APPENDIX D: POPULATION AND DEMAND FORECAST MEMO AND WATER DEMAND VARIABILITY MEMO

Technical Memorandum

To: Matthew S. Dickens, MPA, Sustainability Manager

From: Thomas W. Chesnutt, Ph.D., PStat™, CAP™ and David M. Pekelney, Ph.D.

Date: Sept. 4, 2026

Re: **Housing Growth Rates and Population Data (Person per Household) for SCV Water Demand Forecasting**

Overview

The water demand forecasting approach deployed by SCV Water is based on a high resolution understanding of historical and current land uses, water demand drivers attached to land uses, and a scenario analysis approach to depicting future demand uncertainties.

The sources of data used for SCV Water demand forecasting include:

- SCV Water History of Meters and Use, 1990-present
- US Bureau of Census 2020 Decennial Census, American Community Surveys (conducted on a 2-3 year times step with 2023 being the most recent for SCV)
- Calif. Dept of Finance annual updates in Tables E-5 and E-8
- County Tax Assessor – Parcel data including parcel area and year built
- So. Cal. Assoc. of Gov. Regional Transportation Plan (RTP 2024) – forecasted housing units and population
- US Bureau of Labor Statistics—estimates of employment and unemployment
- Weather Data: NOAA and CIMIS historical daily weather data on precipitation, maximum air temperature, and evapotranspiration.

The types of data used for SCV Water demand forecasting and described in this technical memorandum can be briefly summarized and include:

Service Connections and Volume – SCV Water curates its service connection/meters and metered volume data from customer service billing records. Any specific water meter is associated with location data that can be associated with specific parcels of land through GIS methods. Each land parcel is associated with land uses.

Housing Units – Estimates for the number of occupied housing units come from the U.S. Bureau of Census (2020 decennial census) and from by the California Department of Finance (derived from census data and state administrative data, annually available Tables E-5 and E-8). Estimates of future housing units are addressed through a scenario analysis that identifies an ultimate build out level for the service area and alternative rates of growth for attaining that buildout level.

Population – Estimates for service area population also derive from the U.S. Bureau of Census 2020 decennial census and annual updates from the California Department of Finance. The Southern California Association of Governments (SCAG) uses both sources to inform it's estimates of local area data and future forecasts.

Data not described in this technical memorandum include, at a minimum, the analysis of planned and possible new developments and phasing, estimates of irrigable area per parcel (DWR 2018 or historically estimated by legacy division), most nonresidential demand determinants (for example, future employment, office building square footage, irrigated area, etc.), determinates of passive conservation (plumbing code), or active conservation (conservation/WUE programs, MWELO, customer response to the increasing price of water), and how customer demand for water will change as a result of climate change.

Historical Housing Unit and Population Data Table Used for Demand Forecasting

Table 1 describes the estimated population (POP), housing units (HU), and persons per housing unit (PPHU) resulting from the analysis of Census Data (2020 decennial and annual updates from Calif. DOF) after DCSE conducted the GIS analysis that joined these data to SCV Water individual parcels. Note that these data can be revised when new evidence is available on individual parcels.

Observations:

1. For the year 2020, the best current estimates of population and housing units differ from the OVOV forecast for 2020. We note that the 2020 Census data was not available for either the OVOV planning effort or the 2020 UWMP. It is not unusual to have forecasts of the future differ from what comes to pass over time. Another reason for the difference is the detailed high resolution GIS analysis that includes SCV Water service area only.
2. The housing unit density (Persons per HU), because of observation 1, also differs for the year 2020.
3. The best estimate of housing unit density (informed by the ACS and Calif. DOF annual extrapolations to local areas) declines from 2020 to 2024 for the SCV retail service area.

Table 1: Summary of Estimated SCV Water Estimated Population, Housing Units, and Persons per Housing Unit

Calibration Zone (Division)	Demographic	2020 CENSUS (Thru 4/2020)	2020 Adj. Census (Thru 12/2020)	2021 Adj. Census	2022 Adj. Census	2023 Adj. Census	2024 Adj. Census
CZ2	*POP*	96,030	95,828	96,178	97,615	97,795	98,328
	HU	33,721	33,788	34,121	34,846	35,129	35,543
	Persons/HU	2.85	2.84	2.82	2.80	2.78	2.77
CZ1	*POP*	51,285	51,090	50,790	50,532	50,702	51,818
	HU	14,489	14,493	14,497	14,513	14,653	15,070
	Persons/HU	3.54	3.53	3.50	3.48	3.46	3.44
CZ3	*POP*	129,771	130,092	132,263	132,023	131,564	132,312
	HU	42,421	42,700	43,681	43,873	43,994	44,523
	Persons/HU	3.06	3.05	3.03	3.01	2.99	2.97
Total SCV Retail (CZ 1-3)	***POP***	**277,086**	**277,010**	**279,231**	**280,169**	**280,061**	**282,459**
	HU	**90,631**	**90,981**	**92,299**	**93,232**	**93,776**	**95,136**
	Persons/HU	**3.06**	**3.04**	**3.03**	**3.01**	**2.99**	**2.97**
LA County 36	*POP*	6,119	6,119	6,119	6,119	6,119	6,119
	HU	1,806	1,762	1,762	1,762	1,762	1,762
	Persons/HU	3.39	3.47	3.47	3.47	3.47	3.47
Total SCV Service Area (=Retail+LA 36)	***POP***	**283,205**	**283,129**	**285,350**	**286,288**	**286,180**	**288,578**
	HU	**92,437**	**92,743**	**94,061**	**94,994**	**95,538**	**96,898**
	Person/HU	**3.06**	**3.05**	**3.03**	**3.01**	**3.00**	**2.98**
OVOV	*POP*	290,911					
	HU	82,787					
	Person/HU	3.51					

Source: DCSE and SCV Water, 8-27-2025

Assumptions for Future Scenarios

Housing Unit Growth Rate Scenarios

To develop a range of long-term housing growth rates for use in demand scenarios, SCV Water staff developed an annual time series of residential parcels (with year of building structures construction), taken from the County Tax Assessor data. From these data, an understanding of historical residential growth can be obtained.

