Comparing future patterns of energy system change in 2°C scenarios to expert projections

Mariësse A.E. van Sluisveld [a b*], Mathijs J.H.M. Harmsen [a b], Detlef P. van Vuuren [a b], Valentina Bosetti [c d], Charlie Wilson [e], Bob van der Zwaan [f g h]

[a] Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, The Netherlands
[b] Netherlands Environmental Assessment Agency (PBL), the Hague, The Netherlands
[c] Economic Department, Bocconi University, Milan, Italy
[d] Fondazione Eni Enrico Mattei (FEEM), Milan, Italy
[e] Tyndall Centre for Climate Change Research, University of East Anglia, Norwich, UK
[f] Policy Studies, Energy research Centre of the Netherlands (ECN), Amsterdam, The Netherlands
[g] Faculty of Science (HIMS), University of Amsterdam, Amsterdam, The Netherlands
[h] School of Advanced International Studies (SAIS), Johns Hopkins University, Bologna, Italy

*corresponding author: mariesse.vansluisveld@pbl.nl

Abstract

Integrated assessment models (IAMs) are computer-based instruments used to assess the implications of human activity on the human and earth system. They are simultaneously also used to explore possible response strategies to climate change. As IAMs operate simplified representations of real-world processes within their model structures, they have been frequently criticised to insufficiently represent the opportunities and challenges in future energy systems over time. To test whether projections by IAMs diverge in systematic ways from projections made by technology experts we elicited expert opinion on prospective change for two indicators and compared these with the outcomes of IAM studies. We specifically focused on five (energy) technology families (solar, wind, biomass, nuclear, and carbon capture and storage or CCS) and compared the considered implications of the presence or absence of climate policy on the growth and diffusion of these technologies over the short (2030) to medium (2050) term. IAMs and experts were found to be in relatively high agreement on system change in a business-as-usual scenario, albeit with significant differences in the estimated magnitude of technology deployment over time. Under stringent climate policy assumptions, such as the internationally agreed upon objective to limit global mean temperature increase to no more than 2 °C, we found that the differences in estimated magnitudes became smaller for some technologies and larger for others. Compared to experts, IAM simulations projected a greater reliance on nuclear power and CCS to meet a 2 °C climate target. In contrast, experts projected a stronger growth in renewable energy technologies, particularly solar power. We close by discussing several factors that are considered influential to the alignment of the IAM and expert perspectives in this study.

Keywords

Technology diffusion, Integrated assessment, Climate change, 2 degrees, Expert elicitation

1 Introduction

Integrated assessment models (IAMs) are computer-based instruments used to assess the implications of human activity on the human and earth system. They are simultaneously also used to explore possible response strategies to climate change. Scenarios generated by these models inform policy makers on elements such as the timing of greenhouse gas (GHG) emission reductions, required changes in technological infrastructure, and the potential contribution of different world regions to limiting global temperature increase (e.g. Calvin et al., 2012; Kriegler et al., 2013; Riahi et al., 2015; Tavoni et al., 2015; Weyant and Kriegler, 2014). In the past these scenarios have proven to play an important role in informing society about the effects of future climate and energy policies. For example, the assessment reports by the *Intergovernmental Panel on Climate Change* (IPCC), reviewing model-based scenario literature on global systems change, have helped inform negotiators and heads of state in articulating long-term ambitions in line with the internationally agreed upon objective to limit global mean temperature increase to no more than 2 °C. To illustrate, the IPCC's *fourth Assessment Report* (AR4) has provided the underpinning of the European Union's ambition to reduce GHG emissions by 80%–95% in 2050 compared to 1990 levels (Council of the European Union, 2009; Gupta et al., 2007). Similarly, the IPCC's *fifth Assessment Report* (AR5) has supported the communicated ambition of the G7 during the Paris Agreement to reduce global GHG emissions by 40%–70% in 2050 compared to 2010 levels (G7, 2015; UN, 2015). Due to this rising importance of model-based scenarios in climate change mitigation policy and strategy, interest has sharpened on the evaluation of IAMs and their depictions of achievable technological growth under stringent climate mitigation assumptions (Anderson, 2015; Anderson and Peters, 2016; Fuss et al., 2014).

Literature evaluating the ability of IAMs (and related models) to capture future energy system change has emphasised the difficulty of using formal model validation methods (Schwanitz, 2013). One reason is that IAMs are designed to capture long-run dynamics of aggregated human activity and not the dynamics of more incidental or volatile processes. This means that comparing IAM projections to recent observations has limited relevance for model evaluation (van Vuuren et al., 2010). Instead, other methods have been designed to evaluate the projected patterns in IAMs, including (1) inter-model comparisons, to identify dominant or robust patterns across multiple IAMs (e.g. Kriegler et al., 2015; Riahi et al., 2015; Tavoni et al., 2015), (2) comparative analysis with long-run observational datasets, to assess whether depicted trends on the speed of technological diffusion and scalability of technologies are consistent with historical evidence (e.g. Kramer and Haigh, 2009; van der Zwaan et al., 2013; van Sluisveld et al., 2015; Wilson et al., 2012) and (3) retrospective analysis, to test whether modelled system behaviour can approximate the observed historical developments of its real-world counterpart (e.g. Fujimori et al., 2016; Metayer et al., 2015; Trutnevyte et al., 2016; van Vuuren and O'Neill, 2006). Although such studies provide useful insights on the performance of IAMs, they remain focused on past insights and take little note of current or prospective innovation processes and development. Hence, comparative methods that rely on historical data and trends assume continuity of the past and may therefore be less meaningful in situations where trends are changing (National Research Council, 2010).

Several strands of literature have applied alternative methods to provide insights on future developments (Wilson et al., 2017). Systematically consulting specialists in a field of expertise is one example. Experts are assumed to have the ability to interpret the wealth of (tacit) information on current societal and technological trends and consider their implications for the future. Collecting this knowledge through expert elicitation has the advantage of gauging uncertainties beyond current conditions (Bosetti et al., 2016). For example, various expert elicitations have assessed changes in the costs of electricity generation under various descriptive scenarios on RD&D funding. Examples include elicitations on the future costs of biomass energy (Fiorese et al., 2014), solar PV (Bosetti et al., 2012; Curtright et al., 2008), nuclear energy (Anadón et al., 2012; Baker et al., 2008) and carbon capture and storage (CCS) (Baker et al., 2009; Chan et al., 2011; Nemet et al., 2013; Rao et al., 2006). However, experts are known to be susceptible to cognitive biases (Marquard and Robinson, 2008), affecting the transparency, accuracy and defensibility of their judgements. Moreover, expert judgements are usually limited to a single object of interest and their projections do not stretch out over very long time scales. Given these limitations, expert elicitations may only provide limited guidance on counterfactual developments that remain aligned with the 2 °C objective over time.

In this study we present a comparative analysis of two different analytical methods that are both used to assess future change. We focus particularly on quantitative projections provided by IAMs and quantitative estimates elicited from experts. To our knowledge, expert elicitations have rarely focused on technology deployment, nor have they been directly compared to IAM outcomes. The few expert elicitation studies on growth and diffusion of energy technologies have predominantly focused on driving forces and evaluation criteria (see e.g. Napp et al., 2015; Vaughan and Gough, 2016). As these studies have mostly remained on a qualitative level, they cannot directly be compared to IAM output. We therefore confront existing IAM data with expert projections acquired through a new expert elicitation process. Given how the decarbonisation of the power sector is the principal near and medium-term response strategy in IAMs (Clarke et al., 2014), we are specifically interested in comparing projections for this sector. We focus on the five main families of electricity-supply technologies that contribute the most to decarbonisation in (IAM) projections, which are solar PV, wind, nuclear, biomass, and thermal plants with and without carbon removal technologies (CCS). In the next section we will first elaborate on the selection process for experts and scenarios and describe the applied methodology. Section 3 presents the results of the expert elicitation and the IAM scenarios. Section 4 discusses the factors that are considered to impose influence on the alignment of the IAM and expert perspectives and Section 5 summarises and concludes.

2 Methodology

2.1 Models and scenarios

To study future change from an IAM perspective we use the outcomes of a multi-model inter-comparison study (MIP), which allow us to sample the results of multiple high resolution IAMs that have run under harmonised settings. The benefit of using high resolution IAMs is that they typically represent relevant interactions and feedbacks that can be used to assess the implications of human activity on the system (as opposed to the more highly aggregated IAMs used for cost-benefit analyses) (Edmonds et al., 2012). In this study we specifically focus on an ensemble of high resolution IAMs that have participated in the LIMITS project, a multi-model inter-comparison project aimed at assessing policies and timescales consistent with limiting global mean temperature increase to 2 °C within the 21st century (Kriegler et al., 2013).

