

# Empirically calibrating damage functions and considering stochasticity when integrated assessment models are used as decision tools

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**Abstract** – Benefit-cost integrated assessment models (IAMs), though developed originally for exploratory research, are now being applied as decision-making tools. This application places new demands on model calibration and capabilities. We suggest two directions for increasing the policy applicability of IAMs. First, employ recent work in the impacts community on empirical impact functions, grounded in the observed response of human systems to climate variability, to parameterize and calibrate IAM damage functions. Empirical damage functions can supplement and, in some cases, replace the often-dated damage estimates in IAMs with alternatives that can be directly compared to contemporary observations. Second, explicitly model the interactions between changes in mean climate and stochasticity in natural and human systems (e.g., weather, business cycles). Explicit stochasticity enables consideration of risk aversion with respect to episodic factors, such as extreme weather, thereby providing a natural way to examine the benefits of consumption-smoothing adaptive measures, such as insurance.

**Index terms** – integrated assessment models, damage functions, Earth system models, weather, stochasticity

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## 1 Introduction

The integrated assessment models (IAMs) used for benefit-cost analysis of climate change impacts and mitigation generally trace their intellectual lineage to Nordhaus (1992) and the first version of the DICE model, presented therein. These models have employed simple functional formulas to relate physical climate changes (most typically indexed by change in global mean temperature) to their economic impacts. Most IAMs either have functional representations of or are calibrated against projections of impacts, at relatively low levels of warming, for a few discrete sectors (e.g., agriculture, energy demand, human health); interactions among these sectors and between regions are often ignored (Warren, 2011; Oppenheimer, 2013). While uncertainty in parameters such as climate sensitivity may be considered, these models generally do not explicitly treat the economic impacts of climate variance or other stochastic factors.

For example, Fig. 1 shows estimates of damages by the sectoral calibration of the damage function used by DICE (Nordhaus, 2007, 2008) and the sectoral damage estimates of FUND (Anthoff and Tol, 2012) and ENVISAGE (Roson and Mensbrughe, 2012). In DICE and FUND, two models with long lineages of publications, most of the sectoral studies used for calibration date back more than a decade, to a time when the impact research

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community's understanding and ability to model such impacts was significantly less developed than today (see Kopp et al., 2012, for a synopsis). This lag between empirical impact research and its incorporation into IAMs is understandable: from an academic research perspective, many of the fundamental questions models like DICE and FUND were developed to address are conceptual. For example, how does the social cost of carbon change with different assumptions about discounting, equity, or socio-economic and policy scenarios? In this context, tuning or updating damage calibrations to match the latest impacts literature is not a high priority (although improving models to include unimplemented structural effects such as intersectoral interactions or stochasticity might be).

Nevertheless, the quantitative outputs of benefit-cost IAMs are currently being used to inform policy judgments. In the United States, for example, benefit-cost analyses that help set stringency of Federal regulations that reduce carbon dioxide emissions (such as energy efficiency standards and power plant carbon standards) employ estimates of the social cost of carbon derived from these models. The current range of official U.S. social cost of carbon estimates (\$5-\$70/tonne CO<sub>2</sub> emitted in 2013) are derived by averaging across three IAMs – DICE, PAGE (Hope, 2006) and FUND – at three different discount rates (Interagency Working Group on the Social Cost of Carbon, United States Government, 2010; Kopp and Mignone, 2012). In the context of policy analysis, the quantitative calibration of damage estimates matters greatly, as may omitted features of the climate such as stochasticity. In the remainder of this paper, we propose an approach for tackling each of these elements and illustrate their potential quantitative influence.

