



ODEN INSTITUTE

FOR COMPUTATIONAL ENGINEERING & SCIENCES

ARCTIC OCEAN CIRCULATION(S): MODELS AND OBSERVATIONS - SOME RANDOM THOUGHTS

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Why models?

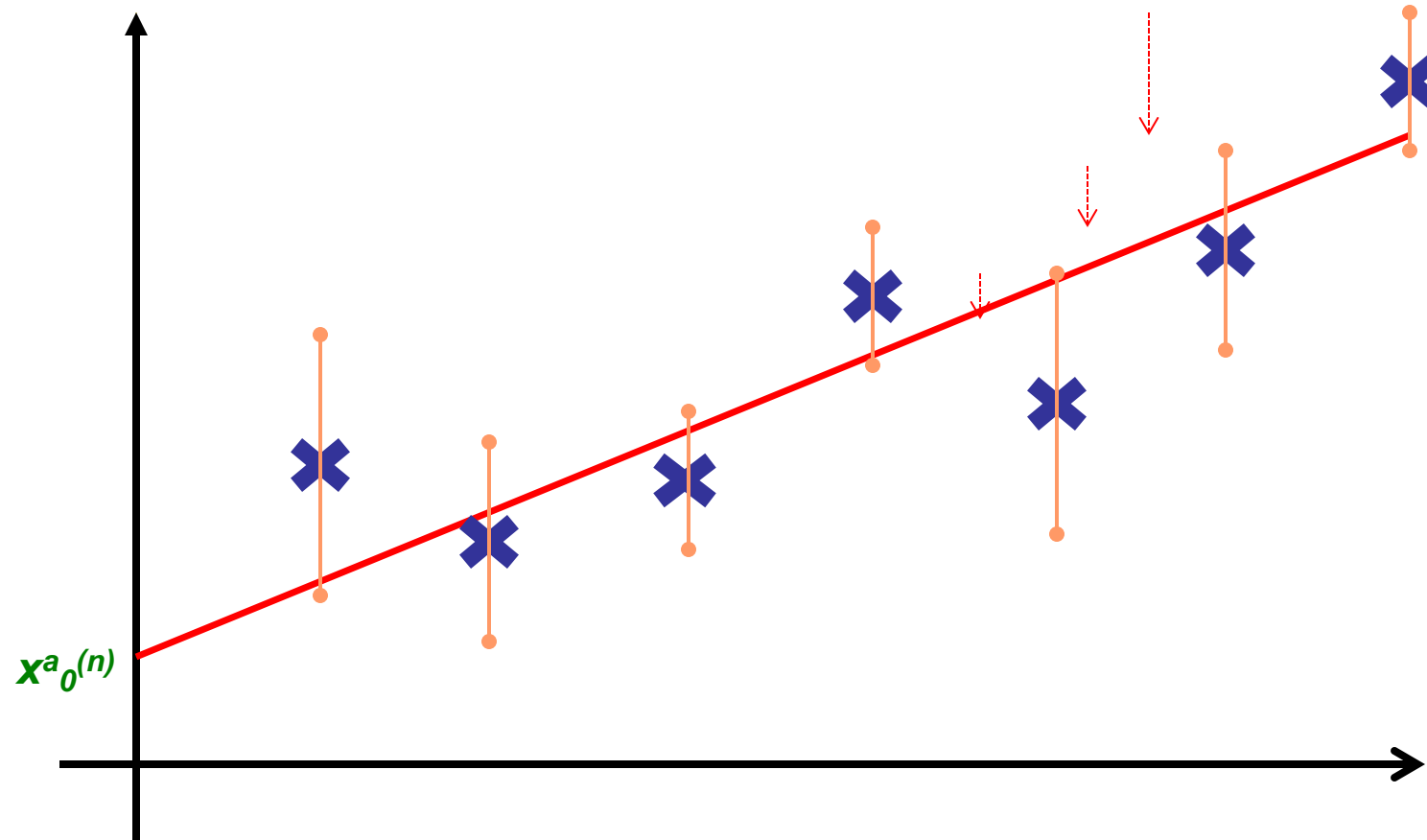
- Their underlying equations of motion remain our best shot at peaking into the future
- Their underlying equations of motions conserve properties, globally and locally (at the fluid parcel level)
- They serve as “dynamics-respecting interpolators” of sparse data
- They enable us to ask WHAT-IF experiments
 - addressing fundamental question of system sensitivity
- We know uncertainties are basic ingredients of models:
 - Initial condition uncertainty
 - Boundary condition (surface forcing, lateral & basal boundary conditions, ...)
 - Model parametric uncertainties
 - Model structural uncertainties (model inadequacy)
 - ...

