

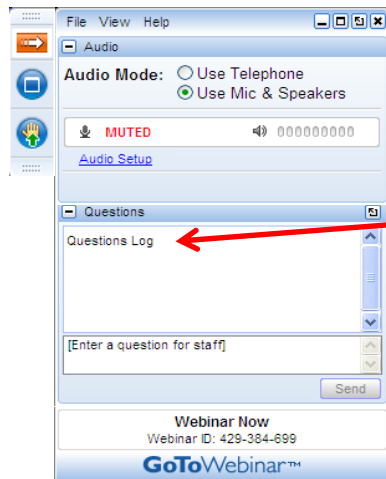
Evaluation of Data Needs to Support Water Quality Models for Setting Nutrient Targets

Tuesday, April 2, 2019
12:00 – 2:00 pm ET



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How to Participate Today



- **Audio Modes**
 - Listen using Mic & Speakers
 - Or, select “Use Telephone” and dial the conference (please remember long distance phone charges apply).
- **Submit your questions using the Questions Pane.**
- **A recording will be available for replay shortly after this web seminar.**

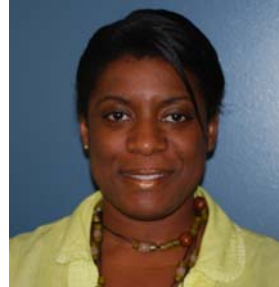


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Today's Moderators



Penelope Moskus
Senior Environmental
Scientist/Project
Manager
LimnoTech



Lola Olabode
Program Director
*The Water Research
Foundation*



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Agenda

- 12:00** Welcome and Introduction
- 12:10** Rationale for the Project/Steve Chapra
- 12:20** Project Overview/Todd Redder
- 12:25** Review of Existing Model Applications/Todd Redder
- 12:35** Relationship between Amount of Data and Model Utility/Dave Dilks
- 12:50** Practical Methods for Assessing Model Uncertainty/Dave Dilks
- 1:15** Requirements for Regulatory Acceptance/Dave Dilks
- 1:30** Summary of Findings and Project Benefits/Steve Chapra
- 1:40** Q&A
- 2:00** Closing



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Today's Speakers

Steve Chapra, Ph.D.
Professor, Civil and
Environmental Engineering
Tufts University



Todd Redder, PE
Environmental/Water
Resources Engineer
LimnoTech



David W. Dilks, Ph.D.
Vice President
LimnoTech



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Acknowledgments

- **Association of Clean Water Administrators** – *Special webcasts*
- **Water Environment Federation** – *Education and Training*
- **ACWA-WEF partnership**- *Permit Writers Workshops*
- **National Association of Clean Water Agencies** –*Committee updates, Briefings, Support to the Utilities*
- **Colorado Monitoring Framework** – *Reg 85, Colorado Water Quality Control Commission*
- **EPA** – *Briefings, Information Exchange and Updates*
- **American Water Resources Association**- *Information Exchange*
- **The California Water and Environmental Modeling Forum** – *Information exchange*
- **Utilities** – *Participation, Information Exchange, Case Studies, Demonstrations, and Implementation of Water Quality Based Discharge Standards.*
- **States** – *Participation, Information Exchange, Case Studies, Demonstrations, and Implementation of Water Quality Based Discharge Standards.*
- **Key Consultants & Academics** – (LimnoTech, Brown & Caldwell, Clements consulting, Arcadis, Dr. Steve Chapra)
- **WRF's Sustainable Integrated Water Management and Nutrients Research** – *Collaboration, Information Exchange, and Strategic communications*



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Research Area Objective

Enable the water quality community to fully participate in the development and implementation of water quality based discharge standards for contaminants (principally nutrients) by developing independent methods for confirming linkages between receiving water quality, wastewater discharges, and other sources.



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Research Projects Receiving Water Linkages in Water Quality (LINK)

Year	Project Title	Research Group		
		Linkages	Permit	Comm.
2019	2019 Roadmap on prioritizing research in both permitting and linkages	X	X	X
2018	Modeling Guidance for Developing Site Specific Nutrient Goals – Demonstration, Screening-Level Application (LINK4T17).	X	X	X
2017	Establishing Methods for Numeric Nutrient Target-Setting (LINK3R16)	X	X	
2015	Developing Site-Specific Nutrient Goals – Demonstration: Boulder Creek, Colorado (LINK2T14)		X	
2015	Modeling Guidance for Developing Site-Specific Nutrient Goals (LINK1T11)		X	
2010	Linking Receiving Water Impacts to Sources and to Water Quality Management Decisions: Using Nutrients as an Initial Case Study (WERF3C10, 2010)		X	



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Rationale for Project

- Nutrient pollution is a serious concern
- The relationship between nutrients and environmental response is complicated
- Guidance is needed on methods for conducting rigorous site-specific assessments to set nutrient targets



Nutrient Pollution is a Serious Concern

- Excess nitrogen and phosphorus is a major water quality concern
 - >10,000 waters impaired nationally
 - Harmful algal blooms are increasing
- EPA has been calling for states to develop numeric nutrient criteria for more than a decade



Relationships between Nutrients and Endpoints Are Complicated

- Response of aquatic plants to nutrient loads are highly dependent on site-specific factors
 - e.g., clarity, shading, habitat, hydrology
- Multiple potential endpoints
 - e.g., hypoxia, harmful algal blooms, aesthetics
- Many endpoints of concern require consideration of multiple levels of relationships
 - Nutrients -> algal growth-> algal toxins

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Methods for Developing Numeric Nutrient Criteria

EPA has defined three categories of approaches

1. Reference condition approach
 - Base numeric nutrient criteria at levels consistent with those observed in relatively pristine (i.e. “reference”) water bodies
2. Stressor-response analysis
 - Empirically derive statistical relationships between in-situ nutrient concentrations and the response variable
3. Process-based (mechanistic) modeling
 - Describe systems using equations representing specific ecological processes, calibrated to site-specific data

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The Most Readily Applied Approaches Can Be Inaccurate

Reference condition approach can be (relatively) easily applied to broad areas, but is potentially very imprecise

