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An exponential-interval sampling method for evaluating equilibrium climate sensitivity via reducing internal variability noise

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Abstract
Equilibrium climate sensitivity (ECS) refers to the total global warming caused by an instantaneous doubling of CO_2 from the preindustrial level. It is mainly estimated through the linear fit between the changes in global-mean surface temperature and top-of-atmosphere net radiative flux, due to the high costs of millennial-length simulations for reaching a stable climate. However, the accuracy can be influenced by the response's nonlinearity and the internal noise, especially when using a limited-length simulation. Here, we propose a new method that derives a new series using an exponential-interval sampling (EIS) method for the original simulation to reduce the noise and estimate the ECS more accurately. Utilizing the millennial-length simulations of LongRunMIP, we prove that the EIS method can effectively reduce the influence of internal variability, and the estimated ECS based on the first 150 years of simulation is closer to the final ECS in the millennial-length simulations than previous estimations with the deviation rate decreased by around 1/3. The ECS in CMIP6 models estimated by the EIS method ranges from 1.93 to 6.78 K, and suggests that the multimodel mean ECS derived from the original series with previous methods could be underestimated.

Keywords: Global warming, Equilibrium climate sensitivity, Internal variability, LongRunMIP, CMIP6

Introduction
Estimating the sensitivity of the climate system to greenhouse gases (GHGs) is a key problem in understanding GHG-induced global warming (Manabe and Stouffer 1980; Meehl et al. 2020; Senior and Mitchell 2000; Stouffer and Manabe 1999; Washington and Meehl 1989). When a climate model is used to simulate the climate response to GHGs, the equilibrium climate sensitivity (ECS) is one of most important metrics for evaluating its climate sensitivity. The ECS is defined as the total warming of the Earth's climate system when it rebalances after an abrupt doubling of CO_2 from the preindustrial level (Hansen et al. 1984; IPCC 2007). However, it is difficult to obtain an exact value of the ECS in a fully coupled climate model because it takes the modeled climate system multiple millennia to rebalance (Dai et al. 2020; Rugenstein et al. 2020; Williams et al. 2008). Therefore, how to obtain a reliable ECS in climate models is of great concern in estimating the climate sensitivity.

Early studies often estimated the ECS using slab ocean climate models in which the atmospheric component is coupled with a slab ocean model without ocean dynamics, since such models respond and reach a new equilibrium much faster than fully coupled models (Washington and Meehl 1984; Wilson and Mitchell 1987). However, the bias in the ECS estimated using slab ocean climate models is unavoidable owing to the lack of dynamic and thermodynamic processes in the deep ocean, even though some studies have suggested that the bias could be small (e.g., Gent and Danabasoglu 2009). As a result,

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alternative statistical methods have been developed to estimate the ECS using relatively short simulations in fully coupled models.

In the climate response to GHG forcing, the energy balance of the climate system can be written as $\Delta N = F - \lambda \Delta T$, in which ΔN is the top-of-atmosphere (TOA) net radiative flux change, ΔT is the change in global-mean surface temperature, F is a constant representing the radiative forcing caused by a doubling of CO_2, and λ is a feedback parameter. An approximate linear relationship between ΔN and ΔT is found in a time-varying climate response before climate models reach equilibrium. Thus, the feedback parameter λ can be estimated as the slope of the linear regression between ΔN and ΔT. Under the assumption that λ remains constant until climate equilibrium is reached, the ΔT in the equilibrium state can be estimated as the T-intercept in the linear regression of ΔN and ΔT (Gregory et al. 2004). This method is widely used to estimate the ECS based on the 150-year simulation of the abrupt4xCO2 experiment in the phase 5 and 6 of the Coupled Model Intercomparison Project (CMIP5 and CMIP6) (Andrews et al. 2012).

However, many studies have suggested that the response of the climate system is nonlinear. The net TOA radiative flux is found to decline sharply with surface temperature change in the first several decades, which is usually considered as the "fast response" (Andrews et al. 2015; Armour et al. 2013; Gregory et al. 2004; Rugenstein et al. 2020). Accordingly, the dN/dT slope, i.e., the feedback parameter λ, shows a tendency to flatten after the fast response. Previous studies have ascribed this flattening of λ to the evolution of the ocean warming pattern, the oceanic heat uptake efficacy, and cloud feedback, among other factors (Armour et al. 2013; Rugenstein et al. 2016a, b; Xie 2020). Given the decrease in λ, including the early response of the ΔN and ΔT in the abrupt4xCO2 simulation can underestimate the ECS (Meehl et al. 2020).

Therefore, increasing the simulation length in the linear regression of ΔN and ΔT seems necessary to improve the ECS estimation. Nevertheless, the ΔT response to an abrupt quadrupling of CO_2 basically follows a quasi-exponential slow-down relative to time (Dunne et al. 2020). After the first few hundred years, the long-term warming signals become very slight, especially compared with the internal noise. As a result, when longer simulations are included in the simple linear regression of ΔN and ΔT, the ΔT after the first few hundred years show little increase but dominate the linear regression due to the large number of data points. In this case, the contribution of ΔT in the slowly warming period is enlarged. Moreover, the influence of internal noise in ΔN and ΔT for the dN/dT slope become more apparent as revealed in previous studies (Dai et al. 2020; Dessler et al. 2018; Gregory et al. 2004; Marvel et al. 2018; Rugenstein and Armour 2021). Therefore, a new method is needed that can retain the very slowly increased signals of global warming ΔT and also can remove the influence of internal noise.

