The 2000–2012 Global Warming Hiatus More Likely With a Low Climate Sensitivity

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**Abstract**  The global warming hiatus during the first decade of the 21st century has posed a challenge to the scientific community, though a leading explanation is that it was caused by internal variability overlaying a forced global warming trend. Here, we apply the Winton-Held two-layer model and show that the probability of the observed 2000–2012 hiatus period to arise from internal variability driven by white noise is larger if climate sensitivity is low. This is due to the delayed response of the oceans that cause the forced trend to increase faster with rising climate sensitivity than does natural variability, leading to a decreasing likelihood of observing the hiatus. The results are confirmed with the latest climate models participating in the Coupled Model Intercomparison Project (CMIP6).

**Plain Language Summary**  The global warming during 2000–2012 was slower than the projections by global climate models. Several studies suggest that this was an expression of natural variability causing deviations from what is expected based on changes in greenhouse gases. In this study, we investigate whether the probability of such an event to occur depends on climate sensitivity, since a higher sensitivity is thought to result in more variability. However, we find that the forced trend increases faster than natural variability, leading to a decreasing likelihood of observing the hiatus.

1. Introduction

The global mean surface temperature of Earth warmed slowly during the 2000–2012 period relative to the surface warming simulated by global climate models (Flato et al., 2013). The observed temperature trend during this period is somewhat data set-dependent with 0.08–0.16 K/decade (Figure 1), while the trend is 0.21 K/decade in the fifth phase of the Coupled Model Intercomparison Project (CMIP5) multimodel mean (Flato et al., 2013) which can be taken to represent their forced temperature trend. Three climate models which participated in the following CMIP6 provided ensembles of at least 10 members, thereby allowing the estimate of their forced trend, also simulate larger 2000–2012 temperature trends that in two of three cases are distinct from observations (0.14–0.26 K/decade; Figure 1). Thus, also the latest edition of climate models has, on average, difficulties simulating the observed hiatus period.

Several studies investigated the potential causes of the hiatus. For instance, some studies attribute the warming hiatus to errors in the external forcing (Kaufmann et al., 2011; Santer et al., 2014; Solomon et al., 2011), whereas others associate it with coverage bias in the observations (Cowtan & Way, 2014; Karl et al., 2015); the data sets used here, with exception of HadCRUT4.6, do not suffer from incomplete coverage. Several other studies have attributed the hiatus to internal variability (Guemas et al., 2013; Meehl et al., 2014; Sévellec & Drijfhout, 2018; Watanabe et al., 2013): if correct, neither a single realization of a climate model nor an ensemble mean is likely to reproduce the hiatus. Meehl et al. (2011) and Watanabe et al. (2013) relate the warming hiatus to the internal variability in ocean heat uptake, drawing of heat from the surface ocean to deeper layers, while Hedemann et al. (2017) suggest that a hiatus could equally likely have been caused by the internal variability in the top-of-atmosphere (TOA) energy imbalance. Several studies investigated the likelihood of such warming hiatuses for the future climate (Guemas et al., 2013; Roberts et al., 2015; Schurer et al., 2015), and for instance, Sévellec et al. (2016) showed that under the RCP8.5 scenario hiatuses are likely to vanish by 2100.

Perhaps inspired by the hiatus period there has been a renewed interest in the possible connection between internal climate variability and climate sensitivity (Colman & Power, 2018; Cox et al., 2018; Lutsko & Takahashi, 2018). In particular Nijsse et al. (2019) investigated whether internal variability driven hiatus periods,
such as that of 2000–2012, would be more likely to occur with a high or a low equilibrium climate sensitivity (ECS), defined as the long-term warming in response to doubled CO$_2$ relative to preindustrial conditions. Using the fluctuation-dissipation theorem (Einstein, 1905; Hasselmann, 1976) applied to a single heat reservoir model they find that the variability of the global temperature trend is proportional to ECS which they evaluate using the CMIP5 models. They found that models with high ECS have stronger temperature variability on time scales of several years to decades, exceeding the increase in the forced historical temperature trend, and hence argue that hiatus periods are more likely to occur in case of a high ECS.

