


# Integration of future water scarcity and electricity supply into prospective LCA

## Application to the assessment of water desalination for the steel industry

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### Abstract

The urgency of tackling global environmental issues calls for radical technological and behavioral changes. New prospective (or ex ante) methods are needed to assess the impacts of these changes. Prospective life cycle assessment (LCA) can contribute by detailed analysis of environmental consequences. A new stream of research has taken up the challenge to create prospective life cycle inventory (LCI) databases, building on projections of integrated assessment models to describe future changes in technology use and their underlying environmental performance. The present work extends on this by addressing the research question on how to project life cycle impact assessment methods for water scarcity consistent with prospective LCI modeling. Water scarcity characterization factors are projected from 2010–2050 using the AWARE method, based on SSP-RCP scenario results of the integrated assessment model IMAGE. This work is coupled with prospective LCI databases, where electricity datasets are adapted based on the energy component of IMAGE for the same scenario. Based on this, an LCA case study of water desalination for the steel industry in Spain is presented. The resulting regional characterization factors show that some regions (i.e., the Iberian Peninsula) could experience an increase in water scarcity in the future. Results of the case study show how this can lead to trade-offs between climate change and water scarcity impacts and how disregarding such trends could lead to biased assessments. The relevance and limitations are finally discussed, highlighting further research needs, such as the temporalization of the impacts.

### KEYWORDS

desalination, industrial ecology, integrated assessment model, new technology, prospective LCA, water scarcity

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## 1 | INTRODUCTION

Environmental issues such as climate change or air pollution require radical changes in technology choice and behavior. Life cycle assessment (LCA) can play a critical role in assessing the environmental performance of these changes (Hauschild et al., 2017). A specific application of this quantitative approach aims at anticipating the environmental impacts of new technologies, products, or processes when launched to the market and at estimating their potential environmental benefits compared to the business as usual. Such approaches are called “anticipatory,” “ex-ante,” or “prospective” LCA (Buyle et al., 2019; van der Giesen et al., 2020). The term “prospective” is adopted in this article. Prospective LCA answers questions such as: “What are the expected environmental impacts of an emerging product system?” (Guinée et al., 2018).

Recently, researchers have worked on recommendations and frameworks to perform such prospective LCA assessment of future production systems (Arvidsson et al., 2018; Cucurachi et al., 2018a; Cucurachi et al., 2018b; Gibon, 2017; Miller & Keoleian, 2015; Thonemann et al., 2020; Tsoy et al., 2020; van der Giesen et al., 2020). A large part of this research is dedicated to the modeling of future technologies, their direct effects (e.g., future performances of the technology, upscaling effects, future penetration, end-users’ behavioral changes), and the related uncertainties. These aspects are particularly relevant when the studied technology and its application are emerging (low maturity): In that case, these are critical unknown factors (Bergerson et al., 2020). In other words, in these cases, practitioners model in detail the so-called foreground life cycle inventory (LCI) of the system of interest to conduct their LCA, that is, the specific processes and flows related to the emerging technology. These assessments rely on existing background LCI databases to model upstream and downstream processes to the foreground system (e.g., production of electricity or end-of-life treatment needed for the emerging technology). The combination of foreground and background data allows creating the LCI results for the entire product system. Finally, practitioners use life cycle impact assessment (LCIA) methods using characterization factors (CFs) to convert the LCI results into environmental impacts.

The LCI and LCIA databases, available in LCA software tools, represent current or past economic exchanges and environmental states. Therefore, Van der Giesen et al. (2020) rightly raised the question for prospective LCA: “Can characterisation factors relevant for the incumbent and new technical systems change over time?” Clearly, when assessing the implementation of an emerging technology, LCIA models should be aligned to the temporal horizon of the foreground LCI to avoid inconsistencies and achieve a proper environmental assessment of a technology.

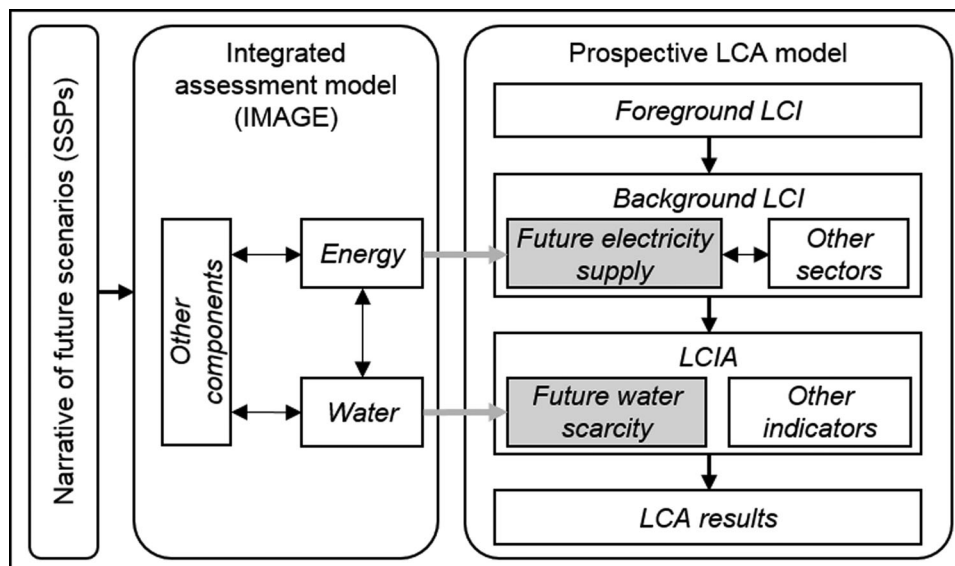
As further proposed by van der Giesen et al. (2020), the combination of integrated assessment models (IAMs) and the LCI is an exciting avenue to align the temporal representativeness of foreground and background LCI systems. Such a development is proposed by Mendoza Beltran et al. (2018), who modify the background LCI database ecoinvent (v3.3) (Wernet et al., 2016) to consider the future electricity mixes, based on shared socio-economic pathway (SSP) (Riahi et al., 2017; van Vuuren et al., 2017) and representative concentration pathway (RCP) scenarios (van Vuuren et al., 2011a) simulated using IMAGE (Stehfest et al., 2014). The latter includes the energy model TIMER that simulates the future market shares and performances of energy technologies based on cost optimization and emission mitigation constraints. The work on LCIA modeling for prospective assessment has been less investigated. Pfister et al. (2011) provide future projections of the water stress index (WSI) based on the WaterGAP 2 model results for climate scenarios developed by Parry et al. (2007).