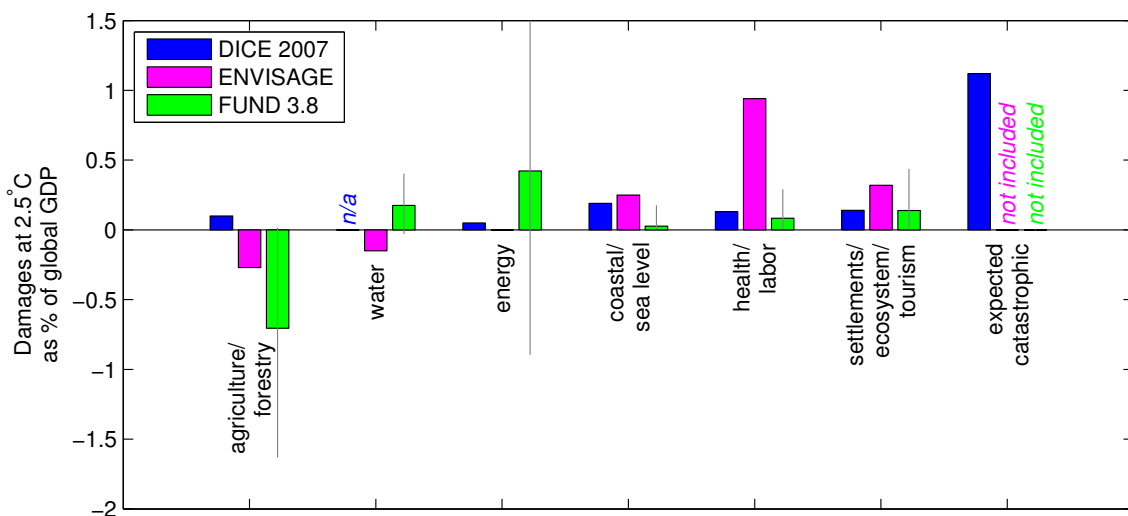


Figure 1: Monetized damage calibration (for DICE 2007) or estimates (for ENVISAGE and FUND 3.8) by sector at 2.5°C, as a percent of global GDP. Error bars for FUND reflect 5th-95th percentiles calculated off the FUND reference scenario. Modified from Kopp and Mignone (2012).

## 2 Empirical calibration of damage functions

Over the last decade, researchers have developed empirical estimates of climate change impacts based on observed historical relationships between environmental conditions and socioeconomic responses, such as agricultural output (e.g., Schlenker and Roberts, 2009), labor productivity (e.g. Hsiang, 2010), or energy demand

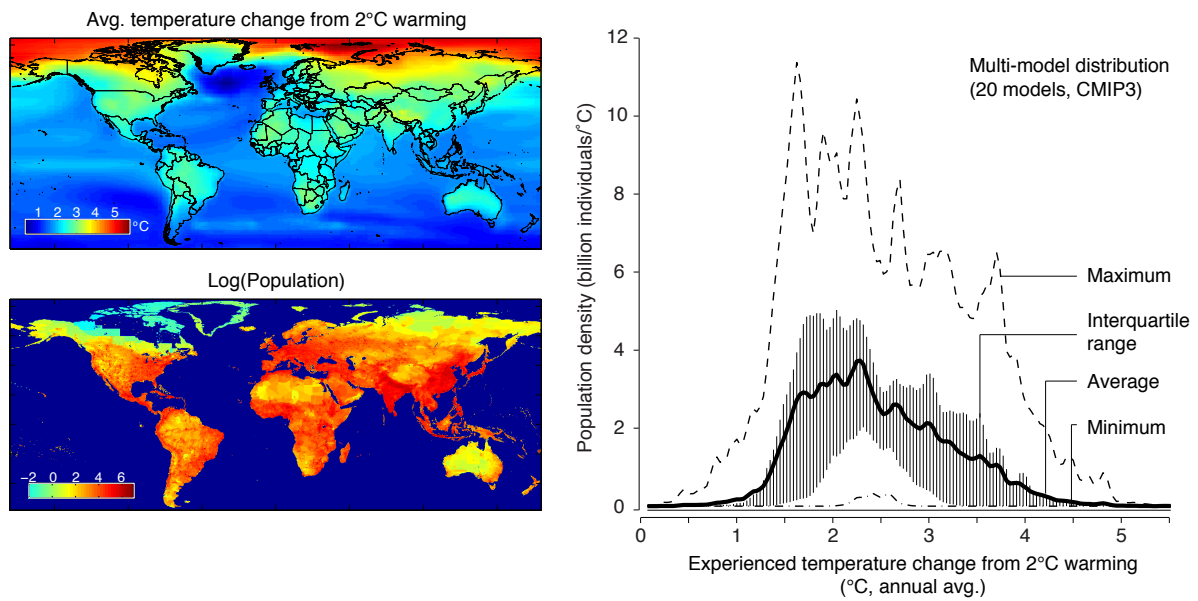


Figure 2: *Upper left:* The global distribution of surface temperature changes associated with 2° warming in global mean temperature, averaged across 20 Earth System Models in CMIP3. *Lower left:* The global distribution of the world population, from the Gridded Population of the World. *Right:* The distribution of temperature changes experienced by individuals, across models.