Dai et al. (2020) recommended an analytic method to evaluate the ECS in which the ΔN and ΔT time series are fitted to an analytic function based on a two-layer climate model and then applied the $\mathrm{d}N/\mathrm{d}T$ slope to estimate unrealized warming. In the fitted analytic function, the influence of internal variability is thoroughly removed, and the relative contributions of ΔT in the early and late response are reasonably set based on the presupposed function. The analytic method can obtain a relatively accurate ECS with only 180 years of simulation, as compared with the final warming in models after multiple millennia (~ 5000 year). However, this method requires a presupposed complex function for fitting.

In this study, a new method is proposed to remove the internal variability and further improve ECS estimation. We derive new series from the original ones via exponential-interval sampling (EIS) to remove most of the internal variability, considered here as noise. The EIS series of ΔN and ΔT show more accurate linear correlation. Based on the regular 150-year abrupt4xCO2 simulation, the EIS method can estimate an ECS that is closer to the result from using a multi-millennium simulation. The rest of the paper is organized as follows: "Models" section describes the models used, and "Methods" section introduces the EIS method developed in this study. "Results" section evaluates the EIS method in terms of decreasing the internal noise, and compares the ECS estimated by four methods. "Summary and discussion" section discusses the results and the broader implications.

Models

The surface temperature (ΔT) and TOA radiative flux (ΔN) in the abrupt4xCO2 and piControl experiments from nine models participating in LongRunMIP (Rugenstein et al. 2019) are used to check the effectiveness of our method for reducing the internal noise and estimating the ECS. LongRunMIP is a model intercomparison project of millennial-length GCM simulations, aimed at obtaining the originally defined ECS. These models are: CESM104 (5900 years), MPIESM11 (4459 years), FAMOUS (3000 years), CNRMCM61 (1850 years), HadGEM2 (1299 years), ECHAM5MPIOM (1001 years), IPSLCM5A (1000 years), MPIESM12 (1000 years), and HadCM3L (1000 years).

In addition, the abrupt4xCO2 experiments from 32 models participating in CMIP6 (Eyring et al. 2016) are used to apply the methods to 150-year datasets.

The 32 models are: ACCESS-CM2, ACCESS-ESM1-5, BCC-CSM2-MR, BCC-ESM1, CESM2, CESM2-FV2, CESM2-WACCM, CESM2-WACCM-FV2, CIESM, CanESM5, E3SM-1-0, EC-Earth3, EC-Earth3-Veg, EC-Earth3-Veg-LR, FGOALS-g3, GFDL-CM4, GFDL-ESM4, GISS-E2-1-G, GISS-E2-1-H, HadGEM3-GC31-LL, HadGEM3-GC31-MM, INM-CM4-8, INM-CM5-0, IPSL-CM5A2-INCA, IPSL-CM6A-LR, KACE-1-0-G, MCM-UA-1-0, MIROC-ES2L, MIROC6, SAM0-UNICON, TaiESM1 and UKESM1-0-LL.

Methods

Previous linear extrapolation methods for the ECS

We apply four methods to estimate the ECS, which are modified from the original method of Gregory et al. (2004), referred to as Method 1 here. Method 1 gives the $\lambda = \mathrm{d}N/\mathrm{d}T$ slope and $\mathrm{ECS} = \theta \times T_{\mathrm{int}}$ through linear fitting over the whole time series of the annual ΔT and ΔN in the abrupt4xCO2 experiment (relative to the piControl run), where T_{int} is the T-intercept. The θ is the ratio of the final warming caused by 2xCO2 forcing to that by 4xCO2 forcing, for calculating a comparable ECS when a 4xCO2 experiment is used. We take $\theta = 3.8749/8.1246 = 0.4769$ according to the radiative forcing for 2xCO2 and 4xCO2 (Byrne and Goldblatt 2014). In order to remove the influence of the fast response, previous studies have usually excluded the first 20 years of the simulation in the linear regression (Andrews et al. 2015), whereas recent studies have tended to expand the length of exclusion to 40–50 years (Dai et al. 2020; Dunne et al. 2020). Method 2 follows previous studies in excluding the fast response in early years, but we start the linear fit from the 50th year for comparing the result with the EIS method. Method 3 divides the final warming ECS into realized and unrealized warming to minimize the bias caused by the flattening of the climate feedback in the linear method (Dai et al. 2020). The realized and unrealized warming are represented by ΔT_{mean} and $\Delta N_{\mathrm{mean}}/b$, respectively. The ΔT_{mean} and ΔN_{mean} are averages over the last 50 years of the simulation, and b is the same slope as in method 2. Hence, $\mathrm{ECS} = \theta \times (\Delta T_{\mathrm{mean}} + \Delta N_{\mathrm{mean}}/b)$.

EIS for improving the linear extrapolation method

In this study, we introduce the new EIS method as Method 4 in an attempt to remove the influence of internal noise, which was ignored in previous methods. Before applying the $\Delta N - \Delta T$ linear fit, we derive new ΔN and ΔT series from the original ones. Considering the ΔT response to an abrupt quadrupling of CO_2 basically follows a quasi-exponential evolution relative to time (Dunne et al. 2020), we cut the total time period into several segments whose centers and lengths both increase exponentially relative to time. After some tests, the central point in each segment is set as $e^{0.2\times t}$, to retain as much data points as possible with the internal noises effectively reduced. Setting the coefficient as 0.25, 0.4 or so can get the similar results (not shown). The values composed of individual segments form the new series. For example, the new point $T(t)$, which corresponds to the original $T(e^{0.2\times t})$, is the average over $T[(e^{0.2\times t-0.2} + e^{0.2\times t})/2] \sim T[(e^{0.2\times t} + e^{0.2\times t+0.2})/2]$. The left-hand boundary is rounded down and the right-hand one is rounded up to an integer, except for the right-hand boundary of the first point and the left-hand boundary of the last point, which are both rounded down.

