JOHN CAMPBELL

Quantifying Uncertainty in Ecosystem Studies

LTER All Scientists Meeting
Estes Park, Colorado
Sept. 10-13, 2012

Agenda

Introductions (what's your biggest source of uncertainty?)

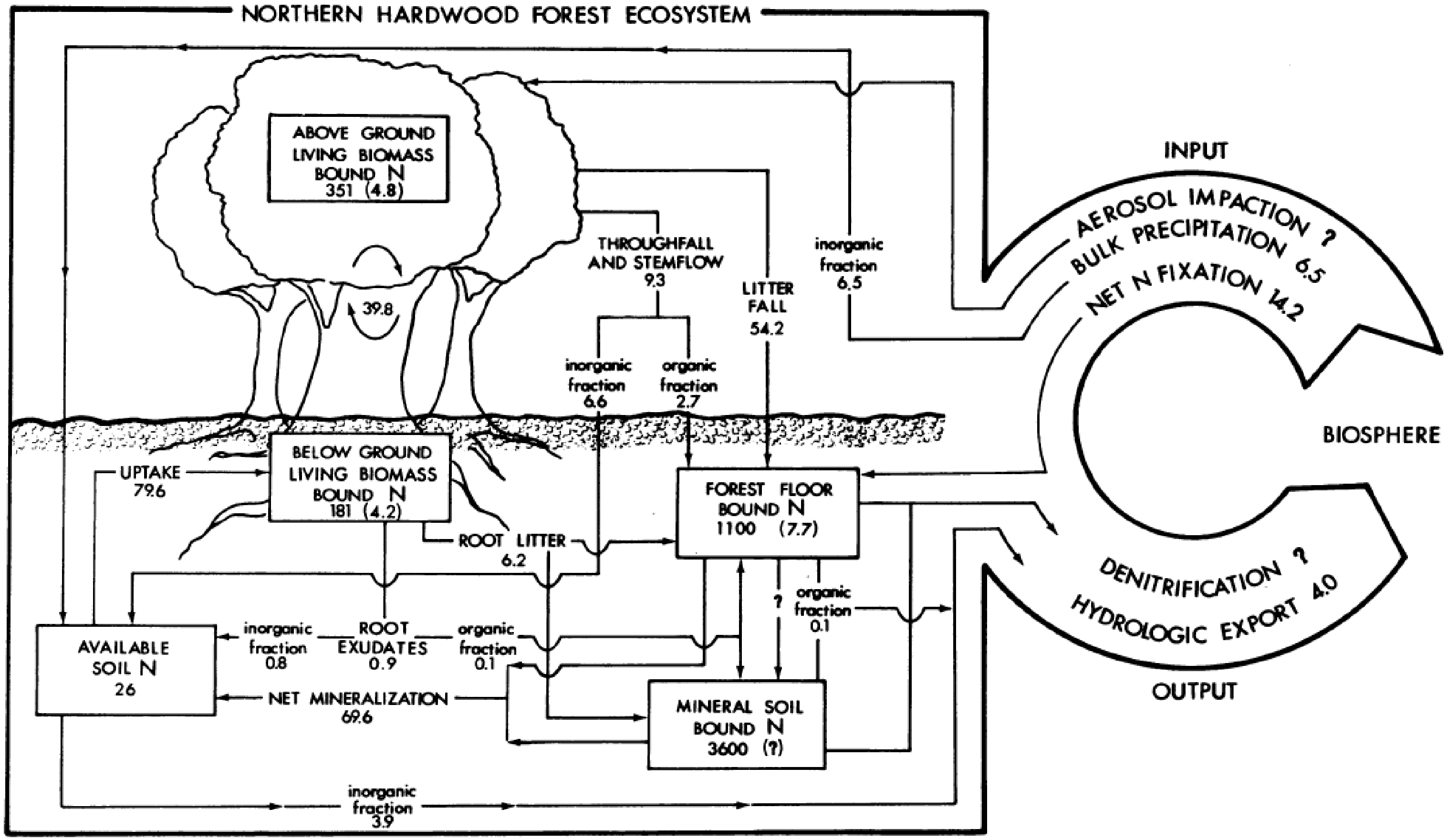
5 minute presentations (5 minutes questions/discussion)

- Mark Harmon: Introduction to sources of uncertainty
- Adam Skibbe: Precipitation interpolation
- Xuesong Zhang: Precipitation
- John Battles: Biomass
- Mark Green: Streams
- Ruth Yanai: Soils
- Jeff Taylor: NEON

Overarching topics: Introduction followed by group discussion

- Craig See: Gaps
- Carrie Rose Levine: Monitoring

A plea for your involvement



Bormann et al. 1977. Science.

What is QUEST?

QUEST is a research network interested in improving understanding and facilitating use of uncertainty analyses in ecosystem research

- **Funding through LNO, NSF**
- **Working group meetings (Boston, Oregon, New York, NH)**
- **Held educational workshops (e.g., ESA)**
- **Several publications**

www.quantifyinguncertainty.org
quantifyinguncertainty@gmail.com

Introduction

- Name
- Affiliation
- Site
- What’s your biggest source of uncertainty?

Discussion Questions

Overarching topics: Intro followed by group discussion

Craig See: Gaps
Carrie Rose Levine: Monitoring

Should we use consistent approaches to estimating uncertainty for every observation?

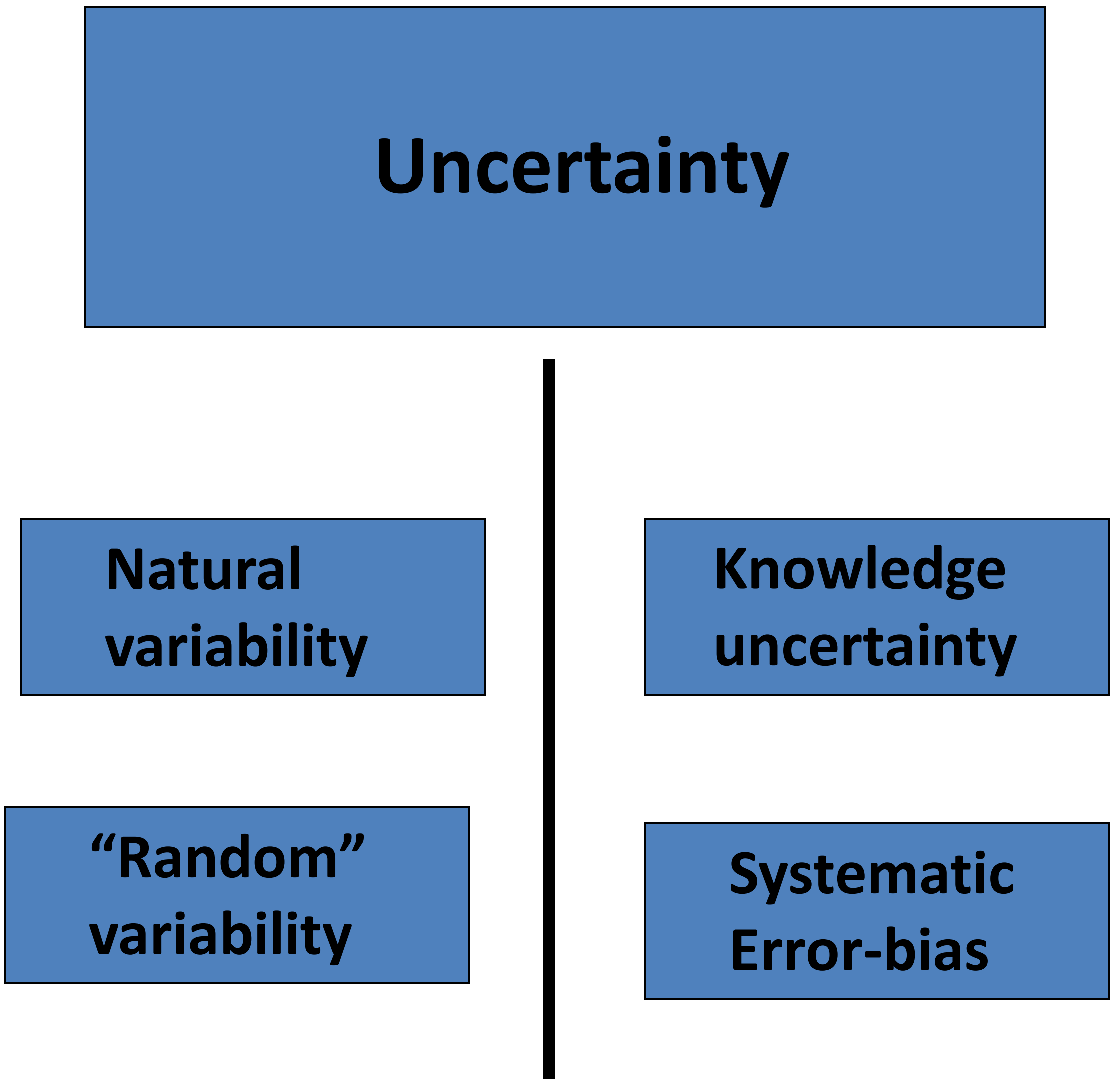
How does one derive an optimal sampling strategy for minimizing uncertainty?

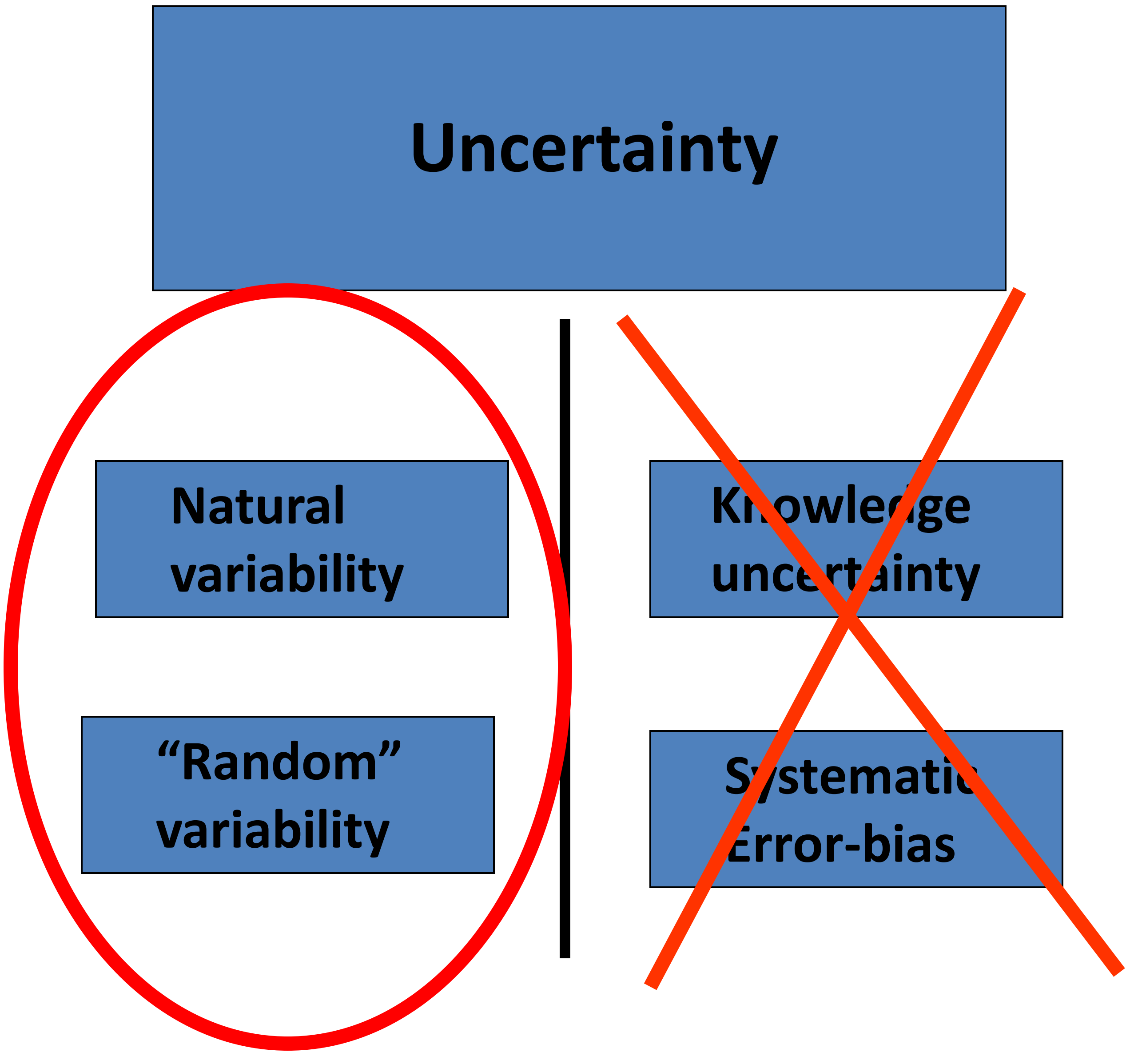
Is it always possible to estimate uncertainty?