2.1.1 Selection of integrated assessment models

The ensemble of models included for study encompasses a set of high resolution IAMs that are widely used to assess systemic change over time and under various pressures, contributing over half the scenarios in the IPCC’s AR5 Scenario Database (IPCC, 2014; Krey et al., 2014b). Next to having contributed to the previous large-scale IPCC assessment reports, they also play a central role in the forthcoming scenario framework which is to be used in future assessment reports (also referred to as SSPs and RCPs, see e.g. Moss et al., 2010; O’Neill et al., 2014 and the Supplementary information for details). As such, the results produced by the models in our ensemble can be considered representative in the field of IAM studies.

The IAMs in this study provide a wide range of possible transition pathways over time and towards the 2 °C objective (see Figure A1 in the Supplementary information). This breadth in outcome is a result of methodological and structural differences between these IAMs, which can be expressed in terms of variation in the coverage of the economy, the degree of foresight, the level of detail in spatial, sectoral and technological resolution, and assumptions or constraints on the speed of technology diffusion (see Table 1) (Kriegler et al., 2015). By combining diverse models in an inter-comparison study, we can assess the robustness of projected long-term developments within a range of embedded structural uncertainty (Wilson et al., 2017). In this study it is therefore more of interest to focus on the collective pattern observed across these IAMs than the individual model responses. To prevent a selective draw of model outcomes, we tested whether the patterns of the current subset of IAM models and scenarios deviate significantly from the full set of result as found in the IPCC's AR5 Scenario Database (IPCC, 2014). We found that the IAM models and scenarios in Table 1 broadly represent the middle of the road in all IPCC's AR5 result (see Annex A in Supplementary information).

Table 1 - Key model characteristics, adapted from Kriegler et al. (2015)

Name*[1]	Time horizon	Model category	Intertemporal Solution Methodology	Tech diversity in low carbon supply	Classification*[2]
AIM-Enduse	2050	Partial equilibrium	Recursive dynamic	High	Medium response
GCAM	2100	Partial equilibrium	Recursive dynamic	High	High response
IMAGE	2100	Partial equilibrium	Recursive dynamic	High	High response
MESSAGE	2100	Partial equilibrium	Intertemporal optimisation	High	High response
REMIND	2100	General equilibrium	Intertemporal optimisation	High	High response
TIAM-ECN	2100	Partial equilibrium	Intertemporal optimisation	High*[3]	High response*[3]
WITCH	2100	General equilibrium	Intertemporal optimisation	Low	Low response

*[1] Sources: AIM-Enduse (Kainuma et al., 2004); GCAM (Clarke et al., 2007); IMAGE (Stehfest et al., 2014); MESSAGE (Messner and Strubegger, 1995); REMIND (Bauer et al., 2013; Luderer et al., 2013); WITCH (Bosetti et al., 2006) and TIAM-ECN (Keppo and van der Zwaan, 2011)

*2 Classification represents a pattern of common model behaviour in response to a carbon tax in terms of cumulated carbon reduction, carbon over energy intensity reduction and structural changes in energy use (primary energy) (Kriegler et al., 2015).

*[2] The TIAM-ECN model was not part of the Kriegler et al. (2015) evaluation study – based on the model characteristics for the TIAM-ECN model it is assumed that it behaves similarly to comparable models.

2.1.2 Scenarios

We analyse two different scenarios that outline a future with and without climate policy. In order to ensure that model responses are clearly traceable to the differences in the model structure, we explicitly selected the standard (idealised) baseline and mitigation scenarios that are created by (solely) harmonising assumptions on the presence or absence of future climate policy. Scenarios that implement richer narratives of change (such as those including detail on the timing of international collaboration or technology availability, see e.g. Krey et al., 2014a; Riahi et al., 2015 for examples) are not further analysed in this work. Our two scenarios are:

1) A baseline (*Baseline*) scenario, describing a business-as-usual case in which there will be no global agreement on international climate policy. Changes in the energy system will therefore mostly be driven by other factors than climate policy, such as growing energy demand linked to demographics and resource price developments which reflect scarcity and innovation. In general the *Baseline* scenario does not entail major technology shifts over time, while greenhouse gas emissions increase over the century, peaking only towards the end of the century as population stabilises (see Tavoni et al. (2015); van Sluisveld et al. (2013) for regional and global decomposition analyses). A business-as-usual scenario allows consideration of system change over time as adopted within the model structure without the influence of additional exogenous pressure.

2) A climate policy (*2 Degrees*) scenario, describing a mitigation pathway that will restrict the increase in global mean temperature to a maximum of 2 °C in the year 2100 (all corresponding to a likely (>66%) probability of meeting 2 °C, see Annex A in the Supplementary information). To maintain narrative simplicity, this scenario assumes an immediate and universal implementation of a global carbon tax to induce the deployment of low-carbon technologies in a most cost-effective manner while ignoring the normative (fair) distribution of efforts. The carbon tax increases the price of energy carriers with a carbon content, creating a price-based preference order in favour of low-carbon or carbon-removal alternatives over unabated fossil-fuel technologies. These additional costs add to the system change drivers already included in the business-as-usual scenario. In general the *2 Degrees* scenario leads to an immediate move away from fossil-fuel dependent technologies and towards a diverse blend of decarbonisation options, such as (1) renewable (non-combustible) power supply; (2) deployment of carbon removal technologies (such as carbon capture and storage, CCS); and (3) energy efficiency improvements.

2.2 Expert elicitation

To collect expert projections along similar assumptions about future climate policy as adopted by IAMs, we employed the lower bound of the CO_2 emission reduction range as reported in the IPCC's *4th Assessment Report* (50%–85% by 2050 compared to 2000 levels) (IPCC, 2007) as an indication of needed transformative change. We used the value of the *4th Assessment Report* (2007) as the *5th Assessment Report* (2014) had not been published yet at the time. As both ranges are considered broadly comparable (Van Vuuren et al., 2015), it is assumed that this does not impose influence to the end result of this study. No other assumptions on future change were provided to the expert to prevent the narrowing of the experts' focus. In the following section we outline our elicitation protocol in more detail.

2.2.1 Expert selection

To gain an alternative perspective on future change, we selected technology experts with a comprehensive view of all the various factors that may stimulate or inhibit the development of a specific technology (both technical aspects, as well as whole energy system dynamics). To identify relevant participants, we drew on the lead authors of technology-focused chapters of key assessment and synthesis products such as the IPCC's *4th Assessment Report* (Sims et al., 2007), the *Global Energy Assessment* (GEA, 2012), the IPCC's *Special Report of Renewable Energy Sources and Climate Change Mitigation* (Edenhofer et al., 2011) and the *Global Status Report* (REN21, 2014). We thus extended earlier selection procedures that identified relevant expertise. Each expert was contacted via email, explained the project aim and invited to take part in the elicitation. To boost sample sizes, participating experts were also requested to propose alternative or additional participants following a snowball sampling technique. This network approach proved particularly useful for identifying bioenergy and nuclear experts in our study.

A total of 39 experts took part in our elicitation (33% of the 117 experts contacted), including representatives of universities or research institutes (51%), member-based organisations dedicated to a specific technology (21%), governmental agencies (15%), private sector (8%) and intergovernmental organisations (5%) (see Table 2 and Annex B in the Supplementary materials). Overall, the participating experts formed a diverse group covering both theoretical and practical knowledge. Per energy supply technology individually, the samples vary in size (see Table 2). Although no rule exists on how many experts are needed in an expert elicitation, five to six specialists are considered to be a lower bound for representing most of the expertise and breadth of opinion, provided that the experts have a broad understanding of the problem (Keeney and von Winterfeldt, 1991; Morgan, 2014). If we compare our sample of experts to other elicitations on future system change (see Bosetti et al., 2016 for an overview), we find that the number of experts sampled in this elicitation are in the range of comparable expert elicitations although near the lower bound for each technology individually.

Table 2 - Overview of invited experts per technology

	Wind	Solar	Nuclear	Biomass	CCS
Number of experts contacted	24	19	16	33	25
Responses	7 (29%)	7 (37%)	6 (38%)	12(36%)	7 (28%)
Year of elicitation	2014-2015	2014-2015	2014-2015	2014-2015	2015-2016
Academia / research institutes	2	3	3	6	6
Governmental agency	1	2	1	1	1
Intergovernmental organisation			2		
Member-based organisations	3	1		4	
Private organisations	1	1		1	
TOTAL	7	7	6	12	7

2.2.2 Elicitation method

In the elicitation, we used both direct and indirect elicitation methods (O'Hagan et al., 2006) to identify and limit possible cognitive biases. Recognised biases in expert elicitations are (1) motivational biases (due to personal interests or other context-related factors), (2) accessibility biases (relating to information first coming to mind), (3) anchoring and adjustment biases (not being able to adjust above or below a benchmark or reference point), and (4) overconfidence bias (as a result of reinforcing evidence found in newly available information) (Martin et al., 2012).

