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Model linking for low-carbon transitions: Technical and conceptual challenges and best practices

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ABSTRACT

Linking existing models to extend energy system and integrated assessment analysis is an increasingly common practice. Despite this, and unlike in the field of environmental and earth sciences, little attention has so far been paid to the details of it, to the trade-offs involved and the way in which the model linking affects the interpretation of the outcomes of the interlinked model system. Our aim in this paper is to first focus on a set of key technical and methodological problems that are common in model linking and suggest how these could be approached in different model linking contexts. We then further explore how model linking may affect the nature of the knowledge produced, and how this should be considered in the model linking process. Reflecting our literature driven assessment of the issues and possible solutions, we compile "a check list" to assist in the process of decision making for model linking.

1. Introduction

Energy-system models (ESMs) and integrated assessment models (IAMs) have been key tools for assessing the progress towards achieving various climate goals, developing pathways consistent with specific climate 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

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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 [1]. The models have extensively influenced decision-making at national and international levels (e.g., Refs. [2–4]), while also playing a central role in producing the scientific evidence underlying climate negotiations and underpinning the agreed climate goals [5,6].

The initial focus of modelling and long-term scenarios was predominantly on technical assessments of the energy system [7,8]. In time, however, and with increasing awareness of the urgency of climate action, the importance of covering more relevant sectors—and the interlinkages between them—has increased (e.g. Refs. [9–13]), and so has the computational capacity to cover these sectors and their interlinkages in more detail, thereby leading to increasingly complex and computationally intensive models. As extending the model boundaries would further complicate the models, a common approach to enabling ever broader and more detailed assessments is to create linkages between existing models, and to endogenise the cross-system interactions through these linkages (e.g. Refs. [14–17]). 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 (e.g. see Refs. [18,19]). 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., Ref. [20])—or for capturing effects of climate action from a sustainability perspective [21]. Model linking has thus not only allowed the model-based analysis to make explicit and cover the impacts of cross-system interactions, which in turn enables more integrated analysis of energy, climate, and sustainability challenges, but also adds a level of detail and granularity previously unavailable. Thus, it can be argued, the benefits of model linking are clear and persuasive.

As common as model linking is for IAMs and ESMs, 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 context specific 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 takes 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 not been at the center 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 assess low-carbon transitions, and carry out a narrative review to identify and discuss a set of key problems that should be addressed when linking models, as well as how these may depend on the characteristics of the specific models involved. We use the outcomes of this review and analysis to propose a practical check-list, to be used when planning a model linking activity.

While model linking has traditionally been mostly a pragmatic endeavor, there also exists research focussing 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. Refs. [9, 22–24]), but these papers are typically general and conceptual, without directly addressing the practical complexities of carrying out the actual model linking. A recent paper [25], while focused on exploring the benefits of linking three specific model types (agent based models, CGE models and IAMs), does also offer an insightful, albeit short, discussion of model linking issues related to e.g. scales, interoperability, and model calibration.

Model linking within the environmental and earth sciences, however, has a much richer literature on model linking as a problem by itself. Models such as Earth System Models, Vegetation Demographic Models, and Land Use Change Models (LUC) generally focus on the biophysical characteristics of the systems, such as atmospheric and ocean physics and chemistry and land cover, ecology and dynamic vegetation growth [26,27].Verburg et al. [28], 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 discussed also 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. [29], in turn, explore the ways in which earth system models and IAMs have been linked, especially focussing 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 their associated challenges, nor suggest ways forward. Similarly, Van Vuuren et al. [27] also discuss linking earth system models and IAMs, with the focus on the nature of the linkage (e.g., one-way linkage or full coupling, the latter interpreted in this paper to imply full integration of an IAM within the earth system model), 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. [26], in turn, discuss human-natural systems model coupling, i.e. tools that link models focused on human decision-making with those describing e.g. the biophysical processes in detail. Their paper zooms in on land use and the type of model links used, and draws eight lessons that, - while reflecting the very specific examples used, - 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, also features in the literature. Belete et al. [30], for example, primarily discuss the technical and software side of model linking, although their take on pre-integration assessment and data interoperability provides important observations, e.g., about variable definitions and purpose of the model integration.

Similarly, Usher and Russell [31] present a framework for integrating infrastructure models - in their case defined as "Models of transport, energy, solid waste, water supply and digital communications [...]" - but with the focus strictly on software implementation, and only briefly noting problems related to model linking across temporal scales.

Finally, and as noted above, many of the potential complications related to model linking are driven by the differences e.g. in the structure, internal rationale and scope of models to be linked, typically in various dimensions. 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 categorized—see e.g. Refs. [32–34], as well as Keppo et al. [35] and the references within. Such "model typologies" can help in understanding how given models to be linked differ, in which dimensions the differences are particularly important, and how the differences affect the interpretation of the modelling outcomes.

