

# Water Quality Monitoring and Models for Decision Making

*Jodi L. Ryder<sup>1</sup>, Emily J. Summers<sup>2</sup>, Kathleen E. Inman<sup>1</sup>*

<sup>1</sup>Environmental Laboratory US Army Engineer Research and Development Center,  
Vicksburg, MS, USA

<sup>2</sup>Department of Oceanography, Texas A&M University, College Station, TX USA

# Preparing for Reservoir Resiliency

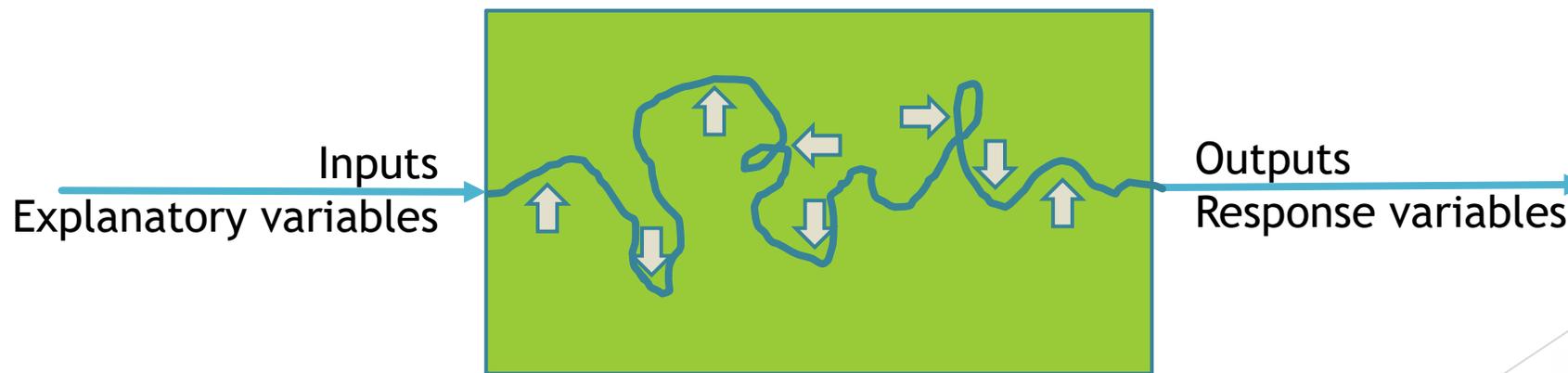
- ▶ USACE Reservoirs have Operating Manuals designed to guide the operational selections to meet applicable requirements
- ▶ Operating ranges are developed based on the project's authorized purposes, stakeholders, and multi-level government
- ▶ Control tends to be limited to the outlet end and specifics vary reservoir-to-reservoir
- ▶ Some reservoirs are operated in concert with others
- ▶ A deviation is a response made outside the range of conditions in the operating manual
- ▶ 2018 HABs and 2020 Wildfires



# “All models are wrong, some are useful”

## -George Box, 1976

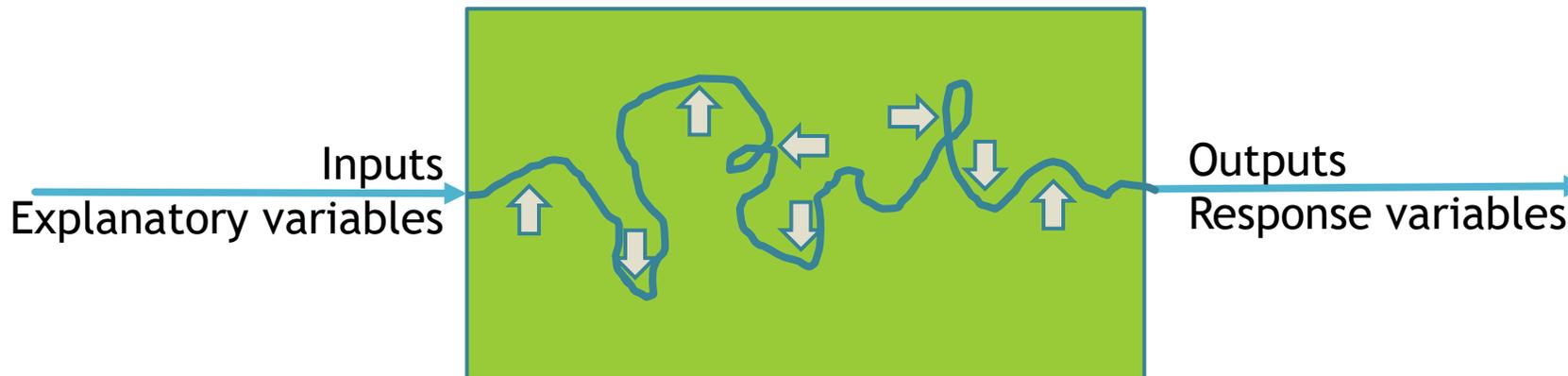
- ▶ A model is any simplification of a system meant to represent key features or responses
- ▶ Models can be empirical, statistical (stochastic), numerical, or even physical
- ▶ Models have inputs, outputs, and parameters
- ▶ Parameters tune the relationship between the inputs and outputs or explanatory and response pairings



# “All models are wrong, some are useful”

## -George Box, 1976

- ▶ Good assumptions are a key component of good modeling
- ▶ Confounding variables or co-varying variables are related to both an explanatory and response variable.
- ▶ Real systems typically have many confounding variables
- ▶ Lurking variables are explanatory variables that aren't included in a model.



# Water quality modeling for restoration

## Specific constituents

- ▶ Habitat conditions
  - ▶ Temperature, Salinity, DO, TDG, Turbidity
- ▶ Nutrient water quality
  - ▶ N, P, C
- ▶ Contaminants
  - ▶ Metals, organics, bio-toxins

## Specific conditions

- ▶ Historical
- ▶ Climate change impacts
- ▶ Event impacts
  - ▶ HABs, Wildfires, Hurricanes
  - ▶ Invasive species introduction
  - ▶ Weather dynamics
  - ▶ Beavers
- ▶ Management decisions
  - ▶ New infrastructure
  - ▶ New operations

# Numerical models

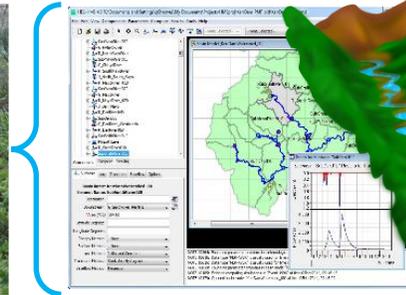
Ideal for complex variable relationships where the driving processes are known

## ▶ Water quality modeling tools:

### ▶ Watershed Runoff:

- ▶ **GSSHA**: Surface and sub-surface water quality modeling and Nature-Based Features design tool

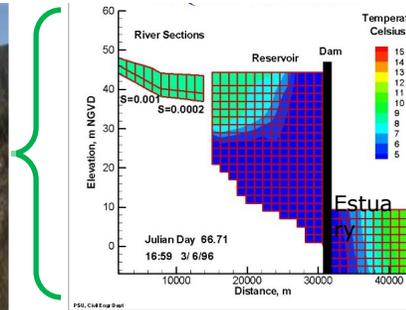
- ▶ **HEC-HMS**: Surface runoff temperature modeling



### ▶ Reservoirs:

- ▶ **CE-QUAL-W2**: 2D reservoir-river hydrodynamics and water quality modeling

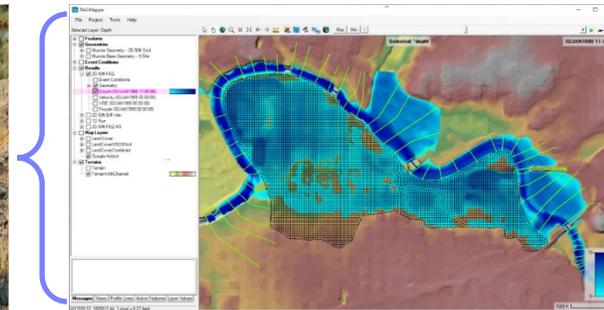
- ▶ **HEC-ResSim**: Reservoir operations and water quality modeling



