

Uncertainty Assessment of Salinity Predictions in Barataria Estuarine System, Louisiana

Seminar at the South Florida Water Management District

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Acknowledgement

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Dealing With Uncertainty

“As we know, there are known knowns.
There are things we know we know.

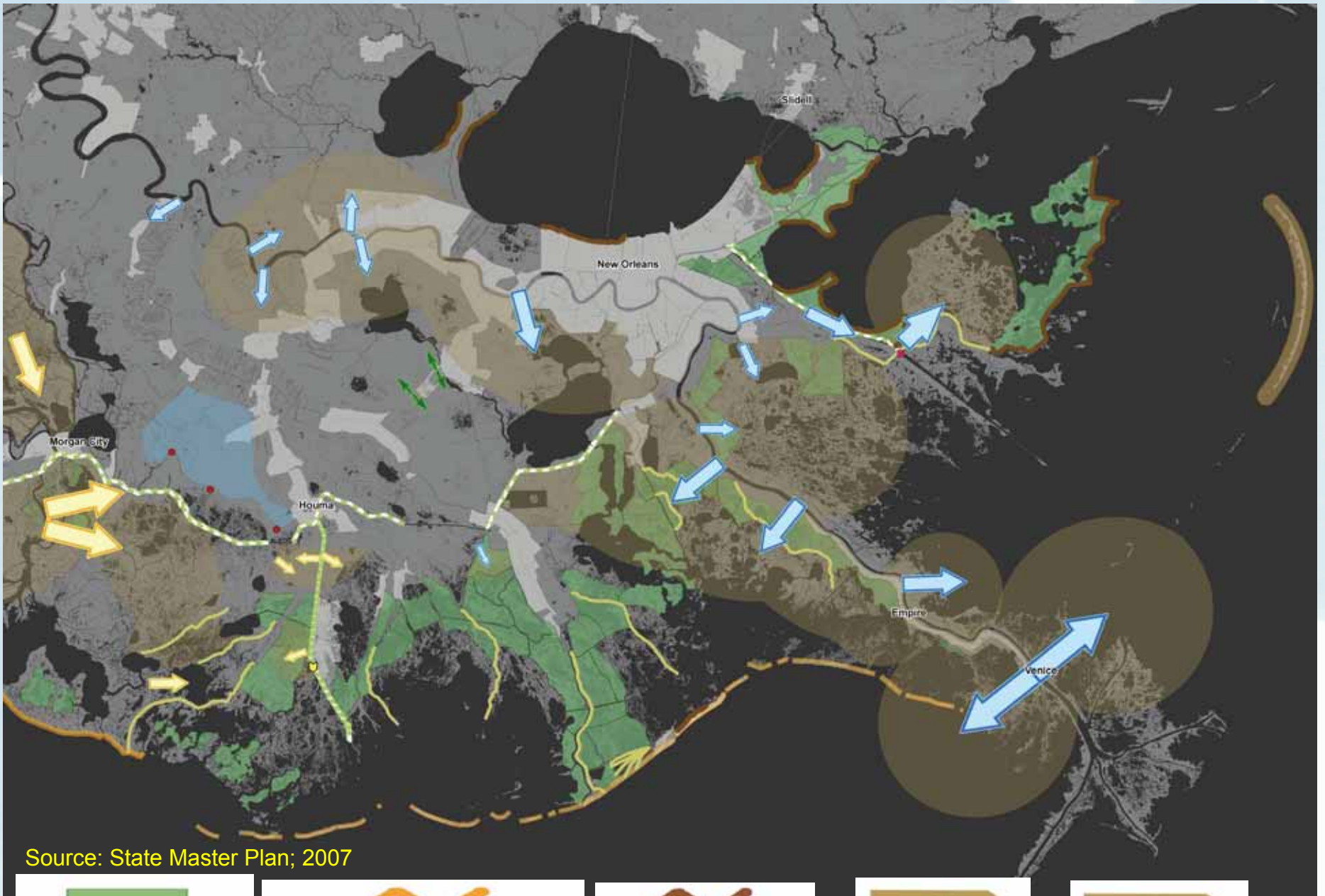
We also know there are known unknowns.
That is to say, *we know there are some things we do not know.*

But there are also unknown unknowns, *the ones we don't know we don't know.*”

Donald Rumsfeld (2004)

Background

- Coastal Louisiana is experiencing the most critical coastal wetland loss in North America.
- Main reason:
 - long-term reductions in freshwater and sediment inputs
- Coastal Restoration Master Plan proposed in 2007 to restore ecosystem sustainability



Source: State Master Plan; 2007

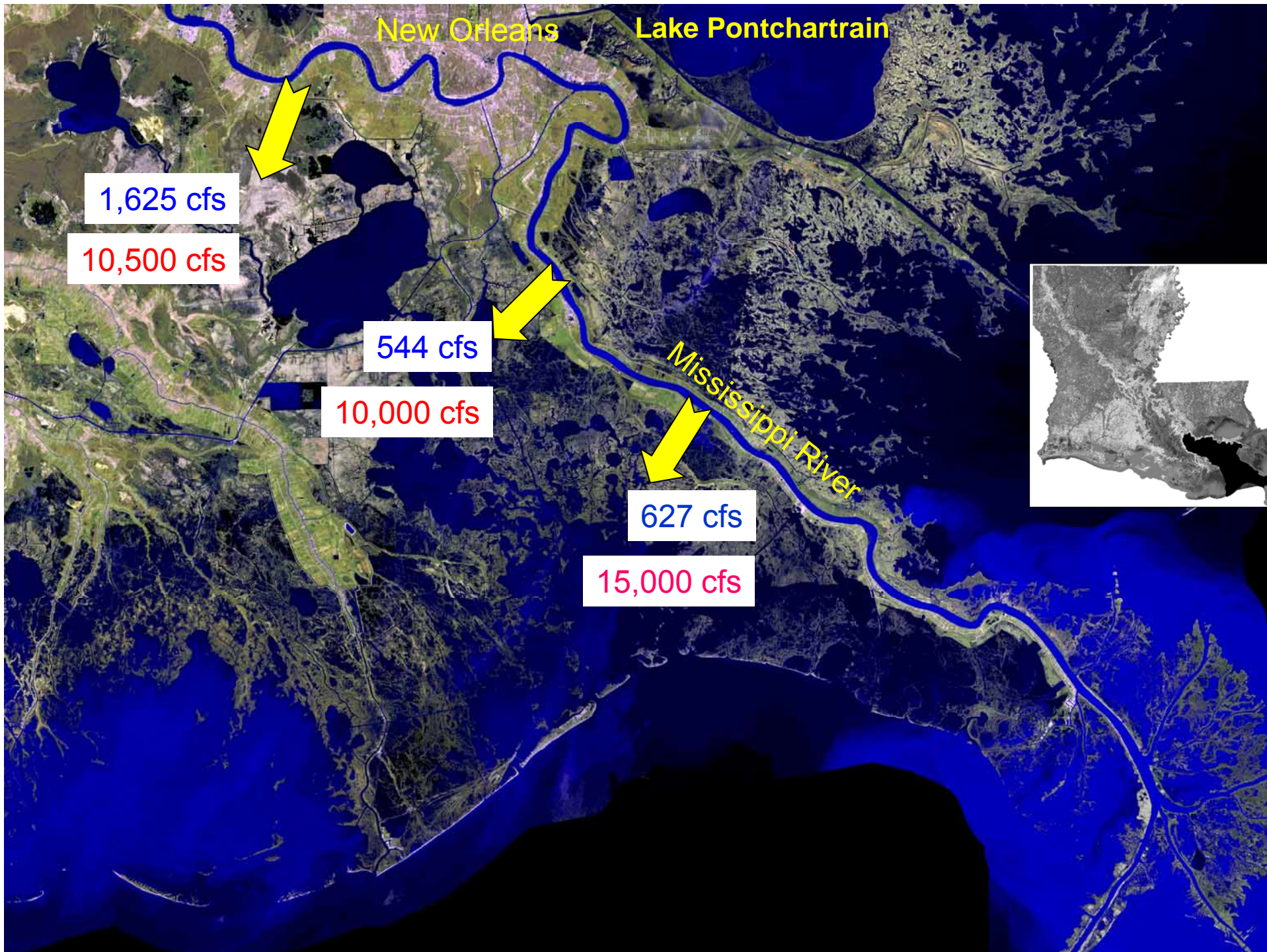

Marsh Restoration using
Dredged Material


Barrier Shoreline Restoration


Shoreline Stabilization in
Strategic Areas

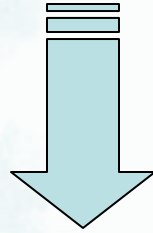

Mississippi River
Diversion


Atchafalaya River
Diversion



Ecological Impacts

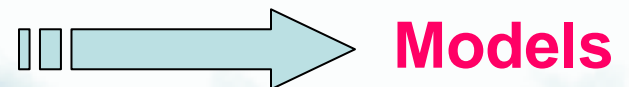
- Alter salinity regime (magnitude, gradient, and pattern)



- Effect on fisheries that depend on diverse estuarine habitats currently found in Louisiana coast

Proposed Restoration Alternatives

- Managers need to strike a balance between:
 - providing river sediment needed to build and sustain wetlands
 - competing objective to maximize diversity of habitats within a basin.
- Managers must be able to predict changes in salinity as a result of proposed restoration



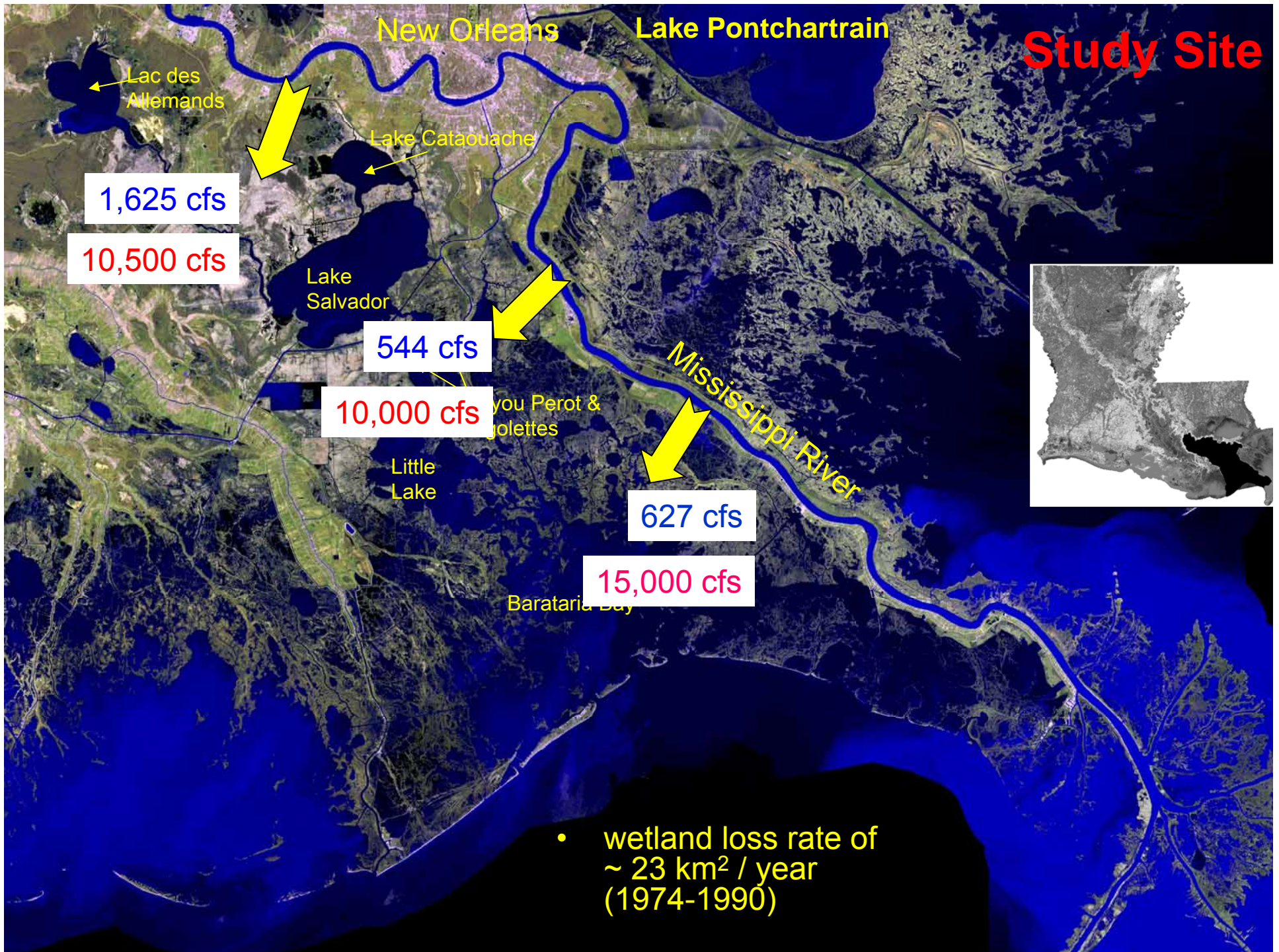
Models are not perfect!

