AIII

Annex III: Scenarios and Modelling Methods

Coordinating Lead Authors:

Céline Guivarch (France), Elmar Kriegler (Germany), Joana Portugal-Pereira (Brazil).

Lead Authors:

Valentina Bosetti (Italy), James Edmonds (the United States of America), Manfred Fischedick (Germany), Petr Havlík (Austria/Czech Republic), Paulina Jaramillo (the United States of America), Volker Krey (Germany/Austria), Franck Lecocq (France), André F.P. Lucena (Brazil), Malte Meinshausen (Australia/Germany), Sebastian Mirasgedis (Greece), Brian O'Neill (the United States of America), Glen P. Peters (Norway/Australia), Joeri Rogelj (Belgium/United Kingdom), Steven Rose (the United States of America), Yamina Saheb (France/Algeria), Goran Strbac (Serbia/United Kingdom), Anders Hammer Strømman (Norway), Detlef P. van Vuuren (the Netherlands), Nan Zhou (the United States of America).

Contributing Authors:

Alaa Al Khourdajie (United Kingdom/Syria), Hossein Ameli (Germany), Cornelia Auer (Germany), Nico Bauer (Germany), Edward Byers (Austria/Ireland), Michael Craig (the United States of America), Bruno Cunha (Brazil), Stefan Frank (Austria), Jan S. Fuglestvedt (Norway), Mathijs Harmsen (the Netherlands), Alan Jenn (the United States of America), Jarmo Kikstra (Austria/the Netherlands), Paul Kishimoto (Canada), Robin Lamboll (United Kingdom/the United States of America), Julien Lefèvre (France), Eric Masanet (the United States of America), David McCollum (the United States of America), Zebedee Nicholls (Australia), Aleksandra Novikova (Germany/the Russian Federation), Simon Parkinson (Canada), Pedro Rochedo (Brazil), Sasha Samadi (Germany), David Vérez (Cuba/Spain), Sonia Yeh (Sweden).

This chapter should be cited as:

IPCC, 2022: Annex III: Scenarios and modelling methods [Guivarch, C., E. Kriegler, J. Portugal-Pereira, V. Bosetti, J. Edmonds, M. Fischedick, P. Havlík, P. Jaramillo, V. Krey, F. Lecocq, A. Lucena, M. Meinshausen, S. Mirasgedis, B. O'Neill, G.P. Peters, J. Rogelj, S. Rose, Y. Saheb, G. Strbac, A. Hammer Strømman, D.P. van Vuuren, N. Zhou (eds)]. In IPCC, 2022: *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA. doi: 10.1017/9781009157926.022

Table of Contents

Preamble

The use of scenarios and modelling methods are pillars in IPCC Working Group III (WGIII) Assessment Reports. Past WGIII assessment report cycles identified knowledge gaps about the integration of modelling across scales and disciplines, mainly between global integrated assessment modelling methods and bottom-up modelling insights of mitigation responses. The need to improve the transparency of model assumptions and enhance the communication of scenario results was also recognised.

This annex on *Scenarios and Modelling Methods* aims to address some of these gaps by detailing the modelling frameworks applied in the WGIII Sixth Assessment Report (AR6) chapters and disclose scenario assumptions and its key parameters. It has been explicitly included in the Scoping Meeting Report of the WGIII contribution to the AR6 and approved by the IPCC Panel at the 46th Session of the Panel.

The annex includes two parts: Part I on *Modelling Methods* summarises methods and tools available to evaluate sectoral, technological and behavioural mitigation responses as well as integrated assessment models (IAMs) for the analysis of 'whole system' transformation pathways; Part II on *Scenarios* sets out the portfolio of climate change scenarios and mitigation pathways assessed in the AR6 WGIII chapters, its underlying principles and interactions with scenario assessments by WGI and WGII.

Part I: Modelling Methods

A.III.I.1 Overview of Modelling Tools

Modelling frameworks vary vastly among themselves, and several key characteristics can be used as basis for model classification (Scrieciu et al. 2013; Dodds et al. 2015; Hardt and O'Neill 2017; Capellán-Pérez et al. 2020). Broadly, literature characterises models along three dimensions: (i) level of detail and heterogeneity, (ii) mathematical algorithm concepts, and (iii) temporal and spatial system boundaries (Krey 2014).

Commonly climate mitigation models are referred to as bottom-up and top-down depending upon their degree of detail (van Vuuren et al. 2009). Generally, bottom-up approaches present more systematic individual technological details about a reduced number of mitigation strategies of a specific sector or sub-sector. These models tend to disregard relations between specific sectors/technologies and miss evaluating interactions with the whole system. On the other hand, top-down approaches present a more aggregated and global analysis, in detriment of less detailed technological heterogeneity. They tend to focus on interactions within the whole system, such as market and policy instrument interactions within the global economy systems. Studies using top-down models are more capable of representing economic structural change than adopting technology-explicit decarbonisation strategies (van Vuuren et al. 2009; Kriegler et al. 2015a). Integrated assessment models (IAMs) typically use a top-down approach to model sectoral mitigation strategies.

Although this dichotomic classification has been mentioned in the literature, since the IPCC's Fifth Assessment Report (AR5), climate mitigation models have evolved towards a more hybrid approach incorporating attributes of both bottom-up and top-down approaches. This is partly due to different modelling communities having different understandings of these two approaches' principles, which can be misleading.

One of the most basic aspects of a modelling tool is how it approaches the system modelled from a solution perspective. A broad interpretation of mathematical algorithm concepts classifies models as simulation and optimisation models. **Simulation models** are based on the evaluation of the dynamic behaviour of a system (Lund et al. 2017). They can be used to determine the performance of a system under alternative options of key parameters in a plausible manner. Most often, simulation models require comprehensive knowledge of each parameter, in order to choose a specific path under several alternatives. On the other hand, **optimisation models** seek to maximise or minimise a mathematical objective function under a set of constraints (Baños et al. 2011; Iqbal et al. 2014). Most often, the objective function represents the total cost or revenue of a given system or the total welfare of a given society. One major aspect of optimisation models is that the solution is achieved by simultaneously binding a set of constraints, which can be used to represent real-life limitations on the system, such as: constraints on flows, resource and technology availability, labour and financial limitations, environmental aspects, and many other characteristics that the model may require (Fazlollahi et al. 2012; Pfenninger et al. 2014; Cedillos Alvarado et al. 2016). Specifically, when modelling climate mitigation responses, limiting carbon budgets is often used to represent future temperature level pathways (Rogelj et al. 2016; Millar et al. 2017; Peters 2018; Gidden et al. 2019).

Another major distinction among modelling tools is related to the solution methodology from a temporal perspective. They can have a perfect foresight intertemporal assumption or a recursive-dynamic assumption. Intertemporal optimisation with **perfect foresight** is an optimisation method for achieving an overall optimal solution over time. It is based on perfect information on all future states of a system and assumptions (such as technology availability and prices) and, as such, today's and future decisions are made simultaneously, resulting in a single path of optimal actions that lead to the overall optimal solution (Keppo and Strubegger 2010; Gerbaulet et al. 2019). Such a modelling approach can present an optimal trajectory of the set of actions and policies that would lead to the overall first-best solution. However, real-life decisions are not always based on optimal solutions (Ellenbeck and Lilliestam 2019) and, therefore, solutions from perfect foresight models can be challenging to be implemented by policymakers (Pindyck 2013, 2017). For instance, perfect foresight implies perfect knowledge of the future states of the system, such as future demand for goods and products and availability of production factors and technology.

Recursive-dynamic models, also known as myopic or limited foresight models, make decisions over sequential periods of time. For each time step, the solution is achieved without information on future time steps. Therefore, the solution path is a series of solutions in short trajectories that, ultimately, is very unlikely to achieve the overall optimal solution over the whole time period considered (Fuso Nerini et al. 2017). Nonetheless, the solution represents a set of possible and plausible policies and behavioural choices of the agents that could be taken in short-term cycles, without perfect information (Heuberger et al. 2018; Hanna and Gross 2020). In between, some models consider **imperfect or adaptive expectations,** where economic decisions are based on past, current and imperfectly anticipated future information (Keppo and Strubegger 2010; Kriegler et al. 2015a; Löffler et al. 2019). Modelling tools can also be differentiated by their level of representation of economic agents and sectors: they can have a full representation of all agents of the economy and their interactions with each other (**general equilibrium**) or focus on a more detailed representation of a subset of economic sectors and agents (**partial equilibrium**) (Cheng et al. 2015; Babatunde et al. 2017; Hanes and Carpenter 2017; Sanchez et al. 2018; Guedes et al. 2019; Pastor et al. 2019) (Annex III.I.2).

The most basic aspect to differentiate models is their main objective function, which includes the detail at which they represent key sectors, systems and agents. This affects the decision on methodology and other coverage aspects. Several models have been developed for different sectoral representation, such as the energy (Annex III.I.3), buildings (Annex III.I.4), transport (Annex III.I.5), industry (Annex III.I.6) and land-use (Annex III.I.7) models.

Modelling exercises vary considerably in terms of key characteristics, including geographical scales, time coverage, environmental variables, technologies portfolios, and socio-economic assumptions. A detailed comparison of key characteristics of global and national models used in this report is presented in Annex III.I.9. Geographical coverage ranges from sub-national (Cheng et al. 2015; Feijoo et al. 2018; Rajão et al. 2020), national (Li et al. 2019; Sugiyama et al. 2019; Vishwanathan et al. 2019; Schaeffer et al. 2020), regional (Vrontisi et al. 2016; Hanaoka and Masui 2020) and global (Gidden et al. 2018; Kriegler et al. 2018a; McCollum et al. 2018; Rogelj et al. 2019b; Drouet et al. 2021) models. Even models with the same geographical coverage can still be significantly different from each other, for instance, due to the number of regions within the model. Models can also have spatially implicit and explicit formulations, which in turn can have different spatial resolution. This distinction is especially important for land-use models, which account for changes in land use and agricultural practices (Annex III.I.7: Land-use modelling). The time horizon, time steps and time resolution are major aspects that differ across models. Model horizon can range from short- to long-term, typically reaching from a few years to up until the end of the century (Fujimori et al. 2019b; Gidden et al. 2019; Rogelj et al. 2019a; Ringkjøb et al. 2020). Time resolution is particularly relevant for specific applications, such as power sector models, which have detailed representation of power technologies dispatch and operation (Soria et al. 2016; Abujarad et al. 2017; Guan et al. 2020).

Life Cycle Assessment (LCA) is an integrated technique to evaluate the sustainability of a product throughout its life cycle. It quantifies the environmental burdens associated with all stages from the extraction of raw materials, through the production of the product itself, its utilisation, and end-life, either via reuse, recycling or final disposal (Rebitzer et al. 2004; Finnveden et al. 2009; Guinée et al. 2011; Curran 2013; Hellweg and Milà i Canals 2014). The environmental impacts covered include all types of loads on the environment through the extraction of natural resources and emission of hazardous substances. For this reason, LCA has the flexibility to evaluate an entire product system, hence avoiding sub-optimisation in a single process and identifying the products and processes that result in the least environmental impact. Thus, it allows for the quantification of possible trade-offs between different environmental impacts (e.g., eliminating air emissions by increasing non-renewable energy resources) (Hawkins et al. 2013; Nordelöf et al. 2014; Gibon et al. 2017) and/or from one stage to other (e.g., reuse or recycling a product to bring it back in at the raw material acquisition phase) (Hertwich and Hammitt 2001a,b). It gives a holistic view of complex systems and reduces the number of parameters for which decisions have to be taken, while not glossing over technical and economical details. In recent years, LCA has been widely used in both retrospective and prospective analysis of product chains in various climate mitigation fields, namely comparing existing energy technologies with planned alternatives (Cetinkaya et al. 2012; Portugal-Pereira et al. 2015), product innovation and development (Wender et al. 2014; Portugal-Pereira et al. 2015; Sharp and Miller 2016), certification schemes (Prussi et al. 2021), or supply chain management (Hagelaar 2001; Blass and Corbett 2018).

Two different types of LCA approaches can be distinguished: Attributional Life Cycle Assessment (ALCA) and Consequential Life Cycle Assessment (CLCA). ALCA aims at describing the direct environmental impacts of a product. It typically uses average and historical data to quantify the environmental burden during a product's life cycle, and it tends to exclude market effects or other indirect effects of the production and consumption of products (Baitz 2017). CLCA, on the other hand, focuses on the effects of changes due to product life cycle, including both consequences inside and outside the product life cycle (Earles and Halog 2011). Thus, the system boundaries are generally expanded to represent direct and indirect effects of products' outputs. CLCA tends to describe more complex systems than ALCA, which are highly sensitive to data assumptions (Plevin et al. 2014; Weidema et al. 2018; Bamber et al. 2020).

Integrated assessment models (IAMs) are simplified representations of complex physical and social systems, focusing on the interaction between economy, society and the environment (Annex III.I.9). They represent the coupled energy-economy-land-climate system to varying degrees. In a way, IAMs differ among themselves on all the topics discussed in this section: significant variation in geographical, sectoral, spatial and time resolution; they rely greatly on socio-economic assumptions; different technological representation; partial or general equilibrium assumptions; differentiated between perfect foresight or recursive-dynamic methodology. The difficulty in fully representing the extent of climate damages in monetary terms may be the most important and challenging limitation of IAMs and it is mostly directed to cost-benefit IAMs. However, all categories of IAMs present important limitations (Annex III.I.9).

Following this brief synopsis of modelling taxonomies, Section I.2 details key aspects of economic frameworks and principles used to model climate mitigation responses and estimate their costs. Sections I.3, I.4, I.5, I.6, and I.7 present key aspects of sectoral modelling approaches in energy systems, buildings, transport, industry, and land use, respectively. Interactions between WGI climate emulators and WGIII mitigation models are described in Section I.8. A review of integrated assessment model approaches, their components and limitations, is presented in Section I.9. Sections I.10 and I.11 present comparative tables of key characteristics and measures of national and global models that contributed to the AR6 WGIII scenario database.

A.III.I.2 Economic Frameworks and Concepts Used in Sectoral Models and Integrated Assessment Models

Several types of 'full-economy' frameworks are used in integrated assessment models. The **general equilibrium** framework – often referred to as Computable General Equilibrium (CGE) – represents the economic interdependencies between multiple sectors and agents, and the interaction between supply and demand on multiple markets (Robinson et al. 1999). It captures the full circularity of economic flows through income and demand relationships and feedbacks including the overall balance of payments. Most CGE approaches used are neoclassical supply-led models with market clearing based on price adjustment. Representative agents usually minimise production costs or maximise utility under given production and utility function, although optimal behaviours are not a precondition *per se*. Most CGE models also include assumptions of perfect markets with full employment of factors although market imperfections and underemployment of factors (e.g., unemployment) can be assumed (Babiker and Eckaus 2007; Guivarch et al. 2011). CGE frameworks can either be static or dynamic and represent pathways as a sequence of equilibria in the second case.

Macro-econometric frameworks represent similar sectoral interdependence with balance of payments as general equilibrium, and are sometimes considered a subset of the general equilibrium framework. They differ from standard neoclassical CGE models in the main aspect that economic behaviours are not micro-founded optimising behaviours but are represented by macroeconomic and sectoral functions estimated through econometric techniques (Barker and Scrieciu 2010). In addition, they usually adopt a demand-led post-Keynesian approach where final demand and investment determine supply and not the other way around. Prices also do not instantaneously clear markets and adjust with lag.

Macro-economic growth frameworks are also full-economy approaches derived from aggregated growth models. They are based on a single macroeconomic production function combining capital, labour and sometimes energy to produce a generic good for consumption and investment. They are used as the macroeconomic component of cost-benefit IAMs (Nordhaus 1993) and some detailed-process IAMs.

The **disaggregation of economic actors and sectors and the representation of their interaction** differ across full-economy frameworks. A main distinction is between models based on full Social Accounting Matrix (SAM) and aggregated growth approaches. On the one hand, SAM-based frameworks – CGE and macro-econometric – follow a multi-sectoral approach distinguishing from several to a hundred different economic sectors or production goods and represent sector-specific value-added, final consumption and interindustry intermediary consumption (Robinson 1989). They also represent economic agents (firms, households, public administration, etc.) with specific behaviours and budget constraints. On the other hand, macro-economic growth frameworks are reduced to a single macro-economic agent producing, consuming and investing a single macroeconomic good without considering interindustry relationships. In some detailed process IAMs, the aggregated growth approach is combined with a detailed representation of energy supply and demand systems that surmises different economic actors and subsectors. However, the energy system is driven by an aggregated growth engine (Bauer et al. 2008).

Partial equilibrium frameworks do not cover the full economy but only represent a subset of economic sectors and markets disconnected from the rest of the economy. They basically represent market balance and adjustments for a subset of sectors under *ceteris paribus* assumptions about other markets (labour, capital, etc.), income, and so on, ignoring possible feedbacks. Partial equilibrium frameworks are used in sectoral models, as well as to model several sectors and markets at the same time – for example, energy and agriculture markets – in energy system models and some detailed process IAMs but still without covering the full economy.

In most models the treatment of **economic growth** follows Solow or Ramsey growth approach based on the evolution through time of production factors, endowment and productivity. Classically, labour endowment and demography are exogenous, and capital accumulates through investment. Partial equilibrium frameworks do not model economic growth but use exogenous growth assumptions derived from growth models. Factors' productivity evolution is assumed exogenous in most cases that is, general technical progress is assumed to be an autonomous process. A few models feature endogenous growth aspects where factor productivity increases with cumulated macroeconomic investment. Models also differ in the content of technical progress and alternatively consider unbiased total factor productivity improvement or labour-specific factor-augmenting productivity. In multi-sectoral macroeconomic models, economic growth comes with endogenous changes of the sectoral composition of GDP known as structural change. **Structural change** results from the interplay between differentiated changes of productivity between sectors and of the structure of final demand as income grows (Herrendorf et al. 2014). If general technical progress is mostly assumed exogenous and autonomous at an aggregated level, **innovation in relation to energy demand and technical systems** follow more detailed specifications in models. Energy efficiency can be assumed an autonomous process at different levels – macroeconomic, sector or technology – or energy technical change can be endogenous

AIII

and induced as a learning by doing process or as a result of R&D investments (learning-by-searching) (Löschel 2002).

Multi-regional models consider interactions between regions through **trade** in energy goods, non-energy goods and services – depending on model scope – and emission permits in the context of climate policy. For each type of goods, trade is usually represented as a common pool where regions interact with the pool through supply (exports) or demand (imports). A few models consider bilateral trade flows between regions. Traded goods can be assumed as perfectly substitutable between regions of origin (Heckscher-Ohlin assumption), such as is often the case for energy commodities, or as imperfectly substitutable (e.g., Armington goods) for non-energy goods. The representation of trade and capital imbalances at the regional level and their evolution through time vary across models and imbalances are either not considered (regional current accounts are balanced at each point in time), or a constraint for intertemporal balance is included (an export surplus today will be balanced by an import surplus in the future), or else trade imbalances follow other rules such as a convergence towards zero in the long run (Foure et al. 2020).

Strategic interaction can also occur between regions, especially in the presence of externalities such as climate change, energy prices or technology spillovers. Intertemporal models can include several types of strategic interaction: (i) a cooperative Pareto optimal solution where all externalities are internalised and based on the maximisation of a global discounted welfare with weighted regional welfare (Negishi weights), (ii) a non-cooperative solution that is strategically optimal for each region (Nash equilibrium) (Leimbach et al. 2017b), and (iii) partially cooperative solutions (Eyckmans and Tulkens 2003; Yang 2008; Bréchet et al. 2011; Tulkens 2019), akin to climate clubs (Nordhaus 2015).

Models cover different **investment** flows depending on the economic framework used. Partial equilibrium models compute energy system and/or sectoral (transport, building, industry, etc.) technology-specific investment flows associated with productive capacities and equipment. Full-economy models compute both energy system and macroeconomic investment, the second being used to increase macroeconomic capital stock. Full-economy multi-sectoral models compute sector-specific (energy and non-energy sectors) investment and capital flows with some details about the investments goods involved.

Full-economy models differ in the representation of **macro-finance**. In most CGE and macro-economic growth frameworks financial mechanisms are only implicit and total financial capacity and investment are constrained by savings. Consequently, investment in a given sector (e.g., low-carbon energy) fully crowds out investment in other sectors. In macro-econometric frameworks, macro-finance is sometimes explicit, and investments can be financed by credit on top of savings, which implies more limited crowding out of investments (Mercure et al. 2019). Macro-financial constraints are usually not accounted for in partial equilibrium models.

Models compare economic flows over time through **discounting**. Table 5 summarises key characteristics of different models assessed in AR6, including the uses of discounting. In cost-benefit analysis (CBA), discounting enables the comparison of mitigation costs and climate change damage. In the context of mitigation and in cost-effectiveness analysis (CEA), discounting allows the comparison of mitigation costs over time.

In optimisation models a social discount rate is used to compare costs and benefits over time. In the case of partial equilibrium optimisation models, the objective is typically to minimise total discounted system cost. The social discount rate is then an exogenous parameter, which can be assumed constant or changing (generally decreasing) over time (e.g., Gambhir et al. (2017), where a 5% discount rate is used). In the case of intertemporal welfare optimisation models, a Ramsey intertemporal optimisation framework is generally used, considering a representative agent who decides how to allocate her consumption, and hence saving, over time, subject to a resource constraint. Ramsey (1928) shows that the solution must always satisfy the Ramsey Equation, which provides the determinants of the social discount rate. The Ramsey Equation is given as follows:

$$\rho = \delta + \eta g_t$$

where ρ is the consumption discount rate (also known as the social discount rate), δ is the utility discount rate (also known as the pure time discount rate, or time preferences rate) which is a value judgement that determines the present value of a change in the utility experienced in the future and hence it is an ethical parameter, g_t is the growth rate of consumption per capita over time, and η is the elasticity of marginal utility of consumption, which is also a value judgement and hence an ethical parameter. The parameter η is also a measure of risk aversion and of society's aversion to inequality within and across generations. The pure time preference rate is an exogenous parameter, but the social discount rate is endogenously computed by the model itself and depends on the growth rate of consumption per capita over time. Note that more complex frameworks disentangle inequality aversion from risk aversion, and introduce uncertainty, leading to extensions of the social discount rate equation (see, for instance, Gollier 2013).

Discounting is also used for *ex post* comparison of mitigation cost pathways across models and scenarios. Values typically used for such *ex post* comparison are 2–5% (e.g., Admiraal et al. 2016). Across this report, whenever discounting is used for *ex post* comparisons, the discount rate applied is stated explicitly.

The choice of the appropriate social discount rate (and the appropriate rate of pure time preference when applicable) is highly debated (e.g., Arrow et al. 2013; Gollier and Hammitt 2014; Polasky and Dampha 2021) and two general approaches are commonly used. Based on ethical principles, the prescriptive approach states that the discount rate should reflect how costs and benefits supported by different generations should be weighted. The descriptive approach identifies the social discount rate to the risk-free rate of return to capital as observed in the real economy, which generally yields higher values.

In CBA the choice of discount rate is crucial for the balance of mitigation costs and avoided climate damages in the long run and a lower discount rate yields more abatement effort and lower global temperature increases (Stern 2006; Hänsel et al. 2020). In CEA, the choice of social discount rate influences the timing of emission reductions to limit warming to a given temperature level. A lower discount rate increases short-term emissions reductions, lowers temperature overshoot, favours currently available mitigation options (energy efficiency, renewable energy, etc.) over future deployment of net negative emission options and distributes mitigation effort more evenly between generations (Emmerling et al. 2019; Strefler et al. 2021b).

Outside social discounting for intertemporal optimisation, discounting is used in simulation models to compute the life cycle costs of investment decisions (e.g., energy efficiency choices, choices between different types of technologies based on their levelised costs). In this case, the discount rate can be interpreted as the cost of capital faced by investors. The cost of capital influences the merit order of technologies and lower capital cost favours capital-intensive technologies over technologies with higher variable costs. Models can reflect regional, sectoral or technology-specific cost of capital – through heterogeneous discount rates for life cycle cost estimates in simulation models (Iyer et al. 2015) or as hurdle rates in energy optimisation models (Ameli et al. 2021). In some cases, simulation models may also produce mitigation pathways following the Hotelling principle and assuming that the carbon price rises at the social discount rate (e.g., Global Change Assessment Model (GCAM) scenarios in the Shared Socio-economic Pathways (SSP) study with carbon prices increasing at 5% yearly (Guivarch and Rogelj 2017)).

A.III.I.3 Energy System Modelling

In the literature, the energy system models are categorised based on different criteria, such as (i) energy sectors covered, (ii) geographical coverage, (iii) time resolution, (iv) methodology, and (v) programming techniques. In the following sections, examples on different types of energy system models applied in Chapter 6 are presented.

A.III.I.3.1 Bottom-up Models

A.III.I.3.1.1 Modelling Electricity System Operation and Planning with Large-scale Penetration of Renewables

A number of advanced grid modelling approaches have been developed (Sani Hassan et al. 2018), such as robust optimisation (Jiang et al. 2012), interval optimisation (Dvorkin et al. 2015), or stochastic optimisation (Meibom et al. 2011; Monforti et al. 2014) to optimally schedule the operation of the future low-carbon systems with high penetration of variable renewable energies. Advanced stochastic models demonstrated that this would not only lead to significantly higher cost of system management but may eventually limit the ability of the system to accommodate renewable generation (Bistline and Young 2019; Hansen et al. 2019; Perez et al. 2019; Badesa et al. 2020). Modelling tools such as *European Model for Power System Investment with Renewable Energy (EMPIRE)* (Skar et al. 2016), *Renewable Energy Mix for Sustainable Electricity Supply (REMix)* (Scholz et al. 2017), *European Unit Commitment And Dispatch model (EUCAD)* (Després 2015), *SWITCH* (Fripp 2012), *GenX* (TNO 2021), and *Python for Power System Analysis (PyPSA)* (Brown et al. 2018) investigated these issues. SWITCH is a stochastic model, in which investments in renewable and conventional power plants are optimised over a multi-year period (Fripp 2012). In GenX the operational flexibility as well as capacity planning is optimised from a system-wide perspective (TNO 2021). PyPSA is an optimisation model for modern electricity systems, including unit commitment of generation plants, renewable sources, storage, and interaction with other energy vectors (Brown et al. 2018).

Furthermore, advanced modelling tools have been developed for the purpose of providing estimations of system-wide inertial frequency response that would assist system operators in maintaining adequate system inertia (Sharma et al. 2011; Teng and Strbac 2017). These innovative models also provide fundamental evidence regarding the role and value of advanced technologies and control systems in supporting cost-effective operation of future electricity systems with very high penetration of renewable generation. In particular, the importance of enhancing the control capabilities of renewable generation and applying flexible technologies, such as energy storage (Hall and Bain 2008; Obi et al. 2017; Arbabzadeh et al. 2019), demand-side response, interconnection (Aghajani et al. 2017) and transmission grid extensions (Schaber et al. 2012) to provide system stability control, is demonstrated through novel system integration models (Lund et al. 2015; Sinsel et al. 2020).

A novel modelling framework is proposed to deliver inertia and support primary frequency control through variable-speed wind turbines (Morren et al. 2006) and PVs (Waffenschmidt and Hui 2016; Liu et al. 2017), including quantification of the value of this technology in future renewable generation-dominated power grids (Chu et al. 2020). Advanced models for controlling distributed energy storage systems to provide an effective virtual inertia have been developed, demonstrating the provision of virtual synchronous machine capabilities for storage devices with power electronic converters, which can support system frequency management following disturbances (Hammad et al. 2019; Markovic et al. 2019). Regarding the application of interconnection for exchange of balancing services between neighbouring power grids, alternative control schemes for high-voltage direct current (HVDC) converters have been proposed, in order to demonstrate that this would reduce the cost of balancing (Tosatto et al. 2020).

A.III.I.3.1.2 Modelling the Interaction between Different Energy Sectors

Several integrated models have been developed in order to study the interaction between different energy vectors and whole-system approaches, such as *Integrated Energy System Simulation model (IESM)* (NREL 2020), *Integrated Whole-Energy System (IWES)* (Strbac et al. 2018), *UK TIMES* (Daly and Fais 2014), and *Calliope* (Pfenninger and Pickering 2018).

IESM is an approach in which the multi-system energy challenge is investigated holistically rather than looking at each of the systems in isolation. IESM capabilities include co-optimisation across multiple

AIII

energy systems, including electricity, natural gas, hydrogen, and water systems. These provide the opportunity to perform hydro, thermal, and gas infrastructure investment and resource use coordination for time horizons ranging from sub-hourly (markets and operations) to multi-year (planning) (NREL 2020).

The IWES model incorporates detailed modelling of electricity, gas, transport, hydrogen, and heat systems and captures the complex interactions across those energy vectors. The IWES model also considers the short-term operation and long-term investment timescales (from seconds to years) simultaneously, while coordinating operation of and investment in local district and national/international level energy infrastructures (Strbac et al. 2018).

The UK TIMES Model ('The Integrated MARKAL-EFOM System') uses linear programming to produce a least-cost energy system, optimised according to a number of user constraints, over medium- to long-term time horizons. It portrays the UK energy system, from fuel extraction and trading to fuel processing and transport, electricity generation and all final energy demands (Taylor et al. 2014; Daly and Fais 2014). The model generates scenarios for the evolution of the energy system based on different assumptions around the evolution of demand and future technology costs, measuring energy system costs and all greenhouse gases (GHGs) associated with the scenario. UKTM is built using the TIMES model generator: as a partial equilibrium energy system and technologically detailed model, it is well suited to investigate the economic, social, and technological trade-offs between long-term divergent energy scenarios.

Calliope is an open source Python-based toolchain for developing energy system models, focusing on flexibility, and high temporal and spatial granularities. This model has the ability to execute many runs on the same base model, with clear separation of model (data) and framework (code) (Pfenninger and Pickering 2018).

A.III.I.3.2 Modelling of Energy Systems in the Context of the Economy

To study the impact of low-carbon energy systems on the economy, numerous integrated assessment modelling tools (top-down models) are applied, such as: *General Equilibrium Model for Economy-Energy-Environment (GEM-E3)* (Capros et al. 2013), *ENV-Linkages* (Burniaux and Chateau 2010), and *Emissions Prediction and Policy Analysis (EPPA)* (Chen et al. 2016).

GEM-E3 is a recursive dynamic computable general equilibrium model that covers the interactions between the economy, the energy system and the environment. It is specially designed to evaluate energy, climate, and environmental policies. GEM-E3 can evaluate consistently the distributional and macro-economic effects of policies for the various economic sectors and agents across the countries/regions (Capros et al. 2013).

The modelling work based on ENV-Linkages (as a successor to the OECD GREEN model) provides insights to policymakers in identifying least-cost policies by taking into account environmental issues, such as phasing out fossil fuel subsidies, and climate change mitigation (Burniaux and Chateau 2010).

In the EPPA model, different processes (e.g., economic and technological) which have impacts on the environment from regional to global at multiple scales are simulated. The outputs of this modelling (e.g., greenhouse gas emissions, air and water pollutants) are provided to the MIT Earth System (MESM), which investigates the interaction between sub-models of physical, dynamical and chemical processes in different systems (Chen et al. 2016).

A.III.I.3.3 Hybrid Models

Hybrid models are a combination of macro-economic models (i.e., top-down) with at least one energy sector model (i.e., bottom-up) that could benefit from the advantages of both mentioned approaches. In this regard, linking these two models can be carried out either manually through transferring the data from one model to the other (soft linking), or automatically (hard linking) (Prina et al. 2020). In this section, some of these models are presented including *World Energy Model (WEM)* (IEA 2020a) and the *National Energy Modelling System (NEMS)* (Fattahi et al. 2020).

The WEM is a simulation model covering energy supply, energy transformation and energy demand. The majority of the end-use sectors use stock models to characterise the energy infrastructure. In addition, energy-related CO_2 emissions and investments related to energy developments are specified. The model is focused on determining the share of alternative technologies in satisfying energy service demand. This includes investment costs, operating and maintenance costs, fuel costs and in some cases costs for emitting CO_2 (IEA 2020a).

The NEMS is an energy-economy modelling system applied for the USA through 2030. NEMS projects consider the production, import, conversion, consumption, and prices of energy, subject to assumptions on macroeconomic and financial factors, world energy markets, resource availability and costs, behavioural and technological choice criteria, cost and performance characteristics of energy technologies, and demographics. NEMS was designed and implemented by the Energy Information Administration (EIA) of the US Department of Energy. NEMS is used by EIA to project the energy, economic, environmental, and security impacts on the United States considering alternative energy policies and assumptions related to energy markets (Fattahi et al. 2020).

A.III.I.4 Building Sector Models

A.III.I.4.1 Models: Purpose, Scope and Types

GHG emissions and mitigation potentials in the building sector are modelled using either a top-down, a bottom-up or a hybrid approach (Figure 1).

The top-down models are used for assessing economy-wide responses of building policies. These models are either economic or technological and have low granularity.

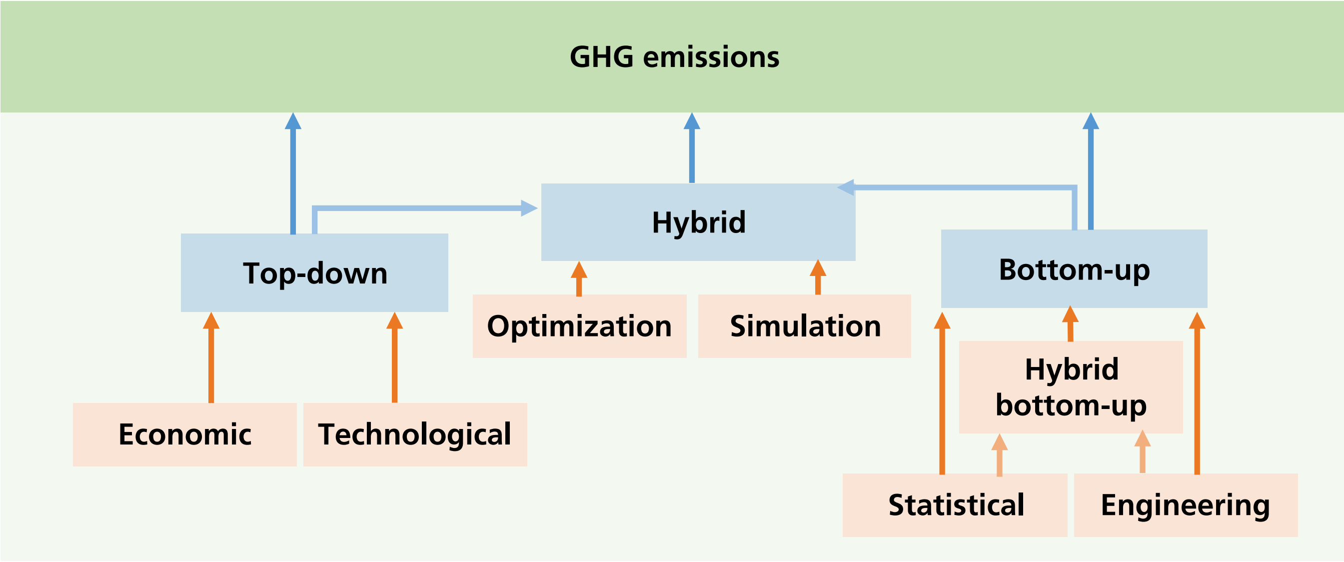


Figure 1 | Modelling approaches for GHG emissions used in the building sector.

The bottom-up models are data intensive and based on microscopic data of individual end uses and the characteristics of each component of buildings. Bottom-up models can be either physics-based, also known as engineering models; data-driven, also known as statistical models; or a combination of both, also known as hybrid bottom-up models. Bottom-up models are useful to assess the technico-economic potentials of the overall building stock by extrapolating the estimated energy consumption of a representative set of invidual buildings (Duerinck et al. 2008; Hall and Buckley 2016; Bourdeau et al. 2019).

Hybrid models used for buildings can be either optimisation or simulation models (Duerinck et al. 2008; Hall and Buckley 2016; Bourdeau et al. 2019) (Figure 1). The latter can also be agent-based models and could be combined with building performance models to allow for an assessment of occupants' behaviour (Papadopoulos and Azar 2016; Sachs et al. 2019a; Niamir et al. 2020). Hybrid models are used for exploring the impacts of resource constraints and for investigating the role of specific technological choices as well as for analysing the impact of specific building policies.

The use of geographical information systems (GIS) layers (Reinhart and Cerezo Davila 2016) combined with machine learning techniques (Bourdeau et al. 2019) allows the creation of detailed datasets of building characteristics while optimising the computing time, thus, leading to a better representation of energy demand of buildings and a more accurate assessment of GHG mitigation potential.

A.III.I.4.2 Representation of Energy Demand and GHG Emissions

Comprehensive models represent energy demand per energy carrier and end use for both residential and non-residential buildings, for different countries or sets of countries, further disaggregated across urban/rural and income groups. Drivers of energy demand considered include population, the floor area per capita, appliances ownership and to some extent occupants' behaviour in residential buildings. The former are included in top-down, hybrid and bottom-up models while the latter is usually included in bottom-up and agent-based models (Niamir et al. 2020; IEA 2021). In non-residential buildings, value added is considered among the drivers.

GHG emissions from buildings are usually modelled on the basis of the estimated energy demand per energy carrier and appropriate emissions factors. The purpose of most building models is to assess the impact of mitigation measures on energy demand in the use phase of buildings and for a given assumption on the per-capita floor area and technological improvement (IEA 2021; Pauliuk et al. 2021b). After decades of ignoring material cycles and embodied emissions (Pauliuk et al. 2017), a few IAMs are now including material stocks and flows (Deetman et al. 2020; IEA 2021; Zhong et al. 2021). However, the top-down nature of these models and the modelling methodology of embodied emissions, which are added onto the emissions estimated in the use phase, questions the policy relevance of these estimates. As of today, the resource efficiency and climate change (RECC) scenario (IRP 2020; Fishman et al. 2021; Pauliuk and Heeren 2021; Pauliuk et al. 2021b;) is the only global scenario identified which includes measures to limit, in the first place, embodied emissions from buildings. The scenario is modelled using the bottom-up ODYM-RECC model.

A.III.I.4.3 Representation of Mitigation Options

The assessment conducted in Chapter 9 was based on the SER (Sufficiency, Efficiency, Renewable), framework with sufficiency being all the measures and daily practices which avoid, in the first place, the demand for energy, materials, water, land and other natural resources over the life cycle of buildings and appliances/equipment, while providing decent living standards for all within the planetary boundaries. By contrast to efficiency, sufficiency measures do not consume energy in the use phase. Efficiency improvement of the building envelope and appliances/equipment are the main mitigation options considered in the existing models and scenarios. They are, usually, combined with market-based and information instruments and to some extent with behaviour change. As of today,

AIII

Grubler et al. (2018), Pauliuk et al. (2021b), Kuhnhenn et al. (2020), Millward-Hopkins et al. (2020), Kikstra et al. (2021), and van Vuuren et al. (2021) are the only six global models/scenarios to include sufficiency measures, out of which detailed data were available only for two scenarios (Pauliuk et al. 2021b; van Vuuren et al. 2021).

In total, 931 scenarios were submitted to the AR6 scenario database, out of which only two scenarios provided detailed data allowing for an assessment of emissions reductions based on the SER framework considered in the building chapter. An additional 78 bottom-up models/scenarios were gathered (Table 1). Mitigation potentials from these scenarios are assessed using either a decomposition analysis (Section 9.3) or an aggregation of bottom-up potential estimates for different countries into regional and then global figures (Section 9.6).

Scenarios considered in the illustrative mitigation pathways included in Chapter 3 were assessed, compared to current policy scenarios. The assessment was possible for only the combined direct CO_2 emissions for both residential and non-residential buildings due to lack of data on other gases as well as on indirect and embodied emissions. The assessment shows mitigation potentials, compared to current policies scenarios, at a global level ranging from 9% to 13% by 2030 and from 58% to 89% in 2050 (Figure 2-b).

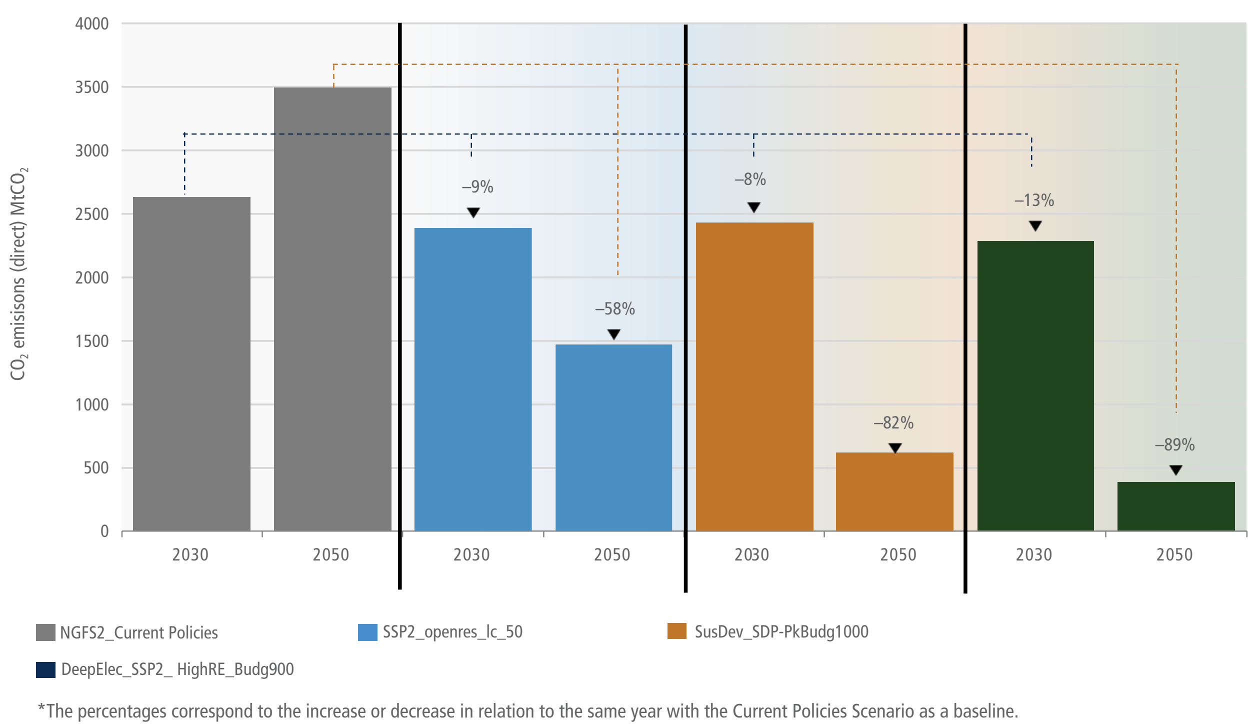
There are great discrepancies in the projected potentials by the IAMs across regions and scenarios. In the deep electrification and high renewable scenario, emissions in Africa are projected to increase by 88% by 2030, followed by a decrease of 97% by 2050, compared to current policies scenario. Similarly, in the sustainable development scenario, emissions in developing Asia are projected, compared to current policies scenario, to increase by 56% by 2030, followed by a decrease of 75% by 2050. Such variations in emissions over two decades in the developing world raise questions about the policy relevance of these scenarios. In developed countries, emissions are projected to go down in all regions across all scenarios, except in SSP2 scenario in Asia-Pacific, where emissions are projected to increase by 18% by 2030 followed by a decrease of 25% by 2050, compared to current policies scenario. It is worth noting that, across all scenarios, Eastern Asia is the region with the lowest estimated mitigation potential compared to the current policies (Figure 2-b).

A.III.I.4.4 Representation of Sustainable Development Dimensions

The link to the Sustainable Development Goals (SDGs) is not always explicit in buildings models/scenarios. However, some models include requirements to ensure access to decent living standards for all (Grubler et al. 2018); Millward-Hopkins et al. 2020; Kikstra et al. 2021) or to specifically meet the 2030 SDG 7 goal (IEA 2020a, 2021).

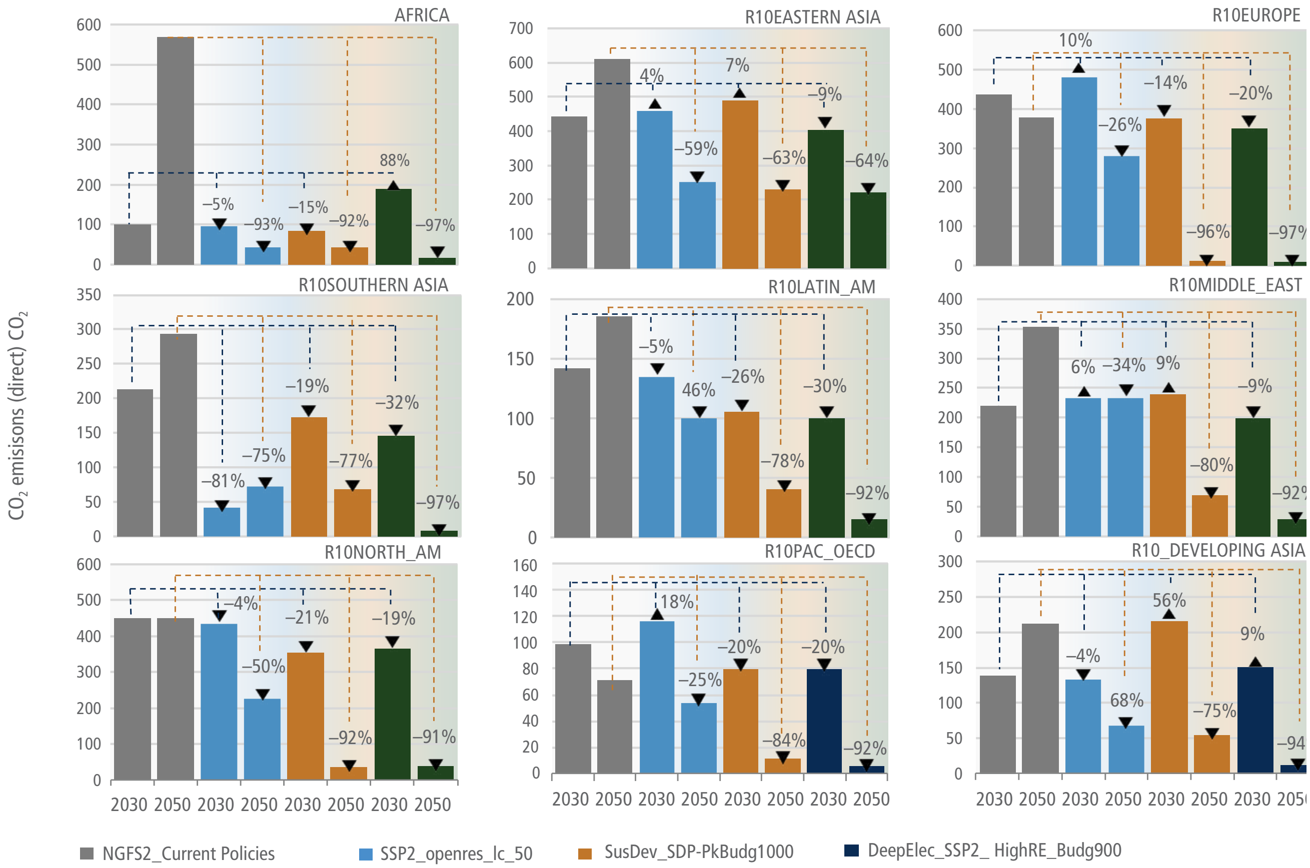
A.III.I.4.5 Models Underlying the Assessment in Chapter 9

The AR6 scenario database received 101 models with a building component, out of which 96 were IAM models and five building specific models. This is equivalent to 931 scenarios. After an initial screening, quality control and further vetting to assess if they sufficiently represented historical trends and climate goals, 43 models (42 IAMs and 1 building-specific model) were kept for the assessment, thus reducing the number of scenarios to assess to 554. The unvetted scenarios are still available in the database.



a) Global

Figure 2 | GHG emissions reductions in the building sector (direct emissions) in scenarios considered as illustrative mitigation pathways in Chapter 3.