The new time series together with the original ones are shown in Fig. 1. The series are demonstrated in a logarithmic coordinate according to the exponential-like response of ΔT and ΔN. As shown in Fig. 1, the EIS method can reduce most internal signals, such as interannual and decadal variabilities, in contrast with the original series, especially in the later response stage. The composed values of exponentially increased segments enlarge the weight of the data points in the fast response period and decrease the weight in the very slow response period. Since the system's response becomes exponentially slower, the EIS method can retain more effective signals in the whole process compared with the running average, which either loses the signals in the first few decades or maintains a lot of noise in later centuries, depending on the sliding window. In a logarithmic coordinate (Fig. 1), these sample points are evenly distributed, indicating a reasonable contribution of the data points in different warming stages. In method 4, $\lambda = b$ and $\mathrm{ECS} = \theta \times (\Delta T_{\mathrm{mean}} + \Delta N_{\mathrm{mean}}/b)$, where b is solved from the linear fit on the new ΔN and ΔT series since the 21st point, the mean of the original points from the 50th to the 62nd year. The ΔT_{mean} and ΔN_{mean} are represented by the last ΔT and ΔN value of the new series from the simulation.

Results

Effectiveness for decreasing noise

The new and original time series of ΔT and ΔN are compared in Fig. 2. The scatters of ΔT and ΔN in the new series follow a much more significant linear relationship than those of the original series, especially during the quasi-steady period, with a relatively smaller ΔT trend. As the length of segments exponentially increases, the new ΔT and ΔN scatters are more well-distributed than the original scatters, leading to the regression coefficient of ΔT and ΔN being more reliable for estimating their linear relationship. As Fig. 3a shows, the correlation coefficient between the ΔT and ΔN of the new series is closer to 1 than that of the original series. We also calculate the $\Delta T - \Delta N$ correlation coefficient using the

