Autonomous Moisture Continuum Sensing Network

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Presentation Contents

- Motivation and Overview
- Background: SoilSCAPE.
- Technical Development ($\text{TRL}_{\text{in}} = 2$):
  - Wakeup-on Radio
  - Machine Learning Decision Making
- Summary

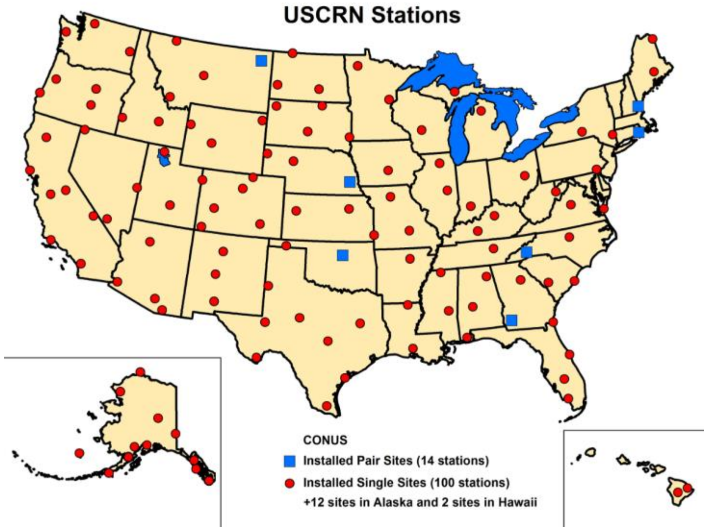
Motivation and Context

- Environmental *in situ* sensor networks:
  - Key components in our study of Earth.
  - Long-term records and observations of different Earth processes, e.g., SCAN, USCRN, AmeriFlux, FluxNet, SoilSCAPE, etc.
  - Near real-time ground truth for Earth Science missions.

    e.g., Cal/Val support for SMAP, etc.
  - Predetermined and fixed sampling rates, e.g., hourly.
  - Solar panels and rechargeable batteries.

AmeriFlux Site, Tonzi Ranch ,CA

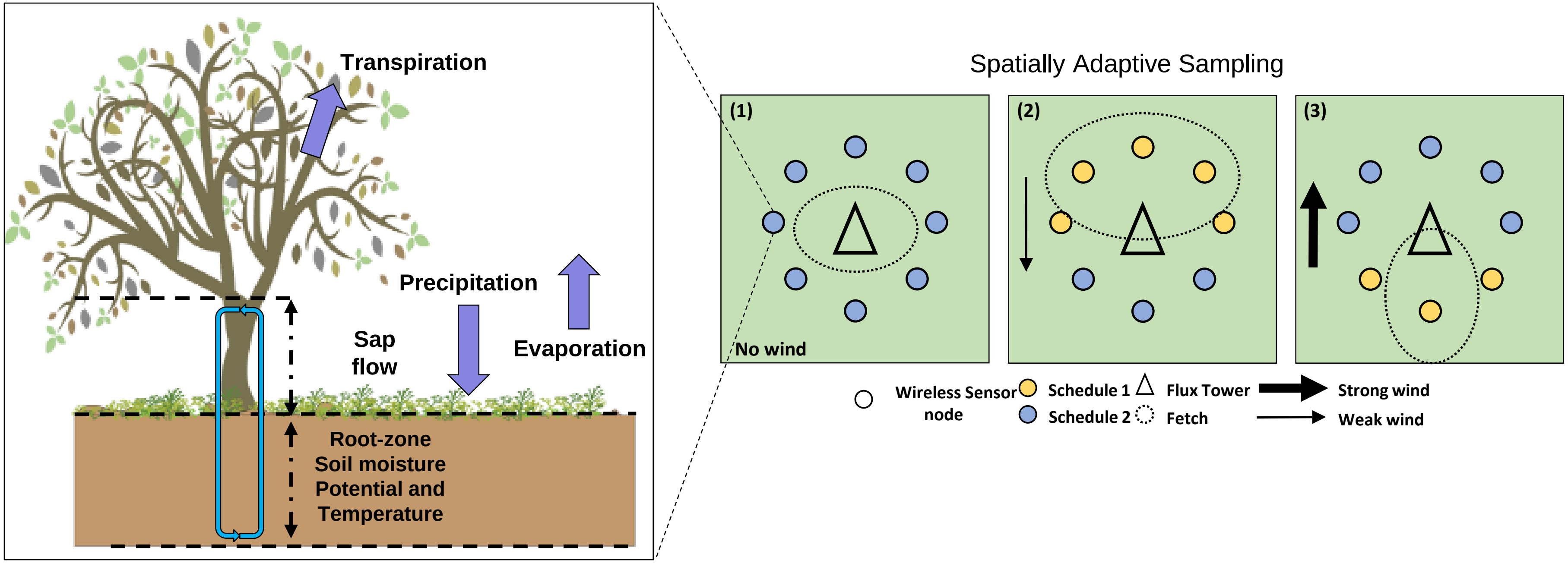
Richard Chen, USC



https://www.ncdc.noaa.gov/crn/

Motivation and Context

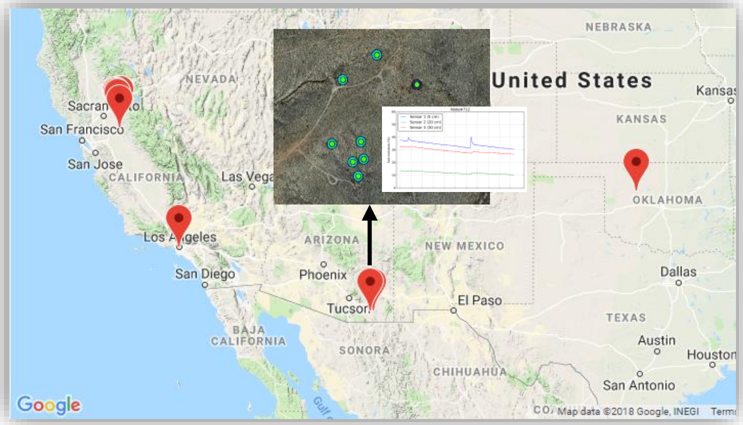
- Keeping track of the soil moisture state is of particular interest.
  - We can learn about biome adaptation to climate change by monitoring the flow and distribution of water between land and atmosphere.
  - A distributed sensor network observing hydrologic processes, both in the spatial and temporal domains, is required.



