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Assessing the social dimension in strategic network optimization for a sustainable development

The case of bioethanol production in the EU

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Abstract

The complexity of social indicators and their subjective and often qualitative nature render their inclusion into quantitative optimization models for network design and strategic decision-making challenging. The social dimension is thus often implemented only rudimentarily, thwarting a holistic sustainability assessment and neglecting many of the social issues addressed in the sustainable development goals (SDGs). This work presents a structured process for including a comprehensive set of social aspects by selecting applicable quantitative and regionalized social indicators. This approach is applied to the case of second-generation bioethanol production in the EU. Based on inter alia the *Guidelines for Social Life Cycle Assessment of Products and Organizations*, the Social Hotspots Database, state-of-the-art literature, as well as previous work, we compile 9 social objective functions and 25 functions for social hotspot identification. They are evaluated alongside 1 economic and 21 environmental LCA-based objective functions in a mixed-integer linear programming (MILP) model. Key results show that social optimization either leads to large, labor-intensive or regionally focused, indicator-driven networks. *Injuries and fatalities* in the feedstock sectors of Central and Eastern European countries is the primary social hotspot. On the level of the overarching SDGs, SDG13 is most congruent with other goals, while SDG7 is hindered by pursuing other goals. This study's approach is novel in strategic network design and the European bioeconomy, and, by operationalizing the social dimension, enables a more holistic life cycle sustainability assessment and the consideration of the SDGs. This article met the requirements for a gold-gold *JIE* data openness badge described at http://jie.click/badges.

KEYWORDS
industrial ecology, multi-objective optimization, second-generation bioethanol, social hotspots, social optimization, sustainable development goals

1 INTRODUCTION

For decades, most companies oriented their strategic supply chain design solely toward economic performance. To address the challenges of our time, the United Nations formulated the sustainable development goals (SDGs; United Nations, 2015) to provide a common ground for peace, prosperity, health and education, and reduced inequality, while tackling climate change and biodiversity loss. In 2019, 72% of over 1000 globally acting companies mentioned the SDGs in their reporting, although only 1% measured their actual performance (PwC, 2019). Companies are hence aware of their role in achieving sustainable development, but not of their actual impact. Incorporating operationalized environmental, economic, and social indicators as early as in strategic decision-making is the basis of aligning with the 17 SDGs.

While the SDGs are the "high-level shared blueprint" (Valdivia et al., 2021, p.1), the life cycle sustainability assessment (LCSA) framework (UNEP, 2011) divides sustainability into three pillars. For the environmental pillar, life cycle assessment (LCA) is a formally defined concept (ISO, 2006) that copes with both the product and the strategic, more aggregated level. Unlike product-specific or site-specific assessments, sustainable decision-making on a strategic and multiregional scale, inherently, relies heavily on aggregated and often generic data. In the field of strategic supply network design, many studies have addressed both LCA-based environmental impacts and economic feasibility in mathematical optimization models (Eskandarpour et al., 2015). The case of social sustainability is more intricate: While taking or not taking a decision has quantifiable repercussions in the economic and environmental dimensions, the social implications of the decision are not always clear ex-ante. The complexity of social indicators, their subjective and often qualitative nature, and a lack of data (Valdivia et al., 2021) render their inclusion into quantitative decision-making models complex. Existing social frameworks, such as the ISO 26000 (ISO, 2011) or the Sustainability Reporting Standards (GRI, 2021), focus on ex post evaluations, which allow for site- or product-specific assessments (Kolotzek et al., 2018; Ren et al., 2015). In contrast, strategic network design is located on a more generic level of aggregation and includes Greenfield problems, where social considerations and their interconnectedness with environmental and economic criteria (Valdivia et al., 2021) need to be quantifiable before strategic decisions are taken.

Although general interest in the inclusion of social issues is observed in the literature (Mujkic et al., 2018), the state-of-the-art implementation of the social dimension is far from being on par with the economic and environmental dimensions (Barbosa-Póvoa et al., 2018). Recently, Messmann et al. (2020) reviewed 91 articles with social objective functions (SOFs) for strategic network design and concluded: (1) most of the reviewed articles (74%) do not cite any existing social framework, and only 14% use frameworks specifically for identifying relevant social issues or quantifiable indicators (Ghaderi et al., 2018; Mota et al., 2015b; Soleimani et al., 2017). Those articles that rely on frameworks tend to cover more social issues, but the reasoning behind the selection is often not transparent, and there is no "best practice" process to build upon. (2) There is only a small number of consistently applied indicators, and only a few studies include several at once (Anvari & Turkay, 2017; Pishvaee et al., 2014; Zhu & Hu, 2017). Job creation is the only issue that is reliably found in the majority (69%) of relevant literature, mainly expressed by the total number of jobs created (Lin et al., 2019; Miret et al., 2016; Ahranjani et al., 2018; Roni et al., 2017). (3) There are hardly any attempts of impact assessment or multidimensional analyses, for example, multicriteria optimization. Studies instead weight and aggregate the aspects by applying, for example, the AHP method (Jakhar, 2015; Sahebjamnia et al., 2018; Shokouhyar & Aalirezaei, 2017). More quantitative approaches, such as the Social Hotspots Database (Benoît-Norris et al., 2018) or the Product Social Impact Life Cycle Assessment database (Ciroth & Eisfeldt, 2016), have not yet been applied in this field. Against this background, this work sets out to provide a best-practice approach for a structured selection of a set of quantitative and operationalizable social indicators for strategic network design.

Since the selection of suitable indicators and their application are case-specific, we present our approach in a case study in the context of the European bioeconomy. Agriculture claims the largest share of anthropogenically used land, which is why the use of renewable raw materials is subject to several tensions (Eurostat, 2021e; Hennig et al., 2016; Thorenz et al., 2018). Anthropogenic land use is associated with high environmental impacts in its current state (Lewandowski, 2015). Utilizing starch, protein, oil-based, or other dedicated energy crops as a source for renewable energy and materials (first generation) as substitutes for fossil-based counterparts competes for land with food security. These conflicts can partly be avoided by using harvesting residues (second generation). The bioeconomy thus represents a challenging application case for multicriteria strategic network planning and is linked to multiple SDGs. Ultimately, we investigate the following research questions, which are addressed in Sections 2 (RQ1) and 3 (RQ2 and RQ3):

- **RQ1**: How can a set of quantitative and operationalizable social indicators for strategic network optimization be derived in a structured manner?
- **RQ2**: What are the social benefits, impacts, and hotspots of socially, environmentally, and economically optimal large-scale production networks for second-generation bioethanol in the EU?
- **RQ3**: Which SDGs are affected, and what are interlinkages between them?

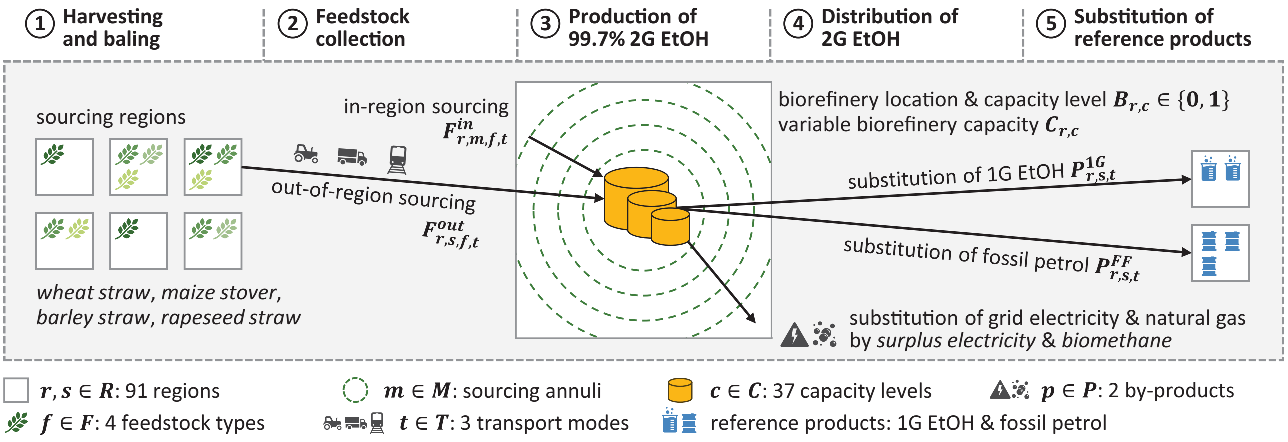

FIGURE 1 Value chain of 2G EtOH and visual problem description, including sets and variables of the MILP model (cf. Supporting Information S1, section 1)

2 | METHODS

Section 2.1 first motivates and describes the case study. This is necessary, as the focal supply chain, the geographical and system boundaries, and the level of aggregation influence the outcome of the indicator selection, which is described in Section 2.2. Sections 2.3 and 2.4 then select social indicators and integrate them into the problem by formulating SOFs and functions for social hotspot identification.

