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An energy future beyond climate neutrality: Comprehensive evaluations of transition pathways

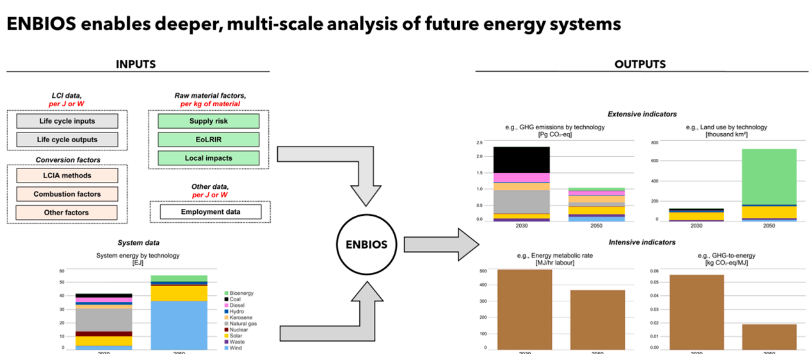
Nick Martin [a], Laura Talens-Peiró [a], Gara Villalba-Méndez [a,b], Rafael Nebot-Medina [c], Cristina Madrid-López [a,*]

[a] Sostenipra Research Group, Institute of Environmental Science and Technology (ICTA-UAB), Autonomous University of Barcelona, Bellaterra (Cerdanyola del Vallès), Catalunya 08193, Spain
[b] Department of Chemical, Biological and Environmental Engineering, Autonomous University of Barcelona, Bellaterra (Cerdanyola del Vallès), Catalunya 08193, Spain
[c] Scientific and Technological Computing Department, Instituto Tecnológico de Canarias, Las Palmas de Gran Canaria, Canarias 35003, Spain

HIGHLIGHTS

- Energy models generally fail to consider impacts beyond direct GHG emissions.
- ENBIOS joins a push to integrate life cycle thinking into energy modelling frameworks.
- Extra dimensions are added via social metabolism and hierarchical analysis.
- Analysis of EU scenarios reveals potential land use, labour and material issues.

GRAPHICAL ABSTRACT



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ABSTRACT

Many of the long-term policy decisions surrounding the sustainable energy transition rely on models that fail to consider environmental impacts and constraints beyond direct greenhouse gas emissions and land occupation. Such assessments offer incomplete and potentially misleading information about the true sustainability issues of transition pathways. Meanwhile, although decision-makers desire greater access to a broader range of environmental, material and socio-economic indicators, few tools currently address this gap. Here, we introduce ENBIOS, a framework that integrates a broader range of such indicators into energy modelling and policymaking practices. By calculating sustainability-related indicators across hierarchical levels, we reach deeper understandings of the potential energy systems to be derived. With ENBIOS, we analyse a series of energy pathways designed by the Calliope energy system optimization model for the European energy system in 2030 and 2050. Although overall emissions will drop significantly, considerable rises in land, labour and critical raw material requirements are likely. These outcomes are further reflected in unfavourable shifts in key metabolic indicators during this period; energy metabolic rate of the system will drop by 25.6%, land requirement-to-energy will quadruple, while the critical raw material supply risk-to-energy ratio will rise by 74.2%. Heat from biomass and electricity from wind and solar are shown to be the dominant future processes across most indicator categories.

* Corresponding author.
E-mail address: cristina.madrid@uab.cat (C. Madrid-López).

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Nomenclature

Glossary

ALOP	agricultural land occupation LCIA method
CRM	critical raw material
EC	European Commission
EJ	exajoules (x10^{18} joules)
EMR	energy metabolic rate (energy per hour of human activity) [MJ/h]
ENBIOS	ENvironmental and BIOeconomic System Assessment
EoLRIR	end-of-life recycling input rate [%]
ESM	energy system model
EU	European Union
Gh	gigahours (x10^9 hours)
GHG	greenhouse gas
GHGMR	GHG metabolic rate (GHG per hour of human activity) [kgCO_2-eq/h]
GWP	global warming potential
GWP100	global warming potential (100-year time horizon) LCIA method
h	hours
HA	human activity [h]
IAM	integrated assessment model
ILO	International Labour Organization
IPCC	Intergovernmental Panel on Climate Change
ISIC	International Standard Industrial Classification
kg	kilograms
kgCO_2-eq	kilograms of carbon dioxide equivalent
km^2	square kilometres
LCA	life cycle assessment
LCI	life cycle inventory
LCIA	life cycle impact assessment
m^2	square metres
MJ	megajoules (x10^6 joules)
MuSIASEM	Multi-Scale Integrated Analysis of Socio-Ecosystem Metabolism
MW	megawatts (x10^6 watts)
PgCO_2-eq	x10^{12} kilograms of carbon dioxide equivalent
pLCA	prospective life cycle assessment
RoW	rest of the world
SENTINEL	Sustainable Energy Transitions Laboratory
solar PV	solar photovoltaic
SR	supply risk [yr]
TL	teralitres (x10^{12} litres or 10^9 cubic metres)
TWh	terawatt-hours (x10^{12} watt-hours)
ULOP	urban land occupation LCIA method
WDP	water depletion LCIA method
WMR	water metabolic rate (water use per hour of human activity) [m^3/h]
yr	years

1. Introduction

Global and local responses to the threat of climate change call for large reductions in the production of greenhouse gases (GHGs) via a rapid transition towards more sustainable energy system configurations. In the European Union (EU), the decarbonization of the economy–where renewable energy technologies replace older fossil fuel-based technologies–acts as one of the five “dimensions” of the energy union strategy [1]. However, while “decarbonised” energy systems are generally seen to represent cleaner and more sustainable alternatives, wider understandings of the impacts and constraints that relate to different energy technologies are often overlooked in decision-making. Indeed, the integrated assessment models (IAMs) and other energy system models (ESMs) used to inform energy-related decisions in the EU and elsewhere tend to only include simplified estimates of direct GHG emissions and obviate other environmental factors–such as raw material or water use– that may limit calculations [2,3].

Incorporating detailed sets of environmental calculations into such models is cumbersome not only from a computational point of view; it is also complicated by the vastly different semantics employed to define energy and environmental dynamics [4]. Nevertheless, continuing to overlook or simplify certain environmental aspects and constraints could result in suboptimal outcomes in proposed transition pathways [5]. What’s more, research suggests that energy decision makers are eager to access more comprehensive information about the range of possible environmental impacts and other limitations that could affect future energy scenarios [6].

