ANALYSIS
https://doi.org/10.1038/s41558-021-00998-8

nature climate change

Sources of uncertainty in long-term global scenarios of solar photovoltaic technology

Marc Jaxa-Rozen ✉ and Evelina Trutnevyte

The deployment of solar photovoltaic (PV) technology has consistently outpaced expectations over the past decade. However, long-term prospects for PV remain deeply uncertain, as recent global scenarios span two orders of magnitude in installed PV capacity by 2050. Here we systematically compile an ensemble of 1,550 scenarios from peer-reviewed and influential grey literature, including IPCC and non-IPCC scenarios, and apply a statistical learning framework to link scenario characteristics with foreseen PV outcomes. We show that a large portion of the uncertainty in the global scenarios is associated with general features such as the type of organization, energy model and policy assumptions, without referring to specific techno-economic assumptions. IPCC scenarios consistently project lower PV adoption pathways and higher capital costs than non-IPCC scenarios. We thus recommend increasing the diversity of models and scenario methods included in IPCC assessments to represent the multiple perspectives present in the PV scenario literature.

The Paris Agreement calls for net anthropogenic CO_2 emissions to be halved within a decade and eliminated by 2050[1]. Widespread adoption of renewable power generation is crucial to this effort[1], with key synergies provided by end-use electrification for transport and heat[2]. Recent development of solar photovoltaic (PV) technology has been remarkable, with installed capacity rising from 25 to 600 GW from 2010 to 2019—the largest net growth of any generation technology[3]. A key to this expansion has been PV's growing cost competitiveness: the benchmark levelized cost of PV electricity fell by 81% in 2009–2019 (ref. [3]), twice the reduction foreseen for the decade by the International Energy Agency[4].

PV prospects are especially relevant for decision-makers and investors concerned with stimulating the adoption of renewable generation for climate action. Solar resources largely exceed global energy demand[5], and several observers expect PV technology to reach a dominant role by mid-century in the electricity sector, with a global installed capacity of more than 20 TW[6–8]. Others anticipate limited prospects for PV expansion due to land use constraints or grid flexibility[9,10]. In either case, further PV deployment requires addressing challenges such as grid integration and adoption of complementary storage technologies[3,11].

Energy systems models and scenarios are common tools to quantify the potential uptake of technologies for guiding investments, planning infrastructures and evaluating policies[12,13]. Over the past decade, these model-based scenarios projected values of PV generation in 2050 from nearly zero to above 300 EJ yr^{-1}, equivalent to capacity exceeding 60 TW (Fig. 1a). Such diversity is expected, given various expert views on PV prospects[14], and it is helpful to avoid false confidence in the face of irreducible uncertainties[15,16]. Nonetheless, given that energy scenarios shape expectations and strategic choices for emerging technologies[17,18], it is essential to explain the origins of this disparity in projected PV outcomes.

Some uncertainty in scenarios until now was attributed to techno-economic parameters: for a given energy model, different cost assumptions can more than double projected PV generation[19,20]. Across multiple models with consistent parametric assumptions, structural choices on power system modelling can similarly shift PV generation by a factor of two[21,22]. More broadly, the institutional background of models and scenarios has been argued to shape their assumptions and results[23]. For example, global scenarios published by fossil fuel firms tend to depict higher fossil energy demand than equivalent scenarios from non-governmental organizations (NGOs), possibly reflecting vested interests[24]. A quantification of the impact of these assumptions on projected PV outcomes is still lacking.

We therefore systematically analyse a new ensemble of 1,550 long-term energy scenarios published since 2010 in peer-reviewed scientific publications, grey literature and two latest scenario databases of the IPCC, focusing on PV global capacity over 2030–2050. We apply a new methodology based on statistical learning methods, where we identify archetypes of scenarios and scenario publications using spectral clustering and topic modelling. We then link general characteristics of scenarios, such as the type of organization, model and structural assumptions, with the projected growth of PV capacity by using a non-linear classifier. The results indicate that general properties of the models and publications are associated with a large portion of the variation in projected PV outcomes. On the basis of these properties alone, the scenarios can be classified into quintiles in terms of PV capacity growth with 73% accuracy. Other scenario properties, such as explicit assumptions on PV costs or, in the case of non-IPCC scenarios, climate and technology policy, are left with a secondary contribution to projected PV adoption.

A framework for analysing uncertainty in global PV scenarios

The new scenario ensemble created in this study combines 1,360 scenarios included in the IPCC SR1.5 and Fifth Assessment Reports (AR5)[25,26], and 190 other systematically selected scenarios published since 2010 in peer-reviewed and grey literature (Supplementary Data 1). Figure 1b,c shows time series for installed PV capacity and generation in the subsets of IPCC and non-IPCC scenarios. Remaining analysis focuses on the equivalent compound annual growth rate (CAGR) of global installed PV capacity, computed from the scenario end date relative to 2010, so that scenarios can be compared across different horizons. We restricted the timeframe of the analysis to 2050, given the scarcity of non-IPCC projections

Renewable Energy Systems, Institute for Environmental Sciences (ISE), Section of Earth and Environmental Sciences, University of Geneva, Geneva, Switzerland. ✉e-mail: marc.jaxa-rozen@unige.ch

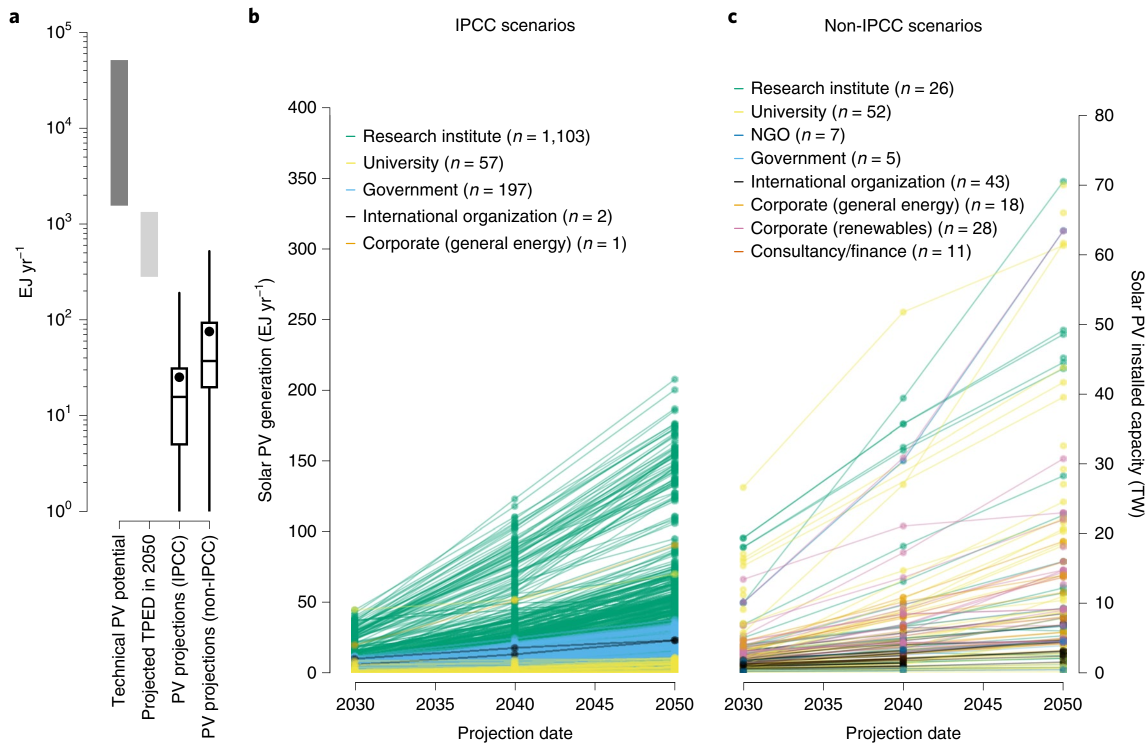

Fig. 1 | Overview of the analysed scenario ensemble. **a**, A range of estimates of global technical PV potential[5], projected TPED in 2050 (ref. [1]) and projected PV generation in 2050 in the scenarios compiled in this study. Box plots show the mean (black marker), median (black line), interquartile range (box) and the minimum–maximum range (whiskers). **b**,**c**, Time series of PV generation and capacity grouped by the type of organization, for 1,360 IPCC scenarios (**b**) and 190 non-IPCC scenarios (**c**) compiled in this study. The *y*-axis values for PV generation and PV installed capacity are related with an average energy yield of 1,370 $\mathrm{kWh\,kW_p^{-1}}$ (ref. [7]).

