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# Drought in the West: Embedded Water Demand Stationarity Compromises System Vulnerability Analysis

## *Case Study*

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**Abstract**

Hydrological drought is challenging managers of western U.S. snowpack-dependent urban water systems. Snowpack, reservoir storage, streamflow dynamics, and demand interactions guide water system management and operations, assuming per-capita demand stationarity. Using the Salt Lake City Department of Public Utilities and two drought scenarios, we investigate water system vulnerability differences between unchanging industry per-capita forecasting methods and dynamic demands driven by hydro-climate-demand relationships. The introduction of dynamic demands estimates a 42% reduction in system vulnerability during supply limiting conditions than the industry methods. These modeled water use behaviors also suggest a reduction in the peak timing and volume (September 2, 55MGD vs. August 2, 89MGD), duration (114 days vs. 144 days), and seasonal volume (16,000ac-ft vs. 25,000ac-ft) of out-of-district supply requests during extreme drought conditions. By relying on forecasts embedded with per-capita demand stationarity assumptions, significant and unlikely system vulnerabilities can misinform operational actions.

*Keywords: Water System Analysis, Stationarity, System Dynamic Modeling, Drought, Climate*

## 1. Introduction

Water managers need to ensure the delivery of clean and reliable water supplies throughout the service area. This task is complicated by uncertainties in climatic and behavioral drivers of water supply and demand, especially in the western United States, where hydrological droughts from below-average snowpack correlate to reduced streamflows and reservoir storage. These surface water conditions can challenge system management to source additional supplies to ultimately maintain system resilience, reliability, and vulnerability (RRV) (Hashimoto et al., 1982). To navigate water system RRV, operators and management leverage water-year streamflow forecasts and system models to assess performance and guide operational decisions (Finnessey et al., 2016). This methodology is routinely supply-focused by evaluating water system response to the timing and duration of peak runoff and low-flows. These streamflow metrics are indicators of challenging surface water conditions to a water system, responsible for critical decisions geared towards groundwater withdrawal, 'out-of-district water purchases, and reduced reservoir storage (Wei et al., 2007; Finnessey et al., 2016). These system analyses are confounded by embedded per-capita demand stationarity not reflecting climate influences on seasonal water use (Milly et al., 2008; Ghiassi et al., 2008; Li et al., 2009; Donkor et al., 2014; Johnson et al., 2021).

Stemming from a change in supply-oriented water management approach, both supply and demand influences on system performance now inform a public water utility's strategic and operational decisions (Billings & Jones, 2011). According to the American Water Works Association, monthly total system demand, annual per-capita demand, and annual demand by customer base are of critical interest to public utility management (Billings & Jones, 2011). These projections inform seasonal forecasts to establish effective management strategies that gauge ecosystem health, set water rates, and most importantly, maintain and improve potable water quality. In practice, municipalities forecast future demands based on historical mean per-capita demands, embedded with stationarity assumptions (Donkor et al., 2014; Billings & Jones, 2011). Integrating these demand forecasting methods in comprehensive systems assessments neglects errors attributed to stationarity (Matthews et al., 2011; Koutsoyiannis & Montanari, 2014).

Relying on unchanging per-capita demands disconnects water system assessments from the variability observed in water use behaviors, introducing the potential of increased uncertainty in system performance. While the focus of water system assessments remains supply-oriented, there exists a need to characterize the impacts of stationarity assumptions in per-capita demands on seasonal water system vulnerability assessments, especially in the drought-prone western U.S. We address this research gap by using a systems approach and out-of-district water requests to investigate the impacts of outdoor demand forecasts type, with and without embedded per-capita demand stationarity, on system vulnerability during two supply-limiting scenarios.

## 2. Methods

### 2.1 Experimental Approach

We use the anticipated water year 2021 drought in the Salt Lake City's Department of Public Utilities (SLCDPU) service area to investigate how the volume and timing of out-of-district water requests differ between demand forecasts embedded in per-capita stationarity and those capturing demand variability in response to key exogenous drivers. Two surface water supply scenarios based on year-to-date (February, 2021) precipitation in the Jordan River basin (National Resource Conservation Service, 2021) are developed using the Central Wasatch Memory-Driven Streamflow Model (CWMDSM), Section 2.3. Two water demand forecasts are created using the Climate-Supply-Development Water Demand Model (CSD-WDM) to investigate the differences in water system vulnerabilities, Section 2.4. The magnitude and timing of SLCDPU water system vulnerabilities are evaluated by integrating the streamflow and demand forecasts into the Salt Lake City Water Systems Model (SLC-WSM), a system (SD) model built to represent the SLCDPU service area, see Section 2.5.