In the following sections we will first discuss the technical considerations for model linking in three key areas emerging from the literature (Section 2), which serves as a foundation for the subsequent discussion on before continuing to discuss how model linking may affect the interpretation of the knowledge derived with the linked model system(Section 3). We conclude by providing our checklist for establishing links between models (Section 4).

2. 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. 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 [36], explore distinct solution spaces and sets of uncertainties for different contexts [37], and, overall, address the diversity of shortcomings associated with exercises of limited spatiotemporal detail in IAMs [38]. The aim, however, may not always be to benefit from the difference in scales, 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. More complex methods also require more human resources for their development.

The first order of trade-offs concerns the *extent of linking* (such as hard linking or soft linking) used for linking across spatial and temporal scales. Soft-linking typically means a linking process in which results are transferred from one model to another more manually, with direct user control, whereas hard-linked models typically run in parallel, constantly exchange data based on predefined algorithms and produce one set of results [39].

For instance, Fattahi et al. [36] 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 IAMs and/or ESMs with different spatial and temporal resolutions. Gong et al. [40], for example, address the lack of temporal detail in an IAM (REMIND) by an iterative soft linkage with an annual, single-region, hourly power system model (DIETER), exchanging data on annual costs and capacities (from REMIND) and average market values (DIETER) until convergence in electricity-prices and quantities is reached. The analysis, however, lacks spatial detail and the scope is limited to one region (Germany). Frysztacki et al. [41] highlight the strong effect that spatial network resolution in electricity system models has on key variables, such as least-cost penetration of variable renewables: If ESMs with low temporal or spatial resolution are soft-linked with high-resolution electricity system models (e.g., hourly dispatch models with numerous nodes to represent an electricity grid), the capacity expansion results from the former may be too low-resolved and sub-optimal, making the dispatch analysis less reliable. Kumar et al. [42] attempt to increase both 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, albeit again doing so for a limited geographical scope.

Rather than linking models [43–45], increase the spatial detail in ESMs by clustering regions with similar demand and/or supply characteristics. Such an approach has the benefit of keeping the computational load manageable, but it loses the information on the topology of infrastructure, making it unsuitable for network-focused analyses. Sahoo et al. [46], on the other hand, break down a province-scale model into geographic regions (municipalities and high-density areas within them), thus retaining a certain level of information on the network topology. The level of granularity achievable by regionalising a model with a feasible computational load, however, depends on the scale of the model. If the model is at national or continental scale, the level of granularity achieved by Sahoo et al. will require significantly higher computational load. Similarly, coupling complex General Circulation Models (GCMs) with IAMs of different complexity and temporal resolution has been addressed by means of different statistical methods (e.g., emulators, machine learning, etc.) [47]. The simplification of processes using averaged relationships in emulators might not, however, be able to capture the nonlinear feedbacks 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 [48].

The second order of trade-offs concerns *how the spatial disaggregation is treated in model links*. Cultice et al. [49] highlight that spatial granularity is necessary in IAMs for representing spatial economic interactions at local and meso scales (the former intended as the set of economic and environmental interactions happening in the order of 1 km, the latter as the processes and dynamics linking local to global realities), and to capture their effects on global dynamics. They also discuss recent progress in detailing spatial economic and biophysical dynamics using multi-scale, multi-module[1] IAMs. However, this level of detail often comes at the cost of reaching spatial equilibrium (i.e. a state at which no agent is better off relocating anymore, given the decisions of other agents [49]), due to the high computational power and time required. On the other hand, when using a single model, the spatial and cross-system detail that can be achieved is usually limited. Using a global IAM (GCAM) but focussing on dynamics within an individual study region, Kyle et al. [50] 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 is the limited representation of drivers and dynamics of land use changes. This includes for instance lack of constraints related to protected lands or

[1] In the literature term "module" is typically used when referring to a smaller component of the full model, often explicitly designed for the model.

productivity [51], inability to show land use changes in each direction [52], or 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 [53]). There exist country-scale model applications that use integrated resource management optimisation techniques to determine land use changes at higher spatial resolution and clustering techniques to reduce computational load [54]. 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 guidance for how the potentially different rationales underlying the models affect the interpretation of the linked model system (see Section 3). Reconciling differences in spatial resolution while ensuring computational feasibility is also a challenge when linking GCMs and IAMs: 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 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 [55,56], suggest a hybrid approach combining statistical downscaling with dynamic feedbacks 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, when linking existing, stand-alone models. Much like stakeholders in societal contexts where decisions are made, strictly formalised modelling frameworks often apply different foresight for their decision-making. While different foresights of linked models can complicate the linking process, it can also be beneficial in better reflecting some aspects of real-world dynamics; decisions made by the agents with short-term foresight (e.g., prioritising immediate gains) will affect also the agents with longer decision horizons (e.g., long-term strategic planning). As an example of linking across time horizons, Leimbach et al. [57] input global tradable energy commodity prices and carbon prices from a perfect-foresight IAM into two myopic-foresight trade models. The latter 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. Different foresights are also common in modelling electricity system capacity planning and dispatch. Kleanthis et al. [58], for example, present a methodological framework in which the capacity expansion tool first plans the system for a longer time horizon and a dispatch tool is then used to test and refine the flexibility options deployed. In the last step, the capacity expansion model is run again, with the additional flexibility options included. This approach does not, however, necessarily lead to an optimal system, as the temporally more granular modelling optimizes flexibility in the context of a specific initial design – and the design can, by definition, not consider possible flexibility issues.