The first two types of bias may be limited via the framing of questions. In order to expose motivational bias, the survey started with a question in which experts were asked to rank the contribution of their technology to total electricity supply within a subset of eight technology families under varying future pathways for 2050. This question functioned as a self-assessment, providing insights on potential biases within a particular group of technology experts compared to the group as a whole. To reduce accessibility biases, we selected and pre-tested metrics based on literature (van der Zwaan et al., 2013; van Sluisveld et al., 2015; Wilson et al., 2012) to ensure their familiarity to both the IAM community and the technology experts. The selected metrics, covering both technology stock and growth over different timescales, are shown in Table 3.

Anchoring and overconfidence biases are harder to overcome given the unfamiliar nature of long-term future development. In order to test the consistency of experts throughout the elicitation protocol, several methods were used. First, to limit overconfidence and anchoring (Morgan, 2014), we asked experts to provide lower limit, mean and upper limit expected values rather than point estimates for future developments under different climate policy assumptions and for different periods in time. Additionally, the experts were asked to provide these quantitative values before they were shown results from IAMs. Secondly, we used the method of 'rephrasing with alternative wording' (Martin et al., 2012; Morgan, 2014). Instead of asking the same questions multiple times with different wordings, we asked experts about two different metrics that are logically interconnected. In this study we chose to focus on (1) total installed capacity which contains information about technology stocks and growth, and (2) market share which contains information about the impact of a technology on the electricity system. We assumed that these metrics are alternative but complementary indicators to describe future technological change in the power sector.

Table 3 - overview of aggregate system metrics included in the expert elicitation

Group	Metric	Description
Wind, Solar, Nuclear, Biomass	Total installed capacity (GW)	Total amount of technology stock
	Share in total electricity production (%)	Contribution of a technology to the electricity mix
CCS	CO_2 capture rate ($MtCO_2$/yr)	Total capture capacity in the power sector
	Share in total electricity production (%)	Contribution of a technology to the electricity mix

In a later stage of the survey, the experts were confronted with a visual representation of the IAM outcome on the same set of metrics. As another means to test for consistency we asked the experts to assess the presented values by using verbal statements on a five-point Likert scale, ranging from "very low" to "very high" with three evenly distributed intermediate steps in between. Although Likert scale results cannot reflect the breadth of possible response in much depth, they were preferred over open-ended questions as they allowed for quick sampling. Moreover, the method yields standardised output which improves the comparability between experts and expert groups. Using verbal statements as a means of expressing a judgement can also allow for more intuitive responses than when asking for numbers, especially when intuition can be considered a more appropriate form of analysis (as may be the case for forward-looking analysis). Their use may be also more desirable over more quantitative probability estimates which are more prone to errors or bias (O'Hagan et al., 2006). To avoid a forced response, the survey also offered experts the option of opting out of any question. For all questions, the experts could also provide (optional) comments to explain their reasoning (see Annex C in the Supplementary materials for the elicitation protocol per technology group).

We distributed the survey online for experts to self-complete in their own time. Advantages of online surveys include geographical flexibility, cost-effectiveness and the option for participants to take the survey at any time and place of choice. However, a limitation of online surveys is that it is hard to know whether the question was understood correctly by the experts, or whether the experts took shortcuts to complete the survey faster, leading to less reliable responses or missing data (Baker et al., 2014). To prevent this we carried out a pre-test with an expert in each technology domain to assess the clarity of the questions, as well as to consider whether questions were being interpreted similarly across various technology expert groups. The pre-tests provided confidence that experts had a good overall understanding of the elicitation metrics shown in Table 3.

2.2.3 Overall structure of the survey

The surveys were carried out between September 2014 and June 2016. To open the elicitation, experts were asked to rank the relative roles of various technologies by their importance (in terms of share in total power supply by 2050). This question was asked to all experts, requiring them to also assess technologies outside their specialist field of expertise. Results are presented and discussed in Section 3.1.

The elicitation groups were then guided through a two-step approach (see Annex C in the Supplementary information for a visual representation), beginning with questions asking for quantitative estimates (lower, mean and upper values) for the metrics shown in Table 3. Experts in each elicitation group were asked to estimate each metric for the technology in their field of expertise for both the near future (2030) and medium-term future (2050) under both *Baseline* and *2 Degrees* assumptions. In a second step, the elicitation groups were asked to qualitatively evaluate technology projections provided by IAMs using the same metrics. Experts could evaluate the IAM values for the near (2030) and medium-term (2050) future under *Baseline* and *2 Degrees* assumptions as "very low", "low", "reasonable", "high" or "very high". The results of this two-step approach are further discussed in Section 3.2.

3 Results

3.1 Comparing power supply system projections

In the first part of the comparative analysis we focused on the relative contribution of specific energy technologies to total electricity supply under *Baseline* and *2 Degrees* policy assumptions by 2050. For experts, ranking the energy technology's contribution to future power supply was an explicit question. For IAMs, a similar ranking was constructed by assigning ranks to the average relative contribution of energy technologies to total power supply (with the largest relative contribution receiving the number one ranked position, the second largest relative contribution the second ranked position, etc.). Results are presented in Figure 1, plotting the mean and spread of expert rankings (y-axis, representing the 10th and 90th percentile of 39 responses) versus the mean and spread from IAM projections (x-axis, representing the 10th and 90th percentile of 7 IAM outcomes). We have added a diagonal line to the graph to represent the position in the plot where experts and IAMs are in consensus about the relative position of an energy technology in a future power supply. A 1-point margin of difference is considered as being broadly in agreement as well (dashed area in Figure 1).

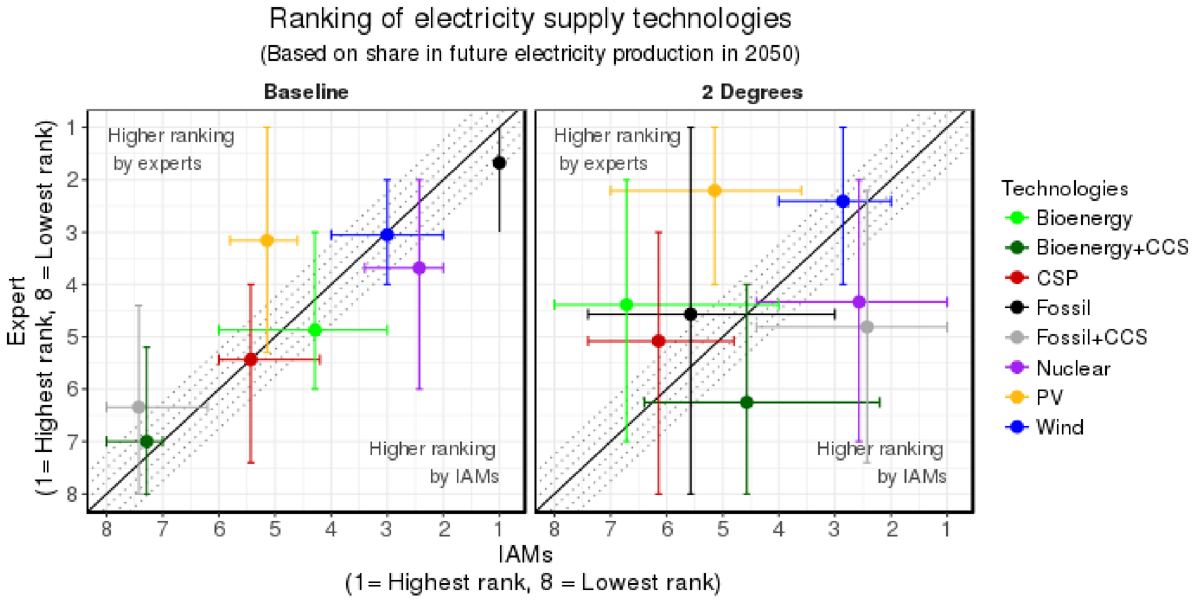

Figure 1 - Mean ranking of energy technologies in the energy system in 2050 for both the experts and IAMs. Rank 1 represents the technology with the largest expected share in electricity supply by 2050, while rank 8 represents the lowest: reading left to right on the x-axis therefore goes from technologies with the smallest share to technologies with the largest shares. Ranges shown are the 10th and 90th percentile of the outcomes from 7 IAMs and 39 experts. The diagonal line indicates agreement; shaded area represents a range of max 1-point difference in rankings.