### 2.2 Study Area

The SLCDPU water service area lies within northern Utah's urban growth-bound Salt Lake Valley, see Figure 1. The snowpack and hydrology in the adjacent Wasatch mountains functions as a natural reservoir, with City (CC), Parley's (PC), Big Cottonwood (BCC), and Little Cottonwood (LCC) creeks supplying over 60% of the municipality's water. This supply is challenged by inter-annual climate variability as a result of the complex topography of the Great Basin and global climate oscillations, for example, annual snow-water-equivalent (SWE) has a standard deviation of $\sigma = 200\,mm/yr$ at the headwaters of Little Cottonwood Canyon, equation 1 (Steenburgh, Halvorson, & Onton, 2000; Steenburgh J. , 2014; Wang, Gillies, Jin, & Hipps, 2010; Wang, Gillies, Martin, Davies, & Booth, 2012).

$$\sigma = \sqrt{\frac{\sum^{i}(x_i - \mu)^2}{N}} \qquad (1)$$

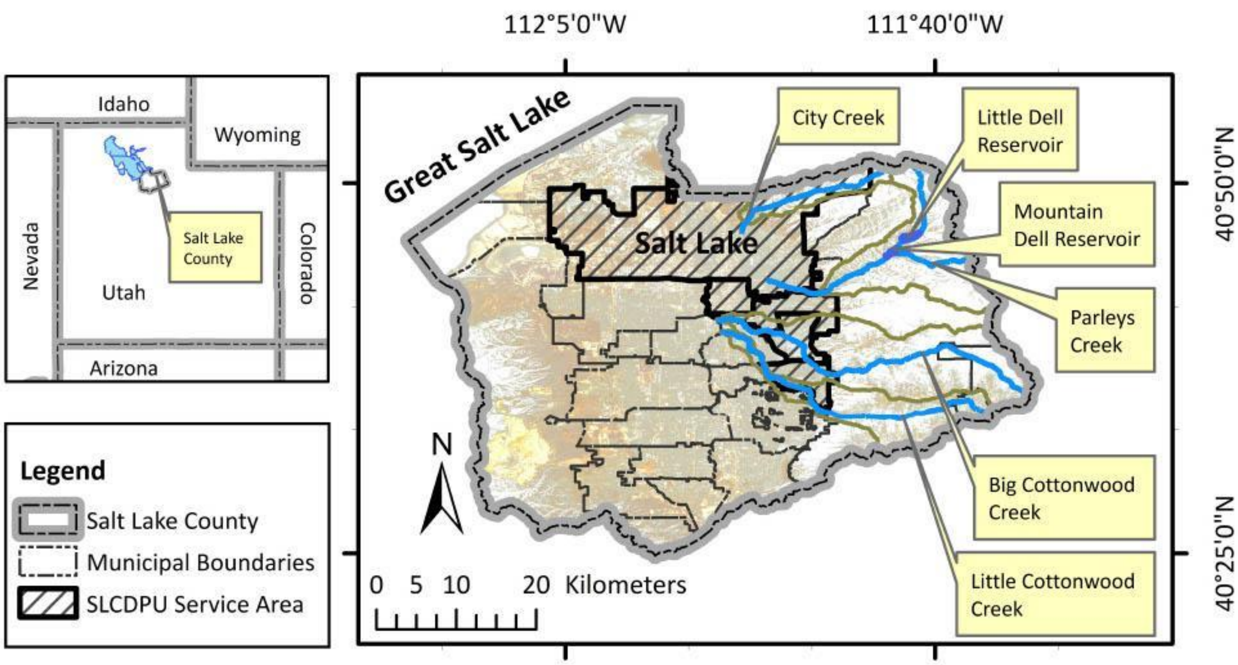


**Figure 1. The SLCDPU water supply region is located in the eastern bench of the Salt Lake Valley in northern Utah with approximately 60% of its surface supply supported by the four labelled Central Wasatch streams.**

The study area's cold semi-arid (*BSk*) to cold desert climate (*BWk*) has four distinct seasons that influence water demands (Peel, Finlayson, & McMahon, 2007). Increases in temperature during spring and the quantity of precipitation determine the beginning of the irrigation season; a hot, dry summer with temperatures exceeding 35.0°C drive high evapotranspiration; and decreasing fall temperatures coupled with the return of precipitation end the irrigation season. From April to October up to ~1000 mm of water can be applied to landscaping (UDWR, 2010; UDWR, 2014).

| Month | Minimum | Mean | Maximum | σ |
|---|---|---|---|---|
| Apr* | 113 | 119 | 267 | 37 |
| May* | 161 | 292 | 438 | 65 |
| Jun* | 288 | 455 | 576 | 74 |
| Jul* | 387 | 548 | 696 | 73 |
| Aug* | 338 | 510 | 632 | 74 |
| Sep* | 272 | 381 | 486 | 55 |
| Oct* | 158 | 231 | 324 | 42 |
| Season* | 280 | 372 | 445 | 46 |
| Season** | 64,088 | 58,248 | 101,895 | 10,570 |

*units in gpcd

**units in acre-feet

**Table 1. Gallons per-capita day (*gpcd*) SLCDPU water use observations from 1980-2017. Season values are averages over April-October. exhibit high variability during the irrigation season.**

The SLCDPU has a nearly complete 40-year record of historical monthly produced water deliveries available. Analysis of historical monthly water use indicates significant year-to-year variability $\sigma = 10{,}600 ac - ft\ or\ \pm 25\%$ of the historical mean) and is illustrated in Table 1. The variance in intra- and inter-annual water use suggests that per-capita water demand may exhibit non-stationarity. Johnson et al. (2021) found that forecasting methods relying on stationarity can over predict municipal monthly water use by 90% and seasonal water use by 40% during supply limiting conditions. By integrating machine learning tools that recognize driver-demand dynamics (air temperature, precipitation, surface water supplies, snowpack, population density), seasonal forecasting accuracy during supply-limiting conditions was reduced to less than 1% of the observed water use. Figure 2 illustrates the limitations of models with per-capita demand stationarity assumptions during drought, average, and surplus supply conditions, and how integrating driver-demand dynamics significantly improves the forecast's accuracy.

