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Working paper

Multidimensional analysis of nexus technologies I: diffusion, scaling and cost trends of desalination

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Abstract

Desalination is analyzed from a multidimensional perspective as the first of a series of 'nexus technologies' that offer potential challenges and opportunities for the integrated management of water, energy and land (Nexus) resources. With a focus on the three desalination technologies with the highest level of technological maturity and commerical applications - multi-effect distillation (MED), multiflash distillation (MSF) and reverse osmosis (RO) –, the analysis describes and quantifies the historical trends in diffusion, scaling and capital cost reductions as a result of economies of scale and learning. Based on the results, it also derives a range of future cost scenarios that can be used as an input for integrated Nexus modelling and scenario development.

The analysis shows that thermal technologies (MED and MSF) are in an advanced growth phase and approaching saturation, with deployment levels likely to peak before 2050. This may be explained by their lower competitiveness in costs and energy efficiency compared to RO, as well as the constraint of their market to the particularly enabling environment of the Middle East. Nevertheless, marginal new market opportunities may come from the coupling with solar energies, especially for MED. RO, in turn, is still at an earlier stage with considerable future growth potential, albeit the uncertainty to develop growth forecasts is also higher.

A parallel analysis to unravel and quantify the economies of scale and learning effects on historical cost reductions reveals that learning has been the dominant driver, with learning rates of 23%, 30% and 12% for MED, MSF and RO respectively. The highest influence of economies of scale effects is found for MED, exhibiting the highest scale power law coefficient (of 0.71) and a 13% difference between the traditional and the descaled learning rate. The application of these results to derive future cost projections leads to limited cost reduction prospects for thermal technologies, with a maximum of 6-8% by 2030 and 8-10% by 2050. As for RO, more substantial reductions are obtained, with ranges of 12-33% by 2030 and 18-66% by 2050 between a moderate logistic shaped growth and a demand pull effect by i.e. SDGs policies.

These findings provide important insights that should be taken into account by modelling frameworks integrating desalination as a possible solution to address water scarcity challenges and pathways to achieve SDG targets, and/or to optimize water-energy-land resource management. Particularly, they can prevent excessively optimistic and unrealistic assumptions of future desalination capacity, as well as an overestimation of learning effects due to the confounding effects of historical upscaling.

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Beatriz Mayor

1. Introduction

1.1 Desalination as a 'nexus technology' to address water, energy and land challenges

Within the framework of the United Nation's Sustainable Development Goals (SDGs) Agenda approved in 2015, understanding the interconnections between the different SDG goals and assessing the tradeoffs and synergies of potential technological and non technological solutions has become a priority to come up with sustainable development pathways. A particular focus has been put at both the international and regional levels on understanding the intrinsic interconnections between water, energy and land systems - the so called water-energy-land (WEL) nexus –, as these are transversal resources that underpin the achievement of most of the SDGs as well as the wellbeing and economic prosperity of regions. Several initiatives have been started by governments, international institutions and the research community with the aim to model and assess the water-energy-land implications of different policies and technology choices, e.g. FAO (2014), Mannschatz et al. (2016), Salam et al. (2017). It is imperative that such modelling exercises understand and integrate the historical trends and dynamics of those technology options in order to come up with realistic assumptions and estimations of technological change.

Amongst these initiatives, the International Institute for Applied Systems Analysis (IIASA) in cooperation with the United Nations Industrial Development Organization (UNIDO) and the Global Environmental Facility (GEF) launched in 2016 an ambitious cross-cutting project entitled 'Integrated Solutions for Water, Energy and Land (IS-WEL)'. IS-WEL aims to explore cost-effective nexus solutions to jointly meet water, land and energy demands under different development and climate pathways. The project involves the integration and upgrade of four robust IIASA models that target the different WEL dimensions – ECHO and CWAT (water), MESSAGE (energy) and GLOBIOM (land use) -, to generate an integrated framework that will be used to assess different nexus solutions across scales. At a global scale, a global hotspot analysis will allow to identify multi-sectorial scarcity hotspots and assess the synergies and trade-offs among sectors and countries; at the regional scale, different portfolios of integrated solutions for local water, energy and land challenges will be assessed in two case studies in the Zambezi and Indus basins (IIASA, 2016).

The work presented in this paper is part of a multidimensional analysis aimed to provide an empirical analysis of a selection of critical 'nexus technologies', as an input to ISWEL integrated modelling and scenario building exercises. The term 'nexus technologies' refers to technologies that can exert potential trade-offs (high resource use, counteracting impacts or environmental externalities) or opportunities (resource efficiency, synergies between technologies or reduced externalities) for the integrated management of water, energy and land systems. The multidimensional analysis is comprised of three steps: first, a selection of a set of representative technologies to be analysed; second, an analysis of historical technological trends including diffusion at the industry and unit level, costs and cost reduction drivers (economies of scale and learning); and third, an analysis of technological performance against a series of nexus indicators. Some examples of relevant nexus technologies identified for the analysis span desalination technologies, irrigation systems, wastewater treatment and reuse technologies and decentralized solar systems.

Desalination was selected as the first of these technological options that can bring important opportunities for meeting the WEL SDGs - particularly the water-related ones -, but also exhibit several challenges. On the one hand, it provides an additional source of fresh water resources that can help fill the water supply gap for human consumption and irrigation in water stressed areas; or an alternative source to alleviate the pressure on fresh water resources in regions with water pollution or overexploitation problems. On the other hand, most desalination technologies also entail considerable energy requirements and upfront investment costs that reflect on the price of the desalinated product, and can constrain their economic viability, return on investments and ultimately market uptake, especially in developing regions (Ghaffour et al., 2013; Gao et al., 2017). However, investment costs and energy efficiency for desalination technologies, amongst other technological characteristics, have not been static over time but instead show a decreasing trend since the first projects were implemented (Ghaffour et al., 2013). This phenomenon is a well known and acknowledged process in technology innovation studies, whereby as technologies advance in the technology innovation cycle from 'research idea' through to widespread market diffusion, they usually experiment upscaling (increase in the unit and production capacities) and learning (cost reductions and other performance improvements as a result of accumulated experience) processes that ultimately result in investment and production costs reductions (Grübler, 1998; Grübler, Wilson, 2014). Despite in depth research has been ongoing on desalination performance and technical advances, economics, energy efficiency and market trends (Karagiannis, Soldatos, 2008; Al-Karaghouli, Kazmerski, 2013; Ghaffour et al., 2013; Alvarado-Revilla, 2015; Stillwell, Webber, 2016; Voutchkov, 2017), there is lack of a detailed characterization and parametric quantification of their historical diffusion, scaling and cost dynamics that can be integrated in modelling approaches and used for scenario development. Furthermore, to date only two studies have applied the learning concept to desalination estimating learning rates for either the whole desalination capacity without distinguishing amongst different technologies, or to one single technology (sea water reverse osmosis) (Sood, Smakhtin, 2014; Caldera, Breyer, 2017).

This paper presents the second step of the multidimensional analysis undertaking a historical trend analysis applied to desalination technologies, with the aim to provide detailed quantiative and qualitative information that can be used for modelling and scenario development purposes. The analysis focuses on the three desalination technologies with the highest level of technological maturity and market deployment, and pursues three main goals: 1) to analyze and quantify the dynamics in industry and unit scaling; 2) to analyze historical capital cost reductions and the role played by economies of scale and learning effects respectively; 3) to develop capital cost projections to 2020, 2030 and 2050. The paper starts with an overview of the current technological and market status of desalination, providing the basis and logic for the selection of the three particular desalination technologies to be analysed. Section 2 presents the methodological approach adopted for the different parts of the analysis that is further developed in section 6. Section 3 presents the results of the analysis, followed by a discusion of the most outstanding findings in section 4. Section 5 highlights the most important conclusions of this analysis.

1.2 Desalination technologies and their level of technological maturity

Since the implementation of the first desalination projects in the late nineteen forties, desalination has moved forward in the technology innovation cycle. Several technological families and designs have emerged to reach different technological maturity and diffusion levels. Desalination technologies are mainly divided into two technological groups according to the principle applied for the desalination process. The first emerging technologies comprised the thermal family, which use thermal energy to heat and distil water. The main thermal technologies are multi-effect distillation (MED), multiflash distillation (MSF) and vapor compression destilation (VCD). During the 60s, a second group of desalination technologies arised leaded by reverse osmosis (RO). This family uses the capacity of membranes to retain salts and the differences in osmotic pressure as the basis for the desalination process. Besides reverse osmosis, membrane technologies span electrodialysis (ED), electrodialysis reversal (EDR), nanofiltration (NF), forward osmosis (FO), pulsed electrodialysis (PE), and captive deionization (CD). In addition to these major groups, other minoritary processes include solar desalination and freezing. Whilst the latter two processes have not yet achieved significant market success, they may become valuable under special circumstances or with further development (Hyawaki, 2008).

Within this technological array, MED, MSF and RO register the highest technical maturity and market deployment levels, accounting together for 92.7% of global installed desalination capacity with 8%, 11% and 73.7% shares respectively (Alvarado-Revilla, 2015). These three technologies are currently within the "diffusion" stage in their technology innovation cycle (Grübler, Wilson, 2014), and have gone through both upscaling and learning processes allowing considerable investment cost and water production cost reductions, along with substantial energy efficiency improvements (Ghaffour, 2013). These characteristics have motivated their selection as the focus of this study. Here follows a brief description of the processes and their technological status, as well as a compilation of the main technological features summarized in table 1.

Multi-effect distillation (MED): MED is the oldest desalination method and is mainly applied for seawater desalination purposes. It uses the principle of alternated evaporation and condensation at reduced ambient pressure in a series of successive effects to finally obtain a condensate of fresh water. The number of effects determines the volume of distilled water obtained and thus the performance ratio, but is limited by the total temperature range available and the minimum allowable temperature difference between consecutive effects (Khawaji et al., 2008). MED plants require both thermal energy for the distillation process and electrical energy for the water pumping system, with typical value ranges of 45 - 230MJ/m^3 (12-19 kWhe/m^3 assuming power plant conversion efficiencies of 30%) and 2 – 2,5 kWh/m^3 respectively (Al-Karaghouli, Kazmerski, 2013). The first plant was constructed in 1945 in Preston, England, albeit the highest deployment is found in the Middle East, with 64% of global installed capacity (Alvarado-Revilla, 2015). Despite being the first commercialized desalination method, it registered a slower market penetration than MSF due to significant salt precipitation (or scaling) problems and higher capital and operation costs (Mezher et al., 2011). Nevertheless, recent studies suggest that MED may replace MSF in future projects thanks to the significant improvements in energy and conversion performances (Mezher et al., 2011). Furthermore, it could even compete with seawater reverse osmosis (SWRO) for the treatment of highly polluted or saline raw waters (Khawaji et al., 2008).
Multistage Flash Distillation (MSF): MSF emerged shortly after MED as an alternative method for sea water desalination. The first plant was constructed in Casablanca (Morocco) in 1950, following

a fast diffusion across the Middle East linked to thermal power plants (Alvarado-Revilla, 2015). The MSF process applies the principle of "flash distillation" by conducting previously heated water under high pressure through successive chambers operating at progressively lower pressures. As the water enters each chamber, it releases part of the pressure and rapidly boils resulting in sudden evaporation or 'flashing'. The vapor generated by the flashing is condensed on heat exchanger tubes to produce a distilled water outflow (Khawaji et al., 2008). MSF plants are usually bigger and operate at higher temperatures than MED, thus entailing higher energy consumptions. Typical MSF thermal and electric energy requirements are in the order of 190-282 MJ/m^3 (16 - 23 kWhe/m^3) and 2.5 – 5 kWh/m^3 respectively.

Reverse Osmosis (RO): RO, as the main representative of membrane technologies, applies external pressure to overcome the intrinsic osmotic pressure of seawater and reverse the natural flow direction across a membrane, leaving the dissolved salts behind (Khawaji et al., 2008). This process requires only electric energy to power the pumps, with typical values ranging between 1.5 and 5 kWh/m^3 depending on the salinity of the feedwater (Al-Karaghouli, Kazmerski, 2013). The first plant was constructed in 1962 in Kuwait, followed by a quick expansion across the Middle East, North America and the Mediterranean countries. RO alone overtook the installed capacity by both MED and MSF together, to finally reach a 73% global market share in 2016 (Alvarado-Revilla, 2015). The success of RO lies in the lower energy requirements as compared to MSF and MED, the application to both sea water and brackish water treatment, several technological improvements, and membrane cost reductions, which together resulted in lower capital and operation costs (Ghaffour et al., 2013). To date there is no other desalination technology that can compete with RO, and it is expected to continue gaining market share, with the only significant competition posed by MED in those countries with cheap oil supplies (Alvarado-Revilla, 2015).

Table 1. Main technological features of MED, MSF and RO desalination technologies. Sources: Alvarado-Revilla, 2015; Al-Karaghouli, Kazmerski, 2013; Greenlee et al., 2009; Eltawil et al., 2009; Khawaji et al., 2008; Ophir et al., 1994.

Feature	**MED**	**MSF**	**RO**
Number of stages	4-31	19-28	NA
Recovery ratio	0-65%	25-50%	35-45% SW[1] 75-90% BW[2]
Tolerated feedwater salinity	No restrictions	No restrictions	<60,000 mg/L
Output water salinity	<10 mg/L	2-10 mg/L	<500 mg/L SW[1] <200 mg/L BW[2]
Brine temperatures	70°C	90-120°C	Same as input
Thermal energy consumption	12-19 kWhe[3]/m^3	16-23 kWhe/m^3	None
Electric energy consumption	2-2.5 kWh/m^3	2.5-5 kWh/m^3	1.5-5 KWh/m^3

[1]SW: Sea water

[2]BW: Brackish water

[3]kWhe: Kilowatt hour equivalent applying a heat conversion efficiency of 30%.