(e.g., Auffhammer and Aroonruengsawat, 2011). Unfortunately, integrating empirical results into IAMs is a difficult task, and few authors pursue such integration. Here, we propose a procedure to streamline integration, making it easier for empirical researchers to present their results in a such a way that they are immediately applicable to IAMs. As more empirical studies are converted into IAM-ready format, we suggest developing an online database that will use Bayesian updating to continuously improve sectoral damage functions for use in IAMs. This system will provide a seamless link between the empirical impacts research community and the IAM research community, thereby ensuring that policy decisions made using IAMs are always based on the best-available empirical research.

Essentially, our approach collapses multidimensional output from global earth systems models into those statistics needed to make impact projections using statistical estimates taken from the empirical research community. Using these summary statistics, we can then project a socioeconomic response based on most empirical estimates, and aggregate these results up to the level of analysis used in IAMs. The basic flow is as follows:

1. Use Earth system model output to develop a probabilistic mapping between global mean temperature change and the distribution of social (or economic) exposure to future climatic changes based on the global distribution of primitive units, i.e. number of humans, dollars of economic production, area of agricultural crop lands, etc. (Figure 2).
2. Summarize global unit-level changes in climatic exposure based on the characteristics of units that are essential for estimating their response to climatic changes, such as the income of populations – which might influence their capacity to adapt (Figure 3).

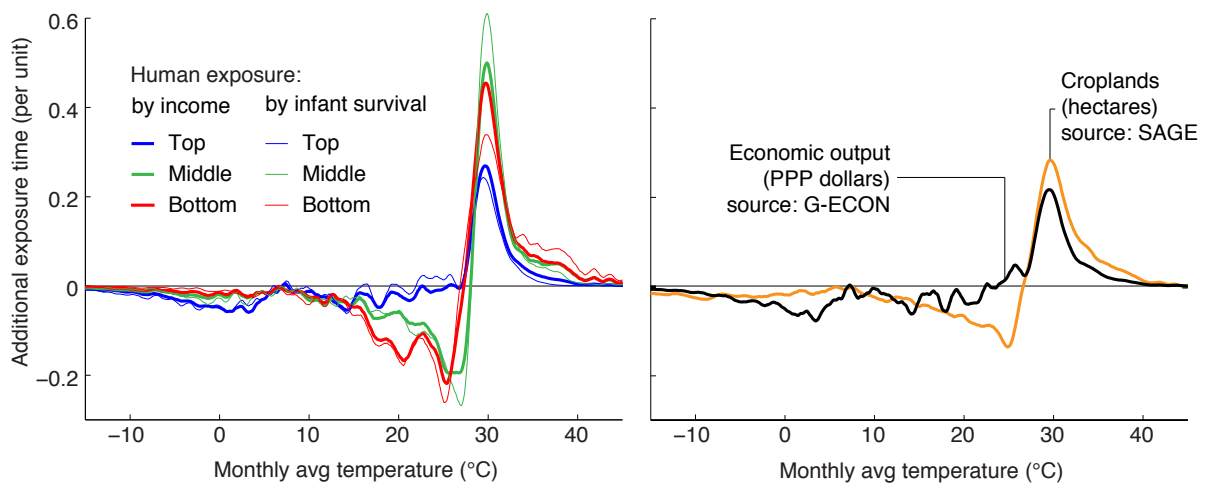


Figure 3: The amount of additional time that a randomly selected unit will be exposed to specified temperatures under 2°C warming in global mean temperature. The global population (left) is stratified into three tiers based on two metrics of vulnerability: income and infant mortality. Also shown is the distribution of economic activity and croplands (right).

