Earth system commitments due to delayed mitigation

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Earth system commitments due to delayed mitigation

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Abstract
As long as global CO2 emissions continue to increase annually, long-term committed Earth system changes grow much faster than current observations. A novel metric linking this future growth to policy decisions today is the mitigation delay sensitivity (MDS), but MDS estimates for Earth system variables other than peak temperature ($\Delta T_{\text{max}}$) are missing. Using an Earth System Model of Intermediate Complexity, we show that the current emission increase rate causes a $\Delta T_{\text{max}}$ increase roughly 3–7.5 times as fast as observed warming, and a millenial steric sea level rise (SSLR) 7–25 times as fast as observed SSLR, depending on the achievable rate of emission reductions after the peak of emissions. These ranges are only slightly affected by the uncertainty range in equilibrium climate sensitivity, which is included in the above values. The extent of ocean acidification at the end of the century is also strongly dependent on the starting time and rate of emission reductions. The preservable surface ocean area with sufficient aragonite supersaturation for coral reef growth is diminished globally at an MDS of roughly 25%–80% per decade. A near-complete loss of this area becomes unavoidable if mitigation is delayed for a few years to decades. Also with respect to aragonite, 12%–18% of the Southern Ocean surface become undersaturated per decade, if emission reductions are delayed beyond 2015–2040. We conclude that the consequences of delaying global emission reductions are much better captured if the MDS of relevant Earth system variables is communicated in addition to current trends and total projected future changes.

1. Introduction

Global CO2 emissions have been rising at a nearly exponential rate of roughly 2% per year over the past three decades (Boden et al 2013). Policy decisions in the next few decades will determine how long this rise continues, if its rate changes, and at what rate emissions can eventually be reduced. These near-term decisions will impact the Earth system and its climate for centuries to millennia (Weaver et al 2007, Plattner et al 2008, Friedlingstein et al 2011, Zickfeld et al 2013), due to the long atmospheric lifetime of CO2 (Archer et al 2009, Joos et al 2013) and the inertia of the climate system. This can be illustrated using idealized CO2 emission scenarios (Stocker 2013), in which global annual emissions continue to increase exponentially at a constant rate $r$ up to a time $t_f$ when a "global mitigation scheme" takes effect. After $t_f$, annual emissions decrease exponentially at a constant rate $s$, which is limited by technological and economic feasibility (den Elzen et al 2007).

The cumulative carbon emissions $C_\infty$ from these or more sophisticated increase-to-decrease scenarios can be linked to future temperature increases using climate models, or using the linear relationship $\Delta T_{\text{max}} = \beta_f C_\infty$ as a good approximation (Allen et al 2009, Matthews et al 2009, Steinacher and Joos 2015), where $\beta_f$ is the peak response to cumulative emissions. This allows the estimate of the lowest achievable temperature target given an emissions reduction profile (Stocker 2013). Conversely, one can also estimate the necessary reduction profiles to achieve certain temperature targets such as the 2 °C target (Friedlingstein et al 2011, Rogelj et al 2011, ...
Peters et al. 2013). Such estimates are evidently dependent on the starting year of emission reductions \( t_1 \), leading to the important complementary question: what are the consequences of delaying mitigation?

In terms of economic cost, this question has been extensively explored (Bozetti et al. 2009, Jakob et al. 2012, Luderer et al. 2013). These studies show that reaching certain climate targets becomes more expensive, and eventually unfeasible, while mitigation is delayed. In terms of Earth system commitments, however, quantitative estimates of the changes caused by delaying mitigation are sparse. Here, ‘Earth system commitments’ refers to future changes in the Earth system that are unavoidable based on the presently chosen emission pathway. Only for global mean temperature, estimates linking mitigation delays to additional commitments exist (Ramanathan 1988, Hare and Meinshausen 2006, Friedlingstein et al. 2011, Allen and Stocker 2014). They were obtained from simple models under specific scenarios, and amount to roughly 0.1 °C−0.5 °C per decade of delay (evaluated at different times between AD 2100 and AD 3000). But limiting temperature changes alone may not be sufficient to meet the ultimate objective of the United Nations Framework Convention on Climate Change (UNFCCC), to prevent ‘dangerous anthropogenic interference with the climate system’ (Steinacher et al. 2013).

The purpose of this study is to determine the additional commitments due to delayed mitigation for a range of policy-relevant quantities. These include \( \Delta T_{\text{max}} \), the thermal expansion component of millennial sea level rise (SSLR), and two ocean acidification metrics. The latter are derived from the extent of sea surface areas that are either undersaturated or strongly supersaturated with respect to aragonite (Steinacher et al. 2013). These areas are highly sensitive to \( \text{CO}_2 \) emissions and relevant for coral reefs (Kleypas et al. 1999, Steinacher et al. 2013, Pörtner et al. 2014) and other shell-forming marine organisms (Orr et al. 2005, Doney et al. 2009, Pörtner et al. 2014). Following Allen and Stocker (2014), we evaluate the mitigation delay sensitivities (MDSs) of these four quantities.

