Water Resources Research

Key Points:
- The historical learning rates of desalination technologies are 3–13% lower than previously reported when scale economies are removed
- Learning is found to be the most influential driver of historical cost reductions of desalination over economies of scale effects
- A trend break over the last 10 years suggests that the present and future learning rates may be lower than the historical rate

Supporting Information:
- Supporting Information S1

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Unraveling the Historical Economies of Scale and Learning Effects for Desalination Technologies

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Abstract As a technology develops and matures, both economies of scale and the lessons learned through experience drive down the cost over time. This article analyzes and separates the effects of economies of scale and learning through experience on historical cost reductions for three mature desalination technologies: multi-effect distillation (MED), multi-stage flash (MSF) distillation, and reverse osmosis (RO). The analysis suggests that learning has been the dominant driver for cost reductions, with learning rates of 23%, 30%, and 12% for MED, MSF, and RO, respectively, when the effects of scale are removed. The highest influence of economies of scale is found for MED, with an exponential scale coefficient of 0.71 and the largest difference between a traditional or scale-free estimation of the learning rate. MSF and RO showed smaller differences between the traditional and de-scaled learning rates (only 3%), pointing at learning as the main factor driving their historical cost reductions. However, a trend break observed over the last 10 years mirrors an exhaustion of the potential for technical improvements, as well as an increasing complexity and nonlinearity of the factors influencing the systems' cost. The findings provide useful data and insights for integrated and economic modeling frameworks, while providing guidance to prevent overestimations of the learning effect due to the confounding influence of economies of scale effects associated to historical unit upscaling processes.

1. Introduction

Within the framework of the United Nation's Sustainable Development Goals (SDGs) Agenda, which was approved in 2015, a particular focus has been put at both the international and regional levels on the identification, understanding, and modeling of technological solutions that can pave the way to meet the ambitious targets. Such modeling approaches require an understanding of the historical trends and dynamics of those technology options in order to come up with realistic assumptions and quantitative estimations that can serve as a basis for scenario development.

Desalination is one of the technological options that can bring important opportunities for meeting the SDGs—particularly the water-related ones—but also poses 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 and 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 upfront investment costs and energy requirements that reflect on the price of the desalinated product and can constrain their economic viability, return on investment, and ultimately market uptake, especially in developing regions (Gao et al., 2017; Ghaffour et al., 2013). However, investment costs for the main commercial desalination technologies, along with energy efficiencies, have not been static over time but have instead shown a decreasing trend since the first projects were implemented (Caldera & Breyer, 2017; Ghaffour et al., 2013). Evidence of this trend can be observed in the evolution of the average specific capital cost over time of the three desalination technologies with the highest level of technological maturity and market uptake: multi-effect distillation (MED), multi-stage flash (MSF) distillation, and reverse osmosis (RO), as shown in Figure 1.

This phenomenon is well known in technology innovation, whereby as technologies advance in the technology innovation cycle from a research idea through to widespread market diffusion, they usually go through upscaling (increase in the unit and production capacities) and learning (cost reductions or other performance improvements as a result of accumulated experience) processes that ultimately result in lower investment and production costs (Arrow, 1962; Grübler, 1998; Grübler & Wilson, 2014). Learning and upscaling processes are linked across the different technology growth stages and have been found to explain a very
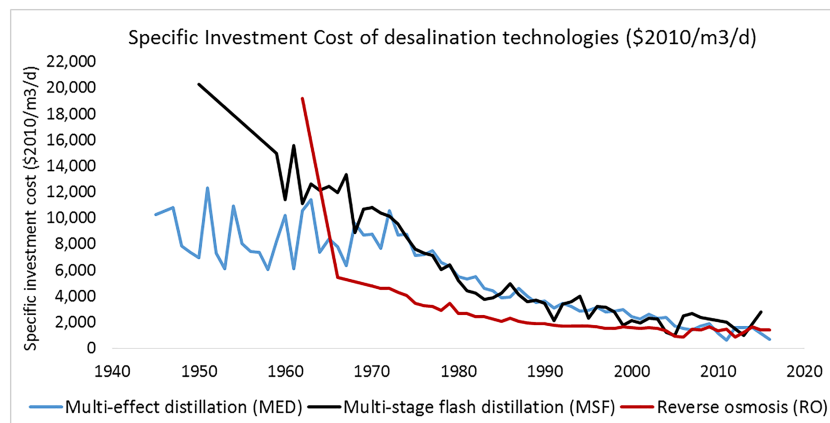
Figure 1. Historical evolution of average specific investment costs for MED, MSF, and RO desalination technologies. Own elaboration with data from Global Water Intelligence (2017a, 2017b).

