result of global warming, desiccation, land use change (37), and re-excavation by increased rates of water erosion (24), as well as the dynamics of SOC replacement at sites of erosion. Based on our analysis, we reject both the notion that agricultural erosion substantially offsets fossil fuel emissions and the view that agricultural erosion is an important source of CO2.

References and Notes
14. Materials and methods are available as supporting material on Science Online.
19. The proportion of eroded carbon being replaced at the eroding sites ranges from 0.11 to 0.55 when all errors are accounted for (Table 1). Based on radiocarbon studies of density separates (32) and bulk fractions (33) and on mass weights of SOC fractions (34) for globally diverse soils that are not generally eroded, the fraction of SOC that turns over within years to decades varies from 15 to 80%. Eroding sites are less studied, and carbon dynamics may be affected by the introduction of exposed subsoil, which is enriched with less reactive carbon substrates but may also provide nutrients for enhanced plant growth.
21. We note that burial of SOC in depositional environments has been shown to substantially reduce decomposition (6, 9, 35) and, therefore, carbon exported beyond watershed boundaries may be assumed to be protected from further decomposition. For our watersheds, the sink term is larger than the carbon export rate (Table 1), which suggests that erosion and deposition induce a sink, irrespective of the fate of the exported carbon.
22. We compared our global results with our high-resolution simulations at various spatial scales and established that our approach provides unbiased and scale-independent estimates of SOC erosion at the continental scale. The range is derived by using the 95% lower/upper confidence level of the replacement term (13 to 45%) using the conservative/extreme model scenario in combination with a low/high global SOC erosion estimate.
25. Supporting online text.
26. There is also indirect evidence that previous estimates of SOC erosion for agricultural land by the degrad. Dev. (30%) (Table 1).
27. There is also indirect evidence that previous estimates of SOC erosion for agricultural land by the degrad. Dev. (30%) (Table 1).
30. The range is obtained by multiplying the low/high global SOC erosion estimates for agricultural land by the average SOC export fraction obtained from our watershed (30%) (Table 1).
38. We thank R. Buddenmeier, S. Billings, A. Nicholas, W. Van Muyen, A. Berge, and H. Van Hemelrijck for help and advice during the course of this work. Much of this work was supported by the European Commission under the Marie Curie IntraEuropean Fellowship Programme. The contents of this work reflect only the authors’ views and not the views of the European Commission. K. Van Oost holds a postdoctoral position at the Fund for Scientific Research Flanders (FWO). J. Six and S. De Gryze were supported by the Kearney Foundation of Soil Science.

Supporting Online Material
www.sciencemag.org/cgi/content/full/318/5850/626/DC1
Materials and Methods
SOM Text
Figs. S1 to S5
Tables S1 to S3
References
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Why Is Climate Sensitivity So Unpredictable?
Gerard H. Roe* and Marcia B. Baker

Uncertainties in projections of future climate change have not lessened substantially in past decades. Both models and observations yield broad probability distributions for long-term increases in global mean temperature expected from the doubling of atmospheric carbon dioxide, with small but finite probabilities of very large increases. We show that the shape of these probability distributions is an inevitable and general consequence of the nature of the climate system, and we derive a simple analytic form for the shape that fits recent published distributions very well. We show that the breadth of the distribution and, in particular, the probability of large temperature increases are relatively insensitive to decreases in uncertainties associated with the underlying climate processes.

The envelope of uncertainty in climate projections has not narrowed appreciably over the past 30 years, despite tremendous increases in computing power, in observations, and in the number of scientists studying the problem (1). This suggests that efforts to reduce uncertainty in climate projections have been impeded either by fundamental gaps in our understanding of the climate system or by some feature (which itself might be well understood) of the system’s underlying nature. The resolution of this dilemma has important implications for climate research and policy.