In this study, we focus on the observed 2000–2012 period (light coral shading in Figure 1). We use a two-layer model (Geoffroy et al., 2013; Held et al., 2010; Winton et al., 2010) with added white noise to the energy balance to investigate how the likelihood of the observed hiatus period 2000–2012 depends on ECS. We show that on decadal time scales the delayed response of the deep ocean to external forcing causes the forced temperature trend increase to be strongly dependent on climate sensitivity. The noise-induced variability also increases with rising climate sensitivity, but at a slower rate. This larger increase in the forced temperature trend with increasing ECS leads to a reduction in the probability of observing the 2000–2012 hiatus. The results are confirmed with the latest CMIP6 models, which exhibit a wider range of ECS than CMIP5, thereby allowing us to verify the results of the two-layer model.

2. Model, Data, and Methods

We apply the widely used Winton-Held two-layer model including a representation of the pattern effect (Geoffroy et al., 2013; Held et al., 2010; Winton et al., 2010) with added white noise to the energy balance to investigate how the likelihood of the observed hiatus period 2000–2012 depends on ECS. We show that on decadal time scales the delayed response of the deep ocean to external forcing causes the forced temperature trend increase to be strongly dependent on climate sensitivity. The noise-induced variability also increases with rising climate sensitivity, but at a slower rate. This larger increase in the forced temperature trend with increasing ECS leads to a reduction in the probability of observing the 2000–2012 hiatus. The results are confirmed with the latest CMIP6 models, which exhibit a wider range of ECS than CMIP5, thereby allowing us to verify the results of the two-layer model.
where $F$ is the external radiative forcing taken from Annex II of the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment report (AR5) (Myhre et al., 2013), $\lambda$ is the climate feedback parameter, $\gamma$ is the heat exchange coefficient between the two layers, $\epsilon$ is the ocean heat uptake efficacy representative of the pattern effect (Geoffroy et al., 2013; Held et al., 2010; Winton et al., 2010), and $N$ is the planetary energy imbalance. The concept of ocean heat uptake efficacy ($\epsilon$) was introduced by Winton et al. (2010) to represent the radiative response associated with the disequilibrium temperature component of the transient temperature response driven by the ocean heat uptake. The ocean heat uptake can induce a spatial pattern of surface temperature change which could in turn impact the radiative imbalance. Stevens et al. (2016) termed this the pattern effect to denote the effect of ocean heat uptake induced spatial pattern of surface temperature on the radiative response, although it is recognized that sea surface temperature patterns are also important in setting the feedback to internal variability and the long-term response (Mauritsen, 2006). A typical value of $\epsilon$ is 1.28 (Geoffroy et al., 2013). In the two-layer model, the ECS is the equilibrium temperature response (where $N = 0$ and $T = T_0$) to the forcing from doubled atmospheric CO$_2$ ($F_{2x}$) given as $ECS = -F_{2x}/\lambda$. For most of this study, we use the following parameters: $F_{2x} = 3.7$ W m$^{-2}$, $\gamma = 0.8$ W m$^{-2}$ K$^{-1}$, $C$ to equivalent of 50 m water layer, $C_d$ equivalent of 1,200-m deep water layer, and $\epsilon = 1$. The latter results in no pattern effect, since when writing out $N$ the term $-(\epsilon - 1)(T - T_d)$ vanishes. We shall also consider the case with a pattern effect. Note that the AR5 historical forcing data continues until 2011 which we extend here till 2012. We decide to simply keep the 2011 radiative forcing value of all the forcing agents to 2012.

In order to simulate the internal global variability with the two-layer model, we add white noise to the forcing (F) and run the model 10,000 times for each value of ECS. Running the model several times generates an ensemble of simulations for each ECS which allows to separate the expected forced response from the internal variability. Throughout the paper we present our discussion when the two-layer model is forced with the AR5 historical forcing plus white noise sampled from a Gaussian distribution centered at zero and with a standard deviation of $\sigma = 1.3$ W m$^{-2}$ on a monthly time scale. Our choice of $\sigma$ is based on the variability in the TOA net radiative flux and the variability associated with exchange between the upper and the deep ocean components. From the AMIP simulations of the CMIP6 models, we estimate the multimodel mean TOA variability to be 0.9 W m$^{-2}$ (Figure S1), whereas a similar amount of variability is related to the ocean component (Hedemann et al., 2017). Adding these in quadrature yields $\sigma = 1.3$ W m$^{-2}$. As we find that there is no relationship between the TOA variability and ECS in CMIP6 models (Figure S2), we add white noise with constant $\sigma$ to the forcing in the two-layer model simulations.