* The percentages correspond to the increase or decrease in relation to the same year with the Current Policies Scenario as a baseline.

b) Regional

Figure 2 (continued): GHG mitigation potentials of scenarios considered in the illustrative mitigation pathways considered in Chapter 3.

After a final screening based on the SER (Sufficiency, Efficiency, Renewable) framework, only two IAMs were kept. Given the top-down nature of IAMs and their weaknesses in assessing mitigation measures, especially sufficiency measures, 78 bottom-up models with technological representation have been included in the assessment (Table 1). These additional bottom-up models were not submitted to the AR6 scenario database. However, scenario owners supplied Chapter 9 with the underlying assumptions and data.

A.III.I.5 Transport Models

A.III.I.5.1 Purpose and Scope of Models

GHG emissions from transport are largely a function of **travel demand, transport mode,** and **transport technology and fuel**. The purpose of transportation system models is to describe how future **demand** for transport can be fulfilled through different **modes** and **technologies** under different climate change mitigation targets or policies. Within a given transport mode, technologies differ by efficiency and fuel use.

Common components of transportation energy systems models mirror these main drivers of GHG emissions. Most models will also quantify how much movement occurs, or the **travel demand** associated with each mode. Models commonly quantify demand through **transportation mode** (e.g., active transit, passenger vehicles, trucks, boats, planes, etc.) or how movement occurs (e.g., passenger travel distance pkm and freight distance tkm). Higher fidelity models provide more nuanced breakdowns of demand by trips of various lengths such as short-, medium-, and long-distance trips or by region (e.g., kilometres or tkm per region). The scope of the model often determines how much information it provides on where and when movement occurs. While larger scale models typically provide aggregate travel demand, higher resolution travel demand models can be integrated into transportation system models and provide much more information on origin and destination of trips, when and where trips occur, and the route of travel taken. This level of detail is not often characterised in the output of system models but can be employed as a 'base' model to determine how travel occurs before aggregation (Edelenbosch et al. 2017a; Yeh et al. 2017).

A key distinguishing feature between different model types is how they control the above components. Our review of the transport energy system models can be broadly divided into three main categories: (i) optimisation models, (ii) simulation models, and (iii) accounting and exploratory models.

Table 1 | Models underlying the assessment in Chapter 9.

Model name/ institution using the model	Model description	Geographic scope	Building type included	Energy demand	Example of publications
World Energy Model (WEM)/International Energy Agency (IEA)	A simulation model with detailed bottom-up building stock model	Global	Residential and non-residential	The building module includes a stock model with detailed technologies, end uses and energy carriers. Activity variables such as floor area and appliance ownership are projected by end use. A cost-based approach, influenced by policy and other constraints, is used to allocate between almost 100 technologies. Energy demand projections are based on country-level historical data for both residential and non-residential buildings. The buildings module is integrated within the wider World Energy Model.	IEA (2020a); IEA (2021)
IMAGE 3.2 model/ Netherlands Environmental Assessment Agency	A modular integrated assessment model using a simulation model for energy demand	Global	Residential and non-residential buildings	Energy demand is calculated as a function of household expenditure and population growth, disaggregating across urban/rural and income groups. The model includes a building stock model (residential) with a detailed description of end uses, energy carrier use and building technologies for both residential and non-residential buildings. A scenario analysis assessing assumptions on lifestyle changes has also been conducted.	van Vuuren et al. (2021)
Resource Efficiency and Climate Change (RECC) model. Research Institutions: Norwegian University of Science & Technology and University of Freiburg. Funding Institutions: UNEP and International Resource Panel	Bottom-up building stock-flow model estimating material and energy flows associated with housing stock growth, driven by input parameters of population and floor area per capita	Global	Residential buildings	Energy demand is calculated the model BuildME, a physical model using the EnergyPlus simulation engine, incorporating country/region-specific projections of envelope and equipment efficiency.	IRP (2020); Fishman et al. (2021); Pauliuk and Heeren (2021); Pauliuk et al. (2021a); Pauliuk et al. (2021b)
A total of 77 bottom-up models out of which 67 were technology-rich and 10 sufficiency-focused	Bottom-up technology-rich models with detailed building and other technology stock models	Three global (all sufficiency models), six regional (regions here refer to regions including several countries), two subnational, and the rest national	Residential and/or non-residential buildings	In most cases, energy demand was modelled by multiplying units of energy consumption of technologies/product/buildings by stocks of corresponding technologies/products and/or buildings at national level. The projected stocks of buildings and/or technologies/products are modelled based on past levels. The potential is demonstrated by replacing the business-as-usual technologies and practices with demonstrated best available or commercially feasible technologies and practices. The studies rely on some or all of the following mitigation options: the construction of new high-performance buildings using building design, forms, and passive construction methods; the thermal efficiency improvement of building envelopes of the existing stock; the installation of advanced heating, ventilation air conditioning systems, equipment and appliances; the exchange of lights, appliances, and office equipment, including ICT, water heating, and cooking; active and passive demand-side management measures; as well as on-site production and use of renewable energy. Many bottom-up studies considered the measures as an integrated package due to their technological complementarity and interdependence, rather than the penetration of individual technologies applied in an incremental manner in or to these buildings.	Department of Environmental Affairs (2014); Alaidroos and Krarti (2015); de Melo and de Martino Jannuzzi (2015); Kusumadewi and Limmeechokchai (2015); Markewitz et al. (2015); Prada-Hernández et al. (2015); Csoknyai et al. (2016); Energetics (2016); Gagnon et al. (2016); Horváth et al. (2016); Nadel (2016); Oluleye et al. (2016); Timilsina et al. (2016); Trottier (2016); Virage-Energie Nord-Pas-de-Calais. (2016); Yeh et al. (2016); ADB (2017); Bashmakov (2017); Chaichaloempreecha et al. (2017); Iten et al. (2017); Khan et al. (2017); Krarti et al. (2017); Kusumadewi and Limmeechokchai (2017); Momonoki et al. (2017); négaWatt (2017); Ploss et al. (2017); Radpour et al. (2017); Streicher et al. (2017); Subramanyam et al. (2017a,b); Wakiyama and Kuramochi (2017); Wilson et al. (2017); de la Rue du Can et al. (2018); Grubler et al. (2018); Novikova et al. (2018a,b); Oluleye et al. (2018); Ostermeyer et al.(2018a,b,c); Tan et al. (2018); Toleikyte et al. (2018); Yu et al. (2018); Zhou et al. (2018); Bierwirth and Thomas (2019); Bürger et al. (2019); Cabrera Serrenho et al. (2019); Colenbrander et al. (2019); de la Rue du Can et al. (2019); Dioha et al. (2019); Duscha et al. (2019); González-Mahecha et al. (2019); Kamal et al. (2019); Krarti (2019); Kwag et al. (2019); Levesque et al. (2019); Minami et al. (2019); Onyenokporo and Ochedi (2019); Ostermeyer et al. (2019b); Butler et al. (2020); Filippi Oberegger et al. (2020); Grande-Acosta and Islas-Samperio (2020); Merini et al. (2020); Millward-Hopkins et al. (2020); Roca-Puigròs et al. (2020); Rosas-Flores and Rosas-Flores (2020); Roscini et al. (2020); Sugiyama et al. (2020b); Brugger et al. (2021); Calise et al. (2021); Sandberg et al. (2021); Xing et al. (2021); Zhang et al. (2020)

i. **Optimisation models:** Identify least cost pathways to meet policy targets (such as CO_2 emission targets of transport modes or economy-wide) given constraints (such as rate of adoption of vehicle technologies or vehicle efficiency standards). For example MessageIX-TransportV5 (Krey et al. 2016) and TIMES (Daly et al. 2014).
ii. **Simulation models:** Simulate behaviour of consumers and producers given prices, policies, and other factors by using parameters calibrated to historically observed behaviours such as demand price elasticity and consumer preferences. For example models by Barter et al. (2015), Brooker et al. (2015) and Schäfer (2017).
iii. **Accounting and exploratory models:** Track the outcomes (such as resources use and emissions) of key decisions (such as the adoption of advanced fuels or vehicle technologies) that are based on 'what-if' scenarios. The major difference between accounting models versus optimisation and simulation models is that key decision variables such as new technologies adoptions typically follow modellers' assumptions as opposed to being determined by mathematical formulations as in optimisation and simulation models. See models in Fulton et al. (2009), IEA (2020a), Gota et al. (2019) and Khalili et al. (2019).

Due to the model types' relative strengths and weaknesses, they are commonly applied to certain problem types (Table 2). Models can do **forecasting,** which makes projections of how futures may evolve, or **backcasting**, which makes projections of a future that meets a predefined goal such as a policy target of 80% reduction in GHG emissions from a historical level by a certain year. Models are often also used to explore 'what-if' questions, to confirm the **feasibility** of certain assumptions/outcomes, and to quantify the **impacts** of a change such as a policy under different conditions. Enhancing fuel efficiency standards, banning internal combustion engines, setting fuel quality standards, and the impacts of new technologies are typical examples of problem types analysed in energy system models.

While these four model types drive the component dynamics in different ways, they commonly include modules that include: learning and diffusion (via exogenous, e.g., autonomous learning, or endogenous learning regarding costs and efficiency: i.e., cost decreases and/or efficiency increases as a function of adoption, and increased diffusion due to lower costs) (Jochem et al. 2018), stock turnover (the performance and characteristics of vehicle fleets including survival ages, mileages, fuel economies and loads/occupancy rates are tracked for each new sales/vehicle stocks), consumer choice (theories of how people invest in new technology and utilise different modes of transport based on their individual preferences given the characteristics of mode or technology) (Daly et al. 2014; Schäfer 2017), or other feedback loops (Linton et al. 2015).

IAMs (Krey et al. 2016; Edelenbosch et al. 2017a) are typically global in scope and seek to solve for feasible pathways meeting a global temperature target (Annex III.I.9). This implies finding least-cost mitigation options within and across sectors. In contrast, global and national transport energy system models (GTEMs/NTEMs) typically only assess feasible pathways within the transport sector (Yeh et al. 2017). The range of feasible pathways can be determined through optimisation, simulation, accounting and exploratory methods, as outlined in Table 2. Some GTEMs are linked to an IAMs model (Krey et al. 2016; Edelenbosch et al. 2017a; Roelfsema et al. 2020). The key difference between IAMs and GTEMs or NTEMs is whether the transportation system is integrated with the rest of the energy systems, specifically regarding energy and fuel production and use, fuel prices, economic drivers such as GDP, and mitigation options given a policy goal. IAMs can endogenously determine these factors because the transport sector is just one of many sectors captured by the IAM. While this gives IAMs certain advantages, IAMs sacrifice resolution and complexity for this broader scope. For example, most IAMs lack a sophisticated travel demand model that reflects the heterogeneity of demands and consumer preferences, whereas GTEM/NTEMs can incorporate greater levels of details regarding travel demands, consumer choices, and the details of transport policies. Consequently, what GTEMs/NTEMs lack in integration with other sectors they make up through more detailed analyses of travel patterns, policies, and impacts (Yeh et al. 2017).

Several noteworthy recent active research areas in long-term transportation energy systems modelling involves the consideration of infrastructure investment and consumer acceptance for non-fossil fuel vehicles including charging for electric vehicles (Jochem et al. 2019; Statharas et al. 2021) and refuelling stations for hydrogen vehicles (Rose and Neumann 2020); and the greater integration of the electric, transport, residential, and industrial sectors in fuel production, storage, and utilisation (Bellocchi et al. 2020; Lester et al. 2020; Olovsson et al. 2021; Rottoli et al. 2021). While national and regional transport energy models have the advantage of exploring these relationships in greater spatial, temporal, and policy details for specific countries or regions (Jochem et al. 2019; Bellocchi et al. 2020; Lester et al. 2020; Rottoli et al. 2021; Statharas et al. 2021), the IAMs have the advantage of examining these interactions across the entire economy at the global level (Brear et al. 2020; Rottoli et al. 2021).

A.III.I.5.2 Inventory of Transportation Models included in AR6

Table 2 | Taxonomy of transport models by method (modelling type) and application (problem type).

Problem Type	Optimisation model	Simulation model	Accounting model	Heuristic model
Backcasting	●			●
Forecasting	●	●	●	
Exploring feasibility space		●	●	●
Impact analysis	●	●	●	

Table 3 | GTEM/NTEMs models evaluated in Chapter 10.

Model name	Organisation	Scope	Resolution	Period	Economy-wide	Method
Mobility model (MoMo)	International Energy Agency (IEA)	Global	Country groups	2050	Soft link	Accounting model
Global Transportation Roadmap	International Council on Clean Transportation (ICCT)	Global	Country groups	2050	No	Accounting model
MESSAGE-Transport V.5	International Institute for Applied Systems Analysis (IIASA)	Global	Country groups	2100	Yes	Optimisation model
Global Change Assessment Model (GCAM)	Pacific Northwest National Laboratory (PNNL)	Global	Country groups	2100	Yes	Partial equilibrium model

The global/national transport energy system models included in the transportation chapter (Chapter 10) are listed below in Table 3.

A.III.I.6 Industry Sector Models

A.III.I.6.1 Types of Industry Sector Models

Industry sector modelling approaches can vary considerably from one another. As with other types of models, a key characteristic of industry sector models is related to their geographical scope. While IAMs are often global in scope, many bottom-up sector models are limited to individual countries or regions. The models' system boundaries also differ, with some models fully considering the use of energy for feedstock purposes and other models focusing only on the use of energy for energetic purposes. Differences between models also exist in regard to differentiation between the industry sector and the energy transformation sector, concerning, for example, refineries and industrial power plants.

A.III.I.6.2 Representation of Demand for Industrial Products

Industry sector models vary in regard to their representation of demand for industrial goods or products. A more detailed representation of demand in a model allows for a more explicit discussion of different types of drivers of industrial demand and therefore a more detailed representation of demand-side strategies such as material recycling, longer use of products or sharing of products.

Particularly, demand for industrial products is often considered in more detail in bottom-up models of the industry sector than in top-down models by taking more drivers into account. These drivers can be, inter alia, population, gross value added, construction activity, transport activity, but also changes in material efficiency, recycling rates and scrap rates as well as product use efficiency (e.g., through longer use of products or sharing of products) (Fleiter et al. 2018; Material Economics 2019; IEA 2020b).

A.III.I.6.3 Representation of Mitigation Options

In most top-down IAMs, some energy-intensive sectors, such as iron and steel or cement, are included separately, at least in a generalised manner, but typically few if any sector-specific technologies are explicitly represented. Instead, energy efficiency improvements in the industry sector and its subsectors are often either determined by exogenous assumptions or are a function of energy prices. Likewise, fuel switching occurs primarily as a result of changes in relative fuel prices, which in turn are influenced by CO_2 price developments. In IAMs that include specific technologies, fuel switching can be constrained based on the characteristics of those technologies, while in IAMs with no technological detail, more generic

Table 4 | Models underlying specific assessments in Chapter 11.

Model name and institution using the model	Model description	Geo-graphic scope	Industrial sectors included/ distinguished	Demand for industrial products	Examples of publications
Industry sector model of the Energy Technology Perspectives model (IEA)	The bottom-up industry sector model is one of four soft-linked models making up the ETP model. The four models are an energy supply optimisation model and three end-use sector models (transport, industry, buildings). Technologies and fuels in the industry sector model are chosen based on cost optimisation.	Global	Aluminium, iron and steel, chemical and petrochemical, cement, pulp and paper and other industry sectors	Demand for industrial products is derived based on country-level historical data on per capita consumption. This per capita consumption is projected forward by using population projections and industry value-added projections. Demand for materials is derived by also taking the build-up of material stocks into account.	IEA (2020b, 2021)
World Energy Model (IEA)	Simulation model consisting inter alia of technologically detailed bottom-up representations of several industry sectors	Global	See ETP model	See ETP model	IEA (2020a, 2021)
Material Economics modelling framework	Modelling tool consisting of several separate bottom-up models	European Union	Steel, chemicals (plastics and ammonia), cement	Demand for industrial products is derived based on scenarios of future activity levels in key segments such as construction, mobility and food production. Separate models additionally explore opportunities for improving materials efficiency and increasing materials circulation.	Material Economics (2019)

constraints on fuel switching in the industry sector are embedded (Edelenbosch et al. 2017b).

In bottom-up models, individual technological mitigation options are represented in detail, especially for energy-intensive sectors such as iron and steel, cement and chemicals. Typically, for each considered technology, not only specific energy demand but also investment and operating costs are included in these models. Investment costs can change over time, either based on an exogenous assumption or on an endogenised process such as a learning rate. While bottom-up models often consider technology-specific learning, IAMs cover technological progress in a more general way associated to industry branches. The uptake of new technologies is typically restricted in bottom-up models, for example by assuming a minimum lifetime for existing stock or by assuming S-shaped diffusion curves (Fleiter et al. 2018). The industrial sector models included in the industry chapter (Chapter 11) are listed in Table 4.

A.III.I.6.4 Limitations and Critical Analysis

Aggregated, top-down models of the industry sector, as used in most IAMs, are typically calibrated based on long-term historical data, for example on the diffusion of new technologies or on new fuels. These models are therefore able to implicitly consider real-life restrictions of the whole sector that bottom-up models (with their focus on individual technologies) may not fully take into account. These restrictions may arise, inter alia, from delays in the construction of infrastructure or market actors possessing incomplete information about new technologies. Furthermore, as IAMs also model the climate system, these models can principally take into account potential repercussions of climate change impacts on the growth rate and structure of economies.

However, a downside of top-down models is that they are typically limited in their representation of individual technologies and processes in the industry sector and particularly of technology-driven structural change. This lack of technological detail limits the usefulness of these models to analyse technology-specific and sector-specific mitigation measures and related policies. Top-down models also tend to have a relatively aggregated representation of industrial energy demand, meaning demand-side mitigations strategies such as recycling, product-service efficiency and demand reduction options are difficult to assess with these models (Pauliuk et al. 2017).

In contrast, technology-rich bottom-up models allow detailed analysis of the potential of new technologies, processes and fuels in individual industrial sectors to reduce GHG emissions. Their often-detailed analysis of the demand side allows demand-side mitigation strategies to be evaluated. Furthermore, radical future changes in technology, climate policy or social norms can more easily be reflected in bottom-up models than in top-down models which are calibrated on past observations. Both types of models are typically not able to account for product substitution (e.g., steel vs plastics) arising from changing production cost differentials or changing product quality due to new production processes. In principle, technology-rich input-output models could fill this gap.

A.III.I.7 Land-use Modelling

Land use related IAM modelling results as presented in Chapter 7 are based on comprehensive land-use models (LUMs) that are either integrated directly, or through emulators, into the integrated assessment framework. Given the increasing awareness of the importance of the land use sector to achieve ambitious climate mitigation targets, LUMs and their integration into IAM systems was one of the key innovations to the integrated assessment over the past decade to allow for an economy-wide quantification of climate stabilisation pathways.

LUMs allow developments in the land-use sector to be projected over time and the impacts of mitigation policies on different economic (markets, trade, prices, demand, supply, etc.) and environmental (land use, emissions, fertiliser, irrigation water use, etc.) indicators to be assessed. The following models submitted scenarios to the AR6 database: AIM (Fujimori et al. 2014, 2017; Hasegawa et al. 2017), EPPA (Chen et al. 2016), GCAM (Calvin et al. 2019), IMAGE (Stehfest et al. 2014), MERGE, MESSAGE-GLOBIOM (Havlík et al. 2014; Fricko et al. 2017; Huppmann et al. 2019), POLES (Keramidas et al. 2017), REMIND-MAgPIE (Kriegler et al. 2017; Dietrich et al. 2019), WITCH (Emmerling et al. 2016).

A.III.I.7.1 Modelling of Land Use and Land-use Change

LUMs represent different land use activities for managed land (agriculture including cropland and pastures, managed forests, and dedicated energy crops) while natural lands (primary forests, natural grasslands, shrubland, savannahs, etc.) act as land reserves that can be converted to management depending on other constraints (Popp et al. 2014a; Schmitz et al. 2014). Typically, the agricultural sector has the greatest level of detail across land use sectors. LUMs include different crop and livestock production activities, some even at the spatially explicit level and differentiated by production system (Havlík et al. 2014; Weindl et al. 2015). Forestry is covered with varying degrees of complexity across LUMs. While some models represent only afforestation/deforestation activities dynamically, others have detailed representation of forest management activities and/or forest industries (Lauri et al. 2017). The models endogenously determine the land allocation of different land use activities as well as land-use changes according to different economic principles (land rent, substitution elasticities, etc.) and/or considering biophysical characteristics such as land suitability (Schmitz et al. 2014; Weindl et al. 2017).

A.III.I.7.2 Demand for Food, Feed, Fibre and Agricultural Trade

LUMs project demand for food, feed, other industrial or energy uses for different agriculture and forestry commodities over time. While partial equilibrium models typically use reduced-form demand functions with greater level of detail at the commodity level, however limited agriculture and forestry, Computable General Equilibrium (CGE) models represent demand starting from utility functions from which it is possible to derive demand functions, and functional forms for income and price elasticities, however for a more limited set of agricultural and forestry commodities but with full coverage of all economic sectors (Valin et al. 2014; von Lampe et al. 2014). Over time, demand for food, feed, and other industrial uses is projected conditional on population and income growth while bioenergy demand is typically informed in partial equilibrium (PE) models by linking with IAMs/energy systems models, and is usually endogenous in CGE/IAMs (Hasegawa et al. 2020). Depending on the model, demand projections are sensitive to price changes (Valin et al. 2014). International trade is often represented in LUMs using either Armington or spatial equilibrium approaches (von Lampe et al. 2014).

A.III.I.7.3 Treatment of Land-based Mitigation Options

Two broad categories of land-based mitigation options are represented in LUMs: (i) reduction of GHG (CO_2, CH_4 and N_2O) emissions from land use, and (ii) carbon sink enhancement options including biomass supply for bioenergy. Each of these categories is underpinned by a portfolio of mitigation options with varying degrees of complexity and parameterisation across LUMs. The representation of mitigation measures is influenced on the one hand by the availability of data for its techno-economic characteristics and future prospects as well as the computational challenge, for example in terms of spatial and process detail, to represent the measure, and on the other hand, by structural differences and general focus of the different LUMs, and prioritisation of different mitigation options by the modelling teams. While GHG emission reduction and CO_2 sequestration options such as afforestation are typically covered directly in LUMs (Hasegawa et al. 2021), carbon sequestration from biomass supplied for bioenergy with carbon capture and storage (BECCS) is usually not accounted for in LUMs but in the energy sector and hence is taken care of directly in the IAMs. Yet, LUMs provide estimates of available biomass for energy production and the impacts of its production.

A.III.I.7.3.1 Treatment of GHG Emissions Reduction

Agricultural non-CO_2 emissions covered in LUMs include CH_4 from enteric fermentation, manure management and cultivation of rice paddies, and N_2O emissions from soils (fertiliser and manure application, crop residues) and manure management and are based on IPCC accounting guidelines (IPCC 2019a). For each of those sources, LUMs typically represent a (sub)set of technical, structural and demand-side mitigation options. Technical options refer to technologies such as anaerobic digesters, feed supplements or nitrogen inhibitors that are either explicitly represented (Frank et al. 2018) or implicitly via the use of marginal abatement cost curves (MACC) (Lucas et al. 2007; Beach et al. 2015; Harmsen et al. 2019). Emission savings from structural changes refer to more fundamental changes in the agricultural sector, for example through international trade, production system changes or reallocation and substitution effects (Havlík et al. 2014). Demand-side options include dietary changes and reduction of food waste (Springmann et al. 2016; Creutzig et al. 2018; Ritchie et al. 2018; Frank et al. 2019; Mbow et al. 2019; Clark et al. 2020; Ivanova et al. 2020; Popp et al. 2010; Rosenzweig et al. 2020). For the forest sector, emission reduction options are mainly targeting CO_2 from deforestation (Overmars et al. 2014; Hasegawa et al. 2017; Rochedo et al. 2018; Bos et al. 2020; Doelman et al. 2020; Eriksson 2020). Mitigation/restoration options for wetlands to reduce emissions from drained organic soils are typically not represented in LUMs (Humpenöder et al. 2020).

There are significant differences between UNFCCC nationally reported GHG inventories and analytical global land use models. According to Grassi et al. (2017), this discrepancy results in a 3GtCO_2-eq difference in estimates between country reports and global models. The difference relies on different methods to classify and assess managed forests and forest management fluxes (Houghton et al. 2012; Pongratz et al. 2014; Smith et al. 2014; Tubiello et al. 2015; Grassi et al. 2017, 2021). While global models account for GHG emissions from indirect human-induced effects and natural effects in unmanaged land, countries only consider fluxes of land use and land-use change in managed land. In order to produce policy-relevant land-use model exercises, reconciling these differences is needed by harmonising definitions and approaches of anthropogenic land and the treatment of indirect environmental change (Grassi et al. 2017).

A.III.I.7.3.2 Treatment of Terrestrial Carbon Dioxide Removal Options including Biomass Supply for Bioenergy

Terrestrial carbon dioxide removal options are only partially included in LUMs and mostly rely on afforestation and bioenergy with carbon capture and storage (BECCS) (Fuss et al. 2014, 2018; Minx et al. 2018; Smith et al. 2019; Butnar et al. 2020). Especially some nature-based solutions (Griscom et al. 2017) such as soil carbon management (Paustian et al. 2016), which have the potential to alter the contribution of land-based mitigation in terms of timing, potential and sustainability consequences, are only recently being implemented in LUMs (Frank et al. 2017; Humpenöder et al. 2020). The representation of bioenergy feedstocks varies across models but typically LUMs have comprehensive representation of a series of crops (starch, sugar, oil, wood/lignocellulosic feedstocks) or residues/byproducts that can be used for liquid and solid bioenergy production (Hanssen et al. 2019).

A.III.I.7.4 Treatment of Environmental and Socio-economic Impacts of Land Use

Aside reporting the implications on agriculture, forestry and other land use (AFOLU) GHG emissions, LUMs can provide a set of environmental and socio-economic impact indicators to assess the quantified climate stabilisation pathways in a broader sustainable development agenda (van Vuuren et al. 2015; Obersteiner et al. 2016; van Vuuren et al. 2019; Frank et al. 2021; Soergel et al. 2021). These indicators typically span from land use area developments (Popp et al. 2017; Stehfest et al. 2019), fertiliser use, irrigation water use and environmental flows (Bonsch et al. 2015; Pastor et al. 2019; Chang et al. 2021; de Vos et al. 2021), and on biodiversity (Leclère et al. 2020; Marquardt et al. 2021), to market impacts on commodity prices and food consumption, or impact on undernourishment (Hasegawa et al. 2018; Doelman et al. 2019; Fujimori et al. 2019a; Hasegawa et al. 2020; Soergel et al. 2021).

A.III.I.8 Reduced Complexity Climate Modelling

Climate model emulators (often referred to as reduced complexity or simple climate models) are used to integrate the WGI knowledge of physical climate science into the WGIII assessment. Hence, emulators are used to assess the climate implications of the GHG and other emissions trajectories that IAMs produce (van Vuuren et al. 2008; Rogelj et al. 2011; Clarke et al. 2014; Schaeffer et al. 2015; Rogelj et al. 2018a). The IAM literature typically uses one of two approaches: comprehensive emulators such as MAGICC (Meinshausen et al. 2011) or Hector (Hartin et al. 2015) or minimal complexity representations such as the representation used in DICE (Nordhaus 2018), PAGE (Yumashev et al. 2019; Kikstra et al. 2021c) and Fund (Waldhoff et al. 2014). In physical science research, a wider range of different emulators are used (Nicholls et al. 2020b, 2021a).

A key application of emulators within IPCC WGIII is the classification of emission scenarios with respect to their global mean temperature outcomes (Clarke et al. 2014; Rogelj et al. 2018a). WGIII relies on emulators to assess the full range of carbon-cycle and climate response uncertainty of thousands of scenarios, as assessed by AR6 WGI. An exercise of such amplitude is currently infeasible with more computationally demanding state-of-the-art Earth system models. Cross-Chapter Box 7.1 in AR6 WGI documents how emulators used in WGIII are consistent with the physical science assessment of WGI (Forster et al. 2021).

Previous IPCC Assessment Reports relied either on the climate output from each individual IAM (IPCC 2000) or a more streamlined approach, where one consistent emulator set-up was used to assess all scenarios. For instance, in AR5 and the Special Report on Global Warming of 1.5°C (SR1.5), MAGICC was used for scenario classification (Clarke et al. 2014; Rogelj et al. 2018a). In recent years, numerous other emulators have been developed and increased confidence and understanding can thus be gained by combining insights from more than one emulator. For example, SR1.5 used MAGICC for its scenario classification, with additional insights provided by the FaIR model (Smith et al. 2018). The SR1.5 experience highlighted that the veracity of emulators 'is a substantial knowledge gap in the overall assessment of pathways and their temperature thresholds' (Rogelj et al. 2018a). Since SR1.5, international research efforts have demonstrated tractable ways to compare emulator performance (Nicholls et al. 2020b), as well as their ability to accurately represent a set of uncertainty ranges in physical parameters (Nicholls et al. 2021b), such as those reported by AR6 WGI (Forster et al. 2021).

Finally, the recently developed OpenSCM-Runner package (Nicholls et al. 2020a) provides users with the ability to run multiple emulators from a single interface. OpenSCM-Runner has been built in collaboration with the WGIII research community and forms part of the WGIII assessment (Annex III.II.2.5.1).

A.III.I.9 Integrated Assessment Modelling

Process-based integrated assessment models (IAMs) describe the coupled energy-land-economy-climate system (Weyant 2009; Krey 2014; Weyant 2017). They typically capture all greenhouse gas (GHG) emissions induced by human activities and, in many cases, emissions of other climate forcers like sulphate aerosols. Process-based IAMs represent most GHG and climate pollutant emissions by modelling the underlying processes in energy and land use. Those models are able to endogenously describe the change in emissions due to changes in energy and land use activities, particularly in response to climate action. But IAMs differ in the extent to which all emissions and the corresponding sources, processes and activities are represented endogenously and, thus, can be subjected to policy analysis.[1] IAMs also differ regarding the scope of representing carbon removal options and their interlinkage with other vital systems such as the energy and land-use sectors.

Typically, IAMs consider multi-level systems of global, regional, national and local constraints and balance equations for different categories such as emissions, material and energy flows, financial flows, and land availability that are solved simultaneously. Intertemporal IAMs can fully incorporate not only flow constraints that are satisfied in each period, but also stock constraints that are aggregated over time and require to balance activities over time. Changes of activities, for example induced by policies to reduce emissions, are connected to a variety of balance equations and constraints and therefore such policies lead to system-wide changes that can be analysed with IAMs. Many IAMs also contain gridded components to capture, for example, land-use and climate change processes where the spatial distribution matters greatly for the dynamics of the system. Processes that operate on smaller spatial and temporal scales than resolved by IAMs, such as temporal variability of renewables, are included by parameterisation and statistical modelling approaches that capture the impact of these subscale processes on the system dynamics at the macro level (Pietzcker et al. 2017).

Global IAMs are used to analyse global emissions scenarios extrapolating current trends under a variety of assumptions and climate change action pathways under a variety of global goals. In recent years, a class of national and regional IAMs have emerged that describe the coupled energy-land-economy system in a given geography. They typically have higher sectoral, policy and technology resolution than global models and make assumptions about boundary conditions set by global markets and international policy regimes. These IAMs are used to study trends and transformation pathways for a given region (Shukla and Chaturvedi 2011; Capros et al. 2014; Lucena et al. 2016).

AIII

[1] See the common IAM documentation at www.iamcdocumentation.eu.

A.III.I.9.1 Types of Integrated Assessment Models

IAMs include a variety of model types that can be distinguished into two broad classes (Weyant 2017). The first class comprises *cost-benefit IAMs* that fully integrate a stylised socio-economic model with a reduced-form climate model to simultaneously account for the costs of mitigation and the damages of global warming using highly aggregate cost functions derived from more detailed models. In the model context, these functions do not explicitly represent the underlying processes, but map mitigation efforts and temperature to costs. This closed-loop approach between climate and socio-economic systems enables cost-benefit analysis by balancing the cost of mitigation and the benefits of avoided climate damages. This can be done in a globally cooperative setting to derive the globally optimal climate policy where no region can further improve its welfare without reducing the welfare of another region (Pareto optimum). Alternatively, it can be assumed that nations do not engage in emission mitigation at all or mitigate in a non-cooperative way, only considering the marginal benefit of their own action (Nash equilibrium). Also, differing degrees of partial cooperation are possible.

The second class of IAMs, called *process-based IAMs*, focuses on the analysis of transformation processes depending on a broad set of activities that induce emissions as side effects. They describe the interlinkages between economic activity, energy use, land use, and emissions with emission reductions and removals as well as broader sustainable development targets. GHGs and other climate pollutants are caused by a broad range of activities that are driven by socio-economic developments (Riahi et al. 2017) and also induce broader environmental consequences such as land-use change (Popp et al. 2017) and air pollution (Rao et al. 2017b). With few exceptions, these models typically do not close the loop with climate change and damages that affect the economy, but focus on emission scenarios and climate change mitigation pathways. Due to the process-based representations of emission sources and alternatives, it is not only possible to investigate the implications of policies on GHG emissions, but also the trade-offs and synergies with social and environmental sustainability criteria (von Stechow et al. 2015) (Annex III.I.9.3). The analysis of different cross-sectoral synergies and trade-offs is frequently termed a nexus analysis, such as the energy-water-land nexus. The analysis can also address socio-economic sustainability criteria such as energy access and human health. Process-based IAMs are also used to explore the synergies and trade-offs of 'common, but differentiated responsibilities' by analysing issues of burden sharing, equity, international cooperation, policy differentiation and transfer measures (Tavoni et al. 2015; Fujimori et al. 2016; Leimbach and Giannousakis 2019; Bauer et al. 2020b).

There exists a broad range of process-based IAMs that differ regarding the economic modelling approaches (Annex III.I.2) as well as the methodology and detail of sector representation (Annex III.I.3–7) and how they are interlinked with each other.

This leads to differences in model results regarding global aggregates as well as sectoral and regional outputs. Several approaches have been used to evaluate the performance of IAMs and understand differences in IAM behaviour (Schwanitz 2013; Wilson et al. 2021), including sensitivity analysis (McJeon et al. 2011; Luderer et al. 2013; Rogelj et al. 2013a; Bosetti et al. 2015; Marangoni et al. 2017; Giannousakis et al. 2021), model comparisons (Clarke et al. 2009; Kriegler et al. 2014a, 2015a; Riahi et al. 2015; Tavoni et al. 2015; Kriegler et al. 2016; Riahi et al. 2017; Luderer et al. 2018; Roelfsema et al. 2020; Riahi et al. 2021; van Soest et al. 2021), model diagnostics (Kriegler et al. 2015a; Wilkerson et al. 2015; Harmsen et al. 2021), and comparison with historical patterns (Wilson et al. 2013; van Sluisveld et al. 2015; Napp et al. 2017).

A.III.I.9.2 Components of Integrated Assessment Models

A.III.I.9.2.1 Energy-economy Component

Typically, IAMs comprise a model of energy flows, emissions and the associated costs (Krey 2014). The demand for exploring the Paris Agreement climate goals led to model developments to make the challenges and opportunities of the associated transformation pathways more transparent. Since AR5 much progress has been achieved to improve the representation of mitigation options in the energy supply sector (e.g., renewable energy integration (Pietzcker et al. 2017), energy trade (Bauer et al. 2016; McCollum et al. 2016; Bauer et al. 2017; Jewell et al. 2018), capacity inertia, carbon removals, and decarbonisation bottlenecks (Luderer et al. 2018)) and technological and behavioural change measures in energy demand sectors such as transport (van Sluisveld et al. 2016; Edelenbosch et al. 2017a; McCollum et al. 2017). An energy sector model can be run as a partial equilibrium model using exogenous demand drivers for final energy and energy services. These models derive mitigation policy costs in terms of additional energy sector costs and area under the marginal abatement costs curve.

Energy models can be also embedded into a broader, long-term macroeconomic context in a general equilibrium model (Bauer et al. 2008; Messner and Schrattenholzer 2000). The demands for final energy and energy services are endogenously driven by an economic growth model that also endogenises the economic allocation problem of macroeconomic resources for the energy sector that crowd out with alternatives. This allows impact analysis of climate policies on economic growth and structural change, investment financing and crowding out as well as income distribution and tax revenue recycling (Guivarch et al. 2011). Moreover, general equilibrium models also derive mitigation costs in terms of GDP losses and consumption losses, which comprise the full macroeconomic impacts rather than only the narrow energy-related costs (Paltsev and Capros 2013).

A.III.I.9.2.2 Land System Component

In recent years, substantial efforts have been devoted to improve and integrate land-use sector models in IAMs (Popp et al. 2014b, 2017). This acknowledges the importance of land-use GHG emissions of the agricultural and forestry sectors as well as the role of bioenergy, afforestation and other land-based mitigation measures. The integration is particularly important in light of the long-term climate goals of the Paris Agreement, for four reasons (IPCC 2019b). First, the GHG emissions from land-use change account for more than 10% of global GHG emissions (Kuramochi et al. 2020) and some sources of CH_4 and N_2O constitute serious mitigation bottlenecks. Second, bioenergy is identified as a crucial primary energy source for low-emission energy supply and carbon removal (Bauer et al. 2020a; Butnar et al. 2020; Calvin et al. 2021). Third, land use-based mitigation measures such as afforestation and reduced deforestation have substantial mitigation potentials. Finally, land-cover changes alter the Earth surface albedo, which has implications for regional and global climate. Pursuing the Paris Agreement climate goals requires the inclusion of a broad set of options regarding GHG emissions and removals, which will intensify the interaction between the energy sector, the economy and the land use sector. Consequently, intersectoral policy coordination becomes more important and the land-related synergies and trade-offs with sustainable development targets will intensify (Calvin et al. 2014b; Kreidenweis et al. 2016; Frank et al. 2017; van Vuuren et al. 2017a; Humpenöder et al. 2018; Bauer et al. 2020d). IAMs used by the IPCC in the AR6 have continuously improved the integration of land-use models with energy models to explore climate mitigation scenarios under varying policy and technology conditions (Rogelj et al. 2018a; Smith et al. 2019). However, feedbacks from changes in climate variables are not included in the land-use sector models, or are only included to a limited degree.

A.III.I.9.2.3 Climate System Component

Reduced complexity climate models (often called simple climate models or emulators) are used for communicating WGI physical climate science knowledge to the research communities associated with other IPCC working groups (Annex III.I.8). They are used by IAMs to model the climate outcome of the multi-gas emissions trajectories that IAMs produce (van Vuuren et al. 2011a). A main application of such models is related to scenario classifications in WGIII (Clarke et al. 2014; Rogelj et al. 2018a). Since WGIII assesses a large number of scenarios, it must rely on the use of these simple climate models; more computationally demanding models (as used by WGI) will not be feasible to apply. For consistency across the AR6 reports, it is important that these reduced-complexity models are up to date with the latest assessments from WGI. This relies on calibrating these models so that they match, as closely as possible, the assessments made by WGI (Annex III.II.2.5.1). The calibrated models can then be used by WGIII in various parts of its assessment.

A.III.I.9.3 Representation of Nexus Issues and Sustainable Development Impacts in Integrated Assessment Models

An energy-water-land nexus approach integrates the analysis of linked resources and infrastructure systems to provide a consistent platform for multi-sector decision-making (Howells et al. 2013). Many of the IAMs that contributed to the assessment incorporate a nexus approach that considers simultaneous constraints on land, water and energy, as well as important mutual dependencies (Fricko et al. 2017; Fujimori et al. 2017; Calvin et al. 2019; Dietrich et al. 2019; van Vuuren et al. 2019). Recently IAMs have also been integrated with life cycle assessment tools in assessing climate mitigation policies to better understand the relevance of life cycle GHG emissions in cost-optimal mitigation scenarios (Portugal-Pereira et al. 2016; Pehl et al. 2017; Arvesen et al. 2018; Tokimatsu et al. 2020). This holistic perspective ensures mitigation pathways do not exacerbate challenges for other sectors or environmental indicators. At the same time, pathways are leveraging potential synergies along the way towards achieving multiple goals.

IAMs rely on biophysical models with a relatively high degree of spatial and temporal resolution to inform coarser-scale economic models of the potentials and costs for land, water and energy systems (Johnson et al. 2019). IAMs leverage population, GDP and urbanisation projections to generate consistent water, energy and crop demand projections across multiple sectors (e.g., agriculture, livestock, domestic, manufacturing and electricity generation) (Mouratiadou et al. 2016). The highly distributed nature of decisions and impacts across sectors, particularly for land and water, has been addressed using multi-scale frameworks that embed regional and sub-regional models within global IAMs (Mosnier et al. 2014; Hejazi et al. 2015; Bijl et al. 2018; Portugal-Pereira et al. 2018). These analyses have demonstrated how local constraints and policies interact with national and international strategies aimed at reducing emissions.

Sustainable development impacts extending beyond climate outcomes have been assessed by the IAMs that contributed to the assessment, particularly in the context of the targets and indicators consistent with the Sustainable Development Goals (SDGs). The representation of individual SDGs is diverse (Figure 3), and recent model development has focused mainly on improving capabilities to assess climate change mitigation policy combined with indicators for economic growth, resource access, air pollution and land use (van Soest et al. 2019). Synergies and trade-offs across sustainable development objectives can be quantified by analysing multi-sector impacts across ensembles of IAM scenarios generated from single or multiple models (McCollum et al. 2013; Mouratiadou et al. 2016). Modules have also been developed for IAMs with the specific purpose of incorporating policies that address non-climatic sustainability outcomes (Cameron et al. 2016; Fujimori et al. 2018; Parkinson et al. 2019). Similar features have been utilised to incorporate explicit adaptation measures and targeted policies that balance mitigation goals with other sustainability criteria (Bertram et al. 2018; McCollum et al. 2018).

A.III.I.9.4 Policy Analysis with IAMs

A key purpose of IAMs is to provide orientation knowledge for the deliberation of future climate action strategies by policymakers, civil society and the private sector. This is done by presenting different courses of actions (climate change and climate action pathways) towards a variety of long-term climate outcomes under a broad range of assumptions about future socio-economic, institutional and technological developments. The resulting climate change and climate action pathways can be analysed in terms of their outcomes towards a set of societal goals (such as the SDGs) and the resulting trade-offs between different pathways. Key trade-offs that have been investigated in the IAM literature are between (i) no, moderate, and ambitious mitigation pathways (Riahi et al. 2017), (ii) early vs delayed mitigation action (Riahi et al. 2015; Luderer et al. 2018), (iii) global action with a focus on economic efficiency equalising

AIII

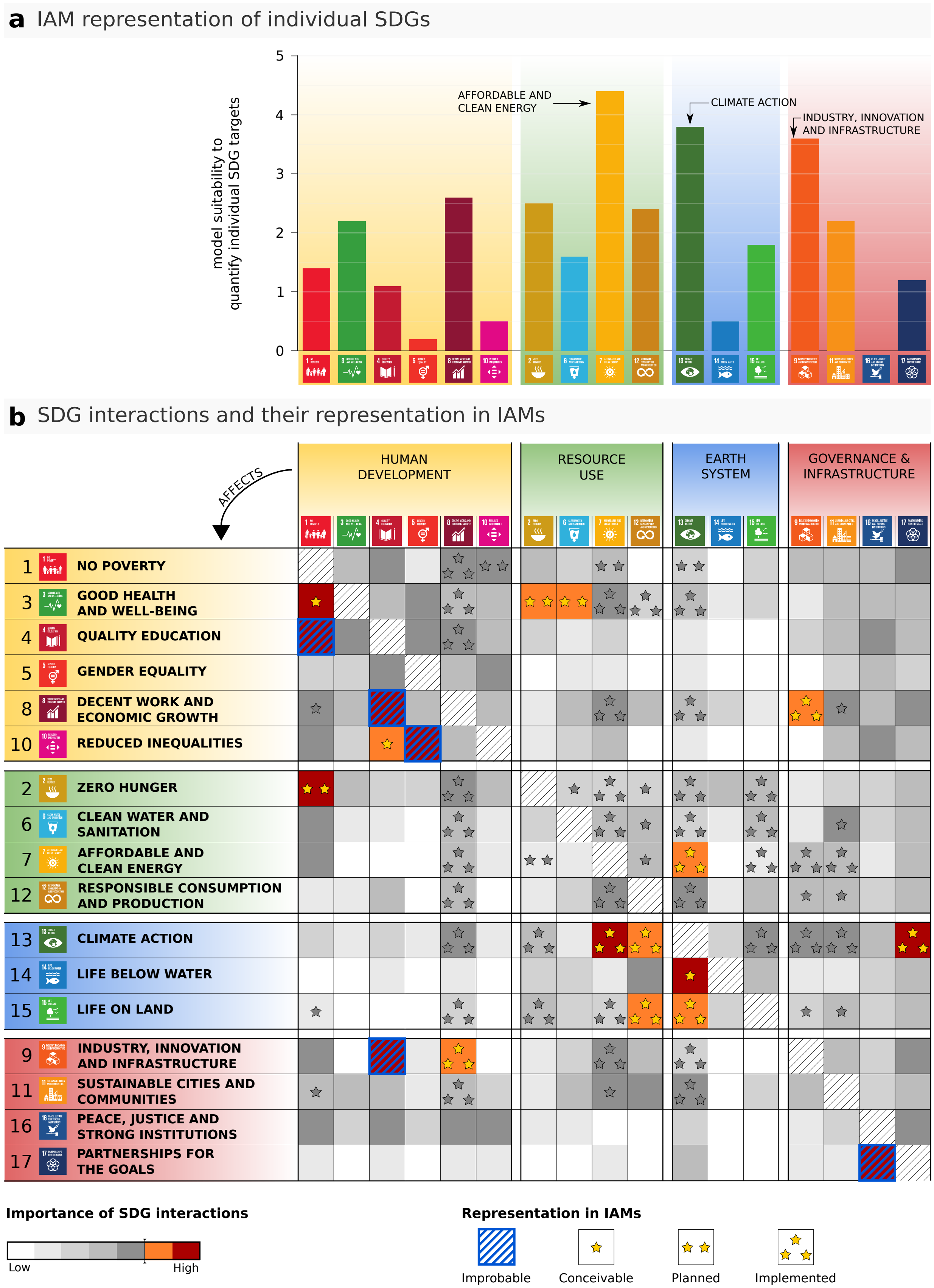


Figure 3 | The representation of Sustainable Development Goals by Integrated Assessment Models. (a) Individual target coverage from a multi-model survey; and **(b)** SDG interactions and coverage by IAM models according to a combination of expert and model surveys. The strength dimension of SDG interactions is indicated by grey shading: darker shades represent strong interactions while white represents no interactions. Orange cells indicate where there is the highest agreement between the importance of interactions and model representation, while blue coloured cells show the most important interactions without model representation. Source: van Soest et al. (2019).

marginal abatement costs across countries and sectors vs regionally and sectorally fragmented action (Blanford et al. 2014a; Bertram et al. 2015; Kriegler et al. 2015b, 2018b; Bauer et al. 2020b; Roelfsema et al. 2020), (iv) pathways with different emphasis on supply-side vs demand-side mitigation measures (Grubler et al. 2018; van Vuuren et al. 2018) or more broadly different sustainable development strategies (Riahi et al. 2012; van Vuuren et al. 2015; Soergel et al. 2021), and (v) pathways with different preferences about technology deployment, in particular with regard to carbon capture and storage (CCS) and carbon dioxide removal (CDR) (Krey 2014; Kriegler et al. 2014a; Riahi et al. 2015; Strefler et al. 2018; Rose et al. 2020; Luderer et al. 2021; Strefler et al. 2021b). Key uncertainties that were explored in the IAM literature are between (i) different socio-economic futures as, for example, represented by the Shared Socio-economic Pathways (SSPs) (Bauer et al. 2017; Popp et al. 2017; Riahi et al. 2017), (ii) different technological developments (Bosetti et al. 2015) and (iii) different resource potentials (Kriegler et al. 2016).