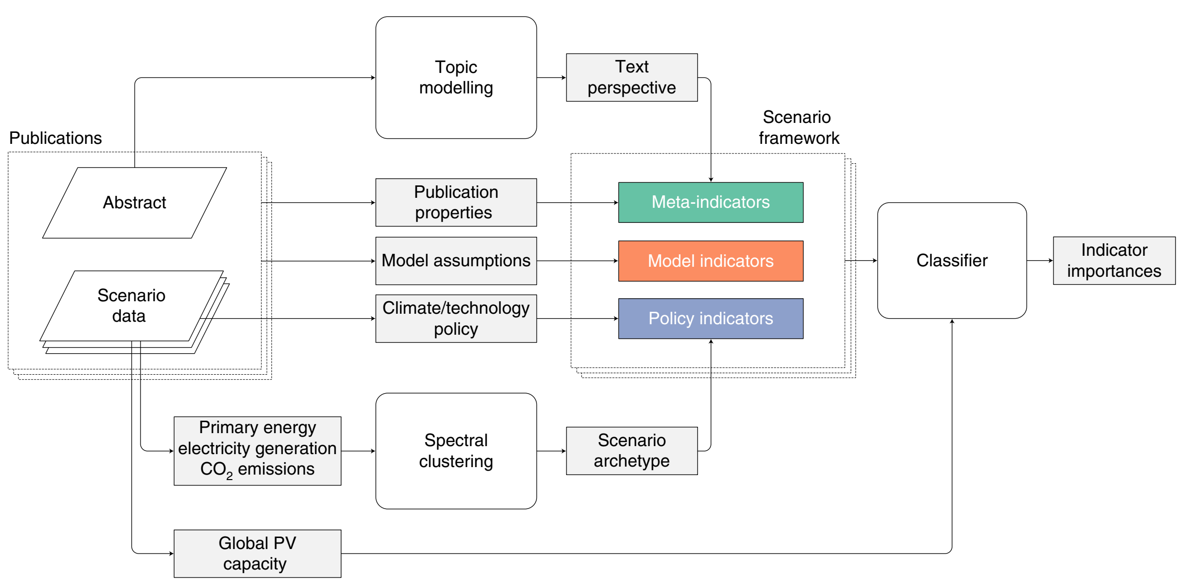

Fig. 2 | Workflow of the analysis and data sources. Primary sources are shown in parallelograms, key data and outputs are shown in grey boxes, and key analytical methods are shown in rounded rectangles.

beyond this date. We use a framework that records three groups of categorical indicators (Fig. 2 and Supplementary Table 1), obtained from the publications or model documentations. First, we record meta-indicators for the date and type of publication, and the type and location of organization. A second group of model indicators tracks categorical data about the model, such as whether it is limited to the PV sector or covers broader energy system dynamics. Finally, policy indicators document general climate mitigation and technology policies assumed in the scenario, if specified.

We extend this framework with additional properties, using statistical methods for clustering and topic modelling (detailed in Methods). Most PV scenarios in our ensemble are embedded in

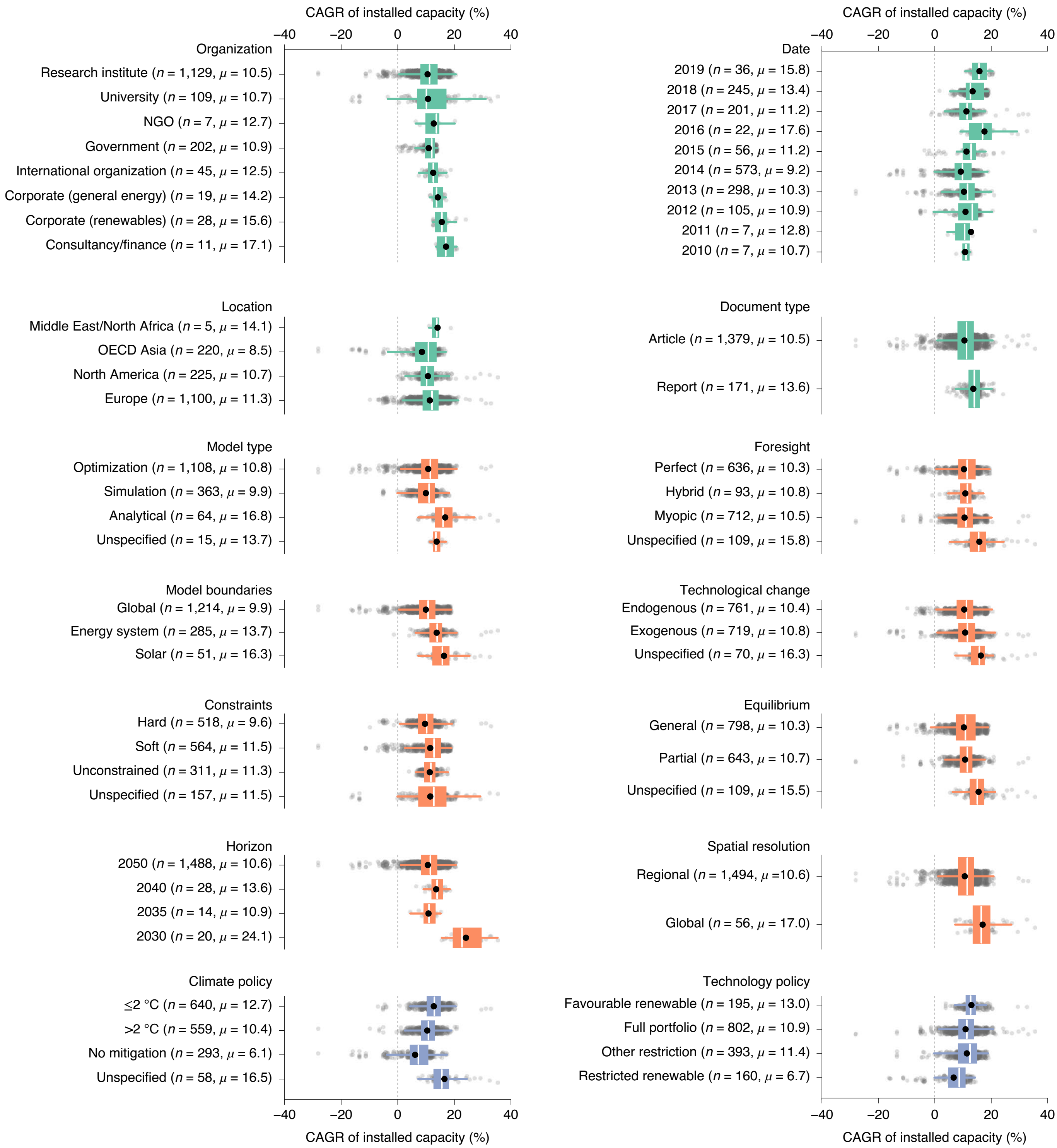

Fig. 3 | Visualization of projected PV growth in the overall ensemble, grouped by indicators. Boxplots show projected capacity CAGR across meta-indicators (green), model indicators (orange) and policy indicators (blue). The projected CAGR is computed from the end year of the scenario (or from 2050, for scenarios reporting values beyond this horizon), relative to historical values for 2010. For each boxplot, the mean μ over the entire ensemble is denoted by a black marker, and the median by a white line. Boxes show interquartile range, whiskers are extended by 1.5 times the interquartile range and light grey markers show individual scenarios. Supplementary Fig. 1 shows disaggregated results for IPCC and non-IPCC scenarios.

long-term scenarios of the global energy system, and PV deployment is therefore conditional on assumptions of energy demand or technological development. To assess the impact of this wider scenario context, we use spectral clustering to group the scenarios across their projected CAGR for three other indicators: share of electricity generation in total primary energy demand (TPED), TPED itself and total energy-related CO_2 emissions. In the subset of 1,392 scenarios that include these three indicators, we identify four representative scenario archetypes that we assign as an additional policy indicator. We then use probabilistic topic modelling