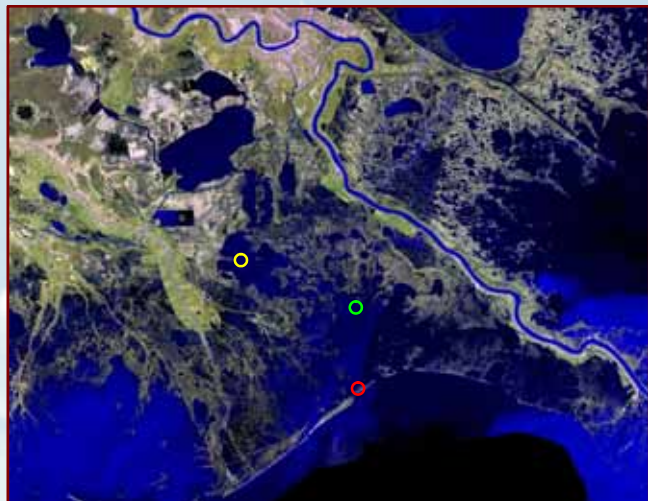
(Lall, Phillips, Reckhow and Loucks, CERP-SFWMD report 2002)

- ❖ Users might wrongly attribute too much accuracy to model predictions and infer unrealistic differences between restoration scenarios when no differences actually exist!
- ❖ Users might digest all sources of uncertainties and wrongly conclude that model predictions are useless!
- ✓ *We need to quantify uncertainties in model predictions to ensure that predictions are properly interpreted.*

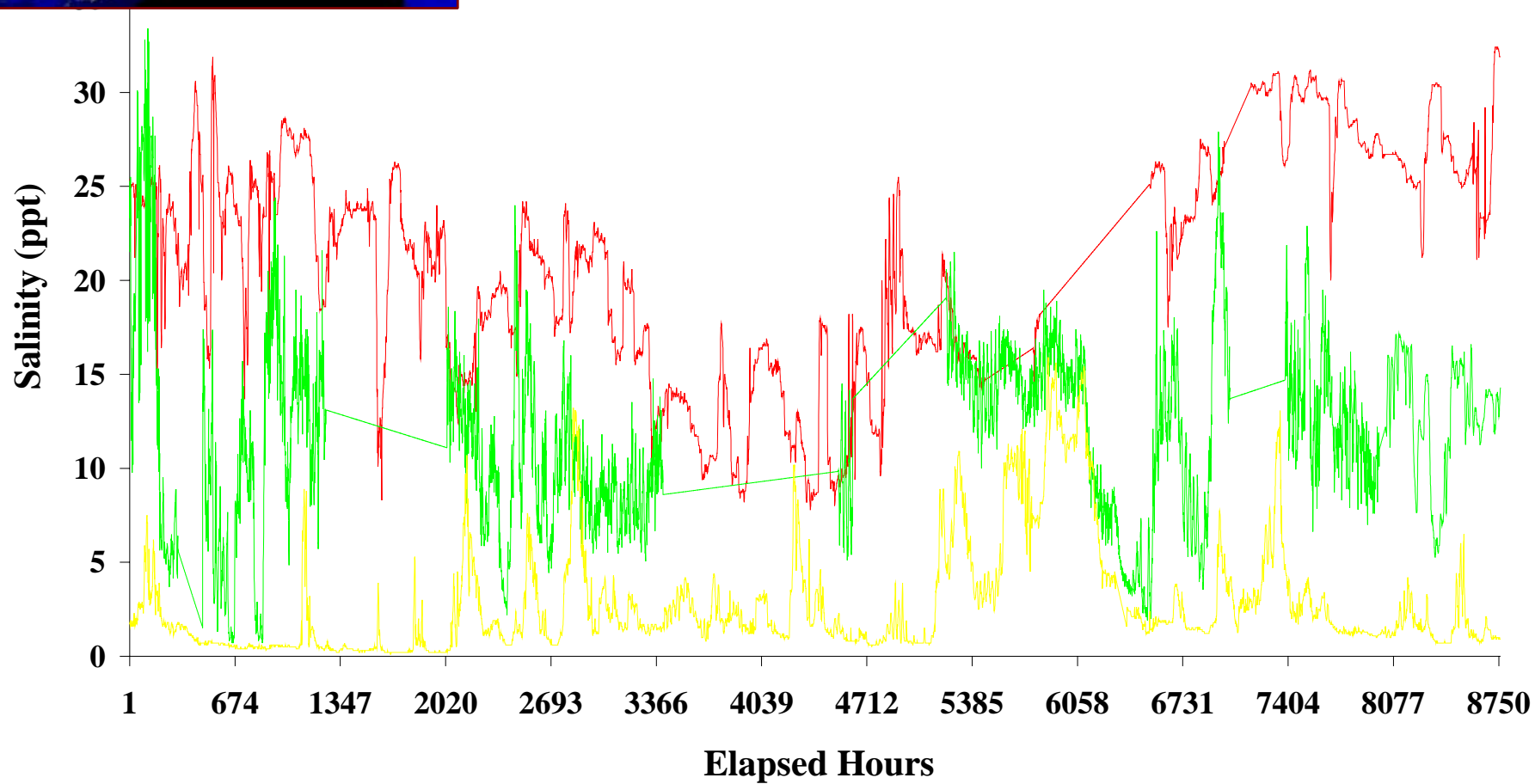
Scope & Objectives

- Examine the utility of mass-balance salinity estuarine models for forecasting salinities under future restoration scenarios
- Investigate sources and magnitudes of uncertainty in salinity forecasts:
 - Analyze sources of uncertainties and identify most significant
 - How do separate sources of uncertainty combine and interact?
 - Should we focus on developing more complex models?
 - Or focus on improving existing data collection strategies?
 - Develop some practical uncertainty analysis tools for model users and in decision making

