



Insufficient forcing uncertainty underestimates the risk of high climate sensitivity

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[1] Uncertainty in climate sensitivity is a fundamental problem for projections of the future climate. Equilibrium climate sensitivity is defined as the asymptotic response of global-mean surface air temperature to a doubling of the atmospheric CO₂ concentration from the preindustrial level (≈280 ppm). In spite of various efforts to estimate its value, climate sensitivity is still not well constrained. Here we show that the probability of high climate sensitivity is higher than previously thought because uncertainty in historical radiative forcing has not been sufficiently considered. The greater the uncertainty that is considered for radiative forcing, the more difficult it is to rule out high climate sensitivity, although low climate sensitivity (<2°C) remains unlikely. We call for further research on how best to represent forcing uncertainty.

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1. Introduction

[2] Atmosphere-Ocean General Circulation Models (AOGCMs) used in the IPCC Fourth Assessment Report show different equilibrium climate sensitivity ranging from 2.1°C to 4.4°C [*Intergovernmental Panel on Climate Change (IPCC)*, 2007, p.631]. Perturbing parameters in AOGCMs reports wider ranges in sensitivity – *Murphy et al.* [2004] find values up to 7°C and *Stainforth et al.* [2005] up to 11°C.

[3] Climate sensitivity can also be estimated by an inversion approach using historical observations over various periods and time scales. The uncertainty range of these estimates is dominated by uncertainties in reconstructions of historical surface air temperature. Uncertainty in historical radiative forcing has received less attention and has not been sufficiently treated. Previous studies [e.g., *Andronova and Schlesinger*, 2001; *Gregory et al.*, 2002; *Knutti et al.*, 2002; *Forest et al.*, 2006] express this forcing uncertainty by introducing an additional parameter to scale a presumed time-evolution of the aerosol forcing, with the exception of a few studies [*Hegerl et al.*, 2006; *Meinshausen et al.*, 2009; *Prather et al.*, 2009]. *Hegerl et al.* [2006] uses different realizations of volcanic and solar forcing. *Meinshausen et al.* [2009] and *Prather et al.* [2009] introduce a variety of parameters to individual forcing terms. The forcing scaling approach does not fully capture radiative forcing uncertainty because it does

not consider the uncertainty in the temporal structure of aerosol forcing, the uncertainty in other forcing terms, and radiative forcing that is not well represented in the model.

[4] We investigate the effect of radiative forcing uncertainty on the estimation of climate sensitivity using an inversion setup of the Aggregated Carbon Cycle, Atmospheric Chemistry, and Climate model (ACC2) version 3.1 [*Tanaka*, 2008]. In Section 2, we discuss the model ACC2, its inversion estimation, and the experimental setup. The results are discussed in Section 3. The paper is concluded in Section 4. This paper is accompanied by auxiliary material that shows a few sensitivity analyses for the main results.⁵

2. Methodology

2.1. Model ACC2

[5] ACC2 is a global-annual-mean Earth system model comprising carbon cycle, atmospheric chemistry, and climate components [*Tanaka et al.*, 2007; *Tanaka*, 2008; *Tanaka et al.*, 2009]. Directly relevant to this study is the climate component, the Diffusion Ocean Energy balance CLimate model (DOECLIM) [*Kriegler*, 2005]. DOECLIM is a land-ocean energy balance model that comprises essentially two boxes: 1) land coupled with the troposphere over land and 2) ocean coupled with the troposphere over the ocean. Coupled to the ocean box is a heat diffusion model that describes heat transfer to the deep ocean. DOECLIM is used to calculate surface air temperature prescribing total radiative forcing, which is the sum of individual forcing terms calculated in the carbon cycle and atmospheric chemistry components. The ocean and land carbon cycle processes are represented by the respective four-reservoir box models tuned to Impulse Response Function models [*Joos et al.*, 1996; *Hooss et al.*, 2001]. ACC2 incorporates parameterizations of atmospheric chemistry processes [*Joos et al.*, 2001] involving direct radiative forcing agents (CO₂, CH₄, N₂O, O₃, SF₆, 29 species of halocarbons, sulfate aerosols (direct effect), carbonaceous aerosols (direct effect), all aerosols (indirect effect), and stratospheric H₂O) and indirect radiative forcing agents (OH, NO_x, CO, and VOC).

