Machine learning based urban water demand (UWD) forecasts incorporating stochastic weather inputs

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Background source: http://www.clevelandwater.com/sites/default/files/your-water_distribution.png

Introduction

- Urban water demand (UWD):
  - **Nonlinear** process [Adamowski et al., 2012];
  - Coupled **human-water-environment** system;
  - Function of **previous** demands, **climate**, socio-economic fluctuations, etc. [House-Peters and Chang, 2011]; and
  - **Outdoor water use** very **important** for system performance (**risk**, **resiliency**, **vulnerability**)…learning about **feedbacks** between humans, water, and the environment…generally **dominated by recent weather**.
- Models/forecasts of water resources time series may be generated using:
  - Deterministic; stochastic; and/or **quasi-stochastic** methods [Chow, 1978].

Introduction

- Opportunity to develop a **quasi-stochastic** model for UWD forecasting (**QS-UWDF**) using a new (**open-source**) stochastic weather generation tool (Chen et al., 2010)*:
  - **Stochastic** weather generation + **historical** UWD used for **input**;
  - **Multiple runs** generated (i.e. to create **ensemble members**);
  - Each run is used to develop a **deterministic machine learning** model; and
  - Each prediction is **combined** in an **ensemble forecast system**.
- **Earlier** stochastic based UWD forecasting approaches:
  - Coupled ANN with either stochastic weather generation (**similar to this presentation**) or GCM projected changes [Yung et al., 2011]; and
  - ARMA applied after removing dominant periodicities [Mamo et al., 2013].

* http://www.mathworks.com/matlabcentral/fileexchange/29136-stochastic-weather-generator--weagets-

Problem Definition

- Given a set of daily UWD records and historical daily weather measurements develop a ***quasi-stochastic*** UWD forecast model (**QS-UWDF**); and
- **Forecast** UWD using the **QS-UWDF** model for the **next 3 days ahead** and **compare performance** against a fully **deterministic** model (i.e. only historical UWD and weather inputs) to asses efficacy of use.

Objectives

- The main goal of this study is to determine if a machine learning based **quasi-stochastic** approach is suitable for short-term (daily) UWD forecasting during outdoor water-use periods by referencing its performance to a **deterministic** model.
- To accomplish our objective we **incrementally combine** the following methods/tools to **produce forecasts** using our proposed **QS-UWDF** model:
  - Input variable selection (**IVS**);
  - Weather Generator of Ecole de Technologie Superiere (**WeaGETS**) [Chen et al., 2010];
  - Support Vector Regression (**SVR**); and
  - Bayesian Model Averaging (**BMA**).

