Seasonal climate change patterns due to cumulative CO₂ emissions

Anti-Ilari Partanen1,2,4, Martin Leduc3 and H Damon Matthews1

1 Concordia University, Department of Geography, Planning and Environment, 1455 De Maisonneuve Boulevard West, Montreal, Quebec, H3G 1M8, Canada
2 Finnish Meteorological Institute, Climate Research, P.O. Box 503, 00101, Helsinki, Finland
3 Ouranos, 550 Sherbrooke West, West Tower, 19th floor, Montreal, Quebec H3A 1B9, Canada
4 Author to whom any correspondence should be addressed.
E-mail: antti-ilari.partanen@concordia.ca

Keywords: CMIP5, cumulative carbon emissions, seasonal climate change, pattern scaling, TCRE

Abstract
Cumulative CO₂ emissions are near linearly related to both global and regional changes in annual-mean surface temperature. These relationships are known as the transient climate response to cumulative CO₂ emissions (TCRE) and the regional TCRE (RTCRE), and have been shown to remain approximately constant over a wide range of cumulative emissions. Here, we assessed how well this relationship holds for seasonal patterns of temperature change, as well as for annual-mean and seasonal precipitation patterns. We analyzed an idealized scenario with CO₂ concentration growing at an annual rate of 1% using data from 12 Earth system models from the Coupled Model Intercomparison Project Phase 5 (CMIP5). Seasonal RTCRE values for temperature varied considerably, with the highest seasonal variation evident in the Arctic, where RTCRE was about 5.5°C per Tt C for boreal winter and about 2.0°C per Tt C for boreal summer. Also the precipitation response in the Arctic during boreal winter was stronger than during other seasons. We found that emission-normalized seasonal patterns of temperature change were relatively robust with respect to time, though they were sub-linear with respect to emissions particularly near the Arctic. Moreover, RTCRE patterns for precipitation could not be quantified robustly due to the large internal variability of precipitation. Our results suggest that cumulative CO₂ emissions are a useful metric to predict regional and seasonal changes in precipitation and temperature. This extension of the TCRE framework to seasonal and regional climate change is helpful for communicating the link between emissions and climate change to policy-makers and the general public, and is well-suited for impact studies that could make use of estimated regional-scale climate changes that are consistent with the carbon budgets associated with global temperature targets.

1. Introduction
Cumulative CO₂ emissions have been shown to be a useful metric to estimate the global-mean temperature change resulting from human CO₂ emissions (Matthews et al 2009, Allen et al 2009). A growing body of research has confirmed that global temperatures respond approximately linearly to cumulative emissions (Matthews et al 2009, Gillett et al 2013, Collins et al 2013, Leduc et al 2015) which has led to the formal definition of this relationship as the ‘transient climate response to cumulative CO₂ emissions’ (TCRE) (Gillett et al 2013, Collins et al 2013). Estimates of the TCRE have now been widely used to compare model responses to cumulative emissions, as well as to estimate the total allowable emissions (or carbon budgets) associated with different levels of global-mean temperature change (Meinshaisen et al 2009, Zickfeld et al 2009, Friedlingstein et al 2014, Rogelj et al 2016).

While useful to inform efforts to meet climate mitigation targets such as 2°C of global warming, the
TCRE is limited in its ability to estimate the likelihood of climate impacts that manifest at the local (rather than global) scale. To expand the utility of the TCRE framework for climate impact assessments, Leduc et al. (2016) recently demonstrated that regional changes in annual-mean temperature can also be linearly related to cumulative CO2 emissions. This analysis suggests that there is considerable potential to quantify regional TCRE (or RTCRE) values based on the patterns of climate response to cumulative emissions as an extension of the current global TCRE framework.