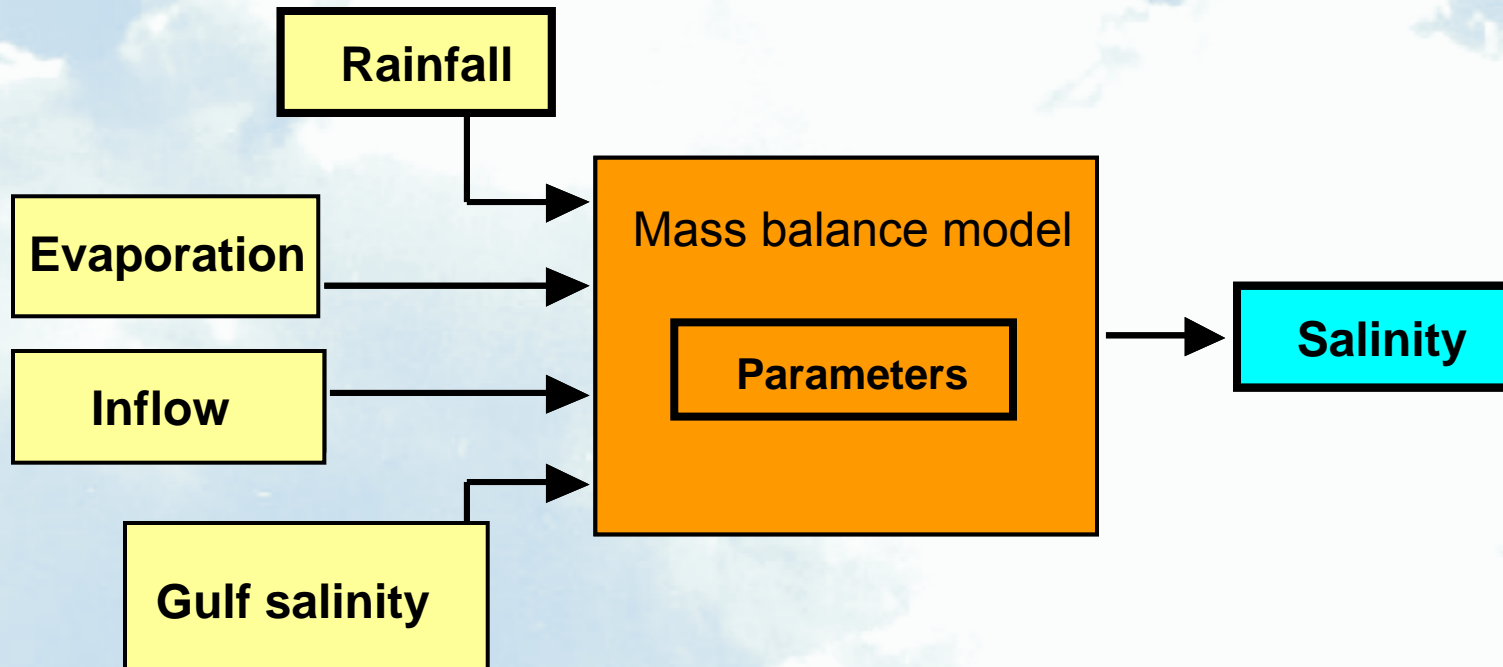




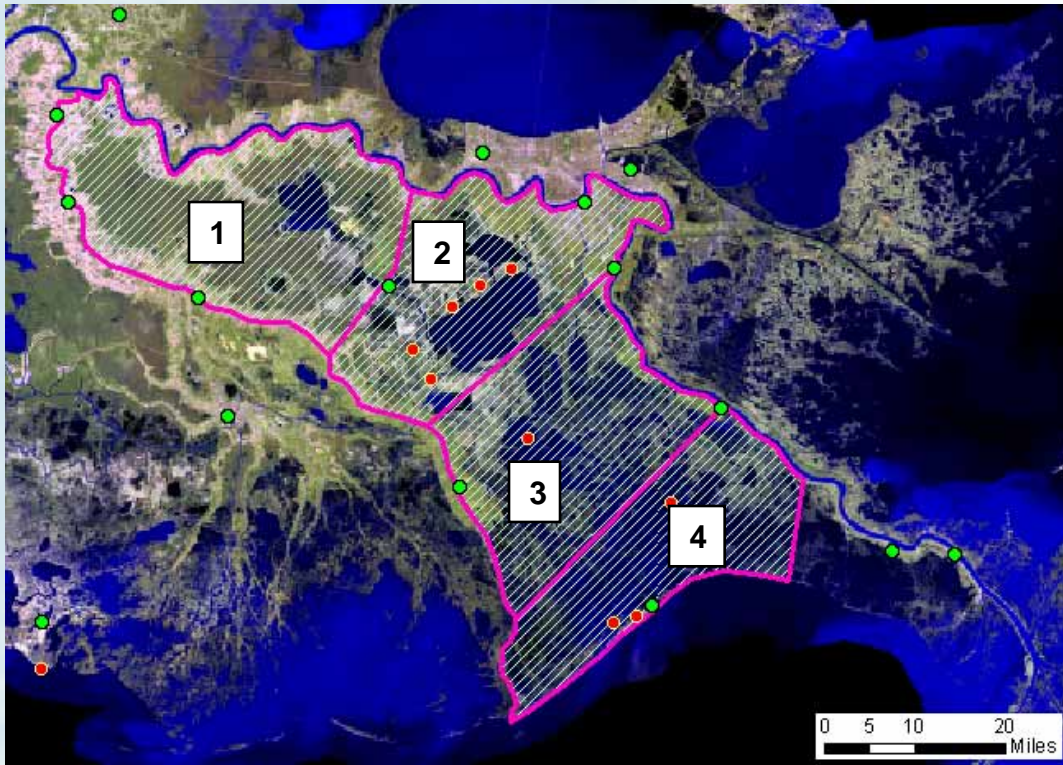
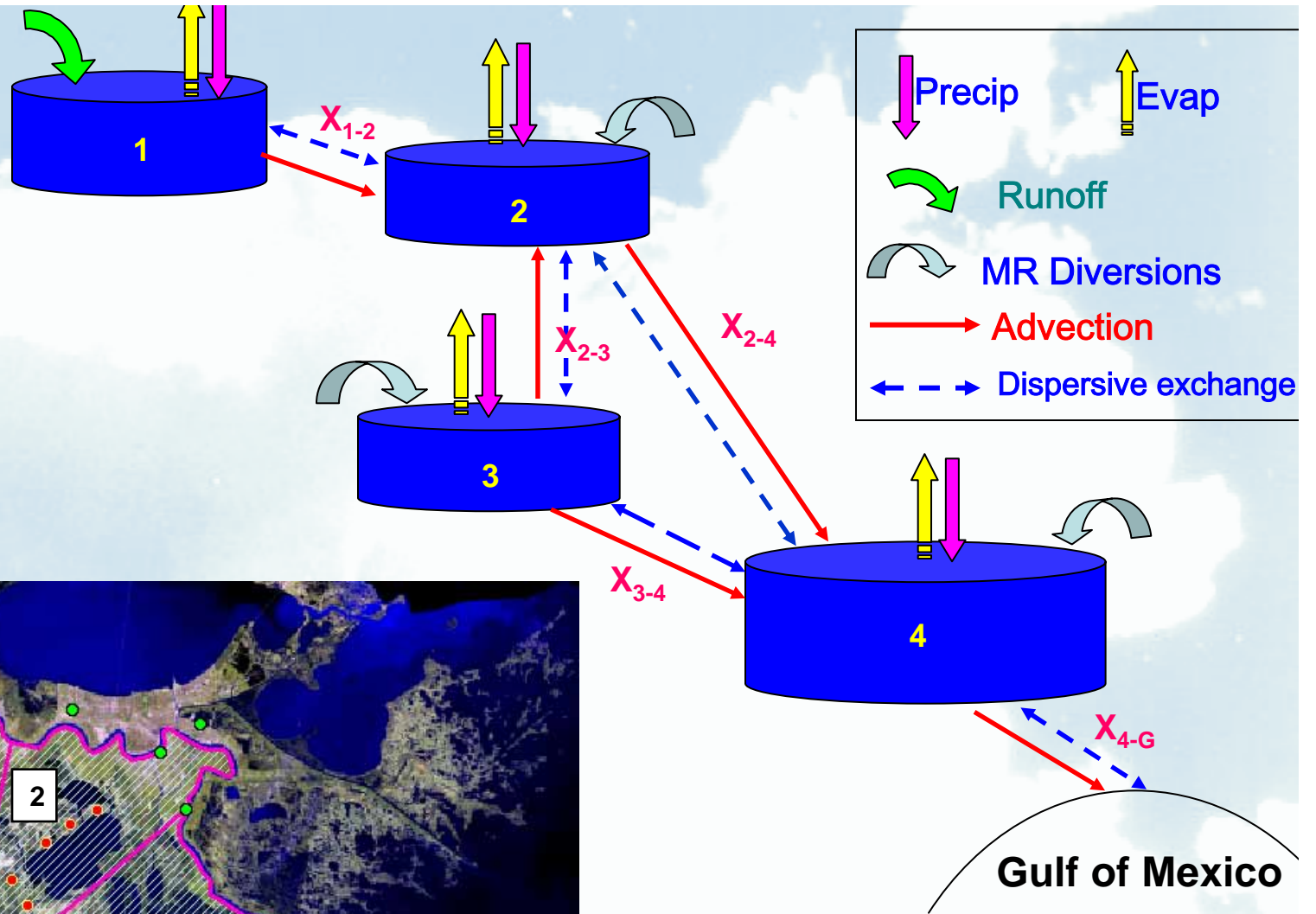
Annual rainfall: ~150 cm
Annual evaporation: ~75 cm



Salinity Mass-balance model

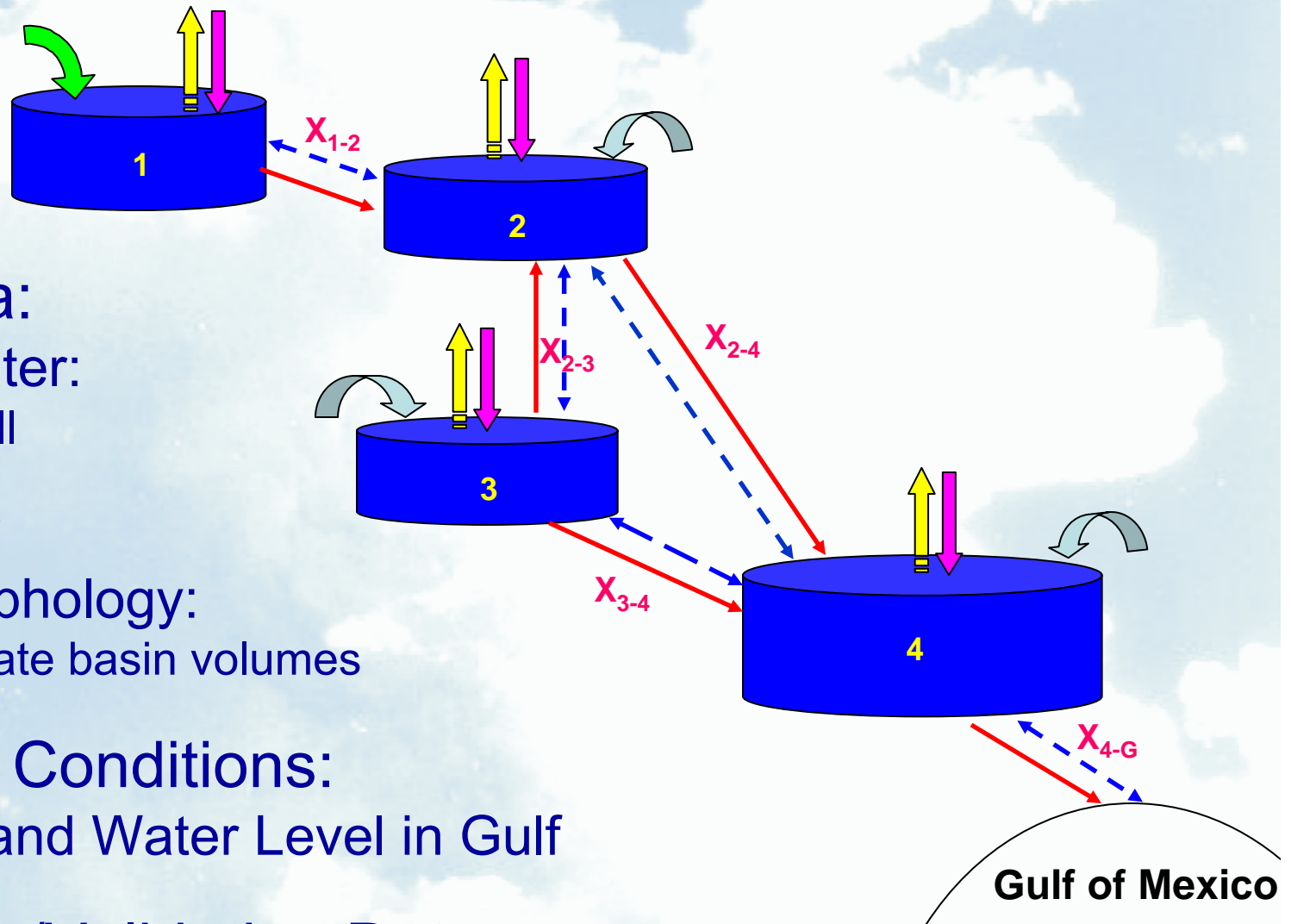


- Account for changes in salinity by:
 - Dilution from freshwater sources/sinks
 - Exchange with Gulf of Mexico
- Intended as screening tools to analyze restoration alternatives

