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Integration of raw materials indicators of energy technologies into energy system models

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HIGHLIGHTS

- Four environmental indicators suitable for use in energy system models are proposed (85)
- The indicators allow direct comparison of decarbonisation potential of renewables (84)
- Gearbox double-fed induction generators are the preferred form of wind turbine (80)
- Cadmium telluride photovoltaics exhibit best overall raw materials outcomes (78)

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ABSTRACT

Raw materials and their related environmental impacts will play a key role in the implementation of renewable energy infrastructures for decarbonization. Despite the growing amount of data quantifying raw materials for energy production technologies, few examples of these data sources are being included in current energy system models. Accordingly, this paper introduces possible pathways for integrating material-specific life cycle assessment outputs and material metabolism indicators into energy system models so that raw material requirements, and their associated impacts, can be accounted for. The paper discusses the availability of life cycle inventories, impact assessment methods and important output indicators. The material metabolism indicators most relevant to the current policy debate surrounding the European Green Deal–namely, material supply risk and contribution of recycled materials to total supply–are also discussed alongside the value of adding this information to energy system models. A methodology for using data from both approaches is offered and operationalised using four sub-technologies of both wind turbines and solar photovoltaic panels as case studies. The results show that considerable variation exists between and within the two groups for all indicators. The technologies with the lowest global warming potential, cumulative energy demand and supply risk are turbines with gearbox double-fed induction generators and cadmium telluride photovoltaics. Furthermore, wind turbines exhibit significantly higher recycling rates than photovoltaics. Ultimately, the integration of such methodologies into energy system models could greatly increase the awareness of raw material issues and guide policies that maximise compatibilities between resource availability and cleaner energy systems.

1. Introduction

The European Green Deal is the latest response by the European Commission (EC) to climate and other environmental related challenges [1]. Its key objective is to decouple economic growth from resource use, and for Europe to become the first carbon neutral economy by 2050. As stated in the plan, around 75% of greenhouse gas (GHG) emissions in the European Union (EU) are generated by the production and use of energy [2] and, in order to decarbonise the EU, it is crucial to increase the share of low carbon technologies in the generation and use of this energy.

Emissions relating to energy generation can be systematically

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Nomenclature

Abbreviations

a-Si	amorphous silicon
C-Si	crystalline silicon
CdTe	cadmium telluride
CED	cumulative energy demand
CIGS	copper indium gallium diselenide
CO_2	carbon dioxide
CRM	critical raw material
CTUh	comparative toxicity unit for humans
DD	direct drive
DFIG	double-fed induction generator
EC	European Commission
EESG	electrically excited synchronous generator
ELCD	European Platform on Life Cycle Assessment
EOL-RIR	end-of-life recycling input rate
EROI	energy return on investment
ESM	energy system model
EU	European Union
EV	electric vehicle
GB	gearbox
GHG	greenhouse gas
GLAD	Global Life Cycle Assessment Data Access
GLAM	Global Life Cycle Assessment Method
GWP	global warming potential
HDS	high demand decarbonisation scenario
IAM	integrated assessment model
ICEV	internal combustion engine vehicles
IEDC	Industrial Ecology Data Commons
IMAGE	Integrated Model to Assess the Global Environment
IR	import reliance
kg	kilogram
kWh	kilowatt-hour
LCA	life cycle assessment
LCI	life cycle inventory
LCIA	life cycle impact assessment
LDS	low demand decarbonisation scenario
MDS	medium demand decarbonisation scenario
MFA	material flow analysis
MJ	megajoule
MSA	material system analysis
MW	megawatt
PMSG	permanent magnet synchronous generator
PV	photovoltaic
SO_2	sulphur dioxide
SR	supply risk
UNEP	United Nations Environment Programme
WGI	world governance indicator
yr	year

Notation

c_i	annual consumption level in EU of material *i* [kg/year]
$EOL\text{-}RIR_i$	end-of-life recycling input rate of material *i* [%]
$EOL\text{-}RIR_{technology}$	net end-of-life recycling input rate of the technology under study [%]
m_i	mass of material *i* contained in the technology under study [kg/MW]
n	number of individual materials in the technology under study
SR_i	Supply risk of material *i* [dimensionless]
$SR_{technology}$	net SR of the technology under study [year/MW]

assessed by the methodology known as life cycle assessment (LCA). LCA evaluates the environmental burdens stemming from a process by considering the entire life cycle of the process under study using a holistic perspective [3]. Results from an LCA are given as environmental impact categories, among them the global warming potential (GWP) measured in terms of greenhouse gas generation in carbon dioxide equivalent (CO_2-eq) units. Blanco et al. point out that most studies that have used LCA in combination with ESM to date have been done ex-post to account for the potential environmental impacts of specific technologies, specific sectors or at a global level under different policy scenarios [4]. These studies have tended to use the environmental impact categories described in the ReCiPe [5] or Impact 2002+ [6] assessment methods to account for potential environmental and human health impacts. However, mineral resource depletion is not included in some cases due to data uncertainty on recycling rates and material balances [7].

Energy supply is addressed from a holistic perspective in the European Green Deal, thus potential dependencies on resources key to reaching the EU goals also need to be addressed. Indeed, one of the EU's major fears appears to be the shift from a fossil fuel to a materials-dependent economy. To avoid this situation, and to identify materials that may potentially become problematic in coming decades, the EC has produced several reports addressing the use of so-called critical raw materials (CRMs). The EU considers CRMs to be materials with high importance to the union's economy (e.g., lithium for electric mobility) and with a potentially high risk regarding their supply [8]. Since 2010, the EC has reviewed and updated the list of CRMs for the EU every three years [9-12]. The methodology relating to CRMs has been also revised and formally presented together with an extensive guideline document [13]. The reports published by the EC highlight the material needs for growing technologies, especially for renewables and electric mobility [14]. In 2020, the EC presented the European Raw Materials Alliance for securing the supply of raw materials within its borders [15]. The report listed borates (batteries), lithium (batteries), natural graphite (batteries), niobium (magnets), silicon metal (PV), and a mix of diverse rare earth elements (batteries and magnets) as materials with 100% import reliance [15].

As the dependencies on raw materials for the development of low carbon energy technologies become more evident, the need to include them as a variable in energy system models is being acknowledged. However, to date, only a small number of energy system models (ESMs) consider environmental impacts. One of the most renowned integrated assessment models (IAMs) used to model energy systems is IMAGE [16,17], a large-scale, ecological-environmental model framework that simulates the environmental consequences of human activities worldwide. It addresses some of the most prominent environmental issues and sustainability challenges such as climate change, land-use change, biodiversity loss, modified nutrient cycles and water scarcity. However, in the latest version (IMAGE 3.0), raw material use is not included.

Raw materials have been addressed in the MEDEAS model created within the framework of the EU H2020 project MEDEAS (https://www.medeas.eu/model/medeas-model). The model contains seven submodules including one that models material requirements [18]. This submodule accounts for the materials needed for energy infrastructure and the energy related to its manufacturing, expressed as an energy return on investment (EROI). Using this approach, the model assesses the implications that mineral depletion may exert on energy transitions in relation to potential mineral supply constraints. The demand of minerals is compared with their currently estimated level of geological availability (reserves and resources) for the qualitative detection of risks of material supply from a global perspective. These concepts are now being further developed within the EU H2020 project LOCOMOTION (https://www.locomotion-h2020.eu) which aims to develop further capabilities for the materials module based on geological supply. In any case, neither project is assessing material metabolism factors beyond the physical quantities that exist; geopolitical and other risk factors relating to material supply between countries are not considered.

So, although some efforts have been made to assess raw materials using a holistic perspective, and several new indicators have been defined [1411], their use in ESMs remains limited. This is partially because a systematic process for collecting and providing such information in an ESM-usable format is yet to be developed.

Accordingly, the present paper proposes the use of LCA data alongside material metabolism approaches as a way of providing a more complete picture of the raw materials use and associated environmental impacts within ESM processes. The paper begins by briefly explaining the LCA methodology and how it could be used to integrate the potential environmental impacts of energy production into ESMs. It also discusses existing LCA data and outlines a simple methodology for creating environmental impact indicators for energy infrastructures per unit of power capacity. Section 3 then investigates existing material metabolism information and how this information can complement LCA results. It expands the methodology further to include material supply parameters for supply risk and recycling rates. The article provides, for the first time, the results of a set of four environmental indicators readily usable in ESM to support the assessment of wind turbines and solar photovoltaic cells. It concludes by confirming the potential of such approaches, the need for further integration of environmental and metabolic data into ESMs and, to aid future policy decision-making, the ongoing need for good quality life cycle and material supply data.

