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Comparing future patterns of energy system change in 2 °C scenarios with historically observed rates of change

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ABSTRACT

This paper systematically compares modeled rates of change provided by global integrated assessment models aiming for the 2 °C objective to historically observed rates of change. Such a comparison can provide insights into the difficulty of achieving such stringent climate stabilization scenarios. The analysis focuses specifically on the rates of change for technology expansion and diffusion, emissions and energy supply investments. The associated indicators vary in terms of system focus (technology-specific or energy system wide), temporal scale (timescale or lifetime), spatial scale (regional or global) and normalization (accounting for entire system growth or not). Although none of the indicators provide conclusive insights as to the achievability of scenarios, this study finds that indicators that look into absolute change remain within the range of historical growth frontiers for the next decade, but increase to unprecedented levels before mid-century. Indicators that take into account or normalize for overall system growth find future change to be broadly within historical ranges. This is particularly the case for monetary-based normalization metrics like GDP compared to energy-based normalization metrics like primary energy. By applying a diverse set of indicators alternative, complementary insights into how scenarios compare with historical observations are acquired but they do not provide further insights on the possibility of achieving rates of change that are beyond current day practice.

1. Introduction

Keeping temperature increase to less than 2 °C with a high likelihood will require substantial changes in energy and land use. Integrated assessment model (IAM) studies on mitigation scenarios can provide insights into the level of the required change over time. IAM-based studies often conclude that the required transition for reaching the 2 °C target is 'technically feasible', depending on the model set-up and assumptions. In the past, such studies generally considered rather idealized conditions such as full participation of all regions and sectors in climate policy. However, more recently, models have also studied the achievability of the 2 °C target under less idealized circumstances assuming limits in technology availability or reduced participation in international climate policy (Clarke et al., 2009; Kriegler et al., 2013b; Riahi et al., 2015; Weyant and Kriegler, 2014). Even in those cases, most models still identify scenarios that reduce emissions in line with the 2 °C target. It should, however, be noted that in their assessment, IAMs mostly account for technological and economic factors that can be easily included in the models. These factors include, for example, mitigation potentials, capital stock turnover

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Table 1
Overview of technology change indicators included for study.

Indicator	Variations	Reference	Metric
(a) Average annual capacity addition	Average annual capacity addition	Eq. (1)	GW/yr
	Normalized average annual capacity addition	Eq. (2)	GW/yr/ $
(b) Technology diffusion	Normalized extent and duration (Δt)	Eq. (3)	GW/EJ/yr
(c) Average annual emission decline rates	Average annual emission decline rate	Eq. (4)	%/yr
	Normalized average annual emission decline rates	Eq. (5)	%/yr
(d) Average annual supply-side investments	Average annual supply-side investments	Eq. (6)	$/yr
	Normalized average annual supply-side	Eq. (7)	%/yr

rates, mitigation costs and inertia in investments patterns. Several other factors are not included such as the role of international negotiations, societal inertia or the time associated with decision-making processes on the one hand and behavioral changes on the other. Clearly, such factors can have a substantial influence on the probable (future) rate of change.

Historically observed rates of change can be important reference points for assessing the difficulty associated with future rates of change – providing possibly also insights in real world factors not covered in the models. In fact, several studies have already tried to compare model results and historical data using different indicators (Kramer and Haigh, 2009; Loftus et al., 2014; Riahi et al., 2015; Tavoni and van der Zwaan, 2009; van der Zwaan et al., 2013; Van Vuuren and Stehfest, 2013; Wilson et al., 2012). In these studies different methods and data sets have been used to confront existing scenarios with historical evidence, meaning that their results and conclusions cannot be easily compared. For instance, Van Vuuren and Stehfest, 2013; Riahi et al., 2015 looked at overall change in emissions or emission intensity. In contrast, the studies of van der Zwaan et al. and Wilson et al. look at absolute and relative changes in the deployment of particular energy technologies. It should also be noted that model comparison projects have shown that models select different pathways in achieving similar goals, and that models can be 'diagnosed' as being more or less responsive to climate policy (Kriegler et al., 2015). In order to represent model uncertainty, it is therefore important to compare the results of a diverse set of IAMs against a standardized set of historical indicators.

In this light, the goal of this study is (1) to systematically compare several methods that use historical evidence as a basis for analyzing the difficulty associated with future energy transitions and (2) to use these methods for evaluating model results. We use the results of a multi-model study to provide insight into the uncertainty resulting from a wide diversity of technology trajectories that are consistent with the 2 °C target. Questions that are addressed are:

- How do historical rates of change compare to future rates of change required under the 2 °C climate objective?
- Do various indicators of technology change depict a coherent storyline?

2. Methodology

2.1. Comparing historical and future rates of change

Historical observations provide an important reference point for the required level of effort to achieve future energy system changes associated with ambitious climate policy objectives. To date, different indicators have been used to compare historical trends with future rates of change, varying in terms of system focus (technology-specific or energy system wide), temporal scale (timescale or lifetime), spatial scale (regional or global) and normalization (accounting for entire system growth). In order to gain a more holistic insight from these analyses we combine and harmonize the methods to encompass an overall similar scope of research. In the following paragraphs the various methods are described first followed by how they are interpreted in the current study. Table 1 and Table 2 provide summaries of the metrics used and scope of study. Fig. 1 provides a visual example of the introduced methods.

2.1.1. Average annual capacity addition

Van der Zwaan et al. investigated historical and future capacity growth by comparing the average annual capacity additions (in GW/yr) in a multi-model context for low-carbon technologies for the short-term (2010–2030) and medium-term (2030–2050) (van

Table 2
Overview of methodologies and the scope of this study.

Indicator	System focus	Temporal scale	Spatial scale	Normalization (Metric)[b]
(a) Average annual capacity addition	Technology specific	Annual[a]	Global	No
	Technology specific	Annual[a]	Global	Yes (GDP)
(b) Technology diffusion	Technology specific	Lifetime	Global	Yes (Primary Energy)[c]
(c) Average annual emission decline rate	Energy system	Annual[a]	Global/National	No
	Energy system	Annual[a]	Global/National	Yes (GDP)
(d) Average annual supply-side investments	Energy system	Annual[a]	Global	No
	Energy system	Annual[a]	Global	Yes (GDP)

[a] On average over a selected period of time.
[b] This study depicts GDP throughout the results as the measure of growth, other metrics of growth are further discussed in Section 4.2.
[c] Normalization only available for primary energy as system growth metric.