The more feedbacks and variables exchanged between models with different foresights, however, the more complicated and iterative the linking process becomes. Does one, for example, run a model with a longer decision horizon first, to provide boundary conditions for the short-term tools, and then recalculate those boundary conditions once the short-terms models have been run? Depending on the temporal granularity of the myopic tools, this can lead to an extensive set of iteration loops (see also section 2.3, on model convergence).

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 (as done by Sahoo et al. [46], see the discussion above). This is more feasible the smaller the scale of the original model. 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. 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 later section).

2.2. System boundaries, variable definitions, and harmonisation

For model linking to be feasible, model 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 system boundaries do not overlap and contact points are 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., Ref. [59]). The output of many IAMs is used as input into simple climate models for climate assessments, with various harmonisation and infilling steps required to make a consistent assessment [60]. More integrated examples are ESMs linked with land-use models and simple climate models, such as the 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 [14] 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 [61].

More complex linking exercises involve partially or fully overlapping system boundaries resulting in larger sets of contact points formed by variables that are endogenous in both models and multiple 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 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 of the TIMES-Sweden model with the EMEC model in a Swedish case [62], the soft-linking between PRIMES and other national energy system models with the global Computable General Equilibrium GEM-E3 Model [63] and linking the ESM EU-TIMES with the NEMESIS macroeconometric model [64]. In these cases, for example, the energy systems are fully encompassed in the economic descriptions, but the latter are more aggregated and abstracted for many of the variables of the former. As a consequence, extensive mappings between variables representing energy and macroeconomy in the involved models need to be created that account for diverging sector boundaries and the representation of variables (e.g. physical units vs. monetary units).

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 supply 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 2.1). For example, an IAM (or ESM) 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 had 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 the needs for heating and cooling in housing), ignoring them can create inconsistencies.

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 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, the 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 [65]. Finally, in absence of full harmonisation, one can try to link models using relative changes (rather than absolute values, see e.g. Ref. [63]), although this naturally harms consistency across the models.

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 [66] as well as the IAMC scenario submission template (also in context of contributing to the IPCC WGIII assessment—see Ref. [67]) can help in harmonising similar system boundaries and variables (including units of measurement) as an intermediary between two models. Other approaches, such as Open Energy Ontology[2] for ESMs and Functional Mock-up Interface for simulation tools, serve a similar purpose.[3] 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 feedbacks are captured and models are iterated until convergence is reached [68]. 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, convergence will not be guaranteed, and it may not always be trivial to communicate the information in a way that allows the other model to react—see also Section 2.1 as well as [26,27,29] for previous work on various approaches to linking and how the information flows between the models.

2.3. 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 [30]. The latter plays a critical role, as the needs for data exchange are radically different between approaches such as soft links and hard links (see Section 2.1). Since hard-linking is usually significantly more time- and resource-consuming [20], soft links have been traditionally used to connect IAMs and ESMs with various types of models, *inter alia* macroeconomic [69–71], Multi-Regional Input and Output [72], technology diffusion [73], or power systems models [74].

For IAMs, this exchange has been facilitated by standards such as the IAMC template,[4] which offers a structured format for exchanging modelling results and has been established in the community through large model intercomparisons, feeding into IPCC assessments [66]. 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. What's more, the specific template may be less suitable for some models, making it burdensome to use [67]. While many efforts to harmonise result variables or region names are underway—e.g., see Ref. [75], the nomenclature Python package,[5] and automated data validation applications[6]—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 [19]. This can be partly addressed by building specific

2 https://openenergyplatform.org/ontology/.
3 https://modelon.com/blog/functional-mock-up-interface-fmi/.
4 https://data.ene.iiasa.ac.at/database/.
5 https://nomenclature-iamc.readthedocs.io/en/stable/.
6 https://github.com/ciceroOslo/iamcompact-validation-ui.

platforms to coordinate the model linking. Such platforms already exist in other research fields, such as the Pegasus system [76], which has been used for over a decade to manage the computational workflows and data exchange between models in astronomy, bioinformatics, physics, and elsewhere. A Pegasus workflow is built by defining the inputs and outputs of different tasks within the model linking application (e.g., run model A based on inputs from model B), which are then executed based on a directed acyclic graph and without requiring a common ontology between models. Recently, Pegasus has been used to coordinate model linking in an IAM [77], 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 [30], 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 [78] or to deliver data to non-modelling stakeholders in order to validate them [79]. There are several examples of web interfaces showing modelling results to experts and non-experts, such as the I^{2}AM PARIS platform [80], the Senses Toolkit [81], or the upcoming Scenario Compass,[7] which could potentially connect to API-enabled models and visualise their results.

