Expanding Integrated Assessment Modelling: Comprehensive and Comprehensible Science for Sustainable, Co-Created Climate Action

29/04/2025

D3.5 Model interlinkages and integration - Update

WP3 – Exchanging – Open & FAIR science, mutual learning

Funded by the European Union

www.iam-compact.eu

Disclaimer

Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Climate, Infrastructure and Environment Executive Agency (CINEA). Neither the European Union nor the granting authority can be held responsible for them.

Copyright Message

This report, if not confidential, is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0); a copy is available here: https://creativecommons.org/licenses/by/4.0/. You are free to share (copy and redistribute the material in any medium or format) and adapt (remix, transform, and build upon the material for any purpose, even commercially) under the following terms: (i) attribution (you must give appropriate credit, provide a link to the license, and indicate if changes were made; you may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use); (ii) no additional restrictions (you may not apply legal terms or technological measures that legally restrict others from doing anything the license permits).

Grant Agreement Number	101056306		**Acronym**	IAM COMPACT	
Full Title	Expanding Integrated Assessment Modelling: Comprehensive and Comprehensible Science for Sustainable, Co-Created Climate Action				
Topic	HORIZON-CL5-2021-D1-01-04				
Funding scheme	HORIZON EUROPE, RIA – Research and Innovation Action				
Start Date	September 2022		**Duration**	36 Months	
Project URL	https://www.iam-compact.eu				
EU Project Advisor	Andreas Palialexis				
Project Coordinator	National Technical University of Athens – NTUA				
Deliverable	D3.5 – Model interlinkages and integration – Update				
Work Package	WP3 – Exchanging – Open & FAIR science, mutual learning				
Date of Delivery	**Contractual**	30/04/2025	**Actual**	29/04/2025	
Nature	Report		**Dissemination Level**	Public	
Lead Beneficiary	Aalto University (Aalto)				
Responsible Author	Ilkka Keppo		**Email**	Ilkka.keppo@aalto.fi	
	Aalto		**Phone**	+358 50 5781103	
Contributors	Behzad Zamanipour, Hesam Ghadaksaz [AALTO]; Alaa Al Khourdajie, Adam Hawkes [Imperial]; Francesco Gardumi [KTH]; Georg Holtz [WI]; Alexandros Nikas, Natasha Frilingou [NTUA]; Georgios Xexakis [HOLISTIC]; Noelia Ferreras Alonso, Adrian Mateo [CARTIF]; Panagiotis Fragkos [E3M]; Shivika Mittal, Ida Sognnæs, Glen P. Peters [CICERO]; Gonzalo Parrado-Hernando [UVa]; Lorenzo Rinaldi, Matteo Vincenzo Rocco [POLIMI]; Dirk van de Ven [BC3]				
Reviewer(s)	Alaa Al Khourdajie [Imperial], Vassilis Stavrakas [UPRC]				
Keywords	Model linking, temporal and spatial scales, system boundaries, data exchange, model epistemology				

EC Summary Requirements

1. Changes with respect to the DoA

No changes with respect to the work described in the DoA.

2. Dissemination and uptake

This deliverable develops and demonstrates a model linking checklist, meant for facilitating decision-making when model linking is considered. It can be used both within the context of the project's studies to make the model linking more robust, and more broadly available by the energy- and climate-economy modelling community.

3. Short summary of results (<250 words)

Over the years, energy-system models (ESMs) and integrated assessment models (IAMs) have become indispensable for evaluating our progress toward climate targets, crafting pathways that align with specific goals, and judging the impact of various mitigation strategies. As the urgency of the climate crisis has grown, so too has the need to encompass a broader range of sectors and the interactions between them. However, expanding a model's boundaries often adds layers of complexity. To address this without overwhelming individual models, researchers frequently link established models together, allowing cross-system dynamics to emerge organically through those connections. Connecting models not only broadens the analytical scope but also deepens detail in particular sectors while preserving the overall systemic context. Despite its widespread use, model linking presents numerous challenges—arising from differing assumptions, structures, data formats, and temporal or spatial scales—that are seldom explored in depth within published studies. In this deliverable, we first discuss four key problems that are central to most model linking activities, then develop a general "checklist" to be used when considering model linking. We finally demonstrate the use of the checklist for a study carried out in the IAM COMPACT project.

4. Evidence of accomplishment

This report.

Preface

IAM COMPACT supports the assessment of global climate goals, progress, and feasibility space, and the design of the next round of Nationally Determined Contributions (NDCs) and policy planning beyond 2030 for major emitters and non-high-income countries. It uses a diverse ensemble of models, tools, and insights from social and political sciences and operations research, integrating bodies of knowledge to co-create the research process and enhance transparency, robustness, and policy relevance. It explores the role of structural changes in major emitting sectors and of political, behaviour, and social aspects in mitigation, quantifies factors promoting or hindering climate neutrality, and accounts for extreme scenarios, to deliver a range of global and national pathways that are environmentally effective, viable, feasible, and desirable. In doing so, it fully accounts for COVID-19 impacts and recovery strategies and aligns climate action with broader sustainability goals, while developing technical capacity and promoting ownership in non-high-income countries.

NTUA – National Technical University of Athens	EL	
Aalto – Aalto Korkeakoulusaatio SR	FI	
AAU – Aalborg Universitet	DK	
BC3 – Asociacion BC3 Basque Centre for Climate Change – Klima Aldaketa Ikergai	ES	
Bruegel – Bruegel AISBL	BE	
CARTIF – Fundacion CARTIF	ES	
CICERO – Cicero Senter for Klimaforskning Stiftelse	NO	
E3M – E3-Modelling AE	EL	
KTH – Kungliga Tekniska Hoegskolan	SE	
POLIMI – Politecnico di Milano	IT	
UPRC – University of Piraeus Research Center	EL	
UVa – Universidad De Valladolid	ES	
WI – Wuppertal Institut fur Klima, Umwelt, Energie GGMBH	DE	
IIMA – Indian Institute of Management	IN	
THU – Tsinghua University	CN	
USMF – University System of Maryland	US	
AAiT – Addis Ababa University	ET	
KEI – International Civic Organisation Kyiv Economics Institute	UA	
RUSL – Raja Rata University of SriLanka	LK	
TUM – Technical University of Mombasa	KE	
UNIGE – Université de Geneve	CH	
Imperial – Imperial College of Science, Technology and Medicine	UK	

Funded by the European Union

Executive Summary

Over the years, energy-system models (ESMs) and integrated assessment models (IAMs) have become indispensable for evaluating our progress toward climate targets, crafting pathways that align with specific goals, and judging the impact of various mitigation strategies. As the urgency of the climate crisis has grown, so too has the need to encompass a broader range of sectors and the interactions between them. However, expanding a model's boundaries often adds layers of complexity. To address this without overwhelming individual models, researchers frequently link established models together, allowing cross-system dynamics to emerge organically through those connections.

Connecting models not only broadens the analytical scope but also deepens detail in particular sectors while preserving the overall systemic context. Despite its widespread use, model linking presents numerous challenges—arising from differing assumptions, structures, data formats, and temporal or spatial scales—that are seldom explored in depth within published studies. In this deliverable, we first identify four fundamental challenges inherent to most model-linking efforts based on literature review (*Section 2*). We then propose a comprehensive checklist (*Section 2.3*) to guide future linkage projects, and finally, we apply this checklist retrospectively to an earlier study conducted during the project (Section 3).

Contents

Table of Figures

Table of Tables

1 Introduction

Energy-system models (ESMs) and integrated assessment models (IAMs) have been key tools for assessing the progress towards various climate targets, developing pathways consistent with specific goals, and assessing the effectiveness of specific mitigation portfolios. Their strength lies in their ability to assess system-wide, cross-system developments, by covering the major components of climate-economy dynamics—including the energy system, the economy, typically an aggregate representation of the climate system, and to different extents land use—while reflecting the impacts of their interactions within and across the different subsystems (Nikas et al., 2019). The models have influenced extensively decision-making at national and international level (e.g. Capros et al. (2016), Chiodi et al. (2015), Van Beek et al. (2020)), while also playing a central role in producing the scientific evidence underlying climate negotiations and underpinning the agreed targets (Shukla et al., 2022, Skea et al., 2021).

The initial focus of modelling and long-term scenarios was predominantly on technical assessments of the energy system (Gaskins and Weyant, 1993, Häfele, 1980). In time, however, and with increasing awareness of the climate urgency the importance of covering more of the relevant sectors—and the interlinkages between them—has increased (e.g. Del Granado et al. (2018), Fuhrman et al. (2023), Hasegawa et al. (2017), Mouratiadou et al. (2016), Soergel et al. (2021)), and so has the computational capacity to cover these sectors and interlinkages thereof in more detail, thereby leading to increasingly complex models. As extending the model boundaries would often complicate this existing complexity, a common approach to enabling broader and more detailed assessments is to create linkages between existing models, and to endogenise the cross-system interactions through these linkages (e.g. Baumstark et al. (2021), Havlík et al. (2011), Huppmann et al. (2019), Krey et al. (2020)). Some IAMs have, over decades, evolved from models with a limited disciplinary focus, such as energy systems, by linking to additional models, modules and extensions for land systems, the economy, the environment, and the climate system. Similarly, model linking has been used for sectoral "deep dives"—i.e., to provide greater detail about a subsector already covered by the larger, system-level model (e.g., Brinkerink et al. (2022))—or for capturing effects of climate action from a sustainability perspective (Nikas, 2024).

As common as model linking is, however, there are no straightforward, standardised, commonly accepted processes to do it; in fact, fairly little attention has been paid to the details, specifications, and requirements associated with model linking. Individual models have been created for different purposes, often with different internal rationales, overlapping system boundaries, and varying variable definitions. Linking models simply by exchanging chosen variables between them is feasible, and thus often done, but overlooks the significant complexities that closer scrutiny would reveal. For example, does the parameterisation of interlinked models reflect similar assumptions about how exogenous factors of the future will unfold? Do the models truly overlap only for the variables that are being exchanged and, if not, should linking take place for all the shared variables for the modelling to be internally consistent–and how should one define which model should take precedence for a given variable? How should one link models that consider time, either for horizon or granularity, differently? If one model aims to find an optimal solution across the given time frame, and another myopically simulates system behaviour based on historical data, how should the results of the combined model be interpreted? Rarely can such methodological choices in model linking be defensible purely on scientific grounds, and trade-offs need to be accepted in practically all model linking exercises. Modellers must often make pragmatic decisions based on a combination of scientific principles, practical constraints, and expert judgment, but the rationale and trade-offs involved in this decision-making have rarely been at the centre of the model-linking exercises, nor in the communication thereof. Our aim in this paper is to focus the attention on the practice of model linking, to identify, discuss, and propose approaches for a set of key problems that should be addressed when linking models, as well as how these may depend on the specific models involved.

While model linking has traditionally been mostly a pragmatic endeavour, there also exists research focusing more on the model linking process itself. Some studies have discussed the issue explicitly or additionally in the context of the energy and economic systems (e.g. Chang et al. (2023), Del Granado et al. (2018), OECD (2024)), but these papers are typically general and conceptual, without directly addressing the practical complexities of carrying out the actual model linking. Model linking within the environmental and earth sciences, however, has a much richer literature on model linking as a problem by itself.

Verburg et al. (2016), for example, highlight model linking in the context of their broader discussion of what is needed for modelling the socio-ecological dynamics of the Anthropocene; although they touch upon many issues also discussed in this paper, such as the problem of "reconciling epistemologies", their main focus is different: what should be captured, and how, to model the Anthropocene. Tan et al. (2023), in turn, explore the ways in which earth system models and IAMs have been linked, especially focusing on the way in which the feedbacks are captured across space and time. In their discussion of remaining gaps and challenges, they briefly highlight issues such as reconciling different spatiotemporal scales and variable definitions but do not further elaborate on them and associated challenges, nor suggest ways forward. Similarly, Van Vuuren et al. (2012) also discuss linking earth system models and IAMs, with the focus on the nature of the linkage (e.g., one-way linkage, full coupling), and the trade-offs the different options bring. They note some general problems that full coupling might bring, drawing on the specific types of models discussed in the paper, and provide some insightful advice about the conditions under which specific linking options may be preferable. Robinson et al. (2018), in turn, discuss human-natural systems model coupling, with a focus on land use and the type of model links, drawing eight lessons that reflect the very specific examples used but are broadly applicable in any model linking activity. Several of the lessons are relevant also for our discussion—reflecting issues related to, e.g., spatiotemporal differences and system boundaries—while also providing practical advice about the way in which aspects such as data exchange and variable naming can be organised.

