Consumptive Water Use: Refining State Water Supply Estimates with Discharge and Withdrawal Data

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Thesis submitted to the Faculty of the

Virginia Polytechnic Institute and State University

in partial fulfillment of the requirements for the degree of

Master of Science

in

Biological Systems Engineering

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April 30, 2019

Blacksburg, Virginia

Keywords: Consumption, Water Use, Water Supply, Withdrawal, Discharge

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(ABSTRACT)

Water scarcity has quickly become one of the most pressing issues in the 21st century. Knowledge of the stress consumption places on water supply is therefore necessary for improved resource management. This research leverages monthly facility level withdrawal and discharge data from two different sources to provide important observations of consumptive water use across several spatial scales and water use sectors in Virginia between 2010-2016. Consumptive water is defined as water which is withdrawn and not returned to a water resource system. Consumption was estimated on statewide, watershed, county, and facility levels. The agriculture/irrigation, aquaculture, commercial, industrial, energy, and municipal sectors were considered for analysis. Facilities were matched between the two data sources by narrowing potential matches by distance and then by facility name using an approximate string distance mechanism. This analysis revealed that inconsistent discharge reporting affects estimates of consumption through time and any errors at finer spatial scales are ultimately masked at coarser levels. Statewide energy consumption in Virginia was found to be between 4-20% considering all available data and 0.4-4% across matched facilities. Non-energy consumption was an estimated 37-51% considering all available data and only 28-33% across matched facilities. Inconsistent reporting of discharge made it difficult to determine if consumption trends truly exist in Virginia, but monthly consumption appears to be persistent through time and slightly increasing in non-energy sectors. Industrial consumption in Virginia was also found to be higher than literature values. Results from this study are beneficial for water supply modeling and planning by providing more refined estimates of the actual stress withdrawals place on water supply.

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(GENERAL AUDIENCE ABSTRACT)

Water scarcity has quickly become one of the most pressing issues in the 21st century. Improved water resource management is critical for sustainable development, especially in historically water-rich states that have not had an urgency to improve water planning. This research provides key information about the impact consumption has on water supply in Virginia, using water use data from two different sources between 2010-2016. Consumptive water is defined as water which is withdrawn and not returned to a water resource system. This includes losses through evaporation, transpiration, conveyance, and incorporation into products and animals. Consumption was estimated on statewide, watershed, county, and facility levels. It was also estimated for the agriculture/irrigation, aquaculture, commercial, industrial, energy, and municipal sectors. Facilities were matched across the two data sources by narrowing potential matches by distance and then by facility name. This study revealed that statewide energy consumption in Virginia is between 4-20% considering all available data and 0.4-4% across matched facilities. Non-energy consumption is then between 37-51% considering all available data and only 28-33% across matched facilities. Inconsistent reporting of return flow data made it difficult to determine if consumption trends truly exist in Virginia, but consumption appears to be persistent through time and slightly increasing in non-energy sectors. Results also suggest that industrial consumption in Virginia may be higher than published literature values. This study ultimately introduces a feasible method for water managers to estimate consumption using data from multiple sources. Results from this approach are beneficial for predicting future water demand and long-term resource planning by providing more knowledge of the actual stress withdrawals place on water supply.

Acknowledgments

I would like to acknowledge all of the people that made this work possible. To Julie, my lovely advisor, thank you for being my sounding board and anchor during the past two years. To Rob and Joey from the Department of Environmental Quality Office of Water Supply, thank you for diving down the thousands of rabbit holes with me and being top notch mentors. I wouldn't have been able to navigate the mess that is self-reported big data without your guidance. To Connor Brogan, who also endured the harsh pains of the ECHO site and laid the foundation for this consumption analysis. To my long life best friends, Teagan and Marissa, thank you for sending your undying support from all over the country and keeping me hopeful. To my acquired friends, Lauren, Hannah, Kat, Kyle, Tyler, Laura, Joe, JC, Sammy, Ben, Chelsea, etc., thank you for the multitude of happy hours, laughs, and unconditional love. I would have never made it through without you guys. And to my mom, thank you for picking up the phone everyday and listening to every minor inconvenience, triumphs, and nuances.

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List of Abbreviations

CWA Clean Water Act

ECHO Enforcement and Compliance History Online

EPA Environmental Protection Agency

JLARC Joint Legislative Audit and Review Commission

MGD Million Gallons per Day

NPDES National Pollution Discharge Elimination System

QA/QC Quality Assurance and Quality Control

SWRP State Water Resources Plan

USGS United States Geological Survey

VDEQ Virginia Department of Environmental Quality

VPDES Virginia Pollution Discharge Elimination System

VWP Virginia Water Protection Permit Program

VWUDS Virginia Water Use Data System

Chapter 1

Introduction

1.1 Introduction

Water is an essential natural resource that is utilized for a vast range of human and environmental purposes. Knowledge of available water supply and how it is being used is therefore crucial for resource management. Current assessments of water resources and trends rely heavily on water withdrawal analysis [41]. However, they do not account for water that is being returned to surrounding resources after use. Estimates of consumptive use, or water that is not returned to a water resource, can aid in the quantification of water availability. By examining historical consumptive use and current practices, more refined projections of water demand can be provided by local and state managers [19].

1.2 Purpose and Scope

The overarching goal of this study is to assess water consumption in Virginia by combining federally maintained discharge data with state maintained withdrawals to calculate consumptive water use. Estimates of consumptive water use are presented for selected economic sectors and spatial scales during the period of 2010-2016 through total volume and per-facility approaches. Monthly and annual consumptive-use estimates and non-parametric trend tests on estimates are also presented. Data are presented in tabular and figure forms, with maps indicating locations of water users and long-term median consumption estimates.

1.3 Water Resources of Virginia

Unlike the arid Southwest regions in the United States, Virginia has historically been a water plentiful state. With rainfall averaging 43 inches per year (national average: 30.21 inches) and a total combined flow of 22.5 billion gallons per day in all freshwater streams, the Commonwealth has been able to meet water demands for its constituents [41]. Withdrawals from surface water (including rivers, streams, and reservoirs) and groundwater (aquifers) supply Virginia with the water needed to support its full range of human and environmental purposes [21]. Of these two sources, surface water withdrawals make up the vast majority of what's used in the state (approx. 90%), where the major river basins include the Potomac, Lower Chesapeake, Mid Atlantic Coastal, James, Albemarle-Chowan, Roanoke, Upper Pee Dee, Kanawha, French Broad-Holston, Upper Tennessee, and the Big Sandy (Figure 1.1). Groundwater withdrawals are concentrated in eastern Virginia and from the coastal plain aquifer [21].

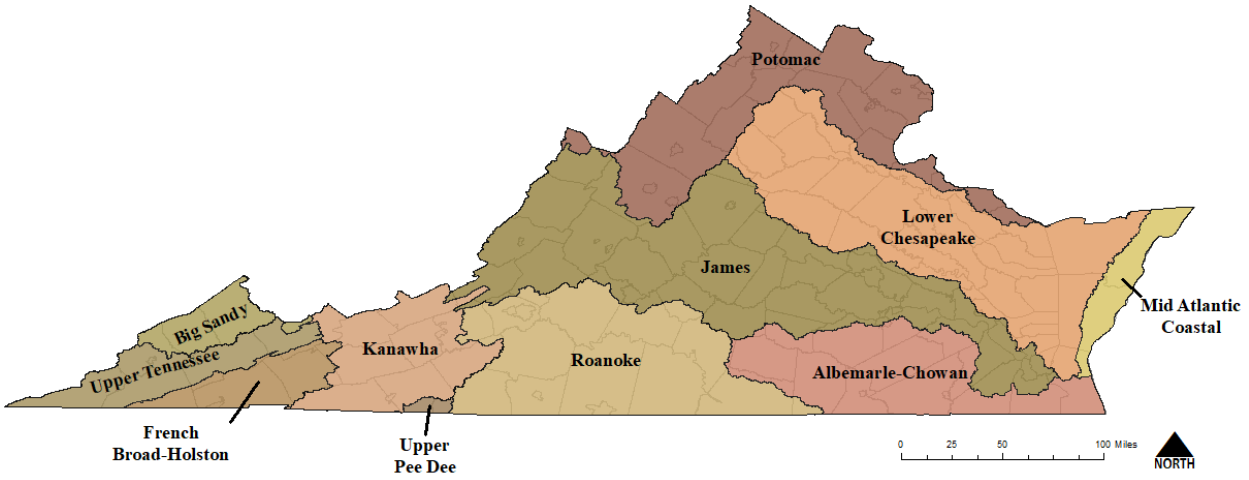

Figure 1.1: Major river basins in Virginia

Although plentiful resources have been advertised, a multi-year drought between 1999-2002 sparked a major shift in management perception for water planners in Virginia's Depart-

ment of Environmental Quality's (VDEQ) Office of Water Supply. During this time, the commonwealth experienced record low flows, leaving several public water systems on the brink of failure with less than 60 days of remaining water supply capacity [37]. Besides the drought, the VDEQ predicted a 32% increase in water demand in 2010 through 2040, while acknowledging gaps in ground and surface water use data across various water use sectors. This prediction, however, overestimated how much water was actually withdrawn between 2010 to 2015 (decrease in demand by 10%) [21]. This discrepancy and the unrefined nature of Virginia's water supply estimates ultimately frames the urgency for improving both water resource modeling and management.

Chapter 2

Review of Literature

2.1 Virginia's State Water Resource Plan

Responsibility for managing water resources in Virginia is divided amongst the State Water Commission, the State Water Control Board, and the Department of Environmental Quality (DEQ) Office of Water Supply [37]. These three entities coordinate legislative activity, develop regulations, and implement water resource planning, respectively [21]. The VDEQ collects and analyzes surface and ground water usage data to understand the impact of reported withdrawals on statewide supply [39]. They direct water supply management for the Commonwealth through five programs including groundwater characterization, water supply planning, water withdrawal permitting and compliance, environmental data and analysis, and drought assessment [41].

Annual reporting of surface and ground water withdrawals is required under the Virginia Water Withdrawal Reporting Regulation (9VAC25-200-10, et seq.) [37]. It requires users exceeding an average of 300,000 gallons per month (or 10,000 gallons per day) to report their water withdrawals, with the exception of crop irrigation [39]. If water is diverted for crop irrigation, reporting is only required for withdrawals exceeding 1 million gallons for a single month [39]. Regardless of whether the user has a permit or not, reporting is required if their withdrawals exceed these thresholds [37]. These thresholds, along with grandfather

clauses, exempt approximately half of surface and groundwater users from reporting water withdrawals [21]. Collectively, in the year 2013, exempt surface water users accounted for an estimated 82% of the total surface water withdrawn statewide [21]. Unfortunately, the VDEQ does not have the authority to impose civil penalties to users that fail to report their water withdrawals [21]. This makes it difficult for the Office of Water Supply to obtain data needed for analysis to reach a better understanding of the pressure withdrawals have on the state's water resources.

In efforts to improve resource management and permitting decisions, the VDEQ drafted the State's first Water Resources Plan (SWRP) in October of 2015 [37]. This document is the first of its kind and was created to be the primary planning mechanism for the Commonwealth of Virginia. It's intended to enable regional and local entities to identify their specific future water needs and plans and consolidate them into a single place. The document outlines assessments of existing water use, sources of supply, population and water demand projections, anticipated deficits, potential new supply sources, and guidance on how to use this information to support sustainable water use [37].

2.1.1 Water Supply Challenges in Virginia

In 2016, the Joint Legislative Audit and Review Commission (JLARC) was appointed by the General Assembly to evaluate the effectiveness of the State Water Resources Plan and its progress towards sustainable water use [21]. Their review includes an overview of water resource planning and management in Virginia, noting water supply challenges and providing recommendations to the VDEQ, in efforts to improve management and modeling efforts. Major challenges involving water supply and the overall water resources plan (Table 2.1) include instability of groundwater withdrawals in the near future, major gaps in ground and surface water use data over several water use sectors, an overall vagueness of the water

supply plan, and a lack of knowledge of the impact of consumptive use on water supply [21].

Table 2.1: Water supply challenges noted in Virginia's 2015 State Water Resources Plan [21].

Challenges	**Recommendations**
Uncertainty of groundwater availability outside of protection areas.	Implement monitoring wells outside of ground water management areas.
Gaps in ground and surface water withdrawal data.	Develop a more efficient approach to registering withdrawing facilities and users to reporting systems.
82% of total surface water withdrawals are unpermitted[21].	Develop and include additional rules that are not currently in VWP permitting regulations.
Unknown impact of consumption on water supply.	Include discharge data when assessing water resources and request reporting of consumptive use in annual reporting.
Climate change may impact water supply.	Evaluate cumulative impact analyses on an annual basis and implement climate change model scenarios.
Two-thirds of local stakeholders haven't read or are not aware of the SWRP.	Improve communication and collaboration with regional and local stakeholders with a comprehensive education and outreach program.

Groundwater confined in aquifers has been a source of low-cost, high quality water for residents located in Eastern Virginia. Fresh water options are often limited along this coastal area, which increases the importance of improving groundwater sustainability. Of the coastal plain aquifer system (which stretches from I-95 to the Chesapeake Bay), the Potomac aquifer is the largest and most productive layer [21]. Even with recent limitations to permitted use, it is expected that withdrawals from the aquifer system will become unsustainable according to long range computer simulations (due to potential increases in both permitted and unpermitted use). Since the VDEQ does not have authority to regulate the growth of unpermitted users, future reductions will need to come from permitted users. Up-to-date understanding of the aquifers, rigorous calibration, and a comprehensive network of

monitoring wells strengthens the VDEQ's ability to model groundwater sustainability [21].

The state also lacks the ability to create accurate predictions of the timing, location, and magnitude of future surface water shortfalls due to insufficient withdrawal data (as mentioned in section 2.1). VAHydro is the model utilized by the VDEQ to simulate and predict surface water flows [38]. Although it is robust and accounts for a wide range of inputs, there is uncertainty and limitation present. This uncertainty stems from the inherent complexity of surface water systems, prediction of future human consumption behavior, uneven data collection, and faulty assumptions [21]. In 2010, the Interstate Commission on the Potomac River Basin predicted that water demand would increase by 32% by 2040, when in reality, water demand decreased by 10% between the years 2000 and 2015 (excluding water used for power generation) [21]. This overestimation of demand assumes water usage corresponds to future population growth and does not consider the adoption of water-efficient technology, conservation techniques, and water that is returned to water resources after use.

The JLARC also deemed the SWRP to not be a useful tool to inform decision-making for regional and local entities. Although the development of a centralized state water supply plan lead to an improved comprehensive database of water withdrawal data, the planning process only incorporated input from 48 stakeholders (including groups and single localities) [21]. Stakeholders, including county and city water planners, are encouraged to provide current and future water demand estimates and their specific management plans; but a vast majority of stakeholders were unaware that a state plan was being developed in 2015 [21]. A survey of 236 stakeholders revealed that over two-thirds have either not heard of the state plan or have heard about and have chosen not to read it [21]. For those that read the plan, most expressed they didn't feel a need to use the plan because it does not set clear priorities or actionable strategies to address those priorities. Water planning should contain sufficient detail to identify effective water supply strategies and inform decision-making. To

do so, water supply estimates can be refined at regional and local scales, so that the plan is tailored towards these regions with a targeted state role.

The key to comprehending the full water budget could be in understanding how consumption impacts water supply; where consumption is defined as water that is removed from a water system and not returned [20]. This includes losses through evaporation, transpiration, conveyance, incorporation into products, and consumption by animals and humans [20]. Consumption is especially important for water management because large water users will not necessarily impact supply if the withdrawn water is returned to its source. For instance, power producing facilities withdraw large volumes of water to cool their equipment, and then discharge it to a surface water source after once-through or re-circulation [20]. Discharges of effluent to surface waters are monitored by the National Pollutant Discharge Elimination System (NPDES), which was established by Section 402 of the Clean Water Act (CWA) [37]. Loss through consumption has the largest impact on water availability; however, current state regulations do not require estimations of consumptive use in annual reports [38]. Consequently, this means current assessments of water supply depend solely on the analysis of water withdrawals, without the input of return flows.

2.2 Consumptive Water Use

Currently, there is not a universally accepted method to estimate consumptive water use. Two common methods include tracking water from when it's withdrawn to when (or if) it's discharged into open waters (equations 2.1 and 2.2), or by applying coefficients from previous publications to estimate consumption [42].

$$\text{Consumptive Use} = \sum_{i=0}^{N} Withdrawal - \sum_{i=0}^{N} Discharge \tag{2.1}$$

$$\text{Consumption Coefficient} = (\sum_{i=0}^{N} Withdrawal - \sum_{i=0}^{N} Discharge)/\sum_{i=0}^{N} Withdrawal \quad (2.2)$$

Consumption often get confused with the phrase "water-use", which only focuses on the gross volume of water withdrawn to predict future supply and demand. The actual stress withdrawals place on water sources can be understood better by analyzing the net water that is first diverted from water sources, returned after use, and ultimately consumed. This concept is visualized in Figure 2.1.

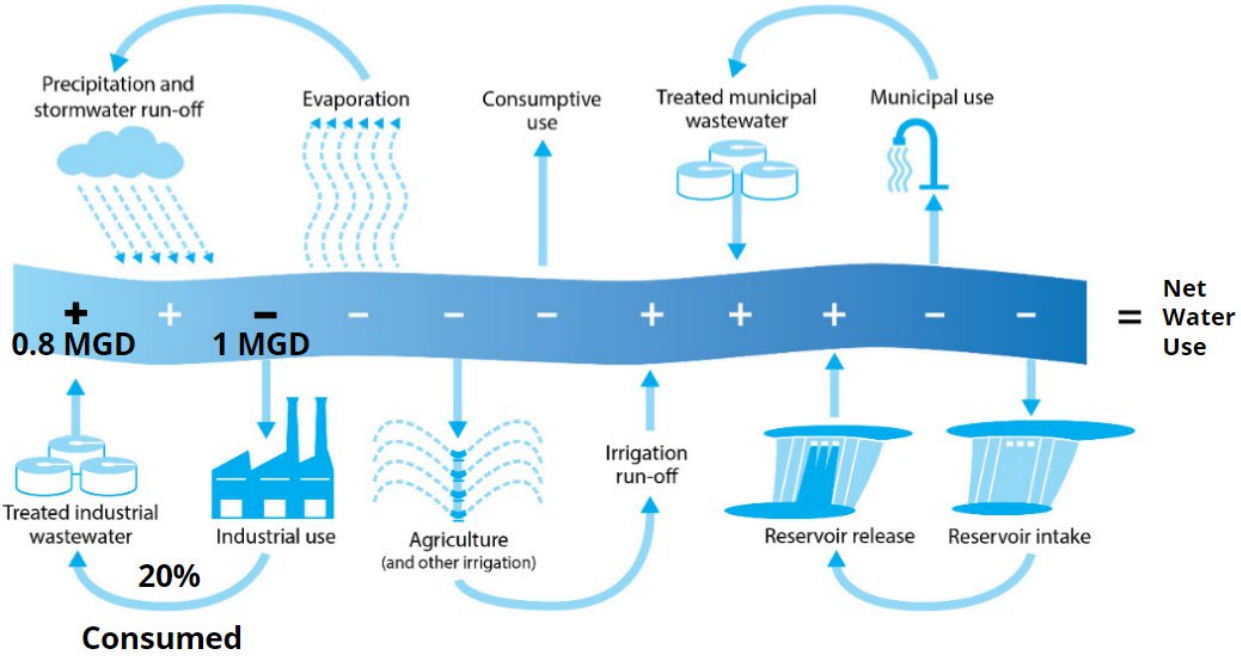

Figure 2.1: Consumptive water use uses a net balance approach to analyze the water that is permanently withdrawn from water resources. Figure adapted from Virginia's Joint Legislative Audit and Review Commission [21].

Often times, the availability and quality of water use data differs significantly by jurisdiction and time. Monthly withdrawals and discharges for major power generation, industrial, public supply, and other metered sites are readily available for analysis, whereas data are typically

scarce for minor users (< 300,000 gal/mon). Other complexities concerning calculating consumptive water use include inter-basin water transfers, water quality degradation, and storm water infiltration, which are discussed in Table 2.2.

2.2.1 Consumptive Use by Water Sector

Water use is categorized into major economic sectors and include, but are not limited to, agriculture, irrigation, commercial, manufacturing, mining, fossil fuel power, hydropower, nuclear power, and public supply [39]. For the purpose of this analysis, these sectors are condensed into Agriculture/Irrigation, Aquaculture, Commercial, Energy (with the exclusion of hydropower), Industrial, and Municipal.

Agriculture/Irrigation

Agriculture and irrigation is associated with high consumptive rates due to evapotranspiration (ET) by crops/plants and conveyance losses. Annual rainfall, soil type, irrigation methods, and the types of crops heavily impact the rate of consumption [42]. Even though water used for irrigation may ultimately runoff into a body of water, this water is not monitored or quantified since it is not considered a point source. Conveyance losses occur in transit from the water source to the agricultural or irrigated land. Variables of conveyance loss include the distance transported, water source, climatic conditions, and the condition of the irrigation canals/ditches/pipes [14]. The decentralized nature of agricultural practices influences a lack of documentation and data provided by farmers. An absence of universal methods also makes evaluation and estimations of consumptive water use in agriculture difficult [14].

Water used for aquaculture and livestock are often included under the agriculture sector [41]. Livestock water use includes the water consumed by livestock (species specific), feed

Table 2.2: Challenges of computing consumptive water use.

Challenges	Description
Data Quality and Availability	Depending on the size of facility and reporting jurisdictions, the quality and quantity of water use data differs significantly. This stunts the ability of water modelers to assess current water resources and project future demands. When detailed data is scarce, coefficients from climatically similar areas are often used to estimate consumptive use [26], [8], [36]. Although this provides insight, these estimations are not as accurate as metered withdrawal and discharge data.
Water Transfers	Users in need of water can buy or lease water rights to meet demands when water resources have already been allocated. These transactions are known as water transfers and commonly occur within municipal water deliveries and waste water collection systems [42]. Inter-basins transfers create a noisy relationship between withdrawals and return flows. For instance, an industrial facility may withdrawal water from a well and purchase additional water from a supplier. Some of that total water may then be treated on-site, while the rest is discharged to surface water. Obtaining this data can be quite difficult and without it, consumption may be overestimated or underestimated.
Delayed Releases	Water used in an energy facility's cooling system may be stored in a cooling lagoon for an extended period of time before being released and reported as a return flow. This delay causes there to be months of no discharge and high withdrawal, skewing the perception of consumption for the monitoring period.
Stormwater Discharges	Polluted stormwater is commonly transferred through Municipal Separate Storm Sewer Systems (MS4s) to be discharged into local water resources [18]. Ms4s are required to obtain NPDES permits and are included amongst the other permits for facilities across the nation. When MS4 outfalls are not correctly labeled, stormwater may be mistaken for effluent exiting a facility. This will grossly underestimate consumption.

production, dairy operation, and farm operation [19]. Aquaculture is the farming of aquatic organisms including algae, fish, and shellfish [19]. Unlike irrigation and livestock, aquaculture

operations often provide ample return flow data required to estimate consumptive use [19]. When data are included among other agricultural practices, overall consumption is pulled lower.

Other than using evapotranspiration models (ex. Blaney-Criddle [17], Hargreaves [32], Penman Monteith [23], etc.) to estimate how much water is actually lost, the use of consumptive use coefficients from climatically similar areas is a common method to estimate consumption for this sector. The average consumption rate for Agriculture/Irrigation in the Mid-Atlantic region of the Unites States ranges from 75-100% [42] (Table 2.4).

Commercial

Shaffer and Runkle define the commercial sector as community areas that are not considered to be residential [42]. This includes golf courses, hotels, military institutions, schools, office buildings, etc. Processes that contribute to consumption include landscape irrigation (including golf courses), sidewalk washing, evaporation from fountains, and a lesser extent from cleaning, clothes washing, and cooking [42]. Indoor commercial water use is assumed to be collected and returned to wastewater treatment plants [20],[31]. Outdoor use is then assumed to be consumed similar to rates in the Agriculture/Irrigation sector (Section 2.2.1) [20].

This allows for data analysts to obtain metered withdrawal and data to calculate the amount of water that is ultimately lost (eq. 2.1 and eq. 2.2). However, commercial facilities are commonly exempt from obtaining permits and reporting due to their smaller size and operations [19]. On average, the consumption rate for commercial use ranges from 4.6-10% [42]. These are typical values for the Great Lakes Basin and Mid-Atlantic area [42]. Further investigation into these coefficients are discussed in the Consumptive Water Use Coefficient Section 2.2.2.

Energy

The energy sector encompasses facilities used for power generation, transmission, and distribution [43]. Cooling water used in power generation is a key component of consumption in the energy sector and a major component of water withdrawals in the US [20]. In the U.S., withdrawals for power generation make up nearly 90% of the total freshwater withdrawn each year [20]. Steam/Rankine cycle plants (ex. coal and nuclear) and combined cycle plants (ex. natural gas) convert heat into mechanical energy [20]. No matter the level of efficiency, there is a need to release the surplus of heat that is created. Exchanges with cooling water accomplishes this task. Two common methods include once-through and recirculating cooling systems.

Once-through systems use withdrawn water to transfer the heat over a single cycle before discharging it [20]. This type of system typically has relatively low consumption, but introduces high thermal loads into surrounding water sources [43]. The warm effluent results in forced evaporation in the receiving water body [20]. Thermal loading affects the livelihood of fish and other species, which prompted changes in EPA regulations under Section 316(b) of the Clean Water Act to promote switching from once-through cooling systems to recirculating methods [43]. Recirculating cooling systems withdrawal a similar amount of water compared to once-through cooling system, but they circulate the water over multiple cycles. The water used in these systems are cooled by ambient air before recycled, which is the main source of loss (evaporation).

A study performed by the Electric Power Research Institute (EPRI) found that consumption for recirculating systems may be estimated around 20%, while once-through systems show more variability with a range from 0.3-1.3% (using the Mississippi River as the study area) [20]. If cooling ponds are used in once-through systems, forced evaporation is estimated up to

50% [20]. Meanwhile, in the Great Lakes Basin and Mid-Atlantic areas, efficient technologies and processes have resulted in consumption rates ranging from 0.1-5% (Table 2.4) [42].

Industrial

Water in the Industrial sector is primarily used for processing, cooling, refining, washing, irrigation of property, etc. [42]. Consumptive use in these sectors originates from evaporation during processes, product incorporation, cleaning, and lawn irrigation [42]. Mining is often defined under the industrial sector and includes water used for the extraction of minerals, quarrying, milling, and preparation [19].

Large industrial water users typically include pulp and paper mills, textile facilities, chemical manufactures, and mining operations [19]. Water for industrial use may be self supplied or provided from a public supplier. As referenced in Table 2.2, deliveries from suppliers can be difficult to track and establish a noisy relationship between withdrawals and their respective return flows. This often leads to under- and over-estimations of consumption rates for facilities.

The ever-growing concern of water pollution stems from industrial processes, which led to the creation of the Clean Water Act in 1977 [42]. This shaped the current data collection methods used today and the changes in how water is used in industrial facilities. Typical consumption rates in the Great Lakes Basin and Mid-Atlantic region of the US range from 4-32.8% (Table 2.4). This is dependent on the technology used and the extent of remediation needed for polluted effluent.

Municipal

Municipal water, also known as public supply and sewage treatment, is supplied to users who, in turn, may use the water for domestic, commercial, energy, or industrial use [29]. Water

for domestic use can be self-supplied or supplied by a public supplier, where self-supplied is harder to regulate due to smaller withdrawals [42]. Domestic uses include water used for drinking, cooking, bathing, flushing toilets, lawn irrigation, etc. Indoor use is assumed to be collected and delivered to wastewater treatment systems or to on-site septic tanks [25].

Table 2.3: Challenges of computing consumption on the municipal supply/treatment level.

Challenges	**Description**
Unaccounted-for Use	Losses occurring through conveyance and degraded infrastructure are unknown.
Unequal Withdrawals and Discharges	Industrial facilities that are self supplied may be returning water to municipal wastewater treatment facilities rather than surrounding open waters.
Differing Customer Base	A particular municipal water treatment facility (public supplier) may serve 200,000 people, but its corresponding wastewater facility may serve 250,000 people. This is due to contributions from private wells and smaller public supply facilities. This creates complexity that is hard to intuitively track [29].
Storm Water Infiltration	Storm water runoff into sewer pipes may be mistaken as return flow to a treatment facility [18]. This skews consumption, making it seem less than it actually is. Ground water infiltration may also enter the treatment system, skewing the perception of return flows. Quantifying these additions of flow are often difficult [25].

Municipal water is among the best measured because of its regulated water supply and treatment facilities. Constant metering of water on multiple levels, including local entities, provides a rich data set. However, direct measurements of consumption doesn't necessarily work at the supply and treatment level. Reasons include unaccounted-for use, unequal withdrawals and discharges, differing customer base, and storm water infiltration (discussed in Table 2.3) [42];[29]. Therefore, most sources compute percent water consumed at higher levels or use literature values [20]. In the Great Lakes Basin area and Mid-Atlantic Region, consumption for the Municipal sector ranges from 10-37% (Table 2.4).

2.2.2 Studies from Climatically Similar Areas

Consumption rates are highly influenced by geographic area and climate. Therefore, consumptive water use studies from climatically similar areas to the Commonwealth of Virginia were investigated (Table 2.4).

Table 2.4: Consumption as a fraction of water lost for major water use sectors from climatically similar studies, the United States, Europe, and the World.

Geographical Area	Agriculture/Irrigation	Commercial	Energy	Industrial	Municipal
Connecticut [35]	-	-	-	-	0.20
Delaware [26]	-	-	0.01	0.04	0.10
Georgia [19]	1.00	0.18	-	0.13	-
Great Lakes [33]	0.75	-	0.004	0.079	0.20
Great Lakes [11]	-	-	0.02	0.10	-
Illinois [29]	0.80	0.096	-	0.33	0.28
Massachusetts [25]	-	0.10	-	0.10	0.15
Ohio [10]	-	-	0.001	0.06	0.20
Pennsylvania [26]	1.00	0.046	0.04	0.084	0.37
Pennsylvania [15]	1.00	0.10	0.012	0.081	0.10
Rhode Island [36]	1.00	0.10	-	0.10	0.15
Rhode Island [24]	1.00	0.08	-	0.04	0.15
Tennessee [28]	1.00	11	0.5	11	24
Wisconsin [9]	1.00	-	0.01	0.10	-
United States [20]	-	-	0.01	0.15	0.28
Europe [27]	0.80	-	0.05	0.20	0.20
World [8]	0.70	-	-	0.11	0.12

Of the studies listed in Table 2.4, Agriculture consumes the most water with coefficients averaging 91.4%. The energy sector consumes the least (1.6%), with the rest averaging below 20%. Studies reporting energy consumption typically analyzed once-through cooling systems, rather than recirculating ones. Common challenges noted in these studies include a lack of quality data [29], inter-basin transfers [25], storm water infiltration [42], and differing customer bases for municipal systems. For studies lacking quality water use data, population data, number of employees, acres irrigated, number of livestock, or any other variable related to volume of water were used to estimate water use [25], [35], [24].

To evaluate the validity of these literature values, methodology was analyzed (Table 2.5). It was discovered three studies used previously published estimates, rather than calculating unique consumptive use; and eleven studies lacked a sufficient explanation of methodology.

Table 2.5: Most consumption studies published original estimates, but did not provide detailed methodology.

Reference	Geographic Area	Original Estimates	Detailed Methods
[35]	Connecticut, New York	Yes	Yes
[26]	Delaware River Basin	No	No
[19]	Georgia	Yes	Yes
[33]	Great Lakes Basin	Yes	No
[11]	Great Lakes	Yes	No
[29]	Illinois	Yes	Yes
[25]	Massachusetts	Yes	Yes
[10]	Illinois, Indiana, Kentucky, and Ohio	Yes	No
[26]	Pennsylvania	Yes	No
[15]	Pennsylvania	Yes	No
[36]	Rhode Island	No	No
[24]	Rhode Island	Yes	Yes
[28]	Tennessee	Yes	No
[9]	Wisconsin	Yes	No
[20]	United States	Yes	Yes
[27]	Europe	Yes	No
[8]	World	No	No

2.2.3 Gaps in Studies

There are distinct opportunities that can be developed on after reviewing the body of literature (Table 2.6). First and foremost, reported return flows can be utilized to estimate unique consumption for the state, rather than relying solely on withdrawal data. Few studies used previously published consumption estimates to estimate the relative amount of water lost in their study area. Employing published coefficients may be particularly useful for estimating consumption in water use sectors that lack sufficient discharge data or have noisy relationships with transfers.

However, there is an inherent variability among water use types, especially in energy gener-

ation and industrial processes (see Table 2.4). All facilities within the same sector will not withdraw identical quantities of water, meaning consumption rates will vary on a facility level. Consumption for a single facility may change seasonally based on operation schedules and public demand. It may also gradually change over time if newer technology/methods are introduced to decrease water use. Using a median consumption coefficient from multiple studies, or a single annual estimate, will mask this variability; which is desired to analyze historic water use trends.

For studies that calculated original estimates, study areas were limited to singular basins [25], counties [35], cities [24], or service areas [29]. As mentioned in Section 2.1, the SWRP is designed to incorporate plans and reports from regional and local entities. However, if only a handful of consumption and water use needs for localities are analyzed, water supply planners cannot create a plan that is relevant and applicable to all stakeholders. Consumption estimates from other locations and sectors may not be accurate for a different location or water use type. Using water use data from across the State and assessing consumption rates over different spatial scales may highlight areas that need improved reporting, assistance in water conservation techniques, drought alerts, etc. Ideally, consumption should be estimated using withdrawals with corresponding discharge records. However, not every withdrawing facility may be discharging into receiving waters (or has associated discharge records in the national database). This is particularly relevant for agriculture and municipal operations. Water withdrawn for irrigation will typically not have a corresponding discharge permit, as it is is considered a non-point source. Water that is metered within municipal treatment and supply facilities differs from other sectors, making it difficult to calculate municipal consumption on facility level. Regardless, attempting to assess consumption on various spatial scales can ultimately provide State planners the level of detail needed to create informed plans and policy actions, without relying on a large number of stakeholders

to provide separate assessments.

Other than limited study areas, exclusion and grouping of sectors often occurs in consumptive use studies. Most studies of consumptive water use focus on major industrial facilities. Required monitoring and reporting of discharge after the NPDES program was established in 1972, with a large focus on industrial effluent [37]. Relative to industrial uses, other sectors have been assumed to have cleaner effluent and smaller consumption rates. Particularly, the Energy sector is left out of analysis because it is assumed to be non-consumptive, although the quantity of water that electric generation facilities withdraw is orders of magnitude higher than other sectors.

The limited focus on select sectors removes valuable data that can be used to better characterize total water consumption and available water resources for the study area. As for categorization, aquaculture is commonly grouped with Agriculture or Commercial facilities. This may be misleading, as aquaculture processes often have lower consumption and may skew the average consumption rates of the sector it belongs to.

Addressing these gaps and estimating consumption rates will ultimately generate a more robust analysis of water use trends in Virginia. The consumption estimates generated from this study can then be compared to climatically similar literature values to provide more insight to regional trends and preconceived notions of consumptive use across water sectors. Ultimately, it's the hope that these results can be utilized by State water planners to create a clearer Water Resources Plan to ensure Virginia stays a water plentiful state for many years to come.

Table 2.6: Gaps in consumptive water use studies.

Gaps	Description
Use of Published Consumption Estimates	Accuracy and specificity is lost when consumptive use is estimated by using coefficients from climatically similar areas. Withdrawal and discharge maintained by the State can be used to calculate original estimates for the study area at question.
Limited Study Areas	Most consumption studies are limited to groups of facilities, single counties, or other small municipalities. With Statewide water resource management in mind, the study area should cover areas all over the state and a much broader range of facilities. The studies also failed to compare consumption over different spatial scales. Perception of water use and consumption will be different depending on if visualization takes a county, watershed, or regional approach.
Limited Sectors	Rather than providing a full analysis on water use over multiple sectors, some consumption studies focused on particular water use types (Table 2.4).
Energy Consumption	The energy sector is often disregarded in consumption analyses because it is assumed to be non-consumptive [41]. Water withdrawn for electricity generation overwhelm the amount of water used for any other sector. Even if the relative consumption for the energy sector is low, the quantity of water lost may be quite large. Therefore, this study analyzes energy consumption.
Aquaculture	Aquaculture is commonly grouped with Agriculture or Commercial facilities. Its lower rates of consumption bring the overall average consumption of the Agriculture sector down, which may be misleading. Analyzing it as its own sector may reveal previously unknown patterns.

Chapter 3

Research Objectives

This study is part of a broader effort with the USGS's Water-Use Data and Research Program, and specifically aims to estimate the consumptive water use in the State of Virginia. There is a need to quantify the amount of water that is being withdrawn and not returned to water resources for immediate use. These estimates of water consumption will be used to answer the following research questions:

- How do characterizations of consumptive use differ depending on water use sector and spatial scale?
- Are there statistically significant trends in consumption through time and do they vary by water use sector?
- How do consumptive coefficients for Virginia compare to literature values?

Accurate estimates of consumptive water use in Virginia can aid the DEQ's capacity to improve permitting, plan for water scarce scenarios, and understand the full water budget. This is accomplished by combining monthly withdrawal data maintained by the VDEQ and monthly discharge data maintained by the EPA. Consumption is calculated using a total volume and median facility approach over several spatial scales (e.g. State, Facility, County, and HUC 6) and water use sectors (e.g. Energy, Industrial, Municipal, Commercial, Agriculture/Irrigation, and Aquaculture).

Chapter 4

Methods

4.1 Data Description

4.1.1 Virginia Pollution Discharge Elimination System (VPDES)

ECHO's REST Services

Section 402 of the Clean Water Act-requires all point source discharges to obtain National Pollutant Discharge Elimination System (NPDES) permit [12]. All states are required to abide by the NPDES program, where governments are encouraged to perform the permitting, administrative, and enforcement responsibilities [2]. In Virginia, NPDES permits are issued by the DEQ (VPDES Program), while the Environmental Protection Agency (EPA) ultimately maintains authority. This requires the Commonwealth to have regulations comparable to the EPA's standards under their Virginia Discharge Elimination System Program (VPDES). Discharge Monitoring Reports (DMRs), which were utilized in this study, are available to the public on the EPA's Enforcement and Compliance History Online System (ECHO). A DMR is a water pollution report prepared by NPDES permitted facilities which contain effluent limits and actual values for each discharged monitored pollutant, where limitations depend on the water quality standards of the receiving water body [2]. ECHO is as-reported from original source databases (i.e. Virginia's NPDES Program) and represents

a snapshot of the data as it existed during extraction [2]. Therefore, data is typically more complete for major permits (Design Flow > 1.0 MGD), while data may vary for smaller facilities [12]. DMRs are routinely updated based on when data is entered for a facility (typically from a week up to three months).

Data can be retrieved using Representational State Transfer (RESTful) web services from the ICIS NPDES database located in ECHO. REST uses HTTP as its underlying protocol to perform API-based (Application Program Interface) tasks [3]. ECHO offers two web services to obtain discharge data; *Facility Search - Water* and *Effluent Charts* [3] [2]. In the *Facility Search - Water* service, there are compliance and enforcement data for over 800,000 regulated facilities in the United States. For each facility, there are 299 possible attributes (known as qcolumns) that include information ranging from facility ID, location, permit type, etc. [3]. In efforts to decrease the curse of dimensionality (800,000 * 299 possible entries), only relevant parameters (e.g. State) and attributes (e.g. FacilityID, Latitude/Longitude, Permit Type) were included in the request URL. Using R (version 3.5.1), the customized request URL was downloaded, parsed (to obtain a query ID), and returned to obtain a list of 1,143 regulated facilities with an NPDES individual permit in Virginia.

With this list of facilities, the *Effluent Chart* REST service was used to obtain all tables of permitted effluent limits, releases, and violations over a defined date range for each effluent outfall. An outfall is a permanent point source that discharges effluent to an open body of water [36]. Each effluent chart provides detailed data of discharge limits, Discharge Monitoring Reports, and NPDES Violations. There are 300 unique Clean Water Act (CWA) parameter codes that represent effluent pollutants defined by the EPA, as well as 183 units of measure [2]. For this study, the parameter code 50050, flow in conduit or thru treatment plant, was passed through the query. It is possible that facilities may report discharge underneath another parameter code, however, code 50050 returned the greatest number of

DMRs for the facilities located in Virginia.

Because of this, it became clear that not every facility acquired from the *Facility Search* REST service returns discharge monitoring reports within the specified date range. This may be due to the selected parameter code, or the presence of permits that were terminated or expired before the year 2010. The time period of data displayed in ECHO is also variable and is considered partially complete before the year 2009 when using the online REST services [3]. As of June 2017, Virginia has recently begun data flow for non-major NPDES permits to ECHO; therefore DMRs may not be accurate for smaller discharging facilities [2]. Pre-processing efforts here include querying for *Flow, in conduit or thru treatment plant* (parameter code = 50050), monthly averages (in MGD), and setting the date range to 01/01/2010-12/31/2016. This date range addresses potential data quality issues that come before the year 2010 in ECHO and matches the latest date of available withdrawal data (discussed in Section 4.1.2).

In the end, 25,849 monthly average discharges from 734 facilities (1,098 outfalls) were extracted from the *Effluent Chart* REST service. It was however discovered that reporting frequencies differ among facilities (i.e. Annually, Semi-Annually, Quarterly, and Monthly) (Table 4.1). For each DMR, there is an attribute labeled *nmbr of submission*, which indicates the number of months represented in the report [2]. Thus, if a facility reports annually, there is only one submitted report, which represents the monthly average discharge across all months within that respective year.

Therefore, additional measures were taken to convert annual, semi-annual, and quarterly submissions into separate monthly submissions for analysis. Of the 25,849 discharge reports, 237 are annual submissions, 361 are semi-annual submissions, and 908 are quarterly. This results in a data frame of 31,812 monthly average discharges from 734 facilities (1,098 out-

Table 4.1: Discharge monitoring reports may be submitted at varying frequencies. Frequency corresponds to the number of months represented in the report.

Reporting Frequency	Facilities	Outfalls	Entries
Annual	23	78	237
Semi-Annually	15	49	361
Quarterly	68	116	908
Monthly	674	860	24,343

falls) between 01/01/2010-12/31/2016. Once conversions were completed, outfall types were labeled using the *perm feature type code* attribute found in each DMR. External outfalls track the water that is leaving the facility as discharge. Internal and internal sum outfalls then track the water that is being used within the facility, while MS4 outalls track stormwater runoff in municipal seperate storm sewer systems [18].

4.1.2 Virginia Wateruse Database System (VWUDS)

Monthly withdrawals from surface and groundwater in Virginia are regulated by the VDEQ Office of Water Supply. Surface water withdrawals (in Million gallons per month (MGM)) are self reported by users under the Virginia Water Protection Permit Program (VWP), which are submitted once a year to represent withdrawals from the previous calendar year [38]. VWPs are required for all surface water withdrawals, unless they qualify for exemption. Ground water withdrawals are collected separately through the Groundwater Characterization Program, which is mandated under the Ground Water Management Act of 1992 [6].

On average, surface water withdrawals make up about 98% of the total water that is withdrawn each year from 2010-2016, where groundwater makes up the remaining 2% (Figure 4.1). Reporting is required for those that exceed 10,000 gal/day on average, or agricultural users that exceed 1 MGM in a single month [41]. This threshold and grandfathering clauses exempts half of surface water users from obtaining a permit [21]. Nevertheless, exempt water

users are encouraged to voluntarily report their water withdrawals.