Background

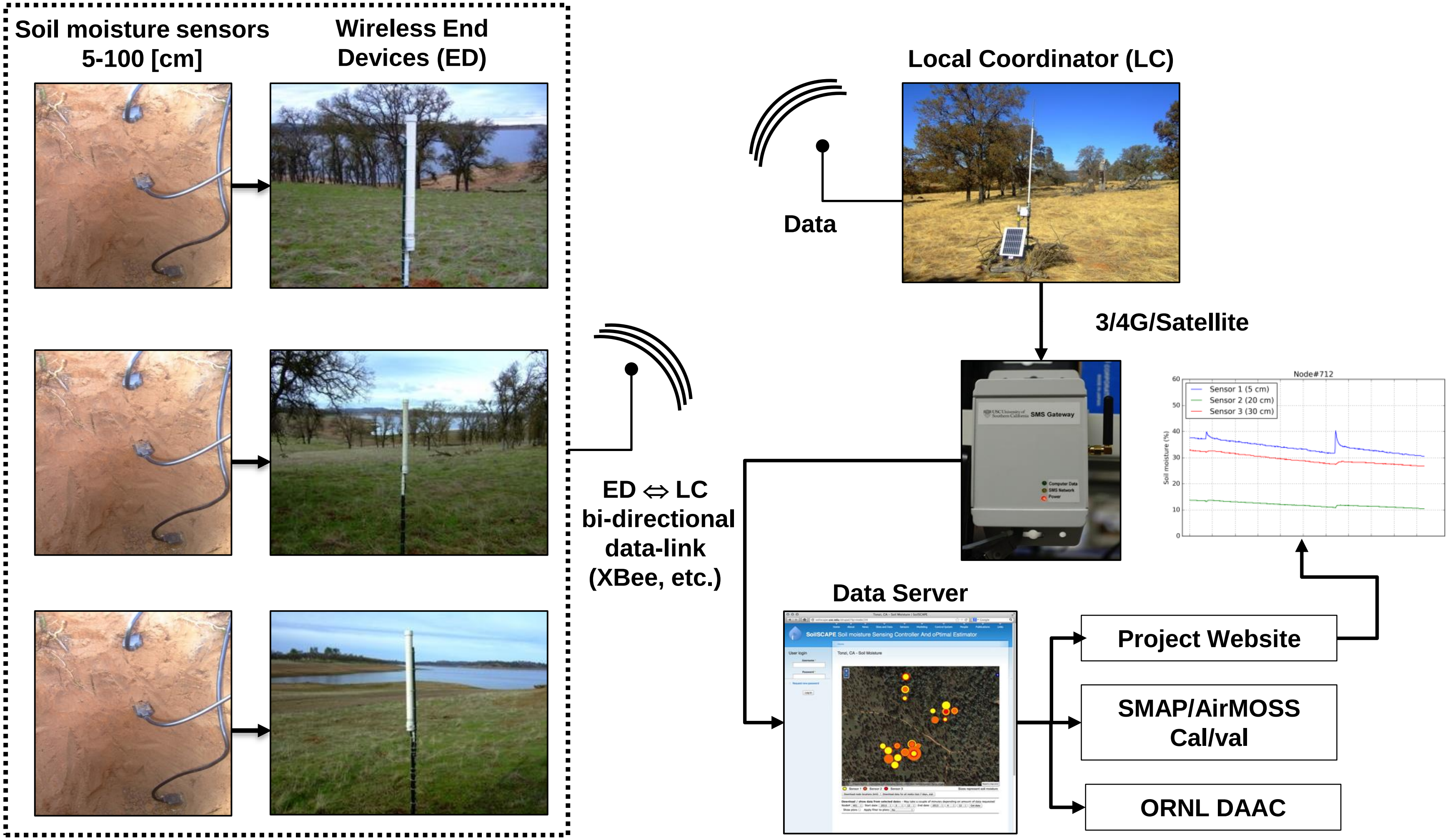
Soil Moisture Sensing Controller and Optimal Estimation (SoilSCAPE)

- Significant heritage from prior ESTO support: SoilSCAPE (PI: Moghaddam, USC)
- Multiple large scale *in situ* wireless sensor networks
    - AK, AZ, and CA with over 3 years of operation
- Fully in-house and custom built hardware and software.
- End-to-end measurement acquisition and distribution.
- AirMOSS & SMAP cal/val support
- 20-min sampling schedule
- Data available for free:
    - soilscape.usc.edu
    - ORNL DAAC



SoilSCAPE Overview

Network Architecture



Soil moisture sensors 5-100 [cm]

Wireless End Devices (ED)

Data

Local Coordinator (LC)

3/4G/Satellite

ED ⇔ LC bi-directional data-link (XBee, etc.)

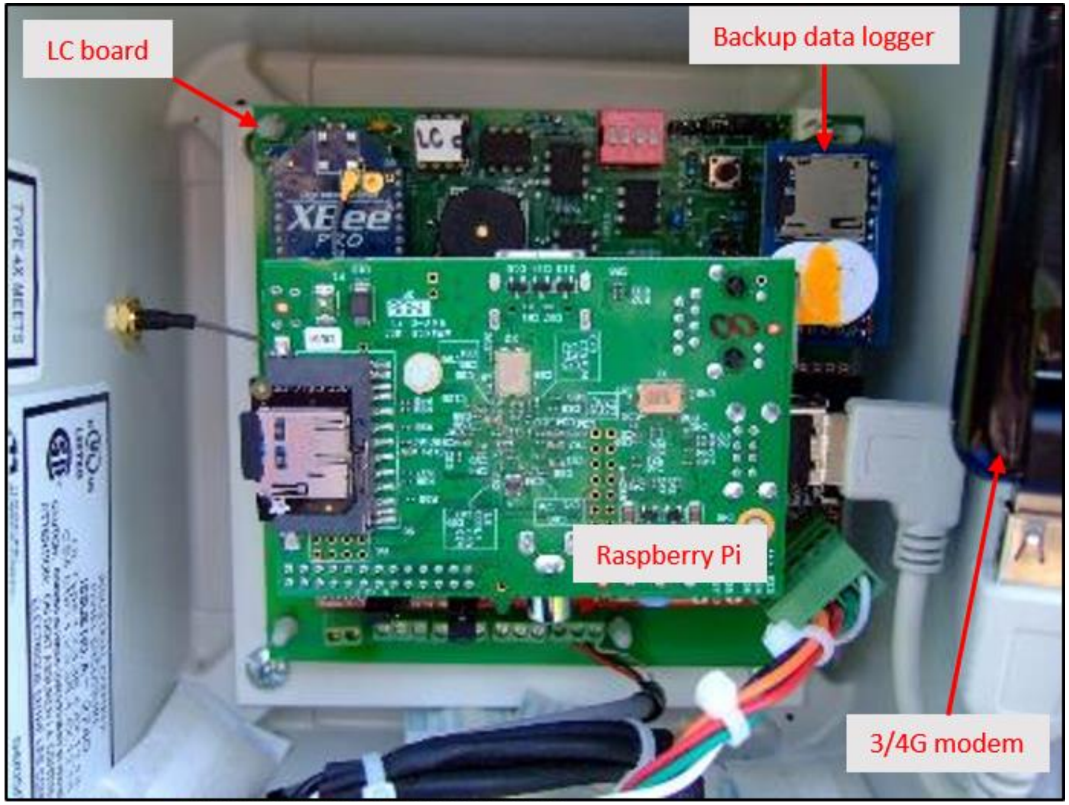
Data Server

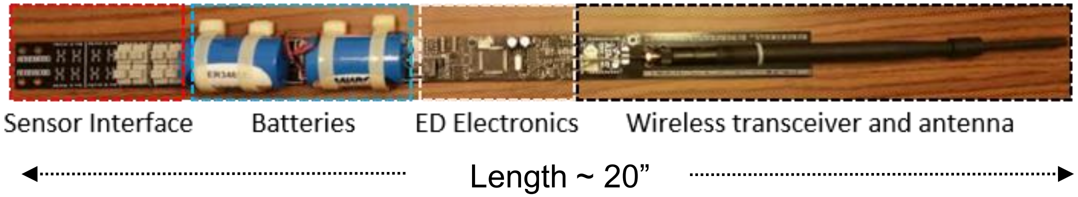
Project Website

SMAP/AirMOSS Cal/val

ORNL DAAC

SoilSCAPE Overview
Local Coordinator (LC) & End Device (ED)





- Over 150 WSN nodes installed
- SoilSCAPE system, end-to-end, TRL~ 7

Project Objectives

SoilSCAPE 2.0!