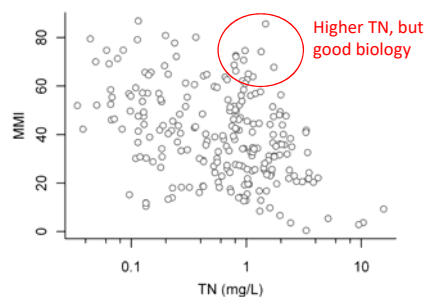
- Doesn't consider the dose-response relationship between nutrients and environmental response
 - Unable to define the threshold where impairment begins
- Doesn't consider potentially important site-specific factors

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The Most Readily Applied Approaches Can Be Inaccurate

Stressor-response analysis considers thresholds, but still not accurate for all sites

- Doesn't consider important site-specific factors



- Correlation does not mean causation

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Simple Approaches Can Result in Expensive Controls

- Existing TMDLs using reference condition-based numeric nutrient criteria have led to some extremely low wasteload allocations to WWTPs for nutrients
 - TP = 0.007 mg/l
 - TN = 0.289 mg/l
- No assessment of site-specific response to nutrient levels conducted

Guidance Is Needed on Rigorous Methods for Nutrient Criteria

- EPA provides guidance for developing nutrient criteria using the reference condition and stressor-response approaches
- Similar guidance is not currently available for the process-based modeling approach
 - Lack of guidance will serve as an impediment for more rigorous approaches being taken

WRF Predecessor Projects on Rigorous Methods for Nutrient Criteria

- LINK1T11
 - Developed a Nutrient Modeling Toolbox/Model Selection Decision Tool to select models for specific sites
- LINK2T14
 - Applied Nutrient Modeling Toolbox to Boulder Creek, CO
- Selection of an appropriate model is not enough, also need sufficient data

Project Overview Project Objectives and Team



Project Objectives

Overarching: Determine how much data is needed to successfully apply a model to set nutrient targets

1. Define relationship between data availability and model utility
2. Assess methods for estimating model uncertainty
3. Provide insight into the regulatory climate regarding consideration of model uncertainty



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Project Team

WRF Issue Area Team	Stakeholder Advisory Panel
<ul style="list-style-type: none"> • Lola Olabode, WRF • Raj Bhattarai, P.E., BCEE, City of Austin, TX • Renee Bourdeau, P.E., Horsley Witten Group • Xueqing Gao, Ph.D., FL Department of Health • Bret Linenfelser, City of Boulder • Steve Peene, Ph.D., ATM • Jim Pletl, Ph.D., HRSD • Paul Stacey, Footprints in the Water, LLC • Thomas Stiles, KDHE • Steve Whitlock, PE, EPA • Matt Wooten, SD No. 1 of Northern Kentucky 	<ul style="list-style-type: none"> • Tom Fikslin, Ph.D. Retired River Basin Commission • Lewis Linker, U.S. EPA Chesapeake Bay Program Office • Mindy Scott, Sanitation District No. 1 of Northern Kentucky • Elizabeth Moore, Montgomery County (OH) Environmental Services
Co-Principal Investigators	Project Manager
<ul style="list-style-type: none"> • David W. Dilks, Ph.D., LimnoTech • Todd M. Redder, PE, LimnoTech • Steven C. Chapra, Ph.D., F. ASCE, Tufts University 	<ul style="list-style-type: none"> • Penelope Moskus, LimnoTech
Project Team	
<ul style="list-style-type: none"> • Victor J. Bierman Jr., Ph.D., BCEEM (Senior Advisor) • Joseph V. DePinto, Ph.D. (Senior Advisor) • Derek Schlea, PE, LimnoTech • Daniel Rucinski, Ph.D., LimnoTech 	<ul style="list-style-type: none"> • Hua Tao, Ph.D., LimnoTech • Scott C. Hinz, LimnoTech • Kyle Flynn, Ph.D., P.E., P.H., KF2 Consulting, PLLC • Nicole Clements, Clements Consulting



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Project Summary Overview of Tasks

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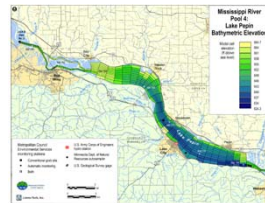
Project Tasks

1. Review existing models applied to set nutrient targets
2. Assess relationship between amount of data and model utility at data-rich case study sites
3. Develop practical methods for assessing model uncertainty
4. Assess requirements for regulatory acceptance

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Review of Existing Model Applications

- Gain insight into how much data was required to support management decisions at other sites
- Develop broad inventory of applications
 - At least five examples from rivers, lakes, and estuaries
 - At least five examples for each key endpoint
 - At least five examples of applications that were, and were not, successful in defining nutrient targets for regulatory purposes



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Inventory of Model Applications

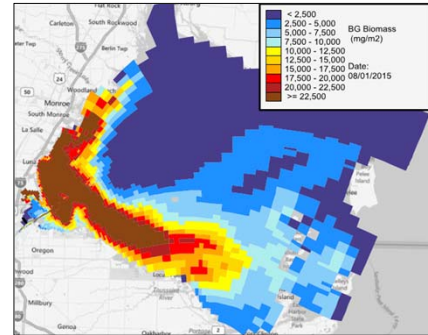
- Gathered 38 nutrient modeling applications
 - Diversity of water bodies within various regions
 - 20 sites with dissolved oxygen, 22 with sestonic chlorophyll, and 7 with attached algae endpoints

Region	U.S. EPA Regions	Estuary	Lake/Impoundment	River
North Central (MT, WY, UT, CO, ND, SD, NE, KS, IA, MO, MN, WI, IL, IN, MI, OH)	5, 7, 8	--	9	4
Northeast (ME, NH, VT, MA, RI, CT, NY, NJ, PA, WV, VA, DE, MD, DC)	1, 2, 3	--	1	3
Northwest (AK, ID, OR, WA)	10	1	2	4
South Central (NM, TX, OK, AR, LA)	6	--	1	--
Southeast (KY, TN, MS, AL, GA, FL, NC, SC)	4	8	7	1
Southwest (AZ, CA, HI, NV)	9	1	1	2
Total		10	21	14

