a power law:

$$\Omega_{SLR} = \alpha \left(\frac{T(t)}{2.5} \right)^{\frac{3}{2}} \tag{22}$$

The damage function for "human settlements and ecosystems", Ω_{hse}, also uses a power function like (22) with, of course, different parameter calibrations.

Finally, human health is based on a power equation very similar to (22), but driven by the regional temperature level. Nordhaus and Boyer (2000, chapter 4) present it with exact parametric values:

$$\Omega_{hh} = 0.002721(T_i)^{0.2243} \tag{23}$$

As mentioned, it is not clear how equations (21), (22) and (23) are integrated into the net (post-damage) function represented in (18). The documentation in Chapter 4 of Nordhaus and Boyer (2000) says that estimates are run for $T(2100) = 0°$, $T(2100) = 2.5°$ and $T(2100) = 6°$. Damages for other T's are found by quadratic interpolation. Finally, the sectoral damages are then added together, e.g.,

$$\Omega_{99} = \Omega_{ag} + \Omega_{om} + \Omega_{nm} + \Omega_{SLR} + \Omega_{hse} + \Omega_{hh} \tag{24}$$

in order to find the total damages for any $T(t)$. This, however, would seem to contradict the simple damage function represented in (20) and the GAMS code for DICE-99. Yet (24) is likely the correct version since it is derived from the appendix in Nordhaus (2010b) – the supporting documentation to the PNAS publication Nordhaus (2010a). In either case this model is outmoded now, replaced by simplified version of damages in DICE 2013.

4 FUND: Framework for Uncertainty, Negotiation and Distribution

The FUND model is the most complex of the economic IAMs, but this comes at a cost to its theoretical underpinnings. To run this complicated algorithm Richard Tol and David Anthoff have written the code in C#. In contrast to Nordhaus's recent reduction in complexity, Tol and Anthoff continue to add more layers of detail to their model. Importantly, FUND's complexity comes from more realistic modelling of climatic relations (e.g., 5-reservoir carbon capture and endogenous non-CO_2 emissions), but with a *less* detailed model of the economy. In FUND the growth rate of GDP is an exogenous random variable. Although overall output is exogenous, population growth endogenously reacts to climatic impacts such as land loss and disease rates, so per capita output growth can be thought of as partially endogenous.[12] Since the FUND algorithm is not an optimization routine, it is a step removed from the general theory on which it is built.

Instead, the complexity of FUND comes from the large number of interacting, randomly parameterized equations. Whereas different scenarios for the DICE model are run by *a priori* choice of fixed parameters, FUND employs Monte Carlo sampling for the choice of parameters. Thus different scenarios are generated from FUND's *a priori* specification of the parameters' probability distributions, and the reported results of the model are the average of 40,000 Monte Carlo simulations. Anthoff and Tol (2013a, Table MC) report that in FUND 3.7.4 there are 73 Monte Carlo variables of which 3 have an exponential distribution, 3 are gamma and 5 are triangular. The remaining 63 are normally distributed, 12 of which are unrestricted and the remaining 51 are truncated by an upper or lower bound. This count, however, underestimates the total number of MC variables since 20 of them are calibrated at the regional and/or annual level. The MC sampling of these 20 variables would occur 16 times

[12] However, this does not mean that climate change-induced deaths (e.g. from storms or diseases) increase wellbeing as measured by GDP per capita. The FUND model imposes a monetary cost to lost human life at an average of 3 times per capita GDP. Thus one death would reduce the numerator by three times as much as the reduction in the denominator of $y_{t,r}$. See equation 32.

for each region, 30 times for each decade (for runs up to the year 2300) or 480 times for regional-decadal variables such as the gross growth rates of population and GDP (Anthoff & Tol, 2013a, Tables P and Y). Such variables vastly increase the total number of random parameters used in each FUND run.

FUND's most recent version (FUND 3.7) is an excellent source for detailed sectoral damage functions. FUND 3.7 contains 9 sectoral damage functions, of which 5 are presented in Section 4.2. There are both direct and indirect damages in FUND. Direct damages are calculated as capital losses in the concerned sector. What we term 'indirect losses' stem from lost life, increased mortality rates and forced emigration. These human tolls are translated into monetary figures via "value of statistical life"-type equations discussed below. Before elaborating on these quantifications, section 4.1 presents the structure of the FUND model. Section 4.3 offers some concluding remarks on this highly detailed economic IAM.

4.1 Foundation of the FUND 3.7 Model

The FUND model can be run as a global average, but is typically run and analyzed across its 16 regions:

1. Australia & New Zealand
2. Central America
3. Canada
4. China, Mongolia and North Korea
5. Eastern Europe
6. Former Soviet Union
7. Japan and South Korea
8. North Africa
9. Middle East
10. South Ameica
11. South Asia
12. Southeast Asia
13. Small Island States
14. Sub-Sharan Africa
15. United States of America
16. Western Europe

For each region the core variables – GDP growth, population, emissions, abatement technology – are normalized such that the values in 2000 equal 100. FUND 3.7 can be run according to five underlying scenarios of gross population and GDP growth. The mean values of these decadal rates are reported in Tables P & Y, P.A1 & Y.A1, P.A2 & Y.A2, P.B1 & Y.B1 and P.B2 & Y.B2 (see Anthoff & Tol, 2013a). For the equations below the initializing values for $Y_{t,r}$ and $P_{t,r}$ (GDP and population in year t and region r) are given by these tables.

FUND relates economic activity to CO_2-eq emissions by the Kaya Identity:

$$\begin{array}{c}\text{Global CO}_2\\\text{Emissions}\end{array} = \begin{array}{c}\text{Global}\\\text{Population}\end{array} \times \frac{\text{Global GDP}}{\begin{array}{c}\text{Global}\\\text{Population}\end{array}} \times \frac{\begin{array}{c}\text{Global Energy}\\\text{Consumption}\end{array}}{\text{Global GDP}} \times \frac{\begin{array}{c}\text{Global CO}_2\\\text{Emissions}\end{array}}{\begin{array}{c}\text{Global Energy}\\\text{Consumption}\end{array}}$$

FUND uses this identity at the regional level for each time period

$$M_{t,r} = P_{t,r} \cdot \frac{Y_{t,r}}{P_{t,r}} \cdot \frac{E_{t,r}}{Y_{t,r}} \cdot \frac{M_{t,r}}{E_{t,r}}$$

$$M_{t,r} = \psi_{t,r} \phi_{t,r} Y_{t,r} \tag{25}$$

which can be written for policy considerations (see below) as

$$M_{t,r} = \left(\psi_{t,r} - \chi^{\psi}_{t,r}\right) \left(\phi_{t,r} - \chi^{\phi}_{t,r}\right) Y_{t,r} \tag{25'}$$

where t is the year index, $r = 1, 2, \ldots, 16$ is the index for the region. $M_{t,r}$ is emissions (in tonnes of CO_2-eq) and $E_{t,r}$ is energy usage in region r in year t. Further, $\phi_{t,r}$ is the energy intensity of production and $\psi_{t,r}$ is the carbon intensity of energy consumption. Thus equation (25) relates gross output to emissions by ratios of the demand ($\psi_{t,r}$) and supply ($\phi_{t,r}$) sides of the economy.

Policy intervention at the regional level can be taken against climate change by policy choice $\tau_{t,r}$, measured in US$/tC. First, policy interventions reduce emissions intensities with a one-period lag:

$$\psi_{t,r} = g^{\psi}_{t-1,r}\psi_{t-1,r} - \alpha_{t-1,r}\tau_{t-1,r} \tag{26}$$
$$\phi_{t,r} = g^{\phi}_{t-1,r}\phi_{t-1,r} - \alpha_{t-1,r}\tau_{t-1,r} \tag{27}$$

Secondly, intervention will reduce emissions directly via the lagged parameter χ in equation (25′)

$$\chi^{\psi}_{t,r} = \kappa^{\psi} + (1-\alpha_{t,r})\tau_{t-1,r} \tag{28}$$
$$\chi^{\phi}_{t,r} = \kappa^{\phi} + (1-\alpha_{t,r})\tau_{t-1,r} \tag{29}$$

The parameter $0 < \alpha < 1$ in equations (26)–(29) determines the extent to which intervention reduces emissions permanently (26 & 27) and temporarily (28 & 29).

If policy intervention ceases, the second set of equations tend toward $\kappa^{\psi}, \kappa^{\phi}$. Stability for the first set of equations depends on the varying (MC) autoregessive parameters g^{ψ}, g^{ϕ}. However, Tables AEEI and ACEI in Anthoff and Tol (2013a) suggest that over any given period the equations (26), (27) are stable since[13]

$$0 < E[g^{\psi}_{t,r}] - 3\sigma_{g^{\psi}} < E[g^{\psi}_{t,r}] + 3\sigma_{g^{\psi}} < 1 \qquad \forall t, r$$
$$0 < E[g^{\phi}_{t,r}] - 3\sigma_{g^{\phi}} < E[g^{\phi}_{t,r}] + 3\sigma_{g^{\phi}} < 1 \qquad \forall t, r$$

These growth rates represent the 'Autonomous Energy Efficiency Improvement' (AEEI) and the 'Autonomous Carbon Efficiency Improvement' (ACEI) that is expected to occur over the next several centuries. The FUND model uses these autonomous improvement in place of a gradual take-up of a zero-emissions backstop technology.

