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Inherent uncertainty disguises attribution of reduced atmospheric CO_2 growth to CO_2 emission reductions for up to a decade

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Abstract

The growth rate of atmospheric CO_2 on inter-annual time scales is largely controlled by the response of the land and ocean carbon sinks to climate variability. Therefore, the effect of CO_2 emission reductions to achieve the Paris Agreement on atmospheric CO_2 concentrations may be disguised by internal variability, and the attribution of a reduction in atmospheric CO_2 growth rate to CO_2 emission reductions induced by a policy change is unclear for the near term. We use 100 single-model simulations and interpret CO_2 emission reductions starting in 2020 as a policy change from scenario Representative Concentration Pathway (RCP) 4.5 to 2.6 in a comprehensive causal theory framework. Five-year CO_2 concentration trends grow stronger in 2021–2025 after CO_2 emission reductions than over 2016–2020 in 30% of all realizations in RCP2.6 compared to 52% in RCP4.5 without CO_2 emission reductions. This implies that CO_2 emission reductions are sufficient by 42%, necessary by 31% and both necessary and sufficient by 22% to cause reduced atmospheric CO_2 trends. In the near term, these probabilities are far from certain. Certainty implying sufficient or necessary causation is only reached after, respectively, ten and sixteen years. Assessments of the efficacy of CO_2 emission reductions in the near term are incomplete without quantitatively considering internal variability.

1. Introduction

Substantial year-to-year variations in the growth rate of global atmospheric CO_2 concentrations show variations that cannot be explained by land-use changes, fossil fuel emissions or the increase of carbon sink capacities due to increasing atmospheric CO_2 concentrations (Friedlingstein *et al* 2019, Peters *et al* 2017). The variations originate instead from the variability of the global carbon cycle in response to climate variability, which is inherent to the physics of the Earth System. For instance, the variations of the tropical land carbon sink is dominated by the El Niño-Southern Oscillation (Jones *et al* 2001, Zeng *et al* 2005), and the pronounced Southern Ocean carbon sink is susceptible to changes in atmospheric circulation patterns (Landschützer *et al* 2015, McKinley *et al* 2017). Therefore, this internal variability of the global carbon cycle in atmospheric CO_2 may disguise the detection of potential CO_2 emission reductions in atmospheric CO_2 observations. But CO_2 emission reductions are required to achieve the targets of the Paris Agreement (UNFCCC 2015). Here we ask what the probability is that a slowdown in atmospheric CO_2 growth is attributable to a policy change implementing CO_2 emission reductions as the difference between Representative Concentration Pathway (RCP) 4.5 and RCP2.6, in the face of internal climate variability. This question becomes policy-relevant as policy-makers assess the efficacy of CO_2 emission reductions in the Global Stocktake every 5 years (Peters *et al* 2017, Schwartzman and Keeling 2020). Furthermore, we ask after how many years this policy change will cause atmospheric CO_2 growth rates to slow down for certain.

The challenge of emissions reductions verification in atmospheric CO_2 concentrations was first outlined by Peters *et al* (2017). We address this challenge by using a large ensemble of Earth System Model (ESM) simulations (Maher *et al* 2019).

We integrate 100 simulations based on the code of a single ESM with slightly perturbed initial conditions that serve as different realizations of the Earth System. Our analysis compares RCP4.5, which is close to the pledged and current policies until 2035 (Rogelj *et al* 2016, Hausfather and Peters 2020), with an emission reductions scenario compatible with the Paris targets under RCP2.6 (figure S4 (https://stacks.iop.org/ERL/15/114058/mmedia)). We attribute a reduction of trend in atmospheric CO_2 concentrations to CO_2 emission reductions in the comprehensive causation framework of Pearl (2000) and Hannart *et al* (2016). In the context of CO_2 emission reductions, necessary causation means that a factual trend reduction would not have occurred without a policy change. By contrast, sufficient causation implies that while a policy change may trigger a trend reduction, this trend reduction is not certain.

We go beyond approaches in previous studies (Tebaldi and Friedlingstein 2013, Peters *et al* 2017, Marotzke 2019, Samset *et al* 2020, Schwartzman and Keeling 2020) by comprehensively diagnosing atmospheric CO_2 variability in an ESM, which is compatible with the terrestrial and oceanic carbon sinks variations. The recently formalized emissions reductions verification of Schwartzman and Keeling (2020) uses an autoregressive model based on the observed carbon imbalance and a different statistical framework. While Tebaldi and Friedlingstein (2013) only focus on causation in a necessary causation sense, we here complete the probabilistic setting by asking also about sufficient causation. We compare two RCP scenarios in a single-model framework; formally only internal variability may undermine the detectability of CO_2 emission reductions. Assessing the contribution of our quantitative results against structural model uncertainty and imperfections is left for future study.