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Review of Existing Model Applications

- Characterized each of the model applications regarding the following features:
 - Data availability
 - Model calibration evaluation
 - Uncertainty assessment
 - Regulatory/management outcome
- Fifteen individual assessments made
 - Ranked on a 1-5 scale



Review of Model Applications

Evaluation Criteria for Data Availability: Model Calibration Data

	High Degree of Rigor: State of the Science		Moderate Rigor		Low Degree of Rigor: Default Values
	5	4	3	2	1
Spatial	Captures all of the important spatial variability; required spatial resolution of data explicitly assessed; data available at desired resolution.	Captures most of the important spatial variability; required spatial resolution of data given consideration; data available at desired resolution.	Captures some of the important spatial variability; spatial variability of data included, with cursory consideration of necessary extent.	Some spatial variability included, but no consideration of necessary extent.	No spatial variability included; necessary extent not considered.
Temporal Resolution	Captures all of the important temporal variability; required temporal resolution explicitly assessed; data available at desired resolution.	Captures most of the important temporal variability; required temporal resolution assumed; data available at desired resolution.	Captures some of the important spatial variability; temporal variability of data included, with less than complete coverage.	Some temporal variability exists, many gaps present.	No temporal variability included; necessary extent not considered.
Temporal Extent	Greater than five years (or steady state periods) of data.	Three to five years (or steady state periods) of data.	Two years (or steady state periods) of data.	One year (or steady state period) or less of data.	No calibration data available.
Parameters	Data available for all state variables, except for those demonstrated to be unimportant.	Data available for all state variables, except for those presumed to be unimportant.	Data available for many state variables, some potentially important parameters absent.	Missing most state variables.	No calibration data available.



Comparison of Successful vs. Unsuccessful Applications

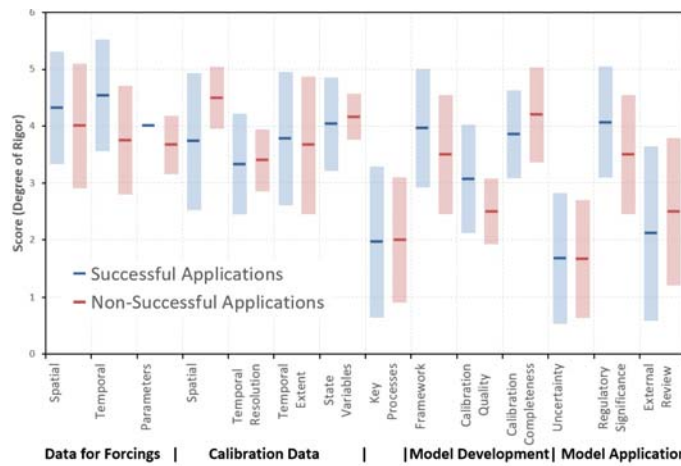
- **Question:** For which parameters did more rigorous data and/or approach lead to an accepted model?
- **Approach:** Statistically compared “rigor” scores between ‘successful’ and ‘unsuccessful’ applications



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Successful vs. Unsuccessful Applications

- No significant difference between successful and unsuccessful applications were found for any of the parameters

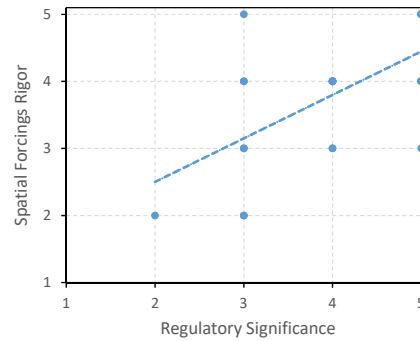


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Regulatory Significance Is Important

- Positive correlation found between degree of rigor and regulatory significance for every factor evaluated.

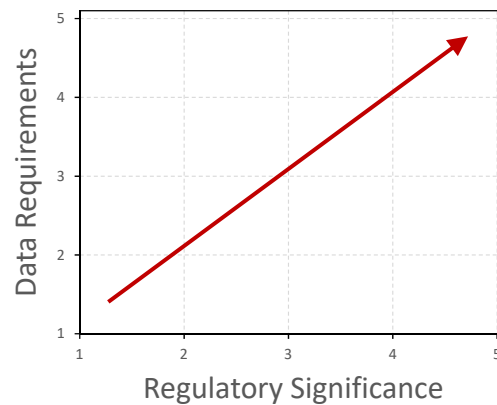
Example
Result:



- Graded approach to model application

Finding: Review of Existing Models

- The amount of data required for a model application depends upon the regulatory significance of the application



Assessment of Relationship between Amount of Data and Model Utility

- Evaluate model robustness by characterizing the uncertainty that results from different levels of data availability
 - Examined through Jackknife Assessment
- Conducted for two data-rich case study sites
 - Truckee River, NV
 - Western Basin of Lake Erie

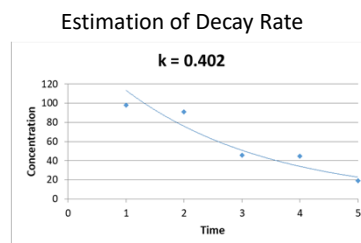


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Jackknife Example

- Conduct calibration multiple times, excluding a portion of the data set each time
- Simple first-order decay example: $C = C_0 e^{-kt}$

Data	
Time	Conc.
1	97.9
2	90.9
3	45.5
4	44.6
5	18.7



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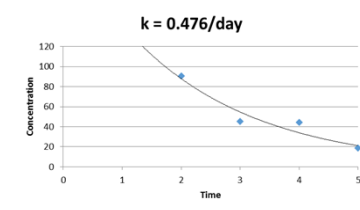
Jackknife Example