Policy intervention against emissions, of course, helps to limit the mean temperature increase above pre-industrial levels. Global mean temperature above pre-industrial norms, T_t, is the primary variable driving the economic damages in the FUND model. As represented in Figure 4, emissions $M_{t,r}$ of various GHGs are translated into temperature change according to the radiative forcing (RF_t in equation

[13]The mean values for each t are reported in Tables AEEI and AECI. The variances are given fixed at $\sigma_{g^{\psi}} = 0.0009$ and $\sigma_{g^{\phi}} = 0.0005$ for all regions and years (Anthoff & Tol, 2013a, Table MC).

31) and depends the climate equilibrium sensitivity[14] (CS) variable. The equation is

$$T_t = \left(1 - \frac{1}{\varphi}\right) + \frac{1}{\varphi}\frac{CS}{5.35\ln 2} \cdot RF_t \tag{30}$$

where φ is the e-folding time (for $CS = 3°$ this is 66 years). Regional temperatures are given by multiplying a fixed regional factor by the global mean temperature, T_t.

The global radiative forcing variable, RF_t, is given by the concentration levels of carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulfur dioxide (SO_2) and, of course, sulfur hexafluoride (SF_6) as:

$$\begin{aligned} RF_t = {} & 5.35\ln\frac{CO2_t}{275} + 0.036\left(\sqrt{CH4_t} - \sqrt{285}\right) \\ & - 0.47\ln\left[1 + 2.01\times10^{-15} CH4_t^{0.75} 285^{0.75} + 5.31\times10^{-15} CH4_t^{2.52} 285^{1.52}\right] \\ & - 0.47\ln\left[1 + 2.01\times10^{-15} N2O_t^{0.75} 790^{0.75} + 5.31\times10^{-15} N2O_t^{2.52} 790^{1.52}\right] \\ & + 2(0.47)\ln\left[1 + 2.01\times10^{-15} 285^{0.75} 790^{0.75} + 5.31\times10^{-15} 790^{2.52} 285^{1.52}\right] \\ & + 0.00052(SF6_t - 0.04) - 0.03\frac{SO2_t}{14.6} - 0.08\frac{\ln\left(1 + \frac{SO2_t}{34.4}\right)}{\ln\left(1 + \frac{14.6}{34.4}\right)} + 0.9 \end{aligned} \tag{31}$$

Equations (30) and (31) are the core of FUND's climate change aspects. Note that abatement strategies reduce emissions or energy intensity directly. This is an important distinction: it allows damages to calculated and monetized separately as they logically (and in the coding) after the policy intervention. Recall that in DICE 2013R, abatement reduced the wedge between gross and net output and hence can be logically determined simultaneously with damages. In other words, policy interventions in FUND reduce the drivers of damages and not the damages themselves. This seems to be a more realistic representation of how policy interacts with the damages of climate change.

[14] Defined as the temperature increase resulting from a doubling of CO_2-eq concentration above the pre-industrial level.

4.2 FUND 3.7 Damage Functions

Economic damages and gains from climate change in FUND are driven by temperature levels above pre-industrial norms, T_t or $T_{t,r}$, and atmospheric concentrations, C_t, of greenhouse gases (GHG). The nine sectors in which damages occur are listed in Table 2, along with a note on what climatic variables are the proximate cause of the damage (-) or gain (+). Although there are nine sectoral damages this section focuses only on items (1)–(5) in Table 2. The first two – agriculture and energy usage – represent, by far, the most significant areas in driving the social cost of carbon estimate (Anthoff & Tol, 2013c). The two tropical storm categories are reviewed because of the large and unambiguous devastation these can have on people and society. Finally, we review the complicated sea level rise mechanism in FUND in section 4.2.5. SLR represents a unique form of damages in that it can directly mitigated via coastal protection. The four areas not covered here (forestry, water resources, ecosystems and human health) are smaller impact sectors. For details on these damage functions see Anthoff and Tol (2013b).

In addition to direct, capital-impacting damages several sectoral damages lead to lost lives and/or forced migration. As one would expect lost life comes from storms and human health sectors. These lives lost are given an economic value according to the Value of a Statistical Life, $VSL_{t,r}$, which is time- and region-specific:[15]

$$VSL_{t,r} = \alpha \left(\frac{y_{t,r}}{24\,963} \right)^{\epsilon} \tag{32}$$

where $\alpha \sim N(200, 100^2)$, but truncated such that $\alpha > 0$, and ϵ is a constant representing is the income elasticity of VSL.[16]

Further, losses of dry land to rising sea levels lead to forced migration. The num-

[15]Certain human health damages raise mortality rates, for which the economic damage is calculated separately from $VSL_{t,r}$. The value of unit of mortality is given as

$$VM_{t,r} = \beta \left(\frac{y_{t,r}}{24\,963} \right)^{\eta}$$

where η is the income elasticity of statistical mortality.

[16]It appears that this parameter is set at different values for different scenarios, $\epsilon = 1, 0.2$ or > 0 (Anthoff & Tol, 2013b, p. 22).

Table 2: FUND Damaged Sectors

SECTOR	Sources of Damage
1) **Agriculture**	$\Delta T_{t,r}$ (-), $T_{t,r}$ (+/-) and C_t from CO_2 fertilization (+)
2) **Energy consumption**	changes in energy usage for heating (-) and cooling (+) from regional population, $P_{t,r}$ and global temperature, T_t
3) **Tropical Storms**	storm intensity driven by $T_{t,r}$
4) **Extra-tropical Storms**	storm intensity driven by CO_2
5) **Sea Level Rise**	T_t drives rising global water levels, S_t, leading to losses of dry and wet lands
6) **Forestry**	T_t and CO_2 (-)
7) **Water Resources**	cost of protection against T_t
8) **Ecosystem**	people's inherent valuation of ecology and biodiversity $(\Delta T_t, P_t, B_t)$
9) **Human Health**	diarrhoea, vector-borne diseases and cardiovascular & respiratory diseases driven by $T_{t,r}$ increasing mortality rates

Source: Anthoff and Tol, 2013b

ber of forced migrants is given by the area lost times the region's average population density. The economic damage of migration is three times the income per capita:

$$\text{Force Migration Cost} = 3 \times y_{t,r} \times \text{pop. density} \times \text{dryland lost} \tag{33}$$

The regions receiving immigrants obtain an economic benefit of 0.4 times its income per capita.[17]

[17]It appears forced migration in FUND 3.7 is determined by a Markov switching matrix with very lower transition probabilities (see Anthoff & Tol, 2013a, Table I).

Given the conversion of human suffering into monetary estimates in equations (32) and (33), we can now assess the five main damage functions modelled by FUND. These are Agriculture, Energy Consumption, Tropical Storms, Extra-Tropical Storms and Sea Level Rise.

4.2.1) Agriculture

The climate change affects agricultural production, $GAP_{t,r}$ in three distinct (and additive) forms: adjustment to change, deviation from the optimal growing temperature and increased fertilization rates from carbon dioxide concentrations. The sum of these impacts equal the total agricultural $A_{t,r}$, damages

$$A_{t,r} = \begin{pmatrix} \text{Farming Adjustment} \\ \text{Rate} \end{pmatrix} + \begin{pmatrix} \text{Difference from} \\ \text{Optimal } T \end{pmatrix} + \begin{pmatrix} \text{Increased Production} \\ \text{from } CO_2 \text{ Fertilization} \end{pmatrix}$$

where $A_{t,r}$ is a proportion of gross agricultural production $GAP_{t,r}$, which increases or decreases according to the sign of $A_{t,r}$ and is converted to a fraction of income by (38) below. The variable notation for agricultural damages (-) and benefits (+) is

$$A_{t,r} = \underbrace{A^r_{t,r}}_{-} + \underbrace{A^l_{t,r}}_{+/-} + \underbrace{A^f_{t,r}}_{+} \tag{34}$$

The signs indicate that adjustment to temperate change, $A^r_{t,r}$, always has a negative impact on agricultural production. The agricultural impact from temperature level is a homogenous quadratic equation with stochastic coefficients. *Most of the time*, the linear coefficient is positive and the squared coefficient is negative, yielding a global maximum that is positive at low levels of temperature increases. Therefore, agriculture may benefit from initial temperature increases as regional mean temperature approach their optimum. Finally, increasing levels of agricultural production, $A^f_{t,r} > 0$ (reduced damages) are modelled as being driven by higher CO_2 concentrations that increase the fertilization rate of plants.

The damage function for farmers' adjustment to temperature change is[18]

$$A^r_{t,r} = \alpha_r \left(\frac{\Delta T_{t,r}}{0.04}\right)^{\beta} + \left(1 - \frac{1}{\rho}\right) A^r_{t-1,r} \tag{35}$$

where $\rho > 1$ is a fixed parameter in all regions which denotes farmers' speed of adaptation. Note that $\alpha_r < 0 \; \forall r$.

$A^l_{t,r}$ is the per cent impact on agricultural production for region r in year t due to the temperature level. Total regional mean temperature change since 1990 is $T_{t,r}$, which has a quadratic impact on production:

$$A^l_{t,r} = \delta^l_r T_{t,r} + \delta^q_r T^2_{t,r} \tag{36}$$

where the regionally-specified parameters have mean values $E[\delta^l_r] > 0$ and $E[\delta^q_r] < 0, \forall r$ (Anthoff & Tol, 2013a, Table A). This quadratic function may be positive (negative) for a small (large) amount of temperature increase.