MARK HARMON

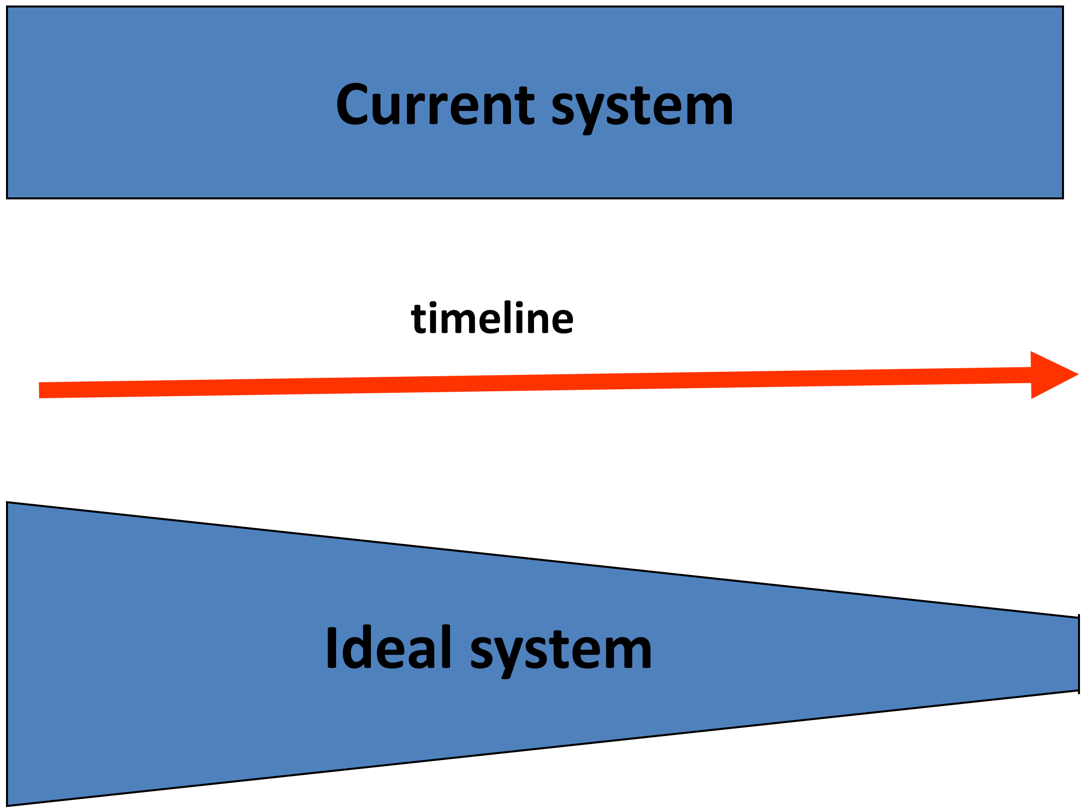
Sources of Uncertainty

- **Measurement error-**technique and technology
- **Sampling error-**natural variability in space and time
- **Regression/conversion (parameter) error-** models used to convert one set of numbers to another
- **Model selection error (structural error)-**uncertainty of knowledge/representation


Uncertainty
Natural variability
"Random" variability
Knowledge uncertainty
Systematic Error-bias

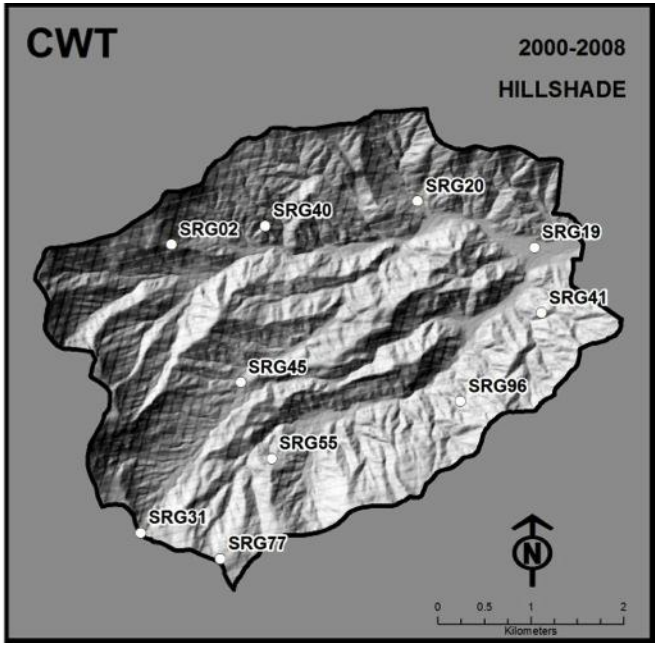

Uncertainty
Natural variability
"Random" variability
Knowledge uncertainty
Systematic Error-bias

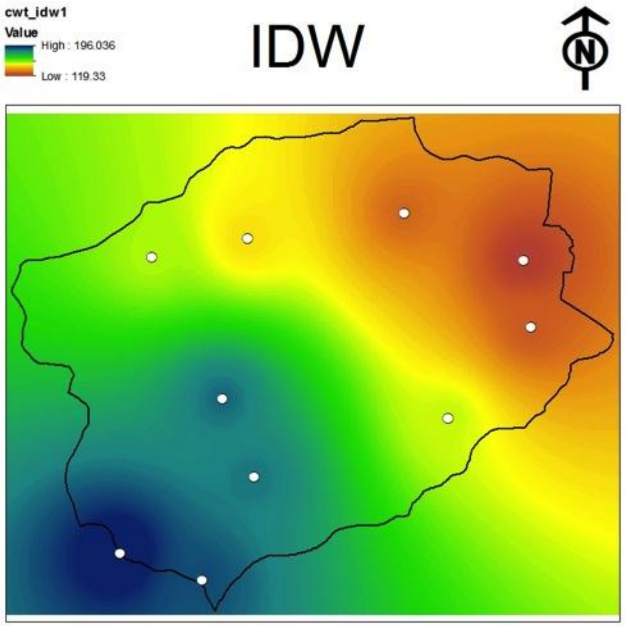
Judging progress objectively

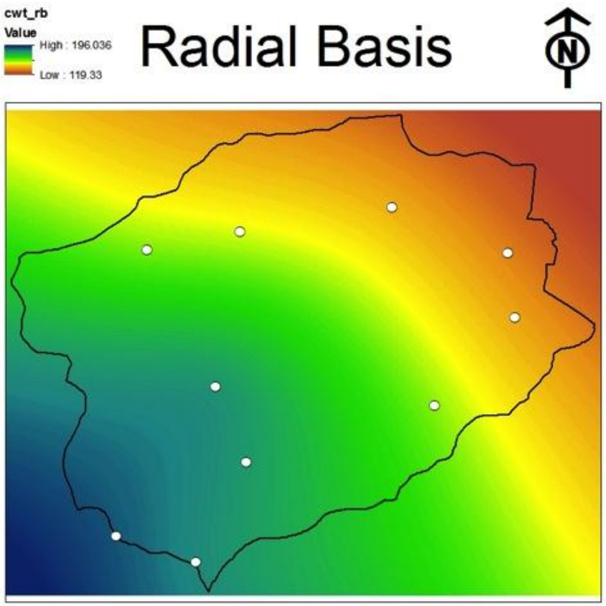


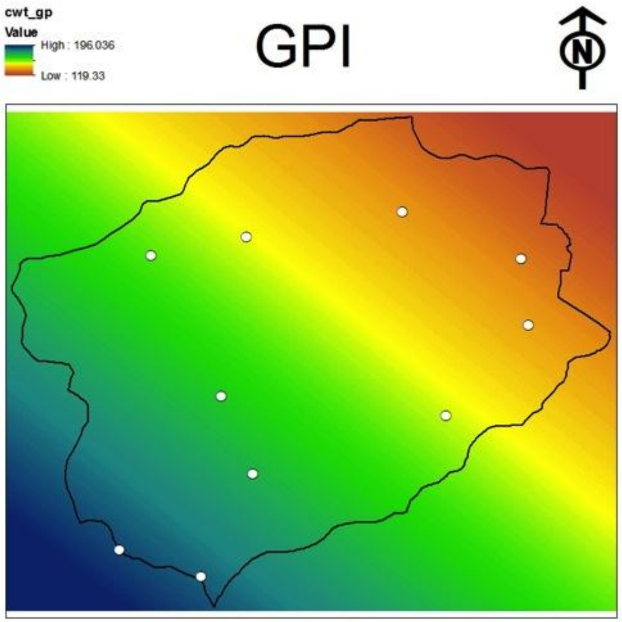
ADAM SKIBBE

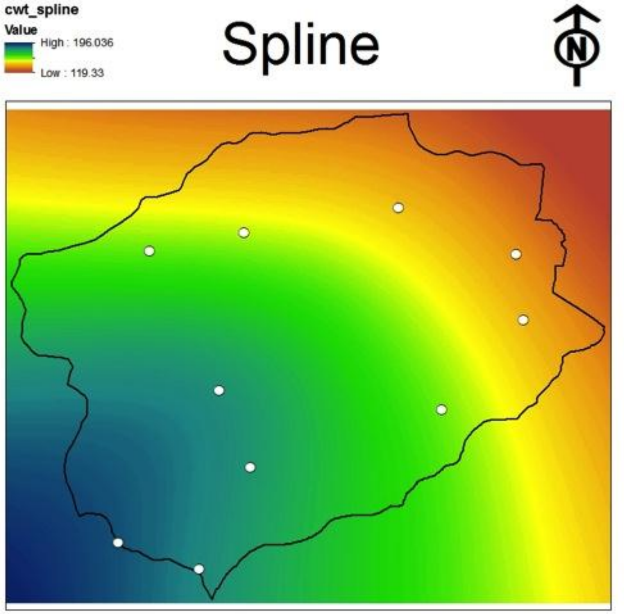
CWT Precip Models











Model Comparisons

Spline	Kernel
High 190	High 182
Low 111	Low 134

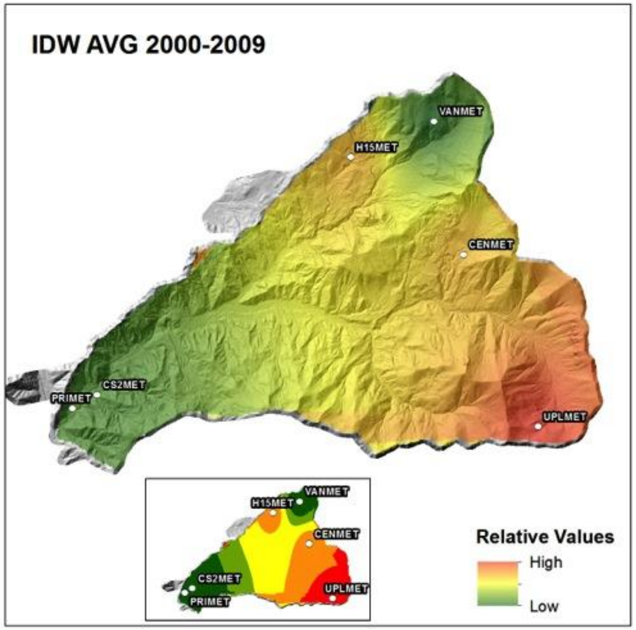
Radial Basis	IDW
High 192	High 183
Low 114	Low 135

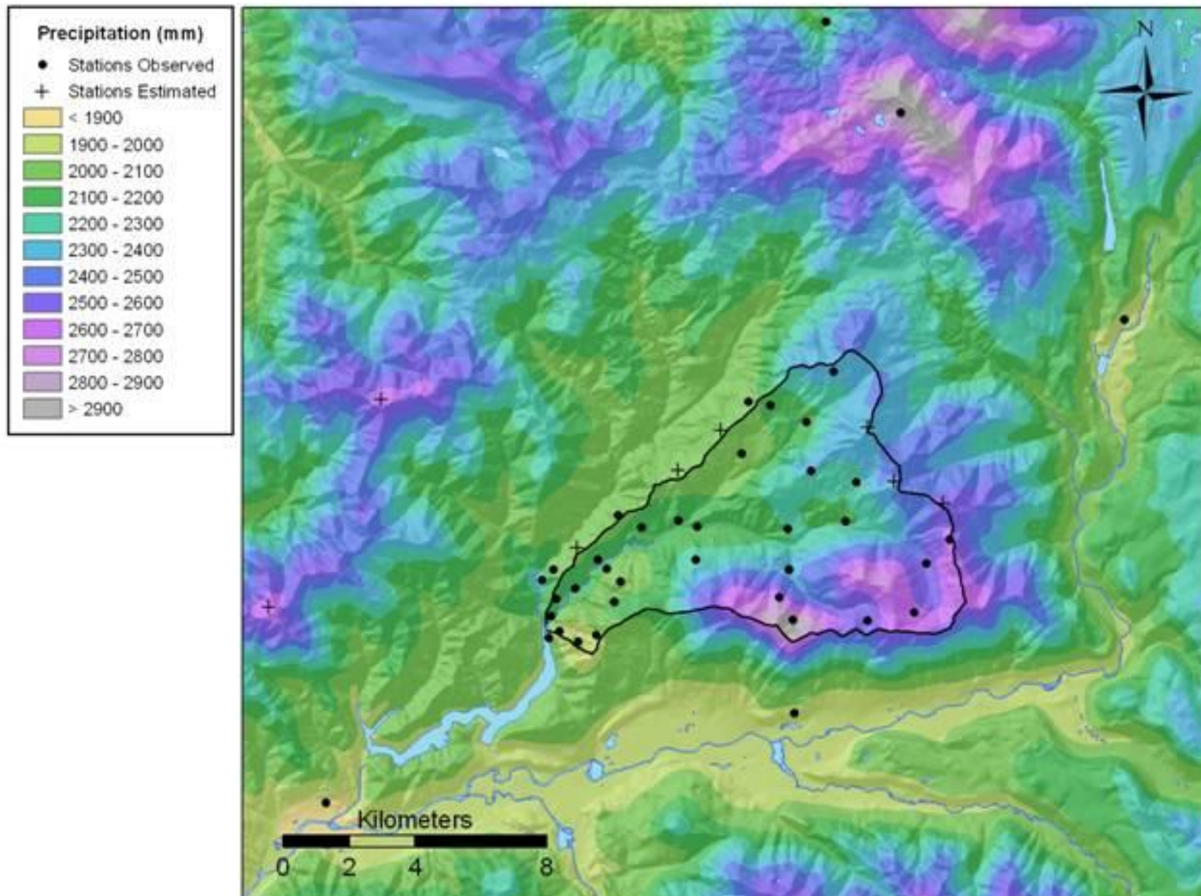
Kriging	Global Polynomial
High 183	High 196
Low 135	Low 119

