Forecasting short-term urban water demands based on the Global Ensemble Forecast System

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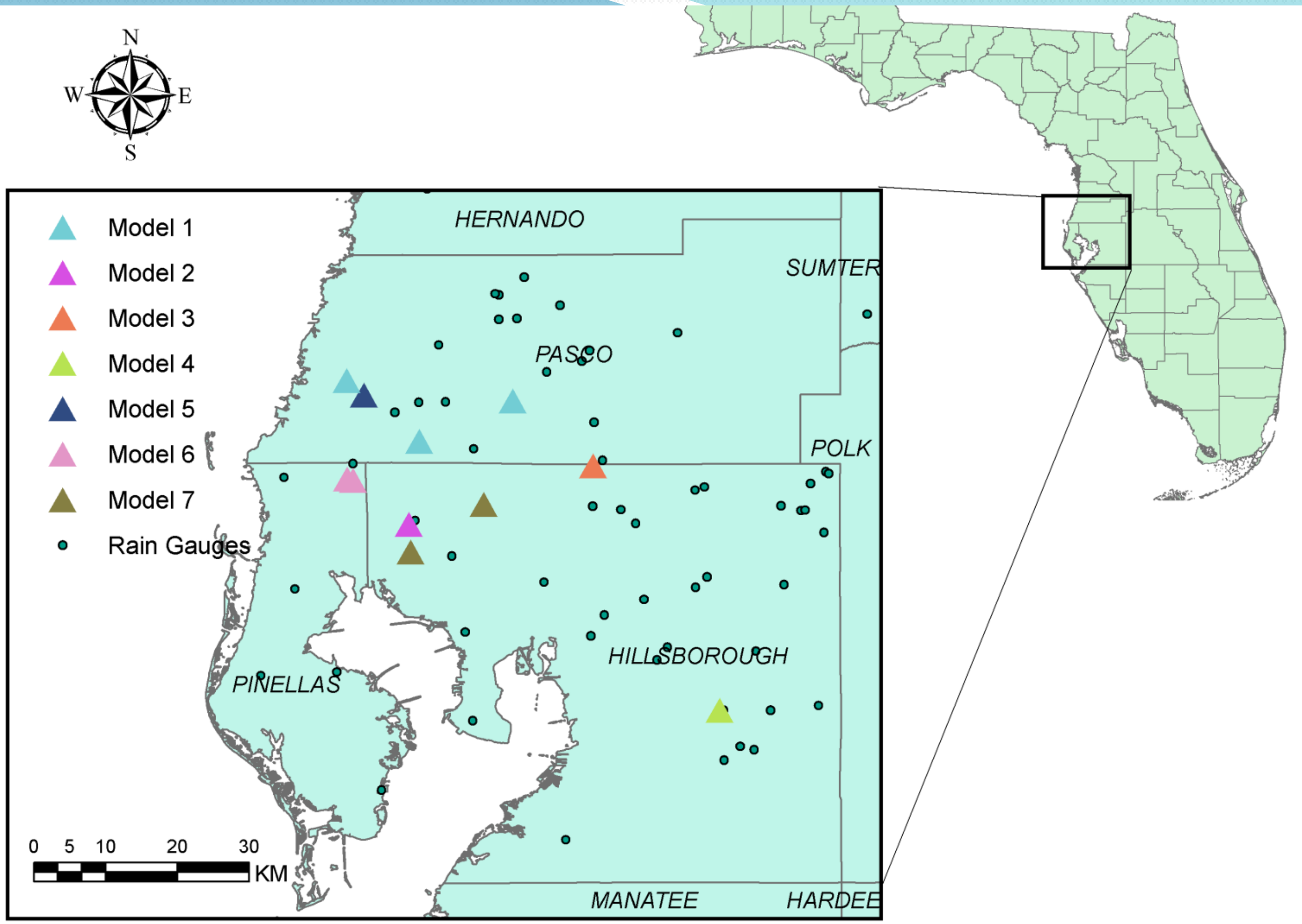
Short-term Water Demand Forecasts in Tampa Bay region

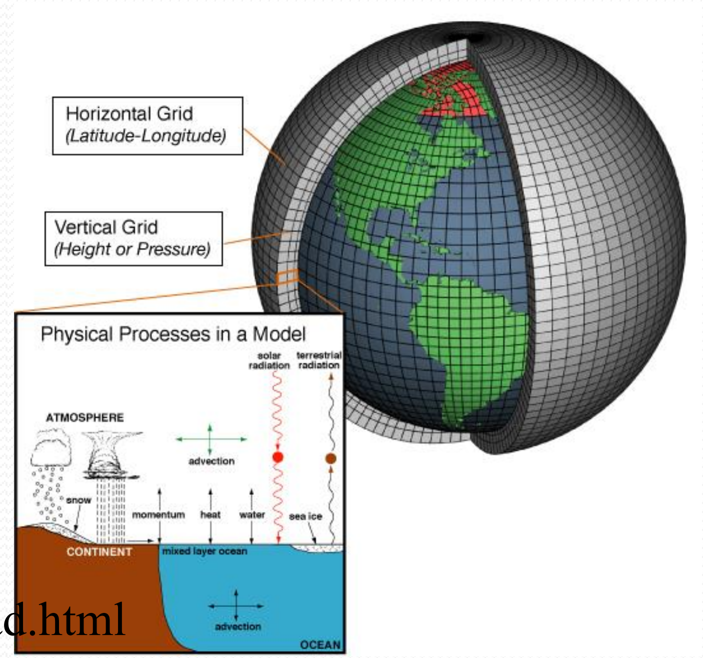
- The Tampa Bay Water makes **short-term water demand forecasts** to optimize water supply management
- The Tampa Bay Water has developed **1-week ahead** weekly water demand forecast models based on auto-regressive integrated moving average models with exogenous variables (**ARIMAX**)