1. Enable the WSN to autonomously “decide” when to collect new data
    - Machine Learning applications + Energy management/awareness
    - Generally speaking:

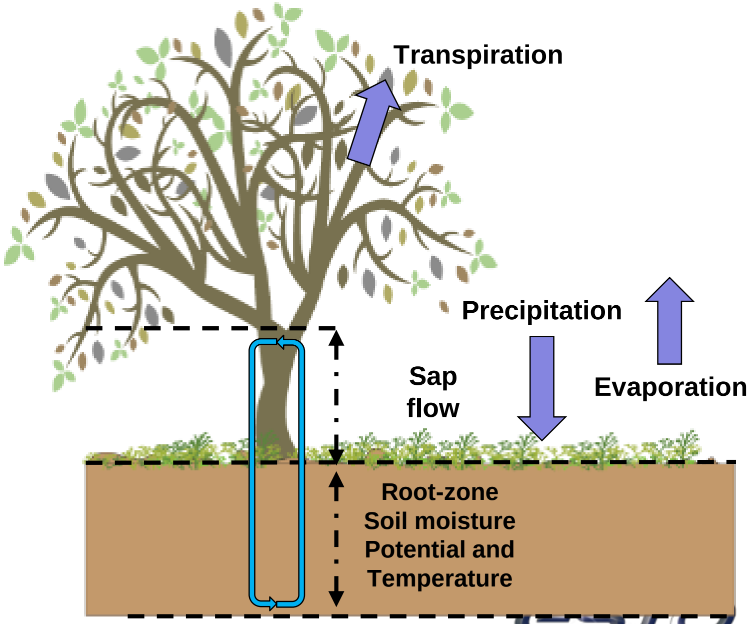
make a “prediction” about current field conditions, then decide whether to acquire new data or not.

2. Wakeup-on-Radio (WoR) wireless module
    - On-demand end-device command and control.

(1) and (2) collectively make the WSN fully autonomous.

Inspiration from Industry:

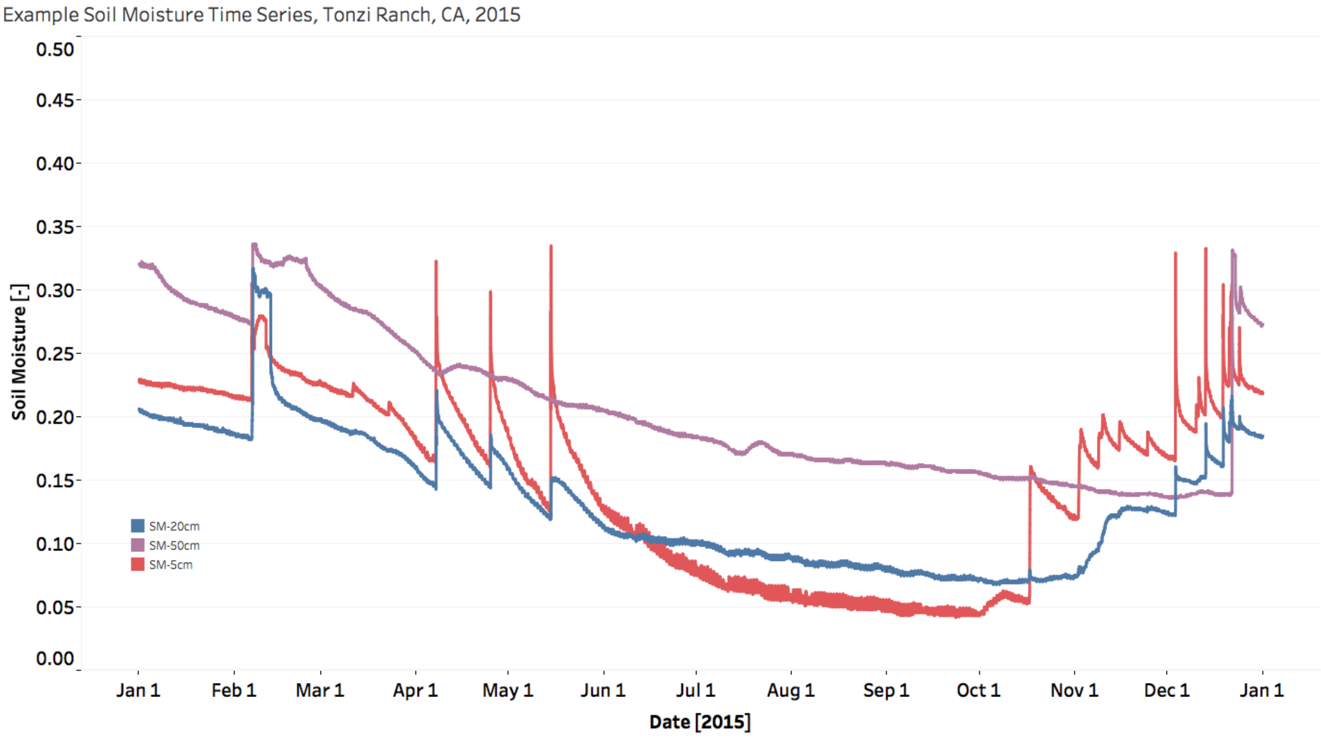
Integrate ML-techniques as components within sensing system, e.g., Apple “Neural Engine”, AI accelerators, TPUs, etc.



Project Objectives

SoilSCAPE 2.0!

- Battery powered devices → finite number of measurements!
- Soil moisture dynamics are highly variable.



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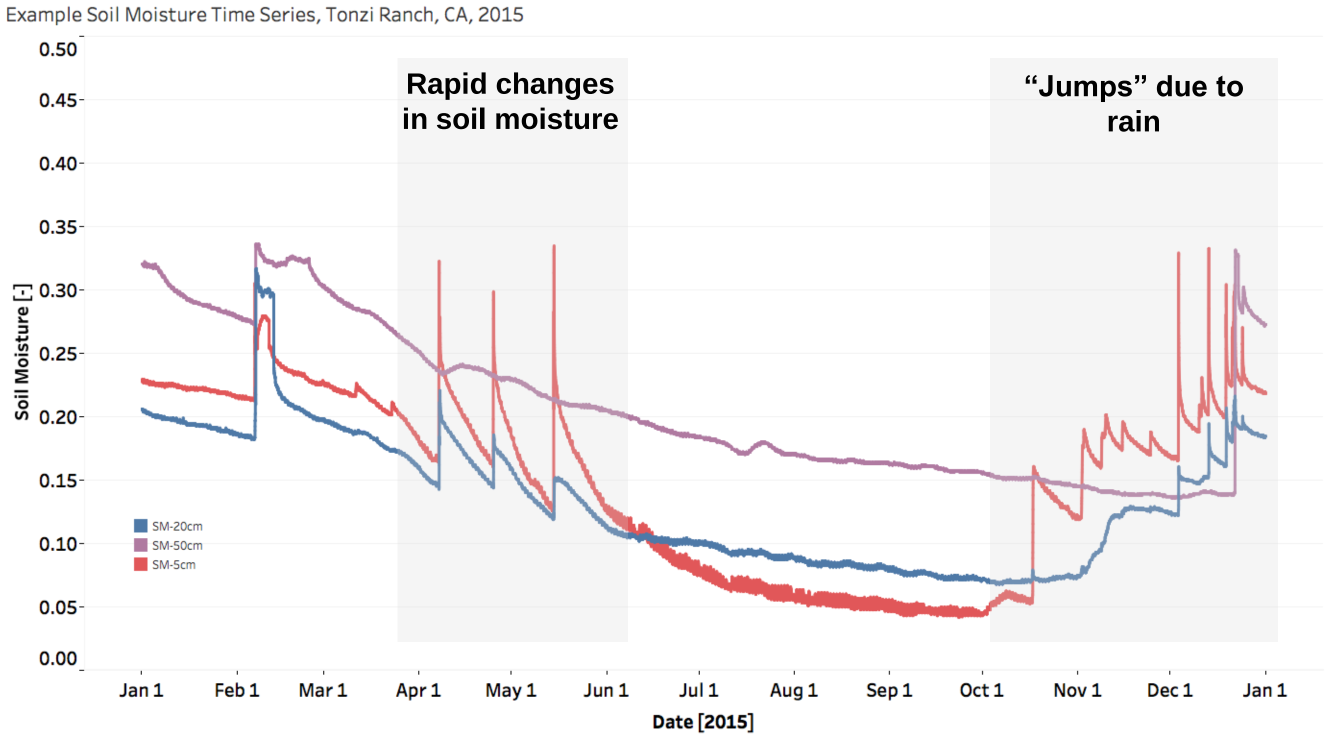

