



TECHNICAL MEMORANDUM

To: Greg Johnson, PE – MCES

From: Uma Vempati, PE
Bailey Hadnott Taylor, PE
Petros Paulos, PE
Yuliana Mendoza
Emily Schabert
Kimley-Horn and Associates, Inc.

Date: March 24, 2026

Subject: White Bear Lake Comprehensive Plan: Study No. 10 – Lawn Watering Restrictions

Executive Summary

The Metropolitan Council Environmental Services (MCES), in coordination with 14 communities hydrologically connected to White Bear Lake, is evaluating strategies to ensure sustainable drinking water supplies while supporting long-term municipal growth. As part of this effort, Study 10 assesses the potential for reducing groundwater use through the implementation of lawn watering restriction policies and smart irrigation control devices to reduce residential outdoor water usage.

Lawn watering restrictions are widely used and can contribute to reduced outdoor water use, but observed savings vary substantially by policy design, enforcement, customer behavior, and local climate. In the White Bear Lake area, historical datasets indicate that residential water use has generally declined over time, including in communities without a restriction policy, making it difficult to isolate the causal effect of restrictions alone. No single restriction type clearly emerged as consistently “best” across communities; policy effectiveness is likely enhanced when paired with public education and, where feasible, dynamic adjustments that better reflect local weather conditions.

Smart irrigation controllers show more consistent, measurable reductions in outdoor water use when properly installed and calibrated, particularly when programs are targeted toward historic high-water users. Published literature and local Twin Cities Metropolitan Area programs suggest average savings of approximately 5,000 to 30,000 gallons per household per year. Depending on assumed adoption levels and development scenario (2025, 2050, and ultimate development), this study estimates total potential annual savings across all 14 White Bear Lake area communities of approximately 23 to 190 million gallons per year. Estimated total costs to implement smart irrigation controllers across all communities are approximately \$1.0 million to \$5.1 million, depending on adoption level (adoption by

20% of the population v. 50% of the population) and development scenario, with potential cost sharing through resident contributions and/or grants.

Enforcement of lawn watering restrictions is typically managed through education, warnings, and progressive fines, often relying on citizen reporting. Regional experience indicates high compliance can be achieved using such methods without resorting to service shutoffs. Advanced Metering Infrastructure (AMI) can improve monitoring by enabling near real-time data collection, customer high-use and leak alerts, and more targeted conservation outreach, but it requires substantial upfront investment plus ongoing network and software costs.

Key uncertainties include:

- gaps in historical datasets that required interpolation and estimation,
- limited post-policy data for communities that implemented restrictions in the last 1-5 years,
- limited Midwest-specific published research,
- the absence of a defined year for reaching ultimate development in each city introduces uncertainty to cost estimates due to variable inflation rates.

These uncertainties affect the precision of savings and cost projections and highlight the need for improved measurement and verification over time.

Recommended next steps are:

- Maintain existing lawn watering restriction policies across the 13 communities that already have them;
- Consider adopting a policy in communities without one (e.g., North Saint Paul);
- Pursue clear public education and, where feasible, weather-informed or dynamic restrictions;
- Expand smart irrigation controller programs with emphasis on proper setup and targeting of high outdoor water users;
- Strengthen measurement and verification (for example, by pairing controller programs with temporary irrigation meters or enhanced metering data); and
- Evaluate phased or targeted AMI deployment options to support monitoring and conservation analytics while balancing capital and ongoing system costs.

Purpose and Scope

Purpose of the Study

The Minnesota legislature has funded the Metropolitan Council of Environmental Services (MCES) to work with the 14 communities in the White Bear Lake area to develop a comprehensive plan that ensures sufficient access to drinking water while supporting municipal growth. The plan will identify strategies to maintain the long-term sustainability of both surface water and groundwater resources for future generations.

Study 10 evaluates the potential water savings that could be achieved through lawn watering restrictions and the use of smart lawn irrigation controllers within the 14 White Bear Lake area communities.

Scope of the Study

To achieve the purpose of the study, the following tasks were performed:

- Review of Case Studies and Best Practices
 - Research regional and national case studies from public water systems that have implemented lawn watering restrictions and/or irrigation technologies. The five identified water restrictions policies are:
 - Even/Odd-day Watering Restrictions (watering allowed only on calendar days matching property address numbers)
 - Watering Restrictions Twice per week
 - Time of Day Watering Restrictions (e.g., watering allowed only during morning and evening hours)
 - Even/Odd-day Restrictions Combined with Time-of-Day Restrictions
 - Twice per Week Restrictions Combined with Time-of-Day Restrictions
 - The three identified irrigation technologies evaluated for potential water savings are:
 - Smart irrigation controllers
 - Soil moisture sensors
 - Weather-based irrigation systems
- Existing Lawn Watering Restrictions
 - Identify and summarize existing lawn watering restrictions and related city codes or ordinances for the 14 White Bear Lake area communities.
- Historical Water Use Analysis
 - Review historical municipal well pumping data from the Minnesota Department of Natural Resources (DNR) Permitting and Reporting System (MPARS) database.
 - Compare water use both before and after lawn watering restrictions were implemented.
 - Estimate historical annual water savings achieved from these restrictions using average gallons per capita per day data.
- Estimated Water Savings from Lawn Watering Policies
 - Estimate potential water savings for all 14 White Bear Lake area communities under the five lawn watering policy options listed above. The analysis:
 - Uses water savings data from regional and national case studies
 - Evaluates savings under three development scenarios:
 - Existing conditions
 - Year 2050 projected demand
 - Ultimate development projected demand
 - Incorporates projected water demand data provided by the Metropolitan Council
- Estimated Water Savings from Smart Irrigation Controllers

- Evaluate the potential water savings from widespread adoption of smart irrigation controllers across the 14 communities. The analysis includes:
 - Assumptions regarding the percentage of customers with irrigation systems
 - Estimated adoption of smart controllers under:
 - Existing conditions
 - Year 2050 development
 - Ultimate development
 - The study also estimates:
 - Average cost per customer to install a smart irrigation controller
 - Total citywide cost for implementation in each community under the three development scenarios
- Monitoring and Enforcement
- Provide recommendations for monitoring and enforcement mechanisms if lawn watering restrictions are implemented or modified. This may include:
 - Use of AMI metering systems
 - Monitoring approaches for outdoor water use
 - Enforcement strategies used by other public water systems

Work Performed

Data Collection and Review

The data for this study was obtained from the following sources:

- Minnesota DNR Permitting and Reporting System (MPARS)
- Metropolitan Council
- ESPWater database, provided by the Metropolitan Council

MPARS permit records related to municipal water supply systems were requested for each of the 14 White Bear Lake area communities. Data was available for most communities and was used to determine total municipal groundwater pumping volumes from 1988 through 2025.

In addition to the MPARS data, the Metropolitan Council provided annual total gallons pumped for each city from the ESPWater database for the years 2014 through 2023. This dataset had been previously reviewed and validated by an MCES consultant, making it more reliable than the raw data entries available in MPARS.

Accordingly:

- ESPWater data was used for the years 2014 to 2023.
- MPARS data was used for the years 1988 to 2013 and 2024 to 2025.

The primary dataset used in this study consisted of MCES data for:

- Residential gallons sold per year,

- total water service population per city, and
- projected water demands for the year 2050 and ultimate development scenarios.

As some datasets were not available for all years, interpolation and estimation methods were applied to address these data gaps. The methods used are outlined below.

Data Processing and Estimation Methods

Water Service Population

MCES provided water service population data for each city from 1990 to 2012 and 2014 to 2023. To address the gap for 2013, linear interpolation was used. For 2024 and 2025, the percentage of each city's population served by municipal water was calculated based on available data, and the average percentage was applied to the total city population to estimate the water service population.

Residential Water Use

MCES provided data on residential gallons sold per city per year for the periods 1990 to 2012 and 2012 to 2022. The identical values for 2012 allowed the datasets to be merged into a single continuous record. To estimate residential water use for 2023-2025, the percentage of residential water use relative to total city water use was calculated for available years, and the average percentage was applied to total water consumption.

Population and Household Data

Total city population and average household size were obtained from MCES population projections available online for each city and year.

Derived Water Use Metrics

Using the datasets described, the following performance metrics were calculated for each city and year.

- Average residential water use per person per day (gallons per capita per day)
- Average residential water use per household per day (gallons per household per day)

These metrics were used to evaluate historical water use trends and estimate potential water savings from lawn watering restrictions. Figure 1 shows the overlap in time series coverage of each data source. The overlap in data shows the years for which a complete dataset was available, namely 2014 to 2022. Data gaps in years without complete datasets were addressed using the methods outlined above, ensuring that all cities had a complete dataset for the years 2000 to 2025.

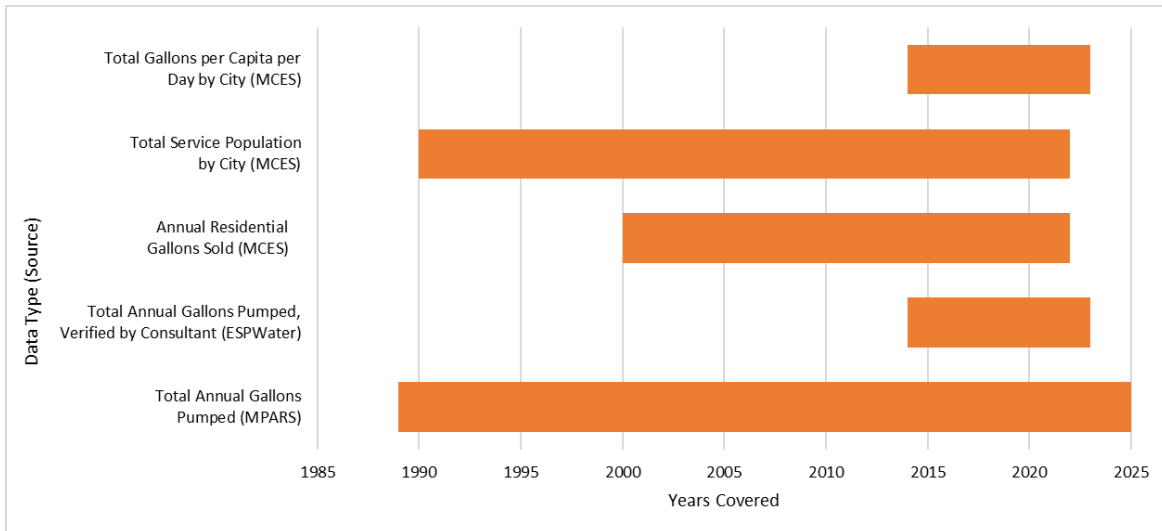


Figure 1. Data Availability by Year

Case Studies Research

The team conducted a review of available case studies on lawn watering restrictions and smart irrigation controllers using the following sources:

- American Water Works Association (AWWA)
- Water Research Foundation (WRF)
- United States Department of Agriculture (USDA)
- Irrigation Association
- Alliance for Water Efficiency
- American Water Resources Association (AWRA)
- University of Minnesota Lawn Water Conservation Educators
- Peer-reviewed scientific research journals

Lawn Watering Restriction Policies

To date, there are relatively few case studies from the Midwestern United States or at the national level that quantify water savings from lawn watering restriction policies. Most available research focuses on regions in the western United States, particularly Utah, Nevada, California, and Colorado, where drought conditions and water scarcity are more severe.

Published studies report a wide range of estimated water savings from lawn watering restrictions, varying from negligible^[1] to approximately 56%^[1,3], depending on policy structure, implementation approach, and study location. In general voluntary restrictions tend to result in lower savings (approximately 4% to 12%),^[1] while mandatory restrictions have shown higher savings (approximately 18% to 56%).^[1]



In 2020, the Alliance for Water Efficiency found that voluntary restrictions did not result in statistically significant reductions in water use, whereas mandatory restrictions produced average annual savings of approximately 18% to 30%.^[4]

It is important to note that many of these studies were conducted during drought conditions, when public awareness and conservation behavior are typically heightened. Therefore, these reported savings may not be directly representative of conditions in non-drought years or in regions such as the Midwest.

Variability and Limitations in Observed Savings

Research indicates that lawn watering restrictions do not consistently result in reduced water use and, in some cases, may lead to increased outdoor water consumption. For example, a 2012 study of communities near Tampa, Florida found that a shift from two-days-per-week to one-day-per-week watering restrictions led to increased irrigation, as homeowners compensated by applying more water per watering event.^[5] Similar findings were reported in a 2016 South Florida study, which concluded that restrictions not aligned with actual weather conditions may encourage overwatering behavior^[6]. These findings suggest that customer response to restrictions can vary significantly and restrictions that are not aligned with actual irrigation needs may lead to unintended outcomes. Factors such as local climate, customer behavior, and policy design all influence the effectiveness of these restrictions.

Additionally, results vary by region. While some western U.S. studies report measurable water savings, studies in other regions have shown mixed or even opposite results. This highlights the importance of considering local conditions, climate, and customer behavior when applying findings from other regions.

Factors Impacting Water Use in Households

- Income: Household income is positively correlated with increased water usage, including increased likelihood of lawn watering during restrictions.^[7]
- Awareness, Behavior & Perceptions: Residents that (1) feel favorably about watering restrictions, (2) believe that they live in a water-scarce city, (3) believe that water restrictions save water, and/or (4) believe in the importance of water conservation, are less likely to water their lawns when restrictions are in place and more likely to use less water overall.)^[7]
- Aesthetic Preferences: Those who value the appearance of a green lawn may use more water regardless of restrictions.^[8] Residents in homeowners' associations (HOAs) or who rent their homes may be required to maintain certain aesthetic standards by their HOA agreements or leases, leading to increased water use.^[9]
- Education: Individual education level is negatively correlated with likelihood of lawn watering during restrictions.^[7]
- Tree Shade: Areas with larger amounts of tree shade tend to have reduced residential water consumption for lawn watering.^[10]

- Irrigable Lot Size: Households with larger lawns or gardens are likely to use a larger amount of water than their peers to maintain plant health.
- Home Age: Older homes may have a higher likelihood of leaky fixtures or pipes and less efficient appliances, leading to unintentional higher water consumption.
- High-Efficiency Appliances and Home Upgrades: Based on statistics from the United States Environmental Protection Agency (EPA), upgrading to WaterSense-labeled products can reduce a household's water usage by tens of thousands of gallons per year.^[11]
- Irrigation Systems: Residents with in-ground irrigation systems tend to use more water both during restrictions and at other times compared to those without irrigation systems, leading to increased household water consumption.^[7,12]
- Hyper-Local Weather Patterns: Increasing observed weekly rainfall totals at an individual's home have a direct negative impact on outdoor water usage.^[6]
- Individual Habits: Personal habits, such as running water while washing dishes, washing multiple partially full loads of laundry, or taking longer showers, lead to variable household water use.^[11]

Key Factors Affecting Effectiveness

The variability in reported water savings is influenced by several factors:

- Combined Conservation Measures: Many studies evaluate lawn watering restrictions alongside other measures such as public education, smart controller adoption, or appliance rebates, making it difficult to isolate the impact of restrictions alone.
- Drought vs. Non-Drought Conditions: Restrictions are often implemented during drought periods, when conservation awareness is higher. These conditions may not reflect typical usage patterns.
- Customer Behavior and Outdoor Water Use Drivers: Household water use is influenced by many factors beyond lawn watering, including property size, landscaping type, and irrigation practices.
- Policy Design and Enforcement: The structure of the restriction (e.g., frequency vs. time-of-day) and the level of enforcement play a significant role in determining effectiveness.

Applicability to White Bear Lake Area

Based on the available research, lawn watering restrictions are widely used and can contribute to reductions in outdoor water use; however, their effectiveness is highly context-dependent. For the White Bear Lake area, Midwest-specific quantitative data are limited, requiring reliance on studies from other regions. Reported savings from national studies should be interpreted cautiously and may represent upper-bound estimates. The effectiveness of restrictions will depend on several factors, including policy structure, customer compliance, enforcement mechanisms, and alignment

with local climate conditions. These considerations support the use of scenario-based water savings estimates in subsequent analyses, rather than relying on a single assumed value.

Smart Irrigation Controllers

Compared with lawn watering restrictions, smart irrigation controllers are generally easier to evaluate because they directly adjust irrigation timing and duration based on site-specific conditions such as weather, soil moisture, and evapotranspiration. As a result, their impact on water use is more measurable, although reported savings still vary depending on installation, calibration, and customer behavior.

