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Modeling Transition Paths for the Energy and Transport Sectors

A Literature Review

Maria Vagliasindi

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Abstract

Meeting the dual challenge of providing reliable and affordable energy and transport to a growing population while reducing environmental impacts, including mitigating greenhouse gas emissions, requires a deep understanding of both the unit- and system-level responses. These responses arise from the ongoing energy and transport system evolution, such as the transition toward lower carbon fuels and the expanded deployment of new low-carbon generation technologies. This literature review takes stock of the advantages and disadvantages of alternative approaches, by offering a taxonomy of the current modeling approach, focusing inter alia on the characteristics of the models. Current analyses often employ integrated assessment models to quantify the effects (for example, economywide greenhouse gas emissions) of various policies and decision processes on representative unit operations. The accuracy of the modeling approaches used to estimate these costs depends on several factors: for example, modeling approaches (ranging from partial equilibrium energy-land models to computable general equilibrium models of the global economy, from myopic to perfect foresight models, and from models with or without endogenous technological change), covered area, time horizon, determination of baseline scenarios, detailed sectoral representation, emissions sources, inclusion of efficiency and renewable energy options, and so forth. Some of the biggest challenges for improving the design and use of integrated assessment models include accounting for the trade-off between efficiency and equity, capturing interactions between impact sectors and feedbacks to the climate system, and dealing with uncertainty and risk. This review focuses on the treatment of the energy and transport sectors.

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Modeling Transition Paths for the Energy and Transport Sectors:

A Literature Review*

Maria Vagliasindi**

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** Maria Vagliasindi is (acting) Chief Economist in the Chief Economist Office of the Infrastructure Practice Group.

1. Introduction

Meeting the dual challenge of providing reliable and affordable energy and transport to a growing population while reducing environmental impacts, including mitigating greenhouse gas (GHG) emissions, requires a deep understanding of both the unit- and system-level responses that arise from the ongoing energy and transport system evolution, such as the transition towards lower-carbon fuels, the expanded deployment of new low-carbon generation technologies. The widespread adoption of renewable generation technologies is of particular significance, because their presence in the system also introduces some challenges linked to their inherent intermittency and variability. The review will look at the current available options for modeling the energy and transport sectors within an integrated framework.

Current analyses often employ integrated assessment models (IAMs) to quantify the effect (e.g., economy-wide GHG emissions) of various policies and decision processes on representative unit operation. The accuracy of the modeling approaches used to estimate these costs depends on several factors: for example, modeling approaches (ranging from partial equilibrium energy–land models to computable general equilibrium models of the global economy, from myopic to perfect foresight models, and from models with or without endogenous technological change), the covered area, time horizon, determination of baseline scenarios, the detailed sectoral representation, emissions sources, inclusion of efficiency and renewable energy options and so forth.

The literature review will take stock of the advantage and disadvantages of alternative approaches, by offering a taxonomy of the current modeling approach, focusing inter alia on the characteristics of the models. The remainder of the paper is structured as follows.

Section 2 provides an overview of IAM models and their evolution over time since Nordhaus's first simple DICE model.

Section 3 focuses on providing a taxonomy over a broad range of IAMs focusing on the modeling approach (Section 3.1), the economic, temporal and spatial coverage (Section 3.2), the sectoral coverage and technological change (Section 3.3), the modeling of renewable energy and substitution effects (Section 3.4), and policy application (Section 3.5).

Section 4 concludes with an overall assessment.

2. IAM models

Based on socioeconomic scenarios, Integrated Assessment Models (IAM) derive consistent pathways for macroeconomic, energy system, and land use variables and project resulting emissions of greenhouse gases and air pollutants over a long horizon. They can address questions, such as "What can happen?", using baseline projections and questions, such as "What should happen?" to reach given mitigation goals.

IAM models are crucial for understanding the nature of climate change, because without formulating a clear framework, it may be hard to capture complex physical and economic. Nordhaus's first integrated assessment model, namely the Dynamic Integrated model of Climate and the Economy (DICE), does so. The single model contains all of the links among carbon dioxide concentrations, the climate, economic damages from climate change, and a model of the economy that produces carbon dioxide emissions – closing the loop (Nordhaus, 1992).

Since its publication in 1994, a sizeable number of papers are currently based on the DICE model. Further contributions and applications were also developed. Just to provide an example, already in 1994, Nordhaus and co-authors pioneered the estimation of the damages from climate change to agriculture (Mendelsohn *et al.* 1994). In a nutshell, agricultural yields may decline as a consequence of climate change, reducing the value of land that is used for cultivating crops.

Nordhaus's contribution to the economics of climate change also extends to the understanding of the paramount importance of uncertainty in climate change. Namely, uncertainty in key parameters that are key assumptions in the models often turns out to be more crucial than uncertainty across different models (Gillingham *et al.* 2018). Based on the DICE model, as reported by Nordhaus (2013), a delay that results in warming of 3° Celsius above preindustrial levels, instead of 2°, could increase economic damages by approximately 0.9 % of global output. The incremental cost of an additional degree of warming beyond 3° Celsius would be even greater. Moreover, these costs are not incurred one-time, but are rather on a recurring basis, because of the permanent damage caused by increased climate change resulting from delay in taking actions to mitigate changes in climate. These temperature increases are far above 1.5-2 ° Celsius target endorsed in the 2015 Paris Agreement, making the commitment under the UN Paris Agreement sub-optimal within the DICE framework. Nevertheless, recent contributions, including Hänsel *et al.* (2020) and Dietz *et al.* (2020), find that even the basic DICE model, when appropriately updated, with more accurate calibration of the carbon cycle and energy balance model or using more reasonable costs and discount rates into the DICE model could find the UN Paris commitment targets optimal.

In principle, the world has accepted the case for a risk management approach based on the UNFCCC commitment to "avoid dangerous interference" in the world's climate system, interpreted in the Paris Agreement's goal to keep global temperature change to "well below 2C above preindustrial levels and pursue efforts… to 1.5C", as opposed to the earlier work, framing the issue more in terms of balancing costs against benefits. The most comprehensive summary of IAM research questions and findings can be found in the IPCC's fifth assessment report, in the chapter from Working Group III (WG3) and a more up-to-date review is included in the IPCC special report on 1.5C.

The DICE model has over time been superseded by much more sophisticated models. IAMs can be applied in a forward-looking manner to explore internally consistent socio-economic-climate futures, often extrapolating current trends (either under a range of assumptions or using counterfactual assumptions) to generate baselines for subsequent climate policy analysis. They can also be used in a back-casting mode to explore the implications of climate policy goals and climate targets for systems transitions and near-to-medium term action. In most IAM-based studies, both applications are used concurrently (Clarke *et al.*, 2009; Edenhofer *et al.*, 2010; Luderer *et al.*, 2012; Kriegler *et al.*, 2016; Riahi *et al.*, 2015; Tavoni *et al.*, 2015).

Often IAMs are defined more narrowly as the subset of integrated pathway models with an economic core and equilibrium assumptions on supply and demand, although non-equilibrium approaches to integrated assessment modeling exist (Guivarch *et al.*, 2011; Mercure *et al.*, 2018). IAMs with an economic core describe consistent price-quantity relationships, where the "shadow price" of a commodity generally reflects its scarcity in the given setting. To this end, the price of greenhouse gas emissions emerging in IAMs reflects the restriction of future emissions imposed by a warming limit. Such a price needs to be distinguished from suggested levels of emissions pricing in multidimensional policy contexts that are adapted to existing market environments and often include a portfolio of policy instruments (Stiglitz *et al.*, 2017).

Despite such characteristics, these models can differ greatly in how detailed the aspects of the system are represented and in how the components interact. For instance, some IAMs place particular focus on macroeconomic feedbacks or particular sectors or technologies. Climate policy analysis often involves comparisons among results from several IAMs in order to provide more robust cost estimates and a clearer representation of uncertainties.

The use of IAMs for climate policy assessments has been framed in the context of solution-oriented assessments (Edenhofer and Kowarsch, 2015; Beck and Mahony, 2017). This approach emphasizes the exploratory nature of integrated assessment modeling to produce scenarios of internally consistent, goal-oriented futures. They describe a range of pathways that achieve long-term policy goals, and at the same time highlight trade-offs and opportunities associated with different courses of action. However, future pathways cannot be completely isolated from society and decision making (Edenhofer and Kowarsch, 2015; Beck and Mahony, 2017). This suggests an interactive approach which engages societal values and user perspectives in the pathway production process. It also requires transparent documentation of IAM frameworks and applications to enable users to contextualize pathway results in the assessment process.

3. Main taxonomy of IAM models

Different modeling frameworks were created for different problems, with each model design tailored to address a specific set of questions. The characteristics of the modeling framework as well as the primary questions that guided its designs must be kept in mind when comparing the model results.

Detailed, process-based IAMs include a diverse set of models ranging from partial equilibrium energy–land models to computable general equilibrium models of the global economy, from myopic to perfect foresight models, and from models with to models without endogenous technological change. IAMs cover most supply-side mitigation options on the process level, while many demand-side options are treated as part of underlying assumptions, which can be varied (Clarke *et al.*, 2014).

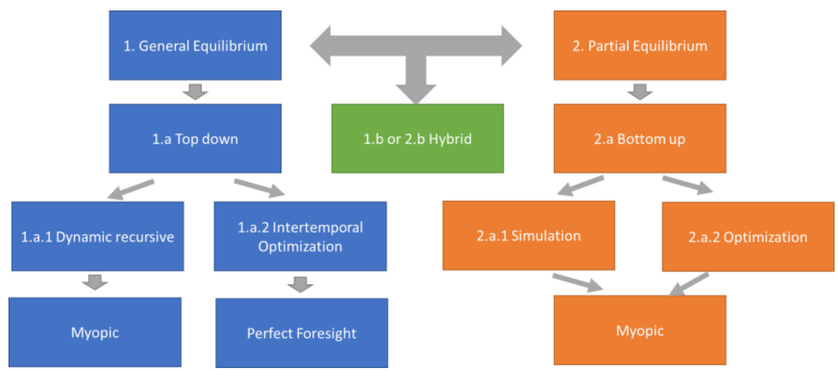
The literature review will take stock of the advantage and disadvantages of alternative approaches, by offering a taxonomy of the current modeling approach, focusing *inter alia* on the characteristics of the models.

3.1 Main taxonomy according to modeling approaches

As summarized in Figure 1, IAMs may be broadly grouped into general equilibrium and partial equilibrium models. General equilibrium models cover the full economy with a more or less detailed representation of specific economic sectors. General equilibrium models are top-down models that provide a highly aggregated representation of economic effects. They have a macroeconomic perspective and focus mainly on the relations between the energy sector and other sectors of the economy. General equilibrium models can use in turn a dynamic recursive approach or intertemporal optimization. Dynamic recursive computable general equilibrium models (CGE) are prominent examples of general equilibrium models, that identify market equilibria for each point in time. In doing so, they are inherently myopic and usually provide a detailed description of the sector composition of the economy. Intertemporal general equilibrium models focus on the intertemporal dynamics of investment in production capital under foresight about future production and consumption. They describe a closed economy but can usually only represent one to three aggregated economic sectors due to the computational burden of intertemporal optimization. IAMs based on conventional top-down models tend to lack an adequate representation of technological flexibility and substitution possibilities and limits.

Partial equilibrium models simplify the data requirements and can permit purposive analysis of a particular sector. They describe processes and markets in one or more sectors in detail – such as the energy sector, including energy demand by economic sectors and technological specifics – and treat the rest of the economy exogenously. Bottom-up models provide a detailed technological representation and typically include no or very limited interactions with the macroeconomic system. IAMs based on the conventional bottom-up approach, without additional macroeconomic modules, do not represent the macro-economic feedbacks of different energy transition pathways, e.g., through rebound effects, investments and households' expenditures feedbacks on the economy. Optimization typically aligns with quantitative-oriented risk assessment and sensitivity analysis, whereas simulation tends to align better with more qualitatively oriented alternative assessment approaches.

Figure 1: Summary of key modeling taxonomy



Researchers have also attempted to bridge the gap between top-down and bottom-up models either by incorporating macroeconomic feedback into bottom-up models or by including technological details in top-down models. Regarding energy-economy linkages, most IAMs are now hybrid constructs, either energy system linked to macroeconomic growth models or multi-sector CGE—or other economywide— models with explicit technologies in key sectors.

The subsections below explore in more detail the key different classes of models and summarize their key assumptions.

General versus partial equilibrium models

As mentioned above, general equilibrium models provide a highly aggregated representation of economic effects and focus mainly on the relations between the energy sector and other sectors of the economy. On the other hand, partial equilibrium models focus on one or more sectors in detail which include no or limited interactions with the macroeconomic system. Partial equilibrium models typically maximize consumer and producer surplus or minimize production costs of sectors over time. They may or may not include foresight of future supply and demand in the optimization process. Policy costs are calculated in terms of sector cost mark-ups or reduction of consumer and producer surplus, typically deduced from the area under the marginal abatement cost curve for greenhouse gas emissions.