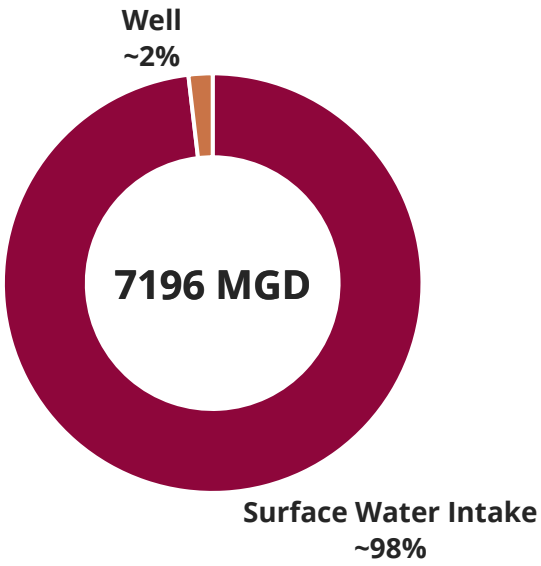

Figure 4.1: Median percentage of water withdrawals by source in Virginia. Median long-term statewide annual withdrawals in million gallons per day in middle.

Regardless of permit status, reported monthly withdrawals are stored in the Virginia Water Use Data System (VWUDS), which is not publicly available, but can be accessed through cooperative efforts with the VDEQ. There are approximately 1.35 million entries that represent monthly withdrawals from 4,132 facilities and 7,119 sources from 01/01/1982-12/31/2017. The data was trimmed to 01/01/2010-12/31/2016 to match the range of the discharge data, and contains 358,4962 entries with 1,860 facilities and 5,110 sources (Figure 4.7; Tables 4.12 and 4.13). Additional attributes such as unique facility ID, withdrawing source ID, owner, facility name, monitoring period end date (yyyy-mm-dd), quantity withdrawn (MGM), facility status, water use sector, coordinates, and source type (well vs. surface water) are included in the data set. The VDEQ recognizes nine water use sectors including agriculture, irrigation, commercial, manufacturing, mining, fossil fuel power, hydropower, nuclear power, and public supply [39]. The main sources of noise originate from self-reported nature of the data. This includes missing/incorrect coordinates on a withdrawing point level and

inconsistent categorization of water use sectors.

4.2 Data Processing

4.2.1 Classification of Water Use Sectors

The self-reporting nature of withdrawal and discharge data, as well as different reporting requirements, promotes inconsistent classification of facilities into water use sectors. Specifically, all facilities in ECHO were categorized as either Industrial (27%), Municipal (68%), or NA (5%). This general classification associates energy producing facilities with industrial facilities. The classification of facilities in the withdrawal data (VWUDS) includes 13 different sectors (see Figure 4.2). Therefore, a semi-supervised learning approach involving text mining and rule-based classification was used to sort unlabeled facilities into one of six water sectors: Agriculture/Irrigation, Aquaculture, Commercial, Energy, Industrial, or Municipal.

In this analysis, power stations, fossil power, and nuclear power facilities were classified in the Energy Sector [20]. Hydropower facilities were not included because they are assumed to be non-consumptive [38]. Municipal facilities include public suppliers, water treatment, and wastewater treatment facilities. Commercial facilities are public centers that are not considered to be residential [42]. This includes golf courses, hotels, schools, prisons, etc. Agricultural/Irrigation facilities include farms, dairy farms, and nurseries. The vast majority of these facilities do not have a corresponding discharge permit associated with them, but aquaculture facilities do. Therefore, aquaculture was analyzed separately from agriculture. Most studies assume water used for agriculture and irrigation of crops is completely lost through evapotranspiration [19]. The industrial sector then covers manufacturing, mining, and industrial waste treatment from facilities.

An incomplete list of Standard Industrial Classification (SIC) codes, which describe the

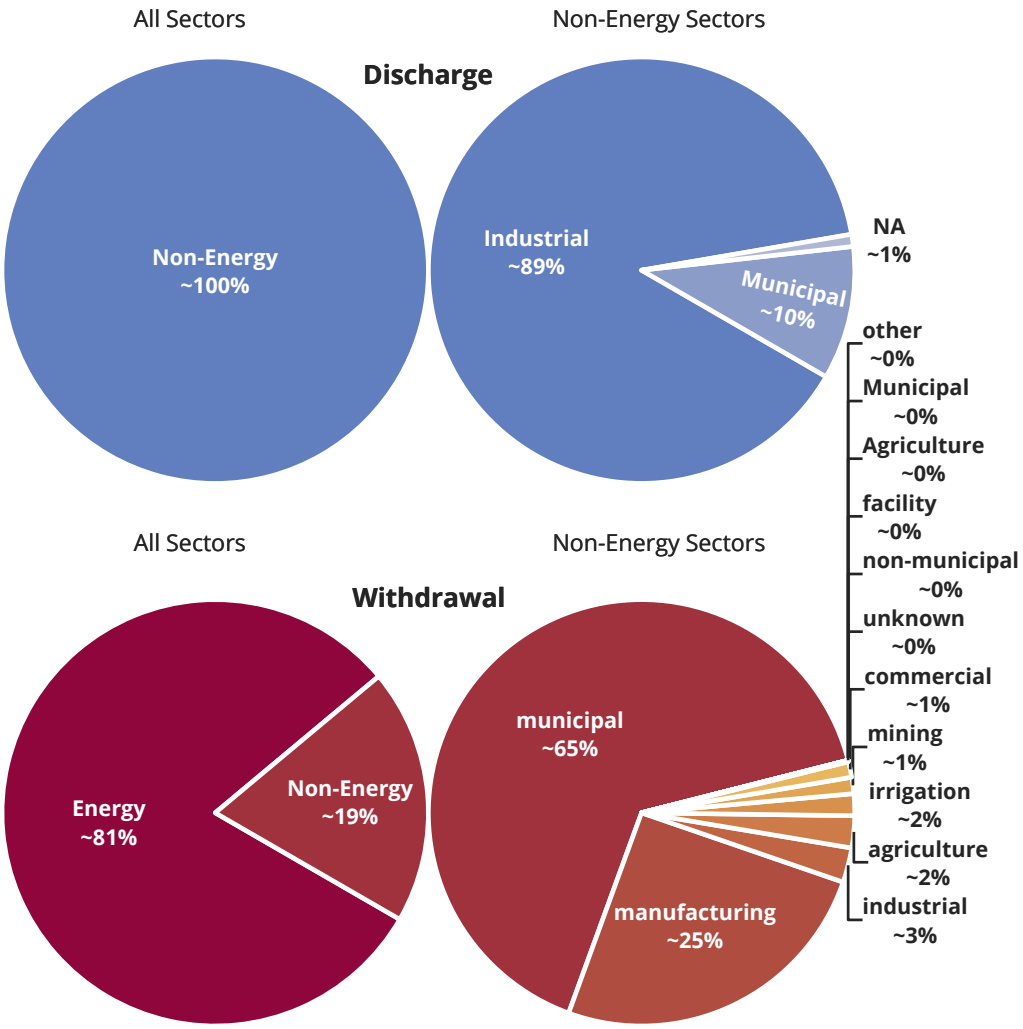

Figure 4.2: Distributions of discharges (top) and withdrawals (bottom) by sector before classification methods, with energy vs. non-energy sectors on the left and non-energy sectors on the right. Annual average in MGD over 2010-2016.

primary use of a business, are available for VPDES permitted facilities in ECHO [3]. These codes were used to initially classify the water sector for each discharging facility. Rule-based classification was then only applied to facilities without an SIC code or obvious sector. Using guidance from domain experts and a training set of 1,793 VWUDS facilities, text mining techniques (using the *findFreqTerms* function in R) were used to find the most frequent terms in facility names by water sector. Table 4.2 shows the top frequent terms found in VWUDS facility names in major VDEQ recognized sectors. This approach is considered to be semi-supervised, because it uses a smaller training set of VWUDS facilities where the labeled water sectors are considered to be "correct", to classify the unknown VPDES records and sort VWUDS facilities.

Table 4.2: Frequent terms found in withdrawing facilities names by major sector (VWUDS).

Agriculture		**Irrigation**		**Commercial**		**Energy**		**Mining**		**Manufacturing**		**Municipal**	
152 Facilities		**426 Facilities**		**401 Facilities**		**19 Facilities**		**55 Facilities**		**101 Facilities**		**639 Facilities**	
Term	**n**	**Term**	**n**	**Term**	**n**	**Term**	**n**	**Term**	**n**	**Term**	**n**	**Term**	**n**
farm	83	farm	142	golf	172	power	13	plant	37	plant	67	service	189
farms	22	farms	79	club	158	station	8	quarry	11	wtp	9	area	188
hog	10	inc	49	course	82	plant	6	prep	8	plt	4	wtp	100
production	10	dairy	19	country	80	combustion	2	mine	5	roanoke	3	water	61
smithfield	10	llc	16	creek	19	facility	2	creek	4	inc	2	system	49
nursery	9	nursery	14	park	17	river	2	big	3	intake	2	town	35
dairy	8	william	10	lake	15	site	2	moss	3	mill	2	park	24
complex	5	hill	9	ridge	12	turbine	2	rock	3			county	20
fish	5	james	9	river	11	fossil	1	stone	3			home	17
hill	4	bain	8	resort	10	nuclear	1	gravel	2			lake	16

The challenge of this approach is finding unique terms in facility names that encapsulate a sector, but are not prevalent in other sectors. For example, the term "INC." is present in a vast majority of industrial facilities, however it is also present in commercial and agricultural facilities. Therefore, INC. and other legal terms (e.g. LLC. and LLP.) should not be used to classify facility type. Using facility names as a basis of classification has its limits, and those limits should be taken into consideration. For instance, there are many withdrawing agricultural facilities that simply include the name of the owner, with no unique terms, in

their facility name. Water treatment plants can also belong in the municipal or industrial sectors. Therefore, the rules created in this process involved domain expertise and several iterations in efforts to decrease training error.

Rules were created using the *grep()* function in R, which searches for terms that match the defined pattern vector. The classification rule for the Energy Sector (Listing 4.1) includes the following patterns:

```
1          if(length(grep('\\bPOWER\\b',Wateruse$Facility_Name[i]))>0|
2               length(grep('\\bPOWER STATION\\b',Wateruse$Facility_Name[i]))
                    >0|
3               length(grep('\\bCOMBUSTION\\b',Wateruse$Facility_Name[i]))>0|
4               length(grep('\\bENERGY\\b',Wateruse$Facility_Name[i]))>0){
5             Wateruse$Reclass_Use_Type[i]<-'Energy'
```

Listing 4.1: Example of rule-based classification for the water use sector attribute based on terms in facility name.

Since terms in facility names may trigger more than one rule, all rules are ordered according to their priority. This implies that rules are induced by sequential covering, removing facilities that are covered by a rule before moving onto the next rule. Classification rules are ordered with energy first and industrial facilities last. Energy facilities withdraw and discharge the most water, therefore their correct classification is the most important as to not skew the distribution of water quantities in the other sectors. Industrial is at the bottom of the rule set due to its lack of unique terms relative to the other sectors. If none of the rules are fired, the class was ultimately assigned to its original classification (which can be referred to the default class). This process was used for both discharging (testing set) and withdrawing (training set) facilities. Distributions of water use sectors before classification are represented in Figure 4.2. Distributions after these classification rules are represented in Figure 4.3 and

were corroborated with results published by the VDEQ in 2015 [21].

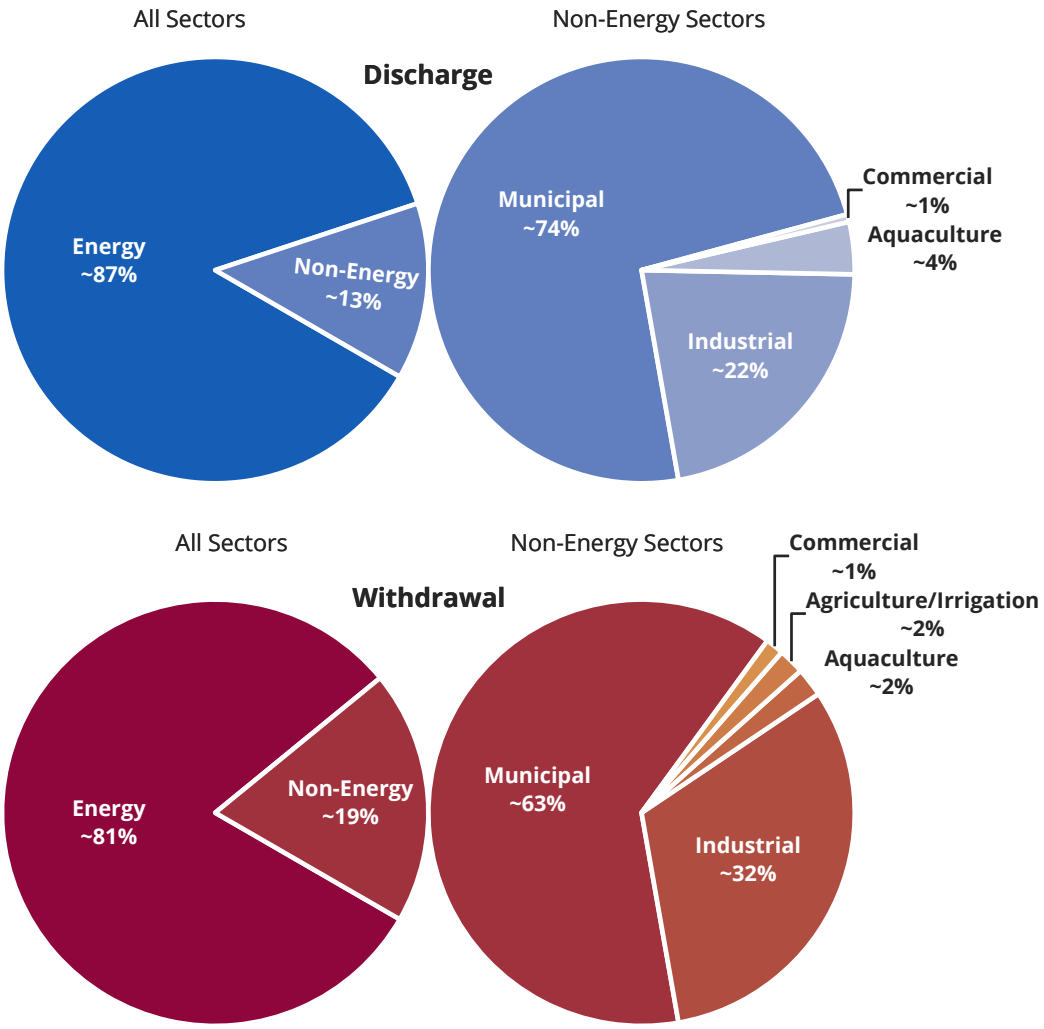

Figure 4.3: Distribution of discharges (top) and withdrawals (bottom) by sector after classification methods, with energy vs. non-energy sectors on the left and non-energy sectors on the right. Annual average in MGD over 2010-2016.

4.2.2 QA/QC Methods of ECHO REST Services Data

Suspected human input errors (Section 4.2.2), inclusion of hydroelectric generating facilities (Section 4.2.2), mislabeling of outfalls (Section 4.2.2), and generalizations of water use sectors (Section 4.2.1) are the main sources of noise in the discharge data obtained from ECHO (Table 4.3). The following sections describe QA/QC procedures used to address these issues.

Hydroelectric and Anomalous DMR Entries

Once discharge data were collected, flows were summed by reporting month (MGD) and plotted to visualize areas that may require quality assurance and control measures (QA/QC). This revealed months with skewed effluent, orders of magnitude higher than expected. Domain experts, Robert Burgholzer and Joseph Kleiner from the VDEQ's Office of Water Supply, were consulted to identify typical ranges for discharge data, based on their knowledge of water withdrawals. Collectively, sources of skewing were identified as the inclusion of hydroelectric power facilities and few accounts of human input error.

Water used for hydroelectric power generation is assumed to be nearly non-consumptive [42]. Therefore, diversions for hydro-power are exempt from annual reporting to the VDEQ [38]. Consequently, withdrawal data for this type of power generation is incomplete for the Commonwealth. Discharges, however, are still reported to the VPDES program and represent a large sum of water [41]. Without corresponding withdrawals, consumption will be skewed greatly. Therefore, seven hydro-power facilities (representing an average additional 45 MGD per year) were excluded from the discharge data (Table 4.4).

As for the suspected human error, criteria were generated using brute force association analysis with guidance from domain expertise. Monthly discharge entries were sorted from high to low reported effluent values (in MGD) and manually examined for common patterns.

Table 4.3: QA/QC Methods applied to VPDES Data retrieved from ECHO REST Services

Challenge	Description	Resolution
Duplicate DMR Entries	There are cases where facilities enter discharge quantities twice for an outfall for a given monitoring period. This leads to double counting of flow and skews estimates of consumption.	Entries were removed using the *!duplicated()* function within R.
Differing Reporting Frequencies	Most facilities report discharges on a monthly basis; however, there are instances of facilities reporting once, twice, and four times out of the year. A single DMR is submitted for the monitoring period and represents a monthly average. Therefore, discharge for the individual months within the monitoring period are not represented. This underestimates facility discharge for the given reporting period.	A function was created to take the singular annual, semi-annual, and quarterly submissions and split them into individual DMRs to represent the monthly average for the given reporting period.
Hydroelectric Generating Facilities	Water utilized for hydropower is considered to be nearly non-consumptive [40]. Hydropower facilities have been removed from the VWUDS data set due to a change in reporting requirements, but discharges are still found within the ECHO system. This adds an overwhelming quantity of discharge to statewide estimates without matching withdrawals to balance it out.	Hydropower facilities with individual NPDES permits were removed from analysis (Subsection 4.2.2).
Anomalous Discharge Quantities	There are instances of suspected human error within the reported effluent values. This includes discharges exceeding median flows by order of magnitude.	Criteria were created to flag entries that exceed design flow, exceed median outfall discharge for a given year by orders of magnitude, and report a design flow of zero. Extreme flagged entries were then replaced with the median outfall discharge for the given year (Subsection 4.2.2)
Mislabeled Outfalls	Outfalls that track stormwater, internal processes, and MS4s are also included in DMRs [18]. By default, each outfall is labeled as external in the ECHO system. Through collaboration with VPDES permitting, this has been deemed to be inaccurate and misleading, creating a surplus of discharge that is not representative of return flows of water that is withdrawn.	Through a case study analysis, outfall classification was confirmed with domain expertise (Table reference to appendix).
Classification of Water Use Sector	ECHO classifies all facilities in the *Facility Search - Water* REST service as either industrial or municipal. This is misleading and limits the ability of a data analyst to estimate consumption on a sector basis.	Standard Industrial Classification codes were used to initially classify a water use sector for each facility. For the unknown records, a semi-supervised learning approach with text-mining and rule-based classification was applied (Section 4.2.1).

Table 4.4: Seven unique discharging hydroelectric facilities retrieved from ECHO were excluded from discharge data.

Year	Facilities	Outfalls	Entries	Discharge (MGD)
2015	6	44	293	45.3
2016	7	45	532	44.6
Ave	**7**	**45**	**413**	**45**

It was found that anomalous entries typically have effluent values that exceed its median outfall discharge for a given year in orders of 100, and sometimes 1,000,000 magnitude. Records with effluent values that exceed its facility's design flow, or report a design flow equal to zero are also noted as suspicious. Using these four criteria as association rules, 3,009 unique DMR entries (out of 30,987) were flagged as anomalous (Table 4.5).

Table 4.5: DMR entries were flagged based on four anomaly criteria. Approximately 10% of entries were flagged.

	Flagging Criteria					
	Design Flow = 0	DMR Value > 100*Median	DMR Value > 10^6*Median	DMR Value > Design Flow	**Total Entries**	**Total Flagged**
DMR Entries	1,940	25	1	1,707	30,987	3,009
Facilities	12	13	1	152	727	162

The flagged entries were then subsetted and examined to indicate which criteria best detects an anomaly (or which does not). This required domain expertise and manual exploration of the discharge records. The top ten flagged entries with the highest difference between its reported effluent and the median flow for its respective outfall were investigated. It became clear that entries with multiple flags were the most suspicious, especially, with the presence of exceeding median outfall discharge for a given year. Exceeding design flow also proved to not be a good indicator of anomalies. Major facilities, like the North Anna Nuclear Power Station, report design flows of 0.0 MGD. While this is an indication that design flow reporting should be examined, it is not a good enough indicator to determine if a discharge entry is erroneous. Since each criteria has its own level of urgency, a decision tree was created

to decide how to resolve the suspicious entries.

Instead of treating each flagging criteria as a node on a decision tree, a singular weighted flag is used as the splitting attribute. Each flag is assigned a subjective weight from 0 to 1 (where 1 indicates the most error potential) and summed to equal an overall weighted value (Table 4.6).

Table 4.6: The criteria used to flag DMR entries were weighted to represent their ability to detect meaningful anomalies.

Design Flow = 0	DMR Value > 100*Median	DMR Value > 10^6*Median	DMR Value > Design Flow	Weighted Flag
0.15	1.0	1.0	0.5	$\sum(Flags)$

If a discharge entry has multiple flags, like Dominion Terminal Associates LLP in Table 4.7, each flag is assigned a binary value of 1. The weights from Table 4.6 are applied to each binary value and summed in a weighted sum column. This continuous attribute is then used to split the flagged entries into two classes: high concern and low concern. If the weighted flag value is greater than or equal to 1, it is labeled as high concern. Otherwise, it is labeled as a low concern. As a result, the entry in Table 4.7 is marked as anomalous.

Table 4.7: Example of anomalous DMR entry given by Dominion Terminal Associates LLP in June of 2016.

Measured Effluent (MGD)	**Median Effluent (MGD)**	**Design Flow (MGD)**	**Date**	**Design Flow = 0**	**DMR Value > 100*Median**	**DMR Value > 10^6*Median**	**DMR Value > Design Flow**	**Weighted Flag**
441,000.00	0.536	1.01	2016-06-01	0	1.0	0	0.5	1.5

Of the 30,987 discharge entries, 3,009 were flagged, and 25 were labeled as a high concern and replaced with its median outfall discharge (Table 4.8). The remaining flagged entries, labeled as low concerns, were left intact. This small percentage of low concerns flags is due to misleading design flows provided by VPDES permits. Some design flows underestimate facility's actual capacities, so when a measured effluent exceeds this limit (even by a minor

amount), it is flagged. This leads to a numerous amount of flagged entries that do not require replacement.

Table 4.8: Flagged DMR entries with weighted flags greater than 1 (approximately 0.8%) were deemed to be true anomalies.

Error Potential	**Low**					**High**
Weighted Flag	**0.0**	**0.15**	**0.5**	**1.0**	**1.5**	**2.5**
DMR Entries	28,159	1,940	1,688	6	18	1

Outfalls

The Clean Water Act parameter code 50050 allows for users to query for flow, in conduit or through a treatment plant in ECHO [2]. A multitude of other parameter codes related to flow exist in the system, but 50050 returns the greatest number of DMRs for the facilities located in Virginia. It is possible to use a combination of multiple parameter codes to obtain discharge records for facilities that do not report under code 50050, but this will increase computational expense and may introduce more noise into the analysis. Because this parameter includes flow through facilities, there is a presence of additional outfalls that track more than the water leaving a facility and entering open waters. Other than external outfalls, internal and MS4 outfalls track internal processes and storm water flows, respectively [2]. Internal outfalls are often identified to ensure tracking of effluent concentrations that may be diluted at the final external outfall ([12]). This ultimately causes a surplus of discharge if not identified and removed from analysis. Unfortunately, accurate labels of outfalls are not represented in ECHO, as a result of being an as-reported data system. Consequently, the default type for outfalls in the Effluent Chart REST service, is external (1,078 out of 1,098).

With the guidance from Andrew Hammond of the VDEQ's Office of VPDES Permitting, it was concluded that outfall IDs labeled with leading zeros (e.g. 001, 002, 003, etc.) are representative of external outfalls, while outfalls leading with other positive integers (e.g.

101, 102, 103, etc.) represent internal outfalls [12]. Typically, it is assumed that outfall 001 is representative of the flow leaving a facility. This assumption, however, doesn't apply to 45 facilities, which lack an outfall ending in 001 in ECHO. It also doesn't apply to facilities that designate their 001 outfall to tracking storm water associated with a regulated industrial activity [12]. Therefore, these facilities were handled on a case-by-case basis (Appendix B). Ultimately, excluding internal outfalls decreases the data set from 1,098 unique outfalls (31,812 DMR entries) to 729 unique outfalls (18,024 DMR entries) from 2010 through 2016.

Figure 4.4 shows total monthly reported discharges in MGD after QA/QC methods in the energy and non-energy sectors. Yearly estimates of total reported discharge in MGD are found within Tables 4.9 and 4.10. Annual estimates were aggregated by summing outfall level discharge for each facility (MGD) per year and dividing by the number of reporting months for each year between 2010 and 2016. Energy discharges are significantly greater than non-energy discharges, and are separated for the entirety of the study. Figures 4.5 and 4.6 then show the physical locations of energy and non-energy VPDES facilities over median annual discharge (averaged over 2010-2016) by county in MGD. The size of each respective facility is based on its median reported discharge over 2010-2016 in MGD. The shape of energy facilities indicates the type of fuel used.

Table 4.9: Total annual reported energy discharge (MGD) per year (2010-2016). Aggregated by facility and year and divided by number of reporting months.

Year	Facilities	Outfalls	Entries	Total Discharges (MGD)	% Change
2010	8	10	103	4,891	
2011	10	12	139	4,810	-1.7%
2012	12	15	152	5,098	6.0%
2013	13	16	182	5,340	4.7%
2014	13	16	191	5,346	0.1%
2015	22	25	237	5,351	0.1%
2016	23	26	309	5,323	-0.5%
Ave	**14**	**17**	**188**	**5,166**	**1.50%**

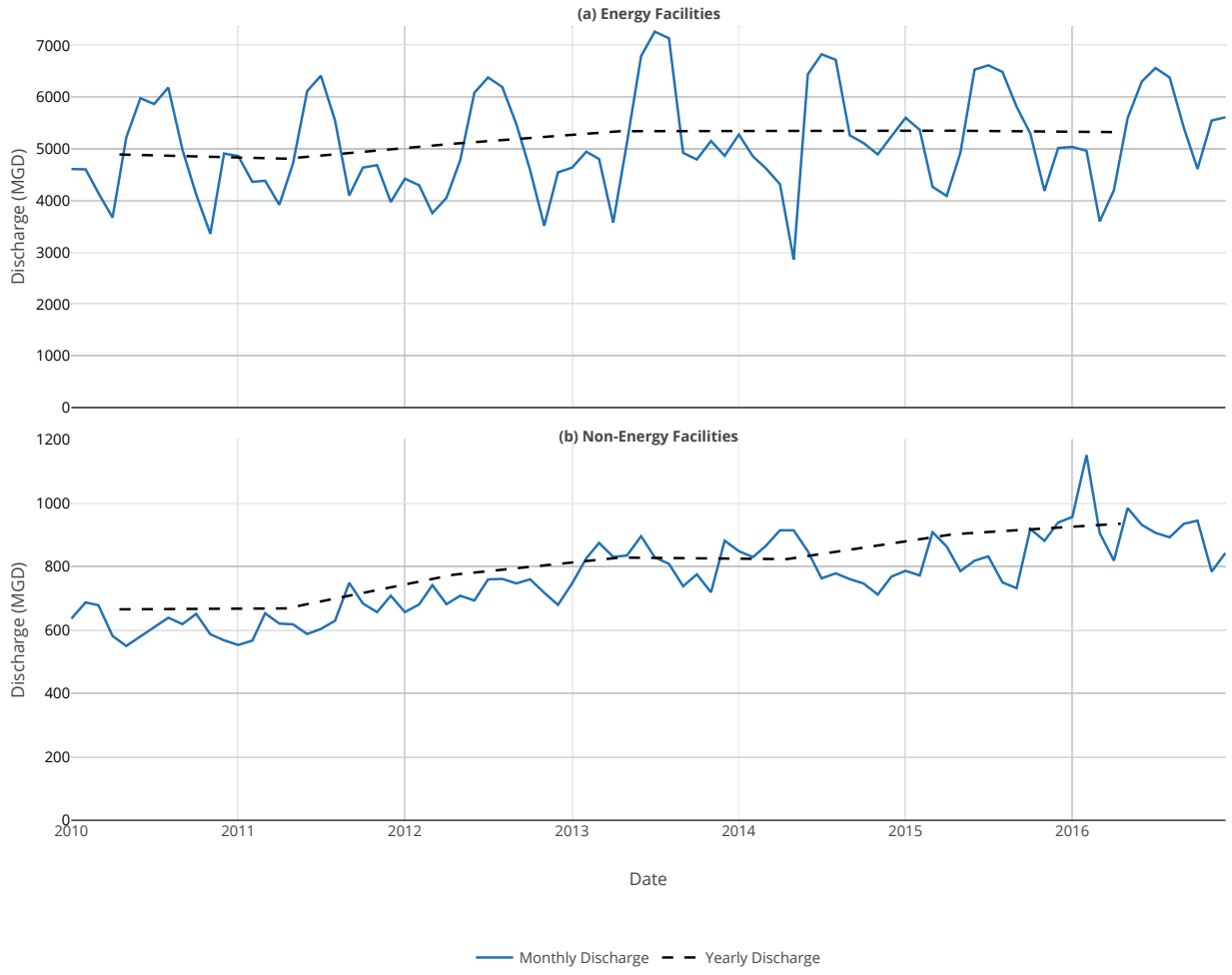

Figure 4.4: Total monthly reported discharge (MGD) after QA/QC methods (2010-2016) for (a) Energy and (b) Non-Energy sectors. Energy represents 85% of total discharge.

Table 4.10: Total annual reported non-energy discharge (MGD) per year (2010-2016). Aggregated by facility and year and divided by number of reporting months.

Year	Facilities	Outfalls	Entries	Total Discharges (MGD)	% Change
2010	81	81	873	665	
2011	104	104	1,109	668	0.4%
2012	121	121	1,315	774	15.9%
2013	118	118	1,390	828	7.0%
2014	119	119	1,411	823	-0.6%
2015	590	590	2,857	902	9.5%
2016	695	695	7,749	935	3.7%
Ave	**261**	**261**	**2,386**	**799**	**6.0%**

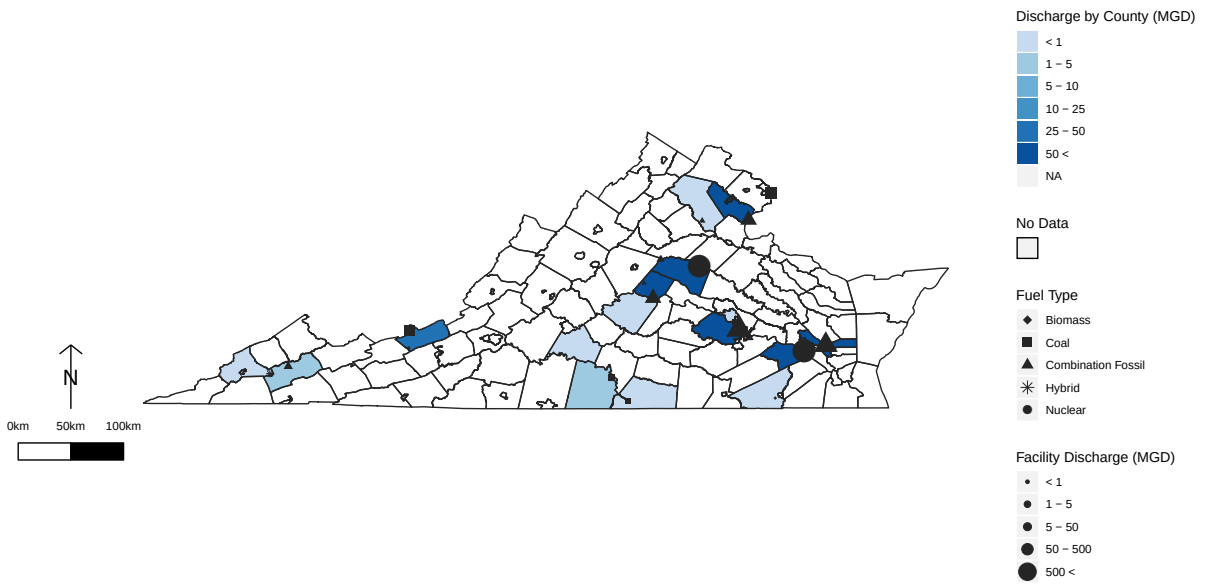

Figure 4.5: Median total annual county energy discharge (MGD) with locations of energy facilities. Size of facility is based on median annual reported discharge in MGD, while the shape indicates type of power facility.

Figure 4.6: Median total annual county non-energy discharge (MGD) with locations of non-energy facilities. Size of facility is based on median annual reported discharge in MGD.

4.2.3 QA/QC Methods of VWUDS Data

Missing/Anomalous Coordinates

Data retrieved from the VWUDS has been vetted by VDEQ employees in the Office of Water Supply. Applied QA/QC methods include identifying suspected unit conversion errors, by comparing five year and two year water withdrawal averages to the current reporting values to detect order of magnitude conflicts [13]. Missing values are also checked for via a "signed and submitted" feature. If a user fails to sign and submit their withdrawal report, they are contacted for a follow-up, starting with larger users (> 1MGD). Other sources of noise, including anomalous coordinates and classification of water use sectors were however addressed in this analysis. Of the 5,110 withdrawing sources in VWUDS, 956 sources are flagged for instances of missing coordinates (either (-9999,9999), (0.1, 0.0), (NA,NA)) or incorrect coordinates that dramatically exceed the physical boundaries of the State (-83 to -75 for Longitude, 36 to 39.5 for Latitude) (Table 4.11). Google Maps and the use of associated information (County Name, Facility Name, Source Name, etc.) were used to locate the exact coordinates of the missing withdrawal locations. Latitudes and Longitudes provided by Google Maps are recorded with an accuracy to six digits. If exact coordinates could not be found (due to lack of sufficient information), the center of the reported city or county was used. This allows for spatial analysis to be performed on the withdrawal data.

Table 4.11: Water withdrawal sources were flagged if coordinates were missing or exceeded the boundaries of Virginia.

Latitude	**Sources**	**Longitude**	**Sources**
>39.46601	185	**>-75.16643**	460
<36.54076	578	**<-83.67539**	276
NA	182	**NA**	182
-99	104	**-99**	276

Figure 4.7 shows monthly reported withdrawal (MGD), with energy withdrawals on the top and non-energy on the bottom. Tables 4.12 and 4.13 show yearly summaries of reported withdrawals in the energy and non-energy sectors, respectively. Figures 4.8 and 4.9 then show the physical distribution of energy and non-energy VWUDS facilities post QA/QC.

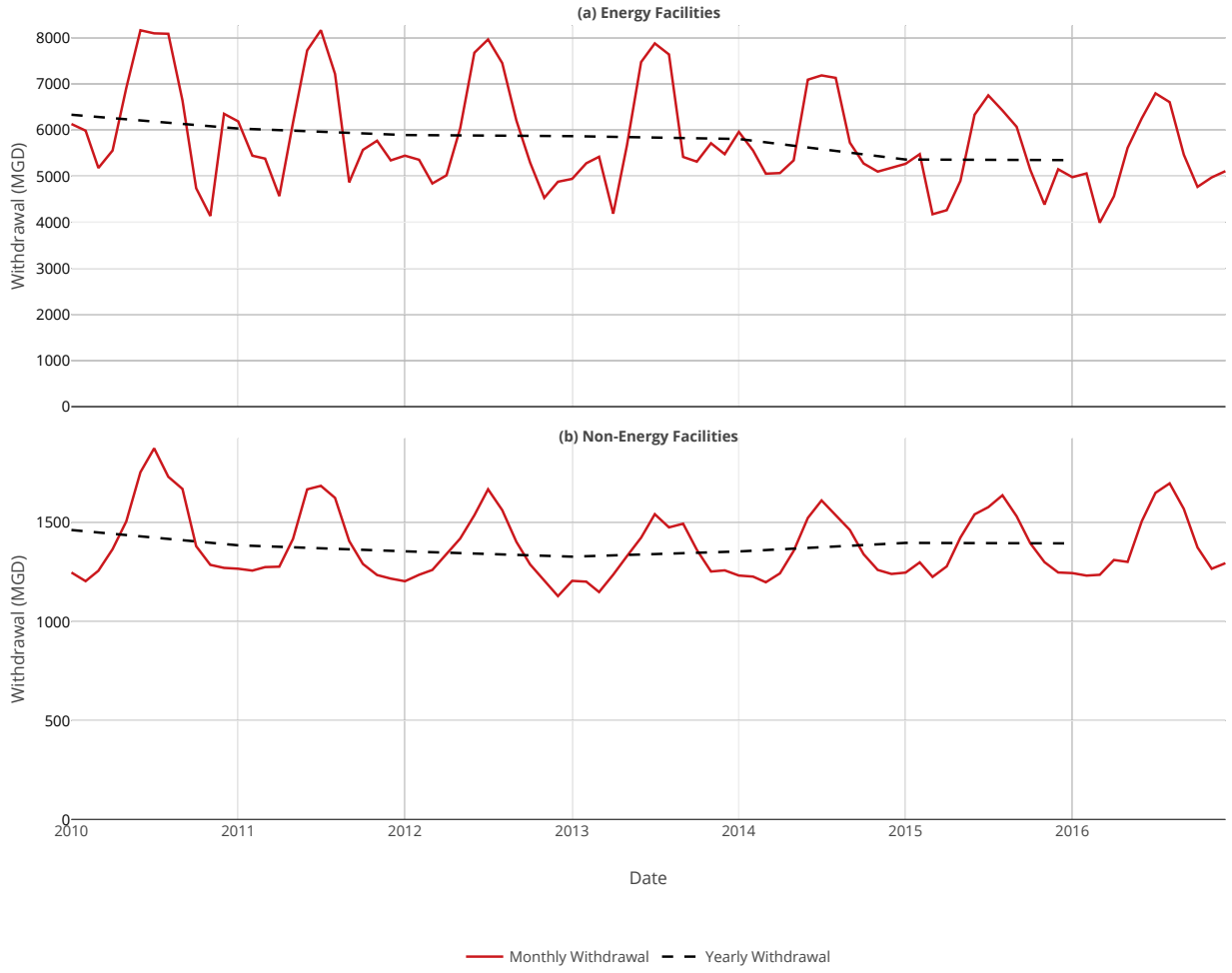

Figure 4.7: Total monthly reported withdrawal (MGD) (2010-2016) for (a) Energy and (b) Non-Energy sectors. Energy facilities (a) represent 80% of total withdrawals on average.

Table 4.12: Total annual reported energy withdrawal (MGD) per year (2010-2016). Aggregated by facility and year and divided by number of reporting months.

Year	Facilities	Sources	Entries	Total Withdrawal (MGD)	% Change
2010	21	66	792	6,331	
2011	21	67	804	6,033	-4.7%
2012	21	68	816	5,892	-2.3%
2013	21	68	816	5,867	-0.4%
2014	20	67	804	5,806	-1.1%
2015	20	64	760	5,360	-7.7%
2016	20	68	774	5,348	-0.2%
Ave	**21**	**67**	**795**	**5,805**	**-2.73%**

Table 4.13: Total annual reported non-energy withdrawal (MGD) per year (2010-2016). Aggregated by facility and year and divided by number of reporting months.

Year	Facilities	Sources	Entries	Total Withdrawal (MGD)	% Change
2010	1,550	4,181	50,183	1,463	
2011	1,546	4,179	50,160	1,386	-5.3%
2012	1,553	4,216	50,604	1,355	-2.2%
2013	1,547	4,200	50,412	1,328	-2.0%
2014	1,684	4,411	52,934	1,355	2.0%
2015	1,655	4,225	48,879	1,398	3.2%
2016	1,646	4,266	49,724	1,396	-0.2%
Ave	**1,597**	**4,240**	**50,414**	**1,383**	**-0.75%**

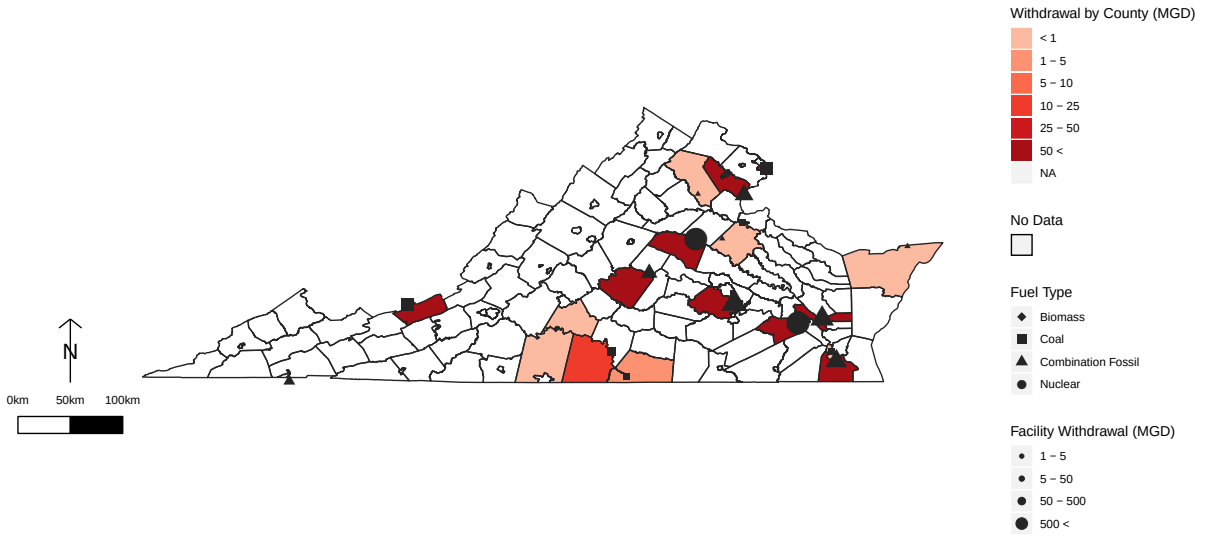

Figure 4.8: Median total annual county energy withdrawal (MGD) with locations of non-energy facilities. Size of facility is based on median annual reported withdrawal in MGD, while the shape indicates the type of power.

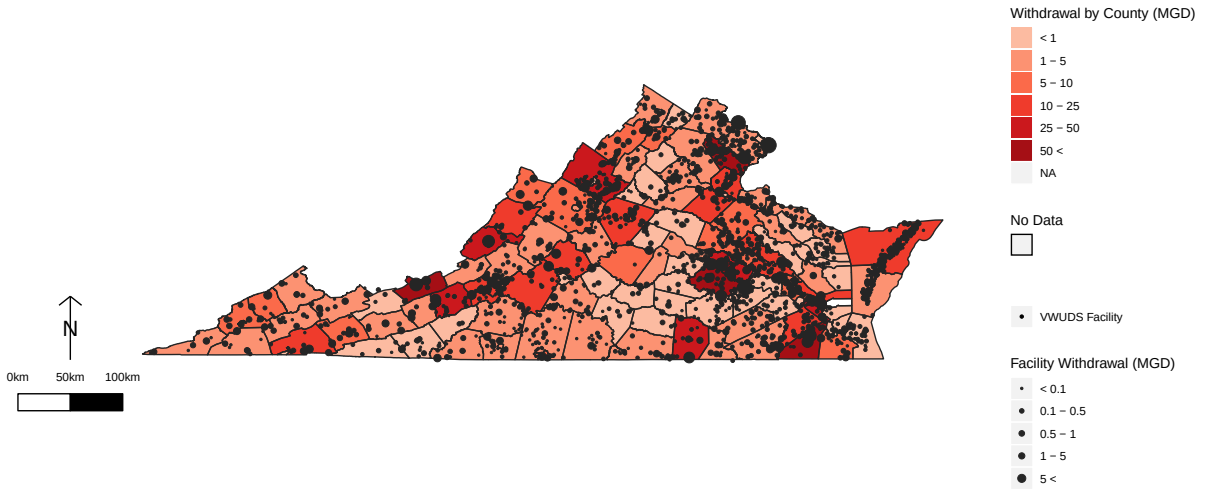

Figure 4.9: Median total annual county non-energy withdrawal (MGD) with locations of non-energy facilities. Size of facility is based on median annual reported withdrawal in MGD.

