



AquaSCALE: Exploring Resilience of Community Water Systems

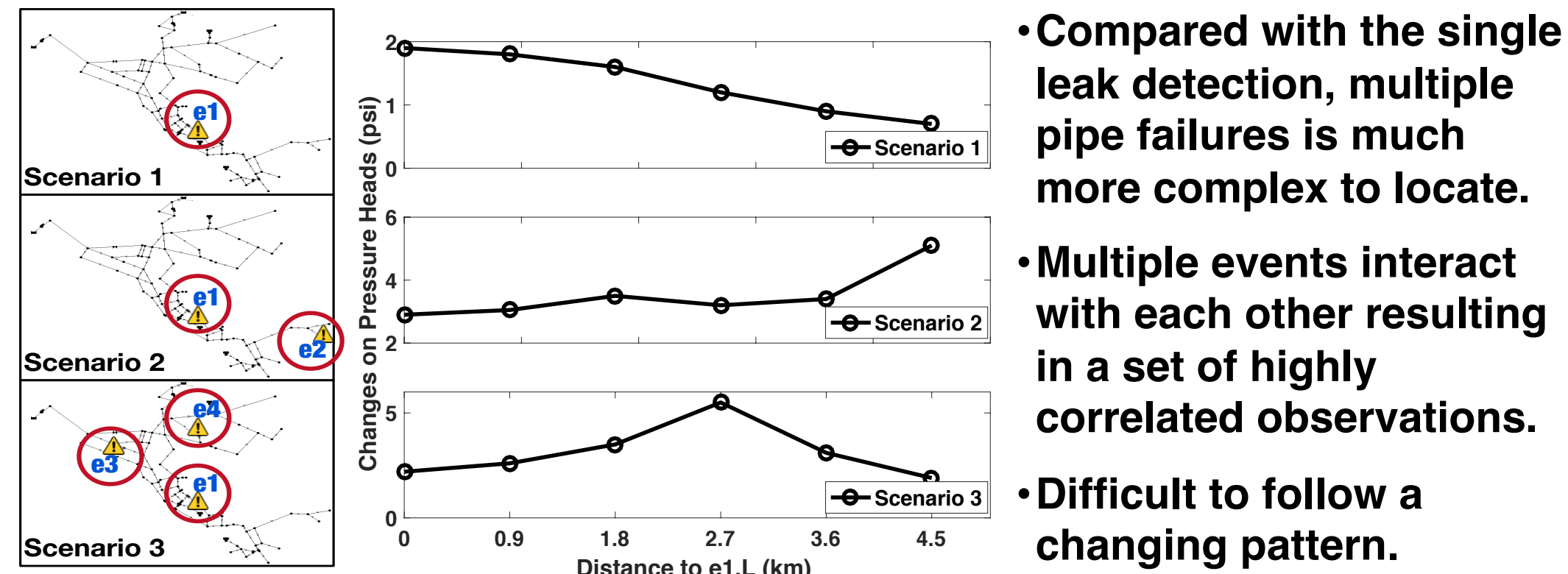
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Ronald T. Eguchi, Georgiana Esquivias, ImageCAT Inc.; Daniel Hoffman, Montgomery County, MD

"A framework to improve the outcomes of water related emergencies"