The use of life cycle assessment (LCA) [7] approaches is one way to address these shortcomings. Within an LCA analysis, the full life cycle of an energy–or any other–process is considered [8]. So, rather than basing quantifications solely on the most obvious or direct aspects of a process, LCA-based approaches require the collection of input–output inventories for all contributing operations, from material extraction through to end-of-life disposal or recycling stages. Input flows include aspects like raw material, land, water and energy use, while output flows include emissions to the atmosphere, water bodies and other ecosystems as well as the products and co-products of a technology. Collectively, this life cycle inventory (LCI) data can be converted into more tangible indicator outputs using predefined life cycle impact assessment (LCIA) methods or other calculations.

LCA approaches have been widely adopted in recent years for comparing different existing and emerging technologies, including those within the energy sector [9,10]. Furthermore, they are beginning to be used to quantify impacts within complete energy systems by aggregating the impacts of the various technological processes that occur within them [11]. Attempts have also been made to integrate LCA data sources directly into energy models [8,12,13], and by creating simplified inventories on-the-fly within IAM simulations [14]. Conversely, within the burgeoning field of prospective life cycle assessment (pLCA) [15–20] information *from* IAMs, input–output models and other sources regarding future variations in energy system configurations–e.g., energy mixes or efficiencies–are used to incorporate provisions for future changes within LCA calculations.

In any event, no existing approaches allow for the detailed inclusion and analysis of LCA-related inputs or outputs across hierarchical levels within energy systems. In this regard, a number of studies have applied relational analysis principles to assessing the social metabolism aspects of energy systems [21,22]. However, such analyses have not attempted to assess environmental impacts or constraints in any detail, nor have they included other socio-metabolic indicators or been able to integrate the resource needs of those systems.

To bridge this gap, we introduce the ENvironmental and BIOeconomic System Assessment (ENBIOS) framework. ENBIOS has been developed to perform sustainability assessments within the energy modelling platform developed as part of the Sustainable Energy Transitions Laboratory (SENTINEL) project [23]. It connects LCA functionality with the relational capabilities of the Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM) approach [24–27]. ENBIOS takes system definition information from ESMs –or any other real or theoretical systems– and combines this with built-in datasets to generate a range of environmental and other indicators at each element in that system. This fundamentally includes the use of LCA-based datasets and methods. However, any number of other user-defined methodologies or datasets can be included in these calculations.

Two broad types of indicators are produced within an ENBIOS simulation. The first of these, *extensive* indicators, are derived using life cycle inventory data and other inputs, such as labor requirements, and provide information about the total size and impacts of the system's components. For example, total energy production, GHG emissions, land requirements or human labour could all be calculated for a given technological process in a system. Combining extensive indicator values for each of these elements then allows a second set of *intensive* indicators to be calculated within the system. Using the previous examples, indicators could be derived to represent the energy produced per hour of labour or GHG emissions per unit of energy, providing useful information about system performance and relations.

The set of extensive and intensive indicators can then be examined within and across hierarchical levels using multi-scale system analysis. This can provide valuable information about the nature of systems at different levels, from individual processes or grouped categories to entire energy systems. For example, visualisations of extensive data could help to identify if higher land requirements are caused by heat or electricity sources in a given scenario, or the relative contributions to labour requirements from different technologies across different scenarios. Likewise, changes in intensive indicators–e.g., a drop in water use per unit of energy–can be compared and traced according to the changes that occur at different hierarchical levels.

Ultimately, the innovation of the framework is rooted in its ability to integrate LCA and MuSIASEM methods for deriving extensive and intensive indicators to evaluate systems from a hierarchical analysis perspective. The flexibility of the framework to different systems and applications allows simple but powerful observations to be made about the different characteristics that exist at different places within a given hierarchy. This, in turn, provides insights into the potential constraints, "hot spots" and possible trade-offs that exist when analysing current or future systems, energy or otherwise.

The article continues in Section 2 with a description of the use of the framework, including summarized descriptions of the LCA and MuSIASEM approaches that form its basis and the various inputs and outputs involved in an ENBIOS simulation. A selection of indicators and possible applications are also discussed. A case study example is then provided in Section 3, based on a projected "climate neutrality" scenario for the European energy system using outputs from the Euro-Calliope model. The article concludes in Section 4 with a discussion of key outcomes, potential issues and a roadmap for further development.

2. The ENBIOS workflow

While previous efforts have attempted to integrate LCA-based thinking with energy system configurations *and* to consider the socio-metabolic dynamics of energy systems, to the best of our knowledge ENBIOS represents the first attempt to consolidate these two perspectives into a single framework. To do this, ENBIOS integrates the high-resolution impact assessment capabilities of LCA with the systemic upscaling capabilities of MuSIASEM. A summary of the ENBIOS workflow is represented in Fig. 1 and detailed in the following sections.

2.1. Preparation

The first step in the development of an ENBIOS simulation is typically to define the system framework within a MuSIASEM environment. To do this one must first define a "dendrogram", a multi-level structure that arranges the system hierarchically into "processor" nodes where the relationships between input and output flows are calculated. Processors can operate in one of two capacities within the "tree" of the dendrogram. "Structural processors" represent the most specific and tangible activities that can easily be located within a spatial–temporal context (e.g., specific technologies like wind turbines or nuclear stations). Meanwhile, "functional processors" represent a less tangible social function (e.g., wind turbines or solar PV panels could exist as "structures" related to the "function" of renewable electricity supply, which itself related to electricity supply and, ultimately, energy supply). In other words, the MuSIASEM usage within ENBIOS, the lower levels of the dendrogram are typically represented by *structures* that are later related to the *functions* they can provide further "up" the hierarchical structure, respecting their multifunctionality.

With the hierarchical definition in place, structural processors are related to a specific activity which must be defined by an LCI listing. Several types of additional data are then also required to enable indicators to be calculated at each processor. The "foreground" scaling information is provided by scenario information such as energy mix and installed capacity data, supplied by outputs from ESMs or other system configuration data. By its nature, this data will differ the most between individual scenarios, where different configurations are being tested, for example. Other "background" input data–e.g., employment rates or constants for raw material calculations–are likely to remain relatively constant from scenario to scenario.