4.2.4 Facility Level Analysis: Matching Facilities

Under ideal conditions, there would be a one-to-one match for every facility in the VWUDS system to the VPDES permitted facilities in ECHO. However, the disconnect in regulations, reporting, and data sources affects the quality and availability of data utilized in this analysis (Table 4.18). There are some withdrawing facilities that won't have a single (or any) discharge facility associated with them. This applies to municipal and agriculture/irrigation operations. Even instances where a facility is reporting withdrawal and discharge, attributes including facility name and coordinates may differ slightly. Despite these challenges, a mechanism was developed to match as many VPDES permitted facilities to their corresponding facility in the VWUDS database 4.10. Matching facilities increases the accuracy of consumption estimates and explores the sources of error in the data.

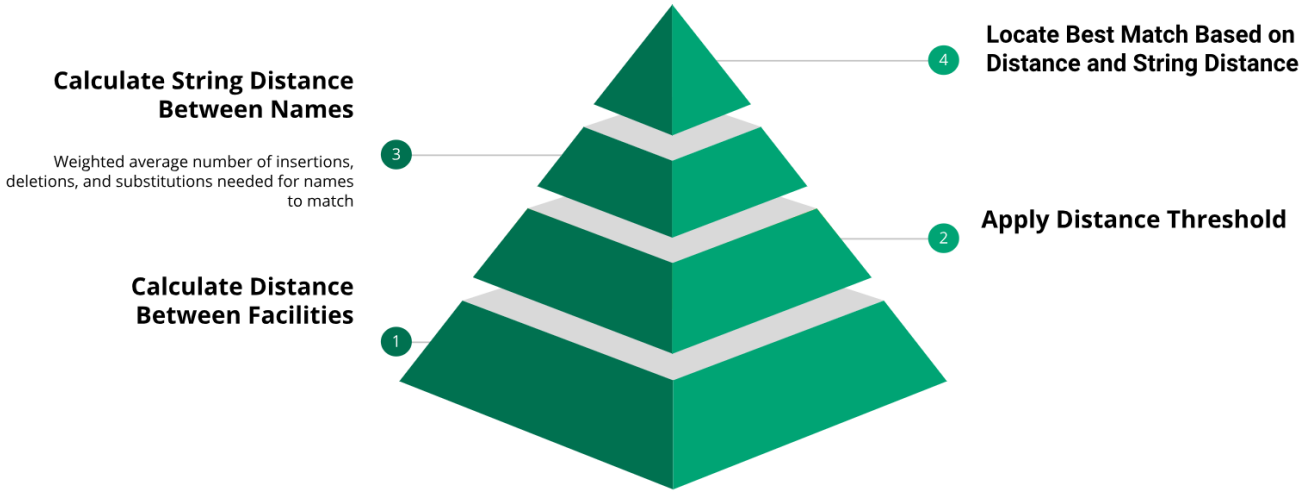

Figure 4.10: Discharging facilities obtained from ECHO were matched to their corresponding withdrawal facility in VWUDS based on distance and facility name.

Potential matches for facilities are first narrowed down by distance and then by facility name. The mechanism was optimised by implementing a search radius from each VPDES facility and using fuzzy logic to compare facility names. The accuracy of facility coordinates and

names may differ depending on the size of the facility. According to ECHO, data is more complete for active and major permitted facilities (Design Flow > 1.0 MGD) [3]. Specifically in Virginia, additional attributes, including owner, average withdrawal/discharge, sector, and county, were used to ensure accurate matching.

Narrowing facilities based on distance is the first step to the matching mechanism. The *distm* function in R calculates the Haversine distance between each singular VPDES facility to every facility in the VWUDS data set; where Haversine is the shortest distance in km between two spatial points, assuming earth is spherically shaped. Computational expense here can be decreased by subsetting facilities by sector or facility size. Regardless, a matrix with the distance between VPDES (left) and VWUDS facilities (top) is populated (Table 4.14).

Table 4.14: The first step of the matching mechanism calculates the haversine distance (km) between each individual VPDES (left) facility to every VWUDS facility (top).

Facility Name	Virginia Electric and power Company: Surry Power Station	Dominion Generation: North Anna Nuclear Power Plant	Bacons Castle Farm LLC: Bacons Castle Farm
Dominion Energy - Surry and Gravel Neck Stations	0.63	138.65	4.87
Dominion - North Anna Power Station	139.21	1.59	141.43

Table 4.14 provides an example of how recorded attributes for a facility that reports withdrawal and discharge to different data sources may vary. Attributes, like facility name and coordinates, may differ for the same facility, depending on the permit and who filed it. This makes matching withdrawing and discharging permits a tedious process. To navigate the inherent error of facility coordinates, a radius threshold of 10 km is applied once distance between facilities is calculated (Table 4.15).

Withdrawing facilities that fall within 10 km of each VPDES facility are subsequently nar-

Table 4.15: A boolean indicates the VWUDS facilities that fall within 10km of each VPDES facility.

Facility Name	Virginia Electric and power Company: Surry Power Station	Dominion Generation: North Anna Nuclear Power Plant	Bacons Castle Farm LLC: Bacons Castle Farm
Dominion Energy - Surry and Gravel Neck Stations	TRUE	FALSE	TRUE
Dominion - North Anna Power Station	FALSE	TRUE	FALSE

rowed by facility name. Since facility names may differ between data sources, a fuzzy string matching approach is applied. Fuzzy matching quantifies how similar two character strings are together. With the inclusion of sliding and trimming, a custom function was created to calculate approximate string distance between facility names. Sliding means the function will ”slide” over the largest distance to accept the minimum, while trimming deletes spaces and unnecessary characters that may increase the relative string distance [16].

This function identifies the weighted number of insertions, deletions, and substitutions needed for the VWUDS facility name to be identical to the facility name in VPDES. Facilities that fall outside the search radius for each VPDES facility is not considered in the approximate string distance comparison and are given a value of 9999. Essentially, the function allows for partial matching and returns the minimum string distance between each potential match (Table 4.16). Code for this function can be found in Appendix A.

Table 4.16: Names of VWUDS facilities that fall within 10 km of each VPDES facility are compared by calculating an approximate string distance.

Facility Name	Virginia Electric and power Company: Surry Power Station	Dominion Generation: North Anna Nuclear Power Plant	Bacons Castle Farm LLC: Bacons Castle Farm
Dominion Energy - Surry and Gravel Neck Stations	25	9999	27
Dominion - North Anna Power Station	9999	14	9999

The minimum string distances, which represent the "best possible matches" based on distance and name, are then selected (Table 4.17). Depending on the facility, the approximate string distance may not be an ideal method of choosing the best possible match. For instance, in Table 4.17, it is known that the Surry Power Station is the same facility in each database. However, the difference in reported owner causes an increase in string distance. Therefore, extra steps must be taken to ensure accurate matching. Additional attributes including county, average discharge and withdrawal (MGD), and water use sector were compared.

Table 4.17: Facilities that are within 10 km and have the lowest approximate string distance between facility names are selected as the best possible match between the two data sources.

VPDES Facility	**Best VWUDS Match**	**Approx String Distance**	**Distance (km)**
Dominion Energy - Surry and Gravel Neck Stations	Virginia Electric and power Company: Surry Power Station	25	0.63
Dominion - North Anna Power Station	Dominion Generation: North Anna Nuclear Power Plant	14	1.59

This facility matching procedure is not appropriate for the municipal sector. As discussed in Section 2.2.1, direct measurement of municipal consumption at the supply and treatment level is complicated. Typically, municipal water consumption is estimated as the difference between wastewater production and water supply at coarser spatial scales [20]. This is because estimates can be confounded by stormwater, unaccounted for use, and differing customer bases. When analyzed, this creates an imbalance of withdrawal vs. discharge, with little verification of the actual end use of water for the facilities. Therefore, at a facility level, municipal consumption is interpreted as negative. With this in mind, the municipal sector is not considered at the facility level scale.

Table 4.18: Challenges/limitations to estimating consumption on the facility level.

Challenge	Description
Municipal Sector	On a facility level, calculating consumptive us for public Supply and treatment facilities is not realistic. Differing customer bases, processing water, and unequal withdrawals to discharges creates a misleading interpretation of water that is consumed. On a spatially aggregate level, consumption for the municipal sector can be implied, but not directly calculated on a facility level.
Data Completeness	ECHO represents data that is "as-reported" from the original database. Discharge data for major water users are typically more complete and accurate. This makes it difficult to match smaller facilities, as their data completeness varies widely (i.e. nonexistent, partial, voluntarily entered, or complete) [3].
Varying Attribute Entries	Attributes for the same facility may vary between permits and data sources. This includes slight changes in facility name and accuracy of coordinates.

4.3 Spatial Analysis

Not all withdrawn and discharges water is associated with matched facilities. To estimate total water consumption estimates that include sectors like municipal and agriculture, some degree of spatial aggregation is necessary. However, this can be confounded by issues such as inter-basin transfers. This study compared multiple levels of spatial aggregation to assess their feasibility for generating aggregate estimates of water consumption.

The spatial scales considered in this study include statewide, facility, county, and HUC 6 watershed (Table 4.19). Generally, consumption is estimated as the fraction of water not returned to water resources (Eq. 2.2).

4.3.1 Statewide Total Volume Analysis

Statewide consumption was calculated with a total volume approach. Monthly consumption estimates were calculated by summing total reported withdrawals and discharges (MGD)

Table 4.19: Description of methods used to quantify and visualize consumption in Virginia.

Scale	Results Presented	Method
Statewide	• Monthly consumption by sector using monthly total reported volume. • Average annual consumption by sector using monthly total reported volume. • All reported facilities vs. matched facilities.	• Sum monthly withdrawals and discharges per reporting month and use Equation 2.2 to calculate fraction of water lost. • Sum withdrawals and discharges by facility and year. Divide by number of reporting months for the given facility and year to return units of MGD. Use Equation 2.2 to calculate fraction of water lost. Take median of the median annual values over 2010-2016.
Facility	• Boxplots representing reported facility consumption rates per month by sector. • Median annual per-facility consumption by sector.	• Median facility reported consumption per reporting month by sector. • Median of the median monthly consumption per year by sector.
County	• Median annual consumption per county by sector. • All reported facilities vs. matched facilities.	• Intersect facilities over county boundaries. Sum withdrawals and discharges by facility and year. Divide by number of reporting months for the given facility and year to return units of MGD. Take median of the median annual values over 2010-2016.
Watershed (HUC 6)	• Median annual consumption per HUC 6 by sector. • All reported facilities vs. matched facilities	• Intersect facilities over HUC 6 boundaries. Sum withdrawals and discharges by facility and year. Divide by number of reporting months for the given facility and year to return units of MGD. Take median of the median annual values over 2010-2016.

per reporting month. These summed monthly withdrawals and discharge are then applied to equations 2.1 and 2.2 to estimate the amount (MGD) and fraction of water lost for the given month. Typically, yearly averages in MGD are estimated by aggregating monthly withdrawals (MGD) and discharges (MGD) and dividing by twelve months. However, this assumption does not work for every facility in this analysis. Although the vast majority of facilities report twelve months out of the year, there are cases of facilities providing partial reporting. Therefore, annual consumption estimates in this study aggregate total reported withdrawals and discharges by facility and year and are divided by the respective number of reporting months. The aggregated annual facility withdrawals and discharges are then passed through equations 2.1 and 2.2 to estimate the amount (MGD) and fraction of water lost for the given year.

4.3.2 Median Facility Consumption Analysis

The caveat of the total volume approach is the influence of large facilities. To remove the bias of facility size, consumption can first be estimated for each facility per month and by sector. This places the same weight on each water using facility, where the statewide monthly consumption estimate is then the median of all of the facility level consumption rates. Annual consumption is then the median of the monthly medians per year and by sector. This approach is limited to facilities with associated withdrawal and discharge entries for given months.

4.3.3 County and HUC 6 Watershed Analysis

The spatial data sets for Virginia Counties [5] and HUC watersheds [4] were obtained from the Census Bureau and the USDA Geo-spatial Data Gateway of Watershed Boundary Data set, respectively. R (version 3.5.1) was used to conduct the spatial analysis on the county

and HUC 6 watershed levels (Figure). Spatial analysis for the county and HUC 6 levels begins by loading the respective geodatabases and extracting the required layers. The layers are then projected using the *spTransform* function within R to GCS North American 1983 and Lambert Conformal Conic. The layers are then clipped to the Virginia State boundaries using *gIntersection*.

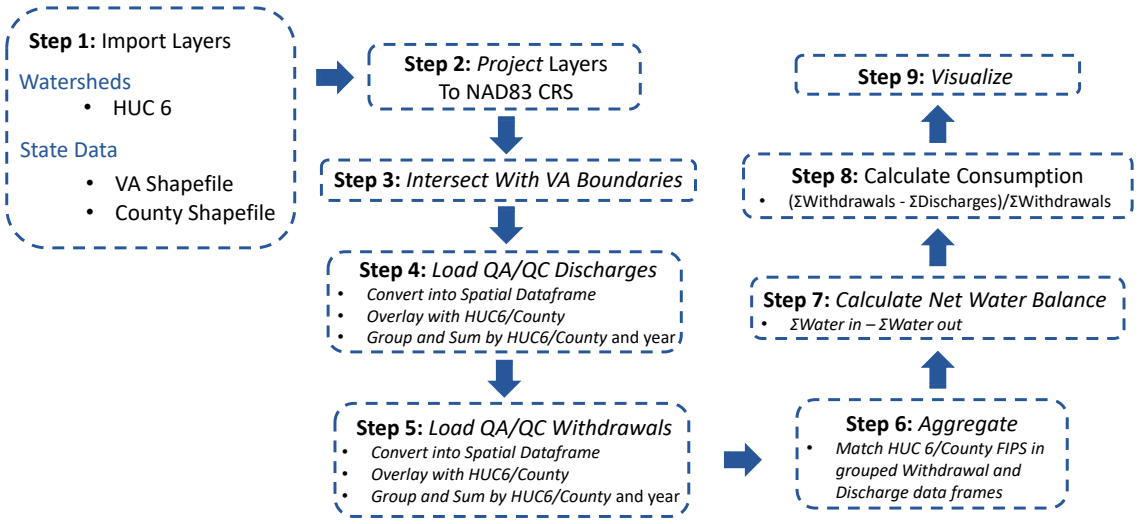

Figure 4.11: County and watershed consumption was estimated with a total volume approach. Withdrawal and discharge was first grouped by facility and year and subsequently divided by the number of reporting months. Annual consumption was calculated using equation 2.2 and long-term median consumption (2010-2016) was displayed as the result.

The cleaned monthly discharge and withdrawal data are then loaded, converted into a spatial dataframe using *SpatialPointsDataFrame*, and overlaid with the HUC6/County layer using *over*. The average monthly discharge and withdrawals are then aggregated by county/watershed and year and divided by the number of reporting months to return annual averages in MGD. The annual averages are then applied to the HUC 6 and County layers using HUC6 and FIPS codes as the matching ID. Separate columns for each year are created that contain

the annual average discharges and withdrawals in MGD for each watershed or county.

Net water balances and consumption are then calculated for each HUC 6 watershed and county from 2010 to 2016. Net water is calculated as the total amount of water coming into the system (discharge), minus the water leaving it (withdrawals) in MGD. Consumption is computed by inputting annual county/watershed discharge and withdrawal into equation 2.2 to return the fraction fo water lost. Missing (e.g. NA and NULL) and impossible values (e.g. INF and NaN) are removed from calculations. Long term averages of net water and consumption from 2010-2016 are calculated using the median. These spatial patterns are then visualised in map form using *ggplot*.

4.4 Trend Analysis

The Mann Kendall Trend Test was used to detect general increasing or decreasing trends (monotonic) in times series data [45]. It's non-parametric in nature, therefore removing the need for a normal distribution of values. The null hypothesis for this test assumes there is no monotonic trend. The alternative hypothesis is that a trend exists (positive or negative). It ultimately analyzes differences in signs between temporal data points. Assumptions include independence in time series entries, meaning that the observations are not serially correlated over time (i.e. auto-correlated). Serial correlation impact the test's ability to detect trends, increasing the potential for a type 1 error (i.e. identifying a significant trend when one isn't actually present) [45].

Auto and partial correlation plots visualize the strength of the relationship between time series observations and previous observations. They can be used to check for seasonality and serial correlation in the statewide monthly consumption estimates (Figure 4.12). Seasonality typically results in a strong positive correlation at 12 months lag and a negative correlation

at six months lag. In essence, all measurements for a given month are similar to each other. Figure 4.12 displays partial auto-correlation plots (PACF) for all reporting facilities on the left and matched facilities on the right.

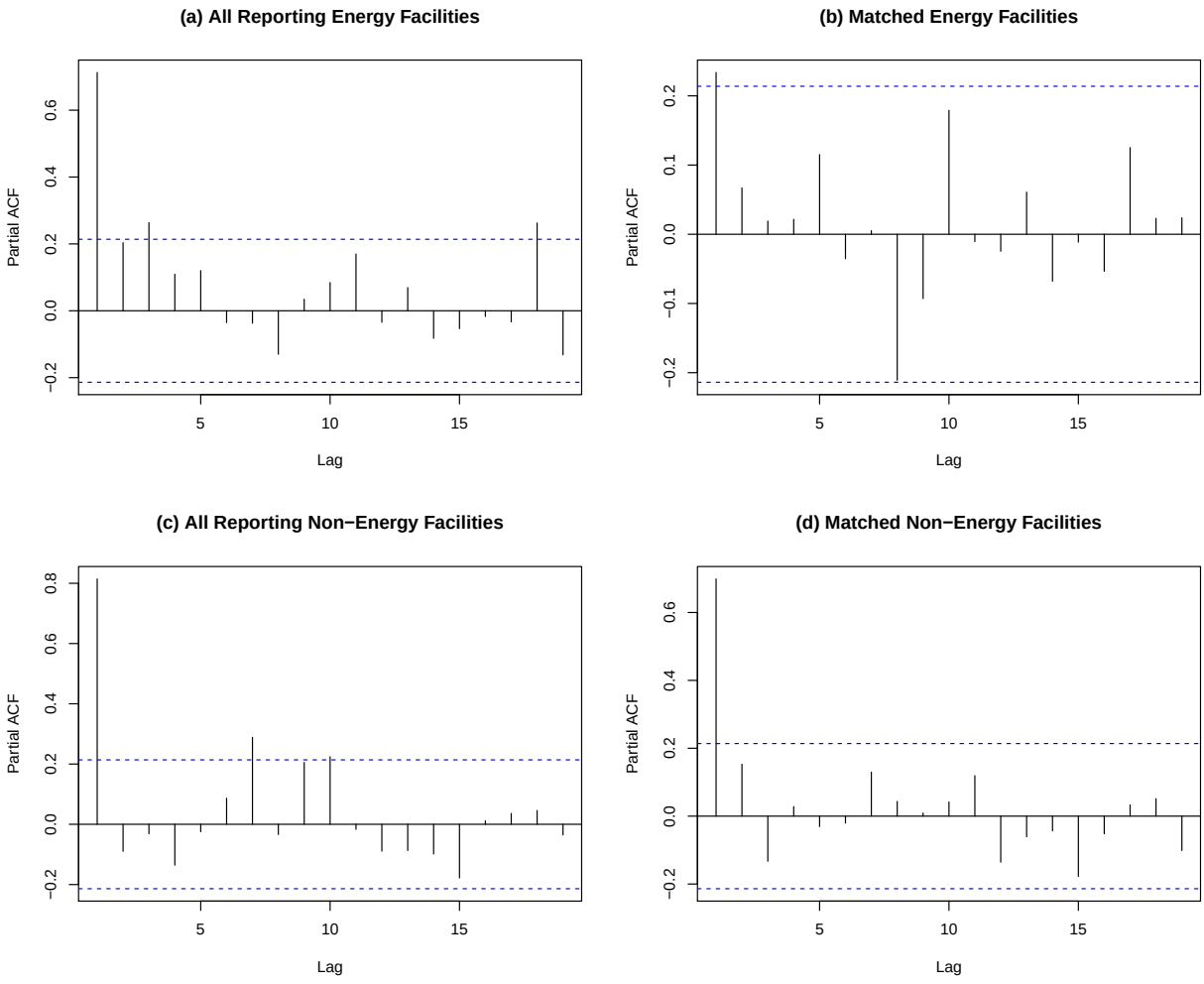

Figure 4.12: Partial auto-correlation plots with 95% confidence intervals (blue striped lines) for (a) All reporting energy facilities, (b) Matched energy facilities, (c) All reporting non-energy facilities, and (d) Matched non-energy facilities

For all reporting facilities, there is weak positive correlation at six months lag and weak negative correlation at 12 months lag. On the other hand, matched facilities show a weak negative correlation at six and 12 months lag. The matched energy facilities are the only PACF plot to not show strong positive correlation at one month lag, which suggests persis-

tence in the data rather than seasonality. It's typical to observe a strong positive correlation at one month lag because that means consumption in any given month is similar to the consumption in the prior month. Ultimately, it can concluded after observing Figure 4.12, that seasonality is not present in the consumption data for all reporting facilities or matched facilities.

The Mann Kendall Test as well as necessary adjustments for auto correlation, can be applied using various packages within R. Multiple approaches including seasonal Mann Kendall, seasonal adjustment, and boot strapping were considered as alternatives. However, since seasonality is not present, it does not need to be adjusted for; thus, the *zyp.trend.vector* function within the *zyp* package can be used [46]. This function computes a pre-whitened linear trend on data which uses a Kendall test for significance. Pre-whitening reduces the power of the test when a trend exists, serving to decrease the type 1 error.

Table 4.20: Mann Kendall tests can be applied to monthly environmental data using various packages in R.

Approach	**Description**
Zyp.trend.vector	Computes a pre-whitened linear trend on data which uses a Kendall test for significance. Prewhitening reduces the power of the test when a trend exists [46].
Seasonal Mann Kendall	Tests for monotonic trend in monthly environmental data. Score is computed separately for each month. Used function as is [34].
Seasonal Mann Kendall w/Seasonal Adjustment	Factors in seasonality and adjust for it so secular trends are exclusively observed. Variables and residuals are regressed before using seasonal Mann Kendall function [34].
Seasonal Mann-Kendall w/Seasonal Adjustment and Block Bootstrap	A re-sampling method to navigate the serial auto-correlation patterns in our consumption data. If consumption is deemed to be dependent on the previous month, bootstrapping is performed in blocks to maintain that auto-correlation. The trick is to select the optimal block size [34].

The Mann Kendall approach using the *zyp.trend.vector* function was applied to major water use sectors with sufficient consumption observations for matched and all reporting facilities

(i.e. Energy, Industrial, Commercial, and Aquaculture). Monthly estimates of consumption from 2010-2016 were used as inputs. The Municipal sector is excluded from analysis since estimations of consumption are difficult to interpret, as mentioned in Section 2.2.1. The Agriculture/Irrigation sector is also not considered for lack of unique consumption estimates.

Chapter 5

Results

5.1 Results from Data Processing

5.1.1 Matching Protocol

Using the mechanism described in Section 4.2.4, 123 facilities, representing approximately 81% and 89% of the total reported annual withdrawal and discharge respectively were matched. Municipal and Agricultural/Irrigation facilities were not included in the matching process, as described in Section 4.2.4. Figure 5.1 (a and c) displays the cumulative number of reporting facilities against the percentage of total average annual reported withdrawal and discharge (2010-2016).

Instantly, the difference in reporting facilities between the two data sources is visualised. Between 2010 and 2016, 1,860 unique facilities report withdrawals in VWUDS, while there are only 726 in the VPDES pulled from ECHO. The cumulative percentage of total reported withdrawal and discharge quickly ascends to 90% around 20 facilities, plateauing to reach ~99% before 200 facilities (Figure 5.1 (b and d)). Of these major facilities, two nuclear power stations are responsible for 52% and 60% of the water that is annually withdrawn and discharged, respectively, on average from 2010-2016. More generally, the energy sector accounts for 81% and 85% of the total reported water that is withdrawn and discharged each

year, respectively (Figure C.1). Thus, even though the facility matching procedure captures a small percentage of facilities, these facilities account for the majority of water withdrawn and discharges in the state.

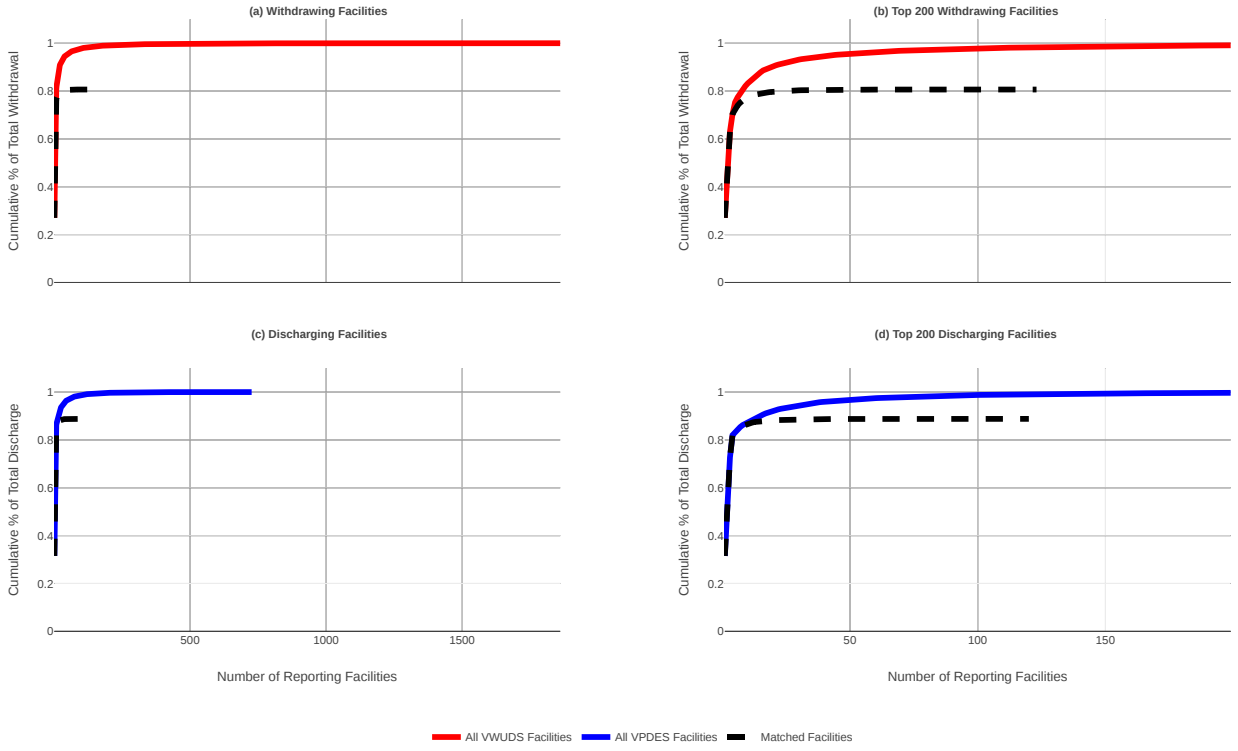

Figure 5.1: Cumulative percentage of total annual reported withdrawal (a) and discharge (c) vs. the number of responsible facilities. The top 200 water using facilities are represented in parts b and d. Averaged over 2010-2016.

5.1.1.1 Matched Withdrawals

Figure 5.2 presents monthly withdrawal (MGD) for all reporting VWUDS facilities (solid line) versus the VWUDS facilities with a corresponding VPDES facility (dashed line). The number of reporting facilities are represented as bar plots behind the monthly withdrawals. Note that the Agriculture/Irrigation and Municipal sectors do not have matched facilities associated with them.

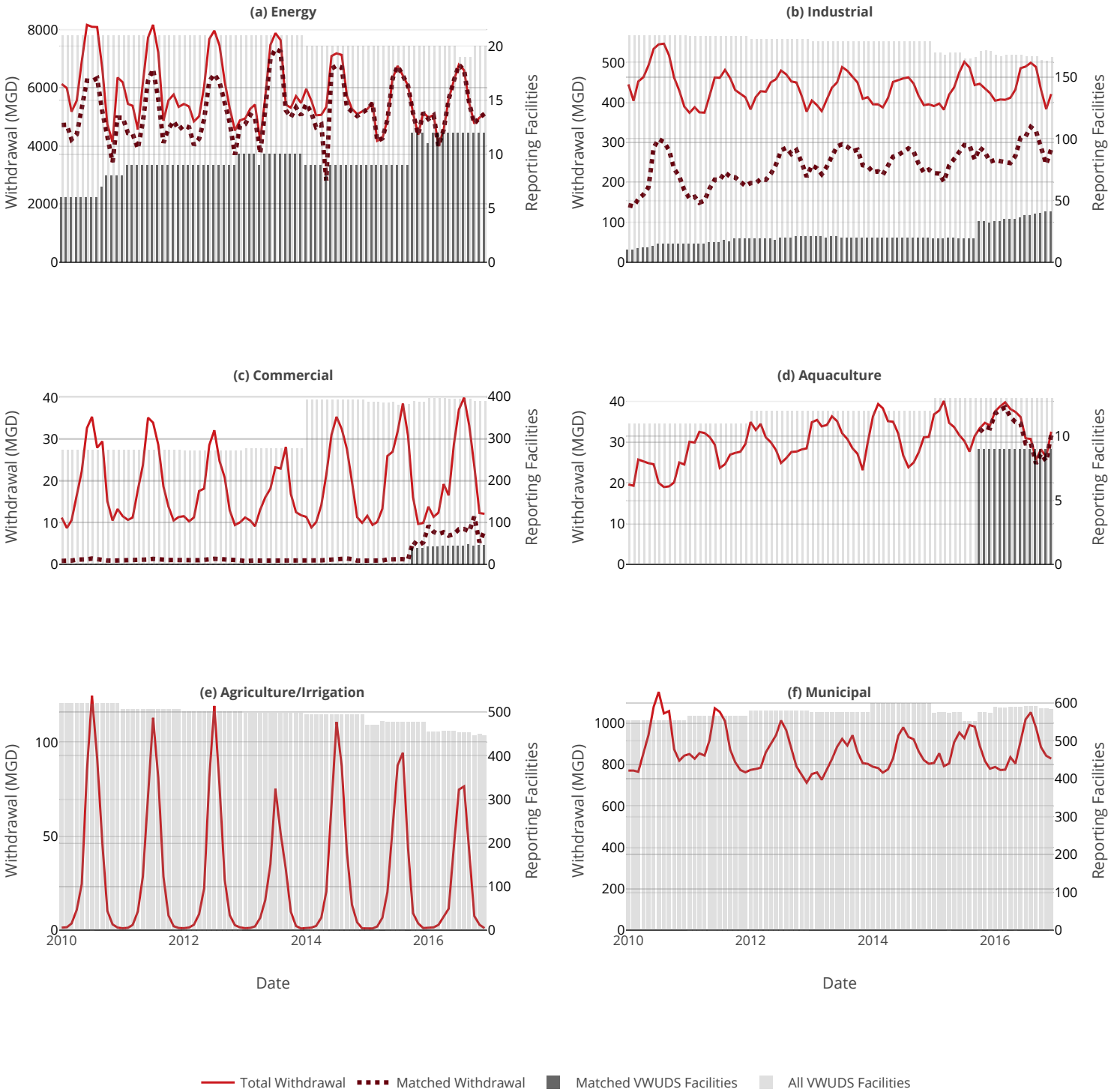

Figure 5.2: Total monthly withdrawals (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for (a) Energy, (b) Industrial, (c) Commercial, (d) Aquaculture, (e) Agriculture/Irrigation, and (f) Municipal facilities (2010-2016)

On average, matched energy VWUDS facilities represent 91% of the total reported energy withdrawals (Table 5.1). Approximately 21 energy facilities report to VWUDS between 2010 and 2016 (Table 5.1). While the amount of reporting facilities does not waver, total reported withdrawals decrease an average of 2.73% per year. The number of matched energy facilities in VWUDS increases slightly from 8 to 12 from 2010-2016 (Figure 5.2(a)). This increase is a product of improved comprehensive reporting of discharge records to the ECHO system through time (Section 5.1.1.2). Therefore, withdrawal records begin to present associated discharge records as time goes on, especially in 2016. Consequently, the quantity of matched withdrawal increases, raising the percentage of total reported withdrawal for the energy sector.

Table 5.1: Comparison of total annual reported energy withdrawal (MGD) per year between all available data and matched facilities (2010-2016).

Year	**All Facilities**	**Matched Facilities**	**Total Withdrawal (MGD)**	**Matched Withdrawal (MGD)**	**% of Total Energy Withdrawal**
2010	21	8	6,331	5,090	80.4%
2011	21	9	6,033	4,931	81.7%
2012	21	10	5,892	5,266	89.4%
2013	21	10	5,867	5,510	93.9%
2014	20	9	5,806	5,443	93.8%
2015	20	12	5,360	5,357	99.9%
2016	20	12	5,348	5,346	99.9%
Ave	**21**	**10**	**5,805**	**5,277**	**91.3%**

Figure 5.3 quantifies energy monthly withdrawals (MGD) by power type. There are two unique nuclear, 6 unique coal, 11 unique combination fossil fuel, and 2 unique biomass facilities that report some type of withdrawal between 2010 and 2016. Of these, both nuclear facilities, 3 coal facilities, 6 combination fossil fuel facilities, and 1 biomass facility was matched with its corresponding discharging facility in VPDES. As time continues, withdrawals for coal and combination fossil fuel facilities appears to be decreasing.

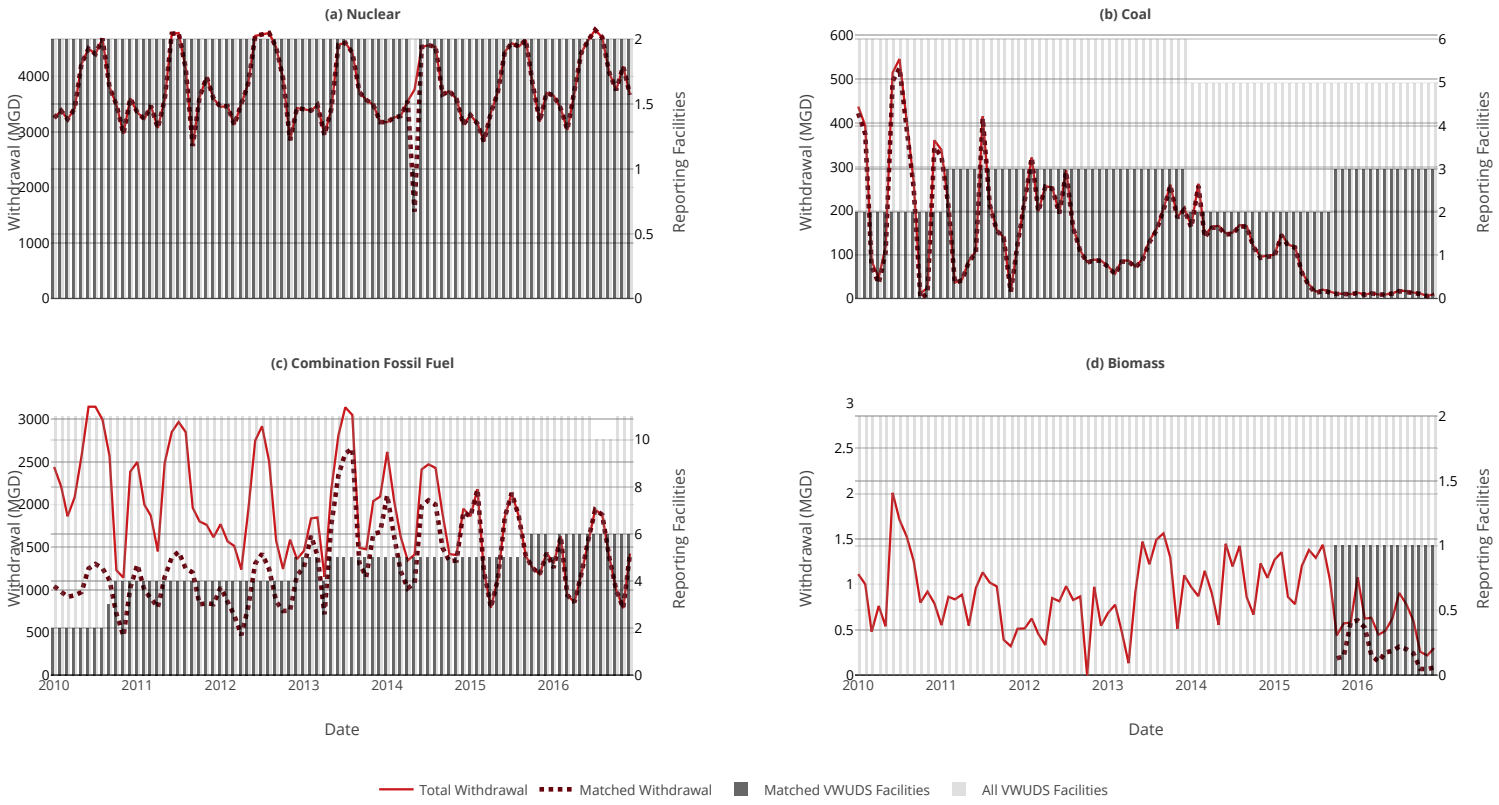

Figure 5.3: Total monthly withdrawals (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for (a) Nuclear, (b) Coal, (c) Combination Fossil Fuel, and (d) Biomass energy facilities (2010-2016)

Water withdrawals for energy facilities are orders of magnitude larger than that of non-energy facilities, therefore they are kept separate. Industrial (b), commercial (c), aquaculture (d), agriculture/irrigation (e), and municipal (f) represent the non-energy withdrawing sectors in this particular analysis (Figure 5.2). Since the agriculture/irrigation and municipal sectors are excluded from the facility-level analysis, only 19.4% of total non-energy withdrawals are captured by matched non-energy VWUDS facilities (Table 5.2). The total number of reporting non-energy VWUDS facilities varies through the years, increasing in 2013, and decreasing after years 2010, 2014, and 2015 (Table 5.2). The amount of matched non-energy VWUDS facilities does not follow this pattern and increases steadily from 2010 to 2014 and jumps from 21 to 83 facilities in 2015. Similar to the energy sector, the total reported withdrawals decreases an average of 0.75% per year, while the withdrawals for matched facilities increase instead.

Table 5.2: Comparison of total annual reported non-energy withdrawal (MGD) per year between all available data and matched facilities (2010-2016).

Year	All Facilities	Matched Facilities	Total Withdrawal (MGD)	Matched Withdrawal (MGD)	% of Total Non-Energy Withdrawal
2010	1,550	16	1,463	248	16.9%
2011	1,546	20	1,386	195	14.0%
2012	1,553	22	1,355	268	19.8%
2013	1,547	22	1,328	264	19.9%
2014	1,684	21	1,355	250	18.5%
2015	1,655	83	1,398	320	22.9%
2016	1,646	98	1,396	328	23.5%
Ave	**1,597**	**40**	**1,383**	**267**	**19.4%**

If the industrial, commercial, and aquaculture sectors are extracted and observed, it's evident that the matched VWUDS facilities capture more of the total reported withdrawal. On average from 2010-2016, 58.4% of total reported industrial withdrawal are captured from the matched industrial VWUDS facilities (Table 5.3). 13.2% of total reported commercial withdrawal is captured by matched commercial VWUDS facilities (Table 5.4), and 97.2% of aquaculture withdrawals are captured by matched VWUDS aquaculture facilities (Table 5.5).

Table 5.3: Comparison of total annual reported industrial withdrawal (MGD) per year between all available data and matched facilities (2010-2016).

Year	All Facilities	Matched Facilities	Total Withdrawal (MGD)	Matched Withdrawal (MGD)	% of Total Reported Withdrawal
2010	191	15	474	247	52.1%
2011	189	19	422	193	45.9%
2012	187	21	434	267	61.5%
2013	185	21	431	263	61.0%
2014	184	20	424	249	58.8%
2015	176	35	438	281	64.3%
2016	175	41	440	288	65.4%
Ave	**184**	**25**	**437**	**255**	**58.4%**

Table 5.4: Comparison of total annual reported commercial withdrawal (MGD) per year between all available data and matched facilities (2010-2016).

Year	All Facilities	Matched Facilities	Total Withdrawal (MGD)	Matched Withdrawal (MGD)	% of Total Reported Withdrawal
2010	274	1	20	1	5.4%
2011	274	1	19	1	5.6%
2012	272	1	17	1	6.6%
2013	277	1	16	1	6.0%
2014	394	1	19	1	5.7%
2015	396	39	20	5	26.5%
2016	403	48	22	8	36.9%
Ave	**327**	**13**	**19**	**13**	**13.2%**

Table 5.5: Comparison of total annual reported aquaculture withdrawal (MGD) per year between all available data and matched facilities (2010-2016).

Year	All Facilities	Matched Facilities	Total Withdrawal (MGD)	Matched Withdrawal (MGD)	% of Total Reported Withdrawal
2010	11		22		0.0%
2011	11		29		0.0%
2012	12		30		0.0%
2013	12		32		0.0%
2014	12		32		0.0%
2015	13	9	34	33	98.1%
2016	13	9	34	32	96.3%
Ave	**12**	**9**	**30**	**33**	**97.2%**

5.1.1.2 Matched Discharges

Figure 5.4 presents monthly discharge (MGD) for all reporting VPDES facilities obtained from ECHO (solid line) versus matched VPDES facilities (dashed line). Note that the Agriculture/Irrigation do not report discharges and the Municipal sector does not have matched facilities associated with them.