An alternative option would be to represent noise induced by exchange between the upper and deep oceans (Menzel & Merlis, 2019). To test if this would affect the results, we applied random time variations to the heat exchange between the two layers in Equation 1, whereby white noise is added to the upper layer while the same amount is subtracted from the deep layer. With this setup we find that the statistics are barely distinguishable (compare Figures 2 and S3). It was therefore decided to keep the simpler formulation with TOA induced noise. Further complication might arise if there exists non-white longer time scale (Kosaka & Xie, 2013) types of noise that could influence global surface temperature variability such as the hiatus period. For instance, alternative forms of noise might be invented that could make the two-layer model mimic for instance ENSO variability (Lutsko & Takahashi, 2018). Nevertheless, we believe that considering such additional types of noise would complicate the study and it is not clear that such complication would lead to scientific advances in the present context: the idea that internal variability is dampened by negative feedback, deep ocean heat uptake and pattern effects would apply equally to global variability driven by white or more red noise. Forced with the AR5 historical forcing (Myhre et al., 2013) and the parameters of the two-layer model set as per the MPI-ESM1.2 (Mauritsen et al., 2019), the temporal evolution of surface temperature anomaly simu-
lated by the two-layer model provides a close approximation to that of much more complex climate models (Figure 1). Visually, the two-layer model generates somewhat stronger cooling and takes slightly longer to recover from some of the volcanic eruptions compared to the complex climate models (Gregory et al., 2016). With this in mind, the two-layer model is a useful emulator of complex model behavior, but unlike those it is feasible to explore systematically how different physical properties affect the results.

For illustration of the hiatus period in Figure 1, we used observations of global mean surface temperature from four different data sets: HadCRUT4.6 (Morice et al., 2012), NOAA GlobalTemp (Smith et al., 2008; Vose et al., 2012), and infilled HadCRUT4 + HadSSt4 and COBE2CRU data sets (Cowtan & Way, 2014). The displayed complex climate models are those from CMIP6 with at least 10 ensemble members available, which is better to compute the model forced trend. We calculate the temperature trends from the slope of an ordinary least-squares linear regression over the 13-year period (2000–2012). The ECS of the models are estimated using the Gregory method (Gregory et al., 2004) using linear regression over years 1–150 in the abrupt4xCO2 experiment. These are 2.9 K for MPI-ESM1.2-HR, 4.5 K for IPSL-CM6A-LR, and 5.1 K for CESM2 (Figure S4). Further, to verify our results with the CMIP6 models, we estimated the 2000–2012 global warming trend from the historical simulations of the CMIP6 models while the variability in 13-years temperature trends is estimated from the piControl simulations of CMIP5 and CMIP6 models (Tables S1 and S2).

3. Results

We start out by evaluating the probability distribution of temperature trends over the 2000–2012 hiatus period (Figure 2a) for a range of ECS. ECS is set by changing the climate feedback parameter ($\lambda$), used as the ECS control parameter (since $\text{ECS} = -\frac{F_\lambda}{\lambda}$ at equilibrium). We find that for a given ECS, the distribution of decadal temperature trends is approximately Gaussian, and as ECS increases the distributions widen, as is to be expected (Hasselmann, 1976; Nijsse et al., 2019). A physical interpretation of this behavior is that the negative feedback parameter, which acts to relax the temperature back toward the expectation value that is externally forced, is weakened (less negative) with increasing ECS resulting in larger and more persistent anomalies (Roe, 2009). It is also clear, and to be expected, that the distributions shift to higher values as ECS increases. However, this forced trend shifts faster than the widening of the distribution such that the probability of low or negative trends decreases with increasing ECS. For instance, the probability of ob-
containing a temperature trend less than or equal to 0.1 K/decade over the hiatus period (Figure 2b) decreases dramatically with ECS.

The reason the forced trend increases faster than the variability is the memory of past forcing carried by the oceans (Held et al., 2010). Figure 3a shows the evolution of surface temperature change of a few CMIP6 climate models to a gradual increase in atmospheric CO$_2$ by 1%/year ($1\text{pctCO}_2$) experiments) with their respective linear fits. The fits join the origin and the mean of the temperature change of 50 years centered around year 70. Changes are with respect to the final 500 years of piControl simulations of the respective CMIP6 models. (b) The ratio of 50-years trend centered around year 70 to that the slope of respective fits for each of the CMIP6 models against ECS. Solid blue shows the ratio of 50-years trend centered around year 70 of a two-layer model simulated for each value of ECS to that of the slope of corresponding linear fit. A ratio larger than one indicates the memory of past forcing carried by the oceans. The vertical red bar shows the range of ratios from 68 $1\text{pctCO}_2$ ensemble members of MPI-ESM1.1. In the absence of oceans, the ratio is always unity (black dashed). The ECS values for the CMIP6 models are taken from Schlund et al. (2020). CMIP, Coupled Model Intercomparison Project; ECS, equilibrium climate sensitivity.