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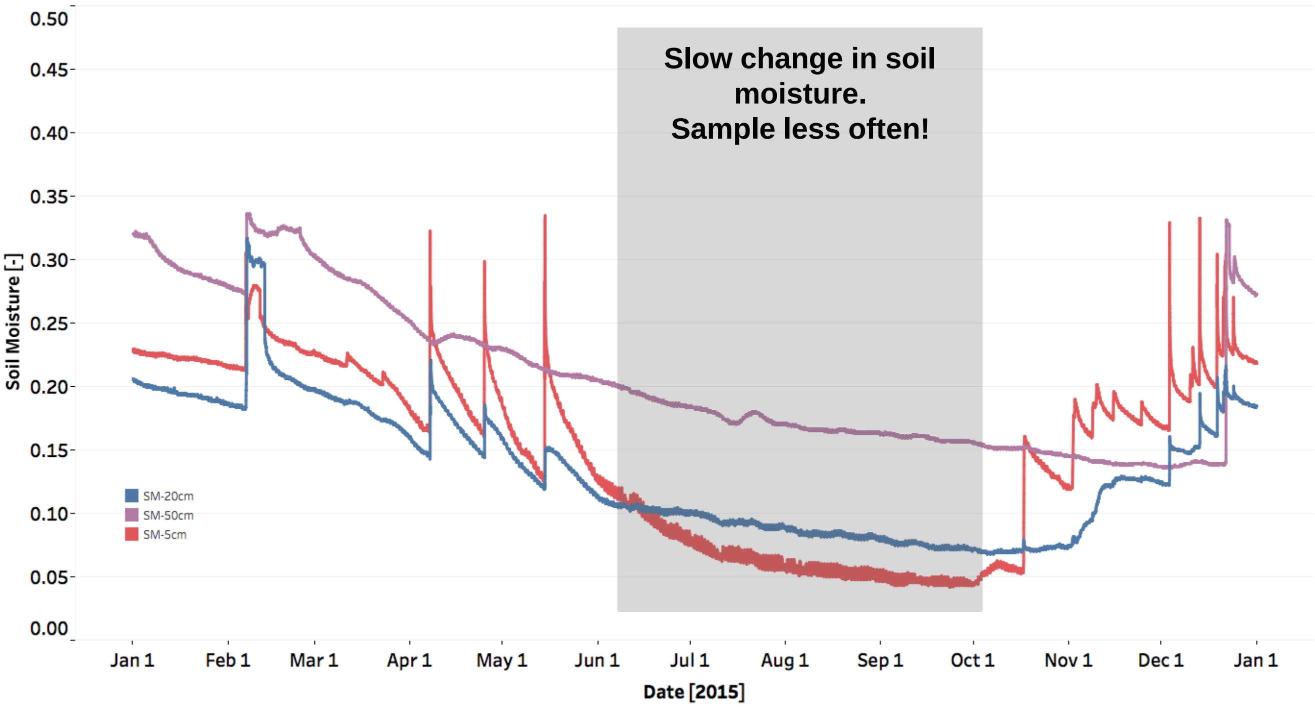

Example Soil Moisture Time Series, Tonzi Ranch, CA, 2015

Slow change in soil moisture.
Sample less often!

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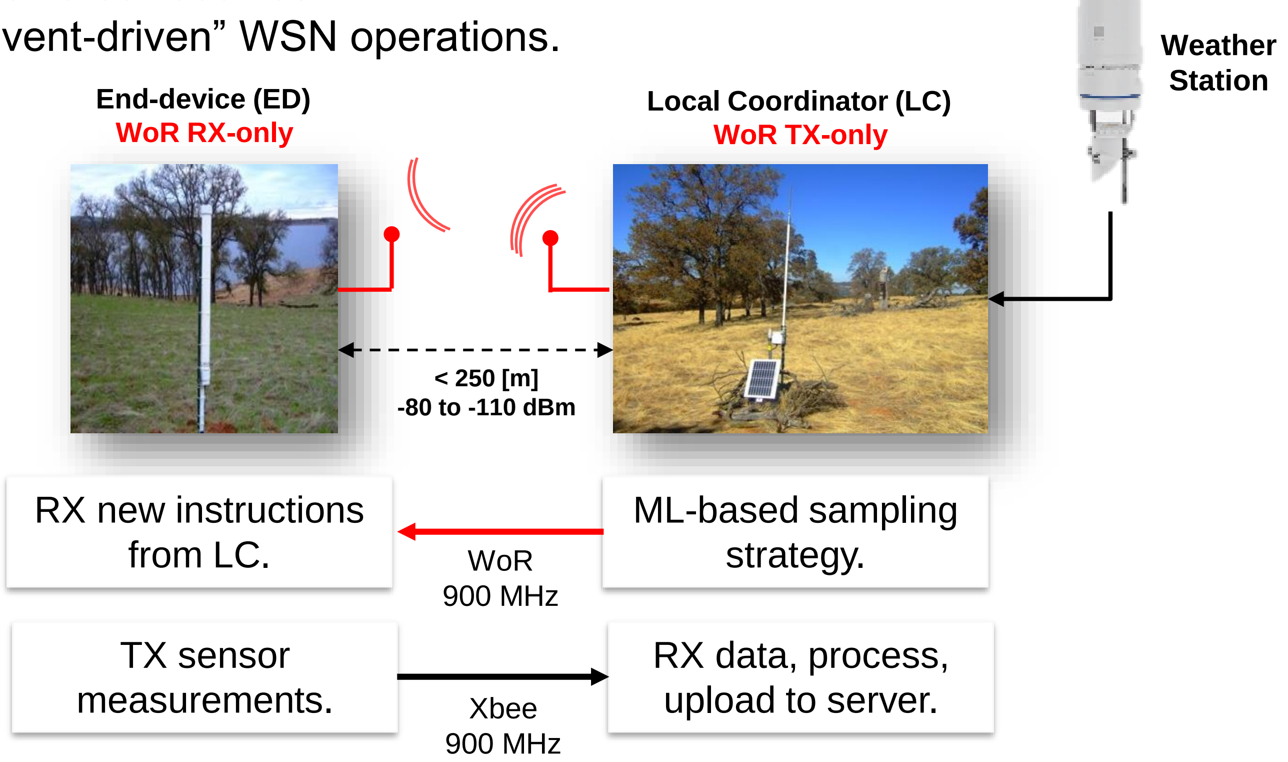
    - Machine Learning Decision Making
- TRL Assessments
- Updated Project Schedule
- Project Finances
- List of Acronym

Wakeup-On Radio (WoR) (1)

- Wakeup-on-Radio
  - Ultra low-powered receives
  - Enables “event-driven” WSN operations.



End-device (ED)
WoR RX-only

Local Coordinator (LC)
WoR TX-only

Weather Station

< 250 [m]
-80 to -110 dBm

RX new instructions from LC.

ML-based sampling strategy.

WoR
900 MHz

TX sensor measurements.

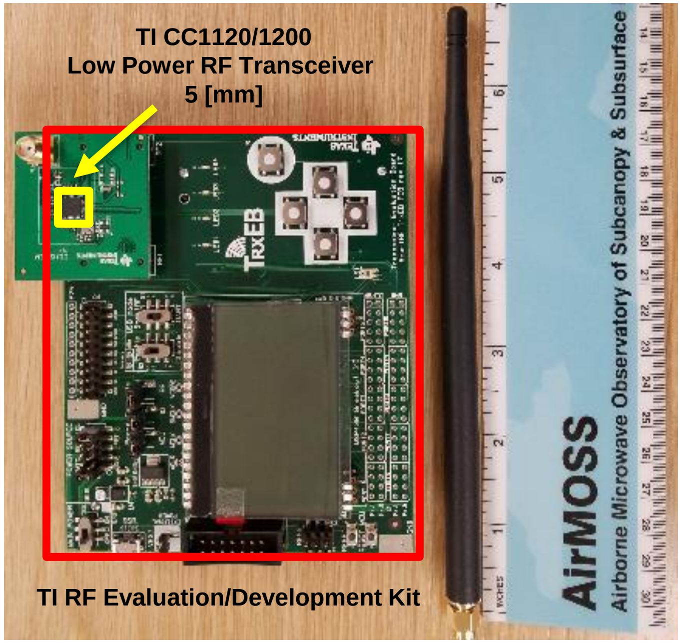
RX data, process, upload to server.

