Stochastic Simulation for Climate Change Risk Assessment and Management

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EXTENDED ABSTRACT

The risk management paradigm has been proposed by a number of national and international research organisations as a useful framework for identifying robust decisions in the face of the inherent uncertainties associated with climate variability and anthropogenic climate change. The pursuance of risk management hinges on four fundamental considerations: a) a threshold for a particular system of interest; b) understanding of the response of that system to climate variability and/or change; c) understanding of the probabilities associated with different climate futures; d) one or more management options or strategies for reducing risk.

Integrating these four components in the process of risk management is a non-trivial task, particularly for complex systems. Stochastic simulation such as Monte Carlo analysis is a useful tool for achieving such integration in a modelling environment. Monte Carlo techniques were applied in the analysis of impact assessment data from the United States to assess the uncertainty associated with the direction and magnitude of different impacts over a range of climate futures and estimates of sectoral responses. Bayesian techniques were used in the quantification of the probabilistic uncertainty associated with global and U.S. changes in climate and sea-level in 2025, 2050, and 2100 using different assumptions regarding future greenhouse gas emissions and climate sensitivity. In addition, the potential for greenhouse gas mitigation to constrain future uncertainty in climate parameters, and thereby reduce climate impacts, was assessed using the WRE 750/550/350 stabilisation scenarios as constraints on future emissions. Monte Carlo simulation was used to integrate posterior probability distributions for climate variables with probabilistic impact response functions for a number of key sectors including agriculture, energy, coastal protection, water resources, freshwater biodiversity, and human mortality.

Impact distributions indicated there is significant uncertainty associated with future climate change impacts. This uncertainty becomes increasingly less constrained as one's time horizon extends further into the future. For a number of sectors, even the direction of impacts (e.g., damages vs. benefits) could not be determined with a high degree of confidence. Nevertheless, the results indicated that significant climate change impacts are likely in future decades including economic impacts of plus-or-minus several billion dollars, thousands of excess deaths, significant reductions in suitable habitat for wildlife, and reductions in runoff and subsequently, water availability. The impact distributions also revealed that where potential benefits are likely, there remains a lower, but not necessarily negligible, probability of significant adverse effects, and vice versa.

Given a particular critical threshold, these impact distributions can be used to estimate the likelihood of threshold exceedences, and subsequently, provide guidance on the need for risk treatment actions. More stringent thresholds create greater perceptions of risk and thus greater demand for risk treatment, while less stringent thresholds have the opposite effect. Greenhouse gas mitigation generally reduced the risk of adverse climate change impacts. However, the benefits of mitigation were quite limited pre-2050, and even in later decades, stringent stabilisation levels were needed to significantly reduce risk. Mitigation largely benefited the avoidance of large-scale consequences, but did little toward avoiding near-term and/or smaller scale consequences, which are likely those of most relevance to current decision-making activities.

Probabilistic risk assessment offers a useful framework for managing decision-making events challenged by uncertainty. Yet there are important challenges to consider. Uncertainty regarding appropriate ranges and distributions for model parameters introduces subjectivity into Bayesian analysis. Uncertainties associated with impact estimates increase rapidly over time, and dynamical system properties can influence estimates of risk. The spatial scale of analysis must be tailored to ensure results are relevant to decision-making. Finally, in order for the development of methodologies for climate change risk analysis to ultimately benefit decision-making, considerable effort must be invested to ensure that risk assessment is combined with societal preferences for impact thresholds, risk aversion, discounting, and risk treatment within the larger context of risk management.

1. INTRODUCTION

The uncertainty associated with the issue of climate change has been described variously as "persistent," "deep," and "irreducible." These uncertainties propagate from both the top-down (e.g., global greenhouse gas emissions and climate sensitivity) as well as from the bottom-up (e.g., regional sectoral climate sensitivity and coping capacity). Such uncertainty creates a range of challenges not only for scientific investigations into climate change and its downstream consequences, but also for decision-making processes. How does one identify the optimal mitigation strategy given indeterminism regarding future climate change and system responses, and, in fact, is this an appropriate framing of the climate challenge? Alternatively, how do Australia's dryland farmers and/or water resource managers identify appropriate actions to reduce their vulnerability to climate given that the past may no longer be a satisfactory analogue for the future?