The key background inputs are taken from LCA databases. Firstly, an LCI listing provides a detailed set of information relating to the masses of individual materials, volumes of water and areas of land required as inputs to a given process–e.g., the production of one unit of energy using a certain technology or process. Outputs to land, water and soil are also given in relation to radiation, waste and several other aspects. LCI data is assigned at each structural processor in the system dendrogram–one LCI

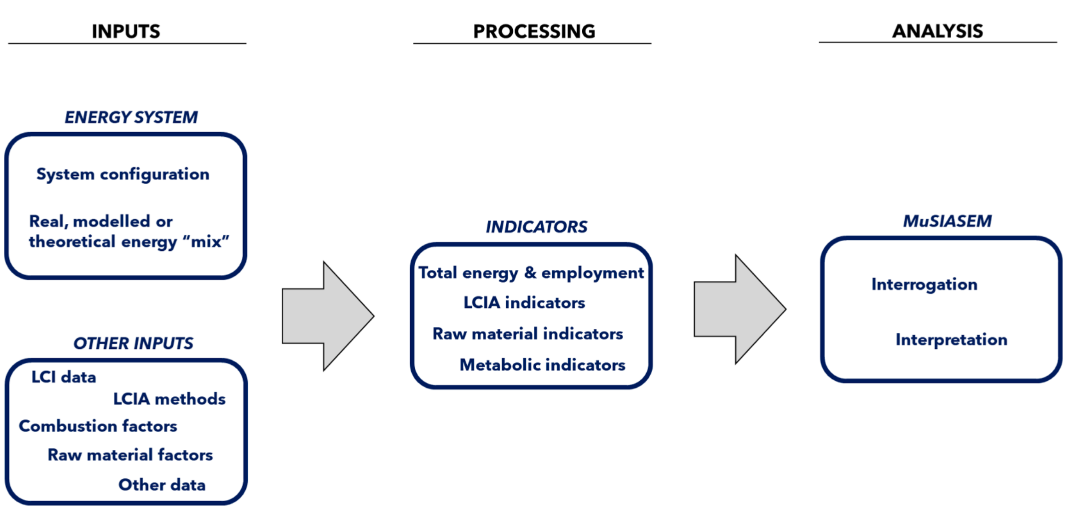

Fig. 1. Overview of general workflow used in the operation of ENBIOS alongside typical inputs and indicators for energy systems.

process per processor–and is provided using the ecospold (.spold) format utilised within the Ecoinvent 3.8 database [28].

Meanwhile, an LCIA "method" defines the way that LCI listings for a given process are transformed into useful final indicators–e.g., global warming potential (GWP), total land and water use, and a raft of other resource and environmental impact metrics. Many methods exist for defining a range of such indicators [29,30]. A number of these LCIA methods can be used with ENBIOS and the required method must be chosen prior to initiating calculations. Furthermore, as LCI processes for fuel production do not consider the combustion of fuels during their final use stage (e.g., the operation of internal combustion engines or home heating using natural gas) the additional GHG emissions for fuels must also be considered. Here, the required emission factors are taken from the Intergovernmental Panel on Climate Change (IPCC) database [31]. It is noted that similar estimates would need to be added to account for the additional contributions from combustion processes when other air pollution indicators are being used.

Aside from life-cycle data, any number of additional socio-metabolic indicator data sources can also be included, provided it has been normalised for installed capacity or for each unit of energy produced. For example, employment data typically specifies the labour required to maintain a given capacity of electricity and heat infrastructure or produce a certain amount of fuel [32,33]. Indicators can also be calculated that use raw materials requirements from LCI data in conjunction with other conversion factors or formulae. Indeed, methods for using LCI data to estimate raw material supply risks, end-of-life recycling input rates (EoLRIR) and local environmental impact and environmental justice threats for individual materials have been hypothesised elsewhere [34,35]. In theory, any number of methodologies and sets of input data could be used to create customised indicators for each process within a defined system, and ENBIOS has been specifically formulated to offer high levels of flexibility to users in this regard. Nevertheless, a summary of typical ENBIOS data inputs for energy systems is shown in Fig. 2.

2.2. Simulation

Once the system hierarchy has been defined and input parameters have been specified, indicators can begin to be produced. The first step is to produce a set of *extensive* results; for all structural and functional processors according to the selected methods as specified in simulation system files. It is important to note here that–unlike most previous attempts to aggregate LCA and other indicators for complete systems–in ENBIOS we do not perform simple linear aggregations on the *results* for individual processors when upscaling to higher hierarchical levels. Rather, the *input variables* themselves are aggregated at each point within the system hierarchy before the calculations are made. That is, we aggregate data inputs over the indicators themselves in order to explore emergent relations. In our previous example, extensive indicators are calculated using the applicable LCI data at the structural processors for wind turbines or solar PV. However, at the functional processor that encompasses these two processors, upscaled LCI data items would need to be summed before the indicator calculations could proceed. While this will not change indicators derived using linear relationships–e.g., GHG emissions derived using characterization factors in LCIA calculations–it is vital for the robustness of the model, and its potential suitability to different applications, that separate calculations are performed in situations where non-linear relationships are involved.

A further round of indicators can then be created by relating the initial indicators to additional data about the internal functioning of the system, thus characterizing the metabolic relationships and constraints that exist within the system. This includes–but is not limited to–the derivation of further *intensive* indicators, which are specific to a given system (e.g., rates, ratios or densities). For example, using the approach shown in Fig. 2, one could report "metabolic rate" indicators based on labour requirements or per-unit-of-energy indicators based on the total amount of energy produced. Indeed, an array of possible intensive indicators is possible based on the number of extensive indicators available. As with the definition of extensive indicators, ENBIOS offers the user great flexibility to define customised intensive indicators of their choosing. In this case, we use the most common MuSIASEM indicator of system functioning–human activity–using the hours of labour associated with the life cycle of each technology.

We calculated all extensive and intensive indicators on a per-unit-of-energy basis, then upscaled and further analysed these indicators examining values at different levels within the system based on the defined energy system hierarchy (i.e., the system configuration or

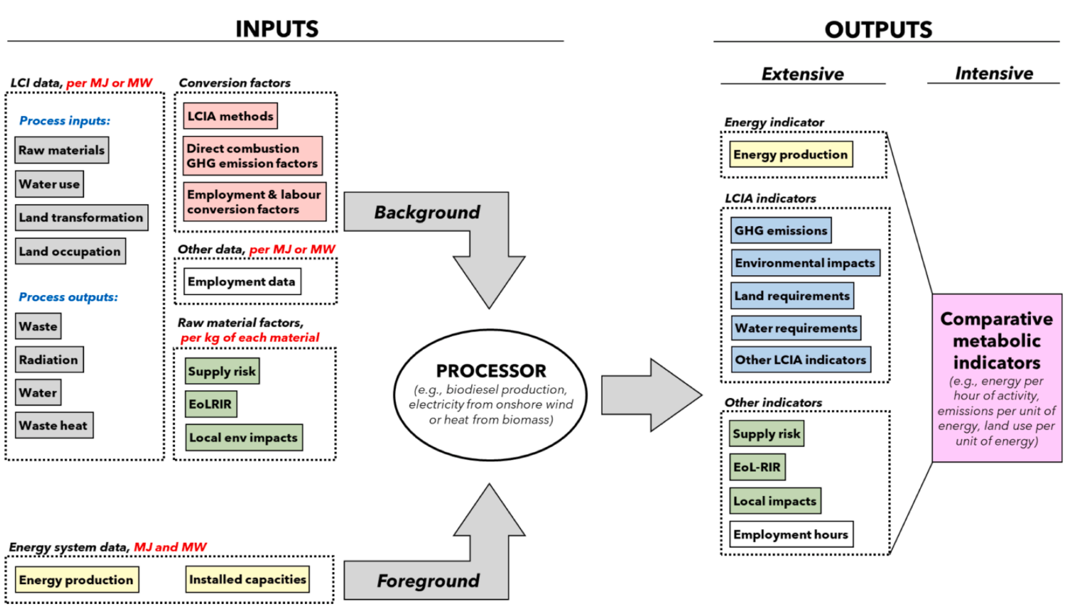

Fig. 2. Overview of typical data and methodological inputs and derived final outputs at each processor in an ENBIOS simulation for a given energy system. LCI data, conversion factors, raw material factors and other such data inputs define the system background and are typically entered at the system definition stage and only updated sporadically. Meanwhile, foreground data inputs for individual energy system configurations change according to each scenario being tested. It is noted that input values are aggregated to previous levels of system hierarchies and that calculations always occur at each processor in a system; indicator outputs themselves are never aggregated directly.