The technical implementation of model linking, often related to linking the type of models discussed above, is also featured in the literature. Belete et al. (2017), for example, primarily discuss the technical and software side of model linking, and their take on pre-integration assessment and data interoperability provides important observations, e.g., about variable definitions and the purpose of the model integration. Similarly, Usher and Russell (2019) present a framework for integrating infrastructure models, focusing strictly on software implementation, and only briefly noting problems related to model linking across temporal scales.

It is important to note that ESMs and IAMs differ from one another in various dimensions. These differences are highly relevant for model linking, as many of the potential complications of model linking are direct consequences of cross-model differences in these dimensions. For example, descriptive simulation models are typically used to explore system dynamics under varying parameters, while optimisation models are prescriptive and aim to minimise costs (or maximise welfare) under constraints, such as carbon budgets (Keppo et al., 2021). Temporal methodologies differ between perfect foresight models, assuming complete future knowledge until the end of the modelling horizon, and recursive-dynamic "myopic" models, which make sequential decisions based on current information at each time step (Harmsen et al., 2021). Sectoral coverage, and the level of detail available for a given sector, may vary considerably and so do technology choice mechanisms (e.g., van de Ven et al. (2022)). Moreover, the dimensions across which models may vary are so numerous, that there is a wide body of papers dedicated only to establishing the different ways in which the models can be categorised—see e.g. Blanco et al. (2022), Connolly et al. (2010), Hall and Buckley (2016), as well as Keppo et al. (2023) and the references within. Understanding how models differ, and in which dimensions the differences are particularly important for linking specific models, is highly important and the use of model typologies can assist in this process.

2 Linking models to analyse low carbon transitions

2.1 Technical considerations for model linking

Here, we will discuss three families of model linking-related technical problems, exploring the nature of the problem, approaches found in the literature, and possible avenues to mitigate the identified issues.

2.1.1 Temporal and spatial scales

Linking models that feature different spatial and temporal resolution allows the analysis of challenges at different geographical and governance scales. For instance, by doing so, one can extract insights into technological transitions that include high penetration of variable renewables, demand response mechanisms, and/or other flexibility options (Fattahi et al., 2020), explore distinct solution spaces and sets of uncertainties for different contexts (Mulugetta et al., 2022), and overall address the diversity of shortcomings associated with exercises of limited spatiotemporal detail in IAMs (Gambhir et al., 2019). The aim, however, may not always be to benefit from the difference in scale or time, but to seek other gains— e.g., in terms of sectoral/technological complementarities, robustness, etc.– and, in the process, find ways of integrating the tools across different spatial and temporal resolutions. There may also exist trade-offs between the different approaches in the literature for downscaling or upscaling results from one model to the other; typically, in the form of providing better consistency at the cost of being computationally intensive, or vice versa.

The first order of trade-offs concerns the extent of linking (as in hard- vs. soft-linking) used for linking across spatial and temporal scales. For instance, Fattahi et al. (2020) suggest hard-linking ESMs with market models as one way to analyse the flexibility potential of cross-border trade in competition with domestic flexibility options; however, since market models typically use mixed-integer linear programming (MILP) to track unit commitment, the energy system-market model combination resulting from the hard-linking would be computationally unmanageable. An emerging body of literature instigates soft-linking among ESMs with different spatial and temporal resolutions, in which case reaching equilibrium solutions between the linked models requires iterative links, thereby increasing the complexity of the modelling framework. Gong et al. (2023) address the lack of temporal detail in one IAM (REMIND) by an iterative soft linkage with an annual, single-region, hourly power system model (DIETER): for each representative year (i.e., a 5-year time step in REMIND), costs and capacities from REMIND are input to DIETER, which in turn returns average market values to REMIND until convergence in power-sector prices and quantities is reached; however, their analysis lacks spatial detail and their scope is limited to one region (Germany). Frysztacki et al. (2021) highlight the strong effect that network resolution in electricity system models has on model variables of importance for decision makers, such as least-cost penetration of variable renewables. They show that if low-resolution ESMs are soft-linked with high-resolution electricity system models (e.g., dispatch models), the capacity expansion results may be too low-resolved (likely sub-optimal), making the dispatch analysis less reliable. Kumar et al. (2023) attempt to increase the temporal and spatial detail in an ESM, by first increasing the temporal resolution of the model itself and then soft-linking it with a geospatial tool for district heating network optimisation; however, similar to Gong et al. (2023), their method's high complexity limits its geographical scope. Millot et al. (2024), Sahoo et al. (2023), Sterl et al. (2022), and Siala and Mahfouz (2019) increase the spatial detail in ESMs by clustering regions with similar demand and/or supply characteristics, allowing geospatial features to be retained in the aggregated ESMs while keeping the computational load manageable; however, their approach loses the information on the topology of infrastructure, making it unsuitable for network-focused analyses. In climate policy modelling, coupling complex Global Climate Models (GCMs) with IAMs of different complexity and temporal resolution remains a major constraint, which has been addressed by means of different statistical methods (e.g., emulators, machine learning, etc.) (Jones et al., 2024). The simplification of processes using averaged relationships in emulators might not, however, be able to capture the nonlinear feedback and may generally limit the capability of the models to assess extreme scenarios. One linking challenge lies in ensuring that climate-driven economic and energy system responses in space and time remain consistent across models. Misalignments between GCMs and IAM scenario assumptions may lead to unrealistic policy insights (Calvin et al., 2013).

The second order of trade-offs concerns the way spatial disaggregation is treated in model links. Cultice et al. (2023) highlight that spatial granularity is necessary in IAMs for representing spatial economic interactions at local and meso scales and their effect on global dynamics. They discuss that, while there has been progress in detailing spatial economic and biophysical dynamics in multi-scale, multi-model IAMs, this often comes at the cost of reaching spatial equilibrium due to the high computational power and time requirements; on the other hand, the spatial, cross-system detail that may be reached within one model is often limited. Using a global IAM (GCAM) but focusing on dynamics within an individual study region, Kyle et al. (2015) demonstrate that different spatial resolutions in the IAM may lead to different magnitudes of land use changes, essentially suggesting that land use changes (and related emissions) may also depend on the IAM's resolution when coupled with a land allocation model. Another challenge in rule-based downscaling lies in the limited representation of drivers and dynamics of land use changes (such as lack of constraints related to protected lands or productivity in (West et al., 2014) or inability to show land use changes in each direction in (Le Page et al., 2016)), as well as averaging errors and misrepresentation of localised effects such as heterogeneous soil fertility or water availability— as in the case of a link between the economic land-use optimisation model MAgPIE and the detailed biophysical model LPJmL (Dietrich et al., 2019). There exist country-scale model applications that use integrated resource management optimisation techniques to determine land use changes at higher spatial resolution— and using, e.g., clustering techniques to reduce computational load like in (Shivakumar et al., 2021). The land allocation results from such applications could be fed back to the IAM as land allocation rules; however, when doing so, the modellers must be aware of and provide explanations for the potentially different rationales underlying the models— see also Section 3.3. For instance, feeding optimisation results from the CLEWs framework to the WILIAM IAM, which is based on exploratory scenarios, would hardly fit into a coherent storyline, since the underlying rationale of the models differs, and there needs to be a clear narrative for linking the two models. Reconciling differences in spatial resolution while ensuring computational feasibility is also a challenge when linking GCMs and IAMs: while despite enhancing regional impact analysis, incorporating high-resolution climate projections into IAMs also increases complexity, computational costs, and inconsistencies due to differences in model structures and assumptions (see also Section 3.2.2). Downscaling techniques can improve the spatial detail of climate modules but may also introduce uncertainties. Pattern scaling is one of the simplest such techniques, which can be improved by including more predictors beyond "global mean temperature" such as "land-sea" temperature contrast; for example, Herger et al. (2015) and van Vuuren et al. (2007) suggest a hybrid approach combining statistical downscaling with dynamic feedback to balance consistency and efficiency.

The third order of trade-offs concerns the model horizons of the linked models. While coupling models with the same approach to foresight provides internal consistency, this may not always be feasible. Much like stakeholders in societal contexts where decisions are made, strictly formalised modelling frameworks apply different foresight for their decision-making; this renders linkages between models of varying types of foresight only unavoidable, but also beneficial in terms of better reflecting some aspects of real-world dynamics. Decisions made by the agent(s) based on short-term foresight (e.g., prioritising immediate gains) can have ripple effects in other areas (e.g., long-term strategic planning). Leimbach et al. (2024) input global tradable energy commodities prices and carbon prices (that may be determined by long-term trade agreements) from a perfect-foresight IAM into two myopic-foresight trade models, which are further linked to a household model, to examine the differences between the distributional effects of climate policy and the distributional effects resulting from macroeconomic structural changes; the more feedbacks and variables exchanged between the models, however, the more complicated and iterative such a linking process becomes. Does one, for example, run a model for the long term to provide boundary conditions for the short-term tools, and then recalculate those boundary conditions once the short-term models have been run? Depending on the temporal granularity of the myopic tools, this can lead to an extensive set of iteration loops.

In synthesis, when seeking higher spatial and temporal granularity, whether by disaggregating one model or by soft-linking models, the clustering of geospatial data can introduce detail in the more aggregated models with limited computational load added. However, clustering methods alone are not suited for analyses where infrastructure networks are in focus, because information on the network topology is essential. In such cases, the aggregated model must feature a level of granularity that preserves the key topological features of the infrastructure—that is, it needs to be regionalised. For one-off links, the use of coupling tools that disaggregate certain datasets of the aggregated model may be more practical. As computational power may be the core constraint, before engaging in the linking process, it may be valuable to carry out a simplified test application to observe how sensitive the results are to the detail added through linking. New techniques such as machine learning can support the coupling of complex climate information and IAMs. Finally, linking models with different foresight horizons can improve the representation of real-world dynamics, but attention should be paid to how the data exchange can be carried out effectively (see the *Section 3.3*).

2.1.2 System boundaries, variable definitions, and harmonisation

For linking itself to be feasible, models' system boundaries need to overlap at least to the extent that some "contact point"–minimum one shared parameter or variable–is included in both models. The most straightforward and easiest case of model linking is when this overlap is limited to one or more variables that are exogenous to one model and endogenous to another. Examples in the literature include linkages between sectoral models, in which models of the mobility, housing, or industry sectors calculate electricity demands of the respective sector, which are then used as input variables of a power sector model (e.g., Karamaneas et al. (2023)). Other examples are ESMs linked with land-use models and simple climate models, such as the full coupling of REMIND with the MAgPIE land-use model and the MAGICC simple climate model to provide fully integrated assessments of the energy-economy-land-climate system (Baumstark et al., 2021) or the economic integration of the WITCH IAM with the FASST(R) air pollution model to internalise health-economic impacts of air pollution into climate policy (Reis et al., 2022).

Another important case of model linkage is when the full scope of one model is a subset of the other model. The objective of such linking exercises is typically reaping benefits from different temporal and spatial scales or granularity of the model, thereby allowing to extract more nuanced insights for particular parts of the system beyond what is typically available in IAMs or large ESMs (e.g., Nikas et al. (2024), Soergel et al. (2021), Van de Ven et al. (2019); see also Section 3.2.1).