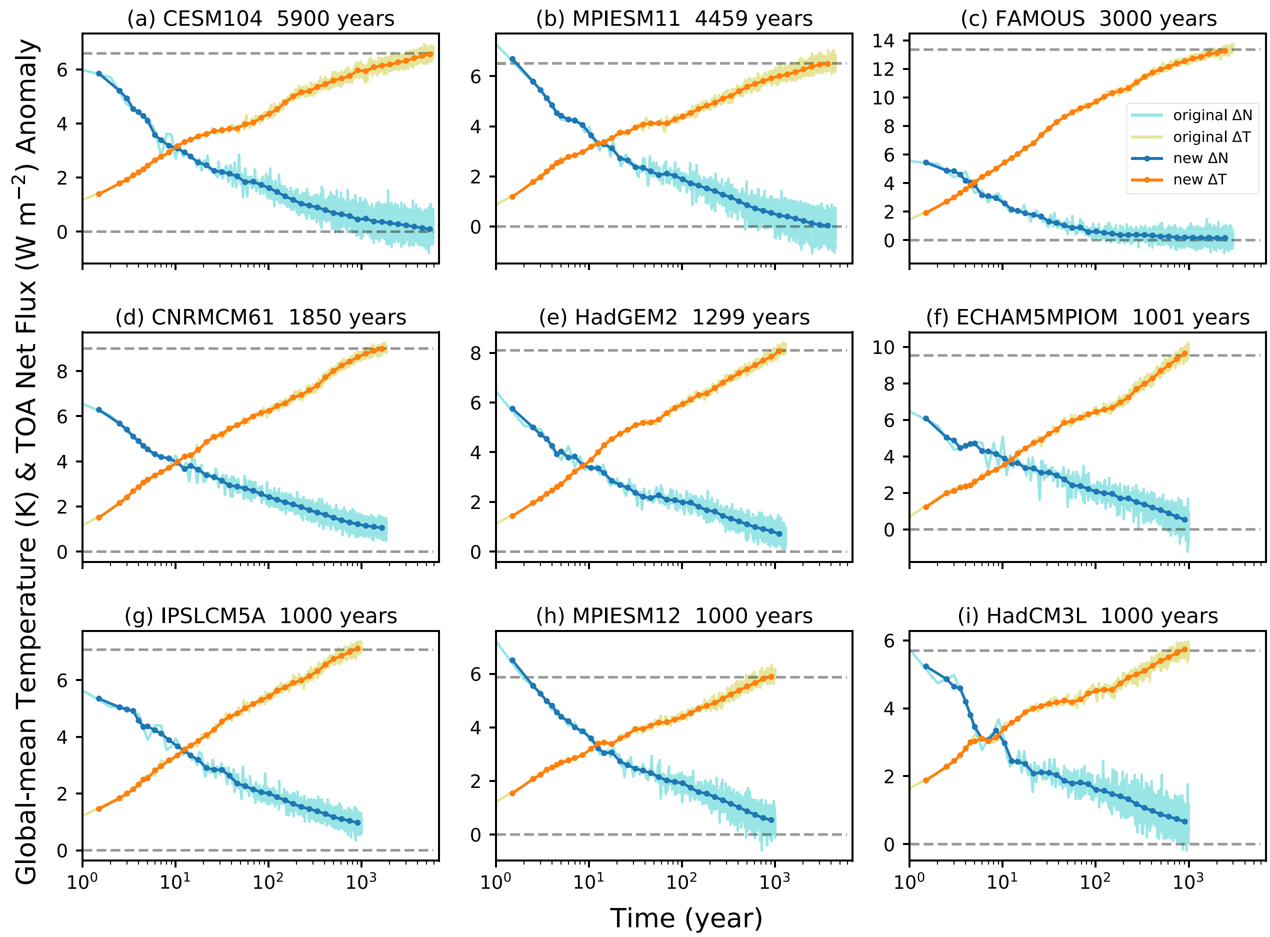

Fig. 1 Time series of the global-mean and annual-mean surface temperature anomaly ΔT and TOA net radiative flux anomaly ΔN in the abrupt4xCO2 (relative to piControl) experiments of LongRunMIP models. The yellow and light blue solid lines are the ΔT and ΔN of the original series, respectively. The orange and blue dotted lines are the ΔT and ΔN of the new series, respectively. The upper dashed grey line is the average ΔT of the last 300 years. The lower dashed grey line marks zero

datasets starting from the 50th year (the 21st point in the new series), and the distance between the results of the two series is even bigger, indicating that the influence of internal variability is greater in the quasi-steady stage. The contrast indicates that the EIS method is efficient at reducing the internal variability and retaining the long-term response signals with more correlated ΔT and ΔN.

Still, we notice that the $\mathrm{d}N/\mathrm{d}T$ slope of the new scatters is close to its original counterpart, while the correlation coefficient is greatly improved toward 1. This is because of the variation in the standard deviation of ΔT and ΔN in calculating the slope. The slope of a linear fit on x and y is calculated as $b = S_y/S_x \cdot r_{xy}$, where S_y and S_x are the standard deviations of the x and y time series, and r_{xy} is the correlation coefficient. While r_{xy} is improved greatly, close to 1, in the EIS method, the ratio of S_y to S_x becomes smaller too, as S_y lessens more than S_x after we reduce the noise. Therefore, the newly estimated slope is more reliable after removing the two errors, although the value could be close to the original one.

The product of the $\mathrm{d}N/\mathrm{d}T$ slope and the $\mathrm{d}T/\mathrm{d}N$ slope should be equal to 1, if ΔT and ΔN are linearly correlated without any noise (Dai et al. 2020). However, the estimated $\mathrm{d}N/\mathrm{d}T$ slope using the original series is not equal to the inverse of the $\mathrm{d}T/\mathrm{d}N$ slope, due to the high-weighted noise during the slow response. The product of the estimated $\mathrm{d}N/\mathrm{d}T$ and $\mathrm{d}T/\mathrm{d}N$ slope is further calculated as a criterion for checking if the noise has been effectively reduced in the EIS method. In Fig. 3b, the product based on the new series is very close to 1, much larger than its counterpart of the original series. This indicates that the real responses of the surface temperature and TOA radiation to an abrupt quadrupling of CO_2 are well-correlated, but they can be blurred by internal variability noise. After the noise has been effectively reduced, the linear fitting method based on the

