Benchmarking Nonresidential Water Use Efficiency Using Parcel-Level Data

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Abstract: Past studies of commercial, industrial, and institutional (CII) water use efficiency have been limited to simple normalization benchmarking measures. Simple normalization ratios (e.g., water use per employee) account for only one driver of water use and are often misleading because of the predominantly skewed nature of water use intensities. In order to improve on benchmarking systems to assess the water use efficiency of CII customers, this paper explores two popular methods used in the energy efficiency field: ordinary least squares (OLS) and data envelopment analysis (DEA). Parcel-level data from Austin, Texas, is used to demonstrate the methods, where a data-driven approach is employed to include average water use, building area, building value, year built, parcel area, and number of employees as measures of input, and annual sales as the economic measure of output. **DOI: 10.1061/(ASCE)WR.1943-5452.0000616.** *© 2015 American Society of Civil Engineers.*

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Introduction

Benchmarking involves the use of performance metrics or models to compare the relative efficiency of entities such as nonresidential establishments. Water use efficiency benchmarking specifically seeks to assess how efficiently comparable establishments use water and can be a useful tool to assist utilities, regulatory bodies, and companies in determining achievable levels of water use efficiency. A U.S. EPA (2009) white paper titled *Water efficiency in the commercial and institutional sector* summarizes many of the information and research needs for the commercial and institutional sectors, citing a lack of subsector specific data, such as water usage by facility and end use, and existing benchmarks by which to set targets. Benchmarking in the nonresidential, or commercial, industrial, and institutional (CII) sectors is complicated primarily by the lack of a standardized classification system for CII water users, and the large heterogeneity across and within sectors with regards to drivers of water use and end-use devices. The lack of a standardized classification system hinders widespread application of benchmarking systems, and though fine-resolution classification systems have been shown to reduce water use variability by creating more homogeneous groups, great variability in water use drivers and end-use devices remains.

Simple benchmarks for water and wastewater utilities including water quality complaints, percent unaccounted for water, and adequacy of water pressure are presented by Ammons (2001), none of which are broken down by CII sector. A review of the available literature indicates that the vast majority of water use efficiency benchmarking for the CII sectors has been limited to simple normalizations of water use (Dziegielewski et al. 2000; Brendle Group 2007; Morales et al. 2011). These simple normalizations are ratios of a single output (i.e., water use) and a single input (e.g., building area, number of employees). Ratios are calculated using average values for a given sample of customers, or at the customer level, from which percentiles of ratios within a given sample are determined. For example, Dziegielewski et al. (2000) presented efficiency benchmarks for schools, hotels/motels, office buildings, restaurants, and food stores based on the 25th percentile of water use intensity ratios normalized by a number of variables (e.g., liters/student/school day for schools, liters/occupied room/day for hotels/motels). Similar water use efficiency ratios have also been presented for Colorado (Brendle Group 2007) and Florida (Morales et al. 2011). Simple normalization ratios are relatively easy to calculate, understand, and implement, but their simplicity also limits their accuracy as a measure of efficiency given that they only account for a single driver of water use. For example, a ratio of water use per building area or employee fails to differentiate a restaurant that has a large ratio because it has inefficient water use fixtures from one that simply has a great deal of business. This is true too in the industrial water use sectors, where Bruneau and Renzetti (2010) showed how the intensity of water use per dollar of output has decreased in Canada despite an increase in total water use. CII water use efficiency benchmarking is also complicated by the difficulty of obtaining true measures of output. Dziegielewski et al. (2000) presented benchmarks normalized by variables that better denote the intensity of activity within a given sector (e.g., meals served for restaurants, occupancies for hotel/motels, transactions for food stores), but these measures of output were obtained through costly survey and audit data and are difficult to readily apply elsewhere.

Given the limitations associated with simple normalization benchmarks, this paper explores two more sophisticated approaches to evaluate water use efficiency in the CII sectors. These two approaches are ordinary least squares (OLS) and data envelopment analysis (DEA), which are predominant methodologies found in the energy use efficiency literature (Chung 2011). To present and compare the two approaches, actual parcel data from Austin, Texas,

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is used. A database-driven methodology is employed to obtain the data used in this analysis by joining water billing, property appraiser, and business databases. This approach allows for multiple input variables (e.g., building area, number of employees, water use) and a true measure of output in annual sales. The following section will present the mathematical framework, assumptions, and advantages/disadvantages of the OLS and DEA approaches. Then the Austin, Texas data will be presented, along with a summary of the database-driven approach employed to obtain the data, for which greater insight is provided in Morales and Heaney (2014). Subsequently, the OLS and DEA benchmarking approaches will be applied to various CII sectors in Austin, Texas, and the results gathered and discussed. The paper will conclude with perspectives on the applicability of the two approaches.

Benchmarking System Methods

Ordinary Least Squares

OLS is a method which seeks to estimate the parameters of a linear regression model by minimizing the sum of the squared vertical distances between observations and the modeled response (Kutner et al. 2004). OLS benchmarking methodologies utilize multiple linear regression and are thus seen as an improvement over simple normalization because they allow for multiple drivers (inputs) of water use to be modeled. Additionally, OLS provides standardized measures of statistical significance and goodness of fit which allows for the determination of which independent variables should be included in the model and how well the model fits the data overall.

