

Advanced Environmental Monitoring Systems (ALTEMIS)

New Paradigm of Long-Term Monitoring

Haruko Wainwright

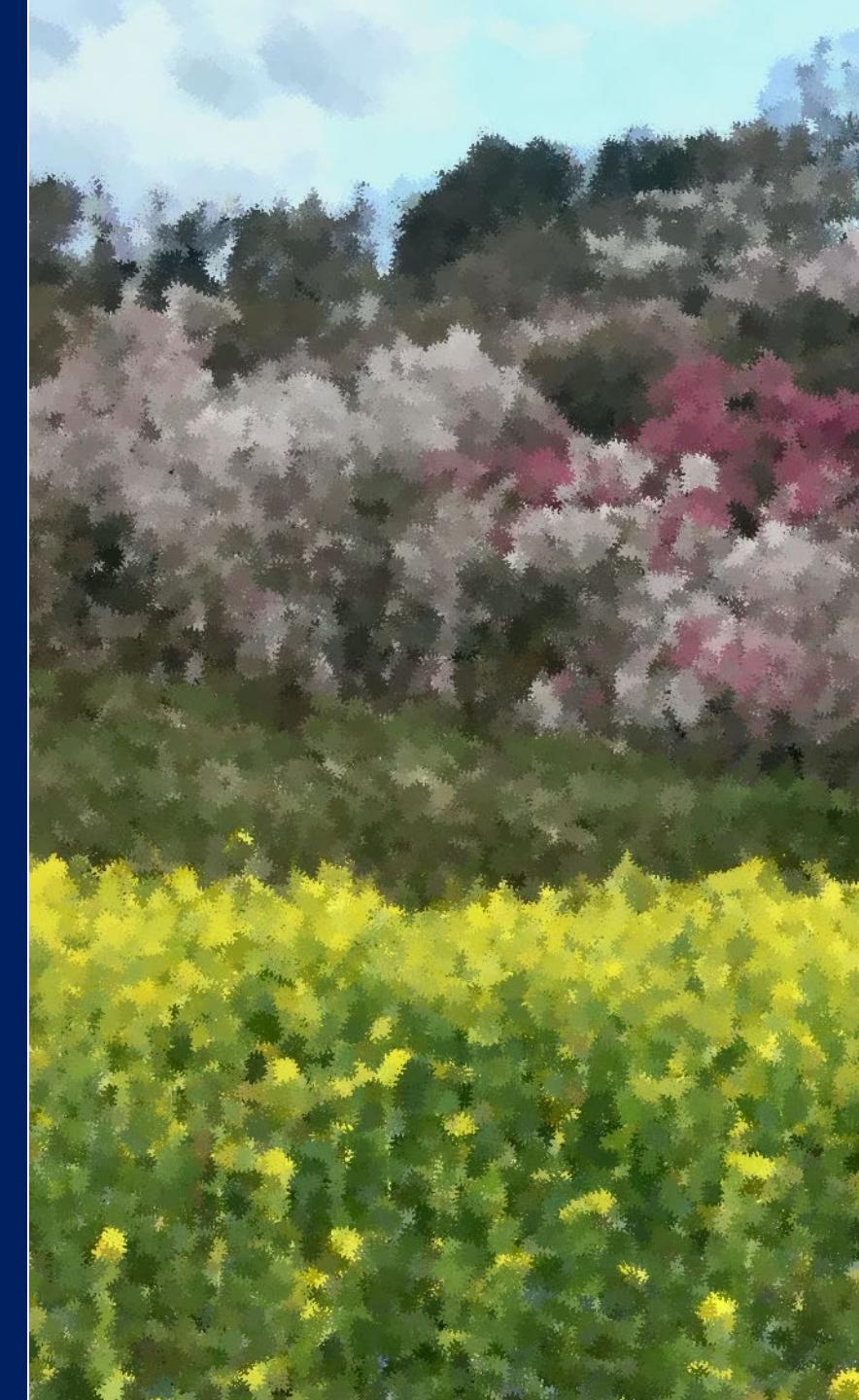
Nuclear Science and Engineering; Civil and Environmental Engineering
Massachusetts Institute of Technology

NSE

Nuclear Science & Engineering at MIT
science : systems : society



Civil and
Environmental
Engineering



ALTEMIS Collaborators

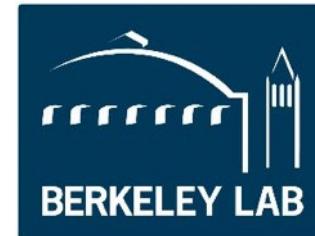
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- Hansell Gonzalez-Raymat
- Tom Danielson
- Holly VerMeulen
- Emily Fabricatore



Lawrence Berkeley National Lab

- Zexuan Xu
- Solchan Han



Massachusetts Institute of Technology

- Haruko Wainwright – Co-Lead

Consultants

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- Pieter Hazenberg
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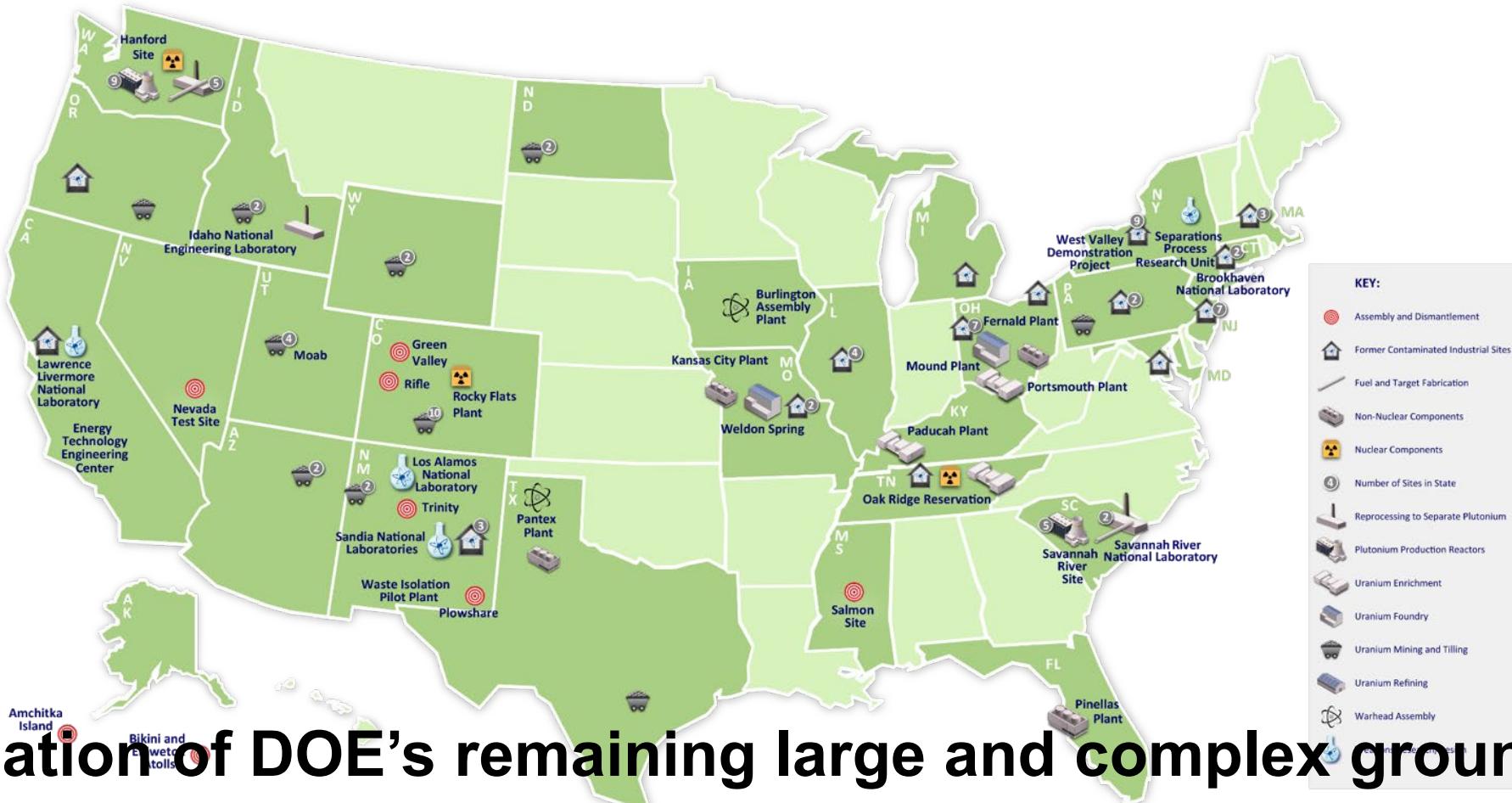
Interns/Graduate Students/Post-Docs

- Lijing Wang
- Kay Whiteaker
- Jayesh Soni
- Aurelien Meray
- Aubrey Litzinger
- Phuong Pham
- Vivian Castillo



DOE-EM-3.21 Office of Technology Operation has sponsored a SRNL-led program since 2020

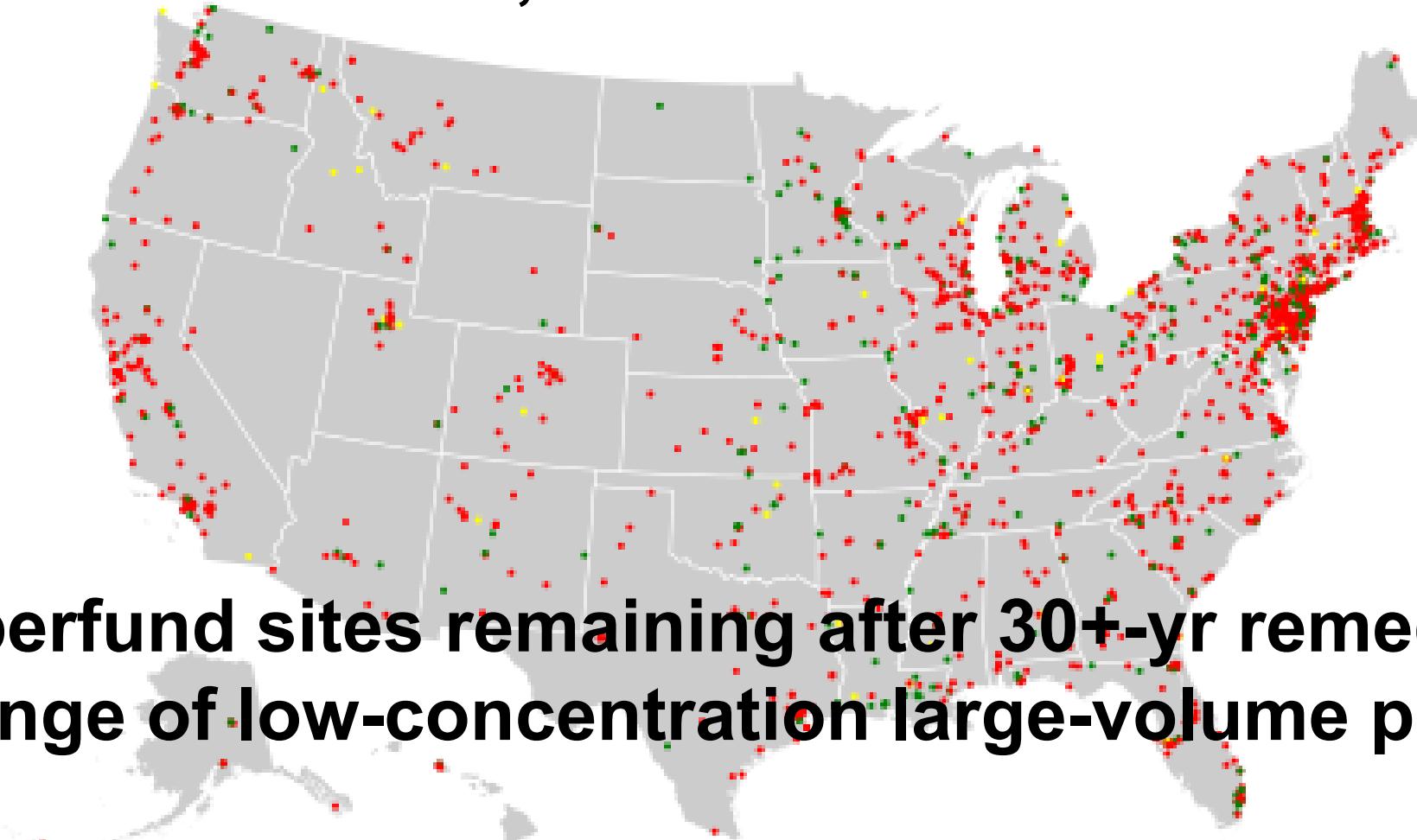
DOE's Legacy Sites



- Remediation of DOE's remaining large and complex groundwater contamination will take decades.
- GAO estimates EM's liability for environmental cleanup across the country will exceed \$550 billion

