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Uncertainty in the evolution of climate feedback traced to the strength of the Atlantic Meridional Overturning Circulation

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Key Points:

- Uncertainty in the Atlantic Meridional Overturning Circulation is the main cause of the model spread in evolution of the warming pattern.
- Warming in Northern Hemisphere extratropics tends to be surface trapped, leading to more positive lapse-rate and cloud feedbacks.
- Models with stronger recovery in Atlantic Meridional Overturning Circulation tend to project a larger increase in net climate feedback.

Abstract

In most coupled climate models, effective climate sensitivity increases for a few decades following an abrupt CO_2 increase. The change in the climate feedback parameter between the first 20 years and the subsequent 130 years is highly model-dependent. In this study, we suggest that the intermodel spread of changes in climate feedback can be partially traced to the evolution of the Atlantic Meridional Overturning Circulation (AMOC). Models with stronger AMOC recovery tend to project more amplified warming in the Northern Hemisphere a few decades after a quadrupling of CO_2. Tropospheric stability then decreases as the Northern Hemisphere gets warmer, which leads to an increase in both the lapse-rate and shortwave cloud feedbacks. Our results suggest that constraining future ocean circulation changes will be necessary for accurate climate sensitivity projections.

Plain Language Summary

How much the Earth's climate will warm in response to increasing carbon dioxide concentration, a number known as climate sensitivity, is an essential metric of the impacts of anthropogenic climate change. Most current global climate models agree that the climate will become more sensitive as time passes, indicating an underestimation of future warming inferred from historical records. In this study, we report that the slow response of oceanic circulation has an influence on this time evolution of climate sensitivity. In the 15 state-of-the-art global climate models we investigate, the models projecting re-strengthening of Atlantic Meridional Overturning Circulation (AMOC) after a few decades of weakening tend to simulate a more significant increase in climate sensitivity. We propose a mechanism as follows: AMOC strengthening causes more enhanced surface warming in the Northern Hemisphere, altering the vertical stability of the global atmosphere. The changes in atmospheric vertical stability then strengthen the radiative feedbacks that amplify greenhouse gas forcing, accounting for the larger increase in climate sensitivity in these models. Our findings emphasize the important contribution of ocean circulation to the intermodel spread in climate change projections.

1 Introduction

Equilibrium climate sensitivity (ECS) refers to the globally-averaged equilibrium surface air temperature response to an abrupt doubling of CO_2 concentration, and it has spanned a range of $1.5-4.5$ K for decades (Charney et al., 1979; Flato et al., 2013). Since it takes thousands of years for coupled models to reach steady state, ECS is usually estimated by assuming the net climate feedback (λ) is time-invariant (Gregory et al., 2004):

$$\mathrm{ECS} = -\mathrm{F}/\lambda. \quad (1)$$

F is radiative forcing of $2\times CO_2$. The "constant λ" approximation has been applied to some atmospheric general circulation models (AGCMs) coupled to slab ocean models, pointing out that the uncertainty in cloud feedback is the main cause of the intermodel spread of ECS (Bony et al., 2006). Many studies, however, have reported a time dependence of λ in atmosphere–ocean coupled general circulation models (AOGCMs), which adds another uncertainty in determining ECS (Block & Mauritsen, 2013; Geoffroy et al., 2013; Armour, 2017). The time dependence of λ has been related to the evolution of the surface warming pattern (Armour et al., 2013; Rose et al., 2014; Zhou et al., 2016).

How the surface warming pattern evolves under CO_2 forcing and how it varies among models are further issues to be confronted in narrowing the uncertainty of ECS. Many have argued for the importance of the ocean in controlling the surface warming pattern (Winton et al., 2010;

Winton et al., 2013; Marshall et al., 2015). For example, Marshall et al. (2015) observed a broad correspondence in SST anomaly between the ocean-only model and multiple AOGCMs, especially the delayed warming in the North Atlantic and the Southern Ocean, suggesting that mechanisms controlling the SST response in coupled models are influenced by ocean processes.

To identify the mechanisms driving the distinct time evolution of climate feedbacks across AOGCMs, we diagnose the time-varying ocean processes, surface warming patterns, and climate feedbacks in fully coupled models (section 2). We show that part of the intermodel spread in climate feedback evolution can be traced to the evolution of the Atlantic Meridional Overturning Circulation (AMOC), via changes in the surface warming pattern and atmospheric stability (section 3). In section 4 we summarize our results and compare them with the previous studies focusing on the multimodel mean.

