

**Updating Key Metrics Regarding  
Outdoor Water Use in Texas  
Community Water Systems**

**TWDB Contract Agreement 2500012883**

**Progress Report 2**

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***Submitted by:***

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### **Project Goals**

1. Characterize changes in outdoor water use during and after the 2011 – 2015 drought.
2. Develop key outdoor water use metrics that incorporate the most recently available data.
3. Evaluate the prospective relationship between outdoor water use and climate drivers.

### **Project Objectives**

1. Analyze annual seasonal single-family (SF) residential water use for at least the 259 community water systems (CWS) evaluated in Technical Note 12-01.
2. Determine the annual percentage of outdoor water use for each CWS and by region.
3. Evaluate CWS monthly intake data and predict outdoor use by developing a seasonal use index.
4. Determine 2011 – 2015 drought and post-drought trends in CWS outdoor water use.
5. Identify and document methodological differences from Technical Note 12-01, if any, used to generate updated CWS outdoor water use data.
6. Assess any trends in CWS gallons per capita demand driven by changes in outdoor water use.
7. Evaluate the prospective relationship between outdoor water use and climate drivers.

## **PROJECT PROGRESS DISCUSSION**

### **Summary**

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We have made significant advances in two key areas since our last progress report:

1. Detailed statistical analysis of data quality issues for CWS with incomplete monthly intake data; and;
2. Validation and benchmarking of our monthly intake-based SF monthly demand estimation methodology against historical TWDB data.

### **Subtask 1. Data Assessment and Collection**

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**Status:** We consider Subtask 1 principally **complete**. However, continuing discussion with TWDB on data availability and quality required to support our analysis needs in Subtask 2 and 3 are possible.

We have collected and processed CWS drought contingency implementation data from TCEQ. We recently requested and received updated drought contingency implementation data from TCEQ that is comprehensive of our study period. These data are ready for joining with CWS data in support of Subtask 2.

## Progress Report 2

We have collected and processed statewide atmospheric data (precipitation, temperature, evapotranspiration, etc.) for the study period. These data are ready to be spatially joined with CWS data in support of Subtask 3.

Upon review of the available CWS water use data provided by TWDB, we have identified the following challenges:

- Lack of Monthly Data: The provided SF and total metered volumes are annual values, whereas monthly data is needed to estimate seasonal trends.
- Incomplete Retail Sales Data: Monthly retail sales remain incomplete for many systems, with particularly significant gaps before 2010.
- Total Metered Volume Data Gaps: Many systems lack total metered volumes, especially before 2010 and for some systems post-2021.
- Total SF Volume Gaps: A few systems lack annual totals of SF use data.

### *Statistical Analysis of Incomplete Monthly Intake Data*

Following TWDB's analysis of the outlier CWSs from the monthly intake comparisons, and observation that some CWSs exhibited problematic reporting patterns (such as December intake values applied to all months or total annual intake concentrated in December), we conducted a comprehensive statistical analysis of all CWSs with incomplete monthly intake data (**Figure 1-2**). Rather than simply removing CWSs flagged with incomplete data, this approach allows us to systematically identify and characterize data quality issues across the entire dataset.

To begin, it is necessary to aggregate intake of differing types as many CWSs report multiple water types (groundwater, surface water, reuse) as separate rows within the dataset. To obtain meaningful CWS-level intake totals for analysis we: (a) combine all water type records for each unique CWS-year combination and (b) aggregate monthly intake values across all water types for each CWS-year.

Next, we implement a sequential two-stage analysis to assess data quality for CWS with incomplete monthly intake data:

#### 1: Percentage of Median Analysis

We first conduct a percentile-based analysis to establish baseline expectations for partial-year reporting. This approach is chosen because it provides intuitive, interpretable results that directly relate to typical CWS performance without assuming normal distributions.

For each CWS-year with incomplete monthly data (1-11 months present) we calculate the percentage the reported partial-year total represents compared to the median annual intake of all CWSs with complete, full-year data as:

$$\text{Percentage of Median (\%)} = (\text{Incomplete Year Total} / \text{Median Annual Complete}) \times 100$$

where Incomplete Year Total = Sum of reported monthly intake values for the incomplete CWS-year and Median Annual Complete = Median annual intake across all CWSs with complete 12-month data.

This metric allows direct assessment of whether a partial-year total falls within reasonable bounds (**Figure 3**) - for example, a CWS reporting only 6 months of data should typically show 40-60% of

median annual values, not 150% or 15%. Moreover, it allows identification of cases where incomplete-year totals are implausibly high (suggesting data entry errors or inappropriate data aggregation) or extremely low (indicating severely incomplete data capture) relative to what complete annual reporting should show.

## 2: Z-Score Standardization Analysis

Building on the percentage analysis, we calculate Z-scores using the standard statistical formula to compare each CWS's percentage of median against the distribution of all incomplete CWSs, allowing us to identify statistical outliers using established criteria. This approach transforms the percentage values into standardized units that directly correspond to probability of occurrence under normal conditions.

$$\text{Z-score} = (\text{Annual Total} - \text{Mean Annual}) / \text{StdDev Annual}$$

where: Annual Total = Individual incomplete CWS's annual intake total, Mean Annual = Mean annual intake for that CWS (calculated from complete 12-month years only), and StdDev Annual = Standard deviation of annual intake for that CWS (from complete years).

We first establish baseline statistics using only complete 12-month data for each CWS, then apply these system-specific means and standard deviations to evaluate how far each incomplete year deviated from that CWS's typical annual intake pattern (**Figure 4**).

Finally, we construct an outlier classification framework. To do so, CWSs are flagged using a hierarchical two-column Boolean system based on standardized statistical thresholds applied to Z-score distributions:

Outlier\_1 $\sigma$  = False, Outlier\_2 $\sigma$  = False - "Within 1 $\sigma$ ": Systems demonstrating acceptable data quality with Z-scores falling within  $\pm 1$  standard deviation of expected values. These systems show minimal deviation from typical reporting patterns and require no additional validation.

Outlier\_1 $\sigma$  = True, Outlier\_2 $\sigma$  = False - "1 $\sigma$ -2 $\sigma$  Outlier": Systems exhibiting moderate data quality issues with Z-scores between 1-2 or -1 to -2 standard deviations. These systems warrant closer examination and potential data verification but may still be suitable for analysis with appropriate caveats.

Outlier\_1 $\sigma$  = True, Outlier\_2 $\sigma$  = True - ">2 $\sigma$  Outlier": Systems displaying severe data quality issues with Z-scores exceeding  $\pm 2$  standard deviations. These systems represent extreme statistical outliers requiring data validation, correction, or exclusion from analysis due to probable systematic reporting errors.

The trendline (**Figure 5**) reveals systematic underreporting bias rather than random measurement errors, with most extreme outliers falling below zero Z-scores. This high correlation between independent statistical measures confirms the framework reliably identifies genuine data quality issues, supporting the justification for intake-based estimation methods when utility reporting is incomplete.

### **Next Steps:**

- Establish error thresholds for CWS exclusion
- Conduct statistical analysis of data quality for additional data sources (as needed)

## **Subtask 2. Methodology Development and Water Use Analysis**

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**Status:** Subtask 2 is progressing and **ongoing**.

We have developed three primary methods (described in our prior report and in **Table 1**) to leverage the available water use data and derive SF monthly use volumes. Each method is related to a primary dataset: retail sales volume, total metered volume, and monthly intake volume.

Of these methods, the monthly intake method provides the most comprehensive data coverage for study CWSs and study years. Therefore, we have chosen to focus on developing and validating the CWS monthly intake method before moving on to testing other methods.