2.2. Inversion for ACC2

[6] In the inverse estimation using ACC2, we obtain a best estimate of uncertain parameters corresponding to the minimum of the following cost function:

$$S(\mathbf{m}) = \frac{1}{2} \left(\sum_{i=1}^a \left(\frac{g_i(\mathbf{m}) - d_{mes,i}}{\sigma_{d,i}} \right)^2 + \sum_{j=1}^b \left(\frac{m_j - m_{prior,j}}{\sigma_{m,j}} \right)^2 \right). \quad (1)$$

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$g_i(\mathbf{m})$ is the forward model projection for data i based on a set of parameter \mathbf{m} . a and b are the total numbers of data and parameters, respectively. $d_{mes,i}$ and $m_{prior,j}$ denote measurement i and prior estimate of parameter j , respectively. m_j is parameter j , the value of which is determined such that the cost function $S(\mathbf{m})$ is minimized. $\sigma_{d,i}$ and $\sigma_{m,j}$ are one-sigma uncertainty ranges for measurement i and for prior estimate of parameter j , respectively. Examples of parameters are climate sensitivity and beta factor (parameterization for CO₂ fertilization). Data include atmospheric concentrations of CO₂, CH₄, and N₂O and global-mean surface air temperature change each year (from year 1750 to 2000). All the parameters and data used in the ACC2 inversion are listed in Tables S1 and S2 of the auxiliary material. The period of our inverse estimation is year 1750–2000.

[7] The cost function (equation (1)) is derived based on the probabilistic inverse estimation theory [Tarantola, 2005]. The cost function is the negative of the argument of the exponential function expressing the joint posterior Probability Density Function (PDF) for all the parameters [Tanaka, 2008, equation (3.2.12)]. This indicates that a low value in cost function corresponds to a large value in PDF and also that these two quantities have an inverse exponential relationship. We assume normal distributions for all the prior uncertainties of the parameters and data. All the parameters and data in the ACC2 inversions are treated independently, implying that fits for time series having strong autocorrelations are over-emphasized. Autoregressive models are not used due to the absence of data to estimate autoregressive propagators for the parameters and data in time series. Implications of the independent error assumption are discussed in section S5 of Text S1.

[8] Our optimization approach is in contrast to previous studies which compute the PDF of climate sensitivity. Calculating a PDF can be done for a problem addressing a small number of uncertainties but is infeasible for our approach, which considers more than one thousand uncertain parameters (Table S2 of the auxiliary material).

[9] In ACC2, the carbon cycle, atmospheric chemistry, and the climate system are linked via feedbacks and therefore jointly affect the estimation of various uncertain parameters in each of these components. In this study, inversion results in the climate component are not sensitive to those in the carbon cycle and atmospheric chemistry components because we do not consider climate-carbon cycle feedbacks in order to focus on the effect of radiative forcing uncertainty (Table S3 of the auxiliary material).

[10] Inverse calculations are performed using the local optimization solver CONOPT3 [Drud, 2006] implemented in the software package GAMS (<http://www.gams.com/>) [Tanaka, 2008, pp. 263–266]. The solutions for inversions are confirmed by performing the same inversions from different initial points.

2.3. Radiative Forcing in ACC2

[11] How radiative forcing is modeled in ACC2 requires clarification for this study. Radiative forcing is represented as the sum of three types of forcing: calculated radiative forcing subject to uncertainties (CO₂, CH₄, and N₂O forcing), prescribed/parameterized radiative forcing without uncertainties (other greenhouse gas, aerosol, volcanic [Ammann

et al., 2003], and solar [Krivova *et al.*, 2007] forcing), and “missing forcing.”

[12] Missing forcing is treated as an independent parameter in each year. The missing forcing term accounts for the uncertainty in the prescribed/parameterized radiative forcing and also represents forcings that are not included in other forcing terms in ACC2 (e.g., albedo forcing and mineral dust forcing). Furthermore, it reflects the interannual and decadal variability in the temperature records, which arises from the non-linear dynamics of the atmosphere and ocean (except for the ENSO-induced change after 1930, which is accounted for based on a regression analysis using the SOI index [Kriegler, 2005, pp. 32–33]). We account for temperature variability from the forcing side because uncertainty in temperature observations is well-defined relative to the uncertainty in radiative forcing. The missing forcing term can express the temporal structure of forcing uncertainty that cannot be captured by the conventional forcing scaling approach.