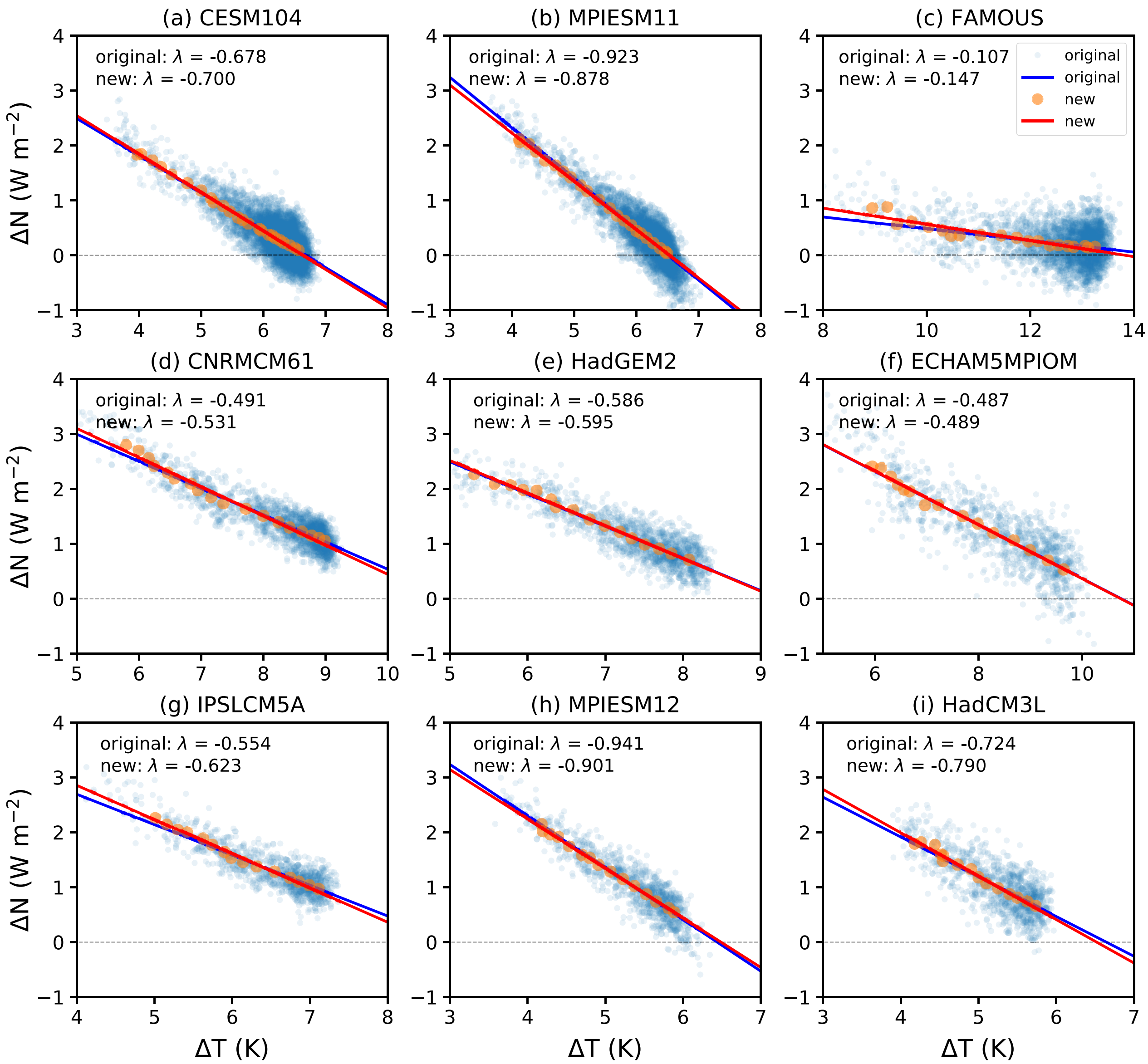

Fig. 2 Scatterplots of the anomalies (relative to piControl) of the global-mean and annual-mean surface temperature ΔT (*x*-axis) and TOA net radiative flux ΔN (*y*-axis) in the abrupt4xCO2 experiments of LongRunMIP models. The original scatters start from the 50th year (blue dots, blue line = linear fit) and the new series starts from the 21st point (average from the original year 50 to 62) (orange dots, red line = linear fit). The slopes of the linear fit on the original and new series are denoted as λ in the top-left corner

well-correlated dN and dT will estimate the ECS more accurately.

Evaluating the methods based on the LongRunMIP

The effectiveness of the EIS method is evaluated using the millennial-length simulations of LongRunMIP. In estimating the ECS, the climate feedback parameter λ is time-varying (Andrews et al. 2015; Rugenstein et al. 2020; Senior and Mitchell 2000; Williams et al. 2008) and also influenced by the internal noise (Armour 2017; Dai et al. 2020), which is more sensitive to the method than the final ECS. Thus, the radiative feedback λ is used as a criterion for checking if the method is stable enough to provide an accurate ECS estimation within a limited simulation. The climate feedback λ is calculated as the slope of the linear fit in varying simulation lengths of LongRunMIP models following (Rugenstein et al. 2020). Figure 4 shows the λ of three methods. Compared with the two traditional methods, the λ of the EIS method becomes stable earlier, to a varying degree, in the models.

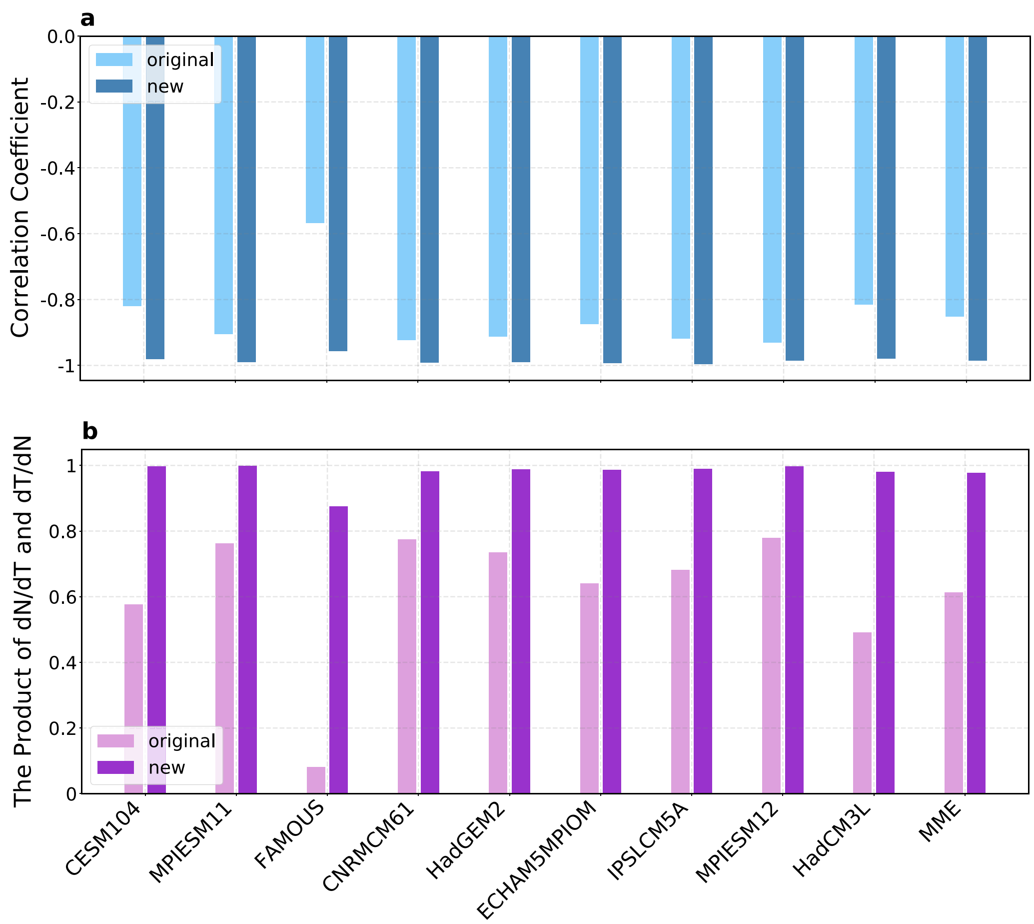

Fig. 3 **a** The correlation coefficient between the global-mean and annual-mean surface temperature anomalies ΔT and TOA net radiative flux anomalies ΔN in the abrupt4xCO2 experiments (relative to the piControl run) of LongRunMIP models. **b** The product of dN/dT (slope of the linear fit between ΔT and ΔN) and dT/dN (slope of the linear fit between ΔN and ΔT)

This result suggests that the EIS method can use a shorter simulation to obtain an ECS close to the eventual ECS in an equilibration state.