The MDS of an Earth system variable is defined as the rate of change in the commitment of that variable with changing \( t_1 \) (i.e., with delay in reducing \( \text{CO}_2 \) emissions), assuming a given emission pathway before and after \( t_1 \). This is a generalization of the definition by Allen and Stocker (2014), who have estimated the MDS of \( \Delta T_{\text{max}} \) analytically using the linear relation \( \Delta T_{\text{max}} = \beta_T C_{\text{C}} \). However, for other policy-relevant quantities, the MDS cannot be estimated analytically. For example, evaluating the spatiotemporal evolution of ocean acidification metrics requires a three-dimensional ocean biogeochemistry model. The model must be computationally efficient to explicitly simulate long-term changes for a large number of scenarios. For this purpose, we choose the Bern3D-LPX model (Ritz et al. 2011, Stocker et al. 2013), an Earth system model of intermediate complexity (EMIC). We examine the dependence of the MDS on the rate of increase (\( \dot{r} \)) and subsequent decrease (\( s \)) in annual emissions. The influence of the equilibrium climate sensitivity (ECS) (IPCC 2013) is also investigated.

This paper is organized as follows. The model and experimental design are described in section 2, along with the Earth system variables that are analyzed. The results are presented in section 3 and discussed in section 4. Section 5 concludes.

2. Methods

We employ the Bern3D-LPX EMIC to evaluate the MDS of four policy-relevant Earth system variables (section 2.2).

2.1. Model description and experimental design

The Bern3D is a three-dimensional frictional geostrophic balance ocean model (Müller et al. 2006) with a prognostic biogeochemistry component (Tschumi et al. 2008) and a sea-ice component, coupled to a single-layer energy and moisture balance model of the atmosphere (Ritz et al. 2011). We use an updated model version (Roth et al. 2014) with improved high-latitude resolution, with a total of 41 × 40 horizontal cells (figure 1) and 32 depth levels (supplementary figure 7). The Bern3D model is coupled to a simplified version of the LPX-Bern dynamic vegetation model (Stocker et al. 2013), which does not include peatlands, dynamic nitrogen or land use changes. This is sufficient for simulating the idealized \( \text{CO}_2 \) emission scenarios, which do not include land use and non-\( \text{CO}_2 \) forcings, and for our analysis which focuses on ocean and atmosphere variables. We do not include non-\( \text{CO}_2 \) forcings such as short-lived climate pollutants in our simulations, because these have a much smaller effect on long-term climate and ocean acidification than \( \text{CO}_2 \) (Caldeira and Kasting 1993, Bowerman et al. 2013, Allen and Stocker 2014).

To assess the influence of the uncertainty in model response, three model versions with ECSs of 1.5 °C, 3.0 °C and 4.5 °C have been constructed, corresponding to the IPCC uncertainty range in ECS (IPCC 2013). The model is tuned to these ECS values by separate 2 × \( \text{CO}_2 \) equilibrium experiments using a simple feedback parameter \( \lambda \). In these experiments, \( \text{CO}_2 \) concentrations are doubled from preindustrial and then kept constant for 5000 years. A term \( \lambda \Delta T(t) \) in the global energy balance accounts for unresolved feedbacks (Ritz et al. 2011), and \( \lambda \) is varied. By fitting the simulated \( \Delta T \) after 5000 years to the prescribed \( \lambda \) values, we obtain a polynomial relation between \( \lambda \) and ECS, where \( \lambda \) values of \( -2.20, -0.70 \) and \( -0.12 \text{ Wm}^{-2} \text{ K}^{-1} \) correspond to ECSs of 1.5 °C, 3.0 °C and 4.5 °C. Only results from the simulations with an ECS of 3.0 °C are shown in the figures.
Corresponding figures for the other values are provided in the supplementary material.

Following a preindustrial spinup of the coupled Bern3D-LPX, each of the three model versions is forced with historical (AD 1750–2013) atmospheric CO₂ concentration data (Etheridge et al 1996, Siegenthaler et al 2005, Dlugokencky et al 2015). Other forcings are kept constant at preindustrial level. The total carbon uptake simulated by the model up to 2011 (488–533 GtC for high to low ECS) is on the lower end of the IPCC (2013) estimates of 555 (470 to 640) GtC. This is due to the rather low carbon uptake of the LPX-Bern model (103–142 GtC in our coupled simulations), while the ocean uptake of the Bern3D model (146–151 GtC) is in good agreement with IPCC estimates. The ECS-dependence of historical carbon uptake is mainly due to the temperature sensitivity of the land biosphere.

Following the historical concentration-driven simulations, the model is run up to AD 3000 and forced by idealized CO₂-only emission scenarios following Stocker (2013):

\[
E(t) = \begin{cases} 
E_0 \cdot e^{r(t-t_0)} & t_0 < t \leq t_f \\
E_0 \cdot e^{r(t-t_0)} \cdot e^{s(t-t_f)} & t > t_f,
\end{cases}
\]

where \(t_0 = 2013\) and \(E_0 = E(t_0) = 9.86\) GtC (Boden et al 2013). Exponential fits of recent fossil fuel emission data (Boden et al 2013) yield an average increase rate \(r\) of 2.0%/yr for the 30 year period 1984–2013, and 2.6%/yr for the last decade 2004–2013. Estimates from economic models suggest that reduction rates \(s\) above 5%/yr are probably not feasible (den Elzen et al 2007). Therefore, the scenario parameters are varied as follows: \(r\) from 0%/yr (constant emissions up to \(t_f\)) to 4%/yr, and \(s\) from 0.5%/yr to 5%/yr, both in steps of 0.5%/yr. To diagnose MDS values valid for three decades, we vary \(t_f\) from 2015 to 2045 in 13 non-equidistant steps (2015, 2018, 2020, 2023, etc), for each combination \((r,s)\). This results in 1170 different idealized scenarios, and a total of 3510 model simulations accounting for the three ECSs selected.

