In the context of Food-Energy-Water (FEW) Nexus: Finding Pathways to Achieve FEW Security given Natural and Anthropogenic Challenges

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LIST OF ACRONYMS

| ABM agent-based modeling |
|--|
| AIC Akaike Information Criterion |
| AP Alluvial Plain |
| AWC available water-holding capacity |
| BAU business-as-usual scenario |
| CP Cumberland Plateau |
| CVSRA cross-validated stepwise regression analysis |
| CWS community water system |
| DBP disinfectant byproducts |
| FEW Food Energy Water |
| FEW-RSH Food Energy Water resource-services-health framework |
| HAM holistic adaptive management scenario |
| HR Highland Rim |
| ICP Inner Coastal Plain |
| IOC inorganic contaminants |
| LOOCV leave-one-out cross validation error |
| MCL maximum contaminant level violations |
| MON monitoring violations |
| NB Nashville Basin |
| NTNC non-transient, non-community water systems |
| PDI Palmer Drought Index |
| PN public notice violations |
| |

PWS public water system, and within the public water systems,

VS, S, M, L, and VL correspond to:

very small public water systems (population served \leq 500);

small public water systems ($501 \le \text{population served} \le 3,300$);

medium public water systems $(3,301 \le \text{population served} \le 10,000)$;

large public water systems (10,001 \leq population served \leq 100,000);

very large public water systems (population served \geq 100,001), respectively.

RAD radionuclides

RPT reporting violations

RV Ridge and Valley

SDWA the Safe Drinking Water Act

SMD soil moisture deficit

SOC synthetic organic contaminants

SSA sub-Saharan Africa

TNC transient non-community water system

TT treatment technique violations

USM Unaka-Smokey Mountain

VOC volatile organic contaminants

Chapter 1

Introduction

1.1 Overview

Food, energy, and water (FEW) resources are critical for the development and survival of societies globally. As such, achieving FEW security has been the focus on the agenda for both governments and international organizations, such as the United Nations through their Sustainable Development Goals (SDGs). However, 12.9% of the world's population still live in hunger, 20% do not have access to electricity, 40% face water scarcity, and 9% have no access to improved water sources (United Nations, 2016). Furthermore, global challenges such as population growth, climate change (and associated extreme weather events), and environmental degradation by anthropogenic activities are increasing pressures and associated difficulties for achieving FEW security.

There are many components of the FEW nexus from both natural aspects (i.e., resource availability and variability) and human capacity aspects (i.e., governance, technological advancement and socio-economic development of a country or society) that may influence the quality and quantity of FEW services (i.e., drinking water, sanitation, food, and energy). The quality and quantity of the FEW services together with human capacity aspects may further impact human health. And often, the societies in the developing world and the developed world face different sets of challenges in the provision of FEW services. There are many open questions related to how FEW interactions occur. The overarching question addressed by this dissertation is "How can social-environmental systems provide, or fail to provide adequate FEW services to society?"

Although it is impossible to represent or simulate the real world by collecting data or running models, in this dissertation study we use data analysis, modeling, and database construction and interrogation methods to address the overarching question of the study. Specifically, we conceive the digital realm powered by databases storing real-life records and information as a sufficient reflection of reality to gain useful insights and explore the range of possible outcomes under various anthropogenic and natural challenges in the FEW arena (Figure 1). We hope that the tools developed in this study will inform the policy and decision-making processes.



Figure 1. Dissertation framework schematic.

Note: On the left in the real world, water, energy, and food in the triangle are part of the resources and environment. Society in the center provides FEW services and protect human health. Human capacity influence the interactions between environment and the society. On the right is the digital realm as a reflection of the real world. We measure, collect, and store the data about resources, environment, and human and society's activities in the database. We create data analysis tools and *in-silico* models to elucidate complex relationships, analyze the data, model the human-nature interactions, and finally address research questions.

1.2 Structure of the dissertation

The dissertation starts from a broad exploratory analysis to unfold and identify the interconnections among the resources, services, and health in each of the three sectors: water, energy, and food. The insights and new knowledge carry over to the next chapter to explore how the FEW nexus is affected by human decisions and behaviors as well as natural variabilities and challenges. The analysis of sectorspecific challenges is demonstrated in chapter 4 in which we combined the data from different aspects and explore the driving factors that influence the water security.

In chapter 2, we study the most important and relevant factors that influence the FEW resources and services and the consequent impacts on health in sub-Saharan Africa. We chose the 38 countries of sub-Saharan Africa (SSA) (where many lack basic access to FEW services (United Nations, 2018a)) because the research questions focused specifically on understanding driving factors that influence the two FEW socio-environment processes: resources-services conversion, and services-health influence. This work provides a broad approach to address the overarching research question for a vulnerable region using readily available data at the level of entire countries that heretofore have been considered in individual resource systems and not in the context of the interconnected FEW nexus.

Policies and decisions are instrumental in the consumption of FEW resources and the utilization of FEW services, as they are supposed to fulfill people's need, remediate an emergency, relocate resources to another region, develop new infrastructures and expand system capacity, or something else. After a policy is enacted, it may have an extensive and deep influence on multiple stakeholders, from the environment to citizens, and ultimately to policy itself. These policies are best understood in the context of institutions at a scale much more disaggregated than of an entire country- mesoscales such as cities or regions, which are the same scales much operational realm of FEW services and the concomitant challenges happen at. Therefore, in chapter 3, we study that how policies, stakeholders, and the environment interact with each

other in the FEW nexus at the city level in Cape Town, South Africa. Specifically, we study how different policies could affect the conditions of the FEW services in Cape Town under the Day-Zero crisis.

While the data collected by government and non-government organizations provide insights about FEW resources, services, and many other types of information, the data all have common issues such as they exist in silos and they may be unavailable for some regions or at finer spatial resolution. Even at the city level in Africa in chapter 3, the issue of data availability limits us from investigating more deeply into sector-specific services, such as water safety and security. For example, drinking water quality data are not typically abundant in developing countries, but there are databases for FEW service quality such as drinking water safety in developed countries such as the United States. Moreover, study the safety and quality of FEW services requires a database that considers a comprehensive list of factors to gain a more fine-grained regional evaluation of a system of interest. In the fourth chapter, we compiled a database that contains drinking water violations and the actual measurement data of the regulated contaminants as well as the natural and socioeconomic factors that may influence the water services to find the possible reasons leading to the potential for unsafe drinking water, using Tennessee, USA as a case study.

We conclude the dissertation by a synthesis in chapter 5 where we summarize the findings we developed about how institutions can provide or fail to provide adequate FEW services to the people living in the societies and provide an outlook for pathways of achieving FEW security globally.

Chapter 2

Contributing Factors to the FEW Resources-Services-Health Processes

2.1 Introduction

Food, energy, and water resources are critical for the development and survival of societies, but still, access to these resources is limited in many parts of the world; currently, billions of people are facing FEW insecurity (United Nations, 2018b). The path to global FEW security is further complicated by challenges such as population growth, climate change (including extreme weather events), and environmental degradation by anthropogenic activities (Biggs et al., 2015).

Researchers have studied the security of the individual resources of FEW for decades, highlighting different metrics or indices of interest for the individual security of resources. Metrics and measurements have generally increased in complexity over time in conjunction with our increased understanding of resource security factors. For example, in the water security domain, indices evolved from the Falkenmark Index (which is a simple measure of physical water resources availability in a country) to consider household, economic, urban, environmental, disaster resilience, and governance aspects (Asian Development Bank, 2016). Similarly, in the energy security domain, approaches evolved from measuring the availability of fossil and other types of energy resources (i.e., energy reserves) to considering diversity of energy resources, import dependence, infrastructure development, societal effects, environmental impact, efficiency, and economic and political factors as important components of energy security (Ang et al., 2015; APERC, 2007). Food security measures also consider social and political aspects such as accessibility and utilization in addition to physical factors (International Food Policy Research Institute, 2015). Health outcomes such as diarrhea and malnutrition are also typically included in the individual resource security metrics. However, individual metrics do not show the interactions and dynamics among the components, which is important because the security of each resource is often connected to the other

resources (e.g., drinking water access impacts utilization aspects of food security, cooking of food relies on energy resources, and water resources are used to generate electricity). Solely addressing or emphasizing scarcity and insecurity issues of any one of the three resources could overlook opportunities for improvement in the other two sectors and fail to capture the synergies (Al-Saidi & Elagib, 2017).

Although there is a consensus on the need for managing FEW resources as a FEW nexus, methods for doing so are relatively underdeveloped (Biggs et al., 2015; McGrane et al., 2018; Perrone & Hornberger, 2014). Statistical and data analysis techniques used to quantify some interrelationships of the FEW nexus have generally applied "black box" approaches (Ozturk, 2015; Zaman et al., 2017) and often did not include critical components such as social-economic factors leading to incomplete evaluation of nexus interactions (Albrecht et al., 2018). For example, Sušnik (2015, 2018) used global data to regress the countries' gross domestic product (GDP) against total/sectoral water withdrawals, total/specific crop production, and electricity consumption/generation, finding strong correlations between GDP per capita and all three resources metrics. Willis et al. (2016) focused on measures of availability and accessibility of FEW resources to produce sub-indices for each resource that were then aggregated to a FEW index for countries globally. Both of these approaches overlooked governance factors, and the resources were siloed such that cross-sectoral influences (e.g., influence of water withdrawals and crop production on electricity consumed) were not considered. Other work has used a variety of techniques to explore parts of the FEW nexus such as global virtual water networks and life cycle analyses (Feng et al., 2014; Konar et al., 2011; Yuan et al., 2018) but have not stressed relationships with governance. Consistent inclusion of governance will be especially important given the potential for and consequences of the conflicts generated by scarcity of resources (Märker et al., 2018).

There is a need to develop a cohesive framework to elucidate key linkages and guide the analyses. Toward this need, we introduce a FEW analytical framework that leverages the theoretical understanding of resource systems to better elucidate nexus interactions (Rasul & Sharma, 2016). Specifically, the framework distinguishes between three domains: resources availability, access to FEW-related services, and FEW-related health outcomes (Figure 2). This FEW resources-services-health (RSH) framework clarifies the complex causal mechanisms between the domains, notably that the conversion of raw resources (e.g., water, arable land, and minerals) into critical services (e.g., drinking water, food, and energy) is needed in order to have an impact on FEW-related health outcomes (e.g., diarrhea, undernourishment, and deaths attributed to air pollution; Dora et al., 2015; WHO, 2018b). Cross-sectoral influences can occur during both the conversion of resources to services (e.g., use of water for energy and use of energy for water) and between the services and health domains (e.g., inadequate provision of water services not only impacts diarrhea rates but also influences nutrient uptake and thus food-related health outcomes such as malnutrition; Dora et al., 2015; Hunter et al., 2010). In addition to physical variables, the dynamics between the domains are mediated by important socioeconomic and governance (SG) capacity variables such as education, political stability, and infrastructure availability; SG variables can influence nexus interactions between resources and service domains as well as between the services and health domains (Figure 2). The FEW-RSH framework provides a comprehensive lens for analyzing and comparing the dynamics and nuances of the FEW nexus that can be applied to regions at any scale. The inclusion of SG in the framework constructs the bridges across disciplinary silos and emphasizes the importance of the human aspect in the FEW nexus.

This study implemented the FEW-RSH framework to understand nexus interrelationships in 38 sub-Saharan African (SSA) countries (Figure 3), a region facing significant resource insecurity (United Nations, 2018a); the Democratic Republic of the Congo was not included in the analyses due to a lack of data. The framework is implemented using a data-driven cross-validated stepwise regression technique to evaluate primary drivers of the service and health outcomes.

2.2 Methods

The data analysis consisted of collecting, categorizing, processing, and regression analysis of FEWrelated data (Figure 4). A cross-validated stepwise regression analysis (CVSRA) method, which systematically evaluates the pool of candidate metrics for each linkage by considering the cross-validation errors of the findings, was implemented to examine and elucidate both sectoral and cross-sectoral linkages (Figure 5 and Table 2). Metrics with the smallest cross-validation errors were selected for each linkage or interlinkage exploration. Analysis was conducted for each of the FEW-services as well as the FEW-health outcomes as dependent variables. Direct sectoral linkages, cross-sectoral linkages between two sectors, and FEW nexus linkages across all three sectors were considered.



Figure 2. Conceptual food, energy, and water-resources-services-health framework.

Note: the framework distinguishes between three domains: (1) resource availability, (2) accessibility to services, and (3) food, energy, and water-related health outcomes for the three sectors: food, energy, and water. The relationships among these three domains are influenced by both direct sectoral and cross-sectoral linkages as well as socioeconomic and governance capacities of regions.

1. Data Collection. All available national-level data were collected from multiple sources (e.g., the United Nations and World Bank; Figure 3 andFigure 6 and Table 8). Metrics that capture human capacity measures that influence the processes between the domains were also included in the data set (Table 9). For each of the metrics listed in Table 8 and Table 9, the most recent data (as of 31 December 2017) were collected to most effectively represent the current FEW-related information and conditions of those countries; we assume that the values did not vary significantly between years. Some of the metrics captured temporal variability of resources, services, or health outcomes (e.g., interannual and seasonal variability of water resources as well as food production and supply variability). Therefore, the data assembled for this analysis generally have a zero time dimension, while the spatial resolution is at the country level. More

data were available for the water sector (38 countries) than energy sector (20) or food (21) sector (Figure 6). Overall, 13 countries had the full set of FEW data analyzed in this research.



Figure 3. The 38 sub-Saharan countries analyzed in this study.

Note: the color gradient indicating gross domestic product per capita in \$US of each region.

2. Data categorization. The collected metrics were first categorized into the three sectors (water, food, and energy) and domains following the FEW RSH framework (Figure 2). The metrics were further categorized into the respective domains: resources, services, and health, which represent the availability of the FEW resources, human accessibility to the processed FEW resources, and

health of the people, respectively (Figure 7). Socioeconomic and governance capacity variables were similarly categorized into general as well as sector-specific variables (Table 9).

- 3. Covariance reduction. Within some of the categories, there were multiple metrics containing overlap- ping information or explaining similar phenomenon (e.g., the six World Bank Governance indicators are calculated from different combinations of the same underlying variables; World Bank, 2018b). We used correlation analysis to first identify highly correlated variables (e.g., the Pearson Correlation Coefficient of Flood occurrence and Total renewable water resources in the water resources domain is -0.76; Table 12). To reduce double-counting and collinearity issues, principal component analysis (PCA) was used to derive independent principal components (PCs) that capture the majority of the variance in the raw metrics. In the regression analysis, fewer PCs were selected than the number of raw metrics, which reduced the dimensionality and improved the robustness of the model performance (Çamdevýren et al., 2005; James et al., 2013). Other metrics were combined (either by summing or differencing) to reduce redundancy (Table 10). These processed variables are referred to as "derived metrics" for clarity. Some of the data with skewed distribution were log10 transformed prior to further analyses (Tables 2 and 10).
- 4. Regression analyses. Relationships between the resources and services domains as well as services and health domains were evaluated using a regression approach. Regression analyses were first implemented to identify important metrics with each sector (i.e., direct-sectoral linkages). The analysis was then repeated to evaluate interactions between the primary sector and one of the remaining sectors (i.e., cross-sectoral linkages). Finally, analyses were implemented to evaluate linkages among all three sectors (i.e., FEW nexus).

Stepwise selection methods are common and widely-used tools to select the best subset of predictors for models when there are many predictors for selection. In the traditional stepwise regression approach, the variable to select or remove in forward or backward method at a certain level (e.g., model with n variables

named as the nth level) is based on F-to-enter or F-to-remove values ($F=t-value^2$). This approach, however, has been criticized for its selection bias, which can lead to inconsistencies in the final model (Whittingham et al., 2006).