2.1 | Problem description

The case study is based on and extends the model presented by Wietschel et al. (2021; Supporting Information S1, section 1). They use multicriteria mixed-integer linear programming (MILP; modeled with IBM ILOG CPLEX 20.1.0.0) to investigate environmental benefits and economic viability of optimal second-generation (2G) bioethanol (EtOH) production networks for petrol and first-generation (1G) EtOH substitution in the EU. 2G bioethanol is based on lignocellulosic harvesting residues (here: wheat, maize, barley, and rapeseed straw). No environmental impacts are allocated for the growth phase; however, impacts of additional N-P-K fertilization to compensate for nutrient losses through straw evacuation are considered (Wietschel et al., 2021). From an LCA perspective, this work approximates the environmental consequences of optimal decisions by predominantly consequential modeling in the foreground system (e.g., avoided burdens), while using attributional background databases (ecoinvent 3.5, accessed with SimaPro 9) with average processes (Schaubroeck et al., 2021) due to a lack of marginal process data (Supporting Information S1, Table S17, gives detailed information on key modeling characteristics).

Figure 1 illustrates the value chain of 2G EtOH and the problem description with sets and variables. The superstructure comprises the 91 NUTS-1 regions of the EU27, in which all decisions are taken. They include feedstock sourcing (inter- or intra-regional) to biorefineries, biorefinery locations and capacities, and bioethanol production and distribution to substitute petrol or first-generation bioethanol. These decisions are taken so as to maximize an economic or 21 environmental objective functions. The environmental dimension comprises 18 impact and 3 damage categories of the LCIA method ReCiPe 2016. The economic dimension is represented by profit maximization in five tax scenarios. Scenario T1 represents the current country-specific taxation of bioethanol. In scenarios T2 and T3, the excise tax is reduced by 50% and 100%, respectively. Finally, scenarios T4 and T5 assume EU-wide carbon taxes of €50 and €375, respectively.

Fertile land is used to meet a wide variety of human needs, and growing global population aggravates the pressure on the limited land. This leads to the socio-economic "food, energy and environment" trilemma (Lewandowski, 2015, p.37), making the inclusion of the social dimension particularly relevant in the given application case. The environmental and economic objectives applied by Wietschel et al. (2021) cover 9 of the 17 SDGs (Supporting Information S2, Details 3). Consequentially, seven socially focused goals and many subordinate social targets of all SDGs are not represented. The approach presented in this section sets out to select and operationalize social indicators to fill the existing gaps and promote all SDGs. The model is then solved for each objective, trade-offs between different social, environmental, and economic categories are analyzed through multiobjective optimization, and social hotspots are evaluated. Lastly, the objectives are matched to 16 of the 17 SDGs (SDG17 is excluded since it rather targets political cooperation to facilitate sustainable development worldwide than explicitly socio-economic or environmental goals), and potentially positive and negative impacts on the attainment of the SDGs are investigated.

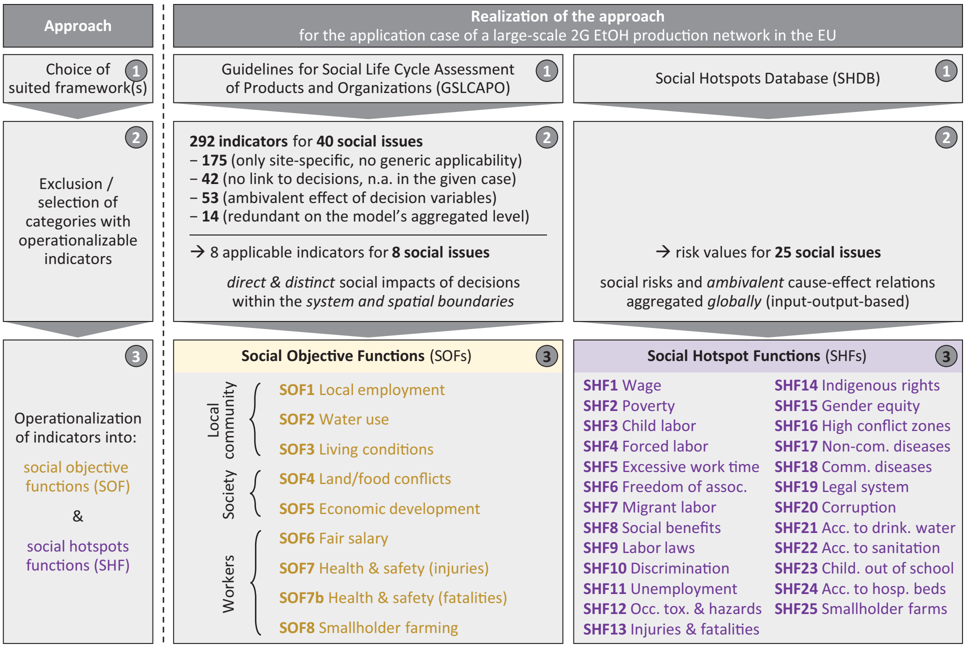

FIGURE 2 Approach for issue and indicator selection, operationalization and definition of indicators, and the formulation of social objective functions and social hotspot functions

2.2 | Selection of issues and indicators

This work presents a structured three-step selection approach (Figure 2) to identify the relevant and quantifiable social issues in the given context. This ensures that the social dimension is not exclusively represented by a single and arbitrarily chosen issue and indicator but covers as many aspects associated with network decisions as possible. In step 1 of the approach, suitable social assessment frameworks are selected. In step 2, relevant and quantifiable social issues are identified, and the irrelevant ones are excluded. Readily (case-specifically) applicable indicators proposed by the selected framework are directly adopted, and suitable operationalized indicators are developed for the remaining issues. In step 3, the indicators are operationalized and integrated in the MILP model. Here, we differentiate between optimizable SOFs, where decisions exert distinctly positive or negative impacts, and social hotspot functions (SHFs), which provide ex post insights into a plethora of potential social issues along the global value chains. The realization of steps 1 to 3 is detailed in Sections 2.3 (for the path toward the SOFs) and 2.4 (for the SHFs).

2.3 | Social objective functions

Step 1 (framework selection): While the SDGs are the overarching and globally accepted framework, their subordinate targets and indicators are not precisely designed to measure the impacts of specific supply chain decisions but rather to evaluate the progress of municipalities, countries, and humankind toward sustainable development. On the other end of the spectrum, there is a vast array of frameworks for evaluating social aspects in specific value chains and for certifying companies. Norms and standards such as the Sustainability Reporting Standards (GRI, 2021), the SA8000 (SAI, 1997), and the ISO 26000 (ISO, 2011) are among the most frequently cited frameworks in network design studies (Messmann et al., 2020) but are often rather designed for site-specific assessments or auditing suppliers and companies' existing supply chains. While the *Guidelines for Social Life Cycle Assessment of Products and Organizations* (GSLCAPO; UNEP, 2020) and their methodological sheets (UNEP, 2021; UNEP SETAC, 2013) also feature mostly site-specific and qualitative indicators, they explicitly focus on decision-making processes and are more product focused through their kinship with environmental LCA. For the case of a bioethanol production network, the GSLCAPO with its indicators for 40 social issues (subcategories)[1] are viewed as a suitable foundation for quantifying distinctly positive or negative social impacts.

