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Predicting the Specific Energy Consumption of Reverse Osmosis Desalination

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Abstract: Desalination is often considered an approach for mitigating water stress. Despite the abundance of saline water worldwide, additional energy consumption and increased costs present barriers to widespread deployment of desalination as a municipal water supply. Specific energy consumption (SEC) is a common measure of the energy use in desalination processes, and depends on many operational and water quality factors. We completed multiple linear regression and relative importance statistical analyses of factors affecting SEC using both small-scale meta-data and municipal-scale empirical data to predict the energy consumption of desalination. Statistically significant results show water quality and initial year of operations to be significant and important factors in estimating SEC, explaining over 80% of the variation in SEC. More recent initial year of operations, lower salinity raw water, and higher salinity product water accurately predict lower values of SEC. Economic analysis revealed a weak statistical relationship between SEC and cost of water production. Analysis of associated greenhouse gas (GHG) emissions revealed important considerations of both electricity source and SEC in estimating the GHG-related sustainability of desalination. Results of our statistical analyses can aid decision-makers by predicting the SEC of desalination to a reasonable degree of accuracy with limited data.

Keywords: desalination, greenhouse gas emissions, multiple linear regression, specific energy consumption, statistical analysis

1. Introduction

Increasing stress on water supplies worldwide, coupled with population growth, has led many water managers to seek alternative water sources to meet demand. Desalination of seawater or brackish water is one such alternative water source, but it has important environmental, economic, and performance tradeoffs [1]. For example, saline sources are abundant and drought-resistant. However, removing dissolved solids (salts) from saline water requires significantly more energy than is required for treating conventional surface water or groundwater sources (see [2,3] and the sources cited therein for representative comparisons). There are other concerns, such as additional cost over conventional water supplies [4,5] and environmental impacts of concentrated salt and waste chemical disposal [6–8]. Despite these concerns, worldwide desalination capacity continues to rise [9].

While desalination capacity is projected to increase globally [10], energy-water planners and policymakers lack straightforward decision support tools that can help estimate the energy requirements of new facilities with minimal site-specific data, for engaging community members in desalination conversations [11]. Full engineering designs typically include energy requirements as part of the plant specifications, yet those plans are usually completed late in the planning process. However, for many stakeholders, it would be valuable to understand the energy implications of different design considerations early in the process, before critical siting decisions and design specifications have been made. Unfortunately, based on personal conversations with policymakers, few such openly accessible easy-to-use tools exist for estimating energy requirements based on specific operational parameters. Commercial membrane manufacturers offer desalination process modeling software, such as ROSA (Reverse Osmosis System Analysis) by Dow [12] and IMSDesign (Integrated Membrane Solutions Design) by Hydranautics [13], but these software packages require detailed inputs regarding operations and water chemistry, which can be a knowledge barrier in early stage decision-making. Furthermore, because the performance depends on a wide range of operational parameters, the actual energy requirements are a non-obvious result of many factors. This manuscript seeks to fill that knowledge gap by use of a meta-regression analysis to create a predictive model of desalination's energy requirements based on a range of relevant factors with minimal data inputs. It is the intent that this methodology would be useful for planners and decision-makers with publicly available data.

In the context of increasing desalination capacity and concern over energy consumption, we surveyed peer-reviewed desalination literature and the DesalData database by Global Water Intelligence [14] and conducted statistical analyses to determine which operational factors most influence the specific energy consumption (SEC)—that is, total desalination plant energy consumption per unit volume of product water, measured in equivalent kWh/m^3—of desalination processes. While published data are limited in terms of scope and specificity, we assembled a database from various sources to reflect as many factors as plausible that we anticipate influence SEC of desalination processes. Scientific- and statistically-based results pertaining to SEC and water cost are presented here in a policy-making context to better aid decision-making regarding future desalination plant installations.

2. Background

Historically, desalination has been confined to areas with scarce water resources and abundant energy supplies needed to drive the desalting processes, such as the Middle East, or other isolated island communities. As the risk and reality of water scarcity faced other areas over time, desalination capacity increased worldwide in locations outside the Middle East as well, including the United States, Spain, Japan, and many others [9]. Worldwide desalination capacity has reportedly increased to a total of nearly 87 million cubic meters per day (m^3/day) as of 2015 [15].

Two primary technologies drive desalination operations: thermal and membrane processes. Thermal-based desalination uses energy in the form of heat (or removed heat in the case of freeze desalination) to separate water from dissolved solids. Common examples of thermal-based desalination systems include multi-stage flash (MSF), multiple effect distillation (MED), and multi-effect boiling (MEB) operations. Membrane-based desalination uses electricity to power high-pressure pumps feeding semi-permeable membranes to filter out dissolved solids. Of the membrane-based desalination technologies commercially available, reverse osmosis (RO) is the most common with applications in both seawater reverse osmosis (SWRO) and brackish water reverse osmosis (BWRO). In both thermal- and membrane-based desalination operations, the end result is a product water stream containing fewer dissolved solids and a concentrate waste stream containing more dissolved solids. With the development of membrane technologies, desalination operations gradually shifted from being primarily thermal-based to more membrane-based, with 56% of the worldwide capacity and 96% of the United States capacity using membrane technologies by 2006 [9]. Many innovative desalination technologies have emerged in recent years, including forward osmosis, humidification–dehumidification, membrane distillation, and others [16,17]; however, RO remains "the benchmark for comparison for any new desalination technology" [18].

A substantial amount of the shift toward membrane-based desalination has been motivated by lower energy requirements, as shown by the equivalent SEC in Table 1. Here, we make the distinction between thermal energy and electrical energy. While both are measured in kilowatt-hours (kWh), the two quantities are not directly comparable. To generate electrical energy (kWh$_e$) in a typical thermal power plant, energy undergoes transformations from chemical to thermal to mechanical to electrical energy. Since each energy transformation incurs some efficiency loss, the direct comparison of thermal energy (kWh_{th}) with electrical energy (kWh_e) is inappropriate. For this analysis, we have converted reported thermal energy values to equivalent electrical energy values using the relationship suggested by Semiat based on an assumed 45% efficiency of a modern power plant [16], such that equivalent electric $kWh/m^3 = kWh_e/m^3 + 0.45\ kWh_{th}/m^3$. Note that this relationship is only appropriate for thermoelectric power plants. For the remainder of this analysis, we will report SEC in equivalent electric kWh/m^3; note, however, that many peer-reviewed literature sources are vague on the distinction between thermal energy and electrical energy use.

Table 1. Specific energy consumption, as reported in literature [9,16,17,19–28], varies for different desalination technologies. Total equivalent specific energy consumption is equal to the sum of kilowatt-hours (electric) and kilowatt-hours (thermal), converted based on an assumed 45% efficiency of a modern power station [16]: equivalent electric $kWh/m^3 = kWh_e/m^3 + 0.45\ kWh_{th}/m^3$.

Technology	Specific Energy Consumption (kWh/m^3)		
	Electric	**Thermal**	**Total Electric Equivalent**
BWRO	0.5–3	–	0.5–3
SWRO	3–6	–	3–6
ED	1–3.5	–	1–3.5
EDR	1–2	–	1–2
MVC	7–15	–	7–15
FO	0.2–0.5	20–150	10–68
MD	1.5–4	4–40	3–22
MSF	2.5–5	40–120	21–59
MED	2–2.5	30–120	15–57
MEB	2	60	30

Notes: BWRO = brackish water reverse osmosis; SWRO = seawater reverse osmosis; ED = electrodialysis; EDR = electrodialysis reversal; MVC = mechanical vapor compression; FO = forward osmosis; MD = membrane distillation; MSF = multi-stage flash; MED = multiple effect distillation; MEB = multi-effect boiling.