Policy analysis with IAMs follows the approach that a baseline scenario is augmented by some kind of policy intervention. To address the uncertainties in baseline projections, the scientific community has developed the Shared Socio-economic Pathways (SSPs) that provide a set of vastly different future developments as reference cases (Annex III.II.1.3,2). Most scenarios used in AR6 are based on the middle-of-the-road reference system (SSP2). Depending on the research interest, the baseline can be defined as a no-policy baseline or it can include policies that either address GHG emissions like the nationally determined contributions (NDCs) or other pre-existing policies such as energy subsidies and taxes. There is no standard definition for baseline scenarios regarding the inclusion of policies. The baseline scenario is augmented by additional policies like a carbon tax aiming towards a long-term climate goal. Hence, the IAM-based policy analysis assumes a reference system like SSP2 within which policy scenarios are compared with a baseline scenario.

Most policy analysis with process-based IAMs apply a mix of short-term policy evaluation and long-term policy optimisation. Policy evaluation applies an exogenous set of policies such as the stated NDCs and evaluates the emission outcomes. Policy optimisation is mostly implemented as a cost-effectiveness analysis: a long-term climate stabilisation target is set to derive the optimal mitigation strategy that equalises marginal abatement cost across sectors, GHGs and countries. This optimal mitigation strategy can be implemented by a broad set of well-coordinated sector-specific policies or by comprehensive carbon-pricing policies.

Most commonly, the baseline scenario is either a no-policy baseline or based on the NDCs applying an extrapolation beyond 2030 (Grant et al. 2020; Roelfsema et al. 2020). The climate policy regimes most commonly applied include a long-term target to be reached. The optimal climate strategy can be phased in gradually or applied immediately after 2020. It can focus on a global carbon price equalising marginal abatement costs across countries or policy intensities can vary across countries and sectors in the near to medium term. The climate policy regime can include or exclude effort-sharing mechanisms and transfers between regions. Also, it can be extended to include additional sector policies such as improved forest protection or fossil fuel subsidy removal. If certain technologies or activities are related to spill-overs such as technology learning, carbon pricing might be complemented by technology support (Schultes et al. 2018). If carbon-pricing policies are fragmented or delayed, additional and early sector policies can help reduce distortions and carbon leakage effects (Bauer et al. 2020b). All these variations to the policy regime can lead to very different transformation pathways and policy costs, which is a core result of the IAM analysis.

By applying sensitivity analysis, IAMs can be used to assess the importance of strategically developing new technologies and options for mitigation and identifying sticking points in climate policy frameworks. The sensitivity analysis evaluates differences in outcomes subject to changes in assumptions. For instance, the assumption about the timing and costs of CCS and CDR availability can be varied (Bauer et al. 2020a). The differences in mitigation costs and the transformation pathways support the assessment of policy prioritisation by identifying and quantifying crucial levers for achieving long-term climate mitigation targets such as R&D efforts and timing of policies.

A.III.I.9.5 Limitations of IAMs

The application of IAMs and their results for providing knowledge on climate change response strategies have been criticised based on four arguments (Gambhir et al. 2019; Keppo et al. 2021). First, there are concerns that IAMs are missing important dynamics, for example with regard to climate damages and economic co-benefits of mitigation (Stern 2016), demand-side responses (Wilson et al. 2012), bioenergy, land degradation and management (Creutzig et al. 2015; IPCC 2019b), carbon dioxide removal (Smith et al. 2016), rapid technological progress in the renewable energy sector (Creutzig et al. 2017), actor heterogeneity, and distributional impacts of climate change and climate policy. This has given rise to criticism that IAMs lack credibility in a set of crucial assumptions, among which stands out the critique on the availability of carbon dioxide removal technologies (Anderson and Peters 2016; Bednar et al. 2019).

These concerns spur continuous model development and improvements in scenario design (Keppo et al. 2021), particularly with regard to improved representations of energy demand, renewable energy, carbon dioxide removal technologies, and land management. IAMs are aiming to keep pace with the development of sector-specific models, including latest advances in estimating and modelling climate damages (Piontek et al. 2019). In places, where dynamic modelling approaches are lacking, scenarios are being used to explore relevant futures (Grubler et al. 2018). Moreover, sector-specific model comparison studies have brought together domain experts and modellers to improve model representations in these areas (Edelenbosch et al. 2017a; Pietzcker et al. 2017; Bauer et al. 2020a; Harmsen et al. 2020; Rose et al. 2020). Although most models are still relying on the concept of a single representative household representing entire regions, efforts are under way to better represent agent heterogeneity and distributional impacts of climate change and climate mitigation policies (Rao et al. 2017a; Peng et al. 2021).

Second, concerns have been raised that IAMs are non-transparent and thus make it difficult to grasp the context and meaning of their results (Skea et al. 2021). These concerns have facilitated a substantial increase in model documentation (see the common IAM documentation at www.iamcdocumentation.eu as an entry point) and open-source models. Nonetheless, more communication tools and co-production of knowledge formats will be needed to contextualise IAM results for users (Auer et al. 2021). When projecting over a century, uncertainties are large and cannot be ignored. Efforts have been undertaken (Marangoni et al. 2017; Gillingham et al. 2018; Harmsen et al. 2021; Wilson et al. 2021) to diagnose key similarities and differences between models and better gauge robust findings from these models and how much they depend on key assumptions (such as, for example, long-term growth of the economy, the monetary implication of climate damages, or the diffusion and cost of key mitigation technologies).

Third, there are concerns that IAMs are describing transformative change on the level of energy and land use, but are largely silent about the underlying socio-cultural transitions that could imply restructuring of society and institutions. Weyant (2017) notes the inability of IAMs to mimic extreme and discontinuous outcomes related to these underlying drivers as one of their major limitations. This is relevant when modelling extreme climate damages as well as when modelling disruptive changes. Dialogues and collaborative work between IAM researchers and social scientists have explored ways to bridge insights from the various communities to provide a more complete picture of high-impact climate change scenarios and, on the other end, deep transformation pathways (Turnheim et al. 2015; Geels et al. 2016; Trutnevyte et al. 2019). The extension of IAM research to sustainable development pathways is giving rise to further inter-disciplinary research on underlying transformations towards the Paris climate goals and other sustainable development goals (Kriegler et al. 2018c; Sachs et al. 2019b).

Finally, there are concerns that IAM analysis could focus on only a subset of relevant futures and thus push society in certain directions without sufficient scrutiny (Beck and Mahony 2017). IAMs aim to explore a wide range of socio-economic, technology and policy assumptions (Riahi et al. 2017), but it remains a constant challenge to capture all relevant perspectives (O'Neill et al. 2020). These concerns can be addressed by adopting an iterative approach between researchers and societal actors in shaping research questions and IAM applications (Edenhofer and Kowarsch 2015). IAM research is constantly taking up concerns about research gaps and fills it with new pathway research, as, for example, occurred for low energy demand and limited bioenergy with CCS scenarios (Grubler et al. 2018; van Vuuren et al. 2018).

A.III.I.10 Key Characteristics of Models that Contributed Mitigation Scenarios to the Assessment[2]

Table 5 | Comparison of modelling characteristics as stated by contributing modelling teams to the AR6 database. Attributes include regional scope, sectoral coverage, type of baseline or benchmark setup as a basis for mitigation policies comparison, technology diffusion, capital vintaging and 'sunsetting' of technologies and variety of discount rates approaches.

		Global integrated and energy models																				National integrated models											
		AIM	C3IAM 2.0	COFFEE 1.1	EPPA 6	IMAGE 3.0 & 3.2	IMACLIM	GCAM	GENeSYS-MOD	GMM (Global MARKAL Model)	McKinsey 1.0	MERGE-ETL	MESSAGEix-GLOBIOM 1.1	MUSE 1.0	POLES	PROMETHEUS	TIAM-ECN 1.1	REmap GRO2020	REMIND 2.1 - MAgPIE 4.2	WEM (World Energy Model)	WITCH	7see6-20_GB	AIM/Enduse-Japan	BLUES 2.0	China DREAM	CONTO-RUS 1.0	E4SMA-EU-TIMES 1.0	STEM (Swiss TIMES Energy Systems Model)	JRC-EU-TIMES	TIMES-China 2.0	TIMES-France	TIMES_PT	TIMES-Sweden 2.0
Regional scope	Global	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●												
	National	●																				●	●	●	●	●		●		●	●	●	●
	Non-global multi-region																										●		●				
Sectoral coverage	Full system (covering all GHGs from all sectors)	●	●	●	●	●	●	●			●	●	●		●		●		●		●			●	●	●			●	●			●
	Energy								●	●				●		●		●		●		●	●				●	●			●	●	
	Buildings								●	●						●		●		●		●	●				●	●					
	Transport								●	●						●		●		●		●	●				●	●					
	Industry								●	●						●		●		●		●	●				●	●					
Characteristics of baseline/ benchmark setup	Well-functioning markets in equilibrium	●	●	●	●	●		●		●	●	●	●	●	●		●	●	●	●	●	●		●	●	●	●	●	●	●		●	●
	Regulatory and/or pricing policies	●	●	●	●	●	●			●	●	●	●		●	●	●	●	●	●	●		●	●	●	●	●	●	●	●		●	●
	Socioeconomic costs & benefits of climate change impacts		●									●						●	●						●								●
	Physical impacts of climate change on key processes	●	●															●										●					

2 The tables are limited to the integrated models that provided the information in response to a survey circulated in 2021, and therefore do not have a comprehensive coverage of all models that submitted scenarios to the AR6 scenario database.

Global integrated and energy models

		AIM	C3IAM 2.0	COFFEE 1.1	EPPA 6	IMAGE 3.0 & 3.2	IMACLIM	GCAM	GENeSYS-MOD	GMM (Global MARKAL Model)	McKinsey 1.0	MERGE-ETL	MESSAGEix-GLOBIOM 1.1	MUSE 1.0	POLES	PROMETHEUS	TIAM-ECN 1.1	REmap GRO2020	REMIND 2.1 - MAgPIE 4.2	WEM (World Energy Model)	WITCH
Technology diffusion	Logit substitution	●				●	●	●							●	●					
	Constant elasticity of substitution		●									●									●
	Lowest marginal cost w/ expansion constraints			●	●				●	●	●	●	●				●	●	●	●	●
	Technology choice depends on agents' preferences													●							
	Technologies w/o constraints or marginal cost w/ expansion constraints																				
Capital vintaging and "sunsetting" of technologies	Single capital stock with fixed lifetime and load factor, early retirement via reduction in load factor possible																				●
	Capital vintaging with fixed lifetime and load factors, early retirement of vintages or reduction in load factors possible		●		●			●		●		●	●			●	●	●	●	●	
	Single capital stock with fixed lifetime and load factor, without early retirement														●						
	Mix of the above for different technologies	●		●		●	●		●		●										
Discount rates	As a property of an intertemporal welfare function (social discount rate)											●							●		●
	In an objective function of an intertemporal optimization, to sum values at different times		●	●		●			●	●			●				●			●	
	To compute lifecycle costs of investment decisions or return on investments, in functions representing agents investment choices				●	●	●	●	●	●		●		●	●	●		●			

National integrated models

		7see6-20_GB	AIM/Enduse-Japan	BLUES 2.0	China DREAM	CONTO-RUS 1.0	E4SMA-EU-TIMES 1.0	STEM (Swiss TIMES Energy Systems Model)	JRC-EU-TIMES	TIMES-China 2.0	TIMES-France	TIMES_PT	TIMES-Sweden 2.0
Technology diffusion	Logit substitution	●											
	Constant elasticity of substitution												
	Lowest marginal cost w/ expansion constraints		●	●	●		●	●	●	●	●	●	
	Technology choice depends on agents' preferences												
	Technologies w/o constraints or marginal cost w/ expansion constraints												●
Capital vintaging and "sunsetting" of technologies	Single capital stock with fixed lifetime and load factor, early retirement via reduction in load factor possible				●								
	Capital vintaging with fixed lifetime and load factors, early retirement of vintages or reduction in load factors possible		●				●	●					●
	Single capital stock with fixed lifetime and load factor, without early retirement					●					●		
	Mix of the above for different technologies	●		●					●	●		●	
Discount rates	As a property of an intertemporal welfare function (social discount rate)								●				
	In an objective function of an intertemporal optimization, to sum values at different times			●			●	●		●	●		●
	To compute lifecycle costs of investment decisions or return on investments, in functions representing agents investment choices		●					●				●	

Table 6 | **Overview of evaluated GHG emissions as stated by contributing modelling teams to the AR6 database: carbon dioxide (CO_2) from energy, industrial processes and land-use change, methane (CH_4) from fossil fuel combustion, from fugitive and process activities, and agricultural biogenic fluxes, nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF_6), sulphur dioxide (SO_2), black and organic carbon, and non-methane volatile organic compounds (NMVOC).** Levels of emission factor (EF) evaluation were classified in four categories: linked to explicit technology but for average fuel, linked to the evolution of other emissions, dependent on average technology classes, and based on an average activity sector.

Type of GHG emissions evaluation	Global integrated and energy models																			
	AIM	C3IAM 2.0	COFFEE 1.1	EPPA 6	IMAGE 3.0 & 3.2	IMACLIM	GCAM	GENeSYS-MOD	GMM (Global MARKAL Model)	McKinsey 1.0	MERGE-ETL	MESSAGEix-GLOBIOM 1.1	MUSE 1.0	POLES	PROMETHEUS	TIAM-ECN 1.1	REmap GRO2020	REMIND 2.1 - MAgPIE 4.2	WEM (World Energy Model)	WITCH
CO_2 energy	a	a	a	a	a	a	a	a	a	a	a	a	a	a	a	a	a	a	a	a
CO_2 industrial processes	a	d	a	a	a	b	a	e	d	a	a	a	a	a	c	a	a	d	a	b
CO_2 land-use change	a	d	a	a	a	b	a	e	e	c	d	a	e	d	e	a	d	a	e	c
CH_4 fossil (combustion)	a	a	a	a	a	b	a	e	e	c	a	a	a	a	c	a	e	a	a	a
CH_4 fossil (fugitive and process)	a	d	a	a	a	b	a	e	e	a	a	a	e	a	c	a	e	c	e	d
CH_4 biogenic	a	e	a	a	a	b	a	e	e	a	d	a	e	d	b	a	e	d	e	c
N_2O	a	d	a	a	a	b	a	e	e	a	d	a	a	d	c	a	e	a	e	c
HFCs	d	e	e	a	a	e	a	e	e	e	d	d	e	c	d	e	e	e	e	d
PFCs	d	e	e	a	a	e	a	e	e	e	d	e	e	c	d	e	e	e	e	d
SF_6	d	e	e	a	a	e	a	e	e	e	d	d	e	c	d	e	e	e	e	d
SO_2	a	a	e	d	a	e	a	e	e	e	d	a	e	a	e	e	a	a	e	a
Black carbon	a	d	e	d	a	e	a	e	e	e	e	a	e	a	e	e	e	a	e	a
Organic carbon	a	d	e	d	a	e	a	e	e	e	e	a	e	a	e	e	e	a	e	a
Non-methane volatile organic compounds (NMVOC)	a	a	e	d	a	e	a	e	e	e	d	a	e	a	e	e	a	a	e	a

Type of GHG emissions evaluation	National integrated models											
	7see6-20_GB	AIM/Enduse-Japan	BLUES 2.0	China DREAM	CONTO-RUS 1.0	E4SMA-EU-TIMES 1.0	STEM (Swiss TIMES Energy Systems Model)	JRC-EU-TIMES	TIMES-China 2.0	TIMES-France	TIMES_PT	TIMES-Sweden 2.0
CO_2 energy	a	a	a	a	a	a	a	a	a	a	a	a
CO_2 industrial processes	a	a	a	a	a	a	c	a	e	e	a	a
CO_2 land-use change	e	e	a	e	d	e	e	e	e	e	e	e
CH_4 fossil (combustion)	e	a	a	a	a	e	e	e	e	e	a	e
CH_4 fossil (fugitive and process)	e	d	a	a	c	e	e	e	e	e	a	e
CH_4 biogenic	e	a	a	e	d	e	e	e	e	e	a	e
N_2O	e	a	a	a	a	e	e	e	e	e	a	e
HFCs	e	c	e	a	b	e	e	e	e	e	e	e
PFCs	e	c	e	a	b	e	e	e	e	e	e	e
SF_6	e	c	e	a	b	e	e	e	e	e	e	e
SO_2	e	e	a	e	b	e	e	e	e	e	e	a
Black carbon	e	e	e	a	e	e	e	e	e	e	e	a
Organic carbon	e	e	e	e	e	e	e	e	e	e	e	a
Non-methane volatile organic compounds (NMVOC)	e	e	a	e	e	e	e	e	e	e	e	a

EF linked to explicit technology w/ or w/o fuel representation: a
EF linked to evolution of other emissions: b
Average EF for technology class: c
EF for sector: d
Not represented: e

A.III.I.11 Comparison of Mitigation and Removal Measures Represented by Models that Contributed Mitigation Scenarios to the Assessment[3]

Table 7 | Overview of demand- and supply-side mitigation and removal measures in the energy, transport, building, industry and AFOLU sectors, as stated by contributing modelling teams to the AR6 database. Levels of inclusion were classified in two dimensions of explicit versus implicit and endogenous or exogenous. An explicit level suggests that the measure is directly represented in the model, while an implicit level refers to measures that are estimated indirectly by a proxy. An endogenous level reflects measures that are included in the dynamics of the model framework, whereas an exogenous level refers to measures that are not part of the model dynamics.

Level of inclusion	Global integrated and energy models																				National integrated models											
	AIM	C3IAM 2.0	COFFEE 1.1	EPPA 6	IMAGE 3.0 & 3.2	IMACLIM	GCAM	GENeSYS-MOD	GMM (Global MARKAL Model)	McKinsey 1.0	MERGE-ETL	MESSAGEix-GLOBIOM 1.1	MUSE 1.0	POLES	PROMETHEUS	TIAM-ECN 1.1	REmap GRO2020	REMIND 2.1 - MAgPIE 4.2	WEM (World Energy Model)	WITCH	7see6-20_GB	AIM/Enduse-Japan	BLUES 2.0	China DREAM	CONTO-RUS 1.0	E4SMA-EU-TIMES 1.0	STEM (Swiss TIMES Energy Systems Model)	JRC-EU-TIMES	TIMES-China 2.0	TIMES-France	TIMES_PT	TIMES-Sweden 2.0
Demand-side measures																																
Energy efficiency improvements in energy end uses	A	B	A	C	A	A	C	B	A	A	C	C	A	C	A	A	A	A	A	C	B	A	A	B	A	A	A	A	A	A	A	A
Electrification of transport demand	A	C	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	B	B	A	A	A	A	A	A	A
Electrification of energy demand for buildings	A	C	A	C	A	C	A	A	A	A	A	A	A	A	A	A	A	A	A	C	B	A	A	B	B	A	A	A	A	A	A	A
Electrification of industrial energy demand	A	C	A	C	A	C	C	A	A	A	A	A	A	C	A	A	A	A	A	C	B	A	A	B	B	A	A	A	A	A	A	A
CCS in industrial process applications	A	A	A	A	A	E	A	E	A	A	A	A	A	A	A	A	A	A	A	C	B	A	A	E	B	A	A	A	A	A	A	A
Higher share of useful energy in final energy	C	B	A	C	A	D	A	D	A	A	C	C	A	A	C	A	C	C	A	C	B	A	A	B	B	A	A	A	A	A	A	A
Reduced energy and service demand in industry	C	C	A	C	A	C	C	D	C	B	C	C	D	C	C	C	B	C	B	C	B	B	A	A	C	C	A	C	C	C	B	A
Reduced energy and service demand in buildings	C	C	D	C	A	D	C	D	C	B	C	C	D	A	A	C	B	C	B	C	B	B	A	B	D	C	A	C	C	C	B	B
Reduced energy and service demand in transport	C	C	A	C	A	A	A	A	D	B	D	C	D	A	C	C	B	C	B	D	B	B	A	B	D	C	A	C	C	C	B	A
Reduced energy and service demand in international transport	C	E	A	C	C	C	C	D	D	B	D	C	D	A	C	C	B	C	B	D	B	E	A	B	E	C	E	C	C	C	E	B
Reduced material demand	C	B	B	C	C	D	E	E	E	A	E	E	E	E	E	E	B	E	B	E	D	B	B	B	D	E	E	C	C	B	B	B
Urban form	E	E	B	E	C	D	E	D	E	E	E	E	E	E	E	E	E	E	C	E	D	B	B	B	E	E	A	E	E	E	E	D
Switch from traditional biomass and modern fuels	B	A	A	B	A	E	A	C	E	B	A	D	A	A	A	A	A	B	A	D	B	E	A	B	B	A	A	A	A	E	A	E
Dietary changes (e.g., reducing meat consumption)	B	E	B	A	B	B	A	E	E	A	E	A	E	E	E	E	E	B	E	E	E	E	B	E	E	E	E	E	E	E	E	E
Food processing	A	E	A	C	B	B	E	E	E	E	A	E	E	E	E	E	E	E	E	E	D	E	A	E	E	E	E	E	E	E	E	E
Reduction of food waste	B	E	E	E	B	E	C	E	E	B	E	B	E	E	E	E	E	B	E	E	E	E	D	E	E	E	E	E	E	E	E	E
Substitution of livestock-based products with plant-based products	A	E	B	A	B	D	E	E	E	B	E	E	E	E	E	E	E	B	E	E	E	E	B	E	E	E	E	E	E	E	E	E

	Explicit	Implicit
Endogenous	A	C
Exogenous	B	D
Not represented	E	

3 The tables are limited to the integrated models that provided the information in responses to a survey circulated in 2021, and therefore do not have a comprehensive coverage of all models that submitted scenarios to the AR6 scenario database.

Level of inclusion	Global integrated and energy models																				National integrated models											
	AIM	C3IAM 2.0	COFFEE 1.1	EPPA 6	IMAGE 3.0 & 3.2	IMACLIM	GCAM	GENeSYS-MOD	GMM (Global MARKAL Model)	McKinsey 1.0	MERGE-ETL	MESSAGEix-GLOBIOM 1.1	MUSE 1.0	POLES	PROMETHEUS	TIAM-ECN 1.1	REmap GRO2020	REMIND 2.1 - MAgPIE 4.2	WEM (World Energy Model)	WITCH	7see6-20_GB	AIM/Enduse-Japan	BLUES 2.0	China DREAM	CONTO-RUS 1.0	E4SMA-EU-TIMES 1.0	STEM (Swiss TIMES Energy Systems Model)	JRC-EU-TIMES	TIMES-China 2.0	TIMES-France	TIMES_PT	TIMES-Sweden 2.0
Supply-side measures																																
Decarbonisation of electricity																																
Solar PV	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	A	A
Solar CSP	E	E	A	E	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	E	A	A	E	A	A	A	A	A	A	E
Hydropower	A	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	A	A	A	D	B	A	A	A	A	A	A	A	A	A	A	A
Nuclear energy	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	A	A	A	A	A	A	A	A	A
Advanced, small modular nuclear reactor designs (SMR)	E	E	E	C	C	E	E	E	A	E	A	E	E	E	C	A	D	E	C	E	B	E	E	E	E	A	A	E	E	E	E	E
Fuel cells (hydrogen)	E	A	A	A	A	E	A	A	A	A	A	A	A	A	A	A	B	A	A	A	B	A	A	B	E	A	A	A	A	A	A	A
CCS at coal and gas-fired power plants	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	E	B	A	A	A	A	A	A	A
Ocean energy (incl. tidal and current energy)	E	E	E	E	C	E	E	A	A	D	A	E	E	A	E	A	A	E	A	E	B	A	E	E	E	A	A	A	A	A	A	E
High-temperature geothermal heat	A	E	A	E	C	E	A	A	A	D	A	A	A	A	C	A	A	A	A	E	B	A	E	E	B	A	A	A	A	A	A	E
Wind (on-shore and off-shore lumped together)	A	A	E	A	A	A	E	A	E	E	A	A	E	E	A	A	A	A	A	A	B	E	E	A	A	A	A	E	E	E	E	E
Wind (on-shore and off-shore represented individually)	E	E	A	E	A	A	A	A	A	A	A	A	A	A	A	A	A	E	A	A	B	A	A	E	A	A	E	A	A	A	A	A
Bio-electricity, including biomass co-firing, without CCS	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	A	B	A	A	A	A	A	A	A
Bio-electricity, including biomass co-firing, with CCS	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	E	E	A	A	A	A	A	A	A
Decarbonisation of non-electric fuels																																
1st generation biofuels	A	E	A	A	A	A	A	E	A	C	A	B	A	A	A	A	A	B	A	A	B	A	A	B	E	A	A	A	A	A	A	A
2nd generation biofuels (grassy/woody biomass to liquids) without CCS	A	E	A	A	A	A	A	A	A	C	A	A	A	A	C	A	A	A	A	A	B	A	A	E	E	A	A	A	A	A	A	A
2nd generation biofuels (grassy/woody biomass to liquids) with CCS	A	E	A	A	A	A	A	A	A	C	A	A	A	A	C	A	E	A	A	A	B	A	A	E	E	A	A	A	A	A	A	A
Solar and geothermal heating	A	E	A	E	C	E	E	A	A	C	A	A	E	A	C	A	A	A	A	E	B	A	A	B	B	A	A	A	A	A	A	A
Nuclear process heat	E	E	E	E	C	E	E	E	A	E	A	E	E	E	C	E	E	E	A	E	B	E	E	E	B	A	A	A	E	E	E	E
Hydrogen from fossil fuels with CCS	E	E	A	A	A	E	C	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	E	E	A	A	A	A	A	A	A
Hydrogen from electrolysis	E	E	A	A	A	E	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	B	E	A	A	A	A	A	A	A
Hydrogen from biomass without CCS	E	E	A	A	A	A	A	E	A	D	A	A	A	A	A	A	A	A	A	E	B	A	A	E	E	A	A	A	E	A	A	A

	Explicit	Implicit
Endogenous	A	C
Exogenous	B	D
Not represented	E	

Level of inclusion	Global integrated and energy models																				National integrated models											
	AIM	C3IAM 2.0	COFFEE 1.1	EPPA 6	IMAGE 3.0 & 3.2	IMACLIM	GCAM	GENeSYS-MOD	GMM (Global MARKAL Model)	McKinsey 1.0	MERGE-ETL	MESSAGEix-GLOBIOM 1.1	MUSE 1.0	POLES	PROMETHEUS	TIAM-ECN 1.1	REmap GRO2020	REMIND 2.1 - MAgPIE 4.2	WEM (World Energy Model)	WITCH	7see6-20_GB	AIM/Enduse-Japan	BLUES 2.0	China DREAM	CONTO-RUS 1.0	E4SMA-EU-TIMES 1.0	STEM (Swiss TIMES Energy Systems Model)	JRC-EU-TIMES	TIMES-China 2.0	TIMES-France	TIMES_PT	TIMES-Sweden 2.0
Hydrogen from biomass with CCS	E	E	A	A	A	E	A	E	A	D	A	A	A	A	A	A	A	A	A	E	B	A	A	E	E	A	A	A	E	A	A	A
Algae biofuels without CCS	E	E	E	E	E	E	E	E	E	E	E	E	A	E	E	E	E	E	C	E	B	E	E	E	E	E	E	E	E	E	E	E
Algae biofuels with CCS	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	C	E	B	E	E	E	E	E	E	E	E	E	E	E
Power-to-gas, methanisation, synthetic fuels, fed with fossil CO_2	E	E	A	A	C	E	E	A	A	E	A	E	E	A	A	A	A	E	A	E	B	A	A	E	E	A	A	A	E	A	A	A
Power-to-gas, methanisation, syn-fuels, fed with biogenic or atmospheric CO_2	E	E	A	E	C	E	E	A	A	E	A	E	E	A	A	A	A	E	A	E	B	A	A	E	E	A	A	A	E	A	A	A
Fuel switching and replacing fossil fuels by electricity in end-use sectors	C	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	B	B	A	A	A	A	A	A	A
Other processes																																
Substitution of halocarbons for refrigerants and insulation	E	E	E	E	A	E	C	E	E	E	E	D	E	C	C	E	E	E	E	C	E	A	E	B	E	E	E	E	E	E	E	E
Reduced gas flaring and leakage in extractive industries	C	E	A	B	C	E	C	E	E	A	E	D	E	A	E	B	E	C	A	C	E	E	A	B	B	E	E	E	E	E	E	E
Electrical transmission efficiency improvements, including smart grids	E	E	A	C	C	E	E	D	C	E	D	E	E	E	C	B	A	E	A	C	D	E	A	B	B	B	C	E	A	E	B	E
Grid integration of intermittent renewables	C	E	A	C	A	C	A	C	C	E	C	A	A	A	C	A	A	A	A	A	D	A	A	A	E	A	A	C	E	E	A	C
Electricity storage	C	D	A	A	A	E	A	A	C	A	C	A	A	A	A	A	A	A	A	A	B	A	A	A	D	A	A	C	A	A	A	A
AFOLU measures																																
Reduced deforestation, forest protection, avoided forest conversion	A	D	A	A	A	B	A	E	E	A	E	A	E	C	E	B	D	A	E	C	E	E	A	E	B	E	E	E	E	E	E	E
Methane reductions in rice paddies	A	E	A	C	A	C	C	E	E	A	E	A	E	C	E	B	E	C	E	C	E	A	A	B	E	E	E	E	E	E	E	E
Livestock and grazing management	A	E	A	C	A	A	C	E	E	A	E	A	E	C	E	B	E	C	E	C	E	A	A	B	D	E	E	E	E	E	E	E
Increasing agricultural productivity	A	C	A	C	A	A	A	E	E	A	E	A	A	C	E	D	D	C	E	E	E	E	A	E	D	E	E	E	E	E	E	E
Nitrogen pollution reductions	A	E	B	C	A	A	A	E	E	A	E	A	E	C	E	D	E	C	E	E	E	A	B	B	B	E	E	E	E	E	E	E
Changing agricultural practices enhancing soil carbon	E	E	E	C	A	E	E	E	E	A	E	E	A	C	E	B	E	E	E	E	E	E	A	E	D	E	E	E	E	E	E	E
Agroforestry and silviculture	E	C	A	E	D	E	E	E	E	B	E	E	E	E	E	B	E	E	E	E	E	E	A	E	D	E	E	E	E	E	E	E
Land-use planning	E	D	A	E	B	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	A	E	B	E	E	E	E	E	E	E
Urban and peri-urban agriculture and forestry	E	E	E	E	D	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E

	Explicit	Implicit
Endogenous	A	C
Exogenous	B	D
Not represented	E	

Level of inclusion	Global integrated and energy models																				National integrated models											
	AIM	C3IAM 2.0	COFFEE 1.1	EPPA 6	IMAGE 3.0 & 3.2	IMACLIM	GCAM	GENeSYS-MOD	GMM (Global MARKAL Model)	McKinsey 1.0	MERGE-ETL	MESSAGEix-GLOBIOM 1.1	MUSE 1.0	POLES	PROMETHEUS	TIAM-ECN 1.1	REmap GRO2020	REMIND 2.1 - MAgPIE 4.2	WEM (World Energy Model)	WITCH	7see6-20_GB	AIM/Enduse-Japan	BLUES 2.0	China DREAM	CONTO-RUS 1.0	E4SMA-EU-TIMES 1.0	STEM (Swiss TIMES Energy Systems Model)	JRC-EU-TIMES	TIMES-China 2.0	TIMES-France	TIMES_PT	TIMES-Sweden 2.0
Fire management and (ecological) pest control	C	E	E	E	D	E	D	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	D	E	E	E	E	E	E	E
Conservation agriculture	E	E	A	E	D	E	E	E	E	E	E	A	E	E	E	D	E	E	E	E	E	E	A	E	E	E	E	E	E	E	E	E
Influence on land albedo of land-use change	E	E	E	E	A	E	E	E	E	E	E	E	E	E	E	E	E	D	E	E	E	E	E	E	E	E	E	E	E	E	E	E
Manure management	A	E	E	E	A	C	C	E	E	A	E	A	E	E	E	B	E	C	E	C	E	A	A	B	E	E	E	E	E	E	E	B
Reduce food post-harvest losses	B	D	E	E	D	E	D	E	E	E	E	B	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E
Recovery of forestry and agricultural residues	E	E	A	E	A	B	A	E	E	E	E	A	E	C	E	E	D	E	E	E	E	E	A	E	B	E	E	E	E	E	E	E
Forest management – increasing forest productivity	C	E	E	C	C	B	D	E	E	E	E	A	E	C	E	E	D	E	E	C	E	E	E	E	D	E	E	E	E	E	E	A
Forest management – increasing timber/biomass extraction	C	E	E	E	C	B	D	E	E	E	E	A	E	C	E	E	D	E	E	C	E	E	E	E	D	E	E	E	E	E	E	A
Forest management – remediating natural disturbances	E	E	E	E	B	B	E	E	E	E	E	E	E	E	E	E	E	E	E	C	E	E	E	E	D	E	E	E	E	E	E	E
Forest management – conservation for carbon sequestration	E	D	E	E	B	B	D	E	E	A	E	A	E	E	E	E	D	E	E	C	E	E	E	E	E	E	E	E	E	E	E	E
Carbon dioxide removal																																
Bioenergy production with carbon capture and sequestration (BECCS)	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	B	A	A	E	E	A	A	A	A	A	A	A
Direct air capture and storage (DACS)	E	E	A	A	A	E	E	A	A	A	A	E	E	A	A	A	A	A	A	A	B	A	A	E	E	E	A	A	A	E	A	E
Mineralisation of atmospheric CO_2 through enhanced weathering of rocks	E	E	E	E	E	E	E	E	E	C	E	E	E	E	E	E	E	A	E	E	E	E	E	E	E	E	E	E	E	E	E	E
Afforestation/Reforestation	A	A	A	A	A	B	A	E	E	C	E	A	E	C	C	B	C	A	E	A	E	E	A	E	B	E	E	E	E	E	E	E
Restoration of wetlands	E	E	E	E	C	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E
Biochar	E	E	E	E	D	E	E	E	E	E	A	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	A	E	E	E	E	E
Soil carbon enhancement, enhancing carbon sequestration in biota and soils	E	E	A	C	D	D	E	E	E	E	A	A	E	C	E	E	E	C	E	E	E	E	A	E	E	E	E	E	E	E	E	E
Material substitution of fossil CO_2 with bio-CO_2 in industrial application	E	E	A	C	A	E	E	E	E	E	A	E	E	E	E	D	E	E	A	E	D	E	A	E	E	A	E	E	E	E	E	E
Ocean iron fertilisation	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E
Ocean alkalinisation	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E
Carbon capture and usage (CCU)																																
Bioplastics, carbon fibre and other construction materials	E	E	A	A	E	E	C	E	A	D	A	E	E	E	A	E	A	E	A	E	E	E	A	E	B	A	E	A	E	E	A	E

	Explicit	Implicit
Endogenous	A	C
Exogenous	B	D
Not represented	E	

Part II: Scenarios

A.III.II.1 Overview on Climate Change Scenarios

Scenarios are descriptions of alternative future developments. They are used to explore the potential implications of possible future developments and how they might depend on alternative courses of action. They are particularly useful in the context of deep uncertainty. Scenarios are conditional on the realisation of external assumptions and can be used to explore possible outcomes under a variety of assumptions.

Future climate change is a prime example for the application of scenarios. It is driven by human activities across the world and thus can be altered by human agency. It affects all regions over many centuries to come. Humankind's response to climate change touches not only on the way we use energy and land, but also on socio-economic and institutional layers of societal development. Climate change scenarios provide a central tool to analyse this wicked problem.

A.III.II.1.1 Purposes of Climate Change Scenarios

Climate change scenarios are developed for a number of purposes (O'Neill et al. 2020). First, they are constructed to explore possible climate change futures covering the causal chain from (i) socio-economic developments to (ii) energy and land use to (iii) greenhouse gas emissions to (iv) changes in the atmospheric composition of greenhouse gases and short-lived climate forcers and the associated radiative forcing to (v) changes in temperature and precipitation patterns to (vi) bio-physical impacts of climate change and finally to (vii) impacts on socio-economic developments, thus closing the loop. Quantitative scenarios exploring possible climate change futures are often called climate change projections and climate change impact projections.

Second, climate change scenarios are developed to explore pathways towards long-term climate goals. Goal-oriented scenarios often carry the word 'pathway' in their name, such as climate change mitigation pathway, climate change adaptation pathway, or more generally climate change transition or transformation pathway. They are sometimes called 'backcasting'[4] scenarios, or 'short backcasts', in the literature, particularly when contrasted with forecasts (Robinson 1982). Goal-oriented/backcasting scenarios are inherently normative and intricately linked to human intervention. They can be used to compare and contrast different courses of actions. For example, they are applied in climate change mitigation analysis by comparing reference scenarios without or with only moderate climate policy intervention, sometimes called baseline scenarios, with mitigation pathways that achieve certain climate goals (Grant et al. 2020). Transformation pathways to climate goals are examples of backcasting scenarios. Among other things, they can be used to learn about the multi-dimensional trade-offs between raising or lowering ambition (Clarke et al. 2014; Schleussner et al. 2016). In addition, different transformation pathways to the same goal are often used to analyse trade-offs between different routes towards this goal (Rogelj et al. 2018a). These scenarios need to be looked at as a set to understand attainable outcomes and the trade-offs between them. With scenarios, context matters.

Third, climate change scenarios are used to integrate knowledge and analysis between the three different climate change research communities working on the climate system and its response to human interference (linked to WG I of the IPCC), climate change impacts, adaptation and vulnerability (linked to WGII) and climate change mitigation (linked to WGIII) (O'Neill et al. 2016; IPCC 2000; van Vuuren et al. 2011b) (Annex III.II.1.3). This involves the adoption of common scenario frameworks that allow the consistent use of, for example, shared emissions scenarios, socio-economic development scenarios and climate change projections (Moss et al. 2010; Kriegler et al. 2012; van Vuuren et al. 2012; O'Neill et al. 2014; van Vuuren et al. 2014). The integrative power of scenarios extends beyond the climate change research community into neighbouring fields such as the social sciences and ecology (Pereira et al. 2020; Rosa et al. 2020). To foster such integration, underlying scenario narratives have proven extremely useful as they allow researchers to develop and link quantitative scenario expressions in very different domains of knowledge (O'Neill et al. 2020).

Fourth, climate change scenarios and their assessment aim to inform society (Kowarsch et al. 2017; Weber et al. 2018; Auer et al. 2021). To achieve this, it is important to connect climate change scenarios to broader societal development goals (Riahi et al. 2012; van Vuuren et al. 2015; Kriegler et al. 2018c; Soergel et al. 2021) and relate them to social, sectoral and regional contexts (Absar and Preston 2015; Frame et al. 2018; Kok et al. 2019; Aguiar et al. 2020). To this end, scenarios can be seen as tools for societal discourse and decision-making to coordinate perceptions about possible and desirable futures between societal actors (Edenhofer and Kowarsch 2015; Beck and Mahony 2017).

A.III.II.1.2 Types of Climate Change Mitigation Scenarios

Different types of climate change scenarios are linked to different purposes and knowledge domains and different models are used to construct them (Annex III.I). Global reference and mitigation scenarios and their associated emissions projections, which are often called emission scenarios, and national, sector and service transition scenarios are key types of scenarios assessed in the Working Group III report. They are briefly summarised below.[5]

A brief description of the common climate change scenario framework with relevance for all three IPCC Working Groups is provided in Annex III.II.1.3, and a discussion how the WGI and WGII assessments relate to the WGIII scenario assessment is given in Annex III.II.2.5.

4 Backcasting is different from hindcasting. Hindcasting refers to testing the ability of a mathematical model to reproduce past events. In contrast, backcasting begins with a desired future outcome and calculates a pathway from the present to that outcome consistent with constraints.

5 The terms mitigation/transition/transformation scenarios and mitigation/transition/transformation pathways are used interchangeably, as they refer to goal-oriented scenarios.

A.III.II.1.2.1 Global mitigation scenarios

Global mitigation scenarios are mostly derived from global integrated assessment models (Annex III.I.9) and have been developed in single model studies as well as multi-model comparison studies. The research questions of these studies have evolved together with the climate policy debate and the knowledge about climate change, drivers, and response measures. The assessment of global mitigation pathways in the Fifth Assessment Report (AR5) (Clarke et al. 2014) was informed, inter alia, by a number of large-scale multi-model studies comparing overshoot and not-to-exceed scenarios for a range of concentration stabilisation targets (Energy Modelling Forum (EMF) study 22: EMF22) (Clarke et al. 2009), exploring the economics of different decarbonisation strategies and robust characteristics of the energy transition in global mitigation pathways (EMF27, RECIPE) (Luderer et al. 2012; Krey and Riahi 2013; Kriegler et al. 2014a), and analysing co-benefits and trade-offs of mitigation strategies with energy security, energy access, and air quality objectives (Global Energy Assessment: GEA) (McCollum et al. 2011; Riahi et al. 2012; McCollum et al. 2013; Rao et al. 2013; Rogelj et al. 2013b). They also investigated the importance of international cooperation for reaching ambitious climate goals (EMF22, EMF27, AMPERE) (Clarke et al. 2009; Blanford et al. 2014b; Kriegler et al. 2015b), the implications of collective action towards the 2°C goal from 2020 onwards vs delayed mitigation action (AMPERE, LIMITS) (Kriegler et al. 2014b; Riahi et al. 2015), and the distribution of mitigation costs and burden-sharing schemes in global mitigation pathways (LIMITS) (Tavoni et al. 2014, 2015). Scenarios from these and other studies were collected in a scenario database supporting the AR5 assessment (Krey et al. 2014). With a shelf life of 8 to 14 years, they are now outdated and no longer part of this assessment.

Since AR5, many new studies published global mitigation pathways and associated emissions projections. After the adoption of the Paris Agreement, several large-scale multi-model studies newly investigated pathway limiting warming to 1.5°C (ADVANCE: Luderer et al. (2018); CD-LINKS: McCollum et al. (2018a); ENGAGE: Riahi et al. (2021); SSPs: Rogelj et al. (2018b)), allowing this report to conduct a robust assessment of 1.5°C pathways. Most scenario studies took the hybrid climate policy architecture of the Paris Agreement with global goals, nationally determined contributions (NDCs) and an increasing number of implemented national climate policies as a starting point, including hybrid studies with participation of global and national modelling teams to inform the global stocktake (ENGAGE: Fujimori et al. (2021); COMMIT: van Soest et al. (2021); CD-LINKS: Schaeffer et al. (2020), Roelfsema et al. (2020)). Multi-model studies covered a range of scenarios from extrapolating current policy trends and the implementation of NDCs, respectively, to limiting warming to 1.5°C–2°C with immediate global action and after passing through the NDCs in 2030, respectively. These scenarios are used to investigate, among others, the end-of-century warming implications of extrapolating current policy trends and NDCs (Perdana et al. 2020); the ability of the NDCs to keep limiting warming to 1.5°C–2°C in reach (Luderer et al. 2018; Vrontisi et al. 2018; Roelfsema et al. 2020), the scope for global accelerated action to go beyond the NDCs in 2030 (van Soest et al. 2021), and the benefits of early action vs the risk of overshoot and the use of net negative CO_2 emissions in the long-term (Bertram et al. 2021; Hasegawa et al. 2021; Riahi et al. 2021). Other large-scale multi-model studies looked into specific topics: the international economic implications of the NDCs in 2030 (EMF36) (Böhringer et al. 2021), the impact of mitigating short-lived climate forcers on warming and health co-benefits in mitigation pathways (EMF30) (Harmsen et al. 2020; Smith et al. 2020b) and the role and implications of large-scale bioenergy deployment in global mitigation pathways (EMF33) (Bauer et al. 2020a; Rose et al. 2020).

A large variety of recent modelling studies, mostly based on individual models, deepened research on a diverse set of questions (Annex III.II.3.2). Selected examples are the impact of peak vs end-of-century targets on the timing of action in mitigation pathways (Rogelj et al. 2019a; Strefler et al. 2021a); demand-side driven deep mitigation pathways with sustainable development co-benefits (Bertram et al. 2018; Grubler et al. 2018; van Vuuren et al. 2018); synergies and trade-offs between mitigation and sustainable development goals (Fujimori et al. 2020; Soergel et al. 2021); and the integration of climate impacts into mitigation pathways (Schultes et al. 2021). There have also been a number of recent sectoral studies with global integrated assessment models and other global models across all sectors, for example the energy sector (IRENA 2020; Kober et al. 2020; IEA 2021) and transport sector (Edelenbosch et al. 2017a; Mercure et al. 2018; Zhang et al. 2018; Fisch-Romito and Guivarch 2019; Rottoli et al. 2021; Lam and Mercure 2021; Paltsev et al. 2022). Very recent work investigated the impact of COVID-19 on mitigation pathways (Kikstra et al. 2021a) and co-designed global scenarios for users in the financial sector (NGFS 2021). In addition to these policy-, technology- and sector-oriented studies, a few diagnostic studies developed mitigation scenarios to diagnose model behaviour (Harmsen et al. 2021) and explore model harmonisation (Giarola et al. 2021).

The scenarios from most of these and many other studies were collected in the AR6 scenario database (Annex III.II.3.2) and are primarily assessed in Chapter 3 of the report. However sectoral chapters have also used the scenarios, including their climate mitigation categorisations, to ensure consistent cross-chapter treatment. Only a small fraction of these scenarios were already available to the assessment of global mitigation pathways in the Special Report on Global Warming of 1.5°C (SR1.5) (Rogelj et al. 2018a) and were included in the supporting SR1.5 database (Huppmann et al. 2018).

A.III.II.1.2.2 National Transition Scenarios

A large number of transition scenarios is developed on a national/regional level by national integrated assessment, energy-economy or computable general equilibrium models, among others. These aim to analyse the implications of current climate plans of countries and regions, as well as long-term strategies until 2050 investigating different degrees of low-carbon development. National/regional transition scenarios are assessed in Chapter 4 of the report.

Recent research has focused on several different types of national transition scenarios that focus on accelerated climate mitigation pathways in the near term to 2050. These include scenarios considered by the authors as tied to meeting specific global climate goals[6] and scenarios tied to specific policy targets (e.g., carbon neutrality or 80–95% reduction from a certain baseline year). A majority of the accelerated national transition modelling studies up to 2050 evaluate pathways that the authors consider compatible with a 2°C global warming limit, with fewer scenarios defined as compatible with 1.5°C global pathways. Regionally, national transition scenarios have centred on countries in Asia (particularly in China, India, Japan), in the European Union, and in North America, with fewer and more narrowly focused scenario studies in Latin America and Africa (Lepault and Lecocq 2021).

A.III.II.1.2.3 Sector Transition Scenarios

There are also a range of sector transition scenarios, both on the global and the country level. These include scenarios for the transition of the electricity, buildings, industry, transport and AFOLU sectors until 2050. Due to the accelerated electrification in mitigation pathways, sector coupling plays an increasingly important role to overcome decarbonisation bottlenecks, complicating a separate sector-by-sector scenario assessment. Likewise, the energy-water-land nexus limits the scope of a separate assessment of the energy and agricultural sectors. Nevertheless, sector transition scenarios play an important role for this assessment as they can usually offer much more technology, policy and behaviour detail than integrated assessment models. They are primarily assessed in the sector chapters of the report. Their projections of emissions reductions in the sectors in the near to medium term is used to check the sector dynamics of global models in Chapter 3 of the report.