2 Materials and Methods

2.1 Model data

We analyze the output from 15 climate models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5) that provide the required variables for our study (Table S1). 150-year simulations with pre-industrial conditions (piControl) and forced with an abrupt quadrupling of atmospheric CO_2 concentration (abrupt4×CO_2) are assessed. To remove any model drift, we calculate the anomalies by subtracting the piControl integration from the corresponding parallel abrupt4×CO_2 integration.

2.2 The evolution of the climate system per 1K global warming

To represent the evolution of the climate system, we define an operator "δ" as follows:

$$\delta X = \left.\frac{dX}{d(GMT)}\right|_{Y21\text{-}150} - \left.\frac{dX}{d(GMT)}\right|_{Y1\text{-}20}. \quad (2)$$

X can be any of the target fields. Ordinary least-squares regression of annual-mean anomalies in X against annual- and global-mean surface air temperature anomaly (GMT) is separately done for the early (years 1-20) and late (years 21-150) periods. The separation at year 20 approximately divides climate responses into fast and slow components (Held et al., 2010; Geoffroy et al., 2013). When X is surface air temperature (TAS), equation (2) gives the "surface warming pattern evolution" (δTAS) (Figure 2a). When X is the global-mean net radiation at the TOA, the terms in equation (2) are the net climate feedback (λ) for the two time periods, and the difference gives the "net climate feedback evolution" (δλ). Different choices of separation year have little influence on the magnitudes of δλ (Andrews et al., 2015). δλ can be further decomposed into various components using the radiative kernel method (Soden et al. (2008); see Text S1).

The terms in equation (2) are chosen to be derivatives with respect to GMT for two reasons (see Figure S1 for GMT evolution). First, the patterns of surface temperature and TOA radiation, expressed per unit of GMT increase, are generally assumed to be constant in a given model. This is an application of the common "pattern scaling" assumption. If pattern scaling holds exactly for X, equation (2) gives δX=0; otherwise, δX measures the deviation from pattern scaling. Second, the change in any X tends to be larger for models which have greater ECS, and hence greater GMT at all time. The use of the derivatives thus in effect normalizes δX with respect to ECS, removing that factor from the consideration of the spread among models in the projected changes.

2.3 AMOC index ($\delta\psi$)

For each model, we first identify the AMOC strength (ψ) as the maximum of the ocean overturning mass streamfunction (variable name *msftmyz* or *msftyyz*) over the North Atlantic (north of 30°N), excluding the overturning shallower than 500 m (Gregory et al., 2005). We then define the "AMOC index ($\delta\psi$)" as per equation (2) with X as the AMOC strength (ψ). The AMOC index quantifies the AMOC evolution from early to late periods in each model and is insensitive to the choice of separation year discussed in section 2.2 (Table S2). Variations in AMOC strength arising from natural variability tend to be substantially smaller than AMOC index values and are unlikely to explain the intermodel spread (see Text S2). With regard to our motivation for taking derivatives with respect to GMT (cf. the previous paragraph), there is no significant correlation of AMOC changes with ECS across models, so the second reason does not apply. The first reason is valid because it makes the early and late terms comparable, by normalizing responses with respect to the magnitude of climate change in the two periods.

3 Results

On average in the 15 CMIP5 coupled climate models analyzed in this study, the climate system becomes more sensitive as it approaches equilibrium, with the multimodel-mean net climate feedback (λ) evolving from -1.37 $\mathrm{Wm^{-2}K^{-1}}$ during the first 20 years of abrupt4×CO_2 simulations to -0.87 $\mathrm{Wm^{-2}K^{-1}}$ during the following 130 years. The difference in multimodel-mean λ (0.50 $\mathrm{Wm^{-2}K^{-1}}$) between the periods is consistent with previous studies (Andrews et al., 2015; Ceppi & Gregory, 2017). At the same time, this time evolution of climate feedback ($\delta\lambda$) is highly model-dependent, ranging from -0.18 to 1.05 $\mathrm{Wm^{-2}K^{-1}}$ across models, a range 2.5 times as large as the magnitude of their multimodel mean.

