Influences of Water Quality and Climate on the Water-Energy Nexus: A Spatial Comparison of Two Water Systems

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Abstract
As drinking water supply systems plan for sustainable management practices, impacts from future water quality and climate changes are a major concern. This study aims to understand the intraannual changes of energy consumption for water treatment, investigate the relative importance of water quality and climate indicators on energy consumption for water treatment, and predict the effects of climate change on the embodied energy of treated, potable water at two municipal drinking water systems located in the northeast and southeast US. To achieve this goal, a life cycle assessment was first performed to quantify the monthly energy consumption in the two drinking water systems. Regression and relative importance analyses were then performed between climate indicators, raw water quality indicators, and chemical and energy usages in the treatment processes to determine their correlations. These relationships were then used to project changes in embodied energy associated with the plants' processes, and the results were compared between the two regions. The projections of the southeastern US water plant were for an increase in energy demand resulted from an increase of treatment chemical usages. The northeastern US plant was projected to decrease its energy demand due to a reduced demand for heating the plant's infrastructure. The findings indicate that geographic location and treatment process may determine the way climate change affects drinking water systems.

Keywords: water quality; climate change; dynamic life cycle energy assessment; spatial comparison of drinking water supply; relative importance analysis; water-energy nexus

1. Introduction

The prosperity of our society relies on a variety of highly interdependent infrastructure systems (e.g., water treatment and distribution, electricity grids, food production and supply network, etc.) working together without major interruptions (Konrad II and Fuhrmann, 2013; Vespignani, 2010). Such interdependencies emerged along with the development of modern infrastructure. They can manifest as the functioning of one infrastructure relies on the functioning or resources provided by other infrastructures or when multiple infrastructures compete for the same resources. The water-energy nexus, for instance, has been widely recognized as a critical type of infrastructure interdependency that, if not understood and managed properly, could bring short and long term problems such as power plant shut downs due to water shortages and pollution (DOE, 2014), energy and financial stresses due to water pumping and treatment (Cherubini et al., 2009; Mo et al., 2016; Searchinger et al., 2008), as well as increased system vulnerability as a result of natural hazards, manmade threats (Hu et al., 2016), and climate change (Conway et al., 2015).

The degree and nature of infrastructure interdependencies continue to evolve under population, technology, climate, and policy changes. For instance, population growth could increase resource demand, and exacerbate the interdependency among their service infrastructures (Siddiqi and Anadon, 2011; Stillwell et al., 2011). Technology changes and utilization of unconventional resources (e.g., using desalinated seawater as a source of drinking water supply) sometimes also increase the degree of interdependency (Hussey and Pittock, 2012; Mo et al., 2014). Short and long term climate variabilities influence the quantity, and sometimes, the quality of available resources, as well as their societal demands, which further change the interdependencies among pertinent infrastructures (Delpla et al., 2009; Vörösmarty et al., 2000). Policies and regulations could have direct and indirect effects on all the aforementioned aspects (Romero-Lankao et al., 2017). Meanwhile, they can also be used as a means to guide the development of infrastructure and to reduce vulnerability resulting from infrastructure interdependency.

Recognition of the importance of infrastructure interdependencies, including the water-energy nexus, has motivated improved understanding of their dynamic complexity to inform future management decisions; yet our understanding of such dynamic changes is still very limited. Quantification of the water-energy nexus requires a comprehensive understanding of both direct and indirect (supply chain) interactions among the pertinent infrastructure. Life cycle assessment (LCA) has been a predominant tool used in previous studies for such quantifications as more data have become available. For example, the life cycle energy consumption of water supply, wastewater treatment (de Faria et al., 2015; Mo and Zhang, 2012), and water reclamation has been studied both separately and as a whole (Mo et al., 2014; Wakeel et al., 2016). Additionally, the life cycle water use of various types of energy supply has also been widely investigated. Nevertheless, most of these studies remain static and not suitable for predictions. Only a few efforts have been made to understand the future potential changes of the water-energy relationships from a life cycle perspective (Fulton and Cooley, 2015; Gerbens-Leenes et al., 2009), especially from the perspective of energy use by water supply. One study of a drinking water plant located in Florida reported that influent water quality could be responsible for about 14.5% of the changes of the plant's total operational embodied energy (Santana et al., 2014). Meanwhile, changes of water source mix combined with water demand growth have been found to significantly increase the electricity consumption of water supply, especially in coastal arid regions (Mo et al., 2014; Stokes-Draut et al., 2017). Efforts have also been made to project the future water-energy interdependence that could result from projected population growth, per capita water demand changes, preferred water supply options, and the required level of service (Hall et al., 2011; Lam et al., 2016). Very few studies have included climate variations in their future projections, and hence could only provide limited understanding of the influence of extreme climate events as well as gradual climate change on the water-energy nexus (Mo et al., 2016). The mechanism of how climate influences water treatment systems is still not well understood. Hence, empirical analysis based upon historical operational data have been suggested and applied (Mo et al., 2016; Santana et al., 2014).

While infrastructure interdependency is inherently complex, the current study adopts an empirical approach to investigate the temporal influences of climate, water quality, and water demand on the embodied energy of water supply. An assessment framework including life cycle energy assessment, regression analysis, relative importance analysis, and prediction analysis was applied. The influence of climate and water quality on the embodied energy of supply water from two surface water supply systems, each with distinct raw water quality, treatment processes, demand pattern, and local climate variations were investigated and compared. This study aims to assist proactive management of water and energy resources in different climates with the ultimate goal of improving the long term resiliency and sustainability of water and energy supply systems under global changes.