### 2.2. Earth system variables and MDS diagnosis

Two physical Earth system variables are analyzed, namely \(\Delta T_{\text{max}}\) and near-equilibrium SSLR. The time when \(\Delta T_{\text{max}}\) is reached generally increases with \(C_{\infty}\) and mostly ranges between roughly 40 and 600 years after present, consistent with Zickfeld and Herrington (2013). Only in some simulations with the highest ECS, there is still a slight warming after 1000 years, in which case \(\Delta T_{\text{max}}\) is evaluated at the end of the model run (AD 3000). SSLR is always evaluated in AD 3000. Although the ocean is not fully equilibrated at that time for some scenarios (supplementary figure 7), this provides a reasonable estimate of near-equilibrium SSLR. We prolonged the one model simulation forced by the highest emission scenario and found that SSLR(3000) reaches about 80% of equilibrium SSLR. For lower emission scenarios, the ocean in AD 3000 is probably even closer to equilibration. For the SSLR computation, the pressure-independent model density is adjusted assuming hydrostatic balance and using a pressure-dependent equation of state (simplified from UNESCO 1981) with the model ocean temperature and salinity. While this pressure adjustment only has a minor effect on short timescales, it becomes very relevant for longer timescales, when temperature changes reach the deep ocean where the pressure and its effect on density are larger. In AD 3000, the adjustment increases SSLR estimates by roughly 30%–90% (depending on ECS and scenario), indicating that SSLR is strongly underestimated if compressibility is neglected.

In addition, we explore two biogeochemical variables derived from the saturation state of aragonite in the surface ocean (\(\Omega_A\), figure 1), which is an important indicator of ocean acidification (Doney et al 2009, Pörtner et al 2014). Following Steinacher et al (2013),

**Figure 1.** Surface ocean aragonite saturation \(\Omega_A\) in AD 2100 for two different \(t_f\), \(\Omega_A\) is shown for an intermediate emission scenario \((r_s = 2.0%/yr, s = 2.5%/yr)\) with (a) \(t_f = 2015\) (immediate emission reductions) and (b) \(t_f = 2045\) (delayed reductions). Areas with \(\Omega_A > 3\) associated with coral reef habitats (Kleypas et al 1999, Steinacher et al 2013) are shown in purple, undersaturated areas \((\Omega_A < 1)\) in gray.
we evaluate $\Omega_A$ changes in terms of surface area fractions. The first is the fraction $A_{SO}$ of the Southern Ocean surface area south of 50° S that becomes undersaturated with respect to aragonite ($\Omega_A < 1$, gray in figure 1), thereby becoming corrosive to aragonitic shells of marine organisms (Orr et al 2005, Doney et al 2009, Pörtner et al 2014). The second is the fractional loss $L_{\Omega_A > 3}$ of the global surface ocean area with more than threefold supersaturation ($\Omega_A > 3$, purple in figure 1), a relevant metric for coral reef habitats (Kleypas et al 1999, Steinacher et al 2013). Both fractions are evaluated at the end of the century (AD 2100). $L_{\Omega_A > 3}$ is calculated as an additional loss commitment due to delaying mitigation, with respect to the preservable $\Omega_A = 3$ area for immediately starting emission reductions (figure 1(a)). This choice and its implications for the MDS are explained at the end of this section.

For example, with emission reductions starting in 2015 at an intermediate $s$ (figure 1(a)), $L_{\Omega_A > 3}$ is 0% by definition and $A_{SO}$ is also 0%, because aragonite undersaturation in the Southern Ocean is entirely mitigated. If reductions are delayed until 2045 (figure 1(b)), $L_{\Omega_A > 3}$ is 96% of the area in figure 1(a), and $A_{SO}$ is 25% of the area south of 50° S.

The MDS of each variable $V$ is diagnosed from a least-squares linear fit of the simulated $V(t_1)$ on $t_1$ (figure 2). Each dot in figure 2 represents a single model simulation forced by an emission scenario uniquely identified by its parameters $(r, s, t_1)$. MDS($V$) is the slope of the linear fit, i.e., MDS$(V) = \Delta V/\Delta t_1$ (given in the figure legend). This diagnosis yields an average MDS over the investigated $t_1$-interval, which is three decades for $\Delta T_{max}$ and SSLR. The $t_1$-interval is shorter for $A_{SO}$ and $L_{\Omega_A > 3}$; for $A_{SO}$, it spans from the first $t_1$ causing $A_{SO} > 0$ to 2045; for $L_{\Omega_A > 3}$, from 2015 to the first $t_1$ causing a near-complete loss of $\Omega_A > 3$ areas, as elaborated in the paragraph below. An MDS fit is not obtained if there are less than three $t_1$-steps within this interval (white regions in figure 4). Note that this average MDS is also a reasonable approximation for instantaneous MDS, because the $t_1$-dependence of all $V(t_1)$ is close to linear within the $t_1$-interval ($R^2 > 0.95$ for most parameters).

Given an achievable reduction rate $s$, the maximum preservable $\Omega_A > 3$ area is obtained by immediately starting emission reductions (figure 1(a)). This area is chosen as the baseline $L_{\Omega_A = 3} = 0$. MDS($L_{\Omega_A = 3}$) therefore indicates what part of the preservable area is lost due to delaying mitigation. Consequently, MDS ($L_{\Omega_A > 3}$) deviates from the other MDS definitions in that the percentages for different $s$ do not correspond to the same absolute area losses, because they scale with this scenario-dependent baseline. Based on the assumption that policy options are limited to $t_1$ for a given $s$, and thus to preserving an $\Omega_A > 3$ area between this baseline and zero, we consider this more relevant than a constant baseline (e.g., preindustrial $\Omega_A > 3$ areas).