To identify the root cause of the intermodel spread of climate feedback evolution, we investigate the evolution of global meridional overturning circulation (GMOC), quantified as the meridional mass streamfunction for the global ocean (Manabe & Stouffer, 1993; Talley et al., 2003). An Empirical Orthogonal Function (EOF) analysis (also known as Principal Component Analysis) of GMOC evolution, applied across models, shows that the AMOC evolution is the main uncertainty of the global ocean circulation response (see Text S3). This is consistent with previous studies highlighting the uncertainty in AMOC projections in CMIP5 models (Cheng et al., 2013; Wang et al., 2014; Heuzé et al., 2015). Based on the AMOC evolution, the 15 CMIP5 models can be classified into three groups, with high, medium, and low AMOC indices ($\delta\psi$; see Figure S2 for the list of models in each composite). In the high AMOC index composite, the AMOC slows down significantly in the initial stage of warming but recovers in strength in the later stage; by contrast, in the low AMOC index composite, the AMOC slows down moderately in the initial warming but continues slowing down as warming proceeds (Figure 1a). It is possible that models in the low index group would eventually project AMOC re-strengthening if the lengths of the simulations were extended. The timing of the re-strengthening could be more than a thousand years after quadrupling CO_2 (Stouffer & Manabe, 2003; Li et al., 2013). The weakening of the AMOC in response to greenhouse-gas forcing is predominantly due to the buoyancy effect of changes in surface heat flux, with the effect of changes in surface water flux being relatively minor (Gregory et al., 2005; Gregory et al., 2016). However, substantially increased meltwater from the Greenland ice sheet, not included in CMIP5 experiments, could further weaken the AMOC (Stouffer et al., 2006; Swingedouw et al., 2009; Sgubin et al., 2015; Swingedouw et al., 2015; Saenko et al., 2017).

The cause of the intermodel spread in AMOC evolution is beyond the scope of this study. Instead, we report that the spread in the AMOC evolution can partly contribute to the intermodel spread in net climate feedback evolution ($\delta\lambda$). $\delta\lambda$ is positively correlated with the AMOC index ($\delta\psi$) (r=0.55; Figure 1b). In the rest of the paper, we will explain why models with higher AMOC index tend to project a larger increase in λ through changes in surface warming pattern and tropospheric stability.

3.1 The uncertainty in the surface warming pattern evolution (δTAS)

As the climate system approaches equilibrium, the multimodel-mean surface warming pattern becomes less pronounced over the Arctic region and the western North Pacific, and more pronounced over the tropical East Pacific and the Southern Ocean (Figure 2a), consistent with Andrews et al. (2015) and Ceppi and Gregory (2017). In most regions over the globe, we note that the evolution of the surface warming pattern (δTAS) is quite model-dependent, since the magnitudes of 1 standard deviation of δTAS across models are larger than the multimodel-mean δTAS. In addition, the first EOF of δTAS across models, explaining 48% of the total variance, exhibits a difference between the northern and southern hemispheres (Figure 2b), suggesting that the degree of hemispheric asymmetry is the main uncertainty in the evolution of the surface warming pattern.

We propose that the intermodel spread of the AMOC evolution is a cause of the spread in δTAS. To visualize the spatial pattern of the AMOC-related δTAS spread, Figure 2c shows the regression slopes of δTAS against the AMOC index. Models with higher AMOC index tend to project increasingly pronounced warming in the Northern Hemisphere (NH) extratropics, and increasingly weak warming in the tropics and Southern Hemisphere (SH) as time passes, and vice versa for models with lower AMOC index (Figures 2c and 2d). Note the remarkable similarity between the AMOC-related spread of δTAS (Figure 2c) and the first EOF of δTAS (Figure 2b) (area-weighted pattern correlation = 0.94). Also, the AMOC index is well correlated with the principal component (PC) corresponding to the first EOF (Figure 2e). We therefore suggest that the varying AMOC evolution is the main cause for the uncertainties in the warming pattern evolution (δTAS). Previous studies have attributed the surface temperature response on decadal and longer timescales to the strength of the deep ocean circulation, based on results from a single model or from the CMIP5 multimodel-mean (Marshall et al., 2015; Trossman et al., 2016). Here we corroborate that attribution by relating the intermodel spread of the surface warming pattern evolution to the varying AMOC evolution among models.