### ▶ Rivers and Floodplains:

- ▶ **HEC-RAS**: 1D River hydraulics and water quality & vegetation modeling

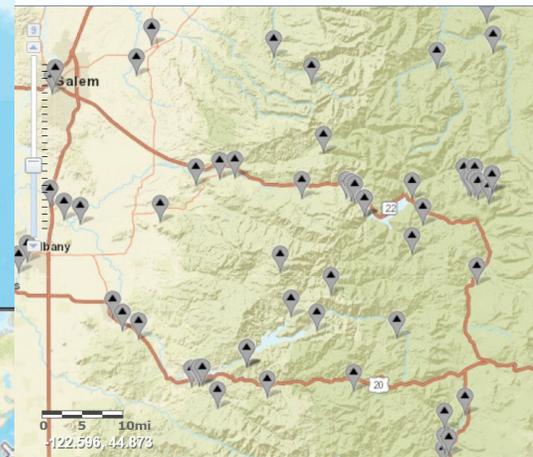
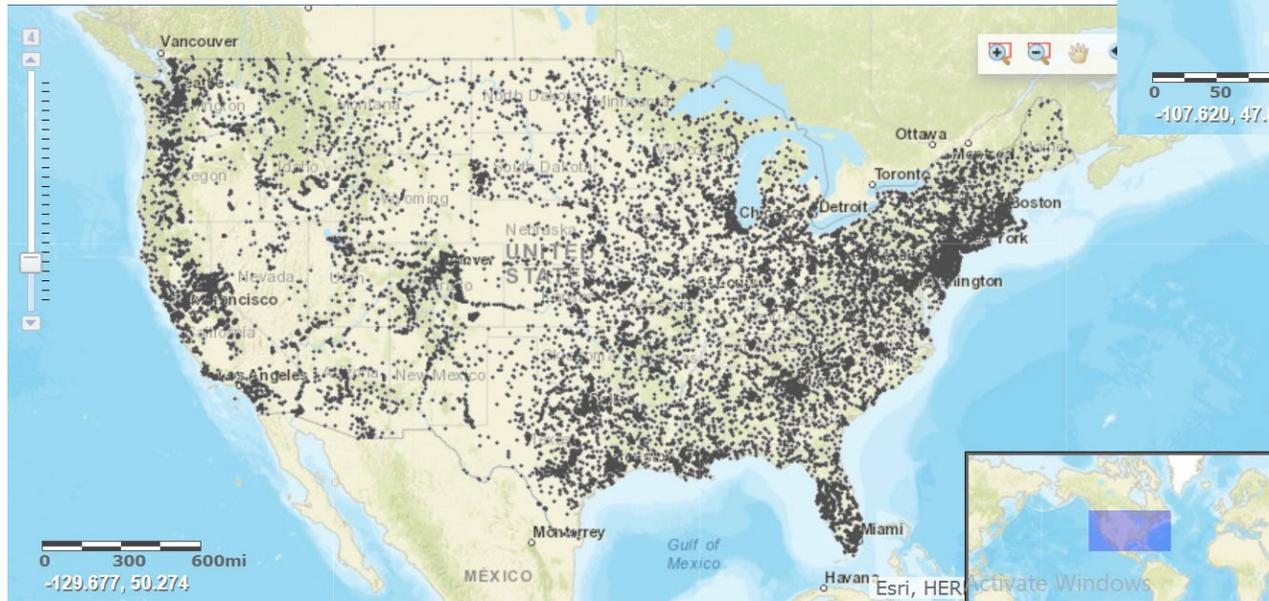
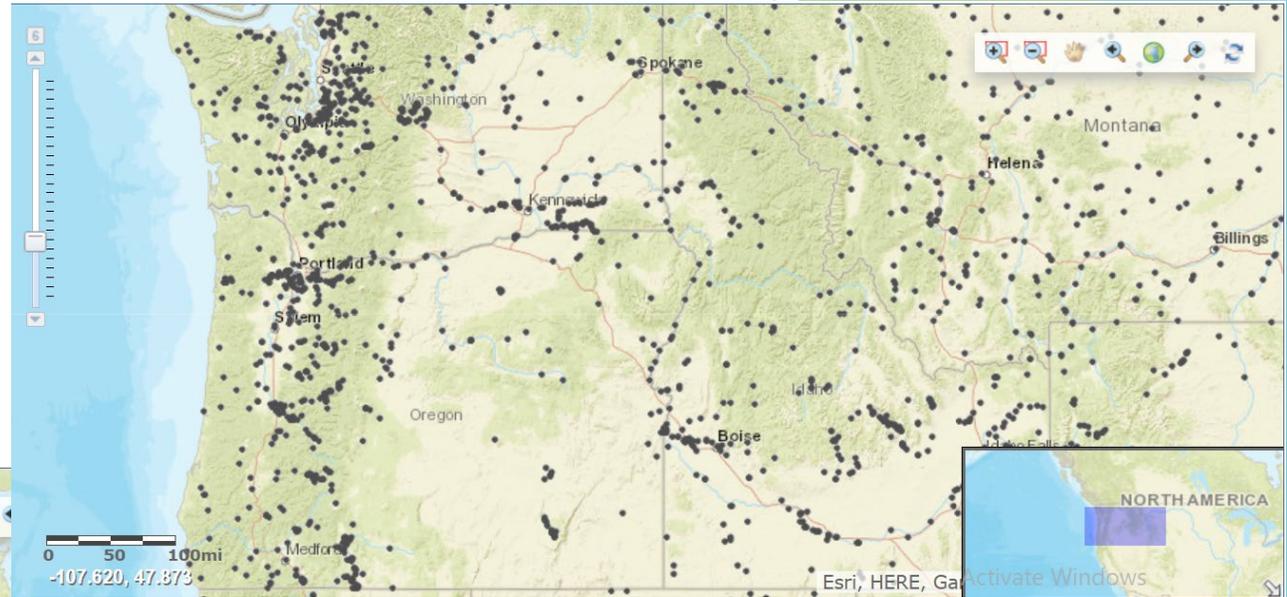
- ▶ **ClearWater-Riverine**: 2D River-floodplain hydraulics and water quality modeling with HEC-RAS-2D



Steissberg, 2022

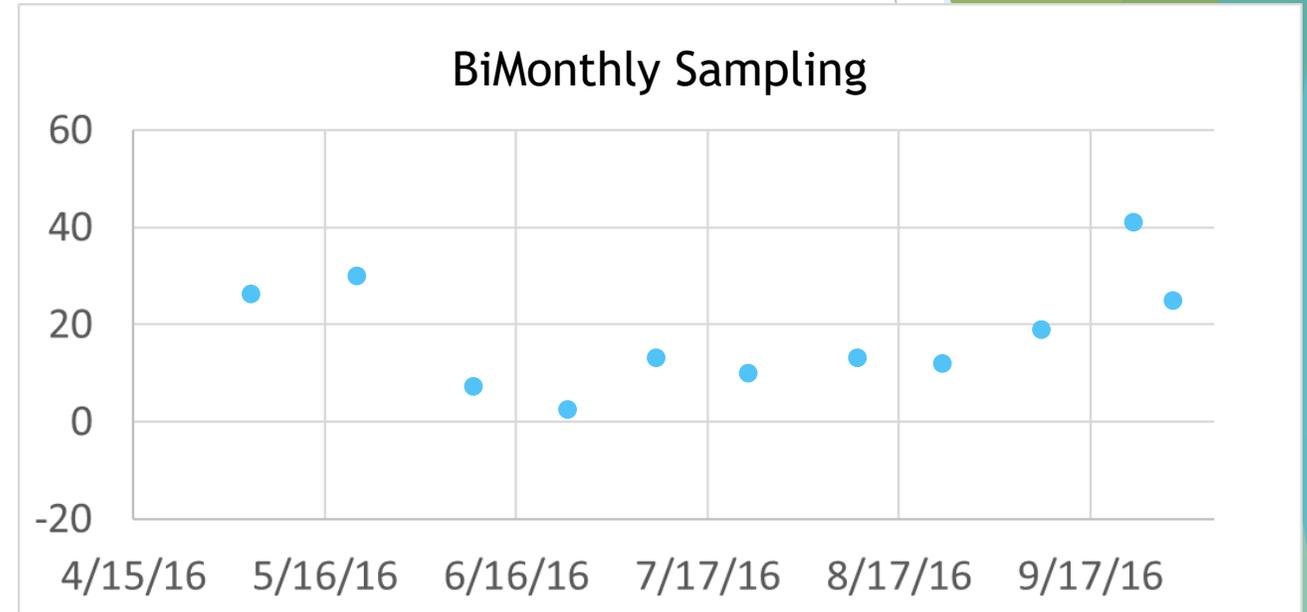
# What was our data system built for?

- ▶ ~3.6 million river miles in the US
- ▶ ~11,110 sites collecting daily data
- ▶ ~121 miles per station
- ▶ 1:3 HUC 12 watersheds has some form of gaging



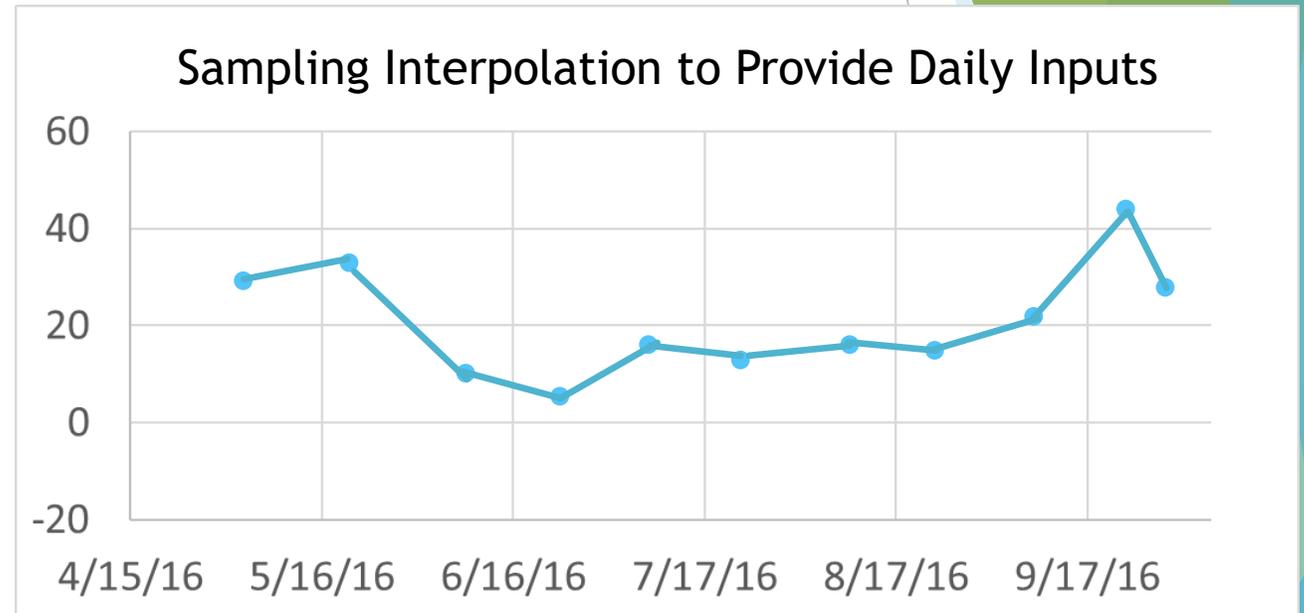
# "The best geologist is he who has seen the most rocks." -H. H. Read, 1940

