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Prospective environmental impact assessment and simulation applied to an emerging biowaste-based energy technology in Europe

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ABSTRACT

The energy sector of the European Union (EU) is expected to progress fast towards a fully-fledged dependency on renewable sources. In such a goal-driven approach, a prospective assessment framework is designed to simulate the environmental consequences engendered by the gradual penetration of a novel biowaste-based energy technology in the EU energy production market. This is done by building a dynamic input-output model reflecting the implementation of the technology over time, following future energy scenarios and hypothetical targets for the EU (number of plants operating in 2030 and 2050). Total impacts, calculated for global warming, photochemical oxidation, acidification, eutrophication and human toxicity are calculated for these scenarios, and for a counterfactual scenario, represented by the same economic system operating without opting for such novel technology. The output of the simulation shows that the technology could bring carbon savings of 220–250 Mt CO_2eq up to 2050 and significant changes in the economy structure such as a reduction of fossil phosphorus production and corresponding generation of revenues from phosphorus recovery in the order of 100–150 billion €. In a more general fashion and beside the case study, the factors affecting the model output, sources of uncertainty and assumptions are presented in order to appraise scope, applicability and limitations of the proposed assessment framework and to prepare its use in decision making.

1. Introduction

Current climate goals, sustainability issues and the energy crisis are pushing the energy sector towards a significant structural change. In 2021 the renewable electricity generation rose by almost 7% worldwide, a record 522 TWh increase. The share of renewables in global electricity generation reached 28.7% in 2021 [1]. The European Union (EU) currently concurs to this transition with a share of ~22% of energy supply from renewables, and an ambitious target to achieve 32% by 2030 [2]. This belongs to a long-term strategic vision of greenhouse gas (GHG) emissions reduction up to 2050 close to climate neutrality [3].

Increased use of bioenergy is considered as one of the main strategies aiming at reducing global GHG emissions [4]. Bioenergy feedstocks include a wide range of products and many processes are available to turn them into different types of energy carriers to be used for electricity, heat or transport [5]. While it is clear that the growth of bioenergy will need to rely on a mix of technologies, special attention should be focused on promoting options which can provide long-term environmental benefits. In particular, it is estimated that biowaste and residues can represent about two-thirds of the feedstock requirement, allowing to avoid negative side effects related to land use change or food security [6].

In this context, appropriate environmental assessment methods are needed, specific to the purpose of understanding how and in which measure the introduction of new technological systems producing bioenergy could be beneficial to the objective at hand [7]. Life cycle assessment (LCA) represents an ISO-standardized tool traditionally used for assessing the environmental potential impacts of products [8,9]. The so-called attributional LCA (ALCA) version of the method allows to measure the environmental performance of any type of goods and services with a flexible and potentially very disaggregated inventory for all the relevant inputs (natural resources, land uses, etc.) and outputs (air and water emissions, solid wastes, etc.) scaled to a precisely-defined functional unit [10]. However, ALCA typically lacks an impact assessment perspective that considers socio-economic systems broader than

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Nomenclature

Abbreviations

ALCA:	attributional life cycle assessment
AP:	acidification potential
CLCA:	consequential life cycle assessment
CPS:	current policy scenario
EP:	eutrophication potential
EU:	European Union
EU-28:	European Union (28 members)
GHG:	greenhouse gas
GWP:	global warming potential
HDO:	hydro-deoxygenation
HTP:	human toxicity potential
IAM:	integrated assessment modeling
IAMs:	integrated assessment models
IEA:	international energy agency
IO:	input-output
IOTs:	input-output tables
LCA:	life cycle assessment
PDF:	probability density function
POCP:	photochemical ozone creation potential
PSA:	pressure swing adsorption
RoW:	rest of the world
SD:	system dynamics
SDS:	sustainable development scenario
TCR:	thermo-catalytic reforming
TSF:	To-Syn-Fuel (European Horizon2020 project).

Notations/Symbols

x, gross output vector
Z, intermediate consumption matrix
A, technical coefficient matrix
a_{ij}, element of A
y, final demand vector
B, environmental stressor matrix
C, characterization matrix
E, allocated stressor matrix
h, impact vector
$sf_{s\rightarrow n}$, substitution factor from substituted to new product
φ, plant size
ν, number of plants
π_i, price of product i
η_i, yield of i
α and β, parameters for the demand-time linear regression
ε_i, energy share in sector i
θ_t, set of substitution factors at time t
ρ_i, specific substitution ratio for i.

Units

t: metric ton
Mt: megaton
h: hour
TWh: erawatthour
TJ: terajoule
kEUR: 1000 euros (2018 if not mentioned otherwise)
°C: degree Celsius

the product-related one and does not take into account the effect of policies and production/technology changes in the market where the investigated product is embedded. This has encouraged the scientific community to develop more sophisticated approaches for the environmental assessment of new or emergent technologies whose introduction in the market necessarily induces more or less relevant changes to existing supply-chains. A well-known example is represented by the environmental impacts associated with the market penetration of new bioenergy technologies, assessed with tools of "consequential" LCA (CLCA) [11,12] and environmentally-extended input-output (IO) analysis [13]. These tools generally attempt to capture the complexity of the wider socio-economic system beyond the technological supply chain, typically through the modeling of economic mechanisms. In particular, CLCA is mostly considered as a theoretical approach which can be applied through the use of a wide spectrum of methods and modeling frameworks [14]. With respect to ALCA, CLCA is focused on understanding the actual environmental consequences of an action or decision, rather than attributing part of the global impacts to specific product systems [15].

1.1. Static and dynamic models combining environmental and economic dimensions

Unless its scope is the global economy, ALCA fails to capture the environmental impacts of a novel technology which aims to spread out on a large scale with decades-long timescale. To evaluate the effects of such technology it is necessary to implement models that expand the system boundaries at a large geographical scale and also capture the main changes over time and the constraints that the novel technology will face. Much effort has been spent to use a more holistic approach than LCA for the assessment of the environmental sustainability of bioenergy systems, often in relation to the European energy sector. For instance, Bentsen et al. [16] employed an optimisation model for the EU energy supply of 2020, focusing on minimizing GHG emissions and considering biomass availability and technology constraints. Similarly, Vadenbo et al. [17] developed a static multi-objective optimisation model combined with CLCA to identify bioenergy strategies that could minimize environmental impacts, and applied this approach to the Danish energy system up to 2025. Even more complex models, far beyond LCA, can be found e.g. in Nieto et al. [18], who adopted a scenario-based analysis in which a macroeconomic model founded on a IO framework is encapsulated within an integrated assessment modeling framework based on system dynamics (SD). Integrated assessment model (IAM) and LCA integration allows the consideration of interrelated global markets and their long-term evolution in response to policy decisions.

IAMs predicting environmental impacts and climate change have a long development history [19,20]. However, research on IAMs has massively grown especially over the last two decades, following the exponential growth of increasingly powerful computation capacity, fast internet and the widespread use of open-source global and regional databases [21]. Among the different types of IAMs existing nowadays, those having a process-based structure offer a suitable framework for physical impact projections at disaggregated economic scales [22,23]. Such a framework is particularly fit for optimizing life cycle-based approaches (such as material flow analysis, environmentally extended input-output analysis or LCA), which can improve the representativeness and accuracy of the environmental impact assessment modeling outputs [14,24,25].

In this regard, recent literature has deeply investigated the advantages and drawbacks of coupling economic and environmental assessment models in order to build effective IAMs to support decision-making. For example, Beaussier et al. [25] distinguish between low-level and high-level couplings. Low-level coupling encompasses couplings where economic and environment models are designed separately, using different variables and assumptions; models are also run separately and the output of the economic model is generally used as input to the environmental model. High-level couplings are conceived, designed and implemented as a whole, where economic and environmental variables of the models are run in closed loops. Although high-level coupling would likely return more representative and customized results, its implementation usually requires more computational and/or mathematical sophistication than in the low-level coupling case, which then becomes the most used solution also when applying LCA and related tools [26,27].

Narrowing the scope to the field of energy analysis, literature on life cycle-based models coupled with other tools suggests multiple solutions, proposing combinations to improve the assessment of energy policy effects (e.g. Onat et al. [28]) and/or the methodological coherence, trying to reduce uncertainty and increase model consistency (e.g. Palazzo et al. [14], Yang [29]). Recent case studies in the energy sector include Fernández Astudillo et al. [30], Luderer et al. [24] and Rauner et al. [31], Uekerdt et al. [32].

Tools coupled with LCA are commonly economic models including partial equilibrium, general equilibrium, IO, agent-based modeling and SD, in which the coupling of partial equilibrium and LCA is the most frequent combination [33]. This results in promising integrated models that foster an alternative conceptualization of CLCA, whereby the "decision" question is determined either by exogenous factors, such as in the case of low-level coupling (e.g. Szekeres & Jeswiet [34], Kumar et al. [35] and Trappey et al. [36]), or endogenous factors, such as in the case of high-level coupling (e.g. Uehara et al. [37] and Wang et al. [38]).