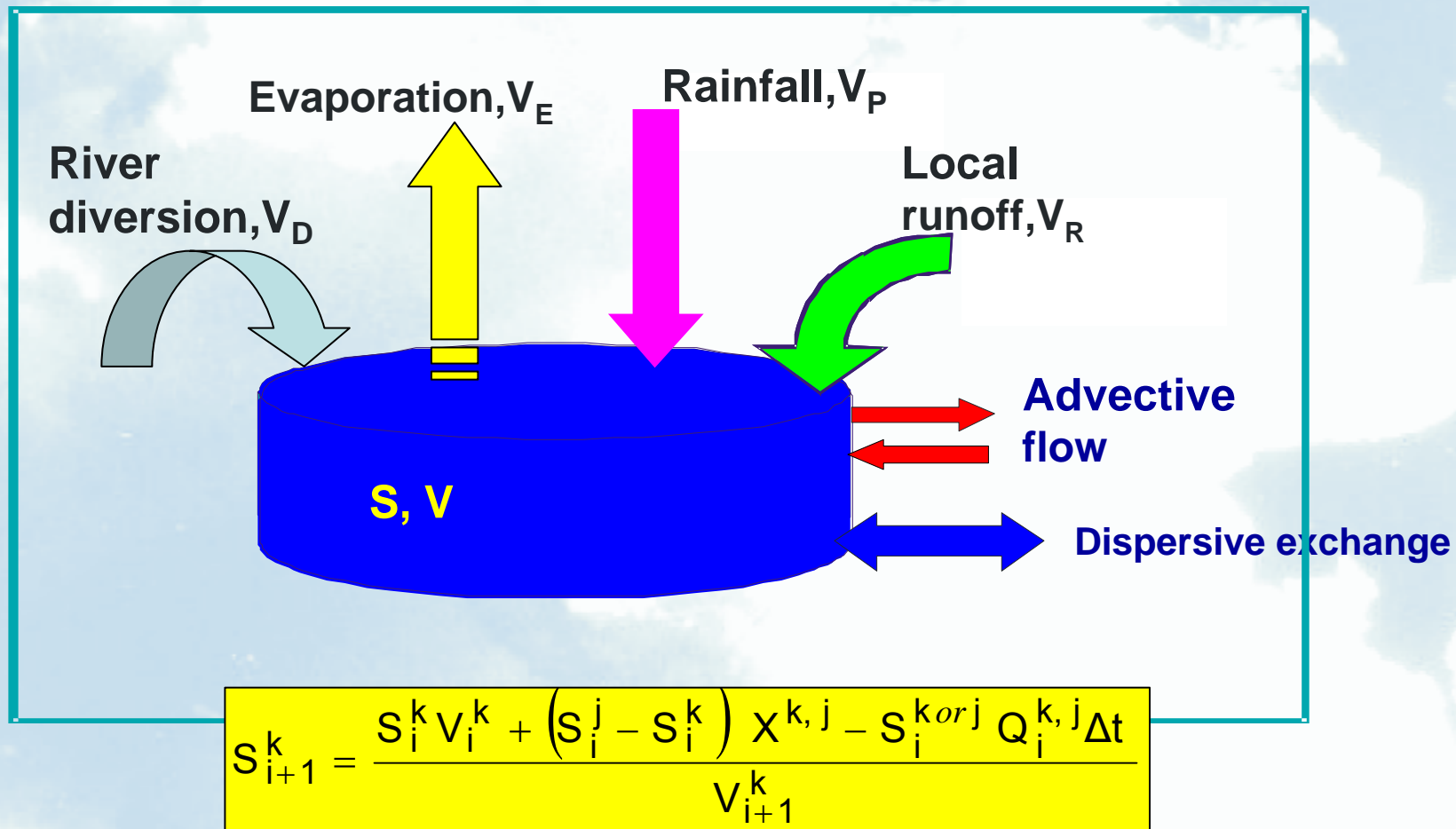


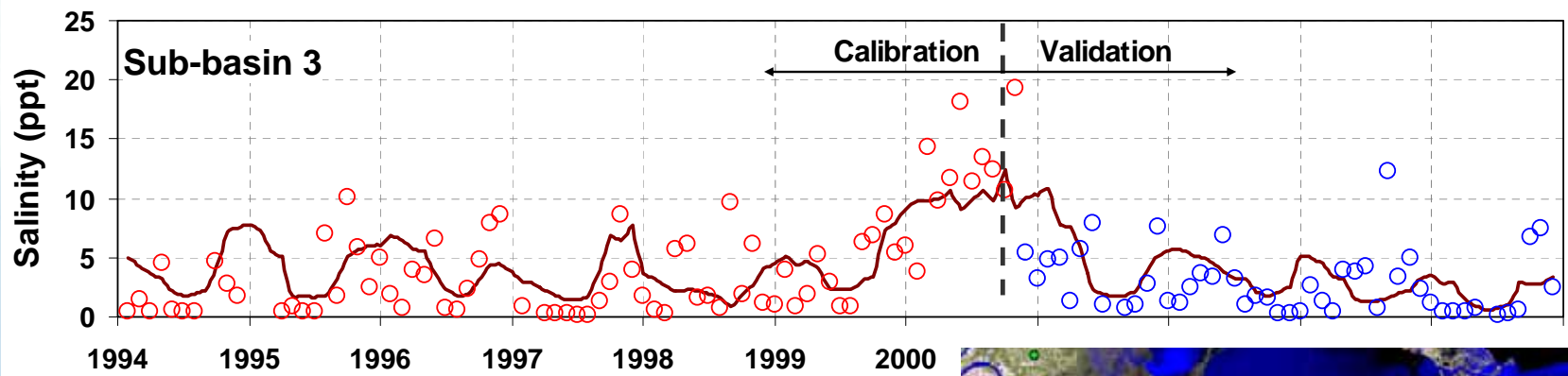
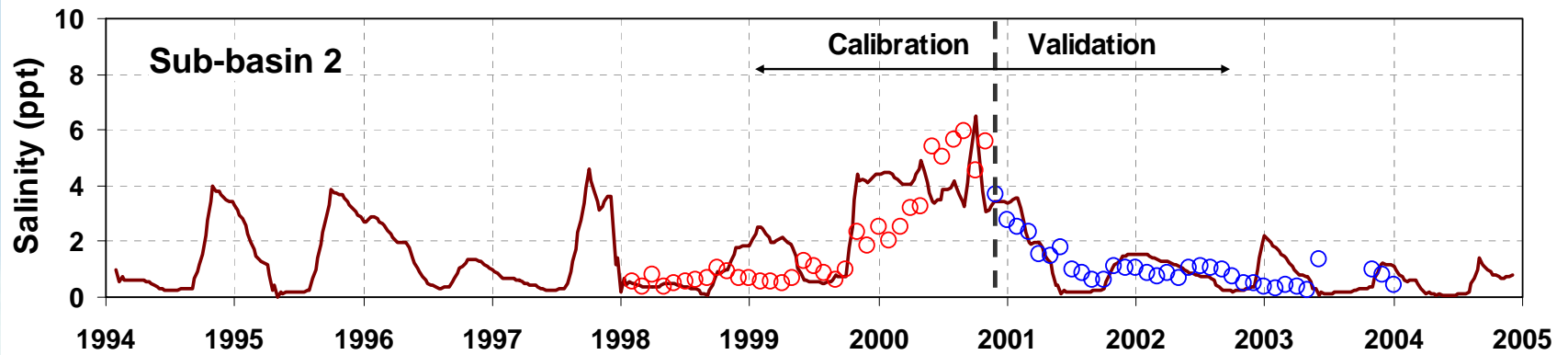
Gulf of Mexico

Data Needs

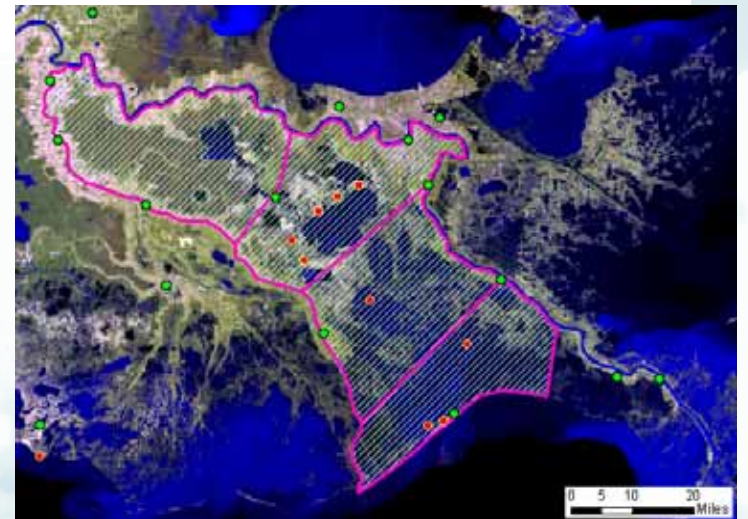
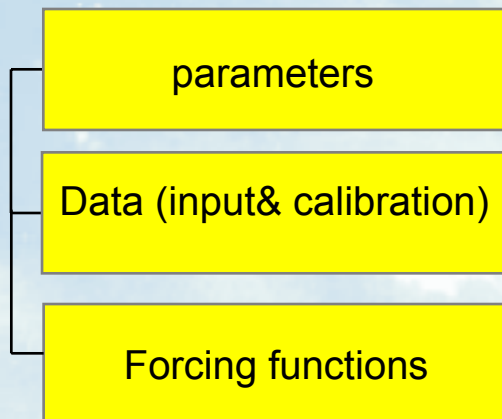


- Input Data:
 - Freshwater:
 - Rainfall
 - ET
 - Runoff
 - Geomorphology:
 - Calculate basin volumes
- Boundary Conditions:
 - Salinity and Water Level in Gulf
- Calibration/Validation Data:
 - Salinity measurements in different basins





Possible
Error sources



Sensitivity & Uncertainty Analysis Approach

– Regionalized Sensitivity Analysis (RSA)

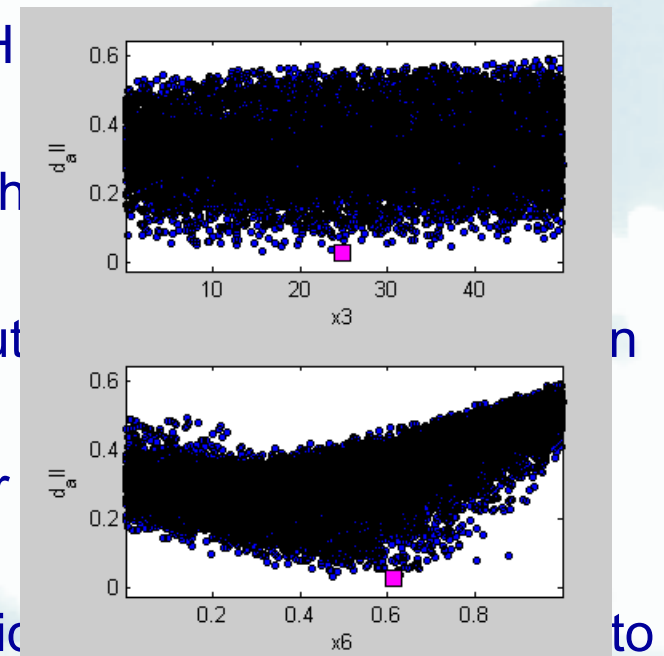
- Hornberger and Spear (1981)
- Freer et al. (1996)

– Generalized Likelihood Uncertainty Estimation (GLUE)

- Beven and Binley, (1992)
- Freer et al. (1996)
- Wagener et al., (2003)

Regionalized Sensitivity Analysis (RSA)

- In the face of model/data error, it is not possible to identify a single best model
- Start from a prior parameter distribution and run a Monte Carlo simulation
- Select a likelihood function (pseudo-probability) to assess acceptability of each model based on residuals from observations
- For every model (parameter set) calculate LH weight based on it
- Parameter sets are ranked according to likelihood into groups.
- For each group cumulative frequency distribution of normalized likelihoods
- A model is sensitive to a particular parameter if there are large differences between frequency distributions
- Parameters with large sensitivity indices are identified and used to improve predictive capabilities