Furthermore, there is reason to expect that seasonal temperature change patterns, as well as patterns of annual-mean and seasonal precipitation, might also scale approximately linearly as a function of cumulative emissions. For many years, researchers have employed a technique known as pattern-scaling to estimate the regional temperature and precipitation changes associated with a given level of global warming (Santer et al. 1990, National Research Council et al. 2011, Tebaldi and Arblaster 2014). This technique is premised on the finding that climate patterns normalized by global-mean temperature remain approximately constant across a wide range of global temperature changes, which has been shown to hold for both annual-mean and seasonal patterns of both temperature and precipitation (National Research Council et al. 2011, Tebaldi and Arblaster 2014, Mitchell 2003). Given a linear global temperature response to cumulative emissions, we therefore expect that it should be possible to extend the pattern-scaling approach from global-mean temperature to cumulative emissions, and apply this to both annual-mean and regional temperature and precipitation change patterns.

In this paper, we calculate annual-mean and seasonal regional temperature and precipitation responses to cumulative CO2 emissions based on an ensemble of models from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012). In addition to the RTCRE patterns, we quantify the robustness of the patterns in terms of inter-model spread, calculate the contribution of internal variability to inter-model spread, and assess to what extent these RTCRE patterns remain stable over time.

### 2. Methods

We used simulation data from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012). Specifically, we analyzed temperature and precipitation data from a scenario where CO2 concentration was rising annually by 1 percent from preindustrial levels (about 285 ppm) to fourfold this level after 140 years (experiment 1pct CO2) (Gillet et al. 2013). As non-CO2 forcings were not considered in this experiment, it allows an excellent opportunity to calculate the effects of cumulative CO2 emissions alone. We used data from 12 earth system models; this model ensemble (table 1) was the same as that used by Leduc et al. (2016), and for each model, only one realization of the experiment was available. In addition to using annual mean values (ANN), we did our analysis using also the means over four seasons: December–January–February (DJF), March–April–May (MAM), June–July–August (JJA), and September–October–November (SON). Regional changes in temperature and precipitation were averaged seasonally, but the scaling was still done using annual global total CO2 emissions.

The data processing methodology that we used is based on that of Leduc et al. (2016). To study the global mean response, we evaluated the TCRE for temperature (TCRE$_T$) as:

$$\text{TCRE}_T(m, t) = \frac{\Delta T_{gm}(m, t)}{E(m, t)}$$

where $\Delta T_{gm}(m, t)$ is change in global mean temperature for model $m$ at time $t$, and $E(m, t)$ is the diagnosed cumulative CO2 emissions. The metric for precipitation (TCRE$_P$) was calculated in the same way as a ratio of change in global mean precipitation and cumulative
emissions. We evaluated TCRE by comparing the means over 20-year average windows at the start of the simulation and at the time of doubling of CO$_2$ concentration, using the model ensemble mean as the best estimate of the TCRE.

RTCRE for temperature (RTCRE$_T$) was evaluated for each model $m$, grid-cell $x$, and time $t$ as:

$$RTCRE_T(m, x, t) = \frac{\Delta T(m, x, t)}{E(m, t)}$$

(2)

where $\Delta T$ is the local change in temperature and $E$ is the diagnosed cumulative CO$_2$ emissions. The metric for precipitation (RTCRE$_P$) was calculated in the same way. As for global mean response, we used 20-year average windows centered at the time of doubling of CO$_2$ concentration to evaluate the annual and seasonal means local changes, which is standard practice when evaluating climate change patterns. As for TCRE, we used the model ensemble mean as the best estimate for RTCRE. We calculated the spatial multi-model means by first interpolating all model data onto the grid of CanESM2 (2.8° of resolution).

To test whether the RTCRE stays constant over time, we calculated RTCRE for different 20-year windows relative to a same reference period (the first 20 years of the time series). We then show to what extent the zonal mean temperature and relative precipitation change remains stable over the 140 year duration of these simulations.

To assess the robustness of the climate change patterns, we calculated the ratio of the RTCRE and inter-model spread defined as:

$$R(x) = \frac{|RTCRE(x)|}{\sigma_{IMS}(x)}$$

(3)

where RTCRE($x$) is the ensemble mean RTCRE change in location $x$ and $\sigma_{IMS}(x)$ is the standard deviation of RTCRE in the model ensemble. Both are evaluated at the time of doubling of the CO$_2$ concentration as described above. The ratio is basically a signal to inter-model spread ratio, which is a convenient measure since the inter-model spread is often the largest where the signal is also large (Leduc et al. 2016).

