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Carbon budgets and energy transition pathways

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Abstract

Scenarios from integrated assessment models can provide insights into how carbon budgets relate to other policy-relevant indicators by including information on how fast and by how much emissions can be reduced. Such indicators include the peak year of global emissions, the decarbonisation rate and the deployment of low-carbon technology. Here, we show typical values for these indicators for different carbon budgets, using the recently compiled IPCC scenario database, and discuss how these vary as a function of non-CO_2 forcing, energy use and policy delay. For carbon budgets of 2000 $GtCO_2$ and less over the 2010–2100 period, supply of low carbon technologies needs to be scaled up massively from today's levels, unless energy use is relatively low. For the subgroup of scenarios with a budget below 1000 $GtCO_2$ (consistent with >66% chance of limiting global warming to below 2 °C relative to preindustrial levels), the 2050 contribution of low-carbon technologies is generally around 50%–75%, compared to less than 20% today (range refers to the 10–90th interval of available data).

1. Introduction

Several publications have recently highlighted the relationship between cumulative CO_2 emissions and long-term temperature change (Allen *et al* 2009, Matthews *et al* 2009, Meinshausen *et al* 2009, Zickfeld *et al* 2009, IPCC 2013, Friedlingstein *et al* 2014). This relationship emerges as a result of the dominant contribution of CO_2 to total anthropogenic warming and the long atmospheric lifetime of CO_2. The policy implication of this relationship is that it is possible to derive so-called 'carbon budgets' that are associated with achieving certain climate targets with a certain probability (Knutti and Rogelj 2015). The strength of such budgets is that they clearly convey the messages that (1) long-term temperature change does not depend on CO_2 emissions at a specific moment in time, but on the accumulated CO_2 emissions over a long time period, (2) that therefore, near-term CO_2 emissions are important as they, too, exhaust the available budget, and (3) finally, that for any stabilisation target, CO_2 emissions will need to be phased out eventually (Anderson *et al* 2008, Matthews and Caldeira, 2008, IPCC 2013, Knutti and Rogelj 2015). There is, however, still flexibility in the timing of CO_2 emissions contributing to the budget, particularly when including the option of negative emissions (Obersteiner *et al* 2001, van Vuuren *et al* 2007, Azar *et al* 2010, Tavoni and Socolow 2013).

In defining emission pathways consistent with specific carbon budgets it is important to realise that these would require major changes in current energy and land-use systems (Clarke *et al* 2014, Kriegler *et al* 2014, Tavoni *et al* 2015). Such transitions will be constrained by socio-economic and technological inertia, manifested, among other things, in capital turnover rates, substitution dynamics, and limitations in implementation potential. This means that there are constraints on the possible pathways that are consistent with specific carbon budgets. Scenarios from integrated assessment models (IAMs) can provide insight into such transition pathways, capturing some of the relevant dynamics (Luderer *et al* 2013, van Vuuren and Stehfest 2013, Rogelj *et al* 2013b, Riahi *et al* 2015, Tavoni *et al* 2015). For the recent IPCC Fifth Assessment Report (AR5), a large set of IAM-based scenarios has been compiled, based on different models and derived for different types of targets, including forcing targets, carbon budget constraints, emission targets and prescribed carbon taxes (Clarke *et al* 2014). The characteristics of these scenarios have been assessed in the IPCC AR5 report.

Given the recent focus on carbon budgets, there is a need for insights into the implications of various carbon budgets, something that can be provided by the IAM-based scenarios. Going significantly beyond earlier assessments, in this paper we use the scenario database to directly explore how different carbon budgets relate to emissions pathways and, subsequently, energy system requirements. We do so by plotting information against a continuous CO_2 budget axis, in contrast to the more aggregated representation for scenario categories often used earlier (e.g. Clarke *et al* 2014). The figures shown here provide more insights into the underlying information (e.g. variance) than the aggregated statistics. We specifically look into the implications of different budgets for (1) emission reductions over time, (2) the contribution of CO_2 and non-CO_2 greenhouse gases, and (3) the scale of the key energy-system transformations underlying these reductions. This provides the possibility to relate CO_2 budgets to policy actions by looking into the continuous relationship between those two aspects. As explained in the section on methods, for each scenario climate information is available in the database based on runs of a probabilistic version of the climate model MAGICC (Meinshausen *et al* 2009, 2011).

2. Methods

The analysis represented here relies on the IPCC AR5 scenario database that contains IAM-based scenarios published in the scientific literature period 2007–2013 (Clarke *et al* 2014). The database was used in chapter 6 of the WG3 contribution to IPCC's Fifth Assessment Report and is available at https://secure.iiasa.ac.at/web-apps/ene/AR5DB/. It was compiled by means of an open call to modelling teams to submit scenarios to the AR5 database. The database includes information on the emissions, energy, land-use, technology and costs characteristics of these scenarios (Krey *et al* 2014). About 1200 scenarios were submitted, including baseline (no new climate policy), optimal policy and other mitigation scenarios. The baseline scenarios, although arguably not very realistic, represent a useful (counterfactual) point of reference for analysis in many studies. The optimal policy scenarios provide insight into least-costs strategies assuming that policies can be introduced in all sectors and regions from a base year onwards. Other mitigation scenarios include various constraints such as the policy delays associated with currently proposed climate policies, as pledged for 2020 and 2030 (Krey *et al* 2014). In the analysis here, we used those scenarios in the database that included information on 21st-century CO_2 emissions (we used the same method as used in AR5 to add a default pathway for land-use related CO_2 emissions in case only energy-related emissions were reported). Because the database was compiled to support AR5 analysis, it contains scenarios published from 2007 onwards, thus including scenarios that assume stringent policies could still be introduced from around 2010 onwards. Other authors have pointed out before that this may lead to possible bias in the results (allowing for a too optimistic view of the feasibility of ambitious climate targets) (Anderson 2015). In particular, this involved the question whether many models already have a peak in emissions in 2010, as in reality global CO_2 emissions increased by around 8.5% in the 2010–2015 period (Le Quéré *et al* 2015). However, the far majority of scenarios have been reported in 10 year steps, meaning that 2020 emissions could still be below the 2010 level without ruling out a 2015 peak. Therefore, we added two additional constraints to only remove those scenarios from the analysis that are clearly inconsistent with historically observed trends. First, all scenarios with 2010 emissions outside the 37.4 ± 3.8 $GtCO_2$ estimated by IPCC AR5 were excluded (Edenhofer *et al* 2014). Second, all scenarios with 2020 emissions more than 25% below 2010 level were excluded. This level is based on a maximum reduction rate of 7% starting from the 2015 emission level (the 7% rate is based on the maximum reduction rates after 2020 and the mean of scenarios showing the most rapid reduction in the 2030–2050 period in Riahi *et al* 2015). Finally, in order to identify whether scenarios that assume an emission peak already in 2015 behave differently, an additional scenario category was added within the optimal scenario group. This additional category shows 2020 emissions below the observed 2015 level (i.e. 8.5% above 2010). In total, 106 scenarios were removed on the basis of these additional constraints.