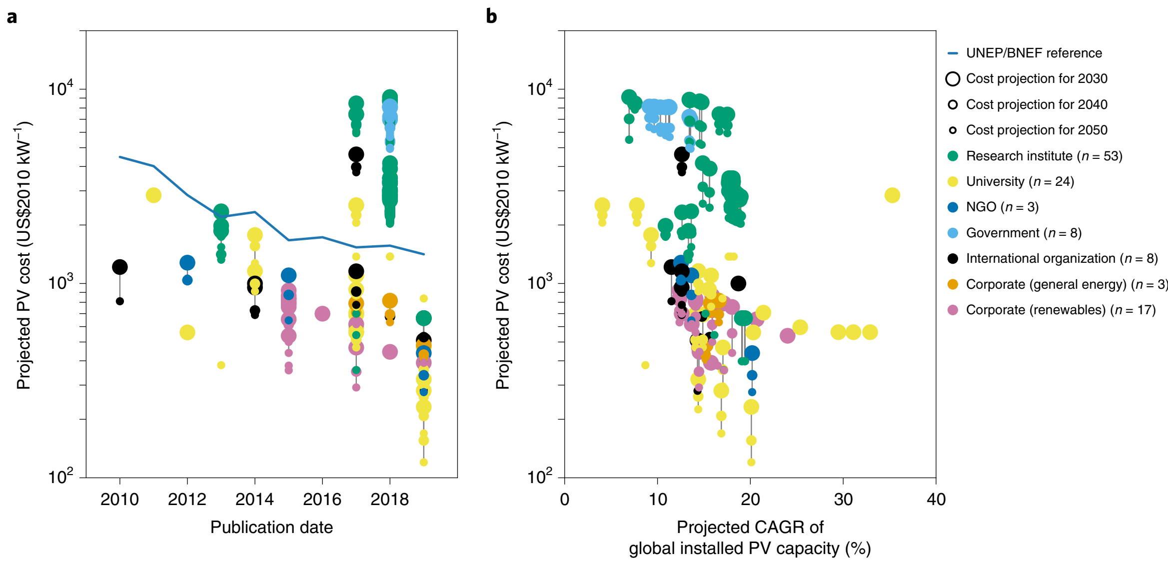

Fig. 4 | PV cost data in the overall scenario ensemble. a, Projected PV costs as a function of the date of publication, grouped by the projection horizon of scenarios (marker sizes) and type of organization (marker colours). The blue line presents actual benchmark costs for utility-scale PV in Germany in the same period[3]. Grey lines link different projection horizons reported in each scenario. **b**, Projected PV capital costs at each reported horizon versus projected CAGR of PV capacity at the end year of each scenario. UNEP, United Nations Environment Programme; BNEF, Bloomberg New Energy Finance. Supplementary Fig. 3 shows disaggregated results and summary statistics for IPCC and non-IPCC scenarios.

to identify dominant text perspectives in the publications and to provide additional context on the points of view that may shape scenarios. We apply latent Dirichlet allocation (LDA) to identify eight dominant topics, based on the abstracts or summaries of the publications. We assign a corresponding meta-indicator for the dominant text perspective.

To understand sources of uncertainty in PV scenarios, we apply the XGBoost non-linear classification algorithm (detailed in Methods) to link these three groups of indicators with the CAGR of global PV capacity. As our analysis focuses on interpreting general patterns, we group the scenarios into equal quintiles, based on their projected CAGR. We then use XGBoost to identify the most influential indicators towards this classification, based on Shapley additive explanation values[27].

Projected PV growth and properties of the scenarios

Figure 3 shows the distribution of CAGR across the meta-indicators as well as model and policy indicators of the scenarios over the full scenario ensemble (Supplementary Fig. 1 shows IPCC and non-IPCC scenarios separately; Supplementary Tables 1–3 report statistics). Overall, European organizations project statistically significantly higher CAGR values than Asian and North American institutions ($\mu = 11.3$ versus $\mu = 8.5$ and $\mu = 10.7$, respectively; $P < 0.001$). The CAGR values in scenarios from universities and research institutes are distributed more broadly than in corporate scenarios, indicating that academic scenarios consider the widest range of uncertainties. Scenarios published in reports project higher CAGR values than scientific articles ($\mu = 13.6$ versus $\mu = 10.5$; $P < 0.001$). CAGR in scenarios from corporate organizations is statistically significantly higher than CAGR from research institutes and universities ($P < 0.01$; Fig. 3 reports the means), except for general energy firms (including fossil fuel firms) versus universities. Although consultancies and renewable-energy-focused firms have higher mean CAGR than general energy firms, these differences are not statistically significant. There is also no significant difference between universities and research institutes, while renewable-energy-focused firms are the only category that have a significantly different CAGR from international organizations, such as the International Energy Agency ($\mu = 15.6$ versus $\mu = 12.5$; $P < 0.05$). The scenarios published in the second half of the 2010s are more optimistic than earlier scenarios, probably owing to revised assumptions reflecting improved technical and economic PV performance[3].

The type and boundaries of models play an important role for CAGR, with a substantial difference in means across categories. Scenarios based on analytical methods have higher CAGR than optimization or simulation models ($\mu = 16.8$ versus $\mu = 10.8$ and $\mu = 9.9$, respectively; $P < 0.001$), and models that focus on only solar technologies foresee higher adoption than energy system models ($\mu = 16.3$ versus $\mu = 13.7$; $P < 0.05$) or global models ($\mu = 16.3$ versus $\mu = 9.9$; $P < 0.001$). Similarly, models that do not explicitly specify technological change or PV growth constraints project higher mean CAGR ($P < 0.001$; Fig. 3 reports the means). If models include constraints, then 'hard' constraints on relative PV growth across time steps are associated with lower mean CAGR than in other categories ($P < 0.001$; Fig. 3), indicating that exogenous constraints may lead to parametric conservatism[28]. Models with exogenous technological change have slightly higher mean CAGR than in the case of endogenized technological change ($\mu = 10.8$ versus $\mu = 10.4$; $P < 0.05$). There are no statistically significant differences between models with perfect and myopic foresight, or between partial equilibrium and general equilibrium models. Non-IPCC scenarios cover diverse projection horizons, while IPCC scenarios uniformly report data to 2050. We find significant differences between these horizons ($P < 0.05$; Fig. 3), except for scenarios ending in 2035 and 2040. This could originate in different growth patterns, such as early exponential growth in shorter-term scenarios versus a saturated logistic curve in long-term scenarios. For scenarios ending in 2050, non-IPCC scenarios have a higher mean CAGR than IPCC scenarios ($\mu = 14.0$ versus $\mu = 10.3$; Supplementary Fig. 1). This difference equates to an installed PV capacity that would be, on average, higher by a factor of 3.7 in non-IPCC scenarios by 2050. We further investigate the impact of projection horizon in Supplementary Fig. 2. The difference between IPCC and non-IPCC scenarios is more pronounced at the near-term 2030 horizon and it is equivalent to an average installed capacity higher by a factor of 4.5 in non-IPCC scenarios.