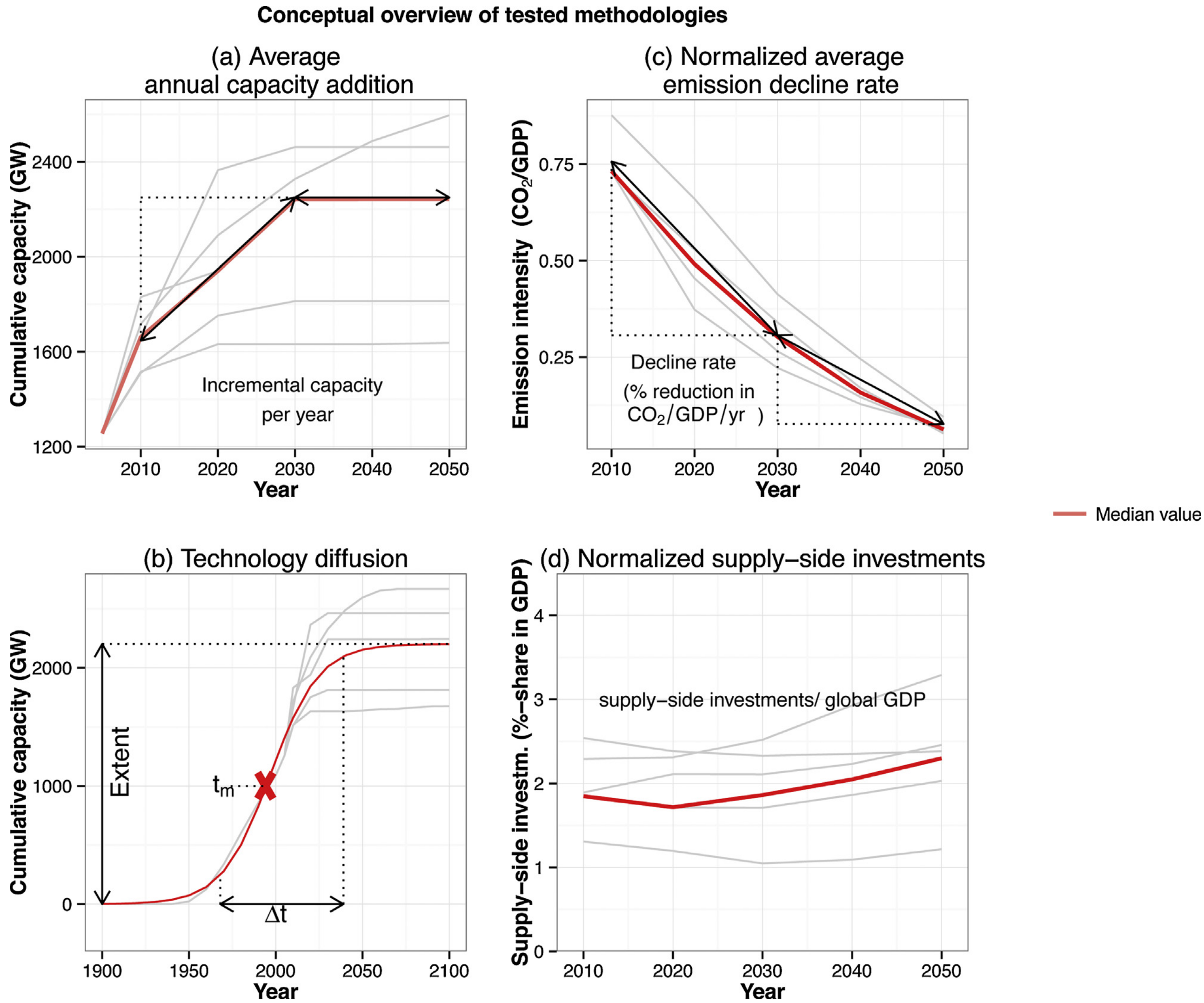


Fig. 1. Conceptual overview of the methodologies and key indicators. Panel (a) and (b) represent cumulative capacity of coal without CCS. Although the figure demonstrates future (modeled) trends the analysis is similar for historical trends.

der Zwaan et al., 2013). The study focused on the absolute rate of change required to reach the 2 °C target compared to rates experienced during historical periods of rapid expansion for established technologies (e.g., natural gas power) and newer technologies (e.g., solar power). The comparison provided easy interpretable insights into the expansion rate for future deployment versus historical figures published in literature and online databases (e.g., EPIA, 2014; Platt's, 2013; US EIA, 2014).

The average capacity addition over a selected period of time (where t_0 and t_n represent respectively the starting and ending point of the timeframe under study) is defined as (see Eq. (1)):

Average annual capacity addition

$$= \frac{\sum_{t=t_0}^{t_n} (\text{newly installed capacity})_t}{t_n - t_0} \; (\text{in GW/yr}) \tag{1}$$

Using this approach, van der Zwaan et al. (2013) concluded that future global expansion rates need to increase significantly, reaching expansion rates well beyond those observed historically in order to stay below the 2 °C target. In particular the expansion of renewable energy technologies would need to be several times larger than the historical rate.

The comparison of absolute future rates with historical rates does not correct for the general growth in the size of the energy or electricity system. It is possible to account for the overall growth by normalizing the absolute indicators with metrics representing total system growth as presented in Eq. (2). Normalization metrics that can be used to represent total system growth are, for example, global GDP (in T$), global primary energy demand (in EJ), total electricity generation capacity (in GW) and total capital investments in the energy system (in billion USD$). For reading considerations, we predominantly use global GDP in the presented outcomes in this study, but discuss the other metrics in Section 4.2.

Normalized average annual capacity addition

$$= \frac{\sum_{t_n=t_0}^{t_n} \left(\frac{\text{Newly installed capacity}}{\text{Normalization metric}}\right)_t}{t_n - t_0} \; (\text{in GW/metric unit/year}) \tag{2}$$

A similar analysis has been done by Loftus et al. (2014), who normalized electricity capacity deployment rates in various global decarbonization scenarios using global GDP. In their study they found that the rates of change are broadly consistent with historical experience. Only specific decarbonization scenarios with imposed restrictions on the implementation of clean and

Table 3
Key model characteristics.

Name	Time horizon	Model category	Intertemporal Solution Methodology
IMAGE	2100	Partial equilibrium	Recursive dynamic
MESSAGE	2100	General equilibrium	Intertemporal optimization
REMIND	2100	General equilibrium	Intertemporal optimization
TIAM-ECN	2100	Partial equilibrium	Intertemporal optimization
WITCH	2100	General equilibrium	Intertemporal optimization

carbon sequestration technologies would lead to unprecedented rates of change for the remaining eligable low-carbon energy technologies (Loftus et al., 2014).

2.1.2. Technology diffusion

Technology growth dynamics are generally characterized by S-shaped curves that show an initial 'formative' phase, followed by rapid diffusion in an 'upscaling' phase and finish into a mature 'growth' phase (Grübler et al., 1999; Wilson, 2012). Growth rates vary over this technology lifecycle, beginning slowly until a lift-off point is reached and growth accelerates. After some time, an inflection point is passed and growth rates level off and eventually saturate, reducing growth to zero.

In this light, Wilson et al. (2012) compared historical and future dynamics of technology diffusion in the energy system by fitting logistic growth curves (with a R-squared fit of 98% or higher) to cumulative capacity time series. The advantage of using cumulative capacity over the technology's lifecycle, as opposed to installed capacity or growth rates during particular time periods, is that short-term volatility and potential selection biases towards specific periods of growth are avoided.

The (symmetrical) logistic function used in this approach is portrayed by Eq. (3). The parameters defining the logistic growth curve are of particular interest, as each parameter represents a specific growth characteristic used in this comparison approach. For example, the parameter defining the steepness of the curve represents the diffusion rate, whereas the parameter defining growth between 10% to 90% of saturation represents the duration of diffusion (also depicted as Δt) and the parameter describing the theoretical asymptote represents the extent of growth or saturation point of a technology (see Eq. (3), Fig. 1 and Supplementary information). To account for the growing size of the energy system, Wilson et al. (2012) normalized the extent of diffusion by the size of the energy system (expressed in primary energy) at the midway point of each technology's lifecycle (the inflection point t_m). The normalized extent and Δt create the extent-duration relationship for the number of technologies included.

$$\text{Technology diffusion} = \frac{\left(\frac{\text{Extent}}{\text{Normalization metric}_{t_m}}\right)}{(1 + e^{-\text{diffusion rate}\times\Delta t})} \tag{3}$$

The main disadvantage of this methodology is that it is not readily comparable to recent observations or to maximum or frontier growth rates over short time periods. Moreover, only historical and future technologies that expose S-curve growth behaviors are included in the analysis. This excludes, for example, wind and solar power technologies which remain to have a rapid growth rate in an expanding energy system and therefore do not conform to S-curve behavior within the time horizon of the model.

The results from the methodology applied by Wilson et al. (2012) showed that the full lifecycles of advanced power generation technologies as modeled in many future scenarios have longer durations than the full lifecycles of energy technologies that have diffused historically. In other words, there is evidence that deep decarbonization scenarios may be somewhat conservative in their long-term technology growth dynamics. However, the authors acknowledged several caveats, including the possibility that comparing long-run historical growth with long-run future growth in this way is problematic. This was specifically the case for the analysis of coal or nuclear power, which combined historical and future growth dynamics in the logistic fitting procedure.

