Uncertainty in Coastal Ocean Modeling

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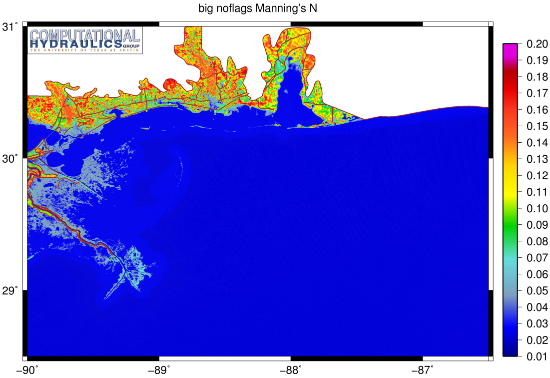
Motivation

Coastal Ocean Modeling

- Oil transport
- Sediment transport
- Dredging feasibility
- **Hurricane storm surge**



Hurricane Storm Surge

Hurricane Katrina -- 2005

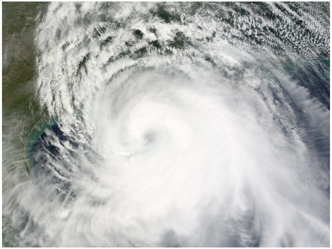
- Category 5
- 1833 fatalities
- $108 billion in damage
- Costliest US hurricane

(Wik, 2012b, Craft, 2011, Blake et al., 2007)

Hurricane Ike -- 2008

- Category 4
- 195 fatalities
- $37.6 billion in damage
- 3rd Costliest US hurricane

(Wik, 2012a, Craft, 2011, Blake et al., 2007)



Advanced Circulation (ADCIRC) Model

- Finite element in space, finite-difference in time
- Validated on Hurricane Ike, Katrina, Gustav, Rita. . .
- Fortran, MPI, C/C++

- storm surge
- tidal and wind driven circulation
- oil movement
- near shore coastal development studies

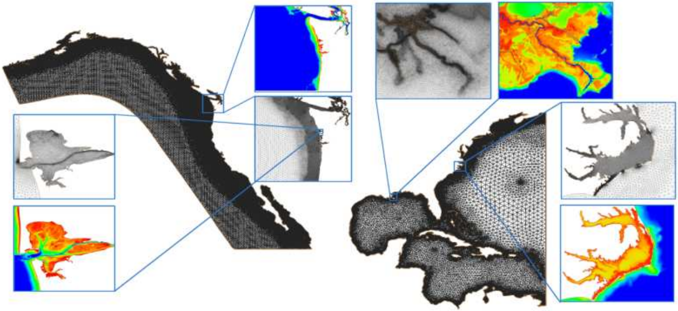


Figure : ADCIRC Coastal Circulation and Storm Surge Model adcirc.org

Shallow Water Equations

"Storm surge is primarily a competition between wind forcing and frictional resistance." (Dawson et al., 2011)

$$\frac{dU}{dt} - fV = -g\frac{\partial[\zeta + P_s/g\rho_0 - \alpha\eta]}{\partial x} + \frac{\tau_{sx}}{\rho_0 H} - \frac{\tau_{bx}}{H\rho_0} + \frac{M_x}{H} - \frac{D_x}{H} - \frac{B_x}{H}$$
$$\frac{dV}{dt} + fV = -g\frac{\partial[\zeta + P_s/g\rho_0 - \alpha\eta]}{\partial y} + \frac{\tau_{sy}}{\rho_0 H} - \frac{\tau_{by}}{H\rho_0} + \frac{M_y}{H} - \frac{D_y}{H} - \frac{B_y}{H}$$

τ_{bx}, τ_{by}	**Bottom stress components**	τ_{sx}, τ_{sy}	**Applied free-surface stress**
ζ	Free-surface elevation relative to the geoid	g	Gravitational acceleration
H	$\zeta + h =$ water depth	h	Bathymetric depth
P_s	Atmospheric pressure at the free surface	ρ_0	Reference density of water
α	Effective earth elasticity factor	η	Newtonian equilibrium tide potential
f	Coriolis coefficient	U, V	Depth-averaged horizontal velocities
M_x, M_y	Vert.-integrated lateral stress gradient	D_x, D_y	Momentum Dispersion
B_x, B_y	Vert.-integrated baroclinic pressure gradient		

(Luettich and Westerink, 2004)

Modeling bottom friction with a spatially varying **Manning's** n value

Bottom friction

$$\frac{\tau_{bx}}{\rho_0} = C_d U \sqrt{U^2 + V^2}; \qquad \frac{\tau_{by}}{\rho_0} = C_d V \sqrt{U^2 + V^2}$$

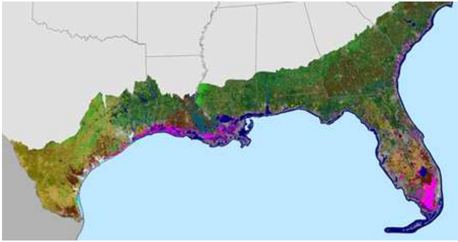
Drag Coefficient

$$C_d(t) = \frac{gn^2}{(h + \eta(t))^{1/3}} = \frac{gn^2}{H^{1/3}}$$

(Luettich and Westerink, 2010, Yen, 2002, 2004, Leopold et al., 1964, Chow, 2008).

NOAA C-CAP Land Coverage and Classification

The Manning's n coefficient is a highly variable spatial parameter often defined on a sub-grid scale, e.g. using land classification data defined pixel-by-pixel from high resolution imagery.