Fig. 1 conceptualizes and summarizes information processing when it comes to coupling LCA with other tools to address consequential energy analysis and policy questions. Such a consequential approach is based on the modeling of interventions which produces outputs relevant to policy goals. Modeling outputs can be either static (one point in time) or dynamic (time-dependent) and calculated as is done in traditional LCA through life cycle inventory (LCI) or impact assessment (LCIA) results. The difference from the traditional LCA is in that the background LCI system is made by an IO table compiled in historical time series e.g. Refs. [12,13,18,25,39,40], complemented by IO tables (IOTs) estimated for future times (e.g.: 2030 and 2050) through the implementation of specific exogenous scenarios generated with the use of specific tools (i.e. low-level coupling). Such a structure has been previously shown effective by Gibon and co-workers [40] or Nieto and co-workers [18], who made use of exogenous models (such as the Global Trade Analysis Project, an example of equilibrium model) to allow structural changes in the IO framework driven by changes in the final demand or other constraints. Other authors successfully implemented a SD approach to model rebound effects associated with the policies [28,41]. This allows incorporating feedback loops describing the causal relationships between drivers, impacts and changes in turn to the baseline inventory (i.e. counterfactual generation). Studies on IAMs for CLCA cover several economic segments of large-scale impact for the society (e.g. mobility, agriculture, energy, housing, …) [42]. Despite these examples, however, integrated models based on a life cycle thinking seem to be rather infrequent regarding the assessment of energy production and consumption flows at continental scale.

This work can be positioned in the depicted state-of-the-art practice. It has the ambition to shed light on the environmental consequences of new technology choices. To do so, it aims at showing how an integration among LCA, SD and IOTs can be performed by expanding the system boundaries to a continental geographic scale. A case study serves the purpose to apply such a framework and to simulate the environmental effects of the gradual implementation of a novel waste biomass-to-energy technology in Europe. The simulation involves targets such as the number of plants and their productive capacity in two phases of technology maturity. The output of such a specific application is purely illustrative of the methodology and results are not intended to support decision-making processes.

2. Materials and methods

2.1. Case study

The reference case study was the system investigated in the European H2020 project "The demonstration of waste biomass to Synthetic Fuels and Green Hydrogen – TO-SYN-FUEL" henceforth noted as TSF [43]. The ambition of this project is to demonstrate the technical and economic viability, as well as the environmental and social sustainability, of a new integrated process which combines Thermo-Catalytic Reforming

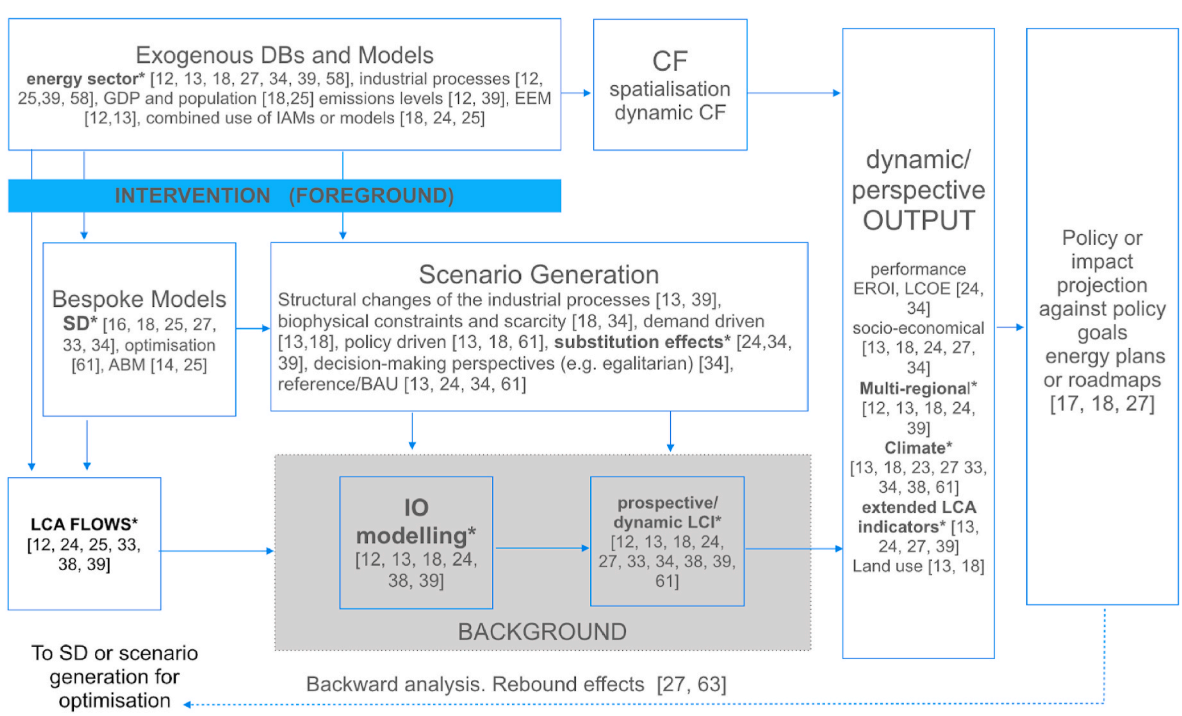

Fig. 1. Conceptualization of hybrid models and tools; boxes symbolize aggregated data and information processing, arrows symbolize flows of information; * contents in bold reflect those appropriate to this work.

(TCR©), a thermochemical process of biomass conversion developed by Fraunhofer UMSICHT with hydrogen separation through Pressure Swing Adsorption (PSA), and Hydro-Deoxygenation (HDO); the integrated process enables the production of a fully equivalent gasoline and diesel substitutes (compliant with EN228 and EN590 European Standards) for use in transport, starting from a waste organic feedstock (sewage sludge). In particular, the study was referring to the decision of implementing this new technology in Europe at industrial scale, according to the targets for future market deployment envisaged by the project (projections to 2030 and 2050), starting from year 2024. The targets (Table 1) were assumed to be reached linearly according to a yearly 0.21% and 4.9% penetration of the technology in the period 2024–2030 and in the period 2030–2050, respectively.

2.2. Modeling approach

First of all, the technology was characterized in its inherent aspects, i.e. inputs and outputs of the corresponding *foreground* system. This is the starting point to retrace a supply chain for a LCA. At this stage it is important to distinguish between elementary and intermediate flows. The former are exchanges with the natural environment, that is, raw material or energy inputs to the economic sectors being studied that have been extracted from the environment without previous human transformation (e.g. natural resources such as water, biomass, minerals, coal, crude oil, …), or material or energy outputs released from those sectors into the environment without subsequent human transformation (e.g. the emissions to the atmosphere from the considered plants). The latter are exchanges between two economic sectors that stay within the technosphere: a product, material or energy flow occurring between activities of the economy which are neither taken nor emitted to the environment (e.g. materials and chemical substances feeding TSF plants) [9]. Those flows that substitute economic activities and, in this sense, provide economic functions are referred to as “functional flows”: they are highlighted in Fig. 2 and Table 2 (see section 2.3). While a classical LCA would then expand the system boundaries with background processes from a database starting from the intermediate flows (e.g. electricity), in this study such flows were translated into monetary terms to include the technology in an IO table of interconnected economic sectors (Equation (1)). When translated into monetary terms, the foreground, i.e. TSF plants production is connected to the economic system of supply and consumption (e.g. diesel oil, waste, inert waste landfill) which can be studied through IOTs. This was used to evaluate how the whole economic system will be affected by the implementation of the technology. The technique applied for the hybridization between LCA and IO analysis was matrix augmentation [44,45]. However, in this case the resulting matrix is not unique, but it was redefined for each time step *t* in a dynamic framework. The equations used were the same as in IO analysis, with time-differentiation in addition:

$$Z_t = A_t \times \widehat{x_{t-1}} \qquad \text{Equation 1}$$

$$x_t = Z_t \times i + y_t \qquad \text{Equation 2}$$

where.

- $\boldsymbol{x}$ = gross output vector
- $\boldsymbol{Z}$ = intermediate consumption matrix
- $\boldsymbol{A}$ = technical coefficient matrix
- $\boldsymbol{y}$ = final demand vector

Table 1
Production targets to 2030 and 2050 set by the European H2020 project TO-SYN-FUEL.

year	Target for European Union
2030	50 plants producing at 3 t/h
2050	300 plants producing at 40 t/h

i = summation vector

The symbol “ × ” is indicating matrix multiplication and the symbol “^” on a vector represents a diagonal matrix with this vector’s elements as diagonal. Also note that in the following dot product is denoted by the symbols “•”.

The technical coefficient matrix $\boldsymbol{A}$ reflects the monetary exchange between each sector in order to produce one currency unit of output for a specific sector. Formally, element a_{ij} represents the monetary amount from sector i used by sector j for a unit output (by definition, $0 \le a_{ij} \le 1$ and $\Sigma_i a_{ij} \le 1$).

$\boldsymbol{A}$ and $\boldsymbol{y}$ were given as inputs, for each time step. Initial values for $\boldsymbol{Z}$ and $\boldsymbol{x}$ were given as well, consistent with initial values of $\boldsymbol{A}$ and $\boldsymbol{y}$. $\boldsymbol{Z}$ and $\boldsymbol{x}$ were recalculated for each time step, in accordance with the equations.

The resulting gross output vector $\boldsymbol{x}$ was then used to obtain the impact vector $\boldsymbol{h}$:

$$h_t = C \times B \times x_t \qquad \text{Equation 3}$$

where $\boldsymbol{B}$ is the matrix of environmental stressors, whose coefficients equal emissions or resource consumption per unit of each sector output, while $\boldsymbol{C}$ is the matrix of characterisation factors, which represents the contribution of environmental stressors in each considered impact category. Coefficients in $\boldsymbol{B}$ and $\boldsymbol{C}$ matrices are here considered static, although in principle this framework would allow for the introduction of time-dependent coefficients.