2.1.3. Average annual emission decline rate

An indicator often used to gain insight into economy-wide changes is the average annual emissions decline rate (Riahi et al., 2015; Van Vuuren and Stehfest, 2013). We define this indicator as given in Eq. (4). Similar to the annual capacity additions (described in Section 2.1.1) we consider the average annual decline rate over a selected period of time (where 'Emissions' describe the total CO_2 emissions and t_0 and t_n represent respectively the starting and ending point of the timeframe under study).

$$\begin{aligned}&\text{Average annual emission decline rate}\\&= \left(1 - \left(\frac{\text{Emissions}_{t_n}}{\text{Emissions}_{t_0}}\right)^{\frac{1}{t_n - t_0}}\right) \times 100\ (\text{in}\ \%/\text{yr})\end{aligned} \tag{4}$$

To account for system growth changes this study also considers the normalized version of the average annual emission decline rate (which is also known as either the intensity decline rate or decarbonization rate if GDP is considered as the normalization

Table 4
Overview of selected historical timeframes per indicator and the used databases

Indicator	Technology	Historical reference	Source
(a) Average annual capacity addition	PV	2003–2013	EPIA (2014)
	Wind	2003–2013	GWEC (2014)
	Nuclear	1980–1990	Platt's (2013)
	Biomass	2005–2011	US EIA (2014)
	Fossil	2003–2012	Platt's (2013)
	CCS	–	–
(b) Technology diffusion	PV	1970s	Wilson et al., (2012)
	Wind	1970s	
	Nuclear	1950s	
	Fossil	Early 1900s	
(c) Average annual emission decline rate	System	1970s–2000	Riahi et al., (2015)
(d) Average annual supply-side investments	System	2000–2013	IEA (2014)

Table 5
Overview of normalization metrics, available historical timeframe and source.

Method	Metric	(Historical) timeframe	Source
Normalization	GDP	1980–2012	The World Bank (2015)
	Primary Energy	1980–2012	US EIA (2014)
	Investments	2000–2013	IEA (2014)
	Capacity|Electricity	1980–2012	US EIA (2014)

metric) (see Eq. (5)).

$$\text{Normalized average annual emission decline rate} = \left(1 - \left(\frac{\left(\frac{\text{Emissions}_{t_n}}{\text{Normalization Metric}_{t_n}}\right)}{\left(\frac{\text{Emissions}_{t_0}}{\text{Normalization Metric}_{t_0}}\right)}\right)^{\frac{1}{t_n - t_0}}\right) \times 100\,(\text{in}\,\%/\text{yr}) \quad (5)$$

The disadvantage of this generic descriptive indicator is that details on underlying drivers of emissions are not visible. Moreover, as emission reduction and emission intensity decline rates have not been major policy goals in the more distant past, a comparison against the long-term historical record can be regarded as having limited relevance. Nevertheless, the study by Van Vuuren and Stehfest (2013) used historical comparisons to conclude that emission reductions as well as decarbonization rates for scenarios consistent with the 2 °C target can be regarded as extremely rapid compared to historical rates of change.

2.1.4. Average annual supply-side investments

Structural changes in the energy system are associated with increasing supply-side investments. As investments are also needed to achieve other social and economic goals there could be constraints in the required pace of change. Therefore, we look into the global investments into electricity generation and supply (including electricity storage and transmission and distribution, but not investments into the fossil fuel extraction sector nor the bio-energy fuel supply costs) to assess the efforts needed to mobilize an energy system transformation that is in line with the 2 °C objective. Demand-side investments are not taken into account as such estimates are subject to considerable uncertainty due to a lack of reliable statistics and definitional issues (McCollum et al., 2013). The general approach is described by Eq. (6) for which the average annual supply-side investments are calculated (where t_0 and t_n represent respectively the starting and ending point of the timeframe under study):

$$\text{Average annual supply} - \text{side investments} = \frac{\sum_{t=t_0}^{t_n}(\text{supply} - \text{side investments})_t}{t_n - t_0}\,(\text{in}\,\$/\text{yr}) \quad (6)$$

As the total amount of investments is coupled to the size of the economy, we normalize the annual supply-side investments (see Eq. (7)). If global GDP is considered as the normalization metric this creates an indicator reflecting investments as percentage in total GDP.

$$\text{Normalized average annual supply} - \text{side investments} = \frac{\sum_{t=t_0}^{t_n}\left(\frac{\text{supply}-\text{side investments}}{\text{Normalization metric}}\right)_t}{t_n - t_0}\,(\text{in}\,\$/\text{metric unit/year})) \quad (7)$$

McCollum et al. (2013) examined absolute rates of change for investments in more detail, concluding that future investment levels remain consistent on the short term although significant increases in investments in both developed and developing countries will be necessary over the next decades under the 2 °C objective.

2.2. Comparing future technological change to historical references

2.2.1. Future rates of change

We demonstrate the indicators by using three scenarios from a five-model study with varying assumptions on long-term international climate policy. A marked advantage of the multi-model approach is that it inherently accounts for technology biases and preferences among individual models. The study here, however, is not a model comparison: we only include the model range as an indication of the uncertainty in model results. We therefore do not discuss the results of individual models in any detail. The focus in the figures is also on the median of the range of model results.

The five global energy-environment models included in this study are: REMIND:(Bauer et al., 2013; Luderer et al., 2013); MESSAGE: (Messner and Strubegger, 1995); IMAGE: (Bouwman et al., 2006); WITCH: (Bosetti et al., 2006) and TIAM-ECN: (Keppo and van der Zwaan, 2011)) (see Table 3). These five models represent a diverse array of different solution frameworks (general equilibrium, partial equilibrium, dynamic recursive, perfect foresight and systems engineering) and differ in a variety of model characteristics, such as coverage of sectors and their disaggregation and in technological and socio-economic assumptions that determine technology diffusion.

The three scenarios that are used in this study are based on different policy assumptions for long-term international climate policy and have been developed as part of the LIMITS project (Kriegler et al., 2013a).

(1) The baseline (*Baseline*) scenario addresses the future energy system and emission developments in the absence of climate policy. This scenario is a best reference for historical rates of change as no climate policy is involved.
(2) The second (*Reference*) scenario reflects current (unilateral) climate policy implementation based on national energy and climate targets for 2020 formulated as unconditional Copenhagen pledges. These targets are then extrapolated post-2020 by assuming similar levels of stringency in the subsequent decades. This scenario represents the current day situation and imposes no additional (technological) restrictions.
(3) The third (*2 Degrees*) scenario is a cost-optimal mitigation scenario that assumes immediate global cooperation toward the long-term target of 2 °C. This scenario represents the most optimistic view on technology availability, availability of carbon sinks and (bio-) resources to attain the 2 °C climate target.

Differences are created due to the varying assumptions on long-term international climate policy, all other factors, such as the penetration and expansion rates of technologies, are treated the same across all scenarios.

The methods and indicators set out in Section 2.1 are comparatively applied on this set of three scenarios. As timing