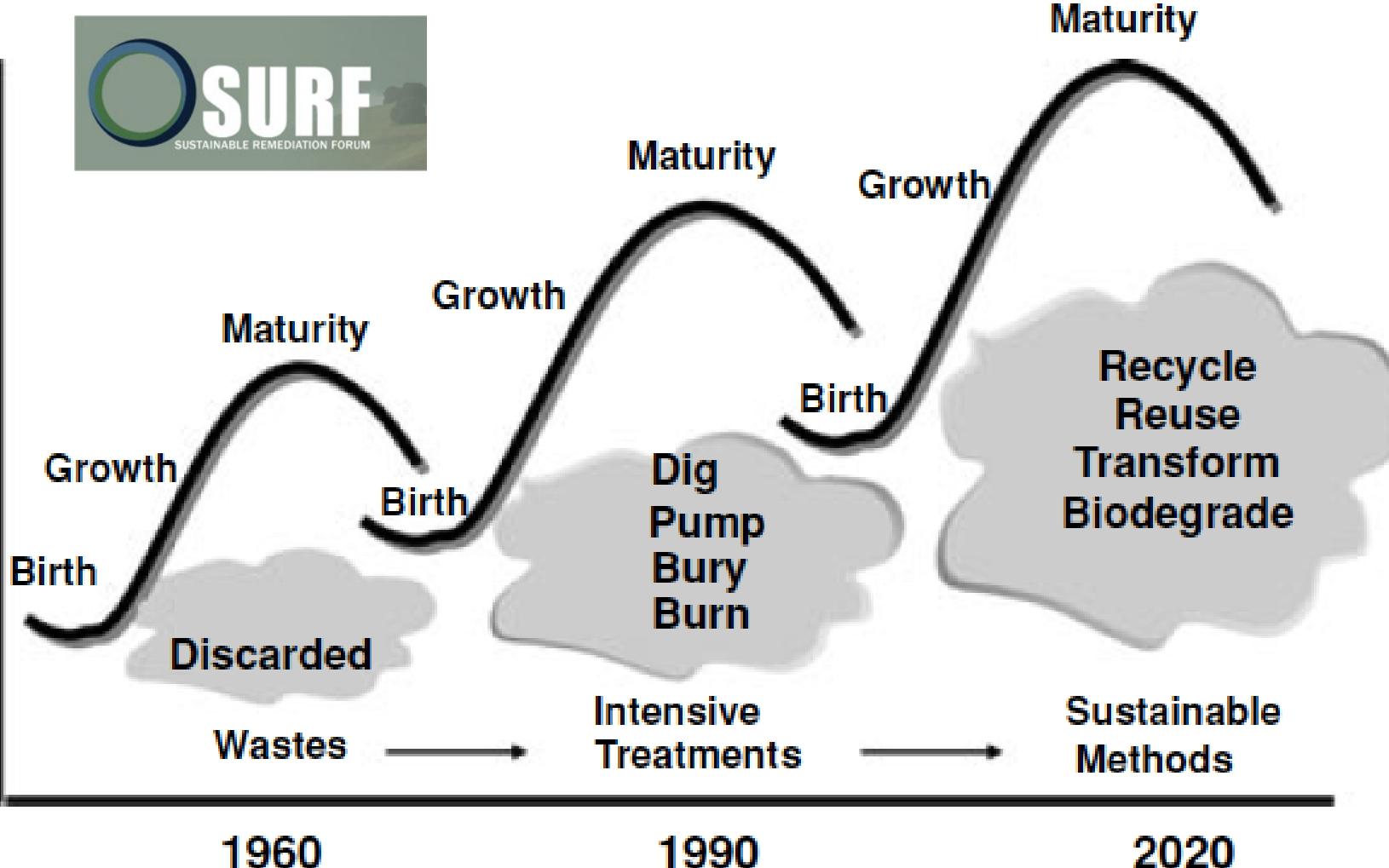
Soil and Groundwater Contamination

- Superfund Sites: >1300 sites (organic/metal/radioactive)
- Brownfield Sites: ~450,000



>900 Superfund sites remaining after 30+-yr remediation
→ Challenge of low-concentration large-volume plume

Environmental Remediation: Evolution



Sustainable Remediation Forum (SURF), "Integrating sustainable principles, practices, and metrics into remediation projects", Remediation Journal, 19(3), pp 5 - 114, editors P. Hadley and D. Ellis, Summer 2009

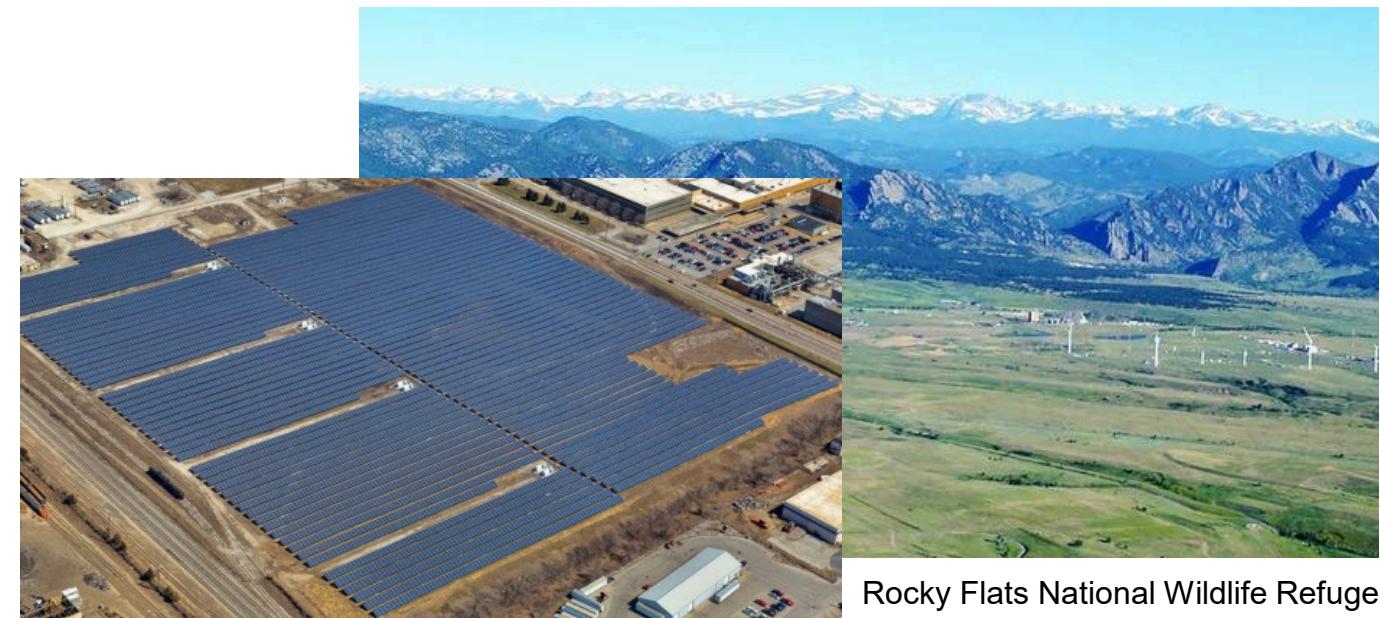
Trade offs: Contaminant removal vs

- Waste
- CO2 emission
- Energy Use
- Ecological Impacts
- Noise, Air pollution

Sustainable Remediation

- Minimize waste/pollution/energy-use/water-use/ecological damages
- Biodegradation, immobilization
- Monitored natural attenuation
- Longer institutional control with alternative/attractive end-use

→ Long-term monitoring



Rocky Flats National Wildlife Refuge

Former Reilly Tar & Chemical Corporation Plant

Environmental Monitoring



- **Data/evidence provides assurance to local communities**
- **Detection of anomalies if they happen**
- **Critical ways to keep operators accountable/responsible**
- **Tackle misinformation and fake news**

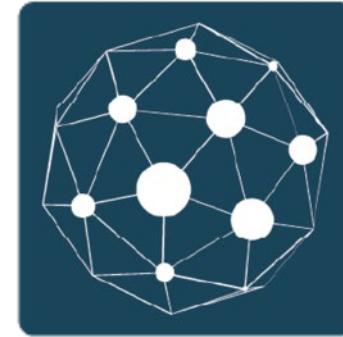
(People are skeptical of modeling results)