What do we mean by “validating the models”?

When we “validate” models ...
... we ***WILL*** find misfits!

NOW WHAT?

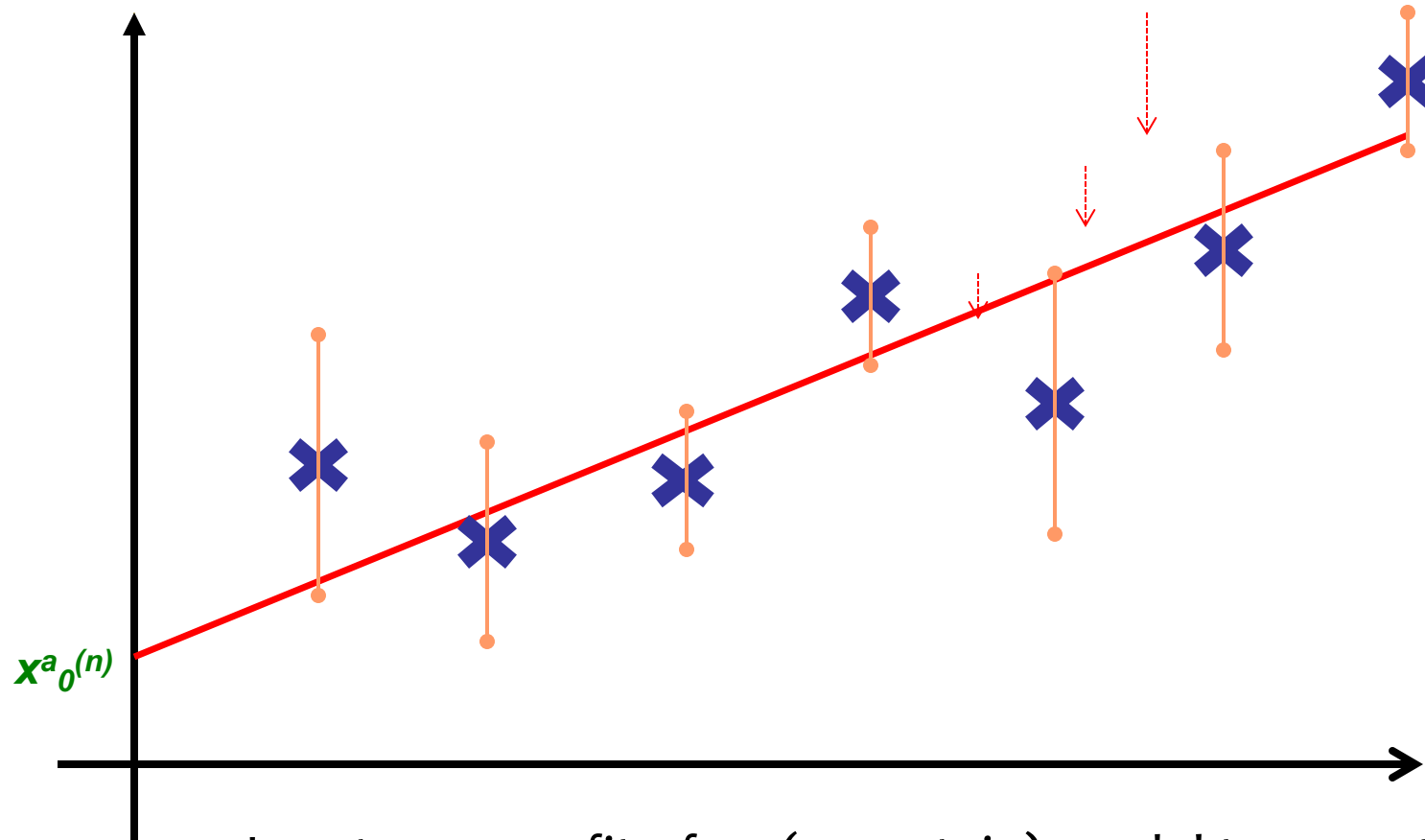
What do we mean by “validating the models”?