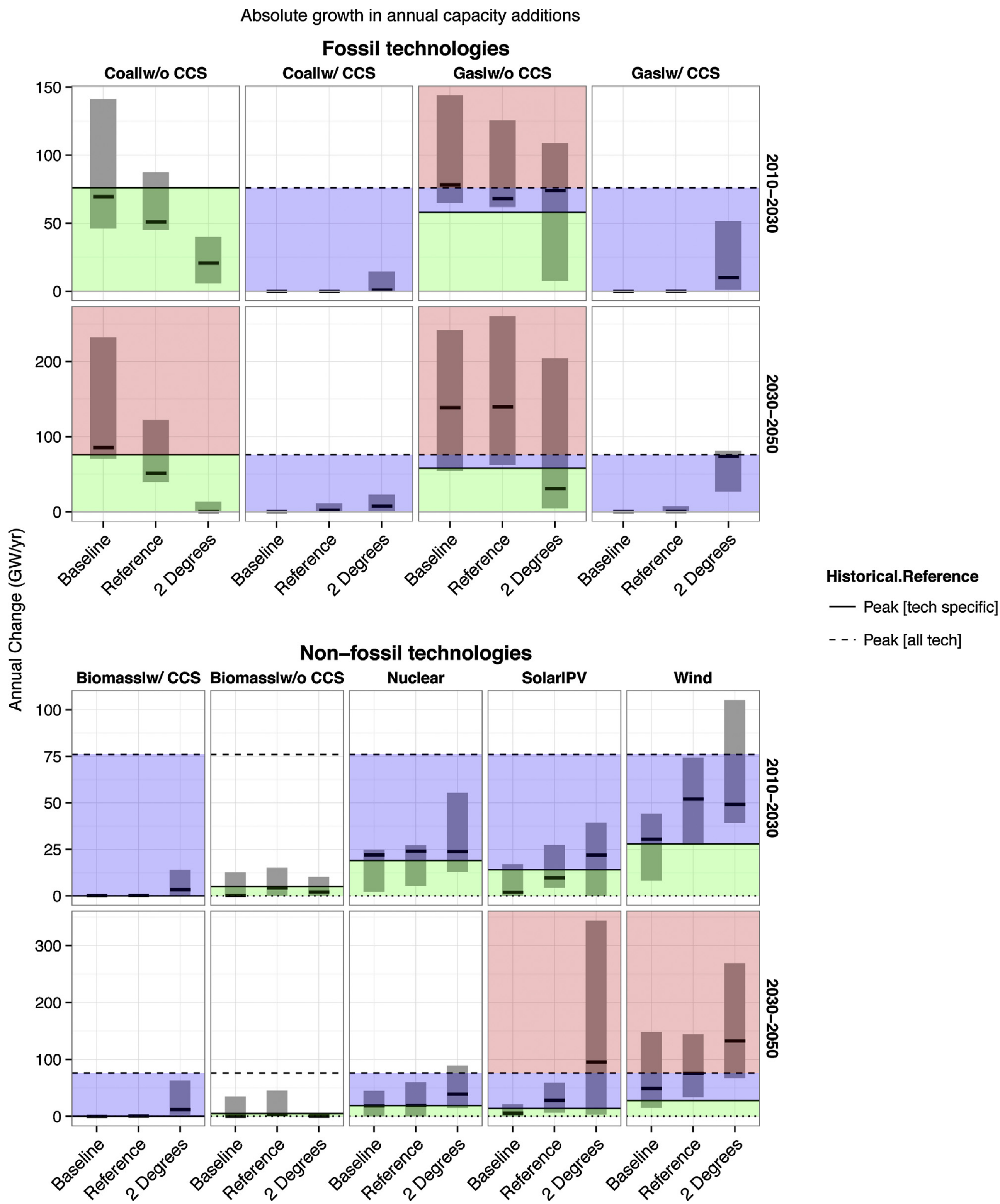


Fig. 2. Average annual capacity additions (over the 2010–2030 and 2030–2050 period) for various electricity-generation technologies under different climate policy assumptions. The horizontal lines indicate the technology-specific peak or maximum value observed historically (solid lines) and the peak value across all technologies which is given by coal without CCS (dotted lines). The green, blue and red areas indicate whether a historical benchmark has been exceeded (red for all-technology peak, blue for technology-specific peak) or not (green). The bars indicate the range of modeled rates of change with the median value highlighted in black inside the bars. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of change is important this study has restricted the analysis to the time period between 2010 and 2050 because it is considered most relevant for current policy and decision making.

2.2.2. Historical references

For the average annual capacity addition indicator, we reconstruct a similar analysis to that of van der Zwaan et al. (2013) by comparing modeled average annual rates of change in

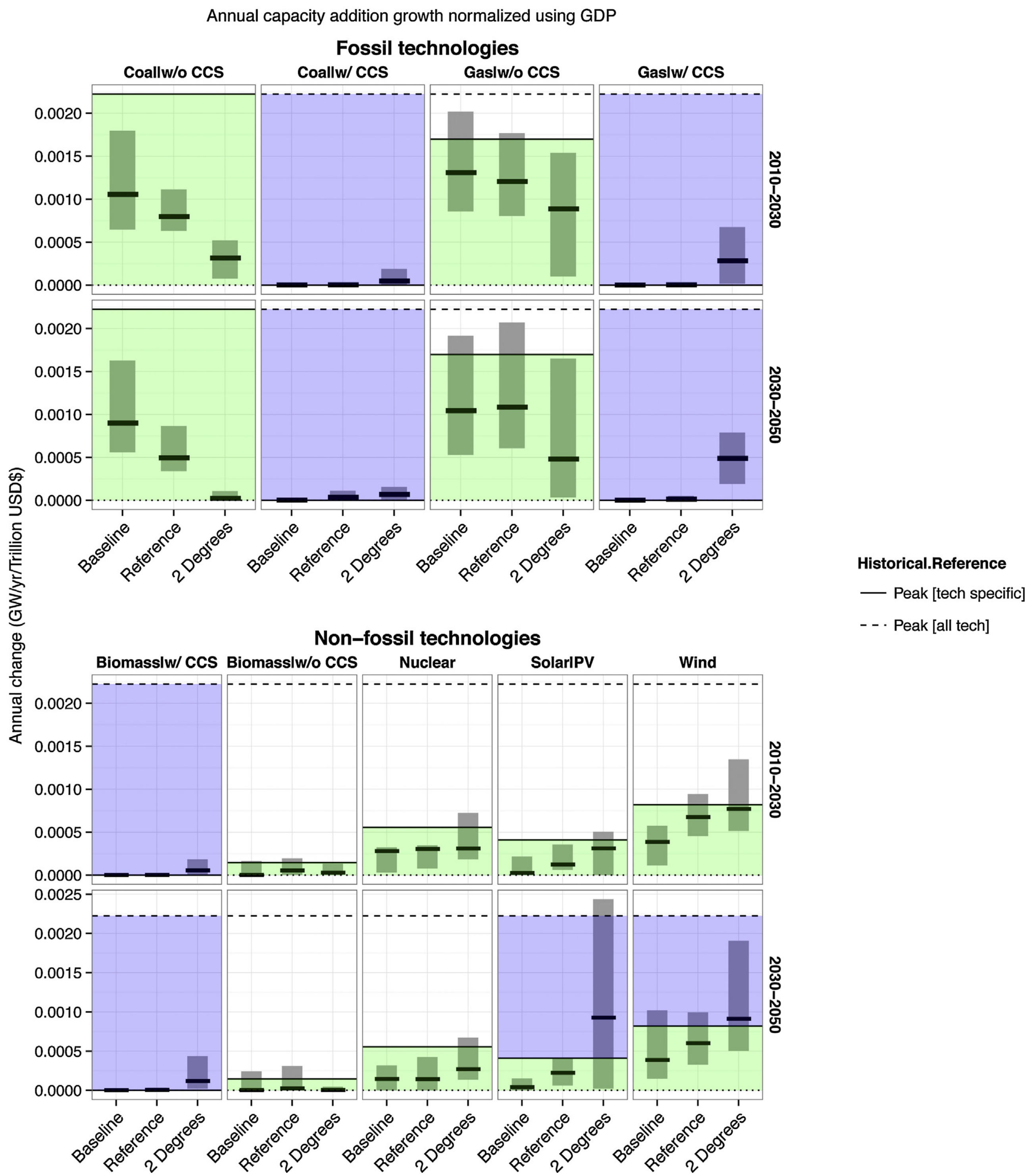


Fig. 3. Average annual capacity additions (GW/yr), normalized using GDP (in trillion US$2005) for both historical data as well as scenario projections. The horizontal lines indicate the technology specific maximum value and the maximum value of any technology in the past. The green, blue and red areas indicate whether a historical benchmark has been exceeded (green below technology specific rate; blue above technology specific rate; red above the historical rate of any technology). The bars indicate the range of modeled rates of change with the median value highlighted in black inside the bars. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

total new installed capacity to historical average annual rates of change. Several databases provided historical data on various technologies (see Table 4) of which the decade with the largest absolute growth in capacity is selected for further analysis.

For the technology diffusion indicator, similar logistic growth curves are constructed as in Wilson et al. (2012) on both historical (if applicable) and future time series. The historical time series begin as far back as the early 1900s (natural gas and coal power), the 1950s (nuclear power), the 1970s (wind power and solar PV), or start no sooner than the 2020s or later (CCS—thus fully based on modeled data only).