Equation (36) is meant to capture the early production benefits from low levels of climate change. For example, at the mean ("best-guess") values for δ^l_r, δ^q_r for Canada, China and the United States, the optimal temperatures increases over the regions' temperatures in 1990 are, respectively, 2.87°C, 1.26 °C and 1.08 °C. These optimal temperatures seem a bit high at first glance, though they are not out of the question. Indeed there is some reason to believe northern countries could slightly increase agricultural production.

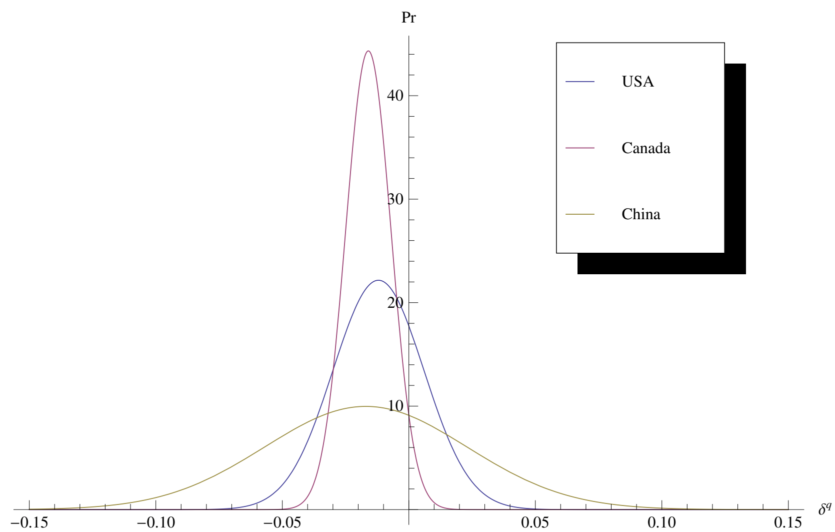
More seriously, FUND 3.7 appears to have a serious parameterization problem as there is a significant chance that $\delta^q_r > 0$.[19] This gives a non-trivial likelihood of the optimal temperature level being unboundedly large. As show in Figure 5, Canada has a fairly small chance of having a positive coefficient on the quadratic term in (36), $\Pr(\delta^q_{CA} > 0) \approx 3.7\%$, but this is non-negligible for the China, $\Pr(\delta^q_{CN} > 0) \approx 33.5\%$, and the United States, $\Pr(\delta^q_{US} > 0) \approx 25.4\%$. In other words, for 1/3

[18] For all ΔT-induced damages the key rate increase is 0.04°C p.a.

[19] Specifically, the distributions for Canada, China and the United States are $\delta^q_{CA} \sim N(-0.016, 0.000081)$, $\delta^q_{CN} \sim N(-0.017, 0.0016)$ and $\delta^q_{US} \sim N(-0.012, 0.000324)$, respectively (Anthoff & Tol, 2013a, Table A).

and 1/4 of FUND's Monte Carlo simulations, respectively, China and the United States' agricultural outputs are strictly, monotonically increasing in temperature levels ($T_{t,r} > 0$) and have no maximum value.

Figure 5: MC probability distribution of δ_r^q for 3 Countries in FUND 3.7



Source: Anthoff & Tol (2013c) Table A

Finally, increased levels of CO_2 concentration above the pre-industrial level are modelled as strictly increasing the level of agricultural production. The logic is that greater CO_2 fertilization eases photosynthesis such that plants grow faster and require less water. Anthoff and Tol (2013b) give this dynamic the functional form

$$A_{t,r}^{f} = \gamma_r \ln \left[\frac{\mathrm{CO}_2}{275} \right] \tag{37}$$

where the denominator is the pre-industrial concentration of 275 CO_2 parts per million. The parameter γ_r ranges from 5.05 for sub-Saharan Africa to over 23 for small islands states and, Australia and New Zealand.

Total agricultural production impacts $A_{t,r}$ are then added to or subtracted from

$GAP_{t,r}$, which is translated into a proportion of income (GDP) according to

$$\frac{GAP_{t,r}}{Y_{t,r}} = \frac{GAP_{1990,r}}{Y_{1990,r}} \left(\frac{y_{1990,r}}{y_{t,r}} \right)^{\epsilon} \tag{38}$$

The income elasticity of agriculture's share in the (per capita) economy is $\epsilon \sim N(0.31, 0.0225)$ but truncated from below such that $\epsilon \geq 0$.

Equation (38) says that the Gross Agricultural Production (GAP) is a declining share of total output, Y, as per capita GDP, y, increases. However $GAP_{t,r}$ may increase as a share of output if the climate change has a significant positive impact on agricultural production, $A_{t,r} \gg 0$. However, the agricultural damages are bounded since $GAP_{t,r} \geq 0$. Hence, the impact of climate change on agriculture in FUND 3.7 has lower bound, thereby limiting potential damages, but no corresponding upper bound on potential benefits.

4.2.2) Energy Consumption

As with agricultural production, the impact of climate change could either increase (damage) or decrease (benefit) energy consumption. FUND models this as changes in regional spending on heating and cooling. Since GHG's will increase global and regional mean temperatures, reduced space heating is a benefit and increased space cooling is damaging. Both are driven by the global mean temperature level (relative to 1990), regional population and income per capita. Total energy consumption is skewed toward damages because the benefits from reduced heating are driven by a logistic function ($\tan^{-1} T_t$) with a global supremum $\frac{\pi}{2}$, whereas damages from increased cooling are exponential (with a MC parameter exponent $\beta \sim N(1.5, 0.25)$ truncated such that $\beta \geq 0$).

A region's benefit from lowered heating expenditure is

$$SH_{t,r} = \frac{\alpha_r^H Y_{1990,r} \cdot \frac{\arctan T_t}{\arctan 1.0} \cdot \left(\frac{y_{t,r}}{y_{1990,r}} \right)^{\epsilon} \cdot \left(\frac{P_{t,r}}{P_{1990,r}} \right)}{\prod_{s=1990}^{t} AEEI_{s,r}} \tag{39}$$

where ϵ is income elasticity of energy consumption (which is derived from a 1995 estimate for the UK). The regional parameter $\alpha_r^H > 0,\ \forall r$ is normally distributed around a positive mean, with low variance and is truncated from below at zero (Anthoff & Tol, 2013a, Tables EFW & MC).

Damages to a region's income from increased expenditure on cooling are

$$SC_{t,r} = \frac{\alpha_r^C Y_{1990,r} \cdot \left(\frac{T_t}{1.0}\right)^{\beta} \cdot \left(\frac{y_{t,r}}{y_{1990,r}}\right)^{\epsilon} \cdot \left(\frac{P_{t,r}}{P_{1990,r}}\right)}{\prod_{s=1990}^{t} AEEI_{s,r}} \tag{40}$$

where, β is a positive, Gaussian exponent and the parameter $\alpha_r^C < 0,\ \forall r$ is truncated from above at zero (Anthoff & Tol, 2013a, Tables EFW & MC). For both equations, $AEEI_{s,r}$ is 'Autonomous Energy Efficiency Improvement' – a variable with a global mean of 1% in 1990 converging to 0.2% in 2200 (Anthoff & Tol, 2013b, pp. 9-10).

4.2.3) Extreme Weather I: Tropical Storms

Tropical storm intensity is driven by temperature change. The economic damages are both direct (capital losses) and indirect (mortalities). Direct tropical storm damage is given by

$$TD_{t,r} = \alpha_r Y_{t,r} \left(\frac{y_{t,r}}{y_{1990,r}}\right)^{\epsilon} \left[(1 + \delta T_{t,r})^{\gamma} - 1\right] \tag{41}$$

Mortalities from storm intensity are given by

$$TM_{t,r} = \beta_r P_{t,r} \left(\frac{y_{t,r}}{y_{1990,r}}\right)^{\epsilon} \left[(1 + \delta T_{t,r})^{\gamma} - 1\right] \tag{42}$$

where $Y_{t,r}$ is regional GDP and $P_{t,r}$ is the population. The parameters α_r and β_r are both positive and are fixed for each region and scenario (Anthoff & Tol, 2013a, Table TS). They represent expected fraction of GDP lost to and population killed by tropical storms in each region. Anthoff and Tol obtain these estimates form the CRED EM-DAT website. The fixed parameter $\delta = 0.04°C$ indicates increased wind speed per degree warming according to the WMO; $\gamma = 3$ since wind power is the cube of windspeed (Anthoff & Tol, 2013b, pp. 19-20).