We investigate a standard metric of climate change: Climate sensitivity is defined as the equilibrium change in global and annual mean surface air temperature, ΔT, due to an increment in downward radiative flux, ΔR0, that would result from sustained doubling of atmospheric CO2 over its preindustrial value (2 × CO2). It is a particularly relevant metric for current discussions of industrial emissions scenarios leading to the stabilization of CO2 levels above preindustrial values (2). Studies based on observations, energy balance models, temperature reconstructions, and global climate models (GCMs) (3–13) have found that the probability density distribution of ΔT is peaked in the range 2.0°C ≤ ΔT ≤ 4.5°C, with a long tail of small but finite probabilities of very large temperature increases. It is important to ask what determines this shape and, in particular, the high ΔT tail, and to what extent we can decrease the distribution width.

Climate consists of a set of highly coupled, tightly interacting physical processes. Understanding these physical processes is a massive task that will always be subject to uncertainty. How do the uncertainties in the physical processes translate into an uncertainty in climate sensitivity? Explanations for the range of predictions of ΔT, summarized in (1–4), have focused on (i) uncertainties in our understand-
ing of the individual physical processes (in particular, those associated with clouds), (ii) complex interactions among the individual processes, and (iii) the chaotic, turbulent nature of the climate system, which may give rise to thresholds, bifurcations, and other discontinuities, and which remains poorly understood on a theoretical level. We show here that the explanation is far more fundamental than any of these.

We use the framework of feedback analysis \((\text{SOM})\) to examine the relationship between the uncertainties in the individual physical processes and the ensuing shape of the probability distribution of \(\Delta T\). Because we are considering an equilibrium temperature rise, we consider only time-independent processes.

Let \(\Delta T = \lambda \Delta R_f\), where \(\lambda\) is a constant. In the absence of feedback processes, climate models show \(\lambda = \lambda_0 = 0.30\) to 0.31 \(\text{K}/(\text{W/m}^2)\) \((\text{where } \lambda_0\) is the reference climate sensitivity) \((16)\), giving an equilibrium increase \(\Delta T_0 \approx 1.2^\circ\text{C}\) in response to sustained \(2 \times \text{CO}_2\). Because of atmospheric processes, however, the climate sensitivity has a value \(\Delta T \neq \Delta T_0\). Conceptually, the forcing \(\Delta R_f\) produces a temperature change \(\Delta T\), which induces changes in the underlying processes. These changes modify the effective forcing, which, in turn, modifies \(\Delta T\). We assume that the total change in forcing resulting from these changes is a constant \(C\) times \(\Delta T\). Thus, \(\Delta T = \lambda_0 \left(\Delta R_f + C \Delta T\right)\), or

\[
\frac{\Delta T}{\Delta R_f} = \lambda = \frac{\lambda_0}{1 - f}
\]

Here, the total feedback factor \(f = \lambda_0 \cdot C\) \((15)\). Clearly, the gain \(G = \Delta T/\Delta T_0 > 1\) if \(f > 0\), which appears to be the case for the climate system. The range \(2^\circ\text{C} \leq \Delta T \leq 4.5^\circ\text{C}\) corresponds to \(1.7 \leq G \leq 3.7\) and \(0.41 \leq f \leq 0.73\). Under our definitions, the feedback factors for individual processes are linearly additive, but the temperature changes, or gains, from individual processes are not [see the supporting online material (SOM)].

The uncertainties in measurements and in model parameterizations can be represented as uncertainties in \(f\). Let the average value of \(f\) be \(f\) and let its SD be \(\sigma_f\), the sum of uncertainties from all the component feedback processes. \(\sigma_f\) can be interpreted in three ways: uncertainty in understanding physical processes, uncertainty in observations used to evaluate \(f\), and, lastly, inherent variability in the strengths of the major feedbacks. If \(\sigma_f\) is fairly small, we see from Eq. 1 that the uncertainty in the gain, \(\delta G\), is

\[
\delta G \approx \frac{1}{(1 - f)^2} \sigma_f = (G)^2 \sigma_f
\]

Thus for \(G \approx 3\) (corresponding to \(\Delta T \approx 3.6^\circ\text{C}\)), uncertainties in feedbacks are magnified by almost an order of magnitude in their effect on the uncertainties in the gain. A second point is that even if \(\sigma_f\) is not large, \(\delta G\) will be large if \(f\) approaches 1: Uncertainty is inherent in a system where the net feedbacks are substantially positive.

