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LETTER

Desalination and sustainability: a triple bottom line study of Australia

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Abstract

For many arid countries, desalination is considered as the final possible option to ensure water availability. Although seawater desalination offers the utilisation of almost infinite water resources, the technology is associated with high costs, high energy consumption and thus high carbon emissions when using electricity from fossil sources. In our study, we compare different electricity mixes for seawater desalination in terms of some economic, social and environmental attributes. For this purpose, we developed a comprehensive multi-regional input-output model that we apply in a hybrid life-cycle assessment spanning a period of 29 yr. In our case study, we model desalination plants destined to close the water gap in the Murray-Darling basin, Australia's major agricultural area. We find that under a 100%-renewable electricity system, desalination consumes 20% less water, emits 90% less greenhouse gases, and generates 14% more employment. However, the positive impacts go hand in hand with 17% higher land use, and a 10% decrease in gross value added, excluding external effects.

Abbreviations

FTE	Full-time equivalents
GHG	Greenhouse gas
GVA	Gross value added
ha	Hectare
hLCA	Hybrid life-cycle assessment
IELab	Industrial Ecology Virtual Laboratory
IO	Input-output
IOT	Input-output table
kha	Kilo hectare
LCA	Life-cycle assessment
MDB	Murray-Darling basin
Mha	Million hectares
MRIO	Multi-regional input-output
RE	Renewable electricity
RO	Reverse osmosis
TBL	Triple bottom line

1. Introduction

Water scarcity affects an increasing proportion of the world's population (Greve *et al* 2018). In Australia, water shortages have intensified over the past two decades (Aijm *et al* 2013). In the 'granary of Australia', the MDB, little precipitation and water over-use has led to environmental issues like high salinity of rivers and fish death (Potter *et al* 2010, Wedderburn *et al* 2012). Over the past few years, Australia faced heat records and intense bushfires (Borchers Arriagada *et al* 2020). The latter put the country in a state of emergency for weeks in early 2020 (Komesaroff and Kerridge 2020).

If using natural resources, improving water management, and measures like wastewater reuse are not sufficient to meet water demand, desalination offers great potential, especially for regions with access to the sea (Crisp 2012, Bell *et al* 2018). However, the technology has some severe drawbacks. The production cost of desalinated water is about twice or three times higher than water from conventional sources (Ziolkowska 2015). Furthermore, effects on the marine ecosystem, high energy consumption and the associated GHG emissions are the primary ecological challenges (Sadhwani *et al* 2005, Stokes and Horvath 2006, Lattemann and Höpner 2008, Shehabi *et al* 2012, Shahabi *et al* 2014, Liu *et al* 2015, Zarzo and Prats 2018, Clark *et al* 2018, Gude and Fthenakis 2020). The use of RE could make a major contribution to environmental sustainability in particular (Jijakli *et al* 2012, Baten and Stummeyer 2013, Cherif *et al* 2016, Alhaj and Al-Ghamdi 2019). However, studies that assess total sustainability by measuring environmental, social and economic indicators are missing (Haddad 2013, Gude 2016).

The motivation of this study is to quantify the three dimensions of sustainability of desalination depending on the used electricity source. Therefore, we apply an LCA approach (Malik *et al* 2016, Hadjikakou *et al* 2019) to measure supply chain effects. We applied an IO-based hLCA for this study (Joshi 1999). The IO analysis goes back to the research work of Wassily Leontief, who received the Nobel Prize for this in 1973 (Leontief 1966). We applied the Australian IELab to compile tailor-made input-output MRIO tables (Lenzen *et al* 2014).

In this study, we simulated fictive desalination plants at 29 sites around the MDB in southeast Australia. The desalination plants were designed to provide the missing water supply in the MDB of 5500 GL in total. The plants were not designed for continuous operation, but take into account an oversize factor of 1.5, allowing load-shifting of the electricity demand. Like all large plants in Australia, the plants are designed as RO systems. For the power supply, we considered five scenarios, with 0, 25, 50, 75 and 100% RE. In the 0% RE scenario, the electricity sector corresponds to the generation mix of the corresponding year in Australia, as shown in the IO data. The electricity mix, as well as the locations of the generators in the 100% RE scenario, were the results of a GIS-based dispatch optimisation model of a previous study (Heihsel *et al* 2019a). The transitional scenarios apply pro-rata combinations of both electricity mixes. The capacities of the technologies wind, biomass, hydro and PV are shown in the table in supplementary material S1, which can be found online (available online at https://stacks.iop.org/ERL/15/114044/mmedia).

To the best of our knowledge, this study is the first comprehensive MRIO TBL study comparing desalination plants in RE and fossil-fuelled electricity scenarios. Thus, we contribute to the research gap in the area of holistic studies on socio-economic and environmental impacts of desalination. The study is structured as follows: In the next chapter, we describe the methodology and the data used. After that, we present our results and end with a conclusion. Further technical details on the methods used can be found in the supplementary material.

2. Methods and data

Two methods are applicable for carrying out LCAs: the bottom-up approach (a process-based LCA) and the top-down approach (based on IOTs) (Finnveden *et al* 2009). The bottom-up approach employs physical process data, allowing very accurate modelling of immediate upstream stages of the value chain. Since the processes are explicitly modelled, the value chain is only reflected to a limited extent due to data availability, and subordinate levels are not considered. Therefore, a truncation error occurs. The top-down approach, on the other hand, uses statistical data on economic sectors, which allows infinite value chains to be modelled. A truncation error, therefore, does not occur, but an aggregation error arises from the aggregation of different processes in industrial sectors. The combination of top-down and bottom-up data in a hybrid approach minimises both errors, which is the advantage of this method (Pomponi and Lenzen 2018).