As shown in Table 1, reported SEC varies widely in practice across desalination technologies. For a given desalination technology, SEC can span a broad range due to different operational and water quality factors. For SWRO, as for many other desalination technologies, the SEC of commercial systems has decreased over time, dropping from an average of 20 kWh/m^3 in 1980 to 1.62 kWh/m^3 in 2005 [9]. While advances have been made in decreasing SEC, especially for RO operations, separating dissolved solids from water requires a minimum amount of energy, which is process-independent [29] but varies with system recovery [30–32]. The theoretical minimum SEC has been calculated based on thermodynamic constraints at approximately 1.06 kWh/m^3 for desalinating raw (incoming) water with total dissolved solids (TDS) concentration of 35,000 mg/L at 50% recovery (defined as the ratio of product water flow to raw water flow) [16,18,33]. As the recovery of a seawater desalination system approaches zero, the minimum theoretical energy approaches 0.7 kWh/m^3 [34]. For BWRO systems, the theoretical minimum specific energy consumption has been calculated at approximately 0.2 kWh/m^3; however, Avlonitis et al. state that a theoretical minimum SEC for BWRO might not exist due to the lack of dominance of concentration polarization across the membrane that is present in SWRO systems [35]. Mathematically, the ideal SEC for desalination increases as temperature increases, yet the opposite is true in actual RO systems as salt and water fluxes increase at higher temperatures [35], with diffusion through the membranes increasing at an estimated rate of 3% to 5% per °C [36] up to varying limits of commercial membranes [37], thereby reducing SEC.

Many operational and water quality factors can influence SEC for a given desalination technology [38–40]. For example, RO facilities with larger treatment capacity often observe economies of scale in terms of SEC due to efficiency gains associated with larger pumps [16]. Similarly, use of energy recovery technologies can substantially reduce the SEC of membrane-based desalination; however, the capital costs of such systems can be prohibitively expensive for small-scale SWRO ($<$100 m^3/day capacity) [41]. In SWRO applications, Pelton turbines (typical energy savings of 35% to 42% compared to a baseline without energy recovery equipment) for energy recovery are generally applicable for $\leq$5000 m^3/day capacity, while isobaric energy recovery devices (typical energy savings of 55% to 60%) are suited for $>$5000 m^3/day [42]. Approaches to reduce SEC include use of high permeability membranes [43], use of energy recovery devices, intermediate chemical demineralization, use of renewable energy, and optimal process configuration [44]. With advanced materials, increased water-solute selectivity has become more important than additional increases in water permeability, since increasing permeability negligibly decreases SEC [45–47]. Since reported energy consumption typically represents 19% to 44% of the cost of desalination [16,23,25,48–50], understanding which factors most significantly affect the SEC of desalination processes becomes important for the future environmental and social sustainability of desalination as an alternative water source.

3. Methodology

To determine the significance level of factors affecting SEC for desalination processes, we completed multiple linear regression analyses of SEC and cost as a function of various factors. The general form of the model is shown in Equation (1):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n + \epsilon \tag{1}$$

where y represents the dependent variable (in this case, SEC or cost), each x_i (for i = 1 … n) is an independent explanatory variable, and each β_i (for i = 0 … n) is a best-fit coefficient such that the error term ϵ is minimized. The use of multiple linear regression statistical techniques assumes certain characteristics about the model and the data on which it is based. In particular, statistical hypothesis testing is recommended to examine significance of individual coefficients, overall model significance, equality of two or more coefficients, satisfaction of restrictions for regression coefficients, stability of the model over time, and the functional form of the model [51].

We used the open-source statistical program R to create our multiple linear regression models. Based on the hypothesis tests for multiple linear regression given in Gujarati [51], we critically examined our model results to check for each of the following criteria:

1. Significance of individual coefficients
2. Overall model significance
3. No (or little) multicollinearity
4. No (or little) heteroscedasticity
5. No (or little) autocorrelation.

The presence of multicollinearity, often quantified with a variance inflation factor, indicates a linear relationship between two or more explanatory variables x_i, which are assumed to be independent. For example, the product water flow rate, q_{pw}, and the raw water flow rate, q_{rw}, are related to each other via the recovery, R, as the ratio between the two explanatory variables. Consequently, some multicollinearity is expected between q_{rw} and q_{pw}. Some suggest, however, that since “sometimes we have no choice over the data we have available for empirical analysis,” a certain degree of multicollinearity is not detrimental to a regression model if the model’s objective is predictive only [51]. Heteroscedasticity and autocorrelation are indications of non-constant variance and serial correlation (trending) among the model residual values (i.e., the difference between observed and predicted values), respectively. Significant heteroscedasticity and autocorrelation would indicate an inappropriate statistical model formulation (e.g., linear model versus non-linear model).

We completed the statistical analyses of SEC and cost using two distinct datasets: (1) data collected from published literature representing small-scale (product water flow: 0.7 to 220 m^3/day) desalination systems; and (2) data reported in the DesalData database representing municipal-scale (product water flow: 2500 to 368,000 m^3/day) systems. The small-scale database contained SEC data of desalination processes reported in peer-reviewed literature published since 2000 [16,19–22,27,35,36,41,42,52–61], including information for the raw water flow rate q_{rw} (m^3/day), product water flow rate q_{pw} (m^3/day), recovery R (unitless), year YR, raw water TDS c_{rw} (mg/L), product water TDS c_{pw} (mg/L), operating (feed) pressure P (bar), energy recovery ER (binary variable, unitless), and temperature T (°C). These desalination factors, summarized in Table 2, represented the explanatory variables in our multiple linear regression model for small-scale desalination facilities, referred to here as the small-scale model. Recovery was included as "inverse recovery" in the models as $\frac{1}{1-R}$ since SEC is proportional to this value [40,47]. The use of energy recovery systems was included as a binary variable with 0 indicating no energy recovery technology and 1 indicating the use of at least one energy recovery device, since the amount of energy savings is not often reported and different energy recovery technologies save similar percentages of operational energy [42]. For literature data where no raw water TDS values were reported, we assumed values of 35,000 mg/L for seawater and 10,000 mg/L for brackish water. Note that while many literature sources include some data on SEC of thermal desalination processes, our database (n = 45) included only RO membrane-based technologies due to the statistical requirement for complete datasets when employing multiple linear regression techniques.

Table 2. Different desalination factors, with ranges in observed values as noted, were used as explanatory variables in the small-scale and municipal-scale models of specific energy consumption.

Factor	Units	Small-Scale Model	Municipal-Scale Model
Year of initial operations	N/A	2003–2015	1988–2012
Raw water TDS	mg/L	1000–40,000	400–52,000
Product water TDS	mg/L	6–1632	10–500
Raw water flow rate	m^3/day	2.04–600	–
Product water flow rate	m^3/day	0.696–220.4	–
Recovery	N/A	0.04–0.81	–
Pressure	bar	4–71	–
Energy recovery *	N/A	0, 1	–
Temperature	°C	18–35	–

Note: * Binary variable.

The municipal-scale database contained SEC data of desalination processes reported in the DesalData database from Global Water Intelligence [14], reflecting actual operations at desalination facilities worldwide. Although the DesalData database is extensive in its reporting with information on over 18,000 facilities, several parameters are either not requested by Global Water Intelligence or not reported by the desalination plants, with 74 facilities reporting SEC. Consequently, our municipal-scale database (n = 36) contained SEC data including year YR, raw water TDS c_{rw} (mg/L), and product water TDS c_{pw} (mg/L) only, to maintain complete datasets.

Based on literature, energy consumption is a non-negligible determinant of the cost of desalinated water, representing as much as 44% of costs [16,23,48–50]. To quantify the statistical significance of SEC related to desalination economics, we completed an economic statistical analysis considering both product water cost p_{pw} (\$/m^3) and engineering-procurement-construction (EPC) price p_{EPC} (\$) based on data from the DesalData database. As a small data sample (n = 16 for p_{pw}; n = 28 for p_{EPC}), these cost data give a limited yet robust view of desalinated water economics.

To complement the multiple linear regression models of the small-scale and municipal-scale databases, we performed relative importance analyses of the coefficient estimates based on the technique presented by Tomidandel and LeBreton [62]. Relative importance analysis partitions the variance explained by a multiple linear regression model among the predictors (i.e., β_i's) such that the relative importance weights of the coefficients sum to the model's R^2 value. Since "standardized regression weights do not appropriately partition variance when predictors are correlated," relative importance analysis is one approach to coping with multicollinearity challenges [62]. We completed the relative importance analyses of factors in our small-scale and municipal-scale databases using a customized version of R code available from Tomidandel and LeBreton [63].