However, the simultaneous integration of both prospective background LCI and LCIA methods has never been attempted. The objective of our work is thus to harmonize the temporal representativeness of the LCA background models with the projected time period of the foreground LCI of technologies under development. To this aim, the assumptions underlying the scenarios and the modeling steps must be consistent. For instance, the combination of WSI factors based on Intergovernmental Panel on Climate Change (IPCC) scenarios for the LCIA step as proposed by Pfister et al. (2011), with electricity datasets based on SSPs scenarios (Riahi et al., 2017) could introduce bias in the results, as the assumptions underlying the scenarios might be conflicting each other. The use of IAMs can improve the alignment, since both human activities (e.g., energy, food supply) and the natural environment (e.g., emissions, land use, water) are modeled based on the same narratives, for example, a consistent SSP-RCP combination.

In this paper, we build further on the work of Mendoza Beltran et al. (2018) to address the research gap of aligning the temporal scope of prospective LCI and LCIA modeling. We focus on water scarcity as an environmental impact and on electricity supply inventories as the most relevant components to update the prospective assessment.

This study aims specifically at (1) developing future water scarcity CFs based on IMAGE scenario water modeling and the AWARE method (Boulay et al., 2018); (2) integrating the developed CFs within a consistent prospective LCA framework including both future background LCI and future LCIA models; (3) testing the developed methodology for a case study; and (4) analyzing the added-value and limitations of the proposed approach compared to existing models.

Concerning the study’s first objective, water stress was chosen because of its sensitivity to climate change. This is a relevant indicator to update for prospective LCA, especially when assessing new technologies optimizing water use. Future water scarcity CFs are developed based on AWARE (Boulay et al., 2018), using water consumption and availability data from the SSP-RCP-based modeling of IMAGE. The AWARE CFs were already updated in literature to account for better geographical resolution (Ansorge & Beránková, 2017; Lee et al., 2019). The projection of AWARE CFs is a novel addition to the existing literature. In addressing the second objective, two SSP-RCP scenarios already used by Mendoza Beltran et al. (2018) are taken, whereas the prospective background LCI is updated to ecoinvent version 3.5 (Wernet et al., 2016). Like in Mendoza Beltran et al. (2018), the “cut-off” LCI system model is used, where waste impacts are attributed to the producer (“polluter pays” principle) and recyclable products



**FIGURE 1** Framework for the prospective LCA with background LCI and LCIA coupled with IAM. In this paper, two components are developed: future electricity supply (update of the work of Mendoza Beltran et al., 2018), and future water scarcity (projection of AWARE CFs)

are burden free (cut-off). Regarding the third objective, we have chosen a case study of a desalination plant replacing the intake of river water with seawater for hot rolling in a steel production plant in Spain. The case study was developed in the European project SPOTVIEW (Sustainable Processes and Optimized Technologies for Industrially Efficient Water Usage; grant agreement No 723577) and is used as an example for which a consistent prospective LCA is useful. The case study is of particular interest since it is in a region which could experience an increase in water stress in the future. Finally, in addressing the fourth objective, results are compared to the existing AWARE CFs applied to the original cut-off system model of ecoinvent version 3.5 (Wernet et al., 2016). The relevance, representativeness, and uncertainty of the different approaches for prospective LCA are further discussed to support LCA practitioners in their modeling choices.

## 2 | METHODS

### 2.1 | LCA-IAM coupling for prospective background modeling

The aim is to develop a prospective LCA background model (including both LCI and LCIA) to assess future systems, in particular emerging technologies. As shown in Figure 1, the approach consists of coupling LCA background data with IAM scenario data. IAMs model the long-term effects (time horizon usually until 2100) of human activities and the natural environment of prospective scenarios following various future socio-economic and climate change narratives. In this paper, scenario data from IMAGE are used to calculate prospective electricity supply inventories, using the ecoinvent version 3.5 cut-off database and prospective water scarcity CFs calculated based on AWARE. The IMAGE data are generated by the energy component (TIMER) and water component (LPJml) for the SSP2 RCP6.0 (or baseline) and SSP2 RCP2.6 (or mitigation) scenarios (van Vuuren et al., 2011b). The SSP2 scenario represents a "Middle of the Road" narrative, where "[...] trends do not shift markedly from historical patterns" (Fricko et al., 2017; O'Neill et al., 2017; Van Vuuren et al., 2017). Medium assumptions are made for drivers like population and economic growth and technology factors, lifestyle patterns, and preferences. RCPs represent emission and concentration trajectories of greenhouse gases affecting the radiative forcing (Van Vuuren et al., 2017), where RCP6.0 limits radiative forcing to 6 W/m<sup>2</sup>, while the more ambitious RCP2.6 limits radiative forcing to 2.6 W/m<sup>2</sup> until 2100. We use the data until 2050, consistent with the goal and scope of the study. As a result, the prospective LCA results are time consistent.

### 2.2 | Computational coupling methodology

For the scenario data of TIMER and LPJml, specific importer functions to the Brightway2 python package (Mutel, 2017) are developed. Mendoza Beltran et al. (2018) already present the integration of the future electricity supply chain (including technological changes such as efficiencies) to

create new versions of ecoinvent v3.3 database (cut-off model) using the baseline year of 2012 and results from several SSPs for the years 2020, 2030, 2040, and 2050. For the present work, the code is updated to be aligned with ecoinvent version 3.5.

The original AWARE method was imported into the Brightway2 package, using the officially published characterization factors.<sup>1</sup> After calculating the prospective AWARE water scarcity CFs (see Section 2.3 for more details), they are also imported into Brightway2, enabling the calculation of the prospective LCA of an emergent technology with the assumed prospective LCI and LCIA changes. Specifically, based on the scenario output files of IMAGE, a Brightway2 project is created with prospective inventory databases (where electricity mixes are adapted according to TIMER) and prospective AWARE methods (where CFs are updated according to LPJml).