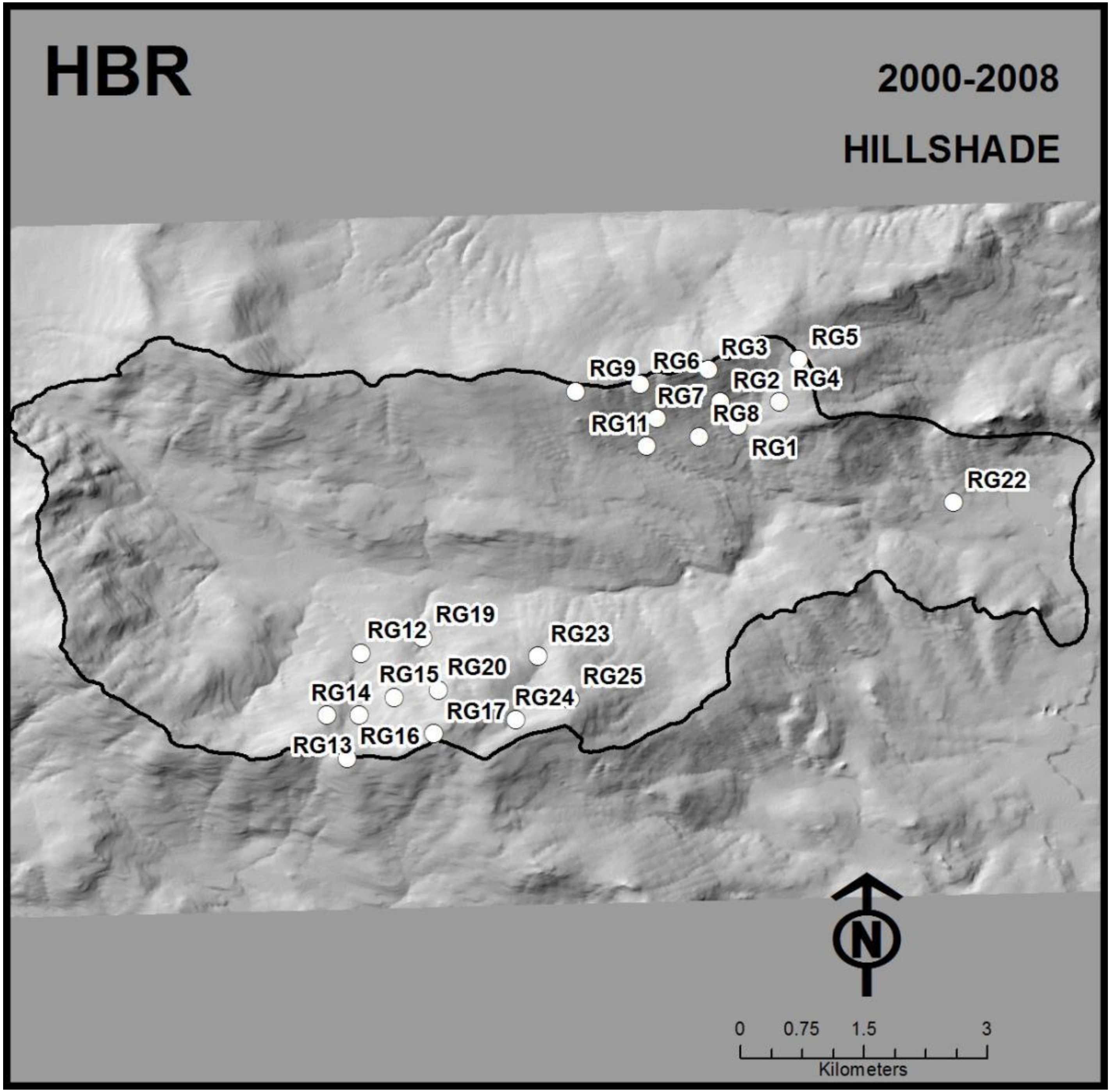
IDW Comparisons

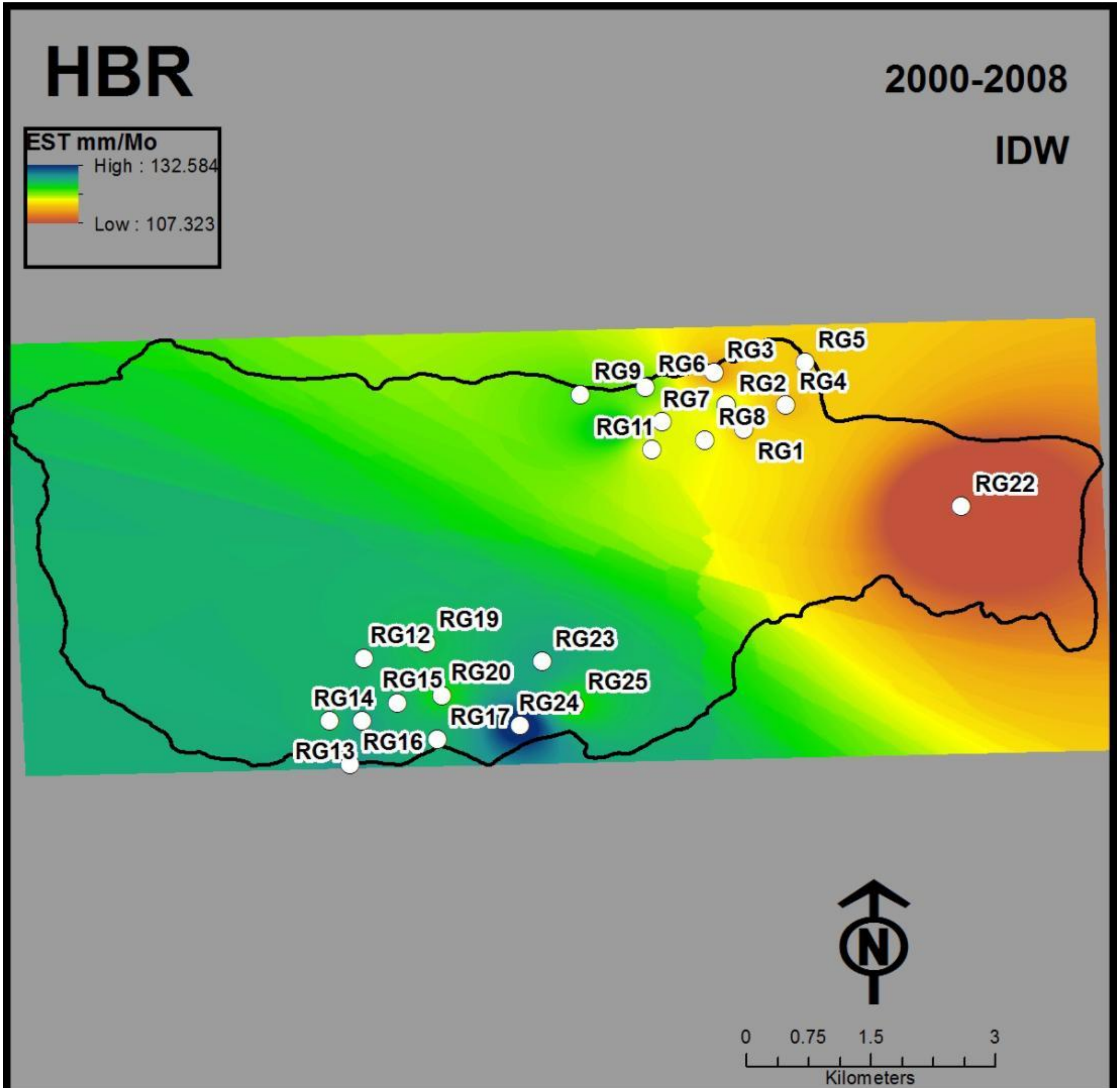
	Area (ha)	ElevMin	ElevMax	ElevRange	ElevMean		PrecipSites	Min	Max	Range	MeanMonthly	MeanAnnual
AND	6369	412.04	1626.92	1214.88	972.9938		6	166.703	209.6488	42.9458	178.3679	2140.4148
CWT	1626	674	1594	920	992.7321		10	135.0287	183.0461	48.01732	157.4323	1889.1876
HBR	3393	117	1004	827	455.2198		24	113.9563	130.4734	16.51717	120.3517	1444.2204
SEV	91931	1418	2651	1233	1634.165		10	14.22249	28.11513	13.89264	20.14921	241.79052

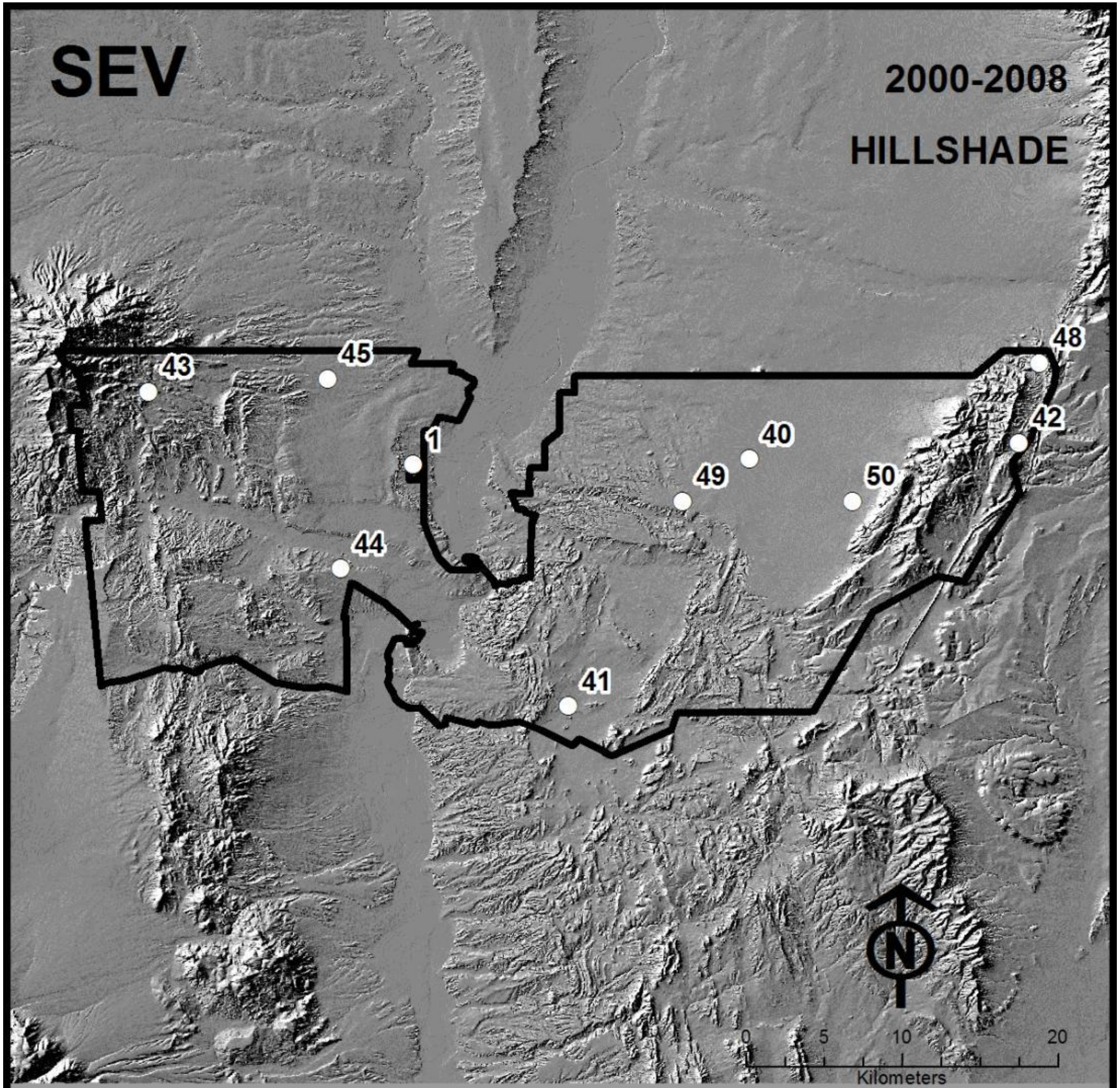
AND Comparisons

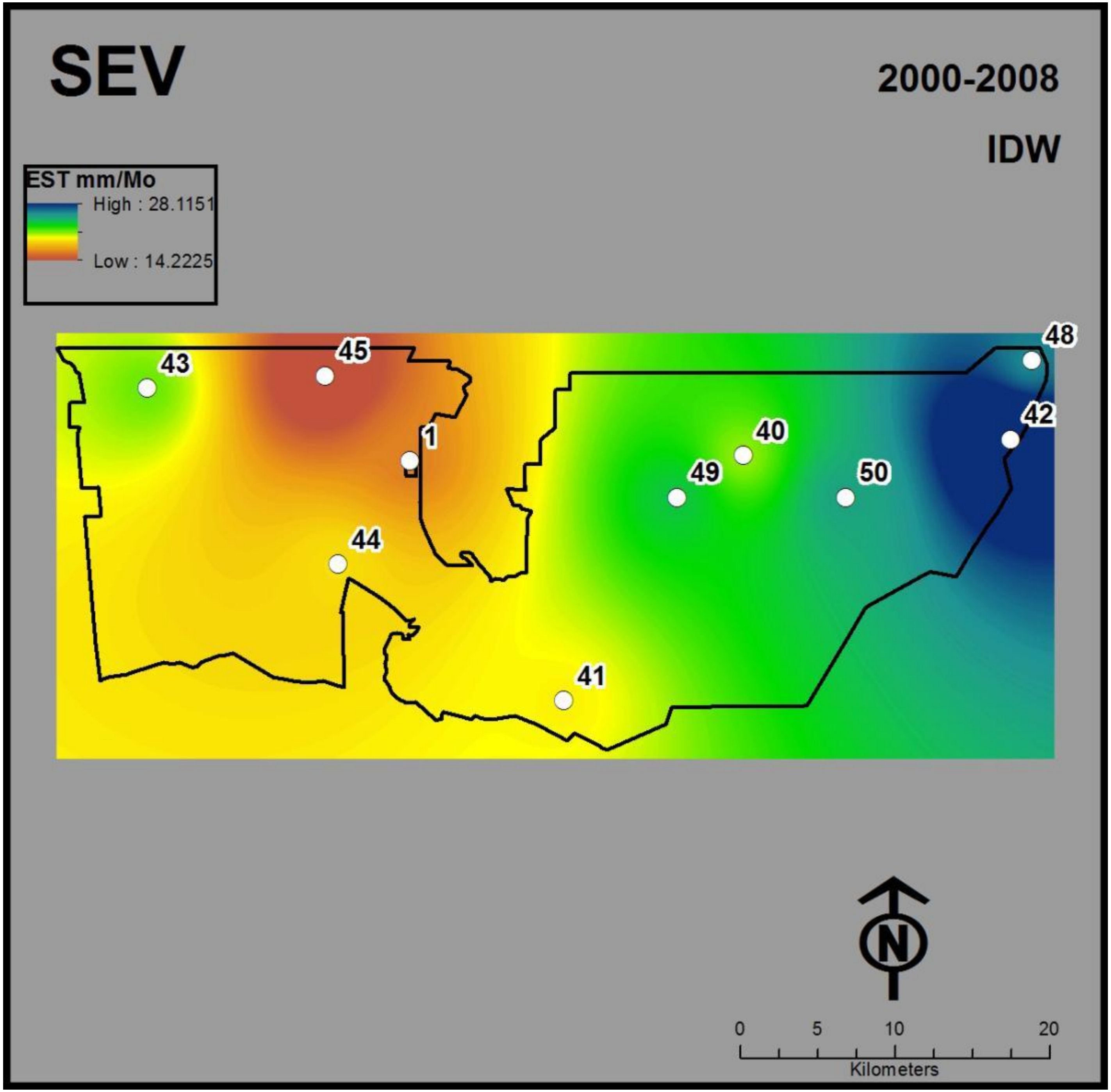





HBR
2000-2008
HILLSHADE
RG1
RG2
RG3
RG4
RG5
RG6
RG7
RG8
RG9
RG11
RG12
RG13
RG14
RG15
RG16
RG17
RG19
RG20
RG22
RG23
RG24
RG25
N
0 0.75 1.5 3
Kilometers


HBR
2000-2008
IDW
EST mm/Mo
High : 132.584
Low : 107.323
RG1
RG2
RG3
RG4
RG5
RG6
RG7
RG8
RG9
RG11
RG12
RG13
RG14
RG15
RG16
RG17
RG19
RG20
RG22
RG23
RG24
RG25
N
0
0.75
1.5
3
Kilometers


SEV
2000-2008
HILLSHADE
43
45
48
1
40
42
49
50
44
41
N
0
5
10
20
Kilometers



SEV
2000-2008
IDW
EST mm/Mo
High : 28.1151
Low : 14.2225
43
45
1
44
41
49
40
50
48
42
N
0
5
10
20
Kilometers

XEUSONG ZHANG

Enhancing Spatial Precipitation Interpolation using Auxiliary Data

Xuesong Zhang

Joint Global Change Research Institute
Pacific Northwest National Laboratory and University of Maryland

Great Lakes Bioenergy Research Center Thrust 4 - Sustainability
Michigan State University

Universal Spatial Variation Model

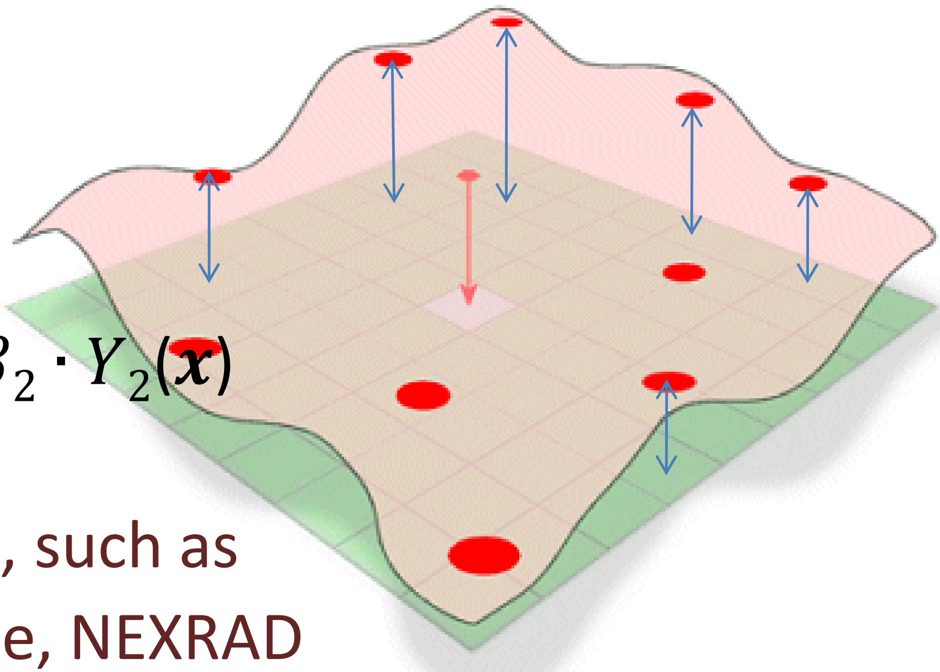
- Materon (1969) proposed a general representation of spatial variables:
  - $Z(\boldsymbol{x}) = m(\boldsymbol{x}) + \varepsilon'(\boldsymbol{x}) + \varepsilon''(\boldsymbol{x})$
  - where $\boldsymbol{x}$ is a spatial location, m is deterministic component, ε' represents a stochastic component driven by unknown factors, ε'' denotes measurement error.
- Basic form of Kriging
  - $Z(\boldsymbol{x}) = m(\boldsymbol{x}) + \varepsilon(\boldsymbol{x})$
- where m is global or locally varying mean, and ε is residual that is spatially correlated.