It is expected that an efficient method can estimate the dN/dT and ECS using a limited simulation close to the dN/dT and ECS directly calculated from millennial-length simulations. We further calculate the deviation rate of the ECS estimated with the first 150-year (200-year) simulation from the ECS directly obtained from the millennial-length simulation. The length of 150 years is the suggested length of the abrupt4xCO2 simulation, and 200 years was suggested in Dai et al. (2020) as the length for a reliable ECS estimation.

Figure 5 shows the deviation rate of the ECS estimated by the short simulation (the first 150 or 200 years) from the eventual ECS by the entire millennial-length simulation based on various methods. When the 150-year simulation and the traditional methods are used, the estimated ECS deviates from the eventual ECS by around 12%, which is consistent with the estimation in Dunne et al. (2020). The deviations of method 4 are apparently smaller than the results using methods 1–3 in the nine LongRunMIP models. The multimodel mean deviation rate of the EIS method is 8.1%, which is decreased by around 1/3 relative to those of the traditional ones, as Fig. 5a shows. The deviations using the 200-year simulation (Fig. 5b) are noticeably reduced relative to those using the 150-year simulation (Fig. 5a) for all methods, and the deviation rate of the EIS method is still the smallest among all methods. This result suggests that although the EIS method is effective for lowering the disagreement between the results using a limited simulation and the millennial-length simulation, it is useful to obtain a more accurate estimate of the ECS by extending the length of the abrupt4xCO2 simulation from the 150 years presently suggested in CMIP to 200 years as suggested in Dai et al. (2020) for a more accurate ECS estimation.