3. Project these distributions of exposure onto empirically derived “dose-response” functions that describe how socio-economic sectors respond to a given “dose” of climatic exposure (eg. Figure 4).
4. Aggregate projected impacts, conditional on changes in global mean temperature, up to the unit of analysis used in IAMs (e.g., geographic regions).
5. Compare and, as desired, integrate (via Bayesian statistics) empirical damage estimates with process-model-based estimates, so as to overcome limits of empirical studies (for example, for out-of-sample projection).
6. Propagate impacts through a macroeconomic model, such as a computable general equilibrium (CGE) model, to translate impacts into output or welfare losses and account for compensatory or amplifying interactions between regions and sectors.
7. Integrate impact estimates across projections that use different empirical studies (via Bayesian statistics) to construct a composite damage functions that are updated in real-time and publicly available via server.

To demonstrate the importance of this calibration procedure, we project the predicted change in United States crop exposure onto the temperature response functions in Figure 4 (obtained from Hsiang et al. (2012)). We plot the projected impact of a 2°C global mean warming for all four major crops in Figure 5, along with the average response (weighted by area-planted). When we compare these responses to comparable “agricultural damage functions” used in three modern IAMs, we note that these empirical estimates suggest agricultural losses under 2°C warming will be roughly an order of magnitude larger in magnitude than the IAM functions predict. This large discrepancy indicates that systematic calibration of IAM damage functions is badly needed.

To illustrate the generalizability of our proposed calibration procedure, we demonstrate that it can easily link a “new” damage function to impacts aggregated across regions used in IAMs. In Figure 6 (upper left panel) we