Both partial and general equilibrium models can include a great variety of low-carbon technology options on the supply and demand sides that can deliver emission reductions in response to climate policy. Most models include a similarly high variety of low-carbon supply options, but some general equilibrium models include a noticeably lower number of options. For simplicity, they focus on energy supply side technologies and do not cover demand-side options for emissions reduction and use of low-carbon fuels (e.g., electricity or hydrogen in transport), even though demand side options are explicitly represented in some models. Nonetheless, the measure illustrates the fact that by modeling the economy as a whole, general equilibrium models may not always include the same level of technological detail as more energy-system-focused partial equilibrium models.

Tables 1a and 1b report separately a first overview of the key modeling approaches proposed by the general and partial equilibrium models included in the review.

Top down versus bottom up modeling

There are broadly two approaches for estimating costs of carbon mitigation from energy systems: top-down and bottom-up models, with this distinction being overcome by hybrid models including features of both top-down and bottom-up models, as characterized in the second column of Tables 1a and 1b.

Top-down models provide a highly aggregated representation of economic and endogenization effects. They yield no or limited characterization of technologies. They represent sectoral economic activities through aggregate production functions. However, their energy-economy interactions provide limited representation of the energy system. One third of the general equilibrium models in Table 1.a falls under this category.

Bottom-up models, namely technologically disaggregated models, provide flow optimization or partial equilibrium representations of the energy sector. Bottom-up models are built with deep technological detail including technical performances and cost structures of future technologies. As such they also reflect an optimistic engineering paradigm. They include a great number of discrete energy technologies to capture the substitution of energy sources on primary and final energy levels. They also include process substitutions and efficiency improvements. Each energy-consuming technology is identified by a detailed description of input-output structures, cost dynamics, and other technical and economic characteristics. However, such models often neglect the macroeconomic impacts of energy policies. The majority of partial equilibrium models, with the exception of GCAM, are bottom up models.

Bottom-up models can be further divided into optimization and accounting models. Optimization models are based on a detailed representation of technologies involved in energy supply and demand. The information on technologies is recorded in terms of their capital, operating costs, and technical efficiencies. Models using optimization algorithms find the lowest costs for an energy system for a given discount rate. These models can analyze different energy markets (oil, gas, coal, etc.) and the interactions between them. Following a partial equilibrium approach with a focus on the energy sector, these models also assume that other sectors are not affected by changes in energy demand or the way this demand is serviced.

In recent years, various bottom-up models have been developed on global and national scales to study energy strategies and planning. These models have different features and are often based on different methodological approaches. However, although these models are useful in predicting future trends, most consider the system as a whole and disregard the relationships between nations. Often, these models employ global or regional frameworks and depict energy systems and sectors of selected nations independently of each other (i.e., they ignore trading relationships and possible variations in production and energy consumption due to changes in trading volumes).

By merging both top-down and bottom-up approaches, hybrid models combine the technological explicitness of bottom-up models with the economic comprehensiveness of top-down models. However, in hybrid modeling, both the bottom-up and top-down aspects are simplified for computational purposes (i.e., to make the model computable). Therefore, by comparison, hybrid models typically have limitations in the amount and detail of their inputs and outputs. These models can be divided into (a) input-output models, (b) neo-Keynesian macroeconomic models, and (c) computable general equilibrium models. Input-output models are based on a system of linear equations that represent an economy as a number of industries. Input-output analysis shows the process by which inputs in one industry sector produce outputs for consumption or for input into another industry sector. Because macroeconomic models assume that every industry exists in an imperfect competition market, they do not calculate an equilibrium solution. Instead, the equilibrating mechanisms of macroeconomic models work through quantity adjustments rather than price. By contrast, general equilibrium models include all sectors of the economy and several interacting markets. The energy demand is estimated through aggregate economic indices (GDP growth, price, and price elasticities). Each sector's production output is simulated by means of a production function that allows for the substitution of a factor of production (labor, capital, energy, and material) based on the elasticity of the substitution. These models assume perfect market equilibrium and do not take into account structural unemployment. These models can be static when they look at a given future year in a single step or dynamic when an entire time transition is covered in multiple time steps. In dynamic models, investments made in one period have an influence on the capital stock of the next period. Two-thirds of the general equilibrium models in Table 1.a fall in this category.

In sum, top-down models lack technological details, whereas bottom-up models lack macroeconomic consistency. To address these challenges, two strategies have been followed. Soft linking has been a practical strategy adapted to run a given scenario on both top-down and bottom-up models. It ensures macroeconomic consistency by making GDP growth comparable, e.g., specific GDP losses due to a carbon tax can also be applied when calculating energy demands in the bottom-up models. Researchers have also attempted to bridge the gap between top-down and bottom-up models either by incorporating macroeconomic feedback into bottom-up models or by including technological details in top-down models. Many of the recent IAMs are increasingly capable of representing technological details and economic interactions because of continuing trend of hybridization (Sugiyama *et al.*, 2013). Partial equilibrium models such as TIAM (Loulou and Labriet 2008), POLES (Criqui et al. 1999), AIM/Enduse (Kainuma et al. 2000), and DNE21+ (Akimoto *et al.* 2008), incorporate some degree of economic effects. On the other hand, general equilibrium models such as MERGE (Richels and Blanford 2008) and ReMIND (Leimbach et al. 2010) explicitly incorporate end-use technologies within a macroeconomic framework in a global IAM based on Ramsey's optimal growth theory, extending classical IAMs. WITCH (Bosetti et al. 2006) is a top-down neoclassical optimal growth model with a specification of energy services. The ReMIND model created by the Potsdam Institute for Climate Impact Research is another example of a hybrid model, integrating technological detail similar to energy system models in the framework of a growth model. MESSAGE-MACRO (Messner and Schrattenholzer 2000) links an energy supply model (Schrattenholzer 1981) with a macroeconomic module and solves it iteratively. The major challenges faced by these models are theoretical consistency, computational complexity, and policy relevance.

Optimal versus recursive modeling

General equilibrium models can use a dynamic recursive approach or intertemporal optimization. Computable General Equilibrium models (CGE) are prominent examples of general equilibrium models. CGE models calculate static equilibria at each point in time prescribing some growth dynamic in between time steps, i.e., they are recursive dynamic. This guarantees not only that all markets are cleared but also that a Pareto-optimum is achieved. Sectoral resolution and the dynamics of relative prices are the main strengths of CGE models. They are inherently myopic and usually provide a detailed description of the sector composition of the economy. Intertemporal general equilibrium models focus on the intertemporal dynamics of investment in production capital under foresight about future production and consumption. They describe a closed economy but can usually only represent one to three aggregated economic sectors due to the computational burden of intertemporal optimization. General equilibrium models typically express policy costs in terms of production losses, consumption losses or welfare measures.

Growth models using an optimizing framework allow endogenous savings and investment decisions with unlimited foresight while many recursive dynamic CGE models restrict optimizing behavior of its agents to a sequence of static equilibria. Hence, the time path of emissions and investments derived by most CGEs are not intertemporally cost-effective. This lack of optimality is not a shortcoming of these models as they try to replicate the outcome of decentralized markets in which market imperfections are inherent.

In contrast to recursive CGE models, an optimal economic growth model allows an understanding of transition paths and an assessment of what decentralized markets could achieve if appropriate policy instruments were applied. On the other hand, most intertemporal economic growth models lack economic detail and offer only limited insights into sectoral dynamics. Finally, simulation models refer to models that start at a given state of the economy; then continue to calculate the next time step. In mathematical terms, they solve initial value problems or boundary value problems given as systems of differential equations. Forty percent of general equilibrium models fall under this category.

Simulation versus Optimization Modeling

The most important difference between the two classes of simulation versus optimization models lies in the crucial assumption whether the model itself can identify the optimal solution or not. Optimization models are expected to be able to make all optimization decisions based on a set of restrictions, rules and presumptions in combination with a limited set of pre-defined economic values. In contrast, simulation models leave it to the user to make all crucial decisions.

Namely, in the optimization approach, the modeler provides information in the form of data, objective functions and boundaries and lets the model identify the optimal solution. In the simulation approach, to establish grounds for decision-making the user identifies a variety of potential system elements and uses the model to calculate consequences of different combinations. Finally, simulation models differ from optimization models in that instead of identifying ‘optimal’ decisions, they simulate, based on observed or assumed relationships between variables, how the system might develop going forward. This difference implies different interpretations for the heterogeneity and decision making of the agents represented in the model—and for the interpretation of the model results more generally. The two approaches also tend to handle risks and uncertainties differently. Optimization typically aligns with quantitative-oriented risk assessment and sensitivity analysis, whereas simulation tends to align better with more qualitatively-oriented alternatives assessment approaches.

For example, simulation models, such as IMAGE, reflect in their parametrization heterogeneity of agents and their implied, heterogeneous preferences whereas cost-driven linear optimization models, generally assume a single representative agent, with a single set of preferences, and would thus suggest that the technology best matching these preferences is the best option for everyone represented by this agent. Arguably investment decisions made in the producing sectors may be more economically rational than those of consumers and policy choice, where many factors beyond financial considerations play a role. Many models have different stylized features to reflect these, beyond cost considerations impacting the choices made. Examples are the use of a multinomial logit equation to depict market heterogeneity (e.g. IMAGE Girod *et al.*, 2012, Daly *et al.*, 2014), risk or hurdle rates to reflect the attitudes that people hold towards risks, and preferences for certain choice features, for example, speed or affluence.

Foresight versus myopic

Optimization models can be further differentiated on the basis of the adopted solution approach. Some optimization models assume perfect foresight behavior, implying that agents have rational expectations about future events. Other models (also known as dynamic recursive models) assume that agents have myopic expectations. The way that IAMs 'solve' over the decision horizon can also vary from model to model. Models do this in time steps, which usually vary from 1 to 10 years. In some models, minimizing costs simultaneously across all time periods (intertemporal optimization) assumes perfect foresight, making strong assumptions in that the agent has full knowledge about the future. Although such assumptions are hardly realistic, exploring cost-optimal pathways can help identify and describe efficient ways to reach a given climate target. Other IAMs work myopically, meaning a time step is solved without full knowledge of the future. Such assumptions may be suitable to explore today's choices which may lock-in infrastructure and raise the cost of climate action later.

Table 1.a Key Modeling taxonomy for General Equilibrium

Model	Equilibrium Concept	Model perspective	Intertemporal Solution Methodology	Myopic/Foresight
MERGE-ETL	General	Hybrid	Intertemporal optimization	Foresight
MESSAGE	General	Hybrid	Intertemporal optimization	Foresight
ReMIND	General	Hybrid	Intertemporal optimization	Foresight
WITCH	General	Hybrid	Intertemporal optimization	Foresight
C3IAM	General	Hybrid	Intertemporal optimization	Foresight
BET EMF33	General	Hybrid	Intertemporal optimization	Foresight
AIM-CGE	General	Top-down	Recursive dynamic	Myopic

GEM-E3-ICCS	General	Top-down	Recursive dynamic optimization	Myopic
IMACLIM	General	Top-down	Recursive dynamic	Myopic
TEA	General	Hybrid	Recursive dynamic	Myopic
GRACE	General	Hybrid	Recursive dynamic	Myopic
IFs	General	Hybrid	Recursive dynamic	Myopic
PHOENIX	General	Top-down	Recursive dynamic	Myopic
POLES	General	Hybrid	Recursive dynamic	Myopic
WorldScan2	General	Top-down	Recursive dynamic	Myopic

Table 1.b Key Modeling taxonomy for Partial Equilibrium

Model	Equilibrium Concept	Model perspective	Intertemporal Solution Methodology	Myopic/Foresight
DNE21+	Partial	Bottom-up	Intertemporal optimization	Foresight
global TIMES	Partial	Bottom-up	Intertemporal optimization	Foresight
global ETP-TIMES	Partial	Bottom-up	Intertemporal optimization	Foresight
COFFEE	Partial	Bottom-up	Intertemporal optimization	Foresight
AIM-Enduse	Partial	Bottom-up	Recursive dynamic	Myopic
GCAM	Partial	Hybrid	Recursive dynamic	Myopic
IMAGE	Partial	Bottom-up	Recursive simulation	Myopic
PROMETHEUS	Partial	Bottom-up	Recursive simulation	Myopic

3.2 Main taxonomy according to the economic, temporal and spatial coverage

As discussed before, IAMs are characterized by a dynamic representation of coupled systems, including energy, land, agricultural, economic and climate systems (Weyant, 2017). They are global in their scope, and typically cover sufficient sectors and sources of greenhouse gas emissions to identify consistency of different pathways with long-term goals of limiting warming to specific levels (Clarke *et al.*, 2014).