Ideally, given such uncertainty, one should opt for decisions that are robust, over the range of potential future outcomes. Traditional deterministic projections or scenarios of future climate or system responses offer little to such an approach, however. There is no single "correct" estimate of future climate change, and, in fact, an infinite number of wrong answers. Instead, uncertainty in climate change and its downstream consequences should be expressed in units of probability or likelihood. This enables one to pursue risk-based impact assessment and management, whereby thresholds for climatic changes and/or specific impacts are integrated with probability distributions for climate, environmental, and socioeconomic variables that influence system outcomes (Jones 2001).

An impact assessment model was constructed which utilised Monte Carlo techniques to stochastically generate probabilistic estimates of future climate change impacts in the United States. Probability distributions for global temperature and sea level and U.S. temperature and precipitation changes in 2025, 2050, and 2100 were based upon Bayesian techniques utilizing an ensemble simulation of global and U.S. climate change from a simple climate model. Posterior probabilities for climate variables were then integrated with probabilistic impact response functions for six different market and nonmarket sectors to generate probability distributions for climate change impacts.

2. PROBABILITY DISTRIBUTIONS FOR GLOBAL AND U.S. CLIMATE CHANGE

2.1. Climate Model Simulations

The range of uncertainty in future average U.S. temperature, precipitation, and sea-level changes was estimated from multiple climate simulation exercises using the publicly available Model for the Assessment of Greenhouse-Gas Induced Climate Change (MAGICC; v.4.1) coupled with a regional climate change scenario generator (SCENGEN) following the methods of Preston (2005a). Global temperature changes and sea-level rise (SLR) in 2025, 2050, and 2100 relative to unperturbed baseline controls were simulated using MAGICC tuned to seven different Atmosphere/Ocean General Circulation Models (GCMs): CSIRO, CSM, HADCM2, HADCM3, ECHM4, GFDL, PCM. Default (mid-range) estimates were used for carbon cycle modelling and aerosol forcing, with variable thermohaline circulation and carbon cycle feedbacks. SLR estimates included low, medium, and high ice-melt paramaterisations. The output from different climate models was used to capture the range of uncertainty associated with climate sensitivity in addition to fundamental differences in model representation of the climate system. To capture uncertainty associated with future global greenhouse gas (GHG) emissions, simulations for each GCM were conducted using the six illustrative scenarios (A1B, A1Fi, A1T, A2, B1, and B2) of the IPCC's Special Report on Emissions Scenarios (SRES; IPCC 2000). Modelling the seven GCMs with the six emissions scenarios resulted in a total of 42 MAGICC simulations of global mean temperature change for each time period. SLR estimates were based upon these 42 simulations with 3 different ice-melt parameterisations (low, medium, and high), resulting in a total of 126 simulations of SLR.

Global mean temperature changes were scaled to the United States (25^{o} to 50^{o}N by 65^{o} to 125^{o}W) for each of the above GCMs and emissions scenarios using the SCENGEN regional modelling tool (with exponential/power law scaling), which downscales global average temperature changes to 5^{o}x5^{o} grid cells using the scaling technique of Santer et al. (1990). Temperature and precipitation changes for individual grid cells were subsequently averaged to yield a model estimate of annual or seasonal U.S. climate changes in 2025, 2050, and 2100. United States SLR for these three time periods was assumed to be equivalent to global means.