Hybrid LCAs are used for carbon footprint studies of products, companies or sectors by extending IO tables with physical environmental satellites (Liu *et al* 2012, Norwood and Kammen 2012, Rodríguez-Alloza *et al* 2019, Heihsel *et al* 2019b). Numerous sustainability studies expand the focus on further economic and social indicators, the so-called TBL (Elkington 1998, Foran *et al* 2005, Onat *et al* 2014, Malik *et al* 2016, Hadjikakou *et al* 2019). The present framework builds on previous research from Heihsel *et al* (2019b).

We extended an existing IO model as follows: In addition to the GHG satellite, we implemented additional indicators, namely water use, land use, employment, and GVA. Furthermore, we extended the regional resolution up to 46 regions. The highly detailed regional resolution enables to aggregate the results according to different regional classifications (Australian states and territories, water catchment and rainfall areas). We increased the time series to the years 1990–2018. Since the existing IO data do not contain RE sectors, we augmented the tables with additional process data. By using hybridised process-data from Yu and Wiedmann (2018), we modelled RE sectors for wind, solar, hydro and biomass technologies. Hereby, we analysed the TBL impacts of the construction and operation period of desalination plants. In this study, we followed the IO-based hLCA approach by Malik *et al* (2014) and Suh and Huppes (2005). A projection of the IO data and the process data into the future would be possible in principle but would be subject to considerable uncertainty when analysing investments spanning decades.

2.1. Input-output and renewable electricity data

To complement the IO data with RE specific data, we used process data from AusLCI. (2020) and Ecoinvent (2014), which Yu and Wiedmann (2018) have hybridised. Yu uses an integrated hLCA framework that includes monetary and physical data. Yu's hLCA framework contains 4463 processes (physical data) and 1284 monetary IO sectors, both in matrix form. For our study, we extracted data from the process-coefficient matrix (the primary life-cycle inventories (LCI) of the processes). Moreover, we utilised the cut-off matrix, which supplements the pure process-based data with IO data. Both matrices describe the production recipe of the technology. While the process-coefficient matrix shows upstream physical pre-processes as inputs to produce a functional unit of the process, the cut-off matrix primarily contains upstream services. Each process is represented by an individual column in the matrices. S2 in the supplementary material shows the structure of the integrated hLCA framework by Yu. The processes extracted for this study are shown in S3. In our hLCA framework, we augmented four RE technologies, namely wind, biomass, hydro and photovoltaic.

Furthermore, adding new sectors to the IO-framework requires physical data for the satellite accounts. Therefore, we collected data for the environmental indicators GHG, water use and land use as well as for the social indicator employment. The electricity generation processes in Yu's LCI have a functional unit of 1 MJ. Hence, we normalised the satellite intensities accordingly. Table 1 summarises the direct intensities of the considered RE technologies. The RE vectors represent the intermediate consumption of the electricity generated and thus take into account both operation and maintenance as well as construction, the latter weighted according to expected lifetime. The construction of RE plants is thus reflected in the indirect effects on an annual basis. The direct intensities of RE thus only refer to direct electricity generation. In the supplementary material S1, we show the LCI data preparation process before augmenting the IO-tables.

2.2. Input-output data

We used the Australian IELab to compile tailor-made IO-tables for our study (Lenzen *et al* 2014). The IELab offers a unique disaggregation level of 1284 IOPC sectors and 2214 SA2 regions. For our study, we created a framework of 64 IO-sectors, including the four augmented RE sectors. Our framework consists of 46 Australian regions. The framework contains both industries and commodities, which means that the intermediate demand framework has a size of $2 \times 64 \times 46 = 5888$ rows and columns. The IELab uses statistical data from ABS (2015f), ABS (2015c), ABS (2015b), ABS (2015d), ABS (2015e) for the IO data and AGEIS (2015), ABS (2015g), ABS (2015a), ABS (2015h) for the social and environmental data, respectively. We created time series IOTs for the years 1990–2018.

2.3. Sector augmentation and re-balancing

Australian IOTs do not include separate RE sectors. Therefore, we post-augmented the IOTs with process data. Columns in IOTs show the input of the production of a particular industry; in other words, it is the recipe of the manufactured commodities. The rows describe the intermediate sales structure of commodities to other industries. While we supplemented columns with the LCI data, we adopted the rows (*i.e.* sales structure) from the structure of the existing electricity sectors. The location of the generators resulted from Heihsel *et al* (2019a).

We compiled separate IOTs for each of the five scenarios with 0, 25, 50, 75 and 100% RE generation. The RE sectors were scaled accordingly. The conventional electricity sectors were scaled according to the complementary value. A schematic diagram of the augmented IOT-framework can be found in the supplementary material S4.

Due to the augmentation of the IOTs, they were no longer balanced, which means that input and output were no longer equal. We used a RAS-type biproportional numerical algorithm to post-balance the IOTs (Lahr and de Mesnard 2004, Malik *et al* 2014).

2.4. Desalination process-data

Heihsel *et al* (2019b) analysed Australia's largest 20 desalination plants, which correspond to 95% of the Australian seawater desalination capacity. For their study, they used process-data from the desaldata database (Global Water Intelligence 2016). We used these data as a weighted-average proxy for the 29 desalination plants. We applied results from Heihsel *et al* (2019a) to specify the capacity and the locations of the plants. We assumed the construction period between 1990 and 1992. We allocated 25% of the capital expenditures (capex) each to the first and the last year. Thus 50% of the capital costs were taken into account for the second year. The operation and maintenance period runs continuously from 1993. Since the desalination plants were used for load shifting scenario in this study, we considered an oversize factor of 1.5.

