Supplementary information

Carbon budget categories and the scenario database

Table S1 provides an overview of the total number of scenarios in each carbon budget class (shown for illustrative purposes in the various figures). The classes correspond to temperature outcomes assuming medium forcing for non-CO_2 forcing agents (see Methods).

Cumulative Carbon range ($GtCO_2$)	**Number of scenarios**					**Median T outcome range in 2100**
	Total	**Optimal**	**Delay**	**Baseline**	**Other**	
525–1025	71	47	24			[1.49, 2.05]
1025–1775	292	192	81		19	[1.58, 2.41]
1775–2475	155	123	14		18	[2.04, 2.57]
2475–3525	29	12			17	[2.62, 3.11]
>3525	222	1		177	44	[2.78, 5.59]

Specifications and goodness of fit of regressions

TABLE S2: Specifications and goodness of fit values of the regressions shown in all figures. Goodness of fit has been computed by means of a pseudo-R-square value(Koenker and Machado, 1999).

Figure 1	**panel a**	**panel b**				
Degree of polynomial	2	2				
Pseudo-R-square						
10th percentile	0.75	0.70				
50th percentile	0.86	0.85				
90th percentile	0.88	0.88				
Figure 3	**panel a**	**panel b**	**panel c**	**panel d**		
Degree of polynomial	3	2	3	3		
Pseudo-R-square						
10th percentile	0.73	0.81	0.65	0.25		
50th percentile	0.76	0.82	0.72	0.26		
90th percentile	0.67	0.73	0.65	0.26		
Figure 5	**panel a**	**panel b**	**panel c**	**panel d**	**panel e**	**panel f**
Degree of polynomial	3	3	3	3	3	3
Pseudo-R-square						
10th percentile	0.14	0.40	0.20	0.60	0.14	0.40
50th percentile – optimal	0.28	0.50	0.43	0.72	0.22	0.48
50th percentile – delay	0.18	0.55	0.27	0.73		
90th percentile	0.22	0.37	0.35	0.57	0.22	0.37
Figure 6	**panel a**	**panel b**	**panel c**	**panel d**	**panel e**	**panel f**
Degree of polynomial	3	3	3	3	3	3
Pseudo-R-square						
10th percentile	0.08	0.12	~0	0.29	0.25	0.0005
50th percentile	0.17	0.15	0.19	0.39	0.20	0.38
90th percentile	0.24	0.26	0.23	0.35	0.32	0.27

Cumulative CO_2 emissions and IPCC AR5-WG3 scenario categories

In the AR5-WG3 IPCC report, the scenarios submitted to the database were categorized on the basis of expected (median) 2100 forcing levels. If models did not report sufficient information on forcing agents other than CO_2, cumulative CO_2 emissions were used to classify scenarios instead. The CO_2 budget criteria in AR5 are described in the Method and Metrics Annex of the WG3 report(Krey et al., 2014). In the paper, we have looked at the relationships between carbon budgets and a set of policy relevant indicators using a continuous cumulative CO_2 emission axis. The graphs also show, for illustrative purposes, coloured horizontal areas corresponding to specific temperature outcomes on the basis of cumulative CO_2 emissions assuming an average non-CO_2 forcing. Clearly, as a result of different levels of non-CO_2 forcing these classifications and the resulting forcing and temperature outcomes are complex as also illustrated in Figure S1 (indicating the CO_2 budgets, the IPCC categories, the horizontal bars used in the paper and the forcing and temperature outcomes). The correlation, however, is strong enough (R^2 near 0.9) for the illustrative purpose between cumulative CO_2 emissions and temperature outcomes used in the main paper.