- Exclude first data point, estimate decay rate

Data

Time	Conc.
1	97.9
2	90.9
3	45.5
4	44.6
5	18.7

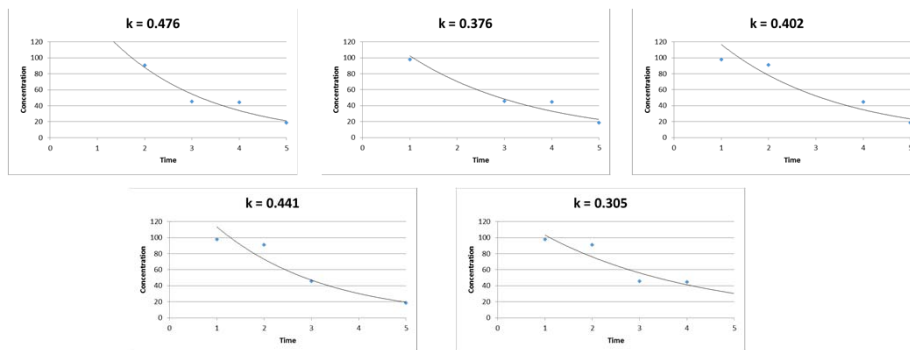
Estimation of Decay Rate



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Jackknife Example

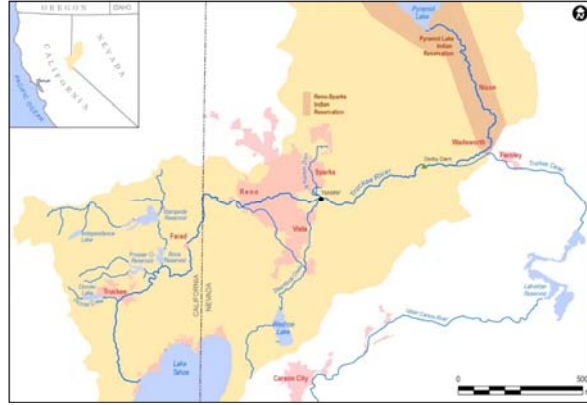
- Repeat by excluding additional data points
- Compile all results to assess uncertainty in parameter(s)



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Jackknife Case Study Sites

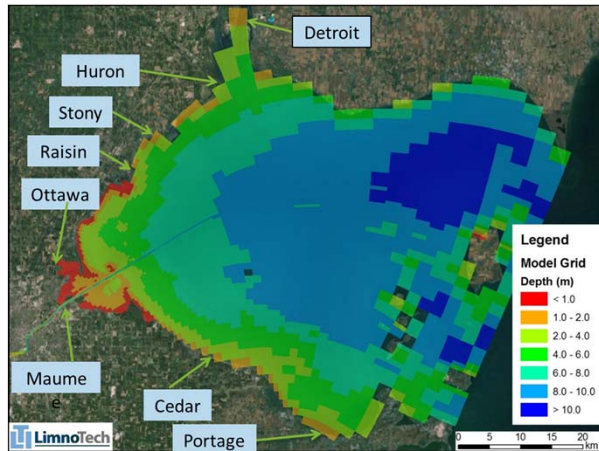
- Truckee R., NV
 - HSPF model developed to assess revision to existing WQS for nitrogen
 - Endpoints of concern were dissolved oxygen, periphyton density



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Jackknife Case Study Sites

- Western Basin of Lake Erie
 - A2EM model developed to assess control of harmful algal blooms
 - Endpoints of concern were harmful algal blooms, chlorophyll *a*



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Combinations Considered during Jackknife Analysis

- 74 combinations of years evaluated for Truckee
 - 6 combinations of five years (leave one out)
 - 15 combinations of four years (leave two out)
 - 20 combinations of three years (leave three out)
 - 15 combinations of two years (leave four out)
 - 6 combinations of one year (leave five out)
 - 12 combinations of half years
- 40 combinations of years evaluated for Lake Erie
 - 5 combinations of four years (leaving one year out)
 - 10 combinations of three years (leave two out)
 - 10 combinations of two years (leave three out)
 - 5 combinations of one year (leave four out)
 - 10 combinations of half years



Processing Jackknife Results

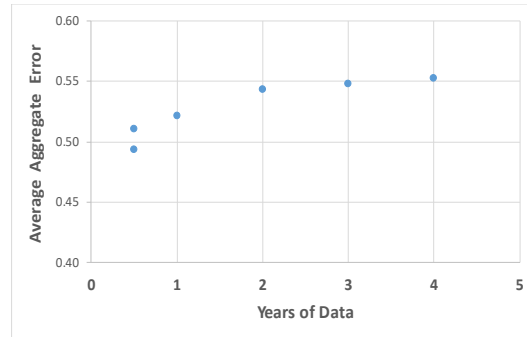
- Evaluated model prediction error for different parameter combinations and different years
 - Maximum benthic algal growth rate
 - Benthic algal respiration rate
 - Reaeration rate escape coefficient