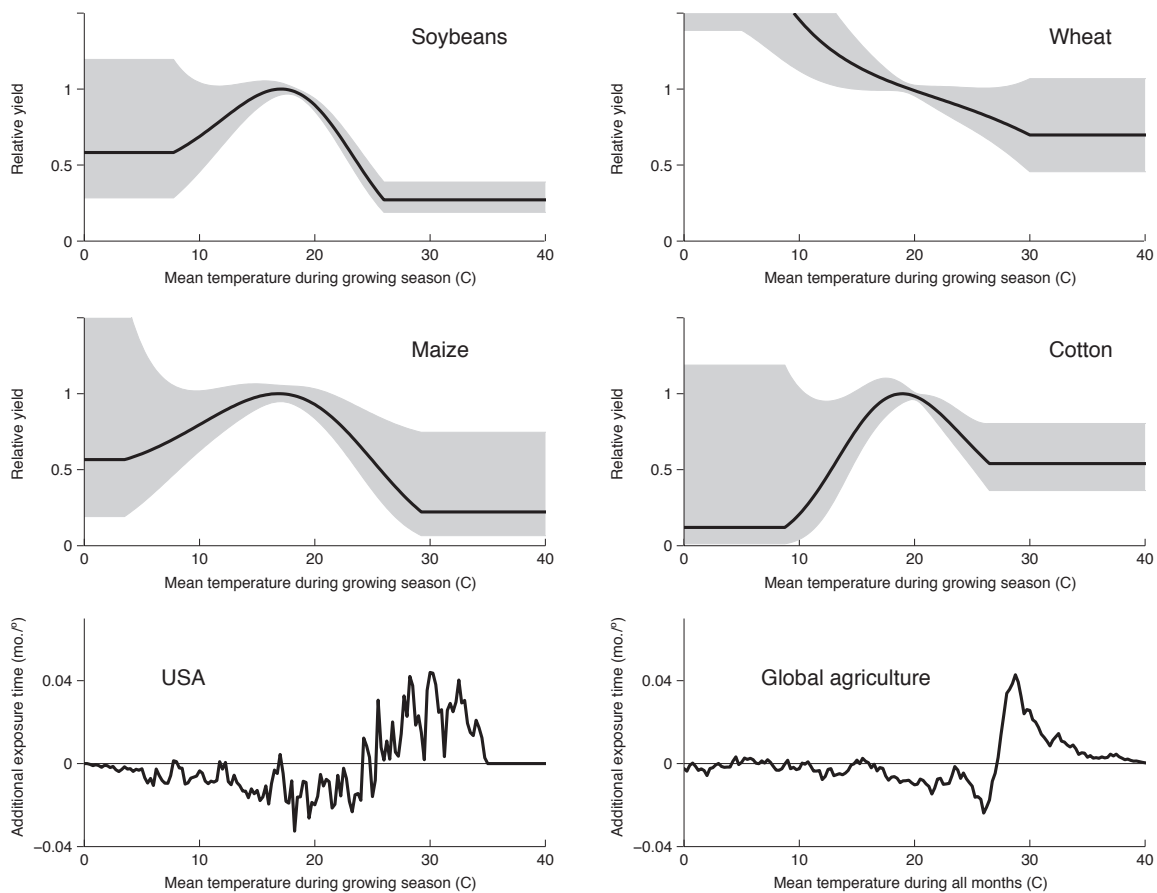


Figure 4: *Top four panels:* Empirically-derived responses of four major crops to growing season temperature in United States counties, from Hsiang et al. (2012). The estimates are based upon comparison of county-level output to county-level average growing season temperature and rainfall (1950-2010). County-level yields is modeled as a polynomial response to temperature and rainfall, accounting for unobserved differences between counties and secular trends. Outside the limits of the temperature data, we conservatively assume constant yields. *Lower panels:* The additional amount of time that croplands in the United States and the world will be exposed to these temperatures under 2°C warming in global mean temperature.

illustrate an empirical estimate for the loss of labor productivity observed at high temperatures Hsiang (2010). Mapping this response function onto the distribution of human exposure to temperature (lower left panel) allows us to estimate region-specific impacts (right panel) based on the regions utilized in FUND.

As parametrizations of adaptation are developed in the empirical literature, these damage function calibrations can be adjusted accordingly.

### 3 The role of stochasticity

Many natural and human systems are stochastic. For example, weather is the manifestation of variance around climatological means; business cycles are manifestations of variance around long-term economic growth. Al-

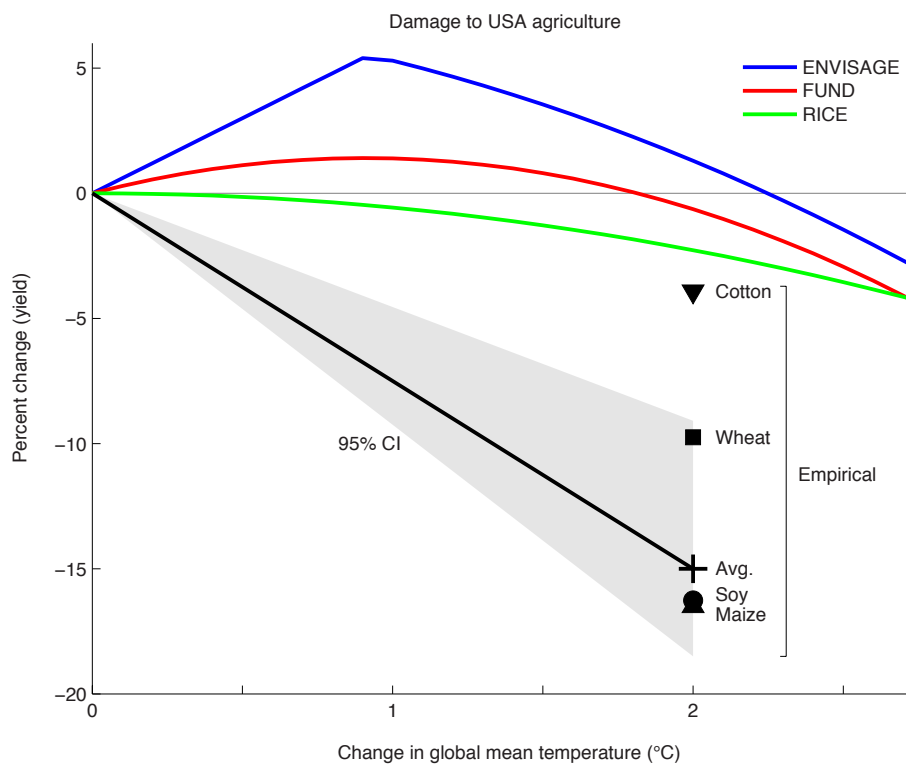


Figure 5: Black: Projected changes in yields using response functions in Figure 4 and the projected exposure of USA croplands. Average changes are averaged by cropland planted in a given crop. The shaded region is the 95% confidence intervals for the average effect across crops. Comparable damage functions (in yield terms for ENVISAGE and FUND and monetized terms for RICE) from ENVISAGE, FUND and RICE are colored.