To overcome the issues of the traditional stepwise regression method, researchers have used the Information-Theoretic model selection such as Akaike Information Criterion (AIC) to penalize models with a high number of variables to prevent overfitting (Whittingham et al., 2006). We chose to use Leave-One-Out Cross Validation (LOOCV) error as the criterion of variable selection. While LOOCV and AIC are asymptotically equivalent (Stone, 1977), LOOCV can explicitly test the prediction error on all data points while systematically removing one variable (in our case, all associated values of a country) from the full data set. The LOOCV is suitable in cases such as ours because there are some high leverage points, and we do not have a large data set. The CVSRA returns the set of independent variables with the minimum LOOCV error (Figure 5). The AIC results are generally consistent with the LOOCV results (Table 11). In three of 32 models, there was a difference in one of the variables selected but in these three instances the chosen metrics for both LOOCV and AIC were from the same category so the difference would not affect our interpretation of the results. While in some cases (Table 11), adding an additional variable can achieve marginally lower LOOCV error, we chose to limit the number of variables allowed to no more than three to control overfit- ting in our data set which has only a modest number of observations. In trimming the number of variables, we considered both the decrease of the LOOCV error of the model and the p value of the additional variable (calculated by the two-tailed t test under standard assumption). For convenience we chose p value of 0.05 as the cutoff point.



Figure 4. Overview of the data analysis methodology.

Note: CVSRA = cross-validated stepwise regression analysis; SG = Socioeconomic and Governance Capacity.



Figure 5. Flow chart of the cross-validated stepwise regression analysis.

Note: *i* is the index of variables inside one running cycle of the algorithm, *j* is the index of the first selected significant variable, *k* is the index of the second selected significant variable, and so on. $CV_ER_nv\#$ means the cross-validation error of independent variable *i* for the linear regression model with # numbers of independent variables.



Figure 6. Countries with available data for the regression analyses.

Note: direct linkage analyses were conducted for (a) water sector (n = 38), (b) energy sector (n = 20), and (c) food sector (n = 21). Cross-sectoral analyses considered the joint set of countries for each of the direct linkage analyses. Food, energy, and water nexus analysis was conducted for (d; n = 13). The colors indicate each country's gross domestic product per capita.



Figure 7. Categorization of the metrics used in the regression analyses by sector and domain.

Note: the "N"s refer to the total number of metrics within each category. The solid blue arrows indicate focus of analysis for direct sectoral linkages, while the dashed red arrows indicate analyses conducted for cross-sectoral and food, energy, and water nexus CVSRAs.

| Sector | Domain | Derived Metric | Explained Variance (%) | Subset (n) |
|--------|--------|---------------------------------|------------------------|---------------|
| W | R | Water availability | 52 | W (38) |
| | | | 50 | E, W-E (20) |
| | | | 48 | F, W-F (21) |
| | | | 57 | FEW (13) |
| W | R | Annual and seasonal variability | 19 | W (38) |
| | | | 23 | E, W-E (20) |
| | | | 19 | F, W-F (21) |
| | | | 20 | FEW (13) |
| E | S | Energy usage | 96 | E, E-W (20) |
| | | | 97 | E-F, FEW (13) |
| F | R | Agricultural area | 59 | F, F-W (21) |
| | | | 52 | F-E, FEW (13) |
| F | R | Land use | 29 | F, F-W (21) |
| | | | 39 | F-E, FEW (13) |
| F | S | Food utilization | 80 | F, F-W (21) |
| | | | 83 | F-E, FEW (13) |
| F | S | Protein balance | 72 | F, F-W (21) |
| | | | 74 | F-E, FEW (13) |
| F | S | U5 malnutrition | 72 | F, F-W (21) |
| | | | 63 | F-E, FEW (13) |
| SG | SG | Overall quality of governance | 72 | W (38) |
| | | | 81 | E, W-E (20) |
| | | | 72 | F, W-F (21) |
| | | | 79 | FEW (13) |
| SG | SG | Political Stability | 13 | W (38) |
| | | | 11 | E, W-E (20) |
| | | | 17 | F, W-F (21) |
| | | | 15 | FEW (13) |

Table 1, Variance Explained by Principal Components

Note: although the number of countries vary, similar percentage of variance is explained in the different sectoral and cross-sectoral analyses. Sectors refer to water (W), food (F), or energy (E) or socioeconomic and governance (SG), while domain refers to resources (R), services (S), or health (H). The subset column notes the combination of countries used in the principal component analysis.

| Sector | Domain | Metric | Unit | Source |
|--------|--------|--|------------------------------|--|
| W | R | Water availability ^a | - | (CRED; Guha-Sapir, 2017; FAO, 2016) |
| | | Annual and seasonal variability ^a | - | (CRED; Guha-Sapir, 2017; FAO, |
| ** 7 | 2 | | 0/ | 2016) |
| W | S | Access to drinking water | % | (FAO, 2016) |
| | | Access to sanitation | % | (FAO, 2016) |
| W | Н | US diarrhea-caused deaths | % | (UNICEF, 2018) |
| Е | R | Non-fossil fuel production ^{a, o} | Mtoe/cap | (International Energy Agency, 2015) |
| | | Fossil fuel production ^{a, b} | Mtoe/cap | (International Energy Agency, 2015) |
| | | Total fossil fuel reserves b | Mtoe/cap | (World Energy Council, 2016) |
| | | Fuel reserves: oil share | % | (World Energy Council, 2016) |
| | | Fuel reserves: gas share | % | (World Energy Council, 2016) |
| Е | S | Energy usage ^a | - | (United Nations, 2017; World |
| | | <i></i> | | Bank, 2018b) |
| Е | Н | Air pollution-attributed deaths | % | (WHO, 2018a) |
| F | R | Agricultural area ^a | % | (FAO, 2018) |
| | | Land use ^a | % | (FAO, 2018) |
| F | S | Food utilization ^a | - | (FAO, 2018) |
| | | Protein balance ^a | - | (FAO, 2018) |
| | | Food supply variability | kcal/cap/day | (FAO, 2018) |
| | | Food production variability | Int\$/cap | (FAO, 2018) |
| F | Н | U5 malnutrition ^a | - | (FAO, 2018) |
| G | SG | GDP per capita ^b | US\$ | (World Bank, 2018b) |
| | | Education index | - | (United Nations, 2013) |
| | | Governance quality ^a | - | (Kaufman & Kraay, 2015) |
| | | Political stability ^a | - | (Kaufman & Kraay, 2015) |
| | | Rural population | % | (FAO, 2016) |
| Е | SG | | Mtoe/cap | (International Energy Agency, |
| | | Import export difference ^a | - | 2015) |
| F | SG | Rail lines density b | Lines per 100km ² | (World Bank, 2018b) |
| | | Arable land with irrigation b | - % | (FAO, 2018) |
| | | \$ Food import/merchandise Export b | Ratio, 3-year average | (FAO, 2018) |
| | | Cereal import dependency ratio | % | (FAO, 2018) |

Table 2, Variables Used in the FEW Data Analysis

Note: sectors refer to water (W), food (F), energy (E), or general (G), while domains refer to resources (R), services (S), health (H), or socioeconomic and governance capacity (SG). U5 = children under 5 years of age. ^a Derived metrics. ^b The data have been log10 transformed. FEW = food, energy, and water; GDP = gross domestic product.

2.3 Results

2.3.1 Regression Results

The metrics (independent and dependent variables) used in the CVSRA were chosen from a subset of PCs (derived metrics) along with several of the original metrics that did not have high correlations with other raw metrics (Table 1 Table 2). The cumulative variance proportions of each PC vary between the derived metrics (Table 1). For instance, PC1 of the water resources metrics explains 52% of the total variance, with PC2 adding another 19% to the total variance explained. Although the absolute magnitude of the variances varies among the different subset countries, the standardized weights were generally consistent for the PCA subset combinations (Table 1). For example, the loadings of the water resources PCs indicate

that PC1 primarily captured availability dimensions of water resources, while PC2 captured variability dimensions of water resources for all four combinations of subset countries. Two PCs derived from a group of correlated metrics can capture at least 71% (such as the six metrics of water resources domain in the Water subset) or as high as 92% of the total variance (the six governance indicators of in the energy data set). For the measurable outcomes of FEW services and health in the second and third domains, one PC can explain at least 63% (the four young age malnutrition metrics in the FEW subset) or up to 97% of the total variance (the two energy usage metrics of energy services domain in the FEW subset) for that particular data set. The results indicate that the PC scores we used in the regression analyses can adequately represent the characteristics of the metrics and data while meeting the purposes of dimensionality and covariance reduction. The described behaviors of the PCs were consistent throughout the PCAs for the country subsets for the individual resources (water, energy, and food) as well as cross-sectoral and overall FEW subsets (Table 1).

In the direct sectoral analysis, SG metrics such as governance quality, political stability, and GDP per capita are the primary metrics capturing conversion of resources to services; access to drinking water and some of the food-specific access metrics are significant variables in the services to health outcomes (Figure 8). All models, including independent and dependent raw and derived metrics used, are listed in Table 11. When cross-sectoral linkages are considered, the fossil fuel reserves are significant predictors for improved access to sanitation as well as food production variability; infrastructure variables such as rail lines density and land equipped with irrigation also emerge as significant for food utilization and energy usage and malnutrition outcomes; food services variables are significant variables for malnutrition and air pollution-attributed deaths (Table 3). Similar patterns are present in the FEW nexus linkages analyses as in the cross-sectoral linkages (Figure 9). No significant metrics emerged for food supply variability in either the direct sectoral or FEW nexus analyses. Overall, SG and infrastructure metrics were the predominant explanatory variables in resources-services paths, while FEW-related services variables were the dominant explanatory variables for FEW-related health outcomes (Figure 10).

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| Sector | Domain | Outcome | Sectors analyzed | Significant variables |
|--------|--------|----------------------------------|------------------|---|
| W | S | Access to safe drinking water | W-E | Rural pop, governance quality, political stability (0.86) |
| | | | W-F | - |
| W | S | Access to improved sanitation | W-E | Fossil fuel reserves: oil share, GDP per capita (0.55) |
| | | | W-F | - |
| F | S | Food utilization | F-W | Rural pop, political stability (0.42) |
| | | | F-E | Rail lines density, land equipped with irrigation (0.48) |
| F | S | Protein balance | F-W | GDP per capita (0.47) |
| | | | F-E | GDP per capita (0.69) |
| F | S | Food supply variability | F-W | - |
| | | | F-E | - |
| F | S | Food production variability | F-W | Political stability (0.20) |
| | | | F-E | Fossil fuel reserves: oil share (0.28) |
| Е | S | Energy usage | E-W | GDP per capita (0.39) |
| | | | E-F | Education index and rail lines density (0.81) |
| W | Н | Diarrhea-caused deaths | W-E | Governance quality (0.23) |
| | | | W-F | Governance quality (0.31) |
| F | Н | U5 malnutrition | F-W | GDP per capita, rail lines density (0.52) |
| | | | F-E | Protein balance, food supply variability (0.67) |
| Е | Н | Air pollution-attributed deaths | E-W | - |
| | | | E-F | Food utilization (0.57) |

Table 3. Significant Variables in the Cross-Sectoral and FEW Nexus Linkages Identified by the CVSRA Analyses

Note. In addition to the general SG metrics, fossil fuel reserves and infrastructure-related SG metrics are also significant variables in the cross-sectoral linkages. Sectors refer to water (W), food (F), or energy (E), while domain refers to services (S) or health (H). For readability, the significant variables were color coded by domain: socioeconomic and governance (purple), food (green), and energy (orange). FEW = food, energy, and water; CVSRA = Cross-Validated Stepwise Regression Analysis; GDP = gross domestic product.



Figure 8. Significant variables from direct sectoral Cross-Validated Stepwise Regression Analysis analyses.

Note: The independent variables and the adjusted R2 are presented on top of each linkage indicated by the blue arrow. Socioeconomic and governance metrics that dominate the resources-services linkages and services together with socioeconomic and governance metrics are the significant variables in the services-health linkages. GDP = gross domestic product.



Figure 9. Significant variables between (a) resources and services domains and (b) services and health domains from food, energy, and water nexus Cross-Validated Stepwise Regression Analysis analyses.

Note: The independent variables and the adjusted R2 are presented on top of each linkage indicated by the blue arrow. In addition to the general presence of socioeconomic and governance metrics, infrastructure and services metrics are also present in the food, energy, and water nexus linkages analyses. Food services metrics are important variables for both food and energy-related health outcomes in the food, energy, and water nexus linkages. GDP = gross domestic product.



Figure 10. Percentage of significant variables.

Note: The variable is categorized by domain for both direct and cross-sector linkages in the resourcesservices models (left) and services-health models (right). SG metrics are colored in variations of purple to indicate different subcategories, orange refers to the energy resources metrics, and sky blue indicates the FEW services metrics. SG metrics dominates the routing of resources through the services domain, while FEW services along with SG metrics affect the services to health outcomes. SG = socioeconomic and governance; FEW = food, energy, and water.

2.3.2 FEW Literature Summary of Selected Countries

In addition to the quantitative data-driven approach, we compiled literature summaries for three of the SSA countries to further explore FEW dynamics and test and verify the strength and limitations of the quantitative approach. These "country profiles" allow us to delve more deeply into the primary dynamics influencing FEW nexus outcomes of three countries that have different values of the country-level variables that we use. Specifically, for three countries we consider characteristics such as regional climate and geographic variations that may or may not be captured in the country-level data to highlight both consistencies with the data-driven results and potential limitations of a country-level data analysis. Nigeria, Senegal, and South Africa were selected for the FEW literature summary, because these countries capture the diversity in GDP and natural resources in SSA and all had data for all FEW-related metrics. Senegal, Nigeria, and South Africa are located in the west, middle, and south of the study region with distinctively different climate and natural resources reserves, and per capita income is in the

relatively low, middle, and high range among the 38 SSA countries included in the study, respectively (Table 4). For each country, peer-reviewed articles, papers from nongovernmental organizations, government reports, and other credible media sources were reviewed to better understand the direct and cross-sectoral linkages between the FEW domains in SSA. The findings from the quantitative analyses and literature summaries were compared to identify FEW areas that require further exploration.

| Metric | Unit | Senegal | Nigeria | South Africa |
|--------------------------------------|--------------|------------------|------------------|------------------|
| Precipitation | mm/year | 690 | 1200 | 500 |
| Total Fossil Fuel Reserves | toe/cap | 0 | 52 | 390 |
| Arable Land | hac/cap | 0.21 | 0.19 | 0.23 |
| GDP per capita | \$/cap | 960 | 2200 | 5300 |
| Education Index Global Rank | percentile | 13 th | 19 th | 37^{th} |
| Government Effective Global Rank | percentile | 39 th | 17 th | 65 th |
| Political Stability Global Rank | percentile | 42 nd | 7 th | 40 th |
| Children Under 5 Diarrhea Deaths | % population | 8.9 | 10 | 8.7 |
| Deaths Attributable to Air Pollution | % population | 1.6 | 2.6 | 2.4 |
| Children Under 5 who are stunted | % population | 19 | 33 | 24 |
| Percentage of rural population | % population | 57 | 52 | 36 |

Table 4. Data Summary of Senegal, Nigeria, and South Africa

Senegal:

Senegal is a country with relatively limited FEW resources. The country has a long-term average of 700 mm of annual precipitation, 3.2×10^6 ha of arable land, but no fossil fuel reserves. Although the economy is growing and on the ascending trend, the GDP per capita and the education index are still low (Table 4). However, Senegal has a relatively effective government with limited instability, violence, and terrorism issues (Kaufman & Kraay, 2015).

Urban-rural disparities in FEW services have been a common issue for decades; Senegalese people living in urban areas consistently have better access to water and sanitation services, more electricity supply, and better access to food (Nordman, 2018; WFP, 2018b; World Bank, 2018a). Due to income inequality and lack of remediating policies, rural people who cannot afford better FEW services often use biomass for cooking, suffer from food insecurity, and utilize unsafe water (Diallo, 2017; Nordman, 2018; WFP, 2018b). The water utilities in Senegal are also vulnerable to power outages. Moreover, Senegal's strong seasonal climate and frequent inclement weather events make it challenging to have consistent access to both water services and food services (CRED; Guha-Sapir, 2017). The geographic proximity of Senegal to the Saharan Desert and the Atlantic Ocean makes the arable land in the country prone to floods, droughts, desertification, and salinization (WFP, 2018b).