2. Potential contribution of LCA methodology to ESM

The LCA methodology is used for evaluating the environmental burden of a process by accounting for the inflow and outflow of materials and energies alongside the wastes released to the environment [3]. Such evaluations are undertaken using a holistic perspective that considers the entire life cycle of the process under study. LCA accounts for the inflows and outflows of the system from 'cradle to grave'; that is, from the extraction, manufacturing, consumption and recycling to the final disposal. The methodology can be divided into four steps: goal and scope definition, inventory analysis, life cycle impact assessment (LCIA) and interpretation. Once the objective and functional unit are defined as part of the goal and scope stage, an inventory analysis is done to quantify the raw material and energy inputs, and to account for the atmospheric emissions, waterborne emissions, solid wastes and other releases over the entire life cycle of a product, process or activity.

Each product system inventoried in this stage can be divided into both foreground and background systems [19]. The foreground system refers to the main process steps and infrastructure related to the focused product or system of the study. Meanwhile, the background system is comprised of the processes needed for the supply of raw materials and energy to the foreground system. This generally includes the more dominant processes outside of the study's focus and are typically out of the direct control of those undertaking the assessment [20]. Commonly, the background system's infrastructure (e.g., the manufacturing of the power plant or the fossil fuels production infrastructure) is included in the secondary data sets used for modelling the background system. The background system deals with almost all material and energy flows going to and coming from the foreground system. Data for the background system is typically taken from existing databases (e.g., ecoinvent v3.7.1 [20], GaBi [21]) while the foreground system can often be quantified using primary data from case studies, peer-review papers and technical reports.

In the stage that follows, an LCIA procedure attempts to establish a link between the materials and energy compiled by the LCI inventories and their potential environmental impacts. Potential environmental burdens are given in the form of impact categories defined and selected to describe the impacts caused by the emissions and the consumption of natural resources. Impact categories can refer to a single-issue such as the cumulative energy demand, or to multiple issues as in the commonly used ReCiPe method [22] which includes 21 indicators. In most multiple issue LCIAs, the emissions and consumption of resources are attributable to three main areas of protection (ecosystem quality, human health and natural resources), which are preceded by several impact indicators that express the impact on the environment as midpoint and/or endpoint indicators [23]. Midpoint indicators represent the actual environmental phenomena caused by the life cycle system, such as 'global warming potential' (CO_2-eq) [24] and 'ozone depletion potential' (kg CFC-11-eq) [25], whereas endpoint indicators are composites that result from a combination of midpoint indicators that reflect the damage on so-called areas of protection [26]. For example, in the ReCiPe method the midpoint indicators for 'global warming potential' and 'ozone depletion' are combined into the endpoint indicator 'damage to human health' [22].

Fig. 1 provides a simple conceptualisation for a potential integration of LCA and ESMs by illustrating where inputs and outputs to these models are situated in relation to the four stages of the LCA framework. Again, the most relevant stages for ESMs within this framework involve the LCI and LCIA calculations. Assessing the LCI includes the background (green) and the foreground (blue) systems. As always, the background system refers to all processes needed to supply the raw materials and energy to the processes of the foreground system. In the case of ESMs, the foreground system refers to the processes needed to manufacture a specific energy technology. For example, for a solar photovoltaic panel the foreground system would include the processes for manufacturing the cells and the frame and the balance of system (wiring, switches, mounting system, solar inverter, battery bank and charger), transport and assembly of all components, operation and maintenance, use, dismantling and transport and all waste disposal operations.

Fig. 1 also displays the most common multiple issue methods used in LCIAs (in dark blue). According to Jungbluth [27], the most frequently used LCIA methods are CML2002 [3], ILCD2010 [26], ReCiPe 2016 [22], the EU Product Environmental Footprint 2018 [28] and ImpactWorld+ [29]. Each of these methods includes a list of impact categories that differ in scope and procedure for characterisation and weighting. In 2016, the United Nations Environment Programme (UNEP) launched a consultation for the creation of a Global Life Cycle Assessment Method (GLAM) with the objective of identifying scientifically robust and applicable methods [30]. Discussions within the scope of GLAM have led to a prolific number of papers discussing LCA indicators, especially regarding resource use and availability indicators [31,32]. Another important aspect highlighted in the figure is the potential contribution of background systems to the overall environmental impacts of renewable energy supply processes [33]. For example, the potential environmental impacts of wind generation are largely influenced by the mix of electricity supplied to the production of raw materials, mostly steel, concrete and aluminium, which are highly energy intensive [34].

2.1. Inputs from LCI

2.1.1. The background system

Two types of inputs are considered for background systems: raw materials and energy. The most common source of data for the assessment of raw materials is the fee-paid ecoinvent database [33]; version 3.7.1 of ecoinvent includes LCIs for the production of about 30 metals, 20 types of industrial minerals and seven forms of primary solid biomass. An extensive list of inventories is available for base metals, especially aluminium, iron and steel, copper, zinc, and nickel, as well as some precious metals like gold, silver and the platinum group metals (platinum, palladium, rhodium), alongside specialty metals such as titanium, tungsten, and uranium. An effort has also been made to include LCIs for other materials that are produced in lower quantities but have

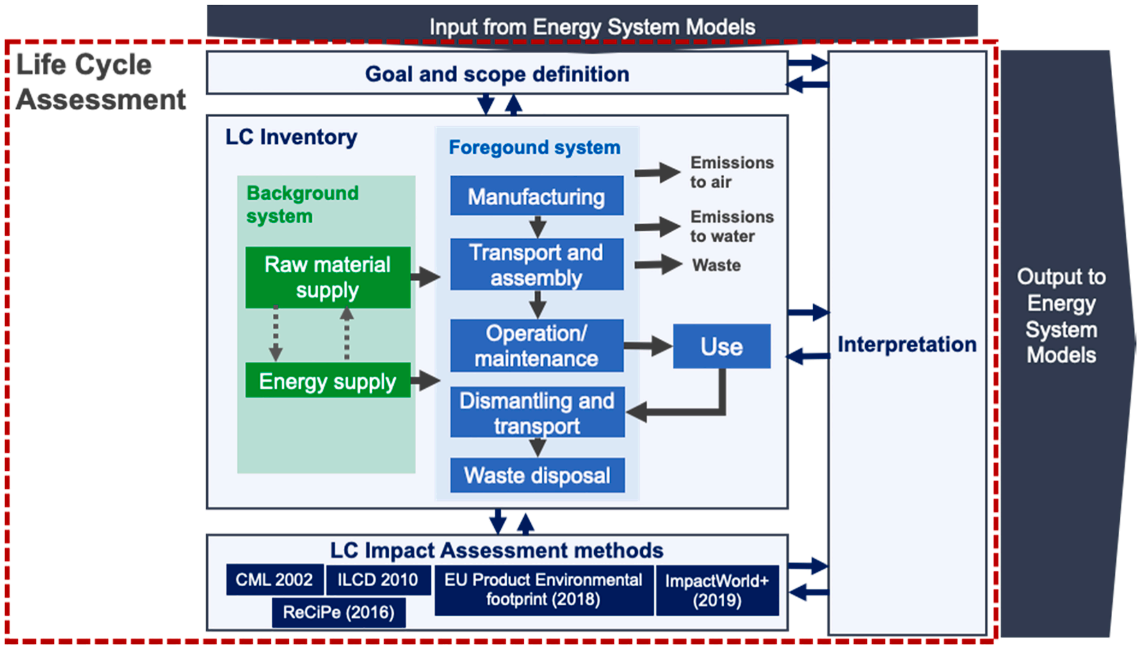

Fig. 1. Possible linkages between energy system models (ESMs) and the life cycle assessment (LCA) framework according to ISO14040 standard. The life cycle inventory (LCI) includes the background system (in green) and foreground system (in light blue). Diverse LCIA methods are represented for illustrative purposes as dark blue rectangles. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

high economic importance such as rare earth elements, indium and gallium. Additional inventory data for the extraction and purification of metals is highly scattered in publications and reports, and funding for generating bespoke data inventories for LCA purposes is often not available. As such, LCA practitioners tend to use existing LCI information within databases such as ecoinvent.