Step 2 (indicator exclusion/selection): We successively reduce the given set of 40 social issues by excluding those of the 292 indicators that cannot be operationalized in this case study for different reasons: 175 indicators are only site specific with no generic applicability in this aggregated Greenfield problem (e.g., the indicator measures social impacts that heavily depend on the actual location of a facility or how an existing facility is operating). Forty-two indicators are not affected by any model decision or do not apply to the case of bioethanol production (e.g., the indicator refers to unrelated products or regions, or model decisions are assumed to not impact the aspects measured by the indicator). For 53, the effect of decisions on this indicator is ambivalent (when the indicator measures impacts that may be associated with the decision, e.g., political circumstances, but the decision's impact cannot be classified as distinctly positive or negative), and 14 indicators are redundant (e.g., when several indicators are proposed that measure the same aspect, e.g., poverty) on the aggregated level of the model (detailed selection and exclusion process in Supporting Information S2, Details 1). This leaves eight social issues, which are the basis for developing SOFs). For some, the GSLCAPO provide readily applicable indicators in this application case; for others, their operationalization and use as parameters in mathematical objective functions is based on existing approaches in this field (Kühnen & Hahn, 2017; Messmann et al., 2020), GSLCAPO's data source suggestions, and own developments (Tables 1 and 2).

Step 3 (objective function formulation): The SOFs represent social fields of action, where strategic network decisions exert distinctly positive or negative impacts. Table 2 lists the SOFs with a verbal description and their generic calculation scheme. The SOFs are formulated as maximization functions as they consider the impacts and benefits of both the network itself and of substituting the two reference products. The specific parameter calculations and objective function formulations are provided in detail in Supporting Information S1 (sections 2.1 and 2.2).

2.4 | Social hotspot functions

Step 1 (framework selection): The SOFs are network centered in their goal and scope, as global implications are mostly beyond the system boundaries of the decision-making process. However, regional decisions in a globalized economic system may also entail global implications. Therefore, and similar to Fürtner et al. (2021), the network-centered SOFs are complemented by results from the Social Hotspots Database V4 (2019) (Benoît-Norris et al., 2018), accessed via SimaPro 9.2.0.1. It provides country- and sector-specific social risks as well as an impact assessment method and is methodologically based on the GSLCAPO. The SHDB uses 160 indicators, data on labor intensity, and the underlying input–output model of the Global Trade Analysis Project (GTAP 9) (Aguiar et al., 2016) to accumulate social risk values along global value chains (so-called social hotspot indices; Benoît-Norris et al., 2018) for 140 countries and 57 sectors in 5 impact categories with 25 subcategories (cf. Supporting Information S2, Details 2). Risk values are expressed in medium risk hour equivalents (mrheq) per USD2011.

Step 3 (hotspot function formulation): The social risk values highlight existing social issues along global value chains in 25 subcategories. They are used to compile 25 SHFs (Supporting Information S1, section 2.3) by composing a product/process system from the 12 different GTAP sectors that the network activities (i.e., decision variables) comprise (Supporting Information S1, Figure S1). The SHDB-based risk entailed in a process is proportional to its economic value, mirroring the economic objective function. Thus, the risk value of a sector (converted to mrheq/EUR2020) in a country is multiplied by the economic value (in EUR2020) associated with decisions (e.g., biorefinery construction costs). For substituted products (e.g., petrol), the economic value can be interpreted as saved costs. The result is an absolute hotspot value (in mrheq), that is, the aggregate of all risks entailed by all decisions taken in the production network. Therefore, production networks of different sizes are hardly comparable in absolute risk values, but the risk accumulated (or saved) per ton of 2G EtOH is more meaningful.

The social risks in different sectors or countries are explicitly *not* provided to induce divestment incentives from regions with high risks but instead aim to shed light on social issues to facilitate a positive development. This may imply that the greatest opportunities for improving social issues can be found in regions with high social risks (Benoit-Norris & Norris, 2015). Due to ambiguous cause–effect relations and the uncertainty, whether activities, expressed by the model's decision variables, are levers for the better or reinforce adverse circumstances, the social hotspot values are not optimized. This contrasts with the social (and economic and environmental) objective functions, where one unit of a decision variable has distinctly positive or negative effects on the respective social indicator. Instead, the 25 hotspot functions are quantified by co-calculation when optimizing other objective functions. This implies that the awareness of risks, for example, for questionable labor practices in a supply chain enables a positive social development and due diligence of the respective operating companies.

3 | RESULTS

Sections 3.1–3.3 correspond to step 4 of the presented approach. Section 3.1 presents the socially, environmentally, and economically optimal production networks, 3.2 discusses the results of Pareto optimization between different pairs of objectives, and 3.3 provides the results of the social hotspot assessment. Section 3.4 corresponds to step 5 and presents the impact of the objective functions on the SDGs semi-quantitatively.

3.1 | Sustainable network planning

Since the production of 2G EtOH is more expensive than 1G EtOH and petrol (Padella et al., 2019), with current country-specific taxation, 2G EtOH can only be sold economically in countries with an excise tax reduction, leading to very small production networks (see Figure S4 in Supporting Information S1). In the following, the economic dimension is represented by tax scenario T3 since an excise tax reduction of 100% in all EU member states offers the most clear-cut economic–environmental trade-offs. Figure 3 presents production networks for selected objective functions of the

TABLE 1 Selected social issues and their indicators, as presented in the GSLCAPO and the methodological sheets

Social issue (subcategory)	Indicator proposed by the methodological sheets	Social objective function (SOF)	Operationalized indicator(s) for the case of 2G EtOH production in the EU	Data sources
Local employment	Unemployment statistics by country	SOF1 *Local employment*	Unemployment rate by region	Eurostat (2021h), World Bank (2021f)
Access to material resources	Levels of industrial water use	SOF2 *Water use*	Water use in the network; water stress level by country	FAO (2021)
Safe and healthy living conditions	Pollution levels by country	SOF3 *Living conditions*	Air emissions in the network; excess mortality from air pollution by region; population density by region	Anderson et al. (2004), EEA (2021), WHO (2021), Eurostat (2021g), Health Effects Institute (2020), WHO (2018), World Bank (2021d, 2021e)
Prevention and mitigation of conflicts	Is the organization doing business in a sector that features linkages to conflicts […]?	SOF4 *Land-food conflict*	Land occupation in the network; agricultural caloric yield by region	Eurostat (2021b), Lee et al. (2016), World Bank (2021a)
Contribution to economic development	Economic situation of the country/region (GDP, […])	SOF5 *Economic development*	GDP per capita by region	Eurostat (2021d), IMF (2021), World Bank (2021c)
Fair salary	Non-poverty wage by country	SOF6 *Fair salary*	Wages by country and sector; poverty threshold by country	Catherine Benoît-Norris et al. (2018), World Bank (2021b)
Health and safety	Number/percentage of injuries or fatal accidents in the organization […]	SOF7a *Workers' health & safety*	Number of non-fatal accidents by days lost, country, and sector; number of employees by country and sector	Eurostat (2021a, 2021f), ILO (2021a, 2021b)
		SOF7b *Workers' health & safety*	Number of fatal accidents by country and sector; number of employees by country and sector	Eurostat (2021a, 2021f), ILO (2021a, 2021b)
Smallholders including farmers	*(New subcategory since 2020, no indicators available yet)*	SOF8 *Smallholder farming*	Area share of small agricultural holdings by region	Eurostat (2021c) FAO (2000, 2010, 2020)

TABLE 2 Social objective functions. DV_r generically represents all decision variables (detailed in Supporting Information S1, section 1), broken down by region r, to illustrate the relation between network decisions and the various social parameters. DV_r thus may stand for feedstock provision and transportation, biorefinery construction, 2G bioethanol production and transportation, and substitution of 1G bioethanol or petrol. The complete mathematical formulation of the SOFs, including substitution, and the calculation and sources of the model parameters are provided in Supporting Information S1 (sections 2.1, 2.2). Similar implementations in existing supply chain optimization literature (Messmann et al., 2020) are cited below the table

