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Coupling an integrated assessment model with an input–output database

Nicolas Dai[a], Qiyu Liu[b], Mengyu Li[a], Arunima Malik[a,c] and Manfred Lenzen[a]

[a]ISA, School of Physics A28, The University of Sydney, Sydney, Australia; [b]Department of Space, Earth and Environment, Energy Technology, Chalmers University of Technology, Goteborg, Sweden; [c]Discipline of Accounting, Sydney Business School, The University of Sydney, Sydney, Australia

ABSTRACT
MESSAGE is an Integrated Assessment Model (IAM) useful for developing anthropogenic climate change scenarios and the evaluation of long-term energy policies. MESSAGE is constrained by its internal scenario generator, which project energy commodity demand inputs based only on population and GDP growth assumptions; the lack of sectoral and supply-chain details prevents modeling impacts from develpoments in non-energy sectors. Here we link MESSAGEix-Australia, a national-level MESSAGE IAM variant, to an input-output scenario builder to generate future energy commodity demands. The coupled IO_IAM framework then captures indirect energy implications of various socio-economic scenarios. Two scenarios were used to demonstrate this capability: first on the policy-based decarbonisation pathways for Australia, and second on the adoption of self-healing roads. This study showcases that a link between IO and IAM methods provides an opportunity for bringing together the strengths of the two approaches for assessing a wide range of sustainability questions.

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Integrated assessment models; Industrial ecology; energy systems modelling; input–output; MESSAGEix

1. Introduction

1.1. Background

The Intergovernmental Panel on Climate Change (IPCC) Shared Socioeconomic Pathways (SSPs) provide scenarios for decision-makers to evaluate emissions trajectories subject to assumptions about population and economic growth, technology developments, and lifestyles. These mitigation pathways are enumerated using Integrated Assessment Models (IAMs; Rogelj et al., 2018). More specifically, the IPCC tends to rely on the detailed process-based variant of IAMs (DP-IAMs), which are bottom-up, disaggregated models that provide complex representations of the interactions between the energy system, land use, the atmosphere, the global carbon cycle, radiative forcing, and the economy (Weyant, 2017). Here, the energy system is at the core of climate change mitigation pathways, where

CONTACT Nicolas Dai nicolas.dai@sydney.edu.au ISA, School of Physics A28, The University of Sydney, NSW 2006, Australia

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IAMs provide a stylised representation of energy production and transformation processes forecasted to meet the final energy requirements of a region's population. Economic variables such as GDP and commodity prices are captured by IAMs through the inclusion of a macroeconomic model.

While some IAMs allow for exogenous parameters describing energy commodity demand, the aggregated nature of these inputs does not typically allow for specifying detailed socio-economic scenarios involving technologies (e.g. low-carbon construction materials) or behaviours (e.g. diets). This shortcoming is also mirrored in their typically low sectoral resolution and lack of supply-chain features, which means that IAM scenarios may miss indirect (supply-chain) impacts such as embodied emissions. For example, IAMs' description of energy consumption associated with material production lacks sufficient detail to model the effects of recycling (Pauliuk & Hertwich, 2016). However, there is some work undertaken using Shared Socioeconomic Pathways to assess the potential of circular waste management systems (Gómez-Sanabria et al., 2022). Industrial ecology methods, such as input–output (IO) analysis, have the advantage of revealing the interactions and interdependence between sectors in an economy (Leontief, 1936).

Several approaches exist where IO analysis has been integrated into energy systems and macroeconomic models (Pauliuk et al., 2017). One of the earliest and most prominent of such integrations is the marriage of engineering-type process analysis with IO analysis into a hybrid Life-Cycle Assessment (LCA) method (Bullard et al., 1978; Heijungs, 2002). IO data have also been subjected to multi-objective Linear Programming for studying economy-energy-environment trade-offs (Daly et al., 2015; Klaassen et al., 1999; Oliveira et al., 2016), and they are routinely included in Computable General Equilibrium (CGE) models, as in the AIM/CGE model (Fujimori et al., 2017; Glynn et al., 2015) that has been applied to study national-level energy systems of Germany (Kuster et al., 2007), the United Kingdom (Strachan & Kannan, 2008) and Korea (Yun et al., 2016).

Two recent publications are of particular relevance to this work: The first describes MEDEAS, an IAM that includes an economy module based on WIOD input–output tables (Capellán-Pérez et al., 2020). The second describes the coupling of MESSAGEix and EXIOBASE (Budzinski et al., 2023). Our study differs from the former and is similar to the latter in that it attempts to use IO tables to extend an existing IAM (MESSAGEix) rather than building an IAM with an internal IO component. Our study differs from the latter in that we developed a national-level model using a detailed national IOT, such as in the approach taken by (Daly et al., 2015) and (Siala et al., 2019), who developed one-way interfaces between IOT and energy system models, albeit without allowing for iterative feedback between the two models.

1.2. Aims, scope, and contribution of this work

The purpose of this study is to develop an integration of an IAM and an IO model to extend the capabilities of both. To this end, we develop a method that contributes two advances: (a) the feeding of an IAM with sectorally and behaviourally detailed socio-economic-demographic scenarios derived from IO data, and (b) the use of IAM's energy carrier mix as a way to project IO data into the future. To serve our purpose, we use the MESSAGE model (Model for Energy Supply Strategy Alternatives and their General Environmental Impact), an IAM developed by the International Institute for Applied Systems Analysis

(IIASA). The SSP scenarios examined by MESSAGE and other IAMs are used by the IPCC to advise policymakers (Fricko et al., 2017).

The MESSAGE model's ability to model technological and behavioural scenarios is limited by how it forecasts energy demands. The MESSAGE model takes a set of final energy requirements as exogenous inputs, broken down into energy carriers such as coal, crude oil, and hydroelectricity, and expressed in energy units. By default, these energy requirements are derived from energy service demands, such as residential and commercial thermal, industrial thermal, industrial feedstock, etc. These service demands are generated via a scenario generator created by fitting historical data on final energy, GDP, and population, along with projected GDP and population from the SSP database. Therefore, MESSAGE does not provide a way to consider the energy requirement of non-energy commodities and the interactions between sectors in value chains, in addition to a lack of supply chain features. Its aggregation over non-energy commodities also prevents the IAM from modelling specific socio-economic-demographic trends that involve, for example, dietary choices or transitions from physical travel to virtual communication.

Therefore, we propose an *IO scenario builder* employing a detailed IO database to build these scenarios. In this approach, final energy requirements input for the IAM are derived from monetary final demand data in the IO database. Second, we propose an *IAM-IO energy-mix adjustment*, by which the IAM-optimised least-cost energy mix is used to adjust the energy system transactions in the IO database. This adjustment of the IO production recipe allows the A matrix to shift over time. The IAM-adjusted IO database is then used by the *scenario builder* in the subsequent time step to compute the final energy requirements for the next period. This final energy requirement is then passed back again into the IAM as the exogenous demand, reinitiating the *energy-mix adjustment* step for the next period, and so on. The IAM-IO loop can be invoked repeatedly, effectively realising a future projection of the IO database's energy-system substructure.

In this study, the MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) IAM framework was selected for having a suitable entry point in the source code as well as for accepting the final energy requirement as an exogenous parameter. One prominent model from the ix modelling platform implementation of the framework is the MESSAGE*ix*-GLOBIOM, which incorporates the GLobal BIOsphere Management (GLOBIOM); this model is used to quantify SSPs (Fricko et al., 2017). A national variant for Australia, MESSAGEix-Australia, was created in this study and then linked to an IO scenario builder constructed using the Australian Industrial Ecology Virtual Laboratory (IELab; Lenzen et al., 2014).