The impact vector $\boldsymbol{h}$ represents the output of the IO module, which was developed in a SD environment. The software Simantics System Dynamics (Version 1.35.0) [46] was used for the modeling.

Finally, in order to assess the consequences of the decision, it is required to compare the results of the scenarios with and without the decision being analyzed. The difference in generated impacts represents the broader environmental consequences related to the implementation of the new technology over the time frame considered.

The steps for building the model are illustrated in detail in the following sections.

2.3. Foreground

The TCR-PSA-HDO combined technology is identified as a unique system providing multiple functions: production of gasoline, diesel, hydrogen, electricity and phosphorus, and sewage sludge management. The production system (Fig. 2) offers an overview of the regional context where the production system is embedded. It is noteworthy that, for the sake of reducing the number of assumptions, the system boundary does not specifically focus on other similar TSF technologies possibly running outside EU-28.

Such technology utilizes sewage sludge as feedstock, to be subjected to pre-treatment in order to remove most of the aqueous component; then, the biomass is sent to the TCR plant, consisting of a pyrolyzer operating at intermediate temperatures (350–500 °C) followed by a catalytic reformer: in the first stage the biomass is decomposed thermally in biochar and volatile compounds, while in the second stage the catalytic properties of the biochar product itself are exploited, so that it is mixed again and placed in contact with the volatile compounds at a higher temperature (650–700 °C), thus determining their upgrading into high quality gas and oil for fuel [47]. From the synthesis gas it is possible to obtain pure hydrogen through the PSA technology, which is based on selective absorption by certain materials at high pressure with respect to compounds contained in a gaseous stream, and subsequent desorption at low pressure. Hydrogen thus obtained is used in the process for the oxygen removal (HDO), to which the oils in output from the TCR are subjected to, acquiring this way the features that will render them suitable for direct use in common transport engines (diesel and gasoline). The char and the residual fraction of syngas may instead be gasified producing heat and power, thus satisfying part of the internal

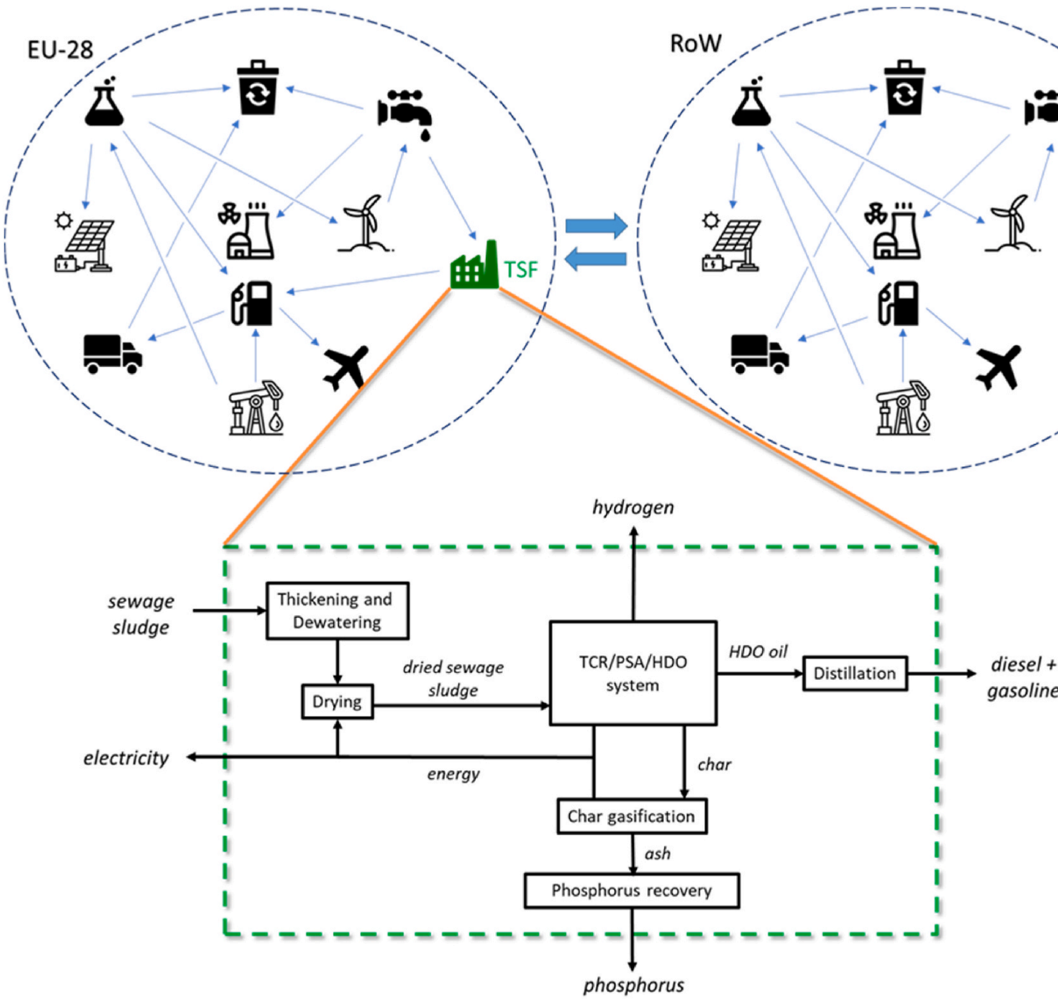

Fig. 2. Overview of the system boundaries of the analysis. (EU-28): European Union (28 members); RoW: Rest of the World; TSF: To-Syn-Fuel technology; TCR: Thermo-Catalytic Reforming; PSA: Pressure Swing Adsorption; HDO: Hydro-Deoxygenation).

Table 2
Functional flows of the foreground system and values referred to 1 plant producing at 3 t/h for 1 year (assuming 7000 operative hours per year).

name	physical value	unit	monetary value	unit
1. TSF Sludge	21,000	t	1890	kEUR
2. TSF Gasoline	430	t	248	kEUR
3. TSF Diesel	681	t	392	kEUR
4. TSF Electricity	25.7	TJ	536	kEUR
5. TSF Phosphorus	1609	t	2923	kEUR

energy demand of the whole process, while excess electricity can be sent to the grid. After gasification, the resulting ash is a waste product rich in phosphorus, which can be eventually recovered as phosphoric acid in feed-grade quality [48]. The use of sludge provides a valuable function (TSF Sludge) because sludge management is no longer required.

The five functions of the system correspond to five functional flows, which were renamed as in Table 2 for their use in the following steps.

Once the physical quantities of the flows have been estimated, both the functional flows and the intermediate flows were converted into monetary terms for their use in the subsequent steps. Specifically, for each flow a sale price (for functional flows) and a purchase price (for intermediate flows) was estimated to perform the conversion. Prices are consistent with the preliminary techno-economic assessment of the TSF project [43]. All monetary values listed in Table 2 are revenues. The monetary value of phosphorus corresponds to the purchase price of phosphoric acid in feed-grade quality obtained during the phosphorus recovery from the biochar ash. The elementary flows remain in physical units and are used later to complete the matrix of environmental stressors ***B***.

2.4. Reference IOTs

Before linking the studied system to the other sectors of the economy, a database describing how sectors in the economy are interlinked is needed. EXIOBASE 3 [49] was chosen, due to its high sectoral and regional detail. In version 3.1, the EXIOBASE monetary IOTs cover the period from 1995 to 2011, however only tables referred to 2011, considered the most representative year, were used to obtain the reference technical coefficient matrix. The product-by-product IOTs include 49 regions (44 countries + 5 rest of the world regions) and classify all sectors through 200 products. For the purposes of the study, the IOTs are aggregated into 2 regions, Europe (EU-28) and Rest of the World (RoW), and 38 products. Furthermore, sectors were aggregated into their specific sector category following the United Nations International Standard Industrial Classification of All Economic Activities (ISIC) system, with the exception of electricity production. Operationally, the Python module "pymrio" [50] was employed to perform the aggregation of the original "200 products × 49 regions" IOTs into the new "38 products × 2 regions" IOTs. The correspondence files used for the aggregation can be found in the Supplementary Material.

2.5. Matrix augmentation

The IOTs representing the world economy were completed with the inclusion of the five products provided by the TSF technology (from Table 2), only for region EU-28 assuming that this technology will be implemented exclusively in Europe. Therefore, matrices $\boldsymbol{A}$ and $\boldsymbol{Z}$ were augmented adding a row and a column for each functional flow. Coefficients in the matrix $\boldsymbol{A}$ have to be defined for each time step in order to make the calculation of Equation (1) possible.

Coefficients in the new rows require to introduce some substitution factors (*sf,* also θ in the following), representing the level of substitution between each new product and their competitive ones, calculated in the following way:

$$sf_{s\rightarrow n}(t) = \frac{x_n(t)}{x_s(t)} \quad \text{Equation 4}$$

where the subscript '*n*' refers to a new product and subscript '*s*' refers to a substituted product. The numerator is the total output of the new product, which is a predicted value, coherent with the target for time *t* (obtained by Table 1). The denominator is the calculated value of total output of the substituted product at time *t*.

The substitution factors were then used to modify the rows of the matrix $\boldsymbol{A}$ for the new products, as well as the substituted products, in the following way:

$$a_{nj}(t) = a_{sj} \cdot sf_{s\rightarrow n}(t) \quad \text{Equation 5}$$

$$a_{sj}(t) = a_{sj} \cdot (1 - sf_{s\rightarrow n}(t)) \quad \text{Equation 6}$$

In this case perfect substitution was considered; therefore the sum of coefficients of a product and their substituted ones was kept constant over time.