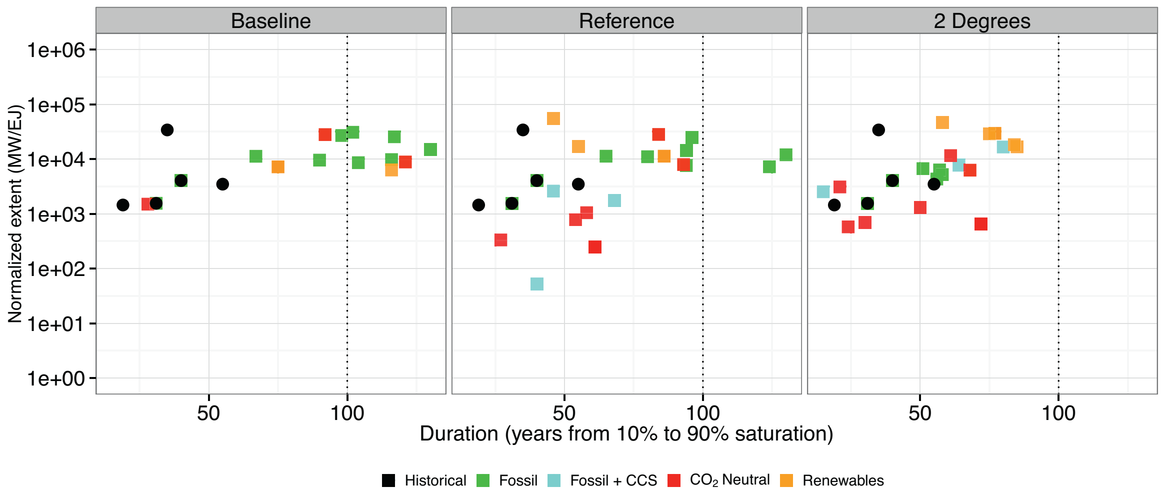


Fig. 4. Capacity growth of energy technologies in 3 future scenarios of the 21st century: extent vs. duration of growth using fitted logistic function parameters. Black dots represent historical extent-duration relationships of various energy-supply technologies (such as nuclear, coal and gas without CCS, hydro and refineries (FCC).

For the average annual emission decline rate indicator, we depict average CO_2 emission and CO_2 intensity reduction rates and compare them to historical national events that led to emission (intensity) reductions (such as oil crises, collapse of political regime) (Riahi et al., 2015; Van Vuuren and Stehfest, 2013).

For the average annual supply-side investments indicator, we show the average annual investments or the share in GDP over the 2010–2050 timeframe and compare them to the historical investments (or share in GDP) over the 2000–2013 timeframe (IEA, 2014).

In order to normalize the absolute indicators, taking into account relative changes in the size of the energy system or economy, we use GDP, primary energy, total energy system investments and total capacity as normalization metrics. The historical period taken into consideration is the 1980–2012 period as most metrics have annual data available in public sources with investments as an exception (see Table 5). The analysis will predominantly focus on global GDP as the main system growth factor, other metrics will be discussed in Section 4.2.

3. Results

In the results below, we show the results of each of the indicators presented in Section 2 for the three LIMITS scenarios and all 5 models as well as the historical reference period.

3.1. Average annual capacity addition

The modeled annual capacity additions (in GW) for the 2010–2030 period are on average consistent with the historical reference across all three scenarios. In the *Baseline* scenario, the expansion rates from 2010–2030 are broadly consistent with historical observations (see Fig. 2). Coal without CCS maintains a constant annual expansion rate whereas gas without CCS will nearly double its current annual expansion rate, matching and overtaking coal without CCS. Under climate constraints, we find a shift away from fossil fuels either shifting to a less carbon-intense substitute (gas) or shifting to non-fossil resources. For solar PV, wind and biomass the expansion rates stay within historical peak observations. The projections of nuclear power capacity growth are also consistent with historically observed expansion rates. However, currently planned additional nuclear capacity between 2015–2019 (World Nuclear Association, 2014) indicates that the expansion rate of nuclear energy will most likely not exceed the 3GW/yr. Hence, given the long inertia in nuclear power plant planning and construction process, the actual expansion rates of nuclear power might continue to be below the deployment rates as depicted in some of the high scenarios (Table 6).

In the 2030–2050 timeframe, the modeled rates of annual capacity additions increase beyond technology-specific expansion rates observed historically. Some even venture into territory that goes beyond overall best system achievement from the past. Under *Baseline* assumptions, this is the case for both coal and gas without CCS, which will expand their growth to unprecedented levels as fossil fuels remain the fuel of choice. Under the 2 °C objective (*2 Degrees*), it will be the growth of solar and wind capacity that becomes particularly rapid, showing deployment rates above the historical peak value of overall system achievements.

The outcomes change if overall system growth between historical and modeled periods is taken into account (by normalizing the average annual capacity indicator using global GDP growth). On the short-term the modeled average annual capacity additions show to remain consistent with technology-specific expansion rates of the past (see Fig. 3). However, although some technologies (wind and solar in particular) will exceed their technology-specific historical reference on the mid-term, all remain in line with the overall best system achievement from the past.

3.2. Technology diffusion

If the extent-duration relationships for all electricity generation technologies and scenarios are assessed (see Fig. 4) we find that all technologies follow the historically observed patterns. However, under *Baseline* assumptions the diffusion durations (Δt) are generally longer (further to the right) and an eventual saturation point (extent) is reached beyond the time horizon of the models involved (presented as a duration that is bigger than a 100 years in Fig. 4).

Once climate policies are introduced (e.g., the *Reference* and *2 Degrees* scenarios), the extent-duration relationships change. All technologies show to shift to the left (shorter diffusion durations). For fossil without CCS technologies this implies a lower capacity saturation level, a shorter lifecycle, and some capacity reduction in the year in which maximum growth is achieved (see the supplementary material online). For clean technologies (fossil with CCS, CO_2 neutral and renewable energy technologies) on the other hand, greater extents of growth are achieved with shorter