We find that the IAMs and experts are broadly in agreement about the role of different technologies under business-as-usual conditions in 2050 (*Baseline*, left panel of Figure 1). Both IAMs and experts expect fossil fuels to remain the dominant energy source, followed by renewable power sources (particularly wind). Some differences are found for the relative position of solar and nuclear power, showing experts' greater preference for solar power and IAMs' preference for nuclear power. Overall, the expert responses reach a wider range of results than IAMs, which appears to be independent of the scenario and to some degree the technology being considered (see also Annex D in the Supplementary information). This difference in perspective could be a reflection of IAMs adopting a more optimal techno-economic perspective, while experts are able to implicitly or explicitly incorporate, for example, socio-political considerations into their assessment.

Under stringent climate policy considerations (*2 Degrees*, right panel of Figure 1) a noticeable difference emerges between IAMs and expert rankings as data points move further away from the diagonal line representing consensus. This deviation is also noticeable among the experts and among the IAMs themselves (reflected by an increasing spread). IAMs tend to rank fossil + CCS, bioenergy + CCS and nuclear technologies in a higher position than experts whereas experts tend to give higher ranks for solar power (both photovoltaic (PV) and concentrated solar power (CSP)) and bioenergy. A major contrast between IAMs and experts is observed in the deployment of bioenergy, whose position directly relates to model preferences for bioenergy + CCS. This may be a reflection of our choice to focus on a standard (idealised) mitigation pathway, as the inclusion of other, non-idealised, mitigation pathways, such as available in AR5 (Clarke et al., 2014) (see Annex D) shows to shift the rank of some technologies in the assumed long-term solution strategy in IAMs (e.g. Fossil + CCS may be replaced with solar PV and bioenergy). Wind power is the main exception, showing an overall consensus between experts and IAMs on its relative position. This could be a result of the large experience base for large-scale wind energy deployment and the observed stable growth over decades.

3.2 Individual technology projections and evaluations

3.2.1 Direct elicitation methods

The experts were then asked next to focus on their technology of expertise and provide quantitative estimates for their short (2030) to medium (2050) term expectations for the metrics as presented in Table 3. In Figure 2 we depict the range of outcomes for the *Baseline* scenario and in Figure 3 for the *2 Degrees* scenario. For comparison, we show elicited results together with IAM outcomes. Alongside this visual comparison of IAM and expert projections, we used a simple statistical test to assess the difference between the means of IAM and expert estimates. As the estimates in both the IAM and expert groups are not consistently normally distributed (based on Shapiro-Wilk normality test, see Annex D in the Supplementary information), we used the Wilcoxon rank sum test for comparing mean differences between the two groups. We used this difference testing mainly to draw out further insights on the magnitude of agreement or disagreement among estimates. Experts were also presented with the mean IAM results and asked to rate the values as "very low" to "very high" with three intermediate steps in between. This combination of quantitative estimates, Wilcoxon rank sum test results, and the qualitative rating exercise, allowed for a thorough comparison of IAM results with the views of the experts.

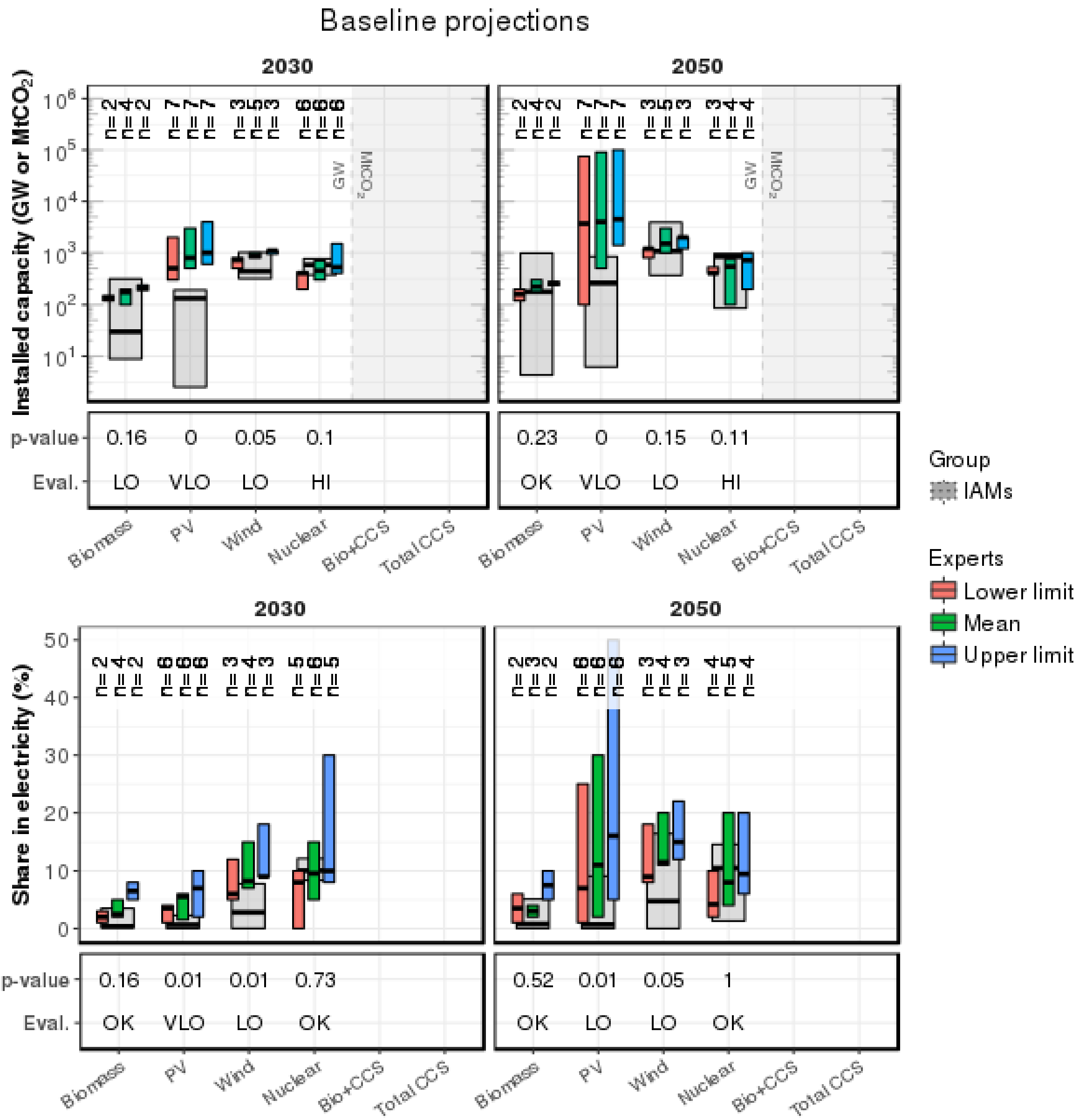

Figure 2- Elicited indicators under *Baseline* assumptions per technology-specific expert group. The broader grey bars represent the breadth in IAM outcomes per technology, with the median value shown as a black line. The smaller coloured bars represent the breadth in expert outcome for their lower, mean and upper estimates, with the median value shown

as a black line. The numbers (n) at the top show the number of elicitations per technology for the quantitative assessment. Experts were free to provide estimates of the lower, mean and/or upper limits, or opt out. This resulted in different sample sizes than those shown in Table 2. The tables below each graph show the p-values of the Wilcoxon rank sum test: p-values <0.05 indicate statistically different means between experts and IAMs. The tables also show the average outcome of the qualitative rating exercise (Eval.) of IAM results: VLO = "Very Low", LO = "Low", OK = "Reasonable", HI = "High", VHI = "Very High" (see Annex F in the Supplementary information for details). Under *Baseline* assumptions no growth and diffusion of technologies such as Bio + CCS and CCS in general are taken into consideration. Some of the data has been cropped for overview purposes, full ranges can be found in Annex E of the Supplementary Information.

Under *Baseline* assumptions (see Figure 2), the experts reported overall higher (median) estimates for installed capacity than projected by IAMs, with nuclear power as an exception. This difference can be observed for both the 2030 and 2050 period. Particularly solar PV shows a substantially higher estimate in the expert projections compared to the IAM projections, with an approximately six-fold higher estimate for installed capacity in 2030 and a twenty-fold higher estimate in 2050 (assuming median values, see also Annex E in the Supplementary information). For the share of technologies in total electricity production, experts also assigned significantly greater roles to solar PV than IAMs. This is consistent with Figure 1. A similar pattern can be observed for wind power at a different level of magnitude. Over time the discrepancy between experts and IAMs diminishes gradually, as is also shown by the increasing p-values in Figure 2.