The most complex linking exercises involve partially overlapping system boundaries for larger sets of (endogenous) variables and flows of information between the models. In these cases, one needs to decide which model(s) determine endogenously the values, and which model(s) use these values as exogenous input. This typically implies very complicated linking exercises, with a high number of contact points (Krook-Riekkola et al., 2017) and potentially the need to do significant changes to one or more participating models to accommodate exogenous input, where formerly endogenous variables would be used in the model's algorithms. In any case, it can be expected that compromises in terms of the consistency between the tools may be necessary. Examples include the soft-linking between PRIMES and other national energy system models with the global Computable General Equilibrium GEM-E3 Model (Fragkos et al., 2017) and linking ESM EU-TIMES with the NEMESIS macro-econometric model (Cassetti et al., 2023).

In all cases, attention must be paid to the definition of the shared variables, i.e., whether these are defined identically (content as well as units of measurement) or not. Even similarly named variables may reflect slightly different real-world entities. For example, when calculating the energy demand of the industry sector, industrial CHP and power plants may be modelled as integral parts of industrial sites in an industry model and their power demand calculated as net balance (i.e., what needs to be provided by the power grid). But, for an energy provision model that is calibrated with statistical data, power generation in these plants and associated primary energy used could be (implicitly) considered as part of the power sector. Another example would be investment costs of industrial plants calculated by an industry model to be used as input into a macro-economic model. The definition of investment costs could differ between both, ranging from pure equipment costs through inclusion of installation costs to also including costs for permits.

Another important consideration is that the results of linked models are often mutually dependent, even if the specific variables are not directly shared. In the above example of a linkage between demand sector models and an electricity provision model, part of the electricity demand– e.g., if some processes in industry are electrified or not–will depend on price signals from the energy sector, while the price of electricity calculated by the electricity system model in turn depends on demand levels calculated by the industry, mobility, and housing models. Challenges also arise if the flow of information goes from a more aggregated variable in one model to a more fine-grained one in another model and thus disaggregation of data is required (see Section 3.2.1). For example, an IAM endogenously calculates, among other outputs, electricity supply on an annual scale and uses resulting electricity costs for endogenously calculating electricity demand based on demand curves. If electricity supply is passed onto an electricity sector model with hourly resolution, e.g., in order to better understand the mix of electricity production technologies required or of grid-related aspects, the electricity costs arising from the electricity sector model may well differ from the ones calculated by the IAM— but if different costs would have been assumed in the IAM, demand (and thus supply) would have differed as well, which would in turn change the input to the electricity model. Similar aggregation issues can exist for any variables—e.g., one model may describe all electric vehicles with one technology, while the other one may distinguish them based on size, cost, or other characteristics.

Furthermore, attention should be paid to background assumptions underlying the model parameterisation, also considering that these may not be found prominently in the models themselves, or in their documentation. Typical examples of such background assumptions are scenarios used for GDP development, population (number and structural composition), international trade, technology costs, climate policies, and weather conditions. If such background assumptions drive key parameters in different models (e.g., assumed weather conditions may influence both agricultural yield and need for heating and cooling in housing), this can create inconsistencies if ignored.

An important element in the process of model linking therefore is the harmonisation of common assumptions and variables. This includes comparison and alignment of underlying narratives and data sources (see also Section 3.2.3)— to the extent that it is possible. Challenges for harmonisation include that the definitions of given input parameters may not be entirely consistent between linked models which may cause significant efforts to identify a consistent mapping of these variables between the models. Practical problems may also arise; for example, if models have large overlaps, harmonisation of these overlaps requires a significant amount of work. Adopting variable values from a harmonisation exercise can also potentially lead to model instability, if it implies that a model enters untested parts of the solution space— see also (Rising, 2017).

Since variable definitions tend to be model-specific, no one-size-fits-all solution exists for the above sketched challenges that arise from diverging variable definitions. The IAM community's work regarding data management and protocols (Cointe, 2024) as well as the IAMC scenario submission template (also in context of the IPCC WGIII submission processes— see Peters et al. (2023)) can help harmonise in similar system boundaries and variables (including units of measurement) as an intermediary between two models. The best practices for dealing with the above sketched issues are (i). encompassing, clear, and detailed model documentation on the one hand and (ii). taking sufficient time as part of model exercises to discuss and report the details of variable definitions and to create consistent model interfaces on the other.

One strategy to mitigate inconsistencies from mutual dependency of dynamics in linked models is to ensure that feedback are captured and models are iterated until some kind of convergence is reached (Kumbaroğlu and Madlener, 2003). Exchanging relevant data between models, in both directions and multiple times in a cascading soft-linking setup, can typically be used to approximate the mutual dependency. However, it may not always be trivial to communicate the information in a way that allows the other model to react— see also Section 3.2.1 as well as (Robinson et al., 2018, Tan et al., 2023, Van Vuuren et al., 2012) for previous work on the various different approaches to linking and how the information flows between the models.

2.1.3 Data exchange implementation

The practical implementation of data exchange between models can also present many challenges. This is unsurprising, since the exchange process depends on a multiplicity of factors such as the development and structure of the models, the programming language used, the availability of model interfaces for interoperability, and the type of interlinkages needed between the models (Belete et al., 2017). The latter plays a critical role, as the needs for data exchange are radically different between approaches such as soft links (i.e., transferring results from one model to the other) and hard links (i.e., running the models in parallel, constantly exchanging data, and producing one set of results). Since hard-linking is usually significantly more time- and resource-consuming (Brinkerink et al., 2022), soft links have been traditionally used to connect IAMs and ESMs with various types of models, inter alia macroeconomic (Fujimori et al., 2024, Messner and Schrattenholzer, 2000, Nishiura et al., 2024), Multi-Regional Input and Output (Budzinski et al., 2024), technology diffusion (Odenweller, 2022), or power systems models (Deane et al., 2012).

This exchange has been facilitated by standards such as the IAMC template[1] , which offers a structured format for exchanging modelling results and has been established in the community through large model intercomparisons, including IPCC assessments (Cointe, 2024). However, this template does not provide a common ontology to use for model exchange, thereby often requiring hard-coded conversions of data from one model to the other. While many efforts to harmonise result variables or region names are underway— e.g., see (Henke et al., 2024), the nomenclature Python package[2], and automated data validation applications[3]— data exchange between linked models often requires manual efforts and the development of ad-hoc scripts for data processing.

An additional challenge is that the linked models are often run by different institutes; thus, practical reasons may force compromises on the linking set up that would not be made in the case of models that are developed and interlinked by the same institute, e.g., MESSAGE and GLOBIOM (Fricko et al., 2017). This can be partly addressed by building specific platforms to coordinate the model linking. Such platforms already exist in other research fields, such as the Pegasus system (Deelman et al., 2015), which has been used for over a decade to manage the computational workflows and data exchange between models in astronomy, bioinformatics, physics, and elsewhere. Recently, Pegasus has been used to coordinate model linking in an integrated assessment model (Clemins et al., 2020), albeit without establishing a paradigm for the IAM community.

Even with a dedicated platform, running the models and passing the data onwards can be a laborious exercise, especially when the portfolio of models is large and the contact points between the models are many. A solution would be to transition to a "model as a service" approach (Belete et al., 2017), where models are built directly as web services or are exposing an application programming interface (API). For instance, models can be uploaded as Docker containers with explicit APIs (as standardised as possible), allowing any user to run them and request specific data for model linking. This could be further combined with user interfaces for orchestrating API communication. APIs could be also used to facilitate harmonisation processes (Giarola et al., 2021) or to deliver data to non-modelling stakeholders in order to validate them (McGookin et al., 2024). There are several examples of web interfaces showing modelling results to experts and non-experts, such as the I2AM PARIS platform (Nikas et al., 2021), the Senses Toolkit (Auer et al., 2021), or the upcoming Scenario Compass[4] , which could potentially connect to API-enabled models and visualise their results.

Model APIs could be especially interesting in bidirectional soft linking, where models run iteratively, using data outputs from one model as data inputs to another, until the results of all models converge between iterations (see e.g., (Nishiura et al., 2024)). The more models are involved, the more contact points (and therefore

---

[1] https://data.ene.iiasa.ac.at/database/
[2] https://nomenclature-iamc.readthedocs.io/en/stable/
[3] https://github.com/ciceroOslo/iamcompact-validation-ui
[4] https://scenariocompass.org/process

Funded by
the European Union

convergence criteria) they have, the more laborious the practical linking mechanisms are, and the more difficult it is to reach convergence between the tools. This is further complicated in case of exchanging data manually, leading the iteration to omit any convergence considerations. Model convergence could be significantly accelerated by using frameworks such as Pegasus to orchestrate the computational workflow between models, especially when combined with APIs to streamline data exchange. Such a structured process could also integrate automated testing using established model diagnostics (e.g., (Harmsen et al., 2021)), which would also ensure the quality of the model linking (Belete et al., 2017).

To sum up, there is ample room for improving current data exchange methodologies for model linking by using standardisation and automation processes. At the very least, modelling teams should opt for a standardised data format such as the IAMC template and agree on the set of variables that will be included. If possible, automated tools such as the nomenclature Python package should be employed to ensure that variable names, units, and regions are consistent among modelling teams. When extensive data linking is expected (e.g., in bidirectional soft linking), the use of standardised interfaces such as the Pegasus system or APIs could potentially reduce errors and ensure the quality of the exchange. While APIs can be time-consuming to develop and many modelling teams may not have the capacity to do so, they can serve as a long-term investment for model developers. Ensuring that a model is easily linkable can potentially increase the likelihood of its use in model linking and other exercises, similar to the way that open-source models such as OSeMOSYS, GCAM, and Calliope have been used and expanded by multiple modelling teams beyond their original developers.

2.2 Model linking as an epistemological problem

The structure of individual models embeds implicit assumptions that shape how their results should be interpreted. Different model types incorporate distinct epistemic values and trade-offs in areas like accuracy, simplicity, and system representation (Silvast et al., 2020). For instance, the choice of system boundaries, spatiotemporal scales, and variable definitions—not to mention the complexity of model linking processes (see Section 3.2)—all shape the nature and validity of knowledge that an individual model can generate. These structural elements often reflect the modeller's conceptualisation of the system and can introduce biases or limitations in the knowledge generated. For instance, a model that assumes constant technological progress may overlook potential disruptive innovations, leading to overly optimistic or pessimistic projections of renewable energy adoption. Model-specific biases are likely to vary from one model to another, which further complicates the interpretation of ensemble data generated through multiple models (Sognnaes and Peters, 2025).

Model linking in energy-system and integrated assessment modelling thus presents key epistemological challenges about the nature and validity of knowledge produced across complex, multi-model systems. By combining diverse conceptual and methodological approaches, model linking introduces three challenges: (1). synthesising distinct knowledge strands, (2). understanding how errors and biases propagate through interconnected frameworks, and (3). interpreting the emergent properties that arise when multiple models are linked. This section explores these three challenges inherent in model linking and proposes frameworks for addressing them.

When models are linked, the synthesis of disparate knowledge strands becomes challenging. For example, coupling a prescriptive, perfect-foresight optimisation ESM (e.g., TIMES) with a descriptive, myopic macroeconomic simulation model (e.g., E3ME) produces a hybrid system with different and conflicting economic-engineering and/or economic solution paradigms. Basically, prescriptive models suggest what should be done, while descriptive models simulate what will happen. Also, the differences between the ways models look at the future are critical, since a myopic decision maker could well decide differently than a perfect foresight decision maker. This raises questions about how to synthesise, interpret, and reconcile knowledge produced under fundamentally different, yet linked, modelling paradigms. One option to addressing this synthesis challenge is to develop explicit frameworks for mapping and documenting the key differences underlying each model component, enabling systematic analysis of where knowledge claims may conflict or complement each other.

Model linking can compound errors and biases across interconnected models or even introduce novel ones

(Goldhaber-Fiebert, 2012). As data and assumptions flow between models, inaccuracies may be amplified more than in any individual model alone. For example, biased renewable energy cost projections in one model could significantly impact investment decisions in linked models, creating compounded errors throughout the system. Furthermore, the interactions between models can create emergent properties that introduce new sources of errors and biases, which are not present in the original models individually. Thus far, there are studies (see Al Khourdajie et al. (2024), Dekker et al. (2023), Fais et al. (2016), Förster et al. (2013), Li et al. (2023), Marangoni et al. (2017), Wachsmuth and Duscha (2019)) that use various methods, such as decomposition and sensitivity analysis, to systematically attribute variations in mitigation scenario outcomes to different drivers, socioeconomic assumptions, model differences, and their interactions, with the aim to improve the robustness of scenario interpretation for policymakers. However, these methods primarily focus on analysing variations in final outcomes, whether for individual or linked models, rather than tracking how errors and biases propagate through the linking process itself, or how they arise and are amplified across linked models.