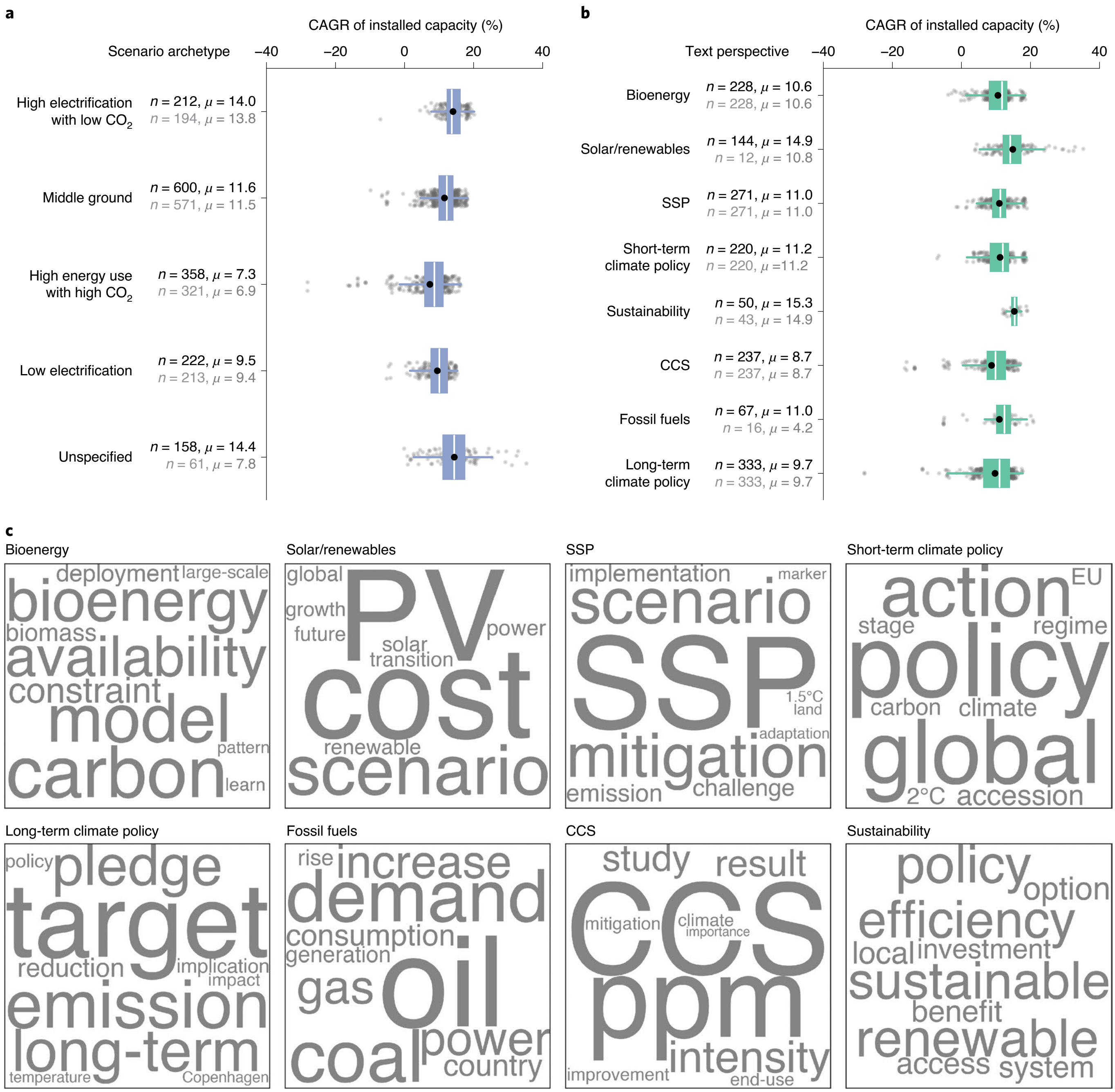

Fig. 5 | Scenario archetypes and text perspectives in the overall ensemble. a, Global PV CAGR in the scenarios, grouped by scenario archetype. Supplementary Fig. 6 presents separate boxplots for IPCC and non-IPCC scenarios; Supplementary Fig. 7 visualizes the scenario archetypes. The projected CAGR is computed from the end year of the scenario (or from 2050, for scenarios reporting values beyond this horizon), relative to historical values for 2010. **b**, Global PV CAGR in the scenarios, grouped by the dominant text perspective. For each boxplot, the mean μ over the entire ensemble is denoted by a black marker, and the median by a white line. Boxes show interquartile range, whiskers are extended by 1.5 times the interquartile range and light grey markers show individual scenarios. Annotations show the count and mean μ of each category within the full ensemble of scenarios (in black text), and within the subset of IPCC scenarios (in grey text). **c**, Text perspectives identified by topic modelling, shown in word clouds with the ten most relevant words in each perspective (detailed in Methods).

All pairwise statistical comparisons for the policy indicators are statistically significant ($P < 0.05$; Fig. 3). As expected, stricter climate and renewable energy policies are associated with higher PV CAGR. Scenarios with a restricted technology portfolio have higher mean CAGR than full-portfolio scenarios, because PV emerges as a stronger mitigation option in the absence of negative emissions technologies. Explicit modelling of climate policies of any kind is associated with lower mean values of CAGR than the scenarios in which policies are not specified, probably because the latter scenarios correspond to more optimistic analytical projections.

We also analyse a subset of 116 scenarios that report PV cost assumptions. We focus on overnight utility-scale capital cost, rather than annualized cost or levelized cost of electricity, because these two are reported in few scenarios (Methods). Projected capital costs in the scenarios decrease over the publication period, mirroring actual values (Fig. 4a). However, some scenarios still project higher

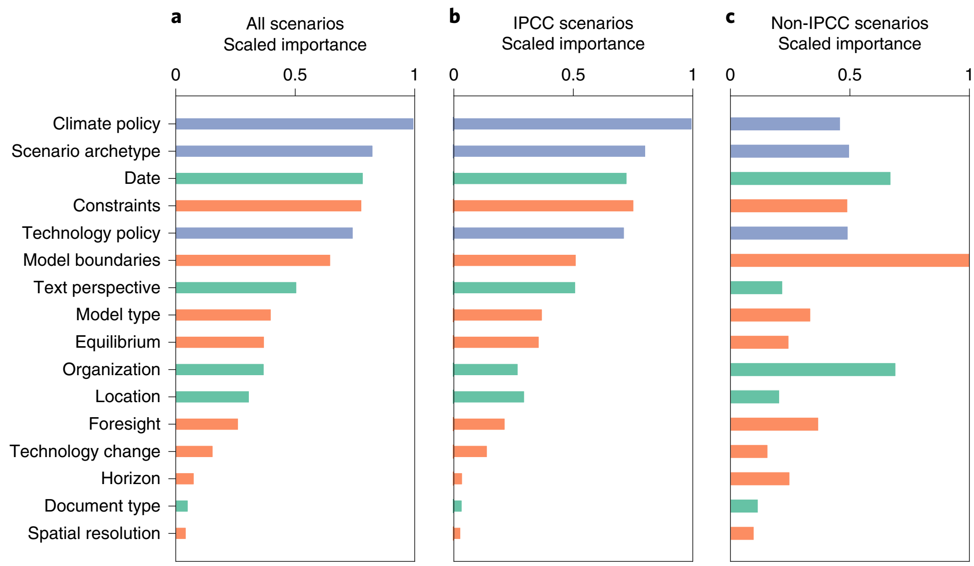

Fig. 6 | Relative importance of scenario indicators for explaining PV growth, estimated using Shapley additive explanation values for the classification of scenarios into CAGR quintiles. a–c, Relative importance of the full ensemble of scenarios (**a**), the IPCC scenarios (**b**) and the non-IPCC scenarios (**c**). Bar colours denote meta-indicators (green), model indicators (orange) and policy indicators (blue).

future costs than the actual benchmark cost for PV at the time of publication, probably owing to the well-known modelling issue of 'assumption drag'[29]. There is also a general link between projected capital costs and projected CAGR (Fig. 4b), where scenarios with high costs tend to project relatively low CAGR. The IPCC scenarios that report PV costs (found in only SR1.5) have relatively high costs compared with non-IPCC scenarios (Supplementary Fig. 3). However, the scenarios still vary substantially: for a given level of PV costs, there is a broad range of CAGR values and vice versa, reflecting other parametric and structural assumptions.

Global PV scenarios that are the primary focus of this study conceal differences in regional PV deployment patterns. Supplementary Figs. 4 and 5 disaggregate the outcomes for Asia and the Middle East with Africa in the scenarios that provide these values. As with global outcomes, some patterns emerge across the types of organization: international organizations tend to foresee higher deployment of PV in Asia, relative to the region's TPED, but comparatively low PV adoption values in Africa. IPCC scenarios show a more diverse range of regional outcomes, including more optimistic pathways for PV growth in Africa and some pessimistic pathways in Asia.

Scenario archetypes and text perspectives

Figure 5a visualizes CAGR across four scenario archetypes identified in a subset of 1,392 scenarios that record variables used for clustering: high electrification with low CO_2 emissions, middle ground, high energy use with high CO_2 emissions and low electrification. These archetypes are visualized in Supplementary Fig. 7, including representative shared socioeconomic pathways (SSPs)[30]. An additional unspecified archetype includes the remaining 158 scenarios, such as the analytical scenarios that do not report TPED. The high-electrification archetype presents the highest mean CAGR for PV among the identified archetypes, because it typically includes high deployment of renewable electricity. The lowest mean CAGR is found in the high-energy high-CO_2 archetype, followed by the low-electrification archetype. All pairwise statistical comparisons show a significant difference ($P < 0.001$; Fig. 5a), except between high-electrification and unspecified scenarios. IPCC scenarios are more strongly associated with middle ground and low-electrification archetypes (Supplementary Fig. 8). Non-IPCC scenarios overrepresent archetypes with high energy use and high electrification, and explore the highest values for CAGR of electricity share (Supplementary Fig. 7), but under-represent the middle ground and low-electrification archetypes.