4.2.4) Extreme Weather II: Extra-tropical Storms

Extra-tropical storm intensity is driven by CO_2 atmospheric concentrations. Direct extra-tropical storm damage is

$$ETD_{t,r} = \alpha_r Y_{t,r} \left(\frac{y_{t,r}}{y_{1990,r}} \right)^{\epsilon} \delta_r \left[\left(\frac{C_{\text{CO2},t}}{C_{\text{CO2},pre}} \right)^{\gamma} - 1 \right] \tag{43}$$

Mortalities from extra-tropical storms are

$$ETM_{t,r} = \beta_r P_{t,r} \left(\frac{y_{t,r}}{y_{1990,r}} \right)^{\epsilon} \delta_r \left[\left(\frac{C_{\text{CO2},t}}{C_{\text{CO2},pre}} \right)^{\gamma} - 1 \right] \tag{44}$$

where $\alpha_r > 0$, $\forall r$ is the benchmark damage from extra-tropical storms and $\beta_r > 0$, $\forall r$ is the benchmark mortality from extra-tropical storm. Both are fixed. Finally, the fixed parameter δ_r is regional storm sensitivity to CO_2 concentration (Anthoff & Tol, 2013b, p. 21). Although it is not clear how δ_r is calibrated, it appears to be a fairly rough estimate since $\delta = 0.21$ for Australia and New Zealand, South Asia and South America, $\delta = 0.13$ for small island states and $\delta = 0.04$ for all other regions (Anthoff & Tol, 2013a, Table ETS).[20]

4.2.5) Land Lost from Sea Level Rise

Global Sea Level Rise, S_t (in metres), is given by

$$S_t = \left(1 - \frac{1}{\varrho} \right) S_{t-1} + \gamma T_t \tag{45}$$

where $\varrho = 500$ is the e-folding time. Clearly (45) is a stable, linear difference equation with a (very) long memory. However, each ratching up of the global mean temperature, T_t, raises the steady-state sea level above the pre-industrial level.

Dryland loss is fundamentally different than other damages because it can be directly abated by policy. All other damages can only be *indirectly* reduced through policy interventions in $\phi_{t,r}, \psi_{t,r}$ and χ^{ψ}, χ^{ψ} in equations (26), (27), (28) and (29).

[20]The parameter $\gamma = 1$ for all scenarios.

However, direct projection of dryland comes at the cost of natural wetlands. That is, dryland protection drives wetland loss beyond that lost “naturally” to rising sea levels.

Sea level rise (SLR) is translated into potential (without abatement) and actual cumulative (with abatement) losses of dryland. The potential cumulative land loss, ζ_r, can only as large as the region's total area in the year 2000:

$$Area_{2000,r} \equiv \zeta_r \leq Area_{t,r}$$

where $Area_{t,r}$ is a region's area in year t.

Conversely, only a proportion of wetlands are thought to be vulnerable to SLR

$$W_r^M \geq W_{t,r}^C$$

where W_r^M is region r's maximum at-risk wetlands, which is assumed to be less than the region's total stock of wetlands, which is set equal to the region's 1990 stock, $W_{1990,r}$. The total accumulated wetlands lost is $W_{t,r}^C$ in region r up to year t.

Potential cumulative dryland loss is

$$\overline{CD}_{t,r} = \min\left\{\delta_r S_t^{\gamma_r}\ ,\ \zeta_r\right\} \tag{46}$$

where $\delta_r \sim N(\mu_r, \sigma_r) > 0$ is the amount of land loss (km^2) for a one metre rise in sea level. It is truncated from below such that it is always positive. The distribution ranges from a high of $\delta_{SEA} \sim N(157\,286, 90\,170^2)$ for Southeast Asia, to a low of $\delta_{CAN} \sim N(970, 970^2)$ for Canada (Anthoff & Tol, 2013a, Table SLR). The exponential parameter, γ_r is calibrated by a digital elevation model but is a normally distributed MC variable that is truncated such that $0 < \gamma_r < 1,\ \forall r$ (Anthoff & Tol, 2013b, p. 11).

A particular year's annual potential dryland loss is the difference between the potential accumulated loss and the actual loss up to that point:

$$\overline{D}_{t,r} = \overline{CD}_{t,r} - CD_{t-1,r} \tag{47}$$

with an actual cumulative loss

$$CD_{t,r} = CD_{t-1,r} + D_{t,r} \tag{48}$$

where $D_{t,r}$ is the actual dryland lost in a particular year.

Coastline protection is the sole difference between actual and potential annual losses such that

$$D_{t,r} = (1 - p_{t,r})\overline{D}_{t,r} \tag{49}$$

where $p_{t,r}$ is the protection policy variable.

Thus dryland would be enveloped by the rising seas at the rate given by $\delta_r S_t^{\gamma_r}$ up to a maximum of ζ_r, where $S_{t,r}$ is driven by the global temperature level. But the actual loss can be slowed (or even stopped) by implementation of policy that protects $p_{t,r}\%$ of the coastline in year t, region r.

Since the dryland loss equations are in km^2, FUND must monetize these direct losses (land value) and indirect costs (forced migration). A region's annual lost dryland is valued according to

$$VD_{t,r} = \varphi \left(\frac{Y_{t,r}/Area_{t,r}}{YA_0} \right)^{\epsilon} \tag{50}$$

where the scaling parameter is φ is a MC variable $\varphi \sim N(4, 4) > 0$, truncated from below. The fixed term $YA_0 = 0.635$ for all regions represents the average income density of the OECD in 1990 (Anthoff & Tol, 2013b, p. 11).

Secondly, the level of forced emigration is the region's average population density times the dry land loss. Thus, annual indirect costs are

$$\text{Emigration Costs} = 3 \times y_{t,r} \times D_{t,r} \times d_{t,r}$$

where density is simple $d_{t,r} = \frac{P_{t,r}}{Area_{t,r}}$. The Markov transition table presented in FUND's documentation appendix determines the (random) allocation of these emigrants to new regions (Anthoff & Tol, 2013a, Table I). The number of immigrants then counts positively toward the recipient region's income. However, each migrant adds only 40% to the host's per capita income, thereby pulling down average income.

Wetland loss is linear in the changing (global) sea level

$$W_{t,r} = \omega_r^s \cdot \Delta S_t + \omega_r^M \cdot p_{t,r} \cdot \ \Delta S_t \tag{51}$$

ω_r^s is the direct loss from rising sea levels, and ω_r^M represents the wetlands lost to coastal protection practices, $p_{t,r}$. Both of these are variables are MC and bounded from below to be positive (Anthoff & Tol, 2013a, Table SLR). As noted these annual losses accumulate to $W_{t,r}^C$ up to a maximum of W_r^M:

$$W_{t,r}^C = \min \left\{ W_{t-1,r} + W_{t,r} \ , \ W_r^M \right\} \tag{52}$$

The value of wetlands is increasing in per capita income and population density, and decreases (as with dryland value, VD) in the initial stock wetland area

$$VW_{t,r} = \alpha \left(\frac{y_{t,r}}{y_0} \right)^\beta \left(\frac{d_{t,r}}{d_0} \right)^\gamma \left(\frac{W_{1990,r} - W_{t,r}^C}{W_{1990,r}} \right)^\delta \tag{53}$$

The last term is the proportion of a region's 1990 'stock' of wetlands remaining. Parameters $y_0 = 25000$ and $d_0 = 27.9$ are normalization constants. The exponents are normally-distributed MC variables, bounded in $0 < \gamma < 1$ and $\beta \sim N(1.16, 0.46^2) > 0$. The scaling parameter α reflects the "net present value of future stream of wetland serves" (Anthoff & Tol, 2013b, p.13), with the distribution $\alpha \sim N(5\,880\,000, 187\,000^2)$.

The final step in the FUND model is to calculate the value of coastal protection, $p_{t,r}$, from a cost-benefit analysis of saved dryland and foregone wetlands. The net-present value of VD given no coastal protection is

$$\text{NPV}VD_{t,r} = \sum_{s=t}^{\infty} \overline{D}_{t,r} VD_{t,r} \left(\frac{1 + \epsilon d_{t,r}}{1 + \rho + \eta g_{t,r}} \right)^{s-t} \tag{54}$$

where $\rho = 0.03$, $\eta = 1$ and $g_{t,r}$ are the pure discount rate, consumption elasticity of marginal utility and the growth rate of per capita income. $\epsilon \sim N(1, 0.04)$ is the income elasticity of dryland value (Anthoff & Tol, 2013b, p.15).

The NPV wetland lost from full coastal protection is

$$\mathrm{NPVV}W_{t,r} = \sum_{s=t}^{\infty} W_{t,r} VW_{t,r} \left(\frac{1}{1+\rho+\eta g_{t,r}} \right)^{s-t} \tag{55}$$

Similarly, the present value of full coastal protection is

$$\begin{aligned} \mathrm{NPVV}P_{t,r} &= \sum_{s=t}^{\infty} \left(\frac{1}{1+\rho+\eta g_{t,r}} \right)^{s-t} \cdot \pi_r \cdot \Delta S_t \\ &= \frac{1+\rho+\eta g_{t,r}}{\rho+\eta g_{t,r}} \cdot \pi_r \cdot \Delta S_t \end{aligned} \tag{56}$$

where π_r is the annual unit cost of coastal protection. π_r is normally distributed and bounded from below to be positive. The range of variables reflects the value and exposure of the coast line. For example, Western Europe is given the MC distribution $\pi_{WEU} \sim N(153.9, 52.6^2) > 0$, whereas Eastern Europe has the distribution $\pi_{EEU} \sim N(3.1, 1.7^2) > 0$.

Taking equations (54), (55) and (56) together, the cost of partial protection in any given year and region is

$$P_{t,r} = \left[1 - \frac{1}{2} \left(\frac{\mathrm{NPVV}D_{t,r} + \mathrm{NPVV}W_{t,r}}{\mathrm{NPVV}P_{t,r}} \right) \right]_{+} \tag{57}$$

FUND takes this functional form from Fankhauser (1995).