Table 2 below depicts the mean annual growth rate over the decades since 1960. The last row includes the most recent historical 15-year period, 2010 to 2024 inclusive.

Table 2: Summary of Housing Growth By Decade

Summary of Housing Growth By Decade			
Decade of Growth	**Mean Annual Growth Rate**	**Std. Dev. Annual Growth Rates**	**Notes**
1960-1969	21.53%	12.0%	Boom-Boom Early Growth in Valley
1970-1979	5.59%	1.5%	Calmer Growth
1980-1989	7.20%	2.8%	Heats back up
1990-1999	2.70%	1.0%	Cooling growth
2000-2009	2.78%	1.9%	Cool growth
2010-2024	1.02%	0.93%	Recent History (15 years)

This pattern of high mean growth early in the development of the Santa Clarita Valley followed by slowing growth and development cycles suggests that the most recent years may be most informative about housing growth rates in the next 15 to 25 years. Growth rate scenarios were developed from the most recent evidence (the 15 years from 2010-2024, inclusive) where the mean growth rate was 1.02% per year, with growth rate variability characterized by a standard deviation of 0.93%. Thus, a central tendency for future growth is taken from the mean annual growth rate (1.02%) of the most recent historical period (Scenario Name: Historical Growth). A high growth rate scenario that assumes a growth rate one standard deviation higher than the mean (1.02%+0.93%=1.95%) and a low growth scenario that assumes half the mean growth rate were developed. Each growth rate will yield a different future year when full build out occurs.

Table 3 summaries a range of potential residential growth rate scenarios for SCV water demand forecasting. The growth rates presented in the prior 2020UWMP designated 2050 as the year of full build out taken from the range of growth in the One Valley One Vision plan (with the high range of 155,000 housing units). This growth scenario is very close to the "High Growth" scenario defined as one standard deviation higher than mean growth. The "Historical Growth" scenario, used in the Baseline Demand forecast, is close to the Southern California Association of Governments (SCAG) forecast of housing unit growth from the 2024 Regional Transportation Plan (RTP), both of which suggesting a full buildout occurring in the 2070's. The "Slow

Growth" scenario of a half of one percent annual growth implies full build out occurring in the next century. [1]

Table 3. SCV Water Housing Growth Rate (High, Historical, Slow)

Housing Unit Growth Rate Scenarios			
Scenario Name	**25 year CAGR Assumption**	**Buildout Year**	**Percentile**
2020 UWMP (SCV Water Designation from OVOV)	1.81%	2050	80%
High Growth	1.95%	2049	84%
Historical Growth – Baseline Demand Forecast	1.02%	2071	50%
SCAG	0.90%	2077	45%
Slow Growth	0.51%	2117	29%

Population Scenarios

The causal model for the WDF-enacted residential demand forecasts[2] is predicated first on the number of housing units which is then multiplied by the number of persons per housing unit (aka housing density by demographers):

$$Estimated\ Population = HousingUnits \cdot \frac{Persons}{HousingUnit}$$

Consistent with this causal path (first housing units followed by persons per housing unit), population scenarios are specified in terms of persons per housing unit.

Table 4 describes a range of population scenarios, specified in terms of persons per housing unit. The first population growth scenario assumes a constant persons per household equal to the most recent Census-derived estimate (2024 housing stock and estimated population) of 2.97 persons per housing unit. The second population growth scenario derives from the SCAG housing unit growth (0.90% CAGR 2025-2050) and population (0.49% CAGR 2025-2050) forecast and implies a decline to 2.56 persons per housing unit by 2050.

[1]Readers should note that given the uncertainty surrounding future housing growth, the numeric growth rate used when enacted in future demand scenarios may be rounded to 1 digit to the right of the decimal point.

[2] We note that the WDF model has a separate capability to forecast future water demand based directly on population (per capita demand) and employment (per employee demand); that capability is not currently being used at SCV Water.

Table 4. SCV Water Population Scenarios

Population per Housing Unit Scenarios	
Growth Level	Person per Housing Unit
1. 2024 Census-derived estimate of persons per housing unit (used in Baseline Demand Forecast). Constant PPHU Implies that population growth is exactly proportionate to housing unit growth.	Constant at 2.97 PPHU
2. SCAG RTP 2024 forecast of housing unit and population. Housing unit growth (0.9%CAGR) and population growth (0.046%) differ, resulting in a declining PPHU.	Declines to 2.56 PPHU

A & N Technical Services, Inc.

Technical Memorandum

To: Matt Dickens, MPA

From: Thomas W. Chesnutt, Ph.D., CAP™ and David M. Pekelney, Ph.D.

Date: January 14, 2026

Re: **SCV Demand Variability—Annual Effect of Weather upon 1922-2024**

Introduction

For purposes of quantifying water demand variability for using in resource reliability modeling, one must estimate how SCV water demand responds to predictable variations. There are numerous forces that drive demand growth in the long term. These include changes in land use patterns and household size, growth in personal income and employment, and price and conservation. In the short term, weather conditions tend to make water demand go up or down in any given year, in addition to short-term drought or economic shocks (e.g., pandemic).

