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Exploring the possibility space: Taking stock of the diverse capabilities and gaps in integrated assessment models

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Abstract

Integrated Assessment Models (IAMs) have emerged as key tools for building and assessing long term climate mitigation scenarios. Due to their central role in the recent IPCC assessments, and international climate policy analyses more generally, and the high uncertainties related to future projections, IAMs have been critically assessed by scholars from different fields receiving various critiques ranging from adequacy of their methods to how their results are used and communicated. Although IAMs are conceptually diverse and evolved in very different directions, they tend to be criticized under the umbrella of “IAMs”. Here we first briefly summarise the IAM landscape and how models differ from each other. We then proceed to discuss six prominent critiques emerging from the recent literature, reflect and respond to them in the light of IAM diversity and ongoing work and suggest ways forward. The six critiques relate to (1) representation of heterogeneous actors in the models, (2) modelling of technology diffusion and dynamics, (3) representation of capital markets, (4) energy-economy feedbacks, (5) policy scenarios, and (6) interpretation and use of model results.

Keywords

Integrated Assessment Model; heterogeneity; technology diffusion; energy-economy feedback; finance; policy scenarios; model interpretation

1. Introduction

Climate change is widely considered to be one of the key, global problems urgently in need of solutions. Examples of recent plans and commitments to address the problem include the European Green Deal (EC, 2019) with the 2050 climate neutrality target, China's recent pledge to reach carbon neutrality by 2060 (Ministry of Foreign Affairs of the People's Republic of China, 2020) and UK's law on reaching carbon neutrality by 2050 (UK Government, 2019). Integrated assessment models (IAMs) are central tools for providing insights about the options available for, and the consequences of, possible strategies for long term greenhouse gas (GHG) emission reductions, by simultaneously capturing the development of several interacting, relevant systems (e.g. energy, economy, land use). Analyses based on such models play a central role in the discussion of mitigation alternatives, implications and determinants of specific actions and their consequences (e.g. IPCC, 2018, UNEP, 2019, CCC, 2008). The influence of the models therefore goes much beyond the academic environment.

Partially due to the central role these models hold, there is a concern in the literature over how the capabilities of, and recommendations from, these models map to the mitigation activities in the real world (e.g. Anderson and Jewell, 2019, Larkin et al., 2018). These models are attempts to capture the key elements of real-world systems, but, as we will discuss in this paper, questions have been raised about whether they are in their current state able to do so.

Additionally, this prominent role and the perceived gaps in model capabilities have raised questions about the way in which model results should be interpreted, used and communicated and to what extent the discussion over long term mitigation strategies should rely on conclusions drawn from these tools (See section 3.6 on Model use and interpretation). Models are always abstractions of reality, i.e. "map is not the territory" (Korzybski, 1931), which suggests that the translation process can be non-trivial. And yet, while all models are wrong, some are useful.

In this paper, we will summarise and discuss six prominent critiques from the literature and reflect the use and capabilities of diverse IAMs against those critiques. In the process, we will also summarise the key characteristics of the various IAMs and illustrate their heterogeneity in methods and capabilities for capturing various elements. We will further suggest next steps for improving the performance and communication of IAMs to the broader climate change community.

2. Integrated assessment models of climate change mitigation

IAMs provide a quantitative description of key processes in the human and earth systems, including the interactions of such processes and systems. Their analytical framework integrates elements from various disciplines such as engineering, economics, climate, and land use. Most IAMs are global in scope, although also, e.g. regional and national IAMs are being developed (Schaeffer et al. 2020). IAMs typically aim to have sufficient coverage of human sources of GHG emissions so they can project anthropogenic emissions over long periods of time, typically to 2050 or 2100. IAMs are utilised for exploring "the solution space" by describing a range of possible pathways that achieve long-term policy goals, such as global climate objectives, and at the same time highlighting feedbacks and trade-offs between choices about the energy system, economy and the environment.

The term "IAM" is used to describe a range of models that work differently, may differ in terms of their system boundaries, level of detail and, generally, were designed to answer different questions (Krey et al., 2019). Detailed process-based, activity focused IAMs have, for example, traditionally been different from cost-benefit IAMs which aggregate these processes into stylised abatement cost and climate damage relationships (Weyant, 2017). Recently, however, these modelling families have been moving closer to each other (e.g. Dennig et al., 2015, Dellink et al., 2019, Takakura et al., 2017, Matsumoto, 2019, van Ruijven et al., 2019). This paper focuses on the global process-based IAMs and their use for assessing global mitigation goals and decarbonisation pathways.

Process-based 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, the IAMs which started as

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3 economic models still have their relative strengths in the representation of the economy (“Economic coverage”
4 in Table 1. See also section 3.4). Some other IAMs core strength is a very detailed energy system, making them
5 more suited for analysing different technological options for decarbonising energy supply (“Technology
6 representation” in Table 1. See also section 3.2). The way IAMs “solve” over the decision horizon can also vary
7 from model to model (“Solution method” in Table 1). Some IAMs try to maximise welfare or minimise costs
8 over time (“optimise”). Other models project based on the trends and dependencies observed in historical time
9 series (“simulate”). Models do this in time steps, which usually vary from one to ten years. In some models,
10 minimising costs simultaneously across all time periods (intertemporal optimisation) assumes “perfect
11 foresight”, meaning that the “agent” knows with full certainty what is available, and required, in the future.
12 Although decisions in the real world are not made with complete knowledge about the future, exploring cost-
13 optimal pathways can help identify and describe efficient ways to achieve a climate target. Other IAMs work
14 “myopically” (recursive-dynamic models), meaning a time step is solved without full knowledge of what comes
15 after, making it possible to explore today’s choices which may lock in infrastructure and raise the cost of climate
16 action later. Finally, simulation models differ from optimisation models in that instead of identifying “optimal”
17 decisions, they simulate, based on observed or assumed relationships between variables, how the system might
18 develop going forward. This difference implies different interpretations for the heterogeneity and decision
19 making of the agents represented in the model - and for the interpretation of the model results more generally.
20 For example, simulation models, such as IMAGE, reflect in their parametrisation the real-world heterogeneity of
21 agents and their implied, heterogeneous preferences (e.g. lowest cost technology does not capture 100% market
22 share, even if this was otherwise feasible), whereas cost-driven linear optimisation models, e.g. like TIAM-
23 UCL, generally assume a single representative agent, with a single set of preferences, and would thus suggest
24 that the technology best matching these preferences is the best option for everyone represented by this agent (see
25 also sections 3.1 and 3.6).

26
27
28 Table 1 illustrates some of the dimensions across which IAMs can differ, using as an example the models the
29 authors of this paper operate and focusing on the areas discussed later in this paper. Models with a detailed
30 description of the energy system at their core (“Technology detail”. See also section 3.2), for example, tend to
31 include a wider and more granular range of technologies than models that have their focus and origins
32 elsewhere, such as in the description of the economic system. As seen from the table, representation of
33 technological change can also vary. For instance, technologies can be represented either as having constant
34 technical characteristics and costs over the time horizon or with endogenously changing costs and/or efficiency
35 over time (Krey et al. 2019). Also, the assumptions about dynamic technology characteristics and costs may be
36 exogenous projections or driven by endogenous learning formulations depending on the deployment of
37 technology (learning by doing) and sometimes also on R&D investments (learning by research). Endogenous
38 formulations for technological change may also be implemented throughout the model or only for key sectors
39 and technologies. Similarly, various approaches exist for capturing how novel technologies diffuse in the system
40 (e.g. hard constraints, adjustment costs, logit formulations, evolutionary formulations).

41
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43 Socio-economic and political dimensions, such as economic growth and behavioural change, are key
44 determinants of how energy and natural resources are used in the future. IAMs differ widely in how these
45 dimensions are represented, both in terms of which elements are modelled and, for the elements that are
46 modelled, how the modelling is done. For instance, capturing decision making in a model is influenced by
47 several factors, such as heterogeneity of modelled actors, how they make decisions - and how granular the
48 description is. How this is implemented in specific IAMs depends on the model and the questions it was built
49 for (see Section 3.1). For instance, IAMs that assume an economically rational social planner will often simulate
50 non-rationality and heterogeneity through exogenous constraints, e.g. minimum market shares for technologies
51 in a given sector.