- ▶ Numerical (process based) models were developed and initially applied when data was acquired by individual sampling events
- ▶ Mindset that a model should confirm what you already know about how the system works



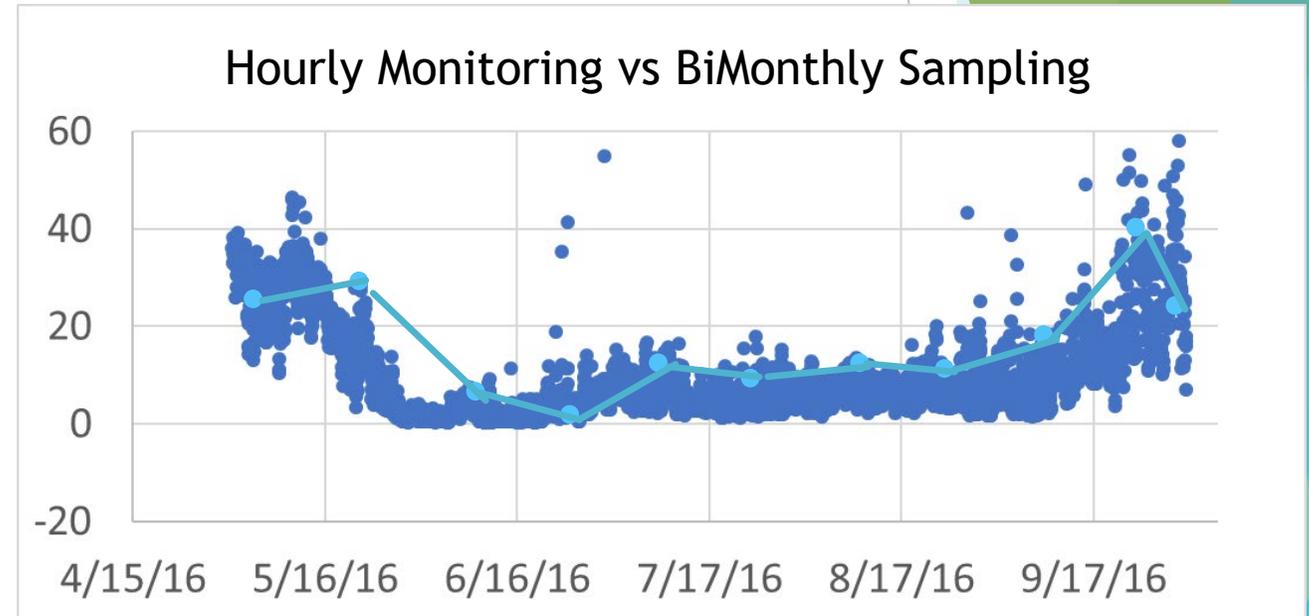
# "The best geologist is he who has seen the most rocks." -H. H. Read, 1940

- ▶ Numerical (process based) models were developed and initially applied when data was acquired by individual sampling events
- ▶ Mindset that a model should confirm what you already know about how the system works
- ▶ Infrequent sampling also interpolated or pre-processed into higher frequency input sets



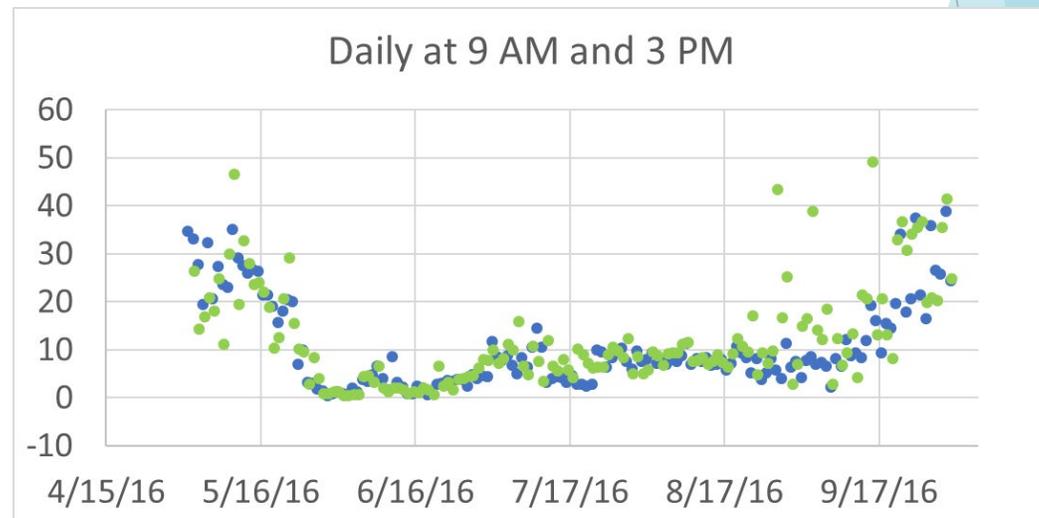
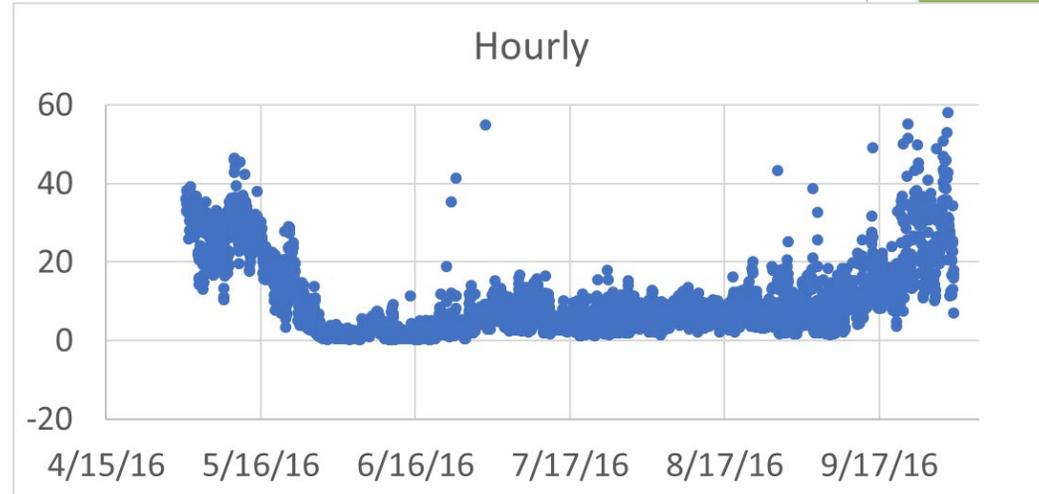
# "The best geologist is he who has seen the most rocks." -H. H. Read, 1940

- ▶ Numerical (process based) models were developed and initially applied when data was acquired by individual sampling events
- ▶ Mindset that a model should confirm what you already know about how the system works
- ▶ Infrequent sampling also interpolated or pre-processed into higher frequency input sets
- ▶ Monitoring can reduce the need to interpolate



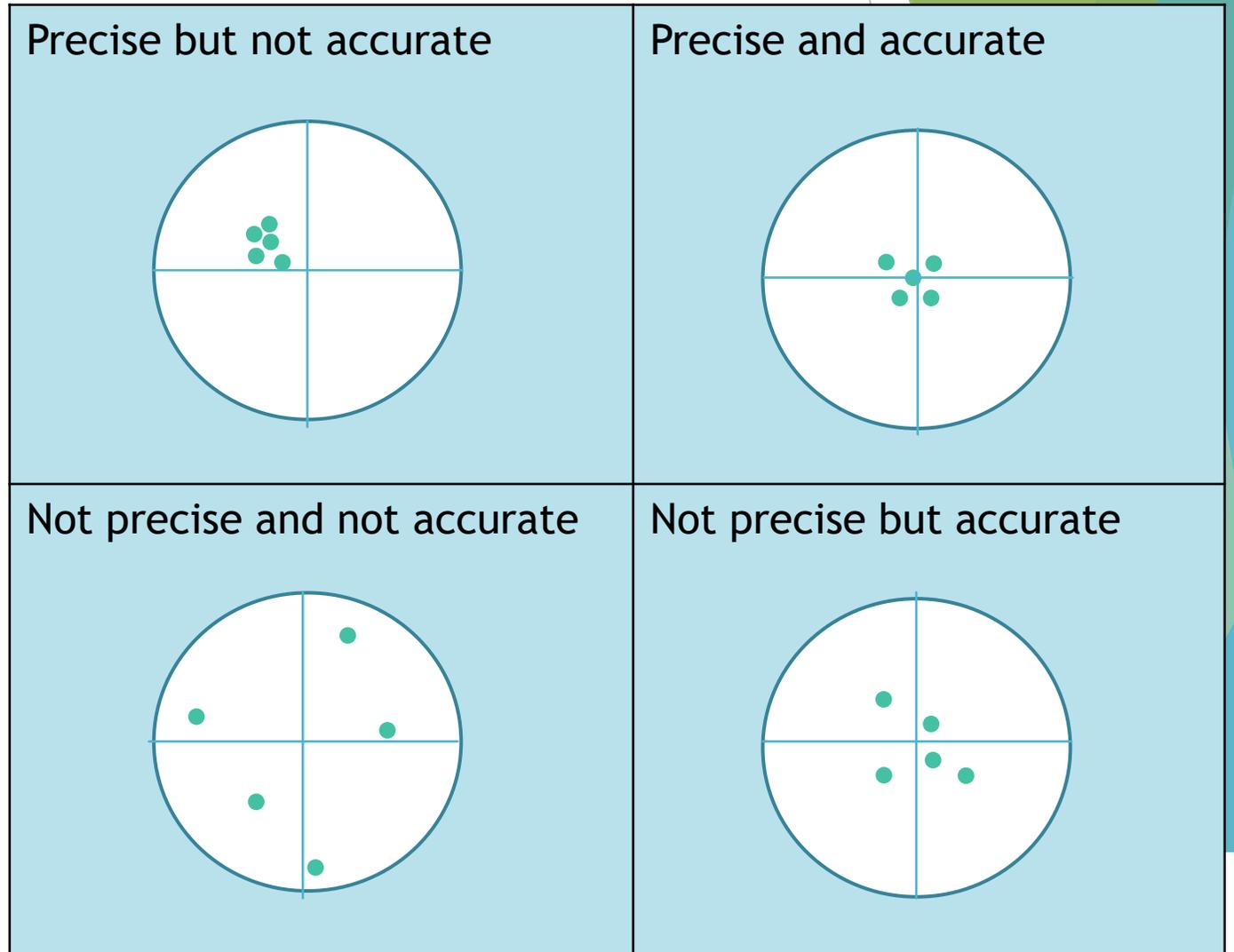
# "The best geologist is he who has seen the most rocks." -H. H. Read, 1940