Linked models can result in new emergent properties of the linked systems, such as their ability to capture cross-sector interactions or produce internally consistent narratives across multiple domains. Indeed, achieving such emergent results may be a key aim of linking models. However, the complex interactions between models can also produce outputs not easily traceable to any single input or assumption, complicating both validation and policy interpretation. For example, linking an ESM that centres on centralised electricity generation with a land-use model focused on ecosystem services might reveal trade-offs between energy policy goals and land-use constraints (and, in turn, between climate and environmental objectives)— insights that neither model could offer independently. In such a combined system, it may be difficult to attribute results to any single input or assumption because the interplay of energy infrastructure, land availability, and ecological integrity emerges only when both models operate together. This complexity can enrich our understanding of cross-sectoral dynamics while simultaneously complicating interpretability and policy guidance.

Looking ahead, it is important to develop a framework that assesses the validity of model linking exercises. This framework should address knowledge synthesis, the propagation of errors and biases, and the interpretation of emergent properties of linked systems, all in the light of the intended purpose of model linking and the potential new insights that it can generate. Key components of this framework would include detailed documentation of linking procedures and assumptions; developing methods for identifying and evaluating errors and biases and understanding how they may propagate through the linked system; and an explicit interpretation stage for the combined model system, similarly to other disciplines— e.g., Laurent et al. (2020). As Silvast et al. (2020) observe, the epistemic values of models are often negotiated alongside non-epistemic values, particularly in applied contexts. In some instances, a model's perceived utility for policy decisions may override considerations of physical accuracy. This interplay between epistemic and non-epistemic values adds another layer of complexity to the interpretation and application of linked models. The selection and interpretation of linked model systems should be considered during the initial design phase, ensuring philosophical compatibility between chosen models and their alignment with the real-world dynamics they aim to represent, thereby minimising conflicts in underlying assumptions.

Practitioners instigating model linking exercises should consider the following steps systematically. First, they should explicitly map the epistemic foundations of each model, including their temporal and spatial scales, key determining assumptions, and methodological approaches; such mapping can enable early identification of potential paradigmatic conflicts and areas where knowledge synthesis might prove challenging. Second, they should assess the potential for error propagation by identifying critical data exchange points between models and by understanding whether and how these may be addressed or at least acknowledged when interpreting the outcomes of the linked systems. Third, they should carefully consider whether the emergent properties from the linked models align with their research objectives and whether they can be adequately validated against empirical data. Throughout this process, modellers should consider trade-offs between complexity vs. tractability, comprehensive system representation vs. result interpretability, and theoretical rigour vs. pragmatic applicability of the modelling framework. These trade-offs should be explicitly documented and justified based on the specific

Funded by
the European Union

research or policy questions being addressed, including clear limitations of the linked system and guidance as to how results should, and importantly should not, be interpreted by end users.

2.3 Conclusions and a way forward

Model linking for energy-system analysis and integrated assessments in support of energy, climate, and sustainability policy should be motivated and thus driven by an explicit need to (better) answer a particular question. This need may be directly associated with the scope of a specific study, meaning that model linking is required only in relation to said study (one-off applications), or it can trace to an ongoing branch of scientific research in the long run, meaning that model linking should result in a strategic modelling framework to be continuously used and further developed. Whichever the case, our focus in this paper has been to highlight some of the areas in which decisions about model linking are not trivial, and to emphasise the significance of the decisions, the documentation of the rationale behind them, and the communication of the implications of the choices and model linkages for interpreting the results.

Based on our discussion as well as on the reviewed literature, we propose a general checklist that can be used for making initial decisions about linking models. As no two models— and thus no two linking tasks— are identical, this checklist is intentionally general: the questions must be addressed and the recommendations interpreted within the context of the specific linking task at hand. When relevant, we acknowledge different requirements and considerations in case the establishment of model links is strategic and long-term rather than circumstantial, one-off activity— acknowledging that the former case requires additional considerations and guardrails. It is also noteworthy that we refrain from discussing here the specific linking approaches (hard linking, bidirectional and unidirectional soft linking, etc.), as these have been previously discussed extensively (see, e.g., van Vuuren et al., 2012). Finally, we recommend the concept of "unlinking" to also be considered: not all questions require an extensive model framework, as this may yield undesired opaqueness; creating the flexibility to easily "unlink" linked tools would add further value to the linking process and the model themselves.

The recommendations included in our checklist, which is summarised in *Table 1*, assume that the trade-offs associated with the model linking process have been considered and deemed beneficial. This means that the level of robustness required for the linking process has been considered, to avoid compromising the integrity of the results or the benefits that can be achieved; this is especially true for long-term/ strategic model linking, which requires considering the level of added complexity, the increase in opaqueness of model dynamics, and the volume of applications that truly need the explicit representation of the cross-model dynamics. Not linking the models should be kept as an option, as the above conditions will not be fulfilled for many model linking possibilities.

Table 1: Checklist for establishing links among ESM and IAM modelling tools.

Type of considerations	Checklist
Linking across temporal and spatial scales	i) If there is an option to link models of similar scope or granularity in terms of time and/ or space, then practitioners should consider linking such models. ii) Considering the role of space and time for the research question at hand, model linking aiming to increase the spatial or temporal granularity of the analysis requires significantly more robust approaches than in the case of simply overcoming differences that exist in the two models. iii) Upscaling and downscaling approaches can be useful for moving data from one model to another– but with limitations (see (v) below). iv) If models with different foresight are linked, attention should be paid to the design and process of data exchange.

	In cases of strategic model-linking for long-term application: v) Limitations to upscaling and downscaling due to important relative positions of data points (in time or space) could render more extensive changes necessary for at least one model; this would imply poor use of resources for a one-off study. vi) The extent to which the spatial and temporal dimensions of the models to be linked can be harmonised should be considered, and the model(s) modified accordingly. vii) As computational power may be the core constraint, a preliminary simplified test application could offer important insights into the sensitivity of model results to the attained increase of detail, and thus to the added value of engaging in the model linking process to begin with.
System boundaries, variable definitions and harmonisation	viii) Common assumptions, key variable definitions, and underlying scenario narratives must be harmonised to the extent possible. When interpreting results, the lack of full harmonisation across all model assumptions must be transparently reflected in the analysis. This includes paying close attention to how variables have been defined in the models to be linked, to ensure the definitions do not differ. ix) Detailed model documentation should be developed and then used during the model linking, to better understand the model assumptions made for model structure, variables and parametrisation. Adequate time within the linking process should be devoted for discussing such assumptions and definitions across modelling teams. In cases of strategic model-linking for long-term application: x) A full mapping of assumptions (explicit and otherwise) and their drivers for the models to be linked can facilitate the process of harmonising assumptions and variable definitions, ensuring consistency across both explicit and background assumptions across the linked model system, and legitimising the produced model framework and its results.
Data exchange implementation	xi) Standardisation (e.g., of data templates and automating processes) can be decisive. The use of dedicated tools developed by the energy-/climate-economy modelling community can help with data exchange, as well as add transparency for variable definitions, model structure, and assumptions. In cases of strategic model-linking for long-term application: xii) Using standardised interfaces or APIs may be more resource-intensive but is highly beneficial, as it can reduce errors and provide a distinct part of the linked model system.
Model linking as an epistemological problem	xiii) Before linking, and in a process similar to that for key assumptions and drivers, the epistemic foundations of the models must be mapped to assess where the rationale of the models may be in conflict; if the areas appear critical, and serious inconsistencies unavoidable, the usefulness of the model linking activity may need to be reconsidered.

	xiv) Documenting the linking process itself can contribute to understanding how the model results should be understood (especially for future use), as well as to legitimising the exercise, in terms of both scientific rigour and policy credibility. xv) Practitioners may need to assess how critical data exchange points (e.g., inconsistencies between variable definitions, or compromises made to facilitate data exchange) may introduce errors as well as how these errors may propagate, especially when two-way feedback are considered between the models (as the latter increase non-linearity and variability); this will help them explicitly discuss and highlight potential issues when interpreting model results. xvi) A separate interpretation stage should be included to explicitly consider and discuss how the potentially different model rationales and various compromises made during the model linking should be interpreted for the results. Special attention should be paid to the emergent properties from the linked system, in terms of whether they can be validated against empirical data. In cases of <u>strategic model-linking for long-term application</u>: xvii) In the light of the epistemological points discussed, for strategic model linking the inconsistencies should be minimised a priori, even at the cost of having to alter one or more of the models– or changing the models to be linked. It is unadvisable to create "permanent" models for which the interpretation of results has obvious ambiguities.

Funded by
the European Union

3 Case study on model linking checklist

In order to demonstrate the presented workflow of the previous section, we conducted an ex-post analysis of a model linking study about the transformation of the EU steel industry which is documented in D4.7 – Sectoral and cross-sectoral analysis deliverable of IAM COMPACT[5]. The current ex-post analysis tries to discuss the four linking-related problem categories in the context of linkages implemented and reflect on the pitfalls and potential improvements.

3.1 Description of Linked Models

As the methodological differences of the models involved in a study can substantially affect the linking process, both in terms of technical and epistemological aspects, here we briefly describe each model.

3.1.1 GCAM[6]

GCAM is a global, partial equilibrium IAM that simulates human-Earth interactions by analysing the relationships between the energy system, agriculture and land use, the economy, and climate. It helps model greenhouse gas (GHG) emissions, energy consumption, energy prices, and trade patterns. The model operates by identifying cost-effective energy system solutions for a given time period before advancing to the next period and repeating the process.

In the linking study, GCAM version 7.0 was used, which incorporates global iron and steel trade, along with modifications to socioeconomic pathways and production technologies to align with other models in the study. GCAM represents the supply and demand for a single "iron and steel" commodity across 32 regions. This version includes 20 technology options for iron and steel production per region, with input coefficients, costs, and technology readiness levels aligned with harmonisation data.

Technology selection each year is determined using a logit function based on price and historically calibrated preferences, ensuring that all available technologies capture a portion of the market rather than allowing a single dominant winner. Iron and steel demand is met through a mix of domestic production and imports from a global trade pool.

3.1.2 TIAM[7]

TIAM (Times Integrated Assessment Model) is a technology-detailed, partial equilibrium IAM that represents the entire energy supply chain—from resource extraction and conversion technologies to delivering energy services to end-users. It balances energy supply and demand across sectors using a least-cost optimisation approach, considering the effects of technology deployment, fuel extraction, and energy price fluctuations over time. The model aims to minimize the total cost of the energy system while meeting energy service demands within predefined emissions constraints.

Key inputs driving future energy service demand projections across all sectors and regions include GDP, population, household size, and sectoral economic shares. In the linking study, steel sector production demand is sourced from GCAM for all scenarios.

3.1.3 MARIO[8]

MARIO is a Python-based modelling tool designed for input-output analysis, making it valuable for evaluating

[5] DOI 10.5281/zenodo.13839232
[6] https://iamparis.eu/detailed_model_doc/30
[7] https://iamparis.eu/detailed_model_doc/59
[8] https://iamparis.eu/detailed_model_doc/71

Funded by
the European Union

economic and environmental impacts as well as scenario-based studies. In the linking study, MARIO was applied to refine the EXIOBASE dataset by integrating new steel production methods and mapping the full supply chain for PV panels and wind turbines for the case of the EU.
The study considered three steel production pathways:

i) Blast Furnace-Basic Oxygen Furnace (BF-BOF) (already included in EXIOBASE),
ii) Direct Reduction with Natural Gas, followed by an electric arc furnace (NG DR-EAF),
iii) Direct Reduction with 100% Electrolytic Hydrogen, followed by an electric arc furnace (100% H_2 DR-EAF),

For the NG DR-EAF method, natural gas was replaced with hydrogen derived from steam reforming, while in the 100% H_2 DR-EAF process, hydrogen was produced through electrolysis. As a result of these adjustments, carbon monoxide's role as a reducing agent in the NG DR-EAF method was excluded. Moreover, in both new processes, the Electric Arc Furnace (EAF) operated solely with Direct Reduced Iron (DRI) instead of scrap, and slag production was omitted.
The updated dataset was then utilised for "what-if" scenario testing, incorporating insights from GCAM. These modified datasets were subsequently analysed using WILIAM to assess macroeconomic and environmental consequences.