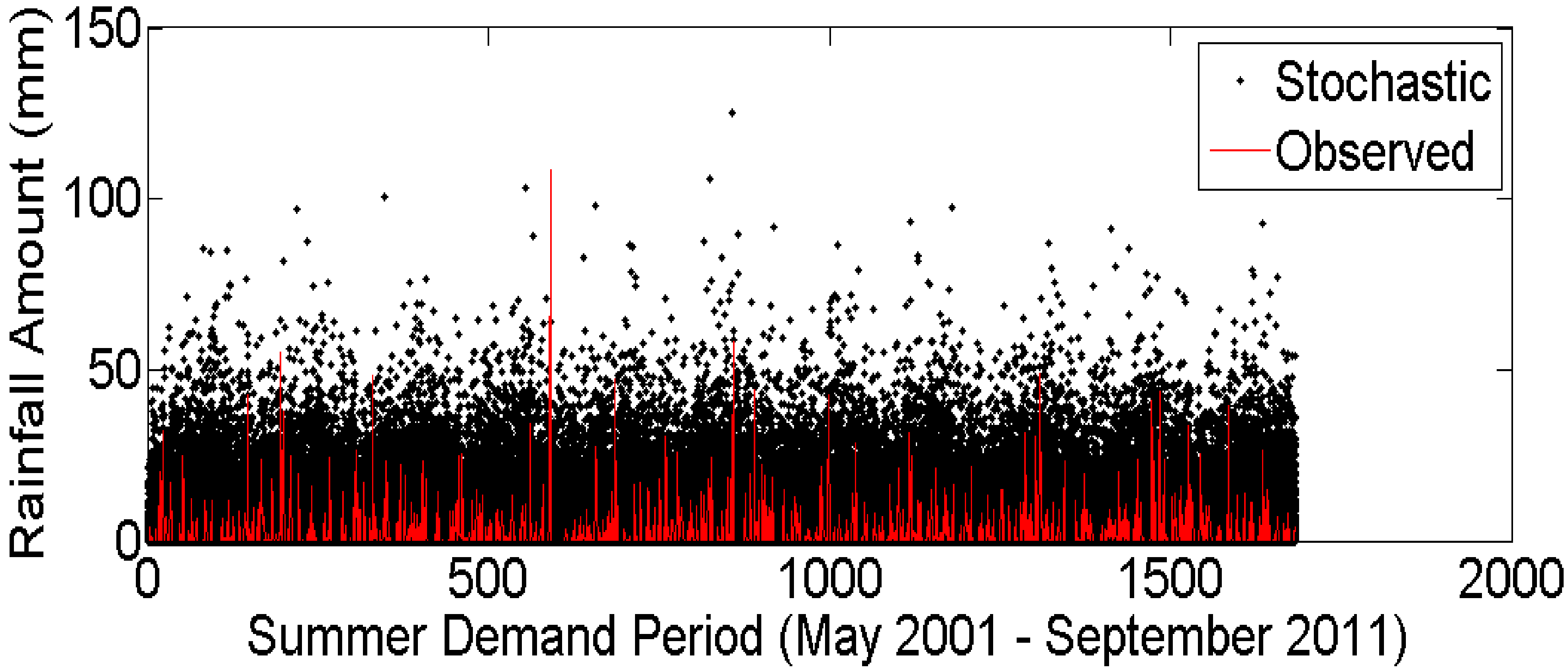
Methodology

- Study site → **Ottawa, Canada**
  - Daily **UWD records** (2001-2011); and
  - Historical daily **weather measurements** (1890-2011):
    - Max and min air temperature and;
    - **Rainfall depth**.
- Cross-correlation analysis **reveals significant dependencies** between UWD and weather up to a ~ **21 day time delay**:
  - **Each time series** (historical UWD and weather inputs) were time delayed **up to 21 days**;
  - Model **inputs**:
    - **Deterministic → Historical** weather measurements **only available up to 1 day time delay** (i.e. only previous information is used);
    - **QS-UWDF → Stochastic** weather inputs were **time lagged up to day of forecast** (i.e. weather on the day of the forecast is considered in the model **in addition to previous 21 days**).

Methodology

- WeaGETS:
  - Rainfall **occurrence**→ first-order Markov model;
  - Rainfall **amount** → mixed exponential distribution; and
  - Max and min **air temperatures** → first-order Markov model (conditioned on wet/dry status).
- SVR → Least- Squares SVR (LSSVR) optimized via PRESS (predicted residual sum of squares) [Cawley and Talbot, 2004]:
  - IVS → Input variables determined via Conditional Mutual Information (**CMI**).
- BMA → Individual LSSVR models combined to provide confidence intervals over ensemble prediction;
- The **2011 summer demand** period (153 records) used for **validating forecasts**; and
- **Forecast quality** determined via: Mean Absolute Error (**MAE**) and Correlation Coefficient (**CC**).

Results (weather generation)



Results (selected input variables)