The monthly intake method uses monthly CWS intake as a proxy for SF monthly demand. In short, we take the ratio of CWS monthly intake over annual intake to create monthly multipliers which are then used with available SF annual demand volumes to calculate monthly SF demand volumes. This method assumes that the relationship between total CWS intake and SF demand are consistent throughout each year.

### *Monthly Intake Method Validation and Benchmarking*

To ensure the reliability of the monthly intake method, we conducted a comprehensive benchmarking analysis comparing our derived monthly SF volumes against CWS-reported data from previous TWDB studies. This validation is essential given that our current methodology relies on monthly intake proportions as a proxy for SF usage patterns where direct CWS reporting is unavailable.

We structure our validation across three distinct periods, each with different data availability characteristics:

Phase 1 [2004–2008]: Complete CWS-reported monthly SF data available for all CWSs from original TWDB studies, allowing direct month-to-month comparison using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics.

Phase 2 [2009–2011]: Limited CWS-reported data available for 17 CWSs only, providing a smaller but important validation subset using the same error metrics.

Current Study Period [2011–2023]: No directly comparable monthly SF data available, necessitating correlation analysis (Pearson and Spearman) to assess seasonal pattern consistency rather than absolute accuracy.

Our benchmarking analysis of Phase 1 data demonstrates robust performance of the intake-based estimation methodology across all validation periods. Analysis of 241 CWSs (**Figure 6, Table 2**) shows that 154 CWSs (64% of CWSs) have RMSE of 25% or less and 190 CWS (79% of CWSs) have MAE of 25% or less. Only 17% and 4% of CWSs show RMSE and MAE values exceeding 50%, respectively. This indicates that our intake-based estimates closely replicate the seasonal patterns observed in CWS-reported data for the vast majority of CWSs.

The smaller subset of the 17 CWSs in Phase 2 shows similar performance patterns (**Figure 7**), with most CWSs achieving acceptable error ranges. Notable outliers included City of Pflugerville and City of Laredo, which may reflect unique system characteristics or reporting inconsistencies during this transitional period.

The correlation analysis of Phase 3 monthly intake-derived SF monthly volumes vs Phase 1 WUS survey-derived SF monthly volumes (**Figure 8-9, Table 3**) reveals robust seasonal alignment between our estimates and patterns expected from the Phase 1 study, with a mean Pearson correlation of 0.77 and a mean Spearman correlation of 0.79. Importantly, 72% of CWSs achieved correlations greater than or equal to 0.75. Only 12% of CWSs showed correlations at or below 0.50, suggesting our methodology captures underlying seasonal trends for the vast majority of CWSs. These results validate that our intake-based approach successfully replicates the monthly distribution patterns that are essential for outdoor water use analysis, particularly the critical summer peaks that drive outdoor usage estimates.

#### *Preliminary Seasonal Analysis of SF Outdoor Use*

After validating our intake-based monthly single-family estimation methodology and establishing robust data quality assessment protocols, we began a preliminary seasonal analysis of 10 CWSs with the largest monthly intake totals and complete monthly intake data across the full study period. This approach ensures that our initial seasonal analysis utilizes the highest quality, most complete datasets available to provide a robust foundation for developing seasonal use indices that can later be applied to the broader CWS population using our validated intake-based estimation methods.

Following the established TWDB methodology from Technical Note 12-01, we implement the core minimum month approach for distinguishing indoor and outdoor water consumption:

$$\text{Outdoor Use} = \text{SF Total Use} - (\text{Monthly Min} \times 12)$$

where: Monthly Min = the lowest SF monthly demand value for the CWS within the year. By nature, this methodology assumes that the month with lowest water consumption represents primarily indoor uses (drinking, cooking, bathing, etc.) with minimal outdoor use.

We then calculate the following key seasonal water use metrics directly in support of project objectives:

- Outdoor/Indoor Ratio: Quantifies the relative magnitude of seasonal variation for each system
- Outdoor Use Percentage: Determines the annual percentage of outdoor water use
- Monthly Distribution Patterns: Establishes seasonal use indices for predicting outdoor use.
- Multi-year Baseline Averages: Computed for the 2004-2008 period to establish reference seasonal patterns for drought impact assessment.

Our preliminary comparison of seasonal indoor and outdoor use metrics between Phase 1 (previous study) and Phase 3 (current intake-based method) shows that the two approaches generally produce consistent interannual patterns, but with some notable differences. Annual outdoor use comparisons (**Figure 10**) reveal that overall volumes are broadly consistent across most systems, with Phase 3 estimates often falling within the same general range as Phase 1. For most systems, Phase 3 reproduces the overall seasonal shape of demand while moderating anomalies observed in Phase 1. Ratio-based metrics such as outdoor/indoor use and outdoor share of total demand tend to align more closely across methods than absolute indoor or outdoor volumes, indicating greater stability in derived seasonal indicators.

Year-to-year comparisons (**Figure 11**) for all 10 CWSs highlight the same general findings as discussed above; outdoor use across CWSs is generally in alignment with Phase 1 results but there are differences and variability from year to year and CWS to CWS. These variances reflect the sensitivity of outdoor estimates to how the minimum month is identified, with higher or lower selections shifting the indoor/outdoor split. In some cases, inconsistencies in the reported monthly intake may also contribute to the magnitude of these divergences.

Seasonal indices (**Figure 12**) illustrate how outdoor use is distributed throughout the year for the current phase (Phase 3) intake-based estimates for the 10 CWS. Both Phase 1 and Phase 3 capture the expected pattern of low use in winter, rising in spring, peaking in summer, and tapering into fall. Across most systems, the seasonal curves are very similar, indicating that both methods identify the same general timing of peak and minimum demand. Where deviations occur, such as Laredo showing elevated January usage (14.2%) and Arlington displaying an unusual dip in February (4.6% compared to 8.2% in January), those anomalies are driven by intake reporting or system-specific usage behaviors rather than systematic differences between methods.

Overall, the comparison highlights both areas of strong agreement and instances of divergence between Phase 1 and Phase 3 intake-based estimates. While Phase 3 reproduces the general seasonal structure and often tracks closely with Phase 1, particularly in ratio-based indicators, some large deviations in outdoor use point to sensitivities in the methodology and the underlying intake data.

**Next Steps:**

- Test alternative methods for estimating SF monthly demand and compare results against the monthly intake method
- Generate final outdoor use data using selected methods
- Produce and document analytical tool for TWDB use

### **Subtask 3. Climate Driver Assessment**

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**Status:** This subtask is dependent on the completion of Subtask 2 and has therefore not yet commenced.

**Table 1:** SF Monthly Demand Calculation Methods

Method	How We Derived It	Alignment with Previous Study	Availability	Strengths	Weaknesses
1. SF from Monthly Retail Sales	Used SF/Total Metered Ratio (y) and multiplied it by the proportion of monthly retail sales to annual retail sales.	Most closely mirrors report because it uses actual sales data, similar to how the study used city-reported (and TWDB-reported) monthly SF volumes.	Available for ~150 systems (but missing total metered for some years) mostly post-2011.	Captures real-world consumption patterns for SF households in later years (2011+), using monthly treated water retail sales.	Only covers ~150 systems, missing 100+ others; also, not available pre-2010/2011.
2. SF from Total Metered / Intake Ratio	Used Total Metered / Annual Intake Ratio (z), then multiplied it by monthly intake to get monthly metered, and then multiplied by y.	Not explicitly in the report, but logical for systems with total metered data (similar to how the study used actual reported volumes).	Available for ~105 systems (but many years lack total metered data, especially pre-2010).	Works well when total metered data is available, preserving physical water system relationships.	Only covers ~105 systems, missing 150+ others; not available for many pre-2010 years, and a few post-2021 years.
3. SF from Monthly Intake Proportion	Used monthly intake / total annual intake to get monthly proportion and scaled it using SF volume.	Not explicitly in the report, but the only other proxy for estimating SF monthly volumes in systems without metered or retail data.	Available for all ~260 systems and complete for all years (2004–2023) since it does not rely on total metered data.	The only method that can be applied across all systems and years, ensuring full coverage.	Assumes intake patterns closely represent actual SF usage, which may not always be true.