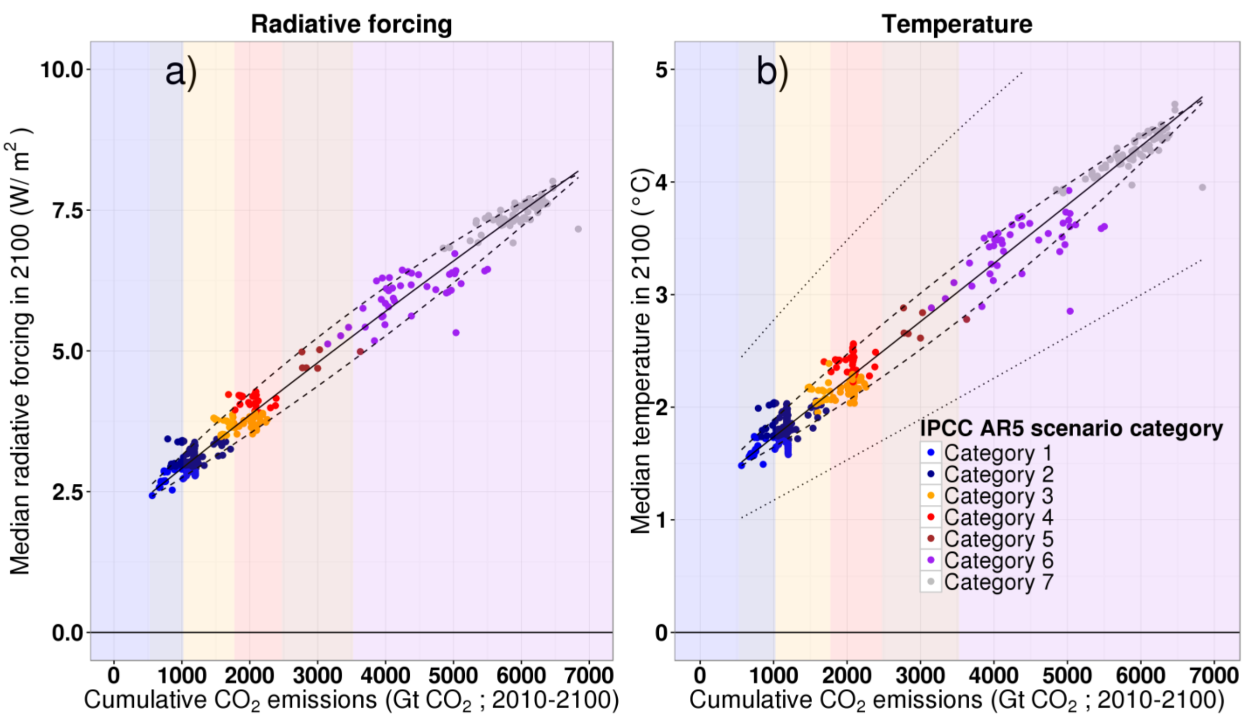


Figure S1: Cumulative CO_2 emissions versus forcing and global mean temperature increase by 2100. The scenarios (dots) are coloured on the basis of the IPCC category assigned in the database. The coloured horizontal areas correspond (from left to right) to staying likely below 1.5, 2, 2.5, 3, 3.5 and >3.5°C on the basis of cumulative CO_2 emissions assuming an average non-CO_2 forcing (see Methods).

21st-century cumulative CO_2 budget vs cumulative budget until the peak

We focused our analysis on the relationship between different pathways and cumulative CO_2 budgets over the 2010–2100 period. These CO_2 budgets correlate well with the 2100 temperature outcome. The maximum temperature during the 21st century (peak temperature) is also often used as a key indicator in addition to the 2100 temperature in the literature. In the figure below, we show peak temperature against the 2010–2100 cumulative emissions and the cumulative emissions over the period between 2010 and the moment of peak temperature (panel c and panel d). For the overall range of scenarios, the differences between the different graphs are relatively small. This can be easily understood, as for high emission scenarios, the maximum 21st-century temperature actually occurs in 2100 (although by then the temperature not yet will have peaked but will continue to increase after 2100). Stringent scenarios, however, show a clear difference, and cumulative CO_2 emissions until the peak show a stronger relationship than the 2010–2100 budget. Nevertheless, the 21st-century emissions and peak temperature also show a reasonable correlation.