Key Resilience Issue – Pipe Leaks

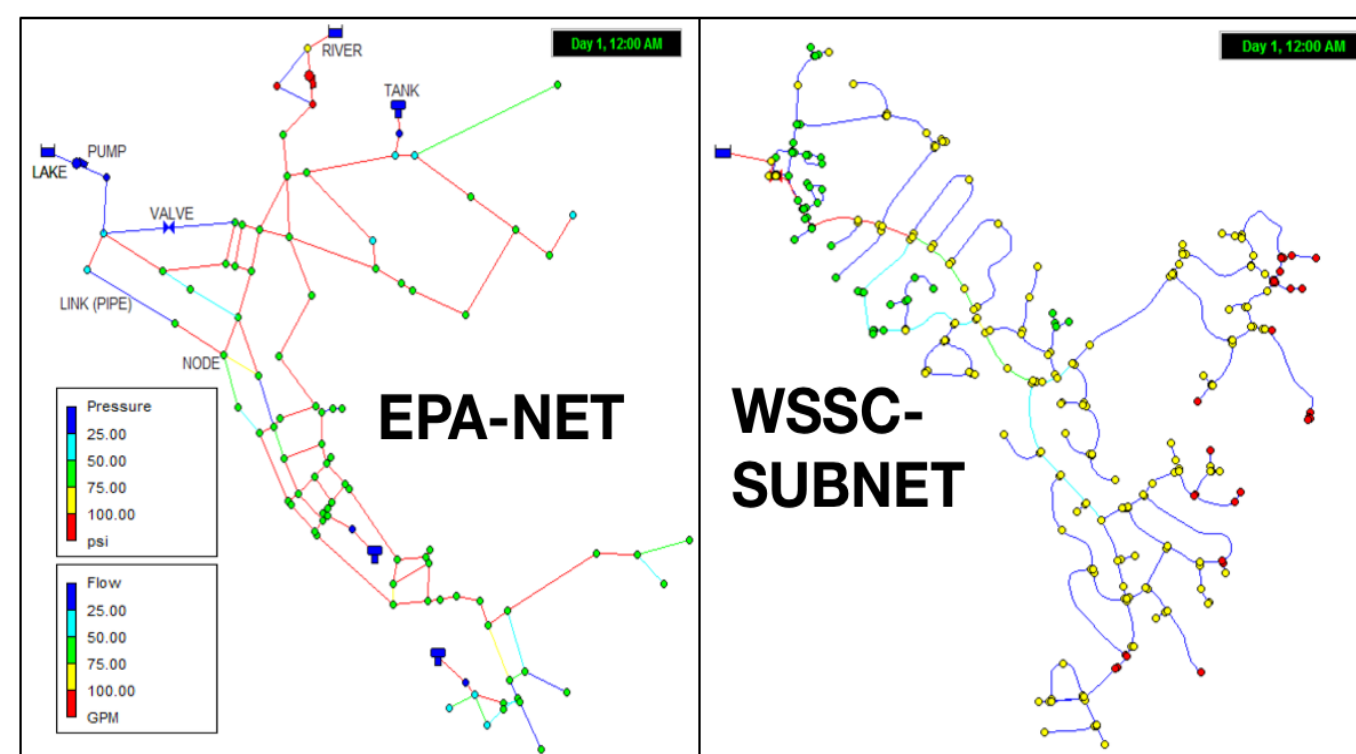
- Pipe break/leak is one of the most frequent types of failures in water networks worldwide.
- Recent reports from agencies (Los Angeles Dept. of Water/Power, Washington Suburban) indicate that communities are experiencing an unusual increase in pipe breaks and leaks.
- Extreme weather and heavy rainfall (e.g. Hurricane Sandy, El Nino 2016) can stress already weakened pipes to the point of causing major breaks.



AquaSCALE is evaluated using two networks.

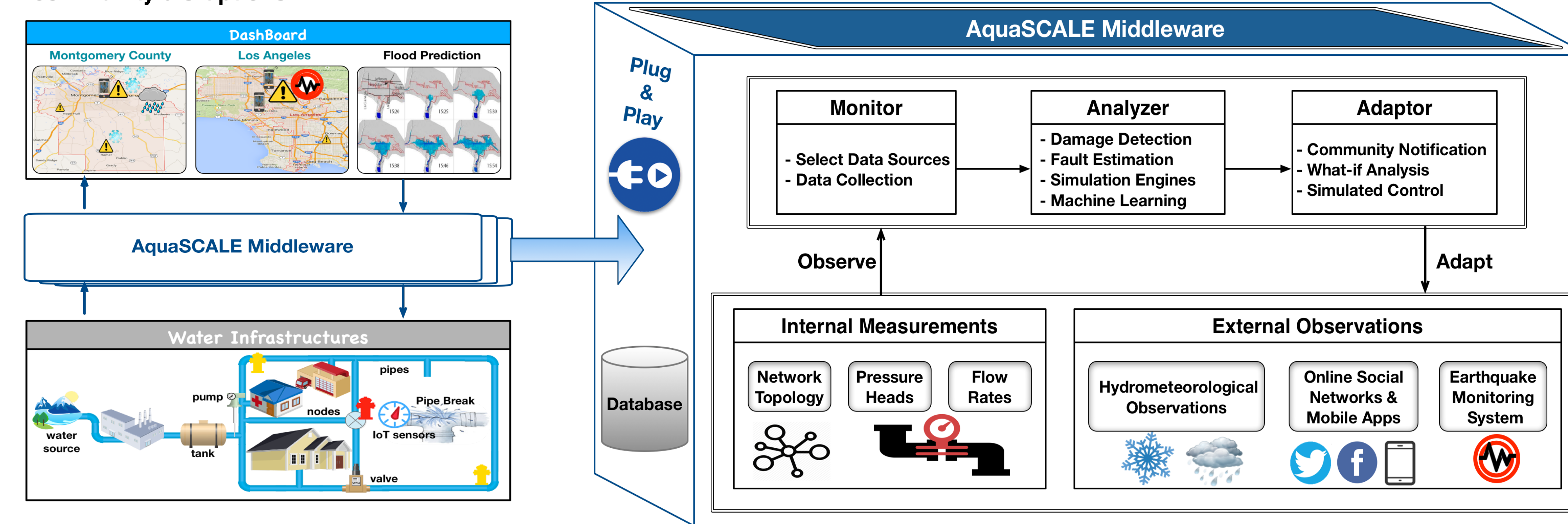
EPA-NET: a canonical network from EPANET. (96 nodes and 118 pipes)