The same reasoning applies to the final demand vector $\boldsymbol{y}$; therefore, its elements were modified in the following way:

$$y_n(t) = y_s \cdot sf_{s\rightarrow n}(t) \quad \text{Equation 7}$$

$$y_s(t) = y_s \cdot (1 - sf_{s\rightarrow n}(t)) \quad \text{Equation 8}$$

In this specific case, it was assumed that the new products are going to substitute the products in the economy as presented in Table 3.

In particular, the assumption related to sewage sludge was based upon the current destination for sewage sludge in Europe. Data referring to 2018 show that about 48% of European sludge is used in the agricultural sector, 27% is incinerated, 8% is used for land reclamation/recultivation, 6% is landfilled and the remaining 11% undergoes "other" management treatments [51]. These percentages have been applied introducing the simplifications shown in Table 3. For what concerns "TSF electricity", it is assumed that the substitution will involve only the electricity production of those plants that would be built otherwise in accordance with the European Investment Bank accounting for renewable energy [52,53]. All energy products generated by TSF plants are expected to be sold in the domestic market within the EU, for this reason the substitution involves only the EU-28 products. On the contrary, "TSF Phosphorus", both for the quantities generated and for the typology of product, is likely to be sold also abroad: it is assumed that the quantities exceeding the production levels corresponding to the 2030 target (the last year in which they are not expected to exceed 10% of the "EU-28 P fertilizers" market volume) will be sold in the RoW region.

Coefficients in the new columns are derived from monetary values of intermediate flows, attributed to the six new products considering economic weights relative to the total revenue of the technology. Prices are being assumed constant over time, which means monetary coefficients are not adjusted any further; each product's input coefficients are therefore constant over time.

Table 3
Assumed correspondence and substitution ratio between new products and other products in the economy.

new products	substituted products
TSF Sludge	EU-28 Inert Waste Incineration (30%) EU-28 Sewage sludge Land Application (50%) EU-28 Inert Waste Landfill (20%)
TSF Gasoline	EU-28 Motor Gasoline
TSF Diesel	EU-28 Diesel Oil
TSF Electricity	EU-28 Electricity (Natural Gas)
TSF Phosphorus	EU-28 P fertilizers, RoW P fertilizers

2.6. Implementing future scenarios

Since the IOTs used in the study refer to 2011, they are not adequate to describe economic scenarios related to the following decades. For this reason, they need to be updated assuming certain trends occurring in the sectors of the economy, which can be expressed by modifying technical coefficients in matrix $\boldsymbol{A}$ for modeling structural changes, and elements in vector $\mathbf{y}$ for modeling changes in final demand of each sector.

For all sectors except the electricity ones, future final demand was modeled based on historical trends, using the values from 1995 to 2011 contained in final demand vectors of EXIOBASE 3, and performing a linear regression.

Matrix $\boldsymbol{A}$ technical coefficients were modified specifically for the electricity sectors, in order to reflect the future electricity mix outlined by future scenarios in the "World Energy Outlook" by the International Energy Agency (IEA) [54]. Data from the IEA report were aggregated to fit into the two regions of the model, and two different scenarios were considered: a current policy scenario (CPS) and a sustainable development scenario (SDS) (Fig. 3). The CPS conveys the consequences of policy inaction, that is, no further energy policy decision is made after 2019 at the global level, de facto serving as a benchmark for this analysis. The SDS, on the contrary, is defined based on climate targets, and contains all the structural changes necessary to reach these targets by 2040. Coefficients in matrix $\boldsymbol{A}$ were thus increased or decreased by factors that reflect the change in the energy mix from year to year. The same scenarios were used to modify the final demand for the electricity sector in the vector $\boldsymbol{y}$.

2.7. Comparative assessment

In order to understand the consequences of the decision analyzed in the study, it is also worth to know what would happen without the decision taking place (the "counterfactual" situation) [55]. For this reason, the model was run considering a first situation in which the technology is not implemented (production by the analyzed technology is fixed at zero for all the time span of the simulation), and a second situation in which the technology is implemented according to the project trends. The environmental consequences were the avoided or additional impacts due to the implementation of the technology, which could be simply derived by arithmetical difference between the impact vectors $\boldsymbol{h}$ (Equation (3)) in the two situations considered, as in the following equation:

$$\Delta h_t = h_{t,dec} - h_{t,nodec} \quad \text{Equation 9}$$

where the subscripts "dec" and "no dec" refer to situations with and without the decision, respectively. The two situations, in consideration of the specific technology, will be indicated as "TSF" and "noTSF" from hereafter. For convenience, in cases where $\boldsymbol{\Delta h_t}$ assumes negative values, its sign is changed to positive and it is referred as "impact savings", which means that the "TSF" situation is characterized by lower impacts than the "noTSF" situation.

The following impact categories were considered in this study: global warming, 100 years (GWP), photochemical ozone creation (POCP), acidification (AP), eutrophication (EP) and human toxicity (HTP)

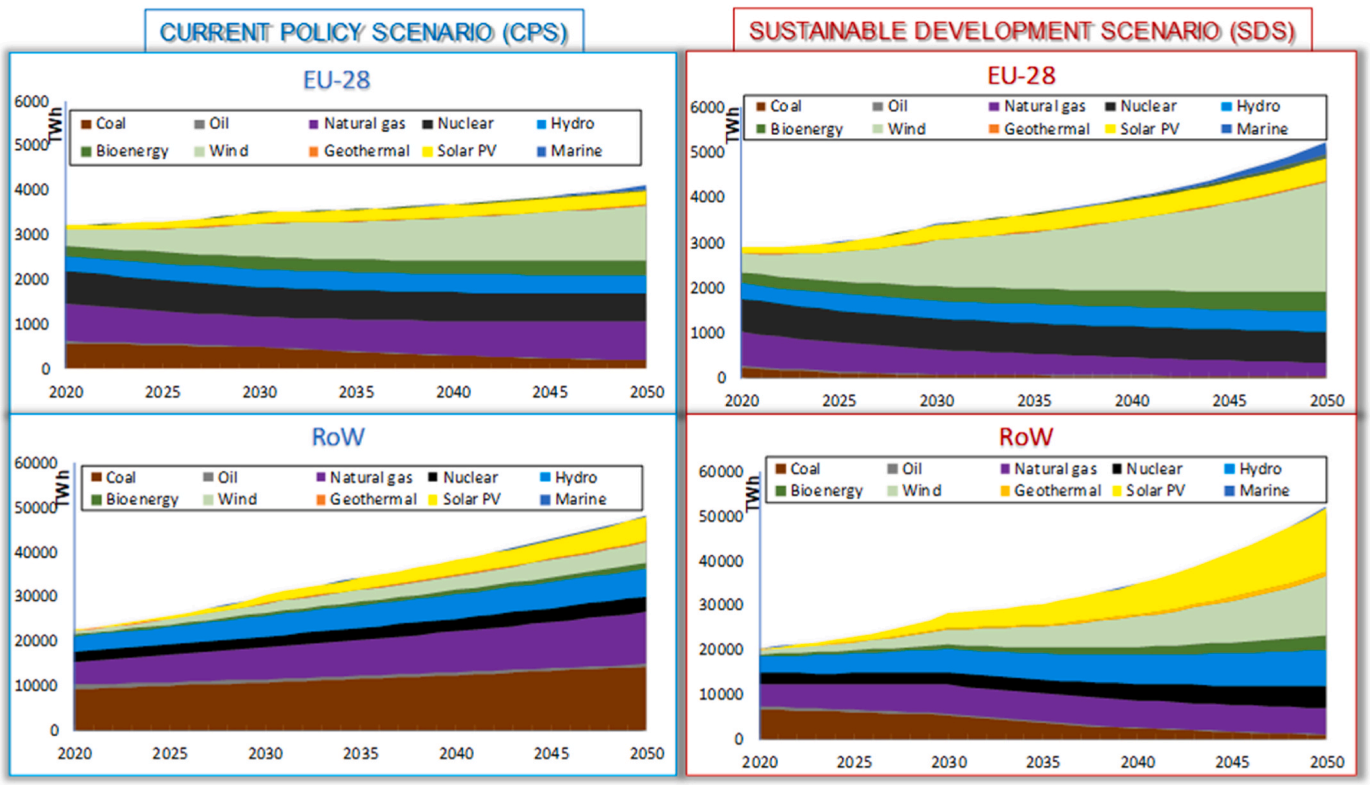

Fig. 3. Electricity scenarios used in the model [54].