2. Methodology

2.1 Study site description

Two large-scale drinking water systems located in Tampa, FL and Boston, MA were selected for this study because coastal cities in the US are the most vulnerable to water supply and demand gaps; they represent two very different climates and have different source water quality (Oki and Kanae, 2006). The Tampa Water Treatment Plant (WTP) provides about 300 megalitre (ML) of water per day to approximately 588,000 customers in a service area of ~550 km^2. It relies on the Hillsborough River as the main water source, and employs a treatment process of rapid mixing, flocculation, sedimentation, pre-ozonation, biologically activated carbon (BAC) filtration, and disinfection to treat the water (Figure 1). Ten types of chemicals are added at different points of the process: 1) sulfuric acid and ferric sulfate are added during rapid mixing for pH adjustment and coagulation, respectively; 2) dry polymer is added during flocculation for larger floc to form; 3) ozone is applied during pre-ozonation to destroy bacteria, viruses, pathogens, and taste- and odor-causing compounds; 4) hydrogen peroxide is used to remove ozone residuals; 5) lime is added to stabilize the pH of the water before it is filtered; 6) chlorine and ammonia are added together during the disinfection stage to form chloramine, a type of disinfectant that minimizes the formation of disinfection byproducts (DBPs); 7) sodium hydroxide is used for final pH adjustment; and, 8) fluoride is added for dental health benefits. Tampa Electric provides the facility with power, and the facility uses kerosene as backup energy. The Boston WTP, on the other hand, supplies around 750 ML of water per day serving 2.55 million customers in 48 communities in east and central MA (Mo et al., 2016). Water obtained from two adjacent reservoirs is used as the source water, and these reservoirs combined hold 1.8 trillion liters. Because of a relatively high raw water quality, the Boston WTP adopts a much simpler treatment chain of ozonation, chlorination, and final pH adjustment (Figure 1; Mo et al., 2016). Seven types of chemicals are added for treatment: 1) liquid oxygen is used for ozone generation and the ozonation process; 2) sodium bisulfite is used for ozone removal; 3) sodium hypochlorite and ammonia are added to form chloramine for disinfection; 4) soda ash is added to raise the water alkalinity for pH buffering; 5) carbon dioxide is used for final pH adjustment; and 6) fluoride is used for dental protection. Furthermore, electricity and natural gas are used for pumping, treatment, and heating, and diesel is used as backup energy.

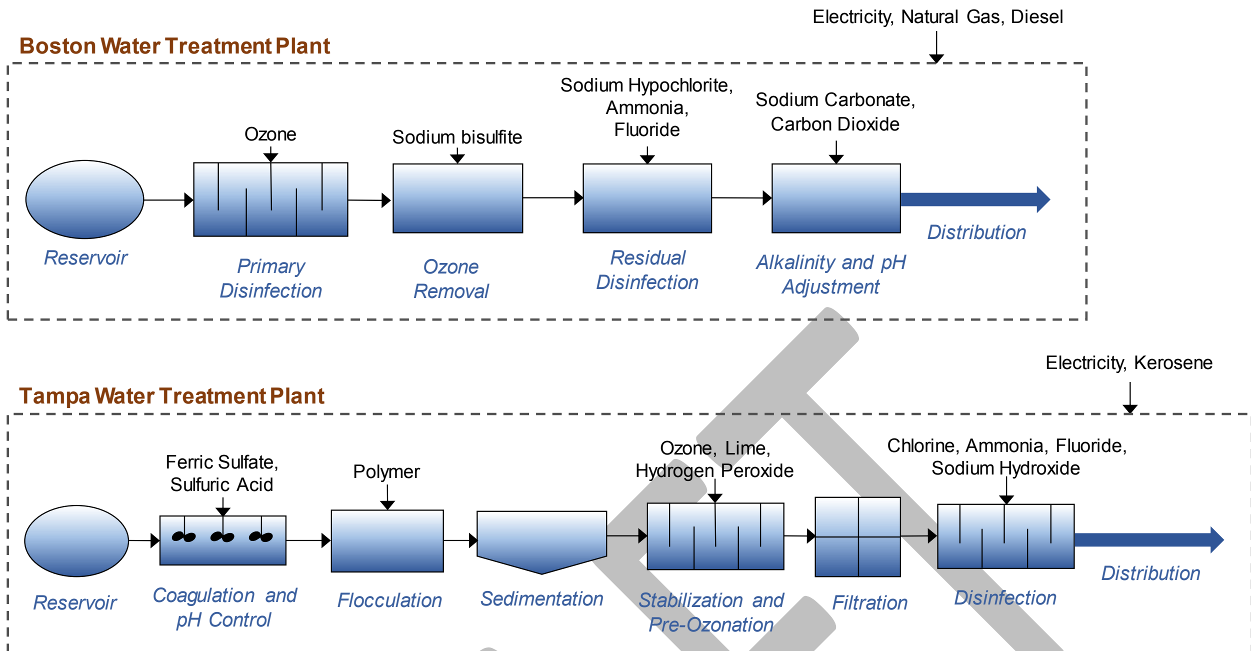

Figure 1. The treatment process flow diagrams for the Boston and Tampa water treatment plants with chemical and energy inputs. The treatment processes reflect conditions during the treatment data records.

Tampa has a humid subtropical climate with strong alternating wet and dry seasonal cycles. The wet season, typically from June to September, has an average monthly rainfall of 17.7 cm, which is around two times higher than the rest of the year (5.86 cm) (Marda et al., 2008). The average monthly temperature in Tampa gets as high as 32.3°C in July and August, and as low as 10.9°C in January. Boston has a humid continental climate with mild summers and cold and snowy winters. Average monthly temperature varies from around 27.4°C in July to around -5.4°C in January. There is no significant intraannual precipitation variation in Boston. The highest amount of precipitation occurs in March (10.9 cm) and the lowest occurs in February (8.2 cm). Climate data of both WTPs were obtained from the National Oceanic and Atmospheric Administration (NOAA) National Climate Data Center, and the observation stations that are closest to the water sources were selected. Available climate data include monthly mean maximum temperature (T_{max}), monthly mean minimum temperature (T_{min}), monthly mean temperature (T_{mean}), and total precipitation amount for the month (P_{total}). Additionally, the greatest observed precipitation (P_{max}) and the monthly total snowfall (S_{total}) are available for the Tampa and Boston WTP, respectively. Air temperature influences water temperature and the amount of space heating and cooling. Precipitation and the associated runoff have a significant effect on water quality.