2.2. Probability Distributions for Temperature and Precipitation Changes

Each of the 42 simulations of global temperature and U.S. temperature and precipitation changes in 2025, 2050, and 2100 from MAGICC and SCENGEN were assigned a probability, which was subsequently used to calculate continuous cumulative probability distributions for climate change. Two different methods were used to assign probabilities to individual climate model simulations. The first method (referred to hear as EQUAL) assumed all models and emissions scenarios performed similarly with respect to simulating future global or U.S. climate conditions (i.e., uniform or uninformed prior). Thus, the probability of a particular model result was calculated using the following equation:

$$P_{S\Delta T} = P_{Sk} \times P_{m\Delta T,k}$$

where $P_{S\Delta T}$ is the probability of a projected temperature change for a particular model and emissions scenario, P_{Sk} is the probability of the k emissions scenario, and $P_{m\Delta T,k}$ is the probability of an individual model result for the k emissions scenario.

The second method for assigning probabilities to climate model simulations (referred to here as REA), weighted the probability of model results based upon performance criteria following the reliability ensemble analysis (REA) methodology of Giorgi and Means (2002, 2003). The REA method weights the results from an ensemble of GCMs based upon an indicator of a model's reliability, which a function of two criteria: 1) the skill with which an individual model reproduces historical climate changes and 2) the extent to which the projections of an individual model converge on the ensemble mean. Each model simulation was assigned a reliability indicator (R_i) based upon its performance with respect to these two criteria using the following formula (Giorgi and Mearns 2002):

$$R_i = \left\{ \left[\frac{\boldsymbol{\varepsilon_T}}{\mathbf{abs(B_{T,i})}}\right]^m \left[\frac{\boldsymbol{\varepsilon_T}}{\mathbf{abs(D_{T,i})}}\right]^n \right\} [1/(m{\star}n)]$$

where ε_T represents historical climate variability based upon the difference in the minimum and maximum value for average global temperature or U.S. temperature and precipitation changes from 30-year running means of (linear) detrended data records. For global temperature variability, minimum and maximum values were derived from global temperature anomalies (1880–2003; Hansen *et al.* 2001; Giorgi and Mearns 2002). For U.S. temperature variability, minimum and maximum values were derived from average annual U.S. temperature anomalies (1880–2003; Hansen *et al.* 2001; Giorgi and Mearns 2002). For U.S. precipitation variability, minimum and maximum values were derived from average annual U.S. precipitation observations (1880–2003; Hansen et al. 2001; Giorgi and Mearns 2002). $B_{T,I}$ represents the average model bias in reproducing the historical (1961–1990) baseline mean temperature climatology for the geographic area under consideration (CRU; New *et al.* 1999). Root-mean square errors among the seven models in reproducing historical global temperature change ranged from 0.20–2.38. Root mean square errors in reproducing U.S. temperature and precipitation changes ranged from 1.2–3.2 and 0.13–0.51, respectively. $D_{T,I}$ represents the distance between an individual model's projection and the ensemble mean, and m and n represent weighting coefficients for the two R_i criteria (here both were assigned equal weights of 1). Reliability indicators were used to assign probabilities to individual model simulations using the following formula (Giorgi and Mearns 2003):

$$P_{S\Delta T} = P_{Sk} \left[\frac{R_{i,k}}{\Sigma R_{j,k}} \right]$$

where $P_{S\Delta T}$ represents the probability of a projected temperature or precipitation change; P_{Sk} is the probability associated with a particular emissions scenario; $R_{i,k}$ represents the reliability indicator for a particular model given the k emissions scenario; and $\Sigma R_{j,k}$ represents the sum of R_i among all climate models for the k emissions scenario.

The probabilities associated with simulated climate changes using the various weighting schemes identified above were subsequently summed and expressed as cumulative probabilities. Climate changes and their cumulative probabilities were then used to estimate continuous cumulative probability distributions via linear interpolation among data points using Analytica™ 2.0 with median Latin hypercube sampling (n=1,000).