2.5. Calculation of the triple bottom line impacts

The TBL framework describes an accounting concept in which all three fields of sustainability are examined. The term was first introduced by Elkington (1998). In our analysis, we assessed water use, land use and GHG emissions as environmental indicators. The social indicator is employment and the economic indicator GVA. To measure the supply chain impacts of the choice of electricity source on the sustainability of seawater desalination, we used the standard IO methodology, which goes back to Leontief (1966). In the following section, we present the basic principles of the methodology.

Let Q be the matrix of the physical satellite accounts containing the social and environmental indicators. The same calculations were applied accordingly to GVA as an economic indicator. Each row within the matrix represents another indicator. For each indicator row i, we got the vector of the intensities by dividing by outputs with

$$\mathbf{q}_i = \mathbf{Q_i}\hat{\mathbf{x}}^{-1}, \tag{1}$$

where $\hat{\mathbf{x}}$ represents the diagonal matrix of the output.

Table 1. Direct intensities of renewable electricity generation.

		Wind	Biomass	Hydro	Photovoltaic
Water use	($L\,MJ^{-1}$)	0.00	1.41	7.22	1.05E-03
Land use	($sqm\,MJ^{-1}$)	3.28E221204	1.75E-05	2.16E-03	1.08E-04
Greenhouse gases	($g\,CO_{2,e}\,MJ^{-1}$)	0.00	2.10	1.60	0.00
Employment	($FTE\,MJ^{-1}$)	4.53E-08	3.15E-07	2.92E-08	3.85E-07

The standard Leontief equation estimates the output $\mathbf{x}$ of the sectors depending on the final demand $\mathbf{y}$ by

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y}, \tag{2}$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{A}$ represents the technical coefficient matrix. The matrix of technical coefficients representing the production recipe of the sectors is defined by $\mathbf{A} = \mathbf{T}\hat{\mathbf{x}}^{-1}$ The Leontief inverse $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ contains the supply chain multipliers. We obtained the supply chain impacts $\mathbf{Q}^{\mathrm{d}}{}_{i}$ $(k \times l)$ from (1) and (2) by

$$\mathbf{Q}_i^{\mathrm{d}} = \hat{\mathbf{q}}_i(\mathbf{I} - \mathbf{A})^{-1}\hat{\mathbf{y}}. \tag{3}$$

Each value in row k and column l in $\mathbf{Q}^{\mathrm{d}}{}_{i}$ shows the contribution of industry k or the product l to the total magnitude of indicator i.

The GVA impacts were determined accordingly to (3), using the GVA intensities $\mathbf{v}$ instead of $\mathbf{q}$. The results can be aggregated into two different representations. The formula $1^{\mathrm{Q}'}\mathbf{Q}_i^{\mathrm{d}}$ shows the impacts caused by the production of commodities. Summing the rows by $\mathbf{Q}_i^{\mathrm{d}}1^{\mathrm{Q}}$ aggregates the impacts by emitting industries. The operator 'transposes the summation vector $\mathbf{1}^{\mathrm{Q}}$ $\mathbf{Q}^{\mathrm{d}}{}_{i}$. Electricity is distributed to the conventional electricity sector and to the RE sectors by the electricity penetration ratio $\lambda = 0, 25, 50, 75\,\text{or}\,100\%$. We allocated the total electricity demand e with $e_c = (1 - \lambda)\,\mathrm{e}$ to the conventional electricity sector and with $e_t = \lambda \mathrm{e}\frac{g_t}{\sum_{t=1}^{4} g_t}$ to the RE sector in the demand vector $\mathbf{y}$. Here, g is the generation of the RE technology t.

2.6. Uncertainties

Prior LCAs similar to ours (e.g. Malik *et al* 2018) have shown that measurement uncertainty contained in information on the satellite account $\mathbf{Q}$ and the supply-use data $\mathbf{T}$ represent the main origins for uncertainties in aggregate results, such as the TBL scores calculated in this work (Malik *et al* 2019). Because of nonlinearities in Leontief's equation (2), the latter are usually determined using Monte-Carlo simulation (Bullard and Sebald 1977, 1988, Lenzen *et al* 2010). Because of particular features in the propagation of errors in the Leontief system (Heijungs and Lenzen 2014), high errors of individual matrix elements cancel each other out because of their stochastic nature (Quandt 1958, Lenzen 2000), and the uncertainties of aggregate results are usually much smaller than matrix errors. Whilst the latter occupy a wide range between typically a few and a few hundred percent (Bullard and Sebald 1977, 1988, Lenzen *et al* 2010), the former hover between about 5% and 20% (see e.g. Lenzen *et al* 2018 and Lenzen *et al* 2020). Given the high similarity of data sources and mathematical procedures, these uncertainty magnitudes also apply to this study.

3. Results and discussion

3.1. Holistic triple bottom line impacts

In our study, we investigated the TBL impacts of seawater desalination depending on the electrical energy supply on the environmental indicators water use, land use and GHG. We used GVA as an economic indicator and employment as a social indicator.