Figure 5b,c presents findings on text perspectives identified in the overall scenario ensemble (Supplementary Figs. 9–13 detail the performance of topic modelling). Publications focused on sustainability or renewable energy show the highest mean CAGR values, followed by publications focused on short-term climate policy or SSPs[30]. The last two perspectives are typically associated with more recent publications, such as the IPCC SR1.5 scenarios (Supplementary Fig. 14). Publications emphasizing carbon capture and storage have the lowest mean CAGR, which is significantly lower than most other perspectives ($\mu = 8.7$ versus $\mu \geq 11.0$; $P < 0.05$), except for bioenergy and long-term climate policy. There are no significant pairwise differences among publications with dominant perspectives on short-term and long-term climate policy, SSPs, bioenergy and fossil-fuel-related publications. We find consistent relationships among organization types, scenario archetypes, text perspectives, and subsets of IPCC and non-IPCC scenarios (Supplementary Fig. 8). Publications with dominant text perspective on solar and renewable energy, for example, overrepresent the archetype of high electrification. The publications with fossil fuel perspective are strongly associated with the archetype of high energy use. Some of the text perspectives, such as SSPs and carbon capture and storage, are exclusively associated with IPCC scenarios (Fig. 5a,b, grey annotations).

Linking scenario properties and projected PV growth

We find that the scenarios can be classified into quintiles of PV CAGR with a relatively high accuracy of 73% using the XGBoost algorithm, on the basis of general indicators from our framework. The model performs especially well for the bottom and top quintiles with lowest and highest CAGR values, but the classification is less reliable for the middle quintiles (Supplementary Fig. 15). Using Shapley additive explanation values[27] to estimate relative variable importance, we show that policy indicators—climate policy, scenario archetypes and technology policy—are ranked among the five most influential variables for the full ensemble of scenarios (Fig. 6a). Other indicators in principle unrelated to scenario definitions, such as publication date, the type of modelling constraints on PV or renewable energy deployment and text perspectives, also play an important role. Despite findings on the role of organization type shown earlier in Fig. 3, this indicator does not emerge to be very influential in the overall classification; the importance of this indicator is influenced by the prevalence of IPCC scenarios in the ensemble, which are dominated by research institutes and universities. When using the same classifier to predict outcomes in the more diverse subset of 190 non-IPCC scenarios (Fig. 6c), the model boundaries, organization type, date and scenario archetypes become most influential.

The relatively strong classification accuracy implies that scenario characteristics kept out of our framework, such as specific techno-economic assumptions, are left with a minor marginal contribution, or are at least not independent of the indicators in our framework. To test this, Supplementary Figs. 16 and 17 present results after including PV capital costs as an additional explanatory variable (detailed in Methods). Overall accuracy remains at 73%, but increases to 77% for the 116 scenarios that include cost data. For the latter scenarios, PV cost assumptions remain less important for projected PV growth than date, scenario archetype, model boundaries and constraints, and climate policy. PV cost assumptions have a non-negligible correlation with several other indicators (Supplementary Fig. 18, last column), such as date, text perspective, archetype and organization type. This probably reflects the progressive revision of scenario assumptions over time as well as organizational factors[31].

Implications for decision-makers and scenario modellers

Our analysis shows that corporate scenarios as well as simpler models are consistently associated with relatively optimistic expectations of PV growth. Scenarios from research institutes and universities span the widest range of uncertainties, including the highest and lowest CAGR, but scenarios with highest PV adoption are mostly found outside the IPCC ensembles. A large portion of the uncertainty in the scenarios is associated with general scenario indicators, such as the type and boundaries of energy model, date of publication and text perspective. It is well recognized that techno-economic assumptions influence scenario outcomes, and that their systematic reporting makes scenarios more interpretable for users[32], but our results also show that projected PV growth in scenarios should be interpreted through the lens of who created these scenarios, when and how. These background characteristics may shape specific assumptions and are ultimately associated with much of the uncertainty in published PV scenarios. Overall prospects for PV are thus best understood in such systematic reviews of scenarios.

The value of organizational and model diversity to generate robust insights from scenarios has been repeatedly underlined[15,23]. Our ensemble of 1,550 PV scenarios reveals multiple complementary perspectives that already exist in peer-reviewed and grey literature. As the next IPCC assessment report is being written, this could benefit from a more diverse set of models and PV scenarios. The IPCC AR5 and SR1.5 scenario ensembles are relatively uniform in their organizational provenance and modelling approach, and they also tend to be relatively conservative about PV growth or capital costs, particularly in the near term. The past decade is already full of examples of PV outpacing expectations[19,33]. This pattern, and the rapid adoption of variable renewable energy in general, points towards a possible structural shift in the energy system. Such a departure from historical trends poses a challenge for developing, evaluating and validating models[34–36], which must acknowledge deep uncertainties[37] surrounding socio-technical change. There is a certain unavoidable inertia in assessing real-world developments (such as PV capital costs), updating model assumptions and publishing revised scenarios. This is compounded by the difficulty of distinguishing short-term fluctuations from fundamental long-term trends[34] and by limited organizational resources[13]. In this setting, ensembles of models that span different levels of complexity and organizational background would contribute to robust insights[35].

Solar PV was an especially relevant case to study because it combines rapid scalability with large technical potential and, as a result, can present a wide spectrum of adoption pathways by mid-century. Similar attributes are found in other granular technologies for climate change mitigation[38], such as electric vehicles, battery storage or heat pumps, which are currently also being implemented in global energy models[39]. Future work could therefore assess large scenario ensembles with a focus on these technologies.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-021-00998-8.

Received: 27 April 2020; Accepted: 26 January 2021;
Published online: 3 March 2021

References

1. Rogelj, J. et al. in *Special Report on Global Warming of 1.5 °C* (eds Masson-Delmotte, V. et al.) Ch. 2 (IPCC, WMO, 2018).
2. Davis, S. J. et al. Net-zero emissions energy systems. *Science* **360**, eaas9793 (2018).
3. *Global Trends in Renewable Energy Investment 2019* (Frankfurt School-UNEP Centre/BNEF, 2019).
4. *World Energy Outlook 2010* (International Energy Agency, 2010).
5. Arvizu, D. et al. in *Special Report on Renewable Energy Sources and Climate Change Mitigation* (eds Edenhofer, O. et al.) 34–212 (IPCC, Cambridge Univ. Press, 2011).
6. Bogdanov, D. et al. Radical transformation pathway towards sustainable electricity via evolutionary steps. *Nat. Commun.* **10**, 1077 (2019).
7. Haegel, N. M. et al. Terawatt-scale photovoltaics: transform global energy. *Science* **364**, 836–838 (2019).
8. Jacobson, M. Z. et al. Impacts of green new deal energy plans on grid stability, costs, jobs, health, and climate in 143 countries. *One Earth* **1**, 449–463 (2019).
9. Hansen, J. P., Narbel, P. A. & Aksnes, D. L. Limits to growth in the renewable energy sector. *Renew. Sustain. Energy Rev.* **70**, 769–774 (2017).
10. *World Energy Outlook 2019* (International Energy Agency, 2019).
11. *Future of Solar Photovoltaic: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation)* (International Renewable Energy Agency, 2019).
12. DeCarolis, J. et al. Formalizing best practice for energy system optimization modelling. *Appl. Energy* **194**, 184–198 (2017).
13. Strachan, N., Fais, B. & Daly, H. Reinventing the energy modelling–policy interface. *Nat. Energy* **1**, 16012 (2016).
14. Trutnevyte, E., Guivarch, C., Lempert, R. & Strachan, N. Reinvigorating the scenario technique to expand uncertainty consideration. *Climatic Change* **135**, 373–379 (2016).
15. Craig, P. P., Gadgil, A. & Koomey, J. G. What can history teach us? A retrospective examination of long-term energy forecasts for the United States. *Annu. Rev. Energy Environ.* **27**, 83–118 (2002).
16. Morgan, M. G. & Keith, D. W. Improving the way we think about projecting future energy use and emissions of carbon dioxide. *Climatic Change* **90**, 189–215 (2008).
17. Konrad, K., Van Lente, H., Groves, C. & Selin, C. in *The Handbook of Science and Technology Studies* (eds Felt, U. et al.) 465–493 (MIT Press, 2017).
18. Wüstenhagen, R. & Menichetti, E. Strategic choices for renewable energy investment: conceptual framework and opportunities for further research. *Energy Policy* **40**, 1–10 (2012).
19. Creutzig, F. et al. The underestimated potential of solar energy to mitigate climate change. *Nat. Energy* **2**, 17140 (2017).
20. Pietzcker, R., Stetter, D., Manger, S. & Luderer, G. Using the Sun to decarbonize the power sector: the economic potential of photovoltaics and concentrating solar power. *Appl. Energy* **135**, 704–720 (2014).
21. Cole, W. et al. *Variable Renewable Energy in Long-Term Planning Models: A Multi-Model Perspective* (National Renewable Energy Laboratory, 2017).
22. Pietzcker, R. et al. System integration of wind and solar power in integrated assessment models: a cross-model evaluation of new approaches. *Energy Econ.* **64**, 583–599 (2017).