though climate damages are often partially realized through shifts in climatological extremes, IAMs have generally not explicitly included year-to-year variability. IAM welfare analysis therefore implicitly assumes perfectly-functioning markets and institutions capable of spreading risk over time and thus allowing the welfare impact of average damages to be a good substitute for the welfare impact of a sequence of actual loss realizations (which vary around this average). Without such markets or institutions, however, the absence of inter-annual variability likely leads to an underestimate of future welfare losses.

The importance of stochasticity is clearly illustrated by the example of sea level change. Most damage due to sea level rise is not due to the permanent inundation of land but to enhanced episodic flooding. Local sea surface height is the sum of long-term anthropogenic and natural trends, multi-year ocean dynamic variability, periodic tidal signals, and storm surges. The ~20 cm of climatically-driven twentieth-century sea level rise led to acute impacts for fifty thousand additional residents of New York City when the city was hit by Superstorm Sandy (Climate Central, 2013); this impact was exacerbated because the storm surge occurred in superposition with pre-existing sea level rise (as well as high tide). IAMs, as they are currently structured, do not capture these kinds of acute impacts and instead would model the impact of a cyclone-induced surge as a small increase in average sea level spread across many years.

Natural system stochasticity is not limited to sea level and flooding; it is ubiquitous and affects most climate change impacts. As another example, consider corn yields. Employing the impact function of Schlenker and

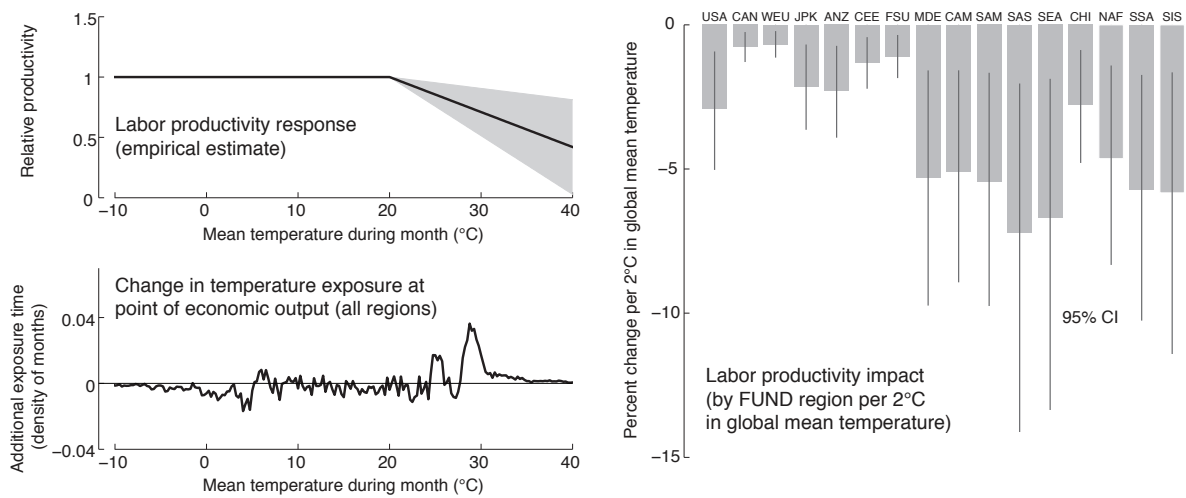


Figure 6: *Top left:* Empirical estimate of the response of labor productivity to temperature exposure with 95% confidence interval (gray) (Hsiang, 2010). The estimate is based upon analysis of the influence of annual, monthly and daily temperature variations on overall economic output (GDP) in 28 countries in the Caribbean and Central America (1970-2006) using panel data disaggregated by industry, and accounting for precipitation, hurricane exposure, unobserved constant differences between countries, secular trends and autocorrelation. *Lower left:* the projected change in temperature exposure of the global population (across all regions) under 2°C warming in global mean temperature. *Right:* the corresponding loss in labor productivity, broken down according to FUND region.