In the following, we demonstrate the application of our linked IAM-IO model by using two scenarios. In the first, IO tables incorporate indirect emissions in the evaluation of incentive-based decarbonisation pathways in Australia. In the second, results from a hybrid LCA study of long-term road surface replacement are incorporated into MESSAGEix-Australia via the IO link without changing the background processes of IAMs as was necessary in prior studies (Mendoza Beltran et al., 2020).

2. Methods

This study involved the development of an Australian IAM model to link to an IO database in the Australian IELab. This section will describe the rationale behind using MESSAGE,

Table 1. IAM selection criteria.

Integrated Assessment Models/Criterion	AIM/CGE	GCAM	IMAGE	MESSAGEix-GLOBIOM	REMIND
Open Access	User manual available online, but source code not accessible	Open Access	User manual available, but source code not accessible	Open Access and full license for development	Access of source code for validation purpose only
Exogenous Final Energy Requirement Generation	Final energy requirements are linked to the income estimation model	Final energy requirement of bioenergy linked to the agricultural model	Hard linked to TIMER model	Exogenous 'scenario generator'	Hard linked to 'Energy transformation Technologies' model

the way MESSAGE Australia was created with publicly available data, how the IELab IO database is used to generate energy demands based on scenarios, and how the IAM-IO energy mix adjustment link is implemented.

2.1. Model selection

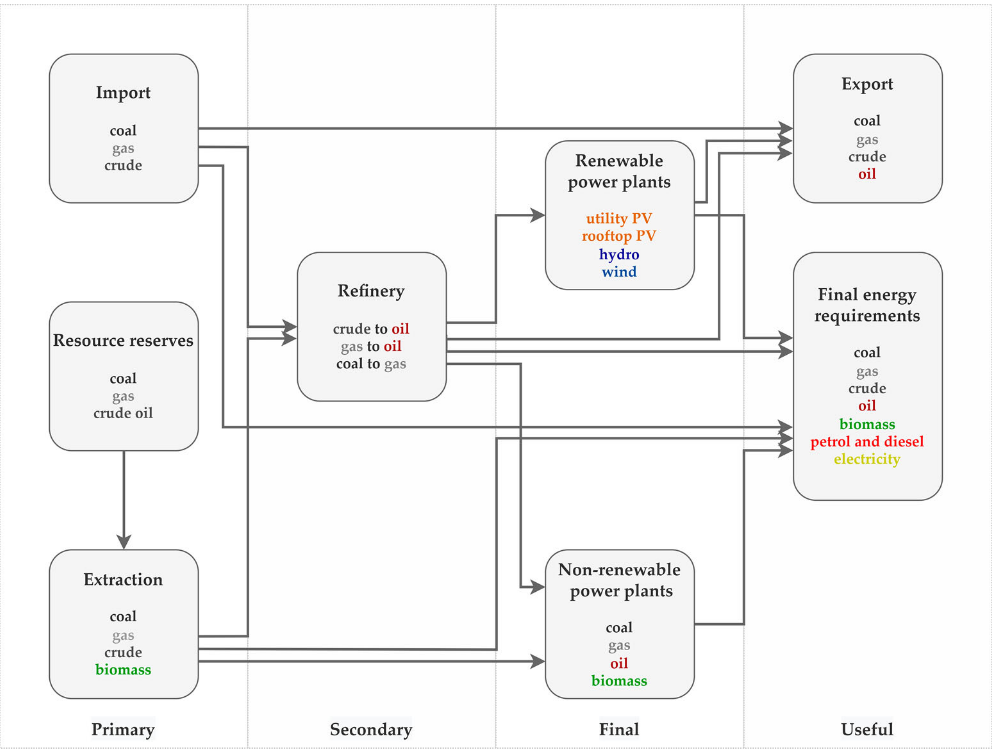
Two important criteria for selecting a suitable IAM for an IAM-IO link are (i) code access and support and (ii) exogenously specified energy demand. This is because the IAM code is first needed for modification and enhancement towards facilitating an iterative IAM-IO interplay. Second, the IAM-IO linking process benefits from the IAM having an exogenous final energy requirement parameter instead of relying on an endogenous component part of the model, because an exogenous IAM component is easily replaced with an IO-based module.

We considered five widely used IAMs during this study: the Asia-Pacific Integrated Assessment Model/Computable General Equilibrium (AIM/CGE; Fujimori et al., 2012), Global Change Analysis Model (GCAM; Thomson et al., 2011), Integrated Model to Assess the Global Environment (IMAGE; Vuuren et al., 2011), Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE; Huppmann et al., 2019), and Regional Model of Investment and Development (REMIND; Bauer et al., 2013). Table 1 shows that MESSAGE is the only model that fully fulfils both our criteria and was, therefore, the chosen model to trial our ideas.

MESSAGE depends on an exogenous scenario model to determine energy demand requirements at each timestep, which we can replace with an IO-based module. Code access is available through MESSAGEix, an open-source implementation of the MESSAGE IAM on the ix-modelling platform. It was developed and maintained by the International Institute for Applied System Analysis (IIASA; Huppmann et al., 2019). The code for ix is open-access and available for researchers to build their own models.

MESSAGEix uses a set of linear programming equations coded in the General Algebraic Modelling System (GAMS) to find the least-cost-optimised final energy requirements of Australia's energy system. MACRO is the macroeconomic model coupled with MESSAGEix to capture and endogenise macroeconomic effects (e.g. commodity prices) on the

Figure 1. Stylised representation of the MESSAGEix-Australia model.



energy system (Messner & Schrattenholzer, 2000). MACRO determines end-use energy demand, given a sequence of optimal savings, investment, and consumption decisions.

2.2. MESSAGEix-Australia model implementation

We first developed MESSAGEix-Australia, a national MESSAGE variant based on Australian data. MESSAGEix-Australia is built with various ‘blocks’ representing commodities or technologies in a hierarchical structure. The MESSAGEix-Australia model includes four levels, starting with the import and extraction of coal, natural gas, and crude oil (primary), via crude oil refining (secondary), and power generation (final), and ending with useful energy for domestic consumption and export. Renewable power plants are constrained by upper bounds derived from resource variability data and reliability criteria (Sullivan et al., 2013). The primary level represents the input of primary commodities into the model through imports and extraction. The secondary level represents the refining process of crude oil into various petroleum products. The final level represents renewable and fossil-fuel based electricity generation. In total, 14 energy commodities represent the Australian energy system (Figure 1).

The Shared Socioeconomic Pathways database compiled by IIASA (Riahi et al., 2017) was used as a starting point for data collection for MESSAGEix-Australia and the MACRO model. The MACRO parameters are taken directly from IIASA’s database (Krey et al., 2016) to ensure consistency with existing studies. Given that MESSAGEix-GLOBIOM was one of the original contributing models of SSP 2 ‘middle of the road’ (Fricko et al., 2017; Riahi et al., 2017), the SSP 2 GDP growth dataset was used in developing MESSAGEix-Australia. We again implemented MESSAGEix-Australia with five-year-stepped results, from 2015 to 2050, to be consistent with the SSPs and focus on medium-range projection of Australia’s energy system.

We follow the approaches of other national-level MESSAGEix models by initially using exogenously supplied final energy requirements data. For example, in the MESSAGEix Brazil and South Africa variants (Lucena et al., 2010; Orthofer et al., 2019), the final energy requirements are derived from data published by the International Energy Agency. For Australia’s business-as-usual (BAU) scenario, final energy requirement data are taken from the Australian Energy Statistics (Department of Industry Science Energy and Resources, 2020). The Department publishes comprehensive annual data sets on the consumption, production, and trade of energy commodities in Australia. We use their statistics on energy consumption as final energy requirements in our BAU scenario. The consumption of refined petroleum products from the AES is also used in the refinery technology parameters. The energy supply and trade data sets are used in the import, export, and extraction parameters. The data set on electricity generation informs the base-year (2015) activities for each power plant type.