3.2 The uncertainty in the tropospheric stability evolution (δEIS)

Varying hemispheric asymmetry in the surface warming pattern evolution can lead to uncertainty in the tropospheric stability response, shown to be a key mechanism for the time evolution of climate feedbacks (Ceppi & Gregory, 2017; Andrews & Webb, 2018). Here we quantify tropospheric stability by calculating the estimated inversion strength (EIS), defined as the difference in potential temperature between 700 hPa and the surface, corrected to account for the dependence of the moist adiabat on mean temperature (Wood & Bretherton, 2006). In general, the multimodel-mean EIS evolution (δEIS, defined using equation (2)) has the opposite sign from the multimodel-mean warming pattern evolution (δTAS) (Figure S3, consistent with Figure 1b in Ceppi and Gregory (2017)). Also, similar to δTAS, δEIS appears to be model-dependent. For example, in the Arctic, the North Atlantic, and the western North Pacific, the negative regression slopes indicate that models with stronger AMOC recovery (high AMOC index) tend to project an increasingly unstable troposphere in these regions, and vice versa for the positive regression slopes in the tropical South Atlantic (Figure 3a). Dominated by the negative correlation in the NH, Figure 3c shows that the global-mean EIS evolution negatively correlates with the AMOC index.

Our interpretation for the link between hemispherically asymmetric warming pattern and global EIS response is as follows. The pronounced warming in the relatively stable NH extratropics tends to remain trapped near the surface, resulting in a more unstable troposphere. The warming is increasingly pronounced if the AMOC index is higher, accounting for the negative regression slopes of δEIS against the AMOC index. In the tropics, consistent with the weak temperature gradient approximation (Sobel et al., 2002), the temperature of the free troposphere is uniform and is determined by the SST over the deep convective regions (e.g., the West Pacific warm pool), where the lapse rate is close to a moist adiabat. The regression slopes of δTAS against the AMOC index are negative in the West Pacific warm pool (Figure 2c). The approximation explains a larger decrease in temperature of the free troposphere throughout the entire tropics for models with higher AMOC index (not shown). Therefore, regions with positive or insignificant regression slopes of δTAS against AMOC index exhibit negative regression slopes of δEIS. Consistently, Figure 3a shows that regions with more positive δTAS relative to the warm pool (red contours) would project more negative δEIS, and vice versa for the regions with more negative δTAS relative to the warm pool (green contours). An exception to this behavior is in the SH extratropics, where the suppressed warming response over Antarctica is not trapped near the surface as in the NH extratropics. Instead, it is vertically uniform and can be ascribed to a more positive southern hemisphere annular mode (SAM). A more positive SAM is characterized by the band of westerly winds contracting toward Antarctica (Figure 3e) and is associated with equivalent barotropic wind and temperature anomalies (Thompson & Wallace, 2000).

3.3 The uncertainty in the climate feedback evolution (δλ)

The AMOC-related spread in global EIS evolution affects the lapse-rate feedback. Figure 4a shows the regression slopes of lapse-rate feedback evolution against the AMOC index, which is strongly anticorrelated with the regression slopes of the EIS evolution (Figure 3a) (area-weighted pattern correlation = -0.92). In the Arctic, the North Atlantic, and most of the North Pacific, the troposphere becomes more unstable in the models with higher AMOC index. A more unstable troposphere indicates a reduced cooling ability of the free troposphere, which then results in a more positive lapse-rate feedback. Since models with a more positive AMOC index tend to project a larger decrease in global-mean EIS (Figure 3c), those models should also feature a larger increase in global-mean lapse-rate feedback. Indeed, Figure 4c shows a positive correlation (r=0.83) between the AMOC index and the global-mean change in lapse-rate feedback. In summary, models with a higher AMOC index tend to project a stronger decrease in the NH tropospheric stability while having little influence on the vertical temperature profile in the SH. This hemispherically asymmetric amplitude of stability response to the varying AMOC evolution results in global-mean changes in EIS and lapse-rate feedback against the AMOC index.

Meanwhile, the EIS evolution also contributes to the evolution of shortwave cloud feedback in specific regions. Figure 4d shows that shortwave cloud feedback becomes more positive in the North Atlantic and the North Pacific mid-latitudes, where δEIS is negative. The destabilization of the lower troposphere acts to reduce low cloud cover, which leads to a more positive shortwave cloud feedback, associated with a higher AMOC index. In the tropics, the degree of ITCZ shift affects the shortwave cloud feedback. Consistent with the energetic framework (Kang et al., 2008; Kang et al., 2009; Friedman et al., 2013), models with higher