4.3 FUND conclusion

As noted FUND 3.7 has five baseline scenarios of economic and population growth. For any of these a business as usual (BAU) valuation of damages can be computed by adding together all of the sectoral direct and indirect damages – five of which have been outlined in detail above. The BAU version of FUND would, presumably, set abatement policies and coastal protection policies equal to zero ($\tau_{t,r} = 0, p_{t,r} = 0,\ \forall t, r$). However, this scenario comparison would differ from FUND's approach to quantifying the social cost of carbon. FUND determines SCC by running the model repeatedly with a pulse of CO_2 emissions in each run (Ackerman & Munitz, 2012a; Anthoff & Tol, 2013c). The sum of these pulses of damages above the BAU level of damages then produces the marginal willingness to pay to offset the marginal tonne of carbon emissions.

Clearly the FUND model offers an extensive menu of sector-specific damages that have been parameterized with great care. However, even with this great detail there remains work to be done. First, many of their physical science sources for functional forms are 2 decades old. Even granting this inertia, there are still a fair number of parametric concerns (as mentioned in the section 4.2.1). Finally, there is also the issue of equity in the FUND and other models reviewed here. Because it is based on a willing-to-pay approach, all sectoral damages (direct and indirect) are scaled in proportion of per capita income, which arguably skews downward the estimation of the social cost of carbon as poorer regions tend to be more vulnerable to the vicissitudes of climate change (IPCC Working Group II, 2014, Chapters 9, 12-14), but the damages there appear low as they may be less able to pay.

5 PAGE: Policy Analysis of the Greenhouse Effect

Chris Hope's Policy Analysis of the Greenhouse Effect (PAGE) models emissions of carbon dioxide (CO_2), methane (CH_4) and sulfur hexafluoride (SF_6). These three GHG emissions feed into atmospheric concentrations, which slowly decay according to a piece-wise differentiable function (Hope, 2006). Decay rates are used in place of a reservoir model. Based on the GHG concentrations, radiative forcing is the sum of a logarithmic concentration function for CO_2, square root concentration function for CH_4, a linear function for SF_6 and an exogenous forcing variable is added to the explicitly modelled gases to capture the impact of other GHGs. Thus the PAGE radiative forcing function is a slightly simplified version of equation (31) in FUND. Rather than go into detail about the environmental aspects of PAGE we briefly discuss its modelling approach in comparison with FUND in Section 5.1 and then summarize the PAGE damage functions in Section 5.2.

5.1 Structure of the PAGE model

The PAGE model is similar to FUND's structure in three areas: random sampling, regionally-specified routines for which there are, thirdly, exogenous rates of economic growth. As with the FUND model, PAGE incorporates uncertainty into its estimates via repetitive random sampling. However, instead of Monte Carlo simulations, the PAGE model uses Latin Hypercube sampling, which is meant to better approximate real-world realizations of random variables (Hope, 2006). For the 80% of parameters which are completely unknown, PAGE assumes a triangular distribution. For the remaining 20% of random parameters normal, log-normal, Pareto or other distributions are used based on the observed phenomena.

PAGE is designed and calibrated for 8 regions, and therefore cannot be run as a singular, global routine. The regions that are separately parameterized are:

1. European Union
2. United States of America
3. Other OECD Countries
4. Africa and the Middle East
5. China and Centrally Planned Asia
6. India and South East Asia
7. Latin America
8. Former Soviet Union and East Europe

PAGE is specifically designed with the EU as the focus region. Therefore, certain variables, such as tolerable temperature levels (see sec. 5.2), are specified by scaling factors relating non-focus regions to the focus region's (the EU's) calibrated value.

Finally, economic growth rates in this model are exogenous. For each region r and time period t there is a specified annual growth rate (in %) of GDP, which is denoted by $GRW_{t,r}$. Because the model is run for 10 discrete time periods of lengths ranging from 1 year to 50 years[21], annual growth rates have to be compounded accordingly.

[21] The time period index runs as $t = 2000, 2001, 2002, 2010, 2020, 2040, 2060, 2080, 2100, 2150, 2200$.

Thus, for any year Y_t in time period t, region r's level of output is given as

$$GDP_{t,r} = GDP_{t-1,r} \cdot \left(1 + \frac{GRW_{t,r}}{100}\right)^{Y_t - Y_{t-1}} \tag{58}$$

In these three respects the PAGE model appears rather similar to the FUND model. However, its approach to computing damages, as we see below, is quite different from both the FUND and DICE models.

5.2 Damage Modelling in PAGE

The baseline model is PAGE2002, which was developed with data and assumptions from the *Third Assessment Report* of the IPCC. This older PAGE vintage was the primary model used in the (Stern, 2007). Hope has since extended and updated the model, the latest version of which is PAGE09. It is based on new research and the *Fourth Assessment Report* of the IPCC. We focus on PAGE2002 since the model's structure is largely unchanged in PAGE09 (Hope, 2011). However, we cannot focus exclusively on PAGE2002 because the damage function in PAGE09 has been slightly amended from its 2002 version. The new version keeps the two basic forms of damages (economic and non-economic impacts), but adds explicit damages from rising sea levels (Hope, 2011).[22]

In PAGE2002 direct damages are modelled in two broad and generic categories: Economic and Non-economic. Both damages are driven by the temperature level and rate of temperature change relative to some *effective* tolerable level and rate. However, it is only a region's realized temperature level, $RT_{t,d,r}$, relative to the tolerable "plateau level" that causes direct impacts, denoted by $I_{t,d,r}$. The subscript index $d = \{0, 1\}$ indicates whether the function is for economic damages ($d = 0$) or for non-economic damages ($d = 1$). The direct impacts, $I_{t,d,r}$, are measured in °C and then translated into monetary value. In addition to these regional damages, PAGE2002 models "damages from a discontinuity", which is an additive, probabilistic impact increasing in likelihood when the global realized temperature, GRT_t, is

[22]Sea level rises were implicitly modelled in PAGE2002, so the advancement is merely an explicit damage equation in PAGE09.

above a certain 'discontinuity threshold', $TDIS$ (Hope, 2006).

For each region, r, there is a natural tolerable temperature level $TP_{d,r}$ (P for plateau) and a natural tolerable rate of temperature change per year $TR_{d,r}$. Both of these are specified as proportions of the focus region, $r = 0$ (the EU), such that:

$$TP_{d,r} = TP_{d,0} \cdot TM_r \qquad \text{and} \qquad TR_{d,r} = TR_{d,0} \cdot TM_r$$

where TM_r is the regional multiplier ($TM_0 = 1$) and, $TP_{d,0}$ and $TR_{d,0}$ are the tolerable rates and level in the focus region. Clearly, the functional forms of damages are the same for both sectors; it is merely the parameter values that differ between the two types of damages.

The natural tolerable levels are fixed for each region and time period. However, the effective tolerable levels can be adjusted by policies aimed at the plateau, $PLAT_{t,d,r}$, or the rate-of-change, $SLOPE_{t,d,r}$. Thus the Adjusted Tolerable Plateau and Rate are specified for each time period and region as:

$$ATP_{t,d,r} = TP_{d,r} + PLAT_{t,d,r} \tag{59}$$

$$ATR_{t,d,r} = TR_{d,r} + SLOPE_{t,d,r} \tag{60}$$

These determine the Adjusted Temperature Level against which the realization of impacts are determined is

$$ATL_{t,d,r} = \min\left\{ATP_{t,d,r}\ ,\ ATL_{t-1,d,r} + ATR_{d,r} \cdot (Y_t - Y_{t-1})\right\} \tag{61}$$

where Y_t is the specific year studied within the (usually) multi-year time period, t.

Equation (61) says that the policy-adjusted, tolerable temperature level is the lesser of the policy-adjusted plateau level and the policy-adjusted tolerable rate of change in regional temperature from last period's tolerable temperature level ($ATL_{t-1,d,r}$). Recall that equations (59)–(61) are specified for each region, time period and for both types of damages modelled in PAGE2002.

Given the region and time period the impact from either damage type, $I_{t,d,r}$, is simply the difference by which the region's realized temperature, $RT_{t,r}$, exceeds the tolerable, adjusted level determined in (61):

$$I_{t,d,r} = \max\left\{0\ ,\ RT_{t,r} - ATL_{t,d,r}\right\} \tag{62}$$

where impacts in (62) are in degrees centigrade. Clearly, unlike FUND, climate change cannot produce positive benefits (i.e., negative damages are excluded by equation 62).

Monetary impacts are determined by a power function. To convert $I_{t,d,r}$ into monetary damages – usually US$ – PAGE2002 specifies GDP-weighted impacts, $WI_{t,d,r}$ for each region. Since PAGE2002 is based on the *Third Assessment Report* the mean temperature increase from a doubling of CO_2 is 2.5°C, which is the baseline against which damages are calibrated. With $W_{d,r}$ indicating the value of a region's economic ($d = 0$) and non-economic ($d = 1$) losses from a temperature increase above 2.5°C we have

$$WI_{t,d,r} = \left(\frac{I_{t,d,r}}{2.5}\right)^{POW} \cdot W_{d,r} \cdot GDP_{t,r} \cdot \left(1 - \frac{IMP_{t,d,r}}{100}\right) \tag{63}$$

where $IMP_{t,d,r}$ is the mitigation policy that directly reduces the monetary losses to the two sectors. It is set to different levels depending on the scenario being tested. Note that in PAGE damages are sequentially prior to abatement.

In addition to the direct damages there are global impacts from discontinuity, $IDIS_t$, which are also measured in °C:

$$IDIS_t = \max\left\{0\ ,\ GRT_t - TDIS\right\} \tag{64}$$

where GRT_t is the global realized temperature. The discontinuity threshold variable is randomly chosen from the triangle distribution $TDIS \sim T(2, 5, 8)$ for each Latin Hypercube run of the model.