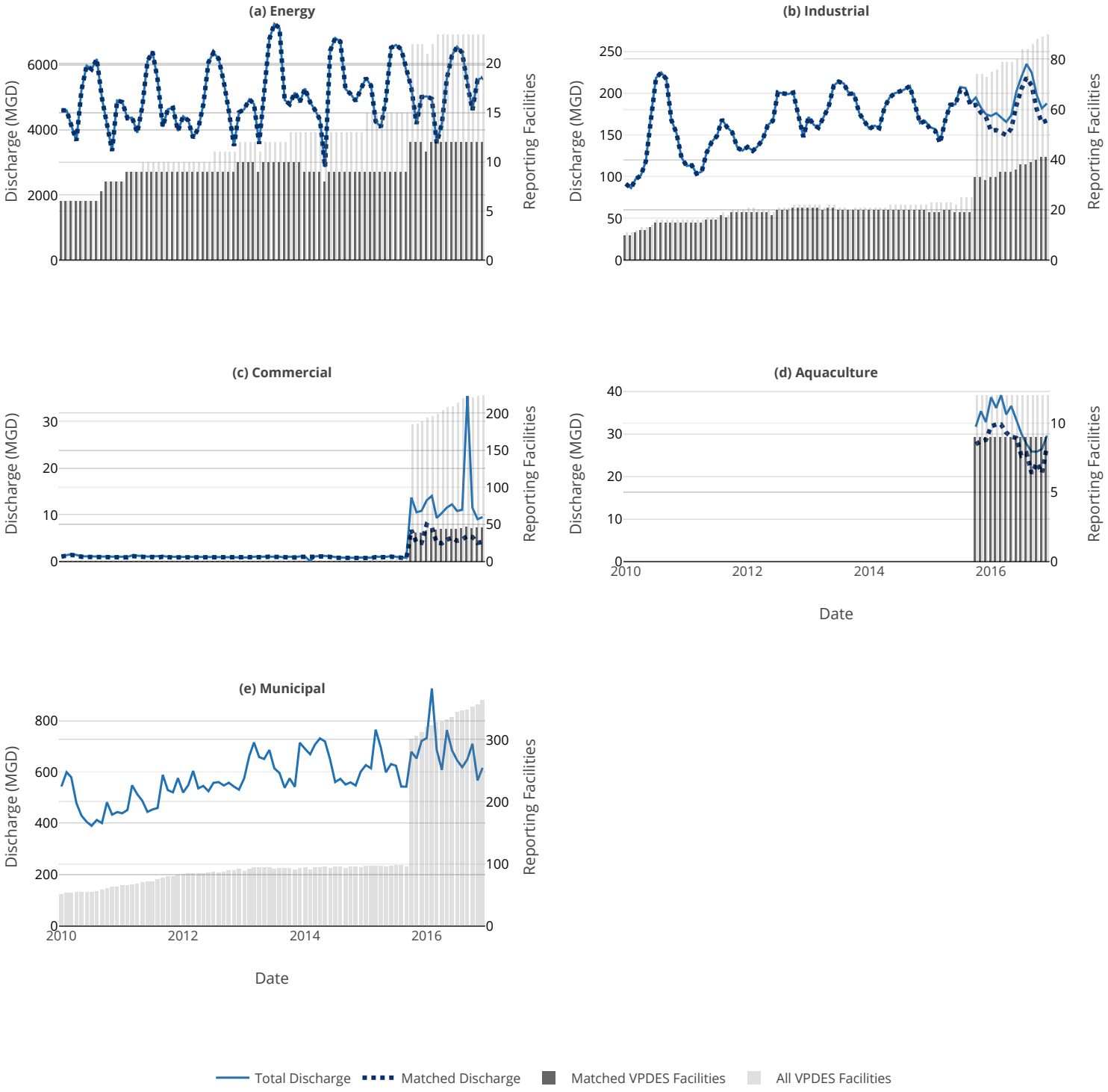

Figure 5.4: Total monthly discharges (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for (a) Energy, (b) Industrial, (c) Commercial, (d) Aquaculture, (e) Agriculture/Irrigation, and (f) Municipal facilities (2010-2016)

Matched energy VPDES facilities represent more than 99% of the total reported discharge, higher than that of the matched VWUDS energy facilities. Matched non-energy VPDES facilities also represent a higher percentage of total reported discharge than that of non-energy VWUDS facilities (approximately 23.4%). The average number of total reporting facilities differs than that of the VWUDS data in both the energy and non-energy sectors.

On average, ECHO reports 14 VPDES energy facilities per year from 2010-2016, with improved comprehensive reporting over time (Table 5.6). Whereas, in VWUDS, an average of 21 energy facilities are reporting withdrawals (Table 5.1). Therefore, not every withdrawing energy facility in VWUDS has associated discharge records located in the national ECHO data system. The types of energy facilities without associated discharge records include combination fossil fuel (c) and coal (b) facilities (Figure 5.6).

Table 5.6: Comparison of total annual reported energy discharge (MGD) per year between all available data and matched facilities (2010-2016).

Year	All Facilities	Matched Facilities	Total Discharges (MGD)	Matched Discharges (MGD)	% of Total Energy Discharge
2010	8	8	4,891	4,891	100.0%
2011	10	9	4,810	4,809	99.9%
2012	12	10	5,098	5,098	99.9%
2013	13	10	5,340	5,340	99.9%
2014	13	9	5,346	5,346	99.9%
2015	22	12	5,351	5,349	99.9%
2016	23	12	5,323	5,320	99.9%
Ave	**14**	**10**	**5,166**	**5,165**	**99.9%**

Figure 5.5 quantifies energy monthly discharges (MGD) by power type. There are two unique nuclear, 5 unique coal, 11 unique combination fossil fuel, and 3 unique biomass facilities that report some type of withdrawal between 2010 and 2016. Of these, both nuclear facilities, 3 coal facilities, 6 combination fossil fuel facilities, and 1 biomass facility was matched with its corresponding withdrawing facility in VWUDS. In contrast to Figure 5.3, it's evident

comprehensive reporting has improved from 2010 to 2016, especially for combination fossil fuel facilities. Reported discharge for coal facilities appears to be decreasing over time, with reports of 0.0 MGD in 2013 and throughout October of 2015 to 2016. This figure also reveals that the matching procedure was able to capture close to all reported discharge for nuclear (a), coal (b), and combination fossil fuel (c) facilities, meaning that the unmatched VWUDS energy facilities are likely not represented within ECHO.

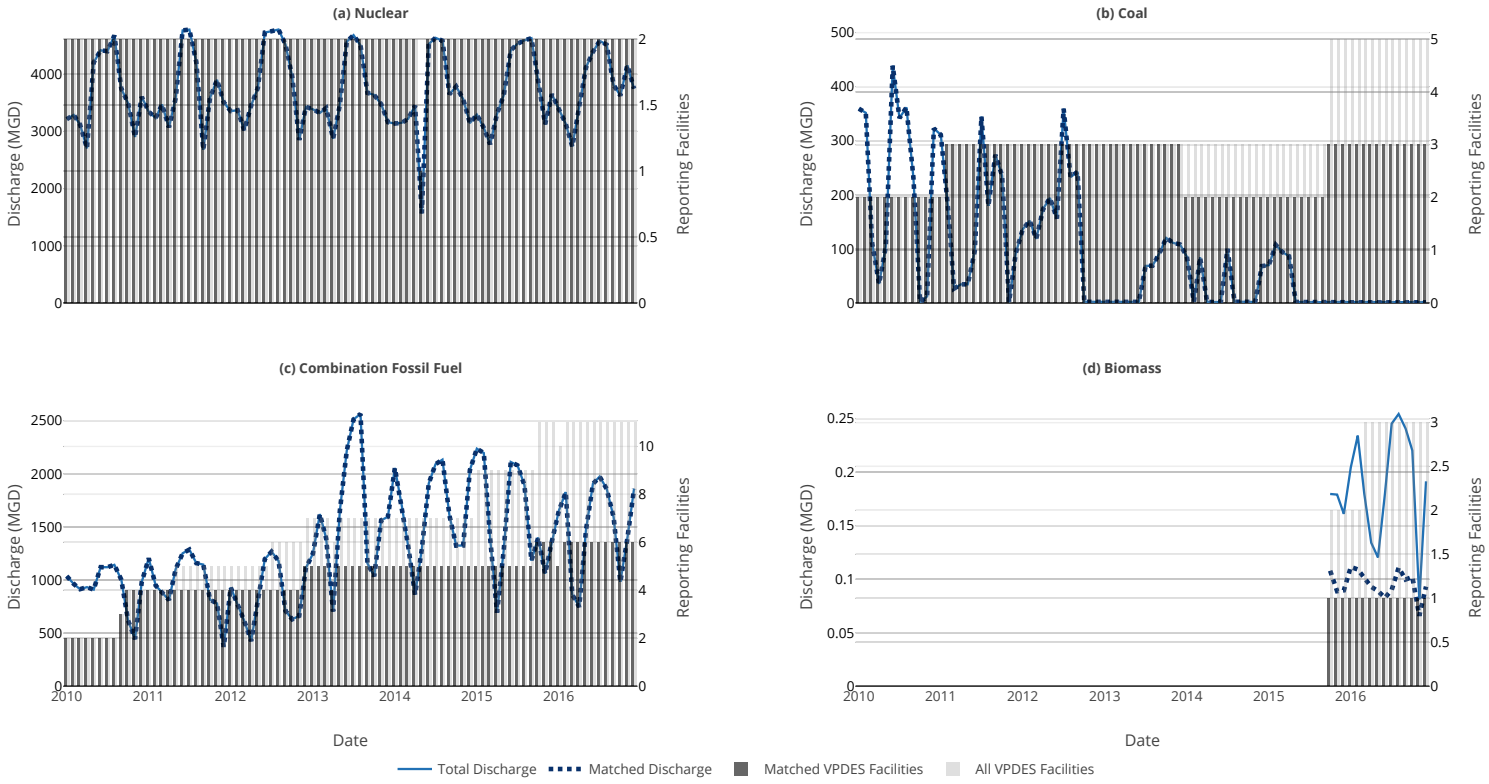

Figure 5.5: Total monthly discharges (MGD) for matched facilities (dashed line) vs. all reporting facilties (solid line) with number of reporting facilities on the secondary y-axis for (a) Nuclear, (b) Coal, (c) Combination Fossil Fuel, and (d) Biomass energy facilities (2010-2016)

When non-energy VPDES facilities are focused on, there is a distinct increase in reporting where there are 81 facilities in 2010 and 695 by 2016 (Table 5.7). The amount of matched facilities displays an increase as well, from 16 in 2010 to 98 by 2016. The total amount of

reported discharge does not follow the same degree of increase, but increases nonetheless from 665 to 935 MGD (an average increase of 6.0% per year). This suggest that although numerous additional facilities are included in the discharge data in later years, most of these facilities are discharging a relatively small volume of water.

Table 5.7: Comparison of total annual reported non-energy discharge (MGD) per year between all available data and matched facilities (2010-2016).

Year	All Facilities	Matched Facilities	Total Discharges (MGD)	Matched Discharges (MGD)	% of Total Non-Energy Discharge
2010	81	16	665	177	26.6%
2011	104	20	668	140	20.9%
2012	121	22	774	185	23.9%
2013	118	22	828	186	22.5%
2014	119	21	823	183	22.2%
2015	590	83	902	222	24.6%
2016	695	98	935	213	22.8%
Ave	**261**	**40**	**799**	**187**	**23.4%**

Matched non-energy facilities represent a larger percentage of total reported discharge compared to withdrawal data because of the lack of return flow data from Agriculture/Irrigation facilities. On average from 2010-2016, 98.1% of total reported industrial discharge is captured from the matched industrial VWUDS facilities (Table 5.8). 75.2% of total reported commercial discharge is captured by matched commercial VPDES facilities (Table 5.9), and 84.9% of aquaculture withdrawals are captured by matched VWUDS aquaculture facilities (Table 5.5).

Table 5.8: Comparison of total annual reported industrial discharge (MGD) per year between all available data and matched facilities (2010-2016).

Year	All Facilities	Matched Facilities	Total Discharge (MGD)	Matched Discharge (MGD)	% of Total Reported Discharge
2010	16	15	176	176	99.9%
2011	20	19	139	139	99.9%
2012	23	21	184	184	99.9%
2013	22	21	186	185	99.9%
2014	22	20	182	182	99.9%
2015	76	35	195	188	96.8%
2016	91	41	200	181	90.4%
Ave	**39**	**25**	**180**	**177**	**98.1%**

Table 5.9: Comparison of total annual reported commercial discharge (MGD) per year between all available data and matched facilities (2010-2016).

Year	All Facilities	Matched Facilities	Total Discharge (MGD)	Matched Discharge (MGD)	% of Total Reported Discharge
2010	2	1	1	1	89.4%
2011	2	1	1	1	88.1%
2012	2	1	1	1	90.5%
2013	2	1	1	1	90.9%
2014	2	1	1	1	91.1%
2015	189	39	12	5	42.1%
2016	228	48	16	6	34.4%
Ave	**61**	**13**	**5**	**2**	**75.2%**

Table 5.10: Comparison of total annual reported aquaculture discharge (MGD) per year between all available data and matched facilities (2010-2016).

Year	All Facilities	Matched Facilities	Total Discharge (MGD)	Matched Discharge (MGD)	% of Total Reported Discharge
2010					0.0%
2011					0.0%
2012					0.0%
2013					0.0%
2014					0.0%
2015	12	9	33	28	84.6%
2016	12	9	32	27	85.2%
Ave	**12**	**9**	**33**	**28**	**84.9%**

5.2 Spatial Analysis

5.2.1 Statewide (Total Volume Approach)

Consumption calculated on the statewide level considers the total volume of withdrawals and discharges reported each reporting month and estimates the fraction of water not returned to water resources. This allows for larger water users to influence the overarching trends over time. At this level, consumption estimates for all available data and matched facility data are compared (Tables 5.11 and 5.12).

Table 5.11: Annual consumption estimates based on all available data per year and by sector. Calculated by aggregating total volume reported by facility and year to estimate fraction of water lost. Long term median estimates represented far right column.

Sector	2010	2011	2012	2013	2014	2015	2016	Median
Agriculture/Irrigation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Aquaculture	1.00	1.00	1.00	1.00	1.00	0.02	0.05	1.00
Commercial	0.94	0.94	0.95	0.94	0.95	0.40	0.26	0.94
Energy	0.23	0.20	0.13	0.09	0.08	0.002	0.005	0.08
Industrial	0.63	0.67	0.58	0.57	0.57	0.56	0.55	0.57
Municipal	0.47	0.40	0.30	0.23	0.25	0.25	0.22	0.25

Table 5.12: Annual consumption estimates based on matched facility data per year and by sector. Calculated by aggregating total volume reported by facility and year to estimate fraction of water lost. Long term median estimates represented far right column.

Sector	2010	2011	2012	2013	2014	2015	2016	Median
Aquaculture						0.15	0.16	0.16
Commercial	0.006	0.10	0.25	0.07	0.23	0.04	0.31	0.24
Energy	0.04	0.02	0.03	0.03	0.02	0.001	0.005	0.024
Industrial	0.29	0.28	0.31	0.30	0.27	0.33	0.37	0.32

When all available data are considered, annual energy consumption is approximately 0.08 (Table 5.11). This rate lowers to 0.024 when only matched facilities are considered (Table 5.12). Agriculture/Irrigation displays the highest consumption of 100% due to a lack of

discharge records in ECHO. The commercial sector is the most variable when all data is considered. If Figure 5.4(c) is referred to, it shows that discharge records for commercial facilities become more comprehensive in the year 2016. This improved data flow to ECHO causes a distinct decrease in consumption. The same can be said for the aquaculture sector, where discharge data is not available in ECHO until 2016 (Figure 5.4(d)). Discharge records for the industrial and municipal sectors are more persistent in ECHO, but only represent about 10% of the total facilities reporting to VWUDS in the same respective sectors (Figure 5.2(b) and (f)).

When only fully matched discharge and withdrawal records are considered, median annual consumption is clearly lower versus when all data is considered (Table 5.12). The most noticeable difference is the commercial sector. The consumption rates here are not as heavily influenced by the lack of associated discharge records available in ECHO. Regardless, commercial consumption rates are still variable throughout the years. This may be due to facilities retrieving self supplied water as well as purchasing water from public suppliers. This leads to higher reported discharge that will not have a corresponding point withdrawal in VWUDS, which is interpreted as negative consumption. Energy consumption appears to remain relatively consistent through the years, with a slight downward trend. The industrial sector is the only one indicating a weak upward trend in consumption over time when only matched facilities are considered. It also appears that consumption in all sectors increases from 2015 to 2016, perhaps suggesting the influence of reporting or warmer climate conditions.

5.2.1.1 Energy vs. Non-Energy Monthly Consumption

There is a limit to how useful annual median consumption estimates can be for water supply planning and management. Therefore, monthly patterns of consumption were investigated for energy and non-energy sectors. When all reported withdrawal and discharge data are considered, the inter-quartile range (IQR) of monthly energy consumption is 4-20% (Figure 5.6(a)). The IQR decreases to 0.4-4%, when the data is narrowed to focus on matched facilities (Figure 5.6(b)).

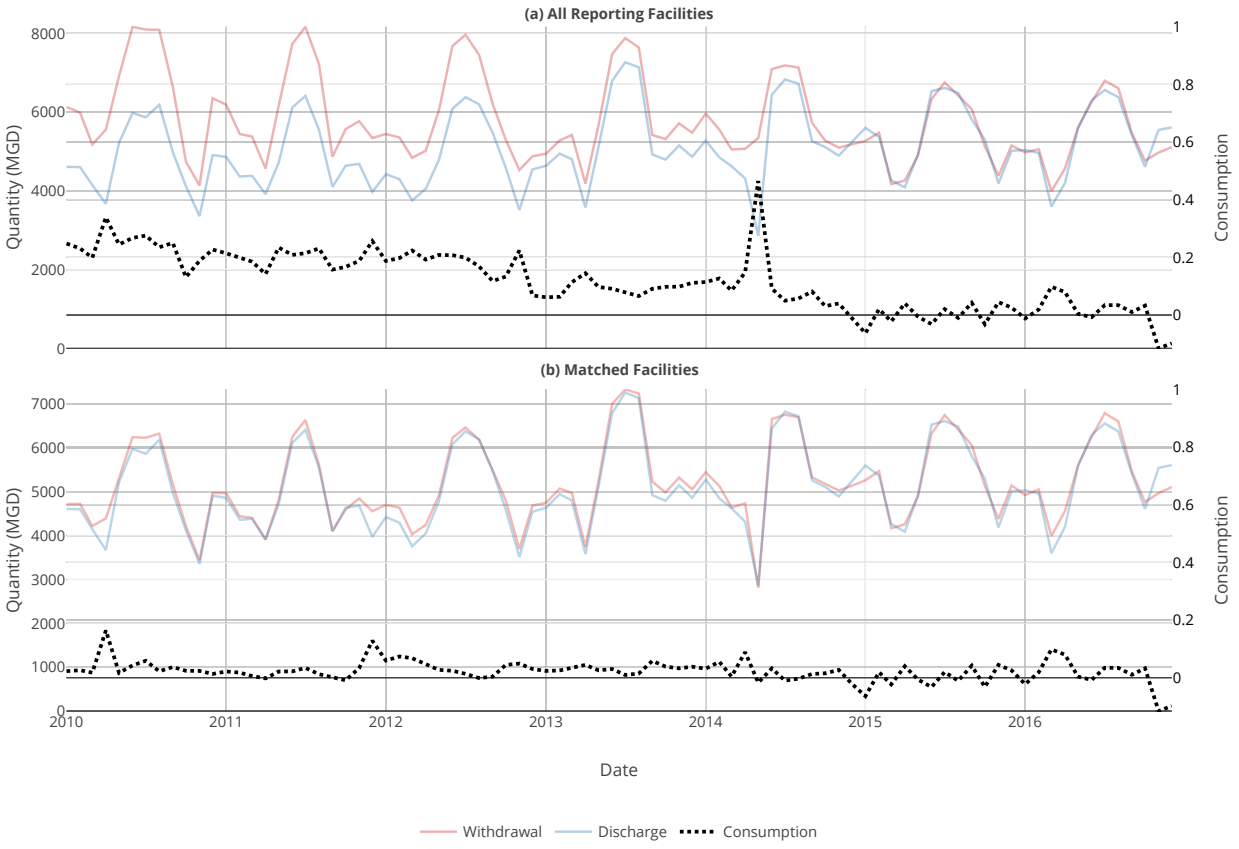

Figure 5.6: Monthly energy consumption estimates based on (a) all available data and (b) matched facility data (2010-2016). Aggregated total volume per reporting month to estimate fraction of water lost.

Monthly reported withdrawals and discharges show patterns of seasonality in the energy

sector, where more water is being withdrawn between June and August. These patterns of seasonality are however not represented in the monthly consumption estimates (Figure 5.6). The matched energy facilities in Figure 5.6(b) close the gap between reported withdrawal and discharge from 2010-2013. Regardless of if the energy facilities are matched, there are cases where more discharge is reported than withdrawal throughout 2015 and 2016.

The IQR of monthly non-energy consumption is 37-52% when all withdrawal and discharge data are considered (Figure 5.7(a)). Monthly consumption become less variable and the IQR decreases to 28-33% when only matched data are considered (Figure 5.7(b))

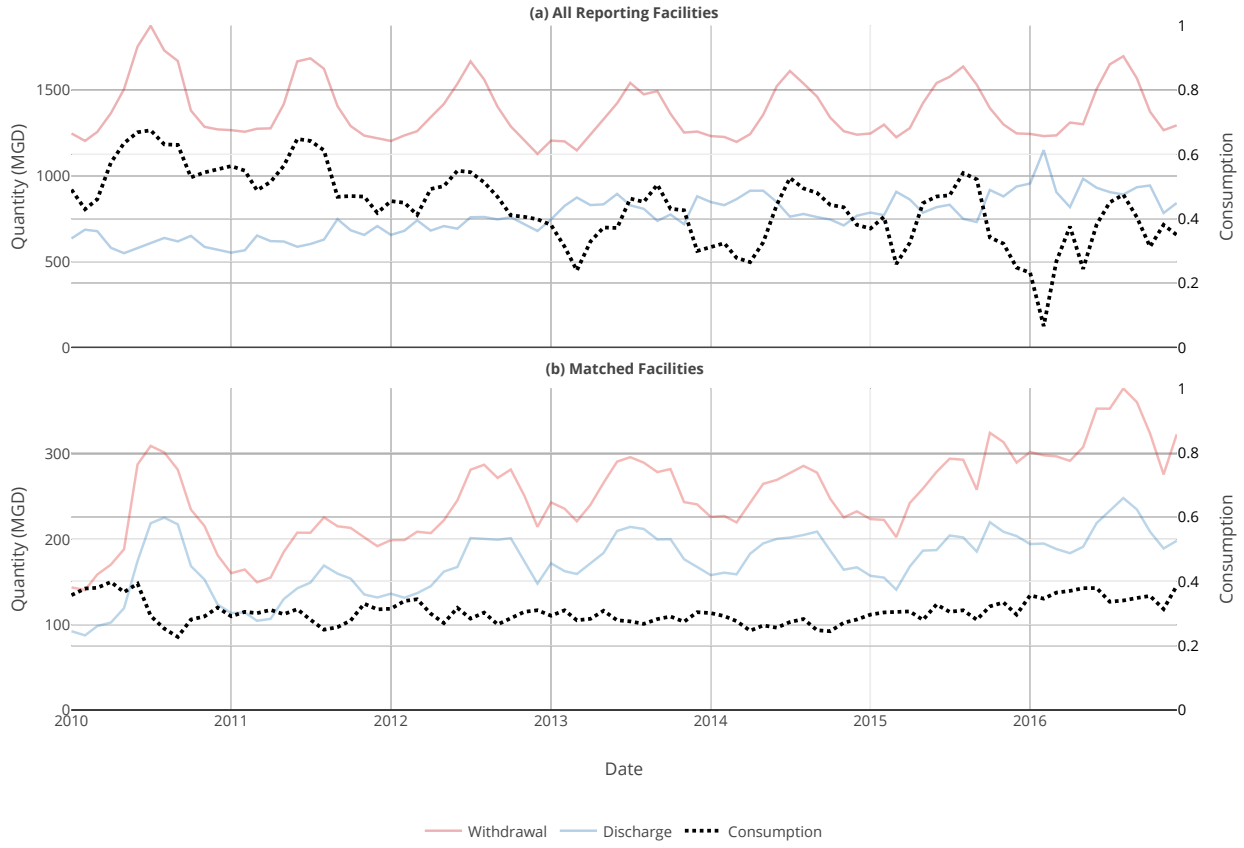

Figure 5.7: Monthly non-energy consumption estimates based on (a) all available data and (b) matched facility data (2010-2016). Aggregated total volume per reporting month to estimate fraction of water lost.

5.2.1.2 Energy Consumption by Fuel Type

To investigate energy consumption further, facilities were separated into their respective power type including, nuclear (2 matched facilities), coal (3 matched facilities), combination fossil fuel (6 matched facilities), and (1 matched facility) biomass (Figure 5.8).

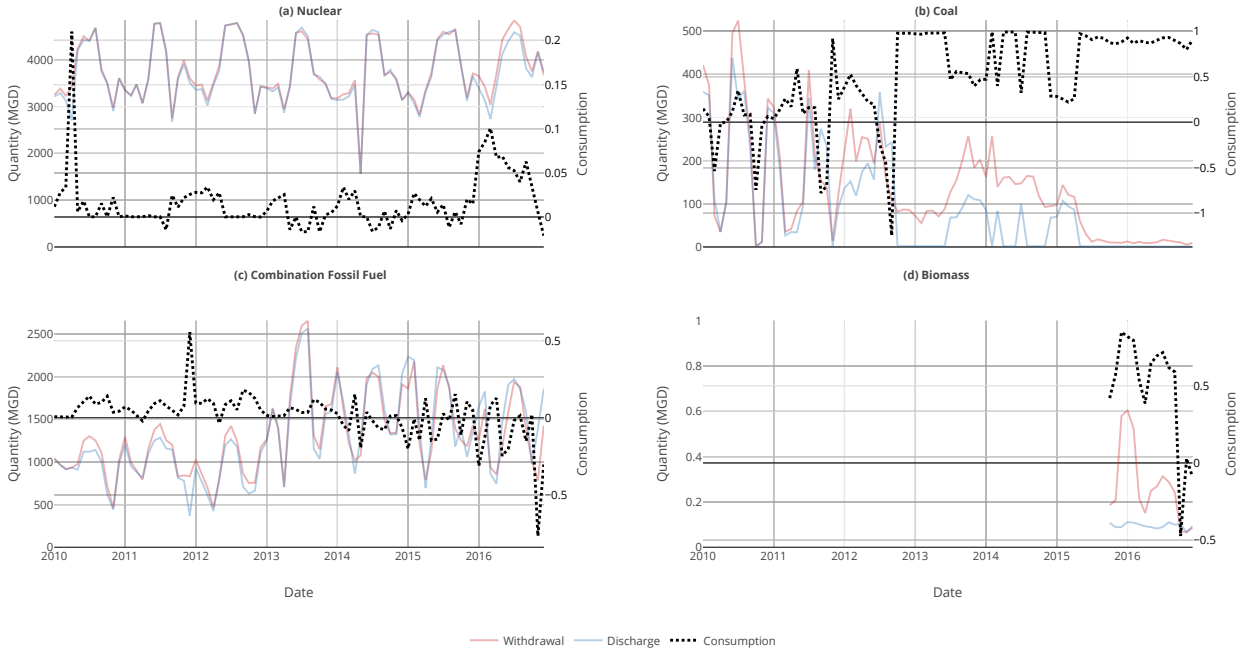

Figure 5.8: Monthly energy consumption estimates based on matched facility data for (a) Nuclear, (b) Coal, (c) Combination Fossil Fuel, and (d) Biomass power type (2010-2016). Aggregated total volume per reporting month to estimate fraction of water lost.

The two nuclear power stations drive the statewide water withdrawal and discharge patterns. The highest reported nuclear consumption is 0.20 in April of 2010. Consumption then remains below 10% and turns negative in months throughout 2013-2015. Three coal facilities fluctuate between -1 and 0.9 between 2010-2012 before rising to between 0.97 and 0.22. The variable consumption for coal facilities is ultimately overshadowed by the consumption trends of the nuclear and combination fossil fuel facilties due to their size. Six combination fossil fuel facilities display high consumption in the summer and low in the winter between 2010-

2013. After 2014, consumption begins to oscillate between 0.15 and -0.20 before remaining negative for the majority of 2016. One biomass facility displays matched data for 2015 and 2016. High consumption is reported in the winter months of 2015 and summer months of 2016, before dipping to negative in October of 2016.

Consumption by rated capacity was also considered for each fuel type (Figure 5.9). Rated capacity is the intended power output of an energy facility in megawatts (MW) [7]. Capacities were obtained for each individual facility through their parent organization websites and averaged for each power type (Table 5.13).

Table 5.13: Average energy facility rated capacity (MW) and consumption (Mgal) per power type.

Sector	**Mean Rated Capacity (MW)**	**Mean Consumption (MGal)**
Biomass	59	5
Coal	350	1,346
Combination Fossil Fuel	647	198
Nuclear	1,733	1,801

Biomass, with the lowest mean rated capacity, displays the lowest consumption per rated capacity of 0.3 MGal of water consumed per MW. Nuclear and combination fossil fuel facilities show similar patterns to their monthly consumption rates, as a percentage of water lost, peaking at around 13 MGal per MW. Even though they are within the same range of cosumption per rated capacity, nuclear facilities have a much higher intended power output. Coal consumes the most water per rated capacity on average and presents a divergent monthly pattern than what is introduced in Figure 5.8. Even though coal facilities displayed consumption rates around 0.90 2015-2016, the quantity of water consumed per MW is below 1.5 MGal/MW.

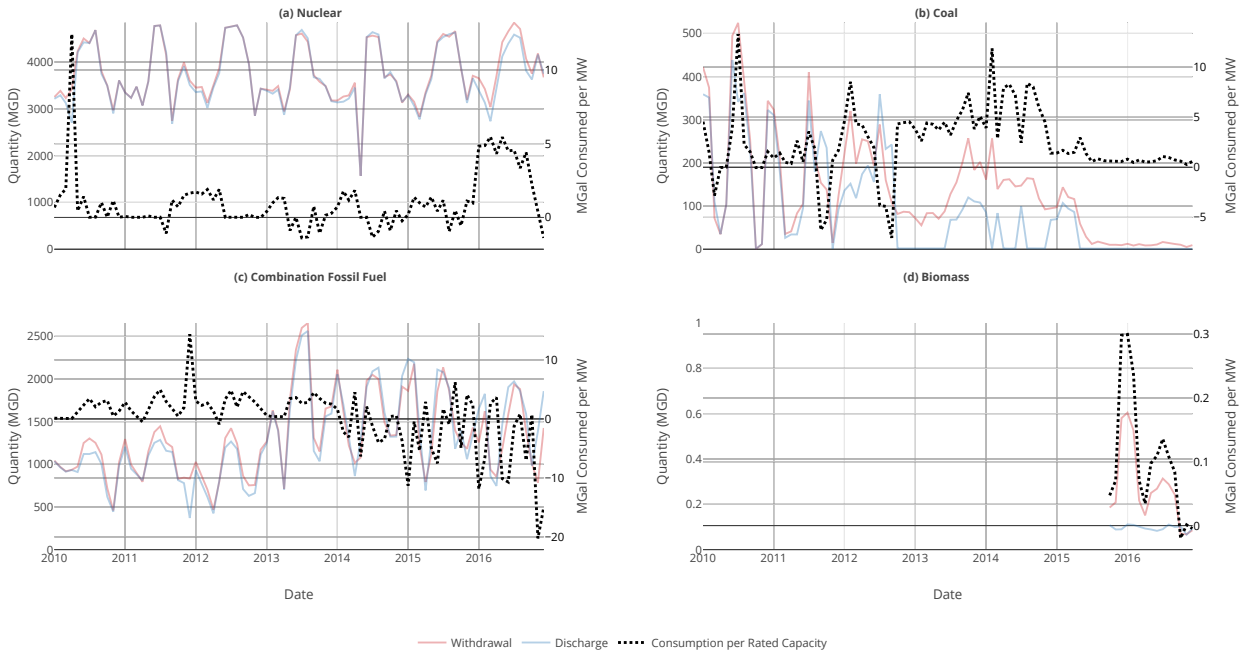

Figure 5.9: Monthly energy consumption per rated capacity (MGal/MW) based on matched facility data for (a) Nuclear; (b) Coal; (c) Combination Fossil Fuel; and (d) Biomass power type (2010-2016). Aggregated total volume per reporting month to estimate quantity of water lost in millions of gallons, divided by average rated capacity per power type.

5.2.1.3 Non-Energy Sectors

Industrial consumption decreases by 0.2 on average when only matched facilities are considered (Figure 5.10). Between 2010 and 2016, monthly consumption rates for matched facilities stay between 0.25 and 0.35. Consumption is highest in 2010 and appears to increase again in 2016. More water is withdrawn around July and dips around January-March. Evident seasonality is not discernible, as higher consumption occurs in winter as well as summer months.

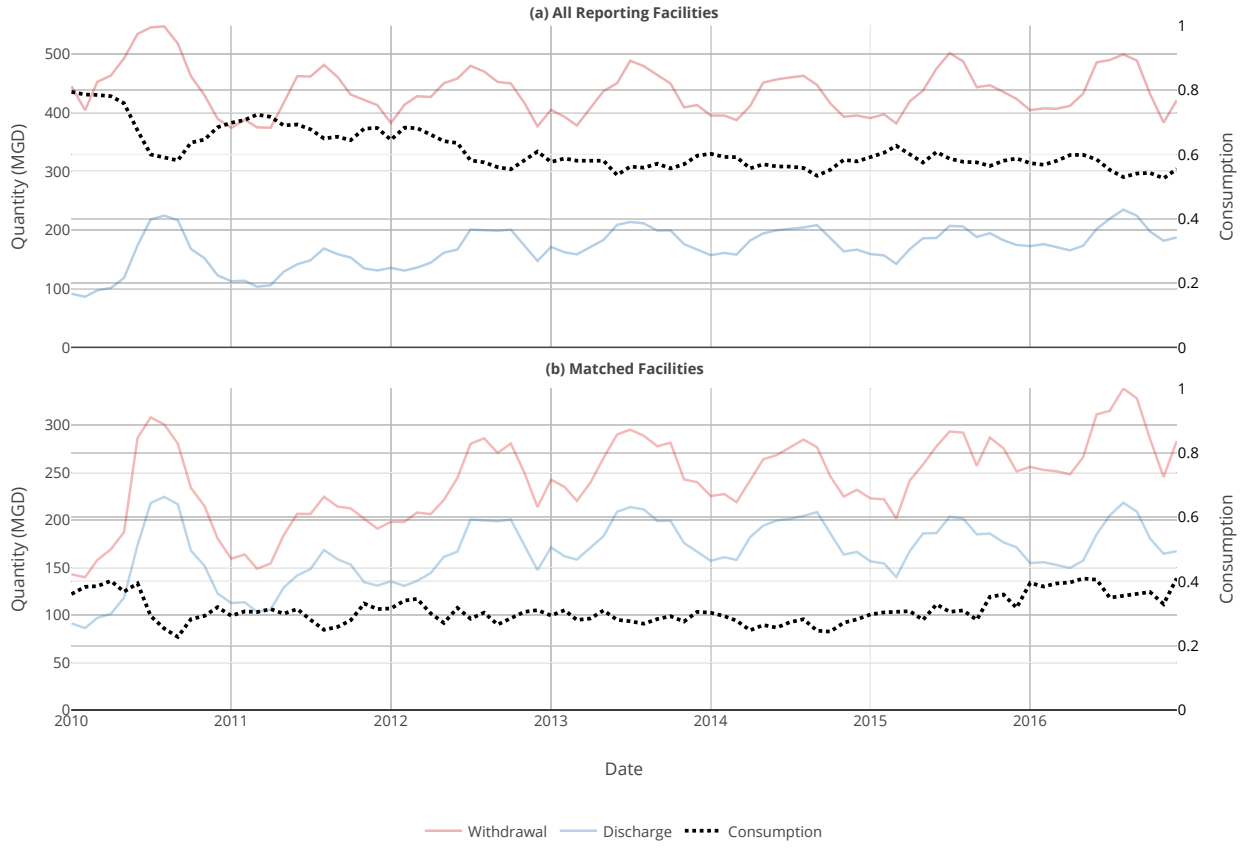

Figure 5.10: Monthly industrial consumption estimates based on (a) all available data and (b) matched facility data (2010-2016). Aggregated total volume per reporting month to estimate fraction of water lost.

Discharge data for aquaculture is only available in ECHO starting in October of 2015. Monthly consumption for all aquaculture facilities is choppy between each month, while it remains near 0.15 during all months for matched operations (Figure 5.11).

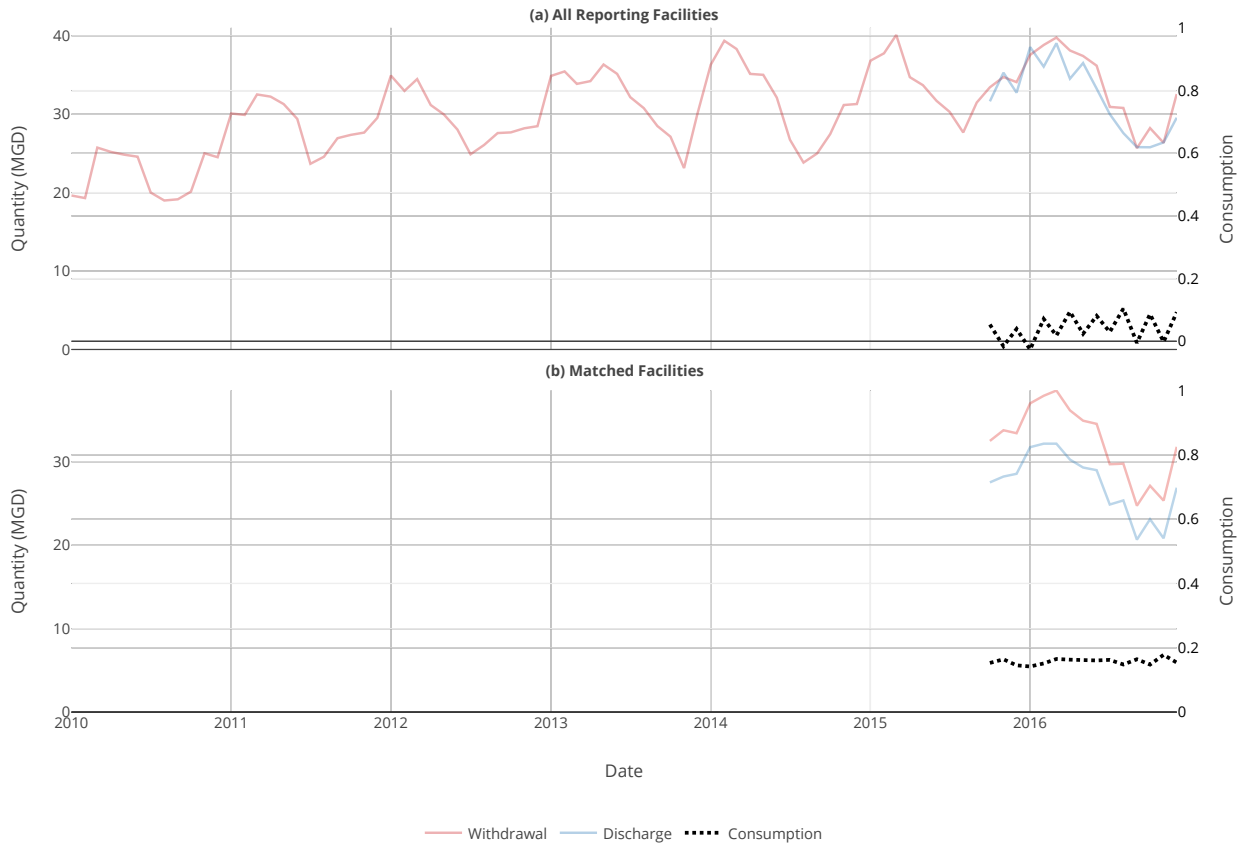

Figure 5.11: Monthly aquaculture consumption estimates based on (a) all available data and (b) matched facility data (b) (2010-2016). Aggregated total volume per reporting month to estimate fraction of water lost.

The commercial sector shows the most difference in consumption estimates between matched and all reporting facilities (Figure 5.12). Similar to aquaculture, discharge data in ECHO is not prevalent for commercial facilities until October of 2015. Once matched, consumption is highest in June to October from 2010-2015, oscillating in an obscure manner. Occurrences of negative consumption also appear in an unclear pattern as well. After 2015, consumption peaks in December, April, July, and October.

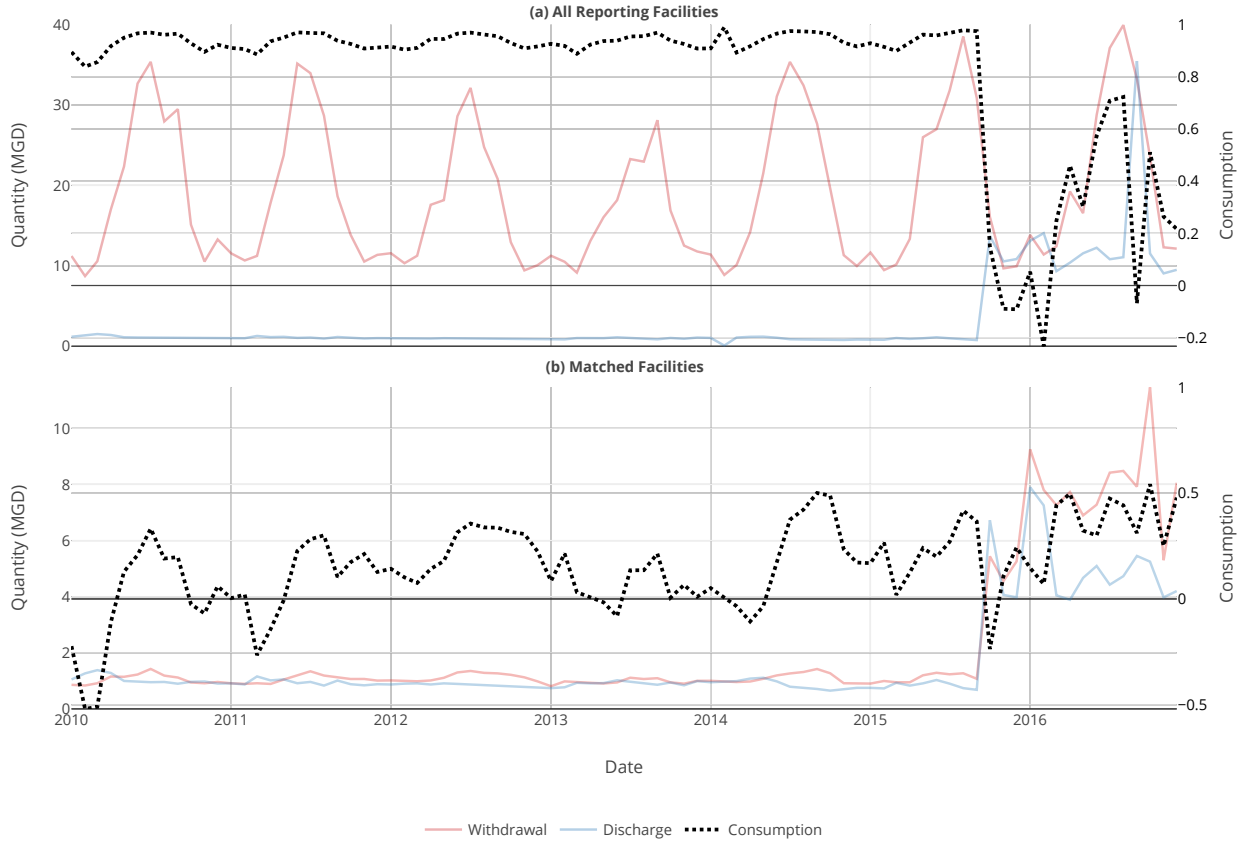

Figure 5.12: Monthly commercial consumption estimates based on (a) all available data and (b) matched facility data (b) (2010-2016). Aggregated total volume per reporting month to estimate fraction of water lost.

Municipal facilities were not included in the matching mechanism described in Section 4.2.4 due to differing customer bases and operations. However, on a statewide level with all facilities, consumption appears to follow a detectable pattern (Figure 5.13). From 2010 to 2016, monthly consumption is highest in the summer months, peaking in either July or September each year. Lowest consumption appears around March, with smaller peaks around February (save 2016).