From a policy-maker's perspective looking into the near-term future, necessary and sufficient causation of CO_2 emission reductions slowing down atmospheric CO_2 trends deal with two different questions (Pearl 2000, Hannart *et al* 2016):

1. Will a policy change towards CO_2 emission reductions suffice to slow down atmospheric CO_2 growth? Other factors, such as a weakening uptake by the natural carbon sinks, may induce an increase in atmospheric CO_2 growth despite policy measures. From the viewpoint of a pathway without CO_2 emission reductions, the uncertainty in this question is based on sufficient causation.
2. Would a factual atmospheric CO_2 growth slowdown have occurred even without the policy change? This question asks whether the policy change was necessary to achieve the policy goal. From the viewpoint of a factual pathway of CO_2 emission reductions and a factual slowdown, the uncertainty in this question is based on necessary causation.

Based on this causation framework, we obtain probabilities that a policy change causes atmospheric CO_2 trends to decline. However, this causation may be far from certain depending on the time-scale assessed. Should CO_2 emission reductions not soon lead to reduced atmospheric CO_2 growth trends, we might face a debate analogous to the warming hiatus debate (Lewandowsky *et al* 2015, Fyfe *et al* 2016) about why CO_2 rises faster despite falling emissions. Therefore, scientists need to communicate the role of internal variability to policy-makers and the public (Deser *et al* 2012).

Marotzke (2019) shows the uncertain effect of emission reductions on global mean surface temperature (GMST) 15-year trends. As atmospheric CO_2 drives the forced GMST signal, the emissions reduction signal should become detectable earlier in atmospheric CO_2. Analyzing the effect of individual climate forcers, Samset *et al* (2020) confirms that anthropogenic CO_2 has the highest potential for emission reduction detection.

In our study, we also ask after how many years internal variability can still obscure the identification of CO_2 emission reductions in atmospheric CO_2. In other words, how long does it take until certainty arises in causation? This is a distinctly different question than the classical time-of-emergence of anthropogenic signals, which asks on which timescales the climate change signal emerges from natural variability (McKinley *et al* 2016). Here, we ask on which timescales a forcing change induced by this policy change causes a climate response considering sufficient and necessary causation (Marotzke 2019). These timescales of CO_2 emission reduction detection might be longer than the periodicity of the Global Stocktake in which policy-makers will assess the efficiency of mitigation measures.

2. Methods

2.1. Causation attribution framework

To identify whether CO_2 emission reductions cause a reduction in atmospheric CO_2 growth, we apply the concept of event causation (Pearl 2000, Hannart *et al* 2016, Marotzke 2019). We use the scenario RCP2.6 as implementing CO_2 emission reductions and RCP4.5 for the near-term future without CO_2 emission reductions (for a detailed justification see section 2.2). Taking a decline in atmospheric CO_2 growth as an effective consequence of CO_2 emission reductions policy, we define a reduction in the linear trend in global atmospheric CO_2 concentration as the policy goal, comparing the period before emission reductions started with the period afterwards. While this response is expected as the forced response averaged over all realizations, the trend of single ensemble members could potentially increase due to internal variability. For a five-year trend period and a scenario separation in 2020, compatible with the switch from RCP4.5 to RCP2.6, we hence compare the trends 2016-2020 and 2021–2025. The fraction of responses in a given scenario s yields the probability of trend reduction P_{RCPs}. The two scenarios serve as either the real world, labeled as factual, or the alternative world, labeled as counter-factual. The probabilities of trend reduction can be translated into a probability $P_{\{S,N\}}$ that the trend reduction is caused by the policy change (Pearl 2000, Hannart *et al* 2016):

- In a currently pledged policy pathway (factual RCP4.5 world) without CO_2 emission reductions in near-term, we ask in advance whether CO_2 emission reductions (a policy change towards the counterfactual RCP2.6) would be *sufficient* to cause a reduction in atmospheric CO_2 trends. The probability P_S means how likely a policy change would be sufficient to cause a reduced trend:

$$P_S = \frac{P_{\mathrm{RCP2.6}} - P_{\mathrm{RCP4.5}}}{1 - P_{\mathrm{RCP4.5}}}. \quad (1)$$

  In our case of CO_2 emission reductions, P_S is important when answering questions whether the policy goal of reduced atmospheric CO_2 growth will be achieved from the perspective of a planner.
- Considering CO_2 emission reductions in RCP2.6 as the factual where in retrospect atmospheric CO_2 trends have indeed declined and no CO_2 emission reductions in RCP4.5 as the counter-factual world, the probability P_N that the policy change was necessary to cause the trend reduction is:

$$P_N = 1 - \frac{P_{\mathrm{RCP4.5}}}{P_{\mathrm{RCP2.6}}}. \quad (2)$$

  In our case of CO_2 emission reductions, P_N is important when answering questions whether the policy goal would not have been reached without the policy change.
- Combining the two aforementioned, P_{NS} describes the probability that the policy change is both *necessary and sufficient* to cause the respective trend reduction:

$$P_{NS} = P_{\mathrm{RCP2.6}} - P_{\mathrm{RCP4.5}}. \quad (3)$$

  This strongest causation probability P_{NS} means how likely a reduced trend would occur in case of a policy change and would not occur without.

