

Valuing Potential Climate Impacts: A Review of Current Limitations and the Research Frontier

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Estimating the economic cost of climate impacts is difficult for many reasons related to complex interactions and uncertainty in the coupled earth-human system. This review paper describes current approaches to valuing climate impacts in integrated assessment models, summarizes eleven primary critiques, and identifies the frontier of climate impacts research that could serve to advance the state of the art.

Introduction

Climate impacts cut across many dimensions, and determining a comprehensive relationship between climate change and social welfare is challenging for many reasons, including complex interactions among physical, natural, and social systems and the heterogeneous nature of climate impacts that vary across space and time. The economic cost of these impacts is estimated using cost-benefit integrated assessment models (IAMs) that simulate the ‘causal chain’ from greenhouse gas (GHG) emissions to climate damages. Though many recent commentaries on the state of climate change economics have pointed to the representation of climate impacts in these models as an area requiring major improvement (Burke et al., 2016; Revesz et al., 2014), there has been no systematic review of the literature base.

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This review proceeds in three parts. The first part describes existing IAM damage functions, focusing on the three models used by the Interagency Working Group (IWG) of the U.S. Government to calculate the social cost of carbon (SCC)—DICE, PAGE and FUND (hereafter the IWG models). The second part summarizes and reviews critiques of these damage functions in the literature. The last part considers opportunities to improve and update model damage functions, discussing substantial advances in both the science and economics of climate change impacts as well as the challenges involved in incorporating findings into damage functions.

Part One: Existing State of IAM Damage Function Calibrations

Aggregate damage functions have long been used in climate-economic analyses to relate projected temperature change to social costs (e.g., Cline, 1992; Nordhaus, 1991, 1992), and the IWG damage functions are remarkably similar to the earliest efforts. The typical functional form of damages is an increasing power function of mean surface temperature change, often quadratic (Kopp et al. 2011; Warren 2011). This simple, compact (if arbitrary) functional form suited the computational constraints of cost-benefit IAMs and the analytical models that preceded them (e.g., Nordhaus 1991). Damage functions tend to be calibrated to point estimates of damages corresponding to a benchmark warming level (e.g., 2 or 3°C), either taking a

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bottom-up, additive sectoral approach as in the RICE model (Nordhaus & Boyer, 2000) or a top-down, aggregate form as in DICE-2013 (Nordhaus & Sztorc, 2013) based on the Tol (2009) meta-analysis. For certain impact categories there exist markets that can inform estimates (e.g., agriculture, forestry, coastal property and structures), while for intangible impacts (e.g., biodiversity, environmental quality, and human health) contingent valuation or hedonic methods are used.

There are several broad approaches to estimating climate damages. Process model or enumerative approaches simulate physical, natural science, and/or engineering processes and their response to climate variables. These have the advantage of being realistic and interpretable (Tol, 2009), though they can be computationally intensive, generally only cover a single link of the causal chain, and require scarce empirical evidence for parameterization (Fisher-Vanden, Popp, & Wing, 2014). Statistical methods use observed weather variations to directly estimate economic impacts in a given sector, though there is the potential for bias from unobserved factors as well other methodological challenges (discussed in more detail in Part 2). Nevertheless, there has been a recent surge in these econometric studies contributing to the empirical basis for estimates of climate change impacts and adaptation (Dell, Jones, & Olken, 2014; Fisher-Vanden et al., 2014). There is also a small literature that applies expert elicitation to gather subjective assessments of climate risks and potential damages, particularly for impact sectors that lack data. Nordhaus (1994a) surveyed about 20 experts to estimate the overall economic impacts of 3 and 6°C warming, while other expert surveys have focused on assessing physical impacts (Bamber & Aspinall, 2013; Kriegler, Hall, Held, Dawson, & Schellnhuber, 2009; Morgan & Keith, 1995; Vaughan & Spouge, 2002).

The remainder of this section will focus on the three publicly-available, highly aggregated, IAMs—DICE, FUND and PAGE—used by the US Government Inter-Agency Working Group (IWG) to calculate the SCC (IAWG, 2010, 2013). These models have long histories and have produced most of the SCC estimates in the recent scientific literature (Tol 2009). The three models differ substantially in terms of their structure, assumptions, and parameterization, as described in Rose, Diaz & Blanford (2017). DICE has two quadratic damage functions that are driven by global mean temperature and SLR respectively, while FUND and PAGE have functions that respond dynamically to a broader set of drivers such as population, per capita income, and technological change. Here we describe the key features of the IWG damage modules, followed by a more detailed discussion of two sectors, agriculture and coastal impacts.

DICE

The DICE model was developed in 1992 by William Nordhaus (Nordhaus, 1992). DICE is an inter-temporal optimization model of economic growth for the world as a single region, balancing the cost of mitigation with the damages from climate change. The IWG did not run the DICE model in its traditional form as an optimization model to compute the SCC, but rather as a simulation model driven by the exogenous socioeconomic scenarios.

The latest SCC estimate used the 2010 version of the DICE model (re-coded in MATLAB and run in-house by IWG). The single region DICE-2010 model is calibrated to the 12-region RICE-2010 model in terms of socioeconomic, technology, and damage parameters. RICE-2010 consists of aggregate damage functions for each region, citing the Tol (2009) meta-analysis of IAM estimates and the IPCC (2007) synthesis of the impact literature as the calibration source (Nordhaus, 2010). DICE has been updated twice since the 2010 version used by the IWG. DICE-2013R also cites the Tol (2009) survey as the starting point for damage calibration, and retains the adjustment factor of 1.25 for omitted or intangible impacts. DICE-2016 uses a quadratic damage function calibrated to a meta-analysis by Nordhaus and Moffat, and implies slightly lower damages of 2.1% GDP loss at 3°C warming (Nordhaus, 2017).

DICE-2010 was the first and only vintage of the model to explicitly include a module for sea level rise (SLR) that computes the physical extent and economic impacts. SLR is decomposed into contributions from four major processes: thermal expansion, melt from glaciers and small ice caps, Greenland Ice Sheet melt, and Antarctic Ice Sheet melt, each parameterized in accordance with the IPCC Fourth Assessment Report (Nordhaus, 2010). Coastal impacts from SLR are removed from the aggregate damage function and reformulated as a function of SLR. The remaining of climate damages are classified as non-SLR damages.

Due to DICE's highly aggregate nature, many features are accounted for in an implicit manner. For example, the effect of adaptation is included implicitly to the extent that the damage function is calibrated to estimates that report the residual damage after accounting for adaptation.

FUND

FUND is based on version 3.8 of the FUND model. FUND was developed in 1993 by Richard Tol, and since 2006 has been co-developed with David Anthoff (Tol 1995). It is the most

disaggregated cost-benefit IAM, covering 14 distinct impact sectors and 16 regions. FUND considers damages for sea level rise, agriculture, forests, heating, cooling, water resources, tropical storms, extratropical storms, biodiversity, cardiovascular respiratory, vector borne diseases, morbidity, diarrhea, and migration, each with a specific damage functional form based on or calibrated to a published impact assessment, with regional parameters based on spatial patterns of warming, estimated impacts, or other regional assumptions and adjustments (Tol 2002a). FUND projects a positive climate impacts in certain sectors (e.g., avoided energy expenditures for space heating, increased productivity in agriculture and forestry), implying net global benefits up to roughly 2.5°C of warming.

Many of FUND's damage functions are formulated with 'dynamic vulnerability', such that exposure or vulnerability to climate impacts changes dynamically over time depending on socioeconomic metrics like population growth, income growth, and technological change. Vulnerability is projected to decrease over the long-run in many impact sectors, e.g., energy consumption declines with energy efficiency, agriculture decreases as a share of overall GDP as economies develop, and exposure to vector-borne diseases will decline with improved health care. Dynamic vulnerability works in both directions, however, and other impact sectors may become more vulnerable over time. For example, water resource impacts will be amplified with population growth, exposure to heat-related disorders will increase with urbanization, and willingness to pay to avoid damages to ecosystems and mortality will increase with higher per capita incomes. The income elasticities are estimated from cross-sectional data or taken from the literature in accordance with Tol (2002b). Dynamic vulnerability is distinct from the concept of climate adaptation, which is a direct response to the expected change in climate. FUND models proactive adaptation in the coastal sector, weighing the cost of retreat against those of protection in order to avoid incurring the worst impacts of SLR in the no adaptation case. FUND does not explicitly include possible high-impact, uncertain consequences of climate change but extreme outcomes are included via the long tails of uncertain parameter distributions.

PAGE

The PAGE model was developed in 1991 by Chris Hope with several updates (e.g., Plambeck 1996, Hope 2006) prior to the current PAGE09 model used by the IWG for the current SCC

estimate (Hope2011a). PAGE specifies four sectors for damages: sea level, economic, non-economic and discontinuity. The SLR damage function is calibrated to Anthoff et al. (2006) and the economic and non-economic damage functions are based on Warren (2006), such that all three have an aggregate impact before adaptation of just under 2% of GDP for a temperature rise of 3°C.² The discontinuity impacts are calibrated to the Nordhaus (1994) expert survey and Ackerman et al. (2009).

The PAGE damage functions for each sector are calibrated for the EU and then adjusted for other regions based on a coastline length scaling factor and assumptions about adaptive capacity. PAGE includes two types of adaptation: 'plateau' increases the tolerable level of SLR or warming without suffering any damages, and 'impact' reduces the remaining damage by a fixed percentage. The adaptation policy and capacity is prescribed for each region at the outset of the PAGE model run and does not depend on the severity of climate change.

Agriculture Spotlight

Of the three models used by the IWG, only FUND has a separate damage function for the agricultural sector. Agricultural damages in FUND are a linear sum of three types of impacts: the level of warming, the CO₂ fertilization effect, and the rate of warming (Anthoff and Tol 2014b). The sum of the three components give the percent of agricultural production impacted by climate change, applied to the gross agricultural product (assumed to decline over time with economic development) to determine overall damages in absolute terms.

The effect of level of warming is a quadratic, parameterized separately for each of the 16 regions in FUND. These quadratics all give positive impacts for moderate warming that become negative at higher levels of warming. Calibration is described in Tol (2002a) and is based on economic studies from the early 1990s: Kane (1992), Reilly (Reilly, Hohnmann, and Kane 1994), Darwin et al. (1995), Fischer et al. (1996) and Tsigas et al. (1996). These are all economic studies using computable general equilibrium (CGE) or agricultural market models combined with GCM projections of climate change and an estimate of the yield impacts. The range over which the level of warming benefits agriculture ranges from 0.75°C in South America to 5.75°C in Canada (Anthoff and Tol 2014b).

2 The aggregate impact is allocated such that 'half of impacts are sea level, one-quarter economic, and one quarter non-economic' according to a comment in the model Excel file. Note that Warren (2006) is a review of four IAMs (DICE, FUND, PAGE, and MERGE), so PAGE is calibrated to the consensus of IAM output, not the impacts literature.

The CO₂ fertilization benefit is formulated in FUND as having a declining marginal effect using a natural logarithm. The effects of CO₂ fertilization are calibrated based on average difference in damages between studies that did and did not include CO₂ effects. Benefits estimated from this meta-analysis vary between regions. A doubling of atmospheric CO₂ concentration benefits agriculture by between 16% (Small Island States) and 2.8% (Canada).

The effect of adaptation, parameterized in the damage function based on the annual rate of climate change, is based on the average difference in impacts between studies that did and did not include adaptation. Damages from the rate of climate change are strictly negative and depend on the rate of temperature change in the current time period as well as damages in the previous time period. Consistent with the observation that there is relatively little known about the rate or effectiveness of private adaptation, the parameters in this damage function are documented as educated guesses (Anthoff and Tol 2014b).