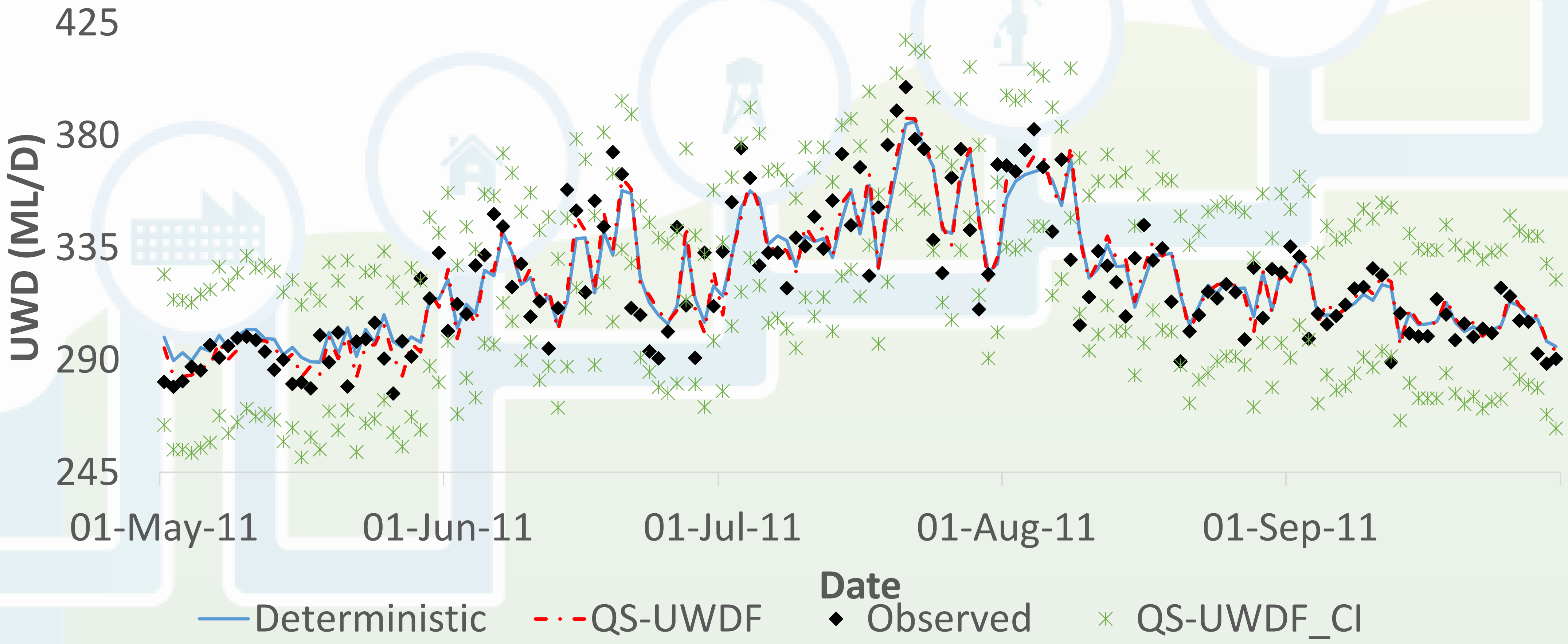
Input Variables (20 in total)

UWD (t)	UWD (t-1)	rain (t-1)	UWD (t-2)	rain (t-2)	UWD (t-4)	rain (t-4)	rain (t-5)	UWD (t-6)	rain (t-7)
rain (t-8)	rain (t-9)	rain (t-11)	rain (t-12)	rain (t-13)	rain (t-14)	rain (t-15)	UWD (t-17)	rain (t-17)	rain (t-19)

Results (short-term UWD forecasts)