52
53 IAMs also vary in terms of their representation of the economy. As depicted in Table 1, IAMs range from partial
54 equilibrium energy - land models (in which the economy is exogenous) to computable general equilibrium
55 models of the global economy, which endogenously capture the interactions between energy, land and the
56 environment with the overall economy. This representation will shape how models represent energy-economy
57 relationships and feedbacks, as discussed further in Section 3.4, and also finance as discussed in Section 3.3.
58 IAMs also differ in terms of their capability to represent specific policies. In Table 1 we score IAMs as low,
59 medium, high representation of policies, depending on the number of policies they can implement (based on
60 IAMC, 2020).

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4 INSERT TABLE 1 HERE
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6 Given the long time horizon and simplifications needed in order to capture the various complex systems in
7 models, pathways suggested by IAMs are generally not meant to be normative, nor provide a blueprint for
8 policy makers (see also Section 3.6). It is also important to keep in mind the multitude of modelling approaches
9 that are captured under the term “integrated assessment model”, even when focusing only on process-based
10 IAMs. The models have been originally created for different core purposes and these are reflected in their
11 structures, level of detail for specific parts of the model and capabilities for capturing various processes. This
12 means that not all models will be equally suited for answering specific questions, as their strengths and
13 weaknesses differ. This, however, also means that a combined portfolio of IAMs is likely to be stronger than
14 any single model.
15

16 17 18 **3. Critiques, responses, and suggestions for future research** 19

20
21 We will, in this section, discuss six prominent areas of IAM critique, that emerge from our assessment of the
22 literature. The referenced articles have been chosen based on our collective expertise of the literature critical of
23 IAMs, with no further constraints on the nature of the critique, and these six broad areas of critique arise from
24 this review process. We see these topic areas as timely and central, but we note also that the nature of our review
25 is a narrative one, whereas a different approach of a systematic review using a specific set of search terms could
26 identify additional, or different, areas of critique. Finally, the modelling community is naturally also aware of a
27 range of additional areas in which the models and model-based assessment could be improved, e.g.
28 harmonisation of assumptions for model comparison exercises, more frequent ex-post studies of model results
29 and further focus on uncertainty. These areas are not part of this review.
30

31 **3.1 Representation of heterogeneity within and across actor groups** 32

33 IAMs have been criticized for neglecting actor heterogeneity, which plays an important role in societal
34 transitions. Modelling the complexity of societal transitions involves representing mechanisms that lead to
35 heterogeneous behaviour (e.g. norms, conventions, conflict, negotiation, strategic behaviour, resistance to
36 change), local initiatives (local heterogeneity), actor interactions, and the evolving system level structures,
37 including social and political processes, governance and institutions (Trutnevyte et al. 2019). The latter is itself
38 also subject to heterogeneous decision-making impacted, e.g., by normative objectives of policy makers. The
39 heterogeneity in different parts of the system leads to important interactions within and between actor groups
40 that can lead to a societal transition. The models, however, are said to remain in the paradigm of a single
41 representative agent (Mercure et al., 2016, Balint et al., 2017), with economically rational, optimizing decision-
42 making based on perfect foresight (De Canio, 1997, De Canio et al., 2001, De Canio, 2003, Laitner et al., 2003
43 Geels et al., 2016, Trutnevyte, 2016). The realism of decision-making as represented in the models is questioned
44 (van Sluisveld et al., 2016; McCollum et al. 2017; Hirt et al. 2020) and hence the model results may overlook
45 effective policies and other levers for climate mitigation (Trutnevyte et al., 2020). The diversity across actor
46 groups is said to be limited to aggregate producers, consumers and a fully informed benevolent social planner
47 implementing policies (Köhler et al., 2018. See also Czupryna et al., 2020), and therefore those social processes
48 emerging from coordinated actions of few actors (lifestyle change, innovation, strategic actions, political
49 processes) (Holtz et al., 2015), are hard to capture in IAMs (McDowall and Geels, 2017). Relatedly, it has also
50 been highlighted that few IAMs represent inequality (Rao et al., 2017) as well as social and distributional
51 impacts (Böhringer and Löschel, 2006).
52
53
54

55 The brief literature summary shows that actor heterogeneity is connected to societal transitions. Therefore, in
56 our response to the raised critiques, we make an attempt to simultaneously disentangle the different roles that
57 heterogeneity plays, while addressing them. Modelling heterogeneity inherently means representing the
58 individual parts of something that initially is treated as a whole. This can be applied at different scales, for
59 example, from the population as a whole to different social groups, or from regional to neighbourhood level
60

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3 down to the individuals. Ultimately this means including more details in IAMs. Within longer time horizons and
4 scope, specificity does not imply greater accuracy as uncertainties increase. The challenge lies therefore in
5 modelling clear and simple relations that capture the complexity but do not overly constrain it (Dowlatabadi
6 1995). A key question that the modeler will need to ask her or himself is therefore what details need to be
7 included in order to capture the overall system behaviour.
8

9
10 There are two important situations when the degree and type of heterogeneity is important to include. The two
11 situations are to a certain extent in opposition to each other, illustrating how the required level of heterogeneity
12 in models will always be based on a case by case approach.
13

14 1) Behaviour is uncoordinated and differs across agents, leading different actors to respond to context and
15 policy incentives differently and be affected differently. A modeler wants to add heterogeneity to evaluate
16 specific detailed policies targeting different groups or inequality, ultimately because the aggregate effect is
17 significantly different from using a mean representative agent (e.g. see Mercure & Lam 2015). IAMs come, as
18 noted, in different shapes and sizes but there are multiple examples of studies where heterogeneity is introduced
19 for this purpose in different frameworks. Ekholm et al (2010) and Daioglou et al. (2012) for example both use
20 bottom-up modelling frameworks and model households with different income levels in developing regions,
21 showing that climate policy can reduce residential GHG emissions, but prevents for lower income classes a
22 transition from traditional biofuels to clean fuels. Dagnachew (2018) demonstrates how increased electricity
23 prices as a result of climate policy can impact the low income classes in sub-Saharan Africa. In a multi-model
24 study McCollum et al. (2018) show the importance of a diverse set of policy measures targeting vehicle buyers,
25 when modelling heterogeneous non-financial consumer preferences towards alternative propulsion vehicles. So far,
26 the research has focused more on consumer heterogeneity, than heterogeneity of businesses, governance and
27 institutions. Identifying and developing the key areas in which the inclusion of heterogeneity is likely to
28 significantly change the conclusions drawn from the models is an ongoing activity in the community and should
29 be continued.
30
31

32 2) Behaviour is coordinated and similar, and actors follow each other's behaviour or repeat their own
33 behaviour. A modeler is interested in this coordinated response when interactions, spill-over and feedback
34 effects between actors could lead to significantly different outcomes than if a single representative agent was
35 used (e.g. see Mercure 2018). Key examples here are inertia, learning and social influence effects. While most
36 IAMs address these system behaviours implicitly, through learning rates, diffusion constraints or enablers (see
37 also "Technology representation" in Table 1), there are also examples of models, or model variants, that
38 explicitly represent the interaction effects between individual agents. Edelenbosch et al. (2018) represent
39 different adopter groups to assess the reinforcing dynamics between social and technical learning in a transition
40 towards electric mobility. Sachs et al. (2019) describe household agents in the MUSE model with varying
41 objectives, where technology choice is influenced by choices made by other agents. Also the E3ME-FTT-
42 GENIE model separates agents at the sectoral level allowing to represent multi-agent influence, behavioural
43 biases (Thaler, 2016) and innovation diffusion (Mercure et al., 2018a, Knobloch et al., 2019), while the
44 PRIMES-Builmo model represents multiple agents in the buildings sector enabling the assessment of
45 distributional impacts of climate policies across income classes (Fotiou et al. 2019). While there is no strict rule
46 in terms of the IAM type that can best consider explicit modelling of such interactions and their consequences,
47 in practise optimisation models (as opposed to simulation models) are likely to be more heavily tied to a single,
48 global decision-making rule with system behaviour addressed implicitly. It is worth noting, however, that there
49 is essentially nearly infinite granularity for actor interactions in the real world and thus the models that do try to
50 capture some of this explicitly focus on doing so for chosen, very specific mechanisms only.
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52
53