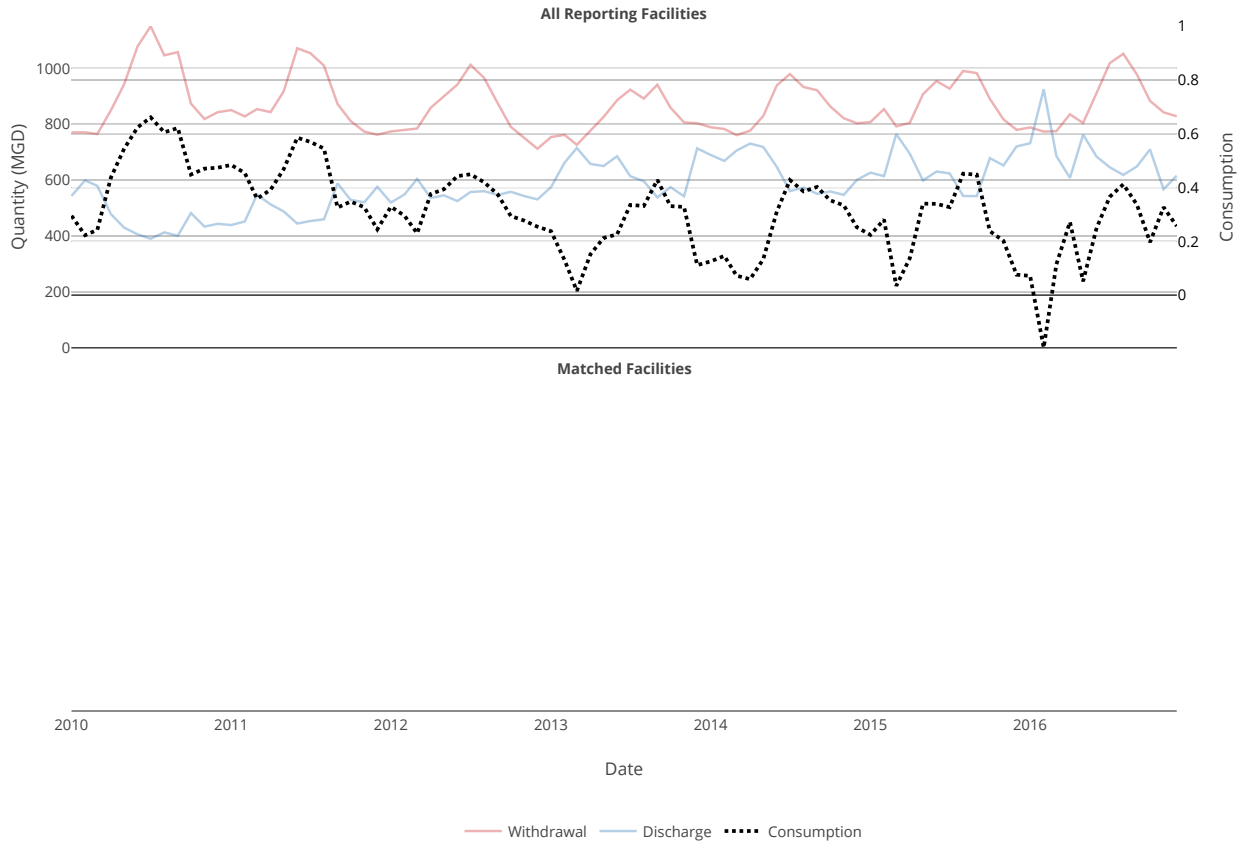

Figure 5.13: Monthly municipal consumption estimates based on (a) all available data and (b) matched facility data (2010-2016). Aggregated total volume per reporting month to estimate fraction of water lost. Municipal facilities were excluded from matching due to noisy facility-level relationship between withdrawal and end-point discharge.

Agriculture/Irrigation facilities do not report return flows, therefore resulting in 100% consumption. Withdrawals for agriculture show distinct patterns of seasonal operations, when precipitation is lowest in the Commonwealth. The peak of each year occurs in July and dips down to around 1 MGD in December through to February. Peak withdrawals between 2012 and 2013 decrease by 40%, but increase again in 2014 before lowering again in 2015 and 2016.

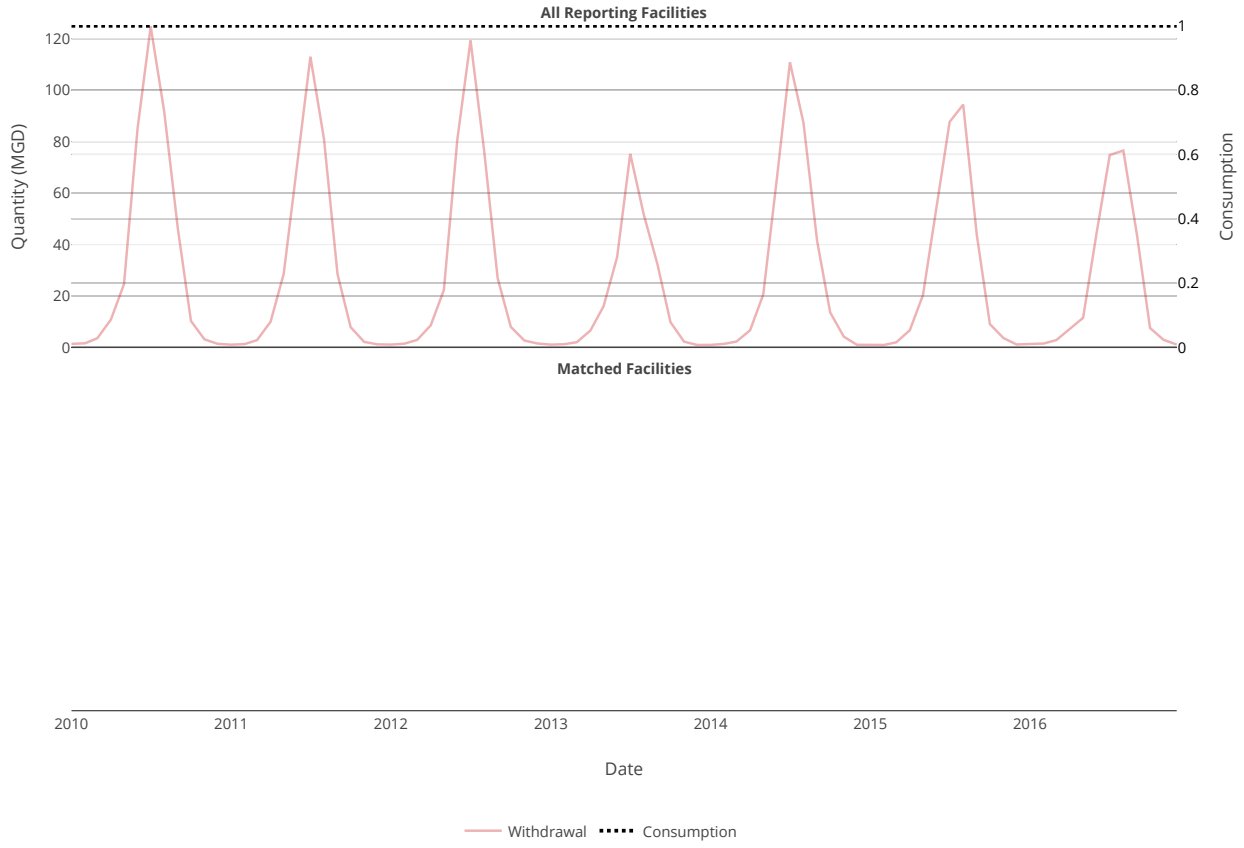

Figure 5.14: Monthly agriculture/irrigation consumption estimates based on (a) all available data and (b) matched facility data (2010-2016). Aggregated total volume per reporting month to estimate fraction of water lost. Assumed to be 100% consumptive in this analysis.

5.2.2 Facility Level

Consumption across facilities was also considered in this study. Rather than summing total reported withdrawals and discharges by reporting month, this approach quantifies how consumption varies across different facilities within the same sector. This aims to exclude outliers and diminish the influence of larger facilities. Figure 5.15 displays the long term median facility consumption in the energy (a), industrial (b), commercial (c), and aquaculture (d) sectors. Consumption was first estimated for each facility per reporting month. Long-term water consumption for each facility was characterized as the median of all of its median monthly consumption between 2010 and 2016. The red dashed lines in Figure 5.15 then indicate the overall median long term consumption across facilities within that respective sector.

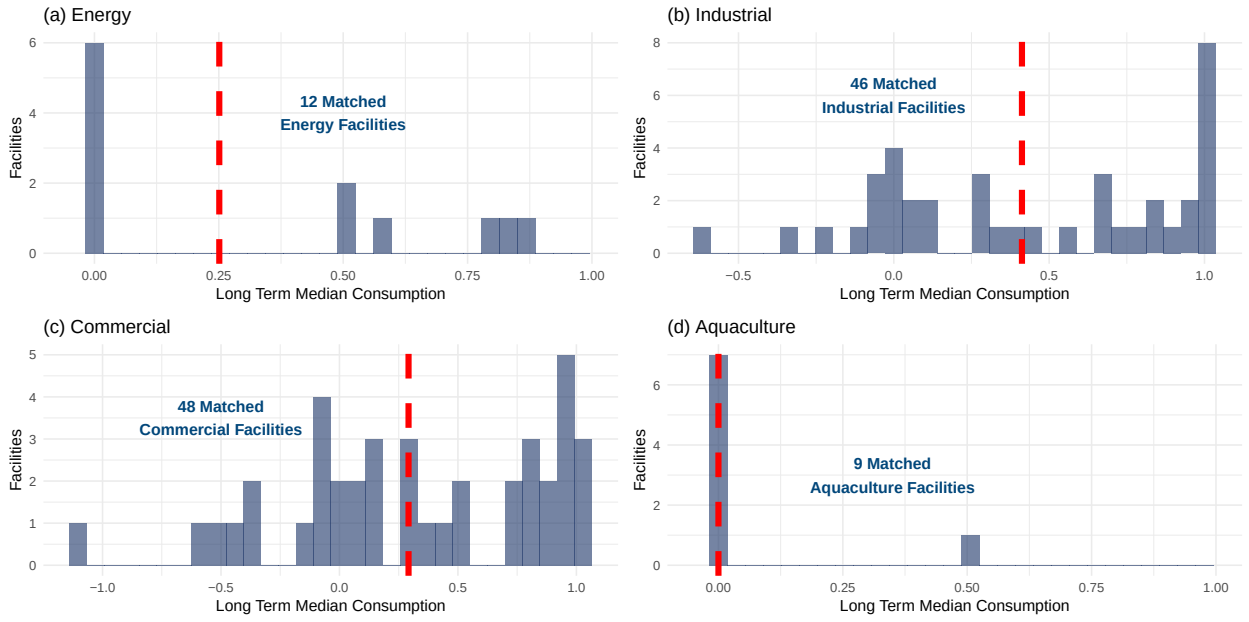

Figure 5.15: Distributions of long term median facility level consumption for (a) Energy, (b) Industrial, (c) Commercial, and (d) Aquaculture sectors (2010-2016). Medians of the distributions are indicated in the red dashed lines.

The long term medians displayed above are broken down by year and sector in Table 5.14.

Here, consumption was estimated for each facility per reporting month. Annual estimates per facility were calculated as the median monthly consumption value for the given year. The values presented in Table 5.14 show the median annual consumption value across facilities within each respective sector. Note that the long term median column analyzed monthly consumption per facility from 2010-2016 and is not the median of each yearly consumption value.

Table 5.14: Median annual facility consumption per year and water use sector (2010-2016). The median long term monthly consumption across facilities is represented in the far right column.

Sector	2010	2011	2012	2013	2014	2015	2016	Long Term Median
Energy	0.014	0.001	0.002	0.007	0.014	0.46	0.31	0.25
Industrial	0.38	0.39	0.42	0.21	0.31	0.41	0.38	0.41
Commercial	0.02	0.12	0.27	0.05	0.18	0.23	0.32	0.29
Aquaculture						0.00	0.00	0.00

5.2.2.1 Energy Facilities

The long term median consumption for energy facilities is 0.25, where median annual consumption is relatively low and consistent between 2010 and 2014 (Table 5.14). This then increases significantly in 2015. To understand this spike better, energy facilities were split by their fuel type. Figure 5.16 examines the differences in long term consumption between nuclear (a), coal (b), combination fossil fuel (c), and biomass (d). Table 5.15 then breaks down the long term median consumption estimates by year and power type. Methods for this figure and table are the same as described for Figure 5.15 and Table 5.14.

Two nuclear power stations in Virginia produce 31% of the total electricity used by the Commonwealth [7]. They also represent approximately 52% of the total water withdrawn each year (Table 5.16). Despite this, the long term median nuclear facility consumption rate is 0.005, with a lower and upper quartile of 0.0003 and 0.0005 respectively between 2010 and

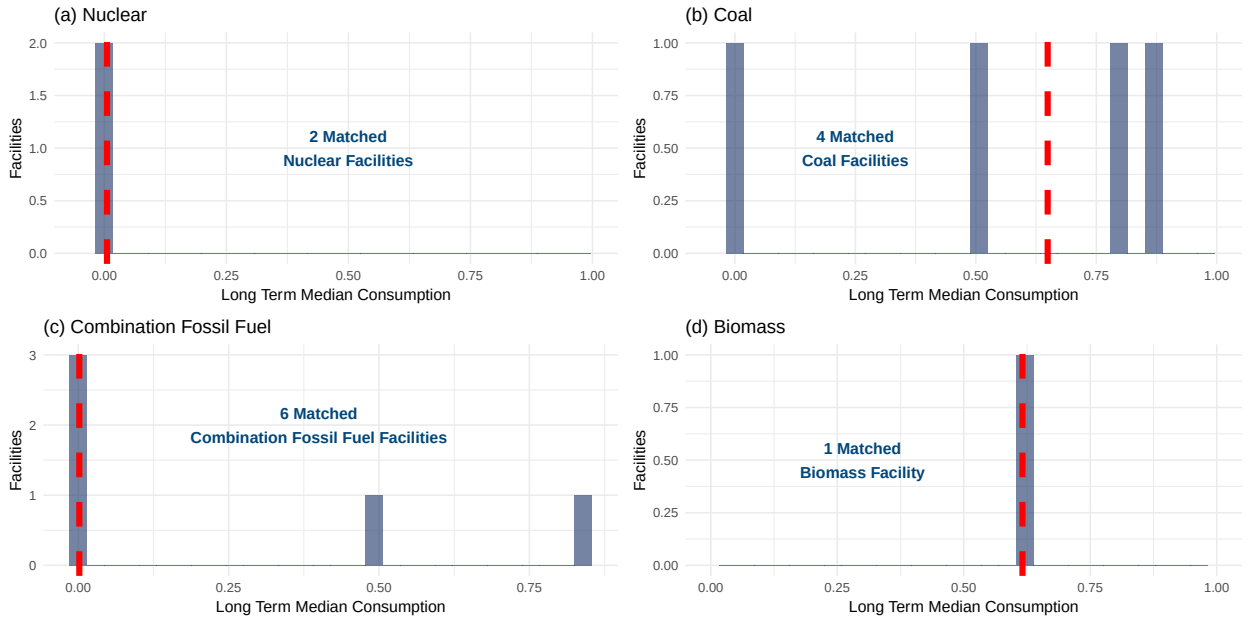

Figure 5.16: Distributions of long term median facility level consumption for (a) Nuclear, (b) Coal, (c) Combination Fossil Fuel, and (d) Biomass energy facilities (2010-2016). Medians of the distributions are indicated in the red dashed lines.

Table 5.15: Median annual facility consumption per year and power type (2010-2016). The median long term monthly consumption across facilities is represented in the far right column.

Sector	2010	2011	2012	2013	2014	2015	2016	Long Term Median
Nuclear	0.014	0.0003	0.0002	0.004	0.004	0.01	0.007	0.005
Coal	0.10	0.20	0.83	0.81	0.93	0.61	0.85	0.65
Combination Fossil	0.18	0.16	0.002	0.001	0.002	0.002	0.002	0.002
Biomass						0.57	0.63	0.60

2016 (Table 5.15). Monthly consumption rates fluctuate throughout the years, but do not display any clear seasonality patterns. Occurrences of reported negative consumption are prevalent in the years 2013 and 2014.

It's clear that the energy facilities operating on coal and biomass are influencing the increased annual consumption estimates observed in 2015 and 2016. The three matched coal facilities present a long term median consumption rate of 0.65, with a lower quartile of 0.31 and an upper quartile of 0.89 for monthly consumption observations. Monthly consumption rates appear to increase after 2010 and remain above 0.5 throughout to 2016.

Combination fossil fuel power stations use multiple generators that use natural gas and distillate oil. The six facilities present an overall median consumption rate of 0.002, with a lower and upper quartile of 0.0006 and 0.63 respectively between 2010 and 2016 for monthly consumption observations. Ranges of monthly reported consumption rates vary widely, increasing during the summer. In 2013, median consumption rates decrease dramatically and stay close to zero with the exception of higher rates during the summer months.

Three biomass facilities utilize wood waste in Virginia. One was matched using the mechanism described in Section 4.2.4 [7]. The overall median reported consumption rate between 2015 and 2016 is 0.60, with a minimum monthly consumption of 0.38 and maximum of 0.85.

5.2.2.2 Non-Energy Facilities

The non-energy sectors in this facility level analysis are comprised of industrial, commercial, and aquaculture facilities. The long term median consumption rate for 46 matched industrial facilities is 0.41, with a lower and upper quartile monthly consumption rate of 0.017 and 0.71, respectively between 2010 and 2016 (Table 5.14). The median monthly consumption fluctuates between 0.3 and 0.5 in 2010-2011. They begin to decline to 0.20 in 2013, but

ultimately increase to around 0.3 and 0.4 through 2016.

Of the 48 matched commercial facilities, consumption observations are not persistent until the year 2016. The long term median consumption rate is 0.29, with a lower and upper quartile monthly consumption rate of 0.01 and 0.82, respectively. Negative consumption occurrences are more frequent among the commercial facilities than that of the energy and industrial sectors.

Consumption estimates for the aquaculture sector are only available for the years 2015 and 2016. For these 9 matched facilities, the median reported consumption is 0.0. The highest observed monthly consumption rates occur around 0.5, but fall outside the whiskers of reported consumption for each month.

5.2.2.3 Case Studies

It can be seen that long term consumption varies across facilities within sectors. This variation could be due to inconsistent reporting, differences in water conservation technologies, or reporting errors. To investigate this concept further, one facility from the energy, industrial, commercial, aquaculture, and municipal sectors were extracted and analyzed (Figure 5.17). Facilities were selected based on data availability and ability to monitor in the future. A municipal facility is presented in these case study results to showcase a smaller water system located in rural Virginia. A smaller water system decreases the influence of unaccounted-for use and differing customer bases. It also gives a glimpse into the typical water use patterns for a water supply and wastewater treatment system.

For the energy sector, the North Anna Nuclear Power Station (Figure 5.17(a)) was selected because it is responsible for approximately 25% of the water that is reported as withdrawn from Virginia each year, on average. This nuclear facility also has an external outfall that

tracks stormwater flows. This has the potential to confound consumption estimates, causing them to be lower than what may be actually be consumed. The discharge represented in Figure 5.17(a) is the best approximation of the actual return flow for the facility, but still exceeds reported withdrawals in several months between 2010 and 2016. Therefore, this facility should be monitored in the future to understand the actual amount of return flow exiting the facility, as well as any forced evaporation into its adjacent cooling pond.

Advansix Resins and Chemicals LLC was then selected as the industrial sector case study (Figure 5.17(b)). This facility is a well known producer of caprolactam, which is the feedstock for nylon polymer production [38]. Although it is a well known industrial facility, it has a fairly steady consumption rate around 40%, well above values reported in literature. This could be a facility that water planners can focus on to implement efficient water conservation technology and practices. Especially if not all withdrawn water is being incorporated into products.

As indicated in Section 4.2, reporting of discharge in the commercial sector did not become persistent and prevalent for several facilities until 2015 and 2016. Therefore, the Mainside STP at the Marine Corps Base in Quantico was selected as the case study study (Figure 5.17(c)). This on-base treatment facility is one of two commercial facilities that provides matched withdrawal and discharge from 2010 through 2016. Like the North Anna Nuclear Plant and several other facilities, this one also reports excess discharge in a handful of months before 2015. It would be interesting to see if this is a consequence of data reporting from Virginia's NPDES program to the EPA, or if the base is accepting water from other sources other than its point source withdrawals for treatment.

As for aquaculture, the majority of fish hatcheries within this analysis report consumption closer to 0%. However, the Marion Fish Hatchery reports consumption around 50-60% (Fig-

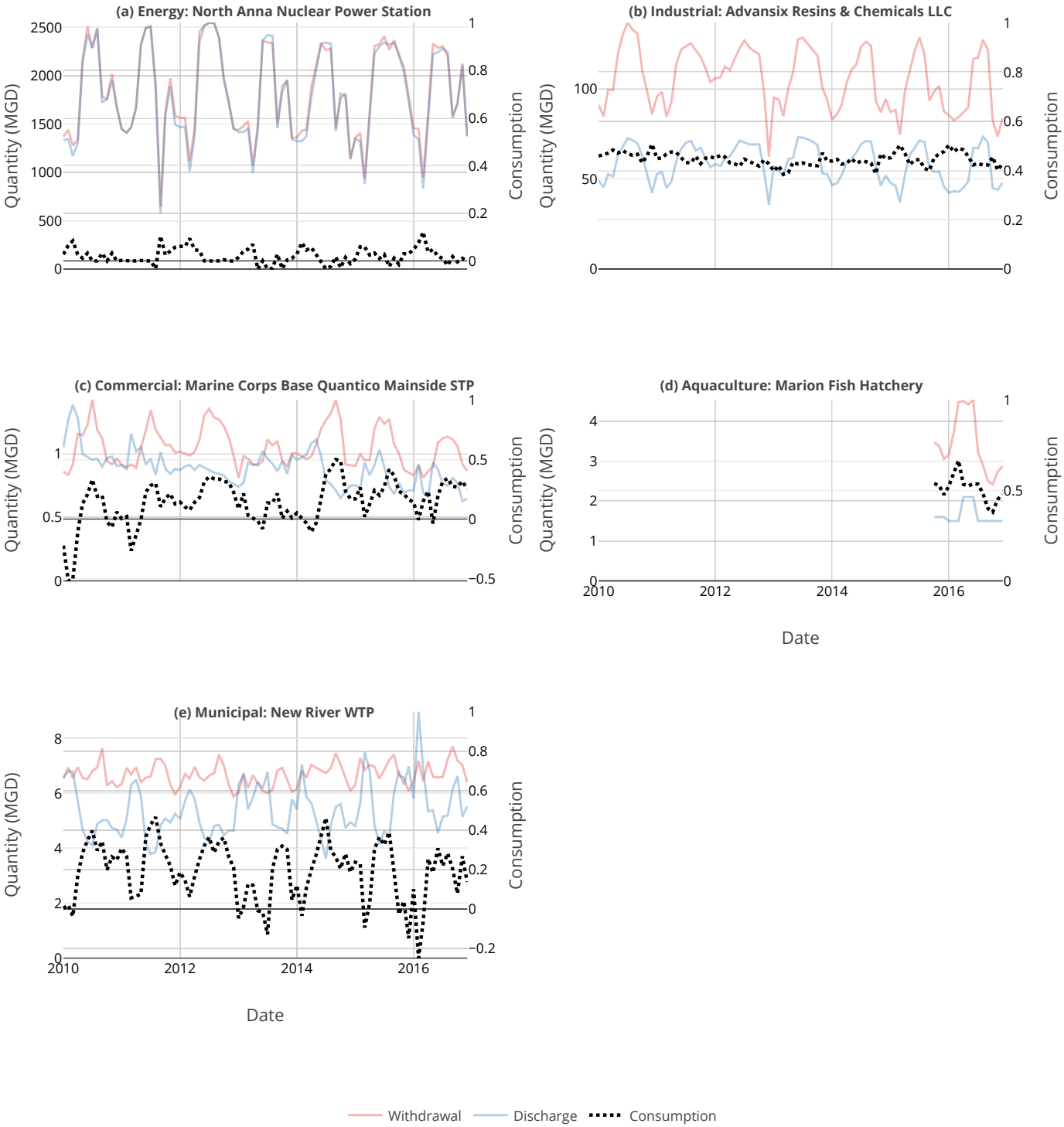

Figure 5.17: Monthly consumption estimates for (a) North Anna Nuclear Power Station, (b) Advansix Resins and Chemicals LLC, (c) Shenandoah Brewery, (d) Marion Fish Hatchery, and (e) New River WTP. Summed total volume per reporting month to estimate fraction of water lost.

ure 5.17(d)). Specifically, this trout hatchery is one of the oldest in the state of Virginia. High consumption may be due to degraded infrastructure or lack of quality discharge reporting. This is a good opportunity for the VDEQ to intervene and investigate this facility's unusually high reported consumption rates.

A case study facility from the municipal sector was also selected; partially to highlight the effects of potential differing customer bases. The New River WTP is located in Radford, Virginia and represents a fairly small municipal system located in a fairly rural area, making it more of a closed system compared to ones located in Richmond and Alexandria (Figure 5.17(e)). Larger populated areas will typically have multiple drinking water facilities, wastewater treatment facilities, and transfers, which causes the noise observed in the municipal sector. Unlike consumption rates from other sectors, this water treatment facility displays seasonality, with more consumption in the summer months. Ultimately, this shows that consumption may be estimated on the facility level for municipal systems with smaller customer bases or one-to-one match between a single supplier and a wastewater treatment facility.

5.2.2.4 Top Paired Facilities in Virginia

The top two energy, industrial, commercial, and aquaculture facilities are presented in Table 5.16. For each facility, the long term average percentage of total reported withdrawal and discharge is given. Median values of consumption as a coefficient and a quantity of water are also provided. Annual reported withdrawal and discharge for each facility were summed and used to calculate an annual consumption value for each year. The presented consumption estimates are then the median value across 2010 and 2016.

Table 5.16: Top two paired water systems in Virginia per sector: 2010-2016.

Facility	**% Total Withdrawal**	**% Total Discharge**	**Median Consumption**	**Median Consumption (MGD)**	**Sector**
Surry Power Station	27%	32%	3.8E-04	0.74	Energy
North Anna Nuclear Power Plant	25%	28%	0.02	34	Energy
Advansix Resins and Chemicals LLC	1.5%	0.9%	0.45	46	Industrial
Covington Plant Westrock	0.5%	0.5%	0.25	10	Industrial
Coursey Spring Fisheries	0.2%	0.2%	-1.3E-16	-1.8E-15	Aquaculture
Terry Place Plant	0.1%	0.1%	0.0	0.0	Aquaculture
Shenandoah Brewery	0.03%	0.02%	0.39	0.89	Commercial
Naval Support Facility Dahlgren	0.004%	0.006%	-72	-0.4	Commercial

5.2.3 County

All available data are compared to matched facility data in this county analysis (Figures 5.18 and 5.19). Energy, industrial, commercial, and aquaculture sectors are considered for matched facilities. All available data results provide consumption estimates for the municipal and agriculture/irrigation sectors. County estimates are presented as median annual rates over 2010-2016.

Monthly reported total volume was first aggregated by facility and year and subsequently divided by the number of respective reporting months. Annual facility estimates were then aggregated by intersecting county per year. The median of the annual estimates is ultimately displayed on the maps in this section.

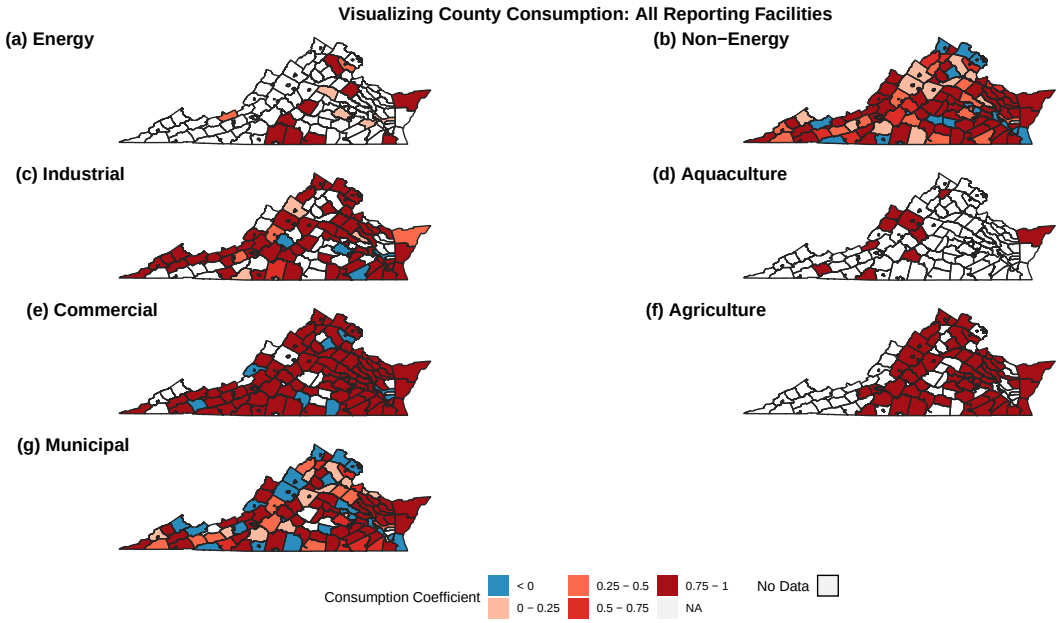

Figure 5.18: Median long-term county consumption considering all available data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Aquaculture, (e) Commercial, (f) Agriculture, and (g) Municipal sectors (2010-2016). Aggregated total volume per facility and year first, and then by county to estimate fraction of water lost.

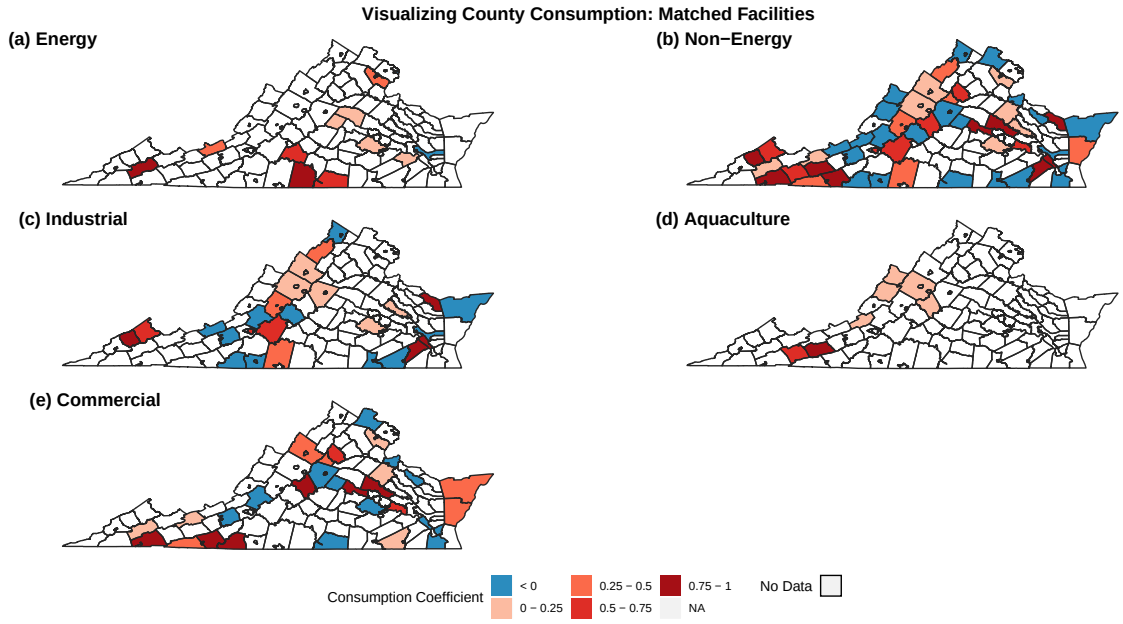

Figure 5.19: Median long-term county consumption considering only matched facility data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Aquaculture, (e) Commercial, (f) Agriculture, and (g) Municipal sectors (2010-2016). Aggregated total volume per facility and year first, and then by county to estimate fraction of water lost.

5.2.3.1 Energy Sector

According to literature, energy consumption typically ranges between 1-5% (Table 2.4). When all available data are considered, energy consumption appears to be higher than expected (Figure 5.20). Counties displaying low consumption include Louisa, Chesterfield, Surry, and York. Median consumption lowers when matched facilities are displayed, but still remain high in the southwest, where coal facilities are located (Figure 5.21).

Matched facility coordinates were paired in Figure 5.21 to present median county consumption as well as median facility consumption in MGD and power type. Even though energy consumption may be low relative to the amount of water withdrawn, the quantity of water lost exceeds that of other sectors. For instance, facilities along the James River consume 0-25% of the water withdrawn, resulting in an average loss of 10 or more MGD.

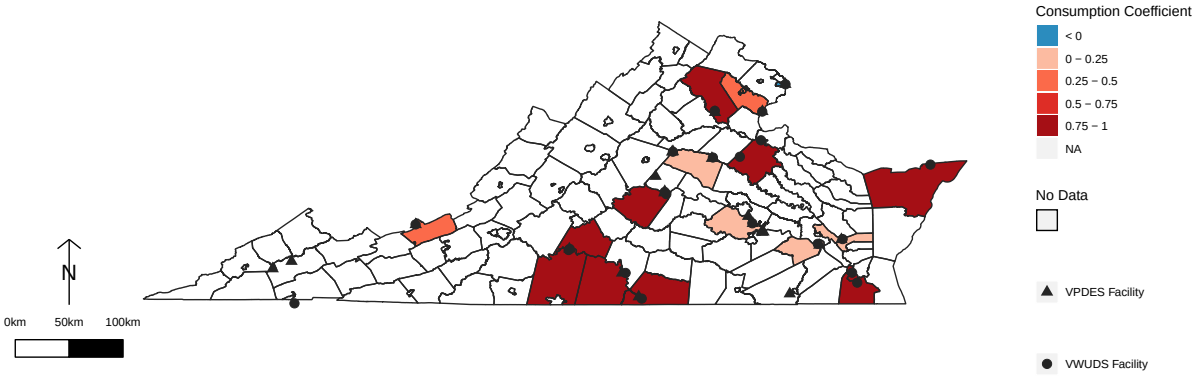

Figure 5.20: Median long-term county energy consumption considering all available data (2010-2016). Aggregated total volume per facility and year first, and then by county to estimate fraction of water lost.

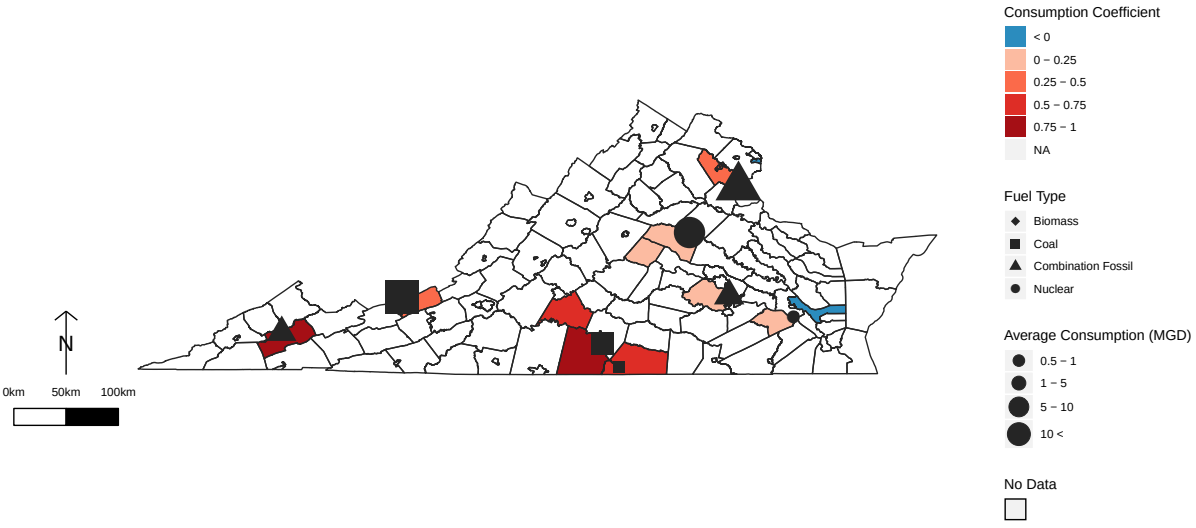

Figure 5.21: Median long-term county energy consumption considering matched facility data (2010-2016). Aggregated total volume per facility and year first, and then by county to estimate fraction of water lost.

5.2.3.2 Non-Energy Sectors

As demonstrated in Figure 5.2, not all withdrawing industrial facilities have persistent associated discharge entries located in ECHO. Therefore, when all available data is projected in a county framework, it appears that consumption is within 75-100% for most counties (Figure 5.22). Nearly all of the reported industrial discharge was captured by matched facilities (Table 5.8), therefore observations of negative consumption are likely due to errors on the facility level.

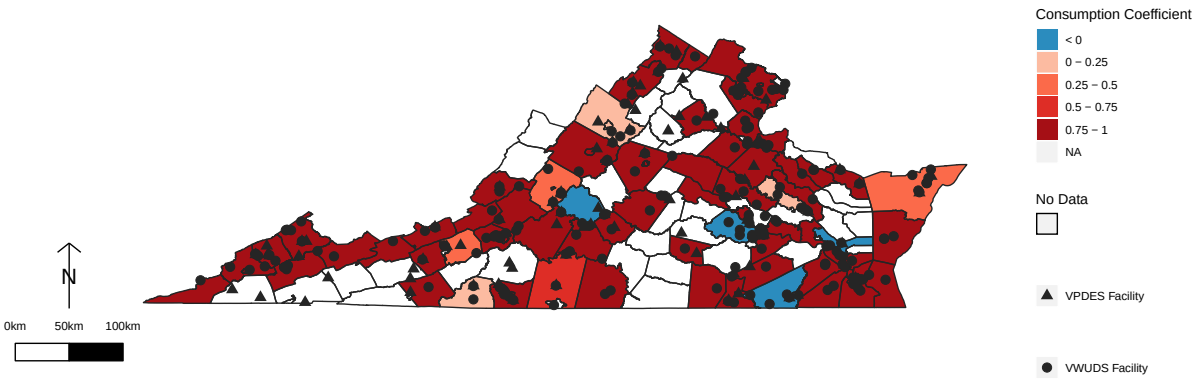

Figure 5.22: Median long-term county industrial consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

When facilities without corresponding discharge/withdrawal records are removed, noticeable pockets are formed, revealing regions lacking significant matched industrial data (Figure 5.23). Higher consumption is observed among mining operations in Dickenson County, paper mill operations near Roanoke, biomass gasification in Bedford County, apparel operations in Pittsylvania, and packing operations in Northumberland. Negative consumption occurs near major water ways including the Chesapeake Bay, York River, James River, and Smith

River.

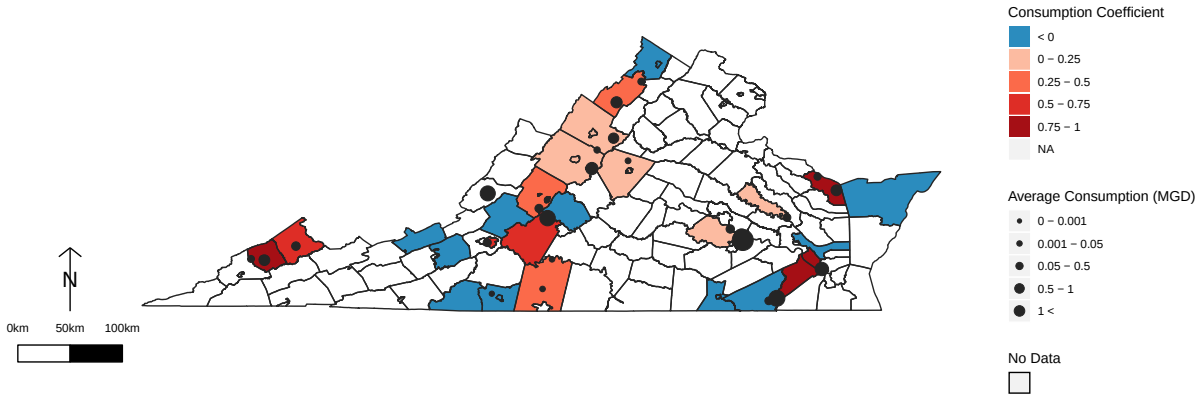

Figure 5.23: Median long-term county industrial consumption considering matched facility data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

Commercial and aquaculture consumption is impacted the most from inconsistent discharge reporting in ECHO (Figures 5.24 and 5.26). Consequently, the lack of discharge data between 2010 and 2015 leads to median consumption rates between 75-100%. All reporting commercial facilities are concentrated around populated city centers including Richmond, Virginia Beach, Alexandria, and other major interstates.

Matched commercial facilities are also located near populated city centers and along I-95 in Virginia (Figure 5.25). Similar to the Industrial facilities, several commercial facilities have negative consumption observations. Therefore, when a county contains a small number of commercial facilities, it may also report negative consumption. Top negative consumption occurs in Chesterfield, Newport News City, and King George County, which are all bordered by major waterways. Higher median consumption is observed in Washington, Nelson, and Carroll County.

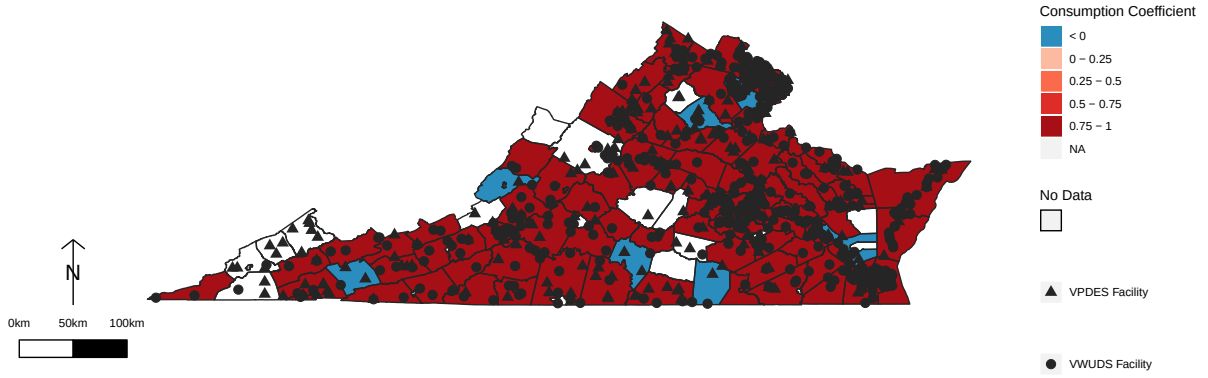

Figure 5.24: Median long-term county commercial consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

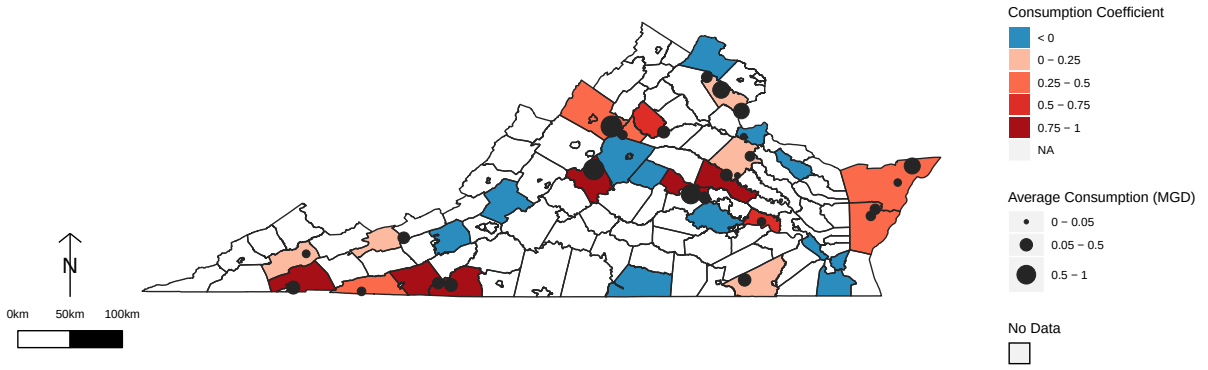

Figure 5.25: Median long-term county commercial consumption considering matched facility data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

The majority of the aquaculture facilities in Virginia are located along the Appalachians (Figure 5.26). Like the commercial sector, discharge data is not persistent until 2016. Thus, when all available data is considered, the median annual consumption appears to be 100% consumptive.