The climate in Senegal not only impacts FEW services but also affects FEW-related health outcomes. For example, researchers studied the prevalence of diarrhea in urban areas of Dakar and two suburbs and found a high prevalence of rotavirus infections in the dry season, while bacterial infections dominated during the wet season (Sambe-Ba et al., 2013). Their work highlights the potential risks of flooding for exposing environmental pathogens to people directly and indirectly from contaminated water and food. Due to higher income inequality and limited access to food, children in rural areas are more likely to be affected by stunting in the country (USAID, 2014).

Despite these challenges, Senegal continues to make progress on the quality of the FEW services, closing the urban-rural gap, and improving people's well-being. This is primarily through a collaborative effort among partner agencies, including utilities, health care sectors at all levels, financial institutions, government, public-private partnerships, and international aid organizations such as the World Bank and Red Cross (Diallo, 2017; World Bank, 2018a).

Nigeria:

Nigeria is a country with abundant FEW resources. The country has a long-term average of 1,000 mm of annual precipitation, 10 billion tonnes of oil equivalent (toe) of oil and gas reserves, and 34×10^6 ha of arable land. Although Nigeria has the largest economy in Africa, with the largest population, the per capita GDP ranking is in the middle for SSA countries while education is low (United Nations, 2013). The country faces significant challenges in political stability and government effectiveness as it is ranked low at 7th and 17th percentiles in the world, respectively (Table 4).

Although the economic conditions are relatively strong, Nigeria still lacks essential infrastructures and financial capacity to provide FEW services (Food Security Portal, 2018; United Nations, 2014). Despite

investments, drinking water supply improvements are slow growing, while sanitation access is decreasing over time (AMCOW, 2011). Nigeria has more than sufficient natural and human resources to grow agricultural products; however, the country experiences deficiencies in food and is heavily dependent on food imports (Food Security Portal, 2018; Matemilola & Elegbede, 2017). Regional conflicts and domestic violence in the northeastern and other parts of Nigeria have not only seriously disrupted the local FEW services but have also displaced a significant number of people and local workforces in FEW sectors (Strauss Center, 2018; WFP, 2018a). Nigeria has a significant amount of fossil fuel reserves and a significant potential in other renewable energy sources (i.e., hydropower and solar); however, the lack of electrical power supply and refining technologies to process crude oil has made many industrial operations unfeasible (Borok et al., 2013).

Nigeria faces serious FEW-related health issues, such as diarrhea, indoor, air pollution, and malnutrition prevalence among children under the age of five (U5). Although diarrhea has decreased by 20% over a decade in Nigeria, over a hundred thousand U5 deaths were attributed to diarrhea in Nigeria in 2015, accounting for 20% of the global U5 diarrhea-caused deaths (Troeger et al., 2017). Some urban areas in Nigeria have built water treatment plants and deliver treated water to the people. This has reduced the presence of Escherichia coli at the taps suggesting the effective removal of microbial contaminants, but heavy metal introduced during the distribution process is posing a greater risk to human health (Etchie et al., 2013). Health disparities are present at the regional scale in Nigeria; some states have a much higher percentage of stunting than other states (USAID, 2018b). In particular, regions with more educated mothers have lower U5 stunting issues, while also present in Senegal, this dynamic is more prevalent in Nigeria (USAID, 2014, 2018b).

After failing to meet the United Nations Millennium Development Goals, the Nigerian government has acknowledged that proper management and effective policies were key to fully utilizing the existing infrastructures, resources, and financial investments. Since then, the government has undertaken a series

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of reforms such as privatization of the water services sector, enhancement of regulations, and function clarification of responsibilities for government institutions to improve FEW services (AMCOW, 2011).

South Africa:

South Africa has limited water resources, with annual precipitation less than 500 mm. In contrast, the country has 21 billion toe of coal reserves and 13×10^6 ha of arable land. South Africa is one of the top economies in SSA, and the nation ranks high at the 65th percentile rank for government effectiveness and at the 40th percentile rank of political stability globally (Table 4).

South African policy is to provide free access to basic water and electricity (6,000 L of water/household/month and 50 kWh of electricity/household/month for indigent households) as well as basic access to affordable food. However, the nation faces challenges in implementing the policy effectively (Gladwin-Wood & Mathebula, 2016; Muller, 2017a). For example, although there are tariffs imposed on high consumption, high water demand and usage in richer parts of the country have led to an unstable and decreasing supply of water for the poorer regions. The affected areas predominantly tend to be rural areas with black communities, which have been historically ignored by service providers even though South Africa became a democracy in 1994 (ANA, 2016; Muller, 2017a; Naicker, 2015). The recent Cape Town water crisis highlights that although infrastructure (such as desalination plants) is being developed, the nation will likely continue to face water shortages (Dawson, 2018; Scott, 2018; Shelly, 2018). Climate change, in particular, is expected to pose a significant risk to South Africa's water-dependent economy and the affordability of FEW services in the future (Misselhorn & Hendriks, 2017; Mission 2017, 2017; Muller, 2017a). The energy sector also faces similar infrastructure challenges from overloading and power outages due to increasing demand, underinvestment, and maintenance failures (Hedden, 2015; Trollip et al., 2014).

Besides its impact on FEW services, water stress is a significant risk factor for health issues in the country. During the Cape Town water crisis, for example, the citizens were requested to heavily conserve

water to avoid a Day Zero disaster, leading to poor sanitation and personal hygiene as well as severe health risks such as dehydration and heat stroke (Mash et al., 2018). Indoor air pollution caused by smoke from burning wood during cooking is a common energy-related health issue for all three countries in the qualitative analyses, leading to many adverse health effects including eye infections, acute and chronic respiratory diseases, birth weight reduction, and cancer (Anozie et al., 2007; Bensch & Peters, 2017; Vegter, 2016). In South Africa, poor indoor air quality is exacerbated by ambient air pollution, which exceeds the particulate matter 2.5 limit set by local and international standards in a majority of the country. The pollution is particularly high in low-income and heavily populated areas around townships, where coal production is concentrated (Altieri & Keen, 2016). Although there are national standards and legislation focused on regulating and improving air quality in South Africa, the policies have been criticized for being too lenient and for lack of enforcement (Hugo, 2018).

South Africa has legislative support and fairly comprehensive regulations as well as the technical expertise and financial capacity to improve FEW services. However, compliance of service providers with and enforcement by government officials of the laws and regulations need to be significantly improved. It would also be advantageous for South Africa to partner with nearby nations and to use international aid to further improve the quality of FEW services and people's well-being through trade and capacity development (USAID, 2018a).

2.4 Discussion

The FEW nexus is characterized by complex factors and dynamics. The FEW-RSH framework aims to untangle the diverse influences by distinguishing three distinctive domains: natural resources, accessibility to critical services, and associated health outcomes (Figure 2). A data-driven quantitative approach guided by the framework was implemented to understand the primary drivers influencing the FEW nexus in SSA countries. Direct and cross-sectoral linkages were evaluated using a CVSRA and a FEW literature summary was leveraged to understand nuances that may have been overlooked in analysis of national-level data sets.

Interestingly, most of the natural resources variables did not emerge as the most significant predictors in the statistical analyses, highlighting the general abundance of natural resources in these countries (Figure 8Figure 10). Oil reserves were found to be important for access to improved sanitation and food production variability, highlighting the energy dependencies of these FEW services (Figure 9). In general, the routing of resources through the services domain was dominated by socioeconomic and governance capacity variables (Figure 10). GDP per capita, governance quality, and political stability were the most prevalent for direct sectoral linkages and infrastructure-related variables such as rail lines density and land equipped with irrigation emerged as significant in the FEW nexus analyses. Despite the potential link between the extraction of raw FEW resources with a portion of domestic GDP as in the case of Nigeria, GDP remains an important proxy of a country's financial capacity that influences the provision of FEW services and the FEW-related health conditions. Governance quality was also a significant correlate of diarrhea-caused deaths in the quantitative analysis. Weak governance can result in poor quality of water services that ultimately threatens people's health. Additional support for this interpretation comes from more detailed reports for three countries (section 2.3.2). Generally, FEW-related health outcomes were more strongly influenced by FEW services, with water and food access issues particularly impacting health in SSA (Figure 10); the significant relationship between food utilization and air quality, in particular, has also been demonstrated using a panel random effect regression in SSA (Zaman et al., 2017). The analyses did not show a connection between the energy services and energy-related health at the country level. However, the FEW literature summary for three countries revealed that indoor air pollution caused by the lack of clean cooking in rural areas leads to health inequality issues at the subnational level.

The statistical findings are generally consistent with the FEW nexus summaries of the three countries. Specifically, Senegal and Nigeria have sufficient raw resources (Table 4) but lack capacities in physical infrastructure and treatment/processing technology that limit people's access to FEW services. The quantitative results also indicated that infrastructure variables are more dominant than resources variables in the resources-services paths (Figure 10). Indicators related to governance and socioeconomic conditions are higher for South Africa than for Senegal and Nigeria (Table 4). Although FEW services are also better in South Africa, health outcomes are not markedly different among the three countries in the FEW literature summary (Table 4). Political instability from regional conflict also had an impact on infrastructure performance and government functions, especially in Nigeria and South Africa. The CVSRA also revealed that political instability is an important determinant to Water and Food Services (Table 3). Good governance is especially important for addressing cascading failures across sectors (e.g., power outages that impact sanitation access and poor cooking practices leading to indoor pollution). The quantitative results confirm the importance of governance as the second most dominant subcategory of variables in both resources-services and services-health paths (Figure 9). These issues are best addressed through an integrated management of infrastructures by governing institutions (Cai et al., 2018; Lele et al., 2013). The country profiles also high-lighted another geographic disparity overlooked in the nationallevel data: urban-rural disparities. There is a consistent inequality of FEW services between rural and urban regions in all three countries. Limited physical infrastructure capacities (e.g., pipelines and railroads) exacerbate these differences by reducing the transfer of resources from abundant to scarce regions (Burgess & Donaldson, 2010).

The education level of a country may affect the FEW nexus as well. Education was identified as a significant determinant for energy usage using CVSRA. Furthermore, the FEW literature summary highlighted the importance of education (especially of the mothers) for impacting U5 stunting, especially in Nigeria.

Investments from domestic GDP (as well as income from foreign companies or aid) are critical for building and maintaining infrastructures and developing GIS applications and other pioneering technologies to increase the security and quality of FEW services (Lele et al., 2013). Improving

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agricultural services (e.g., by reducing food supply variability), in particular, has been recognized to have a significant impact on poverty in SSA (Ozturk, 2017). Improvement of FEW services, such as the improvement of water and sanitation services (Haller et al., 2007), the development and expansion of sustainable energy (Deichmann et al., 2011), and the improvement in irrigation management and agricultural research and development (Thirtle et al., 2003), can also benefit the economy. The case of South Africa highlights, however, that increases in GDP are also associated with higher demand for FEW resources (Sušnik, 2015, 2018). Given climate change impacts on FEW resources, explicit attention is needed to ensure that economic growth pathways incorporate environmental sustainability in SSA (Cumming & von Cramon-Taubadel, 2018).

Although the findings from the data analysis are consistent with the FEW literature summary of the three countries, there are various limitations of the current approach. Notably, this study took a static view of the FEW system in SSA, with temporal variabilities of a country usually represented by a single metric, such as interannual and seasonal variabilities in water resources or production and supply variabilities of food resources. Metrics used in the analysis were not collected at the same time; there were some cases where the year of the metric for a specific country did not match the dates of other countries. Improved data quality and availability would enable better tracking of changes in the different countries' systems over time as well as address issues of collinearity in the metrics. Other techniques such as agent-based modeling can be used to simulate the dynamic relationships between the resources, services, and health domains of FEW sectors (Bonabeau, 2002). Our analysis indicates that in such models, socioeconomic and governance metrics need to be explicitly considered. This approach could be used to evaluate the impact of different adaptation strategies to future changes in climate, urbanization, and other potential disruptions as well as enable incorporation of insights from survey-based and other field methods (T. Gunda et al., 2017). Last but not least, the research was conducted at country scale across sub-Saharan Africa, analyses at smaller scales are needed to better capture spatial-temporal variations of the FEW interactions as well as the effects of the human capacity and natural challenges.

Chapter 3

Modeling the Interactions of Policies, Stakeholders, and the Environment

3.1 Introduction

As we discovered in the previous chapter, the human capacity aspects such as socio-economic factors as well as the quality of governance have significant impact on services and health around the FEW nexus. For the FEW nexus, decisions usually occur at the mesoscale, at city or regional levels (Lant et al., 2019). Furthermore, if we consider policies and decisions as outcomes of public governance, they are instrumental in the consumption of FEW resources and the utilization of FEW services, as they are supposed to fulfill people's needs, remediate an emergency, relocate resources to another region, develop new infrastructures and expand system capacity, or meet other societal needs. In the past, conventional methods such as conducting surveys and collecting data were used to assess how the policies and decisions affected the stakeholders in the target regions. These findings were intended to inform government and other decision-maker activities in subsequent responses, through making adjustments or introduction of new policies based on the lessons learned. Such policy revisions is not robust enough, because pathways for next policy cycle is still unclear. However, using modeling techniques to run simulations could provide useful insights to inform policies such as identifying patterns and providing an ensemble of possible outcomes to quantify the uncertainties.

Simulation modeling is widely used for comparing different policy approaches to managing certain aspects in the complex FEW systems (e.g., irrigation for crops) and for optimizing the system's performance under uncertainty and climatic change (Hyun et al., 2019; Yang et al., 2018). Previous studies have applied agent-based modeling (ABM) techniques to water management in urban settings and interactions between water management policies and hydrology at the watershed scale and beyond (e.g., inter-basin water transfer (Kanta & Zechman, 2014; Murphy et al., 2016). Water-energy

interrelationships, such as hydroelectric dam optimization, have been extensively studied by applying optimization algorithms in simulation models (Dai et al., 2018). Our study investigates holistic management of water resources and performance assessments for all three sectors of the FEW nexus. Specifically, we study how different policies affect the FEW system outcomes and various stakeholders.

We chose Cape Town as a test case for our modeling approach because the city faces extreme stress resulting from a variety of problems, such as changing rainfall patterns, multiple sectors competing for limited resources, and policy and governance conflicts that arise from this inter-sectoral competition (Muller, 2017b). In this chapter, we restrict our analysis to improving the management of existing water supply sources across the food, energy, and water sectors in and around Cape Town and do not consider alternative water or energy sources, such as desalination or solar electricity generation. Our model framework will allow future research to investigate these possibilities.

In 2018, Cape Town almost encountered a "Day Zero" crisis where more than four million of people would have lost access to the municipal water supply. The Cape Town region experienced a sustained decrease in precipitation that started in early 2016. This led to a series of water use restrictions and the imposition of high water tariffs in Cape Town. Water restrictions were structured with multiple levels of severity across different sectors. The most serious restrictions, level 6b, would have limited water consumption for the entire city to 450 million liters per day (MLD), corresponding to 50 liters per person for residential use, and would have completely curtailed agricultural water allocations (DWS, 2018). The wine industry forms an important part of the regional economy of Cape Town and Western Cape Province. The water crisis severely harmed wine production and the health of the vines; some vineyards only received 20% of their demand for irrigation water even before the government completely shut down agricultural water allocation (Browdie, 2018).

Cape Town's rigorous and strict water use restrictions avoided a Day Zero crisis but produced severe hardship and economic losses. June 2018 brought increased rainfall and reservoir storage levels returned

to over 50% of their total capacity. A post-crisis assessment by Ziervogel (2018) summarized a number of problems that contributed to the near Day Zero crisis. These included a lack of collaboration and joint management of the water resources across government agencies—both laterally (across regions) and vertically (between national, provincial, and municipal levels of government)—and the lack of understanding of the local water system. Muller (2017b) also suggested that the water overuse in the agricultural sector in the 2015–16 planting season contributed to the vulnerability of the water supply to diminished rainfall over the next two years.