Several previous studies have attempted to compile life cycle data for metals. Nuss and Eckelman compiled proprietary data from ecoinvent version 2.2 in conjunction with data from various reports and scientific publications [33]. Meanwhile, Van der Voet et al. used ecoinvent version 2.2 to complete an inventory of the background system and datasets from previous studies [35,36] to assess the environmental implications of future demand scenarios of seven major metals: aluminium, copper, iron and steel, lead, nickel, manganese and zinc [37]. The LCIs generated by both studies have not been made available and, therefore, it is not possible to use them directly in future studies. Although some recognised LCI formats do exist (e.g., ecoSPOLD), the general lack of LCI data in formalised formats impedes their use in LCA software tools and restricts their widespread use by LCA practitioners. Furthermore, not disclosing inventory data in published articles and other reports hinders the reproducibility and replicability of the assessment.

Although some initiatives exist for generating fee-free LCIs for raw materials, these tend to only partially cover raw materials and rarely focus specifically on CRMs. The UNEP Global Life Cycle Assessment Data Access network (GLAD), launched in April 2018, aims to address this issue by providing a platform for hosting independent LCA databases, so-called nodes, that are made available in various data formats. One of the main functions offered is the conversion of LCI data from the native format to a format that allows their use in common LCA softwares. In GLAD, LCA practitioners can check the availability of datasets from diverse providers such as IDEA, ecoinvent, USA LCA Digital Commons, SICV Brazil and ELCD [38]. Another less ambitious initiative is the updated database of the DoSE-LCADB [39,40]. This includes current LCI data for agriculture (mainly vegetables), bioenergy (biomass from Populus spp. and soybean biofuel), and manufacturing (cement, natural cork, rubber mix and fertiliser). LCIs for individual raw materials are not yet available, although this looks likely to change in coming years as the database becomes more widely known and more nodes begin to be linked with the GLAD database. Lastly, Paulik and Hasan have created the Industrial Ecology Data Commons (IEDC) prototype which contains around 180 industrial ecology-related datasets from the literature. Datasets are not limited to LCIs and include stocks, flows, process descriptions, input–output tables, material composition of products and other factors [41]. At present this collection only contains inventories for a small number of unit processes for aluminium and steel.

As with raw materials, the major source of LCI information for energy systems is ecoinvent. In an LCA context, energy inputs generally refer to electricity consumption and, thus, are assessed based on the so-called electricity production mix, the share of individual electricity sources, generated from a diverse group of technologies, within a local electricity supply. The composition of this mix changes according to the geographical location of the system under study (i.e., region, country and continent). It also varies from year to year due to changing energy policy measures, economic growth, energy intensity, technology changes, meteorological conditions, and so on [42]. Accordingly, potential environmental impacts can be considered to vary over time and between location.

The number of studies analysing the effects of changing electricity background systems on LCA results is limited. Mendoza Beltrán et al. combined the Integrated Model to Assess the Global Environment (IMAGE) with the ecoinvent database to perform prospective LCAs for electric vehicles (EV) and internal combustion engine vehicles (ICEV) [43]. Changes were mainly focused on the electricity sector as electricity is the largest potential source of variability in the environmental impact results [44]. The development of electricity scenarios firstly included scenario generation using IMAGE; scenarios could then be evaluated using LCIA. The adaptation of inventory parameters within LCA consisted of using and adapting the emission factors of the GHG emissions, mostly from the EU EDGAR [45], and replacing the shares of electricity-producing technologies, both using IMAGE. LCI inventories were adapted to IMAGE by the development of the Wurst software platform, a python-based application that enables the systematic importing, filtering and modification of LCI data (https://github.com/IndEcol/wurst).

2.1.2. The foreground system

Conversely, foreground systems focus on the processes needed to generate a certain amount of energy using a particular energy technology. For example, the LCA for generating one kilowatt-hour (kWh) of electricity from a solar photovoltaic (PV) panel includes all processes from the extraction of raw materials for the manufacturing of the panel to its end-of-life. As many current decarbonisation targets are based on increased electrification of the energy sector by increasing the share of renewable energy technologies, the number of LCIs for these technologies has increased considerably in the past decade. Appendix A includes a list of LCIs available in version v3.7.1 of ecoinvent and the 2020 edition of GaBi, considering different energy sources and energy carriers. While these values suggest that a significant amount of data is already available, new technologies continue to be developed and data for the newest iterations of energy technologies is often not available in a useable format for several years after its introduction. As such, an increased effort is needed to formalise and incorporate such data into databases in a more timely fashion. As an example, over 90% of the LCI listings for solar PV cells in ecoinvent v3.7.1 relate to first-generation cell technologies–41% single crystalline silicon (C-Si), 55% multi-crystalline and 4% ribbon–while only 10% refer to second-generation technologies–50% amorphous silicon (a-Si), 25% cadmium telluride (CdTe) and 25% copper indium gallium diselenide (CIGS). In the 2020 edition of GaBi, 60% of these datasets are dedicated to first-generation cells–38% C-Si, 37% multi-crystalline and 25% ribbon–with 20% describing second-generation cells–40% a-Si, 24% CdTe and 36% CIGS. The remaining 22% refer to general datasets.

It is also notable that neither of these databases currently contain LCI data for the third-generation of cells such as metal halide perovskite cells which are believed to hold significant economic and efficiency advantages over the currently commercialised first and second-generation variants [46]. While not yet in widespread use, these technologies are expected to play a significant role in the emergence of solar PV cells going forward. This highlights the importance of including data relating to burgeoning technologies in prospective energy system assessments and the shortcomings in the current data.

2.2. Inputs from LCIA

Using the collected LCI data, an LCIA attempts to form a connection between the product or system and its potential environmental impacts by creating indicator values relating to specific impacts; the results of the assessment are given in the form of environmental impact categories to help evaluate outcomes in various areas (e.g., potential human health and ecological effects). Environmental impact categories can consider one selected environmental aspect, such as the cumulative energy demand, water footprint or carbon footprint, or combine several environmental impacts to become a ‘method’. Each of the most commonly used methods include a list of impact categories (see Appendix B for an exhaustive list).

As a result of the ongoing discussions surrounding the development of the GLAM [30], attention to resource availability indicators has been increasing in recent years and several publications now provide a comprehensive review of indicators [31,32]. Sonderegger et al. revised the 27 different methods suitable for LCIA for mineral resource use and grouped these methods into four categories: depletion methods, future efforts methods, thermodynamic accounting methods and supply risk methods [31]. The two former methods consider resource depletion from a more ‘traditional’ LCIA perspective, where the availability of mineral resources given a certain stock are considered (depletion method) or the potential increase of extraction and refining costs, surplus energy use and other related aspects are considered under the assumption of ore decline (future effort methods). The two latter methods, however, provide complementary information to LCA outputs regarding the use of cumulative material and energy use for a product (accounted in useful energy or exergy), and the availability of materials based on the supply disruption probability and vulnerability, respectively. Berger et al. [32] built on the analysis of Sonderegger at al. [31] to give recommendations for the application of such methods by formulating seven questions that can be further classified into ‘inside-out’ (i.e., current resource use changing the opportunities for future users to use resources) and ‘outside-in’ (i.e., potential resource availability issues for current resource use). The study concluded that there is a need for methodological enhancement across method categories. Additionally, the authors suggest that future methods increase the number of abiotic resources considered, including secondary resources and anthropogenic stocks, and include the concept of dissipative resources in future developments.

In terms of natural resources, critical raw materials–and metals in particular–have attracted most of the attention in this regard as many of them look set to play a key role in the development of renewable energy technologies [8]. However, at present there is no consensus on a single method or set of methods for measuring resource availability using LCA methodologies and only a small number of approaches are currently available, as listed in Appendix C. Nevertheless, a number of studies have published data for individual raw materials. Nuss and Eckelman performed LCA analyses for 63 metals and reported the results for five main environmental impact categories: the global warming potential (kg CO_2-eq), the cumulative energy demand (CED) (MJ-eq), terrestrial acidification (kg SO_2-eq), freshwater eutrophication (kg P) and human toxicity (CTUh) [33]. The investigation yielded several interesting results. The global CED of metal production is estimated to have been 49 PJ in 2008, which represents 9.5% of the global primary energy demand. Iron and steel (74%) and aluminium (17%) dominate the CED impact category; the remaining 60 metals collectively represented only 9% of the total CED. Globally, the largest environmental impacts are found in the purification and refining of these metals. An environmental assessment of the seven major metals by Van der Voet et al. [37] referred to the CED (MJ-eq) and GHG emissions (kg CO_2-eq) as defined by the CML2002 impact categories [3]. Their results show that the environmental impacts generated by metal production look set to increase gradually, and designate iron as the metal responsible for most impacts and emissions. Both studies provide valuable information about the potential environmental impacts of metals in energy systems.