Most notably, this MDS definition contains information on how much delay would cause a near-complete loss of global $\Omega_A > 3$ areas. We speak of a near-complete loss if less than 5% of preindustrial $\Omega_A > 3$ areas remain by 2100 (e.g., figure 1(b)). For the MDS diagnosis, losses are only fitted up to this value, because further losses are increasingly nonlinear with both cumulative emissions and $t_1$ (figure 2(d)). This indicates that the last remaining 5% of the $\Omega_A > 3$ areas are more resilient to further emissions, which may be a model-specific feature. These cells, located chiefly in the Indian Ocean, start from a particularly strong undersaturation at preindustrial times ($\Omega_A > 4.5$) and therefore require more emissions to cross the $\Omega_A = 3$ threshold. According to our definition, an MDS($L_{\Omega_A > 3}$) of 50%/decade thus indicates that a delay of two decades would cause a near-complete loss, for example.

3. Results

3.1. MDS of physical variables

Firstly, projected changes in the physical variables $\Delta T_{max}$ and SSLR are presented. In agreement with other models and analytical considerations (Allen et al 2009, Matthews et al 2009, Williams et al 2012, Allen and Stocker 2014), these are mainly dependent on $C_{SO}$, which is determined by the scenario parameters $r$, $s$ and $t_1$ (section 2.1). In figures 2(a) and (b), we focus on a business-as-usual increase rate $r = 2{%/yr}$ to analyze the influence of $t_1$ for various $s$. Note that these figures contain much information beyond our MDS analysis. For example, figure 2(a) shows that the lowest achievable temperature target is strongly affected by the choice of $s$, or which $(s, t_1)$ combinations are consistent with meeting the 2°C target according to our model. As these topics have been extensively covered in the recent literature (Friedlingstein et al 2011, Rogelj et al 2011, Peters et al 2013, Stocker 2013), we focus on describing the additional commitments due to delay in emission reductions, quantified by the MDS (section 2.2).

The MDS of $\Delta T_{max}$ and SSLR increase substantially for smaller reduction rates $s$ (figures 2(a) and (b)). With an intermediate ECS, they are estimated at roughly 0.3–0.7 °C/decade for $\Delta T_{max}$ and 8–21 cm/decade for SSLR by AD 3000, for $s$ ranging from 5%/yr down to 0.5%/yr. To better understand the significance of these numbers, they can be compared to the observed rates of warming and SSLR over the last few decades. This is done in table 1, which lists the factors between MDS and model-diagnosed historical rates, along with related quantities as described in the following.

Model-diagnosed historical warming and SSLR rates are comparable to IPCC observed rates (table 1 and footnotes). To enable this comparison, two different time frames are chosen for the diagnosis (1951–2012 for warming and 1970–2011 for SSLR). Historical warming rates in the Bern3D-LPX (0.05 to 0.12 °C/decade) are somewhat lower than observed
rates (0.08–0.14 °C/decade). This is because non-CO₂ forcings, which are overall positive over the historical period (IPCC 2013), are not included in our historical simulations. Nevertheless, the model-diagnosed historical rates are used for the comparison with the MDS, mainly because the IPCC uncertainty range does not uniquely correspond to the ECS uncertainty. Using the IPCC range regardless would result in slightly lower factors in the case of temperature. In the case of SSLR, there would be no difference, as the Bern3D-LPX range corresponding to the ECS uncertainty (0.49–1.13 cm/decade) is in very close agreement with the IPCC uncertainty range (0.5–1.1 cm/decade). While a somewhat lower rate would be expected due to the lack of non-CO₂ forcings, the median CMIP5 rate including these forcings (0.96 cm/decade) is still higher than our intermediate ECS rate (0.84 cm/decade). Also, the projected SSLR (measured by βSSLR) is consistent with estimates by Williams et al (2012) (supplementary section 1.1).

As long as emission reductions are delayed, peak committed warming and millennial SSLR increase much faster than observed warming and SSLR (table 1). While the absolute MDS(ΔTmax) and MDS (SSLR) values scale with ECS, the factors between MDS and historical rates are less strongly affected by the ECS. This is because the historical rates also scale with ECS (see previous paragraph). Nevertheless, the factors increase with increasing ECS because the present-day realized warming fraction (Frölicher and Paynter 2015) is lower in model versions with higher ECS. Here, the realized warming fraction is defined as $T(2013)/T_{eq}(2013)$, where $T_{eq}(2013)$ is the equilibrium temperature corresponding to the transient atmospheric CO₂ concentration. $T_{eq}$ solely depends on the prescribed concentration and ECS, but the three model versions produce different $T(2013)$, resulting in realized warming fractions of 49%–66% (high to low ECS). The maximum factor increases less strongly than the minimum factor, and even decreases
Table 1. Simulated temperature and SSLR changes for different ECSs. Rates of change in projected peak temperature and millenial SSLR while emission reductions are delayed (MDS(ΔTmax) and MDS(SSLR)) are compared to simulated historical rates. MDs are several times larger than historical rates, as indicated by the factors in the last column. Ranges in MDs and factors correspond to the simulated range of emission reduction rates s, from 5%/yr down to 0.5%/yr/yr. The proportionality factors βs and βSSLR for the relations ΔTmax = βsC∞ and SSLR(3000) = βSSLR C∞ are diagnosed from all model scenarios with C∞ < 2 TtC (supplementary section 1.1).