The previous measure of robustness can be interpreted as a standard signal to noise ratio in cases where the internal variability dominates the inter-model spread. To account for this effect, we calculated how the internal variability of the climate affects the RTCRE. As in Leduc et al. (2016), we estimated, using the variance inflation factor from Wilks (2011), that over a N-year period, the effect of internal variability on RTCRE is:

$$\sigma_{IV}(x)^2 = \frac{2\sigma_1(x)^2 + \phi(x)}{N_c^2(1 + \phi(x))}$$

(4)

where $\sigma_1(x)^2$ is the inter-annual variance of the detrended time series of annual mean temperature or relative change in precipitation with respect to the 20 year reference period. $E$ is the cumulative CO$_2$ emissions at the time of doubling of the CO$_2$ concentration, and $\phi(x)$ is autocorrelation of the detrended time series with lag of one year. Autocorrelation with lag of two years was negligible for both variables, and therefore higher-order terms are not needed to calculate the internal variability. We detrended using a fourth-order polynomial fit (Hawkins and Sutton 2009, Leduc et al. 2016). To quantify the contribution of the internal variability to the inter-model spread, we thus calculated the ratio of the effect of internal variability on the RTCRE to the inter-model spread in RTCRE:

$$G(x) = \frac{\sigma_{IV}(x)}{\sigma_{IMS}(x)}$$

(5)

3. Results

3.1. Annual mean temperature and precipitation response

Figures 1(a) and (b) show the change in global mean temperature and precipitation as a function of cumulative CO$_2$ emissions for all 12 models and for the ensemble mean. The plots also contain straight lines representing ensemble mean TCRE at the time of doubling of CO$_2$ concentration. In general, models with a strong temperature response had also a strong precipitation response. The ensemble mean TCRE$_T$ and TCRE$_P$ were 1.68 °C per Tt C and 2.5% per Tt C, respectively. Following the convention established in previous works (Matthews et al. 2009, Gillett et al. 2013, Leduc et al. 2015 and 2016), these values were calculated as a change (in temperature or precipitation) per cumulative CO$_2$ emissions at the time when the atmospheric CO$_2$ concentration has doubled its initial concentration for each model individually before calculating the ensemble mean. Although evaluating TCRE at the time of doubling of CO$_2$ concentration has been shown to be more stable than if it is calculated at a certain amount of cumulative emissions (Leduc et al. 2015), the ensemble mean was very similar using both of these two methods (compare solid and dashed black lines in figures 1 (a) and (b)).

Figures 1(c) and (d) show the ensemble mean annual mean RTCRE for temperature and precipitation. As discussed in Leduc et al. (2016), land areas and especially the Arctic showed a strong temperature response to CO$_2$ emissions mainly due to sea-ice feedback (Kumar et al. 2010, Screen and Simmonds 2010). RTCRE$_T$ values were greater than two times the inter-model spread ($\sigma_{IMS}$) over most of the globe (hatched regions in figure 1(c)). Here we also show the RTCRE$_P$ as a relative change in precipitation per Tt C emitted. The strongest positive response took place at
the Equator in the Pacific Ocean and Northeastern Africa, where RTCRE$_T$ was about 30%–40% per Tt C. Over land areas, precipitation decreased considerably (by 8%–32% per Tt C) in Southern Europe, Northwestern Africa, and Southern parts of North America. RTCRE$_P$ was mostly positive (about 5%–25% per Tt C) at both poles. Unlike for temperature, only over small regions RTCRE$_P$ was greater than 2$\sigma_{\text{IM5}}$, indicating considerably lower robustness as discussed in more detail in section 3.4.