3.1.4 WILIAM[9]

The WILIAM model (Within Limits Integrated Assessment Model) is a newly developed IAM based on system dynamics, designed as an extension of the MEDEAS models. By using system dynamics, WILIAM captures complex feedback loops and non-linear interactions between social, economic, and environmental factors.
The model consists of eight interconnected modules: (1). demographics, (2). society, (3). economics, (4). finance, (5). energy, (6). materials, (7). land and water, and (8). climate. It covers nine regions and 35 countries, including the EU27. WILIAM is highly detailed, featuring a disaggregated structure with 62 economic sectors. Its sectoral classification, particularly the production sub-module, is based on Input-Output Analysis. Among its sectors, WILIAM includes nine dedicated to mining and mineral manufacturing, such as iron production, while steel is categorised within the broader "Manufacture of metal products" sector.

3.1.5 WISEE EDM-I[10]

The WISEE EDM-I is a technology-focused investment modelling framework for specific industrial sectors, developed in Python. It utilizes detailed, site-specific data on production processes, such as asset capacity and age, to optimise costs across multi-step value chains— from iron reduction to steelmaking and steel finishing. The model also accounts for the spatial distribution of production facilities and transport options for intermediate products.
For the linking study, a newly implemented version of EDM-I for the EU steel sector is used. Investments are made to meet predetermined production levels for 20 types of finished steel while factoring in energy and CO_2 prices, as well as constraints like scrap availability. EDM-I is particularly designed to assess the relocation of industrial production capacity within Europe.
The version used in the linking study distinguishes between five iron reduction technologies (Blast Furnace, Blast Furnace with Carbon Capture and Storage, Direct Reduced Iron with/without reformer, and electrolysis), three steelmaking technologies (Basic Oxygen Furnace, Electric Arc Furnace, Submerged Arc Furnace_Basic Oxygen Furnace), and 12 steel finishing technologies. These technologies can be combined into different steel production pathways. Additionally, the model categorizes scrap and steel qualities into five levels, ensuring that specific finished steel demands meet minimum quality requirements.

---

9 https://iamparis.eu/detailed_model_doc/62
10 This model has been renamed to ITOM (Industry Transformation Optimisation Model). https://iamparis.eu/detailed_model_doc/63

Funded by the European Union

3.2 Reflection on the Linkages

The steps of the study and the models involved in each step are shown in *Figure 1*. The study on the EU steel industry used two unidirectional soft-links, namely GCAM~>TIAM and GCAM~>EDM-I, to eventually project the steel production technology mix in the EU and the country-level transition of the steel industry. The study also used two other unidirectional soft links, i.e., GCAM~>MARIO and MARIO~>WILIAM, to provide insights into the economic and labour effects of the steel industry.

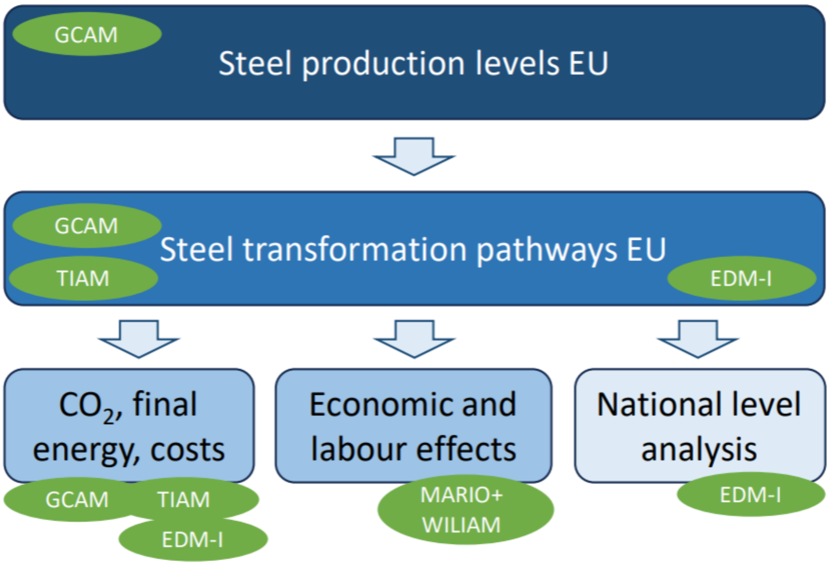

Figure 1: Steps of the analysis and models used in each step.

The data flows between the models are depicted in *Figure 2*. In the first step, GCAM projected the steel production levels in the EU. This fed into the second step of the analysis, which employed TIAM and EDM-I. TIAM considers the steel production levels per world region and does not allow inter-regional steel trade. In addition to the steel production levels, EDM-I used electricity, hydrogen, natural gas, coal, and CO_2 costs resulting from GCAM runs to set its parameters. Furthermore, the EDM-I team translated the GCAM projections for steel projections into steel demands per type of finished steel using Eurofer data and a material flow scenario for EU steel demand, production, and recycling. In the third step, GCAM provided electricity and steel production portfolios as well as the PV and wind capacity additions to MARIO. Then, MARIO produced input-output tables that were fed into WILIAM as off-shoring and on-shoring assumptions to assess the socioeconomic impacts of the transformation.

In this analysis, since the linking activity was more of a one-off linking, we focused on the advice from the previous section that is not for the strategic type of linkages. Besides, we do not reflect on the existing options for the models that are involved in the linking since there are other constraining factors, such as the availability of modelling teams and other resources (see (i) in *Table 1*). The analysis is mainly based on the report, although the authors were approached for their feedback. This means that, in many cases, the analysis cannot directly identify whether the checklist advice was followed, but only speculate on it, based on the structure and nature of the models and the information given. In the following, we explicitly reflect on the four categories of linking problems and refer to related advice from the previous section (i.e., *Table 1*).

Funded by
the European Union

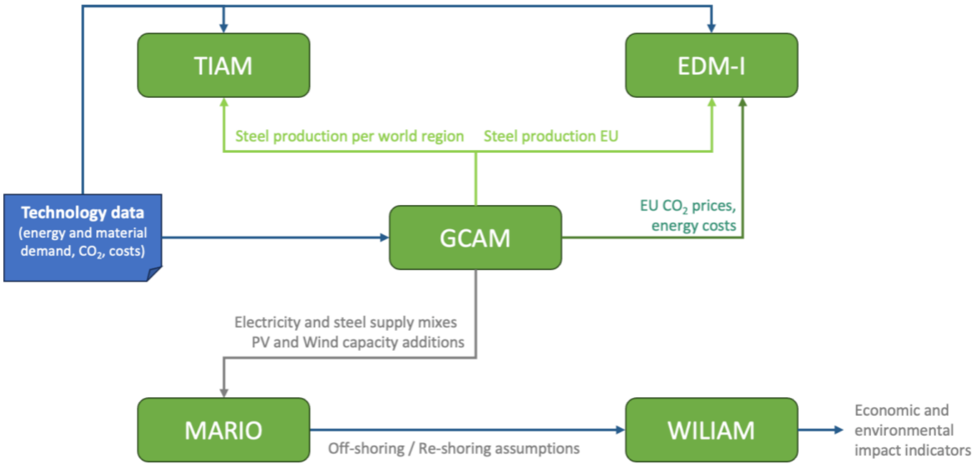

Figure 2: Data flows between models

3.2.1 Temporal & Spatial Scales

Regarding the temporal and spatial scales, such information has not been extensively communicated in the report. It would have been better if the modelling teams had indeed documented the temporal and spatial resolution of the data being exchanged and the temporal resolution of the other influential sectors of the models. Although the linkages did not aim to increase either the temporal or the spatial resolution of the results in any way, attention could have been paid to the implications of exchanging the data between the models with different spatiotemporal scales (see (ii) in *Table 1*).

Another issue is related to linking models with different ways of looking into the future (see (iv) *in Table 1*). More specifically, GCAM, MARIO, and WILIAM treat the time horizon in a myopic manner, whereas TIAM and EDM-I are perfect foresight optimisation models. The inconsistencies that may arise due to this difference were not reported. Such complications usually occur in the interpretation stage, where the results of a model combination need to be evaluated. We elaborate further on this matter in the section related to epistemological aspects of model linking.

Although in GCAM~>TIAM, GCAM~>EDM-I, and GCAM~>MARIO the temporal granularity of the steel production levels, the electricity, and the steel production portfolios was not specified in the report for any of the involved models, the GCAM, TIAM, and EDM-I models operate with yearly averages and 5-year timesteps (except for EDM-I, which operates with averages of five years around the central reported year), thus there would be no inconsistency from this perspective—this was also clarified after getting feedback from the involved teams. Besides, in GCAM, for instance, the steel production commodity was defined in each of 32 regions of the model, but the regional split of TIAM was not presented, potentially differing from what it is in GCAM. The practitioners seemingly used a kind of up- or downscaling method to aggregate or disaggregate the results of GCAM across time and space, to be able to transfer them to TIAM, EDM-I, and MARIO, which could have been communicated transparently (see (iii) in *Table 1*). After discussing with the involved teams, it was indicated that the GCAM, EDM-I, and TIAM teams had spent considerable effort on regional mapping between GCAM and EDM-I, and between GCAM and TIAM. Furthermore, for instance, in MARIO~>WILIAM the spatial disaggregation of both models is unknown. Except for GCAM, which is mentioned to have 32 regions, the number of regions for the other models is not presented in the report. Nevertheless, the main issue from the practitioners' view is that they did not spend enough time to fully document their efforts and the details of the exercise.

3.2.2 System Boundaries, Variable Definitions & Harmonisation

One could argue that, until all model parameters and assumptions are fully harmonised, there remains significant scope to improve integration. Nevertheless, it is almost impossible to fully harmonise the models, and this is why practitioners should usually focus on the most important common assumptions, key variable definitions, and underlying scenario narratives (see (viii) in *Table 1*). The four research teams involved in the linking used a

dataset shared as an Excel table among them, which is provided in the Appendix of deliverable D4.7, and harmonised detailed steel technology data from WISEE EDM-I. The dataset consists of information about energy demand, material use, costs, emissions, lifetime, availability year, and the capacity factor of each steel production technology. It was mentioned that the technological assumptions are broadly consistent with the harmonisation data, although *ideally* each modelling team should have provided the exact data used as input into their models, in order for us to easily evaluate the level of harmonisation conducted in the task (see (ix) in *Table 1*).
Besides the reported information on the harmonisation stage, the teams mentioned that an issue in the process was related to the differences between the models in terms of what is being calculated endogenously and what exogenously. For example, in GCAM, emissions are calculated endogenously from the energy inputs of each production route and do not exactly match the values in the harmonisation dataset, which is based on a more detailed technological model. Another example is that CO_2 Transport & Storage costs are calculated endogenously by GCAM based on storage demand, while it was assumed as an external value for EDM-I.

3.2.2.1 GCAM~>TIAM

GCAM encompasses the global steel industry in various regions and the trades between them, while TIAM does not consider steel trade; thus, it treats the production level of each region exogenously. GCAM and TIAM model the whole energy system and even other systems interacting with the energy system to some extent. As a result, each region's steel production in GCAM is not only driven by the model assumptions about steel production technologies, but also by various other assumptions in even remotely connected sectors of the system.
The models have been partially harmonised based on the guidelines of IAM COMPACT's Broad Scenario Logic[11]. The modelling teams have, however, not described potential issues that could arise due to partial harmonisation of the models. Aside from the technological assumptions, the scenario narratives and their exogenous drivers might become problematic. In the description of TIAM, the corresponding team have mentioned that GDP, population, household size, and sectoral shares of the economy are driving energy service demands across all sectors in each region, while GCAM includes some of these as endogenous variables. Therefore, once TIAM uses the steel production level data from GCAM, it may also need to use some other outputs from GCAM to modify its energy service demands and the narratives behind them. Regarding the variable definitions, GCAM considers "iron and steel commodity". On the other hand, TIAM receives the "steel production demand" from GCAM. The potential differences between the definitions have not been reported.