Twelve raw water quality indicators of the influent from the Tampa WTP are monitored on a daily basis: pH, color, $CaCO_3$ alkalinity, water temperature, specific conductance, threshold odor number (TON), iron, total organic carbon (TOC), specific ultraviolet absorbance (SUVA), turbidity, $CaCO_3$ hardness, and total coliform. Monthly data for these water quality indicators were obtained for a period of ~9 years (Figure S1 in SI). pH influences all stages of water treatment, and it is maintained at the range of 7.1-8.5 to avoid pipe corrosion (CTWD, 2018). Color (tea-like), TOC, and SUVA are related to the amount of natural organic matter (NOM) in the Hillsborough River, which affect the amount of energy and chemicals used during coagulation, flocculation, and pre-ozonation processes. Particularly, SUVA characterizes NOM's aromaticity, which serves as a predictor of DBP formation potential (Hua et al., 2015). Alkalinity reflects water's ability to neutralize acids, which influences the amount of chemicals needed for pH adjustment. Water temperature directly affects the reaction efficiency and chemical solubility throughout the entire treatment train. Specific conductance, hardness, and iron measure the amount of total dissolved ions, calcium and magnesium ions, and iron ions in water, respectively. Depending on the chemical species present in water, these ions could affect the coagulation, flocculation, pre-ozonation (through oxidization of iron), and pH adjustment stages. TON is a measure of the odor and its control requires adjustments to the treatment process. Total coliform indicates the amount of pathogenic bacteria in water and affects the disinfection stage. Color, turbidity, SUVA, and TOC are shown to have the highest levels in the wet season when rainfall is most intense, and total hardness, alkalinity, and specific conductance are at their lowest levels. pH, TON, iron, and total coliform, on the other hand, do not show regular seasonal cycles; they may be influenced by a combined effect of both temperature and precipitation changes. Water temperature, on the other hand, has the most prominent seasonal cycling in response to air temperature changes. The Boston WTP regularly monitors three water indicators: water temperature (T_{water}), pH, and UV_{254} (Figure S2 in SI). UV_{254} is another indicator of NOM in water. It influences the amount of energy and ozone used during the ozonation stage. Water temperature and pH in the Boston WTP have strong seasonal cycles corresponding to air temperature changes. However, UV_{254} does not demonstrate a seasonal cycling pattern.

2.2 Life cycle assessment

We only include the operation phase of the treatment plant in this study as the construction and end-of-life of water infrastructure have been found to be insignificant by previous studies (Mo et al., 2010; Mo et al., 2011) and are less relevant to climate and water quality changes. A functional unit of 1 million liter (ML) of water delivered to end users was adopted. Two types of environmental impacts were estimated using SimaPro 8®, embodied energy and carbon emissions. The embodied energy is estimated using the "Cumulative Energy Demand" method and the carbon emission is estimated using the "IPCC 2013 GWP 100a" method. We use "direct energy" to refer to the energy used onsite of the WTP, and indirect energy to refer to the energy associated with the supply chain of producing and providing chemicals. Embodied energy is the sum of the direct and indirect energy. Monthly chemical and energy usage data were obtained from the two WTPs. A list of corresponding data entries used in SimaPro is provided in Table S1 of the supporting information (SI). We used the seasonal climate variations as a surrogate to model the influence of long term climate change on embodied energy. This is because of a lack of available long term WTP operation records to quantify the historical influence of global climate change. Hence, the results do not consider the cumulative effect of multi-year events, such as prolonged droughts.

2.3 Statistical analysis

Statistical analysis was used to identify the relative contribution of water quality and climate indicators to the change of energy use by the two WTPs as well as to predict the future changes of embodied energy of produced water that could result from climate change. The analysis consisted the following four steps: (1) covariate correlation analysis, (2) variable selection, (3) relative importance analysis, and (4) prediction analysis. Correlation analysis was first performed to identify potentially high collinearities among the climate and water quality indicators for the two WTPs. Negative effects of high collinearity can be reduced by eliminating one of the two variables with extremely high collinearity from the subsequent analyses. However, there are two contradicting factors that need to be considered when selecting the elimination criteria. Noted that from a statistical perspective, no two variables are entirely "independent" and certain levels of collinearity among the variables is always present. A certain amount of collinearity is taken into account in the regression analysis with a result of increased variances in parameter estimation and hence, variables do not have to be intentionally eliminated. As such, the more "independent" variables that are included in the regression analysis, the better explanation of the historical embodied energy changes that can be achieved and hence the regression can be more accurate. On the other hand, extremely high collinearity could mean that these variables essentially represent the same information, and information redundancy could result in over-inflated variances and make the regression analysis inaccurate. This dilemma manifests when determining whether to eliminate water temperature from the analysis as it has a relatively high correlation with air temperature ($r=0.98$ in Tampa WTP and 0.91 in Boston WTP). While a causal relationship exists between the air and water temperatures, they could influence the WTP embodied energy through different paths. For instance, water temperature influences treatment efficiency directly and air temperature influences space and water heating demand. Therefore, both water and air temperatures are kept for the subsequent analyses in this study. Based upon the number of historical observations that are available for the two WTPs, an elimination criteria of $r>0.99$ was selected for this study.

A regression analysis was then performed to identify predictor variables for each type of chemical and energy usages. Three variable selection methods were used, 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). All selected predictor variables were then combined to form the final linear regression model to prevent potential omissions of important variables (Mo et al., 2016). R^2 values were calculated for each regression to estimate the percentage of the chemical and energy usage variations that can be explained by the regression. The standard errors (*s*) and p-values (*p*) were also calculated to characterize the confidence intervals and the observed significance levels of each predictor variable. These values are provided in Table S1 of the SI. Based upon the selected predictor variables, a relative importance analysis was then performed to examine the contribution of the water quality and climate indicators on the embodied energy of the two WTPs. Two relative importance methods were examined: the dominance analysis method (Budescu, 1993) and the decomposition method (Genizi, 1993). The dominance analysis method determines the dominance of one predictor over another by comparing their additional R^2 contributions across all subset models (Azen and Budescu, 2006). The decomposition method, on the other hand, measures the relative importance of a predictor by partitioning the R^2 by averaging over orders. Both methods were performed using the R software utilizing the Relaimpo package (Grömping, 2006). Results from both relative importance methods were calculated and the averages are reported. Once the relative importance of the water quality and climate indicators on each regression was calculated, Equation (1) was used to estimate their overall contribution to the embodied energy.

$$C_{tot}=\sum_j \left(\sum_i RI_{i,j} \times Rsq_j \times C_j\right) \quad (1)$$

Where

- C_{tot} = Total contribution of water quality and/or climate indicators on the WTP embodied energy;
- RI = The relative importance of indicator i on chemical and/or energy type j;
- Rsq = The R^2 value of the regression analysis of chemical and/or energy type j;
- C_j = Contribution of chemical and/or energy type j to the WTP embodied energy;
- i = Water quality and/or climate indicator index; and,
- j = Chemical and/or energy type index.