On top of the physical energy demand and supply data, MESSAGEix requires information on the costs associated with each parameter. The input cost data for various power generation technologies are taken from a GIS-based energy supply-demand study (Li et al., 2020). The parameters for prices of energy commodities are derived from average quarterly spot prices published in Australian Wholesale and Market Statistics by the Australian Energy Regulator (AER; Australian Energy Regulator, 2020). The prices of crude oil and retail petroleum are taken from the Australian Institute of Petroleum (AIP)’s database (Australian Institute of Petroleum, 2020). No official database for coal prices exists, so the average coal prices are synthesised from various grey literature sources (Orthofer et al., 2019; Ycharts, 2020; Index Mundi, 2020).

The IAM is designed with an upper bound placed on renewable power plants. The purpose of these upper bounds is to ensure that the share of renewable power plants grows at a technically feasible rate. Two additional cumulative caps are placed on rooftop PV deployment and on the weighted average of emissions over the entire time horizon in MESSAGEix-Australia. The former cap is calculated based on the estimate of total available rooftop spaces in Australian residential homes, ensuring that the area of rooftop PVs does not exceed available roof space.

Renewable power plant capacity factors are introduced to reflect that they are operating at a variable rate (Sullivan et al., 2013). Fossil-fueled, biomass, and hydropower plants are – at least in principle – operational at nominal capacity 24 h a day. However, this is not the case for renewable power plants; for example, solar PV requires sunshine and wind turbines are dependent on wind speed. The capacity factor dictates that for a percentage of time, solar PV and wind turbines will be offline, and fossil-fuel power plants will kick in to meet the shortfall. Coal-, gas- and oil-based power plants are mutual substitutes; MESSAGEix endogenously determines which fossil-fuel power plant type is recruited.

2.3. IO scenario builder

The IO scenario builder uses an IO database constructed in the Industrial Ecology Lab (IELab; Lenzen et al., 2017), a cloud computing platform that provides users with the capabilities to assemble their own individual IO databases. The IO database constructed for this project features particular detail in energy-related sectors, supported by life-cycle assessment data on crude oil refining (Wang et al., 2004). The two main components of an IO database are the intermediate transactions matrix $\mathbf{T}$ $(N'N)$ and the final demand matrix $\mathbf{Y}$ $(N'M)$, both expressed in monetary units. The sum of intermediate and final demand defines the total output of the economy $(N'1)$

$$\mathbf{X} = \mathbf{T1}^{\mathbf{T}} + \mathbf{Y1}^{\mathbf{Y}}, \tag{1}$$

where $1^{\mathrm{T}} = \{\underbrace{1, 1, \ldots 1}_{N}\}$ and $1^{\mathrm{Y}} = \{\underbrace{1, 1, \ldots 1}_{M}\}$ are row summation operators. Writing

$$\mathbf{X} = \mathbf{AX} + \mathbf{Y1}^{\mathbf{Y}} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{Y1}^{\mathbf{Y}} = \mathbf{LY}1^{\mathbf{Y}}, \tag{2}$$

yields Leontief's fundamental demand-pull formulation, where $\mathbf{A} = \mathbf{T}\hat{\mathbf{X}}^{\mathbf{-1}}$ $(N'N)$ is called the input coefficients matrix, the hat (^) symbol denotes vector diagonalisation, $\mathbf{I}$ is an $N'N$ identity matrix, and $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is Leontief's inverse $(N'N)$. In essence, Equation (2) enables computing the total output $\mathbf{x}$ required to satisfy a given final demand bundle $\mathbf{Y}$. As $\mathbf{T}$ describes the interdependence of intermediate sectors, $\mathbf{L}$ captures both direct and indirect supply-chain effects.

The monetary IO database can be extended to non-monetary dimensions, using so-called satellite accounts $\mathbf{E}$ containing a $J'N$ set of physical indicators (e.g. resources or pollution). In our application, these extensions allow for energy quantities to be included in Equation (2) (Lam et al., 2019), which is necessary for calculating final energy requirements. In analogy to $\mathbf{A} = \mathbf{T}\hat{\mathbf{x}}^{-1}$, we can define satellite coefficients $\mathbf{e} = \mathbf{E}\hat{\mathbf{x}}^{-1}$ $(J'N)$, and extend Leontief's demand-pull equation to

$$\mathbf{E} = \mathbf{E}1^{\mathbf{T}} = \mathbf{ex} = \mathbf{e}(\mathbf{I} - \mathbf{A})^{-1}\mathbf{Y}1^{\mathbf{Y}} = \mathbf{eLY}1^{\mathbf{Y}} = \mathbf{mY}1^{\mathbf{Y}}, \tag{3}$$

The elements of $\mathbf{m} = \mathbf{eL}$ $(J'N)$ are called satellite multipliers. As with $\mathbf{x}$, $\mathbf{mY}$ represents the physical quantities (eg resources or pollution) required to satisfy a given final demand bundle $\mathbf{Y}$. As with $\mathbf{L}$, the multipliers $\mathbf{m}$ capture all direct and indirect supply-chain effects arising from the economic activity given by final demand $\mathbf{Y}$.

Equation (3) precisely represents the IO scenario builder. Using the detailed categories offered in the IO database, a scenario is defined as a future projection of $\mathbf{Y}$ scaled based on a single year's GDP $\mathbf{mY}$ specifies the direct and indirect final energy requirements including those from economic activity in non-energy (e.g. agriculture, construction, services, etc.) industries.

The IO database $\{\mathbf{Q}, \mathbf{T}, \mathbf{Y}\}$ used in this work distinguishes $J = 19$ energy carriers, $N = 142$ industry sectors, and $M = 6$ final demand destinations, where $\mathbf{Q}$ is the IO satellites. The IO database's energy-system substructure counts $N_E = 14$ energy sectors. This large number of categories offers ample opportunities for exploring different socio-economic and technological trajectories.

2.4. IAM-IO coupling

There are three principal steps in the iterative link between MESSAGEix-Australia and the two IO modules (scenario builder and energy mix adjustment) (Figure 2).

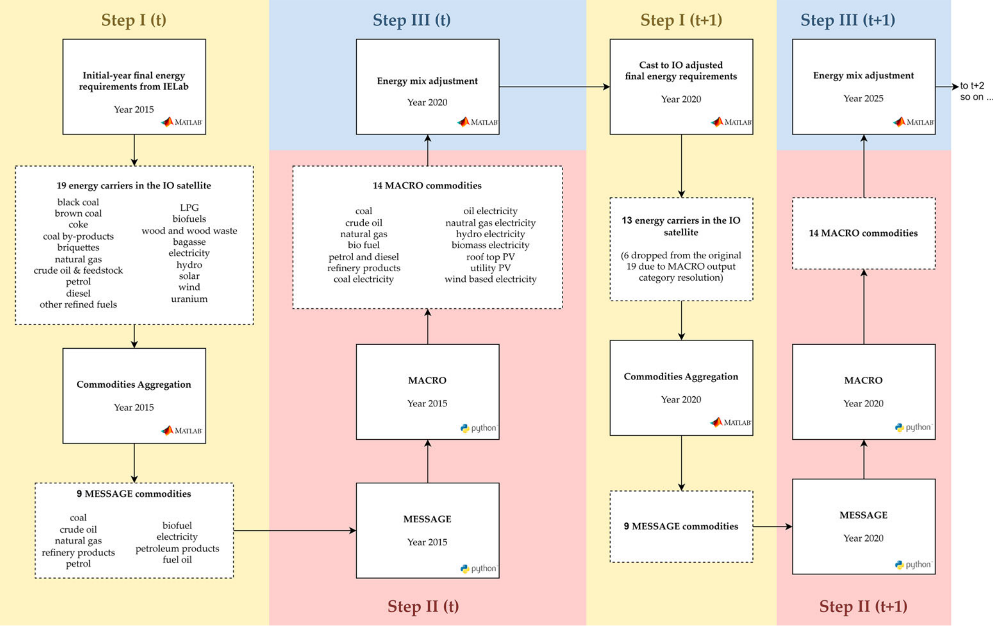
Step I	**Scenario builder** – yellow: the IO database is used to calculate the final energy demand requirements in terms of 19 energy carriers distinguished by the IO satellite **Q**. These 19 carriers are aggregated into the $K = 9$ energy types E^t (i.e. $\mathrm{E}^{t=2015}$) for input into MESSAGE.
Step II	**MESSAGE-MACRO** – red: calling MESSAGEix-Australia, the IAM then generates least-cost-optimised year-t economy-wide energy use for $L = 14$ energy sectors. The original MESSAGE-MACRO formulation is unchanged.
Step III	**Energy mix adjustment** – blue: the optimised energy carrier mix is used to update the energy transactions in the IO database for the next timestep. Then, a new step I ensues, and a new final energy demand requirement (19 energy carriers) is produced using the updated IO data. These 19 carriers are once again aggregated into the 9 MESSAGE-compatible inputs, and a new step I ensues.

