

Learning About Climate Sensitivity

From the Instrumental Temperature Record⁺

David L. Kelly,^{*} Charles D. Kolstad,^{**}
Michael E. Schlesinger^{***} and Natalia G. Andronova^{***}

The debate over the magnitude of anthropogenically induced climate change has raged for over a century (1-6). Today considerable uncertainty remains about the magnitude of greenhouse-gas-induced climate change, particularly the climate sensitivity – the equilibrium change in global-mean surface temperature per unit of radiative forcing. The rapidity at which uncertainty in the climate sensitivity is resolved has significant policy implications. If resolution is expected soon, deferring action until the picture is clearer may be prudent. If uncertainty is likely to be resolved only slowly, then action today on the basis of expected costs and damages may be the wisest course. Here we use a Bayesian learning model, the instrumental temperature record, and IPCC scenarios of future emissions of greenhouse gases and SO₂ to estimate the time required to reduce the uncertainty in the climate sensitivity. We find that more than half a century is required to be 95% confident that the true value of the climate sensitivity lies within $\pm 20\%$ of the estimated value. Further, accelerated control of greenhouse-gas emissions significantly slows this rate of learning, while control of SO₂ emissions accelerates it.

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^{*} Department of Economics, University of California, Santa Barbara, CA 93106 and Department of Economics, University of Miami.

^{**} Department of Economics, School of Environmental Science and Management, and Environmental Studies Program, University of California, Santa Barbara, CA 93106.

^{***} Department of Atmospheric Sciences, University of Illinois, Urbana, IL 61801.

It might seem that it is impossible to shed any light on future resolution of uncertainty; after all, who can know what future research on climate will yield? Our approach is to assume that the process of learning about climate sensitivity that has occurred during the last 100 years will continue to be driven by the instrumental temperature record. Given this assumption, we can use standard statistical methods to quantify the current uncertainty and the rate at which it can be expected to be resolved.

One approach to estimating the climate sensitivity, λ , is to use a simple physical model to simulate the instrumental temperature record in a best-fit, maximum-likelihood sense (7). One such simple physical model is (8, 9):

$$T_t = T_{t-1} + \frac{1}{\alpha} \left[(F_t + F_{SO_4} S_t) - \frac{T_{t-1} - \Gamma}{\lambda} \right] - K(T_{t-1} - O_{t-1}) \quad (1a)$$

$$O_t = O_{t-1} + L(T_{t-1} - O_{t-1}) \quad (1b)$$

where T_t is the annual global temperature ($^{\circ}\text{C}$) difference of the upper ocean in year t from the 1961-1990 average temperature, taken to be synonymous with the surface-air temperature difference, and $T_0 = O_0 = \Gamma$ is the initial temperature difference in some initial year; O_t is the corresponding temperature difference for the deep ocean; F_t is the radiative forcing by greenhouse gases (GHGs), including tropospheric ozone; S_t is the emission rate of sulfur dioxide (SO_2), normalized by its value in 1990 (75 TgS/yr), which is converted to sulfate aerosol in the atmosphere; F_{SO_4} is the radiative forcing by sulfate aerosols in 1990; α is the heat capacity of the upper ocean; and K and L equal the coefficient of heat transfer between the upper and deep ocean divided by their respective heat capacities. Equation (1) can be written as the following statistical model (10),

$$T_t = \frac{\Gamma}{\alpha\lambda} + \beta_1 T_{t-1} + \beta_2 F_t + \beta_3 S_t + K O_{t-1} + \varepsilon_t, \quad (2a)$$

$$O_t = O_{t-1} + L(T_{t-1} - O_{t-1}), \quad (2b)$$

where ε_t is an error term of mean zero. Equation (2) could be estimated from observed records of T_t and O_t , from which $\lambda = \beta_2 / (1 - \beta_1 - K)$ and $F_{SO_4} = \beta_3 / \beta_2$. However, the absence of an observational record for the deep-ocean temperature, O_t , makes it impossible to statistically estimate all of the coefficients. Because it is unlikely that O_t has changed very much over our sample (1856-1995), we make the assumption that O_t is constant and thus roll KO_{t-1} into the constant term. Equation (2a) thus reduces to:

$$T_t = \beta_0 + \beta_1 T_{t-1} + \beta_2 F_t + \beta_3 S_t + \varepsilon_t = \beta X_t + \varepsilon_t, \quad (3)$$

where $\beta = (\beta_0, \beta_1, \beta_2, \beta_3)$ and $X_t = (1, T_{t-1}, F_t, S_t)^T$. Equation (3) can be estimated from the historic record. We perform ordinary least squares (OLS) estimation of Eq. (3), using the instrumental temperature record (1856–1995; 140 observations) (11) and the historical GHG forcing and SO_2 emissions (Fig. 1). Results are summarized in Table 1. Also shown in the table is the implied value of λ . Since we were unable to estimate K in Eq.(2), due to an absence of deep ocean temperature observations, we have used a value of K for computing λ drawn from our much more complex energy-balance-climate/upwelling-diffusion-ocean (EBC/UDO) model (7,12-20).