		2000 mean absolute error				2001 mean absolute error				2002 mean absolute error				2003 mean absolute error				
		Max Growth (/hr)				Max Growth (/hr)				Max Growth (/hr)				Max Growth (/hr)				
		Reaer (/hr)	0.09	0.12	0.15	0.09	0.12	0.15	0.09	0.12	0.15	0.09	0.12	0.15	0.09	0.12	0.15	
Reaeration	/ft	0.02175	0.004125	0.6143	0.2954	0.1386	0.004125	0.6143	0.2954	0.1386	0.004125	0.6143	0.2954	0.1386	0.004125	0.6143	0.2954	0.1386
		0.006875	0.6200	0.5955	0.6249	0.8323	0.7200	0.7791	0.8323	0.7200	0.7791	0.8323	0.7200	0.7791	0.8323	0.7200	0.7791	0.8323
		0.004125	0.6235	0.5938	0.5838	0.8451	0.7555	0.8086	0.8451	0.7555	0.8086	0.8451	0.7555	0.8086	0.8451	0.7555	0.8086	0.8451
		0.029	0.0005	0.6285	0.5894	0.5838	0.8375	0.7350	0.7729	0.8375	0.7350	0.7729	0.8412	0.7940	0.8028	0.8221	0.7742	0.7762
0.00425	0.004125	0.6475	0.6015	0.5839	0.8278	0.7146	0.7957	0.8278	0.7146	0.7957	0.8256	0.8142	0.8151	0.8359	0.7911	0.7778	0.8359	
	0.006875	0.6418	0.5984	0.5776	0.8661	0.7563	0.7500	0.8661	0.7563	0.7500	0.8615	0.7996	0.7890	0.8359	0.7884	0.7763	0.8359	
	0.006875	0.6449	0.6039	0.5801	0.8852	0.7973	0.7312	0.8852	0.7973	0.7312	0.8741	0.7911	0.7796	0.8606	0.7911	0.7760	0.8606	
	0.006875	0.6449	0.6039	0.5801	0.8852	0.7973	0.7312	0.8852	0.7973	0.7312	0.8741	0.7911	0.7796	0.8606	0.7911	0.7760	0.8606	
		2004 mean absolute error				2005 mean absolute error												
		Max Growth (/hr)				Max Growth (/hr)												
		Reaer (/hr)	0.09	0.12	0.15	0.09	0.12	0.15	0.09	0.12	0.15							
Reaeration	/ft	0.02175	0.004125	0.7126	0.6995	0.7784	0.004125	0.7126	0.6995	0.7784	0.004125	0.7126	0.6995	0.7784				
		0.006875	0.7232	0.6841	0.7395	0.7390	0.7371	0.7890	0.7390	0.7371	0.7890							
		0.004125	0.7363	0.6970	0.7421	0.7286	0.7369	0.7811	0.7286	0.7369	0.7811							
		0.029	0.0005	0.7482	0.6910	0.7331	0.7487	0.7194	0.7251	0.7487	0.7194	0.7251						
0.00425	0.004125	0.7687	0.6892	0.7239	0.7383	0.7124	0.7230	0.7383	0.7124	0.7230								
	0.006875	0.7627	0.7125	0.7298	0.7650	0.7210	0.7305	0.7650	0.7210	0.7305								
	0.006875	0.7737	0.7080	0.7177	0.7666	0.7148	0.7099	0.7666	0.7148	0.7099								
	0.006875	0.7692	0.7106	0.7203	0.7531	0.7137	0.7041	0.7531	0.7137	0.7041								



Jackknife Findings

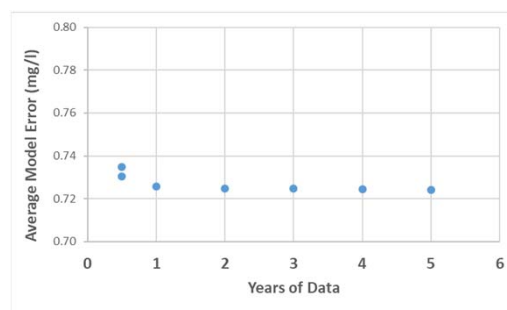
- “Apparent accuracy”* of model decreases with additional data



*How well model describes *available* data

Jackknife Findings

- “Actual model error”* decreases with additional data



*How well model describes *all* data

Findings: Case Study Evaluations

- Traditional metrics for model performance do better with less data
- Rigorous assessment of model performance indicates more years of data result in lower error

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Practical Methods for Assessing Model Uncertainty

- The inability to quantify model uncertainty was identified as limitation of the models in the Nutrient Management Toolbox
- Reviewed applicability of seven methods via testing on real world model applications



Methods That Don't Consider Observed Data

- Sensitivity analysis
- First order variance analysis

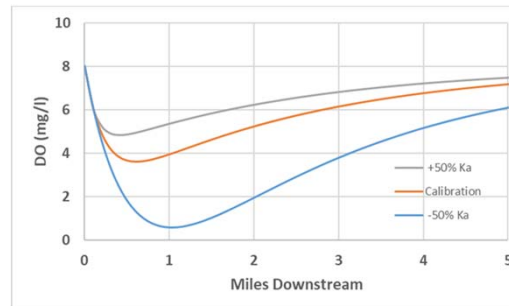
Methods That Do Consider Observed Data

- Generalized sensitivity analysis
- One parameter at a time Bayesian
- Markov Chain Monte Carlo
- Full Bayesian approaches
- Bounding calibration

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Simpler Model Uncertainty Analyses

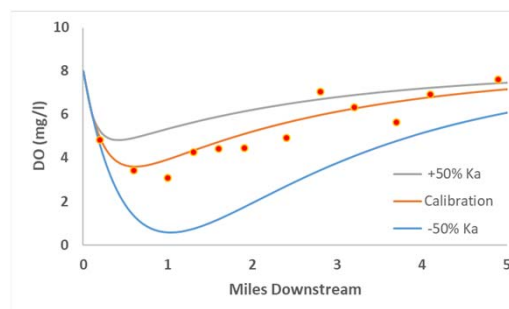
- Sensitivity analysis, first-order error analysis
 - Pre-specify uncertainty in input parameters
 - Simulate range of model response corresponding to given range in inputs



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Simpler Model Uncertainty Analyses

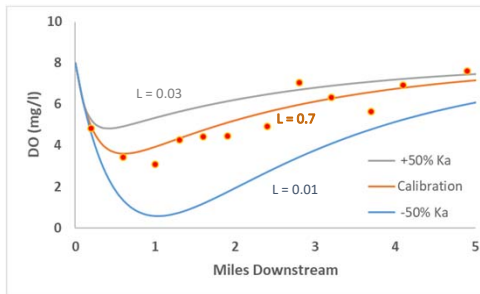
- Do not consider the ability of specified input uncertainty to describe observed data
- Can give credence to model results that are inconsistent with real world



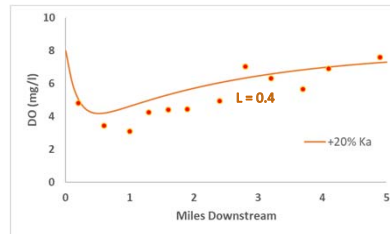
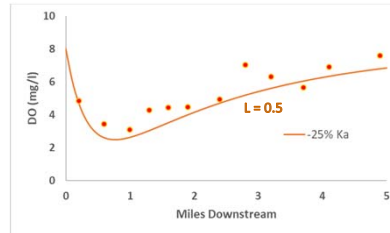
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Bayesian Approaches