WSSC-SUBNET: a real subzone of the WSSC water service area. (299 nodes and 316 pipes)



Goals and Overview

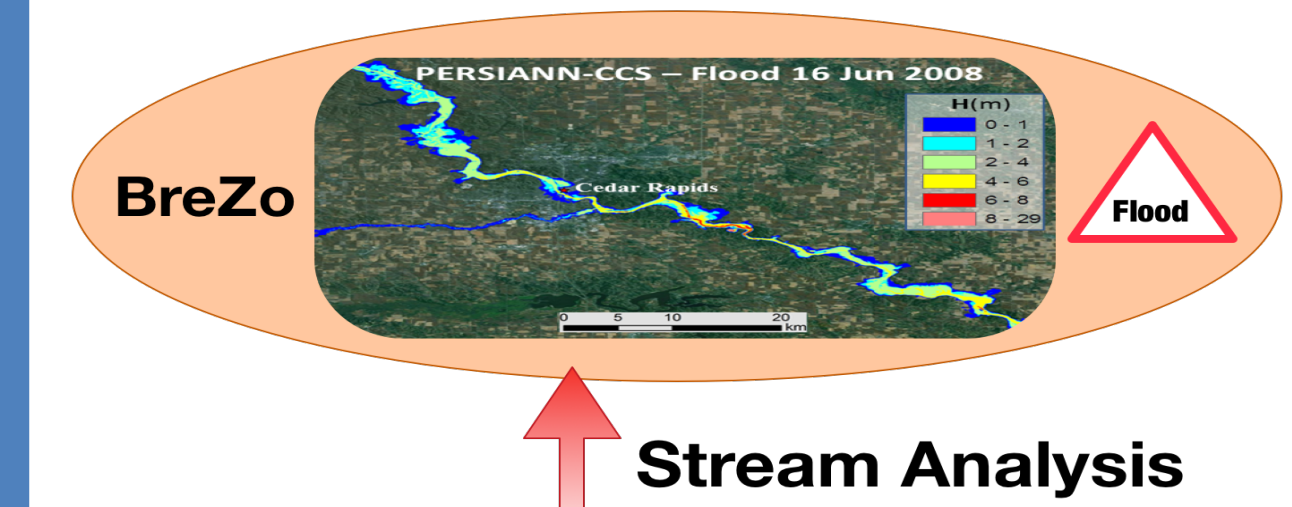
- Water is a precious resource and lifeline service to community worldwide.
- The critical infrastructures have been developed over decades (centuries sometimes) and become complex and vulnerable to failures.
- Pipe breakage is one of the most frequent types of failures that often causes community disruptions.
- Develop methodologies to understand operational performance and resilience issues for real-world community water infrastructures.
- Explore solutions to problems in cyberspace before instantiating them into a physical infrastructure.
- Prevent water service failures by identifying operational degradation in aging infrastructures.
- Improve speed and accuracy of damage estimation in natural disasters and human-made hazards.
- Reduce service restoration time in the event of large hazards.