- ▶ Pre-averaging and filtering data are assumptions
- ▶ Other common assumptions are selecting representative years for calibration and selecting processes to include or ignore
- ▶ Machine learning models (data driven models) attempt to avoid human assumptions



# Arguments against monitoring

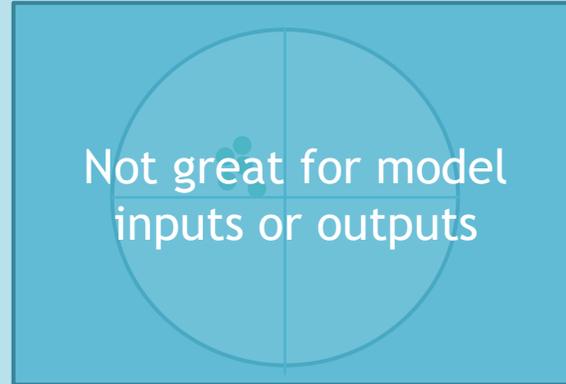
- ▶ Precision - Do repeat measurements get the same value?
- ▶ Accuracy - Do measured values represent the “true” value
- ▶ Most monitoring devices and remote sensed approaches are inherently lower precision than field sampling and lab analysis of water quality



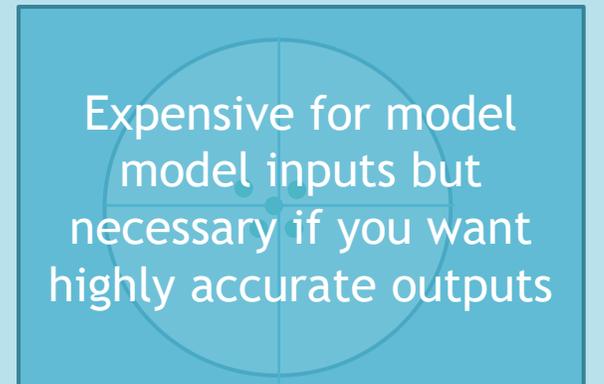
# Precision and Accuracy

- ▶ Precision - Do repeat measurements get the same value?
- ▶ Accuracy - Do measured values represent the “true” value
- ▶ There are tradeoffs
- ▶ Most model outputs are less precise than the inputs

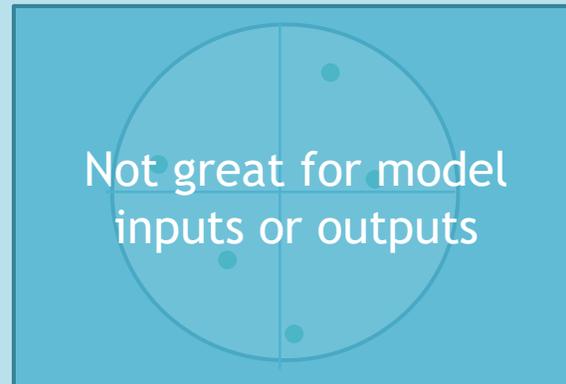
Precise but not accurate



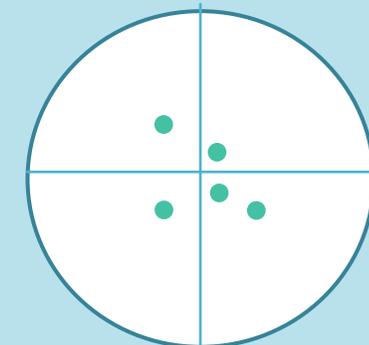
Precise and accurate



Not precise and not accurate



Not precise but accurate

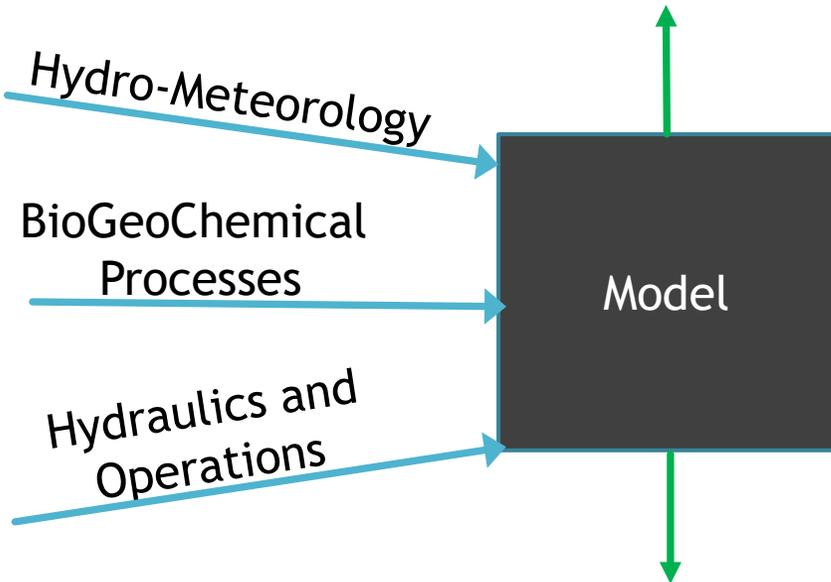


# How to leverage high frequency data?

**Deterministic** = Parameterize constituent relationships using empirical data to build system of equations to that describe system behavior.

CE-QUAL-W2  
CE-QUAL-ICM  
Numerical and analytical

Works best when constituent relationships are well known and static and homogeneous.



**Hybrid, Blended, Physics Informed** = Use deterministic modeling for some constituents and probabilistic for others.

Works best when some aspects of system are well known and homogeneous and others are uncertain, heterogeneous, or dynamic.

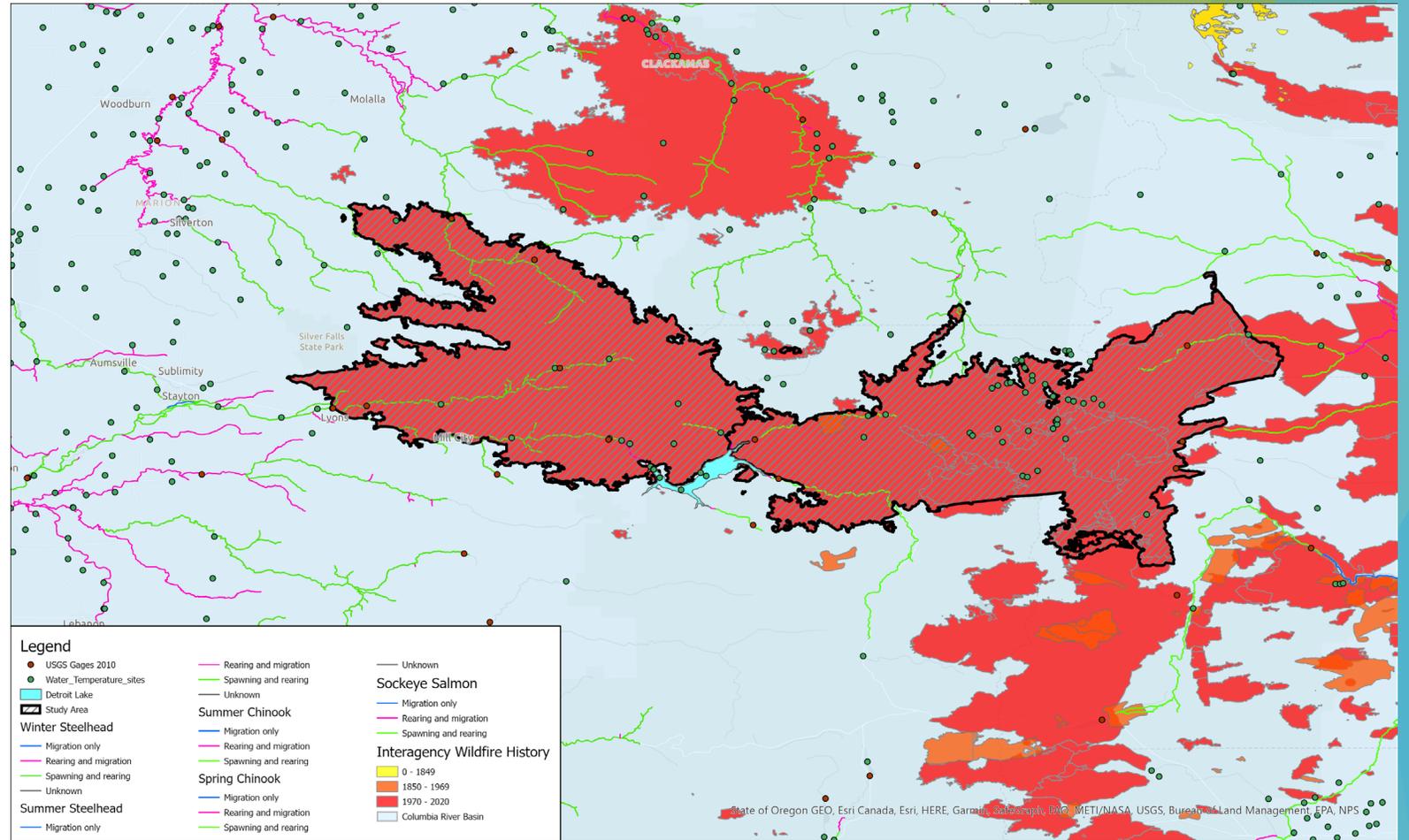
**Probabilistic** = Use statistical parameterization and relationships to build system of equations that describe system behavior.