<table>
<thead>
<tr>
<th>ECs (°C)</th>
<th>βs (°C/TtC)</th>
<th>hist. rate a (°C/decade)</th>
<th>MDS(ΔTmax) (°C/decade)</th>
<th>Factor</th>
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<tbody>
<tr>
<td>1.5</td>
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<td>0.12</td>
<td>0.58–0.85</td>
<td>4.9–7.2</td>
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<table>
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<tr>
<th>ECs (cm/TtC)</th>
<th>βSSLR (cm/decade)</th>
<th>hist. rate b (cm/decade)</th>
<th>MDS(SSLR) (cm/decade)</th>
<th>Factor</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.49</td>
<td>3.4–10.1</td>
<td>6.9–20.6</td>
</tr>
<tr>
<td>3.0</td>
<td>40</td>
<td>0.84</td>
<td>7.8–21.1</td>
<td>9.3–25.1</td>
</tr>
<tr>
<td>4.5</td>
<td>78</td>
<td>1.13</td>
<td>15.5–23.6</td>
<td>13.7–20.9</td>
</tr>
</tbody>
</table>

a Simulated 1951–2012 average rate; to be compared with IPCC 1951–2012 observed rate of 0.12 [0.08–0.14] °C per decade (IPCC 2013).
b Simulated 1971–2010 average rate; to be compared with IPCC 1971–2010 observed rate of 0.8 [0.5–1.1] cm per decade or the corresponding CMIP5 rate of 0.96 [0.51–1.41] cm per decade (Church et al 2013).

in the highest ECS model version, indicating that there is a counteracting effect. This effect is the increasing nonlinearity of the ΔTmax/C∞ relationship at high C∞ with increasing ECS (supplementary figure 5). Both effects may possibly be model-specific, or caused by the tuning of the ECS using a feedback parameter.

Overall however, the range of factors for the considered s range is not much different whether only the medium ECS or all ECS are considered. Including both the ECS uncertainty and the range of achievable s, we summarize: ΔTmax increases roughly 3–7.5 times as fast as observed warming, and near-equilibrium SSLR increases 7–25 times as fast as observed SSLR.

How do these MDs estimates change if r deviates from the business-as-usual r = 2%/yr before emissions start to decrease? For such considerations, r should be viewed as an average increase rate, which is always lower than the peak increase rate in reality, because the transition to decreasing emissions cannot be as sharp as in the idealized scenarios. On the other hand, it is possible that r increases in the near future before approaching the transition. Therefore, we consider r values between 0%/yr (constant emissions up to t1) and 4%/yr (double the 1984–2013 rate). Figure 3 shows MDS(ΔTmax) and MDS(SSLR) for this r-range along with the previously considered s-range. Both MDs scale with r for all s. They increase most rapidly with increasing r if s is low, however not quite as rapidly as analytical estimates suggest (supplementary section 1). In line with increasing changes in cumulative emissions, the s-dependence of MDS(ΔTmax) and MDS(SSLR) increases with increasing r. For comparison, figure 3(b) also shows the MDS of SSLR by AD 2100 (dashed contours), which is much lower than the near-equilibrium MDS(SSLR) (see also supplementary figure 7). Considering r = 2%/yr, it amounts to 1.9–2.4 cm/decade depending on s, which is still more than twice as fast as observed SSLR. In contrast to the MDS of near-equilibrium SSLR, this short-term MDS increases with s, because the difference in cumulative emissions up to 2100 caused by delaying t1 is larger for large s.

3.2 MDS of ocean acidification metrics

Returning to figures 2(c) and (d), we next present the projected changes in the ocean acidification metrics ASO4 and LΩ ranges for a business-as-usual emission increase rate r = 2%/yr/yr. These results are summarized for all model versions with different ECSs in table 2.

Partial aragonite undersaturation of the Southern Ocean surface in AD 2100 can be avoided with sufficiently early and stringent mitigation. Undersaturation (A SO4 > 0%) only occurs if a threshold in cumulative emissions up to 2100 is exceeded. In our model, this threshold ranges from roughly 1.0–1.2 TtC for high to low ECS, due to differences in carbon uptake caused by climate-carbon cycle feedbacks (Plattner et al 2001, Friedlingstein et al 2014). For fixed parameters r and s, this corresponds to a threshold delay in emission reductions, after which the MDS of A SO4 is evaluated. The threshold delay strongly depends on s (figure 2(c)). For s > 1%/yr, undersaturation can be entirely avoided if mitigation starts early enough. In contrast to the threshold delay, MDS(A SO4) is nearly independent of s and ECS. It amounts to 12%–18%/decade, indicating that roughly one sixth of the ocean surface becomes undersaturated per decade of mitigation delay, once the threshold delay is exceeded.

