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Understanding the influence of climate change on the embodied energy of water supply

Weiwei Mo [a, *], Haiying Wang [b], Jennifer M. Jacobs [a]

[a] Department of Civil and Environmental Engineering, University of New Hampshire, Durham, NH, 03824, USA
[b] Department of Mathematics & Statistics, University of New Hampshire, Durham, NH, 03824, USA

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ABSTRACT

The current study aims to advance understandings on how and to what degree climate change will affect the life cycle chemical and energy uses of drinking water supply. A dynamic life cycle assessment was performed to quantify historical monthly operational embodied energy of a selected water supply system located in northeast US. Comprehensive multivariate and regression analyses were then performed to understand the statistical correlation among monthly life cycle energy consumptions, three water quality indicators (UV_{254}, pH, and water temperature), and five climate indicators (monthly mean temperature, monthly mean maximum/minimum temperatures, total precipitation, and total snow fall). Thirdly, a calculation was performed to understand how volumetric and total life cycle energy consumptions will change under two selected IPCC emission scenarios (A2 and B1). It was found that volumetric life cycle energy consumptions are highest in winter months mainly due to the higher uses of natural gas in the case study system, but total monthly life cycle energy consumptions peak in both July and January because of the increasing water demand in summer months. Most of the variations in chemical and energy uses can be interpreted by water quality and climate variations except for the use of soda ash. It was also found that climate change might lead to an average decrease of 3–6% in the volumetric energy use of the case study system by the end of the century. This result combined with conclusions reached by previous climate versus water supply studies indicates that effects of climate change on drinking water supply might be highly dependent on the geographical location and treatment process of individual water supply systems.

1. Introduction

Over the last few decades, water shortage has led to increased adoption of alternative water sources such as imported water, desalinated seawater, and even reclaimed water in many densely populated areas around the world (Lazarova et al., 2012; Yüce et al., 2012; Bischel et al., 2011; Elimelech and Phillip, 2011; Martinez and Clark, 2012; Jiang et al., 2013). While these alternative water sources serve as an important supplement of the dwindling freshwater supply, their adoptions are usually associated with significant short-term and long-term costs in forms of life cycle energy, economic costs, and environmental impacts (Stokes and Horvath, 2009; Mo et al., 2014). For example, producing 1 m^3 of tap water through fresh ground or surface water sources typically consumes around 0.5 kWh of electricity (Goldstein and Smith, 2002), whereas water importation in California requires around 1.6–2.6 kWh and seawater desalination via reverse osmosis uses around 4.4–5.5 kWh to produce the same amount of water (Mo et al., 2014; Klein et al., 2005). These energy and environmental burdens could potentially lead to new or elevated stresses in energy supply, public funds, as well as ecosystem services, which may eventually be partially or fully reflected in water and energy prices, causing ripple effects on social equity and economic development (Kaika, 2003; Rogers et al., 2002). One example is the South-to-North Water Diversion Project in China which is likely to more than double water prices in receiving cities due to the vast project constructional costs and pumping demands (a power capacity of 454 MW to pump water from Yangtze River through the Eastern Route) (Berkoff, 2003; Kuo, 2014).

Climate change is likely to further increase the energy and cost of water supply through combined effects on water quality and availability, service infrastructure, and user demands, challenging

* Corresponding author. 35 Colovos Road, 334 Gregg Hall, Durham, NH, 03824, USA.
E-mail address: Weiwei.mo@unh.edu (W. Mo).

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the sustainable management of both water and energy resources. In the US, the hydrologic cycle is accelerating with increasing flooding and downpours in the northeast as well as more frequent droughts and shrinking snowpack storage in the southwest (Stocker et al., 2013; Barnett et al., 2005). Sea level rise and subsequent seawater intrusion have threatened freshwater availability and quality in many coastal regions (Stocker et al., 2013; Shannon et al., 2008). Already water-stressed regions such as California, Texas, and Arizona are particularly vulnerable to climate change because they are predicted to have the highest temperature increase as well as the greatest precipitation reduction (Stocker et al., 2013; Milly et al., 2005; Bates et al., 2008). Collectively, these climate change effects could impose escalated challenges in providing reliable and low cost water services in the foreseeable future. Utility managers and city planners need to be prepared for such changes so that the most appropriate mitigation and adaptation strategies can be implemented. Therefore, a systematic understanding on the influence of climate change on water supply services especially its indirect effect on energy utilities is imperative, given the lead-time needed for decision making, planning, and construction in water and energy utilities and government agencies.

The energy use of varied forms of water supply has been investigated via different approaches. Traditional energy audits and risk assessments quantify the direct energy used onsite of water systems (Wilkinson, 2000; Elliott et al., 2003; Means, 2004). In the past decade, a proliferated number of life cycle assessments (LCAs) was conducted to examine the life cycle energy use of water supply systems (Stokes and Horvath, 2009; Mo et al., 2014, 2010, 2011; Rothausen and Conway, 2011; Racoviceanu et al., 2007; Lassaux et al., 2007; Godskesen et al., 2010; Lundie et al., 2004; Friedrich et al., 2009; Landu and Brent, 2007; Lyons et al., 2009). These studies have revealed the importance of indirect energy flows associated with providing chemicals and services in water systems in addition to direct energy consumptions, and provided a more comprehensive approach in quantifying the "true" energy embodiment in water systems to inform sustainable management and decision making. Nevertheless, most of these LCAs are static studies focusing on evaluating the energy uses of water supply at given times ("snapshots"), while critical information regarding the trends and dynamic patterns of the life cycle energy in response to exogenous drivers such as climate change is missing (Stokes and Horvath, 2009; Mo et al., 2010, 2011; Racoviceanu et al., 2007; Lyons et al., 2009; Friedrich, 2002). These "snapshots" are mostly taken for a current or past time. Only a few studies have investigated future energy uses based on projected water demand and freshwater availabilities; however, climate change was not considered in either water demand or water availability estimations (Mo et al., 2014; Lundie et al., 2004).

The impacts of climate change on water availability have been widely investigated (Milly et al., 2005; Yates, 1996; Gleick, 1987; O'Hara and Georgakakos, 2008; Muttiah and Wurbs, 2002; Bekele and Knapp, 2010; Matonse et al., 2013), while only a few studies have offered discussion on the influence of climate change on water quality (Whitehead et al., 2009; Mimikou et al., 2000; Senhorst and Zwolsman, 2005; Zwolsman and Van Bokhoven, 2007; Arheimer et al., 2005; Delpla et al., 2009). Nonetheless, water quality could have more acute effects on treatment energy and cost compared with water availability. For instance, increased water temperature and summer drought can lead to enhanced growth of algae and cyanobacteria, cascading the formation of disinfection byproducts and treatment costs (Mimikou et al., 2000; Zwolsman and Van Bokhoven, 2007; Delpla et al., 2009). Storm events and flooding could result in elevated suspended solids, nutrients, and pollutants (e.g., pesticides) fluxes (Whitehead et al., 2009). Seawater intrusion increases groundwater salinity and its associated treatment difficulty in many coastal regions (Barlow and Reichard, 2010). On the other hand, warmer water may increase the reaction rates of treatment processes as well as physical operation of facilities, which may potentially improve treatment efficiency and reduce cost (Crittenden et al., 2012). The degree of these positive and negative effects could vary considerably across regions based on local baseline water and climate profiles, water treatment technologies, and socioeconomic conditions, yet little is known about such tradeoffs to guide management practices.

Therefore, this study primarily investigates the potential effects of climate change on water treatment through changes in water quality parameters for a case study water supply system located in the northeastern US. To achieve this goal, an assessment framework including dynamic life cycle energy assessment, multivariate analysis, and regression analysis were adopted. This study aims to assist proactive management of water and energy resources with the ultimate goal of improving their long term resiliency and sustainability under global changes.