Because desalination is an energy-intensive process, its operation often causes the emission of greenhouse gases (GHGs). These GHG emissions associated with electricity consumption vary in time and space, as different electricity grids rely on different fuels with different associated GHG emissions. To quantify the GHG emissions from SEC at modeled desalination operations, we used empirical SEC and GHG data for U.S. desalination facilities to geographically represent the air emissions from major desalination plants. The resulting GHG analysis represents a first-order quantification of GHG emissions from electricity consumption for desalination; higher order impacts, such as GHG emissions associated with chemical consumption, infrastructure materials, or other operations, are excluded in this estimate.

4. Results

The results of our multiple linear regression and relative importance statistical analyses are presented here, first for the small-scale and municipal-scale desalination models of SEC, followed by economic analysis of product water cost and EPC price.

4.1. Small-Scale Desalination Operations Model

Using literature data on small-scale (0.7 m^3/day $\leq q_{pw} \leq$ 220 m^3/day; n = 45) desalination operations, we created a multiple linear regression model of SEC as a function of eight independent variables: raw water flow, product water flow, inverse recovery, raw water TDS, product water TDS, pressure, energy recovery equipment, and temperature. A summary of the results of our multiple linear regression model for small-scale desalination operations is shown in Table 3 and illustrated in Figure 1. Three values in our small-scale dataset were determined to be outliers based on Rosner's outlier test [64] and were subsequently excluded from the analysis.

Using the five previously mentioned statistical criteria to evaluate the multiple linear regression model, we can state the following:

1. Significance of individual coefficients
   At a significance level (i.e., Pr(>$|t|$)) of 0.05 as is commonly accepted in statistical analysis, all of the individual coefficients of the small-scale model are considered statistically significant since Pr(>$|t|$) $\leq$ 0.05. Since we are making a hypothesis test regarding significance for each coefficient, the value of Pr(>$|t|$) is essentially the probability of observing the estimated value by chance. A lower value of Pr(>$|t|$) indicates a more statistically significant estimate.
2. Overall model significance
   Again using the significance level of 0.05, the small-scale model is highly significant with a p-value of 1.1×10^{-12}. Additionally, the multiple R^2 value of 0.85 indicates that approximately 85% of the variation in SEC can be explained by the multiple linear regression model, making the coefficient estimates a good model fit in predicting SEC.
3. Limited multicollinearity
   Based on rules of thumb [51], multicollinearity is said to exist when the variance inflation factor (VIF) for a given explanatory variable is greater than 10. In our small-scale model of desalination operations, some strong multicollinearity exists with the explanatory variables for raw water flow rate, product water flow rate, raw water TDS, and pressure, as given in the Appendix A,

Table A1. For this predictive analysis, we have not attempted to correct for multicollinearity due to data limitations and, rather, have taken the "do nothing" approach suggested by some statisticians [51].

4. Limited heteroscedasticity
   The residual plots of each of the explanatory variables in our small-scale model, shown in the Appendix A, Figure A1, show some unequal variance across the sample size, indicated by the vertical spread of the residual data. With limited data reported in literature, we proceeded with the heteroscedasticity present in the small-scale model.
5. No (or little) autocorrelation
   In the residual plots shown in the Appendix A, Figure A1, no observable trend is present for each of the variables in our model of desalination factors, indicating no autocorrelation.

Table 3. Multiple linear regression results for the small-scale model of desalination operations (n = 45) revealed a reasonable model fit with highly significant coefficients. Values have been rounded to two significant figures.

Factor	Variable	Coefficient	Estimate	Standard Error	t-Value	Pr(>|t|)
Constant		β_0	7.7	1.2	6.2	3.8×10^{-7}
Raw water flow (m^3/day)	q_{rw}	β_1	3.9×10^{-2}	5.3×10^{-3}	7.3	1.4×10^{-8}
Product water flow (m^3/day)	q_{pw}	β_2	-8.6×10^{-2}	1.5×10^{-2}	−5.9	9.7×10^{-7}
Inverse recovery	$\frac{1}{1-R}$	β_3	1.7	0.21	8.0	1.5×10^{-9}
Raw water TDS (mg/L)	c_{rw}	β_4	6.2×10^{-4}	9.6×10^{-5}	6.4	2.0×10^{-7}
Product water TDS (mg/L)	c_{pw}	β_5	4.2×10^{-3}	1.7×10^{-3}	2.5	1.7×10^{-2}
Pressure (bar)	P	β_6	−0.34	6.0×10^{-2}	−5.7	2.0×10^{-6}
Energy recovery equipment	ER	β_7	−5.4	0.72	−7.6	5.9×10^{-9}
Temperature (°C)	T	β_8	−0.20	4.5×10^{-2}	−4.5	6.5×10^{-5}
multiple R^2 = 0.85; adjusted R^2 = 0.82; F-statistic = 26 (p-value = 1.1×10^{-12})						

With many explanatory variables in the small-scale model, we applied relative importance analysis (from Tonidandel and LeBreton [62]) to estimate the relative weight, or the amount of variance in SEC that is explained, for each variable. The relative weights sum to the R^2 value. These results are summarized in Table 4. When considering statistical significance along with relative weight, water quality parameters (c_{rw} and c_{pw}), pressure, and use of energy recovery equipment emerge as the most important variables in predicting SEC. Although the remaining four factors in the small-scale model each explain some amount of the variation in SEC, as observed by the relative weights in Table 4, a majority of the modeled SEC is explained by water quality, pressure, and energy recovery equipment alone.

Table 4. Relative importance analysis results for the small-scale model of desalination operations (n = 45) revealed a strong dependence on water quality, pressure, and use of energy recovery equipment. Values have been rounded to two significant figures.

Factor	Variable	Relative Weight
Raw water flow (m^3/day)	q_{rw}	0.067 *
Product water flow (m^3/day)	q_{pw}	0.072 *
Inverse recovery	$\frac{1}{1-R}$	0.071 *
Raw water TDS (mg/L)	c_{rw}	0.15 *
Product water TDS (mg/L)	c_{pw}	0.19 *
Pressure (bar)	P	0.12 *
Energy recovery equipment	ER	0.15 *
Temperature (°C)	T	0.034

Note: * relative weight is statistically significant.

Based on the multiple linear regression evaluation criteria and relative importance analysis, our model of small-scale desalination operations is a good statistical fit of the data with predictive capabilities, depending heavily on water quality, pressure, and use of energy recovery equipment. Figure 1 illustrates the observed data as it aligns with the predicted SEC using our multiple linear regression model. While the model overestimates some observed values and underestimates others, the overall model fit is reasonable and appropriate for future use regarding SEC for small-scale (0.7 $m^3/day \leq q_{pw} \leq 220\ m^3/day$) membrane-based desalination processes.

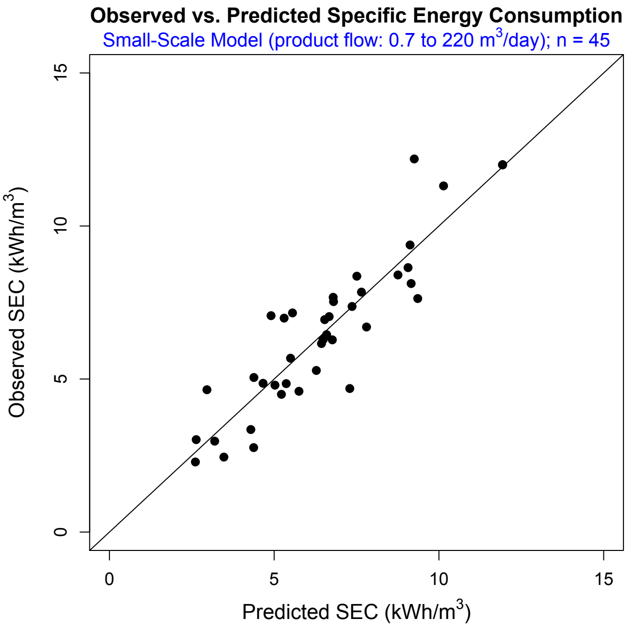

Figure 1. Our model for small-scale desalination operations predicts energy consumption consistent with observed energy consumption.