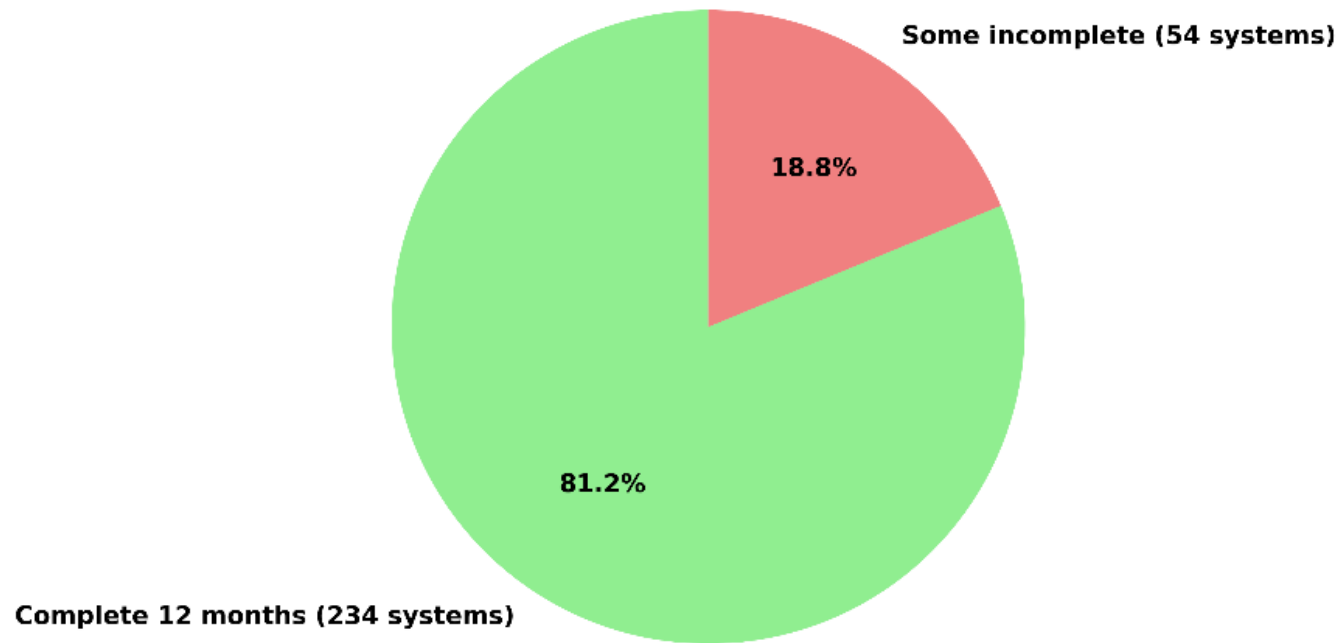
**Table 2:** Summary statistics for validation of monthly intake method against Phase 1 data

Error Range	RMSE	MAE
# (%) of systems $\leq$ 10% error	13 (5%)	48 (20%)
# (%) of systems $\leq$ 25% error	154 (64%)	190 (79%)
# (%) of systems $\leq$ 50% error	201 (83%)	232 (96%)
# (%) of systems $<$ 75% error	229 (95%)	239 (98%)
# (%) of systems $\geq$ 75% error	12 (5%)	3 (1%)

**Table 3:** Summary statistics of Pearson and Spearman correlation coefficients applied to Phase 3 monthly intake method results

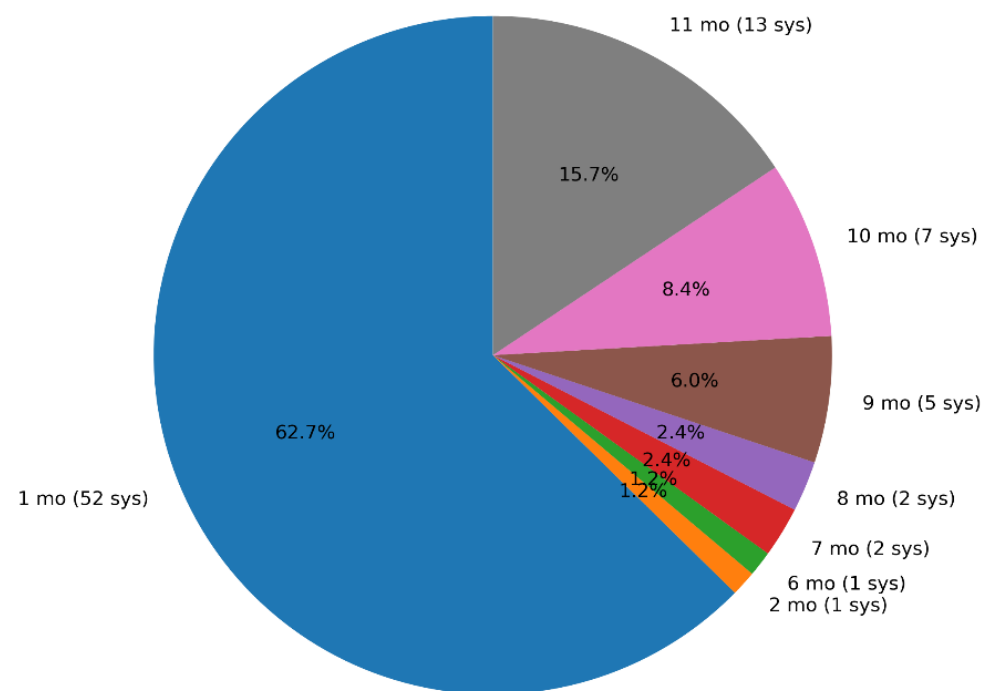
Correlation Range	Pearson	Spearman
# (%) of systems $\geq$ 0.9	102 (43%)	85 (35%)
# (%) of systems $\geq$ 0.8	159 (68%)	147 (63%)
# (%) of systems $\geq$ 0.7	178 (76%)	183 (78%)
# (%) of systems $\geq$ 0.5	207 (88%)	211 (90%)
# (%) of systems $<$ 0.5	28 (12%)	24 (10%)