2. Methodology

2.1. Water quality indicators

Raw water quality is a key factor in determining the selection, design, and operation of water treatment processes (Crittenden et al., 2012). Table 1 provides a list of water quality indicators as well as their influences on six individual treatment processes, including coagulation, filtration, membrane separation, disinfection, ion exchange, and air stripping and aeration. It has to be noted that Table 1 does not exhaust all water quality parameters that are potentially significant to human and ecological health (e.g., heavy metals, nutrients, dissolved oxygen etc.); however, the listed indicators are closely related to chemical dosages, equipment utilization rates, and pre- and post-treatment requirements in drinking water systems' design and actual operation. Most of these water quality indicators are likely to be influenced by climate change (Delpla et al., 2009), which could further affect the daily operation of existing treatment plants as well as their energy demands.

2.2. Study site description

The case study water supply system (CSS) is located on the coast of northeast US serving a population of around 2.55 million. Raw water of the CSS comes from two protected inland reservoirs, which are filled naturally by rain and snow fall on the surrounding watersheds. The two reservoirs have high altitudes, and hence the influence of sea level rise on the water quality is minimum. The CSS utilizes ozone (generated from liquid oxygen) as the primary disinfectant and chloramine (formed by sodium hypochlorite and aqueous ammonia) for residual disinfection. Additionally, sodium bisulfite is used for ozone removal, and sodium hydrofluorosilicic acid is used for tooth health protection. Towards the end of the treatment process, sodium carbonate (soda ash) and carbon dioxide are used for alkalinity and pH adjustment respectively. Three types of energy are directly used onsite of the CSS: 1) electricity is used for pumping, mixing, facility administration etc.; 2) natural gas is primarily used for space and water heating; and, 3) diesel is used as backup power supply. In particular, the local electricity provider has been paying the CSS to go off grid during storms and other extreme climate events in order to relieve regional energy stress and to reduce outages. This interaction between the CSS and the electricity provider further implies the importance of understanding the climate-water-energy nexus and finding solutions to reduce the energy use in water systems.

Monthly flow rates as well as the chemical and energy uses over

Table 1
Important water quality indicators for design and operation of individual drinking water treatment processes and the potential influence of climate change on these water quality indicators.

Water quality indicators	Treatment processes						Potential climate influences
	Coagulation	Filtration	Membrane separation	Disinfection	Ion exchange	Air stripping and aeration	
pH	Optimal pH ranges at 4.5–9.5 depending on coagulants (Crittenden et al., 2012)			Lower pH preferred when using chlorine, and higher pH preferred by ozonation (Hansen et al., 1988)		May affect the distribution of species between ionized and un-ionized forms (Crittenden et al., 2012)	Increased water pH under droughts and warmer climate (Delpla et al., 2009; Van Vliet and Zwolsman, 2008; Psenner and Schmidt, 1992; Prathumratana et al., 2008)
Temperature	Floc formed in colder water tends to be weaker (Crittenden et al., 2012)	Higher temperature preferred for both granular and membrane filtration (Schreiber et al., 2005; Raffin et al., 2012)	Higher temperature preferred for membrane effectiveness (Raffin et al., 2012)	Greatly influences chlorination effectiveness and ozone solubility (Hansen et al., 1988)		Higher temperature preferred (Crittenden et al., 2012)	Increased water temperature under a warmer climate (Delpla et al., 2009; Van Vliet and Zwolsman, 2008; George et al., 2007; Malmaeus et al., 2006)
Alkalinity	High alkalinity makes pH adjustment difficult (Crittenden et al., 2012)			High alkalinity makes pH adjustment difficult (Crittenden et al., 2012)			Increased alkalinity under a warmer climate (Delpla et al., 2009; Psenner and Schmidt, 1992)
Turbidity	Influences coagulant dose (Crittenden et al., 2012)	Determines level of pretreatment, membrane fouling rate, and breakthrough rate (Schreiber et al., 2005; Raffin et al., 2012)	Determines level of prefiltration, pH adjustment, and membrane fouling rate (Crittenden et al., 2012)				Increased surface water turbidity under heavy rainfall events (Hunter, 2003)
Hardness			Controls design of nanofiltration for hardness removal (Van der Bruggen et al., 2004)		Controls the use and regeneration of resin (Hansen et al., 1988)		Increased hardness and salinity when seawater invades freshwater resources
Natural Organic Matters (Total organic carbon, UV_{254}, etc.)	Controls coagulant dose (Crittenden et al., 2012)	Depletes adsorption capacity and increases membrane fouling (Crittenden et al., 2012; Howe and Clark, 2002)	Rapidly increases membrane fouling (Zhu and Elimelech, 1997)	Controls disinfectant does and the formation of disinfection byproducts (Crittenden et al., 2012)			Higher frequencies of algal and cyanobacteria blooms under a warmer climate (Arheimer et al., 2005; Delpla et al., 2009) Weak to fair positive correlation with precipitation (Prathumratana et al., 2008)
Volatile substances						Controls system design (Crittenden et al., 2012)	Increased pesticides fluxes under increased precipitation (Delpla et al., 2009)

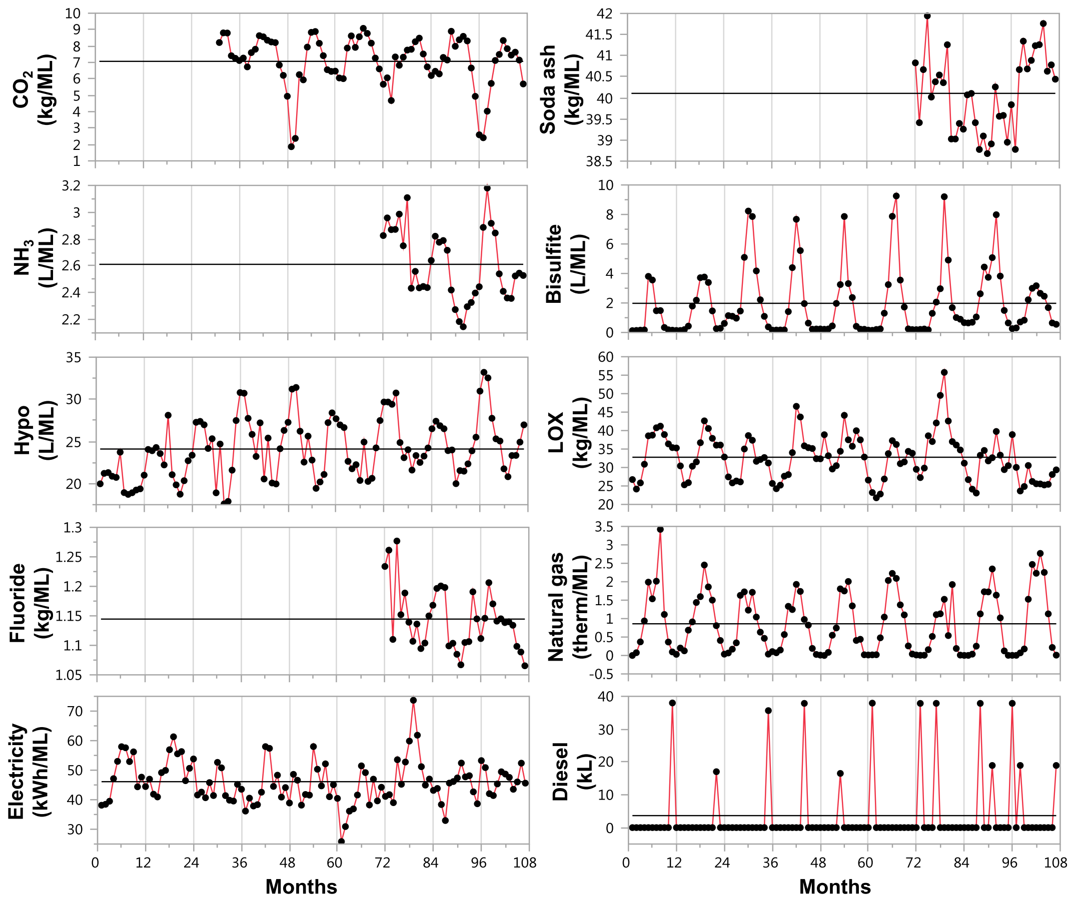

Fig. 1. Monthly chemical and energy uses of the case study water supply system (Note: The starting month, 0th month, corresponds to August of 2005; and the end month, 108th month, corresponds to August of 2014. Diesel amounts shown in the figure only represent the amount of diesel purchased in the specific month instead of consumed.).

