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Materials and Methods

Figs. S1 to S3

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Probabilistic Integrated Assessment of "Dangerous" Climate Change

Michael D. Mastrandrea[1]* and Stephen H. Schneider[2]

Climate policy decisions are being made despite layers of uncertainty. Such decisions directly influence the potential for "dangerous anthropogenic interference with the climate system." We mapped a metric for this concept, based on Intergovernmental Panel on Climate Change assessment of climate impacts, onto probability distributions of future climate change produced from uncertainty in key parameters of the coupled social-natural system—climate sensitivity, climate damages, and discount rate. Analyses with a simple integrated assessment model found that, under midrange assumptions, endogenously calculated, optimal climate policy controls can reduce the probability of dangerous anthropogenic interference from ~45% under minimal controls to near zero.

Article 2 of the United Nations Framework Convention on Climate Change (UNFCCC) states its ultimate objective as "Stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (*1*). This level should be achieved within a time frame sufficient to allow ecosystems to adapt naturally to climate change, to ensure that food production is not threatened, and to enable economic development to proceed in a sustainable manner. Thus, the criteria for identifying "dangerous anthropogenic interference" (DAI) may be characterized in terms of the consequences (or impacts) of climate change (*2*). Although these impacts, and a precise definition of DAI, are subject to considerable uncertainty, a plausible uncertainty range can be quantified from current scientific knowledge (*3*). We argue that climate change policy decisions should be conceptualized in terms of preventing or reducing the probability of DAI, a risk-management framework familiar to policymakers and an outcome to which more than 190 signatories to the UNFCCC have committed.

Research related to global climate change must deal explicitly with uncertainty about future climate impacts. Due to the complexity of the climate change issue and its relevance to international policymaking, careful consideration and presentation of uncertainty is important when communicating scientific results (*2*, *4–7*). Policy analysis regarding climate change necessarily requires decision-making under uncertainty (*8–10*). Without explicit efforts to quantify the likelihood of future events, users of scientific results (including policy-makers) will undoubtedly make their own assumptions about the probability of different outcomes, possibly in ways that the original authors did not intend (*11*, *12*).

Assigning likelihoods to potential future worlds is difficult, as noted by Grübler and Nakicenovic (*13*), because any such estimates will be highly subjective and based on assessments of future societal behavior and values. Uncertainty, they warn, may alternatively be dismissed or replaced by spurious expert opinion. Although the suitability and effectiveness of techniques for presenting uncertain results is context-dependent, we believe that such probabilistic methods are more valuable for communicating an accurate view of current scientific knowledge to those seeking information for decision-making than assessments that do not attempt to present results in probabilistic frameworks (*14*).

We present a metric for assessing DAI: a cumulative density function (CDF) of the threshold for dangerous climate change. We demonstrate its utility by applying it to modeled uncertainty in future climate change using an optimizing integrated assessment model (IAM). IAMs are common policy analysis tools that couple submodels of the climate and economic systems, balance costs and benefits of climate change mitigation to determine an "optimal" policy (*15*), and often exhibit properties not apparent in either submodel alone (*16*).

We chose Nordhaus' Dynamic Integrated Climate and Economy (DICE) model (*17*) for our analysis because of its relative simplicity and transparency, despite its limitations (*16*, *18*). The IAM framework allows us to explore the effect of a wide range of mitigation levels on the potential for exceeding a policy-important threshold such as DAI. We do not recommend that our quantitative results be taken literally, but we suggest that our probabilistic framework and methods be taken seriously. They produce general conclusions that are more robust than estimates made with a limited set of scenarios or without probabilistic presentations of outcomes, and our threshold metric for DAI offers a risk-man-

[1]Interdisciplinary Graduate Program in Environment and Resources, [2]Department of Biological Sciences and Center for Environmental Science and Policy, Stanford University, Stanford, CA 94305, USA.

*To whom correspondence should be addressed. E-mail: mikemas@stanford.edu

agement framework for discussion of future climate change that can be applied to results at all levels of model complexity.