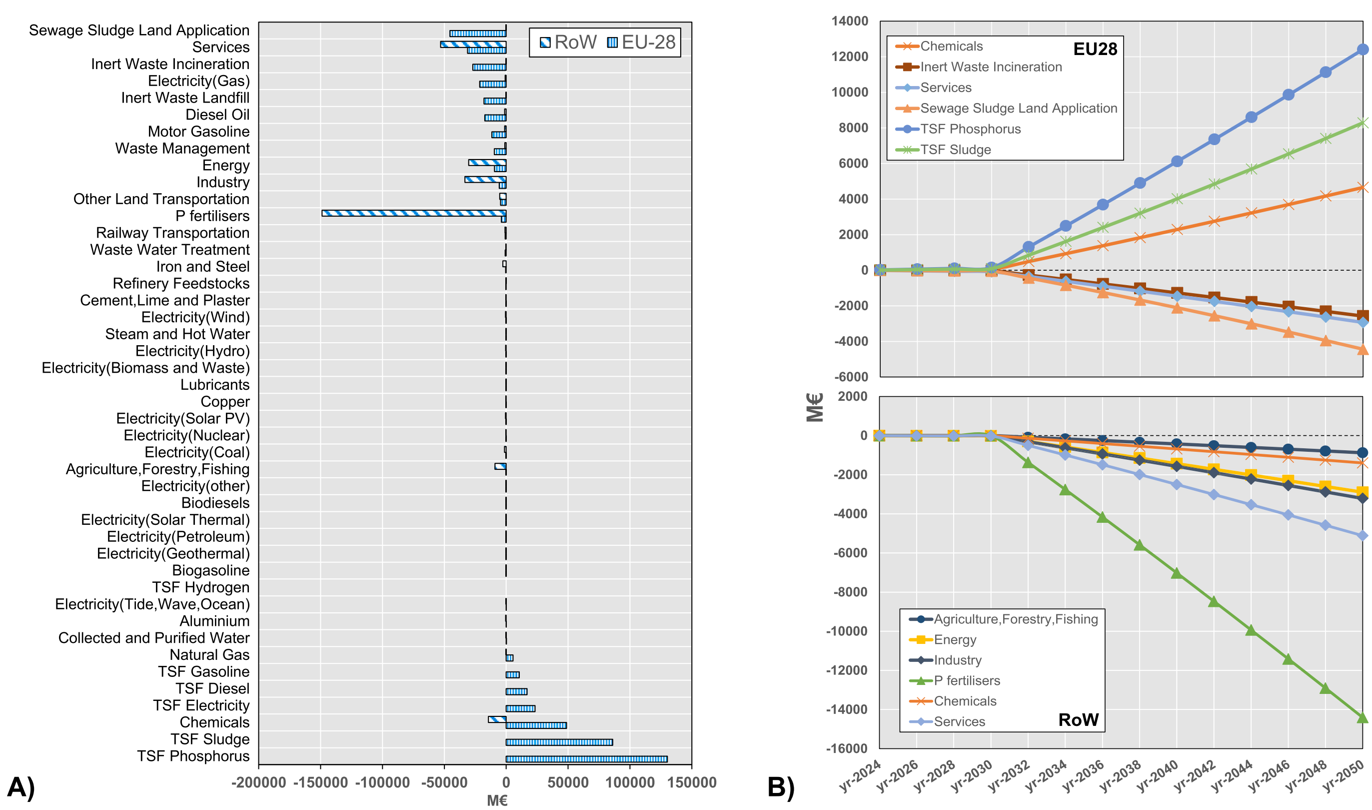

Fig. 4. Change (2024–2050) in sectoral total outputs in the CPS. A) Cumulative change. B) Time trends of change for selected sectors (applied cutoff on the sectors with values in the range −2000 and + 2000 (annual MEUR).

potentials. For the characterisation, the CML 2001 impact assessment method [56] was used.

Impacts were assessed with respect to the total production volume and, in general, for all functions provided by the system. However, it was still useful to refer to a production unit (in terms of revenue) to analyze the performance of the technology from year to year, since the production volume was not constant over time.

3. Results

The results presented in this section are organized showing firstly the outcomes related to sectoral total outputs ($\boldsymbol{x}$) and secondly the outcomes related to environmental impacts ($\boldsymbol{h}$). In the latter, results are shown starting from year 2024 in which the TSF technology is implemented, although the model is calibrated starting from year 1995 and simulated from 2011 (see section 2.6); the objective of the comparative assessment, indeed, was to show the relative outputs, which obviously are different from zero only since the two scenarios differ over time.

3.1. Sectoral total outputs

In the model, the vector $\boldsymbol{x}$ of sectoral total outputs was calculated for each time step with Equation (1). The comparative assessment consists of the arithmetical difference between vector $\boldsymbol{x}$ in "TSF" and "noTSF" situations. In a first step analysis, it is useful to examine the difference in vector $\boldsymbol{x}$, in order to understand which sectors are mostly affected by the introduction of the TSF technology, regardless of the environmental impacts.

In Fig. 4A it can be noted that few sectors of the overall 82 considered in both regions are particularly involved by the change. Obviously, these sectors include the TSF technology itself with positive product outputs, but it can be noticed that other sectors are significantly affected as well. An important positive output can be seen for the chemicals sector in EU-28, with a change in the economic production volume of 48,788 M€ over the timeframe considered by the analysis (i.e. 2024-2050). This is mainly due to the abundance of chemical products required by the TSF system for its functioning. At the same time, product outputs from various sectors are reduced by the presence of the TSF technology, because of direct substitution of the underlying technology (diesel, gasoline, electricity and sludge management in EU-28, P fertilizers in RoW, decreasing by 17,278, 11,598, 21,401, 90,490, and 148,779 M€ respectively) and or because those sectors are indirectly affected, such as services and industry sectors (decreasing by 31,294 and 5565 M€ in EU-28, and by 53,007 and 33,301 M€ in RoW.

Total outputs change linearly with time, as shown on Fig. 4B for the most relevant sectors. This linear trend follows the TSF deployment model described in Section 3.1. In sum, the five product outputs related to TSF technology follow a piecewise linear function with two intervals, as imposed by the model.

3.2. Impacts

In parallel with the calculation of sectoral total outputs, the impact vector h is obtained in the model through Equation (3). Again, through comparative analysis (Equation (9)), it is possible to determine the environmental benefits (or costs) due to the introduction of the TSF technology in the European economy.

Absolute impacts are shown in Fig. 5 for the two IEA policy scenarios. It can be seen that impact savings due to TSF are generally lower in a context of increased environmental policies, as can be expected considering the presence of a technological benchmark performing better from an environmental point of view. More specifically, the main difference between the two scenarios can be noted in the lower values of GWP (>10%) and AP (~10%) for the SDS scenario, while a very small difference can be detected with regard to the HTP impact.

Furthermore, it can be noticed that, although the technology is implemented only in EU-28, a greater part of the environmental benefits occurs in the RoW region (Fig. 5). Specifically, the impacts avoided in the two regions differ by about one order of magnitude, while for the EP impact the contribution of the EU-28 region can be considered even negligible.

It is of interest to evaluate the impact savings due to TSF technology also in relation to the relevance, in economic terms, of the decision analyzed. In support of this, a quantification of the impacts with respect to monetary flows related to TSF technology is provided in Table 4. The 2024–2050 value refers to the ratio between the total impact and the

Table 4
Impact savings of the TSF technology; refer to Fig. 5 for savings across the environmental impact indicator scores.

Indicator	Unit	Savings per output (2024–2050)		Savings per output (annual average)			
		CPS	SDS	CPS	*σ*	SDS	*σ*
GWP	t CO2 eq./M€	960	842	875	*17%*	784	*15%*
POCP	kg C2H4 eq./M€	241	223	213	*22%*	198	*21%*
AP	t SO2 eq./M€	4.99	4.45	4.22	*30%*	3.81	*29%*
EP	kg PO43- eq./M€	448	425	369	*35%*	352	*35%*
HTP	kt 1,4-DB eq./M€	2.17	2.15	1.84	*29%*	1.83	*29%*

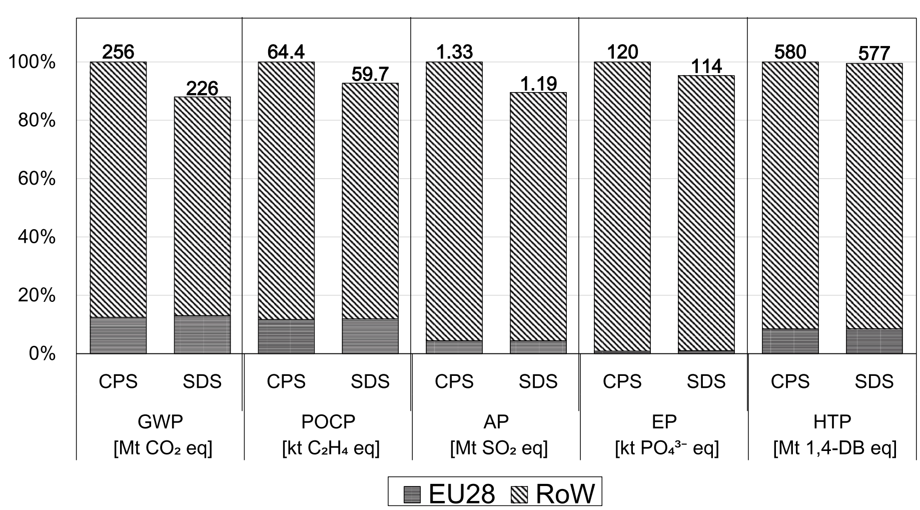

Fig. 5. Comparison of impact savings of the TSF technology in the CPS and SDS scenarios, also considering the contribution (in %) of the EU-28 and RoW regions.

total revenue generated by the TSF plants over all the time span. While the annual average is obtained as an average of the ratio between impacts and revenues calculated for each year of the time frame. The standard deviation of the latter provides a measure of the variability of the impact intensity that can be detected in such a dynamic analysis in which different parameters vary over time, affecting the environmental performance of the assessed technology.