Input Variables	Descriptions
WD (mgd)	Water demand
WeekRain (mm)	Weekly total rainfall
RainDays	number of rainy days (>0.01 inch) in a week
CosRainDays	number of consecutive rainy days in a week
HotDays	number of hot days (>85 F) in a week

Global Ensemble Forecast System (GEFS)

- Retrospective forecasts (**reforecasts**) (Jan 1985 to present) of a newly developed numerical weather prediction model (NWP)
- Forecast range (lead time): 1-16 days
- Time step: convert to weekly
- 11 forecast members
- 1° x 1° resolution



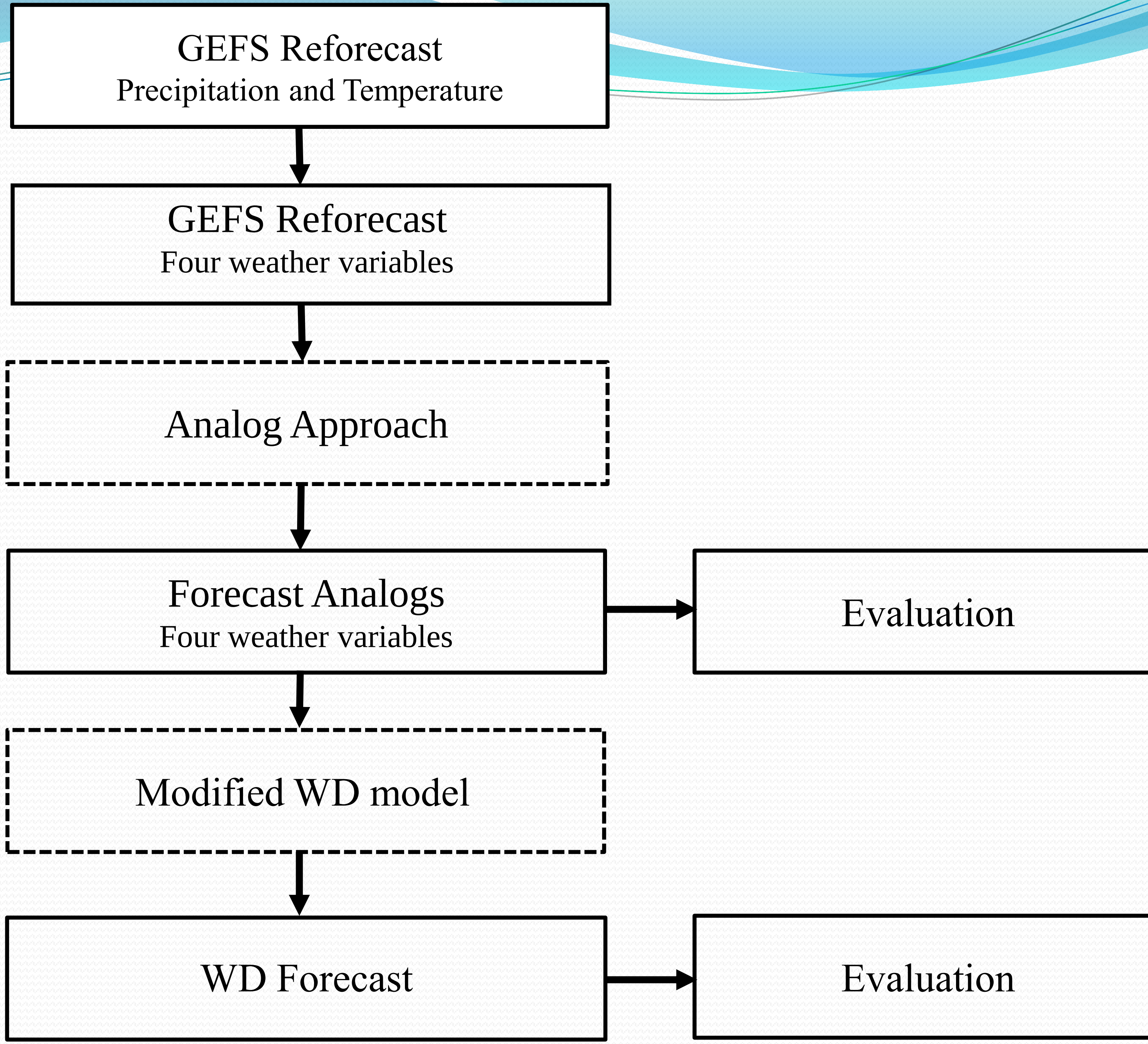
http://www.esrl.noaa.gov/psd/forecasts/reforecast2/download.html