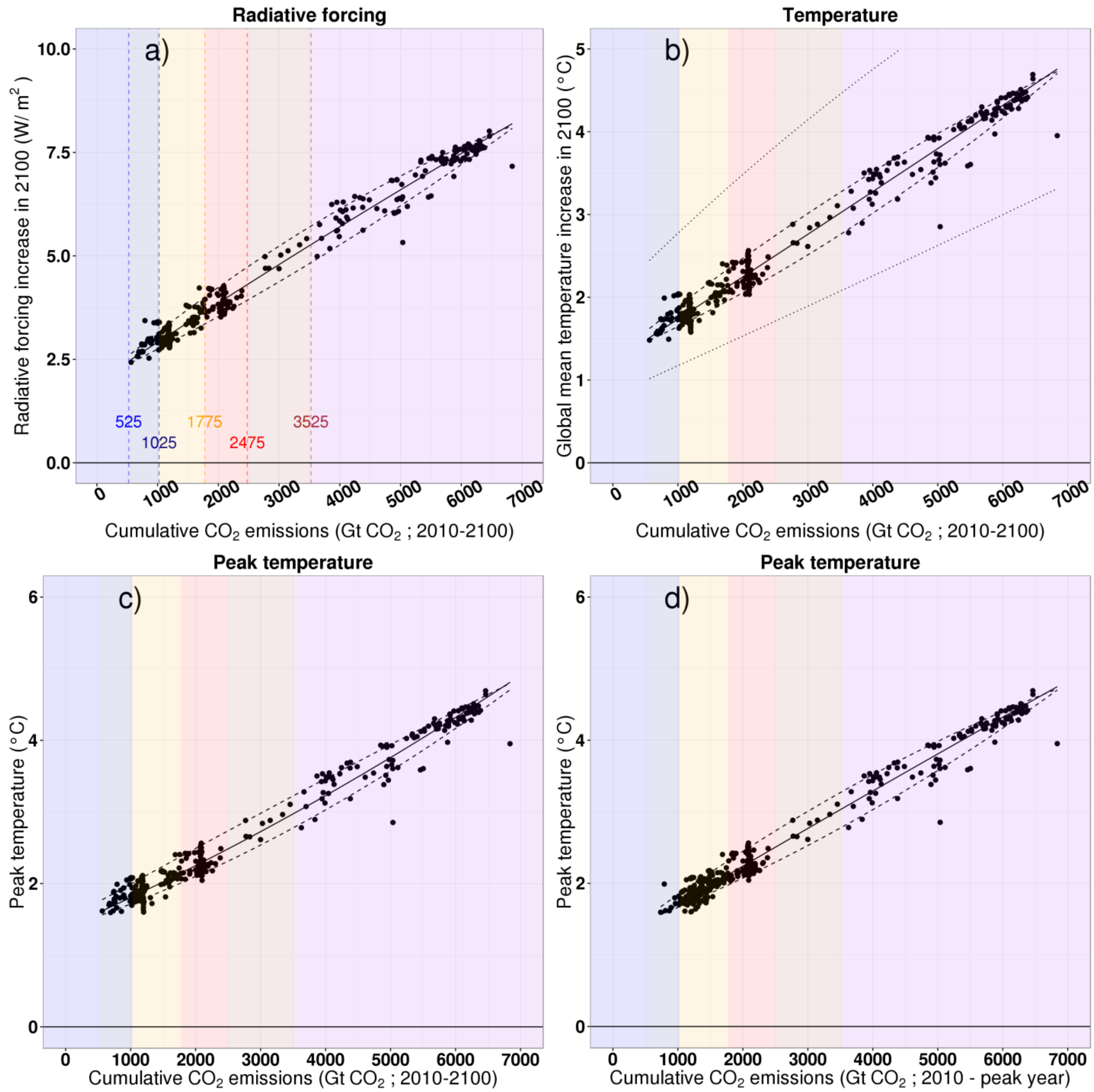
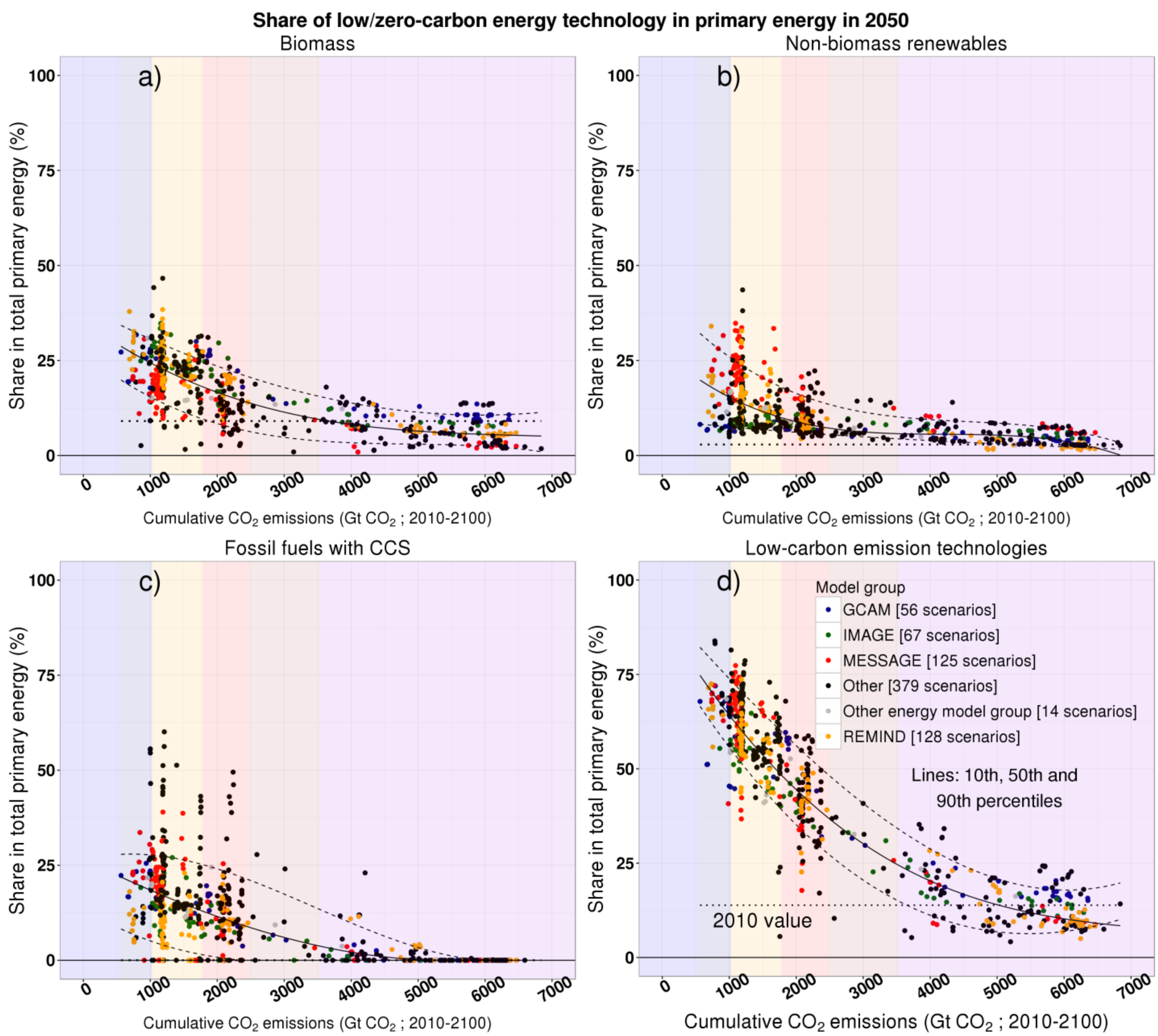