Results from the regression analysis were further used to predict the influence of future climate change on the embodied energy of the water produced from the two WTPs. Climate variation could directly influence the treatment efficiency via changes in chemical solubility and reaction kinetics as well as the space and water heating demand of a WTP, all of which further affect the WTP's energy use. Additionally, climate can alter water quality and hence indirectly change a WTP's energy use. In order to capture the climate change alone, changes of water quality as a result of climate change were modelled via a set of additional regressions using climate indicators as predictor variables and each water quality indicator as a dependent variable. If the regression yields an R^2 value of 0.5 or larger, the regression is deemed statistically significant and the resulting model is used for calculating the future changes of that particular water quality parameter as a result of climate change. On the other hand, an R^2 value of less than 0.5 was assumed to indicate that climate has a weak influence on the particular water quality parameter, and hence no change of the water quality parameter is included. Future changes of volumetric chemical and energy usages at the two WTPs were then calculated applying the same statistical significance cut-off criteria using downscaled climate change projections and the predicted water quality changes calculated from the previous step. These values were then converted into volumetric embodied energy and carbon emission changes using the unit life cycle impact values calculated in Section 2.2 for each chemical and energy type and summed up. Future changes of the total embodied energy also have to take account of the potential water demand change that could result from climate change. The influence of climate change on water demand is modelled via a regression between the climate indicators and the monthly water flow rates for each WTP. Similarly, if the regression results in an R^2 value of 0.5 or larger, climate is considered to have a strong influence on water demand. Hence, the future embodied energy change is calculated as a product of the predicted water demand change and the volumetric embodied energy change.

2.4 Climate change scenarios

Statistically downscaled future temperature and precipitation predictions for both southeast and northeast US were obtained from NOAA (Kunkel, 2013). These predictions were calculated based upon 29 (14 for B1 scenarios and 15 for A2 scenarios) Climate Model Intercomparison Project phase 3 (CMIP3) global climate simulations (Kunkel, 2013). Two emission scenarios provided by the Intergovernmental Panel on Climate Change (IPCC) were investigated, representing the highest (A2 scenario) and lowest bound (B1 scenario) of future climate changes. For each scenario, the lowest, median, and highest temperature and precipitation changes towards the end of this century were considered (Table 1). Percentage changes of snowfall and the greatest observed precipitation were assumed to be the same as precipitation.

Table 1. Downscaled regional temperature and precipitation predictions for the southeast and northeast US

Region	Climate Scenarios		Change in Temperature (°F)			Change in Precipitation (%)		
			2035	2055	2085	2035	2055	2085
Southeast US (Konrad II and Fuhrmann, 2013) (used for Tampa WTP)	A2	Lowest	1.3	2.3	3.9	-9	-14	-23
		Median	2.8	4.4	6.8	2	2	4
		Highest	3.6	5.4	9.6	8	8	11
	B1	Lowest	1.3	1.6	2.5	-9	-11	-12
		Median	2.3	3.1	4.1	1	3	4
		Highest	3.2	3.8	5.2	5	7	9
Northeast US (Kunkel, 2013) (used for Boston WTP)	A2	Lowest	1.7	2.9	4.8	-5	-6	-8
		Median	3.1	4.9	7.9	4	5	9
		Highest	4.5	6.4	11.3	7	10	16
	B1	Lowest	1.7	2.2	3.4	-5	-4	-2
		Median	2.7	3.6	4.6	3	4	6
		Highest	3.4	4.7	6.3	9	8	10

3. Results and Discussion

3.1 Seasonal Embodied Energy Consumptions

Notable seasonal variations of energy consumptions (Figure 2) and carbon emissions (Figure S3 in SI) are evident in both WTPs. For the Boston WTP, summer months generally have a lower volumetric energy consumption than the winter months, which is mainly due to the reduced heating need during summer months corresponding to air temperature changes. The Tampa WTP's volumetric energy consumption shows more diverse variations during a year. Generally, lowest consumptions happen during months with a mild temperature and relatively low precipitation, and highest consumptions occur during months that are relatively wet and the temperature is more extreme. Changes of the volumetric energy consumptions at the Tampa WTP resonate with both temperature and precipitation changes. Two possible reasons might explain the discrepancy of the seasonal trends between the two WTPs. One is the much more prominent wet and dry cycles in Tampa than in Boston that effect water quality parameters. The other is because the Boston WTP has a much larger source water storage than the Tampa WTP (477 billion vs. 1 billion gallons), which provides a considerable buffer on the potential water quality changes due to runoff changes. This shows that climate could potentially change the energy consumption of the WTPs via different pathways, depending on the characteristics of the raw water source.

Volumetric embodied energy consumption in the Tampa WTP is around three times that of the Boston WTP. The difference in pumping needs could not explain the higher volumetric direct energy in the

Tampa WTP, as both WTPs have relatively flat service areas, and the Boston WTP has a much larger pipeline network than the Tampa WTP (~ 6400 miles vs. 2200 miles). Hence, the higher volumetric energy consumption, both direct and indirect, in the Tampa WTP might be primarily contributed by the difference in source water quality of the two WTPs and the treatment technology difference that comes with it, although the economies of scale might also have a partial contribution (water flow at the Boston WTP is around three times of the Tampa WTP). This implies the significance of raw water quality in technology selection and hence the embodied energy consumption, even though both use surface water as a source.

Seasonal climate variations result in a change of 1.2 times the volumetric energy consumption in the Tampa WTP and 1.4 times in the Boston WTP when comparing the highest monthly consumption with the lowest. Furthermore, for both WTPs, direct energy presents a stronger seasonal variation than the indirect energy. For instance, for the Boston WTP, the highest volumetric direct energy consumption (occurring in February, 1,002 MJ/ML) is 48% higher than the lowest (occurs in September, 522 MJ/ML), while the highest volumetric indirect energy consumption (occurs in February, 1,245 MJ/ML) is only 15% higher than the lowest (occurs in May, 1,060 MJ/ML). Similarly, for the Tampa WTP, the highest volumetric direct energy consumption (occurs in November, 4,719 MJ/ML) is 27% higher than the lowest (occurs in March, 3,442 MJ/ML), while the highest volumetric indirect energy consumption (occurs in August, 3,515 MJ/ML) is around 15% higher than the lowest (occurs in February, 2,982 MJ/ML). Direct energy also represents a significant portion of the total embodied energy for both WTPs, ranging from around 33-45% in the Boston WTP to 51-59% in the Tampa WTP. Among the indirect energy contributors, certain chemical usages and treatment processes do present critical seasonal variations (Figure S3 in SI; Mo et al., 2016). For the Boston WTP, chemicals used for ozonation require a much higher consumption of ozone and bisulfite in winter than in summer due to higher natural organic matter (NOM) concentration in winter. Chemicals used for residual disinfection have a higher volumetric consumption in summer than in winter due to increased decay of the residual under higher temperatures. For the Tampa WTP, the volumetric consumption of chemicals used for coagulation (sulfuric acid and ferric sulfate) peak during July to September, as does the amount of ozone used for ozonation. Both are potentially a result of a decrease in water quality during the peak months of heat and precipitation.