http://www.csc.noaa.gov/crs/lca/gulfcoast.html

Table: Manning's n values for LA-GAP classification

2	0.120	High Intensity Developed
3	0.100	Medium Intensity Developed
4	0.070	Low Intesnity Developed
5	0.035	Developed Open Space
6	0.100	Cultivated Land
7	0.055	Pasture/Hay
8	0.035	Grassland
9	0.160	Deciduous Forest
10	0.180	Evergreen Forest
11	0.170	Mixed Forest
12	0.080	Scrub/Shrub
13	0.150	Palustrine Forested Wetland
14	0.075	Palustrine Scrub/Shrub Wetland
15	0.070	Palustrine Emergent Wetland
16	0.150	Estuarine Forested Wetland
17	0.070	Estuarine Scrub/Schrub Wetland
18	0.050	Estuarine Emergent Wetland
19	0.030	Unconsolidated Shore
20	0.030	Bare Land
21	0.025	Open Water
22	0.035	Palustrine Aquatic Bed
23	0.030	Estuarine Aquatic Bed

http://www.csc.noaa.gov/crs/lca/gulfcoast.html

The Stochastic Inverse Problem for ADCIRC

Given

- $\Lambda \subset \mathbb{R}^m$, a compact **parameter domain** with a specified metric (e.g. a finite dimensional representation of possible Manning's n fields),
- $M(Y, \lambda)$ with a solution $Y = Y(\lambda)$, a deterministic **physics based model** (e.g. the Advanced Circulation Model of Oceanic, Coastal and Estuarine Waters (ADCIRC)),
- $Q : \Lambda \to \mathcal{D}$, a map composed of **quantities of interest** (QoI) $Q(\lambda) = (q_1(\lambda), \dots, q_d(\lambda)) \in \mathcal{D} \subset \mathbb{R}^d$ where $q_i(\lambda) := q_i(Y(\lambda))$, for all $\lambda \in \Lambda$ where $d \leq m$

  (e.g. maximum water elevation at d observation stations),
- and an observed (or assumed) **probability density** $\rho_{\mathcal{D}}$ on $\mathcal{B}_{\mathcal{D}}$ for the data domain $\mathcal{D}$.

Assume $\mathcal{D} := Q(\Lambda)$ and that the Jacobian of $Q(\lambda)$ has full rank a.e. in Λ.

The Stochastic Inverse Problem for ADCIRC

Determine

- the **probability density** ρ_Λ on $\mathcal{B}_\Lambda$ for the parameter domain Λ.

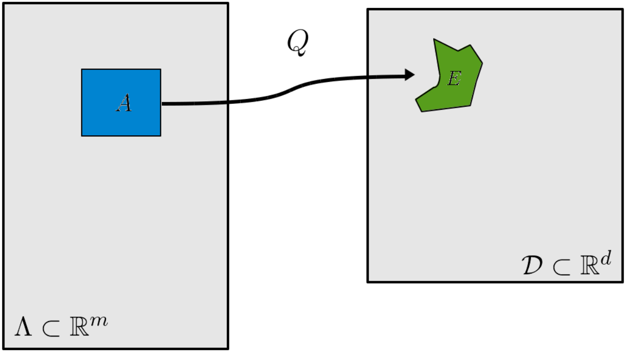
Use ρ_Λ to

- compute **probabilities, $(P(A))$, of arbitrary measurable events** $A \in \mathcal{B}_\Lambda$ (Borel σ-algebra on Λ)
  (e.g. the probability of sets of Manning's n fields),
- identify highly probable regions of Λ (**parameter estimation**)
  (e.g. the most probable set of Manning's n fields),
- etc.

This information is useful for forward uncertainty quantification, parameter estimation, inverse sensitivity analysis, and identification of inverse sets.

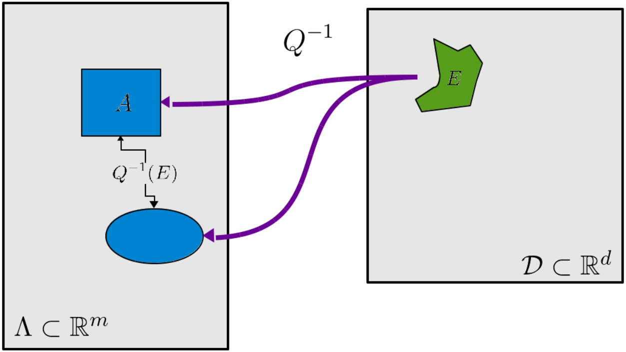
Forward Problem

Given a QoI map $Q : \Lambda \to \mathcal{D}$, a set of parameters $A \in \mathcal{B}_\Lambda$, and a measure μ_Λ. Determine the set of data $E \in \mathcal{B}_\mathcal{D}$ such that $Q(A) = E$ where the push-forward measure is $\mu_\mathcal{D}(E) = \int_E d\mu_\mathcal{D} = \int_{Q^{-1}(E)} d\mu_\Lambda = \mu_\Lambda(Q^{-1}(E))$.



Inverse Problem

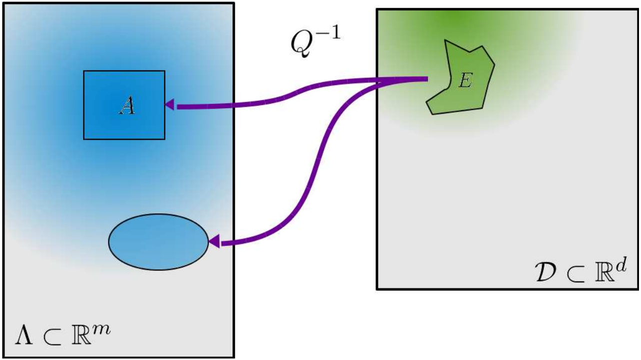
Given a QoI map $Q : \Lambda \to \mathcal{D}$, a set of data $E \in \mathcal{B}_{\mathcal{D}}$, and a measure μ_Λ. Determine the set of parameters $A \in \mathcal{B}_\Lambda$ such that $Q^{-1}(E) = A$ where $\mu_\Lambda(A) = \int_A d\mu_\Lambda = \int_{Q(A)} d\mu_{\mathcal{D}} = \mu_{\mathcal{D}}(Q(A))$.



Inverse Stochastic Problem

Given a QoI map $Q : \Lambda \to \mathcal{D}$, a set of parameters $A \in \mathcal{B}_\Lambda$, a measure μ_Λ, and a density $\rho_\mathcal{D}$ on the data space. *Determine and use ρ_Λ to compute probabilities of events.*

$$P_\Lambda(A) = \int_A \rho_\Lambda d\mu_\Lambda = \int_{Q(A)} \rho_\mathcal{D} d\mu_\mathcal{D} = P_\mathcal{D}(Q(A)).$$



Sample Based Approximation of P_Λ

Theorem

Given

- $Q : \Lambda \to \mathcal{D}$, a QoI map;
- μ_Λ, the measure on the parameter space Λ;
- $\rho_\mathcal{D}$, a probability density on $(\mathcal{D}, \mathcal{B}_\mathcal{D})$, absolutely continuous with respect to $\mu_\mathcal{D}(\cdot) = \mu_\Lambda(Q^{-1}(\cdot))$;
- and an event $A \in \mathcal{B}_\Lambda$

there exists a sequence of simple function approximations to probability densities, $\rho_{\Lambda,N}$ and $\rho_{\mathcal{D},M}$, requiring only calculations of volumes such that

$$P_{\Lambda,N}(A) \to P_\Lambda(A) \text{ as } N, M \to \infty$$

(Butler et al., 2014).