AMOC index, tending to project NH warming, produce a weaker southward ITCZ shift (Figure S4), which results in a more negative (positive) shortwave cloud feedback in the north (south) (Figures 4d and 4e). With positive and negative values generally cancelling out, the AMOC-related spread in tropical mean shortwave cloud feedback evolution contributes little to the global-mean change. Instead, it is the spread in the NH mid-latitudes that largely makes up the positive correlation between the AMOC index and the global-mean change in shortwave cloud feedback (Figure 4f). While some of the spread in shortwave cloud feedback is compensated by the spread in longwave cloud feedback, we note that this compensation mostly happens in the tropics (Figure S5g). In the extratropics, the change in net cloud feedback is dominated by the shortwave component (Figure S5j). Thus, the mechanism described above may explain the positive correlation between the AMOC index and the area-averaged net cloud feedback evolution poleward of 30 degrees (r=0.61). Apart from the influence of tropospheric stability mentioned here, we note that the intermodel spread of cloud feedback could arise from a dependence on parameterization and resolution (Vial et al., 2013; Webb et al., 2015).

In addition to lapse-rate and cloud feedbacks, the AMOC evolution also has an impact on other feedback components. In models with stronger AMOC recovery, for example, albedo feedback becomes more positive in the NH polar region due to more melting ice, where the enhanced warming occurs, and vice versa for the SH polar region with smaller magnitudes (Figure S5a). Similar to longwave cloud feedback, the relative humidity feedback evolves toward more positive (negative) values in the NH (SH) tropics, indicating a northward shift of the ITCZ (Figure S5d). While the varying AMOC evolution influences the pattern evolution of these two feedbacks, the correlations between the AMOC index and the global-mean changes in relative humidity and surface albedo feedbacks are not significant (Figures S5c and S5f). Also, we note that the relationship between the AMOC index and the changes in most of the climate feedback components cannot be explained if assuming time-invariant local feedbacks (Armour et al., 2013). Instead, the evolution of tropospheric stability introduces nonlinearity in local climate feedbacks (Zhou et al., 2016; Ceppi & Gregory, 2017) (see Text S4).

4 Summary and discussion

In this study, we suggest that the intermodel spread in net climate feedback evolution ($\delta\lambda$) can be partially traced to the evolution of the AMOC strength. Models with stronger AMOC recovery tend to project a larger increase in net climate feedback, indicating more sensitive climate over longer timescales. The interpretation for the link between the AMOC evolution and the feedback change is as follows: the strengthening of AMOC over long timescales shifts the location of warming to NH extratropical regions, leading to a global destabilization of the troposphere, and resulting in more positive lapse rate and shortwave cloud feedbacks. Similar relationships between AMOC strength and radiative anomalies are also found in decadal-scale unforced variability in the piControl simulations (see Text S5).

Interestingly, our interpretation that warmer NH leads to more sensitive climate cannot be applied to understanding the evolution of the multimodel-mean climate feedback. For the multimodel-mean, the increase in λ is accompanied by enhanced warming mostly in the SH, especially in the tropical Southeast Pacific and the Southern Ocean (Figure 2a). In our analysis of the intermodel spread, the warming pattern evolution among models includes varying degrees of the north-south contrast (Figure 2b), which contributes to the intermodel spread of the global EIS response and the climate feedback evolution.

The dependence of climate feedbacks on the surface warming pattern has been an active research area. Some studies have focused on the east-west contrast of the surface warming pattern (Ceppi & Gregory, 2017; Zhou et al., 2017; Andrews & Webb, 2018); for example, Zhou et al. (2017) suggest that the cloud feedback is more negative in response to western Pacific warming, and more positive in response to warming in the eastern Pacific. On the other hand, others emphasize the tropics-extratropics contrast, suggesting that the climate will become more sensitive as the ocean heat uptake pattern evolves (Rose et al., 2014; Rugenstein et al., 2016; Liu et al., 2018a; Liu et al., 2018b). By investigating the cause of inter-model spread in the time dependence of climate feedbacks, we identify an additional geographical structure for controlling global-mean climate feedbacks: the variation of SST in the more stable NH high latitudes tends to be more confined in the lower troposphere than the variation of SST in the SH counterparts and is more likely to trigger positive radiative feedbacks. In future work, idealized experiments will be needed to provide a full understanding of the influence of SST patterns on climate feedbacks.