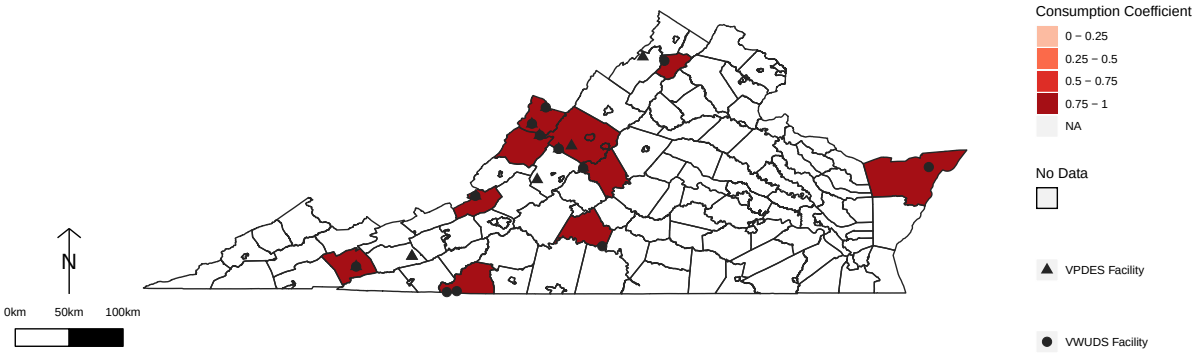

Figure 5.26: Median long-term county aquaculture consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

Matched aquaculture operations are also located along the Appalachians, with none located in Federal waters off of the Coast. Aquaculture consumption on the county level is low, with median rates less than 25% in Craig, Bath, Highland, Augusta, and Nelson County. Higher consumption is observed in Smyth and Wythe County, where the two facilities there are trout hatcheries, one being the oldest in the state.

Agriculture/Irrigation operations are assumed to be completely consumptive in this study (Figure 5.28). Farms are concentrated in the Shenandoah valley and in eastern Virginia. Agricultural data is scarce in the southwest.

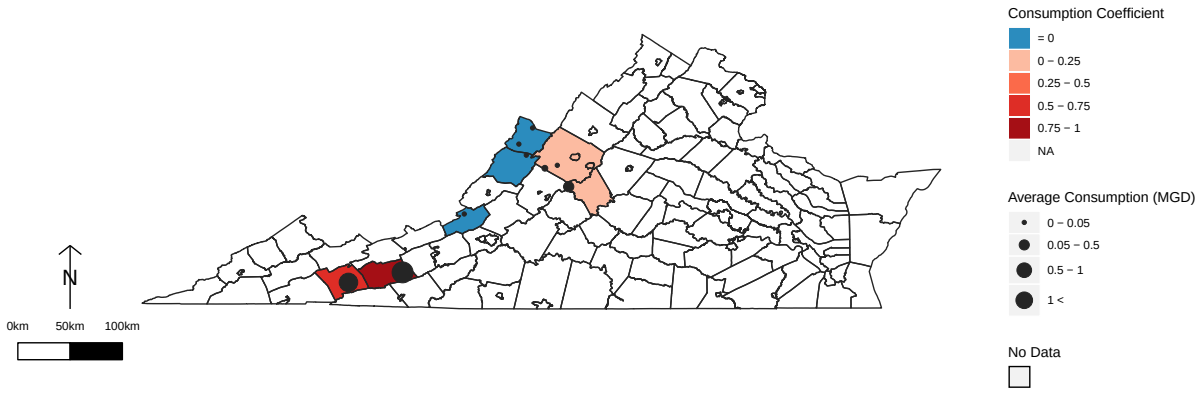

Figure 5.27: Median long-term county aquaculture consumption considering matched facility data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

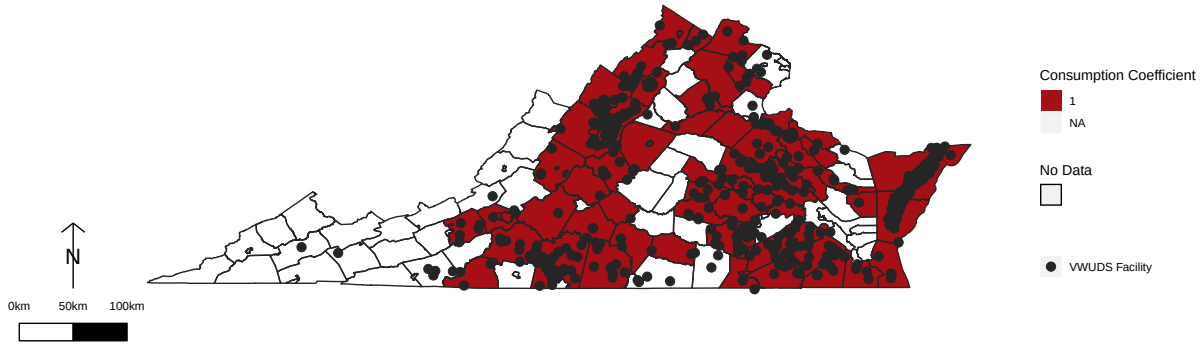

Figure 5.28: Median long-term county agriculture/irrigation consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

The municipal sector was excluded from the matching procedure, but examined for facility location (Figure 5.29). Municipal facilities are distributed across the entire state, with more being concentrated around higher populated regions. If Figure 5.18 is referenced, it appears that the majority of counties reporting negative consumption for all non-energy sectors (b) also report negative consumption for municipal facilities (g), suggesting that the municipal facilities are driving the main consumption trends (when all available data is considered).

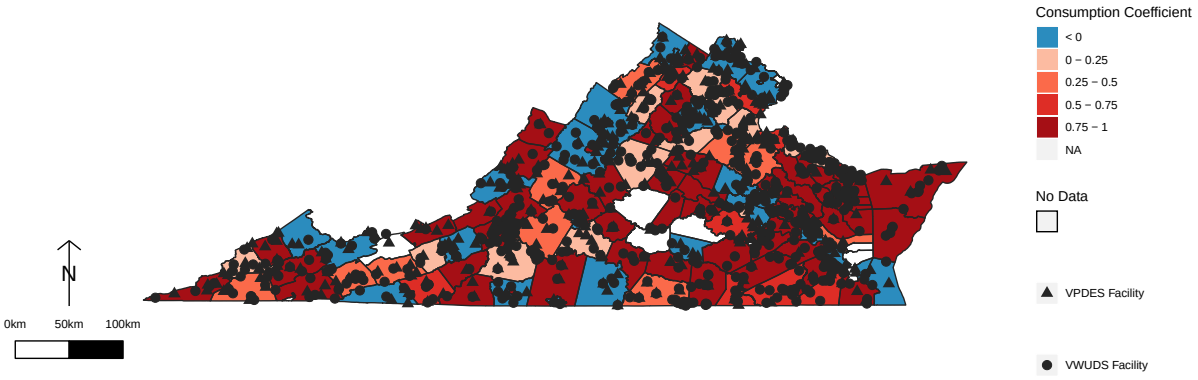

Figure 5.29: Median long-term county municipal consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

5.2.4 HUC 6 Watershed

The HUC 6 watershed analysis compares consumption estimates considering all available data versus fully matched entries (Figures 5.30 and 5.31). Energy, industrial, commercial, and aquaculture sectors are considered for matched facilities. All available data results provide consumption estimates for the municipal and agriculture/irrigation sectors. Watershed estimates are presented as median annual rates over 2010-2016.

Monthly reported total volume was first aggregated by facility and year and subsequently divided by the number of respective reporting months. Annual facility estimates were then aggregated by intersecting watershed per year. The median of the annual estimates is ultimately displayed on the maps in this section.

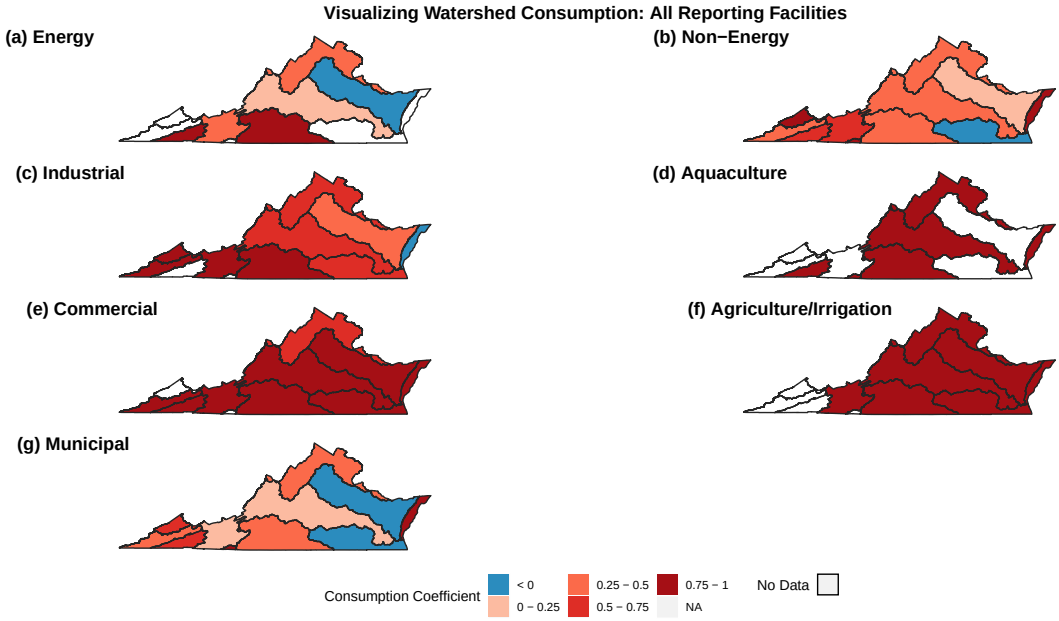

Figure 5.30: Median long-term HUC6 watershed consumption considering all available data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Aquaculture, (e) Commercial, (f) Agriculture/Irrigation, and (g) Municipal sectors (2010-2016).

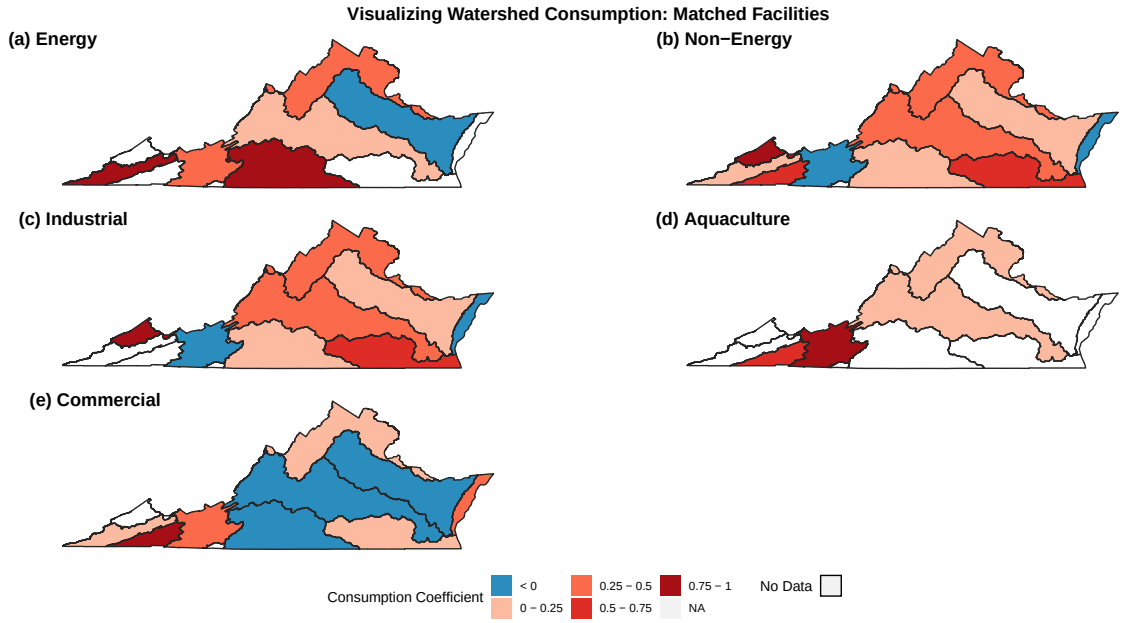

Figure 5.31: Median long-term HUC6 watershed consumption considering all available data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Aquaculture, and (e) Commercial sectors (2010-2016).

5.2.4.1 Energy Sector

When the spatial scale is enlarged to the HUC 6 watershed scale, major energy facilities appear to control the overall consumption trend. Figures 5.32 and 5.33 show that median 2010-2016 consumption estimates are the same between data sets, regardless of if only matched facilities are observed. This further suggests that the facility matching procedure was successful in capturing the majority of reported energy withdrawals and discharges. Even when only matched facilities are observed, there are observations of negative consumption. Here, the negative York county in the previous analysis is influencing the entire consumption trend of the Lower Chesapeake. This indicates that there may be inconsistent reporting or errors at the facility level for the facility located in the southwest corner of the Lower Chesapeake. Other than that, it appears that coal fired power stations consume a higher percentage of water than nuclear stations. Combination Fossil Fuel facilities have a variety

of consumption percentage and quantity.

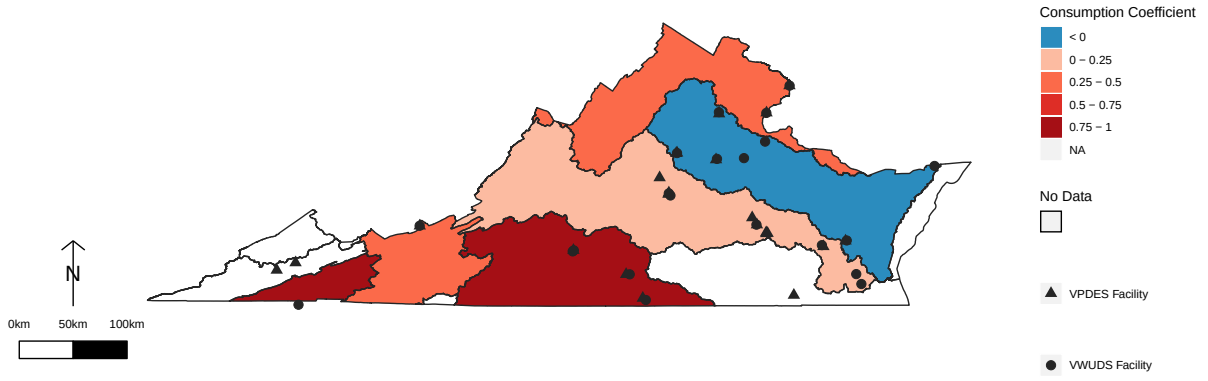

Figure 5.32: Median long-term HUC6 watershed energy consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

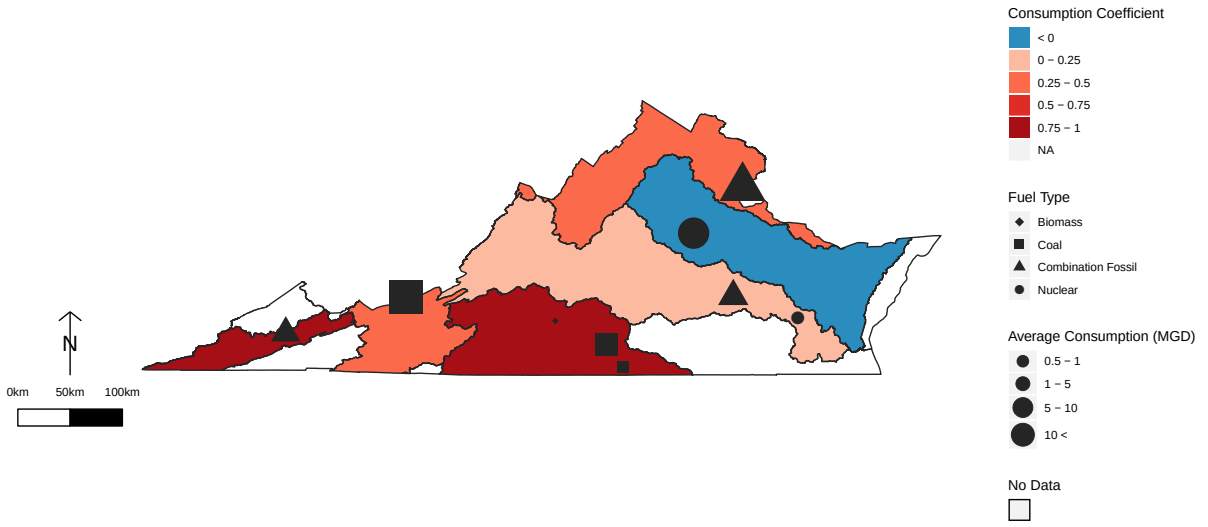

Figure 5.33: Median long-term HUC6 watershed energy consumption considering matched facility data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

5.2.4.2 Non-Energy Sectors

When all reporting industrial facilities are analyzed, consumption is above 50% in the Potomac, James, Big Sandy, Upper Tennessee, Kanawha, Roanoke, Albemarle-Chowan, and Lower Chesapeake watersheds (Figure 5.34). Consumption is however negative in the Mid-Atlantic Coatal watershed, which has multiple facilities located on the western border of the watershed boundaries.

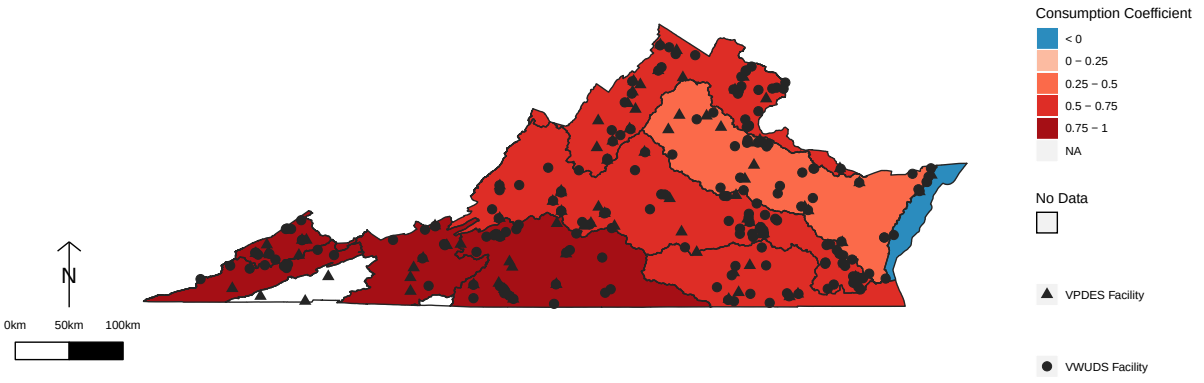

Figure 5.34: Median long-term HUC6 watershed industrial consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

For matched industrial facilities, median watershed consumption is primarily between 0-50% (Figure 5.35). Counties that reported negative consumption are now balanced out by other major industrial facilities. It appears that any errors that are contributing to negative consumption at the smaller scales (i.e. facility and county) are independent of each other and thus tend to cancel each other out when aggregated to larger spatial scales. The Mid-Atlantic Coastal and Kanawha watersheds present negative consumption, with few facilities contributing to the median consumption.

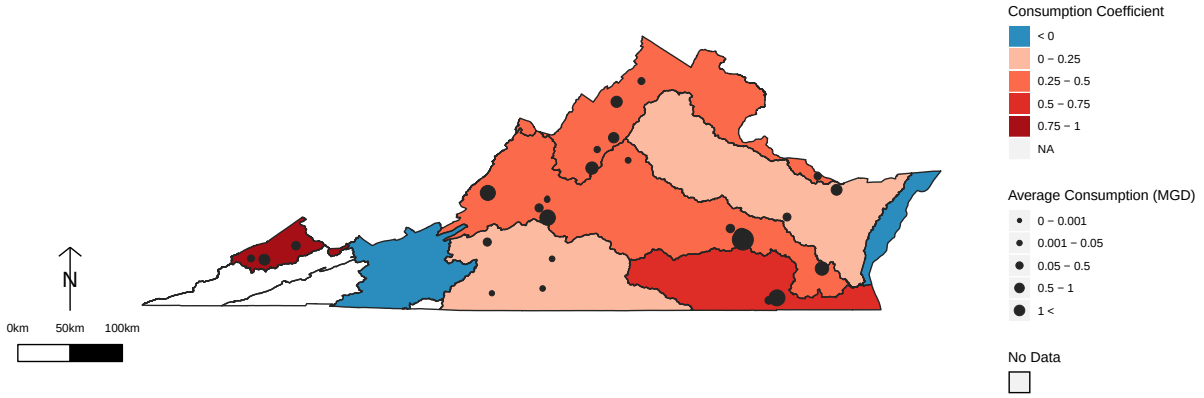

Figure 5.35: Median long-term HUC6 watershed industrial consumption considering matched facility data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

Like the county analysis, commercial watershed consumption is between 75-100% due to inconsistent discharge reporting in ECHO from 2010-2016 (Figure 5.36). When only matched commercial facilities are focused on, it's evident that there a few facilities reporting more discharge than withdrawal that are influencing the overall consumption trend for the Roanoke, James, and Lower Chesapeake (Figure 5.37). The largest commercial facilities influencing negative trends include a shipping and storage facility and a naval facility. Other than these negative observations, the rest of the watersheds present relatively low median consumption estimates less than 25% in the Potomac, Upper Tennessee, and Albemarle-Chowan.

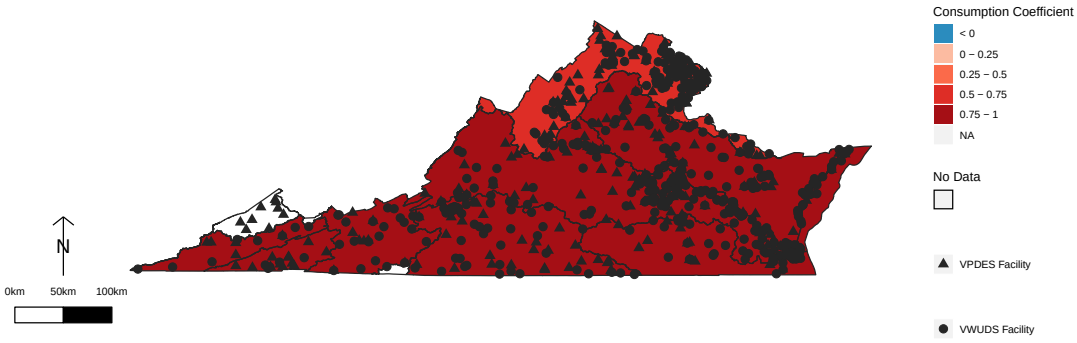

Figure 5.36: Median long-term HUC6 watershed commercial consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

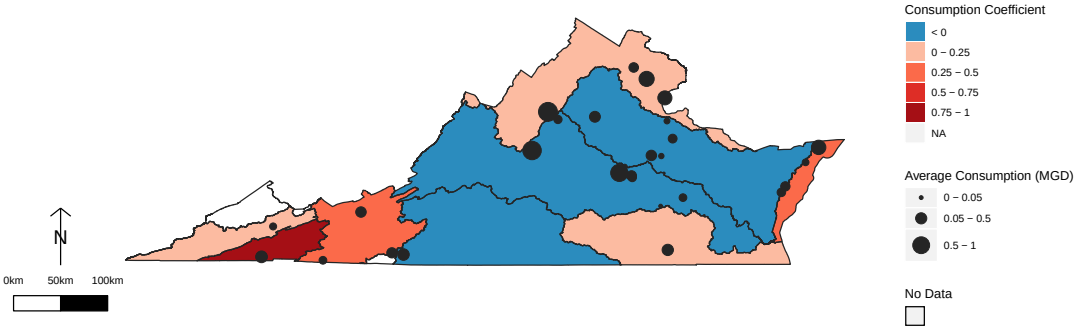

Figure 5.37: Median long-term HUC6 watershed commercial consumption considering matched facility data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

Similar to the county analysis of matched aquaculture facilities, median consumption is 100% in watersheds due to the lack of associated discharge records before 2016 in ECHO (Figure 5.38). Once only fully matched entries are focuses on, median watershed consumption drops close to 0% in the James and Potomac watersheds (Figure 5.39). The facilities with higher consumption in the Kanawha and French Broad-Holston watersheds are both trout fish hatcheries (Marion and Wytheville Trout Hatchery).

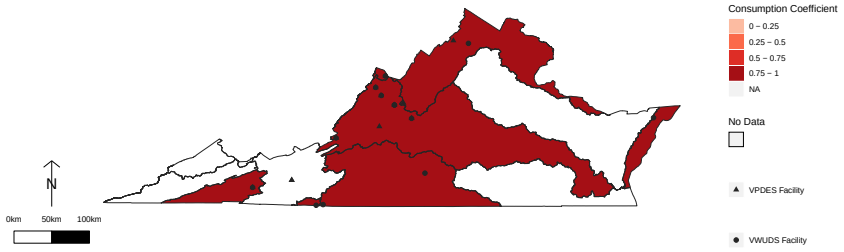

Figure 5.38: Median long-term HUC6 watershed aquaculture consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

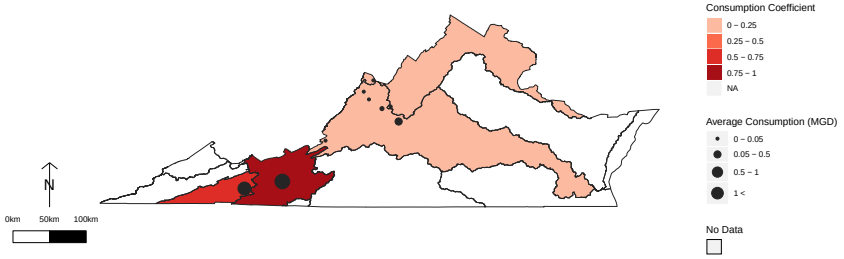

Figure 5.39: Median long-term HUC6 watershed aquaculture consumption considering matched facility data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

All agricultural/irrigation operations are considered to be completely consumptive (Figure 5.40). Since the spatial scale is less refined, the only areas that appear to be scarce of data includes the Big Sandy, Upper Tennessee, French BroadHolston, and Upper Pee Dee watersheds located in Southwest Virginia.

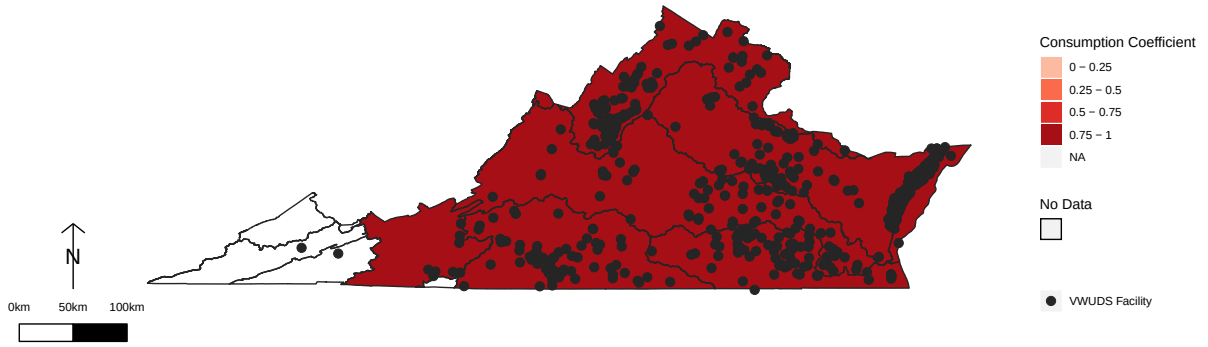

Figure 5.40: Median long-term HUC6 watershed agriculture/irrigation consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

Median consumption estimates for the Municipal sector are less sporadic at the watershed level (Figure 5.40). Perhaps this scale captures potential inter-county transfers that happen at the facility level. The Lower Chesapeake and Albemarle-Chowan display negative consumption which may be due to differing customer bases and deliveries from private wells and domestic users to wastewater treatment facilities.

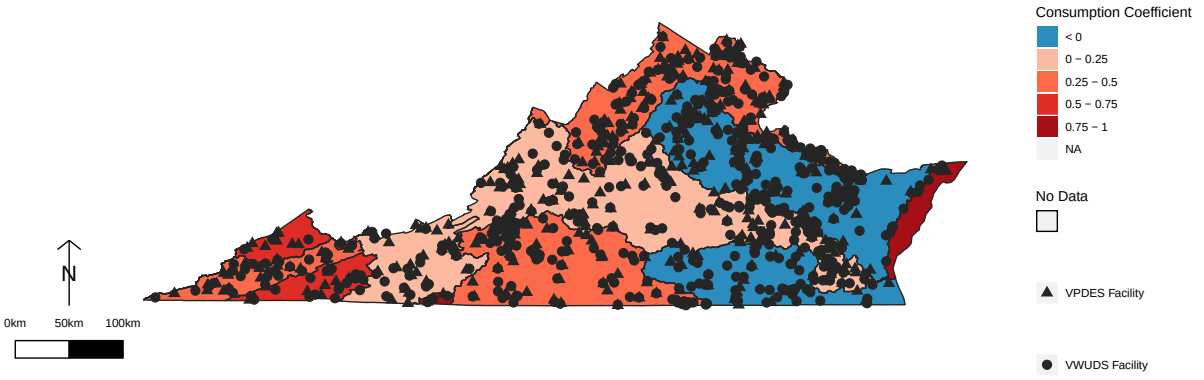

Figure 5.41: Median long-term HUC6 watershed municipal consumption considering all available data (2010-2016). Aggregated total volume per year to estimate fraction of water lost.

5.3 Trend Analysis

To address the second objective of this study, Mann-Kendall trend tests were applied to the monthly 2010-2016 consumption observations at a statewide level, where consumption was estimated as the fraction of water lost based on total reported volume per month (Figure 5.42).

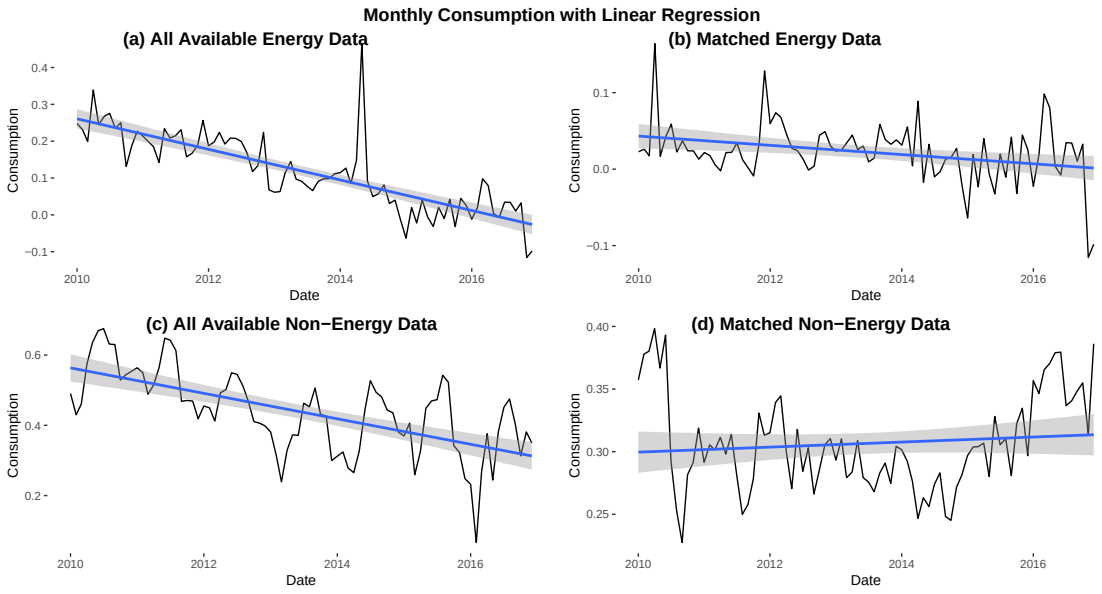

Figure 5.42: Monthly consumption (black line) with linear regression (blue line) considering (a) all available energy data, (b) matched energy facility data, (c) all available non-energy data, and (d) matched non-energy facility data. Consumption estimated by summing total reported withdrawals and discharges each month to estimate the fraction of water lost.

Tests for monotonic trend significance were performed for all available data and fully matched data, first for all sectors and then by sector (Tables 5.17 and 5.18). For all available data, the energy, industrial, commercial, aquaculture, and municipal sectors are considered. Municipal and Agriculture/Irrigation are not included in the trend analysis for matched facilities. Results are reported in tau and p-values. Mann Kendall's tau coefficient measures the rank correlation between consumption and time [45]. If tau is negative, it suggests consumption is decreasing with time, with a positive tau suggests it is increasing. The p-value indicates

the statistical significance of this correlation/trend. Regardless of matching, statewide consumption, which is driven by the energy sector, appears to have a downward trend over time (Table 5.17). However, this trend is only statistically significant when all reporting facilities are considered.

Table 5.17: Mann Kendall's Tau and P-value computed on prewhitened monthly consumption. Energy vs. Non-Energy Sectors.

	Matched Facilities		**All Facilities**	
Sector	**Tau**	**p-value**	**Tau**	**p-value**
Energy	-0.13	0.07	-0.68	5.8E-20
Non-Energy	0.15	0.04	-0.58	6.1E-15

Table 5.18: Mann Kendall's Tau and P-value computed on prewhitened monthly sector consumption.

	Matched Facilities		**All Facilities**	
Sector	**Tau**	**p-value**	**Tau**	**p-value**
Aquaculture	0.10	0.66	-0.16	0.07
Commercial	0.39	2.4E-07	-0.28	1.5E-4
Energy	-0.13	0.07	-0.68	5.8E-20
Industrial	0.20	0.01	-0.72	4.5E-22
Municipal			-0.48	1.01E-10

Commercial and industrial consumption display upward statistically significant trends among the matched facilities (Table 5.18). Matched energy facilities display a downward trend in consumption, but is not significant. Rank correlations are weak (<0.5) among each sector in the matched facilities, suggesting a weaker connection between consumption and time. When all reporting facilities are considered, downward trends in consumption are suggested for each sector, with significance in all except for aquaculture. Trends for all available data are heavily influenced by the increase of reporting discharge facilities within the last 18 months of the data set. Therefore, it is difficult to say if a downward trend truly exists when all data is considered, or whether this is simply an artifact of increased reporting of discharge though time.

5.4 Comparison to Climatically Similar Studies

Ranges of consumption values derived from our data were compared to literature values in three ways:

- Annual statewide consumption values considering all available data, where the ranges indicate the spread of annual consumption values for each year between 2010-2016. Monthly withdrawals and discharges in MGD were summed by facility and year and divided by the number of respective reporting months to return statewide average annual withdrawal and discharge estimates in MGD. Annual consumption estimates used these total reported volumes in MGD to calculate the fraction of water not returned to water resources each year.

- Annual statewide consumption values using the total volume approach, but just with matched facility data only.

- Median annual facility consumption, where consumption was first calculated for each facility per reporting month. Annual facility consumption is the median of the monthly median estimates for each respective year. The distributions displayed in Figure 5.43 show the spread of median annual consumption across 2010-2016.

Figure 5.43 compares the spread of annual consumption estimates from the statewide total volume approach considering all available data (in orange), matched facility data (in blue), and the median facility consumption approach (in pink) to published literature values (in green). From this figure, it is evident that the range of annual total volume consumption estimates are much larger than if only matched facilities are considered. The two largest drawbacks to considering all available data is that results are dominated by large facilities and are potentially skewed by inconsistent discharge reporting before 2015. Therefore, if all

available data is considered, it would imply consumption in Virginia may be higher than what literature suggests, save the agriculture/irrigation sector, where consumption is assumed to be completely consumptive.

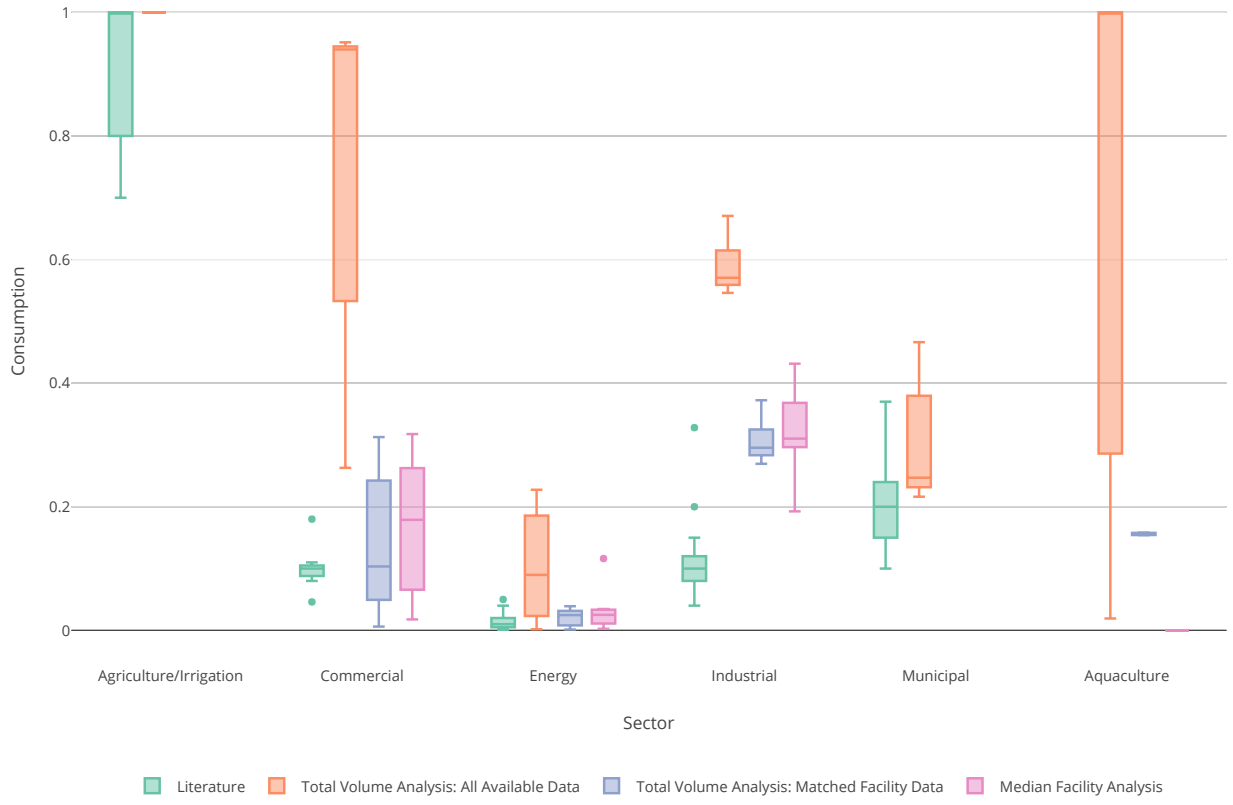

Figure 5.43: Spread of consumption estimates from literature compared to annual estimates derived from our data using a statewide total volume approach considering all available data and matched facility data, and a median facility level . Considering median facility analysis and total volume analysis with all data and matched data.

Be that as it may, when matched facility data is considered, the ranges of consumption are much more comparable to published literature values. In particular, the ranges of energy consumption are the most similar. The median annual energy consumption from the facility level analysis and total volume analysis of matched facilities are 0.015 and 0.025, respectively, whereas literature reports a median of 0.01. It was expected that consumption computed

on the facility level would have higher variation because the approach de-emphasizes the influence of larger facilities on consumption estimates. The comparable ranges of energy consumption between the two analyses also suggests a high success in the matching procedure.

In the commercial sector, the median literature consumption is 0.1, where median consumption is 0.13 and 0.1 for the facility and total volume analysis, respectively. Although median consumption estimates are similar to literature values, the ranges of annual median consumption from this study are larger. This may be due to the improved comprehensive reporting over the years, providing more comparable data for the commercial sector within the last 18 months of the data set. If only the most recent and complete data was included, the range of estimated annual consumption values may narrow.

Industrial consumption appears to be higher than what literature suggests. Published literature reports an annual median consumption of 0.1 for Industrial facilities. However, this study found an annual median of 0.39 and 0.30 during the facility and statewide analysis. The data flow of monthly discharge for smaller industrial facilities (<1 MGD) from the state to ECHO is a known data problem [2]. Perhaps data quality may be influencing higher estimates of consumption.

The municipal sector was excluded from facility matching, therefore there are no values to compare to literature. Annual consumption for all reporting municipal facilities (Figure 5.13) does however range between 0.21 and 0.46, which is comparable to the range of reported literature values. No study analyzed in the literature review had aquaculture as a stand alone sector, as it was included with either agriculture or commercial water use. Median annual consumption was found to be as low as 0.0 in the facility level analysis and a steady 0.16 in the statewide analysis of matched aquaculture facilities.

Chapter 6

Discussion

6.1 Data Availability and Quality

The data used in this study was extracted from two different sources. Withdrawal data located within the Virginia Wateruse Database System was obtained from the VDEQ's modeling system, VA Hydro. Discharge data from Virginia's Pollution Discharge Elimination System was then collected from the EPA's national database, ECHO. Withdrawal data is as-reported from water users from across the state and vetted by VDEQ employees in the Office of Water Supply. While there may be inherent error due to self reporting in the withdrawal data, the opportunity for human error in the discharge data (through conveyance) is much higher. This is because data are first reported by users to the VPDES program and then subsequently to ECHO.

It became clear that the data flow to ECHO for non-major NPDES permittees has issues, and the data may not be accurate for minor Virginian facilities [2]. A distinct improvement of minor facility reporting, however, was noted after the year 2015. This is likely a result of the 2015 NPDES Electronic Reporting Rule (40 CFR 127), which requires NPDES programs to share basic information on all NPDES-permitted facilities, including discharge reports [44]. Historically, major discharging facilities were the priority for data sharing and evaluation, which is evident in the number of reporting VPDES facilities in each sector before 2015 (Fig-

ure 5.4). The new rule was created to eliminate paper reporting, improve transparency of water use activities, and collect more comprehensive reporting from all facilities discharging into the nation's waters [44]. The EPA's ultimately intends on cultivating a rich discharge data set that is electronically available to the public. This aims to improve compliance tracking and opens a line of communication between NPDES programs and regulated facilities to address data quality issues and provide compliance assistance [44]. For this reason, future studies using NPDES data obtained from ECHO should be aware of the chance of diminished data quality for minor users before the December of 2015. Future studies could also compare the data quality between discharge reports obtained from the national database (ECHO) and the state database (DEQ) to identify conveyance errors between the two sources.

6.2 Facility Matching

Despite the noisy relationship centered on discharge data reporting, this analysis revealed that withdrawal and discharge data can be manipulated to quantify insightful conclusions about consumption. Matching withdrawing facilities in VWUDS to discharging permits in VPDES was the most important manipulation to understand if errors originate from missing/unmatched facilities or are on the facility level. Linking facilities using the matching procedure in this study proved to be difficult, even for major water users, because there is a limit to comparing distance and facility name over differing data sources.

Depending on the individual that filed the permit, or reports monthly discharge and withdrawal to the DEQ, inputted attributes for the same facility may vary between databases. For instance, the two nuclear power stations in Virginia, registered different facility names in VWUDS and in NPDES. In VWUDS, they are listed as Surry Power Station and North Anna Nuclear Power Plant. On the other hand, they are listed as Dominion Energy - Surry and Gravel Neck Stations and Dominion - North Anna Power Station in the VPDES pro-

gram. Therefore, matches required confirmation from domain experts in the Office of Water Supply in the DEQ. VWUDS facilities with a match in VPDES have been linked in the VDEQ's VA Hydro modeling system. Future studies could build off of this, to work towards a more complete and comprehensive list.

Regardless of the number of matches, a small number of facilities in Virginia make up the majority of water that is reported as withdrawn and discharged (Figure C.1). Understanding the historic water use patterns of these facilities is therefore essential. Approximately 10% of VWUDS facilities, and 15% of VPDES facilities represent 99% of the total annual reported withdrawal and discharge on average over 2010-2016. Using the matching procedure in this study, 77.4% and 89.8% of annual reported withdrawal and discharge was captured, respectively. (Tables D.1 and D.2).