Table 2 shows the overall results of the TBL footprints from 1990–2018, for the scenarios with only conventional electricity and 100% RE. The first three years represent the construction period of all plants, the years from 1993 onwards represent the operating and maintenance period over 26 yr, which is in the average range of the concession periods of large Australian plants (Global Water Intelligence 2016). The spider plots in figures 1 and 2 show the relative performance of the different scenarios in relation to the 0% RE scenario. The values of the charts are calculated by summing the indicator values of each scenario and relating them to the sum of the indicator values of the 0% RE scenario. The values of the 0% RE scenario are thus always 1, *i.e.* they set the benchmark. In order to show better performance consistently greater than 1, the reciprocal value is formed for indicators for which less is better (for example, GHG, land use, water use). Hence, the normalised index $n_{k,s}$ for key figure k and scenario s (where scenario 0 is the base scenario with 0% RE) in the spider plots result from $n_{k,s} = \frac{\sum_{y=1}^{29} i_{k,s,y}}{\sum_{y=1}^{29} i_{k,0,y}}$ for the key figure employment and GVA (where more is better) and from $n_{k,s} = \frac{\sum_{y=1}^{29} i_{k,0,y}}{\sum_{y=1}^{29} i_{k,s,y}}$ for water use, land use and GHG emissions (where less is better) with y as year of investigation and i as the indicator values. Hence, the spider plots indicate better performances compared to the base scenario outside and weaker performances inside the blue base scenario circle.

We see that RE have a positive impact on water consumption during the entire life cycle. In both scenarios, the construction phase accounts for around

Table 2. Overall results of the TBL footprints of desalination with 0% RE and 100% RE.

		Water use		Land use		Greenhouse gas emission		Employment		Gross value added	
	RE-ratio	0%	100%	0%	100%	0%	100%	0%	100%	0%	100%
	Year	(GL)	(GL)	(kha)	(kha)	(Mt $CO_{2,e}$)	(Mt $CO_{2,e}$)	(10^3 FTE)	(10^3 FTE)	(AU$ bn)	(AU$ bn)
Construction	1990	443	414	5747	5643	50	15	273	272	13	13
	1991	912	852	11 668	11 470	105	31	533	531	26	26
	1992	439	411	5613	5511	51	15	255	253	13	13
	Total	1794	1677	23 029	22 623	206	60	1061	1056	52	52
	Contribution	43%	51%	77%	65%	23%	70%	72%	63%	42%	47%
Operation and maintenance	1993	114	73	582	842	32	1	24	29	2.1	1.7
	1994	109	70	534	785	31	1.4	23	29	2.1	1.6
	1995	105	69	493	752	30	1.3	22	29	2.0	1.6
	1996	103	68	461	723	30	1.3	20	28	2.1	1.7
	1997	101	66	434	663	30	1.2	20	28	2.1	1.7
	1998	97	65	370	625	29	1.2	18	26	2.0	1.7
	1999	88	64	327	592	27	1.1	16	25	1.9	1.6
	2000	89	63	299	552	27	1.1	16	25	2.0	1.6
	2001	85	63	273	563	26	1.1	15	25	1.9	1.7
	2002	94	66	276	620	29	1.1	15	25	2.0	1.7
	2003	87	62	272	576	27	1.0	12	22	2.1	1.8
	2004	85	56	156	378	29	1.0	12	22	2.1	1.8
	2005	64	57	174	377	19	1.1	14	24	2.2	2.1
	2006	63	58	171	339	20	1.1	14	23	2.3	2.2
	2007	59	43	190	237	18	0.9	13	20	2.4	2.2
	2008	60	42	187	234	19	0.9	12	20	2.6	2.4
	2009	62	44	191	237	20	0.9	13	20	2.8	2.6
	2010	56	41	199	246	20	0.8	15	21	3.0	2.6
	2011	67	54	94	241	24	0.9	11	18	3.2	2.7
	2012	103	61	94	273	27	0.8	12	20	3.3	2.8
	2013	115	70	129	269	31	0.7	15	22	4.0	3.0
	2014	113	66	136	280	29	0.7	16	22	4.1	3.1
	2015	96	65	133	287	28	0.7	13	22	4.0	3.1
	2016	90	70	190	473	25	0.7	14	21	3.6	2.9
	2017	108	73	219	499	31	0.7	16	23	3.8	3.0
	2018	121	71	239	494	35	0.8	18	23	4.2	3.2
	Total	2335	1604	6821	12 156	692	26	409	613	70	58
	Contribution	57%	49%	23%	35%	77%	30%	28%	37%	58%	53%