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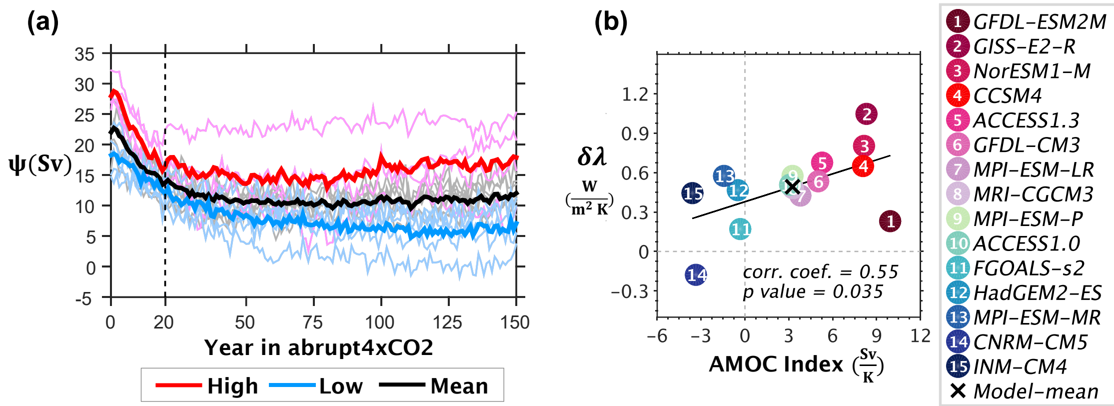

Figure 1. (a) The time evolution of AMOC strength in abrupt4×CO_2 simulations. The strength at year 0 is the 150-year mean in corresponding parallel piControl simulations. The black line indicates the multimodel mean, while the thick red (blue) line indicates the high (low) AMOC index composite mean, and the thin red (blue/gray) lines are from individual models with high (low/medium) AMOC index. (b) δλ versus the AMOC index. Each dot is one model, labeled in the box and colored according to the AMOC index.