Social objective functions
SOF1 (*Local employment*) weights the number of jobs created by the network decisions with a parameter for the regional unemployment rate relative to the EU27 average. In this way, jobs created in regions with higher unemployment rates are favored (Mota et al., 2015a; Zahiri et al., 2017; Zhalechian et al., 2016). $\textit{maximize: } DV_r \ast \textit{job factor}_r \ast \frac{\textit{unemployment rate}_r}{\textit{unemployment rate}_{EU27}}$
SOF2 (*Water use*) weights the water used in the network with country-specific water stress levels, which is also the indicator of SDG6.4 (FAO, 2021) $\textit{maximize: } DV_r \ast \textit{water use} \ast \frac{\textit{water stress level}_r}{\textit{water stress level}_{Europe}}$
SOF3 (*Living conditions*) weights network-induced air emissions with regional population density and the calculatory marginal excess mortality per pollutant of each region. $\textit{maximize: } DV_r \ast \textit{air emissions} \ast \frac{\textit{excess mortality}_r \ast \textit{population density}_r}{\textit{excess mortality}_{EU27} \ast \textit{population density}_{EU27}}$
SOF4 (*Land/food conflict*) weights the potential loss in agricultural production by the network's land occupation by the regional caloric grain yields. This is contrasted with the potential gain in cultivation areas through the substitution of the references (e.g., the substitution of 1G EtOH would free up land that would instead be available for food production). $\textit{maximize: } DV_r \ast \textit{land occupation} \ast \textit{yield}_r \ast \textit{caloric value of wheat}$
SOF5 (*Economic development*) weights the created economic value added by network decisions with a parameter for the regional GDP per capita (calculated as an input-output-based (Aguiar et al., 2016), sector-specific weighted average) relative to the EU27 average. The regional GDP is one of the indicators proposed by the methodological sheets and used as an indicator by the EU in its cohesion reports (European Commission, 2017). The economic value of network activities is assumed to mirror the elements of the economic objective function, i.e., higher costs contribute positively to SOF5. This assumption neglects induced values that, e.g., a newly built facility may add to a local economy but ensures quantifiability (Govindan et al., 2016a; Zhu & Hu, 2017). $\textit{maximize: } DV_r \ast \textit{economic value}_r \ast \frac{\textit{GDP per capita}_{EU27}}{\textit{GDP per capita}_r\ (\textit{global IO}-\textit{based weighted average})}$
SOF6 (*Fair salary*) weights regionally created jobs with the compound fraction between the average sector wage in a country, the country's poverty line, and the wage-poverty ratio on an EU27 average. Therefore, regions with high relative sector wages and a low relative poverty threshold are favored. $\textit{maximize: } DV_r \ast \textit{job factor}_r \ast \frac{\textit{daily wage}_r}{\textit{daily wage}_{EU27}} \ast \frac{\textit{poverty line}_{EU27}}{\textit{poverty line}_r}$
SOF7a and **SOF7b** (*Workers' health and safety*) use 10-year averages of lost employee-years and fatalities, respectively, per employee due to work accidents by country and sector to determine the number of employee-years and lives, respectively, that can be expected to be lost through network decisions or to be saved through substitution. $\text{maximize}: DV_r \ast \textit{job factor}_r \ast \textit{avg.employee} - \textit{years lost}_r;\ \text{maximize}: DV_r \ast \textit{job factor}_r \ast \textit{avg.lives lost}_r$
SOF8 (*Smallholder farming*) focuses on the economic value of feedstock regionally sourced in the network. The value is multiplied with the input-output-based, sector-specific weighted average over the area share of smallholder farms ($\leq$ 2 ha) as well as the fraction of economic value channeled to agriculture. $\textit{maximize: } DV_r^{feedstock} \ast \textit{economic value}_r^{agriculture} \ast \textit{area fraction of small holdings}_{r\ (\textit{global IO}-\textit{based weighted average})}$

SOF1: Ghaderi et al. (2018); Mota et al. (2015a); Pishvaee et al. (2014); Zahiri et al. (2017); Zhalechian et al. (2016); Zhu & Hu (2017); **SOF5**: Ghaderi et al. (2018); Pishvaee et al. (2014); Zahiri et al. (2017); Zhalechian et al. (2016); Zhu & Hu (2017); **SOF6**: Ramos et al. (2019); wages only; **SOF7a**: Chen & Andresen (2014); Devika et al. (2014); Fathollahi-Fard et al. (2018); Govindan et al. (2016b); Mirmohammadi & Sahraeian (2018); Pishvaee et al. (2014); Rahimi et al. (2019); Rahimi & Ghezavati (2018); Rezaei & Kheirkhah (2018); Sahebjamnia et al. (2018); Samadi et al. (2018); Soleimani et al. (2017); Tsao et al. (2018); Zhu & Hu (2017).

three sustainability pillars. The economic optimization leads to a production network of primarily high-capacity biorefineries and is concentrated in countries of Central and Eastern Europe (CEE), with additional biorefineries in the EU's "breadbasket" in central France. Both are characterized by an abundant feedstock supply, and CEE countries additionally yield the economic advantage of below-average costs. The 26 biorefineries can valorize about 47% of the total feedstock potential to produce 11 Mt of second-generation bioethanol, which could substitute 10.8% of the total current petrol demand. The objective value of €1.55 billion (i.e., the profit) is relatively small compared to the network costs of €11.25 billion, which hints at a higher sensitivity toward model parameters. The environmental dimension is represented by the objectives *global warming* and *land use*, which are two relevant (cf. Supporting Information S1, section 3.2) and conflicting (cf. Supporting Information S1, section 3.7.1) environmental impact categories. While optimization of *global warming* leads to 100% utilization of the available feedstock to substitute as much petrol as possible, the objective *land use* exclusively substitutes first-generation ethanol, utilizing 20% of the available feedstock. Optimizing *global warming* results in a total benefit of 58.3 billion tons of CO_2 saved, while optimizing *land use* would only save 7.5 billion tons. Since the entire demand for 1G bioethanol