To define our metric for DAI, we estimated a CDF based on the Intergovernmental Panel on Climate Change (IPCC) "Reasons for Concern" (*3*) (Fig. 1). Each column in the figure represents a reason for concern about climate change in this century, on the basis of dozens of IPCC lead authors' examination of climate impacts literature, thus representing a consensus estimate of DAI. We constructed our CDF by assigning data points at the threshold temperature above which each column becomes red (Fig. 1, solid black line) and assumed that the probability of DAI increases cumulatively at each threshold temperature by a quintile, making the first threshold the 20th percentile (20‰) (*19*). This CDF is a starting point for our analysis of DAI; it facilitates a concrete sensitivity analysis at various thresholds of dangerous climate change. The median, 50‰ threshold for DAI in Fig. 1, DAI[50‰], is 2.85°C (*20*).

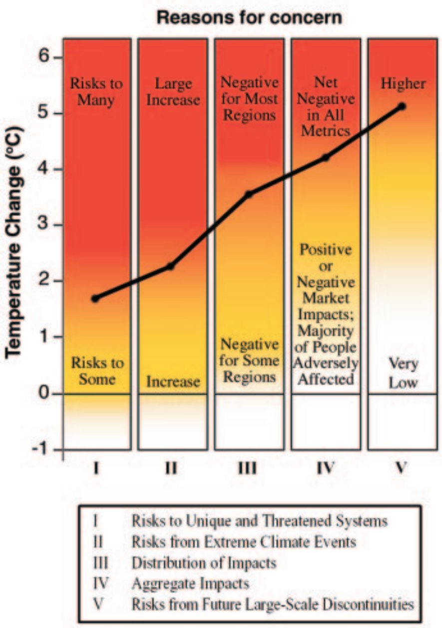

Fig. 1. An adaptation of the IPCC Reasons for Concern figure (*3*), with the thresholds used to generate our CDF for DAI. The IPCC figure conceptualizes five reasons for concern, mapped against climate change through 2100. As temperature increases, colors become redder: White indicates neutral or small negative or positive impacts or risks, yellow indicates negative impacts for some systems, and red means negative impacts or risks that are more widespread and/or greater in magnitude. The risks of adverse impacts from climate change increase with the magnitude of change, involving more of the reasons for concern. For simplicity, we use the transition-to-red thresholds for each reason for concern to construct a CDF for DAI, assuming the probability of DAI increases by a quintile as each threshold is reached (*19*).

We applied this metric for DAI to a spectrum of results based on uncertainty in three key social and natural model parameters—climate sensitivity, climate damages, and discount rate. We focused on these parameters because they are critical determinants of the policy implications of global climate change. Climate sensitivity—the equilibrium surface temperature increase from a doubling of atmospheric CO_2—determines the magnitude of anthropogenic temperature change from a given radiative forcing. The impact of this change is determined by the severity of climate damages from a given global average temperature change, usually reported as a loss of gross economic product. Both factors cannot be determined with high confidence because of the complexity of the system, missing data, and competing frameworks for analysis (*21*). In an IAM, future costs and benefits are compared by discounting their future value at some discount rate. Modeled policy responses to global climate change, where mitigation costs come long before sizeable benefits from avoided climate damages, are very sensitive to this rate. Sensitivity analysis, where uncertain parameters are varied across a likely range of values, is often used to identify and report ranges of uncertainty. When it is possible to define a probability distribution for the uncertain parameter(s), a second method—Monte Carlo (MC) analysis—can expand on a sensitivity analysis by assigning a proba-