- Consider the ability of given parameter values to describe observed data



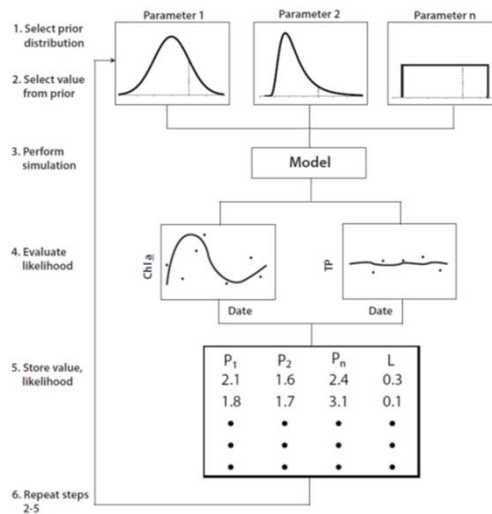
– Quantify goodness of fit with a likelihood function, L



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Bayesian Approaches

- Can also consider prior knowledge of parameter uncertainty
 - Sample priors using Monte Carlo (or Latin Hypercube)



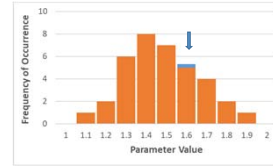
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Bayesian Approaches

- Resulting matrix can be used to:
 - Assess marginal probability distributions

- Construct histograms using likelihood to weight values

P ₁	P ₂	P _n	L
2.1	1.6	2.4	0.3
1.8	1.7	3.1	0.1
•	•	•	•
•	•	•	•
•	•	•	•



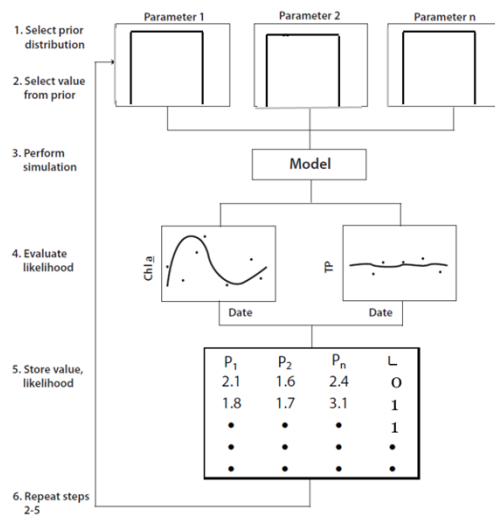
- Examine uncertainty in model predictions
 - Run simulation for each parameter set, weight results by likelihood



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Generalized Sensitivity Analysis

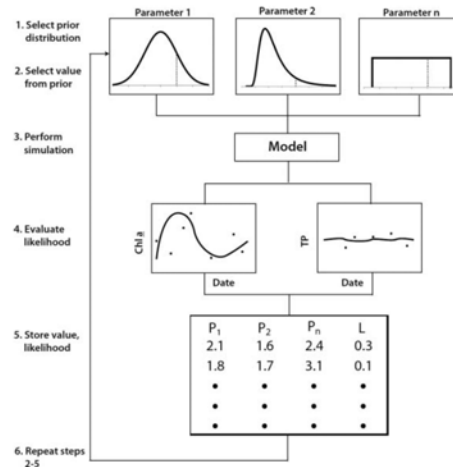
- Similar to Bayesian approach, but
 - Doesn't presume shape of prior distributions
 - Assesses whether each individual simulation "does" or "does not" adequately describe the data



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Bayesian Model Uncertainty Analyses

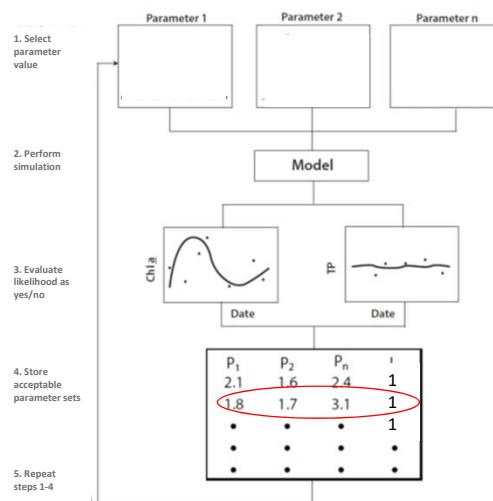
- Can have excessive computational requirements
 - Consideration of ten different values for each of 100 parameters would require 10^{100} (i.e., one Googol) simulations



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Worst Case Bounding Calibration

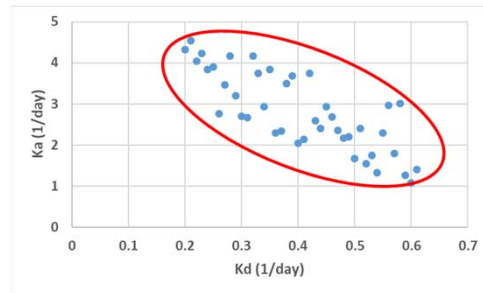
- Similar to generalized sensitivity analysis
 - Use judgment to find acceptable parameter sets
- Conduct scenario analysis using parameter set that generates “worst-case” results



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Markov Chain Monte Carlo

- Bayesian approach with more intelligent parameter selection
 - Use information gained from prior simulations to select values for next simulation
 - Focuses parameter selection on values more likely to adequately describe observed data



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Real World Uncertainty Application

- Applied range of techniques to existing model applications to assess feasibility
 - Truckee R.
 - Worst case bounding calibration, generalized sensitivity analysis
 - Lake Erie
 - Worst case bounding calibration, generalized sensitivity analysis
 - Yellowstone R.
 - One-at-a-time Bayesian, generalized sensitivity analysis, worst case bounding calibration
 - Fountain Lake
 - Markov Chain Monte Carlo

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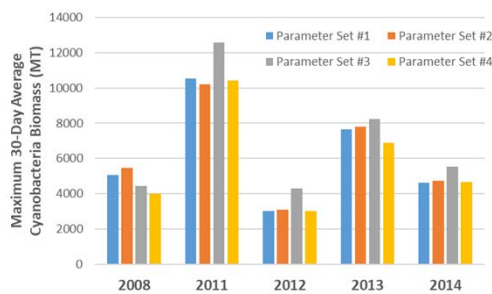
Lake Erie Uncertainty Results