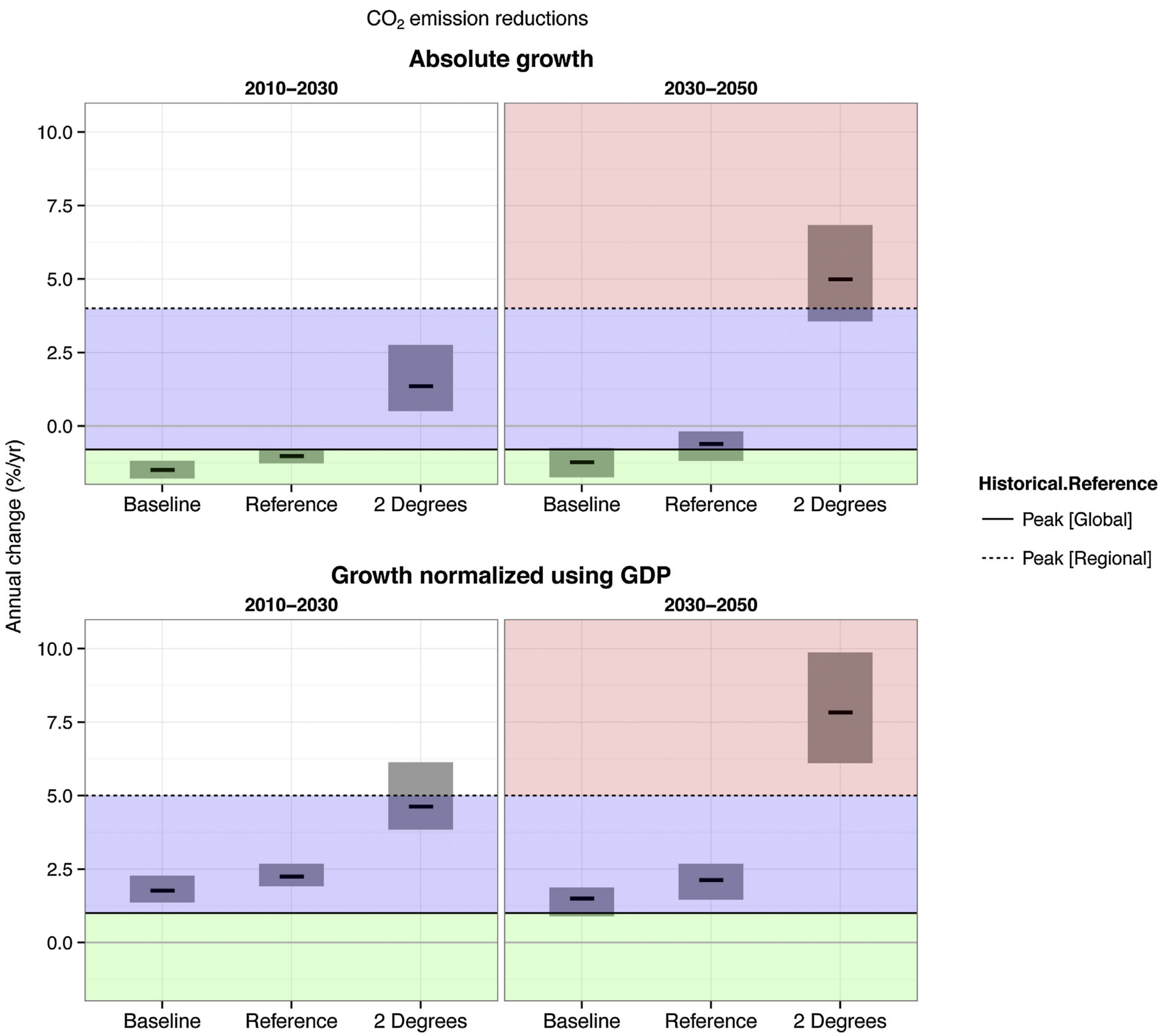


Fig. 5. Average annual emissions decline rates (top) and normalized average annual emission decline rates (bottom). Negative numbers indicate emissions increase. Green area implies consistency with historical evidence for global rates, blue represents values within historical bounds of the fastest regional reduction addressed and red implies beyond historical reference for either considered spatial scale. The bars indicate the range of modeled rates of change with the median value highlighted in black inside the bars. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

diffusion durations. However, despite the shorter diffusion duration, the rates remain above the historically observed reference. In that sense this study is in agreement with Wilson et al. (2012) concluding that the modeled diffusion rates appear to be conservative compared to historically successful technologies.

3.3. Average annual emission decline rate

Fig. 5 shows the average annual emission decline rate and the decline rate normalized using GDP (creating a carbon intensity decline rate or decarbonization rate). Up till today, only rare historical occurrences on a national level have led to significantly higher reduction rates than the global average, which have been negative (−0,8% per year on average throughout the 1970–2010 period) owing to continuously growing emissions worldwide. For example, fairly swift emission reduction rates were observed in Sweden from 1974 to 2000 as a result of policy impulses on greening the Swedish energy system after the oil crisis in 1973 (2–3% per year). Another example is the emission decline rate of 2–4% per year for Eastern European and former Soviet Union countries after the collapse of the Soviet Union (Riahi et al., 2015). To stay in line with the 2 °C objective a sustained global carbon emission reduction rate of about 1% till 2030 is required, remaining within the earlier discussed regional historical boundaries. However, after 2030 the models depict a sustained global carbon emission reduction rate of 5% which goes beyond both global and regional historical achievements.

Similarly, the global decarbonization rate (average annual emission decline rate normalized with GDP) has been around 0.5% over the period 1900–2010 and around 1% over the 1970–2010 (driven by technological change and sectoral shifts) (Van Vuuren and Stehfest, 2013). If compared to the modeled decarbonization rates, we find ranges of 2-3% under *Reference* scenario assumptions whereas the margins expand to 6–10% by 2050 if 2 °C is to be attained at the end of the century. These rates are considerably higher than the global average rate experienced in the past. At the regional level, historically faster rates can be observed than the global average: some Asian regions have managed to achieve

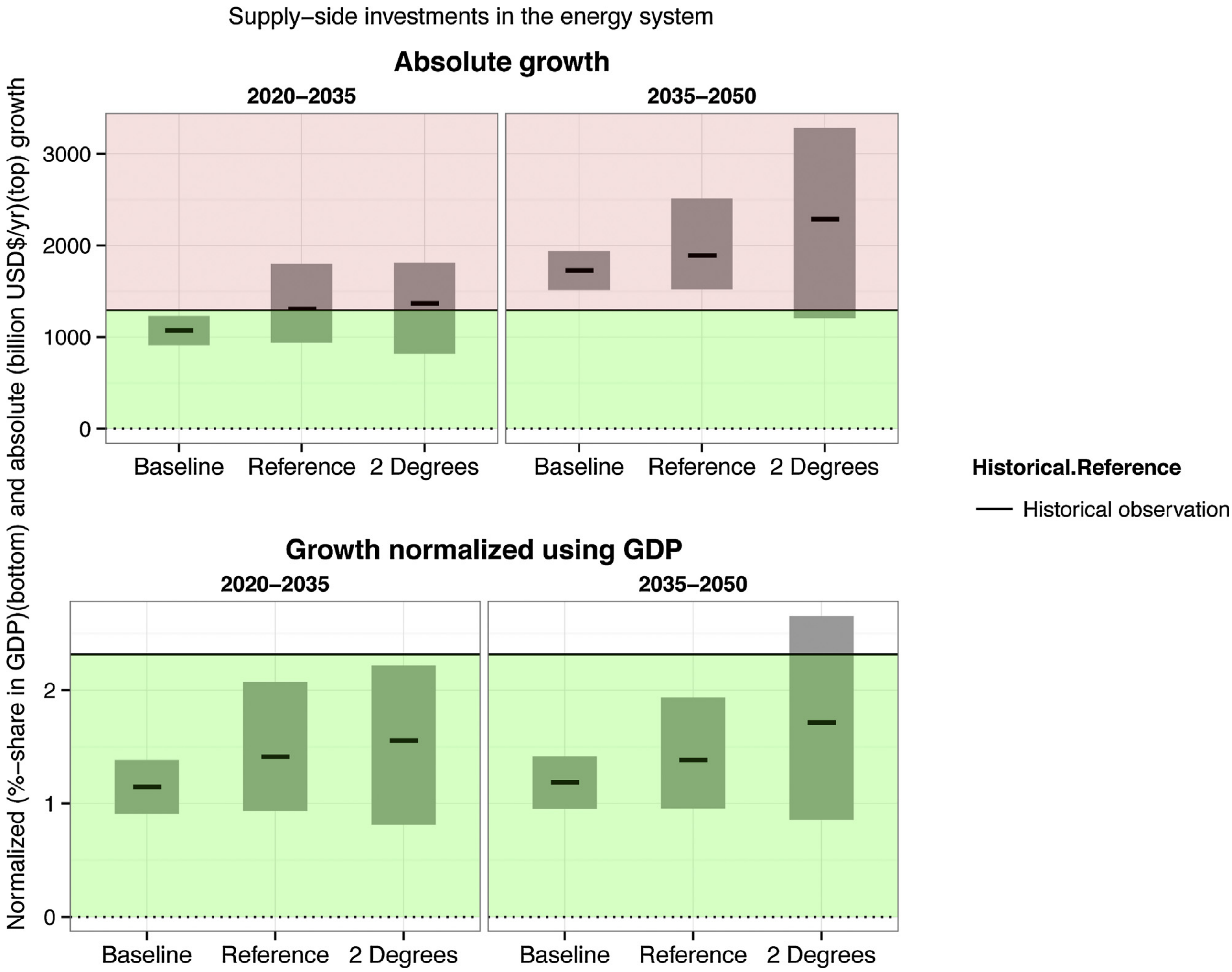


Fig. 6. Average annual supply-side investments (top) and average annual supply-side investments in GDP (bottom). Bars represent the range of model outcomes of respectively *Baseline*, *Reference* and *2 Degrees*. The bars indicate the range of modeled rates of change with the median value highlighted in black inside the bars.[1]

decarbonization rates of 3–5% per year during the late 1980s and early 1990s. This would imply that the global rate would need to increase significantly, but also go beyond the most rapid (local) decarbonization rate experienced in the recent past and maintain this rate (globally) for several decades.