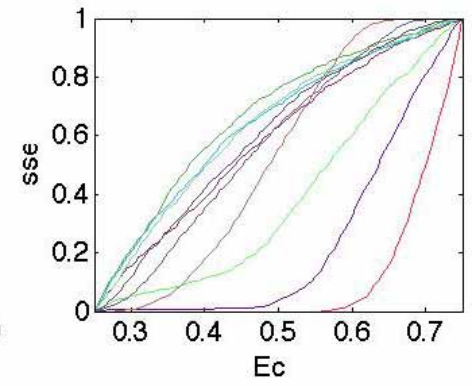
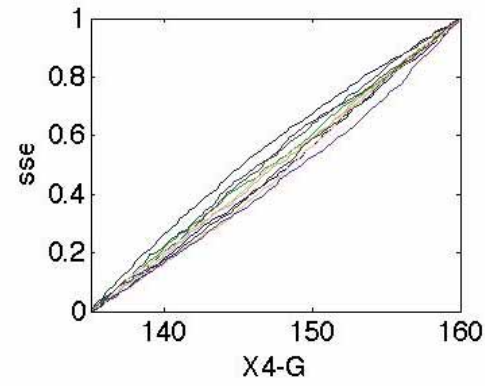
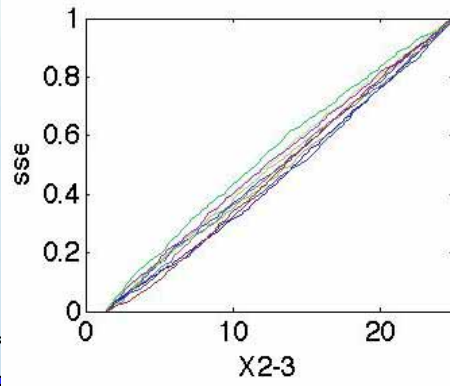
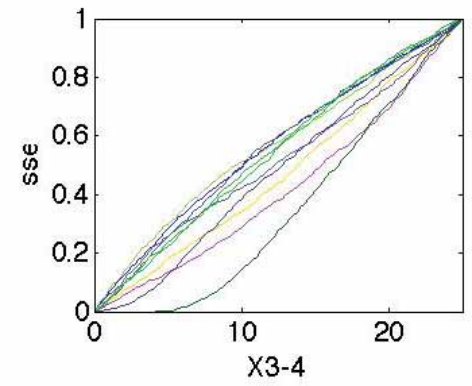
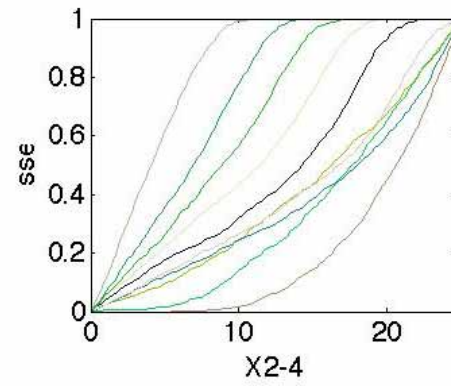
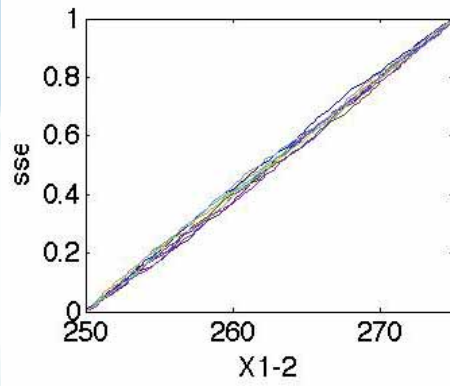
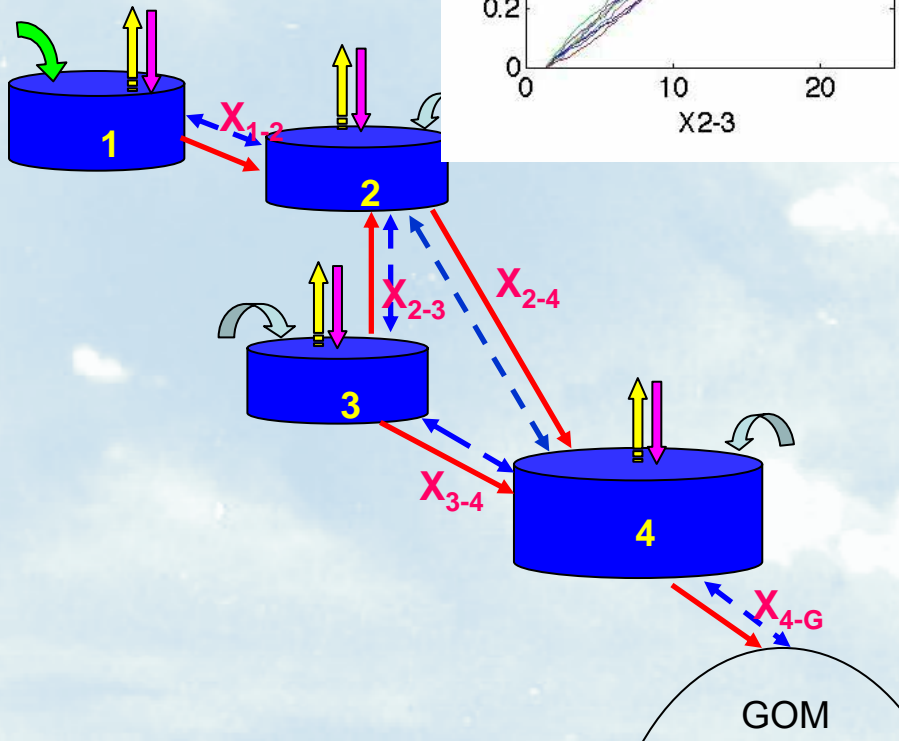
- A likelihood function of a certain parameter set (θ) to describe observed data (S):

$$L(\theta_i | S) : \sigma_\varepsilon^2 = \frac{1}{n-1} \sum_{j=1}^n [S_j - \hat{S}_j(\theta)]^2$$

$$L(\theta_i | S) : B = \frac{1}{n} \sum_{j=1}^n [S_j - \hat{S}_j(\theta)]$$

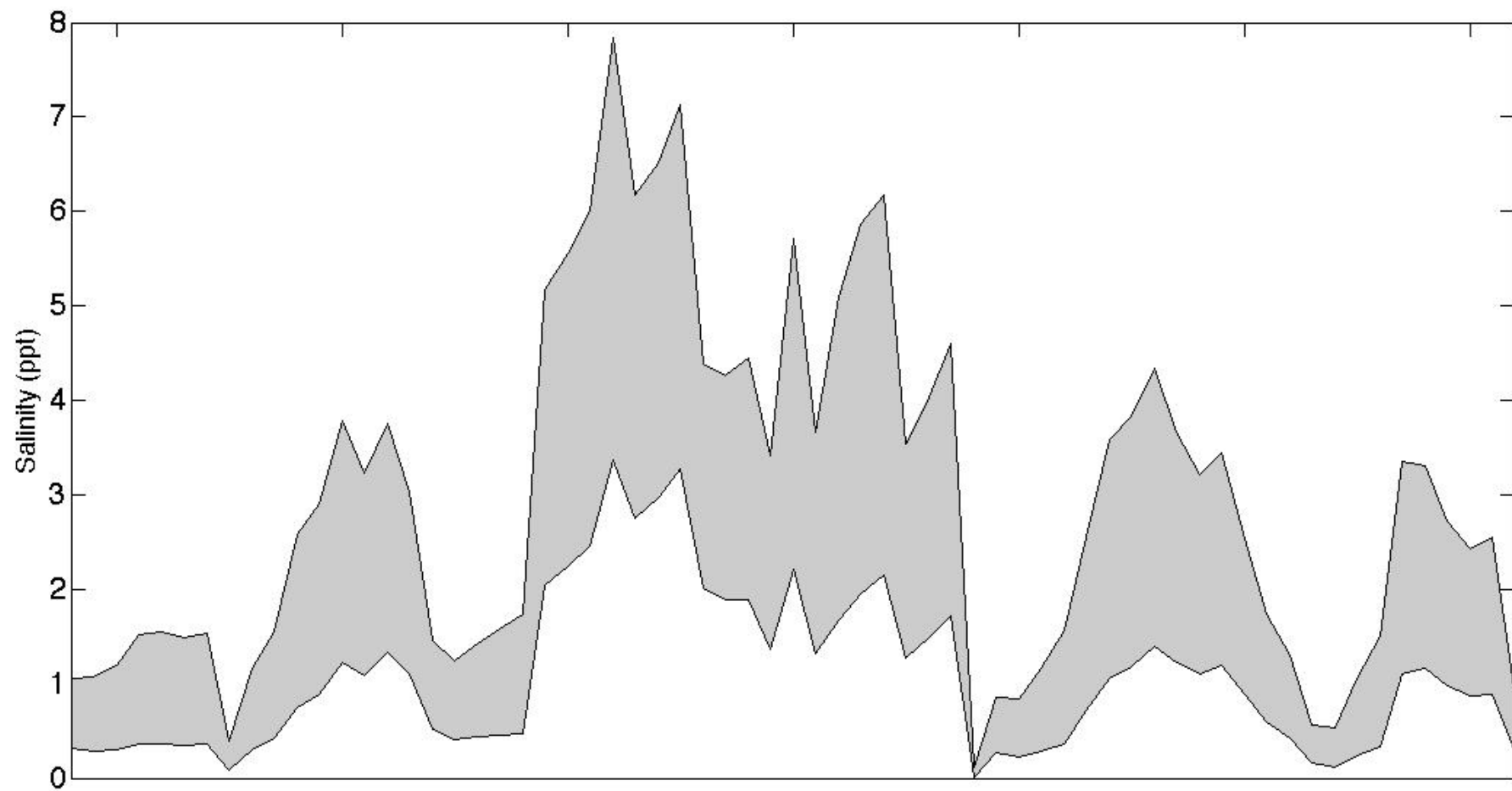
$$L(\theta_i | S) : E = 1 - \frac{\sigma_\varepsilon^2}{\sigma_o^2}$$

Likelihood functions can be defined over the entire basin domain, or over selected parts of it



Generalized Likelihood Uncertainty Estimation (GLUE)

- Prior distribution \rightarrow MC \rightarrow LH \rightarrow weights
- Filter any models that are not behavioral (i.e., $LH < \text{threshold}$)
- Likelihood-weighted behavioral model are used to:
 - Identify posterior parameter distribution
 - Obtain prediction quantiles at any time step



Time Series

Approach for tracking and decomposing sources of uncertainties

- Use the model to establish a reference state for the system
 - Complete & error-free input data and state variables
 - Perfect knowledge of forcing functions & parameters
 - Perfect knowledge of system response
- Corrupt reference state with different sources of uncertainties
- Use GLUE method investigate impact on:
 - Parameter retrieval
 - Prediction uncertainty

Approach

Use a fixed set of
model inputs

Select a Set of
"True" Parameters

Generate "True"
Salinity Observations

Introduce Single or
Combined
Uncertainty Sources

Salinity
Measurement
Errors

Lack of
Calibration
Data

Uncertain
Estimation of
Hydrologic
Forcing inputs

Apply GLUE to estimate:

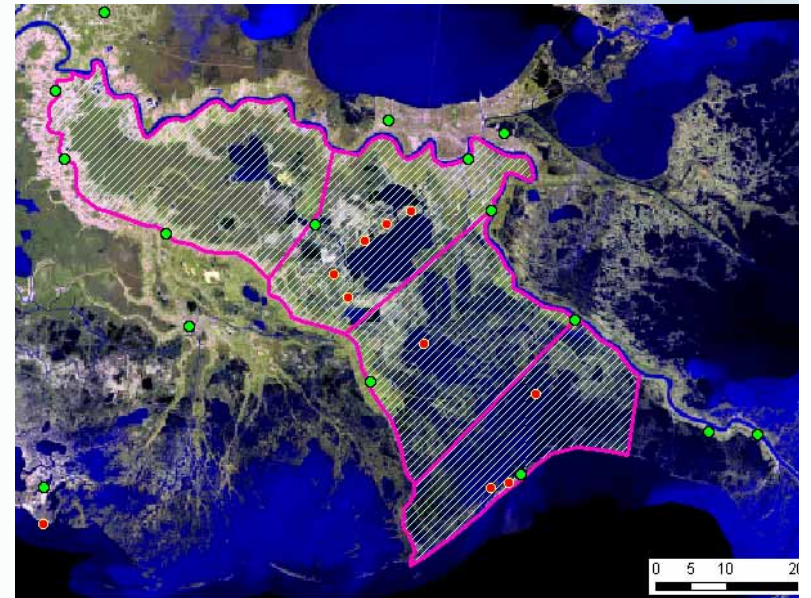
- *Posterior parameter distribution*
- *Model prediction uncertainty*

Modeling uncertainty in salinity data: random errors

- Instrumental errors (usually small)
- Uncertainty due to mismatch between model scales (sub-basin) and observational scales (point measurements).
- σ of differences between point and sub-basin average salinities was found to be ~ 1 to 2 ppt.
- Introduce Gaussian errors with varying levels of variance into salinity calibration data.