Finally, Eq. 2 shows that it is the sum of all the uncertainties in the feedbacks that determines \(\delta G\); the uncertainties in the large positive feedbacks are not more important than the others. For example, a compilation of values of the feedback factors extracted from several GCMs \((17)\) finds considerable inter-model scatter in the albedo feedback, and although the average magnitude of this feedback is not high, this scatter has an important impact on the uncertainty in the total climate sensitivity.

We now derive the shape of the distribution \(h_f(\Delta T)\): the probability density that the climate sensitivity is \(\Delta T\). The important

**Fig. 1.** Demonstration of the relationships linking \(h_f(\Delta T)\) to \(h_f(f)\). \(\Delta T_0\) is the sensitivity in the absence of feedbacks. If the mean estimate of the total feedbacks is substantially positive, any distribution in \(h_f(f)\) will lead to a highly skewed distribution in \(\Delta T\). For the purposes of illustration, a normal distribution in \(h_f(f)\) is shown with a mean of 0.65 and a SD of 0.13, typical to that obtained from feedback studies of GCMs \((17, 18)\). The dot-dashed lines represent 95% confidence intervals on the distributions. Note that values of \(f \geq 1\) imply an unphysical, catastrophic runaway feedback.

**Fig. 2.** Probability density distributions \((A\) and \(B)\) and cumulative probability distributions \((C\) and \(D)\) for climate sensitivity, calculated from Eq. 3, for a range of \(f\) and \(\sigma_f\). In \((C)\) and \((D)\), the gray lines bound the 95% confidence interval. The peak and the shape of the density distributions are sensitive to both \(f\) and \(\sigma_f\) only for \(\Delta T \leq 5^\circ\text{C}\). The cumulative distributions show 50% probability that \(\Delta T \geq 1/(1 - f)\), independent of \(\sigma_f\), and there is little dependence on \(\sigma_f\) of the probability that \(\Delta T > 10^\circ\text{C}\). These features of the distributions imply that diminishing \(\sigma_f\) will have a relatively small impact on uncertainties in sensitivity estimates. See also SOM.
features of this distribution are the location of its peak and the shape and extent of the distribution at large $\Delta T$. We focus on the relationships between these features and the parameters of the feedback distribution, $f$ and $\sigma_f$.

Figure 1 is a schematic picture of the relationships linking $h_f(\Delta T)$ to $h_f(f)$, the probability distribution of $f$. The reason for the long tail of typical climate sensitivity distributions is immediately evident [see also (3)]. Uncertainties in climate processes, and hence feedbacks, have a very asymmetric projection onto the climate sensitivity. As the peak in the $h_f(f)$ distribution moves toward $f = 1$, the probability of large $\Delta T$ also grows. The basic shape of $h_f(\Delta T)$ is not an artifact of the analyses or choice of model parameters. It is an inevitable consequence of a system in which the net feedbacks are substantially positive.

Formally, $h_f(\Delta T)$ is related to $h_f(f)$ by the relationship

$$ h_f(\Delta T) = h_f(f(\Delta T))(df/d\Delta T) = \Delta T / (\Delta T)^2 h_f(1 - \Delta T / \Delta T). $$

As is commonplace, we assume the errors in the feedback factors are normally distributed: $h_f(f) = \left(\frac{1}{\sigma_f \sqrt{2\pi}}\right) \exp \left(-\frac{1}{2} \left(\frac{f - f_0}{\sigma_f}\right)^2\right)$. Although the general features of our results do not depend on this assumption, it facilitates our analysis. Then,

$$ h_f(\Delta T) = \left(\frac{1}{\sigma_f \sqrt{2\pi}}\right) \frac{\Delta T_0}{\Delta T^2} \times \exp \left(\frac{1}{2} \left(1 - \frac{\Delta T - \Delta T_0}{\Delta T}\right)^2\right) $$