Xbee
900 MHz

- Not a feature in most existing networks.
- Design Objectives:
  - Can we add “event-reaction” to SoilSCAPE with ***same*** energy-efficiency?
  - Can we still ***improve*** energy-efficiency of the solution?

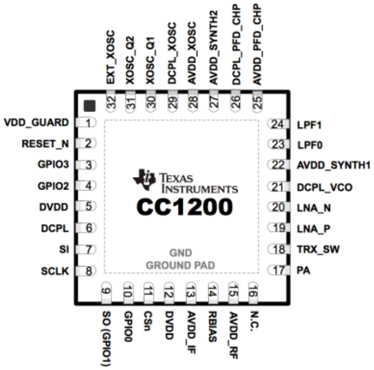
Wakeup-On Radio (WoR) (2)

- Criteria For Evaluating Wireless Wake-up Technologies:
  1) LC-ED distance > 100m (250m is desired, not required)
  2) Energy consumption of new technology < 20 J per day
  3) Wake-up latency <2minutes (i.e., max. time to wake-up ED)
  4) Wake-up likelihood >99%
  5) Implementation feasibility in less than 6-8 months (2-year project)
- Investigating two design options using TI CC1200 RF Transceiver.



TI CC1120/1200
Low Power RF Transceiver
5 [mm]

TI RF Evaluation/Development Kit



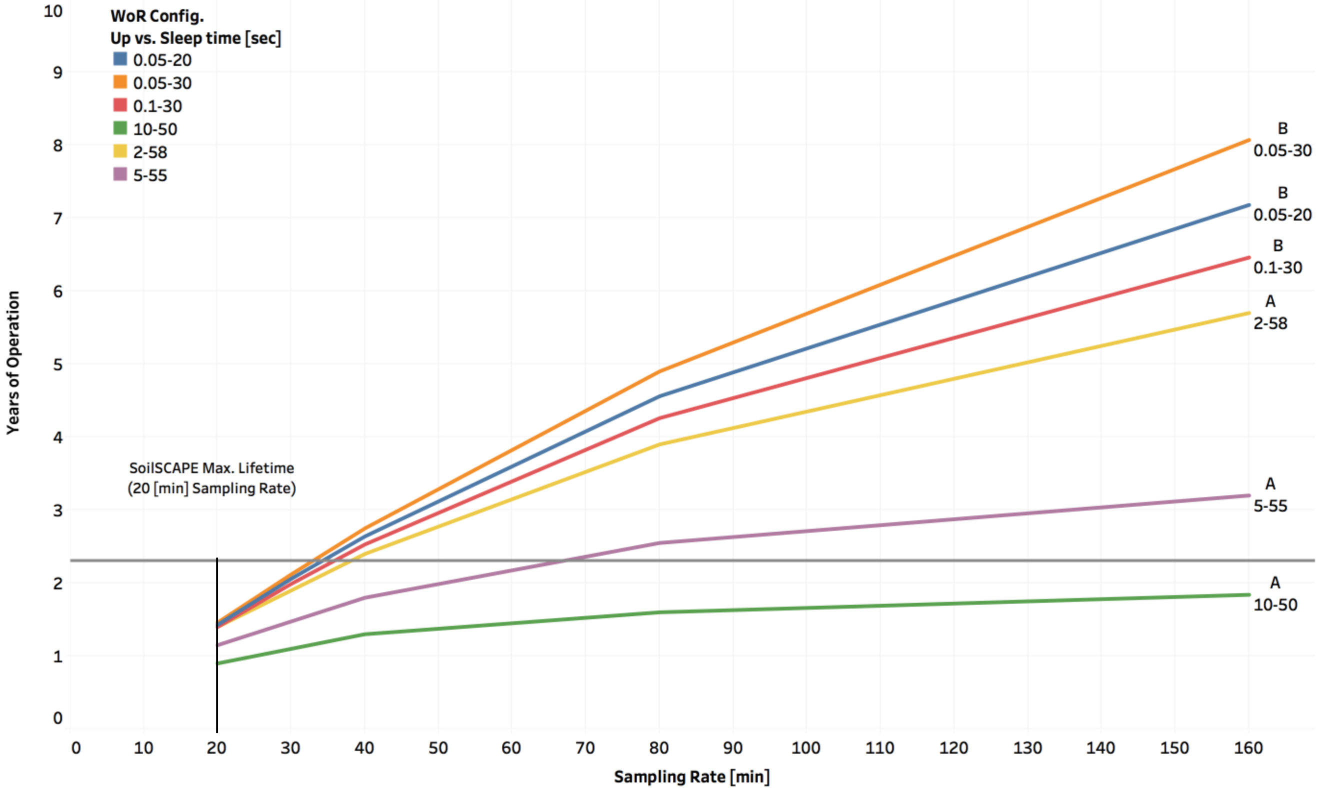
- Chip needs to be integrated within current wireless end-devices.
- Allows for “addressed” WoR, spatially selective wake-ups
- 900 MHz ISM
- 0.5-23 mA Peak current

Wakeup-On Radio (WoR) (3)

Baseline and Expected Lifetime improvement

- Active WoR: must periodically wake-up to check for signal.
- Two custom design option:
  - Option-A: Simpler implementation, less energy efficient. "Wake-up beacons."
  - Option-B: complex, but more energy efficient. CW wake-up signal.

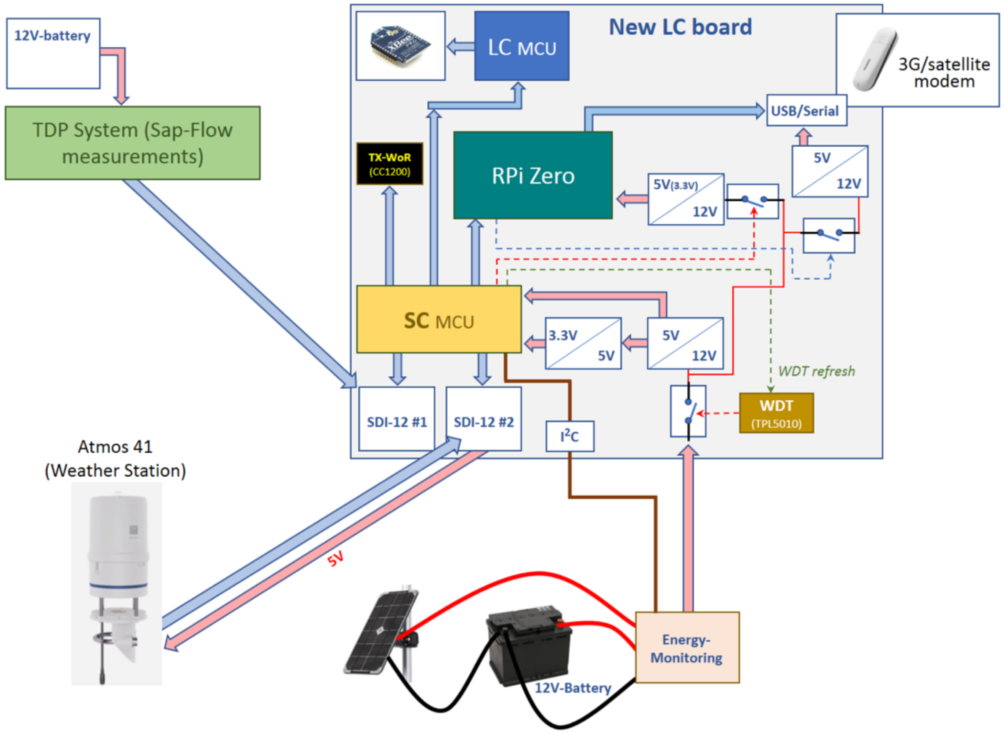
WoR-ED Expected Lifetime Improvement



Wakeup-On Radio (WoR) (4)

New Local Coordinator

- New WSN features too much for current LC.
- Not enough onboard processing power nor memory.