For this study, we designed a model that represented different stakeholders from the municipal, water, energy (hydropower), and food sectors to serve as a test bed for simulating and comparing FEW system outcomes under various policy scenarios. We tested two policy scenarios:

- Business-as-usual (BAU baseline): No joint-management or minimal communication between the departments of Energy, Water, and Food (agriculture). The tariffs of water and threshold levels of reservoir storage for restrictions used in this policy scenario are taken from the city of Cape Town;
- 2. Holistic adaptive management (HAM): Allocate water resources across FEW sectors to satisfy the municipal demand, similarly for hydropower generation, and agricultural production. This policy scenario incorporates a market-driven adaption strategy in which water prices are adjusted in response to changes in the stored water supply.

The BAU policy scenario served as a baseline and the model parameters were calibrated to match the historical system performance (reservoir storage levels, water use). The HAM policy scenario represented an alternative holistic management strategy to optimize performance of the water, energy, and food sectors.

3.2 Study Area

Our model represents the city of Cape Town and its adjacent wine regions including Swartland, Stellenbosch, Breede Valley, Langeberg, Drakenstein, and Witzenberg (Figure 11). The city of Cape Town, with more than 4 million people, consumes more than half of the water from the Western Cape water supply system. The wine regions have over 90,000 hectares of irrigated land for wine grapes (WCDA, 2019) and consume the vast majority of the remaining water. The other urban areas in Western Cape Province consume less than 7% of the water (DWS, 2018).

This region relies mainly on surface water from the six largest reservoirs in Western Cape Province, which have a total storage capacity of 900 billion liters (DWS, 2018). We obtained historical records for rainfall and temperature at weather stations across the region (Figure 11; SAWS, 2019). We used historical records of monthly reservoir storage and water consumption for urban and agricultural sectors (Figure 2) from the Big Six Monitor developed by the University of Cape Town using data provided by the city of Cape Town (CSAG 2019).

Agricultural (wine grape) irrigation starts with the planting season in early October, and peaks in January and February. Agricultural water demand drops to nearly zero during the winter rainy season, which begins at the end of April.

3.3 Model Design

3.3.1 Model Overview

Previous research largely emphasized using simulation models to optimize water consumption by a single sector, but in arid regions where multiple sectors compete for the limited resources, tradeoffs among different sectors require a holistic approach to water allocation. In this model, we account for competition for water resources between municipal, agricultural, and energy (hydropower) sectors within the FEW nexus. We incorporate stakeholders representing all three sectors: residents of Cape Town; farmers; and the manager of the Steenbras hydro-electrical station, which needs to maintain a sufficient storage level in

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the reservoir to generate power. The water allocation among these sectors is overseen by a water manager agent.





Note: The locations of the Porterville, Malmesbury, CT-AWS, Paarl, and Worcester weather stations are indicated by arrows.

This section briefly describes the model design. The NetLogo code for the model, is available at the model repository (Ding et al., 2019). The overview, design concepts, and details (ODD) document of the model is in Appendix B.

We used the model to simulate the ten-year period: 2009–2018, with monthly temporal resolution. The inputs to the model include initial reservoir storage, monthly water inflow, monthly water demand by

sectors, water price, and the price elasticity of demand (Climate System Analysis Group, n.d.; DWS, 2018; Sahin et al., 2016). The initial reservoir storage, monthly inflow, and the baseline monthly demand were taken from historical data. The baseline BAU policy scenario used historical values for the price of water and the HAM policy scenario used adaptive water pricing as described below.

Each month, the water manager receives the requested demand from each stakeholder and determines the allocation to each sector based on the total reservoir storage level and the rules for the chosen policy scenario. The reservoir storage is then updated based on the allocation and the monthly inflow (Algorithm 1). The sub-models and the rules for the two policy scenarios are described in Sections 3.3.2–3.3.6 and Algorithms 2–3.

| Algorithm 1 Main model sequence |
|--|
| Setup: initialize parameters and load input data |
| loop |
| Water manager obtains urban demand // Urban sub-model |
| Water manager obtains agricultural demand // Agricultural sub-model |
| Water manager obtains current reservoir levels // Hydroelectricity sub-model |
| Water manager allocates water according to scenario |
| Update reservoir storage |
| Calculate hydropower generation // Hydroelectricity sub-model |
| <i>tick</i> \leftarrow <i>tick</i> + 1 // Advance to next month |
| end loop |

3.3.2 Urban Sub-Model

For simplicity, we aggregated the urban demand for Cape Town (residential, commercial, and other) into a single representative agent, *CPers*. The *CPers* represents a population of 3.9 million people at the beginning of 2009 with an annual growth rate of 0.8%. In the city of Cape Town, the unrestricted percapita urban water demand is calculated based on the monthly average of urban water usage from 2009–2015 (CSAG. 2019). In all policy scenarios, the monthly municipal water allocation is calculated by the water manager in response to the urban demand using Equation (1):

$$Allocation_{urban,i} = Population_i * Demand_{urban} * (1 - Reduction)$$
(1)

where $Population_i$ is the population at time-step *i*, and *Reduction* is the water reduction ratio based on different policy scenarios .

3.3.3 Agricultural Sub-Model

In the agricultural sub-model, the irrigation demand is calculated using the soil moisture deficit (SMD), where SMD is calculated by a simple water balance approach. We used the Palmer Drought Severity Index (PDSI) tool developed by Jacobi et al. (2013), which uses the Thornthwaite method to calculate the monthly potential evapotranspiration (PET) and applies water balance to calculate the resulting soil moisture content (SMC). This tool is used in agricultural research to assess drought and soil moisture (Gunda et al., 2016; Nawagamuwa et al., 2018). We obtained the available water-holding capacity (AWC) for the soil in each of the agricultural regions from Shulze and Horan (2007) and obtained the monthly rainfall and average temperature for each agricultural region from the closest weather station (SAWS, 2019). We used the PDI tool to calculate the monthly SMD for each agricultural region from these data.

For this study, we focused on the irrigation of vineyards. On average, wine vineyards represent 43% of total irrigation in the Western Cape Province (WCG, 2015). The non-wine crops are mainly located outside our region of interest, so our model allocates 57% of average monthly irrigation demand to non-wine crops and does not apply any water-rationing or price adjustments to it. The irrigation demand by wine vineyards is calculated by the water manager in response to the agricultural demand using equation (2):

$$Demand_{wine,m} = SMD_m * Area * Kc_m * Ef_{wine}$$
(2)

where SMD_m is the soil moisture deficit in month *m*, Area is the irrigation area of each wine region, Kc_m is the Crop Coefficient of wine grapes for month m, and Ef_{wine} is the irrigation efficiency of the vineyard (WSU, 2016). We calibrate the model parameters under the BAU policy scenario to match the historical performance of the system (



). The calibrated model parameters were used in the HAM policy scenario as well.

Figure 12a. Historic versus observed dam storage levels;



Figure 12b. Historical agricultural and urban water consumption.

3.3.4 Hydropower Sub-Model

In the Big Six dam system, the Steenbras Upper Dam is the only pumped-storage hydropower dam. To maintain the maximum generation capacity, the reservoir needs to be maintained at its full level (DWS, 2018). The Steenbras Upper and Lower Dams coordinate their operations: the lower dam pumps the water to the upper dam during off-peak hours, and the upper dam releases water during the peak hours for electricity demand, providing up to 180 megawatts (MW) of electricity to the grid. The storage capacities of the Steenbras Upper and Lower dams are similar, and the combined storage accounts for 10% of the total capacity of the Big Six system. The water supply system in Western Province cannot release water

when the reservoir storage level is below 10% of the total capacity. Thus, we assume that if the total reservoir storage level is above 20% of the total reservoir storage capacity, the Steenbras Upper Dam can remain at full storage, thus achieving its maximum generation capacity. When the total reservoir storage level is lower than 15% of the total storage capacity, water in the Steenbras Upper Dam reservoir will be released for municipal water use, and no hydropower can be generated. In between 15% and 20% of the total reservoir storage, we assume hydropower generation capacity decreases linearly.

3.3.5 Business-as-Usual Policy Scenario

Under the BAU policy (Algorithm 2), the model adopts the restrictions imposed by the city of Cape Town from 2015–2018 (DWS, 2018). There are various levels of restrictions imposed on the study region, with major water use reductions occurring at levels 2, 3, and 6b, which are triggered when combined reservoir storage reaches 50%, 45%, and 20%, respectively, of the maximum storage capacity (DWS. 2018c). At these levels, mandatory reductions of 20%, 30%, and 100% are imposed on agricultural allocations. At levels 2 and 3, municipal allocations are reduced by 20% and 30%, respectively, and additional tariffs are imposed. At level 6b, municipal use is also curtailed to no more than 450 ML/day. Under the BAU policy, the model observes these trigger levels and applies the corresponding allocation reductions to reproduce the historical patterns of water allocation.

| Algorithm 2 Allocations for Business-As-Usual (BAU) scenario |
|--|
| if $V > 0.5 V_{max}$ then |
| Allocate full water demand to each sector // No restriction |
| else if $V > 0.45 V_{max}$ then |
| Allocate 80% of demand to each sector // Level 2 restriction |
| else if $V > 0.2V_{max}$ then |
| Allocate 70% of demand to each sector // Level 3 restriction |
| else |
| // Level 6b restriction |
| Allocate 450 MLD to urban supply |
| Allocate 0 MLD to agriculture |
| end if |

3.3.6 Holistic Adaptive Management Policy Scenario

The BAU policy responds passively to drought: no demand-management is implemented until reservoir storage levels reach trigger points. This policy may avoid system failure during short-lived droughts, but under extended droughts this policy may wait too long before taking action and may thus risk system failure. The recent Cape Town water crisis illustrates such a system failure: it resulted from a combination of factors, including a drought characterized both by historically low rainfall levels and long duration, and by overuse of water during the early stages of this drought (Ziervogel 2018; Muller 2017).

The HAM policy (Algorithm 3) considers the interplay between the agricultural, energy, and urban demand for water and attempts to optimize system performance by holistically managing the demand and allocation for each sector. The HAM policy takes a simple adaptive approach to imposing water use restrictions: Each month, the water manager compares the current reservoir storage level with the seasonally adjusted average pre-drought (2009–2015) storage level corresponding to the current month. If the current reservoir storage level is greater than 90% of the average, the water manager will not impose any restrictions and each stakeholder is allocated their full demand. When the current reservoir storage level is lower than the 90% threshold a mandatory restriction is imposed, reducing allocation to each sector by the ratio ($V_{avg} - V_{current}$)/ V_{avg} , where V_{avg} is the average storage level of the month, and $V_{current}$ is the current storage level of the month. In addition, the water price is raised in order to reduce demand. The relationship between price and demand is described by the demand-elasticity (Equation 3; Sahin et al., 2016):

$$\varepsilon_D = \frac{\% \Delta Demand}{\% \Delta Price}.$$
(3)

| Algorithm 3 | Allocations for | ·Holistic Ada | ptive Management | (HAM) |) scenario |
|-------------|-----------------|---------------|------------------|-------|------------|
|-------------|-----------------|---------------|------------------|-------|------------|

if $V > 0.9V_{max}$ then Allocate full water demand to each sector // No restriction else Calculate desired change in urban consumption: $\%\Delta D$ // Urban sub-model Assign urban tariff based on price-elasticity of demand (E_d) // Urban sub-model Calculate reduced allocation to agriculture: $A = D \times (V_{avg} - V)/V_{avg}$ // Agricultural sub-model Allocate water end if

3.4. Result

3.4.1 Calibration

For each policy scenario, we ran the model ten times each for several different values of key parameters. The monthly storage level of the calibrated model could match the patterns of the historical dam storage relatively well (Figure 12a). For the BAU policy scenario, we varied the irrigation efficiency from 0.6 to 0.7 in steps of 0.01 and for the HAM policy scenario we varied the price elasticity of demand from -0.1 to -0.8 in steps of 0.1. Under the baseline BAU scenario, the monthly reservoir storage levels most closely approximated the historical values for an irrigation efficiency of 0.7 (Figure 12b vs. Figure 13b). The crop coefficient Kc varies from month to month. We started with the values of Kc reported in WSU (2016), and adjusted those values to match the monthly agricultural water consumption to the historical pattern (Figure 12b vs. Figure 14a). The calibrated values for Kc were used for both policy scenarios, and the HAM scenario used 0.7 for the irrigation efficiency.

3.4.2 Demand-Reduction and Allocation

Under the BAU policy, when the water supply is insufficient to meet demand, agricultural and municipal allocations are cut and tariffs on municipal use are raised. Under the HAM policy, prices are gradually raised for both municipal and agricultural users as reservoir levels fall. By all criteria, the holistic adaptive management policy outperformed the baseline. The HAM policy did not result in any curtailment of hydroelectric capacity and it imposed less mandatory reduction of water use. Under the BAU policy, agricultural allocation was reduced to zero several times in 2017–2018 (water-use reduction rose to

100%), whereas under HAM, allocations are cut by less than 60% for both agricultural and municipal users (c and f of Figure 13). July 2017 is the only month in which the municipal water allocation under HAM is less than the lowest allocation at level 6b of the BAU scenario (450 ML/day) (b and e of Figure 14). Patterns of monthly agricultural water allocations are similar for the two policy scenarios (a and d of Figure 14). In general, we see less extreme reduction and less total water allocation in the HAM policy scenario (Figure 13 and Figure 14). Furthermore, the reservoir storage levels under the HAM policy are constantly higher (in a safer zone) than under BAU (Figure 13).



Figure 13. Model simulation results for FEW performance.

Note: (a, d) are average hydropower generation capacity, (b, e) are reservoir storage, and (c, f) are water use reduction from 2009 to 2018. (a–c) corresponds to the business-as-usual (BAU) scenario and (d–f) correspond to the holistic adaptive management (HAM) scenario. The BAU scenario (a–c) is fairly insensitive to variation in irrigation efficiency. The HAM scenario (d–f) shows no sensitivity to demand elasticity because the policy sets prices relative to elasticity. We use BAU to calibrate the irrigation efficiency, and the calibrated value, Kc = 0.7 was used in the HAM scenario.



Figure 14. Model simulation results for water allocations.

Note: (a, d), (b, e), and (c, f) represent agriculture, municipal, and total monthly water allocations from 2009 to 2018, respectively. (a–c) corresponds to the baseline (BAU) scenario and (d–f) correspond to the holistic adaptive scenario. As with Figure 3, the BAU scenario (a–c) is fairly insensitive to variations in irrigation efficiency and the holistic adaptive scenario (d–f) shows no sensitivity to demand elasticity.

3.4.3 Hydropower Generation

Under the holistic adaptive management policy, the hydropower dam never fell below its maximum generating capacity, whereas under the BAU policy hydropower generation had to shut down several times in 2017–2018. Thus, the HAM policy produces significantly better performance in the energy sector because the monthly reservoir levels were maintained constantly above the threshold of 20% of total storage capacity.

3.4.4 Water Price

In the BAU policy, the water tariff set by the city of Cape Town increases for stricter levels of restrictions (CCT, 2019; City of Cape Town, 2018; DWS, 2018). The baseline water price is 5.2 Rand per kilo Liters, R/kL (equivalent of 1.4 US dollars per kilo gallons, USD/kGal) without any restriction. When scarcity reaches level 3 the city of Cape Town imposes high and progressive water tariffs, which rise as household consumption reaches different brackets. The baseline water price for level 3 and level 5 are 15.7 and 24.4 R/kL, respectively, for consumption below 6 kL; for household consumption in the next water usage

bracket between 6 and 10.5 kL, the marginal price rises significantly to 22 and 39 R/kL, respectively (CCT, 2018). In the HAM policy, tariffs are set based on the water price elasticity of demand (ϵ_D) and the necessary curtailment of consumption. Under that policy the water tariff is \leq 35 R/kL even for extremely low values of demand elasticity (Figure 15). When the demand elasticity is within the range of values reported in the literature ([-0.3, -0.8]) (Sahin et al., 2016), the water price is between 5.2 and 15 R/kL.



Figure 15. Monthly water price in the HAM scenario under a range of demand elasticities.