Recent transition scenarios considered overarching accelerated climate mitigation strategies across multiple sectors, including demand reduction, energy efficiency improvement, electrification and switching to low-carbon fuels. The sectoral strategies considered are often specific to national resource availability, political, economic, climate, and technological conditions. Many sectoral transition strategies have focused on the energy supply sectors, particularly the power sector, and the role for renewable and bio-based fuels in decarbonising energy supply and carbon capture and sequestration (CCS). Some studies present comprehensive scenarios for both supply-side and demand-side sectors, including sector-specific technologies, strategies, and policies. Nearly all demand sector scenarios have emphasised the need for energy efficiency, conservation and reduction through technological changes, with a limited number of models also exploring possible behavioural changes enabled by new technological and societal innovations.

A.III.II.1.2.4 Service Transition Scenarios

A central feature of service transition pathways is a focus on the provision of adequate energy services to provide decent standards of living for all as the main scenario objective. Energy services are proxies for well-being, with common examples being provision of shelter (expressed as m^2 per capita), mobility (expressed as passenger-kilometres), nutrition (expressed as kCal per capita), and thermal comfort (expressed as degree-days) (Creutzig et al. 2018). Service transition pathways seek to meet adequate levels of such services with minimal carbon emissions, using combinations of demand- and supply-side options. Ideally this is done by improving the efficiency of service provision systems to minimise overall final energy and resource demand, thereby reducing pressure on supply-side and carbon dioxide removal technologies (Grubler et al. 2018). Specifically, this includes providing convenient access to end-use services (health care, education, communication, etc.), while minimising both primary and end-use energy required. Service transition pathways provide a compelling scenario narrative focused on well-being, resulting in technology and policy pathways that give explicit priority to decent living standards. Furthermore, more efficient service provision often involves combinations of behavioural, infrastructural and technological change, expanding the options available to policymakers for achieving mitigation goals (van Sluisveld et al. 2016, 2018). These dimensions are synergistic, in particular in that behavioural and lifestyle changes often require infrastructures adequately matching lifestyles. Service transition scenarios are primarily assessed in Chapter 5 of the report.

A.III.II.1.3 Scenario Framework for Climate Change Research

A.III.II.1.3.1 History of Scenario Frameworks used by the IPCC

For the first three assessment reports, the IPCC directly commissioned emission scenarios with social, economic, energy and partially policy aspects as drivers of projected GHG emissions. The first set of scenarios, the 'SA90' of the IPCC First Assessment Report (IPCC 1990), had four distinct scenarios, 'business-as-usual' and three policy scenarios of increasing ambition. The set of 'IS92' scenarios used in the Second Assessment Report investigated variations of business-as-usual scenarios with respect to uncertainties about the key drivers of economic growth, technology and population (Leggett et al. 1992). The SRES scenarios from the IPCC Special Report on Emission Scenarios (SRES) (IPCC 2000) were produced by multiple modelling organisations and were used in the Third and Fourth Assessment reports. Four distinct scenario families were characterised by narratives and projections of key drivers like population development and economic growth (but no policy measures) to examine their influence on a range of GHG and air pollutant emissions. Until the Fourth Assessment Report, the IPCC organised the scenario development process centrally. Since then, scenarios are developed by the research community and the IPCC limited its role to catalysing and assessing scenarios. To shorten development times, a parallel approach was chosen (Moss et al. 2010) and representative concentration pathways (RCPs) were developed (van Vuuren et al. 2011b) to inform the next generation of climate modelling for the Fifth Assessment Report. RCPs explored four different emissions and atmospheric composition pathways structured to result in different levels of radiative forcing in 2100: 2.6, 4.5, 6.0 and 8.5 W m^{-2}. They were used as an input to the Climate Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2011) and its results were assessed in AR5 (Collins et al. 2013).

[6] National emission pathways in the near or mid-term cannot be linked to long-term mitigation goals without making additional assumptions about emissions by other countries up to the mid-term, and assumptions by all countries up to 2100 (see Chapter 4, Box 4.1).

A.III.II.1.3.2 Current Scenario Framework and SSP-based Emission Scenarios

The current scenario framework for climate change research (Kriegler et al. 2014c; O'Neill et al. 2014; van Vuuren et al. 2014) is based on the concept of Shared Socio-economic Pathways (SSPs) (Kriegler et al. 2012; O'Neill et al. 2014). Unlike their predecessor scenarios from the SRES (IPCC 2000), their underlying narratives are motivated by the purpose of using the framework for mitigation and adaptation policy analysis. Hence the narratives are structured to cover the space of socio-economic challenges to both adaptation and mitigation. They tell five stories of sustainability (SSP1), middle of the road development (SSP2), regional rivalry (SSP3), inequality (SSP4) and fossil-fuelled development (SSP5) (O'Neill et al. 2017). SSP1, SSP2, and SSP3 were structured to explore futures with socio-economic challenges to adaptation and mitigation increasing from low to high with increasing number of SSP. SSP4 was structured to explore a world with high socio-economic challenges to adaptation but low socio-economic challenges to mitigation, while SSP5 explored a world with low challenges to adaptation but high challenges to mitigation. The five narratives have been translated into population and education (Kc and Lutz 2017), economic growth (Crespo Cuaresma 2017; Dellink et al. 2017; Leimbach et al. 2017a), and urbanisation projections (Jiang and O'Neill 2017) for each of the SSPs.

The SSP narratives and associated projections of socio-economic drivers provide the core components for building SSP-based scenario families. These basic SSPs are not scenarios or goal-oriented pathways themselves (despite carrying 'pathway' in the name), but building blocks from which to develop full-fledged scenarios. In particular, their basic elements do not make quantitative assumptions about energy and land use, emissions, climate change, climate impacts and climate policy. Even though including these aspects in the scenario-building process may alter some of the basic elements, such as projections of economic growth, the resulting scenario remains associated with its underlying SSP. To improve the ability of SSPs to capture socio-economic environments, basic SSPs have been extended in various ways, including the addition of quantitative projections on further key socio-economic dimensions like inequality (Rao et al. 2019), governance (Andrijevic et al. 2020b), and gender equality (Andrijevic et al. 2020a). Extensions also included spatially downscaled projections of, for example, population developments (Jones and O'Neill 2016). By now, the SSPs have been widely used in climate change research ranging from projections of future climate change to mitigation, impact, adaptation and vulnerability analysis (O'Neill et al. 2020).

The integrated assessment modelling community has used the SSPs to provide a set of global integrated energy-land use-emissions scenarios (Bauer et al. 2017; Calvin et al. 2017; Fricko et al. 2017; Fujimori et al. 2017; Kriegler et al. 2017; Popp et al. 2017; Rao et al. 2017b; Riahi et al. 2017; van Vuuren et al. 2017b; Rogelj et al. 2018b) in line with the matrix architecture of the scenario framework (van Vuuren et al. 2014) (Figure 4). It is structured along two dimensions: socio-economic assumptions varied along the SSPs, and climate (forcing) outcomes varied along the Representative Concentration Pathways (RCPs) (van Vuuren et al. 2011b). To distinguish resulting emission scenarios from the original four RCPs (RCP2.6, RCP4.5, RCP6.0, and RCP8.5), they are typically named SSPx–y with x = {1,…,5} the SSP label and y = {1.9, **2.6**, 3.4, **4.5**, **6.0**, 7.0, **8.5**} W m^{-2} the nominal forcing level in 2100. The four forcing levels that were already covered by the original RCPs are bolded here.

The new SSP-based emissions and concentrations pathways provided the input for CMIP6 (Eyring et al. 2015; O'Neill et al. 2016) and its climate change projections are assessed in AR6 (WGI Cross-chapter Box 1.2, WGI Chapter 4). From the original set of more than 100 SSP-based energy-land use-emissions scenarios produced by six IAMs (Figure 4), five Tier 1 scenarios (SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5), and four Tier 2 scenarios (SSP4-3.4, SSP4-6.0, variants of SSP7-3.0, SSP5-3.4) were selected[7] (O'Neill et al. 2016), further processed and harmonised with historic emissions and land-use change estimates (Gidden et al. 2019; Hurtt et al. 2020), and then taken up by CMIP6 models. WGI focuses its assessment of CMIP6 climate change projections on the five Tier 1 scenarios (WGI Chapter 4), but also uses the Tier 2 scenarios where they allow assessment of specific aspects like air pollution. All SSP-based IAM scenarios from the original studies are included in the AR6 emissions scenario database and are part of the assessment of global mitigation pathways in Chapter 3.

IAMs could not identify SSP-based emissions scenarios for all combinations of SSPs and RCPs (Riahi et al. 2017; Rogelj et al. 2018b) (Figure 4). The highest emission scenarios leading to forcing levels similar to RCP8.5 could only be obtained in a baseline without climate policy in SSP5 (SSP5-8.5). Since by now climate policies are implemented in many countries around the world, the likelihood of future emission levels as high as in SSP5-8.5 has become small (Ho et al. 2019). Baselines without climate policies for SSP1 and SSP4 reach up to 6.0–7.0 W m^{-2}, with baselines for SSP2 and SSP3 coming in higher at around 7.0 W m^{-2}. On the lower end, no 1.5°C (RCP1.9) and likely 2°C scenarios (RCP2.6) could be identified for SSP3 due to the lack of cooperative action in this world of regional rivalry. 1.5°C scenarios (RCP1.9) could only be reached by all models under SSP1 assumptions. Models struggled to limit warming to 1.5°C under SSP4 assumptions due to limited ability to sustainably manage land, and under SSP5 assumptions due to their high dependence on ample fossil fuel resources in the baseline (Rogelj et al. 2018b).

A.III.II.1.4 Key Design Choices and Assumptions in Mitigation Scenarios

The development of a scenario involves design choices, in addition to the selection of the model. This section will focus on key choices related to scenario design, and the respective socio-economic, technical, and

[7] Each SSPx-y combination was calculated by multiple IAMs. The specific scenarios developed by the marker models for the associated SSPs (SSP1: IMAGE; SSP2: MESSAGE-GLOBIOM; SSP3: AIM; SSP4: GCAM; SSP5: REMIND-MAgPIE) were selected as Tier 1/Tier 2 scenarios for use in CMIP6. Tier 2 variants include SSP7-3.0 with high emissions of short–lived climate forcers and SSP5-3.4 with high overshoot from following SSP5-8.5 until 2040.

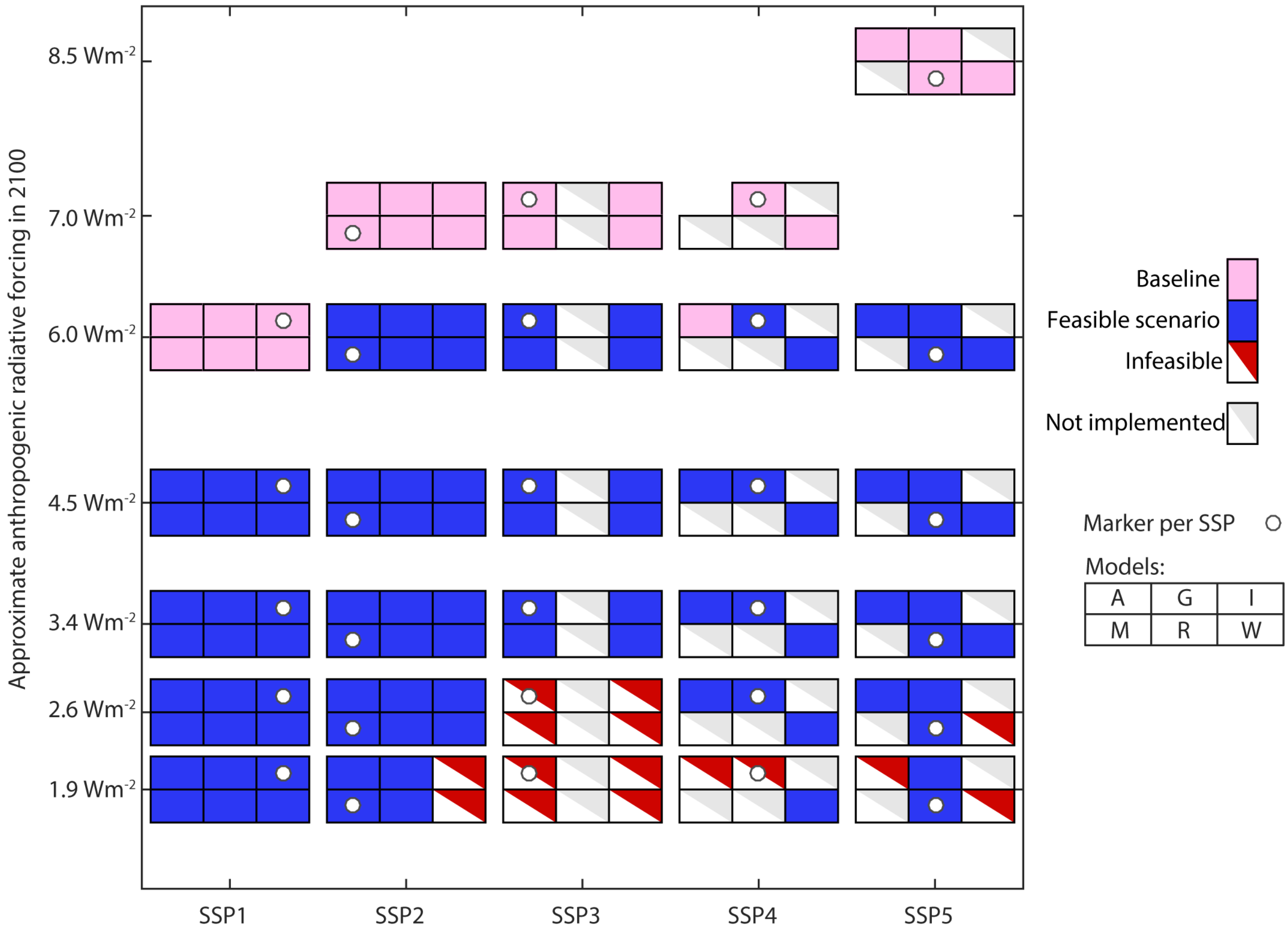


Figure 4 | The SSP/RCP matrix showing the SSPs on the horizontal axis and the forcing levels on the vertical axis. A = AIM, G = GCAM; I = IMAGE, M = MESSAGE-GLOBIOM, R = REMIND-MAgPIE, W = WITCH]. Not all SSP/RCP combinations are feasible (red triangles), and not all combinations were tried (grey triangles). Source: adapted with permission from Figure 5 of Rogelj et al. (2018b). Corresponding scenarios were published in Riahi et al. (2017) and Rogelj et al. (2018b) and included in the AR6 scenario database.

policy assumptions. Model selection cannot be separated from these choices. The various advantages and disadvantages of models are described in Annex III, Part I (Modelling Methods).

Target setting: Goal-oriented scenarios in the climate scenario literature initially focused on concentration stabilisation but have now shifted towards temperature limits and associated carbon budgets. In early model intercomparisons, climate targets were often specified as a CO_2-equivalent concentration level, for example, 450ppm CO_2-eq or 550ppm CO_2-eq (Clarke et al. 2009). These targets were either applied as not-to-exceed or overshoot targets. In the latter case, concentration levels could be returned to the target level by 2100. Overshoot was particularly allowed for low concentration and temperature targets as many models could not find a solution otherwise (Clarke et al. 2009; Blanford et al. 2014b; Kriegler et al. 2014a; Rogelj et al. 2018b). Bioenergy with carbon capture and storage (BECCS) was an important technology that facilitated aggressive targets to be met in 2100. Due to its ability to remove CO_2 from the atmosphere and produce net negative CO_2 emissions, it enabled overshoot of the target, leading to a distinctive peak-and-decline behaviour in concentration, radiative forcing, and temperature (Clarke et al. 2014; Fuss et al. 2014). The mitigation scenarios based on the SSP-RCP framework also applied radiative forcing levels in 2100 (Riahi et al. 2017). Temperature targets were often implemented by imposing end-of-century carbon budgets, that is, cumulative emissions up until 2100. In the case of 2°C pathways, those budgets were usually chosen such that the 2°C limit was not overshoot with some pre-defined probability (Luderer et al. 2018). Arguably, the availability of net negative CO_2 emissions has led to high levels of carbon dioxide removal (CDR) in the second half of the century, although CDR deployment is often already substantial to compensate residual emissions (Rogelj et al. 2018a).

Recent literature has increasingly focused on alternative approaches such as peak warming or peak CO_2 budget constraints to implement targets (Rogelj et al. 2019b; Johansson et al. 2020; Riahi et al. 2021). Nevertheless, due to the availability of net negative CO_2 emissions and the assumption of standard (exponentially increasing) emissions-pricing profiles from economic theory, peak and decline temperature profiles still occurred in a large number of mitigation pathways in the literature even in the presence of peak warming and carbon budget targets (Strefler et al. 2021b). This has led to proposals to combine peak targets with additional assumptions affecting the timing of emissions reductions like a constraint on net negative CO_2

emissions (Obersteiner et al. 2018; Rogelj et al. 2019a; Riahi et al. 2021) and different carbon pricing profiles (Strefler et al. 2021b). These proposals are aiming at a stabilisation rather than a peak and decline of warming under a given warming limit. However, arguments in support of peak and decline warming profiles also exist: the goal of hedging against positive feedback loops in the Earth system (Lenton et al. 2019) and the aim of increasing the likelihood of staying below a temperature limit towards the end of the century (Schleussner et al. 2016). It is also noteworthy that peak and decline temperature pathways are connected to achieving net-zero GHG emissions (with CO_2-eq emissions calculated using GWP100) in the second half of the century (Rogelj et al. 2021).

Efficiency considerations: Process-based IAMs typically calculate cost-effective mitigation pathways towards a given target as a benchmark case (Clarke et al. 2014). In these pathways, global mitigation costs are minimised by exploiting the abatement options with the least marginal costs across all sectors and regions at any time, implicitly assuming a globally integrated and harmonised mitigation regime. This idealised benchmark is typically compared across different climate targets or with reference scenarios extrapolating current emissions trends (UNEP 2019). It naturally evolves over time as the onset of cost-effective action is being set to the immediate future of respective studies. This onset was pushed back from 2010–2015 in studies assessed by AR5 (Clarke et al. 2014) to the first modelling time step after 2020 in studies assessed by AR6.

The notion of cost-effectiveness is sensitive to economic assumptions in the underlying models, particularly concerning the assumptions on pre-existing market distortions (Guivarch et al. 2011; Clarke et al. 2014; Krey et al. 2014) and the discount rate on future values. Those assumptions are often not clearly expressed. Most models have a discount rate of 3–5%, though the range of alternatives is larger. Cost-benefit IAMs have had a tradition of exploring the importance of discount rates, but process-based IAMs have generally not. A lower discount rate brings mitigation forward in time and uses less net negative CO_2 emissions in cases where target overshoot is allowed (Emmerling et al. 2019; Realmonte et al. 2019). While most models report discount rates in documentation, there is arguably too little sensitivity analysis of how the discount rate affects modelled outcomes.

Cost-effective pathways typically do not account for climate impacts below the temperature limit, although recent updates to climate damage estimates suggest a strengthening of near-term action in cost-effective mitigation pathways (Schultes et al. 2021). Recently, the research community has begun to combine mitigation pathway analysis with *ex post* analysis of associated climate impacts and the benefits of mitigation (Drouet et al. 2021). Cost-effective pathways that tap into least cost abatement options globally without considering compensation schemes to equalise the mitigation burden between countries are not compatible with equity considerations. There is a large body of literature exploring international burden-sharing regimes to accompany globally cost-effective mitigation pathways (Tavoni et al. 2015; Pan et al. 2017; van den Berg et al. 2020).

Policy assumptions: Cost-effective mitigation scenarios assume that climate policies are globally uniform. There is a substantial literature contrasting these benchmark cases with pathways derived under the assumption of regionally fragmented and heterogeneous mitigation policy regimes (Blanford et al. 2014b; Kriegler et al. 2015b, 2018b; Roelfsema et al. 2020; van Soest et al. 2021; Bauer et al. 2020b). For example, the Shared Policy Assumptions (Kriegler et al. 2014c) used in the SSP-RCP framework allow for some fragmentation of policy implementation, and many scenarios follow current policies or emission pledges until 2030 before implementing stringent policies (Riahi et al. 2015; Vrontisi et al. 2018; Roelfsema et al. 2020). Other studies assume a gradual strengthening of emissions pledges and regulatory measures converging to a globally harmonised mitigation regime slowly over time (Kriegler et al. 2018b; van Soest et al. 2021). With increasing announcements of mid-century strategies and the rise of net-zero CO_2 or GHG targets, global mitigation scenario analysis has begun to build in nationally-specific policy targets until mid-century (NGFS 2021).

Scenarios limiting warming to below 2°C phase in climate policies in all regions and sectors. Almost all converge to a harmonised global mitigation regime before the end of century (with the exception of Bauer et al. (2020b)). In practice, policies are often a mix of regulations, standards, or subsidies. Implementing these real-world policies can give different outcomes to optimal uniform carbon pricing (Mercure et al. 2019). Modelled carbon prices will generally be lower when other policies are implemented (Calvin et al. 2014a; Bertram et al. 2015). As countries implement more and a diverse set of policies, the need to further develop the policy assumptions in models is becoming apparent (Grant et al. 2020; O'Neill et al. 2020; Keppo et al. 2021).

Socio-economic drivers: Key socio-economic drivers of emission scenarios are assumptions on population and economic activity. There are other socio-economic assumptions, often included in underlying narratives (O'Neill et al. 2017), that strongly affect energy demand per capita or unit of GDP and dietary choices (Bauer et al. 2017; Popp et al. 2017; Grubler et al. 2018; van Vuuren et al. 2018). The SSPs are often used to help harmonise socio-economic assumptions, and further explore the scenario space. Many studies focus on the middle-of-the-road SSP2 as their default assumption, and many use SSP variations to explore the sensitivity of their results to socio-economic drivers (Marangoni et al. 2017; Riahi et al. 2017; Rogelj et al. 2017). While the SSPs help harmonisation, they are not unique and do not fully explore the scenario space (O'Neill et al. 2020). A wider range of narratives describing alternative worlds is also conceivable. The sustainability world (SSP1), for example, is a world with strong economic growth, but sustainability worlds with low growth or even elements of degrowth in developed countries could also be explored. Thus, standardisation of scenario narratives and drivers has advantages, but can also risk narrowing the scenario space that is explored by the literature. Consequently, many studies in the literature have adopted other socio-economic assumptions, for example with regard to population and GDP (Kriegler et al. 2016; Gillingham et al. 2018) and sustainable development trends (Soergel et al. 2021).

Technology availability and costs: Technology assumptions are a key component of IAMs, with some models representing hundreds or thousands of technologies. Despite the importance of technology costs (Creutzig et al. 2017), there has been limited comparison of technology assumptions across models (Kriegler et al. 2015b; Krey et al. 2019). There is, however, a substantial literature on the sensitivity of mitigation scenarios to technology assumptions, including model comparisons (Kriegler et al. 2014a; Riahi et al. 2015), single-model sensitivity studies (McJeon et al. 2011; Krey and Riahi 2013; Giannousakis et al. 2021) and multi-model sensitivity studies (Bosetti et al. 2015). Not only are the initial technology costs important, but also how these costs evolve over time either exogenously or endogenously. Since IAMs have so many interacting technologies, assumptions on one technology can affect the deployment of another. For example, limits on solar energy expansion rates, or integration, may lead to higher levels of deployment for alternative technologies. Because of these interactions, it can be difficult to determine what factors affect deployment across a range of models.

Within these key scenario design choices, model choice cannot be ignored. Not all models can implement aspects of a scenario in the same way. Alternative target implementations are difficult for some model frameworks, and implementation issues also arise around technological change and policy implementation. Certain scenario designs may lock out certain modelling frameworks. These issues indicate the need for a diversity of scenario designs (Johansson et al. 2020) to ensure that model diversity can be fully exploited.

It is possible for many assumptions to be harmonised, depending on the research question. The SSPs were one project aimed at increasing harmonisation and comparability. It is also possible to harmonise emission data, technology assumptions, and policies (Giarola et al. 2021). While harmonisation facilitates greater comparability between studies, it also limits scenario and model diversity. The advantages and disadvantages of harmonisation need to be discussed for each model study.

A.III.II.2 Use of Scenarios in the Assessment

A.III.II.2.1 Use of Scenario Literature and Database

The WGIII assessment draws on the full literature on mitigation scenarios. To support the assessment, as many mitigation scenarios in the literature as possible were collected in a scenario database with harmonised output reporting (Annex III.II.3). The collection of mitigation pathways in a common database is motivated by a number of reasons: First, to establish comparability of quantitative scenario information in the literature which is often only sporadically available from tables and figures in peer-reviewed publications, reports and electronic supplementary information. Moreover, this information is often reported using different output variables and definitions requiring harmonisation. Second, to increase latitude of the assessment by establishing direct access to quantitative information underlying the scenario literature. Third, to improve transparency and reproducibility of the assessment by making the quantitative information underlying the scenario figures and tables shown in the report available to the readers of AR6. The use of such scenario databases in AR5 WGIII (Krey et al. 2014) and SR1.5 (Huppmann et al. 2018) proved its value for the assessment as well as for broad use of the scenario information by researchers and stakeholders. This is now being continued for AR6.

A.III.II.2.2 Treatment of Scenario Uncertainty

The calls for scenarios issued in preparation of this assessment report allowed the collection of a large ensemble of scenarios, coming from many modelling teams using various modelling frameworks in many different studies. Although a large ensemble of scenarios was gathered, it should be acknowledged that only a portion of the full uncertainty space is investigated, and that the distribution of the scenarios within the ensemble reflects the context of the studies the scenarios were developed in. This introduces 'biases' in the ensemble, for example, (i) the topics of the scenario studies collected in the database determine coverage of the scenario space, with large model-comparison studies putting large weight on selected topics over less explored topics explored by individual models, (ii) some models are more represented than others, (iii) only 'optimistic' models (i.e., models finding lower mitigation costs) reach the lowest mitigation targets (Tavoni and Tol 2010). Where appropriate, sampling bias was recognised in the assessment, but formal methods to reduce bias were not employed due to conceptual limitations.

Furthermore, although attempts have been made to elicit scenario likelihoods from expert knowledge (Christensen et al. 2018), scenarios are difficult to associate with probabilities as they typically describe a situation of deep uncertainty (Grübler and Nakicenovic 2001). This and the non-statistical nature of the scenario ensemble collected in the database do not allow a probabilistic interpretation of the distribution of output variables in the scenario database. Throughout the report, descriptive statistics are used to describe the spread of scenario outcomes across the scenarios ensemble. The ranges of results and the position of scenarios outcomes relative to some thresholds of interest are analysed. In some figures, the median of the distribution of results is plotted together with the interquartile range and possibly other percentiles (5th-10th-90th-95th) to facilitate the assessment of results, but these should not be interpreted in terms of likelihood of outcomes.

A.III.II.2.3 Feasibility of Mitigation Scenarios

In order to develop feasibility metrics of mitigation scenarios (Chapter 3, Section 3.8), the assessment relied on the multidimensional feasibility framework developed in Brutschin et al. (2021), considering five feasibility dimensions: (i) geophysical, (ii) technological, (iii) economic, (iv) institutional and (v) socio-cultural. For each dimension, a set of indicators was developed, capturing not only the scale but also the timing and the disruptiveness of transformative change (Kriegler et al. 2018b). All AR6 scenarios (C1–C3 climate categories) were categorised through this framework to quantify feasibility challenges by climate category, time, policy architecture and by feasibility dimension, summarised in Figure 3.43 (Chapter 3).

Scenarios were categorised into three levels of concerns: (i) low levels of concern where transformation is similar to the past or identified in the literature as feasible/plausible, (ii) medium levels of

Table 8 | Feasibility dimensions, associated indicators and thresholds for the onset of medium and high concerns about feasibility (Chapter 3.8).

		Indicators	Computation	Medium	High	Source
Geophysical		**Biomass potential**	Total primary energy generation from biomass in a given year	100 EJ yr^{-1}	245 EJ yr^{-1}	Frank et al. (2021); Creutzig et al. (2014)
Geophysical		**Wind potential**	Total secondary energy generation from wind in a given year	830 EJ yr^{-1}	2000 EJ yr^{-1}	Deng et al. (2015); Eurek et al. (2017)
Geophysical		**Solar potential**	Total primary energy generation from solar in a given year	1600 EJ yr^{-1}	50 000 EJ yr^{-1}	Rogner et al. (2012); Moomaw et al. (2011)
Economic		**GDP loss**	Decadal percentage difference in GDP in mitigation vs baseline scenario	5%	10%	Analogy to current COVID-19 spending Andrijevic et al. (2020c)
Economic		**Carbon price**	Carbon price levels (NPV) and decadal increases	USD60	USD120 and 5×	Brutschin et al. (2021); OECD (2021)
Economic		**Energy investments**	Ratio between investments in mitigation vs baseline in a given decade	1.2	1.5	McCollum et al. (2018)
Economic		**Stranded coal assets**	Share of prematurely retired coal power generation in a given decade	20%	50%	Brutschin et al. (202)1; Global Energy Monitor (2021)
Technological	Established	**Wind/solar scale-up**	Decadal percentage point increase in the wind/solar share in electricity generation	10 pp	20 pp	Brutschin et al. (2021); Wilson et al. (2020)
Technological	Established	**Nuclear scale-up**	Decadal percentage point increase in the nuclear share in electricity generation	5 pp	10 pp	Brutschin et al. (2021); Markard et al. (2020); Wilson et al. (2020)
Technological	New Technologies	**BECCS scale-up**	Amount of CO_2 captured in a given year	3 $GtCO_2$ yr^{-1}	7 $GtCO_2$ yr^{-1}	Warszawski et al. (2021)
Technological	New Technologies	**Fossil CCS scale-up**	Amount of CO_2 captured in a given year	3.8 $GtCO_2$ yr^{-1}	8.8 $GtCO_2$ yr^{-1}	Budinis et al. (2018)
Technological	New Technologies	**Biofuels in transport scale-up**	Decadal percentage point increase in the share of biofuels in the final energy demand of the transport sector	5 pp	10 pp	Nogueira et al. (2020)
Technological	New Technologies	**Electricity in transport scale-up**	Decadal percentage point increase in the share of electricity in the final energy demand of the transport sector	10 pp	15 pp	Muratori et al. (2021)
Socio-cultural		**Total/transport/industry/residential energy demand decline**	Decadal percentage decrease in demand	10 %	20 %	Grubler et al. (2018)
Socio-cultural		**Decline of livestock share in food demand**	Decadal percentage decrease in the livestock share in total food demand	0.5 pp	1 pp	Grubler et al. (2018); Bajželj et al. (2014)
Socio-cultural		**Forest cover increase**	Decadal percentage increase in forest cover	2 %	5 %	Brutschin et al. (2021)
Socio-cultural		**Pasture cover decrease**	Decadal percentage decrease in pasture cover	5 %	10 %	Brutschin et al. (2021)
Institutional		**Governance level and decarbonisation rate**	Governance levels and per capita CO_2 emission reductions over a decade	>0.6 and <20%	<0.6 and >20%	Brutschin et al. (2021); Andrijevic et al. (2020b)

concern that might be challenging but within reach, given certain enablers, (iii) high levels of concern representing unprecedented levels of transformation, attainable only under consistent enabling conditions. Indicator thresholds defining these three levels of concern were obtained from the available literature and developed with additional empirical literature. Table 8 summarises the main indicators used and the associated thresholds for medium and high levels of concern. Finally, we aggregated feasibility concerns for each dimension and each decade, employing the geometric mean, a non-compensatory method which limits the degree of substitutability between indicators, and used for example by the United Nations for the Human Development Index (HDI). Alternative aggregation scores such as the counting of scenarios exceeding the thresholds were also implemented.

A.III.II.2.4 Illustrative Mitigation Pathways

In the IPCC Special Report on Global Warming of 1.5°C (SR1.5), illustrative pathways (IPs) were used in addition to descriptions of the key characteristics of the full set of scenarios in the database to assess and communicate the results from the scenario literature. While the latter express the spread in scenario outcomes highlighting uncertain vs robust outcomes, IPs can be used to contrast different stories of mitigating climate change (Rogelj et al. 2018a).

Following the example of the SR1.5, IPs have also been selected for the AR6 of WGIII. In contrast to SR1.5, the selection needed to cover a larger range of climate outcomes while keeping the number of IPs limited. The selection focused on a range of critical themes that emerged from the AR6 assessment: (i) the level of ambition of climate policy, (ii) the different mitigation strategies, (iii) timing of mitigation actions, and (iv) the combination of climate policy with sustainable development policies. The IPs consist of narratives (Table 9) as well as possible quantifications. The IPs are illustrative and denote implications of different societal choices for the development of future emissions and associated transformations of main GHG-emitting sectors. For Chapter 3, for each of the IPs a quantitative scenario was selected from the AR6 scenario database to have particular characteristics and from diverse modelling frameworks (Table 10).

In total, two reference pathways with warming above 2°C and five Illustrative Mitigation Pathways (IMPs) limiting warming in the 1.5–2°C range were selected. The first reference pathway follows current policies as formulated around 2018 (Current Policies, CurPol) through to 2030 and then continues to follow a similar mitigation effort to 2100. The associated quantitative scenario (NGFS 2021) selected by Chapter 3 leads to about 3°C–4°C warming at the end of the century. The second reference pathway follows emission pledges to 2030 (NDCs) and then continues with moderate climate action over time (Moderate Action, ModAct).

The five IMPs are deep mitigation pathways with warming in the 1.5°C–2°C range. The first IMP pursues gradual strengthening beyond NDC ambition levels until 2030 and then acts to likely limit warming to 2°C (Climate Category C3) (IMP-GS) (van Soest et al. 2021) (Chapter 3.5.3). Three others follow different mitigation strategies focusing on low energy demand (IMP-LD) (Grubler et al. 2018),

Table 9 | Storylines for the two reference pathways and five Illustrative Mitigation Pathways (IMPs) limiting warming to 1.5°C–2°C considered in the report.

		General char.	Policy	Innovation	Energy	Land use, food biodiversity	Lifestyle
CurPol		Continuation of current policies and trends	Implementation of current climate policies and neglect of stated goals and objectives; grey COVID-19 recovery	Business as usual; slow progress in low-carbon technologies	Fossil fuels remain important; lock-in	Further expansion of western diets; further slow expansion of agriculture area	Demand will continue to grow; no significant changes in current habits
ModAct		NDCs in 2030 as announced in 2020, fragmented policy landscape; post-2030 action consistent with modest action until 2030	Strengthening of policies to implement NDCs; some further post-2030 strengthening and mixed COVID-19 recovery	Modest change compared to Cur-Pol	Mostly moving away from coal; growth of renewables; some lock-in in fossil investments	Afforestation/ reforestation policies as in NDCs	Modest change compared to Cur-Pol
IMP	**Neg**	Mitigation in all sectors includes a heavy reliance on carbon dioxide removal that results in net negative global GHG emissions	Successful international climate policy regime with a focus on a long-term temperature goal	Further development of CDR options	Heavy reliance on CDR in power sector and industry; CDR used to compensate fossil fuel emissions	Afforestation/ reforestation, BECCS, increased competition for land	Not critical – some induced via price increases
	Ren	Greater emphasis on renewables: rapid deployment and technology development of renewables; electrification	Successful international climate policy regime; policies and financial incentives favouring renewable energy	Rapid further development of innovative electricity technologies and policy regimes	Renewable energy; electrification; sector coupling; storage or power-to-X technologies; better interconnections		Service provisioning and demand changes to better adapt to high renewable energy supply
	LD	Efficient resource use as well as shifts in consumption patterns globally, leading to low demand for resources, while ensuring a high level of services and satisfying basic needs		Social innovation; efficiency; across all sectors	low demand for energy, while ensuring a high level of energy services and meeting energy needs; modal shifts in transport; rapid diffusion of best available technology in buildings and industry	Lower food and agricultural waste; less meat-intensive lifestyles	Service provisioning and demand changes; behavioural changes
	GS	less rapid introduction of mitigation measures followed by a subsequent gradual strengthening	Until 2030, primarily current NDCs are implemented and gradually strengthened moving gradually towards a strong, universal climate policy regime post-2030		Similar to IMP-Neg, but with some delay	Similar to IMP-Neg, but with some delay	
	SP	Shifting the global pathway towards sustainable development. including reduced inequality and deep GHG emissions reduction	SDG policies in addition to climate policy (poverty reduction; environmental protection)		low demand for energy, while ensuring a high level of energy services and meeting energy needs; renewable energy	Lower food and agricultural waste; less meat-intensive lifestyles; afforestation	Service provisioning and demand changes

Table 10 | Quantitative scenario selection to represent the two reference pathways and five Illustrative Mitigation Pathways warming to 1.5°C–2°C for the assessment in Chapter 3. These quantitative representations of the IMPs have also been taken up by a few other chapters where suitable. The warming profile of IMP-Neg peaks around 2060 and declines to below 1.5°C (50% likelihood) shortly after 2100. While technically classified as a C3, it exhibits the characteristics of C2 high overshoot pathways.

Acronym	Climate Category (II.3.2)	Model	Scenario name in the AR6 scenario database (III.II.3)	Reference
CurPol	C7	GCAM 5.3	NGFS2_Current Policies	NGFS (2021)
ModAct	C6	IMAGE 3.0	EN_INDCi2030_3000f	Riahi et al. (2021)
Illustrative Mitigation Pathways (IMPs)				
Neg	C2*	COFFEE 1.1	EN_NPi2020_400f_lowBECCS	Riahi et al. (2021)
Ren	C1	REMIND-MAgPIE 2.1-4.3	DeepElec_SSP2_ HighRE_Budg900	Luderer et al. (2021)
LD	C1	MESSAGEix-GLOBIOM 1.0	LowEnergyDemand_1.3_IPCC	Grubler et al. (2018)
GS	C3	WITCH 5.0	CO_Bridge	van Soest et al. (2021)
SP	C1	REMIND-MAgPIE 2.1-4.2	SusDev_SDP-PkBudg1000	Soergel et al. (2021)
Sensitivity cases				
Neg-2.0	C3	AIM/CGE 2.2	EN_NPi2020_900f	Riahi et al. 2(021)
Ren-2.0	C3	MESSAGEix-GLOBIOM_GEI 1.0	SSP2_openres_lc_50	Guo et al. (2021)

renewable electricity (IMP-Ren) (Luderer et al. 2021) and large-scale deployment of carbon dioxide removal measures resulting in net negative CO_2 emissions in the second half of the century (IMP-Neg). The fifth IMP explicitly pursues a broad sustainable development agenda and follows SSP1 socio-economic assumptions (IMP-SP) (Soergel et al. 2021). IMP-LD, IMP-Ren and IMP-SP limit warming to 1.5°C (>50%) with no or limited overshoot (C1), while IMP-Neg has a higher overshoot and only returns to nearly 1.5°C (50% chance) by 2100 (close to C2). In addition, two sensitivity cases for IMP-Ren and IMP-Neg are considered that limit warming to 2°C (>67%) (C3) rather than pursuing limiting warming to 1.5°C.

The IMPs are used in different parts of the report. We just mention some examples here. In Chapter 3, they are used to illustrate key differences between the mitigation strategies, for instance in terms of timing and sectoral action. In Chapter 6, Box 6.9 discusses the consequences for energy systems. Chapter 7 discusses some of the land-use consequences. In Chapter 8, the implications of the IMPs are further explored for urban systems where the elements of energy, innovation, policy, land use and lifestyle interact (Chapter 8, Sections 8.3 and 8.4). In Chapter 10, the consequences of different mitigation strategies for mobility are highlighted in different figures. The IMPs are discussed further in Chapter 1, Section 1.3; Chapter 3, Section 3.2; and the respective sector chapters.

A.III.II.2.5 Scenario Approaches to Connect WGIII with the WGI and WGII assessments

A.III.II.2.5.1 Assessment of WGIII Scenarios Building on WGI Physical Climate Knowledge

A transparent assessment pipeline has been set up across WGI and WGIII to ensure integration of the WGI assessment in the climate assessment of emission scenarios in WGIII. This pipeline consists of a step where emissions scenarios are harmonised with historical emissions (harmonisation), a step in which species not reported by an IAM are filled in (infilling), and a step in which the emission evolutions are assessed with three climate model emulators (Annex III.I.8) calibrated to the WGI assessment. These three steps ensure a consistent and comparable assessment of the climate response across emission scenarios from the literature.

Harmonisation: IAMs may use different historical datasets, and emission scenarios submitted to the AR6 WGIII scenario database (Annex III.II.3) are therefore harmonised against a common source of historical emissions. To be consistent with WGI, we use the same historical emissions that were used for CMIP6 and RCMIP (Gidden et al. 2018; Nicholls et al. 2020b). This dataset comprises many different emission harmonisation sources (Velders et al. 2015; Gütschow et al. 2016; Le Quéré et al. 2016; van Marle et al. 2017; Meinshausen et al. 2017; Hoesly et al. 2018), including estimates of CO_2 emissions from agriculture, forestry, and land-use change (mainly CEDS, (Hoesly et al. 2018)) which are on the lower end of historical observation uncertainty as assessed in Chapter 2. The harmonisation is performed so that different climate futures resulting from two different scenarios are a result of different future emission evolutions within the scenarios, not due to different historical definitions and starting points. Sectoral CO_2 emissions from energy and industrial processes and CO_2 from agriculture, forestry, and land-use change were harmonised separately. All other emissions species are harmonised based on the total reported emissions per species. For CO_2 from energy and industrial processes we use a ratio-based method with convergence in 2080, in line with CMIP6 (Gidden et al. 2018, 2019). For CO_2 from agriculture, forestry, and land-use change and other emissions species with high historical interannual variability, we use an offset method with convergence target 2150, to avoid strong harmonisation effects resulting from uncertainties in historical observations. For all remaining fluorinated gases (F-gases), constant ratio harmonisation is used. For all other emissions species, we use the default settings of Gidden et al. (2018, 2019a).

Infilling missing species: Infilling ensures that scenarios include all relevant anthropogenic emissions. This reduces the risk of a biased climate assessment and is important because not all IAMs report all climatically active emission species. Infilling was only performed for scenarios where models provided native reporting of energy and industrial process CO_2, land use CO_2, CH_4, and N_2O emissions to avoid infilling gases that have large individual radiative forcing contributions and cannot be infilled with high confidence. Models that did not meet this minimum reporting requirement were not included in the climate assessment. Infilling is performed following the methods and guidelines in Lamboll et al. (2020). Missing species are infilled based on the relationship with CO_2 from energy and industrial processes as found in the harmonised set of all scenarios reported to the WGIII scenario database that pass the vetting requirements. To ensure high stability to small changes, we apply a Quantile Rolling Window method (Lamboll et al. 2020) for aerosol precursor emissions, volatile organic compounds and greenhouse gases other than F-gases, based on the quantile of the reported CO_2 from energy and industrial processes in the database at each time point. F-fases and other gases with small radiative forcing are infilled based on a pathway with lowest root mean squared difference, allowing for consistency in spite of limited independently modelled pathways in the database.

WGI-calibrated emulators: Using expert judgement, emulators that reproduce the best estimates and uncertainties of the majority of AR6 WGI assessed metrics are recommended for scenario classification use by WGIII (see WGI Cross-Chapter Box 7.1). MAGICC (v7) was used for the main scenario classification, with FaIR (v1.6.2) being used to provide additional uncertainty ranges on reported statistics to capture climate model uncertainty. The WGI emulators' probabilistic parameter ensembles are derived such that they match a range of key climate metrics assessed by WGI and the extent to which agreement is achieved is evaluated (WGI Cross-Chapter Box 7.1). Of particular importance to this evaluation is the verification against the WGI temperature assessment of the five scenarios assessed in Chapter 4 of WGI (SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). The inclusion of the temperature assessment as a benchmark for the emulators provides the strongest verification that WGIII's scenario classification reflects the WGI assessment. The comprehensive nature of the evaluation is a clear improvement on previous reports and ensures that multiple components of the emulators, from their climate response to effective radiative forcing through to their carbon cycles, have been examined before they are deemed fit for use by WGIII.

Scenario climate assessment: For the WGIII scenario climate assessment, emulators are run hundreds to thousands of times per scenario, sampling from an emulator-specific probabilistic parameter set, which incorporates carbon cycle and climate system uncertainty in line with the WGI assessment (WGI Cross-Chapter Box 7.1). Percentiles for different output variables provide information about the spread in individual variables for a given scenario, but the set of variables for a given percentile do not form an internally consistent climate change projection. Instead, joint distributions of these parameter sets are employed by the calibrated emulators. Consistent climate change projections are represented by individual ensemble member runs and the whole ensemble of these individual member runs. To facilitate analysis, multiple percentiles of these large (hundred to thousand member) ensemble distributions of projected climate variables are provided in the AR6 scenario database. The emulators provide an assessment of global surface air temperature (GSAT) response to emission scenarios and its key characteristics like peak warming and year of peak warming, ocean heat uptake, atmospheric CO_2, CH_4 and N_2O concentrations and effective radiative forcing from a range of species including CO_2, CH_4, N_2O and aerosols for each emissions scenario, as well as an estimate of CO_2 and non-CO_2 contributions to the temperature increase. The climate emulator's GSAT projections are normalised to match the WGI Chapter 2 assessed total warming between 1850–1900 and 1995–2014 of 0.85°C.

The GSAT projections from the emulator runs are used for classifying those emissions scenarios in the AR6 database that passed the initial vetting and allowed a robust climate assessment. MAGICC (v7) was selected as emulator for the climate classification of scenarios, as it happens to be slightly warmer than the other considered climate emulator, particularly for the higher and long-term warming scenarios – reflecting long-term warming in line with Earth system models (ESMs) (WGI Cross-Chapter Box 7.1). This means that scenarios identified to stay below a given warming limit with a given probability by MAGICC will in general be identified to have this property by the other emulator as well. There is the possibility that the other emulator would classify a scenario in a lower warming class based on their slightly cooler emulation of the temperature response. Unlike during the assessment of the SR1.5 database in the IPCC SR1.5 report, the updated versions of FaIR and MAGICC are however very close, providing robustness to the climate assessment. MAgiCC and FaIR were both used to assess the overall uncertainty in the warming response for a single scenario or a set of scenarios, including both parametric and model uncertainty. Specifically, the 5th to 95th percentile range across the two emulators is calculated, characterising the joint climate uncertainty range of the two models.