Some IAMs sacrifice sectoral and regional details to provide researchers the ability to explore the fundamental uncertainties. Other IAMs, instead, forego some flexibility in order to provide a more granular detail in the modeling of particular sectors or regions. Each approach has its own set of strengths and weaknesses. Tables 2a and 2b differentiate models depending on the economic, temporal and spatial coverage.

Economic coverage

IAMs have evolved to answer different questions and have therefore developed different aspects of the energy-economy-climate-land systems and their interactions. For instance, IAMs which started as economic models still have their relative strengths in the representation of the economy. It is not surprising that the majority of the general equilibrium models listed in Table 2.a include a representation of the key sectors of the economy. Even within this group, the number of sectors covered ranges from 16 sectors (grouped in 5 more aggregate sectors) to 27 sectors. Other IAMs' core strength is a detailed energy system, making them more suited for analyzing different technological options for decarbonizing energy supply. More than 60 percent of the partial equilibrium models cover exclusively energy supply and demand for all sectors, whereas the remaining models include also land use and agriculture.

Temporal coverage

For most mitigation models, time horizons range from at least 2030 up to 2050 and beyond. Most notably, almost all general equilibrium models go beyond 2050, whereas only 3 out of 8 partial equilibrium models do so. Most baseline scenarios predict little or no change in emissions for the first 20–30 years. Reducing emissions to reach a temperature increase of 2◦C by 2050 requires a rapid reduction in emissions beginning in this decade largely because CO2 emissions remain in the atmosphere for 100 or more years. Cumulative emissions thus are an important element that requires rapid reductions relative to changes in capital stocks, which would require retrofitting existing technologies or switching to advanced technologies.

Spatial coverage

Owing to their aggregate representation, general equilibrium models are well suited for global analyses (Table 2a) in which the world is generally divided into 10 or more regions. They can also be used for regional- and national-level analyses, though the latter approach is more common.

Whereas the coverage of most advanced economies is included in most of the models, the coverage of lower income countries in Sub-Saharan Africa is less widespread and is only done in MESSAGE, WITCH, BET EMF33, AIM-CGE, among the general equilibrium models, and global TIMES and COFFEE among the partial equilibrium models.

Table 2.a Economic, Temporal and Spatial coverage for General Equilibrium

Model	Economic coverage	Temporal dimension	Spatial dimension
MERGE-ETL	Aggregate economic output, detail on energy production and transformation sectors	2000-2150	9 regions: Canada, Australia and New Zealand, China, Eastern Europe and FSU, India, Japan, Mexico and OPEC, Western Europe, US and rest of the world
MESSAGE	Full energy system; supply curves for bio-energy and non-energy mitigation options; iteratively solved with aggregated macro-economic model	Base year:2030, time steps:10, horizon: 2110	11 regions (including Sub Saharan Africa, Asia and China, Eastern Europe, Former Soviet Union, Lattin America, Middle East, North America, OECD, Asia, South Asia, Western Europe)
ReMIND	Closed economy growth model with detailed energy sector	Base year:2005, time steps:5, horizon: 2005-2100	12 Regions
WITCH	Energy, final goods, land use	Base year 2005 with a time horizon of 150 years modeled in 5 year time step (usually reported up to 2100	13 regions, on basis of geography, income and structure of energy demand: Canada, Japan and New Zealand, China and Taiwan, China, Southeast Asia, India, the Republic of Korea and South Africa and Australia, LAC, MENA, EU new and old (15), South Asia (excluding India), SSA, Non EU Eastern Europe, US
C3IAM	27 sectors, which are agriculture products, crops, cattle animal products, raw milk, wool, forestry, fishing, coal, oil, gas, other minerals, other manufacturing, energy-intensive manufacturing, roil, electricity, gas generation and distribution, water, construction, transportation service industry and other services	time horizon from 2011 to 2100 with flexible time steps	12 regions, which are USA, China, Japan, Russian Federation, India, Other Branches of Umbrella Group, European Union, Other West European Developed Countries, Eastern European CIS excluding Russian Federation, Asia excluding China, India and Japan, Middle East and Africa and Latin America
BET EMF33	The model explicitly handles energy service demand and end-use technologies in a global macroeconomic framework. This structure allows a systematic approach to examine trade-offs between advanced energy supply technologies and end-use efficiencies from a long-term global perspective across different mitigation policies and technologies.	Base year:2010, time steps:10, horizon: 2150	13 region, including Brazil, Canada, Australia and New Zealand, China and Taiwan, China, India, Japan, LAC, EU 27 + Switzerland, Norway and Iceland, ,MENA, Asia, LAC, Russian Federation, SSA
AIM-CGE	The whole economic activities are represented , but energy, agriculture and land use are disaggregated.	Base year: 2005. 2005--2100 period. For some applications, the model is run up to 2050. The time step of the model solution is one year.	10 regions: China; Taiwan, China; Korea, Rep.; Hong Kong SAR, China; Singapore, India, Indonesia, Malaysia, the Philippines, and Thailand. Other regions are Latin America, Middle East Asia and North Africa, Sub-Saharan Africa, and the Rest of World (ROW)
GEM-E3-ICCS	General Equilibrium model that includes all economic agents (firms, households, government, rest of the world) and aggregates the economy in 26 economic activities: Agriculture, Coal, Oil, Gas, Power Supply, Ferrous and non ferrous metals, Chemical Products, Other energy intensive, Electric Goods, Transport equipment, Other Equipment Goods, Consumer	Base year: 2014, time steps: 5, horizon: 2100	46 regions

	Goods Industries, Construction, Transport, Market Services, Non Market Services and ten discrete power producing technologies.		
IMACLIM	12 production sectors: 5 energy sectors (coal, oil, gas, electricity, petroleum products), 3 transport sectors (air, water, terrestrial), construction, agriculture, energy-intensive industry and manufacturing & services (composite good). + 2 sectors with auto-production by households: motorized private mobility, non-motorized transport.	2001-2100 in yearly steps	12 regions: USA, Canada, Europe, OECD Pacific, FSU, China, India, Brazil, MENA, SSA, Rest of Asia, Rest of LAC
TEA	16 sectors grouped in 5 macro sectors: Agriculture (represented by 4 goods / sectors); Industry (represented by 6 goods / sectors); Energy (represented by 5 goods / sectors); Transportation (represented by 3 sectors); and Services.	2010--2100 period. The base year is 2010 and the time step is five years	16 Regions (including Africa, Australia and New Zealand, Brazil, Central America, Canada, Caspian region, China, EU and rest of Europe, India, Japan, the Republic of Korea, Middle East, Asia, the Russian Federation, South Africa, South America, United States)
GRACE	All economic activities in the world, as expressed by national accounts data	Base year (2014). The model can be solved yearly until a future year, such as 2050 and 2100 by updating external variables every year.	15 Regions
IFs	A multisector general equilibrium economic model (which uses inventories as buffer stocks and to provide price signals so that the model chases equilibrium over time); it provides labor, investment, and consumption information to partial equilibrium energy and agriculture models.	base year of IFs is 2015 and the model runs recursively in annual time steps through horizons up to 2100.	186 countries
PHOENIX	27 production and investment sectors	2000-2150	GTAP countries
POLES	Industry, services, agriculture	Base year: 2015, time steps: Yearly, horizon: 2015-2100	66 regions (including detailed EU28, all OECD countries and main non-OECD countries)
WorldScan2	16 sectors	2000-2050	16 regions

Table 2.b Economic, Temporal and Spatial coverage for Partial Equilibrium

Model	Economic Coverage	Temporal dimension	Spatial dimension
DNE21+	Energy (bottom-up); energy supply & demand modeled for all sectors	2006-2050 in 5 and 10 years steps	54 regions (America, Canada, Australia, China, India, Russian Federation are divided into further small regions, making a total of 77 regions)
global TIMES	Energy (bottom-up); energy use for all sectors	Base year is 2005 Horizon i (2005-2100) with 5 year time steps up to 2070 and with 10 year time steps beyond	16 regions, including AFR, Australia, Canada, Central and South America, China, Eastern EUROPE, FSU, India, Japan, Mexico, MENA, Other developing Asia, the Republic of Korea, UK, USA, Western Europe
global ETP-TIMES	Energy (bottom-up); energy use for all sectors	Base year: 2014, time steps: 5 years, horizon: 2060	28-39 regions
COFFEE	COFFEE is designed to meet the demand for energy services (exogenous whether run in a stand-alone basis or when linked to the TEA model), given the competition between technologies and energy sources, with the objective of minimizing the total cost of the system.	2010--2100 period. The base year is 2010 and the time step is five years	16 Regions (including Africa, Australia and New Zealand, Brazil, Central America, Canada, Caspian region, China, EU and rest of Europe, India, Japan, the Republic of Korea, Middle East, Asia, the Russian Federation, South Africa, South America, United States)
AIM-Enduse	Energy, agriculture, land use and waste	2005-2050	32 regions
GCAM	Energy, land use and associated products	Base year:2015, time steps:5-year (default), minimum time step is 1-year, horizon: 2100	32 Regions (including USA, Canada, Mexico, Australia and New Zealand, Japan, the Republic of Korea, EU, Europe non-EU, Eastern Europe, the Russian Federation, China, Taiwan, China, Central Asia, South Asia, Southeast Asia, Indonesia, India, Pakistan, Middle East, Africa 4 regions, South Africa, Argentina, Brazil, Central America, Colombia, South America 2 regions)
IMAGE	Detailed energy and land use system. Energy demand from Industry, Transport, Residential and Services.	Base year:1970, time steps:1-5 year time step, horizon: 2100	26 Regions (including USA, Canada, Mexico, Australia and New Zealand, Japan, Western Europe, Eastern Europe, the Russian Federation, China, the Republic of Korea, Ukraine, Asian-Stan, South Asia, Southeast Asia, Indonesia, India, Africa 4 regions, South Africa, Brazil, Central America, South America)
PROMETHEUS	Energy supply (production and international trade of fossil fuels), Energy transformation (electricity production, refining of fuels and production of synthetic fuels, such as liquid biofuels and hydrogen) and energy demand (industry, transport and residential/services/agriculture sector)	1 year time step, usually from 2018 to 2050	10 geographical units, including China, India, North America (USA and Canada), OECD Pacific (Japan, the Republic of Korea, Australia, New Zealand), EU-28, CIS, Middle East and North Africa, Emerging economies and Rest of the world.

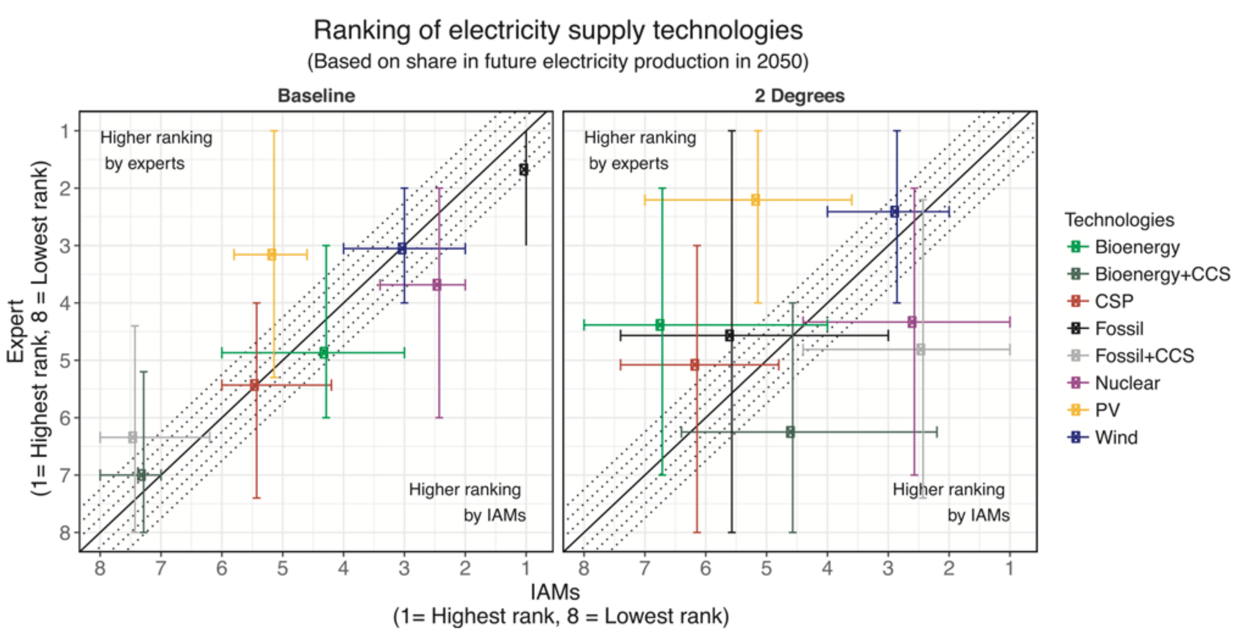
3.3 Main taxonomy according to the sectoral coverage and modeling of technological change

Tables 3a and 3b go into more detail to describe the focus on the energy and transport sectors and the specific forms of technological change used in the models.