Coastal Impact Spotlight

The IWG models formulate coastal damage functions in terms of the level or rate of sea level rise (SLR), which requires the intermediate translation of temperature projections into a corresponding SLR pathway. Each of the models projects SLR in its own way using a component approach or equilibrium function, and notably produce very different SLR projections to drive the damage functions, with FUND projecting twice as much SLR as PAGE in 2050 and 2100.³

Coastal impacts from SLR in DICE are removed from the classic DICE aggregate damage function, and reformulated as a quadratic function of SLR, $D_{SLR} = 0.00518 SLR_t + 0.00306 SLR_t^2$ implying coastal damages are 0.8% of GDP at 1m of SLR, though there is no documented basis for the point estimates used for either the SLR or aggregate non-SLR damage function calibration or the rationale for the quadratic form.

Coastal impacts in FUND are computed at the regional level using a simple process model of adaptation that trades off the cost of retreat against those of protection following the adaptation cost/benefit rule derived in Fankhauser (1995) with cost functions calibrated to Hoozemans et al. (1993), Bijlsma et al. (1995), Leatherman and Nicholls (1995), Nicholls and Leatherman (1995), and Brander et al. (2006). Net damages after adaptation expenditures can be less than half the projected damages without adaptation (Anthoff, Nicholls, and Tol 2010).

This formulation assumes perfect foresight and efficient adaptation to sea level rise, neglecting market and other institutional barriers to adaptation, allowing sea wall protection to be flexibly built each year.

SLR impacts in PAGE are a power function of the height of SLR, $D_{SLR} = wSLR_t^p$. The uncertain exponent p has a mode of 0.7, based on the relationship between exposed land, people, and GDP versus SLR in Anthoff et al. (2006), which finds impacts rise less than linearly with SLR, reflecting the general coastal tendency for the density of land and people to decrease with elevation. The mode of the uncertain parameter w is calibrated to constitute half of the aggregate impact of 3°C reported in Warren et al. (2006), which is based on SLR impacts reported in Anthoff et al. (2006). Diaz (2014) notes it is difficult to reconcile this citation: the PAGE function implies that 0.5 m of SLR in 2100 would cause a 1% loss of world GDP (i.e., \$2 trillion), while Anthoff et al. find \$10–20 billion in damages for 0.5 m SLR for the entire 2080 decade (\$1–2 billion per year), two orders of magnitude smaller than in PAGE. PAGE also accounts for exogenous coastal adaptation to avoid damages from SLR, with coastal adaptation costs based on Anthoff et al. (2006).

Part Two: Limitations of Current Damage Functions

This section describes of published critiques of current damage functions, and discusses related issues and implications for valuation of climate impacts.

1. Extrapolation to High Temperatures

Several authors point out that economic damages at higher levels of warming are largely unknown and that the extrapolation of damage functions beyond calibration points is essentially arbitrary (e.g., Ackerman, 2010; Dietz & Stern, 2014; Weitzman, 2012b). Most of this literature addresses the DICE damage function, which is calibrated to damages at 2.5°C of warming but then extrapolated to higher temperatures using a quadratic functional form. However, the limited calibration basis for impacts at higher temperatures is not unique to DICE. PAGE is calibrated to damages at 3°C of warming and the sector-specific studies underlying FUND damage functions are typically for warming of between 1°C and 2.5°C (Tol 2002a).

Several authors reference the study by Sherwood and Huber (2010) showing that unabated warming will produce wet-bulb temperatures that make large areas uninhabitable as evidence

³ See Diaz (2014) for details on the SLR projection modules.

that the quadratic extrapolation in DICE under-estimates damages at high temperatures (Fisher & Le, 2014; Revesz et al., 2014; Weitzman, 2012a). For example, DICE damages at 6°C and 12°C are equivalent to a loss of 8% and 26% of GDP respectively, yet Sherwood and Huber (2010) find that 12°C of warming would render areas occupied by half the human population uninhabitable. Other studies point to non-linearities or catastrophes at higher temperatures that would increase the convexity of the damage-function such as the abandonment of low-lying areas and island states due to sea-level rise or the non-linear response of crop yields to warming (Fisher & Le, 2014; Hanemann, 2008). Nevertheless, very few impact analyses have been conducted at these higher temperatures.

Weitzman (2012a) considers an alternative damage function that matches DICE damages in the calibration region between 0 and 2.5°C but increases more rapidly with temperature, producing damages of 50% for a warming of 6°C and 99% for 12°C. He argues that damages at these temperatures are important because uncertainty over equilibrium climate sensitivity means the distribution over future temperature change is fat-tailed and that high-temperature damages will therefore dominate the cost-benefit analysis of climate policy (Weitzman, 2009).

The importance of these high-temperature extrapolations is largest when combined with other model structural assumptions. Since very high temperatures are not reached until the distant future, discounting means the damages therefore have little impact a measure like the SCC (Weitzman, 2012a). Ackerman and Stanton (2012) find the Weitzman damage function increases the SCC by approximately a factor of 4 when combined with a fixed 3% discount rate. It is also important when some damages fall on the growth rate rather than output (Dietz & Stern, 2015), or when combined with a fat-tailed temperature distribution to calculate expected utility, particularly with a very low pure rate of time preference and high risk aversion (Weitzman, 2012a).

2. Extrapolation to Other Regions

A further extrapolation critique of damage functions is that the underlying literature consists of impacts estimated for a specific region, which are then applied to other regions the world (Warren et al. 2006; Warren 2011). van den Bergh and Botzen (2014) note that regional extrapolation is prevalent because

damage cost estimates for developing countries are limited by data availability and quality, and caution that extrapolation may fail to account for their relative vulnerability.⁴ Modelers often apply adjustment factors to extrapolate to developing regions (e.g., Nordhaus, 1991; Manne and Richels 1995), though this fails to fully account for geophysical and socioeconomic drivers of impacts.

For example, PAGE defines damage functions for the EU reference region, which are then adjusted to the other regions with linear scale factors ranging from 0.4 to 0.8. Hope (2011a) explains the basis for this formulation as the fact that other regions are on average less vulnerable than the EU for the same sea level and temperature rise because of the long coastline of Europe.⁵ Another example of extrapolation across regions is the FUND damage function for cardiovascular and respiratory mortality, as described in Anthoff & Tol (2014a): ‘Martens (1997) assesses the increase in mortality for 17 countries. Tol (2002a) extrapolates these findings to all other countries’ based on a linear function of extreme temperature.

3. Coverage of Impact Categories

The fact that damage functions have incomplete coverage of known impact sectors is widely acknowledged (IAWG, 2010; Marten et al., 2013; Neumann & Strzepek, 2014; Revesz et al., 2014; Tol, 2002, 2005, 2009; Warren, 2011; Watkiss & Downing, 2008; Watkiss, 2011). Some authors argue that for this reason SCC estimates should be viewed as a lower bound (Howard 2014; van den Bergh and Botzen 2014), however this claim must be considered alongside other known issues with SCC estimation that may cause different biases (e.g., Rose et al. 2017).

Of the IWG models, FUND has the most comprehensive and explicit bottom-up coverage, including climate impacts in 14 sectors: sea level rise, agriculture, forests, heating, cooling, water resources, tropical storms, extratropical storms, biodiversity, cardiovascular respiratory, vector borne diseases, morbidity, diarrhea, migration. Tol (2002a) notes that “the list of omitted impacts is long. It includes amenity, recreation, tourism, extreme weather, fisheries, construction, transport, energy supply, morbidity, and so on. The reason for omitting is that no comprehensive, quantified impact studies have been reported.”

⁴ A distinct concept, regional equity weighting, is discussed later.

⁵ Diaz (2014) notes that this approach appears inconsistent with the fact that PAGE damage functions are calibrated to global studies of climate impacts, not European studies; it is also unclear why the same coastlength scaling factor applies to economic, non-economic, and discontinuity impacts, as well as the cost of adaptation in all four sectors.

DICE accounts for common impact sectors indirectly through its RICE calibration; Nordhaus (2014) states further: “current studies generally omit several important factors (biodiversity, ocean acidification, and political reactions), extreme events (sea-level rise, changes in ocean circulation, and accelerated climate change), impacts that are inherently difficult to model (catastrophic events and very long-term warming), and uncertainty (of virtually all components from economic growth to damages).” An adjustment factor of 1.25 is applied to account for such omitted or intangible impacts. Finally, two of PAGE’s four damage categories (economic and non-economic impacts) use a top-down aggregate function without specifying what is covered or omitted, though the underlying basis for calibration (i.e., Warren et al., 2006) includes both FUND and RICE damage estimates.

Impacts are typically omitted from IAM damage estimates because they are difficult to quantify and therefore lack the requisite underlying IAV and economics literature. Howard (2014) provides a detailed compilation of omitted damage categories that includes damages from acidification and warming in oceans, wildfire, large-scale migration, energy supply, labor and capital productivity, and geopolitical instability. Tol (2009) identifies saltwater intrusion to freshwater resources and tropical storm intensification as well. Neumann and Strzepek (2014) identify less-studied market sectors such as manufacturing, mining, tourism, recreation, finance, and insurance, and also note that many indirect or second-order effects (e.g., malnutrition or business interruptions) have yet to be accounted for, even in the sectors that have a deeper research base. Sussman et al. (2014) emphasize poor coverage of intangible impacts, such as the loss of cultural heritage, historical monuments, charismatic species, and disruptions to ways of life, which are thought to be socially compelling but are challenging and controversial to quantify. Neumann and Strzepek (2014) identify omitted sectors that could potentially be included once the literature basis is more developed, noting that infrastructure, ecosystems, crime, labor, and factor productivity have a few impact estimates but may be incompletely addressed (e.g., ecosystems are largely a sample of convenience) or depend on a single thread of evidence (e.g., crime) or both (e.g., infrastructure).

Watkiss and Downing (2008) and Tol (2009) note that not all omitted impacts will be negative. Warmer temperatures in the Arctic and the corresponding loss of sea ice may afford new shipping routes and other commerce or resource opportunities.

Additionally, certain negative effects of cold weather, such as winter storms and traffic disruptions, may be avoided at low levels of climate change, although these may be balanced out by increased occurrence of heat-related issues. Tourism is also expected to have heterogeneous effects, as tourist revenue is redistributed based on climatic shifts. van den Bergh and Botzen (2014) suggest that negative effects of climate change are thought to dominate omitted or unquantified positive effects, though this question illustrates large remaining research gaps in impact valuation.

4. Treatment of Inter-Sectoral and Inter-Regional Interactions

Many researchers note that the IWG models fail to represent potentially important inter-sectoral and inter-regional interaction effects in their damage modules (Kopp and Mignone 2012; Marten et al. 2013; Warren 2011; IAWG 2010; Howard 2014; Hitz and Smith 2004). Almost all damages in the three IWG model are additive in both regions and sectors, meaning there is no explicit mechanism for interactions of climate change impacts between sectors or regions. The exception is inter-regional migration in FUND that is driven by land inundation from sea level rise, with costs based on per capita income (Anthoff and Tol 2014b). Furthermore, the underlying impacts literature basis for bottom-up damage estimates consists mostly of isolated studies of a given sector and/or region, so inter-sectoral and inter-regional interaction effects are also implicitly unaccounted for (Weyant 2014; Warren 2011; Howard 2014; Huber et al. 2014). To the extent that such interactions could either exacerbate or alleviate the damage to society, the common practice of summing across sectors and regions will produce incomplete SCC estimates.⁶

Water in particular has been recognized for having critical inter-sectoral interactions (e.g., see Field et al. (2014) for discussion of the well-documented water-energy-land-agriculture nexus) that have not yet been fully captured in damage studies (Bell et al. 2014; Warren 2011). Water resources could affect other sectoral damage analyses through a variety of mechanisms: water availability constrains irrigated agriculture and is integral to electricity supply, affecting hydropower resources and cooling of thermal units, and conversely the water system requires energy to pump irrigation groundwater (Neumann and Strzepek 2014). Weyant (2014) points out that finer scales of resolution (e.g., watershed or agro-ecological zone) are needed to capture these complex interactions to address questions about the magnitude and direction of economic impacts.