For those scenarios in the database that contained sufficient information, the carbon-cycle and climate model MAGICC (Meinshausen *et al* 2011) was used by the authors of the IPCC report to add a consistent set of forcing and climate data (and include it in the database). MAGICC is calibrated against more complex atmosphere–ocean general circulation models and it

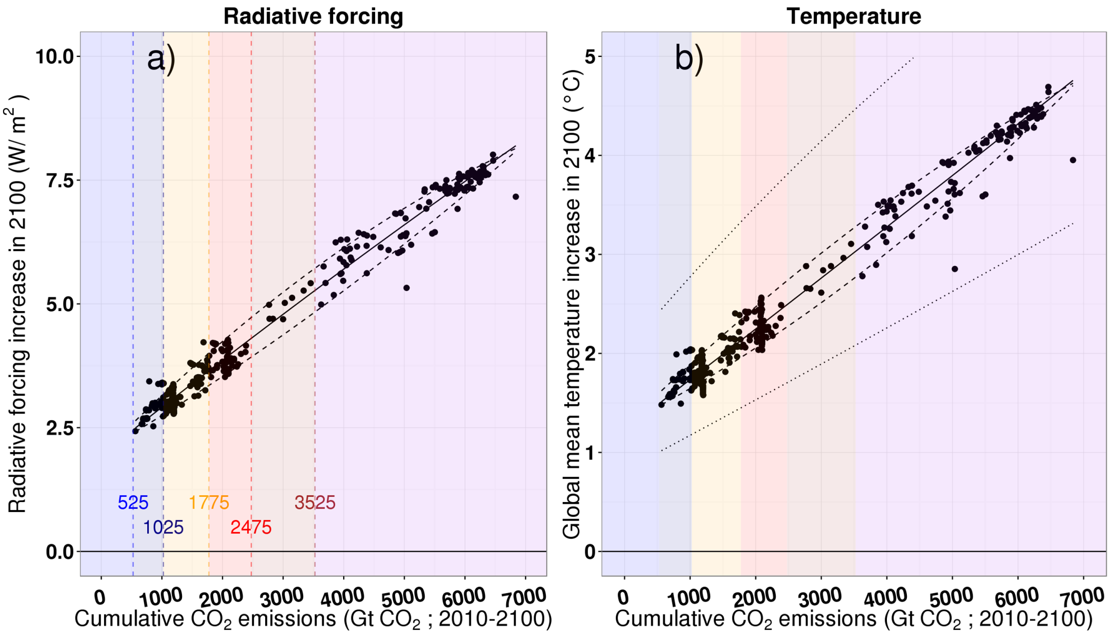

Figure 1. Relationship between cumulative CO_2 emissions and forcing (panel (a)), and cumulative emissions and global mean temperature increase (panel (b)) in scenarios from the IPCC AR5 Scenario Database. Dashed lines indicate 10th and 90th percentile quantile regression (2nd-degree polynomial) of scenario uncertainty using the median climate response. Solid lines show the 50th percentile quantile regression. Dotted lines in panel (b) indicate the 5th and 95th percentiles of the MAGICC temperature results across all scenarios. Quantile regressions are characterised by a goodness of fit parameter (Koenker and Machado 1999) of around 0.7 for the lower (10th) quantile, and 0.8 and higher for the other quantile (see supplementary table S2 for an overview). The coloured vertical areas correspond (from left to right) to staying likely below 1.5 °C, 2 °C, 2.5 °C, 3 °C, 3.5 °C and >3.5 °C on the basis of cumulative CO_2 emissions assuming an average non-CO_2 forcing (see methods).

has been shown to be consistent with the latest complex climate models in terms of mean climate outcomes (including the carbon budget) and, to some degree, also the uncertainty ranges (Rogelj *et al* 2014, Schaeffer *et al* 2015). This implies that the database can provide a link between carbon budgets and a range of important scenario attributes, including energy system parameters and emissions and climate system parameters.

While IAM scenarios provide an important source of information, it is clear that models do not capture all aspects of mitigation strategies. Moreover, the analysis of such models is bounded by assumptions for key uncertainties such as technology change, energy prices and social acceptance of new technologies (Clarke *et al* 2014, Grubb *et al* 2014, Kriegler *et al* 2015a). In general, IAMs focus on identifying low-costs scenarios under clearly specified limitations (e.g. the participation of regions in international climate policy), assuming (fully) functioning markets. The model results are generally meant to be indicative of possible developments given current insights on technology development. It is not easy to assess the implications of the simplifications included in the models. While the assumption of well-functioning carbon markets may imply that models are likely to underestimate costs, the recent rapid development in costs of renewables could also mean that in the long-term, costs could be lower than suggested by the models. Overall, several studies have shown general trends of model output in terms of use of specific technologies (mostly the focus of this article) to be roughly consistent with historical trends (Wilson *et al* 2013) (van Sluisveld *et al* 2015). An other important point is that models mostly focus on technological and economic factors, which means that results say little about political or social feasibility (e.g. regarding the acceptance of carbon-capture-and-storage, CCS). Real-world strategies that deliberately depend on more expensive mitigation options (e.g. the rapid expansion of PV in Germany a few years ago), for instance for political reasons, tend to be underrepresented. In the discussion section, more attention is paid to some key characteristics of IAMs and the implications for our findings.

Two assumptions that play a key role in the overall characteristics of mitigation strategies of IAMs include the timing of climate policy in different regions and sectors and the inclusion of negative emission technologies, which will be shown in this paper. Regarding timing of policies, the AR5 database includes 'optimal scenarios' (which have no further constraints on mitigation technology, timing, or participation) and scenarios that have assumed technology restrictions or delays in policy implementation. If relevant, the scenarios that assume delay have been shown separately in this paper. Similarly, scenarios that show net negative emissions in the second half of the century have been distinguished from scenarios that do not have net negative emissions.