These steps are repeated iteratively, with GHG emissions calculated at each timestep. To integrate the year-on-year output of the IAM with the IOT, we iteratively alternate between the IAM solver and IO database updates.

2.5. Energy mix adjustment

In order to integrate the year-on-year output of the IAM with exogenous demand projections as well as Australia's IO structure, we iteratively alternate between the IAM solver and IO procedures, transforming the output of one into the input of the other. This alternation works as follows: In the first step, starting with the IAM stepping from year t to year $t+1$, we obtain year-$(t+1)$ IAM output $\mathbf{E}^{t+1}$, as $E^{t+1}_{n=1,\ldots,N}$ for $N = 14$ energy carriers. We then

Figure 2. IAM-IO link iteration process.



cast this output into the IO system's $M_\mathrm{e} = 9$ energy sectors, using an $N \times M_\mathrm{e}$ concordance matrix $\mathbf{C}$ as $e_{m=1,\ldots,M_\mathrm{e}}^{t+1} = \sum_{n=1,\ldots,N} E_n^{t+1} C_{n,m=1,\ldots,M_\mathrm{e}}$.

The IO procedures (Section 2.3) provide a year-$(t+1)$ monetary final demand vector $\mathbf{y}^{t+1}$ and input coefficients matrix $\mathbf{A}^{t+1}$. However, the energy sector entries in the IO system are unlikely to obey the energy carrier shares determined by the IAM. Therefore, in the second step, we need impose the year-$(t+1)$ energy carrier shares computed by the IAM onto the year-$(t+1)$ IO quantities. In principle, this could be done by converting the IAM's energy-unit output into monetary values, using energy prices. However, such prices differ substantially between intermediate and final demand, and even between sectors, and are not readily known at the detail contained in the IO classification. A more straightforward way that does not rely on price information is to scale IO entries in the same proportions as year-on-year IAM energy shares.

To accomplish this, we construct an $M_\mathrm{e} \times M_\mathrm{e}$ energy substitution concordance $\mathbf{S}$, in which element (i,j) is 1, if energy carriers substitute for energy carrier j, and 0 otherwise. This means that, by default, diagonal elements S_{ii} of S equal 1. The M_e energy carrier shares $\mu_{m=1,\ldots,M_\mathrm{e}}^{t+1}$ prescribed by the IAM output are then $\mu_m^{t+1} = e_m^{t+1} / \sum_k S_{mk} e_k^{t+1}$. To illustrate this principle, take the example of $\mathbf{e}^{t+1} = \begin{array}{c} \text{Fuel oil} \\ \text{Fossil electricity} \\ \text{Renewable electricity} \end{array} \begin{bmatrix} 46 \\ 50 \\ 20 \end{bmatrix}$, and $\mathbf{S} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix}$, yielding $\mathbf{S}\mathbf{e}^{t+1} = \begin{bmatrix} 46 \\ 70 \\ 70 \end{bmatrix}$ and $\boldsymbol{\mu}^{t+1} = \begin{bmatrix} 1.00 \\ 0.71 \\ 0.29 \end{bmatrix}$. Since fuel oil does not substitute for electricity, its sole and own share is 1. Fossil and renewable electricity substitute for one another, and their shares in their common total of 65 units are 71% and 29%, respectively.

As determined by the IAM, the energy carrier mix undergoes annual changes, which the IO system must represent in order to integrate appropriately into the IAM-IO alternation. This is ensured by scaling the IO monetary quantities in the same way as the IAM scales physical quantities. Assume that, in determining its year-$(t+1)$ output, the IAM has shifted the energy carrier mix from $\mathbf{e}^t$ to $\mathbf{e}^{t+1}$, yielding shares $\boldsymbol{\mu}^t$ and $\boldsymbol{\mu}^{t+1}$. Whilst absolute energy demands scale as $\eta_{m=1,\ldots,M_\mathrm{e}}^t = e_m^y / e_m^{y-1}$ or $\boldsymbol{\eta}^{t+1} = \mathbf{e}^{t+1} \widehat{\mathbf{e}^t}^{-1}$, carrier mixes (ratios) scale as $\sigma_{m=1,\ldots,M_\mathrm{e}}^t = \mu_m^y / \mu_m^{y-1}$ or $\boldsymbol{\sigma}^{t+1} = \boldsymbol{\mu}^{t+1} \widehat{\boldsymbol{\mu}^t}^{-1}$. Using our numerical example above, and assuming $\mathbf{e}^t = \begin{array}{c} \text{Fuel oil} \\ \text{Fossil electricity} \\ \text{Renewable electricity} \end{array} \begin{bmatrix} 40 \\ 60 \\ 5 \end{bmatrix}$ and $\boldsymbol{\mu}^t = \begin{bmatrix} 1.00 \\ 0.92 \\ 0.08 \end{bmatrix}$, we obtain $\boldsymbol{\eta}^{t+1} = \begin{bmatrix} 1.15 \\ 0.83 \\ 3.00 \end{bmatrix}$ and $\boldsymbol{\sigma}^{t+1} = \begin{bmatrix} 1.00 \\ 0.77 \\ 3.63 \end{bmatrix}$. This means that in this illustrative example, fuel oil demand increases by 15%, fossil electricity demand decreases by 17%, and renewable electricity demand increases three-fold. The share of fuel oil within its group of substitutes remains at 100%, the share of fossil within total electricity declines by 23%, and the share of renewable within total electricity increases by 3.63-fold.

In a third step, we now scale the IO system accordingly, as $\mathbf{y}^{t+1} \rightarrow \hat{\boldsymbol{\eta}}^{t+1} \mathbf{y}^{t+1}$ and $\mathbf{A}^{t+1} \rightarrow \hat{\boldsymbol{\sigma}}^{t+1} \mathbf{A}^{t+1}$. Note that the IO system distinguishes $M > M_\mathrm{e}$ sectors, so that the diagonal matrix $\hat{\boldsymbol{\sigma}}$ is constructed as an $M \times M$ identity matrix, with only the M_e energy sectors entries specified as $\boldsymbol{\eta}^{t+1}$ and $\boldsymbol{\sigma}^{t+1}$.