Objectives

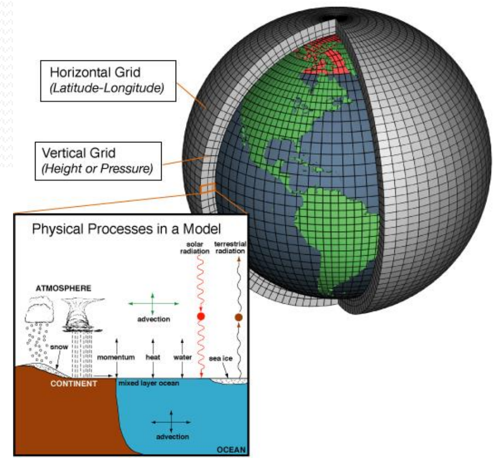
1. To evaluate forecast analogs of water demand related weather variables from reforecasts of the GEFS using station-based observations in the Tampa Bay region

2. To test whether short-term water demand forecasts can be improved using forecast analogs of the GEFS in the Tampa Bay region

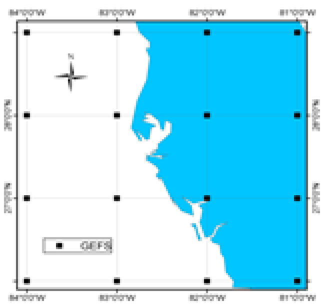
Forecast scheme



Analog approach



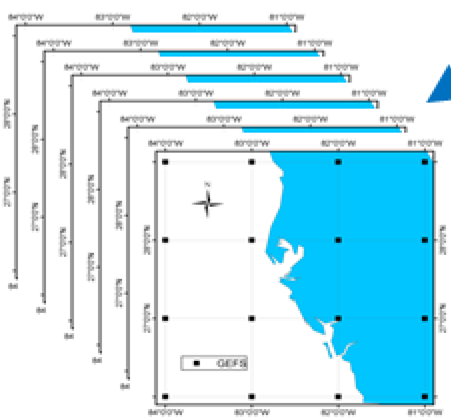
Forecast Date *i.e. Nov 8 2012*



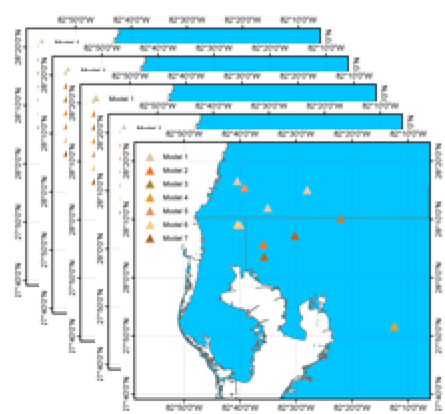
Set Search Window This Day +/- 45 days *i.e. Sep 24 – Dec 23 in historical archive*

Analog Search Engine

Generate probabilistic and deterministic forecast



Locate 75 dates of closest matching Analogs based on average RMSE



Apply the 75 Analog Dates to select analogs for each water demand models at different locations

Forecast Evaluation for Weather Variables

- **Probabilistic Weather Forecasts**: Rank Probability Skill Score (**RPSS**):