3. Results

3.1. IAM information on carbon budgets

Figure 1 shows—consistent with the carbon budget literature—that, for the scenarios included in the database, there is a very strong relationship between cumulative CO_2 emissions and temperature and forcing outcomes. The almost linear relationship between cumulative CO_2 and temperature is uncertain in two ways: first, there is an uncertainty in the slope of the relationship, caused by the uncertainty in the climate system response, and second, there is a scenario uncertainty, shown as a variation around the central relationship, caused by differences in the timing of emission reductions and the reduction in non-CO_2 climate forcers (see also Rogelj *et al* 2015b). The impact of scenario uncertainty is shown by the spread of the individual dots (figure 1(b)), while the two outer lines additionally include the impact of climate system uncertainty. As a result, a range of different climate outcomes is associated with a specific carbon budget. For instance, a carbon budget of around 2500 $GtCO_2$ over the period 2010–2100 may lead to a temperature increase that ranges from 2.4 °C to 2.8 °C compared to pre-industrial level as a result of scenario uncertainty (10th–90th percentile), and 1.7 °C–3.8 °C compared to pre-industrial level if climate response uncertainty is also included. In the IPCC report, the scenarios were categorized on the basis of projected (median) 2100 forcing levels. Throughout this paper, we instead relate policy relevant indicators to a continuous range of cumulative CO_2 emissions. Similar relationships as shown in figure 1 can be drawn for different indicators such as peak temperature. While 2100 temperature correlates well with 21st-century budgets, for stringent scenarios, peak temperature correlates better with the cumulative CO_2 emissions until the peak (see SI). Depending on the type of impacts, it might be more relevant to look at peak temperature or at (long-term) transient temperature.

The vertical bars illustratively couple the results to cumulative CO_2 emissions associated with keeping temperature likely (i.e. >66% chance) below different temperature levels. These vertical bars are also used in subsequent graphs in this article to relate policy-relevant indicators to the climate outcomes. The estimated carbon budgets are based on the 67th percentile temperature outcome which have been approximated by taking the average of the temperature projections for the 50th and 84th percentile for each scenario that was assessed by MAGICC as part of the AR5 Scenario database. For each IPCC AR5 WGIII scenario category, the median 67th percentile temperature outcome was computed over all scenarios, and a piecewise linear line was used to interpolate between these median points. Finally, the width of the illustrative shadings in figures 1–6 (see also supplementary table S1) was computed by determining the intersection of the piecewise linear line with specific temperature levels, like 1.5 °C, 2 °C, 2.5 °C, or 3 °C relative to pre-industrial values.

3.2. Timing of emission reductions

Figure 2 shows the available scenarios as a function of time. For the baseline scenarios, emissions typically increase rapidly until 2050, followed by a slower increase after 2050 (purple lines). For carbon budgets of less than 2500 $GtCO_2$, global carbon emission profiles peak during the 21st century, followed by a distinct decline. For emission budgets of less than 1500 $GtCO_2$, an early emission peak needs to be followed by rapid reductions, mostly resulting in net negative emissions by the end of the century. As discussed by Kriegler *et al* (2015b), the year emissions peak in scenarios strongly depends on scenario assumptions (see figures 2(c) and (d)). While part of the scenario literature looks into cost-optimal trajectories towards long-term climate goals (i.e. based on minimised discounted costs over the century), other scenarios deliberately account for policy delay (i.e. less mitigation action is undertaken in the near term, in line with existing policies, while still aiming for the same long-term global climate objective). The two categories are shown separately in figures 2(c) and (d). The reduction before 2050 strongly depends on the use of negative emissions technologies in the second half of the century. This is shown in figure 3. For CO_2 budgets around 1000 $GtCO_2$ over the 2010–2100 period (which are consistent with a >66% probability of limiting warming to below 2 °C by 2100), most cost-optimal scenarios have negative emissions post-2050. At the same time, they still peak almost immediately (and thus at current emission levels), in order to avoid very expensive rapid reduction rates later on. For higher cumulative CO_2 emission levels, emissions can peak at a later point in time. For instance, under scenarios with a CO_2 budget of 1025–1775 $GtCO_2$ (around 50%–66% probability of limiting global warming to below 2 °C) emissions peak before 2030. In terms of peak year and level, the differences between cumulative CO_2 budgets up to around 2000 $GtCO_2$ are relatively small; emissions peak before 2040—with a median emission level (across all budgets below 2000 $GtCO_2$) that is under 20% above year-2010 emissions. Several multi-model studies have looked into the question how long-term targets could still be reached starting from currently formulated climate policies (pledges) in combination with corresponding policy projections for 2030 (Riahi *et al* 2015, Tavoni *et al* 2015, Kriegler *et al* 2015b). These so-called delay scenarios show a later and higher peak at the global level, compensating the additional emissions by quicker emissions reductions after 2030 and more negative emissions after 2050 (figure 2). Also Peters *et al* (2015) showed that currently formulated policies are inconsistent with an early action emission profile.