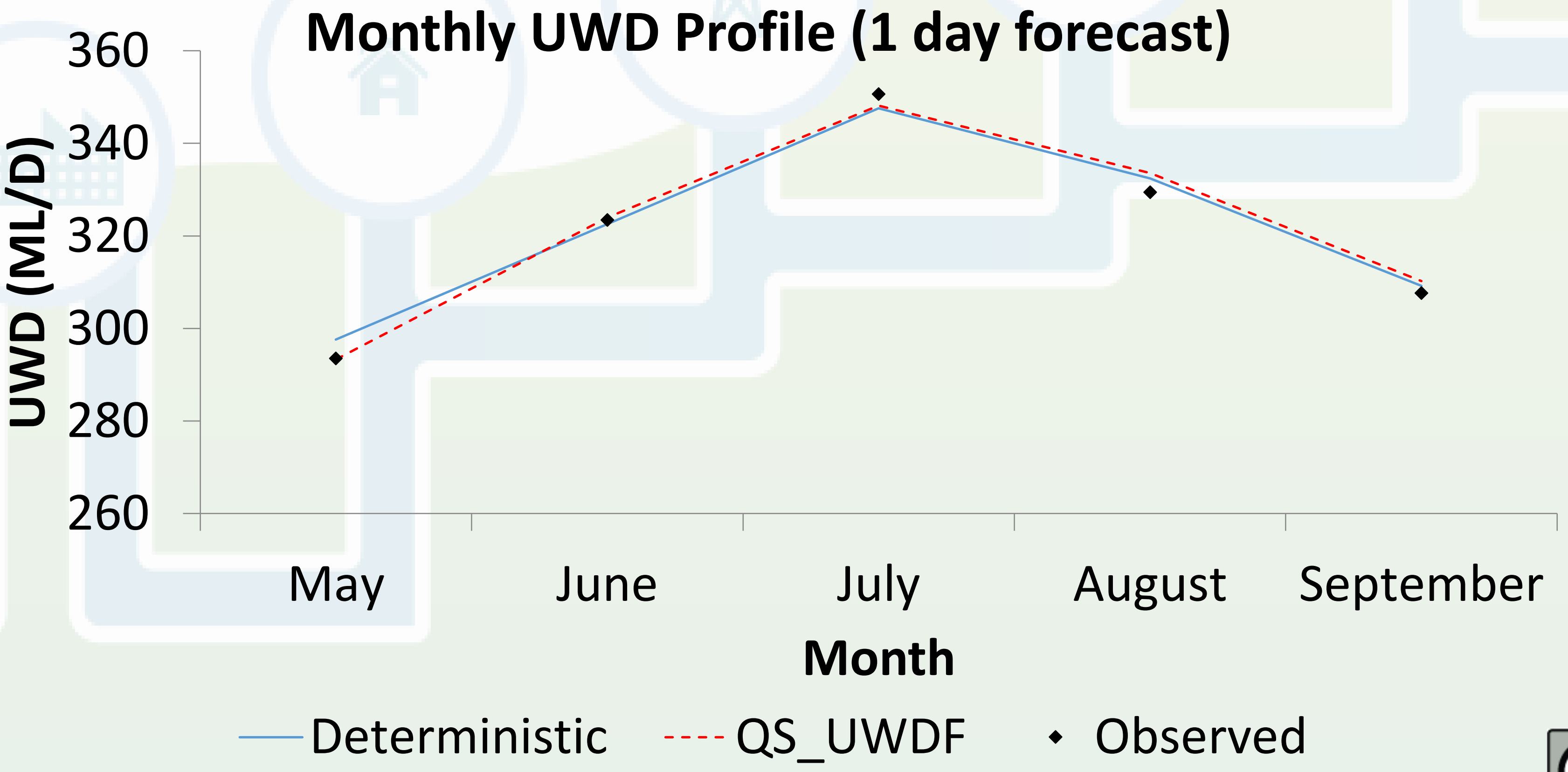
Method	Forecast Lead Time (Days) 1 MAE (ML/D)	CC	2 MAE (ML/D)	CC	3 MAE (ML/D)	CC
Deterministic	13.119	0.789	15.563	0.670	17.146	0.624
QS-UWDF	13.144	0.790	16.462	0.649	18.009	0.615

Results (1 day ahead forecasts)



Conclusions & Recommendations

- **Stochastic weather** inputs or **historical** records are both **viable inputs** for short-term **UWD forecasting** in **Ottawa, Canada;**
- **QS-UWDF** is **competitive** with **deterministic** modeling.



Conclusions & Recommendations

- Deterministic model has better performance **over longer lead times** (e.g. **CC** for QS-UWDF and Deterministic → **1 day**: 0.790 vs. 0.789; **2 day**: 0.649 vs. 0.670; and **3 day**: 0.615 vs. 0.624;
- **QS-UWDF** provide **uncertainty assessment** while deterministic only provides point forecasts; and
- QS-UWDF may be used for **risk**, **resiliency**, and **vulnerability** assessment of water supply systems.

Conclusions & Recommendations

- **Low-frequency variability correction** in weather generation should be explored;
- **Different stochastic simulation methods** should be compared (e.g. WeaGETS vs. k-NN stochastic simulation [Prairie et al., 2006]);
- **Different model ensemble approaches** can be implemented (e.g. via input variable selection);
- **Different machine learning techniques**, such as Extreme Learning Machines [Huang et al., 2006], can be utilized to improve computational efficiency; and
- The **QS-UWDF should be tested on numerous water supply systems** to further explore its practical applications.

THANK YOU!

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