23. Trutnevyte, E., McDowall, W., Tomei, J. & Keppo, I. Energy scenario choices: insights from a retrospective review of UK energy futures. *Renew. Sustain. Energy Rev.* **55**, 326–337 (2016).
24. Carrington, G. & Stephenson, J. The politics of energy scenarios: are International Energy Agency and other conservative projections hampering the renewable energy transition? *Energy Res. Soc. Sci.* **46**, 103–113 (2018).
25. Huppmann, D. et al. *IAMC 1.5 °C Scenario Explorer and Data Hosted by IIASA* (IAMC and IIASA, 2018); https://doi.org/10.22022/SR15/08-2018.15429
26. *IAMC AR5 Scenario Database* (IAMC and IIASA, 2014).
27. Lundberg, S. M. et al. From local explanations to global understanding with explainable AI for trees. *Nat. Mach. Intell.* **2**, 56–67 (2020).
28. Wilson, C., Grubler, A., Bauer, N., Krey, V. & Riahi, K. Future capacity growth of energy technologies: are scenarios consistent with historical evidence? *Climatic Change* **118**, 381–395 (2013).
29. O'Neill, B. C. & Desai, M. Accuracy of past projections of US energy consumption. *Energy Policy* **33**, 979–993 (2005).
30. O'Neill, B. C. et al. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic Change* **122**, 387–400 (2014).
31. Breyer, C. et al. On the role of solar photovoltaics in global energy transition scenarios. *Prog. Photovoltaics* **25**, 727–745 (2017).
32. Weber, C. et al. Mitigation scenarios must cater to new users. *Nat. Clim. Change* **8**, 845–848 (2018).
33. Gilbert, A. Q. & Sovacool, B. K. Looking the wrong way: bias, renewable electricity, and energy modelling in the United States. *Energy* **94**, 533–541 (2016).
34. van Vuuren, D. P. et al. What do near-term observations tell us about long-term developments in greenhouse gas emissions? *Climatic Change* **103**, 635–642 (2010).
35. Wilson, C. et al. *Evaluating Process-Based Integrated Assessment Models of Climate Change Mitigation* (IIASA, 2017).
36. Trutnevyte, E. Does cost optimization approximate the real-world energy transition? *Energy* **106**, 182–193 (2016).
37. Lempert, R. J. Values and uncertainty. *Nat. Clim. Change* **5**, 914–915 (2015).
38. Wilson, C. et al. Granular technologies to accelerate decarbonization. *Science* **368**, 36–39 (2020).
39. McCollum, D. L. et al. Improving the behavioral realism of global integrated assessment models: an application to consumers' vehicle choices. *Transportation Res. D* **55**, 322–342 (2017).

Methods

Scenario ensemble. We systematically selected peer-reviewed publications from the Web of Science and Google Scholar databases that at least minimally included scenarios for global installed PV capacity and/or PV electricity generation for the 2030–2050 horizon. We limited our search to most recent publications that appeared in 2010 or later. The following query was used with appropriate adjustments to the Boolean operators: ((global AND solar AND (pv OR photovoltaic) AND (forecast OR scenario OR scenario OR adoption OR growth OR development) NOT weather NOT irradiance NOT radiation NOT hourly NOT daily)). We used exclusion operators to avoid papers with a focus on, for example, short-term weather-based forecasting of PV irradiance instead of long-term global projections.

This query returned 488 documents in the Web of Science Core Collection and 32,600 documents in the Google Scholar database, from which we retained 1,000 documents with the highest relevance score. The abstracts of these documents were assessed to keep the subset of publications that contained the relevant PV scenarios. Additional publications from the grey literature were identified from earlier reviews of global energy scenarios[24,31,40–42]. This process yielded 190 scenarios from 77 documents, listed in Supplementary Data 1. We combine all these scenarios with 952 scenarios from the IPCC AR5 ensemble that report global values for PV[26] and 407 scenarios from the IPCC SR1.5 ensemble[25]. The total number of scenarios in our ensemble was 1,550.

Numerical values for projected PV capacity, generation and utility-scale PV costs were extracted from the publications by using tabular data when available, or with the WebPlotDigitizer otherwise[43]. In addition to global scenarios, we extracted regional outcomes for non-Organisation for Economic Co-operation and Development (OECD) Asia and the Middle East plus Africa, when available; regional definitions were matched with the standard definitions of these regions used in IPCC SR1.5 scenarios, when possible. We focused on these two regions owing to their large technical PV potential and a wide range of projected PV outcomes[44]. Where available, we also collected scenario data for TPED, total electricity generation and energy-related CO_2 emissions. Only a minority of non-IPCC scenarios report final energy use and their energy accounting methods, and therefore the analysis cannot be done in terms of final energy. We used global and regional TPED to compute a dimensionless scaled regional share for PV capacity $S_{\mathrm{Region,year}}$ (%), shown in Supplementary Figs. 4 and 5 for IPCC and non-IPCC scenarios, respectively:

$$S_{\mathrm{Region,year}} = \frac{\mathrm{PV}_{\mathrm{Region,year}}/\mathrm{PV}_{\mathrm{World,year}}}{\mathrm{TPED}_{\mathrm{Region,year}}/\mathrm{TPED}_{\mathrm{World,year}}},$$

where PV values are in gigawatts and TPED values are in exajoules per year. Based on the installed PV capacity in the scenarios, we computed the equivalent CAGR for each scenario, and used this variable as a primary indicator for our analysis. To compare scenarios more easily across different time horizons, CAGR was calculated from the end year of the scenario (or from 2050, for scenarios reporting values beyond this date), relative to historical values for 2010[45]:

$$\mathrm{CAGR}_{\mathrm{Capacity}} = \left[\left(\frac{\mathrm{PV}_{\mathrm{World,year}}}{\mathrm{PV}_{\mathrm{World,2010}}}\right)^{\frac{1}{\mathrm{year}-2010}}\right] - 1.$$

Supplementary Fig. 2 shows the CAGR computed at a fixed horizon of 2030 instead of the scenario end date, to compare near-term outcomes in the subsets of IPCC and non-IPCC scenarios that report outcomes at this date.

For the subset of 116 scenarios that include capital cost data, we used a similar expression to compute the equivalent projected CAGR of utility-scale PV system capital costs:

$$\mathrm{CAGR}_{\mathrm{Cost}} = \left[\left(\frac{\mathrm{Cost}_{\mathrm{Region,year}}}{\mathrm{Cost}_{\mathrm{Region,2010}}}\right)^{\frac{1}{\mathrm{year}-2010}}\right] - 1,$$

where cost values are in US dollars per kilowatt. These values are tested as an additional explanatory variable for classification (Supplementary Figs. 16 and 17), after grouping them into quintiles to avoid overfitting. For scenarios that include cost data in multiple regions, we used costs for Europe if available, or OECD otherwise. We used a reference historical value for small utility-scale systems in Germany in 2010[3], and converted currencies to US\$2010 using OECD data[46]. We used capital costs in our analysis, rather than annualized capital costs or the levelized cost of electricity, to increase the sample of useable scenarios; only 38 scenarios report data on the levelized cost of electricity (none in the IPCC databases).