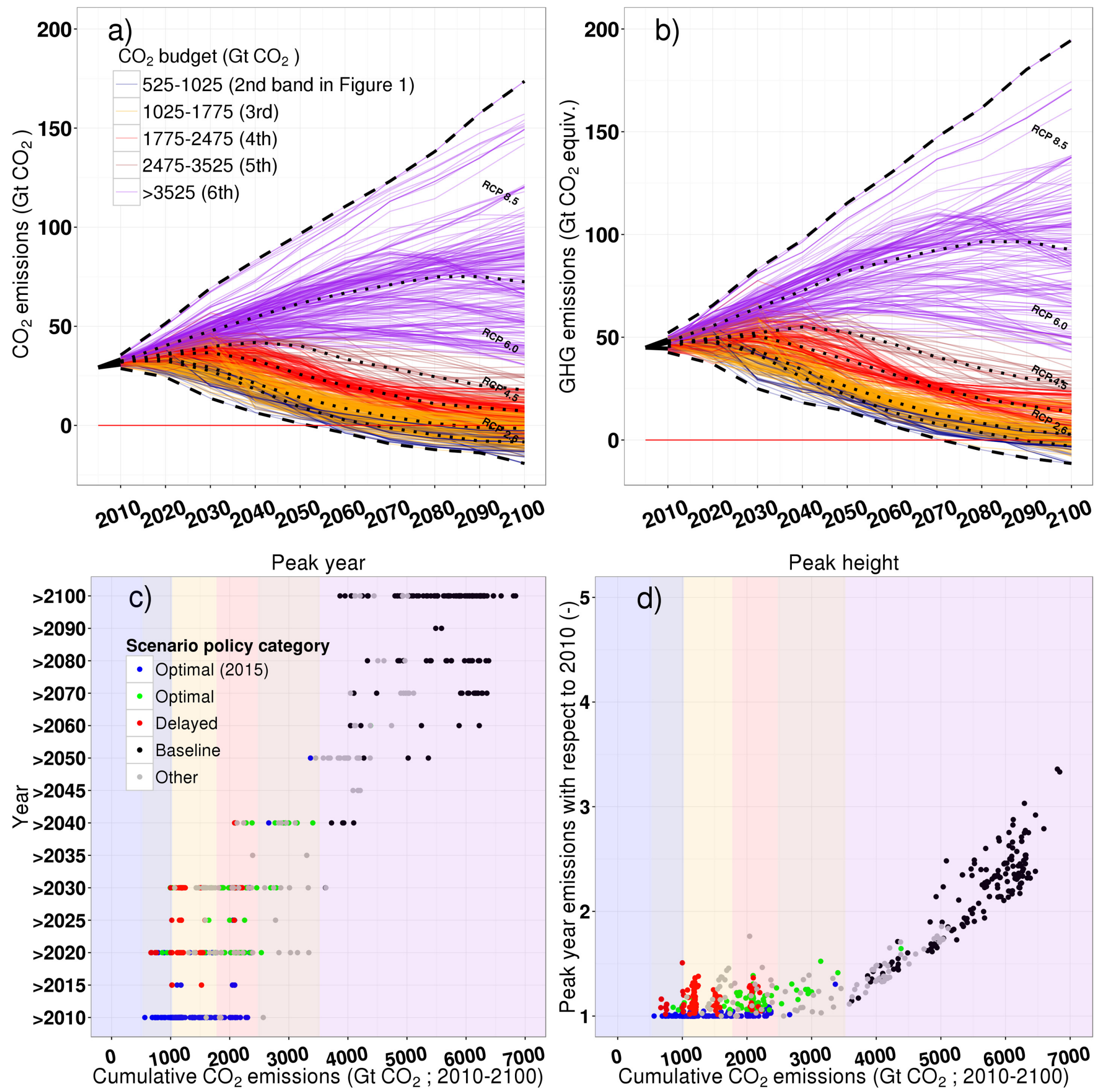

Figure 2. Profiles for CO_2 (panel (a)) and CO_2eq emissions (based on SAR GWP100 as included in the AR5 database, panel (b)) for all scenarios in each of the categories defined in figure 1 (10th–90th percentile), as well as the emission profiles of the RCPs (van Vuuren *et al* 2011). Panel (c) shows the year of the peak in CO_2 emissions, distinguishing optimal and delay scenarios, while panel (d) shows the peak height compared to 2010 emissions. Coloured bands show ranges of cumulative CO_2 emissions consistent with various levels of global-mean temperature increase in 2100, see figure 1 and methods.

The annual emission reduction rate between 2010 and 2050 increases with decreasing cumulative CO_2 emissions (figure 3). Earlier work already showed that average annual emission reduction rates over the full 2010–2050 period do not differ greatly between cost-optimal and delay scenarios, as delay scenarios (developed using models that allow for negative emissions) already catch up with the optimal ones in terms of emission level by 2050 (Riahi *et al* 2015), and compensate for the higher cumulative emissions after 2050. Emission reductions increase steeply for low carbon budgets, but, this critically depends on post-2050 reduction rates and non-CO_2 emission reductions, as will be discussed further. For CO_2 budgets of below 1025 $GtCO_2$, annual emission reductions over the 2010–2050 period are around 2%–6% (computed as compound annual growth rates; range refers to 10–90th percentile). In terms of the decarbonisation rate, i.e. the improvement of the CO_2/GDP ratio over time, the range is between 4.3% and 8.5% per year (figure 3(c)). For comparison, historically, global decarbonisation rates have been mostly around 1%–2% per year (van Vuuren *et al* 2015). Figures 3(a)–(c) also illustrates the influence of the possible negative emissions in the second half of the century, by using a different colour for the scenarios that achieve net negative cumulative emissions over the 2080–2100 period. For low carbon budgets the scenarios with negative emissions (blue) are clearly more frequent than those without (red). There is also some difference in the emission reduction rates (negative emission scenarios show typically lower reduction rates over the full period up to 2050 for a specific carbon budget than those without). At the same time, however, there is a much stronger impact on 2030 emission reduction rates (not shown). The finding that short-term