2. Methods

The methodological approach involved the selection of a set of critical technology dimensions and variables that condition the extent and feasibility of adoption of desalination technologies in various markets. The regression of mathematical models to historical data on the evolution of these variables allows to understand their dynamics and serves as a forecasting model to explore scenarios of future development. This section provides a brief summary of the methodological components of the analysis. A more detailed description of the methodology and the data collection and treatment process, as well as the associated limitations, is provided in section 6.

Technological growth analysis

On the way towards wide market implementation, technologies go through a series of steps or phases known as the 'innovation lifecycle' (Grübler, Wilson, 2014). Several common patterns have been identified and applied for policy and scenario analysis in the case of energy technologies as they evolve and move along this cycle, particularly with regards to the *extent, timing* and *spatial distribution* of technological diffusion at both the technology unit and industry levels (Wilson, 2012; Bento, Wilson, 2015). This study adopts the approach by Wilson (2009, 2012) to estimate the extent, timing and spatial distribution of desalination growth trends at the industry (installed capacity) and unit (average unit capacity) levels by fitting logistic S-shaped curves to historical growth data. Growth is measured in terms of installed capacity and installed units, as these are the most common metrics used both in the literature and by models. Uncertainty and reliability are tested through a set of pre-defined fit quality criteria - 90% confidence and data coverage above 60% of the curve (see section 6) - and sensitivity analyses for non-compliant cases. When validated, the logistic curves are used to generate future industrial deployment and average unit size projections (Martino, 1983; Debecker, Modis, 1994; Modis, 2002, 2007; Kucharavy, De Guio, 2011) as a basis for a cost scenario analysis. Meanwhile, the extent to which the observed dynamics for desalination technologies follow a series of common patterns identified across energy technologies is discussed in section 4.1.

Cost trend analysis

Costs are one of the main factors conditioning the widespread adoption of a technology, and thus its feasibility as a technological solution. Along their life cycle, successful technologies usually experience investment and operation cost reductions that help improve their competitiveness and benefit/cost ratio. This allows them to move beyond specific niche or initial markets, with high willingness to pay, to reach a wider range of potential users (Gruebler, 1998; Gruebler and Wilson, 2014). The analytical focus is put on the study of investment or capital costs, which constitute one of the main variables included by modelling optimization frameworks, while presenting lower regional and context dependency than operation costs. The capital cost trends analysis includes three components: analysis of cost evolution over time, economies of scale and learning.

Time evolution of investment costs. The evolution of technology costs over time and advances in cost reductions resulting from the technology innovation process have been proven to respond to a variety of factors that extend beyond the classical assessment of learning curves (Nemet, 2006). In this study, technology costs are analyzed considering separately the influence of two factors, economies of scale and learning by doing/using, based on the findings by Nemet (2006), Gruebler and Wilson (2014) and Healey (2015).

Economies of scale. Economies of scale are one of the main drivers of capital cost reductions (Joskow, Rose, 1985; McCabe, 1996) and of critical consideration in order to make assumptions on future unit investment costs. They are given by the evolution of capital costs as a function of unit size, as further detailed in section 6.5.

Learning by doing/using. This phenomenon refers to the improvements achieved through the continuous replication and upgrading of the manufacturing process and/or use of the technologies, which together with economies of scale plays the main role in technological cost reductions (Grubler, 1998; Nemet, 2006; Wilson, 2012). It is given by the evolution of specific capital costs as a function of experience. Traditionally, the learning effect has been estimated through the use of learning curves that provide the rate at which specific investment costs (per unit of output or capacity) decrease with increasing installed capacity (Arrow, 1962; McCabe, 1996; Grübler, 1998; McDonald, Schrattenholzer, 2001). However, such method does not account for the scale effect, thus resulting in a presumably overestimated learning rate in which both the learning and the scale effects are confounded (Dutton, Thomas, 1984; Nemet, 2006; Qiu, Anadon, 2012; Healey, 2015). In this study, these effects are estimated separately by applying a cost descaling process to develop descaled learning curves following the methodology by Healey (2015), as further detailed in section 6.6.

Finally, the results from the previous analyses feed a prospective exercise to develop capital cost projections for different technology-specific industrial and unit scale growth scenarios to three time horizons (2020, 2030 and 2050). The scenarios, projection methods, and learning assumptions are summarized in table 2 and appendix 3. More details on the applied methodology are provided in section 6.7.

Table 2. Scenarios, projection methods and assumed learning rates for the different desalination technologies.

Scenarios	**Projection methods**		
	Industrial growth model	Average unit capacity growth model	Learning rate
MED ZERO (no learning)	Logistic	Logistic	0%
MED MOD slow unit upscale	Logistic	Gompertz	12%
MED MOD	Logistic	Logistic	12%
MED BAU	Logistic	Logistic	23%
MSF ZERO	Logistic	Logistic	0%
MSF slow unit upscale - MOD	Logistic	Gompertz	15%
MSF MOD	Logistic	Logistic	15%
MSF BAU	Logistic	Logistic	30%
RO MOD	Logistic	Logistic	12% until 2020 6% after 2020
RO BAU slow unit upscale	10% growth rate	Gompertz	12%
RO BAU	10% growth rate	Logistic	12%
RO HIGH (high learning)	Exponential	Logistic	12% until 2020 20% after 2020
RO SDG boom	10% growth until 2020 20% growth until 2020-2030 15% growth after 2030	Logistic	12% until 2020 20% after 2020

3. Results

3.1 Diffusion and scaling: industry and unit scaling dynamics

The results from the industry and unit scaling analyses suggest that both thermal technologies, and especially MSF, are at an advanced stage in their growth curve and approaching saturation. Table 3 compiles the fit parameters and sensitivity measures for the industry scaling analysis of the three desalination technologies by diffusion regions and at the global scale.

Table 3. Industry scale parameters for MED, MSF and RO desalination technologies. Numbers in grey indicate insufficient fit reliability according to the adopted criteria of minimum R^2 = 0.90 and percentage of saturation (% Sat) above 60% (see section 6.2).

Technology Region	**Cumulative capacity (Ccap)**						**Cumulative units (CUnits)**					
	Ref.	Log fit parameters			Sensitivity		Ref.	Log fit parameters			Sensitivity	
	Ccap 2016 10^6 m^3/d	K 10^6 m^3/d	t_0 year	Δt year	R^2	Sat %	CUnits 2016 10^3#	K 10^3#	t_0 year	Δt year	R^2	Sat %
MED core	0.71	0.8	1991	45	0.99	87	0.70	0.78	1980	58	0.98	90
MED rim	4.36	6.3	2011	22	0.98	70	0.89	1,00	1993	51	0.98	89
MED per	1.75	3.2	2014	59	0.99	55	0.56	0.61	1993	38	0.99	93
MED global	6.82	10.3[1]	2011	39	0.98	65	2.16	2.39	1989	52	0.99	90
MSF core	16.3	19.9	2000	45	0.98	81	0.96	0.99	1984	34	0.99[2]	98
MSF rim	1.2	1.2	1973	40	0.94	100	0.54	0.54	1975	31	0.99[2]	100
MSF per	0.09	0.09	1979	27	0.96[3]	99	0.06	0.06	1979	44	0.97[2]	97
MSF global	17.5	21.1	1999	47	0.98	83	1.57	1.59	1981	34	0.99[2]	99
RO core	29.10	100.5	2024	43	0.99	29	12.46	19.21	2009	47	0.99	65
RO rim	22.13	38.5	2013	28	0.99	57	8.63	10.74	2005	34	0.99	80
RO per	6.76	12.4	2014	25	0.99	54	3.72	7.54	2017	37	0.99	49
RO global	57.99	147.2	2019	35	0.99	39	24.82	37.49	2009	43	0.99	66

[1] A scenario K = Kcore + Krim + Kper is exogenously introduced to avoid implausibly large estimated K values.

[2] Fit adjusted to make logistic fit match real value in 2016 to avoid exceeding 100% saturation.

[3] Regression restricted to time period 1975-2016 to improve fit quality.

The results for MED indicate an advanced stage of diffusion, with higher saturation levels and longer diffusion time periods (Δt) in installed units than in installed capacity, both globally and across regions. This reveals a faster growth in number of units than in installed capacity driven by a relatively delayed process of unit upscaling, as observed in figure 1. Such observation suggests that MED, as the first pioneer desalination technology entering the market, required long initial experimental stages - or formative phase - and the need for deployment of a large number of units with small capacities before scaling up at the unit level was feasible. Meanwhile, the slightly higher difference between saturation levels at the rim, per and global scales suggests that MED deployment will continue in these regions, albeit at a slow pace featured by a small number of new units with rather large unit capacities.

In the case of MSF, the stage of diffusion is even more advanced than in MED. Saturation levels above 80% in both installed capacity and installed units have been achieved in the *core* region and at the global scale, reaching 100% in the *rim* and *per* regions. The duration of diffusion (Δt) in this case is shorter for installed units than for installed capacity, suggesting a relatively early and intense upscaling. Meanwhile, the cumulative and average capacity curves in figure 1 show that this upscaling occurred almost parallel at both the industry and unit scale. These results mirror the later entry of MSF technology in a market already opened by MED, where the possibility of a faster unit upscaling, together with other technical advantages allowing for lower capital costs, prompted a quicker and more extensive diffusion. An extrapolation of the growth curves for MED and MSF places the achievement of their industrial deployment peaks between 2030 and 2050, with installed capacities around 10.3 and 21 million cubic meters per day respectively (see figure 1).

In contrast to the observed situation for thermal technologies, the results for RO reveal an earlier stage in the technology diffusion curve with further room for future growth. In fact, the technology has not yet reached the 60% saturation threshold in the installed capacity curve (as shown by the grey colored entries in table 1), and thus the estimated model parameters should be taken with caution. A faster growth rate is registered at the installed units level, with 60% saturation exceeded in the core and rim regions and at the global scale. When comparing the extent of diffusion (K) amongst technologies, prospects for RO are much higher than for thermal technologies, in line with the historical trends. These diffusion differences were motivated by a series of technological characteristics - modularity that makes it more granular, considerably lower investment costs, lower (and only electrical) energy requirements and thus lower operation costs (Ghaffour et al., 2013)- that facilitated a wider adoption and the penetration of a more spatially distributed market. However, K values for this technology should be taken as a possible scenario given the high level of uncertainty to derive projections at relatively early growth stages.
Looking at the regional and spatial distribution of diffusion, MED and MSF markets have been mostly concentrated in the Middle East (core region for MSF and rim region for MED), prompted by the easy access to cheap thermal energy and, in many cases, even physically coupled to thermal power plants. MSF and RO follow the classic core-rim-periphery sequence with progressively lower Ks and ΔTs indicating a slower but more pervasive diffusion in the core region, and faster but less extensive diffusion in the rim and periphery regions (Grübler, 1990). MED presents a remarkable particularity in this respect, in terms that the diffusion in the rim region reaches a significantly higher extent than in the core. This observation is further developed and contextualized in the discussion section 4.1.

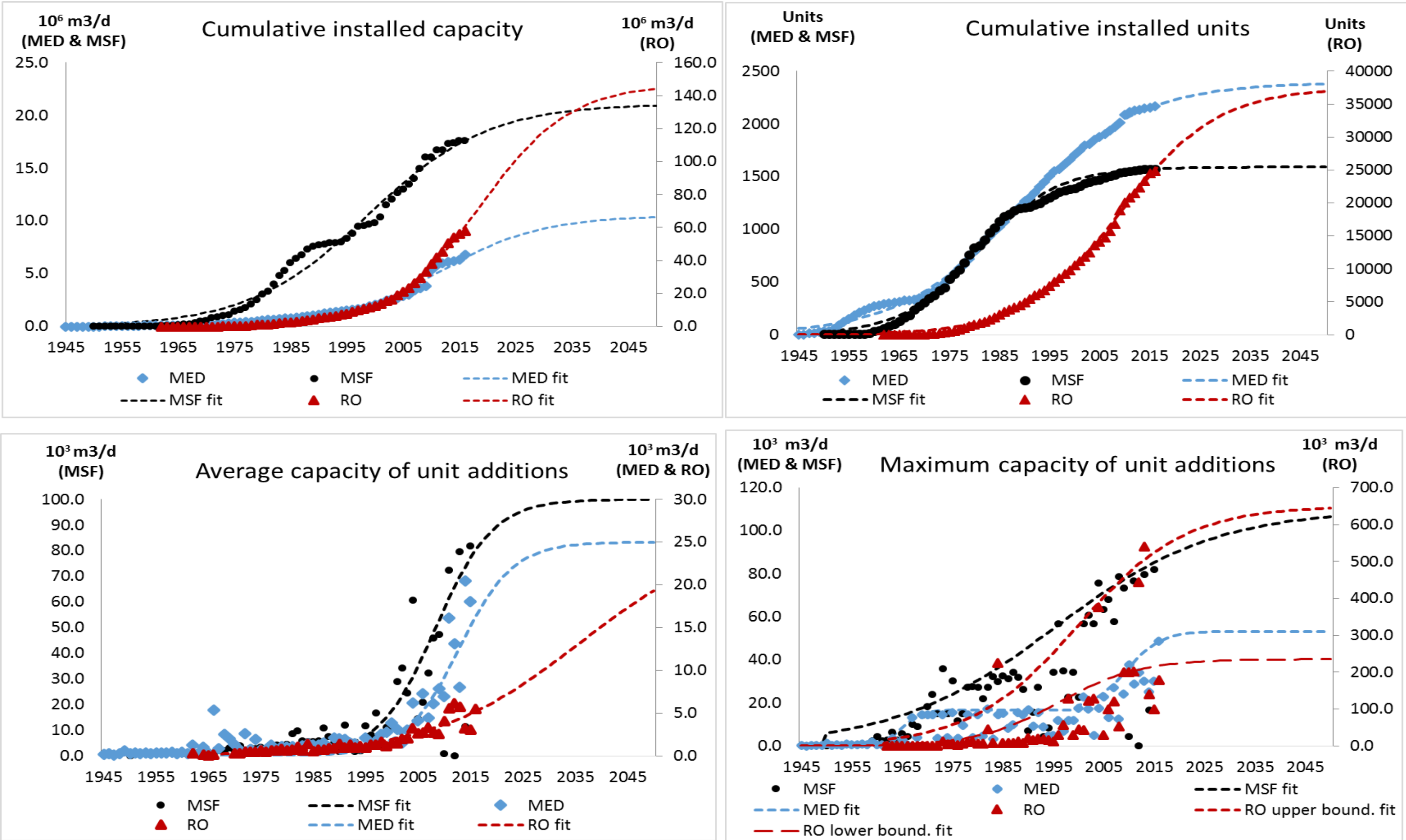


Figure 1. Graphical representation of global historical growth data and logistic fits at the industry and unit levels with trend extrapolations to 2050. Historical data points are represented with a color and symbol code, with red triangles corresponding to RO, blue diamonds to MED and black circles to MSF data. Dashed lines show the modelled trends keeping the same color code (red for RO, blue for MED and back for MSF). Corresponding axes for each technology are indicated in the axis caption.