Energy sector coverage

Only about half of the general equilibrium models distinguish among key categories of energy end users, including the common distinction between residential, commercial, industrial and transport users, while some of the general equilibrium models are characterized by a top-down and a less disaggregated representation of energy end-users. In contrast, all the partial equilibrium models consider a much more granular and bottom-up representation of the different categories of end users. The future energy mix in IAM pathways does not always find agreement among experts. In particular, IAMs have been criticized for their relatively low projections of solar power and for their optimistic projections of CCS and BECCS. van Sluisveld *et al.* (2018) compared the relative ranking of IAMs projections of 2050 electricity generation technologies to the rankings from about 40 experts selected from their collaboration in international reports on climate and energy. Figure 2 shows how experts ranked technologies on the vertical axis compared to the IAM rank on the horizontal axis, for both baseline scenarios (left box) and those limiting warming to 2C (right box).

Figure 2



Source: Sluisveld *et al.* (2018).

Experts ranked solar much higher than IAMs, giving it the highest rank among any technologies, whereas it was ranked only the fifth highest by IAMs. Experts ranked bioenergy (without CCS) higher as well; they had much lower expectations for fossil fuels and bioenergy with CCS, as well as for nuclear.

One key message from these varied projections is that there is no single answer to the question of how the global energy system should change to limit future warming. It is possible to meet climate goals using mainly renewables and biomass, as in the REMIND model. Or the same targets can be met using a combination of renewables, nuclear and fossil fuels with CCS, as in the GCAM model.

Table 3.a Representation of energy, transport sectors and technological change for General Equilibrium

Model	Represented Energy End Use Sectors	Represented Transport sector	Technological change
MERGE-ETL	Energy intensive sector	No disaggregation	Endogenous
MESSAGE	Industry, feedstocks (non-energy use of fuels), residential, commercial, transport	Transport sector representation is very stylized and essentially includes fuel switching and price-elastic demands	Exogenous
ReMIND	Stationary (aggregating industry, buildings), transport	Mobility demands for the 4 modeled transport sub-sectors (Passenger-light duty vehicles (LDV), Freight, Electric Rail, Passenger-Aviation and Buses) are derived in a top-down fashion, since they are input to a nested CES production function that ultimately produces GDP. For the LDV mode, three different technology options (internal combustion engine, battery electric vehicle, and fuel cell vehicle) compete against each other in a linear bottom-up technology model.	Endogenous LBD
WITCH	transport, industry and residential/commercial	Passengers and freight vehicles (both distinguished according to traditional combustion, hybrid, plug in hybrid and electric). The composition of vehicles is determined by a Leontief function of a range of costs (including battery, O&M, fuel and carbon costs)	Partly endogenous
C3IAM	transport, industry and residential/commercial	Intercity passenger transport, urban passenger transport and freight transport. Urban passenger transport is divided into public transport (bus and rail transit), taxi, and private vehicles (cars and electric bikes). Intercity passenger transport is divided into private vehicles and four main business intercity passenger transport (road transport, railway transport, aviation and waterway transport). Freight transport is divided into five main types: road transport, railway transport, aviation transport, waterway and pipeline transport.	Exogenous
BET EMF33	Transport, Power, Heat	Passenger and freight	Exogenous
AIM-CGE	Industry, residential, commercial, transport	Road, Railway, Waterways, Air transport	Exogenous
GEM-E3-ICCS	Firms, households	As regards the transport modes, the sectorial split follows and further extends the classification used by the GTAP database. This extension splits the GTAP data in passenger and freight transport by mode and further disaggregates the modes into rail and road as	Exogenous

		well as distinguishes between public and private transport.	
IMACLIM	Residential, transport, industrial	In static equilibrium, the transport of passengers and freight are characterized by the number and characteristics of household vehicles, the efficiency of the fleet of vehicles, the capacities of the different transport mode and the coefficient of the intermediary energy use and consumption	Endogenous
POLES	Buildings, transport	Several modes are distinguished in the model (road, rail, water, air), for both passenger and goods transport. The competition across vehicle types (6 types of vehicles in cars and trucks: conventional ICE, electric, plugin hybrid, H2 fuel cell, H2 thermal, gas)	Partly Endogenous
TEA	transport, industrial, residential and commercial sectors	The activity of the transportation sector is usually separated into passenger and freight. The energy consumed in this sector is used to achieve a necessary level of activity. In this sense, within the model, the exogenous demand will be expressed in pkm, for passengers, and tkm, for freight.	Exogenous
GRACE	transport, industrial, residential and commercial sectors	Domestic transport in a region is divided into air, sea, and other transport activities, modeled as nested	Exogenous
IFs	Energy demand is estimated as a function of the energy demand per unit GDP and total GDP, with adjustments related to energy prices and energy efficiency	Aggregate	Exogenous
PHOENIX		Ground transportation differs from air and water transport in that we allow for substitution away from conventional transport to hybrid electric (HEV) and/or biofuel backstop technologies when they are cost competitive. The elasticity of substitution is 1.2	Exogenous
WorldScan2	Production sectors using energy as intermediate input and households consuming energy directly.	Aggregated	Exogenous

Table 3.b Representation of energy, transport sectors and technological change for Partial Equilibrium

Model	Represented Energy End Use Sectors	Represented Transport sector	Technological change
DNE21+	Industry, residential, commercial, transport, top-down modeling for other sectors	The type of vehicle includes small passenger car, large passenger car, bus, small truck, and large truck. Vehicle technologies are categorized into internal combustion engines, electric cars, fuel-cell cars, and alternative fuel vehicles, including bioethanol mixed with gasoline, biodiesel mixed with diesel, and CNG. The gasoline and diesel combustion engines for gasoline/diesel are further classified into conventional internal combustion cars (low/high efficiency), hybrid cars, and plug-in hybrid cars.	Partly Endogenous
global TIMES	Transport, Residential and Commercial, Industry and Other (Agriculture).	The transportation sector is characterized by 14 energy-services plus one non-energy use demand segment. Six of the energy-services are considered as generic demands: international and domestic aviation, freight and passenger rail transportation, domestic and international navigation. All other energy-services are for road transport. The non-energy use is predominately the demand lubricants.	exogenous with endogenous technology learning extension
global ETP-TIMES	Transport, industry and residential/commercial	2-3 wheelers, Light duty vehicles (distinguished by Internal combustion (gasoline/diesel/CNG/LPG) (gasoline/diesel/CNG/LPG), Hybrids (gasoline/diesel) Plug-in hybrids (gasoline/diesel) Fuel cell vehicles, Electric vehicles), Heavy duty vehicles (Passenger, Minibuses, Buses, BRT systems, Freight, Medium freight trucks, Heavy freight trucks), Rail (passenger, freight), Air (only passenger) Water (only freight)	Endogenous; exogenous
COFFEE	Transport, industrial, residential and commercial sectors	The activity of the transportation sector is usually separated into passenger and freight. The energy consumed in this sector is used to achieve a necessary level of activity. In this sense, within the model, the exogenous demand will be expressed in pkm, for passengers, and tkm, for freight.	Exogenous
AIM-Enduse	Industry, residential, commercial, transport	Road, Railway, Waterways, Air transport	Exogenous
GCAM	Buildings, transport, industry	Four final demand: long-distance passenger air travel, (other) passenger travel, international freight shipping, and (other) freight. The passenger sector consists of up to five nesting levels, corresponding to different modes (e.g., road, rail), sub-modes (e.g., bus, light duty vehicle), size classes, and drivetrain technologies.	Exogenous
IMAGE	Industry, residential, services, transport	There are seven passenger transport modes - foot, bicycle, bus, train, passenger vehicle, high-speed train, and aircraft.	Endogenous
PROMETHEUS	Industry, transport and residential/services/agriculture sector	The private passenger cars sector is modeled in detail, by distinguishing internal combustion engine cars (using gasoline, diesel, biofuels or hydrogen as a fuel), conventional and plug-in hybrids, electric cars and fuel-cell cars (using hydrogen or gasoline as a fuel).	Endogenous

Transport sector coverage

Some of the general equilibrium models explicitly model the transport sector and also endogenize the choice of technologies. In particular:

- GEM-E3-ICCS distinguishes the technologies for transport means, and endogenizes the choice of technologies in the simulation of investment by sectors providing transport services and the purchasing of durable goods by households. Finally, the operation of the transport means is related to the sectors producing the energy commodities, including alternative fuels, such as electricity and biofuels.
- POLES uses a multinominal logit function that depends on the total cost for the user, considering fixed cost (investment, life-time, user discount rate) and variable cost (consumption per km, fuel price), and is constrained by infrastructure developments for refueling stations.
- GRACE uses CES functions of energy use and other inputs. Importing countries pay a price premium to the international transport sector. This price premium is determined by a fixed transport factor derived from the base year data. The supply of international transport services is depicted by a Cobb-Douglas aggregate of the service good from the individual regions. The Armington aggregate is then distributed between private, public, investment, and intermediate consumption.

A much more detailed representation of the transport sector is reported in some of the partial equilibrium models:

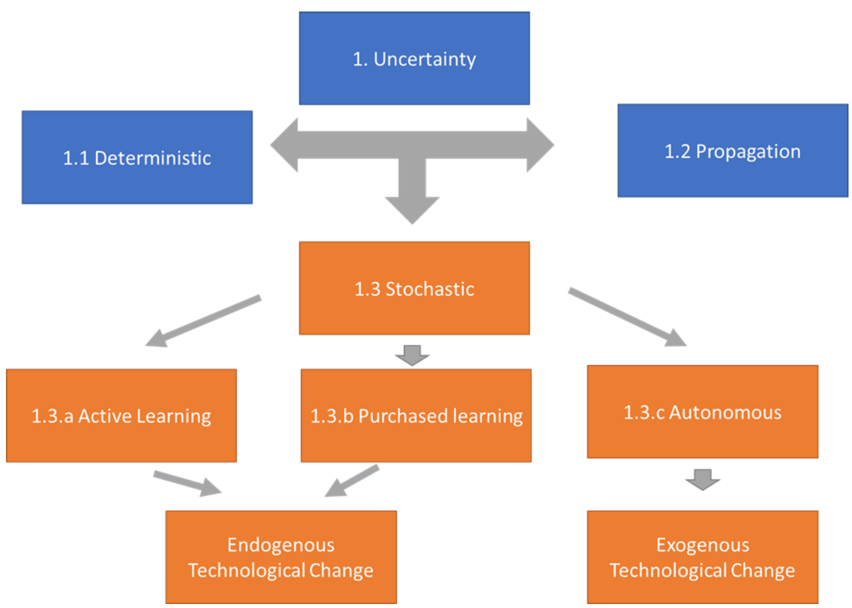
- IMAGE The structural change processes in the transport module are described by an explicit consideration of the modal split. Two main factors govern model behavior, namely the near-constancy of the travel time budget, and the travel money budget over a large range of incomes. Six freight transport modes are included: international shipping, domestic shipping, train, heavy truck, medium truck and aircraft. Vehicles with different energy efficiencies, costs and fuel type characteristics, compete on the basis of preferences and total passenger-kilometer costs, using a multinomial logit equation in both the passenger and freight transport submodules. These substitution processes describe the price induced energy efficiency changes.
- GCAM The passenger sector also includes non-motorized modes (walking and cycling), which are not represented as energy consumers. Their market share in future periods largely depends on income, prices, elasticities, and also the time value of transportation.

Uncertainty and technological change

A relevant feature of IAMs is how they deal with uncertainty and risk. The complexities of both human-induced climate change and the policies designed to address it mean that there are vast uncertainties regarding key model inputs and parameters and important model outcomes (e.g., changes in projected temperatures and precipitation amounts). IAMs and scenarios are developed to analyze climate policies and estimate future pathways of temperature, but no model can replicate the real world completely and no scenario can predict a realized future pathway perfectly. For tractability, every model or scenario has to make some simplifying assumptions, particularly in mathematical representations of economic and climate systems. Different assumptions then lead to different models or scenarios.