54 Arguably investment decisions made in the producing sectors may be more economically rational than those of
55 consumers and policy choice, where many factors beyond financial considerations play a role. The question here
56 is whether, and to what extent, these factors need to be explicitly included in the models to represent the
57 behaviour at the system level. Many models have different stylized features to reflect these beyond cost
58 considerations impacting the choices made. Examples are the use of a multinomial logit equation to depict
59 market heterogeneity (e.g. IMAGE in Table 1), risk or hurdle rates to reflect the attitudes that people hold
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3 towards risks (e.g. TIAM-UCL), and preferences for certain choice feature example speed or affluence (Daly et
4 al. 2014; Girod et al 2012). Reflecting such elements in assumptions embedded, for example, in the
5 parameterisation of the models is, however, by nature less transparent than explicit inclusion in the models,
6 unless a concentrated effort is taken to communicate and document the underlying implications clearly
7 (Trutnevyte et al., 2019).
8

9 10 **3.2 Technology diffusion and dynamics**

11
12 IAMs have been criticised over how they capture the diffusion of technologies, and the processes that determine
13 the speed and shape of these transitions (Köhler et al., 2019, Anderson and Jewell, 2019). For example, co-
14 evolution of technologies and wider contexts in which the technologies exist play a role in technology diffusion,
15 but is generally not explicitly considered in the models, leading to difficulties for directly capturing the drivers
16 of path dependencies, innovation, market drivers and inertia (Geels et al., 2016, Fouquet and Pearson 2012; Hirt
17 et al. 2020). Additionally, authors have argued that, irrespective of how IAMs capture the details of diffusion
18 processes, their outcomes for key technologies are at times too optimistic (e.g. Anderson and Peters 2016,
19 Fleiter et al 2011, Hultman and Koomey 2007, Gambhir et al 2019; Anderson and Jewell, 2019) and sometimes
20 too pessimistic (Fuhrman et al 2019, Wilson et al, 2013). The ability of the models to adequately capture
21 endogenous technological change (Azar and Dowlatabadi, 1999, Grubb et al., 2002, Löschel, 2002, Mercure et
22 al., 2019, Vartiainen et al., 2019), region specific technology policies (Creutzig et al., 2017; Trutnevyte et al.
23 2020) and policies enabling deeper diffusion of low carbon technologies (Gambhir et al 2019) all affect the
24 conclusions drawn from the models, e.g., about costs of mitigation or the feasibility of a rapid diffusion of
25 specific technologies.
26

27
28 Technological learning has shaped energy transitions in several ways (Grübler et al., 1999, Fouquet 2010,
29 Creutzig et al. 2017), leading to reduction of costs, increase of efficiency, and the creation of new services or
30 functionalities. While some IAMs endogenize learning curves (e.g. Krey et al. 2019, Mercure et al. 2019. See
31 also Table 1), i.e. the costs decrease as a function of cumulative installed capacity (learning-by-doing) or
32 cumulative R&D investments (learning-by-research), other IAMs assume exogenously defined cost trajectories
33 (Krey et al. 2019, Rubin et al. 2015), and some IAMs may use a combination of both – endogenous for some
34 technologies, exogenous for others (Clarke et al. 2008; see also Section 2). The solution method of the model
35 (see Table 1) plays an important role in this: Models relying on linear optimisation suffer a significant
36 computational penalty when endogenous learning is included and are thus more likely to rely on exogenous cost
37 projections. What is more, in reality technological change arises from a multitude of human activities and few of
38 these drivers are explicitly represented in the models. While some of the more obvious feedbacks are included in
39 some models, e.g. improved efficiency over time (included in practically all models), changes in input prices for
40 materials and labour (included in detailed general equilibrium models, e.g., CGE models), many other factors -
41 such as changes in the product or service itself (re-design, standardisation of technology), detailed technology-
42 specific policies, spillovers from sectors not covered in detail in the models - remain generally exogenous.
43

44
45 Some of the critiques to IAMs concern the speed at which technologies can be deployed, i.e. how quickly can d
46 a competitive technology be scaled up and what does this depend on in the model. The real world processes
47 behind this are numerous and complex and the speed can be influenced by energy and climate policies (such as
48 those for PV (Creutzig et al. 2017)), but also by factors which are independent of policies, e.g. niche markets
49 (e.g. Fouquet 2016), technology characteristics, fit with the existing infrastructure and knowledge spillovers
50 (Grant et al. 2020) or , public acceptance of PV (Creutzig et al. 2017).

51
52 Historically, factors influencing patterns of technological diffusion in IAMs have been modelled by imposing
53 exogenous constraints (input assumptions), rather than the limits for the speed of deployment being products of
54 endogenously modelled processes (model result). Use of expansion and decline constraints, in which the
55 production or investment in a given period depend on those of the previous period (e.g. investments can grow
56 maximum 5% per year), is common, as can be seen in Table 1. Such constraints can be technology specific, or
57 relate to a group of similar technologies. Sometimes such constraints are extended to include adjustment costs,
58 which allow faster growth/decline, with an additional cost (e.g. Keppo and Strubegger, 2010). Use of
59 multinomial logit function for determining market shares in simulation models, or capital motion equations in
60 macroeconomic tools, reflect inertia for the investments and thus moderate the growth away from the type of
sudden “winner takes it all” outcomes that linear optimisation models can demonstrate (if no explicit constraints

are included). Finally, technology diffusion is also a system characteristic and thus assumptions about technology substitutability and system integration requirements affect both the speed and extent of market share change.

There is an active literature assessing the plausibility of IAM outputs with respect to historically observed diffusion dynamics and stylised facts (Napp et al. 2017; van Ewijk and McDowall 2020; van Sluisveld et al. 2015). On the system level, models generally do characterise the transitions in a way that is qualitatively comparable to empirical evidence (Wilson et al., 2013, van Sluisveld et al. 2015), even if sometimes too conservative (Creutzig et al., 2017), sometimes too optimistic (McDowall, 2016). This relatively good match between forward-looking model results and historical transitions is naturally not evidence for future transitions for specific technologies necessarily following the past patterns - especially when the drivers of faster versus slower historical diffusions are generally abstracted out in the models and thus not explicitly represented. There is an important body of IAM research currently addressing the above described issues. For instance, Mercure et al. (2016) investigated alternative modelling approaches based on complexity dynamics and agent heterogeneity to represent technology adoption and diffusion. McCollum et al. (2017) improved the representation of heterogeneous consumer groups, and thus adaptation of technologies, with varying preferences for vehicle novelty, range, refueling/recharging availability and variety. Edelenbosch et al. 2018 proposed a new model formulation to analyse how technological learning and social learning interact to influence transition dynamics, in this case for electric vehicles. Further research to include a wider range of drivers behind different diffusion rates could be considered, even if the diffusion processes themselves are not explicitly captured. Examples could include improving the parameterization of the diffusion equations based on empirical evidence (e.g. Wilson et al. 2020, Jewell et al., 2019) and more frequent updates of technology data to keep up with costs and performance developments (Grant et al., 2020).

Even if some generalizable patterns can be extracted from empirical research and modelled, fully capturing all that matters for technology diffusion and dynamics is unlikely to be feasible in IAMs. The exploration of future pathways involving disruptive changes, i.e. changes which not necessarily follow the pattern of past transitions, is possible though scenario analyses (e.g. Grubler et al., 2018). Similarly, diffusion constraints in optimisation models should generally be seen as scenario-specific input assumptions in the context of which the model results should be discussed and interpreted. As a consequence, models can provide insights on what the implications of various diffusion assumptions may be for future transitions, but they cannot provide insights into the limits to the diffusion speeds themselves, i.e., what would be needed (e.g. for infrastructures, supply chains, behavioural change) to reach specific levels of deployment growth for a given technology. While many other drivers of technology dynamics are important and would ideally be captured endogenously, this would greatly expand the system boundaries of the models, bringing with it various trade-offs such as increased model complexity, loss of transparency, increased uncertainty of results. Balancing these trade-offs while improving IAMs' capability to represent transformative structural and technological change remains a challenge for the IAM modelling teams.