The analysis of unit scaling using logistic curves provided lower quality fits, which is to be expected given the high variability in yearly average capacities and dependence upon the number and characteristics of the projects (presence of possible outliers). Nevertheless, several strategies were adopted to improve the accuracy of the results and account for uncertainty. First, a diagnosis on a case by case basis was done to identify the different types of uncertainty sources in the irregular fits, and develop a consistent set of sensitivity analyses and strategies to address them. The four different types of uncertainty sources identified and the strategies and criteria applied to each type are described in detail in appendix 1. Second, a specific sensitivity analysis was performed to assess uncertainty in the average unit capacity fits at the global scale, which would be later required to derive projections for the cost scenario analysis. The results showed variabilities in Δt below 0.83%, 0.04% and 1.51% for MED, MSF and RO respectively, and an exponential trend in Ks towards the original value for RO, and thus considered acceptable. A detailed description of the analysis is provided in appendix 2. Table 4 shows the resulting parameters for average and maximum unit capacities.

Table 4. Unit scaling parameters for the three desalination technologies. Numbers in grey indicate that at least one of the quality criteria (minimum $R^2 = 0.90$ and % of saturation (% Sat) > 60%) is not met and thus the uncertainty in the fits is high. An indication of the case type (T1-4) is provided next to the R^2 for the cases with high uncertainty. A brief explanation of the case types is provided as table footnotes. Further detail can be found in appendix 1.

Technology Region	**Average capacity of unit additions (Avcap)**						**Maximum capacity of industry stock (Maxcap)**					
	Ref.	Log fit parameters			Sensitivity		Ref.	Log fit parameters			Sensitivity	
	Avcap 2012-16 10^3 m^3/d	K 10^3 m^3/d	t_0 year	Δt years	R^2, case type	Sat %	Maxcap 2016 10^3 m^3/d	K 10^3 m^3/d	t_0 year	Δt years	R^2, case type	Sat %
MED core	1.7	2.3	1985	84	0.44,T1	100	17.5	45.5	1980	58	0.82	38
MED rim	14.8	15.6	2009	34	0.76,T4	54	48.6	60.0	2006	59	0.93,T2	81
MED per	14.7	22.0	2011	19	0.74,T2	66	25.0	31.7	1988	73	0.99,T3	79
F1								16.2	1965	8	0.99,F1	100
F2								31.7	1988	73	0.99,F2	79
MED global	16.0	22.0	2012	21	0.81,T2	72	48.6	54.0	2003	23	0.85,T3	91
F1								16.7	1965	9	0.99,F1	100
F2								36.6	2009	15	0.97,F2	85
MSF core	80.0	110.0	2008	29	0.88,T2	78	81.8	110.0	1997	65	0.88,T2	75
MSF rim	9.0				No fit,T1		36.0	36.0	1970	12	0.89,T2	100
MSF per	0.1				No fit,T1		15.1	16.0	1969	4	0.99,T2	95
MSF global	80.0	100.0	2008	24	0.87,T2	82	81.8	110.0	1996	71	0.96,T2	74
RO core F1	4.4	28.0	2040	70	0.95,T2	15	540.0	641.6	2002	32	0.99,T4	84
F2							201.6	226.6	1996	30	0.99,T4	89
RO rim F1	6.5	18.5	2024	49	0.87,T4	61	444.0	600.0	2010	17	0.94,T4	74
F2							200.0	418.0	2009	25	0.96,T4	48
RO per	2.9	11.2	2032	75	0.69	36	100.0	103.7	2002	10	0.99	96
RO global F1	4.7	26.7	2036	63	0.84	15	540.0	641.6	2000	17	0.99,T4	84
F2							201.6	235.2	1996	35	0.99,T4	85

T1: Noisy data providing very poor or no fit.
T2: Implausibly high K values requiring adoption of an exogenous scenario.
T3: Multiple phase fits. Envelope fit and fits for phase 1 (F1) and phase 2 (F2) are provided.
T4: Presence of clear outliers shaping a different trend. Envelope fits with outliers (F1) and without outliers (F2) are provided.

Despite the lower accuracy of these results, some conclusions are nonetheless possible. Looking at the average capacity in thermal technologies, MED saturates at lower K values than MSF, with highest averages reported in the Middle East region (core for MSF and rim for MED). This is coherent with the longer formative phase and relatively late unit upscaling process previously observed for MED. The unit scale in this technology may have been limited by the thermal energy consumption, important 'scale formation' problems (excessive precipitation of salts obstructing the system) and the increasing competition from MSF (Khawaji et al., 2008; Arnaldos, personal communication). Thanks to technical improvements and efficiency gains, some remarkable increases have been registered in the last decade. The same situation is observed at the capacity frontier level. MSF, in turn, shows a faster and steeper upscaling phase that occurred almost parallel at the average and maximum capacity levels (see figure 1), especially in the core region (Middle East), as reflected by their similar K values. This phenomenon may have been facilitated by a simpler design, less vulnerability to scale formation, and the association to thermal power plants (Khawaji et al., 2008), which enabled early upscaling experiments at the technology frontier and a quick follow up by the bulk of the industry. Overall, the results suggest that both technologies are very close to saturation at both the average and maximum capacity levels.

In the case of RO, despite the unit upscaling process at the capacity frontier has been steeper than in thermal technologies– particularly influenced by a few giant projects -, the average capacities of unit additions over time have increased at a much lower pace and may remain around 20,000 m^3/d per unit by 2050. An observation that stands out from the table is the considerably higher difference in Ks at the average and maximum capacity levels in RO compared to the thermal technologies. In order to contextualize these differences, the average-to-maximum capacity ratios at the global scale for the three desalination technologies and for a sample of energy supply technologies analyzed by Wilson (2012) are compiled in table 5. The table shows that both thermal technologies are in the upper ratio range, having MSF the highest ratio amongst all technologies, even above the least scalable energy technology, i.e. nuclear power. This mirrors the low scalability of the technology and the homogeneity of the market with a limited variety of applications. RO, in turn, is in the lower ratio range at the level of natural gas and hydropower turbines, which are much more scalable and granular technologies applied for a variety of different applications (gas turbines) and demand sizes (hydropower). Some additional reflection on the particular case of RO is elaborated in the discussion, section 4.1.

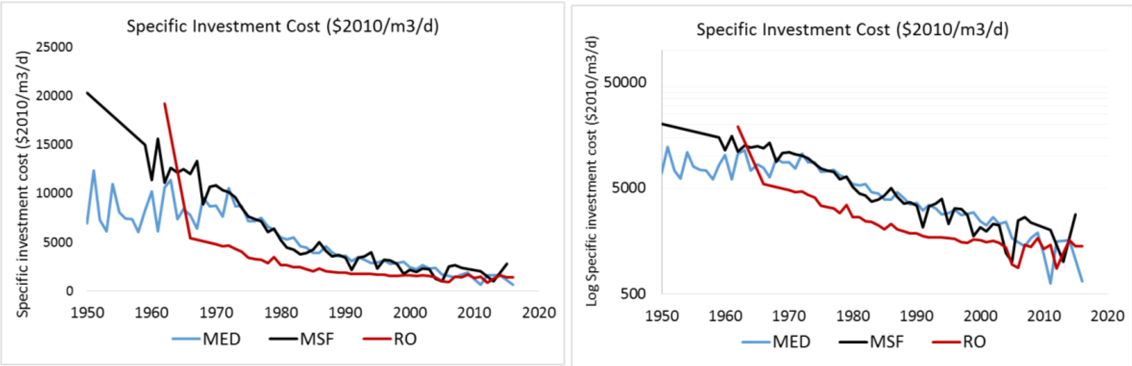
Table 5. Average-to-maximum unit capacity ratios at the global scale for desalination technologies and some examples of energy supply technologies analyzed by Wilson (2012).

	Desalination technologies				**Energy technologies**			
	RO		MSF	MED	Coal power	Natural gas power	Nuclear power	Hydro power
	F1	F2						
Av/max capacity ratio	0.05	0.13	0.91	0.46	0.24	0.07	0.71	0.07

3.2 Capital cost dynamics, economies of scale and learning

Specific capital costs for the three technologies have decreased over the last 5 decades. Figure 2 represents the historical evolution of specific investment costs for the three desalination technologies.

Figure 2. Historical evolution of specific investment costs of desalination technologies represented on a linear scale (figure on the left) and semi-logarithmic scale (figure on the right).



The estimation of economies of scale and learning as main drivers for the observed cost reductions yields the results presented in tables 6 and 7. In the case of learning, both classic (cost vs cumulative capacity) and descaled (descaled cost vs cumulative units) learning rates are provided for comparison. The presented learning rates correspond to the period of maximum growth, as indicated in the *Fit range* row. Further detail on the sensitivity analysis of learning fits for the different growth periods are included in appendix 3.

Table 6. Economies of scale parameters for desalination technologies

Technology	Scale parameter	R^2
MED	0.71	0.72
MSF	0.82	0.88
RO	0.89	0.83

Table 7. Learning rates for desalination technologies

Technology	Traditional learning rate (LR)			Descaled learning rate (LR)		
	LR	R^2	Fit range	LR	R^2	Fit range
MED	36%	0.92	1975-2006	23%	0.97	1968-2006
MSF	33%	0.92	1970-2006	30%	0.97	1970-2006
RO	15%	0.97	1975-2006	12%	0.98	1975-2006

The results show that desalination technologies, particularly the thermal ones, have benefitted from significant economies of scale and learning that explain the considerable specific investment cost reductions observed in Figure 2. MED experienced higher variability in specific costs during the initial market deployment stage (formative phase) until 1970, which marks the beginning of a more homogeneous reduction trend lasting until 2006. This tipping point coincides with the start of a faster industrial growth period (rapid increase in the number of installed units) driven by the industrial take-off in the Middle East, which registers the maximum historical learning rate (22%). Due to its technological configuration, MED exhibits the highest economies of scale effect (exponential scale parameter of 0.71, being 1.0 no economies of scale and increasing the intensity of economies of scale as the parameter decreases) amongst the three. As a result, in spite of the delayed upscaling process, it also presents the highest overestimation in the learning effect when estimated with the traditional learning curve formulation (36%) as compared to the descaled learning curve (22%). This example showcases the importance of separating the scale effect when estimating the learning rates, as for some technologies even relatively small increases in unit size can have an important effect on capital cost reductions.

MSF shows the highest descaled learning rate mirroring the sharpest capital cost reduction amongst the three technologies. Despite having significant economies of scale (0.82), the small difference registered between the classic and the descaled learning rates (only 3 percentage points) suggests that learning played a leading role over economies of scale in historical cost reductions at the average industry level. This period of intense learning process is detected as starting in 1970, along with a boost of industrial deployment in the Middle East that rapidly overtook its thermal sibling. The predominance of learning over scale in MSF is an eye-catching observation considering that it has registered the sharpest unit upscaling process, and will be further analyzed in the discussion section.

In the case of RO, after a sharp cost downfall following the first project in 1962, specific costs have decreased at a constant but much slower pace than in the case of thermal technologies. Due to the modular configuration, RO exhibits the lowest economies of scale (0.89). Consistently, this results in a moderate difference between the traditional and descaled learning rates of 3%, similar to MSF. These two factors suggest that the relevance of scale in cost reductions at the average industrial level have been limited, but it may have had a higher impact in the case of larger scale projects that stand out from the average capacity trend. On this last point, it is noteworthy that some cases of diseconomies of scale have been detected in extremely large projects as analyzed and reported by Caldera (2017)(Caldera, Breyer, 2017), suggesting the possible existence of an upper limit above which the effect of economies of scale turns into a rebound effect. The descaled learning rate obtained for RO is also significant (12%), albeit considerably smaller than that of thermal technologies. However, departing from an overall lower average specific investment costs, this learning rate made RO the most competitive technology rapidly overtaking the other two in the global market. The period of highest learning for RO started slightly later than the other technologies, extending over the years 1975-2006.