⁶ Another limitation of summing bottom-up damage estimates is the fact that impact studies produce estimates that are not comparable due to input assumptions that have not been standardized.

Warren (2011) describes the potential for climate change impacts in one region to affect another, through mechanisms which are both direct (e.g., inter-regional migration in response to desertification, drought, and flooding) and indirect (e.g., higher global food prices from declining agricultural yields in a given region). Tol (2009) notes that most impact studies estimate economic losses from direct costs, ignoring general or partial equilibrium effects. Exceptions include CGE modeling analyses, which can account for important indirect effects from changes in relative prices as well as inter-regional trade (see, e.g., Darwin and Tol (2001) for agriculture and Bosello et al. (2007) for sea level rise).

Related to the issue of inter-sectoral/regional interaction effects as well as omitted impact categories more broadly is the fact that climate impacts are often studied with a narrow scope of analysis, often focusing on the direct effects of climate change on economic assets or production. Oppenheimer (2013) emphasizes the importance of including human responses to climate change in assessing its net impacts, offering the examples of migration, globalization, biofuel production, and changing social vulnerability as influential factors. Calvin et al. (2013) note that the three-way interaction among impacts, adaptation, and mitigation is rarely accounted for in IAMs. Finally, many researchers point out the extreme case of interacting elements: a cascade scenario where impacts of one type trigger a response of another, and this continues to propagate across regions and sectors leading to a far-amplified impact (Huber et al. 2014; The World Bank 2012). Sussman et al. (2014) warn that interdependencies between climatic, ecological, and human systems may lead to such cascading effects.

5. Representation of Adaptation and Technological Change

Representation of adaptation in all three models is highly aggregated and abstract. There are, however, important differences the role adaptation plays in determining damages in each of the models. DICE has no explicit representation of adaptation. Instead, the effect of adaptation is implicitly included to the extent that the aggregate damage function is calibrated to studies that report damages net of adaptation.⁷

FUND includes adaptation as part of the damage functions rather than a policy variable, but explicitly represents adaptation costs in the agriculture and coastal sectors (Anthoff and Tol 2014b). In addition, FUND damage functions have a unique feature termed ‘dynamic vulnerability’, which captures the fact that vulnerability or exposure to climate impacts will change dynamically over time depending on socioeconomic metrics like population growth, income growth, and technological change (Tol 2002b). Although this effect mediates the adverse impacts of changing temperatures in some sectors like health and agriculture, dynamic vulnerability is distinct from the concept of climate adaptation, which is a direct response or investment to reduce climate change impacts.

PAGE includes two types of adaptation, which are classified as plateau and impact (Hope, 2011a). The plateau adaptation increases the adapted tolerable level (e.g., amount of SLR or warming) that a region can tolerate without suffering any damages. The impact adaptation reduces the remaining impact beyond the plateau level by a fixed percentage up to a maximum threshold over the plateau beyond which impacts cannot be reduced for a given region. Net damages are given as the sum of the residual damages plus the cost of adaptation.⁸

Several authors warn that the IAM damage functions that implicitly include private adaptation (for example DICE and some FUND sectors) assume a smooth, instantaneous transition to equilibrium in a new climate state and therefore ignore transition costs that may be substantial (Farmer et al., 2015; Tol, 2009). Firms have to identify a climate signal amidst natural weather variability which may cause costly delays in adaptation (Kelly, Kolstad, and Mitchell 2005; Schneider, Easterling, and Mearns 2000). Other barriers or market failures may limit the rate of adaptation. Empirical quantification of the rate of adaptation and associated adjustment costs is extremely limited, though Hornbeck (2012) finds agricultural adjustment to productivity shocks from the US Dust Bowl took decades. Neumann and Strzepek (2014) point out that the large current ‘adaptation deficit’ calls into question the potential for cost-effective adaptation in the future, noting that assumptions about adaptation learning capacity and pace may be unrealistic. In general, understanding of both the rate and effectiveness of future private adaptation is extremely limited. Both empirical and process-based modeling work is beginning to address this (see Part 2).

⁷ The argument for this approach is that since much of adaptation is a private good undertaken at the local level, adaptation will not necessarily require policy intervention but will instead largely be supplied in the private market.

⁸ Diaz (2014) notes several shortcomings of this formulation of adaptation: 1) The prescribed adaptation policy is set exogenously at the outset of the PAGE model run and does not depend on the severity of climate change. 2) There is an implicit assumption that the cost of undertaking adaptation plus the residual damage is less than the unadapted damage to society, which may not necessarily be the case. 3) Adaptation expenditures could be suboptimal.

A small group of studies has undertaken to modify existing IAMs to explicitly represent adaptation as a public decision variable by incorporating adaptation as a policy variable into DICE (de Bruin, Dellink, & Tol, 2009; Felgenhauer & Webster, 2013), RICE (de Bruin, Dellink, & Agrawala, 2009) and WITCH (Bosello, Carraro, & De Cian, 2010). In doing so, the authors parameterize adaptation cost functions or residual damage functions using information from the impacts literature. Consistent with the observation above that understanding of private adaptation is limited, several authors note the lack of data on the aggregated costs and benefits of adaptation actions required to calibrate these models.

While IAMs commonly represent technological change with respect to mitigation efforts, it is much less typical in damage modules (IAWG 2010). One common approach to representing technological change is through ‘learning-by-doing’, the process by which accumulated experience brings about incremental improvements to production methods, allowing firms to lower costs (Arrow 1962). This relationship can be compactly represented in a learning curve equation (Nemet 2006). Another approach uses a heuristic to account for the energy-saving bias of technical change. The autonomous energy efficiency improvement (AEEI) parameter describes how energy intensity, energy use per unit output across the economy, decreases over time in an autonomous way, regardless of energy prices.

FUND uses the AEEI parameter to account for technological change in energy demand, which affects both the cooling demand and heating demand impact sectors. FUND uses exogenous projections for AEEI at the regional level (Anthoff and Tol 2014a). The global average value is about 1% per year in 1990, converging to 0.2% in 2200. Tol (Tol, 1997) notes that the AEEI parameter, in conjunction with a separate parameter for carbon intensity, is roughly calibrated to match the AEEI implied by the EMF14 standardized scenario.

PAGE includes technological change in adaptation costs in a similar manner. Adaptive costs are specified as a percentage of GDP per unit of adaptation bought and benefit from autonomous technical change, such that the costs come down over time (Hope, 2011a).

6. Out of Date Science

Rose et al. (2017) highlight the fact that the models draw either directly or indirectly on older climate impacts literature, much dating back to the 1990s. Thus, these damage estimates fail to reflect the more recent scholarship from the impacts, adaptation,

and vulnerability (IAV) community. Because many underlying impact studies are dated and because model documentation of the empirical basis for damage functions is sometimes missing, understanding exactly how damage functions were derived is often difficult.

In some cases, there is a circular basis for damage functions being calibrated to IPCC or related summary studies based on IAM results (Pindyck 2013). Rose et al. (2017) traces the underlying studies and independence of different models, noting that damages in both PAGE09 and DICE2010 are calibrated to meta-analyses that include outputs from other IAMs, Warren (2006) and Tol (2009) respectively. These interlinkages suggest that the damage estimates produced by these three models are not independent, which has implications for the IWG experimental design, as it therefore may not be appropriate to average their results with equal weights. Questions of how to aggregate models that are not fully independent into an ensemble average have been explored within the climate science literature because similar questions arise with General Circulation Models (GCMs), many of which share common lineages and parameterizations (Tebaldi and Knutti 2007). Although not fully resolved in the literature, several papers provide guidance on diagnosing and accounting for non-independence in multi-model ensembles (IPCC 2010; Knutti et al. 2010; Bishop and Abramowitz 2013).

7. Representation of Uncertainty

Damage functions have been widely criticized for failing to account for uncertainty in a number of domains (Watkiss 2011; Kopp et al. 2012; M L Weitzman 2009; Howard 2014). Uncertainty can be characterized as parametric (epistemic), due to imperfect knowledge, or stochastic (aleatory), due to natural variability and inherent randomness (Kann and Weyant 2000). Here we will describe the representation of parametric uncertainty and stochastic variability and extreme events, while uncertain climate thresholds will be discussed the next section.

Parametric Uncertainty

IAMs typically deal with parametric uncertainty using sensitivity, scenario, or probabilistic propagation techniques like Monte Carlo simulation (e.g., Nordhaus 2014, Hope 2011, Anthoff and Tol 2013), yet these return a collection of possible outcomes, each corresponding to different conditions, without identifying a single result that accounts for risk, in contrast to stochastic optimization (Kann and Weyant, 2000).

The IWG experimental design accounts for parametric uncertainty in three areas (socioeconomics, climate sensitivity, and the discount rate) with inputs standardized across all models. While DICE considers no additional parametric uncertainty, FUND and PAGE explicitly capture broader parametric uncertainty because the models are run in their native probabilistic mode (IAWG 2013). FUND and PAGE specify independent probability density functions for nearly 500 and 35 uncertainty parameters, respectively, in their damage modules, representing uncertainty around the rate of SLR as a function of temperature or the exponent on the damage function (Anthoff & Tol, 2014a; Hope, 2011a). FUND mostly uses distributions which have tails (e.g., normal, lognormal) as opposed to the truncated triangular distributions in PAGE, though the specific uncertain parameters and specifications are not readily comparable due to model structure (Rose, Diaz, and Blanford 2017). These distribution choices imply different degrees of understanding about the uncertain parameters, though their basis is not well-documented or justified by the modelers.

Stochastic Variability and Extreme Events

Neumann and Strzepek (2014) note that impact studies typically assess gradual, mean changes in temperature and precipitation rather than fully capturing the effects of climate extremes or variability (e.g., storm surge extremes and wildfire events). For example, agricultural impacts will be driven by conditions of shorter duration related to temperature (degree days over some biophysical limit, heat wave) or precipitation (damage from intense rain, drought) not simply the annual mean temperature change. The importance of accounting for impacts due to shifts in the frequency of extreme events or increased climate variability, not just slow incremental trends in the mean of a climate variable has long been recognized (Smith and Tirpak 1989).

Because IAM damage functions are typically formulated in terms of global or regional mean temperature, none of the IWG models explicitly account for this type of stochastic variability in climate outcomes. The effect of stochastic variability and extreme events could be included implicitly if for example the underlying studies used for calibration capture this variability, though this is generally not the case for the IWG models. For example, the coastal impact studies underlying the SLR damage functions are based on assessments of impacts due to changes in global mean sea level alone, without accounting for the additive element of variability in sea level and consequent flood risk. More

recent coastal damage assessments do account for these extreme surge events (Hinkel et al. 2014; Diaz 2016), though Diaz notes a priority for future work is to address nonstationarity in the distribution of such extremes, e.g., incorporating projections by Grinsted et al. (2013) and Buchanan et al. (2015).

