Supporting Online Material

Materials and Methods

The DICE Model

The Dynamic Integrated Climate and Economy (DICE) model (*1*,*2*) couples a simple globally and seasonally-averaged two-box climate model (*3*) with an economic model of similar complexity. The coupled climate-economy system is solved as a simple optimal growth model that maximizes discounted utility—satisfaction—from consumption (subject to a Cobb-Douglas production function) in all considered time periods with perfect foresight. For each set of parameter values, the model determines the "optimal" forecast for future emissions reductions by balancing the costs of reducing emissions with the costs of climate change, represented by a climate damage function. It assumes perfect markets and the imposition of a time-varying carbon tax—calculated endogenously for each time period and usually increasing over time—to internalize the externality of climate damage into economic decisions dependent on the price of carbon energy. Greenhouse gases other than carbon dioxide are specified exogenously. Since its creation, many papers have demonstrated the sensitivity of DICE model results to changing structural assumptions (*4*,*5*,*6*, e.g.).

DICE model results are strongly sensitive to the discount rate, because, in general, the benefits of avoided climate damages from climate mitigation expenditures are not realized until decades after the expenditures are made (since damages are essentially quadratic in terms of global temperature increase, the largest damages are delayed many decades until the largest temperature changes occur, while mitigation costs to avert some of these damages are felt by the economy decades sooner). Specification of the discount rate is partly a normative issue, with a variety of defended options (*7*). Howarth suggests a rate equal to the return on risk-free assets, 0.4% per year (*8*). Azar and Sterner argue that the rate should be zero on ethical grounds (*9*). Weitzman and other authors have suggested time-varying discount rates (*10*). In DICE, Nordhaus chooses 3% for the pure rate of time preference (PRTP) (*1*), which in steady state provides a discount rate of 6%

(*11*). As summarized recently, for example, by Toth, the real discount rate r^* is derived from three factors: the PRTP (a), the elasticity of the marginal utility of consumption (j), and the growth in consumption (f), by the expression $r^* = a + jf$. In the original DICE model in steady state, the PRTP is 3%, the growth in consumption is 3%, the elasticity is 1, and r^* is 6%. Therefore, reducing the PRTP also reduces the discount rate. A high discount rate will trivialize variations in the present value of future climate damages caused by variation in other parameters. To allow investigation of this variation, we set the PRTP to 0% in our calculations (which corresponds to a discount rate of roughly 1% in DICE, a value within, but at the lower end, of the debated range cited above), and perform a sensitivity analysis presented in Fig. 4.

In the DICE model, and in many IAMs, a climate damage function specifying the economic damages from global temperature increase is one of the important linkages between the modeled social and natural systems. For DICE, Nordhaus originally postulated a somewhat weak damage function (*1*). In response to criticism, he performed a decision analytic survey (*12*) for estimates of economic damages from several climate change scenarios of varying severity. Roughgarden and Schneider (*6*) analyzed this dataset and produced probability distributions for climate damages based on survey responses, which provide a broad range of potential climate damage functions both stronger and weaker than the original DICE function. We sample from these probability distributions to produce a range of quadratic-form damage functions. Although many other damage functions could be cited, the Nordhaus survey is well-established in the literature, and allows us to demonstrate transparently and quantitatively the probabilistic framework we believe is needed to analyze the "dangerous anthropogenic interference" (DAI) issue.

Climate Sensitivity

There have been many attempts to estimate the sensitivity of the climate to increasing atmospheric greenhouse gas concentrations. Some early efforts attempted to determine the climate sensitivity from observational data (*13*,*14*). Two decades ago, Gilliland and Schneider (*13*) scaled the observed temperature increases of both hemispheres to natural and anthropogenic forcings via the framework of a simple upwelling-diffusion model, obtaining results that turned out to occur largely inside the IPCC range-to-be (1.5ºC-4.5ºC). These authors pointed out, even back then, that uncertainties in forcing (especially aerosols) precluded confident assessment of climate sensitivity by such semi-empirical means.