Simple Kriging

- Best Linear Unbiased Estimator (BLUE)
- Estimate residual at an unsampled point by a linear combination of the observed residuals at surrounding points.

– $Z(\boldsymbol{u}) - m(\boldsymbol{u}) = \sum_{i=1}^{n} \lambda_i \cdot [Z(\boldsymbol{x}) - m(\boldsymbol{x})]$

- Allow for flexible $m(\boldsymbol{u})$



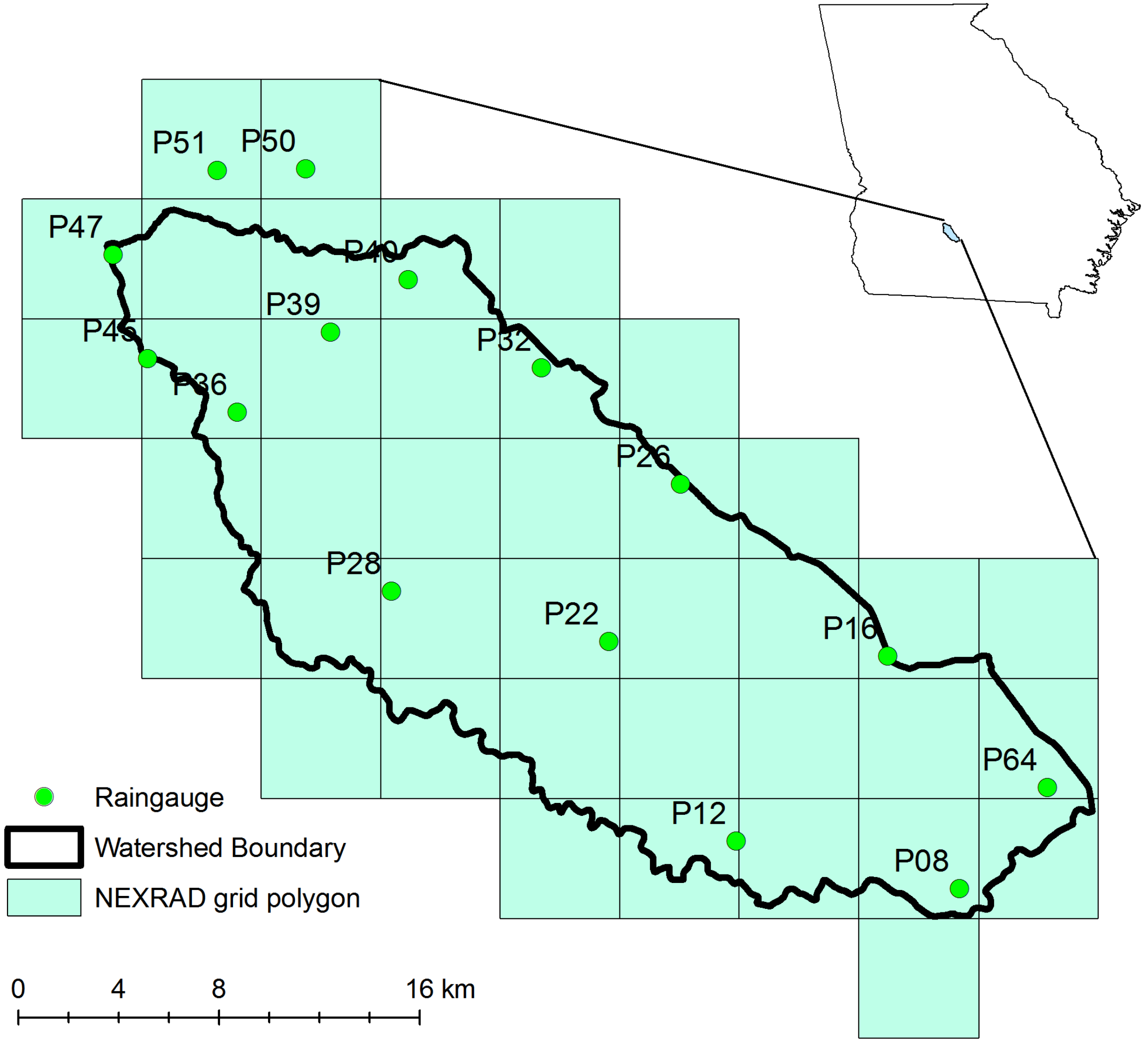
– $m = \frac{1}{n} \sum_{i=1}^{n} Z(\boldsymbol{x})$

– $m(\boldsymbol{x}) = \beta_0 + \beta_1 \cdot Y_1(\boldsymbol{x}) + \beta_2 \cdot Y_2(\boldsymbol{x})$

– where Y_i is external variable, such as

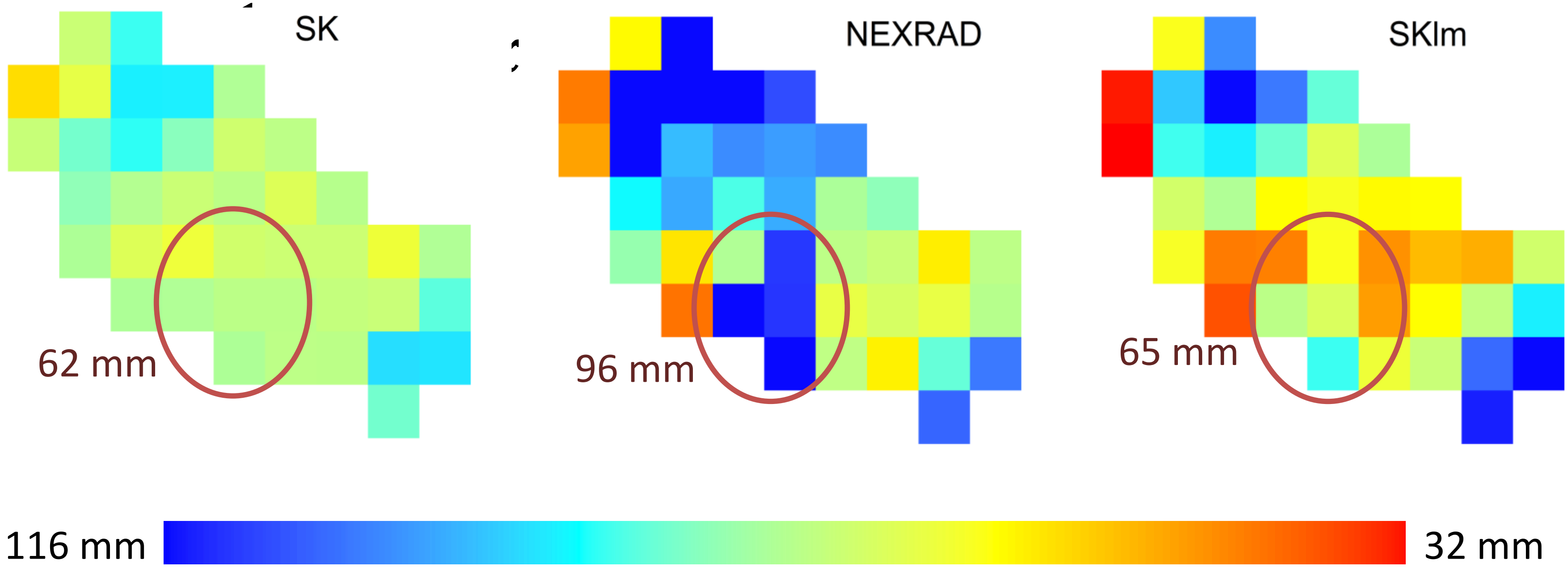
– elevation, spatial coordinate, NEXRAD

An example in Little River Experimental Watershed



Precipitation maps

- Spatial precipitation estimated by different methods on October 3, 2002



Evaluation statistics

- Estimation Efficiency

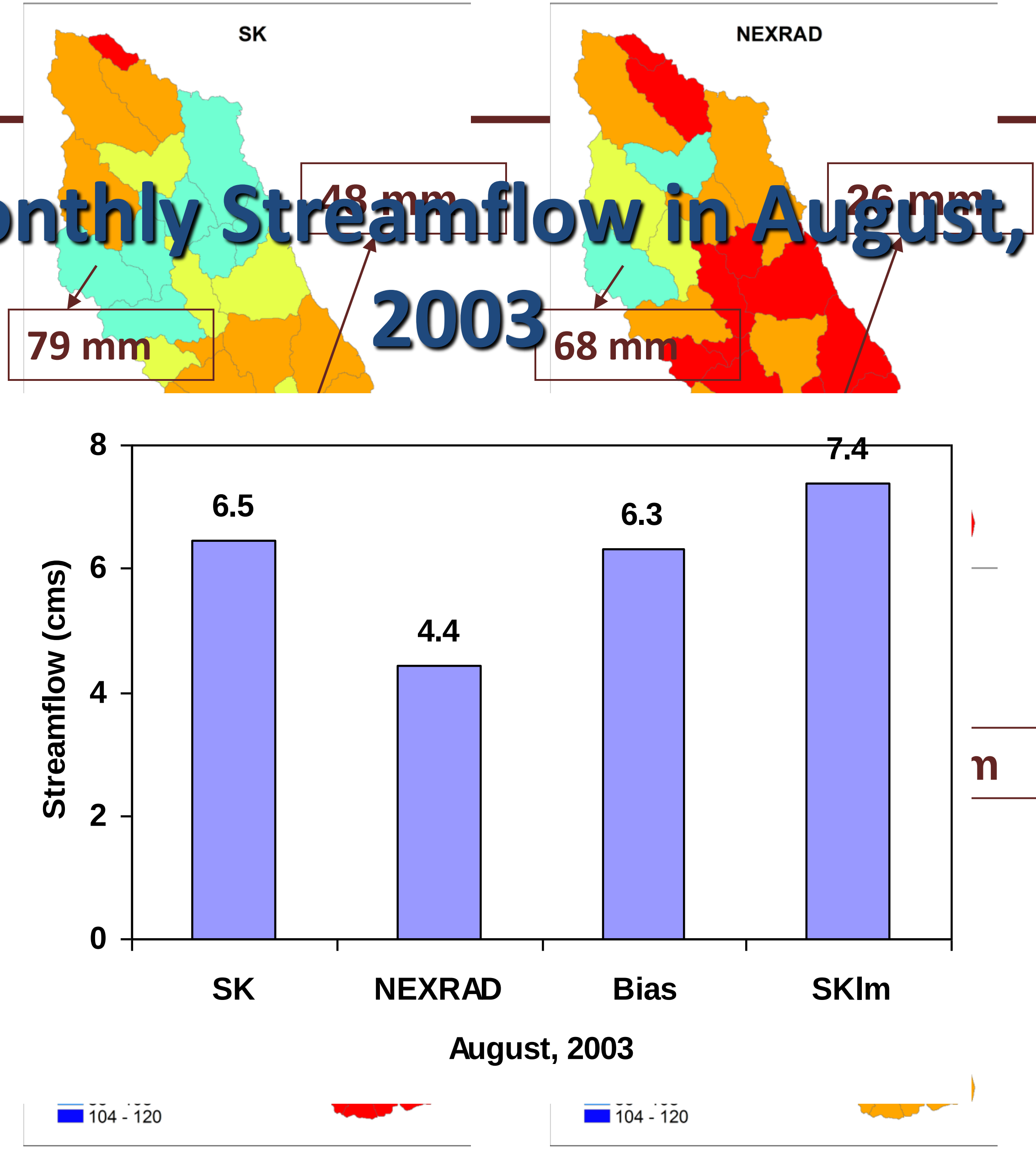
$$EE = 1.0 - \frac{\sum_{i=1}^{n}[\hat{Z}(\boldsymbol{x}) - Z(\boldsymbol{x})]}{\sum_{i=1}^{n}\widehat{[Z}(\boldsymbol{x}) - \bar{Z}(\boldsymbol{x})]}$$