8. Formulation of System Dynamics and Thresholds

Many researchers point out that the IWG damage functions fail to capture the risk of uncertain climate system dynamics in an explicit or credible manner (Deschenes, 2014; Hitz & Smith, 2004; Howard, 2014; IAWG, 2010; Li, Mullan, & Helgeson, 2014; Revesz et al., 2014; Sussman et al., 2014; Warren et al., 2006). Various terms are used to describe these non-marginal system dynamics, including nonlinearities, discontinuities, tipping points, tipping elements, thresholds, regime shifts, surprises, and catastrophic events, and this muddled terminology complicates discussions of already-complex concepts. Kopp et al. (2016) review the inconsistent language around ‘tipping points’ and ‘tipping elements’, and discuss the temporal dimension (e.g., abrupt or not, lag between commitment and realization), potential characteristics (e.g., hysteresis, irreversibility), and magnitude of economic shock for such events.

Known physical system thresholds include ocean thermohaline circulation disruption, methane release from the oceans or permafrost, disintegration of the polar ice sheets, albedo changes (with positive feedback), and forest die-back (Alley 2003; Lenton et al. 2008; National Research Council 2013). These events are non-marginal in that gradual changes in the physical climate may drive other systems over a threshold into a new equilibrium state and have the potential for one or more concerning characteristics that include being abrupt, irreversible, or exhibiting hysteresis (Sussman, Weaver, and Grambsch 2014). The existence of these threats is supported by the geologic record (Alley 2003), but the governing dynamics and thresholds are still not fully understood or quantified due to insufficient data and process models limitations. Kriegler et al. (2009) conduct an imprecise probability assessments for five tipping elements using expert elicitation. While the triggering variable, probability distribution, and consequence of such threshold responses have not yet been credibly incorporated into IAMs for reasons discussed in Diaz and Keller (2016), they are thought to drive up the SCC (Howard 2014; van den Bergh and Botzen 2014).

PAGE explicitly models a type of ‘discontinuity’ impact that covers a number of potential large-scale climate thresholds, which are never satisfactorily defined, as noted in Diaz (2014): Hope (2011a) only cites the Greenland ice sheet disintegration while Hope (2011b) also includes monsoon disruption and thermohaline circulation. van den Bergh and Botzen (2014) similarly comment that PAGE catastrophic outcomes reflect subjective judgements and abstract scenarios rather than well-characterized climate catastrophes. The discontinuity impact is modeled as the expected value of an uncertain event, multiplying the probability (which increases linearly with temperature above a threshold of 3°C) by the consequence (mode of 15% GDP loss).

Neither DICE nor FUND attempts to directly include a climate threshold within the damage module, although DICE’s SLR module decomposes the SLR projection into components and the Antarctic Ice Sheet is assumed to have an initial discharge threshold at 3°C, with a rate that increases linearly with temperature until a maximum rate of 2.5mm/yr is reached at 6 °C (Nordhaus, 2010). To the extent that climate threshold events are conflated with catastrophic damages, these are somewhat accounted for in the IAMs, though Kopp et al. (2016) notes a lack of clarity about what constitutes a catastrophe and recommends the term climate-economic shock instead. The bottom-up basis for the DICE aggregate damage function includes the certainty equivalent damage from a catastrophic impact, formulated such that the likelihood is 1.2% at 2.5°C and 6.8% at 6 °C and the consequence is a loss of GDP between 22 and 44% (varies by region). These catastrophe assumptions are based on Nordhaus’s own ‘pessimistic’ interpretation of the Nordhaus (1994) expert elicitation of the overall economic impacts of 6°C warming, (i.e., a doubled likelihood of survey results to reflect heightened climate concerns).

FUND does not explicitly include high-impact, uncertain consequences of climate change but accounts for the possibility of extreme outcomes via the long tails of uncertain parameter distributions. However, it is worth noting that these are abstract outcomes rather than explicitly modeled feedbacks and system dynamics.

At a more fundamental level, IAM damage functions are implicitly assumed to have symmetric system dynamics in that the function behaves the same for increasing temperature as it does for decreasing temperature. Although the coupled earth and human system is complex to fully understand and model, species extinction and ice sheet loss are known cases of hysteresis or irreversibilities that cannot be ‘undone’ as temperatures are stabilized and then reduced from a peak level.

Several studies have integrated uncertain climate thresholds into IAMs with global stochastic optimization, beginning with Keller et al. (2004) and including more recent work that uses endogenous hazard rates linking the probability of climate catastrophes to warming (Lemoine and Traeger 2014; Cai et al. 2015; Shayegh and Thomas 2014; Diaz and Keller 2016). Diaz (2015) and Kopp et al. (2016) note that moving beyond an abstract or stylized representation of hazard towards one that accounts for each known threat with distinct characteristics will improve the credibility of this approach. Cai Lenton & Lontzek (2016) improve upon these studies in many dimensions, using Kriegler et al.’s (2009) expert elicitation to calibrate likelihoods and the causal interactions between them, account for transition times and carbon cycle effects (e.g., ice sheet collapse could release coastal permafrost), and adjust social planner’s preferences regarding risk aversion and intergenerational equity) and find that the SCC increases substantially. These particular modeling studies use stochastic and dynamic programming to solve for optimal emissions pathways and so are not directly applicable to the IWG effort, although elements of the threshold design could be implemented in a simulation approach (Diaz 2015).

Heal and Millner (2014) warn that IAMs are not designed to treat Knightian Uncertainty (Knight 1921), which differentiates ‘uncertainty’ (unknown probabilities) from ‘risk’ (known probabilities), limiting the usefulness of damage functions and SCC estimates. Many authors point out that there are likely many climate impacts that fall into this category of ‘black swans’ or ‘unknown unknowns’ (e.g., Weitzman 2009). Furthermore, a number of conceptual challenges confront estimation of catastrophic risks, including time consistent preferences, risk aversion, and social versus private discounting.

9. Damages to Output Rather than Growth Rate

Damage functions in all three models are formulated such that losses fall out the level of output, reducing production in the year that damages occur but with no persistent impacts in subsequent years. Recent literature has explored this structural assumption, introducing a number of alternative damage pathways that instead affect the growth rate of output, therefore causing persistent effects.

In the IWG implementation, the underlying factors driving growth in consumption are specified exogenously and are not directly affected by temperature. Specifically, both population and per-capita income are specified exogenously in FUND, GDP growth is given exogenously in PAGE, and growth in labor and total factor productivity (TFP) are given exogenously

in DICE (Anthoff & Tol, 2014; Hope, 2006; Nordhaus & Sztorc, 2013). In the standard intertemporal optimization version of DICE, capital is determined endogenously based on the optimal savings rate so damages to output do lead to an indirect reduction in capital formation, but the IWG simulation mode did not include this endogenous feedback.

The assumption that economic growth will continue largely unaffected by climate change has been criticized in a number of recent publications (Pindyck, 2013; Revesz et al., 2014; Stern, 2013). The question is important because impacts to the growth rate have the potential to greatly increase climate damages compared to a world in which climate change only affects output. Damages to the growth rate have a permanent effect of the size of the economy whereas damages to output are transitory. This means that, if the climate permanently changes, impacts to the growth rate accumulate over time so that even small growth-rate effects will eventually dominate impacts to output (Dell, Jones, and Olken 2012).

Moyer et al. (2014) and Dietz and Stern (2015) both demonstrate the sensitivity of DICE output to assumptions about whether climate damages affect growth rates. Moyer et al. (2014) look at the SCC under BAU emissions when damages are allowed to affect TFP and show large sensitivity. This is driven both by higher damages but also by a lower discount rate if the standard DICE discount rate based on the Ramsey formula is used ($r = \rho + \eta g$). Because damages to TFP slow or reverse economic growth, discount rates are smaller or even negative. If instead the IWG fixed discount rate approach is used, effects on the SCC are smaller, though still large (increase by up to a factor of 10). Dietz and Stern (Simon Dietz and Stern 2015) allow temperature to affect either TFP or the capital stock and solve for the optimal temperature trajectory, which increases the SCC by a factor of 2-3. Both papers present modified versions of the Romer growth model in which temperatures affect growth by affecting the productivity of the R&D sector and therefore the growth in TFP (Dietz & Stern, 2015; Moyer et al., 2014), the depreciation rate of capital (Dietz & Stern, 2015), and the 'knowledge-spillovers' that connect investment in capital to TFP growth (Dietz & Stern, 2015). Both papers conclude that impacts of climate change on economic growth have major implications for the SCC and the optimal mitigation pathway in DICE.

Rather than quantify impacts from the bottom-up on a sector-by-sector basis, an alternative approach is to look at temperature impacts on GDP as a whole. Although this misses important non-market impacts such as health or ecosystem services, it

should capture all climate change impacts on market sectors without the need for individual sector-by-sector analysis. However, even more than with sectoral empirical results, the mechanisms through which these impacts arise are black-boxed. In addition, GDP is a measure of economic activity so the connection between changes in GDP and changes in welfare, even welfare derived from market goods, is unclear. Although much of this literature has appeared only very recently, there are some important emerging findings.

Firstly, this literature has found that the economy as a whole tends to be sensitive to temperature fluctuations, particularly in poorer countries, with the effect only partially explained by the agricultural sector (Heal & Park, 2013). Hsiang (2010) finds large effects of hot temperature shocks on economic output in Central America and the Caribbean for all economic sectors except mining and utilities. Jones and Olken (2010) find that hot temperature shocks negatively affect the growth in exports from poor countries in both agricultural and manufacturing sectors. Deryugina and Hsiang (2014) find substantial effects of hot days on annual income in the United States, including non-farm income. The mechanism driving temperature impacts in sectors not typically considered sensitive to temperature is unclear but may include effects on labor productivity or labor supply.

A second major question addressed in this literature is whether temperature shocks permanently affect the economy by affecting growth rates, which could have large implications for the SCC. Dell, Jones and Olken (2012), Lemoine and Kapnick (2016), and Burke, Hsiang and Miguel (2015) all examine the reduced-form relationship between temperature shocks and economic growth. In general these studies find evidence that temperatures negatively affect growth in poor countries, though they differ in some important respects. Both Dell, Jones and Olken (2012) and Lemoine and Kapnick (2016) find strong interactions between temperature impacts and per-capita income, suggesting impacts are driven by poor economies being more sensitive to temperature fluctuations. Burke, Hsiang and Miguel (M. Burke, Hsiang, and Miguel 2015) instead show evidence for a quadratic relationship between temperature and growth-rates, arguing that large impacts in poor countries arise because they are hotter than rich countries, not because they are poorer. The studies also differ in the extent to which they can confidently distinguish temporary effects of temperature on output from permanent impacts to the growth-rate. Dell, Jones and Olken (2012) use a distributed lag model to argue that warming impacts in poor countries affect the growth-rate. However, the same lag models in Burke, Hsiang and

Miguel (2015) have large confidence intervals that overlap zero, meaning the proportion of temperature impacts falling on growth-rates as opposed to output is unclear. Lemoine and Kapnick (2016) instead use long-differences estimation to argue that temperature changes have persistent effects on growth-rates over decadal timescales. While suggestive, there are still large uncertainties regarding whether growth-rate impacts exist, whether their magnitude depends on temperature or per-capita income, and what mechanisms are driving these effects.⁹

Two papers have incorporated some of the new empirical literature into DICE-2013R in order to examine the implications for optimal climate policy and the SCC. Moore and Diaz (2015) create a two-region version of DICE in which temperature affects growth rates by affecting either TFP or the depreciation rate of capital, calibrating the damage functions to reproduce Dell, Jones and Olken (2012). Even with optimistic adaptation assumptions, they find the SCC along the optimal emissions pathway to be six times higher than using the standard DICE damage function. In supplementary analysis Lemoine and Kapnick (2016) incorporate their long-differences estimate of growth-rate impacts into DICE, finding they do not tend to increase the SCC relative to the standard damage function, and in some cases decreases it significantly. In both papers, the question of how temperature impacts change with per-capita income as poor regions develop is a critical one and something still unresolved in the literature.