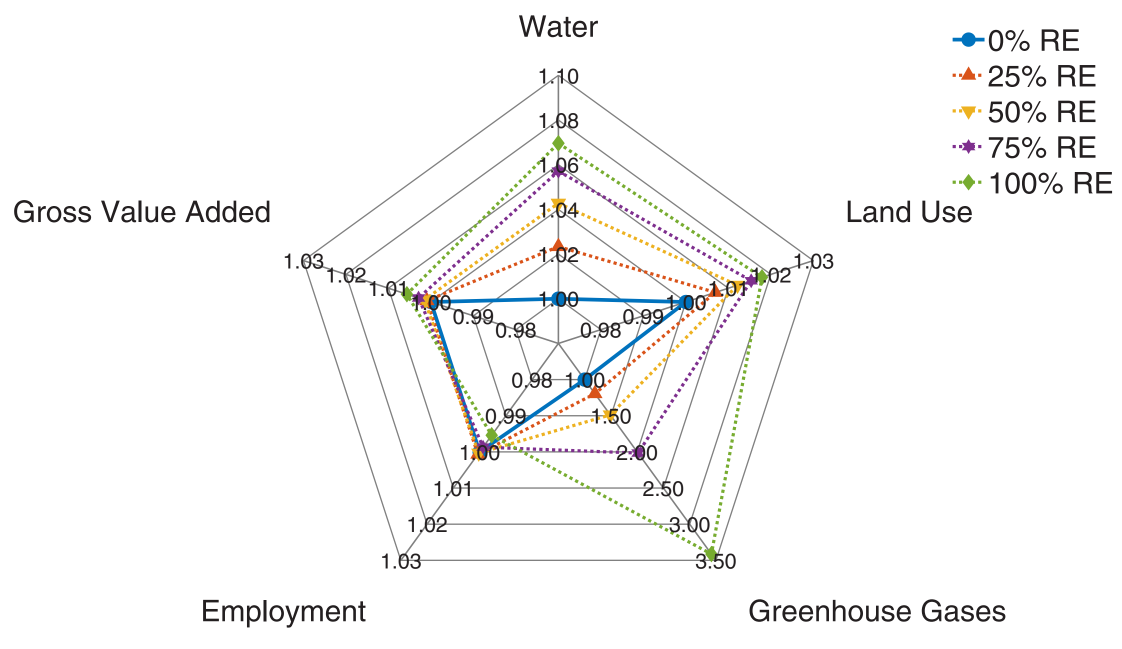

Figure 1. Construction period TBL performances of desalination utilising different electricity mixes.

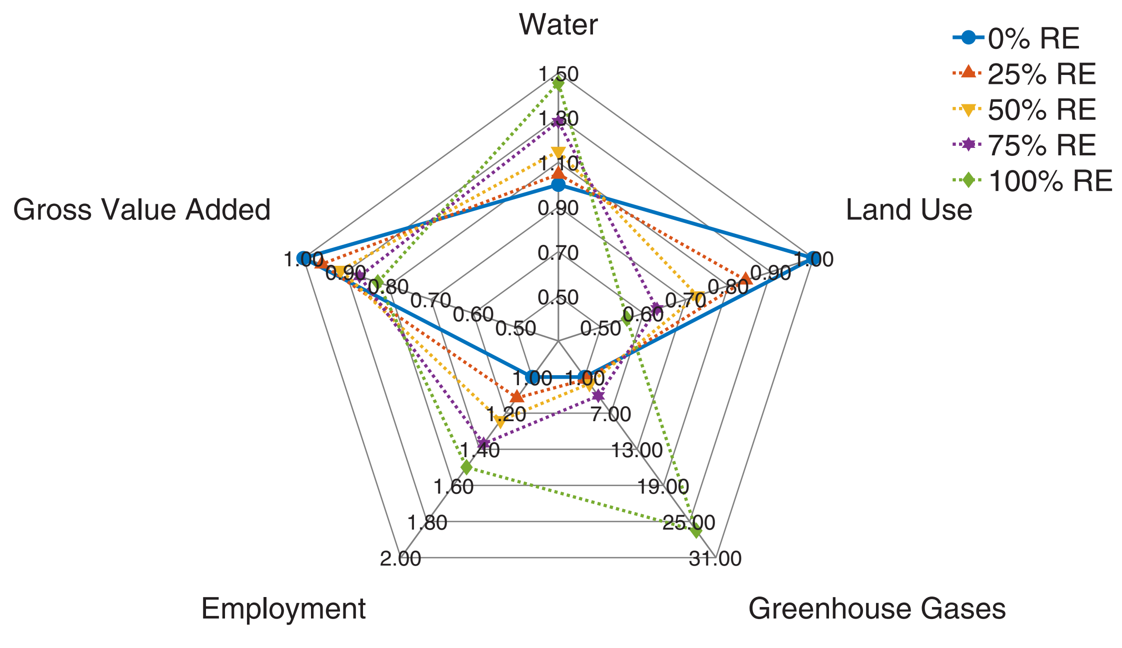

Figure 2. Operation and maintenance period TBL performances of desalination utilising different electricity mixes.

half of the total water consumption. The use of 100% RE would reduce water consumption by 31% in the operating phase and by 7% in the construction phase of desalination plants. Thermal power plants require vast quantities of water due to their technical concept. In particular, the cooling required for the thermodynamic process is highly water-intensive. In coal-fired power plants, the amount of water required to generate electricity can, therefore, account for up to ten times the weight of the coal required (Gleick 1994). Further water is required for the post-treatment of ash and waste disposal. Indirectly, coal mining and recultivation of the landscape are water-intensive. In contrast, the direct water consumption of PV and wind is negligible. Although the water consumption of hydro and geothermal electricity by evaporation and cooling is also substantial, PV and wind dominate the 100% RE system in this case study, which is why water consumption would be significantly reduced.

For the construction, operation and maintenance of the 29 seawater desalination plants, approx. 3300 GL of water would be needed over the entire period of 29 yr when using RE. In contrast, the plants would produce 5500 GL of water per year, *i.e.* over the estimated life cycle of 29 yr, water consumption would amount to 2.3% of the total amount of water produced. With conventional energies, the water consumption share is 2.9%. Over the total period, 21% of water use could be saved by using RE.

Within the construction phase, the land use of desalination would average around 7.5 Mha per year. Moreover, the construction phase is the driver in land use with 77% contribution when using conventional electricity. The use of RE during the construction phase, which would reduce land consumption by 2%, has only a marginal impact. If RE is used in the operational phase, land use would increase significantly by 78%.

RE would have the most significant positive impact on carbon emissions from desalination plants, both during construction and operation. In detail, 206 Mt $CO_{2,e}$ would be generated by the construction using the Australian electricity mix. Only 60 Mt $CO_{2,e}$ would be emitted if Australia had a 100% RE grid. The savings correspond to a reduction of 71%. An even more significant reduction in emissions could be achieved in the operating phase. While 692 Mt $CO_{2,e}$ is emitted in the 0% RE scenario, we see a reduction to 26 Mt with 100% RE. Consequently, carbon emission could be reduced by 96% in the operational period. In the base scenario, the operating phase contributes 77% to carbon emissions. In the RE scenario, the construction phase is the main contributor, with 70% of the total emissions. The results thus show that further measures are needed in other sectors to further reduce emissions during the construction phase.