Several approaches can be taken to measure efficiency using OLS. Taking water use to be the dependent variable for a regression equation, most simply, all observations which have a water use above the regression line, which constitutes the average efficiency, can be considered to be less efficient. However, this approach does not provide a sense of how efficient any given observation is in relation to all other observations or allow for an easily comprehensible normalized efficiency measure from 0 to 1 that would facilitate such comparisons of efficiency. To assist in this effort, a distributional benchmarking approach can be undertaken. Sharp (1998) suggested such an approach where for a given observation the best-fitted regression model is used to arrive at a predicted value from which a percentile table is calculated through the mean values of the distribution of standard errors. A slightly modified version of this approach is employed in the Energy Star benchmarking of buildings by the U.S. EPA and Department of Energy (Kinney and Piette 2002). Chung et al. (2006) proposed a mathematically equivalent approach for benchmarking the energy use efficiency of commercial buildings using standardized independent variables, as shown in Eqs. (1)–(3)

$$X^* = \frac{X - \bar{X}}{S} \tag{1}$$

where X^* = standardized independent variable; X = actual independent variable; $\bar{X}$ = mean of independent variable; S = standard deviation of independent variable.

After determining which variables are significant, via stepwise regression for example, the standardized variables are used to arrive at an OLS regressed model [Eq. (2)]

$$Y = \beta_0 + \beta_1 X_1^* + \beta_2 X_2^* + \ldots + \beta_{p-1} X_{p-1}^* + \varepsilon \tag{2}$$

where Y = dependent variable; β_0 = linear intercept coefficient; $\beta_1, \ldots, \beta_{p-1}$ = slope coefficients of independent variables 1 through $p-1$; $X_1^*, \ldots, X_{p-1}^*$ = standardized independent variables 1 through $p-1$; and ε = error variable.

By incorporating this standardized variable regression equation, a normalized measure of Y is calculated, as shown in Eq. (3)

$$Y_{\text{norm}} = Y_0 - \sum_{i=1}^{p-1} \beta_i X_i^* \tag{3}$$

where Y_{norm} = normalized dependent variable; Y_0 = actual value of Y; β_i = slope coefficients of standardized independent variables 1 through $p-1$ from Eq. (2); and X_i^* = standardized independent variables 1 through $p-1$.

This normalization removes the deviation associated with the significant modeled factors. In this way, the unexplained variability in the linear regression model is attributed to be the relative efficiency of a given entity's use of the resource. The observations used to develop Eq. (2) can then be input into Eq. (3) from which a distribution and corresponding percentile table can be derived. This approach results in a public benchmarking system in that other observations not included in the modeling effort can then utilize Eq. (3) and compare their normalized values to the benchmark percentile table from which a rank or score can be obtained.

The advantages of OLS, which include its ability to account for multiple drivers of demand and provide standardized measures of statistical significance and goodness of fit, along with its public benchmarking formulation capability, have made it the most commonly applied method within the energy efficiency benchmarking literature (Chung 2011). Monts and Blissett (1982) pioneered the approach to assess the energy efficiency and conservation potential of school and university buildings in Texas. OLS has been used to develop energy use benchmarking system for hotels in the United States (Bloyd et al. 1999), Europe (Bohdanowicz and Martinac 2007), and Singapore (Xuchao et al. 2010). OLS offers the additional advantages associated with the further complexities available in regression modeling such as the inclusion of nonlinearity and interaction between variables. OLS has disadvantages; primarily the approach assumes that all residuals are measures of inefficiency while in reality some residuals are likely explained by other factors not included in the modeling effort.

Data Envelopment Analysis

As opposed to OLS, which models the average relationship amongst observations, DEA envelops the observations to arrive at an efficient frontier. The observations on the efficient frontier are taken to be efficient, while the efficiencies of all other observations are determined by their deviations from the efficient frontier (Charnes et al. 1994; Cooper et al. 2007). DEA defines this efficient frontier and evaluates the efficiency of all observations through the use of linear programing (LP). There are a multitude of LP formulations that differ both in how they define the efficient frontier and how the observational deviations from the frontier line are measured. The two most common formulations employed in the literature to arrive at efficiency benchmarking systems using DEA are the Charnes et al. (1978) CCR model and the Baker et al. (1984) BCC model. There are two versions of these models: input oriented and output oriented. Input-oriented models seek to minimize inputs while maintaining at least the same level of outputs, while output-oriented models seek to maximize outputs without requiring any more inputs. Energy use efficiency studies have largely viewed energy use as an input, and thus employed input-oriented models. Hence, this water use efficiency study will also focus on input-oriented models. The primal form of the linearized input-oriented

CCR model is stated in Eq. (4). This model seeks to maximize the measure of efficiency, which in this input-oriented case is calculated in such a way that observations with reduced levels of an input resulting in the same level of output are seen as more efficient. The LP is run n times, once for each observation. Hence, the LP determines the input and output weightings that maximize the measure of efficiency of the observation for which the LP is being run, while ensuring that said weightings do not arrive at a measure of efficiency greater than 1 for any of the observations

$$\max_{v,u}\ w_k = \sum_{r=1}^{s} u_{rk} y_{rk}$$

st.

$$\sum_{i=1}^{m} v_{ik} x_{ik} = 1$$

$$\sum_{r=1}^{s} u_{rk} y_{rj} - \sum_{i=1}^{m} v_{ik} x_{ij} \le 0, \qquad j = 1, \ldots, n$$

$$u_{rk}, v_{ik} \ge \varepsilon, r = 1, \ldots, s, i = 1, \ldots, m \tag{4}$$

where w_k = measure of efficiency for observation k in a set of $j = 1, \ldots, n$ observations; u_{rk} = decision variable and coefficient to weight output $r = \{1, \ldots, s\}$ for observation k; v_{ik} = decision variable and coefficient to weight input $i = \{1, \ldots, m\}$ for observation k; y_{rk} = value of output $r = \{1, \ldots, s\}$ for observation k; x_{ik} = value of input $i = \{1, \ldots, m\}$ for observation k; y_{rj} = value of output $r = \{1, \ldots, s\}$ for observations $j = \{1, \ldots, n\}$; x_{ij} = value of input $i = \{1, \ldots, m\}$ for observations $j = \{1, \ldots, n\}$; and ε = infinitesimal positive number.