**Systems: Complete vs Some Incomplete Data  
(Total Systems: 288)**

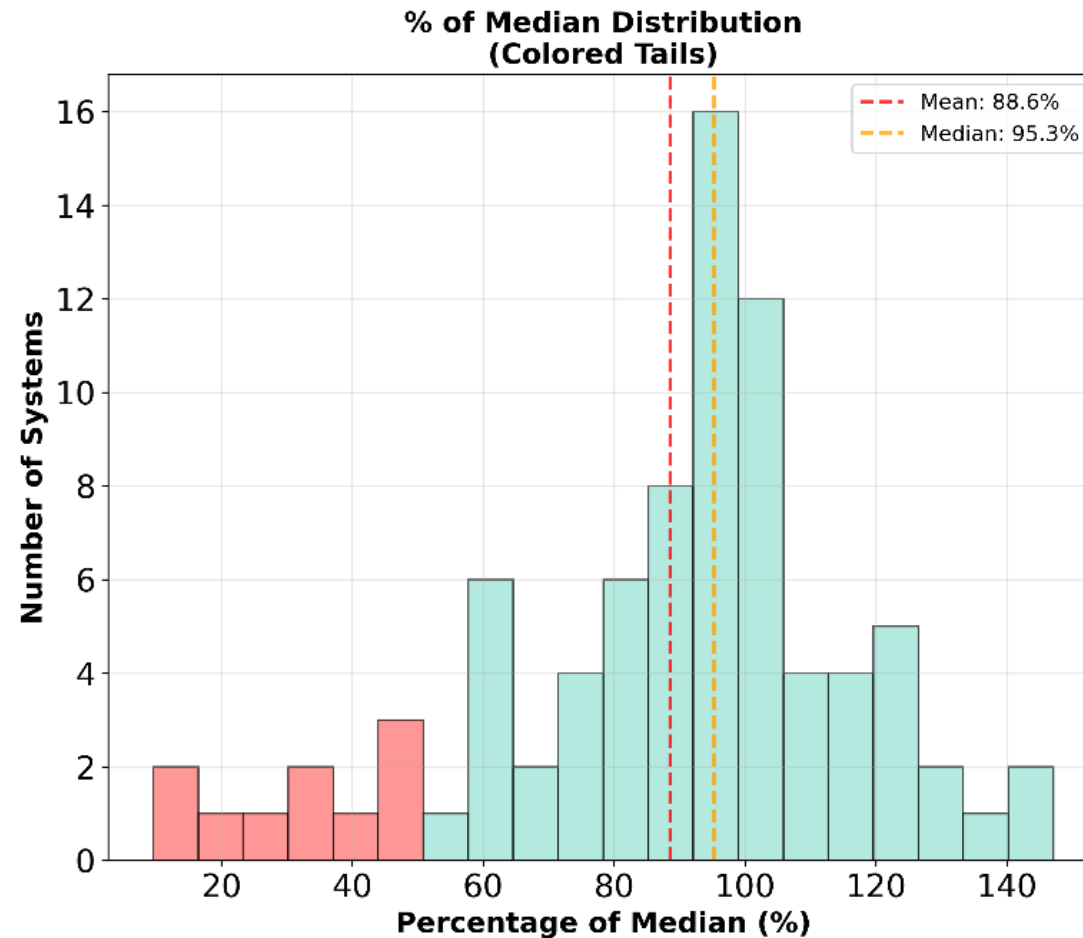


**Figure 1:** Total number of CWS with partial months intake data (2004 - 2024).

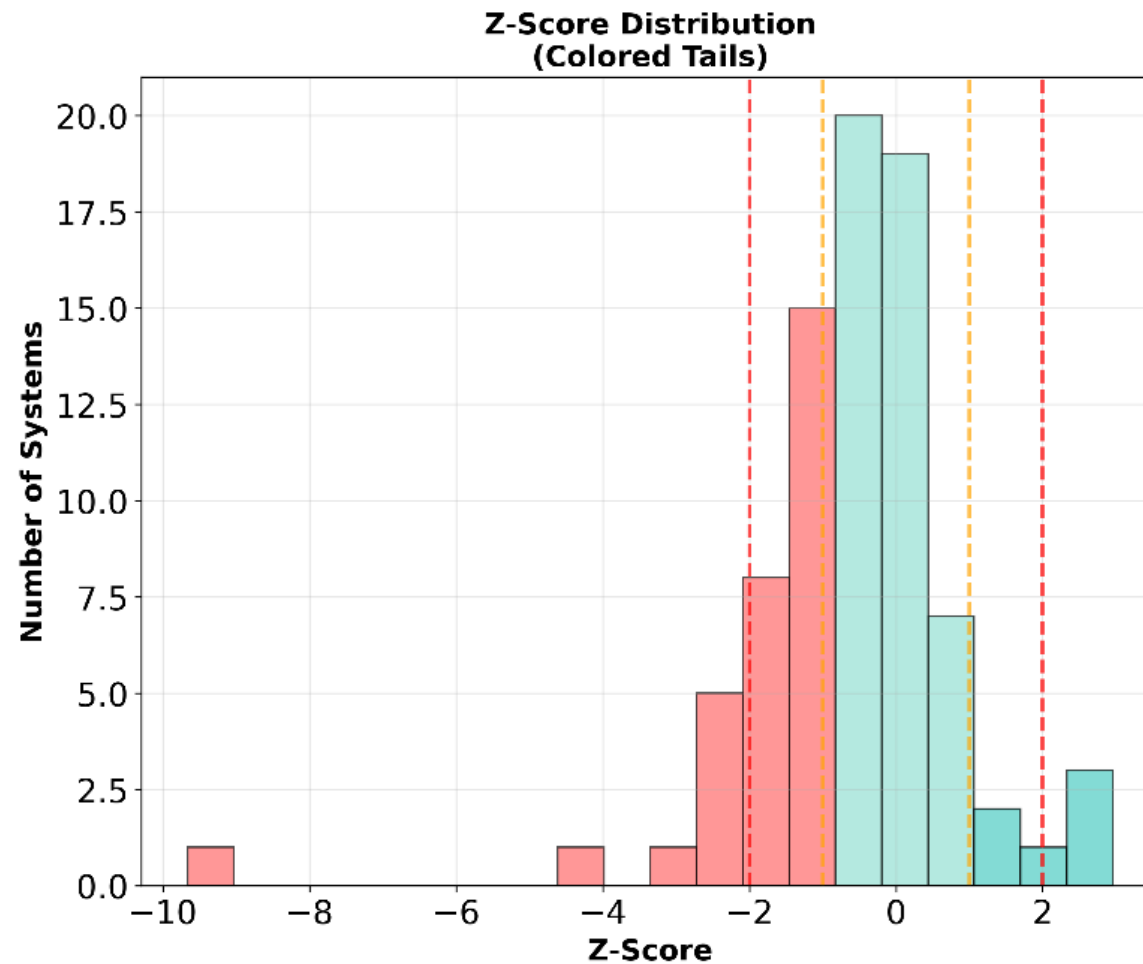
### Incomplete Data Breakdown by Months Present (>0 months)