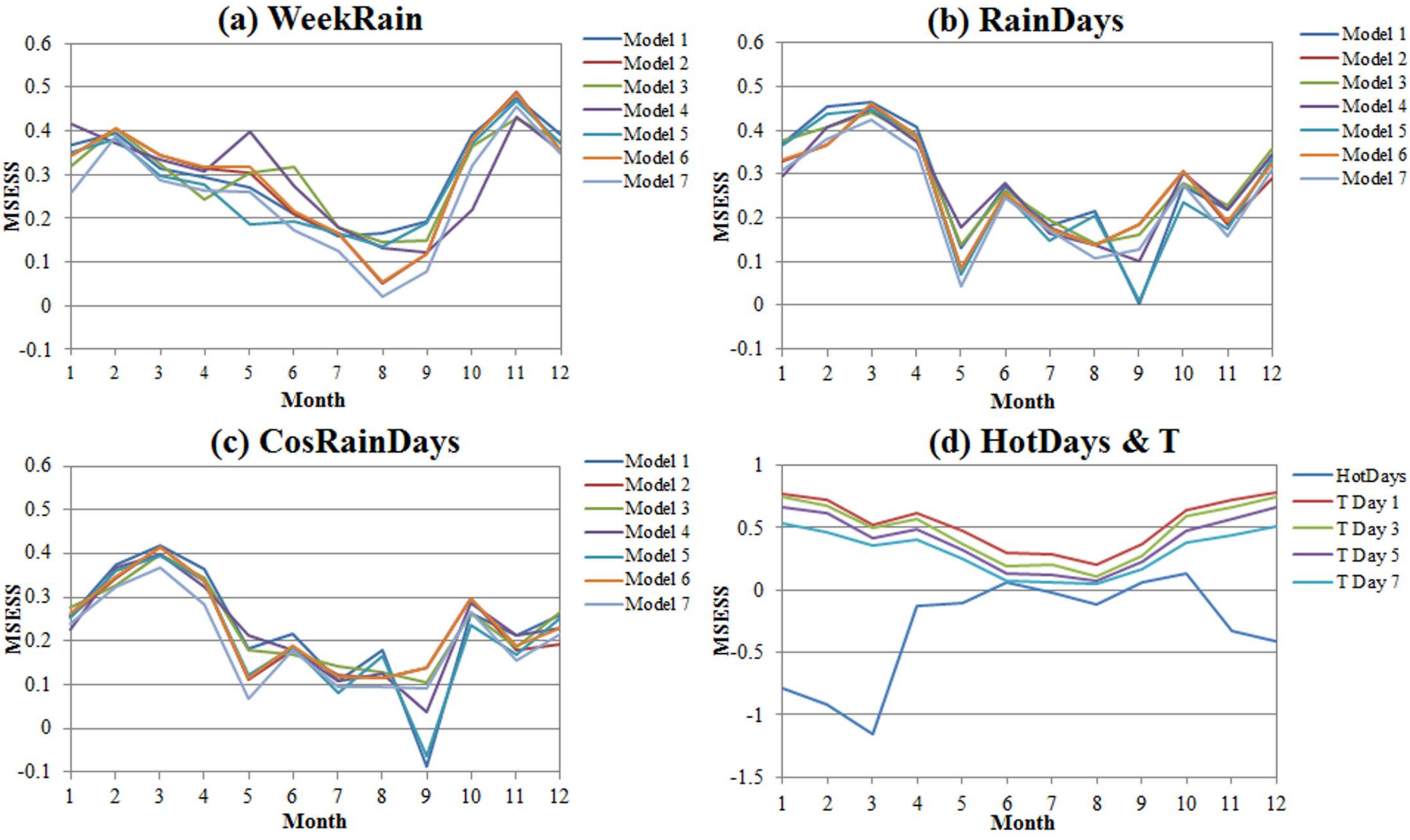
$$RPSS = 1 - \frac{RPSS_{forecast}}{RPSS_{climatology}}$$ -∞ to 1

- **Deterministic Weather Forecasts**: Mean square error skill score (**MSESS**):

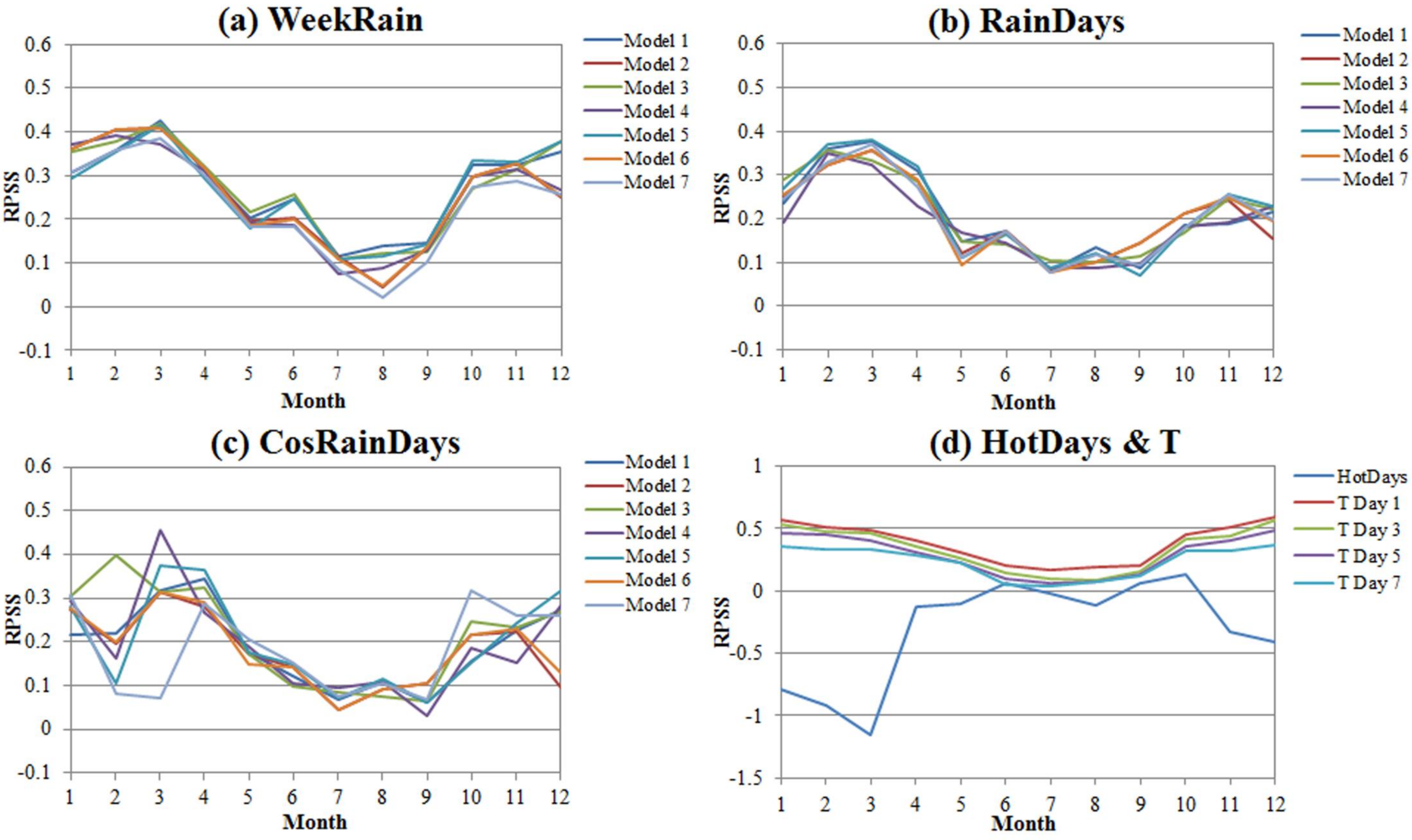
$$MSESS = 1 - \frac{MSE_{forecast}}{MSE_{climatology}}$$ -∞ to 1