Further loss of some Ω3 > 3 areas is unavoidable with s ≤ 5%/yr, but may be reduced by early mitigation. If CO2 emission reductions were to start immediately, roughly 10%–75% of the preindustrial Ω3 > 3 area could be preserved at the end of the century, depending on the achievable s (table 2 and supplementary figure 8(a)). This maximum preservation area defines the baseline for the further loss LΩ ranges due to delay in emission reductions (section 2.2). Such delay increases the loss of Ω3 > 3 areas substantially (figure 2(c) and supplementary figures 8(b) and (c)). This is quantified by the MDS(LΩ), indicating that the remaining Ω3 > 3 area in AD 2100 shrinks rapidly by roughly 25%–80% per decade of delay (for s ≥ 1%/yr). The s-dependence of MDS(LΩ) mainly stems from its s-dependent baseline: The absolute area loss is only slightly s-dependent, but this absolute area loss
Simulated changes in ocean acidification metrics projected for the end of the century, with different ECSs. \( \Omega_{A} \) is the fractional loss of aragonite in Southern Ocean where \( \Omega_{A} < 0 \) (see text). MDSs for both metrics are listed, along with their different kinds of baselines (see footnotes a and b). Ranges correspond to the simulated range of emission reduction rates \( s \), from 5%/yr down to 0.5%/yr.

### Table 2

<table>
<thead>
<tr>
<th>ECS (°C)</th>
<th>Threshold delay (yr AD)</th>
<th>MDS(( \Omega_{A} )) (°C)</th>
<th>MDS(( \Omega_{A} )) (%/decade)</th>
<th>MDS(( \Omega_{A} )) (%/decade)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.5</td>
<td>&lt;2015–2040</td>
<td>15–18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.0</td>
<td>&lt;2015–2038</td>
<td>14–18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.5</td>
<td>&lt;2015–2033</td>
<td>12–15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECS (°C)</td>
<td>Preservable area (% of preind.)</td>
<td>MDS(( \Delta T_{\text{max}} ))</td>
<td>MDS(( \Delta T_{\text{max}} )) (°C)</td>
<td>MDS(( \Delta T_{\text{max}} )) (%/decade)</td>
</tr>
<tr>
<td>1.5</td>
<td>74–11</td>
<td>26–80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.0</td>
<td>73–11</td>
<td>26–79</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.5</td>
<td>73–12</td>
<td>26–78</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\( a \) The first emission reductions starting year \( t_{1} \) for which the Southern Ocean becomes partially undersaturated with respect to aragonite in 2100 (\( \Omega_{A} > 0 \)). Note that this is an approximation because not all \( t_{1} \) are simulated, only \( t_{1} = 2015, 2018, 2020, 2023, \ldots, 2045 \) (section 2.1.).

\( b \) This is the fraction of the preindustrial \( \Omega_{A} > 3 \) area remaining by 2100 if emission reductions start in 2015, i.e., the maximum preservable area for a given \( s \). It is the baseline for MDS(\( \Delta T_{\text{max}} \)) (see text).

\( c \) Only fitted for \( s = 1–5%/\text{yr} \) (see text). The preservable area for \( s = 1%/\text{yr} \) is roughly 25% of preindustrial.

corresponds to a larger part of the preservable baseline for smaller \( s \). Also note that MDS(\( \Delta T_{\text{max}} \)) is only defined up to a near-complete loss (< 5% of the preindustrial area remaining, section 2.2). For \( s = 0.5%/\text{yr} \), a near-complete loss is imminent for delays of 5–8 years, therefore no decadal MDS fit is obtained in this case. For higher \( s \), a near-complete loss becomes unavoidable within roughly 1–4 decades of delay. In summary, our model results indicate that the emissions reduction rate \( s \) is crucial for the future extent of potential coral reef habitats.

Lastly, we also consider the influence of different emission increase rates \( r \) on the MDS estimates for the ocean acidification metrics (figure 4). While MDS (\( \Omega_{A} \)) (colors and solid contours in figure 4(a)) is nearly independent of \( s \), it strongly increases with increasing \( r \). In contrast, the threshold delay for \( \Delta T_{\text{max}} > 0 \) (dashed in figure 4(a)) is influenced by both \( r \) and \( s \). This difference can be explained by the fact that \( \Omega_{A} \) is mainly driven by atmospheric CO2 concentrations. The threshold delay depends on absolute concentrations by 2100, which are determined by cumulative CO2 emissions and uptake, the former depending directly on \( r \) and \( s \). On the other hand, MDS (\( \Omega_{A} \)) depends on the change in concentrations with changing \( t_{1} \), which is mainly influenced by \( r \) in 2100 (\( s \) becomes more important on longer time scales). MDS (\( \Delta T_{\text{max}} \)) (colors and solid contours in figure 4(b)) increases with decreasing \( s \) and increasing \( r \) because, by definition, \( \Delta T_{\text{max}} > 3 \) is related to both the baseline and its changes (section 2.2). Dashed contours in figure 4(b) indicate peak emission times \( t_{1} \) causing a near-complete loss of \( \Omega_{A} > 3 \) areas. Contours beyond \( t_{1} = 2045 \) are missing, but can be inferred from the MDS: e.g., the MDS(\( \Delta T_{\text{max}} \)) = 20%/decade contour should roughly correspond to a near-complete loss after five decades of mitigation delay. On a side note, the \( t_{1} = 2035 \) contour nearly coincides with \( r = s \), indicating that a near-complete loss becomes unavoidable within less than two decades of delay if the achievable \( s \) is smaller than \( r \).
4. Discussion