"energy mix"). A broad range of indicators can then be examined from individual or grouped energy sub-technologies to entire energy systems, and vice versa.

3. Application to European energy scenarios

To demonstrate an application of ENBIOS, the framework was applied to the European energy system using a set of projected scenario results for the years 2030 and 2050 obtained from partners within the SENTINEL project.

3.1. System definition

The dendrogram for the case study system was defined to align with outputs obtained from Euro-Calliope [36], a version of the Calliope model [37] being utilised within the project. The model includes all EU member states (except Malta), together with Albania, Bosnia and Herzegovina, Montenegro, Serbia, Switzerland, the United Kingdom, Iceland and Norway. Euro-Calliope simulates all regional processes of electricity and heat generation at the centralised utility level alongside the most common forms of fuels used for direct consumption (predominantly those for transport, non-centralised electricity and heat generation and use in industrial applications). A representation of the dendrogram is shown in Fig. 3.

Structural processors representing the individual sub-technologies are shown as rounded blocks at the "n-5" level, on the right-hand side of the diagram. Functional processors that represent higher level combinations of these sub-technologies according to energy supply technology type ("n-4"), renewable status ("n-3") and energy carrier type ("n-1") are then shown as square blocks to the left of this column.

3.2. Data inputs

Results obtained from Euro-Calliope that reflect the information for the system under the "climate neutrality" scenario were used here for the years 2030 and 2050 [38]. This includes energy production data in terawatt-hours (TWh) and installed capacity data in megawatts (MW) for 11 sources of utility-level electricity and three sources of utility-level heat. Total production levels (TWh) were also obtained for five sources of fuel supply. Note that no methanol use was included under this particular scenario. LCI data was assigned at each structural processor from the Ecoinvent 3.8 database [28]. All electricity processes are defined per kilowatt-hour (kWh) of energy produced, while heat processes are defined per megajoule (MJ); all inventory items are, thus, initially converted to TWh equivalents according to standard conversions. Fuel production processes are defined per kilogram (kg), which requires the data to be converted to energetic equivalents using known MJ/kg calorific value equivalents [39]. As the case study uses total energy inputs for the European energy system as a whole, generalised LCI process listings for Europe were used, where available. Where these processes are not available, rest of world (RoW) values are used. However, in some cases the RoW values deviate significantly from those of individual European countries, which are often quite similar. In these instances, the European country that represents the highest share for that category in the case study energy mix is used. Lastly, GHG emission factors for combustion of the five fuels–in kg carbon dioxide equivalent (CO_2-eq) per kg fuel–were obtained from the IPCC database [31]. A full listing of the input data is provided in Table S1 of the supplementary information.

Three sample LCIA impact categories from the ReCiPe Midpoint (H) group [40] were chosen in this example: GHG emissions in kg CO_2-eq were derived using the "GWP100" method, total land occupation in m^2 was estimated by summing outputs from the agricultural ("ALOP") and

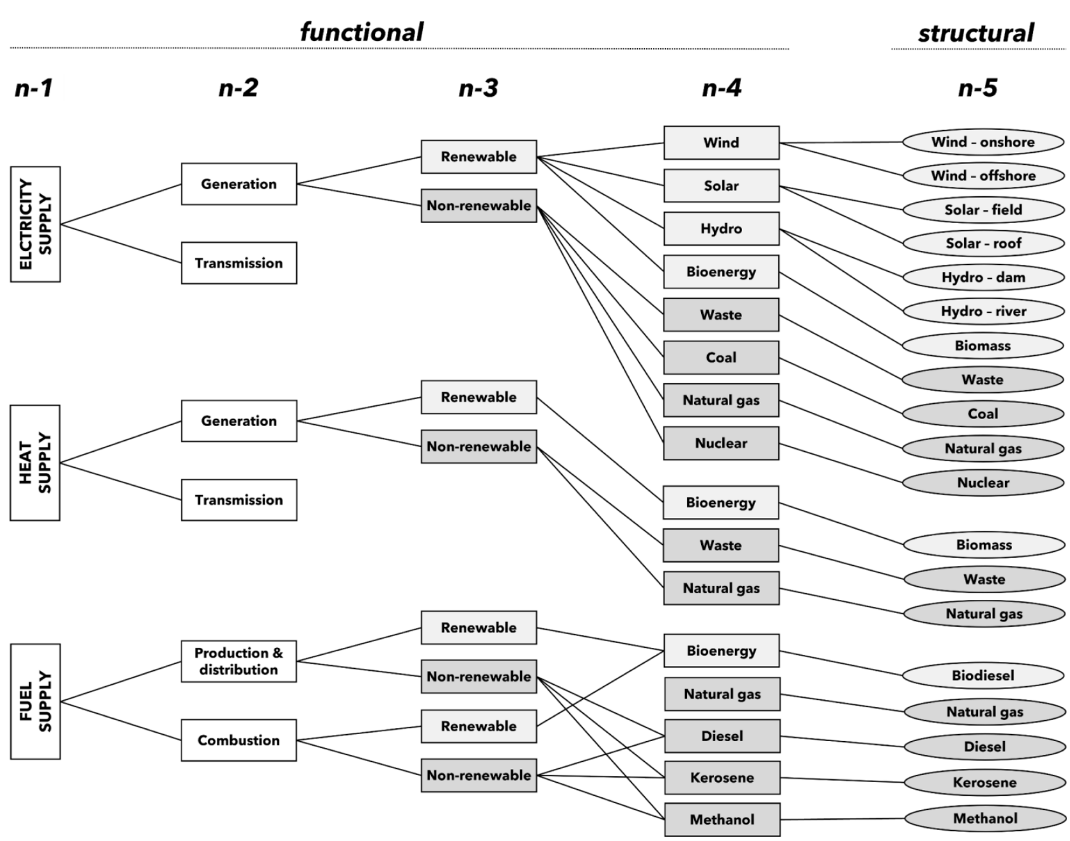

Fig. 3. ENBIOS dendrogram structure for the EU energy system. Structural processors representing specific electricity, heat and fuel supply processes are located on the right side of the figure. Functional processors are shown on the left of the figure.

urban ("ULOP") land occupation methods, while water depletion in m^3 used the "WDP" method.