Framework for analysing the scenarios. The scenarios were compiled in a framework detailed in Supplementary Table 1, which applied a categorical typology grouped by meta-indicators, model indicators and policy indicators. We used the Python pandas library[47] to structure this framework, and the Matplotlib library[48] to visualize the scenarios. The meta-indicators recorded general information about the scenario and publication, such as the type and location of the organization that produced the scenario. The model indicators provide information about the underlying model used to generate the scenarios, such as its boundaries or geographic resolution, and were selected following previous reviews[49,50]. We adjusted the choice of indicators to reduce redundancies or overly specific indicators that would identify individual models or modelling experiments. For instance, rather than explicitly distinguishing between models that represent either overnight technology adoption or dynamic transition pathways[51], we represented this distinction through the combination of indicators for the type of model, foresight and technology expansion constraints. We also did not include indicators for storage modelling, due to the scarcity of data, which would overfit the analysis to specific scenarios. Lastly, policy indicators recorded basic assumptions used in the scenarios in relation to climate mitigation and technology policies, such as the level of climate mitigation. The information required for these indicators was obtained from the publications or model documentation, where available.

For each indicator, we checked for statistical differences across categories, using the Python statsmodels library[52] to run a Kruskal–Wallis test, followed by a post hoc Conover–Iman test with Bonferroni correction. We evaluated correlations between categorical indicator values using Theil's U (Supplementary Fig. 18). This metric accounts for the asymmetry of correlations between indicators with different cardinalities. The resulting asymmetry of row and column pairings in the visualization should be noted; for instance, the text perspective row is quite strongly associated with the document type column ($U = 0.47$), as some perspectives are strongly associated with either academic papers or grey literature reports. The converse is not true ($U = 0.08$), as each document type is associated with multiple text perspectives.

Spectral clustering. We used cluster analysis to identify archetypes of scenarios, separately from their projected PV outcomes, based on the projected CAGR of three other scenario indicators: the share of electricity generation in TPED, TPED itself and energy-related CO_2 emissions. We first retained the subset of 1,392 scenarios that provided these three indicators, out of the total ensemble of 1,550. For each indicator, we computed the equivalent CAGR projected by the scenario from the end year of the scenario (or from 2050, for scenarios reporting values beyond this date), relative to historical values for 2010[45]. The CAGR values for each indicator were linearly scaled over [0,1] across the subset of scenarios. Owing to the lack of information on the energy accounting methods used, we did not account for different equivalency factors in TPED.

We then applied a spectral clustering algorithm to group the scenarios. This approach performs well on irregularly shaped clusters, unlike, for example, centroid-based techniques such as k-means clustering[53], which offered less consistent performance in our application as assessed by a silhouette metric[54]. Spectral clustering follows a graph partitioning approach, using an affinity matrix constructed from a pairwise similarity measure for the samples to be clustered. In this case, we used spectral clustering with a k-nearest neighbours measure as implemented in the scikit-learn Python package[55].

Based on an exploratory visualization of the ensemble, we chose four clusters. This number is sufficient to yield interpretable groupings across the three indicators, and it led to relatively well-balanced cluster sizes. A larger number would have caused overfitting in the classification analysis by identifying individual scenarios or publications. We chose a number of neighbours at $k = 800$ using the silhouette metric[54] to quantitatively assess the separation between clusters, finding stable scores for $k \geq 600$. We then subjectively labelled the resulting clusters as scenario archetypes (Fig. 5a) and assigned the archetypes as an additional policy indicator in the scenario framework. Supplementary Fig. 7 visualizes these archetypes on the indicators used for clustering.

Topic modelling. Probabilistic topic modelling is an unsupervised learning approach that assumes that text documents are composed of mixtures of topics, where a topic is a probability distribution over the vocabulary of terms contained in the documents[56]. We applied the common LDA approach[57], which is a hierarchical Bayesian model. Compared with deterministic methods for topic modelling, such as non-negative matrix factorization[58], LDA requires choosing hyperparameters to set prior distributions. This can be helpful to adjust the relative salience of individual documents in the identified topics[59], which suits this study due to the large variation in document lengths across shorter article abstracts and longer executive summaries.

To prepare the publications for our analysis, we extracted the title, abstract and keywords of each scientific article in the ensemble, and merged them into a single document per article. For scenarios in the IPCC databases, we referred to the publication cited in the metadata of the scenarios if available, and otherwise to the overview publication cited in the AR5 database for the corresponding model intercomparison project. For reports without abstracts, we extracted the executive summary or preface. As each document is typically associated with multiple PV scenarios, particularly in the case of the IPCC overview publications, the number of documents in our ensemble ($n = 127$) is smaller than the number of scenarios. We preprocessed this selection of documents using the Gensim Python package[60] to tokenize documents into lists of terms, and remove punctuation and standard stop words (that is, common words such as 'and', 'or' and so on). We removed numerical data except for climate change targets, which were converted to text (that is, 'two_degrees'). We also manually removed words identifying individual documents, such as the names of model intercomparison projects, institutions and named scenarios. We then used the spaCy Python package[61] to lemmatize remaining terms (for instance, converting verbs of different tenses into present form). Finally, we used the Mallet library[62] to fit an LDA topic model, through the application programming interface provided in Gensim.

To quantify the impact of the selected number of topics and distribution parameters on the quality of the topics that are identified by Mallet, we used the CV topic coherence measure[63] owing to its relatively strong correlation with human interpretability. Supplementary Fig. 9 presents the effect of the two values of the α distribution parameter on the topic coherence over a range of 5–15 topics, as well as dominant words identified for eight topics based on topic-term probability. The topics were relatively robust to the distribution parameter, which tends to have a smoothing effect so that greater values identify a greater number of significant topics per document. We used the distribution parameter of $\alpha = 50/T$, where T is the number of topics, following earlier empirical assessments[64,65], and this yielded subjectively consistent topics. Topic coherence tends to increase with the number of topics, both quantitatively and subjectively, as this allows the topics to be more specific. However, a larger number may cause overfitting, as the topics may then identify individual publications with a particularly salient set of terms. We retained eight topics for further analysis, ensuring that each topic is dominant (that is, has the greatest probability) in at least five documents. Supplementary Fig. 10 shows the count of scenarios and publications for which each topic is predominant. Supplementary Fig. 11 shows a document–topic probability matrix following, for example, ref. [66], indicating that the topics are relatively distinct across documents. We assigned the dominant topic of each scenario as an additional meta-indicator of text perspective in our scenario framework. Supplementary Fig. 12 uses multidimensional scaling[67] to visualize distances between the term frequencies and relative prevalence of each topic within the text ensemble. For instance, the renewable and fossil fuel topics are counterintuitively similar on the multidimensional scaling visualization. Although they differ in the technologies they emphasize, these topics are both typically derived from documents that discuss global long-term energy system trends, and consequently share some vocabulary. Supplementary Fig. 13 details this aspect, using a relevance metric[68] to rank terms associated with each topic, and comparing the topic-specific frequency of relevant terms with their overall frequency. Following empirical guidelines[68] to improve human interpretability, we ranked the terms by setting a parameter $\lambda = 0.7$ to interpolate between baseline topic word probability and the term lift value[69], which highlights particularly rare terms. Figure 5c shows resulting word clouds.

Classification algorithm. To quantitatively link scenario characteristics with projected PV outcomes, we applied the XGBoost learning algorithm[70]. XGBoost is an ensemble method based on gradient-boosted decision trees, which typically provides robust performance on a variety of classification and regression tasks[27]. A tree-based approach is well-suited for this study as our collected scenarios form an ensemble of opportunity, rather than a systematic sampling across the categorical values described in the scenario typology. This causes multiple collinearities between indicators and missing combinations of values. For instance, research institute scenarios and their corresponding text perspectives are clustered around the publication dates that correspond to IPCC reports. In this setting, tree-based ensemble methods are more computationally efficient than neural networks, and more robust than linear regression methods[27].