These probabilities hence describe probabilities that trend reductions over a given trend length are caused by the policy change, but how long do these trends need to be in order to be virtually certain that CO_2 emission reductions caused them? To answer this question, we define *Time to Detection of CO_2 emission reductions in a causation sense* $D_{\{S,N\}}$ as the trend length around CO_2 emission reductions start in 2020 for which $P_{\{S,N\}} > 99\%$, using the probability framing of Mastrandrea (2010). This time-scale marks the maximum range of influence of internal variability over changes in the forced signal due to a policy change.

2.2. Choice of scenarios

We identify RCP2.6 as roughly compatible with the Paris targets (van Vuuren *et al* 2011). Compared to the pre-industrial control, MPI-ESM Grand Ensemble warms by 1.4 ± 0.2 °C in RCP2.6 and 2.2 ± 0.2 °C in RCP4.5 until the end of the century (Suarez-Gutierrez *et al* 2018, Maher *et al* 2019). Anthropogenic CO_2 emissions in RCP2.6 are increasing until 2020; after 2020, emissions are expected to decrease by 2% per year in RCP2.6 until 2030 (figure S3). By contrast, RCP4.5 has similar anthropogenic CO_2 emission levels as RCP2.6 until 2020 and continues a moderate emissions increase until 2040 with a 1% per year increase until 2030 (figures S3, S4). This scenario was designed to reach a forcing stabilization at the end of this century (Thomson *et al* 2011) at about 3 °C warming. Although RCP8.5 is closer to the most recently recorded combined land-use and fossil-fuel emissions, we choose RCP4.5 as a reference scenario, because the differences between RCP4.5 and reported emissions until 2018 originate in land-use change whereas fossil-fuel emissions match (figure S3). More importantly, the levels of projected fossil-fuel emissions based on current and pledged policy until 2035 parallel RCP4.5 (Rogelj *et al* 2016, Hausfather and Peters 2020).

In the above-described comparison under the causal theory framework, we compare trends before and after this policy change to assess causality of this policy change on changes in trends with respect to the period before the policy change. This policy change is assumed to happen in one scenario (RCP2.6), and not in the other one (RCP4.5). Therefore, we require simulations under mostly identical forcing before this policy change. We assume that this policy comes into effect as implemented by the RCP scenarios (Meinshausen *et al* 2011). We identify the combination of RCP2.6 vs RCP4.5 with a scenario split in 2020 as suitable scenario comparison. This scenario combination and timing also describes the present quest aiming for an at most 2 °C warmer world with net emissions reduction of 3% per year over 10 years.

Comparing RCP2.6 with RCP8.5 would be another possible combination. However, RCP8.5 entails higher fossil-fuel CO_2 emissions than recently observed and much higher levels than what current policies pledge for until 2035 (Rogelj *et al* 2016, Hausfather and Peters 2020). Furthermore, RCP2.6 and RCP8.5 separate at a time when emissions in RCP2.6 still grow. This would make the definition of climate event as trend reduction awkward, if our goal is to investigate the effect of policy on possible trend reductions. Therefore we compare RCP2.6 and RCP4.5 and include the comparison against RCP8.5 in the supplementary material.

2.3. Large-ensemble simulations

The Max-Planck-Institute Earth System Model (MPI-ESM) Grand Ensemble comprises 100 members started from different initial conditions branched off a pre-industrial control simulation (Maher *et al* 2019). MPI-ESM contains comprehensive terrestrial and oceanic carbon cycle sub-models, which capture the dynamics of the global carbon cycle (Ilyina *et al* 2013, Schneck *et al* 2013, Li and Ilyina 2018). The Grand Ensemble is based on a model version close to the CMIP5 version (Giorgetta *et al* 2013). To our knowledge this is the largest ensemble of comprehensive climate models available up to date (Branstator and Selten 2009, Kay *et al* 2014, Rodgers *et al* 2015, Kirchmeier-Young *et al* 2016, Frankignoul *et al* 2017, Stolpe *et al* 2018). Its statistics have proven to be useful in investigating internal variability in the Southern Ocean carbon sink (Li and Ilyina 2018) and enable a 1% resolution for climate event probabilities (see section 2.1). From the year 2006 onward, the 100 historical simulations are extended under RCP2.6 and RCP4.5 (Meinshausen *et al* 2011, Taylor *et al* 2011). The Grand Ensemble simulations are forced with a scenario-dependent prescribed atmospheric CO_2 concentration, aerosols, non-CO_2 greenhouse gases and land-use change (Meinshausen *et al* 2011, Taylor *et al* 2011).