2.3. Probability Distributions for Sea-Level Rise

Probability distributions for SLR were calculated using a stochastic SLR generator. The relationship between global mean temperature change and SLR was quantified using a least squares multiple regression model that regressed the 126 MAGICC simulations of SLR in 2025, 2050, and 2100 against the 42 simulations of global mean temperature change and a stochastic dummy variable representing the three different ice melt parameterisations. The regression models for each time period were highly significant ($p<0.0001$) with r^2 values of 0.95, 0.98, and 0.98 in 2025, 2050, and 2100, respectively. Regression coefficients from this regression model were subsequently integrated with the EQUAL and

REA probability distributions for global mean temperature change via Monte Carlo simulation (n=1000) to generate continuous cumulative probability distributions for future SLR.

2.4. Mitigation Scenarios

To assess the sensitivity of climate change impacts to global GHG emissions reductions, a series of climate model simulations were also conducted using three of the Wigley, Richels, Edmonds (WRE) emissions stabilisation scenarios (WRE350/550/750) as upper constraints on future emissions in the MAGICC/SCENGEN ensemble modelling (Wigley *et al.* 1996). The WRE emissions scenarios constrain future GHG emissions in order to achieve a stable atmospheric CO_2 concentration, thus limiting, as a consequence, future radiative forcing and temperature change. Modelling of GHG mitigation cases in MAGICC/SCENGEN was performed for 2025, 2050, and 2100 using each of the three WRE scenarios as well as other SRES scenarios that generated equal or less net radiative forcing for each time period as indicated by MAGICC output. Due to insufficient sample size for REA distributions under the WRE350 constraint, REA weighting was not utilised in the analysis of climate change in response to mitigation. Continuous cumulative probability distributions were estimated for the stabilisation distributions in the same manner as above.

3. IMPACT RESPONSE FUNCTIONS

Continuous impact response functions relating climate and sea level changes to sectoral impacts were calculated based upon a survey of previously published impact assessments (see Preston 2005b). For each sector or impact of interest, multiple estimates were available based upon scenario exercises whereby sectoral responses were estimated for discrete magnitudes of temperature, precipitation, or sea level changes. These data were used to develop reduced-form impact response functions for the six sectors considered in the current study via least-squares regression techniques.

Uncertainty around regression models was estimated by calculating 99.9% confidence intervals for regression coefficients. Regression coefficients and confidence limits were subsequently used to calculate probability distributions for regression coefficients using Analytica™ 2.0. Probability distributions were calculated by assigning the regression coefficients cumulative probabilities of 0.5, and lower and upper 99.9% confidence intervals for regression coefficients cumulative probabilities of 0 and 1, respectively. These cumulative probabilities were then used to generate continuous cumulative probability distributions. Probability distributions for impact response function regression coefficients were subsequently used as parameters in risk modelling. Damage functions for specific sectors are listed below (from Preston 2005b):

3.1 Agriculture

$$\text{Annual Impacts (2000\$)} = 10.01(\Delta T) - 2.22(\Delta T)^2 + 0.54(\Delta P) - 0.02(\Delta P)^2$$

with ΔT and ΔP representing annual temperature (^oC) and precipitation (%) changes, respectively, relative to baselines in the absence of anthropogenic perturbation.

3.2 Energy Costs

$$\text{Annual Costs (\$2000)} = -1.311(\Delta T) + 1.099(\Delta T)^2$$

with ΔT representing the change in annual U.S. temperature (^oC).

3.3 Coastal Protection Costs

$$\text{Costs in 2025 (2000\$)} = 0.94(\Delta SL) + 0.016(\Delta SL)^2$$

$$\text{Costs in 2050 (2000\$)} = 1.22(\Delta SL) + 0.026(\Delta SL)^2$$

$$\text{Costs in 2100 (2000\$)} = 1.49(\Delta SL) + 0.065(\Delta SL)^2$$

with ΔSL representing the change in global sea level (cm) by 2100.

3.4 Terrestrial Runoff

$$\text{Annual Runoff (\% change)} = 1.51(\Delta P) + 11.53(\Delta T) - 2.4(\Delta T)^2 + 16.2$$

with ΔT and ΔP representing annual temperature (^oC) and precipitation (%) change, respectively, relative to baselines in the absence of anthropogenic perturbation.