4.2. Municipal-Scale Desalination Operations Model

The DesalData database from Global Water Intelligence [14] is an extensive repository of data from current and proposed desalination facilities worldwide. Reported data include facility location, technology, suppliers, source water, operational characteristics, and other data. Using operational data from DesalData for municipal-scale (2500 $m^3/day \leq q_{pw} \leq 368{,}000\ m^3/day$; $n = 36$) desalination operations, we created a multiple linear regression model of SEC as a function of the three most complete explanatory variables available in the DesalData database: initial year of operations, raw water TDS, and product water TDS. Two values in our municipal-scale dataset were excluded from the analysis since they reported values below the minimum theoretical energy consumption. A summary of the results of our multiple linear regression model for municipal-scale desalination operations is shown in Table 5 and illustrated in Figure 2. Using the five previously mentioned statistical criteria to evaluate the multiple linear regression model, we can state the following:

1. Significance of individual coefficients
   At a significance level of 0.05, all of the individual coefficients, including the constant, are considered statistically significant in the municipal-scale model, as shown in Table 5.
2. Overall model significance
   Again using the significance level of 0.05, the municipal-scale model is significant with a p-value of 5.5×10^{-14}. In addition to the model's significance, the multiple R^2 value of 0.86 indicates that approximately 86% of the variation in SEC can be explained by the variables in the multiple linear regression model, making the coefficient estimates a strong model fit in predicting SEC.

3. No (or little) multicollinearity
   In our municipal-scale model, no multicollinearity exists in the explanatory variables, as shown by the VIFs less than 10 in the Appendix A, Table A2.
4. No (or little) heteroscedasticity
   The residual plots of each of the explanatory variables in our municipal-scale model, shown in the Appendix A, Figure A2, show minor heteroscedasticity with relatively constant variance across the dataset.
5. No (or little) autocorrelation
   In the residual plots shown in the Appendix A, Figure A2, negligible, if any, observable trends are present for the variables in our municipal-scale model.

Table 5. Multiple linear regression results for the municipal-scale model of desalination operations (n = 36) revealed a reasonable model fit with highly significant coefficients. Values have been rounded to two significant figures.

Factor	Variable	Coefficient	Estimate	Standard Error	t-Value	Pr(>|t|)
Constant		β_0	260	35	7.5	1.4×10^{-8}
Year of initial operations	YR	β_1	−0.13	1.7×10^{-2}	−7.5	1.5×10^{-8}
Raw water TDS (mg/L)	c_{rw}	β_2	8.3×10^{-5}	8.4×10^{-6}	9.8	3.5×10^{-11}
Product water TDS (mg/L)	c_{pw}	β_3	-2.4×10^{-3}	7.1×10^{-4}	−3.4	2.0×10^{-3}
multiple R^2 = 0.86; adjusted R^2 = 0.85; F-statistic = 68 (p-value = 5.5×10^{-14})						

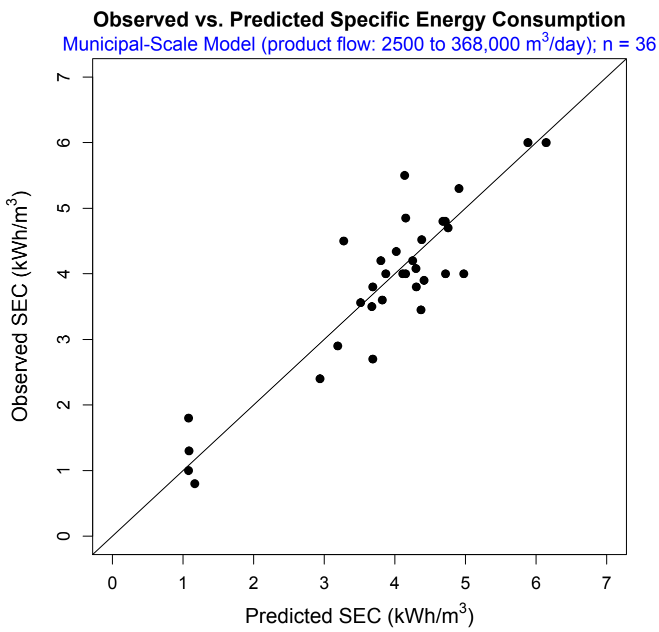

Figure 2. Our model for municipal-scale desalination operations predicts energy consumption consistent with observed energy consumption.

Unlike the small-scale model, our municipal-scale model depends on only three explanatory variables. We performed a relative importance analysis for the municipal-scale model to estimate the distribution of importance between these three variables, as shown in Table 6. Of the three explanatory variables in the municipal-scale model, the relative weights of all of the factors were found to be significant. Two factors—year of initial operations, YR, and raw water TDS, c_{rw}—together explain over 80% of the variation in SEC in the municipal-scale model. Product water TDS, c_{pw}, has lower relative importance since most large-scale desalination facilities treat product water to potable standards, leading to less variation in empirical values.

Table 6. Relative importance analysis results for the municipal-scale model of desalination operations (n = 36) revealed a significant contribution from year, raw water TDS, and product water TDS. Values have been rounded to two significant figures.

Factor	Variable	Relative Weight
Year of initial operations	YR	0.32 *
Raw water TDS (mg/L)	c_{rw}	0.49 *
Product water TDS (mg/L)	c_{pw}	0.050 *

Note: * relative weight is statistically significant.

Like the small-scale model, the municipal-scale multiple linear regression model is a good statistical fit of SEC data based on a small number of explanatory variables. The observed versus predicted SEC values, shown in Figure 2, indicate strong performance of the municipal-scale model over the relatively large range in product water flow rates (2500 to 368,000 m^3/day) based on three factors: year of initial operations, raw water TDS, and product water TDS. Of these factors, year and raw water TDS were found to have the largest relative contribution based on relative importance analysis. More recent years of operations reflect technological advances and increasing energy efficiency in operations, such that modern desalination facilities are associated with lower SEC.

4.3. Economic Analysis

High capital investment costs and increasing cost of water are often cited as critical barriers to expanding the use of desalination as an alternative water supply [4,5]. To evaluate these assertions with municipal-scale data, we performed a multiple linear regression analysis of economic factors for cost of product water (p_{pw}) and EPC price (p_{EPC}) using the DesalData database [14]. Only limited data were available for performing multiple linear regression analysis of p_{pw} (n = 16) and p_{EPC} (n = 28) due to the statistical requirement for complete data observations. The multiple linear regression models of p_{pw} and p_{EPC} with the best model fit (in terms of multiple R^2 and adjusted R^2) were found to be statistically poor, as shown in the Appendix A, Tables A3 and A4. The model of product water cost, p_{pw}, as a function of SEC, year of initial operations, raw water flow, and product water TDS, was an insignificant model with multiple and adjusted R^2 values of 0.41 and 0.20, respectively. Similarly, the model of EPC price, p_{EPC}, as a function of SEC, raw water flow, and product water TDS, was a significant model but exhibited only moderate performance with multiple and adjusted R^2 values of 0.46 and 0.39, respectively. Model goodness-of-fit measures (e.g., R^2) did not improve when we repeated the multiple linear regression analysis using different combinations of the explanatory variables.

Based on the Pearson's correlation coefficients (ρ, ranging from −1 to 1 with 0 representing no correlation) reported in the Appendix A, Table A5, only a slight linear relationship exists between SEC and product water cost with a Pearson's ρ of 0.20. Conversely, we observed approximately zero linear correlation between SEC and EPC price with a Pearson's ρ of −0.041. Based on these results, which are notably limited due to lack of available data, we found limited statistically significant relationships between SEC and economic factors of product water cost and EPC price.

The lack of a strong statistical relationship between SEC and EPC price in our economic analysis reflects the factors considered in other capital cost estimating tools for SWRO. For example, the DesalData capital expense estimating tool predicts costs as a function of raw water flow, raw water TDS, water temperature, and other qualitative or binary variables for pretreatment, intake and outfall locations, second pass, remineralization, permitting, and country of operations [65]. In addition to these cost factors, others include labor and maintenance costs and financing expenses as significant considerations [23,50]. Energy consumption is typically a significant factor in operations, but is not necessarily a direct factor in capital equipment cost.