- **LC MCU**: LC-ED communication (used in SoilSCAPE for +3 years)
- **RPi**: ML-automation and 3G/Satellite Communication
- **SC MSU**: Top-level scheduler, TX-WoR, weather station, sap-flow system.

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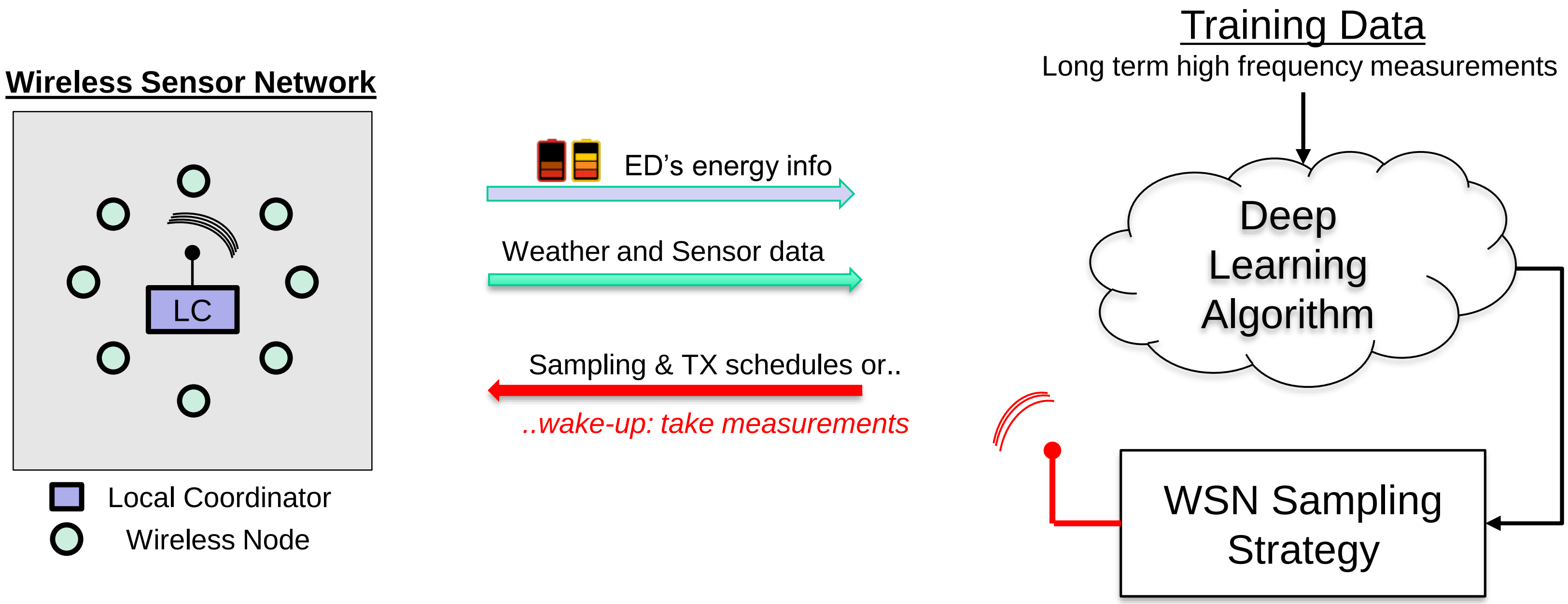
Autonomous WSN
Modular Overview and Architecture



Wireless Sensor Network

LC

▢ Local Coordinator

○ Wireless Node

ED’s energy info

Weather and Sensor data

Sampling & TX schedules or..

..wake-up: take measurements

Training Data

Long term high frequency measurements

Deep Learning Algorithm

WSN Sampling Strategy

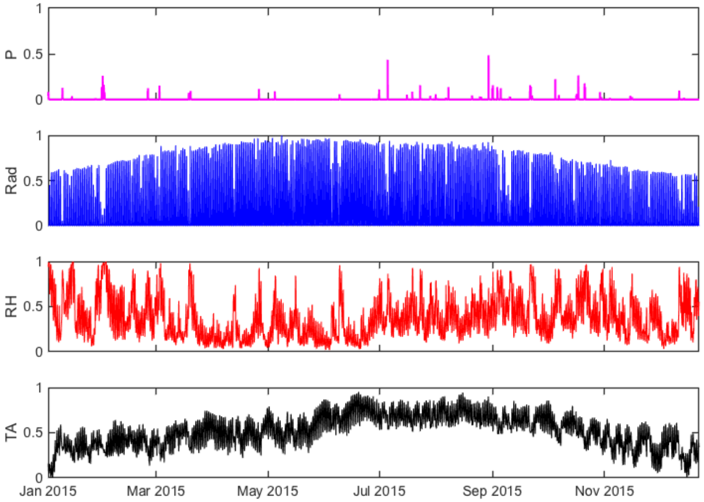
Machine Learning Autonomous Control(1)

“Learn from the environment”

- Expand WSN to include a Weather Station (WS)
    - “Environmental awareness”
    - Event-driven sampling, e.g., rain.

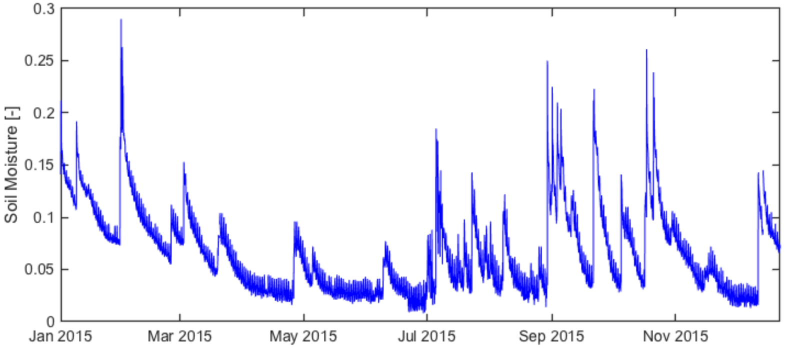
Local Coordinator (LC)

Feature Variables
Precipitation, Radiation, Humidity, Air Temp
(all normalized)



Physically Related

Target: Soil Moisture



- “Jumps” in soil moisture due to rain.
- Decays mostly a function of atmospheric conditions.