As with direct impacts, the discontinuous impact is translated into monetary values by regional weight, here $WDIS_r$, applied to $GDP_{t,r}$. Instead of a power function, however, discontinuity impacts are weighted by a probabilistic factor, $0 <$

$PDIS < 1$. Thus,

$$WIDIS_{t,r} = IDIS_t \cdot \left(\frac{PDIS}{100}\right) \cdot WDIS_r \cdot GDP_{t,r} \tag{65}$$

where the probability $PDIS$ is a random variable (fixed for each run) pulled from $T(1, 10, 20)$.

Taking equation (63) for $d = 0, 1$ and equation (65) together, the total damage for each region in a particular time period is the sum

$$WIT_{t,r} = WI_{t,0,r} + WI_{t,1,r} + WIDIS_{t,r} \tag{66}$$

PAGE aggregates over all the years in each period (via linear midpoint interpolation) to produce the Aggregate Damage for each region

$$AD_{t,r} = WIT_{t,r} \cdot \left(\frac{Y_{t+1} - Y_t}{2} - \frac{Y_t - Y_{t-1}}{2}\right) \tag{67}$$

Finally, the aggregate damages are translated into the global, net present value of damages by use of a regional cost discount rate, $dr_{t,r}$, and a fixed impact rate multiplier, ric. Thus summing and discounting the aggregate damages over all regions and time periods gives the total Discount Damages as

$$DD = \sum_{t,r} AD_{t,r} \cdot \prod_{j=1}^{t} \left(1 + \frac{dr_{j,r} \cdot ric}{100}\right)^{-(Y_j - Y_{j-1})} \tag{68}$$

Equation (68) is the core damage estimate in PAGE2002. It remains the foundation on which PAGE09's updated damages are built.

In PAGE09 the calibrated conversation of direct impacts (in °C) to monetary values becomes (Pycroft, Vergano, Hope, Paci, & Ciscar, 2011):

$$WI_{t,d,r} = \alpha_{d,r} \left(\frac{TR_{t,d,r}}{3.0°C}\right)^{\beta} \cdot GDP_{t,r} \cdot \left(1 - \frac{IMP_{t,d,r}}{100}\right) \tag{69}$$

where $\alpha_{d,r}$ is damage estimate for a 3°C warming – the *Fourth Assessment Report*'s estimate of mean temperature change from a doubling of CO_2. When the realized temperature is greater than 3.0°C then the exponent β has greater impact (it has replaced POW in (63)). β is drawn from $T(1.5, 2, 3)$ in each run of PAGE09.

Unfortunately we have not been able to find, let alone access, the coding for PAGE09, nor were we able to find a summary of the functional relations as there exists for PAGE2002. Thus, we cannot report on the functional form of sea level rise nor on the exact form of its damages. However, Hope (2011, p.5) states

> In PAGE09, sea level impacts before adaptation are a polynomial function of sea level rise, and economic and non-economic impacts before adaptation are a polynomial function of the regional temperature.

which implies that once SLR is modelled it is also translated into monetary damages via an equation with the same form as (69).

Table 3: Calibrated Parameters for Sea Level Rise Impacts in PAGE09

Item	**Unit**	**Variable**	**Distribution**
Calibration sea level rise	m	$SCAL$	$T(0.45, 0.5, 0.55)$
Sea level impact at $SCAL$	% GDP	W_S	$T(0.5, 1.0, 1.5)$
Sea level exponent	none	POW_S	$T(0.5, 0.7, 1)$

This interpretation is supported by the parametric data Hope (2011, Table 4) provides. Table 3 reproduces the sea level rise information from Hope's brief summary of the updated damage estimation in PAGE09. This implies a function in the form

$$W_s = SCAL^{POW_s} \tag{70}$$

where the sea level damage is measured in metres. Despite the imprecise representation of SLR damages in PAGE09, we have at least a sense of this new sectoral damage is incorporated into the latest PAGE vintage.

5.3 PAGE Conclusion

The PAGE model shares similar weaknesses with the FUND model. In particular, the exogenous modelling of economic growth remains a barrier to general equilibrium analysis (see sec. 6.3). Additionally, the regions in PAGE are designed to always be in reference to a focus region. Although the PAGE modelers wish to primarily analyze the EU (Pycroft et al., 2011; Stern, 2007), this approach could lessen the accuracy of the results for non-EU regions. The FUND model has similar drawbacks in its region-to-region extrapolations (e.g., relying on UK housing surveys for heating/income elasticities and US agricultural studies), but these are largely due to limited sector-specific empirical data rather than a design choice.

On the other hand, PAGE strikes a balance between the FUND model's high, even excessive, level of detail and the DICE model's oversimplification of damages. This is especially evidenced by the relatively limited number of distinct forms of the damage function. PAGE approaches fine tuning through calibration rather than by positing a multitude of functional forms. Though arguably less accurate, the chances for compounded misspecification is reduced.

6 Concerns and Critiques

The three integrated assessment models reviewed here are far from academic curiosa. They are influential in European Union climate policy debates[23] and form the basis of US regulatory agencies' carbon cost estimates. Specifically, the US Interagency Working Group on Social Cost of Carbon (2010) relies on the arithmetic average of DICE, FUND and PAGE values for its estimate of the social cost of carbon (Ackerman & Stanton, 2012). With such direct implications for climate policies in the world's largest economies one would hope concerns regarding these IAMs would be relatively minor. However, the models' outstanding issues are broad in scope and appear to magnify *pari passu* with the complexity of design. Although remaining, by

[23]PAGE2002 was the base model for the Stern Report (see Stern, 2007, Part II).

and large, impressive modeling feats, there is a great deal of room for improvement.

This section summarizes three general critiques and concerns related to the economic IAM approach to the social cost of carbon. First, there is an irrevocable tension between economists' use of climate models and the advancement of environmental discoveries. Models estimating SCC borrow findings from climate science, which can be rapidly overshadowed by new findings. Given the non-expertise of economists in such areas, the incorporation of new findings into SCC estimates tends to be delayed and, potentially, misinterpreted. Second, we review the Tol/Ackerman controversy to highlight the coding and mathematical errors that inevitably arise from increasing the complexity of model design. Finally, and most importantly, we discuss the models' infidelities vis-à-vis the general equilibrium theory approach to pricing externalities, which is the conceptual framework upon which each model is built.

6.1 Environmental Research vs. Economic Modeling

The most understandable and unavoidable concern of any climate model is the (im)precision of its formal representation of natural processes. This is particularly challenging for economists whose expertise lies neither in programming IAMs nor in estimating climatic phenomena. The typical SCC model, therefore, is a simplified IAM whose "results approximate those of the most complex climate simulations" (Hope, 2006, p. 21). This pragmatic approach requires occasional reconfiguration of equations or parameters, which the developers of the three models reviewed here have done admirably (see, e.g., Hope, 2010; Nordhaus, 2010b; Anthoff & Tol, 2013c). However, because SCC model calibrations are done with respect to aggregate figures (such as global mean temperature and CO_2 concentrations) recently discovered errors in the basic, underlying functions can persist for undue periods.

Of course, economists are well aware of the empirical weakness of their social cost of carbon estimates. In his seminal review of the literature Tol (2009, p. 38) notes the unresolved issue that "[e]stimates are often based on extrapolation from a few detailed case studies, and extrapolation is to climate and levels of development that are very different from the original case study." Moreover, models are incomplete due to 'missing effects' that are either too minor or too complex to be reliably integrated into SCC estimates (Tol, 2009, p. 43-4). Though widely acknowledged, there is no easy or singular method by which to correct for such shortcomings. This point is demonstrated by the antithetical approaches adopted by William Nordhaus and Richard Tol.

As mentioned in section 3.1, Nordhaus has stepped back from the use of more complicated damage function modelling. While Nordhaus's admission of economists' programming limitations is refreshing (Nordhaus, 2012), designing DICE 2013R with a single damage function (equation 3) forces him to rely on the estimates of other economists. Indeed the calibration of this damage functions comes from the analysis and review of the 200-plus SCC estimates in Tol (2009), with an *ex post* damage addition of 25%, which is meant to account for the missing effects common to all estimates. Under Nordhaus's approach, economists must largely resign themselves to re-calibrating their parameters as climate science advances. Though it is a decidedly secondary (or even tertiary) place for economic models of climate change, this approach is arguably a more efficient division of labour between disciplines.

Relying on secondary climate estimates can bury nuances crucial to the interpretation of new findings. For example, a recent study shows that the over-representation of urban-based weather stations in China has led to the overestimation of the country's warming from 1951 to 2010 (Ge, Wang, & Luterbacher, 2013). By using an urban/rural land-area weighting scheme and accounting for changing land-use patterns, the researchers find the six-decade temperature increase to be between 27% and 12% lower than the standard estimates of temperature change in China. This is an important improvement in estimating historical climate change. However, these new figures may not be as well suited to the needs of economic projections of damages from climate change. If a key economic consequence of global warming is the increasing energy use for indoor cooling, then temperature change estimates weighted by population density are more appropriate than the land-area weights used by climate scientists. In general, the method by which natural scientists aggregate estimates tends to differ from the approach of social scientists. Though this particular example may not be a serious issue on its own, it represents precisely this kind of nuance willfully ignored by Nordhaus's approach.