There are three broad approaches to incorporate uncertainties into economic models of climate change, as represented in Figure 3. The simplest approach, which is not a real uncertainty analysis but can be used as a tool to identify which model parameters should be treated stochastically, is a sensitivity analysis. It answers the question of how sensitive model outputs are to changes in model inputs and involves varying input parameters that are not known with certainty. More demanding, but still relatively simple, is what is termed uncertainty propagation. In this case, there are uncertain parameters in the model, but the agents in the model do not account for them. This implies that there is no learning. Finally, one can for instance take expectations of the output. A more complex implementation involves modeling certain variables as stochastic processes. For computational purposes propagation of uncertainty usually involves sampling from a joint distribution using mostly the Monte Carlo method. The most demanding approach accounts for learning and can be termed sequential decision-making under uncertainty. This implies that models determine optimal policies at more than one point in time, taking into account the available information in each period. Models in this category range from simple two-period decision analysis to an infinite-horizon stochastic optimization. There are three main types of learning: active learning whereby the effect of policy choices on certain key variables (e.g. the effects of emissions on the economy and the climate system) is observed for the purpose of obtaining information about uncertain parameters, purchased learning e.g. from R&D and autonomous learning where the passage of time reduces uncertainty. The first two types of learning imply endogenous technological change, which is also an important issue in the context of climate change. Most existing models though, use autonomous learning and not more than two decision periods. Most existing models are deterministic and, if at all, most modelers have only performed very basic types of uncertainty analysis. Although sensitivity analyses and Monte Carlo simulations are a good place to start, two other crucial dimensions of the climate change problem should be included in any comprehensive attempt to inform climate policy decisions. First, decisions made today can be revisited and modified at any point in the future as new information on climate change damages and mitigation costs becomes available. Thus, decision making about climate change is one of sequential decision making under uncertainty. Models of sequential decision-making under uncertainty are used to determine optimal policies under different aspects of uncertainty and learning. Altogether, uncertainty analysis is very complex and computationally intensive. The second crucial dimension of climate change uncertainty that has yet to be systematically addressed by researchers is assumptions about the decision makers' attitudes toward risk.

Figure 3: Challenges in treatment of uncertainty and technological change



An important issue concerns technological change: specifically, whether technology costs are assumed to be exogenous (that is, specified externally by modeling assumptions), or induced by the cumulative impact of policy, investment, and market growth within a model. Only a limited number of models, irrespective of whether general or partial equilibrium, have been able to endogenize technical change. Few if any models represent path dependence beyond the capital inertia and induced learning, to take account of institutional, social, and behavioral inertia, a limitation acknowledged in some of the leading studies.

Let us consider in turn the specific treatment of uncertainty and technological change.

Treatment of uncertainty

IAMs and scenarios are developed to analyze climate policies and estimate future pathways of temperature, but no model can replicate the real world completely and no scenario can predict a realized future pathway perfectly. For tractability, every model or scenario has to make some simplifying assumptions, particularly in mathematical representations of economic and climate systems. Different assumptions then lead to different models or scenarios.

There is large uncertainty in future temperature projections from climate models, as well as in future economic systems. It is often hard to judge which model or scenario is better, but policy makers have to make their decisions in the face of the model or scenario uncertainty. There are three main types of learning: active learning whereby the effect of policy choices on certain key variables (e.g. the effects of emissions on the economy and the climate system) is observed for the purpose of obtaining information about uncertain parameters, purchased learning e.g. from R&D and autonomous learning where the passage of time reduces uncertainty. The first two types of learning imply endogenous technological change, which is also an important issue in the context of climate change. Most existing models though, use autonomous learning and not more than two decision periods. Models of sequential decision-making under uncertainty are used to determine optimal policies under different aspects of uncertainty and learning. Altogether, uncertainty analysis is very complex and computationally intensive. Most existing models are deterministic and, if at all, most modelers have only performed very basic types of uncertainty analysis.

Finally, the last column of Tables 4a and 4b reports some of the most interesting applications and papers published using the specific IAM model at hand.

Table 4.a Representation of policy, uncertainty and application for General Equilibrium

Model	Policy	Uncertainty	Application
MERGE-ETL	Emission tax Emission pricing cap and trade emission standards Fuel Taxes and Subsidies energy efficiency standards	Deterministic (Scenario analysis); A stochastic version (Monte Carlo analysis) was developed in 2008	Impacts of endogenous technological change on carbon-mitigation policy (Kypreos, 2008) . MERGE-ETL has been applied to explore uncertainty related to global climate and nuclear policies in the wake of the Fukushima disaster, focusing on the impact on Switzerland (Marcucci and Turton 2012)
MESSAGE	Emission tax Emission pricing cap and trade emission standards energy efficiency standards	Scenario analysis; sensitivity analysis; a stochastic version was developed by Kovacevicet al. (2013).	The impacts of wind and solar PV deployment on the structure and operation of the electricity system (Johnson et al. 2017) Policy trade-offs between climate mitigation and clean cook-stove access in South Asia (Cameron et al., 2016).
ReMIND	Emission tax Emission pricing cap and trade fuel taxes and subsidies Portfolio standards Capacity targets	Deterministic (scenario analysis)	The role of renewables in the low-carbon transformation (Bauer et al., 2010) Coupling a Detailed Transport Model (Rottoli et al., 2021)

WITCH	Quantitative climate targets on global temperature, on radiative forcing, on atmospheric carbon concentration, on greenhouse gas emissions or on carbon budget. Carbon taxes and additional subsidies taxes on energy sources	Scenario analysis; a Monte Carlo analysis was introduced in 2008.	Incentives and Stability of International Climate Coalitions (Bosetti et al., 2012) A International energy R&D spillovers and the economics of greenhouse gas atmospheric stabilization (Bosetti et al., 2008)
C3IAM	Emission tax Emission pricing cap and trade fuel taxes and subsidies	Deterministic (scenario analysis)	Self-preservation strategy for approaching global warming targets in the post-Paris Agreement (Wei et al. 2020)
BET EMF33	Advanced technologies	Deterministic (scenario analysis)	Role of end-use technologies in long-term GHG reduction scenarios (Yamamoto et al., 2013 and 2020)
AIM-CGE	Emission tax Emission pricing Capacity targets Emission standards Energy efficiency standards Cap and trade Fuel taxes Fuel subsidies	Deterministic (scenario analysis)	Consequence of Climate Mitigation on the Risk of Hunger (Hasegawa et al., 2013), Assessment of CO3 reductions and economic impacts considering energy-saving investments (Masui et al., 2006). Local air pollutant emission reduction and ancillary carbon benefits of SO2 control policies (Xu& Masui, 2009)
GEM-E3-ICCS	The analysis of market instruments for energy-related environmental policy, such as taxes, subsidies, regulations, emission permits etc., at a degree of detail that is sufficient for national, sectoral and world-wide policy evaluation. The assessment of distributional consequences of programs and policies, including social equity, employment and cohesion.	Deterministic (scenario analysis)	The GEM-E3 model has been extensively used by several DGs of the European Commission for policy analysis and in a series of research projects funded by the European Commission like the MEDPRO and the AMPERE project.
IMACLIM	Energy taxes, Emission trading, technology subsidies or regulation	Scenario analysis	Infrastructures, technical inertia and the costs of low carbon futures (Waisman et al., 2012). The transportation sector and low-carbon growth pathways: modeling urban, infrastructure, and spatial determinants of mobility (Waisman et al., 2013) Sustainability, globalization, and the energy sector (Waisman et al., 2014).
POLES	GHG Policies, Energy taxation policies (carbon pricing fossil fuel subsidies, renewables) Support to specific technologies (including electric vehicles and modal shifts in passenger transport)	Scenario analysis	Pathways to Mexico's climate change mitigation targets (Veyseyet al., 2016), European climate—energy security nexus (Criqui et al., 2012). A global stocktaking exercise of the Paris pledges: Implications for energy systems and economy. (Vandyck et al., 2016).
TEA	The TEA model allows sectoral and international trading of emissions credits (or allowances) that are accounted for along with other trade flows.	Deterministic (scenario analysis)	
GRACE	GRACE can simulate effects of policies of climate mitigation (e.g. carbon tax, carbon market, renewable subsidy, and energy efficiency improvement), climate adaptation measures (e.g. substitution between goods/resources and market responses), climate impact (e.g. climate change impact on crop production and forest growth). the policy options	Deterministic (scenario analysis)	Europe's climate goals and the electricity sector (Gunnar et al., 2012), The effects of energy efficiency improvement in China (GLOMSRØD, S. & WEI, T. 2016, EI, T. & LIU, Y. 2017)

	targeting on specific sectors can be introduced in GRACE as it is a multi-sectoral model.		
IFs	Prepackaged scenario intervention files also allow integrated analysis of scenario sets including the UNEP GEO-4 set and the Shared Socioeconomic Pathway (SSP) set	Deterministic (scenario analysis)	ICT Contribution to Increased Carbon Emissions (Moyer et al., 2012). Scenarios for Vulnerability: Opportunities and Constraints in the Context of Climate Change and Disaster Risk (Birkmann, et al., 2013.) Eradicating Poverty in Fragile States (Burt et al. 2014)
PHOENIX			Impacts of long-term temperature change and variability on electricity investments (Khan et al., 2021)
WorldScan2		Deterministic (scenario analysis & sensitivity analysis)	'Four Futures of Europe' (De Mooij and Tang, 2003, and Lejour, 2003) and its companion 'Four Futures of Energy Markets and Climate Change' (Bollen, Manders and Mulder, 2004)

Table 4.b Representation of policy, uncertainty and application for Partial Equilibrium

Model	Policy	Uncertainty	Application
DNE21+	Based on the scenario setup, energy- and climate-related policies are explicitly represented in DNE21+. This includes carbon pricing, emission cap and trade system, carbon tax, preferred tax on specific energy sources, fuel subsidies, fuel standards and energy standards. In general, these policies are implemented via constraints or a price mark-up on energy sources.	Deterministic (scenario analysis & sensitivity analysis)	Estimates of GHG emission reduction potential by country, sector, and cost (Akimoto et al. 2010) Comparison of marginal abatement cost curves (Akimoto et al. 2012)
global TIMES	A variety of energy and climate policies, including emission taxes, permit trading, specific technology subsidies, technology and resource constraints/targets	Deterministic scenario analysis with Stochastic Programming extension	Bouckaert, S., Assoumou, E., Selosse, S., & Maïzi, N. (2014). A prospective analysis of waste heat management at power plants and water conservation issues using a global TIMES model. Energy, 68, 80–91
global ETP-TIMES	Emission Tax/Pricing, Cap and Trade, Fuel Taxes, Fuel Subsidies, Feed-in-Tariff, Portfolio Standards, Capacity Targets, Emission Standards, Energy Efficiency Standards	Deterministic (scenario analysis & sensitivity analysis); stochastic (Monte Carlo analysis)	IEA ETP reports
COFFEE		Deterministic (scenario analysis & sensitivity analysis)	Development of a global integrated energy model to evaluate the Brazilian role in climate change mitigation scenarios (Rochedo, 2016). The role of biomaterials for the energy transition from the lens of a national integrated assessment model (de Oliveira et al., 2021)
AIM-Enduse	Emission tax Emission standards Energy efficiency standards Fuel taxes Fuel subsidies	Deterministic (scenario analysis & sensitivity analysis)	Applications to China, India, Japan & Vietnam (Kainuma et al., 2003) Consequence of Climate Mitigation on the Risk of Hunger (Hasegawa et al., 2015)
GCAM	Emission tax, Emission pricing Capacity targets, Emission standards Energy efficiency standards, Agricultural producer and consumer subsidies Land protection, Pricing carbon stocks Cap and trade, Fuel taxes, Fuel subsidies Feed-in-tariff, Portfolio standard	Deterministic (scenario analysis & sensitivity analysis)	Power sector investment implications of climate impacts on renewable resources in Latin America (Silvia et a;., 2021). Biojet fuels and emissions mitigation in aviation (Wise et al., 2017).

IMAGE	Energy policies (air pollution, energy access, energy security and bioenergy) Land and biodiversity policies (food, bioenergy, nature conservation) Human development policies (malnutrition, health)	Deterministic (scenario analysis & sensitivity analysis)	Energy systems and climate policy-long-term scenarios for an uncertain future (Van Vuuren, 2007).
PROMETHEUS	The PROMETHEUS model is used to simulate the implications of various energy and climate policy instruments, including GHG policies, energy pricing policies, support policies for specific technologies, efficiency standards. Support to investment in low carbon technologies	Deterministic (scenario analysis & sensitivity analysis)	Investments in Power Generation Under Uncertainty (Fragkos and. Kouvaritakis, 2019, Fragkoset al., 2015)

Treatment of technological change

Let us consider in more detail an important issue concerning technological change, as the direction and scale of innovation are influenced by relative prices, demand and expectations. For example, rising prices induced efficiency improvement in end-use equipment, as described in Newell *et al.* (1999) as well as optimization in vehicle fuel use, as reported by Knittel (2011). Lower solar module prices led to exponential growth in adoption of renewable energy (Taghizadeh-Hesary *et al.*, 2019). "A major systematic review by Grubb & Wieners (2020) documents the evidence and causal mechanisms of cost reductions associated with a doubling of capacity. The key mechanisms of cost reduction include learning-by-doing and learning-by-using, but also economies of scale, together with the development of global supply chains, and growing confidence reducing the perceived risks and hence cost of finance.