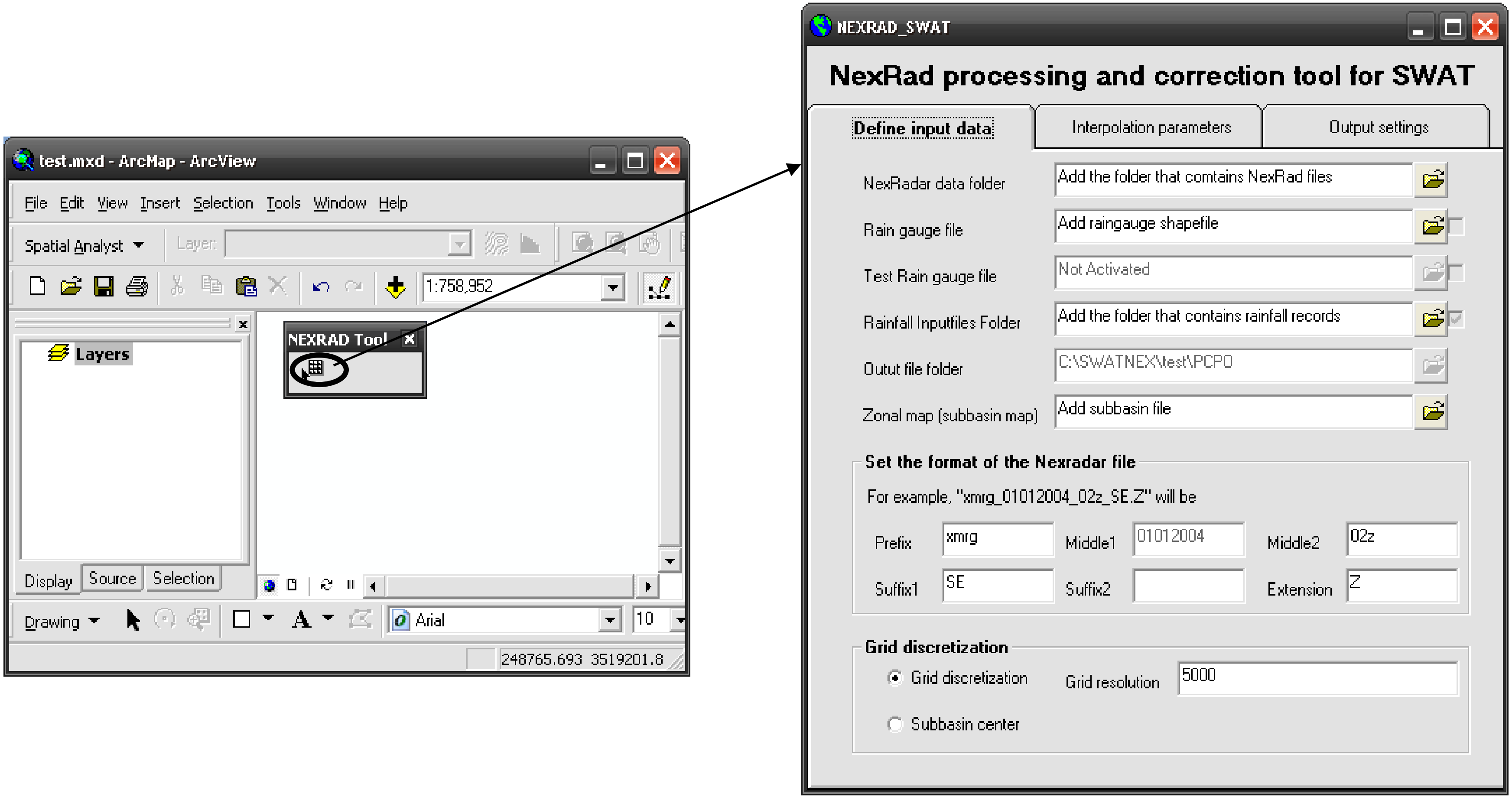
– where $\hat{Z}(\boldsymbol{x})$ estimated precipitation values at $\boldsymbol{x}$, and $\bar{Z}(\boldsymbol{x})$ is mean value of the n rain-gauge observed precipitation values.

Methods / Evaluation coefficients		SK	NEXRAD	SKlm
Oct. 13, 2002	Mean	63.7	73.43	60.95
	SDV	5.84	19.14	16.52
	EE	0.10	-0.26	0.65

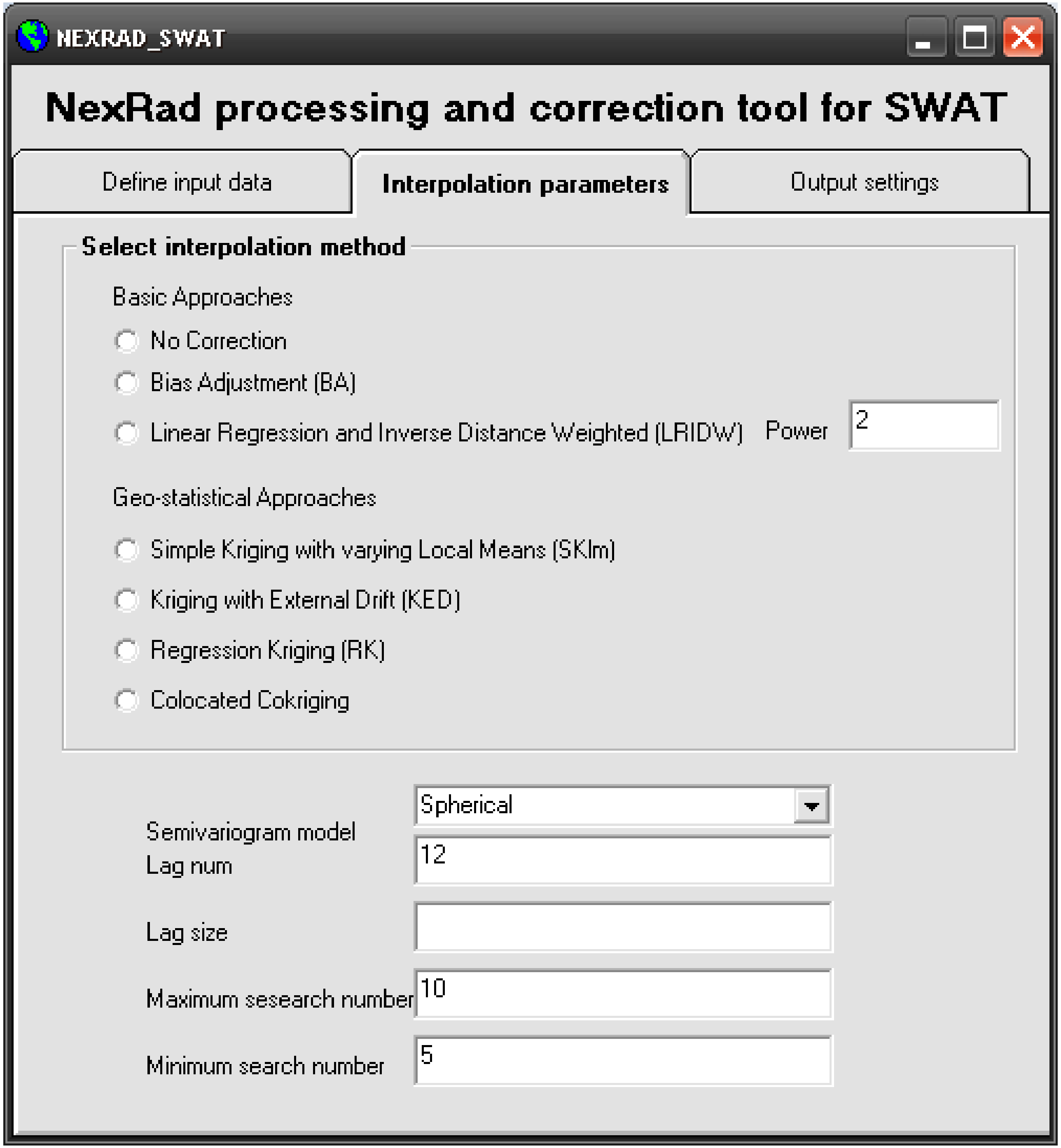
Monthly Streamflow in August, 2003

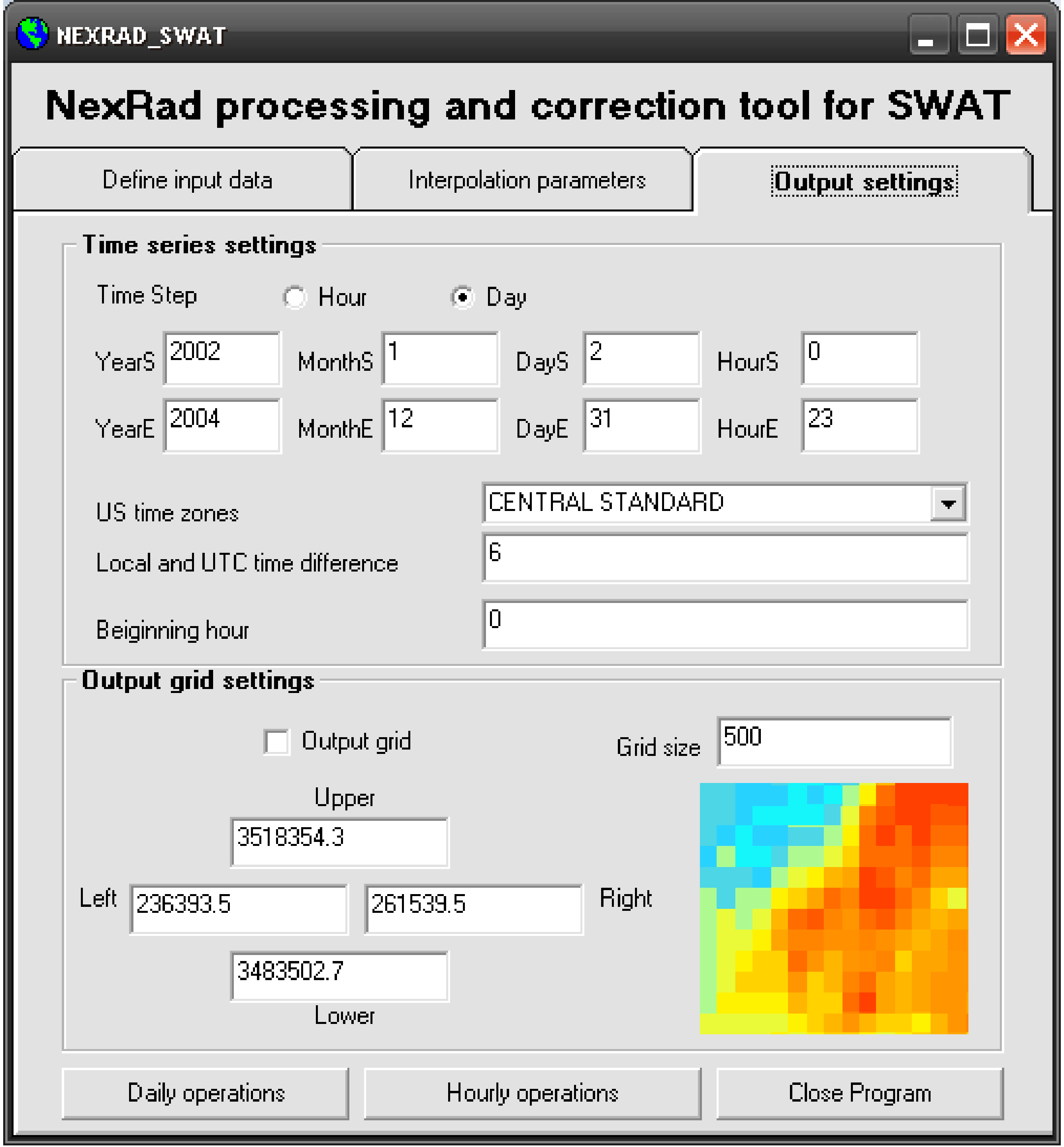
Water Yield Maps in August, 2003





xzhang.pbworks.com


NEXRAD_SWAT
NexRad processing and correction tool for SWAT
Define input data
Interpolation parameters
Output settings
Select interpolation method
Basic Approaches
No Correction
Bias Adjustment (BA)
Linear Regression and Inverse Distance Weighted (LRIDW)
Power
2
Geo-statistical Approaches
Simple Kriging with varying Local Means (SKlm)
Kriging with External Drift (KED)
Regression Kriging (RK)
Colocated Cokriging
Semivariogram model
Spherical
Lag num
12
Lag size
Maximum sesearch number
10
Minimum search number
5


NEXRAD_SWAT
NexRad processing and correction tool for SWAT
Define input data
Interpolation parameters
Output settings
Time series settings
Time Step
Hour
Day
YearS 2002
MonthS 1
DayS 2
HourS 0
YearE 2004
MonthE 12
DayE 31
HourE 23
US time zones
CENTRAL STANDARD
Local and UTC time difference
6
Beiginning hour
0
Output grid settings
Output grid
Grid size
500
Upper
3518354.3
Left
236393.5
261539.5
Right
3483502.7
Lower
Daily operations
Hourly operations
Close Program

Thank you for your attention!

JOHN BATTLES

Estimating uncertainty in forest biomass: What exactly should we be reporting?

QUEST Workshop –LTER ASM 2012
John Battles
Hubbard Brook

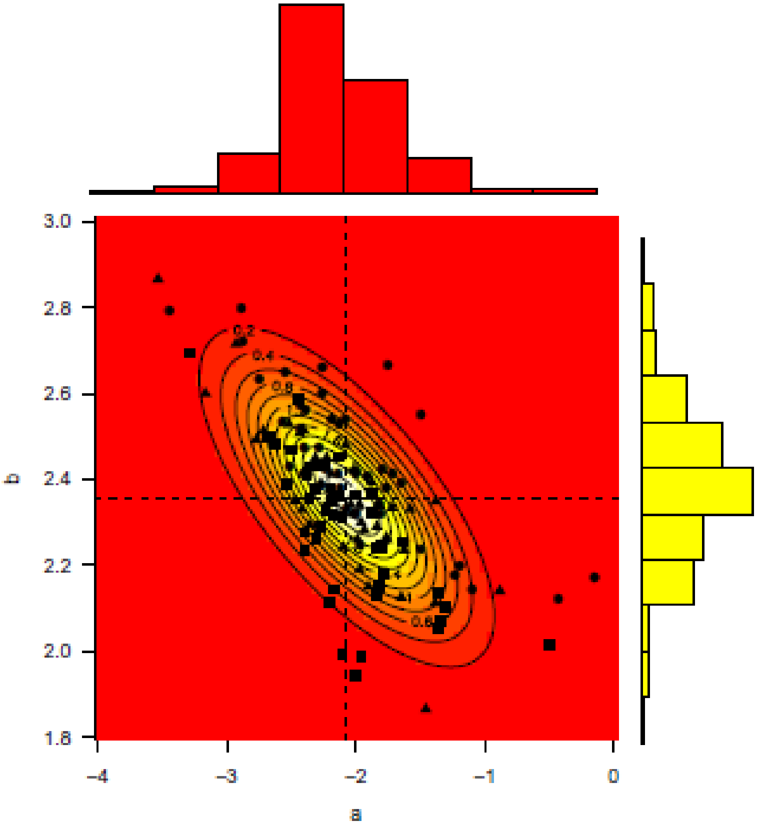
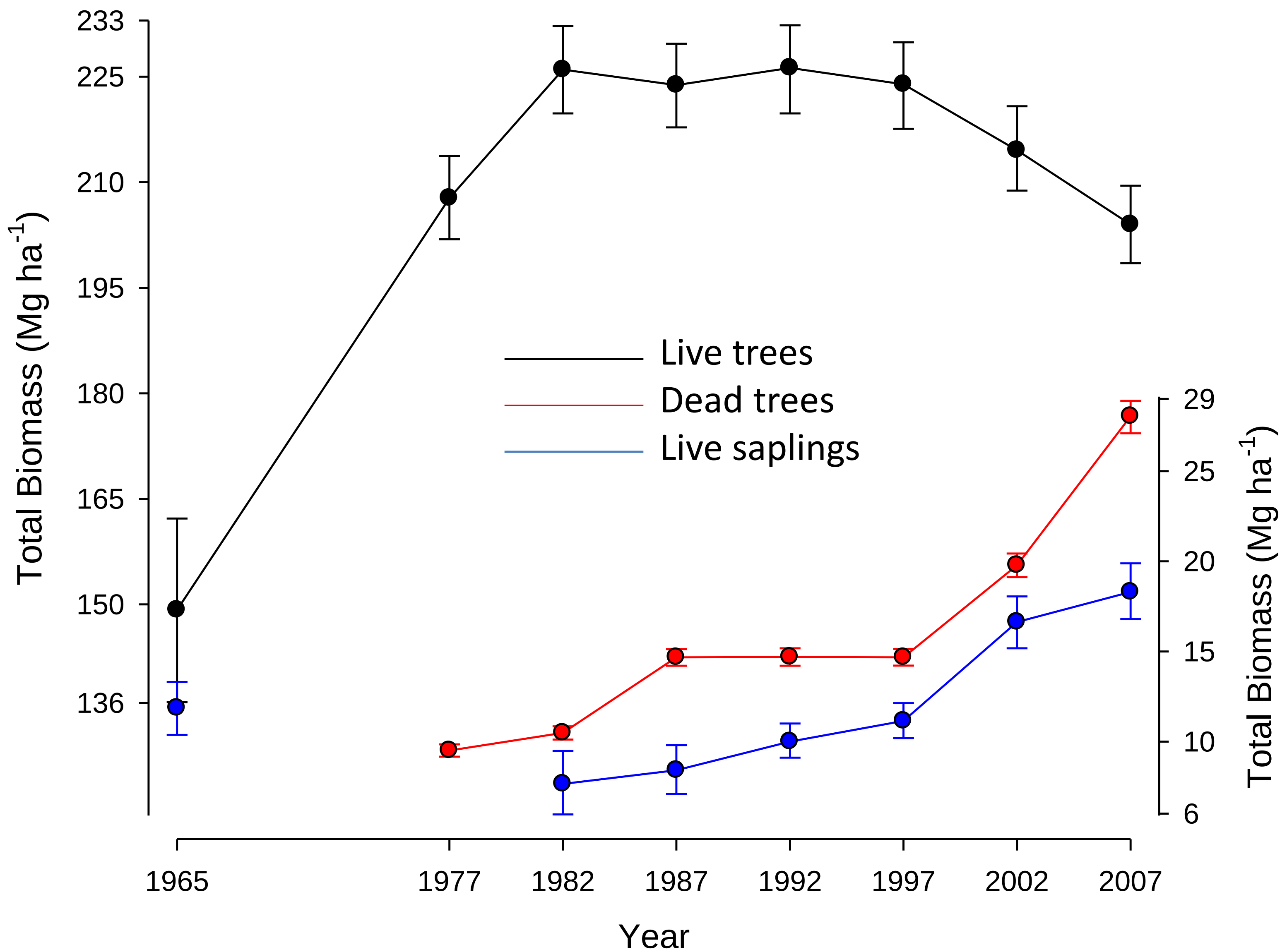