For use in both WUE planning and resource planning, SCV Water needs depiction of the predictable forces that cause demand to vary in the short term to clarify remaining long-term trends and to calibrate long-term water demand forecasts. This memorandum describes an empirical model developed to predict aggregate demand fluctuations. By nature, these models cannot replace long-term predictive models of water demand. However, by providing a better understanding of short-term demand variations, these models can clarify the direction of long-term trends. The explanatory variables in this short-term model include:

- Deterministic functions of calendar time, including
  - The seasonal shape of demand
- Weather conditions
  - measures of maximum daily temperature, contemporaneous and time of year
  - measures of rainfall, contemporaneous and time of year
- Measures to control for long-term growth in demand
  - Population
  - Trend
  - Employment growth different from the trend

The model documented here is used to create high resolution depictions of how variations in weather and the business cycle affect total water demand—as approximated by system production and normalized by service area population—over a wide range of conditions. These model-estimated weather and employment effects can then be used to (1) normalize observed demand and (2) serve as the basis for defining near term variability of demand and any planning dependent upon the trajectory of long-term demand.

Data and Methods

Data

Water demand in the SCV Water service area is approximated in this analysis as the sum of system production. The reader is urged to keep in mind that though these models may be described as "demand" models, the data on which these models are estimated would be better described as "supply" measures.

The second major issue with using production data is the level and magnitude of noise in the data. The data generating mechanism for recording production can change over time as flow meters age or are replaced. The records of flow can also embed non-ignorable meter mis-measurement. To keep data inconsistencies from corrupting statistical estimates of model parameters, this modeling effort employed a sophisticated range of outlier-detection methods and models.

Specification

A Model of Per Capita Water Demand

The model for SCV Water per capita water demand seeks to separate several important driving forces. In the short run, changes in weather can make demand increase or decrease in a given year. In the long run, increased population can drive demand higher. Strong regional economic growth can increase water demand through additional commercial or industrial water use. In addition, a rising economic tide can broadly increase personal income levels and economic activity can encourage or discourage additional population growth. Changes in water rates will change the relative attractiveness of water conservation.

These models are estimated at an aggregate level and, as such, should be interpreted as a condensation of many types of relationships — meteorological, physical, behavioral, managerial, legal, and chronological. Nonetheless, these models depict key short-run and long-run relationships and should serve as a solid point of departure for improved quantification of these linkages.

Systematic Effects

This section specifies a water demand function that has several unique features. First, it models seasonal and climatic effects as continuous (as opposed to discrete monthly, semi-annual, or annual) function of time. Thus, the seasonal component in the water demand model can be specified on a continuous basis, then aggregated to a level comparable to measured water use (e.g. monthly). Second, the climatic component is specified in “difference” form as a similar continuous function of time. The climate measures are thereby made independent of the seasonal component. Third, the model permits interactions of the seasonal component and the climatic component. Thus, the season-specific response of water use can be specific to the season of the year.

The general form of the model is:

Equation 1

$$PerCapitaWaterUse_t[GPCD] = \frac{Use_t}{Pop_t} = f(S_t + C_t + T_t)$$

where ***Use*** is the volumetric quantity of water use within time *t*, ***Pop*** is the annual service area population at time *t*, $\boldsymbol{S_t}$ is a seasonal component, $\boldsymbol{C_t}$ is a climatic component, and $\boldsymbol{T_t}$ is the trend component of GPCD Demand. The function *f* is the functional form of the connection between per capita water use and its explanatory components. Each of these components is described below.

Seasonal Component: A monthly seasonal component could be formed using monthly dummy variables to represent a seasonal step function. Equivalently, one may form a combination of sine and cosine terms in a Fourier series to define the seasonal component as a continuous function of time.[1] The following harmonics are defined for a given day *T*, ignoring the slight complication of leap years:

Equation 2

$$S_t \equiv \sum_{1}^{6}\left[\beta_{i,j} \cdot \sin\left(\frac{2\pi \cdot jT}{365}\right) + \beta_{i,j} \cdot \cos\left(\frac{2\pi \cdot jT}{365}\right)\right] = Z \cdot \beta_S$$

where *T* = (1,...365) and *j* represents the frequency of each harmonic. Because the lower frequencies (annual and semiannual) tend to explain most of the seasonal fluctuation, the higher frequencies (say, bimonthly) can often be omitted with little predictive loss.

The percentage effect of the seasonal component on normal demand is given by:

Equation 3

$$S_t\% = \left[\frac{\exp(\widehat{Y}_t - T_t) - \exp(\widehat{Y}_t - T_t - S_t)}{\exp(\widehat{Y}_t - T_t - S_t)}\right]$$

[1] The use of a harmonic representation for a seasonal component in a regression context dates back to *Hannan* [1960]. *Jorgenson* [1964] extended these results to include least squares estimation of both trend and seasonal components.

where $\widehat{Y}$ is the predicted demand.

Climatic Component: The model incorporates two types of climate measures into the climatic component–rainfall and evapotranspiration. [2] The measures of rainfall and evapotranspiration are then logarithmically transformed to yield:

Equation 4

$$R_t \equiv ln\left[1 + \sum_{t=T}^{T_d} Rain_t\right], ET_t \equiv ln\left[\sum_{t=T}^{E_d} ET_d\right]$$

Though this model extends to monthly measures, for daily measures, *d* takes on the value of one. Because weather exhibits strong seasonal patterns, climatic measures are strongly correlated with the seasonal measures. In addition, the occurrence of rainfall can reduce expected temperature. To obtain valid estimates of a constant seasonal effect, the seasonal component is removed from the climatic measures by construction.