The MDS(ΔTmax) estimates from the Bern3D-LPX are comparable to earlier estimates from less comprehensive models. Hare and Meinshausen (2006) used a one-dimensional climate model (MAGICC) to evaluate a ‘geophysical warming commitment’, defined as ΔT(2100) resulting from a business-as-usual emission increase until a sudden emission stop. For this special case described by s → ∞, they found a decadal increase in this warming commitment by 0.2–0.3 K. This is consistent with our lowest MDS estimates. Friedlingstein et al (2011) found a similar decadal increase in an EMIC, but for s = 3%/yr and ΔT (3000). Reviewing earlier model studies, Ramanathan (1988) reported a decadal increase in committed equilibrium warming of 0.13–0.5 °C/decade. These somewhat lower estimates are also in agreement with our MDS range, considering that equilibrium warming is smaller than the peak ΔTmax and that ΔTmax is reached before AD 3000 in most cases (section 2.2, Zickfeld and Herrington 2015). Using the linear relation ΔTmax = βT C∞, Allen and Stocker (2014) calculated an MDS of 0.4 °C/decade for a scenario that respects the 2 °C target in case of immediate emission reductions. While we did not simulate this exact scenario, our results for intermediate scenarios are consistent with this analytical estimate. For a better comparison, we estimated MDS analytically for all scenarios using model-diagnosed values for β and historical emissions. These analytical fits are in close agreement with the model results except for high-emission scenarios, where the ΔTmax/C∞ relationship becomes increasingly nonlinear, especially for high ECS. This comparison is presented in the supplementary material.

For the other Earth system variables, we do not find earlier results that are directly comparable to MDSs. Realistic simulation of ocean heat uptake, which is essential for the determination of transient SSLR, requires three-dimensional ocean models. However, Williams et al (2012) have shown that, similar to ΔTmax, equilibrium SSLR can be well emulated by the linear relation SSLR = βSSLR C∞. This is also true for the near-equilibrium SSLR simulated by the Bern3D-LPX model, as shown by analytical fits (supplementary section 1). The agreement of simulated and fitted MDS(SSLR) indicates that analytical considerations valid for MDS(ΔTmax) (Allen and Stocker 2014) are also applicable to any other Earth system variable that is linearly related to C∞. This includes their finding that ΔTmax increases at the same rate r as C∞. Examples for other variables that are near-linearly related to cumulative emissions include changes in ocean surface pH and in the Atlantic meridional overturning circulation (Steinacher and Joos 2015). Because SSLR is mainly driven by temperature changes, the ECS range provides a reasonable estimate for uncertainty in MDS(SSLR), which is supported by the model-data agreement of historical SSLR uncertainty (table 1). However, both ΔTmax and SSLR are also affected by the uncertainty in global carbon uptake, which is described further below. While this increases the total uncertainty of the projected changes, the agreement of βT and βSSLR ranges with that of other models (supplementary section 1.1)
suggests that the plausible range of temperature and SSLR responses to CO$_2$ emissions is largely captured by the ECS range in our model.

The total observed global mean sea level rise (GMSLR) in 1971–2010 was 2.5 times as large as observed SSLR over that period (Church et al. 2013). In the future, this ratio is estimated to increase to roughly 5.5, as Church et al. (2015) report a 2000 year GMSLR commitment of 2.3 m/°C, opposed to an SSLR commitment of 0.42 m/°C. Multiplying our MDS/SSLR estimate for an intermediate ECS with this ratio, we get a rough estimate for MDS(GMSLR), amounting to 0.43–1.16 m/decade. This is roughly 20–60 times as fast as the 1971–2010 observed GMSLR of 2.0 cm/decade (Church et al. 2013). These numbers would be even higher for equilibrium GMSLR, mainly because the meltdown of the Greenland ice sheet takes tens of thousands of years (Church et al. 2013). More comprehensive models including contributions from ice sheets and glaciers could be employed to better estimate the MDS of GMSLR, for a smaller set of scenario parameters. This MDS may be time-dependent due to nonlinear ice loss effects.

The ocean acidification metrics are much less affected by the ECS uncertainty than the physical variables. The slight differences for different ECSs (table 2) are due to climate-carbon cycle feedbacks (Plattner et al. 2001, Friedlingstein et al. 2014), most notably the temperature sensitivity of land and ocean carbon uptake. Not only the temperature sensitivities, but also the total magnitude of land and ocean carbon uptake are subject to considerable model uncertainties (Friedlingstein et al. 2014). Treatment of these uncertainties would require using an ensemble of different models, or an ensemble of different parameter sets influencing the carbon uptake (Steinacher et al. 2013). This not feasible here, because the variation of scenario and ECS parameters already requires a large number of model simulations (section 2.1). The land carbon uptake of the Bern3D-LPX model may be too low as indicated by the comparison with historical estimates (section 2.1). This may lead to an overestimation of ocean acidification in the projections. On the other hand, evaluating ocean acidification metrics in AD 2100 underestimates the stress for marine organisms: acidification is strongest after atmospheric CO$_2$ concentrations peak, which may be before or after 2100 depending on scenario. In addition, marine organisms are not only affected by ocean acidification but also by thermal stress (Pörtner et al. 2014).

The scenario uncertainty is partly covered by the variation of the policy-relevant parameters $r$, $\bar{s}$, and $t_1$. The suite of idealized emission scenarios covers a broad range of cumulative emissions, but for emission path-dependent variables (including our ocean acidification metrics), some uncertainty remains on how results would change under a more gradual transition from emission increase to decrease. This probably does not influence the physical variables notably (Caldeira and Kasting 1993, Williams et al. 2012, Zickfeld et al. 2012), although a slight path-dependence was found for SSLR with more drastic path changes (Zickfeld et al. 2012). Non-CO$_2$ forcings are not included in our idealized scenarios, therefore the results of this study only concern mitigation of CO$_2$ emissions. This may lead to an underestimation of projected $\Delta T_{\text{max}}$ (Stocker et al. 2013) and SSLR, but should only slightly affect the CO$_2$-driven $\Omega_s$ metrics, again via climate-carbon cycle feedbacks.