The resulting loose coupling between IAM and LCA is semi-automatized; that is, updated TIMER and LPJml model data (e.g., forthcoming from future versions of the IMAGE model, additional scenario modeling, or time horizons) can be easily implemented. However, as mentioned above, the present work focuses on the SSP2 scenario (combined with two RCPs) for the time horizon of 2050 considered appropriate for the chosen case study and sufficient to understand the feasibility and limitations of the coupling between LCA and IAM.

Regarding geographical representativeness, background LCI and LCIA models represent global exchanges and effects, with different resolutions depending on the dataset or impact indicator. IMAGE water data are provided at 30-min resolution and aggregated at the country and regional level to match ecoinvent geographies. The electricity data from IMAGE covers the world in 26 regions (e.g., Western Europe), while the ecoinvent datasets for electricity are mainly determined at the country level. In Mendoza Beltran et al. (2018), the relative change of the regional electricity mix and technology parameters was used for all the countries encompassed in the IMAGE region. The same approach is followed in the present work.

## 2.3 | Future AWARE CFs calculation

### 2.3.1 | AWARE method

The working group "Water Use in Life Cycle Assessment (WULCA) of the UNEP-SETAC Life Cycle Initiative" developed a consensus method, called Available WATER REMaining (AWARE), to characterize water scarcity in LCA (Boulay et al., 2018). This regionalized method is based on the "availability minus demand" (AMD) factor. AMD can be calculated for the geographical unit  $i$  at a monthly scale:

$$AMD_i = \frac{Availability_i - HWC_i - EWR_i}{Area_i}$$

with:

*Availability*: actual water availability as runoff based on precipitation and evapotranspiration (in m<sup>3</sup>/month);

*HWC*: human water consumption, which includes irrigation, domestic, industrial, and other sectorial demand (in m<sup>3</sup>/month);

*EWR*: environmental water requirements (in m<sup>3</sup>/month), which corresponds to the monthly natural water flow (virtual flow without any human influence) weighted depending on its value compared to the annual average of the natural water flows (weighting factor of 0.6 if the monthly value is below 40% of the average, 0.3 if it is above 80% of the average, and 0.45 for intermediary values, as defined by Pastor et al., 2014);

*Area*: area of the geographical unit  $i$  (in m<sup>2</sup>).

The final CF is the ratio of the  $AMD_{worldavg}$  and the AMD of the geographical unit  $i$  (which can be interpreted as the surface-time equivalent required to generate one m<sup>3</sup> of unused water in this region). The method has set boundaries for the minimal and maximal CF values:

$$\left\{ \begin{array}{l} CF_i = 100 \text{ if } AMD_i < 0 \vee AMD_i < 0.01 \times AMD_{worldavg} \\ CF_i = 1 \text{ if } AMD_i > 10 \times AMD_{worldavg} \\ CF_i = \frac{AMD_{worldavg}}{AMD_i} \text{ otherwise} \end{array} \right.$$

The original AWARE method retrieved water parameters data from the WaterGAP2.2 model (Boulay et al., 2018). Water availability and natural water flows were computed for the interval 1950–2010, while monthly human water consumption was taken for 2010. The long-term period for water availability is a standardized procedure for climate-related data, which can present outliers for specific years.

### 2.3.2 | Computing basin-level CFs

IMAGE data for both SSP-RCP combinations contain the following variables: monthly discharge in hm<sup>3</sup>/day (corresponding to the *Availability* minus the *HWC*), monthly irrigation in mm/month and monthly water use in l/month (where the sum of irrigation and water use is equal to *HWC*), and

monthly natural water discharge in  $\text{hm}^3/\text{day}$  (used to calculate EWR). All these variables are available at grid level (30-min resolution) and from January 1969 to December 2100, except for the natural water flow for which 30-year monthly averages of naturalized historical flow data are available. As they are provided in different units (e.g., irrigation is provided in  $\text{mm}/\text{month}$ ), all variables are first converted to SI units, that is,  $\text{m}^3/\text{month}$ . This is done, for example, by multiplying irrigation in  $\text{m}/\text{month}$  by the surface area of the grid-cell in  $\text{m}^2$ . In addition, the DDM30<sup>2</sup> basin definition and flow accumulation data (both available in 30-min resolution) are used.

The calculation of monthly CFs is first performed at basin scale. To this end, the  $\text{AMD}_i$  for basin  $i$  is determined for a specific month by computing the 30-year monthly average of discharge (which corresponds to  $\text{Availability}_i$  minus the  $\text{HWC}_i$ ) and subtracting the  $\text{EWR}_i$ . All discharge values are recovered from the most downstream cell of the basin (determined based on the DDM30 basin data where the 34 largest basins are subdivided into smaller units). In addition, for each basin  $i$ , monthly  $\text{HWC}_i$  is recorded (by calculating the areal sums of water consumption over the DDM30 basin). Thirty-year monthly averages for discharge and  $\text{EWR}_i$  are computed for the 30-year periods up to an investigated month (i.e., January 1981 to January 2010, for January 2010), like done for the original AWARE approach and as defined by the World Meteorological Organization standards (WMO, 1971). Once the monthly  $\text{AMD}_i$  and  $\text{HWC}_i$  are computed for all DDM30 basins, the yearly  $\text{AMD}_i$  can be calculated by computing the consumption weighted mean of monthly  $\text{AMD}_i$ . The  $\text{AMD}_{\text{worldavg}}$  is defined as the consumption weighted mean of yearly  $\text{AMD}_i$  across all basins. Finally, monthly basin-level CFs are calculated following the method outlined in Section 2.3.1. The consumption weighted mean of monthly CFs allows calculating yearly basin-level CFs. Calculations are done from 2010 (referred to as “current” CFs as this is the reference year for the original AWARE approach) until 2050 (referred to as “future” CFs).