While XGBoost can be used for non-linear regression, the presence of multiple outliers in our scenario ensemble, such as counterfactual scenarios projecting near-zero PV capacity, tends to cause overfitting. As our analysis focuses on interpreting general patterns, we instead grouped the scenarios into quintiles based on their projected PV capacity CAGR. We then used XGBoost for multiclass classification, that is, predicting output quintile based on the input of scenario characteristics. We first encoded the categorical scenario framework indicators as integer variables. We then searched over a hyperparameter grid through the scikit-learn application programming interface to maximize classification accuracy and the area under the receiver operating characteristic curve for each quintile. This search relied on tenfold cross-validation with random shuffling across samples so that the subsets of AR5, SR1.5 and non-IPCC scenarios tended to be represented proportionally to their share in the ensemble. We obtained an ensemble of 300 trees with a maximum depth of four levels, a learning rate of 0.15, a feature (column) sampling rate of 0.6 and a subsampling rate of 0.8. We kept default XGBoost parameters for shrinkage and regularization. We then used Shapley additive explanation values[27] to estimate the importance of the policy indicators, model indicators and meta-indicators on projected PV outcomes. Compared with feature importance metrics based on permutation or on the mean decrease of impurity[71,72], Shapley additive explanation values were found to be more robust across multiple evaluation metrics[73], for instance, by properly accounting for higher-order interactions between features, correlated features, or categorical features with highly imbalanced classes.

We complemented the analysis by including PV capital cost assumptions as an additional explanatory variable (Supplementary Figs. 16 and 17). We implemented this variable using the CAGR of projected PV capital cost computed from the scenario end date, and grouped into quintiles to avoid overfitting to specific cost values and scenarios. Using the same hyperparameter search approach, we used a model comprising 300 trees with a maximum depth of four levels, a learning rate of 0.8, a feature (column) sampling rate of 0.6 and a subsampling rate of 0.8.

Data availability

Data for IPCC SR1.5 and AR5 scenarios are available through the International Institute for Applied Systems Analysis portal[25,26]. Data for non-IPCC scenarios are available in the original sources; metadata for these sources are provided in Supplementary Data 1.

Code availability

The code used for analysis in this study is available from the corresponding author upon request. A code notebook presenting key steps of the analysis is available for download[74].

References

40. Breyer, C. in *Future Energy* 3rd edn (ed. Letcher, T. M.) 727–756 (Elsevier, 2020).
41. Newell, R. G. & Raimi, D. *Global Energy Outlook Comparison Methods: 2019 Update* (Resources for the Future, 2019).
42. *World Energy Insights Brief 2019: Global Energy Scenarios Comparison Review* (World Energy Council, 2019).
43. Rohatgi, A. *WebPlotDigitizer* https://automeris.io/WebPlotDigitizer/ (2019).
44. *Africa Energy Outlook 2019* (International Energy Agency, 2019).
45. *World Energy Outlook 2011* (International Energy Agency, 2011).
46. Exchange Rates (Indicator). *OECD iLibrary* https://doi.org/10.1787/067eb6ec-en (OECD, 2020).
47. McKinney, W. in *Proceedings of the 9th Python in Science Conference* (eds van der Walt, S. & Millman, J.) 51–56 (SciPy, 2010).
48. Hunter, J. D. Matplotlib: a 2D graphics environment. *Comput. Sci. Eng.* **9**, 90–95 (2007).
49. Densing, M., Panos, E. & Hirschberg, S. Meta-analysis of energy scenario studies: example of electricity scenarios for Switzerland. *Energy* **109**, 998–1015 (2016).
50. Krey, V. Global energy–climate scenarios and models: a review. *WIREs Energy Environ.* **3**, 363–383 (2014).
51. Li, F. G. N., Trutnevyte, E. & Strachan, N. A review of socio-technical energy transition (STET) models. *Technol. Forecast. Soc. Change* **100**, 290–305 (2015).
52. Seabold, S. & Perktold, J. in *Proceedings of the 9th Python in Science Conference* (eds van der Walt, S. & Millman, J.) 92–96 (SciPy, 2010).
53. Lucińska, M. & Wierzchoń, S. T. in *Computer Information Systems and Industrial Management* (eds Cortesi, A. et al.) 254–265 (Springer, 2012).
54. Rousseeuw, P. J. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *J. Comput. Appl. Math.* **20**, 53–65 (1987).
55. Pedregosa, F. et al. scikit-learn: machine learning in Python. *J. Mach. Learn. Res.* **12**, 2825–2830 (2011).
56. Steyvers, M. & Griffiths, T. in *Handbook of Latent Semantic Analysis* (eds Landauer, T. K. et al.) 424–440 (Routledge, 2007).
57. Blei, D. M., Ng, A. Y. & Jordan, M. I. Latent Dirichlet allocation. *J. Mach. Learn. Res.* **3**, 993–1022 (2003).
58. Lee, D. D. & Seung, H. S. Learning the parts of objects by non-negative matrix factorization. *Nature* **401**, 788–791 (1999).
59. Bakharia, A. *Interactive Content Analysis: Evaluating Interactive Variants of Non-Negative Matrix Factorisation and Latent Dirichlet Allocation as Qualitative Content Analysis Aids.* PhD thesis, Queensland Univ. Technology (2014).
60. Řehůřek, R. & Sojka, P. in *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks* (eds Calzolari, N. et al.) 45–50 (ELRA, 2010).
61. Honnibal, M. & Montani, I. spaCy 2: natural language understanding with bloom embeddings, convolutional neural networks and incremental parsing. *spaCy* https://spacy.io/ (2017).
62. McCallum, A. K. *MALLET: A Machine Learning for Language Toolkit* http://mallet.cs.umass.edu/ (2002).
63. Röder, M., Both, A. & Hinneburg, A. in *Proceedings of the 8th ACM International Conference on Web Search and Data Mining* (eds Cheng, X. et al.) 399–408 (Association for Computing Machinery, 2015).
64. Griffiths, T. L. & Steyvers, M. Finding scientific topics. *Proc. Natl Acad. Sci. USA* **101**, 5228–5235 (2004).
65. Heinrich, G. *Parameter Estimation for Text Analysis* (vsonix GmbH and University of Leipzig, 2005).
66. Eker, S., Rovenskaya, E., Obersteiner, M. & Langan, S. Practice and perspectives in the validation of resource management models. *Nat. Commun.* **9**, 5359 (2018).
67. Torgerson, W. S. Multidimensional scaling: I. Theory and method. *Psychometrika* **17**, 401–419 (1952).
68. Sievert, C. & Shirley, K. in *Proceedings of the Workshop on Interactive Language Learning, Visualization, and Interfaces* (eds Chuang, J. et al.) 63–70 (Association for Computational Linguistics, 2014).
69. Taddy, M. in *Proceedings of the 15th International Conference on Artificial Intelligence and Statistics (AISTATS)* (eds Lawrence, N. et al.) 1184–1193 (PMLR, 2012).

70. Chen, T. & Guestrin, C. in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (eds Krishnapuram, B. et al.) 785–794 (Association for Computing Machinery, 2016).
71. Altmann, A., Tolosi, L., Sander, O. & Lengauer, T. Permutation importance: a corrected feature importance measure. *Bioinformatics* **26**, 1340–1347 (2010).
72. Strobl, C., Boulesteix, A.-L., Kneib, T., Augustin, T. & Zeileis, A. Conditional variable importance for random forests. *BMC Bioinformatics* **9**, 307 (2008).
73. Lundberg, S. et al. From local explanations to global understanding with explainable AI for trees. *Nat. Mach. Intell.* **2**, 56–67 (2020).
74. Jaxa-Rozen, M. & Trutnevyte, E. Scenario analysis workflow for the manuscript 'Sources of uncertainty in long-term global scenarios of solar photovoltaic technology'. *Zenodo* https://doi.org/10.5281/zenodo.4297227 (2020).

Acknowledgements
This work received funding from the University of Geneva as well as from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 821124 (NAVIGATE). We thank G. Luderer and L. Hirt for their helpful comments on the analysis.

Author contributions
M.J.-R. and E.T. designed the research; M.J.-R. performed the analysis; M.J.-R. and E.T. wrote the article.

Competing interests
The authors declare no competing interests.

Additional information
Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41558-021-00998-8.

Correspondence and requests for materials should be addressed to M.J.-R.

Peer review information *Nature Climate Change* thanks Wesley Cole, Felix Creutzig, Sibel Eker and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.