- Conducted 420 calibration runs to define eight acceptable parameter sets

Growth Rate	Half Saturation	Organic Settling Rate	Blue Green Optimal Growth Temperature
+25%	+50%	Calibration	Calibration
+25%	+50%	+50%	Calibration
+25%	Calibration	-50%	Calibration
+25%	+50%	-50%	Calibration
Calibration	+50%	-50%	+20%
+25%	+50%	-50%	+20%
+25%	Calibration	-50%	+20%
+25%	+50%	Calibration	+20%

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Lake Erie Uncertainty Results



- Findings
 - No single parameter set represents “worst case” for all conditions
 - Computational time is a concern

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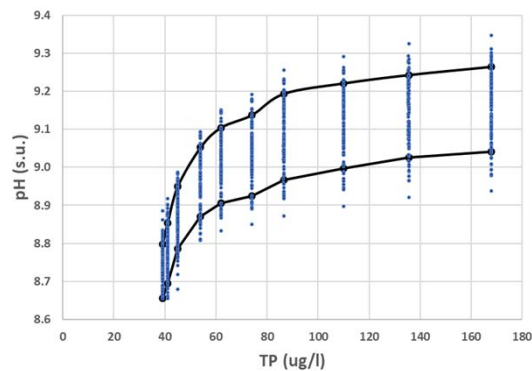
Yellowstone R. Bounding Calibration/ Generalized Sensitivity Analysis

- 177 different parameter sets were identified that resulted in an “acceptable” calibration
- Numeric nutrient criterion scenario runs conducted to evaluate instream pH in response to ten different hypothetical TP concentrations

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Yellowstone R. Bounding Calibration/ Generalized Sensitivity Analysis

- 177 results per concentration allows frequency distributions to be assessed



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Yellowstone R. Findings

- Models with fast execution times are amenable to more rigorous application of uncertainty techniques
 - Generalized sensitivity analysis with more parameters considered or one-at-a-time Bayesian
 - Better suited to evaluate Type I and Type II error

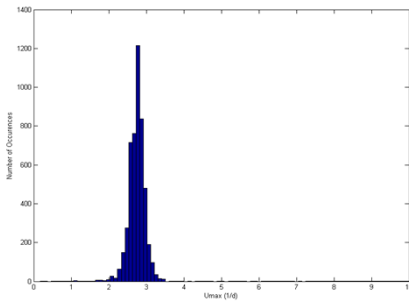
Fountain Lake Phytoplankton Model

- Dynamic spreadsheet model developed to assess management options for controlling algae in a lake receiving wastewater discharge
- Applied Markov Chain Monte Carlo (MCMC)
 - Shuffled Complex Evolution Metropolis algorithm was implemented in MATLAB
 - Tested resources required for different amounts of uncertain parameters

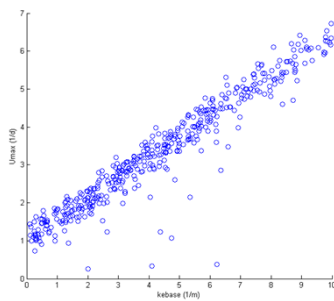
Fountain Lake MCMC

- Time to convergence depends upon number of parameters treated as uncertain

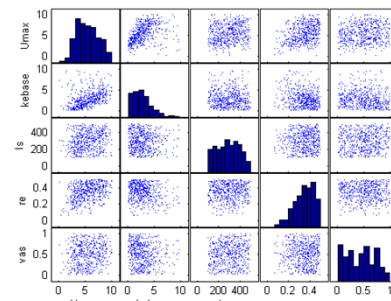
One parameter: 100 iterations



Two parameters: 400 iterations



Five parameters: 5000 iterations



- Feasibly applied to only to simpler models



Review of Uncertainty Analysis Methods

	Advantages	Disadvantages	Summary
Sensitivity Analysis	<ul style="list-style-type: none"> • Simple to apply. • Should be conducted as part of standard modeling practice. 	<ul style="list-style-type: none"> • Does not provide useful information on model uncertainty. 	Insufficient to serve as a stand-alone method for uncertainty assessment, but useful for identifying important parameters.
First Order Variance Analysis	<ul style="list-style-type: none"> • Manageable computational requirements. • Considers combined effect of multiple uncertain parameters. 	<ul style="list-style-type: none"> • Requires prior knowledge of parameter uncertainty. • Assumes linear response between parameter change and model results. 	Potentially suitable if parameter uncertainty is well characterized and model response to uncertainty is linear.
One Parameter at a Time Bayesian	<ul style="list-style-type: none"> • Considers ability of uncertain parameter values to describe observed data. 	<ul style="list-style-type: none"> • Excessive computational requirements for models with long execution times. • Does not consider correlation structure between acceptable input values. 	Potentially suitable for models with shorter execution times.
Bounding Calibration	<ul style="list-style-type: none"> • Considers ability of uncertain parameter values to describe observed data, including correlation structure. • Lower computational requirements. 	<ul style="list-style-type: none"> • "Worst case" parameter set can be difficult to define, and may not exist. • Provides no assessment of Type II errors. 	Potentially suitable for models where worst case parameter set exists and can be readily identified.
Generalized Sensitivity Analysis	<ul style="list-style-type: none"> • Considers ability of uncertain parameter values to describe observed data, including correlation structure. 	<ul style="list-style-type: none"> • Impractical to identify all acceptable parameter combinations. • Decision as to what represents an "acceptable" calibration introduces some subjectivity. 	Suitable if limited to assessment of most important parameters.
Full Bayesian Approaches	<ul style="list-style-type: none"> • Considers ability of uncertain parameter values to describe observed data, including correlation structure. 	<ul style="list-style-type: none"> • Impractical to sample entire range of parameter combinations 	Potentially suitable for models with limited number of parameters and/or shorter execution times.
Markov Chain Monte Carlo	<ul style="list-style-type: none"> • Considers ability of uncertain parameter values to describe observed data. • More efficient than standard Bayesian approaches. 	<ul style="list-style-type: none"> • Requires computer coding to implement. • Impractical computational times for complex models. 	Best suited for research applications, or models with very short execution times.