By way of example for the GWP impact, in Fig. 6 the time trends of impact savings per monetary unit are shown for both electricity scenarios. It can be seen that the main source of variability in both scenarios is determined by the gap between two groups of values (until 2030 and after 2030). Such a gap can be explained considering that after 2030 the TSF technology directly affects also the “P fertilizers” sector in RoW, where highest emissions are associated with the product unit with respect to the equivalent sector in EU-28. Consequently, the TSF technology increases its environmental performance when it becomes more capable of affecting the RoW economy. A second effect, although less evident, can be noticed in the trend: a slight reduction of the impact savings occurs constantly over time, which is attributable to an increase in the use of renewable energy, progressively improving the environmental performance of the technologies against which the bioenergy at hand is measured. The effect of the amount of renewable energy in the electricity mix explains the difference between CPS and SDS scenarios as well. This difference also exhibits a slight increase over time (by ~6% on yearly mean), recalling the growing gap between the two energy scenarios. Similar figures for the other impact categories are provided in the Supplementary Material.

Fig. 7 shows the affected sectors that contribute mostly to the GWP impact change. The graph confirms that the environmental benefits of the TSF technology would mainly come from the substitution of P fertilizers produced in RoW, and secondly from the substitution of electricity produced by gas in EU-28. Interestingly, an important contribution also comes from other sectors in RoW only indirectly affected, especially the “Energy” sector. In this regard, it can be noticed that the main difference between the two scenarios concerns the contribution of electricity by coal in RoW, which is considerably reduced in the SDS. This result is not eventually surprising since it reflects the meaningful difference observed in coal-powered electricity projections between the two scenarios (see Fig. 3), showing the importance of assessing the environmental impact of a given technology in the context of different possible future global scenarios. At the same time, the implementation of the TSF technology will require the production of additional chemicals, used in the TCR-PSA-HDO process, and natural gas to meet the additional demand of thermal energy for the drying of sewage sludge in the pre-treatment phase. Therefore, the analysis suggests that further improvements in the GWP related performance can be obtained implementing solutions for reducing the use of chemical products and for performing the drying of biomass with the only contribution of renewable sources.

4. Discussion

4.1. Output of the simulation in the context of EU target

Results presented in the previous section can now be evaluated in the context of the EU targets. The EU is committed to reduce its GHG emissions by 55% in 2030 with respect to 1990 emission levels, and the most ambitious target for 2050 aspires to reach climate neutrality [57]. Considering the current levels of GHG emissions, it would require an average reduction of 146 Mt CO_2 eq per year to meet the 2030 target and of 128 Mt CO_2 eq per year to meet the 2050 target. This study shows that the TSF technology is capable of saving from 226 to 256 Mt CO_2 eq up to 2050, reaching a top contribution of 0.47–0.54% in 2050 to the EU reduction target. Fig. 8 shows how this contribution would rise over time.

Despite its relatively high increase over time, it is clear that this contribution remains relatively small in absolute terms and marginal for the accomplishment of the EU emission reduction targets. In other words, this model suggests that TSF-based technologies would not make significant changes on a broad continental scale. Nevertheless, if the focus of decision-making regarding the TSF’s role in contributing to climate neutrality goals by 2050 were to be downscaled at the level of single specific countries, then those technologies could potentially become very relevant as small-scale interventions. Moreover, it is worth noticing that, when strictly compared with the share of renewable energy expected to contribute to achieve the 2050 targets in the EU, which is up to 32% of the total GHGs emission savings in the SDS [54], the contribution to savings from the TSF technology increases to around 1.5%.

4.2. Framework strengths, limitations, uncertainties and relative importance of different input factors on the model output

A common problem of any prospective assessment is the uncertainty of the outcome. Typically, this is partially solved by resorting to the use of scenarios [58]. As it has been shown, the proposed dynamic IO framework is prepared to model different scenarios, for example one preserving (CPS) and one transforming (SDS) with respect to upcoming energy policies.

To make this framework reproducible and generalized, it is necessary

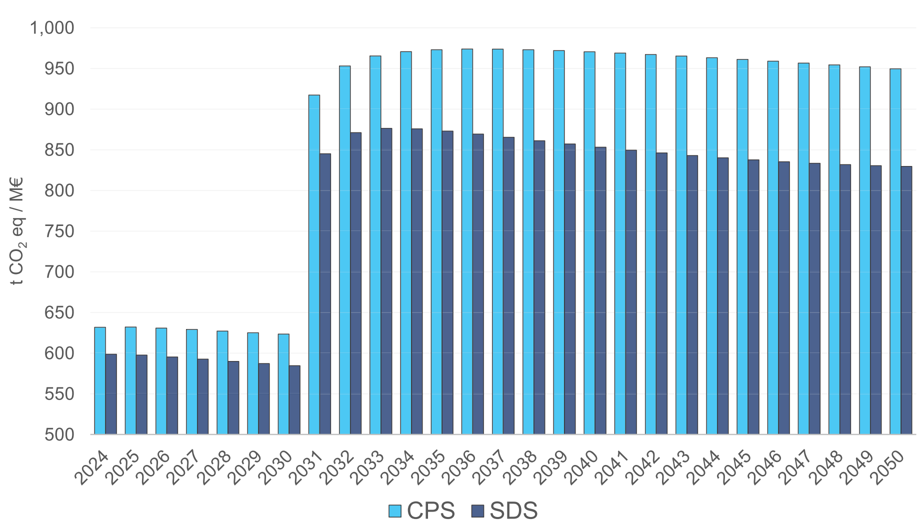

Fig. 6. Yearly GWP impact savings per M€ in the CPS and SDS scenarios.

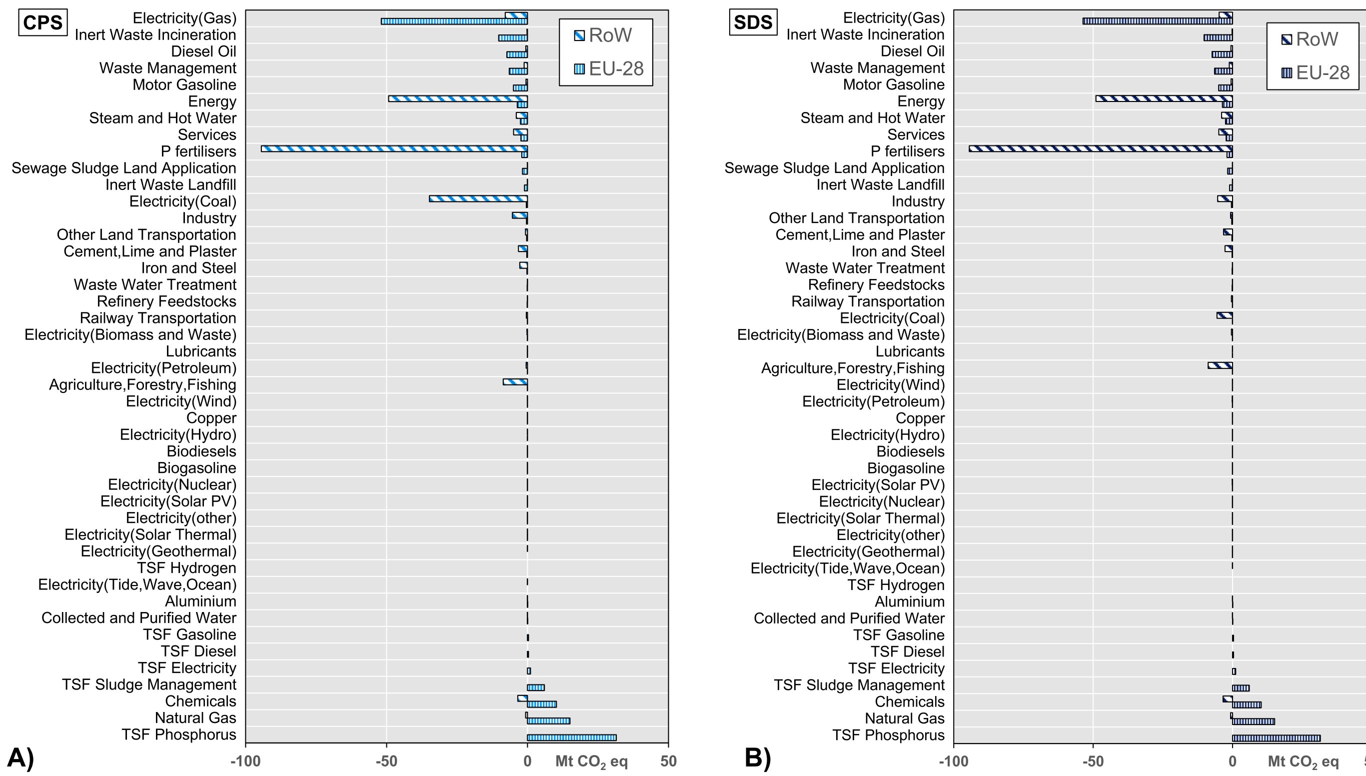

Fig. 7. GWP Impact by sector of the TSF technology in the CPS (A) and SDS (B) scenarios.

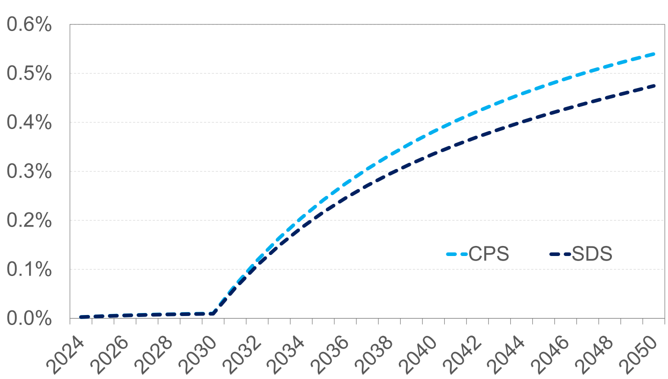

Fig. 8. Yearly contribution (%) of TSF technology to targets of GHG emission reduction of the EU in the period 2024–2050.

to understand and model the source of uncertainties (uncertainty analysis) and those factors most sensitive with respect to the output of the model (sensitivity analysis). To this end the model architecture is illustrated and the factors affecting the output are highlighted together with the model assumptions and related discretionary choices. The computational structure is presented in Fig. 9 and explained through synthetic equations where the input factors are highlighted in red. The specific equations and details about the factors are reported in Supplementary Material.