A Case Study: The Idealized Inlet

The Stochastic Inverse Problem for ADCIRC

Given

- $\Lambda \subset \mathbb{R}^m$, a compact **parameter domain** with a specified metric (e.g. a finite dimensional representation of possible Manning's n fields),
- $M(Y, \lambda)$ with a solution $Y = Y(\lambda)$, a deterministic **physics based model** (e.g. the Advanced Circulation Model of Oceanic, Coastal and Estuarine Waters (ADCIRC)),
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  (e.g. maximum water elevation at d observation stations),
- and an observed (or assumed) **probability density** $\rho_{\mathcal{D}}$ on $\mathcal{B}_{\mathcal{D}}$ for the data domain $\mathcal{D}$.

Assume $\mathcal{D} := Q(\Lambda)$ and that the Jacobian of $Q(\lambda)$ has full rank a.e. in Λ.

The Stochastic Inverse Problem for ADCIRC

Determine

- the **probability density** ρ_Λ on $\mathcal{B}_\Lambda$ for the parameter domain Λ.

Use ρ_Λ to

- compute **probabilities,** $(P(A))$**, of arbitrary measurable events** $A \in \mathcal{B}_\Lambda$ (Borel σ-algebra on Λ)
  (e.g. the probability of sets of Manning's n fields),
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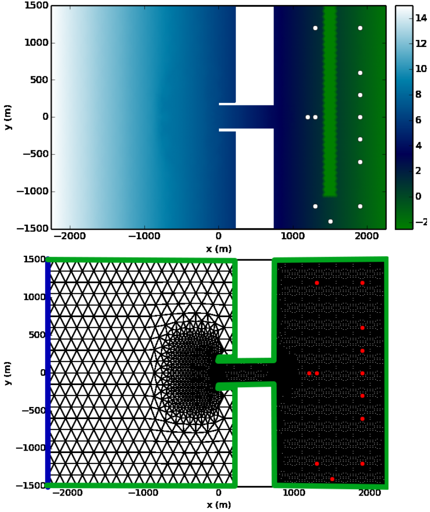
- etc.

This information is useful for forward uncertainty quantification, parameter estimation, inverse sensitivity analysis, and identification of inverse sets.

$M(Y, \lambda)$ with a solution $Y = Y(\lambda)$, a deterministic **physics based model** (e.g. the Advanced Circulation Model of Oceanic, Coastal and Estuarine Waters (ADCIRC))

Computational Domain

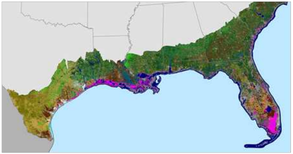


- Open ocean boundary with M_2 tidal amplitude of $1.2[m/s]$
- Land boundary $(\mathbf{u} \cdot \mathbf{n} = 0)$ and no slip
- Earthen jetty between $x = 1420[m], 1580[m]$, and $y = 1500[m], -1050[m]$.

Define $\Lambda \subset \mathbb{R}^m$, a compact **parameter domain** with a specified metric (e.g. a finite dimensional representation of possible Manning's n fields)

Parameter Domain

Mapping Manning's n onto a computational mesh

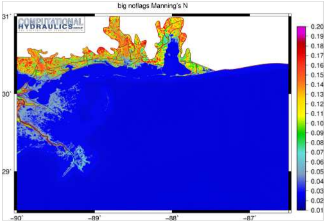


+

spatial average

$\longrightarrow$

Manning's n table

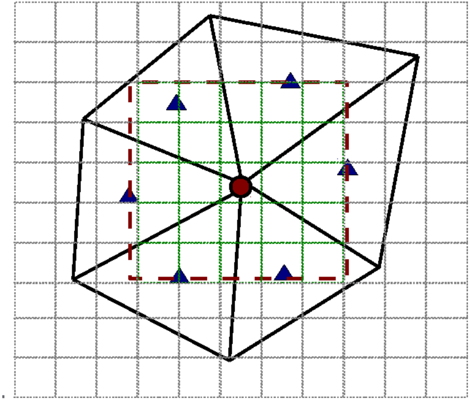


A Mesoscale representation of Manning's n

We can construct a set of land classification meshes $\{\mathbf{b}_i\}_{i=1}^{m}$ such that

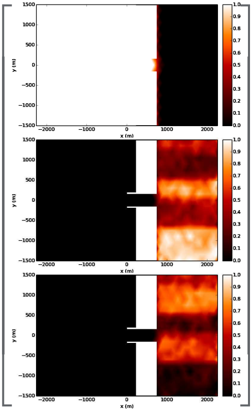
$$\mathbf{n} = [\mathbf{b_1} \ldots \mathbf{b_m}] \cdot \lambda$$

$$\mathbf{n} = \{n_k\}_{k=1}^{N_{nodes}}$$

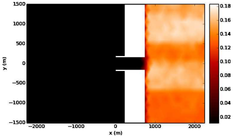


A Mesoscale representation of Manning's n

Let $\boldsymbol{\lambda} = \{\lambda_i\}_{i=1}^{m} \in \mathbb{R}^{+m}$, where λ_i is the Manning's n value associated with the i^{th} land classification and m is the total number of land classifications.



$$\cdot \begin{bmatrix} \lambda_0 \\ \lambda_1 \\ \lambda_2 \end{bmatrix} =$$



A Mesoscale representation of Manning's n

We construct a set of land classification meshes $\{\mathbf{b}_i\}_{i=1}^{m}$ such that

$$\mathbf{n} = [\mathbf{b_1} \ldots \mathbf{b_m}] \cdot \boldsymbol{\lambda}$$
$$\mathbf{n} = \{n_k\}_{k=1}^{N_{nodes}} .$$

The Manning's n value at the k^{th} node in the mesh is n_k.