Advanced Long-term Environmental Monitoring Systems

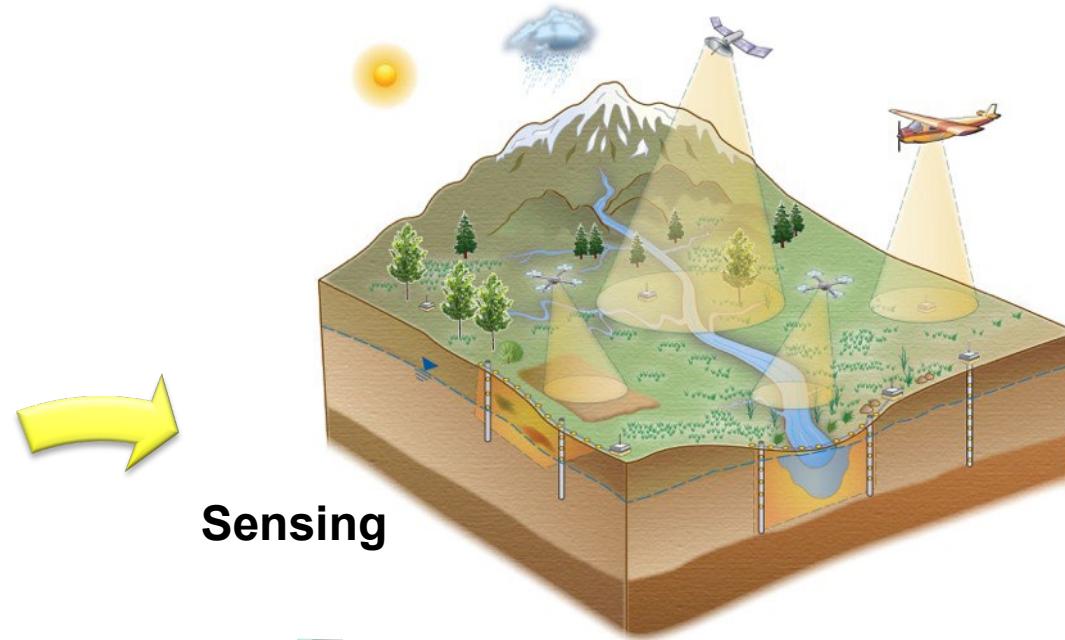


ALTEMIS

www.srnl.gov/fact-sheets/altemis/

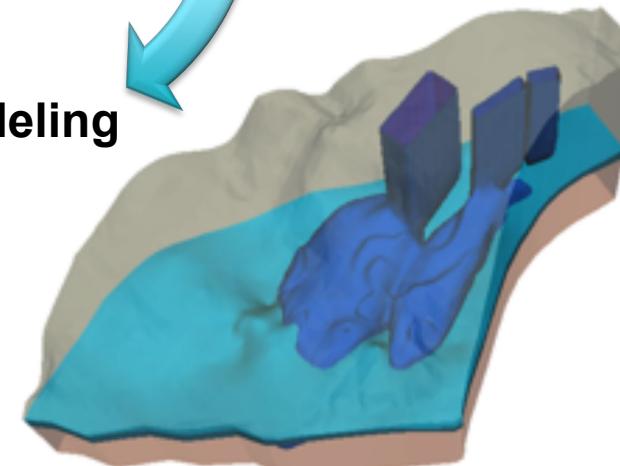


ML/AI



Sensing

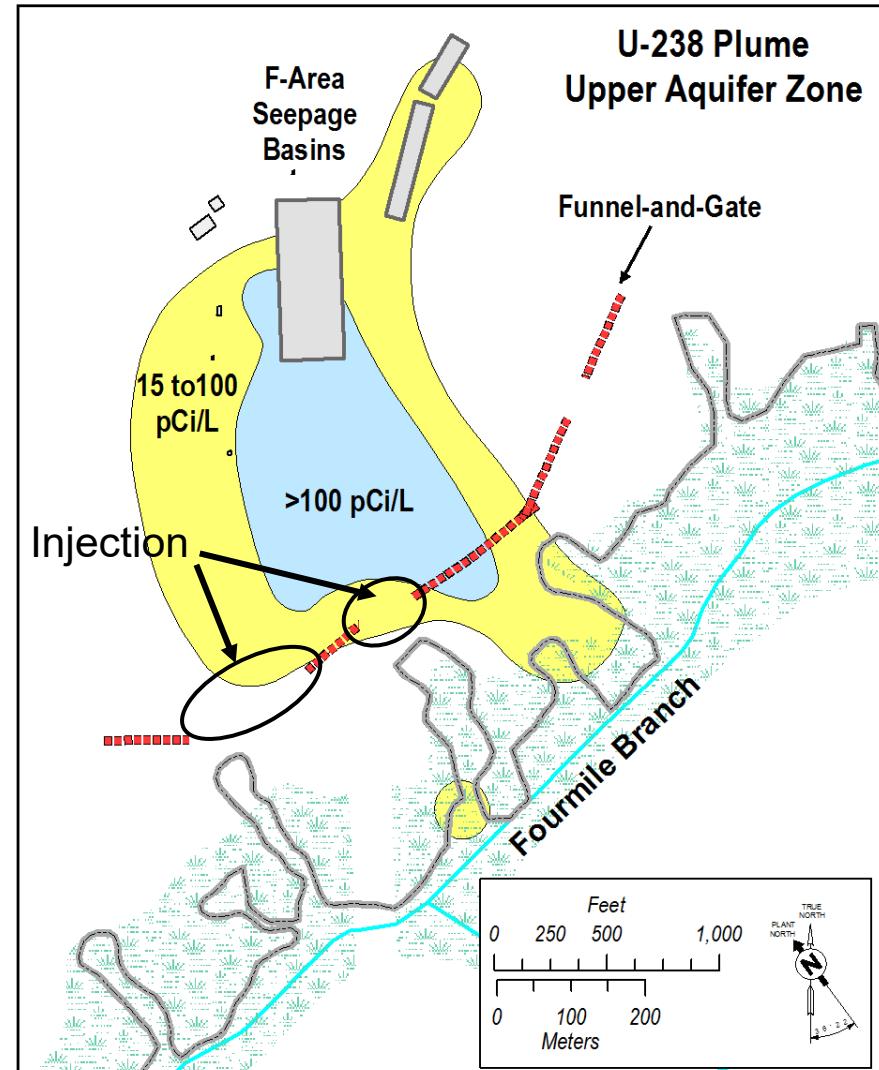
Modeling



*New paradigm for
long-term monitoring*

Savannah River Site F-Area: Testbed

- **Disposal activities:**
 - Low-level radioactive waste from PUREX process (1955–1989)
 - Nitric acid plume: pH 3–3.5, U, ^{90}Sr , ^{129}I , ^{99}Tc , ^3H
- **Remediation approaches**
 - Pump & treat (the filters became highly radioactive; not sustainable)
 - Immobilization of U and ^{129}I



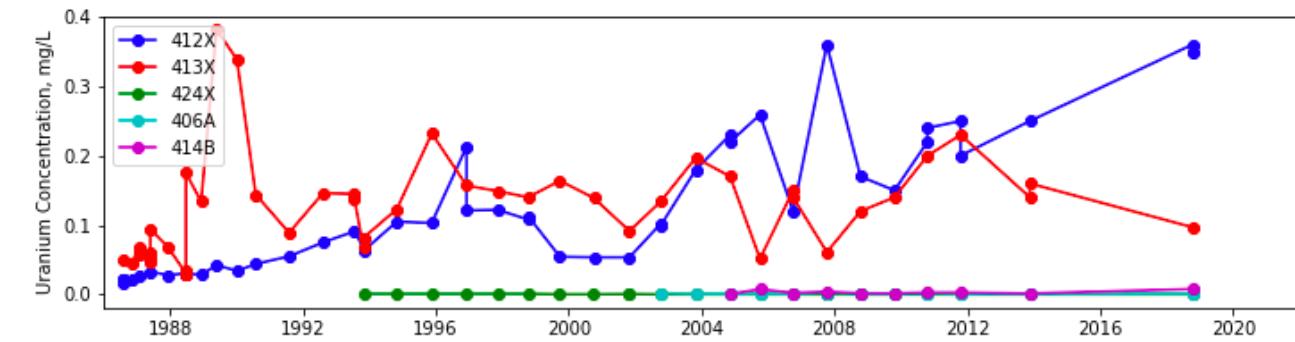
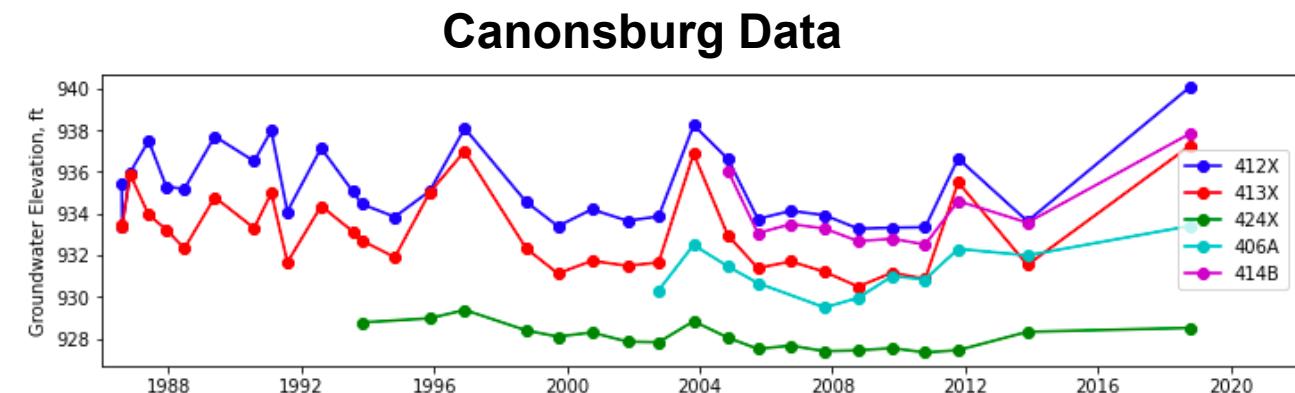
Guided by Real-world Observations

DOE Mound Site

- Dewatering for construction nearby
→ Shift in the groundwater table and plume direction

DOE Canonsburg Site

- Groundwater fluctuation associated with river stages
→ Contaminant concentration changes (hard to explain with sparse measurements)
→ Extreme weathers?



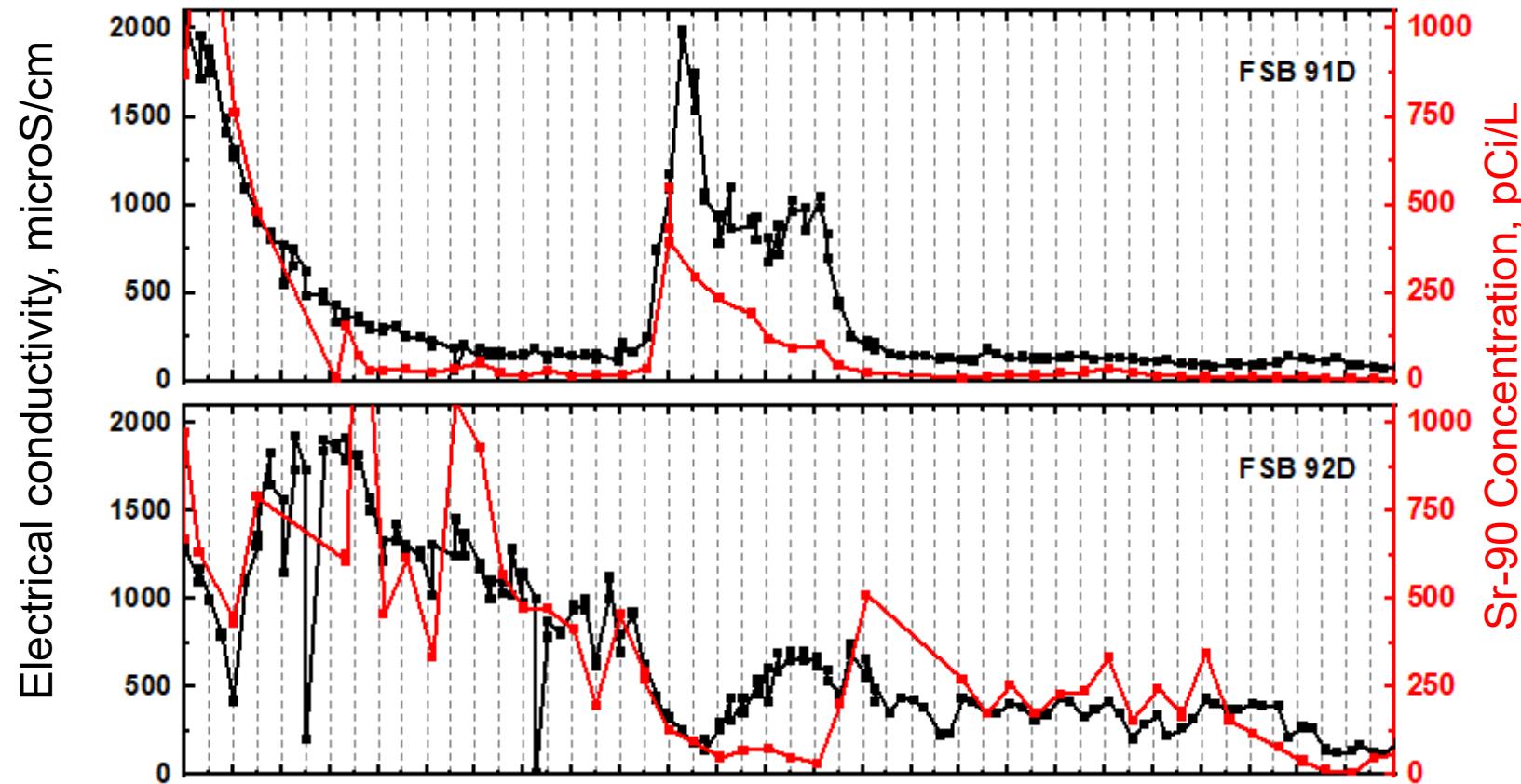
→ Importance of hydrology (e.g., water table) for contaminant mobility and plume migration

Guided by Real-world Observations

DOE Savannah River Site F-Area

- Pump-and-treat system

→ Re-injection increased cations → Sr-90 concentrations increased

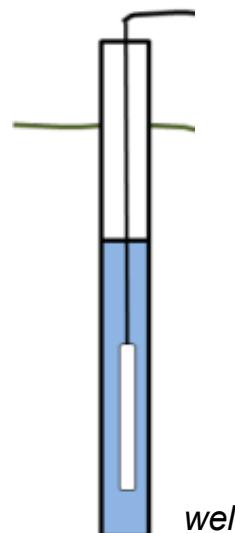


→ Importance of *in situ* measurable proxies (e.g., electrical conductivity)