3.5 Discussion

This model functions as a testbed that can simulate a relatively complex system under different scenarios and compare the outcomes to evaluate different policies or strategies. Where detailed parameters characterizing human behavior or system performance are uncertain the testbed also allows users to test the sensitivity of the system performance to various parameters and to test the robustness of different policies under a range of parameter values. From the results of the model, in general, the holistic adaptive management policy achieved better hydropower generation, conserved more water and avoided zerowater allocation for the agricultural sector. The water price in the HAM scenario is also lower than what the city of Cape Town is currently imposing with level 3 restriction.

Although the HAM policy curtails water allocations more frequently than BAU under less severe drought conditions, the level of water allocation reduction is not devastating to the urban and agricultural users.

For farmers, the less punitive reductions, compared to BAU, can ensure sufficient water to prevent the wines from fallowing even under severe drought conditions. Hydropower generation remains more secure under the HAM policy, across a wide range of parameters.

It is promising to see that a simple adaptive strategy can produce much better FEW system outcome, but further work is needed. The current model uses an agent-based structure, but aggregates each sector into a single representative agent. Future work will explore interactions among multiple heterogeneous agents in each sector, including consideration of economic inequality among Cape Town residents. We also plan to apply the model to studying adaptation to future climatic change, using projections for precipitation trends under different climate scenarios. Precision irrigation and regulated deficit irrigation can improve the economic performance of the vineyards and produce better wines and improve irrigation efficiency in the meantime (WSU, 2016). In the future the municipal and agricultural stakeholders can also be disaggregated to include more diversity and individual behavior in the model. The current model focuses solely on the management of existing water resources, but the model can be modified and expanded in future studies to consider alternative water sources, such as desalination, and the management of food and energy resources and services as well.

An important aspect of future work will be the consideration of economic inequality and equitable access to water. South Africa has one of the highest national rates of economic inequality in the world and Cape Town in particular suffers from severe economic inequality, with a Gini coefficient for income of 0.6 and a poverty rate of 19% (Karuri-Sabina, 2016; Sieff, 2018). Moreover, income inequality correlates strongly with race: on average, white South Africans enjoy considerably greater income and wealth than their black compatriots (Sieff, 2018). Both demand-elasticity and the ability to pay for minimum necessary access to water both vary significantly with household income. South African law guarantees each household 6 kL of water per month free of charge (Muller, 2008), but if the response to severe drought conditions is to impose a tariff even on this base level of water consumption, the economic inequality among Cape Town residents will result in unequal access to water. Under current (BAU) policy, level 3

restrictions in Cape Town impose a minimum price of 15.7 R/kL, or 4.2 USD/kGal (CCT, 2018), which is higher than the average price in the United States (\$3.4 per 1,000 gallons) (DOE, 2017) despite the much higher average household income in the U.S. The response to the 2017–2018 water crisis created a situation in which affluent residents of Cape Town found it "pretty cheap" to fill swimming pools at the same time that poor and lower-middle-class residents struggled to obtain enough water for basic hygiene (Sieff, 2018). Thus, future policy analyses will need to address issues of equitable access to water under conditions of scarcity.

The limitations of food, energy, and water services at country scale across sub-Saharan Africa and regional/city scale such as in Cape Town has been discussed in this and in the previous chapters. Through the analyses, we constantly face issues of lack of data, especially the detailed metrics measuring FEW services quality, which limits the ability to explore more deeply the primary factors influencing the quality of FEW services. However, such data are relatively abundant in developed countries such as the United States.

Chapter 4

Uncover the Water Problems in the US with Geospatial Database

4.1 Introduction

In the previous two chapters, we rely on data to perform simulations and analyses. Due to accessibility reasons, most of the analysis was focused on water quantity-related questions at generally coarse scales. Beyond the impact on FEW quantity, socioeconomic factors also influence FEW quality. Because of the limited data availability overseas, the shift is made to the United States for this chapter. We pilot an indepth study of the primary factors influencing drinking water services in the United States with readily available data.

In the United States, the Safe Drinking Water Act (SWDA) passed in 1974 and amended in 1986 and 1996 is the primary federal law to regulate public water systems (PWSs) to protect the health and wellbeing of people. Still, drinking water quality issues have been reported that could be cause for concern (Allaire et al., 2018; Rubin, 2013).

Under the SWDA, the USEPA and similar state agencies require utilities to monitor drinking water quality where treated water enters the distribution systems and at additional monitoring locations such as critical water users in hospitals. The USEPA's Safe Drinking Water Information System (SDWIS) is the database that stores information on reported water quality violations in public water systems. Additionally, USEPA grants primacy to most state agencies to implement their regulations and management according to the SDWA, leading to some differences in how rules and regulations are enforced across the states.

Analyses using the SDWIS data base provide insights into the overall status of drinking water issues across the U.S. Rubin (2013) considered community water systems (CWSs) in which SDWIS violations

in 2011 were grouped by the characteristics of the CWSs (small, 500-3300, and medium, 3300-10000), water sources (surface vs. groundwater), and types of the violation (Maximum Contaminant Level (MCL), Monitoring, and Reporting), finding only small differences across systems. Allaire et al. (2018) used data from 1982 to 2015 to study the trends of health-based violations (MCL and Treatment Technique, TT) for CWSs. They found that violations in the southwest have been increasing over time and urban areas tend to have fewer violations than rural areas. McDonald and Jones (2018) used data from 2011 to 2015 to study how demographics and socioeconomic status of water systems related to violations; they found that systems serving minorities and others of low socioeconomic status report more violations regardless of the size of the CWS. Eskaf (2015) identified a positive association between monitoring and reporting violations and the financial constraints on a system in 2014 with smaller systems more subject to financial difficulties than large systems. Kirchhoff et al. (2019) focused on MCL violations and enforcement actions in Connecticut, finding that state-ownership, groundwater dependence, and rurality were associated with increasing violations. Marcillo and Krometis (2019) used data from 1999 to 2016 to assess the rural-urban disparity in the frequencies of different types of violations, confirming that remote rural CWSs in Virginia have particularly high and persistent monitoring and reporting violations in comparison to systems in urban area.

Because the SDWIS database contains information only that a violation occurred and not any of the measurements made on the water samples, inferences are necessarily limited. There has been some effort to do analyses that augment the SDWIS data with actual sampling data. Schaider et al (2019) linked the national SDWIS data with data that they compiled on nitrate concentrations and socioeconomic data to support the hypothesis that Hispanic residents, a large proportion who are farm workers, are exposed to higher nitrate levels than the general population. Hill and Ma (2017) used sampling data in addition to SDWIS data to study the influence of shale gas development on drinking water quality, finding some evidence that contaminants related to shale gas development were elevated by up to 3 percent within a 0.5 km distance from the CWS water intake.

Research to date on potential issues related to drinking water and the SWDA raises several questions. Is the variability in reported MCL violations (e.g., Allaire et al. 2018) related to background differences in water quality that reflect differing geology? If the conclusion reached for 2011 by Rubin (2013) that "smaller CWSs appear more likely than larger systems to violate monitoring, reporting, and notification requirements" consistent across years? Are actual concentrations reported in sampling data, even if there is no MCL violation reported in SDWIS, higher for certain systems depending on location, size, population served and so forth? For example, with the MCL for nitrate set by the EPA at 10 mg/L, Schaider et al. (2019) found that the frequency of nitrate concentrations above 5 mg/L was higher in systems serving Hispanic populations than in others. Because there isn't anything fundamental about an MCL, risks can be considered to be proportional to actual concentration so knowing how close sampling measurements are to the MCL is important. Finally, few drinking water studies have investigated the different types of violations for transient non-community systems (TNCs) (e.g., campgrounds) and nontransient, non-community systems (NTNCs) (e.g., schools) along with CWSs. In reality, on a daily basis people may drink water supplied by non-community water systems, such as at work, a hospital, or during a stop while running errands. It is important for drinking water researchers to include all types of public water systems and violations to assess the potential health risks of the public drinking water supply.

To address these gaps in the US drinking water research agenda, we 1) include all types of PWSs- CWSs, TNCs, and NTNCs; 2) include all types of SDWIS violations, both health-based and non health-based violations; 3) include the actual measurement data in this study to assess the drinking water quality. Specifically, we use data for the state of Tennessee which includes SDWIS data, actual concentration data reported to the state primacy agency (Tennessee Department of Environmental Conservation or TDEC), and physical data that we compile to address 3 questions.

Part 1: how do the external and internal factors of the systems including a) the types of systems, a) the
physiographic and geological factors, c) system size by population served, and d) the source of the water
impact drinking water quality? In other words, how are different types of SDWIS violations (i.e., MCL,

Treatment Technique, Monitoring, Reporting, Public Notice, and Other) and the actual sampling concentrations related to factors a - d?

Part 2: how do socioeconomic capacity factors such as income and income inequality impact drinking water quality?

- 2. What is the spatial distribution of violations across the state of Tennessee?
- 3. How close are the measured concentrations of the regulated contaminants in drinking water with respect to the MCL threshold (i.e. adherence to regulatory level) in Tennessee?

4.2 Method

4.2.1 Data Sources

The study area is the state of Tennessee, USA. There are three types of PWSs in the SDWIS database: CWSs such as residential dwellings, NTNCs such as schools and hospitals with their own water supplies, and TNCs such as rest areas and campgrounds. The main difference between CWSs, NTNCs, and TNCs is that the CWSs supply water all year round whereas the others may only supply water during different time periods of a year. In Tennessee, there are 460 CWS, 290 TNCs, and 30 NTNCs active systems serving 7.2 million people (as of Q1 2019). We used three types of data 1) the violation data downloaded from the USEPA's SDWIS database (2011 - 2018), 2) the actual measurement data for the regulated contaminants provided by the public water systems to the Tennessee Department of Environment and Conservation (2011 - 2018; for disinfectant byproducts or DBPs data availability was 2012 - 2018 which covered as many as 678/780 systems and 6.7 million people), and 3) the latest income (2017) and income inequality (2018) data available at the county level obtained from publicly available databases (CHR&R, 2019; FRED, 2019).

The SDWIS database contains the general information of the public water systems (PWS) and any reported violations per the USEPA's drinking water quality standards. We used the five different types of

violations reported in the SDWIS database: Maximum Concentration Level (MCL), Treatment Technique (TT), Monitoring (MON), Reporting (REP), Public Notice (PN), and Other violations.

It is important to clarify the water quality monitoring/reporting mechanism such that how different types of violation may be triggered and reported to the SDWIS database to provide the necessary background knowledge to help us understand the relationships specific to each type of violations. An example routine of water quality monitoring is as follows in Tennessee: the PWSs should take required number of samples across the sampling points periodically determined by the monitoring schedule from the state primacy agency-TDEC. The samples will be sent to the certified laboratories for testing and measurement specific to the contaminants. TDEC indicates that it is more common for the larger PWSs to test their samples (usually biological contaminants such as total coliforms) in their own in-house certified laboratories, whereas smaller PWSs have to send their samples to the commercial laboratories. The laboratories will send the results to TDEC, and TDEC will determine whether there is any violation and what kind of violation it is. Finally, TDEC will upload the violations to SDWIS database if there is any. MCL violation occurs if the average concentration of all the required samples exceeded the MCL of the contaminant. TT violation occurs as the treatment plant failed to comply with the requirements in the removal of specific contaminants (i.e., lead and copper). Reporting of MON and RPT is more complicated. MON and RPT have two distinctions in severity, major or minor. A major MON or RPT violation is classified as a complete failure to monitor or report, whereas a minor one may be caused by providing fewer than the required number of samples, missing the reporting deadline, or not meeting the requirement. Although all monitoring and reporting violations are recorded in the SDWIS database, the annual compliance report only includes major MON/RPT violations (USEPA, 2019). Our research does not distinguish between major and minor MON/RPT violations.

The sampling data for TN includes the raw measurements of inorganic contaminants (IOCs), synthetic organic and volatile organic contaminants (SOCs and VOCs), radionuclides (RADs), and disinfectant byproducts (DBPs). The sampling data of DBPs was stored in a separate file because DBPs have

distinctly different measuring and monitoring methods. For DBPs, different systems begin their monitoring schedule at different times with different requirements for numbers of samples per measurement and sampling frequency. The two specific DBPs of chlorine disinfection, total trihalomethanes (TTHM) and haloacetic acids (HAA5), are included in the sampling data for DBPs. Therefore, we refer the IOCs, SOCs, VOCs, and RADs as group 1 contaminants, while the two DBPs are in group 2. We do not have the actual measurement of total coliforms and E. Coli; therefore the total coliform and E. Coli are excluded from the concentration analysis (research question 3).

We collect the latest income and income inequality data at the county level to represent the socioeconomic capacity of the people. We chose the median household income as well as the income inequality which is calculated by the top 20th percentile of the income of the earners divided by the value at bottom 20th percentile for each of the 95 counties in Tennessee (CHR&R, 2019; FRED, 2019). We use the county level data of income and income inequality to approximate the socioeconomic conditions of the users of all the public water systems collectively at that county (Bernabé et al., 2009).

4.2.2 Statistical Analysis

Categorization:

We examined the composition of the six types of SDWIS violations, MCL, TT, MON, REP, PN, and Other, by categorizing the PWSs four different ways: types of systems, geological regions, system sizes and types of water sources. First, there are 460 CWSs, 290 TNCs, and 30 NTNCs. Second, we categorized each PWS by matching the primary county they serve with one of the seven geological regions in Tennessee. There are 15 PWSs in the Alluvial Plain (AP), 175 PWSs in the Inner Coastal Plain (ICP), 178 PWSs in the Highland Rim (HR), 44 systems in the Nashville Basin (NB), 52 PWSs in the Cumberland Plateau (CP), 165 in the Ridge and Valley (RV), and 151 systems in the Unaka-Smokey Mountain (USM) (Figure 16). Third we categorize the PWSs into different sizes by the population served: very small defined as \leq 500 (VS), small defined as 501 \leq 3,300 (S), Medium defined as 3,301 \leq 10,000

50

(M), large defined as $10,001 \le 100,000$ (L), and very large defined as $\ge 100,001$ (VL) (USEPA, 2019). In Tennessee, there are 348 VS, 163 S, 132 M, 128 L, and 9 VL PWSs. The final category is categorizing the PWSs by their water sources. 151 PWSs use surface water, 120 PWSs use purchased surface water (SWP), 432 PWSs uses ground water (GW),13 PWSs use purchased ground water (GWP), 55 PWSs use ground water under influence of surface water (GUS), and 9 PWSs use purchased ground water under influence of surface water (GUSP) (Table 5).

MCL levels:

To assess the level of concentration reported in the sampling database by contaminants and compare to the MCL, we calculated the percentage difference of each sample (PCT_DIFF_MCL) to the MCL of that specific contaminant using equation (4). The concentrations below MCL were therefore presented as a negative percentage, the ones above MCL were shown as positive percentage, and the MCL is at the 0 mark.

$$PCT_DIFF_MCL = \frac{Concentration - MCL}{MCL}$$
(4)

We looked at MCL levels of the IOCs, RADs, VOCs, and SOCs aggregately and individually. We looked at the DBPs separately with other contaminants because DBPs are primarily introduced into the water because of the disinfection (USEPA, 2019).

In addition to examine the concentration distributions of the aforementioned contaminants, we look at the cumulative distributions of the fraction of samples greater than or equal to the indicated value- the sample concentrations at a certain percentage point below the MCL. Similarly, we also looked at cumulative distributions of the fraction of systems has samples greater than or equal to the indicated value, and the affected population associated with the systems. The affected population is defined as the number of people whose water systems having samples' concentrations greater or equal to the indicated values.

Statistical Methods:

We compared the types of violations in different categories by looking at the ratio of each type of violations (MCL, MON, RPT, PN, TT, and Other) to the total number of violations of that. For example, among all violations of CWSs, the fraction of MCL violations is about 0.13, whereas the fraction of MCL violations among all TNC violations is only about half as much (~0.07).