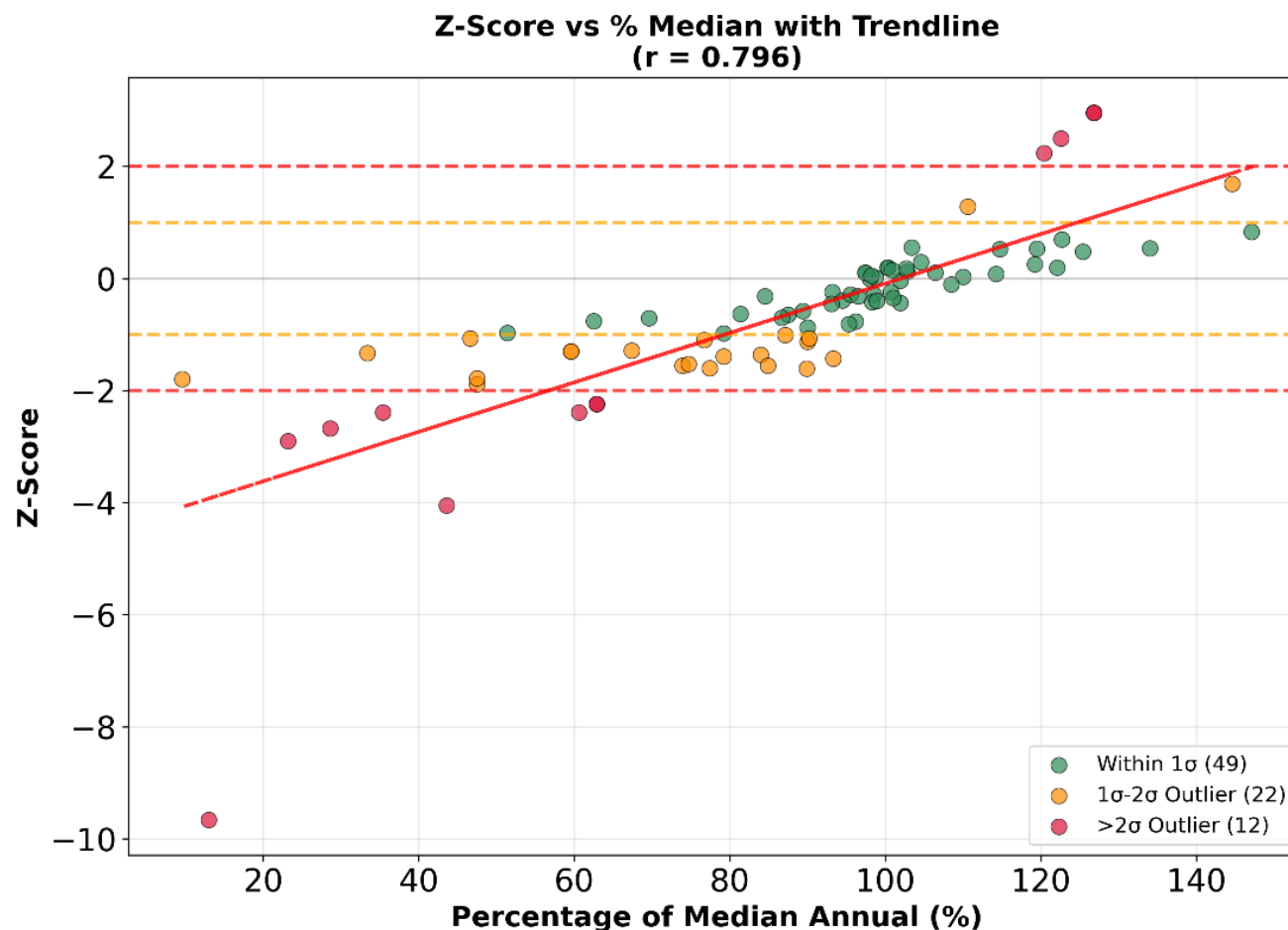
**Figure 2:** Visualizations of incomplete CWS monthly intake data (2004-2023)



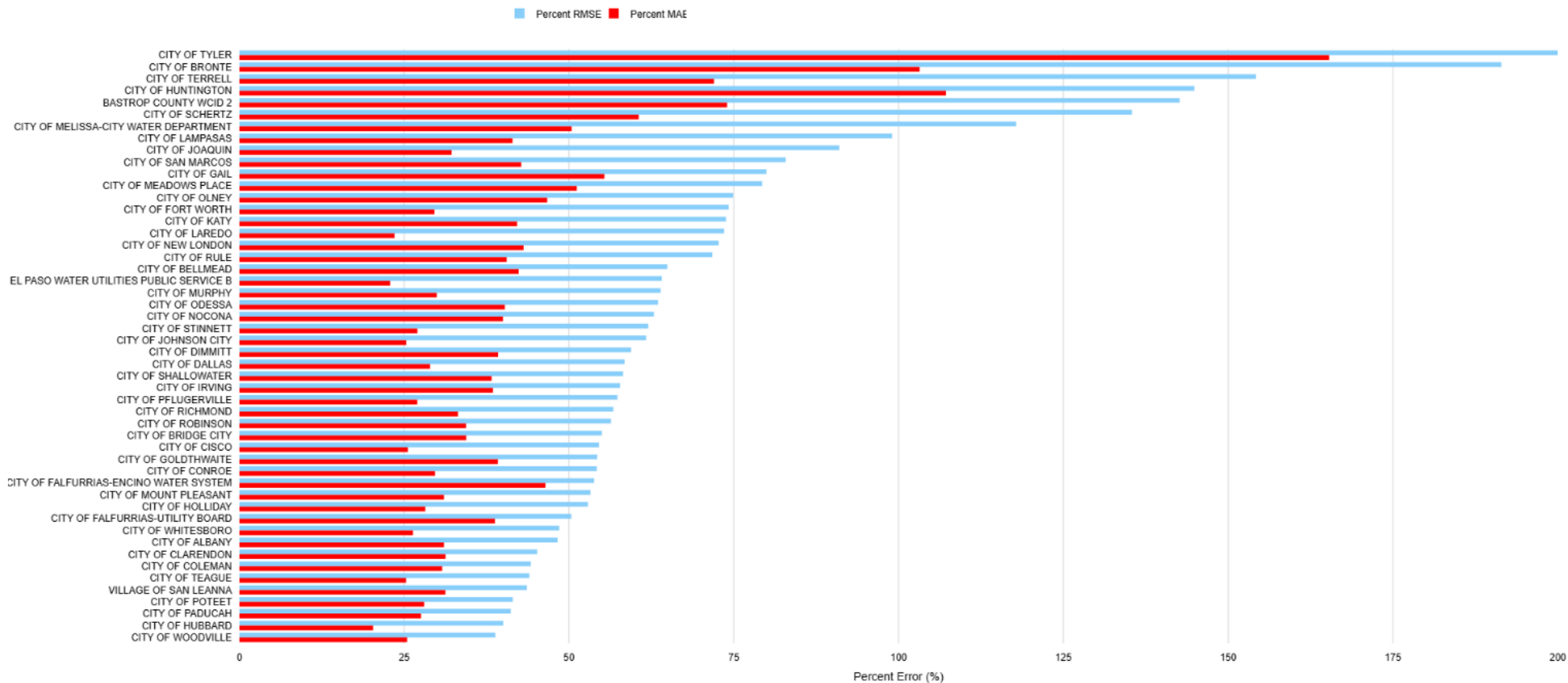
**Figure 3:** Histogram displaying a left-skewed distribution of partial year monthly intakes as a percentage of each system's median annual, revealing a peak concentration of systems around 90-100% of the median, and a tail extending towards lower percentages. The vertical dashed lines show the mean and median values, indicating that typical incomplete systems report about 89-95% of their expected annual totals. Red bars represent systems with significantly lower partial year usage (<50%), and light green bars represent the majority of the systems (50-140%), indicating typical to higher partial year usage patterns.