Current Groundwater Monitoring

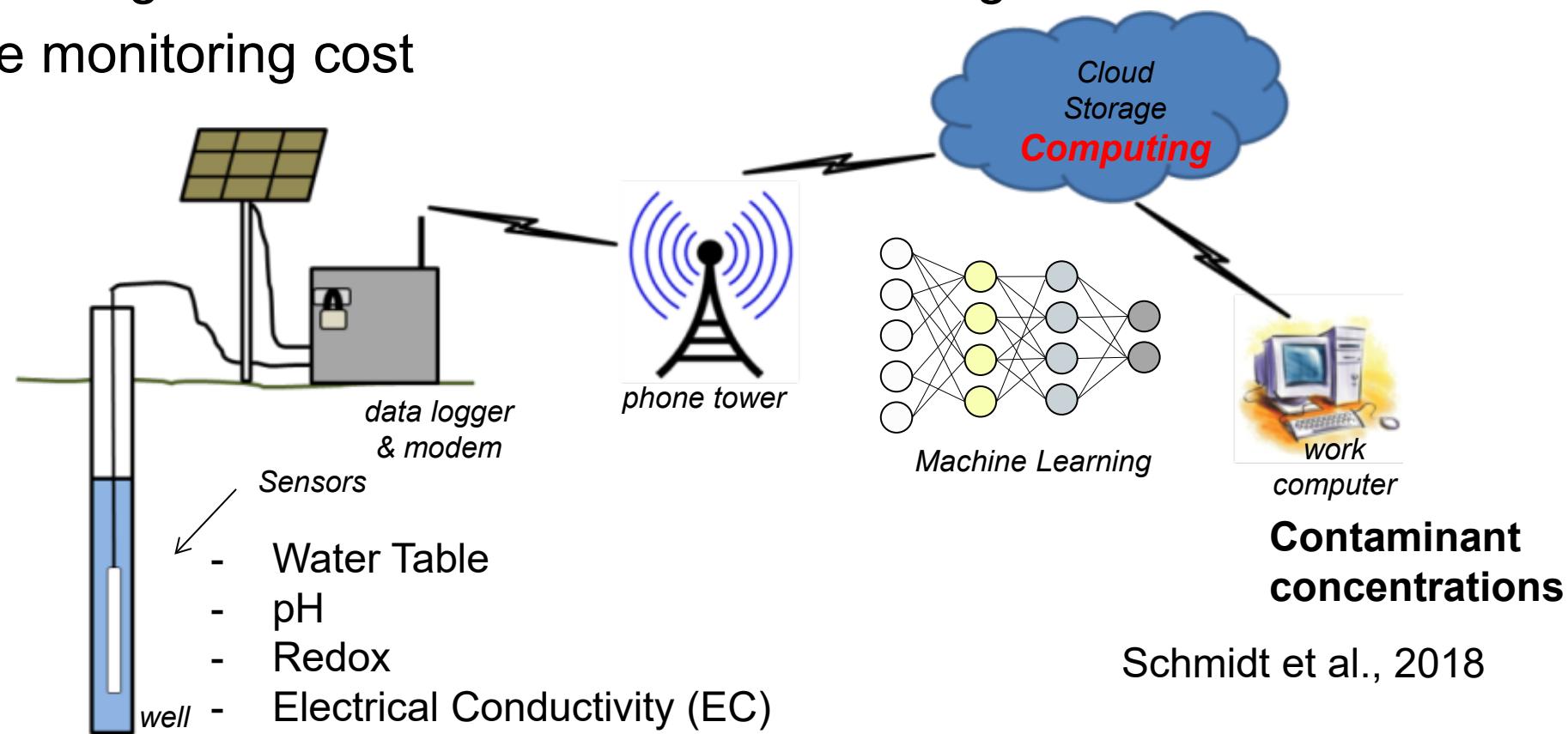
- **Groundwater Sampling → Laboratory Measurements**

- Expensive: 10s – 100s of wells
- Contamination issues (requires training, equipment)
- Temporally sparse: every quarterly, annually → Miss anomalies
- Compliance only (no analytics)

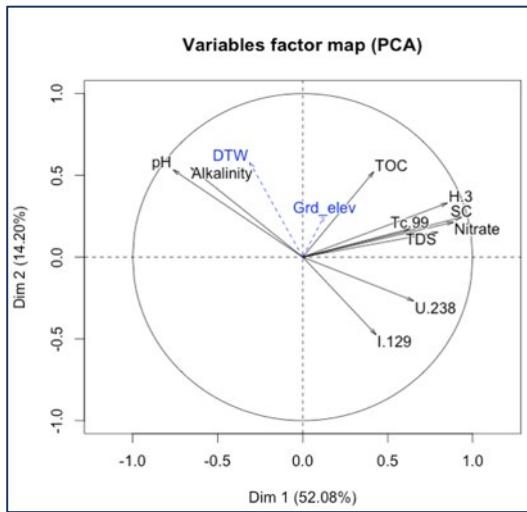


In situ Real-time Monitoring Strategies

- **Low-cost in situ sensors, wireless network, cloud computing**
 - Continuous monitoring of **in situ variables**
 - Detect changes real-time = **Reactive Monitoring** → **Proactive Monitoring**
 - Reduce monitoring cost

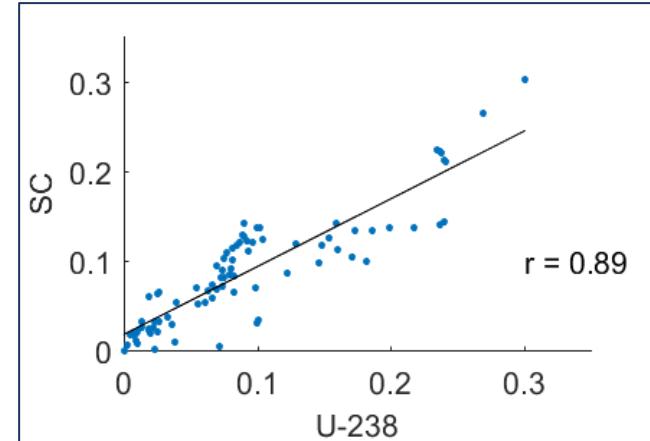


Data Analytics Workflow

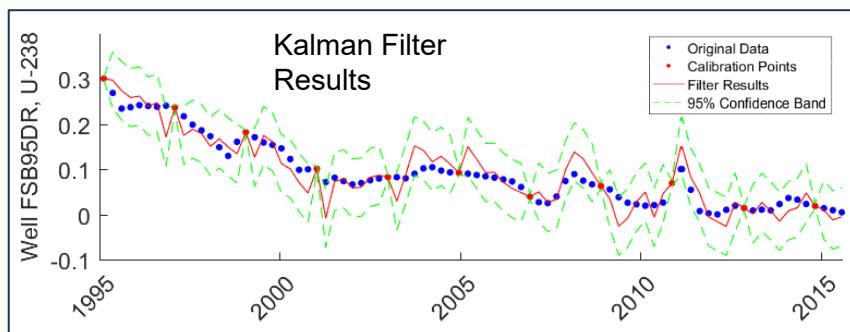


Exploratory Data Analysis

Quantification of Correlations



Contaminant Concentration Estimation
Machine Learning





Article

***In Situ* Monitoring of Groundwater Contamination Using the Kalman Filter**

Franziska Schmidt[†] [ID](#), Haruko M. Wainwright[‡] [ID](#), Boris Faybushenko[§], Miles Denham[¶], and Carol Eddy-Dilek[¶]

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Efficiency & Environment

Scientists develop new method to track groundwater pollutants in real-time

It is expected to reduce the frequency of manual groundwater sampling and lab analysis and therefore cut the monitoring cost

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 Environ. Sci. Technol.

PUBLIC RELEASE: 13-AUG-2018

Algorithm provides early warning system for tracking groundwater contamination

Berkeley Lab researchers devise system to monitor contaminant plumes

DOE/LAWRENCE BERKELEY NATIONAL LABORATORY



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New Algorithm Provides Real-Time Monitoring Of Groundwater Pollutants

By Sam Bonnera | 8 Months Ago



The Technology that Drives Government IT

AI & Automation Cybersecurity Cloud & Infrastructure Data & Analytics Smart Cities & IoT

Machine learning improves contamination monitoring

BY MATT LEONARD | AUG 14, 2018

Because groundwater is [susceptible to pollution](#) from automotive fuel, fertilizer or naturally occurring substances like iron, the Environmental Protection Agency and its state-level counterparts conduct annual or quarterly sampling and analysis.

PyLEnM: A Machine Learning Framework for Long-Term Groundwater Contamination Monitoring Strategies

Aurelien O. Meray, Savannah Sturla, Masudur R. Siddiquee, Rebecca Serata, Sebastian Uhlemann, Hansell Gonzalez-Raymat, Miles Denham, Himanshu Upadhyay, Leonel E. Lagos, Carol Eddy-Dilek, and Haruko M. Wainwright*



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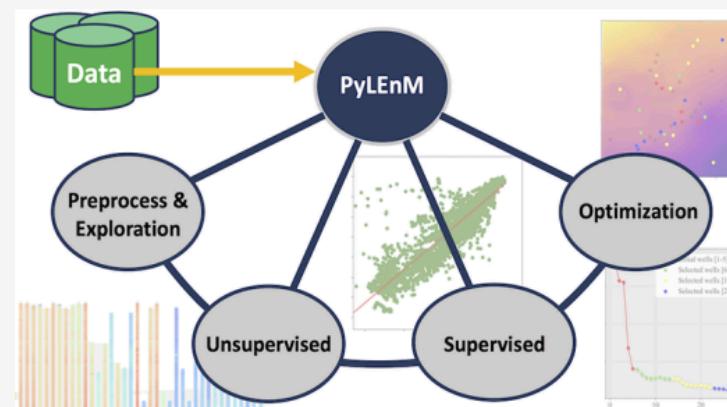
ACCESS |