In a final step, we are now able to utilise the IO capability to compute total energy requirements of monetary final demand, as $\mathbf{E}^{*,t+1} = \mathbf{q}^{t+1}(\mathbf{I} - \mathbf{A}^{t+1})^{-1}\mathbf{y}^{t+1}$. $\mathbf{E}^{*,t+1}$ contains the IO-based adjustments of the year-$(t+1)$ IAM output $\mathbf{E}^{t+1}$. $\mathbf{E}^{*,t+1}$ specifies the direct and indirect energy requirements not just of the energy sectors, but for exogenously specified trajectories of economic activity in energy and non-energy (e.g. agriculture, construction, services, etc.) industries.

3. Scenarios and results

Two scenarios based on policy and technology implementation were modelled using the IAM-IO technique described in the previous section. The first of the two scenarios tested in this study is a decarbonisation pathway facilitated by carbon pricing. The second scenario derives from a hybrid Life Cycle Analysis (LCA) of an advanced road surface construction and maintenance technology (Rodríguez-Alloza et al., 2019).

3.1. Scenario 1 – Australian decarbonization pathway

3.1.1. Scenario description

MESSAGEix-Australia simulates decarbonisation pathways through substitution between carbon-intensive and clean technologies. For example, once carbon taxes or renewable subsidies are introduced, solar PV is expected to replace coal-fired power plants. The MESSAGEix-Australia model is thus able to simulate the decarbonisation of a power grid at a detailed technology level. Using the IAM-IO linked model in this scenario, we will demonstrate how IO adjustment iterations of the IAM-IO linked model results differ from standalone MESSAGEix-Australia forecasts by capturing the impacts of indirect emissions associated with renewable energy. Previous research suggests that the indirect carbon footprint of renewable generation range between 12 to 60 gCO2e per kWh (Wolfram et al., 2016).

3.1.2. Scenario results

The IO-adjusted results reveal that if current policies were to continue into the future, the optimised fuel mix in the year 2050 would be carbon-intensive, featuring significant gas-fired power plants (Figure 3). MESSAGEix-Australia assumes a high growth rate of renewable power plants to account for their rapid market penetration. The share of natural gas-fired power plants increases while coal-fired power plants are slowly phased out due to their high cost. As expected, rooftop and utility PVs show the largest increase, while hydropower plants grow relatively slowly. Notably, wind generation does not grow and will disappear by 2035. We find that coal-fired power plants are phased out by the year 2045.

We now introduce carbon taxes to simulate the decarbonisation of the Australian power grid, initially at 5 USD/tonne, increasing by 5 USD/tonne at each time step, ending at 30 USD/tonne in 2050. No CO2 emissions are assigned to renewable power plants since the model only accounts for direct emissions during the electricity generation process and not the indirect emissions. Using the IO-adjusted scenario, we find that under this policy, Australia's fuel mix will substantially decarbonise by the year 2050 (Figure 4).

The scenario generated using the linked IAM-IO model shows increases in total final electricity requirement, facilitated by indirect supply chain impacts that the IO-scenario-builder captures. For example, every new solar PV unit installed requires manufacturing, transportation, and installation, which generate CO2 emissions that are not reflected in the unlinked MESSAGE variant. The difference in total final electricity requirements between the base IAM results and the IO-adjusted results varies at each time step (Figure 4). The

Figure 3. Energy carrier mix in the BAU scenario, with IO adjustment.

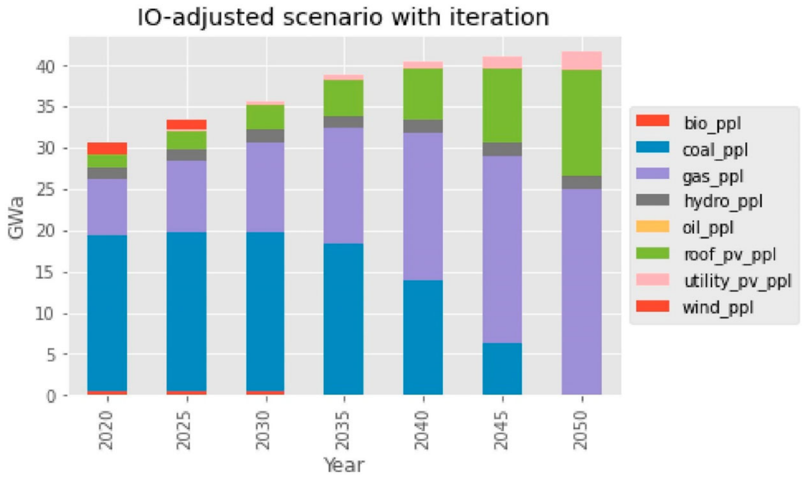
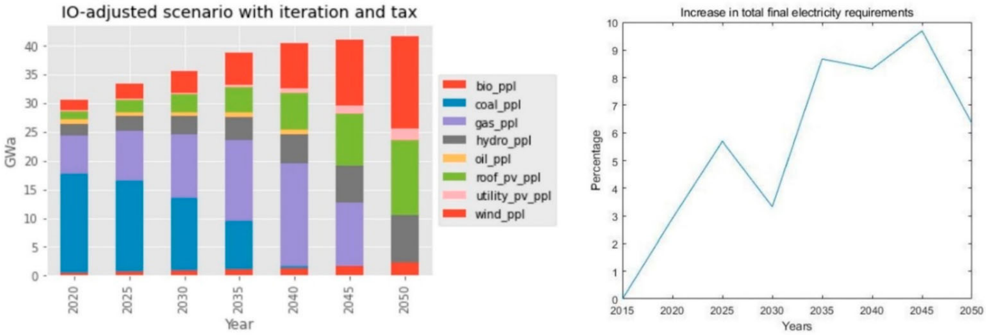


Figure 4. Left: Energy carrier mix in the policy intervention scenario, with IO adjustment. Right: Difference between the standalone and IO-IAM model.



*ppl= power plant

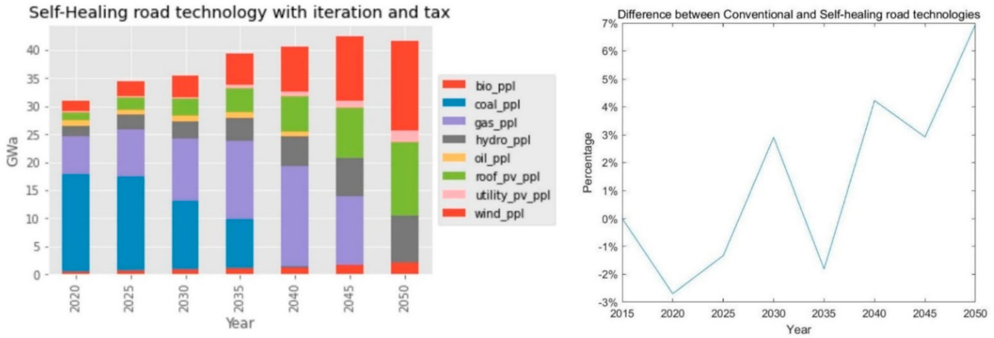
variations are caused by construction and plant life cycles, larger increases in final energy from an IO-adjusted model are expected in periods with more intense construction of new plants (Figure 5).

3.2. Scenario 2 – self-healing roads LCA

3.2.1. Scenario description

To demonstrate the applicability of the linked IAM-IO model to individual technology developments, we evaluated the impact of introducing self-healing roads. These are asphalt pavements where ageing processes are significantly slowed down by means of incorporating nanoparticles, applying induction heating during maintenance, and other rejuvenation measures (Tabaković et al., 2015). The life span of these roads is thus significantly increased, reducing the need for expensive conventional maintenance activities and substantially reducing primary energy use and greenhouse gas emissions (Rodríguez-Alloza et al., 2019).