At the other end of the spectrum is the modelling approach of David Anthoff and Richard Tol's FUND model.[24] Each of the nine damaged sectors in FUND are built on distinct functions sourced from multiple empirical studies (see Anthoff & Tol, 2013b). Yet key sectors rely on outdated, regionally-specific studies to establish the functional form of damages – precisely what Tol (2009) warns against. Of course, all three models lack regionally precise estimates in certain areas. The particular problem of FUND is that it projects Panglossian outcomes for agricultural production in response to climate change simply because it continues to rely on two decade old studies (Ackerman & Munitz, 2012a).[25] Specifically, the quadratic form of the temperature level function, equation (36), is derived from four empirical studies published between 1992 and 1996 (Anthoff & Tol, 2013b, p. 7). These studies are now outdated.

Recent work by Schlenker and Roberts (2009) on US agricultural output evidences the over-optimism of FUND's quadratic function. This is *a fortiori* true given FUND's estimate of the positive production impact from CO_2 fertilization in equation (37), which is strictly increasing in emissions. Schlenker and Roberts (2009) analyze the production of three staple crops (corn, soybeans and cotton) at the county-level in the US from 1950 to 2005. In each case, crop output slowly rises as local exposure frequencies increase from below- to above-average temperatures. This validates the positive output effects from small temperature increases modeled in FUND's equation (36). However, crop output suddenly and steeply declines beyond a particular threshold temperature.[26] The rapid decline is markedly sharp even when estimated with an 8^{th}-order polynomial function (Schlenker & Roberts, 2009, see Fig. 1, p. 15595). The result suggests that a relatively mild concave quadratic

[24]The PAGE model lies somewhere between the approaches of Nordhaus and Tol. The use of multiple (four) types of damages in PAGE09 is similar to FUND. However, the sectors share a common (quadratic) functional form. Thus Hope's efforts are geared toward accurate calibration of these functions, which is more akin to the RICE/DICE approach.

[25]Ackerman and Munitz (2012a) first point out this issue with respect to FUND 3.5, but the problem persists in FUND 3.7

[26]The temperature thresholds are approximately 29° C for corn, 30° C for soybeans and 32° C for cotton (Schlenker & Roberts, 2009, p. 15594)

function (e.g. equation 36) is ill-suited to capture this behaviour.

In addition to the panel analysis Schlenker and Roberts (2009, p. 15596) show that cross-sectional and time series regressions yield the same conclusion: agricultural production suffers severe nonlinear effects from increased exposure to warmer temperatures. These results are especially important for economists. The time series regression shows that even with the enormous productivity gains in agriculture from 1950 onwards there has been no noticeable improvement in crop resilience to extreme temperatures. Secondly, county-level cross-sectional analysis allows for the possibility of year-to-year adaptation by farmers.[27] Evidently adaptation has been inconsequential for larger temperature increases. Finally, although the study takes no explicit account of the fertilization benefits of higher CO_2 concentration, Schlenker and Roberts's focus on total production level impacts suggests that this additive factor, equation (37), should be given little to no weight in a damage function.

The point here is not to single out problems in FUND 3.7. (Indeed, the imprecision found in this model is likely to be, at some level, implicitly built into DICE and PAGE.) Rather, we wish to highlight that even sophisticated economic models can lag for years behind climate science. As another example, all three IAMs treat sea level rise (SLR) as globally uniform, but recent evidence suggests this is not accurate. Kopp (2013) affirms that over the past decade the northeast US seaboard has experienced a more rapid sea-level rise than the global average, although he concludes that it is too early to determine if the recent SLR is "beyond the bounds of 20th-century variability" (Kopp, 2013, p. 5). Conversely, IPCC Working Group II (2014) shows that SLR in East Asia has been much lower than anticipated, whereas the East Pacific waters have risen faster. Since the SLR variability in this region is driven by trade winds it is liable to a quick reversal. Thus, while FUND's use of a digital elevation model to calibrate regions' exposure to SLR incorporates regional damage specificity, it cannot account for regional and temporal differences in the rate of SLR *per se*. With much lower degrees of precision, the DICE and PAGE models do little more than calibrate regional weights in order to estimate the varied impacts from SLR. Such differences may prove important for highly exposed areas such as

[27] They point out that fixed effects panel only allows for within-year planting adaptations.

the eastern United States.

Inevitably, economic models will lag and simplify the climate change models that they seek to build upon. Model inaccuracies are, of course, not eliminated by reducing complexity. In fact using secondary or tertiary estimates of climate damage may simply compound these lagged errors. This view would augur for greater detail in SCC models, albeit with the attendant attention that must be paid to ongoing environmental research. This is certainly the sentiment behind the FUND and, to a lesser extent, PAGE modeling approaches. However, as we discuss in the next section, even the most precisely designed models will face practical coding difficulties. In fact, it was in light of coding error risks that Nordhaus (2012) choose to reduce the complexity of the DICE/RICE model.

6.2 Coding Complexity: The Tol–Ackerman Controversy

In a keynote speech for the European Associate of Environmental and Resource Economists (EAERE) William Nordhaus (2012) discusses the "scary problem of computational complexity." He notes that in the coding industry standard is to expect 1 error per 1000 lines of code, and 1 error per 10,000 lines of "super-clean code". He therefore suspects that "there are multiple errors in our IAMs." Given economists' relative unfamiliarity with coding architecture practices, Nordhaus argues for a reduction in the complexity of cost-of-carbon models. Among the examples of programming errors in economic IAMs that he presents is the potential division by zero in the FUND 3.5 model. This problem was first discovered by Ackerman and Munitz (2012a). However, Anthoff and Tol (2012) vociferously rejected this finding and thereby set off the Tol–Ackerman controversy.

FUND is an impressively complete integration of a climate model with economic damages. As sections 3, 4 and 5 suggest, coding the FUND model requires a much more sophisticated algorithm than the other two models reviewed here. With the help of David Anthoff, Frank Ackerman and Charles Munitz learned to install, run and debug FUND 3.5. They found that the temperature-level damage to agricultural production (the counterpart of version 3.7's $A^l_{t,r}$, our equation 36) contained a coding error which allowed for a possible division by zero.

In FUND 3.5 the optimal temperature for agricultural production is a random parameter, T^*, and the realized temperature level T is generated through the carbon cycle and radiative forcing equations.[28] The temperature level's impact on agricultural output is – as in sec. 4.2.1 – a quadratic function of T, but with linear- and quadratic-term weights determined by deviations of the optimal temperature from a given value (=1.6). Specifically,

$$A^l = \frac{-2AT^*}{10.24 - 6.4T^*} \cdot T + \frac{-2A}{10.24 - 6.4T^*} \cdot T^2 \tag{71}$$

Both T^* and A are regionally-specific Monte Carlo parameters which are chosen 16 times (one for each region) in each of the 40,000 MC runs. Clearly, the denominator of (71) equals zero when $T^* = 1.6$, at which point A^l is undefined in FUND 3.5. In particular as $T^* \to 1.6$ then $|A^l| \to \infty$, implying extreme values are produced in the neighborhood of $T^* = 1.6 \pm \varepsilon$.

Ackerman and Munitz (2012a) report that T^* is normally distributed. Without specifying the distribution they note the critical divide-by-zero value of a region's optimal temperature is within one-quarter of a standard deviation of the distribution's mean:

$$T^* = 1.6 < E[T^*] \pm \frac{1}{4}\sigma_{T^*}$$

Therefore, one can reasonably expect that in at least some of the 40,000 model runs A^l will approach $-\infty$ or $+\infty$, depending on whether $T^* \to 1.6$ from the left or right. This is a crucial problem for Monte Carlo simulations since the reported results are the average of all model runs.

Indeed, the purpose of Monte Carlo simulations is to produce accurate projections given a set of probabilistic variables. However, MC runs with $T^* \approx 1.6$ will skew the averaged A^l results.[29] Moreover, as Ackerman and Munitz (2012a, p. 222) point out, "this problem could become more severe as the number of Monte Carlo iterations rises, since the likelihood of coming dangerously close to the critical value

[28] Time and regional subscripts have been removed for the sake of clarity.

[29] This to say nothing about the inaccuracy of extreme values resulting from computers' floating-point representation of real numbers.

steadily increases." Normally, increasing the number of MC runs should reduce the uncertainty of a projected estimate, but with an equation like (71) the standard error increases with the number of iterations.

In their reply, Anthoff and Tol (2012) note that the diagnostic test run by Ackerman and Munitz is not exactly in the form of equation (71). Ackerman and Munitz (2012a) use the function $F(X) = \frac{1}{X-0.25}$, with $X \sim N(0,1)$, to demonstrate extreme variation that a near division by zero causes. Anthoff and Tol (2012) argue that this misrepresents their formulation in which there is also a normal variable in the numerator. It is not clear why this should matter. Their more effective response is that they perform a diagnostic test by "trim[ming] the realizations that are closest to the suspected division-by-zero" and compare these results to the untrimmed trials; they find no substantial difference in the estimates of agricultural sector damage (Anthoff & Tol, 2012, p. 42).[30] Despite this spirited defense, in FUND versions 3.6 and 3.7 the agricultural damage function is altered such that there is no longer any risk of dividing by zero, e.g. equation (36).