Carbon budgets in WGI and WGIII: The remaining carbon budget corresponding to a certain level of future warming depends on non-CO_2 emissions of modelled pathways. Box 3.4 in Chapter 3 highlighted this key uncertainty in estimating carbon budgets. In this section (Figure 5), we put this into the context of the dependence of carbon budgets on two aspects of the non-CO_2 warming contribution: (i) assumptions on historical non-CO_2 emissions and how they can impact future non-CO_2 warming estimates relative to a recent reference period (2010–2019) (Panel a) and (ii) the scenario set underlying estimates of non-CO_2 warming at the time of reaching net zero CO_2 (Panel b). Both aspects affect the estimated remaining carbon budget by changing the non-CO_2 warming contribution from the base year to the time of reaching net zero CO_2. MAGICC7 is used in WGI in conjunction with different input files for the historical warming. For the reported remaining carbon budget estimates (WGI CB) WGI used the non-CO_2 warming contributions from MAGICC7 in line with Meinshausen et al. (2020) and in line with the CMIP6 GHG concentration projections, while the WGI emulator setup in line with WGI Cross-Chapter Box 7.1 was used for the WGIII climate assessment. The WGIII assessment uses MAGICC7 in line with Nicholls et al. (2021) in line with the emission harmonisation process employed in WGIII (see above). The difference in historical assumptions changes the estimated non-CO_2 contribution by up to about 0.05°C for the lower temperature levels, or slightly more than 10% of the warming until 1.5°C relative to 2010–2019. For peak warming around 2°C relative to pre-industrial levels (about 0.97°C warming relative to 2010–2019 in Figure 5 plots), the difference is

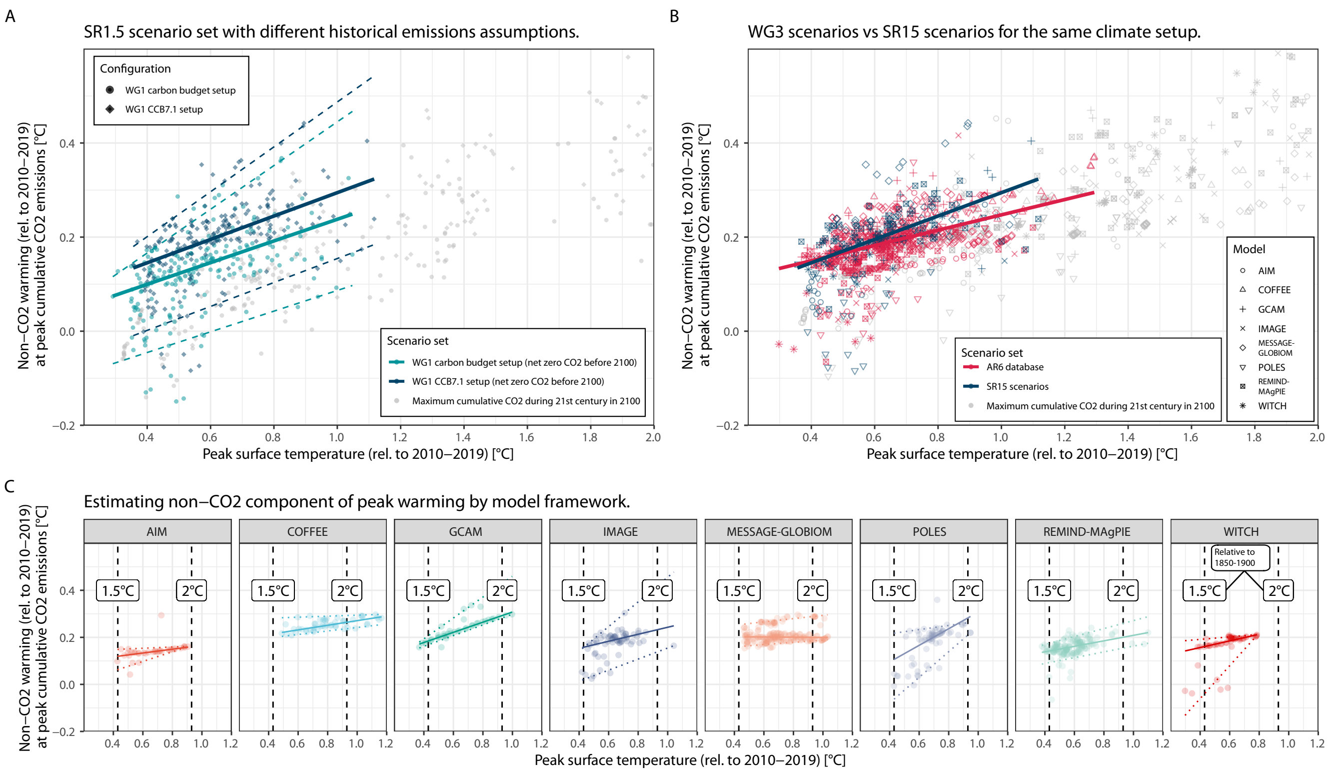


Figure 5 | Comparison of non-CO_2 warming relevant for the derivation of cumulative carbon budgets – and its sensitivity to (a) assumptions on historical emissions and (b) the set of investigated scenarios (right). Panel (c) shows how the relationship across scenarios between peak surface temperature and non-CO_2 warming and peak cumulative CO_2 is different for modelling frameworks. All dashed regression lines are at the 5th and 95th percentiles, solid lines are a regression at the median.

All panels depict non-CO_2 warming in relation to 2010–2019 at the time of peak cumulative CO_2, using MAGICC7. Scenarios that reach net-zero CO_2 this century are coloured, with dots in grey indicating scenarios that do not reach net-zero CO_2 but still remain below 2°C median peak warming relative to 2010–2019 levels in this century. The scenario set 'AR6 database' in **(b)** includes only scenarios of those model frameworks that are shown in panel (c)) which have a detailed land-use model and enough scenarios to imply a relationship.

Panel (a) The WGI remaining carbon budget takes into account the non-CO_2 warming in dependence of peak surface temperatures via a regression line approach (lighter blue-coloured solid line). For the same scenario set, with historical emissions assumptions as used in Cross-Chapter Box 7.1 (darker blue-coloured solid line), a relationship is found with a difference of approximately 0.05°C.

Panel (b) The WGIII database of scenarios tends to imply very similar non-CO_2 warming at peak cumulative CO_2 to the SR15 scenario database, especially around 1.5°C above pre-industrial (0.43°C above 2010–2019 levels), though with slightly lower non-CO_2 warming for higher peak temperatures.

Panel (c) Regressions at the 5th, 50th, and 95th percentiles indicate a model framework footprint affecting the relationship between peak warming and non-CO_2 warming at peak cumulative CO_2.

offset by the difference arising from using either the SR1.5 or AR6 scenario databases (see panel (b) in Figure 5).

Estimates of the remaining carbon budget that take into account non-CO_2 uncertainty are not only dependent on historical assumptions, but also on future non-CO_2 scenario characteristics, which are different across the various scenarios in the AR6 database. In panel (b) of Figure 5, we show how the SR15 database of scenarios, which was used to inform the WGI remaining carbon budget, differs from the larger set considered in the WGIII report (both using MAGICC7 using input files in line with Nicholls et al. (2021)). Overall, there is limited difference in the covered range of non-CO_2 warming at different peak surface temperature levels, leading to no clear change in estimated carbon budgets compared to SR1.5 based on the full scenario database. However, as discussed in Cross-Working Group Box 1 in Chapter 3, and shown in panel (c) of Figure 5, mitigation strategies expressed by both the IAM footprint and scenario design (e.g., dietary change scenarios) can have strong effects on estimated carbon budgets for staying below 1.5°C.

A.III.II.2.5.2 Relating the WGII and WGIII Assessments by use of Warming Levels

WGII sets out common climate dimensions to help contextualise and facilitate consistent communication of impacts and synthesis across WGII, as well as to facilitate WGI and WGII integration, with the dimensions adopted when helpful and possible across WGII (AR6 WGII Cross-Chapter Box 1.1). 'Common climate dimensions' are defined as common global warming levels (GWLs), time periods, and levels of other variables as needed by WGII authors (see below for a list of variables associated with these dimensions). Projected ranges for associated climate variables were derived from the AR6 WGI report and supporting resources and help contextualise and inform the projection of potential future climate impacts and key risks. The information enables the mapping of climate variable levels to climate projections by WGI (AR6 WGI Table SPM.1) and vice versa, with ranges of results provided to characterise the physical uncertainties relevant to assessing climate impacts risk. Common socio-economic dimensions are not adopted in WGII due to a desire to draw on the full literature, inform the broad ranges of relevant possibilities (climate, development, adaptation, mitigation), and be flexible. The impacts literature is wide-ranging and diverse, with a fraction based on global socio-economic scenarios. WGII's approach allows chapters and cross-chapter boxes to assess how impacts and ranges depend on socio-economic factors affecting exposure, vulnerability, and adaptation independently, as appropriate for their literature. For example, WGII Chapter 16 assesses how Representative Key Risks vary under low vs high exposure/vulnerability conditions by drawing on impact literature based on Shared Socio-economic Pathways (SSPs). In general, WGII chapters, when possible and conducive with their literature, used GWLs or climate projections based on Representative Concentration Pathways or SSPs to communicate information and facilitate integration and synthesis, with impacts results characterised according to other drivers when possible and relevant, such as socio-economic conditions.

In the context of common climate dimensions, WGII considers common projected GWL ranges by time period, the timing for when GWLs might be reached, and projected continental-level result ranges for select temperature and precipitation variables by GWL (average and extremes), as well as sea surface temperature changes by GWL and ocean biome. Where available, WGII considers the assessed WGI ranges as well as the raw CMIP5 and CMIP6 climate change projections (ranges and individual projections) from Earth system models (Hauser et al. 2019). With WGII's climate impacts literature based primarily on climate projections available at the time of AR5 (CMIP5) and earlier, or assumed temperature levels, it was important to be able to map climate variable levels to climate projections of different vintages and vice versa. WGII's common GWLs are based on AR6 WGI's proposed 'Tier 1' dimensions of integration range – 1.5, 2.0, 3.0, and 4.0°C (relative to the 1850 to 1900 period), which are simply proposed common GWLs to facilitate integration across and within WGs (WGI Chapter 1). Within WGII, GWLs facilitate comparison of climate states across climate change projections, assessment of the full impacts literature, and cross-chapter comparison. Across AR6, GWLs facilitate integration across Working Groups of climate change projections, climate change risks, adaptation opportunities, and mitigation.

For facilitating integration with WGIII, GWLs need to be related to WGIII's classification of mitigation efforts by temperature outcome. WGII's Chapter 3 groups full century emissions projections resulting from a large set of assessed mitigation scenarios into temperature classes (Chapter 3, Sections 3.2 and 3.3, Annex III.II.2.5.1, and Annex III.II.3.2.1). Scenarios are classified by median peak global mean temperature increase since 1850–1900 in the bands <2°C, 2°C–2.5°C, 2.5°C–3°C, 3°C–4°C, and >4°C, with the range below 2°C broken out in greater detail using estimates of warming levels at peak and in 2100 for which the warming response is projected to be likely higher (33th percentile), as likely higher as lower (median), and likely lower (67th percentile) (Chapter 3, Section 3.2 and Annex III.II.3.2.1). WGII's common GWLs and WGIII's global warming scenario classes are relatable but differ in several important ways. While GWLs represent temperature change that occurs at some point in time, emissions scenarios in a temperature class result in an evolving warming response over time. The emissions scenario warming also has a likelihood attached to the warming level at any point in time, that is, actual warming outcomes can be lower or higher than median warming projections within the range of the estimated uncertainty. Thus, multiple WGII results across GWLs will be relevant to any particular WGIII emissions pathway, including at the peak temperature level.

However, socio-economic conditions are an important factor defining both impacts exposure, vulnerability, and adaptation, as well as mitigation opportunity and costs, that needs special considerations. The WGIII scenario assessment is using additional classifications relating to, inter alia, near-term policy developments, technology availability, energy demand, population and economic growth (Chapter 3, Section 3.3 and Annex III.II.3.2.2), and a set of illustrative mitigation pathways with varying socio-techno-economic assumptions (Annex III.II.2.4, Chapter 3, Section 3.2). Synthesising WGII assessments of climate change impacts and WGIII assessments of climate change mitigation efforts for similar GWLs/global warming scenario classes would have to address how socio-techno-economic conditions affect impacts, adaptation, and mitigation outcomes. Furthermore, a synthesis of mitigation costs and mitigation benefits in terms of avoided climate change impacts would require a framework that ensures consistency in socio-economic development assumptions and emissions and adaptation dynamics and allows for consideration of benefits and costs along the entire pathway (O'Neill et al. 2020) (Cross-Working Group Box 1 in Chapter 3).

A.III.II.3 WGIII AR6 Scenario Database

[*Note: The scenario numbers documented in this section refer to all scenarios that were submitted and not retracted by the literature acceptance deadline of 11 October 2021, and that fulfilled the requirement of being supported by an eligible literature source. Not all those scenarios were used in the assessment, for example some did not pass the vetting process as documented in II.3.1.]*

As for previous IPCC reports of Working Group III, including the Special Report on Global Warming of 1.5°C (SR1.5) (Huppmann et al. 2018; Rogelj et al. 2018a) and the Fifth Assessment Report (AR5) (Clarke et al. 2014; Krey et al. 2014), quantitative information on mitigation pathways is collected in a dedicated AR6 scenario database[8] to underpin the assessment.

By the time of the AR6 literature acceptance deadline of IPCC WGIII (11 October 2021) the AR6 scenario database comprised 191 unique modelling frameworks (including different versions and country setups) from 95+ model families – of which 98 were globally comprehensive, 71 national or multi-regional, and 20 sectoral models – with in total 3,131 scenarios, summarised in Tables 11–17

8 https://data.ece.iiasa.ac.at/ar6/.

(global mitigation pathways), Table 18 (national and regional mitigation pathways) and Table 19 (sector transition pathways).

A.III.II.3.1 Process of Scenario Collection and Vetting

To facilitate the AR6 assessment, modelling teams were invited to submit their available emissions scenarios to a web-based database hosted by the International Institute for Applied Systems Analysis (IIASA).[9] The co-chairs of Working Group III as well as a range of scientific institutions, including the Integrated Assessment Modelling Consortium (IAMC), University of Cape Town and the Centre International de Recherche sur l'Environnement et le Développement (CIRED), supported the open call for scenarios which was subdivided into four dedicated calls:

i. a call for global long-term scenarios to underpin the assessment in Chapter 3 as well as facilitating integration with sectoral Chapters 6, 7, 8, 9, 10 and 11,
ii. a call for short- to medium-term scenarios at the national and regional scales underpinning the assessment in Chapter 4, and
iii. a call for building-focused scenarios to inform the assessment in Chapter 9, and
iv. a call for transport-focused scenarios to inform the assessment in Chapter 10.

A common data reporting template with a defined variable structure was used and all teams were required to register and submit detailed model and scenario metadata. Scenarios were required to come from a formal quantitative model and the scenarios must be published in accordance with IPCC literature requirements. The calls for scenarios were open for a period of 22 months (September 2019 to July 2021), with updates possible until October 2021 in line with the literature acceptance deadline. The data submission process included various quality control procedures to increase accuracy and consistency in reporting. Additional categorisation and processing of metadata over the full database provided a wide range of indicators and categories that were made centrally available to authors of the report to enhance consistency of the assessment, such as: climate, policy and technology categories; characteristics about emissions, energy, socio-economics and carbon sequestration; metadata such as literature references, model documentation and related projects.

For all scenarios reporting global data, a vetting process was undertaken to ensure that key indicators were within reasonable ranges for the baseline period – primarily for indicators relating to emissions and the energy sector (Table 11). As part of the submission process, model teams were contacted individually with information on the vetting outcome with regard to their submitted scenarios, giving them the opportunity to verify the reporting of their data. Checks on technology-specific variables for nuclear, solar and wind energy, and CCS, screen not only for accuracy with respect to recent developments, but also indicate reporting errors relating to different primary energy accounting methods. While the criteria ranges appear to be large, the focus of these scenarios is the medium to long term and there is also uncertainty in the historical values. For vetting of the Illustrative Mitigation Pathways, the same criteria were used, albeit with narrower ranges (Table 11). Selected future values were also vetted and the result of the vetting reported to authors, but not used as exclusion criterion. Where possible the latest values available were used, generally 2019, and if necessary extrapolated to 2020 as most

Table 11 | Summary of the vetting criteria and ranges applied to the global scenarios for the climate assessment and preliminary screening for Illustrative Mitigation Pathways.

	Reference value	Range (IP range)	Pass	Fail	Not reported
Historical emissions (sources: EDGAR v6 IPCC and CEDS, 2019 values)					
CO_2 total (EIP + AFOLU) emissions	44,251 $MtCO_2$ yr^{-1}	±40% (±20%)	1848	23	395
CO_2 EIP emissions	37,646 $MtCO_2$ yr^{-1}	±20% (±10%)	2162	55	49
CH_4 emissions	379 $MtCH_4$ yr^{-1}	±20% (±20%)	1651	139	476
CO_2 emissions EIP 2010–2020 % change	–	+0 to +50%	1742	74	450
CCS from energy 2020	–	0-250 (100) $MtCO_2$ yr^{-1}	1624	77	565
Historical energy production (sources: IEA 2019; IRENA; BP; EMBERS; trends extrapolated to 2020)					
Primary energy (2020, IEA)	578 EJ	±20% (±10%)	1813	73	380
Electricity: nuclear (2020, IEA)	9.77 EJ	±30% (±20%)	1603	266	397
Electricity: solar and wind (2020. IEA, IRENA, BP, EMBERS).	8.51 EJ	±50% (±25%)	1459	377	430
Overall			**1686**	**580**	–
Future criteria (not used for exclusion in climate assessment but flagged to authors as potentially problematic)					
No net negative CO_2 emissions before 2030	CO_2 total in 2030 >0		1867	4	395
CCS from energy in 2030	<2000 $MtCO_2$ yr^{-1}		1518	183	565
Electricity from nuclear in 2030	<20 EJ yr^{-1}		1595	274	397
CH_4 emissions in 2040	100–1000 $MtCH_4$ yr^{-1}		1775	15	476

Rows do not sum to the same total of scenarios as not all scenarios reported all variables. EIP stands for energy and industrial process emissions.

9 https://data.ene.iiasa.ac.at/ar6/#/about.

models report only at five- to 10-year intervals. 2020 as reported in most scenarios collected in the database does not include the impact of the COVID-19 pandemic.

Almost three-quarters of submitted global scenarios passed the vetting. The remaining quarter comprised a fraction of scenarios that were rolled over from the SR1.5 database, and were no longer up to date with recent developments (excluding the COVID-19 shock). This included scenarios that started stringent mitigation action already in 2015. Other scenarios were expected to deviate from historical trends due to their diagnostic design. All historical criteria for reported variables needed to be met in order to pass the vetting.

2266 global scenarios were submitted to the scenario database that fulfilled a minimum requirement of reporting at least one global emission or energy variable covering multiple sectors. 1686 global scenarios passed the vetting criteria described in Table 11. These scenarios were subsequently flagged as meeting minimum quality standards for use in long-term scenarios assessment. Additional criteria for inclusion in the Chapter 3 climate assessment are described in Annex III.II.3.2.1.

A.III.II.3.2 Global Pathways

Scenarios were submitted by both individual studies and model inter-comparisons. The main model inter-comparisons submitting scenarios are shown in Table 12. Model inter-comparisons have a shared experimental design and assess research questions across different modelling platforms to enable more structured and systematic assessments. The model comparison projects thus help to understand the robustness of the insights.

The number of submitted scenarios varies considerably by study, for example from 10 to almost 600 scenarios for the model inter-comparison studies (Table 12). The number of scenarios also varies substantially by model (Table 15), highlighting the fact that the global scenario set collected in the AR6 scenario database is not a statistical sample (Section II.2.2).

Table 12 | Model inter-comparison studies that submitted global scenarios to the AR6 scenario database and for which at least one scenario passed the vetting. Scenario counts refer to all scenarios submitted by a study (in brackets), those that passed vetting (centre) and those that passed the vetting and received a climate assessment (left).

Project	Description	Publication year	Key references	Website	Number of scenarios
SSP model-comparison	The SSPs are part of a new framework that the climate change research community has adopted to facilitate the integrated analysis of future climate impacts, vulnerabilities, adaptation, and mitigation (II.1.3)	2017 / 2018	Riahi et al. (2017); Rogelj et al. (2018b)	https://tntcat.iiasa.ac.at/SspDb	70 / 77 (126)
ADVANCE	Developed a new generation of advanced IAMs and applied the improved models to explore different climate mitigation policy options in the post-Paris framework	2018	Luderer et al. (2018); Vrontisi et al. (2018)	http://www.fp7-advance.eu/	37 / 40 (72)
	Industry sector study	2017	Edelenbosch et al. (2017b)	http://www.fp7-advance.eu/	0 / 6 (6)
CD-LINKS	Exploring the complex interplay between climate action and development, while simultaneously taking both global and national perspectives and thereby informing the design of complementary climate-development policies	2018	McCollum et al. (2018); Roelfsema et al. (2020)	https://www.cd-links.org/	41 / 52 (77)
COMMIT	Exploring new climate policy scenarios at the global level and in different parts of the world	2021	van Soest et al. (2021)	https://themasites.pbl.nl/commit/	41 / 59 (68)
ENGAGE	Exploring new climate policy scenarios at the global level and in different parts of the world	2021	Riahi et al. (2021)	http://www.engage-climate.org/	591 / 591 (603)
EMF30	Energy Modelling Forum study into the role of non-CO_2 climate forcers	2020	Smith et al. (2020a); Harmsen et al. (2020)	https://emf.stanford.edu/projects/emf-30-short-lived-climate-forcers-air-quality	61 / 69 (149)
EMF33	Energy Modelling Forum study into the role of bioenergy	2020	Rose et al. (2020); Bauer et al. (2020a)	https://emf.stanford.edu/projects/emf-33-bio-energy-and-land-use	67 / 68 (173)
EMF36	Energy Modelling Forum study into the role of carbon pricing and economic implications of NDCs	2021	Böhringer et al. (2021)	https://emf.stanford.edu/projects/emf-36-carbon-pricing-after-paris-carpri	0 / 305 (320)

Project	Description	Publication year	Key references	Website	Number of scenarios
NGFS	Study for scenario-based financial risk assessment with details on impacts, and sectoral and regional granularity	2021	NGFS (2020, 2021)	https://www.ngfs.net/ngfs-scenarios-portal	24 / 24 (24) 2 / 2 (2)[10]
PARIS REINFORCE	Study on the long-term implications of current policies and NDCs	2020	Perdana et al. (2020)	https://paris-reinforce.eu	3 / 25 (39)
PARIS REINFORCE	Study with a focus on harmonising socio-economics and techno-economics in baselines	2021	Giarola et al. (2021)	https://paris-reinforce.eu	0 / 8 (16)
CLIMACAP-LAMP	Study on the role of climate change mitigation in Latin America	2016	van der Zwaan et al. (2016)	n.a.	0 / 10 (22)
				Total	**937 / 1336 (1697)**

Table 13 | Single-model studies that submitted global scenarios to the AR6 scenario database and for which at least one scenario passed the vetting. Scenario counts refer to all scenarios submitted by a study (in brackets), those that passed vetting (centre) and those that passed the vetting and received a climate assessment (left).

Title of study	Literature reference[11]	Number of scenarios
Quantification of an efficiency–sovereignty trade-off in climate policy	Bauer et al. (2020b)	4 / 4 (4)
Transformation and innovation dynamics of the energy-economic system within climate and sustainability limits	Baumstark et al. (2021)	18 / 18 (18)
Tracing international migration in projections of income and inequality across the Shared Socio-economic Pathways	Benveniste et al. (2021)	0 / 10 (10)
Targeted policies can compensate most of the increased sustainability risks in 1.5°C mitigation scenarios	Bertram et al. (2018)	3 / 3 (12)
Long term, cross country effects of buildings insulation policies	Edelenbosch et al. (2021)	0 / 8 (8)
The role of the discount rate for emission pathways and negative emissions	Emmerling et al. (2019)	4 / 4 (28)
Studies with the EPPA model on the costs of low-carbon power generation, the cost and deployment of CCS, the economics of BECCS, the global electrification of light duty vehicles, the 2018 food, water, energy and climate outlook and the 2021 global change outlook	Reilly et al. (2018); Morris et al. (2019, 2021); Smith et al. (2021); Fajardy et al. (202)1; Paltsev et al. (2021, 2022)	7 / 7 (10)
Transportation infrastructures in a low carbon world: An evaluation of investment needs and their determinants	Fisch-Romito and Guivarch (2019)	0 / 24 (32)
Measuring the sustainable development implications of climate change mitigation	Fujimori et al. (2020)	5 / 5 (5)
How uncertainty in technology costs and carbon dioxide removal availability affect climate mitigation pathways	Giannousakis et al. (2021)	9 / 9 (9)
A low energy demand scenario for meeting the 1.5°C target and sustainable development goals without negative emission technologies	Grubler et al. (2018)	1 / 1 (1)
Global Energy Interconnection: A scenario analysis based on the MESSAGEix-GLOBIOM Model	Guo et al. (2021)	20 / 20 (20)
Climate–carbon cycle uncertainties and the Paris Agreement	Holden et al. (2018)	0 / 5 (5)
Ratcheting ambition to limit warming to 1.5 °C – trade-offs between emission reductions and carbon dioxide removal	Holz et al. (2018)	6 / 6 (6)
Peatland protection and restoration are key for climate change mitigation	Humpenöder et al. (2020)	0 / 3 (3)
Energy Technology Perspectives 2020	IEA (2020b)	0 / 1 (1)
World Energy Outlook 2020 – Analysis – IEA	IEA (2020a)	0 / 1 (1)
Net Zero by 2050 – A Roadmap for the Global Energy Sector	IEA (2021)	0 / 1 (1)
Global Renewables Outlook: Energy transformation 2050	IRENA (2020)	0 / 2 (2)
Climate mitigation scenarios with persistent COVID-19-related energy demand changes	Kikstra et al. (2021a)	19 / 19 (19)
Global anthropogenic emissions of particulate matter including black carbon	Klimont et al. (2017)	0 / 2 (2)
Global energy perspectives to 2060 – WEC’s World Energy Scenarios 2019	Kober et al. (2020)	0 / 4 (4)
Prospects for fuel efficiency, electrification and fleet decarbonisation	Kodjak and Meszler (2019)	0 / 4 (4)
Short term policies to keep the door open for Paris climate goals	Kriegler et al. (2018b)	18 / 18 (18)
Deep decarbonisation of buildings energy services through demand and supply transformations in a 1.5°C scenario	Levesque et al. (2021)	4 / 4 (4)
Designing a model for the global energy system – GENeSYS-MOD: An application of the Open-Source Energy Modelling System (OSeMOSYS)	Löffler et al. (2017)	0 / 1 (1)
Impact of declining renewable energy costs on electrification in low emission scenarios	Luderer et al. (2021)	8 / 8 (8)

10 The first NGFS scenario publication in 2020 comprised 15 scenarios from the literature and 2 newly developed scenarios. The 15 scenarios are also contained in the database under their original study name.

11 Publication date of scenarios coincides with year of publication.

AIII

Title of study	Literature reference[11]	Number of scenarios
The road to achieving the long-term Paris targets: energy transition and the role of direct air capture	Marcucci et al. (2017)	1 / 1 (3)
The transition in energy demand sectors to limit global warming to 1.5°C	Méjean et al. (2019)	0 / 3 (27)
Deep mitigation of CO_2 and non-CO_2 greenhouse gases toward 1.5°C and 2°C futures	Ou et al. (2021)	34 / 35 (36)
Alternative electrification pathways for light-duty vehicles in the European transport sector	Rottoli et al. (2021)	8 / 8 (8)
Economic damages from on-going climate change imply deeper near-term emission cuts	Schultes et al. (2021)	24 / 24 (24)
A sustainable development pathway for climate action within the UN 2030 Agenda	Soergel et al. (2021)	8 / 8 (8)
Delayed mitigation narrows the passage between large-scale CDR and high costs	Strefler et al. (2018)	7 / 7 (7)
Alternative carbon price trajectories can avoid excessive carbon removal	Strefler et al. (2021b)	9 / 9 (9)
Carbon dioxide removal technologies are not born equal	Strefler et al. (2021a)	8 / 8 (8)
The Impact of U.S. Re-engagement in Climate on the Paris Targets	van de Ven et al. (2021)	0 / 10 (10)
The 2021 SSP scenarios of the IMAGE 3.2 model	Müller-Casseres et al. (2021); van Vuuren et al. (2014, 2021)	40 / 40 (40)
Pathway comparison of limiting global warming to 2°C	Wei et al. (2021)	0 / 5 (5)
	Total	**265 / 350 (421)**

A.III.II.3.2.1 Climate Classification of Global Pathways

The global scenarios underpinning the assessment in Chapter 3 have been classified, to the degree possible, by their warming outcome. The definition of the climate categories and the distribution of scenarios in the database across these categories is shown in Table 14 (Chapter 3, Section 3.2). The first four of these categories correspond to the ones used in the IPCC SR1.5 (Rogelj et al. 2018a) while the latter four have been added as part of the AR6 to capture a broader range of warming outcomes.

For inclusion in the climate assessment, in addition to passing the vetting (Section II.3.1), scenarios needed to run until the end of century and report as a minimum CO_2 (total and for energy and industrial processes (EIP)), CH_4 and N_2O emissions to 2100. Where CO_2 for AFOLU was not reported, the difference between total and EIP in 2020 must be greater than 500 $MtCO_2$. Of the total 2266 global scenarios submitted, 1574 could be assessed in terms of their associated climate response, and 1202 of those passed the vetting process.

Table 14 | Classification of global pathways into warming levels using MAGICC (Chapter 3, Section 3.2).

Description	Definition	Scenarios	
		Passed vetting	All
C1: Limit warming to 1.5°C (>50%) with no or limited overshoot	Reach or exceed 1.5°C during the 21st century with a likelihood of ≤67%, and limit warming to 1.5°C in 2100 with a likelihood >50%. Limited overshoot refers to exceeding 1.5°C by up to about 0.1°C and for up to several decades.	**97**	**160**
C2: Return warming to 1.5°C (>50%) after a high overshoot	Exceed warming of 1.5°C during the 21st century with a likelihood of >67%, and limit warming to 1.5°C in 2100 with a likelihood of >50%. High overshoot refers to temporarily exceeding 1.5°C global warming by 0.1°C–0.3°C for up to several decades.	**133**	**170**
C3: Limit warming to 2°C (>67%)	Limit peak warming to 2°C throughout the 21st century with a likelihood of >67%.	**311**	**374**
C4: Limit warming to 2ºC (>50%)	Limit peak warming to 2°C throughout the 21st century with a likelihood of >50%.	**159**	**213**
C5: Limit warming to 2.5°C (>50%)	Limit peak warming to 2.5°C throughout the 21st century with a likelihood of >50%.	**212**	**258**
C6: Limit warming to3°C (>50%)	Limit peak warming to 3°C throughout the 21st century with a likelihood of >50%.	**97**	**129**
C7: Limit warming to 4°C (>50%)	Limit peak warming to 4°C throughout the 21st century with a likelihood of >50%.	**164**	**230**
C8: Exceed warming of 4°C (≥50%)	Exceed warming of 4°C during the 21st century with a likelihood of ≥50%.	**29**	**40**
No climate assessment	Scenario time horizon <2100; insufficient emissions species reported.	**484**	**692**
	Total:	**1686**	**2266**

Table 15 | Global scenarios by modelling framework and climate category. Table includes number of scenarios that passed all vetting checks and number of all scenarios that received a climate categorisation (in brackets, including those not passing vetting). Unique model versions have been grouped into modelling frameworks for presentation in this table.[12] For a full list of unique model versions, please see the AR6 scenario database.

Model group	C1: Limit to 1.5°C (>50%) with no or limited OS	C2: Return to 1.5°C (>50%) after high OS	C3: Limit to 2°C (>67%)	C4: Limit to 2°C (>50%)	C5: Limit to 2.5°C (>50%)	C6: Limit to 3.0°C (>50%)	C7: Limit to 4.0°C (>50%)	C8: Exceed 4.0°C (≥50%)	No climate assessment	Total with climate categorisation
AIM/CGE+Hub	4 (18)	3 (7)	17 (37)	8 (23)	13 (23)	4 (7)	6 (32)	– (8)	7 (7)	55 (155)
C-ROADS	3 (3)	2 (2)						1 (1)		6 (6)
COFFEE	1 (1)	4 (7)	14 (16)	15 (22)	21 (24)	9 (11)	1 (3)			65 (84)
DNE21+	– (4)		– (7)	– (10)	– (3)	– (4)	– (8)		9 (10)	– (36)
EPPA			1 (3)	3 (4)		1 (1)	2 (2)			7 (10)
En-ROADS	– (2)							– (1)		– (3)
GCAM	6 (10)	6 (9)	13 (17)	9 (16)	6 (13)	– (1)	4 (6)	1 (1)	18 (63)	45 (73)
GCAM-PR					– (1)	1 (3)	2 (3)		13 (14)	3 (7)
GEM-E3	2 (2)	10 (10)	12 (12)	6 (6)	5 (5)	3 (3)	3 (3)		4 (11)	41 (41)
GRAPE-15				– (1)	– (7)	– (8)	– (2)			– (18)
IMAGE	7 (16)	9 (9)	34 (34)	18 (18)	22 (22)	16 (16)	34 (34)	2 (2)	2 (2)	142 (151)
MERGE-ETL	– (1)			1 (1)				– (1)		1 (3)
MESSAGE		– (1)	– (4)	– (3)			– (1)		– (1)	– (9)
MESSAGE-GLOBIOM	20 (20)	43 (48)	59 (61)	39 (40)	57 (59)	20 (22)	28 (33)	– (1)		266 (284)
POLES	4 (14)	10 (15)	26 (26)	24 (26)	20 (21)	11 (12)	19 (23)		1 (1)	114 (137)
REMIND	13 (15)	12 (19)	34 (39)	1 (1)	7 (8)	6 (6)	22 (24)	9 (9)		104 (121)
REMIND-MAgPIE	28 (36)	32 (33)	50 (50)	15 (15)	27 (27)	13 (13)	26 (26)	2 (2)		193 (202)
TIAM-ECN			20 (20)	6 (6)	10 (10)	4 (4)	5 (5)		– (13)	45 (45)
TIAM-UCL			– (4)	– (1)			– (2)			– (7)
TIAM-WORLD					– (3)	– (2)	– (4)		– (2)	– (9)
WITCH	5 (13)	1 (9)	29 (35)	14 (16)	24 (24)	9 (9)	4 (4)	4 (4)		90 (114)
WITCH-GLOBIOM	4 (5)	1 (1)	2 (9)	– (4)	– (8)	– (7)	8 (15)	10 (10)		25 (59)
Total	**97 (160)**	**133 (170)**	**311 (374)**	**159 (213)**	**212 (258)**	**97 (129)**	**164 (230)**	**29 (40)**	**54 (124)**	**1202 (1574)**

12 Scenario numbers by modelling framework combine submissions from different model versions of the same model (indicated by version number or project name in the AR6 scenario database). For the AIM, MESSAGE and REMIND modelling frameworks, the grouping covers the following distinct models (including different versions):
AIM/CGE+Hub: AIM/CGE, AIM/Hub
MESSAGE: MESSAGE, MESSAGE-Transport
MESSAGE-GLOBIOM: MESSAGE-GLOBIOM, MESSAGEix-GLOBIOM.
REMIND: REMIND, REMIND-H13, REMIND-Buildings, REMIND-Transport, REMIND_EU

Table 16 | Global scenarios by modelling framework that were not included in the climate assessment due to a time horizon shorter than 2100 or a limited reporting of emissions species that did not include CO_2 (total emissions or emissions from energy and industry), CH_4 or N_2O. Unique model versions have been grouped into modelling frameworks for presentation in this table.[13] For a full list of unique model versions, please see the AR6 scenario database.

Model framework	Time horizon	Passed vetting	Total
BET	2100	0	16
C-GEM	2030	32	32
C3IAM	2100	5	14
CGE-MOD	2030	32	32
DART	2030	17	32
E3ME	2050	10	10
EC-MSMR	2030	32	32
EDF-GEPA	2030	32	32
EDGE-Buildings	2100	8	8
ENV-Linkages	2060	7	15
ENVISAGE	2030	32	32
FARM	2100	0	13
GAINS	2050	2	2
GEMINI-E3	2050	6	6
GENeSYS-MOD	2050	1	1
Global TIMES	2050	0	14
GMM	2060	4	4
Global Transportation Roadmap	2050	4	4
ICES	2030/2050	32	43
IEA ETP	2070	1	1
IEA WEM	2050	2	2
IRENA REmap GRO2020	2050	2	2
IMACLIM	2050/2080	30	68
IMACLIM-NLU	2100	1	3
LUT-ESTM	2050	0	1
MAgPIE	2100	3	3
MIGRATION	2100	10	10
MUSE	2100	5	11
McKinsey	2050	0	3
PROMETHEUS	2050	7	7
SNOW	2030	32	32
TEA	2030	32	32
TIAM-Grantham	2100	17	19
WEGDYN	2030	32	32
Total		**430**	**568**

13 Scenario numbers by modelling framework combine submissions from different model versions of the same model (indicated by version number or project name in the AR6 scenario database).

Changes in climate classification of scenarios since SR1.5: Since the definition of warming classes was unchanged from SR1.5 for the lower range of scenarios limiting warming to 2°C or lower, changes in overall emissions characteristics of scenarios in these classes from SR1.5 to AR6 would need to come from the substantially larger ensemble of deep mitigation scenarios collected in the AR6 database compared to the SR1.5 database and from updates in the methodology of the climate assessment. Updates since SR1.5 include the methodology for infilling and harmonisation and the use of an updated climate emulator (MAGICC v7) to provide consistency with AR6 WGI assessment (Annex III.II.2.5.1). Out of the full set of SR1.5, 57% of the 411 scenarios that were represented with global temperature assessments in SR1.5 also have been assessed in AR6. Some SR1.5 scenarios could not be taken on board since they are outdated (too early emissions reductions) and failed the vetting or do not provide sufficient information/data to be included in AR6.

Comparison between SR1.5 and AR6 scenarios and associated climate responses are shown in Figure 6, bottom panel. We show that changes in the climate assessment pipeline are minor compared to climate model uncertainty ranges in WGI (in the order of 0.1°C), but show considerable variation due to different scenario characteristics. The updated harmonisation and infilling together have a small cooling effect compared to raw modelled emissions for the subset of 95 scenarios in C1, C2, and C3 that also were assessed in SR15 (SR1.5 Chapter 2, Table 2.4). This is due to both applying more advanced harmonisation methods consistent with the CMIP6 harmonisation used for WGI, and changing the historical harmonisation year from 2010 to 2015. Together with the update in the climate emulator, we find that the total AR6 assessment is remarkably consistent with SR1.5, albeit slightly cooler (in the order of 0.05°C at peak temperature, 0.1°C in 2100).

The lowest temperature category (C1, limiting warming to 1.5°C with no or low overshoot) used for classifying the most ambitious climate mitigation pathways in the literature, indicates that emissions are on average higher in AR6 in the near term (e.g., 2030) and the time of net-zero CO_2 is later by about five years compared to SR1.5 (Figure 6, middle panel). These differences can in part be ascribed to the fact that historical emissions in scenarios, especially among those that passed the vetting, have risen since SR1.5 in line with inventories. This increase has moved the attainable near-term emissions reductions upwards. As a result, the scenarios in the lowest category have also a lower probability of staying below 1.5°C peak warming. Using the WGI emulators, we find that the median probability of staying below 1.5°C in the lowest category (C1) has dropped from about 46% in the SR1.5 scenarios to 38% among the AR6 scenarios. Note that the likelihood of the SR1.5 scenarios limiting warming to 1.5°C with no or limited overshoot has changed from 41% in SR1.5 to 46% in AR6 due to the updated climate assessment using the WGI AR6 climate emulator. Within C1, the vast majority of scenarios that were submitted to AR6 but were not assessed in SR1.5 have median peak temperatures close to 1.6°C. The AR6 scenarios in the lowest category show higher emissions and have a lower chance of keeping warming below 1.5°C, as indicated by the panels showing the distribution of peak warming and exceedance probability in AR6 vs SR1.5, with for instance C1 median peak temperature warming going from 1.55°C in SR1.5 (1.52°C if reassessed with AR6 assessment pipeline) to 1.58°C in AR6.

A.III.II.3.2.2 Policy Classification of Global Scenarios

Global scenarios were also classified based on their assumptions regarding climate policy. This information can be deduced from study protocols or the description of scenario designs in the published literature. It has also been elicited as meta-information for scenarios that were submitted to the AR6 database. There are multiple purposes for a policy classification, including controlling for the level of near-term action (Chapter 3, Section 3.5) and estimating costs and other differences between two policy classes (Chapter 3, Section 3.6). Policy classes can be combined with climate classes, for example to identify scenarios that follow the NDC until 2030 and limit warming to 2°C (>67%).

Table 17 presents the policy classification that was chosen for this assessment and the distribution of scenarios across the policy classes. There is a top-level distinction between diagnostic scenarios, scenarios from cost-benefit analyses, scenarios without globally coordinated action, scenarios with immediate such action, and hybrid scenarios that move to globally coordinated action after a period of diverse and uncoordinated national action. On the second hierarchy level, scenarios are classified along distinctive features of scenarios in each class. Scenarios without globally coordinated action are often used as reference scenarios and come as baselines without climate policy efforts, as an extrapolation of current policy trends or as implementation and extrapolation of NDCs (Grant et al. 2020). Scenarios that act immediately to limit warming to some level can be distinguished by whether or not they include transfers to reflect equity considerations (Tavoni et al. 2015; Bauer et al. 2020c; van den Berg et al. 2020) or by whether or not they assume additional policies augmenting a global carbon price (Soergel et al. 2021). Scenarios that delay globally coordinated action until 2030 can differ in their assumptions about the level of near-term action (Roelfsema et al. 2020; van Soest et al. 2021).

To identify the policy classification of each global scenario in the AR6 database, classes are first assigned via text pattern matching on all the metadata collected when submitting the scenarios to the database. The algorithm first looks for keywords and text patterns to establish whether a scenario represents a global, fragmented, diagnostic or CBA policy setup. Then it looks for evidence on the presence of specific regional policies, delayed actions and transfers of permits. Eventually the different pieces of evidence are harmonised into a single policy categorisation decision. The process has been calibrated on the best-known scenarios belonging to the larger model intercomparison projects, and fine-tuned on the other scenarios via further validation against the related literature, consistency checks on reported emission and carbon price trajectories, exchanges with modellers and supervision by the involved IPCC authors. If the information available is enough to identify a policy category number but not sufficient for a subcategory, then only the number is retained (e.g., P2 instead of P2a/b/c). A suffix added after P0 further qualifies a diagnostic scenario as one of the other policy categories.

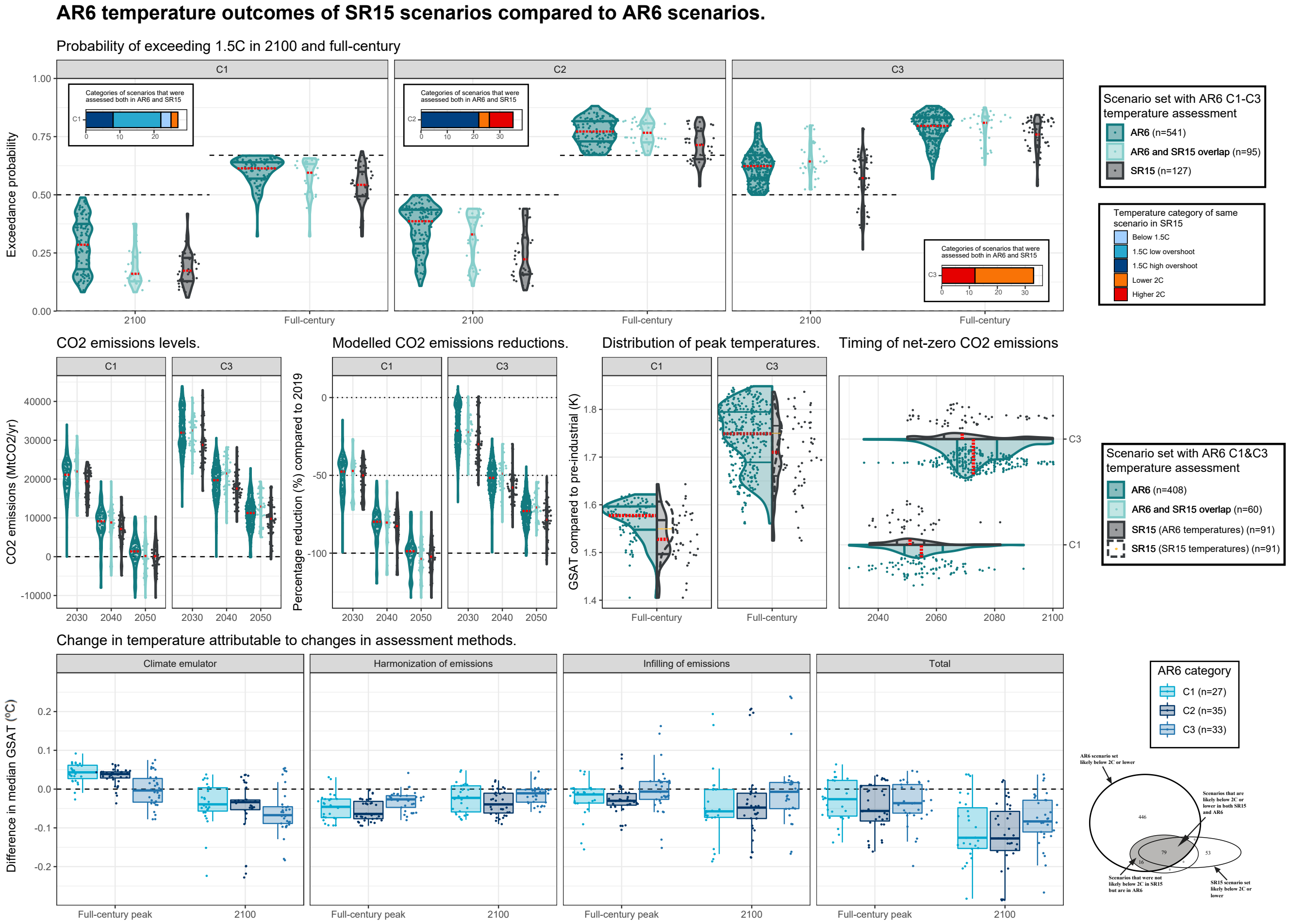


Figure 6 | Comparing multiple characteristics of scenarios underlying SR1.5 Table 2.4 to the AR6 assessment.

Top row: The probability of exceeding 1.5C for scenarios using the AR6 climate assessment pipeline for C1, C2, and C3. All scenarios in AR6 that pass vetting requirements and get climate classification C1, C2, or C3, are labelled as 'AR6' (n=541). The scenarios that are both in the AR6 database (passing the vetting) and were used for SR1.5 Table 2.4, and are classified as C1, C2 and C3 using the AR6 assessment, are labelled as 'AR6 and SR1.5 overlap' (n=95). 'SR1.5 (n=127)' shows all SR1.5 scenarios (except five that were not resubmitted for the AR6 report), including those that failed AR6 vetting, that are classified C1, C2, C3 with the updated AR6 temperature assessment. Dashed lines indicate cut-off temperature exceedance probabilities that align with AR6 category definitions. The violin area is proportional to the number of scenarios. Coloured lines indicate the 25th and 75th percentiles, while the dashed black line indicates the median. The insets in each figure show how the temperature category classifications have changed from SR1.5 to AR6 for those scenarios that are in both databases.

Middle row: Characteristics of CO_2 emissions pathways and the distribution of median peak temperature assessments for C1 and C3. From left to right: (i) Change in CO_2 emissions levels and reductions in 2030, 2040 and 2050 between the AR6 (n=408), AR6 and SR1.5 overlap (n=60) and SR15 sets (n=91). (ii) distribution of scenarios with different median peak temperature scenario outcomes for C1 and C3 for AR6 and SR1.5 (both with AR6 temperature assessment as a solid line and with SR1.5 temperature assessment as a dashed line, with median in yellow). (iii) Year of net-zero CO_2 for C1 and C3 for AR6 and SR1.5. Within C3, 27 AR6 scenarios and 2 SR1.5 scenarios with no net-zero year before 2100 have not been visualised. The violin area is proportional to the number of scenarios. Coloured lines indicate the 25th and 75th percentiles, while the dashed black line indicates the median.

Bottom row: Change in median global mean surface air temperature (GSAT) between the AR6 and SR1.5 climate assessments for both 2100 values and peak temperature values during the 21st century. Positive values indicate that the temperature assessment is higher for the same scenario than the SR1.5 climate assessment. From left to right: (i) the effect of using MAGICCv7 calibrated to the WGI assessment compared with MAGICC6 as used in SR1.5; (ii) the effect of more advanced emissions harmonisation methods; (iii) the effect of more advanced emissions infilling methods; (iv) the total effect which is the sum of the three components. Boxplots show the median and interquartile range, with the whiskers indicating the 95% range.

Table 17 | Policy classification of global scenarios. If the total for a class exceeds the sum of the subclasses, there are scenarios in the class that could not be assigned to a subclass.