### 3.2. Seasonal temperature and precipitation response

Figures 2(a) and (b) show seasonal TCRE$_T$ in DJF and in JJA, respectively. Global mean responses were fairly similar to annual mean response for all seasons in terms of both model spread and ensemble mean. TCRE$_T$ was 1.72, 1.63, 1.64, and 1.73$^\circ$C per Tt C for DJF, MAM, JJA, and SON, respectively. See figures S1(a) and (c) available at stacks.iop.org/ERL/12/075002/mmedia for TCRE$_T$ for MAM and SON, respectively.

Figures 2(c) and (d) show the RTCRE$_T$ during DJF and JJA, respectively. Arctic amplification was most visible during DJF, where the highest value of RTCRE$_T$ was 8.9$^\circ$C per Tt C in some parts of the Arctic. Everywhere below latitude 50$^\circ$N, RTCRE$_T$ was below 3.8$^\circ$C per Tt C. There was little variation inside the latitude band between 40$^\circ$S and 30$^\circ$N; the zonal mean RTCRE$_T$ was between 1.3 and 1.6$^\circ$C per
TtC within this region. For other seasons, the zonal variability of TCRE was considerably lower but land-sea contrasts were still apparent. For JJA, TCRE was below 3.3 °C per TtC everywhere, with the largest values occurring in Northern Eurasia and over parts of the Southern Ocean.

RTCRE was 2.66, 2.40, 2.22, and 2.55 % per TtC for DJF, MAM, JJA, and SON, respectively. RTCRE for annual means (figure S2), DJF (figure 3(a)), MAM (figure S2(b)), JJA (figure 3(b)), and SON (figure S2(d)) were relatively similar in mid-latitudes and near the Equator. The most significant example of seasonal variability was the stronger precipitation response in the Arctic during DJF and SON. RTCRE in the Arctic (above 60°N) was mostly around about 20%–40% per TtC in DJF, whereas for other seasons the values were mostly below 24% per TtC. There were clear seasonal differences also in Southern Africa: a slight positive response (0%–8% per TtC) in DJF and mainly negative response in other seasons (up to about −20% per TtC). Also parts of Australia, Northern America, and Southern America had a different sign of RTCRE in different seasons.

As discussed in section 3.4 and shown with the limited extent of the hatched areas in figures 3(c) and (d) and figures S3(b) and (d), precipitation response had larger inter-model spread and was more sensitive to interannual variability than the temperature response. Therefore, the results on precipitation should be interpreted with caution.

3.3. Stability of climate change patterns over time

Figure 4 shows zonal mean of RTCRE over time for both temperature and precipitation. RTCRE stayed relatively stable over time. However, there was clearly noticeable decrease especially in the Arctic region, but also elsewhere in both annual and seasonal mean values (figures 4(a)–(c), figures S3(a) and (b)). This general decrease is consistent with previous work that has shown that TCRE deviates from linearity at very high levels of cumulative emissions (e.g. Leduc et al 2015, Herrington and Zickfeld 2014) The larger decrease of RTCRE in the Arctic can be attributed mostly to the weakening of the sea-ice albedo feedback (Leduc et al 2016). Although the Arctic amplification manifested mostly during DJF, the relative decrease with respect to time of zonal mean of RTCRE was similar for all DJF and JJA, suggesting that seasonal sea-ice albedo feedback changes are of comparable magnitude to the annual-mean change.

RTCRE stayed also relatively constant over time (figures 4(d) and (e), figures S3(c) and (d)). Different seasons had changes partly in opposite directions that made the annual mean RTCRE more stable. For example, in DJF, precipitation increase over the Arctic was stronger at later years, and weaker in SON. There was also some non-monotonic behavior in the precipitation response. During JJA, at latitudes around 50 °N, precipitation response was positive for the time window of the years 20–40, then negative again for the years 40–80, and changed again to positive for the rest of the experiment. At least part of this variation of sign was related to noise from the early years when both the signal and the emissions were small. Therefore, we show results beginning from the years 60–80 in figure 4. In general, there was not such a clear trend for precipitation as seen in the decreased temperature response over time.