- Positive value indicates the skill is better than climatology
- Cross-Validation was conducted for all forecasts

Deterministic Forecasts for Weather Variables



Probabilistic Forecasts for Weather Variables



Modification of Water demand (WD) model

- In order to use the weather forecast information, we need to modify these WD models
- All input weather variables (except HotDays) of the original WD model were advanced by one week.
- Then the forecast analogs of the weather variables can be used to drive the modified model

Model	POCs	Variables for Original Model	Variables for Modified Model
1	Little Road, US41, Odessa	WD(t), WD(t-1), CosRainDays(t), CosRainDays(t-1), WeekRain(t), HotDays(t)	WD(t), WD(t-1), CosRainDays(t+1), CosRainDays(t), WeekRain(t+1), HotDays(t)

WD Forecast Evaluation

- **Uncertainty of the Ensemble Water Demand Forecasts Driven by Forecast Analogs**:

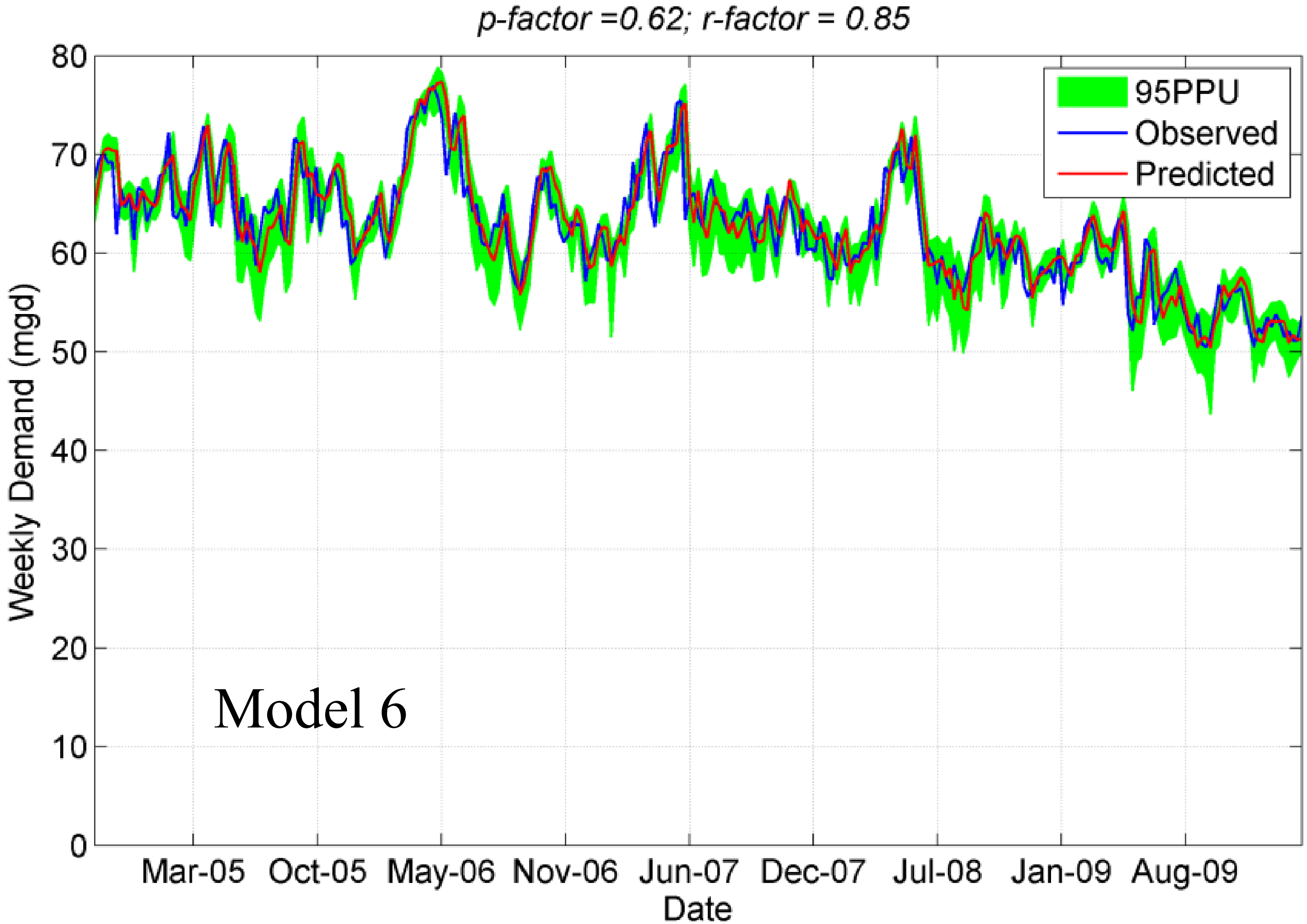
p-factor: the percent of observations covered by the ensemble forecast