The more familiar $T_{2X} = \lambda F_{2X}$ (with $F_{2X} = 4.39 \text{ Wm}^{-2}$) is the equilibrium temperature rise from a doubling of GHG concentration from preindustrial levels (Table 1). Its value of 2.3°C with a standard error of 0.7°C is not inconsistent with IPCC estimates. However, as we shall see later, the time to reach equilibrium from a GHG shock, as implied by the coefficients in Table 1, is unrealistically rapid.

We now define learning, the resolution of uncertainty. We can never be perfectly certain of our estimate of the climate sensitivity. Statistically, at any point in time we will only have a

certain level of confidence in our estimate. We use the 95% confidence level from statistics as our criterion for having learned. We suppose uncertainty is resolved at the time in the future when, for a standard 95% level of confidence, the true climate sensitivity λ will first lie between $(1 - c)\hat{\lambda}$ and $(1 + c)\hat{\lambda}$, where $\hat{\lambda}$ is the then-estimated climate sensitivity and c defines any given confidence interval. Note that uncertainty in the true value of λ does not mean that we are unable to reject the hypothesis that λ is zero.

To be more precise, we are interested in the first point in time at which we fail to reject the hypothesis, H_0 at the 95% level, where $H_0 = \{(1 - c)\hat{\lambda} < \lambda < (1 + c)\hat{\lambda}\}$. For example, when with 95% probability will the true climate sensitivity first lie within $\pm 20\%$ ($c = 0.2$) of the estimated sensitivity? We use Bayes Rule (which uses information optimally and thus is the fastest way to resolve uncertainty from the temperature record) to estimate β and then compute the median time to achieve a particular confidence level for several scenarios of future GHG concentrations and SO_2 emissions, denoted High, Med, and Low, corresponding to their levels (Fig. 1). Med (IS92a) is the IPCC business-as-usual case with expansion in both F_t and S_t . Low (IS92c) is the most aggressive control scenario, both for GHGs and SO_2 . The High (IS92e) case has the largest increase in F_t and S_t .

We take a series of draws from the distribution of our OLS estimate of β and the distribution of ε in the present (1995). Each draw $(\beta_{1994}, \varepsilon)_j$ together with the assumed future F_t and S_t is sufficient to generate from Eq. (3) a sample century (1996-2095) of temperatures $(T_t)_j$. Letting $\hat{\beta}_t$ be the OLS estimate of β based on data through year $t > 1995$ for a particular trajectory, Bayes Rule (21) defines how $\hat{\beta}_t$ will evolve over time as a new observation (Y_t, X_t) is added to the data set, assuming ε is normally distributed with mean zero and variance $1/\rho$:

$$\hat{\beta}_t = [\hat{P}_{t-1} + \rho(X_t X_t')]^{-1} [\hat{P}_{t-1} \hat{\beta}_{t-1} + \rho Y_t X_t] \quad (6a)$$

$$\hat{P}_t = \hat{P}_{t-1} + \rho(X_t X_t') \quad (6b)$$

Here \hat{P}_t is the precision of the estimate $\hat{\beta}_t$ of β , and prime denotes the transpose. For a particular value of c and $(\beta_{1994}, \varepsilon)$, the minimum value of t for which $\text{Prob}\left\{ (1-c)\hat{\lambda} < \lambda < (1+c)\hat{\lambda} \right\} \geq 0.95$, τ_j , is then determined numerically from the sampling distribution for $\hat{\lambda}$ which is generated by Monte Carlo method (1000 draws) from the distribution of the OLS estimate of β .

Let $\tau^+(c)$ be the median value of τ_j taken over 1000 trajectories. $\tau^+(c)$ is the time at which we can expect the true climate sensitivity to be within a prespecified confidence interval ($\pm c\%$). Figure 2a shows $\tau^+(c)$ for each of the three scenarios, that is, the median year when we are 95% sure that the true value of climate sensitivity lies within a specified range ($\pm c\%$) of the estimated value. The results are striking: reducing climate sensitivity from its current uncertainty of approximately $\pm 50\%$ to $\pm 20\%$ will take a long time.

We see from Figure 2 that learning that the value of climate sensitivity lies within $\pm 20\%$ of the estimated value takes nearly a century with the High or Med scenarios. This time is cut to approximately 30 years for the low scenario. The High scenario has high levels of GHGs which increase the temperature signal, but also high SO_2 emissions which reduce the signal. The net effect is that the signal is weaker for “High” than for “Low.”