The experts projected more conservative values for installed capacity for nuclear power in the short-term, which may be a result of assumptions on the economics and likelihood of new construction in the light of the expected retirement of existing capital in the coming decade (World Nuclear Association, 2016). Nonetheless, as seen in the share of nuclear power in total electricity production, the experts assume widely diverging futures for nuclear power, ranging from 'conservative' to 'ambitious' perspectives. For biomass power generation the IAMs reproduce a similar result as observed in Figure 1, showing only limited contribution and growth for this technology, whereas experts are more optimistic for the near to medium-term future. In the *Baseline* scenario no growth or diffusion is considered for power sources combined with carbon capture and storage (CCS) technologies.

Under *2 Degrees* scenario assumptions, several differences between experts and IAMs are found, particularly for solar PV, Bio + CCS and Total CCS (see Figure 3). For solar PV, the growth and diffusion expectations are again significantly different for both the short and medium term, implying either a structural underestimation of solar power development by IAMs, or a systematic underestimation of the challenges of intermittent technologies by experts. For CCS deployment, experts consistently estimated lower values than IAMs. Although some CCS deployment is assumed to materialise in the power sector, we observe that experts are greatly divided about the extent to which this can occur. This may be partly explained by the lack of actual experience in the (commercial) application of CCS and Bio + CCS technologies in the power sector, as well as the large uncertainties surrounding the (joint) application of these technologies (Fuss et al., 2014; Smith et al., 2016). Experts mostly assume the application of CCS technologies linked to fossil-fuel based power plants by 2030, whereas IAMs consider a significant growth of Bio + CCS in 2050. Interestingly, the IAMs appear to be more-or-less in agreement on the depicted magnitude of CCS deployment (as indicated by the rather narrow grey band for this technology family in Figure 3).

We also found some areas of agreement between the estimates of experts and IAMs in a *2 Degrees* scenario. This is clearly observed for wind power in the short-term, showing that IAM and expert estimates converge and reach greater agreement under *2 Degrees* than depicted earlier under *Baseline* considerations (as shown by the p-value and the reasonable or "OK" evaluation for installed capacity). However, IAMs' projected share of wind in power production is considerably lower than adopted by experts, which underscores a difference in the implied capacity factor between experts and IAMs. As the study considers technology "families" on a global scale, this difference may also be an outcome of conflating expectations for (onshore and offshore) wind technologies and regional potentials. For bioelectricity we also observe that the estimates of experts and IAMs converge in a *2 Degrees* scenario, implying that both agree that stringent climate policies can mobilise more large-scale application of biomass in power generation. This is confirmed in the open-ended comments where experts articulated that biomass co-firing can be very effective as it can be installed relatively quickly and retrofitted into existing capital. The experts, however, emphasised that this is only possible if explicit incentives are implemented that move biomass into power generation and away from other applications. Some limits to this alignment can be observed, as perspectives start to diverge again by 2050 (as indicated in the high or "HI" evaluation in Figure 3) which relates to the observed preference of IAMs to deploy bioenergy with CCS instead (Figure 1).

For nuclear power no significant or consistent difference can be observed between experts and IAMs. Both provide higher estimates in the *2 Degrees* scenario than assumed under *Baseline* considerations over the short-term, underlining that both elicitation groups employ implicit near-term assumptions on newly planned capacity. Moreover, despite a greater tendency in IAMs to adopt nuclear energy in the electricity mix (Figure 1), the estimated shares in power production are considered relatively equal between experts and IAMs (as also indicated by a p-value > 0.8).

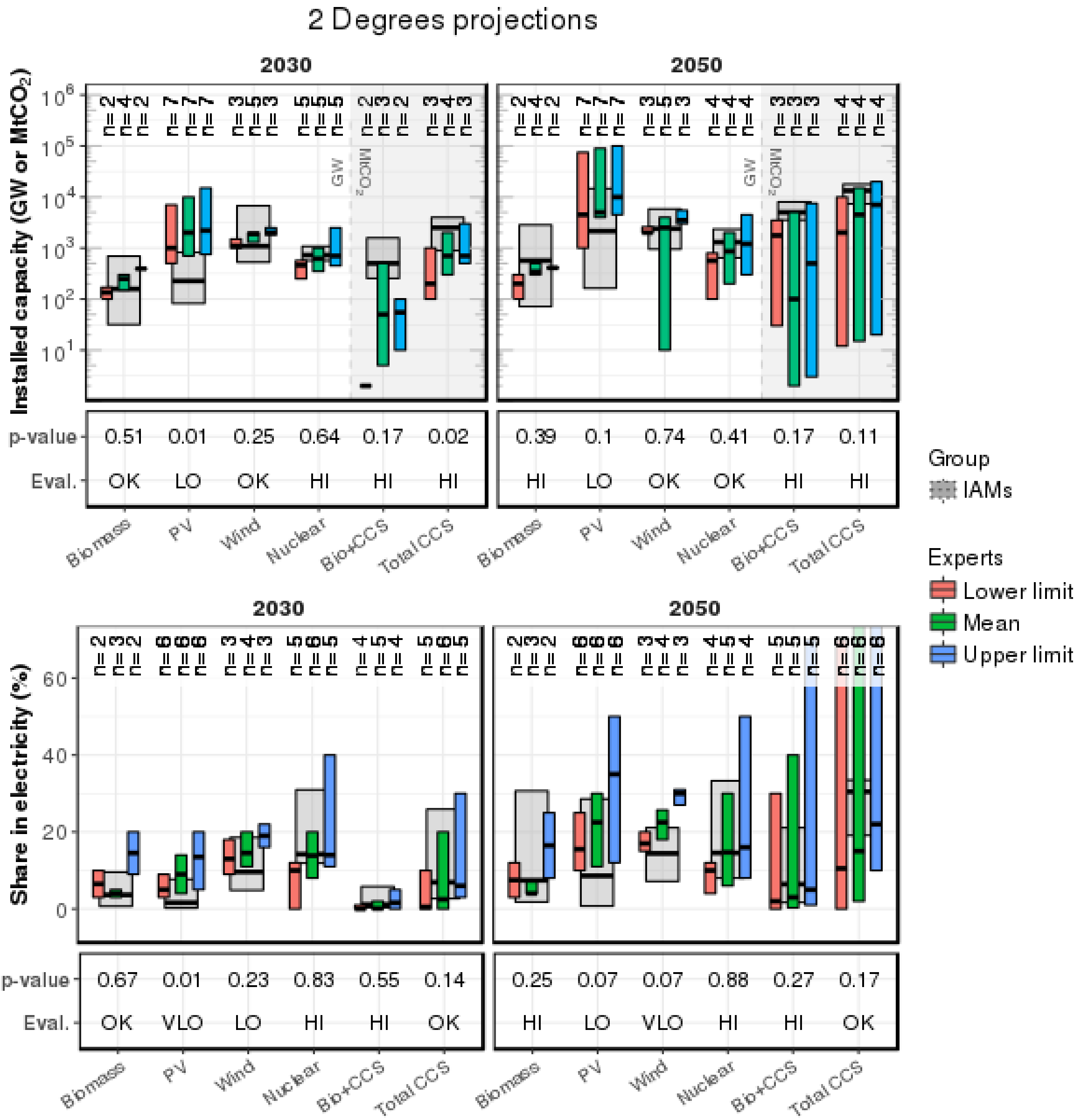

Figure 3 - Elicited indicators under *2 Degrees* assumptions per technology-specific expert group. The broader grey bars represent the breadth in IAM outcomes per technology, with the median value shown as a black line. The smaller coloured bars represent the breadth in expert outcome for their lower, mean and upper estimates, with the median value shown as a black line. The numbers (n) at the top show the number of elicitations per technology for the quantitative assessment. Experts were free to provide estimates of the lower, mean and/or upper limits, or opt out. This resulted in different sample sizes than those shown in Table 2. The tables below each graph show the p-values of the Wilcoxon rank sum test: p-values <0.05 indicate statistically different means between experts and IAMs. The tables also show the average outcome of the qualitative rating exercise (Eval.) of IAM results: VLO = "Very Low", LO = "Low", OK = "Reasonable", HI = "High", VHI = "Very High" (see Annex F in the Supplementary information for details). Some of the data has been cropped for overview purposes, full ranges can be found in Annex E of the Supplementary Information.