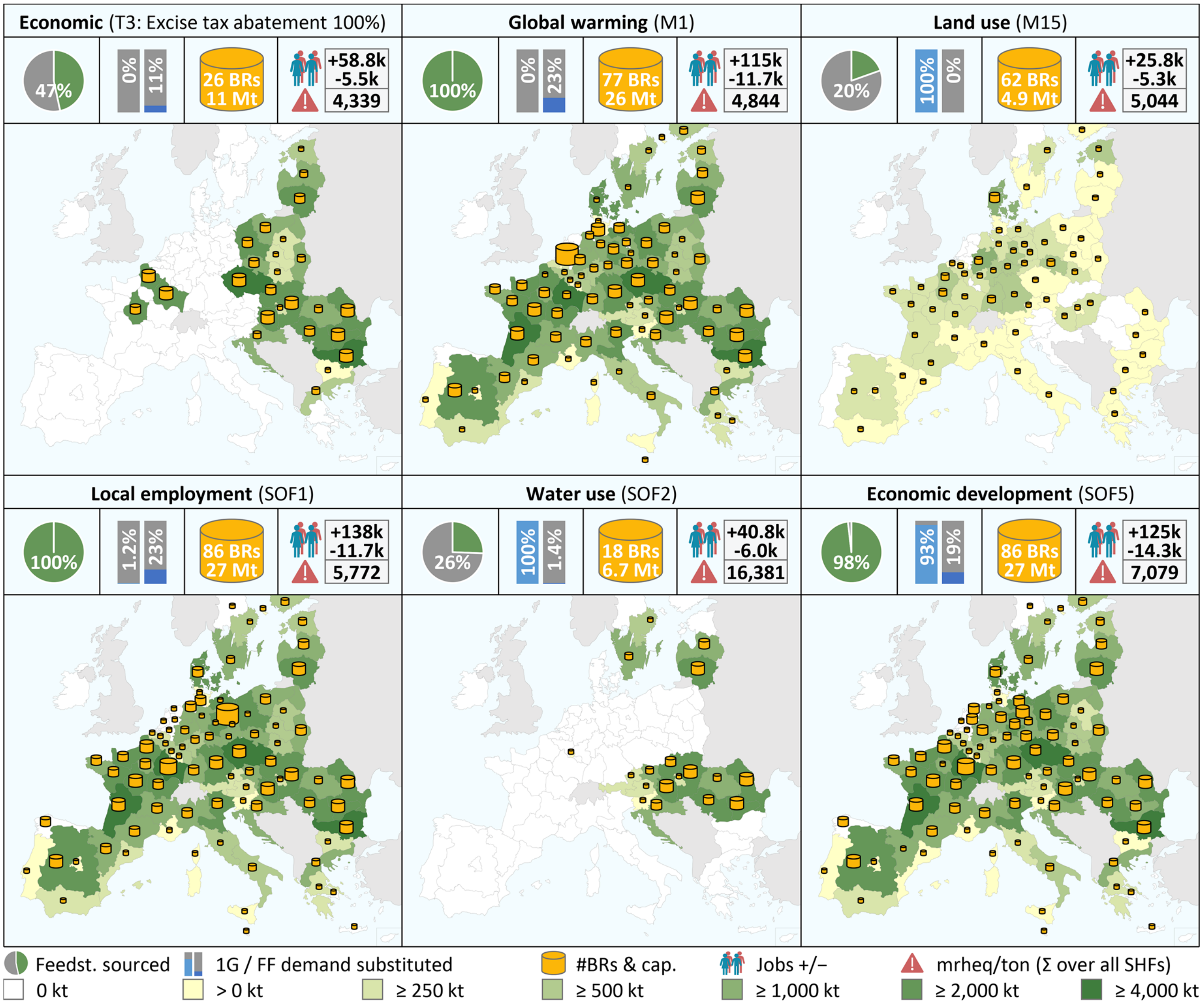

FIGURE 3 Optimal biorefinery locations and capacities (the size of cylinders corresponds to the capacity), and regional amounts of feedstock sourced (green shades, in metric kilotons) for six objectives. The legend also includes respective percentages of total feedstock collected (pie chart), the percentages of 1G demand and fossil petrol demand substituted (bar charts), the total number and total capacity of biorefineries (BRs & cap.), the number of jobs created and lost, as well as the total risk increase over all SHFs (in mrheq per ton). Figures S4-S15 in Supporting Information S1 display analogous information for the economic objective in four tax scenarios, four environmental objectives (E2, M1, M5, and M15), and eight SOFs, and in terms of amounts of feedstock sourced, jobs created, and hotspot values accumulated. Underlying data for Figure 3 are available in Supporting Information S2 (sheet 'Figure data')

is substituted with *land use* optimization, over 11.3 billion m^2 annual cropland eq. could be saved, which would then be free for alternative uses such as additional food production or ecosystem restoration (the implications of this change are beyond the scope of this work). In contrast, the optimization of *global warming* would increase the land use impact of the network by 1.9 billion m^2 annual cropland eq. Apart from minor differences due to slightly adjusted parameters (cf. Supporting Information S1, Appendix 6), the results align with Wietschel et al. (2021).

The SOFs and their results can be divided into results for those SOFs where the network itself yields benefits (SOF1, SOF5, SOF6, and SOF8), and SOFs where benefits are generated through substitution (SOF2, SOF3, SOF4, and SOF7). Results for the former are mainly comparable to the results of the *global warming* optimization. While also suggesting about 100% feedstock sourcing, the substitution decision is less determined by the effects of the substitution itself. Instead, the social objectives aim to exploit opportunities, for example, to create additional jobs or economic value where possible, and subsequently, substitute demand within the model's constraints (cf. Supporting Information S1, section 2.4). Even though optimization of SOF5 (*economic development*) results in the substitution of 93% of the 1G EtOH demand (compared 1.2% for SOF1 and 1.9% for SOF6), the values of SOF1 (*local employment*) and SOF6 (*fair salary*) deteriorate by only 19%, when SOF5 is optimized (cf. Supporting Information S1, Figure S21). These social objectives lead to distinctly negative economic objective values in every tax scenario, especially with SOF5 (T1: –€19.6 billion, T2: –€14.5 billion, T3: –€11.0 billion, T4: –€17.8 billion, T5: –€8.4 billion). The other group of social objectives is more diverse in terms of feedstock sourced (ranging from 1%, SOF7b, to 97%, SOF3), and depend more on the regional characteristics of their parameters. For example, 2G EtOH production for SOF2 only takes place in countries with a low water stress level and also needs the benefits of substituting water-intensive 1G EtOH to operate viably. Lastly, the total risk value displayed in Figure 3 (in mrheq per ton EtOH) reflects global social hotspots connected to the respective solution. A concentration on CEE countries (e.g., SOF2) or a focus on less-developed regions (e.g., SOF5) entails significantly higher social risks than networks with large production capacities in Western European countries (cf. Section 3.3).

3.2 | Pareto optimization

Pareto optimization reveals the leverage of the different social parameters on the regional distribution of the activities. Regional differences are only discernible in nuances once 100% of the available feedstock potential is sourced (Figure 3). If the social dimension were not forced into a tight corset of constraints (Supporting Information S1, section 2.4), the complete production would occur in the region with the highest social parameter value (e.g., the highest unemployment rate). When an economic constraint is introduced in Pareto optimization (applying the equidistant ε-constraint method), and less than 100% of the feedstock is sourced, regional social aspects emerge more clearly.

Figure 4 displays Pareto-optimal frontiers between the economic objective (in tax scenario T3) and SOF1, SOF5, SOF6, and SOF2, visualizing network configurations at three points along the frontier in terms of created jobs.

The single-criteria economic optimization leads to 58,805 additional jobs, mainly in CEE countries and northern France (Figure 3), while 5457 jobs are assumed to be lost due to the substitution of petrol. This net job creation of 53,348 already corresponds to 42.1% of the value when maximizing SOF1 (*local employment*, 126,697). Once SOF1 is introduced as an additional objective, the network starts to shift to regions with high unemployment rates in Spain and Italy (point a). Greece hardly benefits from SOF1 due to its scarce feedstock supply. When sacrificing 11% profit, the pure number of jobs created increases by 30% (from 53,348 to 69,365), but the objective value of SOF1 (in unemployment-weighted job equivalents) improves by more than 49% (from 43,378 to 64,781). These effects become more pronounced with increasing preference for SOF1 (point b). Beyond point (c), where almost all feedstock is sourced, the gradient of the Pareto frontier becomes steeper, meaning that marginal social gains are disproportionately more expensive. Here, only a few regions with a combination of high costs and low unemployment rates are exempted (e.g., Southern Germany, Austria, the Netherlands).

Multicriteria optimization between the economic objective and SOF5 (*economic development*) discriminates economically strong metropolitan regions such as most capital regions and economically strong countries and favors regions in CEE countries and northern France (a and b). Even though regions of central and western Spain also have favorable model parameters due to a comparably low GDP per capita, these regions are not selected. The preference for CEE countries can be explained by the benefits in profitability *and* GDP, while costs indices in Spain hamper profitability. Notably, with a further preference for SOF5 (c), the network is only slightly larger than for (a) and (b), since additional gains for SOF5 are mostly realized by shifts in sourcing and transportation decisions. When higher SOF5 values are obtained, profit drops disproportionately to its lowest value in any of the curves with over −€10 billion.

SOF6 (*fair salary*) favors regions with high sector wages relative to the poverty threshold. Regional differences in Pareto optimization are slightly more pronounced than with the other SOFs. Italy, in particular, profits from SOF6 but also selected regions in France, Spain, and Germany. The Pareto-optimal frontier has, at first, only a small gradient, meaning that SOF6's objective value can be tripled while remaining profitable (point c). After that point, the value again drops disproportionately.

Unlike the afore-shown SOFs, benefits for SOF2 (*water use*) are generated through substitution and not by the network. As the economically preferential regions are coincidentally also, in large parts, regions with a lower water stress level (mostly CEE countries), the network structure does not change much along the Pareto frontier. Trade-offs concern almost only the substitution decision, and positive objective values can be realized for both objectives, as long as petrol is neither exclusively substituted (as left of point a) nor substituted too little (as right of point c).