In addition, a remarkable observation worth mentioning is the detection of a trend break in the descaled learning curves for the three technologies corresponding to the last 10 years (see appendix 3). In the case of thermal technologies, the trend break may reflect the beginning of a 'final slow down' phase marked by the reduction of learning concurrent to the decline in the industrial growth rate. As for RO, the earlier stage of technological maturity and higher level of uncertainty on the possible evolution of future growth rates opens up a wider range of possible learning scenarios. These span from a softening of the historical maximum learning rate (12%) caused by a gradual growth rate reduction, typical from a logistic behavior, through to an increase driven by a demand pull effect, which could push the current industrial deployment towards an exponential model. These possible futures have been captured in this paper in the different cost projections scenarios.

3.3 Capital cost projections to 2020, 2030 and 2050

The results for capital cost projections to 2020, 2030 and 2050 for the three desalination technologies in the different scenarios are provided in table 8.

A first sight look reveals that relatively limited cost reductions may be expected from thermal technologies. MED reports slightly higher cost reduction potentials than MSF thanks to the higher economies of scale. Within MED scenarios, the variability between zero, moderate and historical (BAU) learning scenarios is low, with only 2% cost reduction difference by 2030 and 2050. Meanwhile, the effect of a slower unit upscaling is almost insignificant, with only 1% cost reduction difference between the MED MOD and MED MOD-slow unit upscale scenarios by 2030, and no difference by 2050. A very similar situation is observed for MSF, albeit the variability amongst scenarios is even lower. In this case, a maximum 2% cost reduction difference is registered between the lower and upper boundary learning scenarios (ZERO and BAU). Meanwhile, the variation due to slower unit upscaling between the MOD scenarios only differs in 1% by 2030, as in the case of MED. Overall, the limited growth prospects obtained when projecting historical industrial growth trends for thermal technologies dwarfs the effects of even the most optimistic learning assumptions for these technologies, based on historical records. As a result, cost reductions of 9-11% for MED and 6-8% for MSF by 2050 are obtained resulting in specific costs of 1,594-1,640 $2010/m^3/d and 1,834-1,876 $2010/m^3/d respectively.

Table 8. Average capital cost projections to 2020, 2030 and 2050 for the MED, MSF and RO desalination technologies under different industry growth scenarios.

Technological scenarios	Specific Cost projections ($2010/m^3/d)				Cost reductions (% variation)		
	2011-2016	2020	2030	2050	2016-2020	2016-2030	2016-2050
MED ZERO	1,800	1,718	1,650	1,641	-5	-8	-9
MED slow unit upscale - MOD	1,800	1,748	1,653	1,620	-3	-8	-10
MED MOD	1,800	1,712	1,633	1,618	-5	-9	-10
MED BAU	1,800	1,706	1,615	1,594	-5	-10	-11
MSF ZERO	2,000	1,914	1,882	1,876	-4	-6	-6
MSF slow unit upscale - MOD	2,000	1,931	1,882	1,859	-3	-6	-7
MSF MOD	2,000	1,908	1,869	1,857	-5	-7	-7
MSF BAU	2,000	1,901	1,853	1,834	-5	-7	-8
RO MOD	1,350	1,267	1,163	1,000	-6	-14	-26
RO slow unit upscale – BAU	1,350	1,278	1,134	980	-5	-16	-27
RO BAU	1,350	1,267	1,123	883	-6	-17	-35
RO HIGH	1,350	1,252	1,039	691	-7	-23	-50
RO SDG boom	1,350	1,266	901	453	-6	-33	-66

ZERO: zero learning
MOD: moderate learning
BAU: business as usual
HIGH: high learning

With regards to RO, the scenarios show relatively low sensitivity to differences in unit scale but high sensitivity to differences in industrial growth and learning rates. The slow unit upscale BAU scenario projects similar cost reductions as the BAU scenario until 2030, with a 1% difference. By 2050, the difference sharpens achieving a maximum of 8%. The breach between cost reduction projections by the MOD, BAU and HIGH scenarios is more substantial and also increases over time, amounting to some 3-7% by 2030 and 15-20% by 2050. The SDG boom scenario stands out with the fastest cost decrease, almost doubling cost reductions under the BAU scenario. This brings up, on the one hand, the extent of the cost impacts that a strong stimulation of demand could bring. On the other hand, it is noteworthy that the pulling effect required to double the growth rate between 2020 and 2030 as assumed in the scenario would be substantial. Overall, the scenarios suggest that significant reductions in RO specific investment costs may be expected in the mid and long term under all the assumptions. The predicted specific costs for an average capacity unit range in the order of 901-1,163 m^3/d by 2030 and 453-1,000 by 2050, depending on the future evolution of industrial deployment.
In a cross-technology comparison, RO would increase the cost competitiveness advantages over thermal technologies under all scenarios. Cost differences would range from 30% (2030) and 40% (2050) below MED, and 38% (2030) and 47% (2050) below MSF in the lowest learning scenarios, to 44% (2030) and 72% (2050) below MED, and 51% (2030) and 75% (2050) below MSF for the highest learning scenarios.

4. Discussion

4.1 Technological patterns and dynamics in desalination technologies

The presented analysis allowed to recognize in desalination technologies some of the technological patterns depicted by Wilson et al. (2012) for energy technologies.

The first pattern states that, as technologies diffuse, they go through three stages: 1) a 'formative phase' in which many smaller-scale units are built with only moderate increases in unit capacity; 2) an 'upscaling phase' where large increases in unit capacities are achieved; and 3) a growth phase where a large number of units at large unit capacities is built (Wilson, 2012). This pattern can be also recognized in the three desalination technologies, albeit with some slight particularities. According to our results, MED has experienced a longer formative phase and relatively late unit upscaling process compared to MSF and RO, with the most remarkable increases registered in the last decade. An important factor explaining this delay are the problems of 'scaling' (precipitation of salts that obstruct the system causing performance and yield reductions) faced by the technology, which increases with temperature and evaporation surface area, resulting in higher costs, thus posing a limitation to the number of effects and overall plant size (Mehzer et al., 2011). Meanwhile, larger plants required higher thermal energy inputs, which acted as a second limitation for unit upscaling (Arnaldos, personal communication). MSF, in turn, is less prone to suffer 'scaling' problems, which along with a simpler design and higher operational efficiency provided a comparative advantage. As a result, MSF experienced a faster upscaling and a longer growth phase starting in the Middle East, with spill overs to North America and Western Europe (core and rim regions). Other factors promoting the success and permanence of MSF in the market included the shift towards better materials resulting in an expansion of plant lifespans and lower operation costs (Sommariva, 2010; Alvarado-Revilla, 2015). Overall, the competition with MSF and later with RO played as a third factor reducing the interest and thus experimentation and investment efforts (reduced learning) in MED. It is in the last decade that interest in MED has sprung up again due to the higher energy efficiency and suitability for coupling to solar thermal power (Al-Karaghouli, Kazmerski, 2013; Alvarado-Revilla, 2015). In the case of RO, the technology may be currently approaching the end of the 'upscaling phase' and beginning of the 'growth phase'. However, the strong differences between scales at the average and maximum capacity levels, further discussed below, suggests that the growth phase may play out in increasing installed capacity through a combination of small to medium unit size stand-alone plants and large scale multi-unit projects.

A second pattern refers to the spatial sequence of diffusion, whereby technologies register longer diffusion times in their core regions as the required knowhow and infrastructural and institutional settings are developed (Wilson, 2012). Meanwhile, the rim and periphery benefit from knowledge spillovers enabling a speed up of diffusion, albeit the lack of accompanying contextual settings results in a lower extent of overall diffusion (Grübler, 1998; Grübler, Wilson, 2014). MSF and RO confirm the sequence core-rim-periphery with progressively lower K and ΔT values, indicating a slower but more pervasive diffusion in the core region, and faster but less extensive diffusion in the rim and periphery regions. MED, in turn, presents a remarkable peculiarity in this respect, such that diffusion in the rim region reaches significantly higher extent than in the core. In this case, despite MED was originated and firstly implemented in Western Europe and North America - which constitute their core innovation regions -, it quickly spread to the Middle East parallel to the emergence of MSF. Considered as rim (as a latter implementer partially benefitting from knowledge spill overs), the Middle East conveyed a series of facilitating conditions, i.e. extreme water stress and need for additional resources, high availability of cheap thermal energy and opportunities for technological combinations with thermal plants. Altogether, this environment triggered a faster and extensive industrial settlement and growth accompanied by more intensive technology innovation and learning processes. Meanwhile, in the initial core regions, the entry of RO in the market offering consistently lower energy requirements and investment costs (amongst other technical advantages) relegated MED to a rather marginal growth in specific cases, as reflected in the extremely high saturation levels reported in both installed capacity and installed units (87% and 90% respectively).

A third pattern refers to the average/maximum capacity ratio, whereby high differences between average and maximum unit capacities are associated to technologies with a great variety of market applications and technological variability, whereas a close evolution of both variables are observed in technologies with homogeneous markets (Wilson, 2012). MSF, with the shortest distance between the average and maximum unit capacity curves and very close K values (only 9% difference), has 89% of installed capacity devoted for municipal drinking water supply according to the information in GWI's Desaldata database. MED and RO, with larger differences between Ks at the average and maximum unit capacity levels, have more diverse market applications including municipal drinking water (50% and 53.5%), industrial uses (36% and 34%) and power stations (12.16% and 6%) respectively, and in the case of RO also tourist facilities (2.5%) and irrigation (2%). In the latter, the aforementioned notably lower average/maximum capacity ratio may also be influenced by other factors such as the type of feed waters and the modularity of the technology. RO technology is applied to treat a higher range of water salinities as compared to MED and MSF, for which 89% and 90% of the installed capacity respectively operates with seawater. According to the information in GWI's Desaldata database, as of 2016 the share of RO installed capacity by feed water type was 44% seawater, 30% brackish water, 11% river water and 6% pure water. The feed water type is an essential parameter determining the structure (type of pretreatment), size and cost of the installation (Sommariva, 2010; Gao et al., 2017), and thus could explain a higher level of heterogeneity in unit sizes. Meanwhile, RO allows for a modular configuration enabling the combination of several smaller units (up to 160 in the Rajasthan project in India or 400 in the Army project in Arizona) within a single project. This may have triggered a shift from the classical "vertical upscaling" trend by the construction of bigger units, to a "horizontal upscaling" of projects by concatenating several smaller units, thus reducing the average unit capacity upscaling rate. An exception to this phenomenon would be found in the handful of giant industrial experiments, such as the Wonthaggi project in Australia (440,000 m^3/d) and the Soreq project in Israel (540,000 m^3/d), which shape the upper boundary of the technology's capacity frontier. It is noteworthy, however, that single unit projects have dominated along the technology's history. As of 2016, single unit projects accounted for 80% of the whole industry stock followed by two-unit projects (11%), three-unit projects (3.5%) and four or more (5.5%), and conveying 51%, 9%, 6% and 34% of installed capacity respectively (own analysis with data from Desaldata), with an overall average of 1.6 units per project. However, when zooming into the period 2005-2016, the share diversifies to 60%, 22%, 7% and 11% of installed units and 15%, 12%, 8% and 65% of installed capacity for 1, 2, 3 and 4 or more unit projects respectively. According to these observations, the horizontal upscaling of projects may have started in 2005, along with a slight increase in average unit sizes. A possible trigger may be attributed to the launch in 2004 of large diameter membranes allowing for larger units (Voutchkov, 2017), along with other technological improvements such as high pump pressures, energy recovery devices and membrane cleaning systems (Caldera, Breyer, 2017). A parallel interesting observation is that in some of the exceptionally giant projects built in the last decade, i.e. the aforementioned Australian examples, the quantum leap in capacity frontier came at the expense of an increase in specific capital costs due to diseconomies of scale (up to 6,000 2010$/$m^3$/d). Such examples may play an incentive to push the trend towards the 'horizontal upscaling' rather than the 'vertical upscaling'.

Looking at the growth phase with a prospective lens, the results of this study suggest that MED and especially MSF are currently very close to saturation and will probably achieve their industrial deployment peak before 2050. Several trend studies in the literature argue that thermal processes will remain in the market because they have been widely accepted in the Arabian Gulf area (Khawaji et al., 2008; Alvarado-Revilla, 2015). The regional analysis undertaken highlights that growth will be mainly (and almost solely) concentrated in the Middle East, where these technologies are well rooted and the local market conditions (high water stress, large availability of cheap thermal energy) provide important incentives for their deployment. Meanwhile, these technologies are also more suitable and may be preferred for feed waters with extremely high salt concentrations, where RO finds physical limitations imposed by membrane tolerance (Khawaji et al., 2008). Although some authors believe that MSF will continue to grow and may even have room for further learning processes (Fiorenza et al., 2003; Sommariva, 2010, Mehzer, 2011), the results in the present work support the hypothesis maintained by Ghaffour et al. (2013) and Alvarado-Revilla (2015) of MED overtaking MSF in number of installed units, albeit not in installed capacity. The main factors driving the shift back to MED as preferred technology over MSF are identified in the performance improvements, lower thermal energy and cooling requirements (Mezher et al., 2011; Alvarado-Revilla, 2015). Furthermore, MED seems to be more suitable for coupling with renewable energy technologies, particularly with concentration solar power (Eltawil et al., 2009; Al-Karaghouli, Kazmerski, 2013; Alvarado-Revilla, 2015; Pouyfaucon, García-Rodríguez, 2018), which may offer new opportunities to reduce the energy-water trade-offs while overcoming some of the environmental externalities identified as potential constraints for future desalination growth (Gude, 2016). However, these options are still far from being cost competitive (Pouyfaucon, García-Rodríguez, 2018).