a period of 9 years were obtained from the CSS. Fig. 1 provides the fluctuations of the chemical and energy uses over time. It has to be noted that diesel amounts shown in Fig. 1 only represent the amount of diesel purchased in the specific month instead of consumed. Diesel needs to be stored in order to fulfill its function of emergency electricity generation, yet the dates when diesel is actually consumed were not recorded. Many chemical and energy uses present strong seasonal patterns. For instance, carbon dioxide, bisulfite, liquid oxygen, natural gas, and electricity have higher consumptions during winter months, while sodium hypochlorite has higher consumptions during summer months.

On the basis of the treatment process of the CSS, three raw water quality indicators that may significantly affect the operation of the CSS were further investigated: water temperature (T_{water}), pH, and UV_{254}. Water temperature directly affects the amount of ozone required to achieve the regulatory required target inactivation level by influencing ozone solubility and treatment effectiveness. Higher water pH is used for prevention of leaching of lead and copper from service lines and home plumbing systems, as well as favoring chloramine stability within the distribution system. UV_{254} is a surrogate for the natural organic matter (NOM) concentration and an indicator of ozone dosages in the CSS. It is measured as the absorbance of UV light at a wavelength λ of 254 nm of a filtered water sample measured with a spectrophotometer (Crittenden et al., 2012). Daily data of the three water quality indicators were obtained from the CSS.

Climate data of the CSS were obtained from the National Oceanic and Atmospheric Administration (NOAA) National Climate Data Center, and the closest climate observation station to the two reservoirs were selected. Five climate indicators were used based on the reported data: monthly mean maximum temperature (T_{max}), monthly mean minimum temperature (T_{min}), monthly mean temperature (T_{mean}), total precipitation amount for the month (P_{total}), and total snow fall amount for the month (S_{total}).

2.3. Dynamic life cycle energy assessment

Life cycle energy in the current study is calculated as the amount of primary energy associated with the operation of a water supply system from water intake, treatment, storage, to delivery. Construction and end-of-life of bulk water supply infrastructures were not considered in this study because these activities are less likely to be influenced by water quality changes. The life cycle energy includes both direct energy, referring to the electricity, natural gas, and diesel used onsite, and indirect energy, referring to the energy associated with producing and providing chemicals. The time scale of climate change, although predicted to accelerate rapidly in the coming decades (Stocker et al., 2013), exceeds the operation records of most water treatment facilities. Hence, we investigate the life cycle energy of seasonal climate variations as a surrogate to understand the potential influences of future climate change.

All chemical and energy uses were normalized to a functional unit of 1 ML of water delivered to end users for further analysis. Given that chemical and energy consumptions vary over time, we first estimate the life cycle energy for unit weight/volume use of each type of chemical and energy. These unit weight/volume based life cycle energy was then multiplied with the flow rate normalized monthly chemical and energy uses and summed to estimate the total energy embodiment per functional unit (Eq. (1)). SimaPro 8® was utilized to calculate these life cycle energy and carbon emissions. A list of corresponding data entries used in SimaPro is provided in Table S1 of the supporting information. Specifically, the "Cumulative Energy Demand" method was used to estimate the primary energy associated with extraction, production, and transportation of energy and chemicals used during system operation (Frischknecht et al., 2007), and the "IPCC 2013 GWP 100a" method was used to estimate their carbon emissions (Stocker et al., 2013).

$$E_t = \sum_{i=1}^{n}\left(e_i \times \frac{U_{i,t}}{Q_t}\right) \quad (1)$$

where.

E_t = life cycle energy per functional unit at month t, MJ/ML;
i = chemical and energy type index;
n = the total number of chemical and energy types used in system operation;
e_i = life cycle energy per unit weight or volume of chemical or energy type i, MJ/(weight or volume);
$U_{i,t}$ = weight or volume consumption of chemical or energy type i during month t, weight or volume; and
Q_t = total water production during month t, ML.

2.4. Multivariate and regression analyses

Given the natural complexity and interactions of multiple factors (e.g., treatment train and internal water quality) that potentially influence the operation of water treatment processes, it has been argued that statistical analyses provide an effective means in understanding the influence of raw water quality on the life cycle energy of water supply (Santana et al., 2014). In the current study, a multivariate analysis was conducted in JMP Pro 12® and R software (R Core Team, 2014) to determine the relationships among the five climate indicators (T_{mean}, T_{max}, T_{min}, P_{total}, and S_{total}) and three water quality indicators (T_{water}, pH, and UV_{254}). The multivariate analysis identifies and eliminates highly dependent predictor variables in order to remove redundant information and improves the efficiency of the succeeding regression analysis. This was achieved by utilizing a pairwise method to estimate Pearson correlation coefficients (r) among the predictor variables, with values closer to 1 or -1 indicating stronger positive or negative correlation respectively. When two variables have very strong correlations with each other, only one of them will be used in the following regression analysis.

A comprehensive regression analysis was then performed, which serves two distinct purposes: 1) to identify the predictor variables that potentially influence chemical and energy uses; and 2) to estimate the effects and the relative importance of the selected predictor variables on the chemical and energy uses. While water quality indicators directly affect system operation, climate indicators could have both direct and indirect effects through 1) changing space and water heating/cooling demands and 2) altering raw water quality. Hence, water and climate indicators were simultaneously used as predictor variables in the regression analysis. Firstly, we identify the potentially influential predictor variables utilizing three varied selection methods: the corrected Akaike Information Criterion (AICc) method (Burnham and Anderson, 2002), the Bayesian Information Criterion (BIC) method (Schwarz, 1978), and the Adaptive Lasso method (Zou, 2006). Both AICc and BIC are conventional regression methods with good model selection capabilities, but they both suffer from certain drawbacks. Under certain conditions, AICc could potentially include more variables than necessary while BIC is prone to selecting fewer variables. The Adaptive Lasso method is an advanced method with oracle properties to improve model selection performances (Zou, 2006). After the variable selections have been generated by the three methods, a best subset procedure was performed where all possible models (all combinations of predictor variables) were combined (Eq. (2)). This approach is preferred to the conventional stepwise regression methods because stepwise methods often rule out potential candidate models (Kutner et al., 2004). All predictor variables selected by the three selection methods are then fitted through linear regressions to understand their effects on the chemical and energy uses. While this method could potentially result in selection of uncorrelated variables, the rationale behind is to prevent potential omissions of important variables. The cost of such an approach is only some decrease of efficiency in parameter estimation.

$$V = V_{AICc} \cup V_{BIC} \cup V_{Lasso} \quad (2)$$

where.

V = all variables used for data fitting and regression;
V_{AICc} = variables selected by the AICc method;
V_{BIC} = variables selected by the BIC method; and
V_{Lasso} = variables selected by the Adaptive Lasso method.