Research indicates that “smart” irrigation control devices, such as controllers that use evapotranspiration data and soil moisture sensors, can be effective in reducing residential irrigation water consumption when properly implemented. Although limited research is available for the Midwest, studies from other regions (including the arid Southwest and humid Southeast) show consistent trends that are broadly applicable. A summary of types of smart irrigation controllers is presented in Table 1.

Table 1. Summary of Smart Irrigation Controller Types

Technology Type	Key Findings	Typical Savings Range	Key Considerations	Applicability to White Bear Lake
Weather-Based Sensors	Provide climatic input to irrigation controllers	Moderate to High	Requires proper setup and connectivity	High
Soil Moisture Sensors	Provide soil moisture content as input to irrigation controllers	Moderate to High	Sensor placement and maintenance are critical	High
Smart Controller + Sensors	Combines multiple inputs for optimization	High	Highest performance when properly configured	High
Conventional Controllers	Fixed schedules; no adaptive control	Low	Baseline condition	Existing condition

Key Findings from Literature on Smart Irrigation Controllers

Research indicates that soil moisture sensor-based smart controller systems have demonstrated the highest water savings, with average water use reductions of approximately 47%.^[13] Evapotranspiration (ET)-based smart controller systems have shown average water use reductions of around 30%.^[13,22] Overall, smart irrigation controllers consistently reduce outdoor water use when properly installed and calibrated.



In some instances, water use increased after the installation of smart irrigation controllers. This occurred primarily in homes that were under-irrigating, where controllers adjusted irrigation to meet full plant water requirements,^[12] leading to increased total irrigation demand for those users. The most reliable water savings are achieved when smart irrigation controllers are targeted toward high water-use customers and are properly programmed and calibrated based on site conditions.^[12]

Twin Cities Metropolitan Area Evidence

The most relevant data for this study comes from irrigation system evaluations conducted within the Twin Cities Metropolitan Area. Studies in the City of Woodbury, Vadnais Heights, and Lino Lakes have shown clear water savings advantages for smart irrigation controllers compared to conventional systems. Savings ranged from approximately 15,000 gallons per household per year in Vadnais Heights^[25] to 30,000 gallons per household per year in Woodbury.^[24] Observed reductions in irrigation demand varied significantly by system type and configuration. Woodbury’s studies emphasize the importance of testing smart irrigation control products to find the best option tailored to local conditions.^[24] Implementation details, including sensor reliability and controller programming, strongly influence performance.^[24] The studies demonstrate that factors such as ease of use, total water bill savings, and programming impact the likelihood of resident adoption of smart irrigation controllers.^[24] These findings are particularly relevant for the White Bear Lake area, as they reflect local climate and irrigation practices.

Potential Water Savings from Lawn Watering Restrictions

A summary of the existing water lawn restriction policies for each city is presented in Table 2.

Table 2. Summary of City Lawn Watering Restrictions

City	Restriction Type	City Ordinance Restriction Date
Hugo	Even/Odd Combined with Time of Day Restriction	2001
Lake Elmo	Two Days per Week Combined with Time of Day Restriction	2021
Lino Lakes	Even/Odd Combined with Time of Day Restriction	2023
Mahtomedi	Even/Odd Combined with Time of Day Restriction	2009
New Brighton	Even/Odd Restriction	1998
North Saint Paul	No Current Policy	N/A
Oakdale	Even/Odd Combined with Time of Day Restriction	1995
Shoreview	Even/Odd Combined with Time of Day Restriction	2005
Stillwater	Even/Odd Combined with Time of Day Restriction	2023
Vadnais Heights	Two days per week + time restriction	2017
White Bear Lake	Time of Day Restriction	2022
White Bear Township	Even/Odd Combined with Time of Day Restriction	2009
Woodbury	Two Days per Week Combined with Time of Day Restriction	2023



MCES provided data including residential water usage, residential population, water service population, and water pumped from existing wells. This data was evaluated using multiple methods to understand how lawn watering restrictions affect water usage. These methods are summarized in the following section.

Delta Method

Water usage was calculated in the period before the lawn watering restriction and the period after its implementation. Using this method, seven cities experienced an increase in water usage following the implementation of lawn watering restrictions. Although some case studies indicate that water usage might increase in the initial years after a lawn watering restriction is enacted, a significant general increase is not typically observed. Therefore, this method was not considered indicative of a consistent water usage pattern and was not used to predict water usage in 2050 and at ultimate development.

Table 3 presents each city, their respective lawn watering restriction and its enactment date, the change in water usage (delta) in gallons per year before and after the lawn watering restriction policy was enacted, and the implications of these delta values. The delta before the restriction was calculated by subtracting the residential gallons used in the city's first year of data from the residential gallons used the year the policy was enacted. Therefore, negative values indicate a reduction in water consumption and positive values indicate an increase in water consumption.

Table 3. Delta Before and After Lawn Watering Restriction

City	Restriction Type	Restriction Date	Delta Before Restriction (gal/year)	Delta After Restriction (gal/year)	Implication
Hugo	Even/odd + time restriction	2001	-5,801	7,055	Water savings increase after policy
Lake Elmo	Two days per week + time restriction	2021	-39,245	-6,803	Water savings decrease after policy
Lino Lakes	Even/odd + time restriction	2023	4,145	610	Water savings increase after policy
Mahtomedi	Even/odd + time restriction	2009	7,023	-15,453	Water savings increase after policy
New Brighton	Even/odd	1998	15,963	-11,906	Water savings increase after policy
North Saint Paul	No Current Policy	N/A	N/A	N/A	
Oakdale	Even/odd + time restriction	1995	4,150	-5,283	Water savings increase after policy
Shoreview	Even/odd + time restriction	2005	2,276	-5,267	Water savings increase after policy
Stillwater	Even/odd + time restriction	2023	-8,926	-5,792	Water savings decrease after policy
Vadnais Heights	Two days per week + time restriction	2017	4,040	-2,610	Water savings decrease after policy
White Bear Lake	Time restricted	2022	-4,616	-836	Water savings decrease after policy
White Bear Township	Even/odd + time restriction	2009	12,088	-21,611	Water savings increase after policy
Woodbury	Two days per week + time restriction	2023	-9,420	-5,449	Water savings decrease after policy

Linear Extrapolation Method

Annual per capita residential water usage was graphed over time, and a best-fit line estimate was developed to project usage to 2050 and ultimate development. This usage was calculated by dividing the residential gallons sold per year by the water service population per year. In addition to linear

regressions, the data was also evaluated using exponential and logarithmic regressions. However, R^2 values were less than 0.4 for multiple regression types in all cities, indicating that none of these methods were sufficiently predictive for identifying trends in water usage after a policy was enacted. Figure 2 illustrates this calculation method, using the City of Hugo as a representative example. Additional graphs for the remaining thirteen cities are provided in Appendix A.

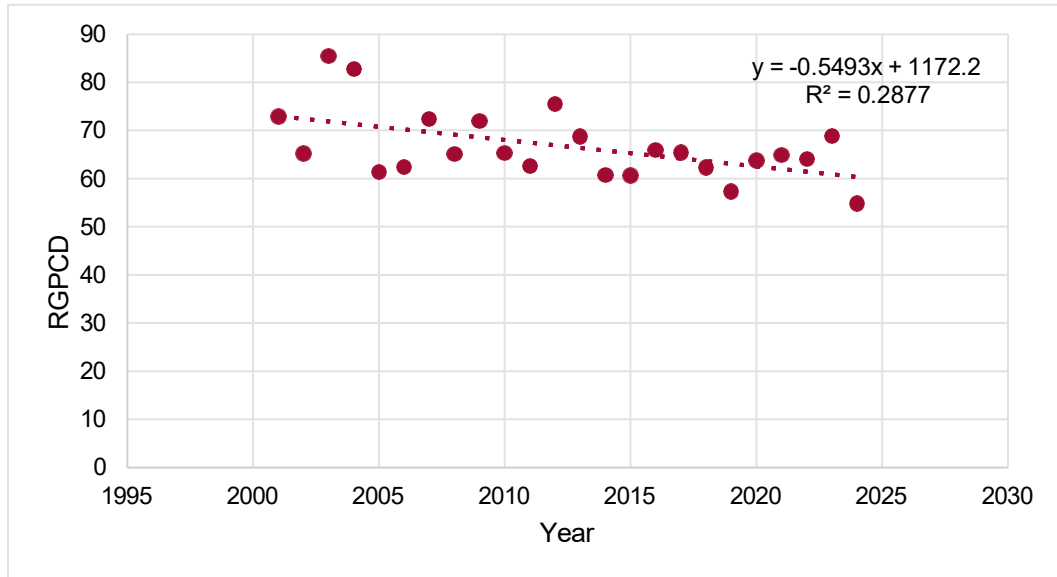


Figure 2. Residential Gallons per Capita per Day (RGPCD) by Year in Hugo

Multiple Linear Regression Method

A regression line was calculated for the periods before and after a city's policy was enacted. Before the policy enactment, some cities showed a slight linear trend with a positive slope (indicating increasing water usage), while others showed a negative slope (indicating decreasing water usage). After the policy was enacted, there was a general overall decrease in water usage. However, the correlation between variables was low (R^2 values often less than 0.4). Using the best-fit line from periods before and after the policy to predict water usage produced unreasonable results for multiple cities, such as estimated water savings of more than 90,000 gallons per household per year. Therefore, it is difficult to attribute the observed downward trend solely to the enactment of a lawn watering policy. The decrease in water usage could also be attributed to more efficient household appliances, community education on water conservation, increased rates, or other factors considered in this study. Due to the low R^2 values and unrealistic results, this method was not selected to predict water usage for the 2050 and ultimate development scenarios, nor water savings. Figures 3 and 4 provide the regression line calculated showing the residential gallons per capita per day in Mahtomedi before and after the policy enactment, respectively.

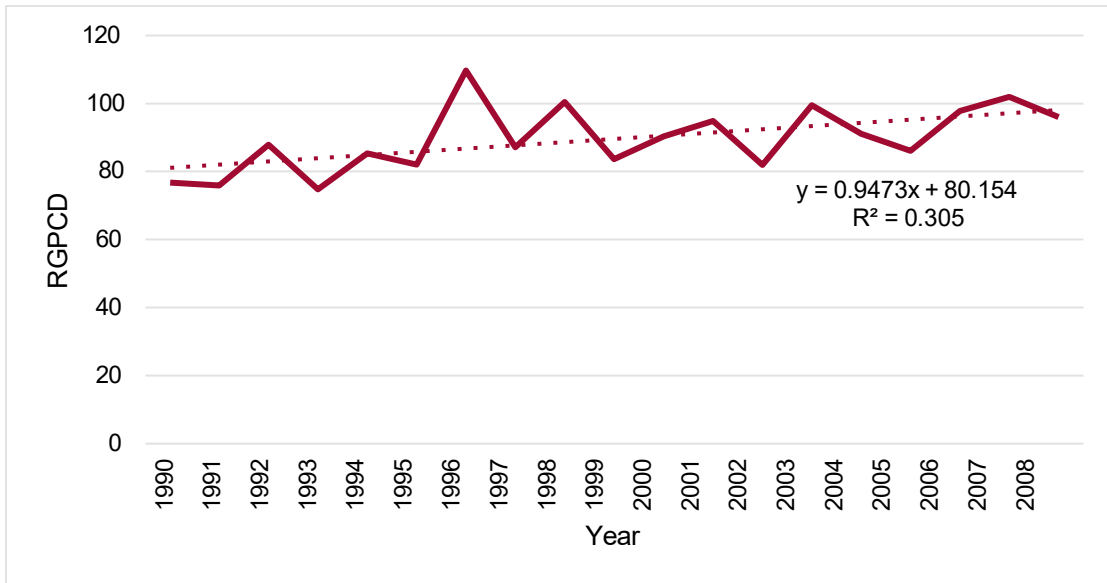


Figure 3. Residential Gallons per Capita per Day in Mahtomedi Before Policy Enactment

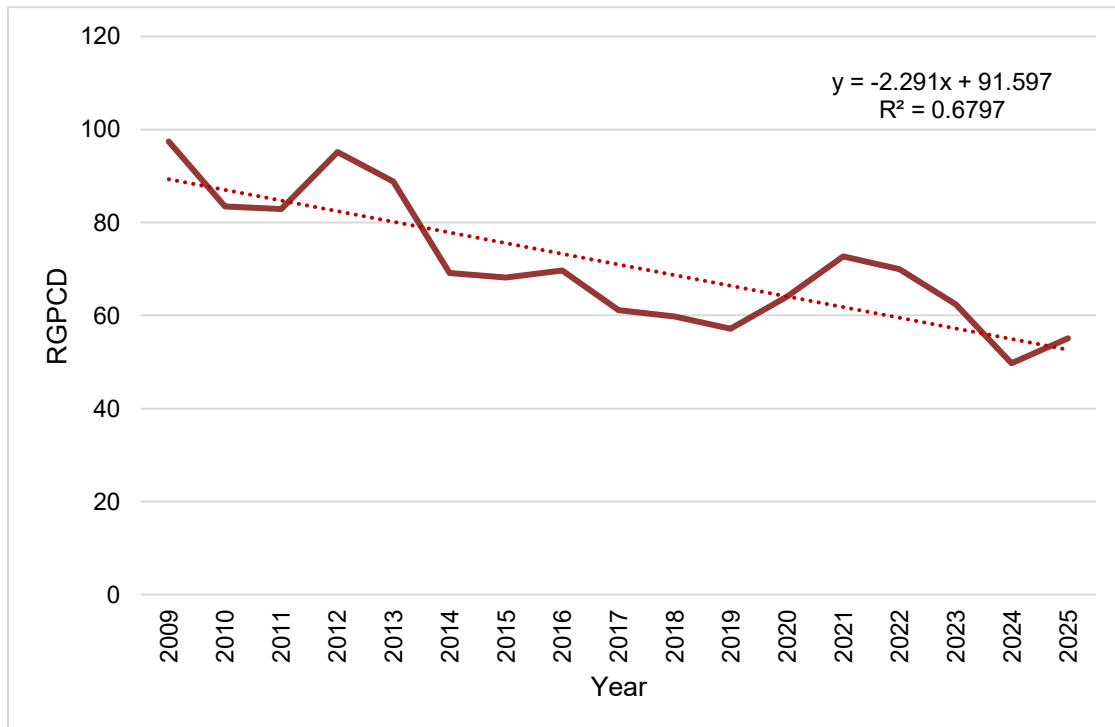


Figure 4. Residential Gallons per Capita per Day in Mahtomedi After Policy Enactment

Median Lot Size Method

To understand typical water usage without a lawn restriction policy, data was collected from cities within and outside of the 14 White Bear Lake area communities that do not have lawn watering restrictions in place. The cities included North Saint Paul, Bloomington, Lino Lakes, Stillwater, White Bear Lake, Woodbury, Fridley, and Newport. For Lino Lakes, Stillwater, White Bear Lake and Woodbury, which are part of the study and enacted their policies within the last five years, data from before their policy enactments serve as a reliable baseline for understanding water usage prior to restrictions. Annual outdoor water usage per household was graphed against median lot size, as shown in Figure 5. It was assumed that the median lot size was a strong predictive independent variable, as cities with larger lots are likely to require more outdoor water for lawn irrigation. However, the data did not show a strong correlation between median lot size and annual outdoor water usage. Therefore, household water usage could not be reliably predicted based on lot size.