3.4. Average annual supply-side investments

Rapid transitions in the energy system are associated with increasing investment flows compared to the status quo, which is reflected in Fig. 6. Both current climate policy (*Reference*) as well as the 2 °C pathway (*2 Degrees*) would require greater investments than the business-as-usual case (*Baseline*), climbing up on the short term to about 1.5 trillion USD per year which is slightly greater than observed historically. Under 2 °C ambitions these investment levels are modeled to nearly double for the subsequent decade, increasing up to 2.5 trillion USD per year on average. Upscaling investments to these levels might pose several difficulties as two-third of the total sum is levied by developing areas (McCollum et al., 2013) which require finance mechanisms other than their own domestic funds (Bowen et al., 2014).

If total supply-side investments are expressed as a share in global GDP, it shows that the ratio remains within the bounds of historical experience. However, by looking into global rates it potentially masks the large differences between regions. The average investment intensity of developing economies was around 3.5%, whereas it was just 1.3% in industrialized countries (McColumn et al., 2014).

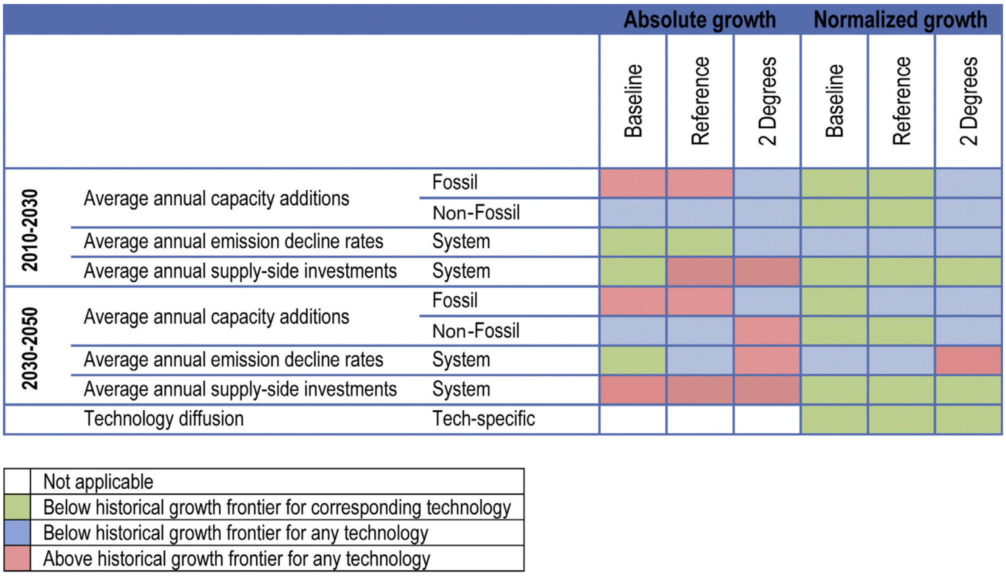
4. Discussion

4.1. Comparative overview of indicators and results

This study uses a diverse set of indicators that assess the consistency of modeled future rates of change with the historical record. The study yields ambiguous insights into the consistency of modeled rates of change with historical observations (see Table 6). Absolute and near-term (2010–2030) rates of change vary in their consistency with historical observations for the three scenarios, although these are mostly within the range of overall system achievements (blue shaded areas on the graphs). By normalizing the indicators to account for system growth shows an overall consistency with historical records. Over the longer term the

[1] For the *Baseline* scenario, the numbers are recalculated, as they were not included in the study of McCollum et al. (2013). Due to data availability, only results for IMAGE and MESSAGE are shown here. The *2 Degrees* scenario includes unilateral climate policy targets till 2020, suspending immediate global action, and therefore deviating from the *2 Degrees* scenario as presented in other graphs. As the *Reference* and *2 Degrees* scenario start to deviate only after 2020 the time periods are amended to 2020–2035 and 2035–2050. The historical observation consists of cumulative energy supply investments and cumulative total GDP from 2000–2013.

Table 6
Summary of comparisons between historical observations and three modeled scenarios using a diverse set of indicators. The fossil and non-fossil technologies are grouped—the table considers the highest rate of change in the group per scenario.



indicators create a near similar picture for the *Baseline* and *Reference* scenarios. However various significant differences emerge under the 2-degree objective (*2 Degrees*), specifically in terms of (absolute) average annual capacity expansion rates, (absolute) average annual energy-supply investments and (absolute and normalized) average annual emission decline rates.

4.2. Methodological diversity and issues

The indicators used vary in focus and scope. In this section we further discuss the influences and sensitivities of the study design on the outcome.

(1) **System focus:** Models are inherently limited in their representation of energy-economy dynamics, and are highly dependent on their technological resolution (number of technologies included), underlying assumptions (on e.g., capital replacement or learning rates) as well as model structure and solution frameworks. In that respect technology-specific indicators are potentially more sensitive to specific model behavior than system-wide indicators. However, in a multi-model set-up these sensitivities are more-or-less balanced out and in that case, as depicted in Table 6, system indicators are not consistently more or less likely to remain consistent with historical observations than technology-specific ones;

(2) **Temporal scale:** Indicators that focus on a specific timeframe (e.g., the average annual capacity additions or average annual emission decline rates) can be sensitive to the selected time period under study. This is especially the case if rapid expansion or declines rates are nested in certain periods of time, which can be either highlighted or numbed down in the longer-term average.
Focusing on the full technology lifecycle, however, can also influence the results. For example, the Wilson et al. (2012) methodology is sensitive to technology projections with a clear logistic growth profile, such as mature historical technologies for which long time-series data are available. As renewable technologies are generally still in their early deployment phase these are not expected to saturate in the timeframe of the model and will therefore not appear as logistic growth profiles in the Wilson et al. methodology. Hence, some modeled rates of change will not find application in the extent-duration analyses. The conservatism in the extent-duration curves could thus be an outcome of the overrepresentation of incumbent technologies;

(3) **Spatial scale:** By focusing on global outcomes an indicator may potentially mask the large differences between regions. In this light the indicator provides only limited insights into the actual challenges that are faced to reach such rates of change.
In the case where a global benchmark is absent (such is the case for (normalized) emission decline rates) we selected a more local (contemporary) achieved peak value. Such a comparison inherently includes selection bias as frontier reduction rates have specifically been selected. However although these regional benchmarks only lasted for a short period of time and emerged under rare circumstances (such as oil crises and regime changes), these specifically underline the difficulty of achieving the needed rates of change;

(4) **Normalization:** The normalization approach is visibly sensitive to the type of system growth metric used (see Fig. 7). Monetary-based normalization metrics (GDP, investments and capacity to some degree as well) result in more conservative rates of change than energy-based normalization metrics (primary energy). As a result, rates of change that are normalized by using monetary-based normalization metrics are less likely to exceed historical rates than those normalized using energy-based metrics. This is in particular true for indicators that experience rapid rates of change (for both technology-specify and system-focus indicators).
Choosing the appropriate normalization metric is important – as the choice for a specific metric could render future rates of change (in)consistent with historical rates. The choice depends according to the authors on (a) the variable being normalized,