### 2.3.3 | Projecting country-level CFs

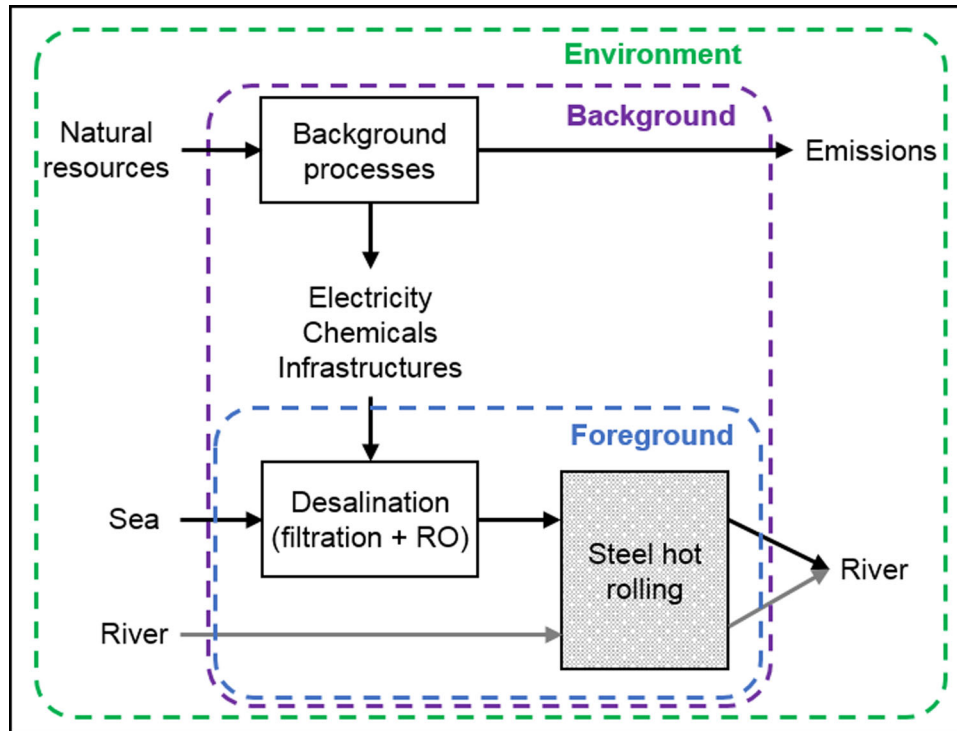
The consumption weighted means of yearly basin-level CFs are computed for each country to compute yearly country-level (and regional) CFs. This is done considering only the  $\text{HWC}_i$  occurring for each basin within the country (or regional) borders (building on the ecoinvent country and region definitions<sup>3</sup>), like for the original AWARE approach.

Since AWARE is currently considered the consensus method, the relative changes to 2010 (the reference year for AWARE) are computed for all yearly country-level (and regional) CFs. These relative changes are then applied to the original AWARE country-level (and regional) CFs until 2050. As for the prospective ecoinvent database for electricity datasets, it was thus decided to apply this relative change approach rather than considering the absolute results from applying IMAGE. Our approach is consistent because the same IAM model runs for the same SSP-RCP scenarios are used to apply relative changes on the LCA background, at the inventory (electricity datasets from ecoinvent 3.5) and impact assessment level (water scarcity from AWARE).

## 3 | CASE STUDY

The prospective LCA framework is applied to a desalination plant replacing river water with seawater for a hot rolling steel factory in Spain from the SPOTVIEW project. The increasing water stress in countries like Spain (driven by climate change and increasing consumption) is a challenge for the sustainability of steelmaking, as the sector uses large amounts of water for cooling (World Steel Association, 2011). The use of seawater is a possible solution for mills located in coastal areas. The case study boundaries were limited to the provision of water for steel since the objective here is not to get a full assessment of the environmental impacts of the steel production but an application case to understand the feasibility, added value, and limitations of the developed prospective methodology. Thus, the processes related to the steel transformation itself are excluded from the evaluation (see Figure 2). The system assesses the impact difference between the reference situation where river water is directly pumped and the SPOTVIEW strategy where the water volume intake is fully replaced by seawater. In this case, a desalination unit with multimedia filtration (sand, anthracite, and gravel) and reverse osmosis (RO), using two passes, is simulated.

The functional unit is the provision of water for the hot rolling of 1 metric ton of steel in Spain. The difference of impacts between the river and seawater use are analyzed based on historical data (2010–2014) and prospective data (2030). The attributional approach is applied to compare the two scenarios for each time period, since the objective is to understand how the desalination unit would operate with an evolving electricity mix and water scarcity, rather than to estimate the consequences of implementing the desalination unit. The required water volume is based on the European average due to confidentiality reasons for the specific plant data. World Steel Association (2011) provided an average of  $5 \text{ m}^3$  of water intake in Europe for the hot rolling of 1 ton of steel. The obtained quality of the desalinated water is expected to be better than the one of river water, possibly leading to a reduced amount of water required (e.g., for washing filters) and pumping energy savings (due to lower scaling). However, for the sake of simplicity, this effect is neglected here, as well as the potential changes due to water losses, as these would not help in assessing our proposed prospective approach. The volume of water released into the river remains thus equal to the intake.



**FIGURE 2** System boundaries of the case study. The processes for the hot rolling of steel are excluded; only the provision of water is included in the foreground. The evaluation is the difference between the reference (gray arrows) and the simulated strategy (black arrows)

As a first proxy, the ecoinvent dataset “tap water production, seawater reverse osmosis, conventional pretreatment, enhance module, two stages” was used to model desalination. It was adapted to improve geographical representativeness (electricity mix and water flows of Spain, other technosphere flows from Europe) and remove flows not considered in the simulated treatment (chlorine for disinfection, polyvinylchloride for the cartridge filters, and adapted waste amount). Modified versions of ecoinvent 3.5 (see Section 2) are created, and results from these modified versions are compared to results of the original version of the ecoinvent 3.5 database.

Only two environmental indicators are considered: water scarcity (with current and future AWARE CFs based on IMAGE modeling) and climate change in terms of global warming potential (CFs from Stocker et al. (2014), with a time horizon of 100 years).