3.2.2.2 GCAM~>EDM-I

EDM-I is completely within the system boundaries of GCAM and needs to receive information about the steel production level and electricity, natural gas, hydrogen, coal, and CO_2 costs from GCAM to operate. The harmonisation of these two models has been done at the level of technological assumptions. As mentioned above, the historical stock could have also been harmonised; however, since EDM-I considers the site-specific information of the plants (e.g., capacity and age), it could be cumbersome. In the description of EDM-I, it is also mentioned that the model captures various transport options for the intermediary products. This presumably falls into the category of freight transport in GCAM. Thus, harmonisation or even data exchange could be done in that sector as well, although potentially not too influential in the final results, based on the teams' feedback. For instance, if the fuel needed for the various transport options is considered in EDM-I, the costs of fuel could have been transferred from GCAM to EDM-I. Furthermore, as EDM-I provides detailed information on the relocation of the steel industry and its transformation within the EU, it could be useful to transfer this data to GCAM to further improve the steel industry transition in GCAM. Consequently, this can change iteratively the steel production levels and even the prices of energy commodities, which were transferred to EDM-I previously.
The definitions of steel production level also differ between the two models. In GCAM, it refers to a general "iron

[11] DOI 10.5281/zenodo.10430888

Funded by the European Union

and steel commodity" but, in EDM-I, it should be translated into steel demands per type of finished steel, which was done in the linking study using the Eurofer dataset and a material flow scenario for EU steel demand, production, and recycling. Finally, regarding the difference in the scenario narratives, at least based on the presented information, there are no major inconsistencies between the models.
The result comparison of TIAM, GCAM, and EDM-I shows inconsistencies between the CO_2 emissions of the EU steel industry reported for 2020. The report identifies two possible explanatory factors for such a difference: first, the share of secondary steel and, second, the consideration of different coal types. This underscores the issues mentioned regarding harmonisation and the variable definitions. Another inconsistent result is related to the direct electricity demand of the EU steel industry for 2020. The report explains the difference between different production volumes and amounts of secondary steel production. A reason for the differences mentioned could be the potentially inconsistent historical stocks in the models, which could have been harmonised as well.

3.2.2.3 GCAM~>MARIO

MARIO is used for input-output analysis. In the linking study, the results for the electricity and steel production portfolios, along with PV and wind capacity additions, were transferred from GCAM to MARIO. Regarding the harmonisation of technological assumptions, it seems that the technologies available in MARIO for steel production are fewer than those in TIAM, GCAM, and EDM-I. This raises questions about the extent to which the models could have been harmonised. More specifically, how were steel production volumes per production route from GCAM mapped to fewer production routes of MARIO? On top of that, since MARIO includes all sectors of the economy and significantly overlaps with the scope of GCAM, data exchange could have been conducted more comprehensively. For example, was the hydrogen production portfolio, which is an important fuel for steel plants in the future, harmonised? This was not clear from the report, but upon exchanges with the modelling teams, it was clarified that indeed both electricity and hydrogen mixes were harmonised.
Furthermore, there could also be a bidirectional stream of data from MARIO to GCAM, as they substantially overlap. For instance, if MARIO can calculate economic impacts on employment and GDP, it could inform GCAM about such ramifications. This could lead to an iterative loop of data exchange, which is certainly difficult and resource-intensive to implement.
Regarding the harmonisation of scenario narratives, since the models have not been fully harmonised, there could be complications in terms of the narratives behind each assumption, but one cannot consistently comment on the level of consistency between the models' assumptions.

3.2.2.4 MARIO~>WILIAM

The input-output tables obtained from MARIO were fed into WILIAM as off-shoring and on-shoring assumptions. These two models consider the whole economy; therefore, the harmonisation could have been done more thoroughly. In addition, as the models have many overlapping variables, there could be a more holistic set of variables being exchanged between the models, rather than only the off-shoring or on-shoring of the steel plants.
Regarding the translation of the input-output tables from MARIO into the input assumptions of WILIAM, the report does not clearly explain which variables in WILIAM were updated using the tables from MARIO and how. Increased transparency in the translation process could better allow us to comment on the issues related to the treatment of different variable definitions across the two models.
Lastly, it was not clear from the report whether the assumptions behind the narratives were harmonised. These assumptions could be about the exogenous parameters that affect the population, GDP, etc. (endogenous variables of WILIAM), which influence various outputs of WILIAM.

3.2.3 Data Exchange Implementation

The report does not discuss any data template used in order to exchange the data from one model to another, nor any automation process (see (xi) in *Table 1*). The data exchange for linkages might have been done manually, which is understandable to some degree, since the activity is a one-off model linking, and is done by four different research teams. However, such a practice could undermine the transparency and accuracy of the data exchange in general. Besides, a less structured data exchange could obscure the potential inconsistencies between the models in terms of the variable definitions, model structure, and model assumptions, either unintentionally or due to various other difficulties in dealing with them.

In the case of this linking study, to increase transparency, one could start by creating a data template in which the exact information exchanged between the models is provided. Furthermore, if the study aimed at a more strategic linking rather than a one-off linking, the modelling teams could come up with a more standardised process, potentially automated, in which standardised interfaces or APIs could be utilised. Nonetheless, establishing such a process requires more resources.

3.2.4 Epistemological Aspects

In general, the practitioners did not discuss the epistemic foundations of the models in detail. In the linking study, GCAM (i.e., a descriptive simulation model) is linked to TIAM and EDM-I (i.e., prescriptive perfect foresight optimisation models), which creates a hybrid multi-model setup with conflicting paradigms. To use both perspectives together, one should be able to reconcile and synthesise the two using, first, a framework to map the differences and, then, a narrative in which the models are parts of a big picture that describes what happens or should happen in the real world (see (xiii) in *Table 1*). For instance, in GCAM~>TIAM and GCAM~>EDM-I, the data about the steel production levels that comes from GCAM is used as an attempt to mimic how the global trade and relocation of steel production plants across the continents can affect the EU steel production level. In TIAM and EDM-I, then, this information was used to suggest the optimal steel production portfolio to reach the climate targets. Indeed, acknowledging the fact that perfect foresight optimisation models do not necessarily show how the future unfolds, however clear to the scientific community, will improve the transparency especially when the non-expert policymakers are being communicated to.

Another area for improvement is the documentation of the linking process, which further enhances the transparency and even accuracy of the analysis, which could potentially be used for policymaking (see (xiv) in *Table 1*). Besides, the documentation contributes to the understanding of how the model results should be used and interpreted for future applications. In the documentation stage, practitioners could note all the critical data exchange points between the models, and at least not make compromises blindly (see (xv) in *Table 1*). Inadequate or unclear documentation can lead to neglecting inconsistencies between variable definitions, mistakes in the identification of data exchange points, and partial harmonisation of assumptions. Such issues, in turn, might introduce errors that may propagate, especially when the linkages are bidirectional, which is not the case here. On the other hand, some of the linkages could have been bidirectional, in which case it would be more probable to observe the error propagation, such as the potential bidirectional link between EDM-I and GCAM, exchanging steel production levels (from GCAM to EDM-I) and steel production portfolio of the EU (from EDM-I to GCAM).

Finally, it could have been better if there were a dedicated section related to the interpretation of insights provided by the model linking (see (xvi) in *Table 1*). In such a section, one could discuss how the results should be evaluated considering disparate epistemic foundations, different perspectives, e.g., prescriptive versus descriptive views, conflicting parametric and structural assumptions, and unalignments in variable definitions. Furthermore, sometimes there might be emergent property from the linked models. Since such a phenomenon may not have any correspondence in the real world, in order for the practitioners to interpret the model outcome, it is suggested to use empirical data to validate the emergent phenomenon. A rigorous interpretation process will facilitate the discussions on potential issues in future works on the linkages, more prominently when the model linking is done for long-term applications. *Table 2* summarises the present analysis of the linkages, reflecting the items in the *Table 1* checklist.

Funded by
the European Union

Table 2: Summary of the linkage evaluation based on the checklist

Type of considerations	Checklist item	GCAM~>TIAM	GCAM~>EDM-I	GCAM~>MARIO	MARIO~>WILIAM
Linking across temporal and spatial scales	(ii)	None of the links aimed at increasing the spatiotemporal granularity of the analysis. The practitioners tried to overcome the differences in the models.			
	(iii)	Practitioners indicated that ***regional mapping*** was done. ***No major*** temporal inconsistency.	Practitioners indicated that ***regional mapping*** was done. ***No major*** temporal inconsistency.	***No*** mention of regional mapping. ***No major*** temporal inconsistency.	***No*** mention of regional mapping. ***No major*** temporal inconsistency.
	(iv)	The foresights are ***different***. This could have been discussed or reflected as inconsistency in the interpretation stage.	The foresights are ***different***. This could have been discussed or reflected as inconsistency in the interpretation stage.	***Both*** are myopic.	***Both*** are myopic.
System boundaries, variable definitions, and harmonisation	(viii)	***Partial*** harmonisation while there is significant overlap, ***non-exhaustive*** identification of potential exchange points between the models, ***some inconsistency*** in underlying narratives and variable definitions, and ***limited*** discussion on the implications of partial harmonisation in the interpretation stage.	***Partial*** harmonisation where there is potential for a more comprehensive one, ***incomplete*** identification of potential exchange points between the models, ***Potential inconsistency*** in variable definitions, and ***limited*** discussion on the implications of partial harmonisation in the interpretation stage.	***Partial*** harmonisation while there is substantial overlap, ***incomplete*** identification of potential exchange points between the models, ***Potential inconsistency*** in underlying narratives and variable definitions, and ***no*** discussion on the implications of partial harmonisation in the interpretation stage.	***Partial*** harmonisation while there is substantial overlap, ***incomplete*** identification of potential exchange points between the models, ***Potential inconsistency*** in underlying narratives and variable definitions, and ***no*** discussion on the implications of partial harmonisation in the interpretation stage.

Type of considerations	Checklist item	GCAM~>TIAM	GCAM~>EDM-I	GCAM~>MARIO	MARIO~>WILIAM
	(ix)	Lack of transparency and detailed documentation	Lack of transparency and detailed documentation	Lack of transparency and detailed documentation.	Lack of transparency and detailed documentation
Data exchange implementation	(xi)	No standardised process of data exchange, e.g., data template and automation			
Model linking as an epistemological problem	(xiii)	The study could have benefited from mapping of epistemic foundations and discussion on how to synthesise and reconcile the models			
	(xiv)	Introduction of model characteristics, but not detailed discussion on how the model results should be understood			
	(xv)	No mention of potential errors due to inconsistencies, error propagation, and compromises made			
	(xvi)	No separate section for model interpretation and discussion of emergent properties			

Funded by the European Union

Bibliography

AL KHOURDAJIE, A., SKEA, J. & GREEN, R. 2024. Climate ambition, background scenario or the model? Attribution of the variance of energy-related indicators in global scenarios. Energy and Climate Change, 5, 100126.

AUER, C., KRIEGLER, E., CARLSEN, H., KOK, K., PEDDE, S., KREY, V. & MÜLLER, B. 2021. Climate change scenario services: From science to facilitating action. One Earth, 4, 1074-1082.

BAUMSTARK, L., BAUER, N., BENKE, F., BERTRAM, C., BI, S., GONG, C. C., DIETRICH, J. P., DIRNAICHNER, A., GIANNOUSAKIS, A. & HILAIRE, J. 2021. REMIND2. 1: transformation and innovation dynamics of the energy-economic system within climate and sustainability limits. Geoscientific Model Development Discussions, 2021, 1-50.

BELETE, G. F., VOINOV, A. & LANIAK, G. F. 2017. An overview of the model integration process: From pre-integration assessment to testing. Environmental modelling & software, 87, 49-63.