2.4. Diagnostic atmospheric CO_2 concentration

CO_2 concentration-driven simulations do not represent a variable atmospheric CO_2 concentration tracer. To quantify the expected variations in global atmospheric CO_2 concentration that are compatible with variations of the global land and ocean carbon sinks, we diagnose a virtual tracer of global atmospheric CO_2 based on the changes due to internal variability of the land and ocean carbon sinks in atmospheric CO_2 [figure S2]. The global residual CO_2 flux $G_{i,s}$ is the difference of CO_2 flux $F_{i,s}$ of the each ensemble member i to the ensemble mean of CO_2 flux F_s:

$$G_{i,s} = \sum_{\text{global}} (F_{i,s} - \frac{1}{M} \sum_{m=1}^{M} F_{m,s}) \tag{4}$$

where $M = 100$ is the number of ensemble members and i the number of a single ensemble member and s the scenario. The ensemble mean F_s is subject to all forcings (anthropogenic fossil-fuel CO_2 emissions, non-CO_2 emissions, land-use change, aerosols) on CO_2 flux, but *no* internal variability. The remaining residual shows the variations of CO_2 flux around neutral flux *only* due to internal variability. The forced atmospheric CO_2 signal f_s is scenario s-dependent and generated by a simplified climate model fed with emissions from integrated assessment models (Meinshausen *et al* 2011) incorporating the strengthening of the carbon sinks with higher CO_2 concentrations and land-use CO_2 emissions. This internal variability component of time-accumulated global CO_2 flux is then superimposed on the smooth atmospheric CO_2 forcing f_s and defines internally varying diagnostic global atmospheric CO_2 concentration $XCO_{2,i,s}$:

$$XCO_{2,i,s}(t) = \sum_{t'}^{t} G_{i,s}(t') \cdot \frac{\text{ppm}}{2.124\text{PgC}} + f_s. \tag{5}$$

We assume that the internal variability of the global carbon cycle to be driven by climate variability. This ignores the short-term effects of atmospheric CO_2 variability on CO_2 flux as in all concentration-driven simulations. Explicitly, for diagnostic atmospheric CO_2, we use as forcing f_s the concentration scenarios generated by the simplified climate model and not directly the CO_2 emissions generated by the integrated assessment models. This assumes that the emission scenarios from the integrated assessment model roughly match the resulting concentration scenarios from the simplified climate model (figure S9). The hereby diagnosed variations of global atmospheric CO_2 capture the observed global atmospheric CO_2 variations (figures 1, S7; Spring and Ilyina (2020)). For a detailed method description and verification in emission-driven simulations, see Supplementary Information section S1.

2.5. Method limitations

The generalisability of our results strongly depend on the strength and timing of the CO_2 emission reductions underlying the two compared scenarios, where causation probabilities $P_{\{N,NS\}}$ are even more sensitive than the probabilities of reducing atmospheric CO_2 trend $P_{\text{RCP}x}$ in scenario x. Here, we present one special case of CO_2 emission reductions as the difference between RCP4.5 and RCP2.6 representing a net 3% annual emission reductions until 2030. There is an active debate whether RCP4.5 (argued for by Hausfather and Peters 2020) or RCP8.5 (argued for by Schwalm *et al* 2020) tracks the current anthropogenic CO_2 emissions pathway best. Also the attribution probabilities are contingent upon whether the climate model simulates realistic magnitudes of internal variability (Marotzke 2019). Furthermore, our attribution method focuses only on one observable variable under internal variability, although atmospheric CO_2 is the most important indicator for CO_2 emission reductions. Lastly, we use the atmospheric CO_2 concentration prescribed to MPI-ESM generated by the simplified climate model based on CO_2 emission scenarios from the integrated assessment model and not the CO_2 emissions from the integrated assessment models themselves to calculate diagnostic