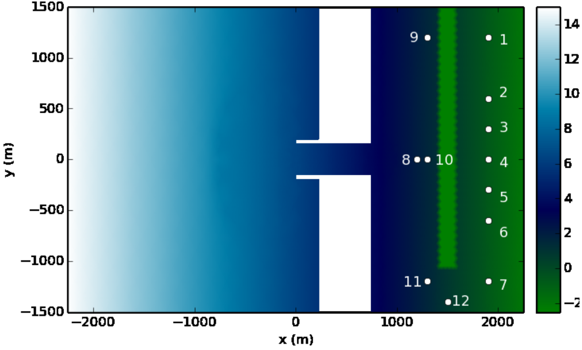
Parameter	Range of Manning's n values	Land Classification
λ_0	0.012	Water
λ_1	$[0.07, 0.15]$	Wetland
λ_2	$[0.1, 0.2]$	Forest

So the compact finite dimensional parameter domain is $\Lambda = [0.07, 0.15] \times [0.1, 0.2] \subset \mathbb{R}^2$.

Quantities of interest (QoI) $Q(\lambda) = (q_1(\lambda), \ldots, q_d(\lambda)) \in \mathcal{D} \subset \mathbb{R}^d$ where $q_i(\lambda) := q_i(Y(\lambda))$, for all $\lambda \in \Lambda$
(e.g. maximum water elevation at d observation stations)

Data Domain

Observation Stations $q_i(\lambda) := q_i(Y(\lambda))$ is the maximum water elevation at the i^{th} observation station.



Data Domain

Choose a set of QoI to define $\mathcal{D}$ and define $\rho_{\mathcal{D}}$.

Prescribe an observed (or assumed) **probability density** $\rho_{\mathcal{D}}$ on $\mathcal{B}_{\mathcal{D}}$.
Assume $\mathcal{D} := Q(\Lambda)$ and that the components of Q are **geometrically distinct**.

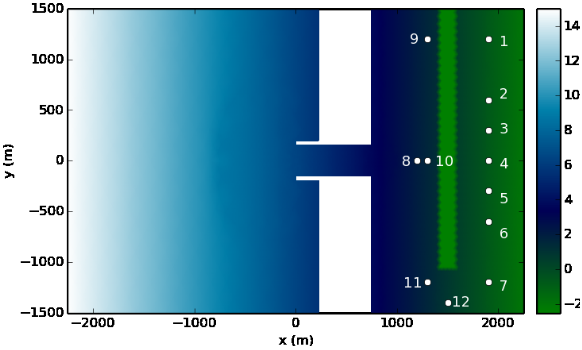
Geometrically Distinct QoI

The Jacobian of $Q(\lambda)$ has full rank a.e. in Λ.

Recall that $Q(\lambda) \in \mathbb{R}^d$ and $d \leq m$ so there are at most m **geometrically distinct** QoI.

Observation Stations

$q_i(\lambda) := q_i(Y(\lambda))$ is the maximum water elevation at the i^{th} observation station.



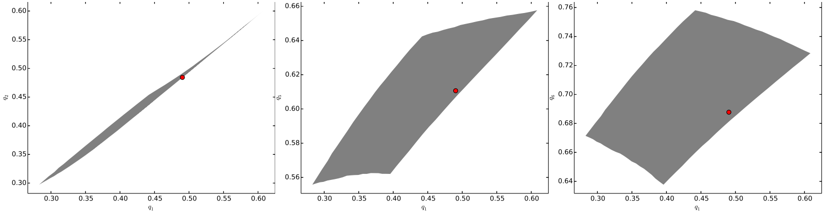
Choosing QoI for a well-conditioned inverse problem

Restrict Q to $Q_{\mathcal{L}} : \mathcal{L} \to \mathcal{D}$ then the accuracy of our solution is dependent on

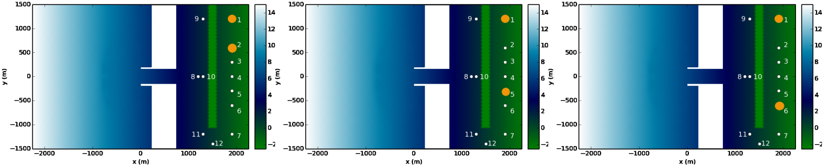
$$\max_i(\text{skew}(J_{Q_{\mathcal{L}}}(\lambda^{(i)}))). \tag{2.1}$$

Large skewness implies less precision in the predictions using the solution of the inverse problem.

Choosing QoI for a well-conditioned inverse problem

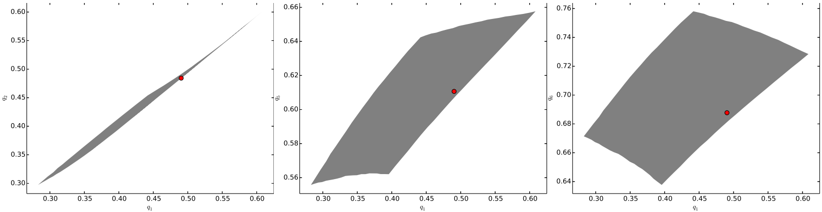


The domain $\mathcal{D} := Q(\Lambda) = \{q_1(\Lambda), q_n(\Lambda)\}$ for $n = 2, 5, 6$. $Q_{reference}$ for $(\lambda_1, \lambda_2) = (0.107, 0.106)$ is marked in red.

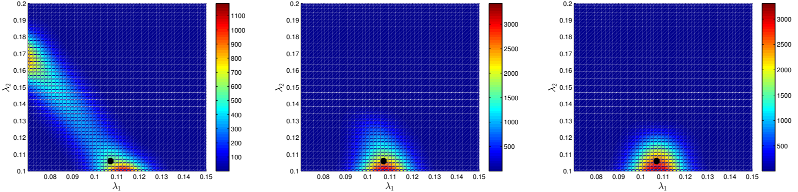


The observation stations. Columns: $Q = (q_1, q_2)$, (q_1, q_5), and (q_1, q_6) for the first, second, and third columns respectively.

Choosing QoI for a well-conditioned inverse problem



The domain $\mathcal{D} := Q(\Lambda) = \{q_1(\Lambda), q_n(\Lambda)\}$ for $n = 2, 5, 6$. The truth $Q_{reference}$ for $(\lambda_1, \lambda_2) = (0.107, 0.106)$ is marked in red.



The approximation of ρ_λ where $\lambda_{reference} = (\lambda_1, \lambda_2) = (0.107, 0.106)$. Columns: $Q = (q_1, q_2)$, (q_1, q_5), and (q_1, q_6) for the first, second, and third columns respectively.