 

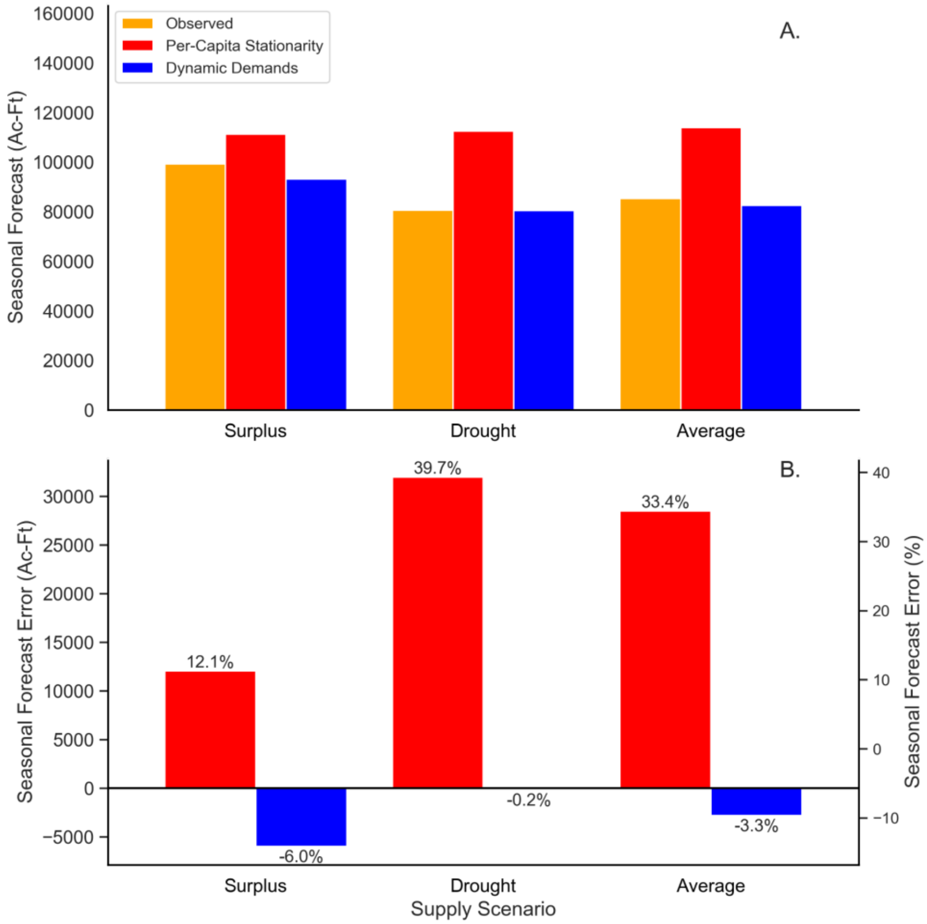


**Figure 2. Seasonal demand forecasting methods relying on stationarity can significantly over-predict water demands (A), leading to high forecasting error (B). Figure adapted from (Johnson et al., 2021).**

### 2.3 Streamflow Forecasting

The CWMDSM is a multivariate linear regression model that considers four metrics to predict the annual watershed discharge: annual precipitation (*P*), winter baseflow ($Q_{BF}$), snowmelt rate ($M_R$), and snowmelt duration ($M_D$) (Brooks et al. 2021). Differing from other streamflow prediction models, this model captures antecedent climate memory by assuming that winter baseflow changes represent the relative change in headwater catchment storage, which is likely controlled by historical climate (Brooks et al., 2021). To estimate streamflow in the Central Wasatch, we use a modified CWMDSM, which has been shown to predict annual streamflow with less than 5% error, using point observations of precipitation and including only climate memory reflected in winter baseflow (or groundwater storage).

To apply this model, we used two annual precipitation regimes (dry and very dry) as predictors. PRISM precipitation was calculated for each Central Wasatch Catchment's area for the period of record of streamflow (1901-2020). PRISM calculates historical precipitation, interpolated using climate-elevation regressions and historic climate station data (Daly et al., 2008). For the very dry scenario, we used precipitation relative to the lowest year on record (1934 water year), where precipitation was approximately 58% of average across all Central Wasatch catchments. For the dry scenario, we used the current state of precipitation (February 2021) using SWE as a proxy variable for precipitation without current PRISM data available. The February 2021 SWE values for the Central Wasatch were below the historically recorded minimum (NRCS Record). From the below-average start of the snow year, we assumed average precipitation for the remainder of the year (resulting in precipitation at 82% of average). We used the two precipitation scenarios to predict streamflow, mean January 2021 baseflow conditions, historical average snowmelt melt rate, and historical average snowmelt duration for all catchments. The final product is daily streamflows calculated as the fraction of total annual flow that occurs on each day of each historical water year, then averaged these across all years and across only the driest 20% of years on record. These yield an estimate of the fraction of total flow occurring on each day of the year under average and dry conditions; multiplying these values by the total predicted annual streamflow gives the predicted daily streamflow values.