high percentage of the historical capital cost reductions for a number of technologies, for example, from aircraft turbines to solar photovoltaic and wind energy technologies (Grübler, 1998; McDonald & Schrattenholzer, 2001; Qiu & Anadon, 2012). The clear manifestation of this phenomenon in the case of desalination is widely acknowledged and discussed in the literature, bringing forward a number of possible underlying factors and learning-related improvements for the different technologies (Borsani & Rebagliati, 2005; Dore, 2005; Ghaffour et al., 2013; Zhou & Tol, 2005). Examples include economies of scale, water recovery ratios, energy efficiency improvements, advances in technical components (e.g., membranes), an increase in the flexibility of build-own-operate-transfer contracts, or the progressive overcoming of salt precipitation problems (Borsani & Rebagliati, 2005; Ghaffour et al., 2013). However, the intermittent effects of upscaling processes have also been argued to get confounded with learning in traditional learning estimations using cumulative capacity-based learning curves and learning rates, leading to the overestimation of the learning effect (Healey, 2015). The learning rate is defined as the rate at which specific costs decline for every doubling of cumulative experience (McDonald & Schrattenholzer, 2001). Such a phenomenon has never been studied for the case of desalination. Furthermore, to date only two studies have looked at the learning concept and estimated learning rates within the desalination field. Sood and Smakhtin (2014) estimated the aggregated learning rate for the cumulative historical desalination deployment (aggregating MED, MSF, and RO technologies) and used it to assess the economic feasibility of desalination and clean energies to alleviate future water stress (Sood & Smakhtin, 2014). The second study by Caldera and Breyer (2017) applied the learning curve model to the particular case of sea water reverse osmosis (SWRO) and developed learning-based capital cost projections to until 2050 (Caldera & Breyer, 2017). However, these studies either lack a sufficient level of technology disaggregation, thus neglecting cross-technology technical and economic differences, or do not account for the scale effect when applying the learning rates to derive cost projections. Furthermore, none of them has been able to completely unravel the role of the historical upscaling and learning processes marking the extent and pace of capital cost reductions.

Understanding and capturing these dynamics and their effects on capital costs is critical for integrated modeling frameworks aimed at designing costing models and assessing future desalination scenarios to alleviate the water supply gap, either as a stand-alone solution or within a broader technological portfolio. Examples of such modeling approaches include the works by Wada et al. (2011), Kim et al. (2016), Hanasaki et al. (2016), Caldera et al. (2016), and Parkinson et al. (2018), spanning global water stress and water availability assessments, hydrological modeling, or cost optimization purposes. Other approaches in the literature to model desalination costs specifically are based on the development of empirical cost models calibrated with historical data on capital costs (Loutatidou et al., 2014) or "total water costs" (annualized capital cost + annual operation and maintenance cost) (Dore, 2005; Gao et al., 2017; Wittholz et al., 2008; Zhou & Tol, 2005). The closest approaches to considering the learning and scale effects through empirical models are found in the works by Gao et al. (2017) and Loutatidou et al. (2014). All these modeling approaches need to consider estimations or make assumptions of the

present and future learning rates for desalination technologies in order to incorporate them to their costing models in desalination.