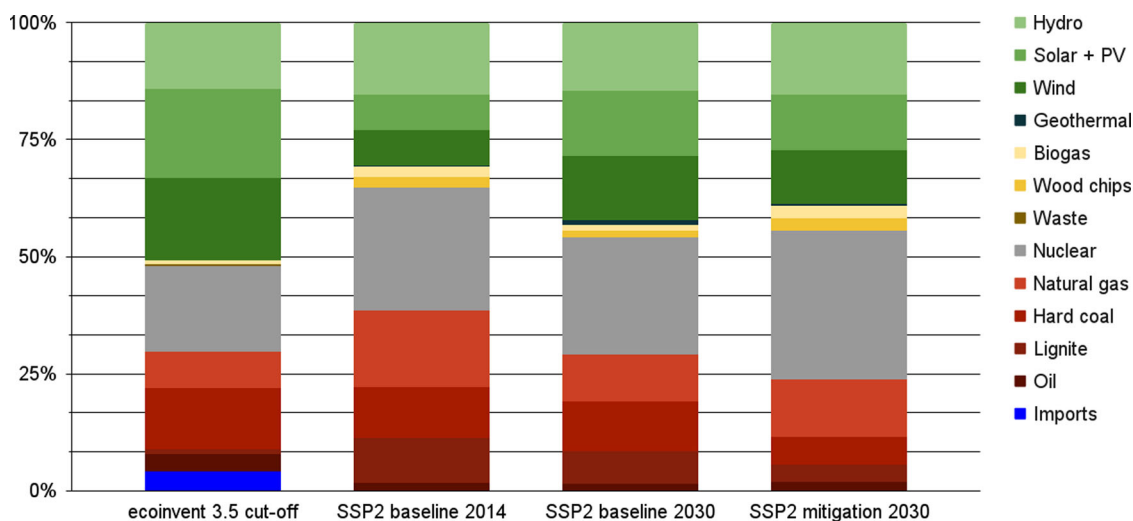
## 4 | RESULTS

### 4.1 | Electricity mix of LCI background database

Figure 3 shows the composition of electricity mixes in Spain for the original and different modified versions of the ecoinvent background database based on TIMER data. The year 2014 from IMAGE SSP2 scenario data is used as a reference to version 3.5 of the ecoinvent cut-off model, for which 2014 data were used to model electricity datasets. One can see that there are some differences between the original electricity mix of Spain in ecoinvent 3.5 and the projected mix according to the TIMER model. TIMER model does not model Spain-specific data, but rather makes projections for larger regions which were used to adapt the original mix for countries within that larger region. This limitation will be discussed in Section 5. Besides this, the projected electricity mixes show that for both SSP2 scenarios, there is an increase of renewable energy sources in 2030 (hydro, solar, wind, and geothermal) compared to 2014. In the case of the SSP2 RCP6.0 (or baseline) scenario, nuclear power is slowly being phased out, while for SSP2 RCP2.6 (or mitigation), nuclear power increases in 2030. The increase in nuclear power for the RCP2.6 scenario allows for a stronger reduction in fossil sources by 2030 compared to the baseline scenario.

### 4.2 | Analysis of current and future water scarcity CFs

Figure 4a shows current basin-level CFs calculated for 2010 based on the IMAGE data for the SSP2 RCP6.0 scenario. Values range from 0.1 to 100. Spatial patterns are comparable to the original AWARE publication (Boulay et al., 2018). A more detailed comparison of IMAGE AWARE and



**FIGURE 3** Composition of electricity mixes of Spain for different version of the ecoinvent 3.5 database. Ecoinvent 3.5 cut-off refers to the original values, while SSP2 2014 baseline, SSP2 2030 baseline, and SSP2 2030 mitigation refer to the mixes adapted according to the IMAGE results. Underlying data for this figure are available in Supporting Information S2

WaterGAP AWARE in 2010 is provided in Supporting Information S1, comparing hydrological variables and CFs at basin and country scale. Focusing on our specific case study, one can see that water scarcity in the southern part of Spain is high (with CFs above 60 for some basins). In general, high water scarcity is observed for basins in several regions of the world, for example, Northern Africa or the Arabian Peninsula.

Figure 4b shows how CF values change between 2010 and 2050 for the SSP2 RCP6.0 scenario. Values can potentially range from close to  $-100$  to  $99.9$ . Looking at the region of interest for our specific case study, CF values seem to slightly increase for some basins on the Iberian Peninsula. Furthermore, especially basins in the Middle East show increasing CFs. Overall, the results suggest that water scarcity will increase in the future under the SSP2 RCP6.0 narrative. A more detailed analysis is provided in Supporting Information S1, as well as a comparison between the SSP2 RCP6.0 and the SSP2 RCP2.6 scenario.

A prior analysis of future water scarcity conducted by Hanasaki et al. (2013a, 2013b) for various SSP scenarios also suggests increases in water scarcity. However, a direct comparison of results is difficult since the AWARE method is based on AMD, while water stress indicators, as applied by Hanasaki et al. (2013a), define water scarcity as a withdrawal to water resources ratio (WWR). Finally, Figure 4c shows the future CF values for 2050.

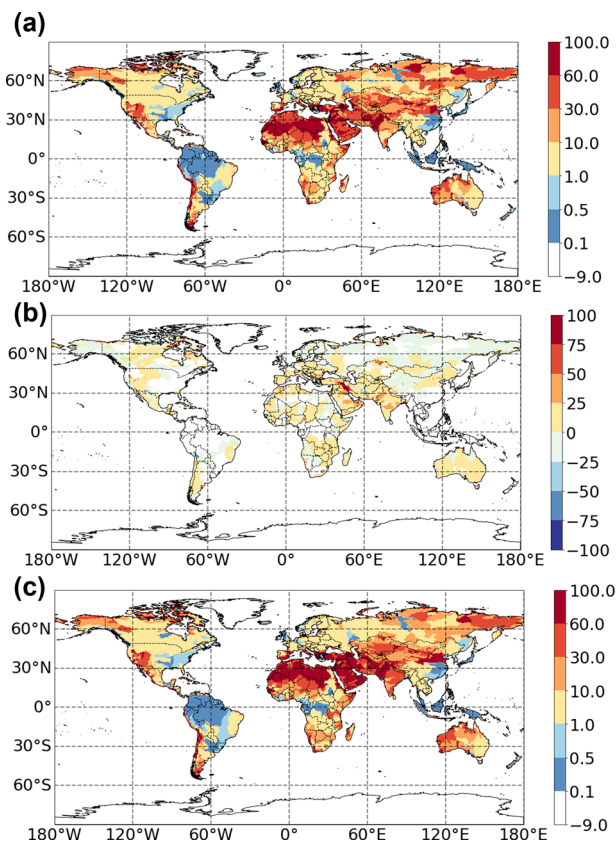
Figure 5 presents: (a) current country-level CFs for 2010 (which correspond to the original AWARE CFs), (b) the absolute changes of CFs between 2010 and 2050, and (c) the projected future CFs for 2050, for the SSP2 RCP6.0 scenario.