3.3 | Social hotspots

Figure 5 shows social hotspots in networks of selected objective functions. Over all the objective functions, SHF6 (*freedom of association, collective bargaining, and right to strike*) is the most relevant hotspot, followed by SHF4 (*forced labor*), SHF12 (*toxics and hazards*), and SHF13 (*injuries and fatalities*) (cf. Supporting Information S2, Figure S3). Significant risks in a country sector are either due to high specific risk values or stem from a high share of network activities, which is why the feedstock sector with its high percentage in the overall production costs has by far the most prominent social hotspots, regardless of SHF.

The economic objective entails the most distinct hotspots and is exposed to 33% higher risk than *global warming* (12,960 compared to 9739 mrheq/t). The relatively high risks can be explained by a focus of activities on CEE countries, which, on average, have higher social hotspot values. The feedstock sector in Romania has the highest contribution in most of the hotspot functions, contributing up to 27% to

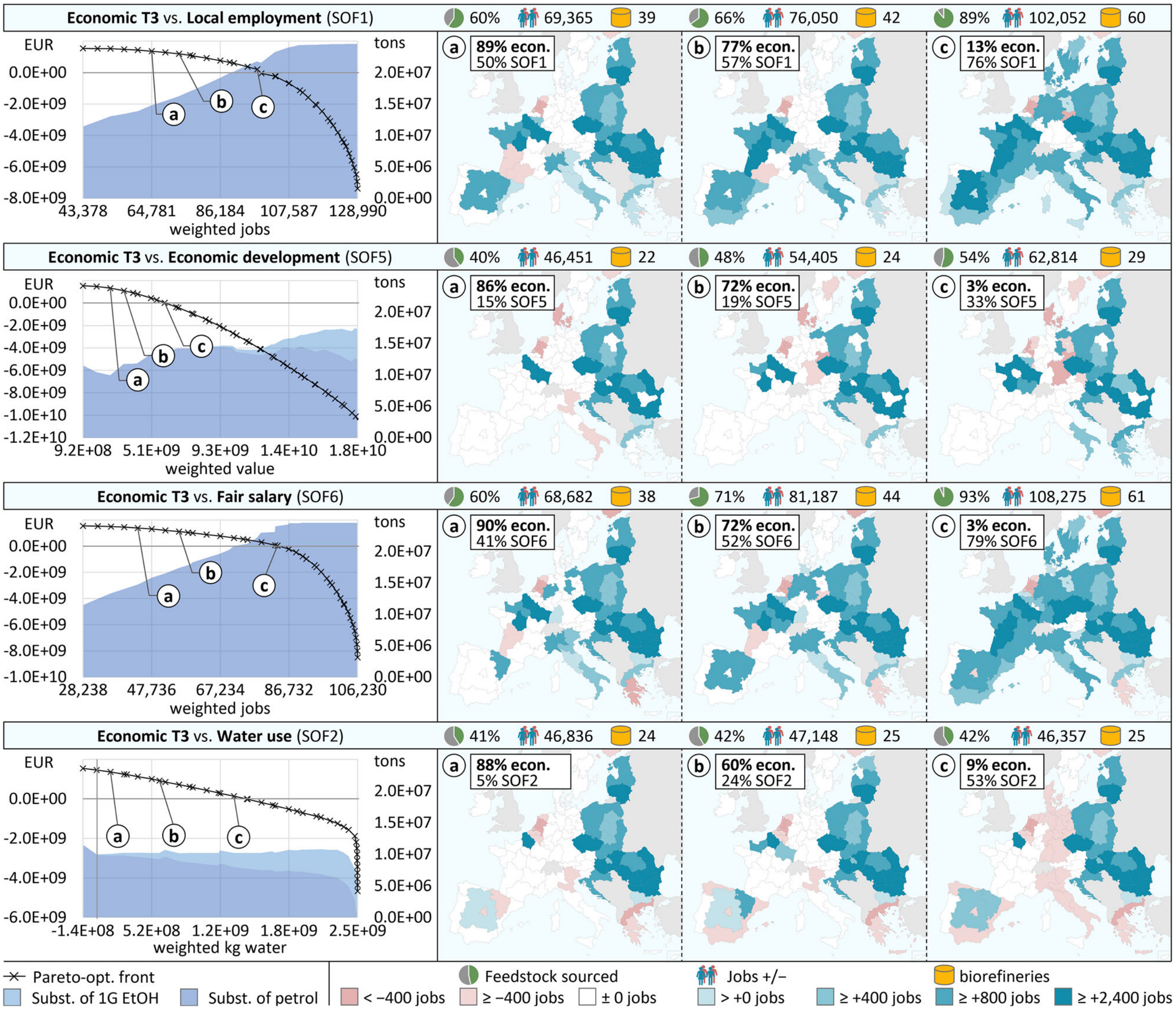

FIGURE 4 Selected Pareto-optimal frontiers between different social objective functions and the economic objective in tax scenario T3. The graphs include the substituted reference products on the secondary axes as stacked area plots. For three Pareto-optimal points, the optimal network design is displayed as maps that visualize the net number of regionally created jobs as blue/red shades. (a) corresponds to the Pareto point closest to 90% of the optimal economic objective value, (b) represents a numerical "compromise point" (i.e., with the shortest Euclidean distance to the two optima), and (c) is the last point with an economic profit. The legend also includes respective percentages of total feedstock collected, the total number of biorefineries, and the net number of jobs created and lost. Figure S17 in Supporting Information S1 displays analogous Pareto curves for pairs of different objectives (economic, E2, SOF1) and the effect on the respective third category. Underlying data for Figure 4 are available in Supporting Information S2 (sheet 'Figure data')

the total *injuries & fatalities* risks. This is mainly attributed to Romania's feedstock sector inherently and the contributing chemicals sector (fertilizer provision). Likewise afflicted with high social risks are Romania's transportation and construction sectors and Hungary's feedstock sector. Networks based on the objectives *global warming* and *land use* are less critical due to networks that are more widely distributed over all countries. Here, Germany and France are also significant hotspots. This is primarily explained by their large share in the value chain (Figure 3) and secondarily (e.g., for SHF16) by above-average indicator values in the SHDB (e.g., in Germany due to violent xenophobic incidents combined with a comparably large proportion of immigrants; Benoît-Norris et al., 2018; HIIK, 2021; UNHCR, 2021). Comparing *land use* with *global warming*, the construction sector is more critical due to smaller biorefineries and resulting lower scale effects. The network of *local employment* optimization slightly emphasizes countries with higher unemployment rates like France or Spain, wherefore they appear among the high-risk countries. *Economic development* favors economically weaker regions. Since this objective in particular benefits from long-distance transportation of EtOH, this sector is also subject to significant risks, especially in terms of SHF4, SHF6, SHF20, SHF10, and SHF23.