Regardless of the power source, the average employment during the construction period would be over 350 000 FTE per year. The construction period therefore contributes significantly to total employment, accounting for around 72% of total jobs. While employment in the 100% RE scenario would decrease slightly during the construction phase, employment during the operation phase would increase significantly to 50%. Hence, jobs would increase by 50% from an average of around 16 000 FTE to around 24 000 FTE per year when using 100% RE.

The construction and operating periods have a similarly high contribution to GVA. In both scenarios, the construction of the 29 plants generates GVA of around AU$52 bn (current prices). If 100% RE were used, GVA would be significantly reduced by 17.5% during the operation and maintenance period. Only AU$58 bn instead of AU$70 bn would be generated. Overall, this leads to a reduction of around 10% of GVA over the entire life cycle of 29 yr. This decline can be explained by the fact that Australia is mining a large proportion of its conventional fuels domestically. However, this calculation does not take the external costs of using conventional energy into account.

3.2. Sectoral implications

In the following section, we identified the sectors that have a significant impact on the indicators. Figure 3 shows the percentage contribution of the different sectors to the overall impact. The upper diagram shows the contribution of each industry where the impacts occur. The lower diagram shows the commodities that trigger the impacts through their demand. The bars compare the 0% RE with the 100% RE scenario. The electricity industry is mainly responsible for water consumption in both scenarios. Furthermore, the decrease in water consumption in the 100% RE scenario is mainly caused by the electricity industry and to a lesser extent by the mining industry. In contrast, the water consumption of the agricultural industry increases with the increasing share of RE in the electricity grid, mainly due to the use of biomass. Moreover, electricity is the most relevant commodity determining water consumption. The decrease in water consumption with 100% RE use is also driven by this commodity.

Land use in both scenarios is dominated by the agricultural industry. The same industry causes additional land use when increasing RE share. While the contribution of the commodity electricity to land use is still relatively small when fossil-based electricity is used, it would more than double if RE were used. The main contributing commodities for land use are civil engineering services and installations, the construction of intakes and outfalls and the manufacturing of equipment and materials.

The electricity industry is the driving force for GHG emissions when desalination is operated and built by utilising conventional electricity. This picture changes with a higher share of RE so that the manufacturing industry plays the most considerable role. If we examine the commodities, a similar picture emerges. Electricity as a commodity, but also the construction of intake and outlet play a significant role in GHG emissions. Both commodities reduce their contribution in increasing the share of RE.

The manufacturing industry substantially contributes to employment. A transition to 100% RE would not change the contribution. However, the electricity sector becomes more critical in the 100% RE scenario, making it the second most job-relevant industry. When looking to commodities, the production of equipment and materials is primarily

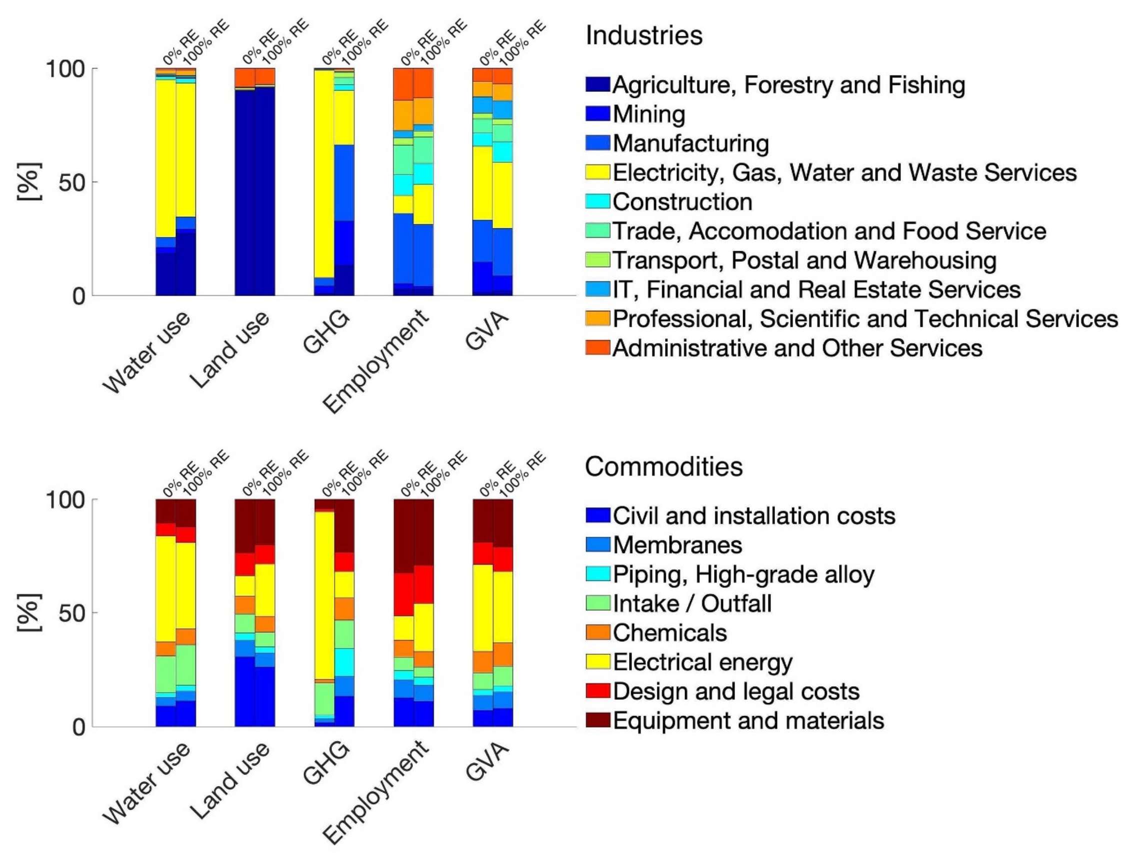

Figure 3. Percentage impact contributions of industries and commodities, comparing the 0% RE and 100% RE scenario.

responsible for job creation. The contribution of the electricity commodity would also increase significantly due to a higher RE-share.