Fig. 2 in Zapata-Cuartas et al. 2012.

W6: Hubbard Brook Reference Watershed
with uncertainty estimates



Sources of uncertainty in forest carbon estimates

Measurement

e.g., diameter and height measurements (tree)

species (tree)

density (plot)

Biomass transfer functions (tree level)

e.g., allometric equations, volume equations, wood density estimates

Sampling error (class level)

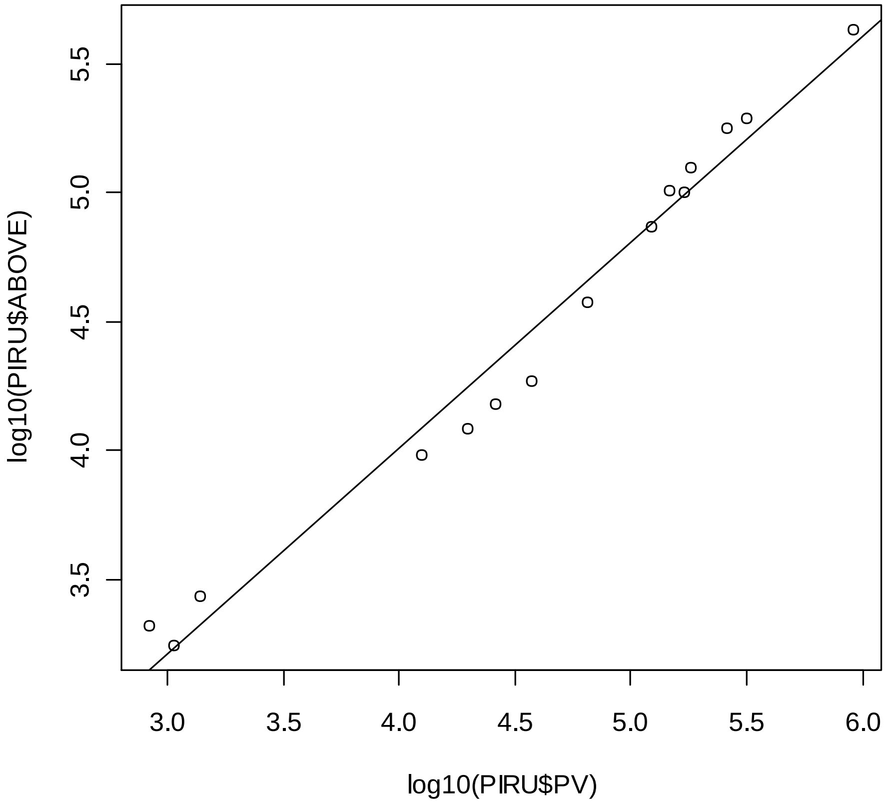
error when plots in a class are aggregated to get central tendencies (e.g., average to get mean value)

Model selection (tree level)

related to transfer function

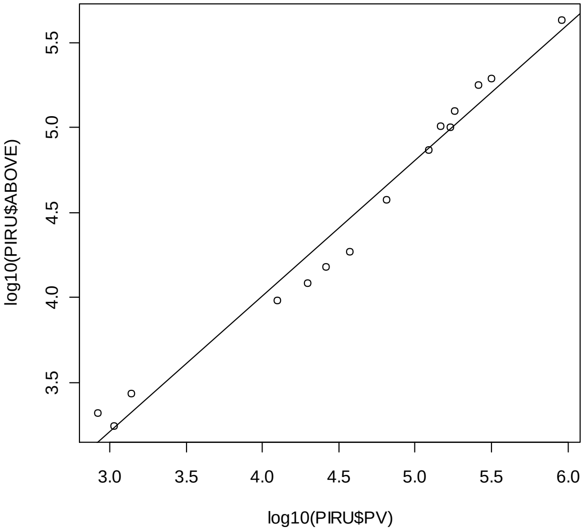
Attention has focused on two aspects:

1. The statistics around the transfer function where tree measurements are used to calculate mass.

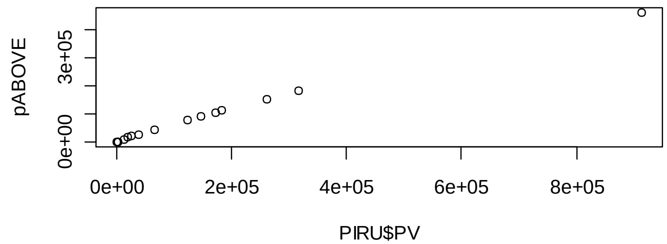


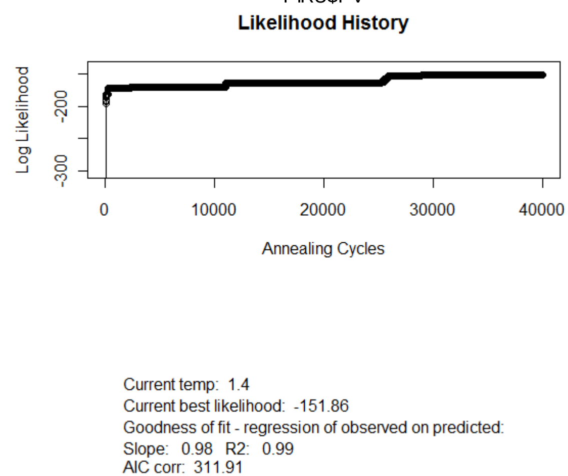
2. Propagating uncertainty as we scale up from trees to plots to stands to forests.

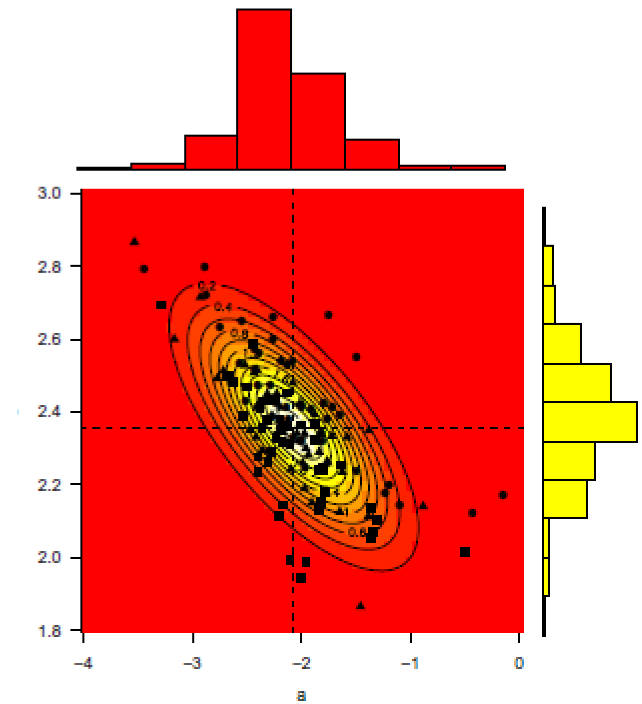
Many ideas on how to best develop transfer functions.



Whittaker et al. 1974.







Zapata-Cuartas et al. 2012. Forest Ecology and Management 277:173–179

Methods for uncertainty assessment

Analytical error propagation
- e.g., Taylor expansions

Monte Carlo simulation

Hierarchical analysis
- e.g., Bayesian state space model
- Nested likelihood functions

Ad hoc approaches
- e.g., various forest offset/carbon accounting protocols

None

Back to the question: What should we be reporting?

1. Science

   Leave to peer review process with expectation uncertainty will be addressed.

2. What about resource managers?

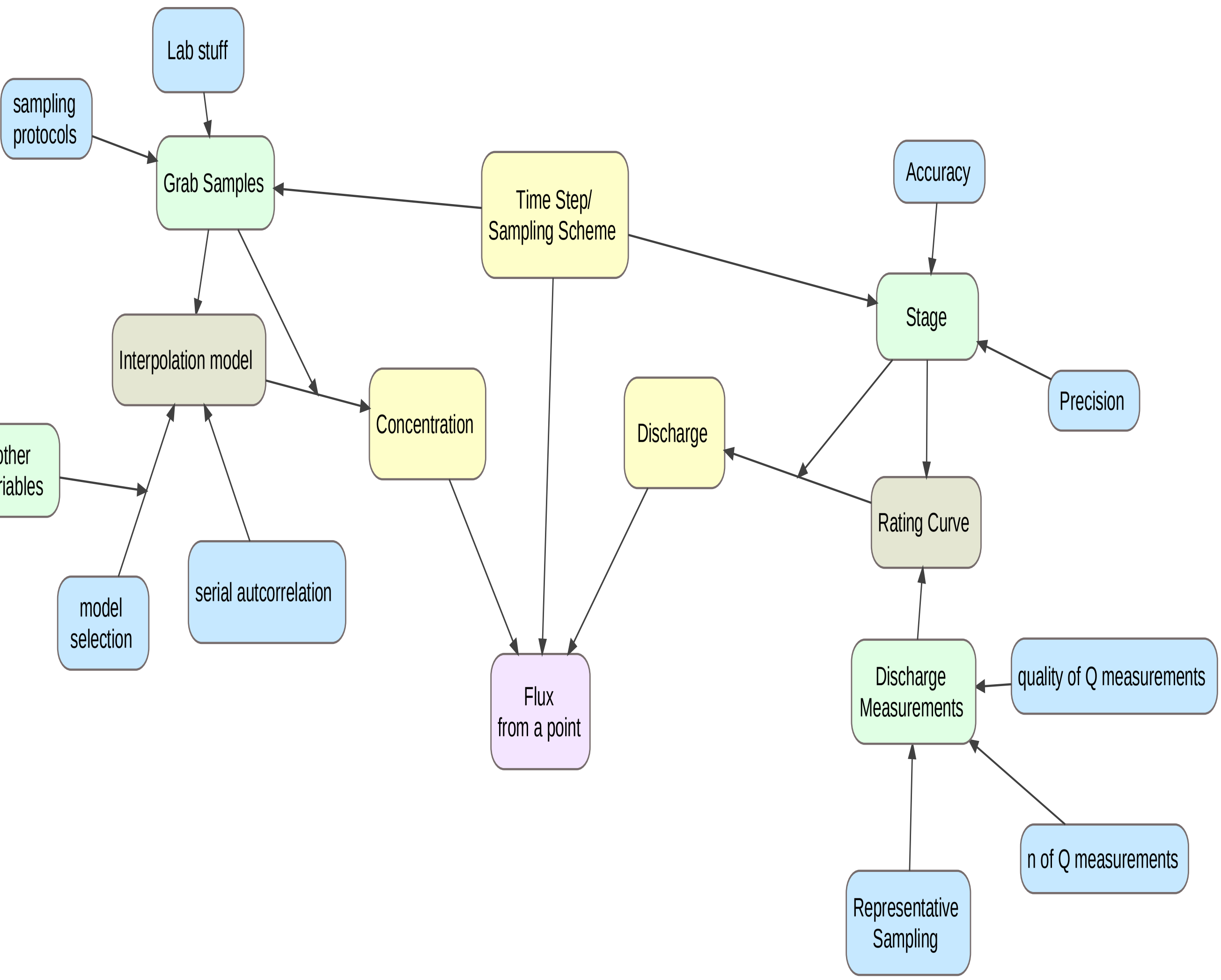
   e.g., National Forest and National Parks now required to monitor forest carbon pools.