Roberts (2009) to daily temperatures from Topeka, Kansas, USA (National Climate Data Center, 2013), we find that corn yield over the interval 1973-1998 should have varied between 60% and 110% of its expected value due to the effects of temperature alone (Fig. 7). The return interval of a 20% loss event (i.e., yield of 80% of its expected value) was about 20 years. In Figs. 8 and 9 we examine the projected effect of warming on expected crop yield, the 5th-95th percentiles of crop yield, and the return intervals of crop loss events. With 1°C of warming, the return interval of a 20% loss event drops to 12 years; with 2°C of warming, to 7 years; and with 4°C of warming, it drops to 1.2 years. Estimates of welfare losses and effective adaptive measures must both take into account the increasing frequency of exceptionally low harvest years and the strain they exert on insurance and safety networks, not just the change in expected agricultural yield. With 1°C of warming, the increased frequency of the 20% loss event, not the minor drop in expected yields, may drive welfare impacts; in their present form, most IAMs can deal only with the latter, not the former.

IAMs could incorporate regional climatological variability into Monte Carlo simulations, employing as a first estimate historical estimates of variance, much as we have in this example. Earth system model estimates of changes in variance could refine this approach. Economic stochasticity has already been incorporated in some studies through the use of dynamic stochastic general equilibrium models (e.g., Gerst et al., 2013). We expect that interactions between economic variability and weather that would emerge from the inclusion of these factors would act in some cases as a dampening factor and in some cases as an amplifying factor to climate damages.

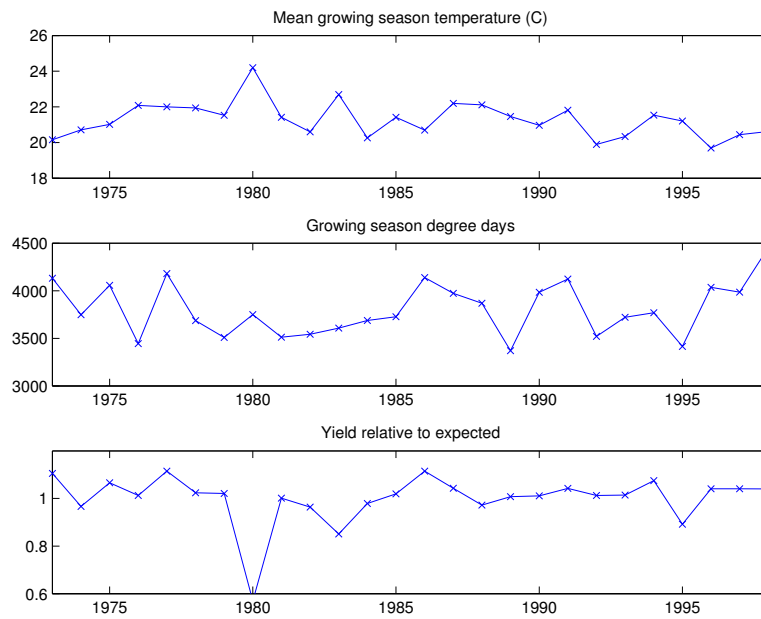


Figure 7: Mean growing season temperature, growing season degree days, and corn yield relative to expected corn yield calculated using the empirical impact function of Schlenker and Roberts (2009) for Topeka, Kansas, 1973-1998. (Data from National Climate Data Center (2013).)

#### 4 Conclusions and next steps

For benefit-cost IAMs to be suitable for real-world policy analysis, their damage estimates need to reflect the available impact literature. It is unreasonable to expect a handful of small research groups, motivated primarily by the pursuit of research questions of academic economics interest, to manage this task on their own. Community infrastructure could therefore make a critical contribution. We propose a procedure for developing this infrastructure, so that empirical researchers will be able to easily “upload” their results so that they can be immediately and automatically integrated (in a Bayesian fashion) into subsequent IAMs.