More recent studies rely on a variety of methods to determine sometimes very different climate sensitivity ranges. Morgan and Keith, using a decision analytic survey (*15*), and Tol and de Vos, using Bayesian updating from the instrumental temperature record (*16*), produced subjective estimates that differ greatly—Morgan and Keith produced a range similar to the IPCC range (though individuals in that survey often suggested values well outside of the IPCC range), Tol and de Vos predicted a 50% chance that the climate sensitivity is above 4.5ºC. Estimates of climate sensitivity based on paleoclimatic data produced a variety of values, for example 1.3ºC (*17*), 5.8ºC (*18*), and a range from 0.7ºC to 10.0ºC (*19*). Recent studies semi-empirically derive probability distributions for climate sensitivity much wider than the IPCC range. We use three such recent probability distributions: the combined distribution from Andronova and Schlesinger (A&S) (*20*), and the expert prior (F Exp) and uniform prior (F Uni) distributions from Forest et al. (*21*). The A&S and F Uni distributions have sizeable right-hand tails of high climate sensitivities. These high values occur due to the currently uncertain and potentially large negative radiative effects of anthropogenic aerosol emissions, as speculated on in 1984 by Gilliland and Schneider (*13*). If aerosols are creating significant net negative radiative effects, the warming observed over the last century would likely have required a high climate sensitivity. The expert prior of F Exp (*21*) was assembled at a time when the potential magnitude of negative aerosol effects was not believed to be as high as it typically is in recent studies. It would be useful for a modern re-elicitation to be performed to test the current state of thinking on this issue, as the two climate sensitivity estimates in Forest et al. (*21*) clearly demonstrate the high sensitivity of the climate sensitivity distribution to prior beliefs about this distribution.

Methods

Definition of "Dangerous Anthropogenic Interference"

As noted in the text (see note *20*), there are many ways that DAI could be interpreted from Fig. 1, or from other sources. Previously, Azar and Rodhe chose 2ºC as their threshold for DAI (*22*), and O'Neill and Oppenheimer chose thresholds between 1 and 3ºC for individual examples of DAI (*23*), without specifying ranges or percentiles for specific DAI thresholds. Our metric for DAI[X‰], where 'X' is a percentile value for a particular DAI threshold temperature, is intended as a first attempt at a probabilistic quantification of this important, policy-relevant threshold. For our metric, we assume that each column's transition-to-red in Fig. 1 represents a threshold for DAI for that specific "reason for concern." Then, by giving equal weight to each reason for concern, and assuming each threshold contributes equally and cumulatively (by a quintile) to the overall probability of DAI, we construct a cumulative density function (CDF) for DAI, as displayed in Fig. S1. We assume the threshold for column V of Fig. 1 to be the magnitude of temperature change above which DAI is "certain" (100^{th} percentile). If each column threshold contributes equally to this limit (column I is 20^{th} percentile, column II is 40^{th} percentile, etc.), the 0^{th} percentile of our CDF must be 1.15ºC to produce a corresponding probability density function (PDF) that is mathematically consistent. We note that Fig. 1 indicates "negative impacts to some systems" (yellow) in columns I and II from the level of warming that has already occurred. However, we choose the transition to impacts that are "widespread and/or greater in magnitude" (red) as our indication of DAI—therefore, our CDF starts above the current level of warming, although this is an arguable assumption (as is 100% probability of DAI above 5°C).

By no means is our CDF the only possible quantification of DAI. Each "reason for concern" need not be given equal weight, nor is it necessary to include all five of these categories, or only these five. We choose to draw our CDF from all five "reasons for concern," because focusing on a subset would mean overlooking information on the concept of DAI already available in well-established, published literature, and would fail to take full advantage of the work done by IPCC lead authors in reviewing available literature and generating these "reasons for concern." Similarly, we do not employ alternate metrics for defining DAI such as the “five numeraires” (*24*)—market impacts, human lives lost, biodiversity loss, distributional impacts, and quality of life. Though they overlap somewhat with the “reasons for concern,” and could also be used to generate a CDF for DAI, this would require a comprehensive worldwide survey of literature based on these categories like that done by the IPCC authors to generate the “reasons for concern.” Such an effort has not yet been undertaken, so we stay in our first analysis with the most widely reviewed and disseminated result, the five IPCC “reasons for concern.”

It should be noted that the IPCC “reasons for concern” were not produced implicitly or explicitly for the purpose of developing a CDF for DAI, but because they represent the consensus on established impacts literature, they are in our view the most comprehensive and credible set of results available, and thus allow the best demonstration of our framework for probabilistic display of DAI. Without doubt, many revisions are already in the works in the literature, and the IPCC may well undertake such a mission to address DAI more explicitly in its fourth assessment (*25*, e.g.).