Prototype Implementation

Integration of Multiple Resources

- Leverages dynamic data from multiple information sources including IoT sensing data, geophysical data, human inputs, and simulation engines.
- Create a sensor-simulation-data integration platform.
- Pipe failures often lead to changes in pressure heads and flow rates.
- The chance of water main breaks rises significantly in the event of extremely cold weather.
- Human reports on leak events can identify the potential damaged region.
- A large-scale pipeline failures or a pipe burst may cause severe flooding.



Cascading Events – Incorporate flood modeling and prediction to capture the impacts of pipe failures.

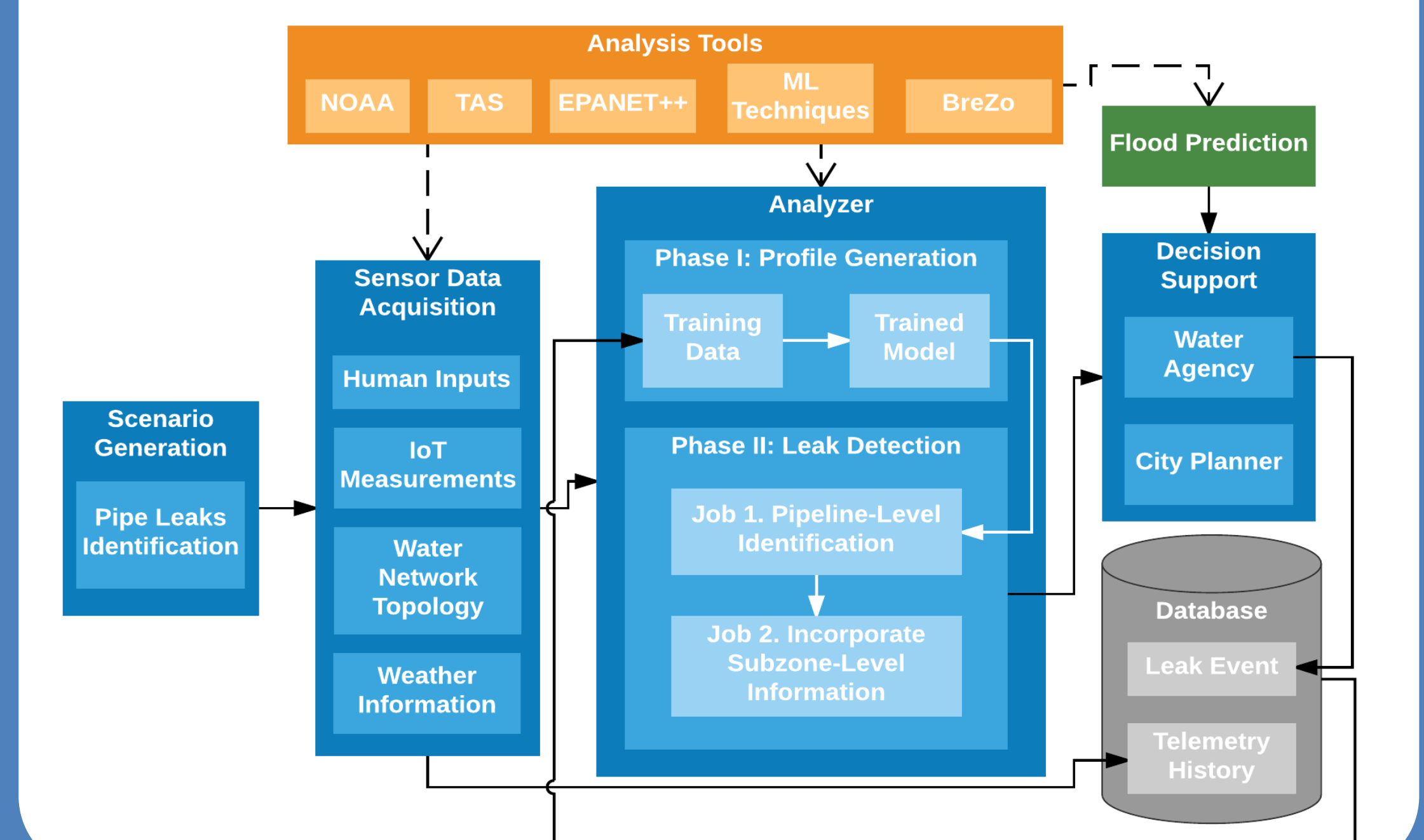
Human Inputs – Integrate a novel Tweet Acquisition System to extract leak-related tweets in an online adaptive manner.