Reverse Osmosis, in turn, is found to stand at an earlier stage in the technology growth curve, and thus exhibit more substantial room for further growth than thermal technologies. The intense growth and rapid overcoming of thermal technologies experimented by RO has been explained as a result of the lower investment and operation costs, which according to Ghaffour et al. (2013) respond to the following factors: drastic reduction in energy requirements thanks to the introduction of energy recovery systems, improvements in membrane technical parameters and water recovery ratios, new intake designs, along with other technical and chemical improvements. The extent and time frame to which this growth trend will continue (or even increase) before it starts bending towards a sigmoidal shape, may be determined by the strength of possible demand-pull drivers - such as exacerbating water scarcity or levering SDG-related policies –, and its success in the competition with other alternative water technologies. As an additional note, some critical thinking on the feasibility limits of stimulated growth assumptions should be made when evaluating the capacity of reverse osmosis desalination to alleviate water scarcity. Considering scenarios where reverse osmosis is deployed to mitigate the water gap in water stressed regions by 2030 would require installed capacities of around 2,400 million m^3/d (Caldera et al., 2016). This implies achieving in 15 years installed capacities that exceed 40 times the capacity deployed in over 50 years of technology history, which is simply impossible. Therefore, historical dynamics should be accounted for in technological scenario development, even when designing breakthrough scenarios.

4.2 Unravelling the role of scale and learning in historical desalination cost reductions

The desalination literature has repeatedly mentioned and emphasized the importance of scale economies and learning to explain the historical capital cost reductions experimented by the three main desalination technologies (Karagiannis, Soldatos, 2008; Ghaffour et al., 2013; Loutatidou et al., 2014; Caldera, Breyer, 2017). However, very few studies have actually measured the extent of those effects individually for the different technologies, and none of them has been able to decouple them.

Sood and Smakhtin (2014) estimated for the first time the learning rate of the global desalination stock considering the three main desalination technologies (MSF, MED and RO), obtaining a learning rate of 29%. He used cumulative capacity as a measure of experience and total water cost - a sum of the amortized capital cost and the operation costs, from which he withdrew the energy cost - as a measure of output. This joint measure provides very general information that overlooks the strong differences amongst the technology types, while not capturing the differential effect of capex and opex, nor the impact of the economies of scale, as pointed out by Caldera and Breyer (2017). The most in depth and detailed estimation of learning curves for desalination to date has been made by Caldera and Breyer (2017) for the case of sea water reverse osmosis (SWRO). These authors estimated the learning rate for the capex of SWRO plants installed in the period 1970-2015 with the aim to make future projections of capex based on empirical data. They obtained a learning rate of 15%, which coincides with the results achieved in the present study for RO when applying the traditional learning curve. However, these authors acknowledge the limitations of the learning curves to estimate future costs due to the exclusion of other drivers such as economies of scale (Caldera, Breyer, 2017).

This limitation is overcome in the present study by considering both parameters separately and estimating a descaled learning rate where the effects of scale have been removed, enabling to avoid an overestimation of the learning effect. It thus presents for the first time an estimation of the effects of scale economies and learning on the evolution of average specific costs individually and independently for the three main desalination technologies.

The obtained scale parameters suggest that thermal technologies have higher economies of scale than RO, unlike stated by Caldera and Breyer (2017). This could be partially explained by the modular configuration of RO promoting 'horizontal scaling' rather than 'vertical scaling', as previously discussed. However, other technological and structural factors could also be involved. With regards to learning, the obtained descaled learning rates are lower than those estimated by the previously cited studies, as it was expected. In the case of MED, the remarkable difference between the traditional and descaled learning rates suggests that, despite the delayed and smoother unit upscaling as compared to MSF, the larger scale effect made this factor more significant in cost reductions. MSF in turn showed the highest descaled learning rate (30%), only 3% lower than the traditional one, pointing at a very intense learning process as the main driver for average cost reductions. This extreme learning has been acknowledged and explained by Borzani and Rebagliati (2005) as a result of the following factors: competition from other technologies leading to development of new costing approaches; technical optimization and knowledge exchange between projects (spillovers); less stringent specifications; and, most importantly, flexibilization of BOOT contracts allowing bidders to develop costing approaches that minimize total plant life costs (including operation) rather than plant construction costs, resulting in further design and optimization flexibility Borzani and Rebagliati (2005). This points at learning as the main driver triggering MSF capital cost reductions and the unit upscaling process, rather than the inverse situation whereby cost reductions are mainly brought about by the unit upscaling. In the latter, further experimentation and learning are constrained, thus limiting further cost reductions, as it happened in the case of nuclear power (Grubler, 2010).

In the case of RO, the estimation of the traditional learning rate provided the same result as the one obtained by Caldera and Breyer (2017). Having the lowest economies of scale, the variation between the traditional and the descaled learning rates for RO is small, resulting in a descaled learning rate of 12%. Two factors that may have had a critical role on this learning effect were the efficiency improvements in membranes and the introduction and optimization of energy recovery devices (Alvarado-Revilla, 2015).

Looking towards the future, the concurrence of three factors suggests that thermal technologies do not exhibit much room for further learning: 1) a trend break in their learning rate, 2) the advanced position in their industry and unit scale curves approaching saturation and 3) the limitation of their market to the Middle East displaced by the competition with RO. Meanwhile, the need for additional unconventional water resources to face water scarcity in an increasing number of regions as a result of climate change plays as a strong market driver to keep demand for additional desalination capacity on the rise. The clear positioning and comparative advantages of RO, mirroring a lower saturation level, point at a continuation and even stimulation of its growing trend and market dominance leading to further learning. However, the extent and time frame of this growth will strongly depend on the competitiveness over other unconventional water technologies, i.e. water treatment and reuse; the advances in other incipient desalination methods, such as membrane distillation; and the implementation and success of demand control and water efficiency policies.

4.3 Using cost projections for modelling purposes

Most economic review studies of desalination report specific investment cost ranges around 900 – 2,000 $/m^3/d$ for MED, 1200 – 2,500 $/m^3/d$ for MSF and 900 – 2,500 $/m^3/d$ for seawater RO (Karagiannis, Soldatos, 2008; Ghaffour et al., 2013). The wide ranges are mainly a result of economies of scale; however, some optimization models do not account for plant scale differences and thus average present and future cost values are required. This study has carried out a projection of present average capital costs for the three technologies considering the scale and learning effects through different average scale and industrial growth scenarios, which can be used for modelling and scenario generation purposes.

Other cost projection exercises found in the literature focus mainly on seawater reverse osmosis and vary in the assumptions and projection methods applied, as summarized in table 9. Loutatidou (2014) built a model to estimate the EPC cost of SWRO plants, which was tested with historical data and used to make specific EPC costs projections to 2030. He found that plant capacity was the variable with highest influence in the EPC cost, followed by installed capacity and award year, which are somehow related. He projected EPC costs actualized to $2013 to 2030 for different SWRO plant capacities assuming a continuation of the 10% annual industrial growth rate, and obtained capex reductions of 33.75% (2.25% per year) for all the plant scale categories. Caldera and Breyer (2017) projected the capital costs of SWRO actualized to $2015 assuming a starting cost of 2,070 $/m^3/d$ in 2015, 15% learning rate and installed capacity growth rates of 10% and 20%. As a result, they obtained cost decreases of 23% and 50% for the lower growth scenario and 34% and 72% for the higher growth scenario by 2030 and 2050 respectively, i.e. a cost projection range of 1,361 to 1,603 $/m^3/d$ for 2030. However, these cost estimations do not take into account effects from scale, as the authors acknowledge.

Given the differences in the actualization date and average reference cost values used for the projections, the results from the cited and the present studies will be compared in terms of relative cost reductions, as presented in table 9.

Table 9. Comparison of cost reduction projections from different studies in the literature.

Industrial growth and learning scenarios	**Unit scale assumptions**	**Cost reductions (%)**	
		2030	**2050**
Loutitadou, 2014 10% annual growth, NA	Cost projections for three different unit scales	35-37%	NA
Caldera and Breyer, 2017 10% annual growth, 15% learning rate 20% annual growth, 15% learning rate	Scale not considered	 23% 34%	 50% 72%
Mayor, 2018 BAU: 10% annual growth, 12% learning rate HIGH: exponential growth, 20% learning rate SDG boom: 10% growth until 2020 20% growth 2020-2030 15% growth 2030-2050	Logistic projection of historical trend in average unit scale	 17% 25% 33%	 35% 50% 66%

The projected cost reductions in this analysis are more conservative than those in the equivalent growth scenarios by the other studies, and only in the highest growth scenarios similar cost reductions are forecasted. The observed differences are mainly due to the different approaches to apply the scale and learning effects in the projections. Our assumption that average unit capacity increases following the observed historical trend also involves that the new installed capacity is achieved with progressively fewer but bigger units. Since learning is associated to the building of new plant units (due to improvements in infrastructure and processes) rather than to capacity per se, it is logical that learning slows down parallel to the reduction in the number of additional units over time (Grübler, 1998; Wilson, 2012). Such phenomenon has been captured in this study through the use of number of units as a measure of experience to derive the learning rates, and the subsequent application to number of units based industrial growth scenarios for the development of cost projections, as opposed to the use of installed capacity by the other studies. The methodological approach presented and the combination of industrial growth and learning scenarios proposed aim to provide modellers with a range of possible cost evolution pathways covering an array of feasible future situations that hold a rational basis from a historical and technological dynamics point of view. From a market perspective, a natural continuation of current trends would lead to the business as usual (BAU) or even moderate (MOD) scenarios, with technology demands contained by the energy dependence penalties on costs and the competition with other alternatives such as water recycling or water transfers. From a technological perspective, Ghaffour et al. (2013) and Alvarado-Revilla (2015) affirm that there is limited room for further cost reductions, and only marginal improvements may be achieved through the optimization of chemical dosing and post-treatment, new cleaning methods without need to shut down the desalination unit, combination with nanofiltration for pretreatment, environmentally friendly intakes, the use of renewable energy, and monitoring and control systems. However, the possibility of a demand pull effect triggered by the increasing water scarcity due to climate change, and/or the implementation of acceleration policies within the SDGs agenda, may open the floor for the more optimistic growth scenarios resulting in a stimulation and acceleration of the learning process in the mentioned lines.

With regards to the thermal technologies, as discussed above the advanced growth stage approaching saturation at the industry and unit scale levels, with market prospects limited to the Middle East, strongly suggest against the hypothesis of a continuation of the historical learning rate. Therefore, for modelling purposes it is recommended to use only the moderate learning scenarios, or/and the zero learning scenarios for low energy demand or climate change mitigation assumptions. Some of the marginal technological and cost reduction opportunities for these technologies may come from combinations with other desalination techniques (MED-RO systems, MED-nanofiltration systems, MSF-RO systems) as well as with renewable energies (CSP) (Khawaji et al., 2008; Mezher et al., 2011).

5. Conclusions

This study has measured and discussed the historical trends in unit and industry scaling and capital costs of the three main desalination technologies (MED, MSF and RO). Building upon this historical trend analysis, it has also derived industry growth and cost projection scenarios considering both learning and scale effects separately.

The historical deployment of desalination technologies was found to follow a very clear logistic growth trend at the industry scale and, to a lesser extent, also at the unit scale. Thermal technologies are found to be well advanced in their growth curves and approaching saturation, with deployment peaks likely to occur before 2050. This may be explained by the lower competitiveness in costs and energy efficiency as compared to RO, which has relegated their market to the particular low-cost energy conditions of the Middle East. Meanwhile, marginal new market opportunities for MED may come from the coupling with concentration solar power. RO, in turn, reports an earlier stage in the growth curve and further room for future growth. However, the uncertainty to make future growth forecasts is higher, and so are the range of possible industrial growth scenarios spanning from a strictly logistic trend, through to a more drastic demand pull driven increase.

Looking at the extent and duration of the diffusion process, desalination technologies are found to overall meet a series of common temporal and spatial diffusion patterns identified in other technological families, particularly energy technologies.
Parallel, a decoupled estimation of the scale and learning effects on historical cost reductions reveals that learning has been the dominant driver for cost reductions of desalination, with descaled learning rates of 23%, 30% and 12% for MED, MSF and RO respectively. The highest influence of scale in cost reductions is found in MED, with an exponential economies of scale factor of 0.71 that plays out in a reduction from a 36% traditional learning rate to a 23% descaled learning rate.

The application of these results to derive future cost projections leads to limited cost reduction prospects for thermal technologies, with a maximum of 6-8% by 2030 and 8-10% by 2050. As for RO, more substantial reductions are obtained, with ranges of 12-33% by 2030 and 18-66% by 2050 between a moderate logistic shaped growth and a demand pull effect by i.e. SDGs policies.

These findings provide important insights that should be taken into account by modelling frameworks integrating desalination as a possible solution to address water scarcity challenges and pathways to achieve SDG targets, and/or to optimize water-energy-land resource management. Particularly, they can prevent excessively optimistic and unrealistic assumptions of future desalination capacity that overestimate/overemphasize the potential of desalination to alleviate water stress, which may promote water supply focused approaches to the problem undermining the water demand management side.

6. Data collection, analysis and associated limitations

6.1 Data sources and treatment

The analysis of desalination technologies applying the above described methodological framework was done using data from the Global Water Alliance's Desaldata database[1] for the period 1945-2016. All available data for each target technology was checked for consistency. A number of data assumptions and treatment steps were applied to ensure data homogeneity, consistency and usability.