Weiss *et al.* (2010) find an average learning rate of 18% across 15 demand-side technologies. Similarly, reviews by Rubin *et al.* (2015), Samadi (2018), and Farmer and Lafond (2016) find learning rates for renewable technologies close to 20% and stable for solar. The average global cost of PV is already well below the projections for 2030 made in the early 2010s. Accordingly, models including specific projections about technology costs over the medium and long period become outdated quite rapidly, particularly when the projections do not vary with the scale of deployment.

The cost reductions reflect learning and development of the industry and its supply chains at scale. Moreover, PV cost variations between countries reflect not just the solar resource, but the maturity and scale of the local PV businesses. In parallel with renewables in electricity generation, the uptake of electric vehicles (EV) and renewably hydrogen-powered fuel cell electric vehicles (FCEV) in the private transport and freight sector has recently been faster than expected and is expected to speed up in the coming decades. This is all happening much faster than in the IAMs' transport sector decarbonization indicators. For light duty transport, electric vehicles are cheaper to run than gasoline, and given battery costs are falling even faster than PV, may be cheaper to buy as the market grows.

The impact of innovation can be quite dramatic, though it involves significant cost and investment in the transition. Competitive tenders of solar PVs in the late decades have repeatedly achieved tariff records, with costs well below the cost of fossil fuel generation even from existing fuel fired plants. Decarbonization has already been more feasible than assumed in most model projections, and the costs continue to decline with deployment, pointing to the need to update the assumptions to reflect most recent developments, and to deal with uncertainty as history is often not the best predictor of future trends.

Although many of these models (e.g., MERGE-ETL) can incorporate induced innovation, several fail to do so, because it adds substantial computational complexity. Most models in the IPCC Assessments were run without induced innovation. Bosetti *et al.* (2015) find that different representations of endogenous technological change in IAMs may still result in similar future energy structures, though the robustness of this finding may be challenged for example, by the dramatic fall in renewables costs since observed.

Only a limited number of models, irrespective of whether general or partial equilibrium, have been able to endogenize technical change. Most notably only 3 out of 15 general equilibrium models (MERGE-ETL, ReMIND, and IMACLIM), 2 of them are partly endogenous (WITCH and POLES) while the other two-thirds of models are still based on exogenous technological change.

Among partial equilibrium models only 2 out of 8 (IMAGE and PROMETHEUS) endogenize technological change, 3 of them (DNE21+, global TIMES and global ETP-TIMES) partly endogenize innovation whereas the other 3 consider only exogenous technical change.

Path dependence is another important feature in IAM models, which entails a transitional cost of moving away from a given path, due to inertia. Seto *et al.* (2016) report quite a few institutional and behavioral factors contributing to carbon lock-in, including technological institutional and behavioral ones. IAM models find it difficult to capture path dependence beyond the capital inertia and induced learning. The improved understanding of carbon lock-in as well as economic insights about "self-fulfilling prophesies" suggest that IAMs still fail to address path dependency (Grubb *et al.*, 2021). Among the ones that succeeded are simulation (rather than optimizing) models, the most detailed linking an econometric model with technology innovation and climate modules (Mercure *et al.*, 2018).

Innovation, through economies of scale and learning-by-doing, makes an established path more attractive. Fouquet and Aghion (2019) identify at least several economic processes driving innovation, including knowledge spillovers (cumulative built innovations based on prior, related innovations in ways, network effects (where the attractiveness of a technology depends upon interrelated networks of other users or suppliers) and complementarities as in the case of renewables and storage.

Path dependence implies that past choices create a new default trajectory, and that there may be many alternative paths. Simplistic interpretation of the existence of a "least-cost, optimum pathway" would imply that countries at a similar stage of economic development would have similar levels of per-capita energy consumption. This is not the case since developed countries with similar per-capita income differ by almost several factors in their primary per-capita energy consumption. Effects of geography and trade can only account for a modest part of these differences. Per-capita CO2 emissions vary even more, though this is also influenced by the endowment of hydro and other low carbon energy sources. Even more striking, there has been no sign of convergence of carbon intensity, over time (Grubb *et al.*, 2021). This stylized fact is consistent with theories of path dependence, in which the institutions, infrastructures, and vested interests in fossil-fuel-intensive countries tend to self-perpetuate, while lower carbon economies may be more able to further decarbonize. Moreover, abatement cost is substantially influenced by assumptions around "hard-to-abate" sectors, rather than climate target stringency (see for instance Mercure *et al*., 2019). The emerging field of agent-based climate-economy models (Farmer *et al.*, 2015) may handle nonequilibrium effects, learning and bounded rationality (Lamperti *et al.*, 2018; Rengs *et al.*, 2020). While some of the more obvious feedbacks are included in some models, e.g. improved efficiency over time (included in practically all models), changes in input prices for materials and labor (included in detailed general equilibrium models, e.g. CGE models), many other factors, such as detailed technology-specific policies, spillovers from sectors not covered in detail in the models, remain generally exogenous.

Some of the criticism of IAMs has to do with the speed at which technologies can be deployed. The real-world processes behind this are numerous and complex and the speed can be influenced by energy and climate policies, but also by factors which are independent of policies, depending on knowledge spillovers or public acceptance of the given technology. IAMs generally modeled patterns of technological diffusion by imposing exogenous constraints, rather considering the speed of deployment endogenously. Use of expansion and decline constraints is common. Such constraints can be technology specific, or relate to a group of similar technologies. Sometimes such constraints are extended to include adjustment costs, which allow faster growth/decline, with an additional cost (e.g. Keppo and Strubegger 2010). Finally, assumptions about technology substitutability and system integration requirements affect both the speed and extent of changes in market shares.

While all models are well calibrated, some models make specific assumptions to explore special scenarios. IMACLIM adopts a pessimistic view of technological change by assuming strong inertia and by neglecting carbon-free energy sources from backstop technologies. AIM/Dynamic-Global focuses on the investment in energy-saving capital as a mitigation option, and largely neglects other options. As a consequence, economic growth cannot be decoupled from emissions.

3.4 Main taxonomy according to the modeling of renewables' intermittency and substitution between different technologies

Tables 5a and 5b report the taxonomy of IAM models, making specific reference to the way in which integration of variable renewable energy is modeled, the substitution between different technologies and the emission considered.

Renewables and intermittency

There has been increasing focus on improving the modeling of integrating variable renewable energy into the power system (Creutzig *et al.*, 2017; Luderer *et al.*, 2017; Pietzcker *et al.*, 2017) and of behavioral change and other factors influencing future demand for energy and food (van Sluisveld *et al.*, 2016; McCollum *et al.*, 2017; Weindl *et al.*, 2017), including in the context of 1.5°C-consistent pathways (Grubler *et al.*, 2018; van Vuuren *et al.*, 2018). The literature on the many diverse CDR options only recently started to develop strongly (Minx *et al.*, 2017). IAMs mostly incorporate afforestation and bioenergy with carbon capture and storage (BECCS) and only in few cases also include direct air capture with CCS (DACCS) (Chen and Tavoni, 2013; Marcucci et al., 2017; Strefler et al., 2018b). Global IAMs also generally do not model electricity grids at an hour-to-hour or day-to-day resolution. This means they cannot consider the weather-related fluctuations that make it challenging to integrate variable renewables, such as wind and solar, into the grid. However, most IAMs do include some mechanism to account for the costs of integration, as reported in detail below, both among general equilibrium and partial equilibrium models.

Among general equilibrium models:

- The power generation sector in AIM/CGE (Fujimori *et al.*, 2012) is disaggregated in great detail to reflect technological change in the power sector, and logit functions are used to determine the share of power supply technologies as a function of their generation costs. The power generation cost is determined by the cost of intermediate inputs and primary factor (capital and labor) cost. Some barriers to variable renewable energy integration, like curtailment and storage, are explicitly taken into account in the recent version of AIM/CGE model (Dai *et al.*, 2017). The storage service is treated as one of the intermediate inputs for the variable renewable energy production sectors, and it is produced by an explicit storage service providing sector. The required input of the storage service is calculated through an exponential function depending on variable renewable energy shares, parameterized to the residual load duration curves developed in the ADVANCE project (Ueckerdt *et al.*, 2017). Curtailment is represented as an additional demand in the electricity balance, and also takes the form of an exponential function depending on variable renewable energy E shares and parameterized to the Ueckerdt *et al.* data.

- In the MESSAGE model (Messner and Strubegger, 1995, Riahi *et al.*, 2012), region- and share-dependent residual load duration curves (Ueckerdt *et al.*, 2017) are used to parameterize how flexibility of the residual non- variable renewable energy system, variable renewable energy curtailment, and wind and solar PV capacity values change with increasing variable renewable energy share (Johnson et al., 2017--in this issue). These equations are translated into step-wise linear functions that describe the contribution of variable renewable energy to capacity adequacy and system flexibility constraints, where increasing deployment requires more firm (backup) capacity and increasing flexibility from the non- variable renewable energy portion of generation. In addition, electricity storage and hydrogen electrolysis technologies are included as options for repurposing both variable renewable energy and non-variable renewable energy production that would otherwise be curtailed. Thermoelectric technologies are represented in two modes of operation, baseload and flexible, to better account for the cost, efficiency, and availability penalties associated with flexible operation and the consequences of variable renewable energy deployment for non-variable renewable energy plant utilization. Since MESSAGE is a least-cost optimization model with perfect foresight, the additional electricity system requirements for integrating variable renewable energy endogenously influence investment decisions within the power sector.

- The energy-economy-climate model REMIND (Luderer *et al.*, 2013, Luderer *et al.*, 2015) is a Ramsey-type general equilibrium growth model of the macro-economy in which inter-temporal global welfare is maximized, combined with a technology-rich representation of the energy system. Its power sector implementation is based on the region-specific residual load duration curves developed in Ueckerdt *et al.* (2017), which capture the effects of adding wind and solar power to the power sector on a) capacity adequacy, b) dispatch, c) storage and d) curtailment. The residual load duration curves are represented by four load bands plus a capacity adequacy equation. The height of these load bands is a polynomial function of wind and solar share, so their height endogenously adjusts with changing variable renewable energy shares. Investments into the different power technologies are optimized with perfect foresight over the full time horizon of the model. Dispatch is represented through the residual load bands. Short-term storage deployment and curtailment are prescribed by polynomial fits of the variable renewable energy-share-dependent residual load duration curves. As the model uses an optimization framework for investments into dispatchable and variable renewable energy technologies, the share-dependent polynomial residual load duration curves formulation enables the model to fully account for the changing marginal value of variable renewable energy in the investment procedure.

- WITCH (Bosetti *et al.*, 2006, Emmerling *et al.*, 2016) is a hybrid model that combines an aggregated, top-down inter-temporal optimal growth Ramsey-type model (with perfect foresight) with a detailed description of the energy sector. Energy technologies – divided between the electric and the non-electric sectors – are nested in a Constant Elasticity of Substitution (CES) framework, which represents the many economic and non-economic drivers leading to limited technology substitution in a stylized way. Energy demand is modeled in average terms over the year. System integration of variable renewable energies is explicitly modeled through two constraints, related to the flexibility and the capacity adequacy of the power generation fleet. A simple modeling of the electric infrastructure and a generic storage technology are implemented as well (Carrara and Marangoni, 2017).

Among general equilibrium models:

- In the integrated assessment framework IMAGE (Stehfest *et al.*, 2014), region-specific residual load duration curves (Ueckerdt et al., 2017) have been combined with a load band approach to capture integration constraints of variable renewable energy resources (De Boer and Van Vuuren, 2017). These constraints include curtailment, storage requirements, backup requirements, and system load factors that decline as the variable renewable energy share increases. The constraints have been translated to cost markups, which are added to a base levelized cost of electricity (LCOE) to form an all-in LCOE. Investments are rule-based and calculated recursively for each time step: a module calculates the required capacity additions to meet demand, and a multinomial logit equation is applied to distribute market share among the available technologies based on the all-in LCOE. Dispatch of technologies occurs according to the merit order.