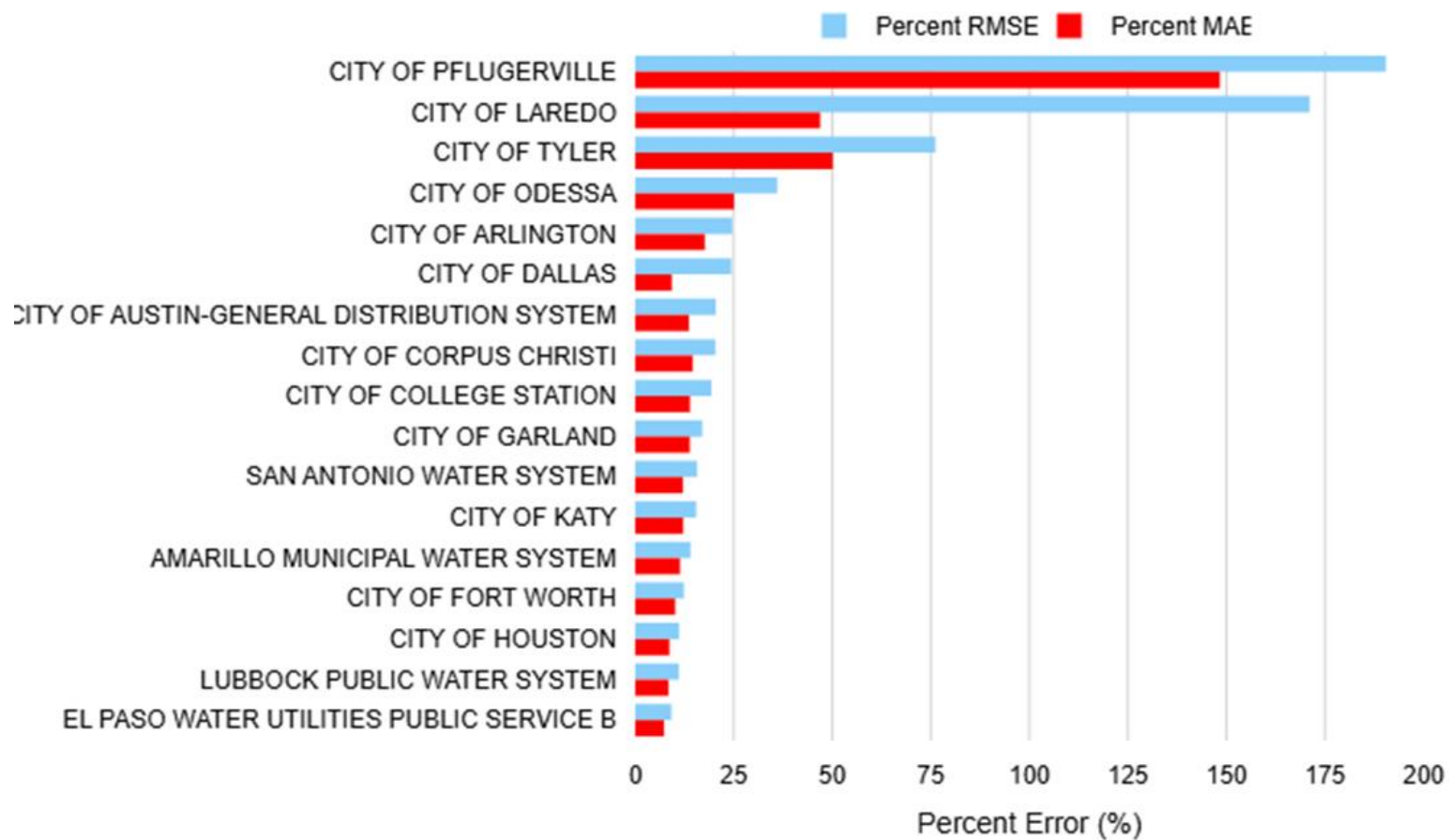
**Figure 4:** The histogram shows the Z-score distribution of systems with incomplete monthly intake, with vertical dashed lines marking statistical thresholds at -2, -1, 1 and 2 standard deviations away from the mean. The distribution is negatively skewed, and displays three distinct colors: red bars for negative Z-scores (partial year totals well below the system's typical annual mean), light green/teal bars for positive Z-scores (partial year totals above the system's annual mean), and the peak around Z-score 0 showing most incomplete systems have partial year totals close to their expected values when accounting for missing months.



**Figure 5:** Scatter plot showing the relationship between systems' partial year monthly intake (as percent of median annual total) and their corresponding Z-scores, with color-coded points representing different outlier categories. The plot reveals that systems reporting higher percentages of their median usage tend to have higher Z-scores, with green points clustering around 80-120% of median near Z-score zero, orange points showing moderate deviations, and red points ( $>2\sigma$ ) representing extreme deviations with either very low percentages (<50%) indicating severe underreporting or very high percentages (>120%) suggesting potential data quality issues. The horizontal dashed lines mark the  $\pm 1\sigma$  and  $\pm 2\sigma$  statistical thresholds used for outlier classification. The strong positive correlation ( $r = 0.796$ ) demonstrates that both statistical methods consistently identify the same problematic systems, validating the dual analytical approach.