Forward Prediction Problem

- Define the inverse problem (Choose Λ, $\mathcal{D}$, $\rho_{\mathcal{D}}$)
- Solve inverse problem
- Define the forward problem (Choose Prediction Space)
- Solve the forward problem

Prediction of time of inundation at $(x_1, y_1) = (1593.75, 1087.5)$ and $(x_2, y_2) = (1593.75, 1012.5)$ for regions in Λ containing 95% of the total probability

Prediction Location	RoI in Prediction Space		
(x, y)	(q_1, q_2)	(q_1, q_6)	Inundation t
(x_1, y_1)	(16:36:50, 19:08:56)	(18:01:36, 19:08:56)	18:36:58
(x_2, y_2)	(26:35:38, 27:18:52)	(27:14:24, 27:19:14)	27:17:08

Forward Prediction Problem

- Define and solve the inverse problem (Choose Λ, $\mathcal{D}$, $\rho_{\mathcal{D}}$)
- Define and solve the forward problem (Choose Prediction Space)

Prediction of time of inundation at $(x_1, y_1) = (1593.75, 1087.5)$ and $(x_2, y_2) = (1593.75, 1012.5)$ for regions in Λ containing 95% of the total probability

Prediction Location (x, y)	RoI in Prediction Space (q_1, q_2)	(q_1, q_6)	Inundation t
(x_1, y_1)	9126s	4040s	18:36:58
(x_2, y_2)	2594s	290s	27:17:08

A Case Study: Hurricane Gustav

The Stochastic Inverse Problem for ADCIRC

Recall that we require

- $\Lambda \subset \mathbb{R}^m$, a compact **parameter domain** with a specified metric (e.g. a finite dimensional representation of possible Manning's n fields),
- $M(Y, \lambda)$ with a solution $Y = Y(\lambda)$, a deterministic **physics based model** (e.g. the Advanced Circulation Model of Oceanic, Coastal and Estuarine Waters (ADCIRC)),
- $Q : \Lambda \to \mathcal{D}$, a map composed of **quantities of interest** (QoI) $Q(\lambda) = (q_1(\lambda), \ldots, q_d(\lambda)) \in \mathcal{D} \subset \mathbb{R}^d$ where $q_i(\lambda) := q_i(Y(\lambda))$, for all $\lambda \in \Lambda$ where $d \leq m$
  (e.g. maximum water elevation at d observation stations),
- and an observed (or assumed) **probability density** $\rho_{\mathcal{D}}$ on $\mathcal{B}_{\mathcal{D}}$ for the data domain $\mathcal{D}$.

Assume $\mathcal{D} := Q(\Lambda)$ and that the Jacobian of $Q(\lambda)$ has full rank a.e. in Λ.

$M(Y, \lambda)$ with a solution $Y = Y(\lambda)$, a deterministic **physics based model** (e.g. the Advanced Circulation Model of Oceanic, Coastal and Estuarine Waters (ADCIRC))

Hurricane Gustav

- August 25, 2008 - September 7, 2008
- Highest winds: 155 mph (250 km/h)
- Fatalities: 153
- Damage: $6.61 billion (2008 USD)

Computational Domain

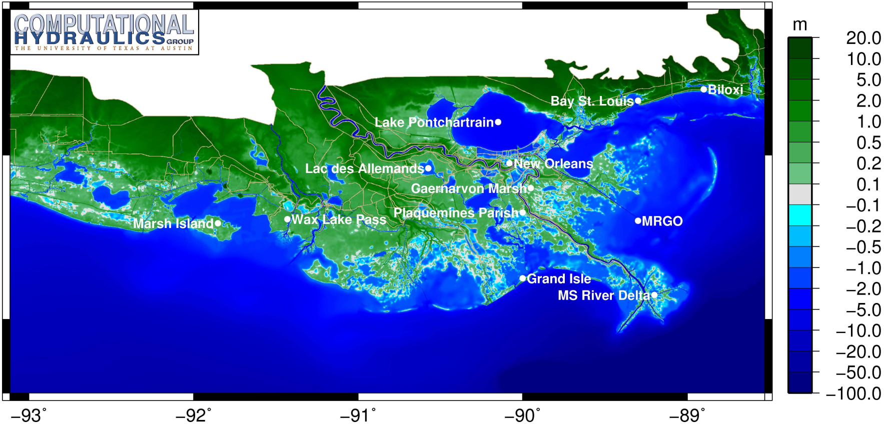
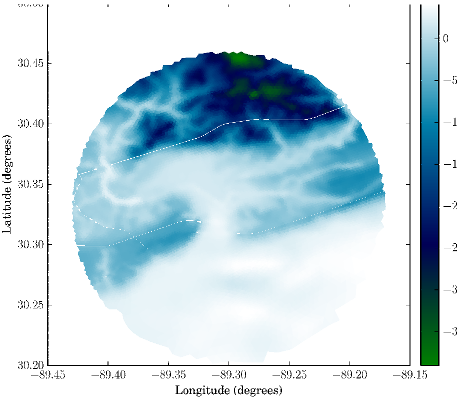
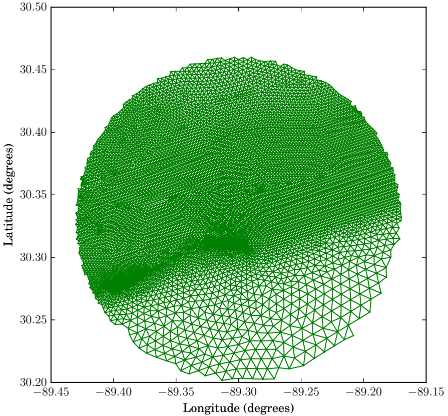


Figure : Bathymetry/topography (m) of the full domain mesh in southeastern Louisiana.

Subdomain Model of Bay St. Louis





Subdomain Model of Bay St. Louis

Subdomain ADCIRC

1. Create full domain ADCIRC model.
2. Create subdomain ADCIRC model.
3. Generate full domain control file to control output of subdomain boundary forcing data.
4. Run ADCIRC on the full domain.
5. Extract subdomain boundary forcing data (elevation, velocity, wet/dry status) from the full domain.
6. Run ADCIRC on the subdomain

Simon (2011), Altuntas (2012), Altuntas and Simon (2013).