5. Policy and Sustainability Implications

High electricity requirements for RO operations often translate into high associated GHG emissions. Since many U.S. electricity and GHG policy decisions are state-based, we quantified the GHG emissions (as carbon dioxide equivalent, CO_2e) associated with selected desalination facilities nationwide, as shown in Figure 3. Since different locations utilize a different mix of electricity fuels (with different associated GHG emissions), electricity consumption and GHG emissions produced in one facility are not necessarily reflective of another site. For example, electricity generated in California produces fewer GHG emissions on average than electricity generated in Texas. Consequently, SWRO operations in California (with higher SEC) have lower associated GHG emissions per unit of desalinated water than BWRO operations in Texas (with lower SEC).

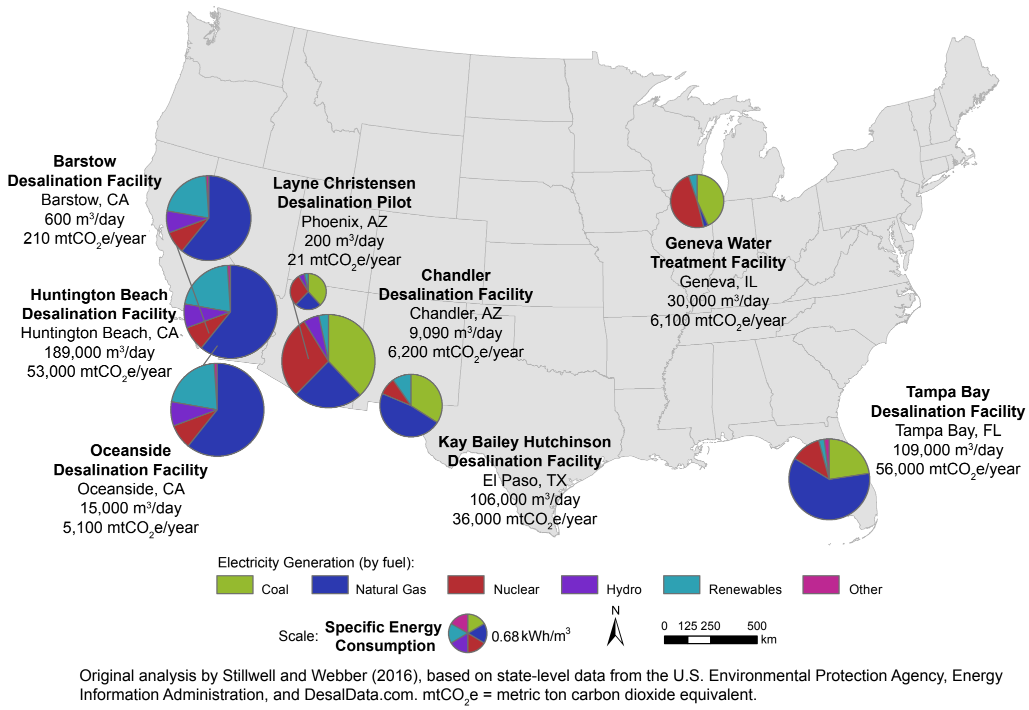

Figure 3. Greenhouse gas emissions associated with electricity consumption for desalination vary with location in selected U.S. desalination facilities. Larger circles correspond to higher specific energy consumption.

In response to severe and on-going drought, cities in California have renewed interest in seawater desalination as a water source; however, energy requirements, environmental impacts, and costs continue to be cited as criticisms. Some view desalination as a risky option when plants are constructed before strong demand exists, yet others view desalination plant construction as a long-term infrastructure investment [66]. Based on our statistical analysis of SEC and associated GHG emissions, desalination in California might lead to fewer GHG emissions than similarly sized operations elsewhere due to the lower CO_2e emissions from California-generated electricity.

The GHG emissions associated with water-related energy reveal the importance of drought management and water conservation as an approach to reducing CO_2e emissions under various state and federal emission policies. Using our municipal-scale multiple linear regression model, we estimated SEC for the recently-opened Carlsbad Desalination Project in southern California to be $SEC_{\text{Carlsbad}} = 3.5 \pm 0.23$ kWh/m^3, with the statistical uncertainty estimate successfully predicting the reported (likely conservative) SEC value of 3.6 kWh/m^3 [67]. Based on the model by Stokes and Horvath [68] of electricity and associated GHG emissions for water in southern California, replacing the current imported water supply in southern California with desalinated water from the Carlsbad facility would increase electricity consumption by a factor of 2.1. Consequently, a target reduction in municipal water use of over 53% is necessary to avoid increasing GHG emissions in response to substituting desalination for the baseline water supplies in southern California. This target reduction percentage might notably decrease over time given the observed trend of increasing cost (both in terms of economics and energy) of marginal water withdrawal and decreasing cost of desalination and reuse [50]. Integrating desalination operations with renewable electricity generation [1,69–71] is another option to increase the sustainability of desalination.

6. Model Limitations

The small-scale and municipal-scale models demonstrate strong statistical goodness-of-fit measures (e.g., R^2, model F-statistic) for predicting SEC in RO desalination; however, these models are empirical and depend on the underlying data. As such, the trends are reflective of the data range under consideration. Caution should be exercised in extrapolating SEC results. SEC has generally decreased over time [9], but the theoretical minimum of 1.06 kWh/m^3 (for c_{rw} = 35,000 mg/L and R = 0.50) constrains the lower bounds [16,18,33]. Actual RO operations are not reversible thermodynamic processes such that SEC is larger than the theoretical minimum [18]. Extrapolating input data, such as initial year of operations or raw water TDS, outside the bound of the empirical data, shown in Table 2, can lead to misleading and incorrect values of SEC.

Although we have compiled a thorough database with information on many desalination factors affecting SEC for both small- and municipal-scale operations, our database is not exhaustive of all the factors that affect energy use in desalination processes. Comparing the small-scale and municipal-scale models, fewer explanatory variables are necessary to predict SEC at the municipal-scale; however, a limited number of variables can miss important factors in a modeling and prediction effort. In particular, very little data were available regarding management of concentrate waste streams, which can affect overall facility sustainability and energy consumption. For inland RO facilities, management and disposal of concentrated dissolved solids and waste chemical streams can be a significant factor influencing overall energy consumption and desalination cost since inland facilities have limited disposal options, including evaporation ponds, zero liquid discharge systems, or deep well injection. Notably some of these disposal options might be socially, politically, or legally unacceptable. Coastal RO facilities typically discharge concentrate waste to a saline surface water body (ocean, bay, or gulf), which has lower associated energy consumption and cost but can still affect overall operations and sustainability.

Other technologies, such as integrating related systems, can also affect energy consumption and cost of desalination operations. For example, co-locating desalination facilities with thermoelectric power plants can be mutually beneficial for both operations by sharing common raw water intake structures, blending of concentrate discharge to reduce adverse environmental impacts, and utilization of elevated temperature raw water to reduce SEC at the desalination facility [72]. Emerging technologies for concentrate management have increased overall product water recovery while generating a solid "waste" gypsum product that can be a marketable by-product when desalination facilities integrate or cooperate with other manufacturers. Such approaches to desalination operations affect the overall SEC and cost, but these technologies and integrated systems are beyond the scope of our statistical analyses.

7. Conclusions

Using meta-data and empirical data of desalination processes compiled from peer-reviewed literature and the DesalData database, we completed multiple linear regression statistical analyses to determine which operational factors affect specific energy consumption in desalination processes.

Based on the statistical evaluation of our models, we show that the best statistical fit for predicting SEC in small-scale (0.7 $m^3/day \leq q_{pw} \leq 220$ m^3/day) RO processes is given as follows:

$$SEC = 7.7 + 3.9 \times 10^{-2} q_{rw} - 8.6 \times 10^{-2} q_{pw} + \frac{1.7}{1-R} + 6.2 \times 10^{-4} c_{rw} + 4.2 \times 10^{-3} c_{pw} - 0.34P - 5.4ER - 0.20T$$

where SEC represents the estimated specific energy consumption (kWh/m^3), q_{rw} is raw water flow rate (m^3/day), q_{pw} is product water flow rate (m^3/day), R is recovery, c_{rw} is raw water TDS (mg/L), c_{pw} is product water TDS (mg/L), P is pressure (bar), ER represents the use of energy recovery systems (a binary variable), and T is temperature (°C). Each of the coefficient estimates was shown to be statistically significant, such that the model is a useful predictive tool in approximating SEC for small-scale RO membrane-based desalination processes. Our model suggests that use of energy recovery equipment, and increasing pressure, temperature, and product water flow rate each decrease SEC overall. Water quality (c_{rw} and c_{pw}), pressure, and use of energy recovery equipment were the most important factors in explaining the variation in SEC, based on relative importance analysis.