3.2.2 Indirect elicitation methods

Experts were also asked to rate the mean (point) estimate of IAM projections for their field of expertise and the metrics as shown in Table 3 using verbal expressions ranging from "very high" to "very low". Overall these ratings were found to be consistent with the direct elicitation outcomes, meaning that visually and statistically different estimates were subsequently evaluated as either (very) high or (very) low, and vice versa. Some exceptions can be found, which may be a result of including a broader spectrum of perspective in the indirect elicitation method (such as found for the Biomass elicitation group, representing a larger sample of experts than considered during the direct elicitation method, see Annex F in the Supplementary information), the demarcation of the assessment classes (in which the average score may sit between labels, such as the case for solar and wind power, see Annex F in the Supplementary information) and possible different interpretations of the verbal expressions among the experts in the rating exercise (O'Hagan et al., 2006). This sensitivity to context may particularly be observed for nuclear power and CCS technologies which could have elicited different patterns of response (intuitive response) than the more direct elicitation methods (analytical response).

4 Discussion

In this study we have identified areas in which IAM projections either compare or diverge in systematic ways from expert interpretations of future energy system change. In the following section we will discuss several aspects that are considered to be of importance to understanding the results.

An important aspect in interpreting the results is time. Both experts and IAM models are exposed to information on long-term historical trends (e.g. of the last thirty years) and short-term historical trends (e.g. of the last five years). However, IAM models are more dependent on long-term historical datasets than experts, as they use these datasets to draw out empirical patterns to build a perspective on the future. In order to account or correct for unforeseen developments over time, IAM models are continuously updated or calibrated, with some years between each modification cycle. During such an interval, IAM studies progressively build on ageing knowledge or model formulations, which particularly affect the (Baseline) representations of emerging technologies in IAMs. This becomes apparent when one looks at modelling efforts of a later date, such as published in Pietzcker et al. (2016), which show a higher use of renewable energy technologies than currently presented in this study. Surprisingly, although the issues and opportunities in system integration have been an active frontier for IAM development (see Pietzcker et al., 2016), these new projections still do not reach the deployment levels as estimated by the experts in this study. It may be argued that IAMs lack the necessary detail or resolution in representing technological progress (Creutzig et al., 2017; Geels et al., 2017; Metayer et al., 2015; Schwanitz, 2013). Or it may be that IAMs are less sensitive to volatile developments, preventing them from over-anchoring to incidental successes. Experts on the other hand, may be affected by short-term successes, as unprecedented growth rates year-on-year may reinforce the experts' perceptions of higher possible future growth rates than considered in IAMs. We argue that wind and solar PV experts may be liable to overconfidence biases (observed to some degree in this study, see Annex D in the Supplementary materials), as both technology groups have seen higher growth rates in recent years than on average over the last decade (see Global Wind Energy Council, 2015; IRENA, 2016). The continued fast growth in renewable energy technologies, a wave of interest in emerging technologies (Melton et al., 2016), and the continued absence of large-scale CCS demonstration projects are all considered salient developments for experts to convey different responses than those provided by IAMs.

A second aspect considered important in interpreting the results is the role of simplification in modelling and scenario analysis. In order to assess global developments over time in a consistent and structured framework, several necessary simplifications of complex real-world processes need to be adopted in IAMs. As a result, IAMs have limitations in their spatial, technological and temporal resolution which inherently compromise their system representativeness and their reflection of current trends and developments. It may be argued that models as a result do not accommodate the breadth of possible transition pathways to be considered under *Baseline* or *2 Degrees* scenarios. Indeed, experts have articulated specific roles for technologies and policy measures in the comment boxes that had not been a part of this assessment (Figure 1). For example, decentralised power systems, geothermal energy or onshore and offshore wind technologies have been mentioned by the experts as important elements in a decarbonisation strategy, but these technologies were not consistently or explicitly represented in the participating IAMs at that time (and therefore not included into the analysis). As IAMs can only depict decarbonisation strategies that are included in the (technology) portfolio, this may have led to an analytical gap between IAMs and experts. Secondly, the *2 Degrees* scenario reflects an idealised best-case scenario with immediate global action in the IAM interpretation. Although narrative simplicity provided advantages to both IAMs and experts, it also carried some vulnerability into the representability and interpretability of the results. Particularly if one considers that the conditions in our current *2 Degrees* formulation are not expected to arise in the real world (e.g. immediate global action), this may have posed challenges for experts to imagine technology developments along a similar trajectory. To test the sensitivity of our analysis to the choice of a scenario, we compared the same expert estimates to the outcomes of other (non-idealised) scenario storylines as given in the IPCC's AR5 Scenario Database (IPCC, 2014). As illustrated in Annex D of the Supplementary information, non-idealised mitigation scenarios appear to show IAM estimates that are closer aligned to the expert expectations for both the ranking (as can be deducted from the central nodes moving towards the diagonal line in Figure D2 of Annex D) as the quantitative projection exercise (particularly showing for solar PV in Figure D4 in Annex D). However, an exception is observed for bioenergy with CCS, which maintains its deviating position under a wide variety of scenario narratives, underscoring again the structural difference in perspective between IAMs and experts for this technology.

A third aspect considered important in interpreting the results is the considered range of result and associated uncertainty. In order to focus on the robust patterns, we have compared the median estimates of IAMs and experts in this study and used the range of outcome as a measure of agreement among the different elicitation groups. In light of the discussions in scenario literature on the differences in needed mitigation efforts between a 1.5 °C and 2 °C objective, it would have been interesting to have also confronted experts with the high estimates of both the IAM and expert projections. Future work could therefore extent the current analysis by confronting the same set of experts with the broader range of outcomes. Such a procedure would bring different sources of knowledge together to reflect on the different outcomes, yielding further insights on the assumed context, depicted magnitudes and the implications of such development over time. This may be particularly relevant in areas for which experts and IAMs have structural differences in perspective. For example, experts articulated an explicit need for policy to move biomass into power generation and away from liquid fuel production in order to reach the levels of deployment as presented in this study. Interestingly, Calvin et al. (2013) found that most of the scrutinised IAMs in this study dedicate a larger share of biomass resources to liquid fuel production than to power generation, implying an substantial increase in the use of bioenergy in both sectors. These differences in scale and perspective underline a more structural disagreement between IAMs and experts on the availability and economics of mitigation alternatives in the liquids and electricity production sectors, which ideally would need to be further discussed in future work.

5 Conclusion

In this study we have used the outcomes of IAMs and the estimates of experts to systematically compare two forward-looking perspectives on future technology deployment. We examine projections by 7 IAMs and 39 experts divided over 5 technology families under two different climate policy scenarios for the near (2030) and medium (2050) term. Our main findings from this analysis are:

Experts and IAMs are broadly in agreement on the development of power system change and technological diffusion over time under Baseline scenario assumptions

The study found agreement between experts and IAMs on the direction of system change under status-quo (*Baseline*) conditions. Overall, the experts and IAMs consider fossil fuels the major power source if climate policy is absent, with some contribution of renewable power sources. Despite agreement on the direction of change, differences are observed in the estimated magnitudes for technology deployment over time. Particularly expert estimates on renewable energy technologies are systematically higher than those projected by IAMs.

Under 2 Degrees scenario assumptions the speed and direction of change in the power sector start to diverge both within and between experts and IAMs

Under stringent climate policy assumptions the observed differences in estimated magnitudes of technology deployment become smaller for some technologies. However, greater systematic differences in the considered direction of change are observed between IAMs and experts. Overall, experts assign a greater role to renewable energy sources in total power production by 2050, particularly for solar PV, whereas IAMs are more likely to deploy nuclear power and thermal power plants with carbon removal technologies. Moreover, experts assume a role for bioenergy in mitigation strategies if deliberate choices are made to utilise this resource in power production, whereas IAMs mostly consider the use of bioenergy if combined with carbon capture and storage technologies. Deviations in the estimated magnitudes for these technologies can be partly attributed to different expectations in the availability and economics of different mitigation options.

Contradictory insights between experts and IAMs highlight areas in need of further (transdisciplinary) study

Although the future is inherently uncertain, by contrasting two different analytical methods in a single comparative analysis, it allows to draw a level of reference while simultaneously evaluating the assumed context, considered magnitudes and the implications of such development over time. The current study described a more static analysis of the expectations of expert and IAMs on future change by drawing insights from a single interaction, but future work could consider a more dynamic approach to further unravel the assumed prerequisites and sensitivities in the estimates. A structural confrontation of different analytical lenses may even be considered the desirable way forward in future studies, particularly in those areas where contradictory insights have been observed between experts and IAMs.

Acknowledgements

The research leading to these results has received funding from the European Union's Seventh Framework Programme FP7/2007–2013 under grant agreement n° 282846 (LIMITS), n° 603942 (PATHWAYS) and the European Union's Horizon 2020 research and innovation programme under grant agreement n° 730035 (REINVENT). CW acknowledges funding support from the European Union's Seventh Framework Programme FP7/2007–2013 under grant agreement n° 308329 (ADVANCE). BvdZ acknowledges the financial assistance from the European Union's Horizon 2020 Programme under grant agreement n° 642260 (TRANSrisk). The authors are indebted to all contributing technology experts for partaking in this research. We would also like to thank Hilke Rösler for her research assistance and the anonymous peer-reviewers for their comments which substantially improved the manuscript.