3.5 Cold-Water Habitat

$$\text{Habitat Loss (\%)} = 8.3\Delta T$$

with ΔT representing JJA temperature (^oC) change relative to baselines in the absence of anthropogenic perturbation.

3.6 Human Population and Mortality

*Annual Mortality (# individuals)=(H_D*DT+AQ_D *DT)*(POP/100,000)*

with H_D and AQ_D representing heat-related and air-quality related deaths per 100,000 individuals, respectively, ΔT representing annual mean temperature (^oC) change, and POP representing total U.S. population in 2025, 2050, or 2100.

4. RISK ANALYSIS

Estimates of the probabilistic uncertainty associated with 2025, 2050, and 2100 U.S. climate change impacts were generated by integrating probability distributions for climate and sea-level changes with the various response functions. For each sector/impact and time period, a series of 1,000 Monte Carlo simulations were conducted using Analytica™ 2.0. Temperature, precipitation, and sea-level changes were sampled at random from the appropriate probability distribution and used as input in the response functions with regression coefficients for those damage functions being similarly sampled at random from their corresponding probability distributions. This procedure was repeated for each of the two weighting schemes for climate and sea-level changes.

5. RESULTS AND DISCUSSION

Impact distributions generated through the integration of climate and sea-level distributions with the sector-specific impact response functions demonstrated the broad range of uncertainty associated with estimates of future U.S. climate

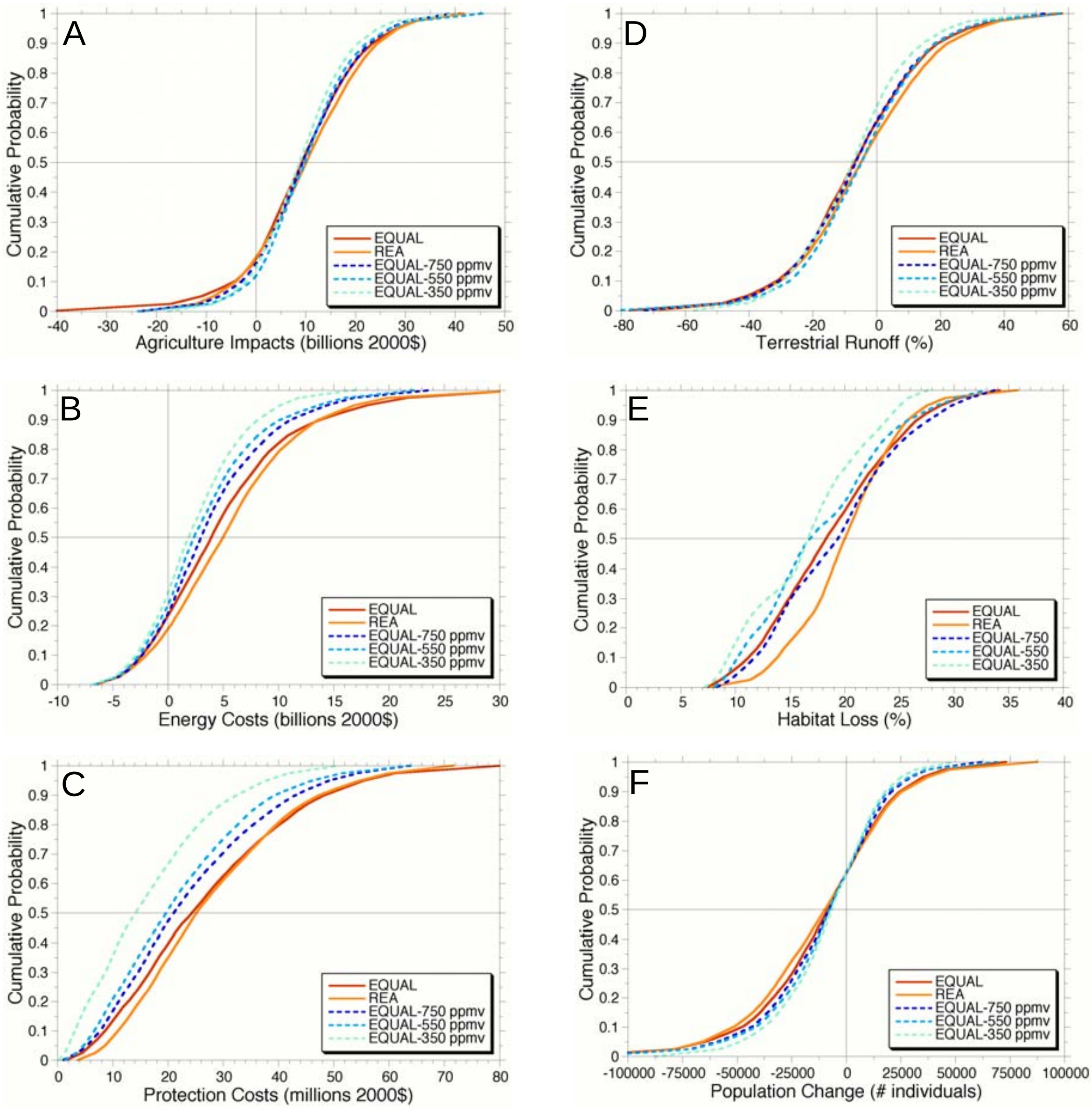
Table 1. Estimated impacts of climate change in 2025, 2050, and 2100. For each time period, estimated impacts are presented as a range corresponding to the 95% confidence intervals. For agriculture, positive numbers indicate benefits while negative numbers indicate costs/damages. For all other sectors, positive numbers indicate costs/damages/mortality, while negative numbers indicate benefits.