Uncertainties of the fitted model were examined using three parameters: the standard errors (s_i), p-values, and the R^2 values. The standard errors could be used to construct confidence intervals of each linear coefficient (a_i). For instance, a 95% confidence level corresponds to the interval of $[a_i - Z_{0.05/2} \times s_i, a_i + Z_{0.05/2} \times s_i]$, where $Z_{0.05/2}$ is a normal quantile with a value of 1.96. p-values indicate the observed significance level of each predictor variable in determining the chemical and energy uses. R^2 values give the percentage of variations in each type of chemical and energy uses that can be explained by the predictor variables. For example, an R^2 value of 0.5 indicates 50% of the variation in a certain type of chemical or energy use can be explained by the fitted model. A relative importance analysis was also performed to further examine the contribution of each predictor variable in the chemical and energy uses. Two relative importance methods were examined: the dominance analysis method (Kruskal, 1987; Lindeman et al., 1980) and the decomposition method (Genizi, 1993). Both methods were performed using the R software utilizing the Relaimpo package (Grömping, 2006).

2.5. Climate change scenarios

Downscaled annual mean temperature and precipitation

Table 2
Future temperature and precipitation changes in northeast US obtained from the National Climate Assessment reports (Kunkel, 2013).

Climate scenarios		ΔTemperature (°C)			ΔPrecipitation (%)		
		2035	2055	2085	2035	2055	2085
A2	Lowest	0.9	1.6	2.7	−5	−6	−8
	Median	1.7	2.7	4.4	4	5	9
	Highest	2.5	3.6	6.3	7	10	16
B1	Lowest	0.9	1.2	1.9	−5	−4	−2
	Median	1.5	2.0	2.6	3	4	6
	Highest	1.9	2.6	3.5	9	8	10

[*] A2 is a high emission scenario with a global CO_2 concentration of 800 ppm by 2100. B1 is a low emission scenario with a global CO_2 concentration of 500 ppm by 2100. Both scenarios are developed by the Intergovernmental Panel on Climate Change (IPCC).

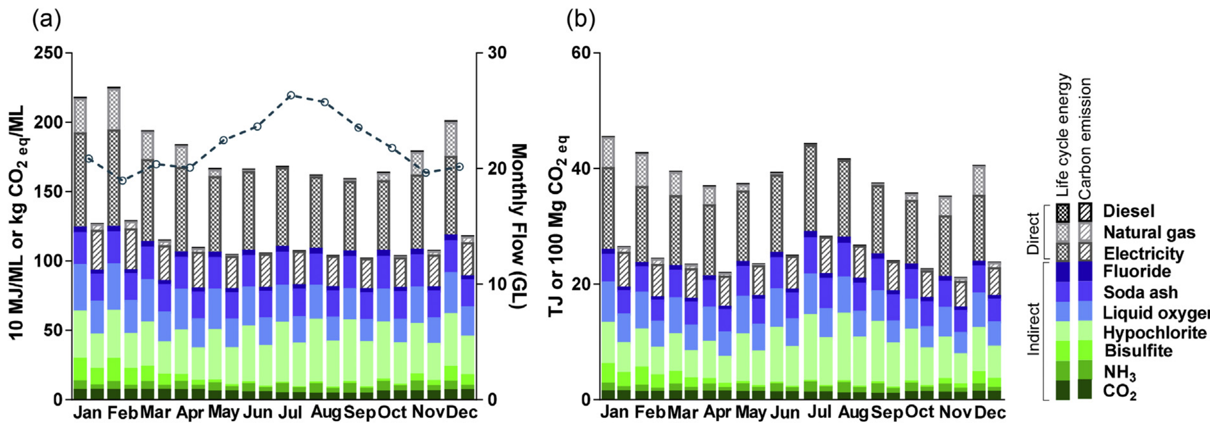

Fig. 2. Life cycle energy and carbon emission of the case study water supply system. (a) shows the monthly life cycle energy consumptions and carbon emissions associated with producing 1 ML of water as well as the monthly total water flow of the case study system; (b) shows the total monthly life cycle energy consumptions and carbon emissions of the case study system.

changes in the northeast US were obtained from the National Climate Assessment reports provided by NOAA (Kunkel, 2013). Future climate changes were estimated for two Intergovernmental Panel on Climate Change (IPCC) generated emission scenarios: 1) the high emission scenario (A2), where global population increases continuously; economic development is primarily regionally oriented; and technological change is slow; 2) the low emission scenario (B1), where global population peaks in mid-century and declines thereafter; economic structures rapidly change towards a service and information economy; and clean and resource efficient technologies are introduced. These downscaled climate change predictions were estimated as multi-model means of 29 (14 for B1 scenarios and 15 for A2 scenarios) Climate Model Intercomparison Project phase 3 (CMIP3) global climate simulations (Kunkel, 2013). Table 2 provides the lowest, median, and highest temperature and precipitation changes towards the end of this century. Percentage changes of snowfall were assumed to be the same as those of precipitation.

3. Results and discussion

3.1. Life cycle energy and carbon emissions

In the case study system, indirect energy and the associated carbon emissions comprises a more significant proportion than the direct energy, representing around 55–67% of the total life cycle energy and around 73–78% of the total carbon emissions in producing 1 ML of water (Fig. 2). Fig. 2(a) shows that the volumetric life cycle energy and carbon emissions have notable variations by month. Generally speaking, summer months present the lowest energy and carbon emissions while winter months present the highest. For example, the average volumetric life cycle energy consumption in February is around 2247 MJ/ML, which is around 41% higher than the energy use in September. Such a difference is primarily contributed by the monthly variations in direct energy consumption, and the reduced heating demand during summer months is the main reason for the changes in direct energy consumption. Total volumetric indirect energy has relatively less change over a year because of the varied peak use time of different chemical species. For example, liquid oxygen and bisulfite, used for ozone disinfection, have higher consumptions during winter due to the lower ozone reaction rates and treatment effectiveness and the need to de-ozonate with bisulfate given the slower ozone decay in colder temperatures. On the other hand, hypochlorite and ammonia, used for residual disinfection, have increased volumetric consumptions during summer due to increased initial and long term decay of the residual with a higher temperature. Volumetric carbon emissions follow a similar trend as volumetric life cycle energy consumptions. Monthly water flow, however, presents a unique trend. Average water demand is the highest during summer, and the lowest during winter. Such a trend can be explained by increased outdoor water uses, such as landscape irrigation and water recreation, during summer time. Fig. 2(b) shows that changes in water flow could have an essential effect on the monthly total life cycle energy and carbon emissions in the CSS. The total life cycle energy and carbon emissions peak in both July and January.

3.2. Multivariate and regression analyses

Three of the five climate indicators, T_{max}, T_{min}, and T_{mean}, are highly positively correlated (Fig. 3), with correlation coefficients above 0.99 ($r > 0.99$). Hence, T_{max} and T_{min} were eliminated from the succeeding regression analysis in order to improve the regression performances. Total precipitation (P_{total}) has very weak correlation with all other climate indicators ($r < 0.11$), indicating no particular wet or dry season in the study area. Snowfall (S_{total}) only happens in winter time, and hence, it is correlated with temperature indicators ($r \approx 0.7$). Among the three water indicators, UV_{254} is relatively independent, while pH and water temperature (T_{water}) have a moderate negative correlation. UV_{254} also has very weak correlations with climate indicators (T_{mean}, P_{total}, S_{total}) ($r < 0.2$). This indicates that climate change might have limited effect on the amount of NOMs in the case study area. Water temperature is highly correlated with air temperature indicators, which can be explained by the air and water heat exchanges. It also has a fair correlation with total snowfall, although the two indicators do not have apparent causal-effect relationship. Similarly, water pH appears to have fair correlations with air temperature indicators mainly because of the high correlations between water and air temperatures. This indicates climate change will potentially affect both water temperature and pH, which might further influence water treatment operation.