Figure S2: Cumulative CO_2 emissions versus 2100 temperature and the maximum in the 21st century (peak temperature).

Influence of model bias

In the AR5 database, a very wide range of different models have contributed to the results. As it has been noticed earlier that individual models can have a specific preference for specific technologies we have looked into the model dependence of the results. So-far, studies suggest that the model itself (and its assumptions) tend to have a larger influence than the type of model. In Figure S3 we have plotted the results of the models that contributed the most scenarios to the database, a group of energy system model output and other models. It can be seen that indeed typical model outcomes can be found in panel a, b, and c (for example, the REMIND model is typically high on biomass consumption while the MESSAGE model relies more on non-biomass renewables). However, at the level of the sum of low-carbon emissions technologies this bias cannot be seen anymore (as here the overall requirements of meeting energy demand and reducing greenhouse gas emissions force models to move towards a more robust finding). The Figures shows that using a range of models – as done in the AR5 database – is important to avoid specific preferences for individual technologies.



Koenker, Machado (1999) Goodness of Fit and Related Inference Processes for Quantile Regression. . Journal of the American Statistical Society 94:1296-1310.

Krey V, Masera O, Blanford G, et al. (2014) Annex II: Metrics & Methodology. in Edenhofer O, Pichs-Madruga R, Sokona Y, et al. (eds.) Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.