DEA models are usually solved using their dual LP formulation since it calculates the slack variables directly. The dual input-oriented CCR model formulation is shown in Eq. (5). The final constraint in Eq. (5) is only applicable to the input-oriented BCC model formulation. Hence, the two model formulations are only distinguished by this one constraint, which is known as the convexity constraint. The CCR model assumes constant returns to scale to define the efficient frontier. Thus, the efficient frontier for CCR models passes through the origin and has a constant slope. The BCC model formulation, through the inclusion of the convexity constraint, assumes variable returns to scale, whereby the efficient frontier is defined by a piecewise linear, concave function. The CCR model's constant returns to scale are said to yield an overall measure of efficiency or (global) technical efficiency. The BCC's variable returns to scale account for a given observation's scale of operation and thus provide an estimate of its (local) pure technical efficiency.

A representation of the CCR constant returns to scale and BCC variable returns to scale is shown in Fig. 1, along with the OLS line. The example in Fig. 1 is of a simple single-input (number of employees), single-output (sales) relationship, meant to highlight how the two DEA approaches envelope the data, while OLS fits a line through the average of the data. In this example, using OLS, observations B, E, and D (to a lesser extent) are said to be efficient since those establishments produce greater sales than the average given their number of employees, observations C and H fall near the OLS line and thus have average efficiency, while observations A, F, and G are said to be inefficient since they fall below the OLS line. Using the CCR model, observation B defines the efficient frontier and is the only observation that is said to be perfectly efficient. The efficiency of all the other observations is based on their distance from this frontier. Observations A, C, D, and E are equidistant from the frontier and thus have the same level of reduced

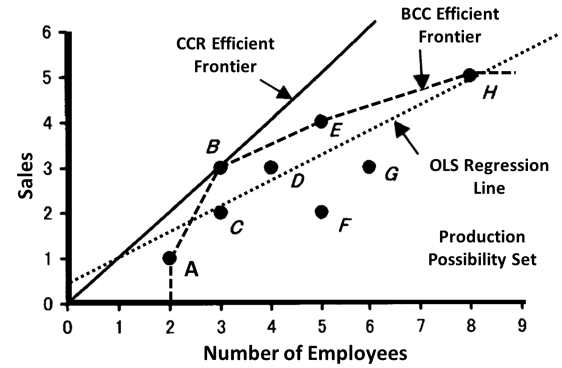


Fig. 1. Example of data envelopment analysis efficient frontiers using CCR (constant returns-to-scale) and BCC (varying returns-to-scale) methods, and ordinary least squares regression line (adapted from Cooper et al. 2007). Example shows single input (number of employees) and single output (sales) for eight establishments labeled A through H

efficiency, while observations F, G, and H are even more inefficient, though equivalently so. Using the BCC model, which factors in scale of operation, observations A, B, E, and H define the variable returns-to-scale efficient frontier and are thus all taken to be perfectly efficient. Observations C and D are slightly less efficient, while F and G are the most inefficient

$$\min_{\theta,\lambda,s^+,s^-} w_k = \theta_k - \varepsilon \sum_{i=1}^{m} s_{ik}^- - \varepsilon \sum_{r=1}^{s} s_{rk}^+$$

s.t.

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_{rk}^+ = y_{rk}, \qquad r = 1, \ldots, s$$

$$\theta_k x_{ik} - \sum_{j=1}^{n} x_{ij}\lambda_j - s_{ik}^- = 0, \qquad i = 1, \ldots, m$$

$$\lambda_j, s_{ik}^-, s_{rk}^+ \ge 0, \quad \forall\ i, j, r$$

$$\sum_{j=1}^{n} \lambda_j \ge 1, \text{(only for BCC formulation)} \tag{5}$$

where θ_k = measure of efficiency for observation k in set of $j = 1, \ldots, n$ observations; s_{ik}^- = slack variables for input constraints; s_{rk}^+ = slack variables for output constraints; and λ_j = dual coefficients or weight assigned to observations.

By solving both the CCR and BCC formulations, the water use efficiency of buildings can be decomposed by the relationship shown in Eq. (6). This decomposition allows for the determination of how much of a given observation's overall efficiency is attributable to inefficient operation (pure technical efficiency) or disadvantageous conditions (scale efficiency)

$$SE = \frac{\theta_{\text{CCR}}^*}{\theta_{\text{BCC}}^*} \tag{6}$$

where SE = scale efficiency; θ_{CCR}^* = global technical efficiency or optimal efficiency measure from CCR run; and θ_{BCC}^* = the local pure technical efficiency or optimal efficiency measure from BCC run.

The DEA formulations can also be adapted to differentiate between discretionary and nondiscretionary input and output variables, the difference being that nondiscretionary variables are not readily adjustable or subject to managerial control. For example, when analyzing water or energy building efficiency, building and parcel areas are useful inputs to include as a measure of size although these inputs are also not readily subject to change. Such inputs and outputs should thus be included in the LP formulation as nondiscretionary variables. Eq. (7) shows the adapted input-oriented CCR and BCC model formulations to account for nondiscretionary variables. As presented in the formulation, only discretionary inputs (I_D) and outputs (O_D) are included within the objective function and the measure of efficiency (θ). All variables are incorporated into the constraints so they still shape the efficient frontier, but only the subvector of discretionary inputs is used to calculate efficiency

$$\min_{\theta,\lambda,s^+,s^-} w_k = \theta_k - \varepsilon \sum_{i \in I_D}^{m} s_{ik}^- - \varepsilon \sum_{r \in O_D}^{s} s_{rk}^+$$

s.t.