### 2.4 Demand Forecasting

The CSD-WDM is a fully automated, python-based (v3.8.5) machine learning optimization algorithm taking in air temperature and precipitation data from the National Land Data Acquisition System (NLDAS), Utah's Governor initiated conservation goals, adjacent Wasatch mountain surface water supplies, monthly Little Cottonwood Canyon snowfall, and service area (population, land-use, density) dynamics to predict a municipality's mean monthly per-capita produced water demand (Johnson et al., 2021). The model has a hierarchical framework where each month of outdoor irrigation (April-October) has a sub-model and a unique set of variable inputs to drive an ordinary least squares (OLS) regression model. During model calibration, the training process evaluates feature correlation with the gallons per-capita water use (*gpcd*), checks for feature collinearity and removes the lesser demand correlated co-linear feature, and performs recursive feature elimination to identify key demand drivers and optimize model accuracy (Johnson et al., 2021). The CSD-WDM is calibrated on thirty years of data from 1980-2017, except for 2015 (drought), 2017 (average), and 2008 (surplus) validation years; see Figure 3 and Table 2. Model accuracy on the validation data is as follows; $R^2 = 0.98$, *mean absolute error = 16.6gpcd*, and *mean absolute percent error = 8.4%*.

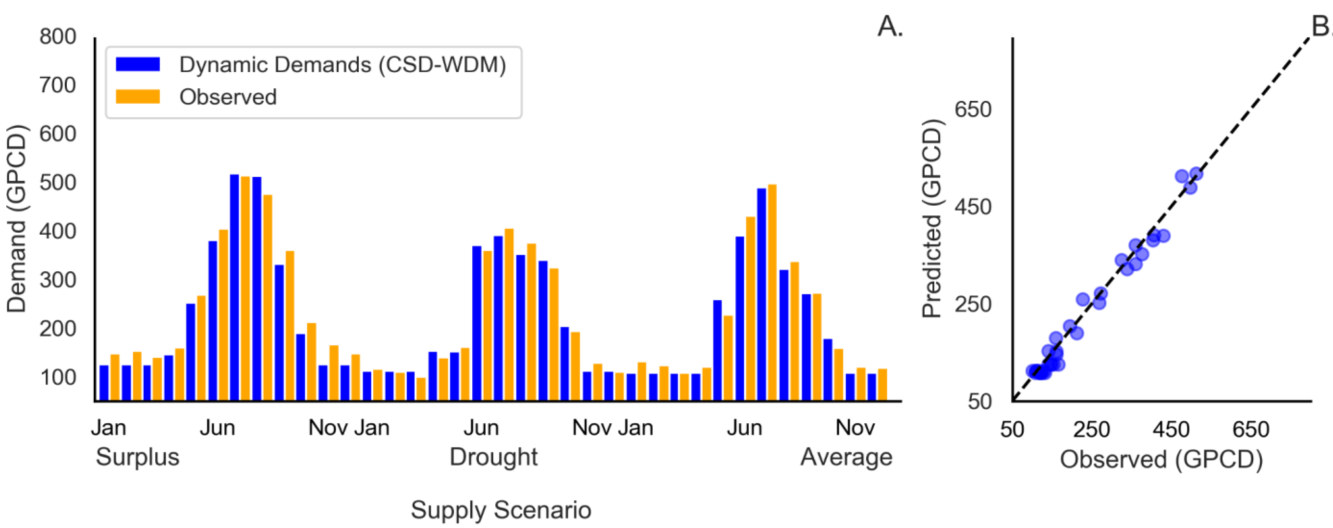


**Figure 3. The CSD-WDM captures water use dynamics in response to drought, average, and surplus supply scenarios (Johnson et al., 2021)**

| Predictor | Apr | May | Jun | Jul | Aug | Sep | Oct | Indoor |
|---|---|---|---|---|---|---|---|---|
| Conservation goal | | | | | | | | 1.00 |
| Population Density[1] | | | | -0.08 | -0.03 | | | |
| Mar LCC Streamflow[2] | 0.01 | | | | 15.05 | | | |
| Apr LCC Streamflow[2] | 0.01 | | | | 0.01 | | | |
| May LCC Streamflow[2] | | | | | 0.01 | | | |
| May BCC Streamflow[2] | | | | | 0.41 | | | |
| Season Snowfall[3] | | | 0.12 | | | | | |
| Apr Mean Temperature[4] | 5.64 | | 8.95 | -3.91 | 3.00 | 4.22 | | |
| May Mean Temperature[4] | | 14.28 | 14.91 | | -0.29 | 3.31 | -2.02 | |
| Jun Mean Temperature[4] | | | | | 1.44 | -3.80 | | |
| Jul Mean Temperature[4] | | | | 31.14 | 11.48 | -7.28 | | |
| Aug Mean Temperature[4] | | | | | 6.31 | 11.93 | | |
| Sep Mean Temperature[4] | | | | | | 8.10 | | |
| Oct Mean Temperature[4] | | | | | | | 5.73 | |
| Apr Precipitation[5] | -0.31 | | | 9.54 | -0.01 | | | |
| May Precipitation[5] | | -1.05 | | | | | | |
| Jun Precipitation[5] | | | -1.99 | | 1.22 | | | |
| Aug Precipitation[5] | | | | | -1.82 | | | |
| Sep Precipitation[5] | | | | | | -0.96 | | |