Employment data that estimates of the number of full-time jobs provided by each installed MW of capacity for each electricity and heat generation category [33] was also obtained for each technology. The data includes employment across the manufacturing, construction and installation periods, as well as the ongoing operation and maintenance tasks occurring within the equipment's lifetime. Decommissioning periods are also included, where appropriate. Consequently, although the lifetimes of energy infrastructure are generally between 20 and 50 years [32], and capacities fluctuate from year to year as equipment is implemented and retired, a total number of job positions can be calculated for each moment in time based on current capacities. Data for fuel production processes is typically given on a per-unit-of-energy basis. Hence, the total amount of fuel supplied within a given period–in this case, one year–contributes to the maintenance of a certain number of

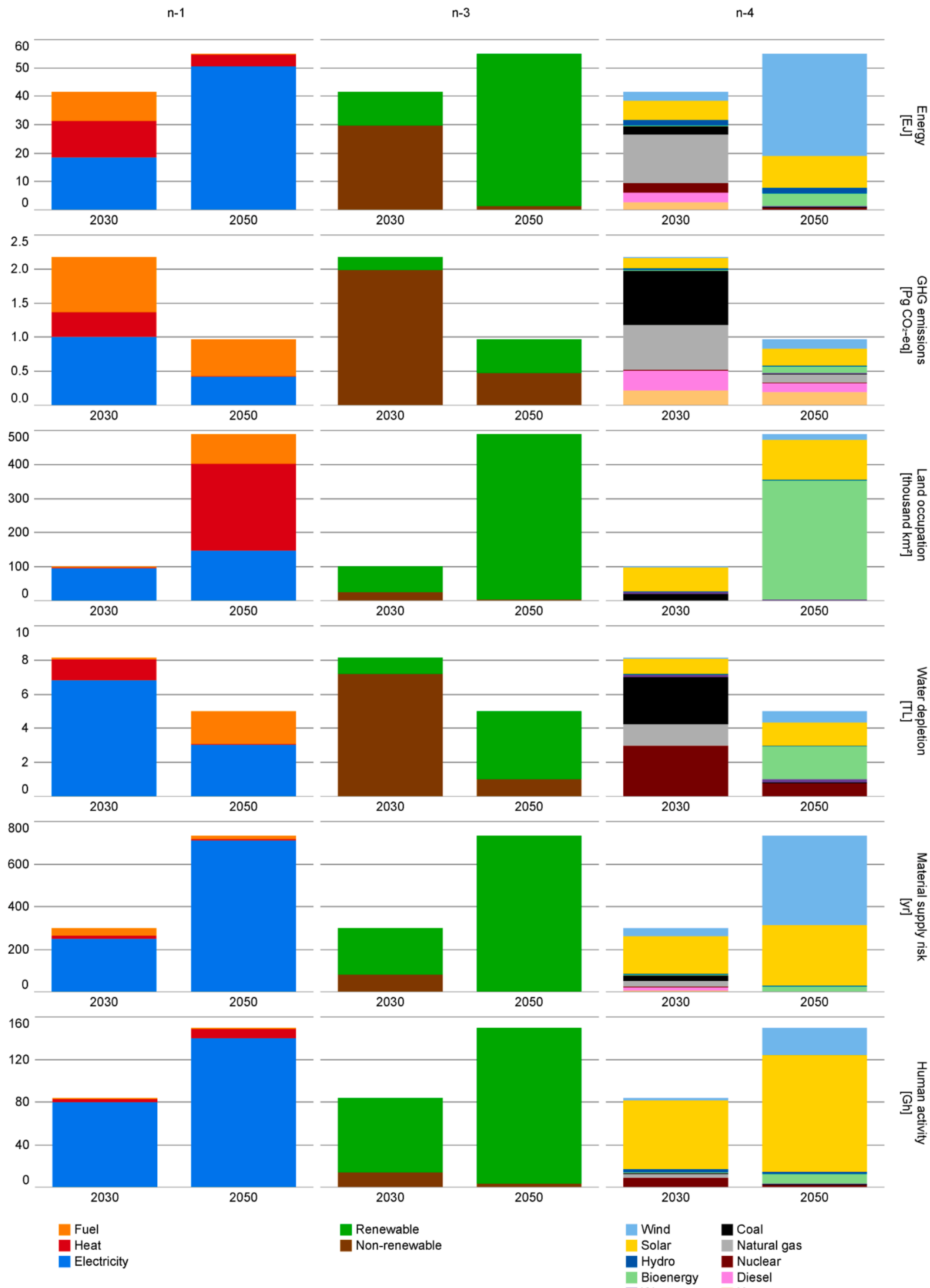

Fig. 4. Results showing outputs for extensive indicators. Results shown for six indicators across three hierarchical level groupings for projected 2030 and 2050 energy mix outcomes under the EU"climate neutrality" scenario.

positions within that timeframe. A full listing of the utilised data is provided in Table S2 of the supplementary information.

In order to fully incorporate labour aspects into the metabolic calculations within ENBIOS, raw job data was then converted into hours of human activity (HA) using estimates of annual working hours from relevant sectors. Here, "mean weekly hours actually worked" data was obtained from the International Labour Organization (ILO) for each country represented in the Euro-Calliope model [41]; data is available for all sectors identified within the International Standard Industrial Classification (ISIC) level 2 definitions, of which four are directly applicable to the energy sector and assigned to each processor. Composite annual values for the full model extent–one for each sector–were then calculated using the weekly hours worked in individual countries, weighted according to ILO employment rate data. The final data for each sector is listed in Table S3 of the supplementary information.

Lastly, raw material factors that enable calculations to be made for material supply risk (SR) according to established methodologies [34,35] were also included. Factors were obtained via external sources [42,43] for the 55 substances contained within the LCI database that are considered to be critical raw materials (CRMs) by the European Commission (EC) [43]. It should be noted that, although SR values are essentially dimensionless, years (yr) are used as units in accordance with the adopted formula.

3.3. Analysis

Results were firstly derived at each of the 19 structural ("n-5") processors for a group of six extensive indicators: the total energy production (directly from Euro-Calliope results), three LCIA indicators, raw material SR and employment-related human activity. A full listing is provided in Table S4 of the supplementary information. Further calculations were then performed in relation to energy supply technology type ("n-4"), renewable status ("n-3") and energy carrier type ("n-1"). The findings are displayed in Fig. 4 and listed in Table S5 of the supplementary information. A summary of the overall percentage changes at the system level are shown in Table 1 alongside a listing of the technology type ("n-4") that makes the most significant contribution to overall system change.