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_{rk}^+ = y_{rk}, \qquad r = 1, \ldots, s$$

$$\theta_k x_{ik} - \sum_{j=1}^{n} x_{ij}\lambda_j - s_{ik}^- = 0, \qquad i \in I_D$$

$$x_{ik} - \sum_{j=1}^{n} x_{ij}\lambda_j - s_{ik}^- = 0, \qquad i \notin I_D$$

$$\lambda_j, s_{ik}^-, s_{rk}^+ \geq 0, \quad \forall\ i, j, r$$

$$\sum_{j=1}^{n} \lambda_j \geq 1, \qquad \text{(only for BCC formulation)} \tag{7}$$

Though data envelopment analysis (DEA) offers certain advantages over OLS, its more limited application is attributed to the fact that DEA provides an internal benchmarking system, whereas simple normalization ratios and OLS offer a public benchmarking system. To incorporate new observations (not previously included in the modeling effort), internal benchmarking systems require the model, in this case the DEA LP, to be rerun with the new and existing observations. This makes applications of internal benchmarking approaches across utilities difficult, since raw data from all the utilities of interest would be required. New observations can be readily applied to public benchmarking systems since they do not need to be incorporated into the model; their values can simply be compared to modeled estimates. In the case of OLS for example, new observations do not need to be used to update the regression equation; they can utilize the previously fitted equation. Still, DEA offers advantages over OLS, principally, that DEA places no restrictions on the functional form of the production relationship, focuses on individual observations as opposed to average values, decomposes overall efficiency into pure technical and scale efficiency, and can handle multiple inputs and outputs simultaneously. Given these advantages, multiple studies have applied DEA to benchmark building energy use. DEA has been employed to benchmark energy use efficiency in government buildings in Taiwan (Lee 2008; Lee and Lee 2009), hotels (Onut and Soner 2006) and manufacturing sectors (Onut and Soner 2007) in Turkey, and single-family homes in the United States (Grosche 2009). Outside of building energy use, Hua et al. (2007) utilized DEA analysis to measure the eco-efficiency of paper mills by way of undesirable pollution outputs. Within the water sector, studies have focused on the application of DEA to evaluate the efficiency of water utilities and agricultural water use. Renzetti and Dupont (2009) and Hernandez-Sancho and Sala-Garrido (2009) used DEA to assess the technical efficiency of municipal water suppliers and wastewater treatment processes, respectively. Ananda (2014) analyzed the efficiencies of urban water utilities by combining DEA and a two-stage double bookstrap procedure. Similarly, Marques et al. (2014) used DEA to benchmark water utilities in Japan. DEA has been used by Fraser and Cordina (1999), Rodriguez-Diaz et al. (2004), Speelman et al. (2008), and Wang (2010) to evaluate water use efficiency of the agricultural sector in Australia, Spain, South Africa, and China, respectively. Outside of its limited applicability as an internal benchmarking system, DEA's disadvantages include its susceptibility to outlier effects, since its measures of efficiency rely on the extreme values in a data set.

Application of OLS and DEA to a Case Study

Austin, Texas Case Study Description

The city of Austin, Texas, was selected as the case study to demonstrate the use of OLS and DEA benchmarking of CII water use efficiency. The city of Austin provided annual average water use data for September 2010 through August 2011 for each of the 17,187 CII premises in its service area. Austin's CII water demands averaged 202 million liters per day over the period for which data were provided, a significant 36% of total water use. Though outdoor water use is understood to generally be a fairly small fraction of total CII water use (Morales et al. 2011), this period of water billing coincides with Stage 1 watering restrictions in Austin, which limited CII irrigation to twice per week at night. The climate in Austin is characterized as humid subtropical, with hot summers and mild winters.

Morales and Heaney (2014) detail the database-driven methodology used to arrive at the input and output data for Austin. The water billing database provided by Austin was spatially joined to the parcel-level Travis County property appraiser database, which provided building and parcel attributes. Also, proprietary business data from InfoGroup were obtained and spatially joined to the other databases to result in an overall parcel-level database which included annual sales as a measure of output and average water use, building area, building value, year built, parcel area, and number of employees as measures of input. The CII parcels were classified using the North American Industry Classification System (NAICS) provided in the business data. NAICS is standardized nationwide taxonomy and is available from various vendors that provide business data across the United States. The NAICS classifications were presented as six-digit codes at the business level. The hierarchical structure of NAICS, however, allowed for classifications to be truncated down to the three-digit level to arrive at more general classes. Five of the top three-digit NAICS water use sectors in Austin, Texas, were used to demonstrate the approach. Summary statistics for the input and output variables of these sectors are shown in Table 1. The sample sizes, N, presented in Table 1, are a result of a certain amount of data loss associated with the joining of the three databases. This data loss is attributed to the imperfect operation of geocoding, the incomplete nature of each database, and their initial spatial scale that required aggregation to the parcel level. For example, the business database was provided at the business level. Being that there could be multiple businesses on a parcel, a filter based on total building area in the business and property appraiser databases matching within 10% was applied to ensure that all business were accounted for. The average values provided in Table 1 can be used to arrive at weighted water use coefficients, a form of simple normalization ratios, as described by Morales and Heaney (2014).