[1] change in demand per persons/km$^2$

[2] change in demand per cfs of streamflow

[3] change in demand per mm of snow

[4] change in demand per °C

[5] change in demand per mm of precipitation

**Table 2. The CSD-WDM's feature selection process identifies 19 water demand drivers whose OLS regression weights are specific to the SLCDPU monthly water demands (Johnson et al., 2021).**

### 2.5 Water Systems Model

The SLC-WSM runs in the GoldSim software environment, an SD tool that integrates sub-models, uses linear programming to allocate water and performs Monte-Carlo simulations (Goldsim, 2013). The model was initially developed for use as a decision support tool to inform the SLCDPU on internal and external factors impacting water system performance (Goharian, 2016; Goharian & Burian, 2018). The SD model aggregates service area demands and prioritizes supplier requests based on management and operations. The order of prioritization is critical to modeling the SLCDPU system operations and is as follows: surface water sources (CC, PC, LCC, and BCC), groundwater, and then Deer Creek reservoir water. From these supplies, the model captures the complex combination of interactions and feedbacks between reservoir operations, water transfer infrastructure, water treatment systems, wells, withdrawal limitations, and more at a daily time step. The coupling of several process modules represents real-world interconnections and responses between different water system components, see Figure 4. This system architecture is critical to identify water system shortages and corresponding RRV (Hashimoto, Stedinger, & Loucks, 1982). A new addition to the model is the integration of a demand module. This module leverages CSD-WDM outputs where previously demand was determined by historical annual water use patterns (embedded per-capita demand stationarity).

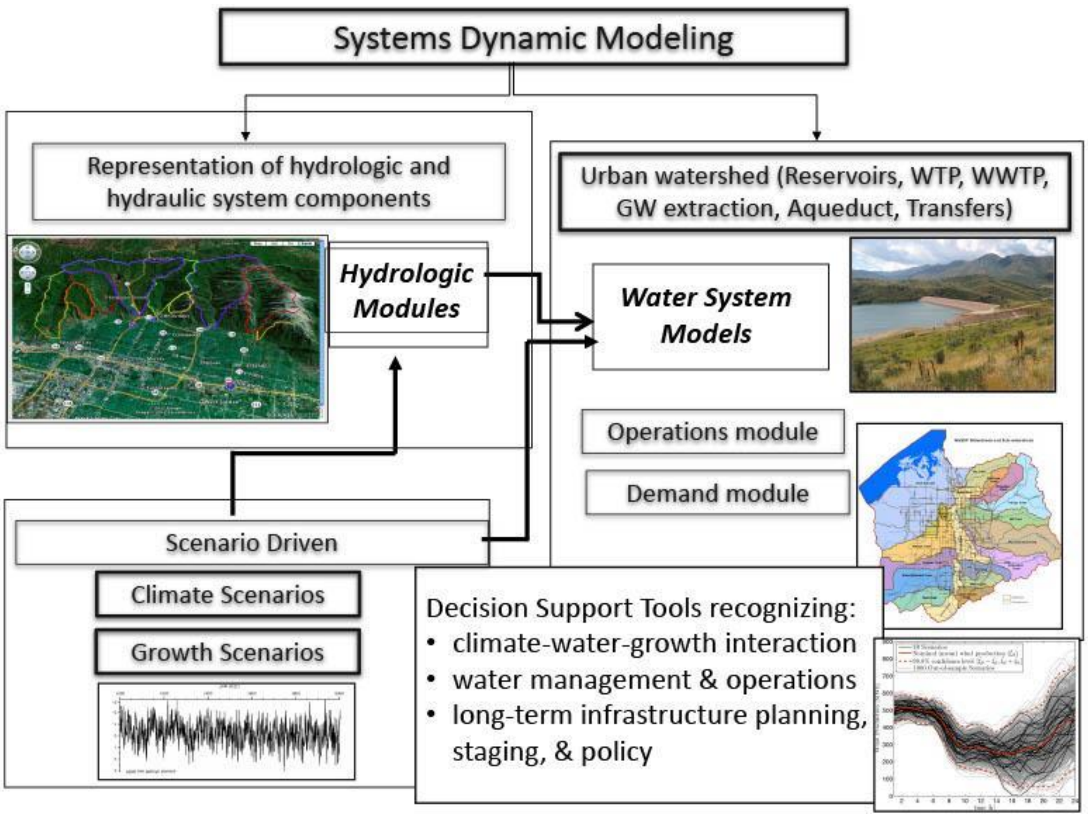


**Figure 4. The systems dynamic model structure connects many components and subsystems that influence the water system.**

Combining hydrologic streamflow and machine learning demand forecasting models, we use four scenarios to investigate per-capita demand stationarity assumptions on water system vulnerability; 1) dry precipitation and embedded per-capita stationarity demands, 2) dry precipitation and dynamic demands, 3) very dry precipitation and embedded per-capita stationarity demands, and 4) very dry precipitation and dynamic demands. The SLCDPU has access to over 50,000ac-ft per year of out-of-district Deer Creek reservoir storage to prevent systematic water shortages or delivery failures. Accessing this water does come at an additional cost to the municipality. Thus, system vulnerability and shortage are defined as water volume exceeding the historical average quantity of water requested from Deer Creek reservoir, referred to as reservoir usage.