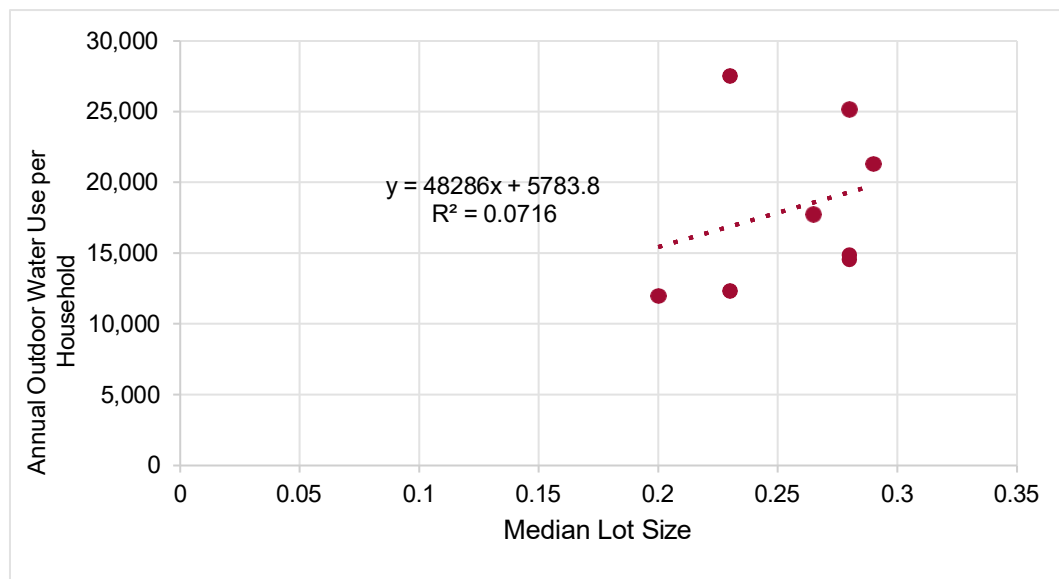


Figure 5. Median Lot Size vs Annual Outdoor Water Use for Cities with No or Recent Lawn Watering Restrictions

Minimum Use Method

For each city, a trendline was fit to three calculated data points – average RGPCD before policy enactment, 10 years after policy enactment, and in the remaining years until 2024. These trendlines were used to extrapolate existing data to calculate average RGPCD in 2050 and ultimate development. However, the extrapolations showed a RGPCD of less than 30 for seven cities (Hugo, Mahtomedi, New Brighton, Stillwater, White Bear Lake, White Bear Township, and Woodbury). Achieving an RGPCD of less than the EPA’s estimated minimum residential water use of 50 gallons per person per day is not realistic for cities in the White Bear Lake area. Therefore, the estimated minimum RGPCD was assumed to be 80% of current use levels, equating to a 20% reduction in residential water use per person, which keeps the RGPCD above the 50 RGPCD EPA minimum. Extrapolation was used to determine when each city is projected to reach their minimum use level. Once a city reaches its minimum use level, it is unlikely to see additional reductions in residential water usage from lawn watering policies. Table 4 summarizes the average RGPCD for each city during the three periods and the year when each city is expected to reach its minimum use level.



Table 4. Average RGPCD Before and After Lawn Watering restriction

City	Restriction Type	Year Enacted	Average RGPCD Before Restriction	20% Reduction from Average RGPCD Before Restriction	10-year Average RGPCD Since Policy	2 nd Stage Average RGPCD After Initial 10 Years	Estimated RGPCD 2050	Estimated RGPCD Ultimate Development
Hugo	Even/odd + time Restriction	2001	76	60.8	70	63	Minimum achieved	Minimum achieved
Lake Elmo	Two days per week + time restriction	2021	87	69.9	Insufficient data to predict water usage			
Lino Lakes	Even/odd + time Restriction	2023	80	64	Policy enacted during drought year – insufficient data to predict water usage			
Mahtomedi	Even/odd + time restriction	2009	90	72	78	62	Minimum achieved	Minimum achieved
New Brighton	Even/odd	1998	79	63.2	87	68	Minimum achieved	Minimum achieved
North Saint Paul	No Restriction in Place		65	52	59	45	Minimum achieved	Minimum achieved
Oakdale	Even/odd + time restriction	1995	69	55.2	82	66	64	54
Shoreview	Even/odd + time restriction	2005	72	57.6	74	62	Minimum achieved	Minimum achieved
Stillwater	Even/odd + time restriction	2023	83	66.4	Policy enacted during drought year – insufficient data to predict water usage			
Vadnais Heights	Two days per week + time restriction	2017	80	64	70	Insufficient data to predict water usage		
White Bear Lake	Time restricted	2022	64	51.2	Policy enacted during drought year – insufficient data to predict water usage			
White Bear Township	Even/odd + time restriction	2009	96	76.8	85	Minimum achieved	Minimum achieved	Minimum achieved
Woodbury	Two days per week + time restriction	2023	98	78.4	Policy enacted during drought year – insufficient data to predict water usage			

Out of the 14 cities in the White Bear Lake area, seven have enacted their lawn watering policies within the last ten years, suggesting that the full impacts of the restrictions may not yet be fully realized. For cities with sufficient data (North Saint Paul, New Brighton, Hugo, Mahtomedi, Oakdale, Shoreview, and White Bear Township), the results are summarized in Figures 6, 7, and 8 below.

North Saint Paul is the only city among the 14 White Bear Lake area communities without a lawn watering restriction policy currently in place. From 1990 to 2002, the RGPCD was 65. Over the next 12 years, RGPCD decreased to 59 without any water lawn restrictions and continues to trend downward. This decline can be attributed to the adoption of more efficient household appliances and general water conservation practices. This indicates that factors other than lawn watering restriction also contribute to decreased water usage.

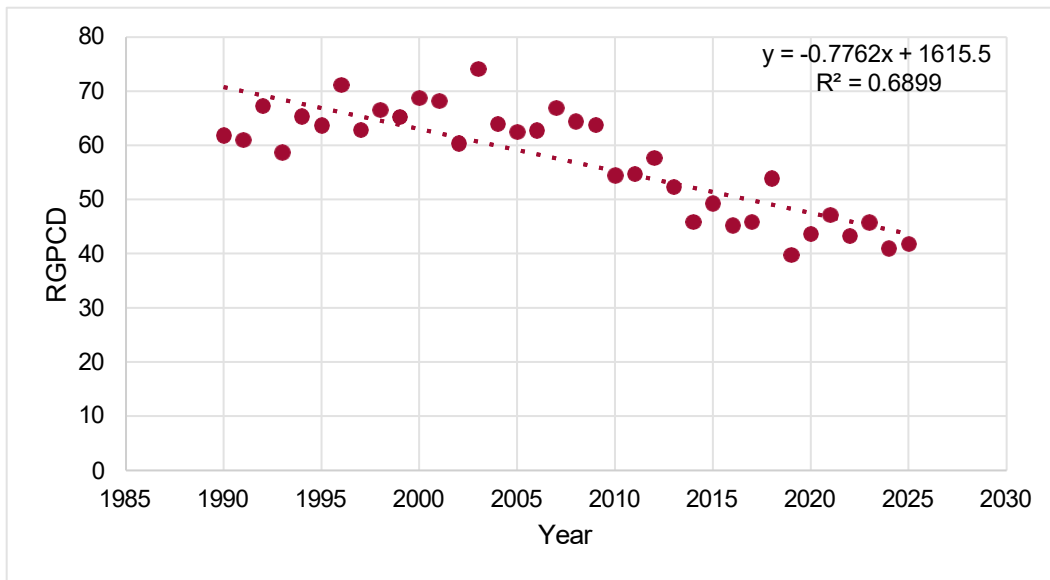


Figure 6. North Saint Paul Residential Gallons Per Capita Per Day

New Brighton operates under an Even/Odd policy without a Time-of-Day restriction. Their water usage increased ten years after the policy was enacted and then decreased subsequently, consistent with patterns observed in literature (Figure 7). Typically, Even/Odd only or Two Days per Week only restrictions do not lead to an overall decrease in water usage due to residents compensating by watering more on their assigned days.

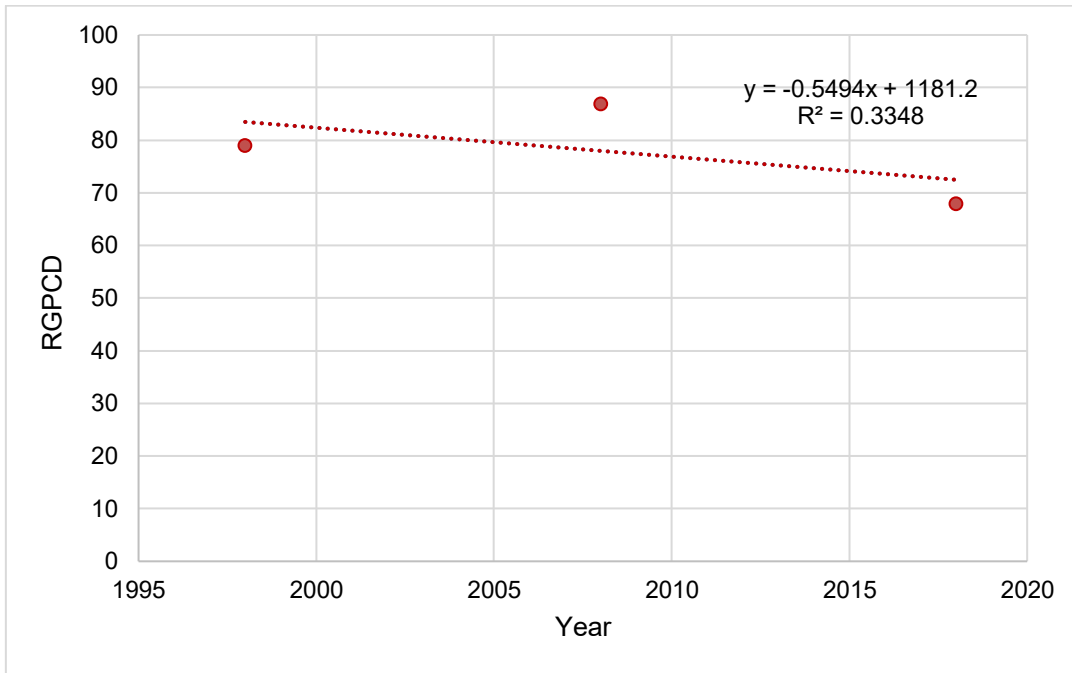


Figure 7. Residential Gallon Per Capita Per Day for Even/Odd Lawn Watering Restriction in New Brighton

Cities with Even/Odd Restriction Combined with Time-of-Day Restriction include Hugo, Mahtomedi, Oakdale, Shoreview, and White Bear Township.

The City of Hugo enacted its policy in 2001 and saw a sustained decline in water usage over the following ten years as seen in Figure 8. Mahtomedi and White Bear Township also experienced reduced water usage in the ten years following the restriction’s implementation. Conversely, Oakdale and Shoreview initially saw increases in water usage after the policy was enacted, followed by a subsequent decline. Figure 8 shows these cities’ estimated reduction in residential water usage, and detailed graphs for each city are available in Appendix B.

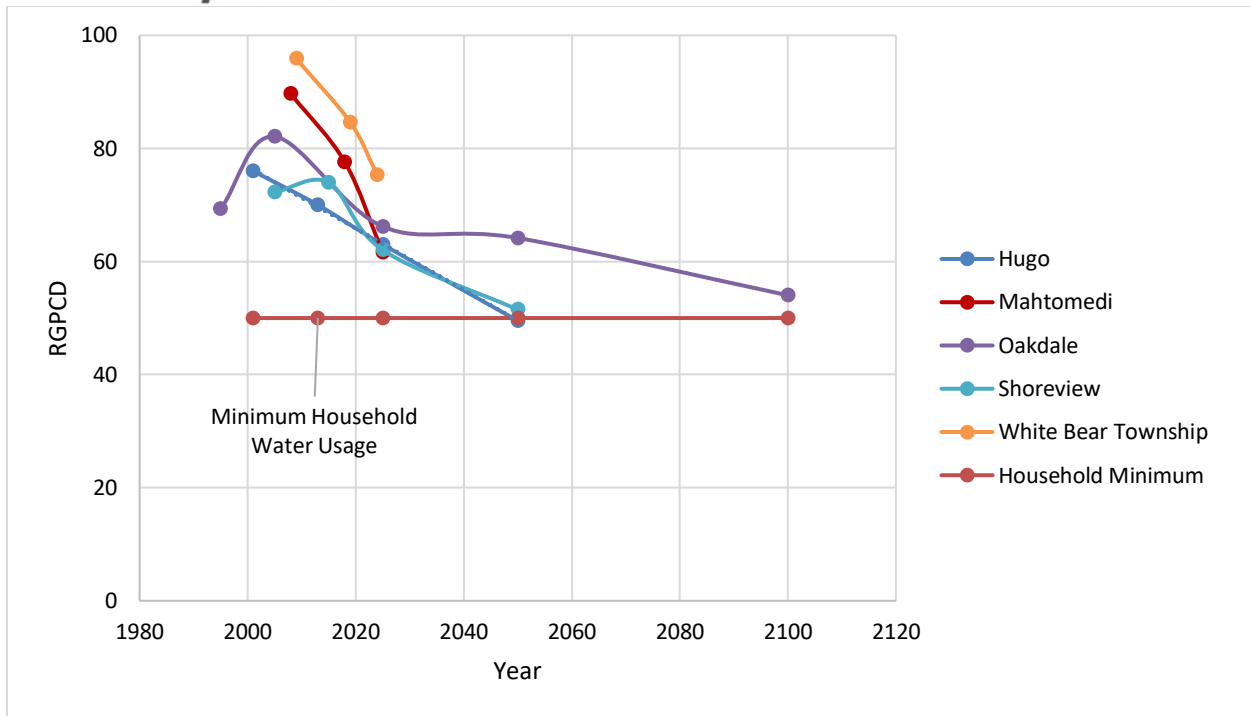


Figure 8. Residential Gallon Per Capita Per Day for Even/Odd + Time of Day Lawn Watering Restriction

Cities that implemented a Two Days per Week Combined with Time-of-Day restriction within the last ten years (Lake Elmo, Vadnais Heights, Woodbury) lack sufficient data to predict water usage for 2050 and the ultimate development scenario. Therefore, a 20% reduction was assumed for future development scenarios.

As indicated in Table 4, most cities saw a decrease in RGPCD after implementing lawn watering restrictions and when predicting water usage in 2050. Table 5 details the reductions in RGPCD along with the projected water service population for 2050, as provided by MCES. These figures were used to calculate the estimated gallons saved in 2050. The estimated savings were then multiplied by the average cost of tap water in across the White Bear Lake area communities (\$0.003 per gallon, per calculations by Hazen and Sawyer) to quantify the financial savings resulting from the reduction in RGPCD.



Table 5. Estimated Cost Savings Based on Water Usage Reduction from Lawn Watering Policies

Restriction Type	City	Reduction in RGPCD	Water Service Population in 2050	Estimated Gallons Saved in 2050	Calculated Cost Savings in 2050	Water Service Population Ultimate	Estimated Gallons Saved Ultimate	Calculated Cost Savings Ultimate
No Policy	North Saint Paul	13	15,750	74,733,750	\$224,201	15,750	74,733,750	\$224,201
Even/Odd Restriction	New Brighton	16	25,000	146,000,000	\$438,000	25,000	146,000,000	\$438,000
Even/Odd Combined with Time of Day Restriction	Hugo	15	21,000	114,975,000	\$344,925	101,054	553,270,650	\$1,659,812
	Lino Lakes	16	25,161	146,940,240	\$440,821	55,700	325,288,000	\$975,864
	Mahtomedi	18	10,881	71,488,170	\$214,465	12,506	82,164,420	\$246,493
	Oakdale	5	40,000	73,000,000	\$219,000	40,000	73,000,000	\$219,000
	Shoreview	14	30,079	153,703,690	\$461,111	36,701	187,542,110	\$562,626
	Stillwater	17	22,937	142,324,085	\$426,972	30,162	187,155,210	\$561,466
	White Bear Township	19	11,000	76,285,000	\$228,855	11,500	79,752,500	\$239,258
Time of Day Restriction	White Bear Lake	13	27,162	128,883,690	\$386,651	36,481	173,102,345	\$519,307
Two Days per Week with Time of Day Restriction	Lake Elmo	17	24,560	152,394,800	\$457,184	28,000	173,740,000	\$521,220
	Vadnais Heights	16	14,746	86,116,640	\$258,350	19,706	115,083,040	\$345,249
	Woodbury	20	110,000	803,000,000	\$2,409,000	110,000	803,000,000	\$2,409,000

Potential Water Savings from Smart Irrigation System Implementation

Published studies report a range of estimated water savings associated with smart irrigation controllers. The Minnesota DNR Water Conservation Reports estimate approximately 9,000 gallons of water saved per household per year following the implementation of a smart irrigation controller.^[21] The University of Minnesota Turfgrass Science Program estimates that smart irrigation controllers can reduce irrigation water consumption by approximately 29%.^[22] These estimates are consistent with broader research findings, indicating that smart irrigation controllers typically reduce household outdoor water use by approximately 30 to 47%, depending on system type, site conditions, and implementation.^[13] Total water savings for each city were calculated using two methods to reflect a range of potential outcomes:

1. Volume-Based Estimate Method: An estimate of 9,000 gallons saved per year per smart irrigation controller implemented, based on Minnesota DNR guidance.
2. Percentage-Based Estimate Method: An estimate of a 30% reduction in household outdoor water usage per smart irrigation controller implemented, based on University of Minnesota research and supported by broader literature.