3.4. Robustness of RTCRE patterns and the contribution of internal variability

In the following, the ratio of RTCRE to inter-model variability (RRT, equation (3)) is used as a measure of robustness of the models’ climate change patterns. In
general, models agreed relatively well in their $\text{RTC}^T$ patterns within the mid-latitudes and the Equator ($R_T$ mostly between 4 and 8, see figures 5(a)–(c)). Even though the signal in the annual means (figure 1(e)) and in DJF (figure 2(e)) was largest at high latitudes, also the model spread was large and thus $R_T$ values were lower than at mid-latitudes and the $\text{RTC}^T$ values were lower than $2\sigma_{\text{IMS}}$. Patterns show important disagreements in the Southern Ocean and in the poles ($R_T$ mostly below 3). figures 5(d)–(f) show
the ratio of internal variability to the inter-model spread (\(G_T\), equation (5)) for temperature. Relative importance of the internal variability was considerably higher for seasonal means than for the annual mean. Especially in North America, Australia, and Europe in DJF, the internal variability component was important relative to the whole inter-model spread with values of \(G_T\) being around 1 (note that \(G_T\) occasionally exceeded 1, because one ensemble member per model is not enough to capture all internal variability and therefore there is some sampling error that affect the evaluation of equations (4) and (5)). In the areas where internal variability dominated the inter-model spread, more (than 1) ensemble members for individual models would help to produce more robust patterns. Conversely, in regions where internal variability was small compared to the inter-model spread, having more members would likely not increase the robustness of the climate change patterns. Rather, the latter case refers to the situation where an improvement of the patterns involves a reduction of the overall uncertainty in regional climate sensitivity. In JJA, the contribution of internal variability to the inter-model spread was small over most of land areas with exception of Australia, Uruguay, and eastern part of the United States.

The robustness (\(R_P\)) (figures 5(g)–(i)) was considerably lower for precipitation than for temperature. The values for \(R_P\) were mostly below 3, which means that the signal is relatively weak compared to the model spread over almost all regions. In particular, in most regions where \(R_P\) was smaller than 0.5, less than 75% of the models agreed on the sign of the change. The robustness was higher in Southern Europe (where precipitation decreased) during JJA and in Siberia and Hudson Bay (where precipitation increased) during DJF with \(R_P\) values of about 2–4.

Internal variability also had a large effect on the robustness of the TCRE\(_P\) metric (figures 5(j)–(l)). Already for the annual results, the ratio between the effect of internal variability on RTCRE\(_P\) and inter-model spread (\(G_{TP}\)) was over 0.8 over large regions reaching values of over 3 in certain areas. Note that regions with \(G_{TP} > 1\) were larger for precipitation, because internal variability was more difficult to calculate accurately for precipitation than for temperature. The large effect of internal variability was clearly visible, when we plotted the regional change in precipitation against cumulative CO\(_2\) emissions over Giorgi regions (figure S4, Giorgi and Francisco 2000). For some regions, such as Australia (figure S5(a)), Sahara (figure S5(b)), Central Asia (figure S5(c)), it was practically impossible to evaluate the mean RTCRE\(_P\) because of the noise generated by internal variability in these low-precipitation regions. Means calculated over larger areas are more likely to be stable. As the Giorgi regions had different areas, ranking of regions with similar amount of noise should be done with caution.

Internal variability had an even larger role in the seasonal analysis. Regions with \(G_P > 1\) were larger and the values of \(G_P\) were considerably greater everywhere compared to the annual results (figures 5(j)–(l)). The noise from internal variability was also very evident in the regional mean plots (figures S6–7), suggesting that it may be difficult to detect the effect of cumulative CO\(_2\) emissions on seasonal precipitation changes over most areas. However, there were some exceptions that show a more robust relationship, notably Greenland (figure S6(i) and figure S7(i)), Alaska (figure S6(h) and figure S7(h)), and North Asia (in JJA, figure S7(u)) had all clear increase in precipitation.

4. Discussion

The patterns of temperature and precipitation change scaled with cumulative CO\(_2\) emissions look very similar to those scaled with global mean temperature change (Tebaldi and Arblaster 2014). This is not surprising, given the near linear relationship between cumulative emissions and global mean temperature change as well as the consistent use of CMIP5 data (although using different scenarios and different model ensembles). This gives us confidence that our approach can be presented as a robust and straightforward extension of established and widely used pattern-scaling techniques.