[1] https://www.desaldata.com/

First, the EPC cost data - which provide the best available information on the final price paid by the contractor on a project basis - were adopted as a proxi for capital investment costs. The EPC cost consists of all the direct capital costs (apart from land cost) of the plant and the EPC contractor's cost of services, including detailed design, contractor permitting, and project management costs (Loutatidou, 2014).

These data were available for 85%, 90% and 48.4% of the projects for MED, MSF and RO technologies respectively. Amongst the projects with missing cost data, 63% (MED), 31% (MSF) and 89% (RO) correspond to projects built after the year 2000. All EPC cost data were converted to US dollars applying the conversion rate corresponding to the contract online date, and then actualized to $2010 using the GDP deflator index available at the World Economic Outlook database[2]. A proxy for specific project costs was calculated by dividing the actualized EPC cost by the project capacity. The resulting specific project costs were compared for consistency, and several outliers with significantly higher costs than the average for the year were identified for MED and RO projects built after year 2000. A more detailed examination case by case of the most striking outliers revealed that these were mainly macro or combined projects for which the EPC price included both the desalination plant and other additional infrastructure, thus resulting in an overestimate of specific costs when divided by the projected plant capacity. To avoid distorsions or overestimations in the computation of annual average trends due to this effect, an upper boundary constraint was set up in \$4,000/m^3/d for RO projects and \$5,000/m^3/d for MED projects for the period 2000-2016 based on capital cost trends reported in the literature. This treatment was especially important considering that the bulk of MED and RO projects with missing cost data were concentrated in that period.

A second assumption relates to the number of units per project. Both thermal and reverse osmosis desalination projects can be comprised by a single unit or plant, or by several units. When information on the number of units composing the project was not available, a single unit project was assumed. In those cases where information on the installed capacity was missing, data were searched for in other sources and, when not found, the projects were excluded from the analysis. The number of projects finally excluded amounted for less than 1% of the total projects.

Finally, a pre-screening of the percentage of projects that are currently offline due to end-of-life or decomissioning was performed in order to assess the need for assumptions on plant decommissioning rates due to industry stock ageing. Resulting percentages of offline plants (including the categories of '*presumed offline*', '*Offline (Decommissioned)*' and '*Offline (Mothballed)*' within the plant status indicator provided by the Desaldata database) over the total industry stock by 2016 were 7.5% for MED, 12.7% for MSF and 6.2% for RO, from which 80-90% were '*presumed offline*' based on the average plant life and the online date. Given the relatively low percentages strongly based on assumptions, the inclusion of a decommissioning component was not deemed necessary.
As a result, the analysis was built upon data from 1,306 MED, 829 MSF and 15,776 RO projects coming online in the periods 1945-2016, 1950-2016 and 1962-2016 respectively. The limitations resulting from the adopted assumptions are discussed in section 4.4.

[2] International Monetary Found, World Economic Outlook database, February 2017. http://data.imf.org/regular.aspx?key=60998112

6.2 Logistic functions to describe technological growth patterns

Amongst the technology innovation literature, the use of S-shaped logistic functions is a common method for describing technological growth patterns (Grubler, 1990, 1998). Similarly, it has been accepted and applied for trend extrapolation purposes when data cover more than half of the S-curve with high fit confidence levels (Martino, 1983; Modis, 2007; Kucharavy, De Guio, 2011). A large record of historical evidence has shown that technologies go through a three stage process during their lifecycle: an initial period of slow growth, a sudden acceleration when the technology reaches high maturity and market confidence, and a final slow down until it reaches a technological deployment maximum (or saturation point) (Grubler et al., 1999). These three stages are well represented by an S-shape curve that, when fitted to the historical cumulative growth data of a given technology, allows to obtain a 3-parameter logistic function as described in box 1.

Box 1. Logistic function and parameters

$y = \frac{K}{1+e^{-b(t-tm)}}$ and $\Delta t = log81 \times b^{-1}$

With:

K = asymptote (saturation level)

b = diffusion rate (steepness)

Δt (delta t) = time period over which y grows from 10% to 90% of *K*

tm = inflection point at *K/2* (maximal growth)

Logistic functions were selected as the most appropriate method to analyse the extent and timing of technological growth for technology comparison and scenario projection, as opposed to other methods such as annual or periodical growth rates. The selection was made following the rational by Wilson (2009), whereby logistic functions provide the following advantages: 1) they allow to measure the extent of growth, not only the rate; 2) a single curve can be used to describe the growth along the different technology lifecycle stages, as opposed to the need to delimitate and measure changing growth rates in the different stages; 3) a single model can be applied to a range of technologies which significantly enhances comparability and reproducibility, 4) they avoid the need for a common denominator or reference unit for comparison (i.e. growth of what?). Therefore, logistic functions were used to characterize growth patterns for the selected desalination technologies at both the industry and unit scales. When fitting logistic functions to historical data, the obtained K and ΔT parameters allow to respectively characterize the extents and rates of scaling for different technologies, as well as making comparisons between them (Wilson, 2009, 2012). The suitability of this model for both types of analysis has been proven for a number of technologies (Wilson, 2012; Grubler, Wilson, 2014; Bento, Wilson, 2016) .

The acceptability of estimated logistic models was set based on two criteria:

- Fit quality: minimum goodness of fit measure (adjusted R^2) of 0.90.
- Sufficient historical data to estimate asymptote: historical data reaches at least 60% of estimated asymptote parameter (K). This criteria was defined by Wilson (2009), as he noted that for technologies with short historical time periods the data are equally well described by logistic and exponential growth curves, so a high goodness of fit for a

logistic model risks false precision. To prevent this situation, he proposed a 60% coverage of the full S-curve range threshold as a fit reliability criteria. In general, it is acknowledged within the technology innovation literature that acceptable logistic fits should cover at least half of the S-curve range (Debecker, Modis, 1994; Modis, 2007).

Growth function parameters were estimated using the "Logistic Substitution Model II" or 'LSM2' software. LSM2 was developed at IIASA and is freely available online.[3]
It should be noted that given the common use of growth rates to derive cost projections in the desalination literature, growth rates of RO at the global scale were also estimated and used in the discussion for comparison with other cost projection studies.

6.3 Industry scaling and spatial diffusion analysis

Industry scaling refers to a rapid and extensive growth in installed capacity or installed units that technologies experiment during their lifecycle (Wilson, 2009). Industry scaling of a technology marks the beginning of the diffusion stage in the technology's innovation cycle, which is characterized by the widespread adoption of the technology over time, in space, and between different social strata (Grubler, 1998).

Industry scaling dynamics of desalination were described fitting logistic functions to historical data series showing the evolution of cumulative installed capacity and cumulative installed units on a yearly basis. The unit level was defined as each self-functioning plant, which can be installed individually or in series in multi-unit projects.

To account for spatial diffusion, the analysis was done both at the global scale and disaggregating the data into initial (core), subsequent (rim) and late stage (periphery) adopting market regions, following the categorization by Grubler (1998). Market regions were singled out by plotting the evolution of cumulative installed units over time by geographical regions, and grouping them based on the timing of commercial uptake and upscaling into the aforementioned market stage categories. The resulting aggregation of geographical regions into diffusion regions for the three analyzed desalination technologies is presented in table 10.

Table 10. Aggregation of geographical regions into diffusion regions for MED, MSF and RO desalination technologies.

	MED	**MSF**	**RO**
Market region	**Geographical regions**		
CORE	WEur + Nam	Mid East	Mid East + Nam
RIM	Mid East	WEur+Lam+EAsPac+Nam	WEur+ EAsPac
PERIPHERY	Lam+SAf+Sas+ EAsPac+EE-CA	SAs+EE-CA+SAf	SAs+EE-CA+SAf

[3] For further information on LSM2 and for downloads:
http://www.iiasa.ac.at/Research/TNT/WEB/Software/LSM2/lsm2-index.html

Region acronyms: East Asia-Pacific (EAsPac), Eastern Europe-Central Asia (EE-CA), Latin America–Caribbean (Lam), Middle East-North Africa (Mid East), North America (Nam), Southern Asia (SAs), Sub-Saharan Africa (SAf) and Western Europe (WEur).

6.4 Unit scaling analysis

Parallel to the growth in industrial capacity, technologies usually experiment a process of increase in size or capacity at the unit level, which has been referred to as up-scaling or unit scaling (Wilson, 2009).

Unit scaling dynamics were analyzed using logistic functions fitted to historical data on average capacity of unit additions and maximum capacity of the industry stock. The former provides a measure of the average trend followed by the industry. It was estimated on a yearly basis by computing the average of new units coming online every given year. The latter indicates the timing of the unit upscaling milestones (or the scale frontier) achieved by the industry. It was estimated by computing on a yearly basis the maximum unit capacity coming online every year, and then estimating the envelope or maximum capacity registered to each given year.

Unit scaling dynamics were similiarly analyzed at the global scale and by market regions, using the aggregation described in section 2.4 above. An additional sensitivity analysis was conducted for average capacity of unit additions at the global scale, since these curves would be used to build the projections in the cost scenario generation section. The analysis tested the variability in K and delta T when taking 100%, 90%, 75% and 50% of the samples and comparing the fits amongst alternative models (see appendix 2).

6.5 Capital cost dynamics and economies of scale

The dynamics of capital costs for the selected desalination technologies were described by analyzing the historical evolution of specific capital costs, as well as the effects of economies of scale and learning.

The evolution of capital costs normalized by the installed capacity - or specific capital costs - was captured by plotting the annual average specific costs over time. Annual averages were computed from new projects coming online every given year with cost data availability.
The economies of scale effect is a common engineering concept that describes the falling marginal costs of production as production capacity or output increases (Wilson, 2012). Economies of scale were assessed using the traditional formula applied in the engineering literature (Eq. 1) (Joskow, Rose, 1985; McCabe, 1996; McNerney et al., 2011), whereby the costs and sizes of two plants relate as follows:

$$[1]\ \text{Cost}(2) = \text{Cost}(1) * (\text{Size }2/\text{Size}1)^{p}$$

where cost and size are the absolute investment cost and total sizes of plants 1 and 2, and p is the exponential scale coefficient with $p<1$ denoting positive economies of scale effects, i.e. specific costs decline at larger scales. Based on this principle and in order to make a comprehensive estimation of the scale effect building upon the maximum number of projects, the scale coefficient was estimated by plotting on a log-log scale the investment costs and project sizes for all the projects with cost data availability for each technology type. Fitting a linear regression to the data, the scale coefficient is given by the slope of the line.

6.6 Learning: traditional and descaled learning

The learning effect makes reference to the reduction in production costs due to improvements in the product quality and production process as a result of experience or 'learning by doing' and 'learning by using' (Arrow, 1962; McCabe, 1996; Grübler, 1998; McDonald, Schrattenholzer, 2001).

Learning phenomena have traditionally been estimated through the so called learning curves, progress curves or experience curves, which describe the technological pattern by representing specific investment costs or unit production costs over a measure of experience, typically cumulative installed capacity or output (units) (Dutton, Thomas, 1984; Argote, Epple, 1990; Grübler, 1998; Argote, 1999). Deriving the linear estimation of the aforementioned learning curve results in the learning rate, which is defined as the rate at which specific costs decline for every doubling of cumulative experience (McDonald, Schrattenholzer, 2001). However, traditional capacity-based learning curves have been argued to overestimate the effects of learning due to the inclusion – or non ex-ante exclusion – of other drivers of cost reductions that conflate with experience (Coulomb, Neuhoff, 2006; Weiss et al., 2010; McNerney et al., 2011; Wilson, 2012). Particularly, in several cases the effect of economies of scale has been found to explain an important part of cost reductions that were usually attributed to learning (Dutton, Thomas, 1984; Nemet, 2006; Qiu, Anadon, 2012; Healey, 2015). Healey (2015) proposed an alternative version of learning curves with special relevance for applications in energy modelling, which represented 'de-scaled' specific investment costs – these are costs where economies of scale effects arising from larger unit sizes have been removed – over cumulative units as a measure of experience. These curves were reported to solve a twofold problem: first, they detached the effect of unit scaling in the estimation of learning, thus allowing for more accurate estimates; and second, they avoided the confusion generated by the fact that both unit scale and experience expressed as cumulative capacity are measured in the same unit (MW in the case of energy technologies and m^3/d in the case of desalination).

Given that the ultimate goal of this work is to provide data for integrated modelling, the learning curve model proposed by Healey (2015) was selected as the most suitable methodology. The computation process was performed in three steps:

1) Descaling the historical series of annual average specific costs for each technology by applying the methodology proposed and described by Healey (2015).
2) Plotting the resulting specific descaled costs over the annual series of cumulative installed units on a log-log scale.
3) Deriving the learning rate through equations 2 and 3:

$$[2]\ Cost_t = Cost_{t0} * (CC_t / CCt_0)^{\alpha}$$

$$[3]\ LR = 1 - 2^{\alpha}$$

where $Cost_t$ is unit cost at time t, $Cost_{t0}$ is the unit cost at the previous time step, CC_t is the cumulative number of units installed by time t, CC_{t0} is the initial cumulative number of units, and α is the learning coefficient. α is obtained as the slope of the linear regression fitted to the data plotted in step 2. Sensitivity and variability were measured by carrying out individual fits for the

different growth stages observed in the data. As a result, two learning rates corresponding to the initial stage and the period of more intense growth were obtained for each technology. The results of this analysis are included in appendix 3.
Additionally, learning rates were also estimated using the traditional learning curves (representing original costs vs cumulative capacity) applying steps 2 and 3, in order to compare the extent of influence of the scale effect.