Volcanic eruptions before the hiatus, such as the 1991 Mount Pinatubo eruption, would have a similar effect on the forced trend in the 2000–2012 period. This is because there will be a surface warming trend sometime after the eruption as the climate recovers from the relatively short-term negative forcing. Indeed, we see that for a given ECS the presence of volcanic forcing substantially reduces the probability of observing a negative 2000–2012 trend in comparison with the case without volcanoes (Figure 2b). It is possible that the two-layer model exaggerates the effect of volcanic eruptions somewhat since it appears to take longer to recover than complex climate models (Figure 1), but in either case the Pinatubo volcanic eruption is expected to reduce the likelihood of a hiatus for a given ECS.

![Figure 3.](image-url) Comparison of temperature trend around year 70 (time of doubled CO$_2$) of a climate model relative to its linear fit. (a) The evolution of change in temperature to atmospheric CO$_2$ increase at 1%/year in the CMIP6 models ($1\text{pctCO}_2$) and a corresponding fit for each model—fit joins the origin and the mean of the temperature change of 50 years centered around year 70. Changes are with respect to the final 500 years of piControl simulations of the respective CMIP6 models. (b) The ratio of 50-years trend centered around year 70 to that the slope of respective fits for each of the CMIP6 models against ECS. Solid blue shows the ratio of 50-years trend centered around year 70 of a two-layer model simulated for each value of ECS to that of the slope of corresponding linear fit. A ratio larger than one indicates the memory of past forcing carried by the oceans. The vertical red bar shows the range of ratios from 68 $1\text{pctCO}_2$ ensemble members of MPI-ESM1.1. In the absence of oceans, the ratio is always unity (black dashed). The ECS values for the CMIP6 models are taken from Schlund et al. (2020). CMIP, Coupled Model Intercomparison Project; ECS, equilibrium climate sensitivity.
Pattern effects, on the contrary, are expected to increase the probability of observing a hiatus. This is because pattern effects can temporarily dampen change on subcentennial time scales; both the forced trends and global variability induced trends are dampened, and in effect a model with a certain ECS behaves as if it had a lower ECS. To demonstrate this, we repeat the experiments with $\epsilon = 1.28$ (Figure 2b), which is a value typically found in global climate models (Geoffroy et al., 2013). We see that this increases the probability for obtaining a negative temperature trend for all ECS, but relatively more so for higher values.

A concern we had when conducting this study was that when we change ECS the overall historical warming also changes. A common idea is that enhanced aerosol cooling can be paired with a higher ECS to compensate for the greater long-term warming (Kiehl, 2007). One can approximate the transient warming as $\Delta T \approx -\Delta F/(\lambda - \epsilon)$ (Jiménez-de-la Cuesta & Mauritsen, 2019). Using this expression for each ECS, and corresponding $\lambda$, we estimated the aerosol cooling necessary to obtain the observed warming from early industrial to early 21st century. The overall results regarding the probability of obtaining negative temperature trends in the hiatus period, however, did not change appreciably (Figures 2b and S5).

The present study is in many ways complementary to a recent study by Nijssse et al. (2019), although the results presented are at odds with their finding that the probability of observing hiatuses in general in CMIP5 models increases with ECS. The discrepancy in the conclusion arises from (1) a different choice of period for estimating how the forced temperature trends depend on ECS—Nijssse et al. (2019) considered 1960–2012 while we focused on the actual 2000–2012 hiatus period—and (2) different estimates of how internal variability of the temperature trends depend on ECS. When combined these two factors resulted in the discrepant outcomes. In the remainder of this section, we shall investigate the causes.