The availability of LCIA estimates for these and other materials allows composite values to be calculated for specific energy infrastructures. If a breakdown of the main material components of a piece of infrastructure (kg of each material) with a given power capacity (MW) is available, a series of material intensities (kg/MW) can be calculated. Values of LCIA indicators for a unit mass of each individual material can then be used to calculate a composite score of the indicator per unit of power capacity. This methodology is formalised for GWP and CED in Appendix D, respectively. Using these two methodologies as examples allows final values–per MW of installed capacity–to be calculated for GWP (kg CO_2-eq/MW) and CED (MJ-eq/MW). Outputs of this type then allow side-by-side evaluations to be made between different energy technologies as the values of the chosen LCIA output category can be directly compared in terms of installed capacity. Furthermore, using assumptions for infrastructure lifetime and typical energy outputs allows values to be calculated–and compared–for each unit of energy produced. It is noted that using the CED as an input to this methodology would return the total energy requirement per unit of produced energy (MJ-eq/MJ, say) which is essentially the inverse of the EROI, a common indicator used in MEDEAS, LOCOMOTION and many other projects.

In any case, some limitations exist in relation to the indicators used in LCA. Firstly, although LCA uses quantitative material and energy input data to account for the potential environmental impacts, this information is not generally used when quantifying material requirements. Similarly, LCA indicators do not provide feedback on the contribution of recycling to the total supply of raw materials. In the EU, both of these issues are progressively gaining more importance [11]. As such, in order to provide more complete environmental assessments in ESM there is a need to develop methodologies that use LCA indicators which capture the potential environmental impacts of energy technologies alongside material specific indicators which give additional information about the raw material supply factors of energy technologies

3. Potential contribution of material metabolism analysis to ESM

The previous section reveals that LCA indicators provide a useful way to assess the environmental performance of the life cycle of an energy system [43]. However, the findings also suggest that other characteristics of energy systems, such as the supply of materials, are poorly captured within LCA methodologies. One of the most overlooked of these is material metabolism. Material metabolism studies offer complementary information about the supply of raw materials as they consider the whole, integrated collection of physical processes that convert raw materials to processed materials, components and finished products [54]. Material metabolism studies, including so-called material flow analysis (MFA) approaches, help practitioners attain a better understanding of the flows and stocks associated with materials, the interconnection between mineral ores and materials, recycling aspects, and shed light on potential future constraints for technology development and diffusion. Some of the most relevant issues quantified by MFA are the supply of raw materials from mineral deposits and from recycling, and the interconnection with other raw materials along the value chain.

Mineral deposits are heterogeneously and unequally distributed across the Earth and the availability of resources depends on various factors such as natural occurrence, concentration (if they are sufficiently attractive to be mined) and accessibility. Geological surveys generally provide figures about geological availability as 'reserves', 'reserve base' and 'resources' [47,48]. However, the lifetimes of many reserves and resources has continually been extended over the last 50 years. Thus, the published reserve figures do not adequately reflect the total amount of mineral potentially available in the long term and should not be used in the evaluation of future material availability [9]. As a result, MFA processes do not, strictly speaking, focus on resource depletion indicators. Rather, they focus on raw material supply indicators, which can refer to either primary production (mining) or secondary production (recycling). Indeed, recycling represents a significant challenge due to the great diversity of applications and end products where materials are embodied, the diversity of products recycled together and the variability of the related processes. Despite such difficulties, a few existing studies supply recycling estimates, which allow meaningful indicators for the secondary supply of raw materials to be defined.

The production of raw materials is highly interconnected, especially those involving metals. Indeed, the topic of by-product dynamics is often discussed [33,49,50], although few publications propose a methodology for providing quantitative estimates [51-53]. Based on the literature available, three different types of by-product metals are distinguished: metals derived from ores of major metals (e.g., germanium, indium), metals that occur without a major metal (e.g., platinum group metals) and metals that can be mined when found in high concentrations (e.g., cobalt, gold). The availability of all three types is largely determined by the availability of the main ore as mine production cannot adapt quickly to meet structural changes in demand patterns. As a result, the supply risk of these metals is high when the volume mined does not match with market demand. Talens Peiró et al. gave one of the first figures illustrating the metabolism of scarce materials and provided production shares between them [50]. Nuss and Eckelman subsequently provided a more complete and detailed illustration of the interlinkages between metals along the supply chain [33]. Obtaining more detailed information about the linkages between raw materials helps identify potential supply restrictions across the value chain that cannot be predicted based on LCA studies. In the EU, the European Commission itself has performed several studies. The first of these identified information and data needs for a complete MFA involving 21 materials and groups of materials in 2012 [55]. The second, from 2015, provided a detailed methodology for developing MFAs [56]. A 2015 study, also referred to as the EC MSA study, illustrated the entire life cycle of materials using a list of parameters which describe physical flows (including import and export flows to each stage of the life cycle) and stocks. The study included a total of 52 parameters divided into three groups: parameters representing physical flows and stocks of materials, parameters relating to policy objectives and criticality, and parameters relating to future supply and demand change. In 2020, the EC also published the latest data relating to raw material supply of critical raw materials [11] and non-critical raw materials factsheets [57]. Employing a material metabolism perspective, the EU also proposed a method for estimating the criticality of resources [58]. This method is considered to be a snapshot of the current situation in the EU and aims to support the development of EU raw materials policy to help monitor supply risk and recycling aspects.

The 2020 CRM assessment sheds further light on the supply of raw materials within the value chain, assuming that raw materials can be supplied in value chains as raw materials, processed materials, components and assemblies [59]. Within value chains, many aspects relating to local supply and demand of materials, the location and characteristics of external supplies, substitutability and end-of-life recycling rates were identified as being relevant to the assessment of future supply constraints. Tellingly, calculations performed within the study found that the EU depends on non-domestic production for more than 80% of the raw materials demanded by its economy [60]. Many of these materials are extracted within a small group of countries which increases the probability of supply shortages and affects the strength of the supply chain.

As a way of monitoring this dependency on non-domestic production, the CRM methodology analysed the import dependencies of specific materials in further detail by assuming that local dependence–or import reliance (IR)–can be calculated as the amount of imports divided by the total supply (imports plus domestically-sourced supply). IR can be calculated for diverse stages across the value chain (e.g., as unprocessed material at the extraction stage or as refined material at the processing stage). The results show that 28 of all 80 materials analysed–and 19 of the 30 materials marked as 'critical'–have an IR of 100%. Many others have IR values well over 50%. This confirms that the EU is highly dependent on imports for many raw materials which are increasingly affected by growing demand pressure from emerging economies and by an increasing number of national policy measures that disrupt the normal operation of global markets. Moreover, the production of many materials is concentrated in a small number of countries (e.g., more than 90% of rare earths and antimony, and more than 75% of germanium and tungsten, are produced in China, 90% of niobium is from Brazil and 77% of platinum from South Africa).

The supply of secondary materials via recycling represents an opportunity to offset overall supply risks, particularly for materials with high dependencies on non-domestic production. Recycling can occur at each of the stages considered along the life cycle of a material or a product (e.g., materials can be recycled at either the extraction stage or the assembly stage). As such, when defining recycling indicators, it is important to define the system boundaries in detail alongside the material flows included in the calculations. The 2020 CRM assessment [60] considers recycling to be a 'risk-reducing factor' and quantifies the supply of secondary materials using the so-called end-of-life recycling input rate (EOL-RIR) indicator. EOL-RIR reflects the total material input into the production stage that comes from recycling of post-consumer scrap and is regarded as a robust measure of the contribution of recycling to meeting materials demand. The results for EOL-RIR suggest that 47 of the 80 materials assessed currently play an insignificant role in the overall EU supply (less than 10% EOL-RIR); the results are starker for the group of more 'critical' materials, where 26 of the 30 materials have EOL-RIR scores less than 10%.