Percentage-based estimates provided a more conservative estimate, while volume-based estimates resulted in higher estimated water savings. These methods were applied across three development scenarios:

- Current conditions (2025)
- Year 2050 projected conditions
- Ultimate development conditions

For each scenario, water savings were evaluated at varying assumed adoption levels, representing the percentage of conventional irrigation controllers converted to smart controllers. Adoption levels of 20%, 30%, 40%, and 50% were analyzed to reflect different degrees of program implementation. This approach allows for the evaluation of a range of potential outcomes based on both conservative and higher-end assumptions of smart irrigation controller performance and adoption.

Values and Data Sources Used to Estimate Total Water Savings

- Household and Water Use Estimates
 - Number of water service households: Estimated by dividing the total water service population (from MCES) by the average number of persons per household for each city.
 - Outdoor water usage per household: The US EPA estimates that approximately 30% of total household water use is used for outdoor purposes, primarily lawn irrigation.^[11] Outdoor water usage was estimated as 30% of the average residential water use per household provided by MCES.
- Irrigation System Assumptions

- Households with irrigation systems: The US EPA estimates that approximately 20% of U.S. households have in-ground irrigation systems. The number of households with irrigation systems in each city was estimated as 20% of total water service households.
- Existing smart irrigation Controllers: Research indicates that approximately 10% of existing irrigation systems in the U.S. are currently smart systems.^[13] Additional research suggests increasing interest in converting to smart systems, with some studies indicating that up to 46% of surveyed households are interested in converting within the next five years.^[20] Local programs in communities such as Lino Lakes, Vadnais Heights, and Woodbury have contributed to increased adoption through rebate and incentive programs.
- Conversion Potential - Based on expected growth in adoption:
 - Approximately 80% of existing irrigation systems were assumed to be convertible to smart systems under the 2050 development scenario.
 - Approximately 70% of existing irrigation systems were assumed to be convertible under the ultimate development scenario.
- Cost Assumptions
 - Cost per smart irrigation controller: Smart irrigation controllers are widely available at retail prices ranging from approximately \$50 to \$300, depending on functionality and system configuration.
 - The City of Woodbury's pilot program (2016–2018) identified cost-effective controller options, including the Rachio 3 Smart Sprinkler Controller.
 - Based on current pricing (2026) and anticipated municipal purchasing discounts, the estimated cost range is \$170 to \$200 per controller. The average cost used in this study is \$185 per controller.

Table 6 provides an overview of the range of potential savings that could be achieved with the implementation of smart irrigation controllers in each development scenario. The “low” and “high” estimates for water savings in Table 6 were calculated using the two methods listed above, with the low estimate representing a 30% savings factor and the high estimate representing the 9,000 gallons per year savings factor.



Table 6. Range of Total Potential Water Savings from Smart Irrigation Controllers by Development Scenario

Percent Conversion	Total Smart Irrigation Controller Water Savings by Development Scenario (Gallons Saved per Year)							
	2025		2050		Ultimate (With Hugo 1)*		Ultimate (With Hugo 2)*	
	Low	High	Low	High	Low	High	Low	High
20%	22,910,000	39,192,000	39,391,000	42,489,000	41,041,000	44,600,000	46,023,000	50,557,000
30%	34,365,000	58,788,000	88,629,000	95,600,000	92,343,000	100,350,000	103,552,000	113,752,000
40%	45,819,000	78,384,000	118,172,000	127,467,000	123,123,000	133,801,000	138,070,000	151,670,000
50%	57,274,000	97,980,000	147,715,000	159,333,000	153,904,000	167,251,000	172,587,000	189,587,000

*Note: The City of Hugo has two Ultimate Development conditions, each with different population and water demand levels. The “Hugo 1” scenario of Ultimate Development uses a water service population of 37,000, whereas the “Hugo 2” scenario uses 101,054. These population estimates are based on MCES’ projections for water demand under varying development scenarios.

Detailed breakdowns of estimated water savings by city in each development scenario are available in Appendix C.

The estimated cost for a smart irrigation controller device averages approximately \$185 for cities purchasing controllers wholesale. To estimate the total cost for a given city to purchase the proposed number of new smart irrigation controllers, this unit cost was multiplied by the number of controllers to be implemented. Additionally, a 30% contingency factor (scaled by a factor of 1.3) was applied to account for taxes, fees, delivery costs, inflation, and labor costs associated with ordering and installing the controllers. This results in an average installation cost of \$240.50 per customer. Table 7 outlines the total projected cost implementing smart irrigation controllers across all 14 communities. A detailed cost breakdown for individual cities is provided in Appendix D.

Table 7. Estimated Cost to Implement Smart Irrigation Controllers in All Communities

Percent Conversion	Cost to Implement Smart Irrigation Controllers in All White Bear Lake Area Communities			
	2025	2050 Development	Ultimate Development (With Hugo 1)	Ultimate Development (With Hugo 2)
20%	\$1,046,000	\$1,137,000	\$1,192,000	\$1,351,000
30%	\$1,571,000	\$2,554,000	\$2,681,000	\$3,039,000
40%	\$2,095,000	\$3,407,000	\$3,575,000	\$4,052,000
50%	\$2,620,000	\$4,261,000	\$4,469,000	\$5,066,000

The values presented in Table 6 represent the total cost for all cities to implement a given number of smart irrigation controllers. However, significant portions of this cost may be alleviated through grant funding or resident contributions. For instance, for the City of Woodbury's smart irrigation controller program, each household is required to contribute \$35 towards the cost of the controller, with the remainder covered by the city. Similarly, residents in Lino Lakes' program pay \$45 per household to receive a smart irrigation controller. These resident contributions account for approximately 20 to 25% of the actual cost of the smart irrigation controller, resulting in significant cost savings for cities that require household contributions.

To enhance data collection capabilities, cities should consider pairing the smart irrigation controllers with irrigation meters in their program implementation. Irrigation meters, which are small flow measurement devices that can be attached directly to a household's outdoor water valve (such as a hose), can provide precise data on water savings. Participants could use an irrigation meter for a designated period of time before and after program participation to collect baseline and post-intervention data. These meters can be purchased from many hardware stores for approximately \$25 to \$30, adding a marginal cost but providing the substantial benefit of demonstrating project success.

Enforcement Strategies

Lawn Watering Policy Enforcement Strategies

The primary enforcement strategy for cities with lawn watering restrictions involves warnings and fines. For example, the City of Woodbury enforces an administrative citation and a \$50 fine for the first violation, with fines doubling for each successive violation within the same calendar year.

Other cities and utilities, such as Saint Paul Regional Water Services (SPRWS), include educational visits and the possibility of water shut-off in their enforcement schedules. During the 2021 drought, SPRWS used the following enforcement schedule^[28]:

- First violation - Educational Notice
- Second violation - Written Warning
- Third Violation - \$50 Fine
- Fourth Violation - \$100 Fine
- Fifth and all additional violations - \$150 Fine + water shut off

Due to high administrative and labor costs associated with constant patrols, most cities rely on residents to submit complaints or reports about their neighbors watering during restricted times. SPRWS found that educational notices, warnings, and fines, issued in responses to citizen complaints achieved 96% compliance with lawn watering restriction policies without resorting to water shut-offs.^[28]

In some regions, citizen reporting mechanisms, educational home visits, warnings, and fines have been less effective. For instance, during periods of excessive drought and wildfires, a municipal water district near Los Angeles, California installed permanent flow restrictor devices on the water shut-off valves of homes that exceeded 150% of their allotted household water budget for four months or

more. This extreme measure was taken only after users failed to reduce their water consumption following warnings, citations, fines, educational notices, and a free home water audit.^[29]

Implementation of AMI Meters

To avoid extreme enforcement measures, the implementation of Advanced Metering Infrastructure (AMI) is recommended. AMI enables the remote collection of water consumption data, automatically transmitting data at predetermined intervals to provide near real-time information. This capability helps quickly identify excessive water use due to irregular watering patterns, non-compliance with lawn watering restriction policies^[34], or leaks. Many AMI utility programs include customer portals that promote water conservation engagement.^[14] Several Minnesota communities, including Saint Paul, Rochester, Owatonna, Elk River, and Shakopee, have begun replacing analog utility meters with AMI meters and are observing water savings from leak identification and policy monitoring.^[31] Case studies from California^[32] and the Canary Islands^[33] report water savings of 5.24 gallons per household per day and 2% of household water usage, respectively. Pairing AMI systems with community education on water conservation has further improved water savings.^[33]

AMI portals can promote water conservation by allowing customers to enable high-usage or leak alerts, providing timely warnings about high-water consumption. These alerts can also notify customers when their water usage approaches higher tier rates. Utilities can use household-specific AMI data to tailor water consumption feedback and promote optimal irrigation, particularly targeting households with significant outdoor water use. The efficacy of AMI portals relies on customer engagement with the portal.^[15]

Complete conversion to AMI meters requires significant investment in infrastructure, as well as ongoing network and software costs. A 2020 study for the Washington Suburban Sanitary Commission (WSSC Water) in the Washington, DC Metropolitan Area estimated that converting 492,000 old water meters to AMI meters by 2026 would cost approximately \$208 million.^[30] Scaling this cost estimate to the estimated service population of each White Bear Lake area community yields the implementation cost estimates shown in Table 8. Future service household estimates included in Table 8 are based on a water service population (from MCES) divided by an average of 2.6 persons per household.

Table 8. Estimated Cost to Implement AMI Meters

City	Water Service Households (2025)	Estimated Total AMI Cost (2025)	Water Service Households (2050)	Estimated Total AMI Cost (2050)	Water Service Households (Ultimate)	Estimated Total AMI Cost (Ultimate)
Hugo 1	5,559	\$2,350,300	8,077	\$3,414,600	14,231	\$6,016,300
Hugo 2	5,559	\$2,350,300	8,077	\$3,414,600	38,867	\$16,431,500
Lake Elmo	4,096	\$1,731,800	9,446	\$3,993,500	10,769	\$4,552,800
Lino Lakes	6,585	\$2,783,900	9,677	\$4,091,200	21,423	\$9,056,900
Mahtomedi	3,685	\$1,557,800	4,185	\$1,769,300	4,810	\$2,033,500
New Brighton	9,922	\$4,194,800	9,615	\$4,065,000	9,615	\$4,065,000
North Oaks	195	\$82,400	2,310	\$976,600	2,310	\$976,600
North Saint Paul	6,225	\$2,631,800	6,058	\$2,561,000	6,058	\$2,561,000
Oakdale	4,469	\$1,889,300	15,385	\$6,504,100	15,385	\$6,504,100
Shoreview	11,339	\$4,793,500	11,569	\$4,890,900	14,116	\$5,967,600
Stillwater	8,115	\$3,430,600	8,822	\$3,729,600	11,601	\$4,904,400
Vadnais Heights	5,713	\$2,415,100	5,672	\$2,397,700	7,579	\$3,204,200
White Bear Lake	11,021	\$4,659,300	10,447	\$4,416,600	14,031	\$5,931,900
White Bear Township	4,859	\$2,054,300	4,231	\$1,788,600	4,423	\$1,869,900
Woodbury	31,479	\$13,308,200	42,308	\$17,886,200	42,308	\$17,886,200
Total with Hugo 1:	113,262	\$47,883,100	147,801	\$62,484,900	178,658	\$75,530,400
Total with Hugo 2:	113,262	\$47,883,100	147,801	\$62,484,900	203,295	\$85,945,600

Findings and Implications

Lawn Watering Restrictions

Lawn watering restriction policies are generally estimated to have a positive impact on city-wide water savings. However, the exact magnitude of the savings attributed directly to policy implementation is difficult to identify without additional data. More restrictive policies can sometimes lead to increased savings,^[3,5,6] although this is not always the case. Such policies are most effective when tailored to an individual community’s habits, needs, and water demands. This study did not identify any specific policy type as consistently producing the greatest water savings. Instead, the presence of any lawn watering restriction policy appears more predictive of water savings than the specific type of policy. Therefore, implementing a policy in cities currently without one, such as North Saint Paul, and maintaining existing policies in the remaining 13 cities, could be effective method for achieving water savings. Furthermore, public education and communication on how to tailor household lawn irrigation based on local weather patterns may provide additional water savings beyond policies alone.^[16] Dynamic policy changes based on local weather conditions may also produce more consistent water savings than static policies not aligned with current rainfall data.^[26]

Smart Irrigation Controllers

Research has reliably demonstrated that smart irrigation controllers result in water savings, with current estimates ranging from approximately 5,000 to 30,000 gallons per controller per year. However, broad implementation can unintentionally increase water consumption by historic under-irrigators. Therefore, programs may produce more reliable water savings when targeted toward historic over-irrigators, as identified using methods from Davis and Dukes' research.^[12] Cities involved in the White Bear Lake area studies, including Lino Lakes, Vadnais Heights, and Woodbury, have already seen promising water savings from implementing smart irrigation controller programs. Additional savings could be realized by implementing similar programs to the remaining 11 White Bear Lake area communities. Individual cities should tailor the resident-paid cost of a smart irrigation controller to balance total program cost with the likelihood of resident participation.^[24]

Monitoring and Enforcement

Compliance with lawn watering restriction policies is typically managed successfully using administrative measures such as warnings, citations, fines, and citizen reporting of violations. To increase water savings or protect water resources during droughts, more extreme enforcement measures, such as flow restrictors, service shut-off, or significant fines, have been effective both within the Twin Cities and nationally. To avoid extreme enforcement measures, implementing infrastructure such as AMI meters can be beneficial. AMI meters enable cities to monitor water use levels over time and provide detailed data on household water usage, facilitating a more precise analysis of water savings from specific interventions.

Risks & Data Needs

- Gaps in data availability required significant amounts of estimation in calculations, introducing uncertainty into final estimates.
- Limited published research exists in the Midwest, and existing research from Florida and the Western United States may not be broadly applicable to the Twin Cities Metropolitan Area due to varying climatic conditions.
- The absence of a defined year for reaching ultimate development in each city introduces significant uncertainty to cost estimates due to variable inflation rates.
- Insufficient data is available on post-policy-implementation water use trends in cities that implemented restrictions in the past 1-5 years. Additional estimates of water savings can be calculated once sufficient data is available.

Summary of Findings

Lawn watering restriction policies are a viable option for reducing overall water consumption in the White Bear Lake area. While these policies can create water demand savings, the specific type of restriction does not significantly impact the amount of savings. Smart irrigation controllers have proven to be effective in achieving water savings when implemented efficiently. Cities within the White Bear Lake area are benefiting from water savings due to these programs. Current monitoring

and enforcement mechanisms for lawn watering restriction policies are generally effective. However, the implementation of AMI meters could further enhance these efforts.