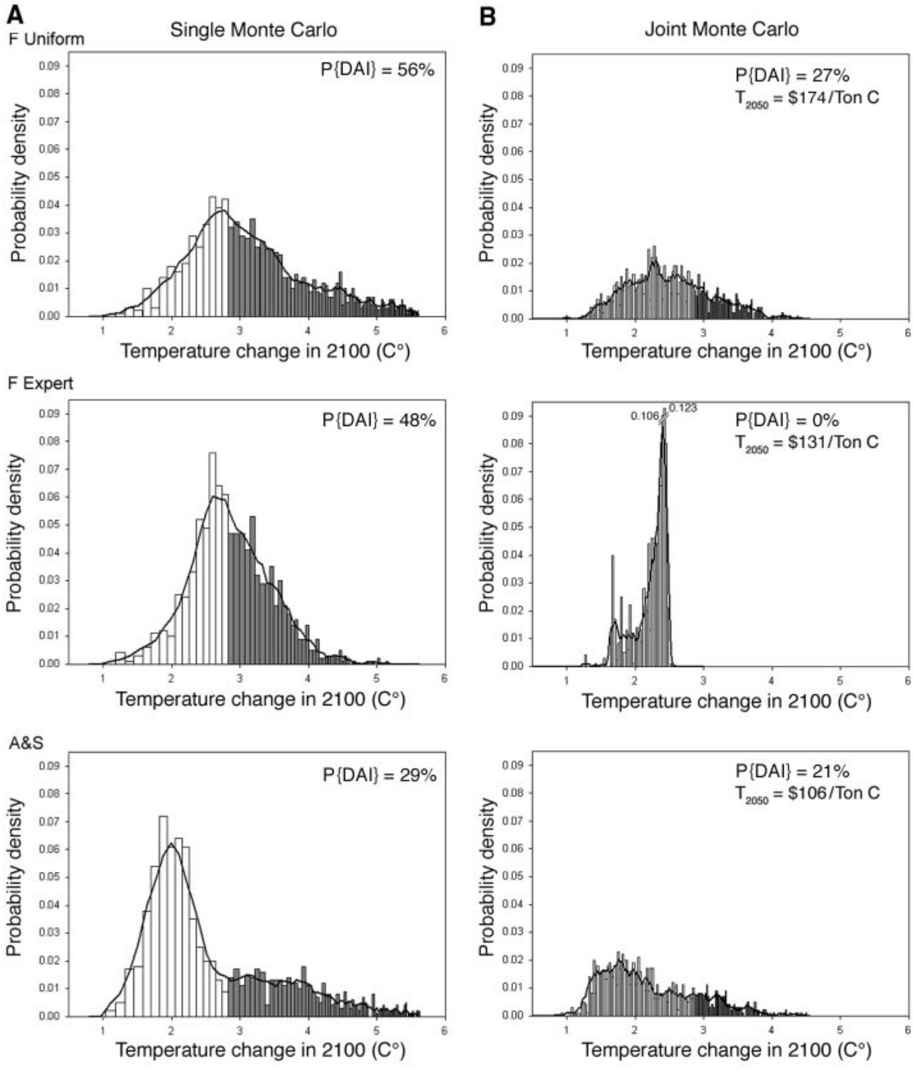

Fig. 2. (**A**) Probability distributions for each climate sensitivity distribution for the climate sensitivity–only MC analyses with zero damages and 0% PRTP (a ~1% discount rate). (**B**) Probability distributions for the joint (climate sensitivity and climate damage) MC analyses. All distributions display a 3-bin running mean and the percentage of outcomes above our median threshold of 2.85°C for dangerous climate change, P{DAI[50‰]}. The joint distributions display carbon taxes calculated in 2050 (T_{2050}) by the DICE model, using the median climate sensitivity from each climate sensitivity distribution and the median climate damage function for the joint Monte Carlo cases (*19*). When we compare the joint cases with climate policy controls (B) to the climate sensitivity–only cases without climate policy controls (A), sufficient carbon taxes reduce the potential (significantly in two out of three cases) for DAI[50‰].

bility distribution to model outcomes run as the parameter is varied. We combined both techniques to evaluate the potential for DAI (*19*).