Class	Definition	Number of scenarios		
		Passed vetting, with climate assessment	Passed vetting	All
P0	**Diagnostic scenario**	**73**	**99**	138
P1	**No globally coordinated climate policy and either**	**207**	**500**	632
P1a	– no climate mitigation efforts	72	124	179
P1b	– current national mitigation efforts	51	59	72
P1c	– NDCs	56	160	184
P1d	– other policy assumptions	24	153	189
P2	**Globally coordinated climate policies with immediate (i.e., before 2030) action and**	**579**	**634**	992
P2a	– without any transfer of emission permits	403	435	610
P2b	– with transfers	70	70	143
P2c	– with additional policy assumptions	45	55	83
P3	**Globally coordinated climate policies with delayed (i.e., from 2030 onwards or after 2030) action, preceded by**	**341**	**451**	502
P3a	– no mitigation commitment or current national policies	3	7	9
P3b	– NDCs	322	426	464
P3c	– NDCs and additional policies	16	18	29
P4	**Cost-benefit analysis**	**2**	**2**	**2**
	Total	**1202**	**1686**	**2266**

A.III.II.3.3 National and Regional Pathways

National and regional pathways have been collected in the AR6 scenario database to support the Chapter 4 assessment. In total more than 500 pathways for 24 countries/regions have been submitted to the AR6 scenario database by integrated assessment, energy-economic and computable general equilibrium modelling research teams. This represents a limited sample of the overall literature on mitigation pathways at the national level. The majority of these pathways originate from a set of larger model intercomparison projects, JMIP/EMF35 (Sugiyama et al. 2020a) focusing on Japan, CD-LINKS (Roelfsema et al. 2020; Schaeffer et al. 2020), COMMIT (van Soest et al. 2021), ENGAGE (Fujimori et al. 2021), and Paris Reinforce (Perdana et al. 2020; Nikas et al. 2021) each covering several countries/regions from the following: Australia, Brazil, China, EU, India, Indonesia, Japan, Korea, Russia, Thailand, USA, Vietnam. The remaining pathways stem from individual modelling studies that submitted scenarios to the database (Table 18).

Table 18 | National and regional mitigation pathways by modelling framework, region and scenario type.

Country/ region[a]	Model	CP	NDC	Other	Total
ARG	IMACLIM-ARG		1	2	3
AUS	TIMES-Australia	1		7	8
BRA	BLUES-Brazil	2	2	15	19
BRA	COPPE_MSB-Brazil			8	8
BRA	IMACLIM-BRA			5	5
CHE	STEM-Switzerland	1		11	12
CHN	AIM/Hub-China	1	1	7	9
CHN	C3IAM		3	11	14
CHN	DREAM-China			1	1
CHN	GENeSYS-MOD-CHN			3	3
CHN	IPAC-AIM/technology-China	1	1	11	13
CHN	PECE-China			2	2
CHN	TIMES-Australia		1		1
CHN	TIMES-China	1	2	8	11
ECU	ELENA-Ecuador			2	2
ETH	TIAM-ECN ETH	1		1	2
EU	E4SMA-EU-TIMES	1			1
EU	eTIMES-EU			23	23
EU	JRC-EU-TIMES			8	8
EU	PRIMES	2	2	9	13
EU	REMIND_EU			9	9
FRA	TIMES-France			8	8
GBR	7see			11	11
IDN	AIM/Hub-Indonesia			2	2
IDN	DDPP Energy			4	4
IND	AIM/Enduse India	1	1	5	7
IND	AIM/Hub-India	1	1	7	9
IND	MARKAL-INDIA	2	3	13	18
JPN	AIM/CGE-Enduse-Japan			6	6
JPN	AIM/Enduse-Japan	3	3	69	75

Country/ region[a]	Model	CP	NDC	Other	Total
JPN	AIM/Hub-Japan	1	2	42	45
JPN	DNE21-Japan		1	30	31
JPN	DNE21+ V.14 (national)	1	1	4	6
JPN	IEEJ-Japan		1	34	35
KEN	TIAM-ECN KEN	1	1	2	4
KOR	AIM/CGE-Korea	1	1	6	8
KOR	AIM/Hub-Korea	1	1	7	9
MDG	TIAM-ECN MDG	1	2		3
MEX	GENeSYS-MOD-MEX			4	4
PRT	TIMES-Portugal		1	3	4
RUS	RU-TIMES	1	1	4	6
SWE	TIMES-Sweden			4	4
THA	AIM/Hub-Thailand	1	2	19	22
USA	GCAM-USA	2	2	9	13
USA	RIO-USA			12	12
VNM	AIM/Hub-Vietnam	1	2	14	17
ZAF	TIAM-ECN AFR			4	4
	Total	29	39	466	534

[a] Countries are abbreviated by their ISO 3166-1 alpha-3 letter codes. EU denotes the European Union.

Notes: CP = current policies, NDC = implementation of Nationally Determined Contributions by 2025/30, Other = all other scenarios.

A.III.II.3.4 Sector Transition Pathways

Sectoral transition pathways based on the AR6 scenario database are addressed in a number of Chapters, primarily Chapter 6 (Energy systems), Chapter 7 (AFOLU), Chapter 9 (Buildings), Chapter 10 (Transport) and Chapter 11 (Industry). These analyses cover both contributions from global IAMs and from sector-specific models with regional or global coverage. The assessments cover a variety of perspectives, including long-term global and macro-region trends for the sectors, sectoral analysis of the Illustrative Pathways, and comparison of the scenarios between full-economy IAMs and sector-specific models on shorter time horizons. These perspectives have a bi-directional utility – to understand how well IAMs are representing sectoral trends from more granular models, and to position sectoral models in the context of full-economy transitions to verify consistency with different climate outcomes.

Table 19 | Overview of how models and scenarios were used in sectoral chapters. All scenario and model counts listed in the table are contained in the AR6 scenario database, with the exception of Chapter 9 (Buildings), which supplemented its dataset with a large number of scenarios separately pulled from the sectoral literature. Scenario counts represents unique model-scenario combinations in the database.

Sector	Number of models	Number of scenarios	Key sections	Key perspectives
Energy systems (Chapter 6)	12 18 13	476 536 776	6.6 6.7 6.7.1	Regional and global energy system characteristics along mitigation pathways and at net-zero emissions specifically: CO_2 and GHG emissions; energy resource shares; electricity and hydrogen shares of final energy; energy intensity; per-capita energy use; peak emissions; energy investments
AFOLU (Chapter 7)	11 14 13 3	384 572 559 4	7.5.1 7.5.2 7.5.4 7.5.5	Regional and global GHG emissions and land use dynamics; economic mitigation potential for different GHGs; integrated mitigation pathways
Buildings (Chapter 9)	80 *(of which 2 are in AR6 scenario database)*	82 *(of which 4 are in AR6 scenario database)*	9.3, 9.6	A mixture of top-down and bottom-up models. The former were either national, regional or global while the latter were global only with a breakdown per end use, building type, technologies and energy carrier
Transport (Chapter 10)	24	1210	10.7	Global and regional transport demand, activity, modes, vehicles, fuels, and mitigation options
Industry (Chapter 11)	14	508	11.4.2	Global final energy use, CO_2 emissions, carbon sequestration, fuel shares

Note 1: The number of models and scenarios reported in the table cannot be summed across chapters, as there is considerable overlap in selected model-scenario combinations across chapters, depending on the filtering processes used for relevant analyses. Moreover, the numbers in the table – and certainly not their sum – are not intended to match those reported for the global pathways assessed by Chapter 3 in Section II.3.2.

Note 2: Numbers shown in the model-count column are arrived at through the authors' best judgement. This has to do with the overlapping nature of unique model versions (within a given model family) as models evolve over time. In this case, model versions with substantial overlap were considered the same model, whereas model versions that differ significantly were counted as unique. For example, MESSAGEix-GLOBIOM 1.0 and MESSAGEix-GLOBIOM_1.1 are counted as the same model, while MESSAGEix-GLOBIOM 1.0 and MESSAGE are counted as different. If instead counting all model versions uniquely, then the following counts would apply to each chapter: Energy systems (30/38/29), AFOLU (18/27/25/4), Buildings (80), Transport (50), Industry (32).

Note 3: The Transport chapter figures in Chapter 10, Section 10.7, are produced from the final AR6 scenario database by the code accompanying this report. The set of model and scenario names appearing in each plot or figure of Section 10.7 varies, depending on whether particular submissions to the database included the specific variables appearing in that plot. Authors advise inspecting the data files accompanying each figure for the set of models/scenarios specific to that figure, or running the code against the final database snapshot to reproduce the figures in question.

References

Absar, S.M. and B.L. Preston, 2015: Extending the Shared Socioeconomic Pathways for sub-national impacts, adaptation, and vulnerability studies. *Glob. Environ. Change*, **33**, 83–96, doi:10.1016/j.gloenvcha.2015.04.004.

Abujarad, S.Y., M.W. Mustafa, and J.J. Jamian, 2017: Recent approaches of unit commitment in the presence of intermittent renewable energy resources: A review. *Renew. Sustain. Energy Rev.*, **70**, 215–223, doi:10.1016/j.rser.2016.11.246.

ADB, 2017: *Pathways to Low-Carbon Development for Viet Nam*. Asian Development Bank, Phillippines, 138 pp.

Admiraal, A.K., A.F. Hof, M.G.J. den Elzen, and D.P. van Vuuren, 2016: Costs and benefits of differences in the timing of greenhouse gas emission reductions. *Mitig. Adapt. Strateg. Glob. Change*, **21(8)**, doi:10.1007/s11027-015-9641-4.

Aghajani, G.R., H.A. Shayanfar, and H. Shayeghi, 2017: Demand side management in a smart micro-grid in the presence of renewable generation and demand response. *Energy*, **126**, 622–637, doi:10.1016/j.energy.2017.03.051.

Aguiar, A.P.D. et al., 2020: Co-designing global target-seeking scenarios: A cross-scale participatory process for capturing multiple perspectives on pathways to sustainability. *Glob. Environ. Change*, **65**, 102198, doi:10.1016/j.gloenvcha.2020.102198.

Alaidroos, A. and M. Krarti, 2015: Optimal design of residential building envelope systems in the Kingdom of Saudi Arabia. *Energy Build.*, **86**, 104–117, doi:10.1016/j.enbuild.2014.09.083.

Ameli, N. et al., 2021: Higher cost of finance exacerbates a climate investment trap in developing economies. *Nat. Commun.*, **12(1)**, doi:10.1038/s41467-021-24305-3.

Anderson, K. and G. Peters, 2016: The trouble with negative emissions. *Science*, **354(6309)**, 182–183, doi:10.1126/science.aah4567.

Andrijevic, M., J. Crespo Cuaresma, T. Lissner, A. Thomas, and C.F. Schleussner, 2020a: Overcoming gender inequality for climate resilient development. *Nat. Commun.*, **11(1)**, 1–8, doi:10.1038/s41467-020-19856-w.

Andrijevic, M., J. Crespo Cuaresma, R. Muttarak, and C.-F. Schleussner, 2020b: Governance in socioeconomic pathways and its role for future adaptive capacity. *Nat. Sustain.*, **3(1)**, 35–41, doi:10.1038/s41893-019-0405-0.

Andrijevic, M., C.-F. Schleussner, M.J. Gidden, D.L. McCollum, and J. Rogelj, 2020c: COVID-19 recovery funds dwarf clean energy investment needs. *Science*, **370(6514)**, 298–300, doi:10.1126/science.abc9697.

Arbabzadeh, M., R. Sioshansi, J.X. Johnson, and G.A. Keoleian, 2019: The role of energy storage in deep decarbonization of electricity production. *Nat. Commun.*, **10**, doi:10.1038/s41467-019-11161-5.

Arrow, K. et al., 2013: Determining benefits and costs for future generations. *Science*, **341(6144)**, 349–350, doi:10.1126/science.1235665.

Arvesen, A., G. Luderer, M. Pehl, B.L. Bodirsky, and E.G. Hertwich, 2018: Deriving life cycle assessment coefficients for application in integrated assessment modelling. *Environ. Model. Softw.*, **99**, 111–125, doi:10.1016/j.envsoft.2017.09.010.

Auer, C. et al., 2021: Climate change scenario services: From science to facilitating action. *One Earth*, **4(8)**, 1074–1082, doi:10.1016/j.oneear.2021.07.015.

Babatunde, K.A., R.A. Begum, and F.F. Said, 2017: Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review. *Renew. Sustain. Energy Rev.*, **78**, 61–71, doi:10.1016/j.rser.2017.04.064.

Babiker, M.H. and R.S. Eckaus, 2007: Unemployment effects of climate policy. *Environ. Sci. Policy*, **10(7–8)**, 600–609, doi:10.1016/j.envsci.2007.05.002.

Badesa, L., F. Teng, and G. Strbac, 2020: Optimal Portfolio of Distinct Frequency Response Services in Low-Inertia Systems. *IEEE Trans. Power Syst.*, **35(6)**, 4459–4469, doi:10.1109/TPWRS.2020.2997194.

Baitz, M., 2017: Attributional Life Cycle Assessment. In: *Goal and Scope Definition in Life Cycle Assessment*, Springer, Dordrecht, The Netherlands, pp. 123–143.

Bajželj, B. et al., 2014: Importance of food-demand management for climate mitigation. *Nat. Clim. Change*, **4(10)**, 924–929, doi:10.1038/nclimate2353.

Bamber, N. et al., 2020: Comparing sources and analysis of uncertainty in consequential and attributional life cycle assessment: review of current practice and recommendations. *Int. J. Life Cycle Assess.*, **25(1)**, doi:10.1007/s11367-019-01663-1.

Baños, R. et al., 2011: Optimization methods applied to renewable and sustainable energy: A review. *Renew. Sustain. Energy Rev.*, **15(4)**, 1753–1766, doi:10.1016/j.rser.2010.12.008.

Barker, T. and S. Scrieciu, 2010: Modeling low climate stabilization with E3MG: Towards a "new economics" approach to simulating energy-environment-economy system dynamics. *Energy J.*, **31** (special issue), 137–164, doi:10.5547/issn0195-6574-ej-vol31-nosi-6.

Barter, G.E., M.A. Tamor, D.K. Manley, and T.H. West, 2015: Implications of modeling range and infrastructure barriers to adoption of battery electric vehicles. *Transp. Res. Rec.*, **2502(1)**, 80–88, doi:10.3141/2502-10.

Bashmakov, I., 2017: Improving the Energy Efficiency of Russian Buildings. *Probl. Econ. Transit.*, **58(11–12)**, 1096–1128, doi:10.1080/10611991.2016.1316099.

Bauer, N., O. Edenhofer, and S. Kypreos, 2008: Linking energy system and macroeconomic growth models. *Comput. Manag. Sci.*, **5(1–2)**, 95–117, doi:10.1007/s10287-007-0042-3.

Bauer, N. et al., 2016: Global fossil energy markets and climate change mitigation – an analysis with REMIND. *Clim. Change*, **136(1)**, 69–82, doi:10.1007/s10584-013-0901-6.

Bauer, N. et al., 2017: Shared Socio-Economic Pathways of the Energy Sector – Quantifying the Narratives. *Glob. Environ. Change*, **42**, 316–330, doi:10.1016/j.gloenvcha.2016.07.006.

Bauer, N. et al., 2020a: Global energy sector emission reductions and bioenergy use: overview of the bioenergy demand phase of the EMF-33 model comparison. *Clim. Change*, **163(3)**, 1553–1568, doi:10.1007/s10584-018-2226-y.

Bauer, N. et al., 2020b: Quantification of an efficiency–sovereignty trade-off in climate policy. *Nature*, **588(7837)**, 261–266, doi:10.1038/s41586-020-2982-5.

Bauer, N. et al., 2020c: Bio-energy and CO_2 emission reductions: an integrated land-use and energy sector perspective. *Clim. Change*, **163(3)**, doi:10.1007/s10584-020-02895-z.

Baumstark, L. et al., 2021: REMIND2.1: transformation and innovation dynamics of the energy-economic system within climate and sustainability limits. *Geosci. Model Dev.*, **14(10)**, 6571–6603, doi:10.5194/gmd-14-6571-2021.

Beach, R.H. et al., 2015: Global mitigation potential and costs of reducing agricultural non-CO_2 greenhouse gas emissions through 2030. *J. Integr. Environ. Sci.*, **12**, 87–105, doi:10.1080/1943815X.2015.1110183.

Beck, S. and M. Mahony, 2017: The IPCC and the politics of anticipation. *Nat. Clim. Change*, **7(5)**, 311–313, doi:10.1038/nclimate3264.

Bednar, J., M. Obersteiner, and F. Wagner, 2019: On the financial viability of negative emissions. *Nat. Commun.*, **10(1)**, 1783, doi:10.1038/s41467-019-09782-x.

Bellocchi, S., M. Manno, M. Noussan, M.G. Prina, and M. Vellini, 2020: Electrification of transport and residential heating sectors in support of renewable penetration: Scenarios for the Italian energy system. *Energy*, **196**, 117062, doi:10.1016/j.energy.2020.117062.

Benveniste, H., J.C. Cuaresma, M. Gidden, and R. Muttarak, 2021: Tracing international migration in projections of income and inequality across

AIII

the Shared Socioeconomic Pathways. *Clim. Change,* **166(39)**, 1–22, doi:10.1007/S10584-021-03133-W.

Bertram, C. et al., 2015: Complementing carbon prices with technology policies to keep climate targets within reach. *Nat. Clim. Change*, **5(3)**, 235–239, doi:10.1038/nclimate2514.

Bertram, C. et al., 2018: Targeted policies can compensate most of the increased sustainability risks in 1.5 °C mitigation scenarios. *Environ. Res. Lett.*, **13(6)**, doi:10.1088/1748-9326/aac3ec.

Bertram, C. et al., 2021: Energy system developments and investments in the decisive decade for the Paris Agreement goals. *Environ. Res. Lett.*, **16(7)**, 74020, doi:10.1088/1748-9326/ac09ae.

Bierwirth, A. and S. Thomas, 2019: *Estimating the sufficiency potential in buildings: the space between under-dimensioned and oversized*. ECEEE Summer Study Proceedings.

Bijl, D.L., P.W. Bogaart, S.C. Dekker, and D.P. van Vuuren, 2018: Unpacking the nexus: Different spatial scales for water, food and energy. *Glob. Environ. Change..*, **48**, 22–31, doi:10.1016/J.GLOENVCHA.2017.11.005.

Bistline, J.E.T. and D.T. Young, 2019: Economic drivers of wind and solar penetration in the US. *Environ. Res. Lett.*, **14(12)**, 1–12, doi:10.1088/1748-9326/ab4e2d.

Blanford, G., J. Merrick, R. Richels, and S. Rose, 2014a: Trade-offs between mitigation costs and temperature change. *Clim. Change*, **123(3–4)**, 527–541, doi:10.1007/s10584-013-0869-2.

Blanford, G.J., E. Kriegler, and M. Tavoni, 2014b: Harmonization vs. fragmentation: Overview of climate policy scenarios in EMF27. *Clim. Change*, **123(3–4)**, 383–396, doi:10.1007/s10584-013-0951-9.

Blass, V. and C.J. Corbett, 2018: Same Supply Chain, Different Models: Integrating Perspectives from Life Cycle Assessment and Supply Chain Management. *J. Ind. Ecol.*, **22(1)**, doi:10.1111/jiec.12550.

Böhringer, C., S. Peterson, T.F. Rutherford, J. Schneider, and M. Winkler, 2021: Climate policies after Paris: Pledge, Trade and Recycle: Insights from the 36th Energy Modeling Forum Study (EMF36). *Energy Econ.*, **103**, doi:10.1016/j.eneco.2021.105471.

Bonsch, M. et al., 2015: Environmental flow provision: Implications for agricultural water and land-use at the global scale. *Glob. Environ. Change*, **30**, 113–132, doi:10.1016/j.gloenvcha.2014.10.015.

Bos, A.B. et al., 2020: Integrated assessment of deforestation drivers and their alignment with subnational climate change mitigation efforts. *Environ. Sci. Policy*, **114**, 352–365, doi:10.1016/j.envsci.2020.08.002.

Bosetti, V. et al., 2015: Sensitivity to energy technology costs: A multi-model comparison analysis. *Energy Policy*, **80**, 244–263, doi:10.1016/j.enpol.2014.12.012.

Bourdeau, M., X. qiang Zhai, E. Nefzaoui, X. Guo, and P. Chatellier, 2019: Modeling and forecasting building energy consumption: A review of data-driven techniques. *Sustain. Cities Soc.*, **48**, doi:10.1016/j.scs.2019.101533.

Brear, M.J., R. Baldick, I. Cronshaw, and M. Olofsson, 2020: Sector coupling: Supporting decarbonisation of the global energy system. *Electr. J.*, **33(9)**, doi:10.1016/j.tej.2020.106832.

Bréchet, T., F. Gerard, and H. Tulkens, 2011: Efficiency vs. Stability in Climate Coalitions: A Conceptual and Computational Appraisal. *Energy J.*, **32(1)**, doi:10.5547/ISSN0195-6574-EJ-Vol32-No1-3.

Brooker, A., J. Gonder, S. Lopp, and J. Ward, 2015: ADOPT: A Historically Validated Light Duty Vehicle Consumer Choice Model. *SAE Technical Papers*, Vol. 2015 (April).

Brown, T., J. Hörsch, and D. Schlachtberger, 2018: PyPSA: Python for Power System Analysis. *J. Open Res. Softw.*, **6**, doi:10.5334/jors.188.

Brugger, H., W. Eichhammer, N. Mikova, and E. Dönitz, 2021: Energy Efficiency Vision 2050: How will new societal trends influence future energy demand in the European countries? *Energy Policy*, **152**, doi:10.1016/j.enpol.2021.112216.

Brutschin, E. et al., 2021: A multidimensional feasibility evaluation of low-carbon scenarios. *Environ. Res. Lett.*, **16(6)**, doi:10.1088/1748-9326/abf0ce.

Budinis, S., S. Krevor, N. Mac Dowell, N. Brandon, and A. Hawkes, 2018: An assessment of CCS costs, barriers and potential. *Energy Strateg. Rev.*, **22**, 61–81, doi:10.1016/j.esr.2018.08.003.

Bürger, V., T. Hesse, B. Köhler, A. Palzer, and P. Engelmann, 2019: German Energiewende—different visions for a (nearly) climate neutral building sector in 2050. *Energy Effic.*, **12(1)**, doi:10.1007/s12053-018-9660-6.

Burniaux, J.-M. and J. Chateau, 2010: *An Overview of the OECD ENV-Linkages model*. OECD, Paris, France, 17 pp.

Butler, C. et al., 2020: *Decarbonisation futures: Solutions, actions and benchmarks for a net zero emissions Australia*. ClimateWorks Australia, Melbourne, Australia, 138 pp.

Butnar, I. et al., 2020: A deep dive into the modelling assumptions for biomass with carbon capture and storage (BECCS): A transparency exercise. *Environ. Res. Lett.*, **15(8)**, 84008, doi:10.1088/1748-9326/ab5c3e.

Calise, F. et al., 2021: Energy and economic assessment of energy efficiency options for energy districts: Case studies in Italy and Egypt. *Energies*, **14(4)**, 1–24, doi:10.3390/en14041012.

Calvin, K. et al., 2014a: EU 20-20-20 energy policy as a model for global climate mitigation. *Clim. Policy*, **14(5)**, 581–598, doi:10.1080/14693062.2013.879794.

Calvin, K. et al., 2014b: Trade-offs of different land and bioenergy policies on the path to achieving climate targets. *Clim. Change*, **123(3–4)**, 691–704, doi:10.1007/s10584-013-0897-y.

Calvin, K. et al., 2017: The SSP4: A world of deepening inequality. *Glob. Environ. Change*, **42**, 284–296, doi:10.1016/j.gloenvcha.2016.06.010.

Calvin, K. et al., 2019: GCAM v5.1: representing the linkages between energy, water, land, climate, and economic systems. *Geosci. Model Dev.*, **12(2)**, 677–698, doi:10.5194/gmd-12-677-2019.

Calvin, K. et al., 2021: Bioenergy for climate change mitigation: Scale and sustainability. *GCB Bioenergy*, **13(9)**, 1346–1371, doi:10.1111/gcbb.12863.

Cameron, C. et al., 2016: Policy trade-offs between climate mitigation and clean cook-stove access in South Asia. *Nat. Energy*, **1(1)**, 1–5, doi:10.1038/nenergy.2015.10.

Capellán-Pérez, I. et al., 2020: MEDEAS: A new modeling framework integrating global biophysical and socioeconomic constraints. *Energy Environ. Sci.*, **13(3)**, 986–1017, doi:10.1039/c9ee02627d.

Capros, P. et al., 2013: *GEM-E3 Model Documentation*. European Commission, Seville, Spain, 154 pp.

Capros, P. et al., 2014: European decarbonisation pathways under alternative technological and policy choices: A multi-model analysis. *Energy Strateg. Rev.*, **2(3–4)**, 231–245, doi:10.1016/j.esr.2013.12.007.

Cedillos Alvarado, D., S. Acha, N. Shah, and C.N. Markides, 2016: A Technology Selection and Operation (TSO) optimisation model for distributed energy systems: Mathematical formulation and case study. *Appl. Energy*, **180**, 491–503, doi:10.1016/j.apenergy.2016.08.013.

Cetinkaya, E., I. Dincer, and G.F. Naterer, 2012: Life cycle assessment of various hydrogen production methods. *Int. J. Hydrogen Energy*, **37(3)**, doi:10.1016/j.ijhydene.2011.10.064.

Chaichaloempreecha, A., P. Winyuchakrit, and B. Limmeechokchai, 2017: Long-term energy savings and GHG mitigations in Thailand's building sector: Impacts of energy efficiency plan. *Energy Procedia*, **138**, 847–852, doi:10.1016/j.egypro.2017.10.110.

Chang, J. et al., 2021: Reconciling regional nitrogen boundaries with global food security. *Nat. Food*, **2(9)**, doi:10.1038/s43016-021-00366-x.

Chen, Y.-H.H., S. Paltsev, J.M. Reilly, J.F. Morris, and M.H. Babiker, 2016: Long-term economic modeling for climate change assessment. *Econ. Model.*, **52**, doi:10.1016/j.econmod.2015.10.023.

Cheng, R. et al., 2015: A multi-region optimization planning model for China's power sector. *Appl. Energy*, **137**, 413–426, doi:10.1016/j.apenergy.2014.10.023.

Christensen, P., K. Gillingham, and W. Nordhaus, 2018: Uncertainty in forecasts of long-run economic growth. *Proc. Natl. Acad.*, **115(21)**, 5409–5414, doi:10.1073/pnas.1713628115.

Chu, Z., U. Markovic, G. Hug, and F. Teng, 2020: Towards optimal system scheduling with synthetic inertia provision from wind turbines. *IEEE Trans. Power Syst.*, **35(5)**, 4056–4066, doi:10.1109/TPWRS.2020.2985843.

Clark, M.A. et al., 2020: Global food system emissions could preclude achieving the 1.5° and 2°C climate change targets. *Science*, **370(6517)**, 705–708, doi:10.1126/science.aba7357.

Clarke, L. et al., 2009: International climate policy architectures: Overview of the EMF 22 International Scenarios. *Energy Econ.*, **31**, S64–S81, doi:10.1016/j.eneco.2009.10.013.

Clarke L., K. Jiang, K. Akimoto, M. Babiker, G. Blanford, K. Fisher-Vanden, J.-C. Hourcade, V. Krey, E. Kriegler, A. Löschel, D. McCollum, S. Paltsev, S. Rose, P.R. Shukla, M. Tavoni, B.C.C. van der Zwaan, and D.P. van Vuuren, 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, UK and New York, NY, USA.

Colenbrander, S., A. Sudmant, N. Chilundika, and A. Gouldson, 2019: The scope for low-carbon development in Kigali, Rwanda: An economic appraisal. *Sustain. Dev.*, **27(3)**, 349–365, doi:10.1002/sd.1906.

Collins, M., R. Knutti, J. Arblaster, J.-L. Dufresne, T. Fichefet, P. Friedlingstein, X. Gao, W.J. Gutowski, T. Johns, G. Krinner, M. Shongwe, C. Tebaldi, A.J. Weaver and M. Wehner, 2013: Long-term Climate Change: Projections, Commitments and Irreversibility. In: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Crespo Cuaresma, J., 2017: Income projections for climate change research: A framework based on human capital dynamics. *Glob. Environ. Change*, **42**, 226–236, doi:10.1016/j.gloenvcha.2015.02.012.

Creutzig, F. et al., 2015: Bioenergy and climate change mitigation: an assessment. *GCB Bioenergy*, **7(5)**, 916–944, doi:10.1111/gcbb.12205.

Creutzig, F. et al., 2017: The underestimated potential of solar energy to mitigate climate change. *Nat. Energy*, **2(9)**, doi:10.1038/nenergy.2017.140.

Creutzig, F. et al., 2018: Towards demand-side solutions for mitigating climate change. *Nat. Clim. Change*, **8(4)**, 260–263, doi:10.1038/s41558-018-0121-1.

Csoknyai, T. et al., 2016: Building stock characteristics and energy performance of residential buildings in Eastern-European countries. *Energy Build.*, **132**, 39–52, doi:10.1016/j.enbuild.2016.06.062.

Curran, M.A., 2013: Life Cycle Assessment: a review of the methodology and its application to sustainability. *Curr. Opin. Chem. Eng.*, **2(3)**, doi:10.1016/j.coche.2013.02.002.

Daly, H.E. and B. Fais, 2014: UK TIMES Model Overview. UCL Energy Institute. https://www.ucl.ac.uk/drupal/site_energy-models/sites/energy-models/files/uk-times-overview.pdf.

Daly, H.E. et al., 2014: Incorporating travel behaviour and travel time into TIMES energy system models. *Appl. Energy*, **135**, 429–439, doi:10.1016/j.apenergy.2014.08.051.

de la Rue du Can, S., D. Pudleiner, and K. Pielli, 2018: Energy efficiency as a means to expand energy access: A Uganda roadmap. *Energy Policy*, **120**, 354–364, doi:10.1016/j.enpol.2018.05.045.

de la Rue du Can, S. et al., 2019: Modeling India's energy future using a bottom-up approach. *Appl. Energy*, **238**(December 2018), 1108–1125, doi:10.1016/j.apenergy.2019.01.065.

de Melo, C.A. and G. de Martino Jannuzzi, 2015: Cost-effectiveness of CO_2 emissions reduction through energy efficiency in Brazilian building sector. *Energy Effic.*, **8(4)**, 815–826, doi:10.1007/s12053-014-9322-2.

de Vos, L., H. Biemans, J.C. Doelman, E. Stehfest, and D.P. van Vuuren, 2021: Trade-offs between water needs for food, utilities, and the environment – a nexus quantification at different scales. *Environ. Res. Lett.*, **16(11)**, doi:10.1088/1748-9326/ac2b5e.

Deetman, S. et al., 2020: Modelling global material stocks and flows for residential and service sector buildings towards 2050. *J. Clean. Prod.*, **245(118658)**, doi:10.1016/j.jclepro.2019.118658.

Dellink, R., J. Chateau, E. Lanzi, and B. Magné, 2017: Long-term economic growth projections in the Shared Socioeconomic Pathways. *Glob. Environ. Change*, **42**, 200–214, doi:10.1016/j.gloenvcha.2015.06.004.

Deng, Y.Y. et al., 2015: Quantifying a realistic, worldwide wind and solar electricity supply. *Glob. Environ. Change*, **31**, 239–252, doi:10.1016/j.gloenvcha.2015.01.005.

Department of Environmental Affairs, 2014: *South Africa's Greenhouse Gas (GHG) Mitigation Potential Analysis*. Department of Environmental Affairs, Pretoria, South Africa, 152 pp.

Després, J., 2015: Modelling the long-term deployment of electricity storage in the global energy system. PhD Thesis, Université Grenoble Alpes, Grenoble, France, https://tel.archives-ouvertes.fr/tel-01231455v1/document.

Dietrich, J.P. et al., 2019: MAgPIE 4 – a modular open-source framework for modeling global land systems. *Geosci. Model Dev.*, **12(4)**, 1299–1317, doi:10.5194/gmd-12-1299-2019.

Dioha, M.O., N.V. Emodi, and E.C. Dioha, 2019: Pathways for low carbon Nigeria in 2050 by using NECAL2050. *Renew. Energy Focus*, **29**(June), 63–77, doi:10.1016/j.ref.2019.02.004.

Dodds, P.E., I. Keppo, and N. Strachan, 2015: Characterising the Evolution of Energy System Models Using Model Archaeology. *Environ. Model. Assess.*, **20(2)**, 83–102, doi:10.1007/s10666-014-9417-3.

Doelman, J.C., E. Stehfest, A. Tabeau, and H. van Meijl, 2019: Making the Paris agreement climate targets consistent with food security objectives. *Glob. Food Sec.*, **23**, 93–103, doi:10.1016/j.gfs.2019.04.003.

Doelman, J.C. et al., 2020: Afforestation for climate change mitigation: Potentials, risks and trade-offs. *Glob. Change.,. Biol.*, **26(3)**, 1576–1591, doi:10.1111/GCB.14887.

Drouet, L. et al., 2021: Net zero-emission pathways reduce the physical and economic risks of climate change. *Nat. Clim. Change*, **11(12)**, 1070–1076, doi:10.1038/s41558-021-01218-z.

Duerinck, J. et al., 2008: *Assessment and improvement of methodologies used for Greenhouse Gas projections*. Vlaamse Instelling voor Technologisch Onderzoek Mol, Belgium, Öko-Institut e.V., Berlin, Germany, and Institute for European Environmental Policy, Brussels, Belgium, https://ec.europa.eu/clima/document/download/1cf69fe3-f5c6-40a0-b5f1-efb9e2b2d8df_en?filename=assessing_methodologies_for_ghg_projections_en.pdf.

Duscha, V., J. Wachsmuth, J. Eckstein, and B. Pfluger, 2019: *GHG-neutral EU2050 – a scenario of an EU with net-zero greenhouse gas emissions and its implications*. Umweltbundesamt, Dessau-Roßlau, Germany, 81 pp.

Dvorkin, Y., H. Pandžić, M.A. Ortega-Vazquez, and D.S. Kirschen, 2015: A hybrid stochastic/interval approach to transmission-constrained unit commitment. *IEEE Trans. Power Syst.*, **30(2)**, 621–631, doi:10.1109/TPWRS.2014.2331279.

Earles, J.M. and A. Halog, 2011: Consequential life cycle assessment: a review. *Int. J. Life Cycle Assess.*, **16(5)**, doi:10.1007/s11367-011-0275-9.

Edelenbosch, O., D. Rovelli, A. Levesque, G. Marangoni, and M. Tavoni, 2021: Long term, cross-country effects of buildings insulation policies. *Technol. Forecast. Soc. Change*, **170**, 120887, doi:10.1016/j.techfore.2021.120887.

Edelenbosch, O.Y. et al., 2017a: Decomposing passenger transport futures: Comparing results of global integrated assessment models. *Transp. Res. Part D Transp. Environ.*, **55**, 281–293, doi:10.1016/j.trd.2016.07.003.

Edelenbosch, O.Y. et al., 2017b: Comparing projections of industrial energy demand and greenhouse gas emissions in long-term energy models. *Energy*, **122**, 701–710, doi:10.1016/j.energy.2017.01.017.

AIII

Edenhofer, O. and M. Kowarsch, 2015: Cartography of pathways: A new model for environmental policy assessments. *Environ. Sci. Policy*, **51**, 56–64, doi:10.1016/j.envsci.2015.03.017.

Ellenbeck, S. and J. Lilliestam, 2019: How modelers construct energy costs: Discursive elements in Energy System and Integrated Assessment Models. *Energy Res. Soc. Sci.*, **47**, 69–77, doi:10.1016/j.erss.2018.08.021.

Emmerling, J. et al., 2016: The WITCH 2016 Model – Documentation and Implementation of the Shared Socioeconomic Pathways. FEEM Working Paper No. 42.2016, Fondazio Eni Enrico Mattei, Milan, Italy, doi:10.2139/ssrn.2800970.

Emmerling, J. et al., 2019: The role of the discount rate for emission pathways and negative emissions. *Environ. Res. Lett.*, **14(10)**, 104008, doi:10.1088/1748-9326/ab3cc9.

Energetics, 2016: *Modelling and analysis of Australia's abatement opportunities*. Report to the Department of Environment. Energetics, 60 p. pp. Australia.

Eriksson, M., 2020: Afforestation and avoided deforestation in a multi-regional integrated assessment model. *Ecol. Econ.*, **169**, doi:10.1016/j.ecolecon.2019.106452.

Eurek, K. et al., 2017: An improved global wind resource estimate for integrated assessment models. *Energy Econ.*, **64**, 552–567, doi:10.1016/j.eneco.2016.11.015.

Eyckmans, J. and H. Tulkens, 2003: Simulating coalitionally stable burden sharing agreements for the climate change problem. *Resour. Energy Econ.*, **25(4)**, doi:10.1016/S0928-7655(03)00041-1.

Eyring, V. et al., 2015: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organisation. *Geosci. Model Dev. Discuss.*, **8(12)**, 10539–10583, doi:10.5194/gmdd-8-10539-2015.

Fajardy, M. et al., 2021: The economics of bioenergy with carbon capture and storage (BECCS) deployment in a 1.5°C or 2°C world. *Glob. Environ. Change*, **68**, 102262, doi:10.1016/j.gloenvcha.2021.102262.

Fattahi, A., J. Sijm, and A. Faaij, 2020: A systemic approach to analyze integrated energy system modeling tools: A review of national models. *Renew. Sustain. Energy Rev.*, **133**, doi:10.1016/j.rser.2020.110195.

Fazlollahi, S., P. Mandel, G. Becker, and F. Maréchal, 2012: Methods for multi-objective investment and operating optimization of complex energy systems. *Energy*, **45(1)**, 12–22, doi:10.1016/j.energy.2012.02.046.

Feijoo, F. et al., 2018: The future of natural gas infrastructure development in the United States. *Appl. Energy*, **228**, 149–166, doi:10.1016/j.apenergy.2018.06.037.

Filippi Oberegger, U., R. Pernetti, and R. Lollini, 2020: Bottom-up building stock retrofit based on levelized cost of saved energy. *Energy Build.*, **210**, 109757, doi:10.1016/j.enbuild.2020.109757.

Finnveden, G. et al., 2009: Recent developments in Life Cycle Assessment. *J. Environ. Manage.*, **91(1)**, 1–21, doi:10.1016/j.jenvman.2009.06.018.

Fisch-Romito, V. and C. Guivarch, 2019: Transportation infrastructures in a low carbon world: An evaluation of investment needs and their determinants. *Transp. Res. Part D Transp. Environ.*, **72**(May), 203–219, doi:10.1016/j.trd.2019.04.014.

Fishman, T. et al., 2021: A comprehensive set of global scenarios of housing, mobility, and material efficiency for material cycles and energy systems modeling. *J. Ind. Ecol.*, **25(2)**, 305–320, doi:10.1111/jiec.13122.

Fleiter, T. et al., 2018: A methodology for bottom-up modelling of energy transitions in the industry sector: The FORECAST model. *Energy Strateg. Rev.*, **22**, doi:10.1016/j.esr.2018.09.005.

Forster, P., T. Storelvmo, K. Armour, W. Collins, J.-L. Dufresne, D. Frame, D.J. Lunt, T. Mauritsen, M.D. Palmer, M. Watanabe, M. Wild, and H. Zhang: 2021, The Earth's Energy Budget, Climate Feedbacks, and Climate Sensitivity. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Foure, J. et al., 2020: Macroeconomic drivers of baseline scenarios in dynamic CGE models: review and guidelines proposal. *J. Glob. Econ. Anal.*, **5(1)**, 28–62, doi:10.21642/jgea.050102af.

Frame, B., J. Lawrence, A.-G. Ausseil, A. Reisinger, and A. Daigneault, 2018: Adapting global shared socio-economic pathways for national and local scenarios. *Clim. Risk Manag.*, **21**, 39–51, doi:10.1016/j.crm.2018.05.001.

Frank, S. et al., 2017: Reducing greenhouse gas emissions in agriculture without compromising food security? *Environ. Res. Lett.*, **12(10)**, 105004, doi:10.1088/1748-9326/aa8c83.

Frank, S. et al., 2018: Structural change as a key component for agricultural non-CO_2 mitigation efforts. *Nat. Commun.*, **9(1)**, doi:10.1038/s41467-018-03489-1.

Frank, S. et al., 2019: Agricultural non-CO_2 emission reduction potential in the context of the 1.5°C target. *Nat. Clim. Change*, **9(1)**, 66–72, doi:10.1038/s41558-018-0358-8.

Frank, S. et al., 2021: Land-based climate change mitigation potentials within the agenda for sustainable development. *Environ. Res. Lett.*, **16(2)**, 24006, doi:10.1088/1748-9326/ABC58A.

Fricko, O. et al., 2017: The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century. *Glob. Environ. Change*, **42**, 251–267, doi:10.1016/j.gloenvcha.2016.06.004.

Fripp, M., 2012: Switch: A Planning Tool for Power Systems with Large Shares of Intermittent Renewable Energy. *Environ. Sci. Technol.*, **46(11)**, doi:10.1021/es204645c.

Fujimori, S., T. Masui, and Y. Matsuoka, 2014: Development of a global computable general equilibrium model coupled with detailed energy end-use technology. *Appl. Energy*, **128**, doi:10.1016/j.apenergy.2014.04.074.

Fujimori, S. et al., 2016: Will international emissions trading help achieve the objectives of the Paris Agreement? *Environ. Res. Lett.*, **11(10)**, 104001, doi:10.1088/1748-9326/11/10/104001.

Fujimori, S. et al., 2017: SSP3: AIM implementation of Shared Socioeconomic Pathways. *Glob. Environ. Change*, **42**, 268–283, doi:10.1016/j.gloenvcha.2016.06.009.

Fujimori, S. et al., 2018: Inclusive climate change mitigation and food security policy under 1.5°C climate goal. *Environ. Res. Lett.*, **13(7)**, doi:10.1088/1748-9326/aad0f7.

Fujimori, S. et al., 2019a: A multi-model assessment of food security implications of climate change mitigation. *Nat. Sustain.*, **2(5)**, 386–396, doi:10.1038/s41893-019-0286-2.

Fujimori, S., J. Rogelj, V. Krey, and K. Riahi, 2019b: A new generation of emissions scenarios should cover blind spots in the carbon budget space. *Nat. Clim. Change*, **9(11)**, 798–800, doi:10.1038/s41558-019-0611-9.

Fujimori, S. et al., 2020: Measuring the sustainable development implications of climate change mitigation. *Environ. Res. Lett.*, **15(8)**, doi:10.1088/1748-9326/ab9966.

Fujimori, S. et al., 2021: A framework for national scenarios with varying emission reductions. *Nat. Clim. Change*, **11(6)**, 472–480, doi:10.1038/s41558-021-01048-z.

Fulton, L., P. Cazzola, and F. Cuenot, 2009: IEA Mobility Model (MoMo) and its use in the ETP 2008. *Energy Policy*, **37(10)**, 3758–3768, doi:10.1016/j.enpol.2009.07.065.

Fuso Nerini, F., I. Keppo, and N. Strachan, 2017: Myopic decision making in energy system decarbonisation pathways. A UK case study. *Energy Strateg. Rev.*, **17**, 19–26, doi:10.1016/j.esr.2017.06.001.

Fuss, S. et al., 2014: Betting on negative emissions. *Nat. Clim. Change*, **4(10)**, 850–853, doi:10.1038/nclimate2392.

Fuss, S. et al., 2018: Negative emissions – Part 2: Costs, potentials and side effects. *Environ. Res. Lett.*, **13(6)**, 063002, doi:10.1088/1748-9326/aabf9f.

Gagnon, P., R. Margolis, J. Melius, C. Phillips, and R. Elmore, 2016: *Photovoltaic Technical Potential in the United States: A Detailed Assessment*. Technical

Report NREL/TP-6A20-65298. National Renewable Energy Laboratory. U.S. Department of Energy. 82 pp.

Gambhir, A. et al., 2017: The Contribution of Non-CO_2 Greenhouse Gas Mitigation to Achieving Long-Term Temperature Goals. *Energies*, **10(5)**, 602, doi:10.3390/en10050602.

Gambhir, A., I. Butnar, P.-H. Li, P. Smith, and N. Strachan, 2019: A Review of Criticisms of Integrated Assessment Models and Proposed Approaches to Address These, through the Lens of BECCS. *Energies*, **12(9)**, 1747, doi:10.3390/en12091747.

Geels, F.W., F. Berkhout, and D.P. van Vuuren, 2016: Bridging analytical approaches for low-carbon transitions. *Nat. Clim. Change*, **6(6)**, 576–583, doi:10.1038/nclimate2980.

Gerbaulet, C., C. von Hirschhausen, C. Kemfert, C. Lorenz, and P.Y. Oei, 2019: European electricity sector decarbonization under different levels of foresight. *Renew. Energy*, **141**, 973–987, doi:10.1016/j.renene.2019.02.099.

Giannousakis, A. et al., 2021: How uncertainty in technology costs and carbon dioxide removal availability affect climate mitigation pathways. *Energy*, **216**, 119253, doi:10.1016/j.energy.2020.119253.

Giarola, S. et al., 2021: Challenges in the harmonisation of global integrated assessment models: A comprehensive methodology to reduce model response heterogeneity. *Sci. Total Environ.*, **783**, 146861, doi:10.1016/j.scitotenv.2021.146861.

Gibon, T., A. Arvesen, and E.G. Hertwich, 2017: Life cycle assessment demonstrates environmental co-benefits and trade-offs of low-carbon electricity supply options. *Renew. Sustain. Energy Rev.*, **76**, 1283–1290, doi:10.1016/j.rser.2017.03.078.

Gidden, M.J. et al., 2018: A methodology and implementation of automated emissions harmonization for use in Integrated Assessment Models. *Environ. Model. Softw.*, **105**, 187–200, doi:10.1016/j.envsoft.2018.04.002.

Gidden, M.J. et al., 2019: Global emissions pathways under different socioeconomic scenarios for use in CMIP6: a dataset of harmonized emissions trajectories through the end of the century. *Geosci. Model Dev.*, **12(4)**, 1443–1475, doi:10.5194/gmd-12-1443-2019.

Gillingham, K. et al., 2018: Modeling uncertainty in integrated assessment of climate change: A multimodel comparison. *J. Assoc. Environ. Resour. Econ.*, **5(4)**, 791–826, doi:10.1086/698910.

Global Energy Monitor, 2021: Global Energy Monitor. https://globalenergymonitor.org/. Acessed November 1 2021.

Gollier, C., 2013: *Pricing the Planet's Future: The Economics of Discounting in an Uncertain World*. Princeton University Press, Princeton, NJ, USA.

Gollier, C. and J.K. Hammitt, 2014: The Long-Run Discount Rate Controversy. *Annu. Rev. Resour. Econ.*, **6(1)**, doi:10.1146/annurev-resource-100913-012516.

González-Mahecha, R.E. et al., 2019: Greenhouse gas mitigation potential and abatement costs in the Brazilian residential sector. *Energy Build.*, **184**, 19–33, doi:10.1016/j.enbuild.2018.11.039.

Gota, S., C. Huizenga, K. Peet, N. Medimorec, and S. Bakker, 2019: Decarbonising transport to achieve Paris Agreement targets. *Energy Effic.*, **12(2)**, 363–386, doi:10.1007/s12053-018-9671-3.

Grande-Acosta, G.K. and J.M. Islas-Samperio, 2020: Boosting energy efficiency and solar energy inside the residential, commercial, and public services sectors in Mexico. *Energies*, **13(21)**, doi:10.3390/en13215601.