The analysis presented in this article aims to disentangle and quantify the differential role played by the economies of scale and learning effects on historical investment cost reductions for the main desalination technologies. The results are compared among technologies and with previous attempts to estimate these parameters and discussed in order to provide insights to the scientific modeling community with views to informing learning assumptions in scenario building.

2. Data Sources and Treatment

The analysis was carried out using data from the Global Water Intelligence's Desaldata database for the period 1945–2016 (Global Water Intelligence, 2017b). Data were checked for consistency, and a number of assumptions and treatments were applied to ensure data homogeneity, consistency, and usability.

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 proxy 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 et al., 2014). These data were available for 85%, 90%, and 48.4% of the projects for MED, MSF, and RO technologies, respectively. All EPC cost data were converted to U.S. dollars, applying the conversion rate corresponding to the contract online date, and then actualized to 2010 values using the GDP deflator index available at the World Economic Outlook database (International Monetary Fund, 2017). 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 the 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 a specific cost overestimate. To avoid this effect, these outliers were removed. The number of outliers removed is detailed in Table 1.

A second assumption was made regarding 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.

Third, projects missing data on the installed capacity that could neither be found in other sources were excluded from the analysis. The number of projects excluded accounted for less than 1% of the total.

The resulting variables and statistics are included in Table 1.

3. Materials and Methods

3.1. Estimation of the Economies of Scale Effect

The effect of economies of scale 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 (equation (1)) (Joskow & Rose, 1985; McCabe, 1996; McNerney et al., 2011), whereby the costs and sizes of two plants relate as follows:

$$\text{Cost } 2 = \text{Cost } 1 \times (\text{Size } 2/\text{Size } 1)^p, \tag{1}$$

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; that is, 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. This scale coefficient usually ranges between 0 and 1, with 1.0 or higher denoting no economies of scale and an increasing intensity of economies of scale as the parameter decreases.

Table 1
Summary Statistics of Data used in the Analysis

Technology	Total number of projects (used for cumulative capacity/units)	No. of projects assumed single unit	No. of projects with cost data	No. of outliers removed	Final sample used for cost-related estimations	Time frame
MED	1,308	55	1,112	3	1,109	1945–2016
MSF	829	49	695	0	695	1950–2016
RO	15,776	4,095	7,223	5	7,218	1962–2016

3.2. Estimation of the Learning Effect: Traditional and De-scaled 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; Grübler, 1998; McCabe, 1996; 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) (L. Argote & Epple, 1990; Linda Argote, 1999; Dutton & Thomas, 1984; Grübler, 1998). Deriving the linear form of the aforementioned learning curve results in the learning rate as defined above. However, it has been argued that traditional capacity-based learning curves 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; McNerney et al., 2011; Weiss et al., 2010; Wilson, 2012). 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; Healey, 2015; Nemet, 2006; Qiu & Anadon, 2012). Healey (2015) proposed an alternative version of learning curves with special relevance for applications in energy modeling, 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/day in the case of desalination).

Given that the ultimate goal of this work is to provide data that can be used for modeling purposes, the de-scaled learning curve model proposed by Healey (2015) was selected as the most suitable methodology. The computation process was performed in three steps:

1. de-scaling 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 de-scaled costs over the annual series of cumulative installed units on a log-log scale; and
3. deriving the learning rate through equations (2) and (3):

$$\text{Cost}_t = \text{Cost}_{t0} * (\text{CC}_t / \text{CC}_{t0})^{\alpha}, \tag{2}$$

$$\text{LR} = 1 - 2^{\alpha}, \tag{3}$$

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. This analysis is further documented in supporting information Tables S1–S3.

In addition, 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 the influence of the scale effect.

Table 2
Economies of Scale Parameters for Desalination Technologies

Technology	Sample	Scale coefficient	R^2	P value
MED	1,107	0.71	0.72	0.000
MSF	694	0.82	0.88	0.000
RO	7,215	0.89	0.83	0.000

4. Results

4.1. Unraveling the Role of Scale and Learning in Historical Desalination Cost Reductions

The results from the estimation of economies of scale and learning effects as main drivers for the historical cost reductions are presented in Tables 2 and 3. In the case of learning, both classic (cost vs. cumulative capacity) and de-scaled (de-scaled cost vs. cumulative units) learning rates are provided for comparison. Further documentation on the economies of scale regressions and sensitivity analysis of learning fits for the different growth periods are provided in supporting information Tables S1 and S2.