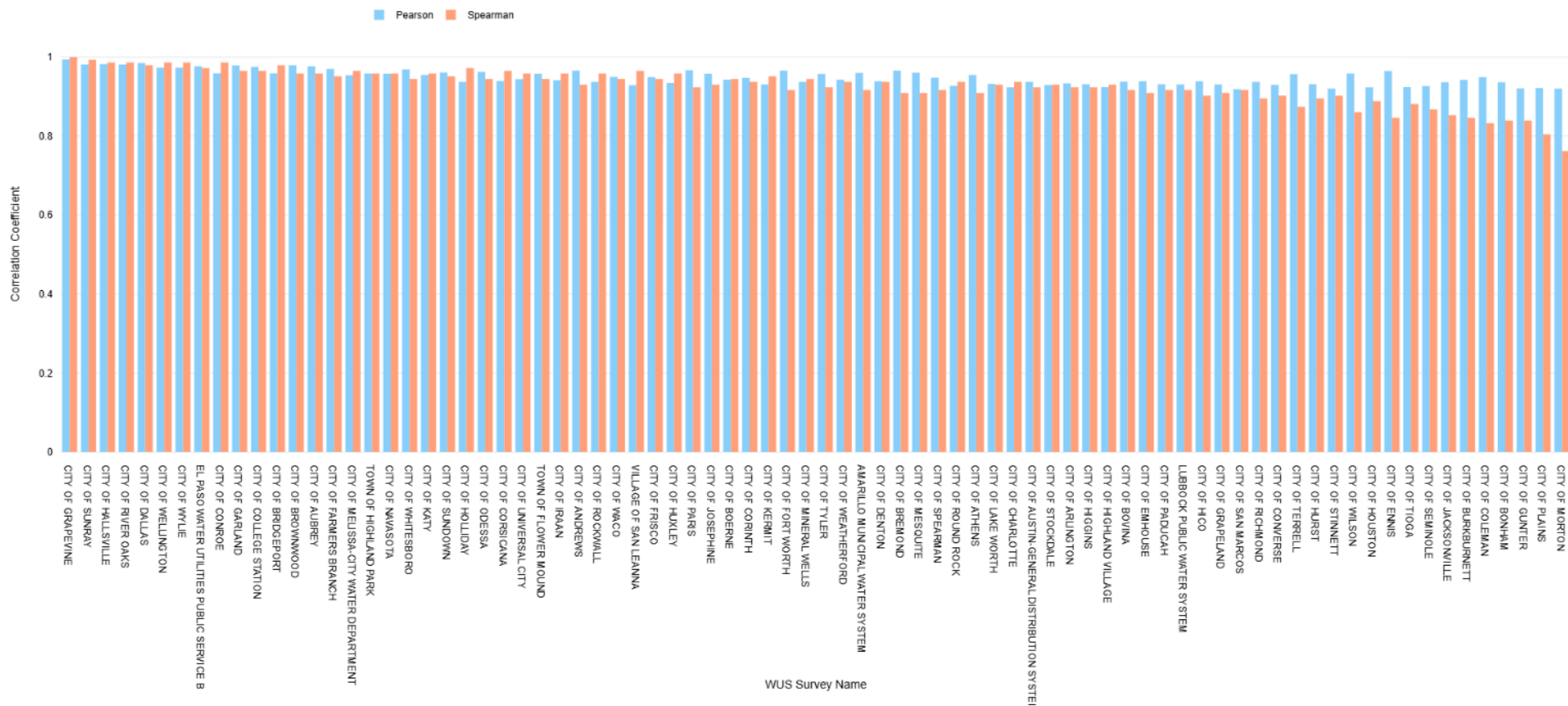


**Figure 6:** Highest error monthly intake method results compared against Phase 1 data (2004-2008)

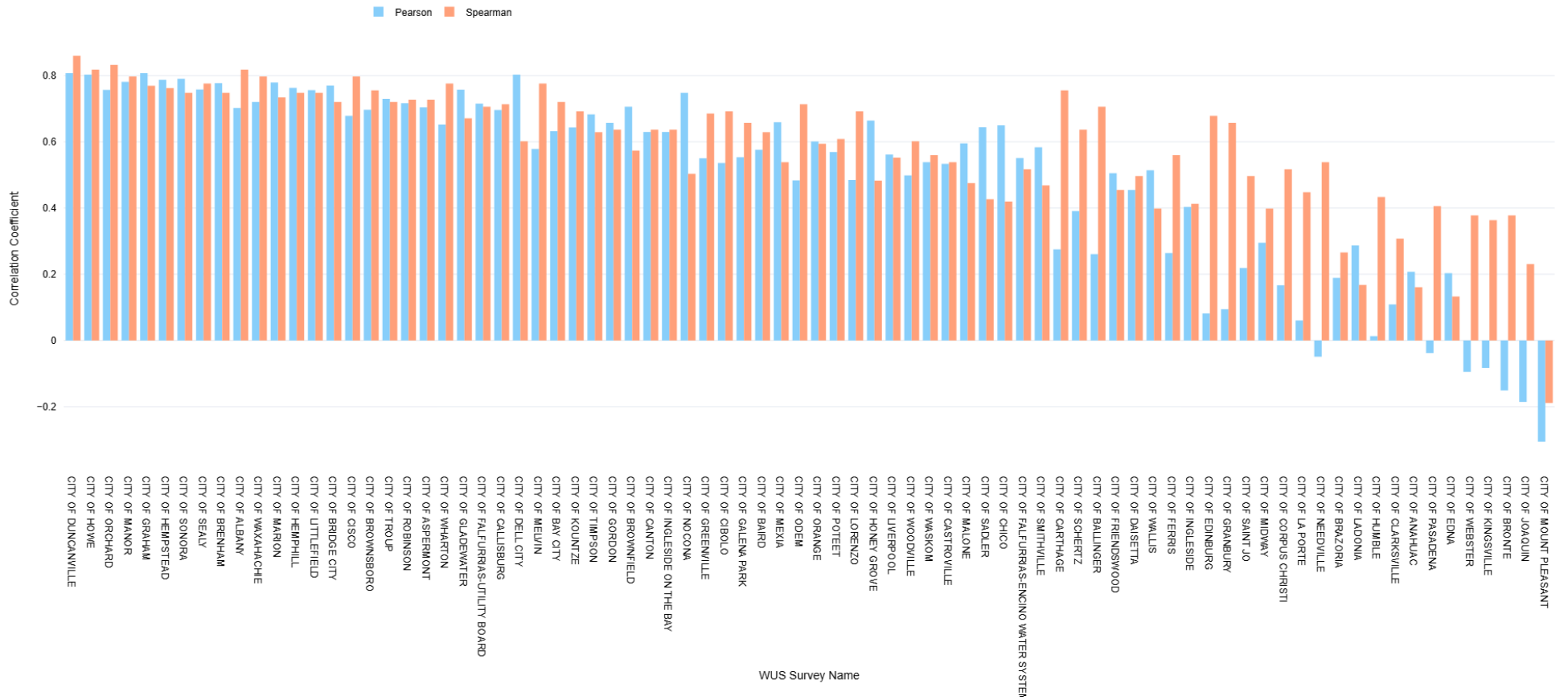


**Figure 7:** Error of monthly intake method results compared against Phase 2 data (2009-2011)

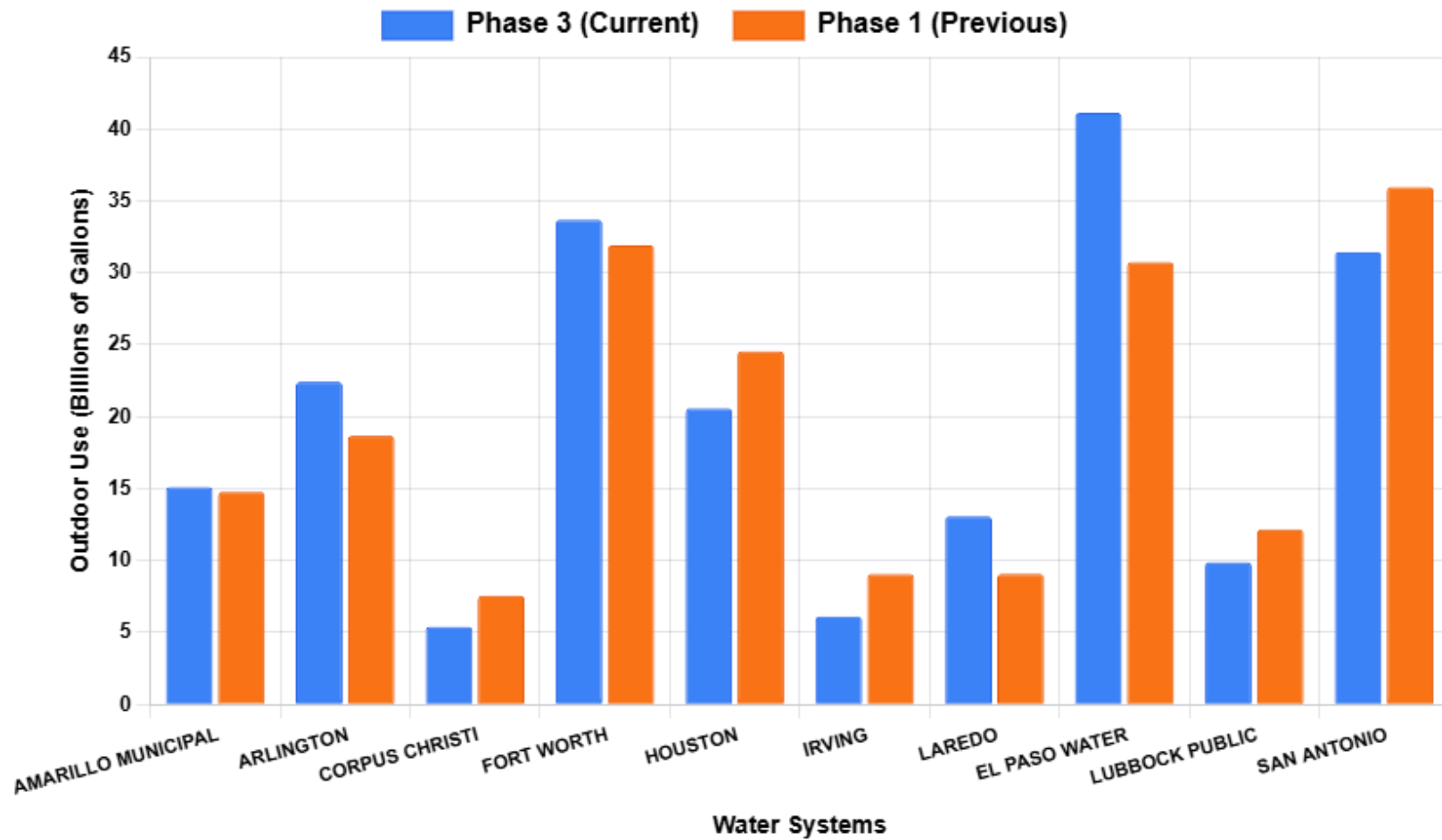




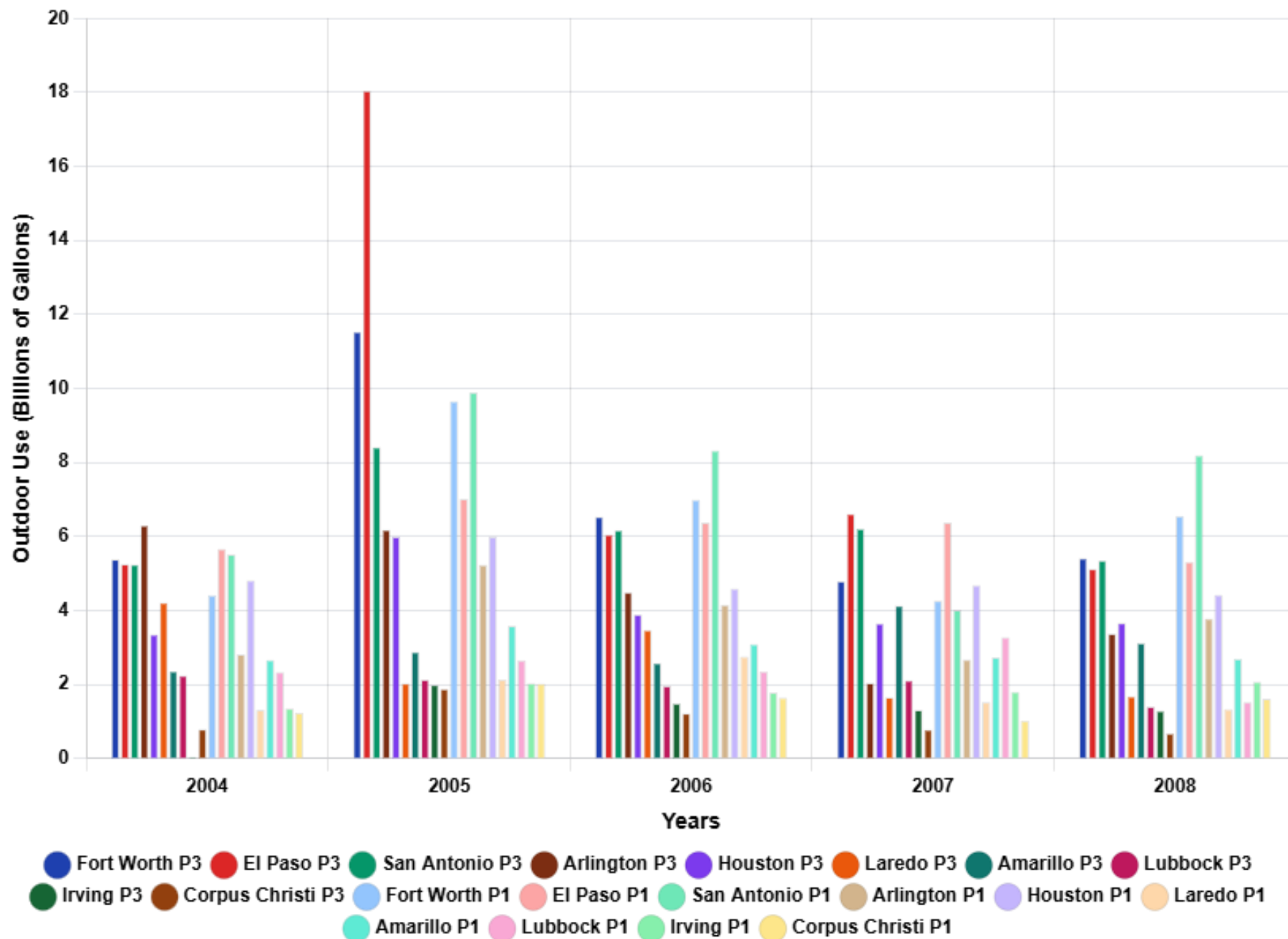
**Figure 8:** Highest correlation values for monthly intake method results (2011-2023)



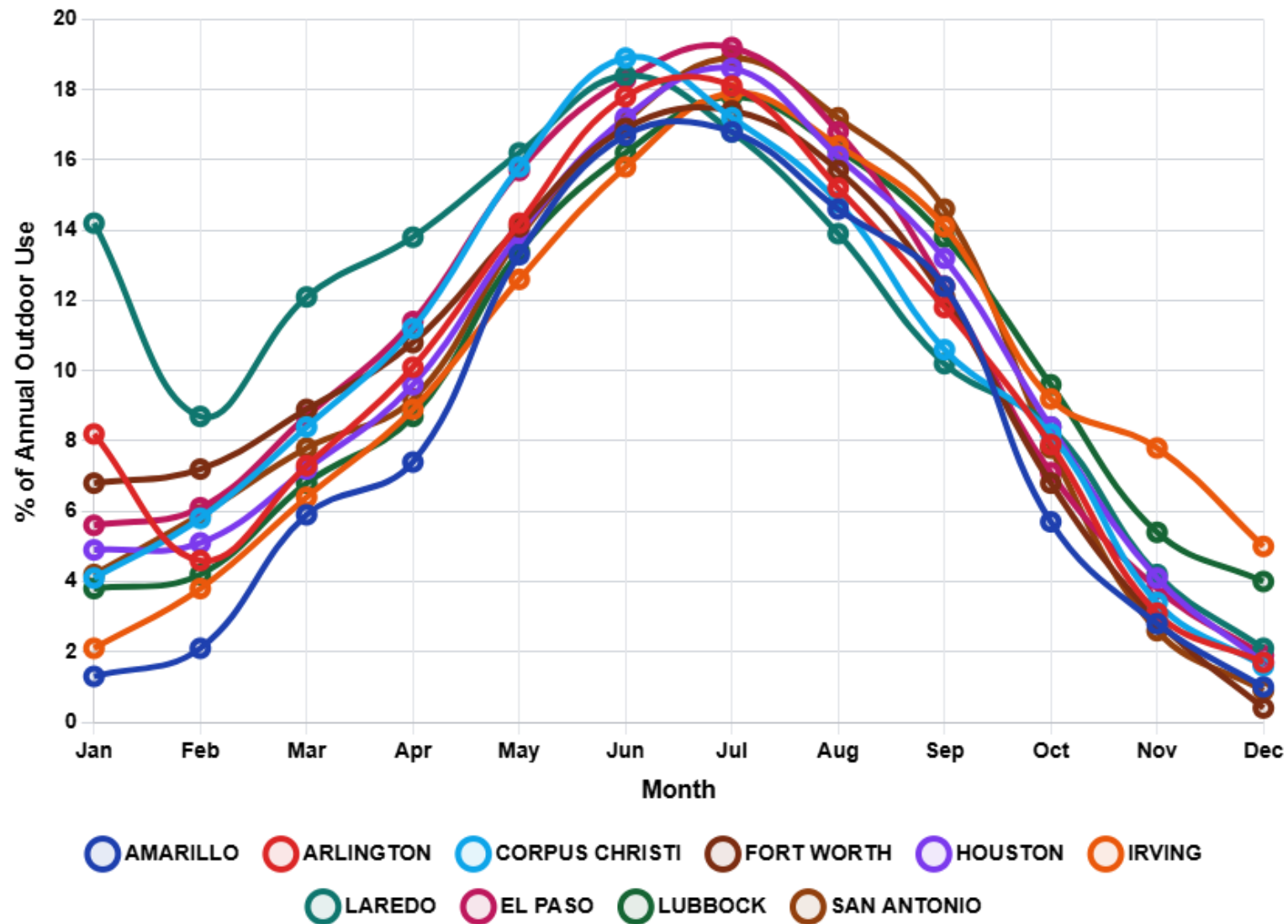
**Figure 9:** Lowest correlation values for monthly intake method results (2011-2023)



**Figure 10:** Bar chart showing Annual Outdoor Use Comparison between previous and current estimates. The plot shows the total outdoor usage, meaning each CWS represents 5 years (2004-2008) of seasonal outdoor use data summed into an annual total.



**Figure 11:** Bar chart showing the yearly outdoor use breakdown for all 10 CWS by year (2004 – 2008).  
Dark colors = Phase 3 (Current) | Light colors = Phase 1 (Previous).



**Figure 12:** Monthly Distribution of Seasonal Use Indices showing the Percentage of Annual Outdoor Use by Month (2004-2008 Average) for the 10 CWS.