Recommendations

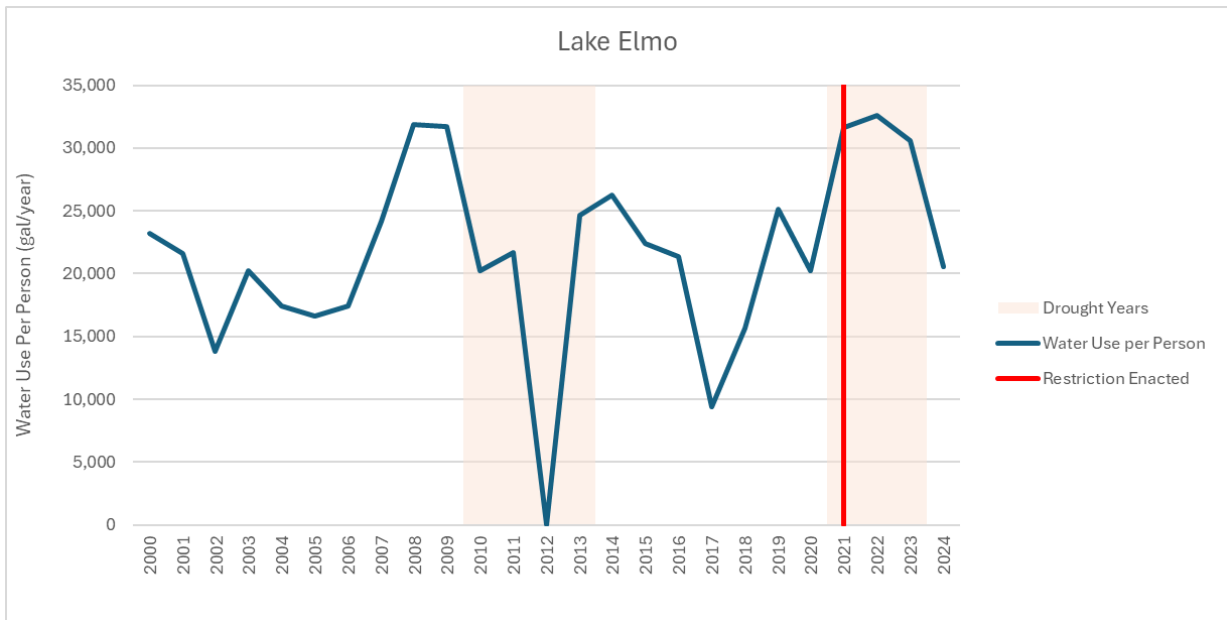
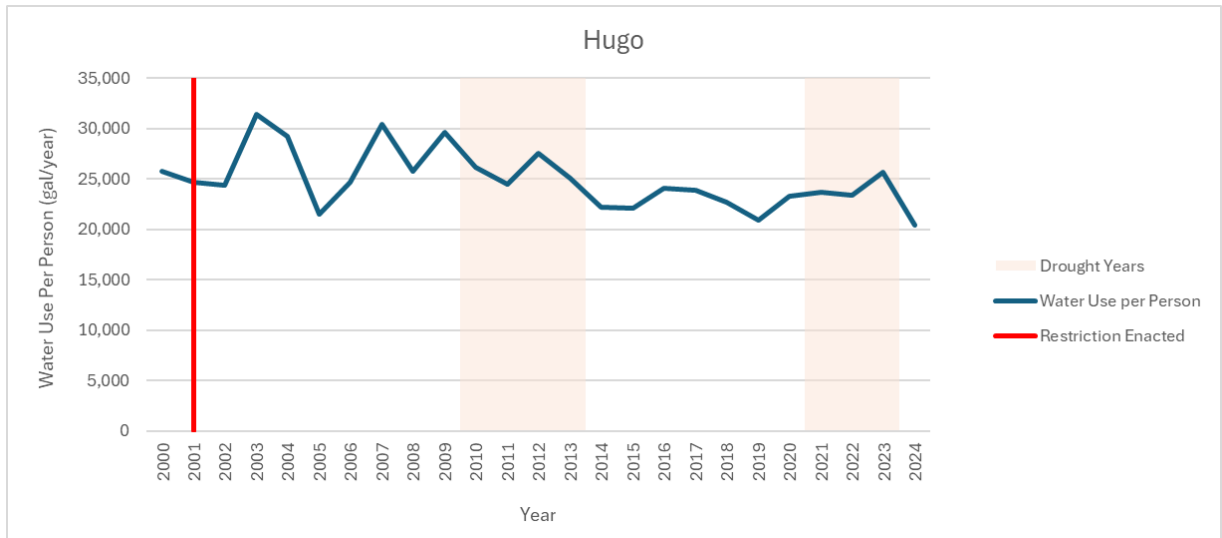
- Individual cities should implement lawn watering restriction policies if they do not currently have one in place. In general, cities should move toward dynamic policies that are adapted based on local weather patterns and tailored to residents' needs to achieve the most significant water savings.
- Cities should implement smart irrigation controller programs to assist residents in lowering their household outdoor water usage. Programs should focus on historic over-irrigators to prevent unintentional increased outdoor water use from historic under-irrigators.
- During the implementation of smart irrigation controller programs, cities should consider gathering baseline and post-installation outdoor water use data through irrigation meters.
- White Bear Lake area communities should consider implementing AMI meters at households on city water service to collect real-time data on water usage. These meters can help cities reduce consumption through ongoing monitoring and provide data to address gaps in existing water demand data.
- White Bear Lake area communities should consider conducting controlled studies on the impact of various lawn watering restriction policies to identify possible causal links between lawn watering restriction policies and water savings.

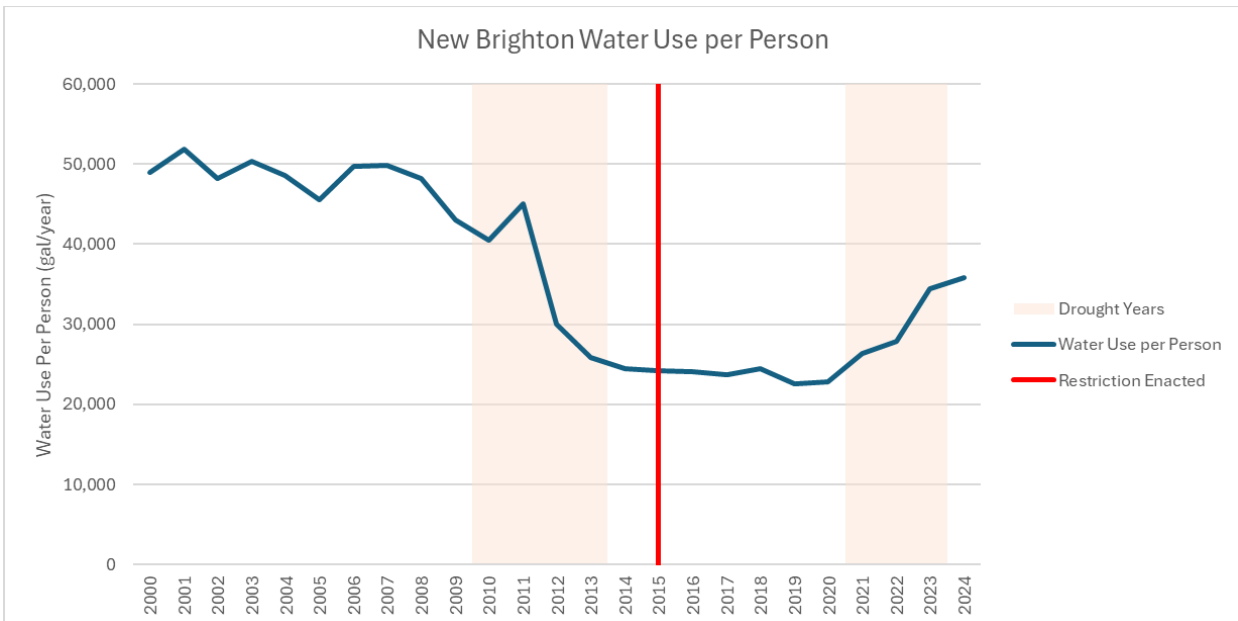
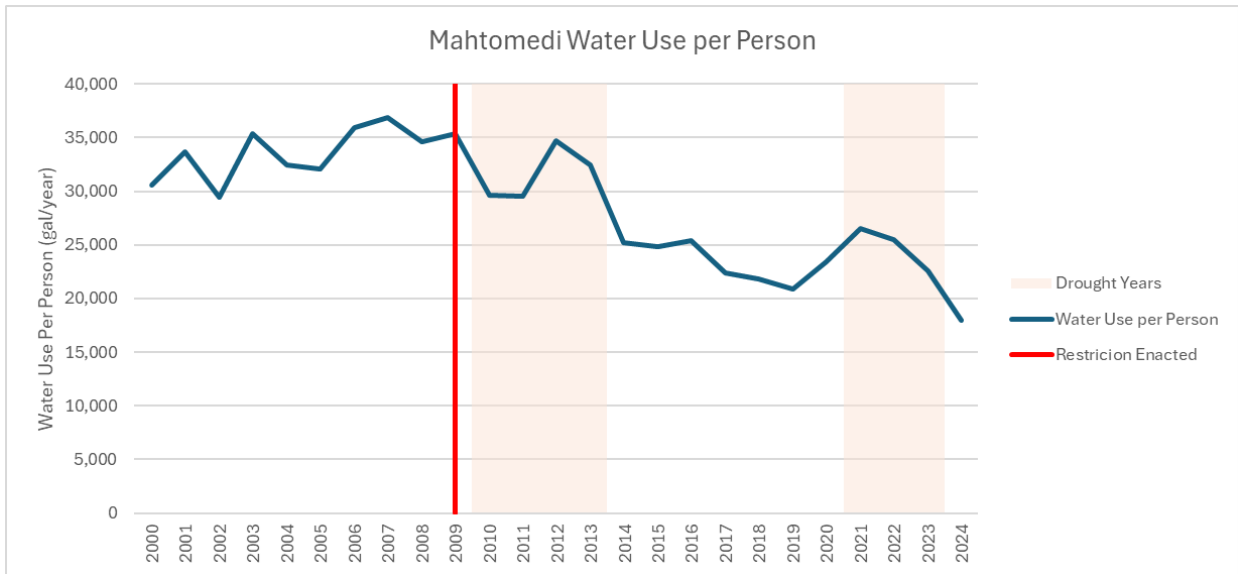


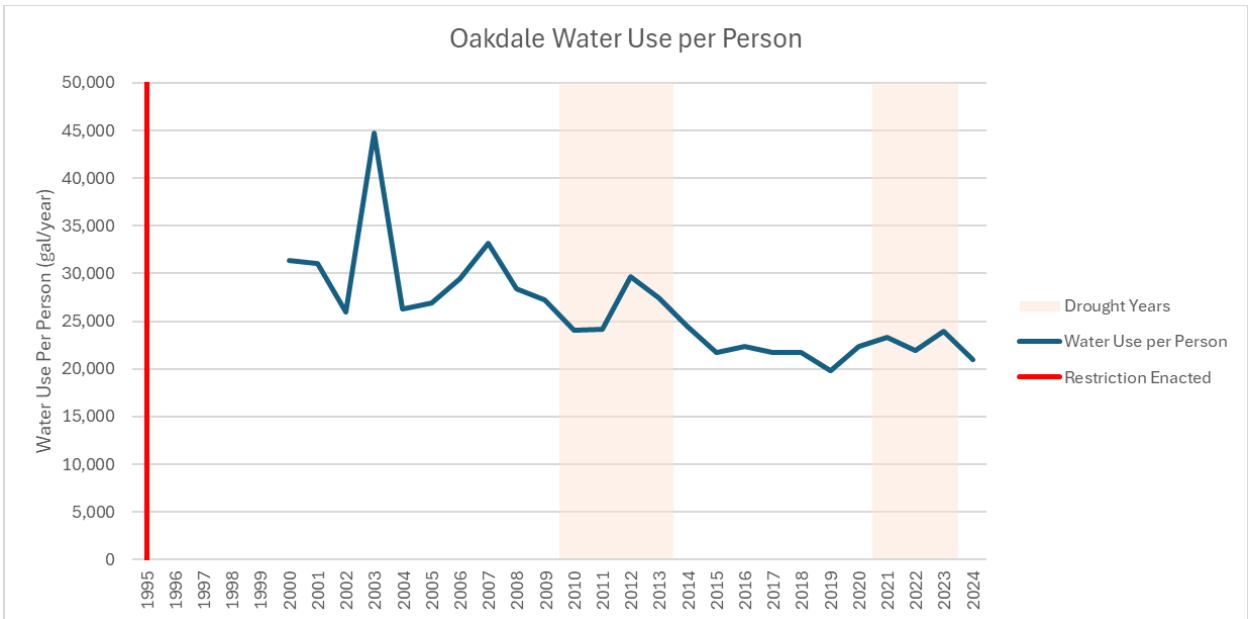
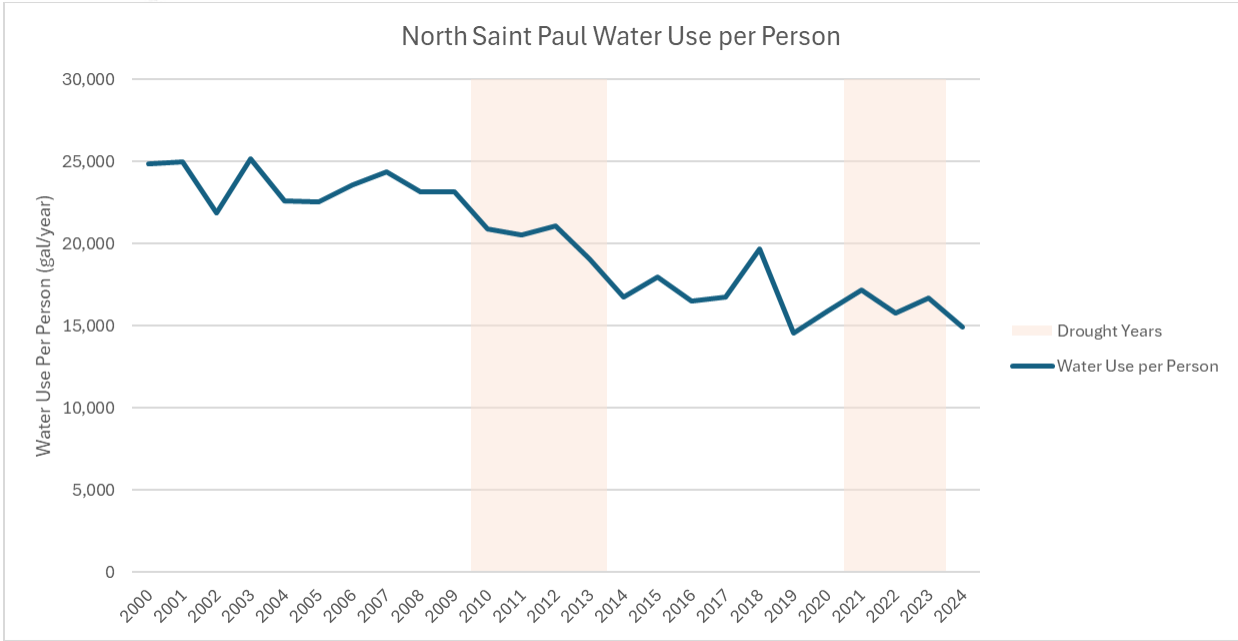
Appendices