The analysis of the learning curves allowed the detection of learning stages or phases coinciding with the different technological growth phases, as described by Mayor (2019) (see Figures S4 and S5 in the supporting information). The initial growth stage corresponds to the first years of deployment when adoption is still slow and learning occurs at a low pace. The intensive growth stage starts when the technology gets cost competitive and starts the industrial upscaling and rapid diffusion phase. This phase is characterized by high technological experimentation and replication resulting in the maximum learning rate, which usually translates in the sharpest cost reductions. The final stage in this study refers to the most recent period starting in 2006, in which a trend break is detected. This period has no clear fit and shows the possible beginning of a new phase. The learning rates presented in Table 3 correspond to the period of maximum growth, as indicated in the Fit range row.

The results show that desalination technologies, particularly the thermal ones, have benefitted from significant economies of scale and learning effects that explain the considerable specific investment cost reductions observed in Figure 1. MED experienced higher variability in average 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 takeoff in the Middle East, which registers the maximum historical learning rate (23%). MED exhibits the highest economies of scale effect (exponential scale parameter of 0.71) among the three. As a result, it also presents the highest overestimation in the learning effect when computed with the traditional learning curve formulation (36%) as compared to the de-scaled learning curve (23%). 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 de-scaled learning rate mirroring the sharpest capital cost reduction among the three technologies. Despite having significant economies of scale (0.82), the small difference registered between the classic and de-scaled 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 again detected as starting in 1970, along with a boost of industrial deployment in the Middle East that rapidly overtook MED. This extreme learning has been acknowledged and explained by Borsani 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, the increase in flexibility of build-own-operate-transfer 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 (Borsani & Rebagliati, 2005).

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. RO exhibits the lowest economies of scale (0.89), which could be explained by the modular configuration. Consistently, there is a moderate difference between the traditional and de-scaled learning rates of 3%, similar to MSF. These two factors suggest that cost reductions at the average industrial level have been limited but 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

Table 3
Learning Rates for Desalination Technologies

Technology	Traditional learning rate (LR)			De-scaled 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

noteworthy that some cases of diseconomies of scale have been detected in extremely large projects as analyzed and reported by Caldera and Breyer (2017), suggesting the possible existence of an upper limit above which the effect of economies of scale turns into a rebound effect. The de-scaled 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, and it rapidly overtook the other two options in the global market. The period of the highest learning for RO started slightly later than the other technologies, extending over the years 1975–2006. Two critical learning drivers for this technology were the efficiency improvements in membrane performance and energy use, especially through the introduction and optimization of energy recovery devices (Alvarado-Revilla, 2015).

In addition, a remarkable observation worth mentioning is the detection of a trend break in the de-scaled learning curves for the three technologies corresponding to the final stage during the period 2006–2015 (see supporting information Table S1). 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 (Mayor, 2019). 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. Nevertheless, the industrial trends reported in the literature suggest that there is limited room for significant improvements in efficiencies, and thus, learning rates equal to or above the historical rate are unlikely (Ghaffour et al., 2013; Pindyck & Rubinfeld, 2013).

5. Discussion

5.1. Unraveling the Role of Scale and Learning

Desalination literature has repeatedly mentioned and emphasized the importance of scale economies and learning to explain the historical capital cost reductions observed in desalination technologies (Borsani & Rebagliati, 2005; Gao et al., 2017; Ghaffour et al., 2013; Karagiannis & Soldatos, 2008; Loutatidou et al., 2014; Mezher et al., 2011; Zhou & Tol, 2005). However, few studies have measured the extent of those effects individually and independently for the different technologies (Caldera & Breyer, 2017; Sood & Smakhtin, 2014; Wittholz et al., 2008). Furthermore, none of them has been able to completely unravel the role of the historical upscaling and learning processes marking the extent and pace of capital cost reductions. This information is of high relevance for the development of costing models and capital cost projections. This knowledge gap is overcome in the present study by considering both parameters separately, while estimating a de-scaled learning rate where the effects of the historical upscaling have been removed. This ultimately results in preventing an overestimation of the learning effect.