Scaling climate change patterns with cumulative CO\(_2\) emissions rather than global mean temperature provides a more direct link between human actions and climate change. Estimating global mean temperature change with TCRE provides an easy-to-understand way of framing the climate response to CO\(_2\) emissions. Our work here, together with Leduc et al (2016) presents a generalized TCRE framework, which links cumulative CO\(_2\) emissions directly to regional and seasonal change in temperature and precipitation. With traditional pattern scaling with global mean temperature, a simple climate model is required to predict the evolution of the global mean temperature according to a given amount of CO\(_2\) emissions (e.g. Goodwin et al 2015). The generalized TCRE framework presented here provides a simple method to link emissions to expected climate change based simply on estimates of anticipated cumulative emissions associated with a given scenario, therefore removing the need to use a simple climate model before pattern scaling.

In theory, this extended TCRE framework could be improved further by employing more advanced methods of pattern scaling. For example, the Time Shift Approach (Herger et al 2015) could be used in almost identical way to the approach we have used here. In this method, the climate change patterns at certain amount of cumulative CO\(_2\) emissions would be directly taken from another simulation at a time of the equivalent cumulative CO\(_2\) emissions. This would
preserve the internal consistency of temperature and precipitation patterns and implicitly take into account non-linearities involved in the retreat of Arctic sea ice. However, the improved accuracy would reduce the conceptual simplicity of scaling climate change patterns with cumulative CO₂ emissions and make it less usable for climate impact studies.

Our analysis here was based on CO₂-only forcing scenarios. The role of non-CO₂ greenhouse gases, aerosols, and land-use change could be evaluated by comparing the results here to analysis of the RCP scenarios with other forcings included. This comparison will be addressed in future work.

5. Conclusions

We analyzed data from an ensemble of 12 CMIP5 models to assess to what extent regional and seasonal changes in temperature and precipitation can be described with a linear relationship to cumulative CO₂ emissions. Overall, seasonal RTCREF was a fairly robust measure across models (signal was greater than two inter-model standard deviations over most of the globe), time and emissions. Thus, cumulative CO₂ emissions can be used to predict temperature change both at global and regional scale for different seasons with almost similar robustness as for the annual means.

For precipitation the picture is more complicated. Although global total precipitation change scaled well with cumulative CO₂ emissions for both annual and seasonal means, the regional change in precipitation was much more uncertain. First, disagreements between different models were large, even on the sign of change. Second, large internal variability made it difficult to extract a clear signal. This was true even when averaged over large regions. This large role of internal variability in precipitation response is, however, not specific to scaling the precipitation response with cumulative CO₂ emissions. The same lack of robustness applies to the patterns scaled with global mean temperature change (Tebaldi and Arblaster 2014), and our results support the hypothesis by Tebaldi and Arblaster (2014) that internal variability can contribute to model disagreements even when 20 year averages are used.

Our analysis demonstrates that cumulative CO₂ emissions can be linearly linked to regional and seasonal changes in temperature and to some degree also to changes in precipitation. This relationship can be used in assessing carbon budgets (van Vuuren et al 2016) also at regional and seasonal level, and in climate impact studies without using even a simple climate model before pattern scaling, and is also a useful concept in communicating with the general public about how climate will respond to continued anthropogenic CO₂ emissions.

Acknowledgments

A.-I. Partanan was supported by a research grant from Emil Aaltonen Foundation. We acknowledge the World Climate Research Programme’s Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the modeling groups (listed in table 1 of this paper) for producing and making available their model output. For CMIP the US Department of Energy’s Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