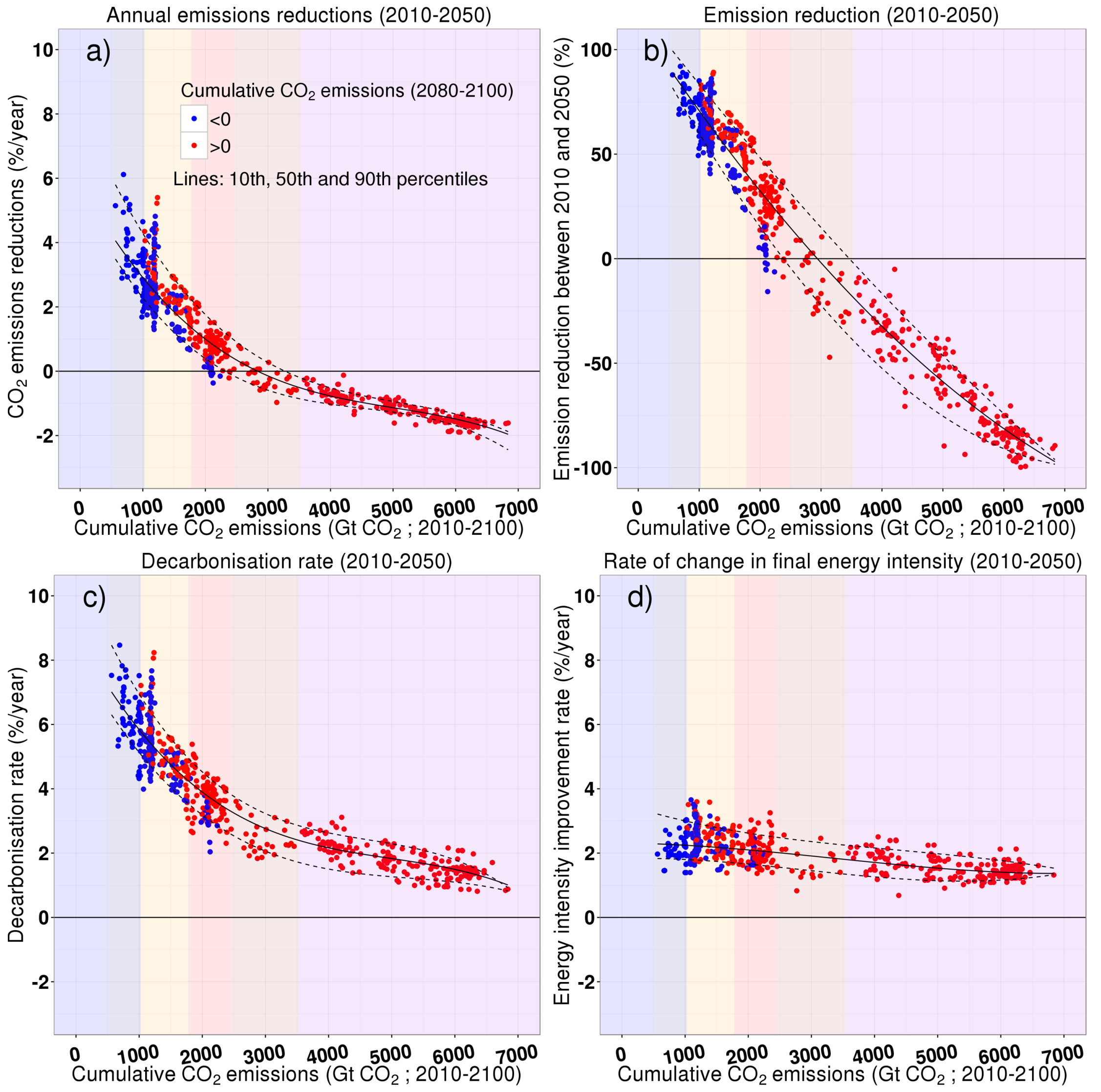

Figure 3. Annual average compound emission reductions rates over the 2010–2050 period, 2050 emission reduction (compared 2050), decarbonisation rate (improvement of CO_2/GDP ratio) and energy intensity improvement rate (energy/GDP ratio) over the 2010–2050 period as a function of the carbon budget. For coloured bands see figure 1 and methods. Fits in panels (a)–(c) show high goodness of fit (0.6 and higher), while the fits in panel (d) are characterised by a reduced one (around 0.25) (see supplementary table S2).

emission reductions consistent with long-term climate targets are dependent on assumptions on long-term mitigation potential (van Vuuren and Riahi 2011, Rogelj *et al* 2013a), is of key importance for international climate negotiations that discuss near-term emission targets.

Finally, scenarios with smaller carbon budgets on average have somewhat higher energy intensity improvements (figure 3(d)), which increase from 1% to 2.5% for high cumulative emissions (budgets above 3500 $GtCO_2$) consistent with the baseline scenario, to between 1.5% and 3% for cumulative emissions below 1775 $GtCO_2$ (comparable to rates achieved in OECD countries during the 1980s). The increase in improvements for energy intensity is clearly less pronounced than for the decarbonisation rate and shows considerable overlap between low and high carbon budgets indicating the importance of fuel substitution (to low carbon fuels) and CCS in low emissions scenarios.

3.3. Non-CO_2 emissions and forcing

A key factor responsible for the spread in 21st-century CO_2 budgets and temperature levels is the forcing of non-CO_2 gases (figure 4(b)). Figure 4(a) indicates that there is a weak correlation between non-CO_2 and CO_2 forcing (r^2 of 0.39 for a linear regression over the whole range), but no correlation at low forcing levels (r^2 of virtually zero for forcing of $<4\ W\ m^{-2}$). The weak correlation arises as a result of common sources of CO_2 and other (non-CO_2) Kyoto gases (e.g. coal and natural gas use) and the multigas policy approach assumed in IAMs calculations (consistent with current policies). The relationship, however, is weak as (1) CO_2 emission reductions are also associated with reductions in SO_2 emissions (which offset part of the

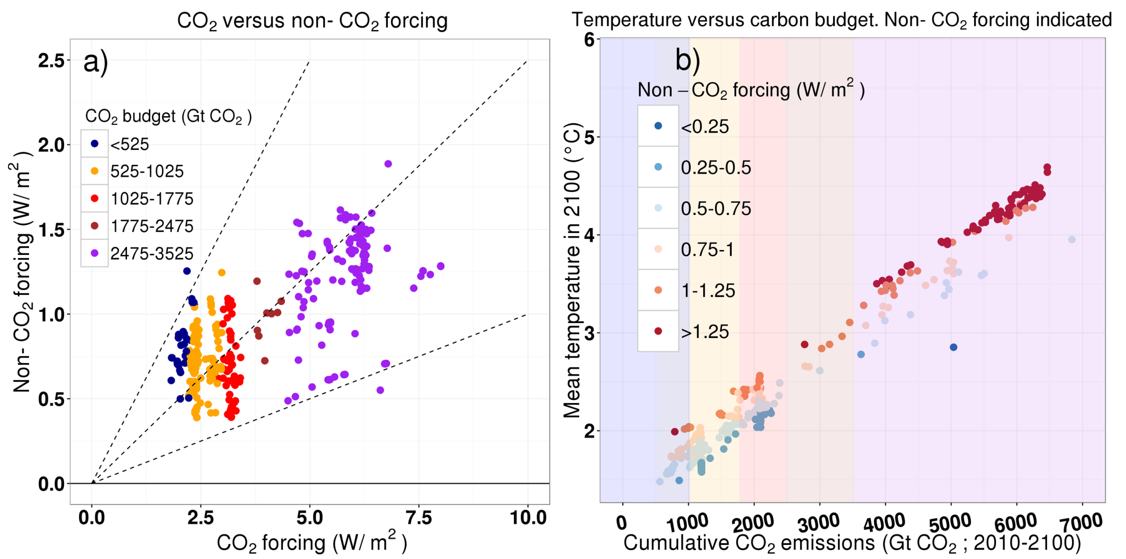

Figure 4. The role of non-CO_2 forcing. Panels show the CO_2 and non-CO_2 forcing in 2100 (lines indicate 33%, 20% and 9% of total forcing coming from non-CO_2 forcing agents) (panel (a)) and the influence of non-CO_2 forcing on the relationship between cumulative CO_2 emissions and temperature (panel (b)). For coloured bands see figure 1 and methods.