We employ this CDF solely as a source of DAI percentiles linked to global average surface temperature thresholds in order to characterize risks derived from probabilistically constructed model results, and do not use the CDF derived from Fig. 1 for actual probabilistic sampling (i.e., no Monte Carlo simulations are performed using our CDF). However, it is interesting to note that the corresponding PDF for our CDF is bimodal. Based on current knowledge of DAI, this form is not automatically unreasonable. A lower level of warming (≤2ºC, e.g.) could "trigger" significant impacts in the first two “reasons for concern” categories, such as disruption of mountaintop ecosystems and low-lying coastal regions, and an increase in frequency of extreme events (these would combine to produce the first DAI PDF mode). Then, warming would increase damages more smoothly until a higher level of warming (≥4ºC, e.g.) “triggers” widespread negative aggregate market damages and potential abrupt climate events represented by the fourth and fifth “reasons for concern” (producing the second DAI PDF mode). We do not claim that such a bimodal PDF is the most realistic possibility for DAI, but given the logic just presented neither do we believe a single-peaked PDF is yet demonstrably more likely. We believe the shape of any DAI PDF will be a growing area of research, and we are certain it will have a major influence on the results of specific integrated assessments of DAI.

This bimodal PDF for DAI is generated by our methods because of the equal weight we give to each of the “reasons for concern.” Greater weight on the middle “reasons for concern” might eliminate this bimodality. We deliberately refrain from assigning subjective unequal weights because we believe this consensus-based task is better left to the broad assessment of the scientific community. We hope this framework will assist such future assessment of DAI—and thus become of increasing interest to analysts and policymakers.

We also note that Nordhaus’ survey (*12*), from which the climate damage probability distributions of Roughgarden and Schneider are derived (*6*), is in itself an implicit quantification of damages from DAI, represented by the survey responses to several scenarios of climate change—including 3ºC increase and 6ºC increase by 2100 (the latter warming is likely to be a potentially “dangerous” change, since in our analysis—derived from the IPCC “reasons for concern”—warming of that magnitude has a probability of one of being “dangerous”). Survey respondents reflected a wide range of disciplinary backgrounds, and are likely to have implicitly assigned different weights to climate impacts when making their economic estimations. Survey respondents were asked to consider non-market impacts, but economist and natural scientist respondents presented very different ranges of damages. This equates with assigning unequal weights to the IPCC “reasons for concern.” Economists may have (implicitly, of course, as the “reasons for concern” had not been produced yet) given more weight to column IV, aggregate market impacts, while natural scientists may have given more weight to columns I and V, low temperature thresholds for “danger” to natural systems and very significant damages from large-scale abrupt changes. However, we defend our choice of equal weights for all “reasons for concern” here as the most basic starting point for our framework, and encourage others to make alternative choices and to maintain transparency at all steps, as we have strived to do here. Regardless, our CDF for DAI, which predicts unavoidable

DAI above an increase of 5.1ºC, is fairly consistent with the damage estimations of the vast bulk of survey respondents—that a 6ºC increase by 2100 would have a significant probability of large negative economic impacts. And, we reiterate, we present our *framework* as noteworthy, not the specific model-dependent quantities we generate in this research.

Monte Carlo Analyses

We first produce single Monte Carlo (MC) analyses varying climate sensitivity in the DICE model (specifying a new climate sensitivity for each run) using the three probability distributions presented above. We record model output for these three analyses, sampling (with replacement) from each of the climate sensitivity probability distributions separately and producing new probability distributions for global average temperature change in 2100 (Fig. 2a). We also present the percentage of model outcomes that fall above our median (50^{th} percentile) threshold, DAI[50%o], of 2.85ºC. These MC analyses are run without a climate damage function in the DICE model. Therefore, the probability distributions for future temperature change are created solely by variation in climate sensitivity.

We then produce joint MC analyses, again varying climate sensitivity and introducing variation in the climate damage function. We use the Roughgarden and Schneider probability distributions to generate quadratic-form damage functions (as described in *6*), specifying damage functions for each integer percentile (5^{th}-95^{th} percentile). These uncertain damages induce the model "agent" to value climate change as an economic cost, generating emissions-restricting policy controls. These policy controls are represented by a time-varying carbon tax calculated endogenously for each model time period. We again produce three MC analyses, sampling from each climate sensitivity distribution separately, and from the percentile damage functions (Fig. 2b). We present the percentage of model outcomes that fall above DAI[50%o], and the carbon tax calculated for 2050 (the midpoint of the time period examined) for a model run using the median damage function and the median climate sensitivity from each distribution. This carbon tax can be viewed as an indicator of overall climate policy level. Each probability distribution of Fig. 2 displays a running mean (solid black line) calculated by averaging each data point (frequency of a given temperature change in 2100) with its neighbors.