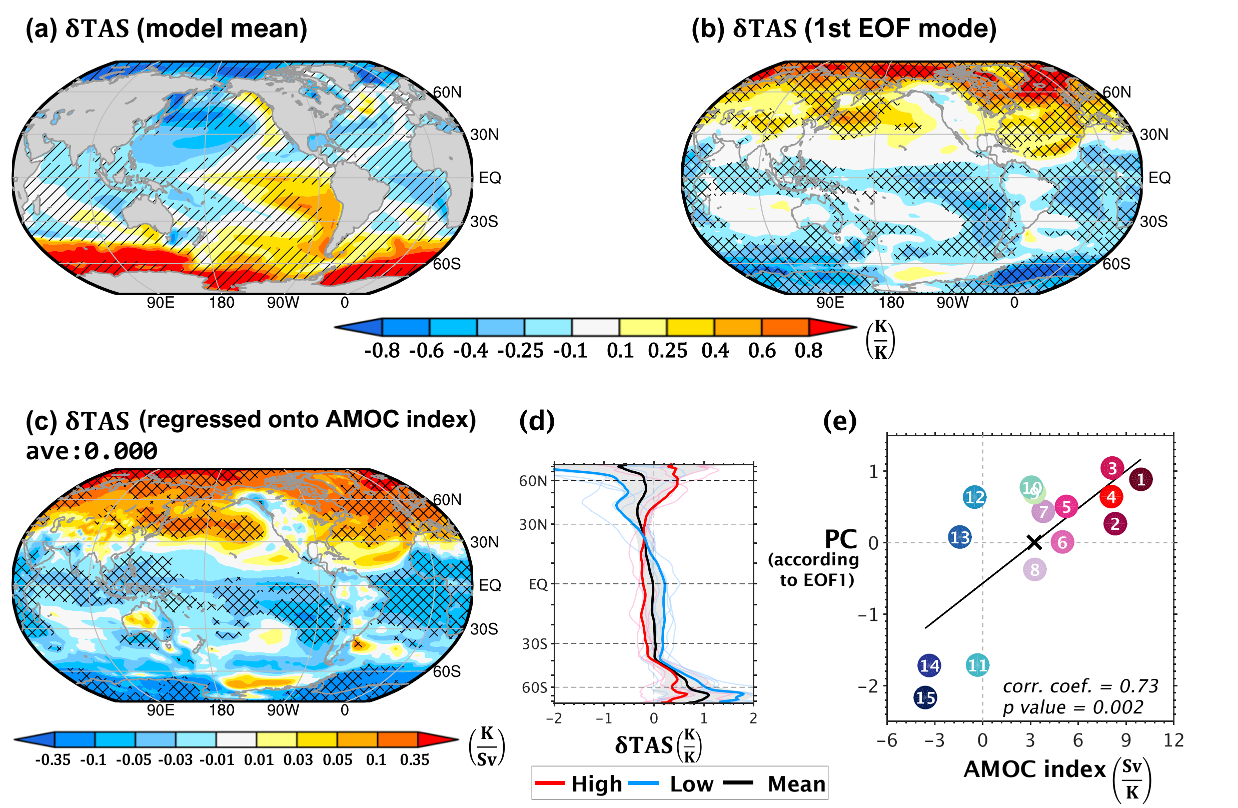

Figure 2. (a) Multimodel-mean pattern evolution of surface air temperature (δTAS). Hatching denotes an absolute multimodel mean < 1 standard deviation across models. (b) The first EOF pattern of δTAS across models. Statistical significance is assessed by regressing δTAS onto the PC according to the first EOF. (c) The regression slopes of δTAS against the AMOC index. (d)

Zonally-averaged δTAS. The meaning of colored lines is the same as in Figure 1a. The gray shading represents the multimodel mean ± 1 standard deviation (K/K) across models. Meshing in (b) and (c) denotes the significance at 95% confidence level. (e) The PC corresponding to the first EOF of δTAS versus the AMOC index.