 Metrics & More

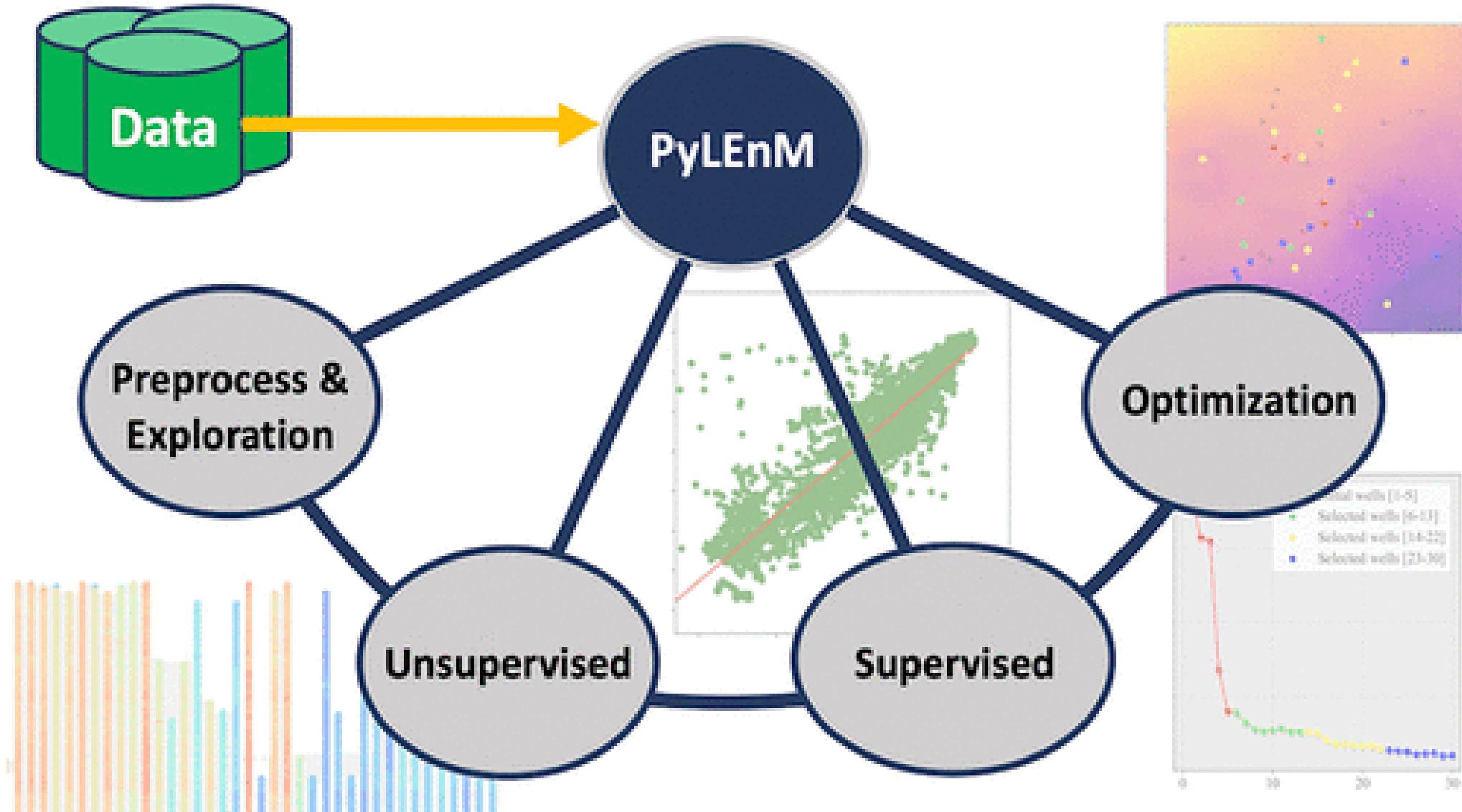
 Article Recommendations

 Supporting Information

ABSTRACT: In this study, we have developed a comprehensive machine learning (ML) framework for long-term groundwater contamination monitoring as the Python package PyLEnM (Python for Long-term Environmental Monitoring). PyLEnM aims to establish the seamless data-to-ML pipeline with various utility functions, such as quality assurance and quality control (QA/QC), coincident/colocated data identification, the automated ingestion and processing of publicly available spatial data layers, and novel data summarization/visualization. The key ML innovations include (1) time series/multianalyte clustering to find the well groups that have similar groundwater dynamics and to inform spatial interpolation and well optimization, (2) the automated model selection and parameter tuning, comparing multiple regression models for spatial interpolation, (3) the proxy-based spatial interpolation method by including spatial

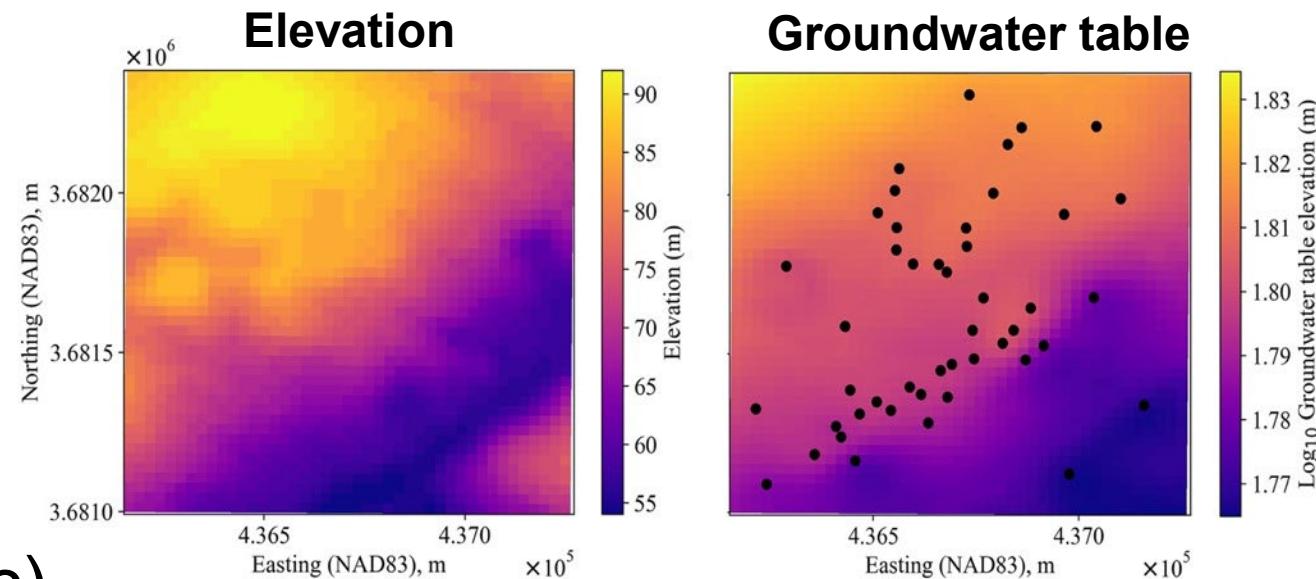


PyLenM: Python for Long-term Env. Monitoring



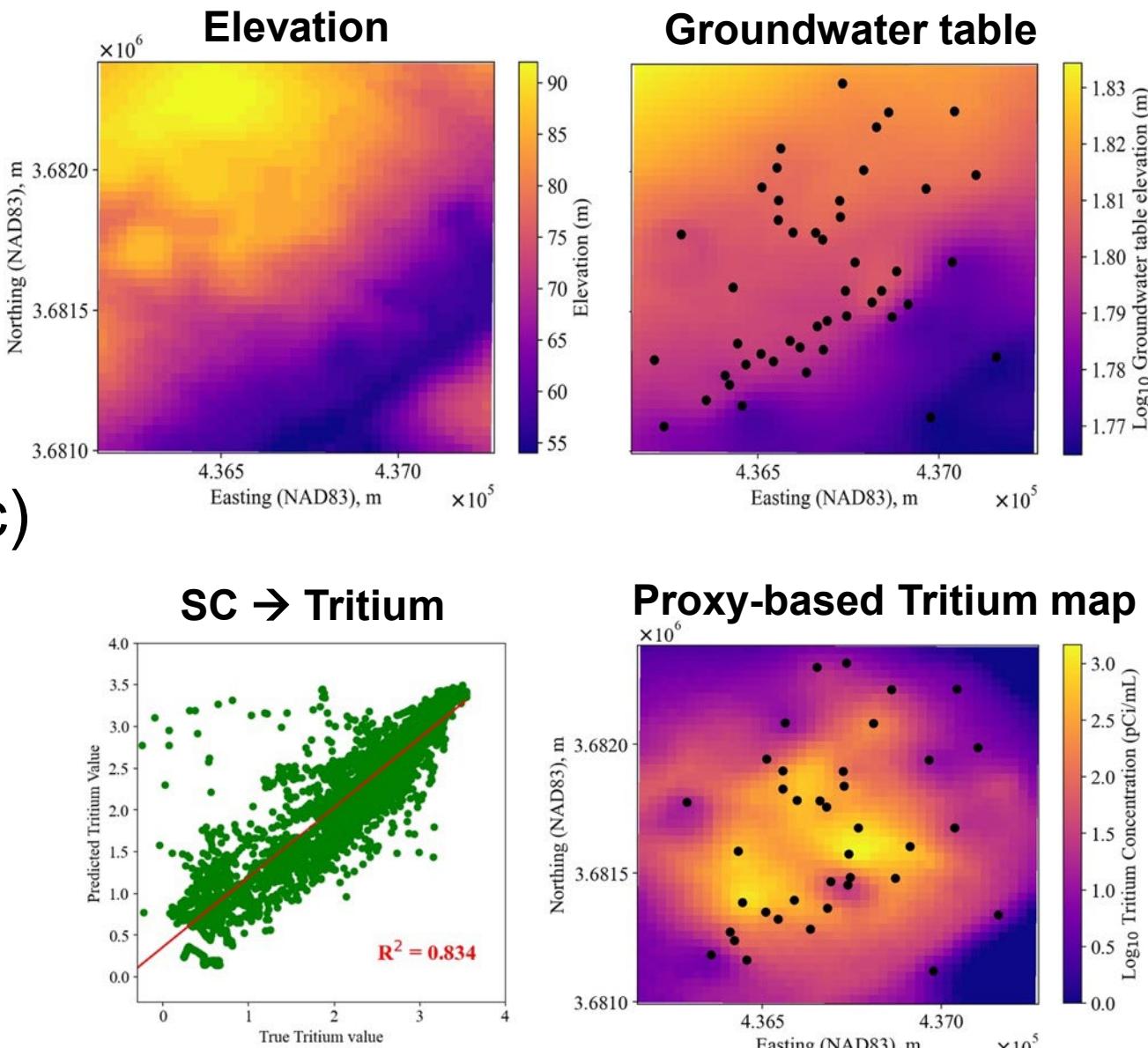
PyLenM: Supervised Learning

- **Spatiotemporal Interpolation**
 - Groundwater table
 - Contaminant concentration
- **Proxy variables**
 - LiDAR elevation data
 - Topographic metrics (slope etc)
 - Distance from the source
 - In situ measurable SC
→ tritium concentration
- **Comparison of multiple ML regression methods**



PyLenM: Supervised Learning

- **Spatiotemporal Interpolation**
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- **Proxy variables**
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→ tritium concentration
- **Comparison of multiple ML regression methods**



PyLenM: Well Placement Optimization

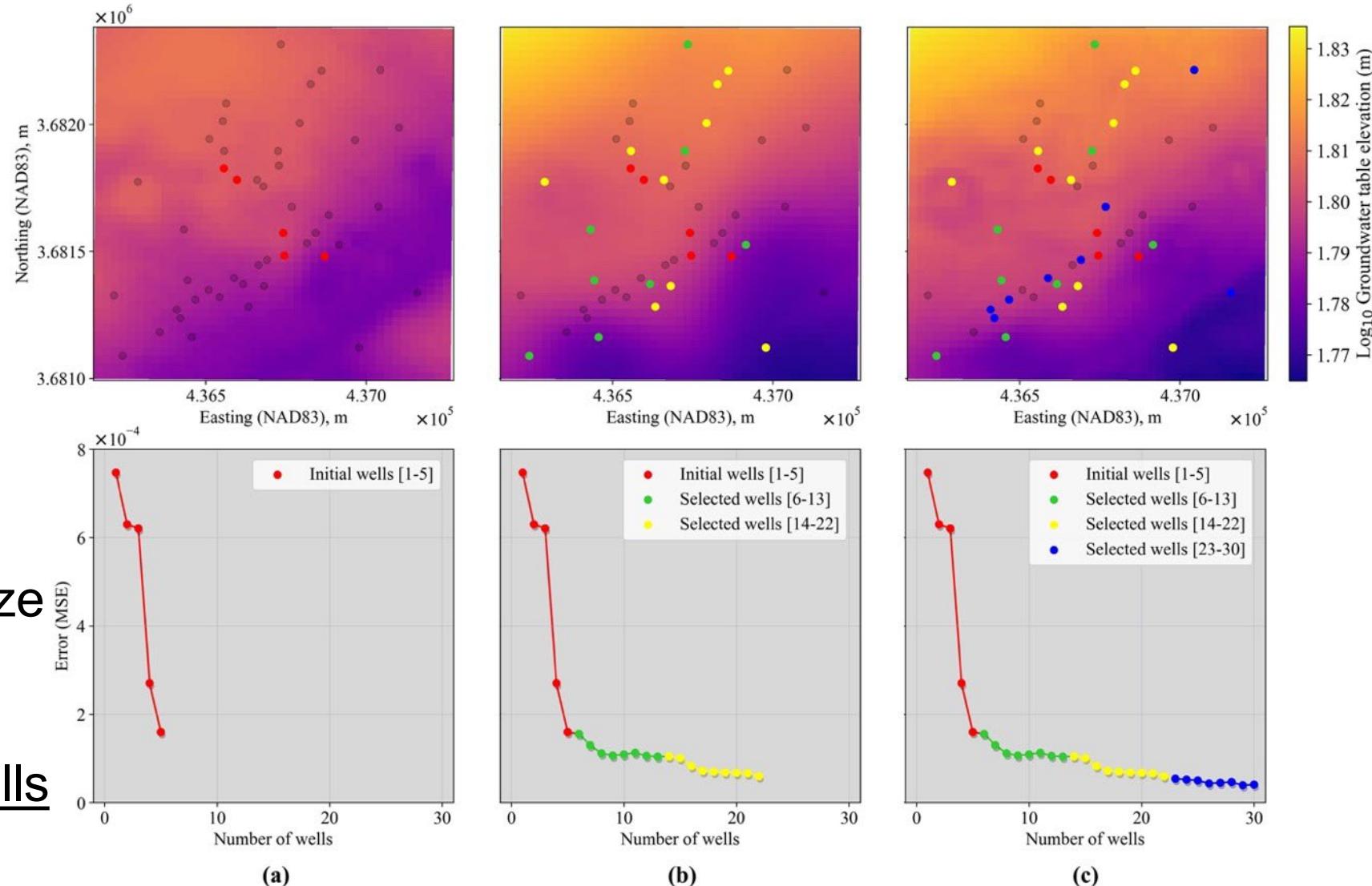
Sub-selection of wells for long-term monitoring