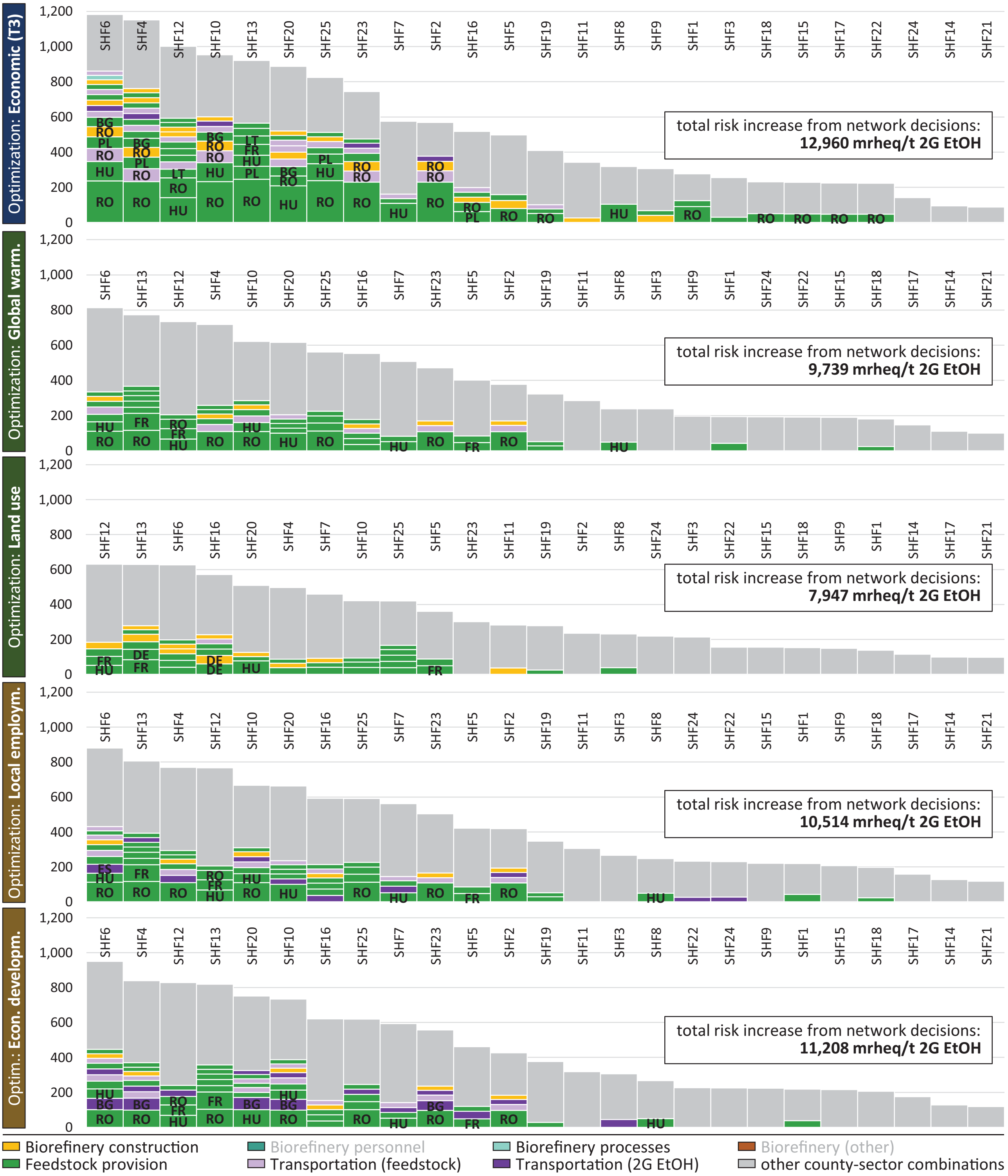

FIGURE 5 Relative contributions of country- and sector-specific social risks to the SHFs, in mrheq / ton 2G EtOH, co-calculated for different objective functions. Each diagram provides the country-sector hotspots with the highest contribution to the respective SHF, not accounting for reduced risks due to substitution. To ensure legibility, single country-sector combinations with risk ≥2% (approx. 23 mrheq/t) of the height of the largest column (SHF6 for economic optimization) and country tags with ≥4% are displayed. Figures S18-S20 in Supporting Information S1 evaluate the category-wise, regional, and process-wise aspects (including substitution) of the hotspot analysis separately and on a more aggregated level. Underlying data for Figure 5 are available in Supporting Information S2 (sheet 'Figure data')

Optimization of objective functions associated with: / Effect on objective functions associated with:	SDG2	SDG3	SDG6	SDG7	SDG8	SDG11	SDG12	SDG13	SDG14	SDG15
SDG2 Zero hunger	−− +++	−− +++	−− ++	−− ++	−− +++	−− +++	−− +++	−− +++	−− +++	−− +++
SDG3 Good health and well-being	−− ++	−− +++	− ++	−− +	−− ++	−− +++	−− +++	−− +++	−− +++	−− +++
SDG6 Clean water and sanitation	−− ++	+ +++	+++	−	−− ++	+ +++	−− +	−− −	+ ++	+ +++
SDG7 Affordable and clean energy	−−	−−	−−	+++	−− +++	−−	−− −	−−	−−	−−
SDG8 Decent work and economic growth	−− ++	−− +++	−− +	−− +++	−− +++	−− ++	−− ++	−− ++	−− ++	−− +++
SDG11 Sustainable cities and communities	− ++	−− +++	+ +++	− +	−− ++	+ +++	− ++	− ++	−− +++	−− +++
SDG12 Responsible consumption and production	−− +++	−− ++	−− +	−− +	−− ++	−− ++	−− +++	−− +++	−− ++	−− ++
SDG13 Climate action	+ +++	+ ++	+	+	o ++	+ ++	o +++	+++	o ++	+ ++
SDG14 Life below water	−− ++	−− +++	+ +++	−− +	−− ++	−− +++	−− ++	−− ++	−− +++	−− +++
SDG15 Life on land	−− ++	−− +++	−− ++	−− +	−− ++	−− +++	−− ++	−− ++	−− +++	−− +++

FIGURE 6 Interlinkages between social, environmental, and economic objective functions on the level of their associated SDGs, based on opportunity cost calculation (percental detriment in one category compared to its optimal value when optimizing another). SDGs with optimized objective functions are displayed on top, affected ones to the left. Categories are assumed to be fully congruent with a detriment of less than −5% (+++), congruent between −5% and −50% (++), slightly congruent between −50% and −95% (+), either neutral or unrelated between −95% and −105% (o), conflicting between −105% and −150% (−), and strongly conflicting with a detriment of more than −150% (−−). Two indications are given for each pair of SDGs, representing the range between the most conflicting and the most congruent relationship between two objective functions of the associated SDGs. The colored shades indicate whether conflicts (red) or congruencies (blue) prevail qualitatively

3.4 | Impact on SDGs

Together with the environmental and economic categories, the SOFs and SHFs cover a broad range of the SDGs. Supporting Information S1 (Table S18) and S2 (Details 3) show the matching of SOFs, SHFs, and environmental and economic objective functions to individual goals, targets, and indicators of the SDGs. By calculating pair-wise opportunity costs (i.e., the percental detriment in one category when optimizing the other; cf. Figure S21, Supporting Information S1), conflicts and congruencies between the different optimizable objective functions, and in turn, the interlinkages between the SDGs associated with these functions, are evaluated (Figure 6). Figure S23 displays the same interlinkages but for affected SDGs associated with the non-optimized SHFs. For insights into the relationships on the level of individual categories, see Figures S24 and S25.

As with conflicts and congruencies on the level of different objective functions, the achievement of SDGs may be hindered or promoted by pursuing different goals. For example, in terms of SDG13, networks optimal for all other goals range from slightly to strongly co-beneficial, yielding the more benefits, the more petrol is substituted. In the case of bioethanol, a large portion of conflicts between environmentally oriented SDGs stems from opposing substitution decisions, wherefore affected SDGs behave ambiguously toward the others. This is the case for SDG2, SDG3, SDG11, SDG14, SDG15, and, with the most pronounced tendencies, SDG**6**. Here, a production network optimal in terms of M1 (*global warming*, SDG13) entails no co-benefits and even jeopardizes the achievement of SDG6. In contrast, the optimization of objective functions of SDG3 always leads to at least small co-benefits for SDG6 (e.g., E1 and SOF3) and even comprises fully congruent objectives (e.g., M14 and M4).

Furthermore, there are conflicts between the three pillars of sustainability, such as with **SDG7** (linked with the economic objective). Here, an optimal network entails minor benefits and some detriments for the other SDGs but pursuing any other goals compromises SDG7 strongly. Divides may also run between different targets within one SDG, depending on the perspective and the sustainability dimension, or even within one target, depending on the context. For example, SDG8 can be divided into two groups: The (corporate and profit-focused) economic objective (target 8.2) together with health and safety issues (target 8.8.1), and (the societal and GDP-focused) SOF5 (target 8.1) together with employment (SOF1; target 8.5.2) and remuneration issues (SOF6; target 8.5.1). The first group is highly conflicting with the second group and all other SDGs, while the second group co-benefits from the others. Similarly, SDG12 with target 12.2 (natural resources) is divided into E3 (*resource availability*) and M17 (*fossil resource scarcity*), and M16 (*mineral resource scarcity*). The former generally benefit from any bioethanol network, particularly from the substitution of petrol, while the latter is impacted by the material requirements of the network itself, with only minor substitution benefits.