10. Assumption of Perfect Substitutability of Environmental Services

All three IAMs assume that temperature damages only affect utility through their effect on consumption of goods. Both Weitzman (2009) and Sterner and Persson (2008) point out that this implies the types of damages caused by climate change can be substituted on a one-for-one basis with increased consumption. This may be appropriate if the primary impact of climate change is on consumption of material goods, but is inappropriate if damages fall on goods that are imperfectly substitutable with higher consumption such as biodiversity or health. This perfect substitutability, combined with exogenously specified growth, almost ensures that absolute welfare will increase over time, despite climate change damages. If instead material goods are imperfectly substitutable with the

environmental services affected by climate change, the relative price of impacted sectors will rise with climate change, causing larger impacts than under perfect substitutability.

Sterner and Persson (2008) investigate the importance of this effect by altering the DICE utility function to include the effects of non-market damages that are only imperfectly substitutable with market goods using a CES utility function. They find that if climate damages are imperfectly substitutable with consumption of material goods, then the optimal emissions pathway in DICE is similar to that implied by the very low pure rate of time preference used in the Stern Review (Stern, 2006; Sterner & Persson, 2008). Results are sensitive to parameters that may be difficult to estimate, however, such as the degree of substitutability between material goods and environmental services, and the fraction of utility today derived from environmental services. The authors also point out that though there may be a range of substitutability between environmental and material goods, calculations will be dominated by goods with lowest substitutability as these will have the largest relative price increase and come to dominate welfare calculations.

Weitzman (2009) points out that the question of how substitutable material goods are with climate damages is empirically difficult to determine but has a very large impact on IAM results, particularly when combined with high temperatures (resulting from fat-tailed probability distributions) and low discount rates (resulting from uncertainty in the discount rate). In a later paper (Weitzman, 2012b) he shows how both the multiplicative damages currently used in IAMs, the CES damages used by Sterner and Persson (Sterner and Persson 2008), and a utility function in which temperature enters additively are members of a general class that can be derived from two axioms: constant relative risk aversion and an analogous constant temperature risk aversion. Giving a numerical example, he shows that choosing an additive utility function rather than the standard multiplicative function increases willingness to pay (WTP) to avoid climate change by a factor of seven, even when damages are calibrated to give the same number for a warming of 2°. He argues the strong dependence of IAM results on obscure details of how temperature enters the utility function that are impossible to determine empirically is an example of deep structural uncertainty that requires caution in interpreting the SCC values.

⁹ In addition to evidence for temperature shocks on economic growth, Hsiang and Jina (2014) use a distributed lag model to show cyclone strikes negatively affect economic growth, not just output. Even accounting for the fact that climate change will decrease cyclone risk in some areas, these growth impacts imply very large negative impacts of climate change.

This issue is identified by the IWG as a reason why the current functional form of damages in the IWG IAMs may be inadequate for accurately representing climate change damages (IAWG 2010).

11. Utility Function and Handling of Risk Aversion

In the IWG report, models were run to produce monetary damages with and without an additional pulse of CO₂ that were then discounted to give the SCC (IAWG 2010; IAWG 2013). This process is consistent with the standard versions of FUND and PAGE which report damages simply in dollar values, leaving aggregation of damages in individual regions to a global value and the conversion to utility to the user.¹⁰ The standard version of DICE however includes a constant elasticity of substitution (CES) utility function with the elasticity of marginal utility of consumption (η) set to 1.45, which was not used in the IWG process (Nordhaus & Sztorc, 2013). Much of the literature regarding risk-aversion in IAMs concerns this utility function and therefore is less relevant to the IWG process which simply uses monetary damages, implicitly using a linear utility function with no risk aversion.

The simple utility function in DICE combined with a single representative agent means that the same η parameter represents preferences over consumption at different time periods, risk aversion, and preferences over income inequality within a given time period. Weitzman (2012a) points out that in the standard DICE model, higher risk aversion tends to lower the SCC because it increases the discount rate. If instead damages are based on an expected utility calculation over a fat-tailed probability distribution of future temperatures, then higher risk aversion substantially increases the SCC. Anthoff, Tol and Yohe (2009) and Newbold and Daigneault (2009) find a similar sensitivity to the risk aversion parameter when climate damages are uncertain in sensitivity analyses using FUND and a modified version of the DICE model respectively.

Recent papers have begun incorporating findings from the asset-pricing literature that show large differences between time and risk preferences by incorporating Epstein-Zin preferences into IAMs. In addition to changing preferences, these papers also allow for the explicit representation of uncertainty in DICE, either over the climate sensitivity (Ackerman and Stanton 2012), damage function (Croston and Traeger 2011;

Daniel, Litterman, and Wagner 2015), or future growth rates (Jensen and Traeger 2014). Because Epstein-Zin utility adds significant computational complexity, this work typically relies on simplified models derived from DICE. Preference parameters derived from asset price returns typically indicate much higher risk aversion (9.5-10) than would be indicated in the standard DICE CES utility function (1.45), and therefore these papers find that disentangling time and risk preferences tends to increase the SCC substantially.

Because the η parameter also captures preferences over intra-temporal inequality, it arises in questions of how to aggregate climate damages occurring to people at different income levels. Several authors have pointed out that using a declining marginal value of consumption for the purposes of time discounting but not in evaluating the importance of damages to different populations is inconsistent and could disguise important distributional impacts (Stern and Persson 2008; Farmer et al. 2015). Since climate damages tend to fall disproportionately on poorer regions, weighting monetary damages by their importance for utility will tend to increase estimates of global damages, a practice sometimes referred to as ‘equity weighting’. Lemoine and Kapnick (2016) aggregate up heterogeneous country-level impacts into global damage functions using different η values and show large differences over a range of plausible values. For regional models, the within-region distribution of climate impacts, as well as the between-region distribution is important for an inequality-averse decision-maker as shown in Anthoff, Hepburn and Tol (2009) for FUND and Dennig et al. (2015) for RICE.

Part Three: Frontier of Climate Impacts Research and Considerations for Damage Functions

Existing Global Aggregate Damage Functions

A number of existing IAMs include global aggregate damage modules that could be considered as candidates for inclusion in the IAWG framework. Here we review four alternative damage formulations – WITCH, MERGE, ENVISAGE, and CRED

WITCH

The WITCH (World Induced Technical Change Hybrid) IAM, originally presented in Bosetti et al. (2006), represents climate damages with 12 region-specific damage functions.

10 An exception is that parts of damages in the coastal sector in FUND use a discount rate derived from the Ramsey rule that implies logarithmic utility (i.e. $\eta=1$) (Anthoff and Tol 2014b).

This module was recently updated with new damage functions and climate adaptation cost curves as described in Emmerling et al. (2016) and Bosello and De Cian (2014). The updated damage module implements a bottom-up approach including 6 impact categories for regional impacts at the calibration point of 2.5°C (Emmerling et al. 2016):

- **Market impacts** – 1) sea-level, 2) agriculture, and 3) energy demand, based on impacts studies conducted as part of the EU FP7 ClimateCost project (see Bosello et al. 2012). The ClimateCost project applied a recursive-dynamic computable general equilibrium (CGE) model to estimate the macro-economic effects of 1.92°C warming on the three impacts sectors, individually and jointly, quantified in terms of % change in GDP. Bosello and De Cian (2014) note that the CGE framework means the market impacts for these sectors are net of autonomous adaptation. Furthermore, they report that the estimates are extrapolated to higher “temperature increases using sector specific assumptions and reasonable judgments based on available knowledge. For the rise in sea levels and agriculture we use a power relationship (Nordhaus and Boyer, 2000) [exponents of 1.5 and 2, respectively]. Energy impacts have been extended using a linear trend.”
- **Non-market impacts** – 4) ecosystem impacts, using updated calculations of the WTP following the approach used in the MERGE model (Manne et al. 2005).
- **Non-market impacts** – 5) health impacts and 6) catastrophic damages from Nordhaus and Boyer (2000) as documented in Nordhaus (2007).

Another key feature of the impact module is that the damage functions are separated into a positive component for beneficial impacts, and a negative component for damages, such that the latter can be offset by adaptation. Bosello and De Cian (2014) describes the nested representation of proactive (stock) and reactive (flow) adaptation for several impact sectors, as well as specific and generic adaptive capacity to determine regional adaptation. This adaptation activity shifts the damage function downward, however the endogenous nature is not readily compatible with the IWG experimental design of exogenous pathways. However, optimal results from WITCH could be used to parameterize an aggregate damage function net of adaptation.

MERGE

An early version of the MERGE IAM included a representation of climate damages that is described in Manne et al (1995) and Manne & Richels (2004), though over the last decade MERGE has only been applied in cost-effectiveness mode (without invoking the damage module) and the formulation is acknowledged to be out of date. Nevertheless, MERGE is cited as the basis for other damage functional forms (e.g., the WTP approach in WITCH).

MERGE differentiates between market and non-market damages, and each affects welfare through different channels. Market damages reduce consumption, while nonmarket damages directly affect the utility function (without lowering GDP or consumption). Market damages are assumed to be a linear function of global mean temperature change, calibrated to estimates of regional GDP loss at 2°C in Mendelsohn et al (2000). One clear defect is the choice of a linear functional form, as the underlying study is formulated with quadratic response functions. Because several regions show benefits at 2°C (before reaching an optimal warming and leading to damages at higher temperatures on a quadratic), the linear form implies that the benefits continue to grow with warming.

Non-market impacts are strictly negative (and are generally larger in magnitude than market damages) are conceptualized in terms of the willingness to pay to avoid impacts associated with temperature rise. The willingness to pay is expressed as a fraction of consumption that rises with per capita income and is quadratic in temperature. This function is calibrated so that a country with per capita income of \$50,000 (and up) would be willing to forgo 4% of its consumption to avoid the impacts associated with a 2°C increase in global average surface temperature relative to pre-industrial. While extremely simple, and not capable of reflecting discontinuous or irreversible damages associated with the possibility abrupt change, this formulation nonetheless provides an intuitive depiction (uncertainty in scale notwithstanding) of the consequences of rising temperatures.

ENVISAGE

Several public comments to OMB suggested applying the World Bank’s Environmental Impact and Sustainability Applied General Equilibrium (ENVISAGE) model to estimate the SCC

11 van der Mensbrugghe (2010) notes that “ENVISAGE is intended to be flexible in terms of its dimensions. The core database—that includes energy volumes and CO2 emissions—is the GTAP database, currently version 7.1 with a 2004 base year. The latter divides the world into 112 countries and regions, of which 95 are countries and the other region-based aggregations. The database divides global production into 57 sectors—with extensive details for agriculture and food and energy (coal mining, crude oil production, natural gas production, refined oil, electricity, and distributed natural gas). Annex 8 provides more detail. Due to numerical and algorithmic constraints, a typical model is limited to some 20-30 sectors and 20-30 regions.”