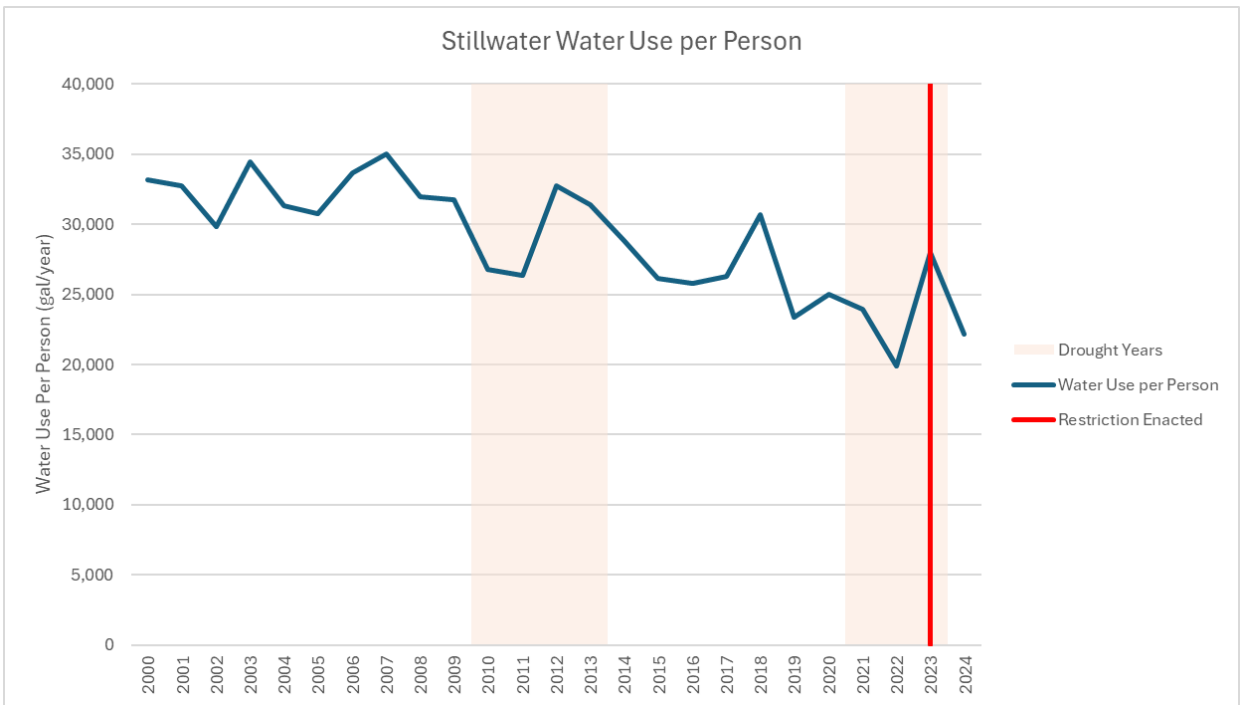
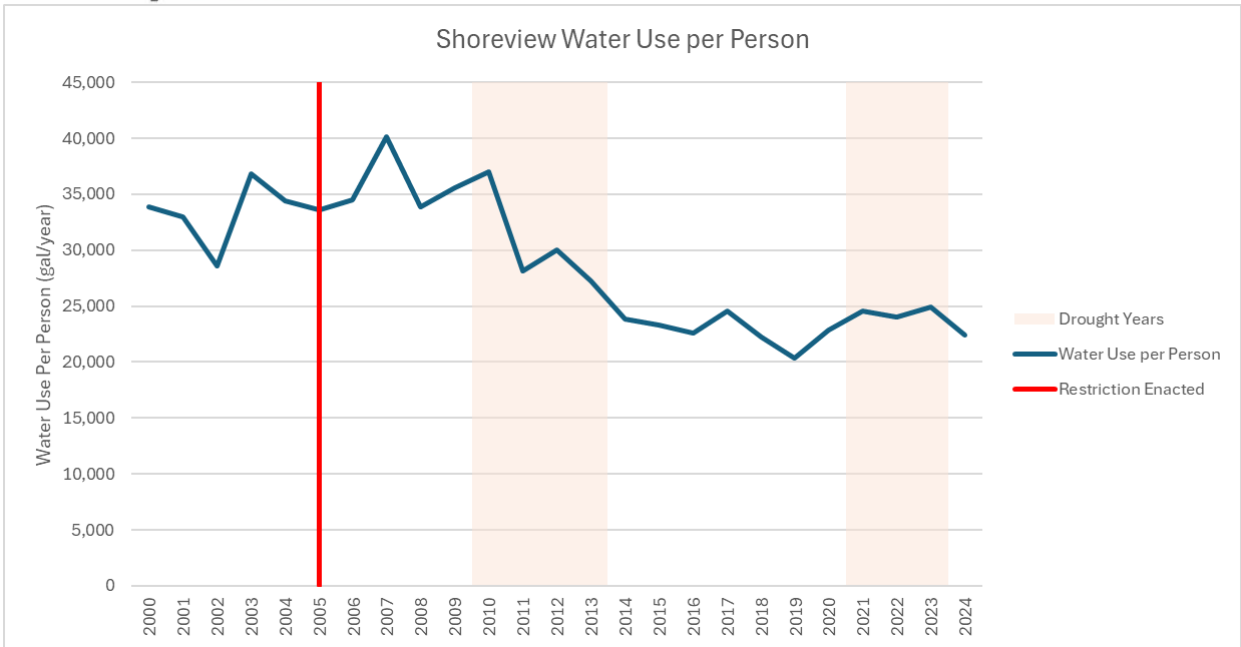
- Appendix A: Policy Enactment Graphs
- Appendix B: Minimum Use Method Graphs
- Appendix C: Estimated Smart Irrigation Controller Water Savings by City
- Appendix D: Estimated Smart Irrigation Controller Implementation Costs by City

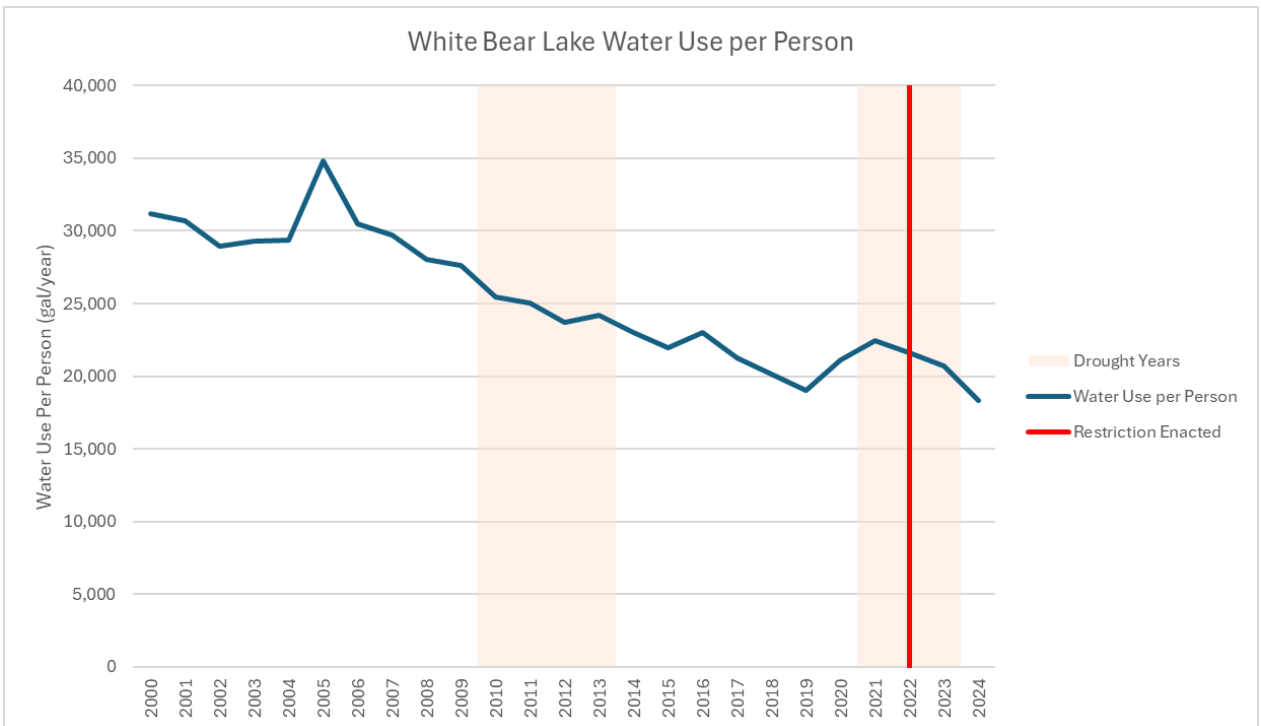
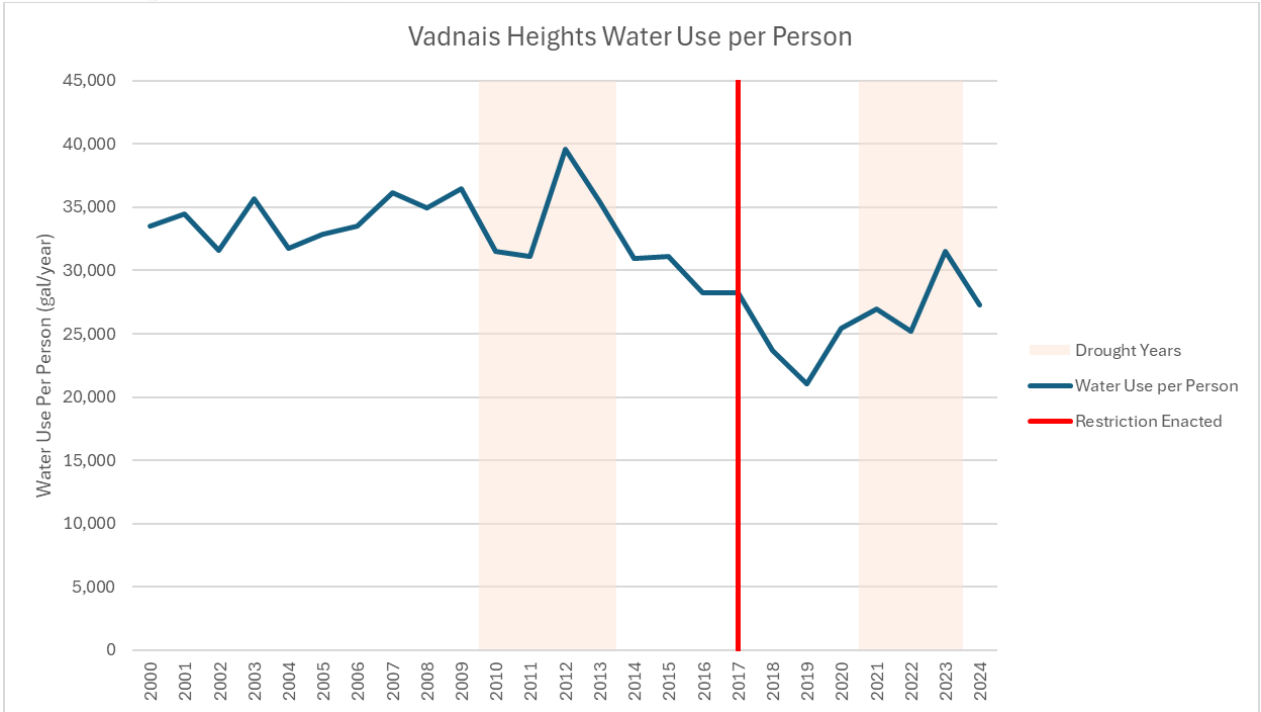
Appendix A: Linear Extrapolation Graphs

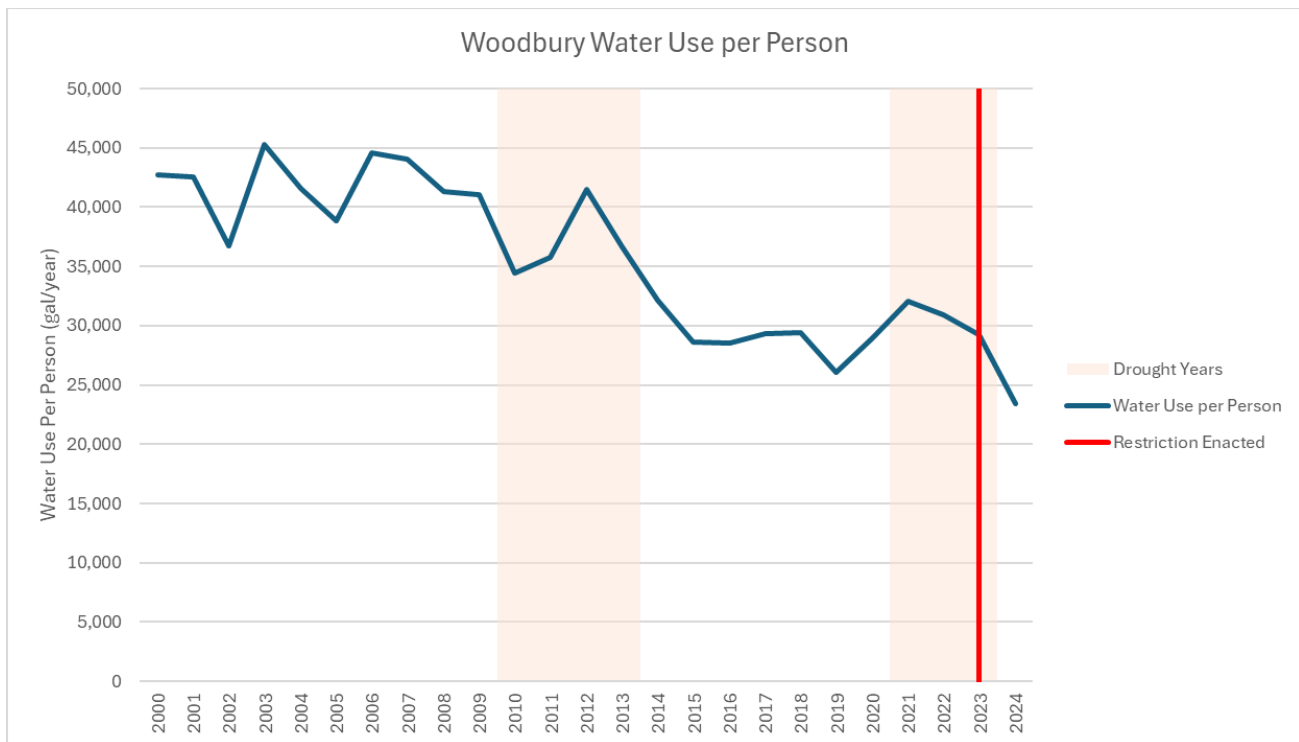
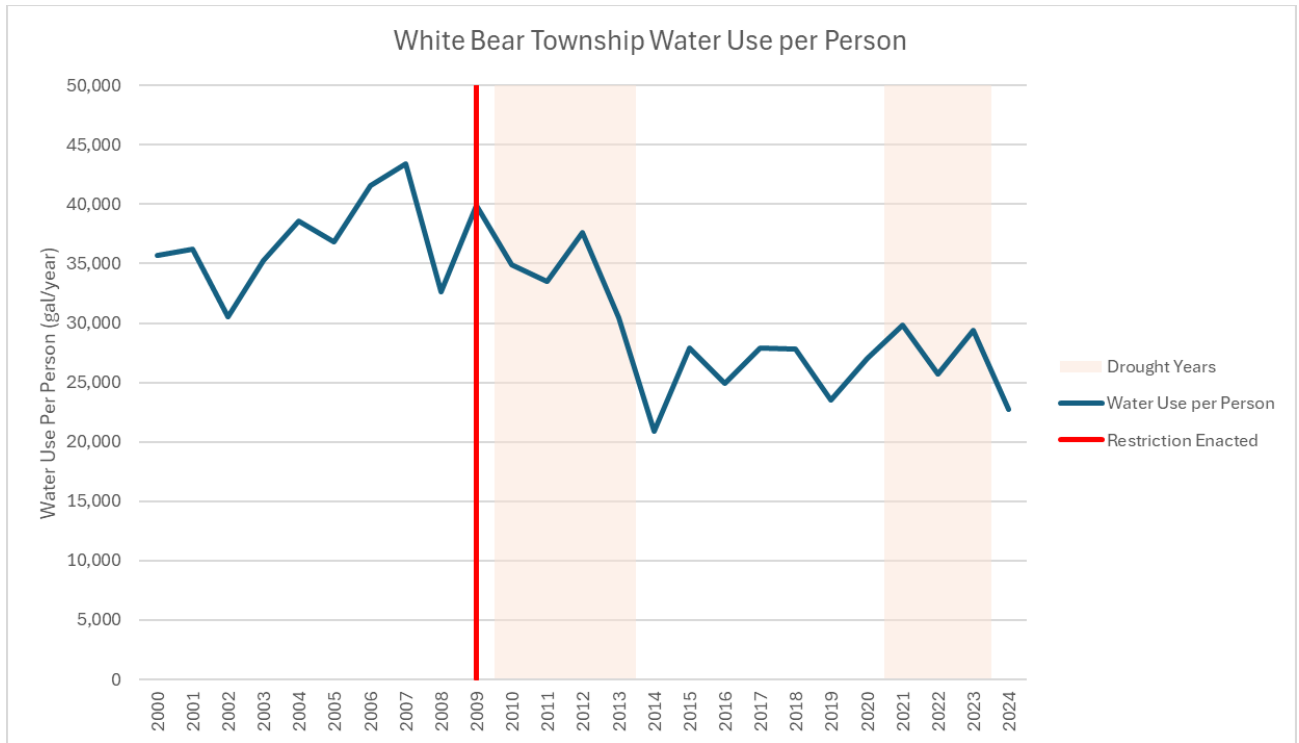