6.7 Capital cost projections to 2020, 2030 and 2050

Economies of scale and learning usually explain a very high percentage of the capital cost reductions over time experimented by technologies along their lifecycle (Grübler, 1998). Therefore, when applied to future projections of industrial deployment and average unit scale capacity, they allow to extrapolate the historical trend and derive approximations of future cost reductions. In the particular case of desalination, Gao (2017) found that the three variables with highest correlation with the capital cost of a RO plant were unit size (due to the scale effect), installed capacity (due to the learning effect) and GDP in the hosting region (reflecting construction cost differentials). For the purpose of this work, the projections were done at the global scale using global data, and thus the third element does not apply.

Specific capital cost projections to 2020, 2030 and 2050 were generated for a series of scenarios of industrial growth and average unit upscaling. Reference specific cost values for the projections were defined by taking an average of specific cost values registered in the last 5 years of the data series, and adjusting them to the average scale capacities taken as a reference for the projections. Cost projections for each scenario were then derived in two steps. In a first step, the obtained scale parameter was applied to the reference cost based on the average unit scale projections for each time horizon, using the above presented economies of scale formula (Eq. 1). In a second step, the learning rate was applied to the scale-adjusted cost based on the installed capacity projections for each time horizon, using the learning formulae (Eq. 2 and 3).

The scenarios were developed under a number of assumptions. In the case of the thermal technologies, a logistic projection of the industrial growth historical trend was used in all the scenarios. This assumption is based on the high saturation and low uncertainty in the logistic fits obtained in the diffusion analysis. At the unit scale level, two average capacity projections were developed following logistic and Gompertz curves, being Gompertz the model providing the second best fit in the sensitivity analysis (see section 6.5 and appendix 2), in order to account for uncertainty. In terms of learning, three learning alternatives - historical rate, half of the historical rate, and zero learning - were considered in order to capture the historical trend break and presumable learning rate reduction observed in the learning curve (see appendix 3). Three scenarios for each technology were developed applying the different learning rates to the logistic projections of industrial and average unit capacity. In order to simplify the number of scenarios, the alternative (Gompertz) unit capacity projection was tested in only one additional scenario assuming the moderate learning rate - which is considered the most probable.

In the case of reverse osmosis, due to the earlier stage in the technology life cycle, leading to higher uncertainty on the possible evolution at the industrial growth level, a wider range of projection models was considered. Three scenarios were firstly developed applying logistic (moderate, MOD), linear continuation of the current 10% growth trend (business as usual, BAU), and exponential (high, HIGH) projections. A fourth scenario (SDG boom) captures the possibility of a demand pull acceleration between 2020 and 2030 at twice the actual growth rate due to facilitating policies to achieve the SDGs, that slightly slows down to a 15% after 2030. At the unit capacity level, the same procedure as in thermal technologies was followed, albeit in this case the Gompertz projection was applied to the business as usual scenario projecting the current trend. In terms of learning, the detection of a recent trend break in the RO curve, as in the case of the thermal technologies, lead to the consideration of several learning alternatives. A low learning at half the historical rate (6%) was applied to the logistic industrial growth projection after 2020, concurrent with the beginning of a gradual slow down phase. For the BAU scenarios, the historical rate (12%) was maintained. As for the case of the high growth scenarios (HIGH and SDG boom), a learning rate of 20% was considered based on a historical leap of 8 percentage points registered between the initial growth stage (4% learning) and the historical maximum growth stage (12%). The resulting set of scenarios, assumptions and projections are summarized in table 2 and appendix 4.

6.8 Limitations of the analysis

There are limitations to this analysis related to data quality constraints and the applied methodological approach.

The first set of limitations are related to the completeness and quality of the data available in the Desaldata database and required assumptions. First, the use of EPC price as an approximation for the capital cost involves a certain overestimation, as EPC price also includes the EPC contractor's cost of services. However, it is necessary as a best available proxy for real capital costs. Second, EPC price data were missing for a significant number of the projects registered in the Desaldata database, especially for online dates later than 2000. This may have reduced the representativeness of the average cost estimations as well as the final tails of the learning curves for the period 2000-2016. Caldera and Breyer (2017) makes a detailed analysis of this phenomenon for RO. Third, the need to assume as 'single unit' those projects lacking data on the number of units may introduce some distortions in the average and maximum capacity estimations. Although individual checks were done for the larger scale projects, a complete check-up of all the projects was impossible due to the considerable number of missing data (4% for MED, 6% for MSF, and 26% for RO). However, the non-checked projects were mostly small scale, so the assumption of a single unit was considered acceptable.

The second set of limitations is related to different aspects of the methodological approach. The selection of S-curves to explain technological growth, and especially to extrapolate future values, has inherently a certain degree of uncertainty as will all trend forecasting models. S-curves have been widely used to describe natural growth patterns in different fields, including technology innovation (Modis, 2007). S-curves have been used for extrapolation and forecasting in the technology forecasting literature, with the general acknowledged observation that the quality of the forecast will improve with the accuracy of the data and the extent of the section of the S-curved covered (Martino, 1983; Debecker, Modis, 1994; Modis, 2002, 2007; Kucharavy, De Guio, 2011). Debecker and Modis (1994) obtained a rule-of-thumb general result that given at least half of the S-curve range and a precision of better than 10% on each historical point, the uncertainty on K will be less than 20% with 90% confidence level. In this study a 60% of saturation threshold and 90% confidence level were adopted following the criteria by Wilson (2009). However, the need to make assumptions on the future evolution of installed capacity and average unit size in order to build the scenarios led to the use of the global scale fitted S-curves as a 'best approach' to make projections, rather than assuming a constant value, even though some of the fits did not meet the stated criteria. This was the case for average unit capacity fits for the three technologies and the cumulative installed capacity fit for RO. The uncertainty was partly addressed by considering several upscaling scenarios at the unit and industry level applying different growth models. It should nevertheless be noted that the level of uncertainty of these projections is high and the results should be taken with caution.

A second limitation relates to the selection of regions for the spatial diffusion analysis. The classification of geographical regions into the different 'diffusion regions' was done based on the timing of diffusion. However, this involves the inclusion within each group of regions with very different characteristics, markets and feed water sources, which may constitute another source of noise in the data reducing the quality of the fits.

Another possible limitation of this study is the adoption of plant units instead of projects as a measure of experience along with installed capacity. This was done to account for the modularity aspect reflecting one of the main differential characteristics amongst the analyzed technologies. An analogy could be made with studies analyzing diffusion of wind energy, where individual windmills are taken as units instead of wind farms (Berry, 2009; Qiu, Anadon, 2012).

A final possible limitation may come from the analysis of RO as a single technology without differentiating between sea water and brackish water desalination plants. Such differentiation would presumably lead to more homogeneous results in the unit scaling analysis, since brackish water plant units tend to be smaller. Meanwhile, the feed water type has been proven as one of the determinants for the capital cost of a RO plant (Loutatidou et al., 2014). Deriving separate average cost estimations and projections for both types of plants would result in more precise estimations. This is considered as a possible follow up of this work.

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Appendixes

Appendix 1. Criteria for addressing uncertainty in average capacity and maximum capacity fits and description of individual cases.

The regression of logistic models to historical data on average and maximum unit capacities presented several cases with lower quality fits and higher levels of uncertainty than the industrial growth regressions. A diagnosis on a case by case basis was done to identify the different types of sources of uncertainty in the irregular fits and develop a consistent set of sensitivity analyses and strategies to address them. The different types of uncertainty sources identified and the strategies and criteria applied to each type are described in tables A1, A2 and A3. The individual cases within each type are singled out in table A4.

Table A1. Type cases, uncertainty sources and strategies applied to reduce uncertainty in average capacity and maximum capacity fits.

Case type	Uncertainty source	Strategy
1	Very noisy data with no fit	Five year moving average to smooth the trend. If fit quality is still below R^2=0.5, considered no fit.
2	Implausibly high K values	Constrain the functions with an exogenous K scenario. Exogenous scenarios were developed on a case by case basis based on a selection of reference trends obtained from a trend literature review and expert consultation (tables A2 and A3).
3	Multi-phase growth	Regression of individual curves for the different phases and an envelope curve for the whole data set.
4	Presence of clear outliers	When there is only one clear outlier that introduces noise, the outlier is ignored. When there are more than one outlier defining a possible different trend, a sensitivity analysis is done providing both fits with and without outliers.

Table A2. Shortlist of critical trends selected from the literature review and expert consultation and taken as reference for determination of exogenous K scenarios in cases type 2.

Technology	Trends
MED	Maximum unit capacities limited by scaling and fouling. Maximum registered operative capacity to date is 54,552 m^3/d presumably for two-unit plant. Manufacturers seem comfortable with unit capacities between 10,000 and 20,000 m^3/d, and higher project capacities are sought through the combination of several unit in parallel.
MSF	Historical average and maximum capacity have evolved closely and parallel over time.

	The deployment rate has decreased considerably in the last decade, with R&D investment efforts shifted towards other technologies with higher market demand (RO). Absence of outlier experiments to exceed current average values.
RO	Wide variety of unit capacities across all regions. Average capacities in the core are overall higher than world averages over time. Maximum capacity in the core has historically upscaled faster and to a higher extent than in the rim.

Table A3. List of experts who provided feedback during the consultations.

Expert name	Position	Institution
Marina Arnaldos	Water Resources, Production and Regeneration Area Manager	Cetaqua
Diego-César Alarcón-Padilla	Head of the solar desalination unit	Plataforma Solar de Almería - CIEMAT

An individual explanation of the cases found within each category type is provided in table A4.

Case type	Case	Description
1	MED Avcap core	Noisy data provided a low fit with R^2=0.2. A 5 year moving average was applied improving R^2 to 0.44.
1	MSF Avcap rim	Very noisy data resulted in no fit. A 5 year moving average was applied without significant improvement. No fit was concluded.
1	MSF Avcap per	
2	MED Avcap per	Recommended average values for K scenario by experts were 10.0-20.0 10^3m^3/d. Best fits were found with scenarios of K= 20.0-25.0 m^3/d. An intermediate scenario of 22.0 10^3m^3/d was assumed.
2	MED Avcap global	Recommended average values for K scenario by experts were 10.0-20.0 10^3m^3/d. Best fits were found with scenarios of K=20.0-25.0 m^3/d. An intermediate scenario of 22.0 10^3m^3/d was assumed.
2	MED Maxcap rim	Best fits were found with scenarios of K>60.0 10^3m^3/d. This threshold value was adopted as a reference scenario taking into account the trends cited in table A2 as limitations for further upscaling.
2	MSF Avcap core	Best fits were found with scenarios of K>110.0 10^3m^3/d. This threshold value was adopted as a reference scenario taking into account the trends cited in table A2 as limitations for further upscaling.
2	MSF Avcap global	Best fits were found with scenarios of K>100.0 10^3m^3/d. This threshold value was adopted as a reference scenario taking into account the trends cited in table A2 as limitations for further upscaling.
2	MSF Maxcap core	The original fit provided by the model was below the historical data in the period from 2005 to 2015. The fit was adjusted with the minimum K allowing to correct for this error with the best fit. The resulting value was adopted of K=110.0 10^3m^3/d was as scenario.

2	MSF Maxcap rim	A scenario assuming saturation has been achieved was considered given the trends in table A2 and the fact that no new plants have been built since 1970. Therefore, the scenario was set as K=highest historical value, in this case k=36.0 $10^3 m^3/d$.
2	MSF Maxcap per	A scenario assuming saturation has been achieved was considered given the trends in table A2 and the fact that no new plants have been built since 1970. Therefore, the scenario was set as K=highest historical value, in this case k=16.0 $10^3 m^3/d$.
2	MSF Maxcap global	The same situation as in Maxcap MSF core was obtained, since the core region has dominated and shaped the global trends. Therefore, the same criteria was adopted to keep consistency.
2	RO Avcap core	Given the uncertainty in the trends and lack of reference data to develop an exogenous scenario, a test with a 5 years moving average was done. The results (K=28.0) are consistent with the trends in table A2, and thus the fit was accepted.
3	MED Maxcap per	A two phase upscaling process was observed. The first phase fit (F1) covers the period 1945-1990. The second phase fit (F2) covers the period 1990-2016. Given the high quality and consistency with trends in table A2, the second phase is regarded as envelope fit for the whole period.
3	MED Maxcap global	A two phase upscaling process was observed. The first phase fit (F1) covers the period the period 1945-2000. The second phase fit (F2) covers the period 2000-2016, where the obtained K value in phase 1 (inflexion point setting the end of phase 1 and beginning of phase 2) was withdrawn from the data points in the second phase in order to reset the departing point before undertaking the second logistic fit. The first row provides the global parameters resulting from a single logistic curve fitted to the whole data set fixing K as the rounded sum of Ks in phase 1 and 2.
4	MED Avcap rim	A single clear outlier in 2012 was ignored in the regression.
4	RO Avcap rim	A single clear outlier in 2016 was ignored in the regression.
4	RO Maxcap core	The possible variability caused by three extremely large outliers was tested. Two alternative fits were generated: an upper boundary with outliers and a lower boundary without outliers (F1 and F2 in table 6 respectively).
4	RO Maxcap rim	
4	RO Maxcap global	

Avcap: average capacity
Maxcap: maximum capacity

Appendix 2. Sensitivity analysis for average capacity of unit additions at the global scale

The sensitivity analysis consists of a test on the variability in K and ΔT when taking 100%, 90%, 75% and 50% of the historical data samples, as well as the variability amongst the best fits from alternative models.