Equation (10) is a reformulation of Equation (3) expressing allocation factors ***w***.

$$H_t = \mathrm{C} \times \mathrm{E} = \mathrm{C} \times \mathrm{B} \times \widehat{x}_t = \mathrm{C} \times \mathrm{B}_0 \bullet w \times (Z_t \times i + y_t) \qquad \text{Equation 10}$$

Allocation factors are constants expressing the relative importance of the total economic flow generated by each of the functional flows indicated in Table 2, the sum of the economic flows of the five products being at the denominator (Equation (11)).

$$w = \frac{\varphi \bullet \nu_t \bullet \pi_i \bullet \eta_i}{\sum_{i=1}^{n} (\varphi \nu_t \pi_i \eta_i)} \qquad \text{Equation 11}$$

$$Z_t \times i + y_t = (A_t \times \widehat{x}_{t-1}) \times i + \alpha_i \bullet y_{t-1} + \beta_i \qquad \text{Equation 12}$$

Equation (12) expands the algorithm in Equation (10) to find ***Z*** and ***y***. The former is obtained from ***A*** and the diagonal matrix of the total output at the previous timestep times the addition vector. Initial values of ***x*** from EXIOBASE are provided at $t = 0$. Demand ***y*** is obtained through a linear regression model resulting in coefficients α (slope) and β (intercept) for any *i*-sector in the model. Again, the initial demand (y_0) is provided by EXIOBASE. Matrix ***A*** is at the core of the computation and is determined by EXIOBASE 3 which provided the initial technical coefficients; these initial conditions were changed through conditional statements as illustrated in Equation (13).

$$A_t = \begin{cases} a_j \bullet w_i \quad \text{if } a_j \in \{\text{TSF new producs}\} \\ a_i \bullet (1+\varepsilon_j) \quad \text{if } a_j \in \{\text{electricity sectors}\} \\ a_i \bullet \theta_t \quad \text{if } a_j \in \{\text{TSF new producs}\} \\ a_i \bullet (1+\theta_j) \quad \text{if } a_j \in \{\text{Substituted}\} \\ a_i \bullet (1+\theta_j) \bullet (1+\varepsilon_j) \quad \text{if } a_j \in \{\text{Substituted}\}\ AND \in \{\text{electricity sectors}\} \\ a_i \bullet \theta_t \bullet (1+\varepsilon_j) \quad \text{if } a_j \in \{\text{TSF new producs}\}\ AND \in \{\text{electricity sectors}\} \end{cases}$$

Equation 13

The technical coefficient reflecting cost structure of each TSF new product—which is read across columns a_j of TSF new products—has been adjusted through its allocation factor ***w*** obtained through Equation (10). For example, 50% of TSF costs (inputs) are from the chemical sectors, both to dispose of sewage sludge and make phosphorus. However, the share market of TSF sludge and TSF phosphorus—i.e. allocation factors—are respectively 17% and 60% of the total economic revenues. Therefore inputs to such products count proportionally more with respect to the other TSF new products.

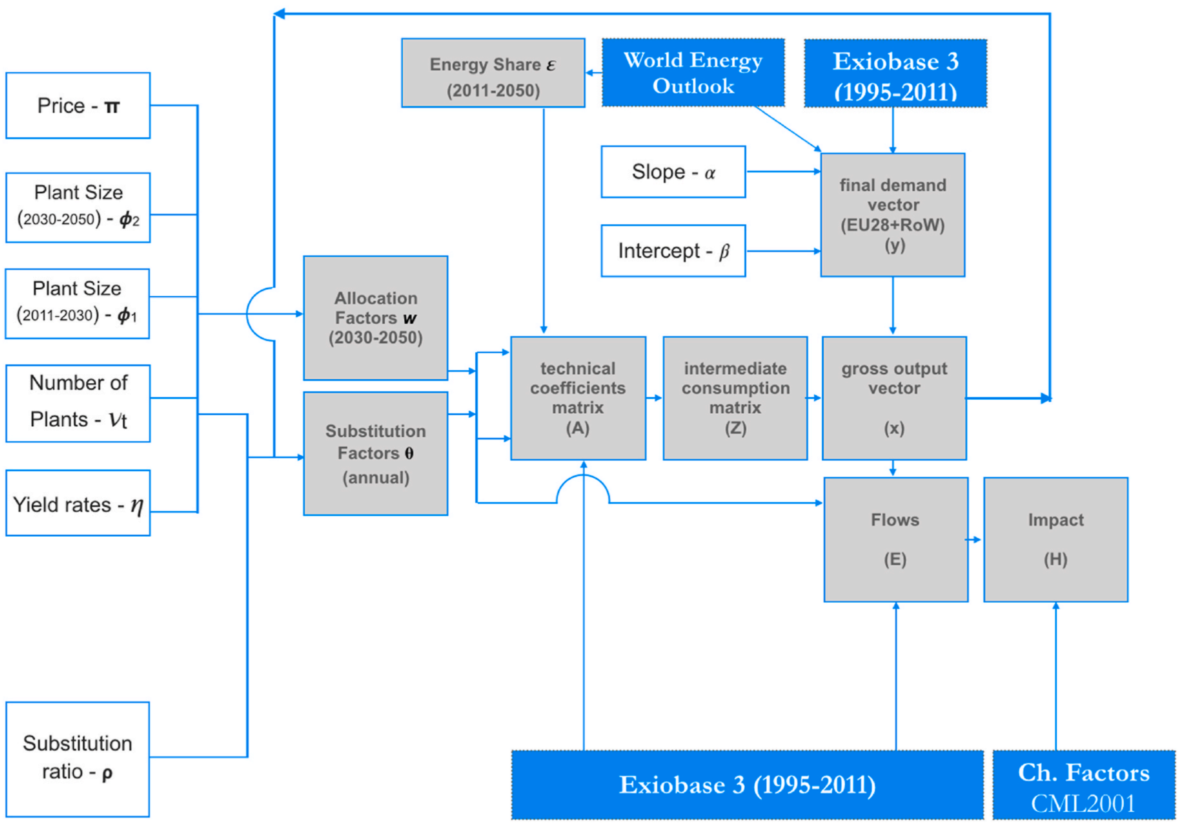

Fig. 9. Model computation structure: input factors are in the empty red-bordered boxes; grey background boxes represent combined intermediary factors and blue background boxes the data sources to run the model.

The substitution factors θ are instead used to adjust the technical coefficients of the sectors in rows, a_i, reflecting the relevance of the i-sector with respect to the output of the j-purchasing sector as explained in Section 2.5. In addition to these factors, the share of the energy sectors of the electricity sectors, ε, originated from the World Energy Outlook (see Fig. 3) are dynamically embodied in matrix $\boldsymbol{A}$.

The substitution factors are computed as indicated in Equation (14) in consideration of specific substitution ratios here denoted by ρ (Table 3).

$$\theta_t = \frac{\pi_i \bullet \eta_i \bullet \varphi \bullet \rho_i \bullet \nu_t}{x_{t-1}} \quad \text{Equation 14}$$

Substitution factors are dynamic factors accounting for the increasing number of plants ν_t at the capacity indicated in Table 3 with respect to the specific product/sector output $\boldsymbol{x}$ at the previous timestep t-1.

While a global sensitivity analysis would require further modeling which was not in scope, some preliminary consideration can be drawn from the analysis of Equations (10)–(14).

a) Most sensitive factors are those displaying the highest substitution factor, θ: phosphorus and sludge display a large output with respect to volumes in the real economy; therefore all input factors at the numerator of $\theta_{phosphorus}$ and θ_{sludge} such as the price π, substitution ratio ρ and yield rate η, are very sensitive with respect to differences in sectoral total outputs (Fig. 4), and impacts (Figs. 5–7, Table 4).
b) Plant size and number of plants equally affect all factors, most and less sensitive ones.
c) It has to be noted that both plant size and number of plants in 2030/2050 represent targets. The variation of the target considerably affects model output, however from a logical point of view they should not be subject to variation if not changing the purpose of the model.
d) The variable slope, α, affects the demand which is an additive factor in the composition of the total output $\boldsymbol{x_t}$. This is a sensitive factor. It is derived from the calibration of the EXIOBASE 3 dataset from 1995 to 2011 (see Section 2.6) and represents the corresponding regression coefficient. The regression model can be computed, adjusted to better fit demand projections through a corrective factor.

A global sensitivity will reveal which factors count the most and deserve additional analysis and modeling also with regard to the uncertainty analysis. With reference to the latter, far to be expanded and realised in detail, the following elements and considerations can prepare the ground for a numerical analysis and can qualitatively explain the main sources of uncertainty. In Table 5 each input factor has been assigned an accuracy band (upper and lower bound) and an appropriate probability density function (PDF) with standard deviation 1. Both the accuracy band and the chosen PDF are a measure of the uncertainty. MATLAB was adopted with functions 'makedist' and 'pdf' to ensure that PDF could reflect the expected distribution as per the statistical parameters in Table 5.