r-factor: the average width ensemble forecast relative to the standard deviation of the observations

p-factor close to 1 represents perfect forecast; r-factor close to 1 represents the same uncertainty as standard deviation

- **Median of Ensemble Water Demand Forecasts (Deterministic)**: coefficient of determination (**R^2**), Coefficient of efficiency (**E**), root mean square error (**RMSE**), and mean absolute error (**MAE**)

WD Forecast Results



Summary of Deterministic WD Forecast Results

Model	Original model				Analog driven (median)			
	R2	E	RMSE	MAE	R2	E	RMSE	MAE
1	0.66	0.65	1.58	1.24	0.70	0.68	1.48	1.14
2	0.74	0.73	1.13	0.86	0.75	0.74	1.12	0.85
3	0.88	0.88	0.42	0.33	0.88	0.87	0.42	0.32
4	0.67	0.64	2.74	2.07	0.71	0.68	2.58	1.97
5	0.67	0.65	0.20	0.15	0.70	0.67	0.20	0.15
6	0.74	0.74	2.84	2.28	0.79	0.77	2.70	2.08
7	0.65	0.63	1.41	1.10	0.68	0.65	1.36	1.03

During validation period from 9/23/2004 to 2/25/2010

Summary

- The analog approach generally showed high skill for forecasting weather variables related to urban water demand

- The analog-driven urban water demand forecast models mostly showed higher skill than the original forecast models implemented by the Tampa Bay Water

- The GEFS showed promising features for advancing short-term urban water demand forecasts

Acknowledgements

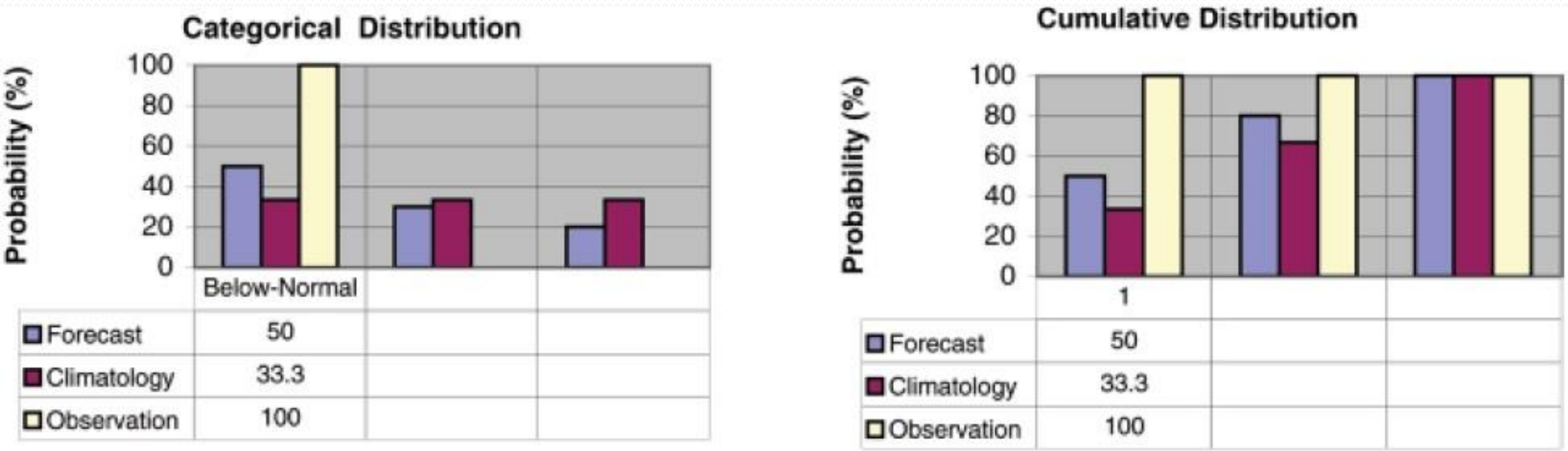
- NOAA Climate Program Office SARP-Water program and NOAA-RISA program