Table 1. Input and Output Average and Standard Deviation Statistics for Select Three-Digit NAICS Sectors in Austin, Texas

Description	Professional, scientific, and technical services	Administrative and support services	Ambulatory health care services	Accommodations	Food services and drinking places
3-digit NAICS	541	561	621	721	722
N	63	34	27	16	101
Year built	1,959 (29)	1,974 (16)	1,968 (18)	1,983 (20)	1,973 (23)
Building area (m^2)	1,077 (1,643)	672 (816)	435 (407)	5,677 (3,843)	416 (331)
Building value ($1,000)	$1,154 ($1,966)	$602 ($1,070)	$484 ($505)	$5,925 ($7,541)	$455 ($353)
Parcel area (m^2)	3,582 (5,334)	3,791 (4,362)	2,514 (2,654)	9,092 (4,783)	2,804 (2,251)
Number of employees	28 (58)	23 (43)	8 (7)	27 (27)	26 (20)
Water use (L/day)	3,013 (4,792)	4,936 (8,532)	1,878 (2,491)	50,081 (51,220)	7,408 (6,492)
Sales ($/day)	$11,315 ($27,518)	$4,688 ($8,874)	$1,795 ($3,455)	$5,038 ($6,995)	$3,553 ($4,627)

Note: Standard deviations are shown in parentheses.

Application of Ordinary Least Squares

The normalized OLS benchmarking approach proposed by Chung et al. (2006) was applied to the Austin, Texas data using the three-digit NAICS sectors described in the previous section. First, stepwise regression on the raw data was carried out to determine which independent variables (annual sales, building area, building value, number of employees, parcel area, year built) were significant predictors of water use for each sector. Using the statistical software package *Minitab*, forward stepwise selection with an alpha of 0.05 to enter new variables into the model was used. This alpha value means that each variable that is entered into the model must have a p-value less than or equal to 0.05, ensuring that each model variable is statistically significant at a 95% confidence level. Once the significant independent variables were identified, their standardized values were determined using Eq. (1), and the mean and standard deviation statistics are presented in Table 1. Multiple linear regression was then carried out using these standardized independent variables to determine their linear relationship to water use. These regression equations, in conjunction with actual water use, can then be used to arrive at a parcel's normalized water use as demonstrated by Eq. (3). Essentially, this approach adjusts a parcel's water use to account for its sector's independent variables which were found to be significant in the modeling effort. Thus, the approach attempts to explain the variability in water use within a given sector. It assumes that the remaining error, not explained by the regression equation, is attributable to water use efficiency.

Application of Data Envelopment Analysis

The DEA methods outlined previously were applied to the parcel data for Austin, Texas. Both the input-oriented CCR and BCC formulations were applied to each of the selected three-digit NAICS sectors. Though the individual DEA LP problems are small, requiring just a single constraint per input and output, nonnegativity restrictions, and a convexity constraint in the case of the BCC formulation, special software is usually necessary since the LPs need to be run n times, to optimize efficiency from the perspective of each unit, or in this case, CII parcel. To handle the large number of optimizations required for this work, LPs were solved using Frontline Systems' *Risk Solver Platform* which functions as an add-in to *Microsoft Excel* and allows multiple optimizations to be run automatically. Nondiscretionary input variables were taken to be building area, building value, parcel area, and number of employees. Water use was also included as an input, but as a discretionary variable. In this way, water use efficiency was singled out. The sole measure of output was taken to be annual sales. All variables were included in the formulation because, as opposed to econometric methods, the effect of multicollinearity is insignificant for DEA (Ahn et al. 1988). Given the five inputs and one output, each LP problem is made up of six constraints, nonnegativity constraints for each of the decision variables, and a convexity constraint in the case of the BCC formulation. The number of decision variables depends on the size of each sector, where there are n λ variables, one for each parcel; six slack variables, one for each input and output; and θ, the measure of efficiency. For example, the Food Services and Drinking Places (NAICS 722) sector in Austin, Texas, having 101 parcels, included 108 decision variables and was composed of six constraints (seven in the case of the BCC formulation), along with 108 nonnegativity restrictions, one for each decision variable. This 108-decision-variable LP needs to be solved 101 times to optimize from the perspective of each parcel.

Results

Results of Ordinary Least Squares

The normalized water use OLS equations for the select three-digit NAICS sectors in Austin, Texas, are presented in Table 2. The standardized independent variables in each equation are ordered from most to least significant. Furthermore, p-values for each of the significant independent variables are also shown in Table 2, along with the overall adjusted-R^2 of each regression equation. The small p-values indicate that all of the independent variables

Table 2. Normalized Water Use Regression Equations and Associated Statistics for Select Three-Digit NAICS Sectors in Austin, Texas

Three-digit NAICS	WU_{norm} (L/day)	P-values	Adj. R^2
541	$WU_0 - (37{,}900)BA^* - (24{,}300)PA^* - (-784)S^* - (1{,}230)NE^*$	$BA = 0.000$; $PA = 0.000$; $S = 0.000$; $NE = 0.013$	0.87
561	$WU_0 - (47{,}200)PA^* - (2{,}510)S^* - (-4{,}190)BV^*$	$PA = 0.000$; $S = 0.000$; $BV = 0.022$	0.54
621	$WU_0 - (1{,}420)NE^* - (11{,}700)PA^*$	$NE = 0.000$; $PA = 0.001$	0.68
721	$WU_0 - (18{,}100)S^*$	$S = 0.000$	0.93
722	$WU_0 - (2{,}930)NE^* - (22{,}200)PA^* - (1{,}660)BV^*$	$NE = 0.000$; $PA = 0.000$; $BV = 0.000$	0.72

Note: BA^* = standardized building area (m^2); BV^* = standardized building value ($1,000); NE^* = standardized number of employees; PA^* = standardized parcel area (m^2); S^* = standardized sales ($/day); WU_{norm} = normalized water use (L/day); WU_0 = actual water use (L/day).