GAM  
Random Forest  
Data Driven

Most useful when constituent relationships have uncertainty but there is lots of field data to fully bracket the uncertainty.

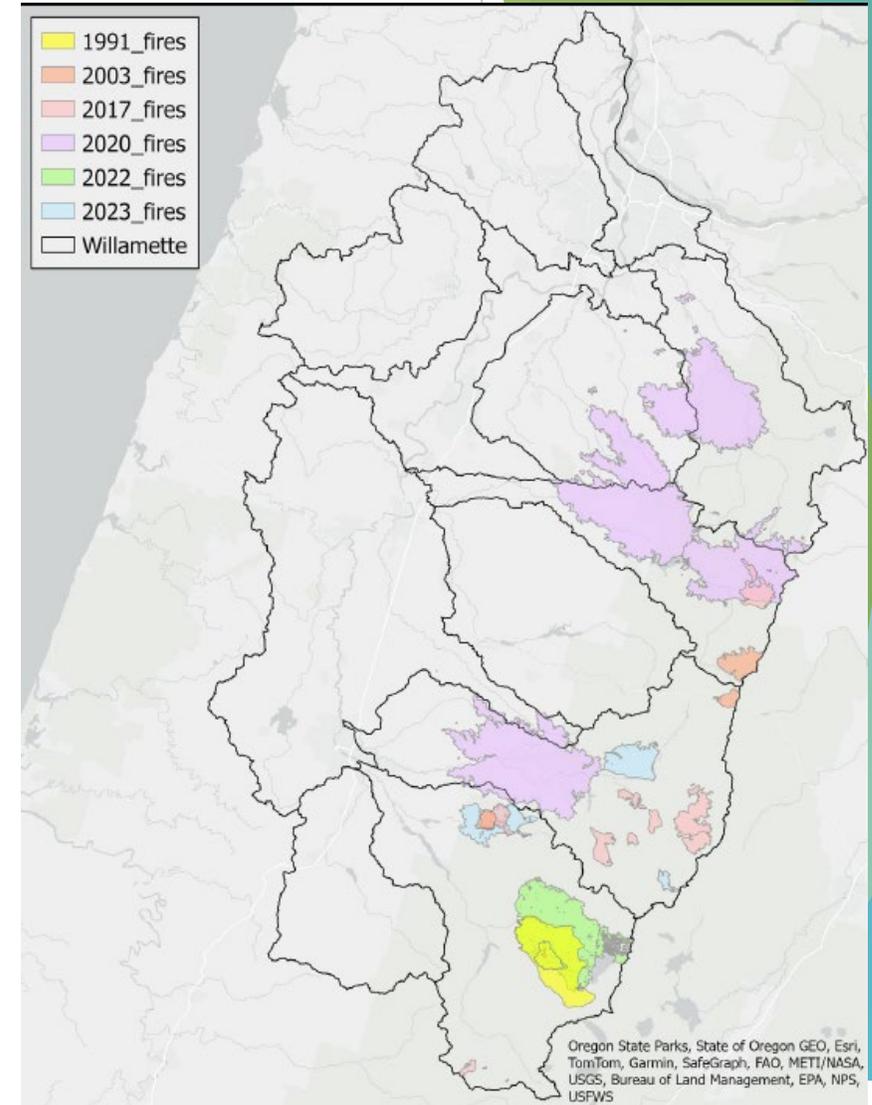
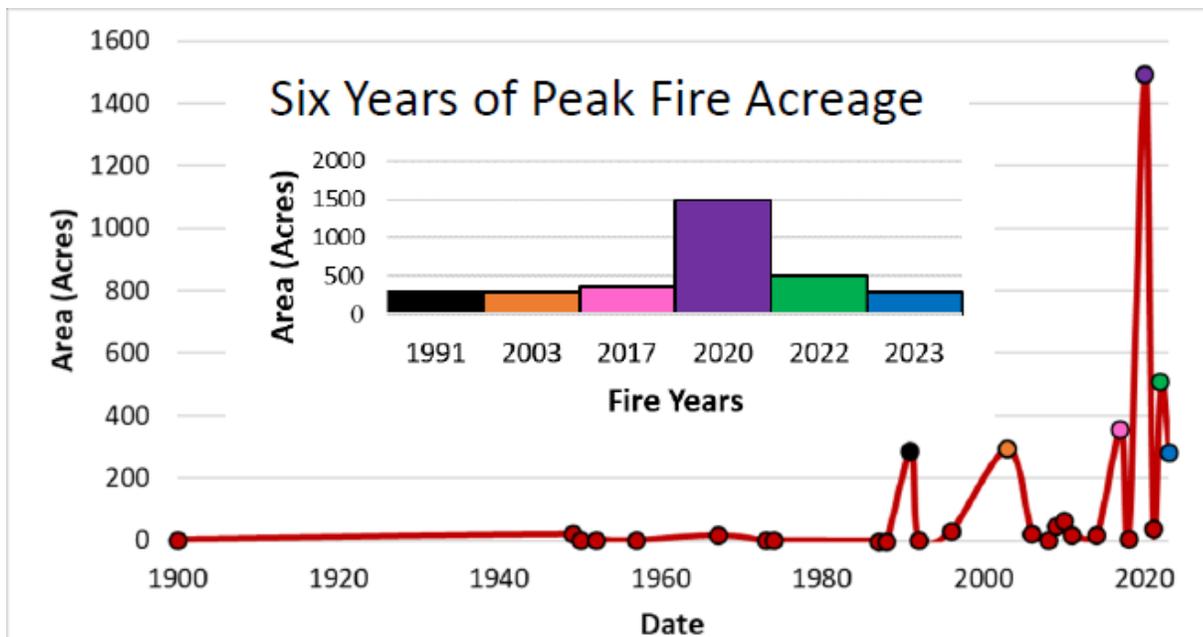
# Water Quality Sensitivity to Watershed Change

**Objective:** Observe post-fire water quality impacts at Detroit Lake, OR and develop modeling strategies to examine the implications of future conditions