Using general circulation models, the IPCC has long estimated the climate sensitivity to lie somewhere between 1.5°C and 4.5°C (*22*), without indicating the relative probability within this range. Other analyses produce both higher and lower values (*19*). Recent studies produce distributions wider than the IPCC range, with significant probability of climate sensitivity above 4.5°C. We used three such probability distributions: the combined distribution from Andronova and Schlesinger (A&S) (*23*), and the expert prior (F Expert) and uniform prior (F Uniform) distributions from Forest *et al*. (*24*).

In the DICE model, 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. We sampled from the probability distributions of Roughgarden and Schneider (*18*), based on an expert elicitation of a much broader range of climate damage functions than in the original DICE model. We used these probability distributions and those for climate sensitivity to conduct MC analyses with the DICE model (*19*). Specification of the third uncertain parameter we considered, the discount rate, has a strong normative component, with a variety of defended options (supporting online text). To prevent a high discount rate from masking variation in model results because of variation in other uncertain parameters (supporting online text), we set the pure rate of time preference (PRTP) to 0%—corresponding to a discount rate of roughly 1%—and performed a sensitivity analysis (*19*). This discount rate falls within the currently debated range, at the lower end (supporting online text).

We examined two types of model output under different assumption sets of the parameters we varied: global average surface temperature change in 2100 (*25*), which we used to evaluate the potential for DAI (*12*); and "optimal" carbon taxes (*26*), which we used to evaluate the magnitude of induced climate policy controls.

We first considered climate sensitivity uncertainty, performing three MC analyses—sampling from each climate sensitivity probability distribution separately (*19*)—without mitigation policy (to ensure that variation in results are from variation in climate sensitivity). We produced probability distributions for global temperature increase in 2100 (Fig. 2A) and indicate the percentage of outcomes that result in temperature increases above DAI[50‰]. The differences in the probability distributions of Fig. 2A show how the range of uncertainty still present among probability estimates of climate sensitivity cascade to uncertainty in our estimates for temperature change in 2100. In all three, a significant percentage of outcomes falls above DAI[50‰] (dark gray).

We introduced climate policy controls by performing a joint MC analysis of temperature increase in 2100, varying both climate sensitivity and the climate damage function (*19*), again indicating the percentage of DAI[50‰] exceedances (Fig. 2B). With the exception of the A&S distribution, for which the single MC analysis showed relatively lower probability of DAI[50‰], the joint MC runs showed significantly lower percentages of DAI[50‰]. It may seem that the most likely outcome of the joint MC runs is a relatively low temperature increase—an optimistic result. However, low temperature change outcomes result from more stringent model-generated climate policy controls, because of the inclusion of climate damages. Time-varying median carbon taxes are more than \$50/ton of C by 2010, and more than \$100/ton of C by 2050 in each joint analysis. Low warming and reduced probability of DAI[50‰] are reached if carbon taxes are high, when higher climate sensitivities and higher climate damage functions sampled from their probability distributions combine to force the model "agent" to react. This policy-relevant complexity is captured through a probabilistic framework.

The analysis above only considers the median DAI[50‰] threshold; therefore, these results do not fully describe the relationship between climate policy and the potential for other thresholds for DAI. We characterized the relationship between climate policy controls and the potential for DAI by calculating a series of single MC analyses, varying climate sensitivity (as in Fig. 2A) for a range of fixed damage functions. For each damage function, ranging from the 10th through the 90th percentile of the climate damage probability distribution (*18*), we performed an MC analysis sampling from each climate sensitivity distribution. We also calculated the carbon tax in 2050 for model runs that use the median climate sensitivity of each probability distribution and the median damage function (*19*).

Averaging the results from each set of three MC analyses, we determined the probability of outcomes that exceed various DAI thresholds at a given 2050 carbon tax under the assumptions described above (*19*) (Fig. 3). Each solid line corresponds to a different percentile threshold, DAI[*X*‰], chosen from our DAI CDF (Fig. 1)—a lower percentile *X* from the CDF represents a lower temperature threshold for DAI (DAI[10‰] = 1.476°C, DAI[50‰] = 2.85°C, for example). At any DAI threshold, climate policy works: Higher carbon taxes lower the probability of considerable future temperature increase and reduce the probability of DAI. Inspecting the median threshold, DAI[50‰] (Fig. 3, thick black line), indicates that a carbon tax by 2050 of \$150 to \$200 per ton of C reduces the probability of DAI[50‰] from ~45% without climate policy controls to nearly zero (*27*).