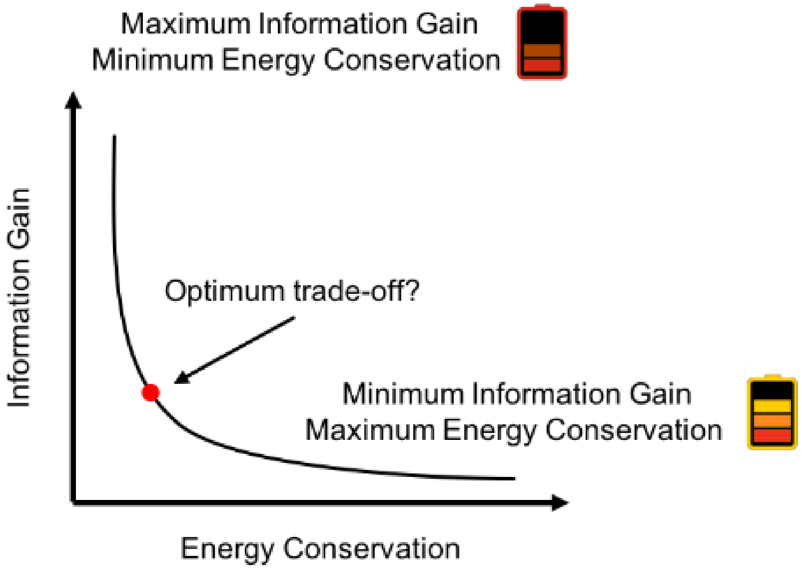
Machine Learning Autonomous Control(2)

“Meta-Objectives”

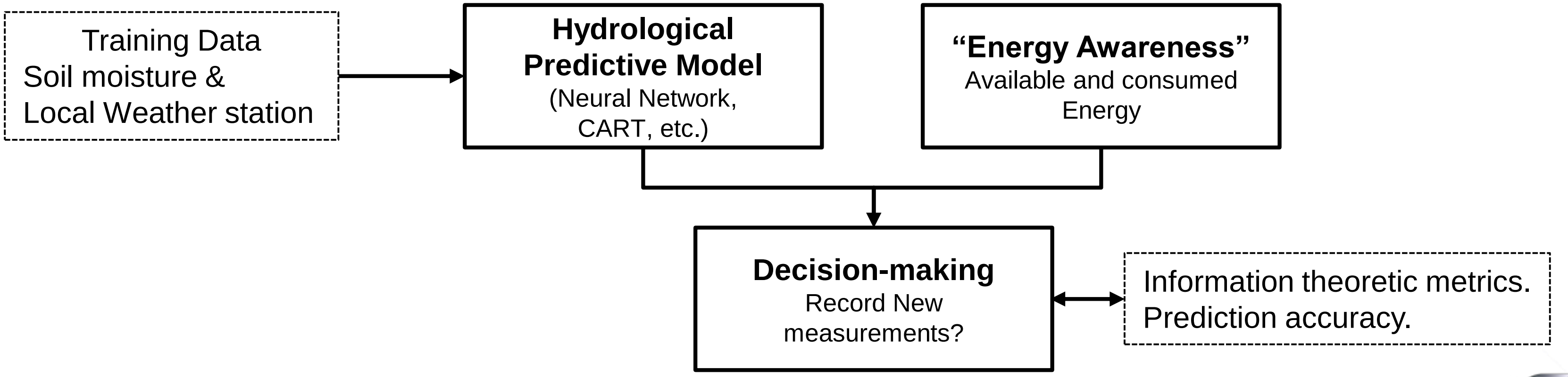
- Two competing objectives define “intelligent” WSN operations:

Minimize Energy Consumption

Maximize Information Content



Modular Implementation:



Training Data
Soil moisture &
Local Weather station

Hydrological Predictive Model
(Neural Network, CART, etc.)

“Energy Awareness”
Available and consumed Energy

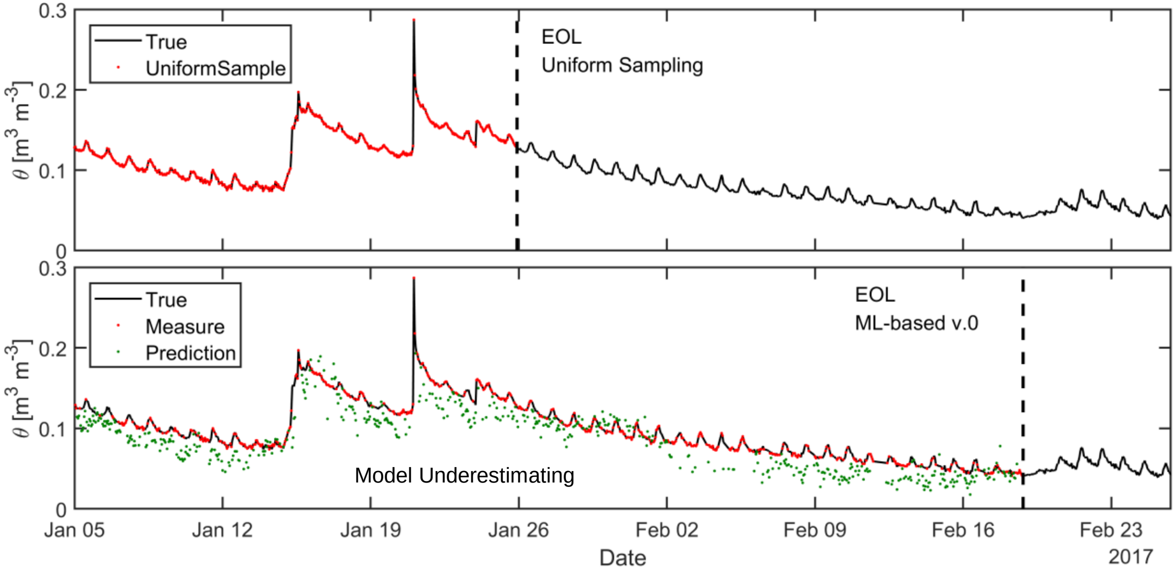
Decision-making
Record New measurements?

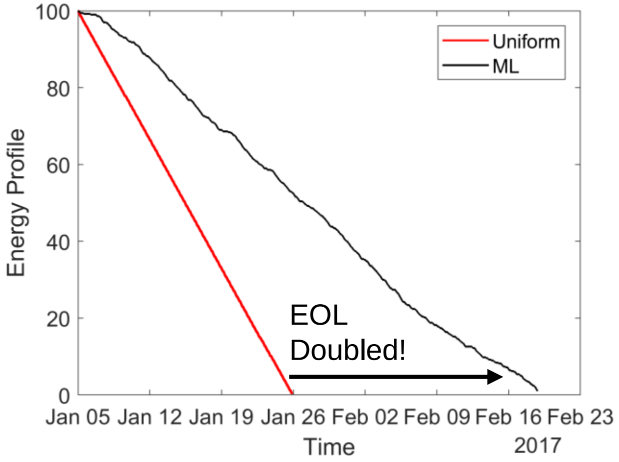
Information theoretic metrics.
Prediction accuracy.

Machine Learning Autonomous Control(3)

Simulation Example: Real-time operation

- One-Step-Ahead soil moisture prediction using prior weather station observations.
- Ensemble Gradient Boosting Regression Trees.
- Simple decision making: If $\begin{cases} \Delta CI > \epsilon_1 \\ \Delta\hat{\theta} > \epsilon_2 \end{cases}$ record new measurement (we can "learn" this too!).