# Case of Modeling for Reservoir Resiliency

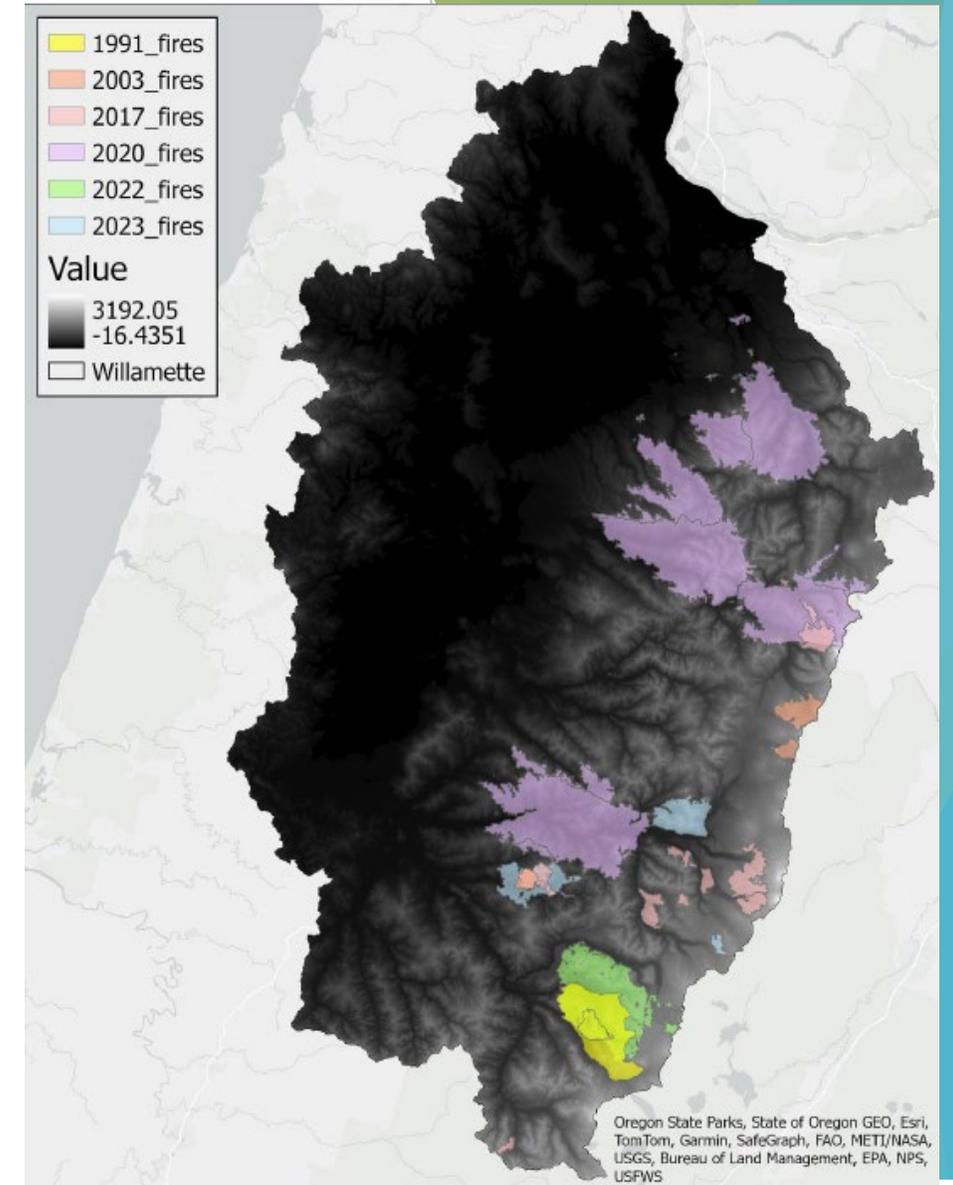
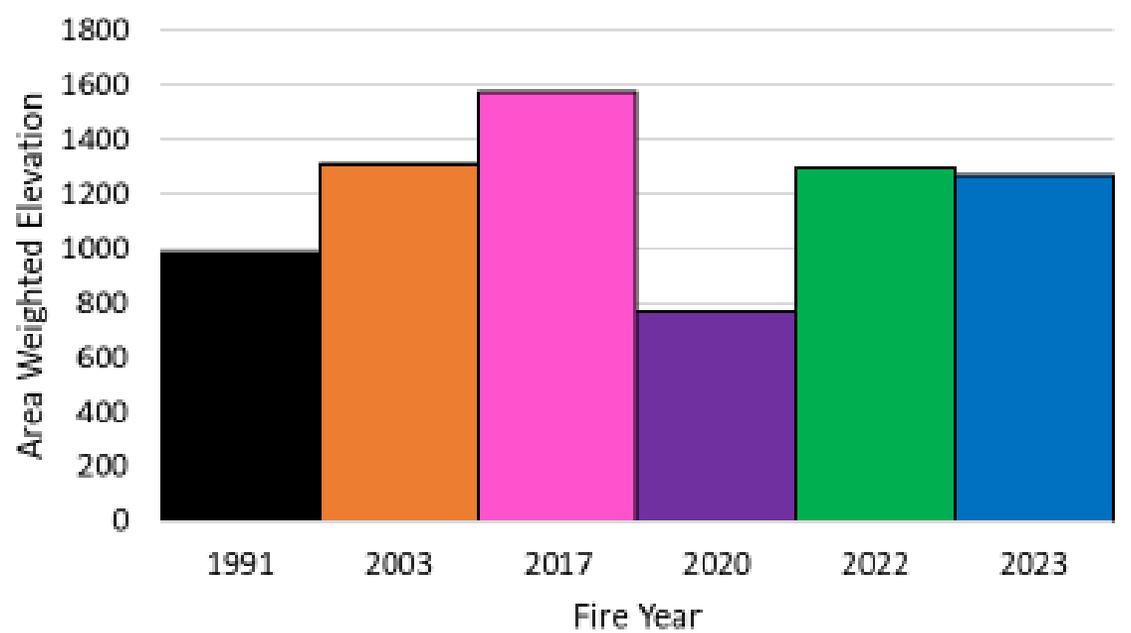
- ▶ Frequency, magnitude, and severity of Cascade fires is increasing
- ▶ Analyzed annual acres burned since 1900



Melendez et al., 2023

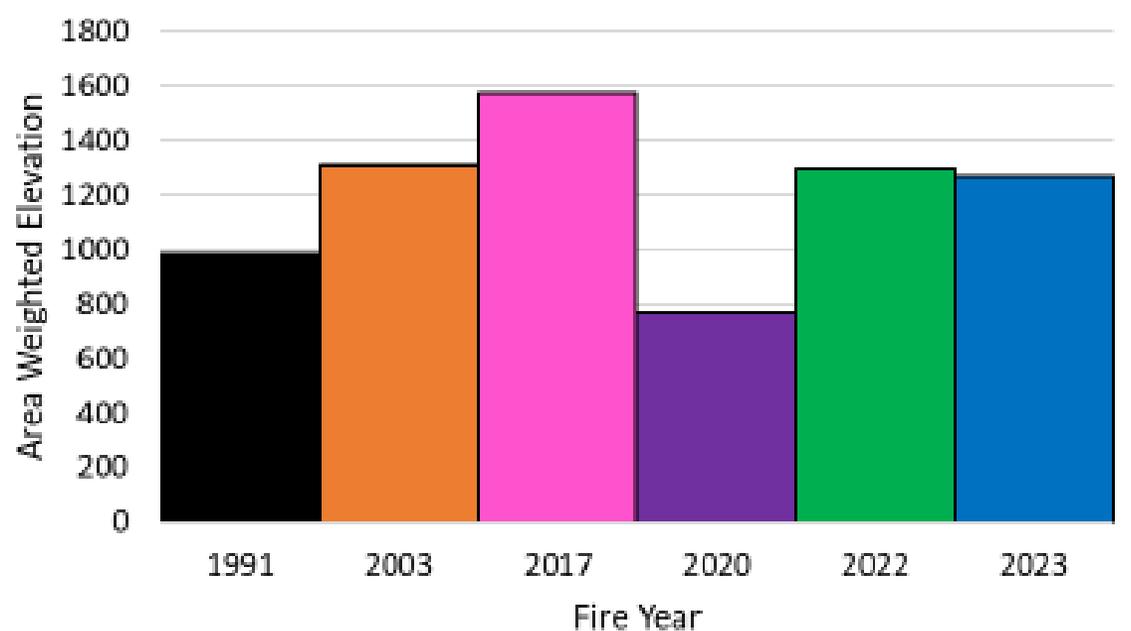
# Preparing for Reservoir Resiliency

- ▶ Frequency, magnitude, and severity of Cascade fires is increasing
- ▶ Analyzed annual acres burned since 1900
- ▶ 2020 was an exceptional year in scale and elevation

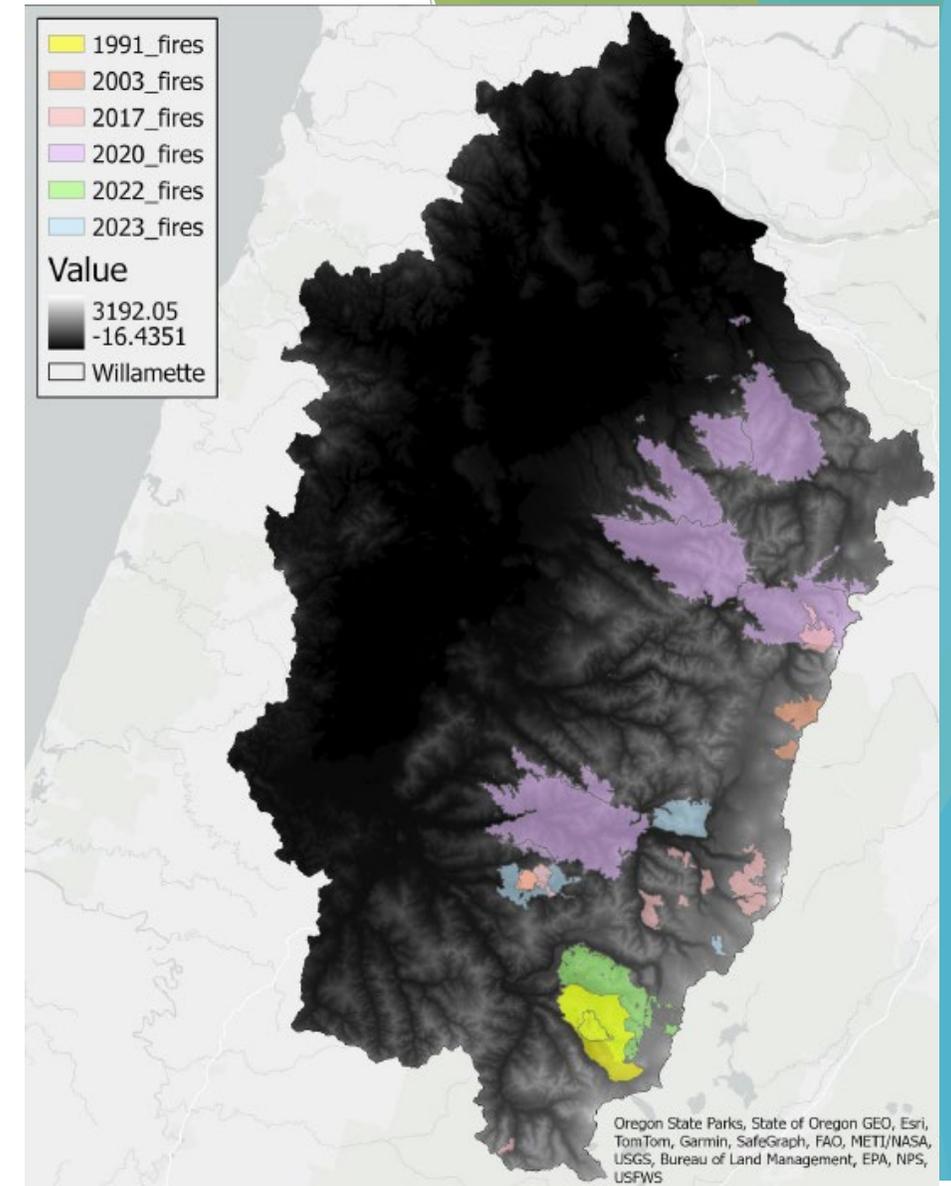


# Preparing for Reservoir Resiliency

- ▶ Frequency, magnitude, and severity of Cascade fires is increasing
- ▶ Analyzed annual acres burned since 1900
- ▶ 2020 was an exceptional year in scale and elevation



What does this mean for future USACE reservoir management and water quality?