The key parameter presented in the 2020 CRM assessment [60] was a supply risk (SR) factor that used aspects of supply concentration, world governance indicators (WGIs), IR (as above), trade restrictions and agreements, supply chain and bottleneck issues, EOL-RIR (as above) and criticality of substitutes to capture a dimensionless composite measure of EU supply risk for each material. Calculations were made for both the mining/extracting and processing/refining stages, and the greater of the two chosen as the final indicator.

A report by Bobba et al. [10] provides data for EU domestic production at the extraction stage (materials in the form of mineral ore) and the processing stage (materials considered refined material). In the EU, most of the materials domestically produced are generated at the processing stage, whereas materials obtained from the extraction stage represent around 20%. In other words, the greatest supply risks are located at the extraction stage of resources. For example, in the wind power supply chain, the risk is reduced along the supply chain from 99% at the extraction stage to 88% at the refining stage, 80% at the component stage to a final 42% at the assembly stage. For solar PV, the supply risk does not vary considerably from the extraction stage (94%) to the assembly stage (99%).

At the larger scale, materials demand can be seen to be driven by technological changes as well as the continual growth of emerging economies. In the EU, raw materials demand is likely to continue to increase as a result of a commitment to becoming a climate neutral economy by 2050. Several studies exist that assess the demand for CRMs coming from several strategic technologies, including wind energy and solar PV technologies. The results are given for low-demand (LDS), medium-demand (MDS) and high-demand (HDS) decarbonisation scenarios [14]. Information relating to the value chains can also help unravel the potential to decarbonise raw material supplies. As 17 of the 24 key materials used in these technologies are supplied as refined materials to the EU, higher GHG emissions will inevitably be associated with the transport of these materials. Accordingly, less opportunity exists to reduce the overall carbon footprint of these technologies.

Expanding upon the methodology proposed for calculating composite LCIA indicators, further methodologies are proposed here for using the values of EOL-RIR and SR for individual raw materials in the EC's 2020 CRM assessment [60] to calculate composite scores for different energy production processes. As with the LCIA indicator values, it is hoped that these new scores can be integrated into ESMs as a way of including material metabolism aspects into the assessment processes relating to a variety of future energy systems. To the best of our knowledge, this is the first time this has been attempted in such a way.

3.1. The circularity of energy technologies in the EU

Eurostat uses the EOL-RIR parameter as an indicator for monitoring the EU's progress towards a circular economy on the thematic area of 'secondary raw materials'. The current paper proposes the use of EOL-RIR as a way of monitoring circularity aspects of energy technologies within ESM practices. The EOL-RIR for a technology can be calculated by considering the EOL-RIR values for individual materials in relation to the overall mass of materials in the item of infrastructure under study, in this case expressed as the material intensity *m*. As rates are expressed as a percentage, the pro-rata EOL-RIR values for each material must be divided by the total mass of all materials to provide the final EOL-RIR value. Accordingly, the composite EOL-RIR for a given technology using inputs from *n* materials is as follows:

$$EOL-RIR_{technology} = \frac{\sum_{i=1}^{n} m_i EOL-RIR_i}{\sum_{i=1}^{n} m_i} \tag{1}$$

The results indicate the overall percentage of recycled materials that occur within end product and provide a better understanding of the circularity of a technology from a material perspective. To assess the circularity of the technology itself, further analysis that assesses the disassembly along with a more detailed analysis of the material recovery from these technologies would need to be further developed.

3.2. The supply risk of energy technologies in the EU

Again, the key output from the 2020 CRM assessment [60] was the SR factor that quantifies the overall supply risk for each material as a dimensionless constant based on a number of physical and geopolitical factors. Initial attempts to define a methodology for creating a composite SR score were based on the same pro-rata approach used for the LCIA outputs (see section S4 of the supplementary information). However, in order to capture the importance of materials that exist in much smaller quantities, an additional parameter was required to normalise the amounts of required materials using some measure of overall abundance of supply. Consequently, in the final formula, each material intensity value, *m*, is normalised by dividing it by the annual consumption level within the EU, *c*. This provides a more useful measure of the significance of using the given amount in relation to the overall supply. Accordingly, the composite supply risk factor for a given technology using inputs from *n* materials is as follows:

$$SR_{technology} = \sum_{i=1}^{n} \frac{m_i SR_i}{c_i} \tag{2}$$

It is noted that, although the final value of SR is essentially dimensionless, the final units are actually the timeframe of the consumption data divided by the unit that the material intensity is based upon. In this example, the final units are, in fact, the relatively meaningless year per MW. Other measures of material intensity, such as kg of materials per MJ of energy or kg of fuel supplied could also be used–highlighting the flexibility of this methodology to different datasets–but would result in different final units of the composite SR score. However, while many types of units can be used, one cannot directly compare final scores that use different units of material intensity and/or consumption data.

4. Case studies: Wind turbines and solar PV panels in the EU

A better understanding of both the typologies and quantities of raw materials used by energy technologies is required to identify technologies that may introduce more significant resource use issues in terms of both environmental impacts and material availability. Inclusion of such factors within ESM projects has the potential to contribute to the current research by allowing for more complete assessments of future energy scenarios to be generated.

Most projected future energy scenarios predict significant increases in the share of renewable energies in the EU energy mix, predominantly via wind turbine and solar PV technologies [11]. And, while utilising such technologies results in far lower day-to-day emissions once in operation, the production of the infrastructure required to implement more renewable energy regimes is often overlooked [61]. In the section that follows, the methodologies for the two LCIA indicators–GWP and CED, as outlined in section S4 of the supplementary materials–are operationalised alongside the methodologies for EOL-RIR and SR outlined in the previous section using material intensity information for the most common wind and solar photovoltaic technologies.

Carrara et al. studied the raw material demands relating to four key infrastructure types for both wind turbine and solar PV technologies [62]. Data from the study provides inputs to case studies using the current methodology. Firstly, inputs are provided for four types of wind turbine: two direct-drive (DD)–electrically excited synchronous generator (EESG) and permanent magnet synchronous generator (PMSG)–and two gearbox (GB) driven–PMSG and double-fed induction generator (DFIG). Material intensity data is supplied for concrete, glass/carbon composites, cast iron, epoxy resin polymers and steel alongside 12 critical metals. These values are provided alongside the corresponding LCIA indicator data–GWP and CED–and material supply data–EOL-RIR, overall annual consumption and SR–for the EU in Table 1. Meanwhile, the study also reports data for installations based on four types of solar PV cell: the first-generation crystalline silicon (C-Si) and three of the newer, second-generation 'thin-film' cells–cadmium telluride (CdTe), copper indium gallium diselenide (CIGS) and amorphous silicon (a-Si). Material intensity data is supplied for concrete, glass, plastic, and steel alongside 10 critical metals. Input data values are provided in Table 2. All sources of data used in the analysis are summarised in Appendix E.

Results for both groups are summarised in Table 3. The results for wind turbines indicate that a significant amount of variation exists between the four types analysed. The results for GWP and CED are all dominated by steel, which contributes around half of the total for all turbine types. The higher level of steel in DD-EESG turbines means that it scores considerably higher than other turbines in both of these categories. The four other non-critical materials, alongside zinc, provide most of the remaining contributions to GWP and CED values. Variation is far higher within the supply risk category. For all turbines, this factor is dominated by amounts of the rare earths dysprosium and neodymium and, to a lesser extent, praseodymium and terbium. Accordingly, the final score for the DD-PMSG turbine is substantially higher than the other turbines owing to higher levels of all four of these metals. The lowest levels of variation occur in the results for EOL-RIR, which are dominated by amounts of concrete and steel. Overall, the most 'desirable' of the four wind turbines analysed is the GB-DFIG turbines which return the lowest scores for GWP, CED and SR and the second highest EOL-RIR.

A significant amount of variation also exists between the four types of PV cells analysed. The results for GWP and CED are again dominated by steel, which contributes between 30 and 40% of the observed levels in both categories. Glass and plastic also influence the final scores in these categories, as does aluminium. Nevertheless, the levels of all materials are assumed to be identical in the material intensities given in [62], so the intensities of the critical metals other than aluminium are ultimately responsible for variations in GWP and CED. Hence, the levels of germanium and silicon in a-Si cells give them the highest scores in these categories. Variation is again significantly higher in the supply risk category. By far the lowest score here is for the first-generation c-Si cells, with only small contributions from silver, aluminium and copper (silicon itself does not make a significant impact). The final SR factor scores for CdTe and CIGS cells are both moderately high, predominantly via the presence of tellurium and indium, respectively. However, by far the highest score in this category was returned for a-Si cells, which is over four times higher than the other cell types. This high score is almost exclusively the result of a requirement for germanium. Lastly, the results for EOL-RIR are almost identical for all turbine types as they are overwhelmingly dominated by concrete and steel which are assumed to be identical in plants for all four cell types. Selecting the most 'desirable' of the four solar PV technologies is less straightforward. CdTe cells return the lowest scores for GWP and CED and the second lowest for SR, making it a strong performer. However, the low SR score for C-Si give it a very strong advantage if this category is prioritised.