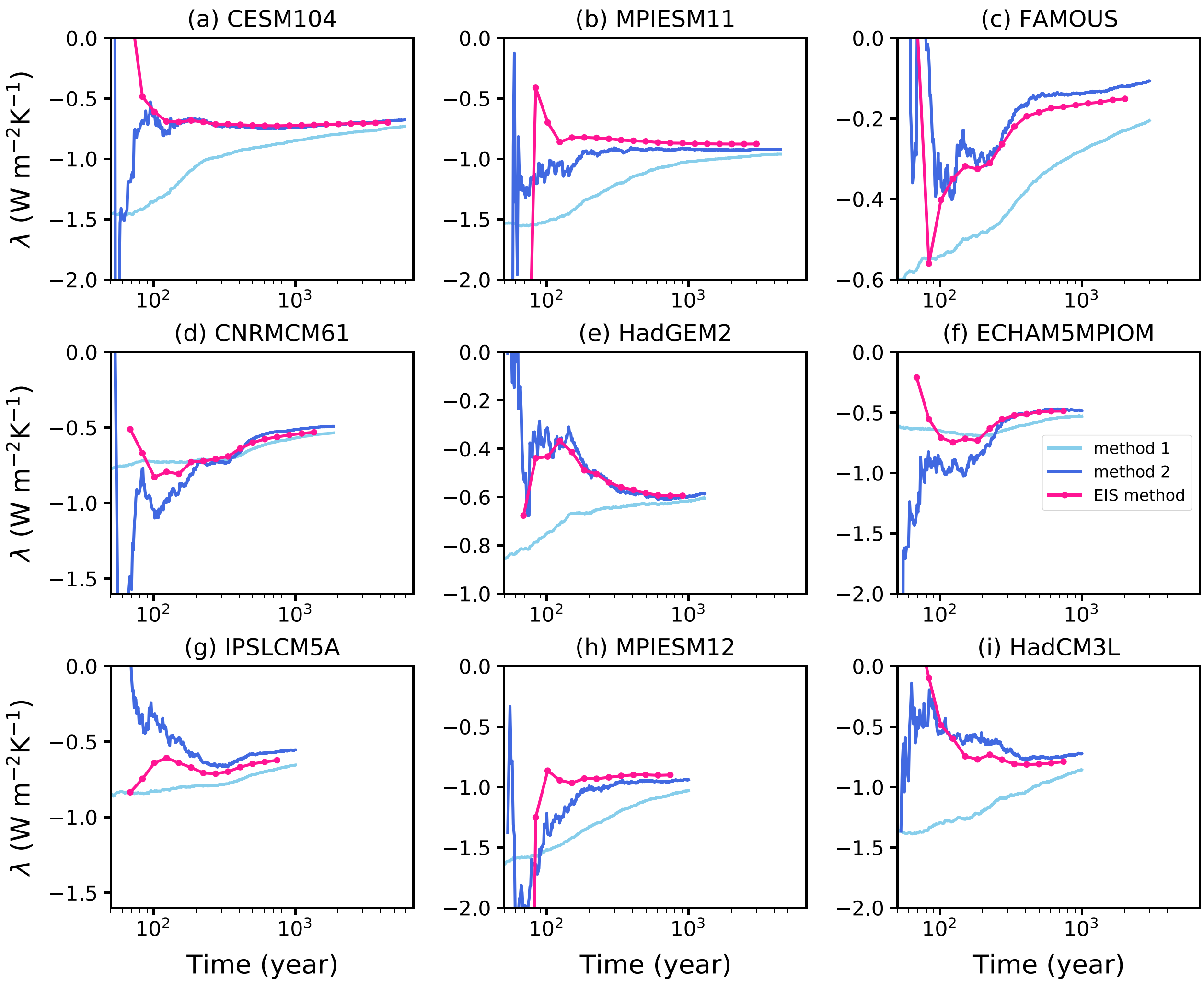

Fig. 4 Time series of the climate feedback λ (the dN/dT slope of the linear fit on the global-mean and annual-mean surface temperature anomalies ΔT and TOA net radiative flux anomalies ΔN) estimated from three methods. The light (dark) blue line is the λ estimated from the linear fit from the 1st (50th) to the plotted year in the original series. The deep pink line is the λ estimated from the linear fit from point 21 to the point whose upper limit of the average range is around the plotted year in the new series

Estimating the ECS in CMIP6 simulations

The EIS method is applied to the 150-year abrupt4xCO2 simulations of 32 CMIP6 models to estimate the ECS. The correlation coefficients between ΔT and ΔN from the 50th original year are shown in Fig. 6a. The ΔT and ΔN are highly correlated from the 50th year with the internal variability noise reduced by the EIS method. As shown in Fig. 6b, the ECSs estimated by method 4 are higher than the estimates by the other three methods, especially method 1, in most models. The multimodel mean ECS of method 4 is 4.20 K, which is around 11.5% larger than its counterpart using method 1 (3.76 K). While the result contradicts the conclusion that internal noise could lead to an overestimated ECS in an ideal framework (Dai and Bloecker 2019; Dai et al. 2020), it is the case, as expected, that the ECS is underestimated owing to the internal variability in the studies based on the simulations with known historical forcings (Dessler et al. 2018; Lewis and Mauritsen 2021).

Summary and discussion

A new method is introduced in this study that reduces the internal variability noise via EIS for estimating the ECS more accurately. The method is based on the fact that the climate system's response to an abrupt quadrupling of CO_2 becomes slower and slighter with time, behaving like exponential functions, and the

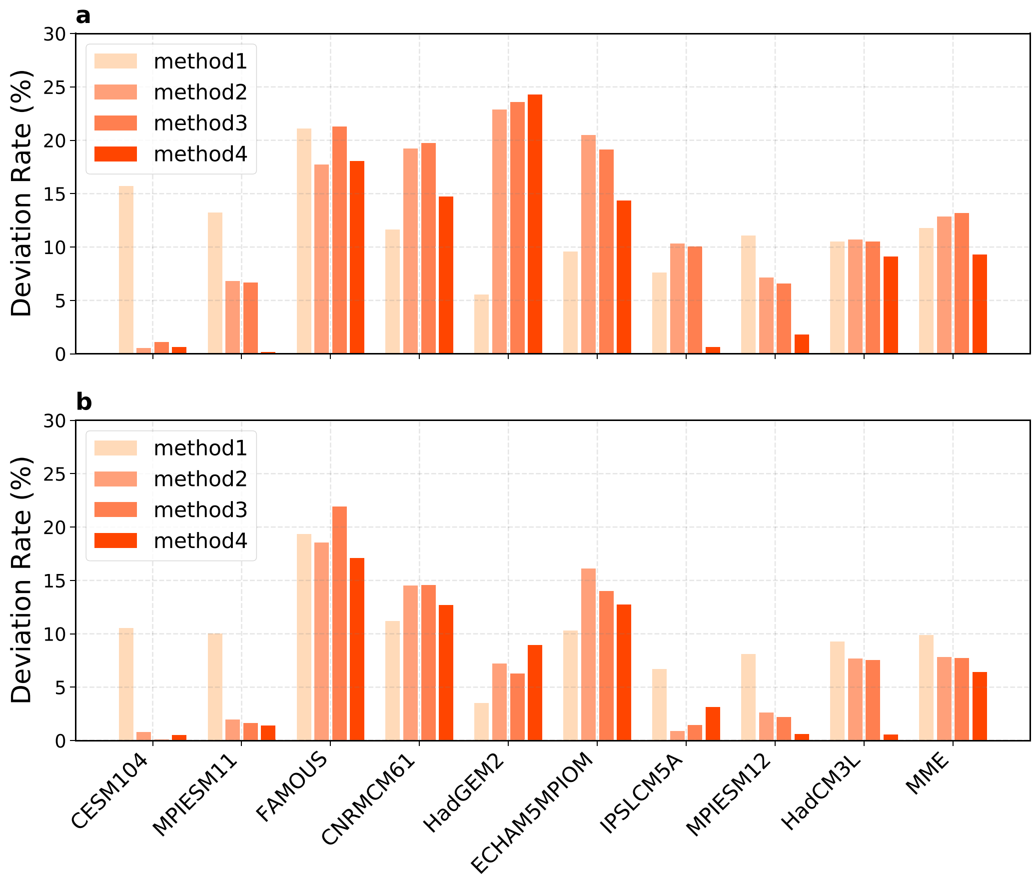

Fig. 5 Deviation rate of the ECS estimated by four methods within limited simulations from the whole simulation in LongRunMIP models: **a** simulation time-limit of 150 years; **b** simulation time-limit of 200 years

noise-to-signal ratio grows with time as well (Geoffroy et al. 2013; Gregory et al. 2004; Wilson and Mitchell 1987). Applying this method to nine LongRunMIP models with at least 1000 years of simulation, we find it sufficient for reducing most noise, and the new global mean surface temperature ΔT and net TOA radiative flux ΔN are strongly linearly correlated from the 50th year. This proves that it is sufficiently accurate to estimate the ECS through a linear fit of ΔT and ΔN with internal noise reduced.