In municipal-scale (2500 $m^3/day \leq q_{pw} \leq 368{,}000$ m^3/day) RO operations, our best statistical fit model for predicting SEC is given as follows:

$$SEC = 260 - 0.13YR + 8.3 \times 10^{-5} c_{rw} - 2.4 \times 10^{-3} c_{pw}$$

where YR is the initial year of operations. Like the small-scale model, each of the coefficient estimates was shown to be statistically significant. Using the municipal-scale model in a predictive capacity, we estimated the SEC for the Carlsbad Desalination Project within quantified uncertainty.

Our model of the factors affecting product water cost and EPC price showed only limited statistically significant relationships with SEC. Consequently, we deduce that other factors absent from the municipal-scale dataset likely have statistically significant influence over product water cost and EPC price, such as concentrate management and disposal or other site-specific information. Future research work could quantify these other factors affecting cost to determine the statistical significance and magnitude of influence on desalinated water cost.

As populations grow and areas continue to experience water stress, desalination might become increasingly attractive as an alternative water supply. Understanding the operational factors that affect SEC and the associated GHG emissions can be useful in a policy-making context to evaluate proposed desalination facilities in terms of environmental and social sustainability. While our multiple linear regression statistical models are based solely on small-scale meta-data and municipal-scale empirical data, the predictive capacity of our models and relative magnitudes and significance of coefficient estimates can prove a useful initial step for estimating SEC for other RO membrane-based desalination processes. This initial modeling step can motivate future in-depth membrane design models and studies as desalination projects move forward.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Statistical Model Details

Appendix A.1. Variance Inflation Factors

Variance inflation factors to check for multicollinearity (when VIF >10) are given for each explanatory variable in our multiple linear regression models in Table A1 through Table A2.

Table A1. Variance inflation factors (VIF) for variables considered in the small-scale multiple linear regression model show some strong multicollinearity where VIF >10. Values have been rounded to two significant figures.

Factor	Variable	Variance Inflation Factor
Raw water flow (m^3/day)	q_{rw}	26
Product water flow (m^3/day)	q_{pw}	20
Inverse recovery	$\frac{1}{1-R}$	2.0
Raw water TDS (mg/L)	c_{rw}	86
Product water TDS (mg/L)	c_{pw}	3.5
Pressure (bar)	P	83
Energy recovery equipment	ER	3.3
Temperature (°C)	T	1.7

Table A2. Variance inflation factors (VIF) for variables considered in the municipal-scale multiple linear regression model show no multicollinearity where VIF >10. Values have been rounded to two significant figures.

Factor	Variable	Variance Inflation Factor
Year of initial operations	YR	1.5
Raw water TDS (mg/L)	c_{rw}	1.2
Product water TDS (mg/L)	c_{pw}	1.6

Appendix A.2. Residual Plots

Residual plots to check for heteroscedasticity and autocorrelation are given for each variable in our multiple linear regression models in Figure A1 through Figure A2. Heteroscedasticity appears as unequal variance (spread) of the residual values. Autocorrelation appears as a general trend among residual values.

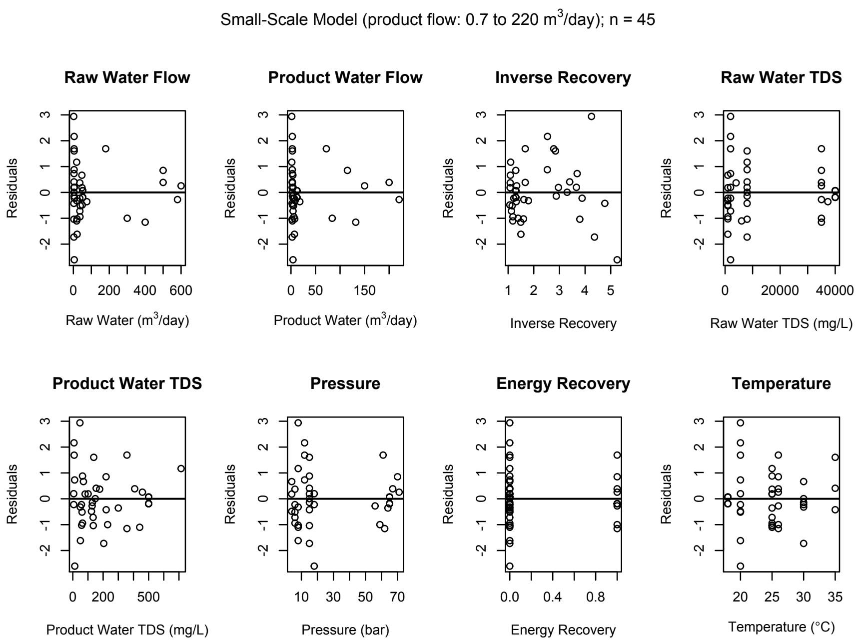

Figure A1. Residual plots for the small-scale desalination multiple linear regression model show some heteroscedasticity, but little trending as autocorrelation.

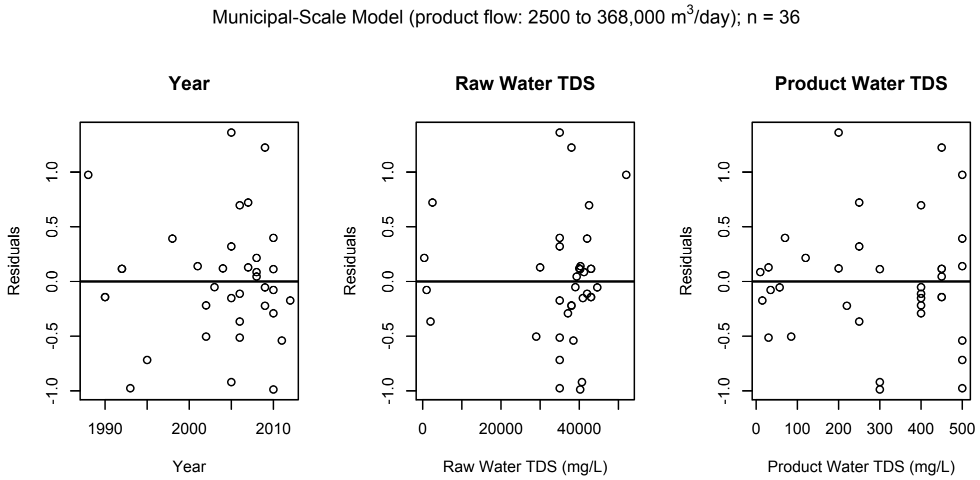

Figure A2. Residual plots for the municipal-scale multiple linear regression model show minor heteroscedasticity and negligible trending indicating autocorrelation.

Appendix A.3. Economic Analysis

The statistical analysis of economic factors revealed a poor to moderate fit for the models of cost of product water (p_{pw}) and EPC price (p_{EPC}), as shown in Table A3 through Table A4. The Pearson's correlation coefficients, shown in Table A5, similarly indicate little to moderate correlation between individual desalination operations and economic factors. Each of these desalination operational factors explains a small amount of the variation in p_{pw} and p_{EPC}, respectively, such that more information is necessary to accurately predict costs.

Table A3. Multiple linear regression results for the municipal-scale model of cost of product water (n = 16) revealed a poor model fit with no significant coefficients. Values have been rounded to two significant figures.