$$x(t) = a + b t$$

a, b are uncertain model inputs

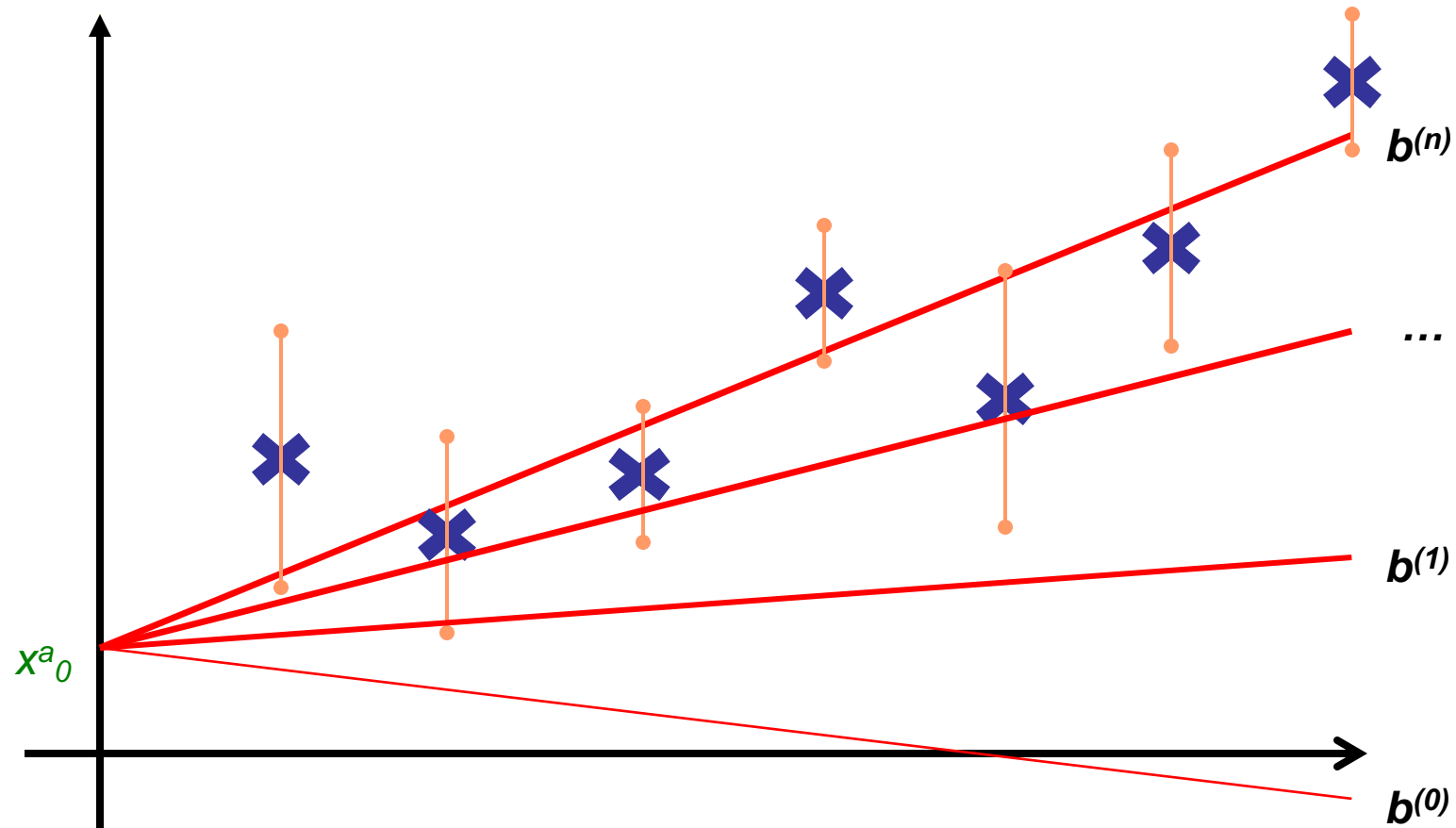