Figure 5. Left: Self-healing road technology scenario with IO adjustment. Right: Difference between conventional road technology fuel mix.



*ppl= power plant

Here we collect data on road length and construction cost for Australian States and Territories for 1970–2015 (Rodríguez-Alloza et al., 2019) and project these 45 years – the life span of a self-healing road – into the future. To this end, we first regress past road length l in regions r by trends over time t, and find that a power function $l_r(t) = l_{0,r}(t - t_{0,r})^{\alpha_r}$ performs better than logarithmic or linear functions in terms of the R^2 performance measure. Based on these regression parameters, we then project road lengths for the 2015–2060 period (see supplementary material).

We use the projected road lengths $l_r(2015 \leq t \leq 2060)$ as well as projected inflation rates as an input into the recursive scheme presented in Equations (4–6) (Rodríguez-Alloza et al., 2019), and establish cost $\mathbf{y}_r(t)$ for roads added in region r and year t. We carry out this calculation for conventional as well as self-healing roads, yielding a sequence of final demand vectors associated with the application of both types of technology. These final demand vectors are then used to calculate the final energy requirements using the IO scenario builder. The results are subsequently fed into MESSAGEix following procedures described in the previous section. The base table and satellite account used for this calculation are identical to the ones used for previous calculations; hence, no modification to the MESSAGEix model is required. This results in a demonstration of the interplay between an LCA study and MESSAGEix.

The road construction LCA study involves many technological processes that are not directly represented in MESSAGEix-Australia, such as bitumen, construction machinery, and road freight forwarding sectors. These sectors and their associated emissions are implicitly accounted for through the corresponding end use of energy products. The IO-scenario-builder utilises the road length calculations to derive these implicit energy uses and converts them into matching commodities in MESSAGEix-Australia to enable the soft link.

3.2.2. Scenario results

The indirect impacts of the supply chain can be observed from the changes in the electricity sector. Direct electricity usage accounts for a small percentage of energy use in the implementation of road technologies, but a larger change can be observed in electricity demand. This is the indirect electricity usage by sectors such as construction machinery and road freight forwarding.

Using our road length estimates and the LCA study, we were able to produce a **y** matrix for every timestep. The results from the soft link are consistent with the original LCA results in terms of energy use trajectories (Rodríguez-Alloza et al., 2019). The only difference is that in MESSAGEix-Australia, these technologies are deployed in 2015 and not 1970. Nevertheless, the embodied-energy balance advantage of self-healing roads is clear.

The differences between the two road technology scenarios result from an interplay between construction and maintenance cycles. The life span and maintenance activity for each of the two road types differ greatly (Rodríguez-Alloza et al., 2019). The dips in 2020, 2035, and 2045 are due to new construction and periodical maintenance costs peaking for self-healing roads. The road construction LCA study involves many technological processes that are not directly represented in MESSAGEix-Australia, such as bitumen, construction machinery, and road freight forwarding sectors. These sectors and their associated emissions are implicitly accounted for through the corresponding end use of energy products.

The results demonstrate that the soft link between IO and MESSAGEix-Australia is a valuable methodology to incorporate existing hybrid-LCA results into MESSAGEix to forecast their impact on energy demands. There are many hybrid-LCA studies into emerging technologies (Teh et al., 2017; Wiedmann et al., 2011), and they could be modelled into MESSAGE through our IO scenario builder.

4. Discussion & future directions

The capabilities of MESSAGEix and IO databases are enhanced through coupling. The IO-scenario-builder captures the interactions between sectors and accounts for final energy requirements fed into MESSAGEix-Australia. Essentially, the IO module provides MESSAGE with a detailed production recipe instead of relying on MACRO’s uni-sectoral representation of the economy. The energy demand computed from IO refers to the energy required throughout the supply chain. Such ‘supply chain-wide’ energy demand goes into MESSAGE-IAM as useful energy inputs, with the corresponding ‘primary energy’ calculated. This feature allows the IAM to account for exogenous demand-side scenarios that are not directly linked to the specified energy commodities, as demonstrated in the hybrid LCA study. The IAM-IO soft-link takes advantage of MESSAGEix’s forecast energy systems into the future to complement the static IO database. Therefore, the coupled model provides a framework to forecast IO databases for the future and to account for supply-side policies. The study has successfully achieved our objective of establishing a soft-linking IO analysis with a DP IAM and demonstrating its application through two scenarios. The inclusion of results from a hybrid LCA study in this study is also a step toward Pauliuk’s vision of incorporating other methods of Industrial Ecology into the IAM community (Pauliuk et al., 2017).

This linked model is useful to policy analysis teams for government and industry associations to demonstrate the long-term indirect impact of technology adoption or behaviour changes in various sectors. For instance, the self-healing roads example used in this project could be extended to various other lower-emissions or recycled building materials that are entering the market to help identify the most promising decarbonisation strategy in the construction sector.

The limitation of this model set-up is that the input–output data are exogenous and not incorporated into the CGE formalism of MACRO. In the interest of runtime, IAMs typically feature economic modules with low sectoral resolution. Therefore, the high resolution of the input–output data comes to the fore in the scenario definitions and in the future projection of production recipes, both of which happen exogenously, i.e. outside the MESSAGE-MACRO cycle. The sectoral resolution of the input–output data surpasses that of the MACRO module, and it is not possible to make the IAM parameters in the model match the IO sectors without completely redesigning MACRO to create an IO-MACRO hard link. Similarly, the energy data in the Australian energy accounts are more detailed than the fuel types in MESSAGE. Hence, a slight aggregation happens whenever exogenous energy demands are passed into MESSAGE. Our approach of using physical ratios for monetary scaling in the input–output table reflects a fundamental assumption made throughout the input–output analysis, which is the constancy of prices across sectors using a particular commodity. In order to circumvent this, mixed- or hybrid-unit IO models may be used, and in this case, the physical IO rows would need to be adjusted using physical quantities supplied by MESSAGE. However, experience with such mixed-unit models is scarce, and physical data are not always available to represent an entire IO-table row by physical flows. Therefore, we have resorted to monetary-only IO tables. For future directions, our linked model will benefit from more detail and complexity. For example, the scaling methodology used by our IO databases scales the final demand matrix using a single uniform ratio of GDP across all sectors. However, due to supply chain dynamics, GDP does not impact all sectors in a consistent manner, and therefore, implementing a sector-by-sector scaling would result in more realistic projections of future energy mix.

It is possible to construct any number of sub-national regions into a MESSAGEix model that explicitly represents all states and territories in a country. Therefore, a more detailed MESSAGEix-Australia could be created to account for interstate interactions and take advantage of an IO table's ability to model sub-national regional dynamics.

MESSAGEix-Australia is relatively simple compared to the global-level MESSAGEix-GLOBIOM model. The scope of MESSAGEix-Australia was limited to the energy system and the economy because we were building upon prior IO-energy system linking studies (Glynn et al., 2015; Siala et al., 2019). Existing studies using national-level MESSAGEix models also exclude modules aside from MESSAGEix and MACRO (Lucena et al., 2010; Orthofer et al., 2019). Therefore, MESSAGEix-Australia so far excludes capabilities that account for the impacts of trade, and the model does not explicitly represent the transport sector. These features could be implemented in future projects.

Some of MESSAGEix-GLOBIOM features are only meaningful at the global level. We imagine that MESSAGEix-GLOBIOM itself (Krey et al., 2016) could be linked with global Multi-Regional Input–Output (MRIO) tables to access data from those modules. For example, the GLOBIOM land use model (Petr Havlík et al., 2018) is a partial equilibrium economic model designed to address various land-use-related issues. The inclusion of the GLOBIOM model could provide a more detailed account of the biofuel extraction process. The MAGICC model is a coupled atmosphere-ocean and carbon cycle model that is usually used in conjunction with MESSAGEix-MACRO to simulate the effect of change in the energy system on the climate system (Meinshausen et al., 2011). Incorporating MAGICC would provide the ability to explore how the IO scenario influences the climate system.