We examined the distributions of the concentration of the contaminants from different groups of PWSs using Pearson's chi-square test. We used the same bin size for the two sets of data for comparison. Because there were some bins that have counts of zero, we took the log10 of the counts to perform the two-sample Pearson's chi-square test.

We analyzed the correlation of different types violations and income and inequality at the county level. We use Spearman's rank correlation coefficient to measure the relationship between two variables.

Statistical Analysis:

We obtained drinking water violations per year (overall and by type), median household income and income inequality, violation frequency, and long-term affected violation at the county level, and performed the Spearman rank correlation analysis. We aggregated the PWSs at the county level to report different types of violations per year by total, MON, TT, MON, RPT, PN, and Other. Those violation results of all PWSs serving same primary county were averaged and reported for each of the 95 counties in Tennessee. In addition, we calculated two indices to reflect the violation conditions at the county level: (1) violation frequency and (2) long-term affected population. We use violation frequency as a measure of repeating violations of a system. The violation frequency (Freq_{violation}) is calculated using equation (5):

$$Freq_{violation} = \frac{\# \ years \ a \ system \ has \ any \ violation}{total \ \# \ of \ years}.$$
(5)

The violation frequencies of all PWSs serving the same primary county then were averaged to create a mean violation frequency for the particular county. The long-term (L.T.) affected population was created to measure the long-term impact of the violations to the people who use the water supplied by the PWSs which is summarized at the county level. The long-term affected population is calculated using equation (6):

$$L.T.affected population = \sum_{i=1}^{n} population served * violation frequency$$
(6)

where n is the total number of PWSs in the county.

Spatial Analysis:

We calculated the Global Moran's I index for each of the variables for 95 counties, which is an index used to measure the spatial autocorrelation ranging from -1 to 1 (IDRE, 2020). Moran's I near 1 indicates spatial clustering pattern (i.e. positive spatial autocorrelation), -1 indicates dissimilar dispersion (i.e. negative spatial autocorrelation) and a zero value indicates complete spatial randomness.



Figure 16. Tennessee geological regions (TDEC, 2010).

| PWS Type | # of systems | Geological Region | # of systems | System Size | # of systems | Water Sources | # of systems |
|----------|--------------|-------------------|--------------|-------------|--------------|---------------|--------------|
| CWS | 460 | AP | 15 | VS | 348 | SW | 151 |
| TNC | 290 | ICP | 175 | S | 163 | SWP | 120 |
| NTNC | 30 | HR | 178 | М | 132 | GW | 432 |
| | | NB | 44 | L | 128 | GWP | 13 |
| | | СР | 52 | VL | 9 | GUS | 55 |
| | | RV | 165 | | | GUSP | 9 |
| | | USM | 151 | | | | |

Table 5 Total number of systems in different categories

4.3 Results:

4.3.1 Links between system characteristics and types of violations:

In the state of Tennessee, we found that the general violation pattern is the dominant prevalence of MON violations regardless of the categories of the PWSs (Figure 17), while other types of violations vary across the four categories: system types, system sizes, physiographic and geological factors, and water sources. Among the two types of health-based violations, the fractions of TT violations are less than the MCL violations except in the very large (VL) PWSs and PWSs using groundwater under the influence of surface water.

Relations to systems types:

In the first category, the CWSs have the largest fraction of MCL violations, while the TNCs have the largest MON violations. The CWSs also have significantly larger fractions of RPT and PN violations compared to the other two types of systems, TNCs and NTNCs (Figure 17).

Relations to physiographic and geological factors:

In the second category, PWSs in Cumberland Plateau (CP) have the largest fraction of the MCL violations, while PWSs in Alluvial Plain (AP) have the smallest fraction of MCL and no TT violations. For the TT violations, PWSs in the Nashville Basin (NB), and CP have the largest fractions compared to other geological regions. MCL and TT violations of PWSs in CP, NB, and Highland Rim (HR) are the top three regions that have the largest fraction of MCL and TT violations combined together. The regions toward the east and west borders of Tennessee have fewer MCL and TT violation and more MON violations than other regions (Figure 17).

Relations to systems sizes:

In the third category, MCL violations are most prevalent among medium (M) and large (L) PWSs. While other sizes of PWSs have similar fractions of MON violations, the VL PWSs only have half of the proportion. In addition, the fraction of RPT violations in VL PWSs is about three times more than the fractions of other sizes of PWSs (Figure 17).

Relations to water sources:

In the fourth category, PWSs using purchased water sources have more MCL violations and fewer TT violations compared to PWSs using non-purchased water sources. PWSs using surface water have larger fractions of MCL and TT violations compared to PWSs using groundwater. On the other hand, PWSs using groundwater sources have larger fractions of MON violations than PWSs using surface water (Figure 17).

4.3.2 Distributions of Sample Concentrations

We examined the concentration distributions of group 1 and group 2 contaminants. Most of the group 1 contaminants are below the MCL, however, there are sharp spikes on the concentration distribution with many concentrations reported exactly at 50%, 25%, and 10% of the MCL level (Figure 18). The DBPs have a small fraction of the samples reported above the MCL, but the concentrations are mostly below 150% of the MCL level (Figure 18).

We examined the cumulative distributions of the sampling concentrations with respect to the MCL for group 1 contaminants (IOC, VOC, SOCs) and group 2 contaminants (HAA5 and TTHM). We expected

that the cumulative distributions of sample concentrations would be smooth and without sharp punctuated increases. However, the group 1 contaminants exhibited unexplained discontinuities in the cumulative distributions (Figure 19). The two DBPs in group 2 met expectations, not having punctuated discontinuities.

Changes in numbers of systems:

For the group 1 contaminants, a punctuated change of fractions of systems with samples greater than or equal to the indicated value occurred at 50% to 51% below MCL (Figure 19). The fraction of systems with samples greater than or equal to the indicated value of 50% below MCL was about 0.1, but as the indicated value moves 1 percent lower, the fraction increases drastically to more than 0.5.

For the group 2 contaminants (DBPs), the curves were much smoother compared to the group 1 contaminants and no punctuated changes was observed. The individual trends of the two DBPs were similar.

Changes in numbers of samples:

For the group 1 contaminants, multiple punctuated changes were observed at 50%, 75%, and 90% below MCL (Figure 19). Furthermore, the concentration distribution of the group1 contaminants indicates that there are sharp spikes on the histograms of sampling results reported exactly at 50%, 25%, and 10% of the MCL level (Figure 18), corresponding to the punctuated changes in Figure 19. A sharp spike is defined as an abnormally large number of samples reported at the same percentage. We assessed the individual concentration distribution of all the contaminants from the sampling data and found there were a large number of volatile organic contaminants and some inorganic contaminants including arsenic, cadmium, chromium, and mercury all displaying sharp spikes at the 10% MCL level, and beryllium, vinyl chloride displaying a sharp spike at the 25% MCL level, and thallium displaying a spike at the 50% MCL level

(see SI table 1). The concentration distributions of the individual contaminants are included in the supplementary materials.

For the DBPs, the fraction of samples greater than or equal to indicated values exhibited a similar smooth increasing trend as concentrations decrease below the MCL level (Figure 19). The shape of the concentration distributions of HAA5 and TTHM looks similar, but they are not from the same distribution $(p < 2.2e^{-16}$ from Pearson's chi-square two-sample test, Figure 18).

Changes in affected population:

For the group 1 contaminants, there were multiple step increases and a punctuated change in population occurred at 50%- 51% below MCL level (Figure 19). Compared to the previous changes in number of violations and number of systems having violations, the punctuated change in population at 50-51% MCL was disproportionally large. The punctuated change of affected population (close to 4 million population increase) indicated that it was not solely driven by the large systems. From the population distribution of the PWSs that demonstrated a punctuated change, the M and L PWSs were dominant (Figure 20). All the VL systems that serve more than 300,000 people were included in the punctuated change. We compared the population distribution of the systems that displayed the punctuated change with systems that did not display such change to the overall population distribution (p = 0.37 from Chi-square two-sample test, Figure 20). Geographically, the systems that displayed punctuated change are concentrated at AP and the northern part of HR and NB (Figure 21).

For the DBPs, the affected population went up with several step changes as concentrations reduced from 100% to 0% of the MCL, and the two largest step changes occurred at different levels for TTHM (57%) and HAA5 (66%) (Figure 19). However, the magnitudes of the step changes are identical which indicates that the changes are driven by the largest two systems serving major cities (Nashville and Memphis which each serve 700 thousand people).





Note: Cumberland Plateau has the largest share of health-based violations. The medium and large systems have the largest fractions of health-based violations. The distribution of types of violations are not significantly different among Community, Transient non-community, and Non-transient non-community water systems.



Figure 18. sampling concentration distributions of 1) Group 1 contaminants (inorganics/organics), haloacetic Acids (HAA5), and total trihalomethane (TTHM), from top to bottom, respectively.

Note: The *p*-value $< 2.2e^{-16}$ from Pearson's chi-square two-sample test of HAA5 and TTHM, which suggests they are from different distributions. The concentration distribution of group 1 contaminants is discontinuous, in contrast to HAA5 and TTHM.



Figure 19. Cumulative distributions of 1) fractions of systems with samples greater or equal to indicated value- concentration below percentages of MCL, 2) fractions of samples greater or equal to indicated value, 3) and affected population for group 1 contaminants of Inorganic, organic, and radionuclides (cyan), TTHM (gold), and HAA5 (black).

Note: The punctuated changes at 50%, 75%, and 90 % of the MCL are indicated by the vertical dash lines in red, magenta, and blue, respectively. Those punctuated changes suggested large amount of samples and systems reported the concentrations of Group 1 contaminants at the previously mentioned percentages of MCL.



Figure 20. log10(population) distributions of 1) the systems having punctuated changes when MCL lowered from 50% to 49%; 2) the complement of systems in part 1 (systems did not have punctuated changes); 3) all systems.

Note: The p-value of Chi-Square test of 1 and 2 is 6.6e-8, and the p-value of Chi-Square test of 1 and 3 is 0.37. The chi-square test indicates that the distribution of the systems with punctuated changes is more likely to come from the distribution of all systems.



Figure 21. Spatial distribution of the systems with punctuated changes.

Note: Intensity of the color represents the fraction: $\frac{\text{\# of systems with punctuated changes}}{\text{\# of systems in the same county}}$. The MCL maps shows slight spatial clustering patterns (*Moran's I* = 0.126, *p*-value = 0).



Figure 22. the overall violation conditions: maps of average total violations per county per year, violation frequency, and long-term affected population.



Figure 23. maps of maximum contaminant level (MCL) violations and Treatment Technique (TT) violations per county per year. Note: MCL and TT violations are health-based violations according to the EPA definition. The MCL maps shows slight spatial clustering patterns (*Moran's I* = 0.022, *p-value* = 0.02).

Relationships between socioeconomic capacity and drinking water quality:

Neither the median household income or income inequality showed a strong association with total, MCL, or monitoring violations at the county level. However, there were weak positive associations observed between income and reporting, public notice, other and TT violations. The weak negative association was observed between income inequality and reporting, public notice, other and TT violations (Table 6) (The complete correlation coefficient matrix with the distribution of the data is in supplementary information). In addition, income inequality was weakly associated with the fraction of the systems that demonstrated punctuated change among all systems in the counties. Therefore we did not find strong evidence indicating a clear relationship between income and income inequality and drinking water violations. However, future research at the scale of the service area of PWSs could better capture the sub-county socioeconomic nuances and differences such as segregation and gentrification when relevant data are available.
Spatial Patterns of drinking water quality

From the Moran's I indices, only the MCL violations (Figure 23), and systems that demonstrated punctuated change (Figure 21) showed slight clustering patterns. Although we found little evidence of spatial clustering, there were several counties in each of the maps that revealed higher values than their neighbors (Table 3, and Figure 22, Figure 23, and Figure 24). Specifically, most of the violations are monitoring violations of inorganic, organic, and microbial contaminants in Humphreys county. DBPs are the most frequent contaminant of the MCL violations in Giles county. TT violations of combined filter effluent and PN violations about notifying public about violations are most prevalent in systems of Marion county. RPT violations of record keeping are most prevalent in Clay county. The only Other violations of siting plan errors are most prevalent in Stewart county. Pickett, Trousdale, Cannon, and Van Buren counties have significant higher values of violation frequency than other counties (Figure 22). Shelby county has the highest value of long-term affected population among all counties, where 106 of 107 records of violations are monitoring violations of different contaminants and one is a reporting violation (Figure 22).

Table 6 Spearman' rank correlation coefficients matrix

| | Total | MCL | MON | RPT | PN | Other | TT | Fraction | Vio Freq |
|-------------------|----------|---------|----------|--------|-------|--------|--------|----------|----------|
| Income | -0.00058 | -0.0503 | 0.0121 | 0.124 | 0.133 | 0.141 | 0.125 | 0.0643 | -0.0681 |
| Income Inequality | -0.0197 | -0.027 | -0.00376 | 0.0609 | 0.033 | -0.234 | -0.181 | 0.146 | 0.0704 |

| Metrics/Indices | Counties with highest values | Number of CWSs | Number of TNCs | Number of NTNC | Total Population Served |
|------------------------------|---------------------------------|----------------|----------------|----------------|----------------------------|
| Total/MON violation per year | Humphreys | 4 | 3 | 8 | 15444 |
| MCL violations per year | Giles | 6 | 0 | 0 | 30259 |
| TT/PN violations per year | Marion | 3 | 2 | 0 | 8648 |
| RPT violations per year | Clay | 2 | 0 | 0 | 9624 |
| OTHER violations per year | Stewart | 6 | 3 | 0 | 7697 |
| Long-Term Affected Violation | Shelby | 6 | 0 | 1 | 939108 |
| Violation Frequency | Pickett | 1 | 0 | 0 | 7060 |
| | Trousdale | 1 | 0 | 0 | 8055 |
| | Cannon | 1 | 0 | 0 | 10505 |
| | Van Buren | 1 | 0 | 0 | 5217 |

Table 7 Counties with highest values of different types of violations and indices



Figure 24. Maps of monitoring (MON) violations, reporting (RPT) violations, Public Notice (PN) violations, and other (OTHER) violations per county per year.

4.4 Discussion

How are the system sizes and types influencing drinking water violations? We first found that very small (VS) and small (S) PWSs predominantly have smaller fractions of MCL violations and a larger proportion of MON violations compared to larger PWSs (medium M and Large L); the exception is 9 of the very large (VL) PWSs. The finding is consistent with TNCs and NTNCs as they also have much smaller

fractions of MCL violations compared to CWSs because most of TNCs and NTNCs are very small (VS) and small (S) PWSs. The finding is contradictory to a prior study which found fewer MCL violations in larger PWSs (Kirchhoff et al., 2019). The smaller fractions of MCL violations found in smaller systems is also contradictory to one of the findings in a national-level analysis (Allaire et al., 2018). One possible reason to explain the finding is that the larger PWSs have greater capacity to test the water and report the result on time (in-house laboratory). Therefore, larger PWSs may have a larger fraction of MCL violations, whereas smaller PWSs may be more prone to MON violations due to stressed technical, managerial, and financial capacity (e.g. additional time required to submit samples to external laboratory for testing) (Balazs & Morello-Frosch, 2013). The EPA monitoring framework and other specific rules of TDEC require large numbers of samples to be tested in a relatively short time period (such as monthly monitoring for total coliform). Larger PWSs equipped with in-house (or on-site) laboratories can handle the load of testing more efficiently compared to smaller PWSs who must send samples to commercial laboratories where the samples may encounter a testing backlog. Handling the testing externally may also increase the probability of missing samples, which could explain the larger fractions of MON violations in smaller PWSs.