A regression analysis was first performed to examine how climate indicators contribute to the water indicators. Only T_{mean}, P_{total}, and S_{total} were used as inputs whereas T_{max} and T_{min} were removed based on the correlation analysis results. Results of this step are provided in the top three rows of Fig. 4. Both T_{mean} and S_{total} was found to be statistically significant contributors of water

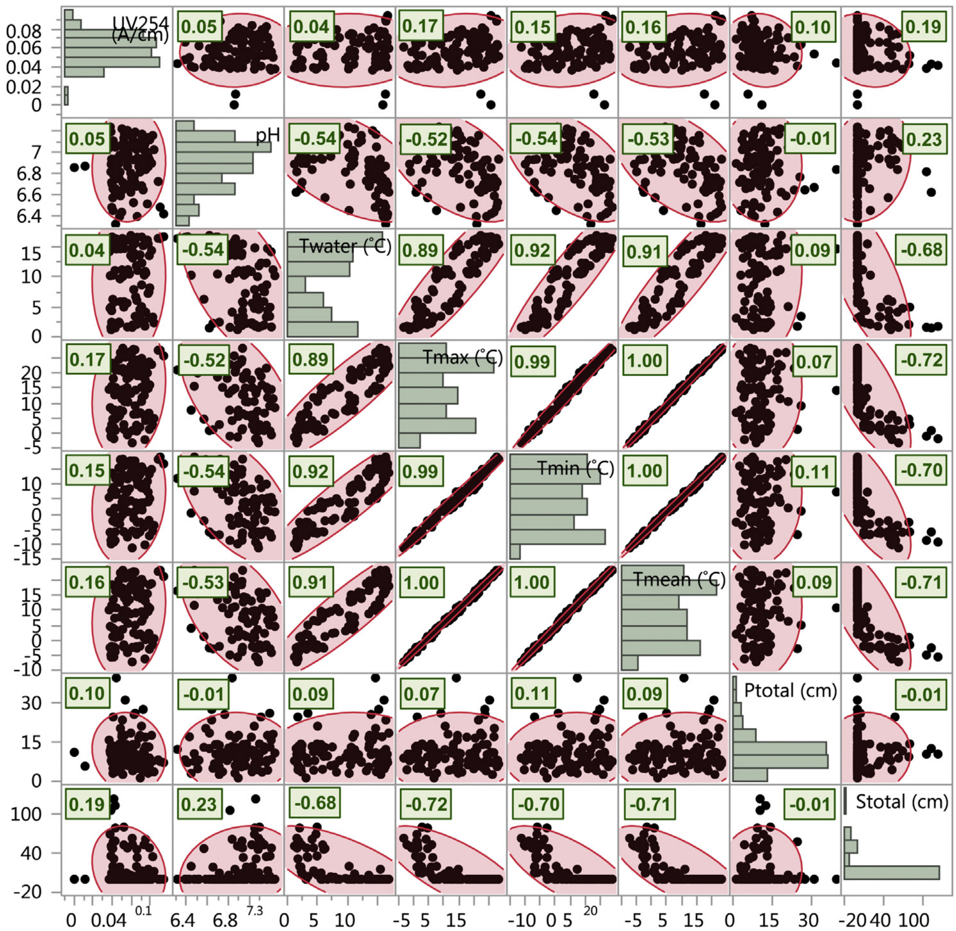

Fig. 3. Correlations among three water quality indicators (UV_{254}, pH, water temperature) and five climate indicators (monthly mean maximum temperature (T_{max}), monthly mean minimum temperature (T_{min}), monthly mean temperature (T_{mean}), total precipitation amount for the month (P_{total}), and total snow fall amount for the month (S_{total})). Numbers in green boxes are the correlation coefficients (r) of the two intersect indicators. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

pH with a relative importance of 85% and 15% respectively. Yet the relatively low R^2 value of 0.33 indicates that the two variables could merely explain a small part of the pH changes. T_{mean} was found to be a very significant contributor of T_{water}, and the changes of T_{mean} can largely explain the changes of T_{water}. S_{total} was also found to be potentially contributing to the changes of UV_{254}, but its contribution could be negligible ($R^2 = 0.03$). A second regression analysis was then performed to examine the contributions of both climate and water indicators to the chemical and energy uses. Soda ash is the only consumption type that can hardly be explained by any of the water or climate indicators (Fig. 4). UV_{254} was found to be an important precursor of the uses of liquid oxygen and electricity (relative importance>45%). This can be explained by the more intense ozone disinfection treatment (higher liquid oxygen usage, electricity for mixing) when the influent water has a higher NOMs level. Raw water pH is statistically significant to the usages of CO_2 and hypochlorite (relative importance>30%). Higher raw water pH decreases the uses of hypochlorite for residual disinfection, but increases the uses of CO_2 for final pH adjustment. Water temperature significantly influences all types of chemical and energy uses except for soda ash. Air temperature (T_{mean}) also has high contributions to the natural gas usages as well as the residual disinfection process. Total precipitation (P_{total}) does not show statistically significant correlations with most chemical and energy uses except for electricity and liquid oxygen, but its contributions to their uses are negligible. Total snowfall (S_{total}) has a high contribution to the bisulfite usages, which might be explained by its statistical correlation with UV_{254}.

3.3. *Future changes of life cycle energy under downscaled climate projections*

We estimate the future changes of the CSS′ life cycle energy on the basis of the regression analyses results presented in Fig. 4. Changes in chemical and energy uses were first estimated and then converted into changes in embodied energy and carbon emissions using the same method as discussed in Section 2.3. Only the regressions with sufficient statistical significance ($R^2 > 0.50$) were included in the projections. More specifically, UV_{254} and pH were not considered because there was no significant climate indicators found in determining their future changes. Potential future changes of hypochlorite, soda ash, and fluoride were also excluded because only weak correlations can be found between them and the climate and water indicators. Hence, the projections of future changes of the CSS' life cycle energy were solely based on future climate (T_{mean}, P_{total}, and S_{total}) changes as well as T_{water} changes caused by changes of T_{mean}. Fig. 5(a) provides the estimated percentage changes of volumetric life cycle energy in the case study water supply system towards the end of the century. Both climate scenarios projected a slight decrease in the volumetric life cycle energy use with the sole influence of climate change. Under the A2 scenario, climate change in the northeast US might lead to an average of 6% decrease in the