3. What about carbon/GHG accounting protocols in states/regions?

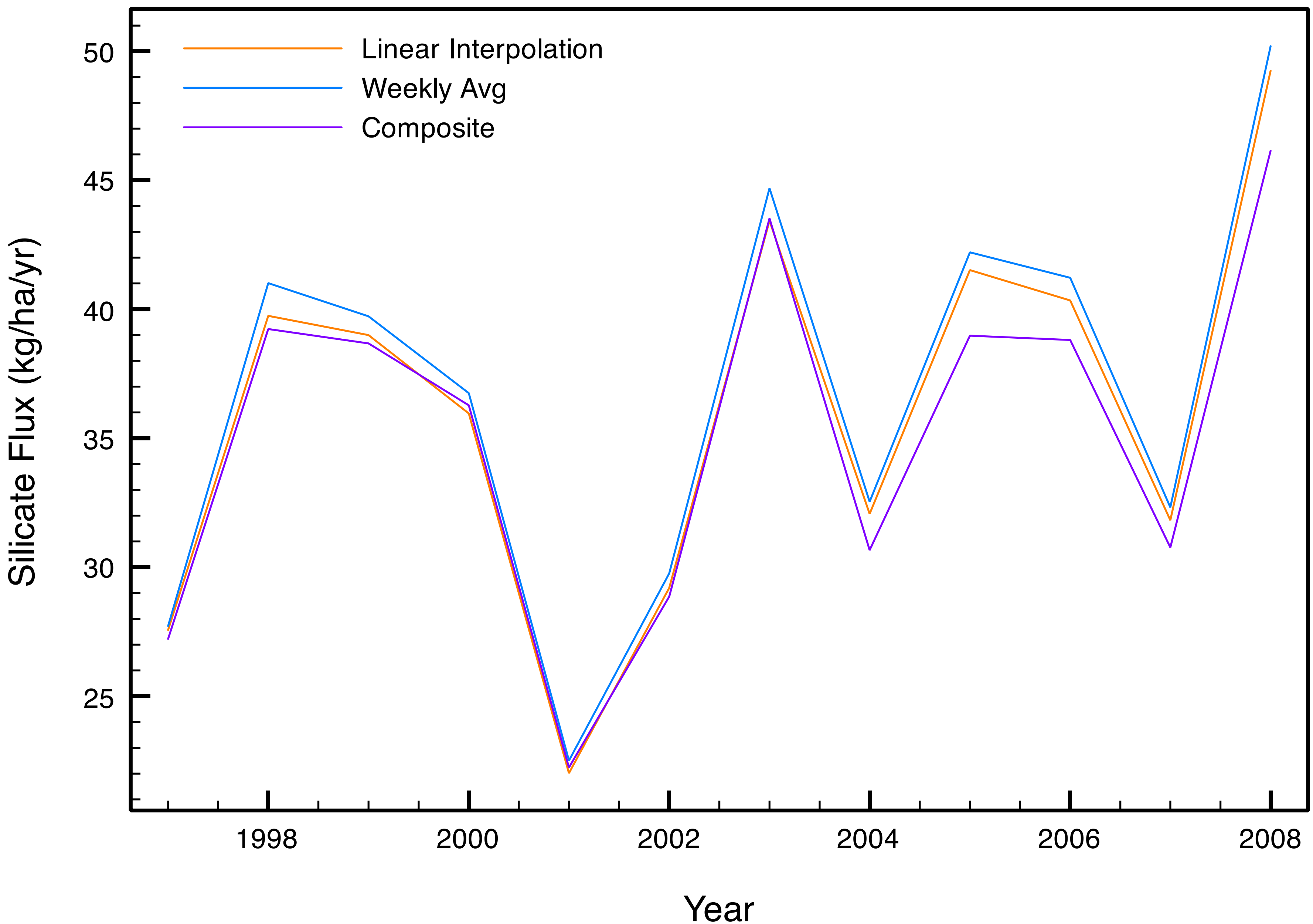
   National standards and international standards

4. What about remote sensing approaches calibrated with biometric results?

MARK GREEN



Lab stuff
sampling protocols
Grab Samples
Time Step/ Sampling Scheme
Accuracy
Stage
Interpolation model
Concentration
Discharge
Precision
other variables
Rating Curve
serial autcorrelation
model selection
Flux from a point
Discharge Measurements
quality of Q measurements
n of Q measurements
Representative Sampling


Linear Interpolation
Weekly Avg
Composite
Silicate Flux (kg/ha/yr)
50
45
40
35
30
25
1998
2000
2002
2004
2006
2008
Year

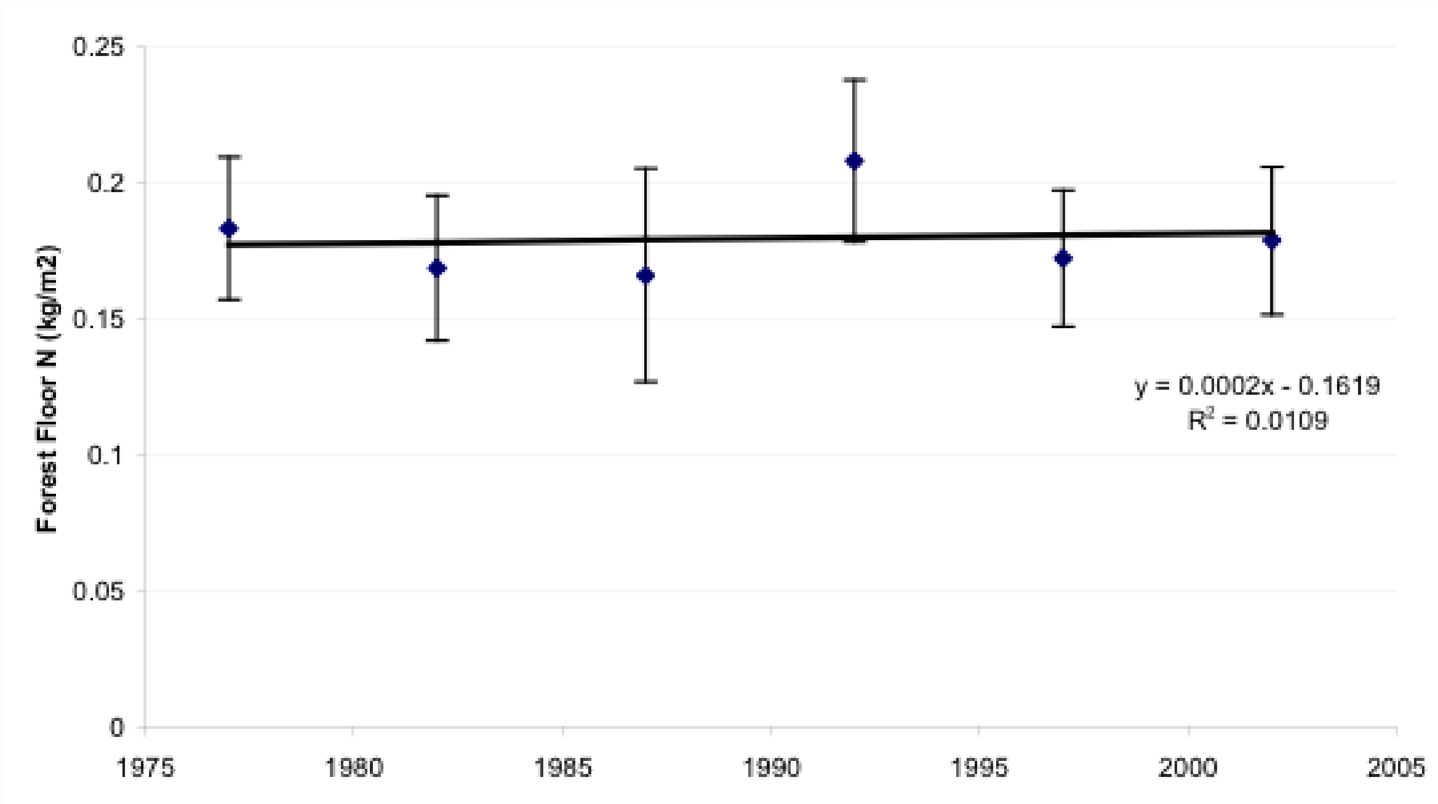
RUTH YANAI

Sources of Uncertainty in Soil Nutrient Contents

Analytical Uncertainty

Sampling Uncertainty

Nitrogen in the Forest Floor
Hubbard Brook Experimental Forest



The change is insignificant (P = 0.84).
The uncertainty is 22 kg/ha/yr.

We can't detect a difference of 1000 kg N/ha in the mineral soil…

Table 7. Total soil pools of N and C and oven-dry mass by soil mapping unit and soil stratum for Watershed 5 at the Hubbard Brook Exp. For. sampled in July 1983.

Mapping unit	n	Soil N content	Soil C content	Soil mass
		kg ha⁻¹	—— Mg ha⁻¹ ——	
			Forest floor	
Tun-Lym	28	1400a†	34a	90a
Berkshire	19	1100a	25a	81a
Skerry	6	1300a	27a	96a
Beckett	2	1100a	25a	61a
			Mineral soil	
Tun-Lym	28	5800a	130a	2500c
Berkshire	19	5600a	120a	3800b
Skerry	6	7100a	150a	4300ab
Beckett	2	5800a	130a	4100abc
			Total solum	
Tun-Lym	28	7200a	160a	2700a
Berkshir	19	6700a	150a	3900b
Skerry	6	8300a	180a	4400ab
Beckett	2	7000a	160a	4200ab

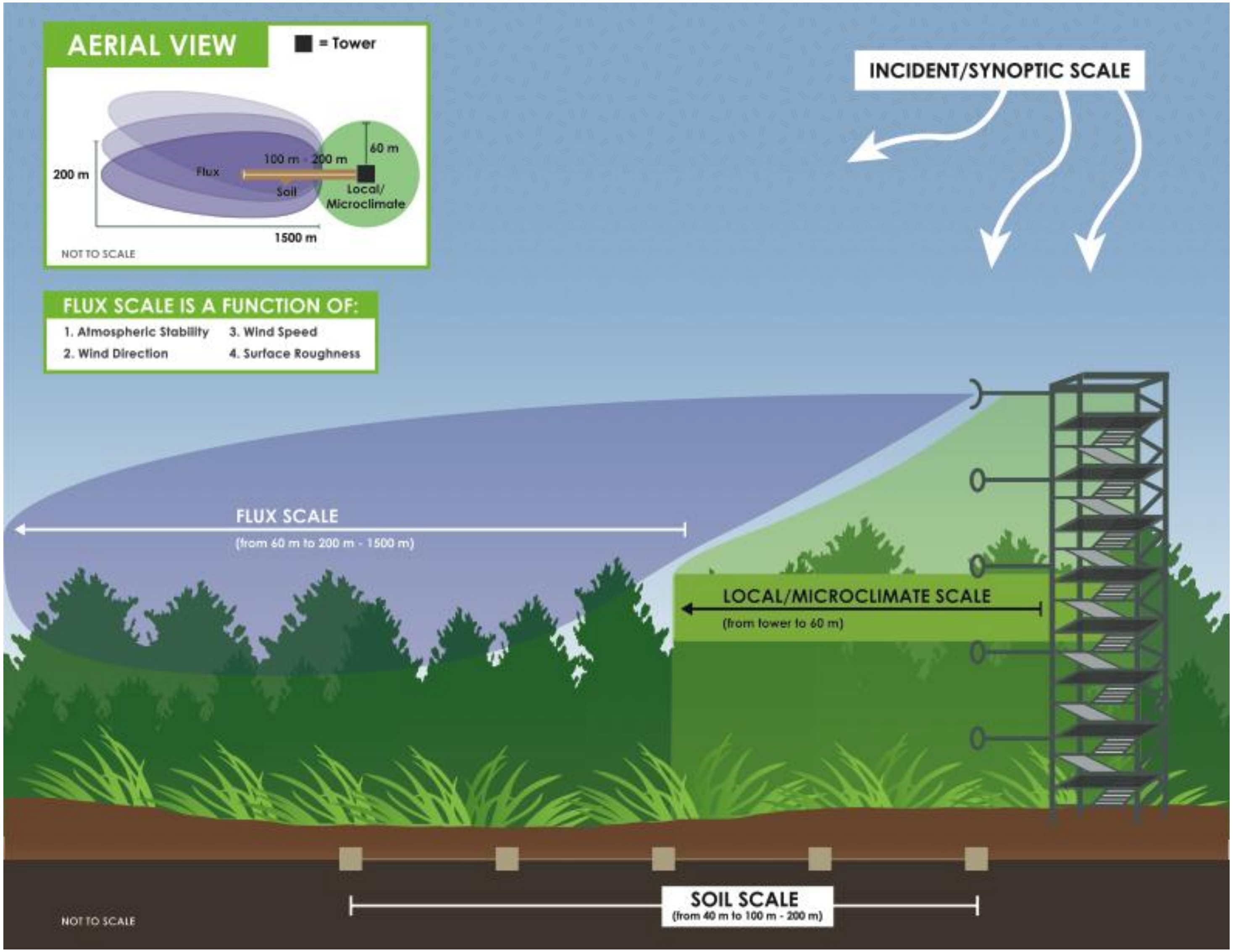
† Mean values within columns in a soil stratum which are followed by the same letter are not significantly different at $p = 0.05$ using Tukey's multiple pairwise comparison.

How should we estimate the uncertainty in change over time in soil N?

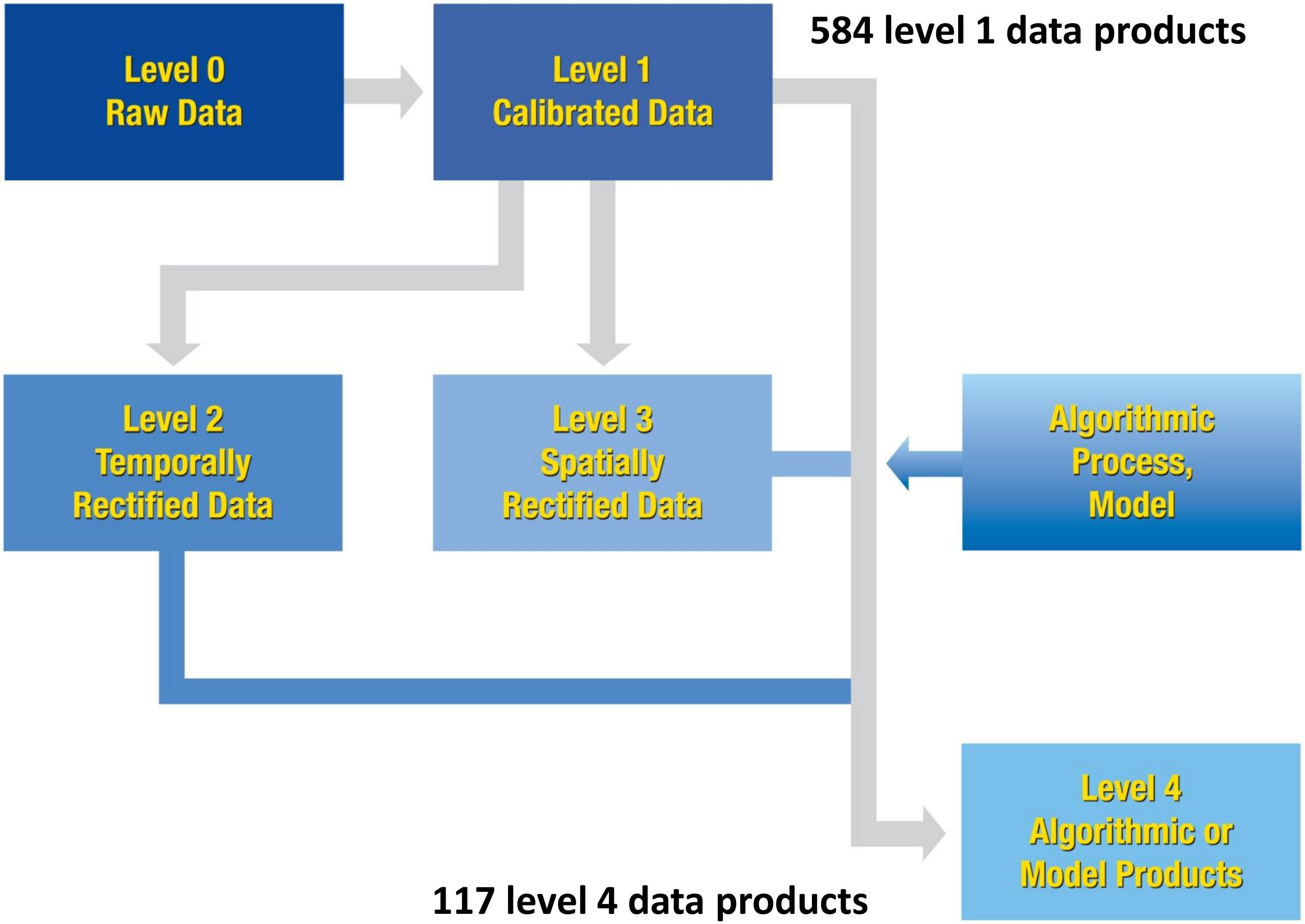
JEFF TAYLOR

A National Observatory: 20 Eco-Climatic Domains

Terrestrial Measurements



NEON Data Products



Challenges

- Coordinating Standardized Approaches

  (Observer Bias)

- Combining Uncertainties Across Scales
- Metadata
- Reprocessing

The National Ecological Observatory Network is a project sponsored by the National Science Foundation and managed under cooperative agreement by NEON Inc.

www.neoninc.org

jtaylor@neoninc.org

CRAIG SEE

Why gap filling?