Specifically, climatic measures are constructed as a departure from their "normal" or expected value at a given time of the year. The expected value for rainfall during the year, for example, is derived from regression against the seasonal harmonics. The expected value of the climatic measures ($\hat{\boldsymbol{C}}=\boldsymbol{Z}\cdot\beta_C$) is subtracted from the original climatic measures:

Equation 5

$$C_t \equiv (R_t - \widehat{R}_t)\cdot\beta_R + (E_t - \widehat{E}_t)\cdot\beta_T$$

The climatic measures in this deviation-from-mean form are thereby separated from the constant seasonal effect. [3] Thus, the seasonal component of the model captures all constant seasonal effects, as it should, even if these constant effects are due to normal climatic conditions. The remaining climate measures capture the effect of climate departing from its normal pattern.

The model can also specify a richer texture in the temporal effect of climate than the usual fixed contemporaneous effect. Seasonally-varying climatic effects can be created by interacting the climatic measures with the harmonic terms. In addition, the measures

[2] Specifically, it uses the total daily precipitation at the Newhall Station 32c (1927-Current) summed to a monthly level. Daily Evapotranspiration/Maximum Air Temperature come from CIMIS Station 204 (Dec. 11 2006-Current) and is also summed to a monthly level. Missing daily values are filled with predictive models using the NOAA Los Angeles Downtown station (WBAN USW00093134).

[3] The logarithmic transformation of the original climate variable implies that the seasonal mean climate effect is a geometric mean. Because the model is estimated on the logarithmic scale the departure-from-mean climatic effects would be more accurately termed departure-from-median. See *Goldberger* [1968].

can be constructed to detect lagged effects of climate, such as the effect of rainfall a month ago on today's water demand.

For applications of the estimated model, the predicted effect of climate on demand on the *log* scale is the difference between predicted demand conditional on actual rainfall and evapotranspiration ($\widehat{Y}$) and the predicted demand conditional on seasonally normal rainfall and evapotranspiration ($\widehat{Y} \mid \hat{\mathbf{C}}$). The predicted effect on the *raw* scale of system GPCD demand[4] is:

Equation 6

$$Monthly\ Weather\ Effect\ (raw\ scale) = \left[\exp\left(\widehat{Y}\right) - \exp(\widehat{Y} \mid \hat{C})\right]$$

These monthly weather effects can be summed for each year and converted to a percentage annual weather effect.

Trend Component : For the SCV Water Demand model, a deterministic annual trend term was used as the primary determinant of trends in per capita water demand in the long term.

Equation 7

$$\boldsymbol{T}_t \equiv AnnualTrend_t \cdot \beta_{Trend} + (ln\,E\,mpDetrended) \cdot \beta_{Emp}$$

Thus, the annual long-term trend in SCV Water Demand from 1995-2023 is captured by β_T while the effects of the business cycle are captured by β_{Emp} the departure of employment from its long-term trend.

Stochastic Effects

To complete the model, we must account for the fact that not every data point will lie on the plane defined by Equation **(1)**. This fundamental characteristic of all systematic models can impose large inferential costs if ignored. Misspecification of this "error component" can lead to inefficient estimation of the coefficients defining the systematic forces, incorrect estimates of coefficient standard errors, and an invalid basis for inference about forecast uncertainty. The specification of the error component involves defining what departures from pure randomness are allowed. What is the functional form of model error? Just as the model of systematic forces can be thought of as an estimate of a function for the "mean" or expected value, so too can a model be developed to explain departures from the mean—i.e., a "variance function" If the vertical distance from any observation to the plane defined by **(1)** is the quantity $\boldsymbol{\varepsilon}$, then the error component is added to Equation **(1)**:

[4] Note that any second order correction to the predicted demand will drop out in the subtraction between the two exponentiated conditional demand predictions.

Equation 8

$$\ln \frac{Use}{Pop} = \boldsymbol{f}(\boldsymbol{S}_t, \boldsymbol{C}_t, \boldsymbol{T}_t) + \varepsilon$$

A variance function is specified where the error is allowed to have a nonconstant variance and skewedness: the equation error is allowed to vary as a function of season, weather, and trend.

$$\varepsilon \sim N(0, \sigma_\varepsilon)$$

$$\sigma_\varepsilon = \mathbf{g}((\boldsymbol{S}_t, \boldsymbol{C}_t, \boldsymbol{T}_t) + \eta$$

$$\eta \sim N\left(0, \sigma_\eta\right)$$

The estimation method is a two stage Weighted Least Squares (WLS) regression. [5] An estimate of the equation error is obtained in a first stage least squares regression. The absolute value of first stage estimated error is then regressed on seasonal, weather, and trend variables. Readers should note that this specification allows detection of increasing demand variability over time and in periods of large weather departures from normal. The reciprocal of the predicted absolute error is then used to weigh the observations of the second stage regression.

Estimated Per Capita Demand Model for SCV Water

Table 1 presents the estimation results for the model of mean monthly per capita system demand in SCV Water. Interpretation of the model follows Table 1.

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[5] This method follows Carroll and Rupert (1988) *Transformation and Weighting in Regression,* Chapman and Hall, page 79-83.