 

## 3. Results

The water system performance suggests different levels of reservoir usage when evaluating per-capita stationarity vs. dynamic demands. For the dry scenario (1 &2), Figure 5(A) 's daily time-step illustrates how the per-capita demand stationarity simulation requests additional reservoir water prior to the historical peak use timing (August 16) and nearly twice the magnitude (75MGD vs. 40MGD). Peak water use further illustrates these errors with above-average reservoir water use up to 44MGD observed on July 28. The total SLCDPU water demand hydrograph increases to peak use (~150MGD) and then tapers off to ~45MGD by the end of October. At a monthly resolution, Figure 5(C) displays the municipality's total August demand exceeds 17,000ac-ft, with over 6,000ac-ft sourced from the reservoir. This is over 4,000ac-ft and nearly 200% more than is requested on average. Seasonally, assuming per-capita stationarity suggests 16,000ac-ft of reservoir water, 7,750ac-ft or 87% more water than the historical mean.

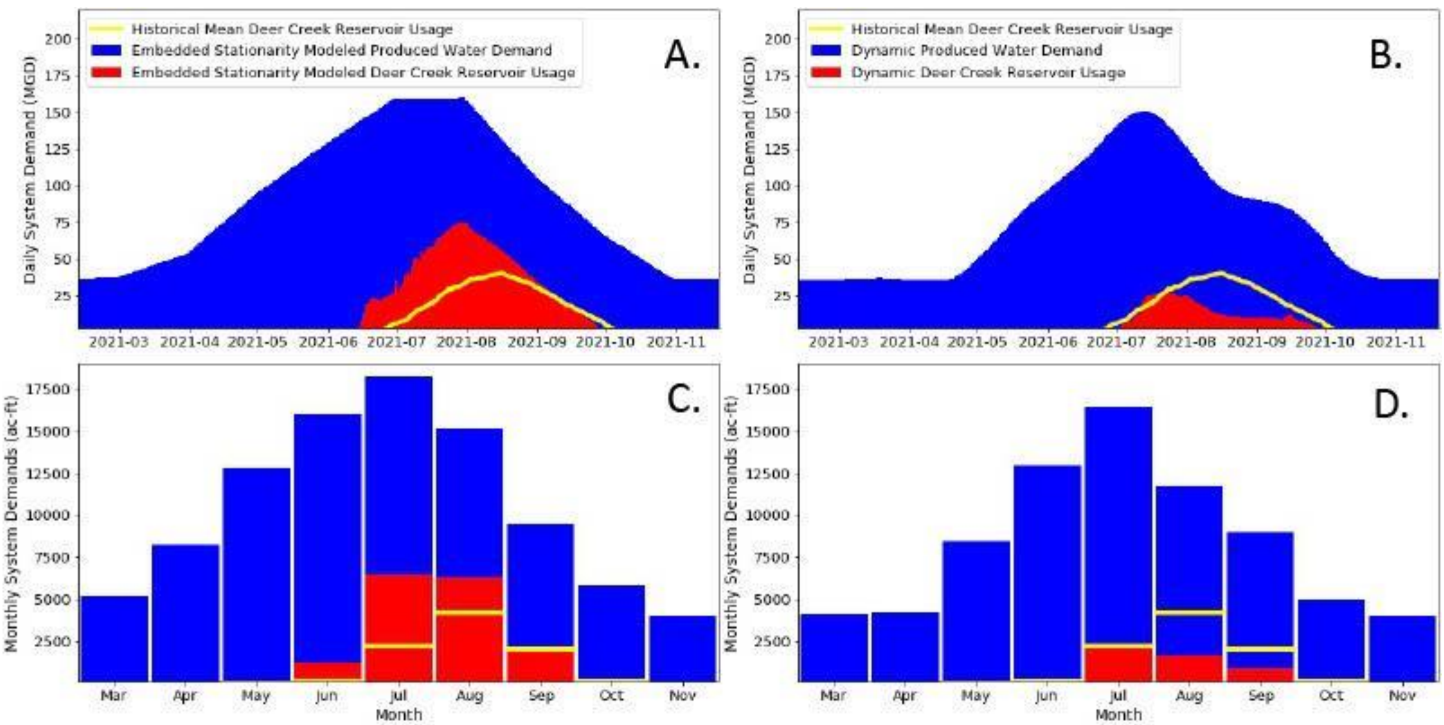


**Figure 5. Daily (A, B) and monthly (C, D) water system performance during dry precipitation scenarios. Stationary per-capita demands (A, C) results in much greater reservoir usage than dynamic demand (B, D). This difference is driven by irrigation behavior reflecting hydro-climate conditions.**

The dynamic CSD-WDM demands in the dry scenario (2) suggest different reservoir water requests. Figure 5(B.) shows that the reservoir usage hydrograph differs in shape from the stationarity case because of climate-driven water behaviors. Peak demand timing is approximately equal to that observed with per-capita stationarity assumptions. However, the duration of excess reservoir requests is much less, eight days vs. 110 days for non-stationarity-based vs. embedded stationarity demand modeling methods. This results from an increase in demand beginning in mid-May, contrasting with the per-capita stationarity-based forecast initiating irrigation in early April. More accurately representing the irrigation season beginning indicates a reduction in system vulnerability, observed with the reservoir requests only exceeding historical use by 6.7MGD on July 14 and maximum daily use of 26.7MGD occurring on July 26. This corresponds to a maximum monthly and seasonal reservoir request of 2,100ac-ft and 4,630ac-ft, with above-average usage being 150ac-ft and 160ac-ft, respectively. This simulation suggests the maximum monthly reservoir requests will be less than 8% and seasonally less than 4% than that observed from the historical mean. To a water system manager, the two demand scenarios convey drastic differences in performance, and subsequently, management actions to mitigate system vulnerability.