2.4. Experimental Design

[13] We compare the standard ACC2 inversion (i.e., expressing radiative forcing uncertainty as missing forcing) with two other ACC2 inversions with alternative representations of radiative forcing uncertainty: one in which, similar to previous studies, it is expressed by an uncertain forcing scaling factor applied to the aerosol forcing, and a second that assumes no forcing uncertainty at all. For all setups, we calculate the relationship between the minimum value of the cost function and the value of climate sensitivity by performing a series of inversions in which climate sensitivity is fixed at values between 1°C and 10°C at intervals of 0.25°C (a total of 111 optimizations). The shape of this relationship indicates both the best estimate of climate sensitivity and the uncertainty of such an estimate. Only the climate sensitivity and the forcing uncertainty are essentially modified from one point in a cost function to another, although the optimization is performed for the entire model (including the carbon cycle component) each time. The inversion in the carbon cycle component is not sensitive to that in the climate component because we assume no climate-carbon cycle feedbacks.

3. Results and Discussion

[14] Figure 1 shows the cost function values for the set of simulations. As these values are clearly elevated for a climate sensitivity of less than 2°C, such a low climate sensitivity is unlikely, in line with the results of the PDF studies. More importantly, if the forcing uncertainty is fully addressed as missing forcing, the cost function curve is almost completely flat at values of climate sensitivity above about 2°C. In this case, the inversion indicates little preference for any value of climate sensitivity in the range 2°C–10°C. In contrast, if the forcing uncertainty is represented as an uncertain scaling factor applied to a fixed temporal trend of aerosol forcing as in the PDF studies, the climate sensitivity appears far better constrained, particularly at high values. It is even better constrained if the uncertainty in the radiative forcing is not considered at all.

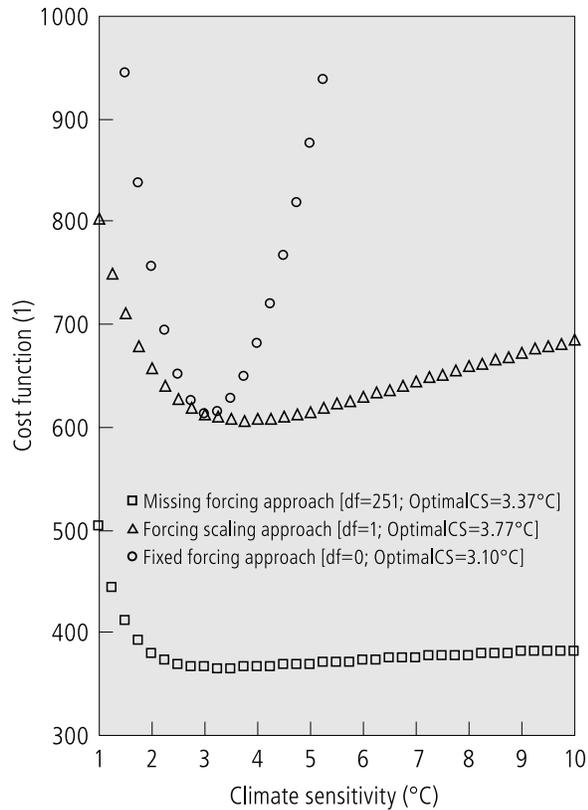


Figure 1. Cost function in the ACC2 inversions under different treatments to radiative forcing uncertainty. Final values of the cost function are computed by optimizations with climate sensitivity fixed at values between 1°C and 10°C at intervals of 0.25°C. Each plot represents a unique inversion result. In square brackets, degrees of freedom for forcing uncertainty and best estimates of climate sensitivity are shown.

[15] Therefore, our analysis suggests that the well-defined peak of the PDF of climate sensitivity in former studies is a consequence of insufficient treatment of the historical development of radiative forcing uncertainty. Including these uncertainties implies that climate sensitivity is less constrained at the high end than previously thought. Our study adds on *Gregory et al.* [2002] that emphasizes the importance of aerosol forcing uncertainty in estimating climate sensitivity. We go one step further by saying that the conventional way of scaling aerosol forcing evolution is not sufficient. The insufficiency of the conventional approach is indicated from

the magnitudes of error terms. In the forcing scaling-based inversion, the temperature error term accounts for 69% of the total cost function while in the missing forcing-based inversion, it accounts for only 31% (Table S3 of the auxiliary material). Such a large temperature error term shifts the cost function curve based on the forcing scaling approach substantially higher than the cost function curve based on the missing forcing approach. This study does not aim to support the conclusion of *Roe and Baker* [2007] that high climate sensitivity cannot be constrained due to its asymmetric influence from positive feedbacks – we rather demonstrate the importance of representing forcing uncertainty in constraining high climate sensitivity.