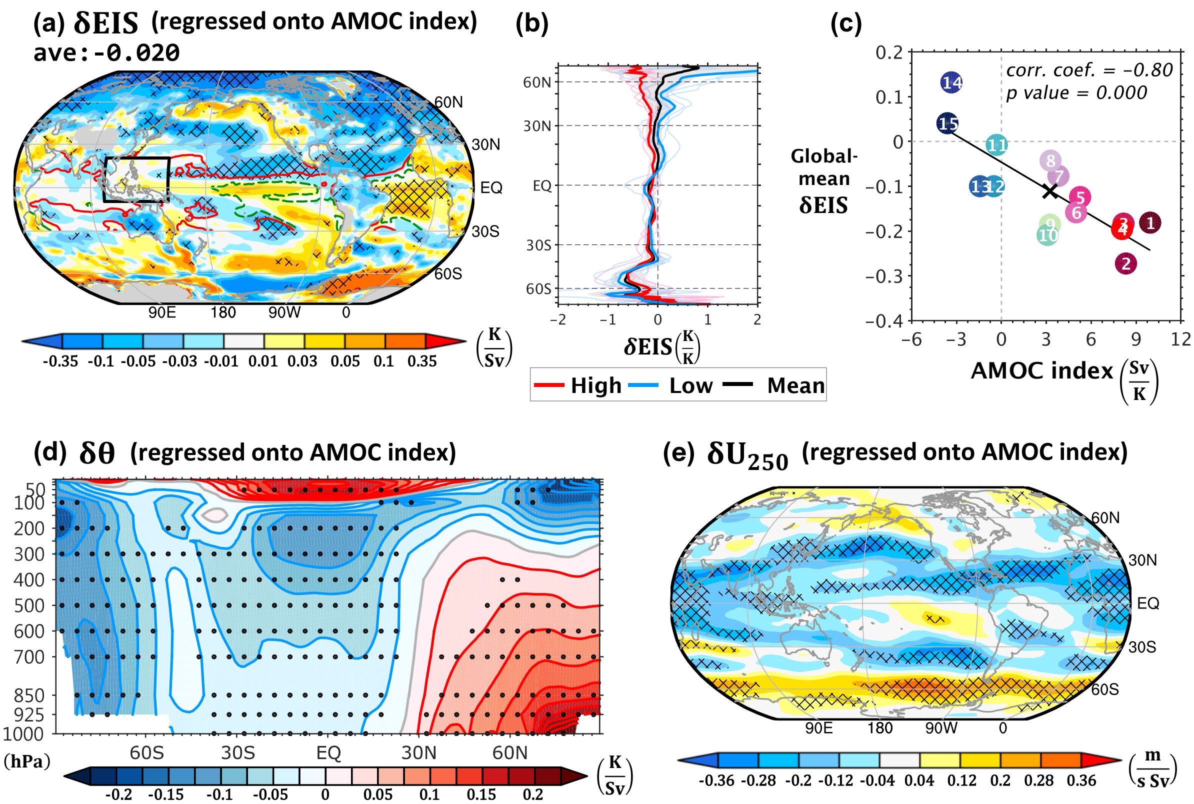

Figure 3. The regression slopes of (a) EIS evolution (δEIS) (d) zonal-mean potential temperature evolution (δθ), and (e) 250 hPa zonal wind evolution (δU_{250}) against the AMOC index. Stippling and meshing denote the significance at 95% confidence level. Contours in (a) denote the anomalous δTAS relative to the warm pool (black box), with solid red (dashed green) indicating a more positive (negative) δTAS. This is done only in the tropics. (b) Zonally-averaged δEIS. The meaning of colored lines and shading is the same as in Figure 2d. (c) Global-mean δEIS versus the AMOC index.

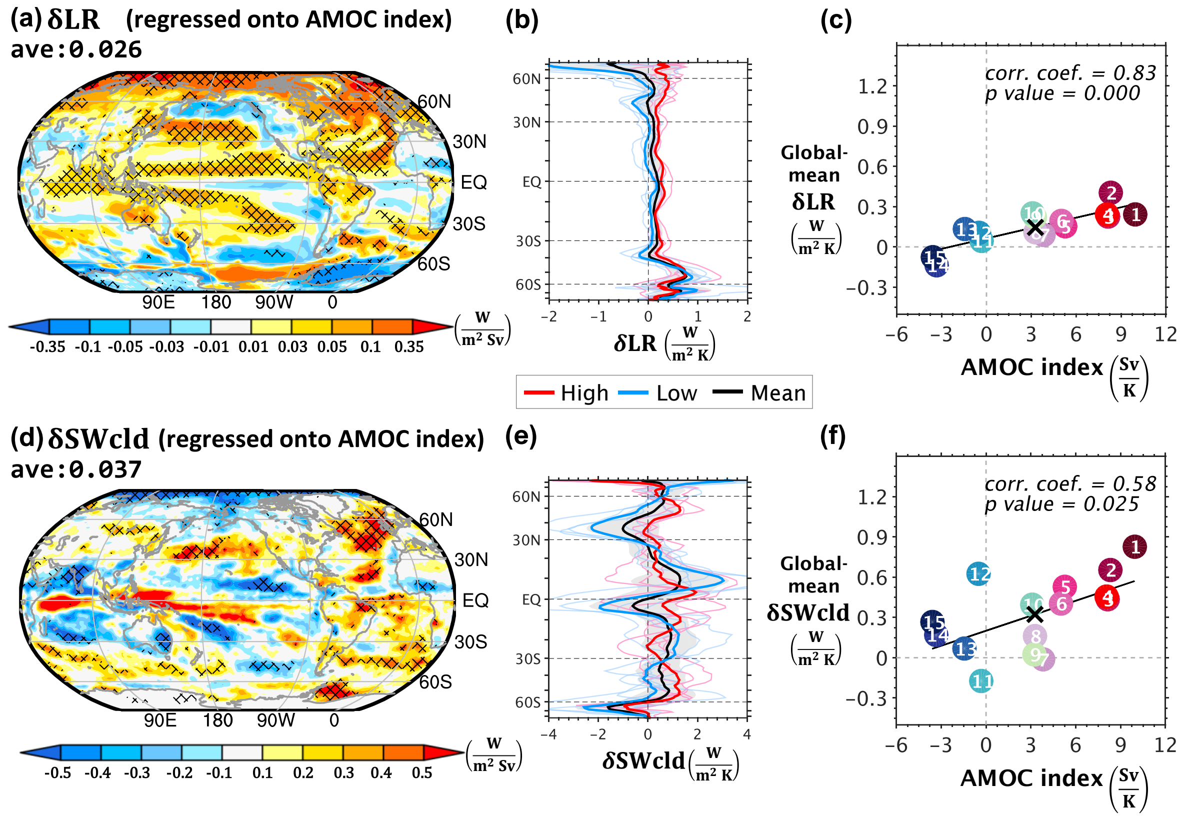

Figure 4. (a) The regression slopes of lapse-rate feedback evolution (δLR) against the AMOC index, with meshing denoting the significance at 95% confidence level. (b) Zonally-averaged δLR. The meaning of colored lines and shading is the same as in Figure 2d. (c) The global-mean δLR versus the AMOC index. (d, e, f) Same as (a, b, c) but for shortwave cloud feedback evolution (δSWcld).