Table 1—Estimated Model of SCV Water Demand Mean

Estimated Model of SCV Water Demand Mean Dependent Variable: Ln SCV Water Per Capita Use (Gl. Per Capita Per Day)		
Independent Variable	**Coefficient**	**Std. Error**
1. Overall Annual Trend 1995 – 2024 (1996=1, 1997=2,...)	-0.01579	0.00055
2. Deviation of ln(Employment, Santa Clarita City) from Trend	0.46990	0.04541
3. First Sine harmonic, 12 month (annual) frequency	-0.22094	0.00647
4. First Cosine harmonic, 12 month (annual) frequency	-0.41766	0.00634
5. Second Sine harmonic, 6 month (biannual) frequency	-0.01494	0.00654
6. Second Cosine harmonic, 6 month (biannual) frequency	-0.01799	0.00629
7. Third Sine harmonic, 4/12 frequency	0.00814	0.00667
8. Third Cosine, 4/12 frequency	0.00729	0.00678
9. Fourth Sine harmonic, 3 month (quarterly) frequency	0.01849	0.00712
10. Fourth Cosine, 3 month (quarterly) frequency	-0.00664	0.00729
11. Contemporaneous Rainfall Deviation [(ln (Rain+1)) – Monthly mean], Newhall Station 32c	-0.14667	0.01391
12. Rainfall Deviation [(ln (Rain+1)) – Monthly mean], Newhall Station 32c, Lag 1 Month	-0.07458	0.00871
13. Rainfall Deviation [(ln (Rain+1)) – Monthly mean], Newhall Station 32c, Lag 2 Months	-0.01957	0.00851
14. Interaction of contemporaneous rain with annual sine harmonic	-0.01255	0.01548
15. Interaction of contemporaneous rain with annual cosine harmonic	0.03532	0.01851
16. Contemporaneous deviation from mean ln (MaxTemp), CIMIS 204, in the month	0.60025	0.09768
17. Interaction of contemporaneous MaxTemp deviation with annual sine harmonic	0.35023	0.13213
18. Interaction of contemporaneous MaxTemp deviation with annual cosine harmonic	0.21142	0.14082
19. Indicator variable for 2015-16 Drought Emergency Mandate	-0.18780	0.02536
20. Indicator variable for 2016-17 Drought Self Certification	-0.12353	0.02826
21. Indicator variable Pandemic Effects in CY 2020	0.03001	0.02718
22. Indicator variable Executive Order, Jan. 2022 to Dec. 2022	-0.06553	0.02690
23. Intercept	5.61757	0.00823
Obs	360	
R^2	0.9573	
Adj R-Squared	0.9546	
Root Mean Squared Error	0.07838	
Time period (Fiscal Years)	Jan. 1995 – Dec. 2024	

Table 2—Estimated Model of SCV Water Demand Variance

Estimated Model of SCV Water Demand Variance Dependent Variable: absolute value of first stage estimated error		
Independent Variable	**Coefficient**	**Std. Error**
1. Overall Annual Trend 1995 – 2024 (1996=1, 1997=2,...)	0.000914	0.000308
2. Deviation of ln(Employment, Santa Clarita City) from Trend	-0.061393	0.029402
3. First Sine harmonic, 12 month (annual) frequency	0.016383	0.003798
4. First Cosine harmonic, 12 month (annual) frequency	0.016278	0.003804
5. Second Sine harmonic, 6 month (biannual) frequency	0.004357	0.003918
6. Second Cosine harmonic, 6 month (biannual) frequency	-0.000998	0.003942
7. Third Sine harmonic, 4/12 frequency	0.000088	0.004138
8. Third Cosine, 4/12 frequency	-0.007687	0.004184
9. Fourth Sine harmonic, 3 month (quarterly) frequency	-0.008974	0.004491
10. Fourth Cosine, 3 month (quarterly) frequency	-0.005931	0.004546
11. Contemporaneous Rainfall Deviation [(ln (Rain+1)) – Monthly mean], Newhall Station 32c	0.019564	0.004863
12. Intercept	0.053146	0.005204
Obs	360	
R^2	0.177	
Adj R-Squared	0.151	
Root Mean Squared Error	0.05037	
Time period (Fiscal Years)	Jan. 1995 – Dec. 2024	

Demand Trends

The first independent variable is an annual trend term (taking on the value 0 for 1995, the value 1 for 1996, the value 2 for 1997, etc.). The estimated coefficient on the annual trend term, $\widehat{\beta_{Trend}}$, is negative and implies an overall decline in per capita system demand of about 1.58 percent per year after controlling for weather and employment variation. [6] Declining per capita demand has been occurring across the U.S. for the last several decades, so SCV Water's experience should be no surprise. [7] The departure of employment growth from trend (Variable 2) [8] and the annual trend term (Variable 1)

[6] The dependent variable uses total system production divided by estimated annual retail population and thus is inclusive of SCV Water's programs to reduce system loss.
[7] See Beecher, J.A. and T.W. Chesnutt, *Declining Sales and Water Utility Revenues: A Framework for Understanding and Adapting.* A White Paper for the Alliance for Water Efficiency National Water Rates Summit –Racine, Wisconsin, October 24, 2012.
[8] We used the Santa Clarita City employment from the Bureau of Labor Statistics (BLS Series Id: LAUCT066908800000005) regressed on the annual trend variable. The residual from the regression equations constitutes the departure of employment from its long-term trend. This 2-Stage Linear Regression (2SLR) partitions the explanation of causal forces from employment: the long-term effects of employment on per capita system demand will be captured by the trend

comprise the long term determinants of per capita system demand trends. The coefficient $\widehat{\beta_{Emp}}$ on employment variation from trend (business cycle) is positive, indicating that employment growth during boom times is associated with higher system GPCD and employment below trend during recession periods is associated with lower system GPCD.