We compare the climate feedback, $\lambda = \mathrm{d}N/\mathrm{d}T$, of the EIS method with three other methods and find that the EIS method can provide a more stable $\mathrm{d}N/\mathrm{d}T$ within limited simulations. Further, we evaluate the EIS method by comparing the ECS estimated from 150 or 200 years and the whole simulation in LongRunMIP models, the longest of which lasts 5900 years. It turns out that the EIS method's ECSs deviate much less than those of the other methods. While a longer simulation is suggested to be better for precisely estimating the ECS (Dai et al. 2020; Dunne et al. 2020), the EIS method can substantially reduce the bias caused by internal noise.

The EIS method is further applied to estimate the ECS in 32 CMIP6 models. With internal noise reduced, the correlation coefficient between ΔT and ΔN from the 50th year in the abrupt4xCO2 simulation is much closer to 1. The ECSs estimated using the EIS method are larger than others in more than half models (18 models). This implies that the internal noise may lead to an underestimation of the ECS through linear fitting. Dai et al. (2020) argued that the noise-to-signal ratio in linear fitting can overestimate the ECS, although the error is almost offset by the inclusion of early data points. In contrast, studies estimating the ECS from historical simulations have found the internal variability to be responsible for an underestimation bias (Dessler et al. 2018; Lewis and Mauritsen 2021). The EIS method successfully reduces the internal variability error source, which is helpful in further studying the estimation of climate sensitivity in models.

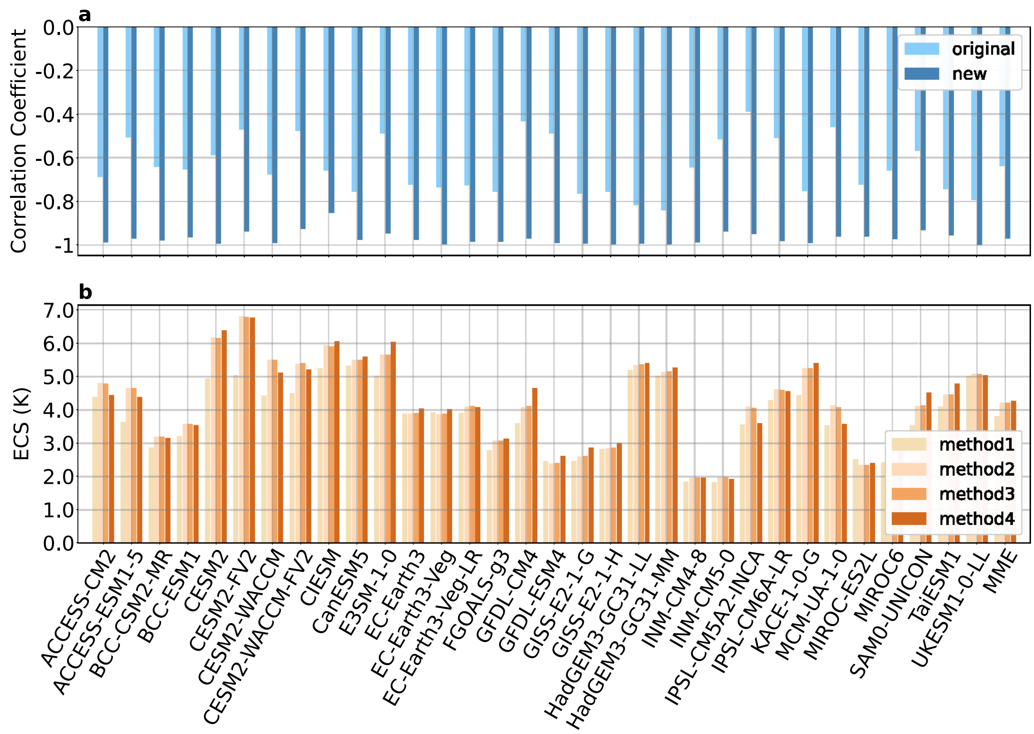

Fig. 6 **a** Correlation coefficient between the global-mean and annual-mean surface temperature anomalies ΔT and TOA net radiative flux anomalies ΔN from the 50th year (21st point) of the original (new) time series in the CMIP6 abrupt4xCO2 experiment (relative to piControl). **b** Comparison of ECS values estimated by four methods in CMIP6 models

Also noticeable is that the intermodel discrepancy of the ECS estimates is much larger than the differences among the estimates based on the four methods, especially in CMIP6. Besides the difference in final warming caused by the cloud feedback, ocean heat uptake and other parameters that influence the strength of the climate response, the various speeds of the response should also be considered. This paper proposes an approach to obtain a more stable climate feedback and therefore extrapolate a more accurate ECS within limited simulations, but further studies are still needed to discuss the underlying mechanisms and therefore further improving the accuracy of ECS estimation.

Author contributions
PH and SL conceived the study. SL conducted the analysis, drew the figures, and wrote the first draft of the paper. PH helped interpret the results and optimized the storyline of the paper. Both authors read and approved the final manuscript.

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Availability of data and materials
The LongRunMIP model datasets analyzed during the current study are provided by http://www.longrunmip.org/. The CMIP6 model datasets are available from the World Climate Research Programme (https://esgf-node.llnl.gov/projects/cmip6/).

Declarations

Competing interests
The authors declare that they have no competing interests.

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