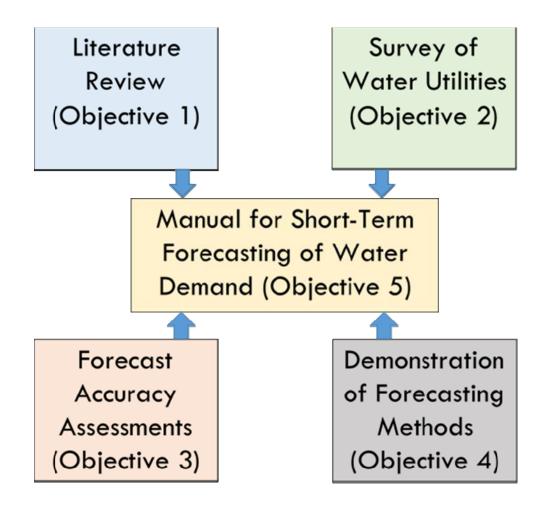
Analysis of the Effectiveness of Short-term Demand Forecasting and Recommendations for Improvement (Project 4501)

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Project 4501 Objectives



Manual for Short-Term Forecasting of Water Demand

Choosing a Forecasting Approach

Implementing a Viable Approach

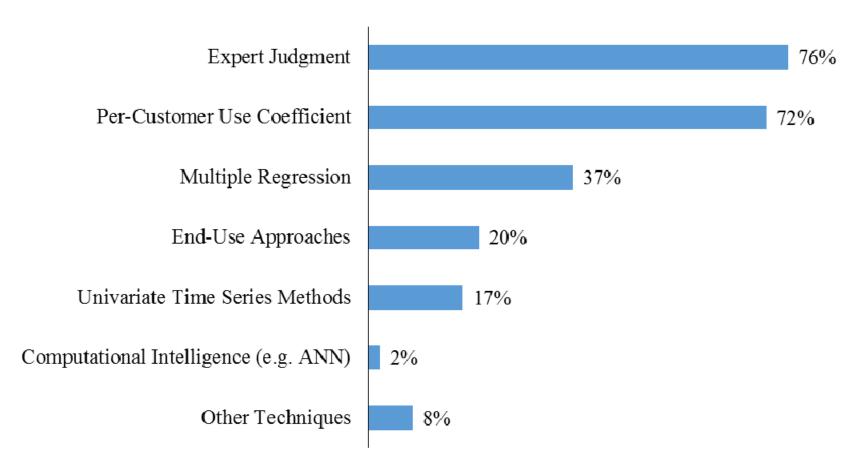
Evaluating the Forecasting Approach

Choosing a Forecasting Approach

Common forecasting techniques

- Expert Judgment
- Per-Unit Use Coefficient
- Multiple Regression Models
- End-Use Models
- Univariate Time Series Methods
- Computational Intelligence Techniques
- Hybrid Approaches

Use of forecasting methodologies by surveyed water utilities



Factors to consider in choosing a forecasting method

- Accuracy track record for each forecasting approach
- Forecast horizon
- Data availability
- Complexity of the forecasting approach
 - Data, staff, and computational requirements
- Importance to the organization of accurate forecasts
- Organizational goals in forecasting
 - Prediction
 - Analyzing scenarios & alternative policies

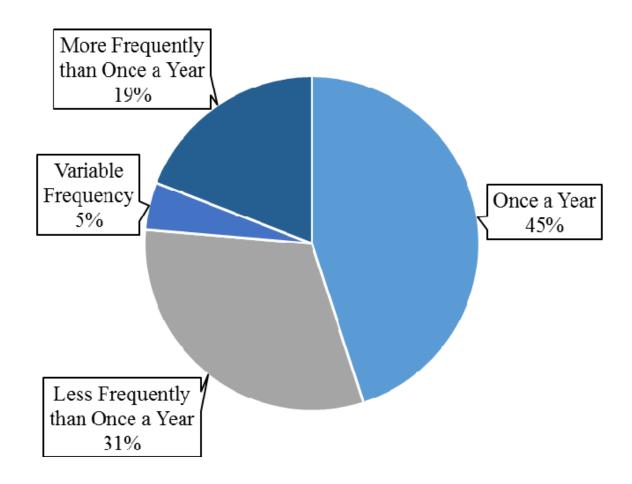
Is it important to quantify causal relationships between water consumption and other key variables? No Is it critical to understand the long-term effects of changes in the stock and utilization of water-consuming appliances? Are survey data available? End-use Multiple regression/ Econometric Time Series Are adequate historical time series data available for local water consumption? No Are there advantages to accounting for the effects of other variables on water use? Is it practical to employ advanced computer software? Computational intelligence Judgmental Univariate time series

Implementing a Viable Forecasting Approach

Non-methodological factors to consider in developing a forecast

- Sample size
- Data quality issues
 - Measurement of key variables
 - Handling of missing/unreliable data
- Level of aggregation
 - Across customer categories
 - Across geographical areas
 - Customer base & water demand per customer
- Vintage of data used for forecasting

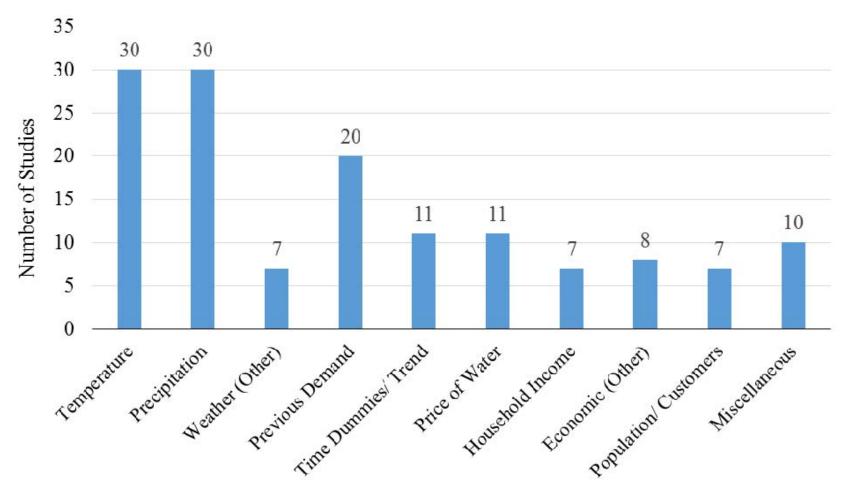
Frequency of forecast re-estimation or updating by water utilities



Historical water demand modeling (en route to developing a forecast)

- Water demand is influenced by factors such as:
 - Price of water
 - Weather conditions
 - Economic conditions
 - Other factors (non-price conservation measures, efficiency of water-using devices, etc.)

Variables used in 53 published studies for short-term forecasting



Linear Transfer Function (LTF) Estimation Methodology:

 Demand is first modeled as a function of lagged values of explanatory variables.

 Any unexplained systematic variation in demand is then modeled using autoregressive (AR) and moving average (MA) parameters.

Estimated LTF Equations for Phoenix: Per-Customer Water Usage

Dependent Variables ->	Single-Family Res.	Multi-Family Res.	Non-Residential
Constant	0.188	-0.010	3.067**
Average Price t	-2.699*	-15.298*	-39.146**
Cooling Degree Days t-1	0.005**	0.037**	0.062**
Days with Rainfall t	-0.099*		-1.563**
Econ. Conditions Index t-11	0.227*		
Rental Vacancy Rate t-11		-1.509*	
Unemployment Rate _{t-15}			-6.063*
AR _{t-1}	-0.593**		-0.481**
AR _{t-8}	-0.342**		
AR _{t-12}		-0.354**	
MA _{t-1}		-0.981**	
MA _{t-4}			-0.581**
R-Squared	0.595	0.691	0.572
F-Statistic	13.482**	23.302**	10.712**

^{*} Probability value <.05; ** Probability value <.01

Estimated LTF Equations for Phoenix: Number of Water Customers

Dependent Variables →	Single-Family Res.	Multi-Family Res.	Non-Residential
С	46.195	12.891	-20.237
Nonfarm Employment _{t-11}	38.122		
Nonfarm Employment _{t-14}			7.926*
Multi-Fam. Housing Starts _{t-15}		0.064**	
AR _{t-2}		-0.549**	
MA _{t-1}	-0.512**		
MA _{t-2}		0.805**	
R-Squared	0.173	0.323	0.080
F-Statistic	5.978**	7.934**	4.775*

^{*} Probability value <.05; ** Probability value <.01

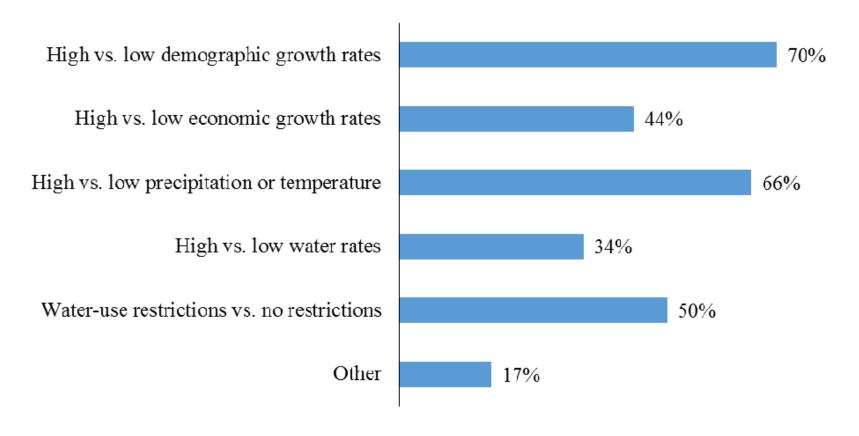
Estimated LTF Equations for El Paso: Customer Base & Per-Customer Usage

Dependent Variable →	Per-Customer Usage	Customers
Constant	0.002	345.198**
Average Price _{t-3}	-2.899**	
Days over 90°F _t	0.089**	
Days over 90°F _{t-1}	0.131**	
Rainfall _{t-1}	-0.396**	
Nonfarm Employment _t	0.121**	
Nonfarm Employment _{t-32}		42.440**
AR _{t-12}	-0.295**	0.369**
AR _{t-18}		-0.175**
MA _{t-1}	-0.706**	-0.299**
MA _{t-3}		0.157*
MA _{t-12}	-0.265**	
R-Squared	0.702	0.237
F-Statistic	59.808**	10.602**

Scenarios & Counterfactuals

- The coefficient estimates in the preceding tables can be used to develop various alternative scenarios, such as the following:
 - What happens if there is a drought?
 - What happens to demand if rates increase?
 - What rate change would be necessary to achieve a given conservation target?
- A counterfactual is similar but asks what would have occurred in the past if some key factor had been different.

Types of scenarios considered by water utilities



Counterfactual example: What would have happened to demand in El Paso if prices had not increased in 2004?



Evaluating the Forecasting Approach

Evaluation methodologies used to assess forecast accuracy:

Criteria based on the size of the forecast error:

- Root Mean Squared Error (RMSE)
- Forecast error differential regression test
 - H₀: Both sets of forecasts are equally accurate

Criteria for evaluating directional accuracy:

- Chi-square test
 - H₀: Forecasted and actual events are independent (i.e. forecasts don't provide useful information for predicting the direction of change)

Summary of Accuracy Results for Utility-Generated Forecasts

- Forecasts were collected from 5 utilities, located in Florida, Texas, Arizona, California, and Australia (numbered to protect anonymity).
- Utility forecasts are compared to random walk alternatives to assess relative accuracy.
- Forecasts are disaggregated in different ways (e.g. by step-length, by geography, by customer class)
- For one utility, there were not enough observations to conduct statistical accuracy tests.

Utility Forecast Accuracy Summary: Root Mean Squared Error (RMSE)

#	Horizon (Freq.)	Methodology	Utility % Better
1	2 Weeks (Daily)	Regression with weather and demographic explanatory variables and lagged demand	71%
2	1 Week (Weekly)	Regression with weather explanatory variables and lagged demand	100%
3	1 Year (Monthly)	Econometric model including price, weather, employment, unemployment rate, and lagged demand	75%
4	2 Years (Monthly)	Expert judgment taking into account climatic & economic conditions	0%
5	4 Years (Annual)	End-use model based on survey data, and data on demographic trends, prices, and conservation policies	0%

Utility Forecast Accuracy Summary: Error Differential Regression Test

#	Horizon (Freq.)	Methodology	% Significantly Better
1	2 Weeks (Daily)	Regression with weather and demographic explanatory variables and lagged demand	29%
2	1 Week (Weekly)	Regression with weather explanatory variables and lagged demand	83%
3	1 Year (Monthly)	Econometric model including price, weather, employment, unemployment rate, and lagged demand	50%
4	2 Years (Monthly)	Expert judgment taking into account climatic & economic conditions	0%
5	4 Years (Annual)	End-use model based on survey data, and data on demographic trends, prices, and conservation policies	NA

Utility Forecast Accuracy Summary: Chi-Square Test of Independence

#	Horizon (Freq.)	Methodology	% Significant
1	2 Weeks (Daily)	Regression with weather and demographic explanatory variables and lagged demand	57%
2	1 Week (Weekly)	Regression with weather explanatory variables and lagged demand	78%
3	1 Year (Monthly)	Econometric model including price, weather, employment, unemployment rate, and lagged demand	75%
4	2 Years (Monthly)	Expert judgment taking into account climatic & economic conditions	0%
5	4 Years (Annual)	End-use model based on survey data, and data on demographic trends, prices, and conservation policies	NA

Questions?