Among the studies focusing on the economies of scale, possibly the most detailed one is the work by Wittholz et al. (2008), who applied the above presented power law coefficient equation (equation (1)) to five desalination technologies and used them as a basis to develop a scale-based cost model. Table 4 shows how these results compare to the present study for the analyzed technologies.

A slight mismatch is detected in the values for MED and MSF. First, Wittholz et al. obtain stronger economies of scale for MED as opposed to our results. Nevertheless, the difference may come from the size of the sample used for the calculation; that is, the use of a considerably bigger sample in this study may presumably provide a more accurate representation of the global industrial deployment. Meanwhile, Wittholz et al. obtain slightly higher economies of scale for RO, similar to MED values. Again, the size of the sample may play a role in this difference. Nevertheless, it is clear that the three technologies move in a value range of 0.7–0.9, and the variations may lie on the number of units of the project along with other technological and structural factors.

In terms of learning, to date only two studies have applied the learning curve concept to desalination. Table 5 shows the results of these studies compared to those presented in this work.

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%. They 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 the energy cost was taken out—as a measure of output.

Table 4
Comparison of Economies of Scale Results With the State of the Art

Technology	Wittholz et al. (2008)			Present study		
	Scale coefficient	Sample size	Time period	Scale coefficient	Sample size	Time period
MED	0.83	34	1970–2005	0.71	1,109	1945–2016
MSF	0.70	64	1970–2005	0.82	695	1945–2016
RO	0.81	112	1970–2005	0.89	7,218	1945–2016

This joint measure provides very general information that overlooks the strong differences among the technology types, while not capturing the differential effect of capex and opex, nor the impact of economies of scale, as pointed out by Caldera and Breyer (2017). These authors obtained a learning rate of 15% for SWRO, which coincides with the results achieved in the present study for RO when applying the traditional learning curve. However, they 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).

The application of de-scaled learning rates in the present study shows that the learning effect has been overestimated by the cited works as a result of an insufficient level of technology disaggregation and/or the confounding effects of unit upscaling. On the first aspect, the obtained cross-technology differences in learning highlight that fitting a single learning rate for the total desalination stock as an aggregated technology or technology cluster can be misleading, especially if the influence of scale is not accounted for. The 29% aggregated learning rate estimated by Sood and Smakhtin (2014) is very much influenced by the effect of the high traditional learning rates exhibited by the thermal technologies. While it provides a fair approximation of the learning trend for MSF, it considerably overestimates the learning effects for MED and especially for RO. Hence, the use of this parameter to model future aggregated desalination cost reductions would be misleading. Furthermore, considering that historical and present growth trends point at RO as the dominant technology in the current (70% of market share as of 2016) and future desalination developments (Alvarado-Revilla, 2015; Mayor, 2019), a better approach would be to adopt RO's learning rate as a proxy for the new global desalination deployment.

Regarding the second aspect, the estimation of the traditional learning rate as a test for comparison provided the same result as the one obtained by Caldera and Breyer (2017) for RO, thus validating the results. As mentioned above, RO shows the lowest economies of scale, and thus, the variation between the traditional and de-scaled learning rates is small, resulting in a de-scaled learning rate of 12%. However, with views to modeling and scenario building exercises, the detection of a trend break in the learning curve for the period 2006–2016 may indicate trend changes, mirroring the uncertainty of certain drivers at stake. On the one hand, the need for additional unconventional water resources to address water scarcity in an increasing number of regions is anticipated to keep demand for additional desalination capacity on the rise or even accelerate it within a frame of active policy responses to the SDG targets (Wada et al., 2011). The clear positioning and comparative advantages of RO, along with its consolidation as a secure option for governments