[16] We can draw this conclusion even though our results are not expressed as PDFs as in previous studies. According to probabilistic inverse estimation theory [*Tarantola*, 2005], our best estimate for climate sensitivity can be interpreted as the peak of the joint posterior PDF for all the parameters. On the other hand, what previous studies have presented corresponds to the marginal posterior PDF for climate sensitivity (obtained by integrating the joint posterior PDF with respect to parameters other than climate sensitivity). Thus, the two approaches reduce the joint posterior PDF differently. Nevertheless, in our case, differences in the value of the cost function qualitatively indicate differences in relative likelihood because the cost function changes monotonically with respect to parameters (section S2 of Text S1). In other words, flatter cost function curves mean less constrained PDFs.

[17] More in detail, Figure 2 presents radiative forcing and temperature time series resulting from missing forcing- and forcing scaling-based inversions. Figure 2 (top) shows that low climate sensitivity is not supported even with the missing forcing approach because the missing forcing goes beyond its 2σ uncertainty range to explain the warming in the late 20th century. Figure 2 (bottom) demonstrates that high climate sensitivity is not acceptable with the forcing scaling approach, which results in excessively strong cooling after large volcanic eruptions in the 19th century. Such results indicate that the forcing scaling approach is too inflexible to deal with the complexity in forcing uncertainty.

[18] Some insights are provided from the estimates of missing forcing (Figure 2, top). The missing forcing is punctuated by large spikes corresponding to volcanic eruptions. In the cases of climate sensitivity of 3, 5, and 10°C, most of these spikes are positive and some others negative, depending on the mismatches between the volcanic forcing and the reconstructed temperature (Figure 2, bottom). The missing forcing after 1900 is highly variable, reflecting the interannual variability of the temperature records. The fluctu-

Figure 2. (top and bottom) Comparison of the results of ACC2 inversions using missing forcing- and forcing scaling-approach. Figures 2 (top) and 2 (bottom) show the inversion results from using the missing forcing- and forcing scaling-approach with climate sensitivity of 1, 3, 5, and 10°C. The forcing scaling factor is estimated to be 0.045, 0.999, 1.214, and 1.398 in the forcing scaling-based inversions with climate sensitivity of 1, 3, 5, and 10°C, respectively. Measurements in Figure 2 (bottom) are compilation of temperature reconstruction [*Jones et al.*, 1998; *Mann and Jones*, 2003] and instrumental records [*Jones et al.*, 2006]. Insert of Figure 2 (bottom) shows the “residuals,” i.e., the difference between prior and posterior values. The residuals are calculated such that the mean measurement during the period 1961–1990 is equal to the corresponding posterior mean. Measurements shown in the main figure are for the missing forcing-based inversion with climate sensitivity of 3°C.