The extensive data outputs reveal several key findings. The most immediate trends observed in the energy production data are the overall increase of energy production within the system boundary, the move towards renewable energy and the increased electrification of the system by 2050. The breakdown of technologies also reflects the forecast dominance of electricity from wind (65.5 %) and solar (20.4 %), heat from biomass (7.6 %) and the phasing out of natural gas, which would drop from 40.9 % of system share in 2030 to 0.1 % by 2050. As expected, net GHG emissions are predicted to drop significantly between 2030 and 2050, reducing by 54.7 %; the highest contributor to this drop is coal, which drops from 34.8 % of system share in 2030 to zero in 2050.

The level of emissions produced in 2050 are predominantly linked to electricity production (43.0 %) and the combustion of fuels produced via electrolysis and hydrogen-to-fuel processes (55.8 %); emissions from centralised heat processes are relatively negligible (1.2 %). Solar PV (24.5 %), wind (14.8 %), natural gas (13.3 %) and bioenergy (9. 6 %) processes are all significant contributors to overall emissions in 2050, and emissions created by combusting kerosene (20.4 %) and diesel (13.8 %) formed from electrolysis processes are also significant. These replace the fossil fuel sources–coal (37.0 %), natural gas (30.1 %), diesel (13.3 %) and kerosene (10.4 %)–predicted to remain as the dominant emitters in 2030.

Conversely, land occupation increases dramatically, largely driven by renewable energy sources. This rise is heavily influenced by the use of bioenergy sources, which accounts 71.1 % of the total required land in 2050, up from 0.8 % in 2030. Water depletion is expected drop by 38.4 %, the changes largely being linked to the move away from fossil fuel processes with higher water requirements, particularly coal and natural gas. Meanwhile, total SR more than doubles between 2030 and 2050 in this example. This is overwhelmingly the result of electricity from wind and solar sources, which contribute 57.0 % and 39.0 % of the total score in 2050, respectively. Lastly, the required number of hours of HA from employment increases by 78.0 % between 2030 and 2050 under this scenario. This is, again, largely driven by increases in wind and solar installations; wind is the dominant contributor here, rising from a 2.4 % share of overall activity in 2030 to a 17.1 % share in 2050.

Additional intensive indicators were then derived by comparing extensive indicators across and between MuSIASEM hierarchical levels. Fig. 5 provides side-by-side comparisons between 2030 and 2050 values for three "metabolic rate" indicators and four indicators that present extensive attributes on a per-MJ basis. Findings are presented for the three previous levels alongside the total system values at level "n". A full listing is provided in Table S6 of the supplementary information. A summary of the overall percentage changes at the system level are shown in Table 2.

The first of these analyses suggests that the energy metabolic rate (EMR) of the European energy system would drop by 25.6 % between 2030 and 2050 under this scenario. This is predominantly the result of the large swing to electricity–and wind and solar technologies in particular–which rises from 44.6 % to 91.5 % of system energy supply (fuels created via hydrogen from electrolysis are included in electricity totals). And, though heat and fuels are seen to provide significantly higher levels of energy per unit of activity, their shares of overall energy production decline from 31.2 % to 7.7 % and 24.2 % to 0.8 %, respectively, during this period. The rapid phasing out of natural gas assumed in the heating sector by 2050 results in the sharp drop observed in the EMR value for heat in this period and, coincidentally, a rise in the overall value for natural gas as its use as a direct fuel remains relatively high (see Fig. 4).

Yet, while more hours of human activity would be required to produce a unit of energy by 2050, findings for the GHG metabolic rate (GHGMR) confirm that significantly less emissions would be produced for each of these labour hours. This reduction is again strongly linked to a substantial change in the share of renewables which, on average, have GHGMR values less than 3 % of those for non-renewables. As a result, overall GHGMR values would reduce by 74.6 % between 2030 and 2050.

Values for the water metabolic rate (WMR)–which decrease at the system level by 65.4 % between 2030 and 2050–are, again, strongly influenced by the dramatic drop in the use of fossil fuels. This is especially true of coal and natural gas, whose extensive water use values represented 34.2 % and 15.5 % of the total contribution, respectively, in 2030 but are expected to be virtually zero by 2050. A fall in the use of nuclear sources of electricity production, from which also have high per-

Table 1
Summary of changes in extensive indicators between projected 2030 and 2050 scenarios. Overall system changes at the "n" level, in relative percentage, are listed for each indicator. The most significant contributors at the "n-4" level, by change in overall percentage share, are also listed.

	Total energy	GHG emissions	Land occupation	Water depletion	Material supply risk	Human activity
Change ("n")	+32.5 %	−55.4 %	+385.8 %	−38.4 %	+146.4 %	+78.0 %
Most significant contributor	Wind	Coal	Bioenergy	Bioenergy	Wind	Wind
Change in share ("n-4")	+58.2 % *(7.3 % to 65.5 %)*	−37.0 % *(37.0 % to zero)*	+70.6 % *(0.8 % to 71.4 %)*	+38.8 % *(zero to 38.8 %)*	+45.2 % *(11.8 % to 57.0 %)*	+14.6 % *(2.4 % to 17.1 %)*