Define $\Lambda \subset \mathbb{R}^m$, a compact **parameter domain** with a specified metric (e.g. a finite dimensional representation of possible Manning's n fields)

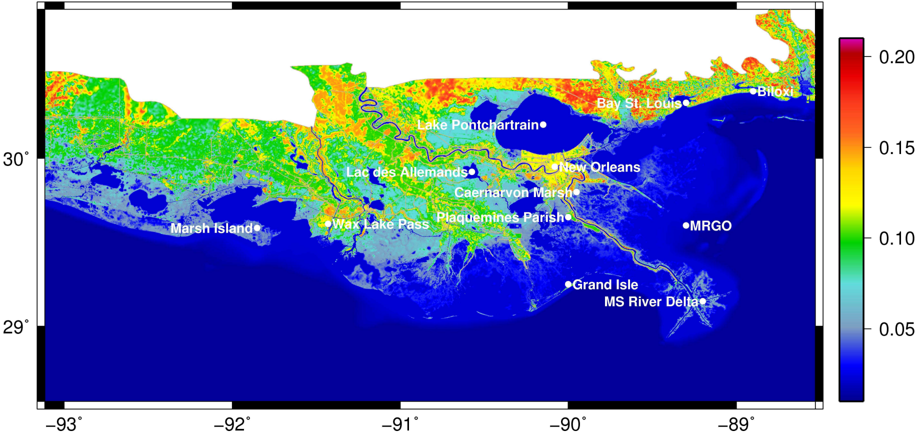
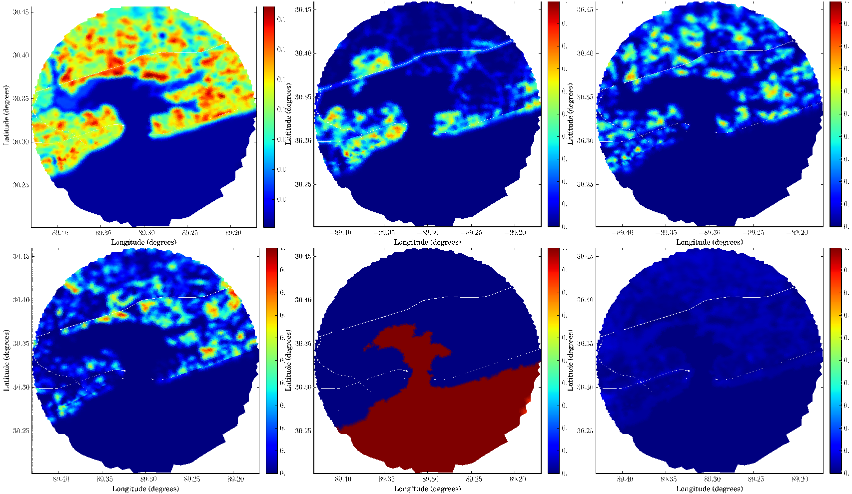


Figure : Manning's n values of the full domain mesh in southeastern Louisiana. (23 different land cover classifications)

Dominant land cover classifications

Percentage	C-CAP Class	Description	Manning's n
23.95	21	Open water	0.025
13.45	10	Evergreen forest	0.180
12.57	13	Palustrine forested wetland	0.150
12.33	4	Low-intensity developed	0.120

Parameter Domain



The mesoscale representation of Manning's n values from basis vectors defining a linear mapping.

Parameter Domain

Parameter	Range of Manning's n values	Land Classification
λ_1	$[0.0396, 0.21]$	4
λ_2	$[0.0594, 0.315]$	10
λ_3	$[0.0495, 0.2625]$	13
λ_4	$[0.00825, 0.04375]$	21

Table : Manning's n ranges for subdomain.

So the compact finite dimensional parameter domain is $\Lambda \subset \mathbb{R}^4$.

Quantities of interest (QoI) $Q(\lambda) = (q_1(\lambda), \ldots, q_d(\lambda)) \in \mathcal{D} \subset \mathbb{R}^d$ where $q_i(\lambda) := q_i(Y(\lambda))$, for all $\lambda \in \Lambda$
(e.g. maximum water elevation at d observation stations)

Data Domain

Observation Stations $q_i(\lambda) := q_i(Y(\lambda))$ is the maximum water elevation at the i^{th} observation station.

Assume $\mathcal{D} := Q(\Lambda)$ and that the components of Q are **geometrically distinct**.

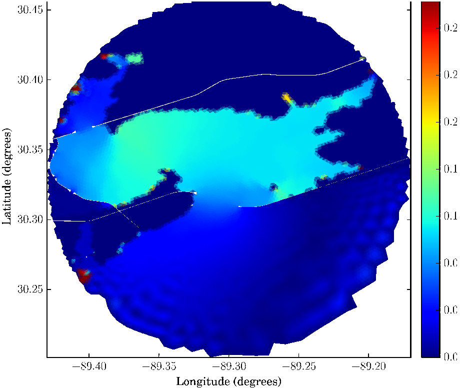
Geometrically Distinct QoI

The Jacobian of $Q(\lambda)$ has full rank a.e. in Λ.

Recall that $Q(\lambda) \in \mathbb{R}^d$ and $d \leq m$ so there are at most m **geometrically distinct** QoI.

Which observation stations should we choose?

Preliminary Study



Maximum difference in subdomain water elevation over a set of 80 preliminary model evaluations. Values shown are $\left(\max_k(Y_i^{(k)}) - \min_k(Y_i^{(k)})\right)$ in $[m]$ where $Y_i^{(k)} = Y_i(\lambda^{(k)})$ is the maximum water elevation at a finite element node i for the k^{th} parameter value $\lambda^{(k)} = (\lambda_1^{(k)}, \lambda_2^{(k)}, \lambda_3^{(k)}, \lambda_4^{(k)})$. Note that to show subtle variations in the bay the color scale has been reduced.

Preliminary Study

	Number of Stations	Number of Data Spaces $\binom{n}{4}$
All	1970	$6.26 \cdot 10^{11}$
Reduced	194	$5.72 \cdot 10^{7}$

Table : Number of possible data spaces for subdomain 16.

Optimal Choice of QoI Based on Skewness

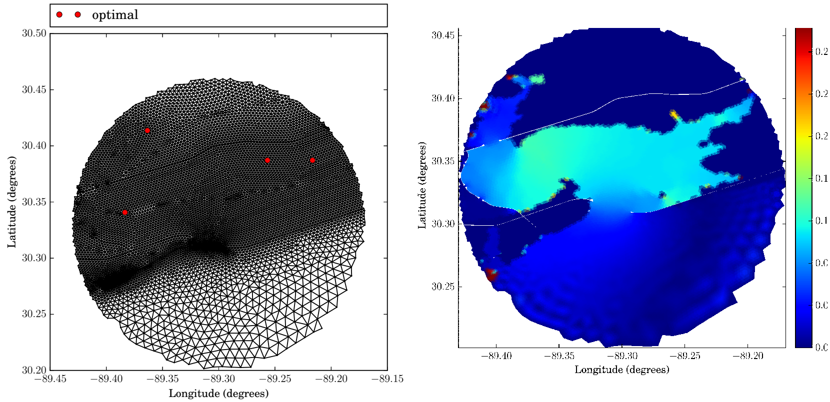


Figure : Left: Optimal maximum water elevation observation stations. Right: Maximum difference in subdomain water elevation..