Impact/Year	**Effect (95% Confidence Interval)**				
	REA	**EQUAL**	**EQUAL-750**	**EQUAL-550**	**EQUAL-350**
Agriculture (change in annual welfare [10^9 2000$])					
2025	-4.3–20.6	-6.6–21.2	-8.9–21.6	-9.2–22.0	-6.3–23.3
2050	-10.5–30.8	-12.8–30.7	-10.2–30.5	-8.3–29.0	-9.2–27.4
2100	-60.7–42.6	-73.4–41.4	-32.1–40.2	-27.8–37.6	3.2–25.0
Energy (change in annual costs 10^9 2000$)					
2025	-5.4–6.3	-5.7–6.3	-5.3–6.5	-5.3–6.7	-5.1–9.0
2050	-4.6–18.5	-4.9–20.9	-4.7–16.1	-4.9–14.8	-4.9–11.3
2100	-5.0–67.1	-4.4–82.0	-4.5–36.2	-4.1–30.4	-5.1–9.2
Coastal Protection (annual protection/abandonment costs [10^6 2000$])					
2025	1.5–16.4	1.1–16.6	0.7–14.4	0.9–14.6	0.5–13.1
2050	7.1–61.3	5.4–60.7	5.0–53.8	3.5–49.6	1.3–41.7
2100	15.8–429.5	10.7–442.6	7.8–340.4	4.9–346.9	0.0–257.4
Terrestrial Runoff (annual % change)					
2025	-34.3–16.8	-36.3–16.4	-36.8–15.3	-38.1–14.1	-36.4–20.4
2050	-42.4–36.0	-43.4–35.0	-42.4–32.5	-39.2–30.5	-37.8–26.0
2100	-100.0–59.8	-100.0–59.4	-59.8–50.7	-57.0–42.6	-33.7–25.2
Cold-Water Habitat (cumulative % reduction)					
2025	9.7–16.5	6.9–18.7	6.7–18.7	6.6–18.7	6.3–15.2
2050	13.5–27.9	9.6–34.2	9.7–31.3	8.9–30.2	8.2–25.6
2100	20.5–50.3	15.1–70.3	13.8–46.6	10.7–38.8	7.1–22.0
Population/Mortality (annual population change [10^3 individuals])					
2025	-39.8–23.2	-37.4–22.1	-36.9–20.3	-38.1–21.0	-48.4–24.9
2050	-72.7–40.6	-71.4–40.9	-66.2–33.1	-63.4–32.1	-53.5–30.6
2100	-133.3–71.7	-133.5–67.0	-96.3–51.7	-91.1–47.4	-47.0–23.9