Modeling uncertainty in salinity data: incomplete coverage

- Uncertainty due to incomplete spatial coverage of salinity data available for calibration.
- To address this issue, salinity data used for model calibration are removed in one or more of the sub-basins.



Uncertainty in estimating areal-rainfall

- Among different freshwater sources in estuarine systems, rainfall is most challenging to quantify; why?
 - insufficient sampling & natural spatial variability
- This introduces uncertainty in evaluating mean-areal rainfall required as input for salinity model calculations.

Modeling rainfall uncertainty

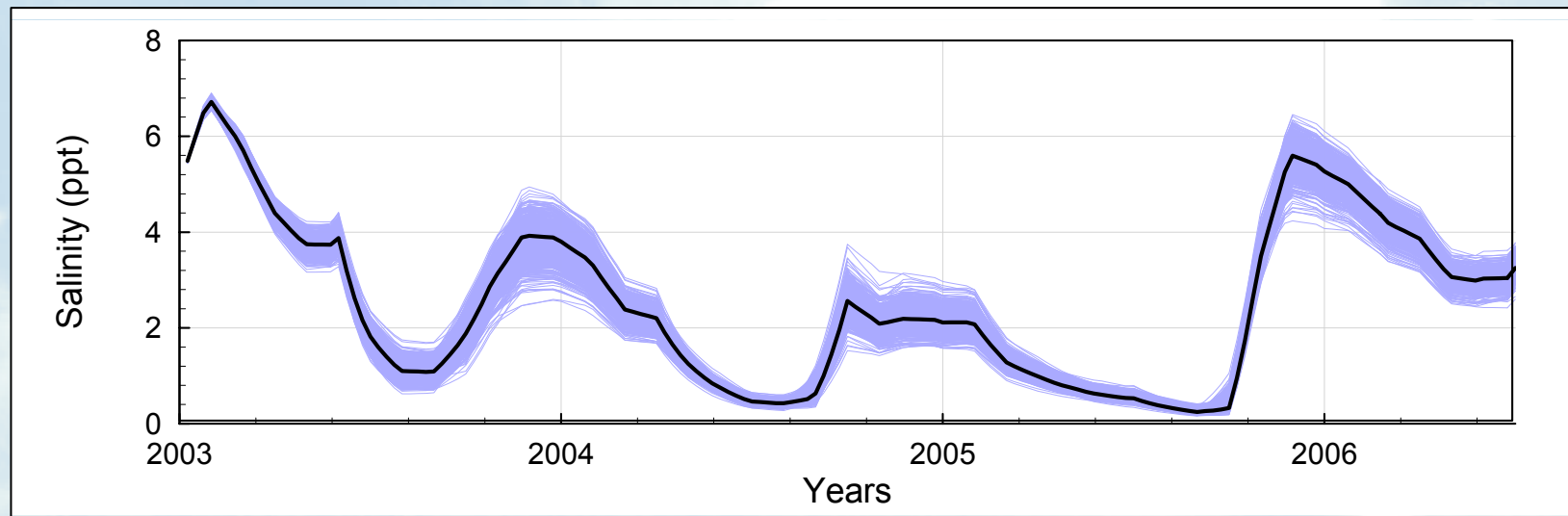
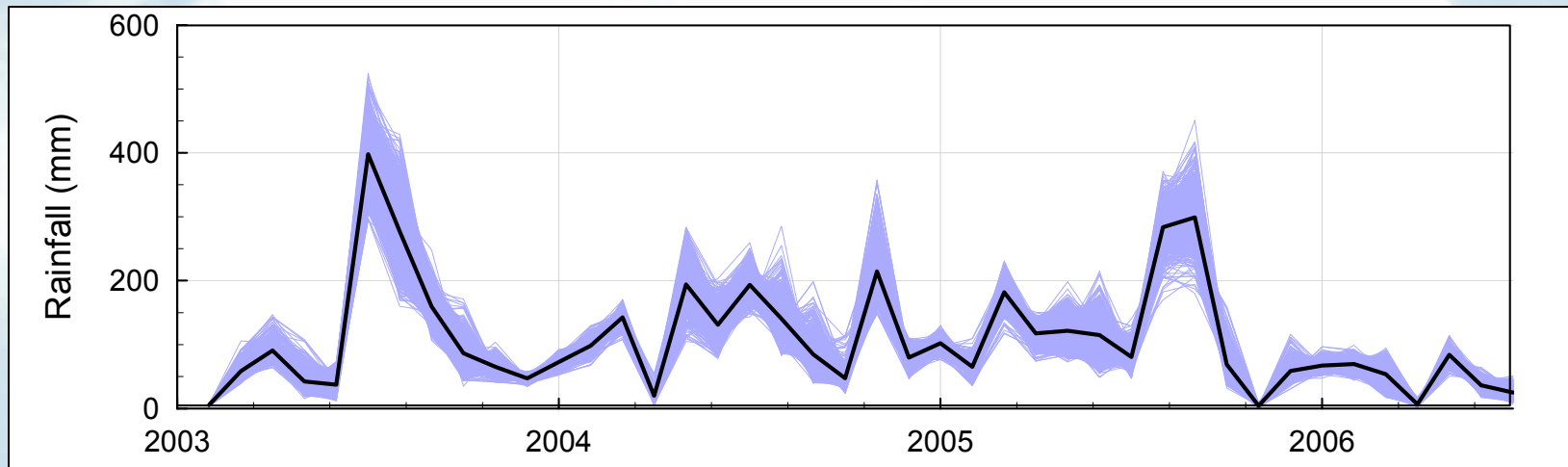
- One scenario of rainfall sampling is examined:
 - a single rain gauge randomly located in each sub-basin domain
- An empirical multiplicative model is used to describe single-gauge sampling errors

$$R_g = \varepsilon(R_a) R_a$$

$$\varepsilon \sim N(1, \sigma_{\varepsilon|R_a}^2);$$

$$\sigma_{\varepsilon|R_a}^2 = \alpha (R_a)^{-\beta}$$

rainfall error model



Uncertainty Metrics

$$B = \frac{\frac{1}{n} \sum_{i=1}^n \left[\frac{1}{N} \sum_{j=1}^N M_{i,j} - O_i \right]}{\bar{O}}$$

Bias

$$UR = \frac{\frac{1}{n} \sum_{i=1}^n (P_{97.5,i} - P_{2.5,i})}{\bar{M}}$$

Uncertainty bounds

Uncertainty Scenario	Uncertainty in model predictions							
	Average bias: <i>B</i> (%)				Average 95% range: <i>UR</i> (%)			
	Sub-basin				Sub-basin			
	1	2	3	4	1	2	3	4
(i)	7.3	1.5	0	0	44.5	17.5	6.7	2.0
(ii)	-0.04	0	0	0	2.9	0.24	0.08	0.02
(iii)	1.39	-0.5	-0.1	-0.1	186	104	64.6	23
(i) & (ii)	132	2.6	-1	0	342	19	7.5	2
(i) & (iii)	8.9	0.7	-0.1	-0.1	195	103	64	23
(ii) & (iii)	199.0	1.4	0.5	-0.1	598	105	63.8	23.7
(i), (ii), & (iii)	255	3.3	0.4	-0.1	569	104	63.8	23.7

- (i) errors in calibration data with $\sigma=1$ ppt,
- (ii) missing calibration data in sub-basin 1
- (iii) uncertain rainfall input.

Uncertainty Scenario	Parameter 95% Confidence Interval		
	X_{1-2} (1.0)	X_{3-4} (4)	E_c (0.75)
(i)	0.14 - 4.3	2.8 - 5.8	0.73 - 0.77
(ii)	0.88 - 1.1	3.9 - 4.0	0.74 - 0.75
(iii)	0.01 - 3.3	3.1 - 9.7	0.65 - 0.81
(i) & (ii)	0.46 - 255	2.5 - 5.7	0.72 - 0.77
(i) & (iii)	0.1 - 5.1	2.9 - 10.3	0.65 - 0.82
(ii) & (iii)	0.01 - 300	2.3 - 9.6	0.66 - 0.83
(i), (ii), & (iii)	0.7 - 290	2.1 - 9.7	0.66 - 0.83

- (i) errors in calibration data with $\sigma=1$ ppt,
- (ii) missing calibration data in sub-basin 1
- (iii) uncertain rainfall input.