It needs to be noted that country-level CFs result from consumption weighted means of basin-level CFs. Even small basins can greatly influence country-level CFs if there is a relatively high HWC within the basin. In contrast to Figure 4, Figure 5 shows the relative changes applied to the original AWARE CFs rather than CFs calculated directly from IMAGE outputs. Overall, however, Figure 5 is highly consistent with what has been observed for the basin level CFs shown in Figure 4.

Since the case study is focused on Spain, Figure 6 presents the changes of CFs for the EU27 between 2010 and 2050. It must be noted that for Cyprus and Malta (due to their small size), IMAGE data did not allow for projections of future CFs; in these cases, the original CF values remain unchanged. All country-level CFs for 2010, 2030 (used for the case study evaluation), and 2050 are provided in Supporting Information S2 of this article.

### 4.3 | Case study results

In Figure 7, the difference of climate change and water scarcity impacts between river water and seawater use for the case study are presented, based on the different databases and time steps. A positive value means that the desalination plant induces higher impacts, and vice versa. First, we observe that the implementation of desalination treatment would create a trade-off between the two indicators; water scarcity decreases thanks to the lack of river water consumption and carbon footprint increase due to additional process installation and operation. The impact of the used chemicals, additional electricity consumption, and needed infrastructure for the desalination on water scarcity is negligible (about 1% to 2% of the benefit compared to the use of river water in Figure 7b). Thus, the changes in electricity supply datasets do not influence this indicator.

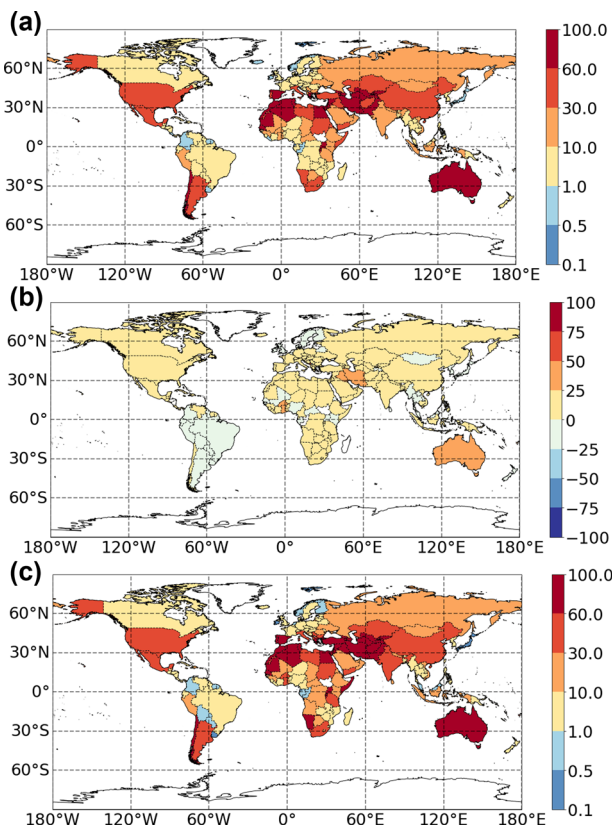


**FIGURE 4** Basin-level characterization factors (CFs) [ $\text{m}^3 \text{ world eq./m}^3$ ] for the SSP2 RCP6.0 scenario; (a) current basin level CFs for 2010; (b) changes in CF values between 2010 and 2050 (a cutoff is applied, where for basins with differences lower than 0.1 no value is shown); (c) future basin level CFs for 2050. We apply the same color scheme as in the AWARE publication (Boulay et al., 2018). Underlying data for this figure are available in Supporting Information S2

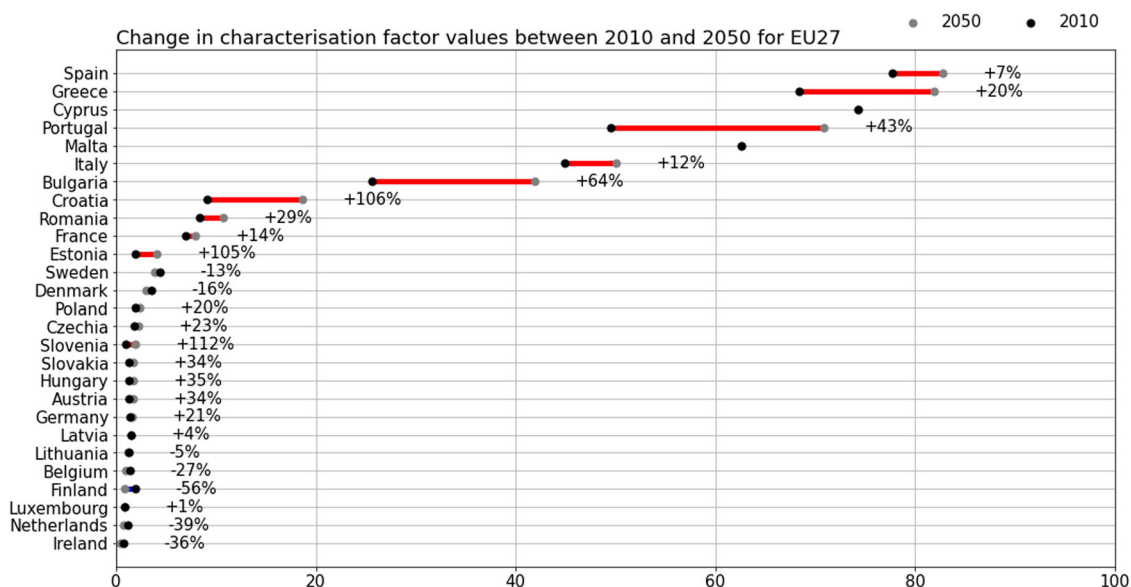
Due to the increased CF for Spain in 2030, the environmental benefits on water scarcity increases by 14% compared to 2014 for both scenarios, which shows the interest in choosing the desalination plant for the sustainable management of water resources in the future. The usage of future CFs derived using the methods presented in Section 2 thus allows to capture an increase in benefits for desalination in Spain, which would have remained unobserved using only the current CFs. Comparing the results for the SSP2 baseline and SSP2 mitigation scenarios shows very small differences, where the 2030 mitigation scenario shows a slightly higher mitigation potential compared to the 2030 baseline scenario. However, in addition, a small rebound effect can be observed for the mitigation scenario, as the impact for chemicals, electricity, and infrastructure also slightly increases due to the higher CFs and differences in electricity mixes of both scenarios. Overall, the SSP2 mitigation scenario performs slightly better than the SSP2 baseline scenario in 2030; however, the difference is very small. A more elaborate comparison between the CFs for both scenarios is provided in Supporting Information S1, which reveals that more significant differences between both scenarios only start to show after 2050.