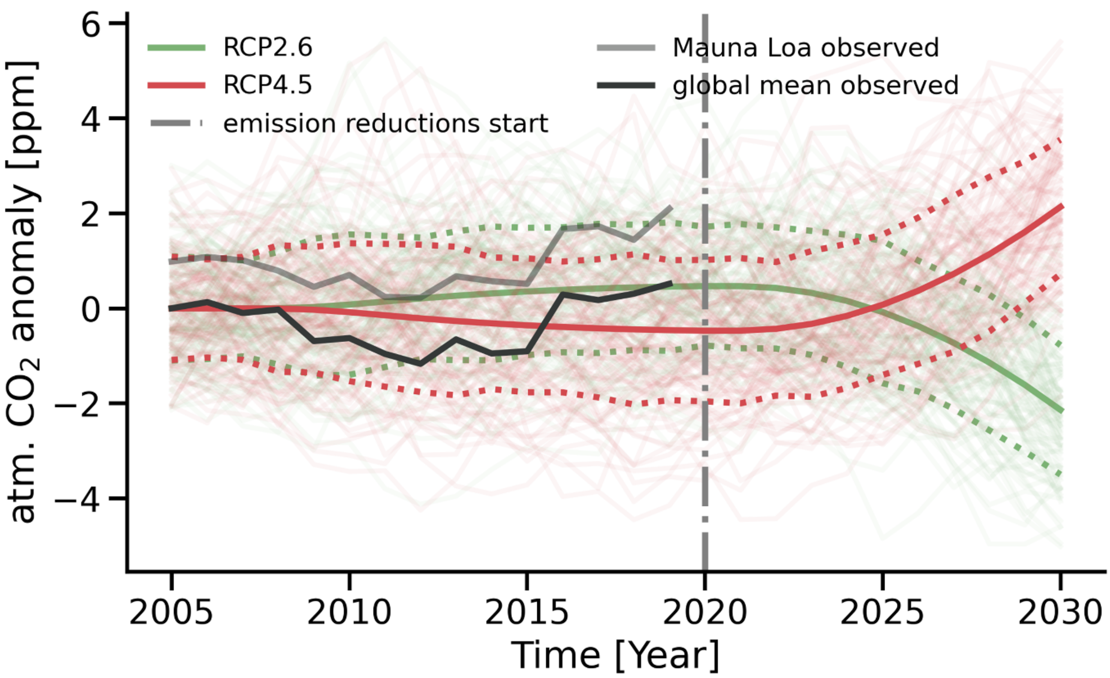

Figure 1. The difference in diagnostic atmospheric CO_2 concentration between CO_2 emission reductions scenario RCP2.6 (green) and currently most likely scenario for the near-term RCP4.5 (red) appears after the start of CO_2 emission reductions in 2020 (vertical dashed gray line). Both scenarios are detrended with the combined scenario mean forcing, see the otherwise identical figure S4 without detrending. Individual ensemble members are shown in faded colors. The forced response (solid green and red) in atmospheric CO_2 follows the prescribed atmospheric CO_2 forcing derived from the a simplified climate model with emissions from integrated assessment models (Meinshausen *et al* 2011). The variation of global mean (black) and Mauna Loa (gray) atmospheric CO_2 observations by NOAA/ESRL (Dlugokencky and Tans 2019), mostly fall within the ensemble standard deviation (dotted green and red).

atmospheric CO_2 Meinshausen *et al* (2011). While this is consistent with the forcing applied to the the climate system in MPI-ESM, this leads to small differences between in the compatible emissions of concentration-driven RCPs and actual CO_2 emissions as discussed by Jones *et al* (2013) and demonstrated for MPI-ESM (figure S9).

3. Probability of CO_2 emission reductions causing changes in atmospheric CO_2 growth trend

We first assess the frequency distributions of five-year trends in atmospheric CO_2. These distributions over the period 2016-2020 in RCP2.6 and RCP4.5 are nearly indistinguishable (figures 1, 2(a) and (d)). The most recent 2015–2019 observations-based estimate for global atmospheric CO_2 (Dlugokencky and Tans 2019) trend is in the upper tercile and thereby captured by our model (figures 2(a) and (d), S7). Comparing the distributions before and after CO_2 emission reductions onset in 2020 in RCP2.6, we find overlapping distributions with a tendency towards lower trends after CO_2 emission reductions (figures 2(a) and (b)). The ensemble mean responds to CO_2 emission reductions with a decrease in trend of 1 ppm over 5 years. The trend reduces in 70 ensemble members, resulting in $P_{\mathrm{RCP2.6}} = 70\%$ (figure 2(c)). This implies that with a 30% probability, atmospheric CO_2 growth will strengthen despite emissions reductions. In RCP4.5, the distributions of atmospheric CO_2 trends before and after 2020 look similar because the emissions rise steadily. Hence, only roughly half of the ensemble members show a reduced trend, with $P_{\mathrm{RCP4.5}} = 48\%$ (figure 2(d)–(f)).

The atmospheric CO_2 may increase more strongly despite the onset of CO_2 emission reductions, when the global carbon cycle triggered by internal climate variability releases more CO_2 than CO_2 emission reductions save. For instance, this is possible when the tropical forests react to higher temperature and less precipitation caused by a strong El Niño event (Jones *et al* 2001, Zeng *et al* 2005). The released CO_2 from the tropical biosphere persists in the atmosphere and can overwhelm the reduction of anthropogenic emissions (figure 1). These stronger atmospheric CO_2 growth trends despite CO_2 emission reductions might occur for trend comparisons around the CO_2 emission reductions start of up to ten years (figure 3).