Table 3. Normalized Water Use (L/Day) Benchmark Percentile Table for Select Three-Digit NAICS Sectors in Austin, Texas

	Three-digit NAICS				
Percentile	541	561	621	721	722
10%	1,411	563	562	33,563	3,821
20%	2,133	3,002	1,086	37,022	4,730
30%	2,519	3,870	1,537	45,241	5,934
40%	2,816	4,524	1,581	46,990	6,723
50%	3,051	4,636	1,766	48,788	6,960
60%	3,276	5,072	2,082	52,365	7,539
70%	3,538	5,925	2,193	55,523	7,938
80%	3,994	7,908	2,613	59,826	9,266
90%	4,542	8,495	3,057	68,432	11,056

Table 4. Data Envelopment Analysis Statistics by Method for Selected Three-Digit NAICS Sectors in Austin, Texas

Three-digit NAICS	N	Average efficiency			Standard deviation efficiency			Coefficient of variation		
		CCR	BCC	SE	CCR	BCC	SE	CCR	BCC	SE
541	63	0.18	0.34	0.59	0.28	0.38	0.34	1.58	1.11	0.59
561	34	0.3	0.51	0.7	0.38	0.44	0.39	1.27	0.87	0.56
621	27	0.35	0.51	0.8	0.28	0.36	0.31	0.8	0.71	0.39
721	16	0.42	0.5	0.86	0.33	0.33	0.31	0.79	0.66	0.36
722	101	0.15	0.36	0.53	0.17	0.33	0.28	1.09	0.9	0.52

included in each model are highly statistically significant. The strongest modeled relationship is found for Accommodation (NAICS 721), where the single variable of sales accounts for 93% of the water use variability in the sector. The positive sign of the sales linear coefficient for this sector reasonably indicates that as sales increase so too does water use. This is sensible for a service sector whose water use is understandably driven by occupancy, for which sales appears to be a good proxy. Administrative & Support Services (NAICS 561) has the weakest relationship with an R^2 of 0.54. For this sector, parcel area, sales, and building value were all found to be statistically significant, with water use increasing with larger parcel areas and sales, and water use decreasing the greater the building value. Overall, the linear regression relationships across the sectors were found to be strong, and the signs of the coefficients reasonable.

The normalized water use for the data employed to arrive at the regression equations can then be determined using the equations in Table 2. The distributions of these normalized water uses are employed to develop a benchmark table to allow for comparison and determination of relative water use efficiency of other observations not included in the modeling effort. The normalized water use benchmark table for the select three-digit NAICS sectors in Austin, Texas, is shown in Table 3 by way of percentile values. As an example of this benchmarking approach, assume a hotel (NAICS 721) uses an average of 40,000 L/day and has sales totaling \$5,500 per day. By applying the equation in Table 2, the normalized water use for this hotel is calculated to be 38,805 L/day. By comparing this normalized value to those in Table 3, this hotel is shown to be rather efficient compared to the hotels included in the modeling effort given that it falls just slightly above the 20th percentile value of normalized water use for hotels.

Results of Data Envelopment Analysis

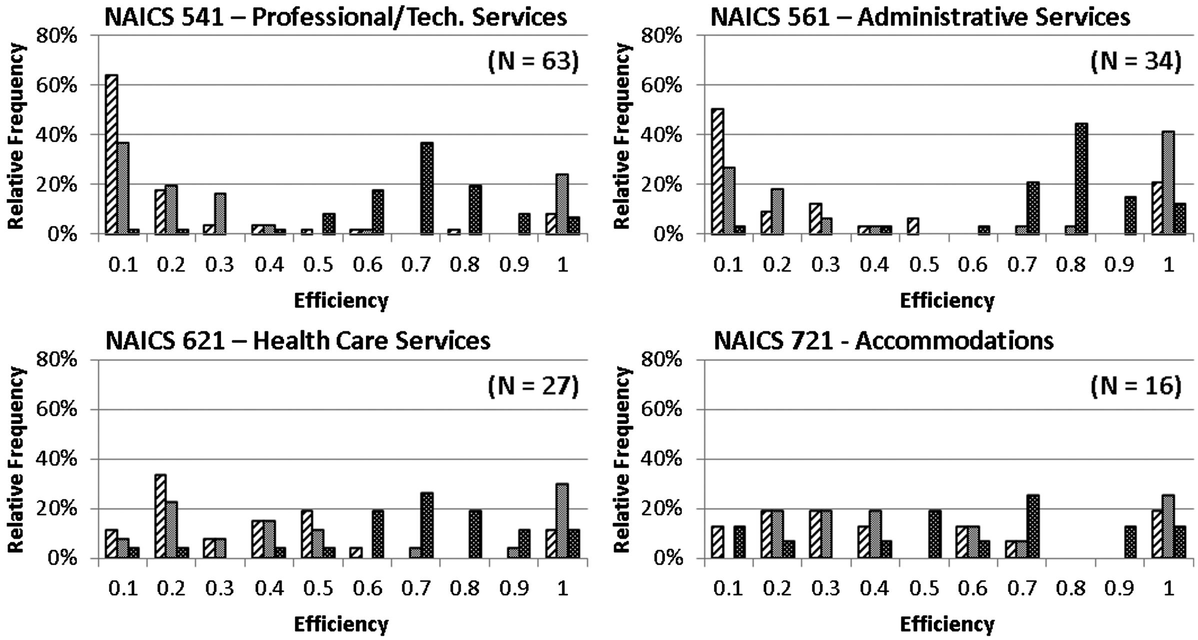
Summary statistics of the various optimizations for the selected three-digit NAICS sectors in Austin, Texas, are shown in Table 4. The five sectors in Table 4 can be grouped into two general categories given their similar efficiency characteristics. Professional, Scientific, and Technical Services (NAICS 541) and Food Services and Drinking Places (NAICS 722) are shown to be, on the average, the least water efficient sectors and share similar statistics on efficiency. These statistics suggest that parcels in these two sectors have the greatest opportunity to improve their water use efficiency. However, these two sectors also have the largest sample sizes in the study. The effect of sample size on the distribution of efficiencies will be discussed in the subsequent subsection. The three remaining sectors (NAICS 561, 621, 721) also appear to behave similarly, with an average CCR (constant returnsto-scale) efficiency between 0.30 and 0.42, and an average BCC (variable returns-to-scale) efficiency between 0.50 and 0.51. These three sectors are shown to have large scale efficiencies (SE), and hence their size or scale is better suited to efficiently use water.