CO_2 warming), and (2) in nearly all models, the mitigation potential for CH_4 and N_2O emission reductions is limited and implemented already at moderate carbon prices (up to USD 100/tCO_2eq). Remaining non-CO_2 emissions include, for instance, methane emissions from free roaming cows and emissions associated with the use of nitrogen fertilizers (Smith *et al* 2014, Gernaat *et al* 2015). As a result, similar minimum forcing levels for non-CO_2 gases are reached both under average and stringent mitigation scenarios. This leads to the increasing share of non-CO_2 forcing at more stringent targets (limitations in non-CO_2 reductions in combination with negative emissions slowly reduce the relative contribution of CO_2 forcing towards the end of the century).

3.4. Energy-system transitions

Staying within low-carbon budgets requires an enormous scale up of the contribution of low-carbon emission technologies (figure 5). Low-carbon emissions technologies are here defined as fossil fuels with CCS, renewable energy, bio-energy (including bio-energy with CCS), and nuclear power, consistent with how they are dealt with in most underlying models. For some of these technologies, there is a strong debate on the effective reduction level for CO_2 emissions. First of all, capture rates in CCS are not likely to be 100% effective and leakage may occur from storage sites. Second, several bio-energy application chains lead to greenhouse gas emissions, with current literature providing a wide range of possible values (Smith *et al* 2014). It should be noted that the scenarios use mostly second-generation biofuels and bio-energy as feedstock in electricity production. Most models do account for some emissions for these technologies, but lower than for conventional use of fossil fuels. In presenting the results we distinguish between baseline scenarios, cost-optimal scenarios, and delay scenarios. In 2010, the contribution of bio-energy, renewable energy and nuclear power was around 14% of world energy use, if we include traditional bio-energy (firewood, charcoal, manure and crop residues). Most scenarios expect the use of traditional bio-energy to be reduced over time. This notwithstanding, under scenarios with low carbon budgets the total contribution of low-carbon emission technologies increases rapidly. In the results for 2030, there is a significant difference between scenarios that assume a delay and those that assume immediate (cost-optimal) emission reductions. This difference, however, has disappeared by 2050. The contribution of low-carbon energy technologies in cost-optimal scenarios with cumulative CO_2 emissions from 2010 to 2100 smaller than 1775 GtCO_2 increases to around 100–300 EJ yr^{-1} by 2030 (20%–50% of primary energy use) and to 200–550 EJ yr^{-1} by 2050 (40%–80% of primary energy use). This implies a scale up by a factor of two to four, between 2010 and 2030, and a further doubling between 2030 and 2050. We have made a distinction between optimal scenarios with and without an emission peak in 2015. While some differences are visible between the categories for 2030 for decarbonisation rates and technology deployment levels, no differences can be found for 2050 (figure 6). In the delay scenarios, the scale up in 2030 is less than in the optimal scenarios, but as a result, an even more rapid deployment is needed between 2030 and 2050 to reach similar deployment levels by 2050 to those in the cost-optimal cases (Riahi *et al* 2015). For higher carbon budgets, the share of low-carbon emission energy remains typically at 2010 level (see figure).