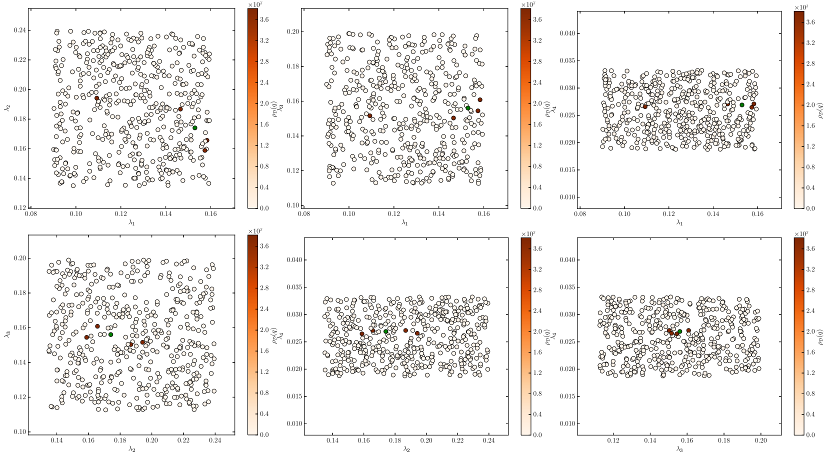
Data Domain

Choose a set of QoI to define $\mathcal{D}$ and define $\rho_{\mathcal{D}}$.

Prescribe an observed (or assumed) **probability density** $\rho_{\mathcal{D}}$ on $\mathcal{B}_{\mathcal{D}}$.

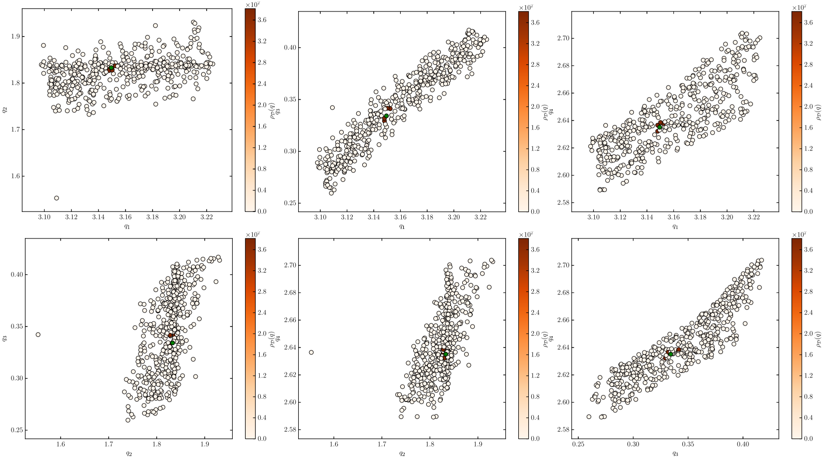
Here, $\rho_{\mathcal{D}}$ is defined as a uniform density on a small rectangular box centered at the reference QoI values associated with $\lambda_{ref} = (0.1523, 0.1751, 0.1561, 0.0269)$.

Uniform i.i.d. samples in the parameter space



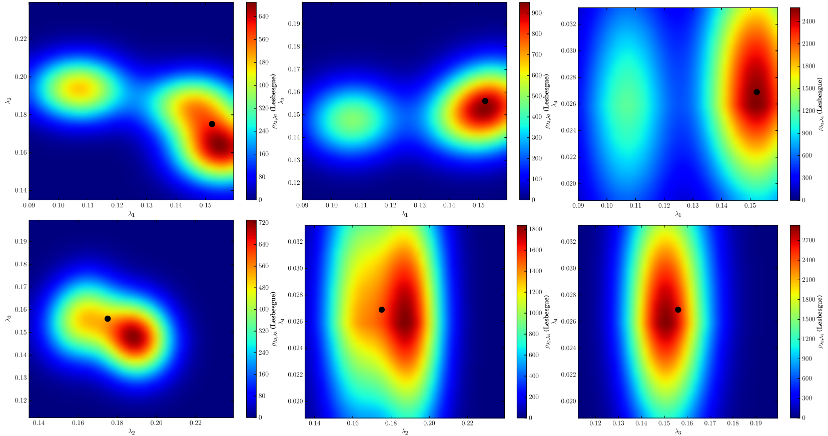
The uniform samples in the parameter space where $\lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4)$ and $\lambda_{ref} =$ (0.1523, 0.1751, 0.1561, 0.0269) is marked in green. The samples are colored by $\rho_{\mathcal{D}}(Q)$. Top: Left to right, (λ_1, λ_2), (λ_1, λ_3), (λ_1, λ_4). Bottom: Left to right, (λ_2, λ_3), (λ_2, λ_4), (λ_3, λ_4).

Uniform i.i.d. samples in the data space using optimal QoI



The uniform samples in the data space for the optimal stations where $Q = (q_1, q_2, q_3, q_4)$ for the optimal set of stations and Q_{ref} is marked in green. The samples are colored by $\rho_{\mathcal{D}}(Q)$. Top: Left to right, $(q_1, q_2), (q_1, q_3), (q_1, q_4)$. Bottom: Left to right, $(q_2, q_3), (q_2, q_4), (q_3, q_4)$.