Total embodied energy consumption is a function of both volumetric energy consumption and water demand. Water demand from the Boston WTP has a strong seasonal trend, which peaks in July mainly due to increased outdoor irrigation. Water demand at the Tampa WTP, however, does not present a strong seasonal trend. An average of the historical monthly water demand record shows it peaks in October, but the intraannual change is relatively small. The seasonal variations of water demand have an essential influence on the total embodied energy, especially in the Boston WTP. When the change of water demand is considered, the total energy consumption in the Boston WTP peaks in both July and January, while the total energy consumption in the Tampa WTP peaks in November. A comparison of these seasonal trends with the intraannual energy demand for the two regions shows that water supply’s energy demand peaks around the same time as the total regional energy demand. This indicates a potential competition of energy between water supply and other energy users, especially given the significance of the direct energy consumptions within both systems. A comparison of the intraannual volumetric energy consumption and water demand trends show that the optimal strategy for reducing total energy consumption and hence alleviate the water-energy nexus competitions could vary over a year. Taking the Boston WTP for example, it might be more effective to conduct water conservation practices (e.g., restriction on irrigation and outdoor water uses) during summer months and energy conservation practices (e.g, reducing space and water heating) during winter months for the Boston WTP to reduce its total energy consumption.

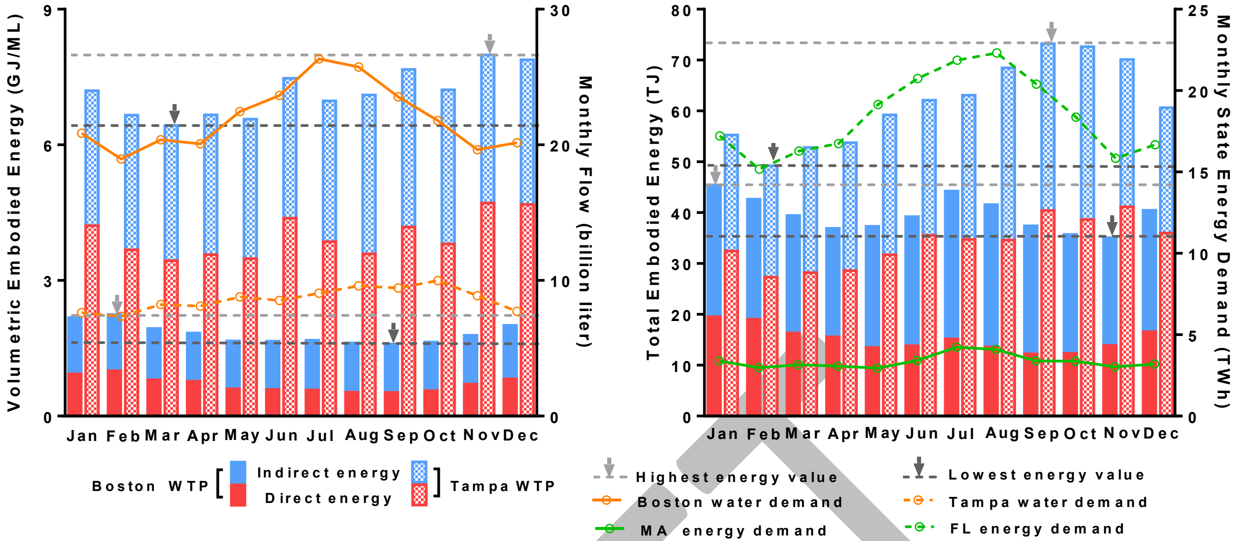

Figure 2. Volumetric and total embodied energy of the Boston and Tampa water treatment plants. The left figure shows the monthly embodied energy consumptions associated with producing 1 million liters of water as well as the monthly total water flow in the two treatment plants; the right figure shows the total monthly embodied energy consumptions of the two treatment plants as well as the regional monthly electricity demand from where the two plants are located.

3.2 Regression Analysis and Relative Importance

Results from the correlation analyses were presented in Figure S4 in the SI. Among the climate indicators, T_{max}, T_{min}, and T_{mean} have very significant positive correlations for both cities 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 performance. Among the water quality indicators, the primary NOM indicator in the Boston WTP, UV_{254}, is relatively independent, while pH and water temperature (T_{water}) have a moderate negative correlation (r=-0.54). In the Tampa WTP, pH, conductance, hardness, and alkalinity have strong positive correlations among each other (r>0.80), all of which are related to the amount of dissolved ions in water. The source of the Tampa WTP, the Hillsborough River, is underlain by limestone and dolomite, which release calcium and/or magnesium (hardness) and carbonate (alkalinity) when water passes through. The release of the minerals consequently contributes to the slightly basic pH and increased conductance. Unlike the Boston WTP, the major NOM indicator in the Tampa WTP, TOC, shares a strong negative correlation with water pH (r=-0.86), which might be resulted from a higher contribution of groundwater (characterized by higher pH and lower TOC) in the river flow during the drier months. Water temperature, on the other hand, only has a weak correlation with the pH, indicating the release of minerals has a weak response to temperature signals. TOC also has a strong positive correlation with iron levels. These two indicators also explain most of the water color changes in the Tampa WTP. SUVA indicates the aromatic character of the dissolved organic matter in the raw water, and hence it shares a moderate positive correlation with TOC. Turbidity, TON, and total coliform are relatively independent indicators in the Tampa WTP. Between the climate and water quality indicators, strong correlations were only found to exist between air and water temperatures in both WTPs (r=0.94 and 0.91in the Tampa and Boston WTP respectively). Despite the concurring effect of water quality degradation and wet season, however, precipitation was found to have no significant statistical correlations with any of the water quality indicators. This indicates the amount of rainfall does not necessarily reflect the degree of water quality degradation, which can be explained by the opposing effect of increased erosion/agitation and dilution under increased precipitation in Tampa.