Appendix B: Minimum Use Method Graphs

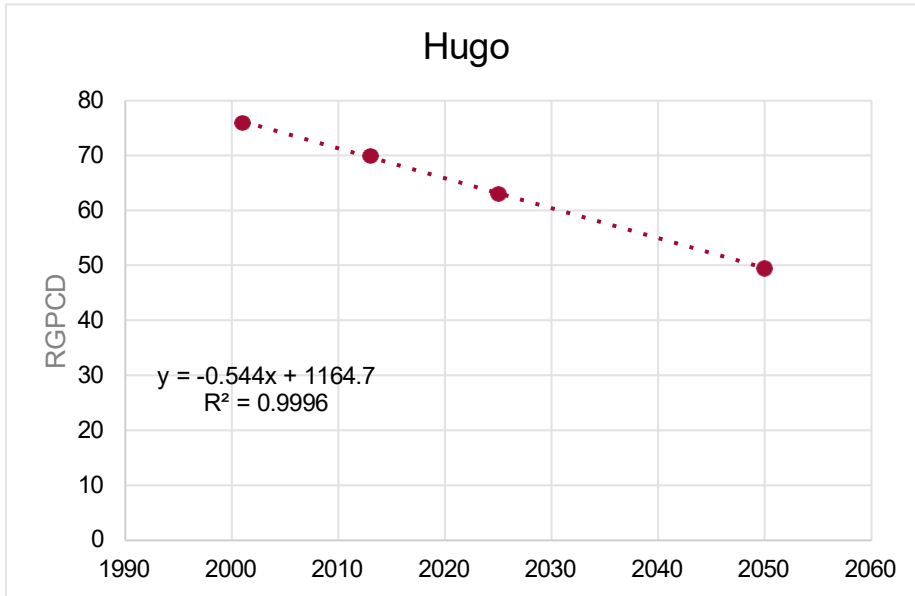


Figure B. 1 Hugo RGPCD vs year

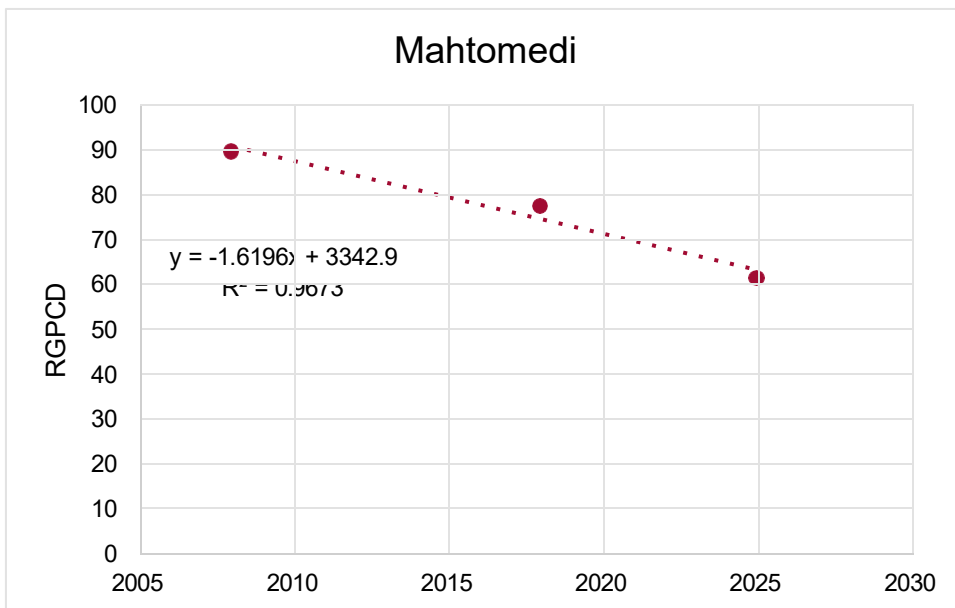


Figure B. 2 Mahtomedi RGPCD vs year

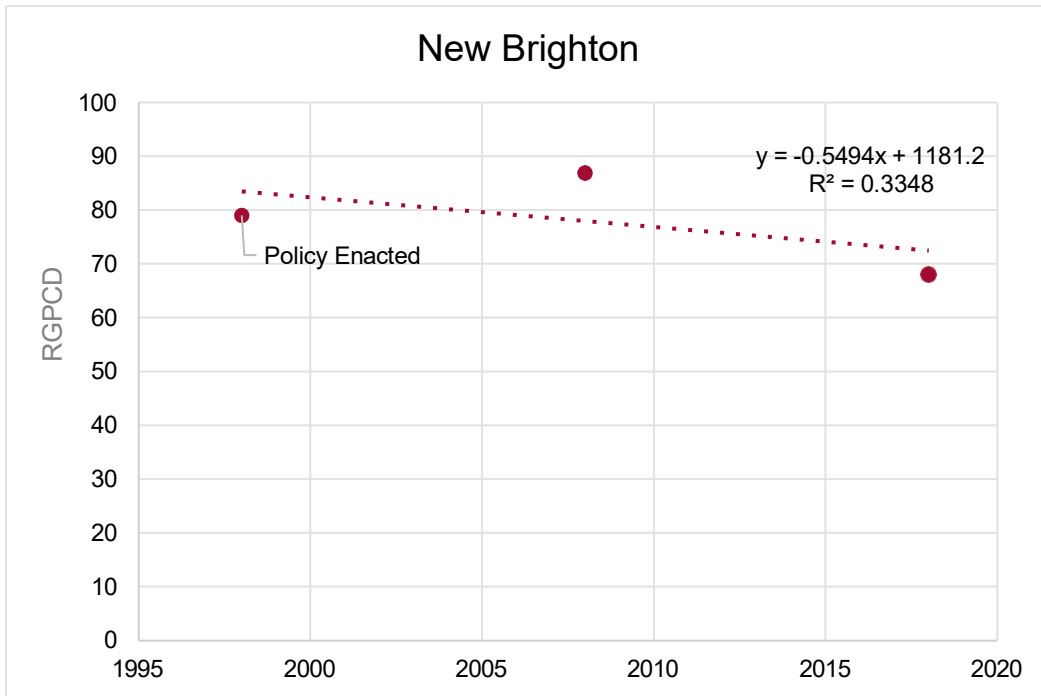


Figure B. 3 New Brighton RGPCD vs year

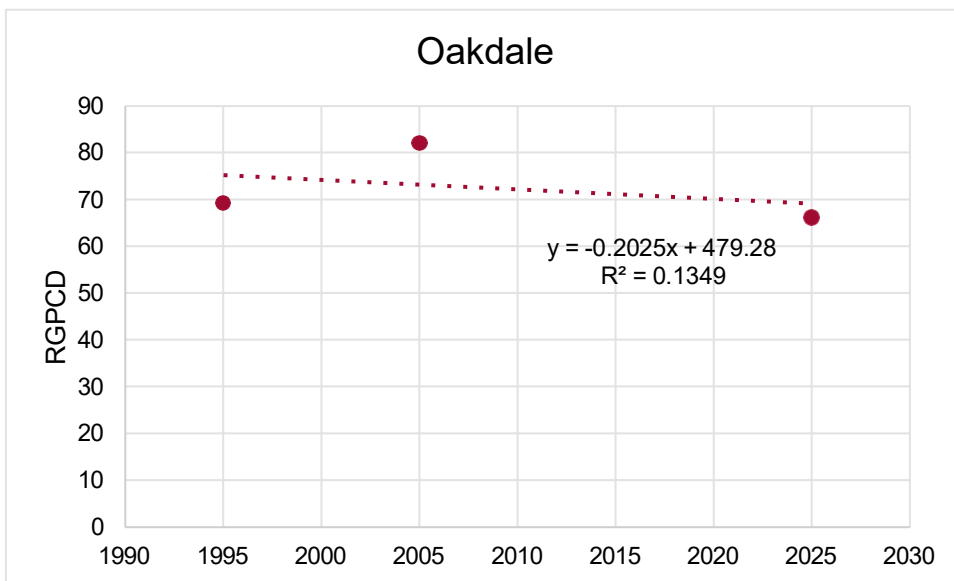


Figure B. 4 Oakdale RGPCD vs year

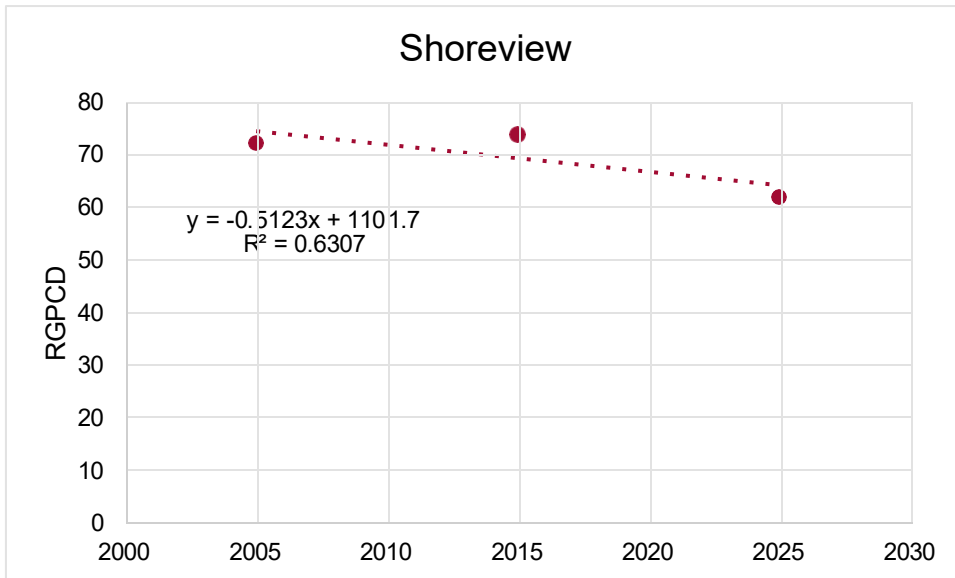


Figure B. 5 Shoreview RGPCD vs year

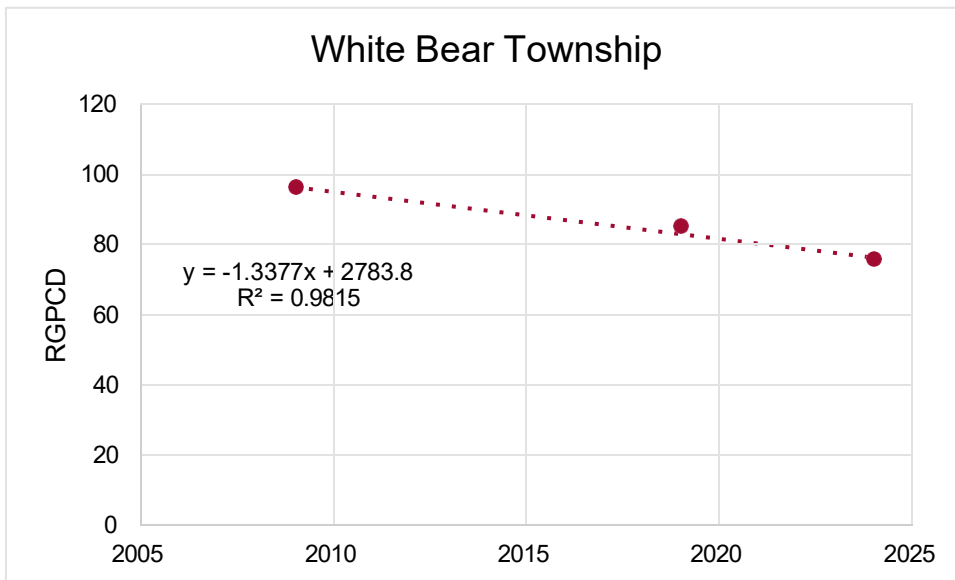


Figure B. 6 White Bear Township RGPCD vs year



Appendix C: Estimated Smart Irrigation Controller Water Savings by City

Table C. 1 Smart Irrigation Controller Water Savings by City at 20% Conversion

City	Water Savings at 2025 Water Use Levels (Gallons Saved per Year)		Water Savings at 2050 Water Use Levels (Gallons Saved per Year)		Water Savings at Ultimate Water Use Levels (Gallons Saved per Year)	
	30% Savings	9,000 gal/year	30% Savings	9,000 gal/year	30% Savings	9,000 gal/year
Hugo 1	929,806	1,801,116	1,866,700	2,231,734	2,877,829	3,440,590
Hugo 2					7,859,895	9,396,903
Lake Elmo	1,059,856	1,327,104	2,573,618	2,464,557	2,567,331	2,458,537
Lino Lakes	1,592,003	2,133,540	2,340,644	2,391,541	4,533,887	4,632,475
Mahtomedi	612,036	1,193,940	924,710	1,147,886	929,958	1,154,400
New Brighton	2,132,495	3,214,728	3,593,536	3,025,210	3,144,344	2,647,059
North Oaks	60,144	24,300	1,646,611	665,280	1,440,785	582,120
North Saint Paul	777,706	2,016,900	1,114,072	1,814,400	974,813	1,587,600
Oakdale	2,112,760	3,981,960	3,503,184	4,626,506	3,065,286	4,048,193
Shoreview	1,771,418	3,673,836	2,758,415	3,579,650	2,944,979	3,821,757
Stillwater	1,517,507	2,629,260	2,421,534	2,642,342	2,786,263	3,040,330
Vadnais Heights	1,057,931	1,851,012	1,503,711	1,733,407	1,758,315	2,026,903
White Bear Lake	1,489,231	3,570,804	2,401,516	3,219,200	2,822,270	3,783,215
White Bear Township	1,013,120	1,574,316	1,139,772	1,213,793	1,042,632	1,110,345
Woodbury	6,783,720	10,199,196	11,602,773	11,733,333	10,152,426	10,266,667
Total Savings with Hugo 1:	22,909,734	39,192,012	39,390,796	42,488,840	41,041,117	44,600,190
Total Savings with Hugo 2:	22,909,734	39,192,012	39,390,796	42,488,840	46,023,184	50,556,503



Table C. 2 Smart Irrigation Controller Water Savings by City at 30% Conversion

City	Water Savings at 2025 Water Use Levels (Gallons Saved per Year)		Water Savings at 2050 Water Use Levels (Gallons Saved per Year)		Water Savings at Ultimate Water Use Levels (Gallons Saved per Year)	
	30% Savings	9,000 gal/year	30% Savings	9,000 gal/year	30% Savings	9,000 gal/year
Hugo 1	1,394,708	2,701,674	4,200,075	5,021,402	6,475,115	7,741,328
Hugo 2					17,684,764	21,143,032
Lake Elmo	1,589,783	1,990,656	5,790,641	5,545,254	5,776,495	5,531,707
Lino Lakes	2,388,005	3,200,310	5,266,449	5,380,966	10,201,246	10,423,069
Mahtomedi	918,055	1,790,910	2,080,598	2,582,743	2,092,405	2,597,400
New Brighton	3,198,743	4,822,092	8,085,456	6,806,723	7,074,774	5,955,882
North Oaks	90,216	36,450	3,704,875	1,496,880	3,241,766	1,309,770
North Saint Paul	1,166,560	3,025,350	2,506,661	4,082,400	2,193,328	3,572,100
Oakdale	3,169,140	5,972,940	7,882,163	10,409,639	6,896,893	9,108,434
Shoreview	2,657,128	5,510,754	6,206,434	8,054,212	6,626,202	8,598,953
Stillwater	2,276,260	3,943,890	5,448,451	5,945,270	6,269,092	6,840,742
Vadnais Heights	1,586,896	2,776,518	3,383,350	3,900,167	3,956,209	4,560,531
White Bear Lake	2,233,847	5,356,206	5,403,411	7,243,200	6,350,107	8,512,233
White Bear Township	1,519,680	2,361,474	2,564,486	2,731,034	2,345,922	2,498,276
Woodbury	10,175,580	15,298,794	26,106,239	26,400,000	22,842,960	23,100,000
Total Savings with Hugo 1:	34,364,601	58,788,018	88,629,290	95,599,890	92,342,514	100,350,427
Total Savings with Hugo 2:	34,364,601	58,788,018	88,629,290	95,599,890	103,552,163	113,752,131