	UV_{254} (A/cm)	pH	T_{water} (C°)	T_{mean} (C°)	P_{total} (cm)	S_{total} (cm)	Int.	R^2
UV_{254} (A/cm)						-0.0001 ^{A} s=0.0001 P=0.055	0.06 s=0.0017 P<0.0001	0.03
pH				-0.02 ^{A,B,L} s=0.0028 P<0.0001 RI = 85.18%		-0.0025 ^{A,B,L} s=0.0009 P=0.0093 RI = 14.82%	7.09 s=0.0415 P<0.0001	0.33
T_{water} (C°)				0.54 ^{A,B,L} s=0.0247 P<0.0001			4.77 s=0.3211 P<0.0001	0.82
NH_3 (L/ML)	4.41 ^{A,B,L} s=2.2227 P=0.0559 RI = 6.88%		0.08 ^{A,B,L} s=0.0139 P<0.0001 RI = 64.89%	-0.04 ^{A,B,L} s=0.0087 P=0.0003 RI = 28.23%			1.94 s=0.1458 P<0.0001	0.56
Bisulfite (L/ML)	-13.47 ^{A} s=8.1961 P=0.1034 RI = 2.36%		-0.25 ^{A,B,L} s=0.0319 P<0.0001 RI = 58.77%			0.02 ^{A,B,L} s=0.0065 P=0.0004 RI = 38.87%	4.81 s=0.6669 P<0.0001	0.69
Hypochlorite (L/ML)		-3.74 ^{A,B,L} s=1.423 P=0.0098 RI = 31.50%	0.42 ^{A,B,L} s=0.0776 P<0.0001 RI = 45.01%			0.03 ^{A,B} s=0.0135 P=0.0416 RI = 23.48%	45.37 s=10.2851 P<0.0001	0.46
Liquid oxygen (kg/ML)	266.78 ^{A,B,L} s=019.5838 P<0.0001 RI = 56.03%	3.80 ^{A} s=1.6475 P=0.023 RI = 10.60%	-0.46 ^{A,B,L} s=0.0906 P<0.0001 RI = 22.12%		-0.009 ^{A} s=0.0485 P=0.0631 RI = 2.85%	0.03 ^{A} s=0.0160 P=0.0503 RI = 8.40%	-3.74 s=11.9024 P=0.7541	0.77
Soda ash (kg/ML)								0
Fluoride (kg/ML)			0.01 ^{A,B,L} s=0.0032 P=0.0039 RI = 69.84%	-0.0035 ^{A} s=0.0020 P=0.0839 RI = 30.16%			1.08 s=0.0180 P<0.0001	0.33
CO_2 (kg/ML)	-0.10 ^{A,B,L} s=0.0243 P<0.0001 RI = 12.38%	0.01 ^{A,B,L} s=0.0019 P<0.0001 RI = 36.22%	-0.84 ^{A,B,L} s=0.0914 P<0.0001 RI = 51.41%				-0.03 s=0.0133 P=0.0632	0.70
Electricity (kWh/ML)	260.92 ^{A,B,L} s=26.6215 P<0.0001 RI = 46.14%	-15.59 ^{A} s=8.4303 P=0.0674 RI = 4.79%	-3.19 ^{A,B,L} s=0.3460 P<0.0001 RI = 43.96%		-1.34 ^{A,B} s=0.6450 P=0.0405 RI = 5.11%		69.22 s=15.7460 P<0.0001	0.66
Natural gas (therm/ML)		-0.32 ^{A} s=0.1745 P=0.0721 RI = 7.76%	-0.05 ^{A,B,L} s=0.0143 P=0.001 RI = 42.60%	-0.06 ^{A,B,L} s=0.0084 P<0.0001 RI = 49.64%			4.07 s=1.236 P<0.0014	0.84

Fig. 4. Outcomes of the regression analyses showing the statistically significant climate indicators of water variables and the statistically significant water and climate contributors to the chemical and energy uses in the case study water supply system. A, B, and/or L indicates that the water quality or climate indicators have been selected by the AICc, the BIC, and/or the Adaptive Lasso method. An empty cell means the corresponding indicator does not affect the corresponding chemical/energy use. Green numbers represent coefficients a_1–a_7 in linear regression equations of the criteria variables in the column. For instance, $NH_3 = a_1 \times UV_{254} + a_2 \times pH + a_3 \times T_{water} + a_4 \times T_{mean} + a_5 \times P_{total} + a_6 \times S_{total} + a_7$. While a_2, a_5, a_6 are all zeros. "s" values are the standard errors of the coefficients represented by the green numbers. "P" values are the observed significance level of each predictor variable. "RI" values are the relative importance of each selected predictor variable in each type of chemical or energy uses. It is reported as an average of the RI values calculated through the dominance analysis method (Kruskal, 1987; Lindeman et al., 1980) and the decomposition method (Genizi, 1993). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

volumetric energy use of the case study system, while under the B1 scenario, an approximate of 3% decrease is likely to occur. This result combined with conclusions reached by previous climate versus water supply studies (Delpla et al., 2009) show that effects of climate change on drinking water supply might be highly dependent on the geographical location and treatment process of individual water supply systems. This result also presents the possibility of climate change having positive effects on the volumetric life cycle energy uses in drinking water supply.

Fig. 5(b) provides the estimated percentage changes of total life cycle energy in the case study water supply system when the potential influence of climate change on the water demand was

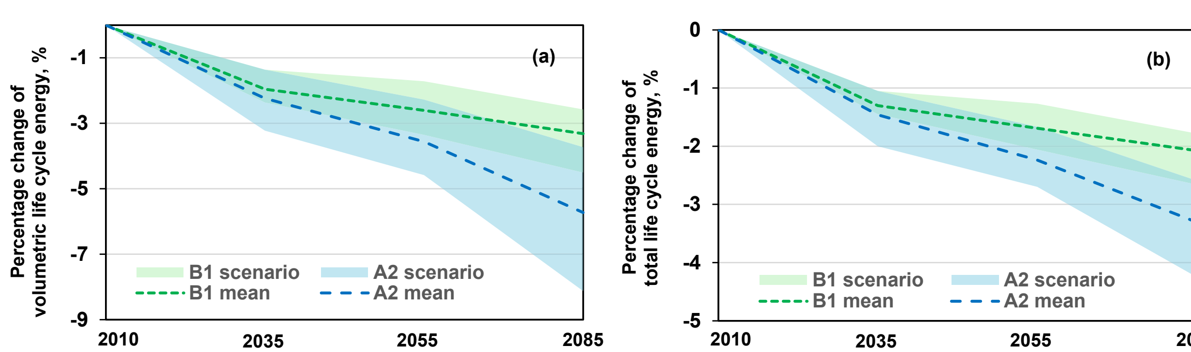

Fig. 5. Percentage change of volumetric life cycle energy (a) and percentage change of total life cycle energy (b) in the case study water supply system towards the end of the century under the IPCC A2 and B1 scenarios.

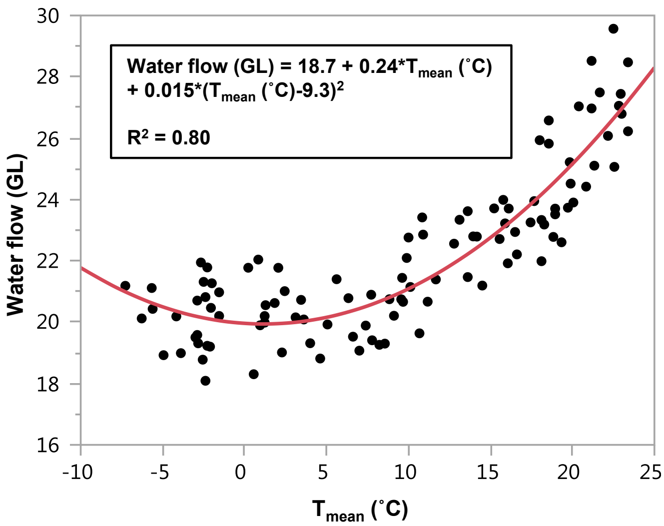

Fig. 6. Fitted model showing the interrelation between monthly mean air temperature and the water flow in the case study system.

considered. The interrelation between water flow and the monthly mean air temperature was fitted using a two-degree polynomial model with an R^2 value of around 0.80. The fitted model is shown in Fig. 6, and also used in the calculations of Fig. 5(b). It was found that the decrease of volumetric energy contributed by climate change overweighs the increase of energy contributed by the increasing of water demand caused by climate change assuming that population does not change. The two combined effects further reduce the potential influences of climate change, which indicates that the overall influence of climate change on the operation of the CSS might be overall insignificant. Nevertheless, given the immigration boom and the rapid population growth happening in the CSS service area, it is likely that the total life cycle energy use of CSS will continue to grow in the future.