This controversy is important as a cautionary tale. Expert programmers are not immune to programming errors, so there is no reason to expect economists to be any less error-prone. However, recognizing and correcting coding mistakes should make economic IAMs progressively more sound. Certainly, there is merit in pressing ahead with these models, though with a healthy recognition of the discipline's limits. On the other hand, given such coding problems (more examples are given in Nordhaus, 2012), one can understand the logic in Nordhaus's decision to return to his, and other economists', area of comparative advantage: building dynamic macroeconomic models. As we discuss below, there is a need for environmental economists to revisit the conceptual framework that the social cost of carbon has been built upon. Advancements in economic integrated assessment modeling have been impressive, but it will be for naught if the link with theory is lost.

[30] In their rejoinder Ackerman and Munitz (2012b, p. 43), somewhat sardonically, note that "It is possible to run a model with a known algebraic defect, and then manually screen the results to determine whether any distortions were caused by the defect but it does not seem to us like an ideal modeling methodology."

6.3 Cost or Benefits? Conceptual Problems in the Social Cost of Carbon

Before one can tackle the practical difficulties of following climate science research and best practices for coding architecture, one must sort through a number of conceptual issues. These include determining the type of growth model to be used (e.g., Nordhaus & Boyer, 2000, chapter 2), the proper discount rate applied to future damages (e.g., Arrow et al., 2013; Stern, 2007, Part II) and the modeling approach to rare but extreme events that are often typified by threshold dynamics (e.g., Jones & Yohe, 2008; Greiner, Grüne, & Semmler, 2010) Greiner et al., 2010. Firstly, and at a more fundamental level, economists must decide upon a methodology for quantifying and aggregating the welfare gains/losses from climate change experienced by people in different regions and societies. On this methodological score the agreement among economists is amazingly widespread. The vast majority of social cost of carbon models use the approach outlined in Fankhauser et al. (1997), known as the willingness to pay (WTP) welfare theory.

Simply put, the WTP approach evaluates the benefits (reduced losses) from avoiding climate change in order to establish how much consumption the representative agent would forego (i.e., would be willing to pay) for such benefits. The flip side of this quantity is the willingness to accept (WTA) climate change, in which a worsening climate would be balanced by the increasing level of consumption made available through higher investment in traditional capital accumulation rather than mitigation (Fankhauser et al., 1997). Posing the problem in WTP/WTA terms ensures that the social cost of carbon estimate measures the marginal benefit (WTP) and/or marginal cost (WTA) of climate change mitigation. Evaluating policies at the margin, of course, is essential for coherent analysis of general equilibrium models. Of course, marginal costs and benefits equate only at the optimum – an obvious but important point that many SCC estimates gloss over by estimating only one marginal value (typically, WTA) and not the other.

In a poignant reminder of the WTP/WTA conceptual foundation Foley et al. (2013) show that, whether in a static or dynamic model, the social cost of carbon has an unambiguous value only along optimal policy paths.[31] This has important implications for quantifying SCC because "[e]stimates of costs and benefits of greenhouse gas mitigation must be conditional on a scenario that specifies a reference path of consumption and environmental quality" (Foley et al., 2013, p. 94). If the baseline is a 'business-as-usual' path (or some other policy path that is suboptimal in climate mitigation) then SCC is an ambiguous value: it depends on whether one measures the costs or benefits from climate change mitigation. Although there is a great deal of uncertainty about the actual impacts from climate change, there is strong evidence that they will be severe (see IPCC, 2012). Given the relatively small amount of investment ($\approx 2\%$ of global GDP) needed to eliminate industrial CO_2 it is likely that marginal benefits will produce very large cost of carbon estimates (Foley et al., 2013, p. 95). Yet all of the models reviewed here base their SCC estimate on the marginal costs. This is a practical necessity since capital loss estimates are observable and, therefore, can be empirically estimated. Yet, this empirical necessity has serious conceptual implications when the marginal cost estimates are just assumed to equal latent benefits. All economic IAMs could benefit form a more complete discussion of this issue.

Finally, there is a serious conceptual issue in using predefined, exogenous growth rates. IAMs without endogenously (optimal or not) determined economic development violate a key tenet of general equilibrium theory: agents' optimal capital allocation. The use of exogenous growth in the FUND and PAGE models means that representative agent's "consumption path is invariant to different scenarios. The cost and benefit of climate change mitigation, however, entail reallocations of resources at a non-marginal scale so that the assumption of exogenous consumption paths does not hold" (Foley et al., 2013, p. 93). That is, the high cost of climate damages predicted by each of the economic IAMs implies very different investment decisions (and hence consumption paths) based on the realized environmental scenario. While it is not clear if the FUND and PAGE models could be redesigned to have some kind of endogenously generated output function, it is a highly advisable next step.

[31]We thank Gregor Semieniuk for bringing this article to our attention. Note as well that the common result $MC \neq MB$ is also discussed in Tol (2009, p. 38-39)

7 Conclusion and Outlook for Future Research

This report provided an overview of how economic damages from climate change are determined in the 3 major integrated assessment models that calculate the social cost of carbon: DICE, FUND and PAGE. These models can be considered the state of the art for economists' modeling of climate change. We began with a review of the IPCC approach to climate modeling and how economic IAMs have developed out of this approach. We then provided a detailed exposition of the damage functions of each economic IAM. We found a great deal of variation in each model's approach to damage function modeling. DICE uses a reduced-form, single equation representation of damages. FUND models each damage separately using as much sectoral detail as possible. The PAGE model uses two reduced-form damage functions (economic and non-economic impacts), but also includes a threshold damage function to account for a climatic tipping point. We have also shown that despite the relative sophistication of these models, a great deal of work remains to be done. Economic models of climate change and the social cost of carbon are still at a nascent stage. We hope to introduce a more complete model of economic dynamics and policy action in future work.

First, the introduction of nonlinear economic and climatic dynamics is essential. For example, the notion that there exists a climatic tipping point beyond which global temperature change becomes self-reinforcing is increasingly accepted among environmental scientists, but has yet to make serious inroads into economic models of climate change. One notable exception is Greiner et al. (2010) who model the Skiba plane in CO_2 concentration-temperature-capital space. The nonlinear (i.e., curvy) Skiba plane divides three-dimensional space into domains of attracting steady states. One attractor is slightly above the pre-industrial CO_2 concentration level; the other is at a very high and dangerous CO_2 level. Depending on the global mean temperature, they find that concentration levels between 170% and 240% of the pre-industrial level represent a sharp tipping point. If carbon emissions were halted at a level below the tipping point, Greiner et al. (2010, p. 72-3) show that CO_2 concentration would slide back to approximately 150% of the pre-industrial level (which is associated with only minor temperature increases). Conversely, at CO_2 levels above the threshold, even zero-emissions scenarios would generate concentrations increasing to 300% of the pre-industrial level of atmospheric CO_2. Even if such non-linearities were a remote possibility (which does not seem to be the case), the precautionary principle would demand that we take decisive abatement action now.[32] At the very least, the leading economic IAMs should all take explicit account of these threshold nonlinearities.

Secondly, the climate change IAMs here reviewed seriously assess only *abatement* policies. Very little attention is paid to responses to climate change damages despite the pressing practical importance of *adaptation*. With the exception of FUND's costal protection variable ($P_{t,r}$ in section 4.2.5) the modeled climate change policies only reduce emissions and, thereby, damages. Abatement policies are no doubt important, but we have reached a point at which a certain level of climate change is inevitable. At a recent talk Michael Oppenheimer (18 November 2013) noted that even if global emissions were to stop today, temperatures would not stop rising for another 40 years, when the current atmospheric CO_2 is finally depleted to an equilibrium level. Therefore, a crucial next step is to embed adaption policies into climate change models. In fact, the urgency of adaptation is a central message in the UN's most recent report on climate change (IPCC Working Group II, 2014).

Unlike abatement policy functions, however, adaptation policy is necessarily specific to the form of damage against which it is directed. PAGE's delineation of economic, threshold and non-economic damages is instructive. Adaptation to economic damages would include lowering cooling costs, protection agricultural production and, as already done in FUND, coastal protection against sea level rise and attendant flooding. These efforts require large investments and, potentially, capital relocation costs. Adaptation to extreme-but-rare events such as tropical storms and wild fires will also require infrastructural development, but the model for such cost estimates would differ greatly from incremental economic damages. Thirdly, one must consider the human and ecological toll of climate change. In addition to

[32]Importantly, the macro-level nonlinearities devised by Greiner et al. (2010) are supported by smaller-scale studies such as the agricultural research of Schlenker and Roberts (2009) discussed in section 6.1 above.

the aforementioned damages, these non-economic impacts come from higher disease rates, extreme heat or cold and lost biodiversity. Again, these non-monetary damages require a very different modeling structure. Finally, in considering adaptive policy responses to climate change, our models must be honed toward the specific risks and capacities of the geographic region in question.

In the coming months our future research will focus precisely on such issues, by asking what kind and how much adaptive and protective infrastructure should be built in order to limit climatic damages. To that end, this report will serve as a primer for a robust and coherent modeling approach to the economic damages of climate change. Ultimately a complete economic policy model should include abatement and adaptation options as well as a transition path for renewable energy sources (e.g. Greiner, Grüne, & Semmler, 2014). However, we have a long way to go before reaching this goal. Our immediate next step is to develop a more generic model for government investment in infrastructure to adapt to, and abate, climatic damage. Indeed, although the impacts will vary from region-to-region and year-to-year, every country will need to invest in new infrastructure against the growing risks induced by climate change.

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