Equation 3 shows how uncertainties in feedbacks lead to uncertainty in the response of a system of linear feedbacks. It can be shown that it is algebraically equivalent to a Bayesian derivation of a “posterior” distribution $h_f(\Delta T)$ based on a uniform previous distribution on feedbacks (SOM). As noted above, several studies have described climate sensitivity distributions similar in form to that indicated in Fig. 1 (4–13), but the particular parameter of Eq. 3 is that it provides a simple interpretation of the shape of these distributions. It is also a function that maps uncertainties in feedback processes onto uncertainties in climate sensitivity and therefore permits an analysis of its parametric dependencies. Figure 2 shows $h_f(T)$ and $p_{\text{cum}}(\Delta T)$, the cumulative probability that the climate sensitivity $\Delta T$ will exceed a given threshold, $\Delta T_c$, for a range of values of $f$ and $\sigma_f$. From Eq. 3, it can be shown that, for all $\sigma_f$, half the area under the curve occurs for $\Delta T < \Delta T_0.5$. Decreasing either $\sigma_f$ or $f$ concentrates the distribution around $\Delta T = \Delta T_0.5$.

The cumulative probability distributions show that decreasing $\sigma_f$ or $f$ steadily reduces the cumulative probability of large climate changes (e.g., $\Delta T \geq 8^\circ C$). However, the probability that $\Delta T$ lies in the interval immediately outside the range of the Intergovernmental Panel on Climate Change (IPCC) (say, $4.5^\circ C \leq \Delta T \leq 8^\circ C$) is very insensitive to $\sigma_f$ and $f$ and changes little with $\Delta T_c$. The cumulative probability distributions (Fig. 2, C and D) are driven by the extreme tail of the $h_f(\Delta T)$ distribution, which is a consequence of our choice of a Gaussian for $h_f(f)$. Even if an $h_f(f)$ without an extreme tail is assumed, the probability distributions in the interval beyond the IPCC range remain insensitive to changes in $\sigma_f$ (SOM).

Thus, foreseeable improvements in the understanding of physical processes, and in the estimation of their effects from observations, will not yield large reductions in the envelope of climate sensitivity. This relative insensitivity of the probability distributions to $\sigma_f$ is also a likely reason why uncertainty in climate sensitivity estimates has not diminished substantially in the past three decades.

We next compare $h_f(\Delta T)$ from Eq. 3 with selected published distributions of climate sensi-

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Fig. 3. Climate sensitivity distributions: (A) from (18), which calculated $(f, \sigma_f)$ of $(0.62, 0.13)$ from a suite of GCM simulations; (B) from (17), which found $(f, \sigma_f)$ of $(0.7, 0.14)$ from a different suite of models; and (C) from the -5700-member multi-ensemble climate prediction net (9, 10) for different choices of cloud processes. [Data were provided courtesy of B. M. Sanderson] (D) Fit of Eq. 3 to the result of (10), which was found by estimating the mode of the probability density and its accompanying $\Delta T$ and solving for $(f, \sigma_f)$ from Eqs. 2 and 3, which yielded values of $(0.67, 0.12)$.