- The new POLES (Mima, 2016) power module now includes several forms of storage technologies as well as load shedding and curtailment of surplus power (Després *et al.*, 2017--in this issue). Each region has an endogenous residual load duration curves of 648 time-slices built from demand, wind and solar variations. They are used to define the seven load bands in which the production technologies compete. Investments for each load band are rule-based and calculated recursively for each time step: a module calculates the required capacity additions to meet demand, and a multinomial logit equation is applied to distribute market share among the available technologies based on the curtailment-adjusted LCOE plus a multiplier representing technology maturity and other non-cost effects on investment. A storage investment mechanism is also implemented based on a computation of its expected economic value. In this way, each region takes into account the integration challenges linked to the gradual development of VRE sources. POLES is the only IAM that follows a model-coupling route and combines a long-term investment planning model with a dispatch model (EUCAD, European Unit Commitment And Dispatch) based on twelve representative days with hourly resolution (Després *et al.*, 2017, Després, 2015, *Nahmmacher et al.*, 2016). Such a model-coupling brings the advantage that it enables representation and analysis of short-term effects, but it also creates the challenges of a) creating a reliable interface to ensure that the results from one model influence the other model (e.g., investment decisions should be influenced by the revenues realized in the dispatch), and b) gathering sufficiently detailed data for the individual regions. Due to lack of data, the current version of POLES only uses the detailed model coupling for the European countries, while the other world regions rely on an aggregated residual load duration curves-based investment and dispatch procedure.

- In the COFFEE model solar resources are split in four steps of increasing capacity factor. Wind resource was estimated considering 12 step curves for and 27 step discrete curves were created combining capacity factor, distance to shore and water depth for onshore and offshore, respectively.

Energy system substitution

IAMs based on top-down models tend to lack an adequate representation of technological flexibility and substitution possibilities and limits, for instance by using constant elasticity of substitution functions for energy modeling which has been shown to fail to match historically observed patterns in energy transition dynamics (Kaya *et al.*, 2017). In contrast, IAMs based on bottom-up approach do not represent the macro-economic feedbacks of different energy transition pathways, such as those coming from rebound effects, as well as additional investments and households' expenditures feedbacks on the economy. These effects can cause radical changes in economic structure, productivity and trade that would affect the rate, direction and distribution of economic growth. This may explain why the decoupling between economic growth and energy use or emissions in IAM scenarios are seen by some as unrealistic (Scrieciu *et al*. 2013, Spangenberg and Polotzek 2019, Nieto *et al*. 2020), in particular for developing regions (Steckel *et al*. 2013). The demand side of the economy is also not adequately represented (Rosen and Guenther, 2016, Lovins *et al.* 2019), so that IAMs may fail to reflect energy efficiency dynamics.

As reported before, in terms of energy-economy linkages, most IAMs are now hybris, either energy system linked to macroeconomic growth models (Bauer *et al.*, 2008) or multi-sector CGE, or other economywide models with explicit technologies in key sectors (Paroussos *et al.*, 2020). With the exception of partial equilibrium models (e.g. TIAM–UCL and IMAGE), most IAMs are able to incorporate some macro-economic feedbacks of energy transition pathways, but substantial different degrees of sophistication. Multisector models based on an input–output structure usually include a more comprehensive representation of energy-economy relationships (Mercure *et al.*, 2019, Paroussos *et al.*, 2019). Most top-down models have also been improved to reflect technological flexibility and substitution possibilities s(Wing, 2006), model linking for specific purpose (Fujimori *et al.*, 2019a, Delzeit *et al.*, 2020).

Finally, IAMs include only limited representation of the life cycle impacts of technology. Models with a macroeconomic budget closure include at least an indirect representation of the global supply chains of all capital investment. In compact growth IAMs, capital investment are included in a composite macroeconomic good, whereas multi-sector models report a more consistent representation with inter-industry flows and specific investment goods, though the related materials flows are accounted for only in monetary units. Conversely, some partial equilibrium IAMs (e.g. COFFEE and IMAGE) can account for material flows in physical units, but miss the full life-cycle linkages. Progress towards expanding IAMs with these features is an active research area (Pauliuk *et al.*, 2017) with different possible routes including adding new features to the models (e.g. adding an investment matrix to track more specific life-cycle linkages in a CGE model (Dai *et al.*, 2016)) or by model linking with IE models (multi-region input–output, life cycle assessment, etc) such as Luderer *et al.* (2019).

Emissions assessment

The baseline applies to all the climate models discussed in this paper, and defining it is a key part of cost assessment. The baseline is a measure of the GHG emissions that would occur in the absence of climate change interventions. The baseline rests on key assumptions about future economic policies at the macroeconomic and sectoral levels, including structure, resource intensity, relative prices, technology choice, and the rate of technology adoption. The baseline also depends on assumptions about future development patterns in the economy, such as population growth, economic growth, and technological change. Climate change policies may have implications in terms of local and regional air pollution. They may also have indirect effects on transportation, agriculture, land use practices, employment, and fuel security. These effects are taken into account within many bottom-up models as well as IAMs. They can be negative or positive. In addition, their inclusion tends to generate higher or lower climate change mitigation costs compared with studies in which they are not included.

For a wide variety of options, and as often demonstrated in IAMs, the costs of mitigation depend on the regulatory framework adopted by national governments to reduce GHGs. The more flexibility allowed by the framework, the lower are the costs of achieving a given reduction. The opposite is expected with inflexible rules and few trading partners. No-regrets options are by definition actions to reduce GHG emissions that have negative net costs. Net costs are negative when options generate direct or indirect benefits large enough to offset the costs of implementing the options. The possibility of achieving no-regrets options implies that people choose not to exercise some carbon-reducing options because of relative prices and preferences. Such options are commonly used when assessing the benefits of scenarios that are focused on increased reduction of climate emissions. For example, compared with a baseline scenario, a faster increase in appliance standards could help achieve rapid no-regrets options.

Table 5.a Representation of renewable energy, substitutions and emissions for General Equilibrium

Model	Renewables and Intermittency	Functional Structure for Energy System Substitution	Emissions
MERGE-ETL	Includes levelized generation costs. Constraints due to intermittent production are described by setting a maximum share on electricity production from wind and solar	Substitution between equivalent technologies with dynamic constraints and share constraints	GHG (CO_2 and NO_2)
MESSAGE	Links intermittent power with the availability of flexible generation (e.g., hydro, gas, other thermal) and back-up/storage capacity	Substitution between equivalent technologies with limitations due to system integration, etc.	GHG and other pollutants
ReMIND	Requires storage and curtails wind and solar depending on the share of wind and solar in power generation	Hybrid: CES at the level of final energy, linear substitution with adjustment costs and capital stocks at the primary and secondary energy levels	GHG and other pollutants
WITCH	Cost penalty for wind with increasing share in electricity to capture spinning reserves, backup capacity, and discarded electricity	Constant elasticity of substitution (CES)	GHG (CO_2 and NO_2)
C3IAM	The evolution of the power mix is calibrated to energy models (i.e. PRIMES for EU and PROMETHEUS for the world).	Substitution occurs through a nested CES function	GHG and other pollutants
BET EMF33	The power generation sub-module in BET takes into account capacity constraints and the lifetime of each generation plant. In addition, it considers the load duration curve, discretized into four sections, ranging from year maximum hours, peak hours, shoulder hours, to bottom hours. BET has a generation constraint on solar and wind, which are intermittent renewables	Linear choice (lowest cost)	CO_2
AIM-CGE	Requires additional storage for intermittent renewables	Energy system cost minimization	GHG and other pollutants
GEM-E3-ICCS	The evolution of the power mix is calibrated to energy models (i.e. PRIMES for EU and PROMETHEUS for the world).	Substitution occurs through a nested CES function	GHG and other pollutants
IMACLIM	Production is distinguished between base and peak demand in a load curve. Constraints due to intermittent production are described by setting a maximum share on wind and solar capacities which depends on the segment.	In the short run static equilibrium, the fixed technologies (Leontief coefficients) prevent substitution among factors. These substitutions are treated between two equilibria in sector-specific dynamic modules.	GHG and other pollutants
POLES	Links intermittent power with the availability of back-up capacity (hydro, gas, other thermal)	Logit sharing depending on costs and political choices	GHG and other pollutants
TEA	As COFFEE	As COFFEE	As COFFEE

GRACE	no	The supply and demand is simulated by nested CES functions.	GHGs include CO2, methane (CH4), nitrous oxide (N2O), fluorinated gases (FGAS)
Ifs	The capital/output (capital/production) ratios for all fuel types decline over time due to technological improvements at rates determined by two user controllable parameters.	Energy system cost minimization	Fossil fuel consumption generates carbon emissions specific to coal, oil, and natural gas use. Net deforestation generates additional carbon emissions or removal.
PHOENIX	Electricity-generating technologies are placed into three nests: base load, intermediate load, and peak load	Energy system cost minimization	GHG and other pollutants
WorldScan2		Nested CES (constant elasticity of substitution) function	GHG and other pollutants

Table 5.b Representation of renewable energy, substitutions and emissions for Partial Equilibrium

Model	**Renewables and Intermittency**	**Functional Structure for Energy System Substitution**	**Emissions**
DNE21+	Electricity demand and supply are formulated for 4 time periods; Useful capacity of wind and solar power depends on time period and share of wind and solar power is limited; Electricity storage options can mitigate limitations	Bottom-up energy system model with substitution calculated endogenously by minimizing total energy system cost	GHG and other pollutants
global TIMES	The temporal resolution is determined by three seasons, summer, winter and intermediate. Each of the season accounts for a third of the whole year or 4 months. These time slices are again split into night and day, where day represents 16 hours and night 8 hours	Renewable production can be constrained through annual bounds on capacity and growth constraints.	Pollutants and non-GHG forcing agents are not explicitly modeled, however additional forcing factor are included in the climate module.
global ETP-TIMES	Expansion and decline constraints system integration constraints	Lowest cost with adjustment penalties. Discrete technology choices with mostly high substitutability in some sectors and mostly low substitutability in other sectors	GHG
COFFEE	COFFEE describes energy conversion technologies based on discrete techniques with pre-defined technological (size, lead time, efficiency, availability, etc.) and economic (overnight costs, fixed and variable O&M costs, contingency factors etc.) variables, thus capturing technological deployment over time in a least cost approach.	Energy system cost minimization	GHG and selected other pollutants
AIM-Enduse	Requires additional storage for intermittent renewables	Energy system cost minimization	Energy and non energy GHG
GCAM	Splits the load duration curve into four distinct pieces in the USA; Requires backup for intermittent renewables in all regions	Logit sharing	GHG and other pollutants

IMAGE	Includes both back up capacity and spinning reserve for intermittent supply options (ISOs). Back up capacity is added to account for the capacity credit (which decreases as a function of penetration of the ISOs). The costs for back up power is allocated to the ISO. Required spinnning reserve of 15% assumed for ISOs.	Multinomial logit formulation describing substitution for technologies and fuels	GHG and other pollutants
PROMETHEUS	The electricity generation module includes 26 power generation technologies and their competition to cover electricity demand for base, medium and peak load	The substitution between different fuels/technological options is modeled based on the "gap", which is defined in terms of the difference between energy demand and the amount of energy that can be satisfied using existing equipment from the previous year, which is not scrapped.	It covers all emissions from the energy sector and the industry sector and can split CO2 emissions by sector (transport, industry, buildings, power generation, refineries, international bunkers, other) and by fuel (coal, oil, natural gas).

3.5 Main taxonomy according to applications

Tables 3a and 3b report in addition to the treatment of uncertainty, the policy whose impact the model is able to represent and applications.

Policy instruments

Top-down models are well suited to assess the macroeconomic impact of energy and environmental policies, especially market-oriented policies (carbon tax and tradable quota), on national and global scales. Because of limited representation efficiency improvements are difficult to convert explicitly into the production function of these models. For top-down models, the most efficient technology lies on the production frontier determined by market behavior. These models can help policy makers to assess the macroeconomic impacts of market instruments such as a carbon tax on energy systems or subsidies on renewable energy generation. Bottom-up models are also used to assess the energy supply and demand aspects of technology-based policies that are not driven by price (e.g., labels and standards). Theoretically, the "most efficient" technology within these models can lie beyond the production frontier determined by market behavior because customers may not actually adopt the technology. This discrepancy provides evidence of an efficiency gap. A high degree of detail regarding technology, such as its cost and efficiency, is included in bottom-up models, which allows researchers to explore the potential of decoupling economic growth from energy demands.

There are many climate-policy instruments, including carbon taxation, cap-and-trade, intensity-based targets, and subsidies (for renewable energy, research for new clean technology, emission reductions, etc.) which have been included in the modeling of IAMs. Each instrument has its advantages and disadvantages. For example, a carbon tax gives a direct price on carbon emissions, so companies can adjust their emissions based on cost-benefit analysis, but there is uncertainty in its effect on total emissions in the real world. A cap-and-trade scheme issues a number of emission allowances for the market to auction and trade, so it provides direct control over future emissions and it would be more straightforward to control temperature increase under some threshold (e.g., 2 or 1.5°C), but it is hard to estimate its economic cost. An intensity-based target scheme requires emissions per unit of economic activity to not exceed given targets, so it may be appealing to developing economies, but there is uncertainty in aggregate emissions and economic costs.