# New Routes to Anticipate Water Quality Outcomes

Capture land use change in novel rainfall-runoff relationships

Improve water quality calibration

Watershed loading models (WQ2)

Capture more spatial information with new ways to do initial conditions and calibration

Capture finer temporal scale with new ways to do boundary conditions and calibration

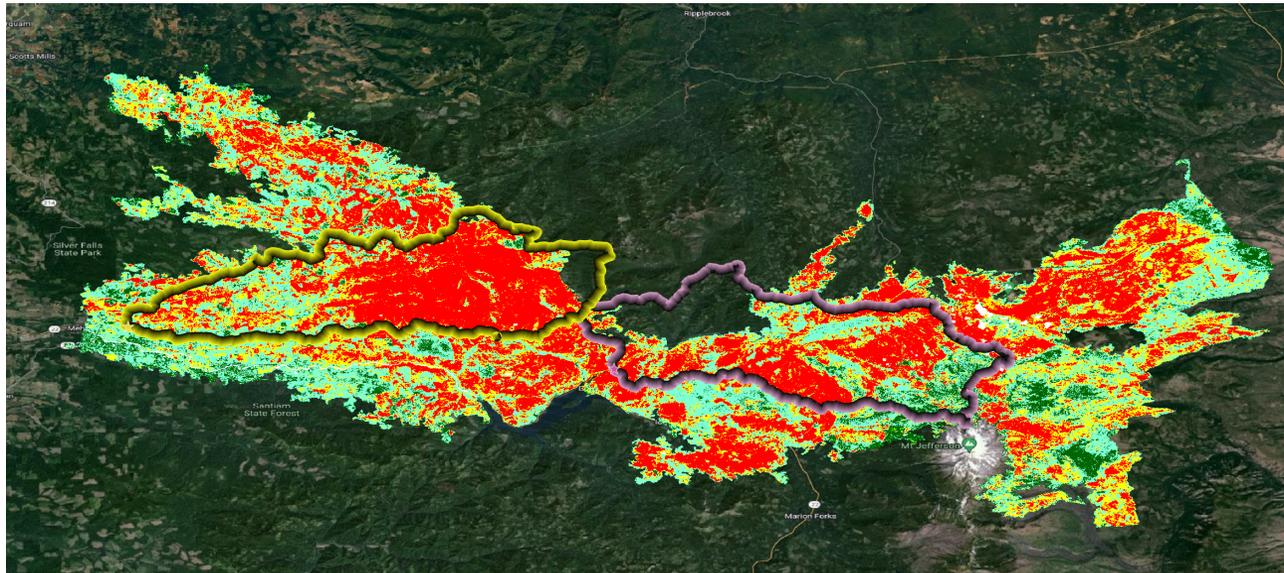
Process based reservoir models

Capture challenging features with post-processing ML

Incorporate new internal processes for HABs and toxins

# Lionshead and Beachie Creek Fire Severity

Watershed	14178000	14179000	14180300	14181500
Low SBS	10.1%	30.1%	4.7%	15.9%
Moderate SBS	7.3%	30.1%	1.4%	16.3%
High SBS	1.7%	9.4%	0.3%	3.8%



Pradhan et al., 2023

# New Routes to Anticipate Water Quality Outcomes

Fire severity and soil conditions

Capture land use change in novel rainfall-runoff relationships

Watershed loading models (WQ2)

Capture more spatial information with new ways to do initial conditions and calibration

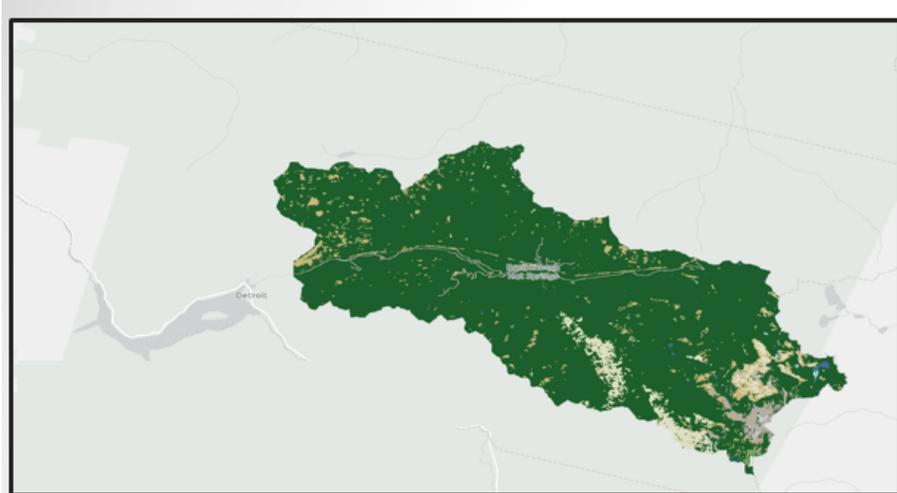
Capture finer temporal scale with new ways to do boundary conditions and calibration

Process based reservoir models

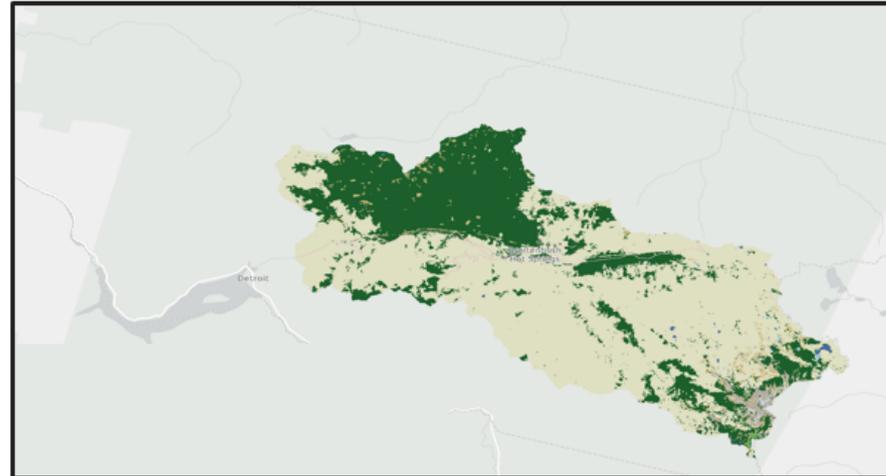
Capture novel processes with with post-processing ML

Incorporate new internal processes for HABs and toxins

# Development of tributary water quality model for post-fire constituent loading changes



NLCD LAND COVER CLASS	Acres	Watershed %
Open Water	153.67	0.23%
Perennial Snow/Ice	47.37	0.07%
Developed, Open Space	450.57	0.67%
Developed, Low Intensity	7.12	0.01%
Developed, Medium Intensity	0.89	0.00%
Barren Land	1091.51	1.62%
Deciduous Forest	84.95	0.13%
Evergreen Forest	59484.84	88.25%
Mixed Forest	94.74	0.14%
Shrub/Scrub	3207.38	4.76%
Herbaceous	2705.88	4.01%
Woody Wetlands	68.50	0.10%
Emergent Herbaceous Wetlands	4.67	0.01%



NLCD LAND COVER CLASS	Acres	Watershed %
Open Water	149.23	0.22%
Perennial Snow/Ice	47.37	0.07%
Developed, Open Space	448.79	0.67%
Developed, Low Intensity	8.01	0.01%
Developed, Medium Intensity	1.78	0.00%
Barren Land	867.12	1.29%
Deciduous Forest	73.39	0.11%
Evergreen Forest	21834.28	32.39%
Mixed Forest	34.69	0.05%
Shrub/Scrub	1376.62	2.04%
Herbaceous	42483.65	63.03%
Woody Wetlands	61.16	0.09%
Emergent Herbaceous Wetlands	16.01	0.02%

Expanding on Pradhan et al., 2023

# New Routes to Anticipate Water Quality Outcomes

Fire severity and soil conditions

Capture land use change in novel rainfall-runoff relationships

Remote sensed LULC

Improve water quality calibration

Expanding tributary sampling

Watershed loading models (WQ2)

Capture more spatial information with new ways to do initial conditions and calibration

Capture finer temporal scale with new ways to do boundary conditions and calibration