References

Anadón, L.D., Bosetti, V., Bunn, M., Catenacci, M., Lee, A., 2012. Expert Judgments about RD&D and the Future of Nuclear Energy. Environmental Science & Technology 46, 11497-11504.

Anderson, K., 2015. Duality in climate science. Nature Geosci 8, 898-900.

Anderson, K., Peters, G., 2016. The trouble with negative emissions. Science 354, 182-183.

Baker, E., Chon, H., Keisler, J.M., 2008. Advanced Nuclear Power: Combining Economic Analysis with Expert Elicitations to Inform Climate Policy.

Baker, E., Chon, H., Keisler, J., 2009. Carbon capture and storage: combining economic analysis with expert elicitations to inform climate policy. Climatic Change 96, 379-408.

Baker, E., Bosetti, V., Jenni, K.E., Ricci, E.C., 2014. Facing the Experts: Survey Mode and Expert Elicitation. FEEM Working Paper No. 1.2014. Available at SSRN: https://ssrn.com/abstract=2384487 or http://dx.doi.org/10.2139/ssrn.2384487

Bauer, N., Mouratiadou, I., Luderer, G., Baumstark, L., Brecha, R.J., Edenhofer, O., Kriegler, E., 2013. Global fossil energy markets and climate change mitigation – an analysis with REMIND. Climatic Change, 1-14.

Bosetti, V., Carraro, C., Galeotti, M., Massetti, E., Tavoni, M., 2006. WITCH: A World Induced Technical Change Hybrid Model. The Energy Journal.

Bosetti, V., Catenacci, M., Fiorese, G., Verdolini, E., 2012. The future prospect of PV and CSP solar technologies: An expert elicitation survey. Energy Policy 49, 308-317.

Bosetti, V., Anadón, L.D., Baker, E., Reis, L.A., Verdolini, E., 2016. The Future of Energy Technologies: An Overview of Expert Elicitations. GGKP Research Committee on Technology and Innovation Working Paper 01 2016.

Calvin, K., Clarke, L., Krey, V., Blanford, G., Jiang, K., Kainuma, M., Kriegler, E., Luderer, G., Shukla, P.R., 2012. The role of Asia in mitigating climate change: Results from the Asia modeling exercise. Energy Economics 34, Supplement 3, S251-S260.

Calvin, K.V., Wise, M., Klein, D., McCollum, D., TAVONI, M., van der Zwaan, B.C.C., van Vuuren, D.P., 2013. A Multi-Model analysis of the regional and sectoral roles of bioenergy in near -and long-term CO2 emissions reduction. Climate Change Economics 04, 1340014.

Chan, G., Anadon, L.D., Chan, M., Lee, A., 2011. Expert elicitation of cost, performance, and RD&D budgets for coal power with CCS. Energy Procedia 4, 2685-2692.

Clarke, L., Lurz, J., Wise, M., Edmonds, J., Kim, S., Smith, S., Pitcher, H., 2007. Model documentation for the minicam climate change science program stabilization scenarios: Ccsp product 2.1 a. Pacific Northwest National Laboratory, PNNL-16735.

Clarke, L., Jiang, K., Akimoto, K., Babiker, M., Blanford, G., Fisher-Vanden, K., Hourcade, J.-C., Krey, V., Kriegler, E., Löschel, A., McCollum, D., Paltsev, S., Rose, S., Shukla, P.R., Tavoni, M., van der Zwaan, B.C.C., van Vuuren, D.P., 2014. Assessing Transformation Pathways. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P.

Eickemeier, B. Kriemann, J. Savolainen, S.Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Council of the European Union, 2009. Brussels European Council 29/30 October 2009 - Presidency conclusions, https://www.consilium.europa.eu/uedocs/cms_data/docs/pressdata/en/ec/110889.pdf.

Creutzig, F., Agoston, P., Goldschmidt, J.C., Luderer, G., Nemet, G., Pietzcker, R.C., 2017. The underestimated potential of solar energy to mitigate climate change. 2, 17140.

Curtright, A.E., Morgan, M.G., Keith, D.W., 2008. Expert Assessments of Future Photovoltaic Technologies. Environmental Science & Technology 42, 9031-9038.

Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Seyboth, K., Matschoss, P., Kadner, S., Zwickel, T., Eickemeier, P., Hansen, G., Schlömer, S., von Stechow, C., 2011. IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation. Cambridge University Press, United Kingdom and New York, NY, USA.

Edmonds, J.A., Calvin, K.V., Clarke, L.E., Janetos, A.C., Kim, S.H., Wise, M.A., McJeon, H.C., 2012. Integrated assessment modeling, Climate Change Modeling Methodology. Springer, pp. 169-209.

Fiorese, G., Catenacci, M., Bosetti, V., Verdolini, E., 2014. The power of biomass: Experts disclose the potential for success of bioenergy technologies. Energy Policy 65, 94-114.

Fujimori, S., Dai, H., Masui, T., Matsuoka, Y., 2016. Global energy model hindcasting. Energy 114, 293-301.

Fuss, S., Canadell, J.G., Peters, G.P., Tavoni, M., Andrew, R.M., Ciais, P., Jackson, R.B., Jones, C.D., Kraxner, F., Nakicenovic, N., Le Quere, C., Raupach, M.R., Sharifi, A., Smith, P., Yamagata, Y., 2014. Betting on negative emissions. Nature Clim. Change 4, 850-853.

G7, 2015. Leaders declaration G7 summit - Think Ahead, Act Together, 7-8 June 2015, Schloss Elmau.

GEA, 2012. Global Energy Assessment - Toward a Sustainable Future, Cambridge University Press, Cambridge, UK and New York, NY, USA and the International Institute for Applied Systems Analysis, Laxenburg, Austria.

Geels, F.W., Sovacool, B.K., Schwanen, T., Sorrell, S., 2017. Sociotechnical transitions for deep decarbonization. Science 357, 1242.

Global Wind Energy Council, 2015. Global status of wind power in 2015.

Gupta, S., Tirpak, D.A., Burger, N., Gupta, J., Höhne, N., Boncheva, A.I., Kanoan, G.M., Kolstad, C., Kruger, J.A., Michaelowa, A., Murase, S., Pershing, J., Saijo, T., Sari, A., 2007. Policies, Instruments and Co-operative Arrangements, In Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. .

IPCC, 2007. Summary for Policymakers. In: Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC, 2014. AR5 Scenario Database, in: III, W.G. (Ed.), https://tntcat.iiasa.ac.at/AR5DB.

IRENA, 2016. Letting in the light - how solar photovoltaics will revolutionise the electricity system.

Kainuma, M., Matsuoka, Y., Morita, T., Masui, T., Takahashi, K., 2004. Analysis of global warming stabilization scenarios: the Asian-Pacific Integrated Model. Energy Economics 26, 709-719.

Keeney, R.L., von Winterfeldt, D., 1991. Eliciting probabilities from experts in complex technical problems. IEEE Transactions on Engineering Management 38, 191-201.

Keppo, I., van der Zwaan, B., 2011. The Impact of Uncertainty in Climate Targets and CO2 Storage Availability on Long-Term Emissions Abatement. Environmental Modeling & Assessment 17, 177-191.

Kramer, G.J., Haigh, M., 2009. No quick switch to low-carbon energy. Nature 462, 568-569.

Krey, V., Luderer, G., Clarke, L., Kriegler, E., 2014a. Getting from here to there – energy technology transformation pathways in the EMF27 scenarios. Climatic Change 123, 369-382.

Krey, V., Masera, O., Blanford, G., Bruckner, T., Cooke, R., Fisher-Vanden, K., Haberl, H., Hertwich, E., Kriegler, E., Mueller, D., Paltsev, S., Price, L., Schlömer, S., Ürge-Vorsatz, D., van Vuuren, D.P., Zwickel, T., 2014b. Annex II: Metrics & Methodology. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Kriegler, E., Tavoni, M., Aboumahboub, T., Luderer, G., Calvin, K.V., Demaere, G., Krey, V., Riahi, K., Rösler, H., Schaeffer, M., van Vuuren, D.P., 2013. What does the 2°C target imply for a global climate agreement in 2020? The LIMITS study on Durban platform scenarios. Climate Change Economics 04, 1340008.

Kriegler, E., Petermann, N., Krey, V., Schwanitz, V.J., Luderer, G., Ashina, S., Bosetti, V., Eom, J., Kitous, A., Méjean, A., Paroussos, L., Sano, F., Turton, H., Wilson, C., Van Vuuren, D.P., 2015. Diagnostic indicators for integrated assessment models of climate policy. Technological Forecasting and Social Change 90, Part A, 45-61.