Model APIs could be especially interesting in bi-directional 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., Ref. [71]). The more models are involved, the more contact points (and therefore 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., Ref. [82]), which would also ensure the quality of the model linking [30]. For instance, the final results derived from models linked for a mitigation study could be used to create diagnostic indicators such as the relative abatement index [82] and compared against benchmarks for feasibility, similar to the vetting process of the 6th Assessment Report of the IPCC.

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 bi-directional 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.

[7] https://scenariocompass.org/process.

3. Model linking as an epistemological problem

The structure of individual models embeds implicit assumptions that shape how their results should be interpreted (e.g. Ref. [83]). Different model types incorporate distinct epistemic values and trade-offs in areas like *accuracy*, *simplicity*, and *system representation* [84]. For instance, the choice of system boundaries, spatiotemporal scales, and variable definitions—not to mention the complexity of model linking processes (see Section 2)—all shape the nature and validity of knowledge that an individual model can generate. These structural elements often reflect the modeller's conceptualization of the system and can introduce biases or limitations in the knowledge generated [85,86]. A model that assumes constant technological progress, for example, may overlook potential disruptive innovations [87], 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 [88].

Beyond the technical hurdles outlined in Section 2, linking models raises deeper epistemological questions, that is, fundamental issues concerning the nature, validity, and interpretation of the 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.

Interpreting how the outcomes of a specific model and modelling exercise should be understood is nontrivial (e.g. Refs. [89–92]). When models are linked, the *synthesis of disparate knowledge strands* becomes ever more challenging. For example, coupling a prescriptive, perfect-foresight optimisation ESM (e.g., TIMES [93]) with a descriptive, myopic macroeconomic simulation model (e.g., E3ME [94]) produces a *hybrid* system with different and conflicting economic-engineering and economic solution paradigms. 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 typologies [35] can assist in this, as they are designed to differentiate models based on the various dimensions in which they may differ, thus providing an initial, more aggregated mapping for the previous.

Model linking can compound *errors and biases* across interconnected models or even introduce novel ones [95]. 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 various studies (see Refs. [96–102]) 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. Developing robust methodologies specifically designed to track and quantify the propagation and potential amplification of uncertainties, errors, and biases through the sequential steps and interfaces of model linking represents a key challenge and an important area for future research.

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 focuses 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., Ref. [103]). As Silvast et al. [84] 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 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.

4. 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 that 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 the key 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 and 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 a circumstantial, one-off activity—acknowledging that the former case requires additional considerations and guardrails. With that said, the one-off suggestions are also a minimum baseline for the strategic linking recommendation, when no new advice is offered for the same topic in the latter. We also refrain here from discussing the specific linking approaches (hard linking, bi-directional and unidirectional soft linking, etc.), as these have been previously discussed extensively (see, e.g., Ref. [27]).

The recommendations included in our checklist 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 important 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.

Credit statement

Conceptualization; IK, Investigation: All authors, Writing – original draft: IK, AAK, FG, GH, AN, GX, NFA, HG, SM, BZ, Writing – review & editing. All authors

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

Type of considerations	Checklist
Linking across temporal and spatial scales	i) If the aim of the linking is not to increase the spatial or temporal granularity of the analysis, and there is an option to link models of similar temporal and/or spatial scope or granularity, then practitioners should prioritise linking such models. ii) Model linking explicitly aiming to increase the spatial or temporal granularity of the analysis requires significantly more robust approaches than if the core purpose of the linking exercise is to simply overcome the spatial and temporal differences that exist in two models linked for other purposes. iii) Upscaling and downscaling approaches (e.g. clustering) can be useful for moving data from one model to another – but with limitations (see (v) below). iv) If models with different foresight assumptions are linked, attention should be paid to the design and process of the 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 vi) The extent to which the spatial and temporal dimensions of the models to be linked can be harmonized 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 harmonized 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 parametrization. Adequate time within the linking process should be devoted to 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, 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, 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 feedbacks 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 strategic model-linking for long-term application: xvii) In the light of the epistemological points discussed, for strategic model linking the inconsistencies should be minimized 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 inadvisable to create "permanent" models for which the interpretation of results has obvious ambiguities.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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