For climate change, no benefits are considered in the assessment. This impact should be minimized to mitigate the environmental trade-off of seawater desalination. The indicator is dominated by electricity use (between 70% and 80% of total impact), as highlighted by other LCA studies on desalination (Zhou et al., 2014). The use of representative data for the electricity supply chain is thus of crucial importance. The impacts for 2030 for the SSP2 RCP6.0 are lower than those for 2014 (−14%) and for the SSP2 RCP2.6 achieves an even stronger reduction (−37%), but the differences with the original ecoinvent 3.5 database are smaller (−7% and −32% for the baseline and mitigation scenario, respectively). Indeed, there is an apparent decrease of fossil fuels between the electricity mixes from IMAGE between 2014 and 2030 (in particular lignite and natural gas), compensated by an increase of renewable energy or nuclear power, for the baseline or mitigation scenario, respectively. Compared to the original ecoinvent 3.5 electricity data, this trend is less obvious, which can be explained by the geographical representativeness of the different models. The electricity mix of Spain in ecoinvent 3.5 already has a significant share of renewable energy compared to other European countries. In particular, the shares for solar and wind energy are higher than the IMAGE data for 2014, aggregated for Western European countries. On the contrary, the share of coal (hard coal and lignite), which is the most carbon-intensive electricity source, is lower in the Spanish mix than in the European average. There is thus a slight mismatch between the spatial resolution of IMAGE and ecoinvent process data.

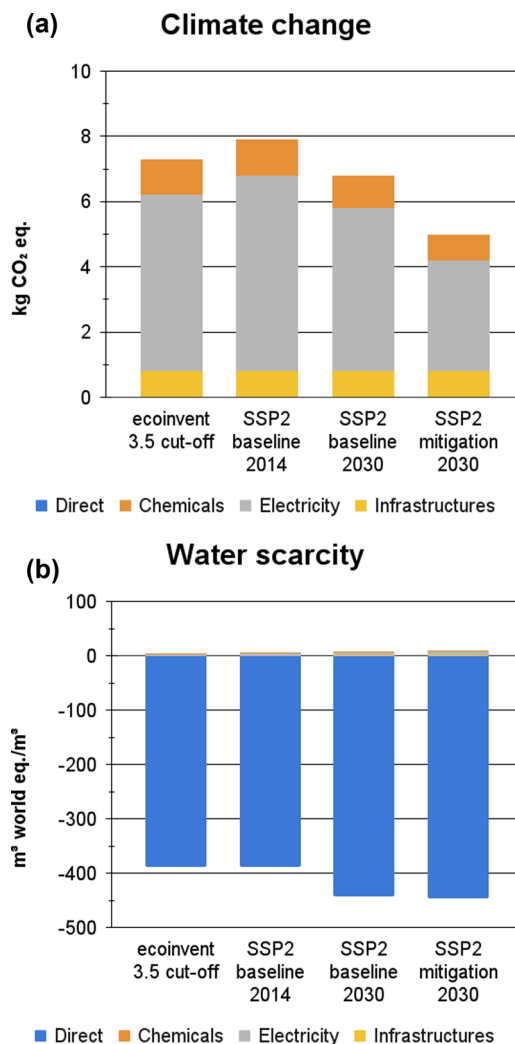




**FIGURE 5** Country-level characterization factors (CFs) [m<sup>3</sup> world eq./m<sup>3</sup>] for the SSP2 RCP6.0 scenario resulting from spatial aggregation of basin level CFs and projection of original AWARE CFs using the observed relative changes. (a) The current CF values for 2010; (b) the changes in CF values between 2010 and 2050 (a cutoff is applied, where for countries with differences lower than 0.1 no value is shown.); (c) the future CF values in 2050. Underlying data for this figure are available in Supporting Information S2



**FIGURE 6** Changes in CF values [m<sup>3</sup> world eq./m<sup>3</sup>] for the SSP2 RCP6.0 scenario between 2010 and 2050 for EU27. Underlying data for the figure are available in Supporting Information S2



**FIGURE 7** LCA case study results for steel factory, replacing 5 m<sup>3</sup> of river water intake with 5 m<sup>3</sup> of seawater (desalinated using reverse osmosis). The columns represent results obtained for the different LCI databases (the original ecoinvent 3.5 cut-off database and the databases modified using SSP2 baseline and SSP2 mitigation), and for current and future AWARE CFs. The two panels show results for (a) climate change impacts and (b) water scarcity impacts. In both cases, impacts are shown for the categories chemicals, electricity, and infrastructure. Underlying data for this figure are available in Supporting Information [S2](#)

## 5 | DISCUSSION AND CONCLUSION

In this section, we discuss the added value and limitations of the proposed prospective LCA background.

First, the development of future water scarcity CFs based on the AWARE method and using IMAGE data raised some constraints. Water outputs from IMAGE do not necessarily fit the exact definition of variables in the AWARE method. Additional computations were necessary to align variables and units. Also, the basin definition can influence the country and regional CFs, especially for smaller countries encompassed in large basins (according to the data), where a finer resolution would better represent the local water scarcity. However, such a finer resolution would also imply a higher computational burden.