(IAWG 2015). The model, documented in van der Mensbrugghe (2010), is a recursive dynamic CGE model with multiple regions and sectors.¹¹ The impact module in ENVISAGE is structured such that impact sectors are differentiated as sources or destinations that interact within a given region, with 7 sources (SLR, agricultural productivity, water availability, labor productivity, tourism, human health, and energy demand) and 7 destinations (labor productivity/stock, capital productivity/stock, land productivity/stock, multi-factor productivity, household consumption of energy, household consumption of market services, and income from abroad).¹² Roson and Sartori (2015) note that this approach to impact pathways allows distinguishing the various mechanisms through which climate can affect the economy. However, while ENVISAGE's CGE formulation accounts for general equilibrium effects such as those from relative prices across regions, it lacks explicit inter-sectoral and inter-regional interaction for climate impact estimation. Roson and van der Mensbrugghe (2012) note that the initial ENVISAGE damage functions are mostly linear functions of mean global temperature change with the exception of quadratic damages for agriculture.

Underlying the damage module in ENVISAGE is detailed analysis by Roson and Sartori (2010; 2015) applied to the GTAP database framework. They initially estimated the effect of 3°C warming on GDP for the 140 countries and regions in the GTAP9 dataset for each climate impact sectors. The more recent GTAP analysis evaluated a wider temperature range (1-5°C) and found that most impacts were non-linear. These results were then used to estimate damage functions that relate changes in average temperature to changes in model parameters in the destination categories (e.g., labor, capital, land, and multi-factor productivity or stocks, household consumption of energy and market services, and income from abroad).

CRED

The Climate and Regional Economics of Development (CRED) model represents damages using an aggregate damage function that is defined at the global level but regionally-adjusted based on vulnerability index (Ackerman, Stanton, and Bueno 2012). Ackerman, Stanton, & Bueno (2013) assumes an aggregate quadratic damage function that is calibrated to a global GDP loss of 0.6% at 1°C. The authors justify this calibration point, which they note is “roughly double the DICE value”, based on the results of potential climate damages in the United States in Ackerman et al. (2008). Global damages are then scaled

to regions using a vulnerability index based on the fraction of GDP in the climate-sensitive industries of agriculture and tourism, share of population exposed to SLR, and freshwater resources per person, and is assumed to be constant over time (Ackerman, Stanton, and Bueno 2012).

Earlier publications including the CREDv1.3 documentation (Ackerman, Stanton, and Bueno 2012) offer multiple damage functions that combine the classic DICE quadratic form with higher powers on the temperature variable following Weitzman (2012a), discussed below, as well as more pessimistic 2C calibration point based on Hanemann (M. Hanemann 2008), which is roughly 2.5 times steeper than Nordhaus.

$$D = a\Delta T^b + c\Delta T^d$$

Weitzman proposes an alternative global aggregate damage function that could be substituted into an IAM damage module or applied in an IWG setting to estimate the SCC. Observing that the DICE function is unrealistically optimistic for high amounts of warming, and noting that all damage functions are “made up”, he proposes a reactive damage function that adds a 6th order damage term that satisfies two conjectured impact outcomes: a 50% consumption loss at 6°C and a 99% consumption loss at 12°C:

$$D = \left(\frac{\Delta T}{20.46}\right)^2 + \left(\frac{\Delta T}{6.081}\right)^{6.754} = 0.0024 \Delta T^2 + 0.0000051 \Delta T^{6.754}$$

High-Resolution IAMs with Climate Impacts

In contrast to the economic damage functions described above, there are a number of high-resolution IAMs that account for climate impacts through biogeophysical processes. These models feature a higher degree of process detail and often finer spatial or temporal scales and can be used to investigate the implications of different climate scenarios on the coupled Earth-human system in terms of resources or other physical measures (as opposed to consumption or welfare). While these models could be used to estimate or inform climate impact response functions, they cannot be used directly to estimate the SCC.

The Global Change Assessment Model (GCAM) at PNNL links economic, energy, land-use, water, and climate systems with high resolution (e.g., 32 energy economy regions, 283 land regions, 233 water basins). Researchers using GCAM have conducted and published assessments of climate impact in several key sectors, including agriculture (Calvin et al. 2013; Kyle et al. 2014; Nelson et al. 2014), energy demand (Zhou et al. 2014; Zhou, Eom, and Clarke 2013), and water resources

(Mohamad I Hejazi et al. 2015; M. I. Hejazi et al. 2014). Documentation and code are available at wiki.umd.edu/gcam.

The Integrated Global Systems Model (IGSM) at MIT (Reilly et al. 2012) uses a multi-model approach to first estimate the physical and biological impacts of climate change and then incorporate those effects into the MIT EPPA CGE model (Paltsev et al. 2005) to determine the economic consequences in a general equilibrium setting (e.g., equivalent variation). Damages are implemented at the country or region level via the Social Accounting Matrix (SAM). IGSM has been used to investigate agriculture-land-water-economy interactions and air pollution health effects, among others. Resources and documentation are available at <http://globalchange.mit.edu/research/IGSM>.

Other well-established models in this category include the Integrated Model to Assess the Global Environment (IMAGE) at PBL Netherlands Environmental Assessment Agency, the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE) at IIASA, and the Regionalized Model of Investments and Technological Development (REMIND) at PIK, among others.

Multi-Sector, Bottom-Up Collaborations

There are a host of ongoing research collaborations evaluating climate impacts from a multi-sector, bottom-up perspective. These efforts have been intentionally structured with an interdisciplinary team, bringing physical scientists together with economists to design more credible and complete modeling frameworks and to improve understanding, communication, and technical implementation. Moreover, many of these projects feature standardized input assumptions and scenarios, often based on the representative concentration pathways (RCPs; Moss et al., 2010) and shared socio-economic pathways (SSPs; Van Vuuren et al., 2012). Previous synthesis efforts (e.g., IPCC-style catalog of sectoral impacts) introduced inconsistent assumptions and caveats that meant the summation of impact estimates was less informative (e.g., “apples and oranges”). The deliberate shift toward harmonization makes individual sector estimates more comparable and better suited for aggregating results across sectors, notwithstanding challenges raised earlier. While these initiatives advance the frontier of climate impact estimation, currently none of these projects offer alternative damage functions for immediate use in the IWG-style IAMs. Furthermore, while CIRA, PESETA, and Roson & Sartori

(2015) report monetized damages, many of the others quantify downstream impacts in various non-monetary units such as percent changes to productivity or crop yields, number of people affected, or coastal area. Table 1 gives several examples of current efforts.¹³

Process-Based Damage Estimates

Agriculture Example

The Agricultural Model Intercomparison Project (AgMIP) has produced global gridded changes in crop yields under different warming scenarios from 7 process-based crop models (Rosenzweig et al. 2014). The economic implications of these yield changes has also been examined using 9 partial- or general-equilibrium economic models (Nelson et al. 2014). Though Nelson et al. (2014) do not report welfare changes, these results should be conducive for the calibration of new damage functions in the agricultural sector.

Individual studies on yield changes with warming were collated and analyzed as part of a meta-analysis for the IPCC based on both process-based and statistical studies (Porter et al. 2014; Challinor et al. 2014). The database gives multi-region, multi-crop yield responses to changing temperature, rainfall and CO₂ concentrations. Moore et al. (2016) re-analyzed data within this database to produce global temperature response functions for four major crops and use these as inputs to the Global Trade Analysis Project (GTAP) CGE model to produce new damage functions for the agricultural sector.

Coastal Example

The first social vulnerability assessment of SLR quantified the land, population, income, and capital in the continental US that would be exposed for two static SLR cases, 4.6 m and 7.6 m, without assuming any coastal adaptation (Schneider and Chen, 1980). Work done by the US EPA in 1989 introduced adaptation measures through a fixed-rule (e.g., protect all coastal zones above a threshold population density) to estimate the total costs of protection, retreat, and inundation (Yohe 1989), and a similar global assessment estimated a cost of \$488 billion to protect the world’s developed coastlines against 1 m of SLR in 2100 (Dronkers et al., 1990).

Yohe (2002) accounted for societal risk attitudes by linking protection standards to income levels; this has been applied to estimate population exposure by Nicholls (2004) and protection costs by Hinkel et al (2014).

¹³ It is worth noting that these current projects have antecedents including multi-sector assessments by Smith and Tirpek (1989) and Mendelsohn and Neumann (2004).

Table 1 – Selection of Multi-Sector Impacts Modeling Collaborations

Project and Lead Institution	Summary and Study Features	Coverage	References
American Climate Prospectus (Risky Business)	ACP presents comprehensive empirical estimates of key economic risks from climate change in the US. Standardized climate scenarios (RCP 2.6, 4.5, 8.5) using statistically downscaled, probabilistic physical climate projections. Impact estimates based on meta-analysis of econometric research, complemented by detailed sectoral models.	Regions: US coverage Sectors: Agriculture, labor productivity, human health, crime and conflict, energy, coastal	Houser, Hsiang, Kopp, & Larsen, 2015 www.climateprospectus.org
AVOID2 UK government	AVOID2 compares impacts of 2 °C compared to a BAU scenario through 2100 using an indicator approach.	Global coverage with multiple regions Sectors: 12 indicators related to water resources, flooding, crop productivity, and energy demand	http://www.avoid.uk.net/
BRACE Benefits of Reduced Anthropogenic Climate change National Center for Atmospheric Research (NCAR)	Evaluates climate impacts in physical and societal measures for two standardized climate scenarios (RCP 8.5 and 4.5) and two socioeconomic scenarios (SSP 3 and 5)	Regions: Global coverage, regions vary Sectors: Heat Extremes & Health, Agriculture and Land Use, Tropical Cyclones, Sea Level Rise, Drought and Conflict	Special issue in Climatic Change, O'Neill et al., 2017 https://chsp.ucar.edu/brace
CIRA Climate Change Impacts and Risks Analysis U.S. EPA	CIRA evaluates impacts in multiple sectors using standardized climate projections with harmonized assumptions to facilitate comparing impacts across sectors and regions and assessing the regional benefits of large-scale mitigation efforts. Reference and mitigation scenarios developed by the IGSM-CAM model. No explicit interaction across sectors. Explicit adaptation in coastal, ag, energy sectors. Phase 2 of project is currently underway and linked to National Climate Analysis (NCA) process.	Regions: US coverage, regions vary by sector Sectors: 6 broad impact sectors based on 20+ detailed impact models Health, Infrastructure, Electricity, Water Resources, Agriculture and Forestry, Ecosystems	Special issues in Climatic Change: Martinich et al. 2015 Marten et al., 2013 www2.epa.gov/cira
ClimateCost European Commission	ClimateCost quantifies impacts and adaptation in physical terms and some economic costs, using consistent climate and socio-economic scenarios. Accounts for general equilibrium effects though not for interaction across regions and sectors. Results implemented in WITCH model.	Regions: primarily EU with China and India Sectors: coasts, health, ecosystems, energy, water and infrastructure	Bosello et al., 2012
Climate Impact Lab	The Climate Impact Lab extends the approach taken by the ACP described above. Seeks to develop plausibly causal estimates of relationship between measures of climate and human welfare in multiple sectors, ultimately producing empirical damage functions.	Regions: Global coverage, regions vary Sectors: Agriculture, crime and conflict, labor productivity, human health, migration, coastal, energy	www.impactlab.org

Table 1 – Selection of Multi-Sector Impacts Modeling Collaborations (continued)