4 | DISCUSSION AND CONCLUSION

This study provides a best-practice approach for a structured and transparent inclusion of a comprehensive set of social aspects. This is done by selecting applicable quantitative and operationalizable social indicators from the *Guidelines for Social Life Cycle Assessment of Products and*

Organizations and the Social Hotspots Database. The approach is applied in a network optimization model for second-generation bioethanol in the EU. The complete set of categories encompasses economic, 21 environmental, and 34 social functions. The model thereby addresses 16 of the 17 SDGs and extends existing work, especially by operationalizing the social dimension. The results allow for identifying socially optimal decisions (SOFss) and evaluating possible social hotspots in global value chains (SHFs).

The different objective functions lead to four fundamentally different network structures, some of which are closely related to the substitution decision. First, economically optimal networks concentrate on lower-cost CEE countries to be competitive with petrol prices in more expensive countries (especially in scenarios T1–T3). The higher the subsidization (excise tax abatement or carbon taxation), the more competitive bioethanol becomes, leading to more extensive production networks. Second, several environmental objectives suggest an exclusive substitution of 1G bioethanol with widely dispersed but capacity-wise small production networks (e.g., *land use*). The third group is similar to the second group in terms of exclusive 1G EtOH substitution, but the networks are small to medium sized and concentrated on regions most favorable in terms of the respective regional social parameters. This is the case for SOF2, SOF4, and SOF7. The fourth principal network structure comprises environmentally optimal solutions that fully exploit the feedstock potential in large production networks. Depending on the environmental objective, 2G bioethanol should either substitute 1G bioethanol *and* petrol (e.g., *ecosystem quality*) or petrol exclusively (e.g., *global warming*). Those SOFs where the benefits (in, e.g., employment and regional development) stem from the network itself, as well as SOF3, fall into this group. Here, the effects of substitution are less decisive than the size of the network itself.

The feedstock sector of Romania constitutes the most significant social hotspot, to which *injuries and fatalities* and *freedom of association* contribute the most. Therefore, when a bioethanol producer decides to invest in these countries, due diligence and supplier auditions are necessary to ensure safe working conditions. In addition, construction and transportation sectors also entail notable risks that would, in practice, need to be assessed in detail. This work takes only an ex post and aggregated look at the co-calculated (not optimized) SHFs, since the risk scores from the SHDB are designed to shed light on potential social grievances without inducing divestment incentives from regions with high risks (Benoit-Norris & Norris, 2015). The approach provides a valuable basis for decision-makers in strategic supply chain design by pointing at hotspots. Subsequent analyses would be necessary in practice to elucidate the circumstances behind each indicator, country, and sector value.

The analysis of interlinkages between SDGs supports the notion that sustainability of strategic decisions is not universal but rather case-specific and varies between a plethora of interlinked social, environmental, and economic criteria. Given the diversity of the different goals, pursuing a specific goal will necessitate concessions in others. SDG8 and SDG12 are prime examples for why one action can benefit or harm not only different sustainability goals differently but also targets and indicators within the same goal. On a more thematic level, particularly the bioeconomy is at the center of tensions between different stakeholders. European policy-makers could use the lever of taxation (Wietschel et al., 2021) to improve the competitiveness of 1G and 2G bioethanol vis-à-vis fossil fuels to foster the achievement of inter alia SDG13 while simultaneously realizing significant benefits in terms of, inter alia, employment (SDG8.5) and regional development (SDG8.1). At the same time, this step could strengthen the energy self-sufficiency of the EU and significantly reduce dependencies on energy imports from countries with a questionable human rights record. This decision needs, however, to be taken consciously. The labor intensity of residue harvesting and transportation and the hereby accumulated risk for adverse social circumstances along the global upstream value chains could create new hotspots that must be monitored. The decision would also put further stress on land, water, mineral resources, and food security, especially in the case of 1G ethanol. The discontinuation of subsiding 1G bioethanol alleviates some of the latter tensions but prevents the full climate, employment, and regional development potential from being unlocked. Especially corporate decision-makers need to be aware of the likely hotspots in their specific value chains (Section 3.3), but also of the potential for environmental and social benefits that adjustments of strategic decisions yield, which could be unlocked with sacrifices in profits (Section 3.2).

It needs to be emphasized that this work does not present a full LCSA, lacking a comprehensive LCC. The study rather aims at advancing the application of SLCA in the field of strategic network design, at presenting results of social and LCA-based environmental optimization on the same level, and at discussing the economic feasibility of these results. Further research should complement this with a comprehensive LCC including different stakeholders (Schaubroeck et al., 2019) and also evaluate a possible aggregation of the results. In this study, we focused on the heterogeneous nature of the various social and environmental categories to inform about the consequences of decisions and possible undesired repercussions. While simple aggregated LCSA "scores" facilitate decision-making by reducing complexity, aggregation also bears the risk of obscuring critical information and requires more elaborate and well-communicated aggregation schemes (Zeug et al., 2021). It also bears mentioning that, while aspects of 16 of 17 SDGs are covered, this study cannot address the interrelationships between all SDGs, as the objective functions only relate to individual subordinate targets or to the goals only ideationally. Furthermore, the most readily applicable indicators are not necessarily those that society and academia should keep relying on in the medium term. While the GDP is a commonly applied indicator in similar studies and European cohesion policy (European Commission, 2017) with undoubted advantages, the measurement of the well-being of the various societal stakeholders should arguably go beyond this metric (Costanza, 2015; Hoekstra, 2019); instead, metrics such as QALY (quality-adjusted life years) have been proposed (Weidema, 2006) and the importance of impact pathways between different area of protection is emphasized (Schaubroeck & Rugani, 2017). In addition, the selected set of indicators is mainly limited by the focus of this study on strategic Greenfield decisions in the European second-generation bioeconomy. Other authors may select or exclude indicators for similar reasons as in the work at hand but compile a different or extended set of indicators when adjusting the application case or scope. Lastly, the results depend on the modeling choices made, such as the selected system boundaries or the modeling approach in the environmental LCA (Brandão et al., 2022). Future research on bioenergy production networks could either apply a strict consequential modeling, to address the consequential nature of the actual change in environmental burdens resulting from the network design decisions (Schaubroeck et al., 2021), or conduct an attributional LCA to focus on the environmental impacts allocated to a specific product system (Sonnemann & Vigon, 2011).

This work illustrates that decision-makers, be it on a corporate level and following one or more business objective functions, or on a political level and using the SDGs as a framework, need to be aware of reciprocities between the various criteria. Subjective experience, socio-cultural conditions, personal values, or attitudes of decision-makers play important roles particularly in environmentally and socially oriented decision-making. This work provides an approach that allows decision-makers to also consider a large number of different quantitatively assessed sustainability aspects and trade-offs between them, thus supporting the rationalization of social and environmental criteria. With evidence-based decision-making under consideration of socio-cultural preconditions, second-generation bioethanol production has the potential to contribute to a socially, environmentally, and economically sustainable development.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Zenodo https://doi.org/10.5281/zenodo.5589667.

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NOTE

[1] The methodological sheets of 2013 proposed 189 generic and specific indicators for the 31 social issues (subcategories) in five stakeholder categories of the 2009 edition of the Guidelines for Social Life Cycle Assessment of Products (GSLCAP). The new 2020 GSLCAPO add nine social issues (subcategories) and a sixth stakeholder category (children). An according new version of the methodological sheets with complementing new indicators was released in 2021. It adopts 107 of the previously existing indicators and adds 103 new, mostly site-specific ones (new generic indicators are often only given in terms of possible data sources, which we count as one). This results in a combined set of 292 indicators (see Supporting Information S2, Details 1).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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