Regression analyses were performed to first examine how climate indicators contribute to water indicators (Table S1 in the SI), then contributions of both climate and water indicators to chemical and energy uses (Tables 2 and S1). Most of the Boston WTP's chemical and energy usages yield a relatively high R^2 value (>0.5), indicating the significance of the climate and water quality indicators in explaining the variances of the chemical and energy usages. On the other hand, only three types of chemicals (ferric sulfate, sulfuric acid, and ozone) in the Tampa WTP have R^2 values larger than 0.5, although these three chemicals represent a significant portion of the indirect energy. One notable difference between the WTPs is that climate and water quality could explain 66% of the electricity consumption variances in the Boston WTP while this number is only 16% for the Tampa WTP. Water temperature has a 44% relative importance (RI) to Boston WTP's explainable electricity variances. Yet in the Tampa WTP, water temperature does not present any statistically significant contribution. This can partly be explained by the less significant interannual water and space heating demand variations due to relatively mild interannual temperature changes and the complex combined effect of both temperature and precipitation on raw water quality in the Tampa WTP.

In the Boston WTP, UV_{254} has a relatively high RI on liquid oxygen and electricity usages (RI>45%), which can be explained by the more intense ozone disinfection treatment (higher liquid oxygen usage, electricity for mixing) when the influent water has a higher NOM concentration. In the Tampa WTP, T_{mean} and influent pH were the significant contributors of ozone usage (R^2 = 0.64) with relative importance of 57% and 43%. Ozone solubility decreases as temperature increases which could explain the relationship between ozone usage and T_{mean}. Ozone dosing is also dependent on pH; higher pH increases the rate of ozone decomposition and decreases the ozone residual (Langlais et al., 1991). In the Boston WTP, 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. In the Tampa WTP, however, influence of temperature on chemical usages is relatively small, with ozone being the only chemical specie that is strongly influenced by temperature. Ferric sulfate is only statistically significant to water quality indicators with the most important being TOC (RI = 27%), color (RI = 26%), and iron (RI = 17%). Ferric sulfate is used as a coagulant to remove NOMs, and iron and TOC contribute to color in the water, which may explain their relationship with ferric sulfate (Bratby, 2006). Similarly, climate indicators were not found to be statistically significant for sulfuric acid. The most significant water quality indicators were alkalinity (RI = 49%) and color (RI = 31%). Higher alkalinity requires larger sulfuric acid dosages to regulate pH which could explain this relationship. In both WTPs, precipitation does not show statistically significant correlations with most chemical and energy uses, except that total snowfall (S_{total}) has a relative high contribution to the bisulfite usages in the Boston WTP, which might be explained by its statistical correlation with UV_{254}.

Table 2. Relative importance of the climate and water quality indicators in explaining the volumetric chemical and energy usages of the Boston and Tampa water treatment plants (the relative importance values of 40% or higher are highlighted in green) and the R^2 values of each regression (the R^2 values of 0.50 or higher are highlighted in blue).

	Chemical and Energy Consumptions	Climate Indicators				Water Quality Indicators													R^2
		T_{mean}	P_{total}	P_{max}	S_{total}	Color	ALKY	Hardness	pH	Cond.	T_{water}	Turb.	TON	Iron	TOC	SUVA	Total Coli.	UV_{254}	
Tampa WTP	Lime		8%				40%		13%			3%	6%		19%	12%			0.42
	Chlorine									17%	10%	28%	34%		11%				0.41
	Fluoride					11%	5%		11%	8%		18%	36%	12%					0.29
	Ferric Sulfate					26%				11%	3%		2%	17%	27%	13%			0.83
	Sulfuric Acid					31%	49%				8%		1%			10%			0.86
	Ammonia								23%		12%	28%	23%		15%				0.29
	Sodium Hydroxide					17%	56%				28%								0.45
	Hydrogen Peroxide			4%							4%	40%		12%	19%	22%			0.45
	Dry Polymer									18%			22%		36%	25%			0.30
	Ozone	57%							43%										0.64

	Emulsion Polymer				21%		79%								0.17
	Kerosene					13%			12%		45%		30%		0.22
	Electricity				30%	28%						42%			0.16
Boston WTP	Ammonia	28%								65%				7%	0.56
	Bisulfite			39%						59%				2%	0.69
	Hypochlorite	23%						32%		45%					0.46
	Liquid Oxygen		3%	8%				11%		22%				56%	0.77
	Soda Ash														0.00
	Fluoride	30%								70%					0.33
	Carbon Dioxide							36%		51%				12%	0.70
	Electricity		5%					5%		44%				46%	0.66
	Natural Gas	50%						8%		43%					0.84

Figure 3 presents the summed contributions of the climate and water quality indicators on the linear variations of both direct and indirect energy in the two WTPs. We separate water temperature from the rest of the water quality indicators because it is highly influenced by air temperature. Overall, climate and water quality explain around 40% (10% direct and 30% indirect) and 55% (25% direct and 30% indirect) of the total embodied energy variations in the Tampa and Boston WTPs respectively. The rest of the embodied energy variations could potentially have resulted from non-linearity, stochastic properties associated with climate, water quality and treatment processes, as well as other factors such as infrastructure aging. In the Tampa WTP, changes of climate and water quality have a much larger influence on the indirect energy variations than the direct energy variations; whereas in the Boston WTP, their influences on direct and indirect energy are similar. Furthermore, water quality indicators present a much stronger influence than the climate indicators in the Tampa WTP; while the climate indicators together with water temperature show slightly larger contribution to energy variations in the Boston WTP compared with other water quality indicators combined. This indicates the extent of climate change's influence on the embodied energy of water supply could vary significantly based upon the spatial location of the treatment plants. Meanwhile, water quality degradation also has varied influence on the embodied energy depending on the local water quality. Figure 3 shows that water quality has a larger impact on indirect energy usage at the Tampa WTP than Boston. This could be attributed to variability of the raw water quality at the plants. Tampa's raw water source originates from a swamp before flowing into the reservoir and has a high concentration of organic matter. The plant has management practices for algal blooms before the water is treated at the plant (Marda et al., 2008). On the other hand, the Boston WTP has been operating without filtration because its source water quality has met turbidity and coliform standards set by the Surface Water Treatment Rule (Alcott et al., 2013). These findings show that poor raw water quality can make a treatment process for drinking water more complex and intensive, which adds to the required direct and indirect energy to reach the desired water quality for the end users.