Applications

1. Analysis of different restoration alternatives
2. Design of a rain-gage network for hydro-ecological purposes

Application: Exploring Restoration Options

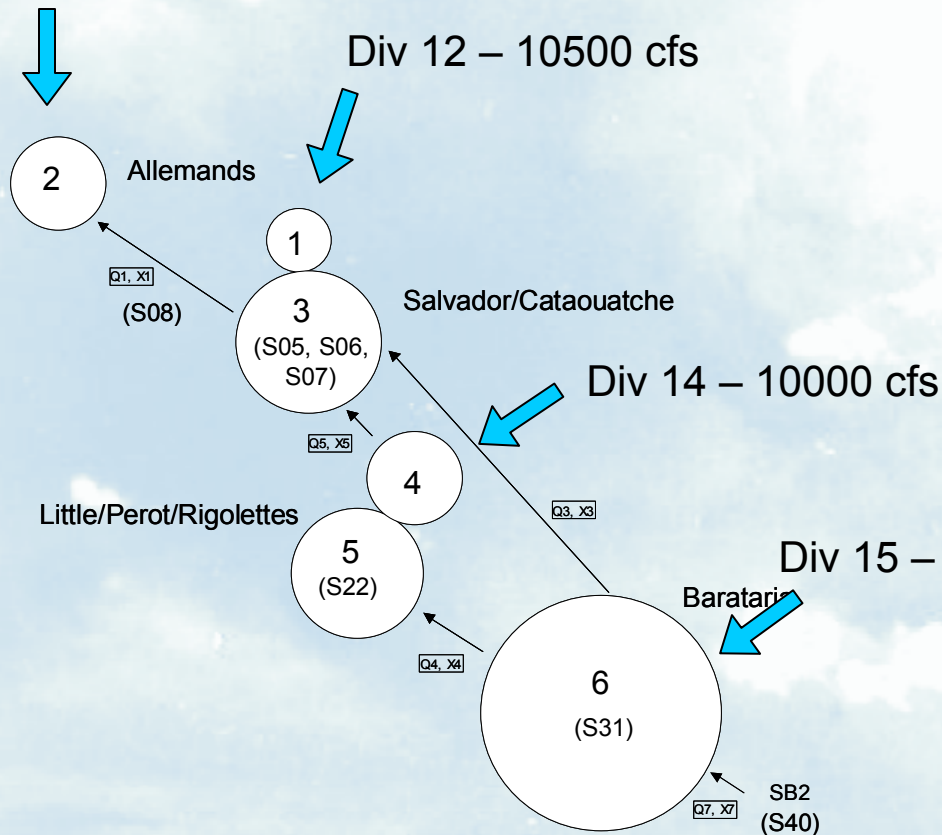
Master Plan Diversions

Div 12 – 5000 cfs
Div 11 – 5000 cfs

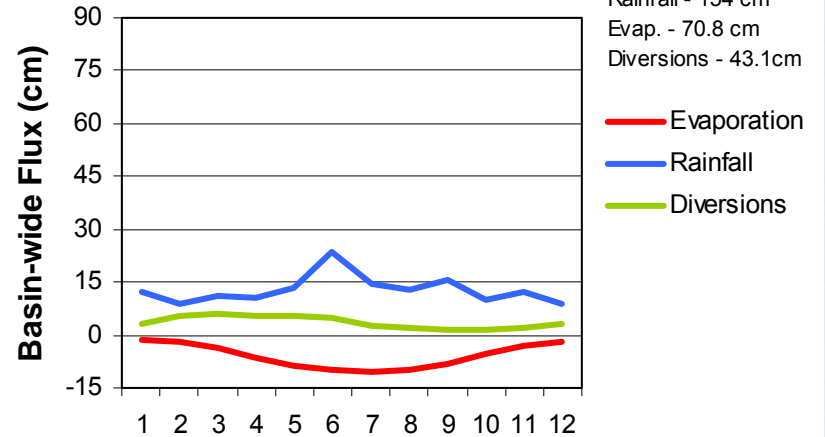
Div 12 – 10500 cfs

Div 14 – 10000 cfs

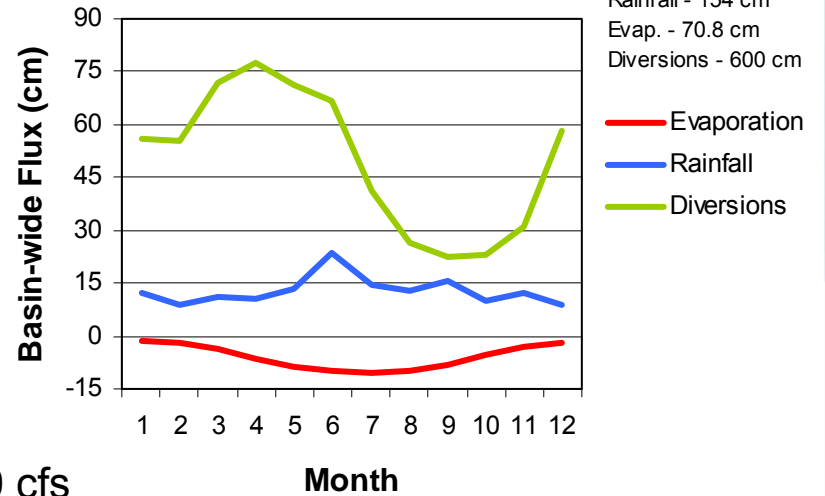
Div 15 – 15000 cfs



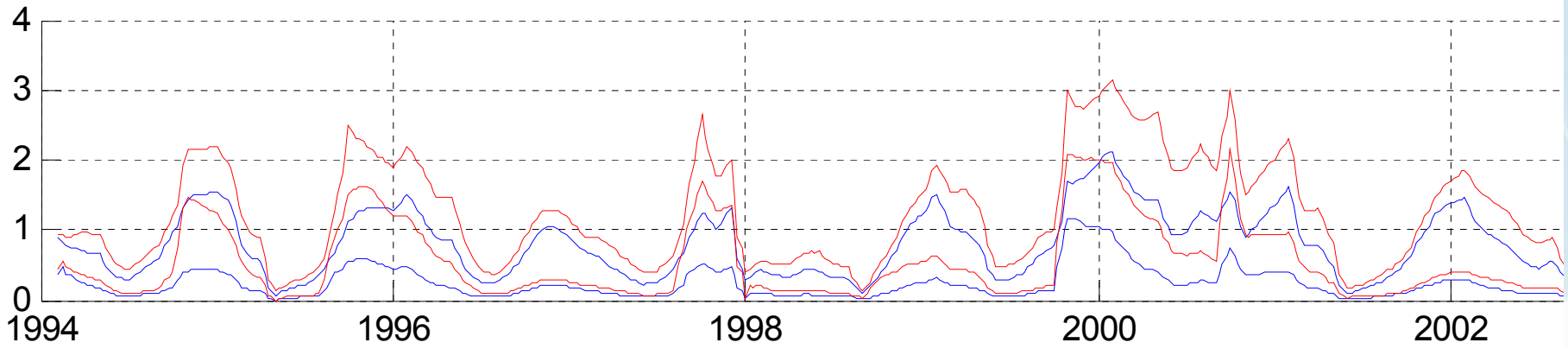
Water Budget - Base Case



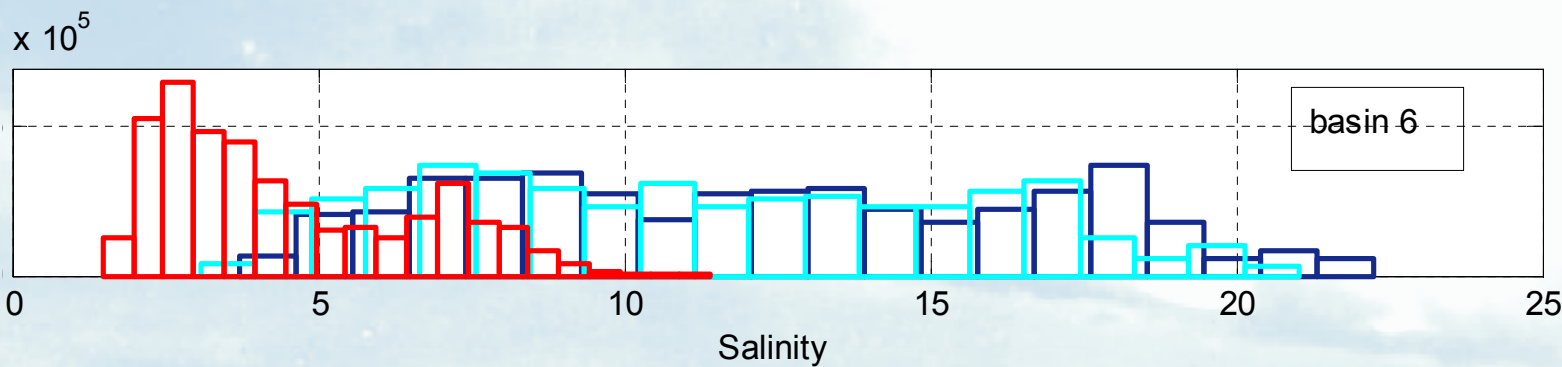
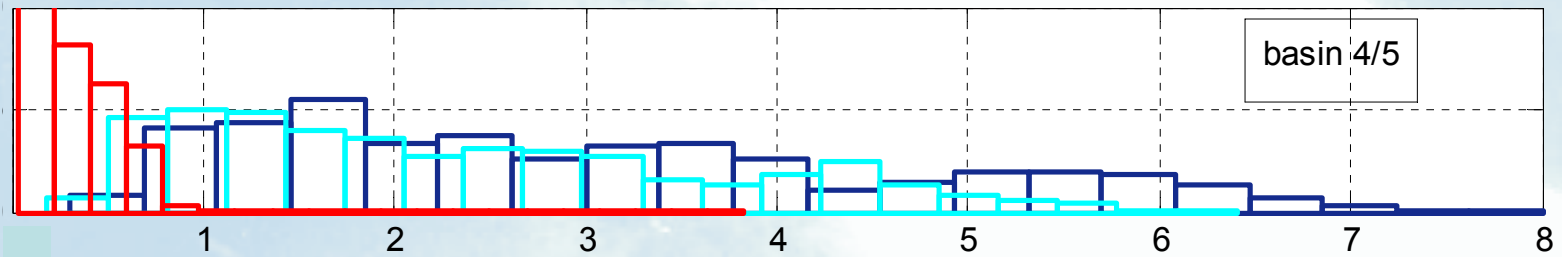
Water Budget - Alt 3



Comparison of Alternatives

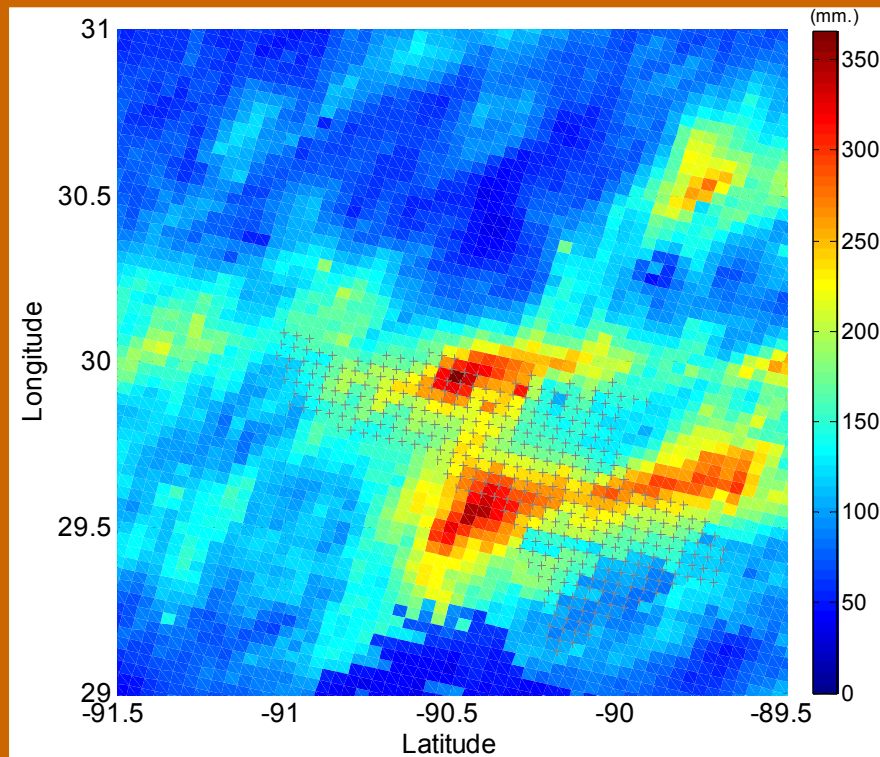
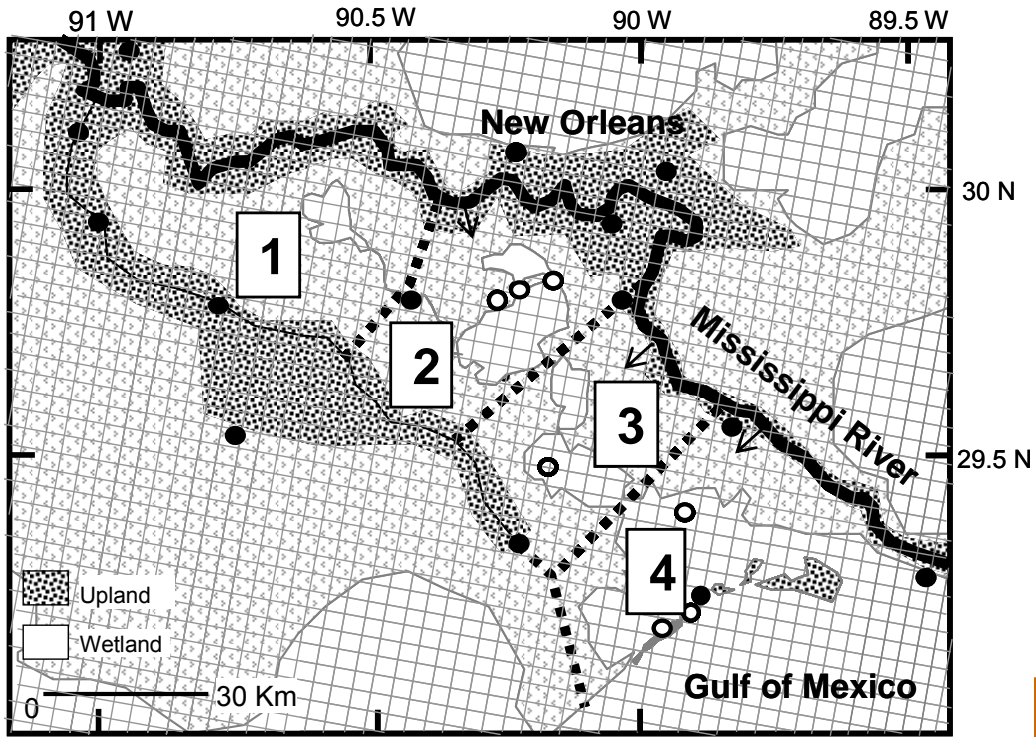