Readers should note that the long-term effect of employment growth in the Valley is but one of the long-term causal forces absorbed by the coefficient on the annual trend (Variable 1). Because employment growth is associated with CII water demand, the causal force would be expected to be positive on GPCD demand (everything else held constant.) Additional causal forces in a downward direction on GPCD demand would include the effects of passive conservation (plumbing code and efficiency standards) and active conservation (WUE programs, system loss control, and the effect of price). [9]

Seasonal Variability

The independent variables 3 to 10—made up of the sines and cosines of the Fourier series described in Equation 2—are used to depict the seasonal shape of GPCD water demand (that is, $S_t = Z \cdot \hat{\beta}_S$); this is the shape of demand in a normal weather year. This seasonal shape is important in that it represents the point of departure for the estimated climate effects (expressed as departure from what is expected in an average month).

Weather Variability

The estimated weather effect is specified in "departure-from-normal" form. Variable 11 is the departure of monthly precipitation from the average precipitation for that month in the season. (Average seasonal precipitation is derived from a regression of monthly precipitation on the seasonal harmonics—exactly equal to monthly precipitation averaged over all years in the record.) Evapotranspiration is treated in an analogous fashion (Variable 16). The contemporaneous weather effects are interacted with the harmonics (Variables 14, 15, 17, and 18) to produce a seasonal shape to both the rainfall and the temperature elasticities. Thus, departures of evapotranspiration from normal produce the largest percentage effect in the spring growing season. Similarly, departures from normal rainfall produce a larger effect upon demand in the summer than in the winter. Lagged effects of precipitation, a one-month lag and a two-month lag, were estimated (Variables 12 and 13).

Drought Emergency and Pandemic Effects

Binary indicators are used to capture customer demand response to the drought emergency (Variables 19 and 20). The indicator variable for 2015-16 Drought Emergency Mandate takes on the value 1 between June 2015 and June 2016 and is zero

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term and the business cycle effects of strong growth and recession are captured by the departure of employment from the long-term deterministic trend, by construction.

[9] Additional causal forces would include increasing household income, a positive force on GPCD consumption as customers can add to the stock of water-using equipment (spas and pools).

elsewhere. The estimated coefficient for this period of state ordered mandatory curtailment targets shows a 18.8 percent reduction in GPCD demand. The Indicator variable for 2016-17 Drought "Self-Certification"—described as a voluntary target by the state but surrounded by state-wide and regional mass media campaigns—shows a still significant 12.4 percent decline from expected GPCD demand.

We used indicator variables for calendar years 2020 in an attempt to detect a work-from-home response to the global pandemic. We were able to detect a significant uptick in 2020 (the coefficient on Variable 21 suggests about 3 percent) [10], but this overall effect did not appear to persist in subsequent years in part due to the statewide Executive Order calling for voluntary conservation (beginning July 1 2021 and ending Dec. 31, 2022.) The effect Executive Order in 2021 appears to offset any Pandemic uptick, but is detectable in 2022 at approximately 6.5 percent.

The constant term (Variable 23) describes the intercept for this equation.

[10] This is consistent with the residential work-from-home effect outweighing any reduction in CII and irrigation demand in the heavily residential SCV Water service area.

Figure 1 plots actual SCV Water Per Capita Demand against the model predictions ($\hat{Y}$) and reveals a very tight fit of predictions to actual. The adjusted R squared statistic suggests that almost 96 percent of the variation around per capita system demand is explained by the model.

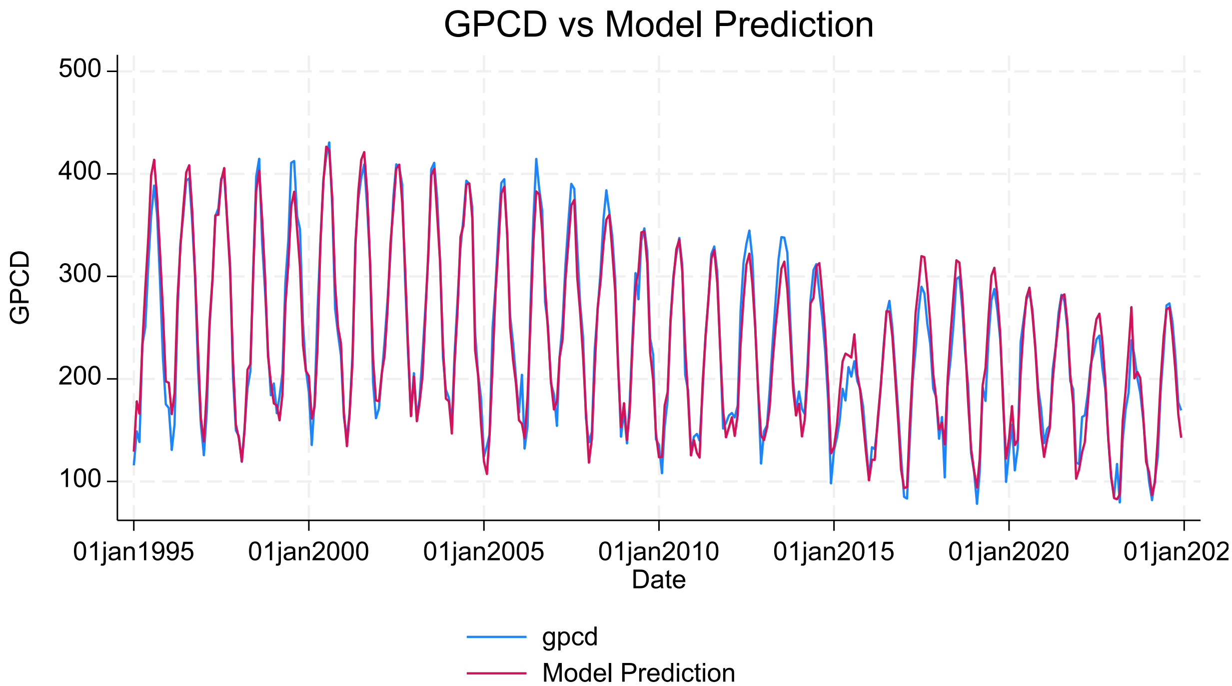

Figure 1—SCV Water Per Capita Demand (GPCD): Actual vs. Model Prediction, Jan. 1995 – Dec. 2024