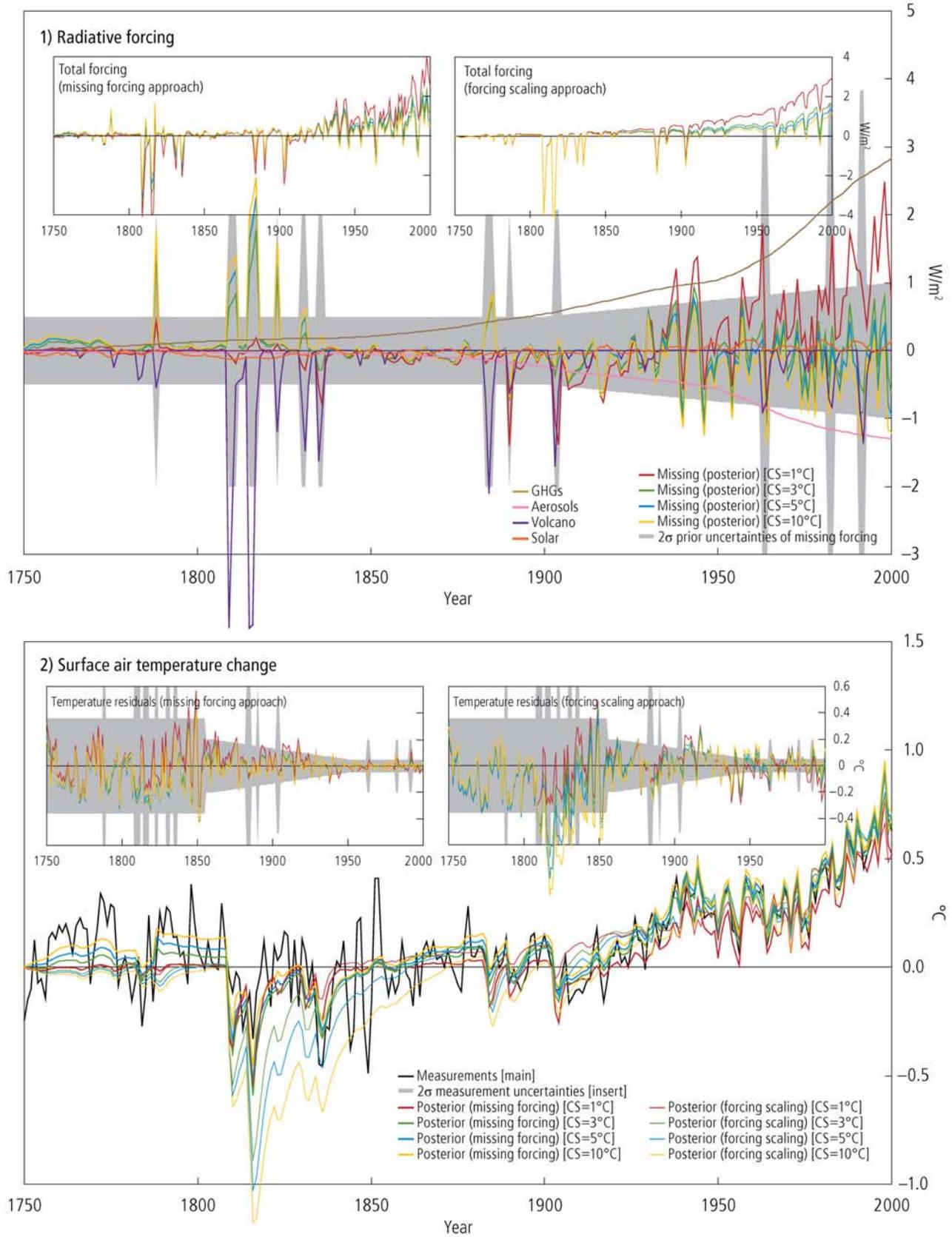


Figure 2

tuation becomes larger toward present as the prior temperature uncertainty gets smaller with an extensive observation network put into place and also as the prior uncertainty of the missing forcing becomes larger to reflect aerosol forcing uncertainty. This results in an increasingly good fit of the temperature observations toward the end of the simulation. The average missing forcing over the last 50 years is small negative, an indication that the aerosol forcing used in ACC2 (total aerosol forcing is -1.3 W/m^2 in year 2000) is slightly underestimated in magnitude.

[19] We do not use a statistical χ^2 test (designed to evaluate the size of residuals) to validate the inversion results because of the nonlinearity of the model and a large number of autocorrelations. Overall, the inversion results can be meaningfully interpreted [Tanaka, 2008, chapter 4 and Appendix A], supporting the validity of the inversion results. We assume a fixed estimate for the ocean diffusivity ($0.55 \text{ cm}^2/\text{s}$ based on Kriegler [2005]), because constraining the ocean diffusivity requires oceanic heat diffusion processes, which are not explicitly modeled in ACC2. A sensitivity analysis (section S4 of Text S1) shows our conclusion is not influenced by different assumptions for ocean diffusivity. We use only one possible prior range of climate sensitivity (mean of 3.5°C with 2σ range of $0.5\text{--}6.5^\circ\text{C}$). There is an argument not to include prior beliefs in inverse estimation [Allen et al., 2006], but our results are not sensitive to prior climate sensitivity because other time series terms in the cost function are dominant. A sensitivity analysis of the prior uncertainty range of missing forcing is provided in section S3 of Text S1.

4. Concluding Remarks

[20] Our ACC2 inversion approach has indicated that by including more uncertainty in radiative forcing, the probability of high climate sensitivity becomes higher, although low climate sensitivity ($<2^\circ\text{C}$) remains very unlikely. Thus in order to quantify the uncertainty in high climate sensitivity, it is of paramount importance to represent forcing uncertainty correctly, neither as restrictive as in the forcing scaling approach (as in previous studies) nor as free as in the missing forcing approach. Estimating the autocorrelation structure of missing forcing is still an issue in the missing forcing approach. We qualitatively demonstrate the importance of forcing uncertainty in estimating climate sensitivity – however, the question is still open as to how to appropriately represent the forcing uncertainty.

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