To start with, the plant size in 2030, expressed by φ_1, can range from 1.5 up to 4.5 t/h. Its accuracy band reflects the varying numbers of subunits composing each plant (each minimum subunit being 0.5 t/h). A normal distribution having 3 as the central value at discrete values of 0.5 is expected because the optimal configuration is known to be 3 t/h. Plant size in 2050 which was set at 40 t/h is uncertain at a higher degree. The TSF project showed that—in account of physical/engineering constraints—the largest operable unit can be 3 t/h and all future plants can be thought of as a combination of 3 and 0.5 t/h sub-units (Andreas Hornung, personal communication April 15, 2021). A lognormal PDF of the plants is reflecting a positively skewed distribution, with this variable at lower values than used in the simulation, median around 20 and a long tail towards the higher size. To account for that, this variable was

Table 5
Uncertainties related to the input factor expressed through lower/upper-bound and PDF. The value of factors from prices onward is reported in Supplementary Material.

Factor	lower-bound	upper-bound	mean (mu)	PDF	Prevalent uncertainties
Plant size target 2030 φ_1 (t/h)	1.5	4.5	3	normal, discrete	varying subunits at 0.5 t/h
Plant size target 2050 φ_2 (t/h)	3	40	3	lognormal, discrete	varying subunits at 3 t/h attainment of the technological maturity
Number of plants (target) ν_{2030}	0	50	2.5	lognormal, discrete	attainment of the target; plants shut down
Number of plants (target) ν_{2050}	0	300	4.5	lognormal, discrete	attainment of the target
Prices π	−50%	50%	π_i	uniform, continuous	economy changes
Yield rates η	−10%	15%	η_i	normal, continuous	technological changes
Substitution ratio ρ	−10%	10%	ρ_i	uniform, continuous	manyfold factors
Slope α(t)	−10%	10%	α_i	uniform, continuous	economy changes
Intercept β	−5%	5%	β_i	normal, continuous	accuracy of EXIOBASE 3

given a log-normal distribution. The target number of operating plants ν (50 and 300 respectively in 2030 and 2050) is uncertain both because the target cannot be attained and also because of random losses/shut down/accidents and interrupted production. Again a log-normal PDF is the most straightforward probability model accounting for such uncertainties in a conservative approach. Price π of TSF new products is held fixed in the model and is expected to vary widely in reality; the uncertainty related to these prices is such that a $\pm$50% variation should be considered. A uniform distribution is signifying an equiprobability of price changes in the long term. The yield rates η of the 5 functional flows (see Section 2.3) depend on the technological performances and might be subject to variability at each plant, temporally as well as in the long term. Expectation for long term technological improvements and consequent higher efficiencies η are reflected in a higher upper-bound. Substitution ratios ρ express the share of substituted sectors and products (e.g. the substitution ratio of sludge incineration is 30%). This depends on the quality of the new TSF products, regulation and trust of end users. As perfect substitution of 100% was assumed for most of new TSF products, the variation of +10% applies only for those ratios below 100%. Slope α and intercept β are derived from the EXIOBASE 3 dataset; while the variation of the former can account for changes in the economy trajectory, the latter is reflecting the inherent uncertainty of EXIOBASE 3.

These elements and considerations would elucidate only a part of the uncertainty.

Uncertainty depends on model assumptions, in the sense that assumptions simplified the model and yet diminished its relevance and adequacy to explain and predict phenomena [59]. These include constant prices, expansion of the technology only in Europe, perfect substitution of new TSF products to mention some.

Should these assumptions be eliminated and translated into additional modeling (e.g. instead of constant prices, dynamic prices generated from an external or developed ad hoc model) that would increase the number of input factors and, consequently, the model uncertainty. The right balance between propagation of errors and the model complexity, i.e. capacity of the model to capture and reflect complex dynamics, require additional elaboration. Here in the following the main assumptions, simplifications and consequent model additions or integrations with other models are reviewed. These have to be regarded as the next steps to improve both the general assessment framework and TSF model.

Structural changes of the economy, such as intermediate consumption matrix of the IO system, were modeled only with regard to electricity sectors; other aspects of future scenarios would require sector-specific modeling, especially regarding the broader energy supply mix, mobility, key industrial sectors. However, economic sectoral modeling is not trivial as these sectors often interplay. Proposals for a more comprehensive IO-based prospective modeling have been made [60–62], but they are data-intensive and no consensus exists yet regarding their robustness. Furthermore, the impacts associated with each economic sector (environmental extensions matrix) were taken constant, although a further development could consist in the inclusion of their variability based on historical trends or other more technical analysis specific to each sector. Another possible improvement could come from the modeling of the final demand (final demand vector) for each economic sector, which was made to vary linearly in accordance with historical trends, and sector-specific consumption projections. A more sophisticated regression modeling would imply a sector-by-sector study also by means of non-linear functions. Additional simplifications regard the economies of scale and/or technological improvements which can occur in the foreground system as long as the technology is developed at a wider scale [63]: in absence of an in-depth analysis, these effects, which could potentially lower the impact of the TSF technology, were neglected.

Moreover, at the basis of this framework there is the consequential thinking according to which the decision context is tested against the counterfactual, i.e. the outcomes that would have occurred in the absence of the decision [64]. Consistently with the consequential approach [65], product multifunctionality of the foreground system is solved with product substitution, in the sense that impacts are never placed outside the system boundaries. IOTs are nonetheless built according to an attributional approach, although the exogenous substitution of products in the augmentation procedure can follow the consequential criterion of choosing marginal products in place of the average ones, as it was the case of electricity corrected by dynamic factors.

It is also possible to develop further the consequential thinking, considering secondary consequences such as price effects, which could result in increased or decreased demand for competing functions. However, in this study, perfect substitution between equivalent functions was assumed and no price effects were modeled. For instance, in the field of biofuels, some attempts exist to model rebound effects on the final demand for fuels, as shown in Smeets et al. [41], Rajagopal et al. [66] and Oladosu [67], which typically involve the use of economic equilibrium models.

The rough aggregation into two regions and a limited number of economic sectors can determine the loss of some technological details which can have a certain relevance on the environmental outcomes. For example, while the role of chemicals in this study appeared to give an important contribution to the impacts, it was not possible to distinguish between different types of chemical products with very different impacts. Furthermore, IO models do not solve some of the typical limitations of LCA models, since they are based as well on a linear structure and on the assumption of unlimited supply of inputs. Nevertheless, the dynamic modeling of the IO structure could be considered a step forward with respect to the fixed input/output relationships, allowing to introduce exogenously substitution of inputs and shifts in the use of energy resources [68]. Another limit, connected to the absence of supply constraints, is the inability to model land use change effects, which is often a relevant aspect to consider in the analysis of bioenergy technologies [69, 70]. However, land use change in the present study was not considered a key topic, since the feedstock of the novel technology is waste biomass, which should not increase the need for land. Additionally, selected external dataset such as EXIOBASE, the World Energy Outlook and the LCIA model CML2001 bring in intrinsic uncertainties whose quantification should be accomplished by —or together with— these dataset providers.

Besides all these simplifications, which are still present as it would be in a traditional LCA, an advantage of the proposed assessment framework is to provide a flexible structure in which the practitioners can include an advanced dynamical modeling for the key elements of any specific case study. The model is developed in the attempt to relax certain fixed assumptions of the static LCA, which would be not realistic for measuring the environmental consequences of an action which unfolds over a large time frame. Among the parameters that are made to vary over time, there are those concerning the scale of the new technology implementation, the background in which the technology is embedded, quantity and type of substituted products.

5. Conclusions

This work presents a framework for assessing the environmental consequences of future potential decisions through a goal-oriented approach. A simulation applied to a bioenergy system related to the TCR-PSA-HDO technology appears to be capable of bringing environmental benefits, producing fuels, energy and phosphorus from a waste biomass source. A relevant part of the benefits would come from the avoided P fertilizers production, especially since the technology is implemented in Europe at a scale high enough to produce phosphorus also for the RoW region market. Along with the fertilizers industry change, the intense use of chemicals required for technology is expected to engender additional production by the chemical sector. This aspect, given its importance on the results, should further be investigated deeply by disaggregating the heterogeneous chemical sector to obtain a more detailed analysis along with modeling market prices of phosphorus and sludge disposal routes. More in general, to use the simulation output for decision making an uncertainty analysis and a review of the assumption shall be performed on the basis of a sensitivity analysis.

Results showed the importance of considering both the variability of the context through dynamic scenarios and extended system boundaries. It also shows through the selected case study how different aspects, such as substitution factors and the specific interplay among different industrial sectors, which are usually overlooked in the conventional framework, can play a decisive role for the outcomes of the analysis.

Although the simulation was focused on different scenarios in the electricity sectors, the same approach could be applied to any sector likely to face important changes in the future. The nature of this framework, conceived for a SD environment, encourages the integration of hybrid LCA with prospective models anticipating future technological and environmental changes.

Credit author statement

Roberto Porcelli: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. Thomas Gibon: Conceptualization, Methodology, Resources, Writing – review & editing. Benedetto Rugani: Conceptualization, Methodology, Resources Conceptualization, Methodology, Writing – review & editing, Visualization. Diego Marazza: Validation, Formal analysis, Data curation, Writing – review & editing, Visualization, Supervision, Funding acquisition. Serena Righi: Writing – review & editing, Funding acquisition, Project administration.

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 will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2023.113172.

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