These probabilities of trend reduction of the two scenarios can be converted into probabilities of trend reduction being *caused* by CO_2 emission reductions (see section 2.1). If asked in advance in 2015, the answer would be that a policy change from RCP4.5 to RCP2.6 representing CO_2 emission reductions starting in 2020 are *sufficient* to cause a five-year trend reduction in atmospheric CO_2 growth by

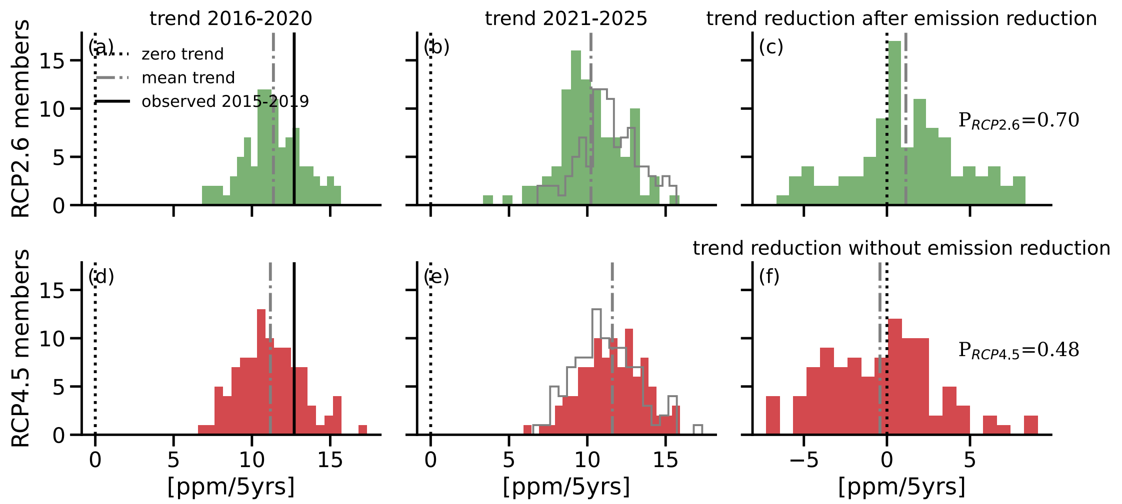

Figure 2. Probability distributions of 5-year trends from 2016 to 2020 and 2021 to 2025 in diagnostic atmospheric CO_2 in a 100-member ensemble following scenarios RCP 2.6 and 4.5: (a) trends before CO_2 emission reductions start in RCP2.6, (b) trend after CO_2 emission reductions started in RCP2.6, distribution of (a) is indicated in gray contours for comparison, (c) trend reduction over time calculated as (a)–(b). (d)–(f) as (a)–(c) but for scenario RCP4.5. $P_{RCP2.6}$ marks the probability of trend reduction over time in the CO_2 emission reductions scenario, $P_{\mathrm{RCP4.5}}$ marks the probability of trend reduction over time in RCP4.5. Vertical dashed gray lines show ensemble-mean trends per scenario. Dotted black vertical lines mark zero trends. Recent observational atmospheric CO_2 trends between 2015 and 2019 from NOAA/ESRL (Dlugokencky and Tans 2019) are shown in solid black.

$P_S = 42\%$ (figure 3). Here, this policy change works toward a trend reduction, but the trend reduction might also be prevented by internal variability. Asking from a 2025 perspective looking into the recent past, CO_2 emission reductions in 2020 were *necessary* by $P_N = 31\%$ to cause trend reductions (figure 3). This policy change causes the five-year trend reduction in a *necessary and sufficient* sense by $P_{NS} = 22\%$ (figure 3, dark blue in box). These results show that CO_2 emission reductions are far from certain to cause trend reductions in global atmospheric CO_2 growth when considering five-year trends.

To estimate the time-scales when CO_2 emission reductions are virtually certain to cause reduced atmospheric CO_2 growth trends, we consider trends calculated over different time window lengths around the CO_2 emission reductions start. As expected, the shorter the trend-lengths considered, the more dominant internal variability is. Therefore, trend reductions are less likely occurring in the CO_2 emission reductions scenario. The 3-year-trend probabilities of trend reduction even overlap with the 50% random forecast (figure 3). Conversely, when longer trends are considered, the influence of the signal of emissions change becomes stronger. CO_2 emission reductions reduce atmospheric CO_2 trends in RCP2.6 virtually for certain only when considering ten-year-trends (figure 3). In contrast, trend reductions are still possible due to internal variability despite the absence of CO_2 emission reductions for much longer in RCP4.5 (figure 3). Note that under RCP4.5 the annual anthropogenic CO_2 emissions increase very little until the 2040 s. Therefore, a few members can still have reduced trends over time. Consequently, $P_{\mathrm{RCP4.5}}$ does not drop to 1% until 2042.