Table C. 3 Smart Irrigation Controller Water Savings by City at 40% Conversion

City	Water Savings at 2025 Water Use Levels (Gallons Saved per Year)		Water Savings at 2050 Water Use Levels (Gallons Saved per Year)		Water Savings at Ultimate Water Use Levels (Gallons Saved per Year)	
	30% Savings	9,000 gal/year	30% Savings	9,000 gal/year	30% Savings	9,000 gal/year
Hugo 1	1,859,611	3,602,232	5,600,100	6,695,203	8,633,487	10,321,771
Hugo 2					23,579,686	28,190,710
Lake Elmo	2,119,711	2,654,208	7,720,855	7,393,672	7,701,993	7,375,610
Lino Lakes	3,184,007	4,267,080	7,021,932	7,174,622	13,601,661	13,897,426
Mahtomedi	1,224,073	2,387,880	2,774,130	3,443,657	2,789,874	3,463,200
New Brighton	4,264,990	6,429,456	10,780,608	9,075,630	9,433,032	7,941,176
North Oaks	120,288	48,600	4,939,834	1,995,840	4,322,355	1,746,360
North Saint Paul	1,555,413	4,033,800	3,342,215	5,443,200	2,924,438	4,762,800
Oakdale	4,225,520	7,963,920	10,509,551	13,879,518	9,195,857	12,144,578
Shoreview	3,542,837	7,347,672	8,275,245	10,738,949	8,834,936	11,465,271
Stillwater	3,035,014	5,258,520	7,264,602	7,927,027	8,358,789	9,120,989
Vadnais Heights	2,115,862	3,702,024	4,511,133	5,200,222	5,274,945	6,080,709
White Bear Lake	2,978,462	7,141,608	7,204,548	9,657,600	8,466,809	11,349,644
White Bear Township	2,026,240	3,148,632	3,419,315	3,641,379	3,127,896	3,331,034
Woodbury	13,567,441	20,398,392	34,808,319	35,200,000	30,457,279	30,800,000
Total Savings with Hugo 1:	45,819,468	78,384,024	118,172,387	127,466,520	123,123,352	133,800,569
Total Savings with Hugo 2:	45,819,468	78,384,024	118,172,387	127,466,520	138,069,551	151,669,508



Table C. 4 Smart Irrigation Controller Water Savings by City at 50% Conversion

City	Water Savings at 2025 Water Use Levels (Gallons Saved per Year)		Water Savings at 2050 Water Use Levels (Gallons Saved per Year)		Water Savings at Ultimate Water Use Levels (Gallons Saved per Year)	
	30% Savings	9,000 gal/year	30% Savings	9,000 gal/year	30% Savings	9,000 gal/year
Hugo 1	2,324,514	4,502,790	7,000,124	8,369,004	10,791,858	12,902,214
Hugo 2					29,474,607	35,238,387
Lake Elmo	2,649,639	3,317,760	9,651,069	9,242,091	9,627,491	9,219,512
Lino Lakes	3,980,008	5,333,850	8,777,415	8,968,277	17,002,077	17,371,782
Mahtomedi	1,530,091	2,984,850	3,467,663	4,304,571	3,487,342	4,329,000
New Brighton	5,331,238	8,036,820	13,475,760	11,344,538	11,791,290	9,926,471
North Oaks	150,360	60,750	6,174,792	2,494,800	5,402,943	2,182,950
North Saint Paul	1,944,266	5,042,250	4,177,768	6,804,000	3,655,547	5,953,500
Oakdale	5,281,900	9,954,900	13,136,939	17,349,398	11,494,821	15,180,723
Shoreview	4,428,546	9,184,590	10,344,056	13,423,686	11,043,670	14,331,589
Stillwater	3,793,767	6,573,150	9,080,752	9,908,784	10,448,487	11,401,236
Vadnais Heights	2,644,827	4,627,530	5,638,916	6,500,278	6,593,681	7,600,886
White Bear Lake	3,723,078	8,927,010	9,005,685	12,072,000	10,583,511	14,187,056
White Bear Township	2,532,800	3,935,790	4,274,144	4,551,724	3,909,871	4,163,793
Woodbury	16,959,301	25,497,990	43,510,399	44,000,000	38,071,599	38,500,000
Total Savings with Hugo 1:	57,274,335	97,980,030	147,715,483	159,333,150	153,904,190	167,250,711
Total Savings with Hugo 2:	57,274,335	97,980,030	147,715,483	159,333,150	172,586,939	189,586,885



Appendix D: Estimated Smart Irrigation Controller Implementation Costs by City

Table D. 1 Estimated Cost to Implement Smart Irrigation Controllers by City

	2025 Development Levels				2050 Development Levels				Ultimate Development Levels			
Conversion Level	20%	30%	40%	50%	20%	30%	40%	50%	20%	30%	40%	50%
City												
Hugo 1	\$48,000	\$72,000	\$96,000	\$120,000	\$60,000	\$134,000	\$179,000	\$224,000	\$92,000	\$207,000	\$276,000	\$345,000
Hugo 2									\$251,000	\$565,000	\$753,000	\$942,000
Lake Elmo	\$35,000	\$53,000	\$71,000	\$89,000	\$66,000	\$148,000	\$198,000	\$247,000	\$66,000	\$148,000	\$197,000	\$246,000
Lino Lakes	\$57,000	\$86,000	\$114,000	\$143,000	\$64,000	\$144,000	\$192,000	\$240,000	\$124,000	\$279,000	\$371,000	\$464,000
Mahtomedi	\$32,000	\$48,000	\$64,000	\$80,000	\$31,000	\$69,000	\$92,000	\$115,000	\$31,000	\$69,000	\$93,000	\$116,000
New Brighton	\$86,000	\$129,000	\$172,000	\$215,000	\$81,000	\$182,000	\$243,000	\$303,000	\$71,000	\$159,000	\$212,000	\$265,000
North Oaks	\$1,000	\$1,000	\$1,000	\$2,000	\$18,000	\$40,000	\$53,000	\$67,000	\$16,000	\$35,000	\$47,000	\$58,000
North Saint Paul	\$54,000	\$81,000	\$108,000	\$135,000	\$48,000	\$109,000	\$145,000	\$182,000	\$42,000	\$95,000	\$127,000	\$159,000
Oakdale	\$106,000	\$160,000	\$213,000	\$266,000	\$124,000	\$278,000	\$371,000	\$464,000	\$108,000	\$243,000	\$325,000	\$406,000
Shoreview	\$98,000	\$147,000	\$196,000	\$245,000	\$96,000	\$215,000	\$287,000	\$359,000	\$102,000	\$230,000	\$306,000	\$383,000
Stillwater	\$70,000	\$105,000	\$141,000	\$176,000	\$71,000	\$159,000	\$212,000	\$265,000	\$81,000	\$183,000	\$244,000	\$305,000
Vadnais Heights	\$49,000	\$74,000	\$99,000	\$124,000	\$46,000	\$104,000	\$139,000	\$174,000	\$54,000	\$122,000	\$162,000	\$203,000
White Bear Lake	\$95,000	\$143,000	\$191,000	\$239,000	\$86,000	\$194,000	\$258,000	\$323,000	\$101,000	\$227,000	\$303,000	\$379,000
White Bear Township	\$42,000	\$63,000	\$84,000	\$105,000	\$32,000	\$73,000	\$97,000	\$122,000	\$30,000	\$67,000	\$89,000	\$111,000
Woodbury	\$273,000	\$409,000	\$545,000	\$681,000	\$314,000	\$705,000	\$941,000	\$1,176,000	\$274,000	\$617,000	\$823,000	\$1,029,000
Total Cost with Hugo 1:	\$1,046,000	\$1,571,000	\$2,095,000	\$2,620,000	\$1,137,000	\$2,554,000	\$3,407,000	\$4,261,000	\$1,192,000	\$2,681,000	\$3,575,000	\$4,469,000
Total Cost with Hugo 2:	\$1,046,000	\$1,571,000	\$2,095,000	\$2,620,000	\$1,137,000	\$2,554,000	\$3,407,000	\$4,261,000	\$1,351,000	\$3,039,000	\$4,052,000	\$5,066,000

BIBLIOGRAPHY

[#] Author, *Title*, (Year), Location or host of source. Available: URL if applicable

[1] Mayer, Lander, and Glenn, *Phase 1 – Analysis of Published Research*, (2015), Alliance for Water Efficiency Library. Available: <https://allianceforwaterefficiency.org/wp-content/uploads/2019/06/AWE-OWSRI-Phase-1-Final-Report-01-2015-60b.pdf>

[2] Boyer, Dukes, Duerr, and Bliznyuk, *Water Conservation Benefits of Long-Term Residential Irrigation Restrictions in Southwest Florida*, (2018), Journal AWWA. Available: <https://doi.org/10.5942/jawwa.2018.110.0019>

[3] Kenney, Klein, and Clark, *Use and Effectiveness of Municipal Water Restrictions During Drought in Colorado*, (2004), Journal of the American Water Resources Association. Available: https://sciencepolicy.colorado.edu/admin/publication_files/resource-296-water_restrictions_jawra.pdf

[4] Alliance for Water Efficiency Outdoor Water Savings Research Institute, *Use and Effectiveness of Municipal Irrigation Restrictions During Drought*, (2020), Alliance for Water Efficiency Library. Available: <https://allianceforwaterefficiency.org/resource/use-and-effectiveness-municipal-irrigation-restrictions-during-drought/>

[5] Ozan and Alsharif, *The effectiveness of water irrigation policies for residential turfgrass*, (2012), Land Use Policy. Available: <https://doi.org/10.1016/j.landusepol.2012.08.001>

[6] Survis, *Beyond Water Restrictions: Informing Effective Lawn Watering Behavior*, (2016), ProQuest. Available: <https://www.proquest.com/openview/afb861125c9c680e9ef6895e158f2496/1?pq-origsite=gscholar&cbl=18750>

[7] Barnes, Yue, and Watkins, *Homeowner perceptions of watering restriction scenarios in the Minneapolis-St. Paul metropolitan area*, (2021), Crop, Forage & Turfgrass Management. Available: <https://doi.org/10.1002/cft2.20131>

[8] Cominola, Preiss, Thyer, Maier, Prevos, Stewart, and Castelletti, *The determinants of household water consumption: A review and assessment framework for research and practice*, (2023), Nature Partner Journals – Clean Water. Available: <https://doi.org/10.1038/s41545-022-00208-8>

[9] Carr and Kramer, *Homeowners' associations: Barriers or bridges to more sustainable residential development?*, (2022), Landscape and Urban Planning. Available: <https://doi.org/10.1016/j.landurbplan.2022.104419>

- [10] Troy, Taylor, Follingstad, and Heris, *The impact of urban tree shade on residential irrigation demand in a semi-arid Western U.S. City*, (2024), Sustainable Cities and Society. Available: <https://doi.org/10.1016/j.scs.2023.105026>
- [11] United States Environmental Protection Agency, *WaterSense Statistics and Facts*, (2026) Available: <https://www.epa.gov/watersense/statistics-and-facts>
- [12] Davis and Dukes, *Methodologies for Successful Implementation of Smart Irrigation Controllers*, (2014), Journal of Irrigation and Drainage Engineering. Available: [https://doi.org/10.1061/\(ASCE\)IR.1943-4774.0000804](https://doi.org/10.1061/(ASCE)IR.1943-4774.0000804)
- [13] Lunstad and Sowby, *Smart Irrigation Controllers in Residential Applications and the Potential of Integrated Water Distribution Systems*, (2023), Journal of Water Resources Planning and Management. Available: <https://doi.org/10.1061/JWRMD5.WRENG-5871>
- [14] United States Environmental Protection Agency, *Advanced Metering Infrastructure*, (2025), Available: <https://www.epa.gov/watersense/advanced-metering-infrastructure#facilities>
- [15] Akesson, Hahn, Kacha, Leavell, and Ong, *Increasing Consumer Benefits & Engagement in AMI-based Conservation Programs*, (2022), Journal AWWA, Available: <https://www.awwa.org/wp-content/uploads/AMI-Increasing-Consumer-Benefits.pdf>
- [16] Survis, *The rain-watered lawn: Informing effective lawn watering behavior*, (2017), Journal of Environmental Management. Available: <https://doi.org/10.1016/j.jenvman.2017.04.081>
- [17] Lee, Taylor, and Berglund, *Water Use in the Landscape: A Comparison of Water Quality and Irrigation Technologies on Behavior*, (2021), AGU Water Resources Research. Available: <https://doi.org/10.1029/2020WR028853>
- [18] United States Environmental Protection Agency, *The WaterSense Current: Spring 2019 – April Showers Could Mean Water Waste*, (2019). Available: <https://www.epa.gov/watersense/watersense-current-spring-2019>
- [20] Khachatryan, Rihn, Suh, and Dukes, *Homeowners' Preferences for Smart Irrigation Systems and Features*, (2024), University of Florida Institute of Food and Agricultural Sciences. Available: <https://ask.ifas.ufl.edu/publication/FE1080>
- [21] Minnesota Department of Natural Resources, *Water Conservation Report Summaries for Public Water Suppliers – North and East Metro Groundwater Management Area*, (2021), MNDNR Water Conservation Reporting. Available: <https://files.dnr.state.mn.us/waters/gwmp/area-ne/water-conservation-report-summaries-public-water-suppliers.pdf>
- [22] University of Minnesota Turfgrass Science Program, *Reducing Lawn Watering Through Smart Irrigation Systems and Changed Mowing Practices*, (2023), Metropolitan Council. Available: <https://metro council.org/Wastewater-Water/Planning/Water-Supply-Planning/Images/Irrigation-controllers-and-mowing-height.aspx>

- [23] Rachio, *Rachio 3 Smart Sprinkler Controller*, (2026). Available: <https://rachio.com/products/rachio-3>
- [24] City of Woodbury, *Residential Smart Irrigation Controller Program*, (2026). Available: <https://www.woodburymn.gov/467/Residential-Smart-Irrigation-Controller->
- [25] City of Vadnais Heights, *Residential Water Efficiency Rebates*, (2026). Available: <https://www.cityvadnaisheights.com/1013/Residential-Water-Efficiency-Rebates>
- [26] Survis, Root, and Pathak, *Identifying Seasonal Opportunities to Save Water: Using Weekly Rainfall and Evapotranspiration Patterns to Evaluate Outdoor Water Restriction Policy in South Florida*, (2017), *Water Conservation Science and Engineering*. Available: <https://doi.org/10.1007/s41101-017-0032-4>
- [27] City of Woodbury, *Lawn & Landscape Watering Policy*, (2026). Available: <https://www.woodburymn.gov/1056/Lawn-Landscape-Watering-Policy>
- [28] Kare11 News, *St. Paul to issue watering fines for first time since 1988*, (2021). Available: <https://www.kare11.com/article/news/local/breaking-the-news/st-paul-to-issue-watering-fines-for-the-first-time-since-1988/89-599e702c-c62b-4730-a6f7-5e649bbb18b6>
- [29] American Water Works Association, *California water district going to extreme lengths to make every drop count*, (2022), *AWWA Articles Archive*. Available: <https://www.awwa.org/AWWA-Articles/california-water-district-going-to-extreme-lengths-to-make-every-drop-count/>
- [30] Arcadis, *2020 AMI Cost-Benefit Analysis*, (2020). Available: <https://www.wsscwater.com/sites/default/files/sites/wssc/files/ami/AMI%20Cost%20Benefit%20Analysis%20-2.pdf>
- [31] Saint Paul Regional Water Services, *Advanced Metering Infrastructure Being Implemented*, (2025), *SPRWS Newsletter*. Available: <https://www.stpaul.gov/departments/saint-paul-regional-water-services/about-sprws/sprws-newsletter/advanced-metering>
- [32] Rupiper, Good, Ackerman, Gregory, Jessoe, and Loge, *AMI water meters deliver end-use water and financial savings in leaky households: experimental evidence from California*, (2024), *IOP Science*. Available: <https://iopscience.iop.org/article/10.1088/1748-9326/ad7bce>
- [33] Daminato, Diaz-Farina, Filippini, and Padrón-Fumero, *The impact of smart meters on residential water consumption: Evidence from a natural experiment in the Canary Islands*, (2021), *Resource and Energy Economics*. Available: <https://doi.org/10.1016/j.reseneeco.2021.101221>
- [34] Moore and Hughes, *Advanced Metering Infrastructure: Lifeblood for Water Utilities*, (2008), *Journal AWWA*. Available: <https://doi.org/10.1002%2Fj.1551-8833.2008.tb09605.x>