Factor	Variable	Coefficient	Estimate	Standard Error	*t*-Value	Pr(>|*t*|)
Constant		β_0	200	100	−2.0	0.076
SEC	*SEC*	β_1	0.21	0.14	1.5	0.15
Year of initial operations	*YR*	β_2	0.10	0.051	2.0	0.074
Raw water flow (m^3/day)	q_{rw}	β_3	-3.2×10^{-6}	1.7×10^{-6}	−1.9	0.086
Product water TDS (mg/L)	c_{pw}	β_4	-1.2×10^{-3}	8.9×10^{-4}	−1.3	0.22
multiple R^2 = 0.41; adjusted R^2 = 0.20; F-statistic = 1.9 (p-value = 0.17)						

Table A4. Multiple linear regression results for the municipal-scale model of EPC cost (n = 28) revealed a moderate model fit with significant coefficients. Values have been rounded to two significant figures.

Factor	Variable	Coefficient	Estimate	Standard Error	*t*-Value	Pr(>|*t*|)
Constant		β_0	4.6×10^7	1.1×10^8	0.43	0.67
SEC	*SEC*	β_1	4.8×10^7	2.1×10^7	2.3	0.030
Raw water flow (m^3/day)	q_{rw}	β_3	1.1×10^3	3.8×10^2	2.9	0.0070
Product water TDS (mg/L)	c_{pw}	β_4	-6.9×10^5	2.0×10^5	−3.4	0.0023
multiple R^2 = 0.46; adjusted R^2 = 0.39; F-statistic = 6.8 (p-value = 0.0017)						

Table A5. Pertinent Pearson's correlation coefficients (ρ) for different municipal-scale desalination factors and economic considerations of cost of product water, p_{pw}, and EPC price, p_{EPC}, reveal little to moderate correlation between factors. Values have been rounded to two significant figures.

Correlation	p_{pw}	p_{EPC}
SEC	0.20	−0.041
c_{rw}	0.24	0.061
c_{pw}	−0.38	−0.47

References

1. Grubert, E.A.; Stillwell, A.S.; Webber, M.E. Where does solar-aided seawater desalination make sense? A method for identifying sustainable sites. *Desalination* **2014**, *339*, 10–17.
2. Stillwell, A.S.; King, C.W.; Webber, M.E.; Duncan, I.J.; Hardberger, A. The Energy-Water Nexus in Texas. *Ecol. Soc.* **2011**, *16*, 2.
3. Sanders, K.T. Critical Review: Uncharted Waters? The Future of the Electricity-Water Nexus. *Environ. Sci. Technol.* **2015**, *49*, 51–66.
4. Zhou, Y.; Tol, R.S.J. Evaluating the costs of desalination and water transport. *Water Resour. Res.* **2005**, *41*, 1–10.
5. Reddy, K.V.; Ghaffour, N. Overview of the cost of desalinated water and costing methodologies. *Desalination* **2007**, *205*, 340–353.
6. Einav, R.; Harussi, K.; Perry, D. The footprint of desalination processes on the environment. *Desalination* **2002**, *152*, 141–154.
7. Lattemann, S.; Höpner, T. Environmental impact and impact assessment of seawater desalination. *Desalination* **2008**, *220*, 1–15.
8. Younos, T. Environmental Issues in Desalination. *J. Contemp. Water Res. Educ.* **2005**, *132*, 11–18.
9. Zander, A.K.; Elimelech, M.; Furukawa, D.H.; Gleick, P.; Herd, K.; Jones, K.L.; Rolchigo, P.; Sethi, S.; Tonner, J.; Vaux, H.J.; et al. *Desalination: A National Perspective*; Technical Report; Committee on Advancing Desalination Technology, National Research Council: Washington, DC, USA, 2008.
10. Buffle, M.O. Water, Water, Everywhere, Many a Drop to Drink. Available online: http://www.robecosam.com/en/sustainability-insights/library/foresight/2013/Water-water-everywhere-many-a-drop-to-drink.jsp (accessed on 7 January 2013).
11. Cooley, H.; Gleick, P.H.; Wolff, P. *Desalination, With a Grain of Salt: A California Perspective*; Technical Report; Pacific Institute: Oakland, CA, USA, 2006.
12. Dow Water & Process Solutions. ROSA System Design Software. Available online: http://www.dow.com/en-us/water-and-process-solutions/resources/design-software/rosa-software (accessed on 18 November 2016).
13. Hydranautics. IMSDesign: Integrated Membranes Solution Design. Available online: http://www.hydranauticsprojections.net/imsd/downloads/ (accessed on 18 November 2016).
14. Global Water Intelligence. DesalData.com. Available online: http://desaldata.com (accessed on 12 July 2016).
15. International Desalination Association. Desalination By the Numbers. Available online: http://idadesal.org/desalination-101/desalination-by-the-numbers/ (accessed on 30 June 2015).
16. Semiat, R. Energy Issues in Desalination Processes. *Environ. Sci. Technol.* **2008**, *42*, 8193–8201.
17. Huehmer, R.; Wang, F. Energy in Desalination: Comparison of Energy Requirements for Developing Desalination Techniques, 2009. In Proceedings of the AWWA Membrane Technology Conference, Memphis, TN, USA, 15–18 March 2009.
18. Elimelech, M.; Phillip, W.A. The Future of Seawater Desalination: Energy, Technology, and the Environment. *Science* **2011**, *333*, 712–717.
19. Fritzmann, C.; Löwenberg, J.; Wintgens, T.; Melin, T. State-of-the-art of reverse osmosis desalination. *Desalination* **2007**, *216*, 1–76.
20. Darwish, M.A.; Al Asfour, F.; Al-Najem, N. Energy consumption in equivalent work by different desalting methods: Case study for Kuwait. *Desalination* **2002**, *152*, 83–92.
21. McGinnis, R.L.; Elimelech, M. Energy requirements of ammonia-carbon dioxide forward osmosis desalination. *Desalination* **2007**, *207*, 370–382.