Finally, we demonstrated the effect of varying the discount rate. As before, we ran MC analyses varying climate sensitivity, but at different values for PRTP and with the climate damage function fixed at the median level (*19*). A higher PRTP increases the discount rate, implying that future climate damages are valued less and calculated policies will be weaker. Averaging over the outcomes for each climate sensitivity distribution, we determined the relationship between the discount rate and the probability of DAI at different temperature threshold levels (Fig. 4). As expected, increasing the discount rate shifts higher the probability distri-

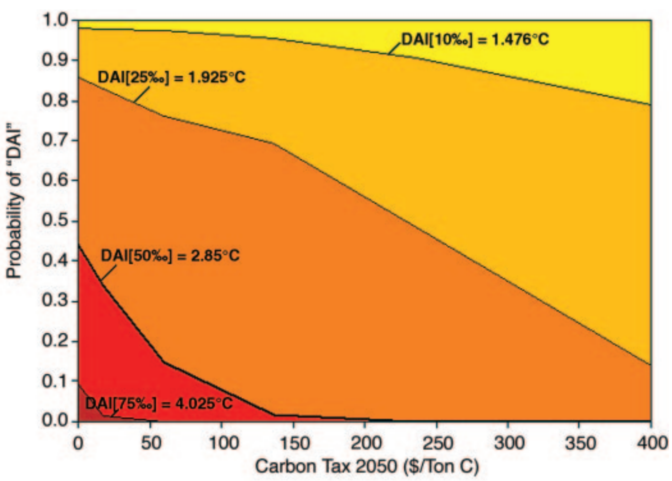

Fig. 3. The modeled relationship between carbon taxes in 2050 (a proxy for general climate policy controls) and the probability of DAI in 2100 (*19*). Each color band represents a different percentile range from the DAI threshold CDF—a lower percentile from the CDF representing a lower temperature threshold for DAI, as indicated. The solid lines indicate the percentage of outcomes exceeding the stated threshold for DAI[*X*‰], where *X* is the percentile from the DAI CDF derivable from Fig. 1, for any given level of climate policy controls. At any DAI[*X*‰] threshold, climate policy controls significantly reduce the probability of DAI, and at the median DAI[50‰] threshold (thicker black line), a 2050 carbon tax of >\$150/ton of C is the model-dependent result necessary to reduce the probability of DAI from ~45% to near zero. [With a 3% PRTP, this carbon tax is an order of magnitude less and the reduction in DAI is on the order of 10% (*27*).]

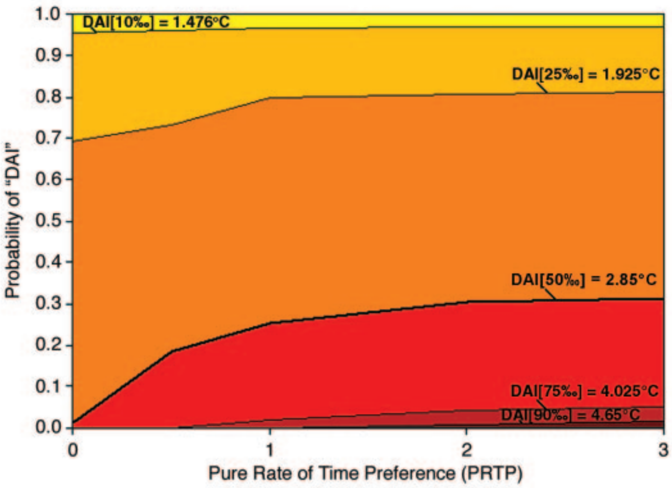

Fig. 4. The modeled relationship between the PRTP—a factor determining the discount rate—and the probability of DAI in 2100 (*19*). Increasing the PRTP (and therefore the discount rate) reduces the present value of future climate damages and increases the probability of DAI[*X*‰] as indicated, where *X* is the percentile from the DAI CDF derivable from Fig. 1. The solid lines indicate the percentage of outcomes above the stated threshold for DAI[*X*‰] for any given level of PRTP or DAI percentile threshold *X*. At our median threshold DAI[50‰] (thicker black line), the probability of DAI[50‰] rises from near zero with a 0% PRTP to 30% with a 3% PRTP, as originally specified in the DICE model.