References

Allen M R, Frame D J, Huntingford C, Jones C D, Lowe J A, Meinshausen M and Meinshausen N 2009 Warming caused by cumulative carbon emissions towards the trillionth tone Nature 458 1163–6
Collins M et al 2013 Long-term climate change: projections, commitments and irreversibility Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge: Cambridge University Press) pp 1029–136
Friedlingstein P et al 2014 Persistent growth of CO₂ emissions and implications for reaching climate targets Nat. Geosci 7 709–15
Gillett N P, Arora V K, Matthews H D and Allen M R 2013 Constraining the ratio of global warming to cumulative CO₂ emissions using CMIP5 simulations J. Clim. 26 6844–58
Giorgi F and Francisco R 2000 Uncertainties in regional climate change prediction: a regional analysis of ensemble simulations with the HADCM2 coupled AOGCM Clim. Dyn. 16 169–82
Goodwin P, Williams R G and Ridgwell A 2015 Sensitivity of climate to cumulative carbon emissions due to compensation of ocean heat and carbon uptake Nat. Geosci. 8 29–34
Hawkins E and Sutton R 2009 The potential to narrow uncertainty in regional climate predictions Bull. Am. Meteorol. Soc. 90 1095–107
Herger N, Sunderson B M and Knutti R 2015 Improved pattern scaling approaches for the use in climate impact studies Geophys. Res. Lett. 42 5486–94
Herrington T and Zickfeld K 2014 Path dependence of climate and carbon cycle response over a broad range of cumulative carbon emissions Earth Syst. Dyn. 5 409–22
Kumar A, Perlwitz J, Eschelid J, Quan X, Xu T, Zhang T, Hoerling M, Jha B and Wang W 2010 Contribution of sea ice loss to Arctic amplification Geophys. Res. Lett. 37 L21701
Leduc M, Matthews H D and de Elia R 2015 Quantifying the limits of a linear temperature response to cumulative CO₂ emissions J. Clim. 28 9955–68
Leduc M, Matthews H D and de Elia R 2016 Regional estimates of the transient climate response to cumulative CO₂ emissions Nat. Clim. Change 6 474–8
Matthews H D, Gillett N P, Stott P A and Zickfeld K 2009 The proportionality of global warming to cumulative carbon emissions Nature 459 829–32
Meinshausen M, Meinshausen N, Hare W, Raper S C B, Frieler K, Knutti R, Frame D J and Allen M R 2009 Greenhouse-gas emission targets for limiting global warming to 2°C Nature 458 1158–62

Meinshausen M, Meinshausen N, Hare W, Raper S C B, Frieler K, Knutti R, Frame D J and Allen M R 2009
Mitchell T D 2003 Pattern scaling: an examination of the accuracy of the technique for describing future climates Clim. Change 60 217–42
National Research Council 2011 Climate Stabilization Targets: Emissions, Concentrations, and Impacts over Decades to Millennia (Washington, DC: The National Academies Press)

Rogelj J, Schaeffer M, Friedlingstein P, Gillett N P, van Vuuren D P, Riahi K, Allen M and Knutti R 2016 Differences between carbon budget estimates unravelled Nat. Clim. Change 6 245–52

Santer B D, Wigley M L T, Schlesinger M E and Mitchell J F B 1990 Developing Climate Scenarios from Equilibrium GCM Results (Hamburg: Max Planck Institute for Meteorology)

Screen J A and Simmonds I 2010 The central role of diminishing sea ice in recent Arctic temperature amplification Nature 464 1334–1337

Taylor K E, Stouffer R J and Meehl G A 2012 An overview of CMIP5 and the experiment design Bull. Am. Meteorol. Soc. 93 485–98

Tebaldi C and Arblaster J M 2014 Pattern scaling: its strengths and limitations, and an update on the latest model simulations Clim. Change 122 439–71

van Vuuren D P, van Soest H, Riahi K, Clarke L, Krey V, Kriegler E, Rogelj J, Schaeffer M and Tavoni M 2016 Carbon budgets and energy transition pathways Environ. Res. Lett. 11 075002

Wilks D S 2011 Statistical Methods in the Atmospheric Sciences (International Geophysics Series vol 100) 3rd edn (Cambridge, MA: Academic)

Zickfeld K, Eby M, Matthews H D and Weaver A J 2009 Setting cumulative emissions targets to reduce the risk of dangerous climate change Proc. Natl Acad. Sci. 106 16129–34