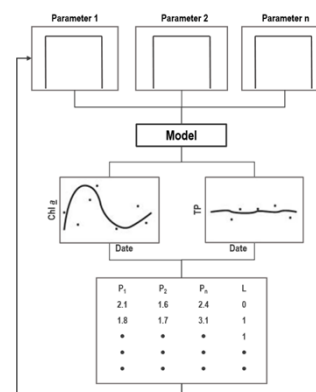
Model Uncertainty Finding #3

- Computationally tractable approaches (sensitivity analysis, first order variance analysis) provide limited information
- Approaches that consider ability of parameter values to describe observed data are computationally impractical for highly parameterized models
- “Worst-case” parameter set varies with environmental conditions

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“Practical” Uncertainty Analysis

- Builds off of typical modeling best practices
 1. Conduct model sensitivity analysis
 2. Define “acceptable” model calibration
 3. Maintain a model run log during calibration process
 4. Supplement acceptable parameter sets as practical
 5. Conduct scenario evaluations using all acceptable parameter sets



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Requirements for Regulatory Acceptance

- “How good does a model need to be (or how much data is required) for it to be accepted?”
- Addressed in two ways
 - Interviewed regulatory staff from six States
 - Reviewed common factors for “accepted” model applications in model inventory

Findings on Regulatory Acceptance

- Formal protocols for assessing the quality of modeling are not applied on a widespread basis
 - Steps are being made
- Confounding factors
 - Variation in data requirements across endpoints and water body types
 - Difficulties in quantifying model uncertainty
 - Lack of protocols for incorporating uncertainty in decision making
- Presence of external review panel facilitates model acceptance

Regulatory Acceptance Recommendations (Pt. 1)

- Consider inclusion of peer review input at project outset for potentially contentious situations
- Apply model prior to data collection to assess spatial and temporal requirements

Regulatory Acceptance Recommendations (Pt. 2)

- Include consideration of uncertainty during decision-making to assess likelihood of requiring nutrient targets that are:
 - too lenient to protect the designated use
 - more stringent than necessary to protect the designated use

Monitoring Recommendations

- Although “one size doesn’t fit all”, monitoring recommendations are provided for different water body types

Category	Data Requirements
Model Forcing Functions	Monitoring station(s) at upstream boundary (or boundaries, for a branched system).
Spatial Coverage	Monitoring station at each tributary or point source that the scoping model indicates will change instream concentration of any state variable of concern by more than a predetermined amount (e.g. 1%). If economically feasible, samples above and below the mixing zone of major inputs should be collected. Sufficient to capture any important temporal variability in forcing functions:
Temporal Frequency	<ul style="list-style-type: none"> • If dissolved oxygen is an endpoint of concern, continuous dissolved oxygen and temperature at all boundaries where the diel signal from the source propagates throughout the model. • Three to four sampling periods per independent survey event for other forcing functions, unless observed variability dictates more frequent sampling.
Temporal Extent	Duration of sampling should be longer than time of travel from upstream to downstream boundary.
Sampling Parameters	Loads of all nutrient forms and organic carbon represented as state variables in the selected model framework.
Ambient Calibration Data	Dissolved oxygen, temperature, flow, suspended solids, conductivity.
Spatial Coverage	Stations located with sufficient resolution to capture any significant (e.g. >10% change) gradient in important state variables as predicted by the scoping model. Stations located no more than 0.5 days travel time apart in absence of spatial gradients. Additional stations located corresponding to any significant resource areas of concern. Sufficient to capture any important temporal variability in forcing functions:
Temporal Frequency	<ul style="list-style-type: none"> • Continuous dissolved oxygen and pH, if these are endpoints of concern. • Three to four sampling periods per independent survey event for other calibration parameters, unless observed variability dictates more frequent sampling.
Sampling Parameters	Concentrations of all state variables considered by the model.
Number of Events	Minimum of two independent survey events representative of critical (or near critical) environmental conditions.
Key Processes	Sediment oxygen demand, if dissolved oxygen is an endpoint of concern.

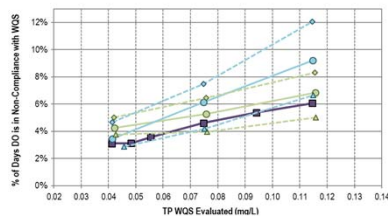


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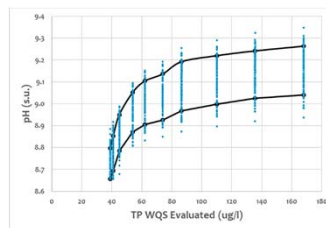
Consideration of Uncertainty

- Use uncertainty analysis results to examine the risks associated with requiring nutrient targets that are:
 - too lenient to protect the designated use
 - more stringent than necessary to protect the designated use
- Depending on uncertainty method used, can either examine:

Range of results



Probability of each type of error



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Summary of Key Findings

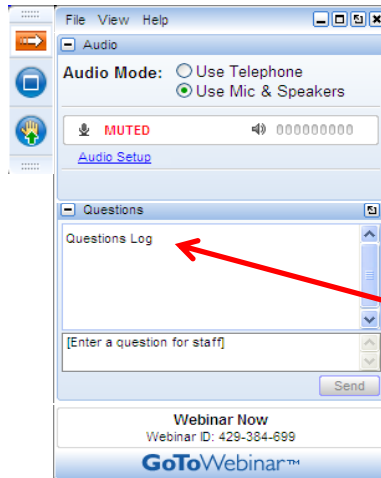
- More data does not translate into improved model performance*
- Quantity of data necessary to support a model varies widely
- Methods to accurately define uncertainty are not easily applied
- Regulatory requirements for amount of data/model performance are not clearly defined

*For most commonly used calibration metrics

Project Benefits

- Guidelines developed summarizing data requirements to support models for different endpoints and water body types
- Practical method proposed for conducting uncertainty analysis on complex models
- Guidance developed on maximizing likelihood of model acceptance

Questions for Our Speakers?



- **Submit your questions using the Questions Pane.**

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Thank you!

For additional information, contact:
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lolabode@waterrf.org

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