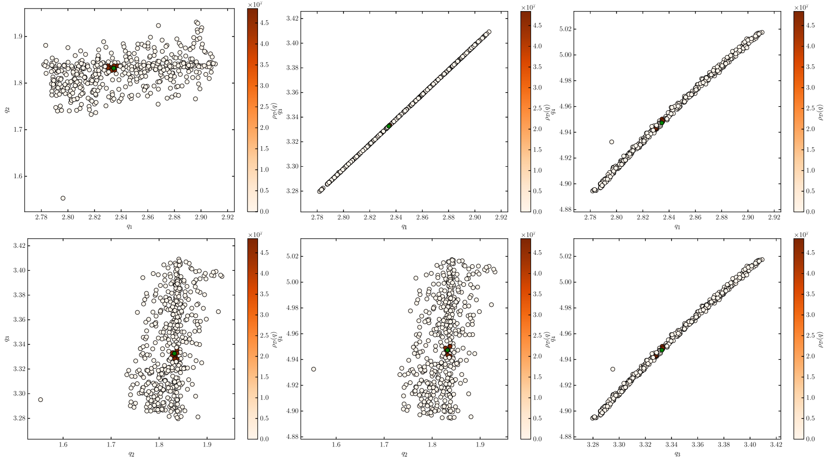
Approximated ρ_Λ using optimal QoI



Plots the marginals of ρ_Λ using uniform samples using optimal stations. The reference value is illustrated by a black circle. Top: Left to right, $(q_1, q_2), (q_1, q_3), (q_1, q_4)$. Bottom: Left to right, $(q_2, q_3), (q_2, q_4), (q_3, q_4)$.

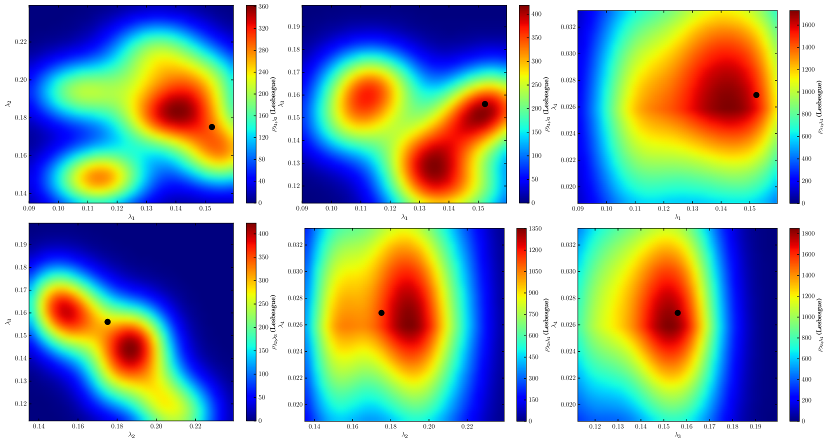
What if we choose a suboptimal set of stations?

Uniform i.i.d. samples in the data space using suboptimal QoI



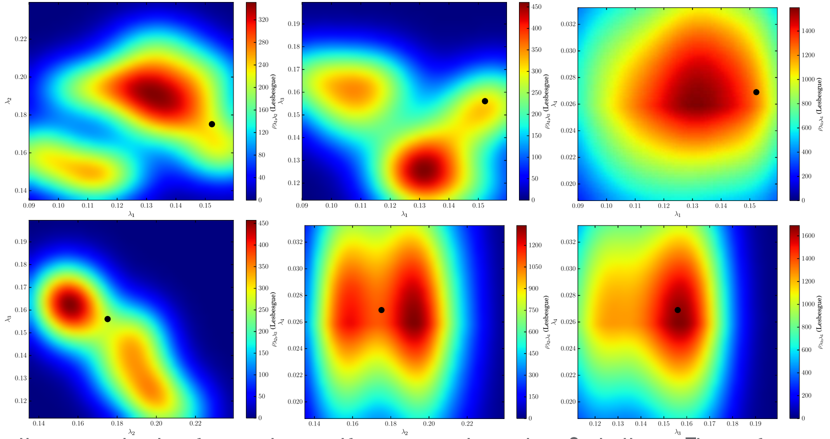
The uniform samples in the data space for the suboptimal stations and Q_{ref} is marked in green. Top: Left to right, $(q_1, q_2), (q_1, q_3), (q_1, q_4)$. Bottom: Left to right, $(q_2, q_3), (q_2, q_4), (q_3, q_4)$.

Approximated ρ_Λ using suboptimal QoI



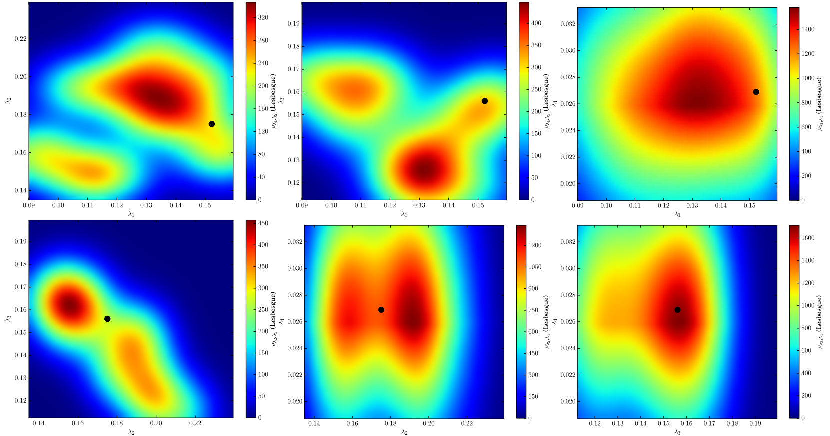
Plots the marginals of ρ_Λ using uniform samples using suboptimal stations. The reference value is illustrated by a black circle. Top: Left to right, $(q_1, q_2), (q_1, q_3), (q_1, q_4)$. Bottom: Left to right, $(q_2, q_3), (q_2, q_4), (q_3, q_4)$.

Approximated ρ_Λ using 3 QoI



Plots the marginals of ρ_Λ using uniform samples using 3 stations. The reference value is illustrated by a black circle. Top: Left to right, (q_1, q_2), (q_1, q_3), (q_1, q_4). Bottom: Left to right, (q_2, q_3), (q_2, q_4), (q_3, q_4).

Approximated ρ_Λ using 2 QoI



Plots the marginals of ρ_Λ using uniform samples using 2 stations. The reference value is illustrated by a black circle. Top: Left to right, (q_1, q_2), (q_1, q_3), (q_1, q_4). Bottom: Left to right, (q_2, q_3), (q_2, q_4), (q_3, q_4).

Conclusion and Future Work

Summary

- QoI choice influences the condition of the stochastic inverse problem.
- The stochastic inverse problem influences experimental design.
- Adaptive sampling identifies regions of interest (high probability) for stochastic inverse problems.

Next Steps

- Additional physical domains, forcing, and parameters.
- Using field data to construct $\rho_{\mathcal{D}}$.
- Using surrogate models.

Thanks!

Questions?

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