The electricity industry is the largest contributor to GVA, but the contribution decreases as RE increases. With an increasing share of RE, the mining industry would also reduce its contribution to GVA. On the other hand, the construction industry would increase its GVA contribution by increasing the share of RE. In all scenarios, the second most important industry sector in terms of GVA is the manufacturing industry. In both scenarios, the commodity electricity is the main driver of GVA, although the share is reduced by increasing the RE share.

3.3. Regional implications

Figure 4 shows the percentage change in the indicator totals for each of the 46 regions over the entire life cycle when switching from conventional electricity to 100% RE. Red indicates a reduction, green an increase of the indicator. The relative change for each region is given by $p_{k,r} = \frac{\sum_{y=1}^{29} i_{k,RE100,r,y}}{\sum_{y=1}^{29} i_{k,\,RE0,\,r,y}}$ where i is the total amount of the indicator of the key figure k, RE100 is the 100% RE scenario and RE0 is the 0% RE scenario. Furthermore, r indicates the region and y the year. It should be noted that especially regions that previously achieved relatively low values and have now experienced a high relative increase may still show low values in absolute terms. The diagram only shows the relative changes to the values in the 0% RE scenario. The key messages of the chart are the relative change in the indicator values in individual regions and, in particular, the shift in the indicator values, but not the absolute level of these values. The maps on the bottom show the classification of the 46 regions, aggregated to Australian states and territories, water catchments (with the MDB) and rainfall areas. The map of the states and territories also shows the locations of the desalination plants.

Throughout the Eastern Region, water consumption would increase, particularly in MDB areas, through greater integration of RE. As the desalination plants in our case study were built to address water scarcity in this area, this is an unsatisfactory result. However, we have seen in section 3.1 that water consumption is only about 2% of total production, so the additional consumption is relatively small. By contrast, water consumption is reduced in the direct coastal areas of the east coast, where most of the economic activity and population is located. Although these regions face higher rainfall than other areas off the coast, these regions are subject to long-term water stress due to high population density and economic activity. Victoria, in particular, would have to cope

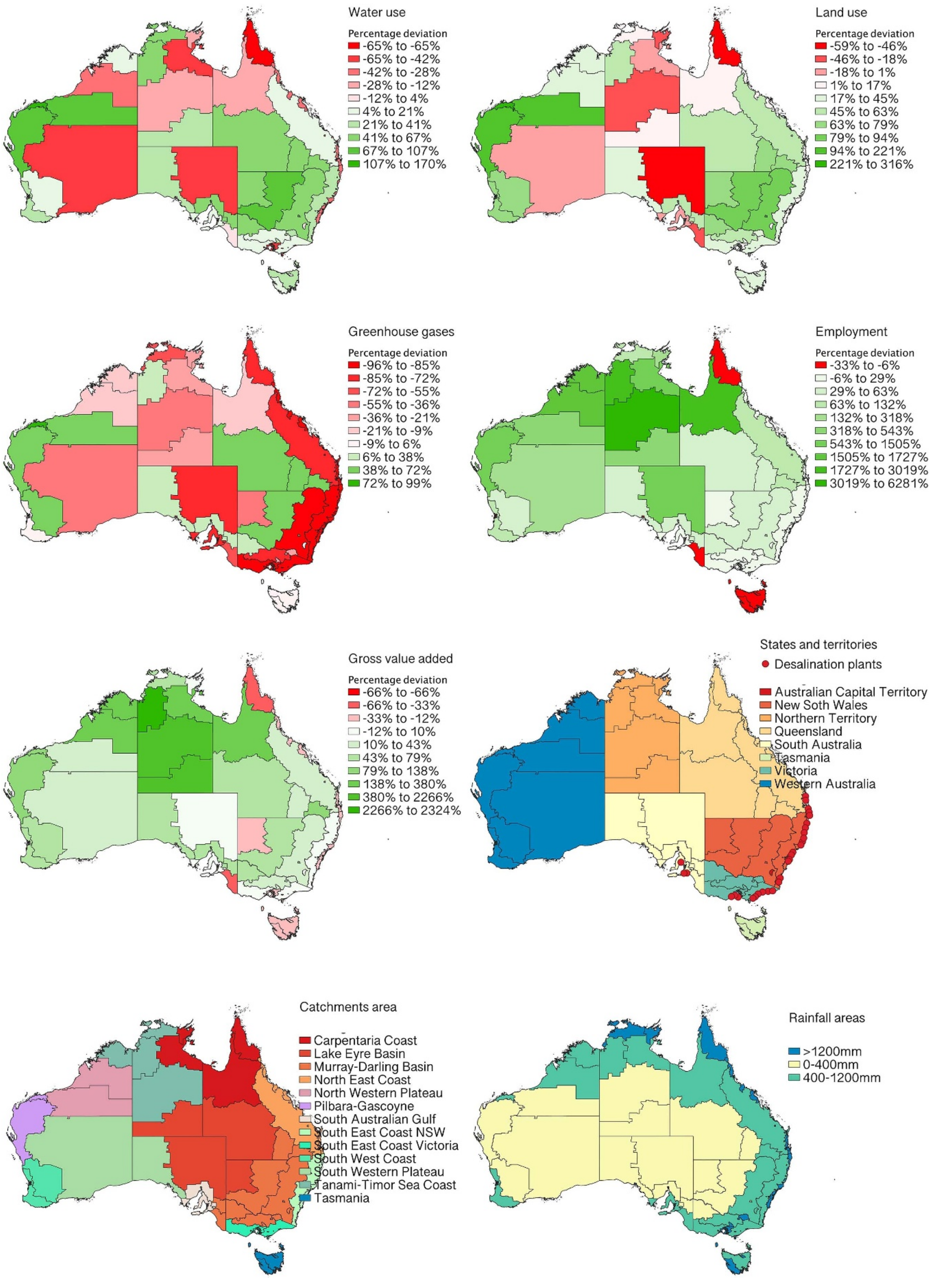

Figure 4. Relative changes of the TBL indicators in the analysed 46 regions.