Methods – Modification of WD model

Model	POCs	Variables for Original Model	Variables for Modified Model
1	Little Road, US41, Odessa	WD(t), WD(t-1), CosRainDays(t), CosRainDays(t-1), WeekRain(t), HotDays(t)	WD(t), WD(t-1), CosRainDays(t+1), CosRainDays(t), WeekRain(t+1), HotDays(t)
2	Cosme	WD(t), CosRainDays(t), CosRainDays(t-1)	WD(t), CosRainDays(t+1), CosRainDays(t)
3	Lake Bridge	WD(t), CosRainDays(t), CosRainDays(t-1), WeekRain(t)	WD(t), CosRainDays(t+1), CosRainDays(t), WeekRain(t+1)
4	Lithia	WD(t), CosRainDays(t), RainDays(t), HotDays(t)	WD(t), CosRainDays(t+1), RainDays(t+1), HotDays(t)
5	Maytum	WD(t), WD(t-1), RainDays(t)	WD(t), WD(t-1), RainDays(t+1)
6	Pinellas, Keller	WD(t), CosRainDays(t), CosRainDays(t-1), WeekRain(t), HotDays(t)	WD(t), CosRainDays(t+1), CosRainDays(t), WeekRain(t+1), HotDays(t)
7	NWH, Lake Park	WD(t), CosRainDays(t), CosRainDays(t-1), WeekRain(t), HotDays(t)	WD(t), CosRainDays(t+1), CosRainDays(t), WeekRain(t+1), HotDays(t)

Methods – Forecast Evaluation

- **Probabilistic Weather Forecasts**: Rank Probability Skill Score (RPSS):



$$RPS_{fcst} = (CP_{f1} - CP_{o1})^2 + (CP_{f2} - CP_{o2})^2 + (CP_{f3} + CP_{o3})^2 = (.5 - 1.0)^2 + (.8 - 1.0)^2 + (1.0 - 1.0)^2 = 0.29$$

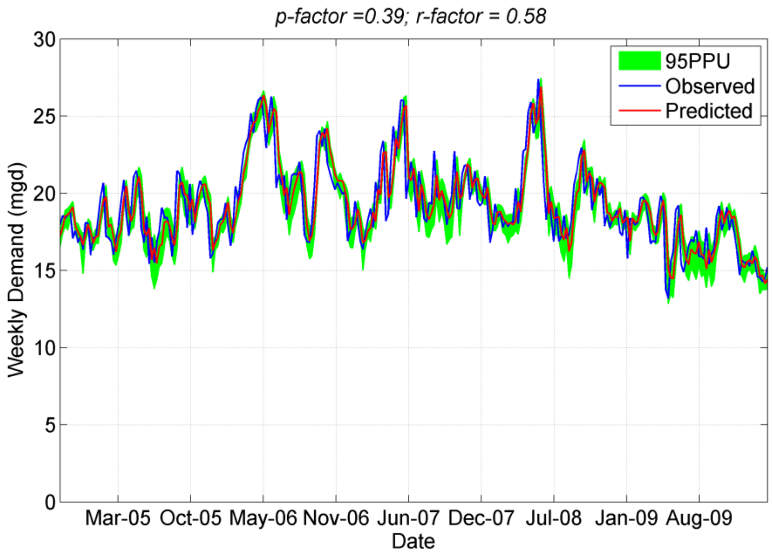
$$RPS_{clm} = (CP_{c1} - CP_{o1})^2 + (CP_{c2} - CP_{o2})^2 + (CP_{c3} + CP_{o3})^2 = (.33 - 1.0)^2 + (.67 - 1.0)^2 + (1.0 - 1.0)^2 = 0.56$$

$$RPSS = 1.0 - \frac{RPS_{fcst}}{RPS_{clm}} = 1.0 - \frac{0.29}{0.56} = 0.48$$

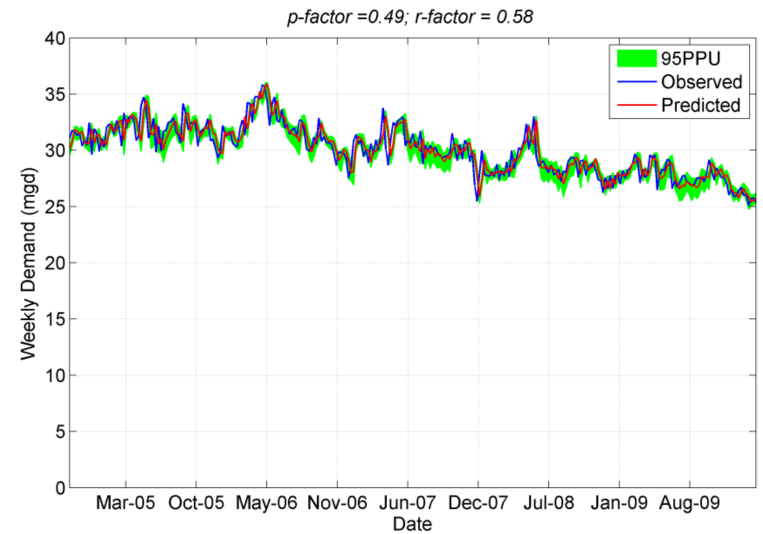
(from Goddard et al. 2013)