Project and Lead Institution	Summary and Study Features	Coverage	References
ENVISAGE CGE analysis Roson and Sartori	Roson and Sartori estimate effect of 1-5°C warming on GDP for the 140 countries and regions in the GTAP9 dataset. Accounts for general equilibrium effects though not for interaction across regions and sectors. Implemented in ENVISAGE model	Regions: Global coverage, regional aggregation is flexible Sectors: labor, capital, land, and multi-factor productivity or stocks, household consumption of energy and market services, and income from abroad	Roson and Sartori, 2010; 2015
ISI-MIP Inter-Sectoral Impact Model Intercomparison Project Potsdam Institute for Climate Impact Research (PIK)	ISI-MIP harmonizes independent models of different sectors and scales with standardized bias-corrected climate input data. No dynamic links between models or explicit interaction across sectors. Explicit adaptation in coastal, agriculture, energy sectors. Builds upon existing sectoral model intercomparison efforts (e.g., AgMIP, WaterMIP)	Global coverage, regions vary by sector Sectors: 7 broad impact sectors based on a variety of detailed impact models Water, Agriculture, Biomes, Infrastructure, Health/ Malaria, Fishery, Permafrost	Huber et al., 2014; Warszawski et al., 2014 www.pik-potsdam.de/research/climate-impacts-and-vulnerabilities/research/rd2-cross-cutting-activities/isi-mip
PESETA Projection of Economic impacts of climate change in Sectors of the European Union based on bottom-up Analysis European Commission	PESETA integrates multiple impact sectors in a single, internally-consistent economic modelling framework for Europe. The latest results assess physical impacts in the 2080s in terms of agriculture yield change, number of people affected by sea level rise and river flooding, impacts to tourism, and changes in hot and cold-related mortality. Standardized climate model scenarios for 2.5°C, 3.9°C, 4.1°C, and 5.4°C.	Regions: Europe Sectors: agriculture, energy, river floods, forest fires, transport infrastructure, coastal areas, tourism, human health, habitat suitability	Phase 2 Ciscar et al., 2014 Phase 1 Ciscar et al., 2009 http://peseta.jrc.ec.europa.eu/
Program on IAM Development, Diagnostics and Inter-comparisons (PIAMDDI)	While not a coordinated multi-sector assessment, this research collaboration focuses on advancing impact assessments and methodologies (e.g., downscaling, uncertainty analysis, etc.) in specific sectors, including agriculture, water resources, energy, and sea level rise among others.	Various	http://piamddi.stanford.edu/

Fankhauser (1995) and Yohe et al (1995) formulated cost-benefit models to determine the economically optimal level of protection based on the relative cost of protection and retreat, building off earlier work by van Danzig (1956). Fankhauser derived a reduced-form equation to approximate the optimal fraction of protection for a given coastline based on the present value cost ratio of protection to inundation. (Fankhauser's reduced-form cost-benefit rule has been formalized in the FUND model, which has been used for numerous analyses of the economic impacts of SLR, e.g., Darwin and Tol, 2001; Nicholls et al, 2008; Tol, 2007; Anthoff et al, 2010.) One limitation of such cost-benefit rules is that by simplifying the optimal result to a closed-form equation it cannot interact dynamically with

changing climate impacts, and the approximation is often further exacerbated by the low spatial resolution and limited temporal structure common to many global and regional analyses.

Progress in the geophysical dimension was afforded by the Dynamic Interactive Vulnerability Assessment (DIVA), a geospatial analysis tool that partitions world's coastlines into 12,148 distinct segments, combining global scope with high spatial resolution (Vafeidis et al, 2008). (Prior to DIVA, the original global coastal dataset was the Global Vulnerability Analysis (GVA), consisting of 192 coastal segments (Hoozemans et al, 1993). Despite this pioneering effort,

country-level resolution is not sufficient to inform adaptation decisions that are inherently local. Advances in computing technology and remote sensing have enabled more detailed and accurate coastal datasets.) Several regional and global studies that account for additional damage factors related to vertical land movement, storm surge flooding, and wetlands have been published with DIVA (see Hinkel et al, 2012, 2013, 2014). A recent DIVA assessment of fixed-rule adaptation under a range of socioeconomic scenarios, digital elevation models, and SLR projections estimated annual costs in 2100 of \$12-71 billion for coastal protection with \$11-95 billion in flood damages (Hinkel et al, 2014).

Sugiyama et al (2008) apply DIVA's increased spatial resolution to reprise Fankhauser's reduced-form approach. Their analytical model of optimal coastal adaptation adds capital stock, adjusts vertical population distribution, and uses nonlinear SLR scenarios. This reduced-form cost-benefit rule is then applied at the spatial resolution of DIVA's coastal segments, though the study omits local SLR and flood damage and does not produce global cost estimates. Diaz (2016) presents the Coastal Impact and Adaptation Model (CIAM), an optimization model that evaluates several adaptation options at the local (DIVA segment) level based on their socioeconomic characteristics and the potential impacts of relative SLR and uncertain sea level extremes. Following a least-cost adaptation strategy, global net present costs through 2100 can be reduced by a factor of seven to less than \$1.7 trillion. The model results are also parameterized and compactly represented in a set of adaptation and damage functions.

A final dimension in the coastal impact literature is the distinction between direct cost estimates and welfare effects. Early studies by Darwin and Tol (2001) and Deke et al (2001) used computable general equilibrium (CGE) models in order to estimate the economy-wide effects of coastal impacts and adaptation. Bosello et al (2007) confirms the importance of CGE approach and finds that direct costs may underestimate the actual welfare loss to society. It is also worth noting that the coastal impact literature often omits damages due to erosion, saltwater intrusion, ocean acidification, coastal tourism and recreation, and international migration, in addition to interactions with other impact sectors.

Empirical Literature

There has been a resurgence of interest in the empirical estimation of climate change impacts over the last 10 years. Much of this work uses reduced-form methods – identifying the impacts of temperature or rainfall variation on specific sectors or the

whole economy without identifying the specific mechanisms by which these impacts occur. In contrast to process-based models which model known mechanisms of action between climate and economic variables, claims for causality in empirical studies rest on plausibly exogenous variation in climate variables. Most recent empirical work therefore uses panel data and fixed-effects to control for all time-invariant unobservable characteristics of different places, thereby reducing problems of omitted-variable bias and improving confidence that the variation used to identify climate change impacts is exogenous and that the relationship identified is causal (Dell, Jones, and Olken 2014).

While the findings of this literature are generally relevant to damage functions, there has as yet been few direct linkages between empirical findings and IAM damage functions. This section briefly reviews specific sectors where substantial empirical advances have been made, then progress on top-down damage estimates based on income or GDP, and then discusses general issues around incorporating these findings into IAM damage functions. In addition, two useful multi-sectoral reviews of findings from recent empirical studies using panel data are Dell, Jones and Olken (2014) and Carleton and Hsiang (2016).

Sector-Specific Empirical Literature

Agriculture

A large fraction of the empirical literature is focused on agriculture. While earlier work used cross-sectional regressions to examine the impacts of climate variables on either agricultural land-values or profits (Mendelsohn, Nordhaus, & Shaw, 1994; Schlenker, Hanemann, & Fischer, 2005), more recent studies often look at impacts on crop yields using panel data and fixed-effects. Studies tend to be concentrated in a few geographic regions and a few crops, with a notable focus on US maize yields (Burke & Emerick, 2016; Butler & Huybers, 2012; Deschênes & Greenstone, 2007; Lobell et al., 2014; Schlenker & Roberts, 2009). There are however a growing number of studies looking at other regions and crops including rice in India and Indonesia (Welch et al. 2010; Levine and Yang 2006), wheat in the United States (Tack, Barkley, and Nalley 2015), and maize and other important crops in sub-Saharan Africa (Lobell, Banziger, Magorokosho, & Vivek, 2011; Schlenker & Lobell, 2010). A few studies examine multiple crops at a global scale (Lobell & Field, 2007; Lobell, Schlenker, & Costa-Roberts, 2011), and some examine other economic variables such as profits (Guiteras 2009; Deschênes and Greenstone 2007), agricultural wages (Jayachandran 2006) or incomes (Yang and Choi 2007).

In general findings from this literature show highly non-linear effects of temperature on crop yields, with large negative impacts at higher temperatures. Most of the literature uses either growing degree days or a quadratic in growing-season temperature to capture this non-linearity. Some studies also use more specific climate variables such as minimum and maximum temperatures (Welch et al. 2010) or vapor pressure deficit (VPD) (Lobell et al., 2014).

Energy Demand

Empirical estimates of climate change impacts on energy demand are reviewed in Auffhammer and Mansur (Auffhammer and Mansur 2014). Studies have a heavy geographic emphasis on the United States and western Europe and on the residential as opposed to the commercial or industrial sectors. The authors distinguish between impacts on the intensive margin (short-run changes in energy use conditional on existing investments) and the extensive margin (long-term changes driven by changing investment decisions such as installing air conditioning). On the intensive margin response functions show an asymmetric inverse-U shape with warming causing small declines in energy demand at lower temperatures and large increases at higher temperatures. Work on the extensive margin has focused largely on air conditioner adoption and has found climate variables including cooling degree days, relative humidity and wind speed to be determinants of air conditioner penetration (Biddle 2008). Studies in developing countries have shown air conditioner penetration to be highly sensitive to income (Davis and Gertler 2015).

Morbidity and Mortality

Climate change will alter exposure to both hot and cold extremes. In general, studies find increases in mortality from hot extremes to be larger than decreases in mortality from cold extremes, particularly when combined with high humidity (Deschênes and Greenstone 2011; Barreca 2012a; Curriero et al. 2002), though there is some evidence of “harvesting”, meaning heat extremes change the timing but do not increase the total number of deaths over a period of weeks to months (Deschenes and Moretti 2009; Braga, Zanobetti, and Schwartz 2001; Hajat et al. 2005). There is evidence that people will be able to adapt to climate change as the marginal impact of hot temperatures tends to be smaller in places that are already hot and have high air conditioning penetration (Barreca et al. 2013; Braga, Zanobetti, and Schwartz 2001). Some papers have also found high temperatures affect fetuses in-utero, with possibly long-lasting impacts on future productivity (Deschênes, Greenstone, and Guryan 2009; Fishman, Russ,

and Carrillo 2015). Climate change will also affect health and mortality through changes in the ranges of disease vectors and through altered nutrition by impacts on agricultural productivity. There has been relatively less work on these pathways, though there is evidence that they are important in developing countries (Burgess et al. 2011; Kudamatsu, Persson, and Strömberg 2012; Maccini and Yang 2009).

Labor Supply and Productivity

A number of studies, both experimental and in field settings, has found that task performance declines at higher temperatures (Heal & Park, 2013; Seppanen, Fisk, & Lei, 2006). Graff Zivin, Hsiang and Neidell (2015) find short-run temperature shocks affect cognitive performance on math tests, but no evidence for long-run effects. Graff Zivin and Neidell (2014) also find that labor supply in sectors highly exposed to weather decreases at hotter temperatures within the United States. In a global analysis, Heal and Park (2013) find productivity impacts of hot temperatures to be mediated by the penetration of air-conditioning.

Conflict, Crime and Migration

Hsiang, Burke and Miguel (2013) perform a meta-analysis of 10 studies examining the relationship between temperature and inter-group conflict and 8 studies relating temperature to interpersonal violence and find a statistically-significant relationship in both cases. A number of studies also examine the relationship between rainfall anomalies (both floods and droughts) and civil conflict and find a connection, though the conclusions are not unambiguous (Dell, Jones, and Olken 2014). Several studies have found evidence for weather-induced migration, mostly related to negative impacts on agricultural production from both temperature and rainfall shocks (Mueller, Gray, and Kosec 2014; Feng, Oppenheimer, and Schlenker 2012; Hornbeck 2012).