The low causation probabilities over short time-scales show the inability to clearly attribute reduced atmospheric CO_2 trends to a policy change from RCP4.5 to RCP2.6 due to the large internal variability. The longer the time-scales considered, the stronger the two scenario pathways differ, and the attribution probabilities rise. If $P_{\mathrm{RCP2.6}} > P_{\mathrm{RCP4.5}}$ as assumed by the response to CO_2 emission reductions, P_S increases more quickly than P_N when $P_{\mathrm{RCP2.6}}$ approaches 1 faster than $P_{\mathrm{RCP4.5}}$ 0. Therefore, in the context of the scenarios RCP2.6 and RCP4.5, $P_S > P_N$ (Marotzke 2019). This means that in our context, sufficient causation is a stronger causation facet than necessary causation. Sufficient causation P_S describes whether the objective of reduced atmospheric CO_2 trends is met, which might be prevented by internal variability. As soon as growth trends decline in all realizations ($P_{RCP2.6} = 1$), also P_S saturates. In contrast, necessary causation P_N describes whether the response of reducing atmospheric CO_2 would only have happened in the presence of CO_2 emission reductions. Therefore, as long as trend reductions are possible even without CO_2 emission reductions, necessary causation will not be certain, that is, if $P_{\mathrm{RCP4.5}} > 0$, then $P_N < 1$.

The time to detection of CO_2 emission reductions $D_{\{S,N\}}$ describes after how many years this policy change is virtually certain to cause atmospheric CO_2 growth trends to decline. CO_2 emission reductions sufficiently cause trend reductions after $D_S = 10$ years and necessary cause of reduction after $D_N = 27$ years. We note that once sufficient

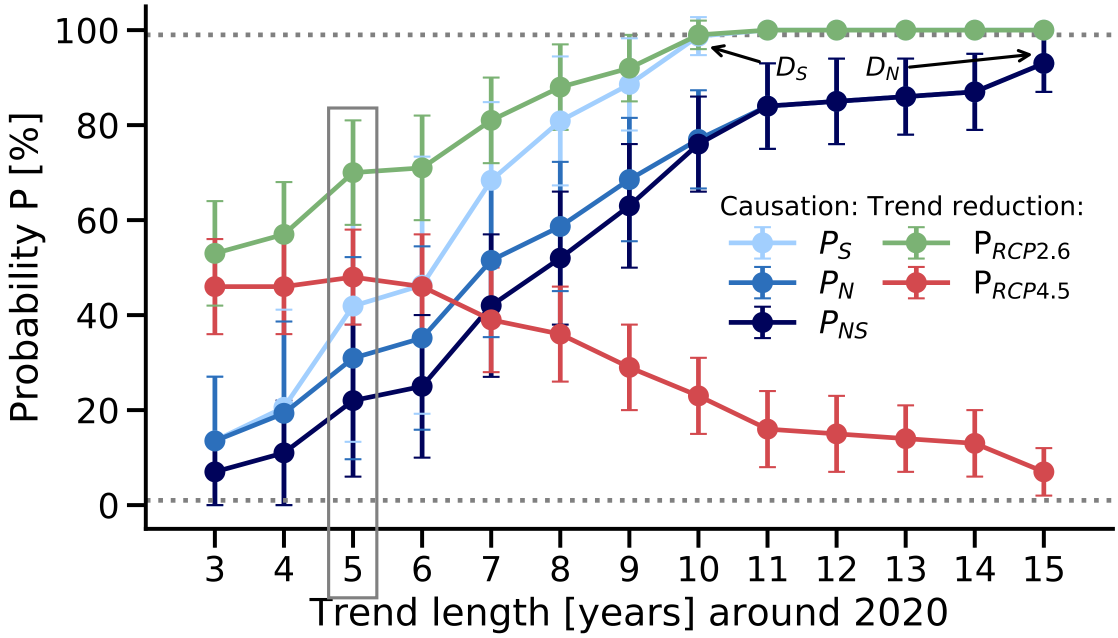

Figure 3. Probabilities of trend reduction in diagnostic atmospheric CO_2 between periods of varying trend length before and after CO_2 emission reductions start in 2020. $P_{\mathrm{RCP2.6}}$ (green) shows the probability of trend reduction in CO_2 emission reductions scenario RCP2.6. $P_{RCP4.5}$ (red) shows the probability of trend reduction in the currently most likely scenario for the near-term RCP4.5. P_S (pale blue) show the probability that a change from RCP4.5 to RCP2.6 causes the respective trend reduction in a sufficient causation sense. P_N (blue)show the probability that a change from RCP4.5 to RCP2.6 causes the respective trend reduction in a necessary causation sense. P_{NS} (dark blue) shows the probability that change from RCP4.5 to RCP2.6 causes the respective trend reduction in a sufficient and necessary causation sense. Error bars show the 1% and 99% confidence intervals based on bootstrapping with replacement. Dotted lines show 99% confidence interval for time of virtual certainty in trend reduction or causation ($D_{\{S,N\}}$). Results for policy-relevant five-year trends are highlighted in the gray box.