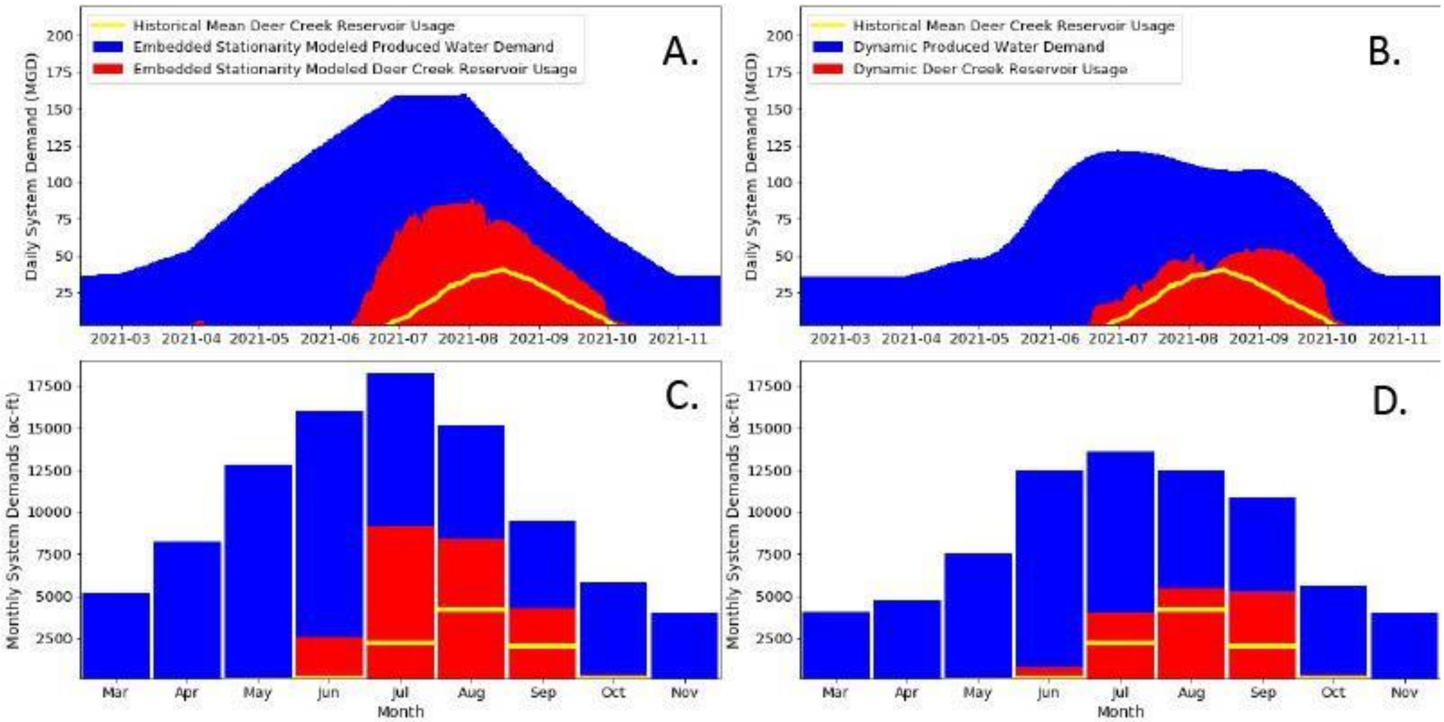


**Figure 6. Daily and monthly per-capita demand stationarity assumptions (A. and C.) over predict the very dry scenario's peak Deer Creek Reservoir water use and do not capture the extended irrigation season demands. Dynamic demands capture water use behaviors that reduce overall system vulnerability in supply-limiting hydro-climate conditions (B. and D.).**

Water system performance shows significantly greater reservoir usage within the very dry precipitation scenario (3 & 4). Figure 6(A) displays how the reduction in surface water flows and daily climate-independent demands suggest a significant increase in peak reservoir use, 89MGD (August 3), and a 150% increase over the historical average (36MGD). Above-average reservoir use exceeds 650% as demand outpaces limiting surface water supplies at the beginning of the irrigation season. The per-capita demand stationarity assumptions lead to a total of 144 days of reservoir requests and maximum monthly and seasonal reservoir water requests of 9100ac-ft and 25,000ac-ft, respectively, see Table 3 and Figure 6(C). Should SLCDPU management need to reduce reservoir usage to the historical average in this climate scenario, a 35% reduction in outdoor water use would be necessary.