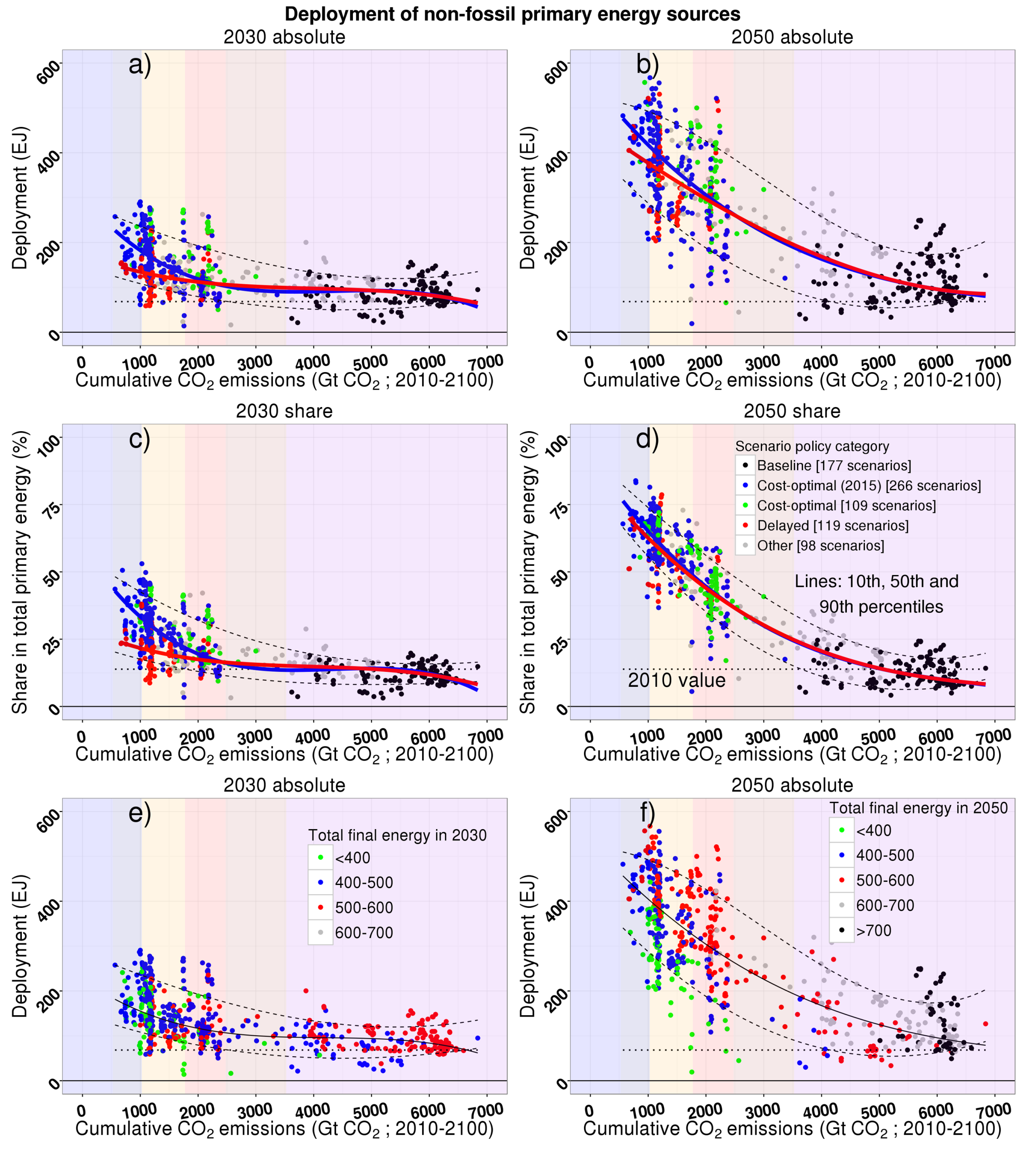

Figure 5. Low-carbon emissions energy use in 2030 and 2050 (primary energy). Panels show (a) and (b) absolute values and (c) and (d) % of total primary energy use for different scenarios categories. Lines indicate the best fit correlation (3rd degree polynomial) for respectively optimal (blue) and delay scenarios (red) , while the dashed lines indicate the 10th–90th percentile for all categories. Panels (e) and (f) show absolute deployment level as function of different levels of energy demand. For coloured bands see figure 1 and methods. Goodness of fit for all regressions is provided in supplementary table S2.

The required scale up depends critically on the volume of energy consumption as shown in figures 5(e) and (f). This is most noticeable for 2050, where the deployment level of low carbon technologies shows a clear gradient under different energy consumption levels; low energy demand levels (e.g. below 400–500 EJ yr^{-1}) lead to considerably less low carbon technology deployment than high energy demand levels. In other words, energy conservation can significantly reduce the demand for low carbon technologies (Riahi *et al* 2012).

In figure 6, we further differentiate the information in terms of different energy technologies, i.e. biomass, non-biomass renewables and fossil fuels with CCS. Again, a distinction is made between delay and cost-optimal scenarios. The share of both bio-energy and non-biomass renewables strongly increases for low cumulative CO_2 emissions, especially in 2050, but also under cost-optimal scenarios in 2030. Total bio-energy use in the cost-optimal response for low CO_2 budgets (<1775 $GtCO_2$) in the scenarios increases to 40–120 EJ by 2030 (or 5%–23% of primary energy, 10th–90th percentile, median of 75 EJ yr^{-1}) and to 75–200 EJ by 2050 (10%–35% of primary energy, median of 140 EJ yr^{-1}). For less stringent budgets, the bio-energy use contribution can be less both in 2030

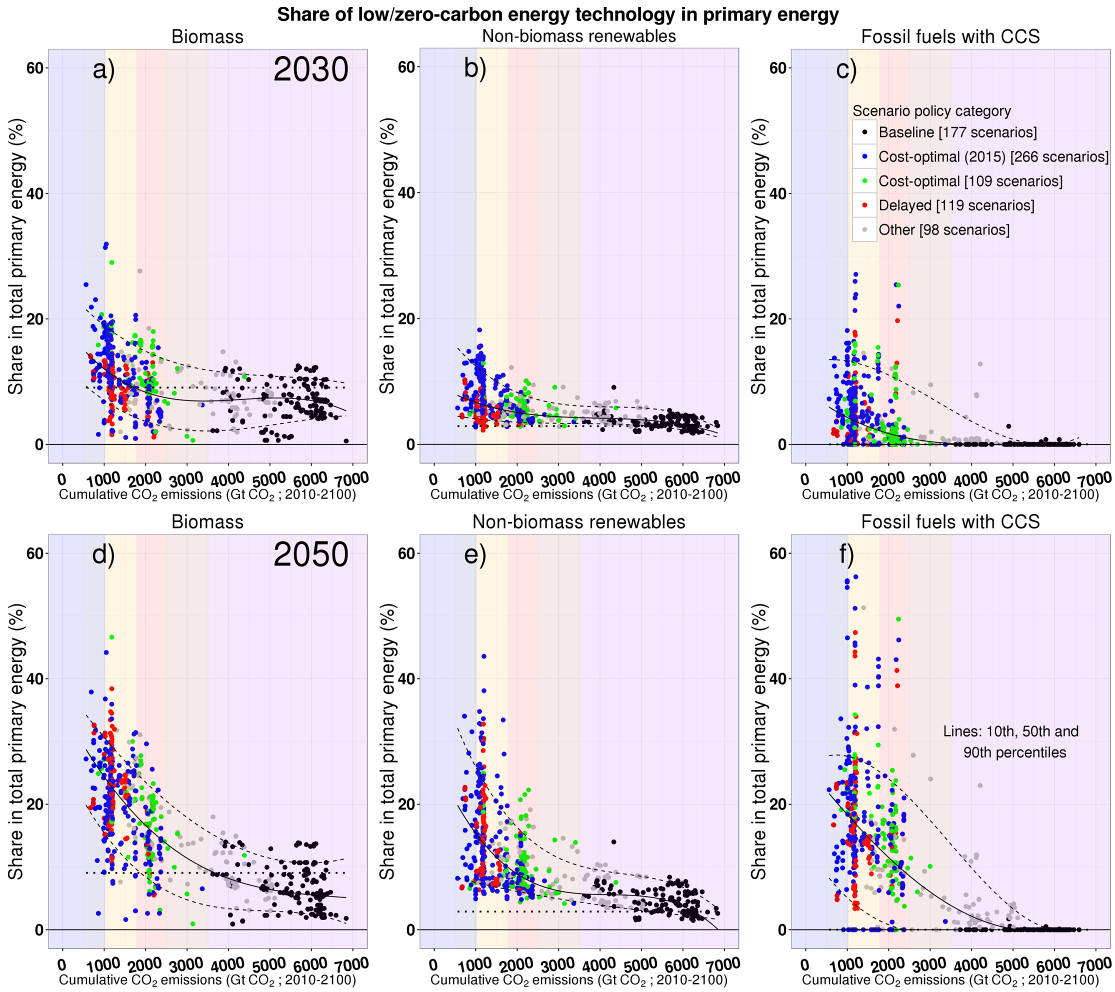

Figure 6. Share of biomass, non-biomass renewable energy and CCS in total primary energy (distinguishing cost-optimal, delay and baseline scenarios). For coloured bands see figure 1 and methods. Goodness of fit characteristics of all regressions are provided in supplementary table S2.

and 2050. Clearly, there has been considerable debate on the land-use impacts of bio-energy production in relation to food production, and biodiversity protection and even the consequences for indirect emissions (see earlier remarks). In some of the IAM models these factors are accounted for, but this should be seen in the context of considerable scientific uncertainties (Searchinger *et al* 2008, Popp *et al* 2014). The recent IPCC report estimated that most likely 100 EJ yr^{-1} could be produced sustainably in 2050, while a high estimate could go up to around 300 EJ. The contribution of all other renewables by 2030 is considerably less than bio-energy. For low carbon budgets, however, their deployment catches up by 2050—indicating a massive scale up over the whole period. The range of deployment for each low carbon technology is very large, as a result of the possibility of substitution.