Application to the Historical Effect of Weather on SCV Demand Variability

From the statistically estimated model documented above, one can calculate the effect of weather on per capita water demand as the difference between two predictions: a prediction of demand conditional on actual weather and a prediction of demand "as if" weather were normal (that is, centered on its historical average). [11] Equation 6 specifies this relationship in percentage terms. Figure 2 presents a histogram and Figure 3 present a time plot of the estimated annual effect of Weather upon SCV Water Demand.

[11] Normal weather is defined as the average values of each weather variable in each month over the period of record 1922-2024.

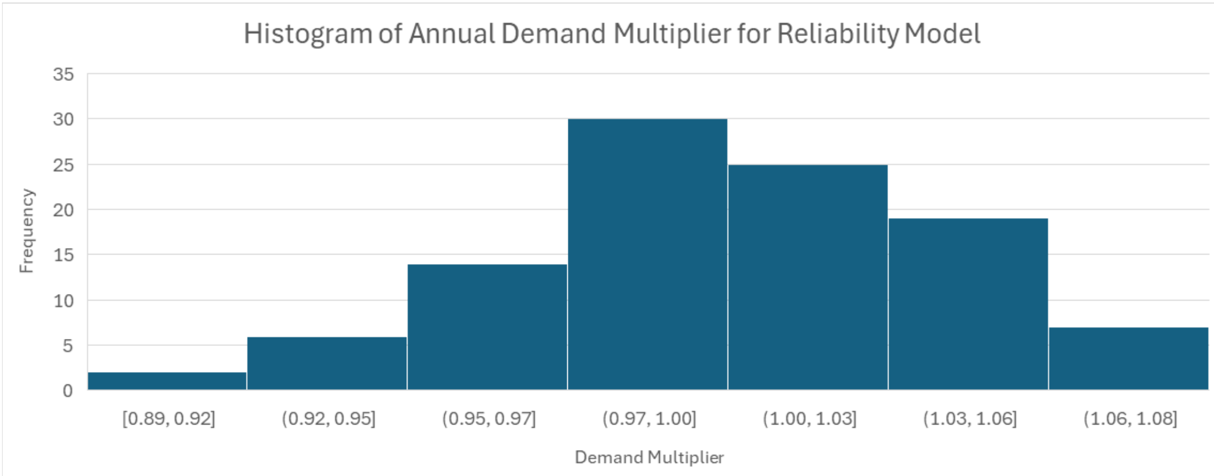

Figure 2—Histogram of the Estimated Annual Effect of Weather on SCV Water Demand, 1922-2024

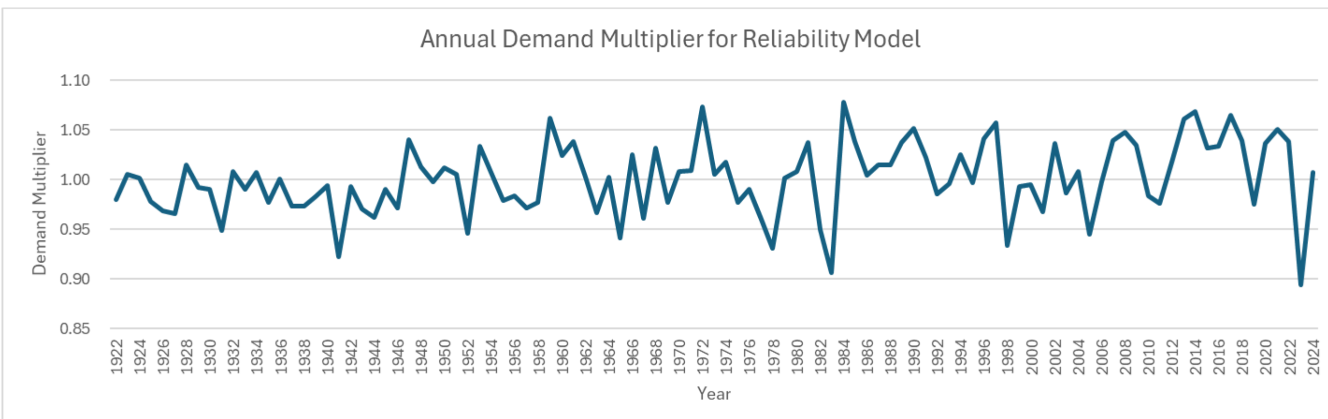

Figure 3—Estimated Annual Effect of Weather on SCV Water Demand Over Time, 1922-2024

Table 3 presents the tabular form of this estimated effect of weather over the historical period, the three year moving average, and the 5 year moving average.