WD Forecasts

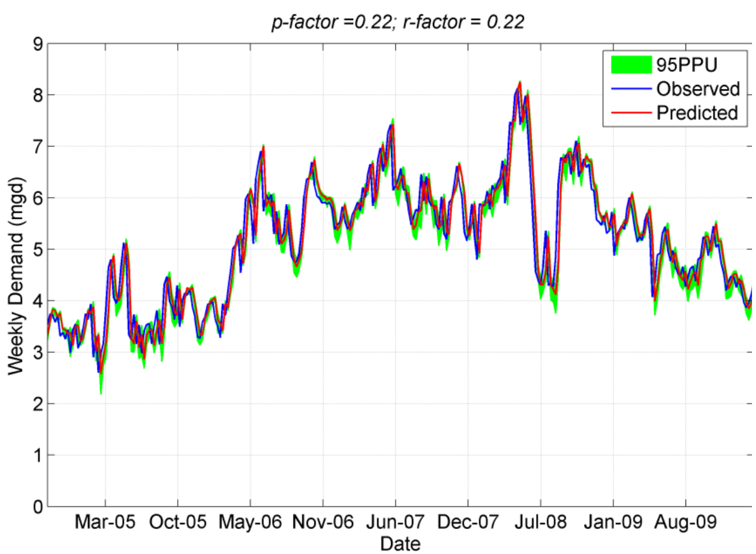
Model 1



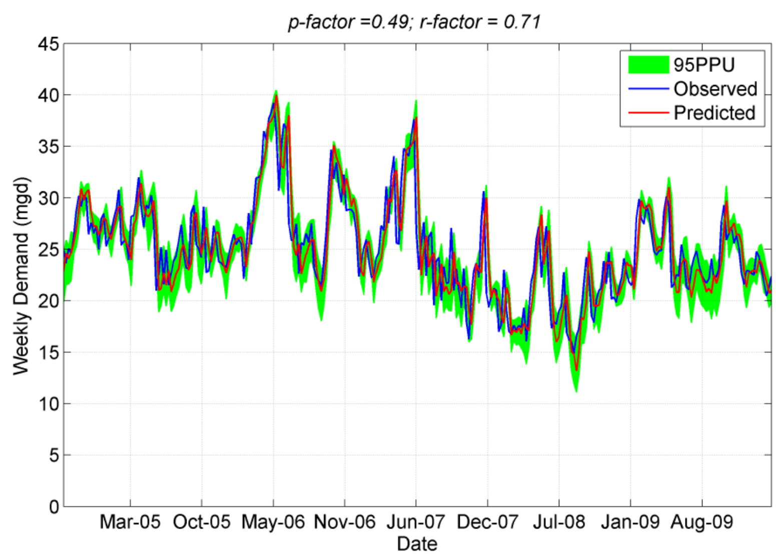
Model 2



Model 3

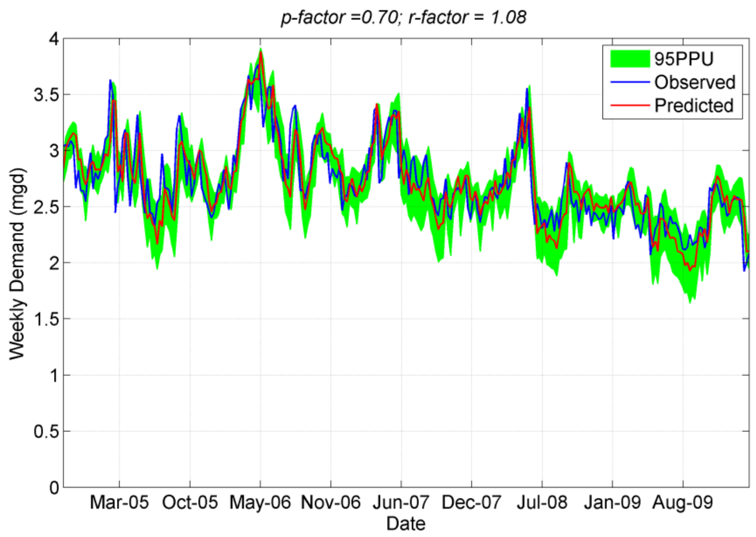


Model 4



WD Forecasts

Model 5



Model 6

Model 7