It is noted that the scores for GWP, CED and SR are all significantly higher in wind turbines when compared to solar PV facilities on a per MW basis. For GWP and CED, this is explained by the far higher levels of concrete and steel required in wind turbine structures, while the differences for supply risk are predominantly due to the presence of rare earth materials in wind turbine generator systems. Conversely, high levels of recovery and/or recycling for concrete and steel mean that overall EOL-RIR rates are higher for wind turbines. Nevertheless, the results strongly indicate that production of a single MW of electricity generation capacity via new wind turbine installations is considerably less desirable than solar PV panels in terms of GWP, CED and SR. Although many other aspects ultimately affect the adoption of different technologies, these simple findings suggest that certain elements of wind turbine designs would need to be improved if they were to become comparable to solar PV panels in the aspects investigated. For example, new wind turbine generators should be designed to include features that facilitate their repairability by allowing access, disassembly and the replacement of specific parts. Extending the service life using these design features would enhance the remanufacturing and reuse of these parts and reduce their dependency on imports. Extending the lifespans of foundations, blades and other components may also improve their desirability in relation to other renewable energy technology options. Collectively, these measures would result in lower SR and higher EOL-RIR values.

The given case studies confirm the effectiveness of employing a relatively simple methodology for obtaining useful information regarding emissions, embedded energy, supply risk factors and recycling rates that allow robust comparisons to be made between technologies using readily available data. Furthermore, the exercise demonstrates that including raw materials assessments in ESM can help to visualise the relevance of certain materials in achieving energy targets and, therefore, to urge the development of new resource management measures directed to ensure the supply of key raw materials and/or

Table 1
LCIA indicators, EU material supply data and specific material inputs for four wind turbine sub-technology case studies.

Material	LCIA indicators[a]		EU material supply data[a]			Case study material inputs[b]			
	GWP	CED	Consumption	SR	EOL-RIR	Material intensity			
						DD-EESG	DD-PMSG	GB-PMSG	GB-DFIG
	[kg CO_2-eq/MW]	[MJ/MW]	[kg/yr]		[%]	[kg/MW]	[kg/MW]	[kg/MW]	[kg/MW]
Concrete	0.12	0.9			90.0%	369,000	243,000	413,000	355,000
Glass/carbon composites	2.45	37.9			19.0%	8,100	8,100	8,400	7,700
Cast iron	1.91	20.9			85.0%	20,100	20,100	20,800	18,000
Polymers (epoxy resins)	4.70	97.3			1.0%	4,600	4,600	4,600	4,600
Steel	1.45	17.3			85.0%	132,000	119,500	107,000	113,000
Aluminium (Al)	9.36	107.7	5,252,000,000	0.59	12.4%	700	500	1,600	1,400
Boron (B)	1.42	22.4	62,850,000	3.19	1.0%		6	1	
Chromium (Cr)	0.04	0.7	1,200,000,000	0.86	21.0%	525	525	580	470
Copper (Cu)	1.23	19.6	4,000,000,000	0.32	17.0%	5,000	3,000	950	1,400
Dysprosium (Dy)	59.60	1,170.0	14,000	6.20	0.0%	6	17	6	2
Manganese (Mn)	2.95	36.9	800,000,000	0.93	8.0%	790	790	800	780
Molybdenum (Mo)	16.93	232.1	60,000,000	0.94	30.0%	109	109	119	99
Neodymium (Nd)	49.60	733.7	100,000	6.07	1.3%	28	180	51	12
Nickel (Ni)	6.50	111.0	460,000,000	0.49	17.0%	340	240	440	430
Praseodymium (Pr)	78.43	1,158.4	41,000	5.49	10.0%	9	35	4	
Terbium (Tb)	297.00	5,820.0	24,000	5.51	6.0%	1	7	1	
Zinc (Zn)	2.76	49.4	4,000,000,000	0.34	31.0%	5,500	5,500	5,500	5,500

[a] See Table E1 in Appendix E for detailed description of data sources, b Material intensities taken from [11].

Table 2
LCIA indicators, EU material supply data and specific material inputs for four solar photovoltaic sub-technology case studies.

Material	LCIA indicators[a]		EU material supply data[a]			Case study material inputs[b]			
	GWP	CED	Consumption	SR	EOL-RIR	Material intensity			
						c-Si	CdTe	CIGS	a-Si
	[kg CO_2-eq/MW]	[MJ/MW]	[kg/yr]		[%]	[kg/MW]	[kg/MW]	[kg/MW]	[kg/MW]
Concrete	0.12	0.9			90.0%	60,700	60,700	60,700	60,700
Glass	0.97	12.3			40.0%	46,400	46,400	46,400	46,400
Plastic	3.62	90.8			32.5%	8,600	8,600	8,600	8,600
Steel	1.45	17.3			85.0%	67,900	67,900	67,900	67,900
Aluminium (Al)	9.36	107.7	5,252,000,000	0.59	12.4%	7,500	7,500	7,500	7,500
Cadmium (Cd)	5.52	93.4	700,000	0.34	30.0%		50		
Copper (Cu)	1.23	19.6	4,000,000,000	0.32	17.0%	4,600	4,600	4,622	4,600
Gallium (Ga)	169.31	2,605.6	27,000	1.26	0.0%			4	
Germanium (Ge)	170.00	2,890.0	39,000	3.89	2.0%				48
Indium (In)	119.37	2,101.3	30,000	1.79	0.0%			15	
Selenium (Se)	3.44	60.2	1,000,000	0.41	1.0%			35	
Silicon (Si)	49.42	964.9	433,000,000	1.18	0.0%	4			150
Silver (Ag)	512.52	7,858.7	3,800,000	0.68	19.0%	20			
Tellurium (Te)	6.94	125.4	30,000	0.51	1.0%		52		

[a] See Table E2 in Appendix E for detailed description of data sources, b Material intensities taken from [11].

Table 3
Final indicator results for wind turbine and solar PV case studies (per MW of installed capacity). Lowest values of GWP, CED and supply risk and highest value of EOL-RIR are shaded in green.

		Net GWP	Net CED	Net SR	Net EOL-RIR
		[10^3 kg CO_2-eq]	[GJ]	[-]	[%]
Wind turbines	DD-EESG	353	4,382	0.006	85.2%
	DD-PMSG	326	4,166	0.025	84.1%
	GB-PMSG	329	4,058	0.006	85.9%
	GB-DFIG	319	3,960	0.002	85.5%
Solar PV	C-Si	268	3,640	0.000	69.2%
	CdTe	258	3,490	0.001	69.2%
	CIGS	260	3,523	0.001	69.2%
	a-Si	273	3,762	0.005	69.1%

components for renewable energy technologies.

5. Discussion and conclusions

Renewable energy technologies are evolving as a promising way of reducing global warming potential and the effects of climate change. Meanwhile, energy system models represent a powerful tool for forecasting possible low carbon future energy scenarios. Although, from a system perspective, environmental implications aside from greenhouse gas emissions need to be addressed to ensure the implementation of the most sustainable energy systems, most present-day energy system models cannot provide information about the other potential environmental and raw materials implications of the systems they replicate. This paper proposes a methodology that combines indicators based on life cycle assessment and material metabolism studies with the objective of providing complete and valuable new information for exploring potential climate policy pathways for reducing greenhouse gas emissions from a holistic perspective. This includes additional information about the potential reduction of greenhouse gas emissions, total energy demand and, more importantly, a better understanding of the possible limitations on obtaining projected installed capacities based on disruptions of raw material supply. Such information will lead to the identification of renewable energy technologies with lower environmental footprints in terms of greenhouse gas emissions while allowing more sustainable and realistic energy system options to be pinpointed using a range of material supply indicators.