How does source water influence drinking water violations? We found that the PWSs using groundwater are associated with smaller fractions of MCL violations in Tennessee. A probable reason is that the raw groundwater may be cleaner as the physical, chemical, and biological contaminants are gradually removed when the groundwater filtrates through the vadose zone and the aquifer (Moore, 2005). In addition, PWSs using groundwater also need to treat the water to comply with the regulations. PWSs using surface water solely rely on treatment methods, with no help of the natural earth filter inherently linked with the groundwater. As such, PWSs from Alluvial Plain, Ridge and Valley, and Unaka-Smokey Mountain that source water from deep-underground aquifers, such as the Memphis Sand and the East Tennessee Aquifer have the lowest fractions of MCL violations in Tennessee (Brahana et al., 1986; Parks & Carmichael, 1990). In addition to groundwater vs. surface water, PWSs using purchased water experience higher fractions of MCL violations in Tennessee, which is contradictory to the results of a national level research (Allaire et al., 2018). Allaire et al. (2018) attribute the lower MCL violations of PWSs using purchased water to the purchased source being private wholesalers (1) with high capacity to comply with drinking water standards and (2) who are more vulnerable to lawsuits if supplied drinking water does not meet regulatory standards. In Tennessee, the majority of the PWSs including wholesalers are public-owned so such an explanation may not be suitable. One probable reason is that the purchased water is subject to contamination through the distribution network or during storage. For instance, the common practice for ensuring drinking water quality through distribution is to keep the disinfectant (typically residual chlorine) at a certain level that can keep the water sanitized but not harmful for human consumption. DBPs are formed when organic matter reacted with the chlorine. The DBP-forming process can be affected by various factors such as the specific chemicals and the doses for disinfection, the concentration of the precursors that react with the chemical, the pH, temperature, and water age (USEPA, 2019). Another reason pointed out by an EPA study is that the system's water received from the wholesaler at the interconnection may continue to rise in DBP concentration level as the disinfectants keep reacting during the distribution process (USEPA, 2019).

How do physiographic and geological factors influence drinking water violations? We found that PWSs in Nashville Basin (NB) and Cumberland Plateau (CP) have much higher fractions of MCL violations compared to other regions. The potential reason could be the relatively high concentrations of contaminants such as regulated IOCs that are naturally present on the top soil layers (~1 m) in Tennessee, particularly concentrated in HR, NB, and CP (Smith et al., 2014). In Tennessee, the concentrations of antimony, arsenic, beryllium, cadmium, (total Carbon, organic carbon), chromium, mercury, and thallium generally are higher than national average, and highest concentrations of the listed contaminants are concentrated at northeast HR, the north NB, and northwest CP (hereafter the first concentrated region), and the Alluvial Plain (hereafter the second concentrated region) (Figure 8; Smith et al., 2014).

How do where people live influence water quality? An interesting finding of the research is that many of the PWSs that displayed punctuated change in reported concentrations of the contaminants exactly at the 50% MCL level are located within the two aforementioned concentrated regions (Figure 21). There are two possible contributing factors to explain this finding. The first is that there may be high concentrations of naturally occurring contaminants. The second is that the EPA monitoring schedule grants waivers if the concentrations of the regulated contaminants of the PWSs are below a certain threshold, 50% of the MCL (USEPA, 2004) so there is no benefit in precise measurements below that level. USEPA requires frequent sampling and monitoring of the regulated contaminants (i.e., monthly or quarterly) if the PWSs do not have waivers. For PWSs who have waivers of certain contaminants, the waiver has to be renewed at 3, 6, or 9 years dependent on the group of contaminants, or until TDEC requires renewal. For all PWSs, it is reasonable to treat the water under the threshold to acquire the waivers, so that they can save money and effort from sampling and testing the water frequently. For PWSs in the concentrated regions, when the raw concentrations of the regulated contaminants are above the threshold level, the PWSs may treat the water at or below the threshold in order to acquire the waiver.

It is also interesting to see that the first concentrated region has the highest fractions of the MCL violations whereas the second concentrated region has the lowest. One probable reason is that most of the PWSs in the first concentrated regions are using surface water, whereas all PWSs in the second concentrated region (AP) are sourcing groundwater, and groundwater sources have better quality as highlighted in the second relationship.

The counties with highest values varied spatially in Tennessee; however there are some commonalities among them (Figures 21, 22, 23 and 24). All four counties, Pickett, Trousdale, Cannon, and Van Buren, had the highest violation frequencies and use surface water where large river bodies (i.e., the Cumberland River, and large reservoirs with hydropower generation capacity including Dale Hollow lake, Cordell Hull lake, and Center Hill lake) run through or nearby their land. Large impoundment of water create issues that impact water quality such as eutrophication, low dissolved oxygen due to the photosynthesis of excess algae, etc. While we do not know the source water quality at times when monitoring violations of various inorganics and organic contaminants occurred, most of the MCL violations were DBPs (Appendix C) so it may be that source waters were high in dissolved organic carbon at these times. Another probable cause could be human error or capacity limitations; for example, many repeating MCL violations of DBPs might be because of errors made by the water system operator. A few water systems had a treatment technique violation due to lack of qualified water system operators.

Excessive numbers and frequency of monitoring and reporting violations of all types of public water systems are of concern. Much previous research has focused on the MCL and TT violations because these are explicitly associated with health risks. However, if a system fails to measure arsenic or some other contaminant, the resulting major or minor monitoring reporting violation could simply mask a problem. At the time of a monitoring violation, neither the authorities nor consumers can have confidence that the drinking water is safe. The uncertainties associated with monitoring violations require attention in the current public water systems operations as well as monitoring and law enforcement.

How close are the sample measurements to the MCL? Most of the samples are below the MCL, most of the samples in violation are below 150% of MCL. However, we saw spikes at 10%, 25%, and 50% of the MCL level for group 1 contaminants. The concentration distributions indicated that a large numbers of samples are reported exactly at the three percentages. The low concentrations of the sampling results ruled out the possibility of the detection limit being at these three percentages. One possible reason could be some staff at laboratories reported the results approximately to the three percentage levels for convenience. This may not be a significant issue since the concentrations are still relatively low. Nevertheless, higher concentrations of contaminants, even under the MCL, may be harmful to certain vulnerable groups of people who are more sensitive than an average person such as pregnant women, people with certain diseases, and children at young ages.

This analysis of the quality of water services combined the data from both natural and human aspects that enables the research to holistically assess the driving factors to the water quality issues. This analysis created a geospatial database for drinking water quality in which future analysis can incorporate more specific factors such as land-use, nutrients in the source water, and detailed sociodemographic information of the region using the unique geospatial location as the key. The analytical framework can also be adapted and tweaked to study energy and food services.

Chapter 5

Synthesis

Throughout this dissertation, we have explored the successes and failures of the provision of food, energy, and water services as human beings interact with nature in the socio-environmental system in both developing and developed world. With the help of the Food-Energy-Water Resources-Services-Health (FEW RSH) framework, we examined the FEW-related resources availability as well as services and health conditions for the people from 38 sub-Saharan African countries in Chapter 2. Driven mostly by the governance and socioeconomic capacity, the quality of the FEW services and FEW-related health outcomes vary significantly across sub-Saharan Africa. This finding propelled us to study the FEW provision issues with an emphasis on human factors of governance and managerial and financial capacity at a smaller scale that could better capture the nuances of human-natural interactions. We built an agentbased model for the city of Cape Town to study how could the city avoid the Day Zero crisis. We found if the policymakers take actions earlier and are adaptive to extreme weather events and climate change in general, crises can be avoided by a much larger margin. The studies we have done in SSA often led us to a common obstacle of data limitation which prevent us from doing analysis of some specific research objectives such as determining factors that influence the quality of drinking water. Thus, in chapter 4 we studied the drinking water quality of Tennessee in United States, where water quality data and other data in general are readily available. Beyond water system characteristics such as size, type, geology, and water sources, human capacity such as the qualification of the water system operators also influence the water quality. The dissertation covers many places at different scales, but the results yield some commonalities.

Governance has appeared frequently in the study which implies the prominence of governance as a factor that could lead to FEW security or insecurity. The overall governance issues as well as the specific issues of political instability in SSA countries led to many problems far beyond lack of food, energy, and water. Disruptive events such as civil wars displaced the local people leading to loss of access to social services including FEW activities, their properties, and even their lives. The effectiveness of the governance also influences how governments handle emergency situations. If governments can be more effective and act swiftly in situations where they deal with drought, flood, or any other extreme events, the damage could be controlled or even avoided just like the Day Zero crisis in Cape Town. Rule of law is an important measure in governance quality to ensure justice and prevent misuse or abuse of power. The Safe Drinking Water Act or the South African law to guarantee free basic water are good examples of laws made with good will. But it depends on the policymakers to abide, interpret, and execute correctly to really protect the people and provide safety.

If governance is a specific kind of human capacity, human capacity in general plays a broader and eminent role in influencing the FEW services provision as well as people's quality of life under anthropogenic and natural challenges such as climate change and population growth. In the developing world, lack of FEW services is partly due to lack of infrastructure, such as treatment facilities, sanitary equipment, distribution network, so forth, and remedies cannot be realized without increased financial capacity. But it is not the case that a country with adequate financial capacity will be guaranteed to have excellent FEW infrastructure; examples include Nigeria and even in some regions of developed countries. Even with adequate physical infrastructure, lack of human capacity contributes to failures in the provision of FEW services. Examples in my work include the Cape Town's policymakers' reluctance to act during a drought period and water quality violations due to errors made by water system operators in Tennessee. Education is the foundation for developing human capital and human capacity to create values, rejuvenate an economy and improve FEW and all social services. Emphasizing education also helps by embracing research through which we discover issues and search for solutions. Through research, we can develop models or use other techniques to search for pathways to achieve FEW security even under pressures from supply instability due to climate change and demand increase because of population growth. Through the research in this dissertation, we confronted a common issue- data limitation, an issue for research in general. We might want to think what information we need and plan on how to store and use it for future research. In the research of FEW nexus or coupled human-natural systems, we are linking the natural environment with human actions which must consider stakeholders from resource managers like the policymakers to resources consumers like people working in the farms, energy plant, water treatment facilities, and even the general population. The data-driven approach we are undertaking requires that data reflect the information from both the natural environment and the activities and behaviors of the stakeholders. But often the data either are not collected or are difficult to find because they exist in silos. We need to think about the database structure in which the following are considered: 1) what kind of data need to be included and who will benefit; 2) what is the finest fidelity the data should capture both spatially (i.e. point, regional, or national) and temporally (i.e. real-time, daily, or yearly); and 3) how can data be connected to other databases. For instance, the drinking water quality database in Chapter 4 could be expanded to a large geospatial database which includes real-time water quality data at the tap level, land-use information, nutrient data in the stream, and more data reflecting the sociodemographic and socioeconomic information of the region. The database will prompt interdisciplinary research across natural and social sciences. The database could be further expanded through the unique locations as primary keys.

Moving forward, we need to put research into action and use science to inform policy. The research outcome from the SSA and in the United States should go beyond journal publications. In addition to these traditional outlets, we could go to the community and engage with farmers, water managers, policy makers, and other stakeholders. Specifically, we can work with them on how to use the tools we developed to address the issues of FEW security. We need to find innovative ways to use scientific research to inform the policy and decision-making process. For instance, we could push the research outcomes to social media and create podcasts to engage a broader audience. Only if we work together can we find the pathway to achieve FEW security for the world.

Appendix A: Supplementary Tables of Chapter 2

Table 8. Details about the various metrics (including sources, and years) evaluated for the resources, services, and health domains.

| Sector | Domain | Metric | Unit | Vear | Source | Sub-category: metrics in the same |
|--------|-----------|--|---|--------------|---|--|
| Sector | Domani | | , , | 1001 | The set o | Domain and Sector with related concepts |
| | | Long-term annual precipitation depth | mm/year | 2014 | (FAO, 2016) | Water-availability-variability-inclement |
| | | I otal renewable water sources per cap | log10(10° m°/yr/cap) | 2014 | (FAO, 2016) | Water-availability-variability-inclement |
| Water | Recourses | Second variability | dim-less | 2013 | (FAO, 2016) (FAO, 2016) | Water-availability-variability-inclement |
| water | Resources | Flood occurrence | dim-less | 2013 | (FAO, 2016) | Water-availability-variability-inclement |
| | | Flood occurrence | ullii-less | 2013 | (CRED: Guba-Sanir | water-availability-variability-inclement |
| | | Drought frequency | number of events | 2016 | 2017) | Water-availability-variability-inclement |
| Watan | Comisso | Total population with access to safe drinking-water | % | 2015 | (FAO, 2016) | |
| water | Services | Total Population with access to improved sanitation | % | 2015 | (FAO, 2016) | |
| Water | Health | Diarrhea as a cause of death for children under 5 | % | 2015 | (UNICEF, 2018) | |
| | | Total-non-fossil fuel production | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Non-fossil-fuel-production |
| | | Nuclear production* | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Non-fossil-fuel-production |
| | | Hydro production* | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Non-fossil-fuel-production |
| | | Geothermal, solar, and other renewables production* | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Non-fossil-fuel-production |
| | | Biofuel waste production* | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Non-fossil-fuel-production |
| | | Total-fossil-fuel production | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Fossil-fuel-production |
| | | Coal production* | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Fossil-fuel-production |
| Energy | Resources | Crude oil production* | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Fossil-fuel-production |
| | | Oil products production* | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Fossil-fuel-production |
| | | Net imports# | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Fossil-fuel-production |
| | | Natural gas production* | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Fossil-fuel-production |
| | | Energy export [#] | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Fossil-fuel-production |
| | | Fossil fuel reserves | Mtoe/cap | 2016 | (World Energy Council, 2016) | Fossil-fuel-reserve |
| | | Total fossil fuel reserves Oil share | % | 2016 | (World Energy Council, 2016) | Fossil-fuel-reserve |
| | | Total fossil fuel reserves Natural Gas share | % | 2016 | (World Energy Council, 2016) | Fossil-fuel-reserve |
| Energy | Services | Electricity consumption per capita Energy supply per capita | kwh/person Gigajoules/person | 2014 2013 | (World Bank, 2018b) (United Nations, 2017) | Energy-Service Energy-Service |
| Energy | Health | Causes of Death attributable to Air Pollution | % of population | 2015 | (WHO, 2018a) | |
| | | Percentage of total country area cultivated | % | 2015 | (FAO, 2018) | Land-availability-variability |
| Food | Resources | Permanent crops | % | 2015 | (FAO, 2018) | Land-availability-variability |
| 1000 | 100001000 | Permanent meadows and pastures Land degradation (% territory) | % % | 2015 2003 | (FAO, 2018) (ISRIC, 2003) | Land-availability-variability Land-availability-variability |
| | | Per capita food supply variability | kcal/cap/day | 2011 | (FAO, 2018) | |
| | | Per capita food production variability | Int.l dollar /cap constant (2004-06) | 2013 | (FAO, 2018) | |
| Food | Services | Share of dietary energy supply derived from cereals, roots, and tubers, | %, 3-yr avg | 2009-2011 | (FAO, 2018) | Protein-balance |
| 1000 | Dervices | Average protein supply | g/cap/day, 3-yr avg | 2009-2011 | (FAO, 2018) | Protein-balance |
| | | Average supply of protein of animal origin | g/cap/day, 3-yr avg | 2009-2011 | (FAO, 2018) | Protein-balance |
| | | Average dietary energy supply adequacy | %, 3-yr avg | 2013-2015 | (FAO, 2018) (FAO, 2018) | Food-utilization |
| | | Depth of the food deficit | kcal/cap/day, 3yr avg | 2015 | (FAO, 2018) (FAO, 2018) | Food-utilization |
| | | Percentage of children under 5 years of age | 0/2 | 2012 | (EAO 2018) | Young-age-malnutrition |
| | | who are stunted, Percentage of children under 5 years of age | 20 % | 2012 | (FAO. 2018) | Young-age-mainutrition |
| Food | Health | affected by wasting Percentage of children under 5 years of age | % | 2012 | (FAO, 2018) | Young-age-malnutrition |
| | | who are underweight Percentage of children under 5 years of age | % | 2012 | (FAO, 2018) | Young age-mainutrition |
| | | who are overweight | /0 | 2012 | (1 AO, 2010) | r oung-age-manutition |

Table 9. Details about the various metrics (including sources, and years) evaluated for the socioeconomic and governance domain for all three sectors.