IoT Measurements – Using a commercial grade hydraulic simulator EPANET enhanced with the support for IoT sensors and failure modeling.

Geophysical Data – Integrate NOAA to supply information pertaining to the state of the atmosphere including weather warning and forecasts.

Leaks Identification Workflow

- The initial implementation of AquaSCALE is designed as a workflow based system comprised of multiple components.
- Scenario Generation Module enables providing meaningful and diverse water contexts to the framework by generating a range of situations.
- Sensor Data Acquisition Module enables gathering of real-time field information and projecting the effects on the simulation outcomes.
- Analytics Module is used to plug and unplug specific information at will depending on the specific context of applications.
- Decision Support Module enables users/operators/analysts to interact.



A Composite Leak Identification Algorithm

- A two-phase approach enables an accurate and timely leak events identification.
- Phase I – the profile model is generated offline. Phase II – additional observations are integrated with the predicted results from the profile model when the live data coming in.
- Proposed a hybrid approach HybridRSL, a combination of RF and SVM via LR.
- Remain robust with decreasing number of IoT devices

Algorithm 1 Training Profile Models

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1: Input water network topology  $T$ , IoT measurements  $X$ , true leak events  $Y_v$  and classifiers  $f_v$  for  $v \in V$ 
2: Output the profile model  $f = \{f_v : v \in V\}$ 
3: Objective update  $f_v$  to best fit training samples
4: for  $v$  in  $V$  do
5:    $f_v \leftarrow \text{fit}(T, X, Y_v)$ 
6: end for
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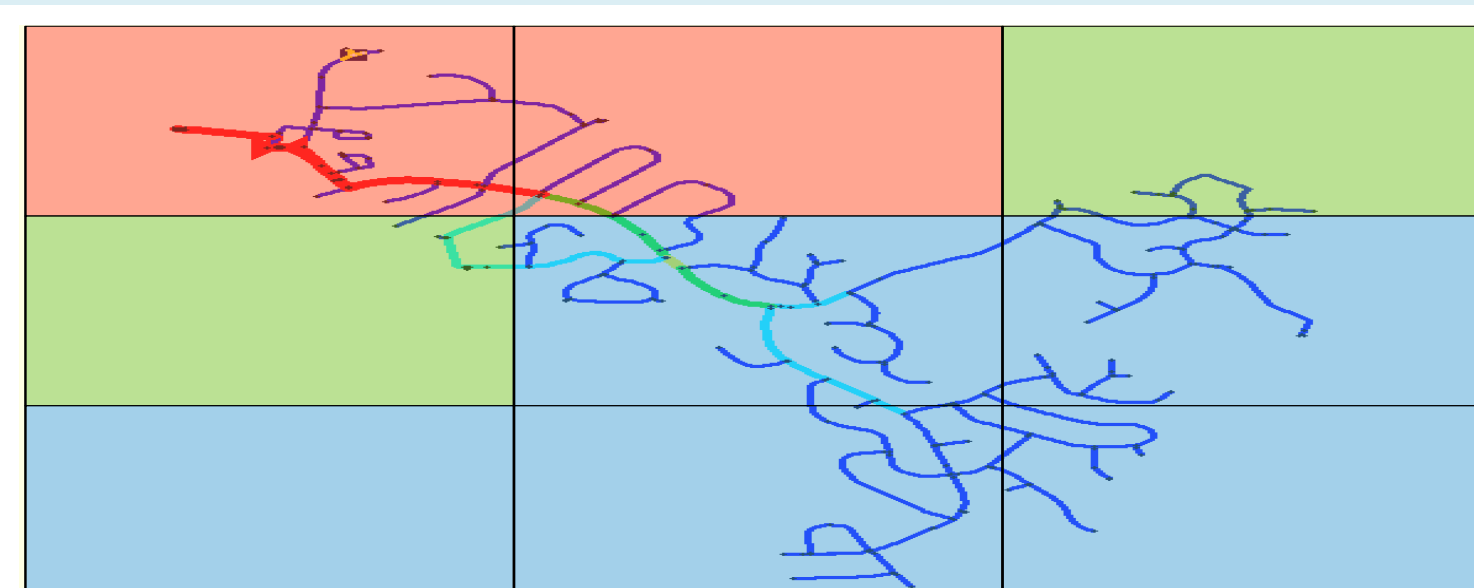
Algorithm 2 Inferring Leak Events