The proposed methodology for calculating composite indicators for energy supply technologies demonstrates that useful and informative information can be calculated relatively simply from material intensity data in conjunction with life cycle impact assessment outputs and material supply data. In that sense, the methodology proposed offers, on one hand, a clear definition of a set of indicators that support a more complete assessment of energy technologies alongside existing life cycle assessment studies. On the other hand, the use of established and reliable data sources (ecoinvent and official EU data) allows bespoke data in a readily usable format to be easily elaborated by energy system modellers.

Additionally, while the given examples use data inputs for the European Union based on a single megawatt of installed capacity, the methodology could easily be adapted to data sources from other regions, for smaller or larger scales and for net energy units. The simplicity of the approach also means that any number of other life cycle impact assessment or material supply data sources could be adapted and applied. The study has demonstrated that a variety of life cycle assessment and material metabolism data is already available that can be used to assess many forms of fossil-based and renewable energy technologies using the proposed methodology and, ultimately, to include the derived indicators in energy system models or similar investigations. For some technologies, greater effort is needed to improve the availability of life cycle inventory data in a useable and formalised format (e.g., the ecoSPOLD standard), particularly for newer solar, geothermal and fuel cell technologies and the myriad electricity storage options available, to name a few. For biomass-derived products used for energy purposes, the data currently available regarding material metabolism studies is limited. For instance, the 2020 European Commission Non-Critical Raw Materials report included supply risk and end-of-life recycling input rate data for three biomass materials (natural cork, natural teakwood and sapele wood) mainly used for construction material and high-end furniture and, thus, of little relevance for energy system models. With the increasing importance of the circular bioeconomy in the European Union, more material metabolism studies of biomass-derived products are likely to be available shortly. As such, applying the indicator calculation methodologies proposed in this paper will soon become feasible for a range of biomass applications. In that sense, it is thought that the potential of the methodology for comparing competing subtechnologies within a field could be especially useful.

Although the present study is limited in its investigation of material metabolism indicators to supply risk and end-of-life recycling input rate, it is thought that import reliance–included in the European Commission's calculations of supply risk scores for individual materials–could also be used to provide critical information as a standalone indicator. While the European Commission leans heavily on the supply risk factor for quantifying the overall criticality of materials, it is recognised that import reliance is more relevant in terms of greenhouse gas emissions as it essentially provides information about the transport requirements for obtaining the raw materials for producing energy infrastructure. As such, it could be considered to be a proxy environmental impact indicator and worthy of further investigation using similar analysis techniques to the current study, particularly as a readily available dataset already exists–at least for the European Union–for the set of most critical raw materials. For now, such approaches could be used in conjunction with the many energy system models and datasets already in existence for European Union and other global and local energy systems to obtain more accurate information regarding materials metabolism. This would enable more informed strategy decisions to be made by climate and resource management policymakers. As wind and solar energy look likely to remain a policy priority in many European countries in coming years, the European Union will need to emphasise the importance of better wind turbine and solar photovoltaic designs, including the implementation of circular economy strategies such as repair and remanufacture, as they strive to meet decarbonisation goals. Demand for such indicators looks set to increase, particularly as new regulations continue to include them as requirements. Consideration of the indicators proposed in this paper represents a vital first step in progressing towards a more complete methodology for the modelling and identification of more sustainable energy systems.

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CRediT authorship contribution statement

Laura Talens Peiró: Conceptualization, Methodology, Writing – original draft. **Nick Martin:** Methodology, Investigation, Writing – original draft. **Gara Villalba Méndez:** Supervision. **Cristina Madrid-López:** Writing – review & editing.

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.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.118150.

References

[1] European Commission. The European Green Deal. European Commission 2019;53:24. https://doi.org/10.1017/CBO9781107415324.004.
[2] IEA. European Union 2020: Energy Policy Review. Iea 2020.
[3] Guinée J. Handbook on Life Cycle Assessment. Springer 2002. https://doi.org/10.1007/0-306-48055-7.
[4] Blanco H, Codina V, Laurent A, Nijs W, Maréchal F, Faaij A. Life cycle assessment integration into energy system models: An application for power-to-methane in the EU. Appl Energy 2020;259:114160. https://doi.org/10.1016/j.apenergy.2019.114160.
[5] Igos E, Rugani B, Rege S, Benetto E, Drouet L, Zachary DS. Combination of equilibrium models and hybrid life cycle-input-output analysis to predict the environmental impacts of energy policy scenarios. Appl Energy 2015;145:234–45. https://doi.org/10.1016/j.apenergy.2015.02.007.
[6] García-Gusano D, Iribarren D, Martín-Gamboa M, Dufour J, Espegren K, Lind A. Integration of life-cycle indicators into energy optimisation models: The case study of power generation in Norway. J Cleaner Prod 2016;112:2693–6. https://doi.org/10.1016/j.jclepro.2015.10.075.
[7] Volkart K, Mutel CL, Panos E. Integrating life cycle assessment and energy system modelling: Methodology and application to the world energy scenarios. Sustainable Production Consumption 2018;16:121–33. https://doi.org/10.1016/j.spc.2018.07.001.
[8] Nuss P, Blengini GA. Towards better monitoring of technology critical elements in Europe: Coupling of natural and anthropogenic cycles. Sci Total Environ 2018;613–614:569–78. https://doi.org/10.1016/j.scitotenv.2017.09.117.
[9] Commission E. Critical Raw Materials for the European Union. Brussels: Belgium; 2010.
[10] Hollins O, Faunhofer ISI. Study on Critical Raw Materials at EU level 2014:1–166.
[11] European Commission. Study on the review of the list of Critical Raw Materials - Final Report. 2020. https://doi.org/10.2873/11619.
[12] Deloitte Sustainability, Bristish Geological Survey, Bureau de Recherches Géologiques et Minières, Netherlands Organisation for Applied Scientific Research. Study on the review of the list of Critical Raw Materials - Criticality Assessments. Luxenbourg: 2017. https://doi.org/10.2873/876644.
[13] Commission E. Methodology for establishing the EU list of Critical Raw Materials. Publications Office of the European Union 2017:1–25. https://doi.org/10.2873/769526.
[14] Bobba S, Carrara S, Huisman J, Mathieux F, Pavel C. Critical Raw Materials for Strategic Technologies and Sectors in the EU - a Foresight Study. Ispra 2020. https://doi.org/10.2873/58081.
[15] European Commission. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committe of the regions on Critical Raw Materials resilience: charting a path towards greater Security and sustainability. Brussels: 2020. https://doi.org/10.1007/978-3-030-40268-6_9.
[16] Stehfest E, van Vuuren D, Kram T, Bouwman L, editors. Integrated Assessment of Global Environmental Change with IMAGE 3.0. The Hague, The Netherlands: PBL publishers; 2014.
[17] PBL Netherlands Environmental Assessment Agency. IMAGE 3.0 2020. https://models.pbl.nl/image/index.php/Welcome_to_IMAGE_3.0_Documentation.
[18] Capellán-Pérez I, de Blas I, Nieto J, de Castro C, Miguel LJ, Carpintero Ó, et al. MEDEAS: A new modeling framework integrating global biophysical and socioeconomic constraints. Energy Environ Sci 2020;13(3):986–1017. https://doi.org/10.1039/C9EE02627D.
[19] Guinée JB, Heijungs R, Huppes G, Zamagni A, Masoni P, Buonamici R, et al. Life Cycle Assessment: Past, Present, and Future. Environ Sci Technol 2011;45(1):90–6. https://doi.org/10.1021/es101316v.
[20] Wernet G, Bauer C, Steubing B, Reinhard J, Moreno-Ruiz E, Weidema B. The ecoinvent database version 3 (part I): Overview and methodology. Int J Life Cycle Assess 2016;21(9):1218–30. https://doi.org/10.1007/s11367-016-1087-8.