| Sector | Domain | Metric | Unit | Year | Source | Sub-category: metrics in the same Domain and Sector with related |
|---------|-------------------|--|-----------------------------|---------------|--|---|
| | | | | | | concepts |
| | | GDP per cap | log10(current US \$) | 2015 | (World Bank, 2018b) | Socio-economic-development |
| | | Education Index | dim-less | 2013 | (United Nations, 2013) | Socio-economic-development |
| | | Voice and Accountability | dim-less | 2015 | (Kaufman & Kraay, 2015) | Governance |
| | | Political Stability and Absence of Violence/Terrorism | dim-less | 2015 | (Kaufman & Kraay, 2015) | Governance |
| General | Human | Government Effectiveness | dim-less | 2015 | (Kaufman & Kraay, 2015) | Governance |
| | Capacity | Regulatory Quality | dim-less | 2015 | (Kaufman & Kraay, 2015) | Governance |
| | | Rule of Law | dim-less | 2015 | (Kaufman & Kraay, 2015) | Governance |
| | | Control of Corruption | dim-less | 2015 | (Kaufman & Kraay, 2015) | Governance |
| | | Rural Population [†] | 1000 inhabitants | 2015 | (FAO, 2016) | Socio-economic-development |
| | | Population [†] | 1000 inhabitants | 2015 | (FAO, 2016) | Socio-economic-development |
| Energy | Human Capacity | import export difference | Mtoe/cap | 2015 | (International Energy Agency, 2015) | Energy-specific-economic- capacity |
| | | Rail lines density | per 100 sq. km of land area | 2014 | (World Bank, 2018b) | Food-specific-Infrastructure- development |
| Food | Human | Percent of arable land equipped for irrigation | % | 2012- 2014 | (FAO, 2018) | Food-specific-Infrastructure- development |
| | Capacity | Value of food imports over total merchandise exports | %, 3-yr avg | 2011- 2013 | (FAO, 2018) | Food-specific-economic-capacity |
| | | Cereal import dependency ratio | % | 2009- 2011 | (FAO, 2018) | Food-specific-economic-capacity |

| Sector | Domain | Derived Metric | Associated Metrics | Methods |
|--------|--------|---------------------------------|--|------------|
| W | R | Water Availability | Long-term annual precipitation depth Total renewable water sources per cap Inter-annual variability Seasonal variability Flood occurrence Drought frequency | PCA: PC 1 |
| W | R | Annual and Seasonal Variability | Long-term annual precipitation depth Total renewable water sources per cap Inter-annual variability Seasonal variability Flood occurrence Drought frequency | PCA: PC 2 |
| Е | R | Non-Fossil Fuel Production | Hydro production Geothermal, solar, and other renewables production Biofuel waste production | log10(Sum) |
| | | Fossil Fuel Production | Coal production Crude oil production Oil products production Natural gas production | log10(Sum) |
| Е | S | Energy Usage | Electricity consumption Energy supply | PCA: PC 1 |
| F | R | Agricultural Area | Total country area cultivated Permanent crops Permanent meadows and pastures Land deeradation | PCA: PC 1 |
| F | S | Land Use | Total country area cultivated Permanent crops Permanent meadows and pastures Land deeradation | PCA: PC 2 |
| F | S | Food Utilization | Cereals, roots, and tubers in dietary energy supply Average protein supply Average supply of protein of animal origin Average dietary energy supply adequacy Prevalence of undernourishment Depth of the food deficit | PCA: PC 1 |
| F | S | Protein Balance | Cereals, roots, and tubers in dietary energy supply Average protein supply Average supply of protein of animal origin Average dietary energy supply adequacy Prevalence of undernourishment Depth of the food deficit | PCA: PC 2 |
| F | Н | U5 malnutrition | U5 who are stunted U5 affected by wasting U5 who are underweight U5 who are overweight | PCA: PC 1 |
| G | SG | Overall Quality of Governance | Voice and Accountability Political Stability and Absence of Violence/Terrorism Government Effectiveness Regulatory Quality Rule of Law Control of Corruption | PCA: PC 1 |
| G | SG | Political Stability | Voice and Accountability Political Stability and Absence of Violence/Terrorism Government Effectiveness Regulatory Quality Rule of Law Control of Corruption | PCA: PC 2 |
| Е | SG | Import Export Difference | Net imports Energy Export | Difference |

Table 10, Metrics and methods used to develop derived metrics.

Table 11. The detailed statistics of all models of linkages and interlinkages exploration of the FEW nexus.

Table 11 is uploaded separately to a GitHub repository: <u>https://github.com/ding-k/Earth-s-Future-Supporting-Information-Code-and-Data</u>.

Table 12. The correlation matrices of the Food, energy, and water resource-services, services- health, and human capacity raw metrics.

Table 12 is uploaded separately to a GitHub repository: <u>https://github.com/ding-k/Earth-s-Future-Supporting-Information-Code-and-Data</u>.

Appendix B: Overview Design concepts, Details of the Cape Town Agent-Based Model

B1 Purpose

We build this ABM close to the reality of the stakeholders from the municipal, water, energy (hydropower), and food sector, so we have a test bed to simulate and compare the FEW system outcomes under various policy scenarios. We test two policy scenarios:

- Business-as-usual (baseline): no joint-management or minimal communication between the departments of Energy, Water, and Food (agriculture). The tariffs of water and threshold levels of dam storage for restrictions used in this scenario are from the city of Cape Town;
- Holistic-adaptive-management: allocate water resources across FEW sectors to satisfy the municipal demand, similarly for hydropower generation, and agricultural production. This scenario also Incorporate some basic climate adaption strategies and adjusting water demand using water price elasticity of demand theory to manage water shortage.

Specifically, we use the scenario 1 to calibrate and set up the baseline to match the actual patterns of the system outcomes (i.e., dam storage levels, water use) under the existing management policies. Whereas scenario 2, we propose a new holistic management strategy to optimize the outcomes of water, energy, and food sector.

We also want to compare the modeling results of different policy scenarios for a range of future climate scenarios.

B2 Entities, State Variables, and Scales

There are four types of agents represented in this model:

1. Water Manager (Western Cape Department of Water Services):

Allocation for each of the water user agent, total dam storage of this month, total storage capacity

2. Energy Manager:

maximum capacity and actual capacity of this month

3. Farmers:

water demand, rainfall, temperature, soil moisture deficit and available water content of the month, Irrigation Area

4. Citizens:

water demand, population, population growth rate

The scale for the model is the city of cape town and the wine grape crop fields in Cape Wineland. The model is simulating from 2009-1 to 2018-12 for the retrofit of historic run. The time step is monthly.

B3 Process Overview and Scheduling

The model simulates a ten-year monthly run from January 2009 to December 2018 for each of the policy scenarios at the monthly scale. The general inputs of the model include initial dam storage, monthly water inflow, monthly water demand by sectors, and water price and its price elasticity of demand (CSAG, 2019; Sahin et al., 2016; DWS, 2018). At the beginning of each month or tick in the model, the water manager asks the demand of each stakeholder and the check the dam level before allocation, then depends on the scenarios, the allocation for each sector is calculated accordingly. At the end of each month or tick, the dam storage is updated based on the current allocation and the inflow.

In Scenario 1, we use the restrictions set up by the city of Cape Town from 2015 to 2018. There are various levels of restrictions imposed on the study region. However, the major water use reductions occur at level 2, level 3, and level 6b, where 20% municipal demand reduction, 30% municipal demand reduction, and a strict 450 MLD municipal use restriction with zero agricultural water allocation are triggered when the total dam storage level is lower than 50%, 45%, and 20%, respectively.

The scenario 2 takes a simple adaptive approach on imposing water use restrictions, where for each month or tick, the water manager compares the current dam storage level with the pre-drought (2009 to 2015) monthly average of dam storage level of this month. If the current dam storage level is greater than 90% of the average, the water manager will not impose any restrictions and all stakeholders acquired their demanded water since it is in the normal range of variation. When the current dam storage level is lower than the threshold, the reduction of this month is simply the ratio of $(V_{avg} - V_{current})/V_{avg}$. In addition, we use water price elasticity of demand so we can adjust the water price to reduce the demand to the targeted level.

After the storage has been updated, the tick advances and the loop continues until the end of tick 120 or 2018-12.

B4 Design Concepts

B4.1 Emergence

Population is growing over time at an annual rate of 0.8%.

B4.2 Adaptation

In Scenario 2, the adaption is the simple reduction if the storage level is lower than the threshold.

B4.3 Objectives

The objective of the ABM is to optimize the system outcomes for all the stakeholders in the model.

B4.4 Learning

No learning if we don't include weather forecast? Farmers will learn to save water by use weather information.

B4.5 Prediction

Currently there is no prediction, but it is within the scope of phase 2 of this project.

B4.6 Sensing

Water managers can sense the dam storage level. Farmers can sense the rain and the temperature, and therefore the soil moisture.

B4.7 Interaction

Interactions is between the managers and the stakeholders through the demand and allocation.

B4.8 Stochasticity

In the future of phase 2, the future weather conditions is going to be a stochastic model. Potential extreme weather events. The stakeholders, instead of the current homogeneous state, will be diversified stochastically.

B4.9 Collectives

Rain, Temperature, soil moisture deficit, water price, Energy generation, Water demand and allocation of each stakeholders.

B4.10 Observation

Soil Moisture, temperature, dam storage level, precipitation, water price.

B4.11 Initialization

The water manager will start with the upper limit of 920,000 ML, and the actual storage volume at the end of 2008.

B5 Input Data

Historic weather and inflow information. Unrestricted water demand. The soil moisture deficit was and input calculated using the tool developed by Jacobi et. al. (2013).

B6 Submodels

B6.1 Urban Demand Submodel

Capetonians and their urban demand is represented by a single agent, CPers. For simplicity, we aggregated the residential, commercial, and other miscellaneous water demand all together and averaged to individual urban water demand. The Cpers has 3.875 million people at the beginning of 2009 with an annual growth rate of 0.8%. In the city of Cape Town, the unrestricted individual urban water demand is calculated based on the monthly average of the urban water usage between 2009 to 2015 (CASG 2019). In all policy scenarios, the real municipal water allocation of the month is calculated using equation:

$$Allocation_{urban,i} = Population_i * Demand_{urban} * (1 - Reduction)$$

where *Population_i* is the population of the year of this month, *i*; and *Demand_{urban}* is the individual demand for municipal water users.

B6.2 Agriculture Submodel

In the agricultural sub-model, the irrigation demand is calculated using the soil moisture deficit (SMD), where SMD is calculated by a simple water balance approach. We adopted the Palmer Drought Index calculating tool developed by (Jacobi 2013), which the monthly potential evapotranspiration (PET) and soil moisture content (SMC) are calculated by Thornthwaite method and by the water balance, respectively. It is a useful tool that provides relatively accurate results which have been used in agricultural research to assess drought and soil moisture (Gunda et al, 2016, Nawagamuwa et al, 2018). We estimated the AWC for each of the wine regions from the AWC map of the region (Schulze and

Horan, 2007), and the SMD was calculated by this tool using the monthly rainfall and temperature data from the closest weather station.

In this study, we specifically focused on the irrigation of the vineyards. On average, the share of irrigation for non-wine crops is 57 % (Western Cape Government, 2015). In the model, we fix the 57% of the total agricultural water usage for the non-wine crops, because those crops are mainly located outside of our study region. We only manage the water allocation of the wine grapes in this model. The irrigation of the wine grapes is calculated using equation:

$$Demand_{wine,m} = SWD_m * Area * KC_m * Ef_{wine}$$

where SWD_m is the soil moisture deficit of this month, Area is the irrigation area of each wine region, KC_m is the Crop Coefficient of wine grapes of this month, and Ef_{wine} is the irrigation efficiency of the vineyard (WSU, 2016). We calibrate the model parameters under scenario 1 to match the historical patterns. The calibrated model parameters are carried on and used in scenario 2 as well.

B6.3 Hydropower Submodel

In the Big Six dam system, only Steenbras upper Dam is a pump-storage hydropower dam. To maintain the maximum generation capacity, the Steenbras Upper Dam needs to keep at full level (DWS, 2018). The Steenbras Upper and Lower Dams operate together, where the lower dam pumps the water to the upper dam during off-peak hours, and the upper dam releases water during the peak hours that provide up to 180 megawatts (MW) to offload the pressure from the electricity grid. The storage capacities of the Steenbras Upper and Lower dams are similar, and the combined storage accounts for 10% of the total capacity. The water supply system in Western Province cannot release water when the dam storage level is below 10% of the total capacity. Thus, we assume that if the total dam storage level is above 20% of the total dam storage capacity, the Steenbras Upper Dam can remain at full storage, and so is the maximum generation capacity. When the total dam storage level is lower than 15% of the total dam storage capacity, the water withheld in the Steenbras Upper dam will be released for the municipal water

use, and no hydropower can be generated. In between 15% and 20% of the total dam storage, we assume the hydropower generation capacity decreases linearly.

Appendix C: Supplementary Information for Chapter 4

Violations summary for counties with highest values of different types of violations and indices: In Humphreys county, there are 4 CWSs, 3 NTNCs, and 8 TNCs serving 15444 people. Monitoring violations are dominant in the violation database in which most of the systems have major routine violations for different inorganic, organic, and microbial contaminants.

In Gilles county, there are 6 CWSs serving 30259 people. All systems except the Large PWS- Pulaski water system are using purchased surface water. The dominant MCL contaminant is HAA5, one of the two common disinfectant by-products in the systems who use purchased surface water. On the contrary, no DBP MCL violations was found in Pulaski water system who treat its own water.

In Marion county, there are 3 CWSs and 2 TNCs serving 8648 people. The most frequent treatment technique violation is monthly combined filter effluent which could be found in both CWS and TNC systems. The most frequent public notice violation is public notice rule linked to violation from River Landing Condominium system.

In Clay county, there are 2 CWSs serving 9624 people. The most frequent reporting violation is the recording keeping with rule code that could only be found in Northwest Clay County Utility system. There was one record found in the other PWS, Celina Water System, which was associated with the consumer confidence report adequacy, availability, and content.

In Stewart county, there are 6 CWSs and 3 TNCs serving 7697 people. There is 5 records of the only one kind of Other violation, sample siting plan errors for revised total coliform rule in the SDWIS database in Tennessee. There are two records in Stewart county found in two different CWSs. The other three cases can be found in Humphreys, Robertson, and Grainger.

There is only one CWSs in each of the four counties where they has high violation frequencies, Pickett, Trousdale, Cannon, and Van Buren. In Pickett county, the Byrdstown water department (medium system serving 7060 people) resulted mostly in major routine violations of the inorganic, organic, and microbial contaminants. Byrdstown water department also have repeating disinfectant by-products MCL violations from 2014 to 2018. In Trousdale county, the Hartsville-Trousdale Water/Sewer Utility District (medium system serving 8055 people) mostly resulted in major and minor routine reporting violations of different contaminants. In Cannon county, the Woodbury water system (Large system serving 10505 people) resulted in various types of violation with mostly monitoring and reporting violations in the study period except 2018. In Van Buren county, the Spencer water system (medium system serving 5217 people) resulted in 14 records of health-based violations (11 MCL violations and 3 TT violations) and 15 monitoring violations. The MCL violations are all disinfectant by-products violations. It is worth noting that Spencer water system has a qualified operator failure violation as one of the treatment technique violations in 2018. All the systems except the one in Pickett were among the systems having punctuated changes.



Figure 25. Individual concentration distributions of inorganic contaminants (IOC). Red dashed line in each subplot indicates the Maximum Contamination Level (0% difference from MCL).



Figure 26. Individual concentration distributions of radionuclides (RAD). Red dashed line in each subplot indicates the Maximum Contamination Level (0% difference from MCL).



Figure 27. individual concentration distributions of Synthetic Organic Contaminants (SOC). Red dashed line in each subplot indicates the Maximum Contamination Level (0% difference from MCL).



Figure 28. Individual concentration distributions of volatile organic contaminants (VOC).

Table 13. Summary of concentration distributions of IOC, RAD, SOC, and VOC.

Table 13 is uploaded separately to a GitHub repository: <u>https://github.com/ding-k/TN_Drinking_Water</u>.

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