Table 5
Comparison of Learning Rates From Different Studies in the Literature

Study and analyzed technology	Measure of experience	Learning rates (%)	
		Traditional	De-scaled
Sood and Smakhtin (2014)			
Aggregated MSF, MED, and RO	Cumulative capacity	29	NA
Caldera and Breyer (2017)			
SWRO	Cumulative capacity	15	NA
Present study			
MED	Cumulative units	36	23
MSF	Cumulative units	33	30
RO	Cumulative units	15	12

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with proved returns of investment and eligibility to access financial instruments, point at a continuation of its growing trend and market dominance in the short-medium term (Alvarado-Revilla, 2015). However, some studies affirm that most of the possible technical improvements in RO have already been achieved, and only marginal future cost reductions may be expected from optimization adjustments and combination with other technologies, that is, nanofiltration or renewable energies (Ghaffour et al., 2013). Furthermore, there are additional aspects influencing the cost of desalination projects that cannot be captured or included in the learning rate of desalination plants but that will highly condition the future cost trends of desalination projects. These factors include costs of transportation and delivery of desalinated water to the end users, specific macroeconomic policies of the different regions and countries, monopoly drivers, and economic interests, among others (Barry & Coombes, 2018; Stiglitz & Dasgupta, 1982). When taking the whole financial, technical, and organizational system surrounding desalination projects into account, cost trends become nonlinear, nonstationary, and very context specific, which results in high uncertainties when trying to derive general averages and projections for modeling purposes (Stiglitz & Dasgupta, 1982). Nevertheless, some authors argue that when considering the whole output cost (produced water cost)—that internalizes operation costs such as energy use or scale of delivery—the trend may point to an increasing costs due to the higher complexity of the systems and their settings (Pindyck & Rubinfeld, 2013).

On the whole, assumptions of future learning rates based on current industrial trends should consider more conservative learning rates than the historical trend for the three technologies and especially for the thermal ones given their limited growth prospects (Mayor, 2019).

5.2. 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 (see Table 1), 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) make a detailed analysis of this phenomenon for RO.

A second limitation may come from the analysis of RO as a single technology without differentiating between sea water and brackish water desalination plants. The feed water type has been proved as one of the determinants for the capital cost of a RO plant (Loutatidou et al., 2014). Deriving separate learning and economies of scale estimations for both types of plants would increase the accuracy and granularity of the results. This is considered as a possible follow-up to this work.

6. Conclusions

This study has measured, unraveled, and discussed the separate roles of economies of scale and learning as drivers for historical cost reductions in the three main commercial desalination technologies.

A decoupled estimation of the scale and learning effects reveals that learning has been the dominant driver for historical desalination cost reductions, with de-scaled learning rates of 23%, 30%, and 12% for MED, MSF, and RO, respectively. The highest influence of scale on cost reductions is found in MED, with a power law scale coefficient of 0.71 that results in a reduction from a 36% traditional learning rate to a 23% de-scaled learning rate. MSF and RO showed smaller differences between the traditional and de-scaled learning rates (only 3%), pointing at learning as the main factor driving their historical cost reductions. However, a trend break observed over the last 10 years mirrors an exhaustion of the potential for technical improvements, as well as an increasing complexity and nonlinearity of the factors influencing the systems' cost. Therefore, assumptions of future learning rates based on current industrial trends should consider more conservative learning rates than the historical trend for the three technologies and especially for the thermal ones given their limited growth prospects.

These findings aim to provide important insights that should be taken into account by modeling frameworks integrating desalination as a possible solution to address water scarcity challenges and assessing cost-based competition among technologies. Particularly, they warn about the risk of overestimation of the learning effect due to the confounding influence of historical unit upscaling at the average industry level or due to an extrapolation of the historical learning trend without consideration of the most recent deviations.

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