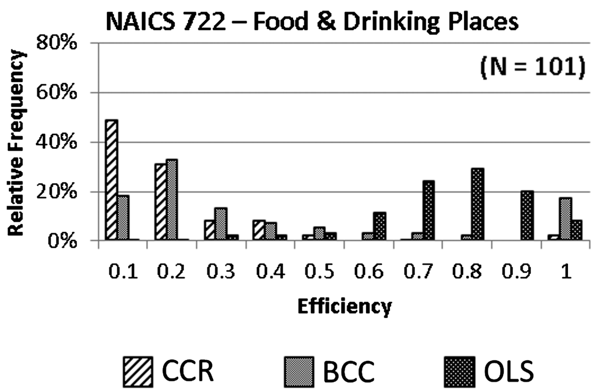
Further insight into the distribution of water use efficiencies is provided in Fig. 2 with histograms of the CCR and BCC measures of efficiencies for the select three-digit NAICS sectors in Austin, Texas. Here, the shifting of efficiencies from the CCR, constant returns to scale, which is often referred to as overall efficiency, and the BCC, variable returns to scale, or pure technical efficiency, is evident. Professional, Scientific, and Technical Services (NAICS 541) is shown to have the greatest fraction of observations with water use efficiencies less than or equal to 0.1. Ambulatory Health Care Services (NAICS 621) and Accommodation (NAICS 721) are shown to have the most widespread distribution of efficiencies over the various bins. This more homogeneous distribution of observations indicates that these sectors appear to be less susceptible to outlier effects. The percentage of bins that make up the efficient frontier for each sector and method is also provided in Fig. 2. Administrative and Support Services (NAICS 561) has the largest fraction of efficient observations at 20 and 40% for the CCR and BCC methods, respectively. This large fraction of perfectly efficient observations helps explain why the average statistics for NAICS 561 compare favorably to those of NAICS 621 and 721 in Table 4, despite having a differing distribution of efficiencies. NAICS 561 shows two extreme peaks in the distribution unlike NAICS 621 and 721. The large number of observations with perfect efficiency scores of 1 skews the averages to more closely match those of NAICS 612 and 721. This highlights the importance of analyzing the efficiency distributions alongside the average statistics.

Comparison of OLS and DEA Results

In order to more readily compare the results from the OLS and DEA efficiency benchmarking approaches, distributions of the normalized OLS water use values arrived at by the equations in Table 2 were also plotted in Fig. 2. These distributions are different from the percentile table (Table 3), in that they provide the relative frequency of normalized water use values within equally sized bins. To comply with the definition of efficiency in DEA, the lower the normalized water use value, the closer the efficiency score is to 1, and the more efficiently the observation or parcel is said to use water.

As is evident by the histograms in Fig. 2, the efficiency benchmarking results between OLS and DEA are drastically different. This is not surprising given that the approaches are inherently dissimilar both in how they define efficiency and the mathematical frameworks in which they operate. While OLS fits a linear function through the average of the data, DEA envelops the data and does not assume a functional form. Hence, the DEA efficiency histograms





	Correlation Coefficient, r		
NAICS	CCR & BCC	OLS & CCR	OLS & BCC
541	0.83	-0.37	-0.54
561	0.71	-0.31	-0.14
621	0.69	-0.64	-0.44
721	0.86	-0.32	-0.31
722	0.71	-0.55	-0.63

Fig. 2. Histograms of efficiency measures calculated by the CCR and BCC data envelopment methods, and the distribution of normalized water use by OLS for selected 3-digit NAICS in Austin, Texas. Table at bottom right shows the correlation coefficients between the various methods of accessing efficiency

often show the greatest relative frequencies in the two extremes (0.1–0.2 or very inefficient, and 1 or perfectly efficient). OLS on the other hand, essentially fills the void that the DEA histograms leave behind, generally demonstrating a singular peak around an efficiency score of 0.7–0.8. This pattern of efficiencies between OLS and DEA is most apparent in NAICS 541, 561, and 722, which also correspond to the sectors with the largest sample sizes. Accommodation (NAICS 721) has the smallest sample size at 16 observations and also shows the most dissimilar pattern. Hence, sample size limitations are likely at play here. Montgomery et al. (2011) suggest using between 5 and 20 bins and that the number of bins is approximately equal to the square root of N. The sample sizes in this study range from 16 to 101. Thus, the histograms shown in Fig. 2 offer only a preliminary view of the emerging distributions. For example, the histograms for Food Services and Drinking Places (NAICS 722) with a $N = 101$ show the prevalence of CCR and BCC in the lower efficiency ranges, while OLS is present in the higher efficiency ranges. By contrast, NAICS 721 with $N = 16$ indicates only a seemingly uniform pattern. As N increases, one would expect the DEA and OLS distributions to continue to define themselves and more closely match those of NAICS 722.

To provide further assistance in interpreting the results, Fig. 2 also includes correlation coefficients (which by definition range from -1 to 1), for the data in the histograms. Across sectors the correlation coefficient between benchmarking approaches is similar. CCR and BCC, the two DEA approaches, are not surprisingly positively and fairly strongly correlated. The OLS and DEA approaches are negatively and generally weakly correlated. As for trends based on sample size, there is no trend in the correlation of CCR and BCC and of OLS and CCR. The correlation coefficients between OLS and BCC do however show a reasonably strong trend, in that as sample size increases, the correlation coefficient becomes more negatively correlated. Such results again should be interpreted with caution since they are based on a sample size of five sectors, but the trend does appear to reinforce the assertion that as sample sizes increase, the DEA results shift to the extremes, primarily to the lower efficiencies, while the OLS results converge toward 0.7–0.8.