with a significant increase in water consumption at 100% RE.

The densely populated areas on the east coast would not face any significant change in land use when shifting to RE. In order to provide water in the MDB, demand is generated at the desalination plant sites shown in the states and territories diagram. Compared to centralised power plants, which are mostly located near the coast, the demand for the construction and operation of decentralised RE plants also generates a decentralised demand. Decentralisation is also reflected in land use, which is why areas in eastern Australia and in the MDB in particular are increasingly used in the 100% RE scenario. In central Australia, on the other hand, land use would tend to decrease, while on the west coast, land use would increase significantly.

On the east coast, where economic activities take place, we see an obvious reduction in carbon emissions at 100% RE. The entire east coast with its high population density and economic activity would significantly reduce carbon emissions from desalination by switching to RE. In areas where decentralised RE increase economic activity, emissions would increase, e.g. inland in eastern Australia or on the west coast.

If desalination is built and operated on the basis of RE instead of conventional electricity, fewer jobs would be created in a few regions in the north and south, including Tasmania. On the other hand, employment would increase in the inland areas. All areas in central and western Australia would see an increase in employment, as RE is much more decentralised than conventional power stations. Diversification of employment is beneficial for a country like Australia, where population and economic activity are concentrated in a few areas, while there are large unused areas in the hinterland.

Like employment, GVA would be regionally diversified due to the increasing use of RE. However, GVA would decrease in the economic areas of the east coast, especially in the north, but also in Tasmania. In the Northern Territory, GVA would increase significantly. From an economic point of view, such a development would be beneficial as economic activity diversifies into areas with lower population density and less economic activity.

4. Conclusion

In our IO-based hLCA assessment, we showed the comprehensive TBL sustainability impacts of seawater desalination, depending on the utilised electricity source. Using social, economic ecological indicators, we explained in detail which sectors and regions contribute positively or negatively to the sustainability of desalination through a 100% RE grid.

With higher RE penetration, we measured rising employment but also falling GVA. Even if there is a trade-off between employment and GVA, the assessment shows that a higher RE share would contribute to regional diversification of economic activity. In fact, the spatial diversification of GVA is itself a value, as the local concentration of GVA increases the cost of land use. Therefore, decentralised GVA prevents price increases caused by land scarcity. While desalination with conventional electricity generates higher GVA through domestic fuel mining, this economic benefit is not sustainable in the light of the Paris Agreement.

Furthermore, the environmental performance of desalination with RE is highly beneficial. The application of a 100% RE system reduces the carbon emissions of desalination during construction by 71% and during operation by 96%. The benefit becomes even more evident when we monetise the reduced external costs. Let us assume an external cost of AU$100 per tonne of CO_2 and 25 Mt as an average amount of carbon emissions reduced by RE during an operating year. Then the reduction in external costs through avoided emissions would result in savings of AU$3.75 bn per year. In contrast, the total loss of GVA over the same period is some hundred million dollars. However, our analysis shows that about 30% of the carbon emissions during the construction period of the desalination plants cannot be reduced by 100% RE. Hence, further measures are still needed.

The results clearly show that RE and desalination benefit from synergy effects. Due to the high energy consumption, this applies in particular to desalination, but similar effects can also be expected for other water supply technologies due to the technical similarities. Due to the consequences of climate change, it is to be predicted that Australia's water problems will increase in the future. Policymakers should, therefore, aim for a common strategy for Australia's water and energy supply. The scope of consideration should be as broad as possible and should also include, for example, other related problems such as the discharge of brine with increased desalination use.

Our holistic assessment approach has several strengths for the analysis of infrastructure projects. Since we examined all three areas of sustainability using an hLCA framework, the results are directly comparable. We used the same system boundaries, the same assumptions and framework conditions, and the same economic linkages. Trade-offs, such as GVA and GHG emissions, can be compared directly. The methodology is particularly useful for practitioners to estimate the impact of infrastructure projects in the early planning phase. The political value of the findings is substantial. Our MRIO approach allows detailed regional and sectoral conclusions. The highly disaggregated analysis enables long-term economic policies, e.g. due to changes in regional water use, employment or economic activities.

The sustainability of seawater desalination plants depends in particular on regional factors such as local energy supply or industrial interconnections. In order to make these influences apparent, regional economic data are indispensable. The hLCA approach with the use of the IELab offers an efficient and effective possibility to break down statistical data to create tailor-made IOTs. The achievable granularity depends in particular on local data availability, whose quality is increasing worldwide. In recent years, IELabs for Australia, China, Indonesia, Taiwan, Japan, and the USA have been created that can be used for these assessments (Geschke and Hadjikakou 2017).

Further research is needed on the effects of large quantities of brine intake on marine biology. Furthermore, the development of new membranes promises remarkable increases in desalination efficiency. The associated effects on sustainability also require further research.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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