Greedy algorithm

- Reference map created using all the wells
- Interpolation with one additional well at a time
- Find the well that minimize the overall error

Minimum-but-sufficient # wells

- Error convergence



In situ Data Monitoring: Proxy-based Estimation

Water Table

Tritium



Vulnerability Zone Concept

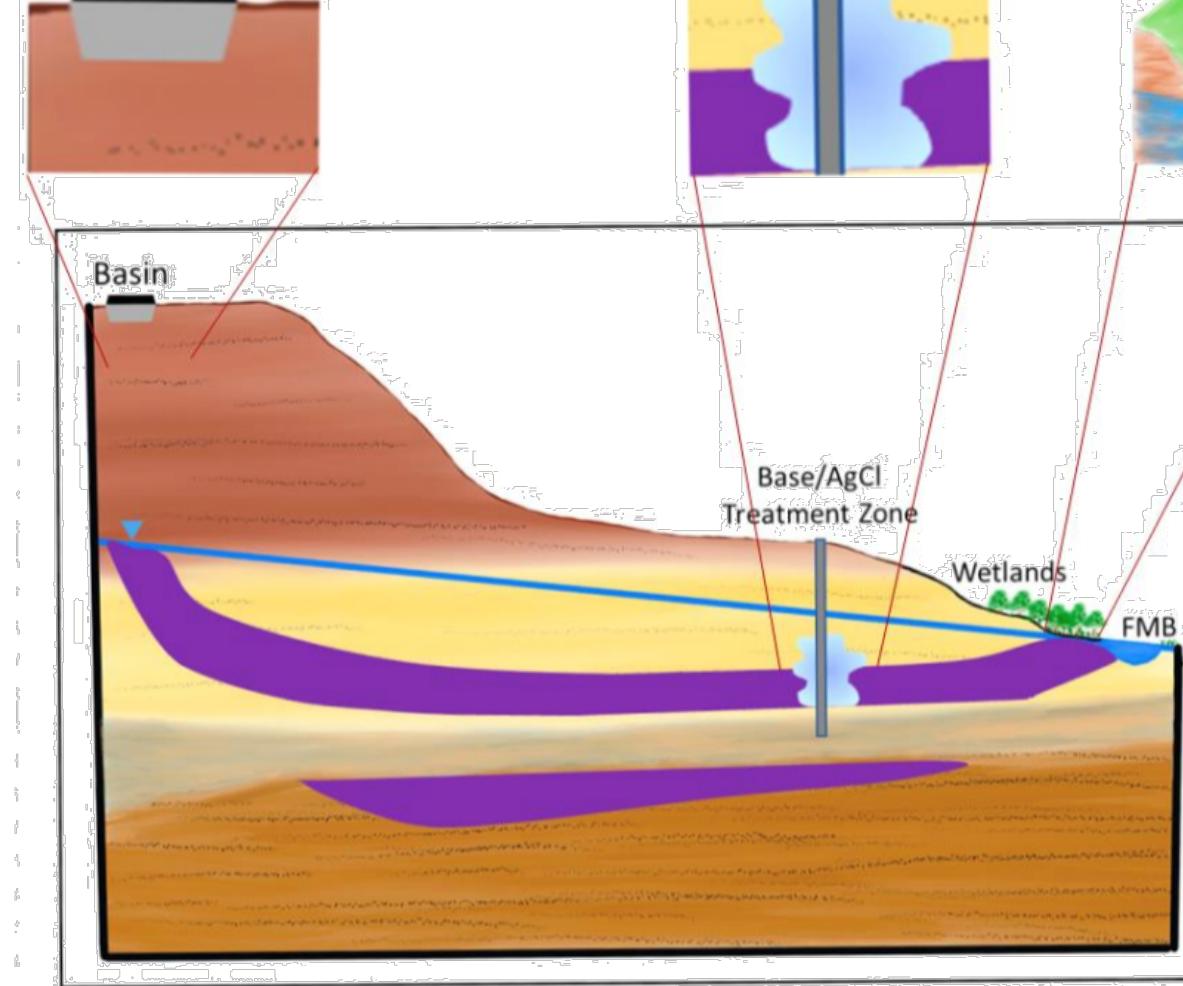
Source zone
Surface barriers



Treatment zone
In situ remedies

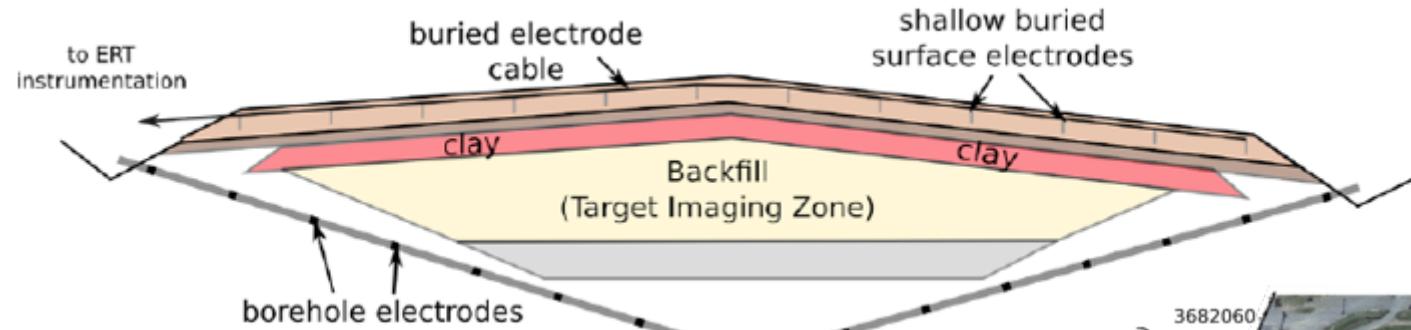


Seep zone/wetland
Last line of defense
Contaminant accumulation



Denham et al., 0220

Cap/Surface Barrier Monitoring

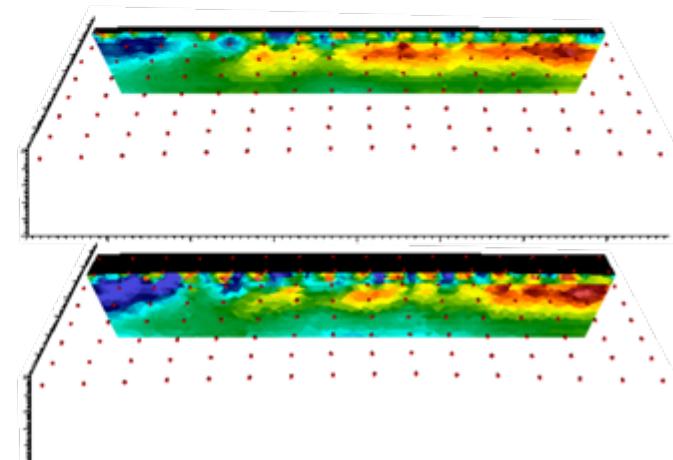
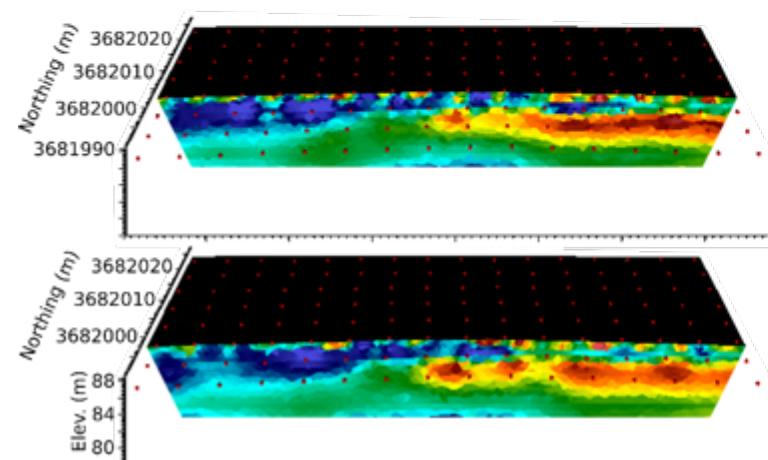
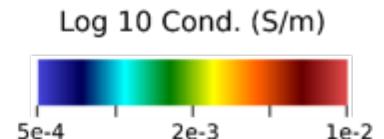
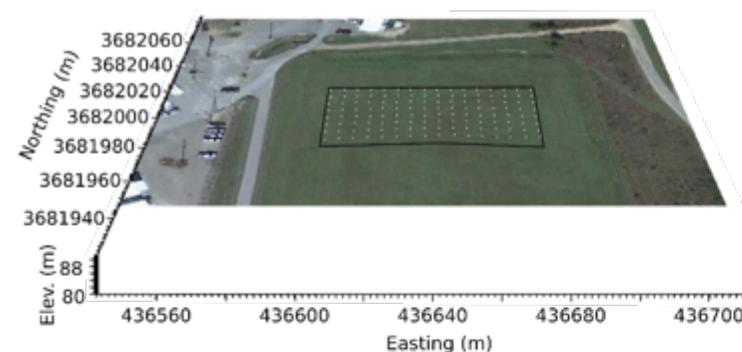


Cap/Surface Barrier

- Limit infiltration
- Concerns: plants, animals, erosions

Electrical Resistivity tomography monitoring

- Electrodes at and below the surface
- Image and detect anomalies continuously

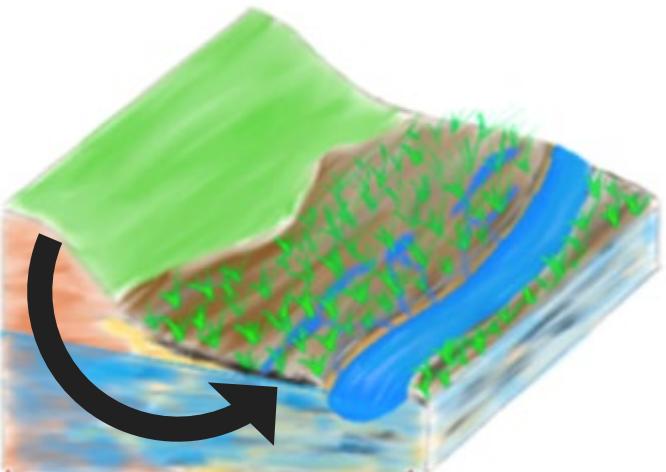


Groundwater Seep Zone Monitoring

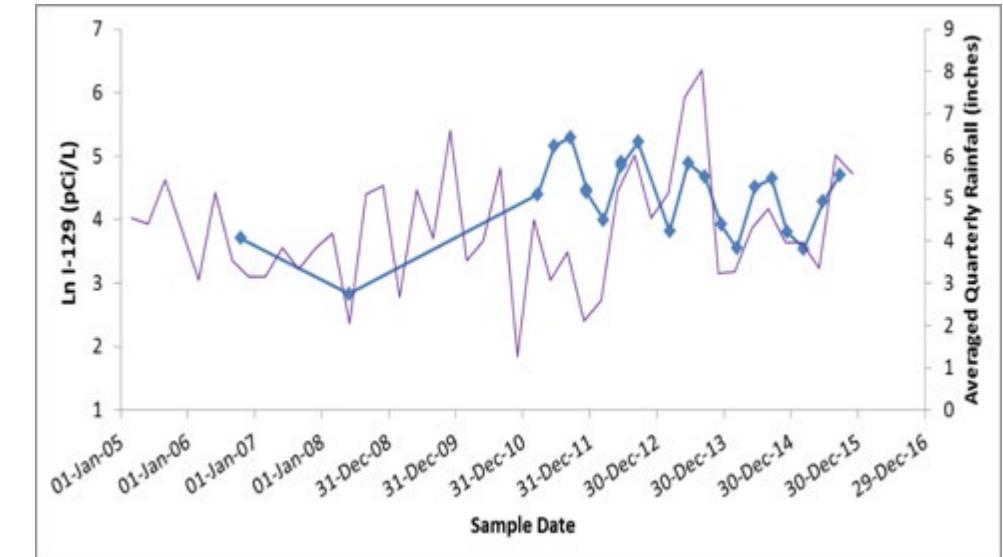
Last line of defense

- Clay/organic-rich soil
- Sequester/accumulate contaminants

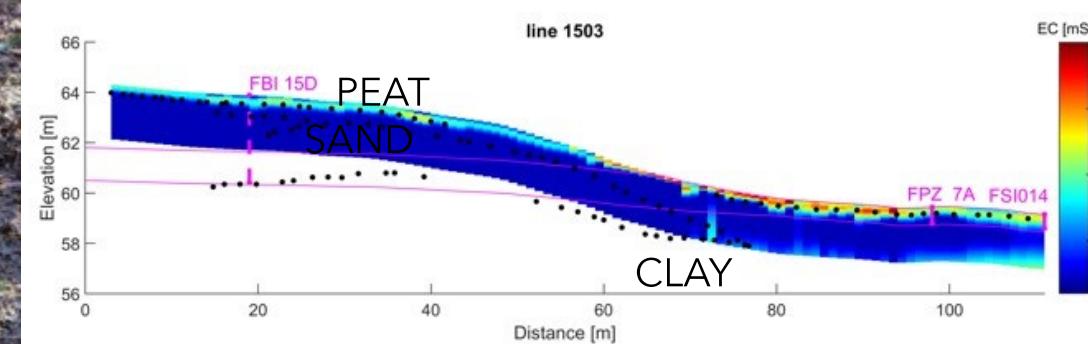
→ Vulnerability: changes in geochemistry etc