These dissimilar results when comparing OLS and DEA are not unique. Cubbin and Tzanidakis (1998) found their efficiency rankings of water utilities to vary significantly between OLS and DEA. They concluded that sample size does play a role, especially within DEA, where outliers could easily skew the measures of efficiency. They also highlighted the built-in checks and objectivity in OLS, which takes the same weightings for inputs across all observations, unlike DEA.

Summary and Conclusions

Two prominent benchmarking approaches were used to evaluate nonresidential water use efficiency: OLS and DEA. Each of these approaches was shown to be an improvement over simple normalization ratios, the state of practice, in that they allow for multiple inputs and thus provide a more accurate measure of efficiency. The two benchmarking approaches were applied to actual parcel-level data from Austin, Texas. The data were obtained through the database-driven approach described by Morales and Heaney (2014), which allows for nationwide application of these benchmarking methodologies through the use of water billing, property appraiser, and business databases, since such databases should be available throughout the United States. Cross-utility comparisons of water use are further facilitated by the NAICS classifications, which are standardized throughout all of North America and also available from the business data.

Most fundamentally, OLS and DEA differ in the type of benchmarking systems that they provide. OLS offers a public benchmarking system where the regressed relationships can be applied to data not included in the modeling effort to obtain a measure of efficiency. Thus, OLS is the preferred benchmarking system in comparisons of water use efficiency across utilities and other study areas. DEA provides for an internal benchmarking system in that in order to obtain a measure of efficiency for data not included in the original modeling effort, the new data need to be included and the model updated. This internal benchmarking classification likely limits the application of DEA to case studies of water use unless a nationwide clearinghouse of water use data can be structured. The two approaches also differ in that OLS focuses on average values in the data, while DEA utilizes the values at the boundaries. Though this provides a more limited measure of efficiency, it also makes OLS less susceptible to the effect of outliers and erroneous values in the data. Another difference is provided in that DEA allows for the decomposition of efficiency into scale and technical efficiencies. Both approaches are susceptible to sample size effects, especially DEA, where outliers are more likely to have a sizable effect on the measures of efficiency.

The results of this study indicate that the DEA and OLS approaches described not only rely on different mathematical techniques and definitions of efficiency, but their distributions of efficiencies are also drastically different. Across the sectors, the general trend indicates that as sample sizes increase, the distribution DEA efficiency scores will shift to the two extremes, with the bulk of the observations taken to be highly inefficient (0.1–0.2). As for OLS, its distributions of efficiencies seem to converge around 0.7–0.8 as sample sizes increase. This indicates several key points. There does appear to be a minimum sample size threshold, approximately $N = 30$, where the true distributions of efficiencies seem to define themselves. DEA is also much more susceptible to outlier effects since its measure of efficiency is based on the frontier of the data, while OLS is not as susceptible to outlier effects since its focus is on the average. DEA's susceptibility to outliers, at least in part, makes it so that the bulk of observations get labeled as highly inefficient (0.1–0.2), and this effect appears to become more amplified as sample sizes increase. The DEA mathematical framework, which assumes no functional form and optimizes the efficiency score of any given observation, likely intensifies the shift toward the extremes since only one outlier or erroneous variable could have a significant effect. Thus OLS certainly has some clear advantages over DEA, including its relative robustness to outliers; its seemingly more reasonable distributions of efficiencies; and its more process-oriented, multivariate description of the performance functions.

The application of water use statistics and benchmarks presented in this paper should be done with caution outside of the Austin, Texas area, understanding that there is a level of uncertainty that cannot be quantified until more utilities from across the country apply this approach. The intent of this paper is for this methodology to be applied elsewhere, where site-specific water use statistics can be developed, applied in utility or regional modeling/benchmarking efforts, and compared to the values presented for Austin, Texas. The focus of this paper is on presenting a data-driven methodology and associated benchmarking applications for this approach. Though outdoor water use has been shown to be a fairly small fraction of CII water use (Morales et al. 2011), its significance varies by sector and region.

In general, the data-driven approach described in Morales and Heaney (2014) and its ability to facilitate water use efficiency benchmarking of CII customers, as discussed in this paper, helps the field of urban water demand modeling by improving our understanding of the highly variable CII sectors of potable water use. The application of more sophisticated benchmarking techniques such as OLS and DEA advance our capability to address the complexity associated with the CII water sectors and their many drivers of water use. The methods described in this paper help utilities evaluate the water use efficiency of their CII sectors and target inefficient customers for their water demand management efforts. The database-driven methodologies in this paper allow for a standardized approach that can be readily duplicated and results compared across utilities and regulatory agencies. Additionally, these benchmarking approaches can be implemented at smaller and more private scales. For example, a company can use the same benchmarking methodologies to evaluate the efficiency of the various branches within their organization. This is perhaps the most effective scale for implementation since a company, as opposed to a utility or regulatory agency, has greater control over the various drivers of water use efficiency.

Future work should apply these data-driven benchmarking methodologies to other areas which would provide insight into the geographic differences in CII water use efficiency and the associated effects of climate, land value, etc. The use of additional longitudinal data such as multiple years of water billing and business information would help address trends in efficiency, seasonal effects, and the effects of weather and the economy. As more results from other utilities become available, our understanding of CII water use will strengthen and provide for a more certain determination of achievable levels of water use efficiency in the CII sectors.

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