BLANCO, H., LEAVER, J., DODDS, P. E., DICKINSON, R., GARCÍA-GUSANO, D., IRIBARREN, D., LIND, A., WANG, C., DANEBERGS, J. & BAUMANN, M. 2022. A taxonomy of models for investigating hydrogen energy systems. Renewable and Sustainable Energy Reviews, 167, 112698.

BRINKERINK, M., ZAKERI, B., HUPPMANN, D., GLYNN, J., GALLACHÓIR, B. Ó. & DEANE, P. 2022. Assessing global climate change mitigation scenarios from a power system perspective using a novel multi-model framework. Environmental Modelling & Software, 150, 105336.

BUDZINSKI, M., WOOD, R., ZAKERI, B., KREY, V. & STRØMMAN, A. H. 2024. Coupling energy system models with multi-regional input-output models based on the make and use framework–insights from MESSAGEix and EXIOBASE. Economic Systems Research, 36, 508-526.

CALVIN, K., WISE, M., CLARKE, L., EDMONDS, J., KYLE, P., LUCKOW, P. & THOMSON, A. 2013. Implications of simultaneously mitigating and adapting to climate change: initial experiments using GCAM. Climatic Change, 117, 545-560.

CAPROS, P., DE VITA, A., TASIOS, N., SISKOS, P., KANNAVOU, M., PETROPOULOS, A., EVANGELOPOULOU, S., ZAMPARA, M., PAPADOPOULOS, D. & NAKOS, C. 2016. EU Reference Scenario 2016-Energy, transport and GHG emissions Trends to 2050.

CASSETTI, G., BOITIER, B., ELIA, A., LE MOUËL, P., GARGIULO, M., ZAGAMÉ, P., NIKAS, A., KOASIDIS, K., DOUKAS, H. & CHIODI, A. 2023. The interplay among COVID-19 economic recovery, behavioural changes, and the European Green Deal: An energy-economic modelling perspective. Energy, 263, 125798.

CHANG, M., LUND, H., THELLUFSEN, J. Z. & ØSTERGAARD, P. A. 2023. Perspectives on purpose-driven coupling of energy system models. Energy, 265, 126335.

CHIODI, A., TAYLOR, P. G., SEIXAS, J., SIMÕES, S., FORTES, P., GOUVEIA, J. P., DIAS, L. & Ó GALLACHÓIR, B. 2015. Energy policies influenced by energy systems modelling—case studies in UK, Ireland, Portugal and G8. Informing Energy and Climate Policies Using Energy Systems Models: Insights from Scenario Analysis Increasing the Evidence Base, 15-41.

CLEMINS, P., TURNBULL, S., RODGERS, M. & ZIA, A. 2020. Implementing a Loosely-Coupled Integrated Assessment Model in the Pegasus Workflow Management System. Practice and Experience in Advanced Research Computing 2020: Catch the Wave.

COINTE, B. 2024. The AR6 Scenario Explorer and the history of IPCC Scenarios Databases: evolutions and challenges for transparency, pluralism and policy-relevance. npj Climate Action, 3, 3.

CONNOLLY, D., LUND, H., MATHIESEN, B. V. & LEAHY, M. 2010. A review of computer tools for analysing the integration of renewable energy into various energy systems. Applied energy, 87, 1059-1082.

CULTICE, B., IRWIN, E. & JONES, M. 2023. Accounting for spatial economic interactions at local and meso scales

Funded by the European Union

in integrated assessment model (IAM) frameworks: challenges and recent progress. Environmental Research Letters, 18, 035009.

DEANE, J., CHIODI, A., GARGIULO, M. & GALLACHÓIR, B. P. Ó. 2012. Soft-linking of a power systems model to an energy systems model. Energy, 42, 303-312.

DEELMAN, E., VAHI, K., JUVE, G., RYNGE, M., CALLAGHAN, S., MAECHLING, P. J., MAYANI, R., CHEN, W., DA SILVA, R. F. & LIVNY, M. 2015. Pegasus, a workflow management system for science automation. Future Generation Computer Systems, 46, 17-35.

DEKKER, M. M., HOF, A. F., VAN DEN BERG, M., DAIOGLOU, V., VAN HEERDEN, R., VAN DER WIJST, K.-I. & VAN VUUREN, D. P. 2023. Spread in climate policy scenarios unravelled. Nature, 624, 309-316.

DEL GRANADO, P. C., VAN NIEUWKOOP, R. H., KARDAKOS, E. G. & SCHAFFNER, C. 2018. Modelling the energy transition: A nexus of energy system and economic models. Energy strategy reviews, 20, 229-235.

DIETRICH, J. P., BODIRSKY, B. L., HUMPENÖDER, F., WEINDL, I., STEVANOVIĆ, M., KARSTENS, K., KREIDENWEIS, U., WANG, X., MISHRA, A. & KLEIN, D. 2019. MAgPIE 4–a modular open-source framework for modelling global land systems. Geoscientific Model Development, 12, 1299-1317.

FAIS, B., KEPPO, I., ZEYRINGER, M., USHER, W. & DALY, H. 2016. Impact of technology uncertainty on future low-carbon pathways in the UK. Energy Strategy Reviews, 13, 154-168.

FATTAHI, A., SIJM, J. & FAAIJ, A. 2020. A systemic approach to analyze integrated energy system modelling tools: A review of national models. Renewable and Sustainable Energy Reviews, 133, 110195.

FÖRSTER, H., SCHUMACHER, K., DE CIAN, E., HÜBLER, M., KEPPO, I., MIMA, S. & SANDS, R. D. 2013. European energy efficiency and decarbonization strategies beyond 2030—a sectoral multi-model decomposition. Climate Change Economics, 4, 1340004.

FRAGKOS, P., TASIOS, N., PAROUSSOS, L., CAPROS, P. & TSANI, S. 2017. Energy system impacts and policy implications of the European Intended Nationally Determined Contribution and low-carbon pathway to 2050. Energy Policy, 100, 216-226.

FRICKO, O., HAVLIK, P., ROGELJ, J., KLIMONT, Z., GUSTI, M., JOHNSON, N., KOLP, P., STRUBEGGER, M., VALIN, H. & AMANN, M. 2017. The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century. Global Environmental Change, 42, 251-267.

FRYSZTACKI, M. M., HÖRSCH, J., HAGENMEYER, V. & BROWN, T. 2021. The strong effect of network resolution on electricity system models with high shares of wind and solar. Applied Energy, 291, 116726.

FUHRMAN, J., BERGERO, C., WEBER, M., MONTEITH, S., WANG, F. M., CLARENS, A. F., DONEY, S. C., SHOBE, W. & MCJEON, H. 2023. Diverse carbon dioxide removal approaches could reduce impacts on the energy–water–land system. Nature Climate Change, 13, 341-350.

FUJIMORI, S., OSHIRO, K., NISHIURA, O., HASEGAWA, T. & SHIRAKI, H. 2024. Integration of a computable general equilibrium model with an energy system model: Application of the AIM global model. Environmental Modelling & Software, 178, 106087.

GAMBHIR, A., BUTNAR, I., LI, P.-H., SMITH, P. & STRACHAN, N. 2019. A review of criticisms of integrated assessment models and proposed approaches to address these, through the lens of BECCS. Energies, 12, 1747.

GASKINS, D. W. & WEYANT, J. P. 1993. Model comparisons of the costs of reducing CO 2 emissions. The American Economic Review, 83, 318-323.

GIAROLA, S., MITTAL, S., VIELLE, M., PERDANA, S., CAMPAGNOLO, L., DELPIAZZO, E., BUI, H., KRAAVI, A. A., KOLPAKOV, A. & SOGNNAES, I. 2021. Challenges in the harmonisation of global integrated assessment models: A comprehensive methodology to reduce model response heterogeneity. Science of The Total Environment, 783, 146861.

GOLDHABER-FIEBERT, J. D. 2012. Accounting for biases when linking empirical studies and simulation models. SAGE Publications Sage CA: Los Angeles, CA.

GONG, C. C., UECKERDT, F., PIETZCKER, R., ODENWELLER, A., SCHILL, W.-P., KITTEL, M. & LUDERER, G. 2023. Bidirectional coupling of the long-term integrated assessment model REgional Model of INvestments and Development (REMIND) v3. 0.0 with the hourly power sector model Dispatch and Investment Evaluation Tool with Endogenous Renewables (DIETER) v1. 0.2. Geoscientific Model Development, 16, 4977-5033.

HÄFELE, W. 1980. A global and long-range picture of energy developments. Science, 209, 174-182.

HALL, L. M. & BUCKLEY, A. R. 2016. A review of energy systems models in the UK: Prevalent usage and categorisation. Applied Energy, 169, 607-628.

HARMSEN, M., KRIEGLER, E., VAN VUUREN, D. P., VAN DER WIJST, K.-I., LUDERER, G., CUI, R., DESSENS, O., DROUET, L., EMMERLING, J. & MORRIS, J. F. 2021. Integrated assessment model diagnostics: key indicators and model evolution. Environmental Research Letters, 16, 054046.

HASEGAWA, T., FUJIMORI, S., ITO, A., TAKAHASHI, K. & MASUI, T. 2017. Global land-use allocation model linked to an integrated assessment model. Science of The Total Environment, 580, 787-796.

HAVLÍK, P., SCHNEIDER, U. A., SCHMID, E., BÖTTCHER, H., FRITZ, S., SKALSKÝ, R., AOKI, K., DE CARA, S., KINDERMANN, G. & KRAXNER, F. 2011. Global land-use implications of first and second generation biofuel targets. Energy policy, 39, 5690-5702.

HENKE, H., DEKKER, M., LOMBARDI, F., PIETZCKER, R., FRAGKOS, P., ZAKERI, B., RODRIGUES, R., SITARZ, J., EMMERLING, J. & FATTAHI, A. 2024. Comparing energy system optimisation models and integrated assessment models: Relevance for energy policy advice. Open Research Europe, 3, 69.

HERGER, N., SANDERSON, B. M. & KNUTTI, R. 2015. Improved pattern scaling approaches for the use in climate impact studies. Geophysical Research Letters, 42, 3486-3494.

HUPPMANN, D., GIDDEN, M., FRICKO, O., KOLP, P., ORTHOFER, C., PIMMER, M., KUSHIN, N., VINCA, A., MASTRUCCI, A. & RIAHI, K. 2019. The MESSAGEix Integrated Assessment Model and the ix modelling platform (ixmp): An open framework for integrated and cross-cutting analysis of energy, climate, the environment, and sustainable development. Environmental Modelling & Software, 112, 143-156.

JONES, C. G., ADLOFF, F., BOOTH, B. B., COX, P. M., EYRING, V., FRIEDLINGSTEIN, P., FRIELER, K., HEWITT, H. T., JEFFERY, H. A. & JOUSSAUME, S. 2024. Bringing it all together: science priorities for improved understanding of Earth system change and to support international climate policy. Earth System Dynamics, 15, 1319-1351.

KARAMANEAS, A., KOASIDIS, K., FRILINGOU, N., XEXAKIS, G., NIKAS, A. & DOUKAS, H. 2023. A stakeholder-informed modelling study of Greece's energy transition amidst an energy crisis: The role of natural gas and climate ambition. Renewable and Sustainable Energy Transition, 3, 100049.

KEPPO, I., BUTNAR, I., BAUER, N., CASPANI, M., EDELENBOSCH, O., EMMERLING, J., FRAGKOS, P., GUIVARCH, C., HARMSEN, M. & LEFEVRE, J. 2021. Exploring the possibility space: taking stock of the diverse capabilities and gaps in integrated assessment models. Environmental Research Letters, 16, 053006.

KEPPO, I., GHADAKSAZ, H., ZAMANIPOUR, B., KORSBAKKEN, J. I., GAMBHIR, A., F., N. & NIKAS, A. 2023. IAM_COMPACT_D3.4_Model_Interlinkages_&_Integration. Zenodo.