Credit: Don Buso


Credit: Odonfiction.wordpress.com

What do you do?

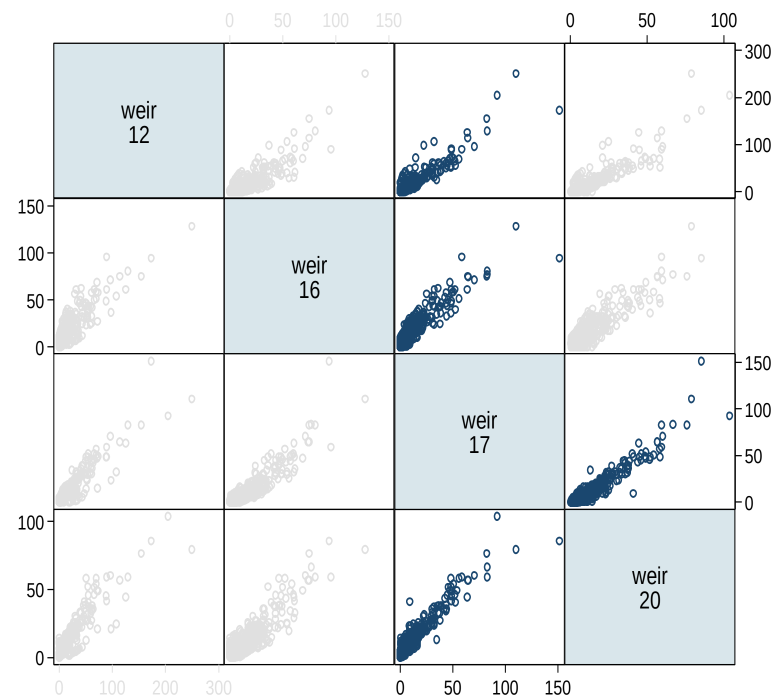
- Sometimes its not important (finding mean)
- Sometimes we need a continuous records (calculating pools, fluxes)
- Often a reasonable estimate can be made based on other available data

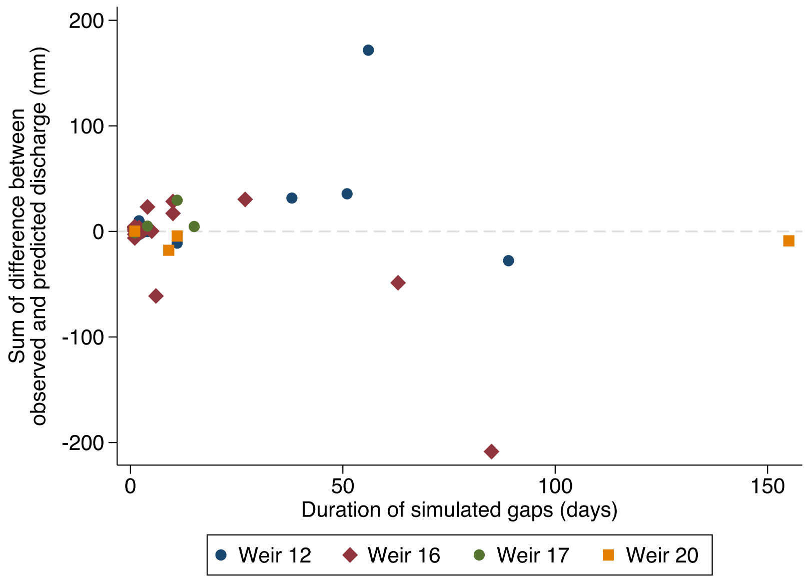
Gap filling (imputation) methods

- Use of historical averages
- Bayesian Bootstrapping
- Expectation-maximization algorithm
- Use neighboring values
  - Direct substitution
  - Regression

All gap filling methods introduce new error into the final total!

Streamflow gaps at Wakayama

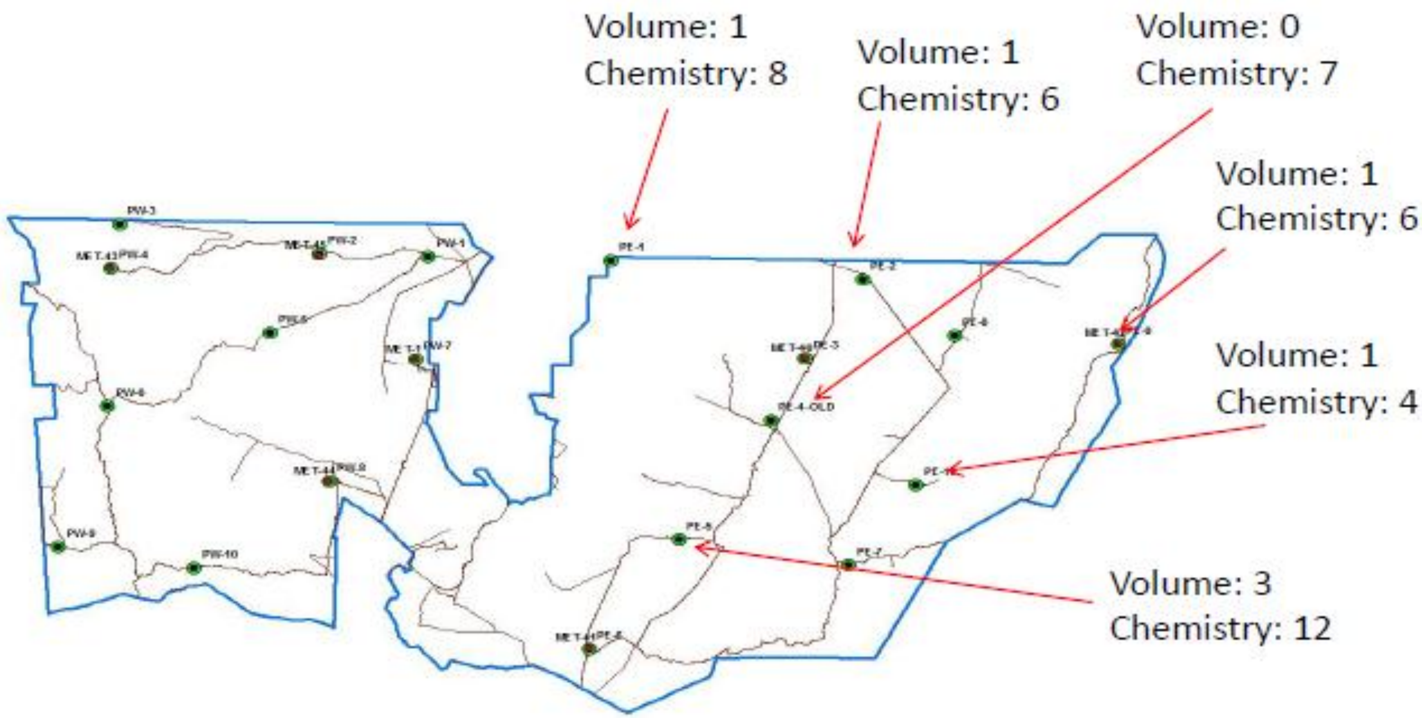




Eiji Matsuzaki

Precipitation gaps at Sevilleta

Volume and chemistry measurements taken from 20 collectors across SEV from 1989-1995.



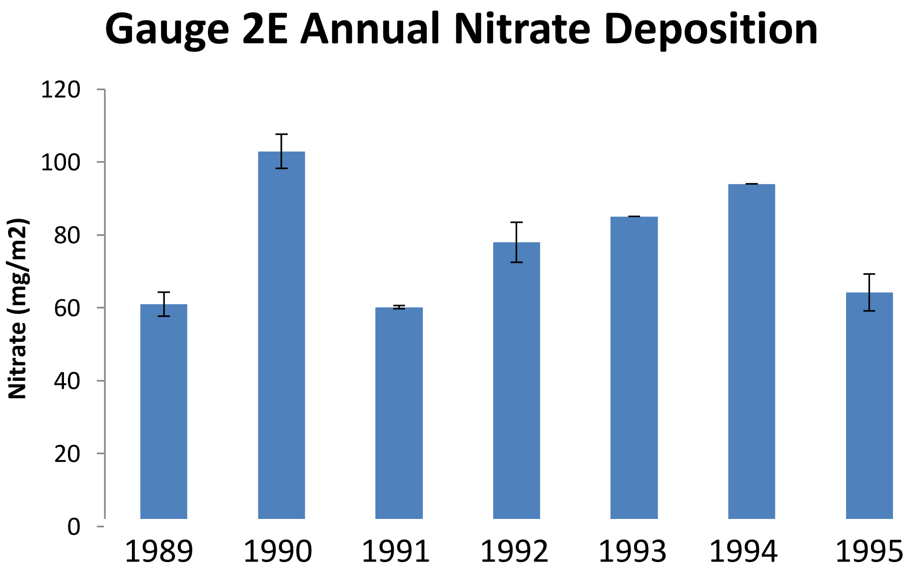
How do we incorporate "gap uncertainty" into annual nitrate deposition estimates?

Statistics

- Stepwise regressions using neighboring gauges as predictor variables
- 68.2% PI →

$$\hat{y}_h \pm t_{(\alpha/2, n-2)} \times \sqrt{MSE\left(1 + \frac{1}{n} + \frac{(x_h - \bar{x})^2}{\sum (x_i - \bar{x})^2}\right)}$$

- Relative errors add



CARRIE ROSE LEVINE

Statistical Approaches

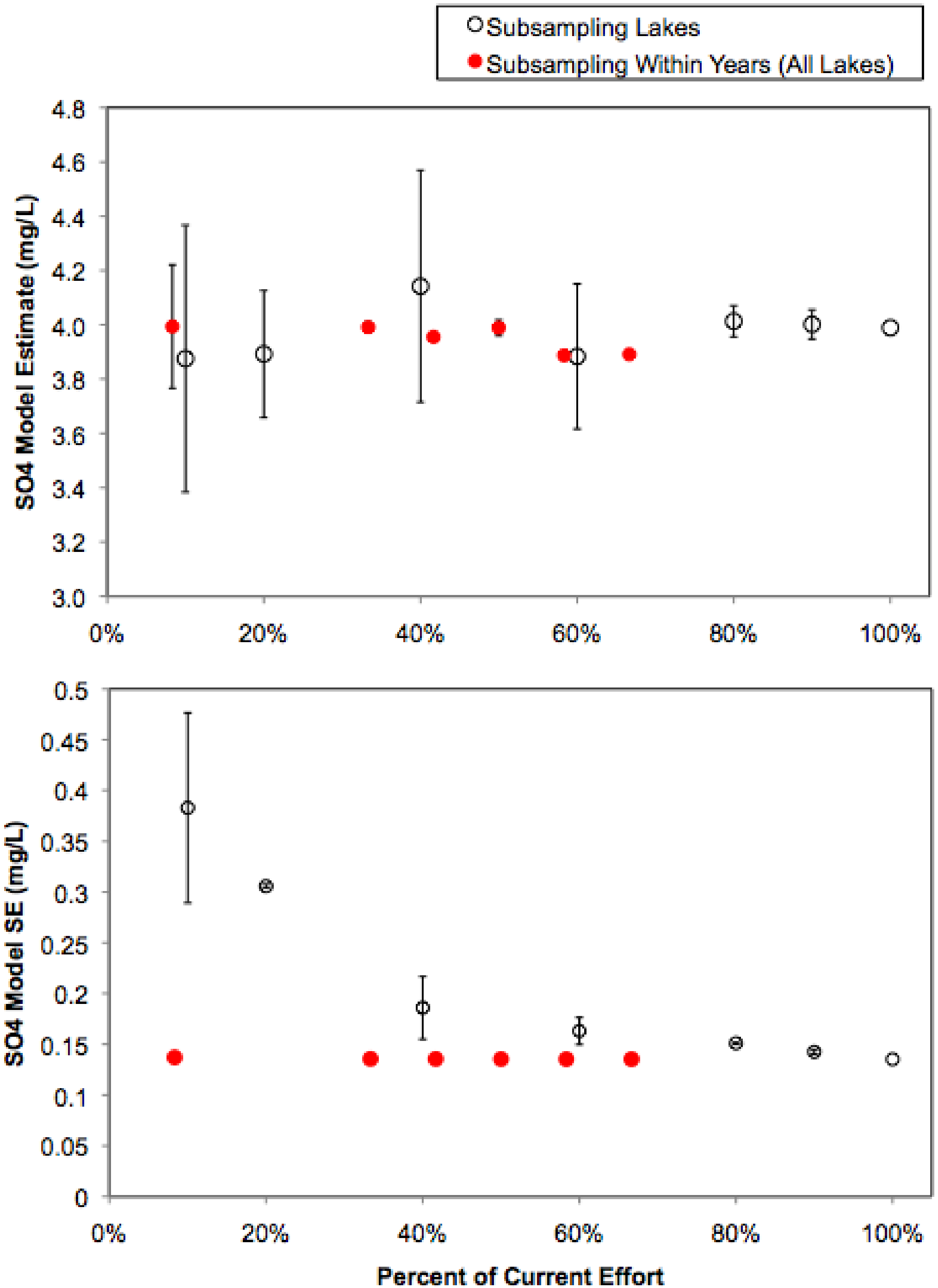
We used certain data analysis methods depending on the available data (pg. 7).

Model Type	Time Series	Multiple Sites
Repeated measures mixed effects model	X	X
Detectable difference analysis		X
Mann Kendall trends test and General Linear Model	X	

Repeated measures mixed effects model: a generalized linear model that can include random as well as fixed effects. Time series within each site treated as a repeated measure, and random subsamples of sites were selected to generate hypothetical sampling schemes.

Detectable difference analysis: describes the ability to detect significant changes in a future survey. The input variables include the sample size and standard deviation of the original survey and an alpha and power level.

Mann Kendall trends test and General Linear Model: Mann Kendall test was used to assess trends in time series based on the Kendall rank correlation. When sampling took place throughout the year and seasonal trends were present, we used a Seasonal Mann Kendall trend test. General linear regression and the standard error of the were used to assess slope and the uncertainty in trends



Model estimate and model standard error of long-term average concentrations of SO_4 (mg L^{-1}) based on a repeated-measures mixed-effects model using 50 random iterations for each simulated subsample size. Open symbols show models that reduced the number of lakes sampled, and red symbols show models that reduce the number of months sampled per year for all lakes.