1.1. MED TECHNOLOGY

Logistic fits for average capacity of unit additions of MED in the world region including 100%, 90%, 75% and 50% of available data points.

Fit number	Data points	% of data points	K*	T0	ΔT	Alpha	R^2
FIT 1	70	100	22,000	2,012	21	0.19	0.85
FIT 2	63	90	22,000	2,012	21	0.19	0.85
FIT 3	53	75	22,000	2,012	21	0.19	0.84
FIT 4	35	50	22,000	2,012	20	0.20	0.84

* Exogenous scenario set up based on expert consultation to avoid exponential values.

Variability amongst fits.

Fit number	% of data points	% of change in K from FIT 1	% of change in T0 from FIT 1	% of change in ΔT from FIT 1
FIT 2	90	0.000	0.000	0.001
FIT 3	75	0.000	0.000	0.005
FIT 4	50	0.000	0.000	4.762

Regression results from different models for average capacity of unit additions of MED.

Model	K	T0	ΔT	Alpha	R^2
Logistic	22,000	2011	21	0.20	0.87
Gompertz	22,000	2009	24		0.85
Sharif-Khabir	NF*	NF	NF	NF	NF
Floyd	NF	NF	NF	NF	NF

*NF: No fit provided by the LSM2 program.

Variability amongst models.

	% variation from logistic		
Model	K	T0	ΔT
Gompertz	0.00	0.15	-14.29

1.2. MSF TECHNOLOGY

Logistic fits for average capacity of unit additions of MSF in the world region including 100%, 90%, 75% and 50% of available data points.

Fit number	Data points	% of data points	K*	T0	ΔT	Alpha	R^2
FIT 1	58	100	100,000	2008	24	0.19	0.88
FIT 2	52	90	100,000	2008	24	0.19	0.87
FIT 3	44	75	100,000	2008	24	0.19	0.86
FIT 4	29	50	100,000	2008	23	0.20	0.83

* Exogenous scenario set up based on expert consultation to avoid unrealistically high projected K values.

Variability amongst fits.

Fit number	% of data points	% of change in K from FIT 1	% of change in T0 from FIT 1	% of change in ΔT from FIT 1
FIT 2	90	0.000	0.000	0.000
FIT 3	75	0.000	0.000	0.002
FIT 4	50	0.000	0.002	0.045

Regression results from different models for average capacity of unit additions of MSF.

Model	K	T0	ΔT	Alpha	R2
Logistic	100,000	2008	24	0.18	0.88
Gompertz	100,000	2005	27		0.86
Sharif-Khabir	NF*	NF	NF	NF	NF
Floyd	NF	NF	NF	NF	NF

*NF: No fit provided by the LSM2 program.

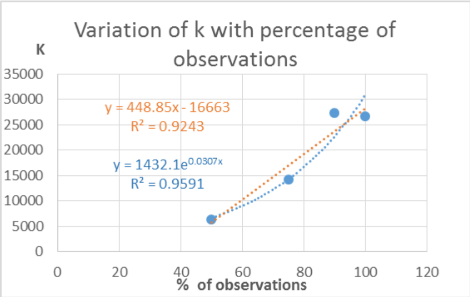
Variability amongst models.

	% variation from logistic		
Model	K	T0	ΔT
Gompertz	0.00	0.17	-12.82

1.3. REVERSE OSMOSIS TECHNOLOGY

Logistic fits for average capacity of unit additions of RO in the world region including 100%, 90%, 75% and 50% of available data points.

Fit number	Data points	% of data points	K	T0	ΔT	R^2
FIT 1	51	100	26,692	2036	63	0.84
FIT 2	46	90	27,359	2037	63	0.82
FIT 3	38	75	14,260	2023	55	0.80
FIT 4	26	50	6,425	2007	32	0.75



Variability amongst fits.

Fit number	% of data points	% of change in K from FIT 1	% of change in T0 from FIT 1	% of change in ΔT from FIT 1
FIT 2	90	-2.499	-0.025	-0.010
FIT 3	75	46.577	0.645	0.388
FIT 4	50	75.929	1.434	1.508

Regression results from different models for average capacity of unit additions of RO.

Model	K	T0	ΔT	Alpha	R^2
Logistic	26,692	2036	63	0.07	0.84
Gompertz	26,692	2036	120		0.83
Sharif-Khabir	NF*	NF	NF	NF	NF
Floyd	NF	NF	NF	NF	NF

*NF: No fit provided by the LSM2 program.

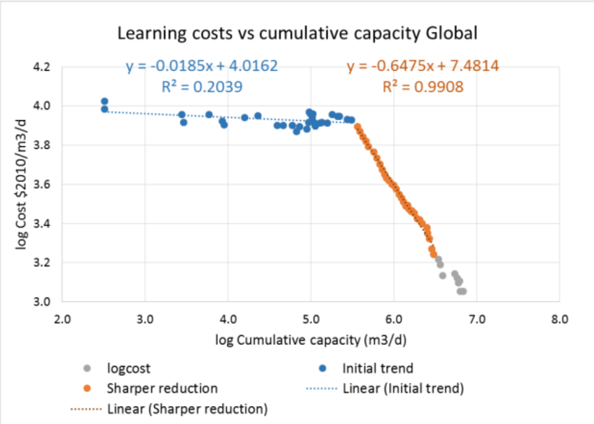
Variability amongst models.

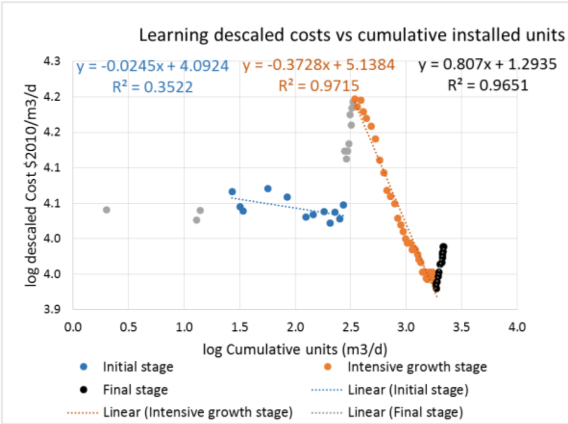
	% variation from logistic		
Model	K	T0	ΔT
Gompertz	0.00	-0.01	-91.37

Appendix 3. Learning curves and rates for desalination technologies at the global scale

3.1 Learning curves for MED

Traditional and descaled learning curves for MED in the different growth stages.



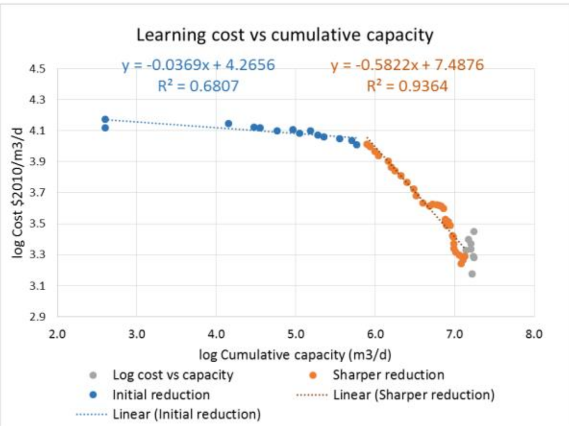


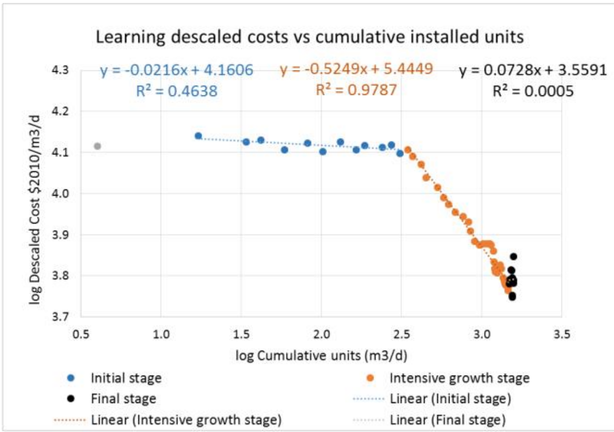
Learning rates MED

Parameters	Initial stage	Intensive growth stage	Parameters	Initial stage	Intensive growth stage	Final stage
Coefficient (a)	-0.02	-0.65	Coefficient (a)	-0.004	-0.37	0.82
Progress rate (2^a)	0.99	0.64	Progress rate (2^a)	1.00	0.77	1.77
Learning rate (1-PR)	0.01	0.36	Learning rate (1-PR)	0.02	0.23	-0.77
R^2	0.20	0.99	R^2	0.35	0.97	0.97

3.2 Learning curves for MSF

Traditional and descaled learning curves for MSF in the different growth stages.



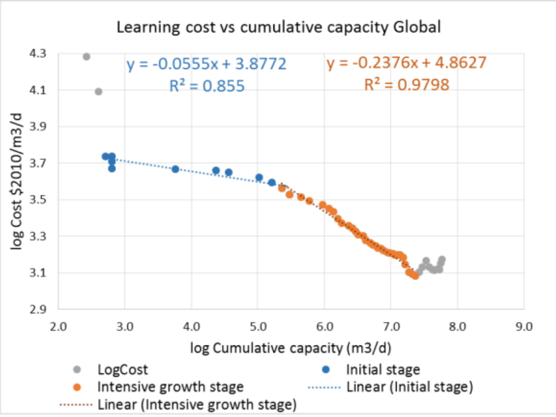


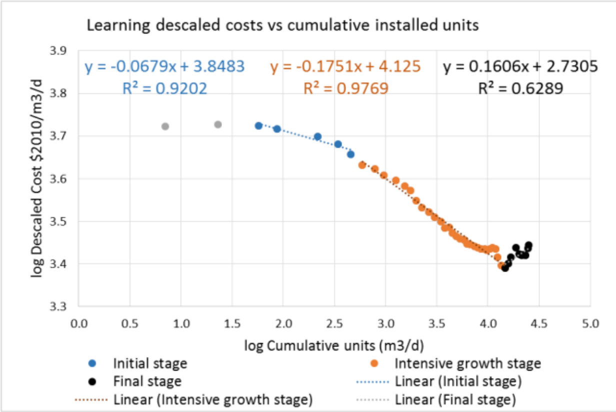
Learning rates MSF

Parameters	Initial stage	Intensive growth stage	Parameters	Initial stage	Intensive growth stage	Final stage
Coefficient (a)	-0.04	-0.58	Coefficient (a)	-0.02	-0.52	0.04
Progress rate (2^a)	0.97	0.67	Progress rate (2^a)	0.98	0.70	1.03
Learning rate (1-PR)	0.03	0.33	Learning rate (1-PR)	0.02	0.30	-0.03
R^2	0.68	0.93	R^2	0.46	0.97	0.00

3.3 Learning curves for RO

Traditional and descaled learning curves for RO in the different growth stages.





Learning rates RO

Parameters	Initial stage	Intensive growth stage	Parameters	Initial stage	Intensive growth stage	Final stage
Coefficient (a)	-0.07	-0.24	Coefficient (a)	-0.06	-0.18	0.16
Progress rate (2^a)	0.95	0.85	Progress rate (2^a)	0.96	0.88	1.12
Learning rate (1-PR)	0.05	0.15	Learning rate (1-PR)	0.04	0.12	-0.12
R^2	0.85	0.95	R^2	0.92	0.97	0.63

Appendix 4. Reference data and projections for the cost scenarios

Scenarios	Assumptions												
	Reference: 2016				2020			2030			2050		
	Specific costs ($2010/ m^3/d)	Installed Capacity (10^6 m^3/d)	Installed units	Av. unit Capacity (10^3 m^3/d)	Installed Capacity (10^6 m^3/d)	Installed Units (10^3 #)	Av. unit Capacity (10^3 m^3/d)	Installed Capacity (10^6 m^3/d)	Installe d units (10^3 #)	Av. unit Capacity (10^3 m^3/d)	Installed Capacity (10^6 m^3/d)	Installe d units (10^3 #)	Av. unit Capacity (10^3 m^3/d)
MED ZERO	1,800	6.82	2,164	15.0	7.52	2.19	20.0	9.29	2.23	24.2	10.35	2.25	25.0
MED MOD slow unit upscale					7.52	2.20	18.5	9.29	2.27	22.7	10.35	2.29	24.7
MED MOD					7.52	2.19	20.0	9.29	2.23	24.2	10.35	2.25	25.0
MED BAU					7.52	2.19	20.0	9.29	2.23	24.2	10.35	2.25	25.0
MSF ZERO	2,000	17.57	1,572	80.0	19.50	1.59	89.4	22.06	1.62	98.1	24.25	1.64	100.0
MSF MOD slow unit upscale					19.50	1.59	83.6	22.06	1.62	94.4	24.25	1.64	99.4
MSF MOD					19.50	1.59	89.4	22.06	1.62	98.1	24.25	1.64	100.0
MSF BAU					19.50	1.59	89.4	22.06	1.62	98.1	24.25	1.64	100.0
RO MOD	1,350	57.96	24,922	4.7	79.51	28,24	6.5	120.30	32.12	10.5	148.98	33.61	19.3
RO BAU slow unit upscale					84.70	29.53	5.8	219.90	46.02	8.2	1,479.21	141.42	13.2
RO BAU					84.70	29.03	6.5	219.90	41.91	10.5	1.479.21	107.16	19.3
RO HIGH					96.50	30.85	6.5	263.60	46.76	10.5	1.966.91	135.02	19.3
RO SDG boom					84.86	29.06	6.5	525.43	71.02	10.5	8,599.47	489.36	19.3