3.3 Representation of capital markets and finance

Analysing the finance of green investments and the role of capital markets is a rather new strand in climate economics research. Interest has been kick-started by demand from policy-makers following concerns expressed amongst central bankers and the financial community in general. IAMs began to deliver relevant insights and results about e.g. adequacy of carbon pricing to cover the financing needs of stringent mitigation (Bowen et al., 2014), how national institutions affect investment risk, cost of financing and, as a consequence, the distribution of mitigation costs (Iyer et al., 2015; Sweerts et al., 2019), alternative model formulations for availability and cost of finance (Mercure et al. 2018a). Some of this research have been criticised for not representing the financial system and its interactions with low-carbon investment and the real economy in an adequate way.

IAMs that are based on neoclassical economic growth and general equilibrium models, in which limited savings are allocated to borrowers by banks and capital markets, face a problem that is known as the Lucas Paradox (Lucas, 1990) – the observation that capital flows from developing to developed countries, whereas standard economic theory of perfect capital markets suggest the opposite flow direction. Thus, under the assumption of perfect capital markets, simulated capital flows are at odds with observed global patterns. Most general equilibrium IAMs of this type therefore avoid to explicitly represent capital trade and current account

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3 imbalances – whereas partial equilibrium models by default do not capture these variables at all, as they do not
4 depict the entire economy. Given the role that capital trade has on foreign investments (including green
5 investments), this is considered to be a drawback of IAMs. Staub-Kaminski et al. (2014) indicate imperfect
6 financial markets as one of the real-world imperfections that are not included in most IAMs but which are
7 crucial in assessing mitigation costs.
8

9 The inadequate treatment of the financial system in IAMs can lead to a possible overestimation of the
10 “crowding-out” of green investment on investment in other parts of the economy (Pollitt and Mercure, 2017,
11 Mercure et al., 2018a). On the other hand, assuming that there is no “crowding-out” and agents have access to
12 unlimited low-cost financial resources could also be misleading (Mercure et al, 2018a, Paroussos et al. 2019).
13 Ultimately, the representation of the allocation of financial resources in models has insufficient detail while
14 theory lacks consensus within the economics academic community and beyond the world of IAMs.
15

16 Whether a rapid low-carbon transition affects national income is a long-standing debate (Edenhofer et al. 2010,
17 Clarke et al. 2014). However, more recent evidence and debates suggest that it may be financial stability that
18 could be most affected by the transition, as financial risk is re-organised and re-allocated between different types
19 of activities (Mercure et al 2016, 2018b; Battiston et al 2017). This suggests that scholars have been overlooking
20 the systemic risk aspect of the problem. The debate also touches on whether a low-carbon transition actually
21 creates new sectors and occupations in the economy, while it destroys others, which, with higher innovation
22 potential, can foster accelerated growth with concurrent structural change. The latter is contingent on how we
23 understand finance to be allocated to borrowers in the economy. If banks are understood as creators of finance,
24 where loans are created first and savings arise as a result, then the transition leads to sectoral growth and
25 structural change (see e.g. Lavoie 2014, Mcleay et al 2014). Otherwise, if banks are understood as channels of
26 transmission for limited savings to reach borrowers, then the finance of low-carbon innovation and
27 technological change may lead to crowding-out of resources in other productive sectors of the economy (see
28 Mercure et al 2018a, Paroussos et al, 2020). Thus, how the availability of finance is treated in IAMs is a key
29 issue for interpreting their outcomes from the macroeconomic standpoint (Capros et al, 2014). At the same time,
30 conceptual dissent over how this actually works in reality hinders progress.
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32 To improve the representation of capital markets in IAMs, models take one of two approaches, depending
33 whether they are based on supply-driven or demand-led macroeconomic theoretical foundations (Capros et al.,
34 1990). The inclusion of the financial sector in CGE IAMs improves their simulation properties by: (i) Allowing
35 the introduction of financing schemes regarding the repayment of loans, which reduces the crowding-out effect
36 in decarbonisation scenarios and more realistically represent the transition. (ii) Calculating detailed budgeting of
37 debt across years and agents’ disposable income, ensuring a more realistic representation of finance sector (iii)
38 Considering the impact of debt accumulation and debt sustainability in the ability of agents to borrow through
39 effects on interest rates (Paroussos et al, 2020). In the demand-led macro-economic approach, finance is created
40 according to demand and can lead to bubbles (Pollitt and Mercure 2018), and the key improvement is
41 adequately representing the perception by financial institutions of the credit-worthiness of borrowers, to identify
42 where and when banks may refuse to lend. Examples of recent work for modelling finance in supply-driven
43 macroeconomics include Bachner et al (2019), who explored determinants of the weighted average costs of
44 capital (WACC) in Europe’s electricity sector, building on a CGE model coupled with electricity modelling and
45 Paroussos et al. (2019), who showed that the provision of low-cost finance can effectively reduce investment
46 costs for decarbonisation enabling developing countries to take full advantage of technological diffusion with
47 positive economic impacts globally. Leimbach and Bauer (2020) investigate potential market feedback
48 mechanisms between climate policies, energy sector transformation and capital markets and in particular asks to
49 which extent the representation of capital market imperfection (based on debt constraints, risk premia on capital
50 trade and savings wedges that cover unobserved institutional conditions) changes the global and regional costs
51 of climate change mitigation. Results show significant changes of regional mitigation costs, while on the global
52 level, higher costs for financing the capital-intensive transformation of the energy system and reduced costs that
53 result from lower baseline GHG emissions under imperfect capital markets compensate each other.
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56 Future research regarding capital markets should address in a more definitive way how the allocation of
57 financial resources should be modelled, and whether the creation of financial capital is crowded-out and limited
58 by savings, or whether financial capital and purchasing power are created by financial institutions as they lend.
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3 Policy questions related to this concern are whether a rapid energy transition reduces macroeconomic activity
4 overall or accelerates activity but increases systemic risk and structural change.
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8 **3.4 Energy-Economy feedbacks**

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10 IAMs have been criticised for the way they represent the economy. In particular, IAMs were criticised for relying
11 on first-best economic assumptions of perfectly functioning markets omitting important aspects of real-world
12 frictions with key implications for macroeconomic dynamics and hence least-cost assessment (Victor, 2015). In
13 addition, IAMs have been criticised for the way they capture energy–economy relationships and feedbacks. As
14 argued by Hourcade et al. (2006), IAMs based on “conventional Top-Down” models tend to lack an adequate
15 representation of technological flexibility and substitutions possibilities and limits (for instance by using Constant
16 Elasticity of Substitution – CES - functions for energy modeling which has been shown to fail to match historically
17 observed patterns in energy transition dynamics (Kaya et al., 2017)). Conversely, IAMs based on “conventional
18 Bottom-Up” approach, without additional macroeconomic modules, do not represent the macro-economic
19 feedbacks of different energy transition pathways, e.g., through rebound effects, investments and households’
20 expenditures feedbacks on the economy. These effects can imply changes in economic structure, productivity and
21 trade that would affect the rate, direction and distribution of economic growth. More recently, adding an industrial
22 ecology (IE) perspective, Pauliuk et al. (2017) state that IAMs “incoherently describe the life-cycle impacts of
23 technology” with missing energy-material-economy linkages related to installed capital and infrastructures.
24 Overall, the decoupling between economic growth and energy use or emissions in IAM scenarios are seen by
25 some as unrealistic (Nieto et al., 2020; Scricciu et al., 2013; Spangenberg and Polotzek, 2019), in particular for
26 developing regions (Steckel et al., 2013). Finally, authors have pointed out the weak representation of the demand
27 side of the economy (Rosen and Guenther, 2015, 2016) with limited “granularity” and “imbalanced analytic
28 methods and structures” (Lovins et al., 2019), so that IAMs are not able to capture energy efficiency dynamics
29 and potential adequately.
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34 First of all, most IAMs do rely on conventional economics either through optimal growth models with perfect
35 foresight or as recursive-dynamic CGE models with limited market imperfections. However, some IAMs also
36 have long explored the implications of second-best formulations, while others operate out of equilibrium. For
37 instance, Fragkos and Paroussos (2018) use a CGE model to include equilibrium unemployment to assess the
38 employment implications of renewables expansion in the EU, and Guivarch et al. (2011) use a CGE model to
39 show how labour market imperfections strongly impact the cost of climate policies. Leimbach and Bauer (2020)
40 have done a corresponding exercise for capital market imperfections using an optimal growth model. Waisman et
41 al. (2012) explore the consequence of technical inertia under imperfect foresight for mitigation costs using a CGE
42 model, and Pollitt and Mercure (2018) show, using a macroeconomic demand-led model, that mitigation can
43 increase the speed of economic growth if economic resources are not assumed under full employment. Similarly,
44 inefficient and region-specific discount rates and risk premia have been implemented in the GCAM model taking
45 into account real-world inefficiencies (Iyer et al. 2015). Beyond those experiments, it is difficult to state which
46 second best features should be mainstreamed in IAMs in the absence of a unified theory of second best economics.
47 However, further studies should at least aim at better reflecting the plurality of the visions of the economy,
48 including alternative growth paradigms as in MEDEAS (D’Alessandro et al., 2020).
49