change impacts (Table 1). The range of plausible impacts often spanned an order of magnitude, and for some sectors, simply the direction of impacts (i.e., positive or negative) could not be identified with a high degree of confidence. Although this analysis reveals the difficulty of identifying a single best-estimate of future impacts, it enables one to evaluate which magnitudes are *likely* to occur, including economic impacts of plus-or-minus several billion dollars, thousands of excess deaths, significant reductions in suitable habitat for wildlife, and reductions in runoff and subsequently, water availability. The impact distributions also reveal that where potential benefits are likely, there remains a lower, but not necessarily negligible, probability of significant adverse effects, and vice versa.

How does one use information about probabilities to manage risk and make better decisions? The successful management of risk first requires some *a priori* criteria or context that articulates what risks are of concern, what magnitude of impact is considered excessive (i.e., beyond society's ability or willingness to cope) and what options are available for reducing risk (Australian Standards 1999; Jones, 2004). For example, Figure 1 presents cumulative probability distributions for impacts to each sector in 2050. If one assumes that society is primarily concerned with the likelihood of adverse consequences (regardless of magnitude), then Figure 1 indicates that for coastal protection costs and habitat loss, adverse effects are certain. For energy and water resources there is a high risk of adverse impacts.

Figure 1. Probability distributions for climate change impacts in 2050 for six market and nonmarket sectors (A: Agriculture, B: Energy, C: Coastal Protection, D: Terrestrial Runoff, E: Cold-Water Habitat, F: Mortality). EQUAL and REA distributions represent no mitigation cases, while EQUAL-750/550/350 represent results assuming emissions are constrained according to one of the WRE stabilisation scenarios.



For human mortality, the odds of adverse effects are almost even, and for agriculture, the risk of adverse impacts is relatively low.

If society judges these risks to be too high, how can risk treatment reduce the risk of adverse effects? In the current study, a series of CO_2 stabilisation pathways was utilised to illustrate the sensitivity of climate change impacts to risk treatment efforts in the form of GHG mitigation. In general, mitigation constrained the range of future impacts (Table 1, Figure 1). But how effective is mitigation at reducing the likelihood of specific impacts such as (as above) the risk of adverse effects? Interestingly, mitigation reduces the likelihood of adverse effects to agriculture and energy, but has little to no effect for the other sectors. Thus, given these management criteria, mitigation does not appear to be a particularly effective strategy for treating risk.

However, by changing the risk management criteria, a decision-maker may arrive at a very different conclusion regarding the efficacy of mitigation. Quite often it is not simply adverse effects *per se* that are of concern, but large-scale consequences. Economic losses of a few million dollars are of little impact to an economy the size of the United States'. However, institutions may want to ensure that losses of $50 billion or more are avoided. Such losses are indeed possible by 2100 for both the agricultural and energy sectors (Table 1), albeit at relatively low probabilities. A modest hedge, such as mitigation consistent with a 750 ppmv stabilisation pathway, eliminates the likelihood of such losses. Given these criteria, GHG mitigation yields potentially valuable benefits.

What is clear from this theoretical exercise is that successfully using probabilistic information about climate change consequences to improve decision-making under uncertainty necessitates incorporating objective risk analysis into a larger risk management decision-making framework. Establishing such a framework generally falls outside the purview of the climate change research community, because it is fundamentally a subjective exercise. Nations, communities, industries, and institutions must first engage in evaluating what resources should be protected, what magnitude of impacts are of concern, what are acceptable risks, and what are the range of treatment options available for reducing risk.

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