The dependence of the forced trend on ECS is stronger during the 2000–2012 hiatus period than during the longer 1960–2012 period (Figure 4a). Single realizations of CMIP6 models scatter around the predicted relationship by the two-layer model with about two-thirds of CMIP6 models falling within one standard deviation, displayed as a red shaded band, as is to be expected from random internal variability. At the same time, the two-layer model predicts a weaker relationship for the 1960–2012 period, which in turn is virtually identical to that found by Nijssse et al. (2019) for the CMIP5 models. Thus, the difference in obtained forced trend dependency on ECS is almost entirely due to a different choice of periods.
An equally large discrepancy, but with opposite sign, is found between the dependency of trend variability on ECS (Figure 4b): the two-layer model predicts an increase of trend variability that is substantially weaker than Nijsse et al. (2019) found for the CMIP5 models. Note, here, that Nijsse et al. (2019) calculated 10-years trend variability, whereas other displayed data is for 13-years trends, Figure S6 explores the effect of this in more detail. Large variability in two CMIP5 models with relatively high ECS supported the strong relationship assumed in Nijsse et al. (2019). However, no CMIP6 models exhibit such strong variability, despite spanning a broader range extending to higher ECS. Instead the CMIP6 models provide clear support for the weaker relationship predicted by the two-layer model applied in the present study.

In light of these results, it is interesting to ask if the fact that we have observed a weak warming trend during 2000–2012 could help constrain ECS? Whereas the observed warming trend overlaps with the mean forced warming for ECS in the range 1.5–2.5 K, for larger ECS random cooling arising from internal variability is required in order to replicate the weak observed warming (Figure 4a). Yet, even for ECS close to 5 K it is possible to find single realizations from CMIP6 models that replicate the observed. On top, if there are stronger pattern effects in the real world than that simulated by CMIP6 models, then the forced transient warming for a given ECS is reduced and hence the probability of observing the hiatus increased (Figure 2b). Thus, the observed warming hiatus period is not a strong constraint on ECS, at least on its own.

4. Conclusions

The global surface temperature evolved slower than predicted on average by climate models in the first decade of the 21st century (2000–2012). In this study, we explore the possibility that this period of weaker than expected warming is related to natural variability and how the corresponding probability of observing the hiatus depends on the climate sensitivity. We apply a two-layer model forced with estimates of natural and anthropogenic radiative forcing for the period 1850–2012, with random white noise added to the radiation balance to emulate internal variability. Whereas the internal variability in the temperature trend over the 2000–2012 period increases with climate sensitivity, it is by far exceeded by the increase in the forced temperature trend. As a result, the probability of seeing weak or negative temperature trends over this period decreases with increasing climate sensitivity.

The underlying mechanism for the strengthening forced temperature trend is that the oceans carry memory of forcing applied before year 2000. This applies to both greenhouse gas warming, a behavior recovered also in the highly idealized 1pctCO2 experiment, as well as from volcanic forcing before year 2000, most notably the 1991 Mount Pinatubo eruption. Considering pattern effects generally increases the probability of observing negative temperature trends, in particular, for higher climate sensitivities. Uncertainty in aerosol forcing, however, had little influence on the results.

We confirm our results from the simple two-layer model with the latest CMIP6 models, which exhibit a wider range of ECS than the CMIP5 models. The variability in temperature trends as function of ECS derived from the two-layer model is consistent with the relationship found from the CMIP6 models. Similarly, the global warming trend during 2000–2012 in individual CMIP6 runs plotted against ECS is within ±1 standard deviation of the forced temperature trend simulated by the two-layer model, to the extent that it is to be expected. These new CMIP6 models verify our result that the probability of observing the 2000–2012 hiatus decreases with rising climate sensitivity. That said, the observed hiatus period is hardly a strong constraint on ECS in its own right, though combined with other lines of evidence the hiatus may help support an upper bound close to 5 K (Sherwood et al., 2020).

Data Availability Statement

CMIP5 and CMIP6 model output are freely available from the Lawrence Livermore National Laboratory (https://esgf-node.llnl.gov/search/cmip5/, World Climate Research Programme (WCRP), 2011 and https://esgf-node.llnl.gov/search/cmip6/, WCRP, 2019). The observed global mean surface temperature from four different data sets, HadCRUT4.6 (Morice et al., 2012), NOAA GlobalTemp (Smith et al., 2008; Vose et al., 2012), and infilled HadCRUT4 + HadSSt4 and COBE2CRU data sets (Cowtan & Way, 2014) are obtained from https://www.metoffice.gov.uk/hadobs/hadcrut4/, https://www.ncdc.noaa.gov/
noaa-merged-land-ocean-global-surface-temperature-analysis-noaaglobaltemp-v5, and https://www-users.york.ac.uk/~kdc3/papers/coverage2013/series.html, respectively. The codes and processed observational data, CMIP5 and CMIP6 model data, and AR5 forcing data used to produce the figures of this paper will be publicly available at the time of publication on Zenodo at https://doi.org/10.5281/zenodo.4706685.

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