50 Regarding energy-economy linkages, most IAMs are now hybrid constructs, either energy system linked to
51 macroeconomic growth models (Bauer et al., 2008) or multi-sector CGE - or other economy-wide - models with
52 explicit technologies in key sectors (Paroussos et al, 2020). Except for partial equilibrium models (e.g. TIAM-
53 UCL and IMAGE, see Table 1), most IAMs are thus capable of capturing some macro-economic feedbacks of
54 energy transition pathways, but with contrasted degrees of sophistication depending on the model. Multisector
55 models based on an Input-Output (I-O) structure usually include a more comprehensive representation of energy-
56 economy relationships (Mercure et al, 2019, Paroussos et al, 2019), whereas the energy system is more simply
57 linked to aggregated economic growth in other models. Most “Top-down” models have also been improved to
58 better capture technological flexibility and substitution possibilities (e.g., explicit technologies in CES production
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3 functions (Wing, 2006), model linking for specific purpose (Delzeit et al., 2020; Fujimori et al., 2019a) or as
4 mainstreamed in the IAM (Lanz and Rausch, 2011; Sassi et al., 2010).
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6 From an industrial ecology perspective, IAMs include only limited representation of the life-cycle impacts of
7 technology. Models with a macroeconomic budget closure include at least an indirect representation of the global
8 supply chains of all capital investment. In compact growth IAMs, capital investment, related to whatever
9 technology or type of infrastructure, only consists of a composite macroeconomic good whereas multi-sector
10 models include a more consistent representation with inter-industry flows and specific investment goods even if
11 related materials flows are only accounted for in monetary units. Conversely, some partial equilibrium IAMs (e.g.
12 COFFEE and IMAGE, see Table 1) can account for material flows in physical units but miss the full life-cycle
13 linkages due to absence of macroeconomic closure. Progress towards expanding IAMs with IE features is an
14 active research area (Pauliuk et al., 2017) with different possible routes including adding new features to the
15 models (e.g., adding an investment matrix to track more specific life-cycle linkages in a CGE model (Dai et al.,
16 2016)) or by model linking with IE models (multi-region input-output (MRIO), Life cycle assessment (LCA),
17 etc.) such as Luderer et al. (2019).
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21 Likewise, IAMs capture adequately the “demand” of clean energy technologies or products, but usually fail to
22 represent the “upstream” industrial implications of mitigation (Karkatsoulis et al, 2016) and the potential domestic
23 industry effects that being a global technology leader might bring about (De Cian et al, 2013) and thus their results
24 for specific regions/countries can be misleading. Again, the inclusion of multiple economic sectors in IAMs can
25 improve their simulation properties with regard to industrial, trade and distributional impacts of climate policies,
26 as demonstrated with the enhanced CGE modelling in (Paroussos et al, 2019).
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29 Overall, the decoupling between economic growth and energy consumption/emissions envisioned in climate
30 stabilization scenarios is much stronger than historically observed, and no absolute lasting decoupling has been
31 experienced so far at the global level (Hickel and Kallis, 2020), casting legitimate doubts about the feasibility of
32 long term decoupling projections. Yet, it is also clear that the very nature of the low carbon transformation is to
33 divert from the historical trend. An alternative simulation model, emphasizing energy constraints and using a
34 system dynamics framework with input-output analysis, shows that meeting stringent climate targets may only be
35 feasible under a de-growth pathway (Nieto et al., 2020). However, this critique points to mechanisms that are, in
36 fact, present in IAMs with endogenous economic growth, namely that the growth is actually constrained by energy
37 availability (Foure et al., 2020). Moreover, other aspects of the energy life-cycle constraints are already taken into
38 account through capital investment and I-O relationships in multi-sector IAMs similar as in stock-flow consistent
39 input-output or system dynamics models. Yet, this topic deserved further future research, also in combination
40 with empirical estimates of growth impacts due to the impacts from climate change (Burke et al. , 2015), which
41 can similarly lead to disruptive growth patterns (Hänsel et al., 2020).
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45 **3.5 Scenarios of policy instruments and policy making**

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47 A major critique about IAMs concerns cost-effective climate change mitigation scenarios and the role of carbon
48 pricing frameworks. The critique addresses various aspects of the political and socio-technical feasibility of
49 transition scenarios related to carbon pricing. First, the effectiveness of carbon pricing is questioned because it
50 does not target the technology transition process directly (Patt and Lilliestam 2018, Rosenbloom et al. 2020).
51 Second, the focus on carbon pricing does not capture interaction between policies and technology innovation
52 (Geels et al. 2017a, Geels et al. 2017b, Grubb et al. 2002, Rosenbloom et al. 2020). Third, the effectiveness and
53 cost-efficiency of carbon pricing is questioned because IAM models often make the idealized assumption over
54 uniform pricing across GHGs, sectors, and countries, and over agent response to the price signal
55 (Hourcade and Gilotte 2000, Patt 2015). Fourth, the aim to achieve climate change stabilization ignores trade-
56 offs and synergies with other societal targets such as the SDGs (Geels et al., 2016). Finally, the introduction of
57 policies needs to consider in the modelling the political process because actors play active roles that feedback
58 onto the policy framework (Cherp et al. 2018, Jewell and Cherp 2020, Pye et al. 2020).
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3 *Effectiveness of carbon pricing.* The critique relates to the effectiveness to trigger technological transition
4 dynamics, which is a key interest of socio-technical energy transition (STET) research (Patt and Lilliestam,
5 2018, Rosenbloom et al. 2020). Cost-effectiveness analysis in optimisation IAMs, in a first step, is agnostic to
6 policy instruments, as these tools are used to identify optimal mitigation strategies, which satisfy the condition
7 that abatement measures are undertaken up to a certain level of marginal cost across all sectors, countries and
8 GHG gases.
9