Table 3—Effect of Weather on SCV Water Demand (GPCD)

Effect of Weather on SCV Demand			
Year	Annual Effect of Weather on SCV Demand	3-Year Moving Average	5-Year Moving Average
1922	0.9799		
1923	1.0052		
1924	1.0019	0.9957	
1925	0.9781	0.9950	
1926	0.9688	0.9829	0.9868
1927	0.9657	0.9709	0.9839
1928	1.0148	0.9831	0.9858
1929	0.9920	0.9908	0.9839
1930	0.9904	0.9991	0.9864
1931	0.9490	0.9772	0.9824
1932	1.0081	0.9825	0.9909
1933	0.9906	0.9826	0.9860
1934	1.0067	1.0018	0.9890
1935	0.9767	0.9914	0.9862
1936	1.0008	0.9948	0.9966
1937	0.9731	0.9836	0.9896
1938	0.9734	0.9825	0.9862
1939	0.9822	0.9763	0.9813
1940	0.9941	0.9832	0.9847
1941	0.9222	0.9662	0.9690
1942	0.9933	0.9699	0.9730
1943	0.9708	0.9621	0.9725
1944	0.9624	0.9755	0.9686
1945	0.9897	0.9743	0.9677
1946	0.9710	0.9744	0.9775
1947	1.0404	1.0004	0.9869
1948	1.0128	1.0081	0.9953
1949	0.9976	1.0169	1.0023
1950	1.0119	1.0074	1.0067
1951	1.0050	1.0048	1.0135
1952	0.9462	0.9877	0.9947
1953	1.0333	0.9948	0.9988

1954	1.0072	0.9956	1.0007
1955	0.9785	1.0063	0.9940
1956	0.9839	0.9899	0.9898
1957	0.9709	0.9778	0.9948
1958	0.9773	0.9774	0.9836
1959	1.0618	1.0033	0.9945
1960	1.0244	1.0212	1.0037
1961	1.0383	1.0415	1.0145
1962	1.0026	1.0218	1.0209
1963	0.9669	1.0026	1.0188
1964	1.0028	0.9907	1.0070
1965	0.9415	0.9704	0.9904
1966	1.0251	0.9898	0.9877
1967	0.9607	0.9757	0.9794
1968	1.0313	1.0057	0.9923
1969	0.9773	0.9898	0.9872
1970	1.0085	1.0057	1.0006
1971	1.0090	0.9983	0.9974
1972	1.0734	1.0303	1.0199
1973	1.0054	1.0293	1.0147
1974	1.0172	1.0320	1.0227
1975	0.9767	0.9998	1.0164
1976	0.9903	0.9947	1.0126
1977	0.9597	0.9755	0.9899
1978	0.9303	0.9601	0.9748
1979	1.0018	0.9639	0.9718
1980	1.0082	0.9801	0.9781
1981	1.0370	1.0157	0.9874
1982	0.9497	0.9983	0.9854
1983	0.9062	0.9643	0.9806
1984	1.0778	0.9779	0.9958
1985	1.0379	1.0073	1.0017
1986	1.0043	1.0400	0.9952
1987	1.0147	1.0190	1.0082
1988	1.0149	1.0113	1.0299
1989	1.0369	1.0222	1.0218
1990	1.0514	1.0344	1.0245
1991	1.0222	1.0369	1.0280
1992	0.9851	1.0196	1.0221
1993	0.9962	1.0012	1.0184
1994	1.0248	1.0020	1.0159
1995	0.9969	1.0059	1.0050

1996	1.0408	1.0208	1.0087
1997	1.0570	1.0316	1.0231
1998	0.9334	1.0104	1.0106
1999	0.9931	0.9945	1.0042
2000	0.9948	0.9738	1.0038
2001	0.9679	0.9853	0.9892
2002	1.0364	0.9997	0.9851
2003	0.9867	0.9970	0.9958
2004	1.0077	1.0103	0.9987
2005	0.9449	0.9798	0.9887
2006	0.9981	0.9836	0.9948
2007	1.0391	0.9940	0.9953
2008	1.0479	1.0284	1.0075
2009	1.0345	1.0405	1.0129
2010	0.9837	1.0220	1.0207
2011	0.9757	0.9980	1.0162
2012	1.0176	0.9924	1.0119
2013	1.0606	1.0180	1.0144
2014	1.0688	1.0490	1.0213
2015	1.0320	1.0538	1.0309
2016	1.0339	1.0449	1.0426
2017	1.0647	1.0435	1.0520
2018	1.0387	1.0458	1.0476
2019	0.9751	1.0262	1.0289
2020	1.0361	1.0166	1.0297
2021	1.0502	1.0204	1.0329
2022	1.0381	1.0414	1.0276
2023	0.8939	0.9940	0.9987
2024	1.0072	0.9797	1.0051
Std. dev. 1922-2024	3.62%		
Std. dev. 1995-2024	4.17%		

Note that the variation of the percentage annual effect of weather is summarized at the bottom of the table and is useful for risk analysis. The standard deviation of annual weather effects, taken over the years 1922-2024, is about 3.6 percent. Applying additional distributional assumptions (normality and stationarity [12]), then 1.96 standard deviations to either side would define an interval expected to contain about 95% of the observed data: about 7.2 percent either way in any year *assuming* weather is

[12] Climate is increasingly recognized as a non-stationary processes, meaning that the statistical properties of climate variables, such as mean and variance, change over time.

"stationary".[13] The cool and wet weather in 2023 yielded an effect of weather on system demand of -11 percent, about 3 standard deviations out. While this is very surprising by historical standards of 1922-2024, it may be only somewhat surprising in the future with increased variability of long-term climate. An empirical basis for defining the point of departure for weather variability will be handy for the resource reliability modeling that depicts possible futures in the SCV Water service area.

[13] Readers with familiarity with the literature on global climate change know that the assumption of a "stationary" weather generating function has been repeatedly rejected by empirical evidence. The literature focuses on how to integrate non-stationary into adaptive planning for climate change. For a recent example see Schlef et al., "Incorporating non-stationarity from climate change into rainfall frequency and intensity-duration-frequency (IDF) curves" *Journal of Hydrology,* January 2023, https://doi.org/10.1016/j.jhydrol.2022.128757

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