In this study, a soft link was accomplished by manually moving data between the IO database running on a MATLAB environment and IAM running on a Python environment. The potential implementation of a hard link between IO and MESSAGEix would offer significant benefits by fully integrating the two modules and allowing it to operate from a single point of entry. IO databases and IAMs carry uncertainties that are potentially compounded when linked together. This becomes more complex when results from existing LCA studies are included. A hard-link process will help to identify, reduce, and quantify uncertainties holistically. Another advantage of a hard link would be the ability for users of an IO database, such as IELabs (Geschke & Hadjikakou, 2017), to easily obtain the IAM model implication of their IO scenario analysis. This integration with IO databases will help build a diverse set of modelling results for both the Industrial Ecology and IAM communities to interpret.

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Model availability

Calculations provided in this study were undertaken in the Australian Industrial Ecology Virtual Laboratory. Model and code are available from the authors upon request.

ORCID

Nicolas Dai http://orcid.org/0000-0002-5924-6326

References

Australian Energy Regulator. (2020). Market Stastics Charts, Australian Government. https://www.aer.gov.au/industry/registers/charts

Australian Institute of Petroleum. (2020). Pricing. https://www.aip.com.au/pricing

Bauer, N.,Mouratiadou, I., Luderer, G., Baumstark, L., Brecha, R. J., Edenhofer, O., & Kriegler, E. (2013). Global fossil energy markets and climate change mitigation – an analysis with remind. *Climatic Change*, *136*(1), 69–82. https://doi.org/10.1007/s10584-013-0901-6

Budzinski, M., Wood, R., Zakeri, B., Krey, V., & Strømman, A. H. (2023). 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*, 1–19. https://doi.org/10.1080/09535314.2022.2158065

Bullard, C. W., Penner, P. S., & Pilati, D. A. (1978). Net energy analysis: Handbook for combining process and input-output analysis. *Resources and Energy*, *1*(3), 267–313. https://doi.org/10.1016/0165-0572(78)90008-7

Capellán-Pérez, I., de Blas, I., Nieto, J., de Castro, C., Miguel, L. J., Carpintero, Ó, Mediavilla, M., Lobejón, L. F., Ferreras-Alonso, N., Rodrigo, P., Frechoso, F., & Álvarez-Antelo, D. (2020).

MEDEAS: A new modeling framework integrating global biophysical and socioeconomic constraints. *Energy & Environmental Science*, *13*(3), 986–1017. https://doi.org/10.1039/C9EE02627D

Daly, H. E., Scott, K., Strachan, N., & Barrett, J. (2015). Indirect CO2 emission implications of energy system pathways: Linking IO and TIMES models for the UK. *Environmental Science & Technology*, *49*(17), 10701–10709. https://doi.org/10.1021/acs.est.5b01020

Department of Industry, Science, Energy and Resources. (2020). Australian Energy Update 2020, Australian Energy Statistics, September, Canberra, 2203–8337.

Fricko, O., Havlik, P., Rogelj, J., Klimont, Z., Gusti, M., Johnson, N., Kolp, P., Strubegger, M., Valin, H., Amann, M., Ermolieva, T., Forsell, N., Herrero, M., Heyes, C., Kindermann, G., Krey, V., McCollum, D. L., Obersteiner, M., Pachauri, S., … Riahi, K. (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. https://doi.org/10.1016/j.gloenvcha.2016.06.004

Fujimori, S., Hasegawa, T., Masui, T. (2017). AIM/CGE V2.0: Basic feature of the model. In S. Fujimori (Ed.), *In post-2020 climate action: Global and Asian perspectives* (pp. 305–332). Springer Singapore.

Fujimori, S., Masui, T., & Matsuoka, Y. (2012). AIM/CGE [basic] manual.

Geschke, A., & Hadjikakou, M. (2017). Virtual laboratories and MRIO analysis – an introduction. *Economic Systems Research*, *29*(2), 143–157. https://doi.org/10.1080/09535314.2017.1318828

Glynn, J., Fortes, P., Krook-Riekkola, A., Labriet, M., Vielle, M., Kypreos, S., Lehtilä, A., Mischke, P., Dai, H., Gargiulo, M., Helgesen, P. I., Kober, T., Summerton, P., Merven, B., Selosse, S., Karlsson, K., Strachan, N., Ó Gallachóir, B. (2015). Economic impacts of future changes in the energy system—global perspectives. In G. Giannakidis (Ed.), *In informing energy and climate policies using energy systems models: Insights from scenario analysis increasing the evidence base* (pp. 333–358). Springer International Publishing.

Gómez-Sanabria, A., Kiesewetter, G., Klimont, Z., Schoepp, W., & Haberl, H. (2022). Potential for future reductions of global GHG and air pollutants from circular waste management systems. *Nature Communications*, *13*(1), 106. https://doi.org/10.1038/s41467-021-27624-7

Havlík, P., Valin, H., Mosnier, A., Frank, S., Lauri, P., Leclère, D., Palazzo, A., Batka, M., Boere, E., Brouwer, A., Deppermann, A., Ermolieva, T., Forsell, N., di Fulvio, F., & Obersteiner, M. (2018). *GLOBIOM documentation*. International Institute for Applied Systems Analysis.

Heijungs, R. (2002). *The computational structure of life cycle assessment*. Kluwer Academic Publishers.

Huppmann, D., Gidden, M., Fricko, O., Kolp, P., Orthofer, C., Pimmer, M., Kushin, N., Vinca, A., Mastrucci, A., Riahi, K., & Krey, V. (2019). The MESSAGE integrated assessment model and the ix modeling platform (ixmp): An open framework for integrated and cross-cutting analysis of energy, climate, the environment, and sustainable development. *Environmental Modelling & Software*, *112*, 143–156. https://doi.org/10.1016/j.envsoft.2018.11.012

Index mundi. (2020). Coal, Australian thermal coal Monthly Price - US Dollars per Metric Ton, Index mundi. https://www.indexmundi.com/commodities/?commodity=coal-australian&months=60

Klaassen, M. A. W., Vos, D., Seebregts, A. J., Kram, T., Kruitwagen, S., Huiberts, R. G. J., & Van Ierland, E. C. (1999). MARKAL-IO Linking an input-output model with MARKAL. In *MARKAL-IO Het verbinden van een invoer-uitvoer model met MARKAL*: ECN.

Krey, V., Havlik, P., Fricko, O., Zilliacus, J., Gidden, M., Strubegger, M., Kartasasmita, G., Ermolieva, T., Forsell, N., Gusti, M., Johnson, N., Kindermann, G., Kolp, P., McCollum, D. L., Pachauri, S., Rao, S., Rogelj, J., Valin, H., Obersteiner, M., & Riahi, K. (2016). *MESSAGE-GLOBIOM 1.0 documentation*. International Institute for Applied Systems Analysis (IIASA).

Küster, R., Ellersdorfer, I. R., & Fahl, U. (2007). *A CGE-analysis of energy policies considering labor market imperfections and technology specifications*.