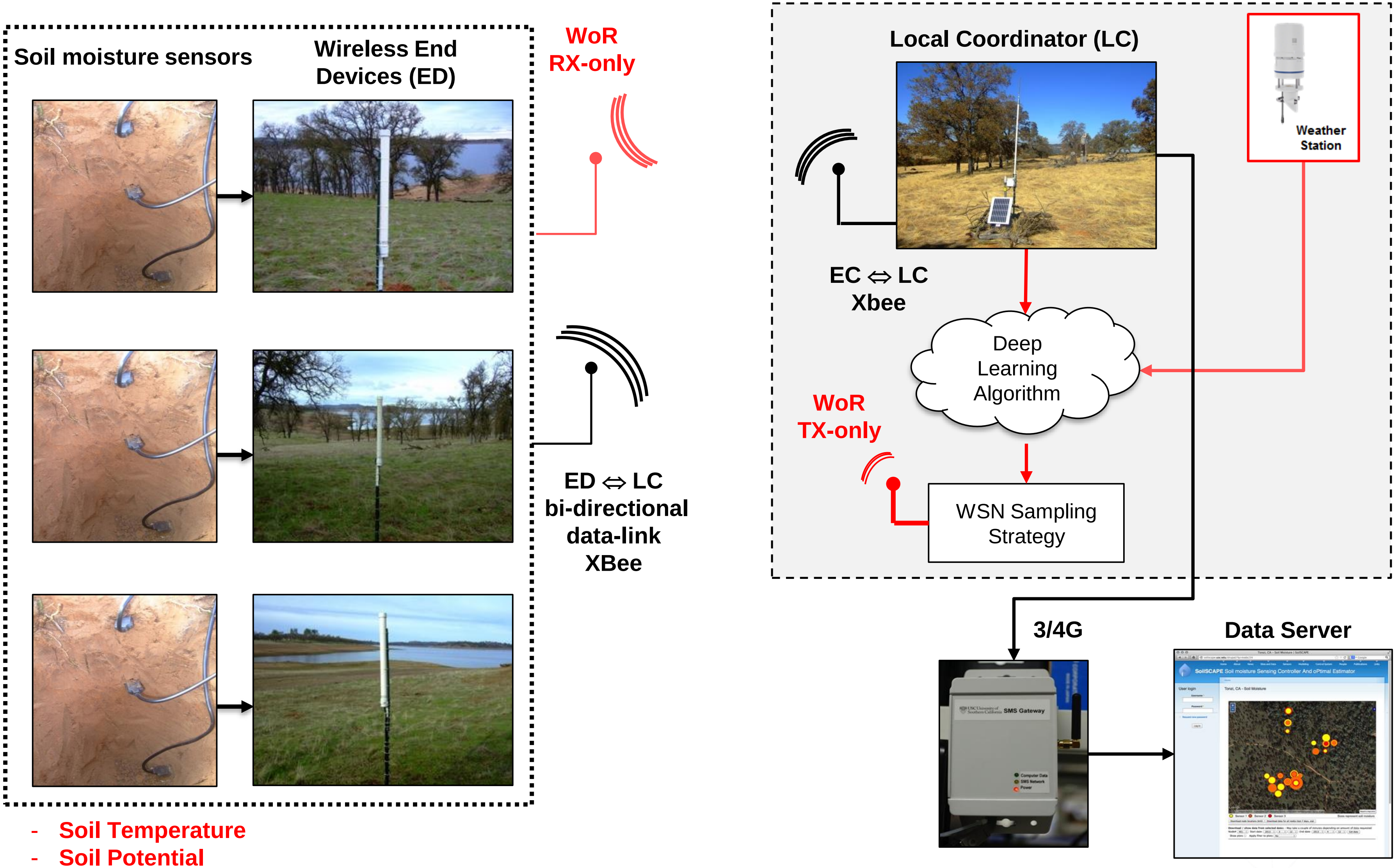




- True vs. **Precited** Error standard deviation 0.0135 [m^{3}m^{-3}], with R^2 = 0.8
- Error less than 0.04 [m^{3}m^{-3}] generally accepted.
- But, plenty of room for improvement.

Network Overview

Putting everything together



Soil moisture sensors

Wireless End Devices (ED)

WoR RX-only

ED ⇔ LC bi-directional data-link XBee

Local Coordinator (LC)

Weather Station

EC ⇔ LC Xbee

Deep Learning Algorithm

WoR TX-only

WSN Sampling Strategy

3/4G

Data Server

- Soil Temperature
- Soil Potential
- Sap-flow

Summary

- Desire for “fully autonomous” wireless *in situ* sensing networks
    - Maximize information content vs. minimize energy use.
    - Close-up view of biome adaptation and dynamics at Plant/Plot level.
- Planned field work for Summer 2018
    - Small-scale field deployment, Southern AZ.
    - Prototype WoR and new LC demonstration.
- Plans for Year 2:
    - Improvements in prediction and ML models.
    - New End-device and LC boards.
    - External Sap-flow systems.
    - Larger-scale field deployment.

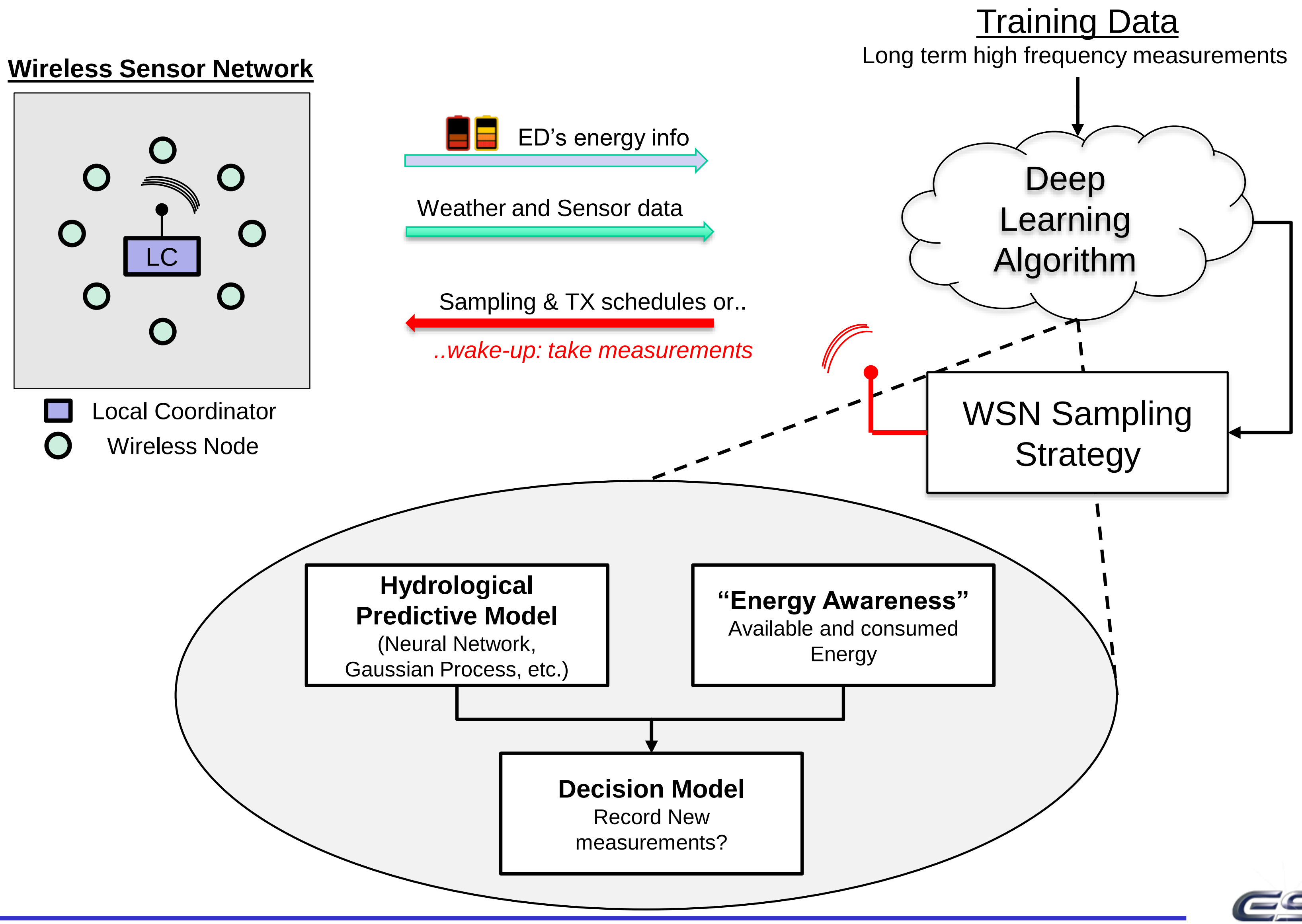

Richard Chen, USC

Many thanks to ESTO for their generous support!

Thank you!

rakbar@mit.edu

Autonomous WSN
Modular Overview and Architecture



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Training Data

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Deep Learning Algorithm

WSN Sampling Strategy

Hydrological Predictive Model
(Neural Network, Gaussian Process, etc.)

“Energy Awareness”
Available and consumed Energy

Decision Model
Record New measurements?