Top-Down Empirical Literature

Rather than quantify impacts from the bottom-up on a sector-by-sector basis, an alternative approach is to look at temperature impacts on GDP as a whole. Although this misses important non-market impacts such as health or ecosystem services, it should capture all climate change impacts on market sectors without the need for individual sector-by-sector analysis. However, even more than with sectoral empirical results, the mechanisms through which these impacts arise are black-boxed. In addition, GDP is a measure of economic activity so the connection between changes in GDP and changes in welfare, even welfare derived from market goods, is unclear. Although

much of this literature has appeared only very recently, there are some important emerging findings.

Firstly, this literature has found that the economy as a whole tends to be sensitive to temperature fluctuations, particularly in poorer countries, with the effect only partially explained by the agricultural sector (Heal & Park, 2013). Hsiang (2010) finds large effects of hot temperature shocks on economic output in Central America and the Caribbean for all economic sectors except mining and utilities. Jones and Olken (2010) find that hot temperature shocks negatively affect the growth in exports from poor countries in both agricultural and manufacturing sectors. Deryugina and Hsiang (2014) find substantial effects of hot days on annual income in the United States, including non-farm income. The mechanism driving temperature impacts in sectors not typically considered sensitive to temperature is unclear but may include effects on labor productivity or labor supply.

A second major question addressed in this literature is whether temperature shocks permanently affect the economy by affecting growth rates, which could have large implications for the SCC. Dell, Jones and Olken (2012), Lemoine and Kapnick (2016), and Burke, Hsiang and Miguel (2015) all examine the reduced-form relationship between temperature shocks and economic growth. In general these studies find evidence that temperatures negatively affect growth in poor countries, though they differ in some important respects. Both Dell, Jones and Olken (2012) and Lemoine and Kapnick (2016) find strong interactions between temperature impacts and per-capita income, suggesting impacts are driven by poor economies being more sensitive to temperature fluctuations. Burke, Hsiang and Miguel (2015) instead show evidence for a quadratic relationship between temperature and growth-rates, arguing that large impacts in poor countries arise because they are hotter than rich countries, not because they are poorer. The studies also differ in the extent to which they can confidently distinguish temporary effects of temperature on output from permanent impacts to the growth-rate. Dell, Jones and Olken (2012) use a distributed lag model to argue that warming impacts in poor countries affect the growth-rate. However, the same lag models in Burke, Hsiang and Miguel (2015) have large confidence intervals that overlap zero, meaning the proportion of temperature impacts falling on growth-rates as opposed to output is unclear. Lemoine and Kapnick (2016) instead use long-differences estimation to argue that temperature changes

have persistent effects on growth-rates over decadal timescales. While suggestive, there are still large uncertainties regarding whether growth-rate impacts exist, whether their magnitude depends on temperature or per-capita income, and what mechanisms are driving these effects.¹⁴

Two papers have incorporated some of the new empirical literature into DICE-2013R in order to examine the implications for optimal climate policy and the SCC. Moore and Diaz (2015) create a two-region version of DICE in which temperature affects growth rates by affecting either TFP or the depreciation rate of capital, calibrating the damage functions to reproduce Dell, Jones and Olken (2012). Even with optimistic adaptation assumptions, they find the SCC along the optimal emissions pathway to be six times higher than using the standard DICE damage function. In supplementary analysis Lemoine and Kapnick (2016) incorporate their long-differences estimate of growth-rate impacts into DICE, finding they do not tend to increase the SCC relative to the standard damage function, and in some cases decreases it significantly. In both papers, the question of how temperature impacts change with per-capita income as poor regions develop is a critical one and something still unresolved in the literature.

Incorporation of Reduced-Form Empirical Results into IAM Damage Functions

Although the literature cited above is relevant to the calculation of climate change costs, very few results in empirical papers have been incorporated into IAMs. Here we review four main issues that arise in translating empirical results to damage functions.

Adaptation

The new empirical literature on climate change impacts uses fixed-effects to remove time-constant variation and therefore improve confidence that estimated effects are causal and not caused by spurious relationships driven by variables omitted from the regression. However, fixed-effects also mean that the variation used to estimate the regression comes from short-term, unexpected fluctuations in weather. If there are actions people can take in response to long-term changes in climate that are not available in response to short-term, unanticipated weather fluctuations then the panel estimator will not necessarily give the long-run equilibrium impacts of a change in climate (Schlenker, 2010).

14 In addition to evidence for temperature shocks on economic growth, Hsiang and Jina (2014) use a distributed lag model to show cyclone strikes negatively affect economic growth, not just output. Even accounting for the fact that climate change will decrease cyclone risk in some areas, these growth impacts imply very large negative impacts of climate change.

Even the theoretical question of whether damage functions should include or exclude adaptation is not fully resolved. Some authors have argued that since climate change is a gradual process adaptation will occur rapidly relative to the rate of climate change and that the relevant damage function is therefore one that includes the net benefits of long-run adaptations (Mendelsohn, Nordhaus, and Shaw 1994). Others have argued that learning and transition costs mean that adaptation will be slow and that estimates of climate change damages should therefore include adjustment costs that will be partly determined by the short-run response given by panel estimators (Quiggin and Horowitz 1999). There is little empirical work on the rate of adaptation, though some evidence from US agriculture suggests it could be slow and adjustment costs correspondingly substantial (Kelly, Kolstad, and Mitchell 2005; Hornbeck 2012).

Two approaches have been suggested that combine the benefits of fixed-effects specifications with long-run climate variation that will capture more adaptation than standard panel estimators. Long-differences estimation uses idiosyncratic variation in decadal climate trends across space to estimate the medium-run impacts of climate change (Burke & Emerick, 2016; Dell et al., 2012). Another approach is to allow the marginal effects of warming to vary with temperature. This can be done either explicitly by estimating separate marginal effects for each location and then modeling these coefficients as a function of climate (Butler and Huybers 2012b; Auffhammer and Aroonruengsawat 2012; Hsiang and Narita 2012) or implicitly by estimating a non-linear panel model (for example Burke et al., 2015).¹⁵ Under certain assumptions, including that adaptation technologies are continuous, these marginal effects can be integrated out to give the long-run impacts of warming including the net benefits of adaptation (Wolfram Schlenker, Roberts, and Lobell 2013; Hsiang 2016).

Relationship of Climate Variables to Global Temperature

Damages in FUND, PAGE and DICE depend on global average temperature change but this is not typically used as an explanatory variable in the empirical literature. Instead, the papers discussed above are based on local temperature, often use non-linear transformations of temperature, and sometimes use other climate variables such as relative humidity, solar radiation or rainfall. While not theoretically complex, in some cases

the work necessary to translate these variables into functions of global average temperature change is substantial, requiring use of observational climate datasets and climate model output. The different steps involved for different functional forms and independent variables are summarized in Table 2, organized from least to most complex.

Step 1 is relatively straightforward and is in fact already implemented in FUND, which includes a linear pattern-scaling from global to regional warming used in the agriculture and health damage functions (Anthoff and Tol 2014b). Steps 2–4 however can rapidly become time-consuming and complex. Steps 3–4 require knowledge of climate model output, possibly including bias correction methods, that may be unfamiliar to most economists (Leard and Roth 2015). More complex climate modules within the IAMs that output regional temperatures or other climate variables would reduce the need for these translation steps.

Extrapolation and Generalization

Relying on empirical results to estimate climate damages requires extrapolating in a number of dimensions. Firstly, calculating a global SCC requires damage functions that have global coverage whereas empirical studies are often limited to specific regions or countries. Panel models rely on intertemporal variation for identification and therefore can only be reliably estimated using data collected in a comparable manner over a relatively long period. This is part of the reason why the geographic focus of most of the papers described above is the United States and western Europe. However, IAM damage functions are based on global impacts, which requires either new studies (where data is available) or geographic extrapolation of existing results, which may add significantly to the uncertainty in damage estimates.

Secondly, creating damage functions based on empirical results may require extrapolating beyond the range of temperature observed historically. Local warming expected over the 21st century will push many locations beyond the bounds of historical weather variability, in some cases (particularly in the tropics) within just a few decades (Mora et al. 2013; Diffenbaugh and Scherer 2011; Hawkins and Sutton 2012). Since several empirical papers have documented thresholds for impacts (Deryugina & Hsiang, 2014; Schlenker & Roberts, 2009), smoothly extrapolating a response function to higher

¹⁵ A model that is non-linear in temperature allows the marginal effects of warming to vary smoothly with temperature. Since most observations of hot temperatures come from locations that are already hot, the marginal effect of hot temperatures in a panel setting will be estimated mostly from locations that should be adapted to those temperatures.

Table 2 – Considerations for incorporating impact study results into global damage functions

Functional Form and Explanatory Variable	Notes	Translation Steps	Example Empirical Paper
Linear function of average local temperature	Temperature change over land and at higher latitudes is typically higher than global average temperature change.	Pattern-scaling between local and global temperature change	Dell, Jones and Olken (2012)
Non-linear function of average local temperature	The definition of baseline temperature may differ depending on the dependent variable. For example, many agricultural papers use crop-specific growing-season temperatures, in which case this step also requires knowing planting and harvest dates and growing areas.	Use climate model output to find local change in daily temperature distributions as a function of global warming. Or parameterize change in historic daily temperature distribution as a function of average warming.	Burke, Hsiang and Miguel (2015)
Function of degree days or days binned by temperature	Only a subset of climate models and observational datasets report daily temperature data.	Use climate model output to find local change in daily temperature distributions as a function of global warming. Or parameterize change in historic daily temperature distribution as a function of average warming.	Schlenker and Roberts (2009)
Functions of climate variables other than temperature	This parameterization may differ substantially between climate models, meaning multiple models would be required to ensure robust results.	Use climate model output to parameterize relationship between local changes in other climate variables and global average temperature.	Barreca (2012b)

temperatures may be unwarranted. Moreover, critiques of existing damage functions have emphasized the lack of an empirical basis for impacts at high levels of warming (6°C and above) and, under certain specifications, the sensitivity of the SCC to these numbers. Empirical results based on historical weather variation will not necessarily be able to constrain impacts at these very high temperatures.

Finally, some types of climate impacts are simply not well-suited to empirical estimation because they represent a completely new state of the world without good historical analogies. Examples include the effects of CO₂ fertilization (which are typically omitted from empirical estimates of climate change impacts on agriculture), long-term sea-level rise, or ocean acidification. Quantifying these impacts will require other forms of data such as experimental studies or process-based modeling.

Welfare Metrics

IAM damage functions parameterize the change in economic welfare with global temperature, but not all empirical studies examine variables that are immediately interpretable as changes in welfare. GDP is often used informally as a proxy for

welfare, but the connection between GDP and social welfare is complex. As noted above, GDP measures economic activity and is only an imperfect measure of welfare derived from market goods. Top-down studies that instead look at income (Deryugina and Hsiang 2014) or consumption may come closer to approximating climate change impacts on welfare. In addition, GDP does not capture welfare derived from non-market goods such as health or ecosystem services. Depending on substitutability assumptions, these non-market sectors may be critical determinants of the SCC.

Sectors differ widely in the ease with which empirical findings can be converted into welfare changes. Health impacts can be monetized simply (though sometimes controversially) using the value of a statistical life. In other cases, such as agricultural or labor productivity, warming everywhere simultaneously may result in substantial price changes, in which case general equilibrium models are required to determine welfare impacts. For heavily traded commodities such as food, the terms-of-trade effects of price changes may be an important (or even a dominant) component of regional welfare change (Moore et al. 2016). For some empirical results such as conflict, crime, or migration, quantifying welfare changes may be extremely difficult.

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