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1: Input water network topology  $T$ , IoT measurements  $X$ , profile model  $f$ , leak probability due to frozen  $p_{v,cy}(\text{leak}/\text{freeze})$  and human inputs  $C$ 
2: Output an updated set of leak locations  $S$ 
3: Objective minimize  $E[y]$  in (7)
4: /* Pipeline-level Identification */
5:  $P = f \cdot \text{predict\_proba}(T, x); S = f \cdot \text{predict}(T, x)$ 
6: for  $v$  in  $V$  do
7:   if  $v$  is detected to be frozen then
8:      $p_v(1) = \min\{1, p_v(1) + p_{v,cy}(\text{leak}/\text{freeze})\}$ 
9:      $p_v(0) = 1 - p_v(1)$ 
10:     $S = S \cup \{v\}$  if  $p_v(1) > p_v(0)$ 
11:  end if
12: end for
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13: /* Incorporate Subzone-level Information */
14:  $C = \{c : c = \{v : |l_c - l_v| < \gamma \wedge v \in V\}\}; \Phi_{c \in C} = \text{Inf}$ 
15: for  $c$  in  $C$  do
16:   if  $\exists v \in S$  for  $\forall v \in c$  then
17:      $\Phi_c = 0$ , break
18:   end if
19:   if  $\Phi_c \neq 0$  then
20:      $v^* = \arg \max_{v \in c} H(y_v)$ 
21:     if  $H(y_{v^*}) > 1$  then
22:        $p_{v^*}(1) = 1, p_{v^*}(0) = 0, S = S \cup \{v^*\}$ 
23:     end if
24:   end if
25: end for
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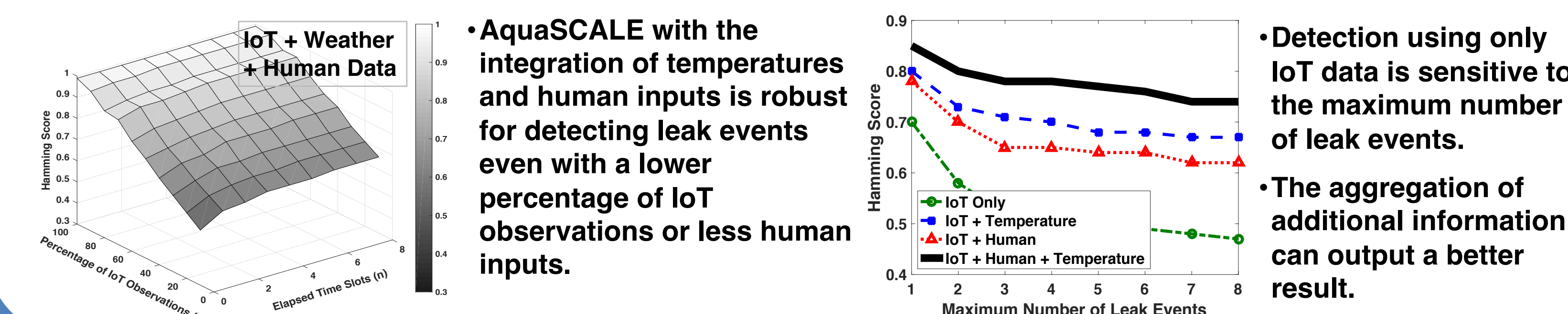
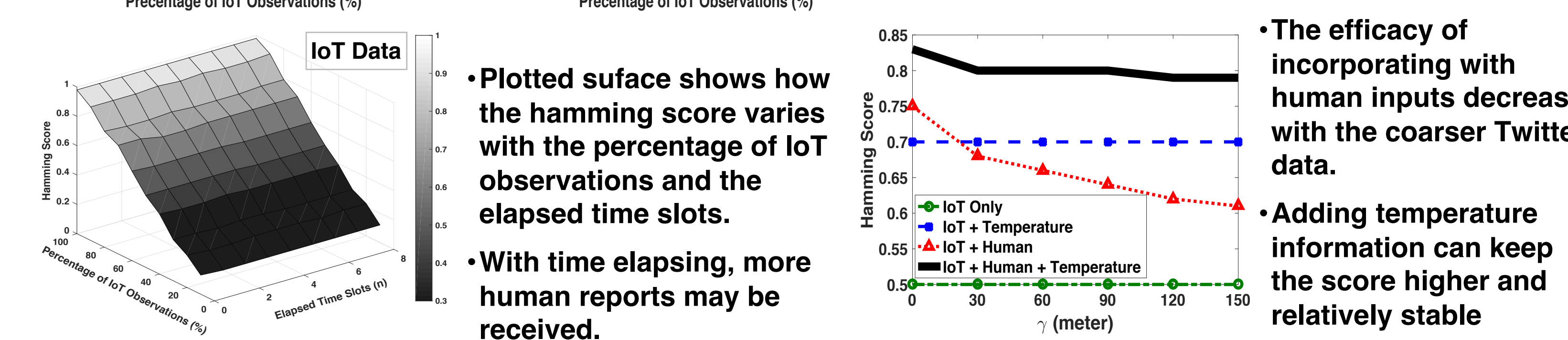
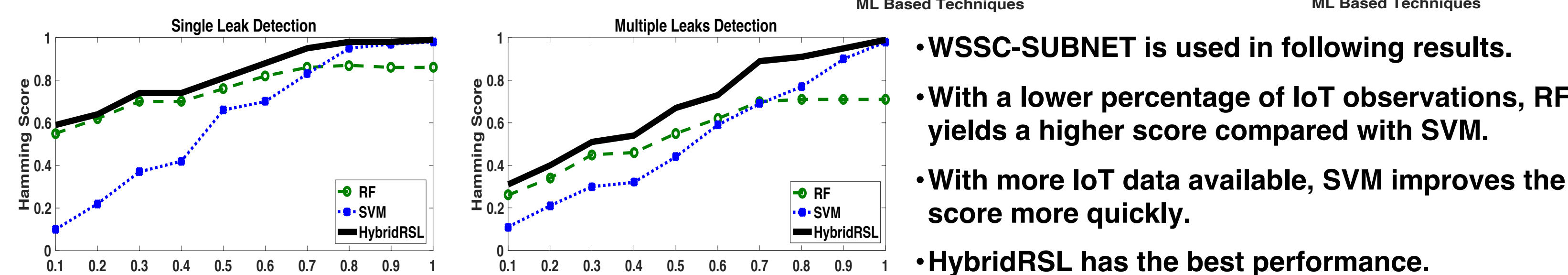
- In Phase I, the objective is to train a set of classifiers to generate a robust profile model.
- Use an extensive amount of measurements collected in water infrastructures.

- In Phase II, multiple data sources are sequentially aggregated to infer leak locations from combinations of information.
- IoT measurements and ambient temperatures are relatively stable data sources compared with human inputs.
- Use IoT and temperature streams for pipeline-level predictions.
- Use additional human inputs for incorporating subzone-level information.



Experimental Study

- Comparison of multiple Machine Learning (ML) techniques for single leak event identifications using full and 10% IoT observations on EPA-NET water network.
- SVM and RF can keep a better performance with 10% IoT observations.



- WSSC-SUBNET is used in following results.
- With a lower percentage of IoT observations, RF yields a higher score compared with SVM.
- With more IoT data available, SVM improves the score more quickly.
- HybridRSL has the best performance.

- Plotted surface shows how the hamming score varies with the percentage of IoT observations and the elapsed time slots.
- With time elapsing, more human reports may be received.

- AquaSCALE with the integration of temperatures and human inputs is robust for detecting leak events even with a lower percentage of IoT observations or less human inputs.
- The efficacy of incorporating with human inputs decrease with the coarser Twitter data.
- Adding temperature information can keep the score higher and relatively stable.
- Detection using only IoT data is sensitive to the maximum number of leak events.
- The aggregation of additional information can output a better result.