Luderer, G., Leimbach, M., Bauer, N., Kriegler, E., 2013. Description of the REMIND model (Version 1.5).

Marquard, J.L., Robinson, S.M., 2008. Reducing Perceptual and Cognitive Challenges in Making Decisions with Models, in: Kugler, T., Smith, J.C., Connolly, T., Son, Y.-J. (Eds.), Decision Modeling and Behavior in Complex and Uncertain Environments. Springer New York, New York, NY, pp. 33-55.

Martin, T.G., Burgman, M.A., Fidler, F., Kuhnert, P.M., Low-Choy, S., McBride, M., Mengersen, K., 2012. Eliciting Expert Knowledge in Conservation Science Obtención de Conocimiento de Expertos en Ciencia de la Conservación. Conservation Biology 26, 29-38.

Melton, N., Axsen, J., Sperling, D., 2016. Moving beyond alternative fuel hype to decarbonize transportation. Nature Energy 1, 16013.

Messner, S., Strubegger, M., 1995. User's guide for MESSAGE III. International Institute for Applied Systems Analysis (IIASA).

Metayer, M., Breyer, C., Fell, H.J., 2015. The projections for the future and quality in the past of the World Energy Outlook for solar PV and other renewable energy technologies, Energy Watch Group.

Morgan, M.G., 2014. Use (and abuse) of expert elicitation in support of decision making for public policy. Proceedings of the National Academy of Sciences 111, 7176-7184.

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., Van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747-756.

Napp, T., Gambhir, A., Thomas, R., Hawkes, A., Bernie, D., Lowe, J., 2015. Exploring the feasibility of low-carbon scenarios using historical energy transitions analysis.

National Research Council, 2010. Persistent Forecasting of Disruptive Technologies. The National Academies Press, Washington, DC.

Nemet, G.F., Baker, E., Jenni, K.E., 2013. Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios. Energy 56, 218-228.

O'Hagan, A., Buck, C.E., Daneshkhah, A., Eiser, J.R., Garthwaite, P.H., Jenkinson, D.J., Oakley, J.E., Rakow, T., 2006. The Elicitation of Probabilities, Uncertain Judgements: Eliciting Experts' Probabilities. John Wiley & Sons, Ltd, pp. 61-96.

O’Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Climatic Change 122, 387-400.

Pietzcker, R.C., Ueckerdt, F., Carrara, S., de Boer, H.S., Després, J., Fujimori, S., Johnson, N., Kitous, A., Scholz, Y., Sullivan, P., 2016. System integration of wind and solar power in Integrated Assessment Models: A cross-model evaluation of new approaches. Energy Economics.

Rao, A.B., Rubin, E.S., Keith, D.W., Granger Morgan, M., 2006. Evaluation of potential cost reductions from improved amine-based CO2 capture systems. Energy Policy 34, 3765-3772.

REN21, 2014. Global Status Report.

Riahi, K., Kriegler, E., Johnson, N., Bertram, C., den Elzen, M., Eom, J., Schaeffer, M., Edmonds, J., Isaac, M., Krey, V., Longden, T., Luderer, G., Méjean, A., McCollum, D.L., Mima, S., Turton, H., van Vuuren, D.P., Wada, K., Bosetti, V., Capros, P., Criqui, P., Hamdi-Cherif, M., Kainuma, M., Edenhofer, O., 2015. Locked into Copenhagen pledges — Implications of short-term emission targets for the cost and feasibility of long-term climate goals. Technological Forecasting and Social Change 90, Part A, 8-23.

Schwanitz, V.J., 2013. Evaluating integrated assessment models of global climate change. Environmental Modelling & Software 50, 120-131.

Sims, R.E.H., Schock, R.N., Adegbululgbe, A., Fenhann, J., Konstantinaviciute, I., Moomaw, W., Nimir, H.B., Schlamadinger, B., 2007. Chapter 4: Energy Supply, Internation panel of climate change.

Smith, P., Davis, S.J., Creutzig, F., Fuss, S., Minx, J., Gabrielle, B., Kato, E., Jackson, R.B., Cowie, A., Kriegler, E., van Vuuren, D.P., Rogelj, J., Ciais, P., Milne, J., Canadell, J.G., McCollum, D., Peters, G., Andrew, R., Krey, V., Shrestha, G., Friedlingstein, P., Gasser, T., Grubler, A., Heidug, W.K., Jonas, M., Jones, C.D., Kraxner, F., Littleton, E., Lowe, J., Moreira, J.R., Nakicenovic, N., Obersteiner, M., Patwardhan, A., Rogner, M., Rubin, E., Sharifi, A., Torvanger, A., Yamagata, Y., Edmonds, J., Yongsung, C., 2016. Biophysical and economic limits to negative CO2 emissions. Nature Clim. Change 6, 42-50.

Stehfest, E., van Vuuren, D.P., Kram, T., Bouwman, L., Alkemade, R., Bakkenes, M., Biemans, H., Bouwman, A., den Elzen, M., Janse, J., Lucas, P.L., van Minnen, J., Muller, M., Prins, A.G., 2014. policy applications Integrated Assessment of Global Environmental Change with IMAGE 3.0 - Model description and policy applications.

Tavoni, M., Kriegler, E., Riahi, K., van Vuuren, D.P., Aboumahboub, T., Bowen, A., Calvin, K., Campiglio, E., Kober, T., Jewell, J., Luderer, G., Marangoni, G., McCollum, D., van Sluisveld, M., Zimmer, A., van der Zwaan, B., 2015. Post-2020 climate agreements in the major economies assessed in the light of global models. Nature Clim. Change 5, 119-126.

Trutnevyte, E., McDowall, W., Tomei, J., Keppo, I., 2016. Energy scenario choices: Insights from a retrospective review of UK energy futures. Renewable and Sustainable Energy Reviews 55, 326-337.

UN, 2015. Paris Agreement.

van der Zwaan, B.C.C., Rösler, H., Kober, T., Aboumahboub, T., Calvin, K.V., Gernaat, D.E.H.J., Marangoni, G., McCollum, D., 2013. A cross-model comparison of global long-term technology diffusion under a 2°C climate change control target. Climate Change Economics 04, 1340013.

van Sluisveld, M.A.E., Gernaat, D.E., Ashina, S., Calvin, K.V., Garg, A., Isaac, M., Lucas, P.L., Mouratiadou, I., Otto, S.A., Rao, S., 2013. A multi-model analysis of post-2020 mitigation efforts of five major economies. Climate Change Economics 4, 1340012.

van Sluisveld, M.A.E., Harmsen, J.H.M., Bauer, N., McCollum, D.L., Riahi, K., Tavoni, M., van Vuuren, D.P., Wilson, C., van der Zwaan, B., 2015. Comparing future patterns of energy system change in 2 °C scenarios with historically observed rates of change. Global Environmental Change 35, 436-449.

van Vuuren, D.P., O'Neill, B.C., 2006. The Consistency of IPCC's SRES Scenarios to 1990–2000 Trends and Recent Projections. Climatic Change 75, 9-46.

van Vuuren, D.P., Edmonds, J., Smith, S.J., Calvin, K.V., Karas, J., Kainuma, M., Nakicenovic, N., Riahi, K., van Ruijven, B.J., Swart, R., Thomson, A., 2010. What do near-term observations tell us about long-term developments in greenhouse gas emissions? Climatic Change 103, 635-642.

Van Vuuren, D.P., van Sluisveld, M.A.E., Hof, A.F., 2015. Implications of long-term scenarios for medium-term targets (2050), publication number: 1871, The Hague: PBL Netherlands Environmental Assessment Agency.

Vaughan, N.E., Gough, C., 2016. Expert assessment concludes negative emissions scenarios may not deliver. Environmental Research Letters 11, 095003.

Weyant, J., Kriegler, E., 2014. Preface and introduction to EMF 27. Climatic Change 123, 345-352.

Wilson, C., Grubler, A., Bauer, N., Krey, V., Riahi, K., 2012. Future capacity growth of energy technologies: are scenarios consistent with historical evidence? Climatic Change 118, 381-395.

Wilson, C., Kriegler, E., van Vuuren, D.P., Guivarch, C., Frame, D., Krey, V., Osborn, T.J., Schwanitz, V.J., Thompson, E.L., 2017. Evaluating Process-Based Integrated Assessment Models of Climate Change Mitigation, http://pure.iiasa.ac.at/14502/1/WP-17-007.pdf.

World Nuclear Association, 2016. Plans For New Reactors Worldwide. World Nuclear Association.