I-129 Concentration seasonal dynamics



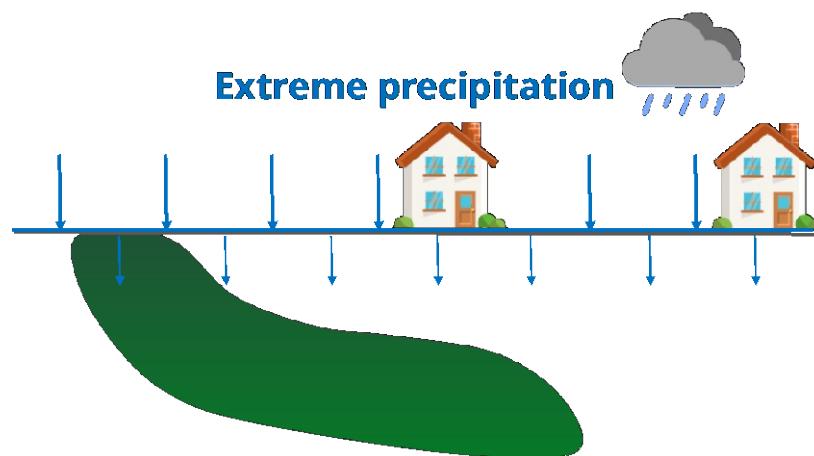
GPR/EM Subsurface Characterization



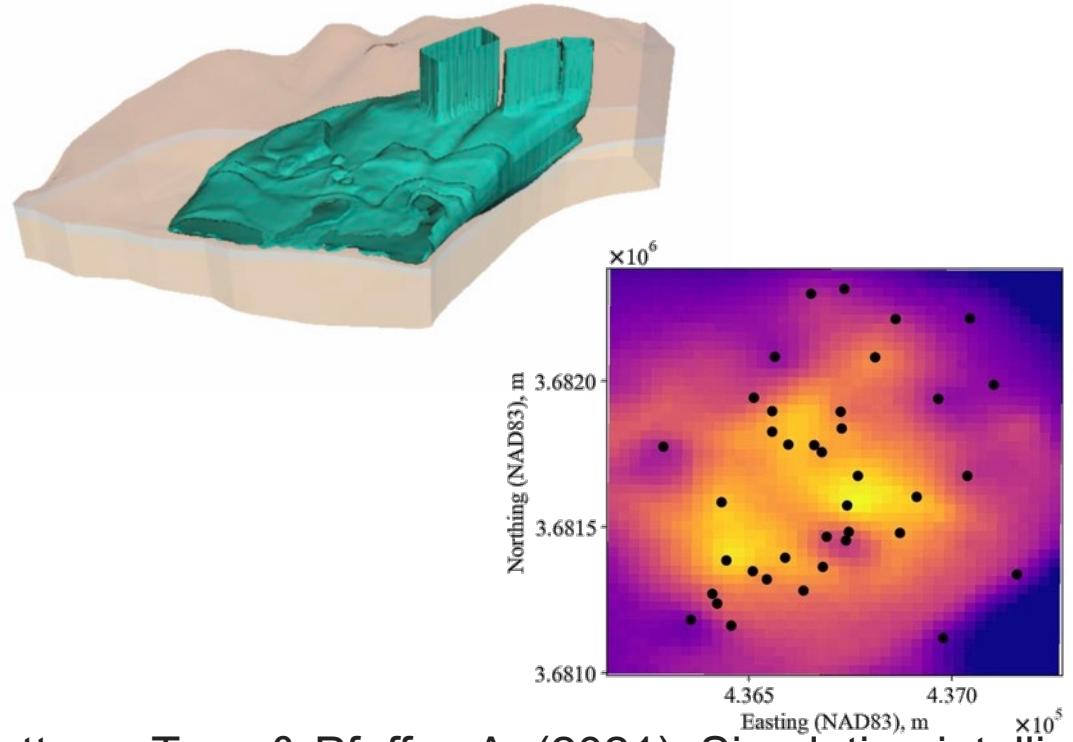
- Geochemical characterization
- Distributed sensor network
- Geophysics

Simulation Intelligence: Simulations x ML/AI

**Climate Change Impact on
Groundwater contamination**
→ Emulator with Fourier Neural
Operator



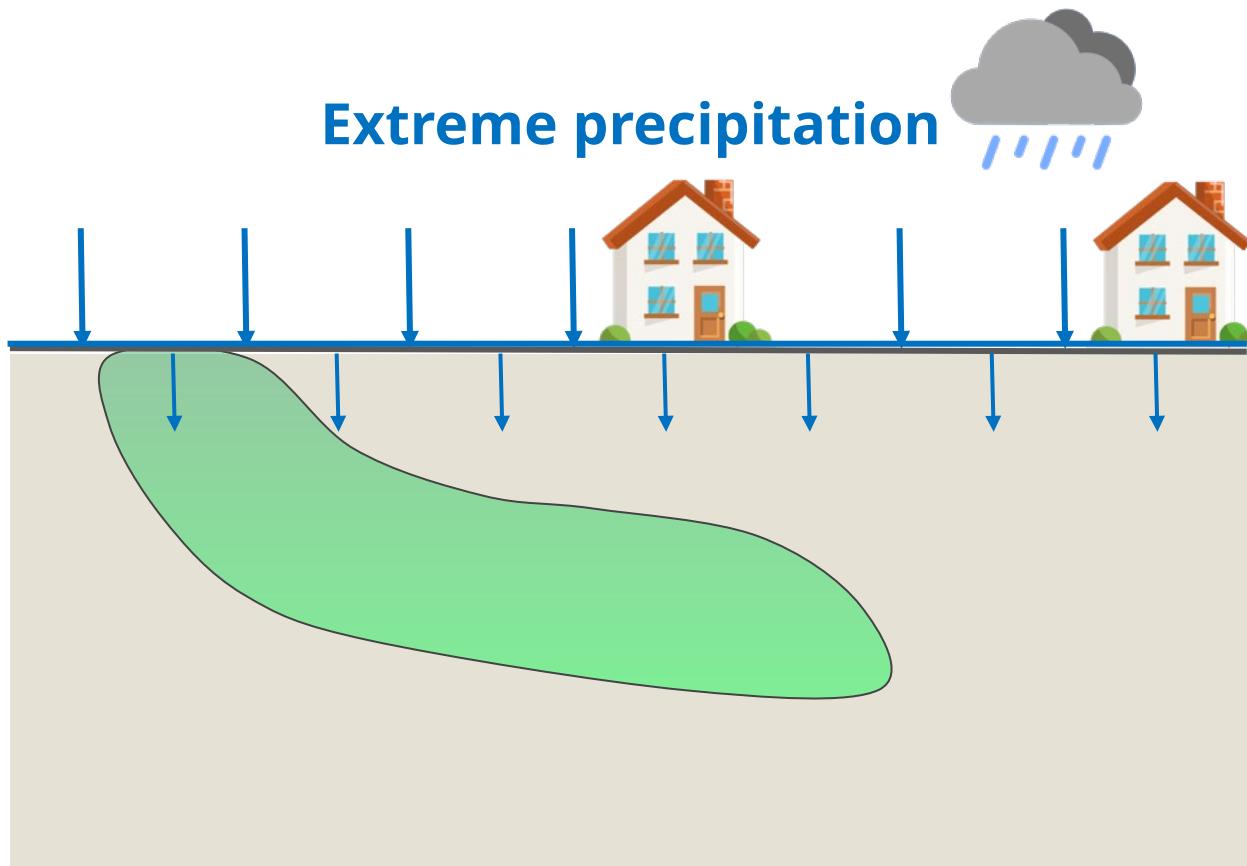
Physics-informed interpolation
→ Model-data integration with
Bayesian hierarchical model



In collaboration with NASA Frontier Development Lab

Lavin, A., Zenil, H., Paige, B., Krakauer, D., Gottschlich, J., Mattson, T., ... & Pfeffer, A. (2021). Simulation intelligence: Towards a new generation of scientific methods. *arXiv preprint arXiv:2112.03235*.

Climate Change Impacts on Contamination



Higher precipitation

- Re-mobilize residual contaminants?
- Dilute concentrations?
→ Change management strategies?
→ Change monitoring configuration?
- But computation is pretty heavy
- We can't run simulation on laptops

Deep Learning-based Emulator: Digital Twin



HPC
Clusters



Parameters
from PDF

$$\{p_1, p_2, \dots, p_N\}$$

Simulations:

$$\phi = f(p)$$
$$\{\phi_1, \phi_2, \dots, \phi_N\}$$

Regressions:

$$\phi \sim f(p)$$

Emulator
predictions

$$\phi = f_{\text{emulate}}(p)$$

Statistical representation of physical models

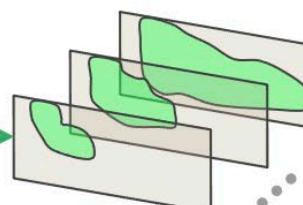
Input:

Climate + Subsurface
Parameters

Emulator

Output:

Plumes

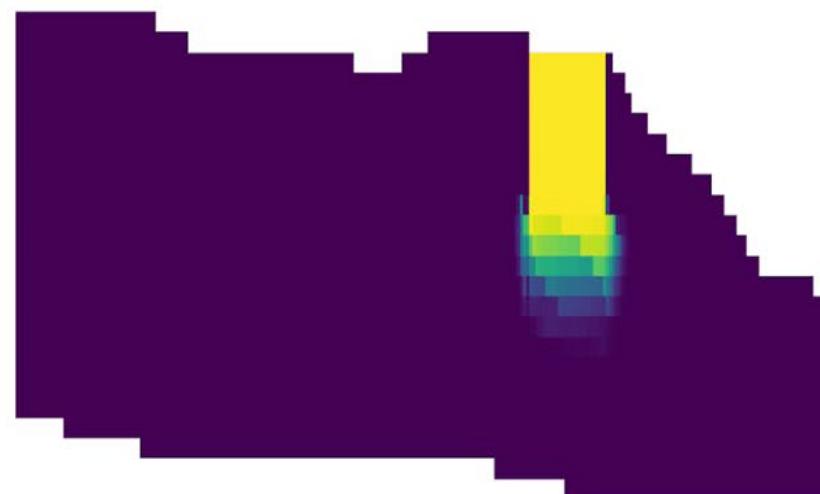


Emulator-based Plume Prediction

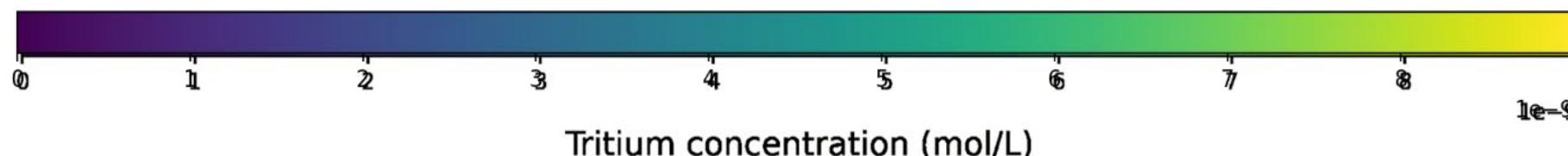
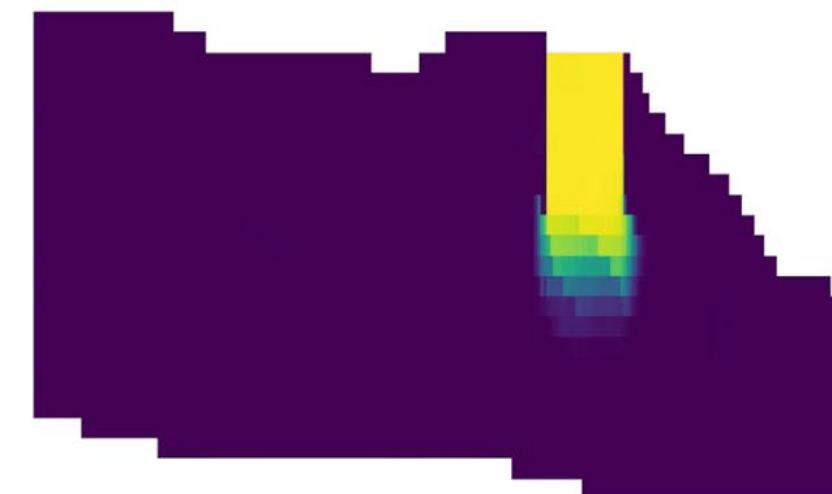
1955

Contaminant Concentration

TRUTH

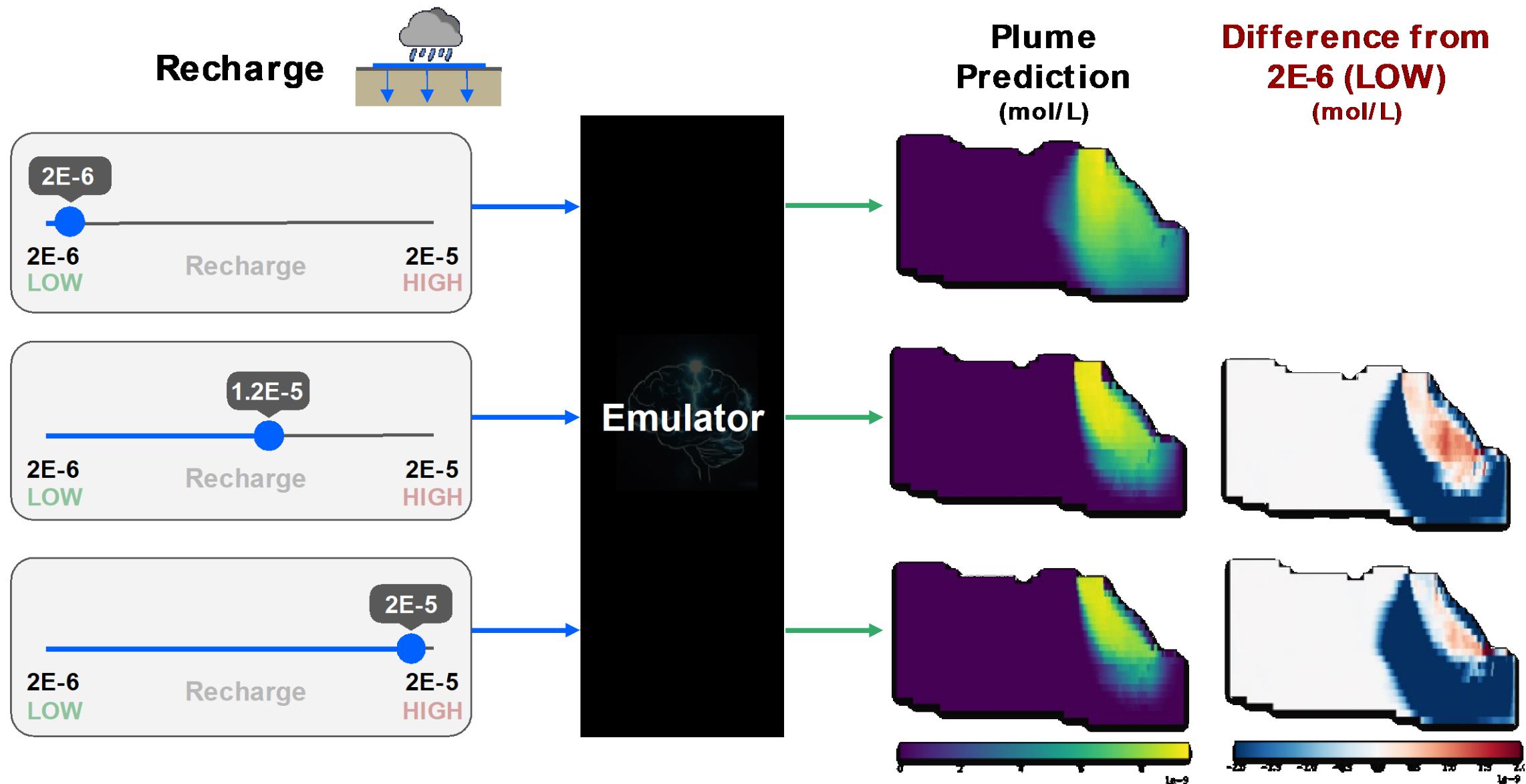


PREDICTION



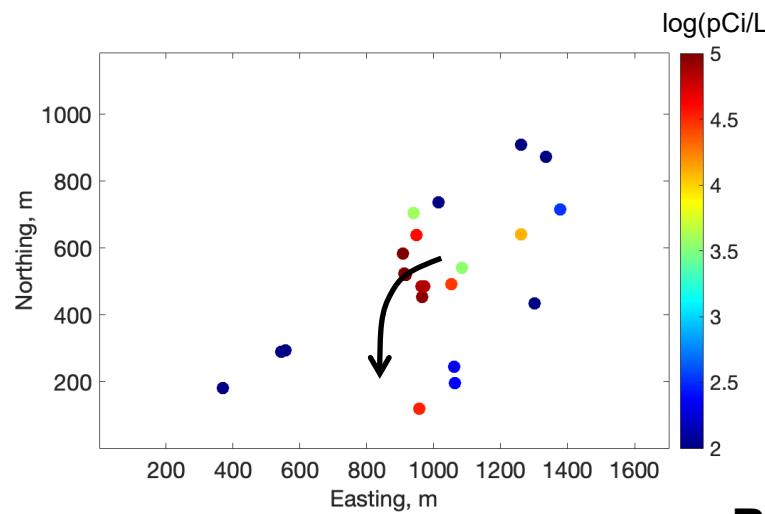
Tritium concentration (mol/L)

Off-Line Climate Change Assessment

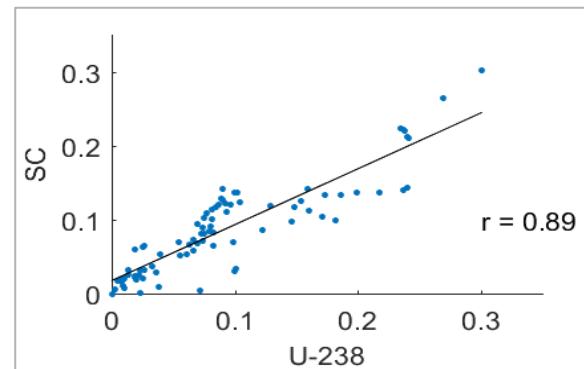


Physics-informed Spatiotemporal Interpolation

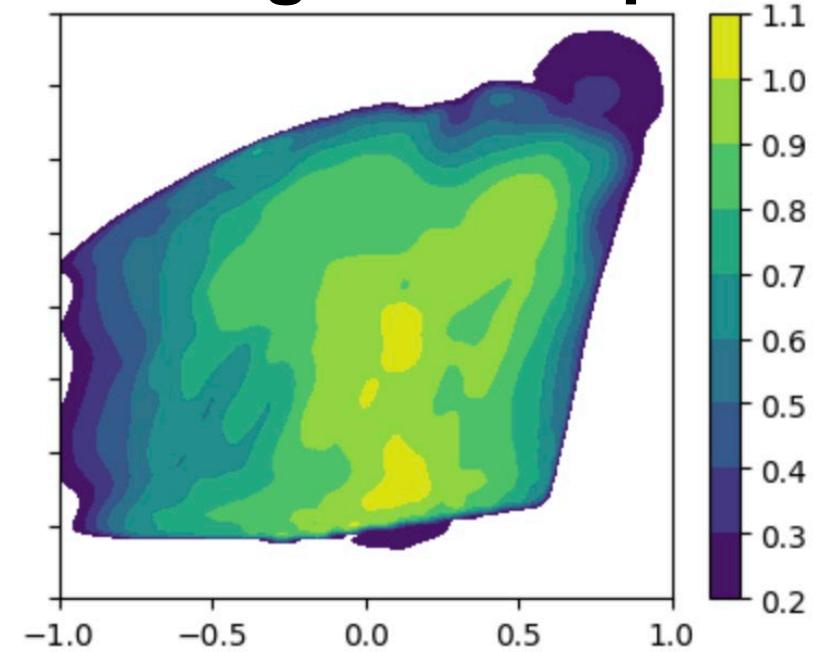
Concentrations at Wells (2015)



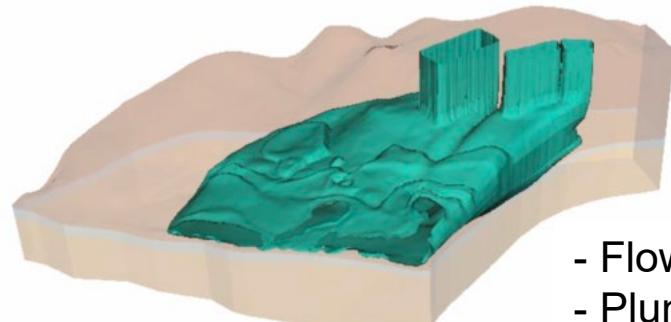
In situ Sensor Data



Integrated map



Reactive Transport Model



- Flow direction
- Plume source

Multiscale data integration
using Bayesian hierarchical
model with Gaussian Process
Models, Wainwright et al.
(2017)

Pathway to Adaptation

- **Understand regulations**
 - Stepwise implementation: in situ sensor deployment
 - Reducing sampling frequencies is easier
 - Then reducing # variables and reducing # wells
- **Emphasize additional safety assurance**
 - Continuous monitoring → early warning, explaining anomalies
 - Guide monitoring strategies (e.g., climate change)
- **Autonomous monitoring → AI-assisted monitoring**
 - Anomaly detection → instrument failure, system changes
 - Realistic plume visualization
 - Digital twin → simulate what can happen in the future

Summary

- **Motivation: Sustainable remediation**
 - Net environmental impact: contaminant removal vs other side effects
 - Long-term institutional controls with passive remediation, monitored natural attestation
- **ALTEMIS Project**
 - **Long-term monitoring with new sensor technologies**
 - In situ real-time monitoring with low-cost low-maintenance sensors
 - Vulnerable concepts to guide key technology implementation strategies
 - **PyLenM: Python for Long-term Environmental Monitoring**
 - ML framework from data exploration to mapping and well optimization
 - Open-source python package for groundwater data analytics
 - **Simulation Intelligence: Simulations x ML/A**
 - Emulators for evaluating climate change impact on residual contamination
 - Physics-informed spatial interpolation (physics-informed monitoring)
 - **Pathway to adaptation**

Thank You!

Contact

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Acknowledgment

DOE Office of Environmental Management