Subsidies to renewable energy can help renewable energy firms to improve their market shares and competitivity with fossil fuel energy firms, but there is uncertainty in its effect on controlling total emissions. Carbon tax is the most popularly debated policy, and it is often estimated to be equal to the social cost of carbon if it is not explicitly modeled (as in Baldwin, Cai, & Kuralbayeva, 2020), and if emissions control has not reached its limit (Cai et al., 2017; Cai & Lontzek, 2019). However, it could be challenging to implement a carbon tax policy in some countries. Instead, the cap-and-trade scheme may be implemented at a regional level. For example, there are currently cap-and-trade programs like the European Union Emissions Trading Schedule, the Regional Greenhouse Gas Initiative, and the California cap-and-trade program, although these programs require careful design to make them effective.

Policy comparisons among the climate policy instruments have been conducted in the literature. Goulder and Parry (2008) review many instrument choices in climate policy with different evaluation criteria, including economic efficiency and cost-effectiveness, distribution of benefits or costs (across income groups, ethnic groups, regions, generations, etc.), ability to address uncertainties, and political feasibility. Fischer and Springborn (2011) compare carbon tax, cap-and-trade, and intensity-based targets in a DSGE model with stochastic productivity. Heutel (2012) compares the optimal emissions tax rate and the optimal emissions quota. Drouet *et al.* (2015) discuss selection of climate policies under uncertainties. Goulder *et al.* (2016) argue that under plausible conditions a more conventional form of regulation, a clean energy standard, is more cost-effective than emissions pricing such as carbon taxation or cap-and-trade. Meckling, Sterner, and Wagner (2017) investigate the combination and sequence of policies to avoid environmental, economic, and political dead ends in decarbonizing energy systems. Rozenberg, Vogt-Schilb, and Hallegatte (2020) compare the impact of mandates (for new power plants, buildings, and appliances), feebates (programs that tax energy-inefficient equipment and subsidize energy-efficient equipment), energy efficiency standards, and carbon pricing in a simple model with clean and polluting capital, irreversible investment, and a climate constraint. They find that carbon prices are efficient but can cause stranded assets, while feebates and mandates do not create stranded assets. Baldwin *et al.* (2020) compare a carbon tax with a subsidy for renewable energy using a DSGE model, which is based on the full DICE model but adds renewable and nonrenewable energy sectors as well as a government that decides the optimal dynamic carbon tax or subsidy. They find that a carbon tax is more efficient under a stringent climate target, while a subsidy is more efficient under a mild climate target.

Barrage (2020) characterizes and quantifies optimal carbon taxes in a dynamic general equilibrium climate–economy model with distortionary fiscal policy. He finds that optimal carbon tax schedules are 8%–24% lower when there are distortionary taxes, compared to the setting with lump-sum taxes considered in the literature. Hafstead and Williams (2020) examine the role for tax adjustment mechanisms, which automatically adjust the carbon tax rate based on the level of actual emissions relative to a legislated target, and the trade-offs of alternative designs. They show that tax adjustment mechanisms in carbon tax design can substantially reduce emissions uncertainty. Kalkuhl *et al.* (2020) find that the time-consistent policy is the "all-or-nothing" policy with either a zero carbon tax or a prohibitive carbon tax that leads to zero fossil investments, and it is the lobbying power of owners of fixed factors (land and fossil resources), rather than fiscal revenue considerations or the lobbying power of renewable or fossil energy firms, that determines which of the two outcomes (all or nothing) is chosen. Van der Ploeg and Rezai (2020) allow for immediate or delayed carbon taxes and renewable subsidies that will cause discrete jumps in the present valuation of physical and natural capital, and then investigate how the legislative "risk" of tipping into policy action affects the time at which the fossil era ends, the profitability of existing capital, and the green paradox effects (Sinn, 2008).

4. Toward an overall assessment

There are several key messages emerging from the literature review that are worth emphasizing ahead of presenting some of the key challenges of IAM models. First, researchers have attempted to bridge the gap between top-down and bottom-up models either by incorporating macroeconomic feedback into bottom-up models or by including technological details in top-down models. Regarding energy-economy linkages, most IAMs are now hybrid constructs, either energy system linked to macroeconomic growth models or multi-sector CGE—or other economywide— models with explicit technologies in key sectors.

Second, IAMs have made substantive progress in dealing with uncertainty and risk. As noted, IAMs and scenarios are developed to analyze climate policies and estimate future pathways of temperature, but no model can replicate the real world completely and no scenario can predict a realized future pathway perfectly. For tractability, every model or scenario has to make some simplifying assumptions, particularly in mathematical representations of economic and climate systems. Different assumptions then lead to different models or scenarios. There are three broad approaches to incorporate uncertainties into economic models of climate change. The simplest approach, which is not a real uncertainty analysis but can be used as a tool to identify which model parameters should be treated stochastically, is a sensitivity analysis. A more complex implementation involves modeling certain variables as stochastic processes. For computational purposes, propagation of uncertainty usually involves sampling from a joint distribution using mostly the Monte Carlo method. The most demanding approach accounts for learning and can be termed sequential decision-making under uncertainty. This implies that models determine optimal policies at more than one point in time, taking into account the available information in each period.

Third, endogenous technological change is also an important issue in the context of climate change. Most existing models though, use autonomous learning and not more than two decision periods. Most existing models are deterministic and, if at all, most modelers have only performed very basic types of uncertainty analysis. Although sensitivity analyses and Monte Carlo simulations are a good place to start, two other crucial dimensions of the climate change problem should be included in any comprehensive attempt to inform climate policy decisions. First, decisions made today can be revisited and modified at any point in the future as new information on climate change damages and mitigation costs becomes available. Thus, decision making about climate change is one of sequential decision making under uncertainty. Models of sequential decision-making under uncertainty are used to determine optimal policies under different aspects of uncertainty and learning. Altogether, uncertainty analysis is very complex and computationally intensive. The second crucial dimension of climate change uncertainty that has yet to be systematically addressed by researchers is assumptions about the decision makers' attitudes toward risk.

An important issue concerns technological change: specifically, whether technology costs are assumed to be exogenous (that is, specified externally by modeling assumptions), or induced by the cumulative impact of policy, investment, and market growth within a model. Only a limited number of models, irrespective of whether general or partial equilibrium, have been able to endogenize technical change. Few if any models represent path dependence beyond the capital inertia and induced learning, to take account of institutional, social, and behavioral inertia, a limitation acknowledged in some of the leading studies.

Last but not least, the variations across model structures and key assumptions yield different results. Some of these variations and their impacts are briefly discussed below:

- Assumptions about energy demand drivers (i.e., GDP and population) differ across models. For example, the range of near- and long-term GDP growth assumed by different models shows great variation. However, many frameworks model drivers endogenously: for example, general equilibrium models project GDP endogenously, whereas other frameworks (bottom-up models) require those drivers as exogenous inputs.

- Differences in assumptions about resource costs and performance parameters reflect the modeling teams' assumptions about the relative costs associated with energy production from different technologies.
- How models represent the growth of technologies is also important. For CCS, nuclear, wind, solar, and hydroelectric technologies as well as, although to a lesser degree, fossil technology for electricity generation, the variation among models is great. As we have seen, some of them can assume no constraint, a growth-rate constraint, a constraint on the share of technologies, or no technology at all.
- The process of calibrating base year shares as well as how this calibration affects the future evolution of technologies are important. Many models, such as GCAM and general equilibrium models, calibrate energy systems to the base year share of technologies, whereas other models, such as MESSAGE and AIM-Enduse, do not calibrate base year shares. Thus, in the former models, the base year shares affect the evolution of future energy systems. This process represents the degree to which base year capital stocks turn over and affect the future capital stocks of different technologies.
- The representation of regional resource bases varies across models. Resource bases are not critical for fossil technologies, as these are globally traded commodities, but they are essential for determining the share of renewable energy sources and CCS technologies. For solar power, for example, some models assume regional production limits, some assume regional supply curves, some CGE models assume a fixed factor, and other models assume no limits. Similar differences in assumptions for other technologies are also present across models. However, each model provides its own representation of the different technologies. For example, GCAM represents solar and wind with supply curves and bioenergy with endogenous land competition. In addition, although there is no limit for CCS supplies, regional resource bases in Japan and the Republic of Korea are constrained.
- Though most models include technology cost as an exogenous assumption, some modeling frameworks, such as WITCH, model technology costs endogenously.
- Finally, solution algorithms differ across models. Most technology-detailed bottom-up models are based on an intertemporal modeling framework, whereas others, such as GCAM, are myopic and their solution algorithm is recursive dynamic.

There are now many criticisms of Integrated Assessment Models (IAM) and these range from technical disputes regarding appropriate quantities for variables to more fundamental critiques of the assumptions, concepts and purposes of IAMs (for the latter see also Dale, 2018; Hickel, 2018; Murphy, 2018). IAMs give the impression of being rooted in data, which tends to give them status as science as well as policy influence in key decision making and advisory circles (governments, the IPCC, etc.). Climate and economy focused IAMs are, however, deeply unrealistic in how they represent energy, environment and human systems and the relation between them.

The recent IPCC Global Warming of 1.5°C report (IPCC, 2018) and the deficits published in the annual UNEP Emissions Gap reports (see Christensen & Olhoff, 2019) have placed greater pressure on governments across the world to immediately increase investment in mitigation and adaptation and take more urgent action to reduce emissions – and this has resulted in further negotiations via the COP process and the UNFCCC and different countries are now beginning to announce they will aim for 'net zero' emissions by mid-century (though currently statutory commitments, detailed plans and implementation are mainly lacking and there is considerable skepticism regarding what 'net' might mean). Still, it is increasingly clear that more delay and gradual incremental change will be insufficient. Moreover, it remains the case that the IPCC approach to change is itself not sufficiently ambitious. IPCC reports include various 'simulated scenarios' generated from IAMs.

Some of the biggest challenges for improving the design and use of IMAs include what to count and how to count it. The application of IAMs to climate policy has generally been focused on issues related to efficiency. Accordingly, equity considerations have rarely been addressed directly. This is unfortunate because equity and fairness issues often dominate the political debate concerning what to do about climate change. For example, a policy maker in a low income country might be more interested in alleviating energy poverty by improving energy access and/or reducing poor air quality than in reducing climate change impacts per se, while a decision maker in a high income country might be more interested in trading off the reductions in economic output that result from reducing emissions against the losses from increases in the projected losses from extreme weather events in both poor and rich coastal regions. Moreover, this shortcoming is not easily fixed after a model with an efficiency-based optimizing architecture has been run, because of the many equity trade-offs and approximations that are typically made when such models are constructed in the first place. Even in this case, this process necessarily requires a number of important value judgments concerning whose preferences to count and how to weigh them against one another (cf., Sussman, Weaver, and Grambsch 2015).

The treatment of intertemporal discounting and intergenerational equity is another related and important challenge to be considered. To summarize, intertemporal equity is extremely important in determining the appropriate rate of implementation of policies designed to reduce carbon emissions. Low discount rates generally make rapid implementation of such policies much more urgent than high discount rates because damages are projected to grow steadily over time at a much more rapid rate than mitigation costs. Climate change impact assessments can be especially sensitive to the baseline assumed, especially in cases where "tipping points" may be reached; the closer the tipping point is to the baseline the more likely it is to be triggered.

Capturing interactions between impact sectors and feedbacks to the climate system. A formidable challenge for all IAMs is capturing important interactions between impacted sectors and regions, and feedbacks that can occur between the impacted sectors and atmospheric concentrations of GHGs, temperatures, and precipitation. IAMs have made slow, but steady, progress on these effects over the last 20 years, with great emphasis increasingly being placed on interactions among the global energy, water, land, and food systems.

This is broad agreement that the global energy system must be increasingly electrified, while shifting away from fossil fuels and towards renewables, in order to meet stringent climate goals. The IAM baseline scenarios continue to be dominated by fossil fuels, though the relative shares of coal, oil and gas vary considerably across the different IAMs. For example, the IMAGE IAM envisages nearly twice the coal consumption and half the oil consumption of WITCH. Similarly, the REMIND model sees significant deployment of renewable energy even without climate policy, due to falling costs, whereas AIM, GCAM and IMAGE have relatively low renewables growth. This is largely because REMIND models the "learning by doing" that has seen renewable energy costs fall as deployment increases, whereas most other IAMs do not. IAM scenarios that limit warming to below 2C also differ substantially in their energy mix. Some, such as GCAM and REMIND, completely eliminate coal use in favor of biofuels and technologies such as bioenergy with carbon capture and storage (BECCS). Others include a sizable amount of both coal and gas coupled to carbon capture and storage.

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