Grant, N., A. Hawkes, T. Napp, and A. Gambhir, 2020: The appropriate use of reference scenarios in mitigation analysis. *Nat. Clim. Change*, **10(7)**, 605–610, doi:10.1038/s41558-020-0826-9.

Grassi, G. et al., 2017: The key role of forests in meeting climate targets requires science for credible mitigation. *Nat. Clim. Change*, **7**, 220–226, doi:10.1038/nclimate3227.

Grassi, G. et al., 2021: Critical adjustment of land mitigation pathways for assessing countries' climate progress. *Nat. Clim. Change*, **11(5)**, 425–434, doi:10.1038/s41558-021-01033-6.

Griscom, B.W. et al., 2017: Natural climate solutions. *Proc. Natl. Acad. Sci.* **114(44)**, 11645–11650, doi:10.1073/pnas.1710465114.

Grubler, A. et al., 2018: A low energy demand scenario for meeting the 1.5°C target and sustainable development goals without negative emission technologies. *Nat. Energy*, **3(6)**, 515–527, doi:10.1038/s41560-018-0172-6.

Grübler, A. and N. Nakicenovic, 2001: Identifying dangers in an uncertain climate. *Nature*, **412(6842)**, 15, doi:10.1038/35083752.

Guan, J., H. Tang, K. Wang, J. Yao, and S. Yang, 2020: A parallel multi-scenario learning method for near-real-time power dispatch optimization. *Energy*, **202**, doi:10.1016/j.energy.2020.117708.

Guedes, F. et al., 2019: Climate-energy-water nexus in Brazilian oil refineries. *Int. J. Greenh. Gas Control*, **90**, doi:10.1016/j.ijggc.2019.102815.

Guinée, J.B. et al., 2011: Life Cycle Assessment: Past, Present, and Future. *Environ. Sci. Technol.*, **45(1)**, doi:10.1021/es101316v.

Guivarch, C. and J. Rogelj, 2017: Carbon price variations in 2°C scenarios explored. Carbon Pricing Leadership Coalition, 15 pp, http://pure.iiasa.ac.at/14685 (Accessed October 28, 2021).

Guivarch, C., R. Crassous, O. Sassi, and S. Hallegatte, 2011: The costs of climate policies in a second-best world with labour market imperfections. *Clim. Policy*, **11(1)**, 768–788, doi:10.3763/cpol.2009.0012.

Guo, F., B. van Ruijven, B. Zakeri, V. Krey, and K. Riahi, 2021: *Global Energy Interconnection: A scenario analysis based on the MESSAGEix-GLOBIOM Model.* IIASA Report, IIASA, Laxenburg, Austria, 20 pp. http://pure.iiasa.ac.at/id/eprint/17487/.

Gütschow, J. et al., 2016: The PRIMAP-hist national historical emissions time series. *Earth Syst. Sci. Data*, **8(2)**, 571–603, doi:10.5194/essd-8-571-2016.

Hagelaar, G., 2001: Environmental supply chain management: using life cycle assessment to structure supply chains. *Int. Food Agribus. Manag. Rev.*, **4(4)**, doi:10.1016/S1096-7508(02)00068-X.

Hall, L.M.H. and A.R. Buckley, 2016: A review of energy systems models in the UK: Prevalent usage and categorisation. *Appl. Energy*, **169**, 607–628, doi:10.1016/j.apenergy.2016.02.044.

Hall, P.J. and E.J. Bain, 2008: Energy-storage technologies and electricity generation. *Energy Policy*, **36(12)**, 4352–4355, doi:10.1016/j.enpol.2008.09.037.

Hammad, E., A. Farraj, and D. Kundur, 2019: On Effective Virtual Inertia of Storage-Based Distributed Control for Transient Stability. *IEEE Trans. Smart Grid*, **10(1)**, 327–336, doi:10.1109/TSG.2017.2738633.

Hanaoka, T. and T. Masui, 2020: Exploring effective short-lived climate pollutant mitigation scenarios by considering synergies and trade-offs of combinations of air pollutant measures and low carbon measures towards the level of the 2°C target in Asia. *Environ. Pollut.*, **261**, doi:10.1016/j.envpol.2019.113650.

Hanes, R.J. and A. Carpenter, 2017: Evaluating opportunities to improve material and energy impacts in commodity supply chains. *Environ. Syst. Decis.*, **37(1)**, 6–12, doi:10.1007/s10669-016-9622-5.

Hanna, R. and R. Gross, 2020: How do energy systems model and scenario studies explicitly represent socio-economic, political and technological disruption and discontinuity? Implications for policy and practitioners. *Energy Policy*, **149**, doi:10.1016/j.enpol.2020.111984.

Hänsel, M.C. et al., 2020: Climate economics support for the UN climate targets. *Nat. Clim. Change*, **10(8)**, 781–789, doi:10.1038/s41558-020-0833-x.

Hansen, K., C. Breyer, and H. Lund, 2019: Status and perspectives on 100% renewable energy systems. *Energy*, **175**, 471–480, doi:10.1016/j.energy.2019.03.092.

Hanssen, S.V. et al., 2020: Biomass residues as twenty-first century bioenergy feedstock – a comparison of eight integrated assessment models. *Clim. Change*, **163(3)**, 1569–1586, doi:10.1007/s10584-019-02539-x.

Hardt, L. and D.W. O'Neill, 2017: Ecological Macroeconomic Models: Assessing Current Developments. *Ecol. Econ.*, **134**, 198–211, doi:10.1016/j.ecolecon.2016.12.027.

Harmsen, J.H.M. et al., 2019: Long-term marginal abatement cost curves of non-CO_2 greenhouse gases. *Environ. Sci. Policy*, **99**(March), 136–149, doi:10.1016/j.envsci.2019.05.013.

Harmsen, M. et al., 2020: The role of methane in future climate strategies: mitigation potentials and climate impacts. *Clim. Change*, **163(3)**, 1409–1425, doi:10.1007/s10584-019-02437-2.

Harmsen, M. et al., 2021: Integrated assessment model diagnostics: key indicators and model evolution. *Environ. Res. Lett.*, **16(5)**, 54046, doi:10.1088/1748-9326/abf964.

Hartin, C.A., P. Patel, A. Schwarber, R.P. Link, and B.P. Bond-Lamberty, 2015: A simple object-oriented and open-source model for scientific and policy analyses of the global climate system – Hector v1.0. *Geosci. Model Dev.*, **8(4)**, 939–955, doi:10.5194/gmd-8-939-2015.

Hasegawa, T., S. Fujimori, A. Ito, K. Takahashi, and T. Masui, 2017: Global land-use allocation model linked to an integrated assessment model. *Sci. Total Environ.*, **580**, 787–796, doi:10.1016/j.scitotenv.2016.12.025.

Hasegawa, T. et al., 2018: Risk of increased food insecurity under stringent global climate change mitigation policy. *Nat. Clim. Change*, **8(8)**, 699–703, doi:10.1038/s41558-018-0230-x.

Hasegawa, T. et al., 2020: Food security under high bioenergy demand toward long-term climate goals. *Clim. Change*, **163(3)**, doi:10.1007/s10584-020-02838-8.

Hasegawa, T. et al., 2021: Land-based implications of early climate actions without global net-negative emissions. *Nat. Sustain.*, **4(12)**, 1052–1059, doi:10.1038/s41893-021-00772-w.

Havlik, P. et al., 2014: Climate change mitigation through livestock system transitions. *Proc. Natl. Acad. Sci.*, **111(10)**, 3709–3714, doi:10.1073/pnas.1308044111.

Hawkins, T.R., B. Singh, G. Majeau-Bettez, and A.H. Strømman, 2013: Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *J. Ind. Ecol.*, **17(1)**, doi:10.1111/j.1530-9290.2012.00532.x.

Hejazi, M. et al., 2014: Long-term global water projections using six socioeconomic scenarios in an integrated assessment modeling framework. *Technol. Forecast. Soc. Change*, **81(1)**, 205–226, doi:10.1016/j.techfore.2013.05.006.

Hejazi, M.I. et al., 2015: 21st century United States emissions mitigation could increase water stress more than the climate change it is mitigating. *Proc. Natl. Acad. Sci.*, **112(34)**, 10635–10640, doi:10.1073/pnas.1421675112.

Hellweg, S. and L. Milà i Canals, 2014: Emerging approaches, challenges and opportunities in life cycle assessment. *Science*, **344(6188)**, 1109–1113, doi:10.1126/science.1248361.

Herrendorf, B., R. Rogerson, and Á. Valentinyi, 2014: Growth and Structural Transformation. In: *Handbook of Economic Growth*, Vol. 2, pp. 855–941.

Hertwich, E.G., and J.K. Hammitt, 2001a: A decision-analytic framework for impact assessment part I: LCA and decision analysis. *Int. J. Life Cycle Assess.*, **6(1)**, doi:10.1007/BF02977588.

Hertwich, E.G. and J.K. Hammitt, 2001b: A decision-analytic framework for impact assessment part 2 - Midpoints, endpoints, and criteria for method development. *Int. J. Life Cycle Assess.*, **6(5)**, doi:10.1007/BF02978787I.

Heuberger, C.F., I. Staffell, N. Shah, and N. Mac Dowell, 2018: Impact of myopic decision-making and disruptive events in power systems planning. *Nat. Energy*, **3(8)**, 634–640, doi:10.1038/s41560-018-0159-3.

Ho, E., D. V Budescu, V. Bosetti, D.P. van Vuuren, and K. Keller, 2019: Not all carbon dioxide emission scenarios are equally likely: a subjective expert assessment. *Clim. Change*, **155(4)**, 545–561, doi:10.1007/s10584-019-02500-y.

Hoesly, R.M. et al., 2018: Historical (1750–2014) anthropogenic emissions of reactive gases and aerosols from the Community Emissions Data System (CEDS). *Geosci. Model Dev.*, **11(1)**, 369–408, doi:10.5194/gmd-11-369-2018.

Holden, P.B. et al., 2018: Climate–carbon cycle uncertainties and the Paris Agreement. *Nat. Clim. Change, 2018 87*, **8(7)**, 609–613, doi:10.1038/s41558-018-0197-7.

Holz, C., L.S. Siegel, E. Johnston, A.P. Jones, and J. Sterman, 2018: Ratcheting ambition to limit warming to 1.5°C-trade-offs between emission reductions and carbon dioxide removal. *Environ. Res. Lett.*, **13(6)**, doi:10.1088/1748-9326/aac0c1.

Horváth, M., D. Kassai-Szoó, and T. Csoknyai, 2016: Solar energy potential of roofs on urban level based on building typology. *Energy Build.*, **111**, 278–289, doi:10.1016/j.enbuild.2015.11.031.

Houghton, R.A. et al., 2012: Carbon emissions from land use and land-cover change. *Biogeosciences*, **9(12)**, 5125–5142, doi:10.5194/bg-9-5125-2012.

Howells, M. et al., 2013: Integrated analysis of climate change, land-use, energy and water strategies. *Nat. Clim. Change*, **3(7)**, 621–626, doi:10.1038/nclimate1789.

Humpenöder, F. et al., 2018: Large-scale bioenergy production: How to resolve sustainability trade-offs? *Environ. Res. Lett.*, **13(2)**, 24011, doi:10.1088/1748-9326/aa9e3b.

Humpenöder, F. et al., 2020: Peatland protection and restoration are key for climate change mitigation. *Environ. Res. Lett.*, **15(10)**, doi:10.1088/1748-9326/abae2a.

Huppmann, D., J. Rogelj, E. Kriegler, V. Krey, and K. Riahi, 2018: A new scenario resource for integrated 1.5 °C research. *Nat. Clim. Change*, **8(12)**, 1027–1030, doi:10.1038/s41558-018-0317-4.

Huppmann, D. et al., 2019: The MESSAGEix Integrated Assessment Model and the ix modeling platform (ixmp): An open framework for integrated and cross-cutting analysis of energy, climate, the environment, and sustainable development. *Environ. Model. Softw.*, **112**, 143–156, doi:10.1016/J.ENVSOFT.2018.11.012.

Hurtt, G.C. et al., 2020: Harmonization of global land use change and management for the period 850–2100 (LUH2) for CMIP6. *Geosci. Model Dev.*, **13(11)**, 5425–5464, doi:10.5194/gmd-13-5425-2020.

IEA, 2020a: *World Energy Model*. International Energy Agency, Paris, France, 112 pp.

IEA, 2020b: *Energy Technology Perspectives 2020*. International Energy Agency, Paris, France, 400 pp.

IEA, 2021: *Net Zero by 2050: A Roadmap for the Global Energy Sector*. International Energy Agency, Paris, France, 224 pp.

IPCC, 1990: *Climate change: the IPCC scientific assessment* [J.T. Houghton, G.J. Jenkins and J.J. Ephraums (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA.

IPCC, 2000: *Special report on emissions scenarios (SRES): A special report of Working Group III of the Intergovernmental Panel on Climate Change* [N. Nakicenovic, J. Alcamo, G. Davis, B. de Vries, J. Fenhann, S. Gaffin, K. Gregory, A. Griibler, T.Y. Jung, T. Kram, E.L. La Rovere, L. Michaelis, S. Mori, T. Morita, W. Pepper, H. Pitcher, L. Price, K. Riahi, A. Roehrl, H.H. Rogner, A. Sankovski, M. Schlesinger, P. Shukla, S. Smith, R. Swart, S. van Rooijen, N. Victor, Z. Dadi (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA.

IPCC, 2019a: *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories* [Calvo Buendia, E., Tanabe, K., Kranjc, A., Baasansuren, J., Fukuda, M., Ngarize, S., Osako, A., Pyrozhenko, Y., Shermanau, P. and Federici, S. (eds). IPCC, Switzerland.

IPCC, 2019b: *Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems* [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D.C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK, and New York, NY, USA.

Iqbal, M., M. Azam, M. Naeem, A.S. Khwaja, and A. Anpalagan, 2014: Optimization classification, algorithms and tools for renewable energy: A review. *Renew. Sustain. Energy Rev.*, **39**, 640–654, doi:10.1016/j.rser.2014.07.120.

IRENA, 2020: *IRENA 2020 – Global Renewables Outlook: Energy transformation 2050*. International Renewable Energy Agency, Abu Dhabi, 291 pp.

IRP, 2020: *Resource Efficiency and Climate Change: Material Efficiency Strategies for a Low-Carbon Future*. Hertwich, E., Lifset, R., Pauliuk, S., Heeren, N. A report of the International Resource Panel. United Nations Environment Programme, Nairobi, Kenya.

Iten R. et al., 2017: *Auswirkungen eines subsidiären Verbots fossiler Heizungen*. Infras, TEP Energy, Zürich/Bern, Switzerland.

Ivanova, D. et al., 2020: Quantifying the potential for climate change mitigation of consumption options. *Environ. Res. Lett.*, **15(9)**, 093001, doi:10.1088/1748-9326/ab8589.

Iyer, G.C. et al., 2015: Improved representation of investment decisions in assessments of CO_2 mitigation. *Nat. Clim. Change*, **5(5)**, 436–440, doi:10.1038/nclimate2553.

Jewell, J. et al., 2018: Limited emission reductions from fuel subsidy removal except in energy-exporting regions. *Nature*, **554(7691)**, 229–233, doi:10.1038/nature25467.

Jiang, L. and B.C. O'Neill, 2017: Global urbanization projections for the Shared Socioeconomic Pathways. *Glob. Environ. Change*, **42**, 193–199, doi:10.1016/j.gloenvcha.2015.03.008.

Jiang, R., J. Wang, and Y. Guan, 2012: Robust unit commitment with wind power and pumped storage hydro. *IEEE Trans. Power Syst.*, **27(2)**, 800–810, doi:10.1109/TPWRS.2011.2169817.

Jochem, P., J.J. Gómez Vilchez, A. Ensslen, J. Schäuble, and W. Fichtner, 2018: Methods for forecasting the market penetration of electric drivetrains in the passenger car market. *Transp. Rev.*, **38(3)**, 322–348, doi:10.1080/01441647.2017.1326538.

Jochem, P., E. Szimba, and M. Reuter-Oppermann, 2019: How many fast-charging stations do we need along European highways? *Transp. Res. Part D Transp. Environ.*, **73**, doi:10.1016/j.trd.2019.06.005.

Johansson, D.J.A., C. Azar, M. Lehtveer, and G.P. Peters, 2020: The role of negative carbon emissions in reaching the Paris climate targets: The impact of target formulation in integrated assessment models. *Environ. Res. Lett.*, **15(12)**, 124024, doi:10.1088/1748-9326/abc3f0.

Johnson, N. et al., 2019: Integrated Solutions for the Water-Energy-Land Nexus: Are Global Models Rising to the Challenge? *Water*, **11(11)**, 2223, doi:10.3390/w11112223.

Jones, B. and B.C. O'Neill, 2016: Spatially explicit global population scenarios consistent with the Shared Socioeconomic Pathways. *Environ. Res. Lett.*, **11(8)**, 084003, doi:10.1088/1748-9326/11/8/084003.

Kamal, A., S.G. Al-Ghamdi, and M. Koç, 2019: Role of energy efficiency policies on energy consumption and CO_2 emissions for building stock in Qatar. *J. Clean. Prod.*, **235**, 1409–1424, doi:10.1016/j.jclepro.2019.06.296.

KC, S. and W. Lutz, 2017: The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. *Glob. Environ. Change*, **42**, 181–192, doi:10.1016/j.gloenvcha.2014.06.004.

Keppo, I. and M. Strubegger, 2010: Short term decisions for long term problems – The effect of foresight on model based energy systems analysis. *Energy*, **35(5)**, 2033–2042, doi:10.1016/j.energy.2010.01.019.

Keppo, I. et al., 2021: Exploring the possibility space: taking stock of the diverse capabilities and gaps in integrated assessment models. *Environ. Res. Lett.*, **16(5)**, 053006, doi:10.1088/1748-9326/abe5d8.

Keramidas, K., A. Kitous, J. Després, and A. Schmitz, 2017: *POLES-JRC Model Documentation*. Publications Office of the European Union, Luxembourg, 78 pp.

Khalili, S., E. Rantanen, D. Bogdanov, and C. Breyer, 2019: Global Transportation Demand Development with Impacts on the Energy Demand and Greenhouse Gas Emissions in a Climate-Constrained World. *Energies*, **12(20)**, 3870, doi:10.3390/en12203870.

Khan, M.M.A., M. Asif, and E. Stach, 2017: Rooftop PV potential in the residential sector of the kingdom of Saudi Arabia. *Buildings*, **7(2)**, doi:10.3390/buildings7020046.

Kikstra, J.S. et al., 2021a: Climate mitigation scenarios with persistent COVID-19-related energy demand changes. *Nat. Energy*, **6(12)**, 1114–1123, doi:10.1038/s41560-021-00904-8.

Kikstra, J.S., A. Mastrucci, J. Min, K. Riahi, and N.D. Rao, 2021b: Decent living gaps and energy needs around the world. *Environ. Res. Lett.*, **16(9)**, doi:10.1088/1748-9326/ac1c27.

Kikstra, J.S. et al., 2021c: The social cost of carbon dioxide under climate-economy feedbacks and temperature variability. *Environ. Res. Lett.*, **16(9)**, doi:10.1088/1748-9326/ac1d0b.

Klimont, Z. et al., 2017: Global anthropogenic emissions of particulate matter including black carbon. *Atmos. Chem. Phys.*, **17(14)**, 8681–8723, doi:10.5194/ACP-17-8681-2017.

Kober, T., H.W. Schiffer, M. Densing, and E. Panos, 2020: Global energy perspectives to 2060 – WEC's World Energy Scenarios 2019. *Energy Strateg. Rev.*, **31**, 100523, doi:10.1016/J.ESR.2020.100523.

Kodjak, D. and D. Meszler, 2019: *Prospects for fuel efficiency, electrification and fleet decarbonisation*. Global Fuel Economy Initiative, London, UK, 31 pp.

Kok, K., S. Pedde, M. Gramberger, P.A. Harrison, and I.P. Holman, 2019: New European socio-economic scenarios for climate change research: operationalising concepts to extend the shared socio-economic pathways. *Reg. Environ. Change*, **19(3)**, 643–654, doi:10.1007/s10113-018-1400-0.

Kowarsch, M. et al., 2017: A road map for global environmental assessments. *Nat. Clim. Change*, **7(6)**, 379–382, doi:10.1038/nclimate3307.

Krarti, M., 2019: Evaluation of Energy Efficiency Potential for the Building Sector in the Arab Region. *Energies*, **12(22)**, 4279, doi:10.3390/en12224279.

Krarti, M., F. Ali, A. Alaidroos, and M. Houchati, 2017: Macro-economic benefit analysis of large scale building energy efficiency programs in Qatar. *Int. J. Sustain. Built Environ.*, **6(2)**, 597–609, doi:10.1016/j.ijsbe.2017.12.006.

Kreidenweis, U. et al., 2016: Afforestation to mitigate climate change: Impacts on food prices under consideration of albedo effects. *Environ. Res. Lett.*, **11(8)**, doi:10.1088/1748-9326/11/8/085001.

Krey, V., 2014: Global energy-climate scenarios and models: a review. *Wiley Interdiscip. Rev. Energy Environ.*, **3(4)**, 363–383, doi:10.1002/wene.98.

Krey, V. and K. Riahi, 2013: Risk hedging strategies under energy system and climate policy uncertainties. *Int. Ser. Oper. Res. Manag. Sci.*, **199**(August), 435–474, doi:10.1007/978-1-4614-9035-7_17.

Krey V., O. Masera, G. Blanford, T. Bruckner, R. Cooke, K. Fisher-Vanden, H. Haberl, E. Hertwich, E. Kriegler, D. Mueller, S. Paltsev, L. Price, S. Schlömer, D. Ürge-Vorsatz, D. van Vuuren, and T. Zwickel, 2014: 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, UK and New York, NY, USA.

Krey, V. et al., 2016: *MESSAGE-GLOBIOM 1.0 Documentation*. International Institute for Applied Systems Analysis, Laxenburg, Austria.

Krey, V. et al., 2019: Looking under the hood: A comparison of techno-economic assumptions across national and global integrated assessment models. *Energy*, **172**, 1254–1267, doi:10.1016/j.energy.2018.12.131.

Kriegler, E. et al., 2012: The need for and use of socio-economic scenarios for climate change analysis: A new approach based on shared socio-economic pathways. *Glob. Environ. Change*, **22(4)**, 807–822, doi:10.1016/j.gloenvcha.2012.05.005.

Kriegler, E. et al., 2014a: The role of technology for achieving climate policy objectives: Overview of the EMF 27 study on global technology and climate policy strategies. *Clim. Change*, **123(3–4)**, 353–367, doi:10.1007/s10584-013-0953-7.

Kriegler, E. et al., 2014b: What does the 2°C target imply for a global climate agreement in 2020? The limits study on Durban Platform scenarios. *Clim. Change, Econ.*, **4(4)**, doi:10.1142/S2010007813400083.

AIII

Kriegler, E. et al., 2014c: A new scenario framework for climate change research: The concept of shared climate policy assumptions. *Clim. Change*, **122(3)**, 401–414, doi:10.1007/s10584-013-0971-5.

Kriegler, E. et al., 2015a: Diagnostic indicators for integrated assessment models of climate policy. *Technol. Forecast. Soc. Change*, **90**(PA), 45–61, doi:10.1016/j.techfore.2013.09.020.

Kriegler, E. et al., 2015b: Making or breaking climate targets: The AMPERE study on staged accession scenarios for climate policy. *Technol. Forecast. Soc. Change*, **90**, 24–44, doi:10.1016/j.techfore.2013.09.021.

Kriegler, E. et al., 2016: Will economic growth and fossil fuel scarcity help or hinder climate stabilization?: Overview of the RoSE multi-model study. *Clim. Change*, **136(1)**, 7–22, doi:10.1007/s10584-016-1668-3.

Kriegler, E. et al., 2017: Fossil-fueled development (SSP5): An energy and resource intensive scenario for the 21st century. *Glob. Environ. Change*, **42**(Supplement C), 297–315, doi:10.1016/j.gloenvcha.2016.05.015.

Kriegler, E. et al., 2018a: Pathways limiting warming to 1.5°C: a tale of turning around in no time? *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, **376(2119)**, 20160457, doi:10.1098/rsta.2016.0457.

Kriegler, E. et al., 2018b: Short term policies to keep the door open for Paris climate goals. *Environ. Res. Lett.*, **13(7)**, 074022, doi:10.1088/1748-9326/aac4f1.

Kriegler, E. et al., 2018c: *Transformations to Achieve the Sustainable Development Goals – Report prepared by The World in 2050 Initiative*. International Institute for Applied Systems Analysis, Laxenburg, Austria, 157 pp.

Kuhnhenn, K., L. Costa, E. Mahnke, L. Schneider, and S. Lange, 2020: *A Societal Transformation Scenario for Staying Below 1.5°C*. Heinrich Böll Foundation, Berlin, Germany, 100 pp.

Kuramochi, T. et al., 2020: Global Emissions Trends and G20 Status and Outlook. *In Emissions Gap Report 2020.* UNEP, Nairobi, Kenya.

Kusumadewi, T.V. and B. Limmeechokchai, 2015: Energy Efficiency Improvement and CO_2 Mitigation in Residential Sector: Comparison between Indonesia and Thailand. *Energy Procedia*, **79**, 994–1000, doi:10.1016/j.egypro.2015.11.599.

Kusumadewi, T.V. and B. Limmeechokchai, 2017: CO_2 Mitigation in Residential Sector in Indonesia and Thailand: Potential of Renewable Energy and Energy Efficiency. *Energy Procedia*, **138**, 955–960, doi:10.1016/j.egypro.2017.10.086.

Kwag, B.C., B.M. Adamu, and M. Krarti, 2019: Analysis of high-energy performance residences in Nigeria. *Energy Effic.*, **12(3)**, 681–695, doi:10.1007/s12053-018-9675-z.

Lam, A. and J.-F. Mercure, 2021: Which policy mixes are best for decarbonising passenger cars? Simulating interactions among taxes, subsidies and regulations for the United Kingdom, the United States, Japan, China, and India. *Energy Res. Soc. Sci.*, **75**, 101951, doi:10.1016/j.erss.2021.101951.

Lamboll, R.D., Z.R.J. Nicholls, J.S. Kikstra, M. Meinshausen, and J. Rogelj, 2020: Silicone v1.0.0: an open-source Python package for inferring missing emissions data for climate change research. *Geosci. Model Dev.*, **13(11)**, 5259–5275, doi:10.5194/gmd-13-5259-2020.

Lauri, P. et al., 2017: Impact of the 2°C target on global woody biomass use. *For. Policy Econ.*, **83**, doi:10.1016/j.forpol.2017.07.005.

Le Quéré, C. et al., 2016: Global Carbon Budget 2016. *Earth Syst. Sci. Data*, **8(2)**, 605–649, doi:10.5194/essd-8-605-2016.

Leclère, D. et al., 2020: Bending the curve of terrestrial biodiversity needs an integrated strategy. *Nature*, **585(7826)**, 551–556, doi:10.1038/s41586-020-2705-y.

Leggett, J., W.J. Pepper and R.J. Swart, 1992: Emissions scenarios for the IPCC: an update. In: *Climate Change 1992 Supplementary Report to the IPCC Scientific Assessessment* [J.T. Houghton, B.A. Callander and S.K. Varney (eds.)], Cambridge University Press, Cambridge, UK and New York, USA, pp. 69–95.

Leimbach, M. and A. Giannousakis, 2019: Burden sharing of climate change mitigation: global and regional challenges under shared socio-economic pathways. *Clim. Change*, **155(2)**, 273–291, doi:10.1007/s10584-019-02469-8.

Leimbach, M., E. Kriegler, N. Roming, and J. Schwanitz, 2017a: Future growth patterns of world regions – A GDP scenario approach. *Glob. Environ. Change*, **42**, 215–225, doi:10.1016/j.gloenvcha.2015.02.005.

Leimbach, M., A. Schultes, L. Baumstark, A. Giannousakis, and G. Luderer, 2017b: Solution algorithms for regional interactions in large-scale integrated assessment models of climate change. *Ann. Oper. Res.*, **255(1–2)**, 29–45, doi:10.1007/s10479-016-2340-z.

Lenton, T.M. et al., 2019: Climate tipping points — too risky to bet against. *Nature*, **575(7784)**, 592–595, doi:10.1038/d41586-019-03595-0.

Lepault, C. and F. Lecocq, 2021: Mapping forward-looking mitigation studies at country level. *Environ. Res. Lett.*, **16(8)**, 83001, doi:10.1088/1748-9326/ac0ac8.

Lester, M.S., R. Bramstoft, and M. Münster, 2020: Analysis on Electrofuels in Future Energy Systems: A 2050 Case Study. *Energy*, **199**, doi:10.1016/j.energy.2020.117408.

Levesque, A., R.C. Pietzcker, and G. Luderer, 2019: Halving energy demand from buildings: The impact of low consumption practices. *Technol. Forecast. Soc. Change*, **146**, 253–266, doi:10.1016/j.techfore.2019.04.025.

Levesque, A., R.C. Pietzcker, L. Baumstark, and G. Luderer, 2021: Deep decarbonisation of buildings energy services through demand and supply transformations in a 1.5°C scenario. *Environ. Res. Lett.*, **16(5)**, 54071, doi:10.1088/1748-9326/ABDF07.

Li, N. et al., 2019: Air Quality Improvement Co-benefits of Low-Carbon Pathways toward Well Below the 2 °C Climate Target in China. *Environ. Sci. Technol.*, **53(10)**, 5576–5584, doi:10.1021/acs.est.8b06948.

Linton, C., S. Grant-Muller, and W.F. Gale, 2015: Approaches and Techniques for Modelling CO_2 Emissions from Road Transport. *Transp. Rev.*, **35(4)**, 533–553, doi:10.1080/01441647.2015.1030004.

Liu, J. et al., 2017: PV-based virtual synchronous generator with variable inertia to enhance power system transient stability utilizing the energy storage system. *Prot. Control Mod. Power Syst.*, **2(1)**, doi:10.1186/s41601-017-0070-0.

Löffler, K. et al., 2017: Designing a model for the global energy system-GENeSYS-MOD: An application of the Open-Source Energy Modeling System (OSeMOSYS). *Energies*, **10(10)**, 1468, doi:10.3390/en10101468.

Löffler, K., T. Burandt, K. Hainsch, and P.Y. Oei, 2019: Modeling the low-carbon transition of the European energy system – A quantitative assessment of the stranded assets problem. *Energy Strateg. Rev.*, **26**, doi:10.1016/j.esr.2019.100422.

Löschel, A., 2002: Technological change in economic models of environmental policy: A survey. *Ecol. Econ.*, **43(2–3)**, 105–126, doi:10.1016/S0921-8009(02)00209-4.

Lucas, P.L., D.P. van Vuuren, J.G.J. Olivier, and M.G.J. den Elzen, 2007: Long-term reduction potential of non-CO_2 greenhouse gases. *Environ. Sci. Policy*, **10(2)**, 85–103, doi:10.1016/j.envsci.2006.10.007.

Lucena, A.F.P. et al., 2016: Climate policy scenarios in Brazil: A multi-model comparison for energy. *Energy Econ.*, **56**, 564–574, doi:10.1016/j.eneco.2015.02.005.

Luderer, G. et al., 2012: The economics of decarbonizing the energy system – results and insights from the RECIPE model intercomparison. *Clim. Change*, **114(1)**, 9–37, doi:10.1007/s10584-011-0105-x.

Luderer, G. et al., 2013: Economic mitigation challenges: how further delay closes the door for achieving climate targets. *Environ. Res. Lett.*, **8(3)**, 34033, doi:10.1088/1748-9326/8/3/034033.

Luderer, G. et al., 2018: Residual fossil CO_2 emissions in 1.5–2°C pathways. *Nat. Clim. Change*, **8(7)**, 626–633, doi:10.1038/s41558-018-0198-6.

Luderer, G. et al., 2021: Impact of declining renewable energy costs on electrification in low emission scenarios. *Nat. Energy*, accepted, doi:10.1038/s41560-021-00937-z.

Lund, H. et al., 2017: Simulation versus optimisation: Theoretical positions in energy system modelling. *Energies*, **10(7)**, doi:10.3390/en10070840.

Lund, P.D., J. Lindgren, J. Mikkola, and J. Salpakari, 2015: Review of energy system flexibility measures to enable high levels of variable renewable electricity. *Renew. Sustain. Energy Rev.*, **45**, 785–807, doi:10.1016/j.rser.2015.01.057.

Marangoni, G. et al., 2017: Sensitivity of projected long-term CO_2 emissions across the Shared Socioeconomic Pathways. *Nat. Clim. Change*, **7(2)**, 113–117, doi:10.1038/nclimate3199.

Marcucci, A., S. Kypreos, and E. Panos, 2017: The road to achieving the long-term Paris targets: energy transition and the role of direct air capture. *Clim. Change*, **144(2)**, 181–193, doi:10.1007/s10584-017-2051-8.

Markard, J., N. Bento, N. Kittner, and A. Nuñez-Jimenez, 2020: Destined for decline? Examining nuclear energy from a technological innovation systems perspective. *Energy Res. Soc. Sci.*, **67**, 101512, doi:10.1016/j.erss.2020.101512.

Markewitz, P., P. Hansen, W. Kuckshinrichs, and J.F. Hake, 2015: Strategies for a low carbon building stock in Germany. 8th International Scientific Conference on Energy and Climate Change, Athens, Institute of Energy and Climate Research, Systems Analysis and Technology Evaluation (IEK-STE), Jülich, Germany.

Markovic, U., Z. Chu, P. Aristidou, and G. Hug, 2019: LQR-Based Adaptive Virtual Synchronous Machine for Power Systems With High Inverter Penetration. *IEEE Trans. Sustain. Energy*, **10(3)**, 1501–1512, doi:10.1109/TSTE.2018.2887147.

Marquardt, S.G. et al., 2021: Identifying regional drivers of future land-based biodiversity footprints. *Glob. Environ. Change*, **69**, doi:10.1016/j.gloenvcha.2021.102304.

Material Economics, 2019: *Industrial Transformation 2050 - Pathways to Net-Zero Emissions from EU Heavy Industry*. University of Cambridge Institute for Sustainability Leadership, Cambridge, UK, 208 pp.

Mbow, C., C. Rosenzweig, L.G. Barioni, T.G. Benton, M. Herrero, M. Krishnapillai, E. Liwenga, P. Pradhan, M.G. Rivera-Ferre, T. Sapkota, F.N. Tubiello, Y. Xu, 2019: Food Security. In: *Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D.C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA.

McCollum, D.L., V. Krey, and K. Riahi, 2011: An integrated approach to energy sustainability. *Nat. Clim. Change, 2011 19*, **1(9)**, 428–429, doi:10.1038/nclimate1297.

McCollum, D.L. et al., 2013: Climate policies can help resolve energy security and air pollution challenges. *Clim. Change*, **119(2)**, 479–494, doi:10.1007/s10584-013-0710-y.

McCollum, D.L. et al., 2016: Quantifying uncertainties influencing the long-term impacts of oil prices on energy markets and carbon emissions. *Nat. Energy*, **1(7)**, 16077, doi:10.1038/nenergy.2016.77.

McCollum, D.L. et al., 2017: Improving the behavioral realism of global integrated assessment models: An application to consumers' vehicle choices. *Transp. Res. Part D Transp. Environ.*, **55**, 322–342, doi:10.1016/j.trd.2016.04.003.

McCollum, D.L. et al., 2018: Energy investment needs for fulfilling the Paris Agreement and achieving the Sustainable Development Goals. *Nat. Energy*, **3(7)**, 589–599, doi:10.1038/s41560-018-0179-z.

McJeon, H.C. et al., 2011: Technology interactions among low-carbon energy technologies: What can we learn from a large number of scenarios? *Energy Econ.*, **33(4)**, 619–631, doi:10.1016/j.eneco.2010.10.007.

Meibom, P. et al., 2011: Stochastic optimization model to study the operational impacts of high wind penetrations in Ireland. *IEEE Trans. Power Syst.*, **26(3)**, 1367–1379, doi:10.1109/TPWRS.2010.2070848.

Meinshausen, M., S.C.B. Raper, and T.M.L. Wigley, 2011: Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 1: Model description and calibration. *Atmos. Chem. Phys.*, **11(4)**, 1417–1456, doi:10.5194/acp-11-1417-2011.

Meinshausen, M. et al., 2017: Historical greenhouse gas concentrations for climate modelling (CMIP6). *Geosci. Model Dev.*, **10(5)**, doi:10.5194/gmd-10-2057-2017.

Meinshausen, M. et al., 2020: The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500. *Geosci. Model Dev.*, **13(8)**, 3571–3605, doi:10.5194/gmd-13-3571-2020.

Méjean, A., C. Guivarch, J. Lefèvre, and M. Hamdi-Cherif, 2019: The transition in energy demand sectors to limit global warming to 1.5 °C. *Energy Effic.*, **12(2)**, 441–462, doi:10.1007/s12053-018-9682-0.

Mercure, J.-F., A. Lam, S. Billington, and H. Pollitt, 2018: Integrated assessment modelling as a positive science: private passenger road transport policies to meet a climate target well below 2 °C. *Clim. Change*, **151(2)**, 109–129, doi:10.1007/s10584-018-2262-7.

Mercure, J.-F. et al., 2019: Modelling innovation and the macroeconomics of low-carbon transitions: theory, perspectives and practical use. *Clim. Policy*, **19(8)**, 1019–1037, doi:10.1080/14693062.2019.1617665.

Merini, I., A. Molina-García, M. Socorro García-Cascales, M. Mahdaoui, and M. Ahachad, 2020: Analysis and comparison of energy efficiency code requirements for buildings: A Morocco-Spain case study. *Energies*, **13(22)**, doi:10.3390/en13225979.

Messner, S. and L. Schrattenholzer, 2000: MESSAGE-MACRO: Linking an energy supply model with a macroeconomic module and solving it iteratively. *Energy*, **25(3)**, 267–282, doi:10.1016/S0360-5442(99)00063-8.

Millar, R.J. et al., 2017: Emission budgets and pathways consistent with limiting warming to 1.5°C. *Nat. Geosci.*, **10(10)**, 741–747, doi:10.1038/ngeo3031.

Millward-Hopkins, J., J.K. Steinberger, N.D. Rao, and Y. Oswald, 2020: Providing decent living with minimum energy: A global scenario. *Glob. Environ. Change*, **65**, 102168, doi:10.1016/j.gloenvcha.2020.102168.

Minx, J.C. et al., 2018: Negative emissions – Part 1: Research landscape and synthesis. *Environ. Res. Lett.*, **13(6)**, 063001, doi:10.1088/1748-9326/aabf9b.

Momonoki, T., A. Taniguchi-Matsuoka, Y. Yamaguchi, and Y. Shimoda, 2017: Evaluation of the greenhouse gas reduction effect in the Japanese residential sector considering the characteristics of regions and households. *Build. Simul. Conf. Proc.*, **1**, 494–501, doi:10.26868/25222708.2017.718.

Monforti, F. et al., 2014: Assessing complementarity of wind and solar resources for energy production in Italy. A Monte Carlo approach. *Renew. Energy*, **63**, 576–586, doi:10.1016/j.renene.2013.10.028.

Moomaw, W., F. Yamba, M. Kamimoto, L. Maurice, J. Nyboer, K. Urama, T. Weir, 2011: Introduction. In *Special Report on Renewable Energy Sources and Climate Change Mitigation* [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C.von Stechow (eds.)], pp. 161–208, Cambridge University Press, Cambridge, UK and New York, NY, USA.

Morren, J., S.W.H. de Haan, W.L. Kling, and J.A. Ferreira, 2006: Wind turbines emulating inertia and supporting primary frequency control. *IEEE Trans. Power Syst.*, **21(1)**, 433–434, doi:10.1109/TPWRS.2005.861956.

Morris, J. et al., 2019: Representing the costs of low-carbon power generation in multi-region multi-sector energy-economic models. *Int. J. Greenh. Gas Control*, **87**, 170–187, doi:10.1016/j.ijggc.2019.05.016.

Morris, J., H. Kheshgi, S. Paltsev, and H. Herzog, 2021: Scenarios for the deployment of carbon capture and storage in the power sector in a portfolio of mitigation options. *Clim. Change Econ.*, **12(01)**, 2150001, doi:10.1142/S2010007821500019.

Mosnier, A. et al., 2014: Modeling Impact of Development Trajectories and a Global Agreement on Reducing Emissions from Deforestation on Congo Basin Forests by 2030. *Environ. Resour. Econ.*, **57(4)**, 505–525, doi:10.1007/s10640-012-9618-7.

Moss, R.H. et al., 2010: The next generation of scenarios for climate change research and assessment. *Nature*, **463(7282)**, 747–756, doi:10.1038/nature08823.

Mouratiadou, I. et al., 2016: The impact of climate change mitigation on water demand for energy and food: An integrated analysis based on the Shared Socioeconomic Pathways. *Environ. Sci. Policy*, **64**, 48–58, doi:10.1016/j.envsci.2016.06.007.

Müller-Casseres, E., O.Y. Edelenbosch, A. Szklo, R. Schaeffer, and D.P. van Vuuren, 2021: Global futures of trade impacting the challenge to decarbonize the international shipping sector. *Energy*, **237**, 121547, doi:10.1016/J.ENERGY.2021.121547.

Muratori, M. et al., 2021: The rise of electric vehicles – 2020 status and future expectations. *Prog. Energy*, **3(2)**, 22002, doi:10.1088/2516-1083/abe0ad.

Nadel, S., 2016: *Pathway to Cutting Energy Use and Carbon Emissions in Half*. American Council for an Energy-Efficient Economy, Washington, D.C, USA, 43 pp.

Napp, T. et al., 2017: Exploring the Feasibility of Low-Carbon Scenarios Using Historical Energy Transitions Analysis. *Energies*, **10(1)**, 116, doi:10.3390/en10010116.

négaWatt, 2017: *Scénario négaWatt : Un scénario de transition énergétique*. négaWatt, 4 pp.

NGFS, 2020: *NGFS climate scenarios for central banks and supervisors*. Network for Greening the Financial System, https://www.ngfs.net/sites/default/files/medias/documents/820184_ngfs_scenarios_final_version_v6.pdf (Accessed August 22, 2022).

NGFS, 2021: *NGFS Climate Scenarios for central banks and supervisors*. Network for Greening the Financial System, https://www.ngfs.net/en/ngfs-climate-scenarios-central-banks-and-supervisors-june-2021 (Accessed October 29, 2021).

Niamir, L., O. Ivanova, T. Filatova, A. Voinov, and H. Bressers, 2020: Demand-side solutions for climate mitigation: Bottom-up drivers of household energy behavior change in the Netherlands and Spain. *Energy Res. Soc. Sci.*, **62(101356)**, 101356, doi:10.1016/j.erss.2019.101356.

Nicholls, Z. et al., 2020a: OpenSCM-Runner: Thin wrapper to run simple climate models (emissions driven runs only). *GitHub Repos.*, https://github.com/openscm/openscm-runner (Accessed August 22, 2022).

Nicholls, Z. et al., 2021: Reduced Complexity Model Intercomparison Project Phase 2: Synthesizing Earth System Knowledge for Probabilistic Climate Projections. *Earth's Future*, **9(6)**, 29, doi:10.1029/2020EF001900.

Nicholls, Z. et al., 2020b: Reduced Complexity Model Intercomparison Project Phase 1: Introduction and evaluation of global-mean temperature response. *Geosci. Model Dev.*, **13(11)**, 5175–5190, doi:10.5194/gmd-13-5175-2020.

Nikas, A. et al., 2021: Where is the EU headed given its current climate policy? A stakeholder-driven model inter-comparison. *Sci. Total Environ.*, **793**, 148549, doi:10.1016/J.SCITOTENV.2021.148549.

Nogueira, L.A.H., G.M. Souza, L.A.B. Cortez, and C.H. de Brito Cruz, 2020: Biofuels for Transport. In: *Future Energy* [Letcher, T.M., (ed.)], Elsevier, Amsterdam, The Netherlands, pp. 173–197.

Nordelöf, A., M., Messagie, A.-M. Tillman, M. Ljunggren Söderman, and J. Van Mierlo, 2014: Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles – what can we learn from life cycle assessment? *Int. J. Life Cycle Assess.*, **19(11)**, doi:10.1007/s11367-014-0788-0.

Nordhaus, W., 1993: Optimal greenhouse-gas reductions and tax policy in the DICE model. *Am. Econ. Rev. (United States)*, **83:2(2)**, 313–317.

Nordhaus, W., 2015: Climate Clubs: Overcoming Free-Riding in International Climate Policy. *Am. Econ. Rev.*, **105(4)**, 1339–1370, doi:10.1257/aer.15000001.

Nordhaus, W., 2018: Evolution of modeling of the economics of global warming: changes in the DICE model, 1992–2017. *Clim. Change*, **148(4)**, 623–640, doi:10.1007/s10584-018-2218-y.

Novikova, A., T. Csoknyai, M. Jovanovic-Popovic, B. Stankovic, and Z. Szalay, 2018a: Assessment of decarbonisation scenarios for the residential buildings of Serbia. *Therm. Sci.*, **22**(Suppl. 4), 1231–1247, doi:10.2298/TSCI171221229N.

Novikova, A., T. Csoknyai, and Z. Szalay, 2018b: Low carbon scenarios for higher thermal comfort in the residential building sector of South Eastern Europe. *Energy Effic.*, **11(4)**, 845–875, doi:10.1007/s12053-017-9604-6.

NREL, 2020: Integrated Energy System Simulation. The National Renewable Energy Laboratory, US Department of Energy, https://www.nrel.gov/grid/integrated-energy-system-simulation.html (Accessed December 19, 2020).

O'Neill, B.C. et al., 2014: A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Clim. Change*, **122(3)**, 387–400, doi:10.1007/s10584-013-0905-2.

O'Neill, B.C. et al., 2016: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.*, **9(9)**, 3461–3482, doi:10.5194/gmd-9-3461-2016.

O'Neill, B.C. et al., 2017: The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Glob. Environ. Change*, **42**, 169–180, doi:10.1016/J.GLOENVCHA.2015.01.004.

O'Neill, B.C. et al., 2020: Achievements and needs for the climate change scenario framework. *Nat. Clim. Change*, **10(12)**, 1074–1084, doi:10.1038/s41558-020-00952-0.

Obersteiner, M. et al., 2016: Assessing the land resource–food price nexus of the Sustainable Development Goals. *Sci. Adv.*, **2(9)**, e1501499, doi:10.1126/sciadv.1501499.

Obersteiner, M. et al., 2018: How to spend a dwindling greenhouse gas budget. *Nat. Clim. Change*, **8(1)**, 7–10, doi:10.1038/s41558-017-0045-1.

Obi, M., S.M. Jensen, J.B. Ferris, and R.B. Bass, 2017: Calculation of levelized costs of electricity for various electrical energy storage systems. *Renew. Sustain. Energy Rev.*, **67**, 908–920, doi:10.1016/j.rser.2016.09.043.

OECD, 2021: *Effective Carbon Rates 2021*. OECD Publishing, Paris, France. https://www.oecd-ilibrary.org/taxation/effective-carbon-rates-2021_0e8e24f5-en.

Olovsson, J., M. Taljegard, M. Von Bonin, N. Gerhardt, and F. Johnsson, 2021: Impacts of Electric Road Systems on the German and Swedish Electricity Systems – An Energy System Model Comparison. *Front. Energy Res.*, **9**, doi:10.3389/fenrg.2021.631200.

Oluleye, G., L. Vasquez, R. Smith, and M. Jobson, 2016: A multi-period Mixed Integer Linear Program for design of residential distributed energy centres with thermal demand data discretisation. *Sustain. Prod. Consum.*, **5**, 16–28, doi:10.1016/j.spc.2015.11.003.

Oluleye, G., J. Allison, N. Kelly, and A.D. Hawkes, 2018: An optimisation study on integrating and incentivising Thermal Energy Storage (TES) in a dwelling energy system. *Energies*, **11(5)**, 1–17, doi:10.3390/en11051095.