Salinity Distributions

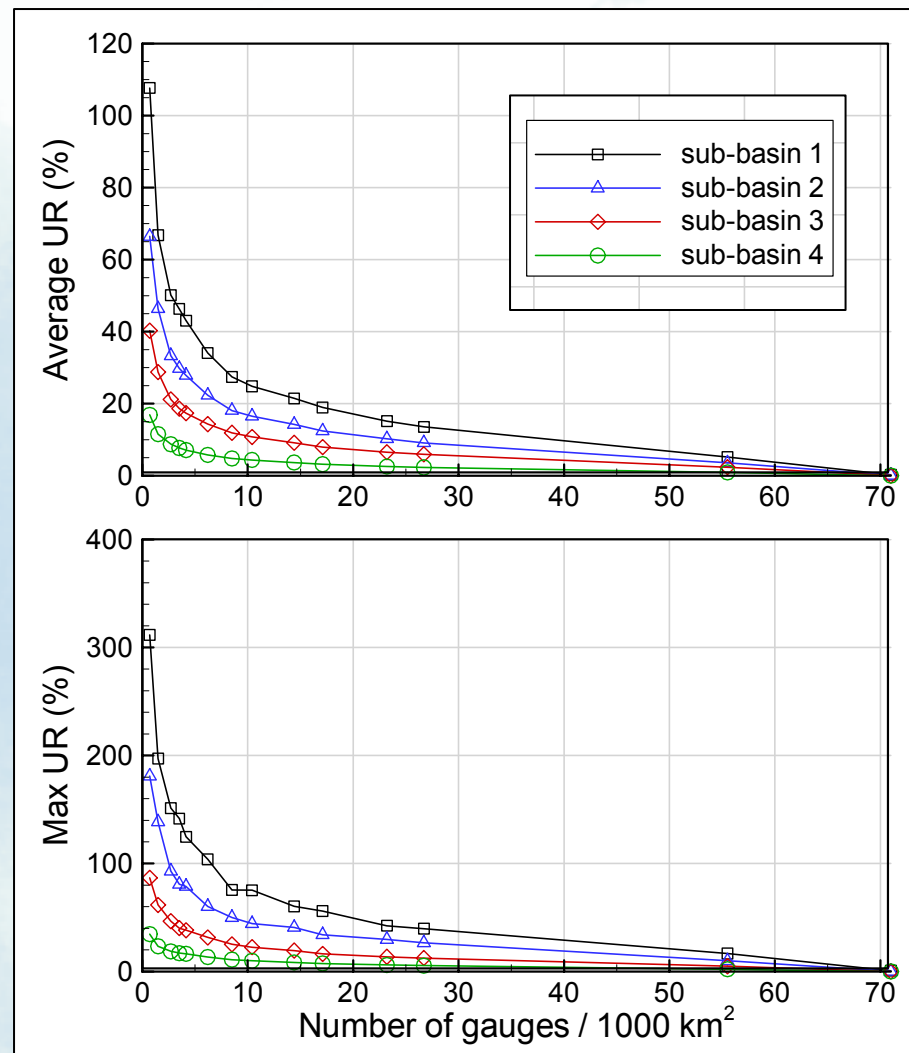


Applications

1. Analysis of different restoration alternatives
2. Designing a rain-gage network for hydro-ecological purposes



Designing a rain-gage network for hydro-ecological purposes



Summary

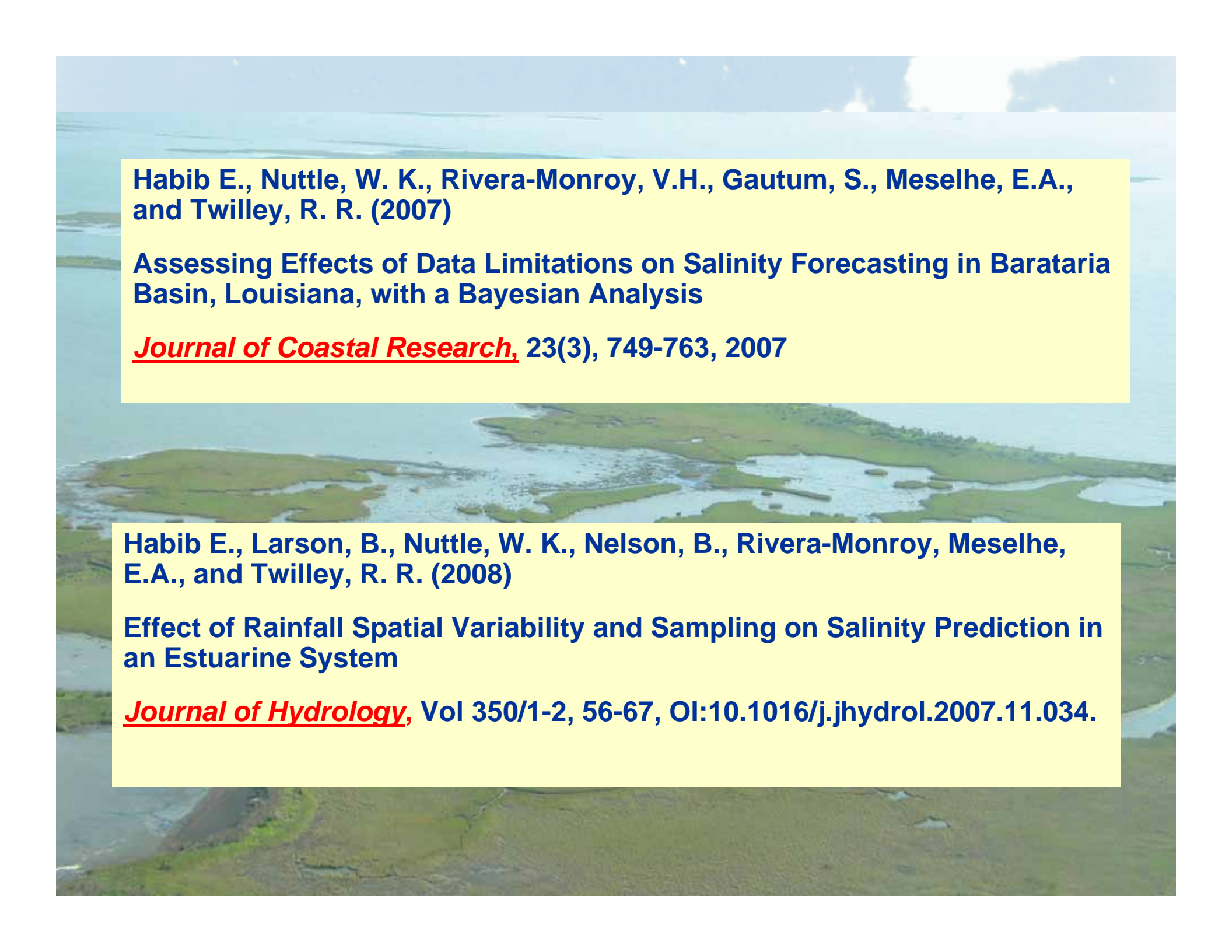
- This study demonstrates the kind of information that uncertainty analysis can provide to managers charged with restoration of estuarine systems.
- Uncertainty information becomes critical to assuring consistency in decision-making when different restoration activities are assessed for potential implementation
- Of the three investigated sources of uncertainty, uncertainty in rainfall volumes has the most significant impact on salinity predictions in Barataria basin.
- Limitations on salinity data available for calibration also contribute to uncertainties in the model parameters.
- Different sources of uncertainty combine in such a way as to amplify their separate effects.

Practical Implications

- Further development and optimization of a monitoring network to facilitate model construction, calibration and validation
- At a minimum, salinity monitoring should support a meso-scale network that captures spatial mean behavior in each sub-basin
- Improve sampling densities of rainfall to accurately capture basin-average volumes
- We need better ET estimates. For evaporation and solar radiation, at least two stations are needed.
- Radiation data also will help to develop and validate water quality models

Future work

- The analysis presented in this study is illustrative, rather than comprehensive.
- Analysis of uncertainty of other factors (ET estimates, influence of MR flow, basin geomorphology).
- Examine uncertainties of other ecological models and water quality variables
- Extend the model to include nutrient calculations and develop probabilistic forecasts of algae bloom outbreaks in large water bodies
- Link and propagate the uncertainty information to benefit assessment calculations
- Investigate how natural variability of climatic processes can affect our ability to forecast and interpret how different restoration strategies may work as intended (100-year planning horizon)



Habib E., Nuttle, W. K., Rivera-Monroy, V.H., Gautum, S., Meselhe, E.A., and Twilley, R. R. (2007)

Assessing Effects of Data Limitations on Salinity Forecasting in Barataria Basin, Louisiana, with a Bayesian Analysis

Journal of Coastal Research, 23(3), 749-763, 2007

Habib E., Larson, B., Nuttle, W. K., Nelson, B., Rivera-Monroy, Meselhe, E.A., and Twilley, R. R. (2008)

Effect of Rainfall Spatial Variability and Sampling on Salinity Prediction in an Estuarine System

Journal of Hydrology, Vol 350/1-2, 56-67, [OI:10.1016/j.jhydrol.2007.11.034](https://doi.org/10.1016/j.jhydrol.2007.11.034).