10 There are two different policy approaches to implement the mitigation strategy. First, climate policies address
11 emissions and environmental outcomes directly, e.g. via carbon pricing or emission standards. These policies
12 change the overall economic landscape affecting the economic competitiveness and feasibility of investment and
13 production decisions across all technologies. Alternatively, energy and sectorial policies aim to control the use
14 and production of selected technologies and activities directly by subsidies, feed-in tariffs or technology
15 mandates that in turn affect emissions indirectly by compromising economic competitiveness and feasibility of
16 freely emitting technologies. Hence, the cost-effective mitigation strategy could be implemented directly by a
17 comprehensive package investment programs and energy efficiency programs or by implementing carbon
18 pricing policies. There is a fundamental trade-off between both approaches. Policies affecting emissions directly
19 (like carbon pricing) leave technology selection issues to decentralised decision makers, whereas policies
20 targeting technologies directly are uncertain about the emission outcomes that are only affected indirectly. From
21 model comparison studies it is well known that cap-and-trade systems lead to very different patterns of
22 technology deployment and energy use (Edenhofer et al., 2010, Kriegler et al., 2014, Bauer et al., 2017)).
23 However, technology oriented policies imply different emissions and can lead to rebound and leakage effects
24 that would require additional policies (Böhringer et al., 2012, Bauer et al., 2015, Otto et al., 2015). Energy
25 related policies must assume a very high level of information about the system at the level of policy makers,
26 whereas the information requirements using carbon pricing policies is substantially lower. Up to our knowledge,
27 a selection and prioritization of what technologies should be supported - when, by how much and where - has
28 not been presented in the STET literature. This would require very detailed information about technologies,
29 interacting systems and behavior, if an environmental target shall be achieved. Although scenarios derived with
30 IAMs could form the basis for such strategy, the STET community has not taken advantage of it.
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33 *Policy mixes and innovation.* The critique questions the use of carbon pricing as the dominant instrument to
34 trigger transitions and technological change. It is granted that carbon pricing mechanisms per se are not
35 empirically known as a key factor promoting the development of new technologies in the early phases of
36 innovation. (Geels et al. 2017a, Grubb et al. 2002, Rosenbloom et al. 2020). Carbon pricing can drive and direct
37 technological change by affecting behaviour, but usually does not fully internalize the positive effects of
38 spillovers. Intra-temporal spillovers relate to knowledge transfers and information pooling, whereas inter-
39 temporal spillovers materialize through research and learning processes - basic features in IAMs since the 1990s
40 (Messner 1997, Edenhofer et al 2005, Manne and Barreto 2004, Kypreos and Bahn 2003). Spillovers are in turn
41 a reason for additional public policies to address them and, thus, overcome additional scarcities caused by
42 carbon pricing (Kverndokk et al., 2007, Goulder et al., 2000). A particular issue with IAM analysis, that is not
43 often discussed, is that spillovers can be implicitly solved, without representing the policies explicitly. For
44 instance, IAMs with endogenous technological change (see “Technological change” in Table 1) derive a social
45 and intertemporal optimal solution assuming implicit support policies that optimally internalize intra- and inter-
46 temporal spillovers (Schultes et al 2018, Hedenus et al 2006). In this context, a key methodological issue that
47 has been much criticized, but often not put into proper perspective is the modeling assumption of perfect
48 information and foresight (e.g. de Canio 1997, de Canio 2003, Fuso Nerini et al., 2017). The assumption allows
49 deriving the timing and magnitude of technology specific support policies based on intertemporal spillovers due
50 to technological learning, adjustment costs, etc.. Assuming perfect foresight in IAMs moderates the support for
51 specific technologies depending on the strength of climate policies and the potential to supply clean energy in
52 the future. Suppose a technology is found to be worth specific support to induce technology learning. In that
53 case, the support level should start relatively high and decline as techno-economic performance improves and
54 less support is required to reach break-even levels. Furthermore, technology support and other regulatory
55 policies can also be a temporary substitute for carbon pricing if the institutional challenge to introduce
56 comprehensive carbon pricing schemes leads to substantial implementation delays (Bauer et al. 2012, Bertram et
57 al. 2018).
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3 In this context, technology maturity assumptions are frequently highlighted: The critique states the necessity to
4 study the technological innovation process in a broader social and political context rather than make
5 assumptions on technology availability (Geels et al. 2017a, Geels et al. 2017b). For a comprehensive systems
6 analysis this is a very demanding criterion. Long-term projections about global energy systems assume future
7 technology development. If only currently status-quotecnologies would be allowed, energy use could hardly be
8 maintained at current levels (Rogner, 1997). Such a static technology landscape is not only very restrictive, but
9 also difficult to justify in light of past and ongoing technological developments. The mitigation technologies
10 most frequently called into question are those relying on carbon capture and storage, particularly in combination
11 with bioenergy (Kemper, 2015, Anderson and Peters, 2016). The critique concerns technology maturity for
12 large-scale deployment and, therefore, scenarios with high deployment fail a feasibility test. This critique,
13 however, misses the crucial point of many IAM analyses. Many IAM publications studying future technologies,
14 test the sensitivity of technology availability and techno-economic parameters to identify and quantify the value
15 of technology available and performance (e.g. via RD&D, improving social acceptance). The sensitivity analysis
16 approach, a standard technique in IAM scenario analysis (e.g. Tavoni and van der Zwaan 2011, Kriegler et al.
17 2014), compares scenarios with varying availability of technologies to draw conclusions about the importance of
18 maturing and making socially acceptable certain technologies and mitigation options. To advance maturity and
19 deployment of technologies identify as key to achieve environmental targets, specific policies and measures are
20 then discussed. As a result the same environmentnatl target would be achieved with a lower carbon price.

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23 *Uniform carbon pricing.* The critique of uniform carbon prices (Hourcade and Gilotte 2000, Patt 2015) is not a
24 model critique but concerns the assumptions about policy scenarios (Trutnevyte et al. 2020). IAMs can
25 incorporate prices differentiated by time, regions, GHGs and emission sources (e.g. see Mercure et al 2018a,b,
26 Bauer et al., 2020). The choice of coverage of carbon pricing is inevitably a political decision by the modeller.
27 The level and differentiation can be chosen to meet certain conditions that can include criteria of fairness, policy
28 promotion mechanisms, existing exemptions from regulations, etc. Actually, the solution with uniform carbon
29 prices could be considered as a case with multiple carbon prices that are adjusted to meet the criterion of cost-
30 minimisation in models of perfect foresight to achieve an emission target. The distributional burden of the
31 policies can be adjusted by transfers or emission permit distribution. The distributional criteria can also be
32 achieved by differentiating carbon prices (Bauer et al., 2020). In models with multiple market failures such as
33 international or intertemporal spillovers uniform carbon prices might not be optimal (see above), but this
34 motivates complementary policies rather than deviations from uniform carbon prices. Carbon price
35 differentiation may cause additional risks because market distortions that have been suggested to lead to (i)
36 leakage effects that undermine the effectiveness to reduce total GHG emissions criteria (Otto et al., 2015,
37 Arroyo- Currás et al., 2015, Böhringer et al., 2012, Bauer et al., 2020) and (ii) drive environmental degradation
38 that undermine sustainability (González-Eguino et al. 2017, Wise et al. 2009, Bauer et al., 2020).

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41 *Trade-offs and synergies with other societal aims.* The critique that climate mitigation scenarios derived with
42 IAMs ignore interactions with other SDGs (Geels et al., 2016) is unsubstantiated. IAMs have been used to
43 investigate synergies and trade-offs between climate policies and non-climate objectives (e.g. Paroussos et al,
44 2019, Fragkos and Paroussos, 2018). In the energy sector the most important contributions include modern
45 energy access, air pollution, water use, toxicology, resource and material use, and energy dependency.
46 Regarding the land-use sector, the most prominent contributions consider food price impacts and hunger,
47 deforestation and afforestation as well as irrigation and fertilizer use. Moreover, IAMs have been used to
48 investigate the exemption of the land-use sector for the consequences of reaching climate change stabilization
49 targets (i.e. carbon price differentiation) as well as interactions of other policies like forest protection or coal-
50 phase out policies with the achievability of climate targets (e.g. Rauner et al. 2020, Bertram et al. 2018).