Onyenokporo, N.C. and E.T. Ochedi, 2019: Low-cost retrofit packages for residential buildings in hot-humid Lagos, Nigeria. *Int. J. Build. Pathol. Adapt.*, **37(3)**, 250–272, doi:10.1108/IJBPA-01-2018-0010.

Ostermeyer, Y. et al., 2018a: *Building Market Brief. United Kingdom*. CUES Foundation, Delft, The Netherlands, 70 pp.

Ostermeyer, Y. et al., 2018b: *Building Market Brief. France*. CUES Foundation, Delft, The Netherlands, 70 pp.

Ostermeyer, Y. et al., 2018c: *Building Market Brief. The Netherlands*. CUES Foundation, Delft, The Netherlands, 70 pp.

Ostermeyer, Y. et al., 2019a: *Building Market Brief. Poland*. CUES Foundation, Delft, The Netherlands, 64pp.

Ostermeyer, Y. et al., 2019b: *Building Market Brief. Germany*. CUES Foundation, Delft, The Netherlands, 70 pp.

Ou, Y. et al., 2021: Deep mitigation of CO_2 and non-CO_2 greenhouse gases toward 1.5°C and 2°C futures. *Nat. Commun.*, **12(1)**, 6245, doi:10.1038/s41467-021-26509-z.

Overmars, K.P. et al., 2014: Estimating the opportunity costs of reducing carbon dioxide emissions via avoided deforestation, using integrated assessment modelling. *Land use policy*, **41**, 45–60, doi:10.1016/j.landusepol.2014.04.015.

Paltsev, S. and P. Capros, 2013: Cost Concepts for Climate Change Mitigation. *Clim. Change Econ.*, **04**(supp01), 1340003, doi:10.1142/S2010007813400034.

Paltsev, S. et al., 2021: *2021 Global Change Outlook: Charting the Earth's Future Energy, Managed Resources, Climate, and Policy Prospects*. MIT, Cambridge, MA, USA, 52 pp.

Paltsev, S., A. Ghandi, J. Morris, and H. Chen, 2022: Global Electrification of Light-duty Vehicles: Impacts of Economics and Climate Policy. *Econ. Energy Environ. Policy*, **11(1)**, (In press), doi:10.5547/2160-5890.11.1.spal.

Pan, X., M. den Elzen, N. Höhne, F. Teng, and L. Wang, 2017: Exploring fair and ambitious mitigation contributions under the Paris Agreement goals. *Environ. Sci. Policy*, **74**, 49–56, doi:10.1016/j.envsci.2017.04.020.

Papadopoulos, S. and E. Azar, 2016: Integrating building performance simulation in agent-based modeling using regression surrogate models: A novel human-in-the-loop energy modeling approach. *Energy Build.*, **128**, 214–223, doi:10.1016/j.enbuild.2016.06.079.

Parkinson, S. et al., 2019: Balancing clean water-climate change mitigation trade-offs. *Environ. Res. Lett.*, **14(1)**, 014009, doi:10.1088/1748-9326/aaf2a3.

Pastor, A.V. et al., 2019: The global nexus of food–trade–water sustaining environmental flows by 2050. *Nat. Sustain.*, **2(6)**, 499–507, doi:10.1038/s41893-019-0287-1.

Pauliuk, S. and N. Heeren, 2021: Material efficiency and its contribution to climate change mitigation in Germany: A deep decarbonization scenario analysis until 2060. *J. Ind. Ecol.*, **25(2)**, 479–493, doi:10.1111/jiec.13091.

Pauliuk, S., A. Arvesen, K. Stadler, and E.G. Hertwich, 2017: Industrial ecology in integrated assessment models. *Nat. Clim. Change*, **7(1)**, 13–20, doi:10.1038/nclimate3148.

Pauliuk, S. et al., 2021a: Linking service provision to material cycles: A new framework for studying the resource efficiency–climate change (RECC) nexus. *J. Ind. Ecol.*, **25(2)**, 260–273, doi:10.1111/jiec.13023.

Pauliuk, S. et al., 2021b: Global scenarios of resource and emission savings from material efficiency in residential buildings and cars. *Nat. Commun.*, **12(1)**, doi:10.1038/s41467-021-25300-4.

Paustian, K. et al., 2016: Climate-smart soils. *Nature*, **532(7597)**, 49–57, doi:10.1038/nature17174.

Pehl, M. et al., 2017: Understanding future emissions from low-carbon power systems by integration of life-cycle assessment and integrated energy modelling. *Nat. Energy*, **2(12)**, 939–945, doi:10.1038/s41560-017-0032-9.

Peng, W. et al., 2021: Climate policy models need to get real about people – here's how. *Nature*, **594**, 174–176, doi:10.1038/d41586-021-01500-2.

Perdana, S.P. et al., 2020: A multi-model analysis of long-term emissions and warming implications of current mitigation efforts. *Nat. Clim. Change*,

Pereira, L.M. et al., 2020: Developing multiscale and integrative nature–people scenarios using the Nature Futures Framework. *People Nat.*, **2(4)**, 1172–1195, doi:10.1002/pan3.10146.

Perez, M., R. Perez, K.R. Rábago, and M. Putnam, 2019: Overbuilding & curtailment: The cost-effective enablers of firm PV generation. *Sol. Energy*, **180**, 412–422, doi:10.1016/j.solener.2018.12.074.

Peters, G.P., 2018: Beyond carbon budgets. *Nat. Geosci.*, **11(6)**, 378–380, doi:10.1038/s41561-018-0142-4.

Pfenninger, S. and B. Pickering, 2018: Calliope: a multi-scale energy systems modelling framework. *J. Open Source Softw.*, **3(29)**, 825, doi:10.21105/joss.00825.

Pfenninger, S., A. Hawkes, and J. Keirstead, 2014: Energy systems modeling for twenty-first century energy challenges. *Renew. Sustain. Energy Rev.*, **33**, 74–86, doi:10.1016/j.rser.2014.02.003.

Pietzcker, R.C. et al., 2017: System integration of wind and solar power in integrated assessment models: A cross-model evaluation of new approaches. *Energy Econ.*, **64**, 583–599, doi:10.1016/j.eneco.2016.11.018.

Pindyck, R.S., 2013: Climate change policy: What do the models tell us? *J. Econ. Lit.*, **51(3)**, 860–872, doi:10.1257/jel.51.3.860.

Pindyck, R.S., 2017: The use and misuse of models for climate policy. *Rev. Environ. Econ. Policy*, **11(1)**, 100–114, doi:10.1093/reep/rew012.

Piontek, F. et al., 2019: Economic Growth Effects of Alternative Climate Change Impact Channels in Economic Modeling. *Environ. Resour. Econ.*, **73(4)**, 1357–1385, doi:10.1007/s10640-018-00306-7.

Plevin, R.J., M.A. Delucchi, and F. Creutzig, 2014: Using Attributional Life Cycle Assessment to Estimate Climate-Change Mitigation Benefits Misleads Policy Makers. *J. Ind. Ecol.*, **18(1)**, doi:10.1111/jiec.12074.

Ploss, M., T. Hatt, C. Schneider, T. Rosskopf, and M. Braun, 2017: *Modellvorhaben "KliNaWo": Klimagerechter Nachhaltiger Wohnbau*. Dornbirn, Austria.

Polasky, S. and N.K. Dampha, 2021: Discounting and Global Environmental Change. *Annu. Rev. Environ. Resour.*, **46(1)**, doi:10.1146/annurev-environ-020420-042100.

Pongratz, J., C.H. Reick, R.A. Houghton, and J.I. House, 2014: Terminology as a key uncertainty in net land use and land cover change carbon flux estimates. *Earth Syst. Dyn.*, **5(1)**, 177–195, doi:10.5194/esd-5-177-2014.

Popp, A., H. Lotze-Campen, and B. Bodirsky, 2010: Food consumption, diet shifts and associated non-CO_2 greenhouse gases from agricultural production. *Glob. Environ. Change*, **20(3)**, 451–462, doi:10.1016/j.gloenvcha.2010.02.001.

Popp, A. et al., 2014a: Land-use transition for bioenergy and climate stabilization: Model comparison of drivers, impacts and interactions with other land use based mitigation options. *Clim. Change*, **123(3–4)**, 495–509, doi:10.1007/s10584-013-0926-x.

Popp, A. et al., 2014b: Land-use protection for climate change mitigation. *Nat. Clim. Change*, **4(12)**, 1095–1098, doi:10.1038/nclimate2444.

Popp, A. et al., 2017: Land-use futures in the shared socio-economic pathways. *Glob. Environ. Change*, **42**, 331–345, doi:10.1016/j.gloenvcha.2016.10.002.

Portugal-Pereira, J., J. Nakatani, K.H. Kurisu, and K. Hanaki, 2015: Comparative energy and environmental analysis of Jatropha bioelectricity versus biodiesel production in remote areas. *Energy*, **83**, doi:10.1016/j.energy.2015.02.022.

Portugal-Pereira, J. et al., 2016: Overlooked impacts of electricity expansion optimisation modelling: The life cycle side of the story. *Energy*, **115**, 1424–1435, doi:10.1016/j.energy.2016.03.062.

Portugal-Pereira, J. et al., 2018: Interactions between global climate change strategies and local air pollution: lessons learnt from the expansion of the power sector in Brazil. *Clim. Change*, **148(1–2)**, 293–309, doi:10.1007/s10584-018-2193-3.

Prada-Hernández, A., H. Vargas, A. Ozuna, and J.L. Ponz-Tienda, 2015: Marginal Abatement Costs Curve (MACC) for Carbon Emissions Reduction from Buildings: An Implementation for Office Buildings in Colombia. *Int. J. Civ. Struct. Eng.*, **2(1)**, 175–183.

Prina, M.G., G. Manzolini, D. Moser, B. Nastasi, and W. Sparber, 2020: Classification and challenges of bottom-up energy system models – A review. *Renew. Sustain. Energy Rev.*, **129**, doi:10.1016/j.rser.2020.109917.

Prussi, M. et al., 2021: CORSIA: The first internationally adopted approach to calculate life-cycle GHG emissions for aviation fuels. *Renew. Sustain. Energy Rev.*, **150**, doi:10.1016/j.rser.2021.111398.

Radpour, S., M.A. Hossain Mondal, and A. Kumar, 2017: Market penetration modeling of high energy efficiency appliances in the residential sector. *Energy*, **134**, 951–961, doi:10.1016/j.energy.2017.06.039.

Rajão, R. et al., 2020: The rotten apples of Brazil's agribusiness. *Science*, **369(6501)**, 246–248, doi:10.1126/science.aba6646.

Ramsey, F.P., 1928: A Mathematical Theory of Saving. *Econ. J.*, **38(152)**, doi:10.2307/2224098.

Rao, N.D., B.J. Van Ruijven, K. Riahi, and V. Bosetti, 2017a: Improving poverty and inequality modelling in climate research. *Nat. Clim. Change*, **7(12)**, 857–862, doi:10.1038/s41558-017-0004-x.

Rao, N.D., P. Sauer, M. Gidden, and K. Riahi, 2019: Income inequality projections for the Shared Socioeconomic Pathways (SSPs). *Futures*, **105**, 27–39, doi:10.1016/j.futures.2018.07.001.

Rao, S. et al., 2013: Better air for better health: Forging synergies in policies for energy access, climate change and air pollution. *Glob. Environ. Change*, **23(5)**, 1122–1130, doi:10.1016/J.GLOENVCHA.2013.05.003.

AIII

Rao, S. et al., 2017b: Future air pollution in the Shared Socio-economic Pathways. *Glob. Environ. Change*, **42**, 346–358, doi:10.1016/j.gloenvcha.2016.05.012.

Realmonte, G. et al., 2019: An inter-model assessment of the role of direct air capture in deep mitigation pathways. *Nat. Commun.*, **10(1)**, 1–12, doi:10.1038/s41467-019-10842-5.

Rebitzer, G. et al., 2004: Life cycle assessment. *Environ. Int.*, **30(5)**, doi:10.1016/j.envint.2003.11.005.

Reilly, J. et al., 2018: *Food, Water, Energy, Climate Outlook: Perspectives from 2018*. MIT, Cambridge, MA, USA, 48 pp.

Reinhart, C.F. and C. Cerezo Davila, 2016: Urban building energy modeling – A review of a nascent field. *Build. Environ.*, **97**, 196–202, doi:10.1016/j.buildenv.2015.12.001.

Riahi, K. et al., 2012: Chapter 17: Energy Pathways for Sustainable Development. In: *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, pp. 1203–1306.

Riahi, K. et al., 2015: Locked into Copenhagen pledges – Implications of short-term emission targets for the cost and feasibility of long-term climate goals. *Technol. Forecast. Soc. Change*, **90**, 8–23, doi:10.1016/j.techfore.2013.09.016.

Riahi, K. et al., 2017: The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Glob. Environ. Change*, **42**, 153–168, doi:10.1016/J.GLOENVCHA.2016.05.009.

Riahi, K. et al., 2021: Long-term economic benefits of stabilizing warming without overshoot – the ENGAGE model intercomparison. *Rev.*,. doi:10.21203/rs.3.rs-127847/v1.

Ringkjøb, H.K. et al., 2020: Short-term solar and wind variability in long-term energy system models – A European case study. *Energy*, **209**, doi:10.1016/j.energy.2020.118377.

Ritchie, H., D.S. Reay, and P. Higgins, 2018: The impact of global dietary guidelines on climate change. *Glob. Environ. Change*, **49** (June 2017), 46–55, doi:10.1016/j.gloenvcha.2018.02.005.

Robinson, J.B., 1982: Energy backcasting A proposed method of policy analysis. *Energy Policy*, **10(4)**, 337–344, doi:10.1016/0301-4215(82)90048-9.

Robinson, S., 1989: Chapter 18: Multisectoral models. In: *Handbook of Development Economics*, Vol. 2, Chenery, H. and T.N. Srinivasan (eds.), Elsevier, Amsterdam, The Netherlands, pp. 885–947.

Robinson, S., A. Yúnez-Naude, R. Hinojosa-Ojeda, J.D. Lewis, and S. Devarajan, 1999: From stylized to applied models: Building multisector CGE models for policy analysis. *North Am. J. Econ. Financ.*, **10(1)**, 5–38, doi:10.1016/S1062-9408(99)00014-5.

Roca-Puigròs, M., R.G. Billy, A. Gerber, P. Wäger, and D.B. Müller, 2020: Pathways toward a carbon-neutral Swiss residential building stock. *Build. Cities*, **1(1)**, 579–593, doi:10.5334/bc.61.

Rochedo, P.R.R. et al., 2018: The threat of political bargaining to climate mitigation in Brazil. *Nat. Clim. Change*, **8(8)**, 695–698, doi:10.1038/s41558-018-0213-y.

Roelfsema, M. et al., 2020: Taking stock of national climate policies to evaluate implementation of the Paris Agreement. *Nat. Commun.*, **11(1)**, 2096, doi:10.1038/s41467-020-15414-6.

Rogelj, J. et al., 2011: Emission pathways consistent with a 2°C global temperature limit. *Nat. Clim. Change*, **1(8)**, doi:10.1038/nclimate1258.

Rogelj, J., D.L. McCollum, A. Reisinger, M. Meinshausen, and K. Riahi, 2013a: Probabilistic cost estimates for climate change mitigation. *Nature*, **493(7430)**, 79–83, doi:10.1038/nature11787.

Rogelj, J., D.L. McCollum, and K. Riahi, 2013b: The UN's "Sustainable Energy for All" initiative is compatible with a warming limit of 2 °C. *Nat. Clim. Change, 2013 36*, **3(6)**, 545–551, doi:10.1038/nclimate1806.

Rogelj, J. et al., 2016: Differences between carbon budget estimates unravelled. *Nat. Clim. Change*, **6(3)**, 245–252, doi:10.1038/nclimate2868.

Rogelj, J. et al., 2017: Understanding the origin of Paris Agreement emission uncertainties. *Nat. Commun.*, **8**, 15748, doi:10.1038/ncomms15748.

Rogelj, J., D. Shindell, K. Jiang, S. Fifita, P. Forster, V. Ginzburg, C. Handa, H. Kheshgi, S. Kobayashi, E. Kriegler, L. Mundaca, R. Séférian, and M.V.Vilariño, 2018a: Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development. In: *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty* [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Rogelj, J. et al., 2018b: Scenarios towards limiting global mean temperature increase below 1.5°C. *Nat. Clim. Change*, **8(4)**, 325–332, doi:10.1038/s41558-018-0091-3.

Rogelj, J., P.M. Forster, E. Kriegler, C.J. Smith, and R. Séférian, 2019a: Estimating and tracking the remaining carbon budget for stringent climate targets. *Nature*, **571(7765)**, 335–342, doi:10.1038/s41586-019-1368-z.

Rogelj, J. et al., 2019b: A new scenario logic for the Paris Agreement long-term temperature goal. *Nature*, **573(7774)**, 357–363, doi:10.1038/s41586-019-1541-4.

Rogelj, J., O. Geden, A. Cowie, and A. Reisinger, 2021: Net-zero emissions targets are vague: three ways to fix. *Nature*, **591(7850)**, 365–368, doi:10.1038/d41586-021-00662-3.

Rogner, H.-H. et al., 2012: Chapter 7: Energy Resources and Potentials. In: *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, pp. 423–512.

Rosa, I.M.D. et al., 2020: Challenges in producing policy-relevant global scenarios of biodiversity and ecosystem services. *Glob. Ecol. Conserv.*, **22**, e00886, doi:10.1016/j.gecco.2019.e00886.

Rosas-Flores, J.A. and D. Rosas-Flores, 2020: Potential energy savings and mitigation of emissions by insulation for residential buildings in Mexico. *Energy Build.*, **209**, doi:10.1016/j.enbuild.2019.109698.

Roscini, A.V., O. Rapf, and J. Kockat, 2020: *On the way to a climate-neutral Europe. Contribution from the building sector to a strengthened 2030 climate target*. Buildings Performance Institute Europe, Brussels, Belgium, 24 pp.

Rose, P.K. and F. Neumann, 2020: Hydrogen refueling station networks for heavy-duty vehicles in future power systems. *Transp. Res. Part D Transp. Environ.*, **83**, doi:10.1016/j.trd.2020.102358.

Rose, S.K. et al., 2020: An overview of the Energy Modeling Forum 33rd study: assessing large-scale global bioenergy deployment for managing climate change. *Clim. Change*, **163(3)**, 1539–1551, doi:10.1007/s10584-020-02945-6.

Rosenzweig, C. et al., 2020: Climate change responses benefit from a global food system approach. *Nat. Food*, **1(2)**, 94–97, doi:10.1038/s43016-020-0031-z.

Rottoli, M., A. Dirnaichner, R. Pietzcker, F. Schreyer, and G. Luderer, 2021: Alternative electrification pathways for light-duty vehicles in the European transport sector. *Transp. Res. Part D Transp. Environ.*, **99**, 103005, doi:10.1016/J.TRD.2021.103005.

Sachs, J., Y. Meng, S. Giarola, and A. Hawkes, 2019a: An agent-based model for energy investment decisions in the residential sector. *Energy*, **172**, 752–768, doi:10.1016/j.energy.2019.01.161.

Sachs, J.D. et al., 2019b: Six Transformations to achieve the Sustainable Development Goals. *Nat. Sustain.*, **2(9)**, 805–814, doi:10.1038/s41893-019-0352-9.

Sanchez, D.L., N. Johnson, S.T. McCoy, P.A. Turner, and K.J. Mach, 2018: Near-term deployment of carbon capture and sequestration from biorefineries in the United States. *Proc. Natl. Acad. Sci.*, **115(19)**, 4875–4880, doi:10.1073/pnas.1719695115.

Sandberg, N.H., J.S. Næss, H. Brattebø, I. Andresen, and A. Gustavsen, 2021: Large potentials for energy saving and greenhouse gas emission reductions from large-scale deployment of zero emission building technologies in a national building stock. *Energy Policy*, **152**, doi:10.1016/j.enpol.2020.112114.

Sani Hassan, A., L. Cipcigan, and N. Jenkins, 2018: Impact of optimised distributed energy resources on local grid constraints. *Energy*, **142**, 878–895, doi:10.1016/j.energy.2017.10.074.

Schaber, K., F. Steinke, and T. Hamacher, 2012: Transmission grid extensions for the integration of variable renewable energies in Europe: Who benefits where? *Energy Policy*, **43**, 123–135, doi:10.1016/j.enpol.2011.12.040.

Schaeffer, M. et al., 2015: Mid- and long-term climate projections for fragmented and delayed-action scenarios. *Technol. Forecast. Soc. Change*, **90**(PA), 257–268, doi:10.1016/j.techfore.2013.09.013.

Schaeffer, R. et al., 2020: Comparing transformation pathways across major economies. *Clim. Change*, **162(4)**, 1787–1803, doi:10.1007/s10584-020-02837-9.

Schäfer, A.W., 2017: Long-term trends in domestic US passenger travel: the past 110 years and the next 90. *Transportation (Amst).*, **44(2)**, 293–310, doi:10.1007/s11116-015-9638-6.

Schleussner, C.-F. et al., 2016: Differential climate impacts for policy-relevant limits to global warming: the case of 1.5 °C and 2 °C. *Earth Syst. Dyn.*, **7(2)**, 327–351, doi:10.5194/esd-7-327-2016.

Schmitz, C. et al., 2014: Land-use change trajectories up to 2050: Insights from a global agro-economic model comparison. *Agric. Econ. (United Kingdom)*, **45(1)**, 69–84, doi:10.1111/agec.12090.

Scholz, Y., H.C. Gils, and R.C. Pietzcker, 2017: Application of a high-detail energy system model to derive power sector characteristics at high wind and solar shares. *Energy Econ.*, **64**, 568–582, doi:10.1016/j.eneco.2016.06.021.

Schultes, A. et al., 2018: Optimal international technology cooperation for the low-carbon transformation. *Clim. Policy*, **18(9)**, 1165–1176, doi:10.1080/14693062.2017.1409190.

Schultes, A. et al., 2021: Economic damages from on-going climate change imply deeper near-term emission cuts. *Environ. Res. Lett.*, **16(10)**, 104053, doi:10.1088/1748-9326/AC27CE.

Schwanitz, V.J., 2013: Evaluating integrated assessment models of global climate change. *Environ. Model. Softw.*, **50**, 120–131, doi:10.1016/j.envsoft.2013.09.005.

Scrieciu, S., A. Rezai, and R. Mechler, 2013: On the economic foundations of green growth discourses: The case of climate change mitigation and macroeconomic dynamics in economic modeling. *Wiley Interdiscip. Rev. Energy Environ.*, **2(3)**, 251–268, doi:10.1002/wene.57.

Serrenho, A.C., M. Drewniok, C. Dunant, and J.M. Allwood, 2019: Testing the greenhouse gas emissions reduction potential of alternative strategies for the English housing stock. *Resour. Conserv. Recycl.*, **144**, 267–275, doi:10.1016/j.resconrec.2019.02.001.

Sharma, S., S.H. Huang, and N.D.R. Sarma, 2011: System inertial frequency response estimation and impact of renewable resources in ERCOT interconnection. IEEE Power and Energy Society General Meeting, IEEE, doi:10.1109/PES.2011.6038993.

Sharp, B.E. and S.A. Miller, 2016: Potential for Integrating Diffusion of Innovation Principles into Life Cycle Assessment of Emerging Technologies. *Environ. Sci. Technol.*, **50(6)**, doi:10.1021/acs.est.5b03239.

Shukla, P.R. and V. Chaturvedi, 2011: Sustainable energy transformations in India under climate policy. *Sustain. Dev.*, **21(1)**, 48–59, doi:10.1002/sd.516.

Sinsel, S.R., R.L. Riemke, and V.H. Hoffmann, 2020: Challenges and solution technologies for the integration of variable renewable energy sources – a review. *Renew. Energy*, **145**, 2271–2285, doi:10.1016/j.renene.2019.06.147.

Skar, C., G. Doorman, G.A. Pérez-Valdés, and A. Tomasgard, 2016: *A multi-horizon stochastic programming model for the European power system*. CenSES working paper 2/2016, Centre for Sustainable Energy Studies, Norwegian University of Science and Technology, Trondheim, Norway, 30 pp. https://www.ntnu.no/documents/7414984/202064323/1_Skar_ferdig.pdf/855f0c3c-81db-440d-9f76-cfd91af0d6f0.

Skea, J., P. Shukla, A. Al Khourdajie, and D. McCollum, 2021: Intergovernmental Panel on Climate Change: Transparency and integrated assessment modeling. *WIREs Clim. Change*, **12(5)**, e727–e727, doi.org/10.1002/wcc.727.

Smith, C.J. et al., 2018: FAIR v1.3: A simple emissions-based impulse response and carbon cycle model. *Geosci. Model Dev.*, **11(6)**, 2273–2297, doi:10.5194/gmd-11-2273-2018.

Smith, E. et al., 2021: The cost of CO_2 transport and storage in global integrated assessment modeling. *Int. J. Greenh. Gas Control*, **109**, 103367, doi:10.1016/j.ijggc.2021.103367.

Smith P., M. Bustamante, H. Ahammad, H. Clark, H. Dong, E.A. Elsiddig, H. Haberl, R. Harper, J. House, M. Jafari, O. Masera, C. Mbow, N.H. Ravindranath, C.W. Rice, C. Robledo Abad, A. Romanovskaya, F. Sperling, and F. Tubiello, 2014: Agriculture, Forestry and Other Land Use (AFOLU). 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, UK and New York, NY, USA.

Smith, P. et al., 2016: Biophysical and economic limits to negative CO_2 emissions. *Nat. Clim. Change*, **6(1)**, 42–50, doi:10.1038/nclimate2870.

Smith, P., J. Nkem, K. Calvin, D. Campbell, F. Cherubini, G. Grassi, V. Korotkov, A.L. Hoang, S. Lwasa, P. McElwee, E. Nkonya, N. Saigusa, J.-F. Soussana, M.A. Taboada, 2019: Interlinkages Between Desertification, Land Degradation, Food Security and Greenhouse Gas Fluxes: Synergies, Trade-offs and Integrated Response Options. In: *Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems* [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Portner, D.C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Smith, S.J. et al., 2020a: Impact of methane and black carbon mitigation on forcing and temperature: a multi-model scenario analysis. *Clim. Change*, **163(3)**, 1427–1442, doi:10.1007/s10584-020-02794-3.

Smith, S.J. et al., 2020b: The Energy Modeling Forum (EMF) –30 study on short-lived climate forcers: introduction and overview. *Clim. Change*, **163(3)**, 1399–1408, doi:10.1007/s10584-020-02938-5.

Soergel, B. et al., 2021: A sustainable development pathway for climate action within the UN 2030 Agenda. *Nat. Clim. Change*, **11(8)**, 656–664, doi:10.1038/s41558-021-01098-3.

Soria, R. et al., 2016: Modelling concentrated solar power (CSP) in the Brazilian energy system: A soft-linked model coupling approach. *Energy*, **116**, 265–280, doi:10.1016/j.energy.2016.09.080.

Springmann, M., H.C.J. Godfray, M. Rayner, and P. Scarborough, 2016: Analysis and valuation of the health and climate change cobenefits of dietary change. *Proc. Natl. Acad. Sci.*, **113(15)**, 4146–4151, doi:10.1073/pnas.1523119113.

Statharas, S., Y. Moysoglou, P. Siskos, and P. Capros, 2021: Simulating the Evolution of Business Models for Electricity Recharging Infrastructure Development by 2030: A Case Study for Greece. *Energies*, **14(9)**, doi:10.3390/en14092345.

Stehfest, E. et al., 2014: *Integrated Assessment of Global Environmental Change with IMAGE 3.0 – Model description and policy applications*. PBL Netherlands Environmental Assessment Agency, The Hague, The Netherlands, 370 pp.

AIII

Stehfest, E. et al., 2019: Key determinants of global land-use projections. *Nat. Commun.*, **10(1)**, 1–10, doi:10.1038/s41467-019-09945-w.

Stern, N. 2006: The Stern Review on the Economic Effects of Climate Change. *Popul. Dev. Rev.*, **32(4)**, doi:10.1111/j.1728-4457.2006.00153.x.

Stern, N., 2016: Economics: Current climate models are grossly misleading. *Nature*, **530(7591)**, 407–409, doi:10.1038/530407a.

Strbac, G. et al., 2018: *Value of Flexibility in a Decarbonised Grid and System Externalities of Low-Carbon Generation Technologies: For the Committee on Climate Change*. Imperial College and NERA, London, UK.

Strefler, J. et al., 2018: Between Scylla and Charybdis: Delayed mitigation narrows the passage between large-scale CDR and high costs. *Environ. Res. Lett.*, **13(4)**, 044015, doi:10.1088/1748-9326/aab2ba.

Strefler, J. et al., 2021a: Carbon dioxide removal technologies are not born equal. *Environ. Res. Lett.*, **16(7)**, 74021, doi:10.1088/1748-9326/ac0a11.

Strefler, J. et al., 2021b: Alternative carbon price trajectories can avoid excessive carbon removal. *Nat. Commun.*, **12(1)**, 2264, doi:10.1038/s41467-021-22211-2.

Streicher, K.N., D. Parra, M.C. Buerer, and M.K. Patel, 2017: Techno-economic potential of large-scale energy retrofit in the Swiss residential building stock. *Energy Procedia*, **122**, 121–126, doi:10.1016/j.egypro.2017.07.314.

Subramanyam, V., M. Ahiduzzaman, and A. Kumar, 2017a: Greenhouse gas emissions mitigation potential in the commercial and institutional sector. *Energy Build.*, **140**, 295–304, doi:10.1016/j.enbuild.2017.02.007.

Subramanyam, V., A. Kumar, A. Talaei, and M.A.H. Mondal, 2017b: Energy efficiency improvement opportunities and associated greenhouse gas abatement costs for the residential sector. *Energy*, **118**, 795–807, doi:10.1016/j.energy.2016.10.115.

Sugiyama, M. et al., 2019a: Japan's long-term climate mitigation policy: Multi-model assessment and sectoral challenges. *Energy*, **167**, 1120–1131, doi:10.1016/j.energy.2018.10.091.

Sugiyama, M., A. Taniguchi-Matsuoka, Y. Yamaguchi, and Y. Shimoda, 2019b: Required Specification of Residential End-use Energy Demand Model for Application to National GHG Mitigation Policy Making – Case Study for the Japanese Plan for Global Warming Countermeasures. *Proceedings of Building Simulation 2019: 16th Conference of IBPSA*, Vol. 6, pp. 3706–3713.

Sugiyama, M. et al., 2020: EMF 35 JMIP study for Japan's long-term climate and energy policy: scenario designs and key findings. *Sustain. Sci.*, **Rev**.

Tan, X., H. Lai, B. Gu, Y. Zeng, and H. Li, 2018: Carbon emission and abatement potential outlook in China's building sector through 2050. *Energy Policy*, **118**(March), 429–439, doi:10.1016/j.enpol.2018.03.072.

Tavoni, M. and R.S.J. Tol, 2010: Counting only the hits? The risk of underestimating the costs of stringent climate policy: A letter. *Clim. Change*, **100(3)**, 769–778, doi:10.1007/s10584-010-9867-9.

Tavoni, M. et al., 2014: The distribution of the major economies' effort in the Durban Platform scenarios. *Clim. Change Econ.*, **4(4)**, doi:10.1142/S2010007813400095.

Tavoni, M. et al., 2015: Post-2020 climate agreements in the major economies assessed in the light of global models. *Nat. Clim. Change*, **5(2)**, 119–126, doi:10.1038/nclimate2475.

Taylor, K.E., R.J. Stouffer, and G.A. Meehl, 2011: An Overview of CMIP5 and the Experiment Design. *Bull. Am. Meteorol. Soc.*, **93(4)**, 485–498, doi:10.1175/BAMS-D-11-00094.1.

Taylor, P.G., P. Upham, W. McDowall, and D. Christopherson, 2014: Energy model, boundary object and societal lens: 35 years of the MARKAL model in the UK. *Energy Res. Soc. Sci.*, **4**(C), 32–41, doi:10.1016/j.erss.2014.08.007.

Teng, F. and G. Strbac, 2017: Full Stochastic Scheduling for Low-Carbon Electricity Systems. *IEEE Trans. Autom. Sci. Eng.*, **14(2)**, 461–470, doi:10.1109/TASE.2016.2629479.

Timilsina, G., A. Sikharulidze, E. Karapoghosyan, and S. Shatvoryan, 2016: *How Do We Prioritize the GHG Mitigation Options? Development of a Marginal Abatement Cost Curve for the Building Sector in Armenia and Georgia*. World Bank, Washington, DC, USA, 37 pp.

TNO, 2021: *GenX: Configurable Capacity Expansion Model*. MIT. https://tlo.mit.edu/technologies/genx-configurable-capacity-expansion-model.

Tokimatsu, K. et al., 2020: Toward more comprehensive environmental impact assessments: interlinked global models of LCIA and IAM applicable to this century. *Int. J. Life Cycle Assess.*, **25(9)**, 1710–1736, doi:10.1007/s11367-020-01750-8.

Toleikyte, A., L. Kranzl, and A. Müller, 2018: Cost curves of energy efficiency investments in buildings – Methodologies and a case study of Lithuania. *Energy Policy*, **115**, 148–157, doi:10.1016/j.enpol.2017.12.043.

Tosatto, A., G. Misyris, A. Junyent-Ferré, F. Teng, and S. Chatzivasileiadis, 2020: Towards Optimal Coordination between Regional Groups: HVDC Supplementary Power Control. *IEEE Trans. Power Syst.*, **37**(1), 1–8.

Trottier, 2016: *Canada's challenge & opportunity. Transformations for major reductions in GHG emissions*. David Suzuki Foundation and partners, Ottawa, Canada, 321 pp.

Trutnevyte, E. et al., 2019: Societal Transformations in Models for Energy and Climate Policy: The Ambitious Next Step. *One Earth*, **1(4)**, 423–433, doi:10.1016/j.oneear.2019.12.002.

Tubiello, F.N. et al., 2015: The Contribution of Agriculture, Forestry and other Land Use activities to Global Warming, 1990–2012. *Glob. Change Biol.*, **21(7)**, 2655–2660, doi:10.1111/gcb.12865.

Tulkens, H., 2019: *Economics, Game Theory and International Environmental Agreements*. World Scientific Publishing Co. Pte. Ltd. ISBN: 9789813141223.

Turnheim, B. et al., 2015: Evaluating sustainability transitions pathways: Bridging analytical approaches to address governance challenges. *Glob. Environ. Change*, **35**, 239–253, doi:10.1016/j.gloenvcha.2015.08.010.

UNEP, 2019: Bridging the Gap: Enhancing Mitigation Ambition and Action at G20 Level and Globally in UNEP *Emissions Gap Report 2019*. UNEP, Nairobi, Kenya.

Valin, H. et al., 2014: The future of food demand: Understanding differences in global economic models. *Agric. Econ. (United Kingdom)*, **45(1)**, 51–67, doi:10.1111/agec.12089.

van de Ven, D.-J. et al., 2021: The Impact of U.S. Re-engagement in Climate on the Paris Targets. *Earth's Future*, **9(9)**, e2021EF002077-e2021EF002077, doi:10.1029/2021EF002077.

van den Berg, N.J. et al., 2020: Implications of various effort-sharing approaches for national carbon budgets and emission pathways. *Clim. Change*, **162(4)**, 1805–1822, doi:10.1007/s10584-019-02368-y.

van der Zwaan, B.C.C., K. V Calvin, and L.E. Clarke, 2016: Climate Mitigation in Latin America: Implications for Energy and Land Use: Preface to the Special Section on the findings of the CLIMACAP-LAMP project. *Energy Econ.*, **56**, 495–498, doi:10.1016/J.ENECO.2016.05.005.

van Marle, M.J.E. et al., 2017: Historic global biomass burning emissions for CMIP6 (BB4CMIP) based on merging satellite observations with proxies and fire models (1750–2015). *Geosci. Model Dev.*, **10(9)**, 3329–3357, doi:10.5194/gmd-10-3329-2017.

van Sluisveld, M.A.E. et al., 2015: Comparing future patterns of energy system change in 2°C scenarios with historically observed rates of change. *Glob. Environ. Change*, **35**, 436–449, doi:10.1016/j.gloenvcha.2015.09.019.

van Sluisveld, M.A.E., S.H. Martínez, V. Daioglou, and D.P. van Vuuren, 2016: Exploring the implications of lifestyle change in 2°C mitigation scenarios using the IMAGE integrated assessment model. *Technol. Forecast. Soc. Change*, **102**, 309–319, doi:10.1016/j.techfore.2015.08.013.

van Sluisveld, M.A.E. et al., 2018: Comparing future patterns of energy system change in 2°C scenarios to expert projections. *Glob. Environ. Change*, **50**(March), 201–211, doi:10.1016/j.gloenvcha.2018.03.009.

van Soest, H.L. et al., 2019: Analysing interactions among Sustainable Development Goals with Integrated Assessment Models. *Glob. Transitions*, **1**, 210–225, doi:10.1016/j.glt.2019.10.004.

van Soest, H.L., Aleluia Reis, L., Baptista, L.B. *et al.* Global roll-out of comprehensive policy measures may aid in bridging emissions gap. *Nat Commun* **12**, 6419 (2021). https://doi.org/10.1038/s41467-021-26595-z

van Vuuren, D. et al., 2021: *The 2021 SSP scenarios of the IMAGE 3.2* *model*. PBL Netherlands Environmental Assessment Agency, The Hague, The Netherlands.

van Vuuren, D.P. et al., 2008: Temperature increase of 21st century mitigation scenarios. *Proc. Natl. Acad. Sci.*, **105(40)**, doi:10.1073/pnas.0711129105.

van Vuuren, D.P. et al., 2009: Comparison of top-down and bottom-up estimates of sectoral and regional greenhouse gas emission reduction potentials. *Energy Policy*, **37(12)**, 5125–5139, doi:10.1016/j.enpol.2009.07.024.

van Vuuren, D.P. et al., 2011a: How well do integrated assessment models simulate climate change? *Clim. Change*, **104(2)**, 255–285, doi:10.1007/s10584-009-9764-2.

van Vuuren, D.P. et al., 2011b: The representative concentration pathways: an overview. *Clim. Change*, **109(1–2)**, 5–31, doi:10.1007/s10584-011-0148-z.

van Vuuren, D.P. et al., 2012: A proposal for a new scenario framework to support research and assessment in different climate research communities. *Glob. Environ. Change*, **22(1)**, 21–35, doi:10.1016/j.gloenvcha.2011.08.002.

van Vuuren, D.P. et al., 2014: A new scenario framework for Climate Change Research: Scenario matrix architecture. *Clim. Change*, **122(3)**, 373–386, doi:10.1007/s10584-013-0906-1.

van Vuuren, D.P. et al., 2015: Pathways to achieve a set of ambitious global sustainability objectives by 2050: Explorations using the IMAGE integrated assessment model. *Technol. Forecast. Soc. Change*, **98**, 303–323, doi:10.1016/j.techfore.2015.03.005.

van Vuuren, D.P. et al., 2017a: Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm. *Glob. Environ. Change*, **42**, 237–250, doi:10.1016/j.gloenvcha.2016.05.008.

van Vuuren, D.P. et al., 2017b: The Shared Socio-economic Pathways: Trajectories for human development and global environmental change. *Glob. Environ. Change*, **42**, 148–152, doi:10.1016/j.gloenvcha.2016.10.009.

van Vuuren, D.P. et al., 2018: Alternative pathways to the 1.5°C target reduce the need for negative emission technologies. *Nat. Clim. Change*, **8(5)**, 391–397, doi:10.1038/s41558-018-0119-8.

Van Vuuren, D.P. et al., 2019: Integrated scenarios to support analysis of the food–energy–water nexus. *Nat. Sustain.*, **2(12)**, 1132–1141, doi:10.1038/s41893-019-0418-8.

Velders, G.J.M., D.W. Fahey, J.S. Daniel, S.O. Andersen, and M. McFarland, 2015: Future atmospheric abundances and climate forcings from scenarios of global and regional hydrofluorocarbon (HFC) emissions. *Atmos. Environ.*, **123**, 200–209, doi:10.1016/J.ATMOSENV.2015.10.071.

Virage-Energie Nord-Pas-de-Calais., 2016: *Mieux Vivre en Région Nord-Pas-de-Calais – Pour un virage énergétique et des transformations sociétales*. 28 pp.

Vishwanathan, S.S., P. Fragkos, K. Fragkiadakis, L. Paroussos, and A. Garg, 2019: Energy system transitions and macroeconomic assessment of the Indian building sector. *Build. Res. Inf.*, **47(1)**, 38–55, doi:10.1080/09613218.2018.1516059.

von Lampe, M. et al., 2014: Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison. *Agric. Econ.*, **45(1)**, doi:10.1111/agec.12086.

Von Stechow, C. et al., 2015: Integrating Global Climate Change Mitigation Goals with Other Sustainability Objectives: A Synthesis. *Annu. Rev. Environ. Resour.*, **40(1)**, 363–394, doi:10.1146/annurev-environ-021113-095626.

Vrontisi, Z., J. Abrell, F. Neuwahl, B. Saveyn, and F. Wagner, 2016: Economic impacts of EU clean air policies assessed in a CGE framework. *Environ. Sci. Policy*, **55**, 54–64, doi:10.1016/j.envsci.2015.07.004.

Vrontisi, Z. et al., 2018: Enhancing global climate policy ambition towards a 1.5 °C stabilization: A short-term multi-model assessment. *Environ. Res. Lett.*, **13(4)**, 44039, doi:10.1088/1748-9326/aab53e.

Waffenschmidt, E. and R.S.Y. Hui, 2016: Virtual inertia with PV inverters using DC-link capacitors. 2016 18th European Conference on Power Electronics and Applications, EPE 2016 ECCE Europe, IEEE.

Wakiyama, T. and T. Kuramochi, 2017: Scenario analysis of energy saving and CO_2 emissions reduction potentials to ratchet up Japanese mitigation target in 2030 in the residential sector. *Energy Policy*, **103**, 1–15, doi:10.1016/j.enpol.2016.12.059.

Waldhoff, S., D. Anthoff, S. Rose, and R.S.J. Tol, 2014: The Marginal Damage Costs of Different Greenhouse Gases: An Application of FUND. *Economics*, **8(1)**, 1–33, doi:10.5018/economics-ejournal.ja.2014-31.

Warszawski, L. et al., 2021: All options, not silver bullets, needed to limit global warming to 1.5 °C: a scenario appraisal. *Environ. Res. Lett.*, **16(6)**, 64037, doi:10.1088/1748-9326/abfeec.

Weber, C. et al., 2018: Mitigation scenarios must cater to new users. *Nat. Clim. Change*, **8(10)**, 845–848, doi:10.1038/s41558-018-0293-8.

Wei, Y.-M. et al., 2021: Pathway comparison of limiting global warming to 2°C. *Energy Clim. Chane.*, **2**, 100063, doi:10.1016/J.EGYCC.2021.100063.

Weidema, B.P., M. Pizzol, J. Schmidt, and G. Thoma, 2018: Attributional or consequential Life Cycle Assessment: A matter of social responsibility. *J. Clean. Prod.*, **174**, doi:10.1016/j.jclepro.2017.10.340.

Weindl, I. et al., 2015: Livestock in a changing climate: production system transitions as an adaptation strategy for agriculture. *Environ. Res. Lett.*, **10(9)**, 094021, doi:10.1088/1748-9326/10/9/094021.

Weindl, I. et al., 2017: Livestock and human use of land: Productivity trends and dietary choices as drivers of future land and carbon dynamics. *Glob. Planet. Change*, **159**, 1–10, doi:10.1016/J.GLOPLACHA.2017.10.002.

Wender, B.A. et al., 2014: Anticipatory life-cycle assessment for responsible research and innovation. *J. Responsible Innov.*, **1(2)**, doi:10.1080/23299460.2014.920121.

Weyant, J., 2017: Some Contributions of Integrated Assessment Models of Global Climate Change. *Rev. Environ. Econ. Policy*, **11(1)**, 115–137, doi:10.1093/reep/rew018.

Weyant, J.P., 2009: A perspective on integrated assessment. *Clim. Change*, **95(3–4)**, 317–323, doi:10.1007/s10584-009-9612-4.

Wilkerson, J.T., B.D. Leibowicz, D.D. Turner, and J.P. Weyant, 2015: Comparison of integrated assessment models: Carbon price impacts on U.S. energy. *Energy Policy*, **76**, 18–31, doi:10.1016/j.enpol.2014.10.011.

Wilson, C., A. Grubler, K.S. Gallagher, and G.F. Nemet, 2012: Marginalization of end-use technologies in energy innovation for climate protection. *Nat. Clim. Change*, **2(11)**, 780–788, doi:10.1038/nclimate1576.

Wilson, C., A. Grubler, N. Bauer, V. Krey, and K. Riahi, 2013: Future capacity growth of energy technologies: Are scenarios consistent with historical evidence? *Clim. Change*, **118(2)**, 381–395, doi:10.1007/s10584-012-0618-y.

Wilson, C. et al., 2020: Granular technologies to accelerate decarbonization. *Science*, **368(6486)**, 36–39, doi:10.1126/science.aaz8060.

Wilson, C. et al., 2021: Evaluating process-based integrated assessment models of climate change mitigation. *Clim. Change*, **166(1–2)**, 3, doi:10.1007/s10584-021-03099-9.

Wilson, E. et al., 2017: *Energy Efficiency Potential in the U. S. Single-Family Housing Stock*. National Renewable Energy Laboratory, Golden, CO, USA, 157 pp.

Xing, R., T. Hanaoka, and T. Masui, 2021: Deep decarbonization pathways in the building sector: China's NDC and the Paris agreement. *Environ. Res. Lett.*, **16(4)**, doi:10.1088/1748-9326/abe008.

Yang, Z., 2008: *Strategic Bargaining and Cooperation in Greenhouse Gas Mitigations – An Integrated Assessment Modeling Approach*. MIT Press, London, UK.

Yeh, S. et al., 2016: A modeling comparison of deep greenhouse gas emissions reduction scenarios by 2030 in California. *Energy Strateg. Rev.*, **13–14**(August 2016), 169–180, doi:10.1016/j.esr.2016.10.001.

Yeh, S. et al., 2017: Detailed assessment of global transport-energy models' structures and projections. *Transp. Res. Part D Transp. Environ.*, **55**, 294–309, doi:10.1016/j.trd.2016.11.001.

Yu, S. et al., 2018: Implementing nationally determined contributions: building energy policies in India's mitigation strategy. *Environ. Res. Lett.*, **13(3)**, 034034, doi:10.1088/1748-9326/aaad84.

Yumashev D. et al. 2019: Climate policy implications of nonlinear decline of Arctic land permafrost and other cryosphere elements. *Nat. Commun.*, **10(1)**, 1900, doi:10.1038/s41467-019-09863-x.

Zhang, R., S. Fujimori, and T. Hanaoka, 2018: The contribution of transport policies to the mitigation potential and cost of 2°C and 1.5°C goals. *Environ. Res. Lett.*, **13(5)**, 054008, doi:10.1088/1748-9326/aabb0d.

Zhang, S. et al., 2020: Scenarios of energy reduction potential of zero energy building promotion in the Asia-Pacific region to year 2050. *Energy*, **213**, doi:10.1016/j.energy.2020.118792.

Zhong, X. et al., 2021: Global greenhouse gas emissions from residential and commercial building materials and mitigation strategies to 2060. *Nat. Commun.*, **12(1)**, 6126, doi:10.1038/s41467-021-26212-z.

Zhou, N., N. Khanna, W. Feng, J. Ke, and M. Levine, 2018: Scenarios of energy efficiency and CO_2 emissions reduction potential in the buildings sector in China to year 2050. *Nat. Energy*, **3(11)**, 978–984, doi:10.1038/s41560-018-0253-6.