bution of future temperature increase—a lower level of climate policy controls becomes "optimal" and thus increases the probability of DAI. At DAI[50‰] (Fig. 4, thick black line), the probability rises from near zero with a 0% PRTP to 30% with a 3% PRTP, as specified in the original DICE model. It is also clear that at PRTP values higher than 1%, the "optimal" outcome becomes increasingly insensitive to variation in future climate damages driven by variation in climate sensitivity.

The DICE model is a highly simplified representation of the climate and the economy, and its specific predictions for temperature increase or carbon tax are subject to considerable uncertainty (*28*). Although it cannot provide high-confidence quantitative answers, it is a transparent model for examining trends and processes, and its qualitative insights should be considered seriously. We present our probability distributions for future climate change to demonstrate three issues: (i) Very different levels are possible for the probability of DAI depending on its definition. (ii) Regardless of its definition, conventional climate policy controls would bring about significant reduction in the probability of DAI. (iii) This probabilistic framework is an effective method for conceptualizing climate change policy decisions.

We chose to create a CDF for DAI based on one plausible interpretation of IPCC work. In certain regions and for certain sectors, different groups might set thresholds for DAI at very different levels. Selection of that threshold can only be made through a decision-making process that combines social and natural assessments, evaluates the effects of climate change and their likelihood, and incorporates value judgments on inherent trade-offs. However, our research shows that regardless of the threshold for DAI, climate policy will reduce the likelihood of exceeding that threshold, and we suggest that this is an effective way to present model results and to demonstrate the value of climate policy, in risk-management terms that policymakers often employ.

Uncertainty in future states of natural and social systems will never be completely removed until future events are directly observed. This unalterable fact requires societies wishing to assess and influence future trends to act on the best current knowledge in the face of uncertainty. We believe that a probabilistic framework—probability distributions and risk diagrams such as Fig. 3—are an effective representation of state-of-the-art results of scientific assessments and should be understood by a wide audience, including policymakers. Policymakers have considerable experience dealing with uncertainty and risk management. For example, "acceptable risk" thresholds for nuclear power, cancer, vehicular safety, etc., are commonplace, even if controversial. The probability of DAI in many of the scenarios we discuss is far higher (by tens of percent) than the "accepted" threshold in some of these fields (though, of course, the dangers are all different). Thus, this research suggests a clear message: It is possible that some thresholds for dangerous anthropogenic interference with the climate system are already exceeded, and it is likely that more such thresholds are approaching. Despite great uncertainty in many aspects of integrated assessment, prudent actions can substantially reduce the likelihood and thus the risks of dangerous anthropogenic interference.

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15. We do not imply preference of the optimization framework over the methods used in other studies; in truth, we openly acknowledge the flaws many have identified in the general method (*29*) and in the DICE model we use (*17*), having ourselves contributed to this literature (*16*). There are other effective frameworks for analysis, such as the "robust strategies" approach (*29*). However, as the DICE family of models does allow a quantitative opportunity to explore methods and model uncertainties explicitly, has influenced policy decisions in the past, and continues to be used, we chose to present the influence of the most current scientific information on IAM results. The main virtue of this approach is transparency through a method to reframe the diagnosis of DAI with probabilistic IAMs.
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19. Materials and methods are available as supporting material on *Science* Online.
20. There are many ways that DAI could be interpreted from this figure, or from other sources. Each reason for concern could provide its own probability distribution for DAI; each reason for concern could be given its own weight based on some definition of its likelihood; or categories or metrics for assessing DAI other than those displayed could be used. The evaluation of DAI will likely be different depending on geographical location, socioeconomic standing, and ethical value system. For a first attempt at this definition, we used the simplest possibility—equal weight for all five categories. As seen in Figs. 3 and 4, we may already have committed to exceedance of a DAI[10‰] (1.476°C) threshold, as the probability of this threshold being crossed by 2100 is near unity. As the temperature increase exceeds the orange-to-red threshold of more categories, we believe a greater number of people will agree that dangerous change is occurring or will likely occur. Thus, we use all reasons for concern instead of just one, assuming equivalence of the danger from each category. We present a traceable account (*11*) of our assumptions in creating this definition (*19*), and we believe a similar account should be made each time such a definition is created by any analyst. We know of one other effort to create a CDF for dangerous climate change, presented by Wigley (*30*). Previously, Azar and Rodhe chose 2°C as their threshold for DAI (*31*), and O'Neill and Oppenheimer chose thresholds between 1° and 3°C for individual examples of DAI (*32*), without specifying ranges or percentiles in any of these cases.
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25. Transient temperature change in 2100 is not, in general, equilibrium change. The inertia of the climate system is such that climate change will continue long after greenhouse gas concentrations are stabilized or emissions eliminated. Some outcomes that avoid exceeding a DAI threshold until 2100 will exceed that threshold in the next century. Therefore, the time horizon of analysis will affect the potential for DAI. However, what is "dangerous" is itself a function of adaptive capacity, not a static quantity, dependent on social and economic development. So, the very threshold for any percentile *X*, DAI[*X*‰], can itself change with time and social conditions.
26. In the DICE model, carbon taxes serve as a proxy for general climate policy controls. Thus, we do not present carbon tax data as a preferred method for mitigation or a required method to produce our results. Instead, these results should be seen as a method to provide insights into coupled model behavior, using the carbon tax in DICE as a measure of the magnitude of climate policy controls.
27. Results such as this are extremely sensitive to the discount rate. For example, the increase in the climate damage function indicated above that produces a ~45% reduction in the probability of DAI[50‰] with a 0% PRTP produces a reduction of only ~10% and an order of magnitude lower "optimal" carbon tax when we used 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 because of changes in parameters other than the discount rate, and observing variation in model results due to other parameters is central to our analysis.
28. We consider three of these sources of uncertainty in the three parameters we varied, but there are other important sources of uncertainty. The DICE model does not consider adaptation, as opposed to mitigation, which theoretically would shift the probability distribution for DAI to higher temperature levels. A highly adaptive society would be less likely to experience dangerous impacts, although this would not be as likely to apply to the first reason for concern, damages to natural systems. The DICE model also only considers mitigation policies for CO_2. It does not account for "knock-on" impacts of CO_2 reductions on emissions of other atmospheric substances, and it specifies a fixed path for non-CO_2 greenhouse gases. Alternative emissions pathways for non-CO_2 gases and for other anthropogenic radiative forcing agents such as aerosols would also affect the potential for DAI.
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Timing, Duration, and Transitions of the Last Interglacial Asian Monsoon

Daoxian Yuan,[1] Hai Cheng,[2] R. Lawrence Edwards,[2]* Carolyn A. Dykoski,[2] Megan J. Kelly,[2] Meiliang Zhang,[1] Jiaming Qing,[1] Yushi Lin,[1] Yongjin Wang,[3] Jiangyin Wu,[3] Jeffery A. Dorale,[4] Zhisheng An,[5] Yanjun Cai[5]

Thorium-230 ages and oxygen isotope ratios of stalagmites from Dongge Cave, China, characterize the Asian Monsoon and low-latitude precipitation over the past 160,000 years. Numerous abrupt changes in $^{18}O/^{16}O$ values result from changes in tropical and subtropical precipitation driven by insolation and millennial-scale circulation shifts. The Last Interglacial Monsoon lasted 9.7 ± 1.1 thousand years, beginning with an abrupt (less than 200 years) drop in $^{18}O/^{16}O$ values 129.3 ± 0.9 thousand years ago and ending with an abrupt (less than 300 years) rise in $^{18}O/^{16}O$ values 119.6 ± 0.6 thousand years ago. The start coincides with insolation rise and measures of full interglacial conditions, indicating that insolation triggered the final rise to full interglacial conditions.

The characterization of past climate is often limited by the temporal resolution, geographic coverage, age precision and accuracy, and length and continuity of available records. Among the most robust are ice core records (*1*, *2*), which characterize, among other measures of climate, the oxygen isotopic composition of precipitation. Although many such records are benchmarks, they are limited to high-latitude or high-elevation sites, which record the oxygen isotopic composition of the last fraction of atmospheric moisture remaining after transit from moisture source regions. Cave calcite also contains information about the isotopic composition of meteoric precipitation, is widespread, and can be dated with ^{230}Th methods. Thus, caves may yield well-dated, low-latitude, low-elevation records that characterize atmospheric moisture earlier in its transit from source regions. We report here on such a record of Asian Monsoon precipitation, which covers most times since the penultimate glacial period, about 160 thousand years ago (ka).

We have previously reported a cave oxygen isotope record of the East Asian Monsoon (*3*) from Hulu Cave, China [32°30′N, 119°10′E; elevation 100 m; cave temperature 15.7°C; mean annual precipitation $\delta^{18}O_{VSMOW} = -8.4$ per mil (‰) (VSMOW, Vienna standard mean ocean water); and mean annual precipitation 1036 mm] (table S1), covering the last glacial period [75 ka to 10 thousand years (ky) before the present]. We now report similar data from Dongge Cave, China, 1200 km WSW of Hulu Cave, a site affected by the Asian Monsoon. The Dongge record more than doubles the time range covered in the Hulu record and overlaps the Hulu record for ~35 ky, allowing comparison between sites. Highlights include the timing and rapidity of the onset (*4*) and end of the Last Interglacial Asian Monsoon and the degree of Last Interglacial Monsoon variability.

Dongge Cave is 18 km SE of Libo, Guizhou Province (25°17′N, 108°5′E), at an elevation of 680 m. The cave temperature (15.6°C), mean annual $\delta^{18}O$ of precipitation (−8.3‰), and seasonal changes in precipitation and $\delta^{18}O$ of precipitation are similar to those at Hulu, with mean annual precipitation being higher (1753 mm) (table S1). Stalagmites D3 and D4 were collected ~100 m below the surface, 300 and 500 m from the entrance, in the 1100-m-long main passageway. D3 is 210 cm and D4 is 304 cm long, with the diameters of each varying between 12 and 20 cm. Stalagmites were halved vertically and drilled along growth axes to produce subsamples for oxygen isotope analysis (*5*) and ^{230}Th dating by thermal ionization (*6*, *7*) and inductively coupled plasma mass spectroscopy (*8*). Sixty-six ^{230}Th dates from D3 and D4 (table S2) and 10 dates from Hulu Cave stalagmite H82 (table S3), all in stratigraphic order, have 2σ analytical errors of ±80 years at 10 ky and ±1 ky at 120 ky. Six hundred and forty $\delta^{18}O$ measurements have spatial resolution corresponding to 20 years to 2 ky for different portions of D3 and D4

[1]Karst Dynamics Laboratory, Ministry of Land and Resources, 40 Qixing Road, Guilin 541004, China. [2]Department of Geology and Geophysics, University of Minnesota, Twin Cities, MN 55455, USA. [3]College of Geography Science, Nanjing Normal University, Nanjing 210097, China. [4]Department of Geoscience, University of Iowa, Iowa City, IA 52242, USA. [5]State Key Lab of Loess and Quaternary Geology, Institute of Earth Environment, Chinese Academy of Sciences, Xi'an 710075, China.

*To whom correspondence should be addressed. E-mail: edwar001@umn.edu