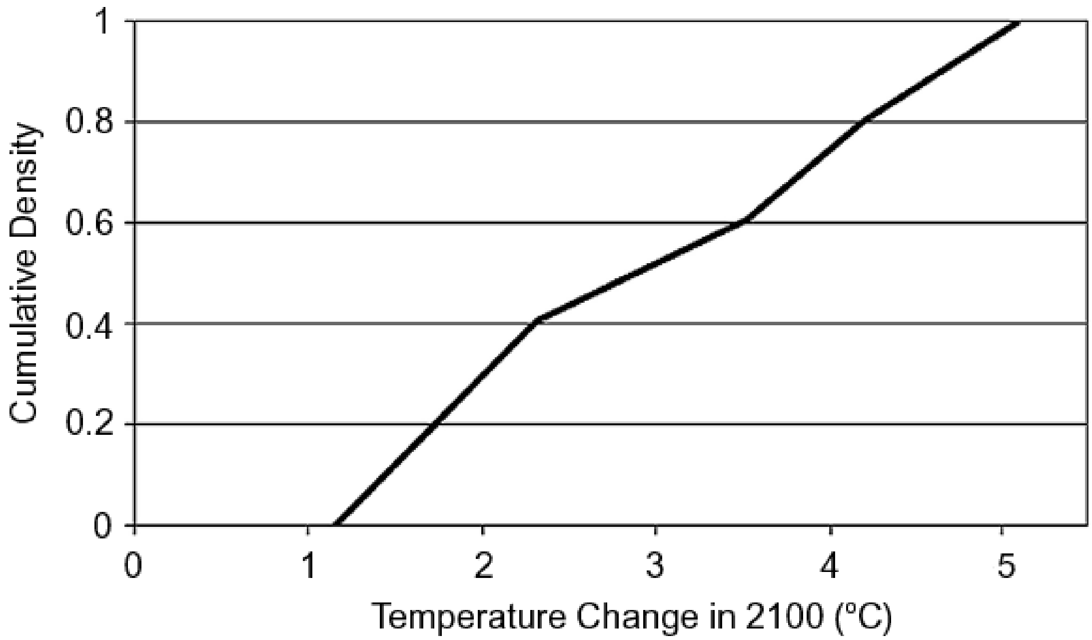
Each MC analysis results in a probability distribution of temperature change in 2100, from which the percentage of outcomes above any threshold for DAI from our CDF (Fig. S1) can be determined. We perform single MC analyses varying climate sensitivity as in Fig. 2a, but with a range of fixed climate damage functions (10^{th}-90^{th} percentile), to create Fig. 3. For each fixed climate damage function, we produce three probability distributions of temperature change in 2100, one for each climate sensitivity distribution. We record the carbon tax calculated for 2050 for model runs using the median climate sensitivity of each distribution and each fixed damage function. Finally, we evaluate the percentage of outcomes in each of these probability distributions of temperature change that exceed DAI[50‰] (as in Fig. 2), and other thresholds for DAI, DAI[X‰], chosen from our CDF, 'X' representing the percentile of that temperature threshold. This process establishes a basis for comparing carbon tax with the probability of DAI[X‰]. Each solid line in Fig. 3 corresponds to one of these temperature thresholds at percentile 'X' of our CDF, as indicated. Figure 3 represents the average of the results generated using each climate sensitivity distribution. For example, the point on the thicker black line at $0/Ton C is the average of the percentages of DAI[50‰] displayed in Fig. 2a. Inspecting this median threshold, DAI[50‰], indicates that a carbon tax by 2050 of $150-$200/Ton C reduces the probability of DAI[50‰] from ~45% without climate policy controls to nearly zero.

As noted in the text, results such as this are extremely sensitive to the discount rate. The increase in the climate damage function indicated above that produces a ~45% reduction in the probability of DAI[50‰] using a 0% PRTP, produces a reduction of only ~10% and an order of magnitude lower "optimal" carbon tax when using a 3% PRTP, the value employed by the original DICE model. We chose to use a 0% PRTP for Fig. 3 exactly for this reason—that using a high discount rate masks the variation in model results due to changes in parameters other than the discount rate, and observing variation in model results due to other parameters is central to our analysis.

Figure 4 is constructed by a similar method. In this case, the climate damage function is fixed throughout at the median level, and instead of varying the damage function, each set of three single MC analyses (one for each climate sensitivity distribution) is performed with a different PRTP. The results for each set of single MC analyses are averaged to produce Fig. 4.

Figure

FIGURE S1:



Our cumulative density function (CDF) for “dangerous anthropogenic interference” (DAI) with the climate system, derived from the Intergovernmental Panel on Climate Change (IPCC) “Reasons for Concern” (*26*) and displayed in Fig. 1. We construct our CDF by assigning data points at the threshold temperature above which each “reason for concern” column becomes red, and assume that the probability of DAI increases cumulatively and equally at each threshold temperature by a quintile.

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