In addition, the IMAGE (more specifically the LPJml) model differs from the WaterGAP model which is used to produce the original AWARE characterization factors. A more detailed basin-level comparison of all relevant variables necessary to produce the AWARE characterization factors from both models is provided in the Supporting Information [S1](#) to this article. The comparison reveals both random (i.e., for water availability and demand) and systematic (i.e., for basin surface areas) differences. The comparison of CFs for the reference year 2010 shows that although both models seem to identify similar regional water scarcity hotspots, significant differences can be observed both at the basin- and country-level. For the present work, we therefore chose to use the original AWARE CFs as a reference and apply to them the relative changes observed for the IMAGE-based AWARE CFs between 2010 and any given year. This approach can create some bias in the results, since the AWARE method provides CFs within a fixed range of values, between 0.01 and 100. Variations beyond these threshold values are therefore lost, for example, a basin with an

initial CF of 100 would keep this value, even if a relative increase of CF was obtained with the IMAGE-based prospective simulations. The coupling of the background LCI database and LCIA method with an IAM such as IMAGE showed several advantages. The simulated prospective scenarios rely on consensual narratives (e.g., from IPCC) that are defined for different sectors. The SSP-RCP pathways provide the scenario definition, for which IMAGE models the resulting technological development (i.e., electricity mixes) using TIMER, as well as the impact of the climate change level on the water availability using LPJml. Therefore, the IAM output can be a coherent source of data to evaluate future environmental impacts, despite the inherent uncertainties of such an exercise. The coupling of LCA and IAM data also has the advantage of potentially covering different economic sectors in a consistent manner and environmental indicators besides water scarcity and electricity supply as covered in this study.

Recently, other studies have coupled LCA with other prospective tools to make projections of environmental impacts. However, this exercise is often limited to the energy sector, for example, coupling LCA with energy modeling tools. Although energy is a crucial component of our economy, and directly related to climate change impacts, the extension to other sectors is necessary to increase the representativeness of prospective LCA.

The premise tool (Sacchi et al., 2021), currently under development, updates processes of the energy, transportation, cement, and steel sector. The tool can use results from the REMIND (Luderer et al., 2015) and the IMAGE model (Stehfest et al., 2014). Regarding LCI modeling, the present work follows the logic of the premise tool, while being focused on electricity mixes only. Another example of a tool which updates the LCI is the futura tool (Joyce & Björklund, 2021), which however does not build on an IAM to construct the future scenario data. Regarding LCIA modeling, the present work is complementary to premise, which provides updated versions of ecoinvent 3.7 for the same IMAGE scenarios.

Regarding prospective LCIA CFs, only Pfister et al. (2011) made such projections, thanks to the WaterGAP model, yet keeping the background LCI model unchanged. The background LCI and LCIA models updated with IAM data, as shown in this work, could be similarly expanded to other sectors and environmental indicators and various SSPs or other relevant scenarios. This expansion could provide a range of possible future environmental impacts and thus give an estimate of uncertainty for the prospective evaluation. Moreover, since several IAMs exist, another interesting research avenue is to perform multiple simulations for each SSP using multi-model ensembles to capture uncertainty induced by modeling choices, like what has been advocated and applied in the field of climate science (Jebeile & Crucifix, 2020).

The use of IAM has limitations nevertheless. As observed in Section 4, while the temporal resolution is relatively high (monthly or yearly data up to 2100), the geographical resolution is generally low, although it covers the entire world. In TIMER, energy supply and demand are modeled for 26 World regions, while in ecoinvent, electricity datasets are modeled at the country level. Such geographical mismatch induces a loss of geographical representativeness in the prospective datasets that can imply a significant limitation depending on the scope of the study. This limitation can be easily overcome by downscaling algorithms (Van Vuuren et al., 2007). In the case of water scarcity, IMAGE variables are at a high geographic resolution enabling the calculation of the variables at coarser resolutions, for instance, at country or basin levels, as used in the AWARE method, in which case the geographic resolution represents an advantage, despite the additional computational steps necessary to align variables and units.

Potential feedback of LCA results into the current version of IMAGE would require running the entire IAM (or at least sub-models) with new inputs, which is not feasible through the user support system. Such flow of information could be interesting to model changes induced by the studied process system on the rest of the economy.

To conclude, we focused here on a prospective research question, "What are the expected environmental impacts of an emerging product system?" Our approach revealed how it is important to consider future changes in the economy, technology, and environmental parameters as both the human and the natural systems will change. We create prospective LCI and LCIA using IAM scenario data for the long-term future. Future LCIs are developed for electricity supply and could be expanded to other economic sectors for complete and more coherent prospective assessments. To calculate future LCIA, water scarcity is chosen as a relevant impact particularly affected by climate change. The development of prospective CFs showed advantages such as the usefulness of the geographic and temporal resolution of the IAM data. However, it was hampered by the need to reproduce the AWARE approach requiring vast data manipulation.

We have computed water scarcity CFs following the approach of Boulay et al. (2018) yet using 30-year monthly averages for HWC data. Boulay et al. (2020) further specify that their original approach results in marginal CFs and propose non-marginal CFs that could be favored in the case of large water volumes consumed.

Finally, it should be noted that product systems, and thus their impacts, are actually spread over time (Beloin-Saint-Pierre et al., 2020). Much like most LCA studies, we made the simplification to ignore the distribution of impacts over time, that is, presuming that the product system occurs in a specific year. Distributing impacts over time can be addressed using a dynamic LCA approach to pinpoint when processes, emissions, and resources occur, coupled with time-dependent LCIA methods. This has been already well studied in the literature (Beloin-Saint-Pierre et al., 2020; Cardellini et al., 2018; Collinge et al., 2013; Levasseur et al., 2010) but only recently applied for the complete background system (Pigné et al., 2019). The implications for the present work should thus be further investigated.

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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 available from the corresponding author upon reasonable request.

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## NOTE

<sup>1</sup><http://wulca-waterlca.org/aware/download-aware-factors/>

<sup>2</sup><https://www.uni-frankfurt.de/45218101/DDM30>

<sup>3</sup><https://geography.ecoinvent.org/>

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