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53 *Consideration of political processes.* Finally, IAM analyses inform about the impact of policies and the
54 achievability of societal targets. In this context, policy makers are partners for communication about policies
55 rather than the subject of the investigation in policy processes, as often is the case in socio-technical transitions
56 analysis (Cherp et al., 2018. See also Jewell and Cherp, 2020 and Pye et al., 2020). The integration of policy
57 process and opinion formation about climate change into a dynamic model structure, however, can lead to
58 outcomes that are difficult to interpret. IAM research shows that such feedback loops can lead to a dialectic
59 pattern: weak policies in the near-term cause huge climate impacts that induce stronger policies later, whereas
60 ambitious policies in the near-term cause economic disruptions that substantially weaken longer-term policies
(Janssen and de Vries, 1998). The modelling result is also problematic and difficult to communicate to policy

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3 makers because it says that near-term action shall be in contradiction to the long-term target to provoke the
4 intended reaction in opinion formation. In a historical perspective political processes are reflexive and respond
5 to expectations about the future – including those produced by models – and therefore efforts to incorporate
6 political feedbacks into models can only ever be partial. However, IAMs do not aim at explaining political
7 processes historically, but to form the scientific basis for rational policy making for the long-term future.
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10 11 **3.6 The use and interpretation of model results** 12

13 Modeller judgement has an important role in defining numerous details about how the system is modelled (e.g.
14 what technologies to include/exclude), but such subjective decisions, often driven by non-epistemic values and
15 norms, are rarely made explicit (Schneider 1997, Beck and Krueger 2016, Haikola et al. 2019, Anderson and
16 Jewell 2019), and the documentation process of IAMs and repeatability of IAM analysis have been criticised
17 (Rosen 2015a, Rosen and Guenther 2016, Rosen 2015b, DeCarolis et al. 2012). Concerns have also been raised
18 about how policymaker demands for analysis may shape modelling choices and to what extent this is legitimate
19 (Beck and Mahony 2017, Low and Schäfer 2020) or damaging (Geden 2015). On the other hand, limited
20 participation of stakeholders in the modelling processes has also been highlighted (Doukas et al. 2018, Low and
21 Schäfer 2020).
22

23 Another concern relates to how some issues are more on the foreground than others and thus distort the
24 discussions about what is important and feasible (Ellenbeck and Lilliestam 2019, Low and Schäfer 2020). For
25 example, technology cost and availability have generally been a more prominent theme than equity (Klinsky and
26 Winkler 2018, Anderson 2015, Anderson and Peters 2016) and issues of political or social feasibility are often
27 of secondary focus in IAM-based analyses (Vaughan and Gough 2016). Such biases can also affect the realism
28 of the scenarios (Ellenbeck and Lilliestam 2019, Low and Schäfer 2020) and scenario intercomparison project
29 induced group think (Cointe et al. 2019) and reliance on “common practise” in the field (Ellenbeck and
30 Lilliestam 2019) can further strengthen these dynamics.
31

32 Finally, the interpretation of the model results is often ambiguous; do they really only explore the possibility
33 space (Low and Schäfer 2020), or do they go beyond that and suggest real world responses to policies, or
34 preferable pathways to follow? And if the former, how is the full possibility space defined (McCollum et al.
35 2020. See also Trutnevyte et al., 2016, Craig et al., 2002)? Critics argue that the interpretation requires
36 judgement that draws on non-epistemic criteria (Beck and Krueger 2016), that the mapping from “model land”
37 to the real world does not get the attention it deserves (Thompson and Smith 2019) and that sometimes
38 modellers do not appear to agree on the appropriate approach to interpretation (Haikola et al. 2019).
39

40 Integrated assessment models are large and complex, which creates practical difficulties for transparency and
41 explicit documentation of the numerous choices made by the modellers. There is much activity and discussion in
42 the community to improve transparency (e.g. Krey et al, 2019, Huppmann et al., 2019, Howells et al., 2011,
43 IAMC, 2020 DeCarolis et al, 2012., Pfenninger et al., 2017, Pfenninger et al., 2018, Cao et al., 2016) and the
44 direction of travel is clear, but having, and transmitting, a full understanding of the various choices made in the
45 modelling process is likely to remain a challenge.
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47 For example, it would be challenging to highlight and communicate, for all technologies in a given model, why
48 some of them are considered separately, but others are aggregated under broader categories, what underlying
49 assumptions drive specific numeric values used for the parameters and so forth. While this is commonly done
50 for assumptions at the core of a specific exercise (e.g. Bauer et al., 2012, McCollum et al., 2014, Butnar et al.,
51 2020), results are greatly affected also by the assumptions made elsewhere in the models (see also Dodds et al.,
52 2015). What is more, documentation is not always as helpful for non-experts as one would hope, since the
53 implications of specific assumptions only become clear when one understands the model well. Similarly,
54 making code and data publicly available is valuable, and people are increasingly doing this, but few people
55 know how to run and critique a model of this kind. With that said, open sourcing can enable extended user
56 groups and with more expert users, there is a greater potential for scrutiny and challenge.
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58 Modellers respond to demand for analysis and in the case of IAMs this demand is created by both scientific and
59 policy related drivers - and it is thus of key importance that IAM teams provide analysis that is, following Cash
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3 et al. 2003, “salient, credible and legitimate”. Salience here is the policy relevance; proximity to policymakers is
4 required for modelling to be salient, i.e., it needs to speak to the policy agenda. Clearly, this is crucial: failure to
5 be policy-relevant undermines the goals of the modelling. However, proximity to politics can sometimes risk
6 undermining perceived credibility, i.e. scientific robustness, if too many decisions are made for non-scientific
7 reasons (i.e. so that the results appeal to policy audiences). IAM teams work closely with governments but are
8 not directly controlled by them. Most are either academic units or in arms-length institutions that are granted
9 intellectual freedom. This helps to balance the credibility dimension and the salience dimension.

10
11 Following the above, IAM exercises are often said to explore the possibility space but what is not included
12 within the boundaries of the space to be explored cannot be found. The ‘map’ created by modellers reveals and
13 elevates mapped pathways in the political arena; but it also leaves possibilities unmapped. As discussed, those in
14 positions of political power influence which possibilities are mapped by the modellers, the implication being
15 that the interests and perspectives of those that lack political power may be overlooked – and there is perhaps a
16 need to counterbalance the resulting power bias of scenarios with efforts to engage more diverse perspectives
17 (e.g. Grubler et al. 2018) and thus improve the legitimacy of the analysis. The IAM community should not
18 overlook the value of exploring the more marginalized perspectives, examining broader ranges of issues or
19 possibilities (as also advocated by McCollum et al., 2020). A tendency to reproduce the perspectives of the
20 powerful is not, of course, an inherent feature of IAMs. Indeed, in the past energy and environment modellers
21 have often played an important role in bringing onto the political agenda issues or perspectives that were
22 previously marginal, such as the potential for renewable energy.

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25 The challenge for IAM modellers is thus to stay politically relevant, while also creating space for more diverse
26 voices and perspectives. This likely requires expanding the range of interests engaged, ideally beyond the
27 typical range of expert stakeholder participants in IAM workshops. Ultimately, if the scenarios and models
28 overlook important perspectives, the resulting knowledge will not be seen as legitimate by some stakeholders –
29 and as a result will be less useful to policy (Cash et al., 2003).

30
31 As for how the analysis of the results is focused, traditionally attention has been especially paid to costs and
32 technologies, but this has also been central for the users of the analysis (e.g. EC, 2007, DTI, 2003. See also
33 Taylor et al., 2014) and thus not driven exclusively by the modelling community itself. The discussion has been
34 recently changing, with more focus on the wider impacts to the society, including how such impacts are
35 distributed, and this shows also in the focus of the modelling and analysis (e.g. Taconet et al., 2020, Liu et al.,
36 2016 Fujimori et al., 2019b, van Vuuren et al., 2015, Bertram et al 2018, Fujimori et al. 2020, Parkinson et al.
37 2019, Jewell et al. 2014). In that sense IAMs do not generate the narratives about what is important and what
38 not, but do amplify them (for a different view on this conclusion, see McLaren and Markusson, 2020).

39
40 Model interpretation, mapping of meaning from model results to the real world, has been a topic in IAM/energy
41 modelling at least since the early 80s (Häfele, 1981, Keepin and Wynne, 1984, Wynne, 1984, Häfele and
42 Rogner, 1984). This discussion often combines issues related to model interpretation to those of clear and
43 consistent model communication, i.e. what is the information and insights that can be retrieved from the model
44 analysis and is the communication of results consistent with this. Better and explicit recognition of what are the
45 limits of what specific IAMs can say about particular topics could help, but one would also need to ensure that
46 the practise is consistent with this; even when most models can, in principle, provide results that appear to
47 provide insights for a specific question, the interpretation of these answers is not uniform and some IAMs may
48 be entirely inappropriate for the specific question, e.g. due to lack of sectoral coverage, and should thus not
49 contribute to the specific exercise. Thinking about an “interpretation phase” as a discrete phase of work, as is
50 done in some other fields (e.g. Laurent et al., 2020), could help with this process and lead to more transparency
51 about how modellers themselves interpret the results. For example, do we understand our models as “credible
52 worlds” and if so, how are we making the inductive inferences from the ‘credible world’ of ‘model land’ to the
53 real world (Sugden, 2000)?