Figure 2b decouples the effects of GHG concentrations from sulfate aerosols by fixing SO_2 emissions at the levels associated with Med, the mid-range emission scenario. Figure 2b shows that controlling GHG emissions slows down the rate of learning about climate sensitivity. The most rapid learning occurs when we have the largest signal from GHGs: over 50 years to achieve a $\pm 20\%$ confidence band. Aggressive control makes the climate change trend more difficult to see within the noisy temperature record. The learning model has difficulty discerning between random warm and cold years and the warm years due to emission of GHGs. Figure 2c shows the result for GHG concentrations set at their level in the Med scenario, and varying SO_2 emission

rates. Here aggressive control of SO_2 increases the upward trend in temperature and thus makes the climate change more visible within the noisy temperature record.

As mentioned earlier, one troubling feature of Eq. (3) as estimated with the instrumental record is that the response from an instantaneous and permanent increase in GHG forcing is surprisingly, and unrealistically, rapid. Since the effect on the temperature n years after a hypothetical shock occurs is $\beta_1^n T_0$, where T_0 is the temperature at the time the shock occurred, the closer β_1 is to unity, the slower the response to a forcing shock. Because of this, we have also estimated Eq. (3) assuming a value of β_1 that is consistent with the physical model; in fact, we use a value obtained from our more detailed EBC/UDO model. We obtain β_1 estimates by simulating the effects of a CO_2 doubling for 245 years (equal in time to 1856-2100), using the EBC/UDO model, for three different assumed temperature sensitivities, T_{2x} , and then use the generated data to estimate the appropriate coefficient values in Eq. (1) with O_t neglected. For $T_{2x} = 1.5^\circ\text{C}$, 2.5°C , and 4.5°C , the results imply $\beta_1 = 0.87941$, 0.92277 and 0.95167 , respectively. Consequently, we have also estimated Eq. (3) assuming a fixed value for β_1 of 0.9, and then estimated the equation again assuming $\beta_1 = 0.94$.

Table 2 shows how the learning times vary with the assumed value of β_1 . The table clearly demonstrates that increasing the value of β_1 only serves to slow down learning about climate sensitivity. This is as would be expected since fixing β_1 leads to a poorer fit of Eq. (3) to the instrumental record, and thus more error. This logically increases the amount of time necessary to reduce the error in the estimate of climate sensitivity.

In conclusion, using a simplified model of learning we have shown that achieving some confidence regarding the value of climate sensitivity may take many decades. Although additional factors could be included in our model (such as volcanoes, the sun, and regional temperature variations), the results suggest a very slow resolution to the question of the magnitude of climate sensitivity. This notwithstanding, we have shown that accelerated control of GHGs and SO_2 emissions will have opposing effects on the rate at which we learn about

climate sensitivity, the former slowing learning and the latter accelerating it. The policy implication is that if we wait until uncertainty is resolved before controlling emissions of greenhouse gases, we may wait a very long time.

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Figure Captions

Figure 1. (a) Global average temperature relative to 1961-1990 ($^{\circ}\text{C}$); (b) Radiative forcing due to greenhouse gases (GHGs) (22), and (c) SO_2 emission (22) normalized by its 1990 value of 75 TgS/yr.

Figure 2 (a) Median year τ^+ (c) at which we can be 95% sure that the true climate sensitivity is within $\pm c\%$ of the estimated climate sensitivity, under emissions assumptions associated with the Low, Med and High scenarios. (b) as in (a), except with the SO_2 emission scenario fixed at the Med(IS92a) scenario; (c) as in (a), except with the CO_2 emission scenario fixed at the Med (IS92a) scenario. Parameter estimates as in Table 1.

Table 1. Ordinary Least Squares Estimates of Parameters in Equation (3)

Quantity	Estimate	Standard Error
β_0	-0.2209	0.0428
β_1	0.5589	0.0712
β_2	0.2295	0.0751
β_3	-0.2517	0.1455
ϵ	NA	0.1008
λ	0.5350	0.1592
T_{2x}	2.3486	0.6988

NB: 1. $\lambda \equiv \beta_2 / (1 - \beta_1 - K)$ computed using $K = 0.012$ from complex energy-balance-climate/upwelling-diffusion-ocean (EBC/UDO) model (7,12-20).

2. $T_{2x} \equiv \lambda F_{2x}$, with $F_{2x} = 4.39 \text{Wm}^{-2}$.