Fig. 4. Climate sensitivity distributions from various studies with the use of a wide variety of methods (black lines) and overlaid with a fit of Eq. 3 (green lines), as described in Fig. 3: (A) from (11), fit with $(f, \sigma_f) = (0.58, 0.17)$ and $(0.63, 0.21)$; (B) from (8), fit with $(f, \sigma_f) = (0.67, 0.10)$ and $(0.60, 0.14)$; (C) from (6), fit with $(f, \sigma_f) = (0.64, 0.20)$ and $(0.56, 0.16)$; (D) from (4), fit with $(f, \sigma_f) = (0.82, 0.11)$, $(0.65, 0.15)$, and $(0.15, 0.28)$; (E) from (5), fit with $(f, \sigma_f) = (0.86, 0.35)$ [see also (29)]; and (F) from (12), fit with $(f, \sigma_f) = (0.72, 0.17)$, $(0.75, 0.19)$, and $(0.77, 0.21)$.
tivity. Figure 3 shows a distribution, determined from the multi-ensemble climateprediction.net experiment, for different representations of several cloud processes (9, 10). Independent estimates of feedback parameters for two different suites of GCMs (17, 18) determine values for \( \langle T, \sigma_f \rangle \) of \((0.70, 0.14)\) and \((0.62, 0.13)\), respectively (19). We calculate the implied climate sensitivity distributions from Eq. 3. These match the numerically derived distributions of \((10)\) quite well. We obtained a closer match by solving Eq. 3 for the \( T \) and \( \sigma_f \) that effectively characterize the feedback processes within the model used by \((9, 10)\) and used these parameters to generate the distribution.

Fits to several other published distributions (obtained by a wide variety of techniques), shown in Fig. 4, are also quite successful, with values \( 0.15 \leq \langle T \rangle \leq 0.86 \) and \( 0.10 \leq \sigma_f \leq 0.35 \). Some differences are seen, especially in the tail of the distributions. This is to be expected because some studies explicitly analyze the non-Gaussian distribution of uncertainties in the physics and various a priori assumptions. Nonetheless, all of these published distributions are, to a good approximation, consistent with propagation of physical-process uncertainties in a simple system of linear feedbacks. The shape of \( h_f(\Delta T) \), including its tail, is crucially dependent on the magnitude of \( T \), which we have assumed is independent of \( \Delta T \). Is there any chance that, as warming continues, the probability of extreme values of \( \Delta T \) will actually diminish? This might result if the feedback factors are functions of temperature. We have performed a preliminary analysis of the changes in the \( h_f(\Delta T) \) distribution that would result from adding nonlinear terms in the Stefan-Boltzmann and water vapor feedbacks (SOM). This analysis shows that these second-order effects are, to a good approximation, consistent with propagating uncertainties in a simple system of linear feedbacks.

Second, Soden and Held (13) found a mean and SD of \((0.11, 0.06)\) for the albedo feedback factor; \((0.17, 0.11)\) for the cloud feedback factor; and \((0.42, 0.06)\) for the water vapor and lapse rate feedback combinations. Second, Soden and Held (13) found a mean and SD of \((0.09, 0.02)\) for the albedo feedback factor; \((0.22, 0.12)\) for the cloud feedback factor; and \((0.31, 0.04)\) for the water vapor and lapse rate feedbacks combined. The water vapor and lapse rate feedbacks are typically combined because models show a strong negative correlation between the two. Although the combined feedback for water vapor and lapse rate has the largest magnitude, the greatest contributor to uncertainty is the cloud feedback.


23. Researchers (17, 18) estimated mean and SD of feedback factors calculated from two different suites of climate models, first, Colman (22) found a mean and SD of \((0.11, 0.06)\) for the albedo feedback factor; \((0.17, 0.11)\) for the cloud feedback factor; and \((0.42, 0.06)\) for the water vapor and lapse rate feedback combinations. Second, Soden and Held (13) found a mean and SD of \((0.09, 0.02)\) for the albedo feedback factor; \((0.22, 0.12)\) for the cloud feedback factor; and \((0.31, 0.04)\) for the water vapor and lapse rate feedbacks combined. The water vapor and lapse rate feedbacks are typically combined because models show a strong negative correlation between the two. Although the combined feedback for water vapor and lapse rate has the largest magnitude, the greatest contributor to uncertainty is the cloud feedback.


25. The curve from (5) is a numerical calculation from climate observations and uses an equation isomorphic to Eq. 3.