54 55 **4. Concluding remarks**

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59 Integrated assessment models have played a central role for academic and policy focused assessment of climate
60 change and mitigation and, even with their shortcomings, there are few alternatives that can provide what they

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3 provide: Internally consistent, virtual laboratories of the complex, interacting social, economic, technical and
4 physical systems. The models cannot predict the future, but without them the simultaneous consideration of
5 these systems and the rules governing them would certainly be more difficult.
6

7
8 Our review and analysis of the literature critical to IAMs in the six identified areas has highlighted a number of
9 critical items for future IAM development and use. In modelling *heterogeneity*, a key consideration is the trade-
10 off between added complexity and better representation of overall system behaviour. There are circumstances
11 under which diverging behaviours play an important role and identifying these areas and developing the models
12 further to capture them better should be continued. At the same time, elements that can be represented through
13 more aggregated formulation should not be unnecessarily complicated, but the underlying rationale and
14 assumptions should be clearly communicated. For *technology diffusion*, it is unlikely that the models would ever
15 be able to fully capture endogenously the complex and numerous processes that determine technology
16 dynamics. With that said, empirically derived explanatory factors can add detail and robustness to the
17 formulations and a wider use of these “stylised facts” in model parametrisation could help better reflect the
18 differences across the technology options.
19

20 Modelling of *capital markets*, and crowding-out effects in particular, is complicated not only by modelling
21 inadequacies, but also by the lack of consensus in the broader economic theory on how creation of finance
22 should be understood. Progressing on this would directly contribute also to how finance should be modelled. In
23 the meantime, supply-driven macroeconomic tools can further improve their capabilities by explicit inclusion of
24 financing schemes, detailed budgeting of debt and linking interest rates to debt accumulation and debt. A key
25 area of development for demand lead models is better representation of how financial institution perceive the
26 credit worthiness of borrowers, and how this affects the allocation of financial resourcesfinance to them. *Energy*
27 *Economy feedback* representation in IAMs has faced critiques especially for the so called “first best
28 assumptions”. There have been activities in this area, but it remains difficult to identify which specific “second
29 best” elements would be essential to integrate in the models. With that said, it would benefit the community to
30 include a broader range of visions for the economy, including those that emerge from alternative paradigms.
31 This is especially true as often IAM scenarios show strong decoupling of emissions and economic growth,
32 which has not been observed for sustained periods of time on the global level.
33

34 Representation of *policy instruments*, and carbon price in particular, in IAM scenarios does not directly reflect
35 model capabilities, but rather the way in which the models are used. We argue that while the critiques do point
36 out a range of valid concerns and useful perspectives, there are clear trade-offs in constructing the policy
37 modelling radically differently and it is unclear whether the alternative policy formulations would increase the
38 usefulness of the analysis. *Interpretation and use* of model results has been an especially active area of critiques,
39 as it often is the contact point between IAM and non-modelling communities. While communication can be
40 improved with the continued efforts to increase transparency, this will always be somewhat limited by the high
41 complexity of the tools and the particular expertise that is required to understand what specific choices in the
42 modelling mean for the interpretation of the results. Open-sourcing of the tools does help in expanding the user
43 group, which can bring with added scrutiny of the tools. Similarly, reflecting more diverse interests and
44 perspectives in the formulation of the scenario frameworks, beyond those emerging from the position of
45 political power, can further increase the credibility and legitimacy of the analysis. Finally, more attention should
46 be given to the differences across the IAMs, to how that affects the nuanced interpretation of results and the
47 questions for which the models are appropriate
48

49 While the models have come a long way and are constantly being improved, gaps remain, and always will.
50 Models are an abstraction of the real world and can never be expected to fully capture the latter. This does not
51 mean that they cannot be useful for understanding key dynamics of it better - or that they could not be improved.
52 In addition to technical model improvements that address perceived shortcomings, modellers should also further
53 continue the efforts to make the models more transparent and open to the end users of model analysis. A key
54 element in this is also a better and more consistent communication of how the model results should be
55 interpreted and how they can, and cannot, be used.
56

57 The richness of modelling approaches and areas of focus is a strength for the community - the portfolio of
58 IAMs, when using specific models in appropriate contexts, provides a much stronger analytical platform for
59 long term climate change mitigation analysis than any single model could. Collaborative platforms, such as the
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3 Integrated Assessment Modeling Consortium (IAMC, <https://www.iamconsortium.org>), should provide an
4 excellent tool for the community to further communicate the strengths and weaknesses of various tools – and
5 how they can further be improved.
6

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8

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21 **Declarations**

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Table 1. Illustrative example of heterogeneity of global IAMs, covering the geographical scope, economic coverage, solution method, technology and policy instruments representation, and model transparency of a set of global IAMs. All the data in the table is based on IAMC (2020).

Integrated Assessment model	Geographical scope	Economic coverage ^a	Solution method ^b	Technology representation			Policy instruments ^e	Model transparency ^f
				Technology detail ^c	Technological change	Technological diffusion ^d		
REMIND-MAgPIE	Global, 12 regions	REMIND: GE, MAgPIE: PE of the agricultural sector	REMIND: IO/NLP MAgPIE: RD/S	High Energy High land-use	Partially endogenous for energy, Endogenous agriculture productivity	High substitutability	Medium	DC
MESSAGEix-GLOBIOM	Global, 11 regions	GE	MESSAGEix: IO/LP, GLOBIOM: RD/LP	High Energy High land-use	Exogenous Energy Conversion and Energy end-use	High substitutability Exp/Decl and SI constraints	Medium	DC (C for MESSAGEix)
IMAGE	Global, 26 regions	PE	RD/S	High Energy High land-use	Endogenous energy end-use, Exogenous material use and Agriculture	Technology choice by mlogit functions Exp/Decl and SI constraints	High	D

WITCH	Global, 17 regions	GE	IO/NLP	Low Energy, Low land-use	Endogenous (incl, R&D) energy end-use Exogenous Agriculture	Nested CES production function Exp/Decl and SI constraints	Medium	DC
ImaclimR-World	Global, 12 regions	GE	RD/S	Medium Energy No land-use	Endogenous energy conversion and end-use	Technology choices by logit functions; Exp/Decl and SI constraints	Low	D
TIAM-UCL	Global, 16 regions	PE	IO/LP	High Energy No land-use	Exogenous Energy Conversion and Energy end-use	Exp/Decl constraints	Low	DC
GEM-E3	Global, 46 regions	GE	RD/NLP	Medium Energy Low land-use	Exogenous total factor, Labour, Capital productivity. Endogenous for low-carbon technologies (incl R&D)	Mixed high/ low substitutability Exp/Decl constraints	Medium	D

E3M3-FTT	Global, 61 regions	Non-equilibrium demand-led	ME	High energy Low land-use	Endogenous energy conversion and energy end use	Evolutionary modelling (replicator dynamics),	High	D
COFFEE-TEA	Global, 18 regions	COFFEE is PE, TEA is GE	COFFEE IO/LP, TEA is RD/S	Detailed Energy Medium land-use	Endogenous energy conversion, end-use, material use, Agriculture	Mixed high and low substitutability SI constraints	High	D

^aGE: General Equilibrium (closed economy) and PE: Partial Equilibrium, ^bIO/(N)LP: Inter-Temporal Optimisation/(Non) Linear Programming (perfect foresight), RD/S: Recursive-dynamic/Simulation, RD/(N)LP: Recursive-dynamic/(Non) Linear Programming, ME: Macroeconometric simulation; ^cQualitative assessment based on IAMC, 2020, with high/medium/low energy representation standing for detailed energy system/limited number of energy sectors/only electricity generation. For land-use high/medium/low represent the degree of coverage of land cover classes, agricultural commodities, and agriculture and forestry demands. ^dExpansion and Decline and System Integration constraints; ^eBased on IAMC, 2020, with number of policies represented in the model (of max 14): Low ≤ 5 , medium: 5-9, high ≥ 10 . ^fD: Online documentation available, C: Open source code, I: Input data publicly available.

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