It is evident that the MDS does not carry the full information on future Earth system changes. In the case of $\Delta T_{\text{max}}$ and SSLR, the consequences of adopting a lower reduction rate $s$ are not entirely reflected in the increase in MDS, as the 2015 committed $\Delta T_{\text{max}}$ and SSLR also increase markedly. For example, choosing $s = 1%/\text{yr}$ instead of $s = 2%/\text{yr}$ does not only increase MDS($\Delta T_{\text{max}}$) by 0.11 °C/decade, but additionally increases 2015 committed $\Delta T_{\text{max}}$ by 0.76 °C (figure 2(a)). Similarly, while MDS($A_{SO}$) is weakly influenced by $s$, the threshold delay for $A_{SO} > 0$ strongly depends on $s$. Finally, MDS($A_{47.3}$) contains information on allowable delays before a near-complete loss of $\Omega_s > 3$ areas, but not on absolute area losses. Overall, the MDS is thus most useful for assessing the choice of the emission reduction starting time $t_1$ given a reduction rate $s$ that is independently limited, e.g., by economic considerations. In reality, target values for $s$ and $t_1$ cannot be chosen independently. They are linked both in terms of feasibility, e.g., due to technological advances before $t_1$ or the lock-in of carbon intensive infrastructure (Jakob et al. 2012), and in terms of impacts on the future Earth system (this study). Nonetheless, communicating the MDS of relevant Earth system variables, in addition to the classical reporting of current trends and total projected future changes, would permit a more transparent assessment of the Earth system impacts of these choices.

5. Conclusions

Our model results support the analytical finding of Allen and Stocker (2014) that peak committed warming increases much faster than observed warming, at least as long as global emission reductions are delayed. In addition, these results show that delaying emission reductions also increases the committed changes in other Earth system variables rapidly. Like peak temperature, any Earth system variable that is linearly related to cumulative emissions increases at the same relative rate as annual emissions. While emissions continue to increase at the current rate, peak committed temperatures rise 3–7.5 times as fast as 1951–2012 global mean temperatures, and millennial SSLR increases 7–25 times as fast as 1971–2010 SSLR, depending on the rate of emission reductions after emissions peak. For an intermediate ECS, this
corresponds to an absolute MDS of 0.3–0.7 °C/decade for \( \Delta T_{\text{max}} \) and 8–21 cm/decade for SSLR. In order to better constrain these absolute ranges, the uncertainty associated with ECS should be reduced. Based on a rough estimate, the MDS of total sea level rise is much larger than the MDS of SSLR, and its factor compared to recent rates may also be larger.

Our results further show that ocean acidification metrics by AD 2100 are very sensitive to delays in emission reductions now, especially the loss of surface ocean areas with more than threefold aragonite supersaturation. Depending on the achievable rate of emission reductions, a near-complete loss of such areas by the end of the century becomes unavoidable within a few years or decades of delay.

In view of communicating future climate risks, MDSs are highly informative as they link policy decisions today with long-term consequences in the Earth system. By comparing MDSs with the current trends, the full extent of Earth system changes due to delay in reducing anthropogenic CO₂ emissions becomes evident.

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References

Boden T A, Marland G and Andres R J 2013 Global, Regional, and National Fossil-Fuel CO₂ Emissions Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, US Department of Energy, Oak Ridge, Tenn., USA
Caldeira K and Kasting J 1993 Insensitivity of global warming potentials to carbon dioxide emission scenarios Nature 366 251–3
Dlugokencky E, Tans P and Keeling R 2015 Atmospheric CO₂ data NOAA/ESRL (www.esrl.noaa.gov/gmd/ccgg/trends/) and Scripps Institution of Oceanography (scrippscps2.ucsd.edu/)
Hare B and Meinshausen M 2006 How much warming are we committed to and how much can be avoided? Clim. Change 75 111–49
Smith S M and Allen M R 2013 The role of short-lived climate pollutants in meeting temperature goals Nat. Clim. Change 3 1021–4
Tenn., USA

Roth R, Ritz S P and Joos F 2014 Burial-nutrient feedbacks amplify the sensitivity of atmospheric carbon dioxide to changes in organic matter remineralisation Earth Syst. Dyn. 5 321–43
Steinacher M and Joos F 2015 Earth system responses to cumulative carbon emissions Biogeoosci. Discuss. 12 9839–77
Steinacher M, Joos F and Stocker T F 2013 Allowable carbon emissions lowered by multiple climate targets Nature 499 197
Stocker T F 2013 The closing door of climate targets Science 339 280–2
Tschumi T, Joos F and Parekh P 2008 How important are Southern Hemisphere wind changes for low glacial carbon dioxide? A model study Paleoceanography 23 PA4208
UNESCO 1981 Tenth report of the joint panel on oceanographic tables and standards Unesco Technical Papers in Marine Science 36
Zickfeld K and Herrington T 2013 The time lag between a carbon dioxide emission and maximum warming increases with the size of the emission Environ. Res. Lett. 10 031001
Zickfeld K et al 2013 Long-term climate change commitment and reversibility: an EMIC intercomparison J. Clim. 26 5782–809