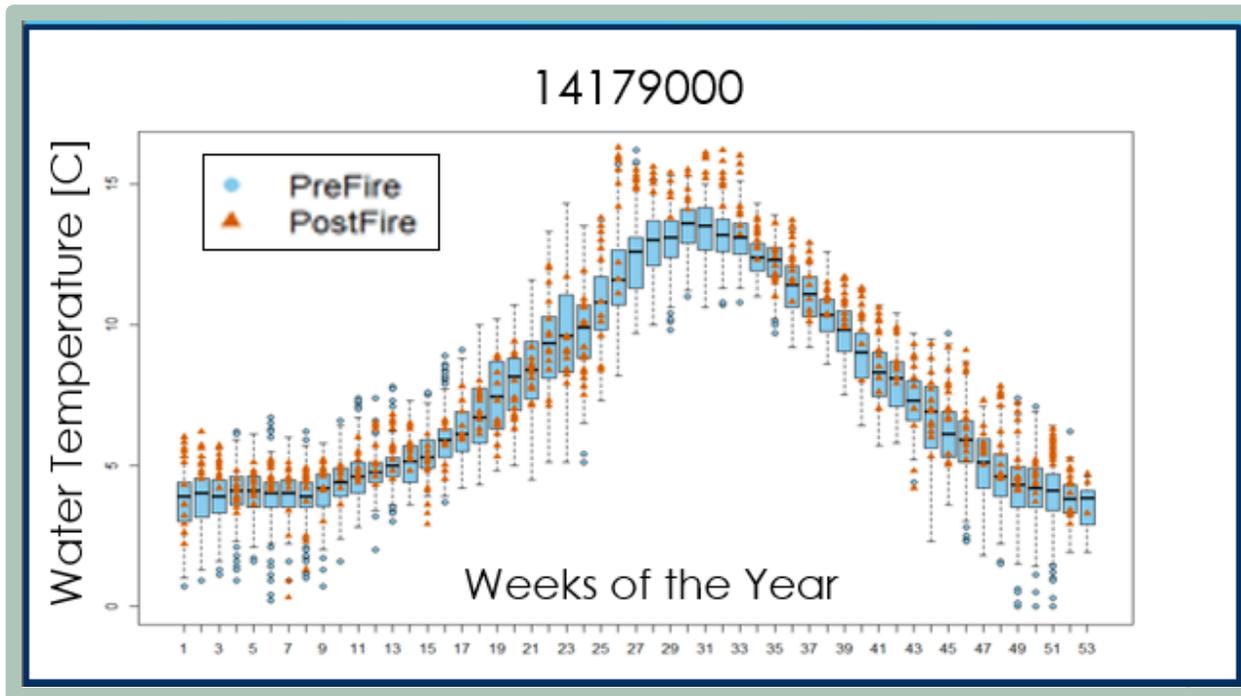
Process based reservoir models

Capture novel processes with with post-processing ML

Incorporate new internal processes for HABs and toxins

# Observations of post-fire changes

Gauge	Burned/Unburned	Water Temperature	Water Temperature p-value sig	Discharge	Discharge p-value sig	Regional Air Temperature	Regional Air Temperature p-value sig
14179000	Burned	<2.2e-16	Significant	0.07413	Non-Significant	0.01109	Significant
14182500	Burned	1.47E-09	Significant	0.2472	Non-Significant	0.01112	Significant
14185000	Unburned	1.44E-06	Significant	4.50E-05	Significant	0.01112	Significant



Inman et al., 2023

# New Routes to Anticipate Water Quality Outcomes

Fire severity and soil conditions

Capture land use change in novel rainfall-runoff relationships

Remote sensed LULC

Improve water quality calibration

Expanding tributary sampling

Watershed loading models (WQ2)

Capture more spatial information with new ways to do initial conditions and calibration

Capture finer temporal scale with new ways to do boundary conditions and calibration

High frequency monitoring data

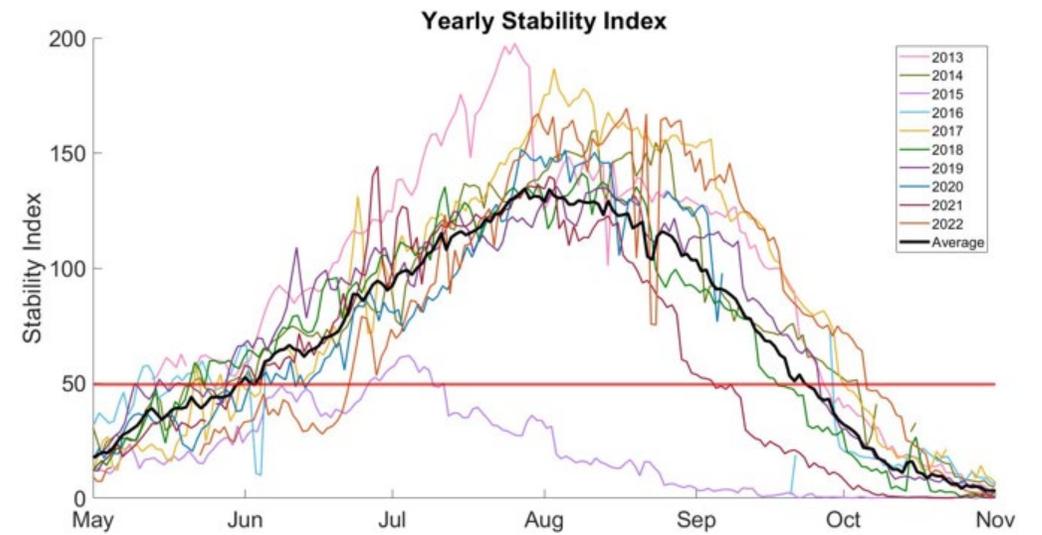
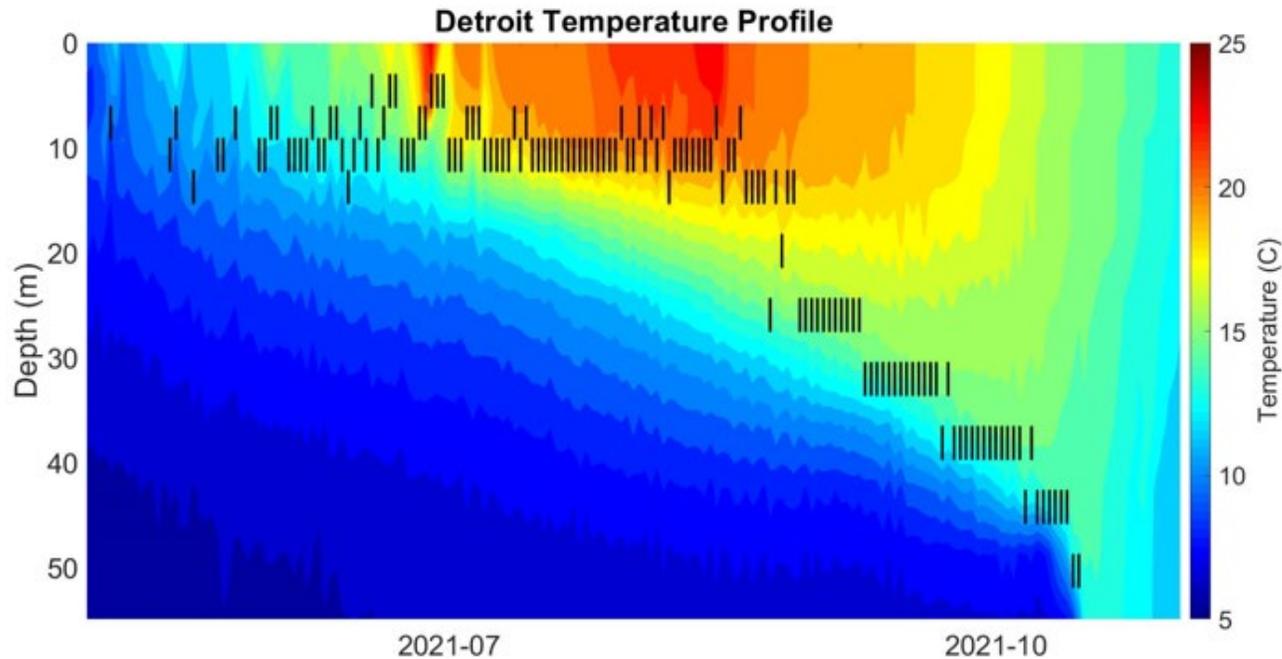
Process based reservoir models

Capture challenging relationships with post-processing ML

Incorporate new internal processes for HABs and toxins

# Translating monitoring into process informed inputs

- ▶ SIVA is a MATLAB code developed to calculate a stability index based on multi-level water temperature observations.



**Dilichiospermum blooms regularly occur during stratification periods on Detroit Lake**

# New Routes to Anticipate Water Quality Outcomes

Fire severity and soil conditions

Capture land use change in novel rainfall-runoff relationships

Remote sensed LULC

Improve water quality calibration

Expanding tributary sampling

Watershed loading models (WQ2)

Remote sensed water quality

New ways to do initial conditions and calibration

Incorporate new internal processes for HABs and toxins

Capture finer temporal scale with new ways to do boundary conditions and calibration

Process based reservoir models

High frequency monitoring data

Development of process informed parameters for ML

Alternative models

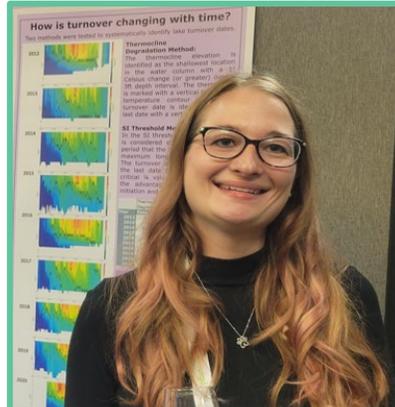
Capture challenging relationships with post-processing ML

Thank You!

Dr. Jodi L. Ryder



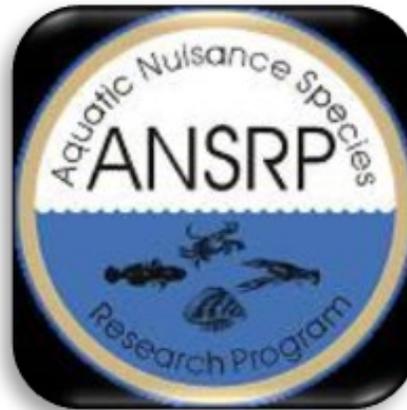
Water Quality and  
Contaminant Modeling  
Jodi L. Ryder  
[Jodi.L.Ryder@usace.army.mil](mailto:Jodi.L.Ryder@usace.army.mil)  
601-631-1852



Emily Summers  
TAMU - ORISE



Kathleen Inman



# New Routes to Anticipate Water Quality Outcomes