The findings from this study combined with many other previous discussions on the influence of climate change on water quality show that the effects of climate change on water supply could vary significantly over geographical regions and treatment processes. For example, some researchers have pointed out that an increasing temperature is likely to raise raw water NOM levels (Mimikou et al., 2000; Zwolsman and Van Bokhoven, 2007; Delpla et al., 2009) and the resulting disinfection byproducts (DBPs) levels in drinking water supply (Delpla et al., 2009; Zhang et al., 2005), indicating increased treatment and energy use in water supply systems. However, the NOM levels (as indicated by UV_{254}) of the current CSS are insignificantly correlated with climate indicators, which could be contributed by an increased number of waterfowl roosting at the open water in the two reservoirs during winter when nearby smaller ponds freeze. On the opposite, the CSS will benefit from a warmer climate because of the resulted higher treatment effectiveness and reduced water and space heating needs. This indicates the necessity of identifying important local water quality determinants as well as their correlations with climate variations. It is also important to understand how these water quality variables affect water system operations considering the varied treatment technologies applied and management strategies adopted.

4. Conclusions

Climate change is commonly perceived as having negative impacts on water quantity and quality as well as drinking water treatment, yet many uncertainties remain on how factors such as geographical locations, local water sources, and water treatment technologies could potentially influence the effect of climate change on drinking water supply. The current study of a disinfection dominated water supply system located in the northeast US found that future climate change might slightly reduce energy and chemical uses under both highest emission and lowest emission scenarios generated by the IPCC. Although a warmer climate is likely to increase water demand in the case study area, this effect is overweighed by the effects of climate change on the volumetric life cycle energy use in the water supply system. The outcome of this study indicates the importance of considering geographical locations, local environmental factors, water treatment technologies, and even management strategies in understanding and quantifying the potential influence of climate change on water systems.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.watres.2016.03.022.

References

Arheimer, B., Andréasson, J., Fogelberg, S., Johnsson, H., Pers, C.B., Persson, K., 2005. Climate change impact on water quality: model results from southern Sweden. AMBIO A J. Hum. Environ. 34 (7), 559–566.
Barlow, P.M., Reichard, E.G., 2010. Saltwater intrusion in coastal regions of North America. Hydrogeol. J. 18 (1), 247–260.
Barnett, T.P., Adam, J.C., Lettenmaier, D.P., 2005. Potential impacts of a warming climate on water availability in snow-dominated regions. Nature 438 (7066), 303–309.
Bates, B., Kundzewicz, Z.W., Wu, S., Palutikof, J., 2008. Climate Change and Water. Intergovernmental Panel on Climate Change (IPCC).
Bekele, E.G., Knapp, H.V., 2010. Watershed modeling to assessing impacts of potential climate change on water supply availability. Water Resour. Manag. 24 (13), 3299–3320.
Berkoff, J., 2003. China: the South-North water transfer project—is it justified? Water Policy 5 (1), 1–28.
Bischel, H.N., Simon, G.L., Frisby, T.M., Luthy, R.G., 2011. Management experiences and trends for water reuse implementation in Northern California. Environ. Sci. Technol. 46 (1), 180–188.
Burnham, K.P., Anderson, D.R., 2002. Model Selection and Multimodel Inference: a Practical Information-theoretic Approach. Springer Science & Business Media.
Crittenden, J.C., Trussell, R.R., Hand, D.W., Howe, K.J., Tchobanoglous, G., 2012. MWH's Water Treatment: Principles and Design. Wiley.
Delpla, I., Jung, A.-V., Baures, E., Clement, M., Thomas, O., 2009. Impacts of climate change on surface water quality in relation to drinking water production. Environ. Int. 35 (8), 1225–1233.
Elimelech, M., Phillip, W.A., 2011. The future of seawater desalination: energy, technology, and the environment. Science 333 (6043), 712–717.
Elliott, T., Zeier, B., Xagoraraki, I., Harrington, G.W., 2003. Energy Use at Wisconsin's Drinking Water Facilities. Department of Civil and Environmental Engineering, University of Wisconsin–Madison.
Friedrich, E., 2002. Life-cycle assessment as an environmental management tool in the production of potable water. Water Sci. Technol. 46 (9), 29–36.
Friedrich, E., Pillay, S., Buckley, C., 2009. Carbon footprint analysis for increasing water supply and sanitation in South Africa: a case study. J. Clean. Prod. 17 (1), 1–12.
Frischknecht, R., Jungbluth, N., Althaus, H., Bauer, C., Doka, G., Dones, R., Hischier, R., Hellweg, S., Humbert, S., Köllner, T., 2007. Implementation of Life Cycle Impact Assessment Methods (Ecoinvent report).
George, G., Hurley, M., Hewitt, D., 2007. The impact of climate change on the