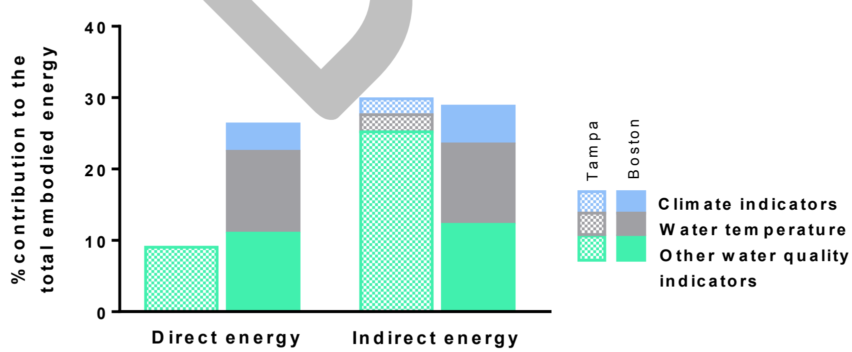

Figure 3. Percent contributions of the climate and water quality indicators in explaining the historical variations of the direct and indirect embodied energy consumptions in the Boston and Tampa water treatment plants. Water temperature is separated from other water quality indicators because of its significant correlation with air temperature.

3.3 Influence of Climate Change on Future Energy Consumption

Figure 4 presents the influence of climate change on the two WTPs using predictions of volumetric (energy/ML) and total energy consumption under different downscaled climate scenarios. The A2 scenarios for both locations predict larger changes in temperature and precipitation than the B1 scenarios. At the Tampa WTP, the volumetric and total energy percent changes were the same because there was no significant relationship between the climate and flow demand (R^2=0.20). Boston's water demand is predicted to increase with temperature (R^2=0.80), so the volumetric and total life cycle energy predictions differ. Tampa's embodied energy is predicted to increase in the three analyzed time periods: 2035, 2055, and 2085, and the A2 climate projections result in a larger increase than the B1 projections. This is because temperature has a strong positive relationship with ozone which has the largest embodied energy of all chemicals used at the Tampa WTP (Table S1 in SI). For the Boston WTP, the volumetric and total embodied energy is predicted to decrease in the three time ranges. The A2 projections result in a larger decrease than the B1 projections at Boston. This is because the increase in temperature decreases the amount of natural gas required to heat the plant. In both locations, the magnitude of the percent change increases over time. The opposite trends in the two WTPs indicate that the influence of climate change on embodied energy is dependent on the WTPs' local climate, influent water quality, and treatment process. Since Boston's climate includes colder temperatures than Tampa for much of the year, an increasing temperature will lower the embodied energy demand because the WTP building will not require as much heat. This effect is infrastructure based. In contrast, climate change will increase the embodied energy demand of the Tampa WTP mainly because of a predicted higher ozone usage. This effect is water treatment process based. The findings of this study show that geographic location and treatment process need to be considered for predicting future energy changes at drinking water plants.

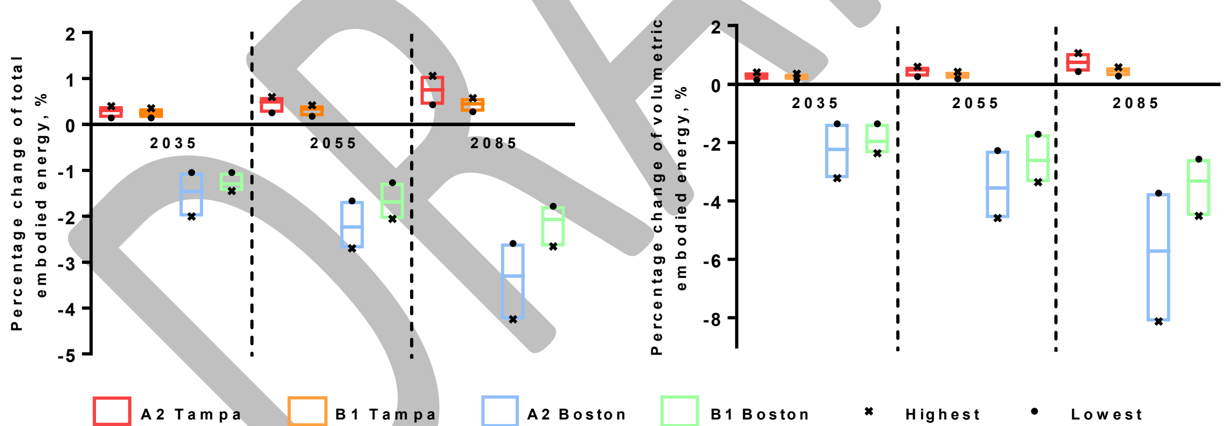

Figure 4. Predicted climate-resulted future changes of volumetric (left) and total (right) embodied energy changes in the Boston and Tampa water treatment plants.

4. Conclusions

This study comparing the effects of climate change on the embodied energy of drinking water in two different regions of the US found that the potential impacts of climate and water quality changes on the embodied energy of water supply vary depending on local conditions. Intraannual volumetric energy changes were found to be less uniform and predictable in Tampa than in Boston, and Boston's intraannual water demand fluctuations are more dramatic than Tampa's. The total embodied energy at both WTPs peaks at a similar time as the regional energy demand. This shows that the energy required for water treatment could compete with other types of energy use. To minimize the competition, Boston and Tampa could conduct water conservation practices to reduce energy consumption during peak months.

Water quality has a much larger contribution to the direct and indirect energy variances at the Tampa WTP than the Boston WTP. As pollution and stress on water sources increases globally in the future, more of the lower quality alternative water sources, such as brackish water, seawater, or even reclaimed water, are expected to be utilized as drinking water sources. The energy implications of such shifts can be potentially significant. This is partially reflected in this study; the two WTPs investigated have a threefold difference in their volumetric embodied energy while both of them rely on conventional surface water. The two WTPs also demonstrate opposite trends of energy use under predicted climate projections, with a reduced embodied energy in the Boston WTP and an increased embodied energy in the Tampa WTP. The differences in projections show that climate change's effects on the treatment process are highly spatially variable, and these effects need to be examined on a case-by-case basis.

Acknowledgement
The authors are grateful for the technical support of Dr. Mark Santana, the Massachusetts Water Resources Authority, and the David L. Tippin Water Treatment Plant. We would like to acknowledge the support of the National Science Foundation under a CBET Award (#CBET-1706143). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

Alcott, E., Ashton, M.S., Gentry, B.S., 2013. Natural and engineered solutions for drinking water supplies: lessons from the northeastern United States and directions for global watershed management. CRC Press.