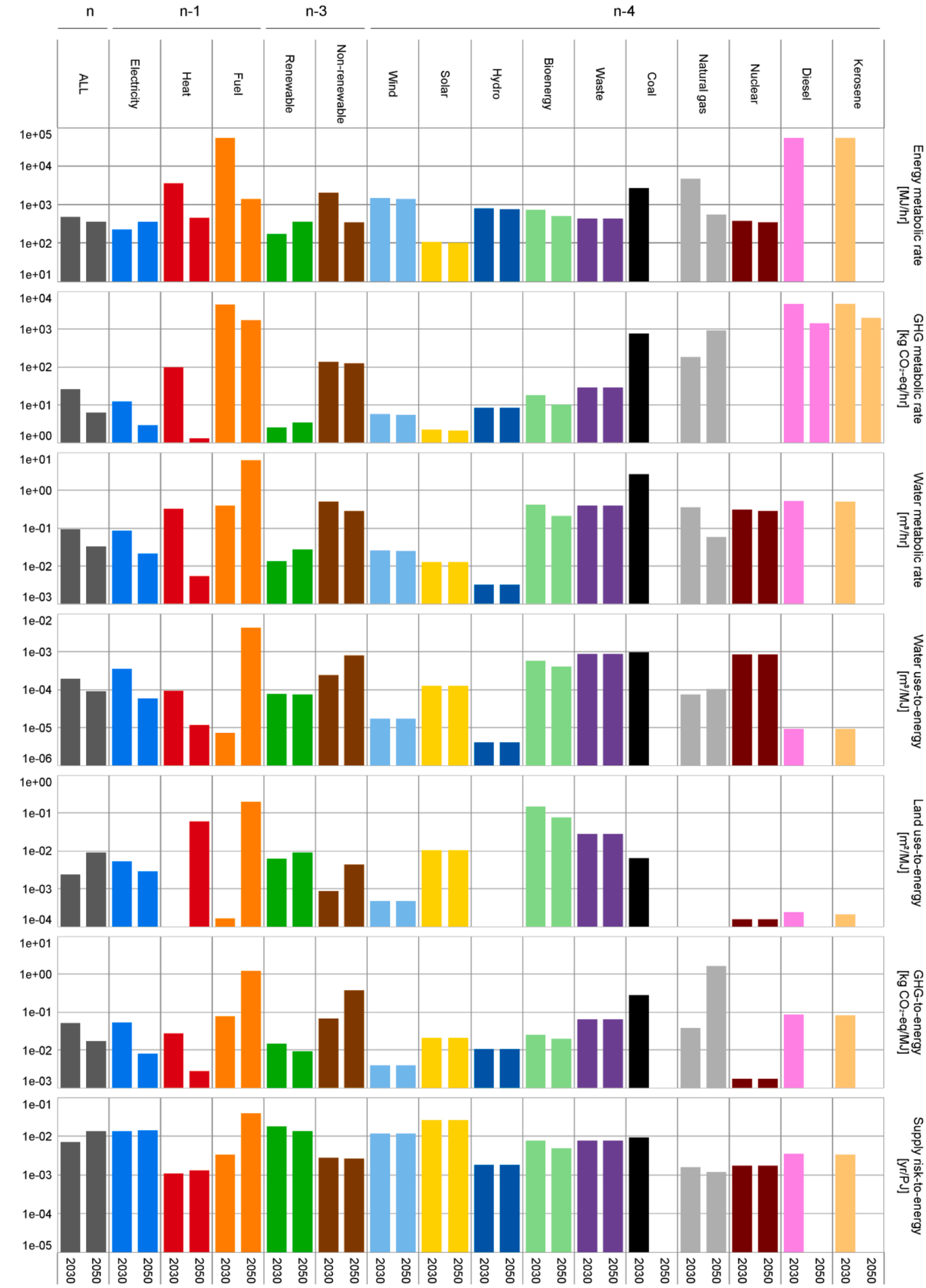

Fig. 5. Results showing outputs for intensive indicators. Results shown for seven indicators over complete system and three hierarchical level groupings for projected 2030 and 2050 energy mix outcomes under the EU"climate neutrality" scenario.

Table 2
Summary of changes in intensive indicators between projected 2030 and 2050 scenarios. Overall system changes at the "n" level, in relative percentage, are listed for each indicator.

	Energy metabolic rate	GHG metabolic rate	Water metabolic rate	Water use-to-energy	Land use-to-energy	GHG-to-energy	Supply risk-to-energy
Change ("n")	−25.6 %	−74.9 %	−65.4 %	−53.5 %	−66.3 %	+266.7 %	+86.0 %

MJ water requirements, is also a factor. Moreover, an increase of technologies with relatively low water requirements such as wind and solar energy would help to reduce overall water use. Very similar results are observed for the water use-to-energy ratio, where the system-wide result is seen to reduce by 53.5 % by 2050.

Meanwhile, the land use-to-energy ratio is predicted to almost quadruple between 2030 and 2050 under this scenario, predominantly due to the dramatic shift towards bioenergy (see Fig. 4). Overall land occupation for the system in 2050 was calculated to be around 4.9 times that in 2030, the contribution from bioenergy increasing from 0.8 % in 2030 to 71.4 % in 2050; 51.8 % of this contribution is from heat derived from biomass. This is also reflected in the dramatic rise in the intensive value of heating witnessed at the "n-1" level. In this sense, it is noted that natural gas, nuclear energy, diesel and kerosene require considerably lower areas of land according to this metric.

The net amount of GHG emissions produced per unit of supplied energy is a key system indicator for analysing system performance alongside emissions reduction targets. In this scenario, an overall reduction of 66.3 % is observed in this indicator between 2030 and 2050. Again, overall system emissions are likely to remain dominated by non-renewable energy forms in 2030, although by 2050 the dominance of renewables would mean that a relatively large share of emissions would also be provided by renewables (51 %). Nevertheless, GHG-to-energy ratios for renewables remain predictably lower than non-renewables–around 40 times lower at the "n-3" level in 2050–and wind technologies comfortably provide the best outcomes within the group. However, it is noted that nuclear power is the lowest of the technologies examined and produces less than half of the emissions of wind energy.

Finally, the level of extensive SR in the 2050 system is almost 2.5 times that of the 2030 system, reflecting a substantial rise in potential supply disruptions during this period. Again, these values are rooted predominantly in contributions from wind (57 %) and solar (39 %) technologies. Analysis of SR-to-energy ratios confirms that solar and wind are substantially higher than all other categories at the "n-4" level; both are between 1.5 and 21.1 times higher than other technologies. Consequently, a net increase of 86 % is observed in the level of expected SR per unit of energy for the system as a whole between 2030 and 2050.

4. Discussion and conclusions

The ENBIOS framework brings a systemic approach to the assessment of environmental impacts and constraints within energy systems using a methodology that combines the high resolution of LCA methodologies with the multi-level functionality of the MuSIASEM approach. Furthermore, in the version presented here, we offer a first attempt at systematizing the integration of raw material indicators into energy modelling practices. Ultimately, ENBIOS has been designed to enable the relationships between indicators at different hierarchical levels to be analysed and the trade-offs between different energy transition pathways to be compared–with each other and with defined benchmarks–-with the aim of informing better energy policy decision making. Full sets of indicators can be produced for multiple energy system scenarios, derived from different system configurations or across different regions and timeframes. Analysis of indicators can derive further information about preferred options, depending on the preferences or perceived limitations of policymakers, and determine whether certain scenarios are more–or less–technically feasible than others in terms of land use, raw material supply issues, employment or other socio-economic factors. The ability to observe indicator data across and between levels also allows problem areas such as constraint hotspots to be more easily identified.

The capabilities of ENBIOS were demonstrated using inputs from a "climate neutrality" scenario for the European energy system in 2030 and 2050. Extensive outputs revealed that system changes in this period–where a rapid switch is made towards renewables, particularly wind and solar electricity and heat from biomass–would result in a significant reduction in GHG emissions. However, although water requirements are unlikely to present serious issues, land occupation, material SR and labour requirements are all likely to rise dramatically. It is recognised that the values of land use derived can refer to many different types of use. For example, the land required by a nuclear plant is vastly different from land required for a hydropower dam or wind far. Nevertheless, here, the land use totals are largely related to biomass plantations. Meanwhile, material issues are strongly linked to wind and solar infrastructure, while the higher labour needs for solar contribute far more than wind or biomass operations.