The same trends are observed for fossil fuels with CCS. Here, the spread is even larger, ranging from no CCS application to deployment levels similar to those of bio-energy or other renewables by 2050. Scenarios with no CCS deployment are the result of specific studies in which CCS deployment is not allowed. Another distinction is that CCS deployment is only observed for the lowest categories—while CCS is hardly used for high carbon budgets (in contrast to the other technologies).

4. Discussion and conclusions

Our analysis depends on IAM scenarios published in the literature over the 2007–2013 period and submitted to the AR5 scenario database. Several limitations are therefore related to potential sampling bias in the scenario set of this database. First of all, our results clearly depend on the subjective assumptions made by researchers publishing IAM model results about future factors that are inherently uncertain. In that context, while models provide (based on these assumptions) information on technological and economic factors that characterize decarbonisation scenarios and the possibility to implement them, they provide little information on socio-political factors that are essential for feasibility in the real world (e.g. the acceptance of large scale CCS use). Another key assumption is development of fossil fuel prices. IAM models mostly focus on long-term trends and many of the models contained in the analysis published in the 2007–2013 period did not use the high fossil fuel prices observed at that time. Similarly, the question whether current low oil prices would influence the results would require an assessment of whether oil prices are expected to remain low over a long period of time. For many models, fossil fuel prices are endogenously calculated and the fossil fuel prices are in fact relatively low in most mitigation scenarios anyway. Results presented here can therefore be expected to be reasonably robust in the light of the recent oil price development. Second, research projects recently have put more emphasis on stringent climate targets than on weak climate targets. As a result—a relatively large share of scenarios is found with cumulative CO_2 emissions of the order of 800–2000 $GtCO_2$. Third, while several research projects have looked into delay scenarios for stringent targets, very few studies looked into delay scenarios for less stringent targets (an exception is (O'Neill *et al* 2010)). Fourth, some research projects and models have contributed more to the database than others, possibly influencing the results with respect to the primary energy mix. For this reason, we looked into the position of those models that have submitted most scenarios to the database in figure 5 (see appendix) and found that indeed some models have a preference for specific technologies. This emphasises the importance of a multi-model approach, including a much wider range for outcomes of individual technologies than provided by single models. Interestingly, no specific model bias can be found for the sum of all low-carbon technologies. Finally, virtually none of the scenarios submitted to the database return warming to below 1.5 °C by 2100 with a likelihood of more than 50%, although a study published more recently provides an overview of such scenarios (Rogelj *et al* 2015a). Overall, however, we consider the conclusions in terms of aggregated characteristics such as decarbonisation rates, the contribution of different gases and the up-scaling of non-CO_2 emitting technologies to be relatively robust against possible biases in method (given the focus on the role of policy-delay and negative emissions). This is, among others, due to the large number of different models represented in the database. Outcomes for specific technologies, however, may depend on common assumptions across the IAM community (e.g. most models assume that CCS technology can be developed at large scale). An important limitation is that the database approach cannot easily handle information on scenarios that were not feasible in a specific model (e.g. due to limited mitigation potential). This problem was noted before in a critical review of the AR4 analysis (Tavoni and Tol 2010). Individual model studies can correct for this by carefully reporting the non-feasible results (Rogelj *et al* 2013a). The more aggregated approach presented here has the advantage of a much higher number of scenarios (and exploration of uncertainty) but makes it more difficult to account for such bias. For this reason, we have not included parameters that may be more sensitive to this issue such as costs, while presented indicators are generally hardly affected. Finally, the results can be prone to collective biases in the IAM models, such as their focus on supply-side technologies. This risk is partly mitigated by the fact that the database includes results from a very large range of models and model types, but it should still be realized that the majority focus on cost-optimal solutions.

The analysis thus clearly shows that for stringent carbon budgets (e.g. those consistent with the goals currently discussed in international policy making) a distinct emission corridor can be identified from scenarios published in the literature. A carbon budget of 1000 $GtCO_2$, for instance, is consistent with an emission peak before 2020 and decarbonisation rates of 4.5%–8% per year. At the same time, the analysis also shows that there is still some flexibility in such indicators, which increases for higher budgets. For low budgets, the difference between cost-optimal and delay scenarios plays an important role for 2030. For 2050, however, this distinction is not so important. Interestingly, the relationship between cumulative emissions and the emission reduction rate seems to be relatively strong, while for the emissions peak, nearly all mitigation scenarios show a very early emission peak. The results show that non-CO_2 forcing is the most important factor determining deviations from the default relationship between cumulative emissions and temperature.

Above all, we show that carbon budgets that are consistent with the 2 °C target, generally, require a massive scale up of low carbon technologies. While this general relationship is obvious, the paper provides key insight into the quantitative characteristics of these relationships, given the current scenario literature. For the 1000 $GtCO_2$ budget, the contribution of such technologies is around 50%–75% in 2050 in the assessed scenarios. For renewable energy, bio-energy and CCS technologies, similar rapid expansions are found, with each of these technologies reaching shares in primary energy use of between 15% and 30% by 2050 (typical median values). The level of deployment, however, clearly depends on energy demand. In low energy demand scenarios, scale up requirements can be halved. The deployment in 2030 depends strongly on the timing of policies. However, delays in mitigation need to be compensated for by more rapid deployment rates over the 2030–2050 period. Previous studies (see references earlier) have shown that this rapid deployment comes at significantly increased transition challenges and a larger amount of stranded fossil fuel assets, leading to overall higher costs. It will therefore be important in the international climate negotiations to identify credible pathways for scaling up demand- and supply-side technologies, even in the short-term, if countries aim to implement the stringent targets now being discussed against relatively low costs.

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