Azen, R., Budescu, D.V., 2006. Comparing predictors in multivariate regression models: An extension of dominance analysis. Journal of Educational and Behavioral Statistics 31, 157-180.

Bratby, J., 2006. Coagulation and flocculation in water and wastewater treatment. IWA publishing.

Budescu, D.V., 1993. Dominance analysis: A new approach to the problem of relative importance of predictors in multiple regression. Psychological bulletin 114, 542.

Burnham, K.P., Anderson, D.R., 2002. Model selection and multimodel inference: a practical information-theoretic approach. Springer Science & Business Media.

Cherubini, F., Bird, N.D., Cowie, A., Jungmeier, G., Schlamadinger, B., Woess-Gallasch, S., 2009. Energy- and greenhouse gas-based LCA of biofuel and bioenergy systems: Key issues, ranges and recommendations. Resources, conservation and recycling 53, 434-447.

Conway, D., Van Garderen, E.A., Deryng, D., Dorling, S., Krueger, T., Landman, W., Lankford, B., Lebek, K., Osborn, T., Ringler, C., 2015. Climate and southern Africa's water-energy-food nexus. Nature Climate Change 5, 837-846.

CTWD, 2018. City of Tampa Water Department, Florida; Water Performance Charts.

de Faria, A.B., Spérandio, M., Ahmadi, A., Tiruta-Barna, L., 2015. Evaluation of new alternatives in wastewater treatment plants based on dynamic modelling and life cycle assessment (DM-LCA). Water research 84, 99-111.

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. Environment International 35, 1225-1233.

DOE, 2014. The water-energy nexus: challenges and opportunities. US Department of Energy

Fulton, J., Cooley, H., 2015. The water footprint of California's energy system, 1990–2012. Environmental science & technology 49, 3314-3321.

Genizi, A., 1993. Decomposition of R2 in multiple regression with correlated regressors. Statistica Sinica 3, 407-420.

Gerbens-Leenes, P., Hoekstra, A., Van der Meer, T., 2009. The water footprint of energy from biomass: A quantitative assessment and consequences of an increasing share of bio-energy in energy supply. Ecological economics 68, 1052-1060.

Grömping, U., 2006. Relative importance for linear regression in R: the package relaimpo. Journal of statistical software 17, 1-27.

Hall, M.R., West, J., Sherman, B., Lane, J., de Haas, D., 2011. Long-term trends and opportunities for managing regional water supply and wastewater greenhouse gas emissions. Environmental science & technology 45, 5434-5440.

Hu, F., Yeung, C.H., Yang, S., Wang, W., Zeng, A., 2016. Recovery of infrastructure networks after localised attacks. Scientific reports 6.

Hua, G., Reckhow, D.A., Abusallout, I., 2015. Correlation between SUVA and DBP formation during chlorination and chloramination of NOM fractions from different sources. Chemosphere 130, 82-89.

Hussey, K., Pittock, J., 2012. The energy–water nexus: managing the links between energy and water for a sustainable future. Ecology and Society 17, 31.

Konrad II, C.E., Fuhrmann, C.M., 2013. Climate of the southeast USA: past, present, and future, Climate of the Southeast United States. Springer, pp. 8-42.

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.

Lam, K.L., Lant, P.A., O'Brien, K.R., Kenway, S.J., 2016. Comparison of water-energy trajectories of two major regions experiencing water shortage. Journal of environmental management 181, 403-412.
Langlais, B., Reckhow, D.A., Brink, D.R., 1991. Ozone in water treatment: application and engineering, American Water Works Research Foundation. CRC press.
Marda, S., Kim, D.-I., Kim, M.-J., Gordy, J., Pierpont, S., Gianatasio, J., Amirtharajah, A., Kim, J.-H., 2008. Plant conversion experience: ozone BAC process installation and disinfectant residual control. Journal (American Water Works Association) 100, 117-128.
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. Environmental science & technology 44, 9516-9521.
Mo, W., Wang, H., Jacobs, J.M., 2016. Understanding the influence of climate change on the embodied energy of water supply. Water Research 95, 220-229.
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. Environmental science & technology 48, 5883–5891.
Mo, W., Zhang, Q., 2012. Can municipal wastewater treatment systems be carbon neutral? Journal of environmental management 112, 360-367.
Mo, W., Zhang, Q., Mihelcic, J.R., Hokanson, D.R., 2011. Embodied energy comparison of surface water and groundwater supply options. Water research 45, 5577-5586.
Oki, T., Kanae, S., 2006. Global hydrological cycles and world water resources. Science 313, 1068-1072.
Romero-Lankao, P., McPhearson, T., Davidson, D.J., 2017. The food-energy-water nexus and urban complexity. Nature Climate Change 7, 233-235.
Santana, M.V., Zhang, Q., Mihelcic, J.R., 2014. Influence of Water Quality on the Embodied Energy of Drinking Water Treatment. Environmental science & technology 48, 3084-3091.
Schwarz, G., 1978. Estimating the dimension of a model. The annals of statistics 6, 461-464.
Searchinger, T., Heimlich, R., Houghton, R.A., Dong, F., Elobeid, A., Fabiosa, J., Tokgoz, S., Hayes, D., Yu, T.-H., 2008. Use of US croplands for biofuels increases greenhouse gases through emissions from land-use change. Science 319, 1238-1240.
Siddiqi, A., Anadon, L.D., 2011. The water–energy nexus in Middle East and North Africa. Energy policy 39, 4529-4540.
Stillwell, A., King, C., Webber, M., Duncan, I., Hardberger, A., 2011. The energy-water nexus in Texas. Ecology and Society 16.
Stokes-Draut, J.R., Taptich, M.N., Kavvada, O., Horvath, A., 2017. Evaluating the electricity intensity of evolving water supply mixes: The case of California's water network. Environmental Research Letters.
Vespignani, A., 2010. Complex networks: The fragility of interdependency. Nature 464, 984-985.
Vörösmarty, C.J., Green, P., Salisbury, J., Lammers, R.B., 2000. Global water resources: vulnerability from climate change and population growth. science 289, 284.
Wakeel, M., Chen, B., Hayat, T., Alsaedi, A., Ahmad, B., 2016. Energy consumption for water use cycles in different countries: a review. Applied Energy 178, 868-885.
Zou, H., 2006. The adaptive lasso and its oracle properties. Journal of the American statistical association 101, 1418-1429.