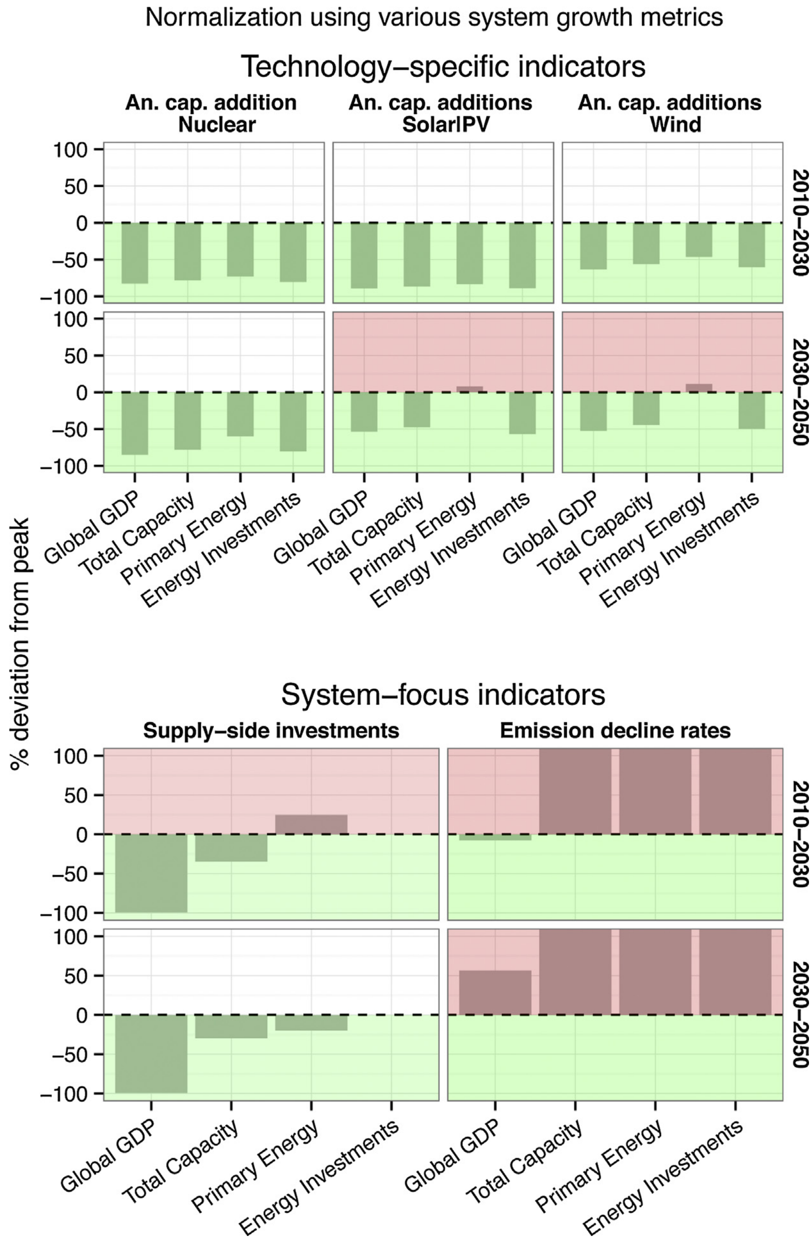


Fig. 7. Deviation of the median model value from the maximum peak benchmark per indicator for each considered normalization metric. Positive values indicate that the indicator exceeded historical experience whereas negative values imply consistency with historical observations. For plotting convenience the annual capacity additions are limited to nuclear, solar PV and wind technologies. Moreover, the investments indicator is plotted on the 2010–2030 and 2030–2050 timeframe but these represent the timeframes as depicted in Section 3.4. The picture focuses on the 2 °C objective.

and (b) the question being asked. For example, if the modeled variable is annual capacity additions, then (a) suggests using historical primary energy or capacity as the normalization metric, unless (b) the specific question is whether investment requirements in new capacity are in line with historical observations.

In sum, the results of the indicators discussed in this study are associated with several methodological considerations. Applying a wide set of indicators therefore offers alternative, complementary insights into how scenarios compare with historical observations on two different scales (e.g., technology-specific and system-wide indicators and the choice for normalization). Although none of the indicators provide conclusive insights as to the achievability of scenarios they are useful ways to contribute to scenario evaluation and provoke critical interpretation of results.

4.3. Expanding the scope of research

By applying a diverse set of indicators one can gain more holistic insights into how scenarios compare with historical observations. Further research in line with this study could focus on:

(1) **Fine-tuning and extending the scope of current indicators:** Two fundamental regularities of successful technology diffusion patterns are described in Kramer and Haigh (2009). According to their study, the build rate of new and existing energy technologies follow two 'laws' which have been fairly

consistent across energy technologies in the past. The first law describes how technologies grow quickly for the first two decades at exponential rates (±26%/yr) until 'materiality' is reached, defined as a ±1% share of the global energy system. The second law states that after materiality, growth rates level down to an eventual equilibrium or constant market share. Although the expansion phase and the maturing growth phase characterized by Wilson et al. (2012) broadly correspond with these 'fundamental laws', this could be embedded more clearly within the historical comparison methods. Moreover, additional insights may also be acquired by distinguishing between expanding systems (adding new capacity) and stabilizing systems (substituting existing capacity);

(2) **Introducing additional comparison methods:** Modeled rates of change could be compared against actual trends over the same period of time, for instance a decade after the original projection was made. An example of such an exercise is found in Van Vuuren and O'Neill (2006). If short-term model trajectories are significantly inconsistent with historical trajectories, it could expose conservatism in the long-term scenario logic and the assumptions on the driving forces. This methodology is, however, only useful if historical trends include similar climate policies as included in the model projections;

(3) **Including demand-side indicators:** Historical and future emissions and their driving forces have also previously been studied by applying the Kaya-identity (Kaya, 1990). The Kaya-decomposition analysis is applied in numerous studies (i.e., Steckel et al., 2011; Zhang et al., 2009) to examine the implications of changes in total CO_2 emissions on affluence (representing growth of economic activities), change in energy intensity (i.e., total primary energy over GPD reflecting efficiency and consumption patterns) and the carbon intensity (i.e., total CO_2 emissions over total primary energy). The three components could be assessed in tandem or as separate indicators in comparative work of prospective studies and historical records. This study has a greater energy supply orientation as all indicators focus on either energy supply technologies, investments or the carbon intensity of energy supply but future work could also include demand side indicators such as energy intensity and affluence;

(4) **Going beyond the historical benchmark:** This study considers history as an important benchmark, though history provides only limited information when looking at innovation. For example the results provide no further information about, amongst others, the drivers of technological change, (perceived) risks, scalability, structure of the industry or role of institutions. Expert elicitation could expand the knowledge on critical implementation barriers and further test the feasibility of prospective studies. Several prospective studies on technology development use expert elicitation protocols as a research tool to assess the feasibility of emerging (carbon-free) energy technologies (see for example Bosetti et al., 2012; Jenni et al., 2013; Fiorese et al., 2014). Experts can go beyond the historical benchmark by providing probabilistic information on the likelihood that technologies will overcome particular hurdles and estimate the overall probability of success for each technology (Baker et al., 2009).

5. Conclusions

In this study we have compared indicators of change in future scenarios to historical trends for various degrees of climate policy. The analysis confronts scenario data from the LIMITS project to four methodologies that focus on different indicators of technology change, such as the average annual capacity additions, technology diffusion and changes in emission trends or investments. The main conclusions of this analysis are:

The achievability of future rates of change depends on the indicator used

In this study, we assessed a variety of indicators to look at the rate of future change versus historically achieved rates of change. This comparison provides some insight into the effort involved in achieving these scenarios but is highly dependent on: (1) selecting the historical benchmark, (2) normalization, (3) data availability as well as the (4) underlying economic and technological assumptions, model structures and the included level of technological detail in the models. Although none of the indicators provide conclusive insights as to the achievability of scenarios they are useful ways to contribute to scenario evaluation and provoke critical interpretation of results.

Indicators highlight that absolute rates of change in scenarios achieving the 2 degree target are rapid in the medium term compared to historically achieved rates of change

In absolute terms we have observed that projections are more-or-less in line with reported achievements on the short-term, but these increase to unprecedented levels by mid-century. Specifically the average annual capacity addition rates for solar and wind and the required energy-supply investments are particularly strong under 2 °C constraints, showing rates above the historical peak value of overall system achievements by 2030.

Methods that look at relative rates of change by comparing the change to overall system change conclude that future rates of change are generally within the range of successful transitions in the past

Indicators that account for the growth in the overall system show that the modeled rates of change in the scenarios are lower compared to the rates of change in the past. We find that monetary-based normalization metrics (GDP, investments and to some degree capacity) result in less conservative normalization than energy-based normalization metrics (primary energy). This is in particular true for indicators that experience rapid rates of change (for both technology-specific and system-focus indicators).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.gloenvcha.2015.09.019.

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