Lam, K. L., Kenway, S. J., Lane, J. L., Islam, K. M. N., & Bes de Berc, R. (2019). Energy intensity and embodied energy flow in Australia: An input-output analysis. *Journal of Cleaner Production*, *226*, 357–368. https://doi.org/10.1016/j.jclepro.2019.03.322

Lenzen, M., Geschke, A., Abd Rahman, M. D., Xiao, Y., Fry, J., Reyes, R., Dietzenbacher, E., Inomata, S., Kanemoto, K., Los, B., Moran, D., Schulte in den Bäumen, H., Tukker, A., Walmsley, T., Wiedmann, T., Wood, R., & Yamano, N. (2017). The global MRIO Lab – charting the world economy. *Economic Systems Research*, *29*(2), 158–186. https://doi.org/10.1080/09535314.2017.1301887

Lenzen, M., Geschke, A., Wiedmann, T., Lane, J., Anderson, N., Baynes, T., Boland, J., Daniels, P., Dey, C., Fry, J., Hadjikakou, M., Kenway, S., Malik, A., Moran, D., Murray, J., Nettleton, S., Poruschi, L., Reynolds, C., Rowley, H., … West, J. (2014). Compiling and using input–output frameworks through collaborative virtual laboratories. *Science of The Total Environment*, *485-486*, 241–251. https://doi.org/10.1016/j.scitotenv.2014.03.062

Leontief, W. W. (1936). Quantitative input and output relations in the economic systems of the United States. *The Review of Economics and Statistics*, *18*(3), 105–125. https://doi.org/10.2307/1927837

Li, M., Lenzen, M., Wang, D., & Nansai, K. (2020). GIS-based modelling of electric-vehicle–grid integration in a 100% renewable electricity grid. *Applied Energy*, *262*, 114577.

Lucena, A., Schaeffer, R., & Szklo, A. (2010). Least-cost adaptation options for global climate change impacts on the Brazilian electric power system. *Global Environmental Change*, *20*(2), 342–350. https://doi.org/10.1016/j.gloenvcha.2010.01.004

Meinshausen, M., Raper, S. C. B., & Wigley, T. M. L. (2011). Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – part 1: Model description and calibration. *Atmospheric Chemistry and Physics*, *11*(4), 1417–1456. https://doi.org/10.5194/acp-11-1417-2011

Mendoza Beltran, A., Cox, B., Mutel, C., Vuuren, D. P., Font Vivanco, D., Deetman, S., Edelenbosch, O. Y., Guinée, J., & Tukker, A. (2020). When the background matters: Using scenarios from integrated assessment models in prospective life cycle assessment. *Journal of Industrial Ecology*, *24*(1), 64–79. https://doi.org/10.1111/jiec.12825

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

Oliveira, C., Coelho, D., & Antunes, C. H. (2016). Coupling input–output analysis with multiobjective linear programming models for the study of economy–energy–environment–social (E3S) trade-offs: A review. *Annals of Operations Research*, *247*(2), 471–502. https://doi.org/10.1007/s10479-014-1773-5

Orthofer, C. L., Huppmann, D., & Krey, V. (2019). South Africa after Paris—fracking Its Way to the NDCs? *Frontiers in Energy Research*, *7*, 20. https://doi.org/10.3389/fenrg.2019.00020

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

Pauliuk, S., & Hertwich, E. G. (2016). Prospective models of society's future metabolism: What industrial ecology Has to contribute. In R. Clift & A. Druckman (Eds.), *Taking stock of industrial ecology*(pp. 21–43). Springer International Publishing.

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Samir, K. C., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., … Tavoni, M. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rodríguez-Alloza, A. M., Heihsel, M., Fry, J., Gallego, J., Geschke, A., Wood, R., & Lenzen, M. (2019). Consequences of long-term infrastructure decisions—the case of self-healing roads and their CO2 emissions. *Environmental Research Letters*, *14*(11), 114040. https://doi.org/10.1088/1748-9326/ab424a

Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., Handa, C., Kheshgi, H., Kobayashi, S., Kriegler, E., Mundaca, L., Seferian, R., Vilarino, M. V., Calvin, K., Edelenbosch, O., Emmerling, J., Fuss, S., Gasser, T., Gillet, N., … Zhou, W. (2018). Chapter 2: Mitigation pathways compatible with 1.5°C in the context of sustainable development. In G. Flato, J. Fuglestvedt, R. Mrabet & R. Schaeffer (Eds.), *Global warming of 1.5 °C an IPCC special report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways, in the* *context of strengthening the global response to the threat of climate change: Intergovernmental panel on climate change* (pp. 93–174). IPCC.

Siala, K., de la Rúa, C., Lechón, Y., & Hamacher, T. (2019). Towards a sustainable European energy system: Linking optimization models with multi-regional input-output analysis. *Energy Strategy Reviews*, *26*, 100391. https://doi.org/10.1016/j.esr.2019.100391

Strachan, N., & Kannan, R. (2008). Hybrid modelling of long-term carbon reduction scenarios for the UK. *Energy Economics*, *30*(6), 2947–2963. https://doi.org/10.1016/j.eneco.2008.04.009

Sullivan, P., Krey, V., & Riahi, K. (2013). Impacts of considering electric sector variability and reliability in the MESSAGE model. *Energy Strategy Reviews*, *1*(3), 157–163. https://doi.org/10.1016/j.esr.2013.01.001

Tabaković, A., Schlangen, E. (2015). Self-Healing technology for asphalt pavements. In M. Hager (Ed.), *In self-healing materials. Advances in polymer science* (pp. 1–22). Springer. https://doi.org/10.1007%2F12_2015_335

Teh, S. H., Wiedmann, T., Castel, A., & de Burgh, J. (2017). Hybrid life cycle assessment of greenhouse gas emissions from cement, concrete and geopolymer concrete in Australia. *Journal of Cleaner Production*, *152*, 312–320. https://doi.org/10.1016/j.jclepro.2017.03.122

Thomson, A. M., Calvin, K. V., Smith, S. J., Kyle, G. P., Volke, A., Patel, P., Delgado-Arias, S., Bond-Lamberty, B., Wise, M. A., Clarke, L. E., & Edmonds, J. A. (2011). RCP4.5: a pathway for stabilization of radiative forcing by 2100. *Climatic Change*, *109*(1–2), 77–94. https://doi.org/10.1007/s10584-011-0151-4

Vuuren, D., Stehfest, E., Elzen, M., Kram, T., Vliet, J., Deetman, S., Isaac, M., Klein Goldewijk, K., Hof, A., Mendoza Beltran, A., Oostenrijk, R., & van Ruijven, B. (2011). RCP2.6: exploring the possibility to keep global mean temperature increase below 2°C. *Climatic Change*, *109*(1–2), 95–116. https://doi.org/10.1007/s10584-011-0152-3

Wang, M., Lee, H., & Molburg, J. (2004). Allocation of energy use in petroleum refineries to petroleum products. *The International Journal of Life Cycle Assessment*, *9*(1), 34–44. https://doi.org/10.1007/BF02978534

Weyant, J. (2017). Some contributions of integrated assessment models of global climate change. *Review of Environmental Economics and Policy*, *11*(1), 115–137. https://doi.org/10.1093/reep/rew018

Wiedmann, T. O., Suh, S., Feng, K., Lenzen, M., Acquaye, A., Scott, K., & Barrett, J. R. (2011). Application of hybrid life cycle approaches to emerging energy technologies – the case of wind power in the UK. *Environmental Science & Technology*, *45*(13), 5900–5907. https://doi.org/10.1021/es2007287

Wolfram, P., Wiedmann, T., & Diesendorf, M. (2016). Carbon footprint scenarios for renewable electricity in Australia. *Journal of Cleaner Production*, *124*, 236–245. https://doi.org/10.1016/j.jclepro.2016.02.080

Ycharts. (2020). Australia Coal Price (I:ACPNM), Ycharts. https://ycharts.com/indicators/australia_coal_price

Yun, T., Cho, G., & Kim, J.-Y. (2016). Analyzing economic effects with energy mix changes: A hybrid CGE model approach. *Sustainability*, *8*(10), 1048. https://doi.org/10.3390/su8101048