The matching procedure was also limited by the data available in ECHO. If Figures 5.2 and 5.4 are examined, it's clear that almost all of the industrial discharge pulled from ECHO is represented by matched facilities. This is not the case for VWUDS industrial facilities, where only approximately 58% of total reported withdrawals are captured by matched facilities on average (Table 5.3). This is evident in the commercial sector as well, where the total quantity of reported discharge is not persistent until 2015, but withdrawal data is.

This suggests that there are VWUDS facilities that do not have corresponding discharge monitoring reports located in ECHO. This does not mean to say they do not discharge any water, it just means it is not represented in the national database. For instance, the second largest industrial water user, Celanese Acetate LLC: Celco Plant, used about 56 MGD on average over 2010-2016, but does not have paired discharge data in ECHO. However, a report of current conditions drafted by the Celco Plant in 2006 indicated that the facility discharged 70 MGD from multiple outfalls into the New River, on average [30]. The absence

of data may be due to the types parameters passed through the ECHO REST Services. In this study, flow in conduit or through facility was examined. There is a multitude of other parameters concerned with flow, including "Flow, discharge", "Flow, return factor", and "Flow, maximum during 24 hour period". Using North Anna Nuclear Power Station as an example, no data was returned for any of these parameters. As the case may be, future studies can investigate the various effluent parameters to return the highest amount of DMR entries.

The ability to pair facilities dramatically changes the perception and variability of consumption throughout the state. If all available data is considered, it appears that non-energy consumption in Virginia is typically between 37-51% and energy consumption is between 3-20% (Figures 5.7(a) and 5.6(a)). This lowers to 28-33% and 0.4-4%, respectively, if only fully matched entries are analyzed (Figures 5.7(b) and 5.6(b)). Being able to push through the data refines consumption estimates and identifies facilities that may contain reporting errors or are not within compliance. This became clear after calculating consumption through a total volume approach and a median facility level approach.

6.3 Statewide Total Volume Analysis

The first approach to calculating consumption was by summing the total volume of withdrawal and discharge per month and then calculating the fraction of water that is lost. By doing this, large water users, primarily in the energy sector, influence the overall consumption trends in the state. The advantage to this approach is that errors on the facility level for minor facilities (< 1 MGD) are weighted lower than if there are errors among the major facilities. It also conveys the water movement that is actually occurring within the state. This could be seen as a disadvantage, however, as the variability of consumption among facilities within the same sector are masked by the shear volume from major water users.

6.4 Median Facility Consumption Analysis

Consumption was also calculated on a facility level, in efforts to quantify the variation of consumption across facilities within the same sector. This aims to normalize facility size, such that consumption trends are not biased by the large water users. Monthly and annual estimates are the median of reported facility consumption, protecting the analysis from outliers and erroneous entries.

Another advantage of this approach is the exposure of inconsistent reporting or months of in-operation (Figure 5.15). As explained in Section 6.1, discharge data for minor or inactive discharge should be accepted with scrutiny. There are several months for paired facilities where excess discharge is being reported. This analysis focused on facilities that are assumed to be self-supplied. However, it is possible for commercial, industrial, and aquaculture facilities to purchase water from suppliers, which increases their quantity of discharged effluent. Studies in the future can implore facility transfers and deliveries to understand these patterns more and refine consumption estimates.

Naturally, the disadvantage to this approach is the equal contribution from each facility in each sector. In reality, two facilities with consumption rates of 50% should be treated different if one withdrawals 100 MGD vs. 1 MGD. For that reason, future studies could do a combination of the total volume and facility level approach, by assigning weights to major water users or narrow analysis to facilities that withdrawal more than 1 MGD on average.

6.5 Comparison to Literature Values

Results from the total volume and median facility analysis were ultimately compared to literature values from climatically similar areas (Figure 5.43). Annual estimates were com-

pared to diminish the effect of monthly variation and the effect of data increase within the last 18 months of the data set. Although annual consumption total volume and facility level estimates for the commercial sector have a larger range than what was found in literature, they have comparable upper and lower quartile values. This suggests that given the data, median estimates of facility level consumption are comparable to total volume commercial consumption estimates. This was interesting, because it was expected that variation on the facility level would be much higher. The median literature commercial values overlaps with the estimates from the total volume and facility level analysis, implying that if there is growth in the commercial sector, there is a good chance it will have consumption from 10-20%.

Estimates for the energy sector are the most similar to literature values, staying well below 5% consumption. The inter-quartile ranges for industrial consumption between the total volume and facility level analysis overlap, but differ significantly from literature values. This difference may describe the types of industry that are located in Virginia, and indicates that state water planners should focus on these facilities. The top consumptive industries in the state include mining and packing operations. They may need assistance to reduce the amount of water they lose during processing or there are errors within their discharge data. Ultimately, future studies should obtain more data (i.e. more years and facilities) to refine this.

Statewide aquaculture consumption is relatively lower than other sectors (except for energy), and on a facility level, it averages close to zero percent consumption Table 5.14. Two of the oldest aquaculture facilities report consumption rates much higher than the other seven facilities, reporting estimates upwards of 75%, which influences the overall consumption in the total volume analysis. Using this information, state water planners can collaborate with these facilities with ”unusual” estimates and identify if they are truly consuming that much

water, or have inputted discharge quantities incorrectly. Ultimately, the main takeaway from this comparison is that the variation in annual consumption estimates from the facility level analysis and total volume analysis are comparable.

6.6 Trend Analysis

Figure 5.4 shows reported discharge vs. the number of reporting facilities on the y-axis. It's evident that within the past couple of years, the data flow from Virginia's DEQ to ECHO's national database has improved. The total number of reporting withdrawing facilities however, does not follow this same increase in 2016 (Figure 5.2). In fact, the number of reporting VWUDS facilties shows a decrease for energy and non-energy sectors after 2013 (Tables 4.12 and 4.13). Therefore, consumption trends may be misleading and a result of more comprehensive discharge reporting between data sources.

Consumption has a weak negative trend without statistical significance, considering total volume from matched facilities. Interestingly enough, when matched facilities are separated by sector, it appears that energy consumption is the only one with a downward trend (however not significant) (Table 5.18). The industrial and commercial sectors display significant upwards trends in consumption, while aquaculture displays a weak upward trend. Specifically, discharge data for aquaculture is only available for the years 2015 and 2016, therefore any increase would be noted as an "upward trend". This suggests that energy consumption is relatively persistent in Virginia and that data quality before the implementation of the 2015 NPDES Electronic Reporting Rule has an impact on consumption estimates for non-major facilities in non-energy sectors.

The influence of improved discharge reporting is more evident when all available data are considered. When total volume from all reporting facilities are analyzed, all sectors display

downward consumption trends, all significant except for aquaculture. Consumption rates start very high in 2010 and decrease dramatically around 2015, when discharge data becomes more comprehensive (Table 5.11). Thus, trends are detected, when they may not actually exist.

6.7 County and Watershed Analysis

Analysis of consumption was also performed on the county and watershed scales. Estimations on these scales were calculated using the total volume approach and displaying the median annual consumption rate over 2010-2016. This analysis revealed likely errors on the facility level that cancel each other out when aggregated on the statewide level, and that as scale becomes more refined errors are highlighted. Confidence in this analysis is not high since accuracy of coordinates is unknown. Many facilities in the VWUDS did not include facility coordinates, inputted them incorrectly, or listed the location of the facility's headquarters. Despite this obstacle, missing coordinates were manually located and used to analyze spatial consumption.

Consequently, if VWUDS and VPDES facility coordinates are not directly paired, points can straddle physical boundaries. This might be a reason why errors appear more prominent at finer spatial scales. This occurred frequently near major water ways, like the Chesapeake Bay, York River, and James River; where consumption tended to be negative on one side and high on the other. To diminish this effect, coordinates were paired for matched facilities, using facility coordinates supplied by VPDES. These were used rather than VWUDS because less than 1% of VPDES facilities in ECHO have missing coordinates [3]. Even with paired coordinates, the confidence in spatial consumption estimates is low, due to the low representation of facilities within each county and watershed. Instead of using facility coordinates, future studies could perhaps utilize the listed county or city instead. Once spatial

estimates are clearer, investigation of negative consumption along major waterways could be performed as well.

6.8 Energy Consumption

In several published studies, the energy sector is often assumed to be non-consumptive. This comprehensive study has revealed that even though energy consumption is relatively low on the statewide level, the quantity of water consumed is far larger than most non-energy sectors. Using the total volume consumption approach, monthly energy consumption for matched facilities is primarily in between 0.4-4%. This however corresponds to a loss of 23-193 MGD. The most interesting revelation from the energy analysis was the difference between power types. In the total volume approach, consumption is heavily influenced by the two nuclear power stations in Surry and Louisa County, which withdraw an average of 1,947 and 1,783 MGD over 2010-2016 (approximately 51% of the total reported water use). Consumption for these two facilities are fairly low, rarely exceeding 5% (Figures 5.8(a) and 5.16(a)). The 3 matched coal, 6 combination fossil fuel, and 1 biomass facility present much higher consumption rates, especially than what literature suggests.

The most distinct difference is within the coal facilities, which report consumption between 50-90% from 2013-2016. This may be contributed to the phase out of coal facilities across Virginia. The commonwealth aims to generate 15% of electricity from renewable sources by 2025 [7]. Many coal facilities, consequently, shut down or switched to natural gas around 2012-2014. The Potomac River Generation station shut down in October of 2012, following heavy opposition from activists [1]. The Glen Lyn station stopped operations in April of 2015 due to lack of compliance with EPA regulations [22]. Other stations including Bremo, Southhampton, Hopewell, and Altavista switched to either natural gas or biomass [7]. This phase out may have affected the quality the reported discharge for the respective

coal facilities. Future studies could focus on these particular facilities to categorize their power type more efficiently and understand their water use better.

Similar to industrial water use, nearly all of the reported energy discharge is captured by matched facilities in this analysis. There are, however, energy facilities in VWUDS without corresponding discharge records in ECHO. This discrepancy may be due to changes in owners, operators, and permit holders. Regardless, this is powerful information for the Office of VPDES permits to be aware of since energy facilities are responsible for nearly 80% of the total freshwater withdrawn every year in the Commonwealth.

6.9 Policy and Management

The State's Water Resources Plan and future plans will benefit from this analysis because discharge data has not been considered when analyzing water use in the state of Virginia. This analysis serves to highlight areas that require more attention, whether that's reaching out to users for better reporting or large users that are consuming more than they are returning. In particular, industrial and energy facilities could be focused on because they use the most water and have higher than typical consumptive use rates compared to climatically similar areas. And even though agriculture/irrigation facilities were not included in facility matching, newer irrigation techniques can be implemented to reduce the quantity of water that is lost through evapotranspiration.

There's also the question of which spatial scale should be used to inform management decisions. Water supply management requires a level of specificity that aids stakeholders to move towards more sustainable practices, but isn't too specific that it isn't applicable to everyone. With this being said, policy makers can leverage the figures created in this study to influence more specific water supply planning and management techniques than what is

currently available.

It is safe to assume that water use in Virginia will not become completely sustainable within the next 1-3 years. Systemic change can often take decades to be implemented. In the case of sustainable water, it will take a long time to acquire appropriate funding and phase out the older practices and technologies. With continuous communication and reassessments (adaptive management) of each stakeholder's water needs and uses, the DEQ can provide guidance. Perhaps in future, discharge or estimates of consumption can be provided in the reporting process to VWUDS. This collaboration would make it easier for data analysts to validate results and make meaningful decisions.

Chapter 7

Conclusions

Although it has been perceived that water supply in Virginia is not a concern, recent droughts and gaps in data have sparked an urgency for improved water resource management. This study leverages state maintained withdrawal data and federally maintained discharge data to quantify the fraction of water lost, on a monthly and annual basis in the Commonwealth. Consumption was estimated using a total volume and median facility level approach on a statewide, facility, county, and HUC 6 watershed scale. Trends were later assessed and compared to consumption values found in literature. It was discovered that not all withdrawal records have associated discharge records, therefore a matching procedure was created to pair facilities between the two data sources.

This led to key insights in consumptive use within Virginia. When paired facilities are considered, energy consumption in Virginia is typically between 0.4-4%. Non-energy consumption was found to be between 28-33%, with industrial, commercial, and aquaculture ranging from 25-35%, 10-20%, and 15-16% respectfully. On a facility level basis, variation of monthly reported consumption was higher than what was calculated using total volume, but median annual values were comparable the two approaches. There are concerns with uncertainty in county and watershed consumption assessments due to the small sample size of facilities and facility coordinate accuracy.

Consumption trends were found to be not significant among matched facilities, suggesting

consumption in Virginia is persistent over time and that more data is required to capture meaningful trends. Regardless, this study was the first of its kind to analyze consumption in Virginia and identify areas in need of data quality and availability improvement. Essentially, this assessment identified how to use discharge data from the EPA's ECHO site to quantify consumption over several sectors and spatial scales to receive a better understanding of water availability to effectively inform water resource planning and management.

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Appendices

Appendix A

Data and R Code Repository

Data and code, in R programming language, used in this study are available online in the following GitHub Repository: Consumptive Water Use: Refining State Water Supply Estimates with Discharge and Withdrawal Data

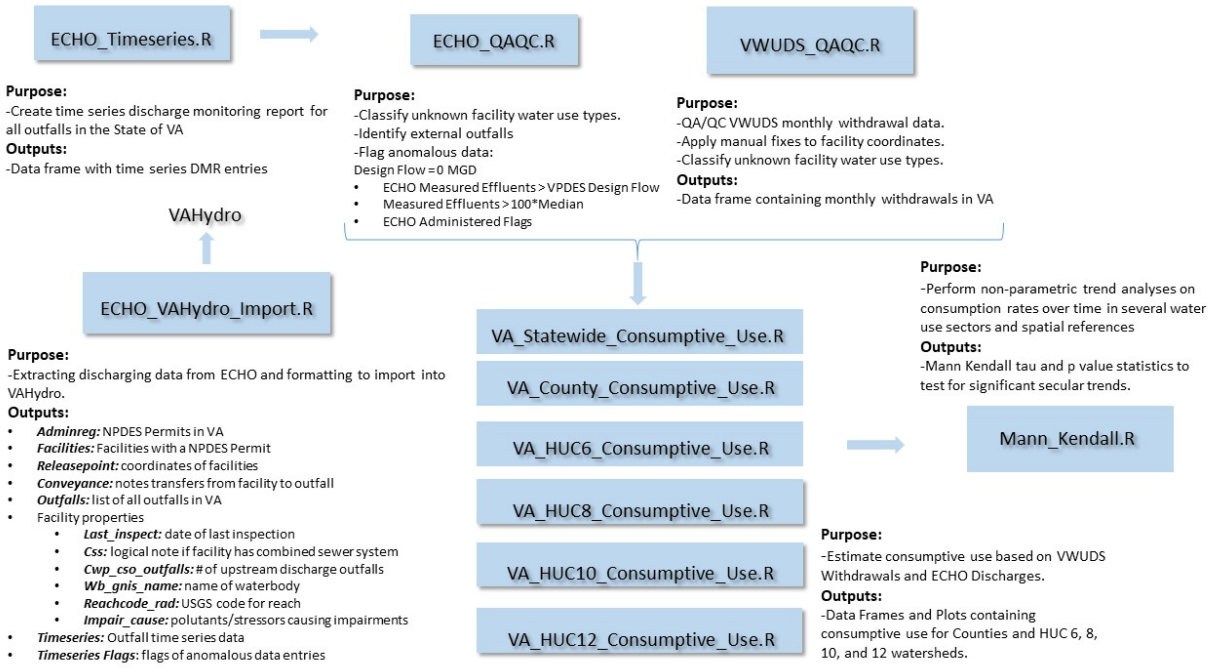

Figure A.1: Process flow diagram of code used for data importing, cleaning, and analysis.

A review of the contents within this repository is found in Table A.1.

Table A.1: R Code Repository Contents

Folder	Purpose	Contents
ECHO Scripts	Utilize the EPA's Enforcement and Compliance Online History (ECHO) Representation State Transfer (REST) Services to extract data on facilities regulated under the Clean Water Act (CWA) and managed under the National Pollutant Discharge Elimination System (NPDES) Program. The extracted data is then cleaned in the ECHO QAQC.R script.	• ECHO Timeseries.R • ECHO Timeseries MD.Rmd • Codebook-for-ECHO-Timeseries.Rmd • ECHO QAQC.R • Codebook-forECHOInterface.md • ECHOInterface MD.Rmd • ECHOInterface McCarthy.R
VWUDS Scripts	This code serves to import and analyze withdrawal data from the Virginia Water Use Database System (VWUDS). Withdrawal data is obtained from the VDEQ's VA Hydro system, which is only available through collaboration. Please contact the Office of Water Supply if you are interested in collaboration. Withdrawal data is cleaned in the VWUDS QAQC.R script.	• VWUDS QAQC.R
Facility Matching	This code serves to match withdrawal facilities to a discharge facility. There are two methods to matching: • 1: First is to create a search radius from each discharge facility and then indicate the withdrawal facilities that fall within that radius. • 2: Then we take the facilities that fall within the search radius and match them by facility name (using fuzzy logic)	• Facility Matching.R
Statewide Analysis	The purpose of this script is to compare withdrawals, discharges, and consumption over time on a state-wide level for the Commonwealth of Virginia.	• VA-Statewide-Consumptive-Use.R
Spatial Analysis	These scripts calculate consumptive use by performing a water balance over several spatial scales.	• VA-County-Consumptive-Use.R • VA-HUC6-Consumptive-Use.R • VA-HUC8-Consumptive-Use.R • VA-HUC10-Consumptive-Use.R • VA-HUC12-Consumptive-Use.R
Trend Assessments	The Mann Kendall Trend Test looks for general increasing or decreasing trends. It's non-parametric in nature, therefore removing the need for a normal distribution of values. The null hypothesis for this test assumed there is no monotonic trend. The alternative hypothesis is that a trend exists (positive, negative, or non-null).	• Mann-Kendall.R

Appendix B

Outfall Classification

Table B.1: Atypical outfall classifications that are representative of facility discharge.

VPDES Facility ID	Facility Name	External Outfall(s)	Additional Notes
VA0004090	DOMINION ENERGY- SURRY AND GRAVEL NECK STATIONS	001	001 is a cooling outfall. Includes discharges from internal outfalls 101-122
VA0052451	DOMINION - NORTH ANNA POWER STATION	001	001 is a cooling outfall. Includes stormwater flows from Lake Anna. Stormwater flows are not measured.
VA0004146	DOMINION ENERGY - CHESTERFIELD POWER STATION	001, 002, 003	001, 002, and 003 are cooling outfalls.
VA0004103	DOMINION - YORKTOWN POWER STATION	001 and 002	001 includes discharges from internal outfalls 101-112. 002 includes discharges from internal outfalls 202-205.
VA0084069	DOMINION ENERGY - MECKLENBURG POWER STATION	101	
. VA0001015	AMERICAN ELECTRIC POWER - CLINCH RIVER PLANT	003	
VA0000370	APCO - GLEN LYN	005	
VA0066630	HOPEWELL WATER RENEWAL	101	
VA0003026	GP BIG ISLAND LLC	002	
VA0002160	APPAREL AND ADVANCED TEXTILES LLC - WAYNESBORO	101	
VA0003646	WESTROCK VIRGINIA LLC - COVINGTON	003	Does not have a 001 outfall
VA0000248	US ARMY - RADFORD ARMY AMMUNITION PLANT	006	Does not have a 001 outfall
VA0001589	RES DBA STEEL DYNAMICS ROANOKE BAR DIVISION	005	Does not have a 001 outfall
VA0004804	HUNTINGTON INGALLS INCORPORATED - NN SHIPBLDG DIV	021	Does not have a 001 outfall
VA0091251	COURSEY SPRINGS FISH CULTURAL STATION	007	Does not have a 001 outfall
VA0091243	MONTEBELLO FISH CULTURAL STATION	002	Does not have a 001 outfall
VA0090590	COVIA HOLDINGS CORPORATION - GORE FACILITY	007	Does not have a 001 outfall
VA0020681	JAMES RIVER CORRECTION CENTER	002	Does not have a 001 outfall
VA0003433	SOLENIS LLC	002	Does not have a 001 outfall
VA0003867	OMEGA PROTEIN - REEDVILLE	002	Does not have a 001 outfall
VA0092436	ILUKA RESOURCES INC - BRINK	101	Does not have a 001 outfall
VA0001597	NORFOLK SOUTHERN RAILWAY CO - SHAFFERS CROSSING	002	Does not have a 001 outfall
VA0020702	VIRGINIA CORRECTIONAL CENTER FOR WOMEN	002	Does not have a 001 outfall
VA0004774	FRAMATOME INC - MAR	004	Does not have a 001 outfall
VA0022802	BASHAM SIMMS WASTEWATER FACILITY	002	Does not have a 001 outfall
VA0024147	FORK UNION MILITARY ACADEMY STP	002	Does not have a 001 outfall
VA0084212	CHURCHVILLE WTP	003	Does not have a 001 outfall
VA0089010	SAN DAMIANO SPIRITUAL LIFE CENTER	002	Does not have a 001 outfall

Table B.2: Atypical outfall classifications that are representative of facility discharge continued.

VPDES Facility ID	Facility Name	External Outfall(s)	Additional Notes
VA0088277	PILOT-4649	002	Does not have a 001 outfall
VA0089214	FLYING J NO 752	003	Does not have a 001 outfall
VA0089541	MWAA - WASHINGTON DULLES INTERNATIONAL AIRPORT	021	Does not have a 001 outfall
VA0090263	TOWN OF BROADWAY REGIONAL WWTF	003	Does not have a 001 outfall
VA0090271	SHEETZ TRAVEL CENTER No 701	002	Does not have a 001 outfall
VA0091871	SPECIALTY COATING AND LAMINATING LLC	202	Does not have a 001 outfall
VA0092371	SHENANDOAH SENIOR LIVING	002	Does not have a 001 outfall
VA0092657	FLYING J TRAVEL PLAZA 749	002	Does not have a 001 outfall
VA0092851	LOVES TRAVEL STOPS AND COUNTRY STORES - MEADOWVIEW	101	Does not have a 001 outfall
VA0090956	LOVES TRAVEL STOPS AND COUNTRY STORES 239	101	Does not have a 001 outfall
VA0092142	FRANKLIN COUNTY - SANITARY LANDFILL	102	Does not have a 001 outfall
VA0088846	SHEN VALLE LOGISTICS STP	006	Does not have a 001 outfall
VA0077399	LACEY SPRING ELEMENTARY SCHOOL STP	002	Does not have a 001 outfall
VA0067245	TOWN OF BOONES MILL - SEWAGE TREATMENT PLANT	002	Does not have a 001 outfall
VA0071528	VIMS GLOUCESTER POINT	004	Does not have a 001 outfall
VA0053813	COLONNAS SHIPYARD INC	009	Does not have a 001 outfall
VA0002151	US MARINE CORPS - MCB QUANTICO - NREAB INDUSTRIAL	030	Does not have a 001 outfall
VA0003492	ASHLAND SPECIALTY INGREDIENTS GP	005	Does not have a 001 outfall
VA0005819	APPOMATTOX RIVER WATER AUTHORITY	004	Does not have a 001 outfall
VA0025151	WAYNESBORO WWTP	002	Does not have a 001 outfall
VA0026891	WARSAW WASTEWATER TREATMENT PLANT	002	Does not have a 001 outfall
VA0029785	LINCOLN TERMINAL COMPANY	007	Does not have a 001 outfall. Shut down.
VA0052655	ALBEMARLE US INC	004	Does not have a 001 outfall.
VA0052906	DOSWELL TRUCK STOP	002	Does not have a 001 outfall.
VA0073091	GENERAL DYNAMICS NASSCO-NORFOLK - LIGON FACILITY	003	Does not have a 001 outfall.
VA0088374	CROP PRODUCTION SERVICES INCORPORATED - SEALSTON	003	Does not have a 001 outfall.

Appendix C

Top Water User Systems

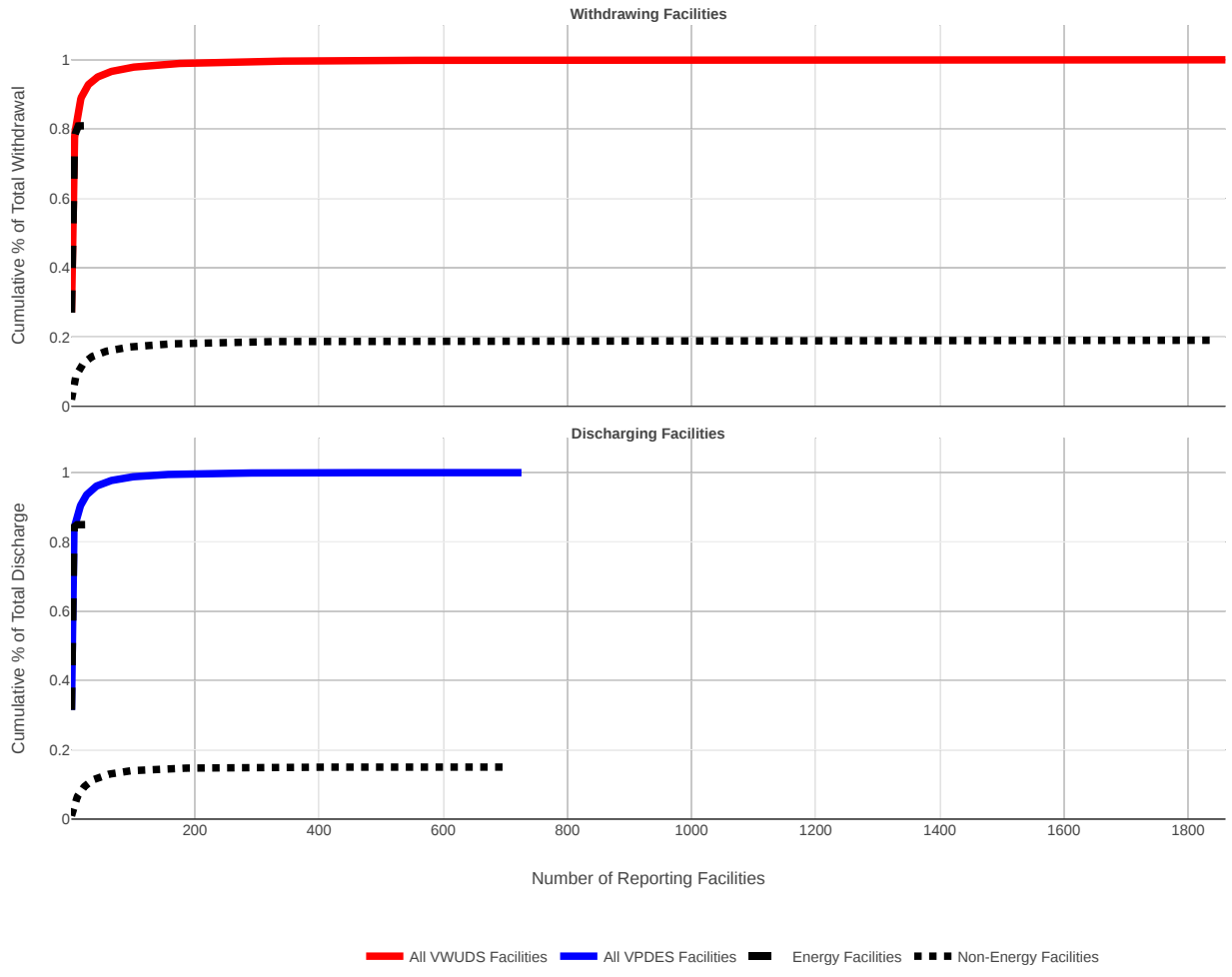

Figure C.1: Average cumulative percentage of annual reported withdrawal and discharge for energy (dashed black line) and non-energy sectors (dotted black line) (2010-2016).

Table C.1: Top energy water users. Consumption estimated by aggregating total volume per year and dividing by number of reporting months to calculate fraction of water lost.

		Consumption as a Coefficient							
Facility	**Power Type**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**Average**
Surry Power Station	Nuclear	0.03	3.7E-04	3.8E-04	3.4E-04	3.0E-04	4.7E-04	0.07	3.8E-04
North Anna Nuclear Power Plant	Nuclear	0.02	0.01	0.02	0.00	0.01	0.02	0.02	0.02
Chesterfield Power Station	Combination Fossil	1.9E-03	0.05	2.0E-03	1.6E-03	2.2E-03	1.9E-03	1.5E-03	1.9E-03
Yorktown Fossil Power Plant	Combination Fossil	NA	NA	1.3E-03	1.0E-03	-0.27	-0.49	-0.92	-0.27
Possum Point Power Station	Combination Fossil	0.42	0.35	0.49	0.49	0.48	0.56	0.51	0.49

Table C.2: Top industrial water users. Consumption estimated by aggregating total volume per year and dividing by number of reporting months to calculate fraction of water lost.

	Consumption as a Coefficient							
Facility	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**Average**
Advansix Resins and Chemicals LLC: Hopewell Plant	0.47	0.45	0.44	0.42	0.44	0.45	0.45	0.45
Covington Plant Westrock	NA	NA	0.20	0.18	0.25	0.27	0.30	0.25
Spruance Plant	0.11	0.05	-0.05	-0.14	-0.10	-0.09	0.06	-0.05
West Point Mill Water System	0.06	-0.11	0.09	0.03	-0.15	0.05	0.08	0.05
Franklin Virginia Mill	NA	NA	0.76	0.81	0.82	0.81	0.83	0.81

Table C.3: Top aquaculture water users. Consumption estimated by aggregating total volume per year and dividing by number of reporting months to calculate fraction of water lost.

	Consumption as a Coefficient							
Facility	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**Average**
Coursey Spring Fisheries						-2.5E-16	0.0	-1.3E-16
Terry Place Plant						0.0	0.0	0.0
Marion Fish Cultural Station						0.52	0.52	0.52
Paint Bank Fish Cultural Sta.						-2.1E-16	0.0	-1.0E-16
Monterey Plant						0.0	0.0	0.0

Table C.4: Top commercial water users. Consumption estimated by aggregating total volume per year and dividing by number of reporting months to calculate fraction of water lost.

	Consumption as a Coefficient							
Facility	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**Average**
Shenandoah Brewery						0.23	0.56	0.39
Dahlgren Base						0.0	0.0	0.0
Fort A. P. Hill Water System						0.52	0.52	0.52
North Spring Behavioral Healthcare							-0.57	-0.57
Newton Mobile Home Court INC						-1.30	-1.17	-1.24

Appendix D

Matched Facilities

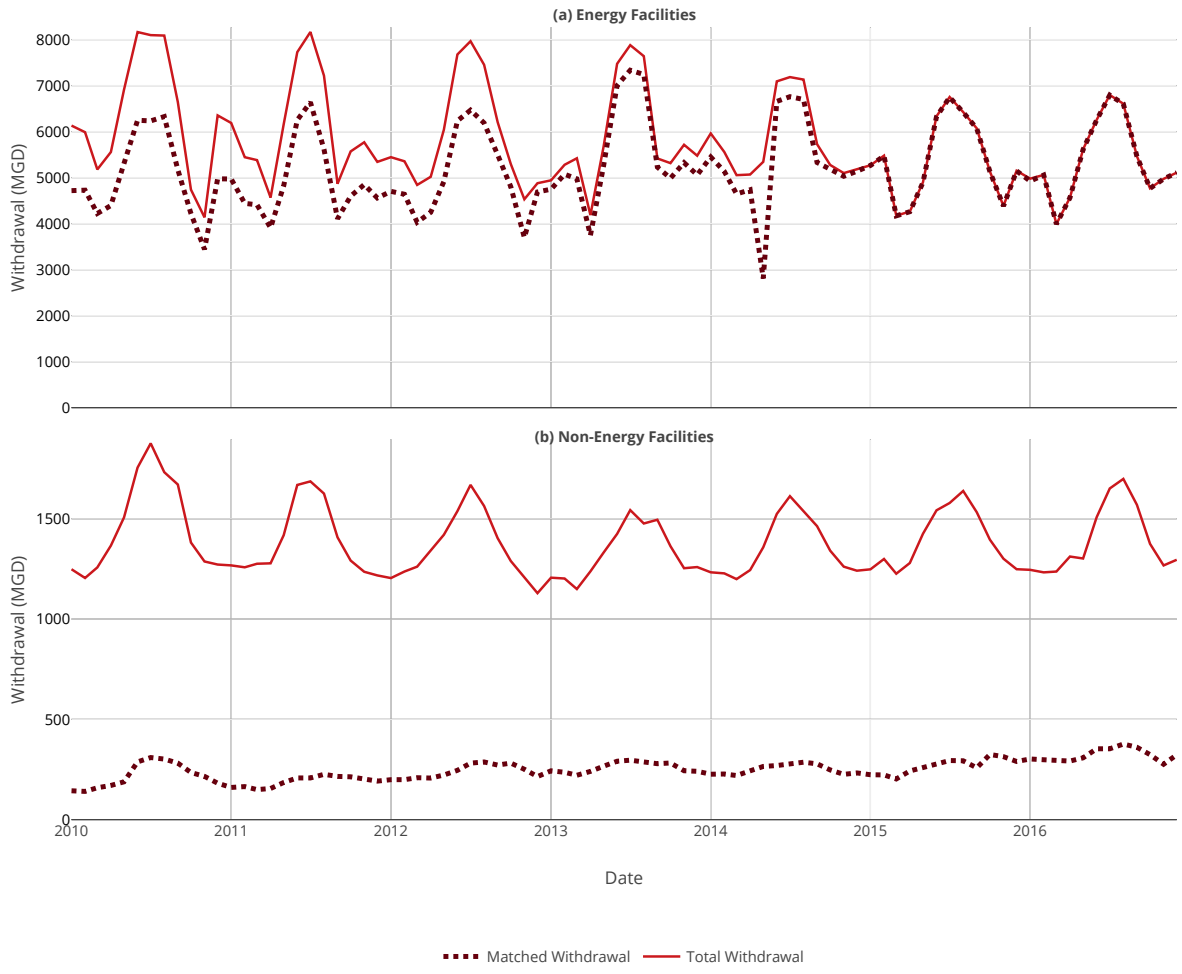

Figure D.1: Total monthly withdrawals (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for (a) energy and (b) non-energy facilities (2010-2016).

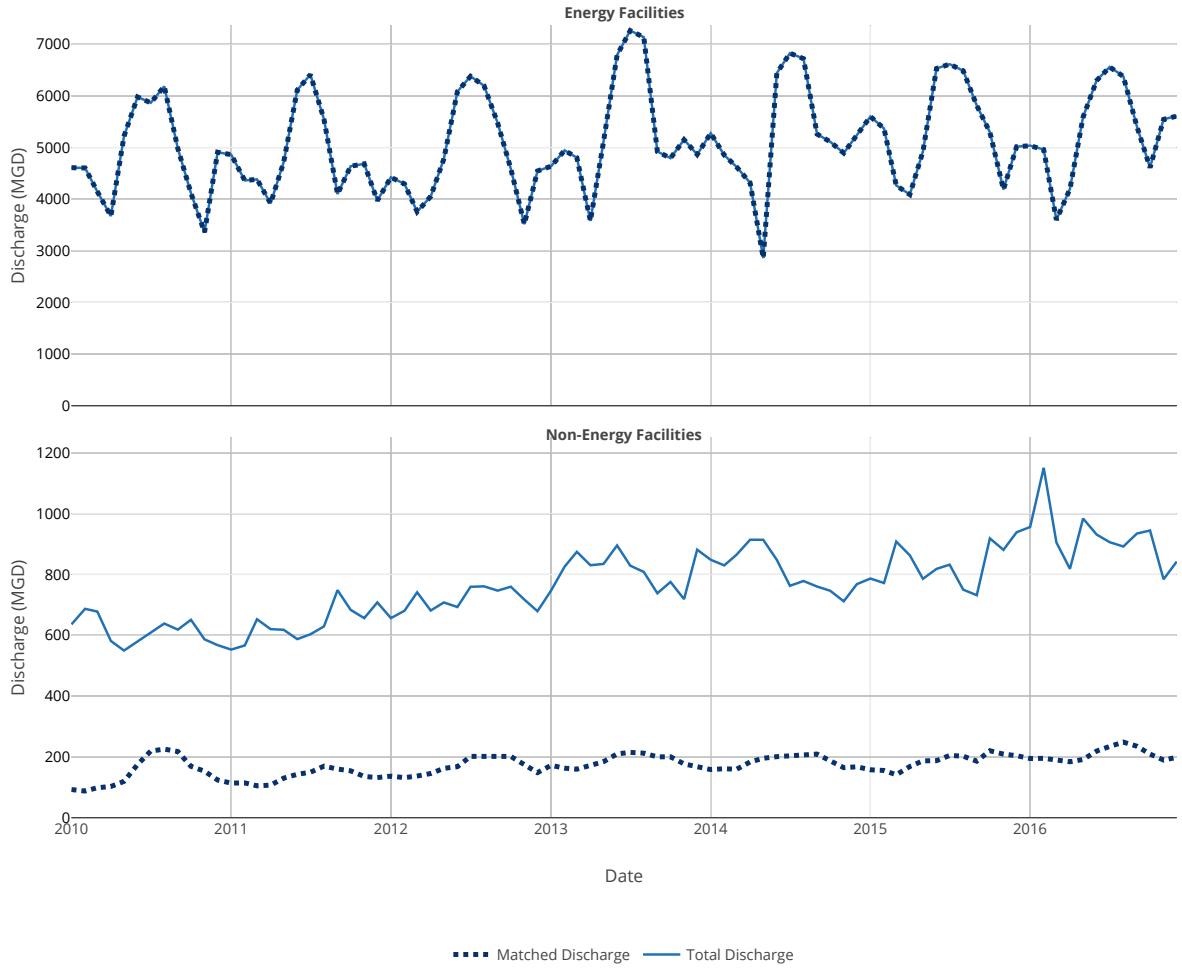

Figure D.2: Total monthly discharges (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for (a) energy and (b) non-energy facilities (2010-2016).

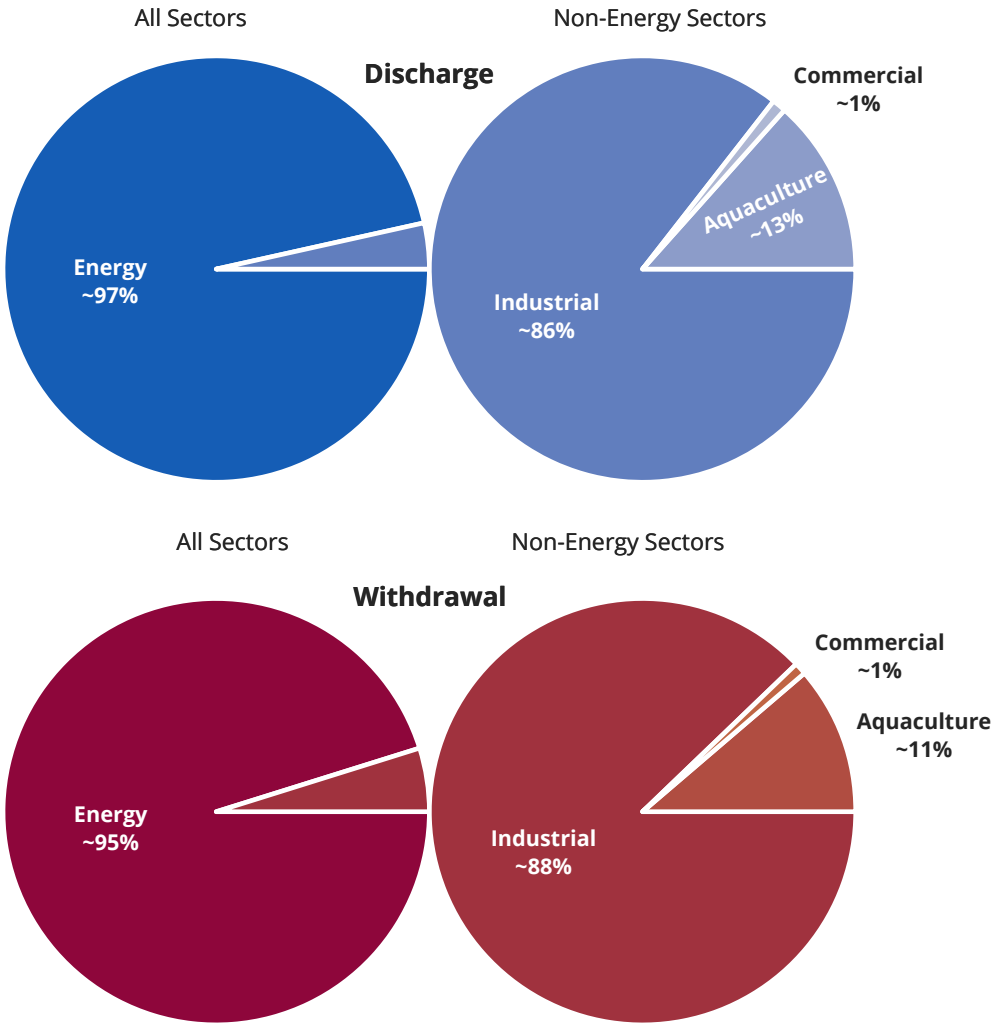

Figure D.3: Distribution of discharges (top) and withdrawals (bottom) by sector for matched facilities, with energy vs. non-energy sectors on the left and non-energy sectors on the right. Annual average in MGD over 2010-2016.

D.1 All Sectors

Table D.1: Comparison of total annual reported withdrawal (MGD) per year between all available data and matched facilities (2010-2016). Considers all sectors.

Year	All Facilities	Matched Facilities	Total Withdrawal (MGD)	Matched Withdrawal (MGD)	% of Total Reported Withdrawal
2010	1,571	23	7,795	5,338	68.5%
2011	1,567	27	7,419	5,126	69.1%
2012	1,574	29	7,247	5,533	76.4%
2013	1,568	29	7,196	5,774	80.2%
2014	1,704	28	7,160	5,693	79.5%
2015	1,675	96	6,758	5,677	84.0%
2016	1,666	111	6,734	5,675	84.2%
Ave	**1,618**	**50**	**7,180**	**5,545**	**77.4%**

Table D.2: Comparison of total annual reported discharge (MGD) per year between all available data and matched facilities (2010-2016). Considers all sectors.

Year	All Facilities	Matched Facilities	Total Discharge (MGD)	Matched Discharge (MGD)	% of Total Reported Discharge
2010	89	24	5,556	5,068	91.2%
2011	114	29	5,478	4,949	90.3%
2012	133	32	5,873	5,283	90.0%
2013	131	32	6,169	5,526	89.6%
2014	132	30	6,170	5,529	89.6%
2015	613	95	6,253	5,571	89.1%
2016	719	110	6,258	5,534	88.4%
Ave	**276**	**50**	**5,965**	**5,351**	**89.8%**

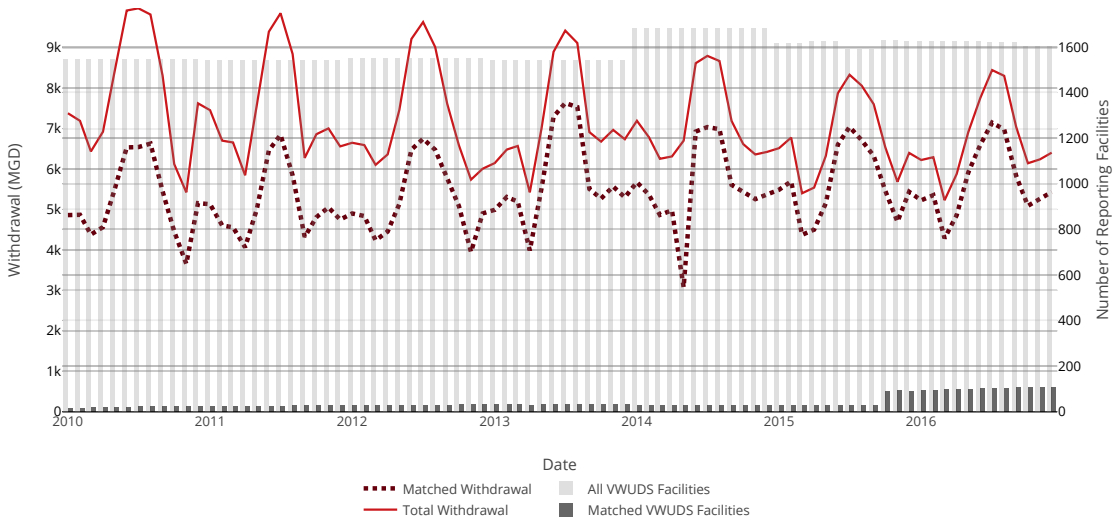

Figure D.4: Total monthly withdrawals (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for all sectors.