causation is certain, $P_S = 1$ in 2030 see (1), necessary causation and causation both necessary and sufficient coincide, $P_N = P_{NS}$; compare (2) and (3) with $P_{\mathrm{RCP2.6}} = 1$. Virtual certainty in $P_{\{N,NS\}}$ is hindered by $P_{\mathrm{RCP4.5}}$ above 1%. Due to the slow increase in emissions in the 2030 s, internal variability allows a few members to have increasing trends. Taking a less strict threshold of 95% certainty like in Tebaldi and Friedlingstein (2013), we obtain $D_N = D_{NS} =$ 16 years. This time-scale of CO_2 emission reductions detection in a necessary causation sense D_N is a bit longer than the similarly defined estimate based on IPSL-CM5A-LR (Tebaldi and Friedlingstein 2013, table 1). Our analysis also shows that whether this policy change from RCP4.5 to RCP2.6 can be identified as the cause of reduced atmospheric CO_2 trends after 10 or 16 years depends on the causation attribute. The differently defined emission reduction detection protocol of Schwartzman and Keeling (2020) finds a similar detection delay of 9 ± 4 years for comparable 2% net annual emissions reduction.

4. Summary and conclusions

In the context of potential future CO_2 emission reductions, we ask whether atmospheric CO_2 growth trend reductions in the near term can be attributed to a policy change. We focus on one specific pathway of CO_2 emission reductions interpreted as a policy change from scenario RCP4.5 without near-term CO_2 emission reductions to emissions reduction scenario RCP2.6 designed to achieve for the Paris targets representing 3% net annual CO_2 emission reductions until 2030. We apply a causation framework comprising two perspectives of policy elaboration (Hannart *et al* 2016, Marotzke 2019). We diagnose atmospheric CO_2 variations compatible with the natural carbon sinks variations and compare growth trends of atmospheric CO_2 before and after the onset of CO_2 emission reductions in 2020 in RCP2.6. While 5-year trends reduce in 70% of all realizations in the CO_2 emission reductions scenario RCP2.6 (consequentially implying increasing trends despite of CO_2 emission reductions by 30%), there is 48% probability of trend reductions in RCP4.5. This translates into CO_2 emission reductions from RCP4.5 to RCP2.6 being sufficient to cause a five-year trend reduction beforehand by 42% and in hindsight necessary by 31%. The probability that this policy change is both necessary and will suffice to bring the desired outcome considering five-year trends is only 22%. These probabilities are far from certain for up to a decade. It takes ten or 16 years of CO_2 emission reductions from RCP4.5 to RCP2.6 to virtually certainty cause a trend reduction in a sufficient or necessary causation sense, respectively. Communicating these probabilities in a clear manner is challenging but needed to inform policy-makers about the impact of internal variability on CO_2 emission reduction causation in the Earth system (Deser *et al* 2012, Hannart *et al* 2016, Howe *et al* 2019).

The five-year Global Stocktake following the Paris Agreement (UNFCCC 2015) makes the five-year internal variability highlighted in this study especially relevant for policy-makers. This study demonstrates the inherent uncertainty in near-term atmospheric CO_2 projections. As a partial solution to this challenge, initialized ESM-based prediction systems can reduce this uncertainty by predicting natural variations of the global carbon cycle. Global oceanic CO_2 flux is predictable for two to three years (Li *et al* 2019, Lovenduski *et al* 2019) and global atmospheric CO_2 variations have the potential to be predicted for up to three years in advance (Spring and Ilyina 2020). These multi-year ESM-based predictions of the global carbon cycle thereby bring added value about the expected natural variations of atmospheric CO_2 to policy-makers in the Global Stocktake process (UNFCCC 2015).

Our analysis shows that it is crucial to have realistic expectations of the efficacy of climate policy in the near term (Marotzke 2019, Samset *et al* 2020). Also Schwartzman and Keeling (2020) find a detection delay of up to a decade in a different approach. Even if anthropogenic emissions begin to decline after 2020, there still remains a substantial probability that atmospheric CO_2 trends will not have declined five years afterwards. In this case, the effects of CO_2 emission reductions on other iconic climate variables, such as global mean surface temperature, very likely get delayed even longer (Marotzke 2019). The likelihood of this happening is substantial. For instance, there is a three-out-of-ten chance that atmospheric CO_2 rises even stronger in the five years after CO_2 emission reductions started compared to before. Assuming the evolution of the RCPs (Meinshausen *et al* 2011) and the magnitude of internal variability in the global CO_2 fluxes in MPI-ESM-LR, such increasing atmospheric CO_2 growth trends despite CO_2 emission reductions from RCP4.5 to RCP2.6 are possible for up to a decade. Although this analysis relies on only a single model, internal variability may disguise CO_2 emission reductions efforts in the Earth System for a couple of years. Should this be the case, climate science should explain the observed atmospheric CO_2 evolution honoring internal variability. Policy makers should rather be informed by initialized predictions about the internal variability in the near-term evolution of atmospheric CO_2 (Betts *et al* 2018, Spring and Ilyina 2020). Evaluation of CO_2 emission reduction efficacy from an atmospheric CO_2 perspective needs to take internal variability, and therefore longer than 5-year trends, into account.

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