Further analysis of the system, via composite intensive indicators, provided further insights. At the system level, positive outcomes were observed for overall reductions in GHGMR (74.9 %), WMR (65.4 %), water-to-energy (53.5 %) and GHG-to-energy (66.3 %) ratios. Even so, an EMR reduction of 25.6 % suggests that the system would generate less energy per unit of human activity in 2050, which could have implications on labour markets. Ratios of land use-to-energy and SR-to-energy are both also projected to increase markedly. Indeed, the consequences of different energy transition pathways on both of these issues is increasingly being highlighted and could result in wider ecological, political and environmental justice concerns [36,44,45].

Looking specifically to the three key processes at the "n-5" level–electricity from wind and solar, and heat from biomass–reveals their influence on overall system indicators. Again, the high labour requirement for solar infrastructure has a strong influence on lowering all metabolic rate values. Very low water requirements for wind turbines have positive effects on both water-related indicators. Similarly, their low GHG-to-energy ratios tend to dictate wider outcomes for this indicator. Extremely high land use-to-energy ratios for biomass result in their total dominance in this regard. Finally, high SR-to-energy ratios for wind and solar infrastructure are highly influential on the score reductions for this indicator.

The case study provides a simple illustration of the ability of ENBIOS to perform deeper analyses on the different relationships that exist within current and future energy systems, relationships that quantify constraints and areas of concern across different system levels. While this example provides a broad demonstration using potential European energy system configurations for illustrative purposes, it is noted that greater detail is possible and that future studies will aim to utilise system dendrograms that incorporate separate consideration of individual regions or countries, where LCA data exists. For example, outputs from the Euro-Calliope model are provided for 35 individual countries and separate definitions are often available for LCA processes at the national level. What's more, shares of energy within technological groups could be further delineated into sub-technologies where suitable LCA data is available. While a lack of data is observed for certain technologies–such as wind and hydropower–a large selection of different LCA processes are defined for solar and biomass sub-technologies. This would allow far more detailed analyses to be undertaken. To that end, an implementation and expansion of the ENBIOS framework in a python package has been created and is now in beta version [46].

In this regard, the validity of the LCIA indicators used in the case study was tested by comparing them against the range of available results for individual European countries. The investigation found that most individual values for GHG emissions, land occupation and water depletion were within 2–3 % of the values used to represent Europe as a whole in the case study. The most significant differences by far were observed for waste incineration, where values could be several *times* higher or lower than others. The process used to represent Europe in the analysis is for Germany, which is the current and projected largest adopter of waste incineration. As such, the best possible representation is being used. However, it is recognised that a considerable amount of uncertainty is inherent within the results for waste incineration as a result of the variability in the regional data. Variations of 10–20 % are observed in the values for natural gas, coal, wind turbines and solar PV cells, suggesting that more regionally detailed investigations are also likely to improve the accuracy of results for these technologies.

It is also noted that in this work we derived sets of indicators using system configuration data taken *from* energy models. However, it is hoped that information produced by the framework could also be integrated *into* such models to be used as constrains. This, of course, would require the ENBIOS python module to be included within the broader architecture of an integrated model in order to become a truly interactive element of its system optimisation calculations. In this sense, it is also important to note that, while ENBIOS has been primarily formulated to analyse energy systems, it has been designed to be adaptable to any type of hierarchical system and could, theoretically, be used in any number of other applications where multi-level analysis is required, such as agricultural systems. This is especially true if users also require LCA functionalities to be integrated into their analysis.

In any case, despite the potential of the framework in its current form, a number of limitations are noted. Firstly, as with many LCA-related applications, assessments are limited to using static information based on current inventories. That is, the derived outputs for future processes do not contain allowances for future improvements in the background systems that supply energy and material inputs. For example, the mix of electricity inputs used in creating or transporting a wind turbine in 2040 is essentially "locked" in its current configuration. In reality, many of these inputs would, themselves, produce less emissions or include higher amounts of recycled content as greener energy practices and circularity initiatives are implemented. It is hoped that the further integration of pLCA concepts–which enable the modification of background systems in modelled environments of this kind–can be included in the python module. This would allow users to manipulate LCI data assumptions to reflect future developments. Nevertheless, current ENBIOS assessments are capable of providing indications of key bottleneck hotspots in terms of required technological or sourcing improvements, using current conditions as reference benchmarks.

Similarly, it is acknowledged that variations may well occur to many of the input parameters used within the calculations for extensive indicators. For example, in the case study presented here, values of SR for individual materials are likely to change over time as reserve amounts and geo-political aspects fluctuate. Likewise, improvements in manufacturing or increased levels of automation may result in lower labour requirements, particularly for newer technologies like wind turbines, solar PV cells or biofuel production. Naturally, the extent of these improvements is difficult to predict, although learning curves or other approaches could be applied [47]. However, the architecture of ENBIOS means that it is simple to change input parameters of this kind for investigating multiple future scenarios.

Several issues relating to LCA data availability have also been identified. Although Ecoinvent and other major LCI databases contain several thousand energy-related processes, a lack of good quality data remains for some common processes, especially for newer technologies. For example, innovations on wind, solar PV and bioenergy technologies are underrepresented and energy storage technologies are not yet represented beyond the production of lithium-ion cells. Accordingly, they have not been included in the current analysis. Moreover, most quality LCA data sources are paywalled, which could seriously restrict access to calculations.

ENBIOS joins a growing move towards the wider inclusion of sustainability concepts in energy modelling processes. The key to further progress in this area would seem to lie in the ability to place related data and operations into environments that are also compatible with the models themselves. As such, open-source applications such as Wurst [48], PREMISE [19] and the ENBIOS module that operate within Python environments are making it easier to import model output data and manipulate and automate the processing of life cycle data. Again, the ability to return outputs from applications such as ENBIOS back into energy models directly to achieve genuine two-way synthesis would greatly improve the ability of models to integrate the power of LCA and other high resolution environmental data in this manner. This would result in modelling platforms that include far better representations of environmental impacts and constraints as we strive to implement cleaner and more sustainable energy systems as safely, efficiently and rapidly as possible.

CRediT authorship contribution statement

Nick Martin: Conceptualization, Methodology, Formal analysis, Data curation, Visualization, Writing - original draft, Writing - review & editing. **Laura Talens-Peiró:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Gara Villalba-Méndez:** Writing – review & editing, Funding acquisition. **Rafael Nebot-Medina:** Methodology, Writing - review & editing. **Cristina Madrid-López:** Conceptualization, Methodology, Visualization, Project administration, Funding acquisition, Supervision, 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.

Data availability

Data used is in the supplementary tables

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Appendix A. Supplementary material

Detailed listings of key model inputs and case study results are available in Tables S1 to S6 of the supplementary information.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2022.120366.

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