KREY, V., HAVLIK, P., KISHIMOTO, P., FRICKO, O., ZILLIACUS, J., GIDDEN, M., STRUBEGGER, M., KARTASASMITA, G., ERMOLIEVA, T. & FORSELL, N. 2020. Messageix-globiom documentation-2020 release.

KROOK-RIEKKOLA, A., BERG, C., AHLGREN, E. O. & SÖDERHOLM, P. 2017. Challenges in top-down and bottom-up soft-linking: Lessons from linking a Swedish energy system model with a CGE model. Energy, 141, 803-817.

KUMAR, S., THAKUR, J., CUNHA, J. M., GARDUMI, F., KÖK, A., LISBOA, A. & MARTIN, V. 2023. Techno-economic

Funded by
the European Union

optimisation of the industrial excess heat recovery for an industrial park with high spatial and temporal resolution. Energy Conversion and Management, 287, 117109.

KUMBAROĞLU, G. & MADLENER, R. 2003. Energy and climate policy analysis with the hybrid bottom-up computable general equilibrium model SCREEN: the case of the Swiss CO 2 act. Annals of Operations Research, 121, 181-203.

KYLE, P., THOMSON, A., WISE, M. & ZHANG, X. 2015. Assessment of the importance of spatial scale in long-term land use modelling of the Midwestern United States. Environmental Modelling & Software, 72, 261-271.

LAURENT, A., WEIDEMA, B. P., BARE, J., LIAO, X., MAIA DE SOUZA, D., PIZZOL, M., SALA, S., SCHREIBER, H., THONEMANN, N. & VERONES, F. 2020. Methodological review and detailed guidance for the life cycle interpretation phase. Journal of industrial ecology, 24, 986-1003.

LE PAGE, Y., WEST, T. O., LINK, R. & PATEL, P. 2016. Downscaling land use and land cover from the Global Change Assessment Model for coupling with Earth system models. Geoscientific Model Development, 9, 3055-3069.

LEIMBACH, M., HUEBLER, M., MAHLKOW, H., MONTRONE, L., BUKIN, E., FELBERMAYR, G., KALKUHL, M., KOCH, J., MARCOLINO, M. & POTHEN, F. 2024. Macroeconomic structural change likely increases inequality in India more than climate policy. Environmental Research Letters, 19, 044070.

LI, P.-H., PYE, S., KEPPO, I., JAXA-ROZEN, M. & TRUTNEVYTE, E. 2023. Revealing effective regional decarbonisation measures to limit global temperature increase in uncertain transition scenarios with machine learning techniques. Climatic Change, 176, 80.

MARANGONI, G., TAVONI, M., BOSETTI, V., BORGONOVO, E., CAPROS, P., FRICKO, O., GERNAAT, D. E., GUIVARCH, C., HAVLIK, P. & HUPPMANN, D. 2017. Sensitivity of projected long-term CO2 emissions across the Shared Socioeconomic Pathways. Nature Climate Change, 7, 113-117.

MCGOOKIN, C., SÜSSER, D., XEXAKIS, G., TRUTNEVYTE, E., MCDOWALL, W., NIKAS, A., KOASIDIS, K., FEW, S., ANDERSEN, P. D. & DEMSKI, C. 2024. Advancing participatory energy systems modelling. Energy Strategy Reviews, 52, 101319.

MESSNER, S. & SCHRATTENHOLZER, L. 2000. MESSAGE–MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively. Energy, 25, 267-282.

MILLOT, A., LUBELLO, P., TENNYSON, E. M., MUTEMBEI, M., AKUTE, M., MENTIS, D., PYE, S., HAWKES, A. & STERL, S. 2024. The map behind the roadmap—Introducing a geospatial energy model for utility-scale solar and wind power buildout in Kenya. Cell Reports Sustainability, 1.

MOURATIADOU, I., BIEWALD, A., PEHL, M., BONSCH, M., BAUMSTARK, L., KLEIN, D., POPP, A., LUDERER, G. & KRIEGLER, E. 2016. The impact of climate change mitigation on water demand for energy and food: An integrated analysis based on the Shared Socioeconomic Pathways. Environmental Science & Policy, 64, 48-58.

MULUGETTA, Y., SOKONA, Y., TROTTER, P. A., FANKHAUSER, S., OMUKUTI, J., SOMAVILLA CROXATTO, L., STEFFEN, B., TESFAMICHAEL, M., ABRAHAM, E. & ADAM, J.-P. 2022. Africa needs context-relevant evidence to shape its clean energy future. Nature Energy, 7, 1015-1022.

NIKAS, A. 2024. Projecting progress in sustainable development goals vis-à-vis climate action in climate-economy models. PLOS Climate, 3, e0000449.

NIKAS, A., DOUKAS, H. & PAPANDREOU, A. 2019. A detailed overview and consistent classification of climate-economy models. Understanding risks and uncertainties in energy and climate policy: Multidisciplinary methods and tools for a low carbon society, 1-54.

NIKAS, A., FRILINGOU, N., HEUSSAFF, C., FRAGKOS, P., MITTAL, S., SAMPEDRO, J., GIAROLA, S., SASSE, J.-P., RINALDI, L. & DOUKAS, H. 2024. Three different directions in which the European Union could replace Russian natural gas. Energy, 290, 130254.

NIKAS, A., SKALIDAKIS, S., SORMAN, A. H., GALENDE-SANCHEZ, E., KOASIDIS, K., SEREPAS, F., VAN DE VEN, D.-J., MORENO, J., KARAMANEAS, A. & KOUTSELLIS, T. Integrating integrated assessment modelling in support of the Paris Agreement: The I2AM PARIS platform. 2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA), 2021. IEEE, 1-8.

NISHIURA, O., KREY, V., FRICKO, O., VAN RUIJVEN, B. & FUJIMORI, S. 2024. Integration of energy system and computable general equilibrium models: An approach complementing energy and economic representations for mitigation analysis. Energy, 296, 131039.

ODENWELLER, A. 2022. Climate mitigation under S-shaped energy technology diffusion: Leveraging synergies of optimisation and simulation models. Technological Forecasting and Social Change, 178, 121568.

OECD 2024. Approaches to linking models to assess the impacts of climate change mitigation actions on greenhouse gas emissions. Inclusive Forum on Carbon Mitigation Approaches Papers, No. 6.

PETERS, G. P., AL KHOURDAJIE, A., SOGNNAES, I. & SANDERSON, B. M. 2023. AR6 scenarios database: an assessment of current practices and future recommendations. npj Climate Action, 2, 31.

REIS, L. A., DROUET, L. & TAVONI, M. 2022. Internalising health-economic impacts of air pollution into climate policy: a global modelling study. The Lancet Planetary Health, 6, e40-e48.

RISING, J. A. 2017. A flexible approach to model coupling through probabilistic pooling. Environmental Modelling & Software, 93, 409-417.

ROBINSON, D. T., DI VITTORIO, A., ALEXANDER, P., ARNETH, A., BARTON, C. M., BROWN, D. G., KETTNER, A., LEMMEN, C., O'NEILL, B. C. & JANSSEN, M. 2018. Modelling feedbacks between human and natural processes in the land system. Earth System Dynamics, 9, 895-914.

SAHOO, S., VAN STRALEN, J. N., ZUIDEMA, C., SIJM, J. & FAAIJ, A. 2023. Regionally integrated energy system detailed spatial analysis: Groningen Province case study in the northern Netherlands. Energy Conversion and Management, 277, 116599.

SHIVAKUMAR, A., ALFSTAD, T. & NIET, T. 2021. A clustering approach to improve spatial representation in water-energy-food models. Environmental Research Letters, 16, 114027.

SHUKLA, P. R., SKEA, J., SLADE, R., AL KHOURDAJIE, A., VAN DIEMEN, R., MCCOLLUM, D., PATHAK, M., SOME, S., VYAS, P. & FRADERA, R. 2022. Climate change 2022: Mitigation of climate change. Contribution of working group III to the sixth assessment report of the Intergovernmental Panel on Climate Change, 10, 9781009157926.

SIALA, K. & MAHFOUZ, M. Y. 2019. Impact of the choice of regions on energy system models. Energy Strategy Reviews, 25, 75-85.

SILVAST, A., LAES, E., ABRAM, S. & BOMBAERTS, G. 2020. What do energy modellers know? An ethnography of epistemic values and knowledge models. Energy Research & Social Science, 66, 101495.

SKEA, J., SHUKLA, P., AL KHOURDAJIE, A. & MCCOLLUM, D. 2021. Intergovernmental Panel on Climate Change: Transparency and integrated assessment modelling. Wiley Interdisciplinary Reviews: Climate Change, 12, e727.

SOERGEL, B., KRIEGLER, E., WEINDL, I., RAUNER, S., DIRNAICHNER, A., RUHE, C., HOFMANN, M., BAUER, N., BERTRAM, C. & BODIRSKY, B. L. 2021. A sustainable development pathway for climate action within the UN 2030 Agenda. Nature Climate Change, 11, 656-664.

SOGNNAES, I. & PETERS, G. 2025. Influence of individual models and studies on quantitative mitigation findings in the IPCC Sixth Assessment Report.

STERL, S., HUSSAIN, B., MIKETA, A., LI, Y., MERVEN, B., BEN TICHA, M., ELABBAS, M., THIERY, W. & RUSSO, D. 2022. An all-Africa dataset of energy model "supply regions" for solar photovoltaic and wind power. Sci Data. 2022; 9 (1): 664.

TAN, J., DUAN, Q., XIAO, C., HE, C. & YAN, X. 2023. A brief review of the coupled human-Earth system modelling:

Current state and challenges. The Anthropocene Review, 10, 664-684.

USHER, W. & RUSSELL, T. 2019. A software framework for the integration of infrastructure simulation models. Journal of Open Research Software, 7.

VAN BEEK, L., HAJER, M., PELZER, P., VAN VUUREN, D. & CASSEN, C. 2020. Anticipating futures through models: the rise of Integrated Assessment Modelling in the climate science-policy interface since 1970. Global Environmental Change, 65, 102191.

VAN DE VEN, D.-J., NIKAS, A., KOASIDIS, K., FOROULI, A., CASSETTI, G., CHIODI, A., GARGIULO, M., GIAROLA, S., KÖBERLE, A. C. & KOUTSELLIS, T. 2022. COVID-19 recovery packages can benefit climate targets and clean energy jobs, but scale of impacts and optimal investment portfolios differ among major economies. One earth, 5, 1042-1054.

VAN DE VEN, D.-J., SAMPEDRO, J., JOHNSON, F. X., BAILIS, R., FOROULI, A., NIKAS, A., YU, S., PARDO, G., DE JALÓN, S. G. & WISE, M. 2019. Integrated policy assessment and optimisation over multiple sustainable development goals in Eastern Africa. Environmental Research Letters, 14, 094001.

VAN VUUREN, D. P., BAYER, L. B., CHUWAH, C., GANZEVELD, L., HAZELEGER, W., VAN DEN HURK, B., VAN NOIJE, T., O'NEILL, B. & STRENGERS, B. J. 2012. A comprehensive view on climate change: coupling of earth system and integrated assessment models. Environmental research letters, 7, 024012.

VAN VUUREN, D. P., LUCAS, P. L. & HILDERINK, H. 2007. Downscaling drivers of global environmental change: Enabling use of global SRES scenarios at the national and grid levels. Global environmental change, 17, 114-130.

VERBURG, P. H., DEARING, J. A., DYKE, J. G., VAN DER LEEUW, S., SEITZINGER, S., STEFFEN, W. & SYVITSKI, J. 2016. Methods and approaches to modelling the Anthropocene. Global Environmental Change, 39, 328-340.

WACHSMUTH, J. & DUSCHA, V. 2019. Achievability of the Paris targets in the EU—the role of demand-side-driven mitigation in different types of scenarios. Energy Efficiency, 12, 403-421.

WEST, T. O., LE PAGE, Y., HUANG, M., WOLF, J. & THOMSON, A. M. 2014. Downscaling global land cover projections from an integrated assessment model for use in regional analyses: results and evaluation for the US from 2005 to 2095. Environmental Research Letters, 9, 064004.

Funded by
the European Union