22. Veza, J.M.; Peñate, B.; Castellano, F. Electrodialysis desalination designed for off-grid wind energy. *Desalination* **2004**, *160*, 211–221.
23. Al-Karaghouli, A.; Kazmerski, L.L. Energy consumption and water production cost of conventional and renewable-energy-powered desalination processes. *Renew. Sustain. Energy Rev.* **2013**, *24*, 343–356.
24. McGovern, R.K.; Lienhard V, J.H. On the potential of forward osmosis to energetically outperform reverse osmosis desalination. *J. Membr. Sci.* **2014**, *469*, 245–250.
25. Miller, S.; Shemer, H.; Semiat, R. Energy and environmental issues in desalination. *Desalination* **2015**, *366*, 2–8.
26. Schallenberg-Rodríguez, J.; Veza, J.M.; Blanco-Marigorta, A. Energy efficiency and desalination in the Canary Islands. *Renew. Sustain. Energy Rev.* **2014**, *40*, 741–748.
27. Carta, J.A.; González, J.; Cabrera, P.; Subiela, V.J. Preliminary experimental analysis of a small-scale prototype SWRO desalination plant, designed for continuous adjustment of its energy consumption to the widely varying power generated by a stand-alone wind turbine. *Appl. Energy* **2015**, *137*, 222–239.
28. Ghalavand, Y.; Hatamipour, M.S.; Rahimi, A. A review on energy consumption of desalination processes. *Desalin. Water Treat.* **2015**, *54*, 1526–1541.
29. Gordon, J.M.; Chua, H.T. Thermodynamic perspective for the specific energy consumption of seawater desalination. *Desalination* **2016**, *386*, 13–18.
30. Lin, S.; Elimelech, M. Staged reverse osmosis operation: Configurations, energy efficiency, and application potential. *Desalination* **2015**, *366*, 9–14.
31. Mazlan, N.M.; Peshev, D.; Livingston, A.G. Energy consumption for desalination—A comparison of forward osmosis with reverse osmosis, and the potential for perfect membranes. *Desalination* **2016**, *377*, 138–151.
32. Shrivastava, A.; Rosenberg, S.; Peery, M. Energy efficiency breakdown of reverse osmosis and its implications on future innovation roadmap for desalination. *Desalination* **2015**, *368*, 181–192.
33. Feinberg, B.J.; Ramon, G.Z.; Hoek, E.M.V. Thermodynamic Analysis of Osmotic Energy Recovery at a Reverse Osmosis Desalination Plant. *Environ. Sci. Technol.* **2013**, *47*, 2982–2989.
34. Spiegler, K.S.; El-Sayed, Y.M. The energetics of desalination processes. *Desalination* **2001**, *134*, 109–128.
35. Avlonitis, S.A.; Avlonitis, D.A.; Panagiotidis, T. Experimental study in the specific energy consumption for brackish water desalination by reverse osmosis. *Int. J. Energy Res.* **2012**, *36*, 36–45.
36. Wilf, M.; Klinko, K. Optimization of seawater RO systems design. *Desalination* **2001**, *138*, 299–306.
37. Wilf, M.; Klinko, K. Performance of commercial seawater membranes. *Desalination* **1994**, *96*, 465–478.
38. Atab, M.S.; Smallbone, A.J.; Roskilly, A.P. An operational and economic study of a reverse osmosis desalination system for potable water and land irrigation. *Desalination* **2016**, *397*, 174–184.
39. Choi, J.S.; Kim, J.T. Modeling of full-scale reverse osmosis desalination system: Influence of operational parameters. *J. Ind. Eng. Chem.* **2015**, *21*, 261–268.
40. Zhu, A.; Christofides, P.D.; Cohen, Y. Effect of Thermodynamic Restriction on Energy Cost Optimization of RO Membrane Water Desalination. *Ind. Eng. Chem. Res.* **2009**, *48*, 6010–6021.
41. Avlonitis, S.A.; Kouroumbas, K.; Vlachakis, N. Energy consumption and membrane replacement cost for seawater RO desalination plants. *Desalination* **2003**, *157*, 151–158.
42. Peñate, B.; García-Rodríguez, L. Energy optimisation of existing SWRO (seawater reverse osmosis) plants with ERT (energy recovery turbines): Technical and thermoeconomic assessment. *Energy* **2011**, *36*, 613–626.
43. Ruiz-García, A.; Nuez, I. Long-term performance decline in a brackish water reverse osmosis desalination plant. Predictive model for water permeability coefficient. *Desalination* **2016**, *397*, 101–107.
44. Li, M. Reducing specific energy consumption in Reverse Osmosis (RO) water desalination: An analysis from first principles. *Desalination* **2011**, *276*, 128–135.
45. Werber, J.R.; Osuji, C.O.; Elimelech, M. Materials for next-generation desalination and water purification membranes. *Nat. Rev. Mater.* **2016**, *1*, 1–15.
46. Werber, J.R.; Deshmukh, A.; Elimelech, M. The Critical Need for Increased Selectivity, Not Increased Water Permeability, for Desalination Membranes. *Environ. Sci. Technol. Lett.* **2016**, *3*, 112–120.
47. Werber, J.R.; Deshmukh, A.; Elimelech, M. Can batch or semi-batch processes save energy in reverse-osmosis desalination? *Desalination* **2017**, *402*, 109–122.
48. Elhassadi, A. Horizons and future of water desalination in Libya. *Desalination* **2008**, *220*, 115–122.
49. Greenlee, L.F.; Lawler, D.F.; Freeman, B.D.; Marrot, B.; Moulin, P. Reverse osmosis desalination: Water sources, technology, and today's challenges. *Water Res.* **2009**, *43*, 2317–2348.

50. Ghaffour, N.; Missimer, T.M.; Amy, G.L. Technical review and evaluation of the economics of water desalination: Current and future challenges for a better water supply sustainability. *Desalination* **2013**, *309*, 197–207.
51. Gujarati, D.N. *Basic Econometrics*, 4th ed.; McGraw-Hill Companies: New York, NY, USA, 2003.
52. Busch, M.; Mickols, W.E. Reducing energy consumption in seawater desalination. *Desalination* **2004**, *165*, 299–312.
53. Jacangelo, J.G.; Oppenheimer, J.A.; Subramani, A.; Badruzzaman, M. Desalination Strategies for Energy Optimization and Renewable Energy Use. *IDA J.* **2012**, *4*, 28–33.
54. Ma, Q.; Lu, H. Wind energy technologies integrated with desalination systems: Review and state-of-the-art. *Desalination* **2011**, *277*, 274–280.
55. Macedonio, F.; Curcio, E.; Drioli, E. Integrated membrane systems for seawater desalination: Energetic and exergetic analysis, economic evaluation, experimental study. *Desalination* **2007**, *203*, 260–276.
56. Mohamed, E.S.; Papadakis, G. Design, simulation and economic analysis of a stand-alone reverse osmosis desalination unit powered by wind turbines and photovoltaics. *Desalination* **2004**, *164*, 87–97.
57. Mohsen, M.S.; Jaber, J.O. A photovoltaic-powered system for water desalination. *Desalination* **2001**, *138*, 129–136.
58. Park, G.L.; Schäfer, A.I.; Richards, B.S. The effect of intermittent operation on a wind-powered membrane system for brackish water desalination. *Water Sci. Technol.* **2012**, *65*, 867–874.
59. Swift, A.; Rainwater, K.; Chapman, J.; Noll, D.; Jackson, A.; Ewing, B.; Song, L.; Ganesan, G.; Marshall, R.; Doon, V.; et al. *Wind Power and Water Desalination Technology Integration*; Technical Report Desalination and Water Purification Research and Development Program Report No. 146; U.S. Department of the Interior, Bureau of Reclamation: Texas Tech University, Lubbock, TX, USA, 2009.
60. Takabatake, H.; Noto, K.; Uemura, T.; Ueda, S. More than 30% energy saving seawater desalination system by combining with sewage reclamation. *Desalin. Water Treat.* **2013**, *51*, 733–741.
61. Weiner, D.; Fisher, D.; Moses, E.J.; Katz, B.; Meron, G. Operation experience of a solar- and wind-powered desalination demonstration plant. *Desalination* **2001**, *137*, 7–13.
62. Tonidandel, S.; LeBreton, J.M. Relative Importance Analysis: A Useful Supplement to Regression Analysis. *J. Bus. Psychol.* **2011**, *26*, 1–9.
63. Tonidandel, S.; LeBreton, J.M. Relative Importance Analysis: Programs for Calculating Relative Weights in Multiple, Multivariate, and Logistic Regression. Available online: http://relativeimportance.davidson.edu/multipleregression.html (accessed on 18 November 2016).
64. McCuen, R.H. *Modeling Hydrologic Change: Statistical Methods*, 1st ed.; Taylor & Francis Group: Boca Raton, FL, USA, 2003.
65. Global Water Intelligence. SWRO Cost Estimator. Available online: http://desaldata.com/cost_estimator (accessed on 30 June 2016).
66. Gorman, S. California Drought Renews Thirst for Desalination Plants. Available online: http://www.reuters.com/article/2015/04/15/us-usa-desalination-california-idUSKBN0N601V20150415 (accessed on 14 April 2015).
67. Carlsbad Desalination Project. *Energy Minimization and Greenhouse Gas Reduction Plan*; Technical Report; Poseidon Resources: Carlsbad, CA, USA, 2008.
68. Stokes, J.R.; Horvath, A. Energy and Air Emission Effects of Water Supply. *Environ. Sci. Technol.* **2009**, *43*, 2680–2687.
69. Clayton, M.E.; Stillwell, A.S.; Webber, M.E. Implementation of Brackish Groundwater Desalination Using Wind-Generated Electricity: A Case Study of the Energy-Water Nexus in Texas. *Sustainability* **2014**, *6*, 758–778.
70. Gold, G.M.; Webber, M.E. The Energy-Water Nexus: An Analysis and Comparison of Various Configurations Integrating Desalination with Renewable Power. *Resources* **2015**, *4*, 227–276.
71. Kjellsson, J.B.; Webber, M.E. The Energy-Water Nexus: Spatially-Resolved Analysis of the Potential for Desalinating Brackish Groundwater by Use of Solar Energy. *Resources* **2015**, *4*, 476–489.
72. Voutchkov, N. Power Plant Co-Location Reduces Desalination Costs, Environmental Impacts. Available online: http://www.waterworld.com/articles/iww/print/volume-8/issue-1/columns/product-focus/power-plant-co-location-reduces-desalination-costs-environmental-impacts.html (accessed on 18 November 2016).