[21] Kupfer T, Baitz M, Colodel CM, Kokborg M, Schöll S, Rudolf M, et al. GaBi databases & modeling principles 2020. Sphera; 2020.
[22] Huijbregts MAJ, Steinmann ZJN, Elshout PMF, Stam G, Verones F, Vieira M, et al. ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. Int. J. Life Cycle Assessment 2017;22:138–47. https://doi.org/10.1007/s11367-016-1246-y.
[23] Dewulf J, Benini L, Mancini L, Sala S, Blengini GA, Ardente F, et al. Rethinking the area of protection "natural resources" in life cycle assessment. Environ Sci Technol 2015;49(9):5310–7. https://doi.org/10.1021/acs.est.5b00734.
[24] IPPC. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom and New York, NY, USA,: 2013.
[25] World Meteorological Organisation. Scientific Assessment of Ozone Depletion: 1998. Geneva: Switzerland; 1999.
[26] Tobergte DR, Curtis S. ILCD Handbook. vol. 53. 2013. https://doi.org/10.278/33030.
[27] Jungbluth N. Description of life cycle impact assessment methods. ESU-Services Ltd 2020;39.
[28] Sala S., Benini L., V. C, B. VL, V. DL, R. P. Suggestions for the update of the Environmental Footprint Life Cycle Impact Assessment: Impacts due to resource use, water use, land use, and particulate matter - EUR 28636 EN. 2019. https://doi.org/10.2760/78072.
[29] Bulle C, Margni M, Patouillard L, Boulay AM, Bourgault G, De Bruille V, et al. IMPACT World+: a globally regionalized life cycle impact assessment method. Int J Life Cycle Assess 2019;24(9):1653–74. https://doi.org/10.1007/s11367-019-01583-0.
[30] Frischknecht R, Jolliet O. Global Guidance for Life Cycle Impact Assessment Indicators - Volume 1. vol. 1. Paris, France: 2016.
[31] Sonderegger T, Berger M, Alvarenga R, Bach V, Cimprich A, Dewulf J, et al. Mineral resources in life cycle impact assessment: Part I - A critical review of existing methods. Int J Life Cycle Assess 2020;25(4):784–97. https://doi.org/10.1007/s11367-020-01736-6.
[32] Berger M, Sonderegger T, Alvarenga R, Bach V, Cimprich A, Dewulf J, et al. Mineral resources in life cycle impact assessment: Part II - Recommendations on application-dependent use of existing methods and on future method development needs. Int J Life Cycle Assess 2020;25(4):798–813. https://doi.org/10.1007/s11367-020-01737-5.
[33] Nuss P, Eckelman MJ, Janssen PJ. Life cycle assessment of metals: A scientific synthesis. PLoS ONE 2014;9(7):e101298. https://doi.org/10.1371/journal.pone.0101298.
[34] Garrett P, Rønde K. Life cycle assessment of wind power: Comprehensive results from a state-of-the-art approach. Int J Life Cycle Assess 2013;18(1):37–48. https://doi.org/10.1007/s11367-012-0445-4.
[35] Verboon M. Environmental impacts of nickel production, 2010 –2050. An assessment of the environmental impacts of metal demand and supply scenarios using life cycle assessment. Leiden University & Delft University of Technology, Den Haag, Netherlands., 2016.
[36] Kuipers K. Environmental implications of alternative global copper supply scenarios and the supply criticality of selected copper by-product metals. Trondheim, Norway: Leiden University & Delft University of Technology; 2016.
[37] Van der Voet E, Van Oers L, Verboon M, Kuipers K. Environmental Implications of Future Demand Scenarios for Metals: Methodology and Application to the Case of Seven Major Metals. J Ind Ecol 2019;23(1):141–55. https://doi.org/10.1111/jiec.2019.23.issue-110.1111/jiec.12722.
[38] Ciroth A, Arbuckle P, Cherubi E, Ugaya C, Edelen A. Task 3: Core meta-data descriptors and guidance on populating descriptors. 2017.
[39] Talens Peiró L, Gabarrell i Durany X, Martinez Gasol C, Rieradevall Pons J. LCADB database (i-depot 120008) 2019.
[40] Talens Peiro L, Gabarrell i Durany X. DoSE database (i-depot:120009), 2019.
[41] Paulik S, Hasan MM. Industrial Ecology Data Commons prototype 2020. http://www.database.industrialecology.uni-freiburg.de.
[42] Díaz A, Marrero GA, Puch LA, Rodríguez J. Economic growth, energy intensity and the energy mix. Energy Econ 2019;81:1056–77. https://doi.org/10.1016/j.eneco.2019.05.022.
[43] Mendoza Beltran A, Cox B, Mutel C, Vuuren DP, Font Vivanco D, Deetman S, et al. When the background matters: Using scenarios from integrated assessment models in prospective life cycle assessment. J Ind Ecol 2020;24(1):64–79. https://doi.org/10.1111/jiec.v24.110.1111/jiec.12825.
[44] Cox B, Mutel CL, Bauer C, Mendoza Beltran A, Van Vuuren DP. Uncertain Environmental Footprint of Current and Future Battery Electric Vehicles. Environ Sci Technol 2018;52:4989–95. https://doi.org/10.1021/acs.est.8b00261.
[45] DG JRC. Emissions Database for Global Atmospheric Research (EDGAR) n.d.
[46] Wilson GM, Al-Jassim M, Metzger WK, Glunz SW, Verlinden P, Xiong G, et al. photovoltaic technologies roadmap. J Phys D Appl Phys 2020;53(49):493001. https://doi.org/10.1088/1361-6463/ab9c6a.
[47] British Geological Survey. What is the difference between resources and reserves? n.d. https://www2.bgs.ac.uk/mineralsuk/mineralsYou/resourcesReserves.html.
[48] U.S. Geological Survey. Mineral commodity summaries 2020. Reston, VA: U.S. Geological Survey; 2020. https://doi.org/10.3133/mcs2020.
[49] Verhoef EV, Dijkema GPJ, Reuter MA. Process knowledge, system dynamics, and metal ecology. J Ind Ecol 2004;8:23–43.
[50] Peiró LT, Méndez GV, Ayres RU. Material flow analysis of scarce metals: Sources, functions, end-uses and aspects for future supply. Environ Sci Technol 2013;47(6):2939–47. https://doi.org/10.1021/es301519c.
[51] Graedel TE, Barr R, Chandler C, Chase T, Choi J, Christoffersen L, et al. Methodology of Metal Criticality Determination. Environ Sci Technol 2012;46(2):1063–70. https://doi.org/10.1021/es203534z.
[52] Nassar NT, Graedel TE, Harper EM. By-product metals are technologically essential but have problematic supply. Sci Adv 2015;1:1–10. https://doi.org/10.1126/sciadv.1400180.
[53] Roelich K, Dawson DA, Purnell P, Knoeri C, Revell R, Busch J, et al. Assessing the dynamic material criticality of infrastructure transitions: A case of low carbon electricity. Appl Energy 2014;123:378–86. https://doi.org/10.1016/j.apenergy.2014.01.052.
[54] Ayres RU. Industrial metabolism. In: Ausubel J, Sladovich HE, editors. Technology and environment. Washington DC: National Academy Press; 1989.
[55] European Commission. Data needs for a full raw materials flow analysis. Norfolk: 2012.
[56] Petiot C, Planchon M, De Prado Trigo A, Devauze C. Study on Data for a Raw Material System Analysis: Roadmap and Test of the Fully Operational MSA for Raw Materials. BIO by Deloitte: IFEU, Charles University Environment Center, ERA Technology; 2015.
[57] European Commission. Study on the EU's list of Critical Raw Materials (2020), Factsheets non-Critical Raw Materials. Brussels, Belgium: 2020. https://doi.org/10.2873/11619.
[58] Blengini GA, Nuss P, Dewulf J, Nita V, Peirò LT, Vidal-Legaz B, et al. EU methodology for critical raw materials assessment: Policy needs and proposed solutions for incremental improvements. Resour Policy 2017;53:12–9. https://doi.org/10.1016/j.resourpol.2017.05.008.
[59] European Commission. Study on the EU's list of Critical Raw Materials (2020), Factsheets on Critical Raw Materials. 2020. https://doi.org/10.2873/867993.
[60] European Commission. Study on the review of the list of Critical Raw Materials – Non Critical Raw Materials Factsheets. 2020. https://doi.org/10.2873/92480.
[61] Amponsah NY, Troldborg M, Kington B, Aalders I, Hough RL. Greenhouse gas emissions from renewable energy sources: A review of lifecycle considerations. Renew Sustain Energy Rev 2014;39:461–75. https://doi.org/10.1016/j.rser.2014.07.087.
[62] Carrara S, Alves Dias P, Plazzotta B, Pavel C. Raw materials demand for wind and solar PV technologies in the transition towards a decarbonised energy system, EUR 30095 EN. Luxembourg: Publication Office of the European Union; 2020. https://doi.org/10.2760/160859.