Integrating dynamic demands into the very dry precipitation simulation (4) suggests the reduction in surface water supplies stresses the system and results in above-average reservoir requests. The municipality's water demand quickly increases with June irrigation but plateaus after 121MGD, ~30MGD less than the dry scenario demands. In response to significantly below-average snowpack, to "survive the drought" voluntary actions are taken, reducing the magnitude of peak system demands by nearly 20%. This correlates to a different pattern in reservoir requests than the other simulations. Figure 6(B) illustrates this increase in daily reservoir requests prior to and after the historical peak. This simulation's peak reservoir request (55MGD) occurs from late August to mid-September rather than the historical peak at the end of July/beginning of August. While municipal water demand decreases as fall approaches, the local surface water supplies enter their 200-year low-flow state (Log-Pearson type III), which severely stresses the system.

| Temporal Scale/Metric | Per-Capita Stationarity | Dynamic Demands | Reduction in Reservoir Use / Vulnerability |
|---|---|---|---|
| Maximum Daily Deer Creek Reservoir Use | 88.9MGD | 54.7MGD | 38% |
| Maximum Monthly Deer Creek Reservoir Use | 9140ac-ft | 5460ac-ft | 40% |
| Seasonal Deer Creek Reservoir Use | 24,700ac-ft | 15750ac-ft | 36% |

**Table 3. Per-capita stationarity assumptions display more significant daily, monthly, and seasonal Deer Creek reservoir use in the very dry simulation than demands coupled to dynamic water use behaviors. The integration of dynamic demands suggests reductions in reservoir use.**

Comparing the very dry simulation's water system performance with and without embedded per-capita demand stationarity assumptions indicates the timing and volume of additional reservoir requests are more severe when demands do not reflect dynamic service area conditions. For example, we observe a 38%, 40%, and 36% reduction in maximum daily, monthly, and total seasonal system vulnerability by integrating dynamic demands in the system assessment, respectively. This per-capita demand stationarity simulation suggests an additional month of reservoir water use than the dynamic demand forecast, 144 days vs. 114 days. These water systems simulations and analyses present significant differences in the decision-making criteria that water resource management relies upon to base operational decisions.

## 4. Discussion

Water system performance simulations should provide management with a tool that can evaluate system operations to a range of supply conditions to inform critical operational decisions. Our comparison of demand forecasting methodologies with and without embedded per-capita demand stationarity assumptions suggests two very different vulnerability scenarios attributed to the irrigation season duration and intensity. The differences in forecasted system vulnerability (reservoir peak use, request duration, and total requests) require different management approaches to bring requests back to historical averages. Anticipating and preparing for these requests is critical to the reservoir storage-release operations at Deer Creek reservoir and many others in the western U.S., where multiple utilities have a stake in the water storage and there are minimum release requirements for aquatic ecosystems.

This study identifies significant decision-making implications from assuming per-capita demand stationarity in seasonal water system assessments. In the dry precipitation simulation, reducing the volume of excess reservoir requests to the historical average requires a 10% reduction in outdoor water. Demand-sided management activities promoting community engagement in water conservation awareness, such as pamphlets distributed by mail and included with water bills, email newsletters, etc., can achieve this reduction (Inman & Jeffrey, 2006; Liu, Giurco, & Mukheibir, 2015). However, curtailing water demands does not address differences in irrigation season duration or peak use. When solving the dry precipitation simulation with dynamic demands, no actions are required as SLC-WSM suggests below-average seasonal Deer Creek reservoir water.

Developing solutions for the increased system vulnerabilities in the very dry climate scenario requires a much more aggressive conservation approach. The per-capita demand stationarity simulation requires over a 35% reduction in average monthly outdoor irrigation use, a significant short-term reduction that could lead to severe economic consequences to end-users (DeOreo, 2006). The dynamic demand simulation only requires an overall 13% reduction in outdoor water use to bring the reservoir requests to historical average levels. This simulation also suggests that a change in the peak reservoir requests from an extended irrigation season could pose additional challenges for system management. This would inform operations that aggressive management action will likely be necessary to address an anticipated increase in September out-of-district requests. While the very dry scenario presents significant operational challenges, a systems approach recognizing non-stationarity in supply and demand provides a more comprehensive vulnerability assessment to base operational decisions.

## 5. Conclusion

These results indicate per-capita demand stationarity in water system forecasts increases the uncertainty of system vulnerabilities. By using dynamic demand forecasts reflecting service area-demand interactions in simulated dry and very dry precipitation scenarios, we find the timing, magnitude, and duration of system vulnerabilities significantly different from those assuming per-capita demand stationarity. The dynamic demand forecasts capture water use behaviors that reduce the duration of peak demands (24 days vs. 61 days), even with greater evapotranspiration rates. The very dry precipitation scenario highlighted greater overall system vulnerability, but by recognizing dynamic drivers to municipal water demands, the duration (114 days) and intensity (55MGD) is much less than when relying on per-capita demand stationarity, 144 days and 89MGD. This results in a 38%, 40%, and 36% reduction in maximum daily, monthly, and total seasonal system vulnerability. Integrating water demand non-stationarity into comprehensive systems analysis advances the insight surrounding water system performance, critical in developing management actions to cope with hydrological droughts and variable climate conditions.

## Acknowledgments

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## Software Availability

CSD-WDM, Version 1.0, Ryan Johnson, Software is in Public Domain, Available starting June 1, 2021, Retrievable at https://github.com/whitelightning450/Water-Demand-Forecasting

 

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