Table 2. Estimated Learning Times for Three Models.

c	$\beta_1 = 0.5589^*$			$\beta_1 = 0.9$			$\beta_1 = 0.94$		
	IS92e	IS92a	IS92c	IS92e	IS92a	IS92c	IS92e	IS92a	IS92c
5	>2100	>2100	>2100	>2100	>2100	>2100	>2100	>2100	>2100
10	>2100	>2100	2077	>2100	>2100	>2100	>2100	>2100	>2100
15	2096	2085	2056	>2100	>2100	>2100	>2100	>2100	>2100
20	2089	2073	2033	>2100	>2100	>2100	>2100	>2100	>2100
30	2067	2039	2011	>2100	>2100	2081	>2100	>2100	>2100
50	2001	2001	2000	>2100	2081	2044	>2100	>2100	>2100

*Results from Eq. (3) with all parameters estimated. Other cases involve β_1 fixed at indicated value during estimation of Eq. (3).

NB:

>2100 states that learning is resolved at some time after the year 2100, due to a lack of estimates of greenhouse gas and sulfate forcing post-2100.

Learning time is defined as the first year in which we expect to be 95% confident that the true climate sensitivity is within $\pm c\%$ of the estimated climate sensitivity.

Figure 1:

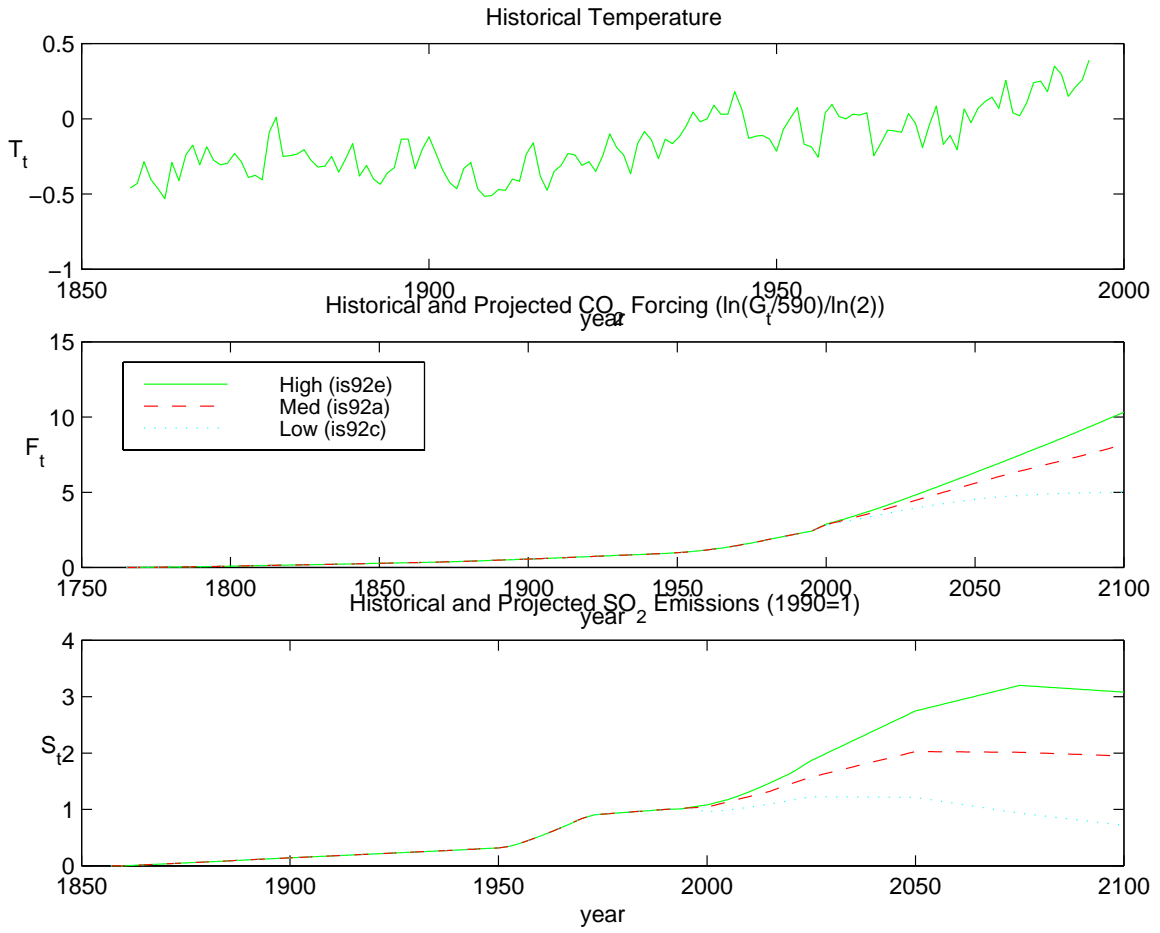


Figure 2:

