SUSTAINABLE Water Management Conference

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Integrating Water Efficiency Standards and Codes into Long-Term Demand Forecasting

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PACIFIC INSTITUTE

Water Research Foundation

Report #4495 (Forthcoming)

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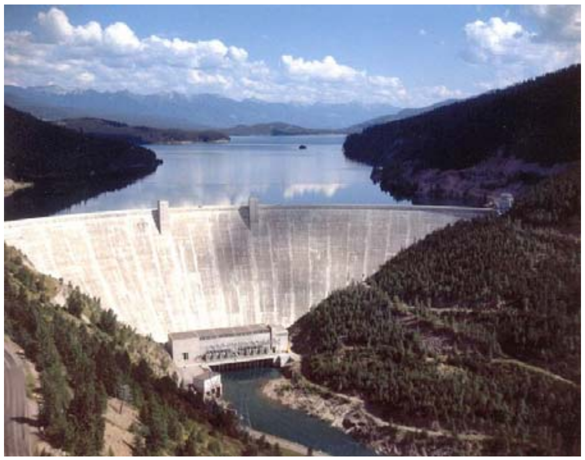
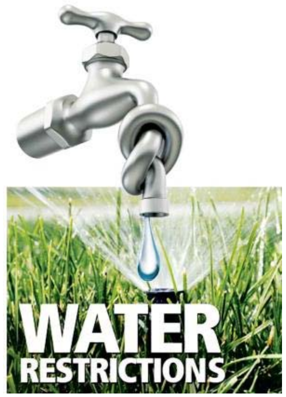
Outline

- Demand Forecasting Overview
- Efficiency Standards and Codes
- Stock Modeling
- Collecting and Incorporating Data
- Characterizing Uncertainty
- Guidance and Recommendations

Water Demand Forecasting





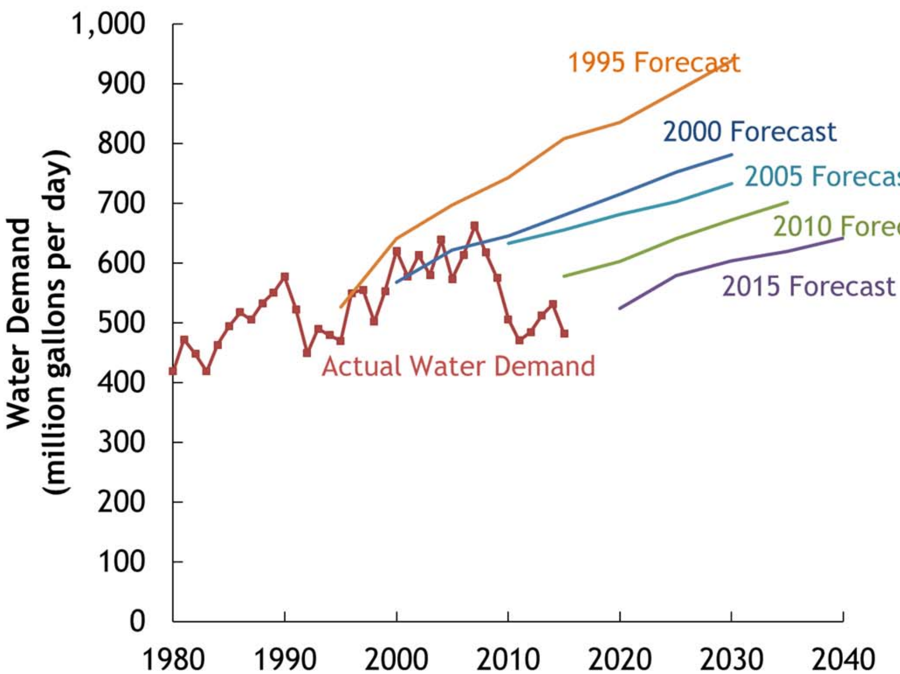
Accurate demand forecasting is essential.

Underestimating future water demand could contribute to water supply shortfalls, temporary increases in water bills, and the imposition of emergency cutbacks.

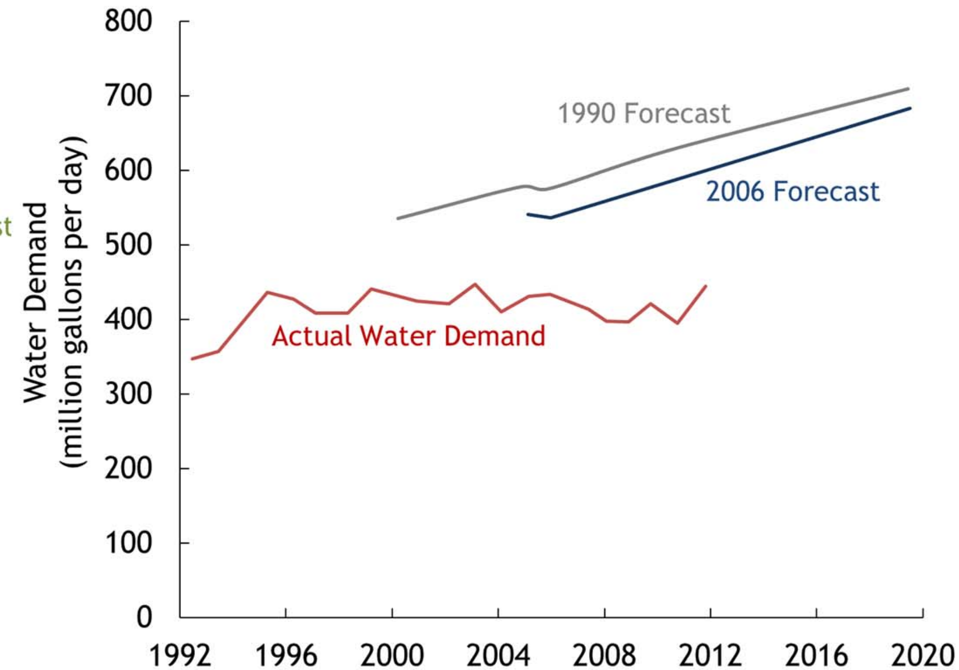
Overestimating demand can lead to costly investment in unneeded infrastructure and water sources, with higher water bills and potential environmental impacts.

Top Left: Hungry Horse Dam, Montana, Dept. of Interior via Wired.com; Top Right: City of Lancaster, Texas; Bottom: Tampa Bay Desalination Plant, Florida, wateronline.com

Forecasts often overestimate demand



San Diego, California

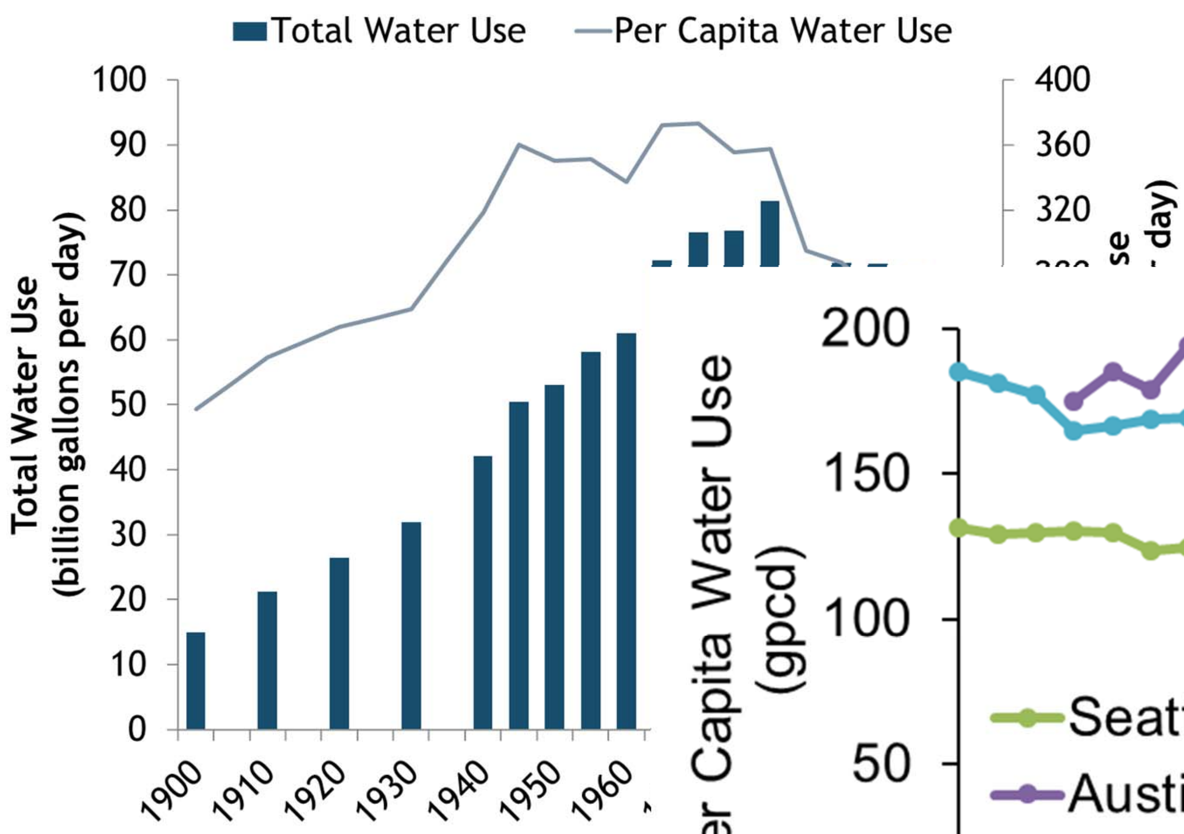


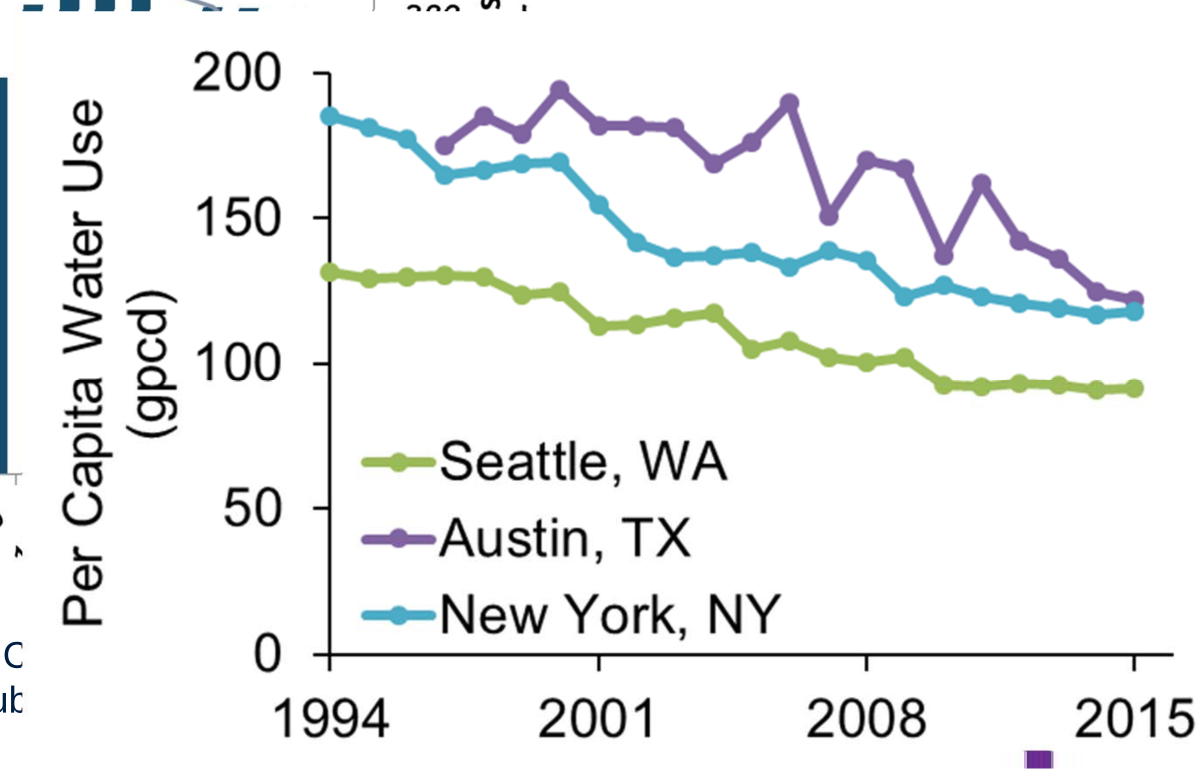
Phoenix, Arizona

Heberger, Donnelly, and Cooley, 2016. “A Community Guide for Evaluating Future Urban Water Demand.” Pacific Institute, Oakland, CA.

Municipal Water Use in the U.S.

Per capita water use in the U.S. is **declining**, at least partially due to efficiency standards and codes.





Donnelly and Cooley (2015); New York C
(2016); City of Austin (2017); Seattle Pub
Utilities (2016)

Research Objective

WRF Report #4495

Develop guidance to help water planners and managers increase the reliability of their water demand forecasts by accounting for efficiency standards and codes.

Water-Use Efficiency Standards

	Units	Federal Standards	WaterSense or ENERGY STAR minimum efficiency	Ultra-high efficiency
Single-flush tank-type toilets	gpf	1.6	1.3	0.79
Dual-flush tank-type toilets	gpf	1.6	1.6 (full)/ 1.1 (reduced)	0.95 (full)/ 0.5 (reduced)
Commercial toilets (flushometer valve)	gpf	1.6	1.28	1.0
Showerheads	gpm	2.5	2	0.75
Bathroom faucets	gpm	2.2	1.5	1.0
Commercial pre-rinse spray valves	gpm	1.6	1.28	0.65
Residential clothes washers	IWF	4.7 (front- load) 6.5 (top-load)	3.7 (front-load) 4.3 (top-load)	2.6
Commercial clothes washers	IWF	4.1 (front-load) 8.8 (top-load)	4.5	3.7
Residential dishwashers	gallons per cycle	5.0	3.5	1.95

Demand Forecasting Methods

Four methods for long-term demand forecasting:

(1) **Extrapolation models:** Population x Water Use Factor

(2) **Econometric or regression models:**

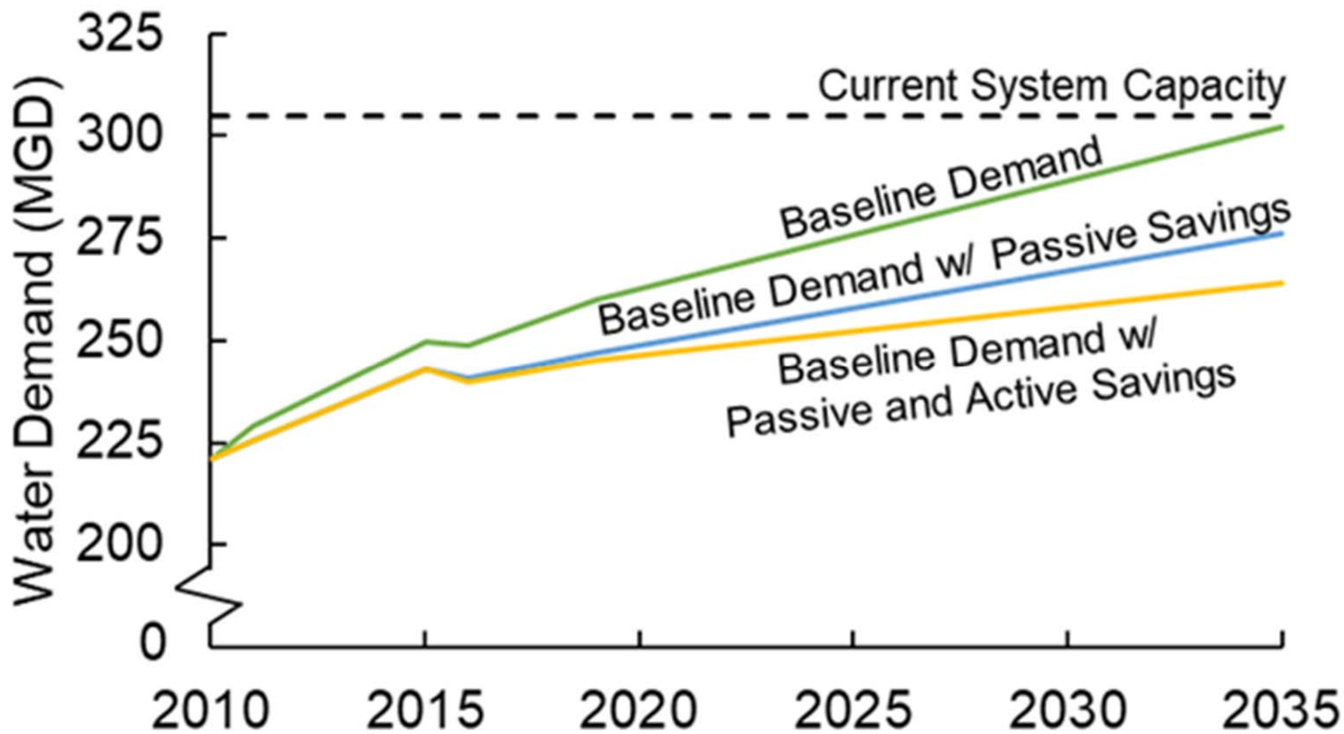
Demand = f(growth, water price, new development, etc.)

(3) **Comprehensive end use ('bottom up') models**: water use projected by end uses individually and then summed.

(4) **Hybrid models:** Extrapolation or econometric models with correction factor for conservation (guesstimate or modeled)

Base Models with Corrections Models

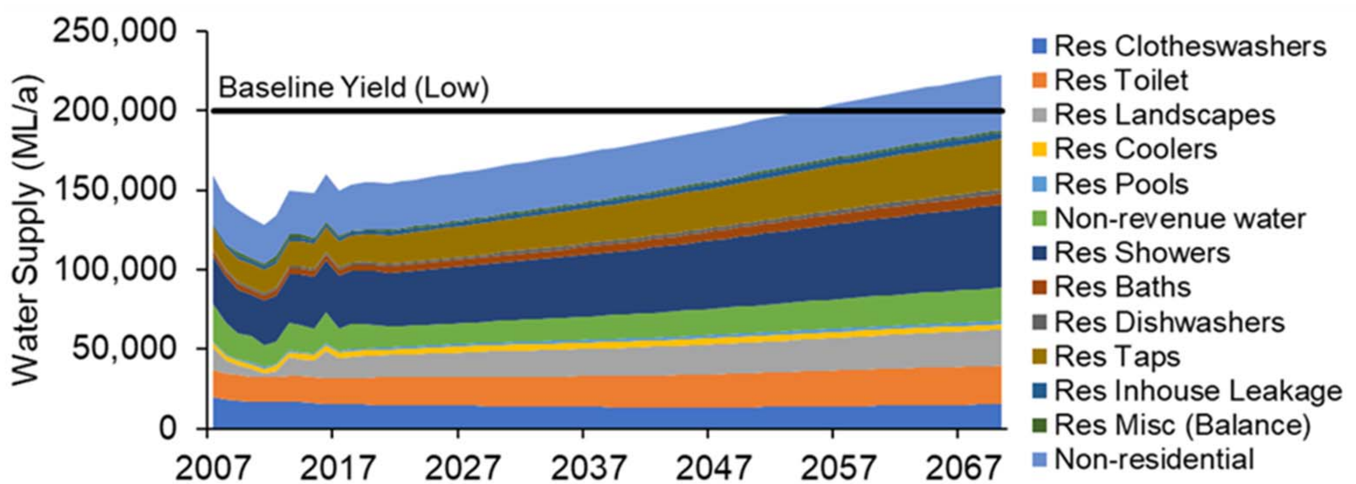
Baseline Econometric or Extrapolation Model
with a Correction Factor for Efficiency



Modified from Tampa Bay Water. (2013).
"Water Demand Management Plan"

Comprehensive End Use Modeling

- Water use projected for each end use as a **function of stock, efficiency, and behavior**.
- Water use is a function of economic/price impacts, technology, development, and changing efficiency.
- Allows for co-variation between economy and efficiency.



Peter Roberts, Yarra Valley Water, Melbourne, AUS

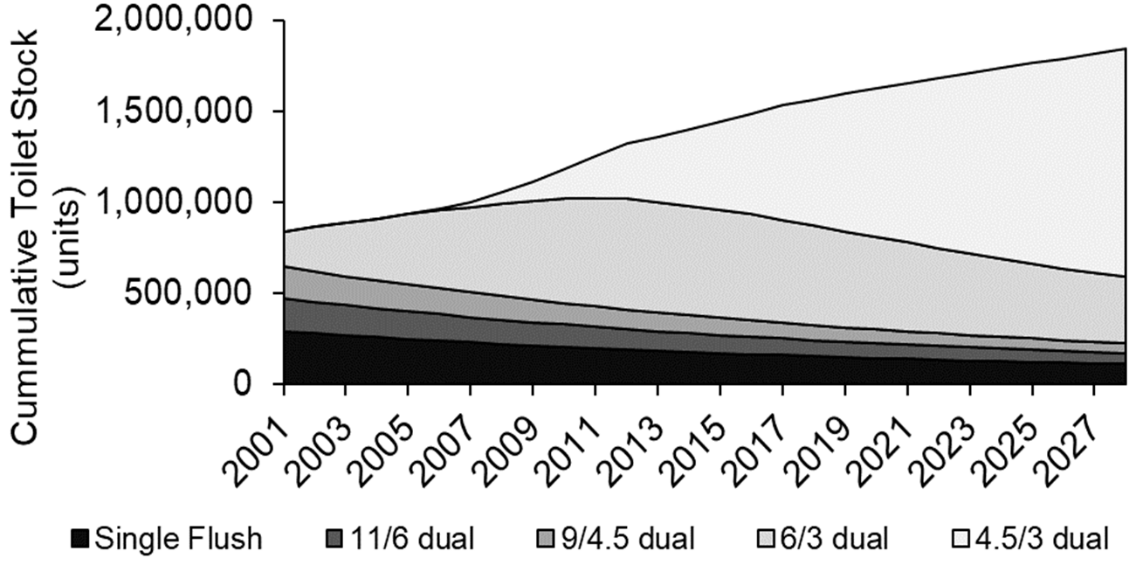
Modeling Water by End Use

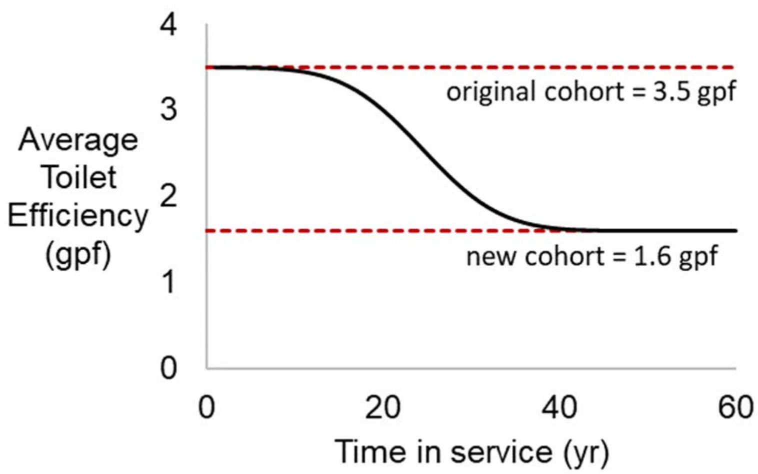
End Use Analysis can be used as part of correction factors or comprehensive end use modeling.

$$\frac{Total\ Vol}{Day} = \overbrace{\left(\#of\ Homes \times \frac{\#\ of\ Homes\ w/\ DW}{\#\ of\ Homes} \times \frac{\#\ of\ DW}{\#\ of\ Homes\ w/\ DW}\right)}^{\text{Total Stock of Dishwashers}} \times \overbrace{\frac{Volume}{Use}}^{\text{Technology (Efficiency)}} \times \overbrace{\frac{Uses}{DW \times Day}}^{\text{Behavior}}$$

Stock Model Components

Stock models simulate the turnover of cohorts of devices using **replacement distribution** and a **device lifetime**.





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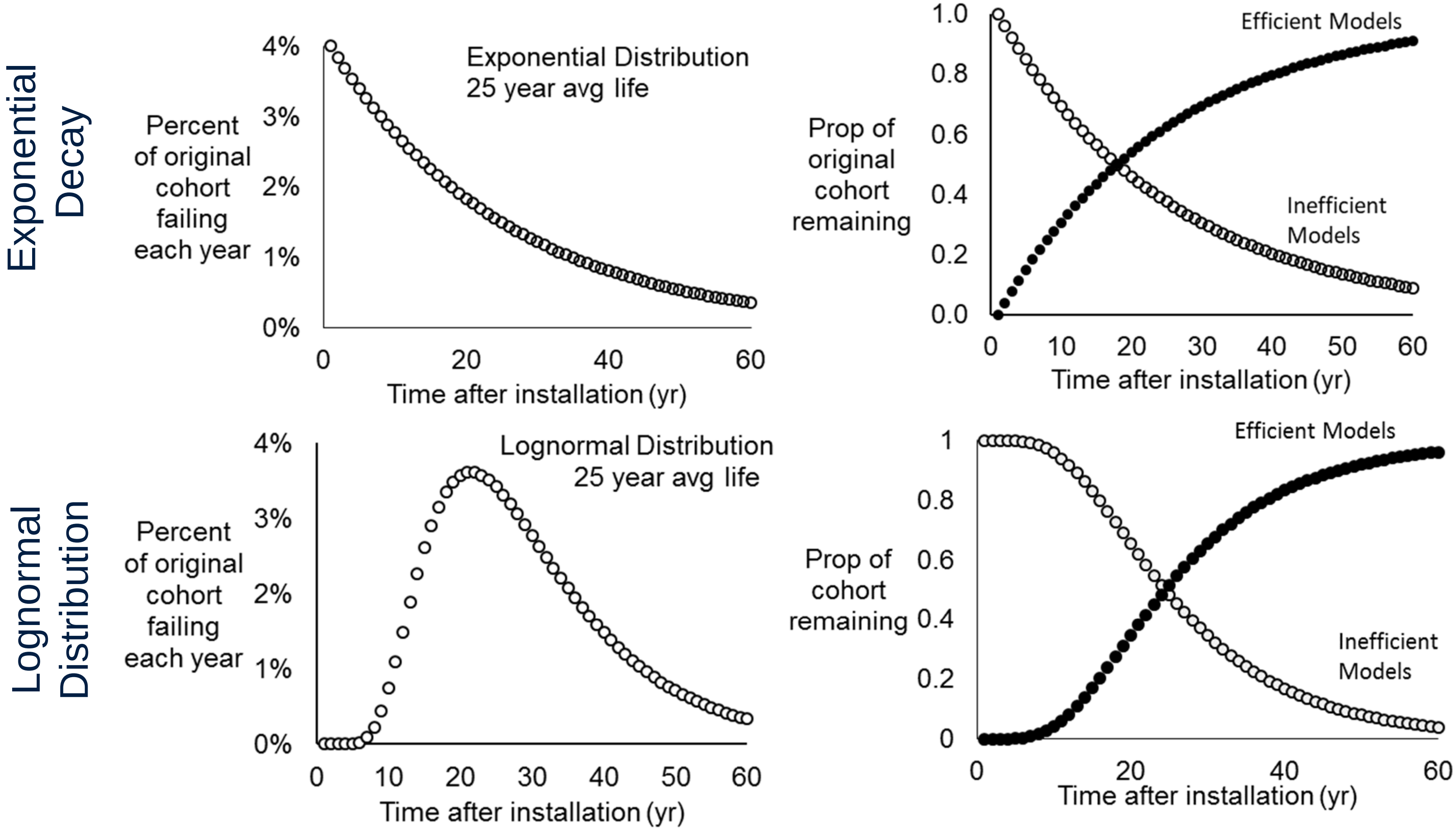
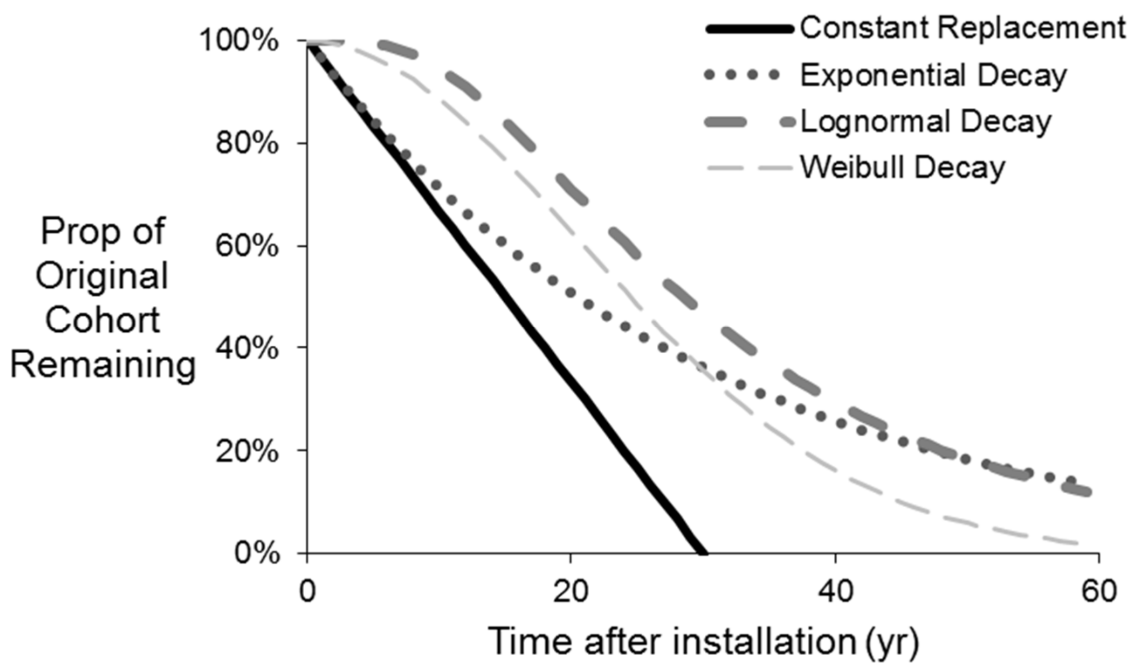
Replacement Distributions



Diringer et al., forthcoming. WRF Project #4495

Choosing a Replacement Rate

- Water Sector: Australia study showed that lognormal decay best fit the replacement rates of toilets (Snelling 2007)
- Energy Sector: Weibull distributions of replacement rates fit with sales data



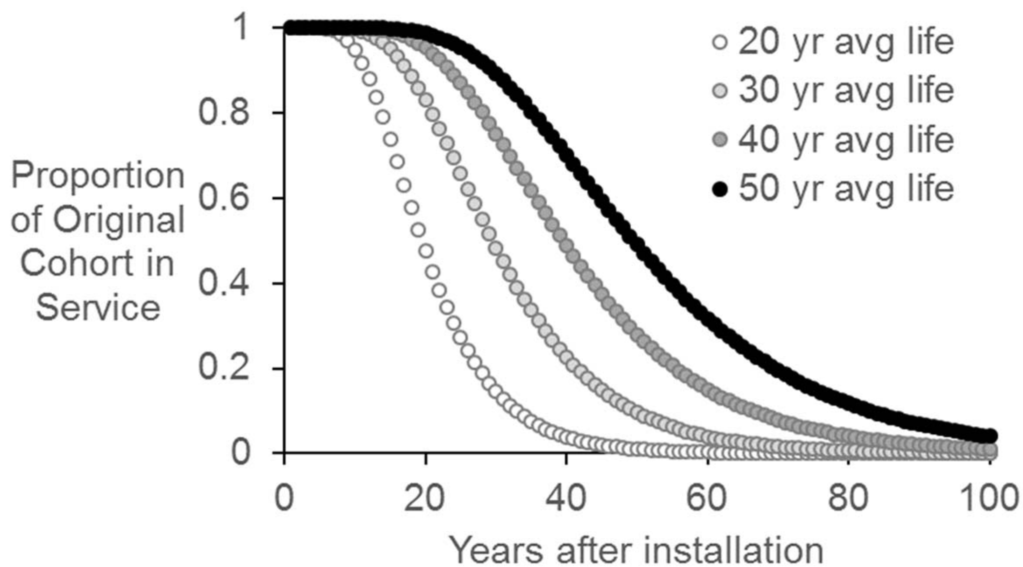
The replacement function can dramatically affect the modeled current stock and future conservation savings.

Diringer et al., forthcoming. WRF Project #4495

Impact of Device Lifetime on Models

Device	Range of Device Lifetime
Showerheads	5 – 12 years
Toilets	20 – 30 years
Dishwashers	10 – 15.5 years
Clothes Washers	8 – 20 years

If an analyst forecasts a 20-year average life and the devices last 30 years, that leads to a 17% difference in water usage.



Diringer et al., forthcoming. WRF Project #4495

Example of Stock Modeling

Tampa Bay Water, Demand Management Plan (2013)

Step 1: Separate households by age based on new legislation

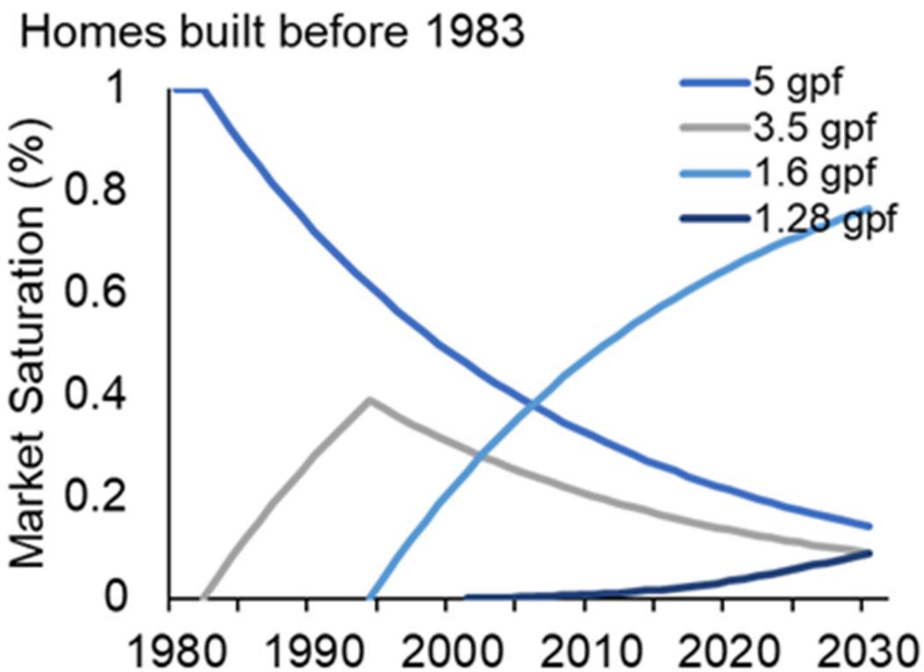
- Pre-1984: 5 gpf toilets
- 1984–1994: 3.5 gpf
- 1994–Present: 1.6 gpf

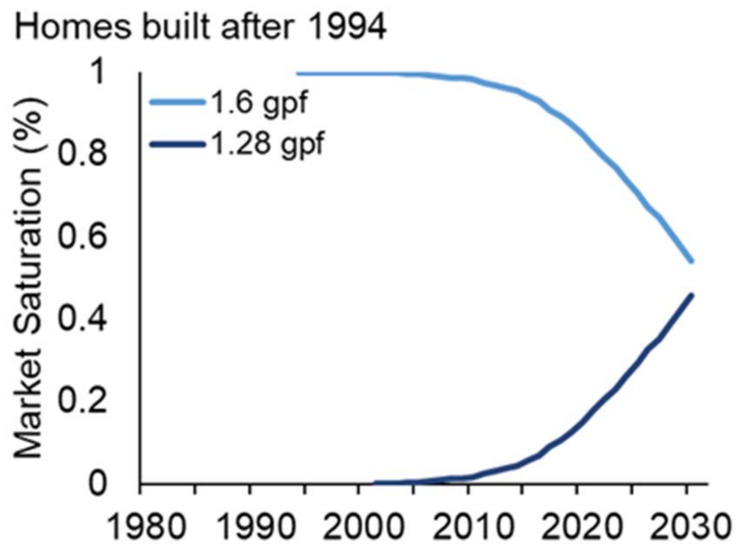
Datasets:

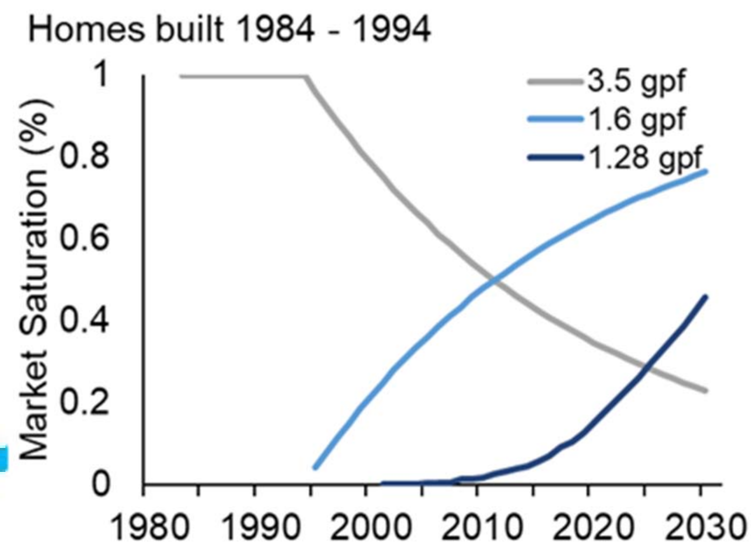
- **Billing and conservation program data**
- **Water use data**
- **Water Efficiency Program Library (WEPL)**
- **Parcel data**
- **Market share of WaterSense devices**
- **Projected population growth (Moody's Analytics)**

Example of Stock Modeling

Step 2: Run stock model with decay function for each housing group.







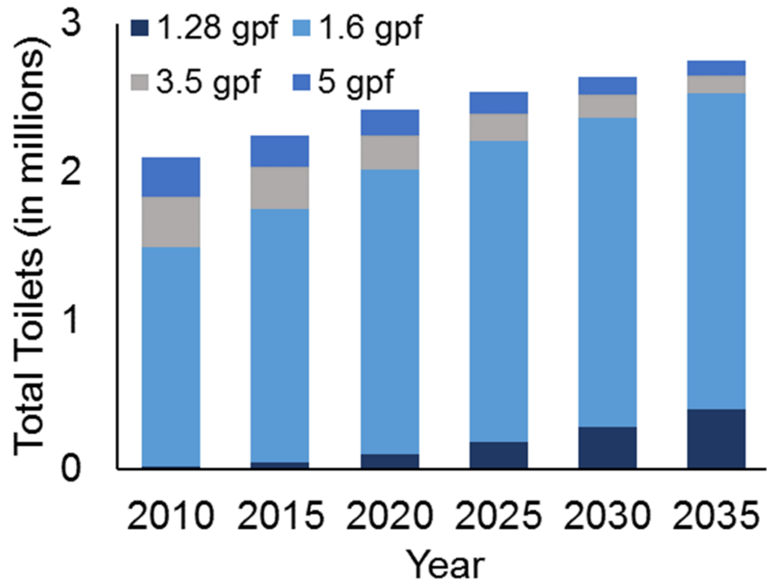
Data provided by Tampa Bay Water. (2013). Water Demand Management Plan.
Diringer et al., forthcoming. WRF Project #4495

Example of Stock Modeling

Step 3: Determine total stock of toilets in the service area.

Step 4: Multiply stock of toilets by distribution of toilet efficiencies.

Step 5: Adjust per capita water demand by changing average toilet efficiency.



Next Step: (1) Validate model with surveys, in-person assessments, or flow trace analyses. (2) Examine uncertainty in forecast using Monte Carlo or scenario testing.

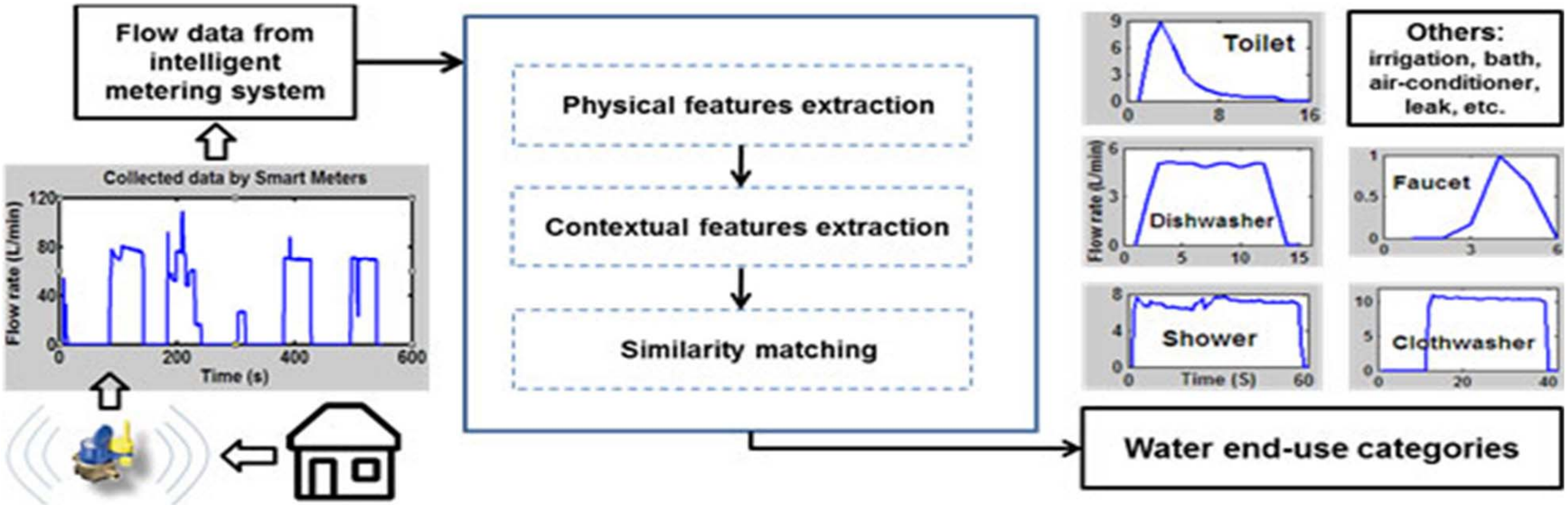
Data provided by Tampa Bay Water. (2013). Water Demand Management Plan.
Diringer et al., forthcoming. WRF Project #4495

Datasets for Stock Modeling

<table>
<tr><th></th><th>Study Outcomes</th><th>Data Collection Method</th><th>Residential Water Demand</th><th>Total Stock</th><th>Efficiency</th><th>Behavior</th></tr>
<tr><td>REUWS 1999, 2016</td><td>End uses of water, single-family homes, Not nationally representative</td><td>Customer survey, flow monitoring</td><td>Average indoor and outdoor residential water demand</td><td>Single flush/dual flush toilets, CW, DW, showers, bathtubs</td><td>Calculated water efficiency per use</td><td>Toilet, faucet, DW, CW, bathtub, shower</td></tr>
<tr><td>RECS 1987, 1990, 1993, 1997</td><td rowspan="2">Residential energy use, single and multi-family homes, nationally representative</td><td rowspan="2">In-person, paper, or online survey</td><td rowspan="2">None</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>RECS 2001, 2005, 2009, 2015</td><td>DW, CW Presence/ Absence</td><td>CW: Top Loading vs. Front Loading</td><td>Self-reported DW, CW use per week</td></tr>
</table>

Collecting Data

- Surveys for end uses of water
- In-person assessments
- High-resolution flow trace analyses
- Advanced Metering Infrastructure (AMI)

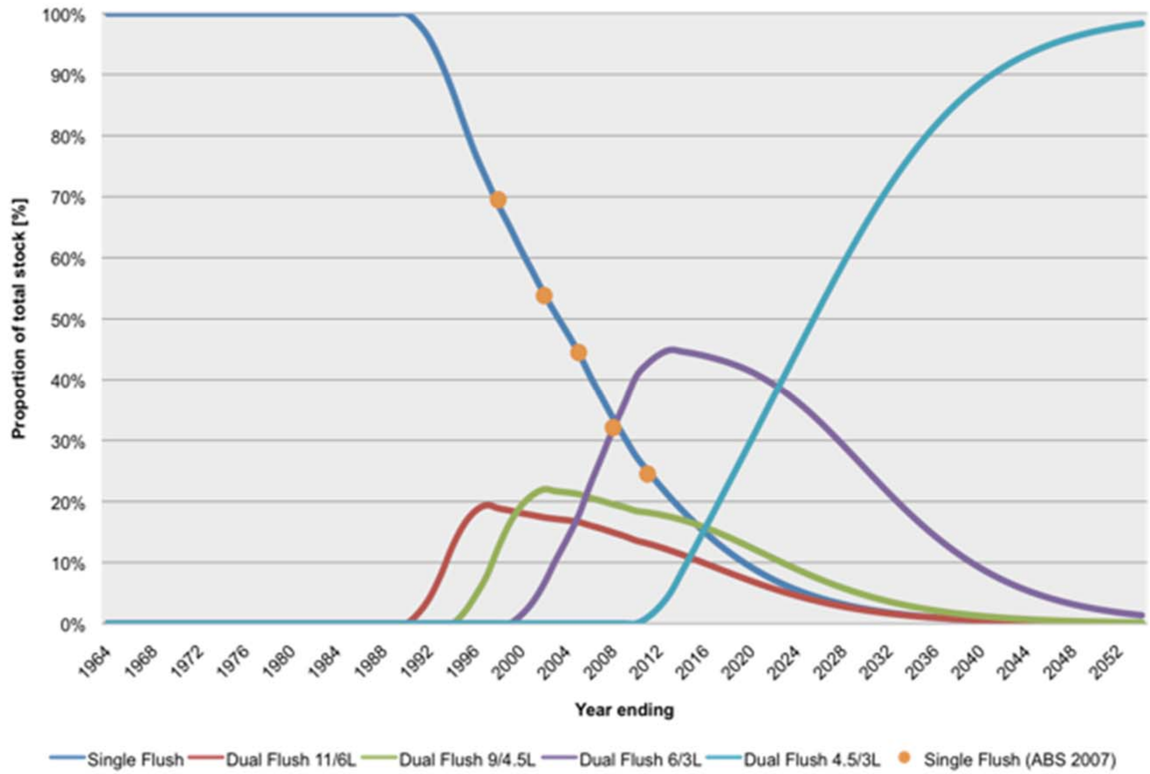


Stewart. (2015). "Hydroinformatics - Big Data Solutions for Water Savings."

Incorporating Data

Study data be incorporated into models, used to calibrate models, and/or verify model results.

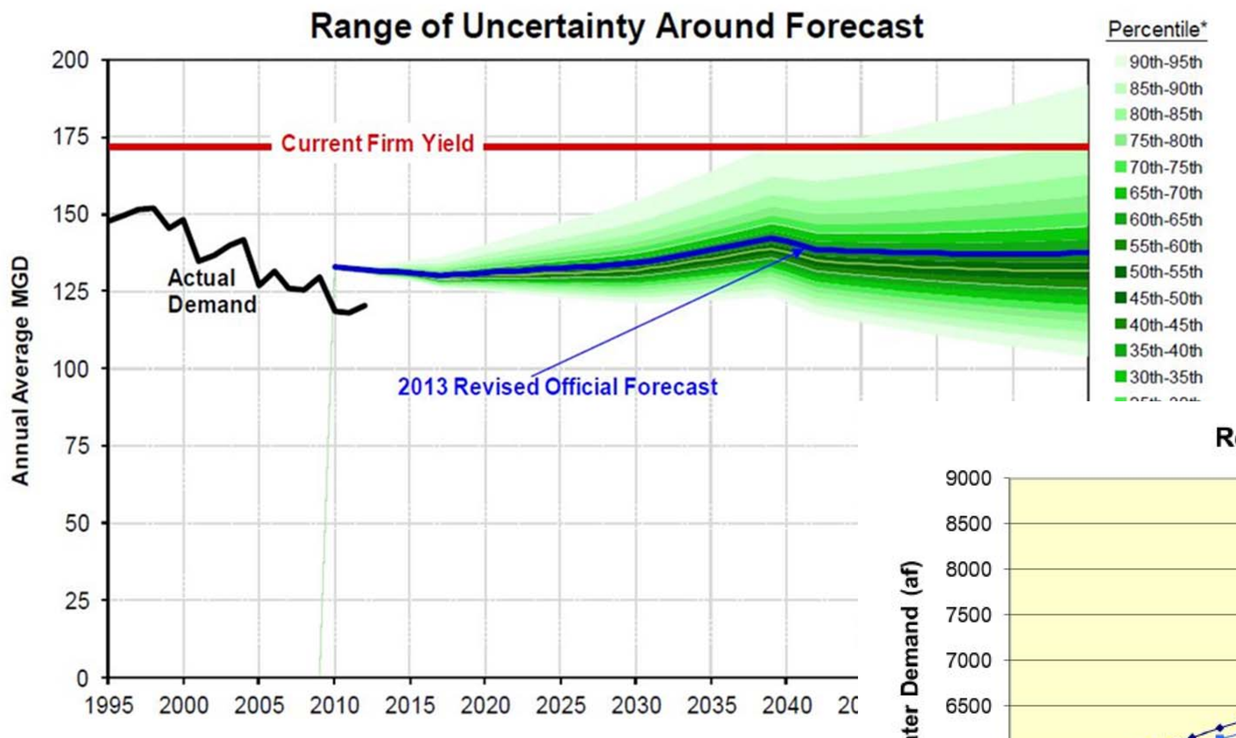
Market share from Australia for toilet, where the orange dots represent census data to calibrate the changing stock.



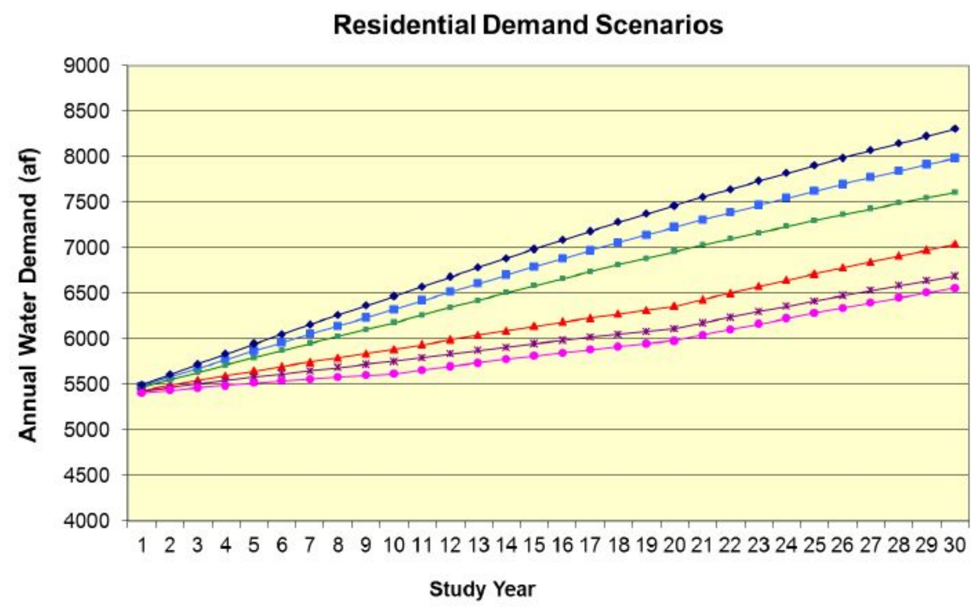
McKibbin et al. (2010). “A New National Tool for Integrated Water Resource Planning.”

Characterizing Uncertainty

Multiple scenarios and Monte Carlo simulations can be used to provide a range of predicted future water demand.



Check out WRF 4558 (Kiefer et al., 2016) Uncertainty in Long-Term Water Demand Forecasting



(above) Flory, 2013. "Forecasting Water Demand in Seattle."
(right) Aquacraft, 2015. "Residential Demand Forecasting Model."

Guidance and Recommendations

1. Improve overall forecasting methods

- Examine the accuracy of demand forecasts and monitor trends in water use.
- Incorporate stock models into demand forecasts to capture efficiency improvements resulting from standards and codes.
- Integrate uncertainty into demand forecasts.

2. Improve stock modeling for demand forecasts

- Determine current stock and efficiency of devices.
- Develop realistic device lifetimes and replacement rates.

3. Anticipate the Future

- Anticipate future standards and codes.
- Investigate AMI technologies for collecting water data

Acknowledgements

Project Advisory Committee

Veronica Blette, U.S. EPA WaterSense Program
David Bracciano, Tampa Bay Water
Benedykt Dziegielewski, formerly Southern Illinois University
Douglas Frost, City of Phoenix Water Services Department
Margaret Hunter, Senior Project Manager, American Water

Participating Utilities

City of Austin, TX; Cobb County Water System, GA; East Bay Municipal Utility District, CA; Irvine Ranch Water District, CA; Long Beach Water Department, CA; San Antonio Water System, TX; San Diego County Water Authority, CA; San Francisco Water and Power, CA; Yarra Valley Water, Melbourne, Australia

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