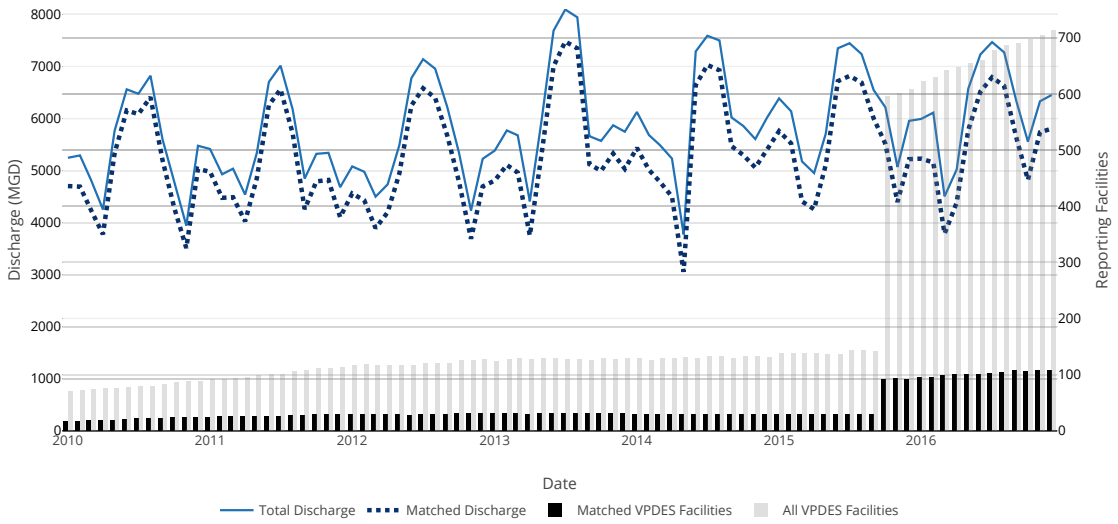

Figure D.5: Total monthly discharges (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for all sectors.

D.2 Energy Sector

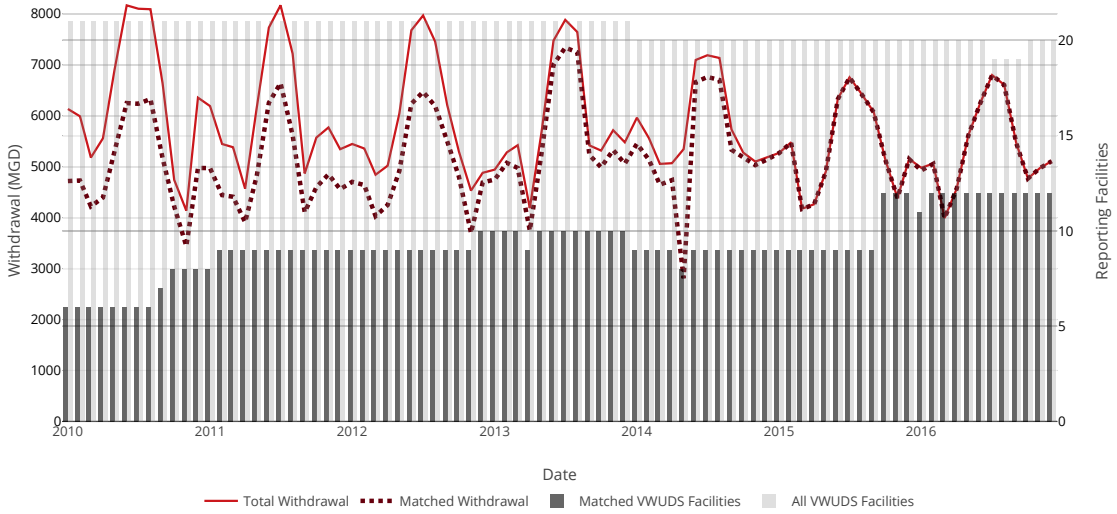

Figure D.6: Total monthly withdrawals (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for the energy sector.

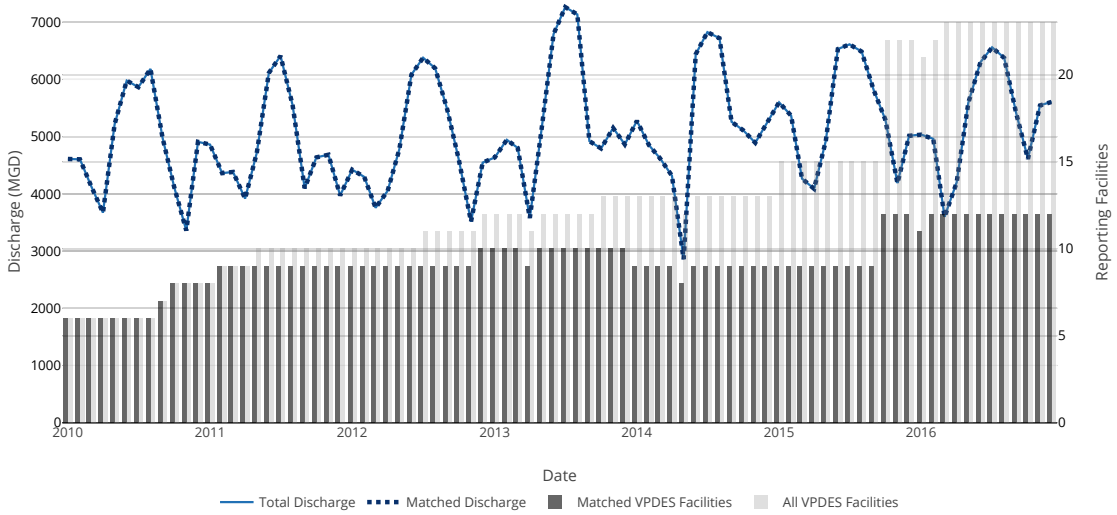

Figure D.7: Total monthly discharges (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for the energy sector.

D.3 Industrial Sector

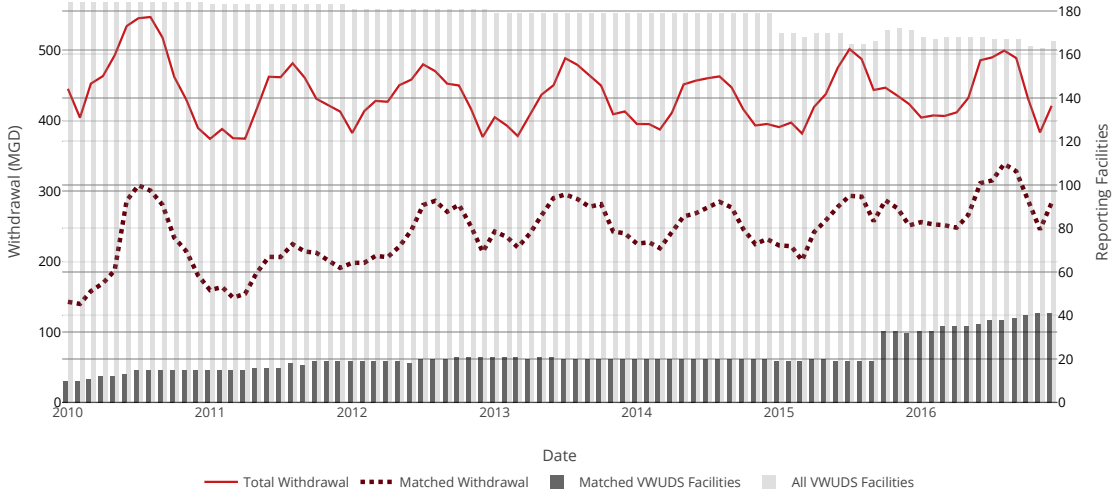

Figure D.8: Total monthly withdrawals (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for the industrial sector.

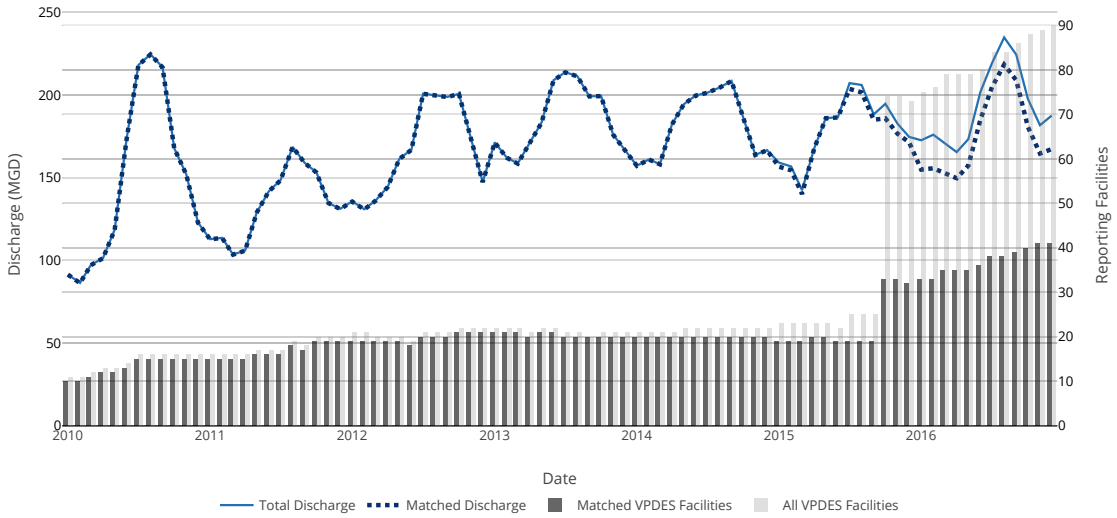

Figure D.9: Total monthly discharges (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for the industrial sector.

D.4 Commercial Sector

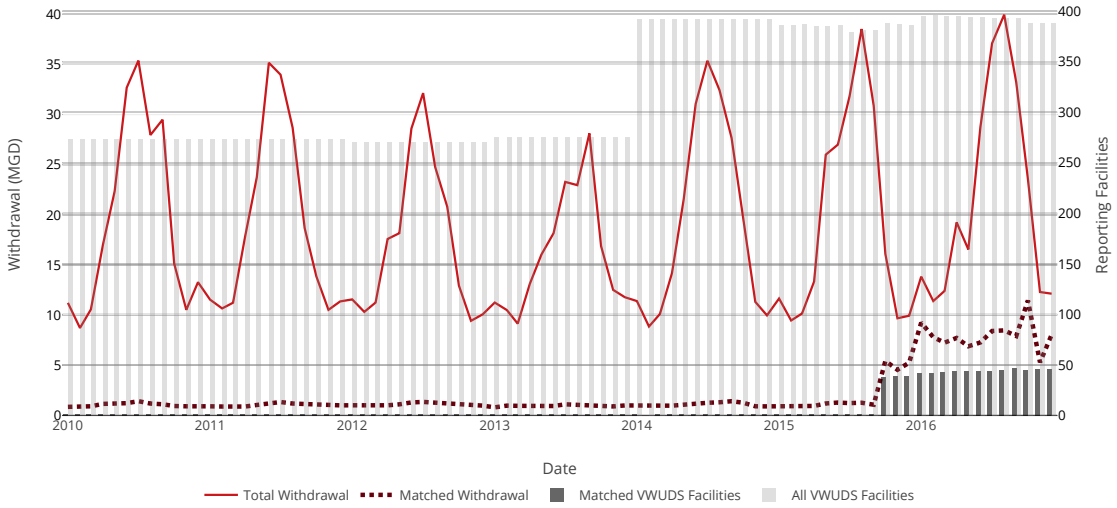

Figure D.10: Total monthly withdrawals (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for the commercial sector.

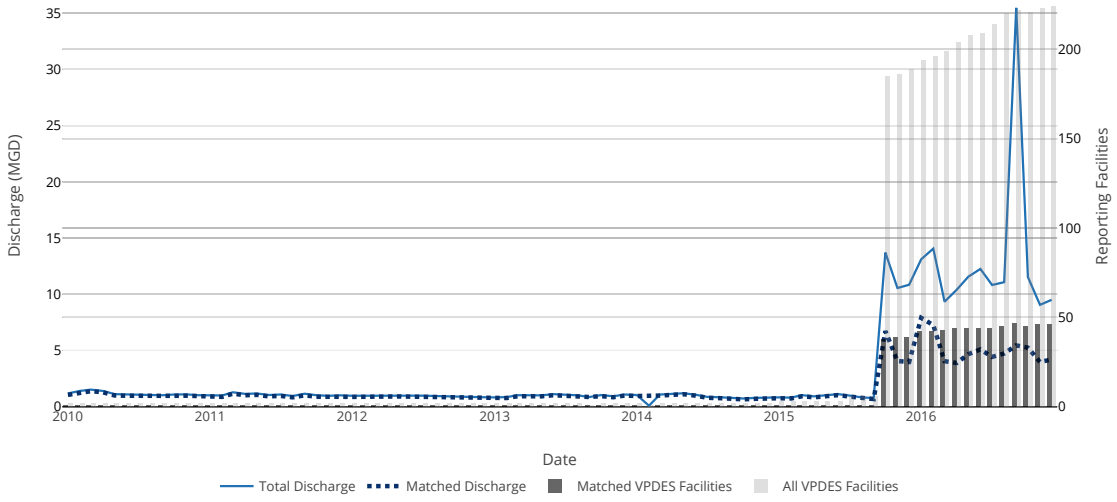

Figure D.11: Total monthly discharges (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for the commercial sector.

D.5 Aquaculture Sector

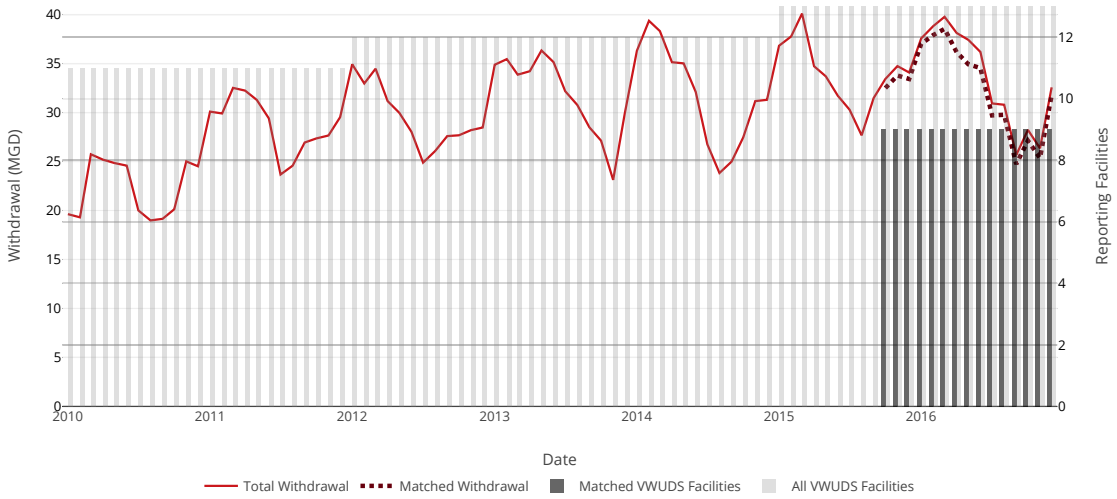

Figure D.12: Total monthly withdrawals (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for the aquaculture sector.

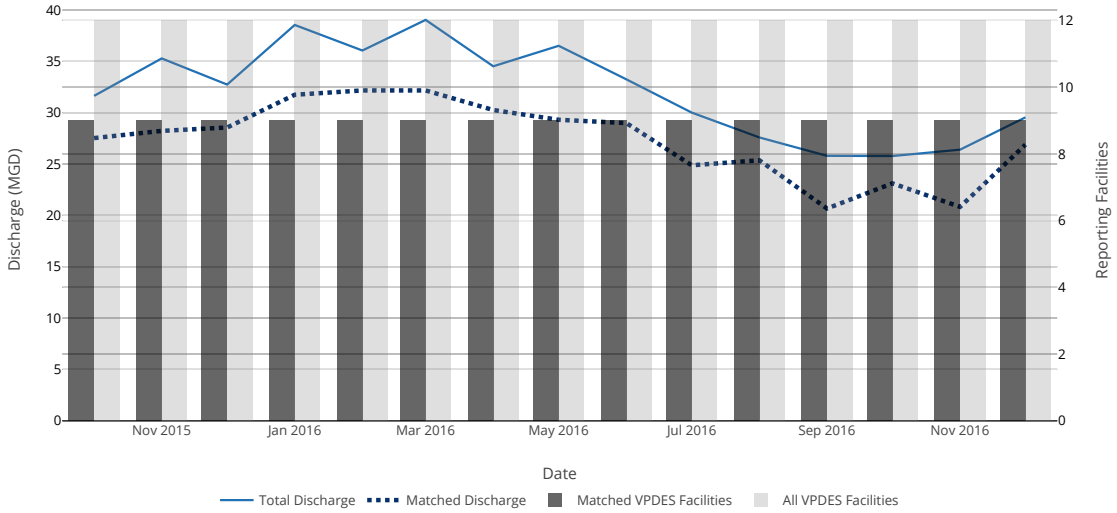

Figure D.13: Total monthly discharges (MGD) for matched facilities (dashed line) vs. all reporting facilities (solid line) with number of reporting facilities on the secondary y-axis for the aquaculture sector.

D.6 Agricultural/Irrigation Sector

Table D.3: Total annual reported Agricultural/Irrigation withdrawals (MGD) (2010-2016).

Year	All Facilities	Total Withdrawal (MGD)
2010	520	34
2011	506	29
2012	502	29
2013	498	20
2014	495	30
2015	484	27
2016	460	23
Ave	**495**	**27**

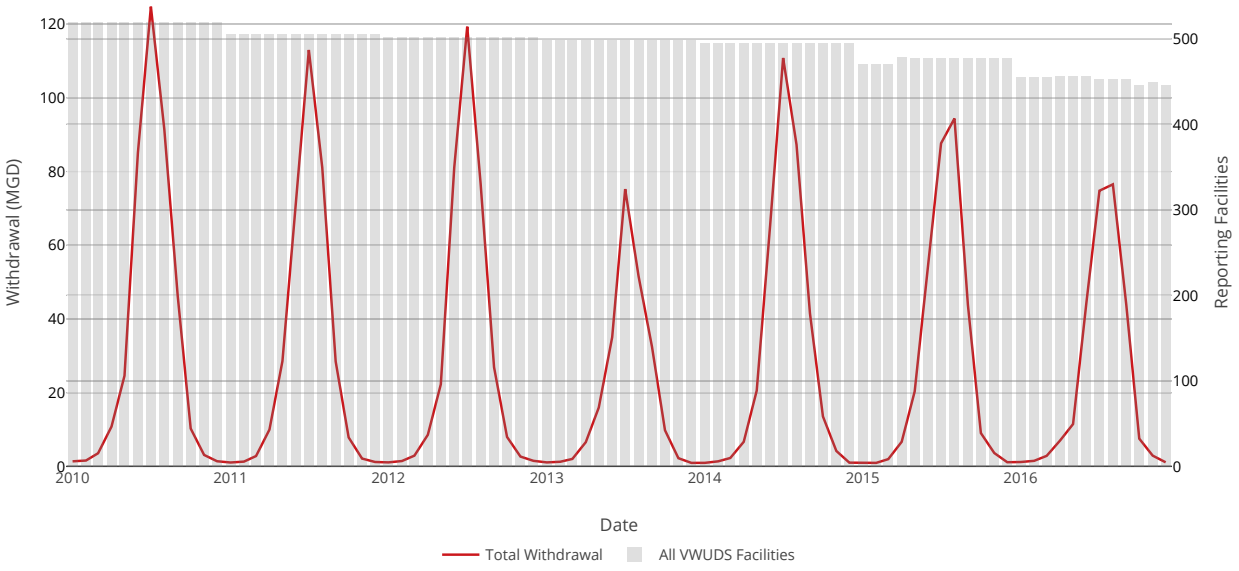

Figure D.14: Total monthly withdrawals (MGD) for all reporting agriculture/irrigation facilities.

Appendix E

Consumption Analysis

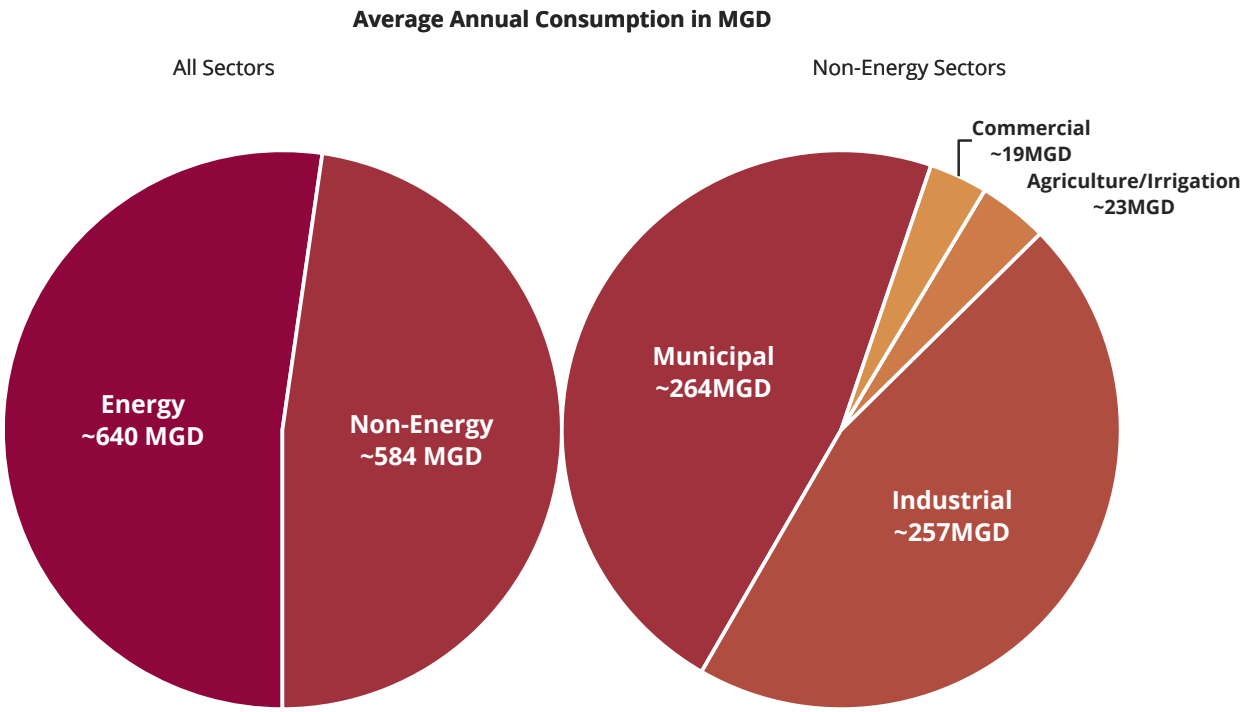

Figure E.1: Median long-term annual consumption for Energy vs. Non-Energy sectors (left) and non-energy sectors (right) considering all available data (2010-2016). Consumption aggregated as total volume reported for year.

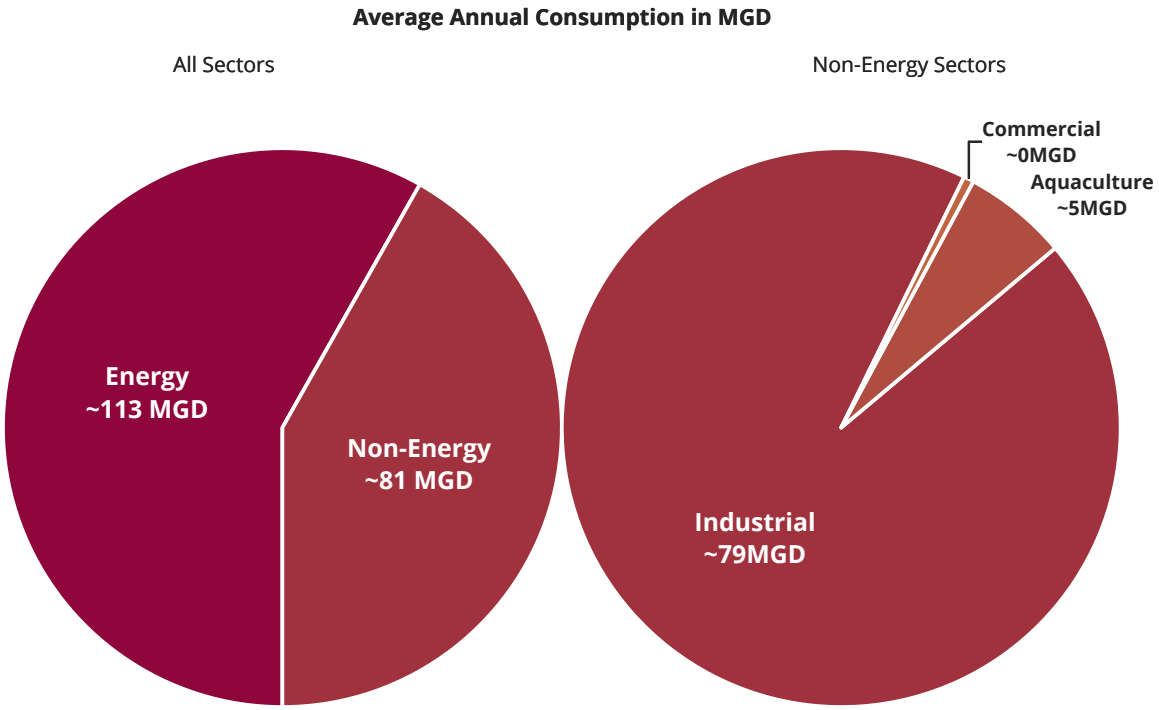

Figure E.2: Median long-term annual consumption for Energy vs. Non-Energy sectors (left) and non-energy sectors (right) considering matched facility data (2010-2016). Consumption aggregated as total volume reported for year.

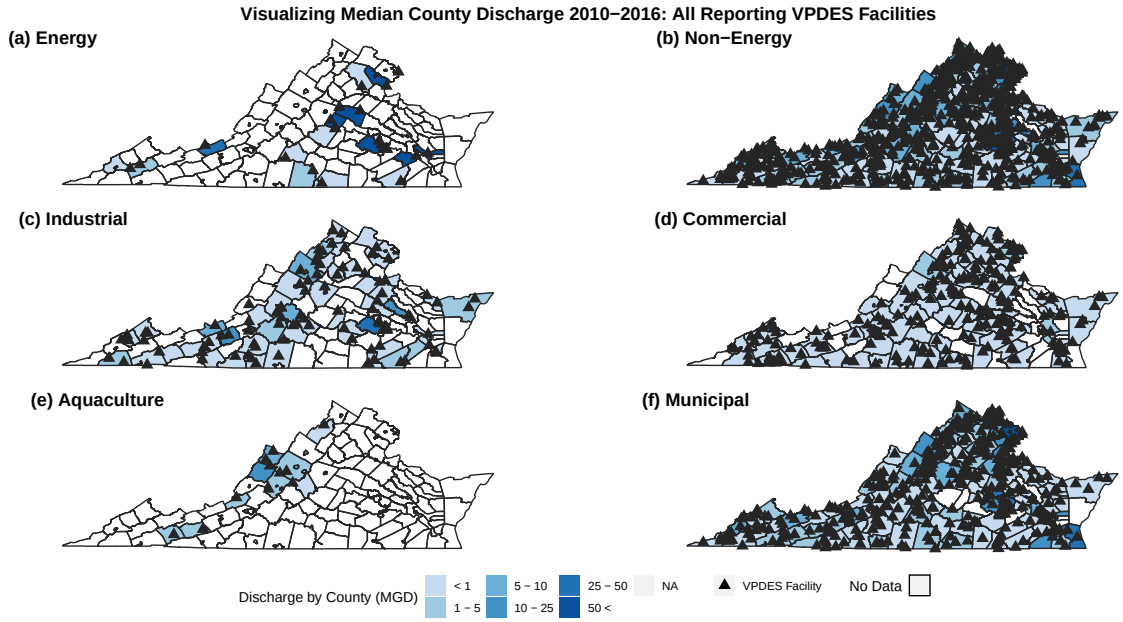

Figure E.3: Median long-term annual county discharge (MGD) considering all available data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Commercial, (e) Aquaculture, and (f) Municipal sectors (2010-2016).

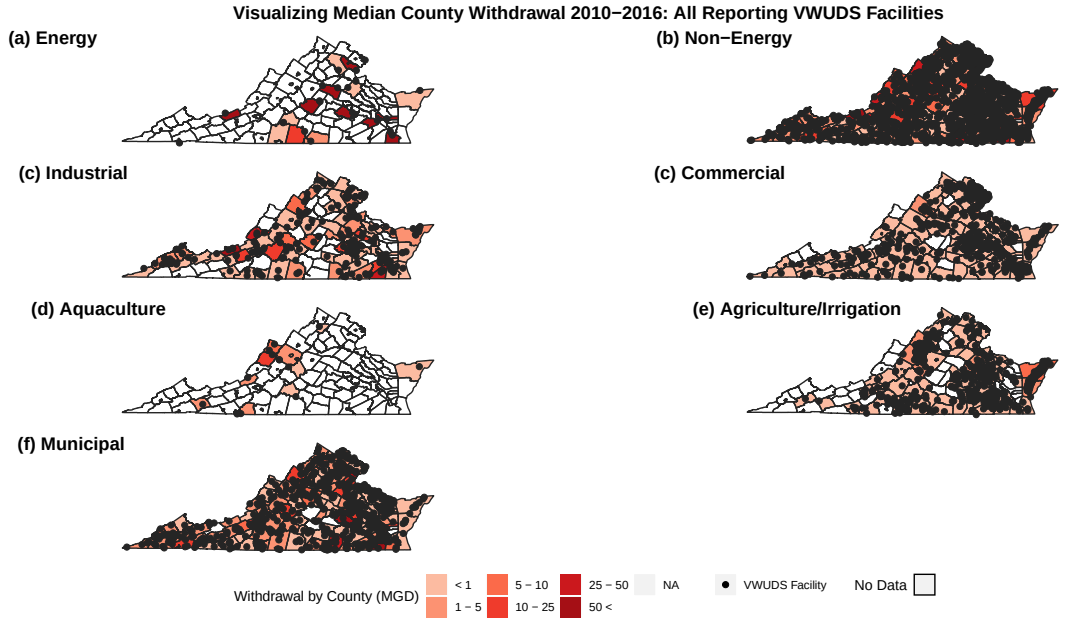

Figure E.4: Median long-term annual county withdrawal (MGD) considering all available data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Commercial, (e) Aquaculture, (f) Municipal, and (g) Municipal sectors (2010-2016).

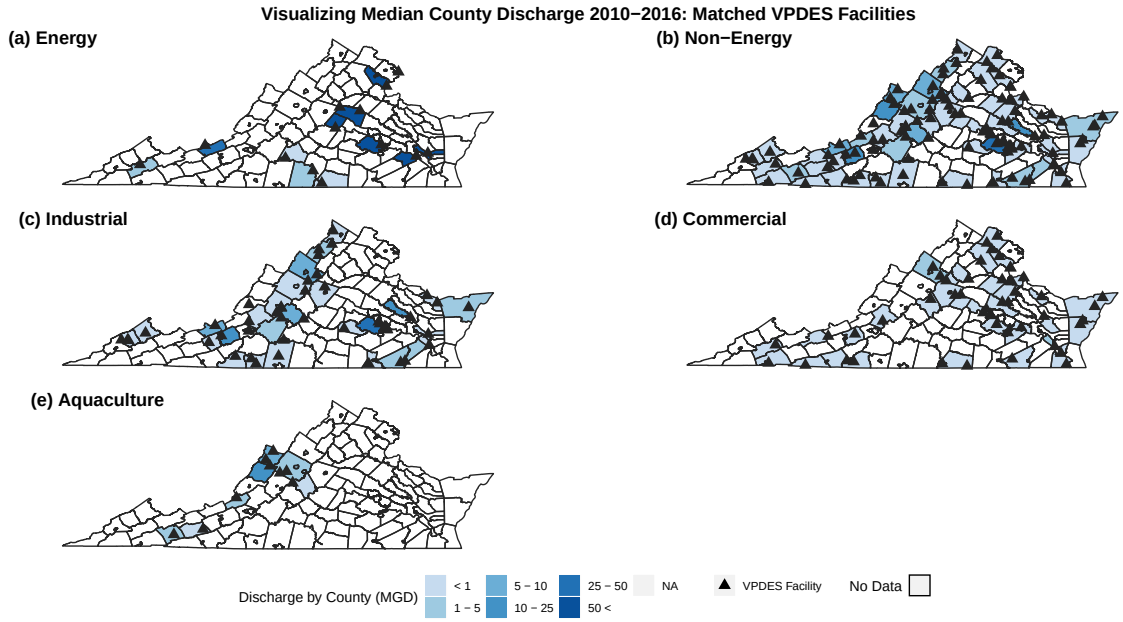

Figure E.5: Median long-term annual county discharge (MGD) considering matched facility data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Commercial, (e) Aquaculture, and (f) Municipal sectors (2010-2016).

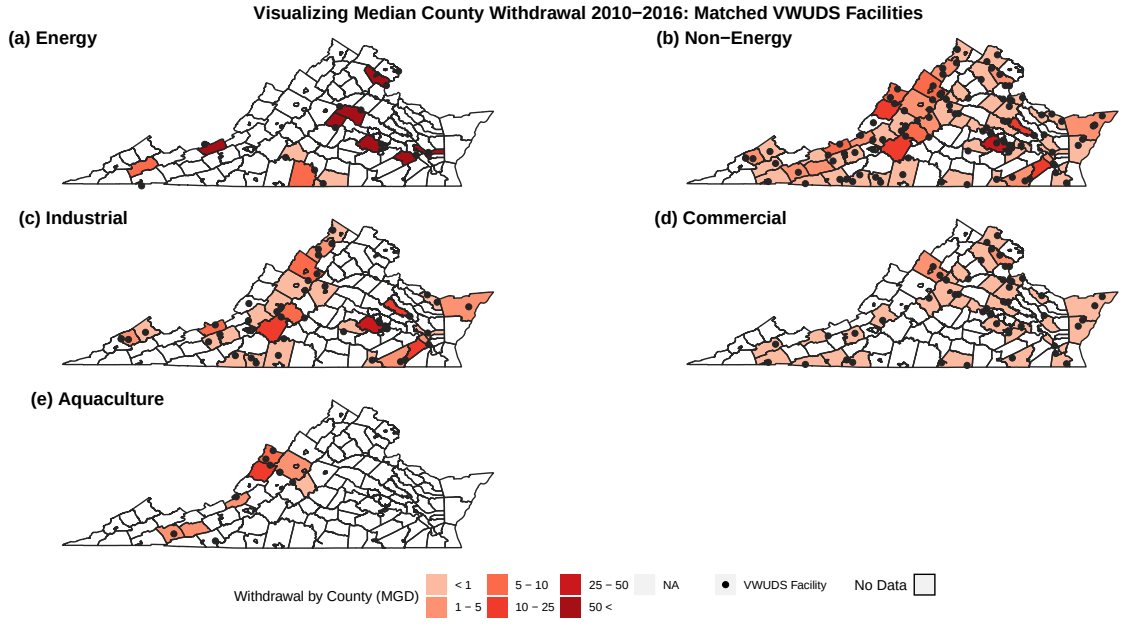

Figure E.6: Median long-term annual county withdrawal (MGD) considering matched facility data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Commercial, (e) Aquaculture, and (f) Municipal sectors (2010-2016).

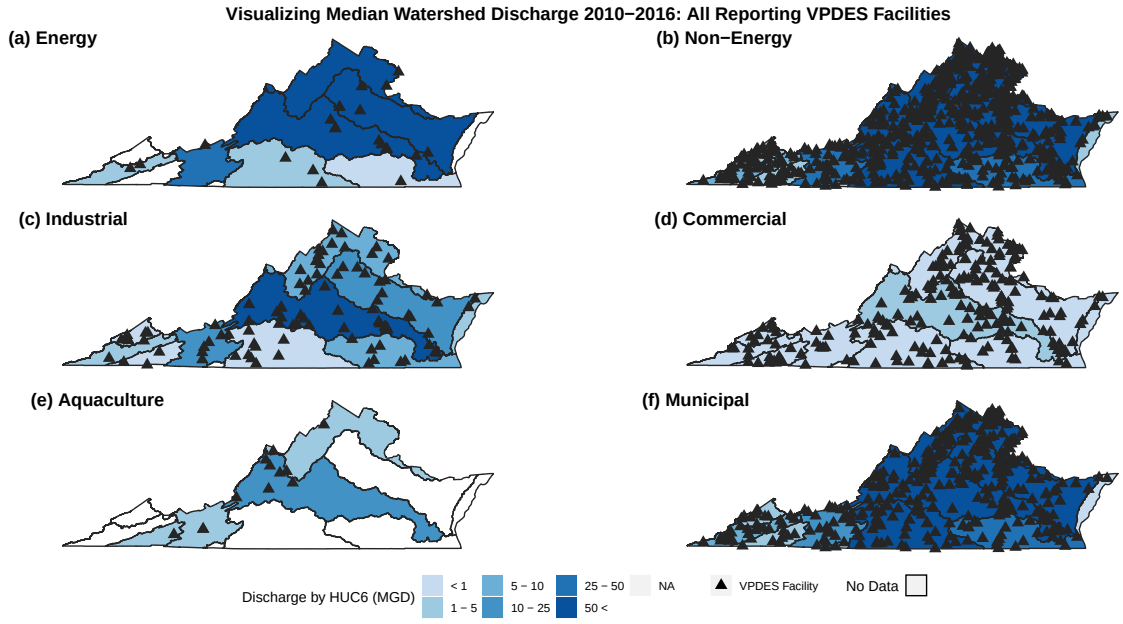

Figure E.7: Median long-term annual HUC6 watershed discharge (MGD) considering all available data for (a) Energy, (b) Non-Energy, (c) Industrial; (d) Commercial; (e) Aquaculture; and (f) Municipal sectors (2010-2016).

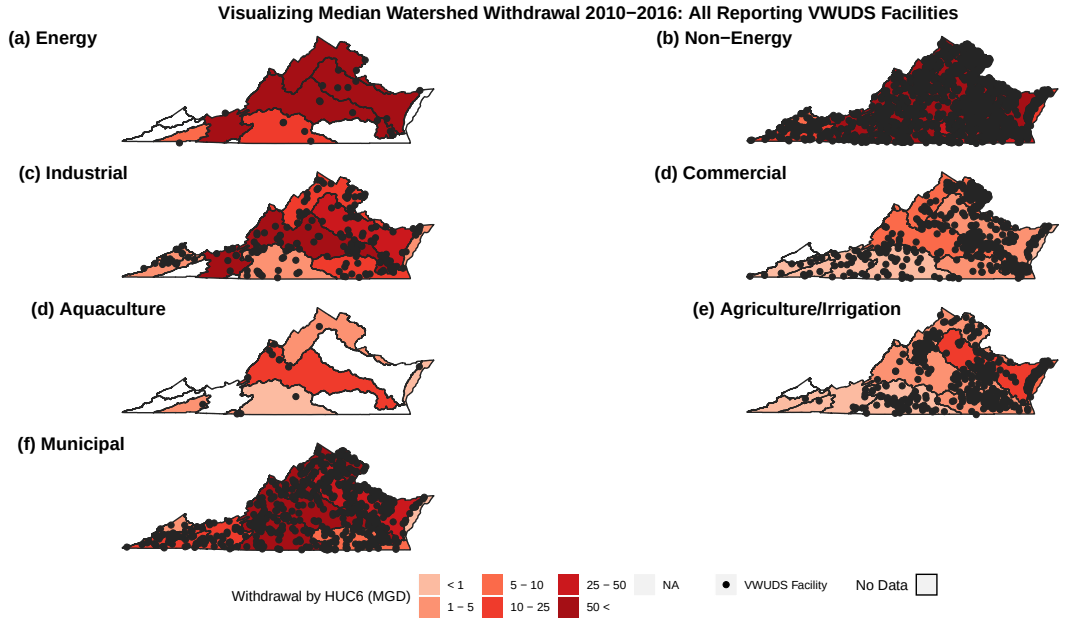

Figure E.8: Median long-term annual HUC6 watershed discharge (MGD) considering all available data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Commercial, (e) Aquaculture, (f) Agriculture/Irrigation, and (g) Municipal sectors (2010-2016).

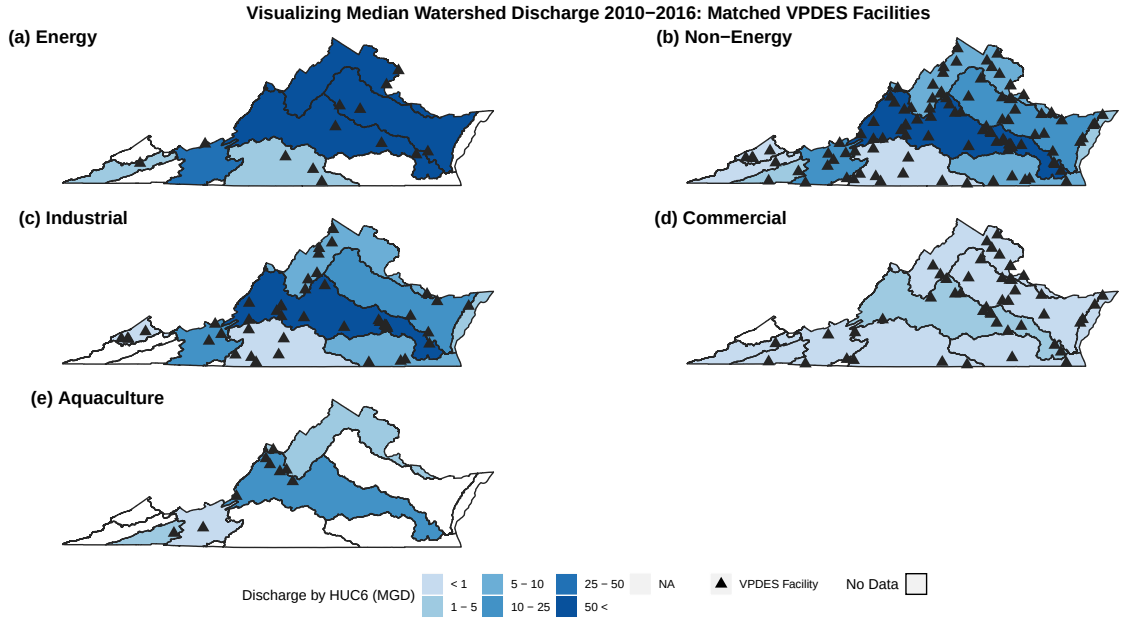

Figure E.9: Median long-term annual HUC6 watershed discharge (MGD) considering matched facility data for (a) Energy, (b) Non-Energy, (c) Industrial, (d) Commercial, and (e) Aquaculture sectors (2010-2016).