We also note that no existing IAM takes into account natural climatic stochasticity (weather), but whether impacts are distributed smoothly through time or concentrated in extreme events will significantly affect both the nature of suitable adaptation mechanisms and, in the absence of perfect safety nets, the nature of the associated welfare impacts. An IAM drawing upon gridded estimates of climate variability would provide a more realistic picture for many categories of impacts.

#### Acknowledgements

REK was supported by a grant from the U.S. Department of Energy and the U.S. Climate Change Technology Program.



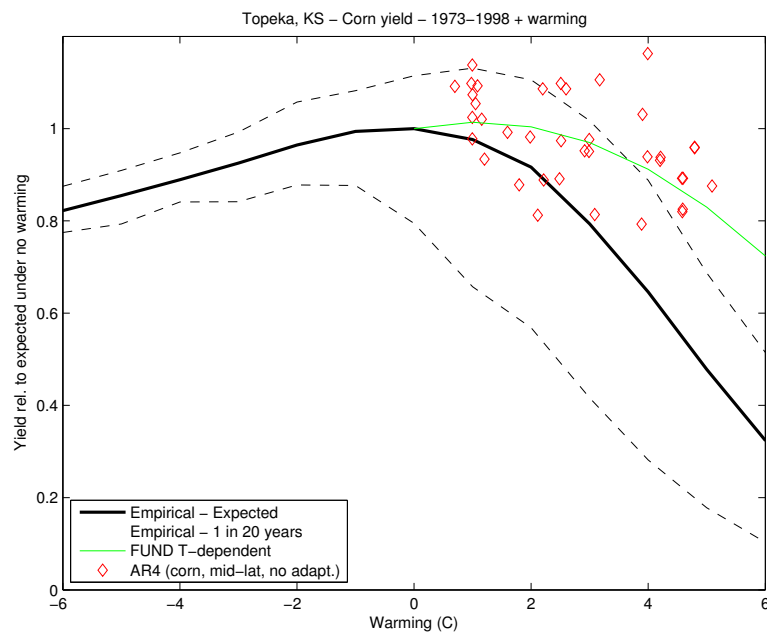


Figure 8: Expected crop yield (heavy black curve) and 5th and 95th percentiles of crop yield (dashed lines) for Topeka, Kansas, using daily temperatures from 1980-2012 incremented by different levels of warming. For comparison, crop yields from the models summarized in IPCC AR4 for mid-latitudes and no adaptation (Easterling et al., 2007) are indicated by the red diamonds and the temperature-dependent term of U.S. agricultural product change from FUND 3.6 is shown in green Anthoff and Tol (2012).

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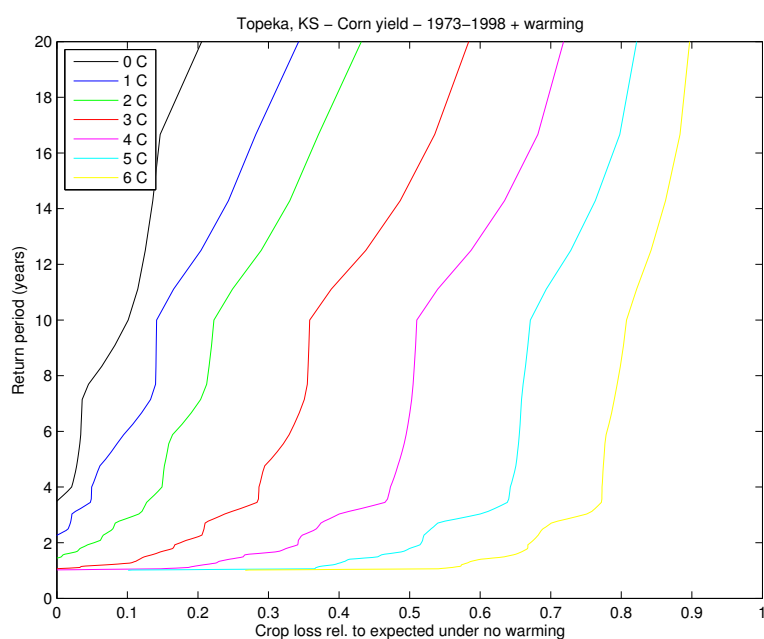


Figure 9: Return periods of corn crop loss events with different levels of warming.

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