physical characteristics of the larger lakes in the English lake district. Freshw. Biol. 52 (9), 1647–1666.
Genizi, A., 1993. Decomposition of R2 in multiple regression with correlated regressors. Stat. Sin. 3, 407–420.
Gleick, P.H., 1987. The development and testing of a water balance model for climate impact assessment: modeling the Sacramento basin. Water Resour. Res. 23 (6), 1049–1061.
Godskesen, B., Zambrano, K., Trautner, A., Johansen, N., Thiesson, L., Andersen, L., Clauson-Kaas, J., Neidel, T., Rygaard, M., Kloverpris, N., 2010. Life cycle assessment of three water systems in Copenhagen-a management tool of the future. Water Sci. Technol. 10 (6).
Goldstein, R., Smith, W., 2002. Water & Sustainability. In: US Electricity Consumption for Water Supply & Treatment-the Next Half Century, vol. 4. Electric Power Research Institute, Palo Alto, CA.
Grömping, U., 2006. Relative importance for linear regression in R: the package relaimpo. J. Stat. Softw. 17 (1), 1–27.
Hansen, S.A., Dostal, K.A., Crosby, C., 1988. EPA treatability database. USATHAMA 15, 245.
Howe, K.J., Clark, M.M., 2002. Fouling of microfiltration and ultrafiltration membranes by natural waters. Environ. Sci. Technol. 36 (16), 3571–3576.
Hunter, P., 2003. Climate change and waterborne and vector-borne disease. J. Appl. Microbiol. 94 (s1), 37–46.
Jiang, Z., Li, X., Ma, Y., 2013. Water and energy conservation of rainwater harvesting system in the loess plateau of China. J. Integr. Agric. 12 (8), 1389–1395.
Kaika, M., 2003. The water framework directive: a new directive for a changing social, political and economic European framework. Eur. Plan. Stud. 11 (3), 299–316.
Klein, G., Krebs, M., Hall, V., O'Brien, T., Blevins, B.B., 2005. California's Water–energy Relationship. California Energy Commission.
Kruskal, W., 1987. Relative importance by averaging over orderings. Am. Statistician 41 (1), 6–10.
Kunkel, K.E., 2013. Regional Climate Trends and Scenarios for the US National Climate Assessment. US Department of Commerce, National Oceanic and Atmospheric Administration, National Environmental Satellite, Data, and Information Service.
Kuo, L., 2014. China Has Launched the Largest Water-pipeline Project in History. The Atlantic. Atlantic Media Company 7.
Kutner, M.H., Nachtsheim, C., Neter, J., 2004. Applied Linear Regression Models. McGraw-Hill/Irwin.
Landu, L., Brent, A.C., 2007. Environmental life cycle assessment of water supply in South Africa: the Rosslyn industrial area as a case study. Water SA 32 (2), 249–256.
Lassaux, S., Renzoni, R., Germain, A., 2007. Life cycle assessment of water from the pumping station to the wastewater treatment plant. Int. J. Life Cycle Assess. 12 (2), 118–126.
Lazarova, V., Choo, K.-H., Cornel, P., 2012. Water-energy Interactions of Water Reuse. IWA Publishing, London, U.K.
Lindeman, R.H., Merenda, P.F., Gold, R.Z., 1980. Introduction to Bivariate and Multivariate Analysis. Scott, Foresman Glenview, IL.
Lundie, S., Peters, G.M., Beavis, P.C., 2004. Life cycle assessment for sustainable metropolitan water systems planning. Environ. Sci. Technol. 38 (13), 3465–3473.
Lyons, E., Zhang, P., Benn, T., Sharif, F., Li, K., Crittenden, J., Costanza, M., Chen, Y., 2009. Life cycle assessment of three water supply systems: importation, reclamation and desalination. Water Sci. Technol. Water Supply 9, 439–448.
Malmaeus, J.M., Blenckner, T., Markensten, H., Persson, I., 2006. Lake phosphorus dynamics and climate warming: a mechanistic model approach. Ecol. Model. 190 (1), 1–14.
Martinez, C.J., Clark, M.W., 2012. Reclaimed Water and Florida's Water Reuse Program. https://edis.ifas.ufl.edu/ae448.
Matonse, A.H., Pierson, D.C., Frei, A., Zion, M.S., Anandhi, A., Schneiderman, E., Wright, B., 2013. Investigating the impact of climate change on New York City's primary water supply. Clim. Change 116 (3–4), 437–456.
Means, E., 2004. Water and Wastewater Industry Energy Efficiency: a Research Roadmap. Awwa Research Foundation.
Milly, P.C., Dunne, K.A., Vecchia, A.V., 2005. Global pattern of trends in streamflow and water availability in a changing climate. Nature 438 (7066), 347–350.
Mimikou, M., Baltas, E., Varanou, E., Pantazis, K., 2000. Regional impacts of climate change on water resources quantity and quality indicators. J. Hydrol. 234 (1), 95–109.
Mo, W., Nasiri, F., Eckelman, M.J., Zhang, Q., Zimmerman, J.B., 2010. Measuring the embodied energy in drinking water supply systems: a case study in the Great Lakes Region. Environ. Sci. Technol. 44 (24), 9516–9521.
Mo, W., Wang, R., Zimmerman, J.B., 2014. An energy-water nexus analysis of enhanced water Supply scenarios: a regional comparison of Tampa Bay, Florida and San Diego, California. Environ. Sci. Technol. 48 (10), 5883–5891.
Mo, W., Zhang, Q., Mihelcic, J.R., Hokanson, D.R., 2011. Embodied energy comparison of surface water and groundwater supply options. Water Res. 45 (17), 5577–5586.
Muttiah, R.S., Wurbs, R.A., 2002. Modeling the impacts of climate change on water supply reliabilities. Water Int. 27 (3), 407–419.
O'Hara, J.K., Georgakakos, K.P., 2008. Quantifying the urban water supply impacts of climate change. Water Resour. Manag. 22 (10), 1477–1497.
Prathumratana, L., Sthiannopkao, S., Kim, K.W., 2008. The relationship of climatic and hydrological parameters to surface water quality in the lower Mekong River. Environ. Int. 34 (6), 860–866.
Psenner, R., Schmidt, R., 1992. Climate-driven pH control of remote alpine lakes and effects of acid deposition. Nature 356 (6372), 781–783.
R Core Team, 2014. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, ISBN 3-900051-07-0, 2012.
Racoviceanu, A.I., Karney, B.W., Kennedy, C.A., Colombo, A.F., 2007. Life-cycle energy use and greenhouse gas emissions inventory for water treatment systems. J. Infrastruct. Syst. 13 (4), 261–270.
Raffin, M., Germain, E., Judd, S., 2012. Influence of backwashing, flux and temperature on microfiltration for wastewater reuse. Sep. Purif. Technol. 96, 147–153.
Rogers, P., Silva, R.d., Bhatia, R., 2002. Water is an economic good: how to use prices to promote equity, efficiency, and sustainability. Water Policy 4 (1), 1–17.
Rothausen, S.G., Conway, D., 2011. Greenhouse-gas emissions from energy use in the water sector. Nat. Clim. Change 1 (4), 210–219.
Santana, M.V., Zhang, Q., Mihelcic, J.R., 2014. Influence of water quality on the embodied energy of drinking water treatment. Environ. Sci. Technol. 48 (5), 3084–3091.
Schreiber, B., Brinkmann, T., Schmalz, V., Worch, E., 2005. Adsorption of dissolved organic matter onto activated carbon—the influence of temperature, absorption wavelength, and molecular size. Water Res. 39 (15), 3449–3456.
Schwarz, G., 1978. Estimating the dimension of a model. Ann. Stat. 6 (2), 461–464.
Senhorst, H., Zwolsman, J., 2005. Climate change and effects on water quality: a first impression. Water Sci. Technol. 51 (5), 53–59.
Shannon, M.A., Bohn, P.W., Elimelech, M., Georgiadis, J.G., Marinas, B.J., Mayes, A.M., 2008. Science and technology for water purification in the coming decades. Nature 452 (7185), 301–310.
Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M., 2013. Climate Change 2013: the Physical Science Basis. Intergovernmental Panel on Climate Change. Working Group I Contribution to the IPCC Fifth Assessment Report (AR5). Cambridge Univ Press, New York.
Stokes, J.R., Horvath, A., 2009. Energy and air emission effects of water supply. Environ. Sci. Technol. 43 (8), 2680–2687.
Van der Bruggen, B., Koninckx, A., Vandecasteele, C., 2004. Separation of monovalent and divalent ions from aqueous solution by electrodialysis and nanofiltration. Water Res. 38 (5), 1347–1353.
Van Vliet, M., Zwolsman, J., 2008. Impact of summer droughts on the water quality of the Meuse River. J. Hydrol. 353 (1), 1–17.
Wilkinson, R., 2000. Methodology for Analysis of the Energy Intensity of California's Water Systems, and an Assessment of Multiple Potential Benefits through Integrated Water-energy Efficiency Measures. University of California, Santa Barbara, Environmental Studies Program, Santa Barbara, CA.
Whitehead, P., Wilby, R., Battarbee, R., Kernan, M., Wade, A.J., 2009. A review of the potential impacts of climate change on surface water quality. Hydrol. Sci. J. 54 (1), 101–123.
Yates, D.N., 1996. WatBal: an integrated water balance model for climate impact assessment of river basin runoff. Int. J. Water Resour. Dev. 12 (2), 121–140.
Yüce, S., Kazner, C., Hochstrat, R., Wintgens, T., Melin, T., 2012. Water-energy interactions of water reuse. In: Lazarova, V., Choo, K.-H., Cornel, P. (Eds.), pp. 243–256.
Zhang, X., Echigo, S., Lei, H., Smith, M.E., Minear, R.A., Talley, J.W., 2005. Effects of temperature and chemical addition on the formation of bromoorganic DBPs during ozonation. Water Res. 39 (2), 423–435.
Zhu, X., Elimelech, M., 1997. Colloidal fouling of reverse osmosis membranes: measurements and fouling mechanisms. Environ. Sci. Technol. 31 (12), 3654–3662.
Zou, H., 2006. The adaptive lasso and its oracle properties. J. Am. Stat. Assoc. 101 (476), 1418–1429.
Zwolsman, J., Van Bokhoven, A., 2007. Impact of summer droughts on water quality of the Rhine River-a preview of climate change? Water Sci. Technol. 56 (4), 45–55.