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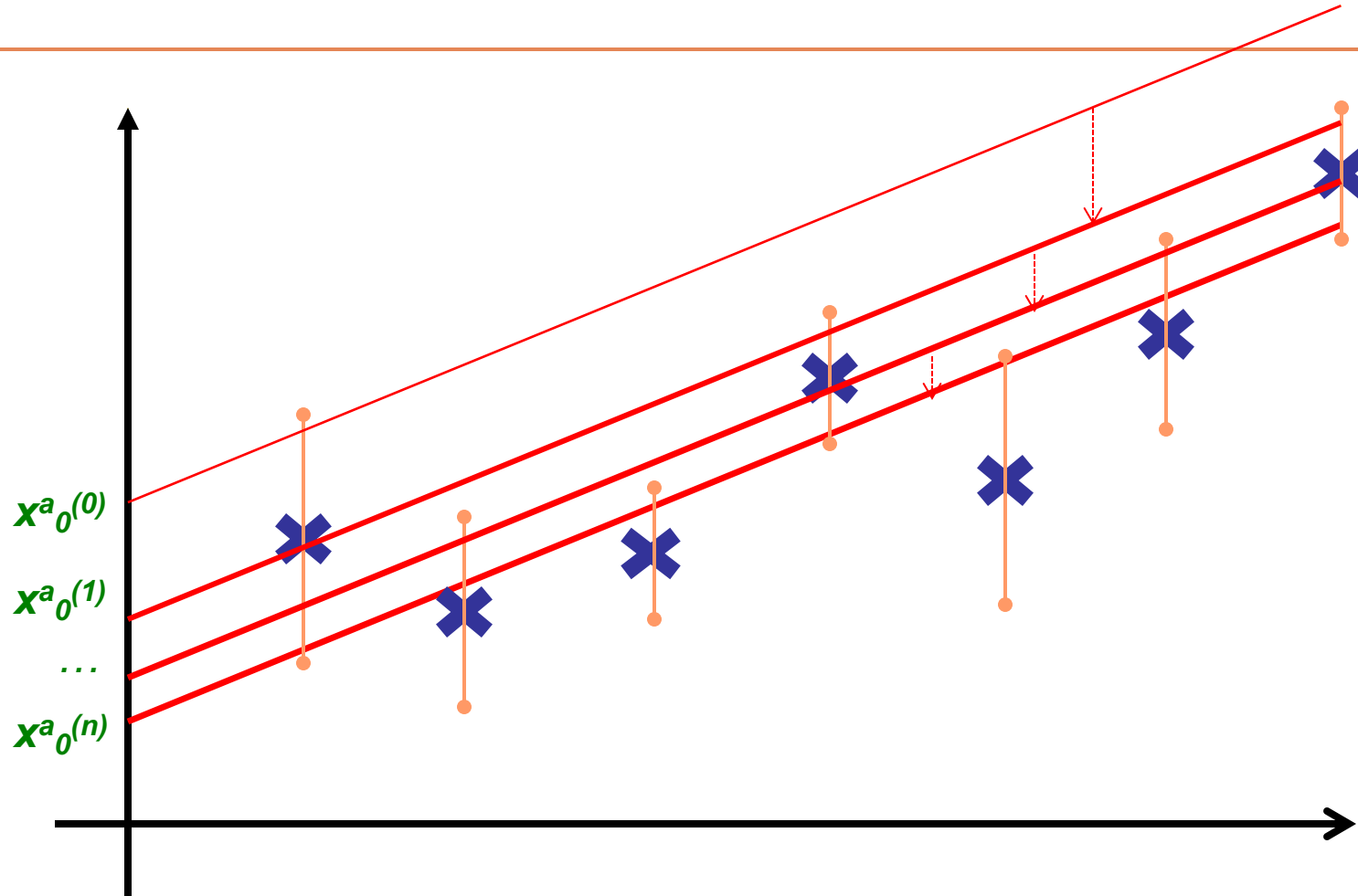
Least-squares fit of an (uncertain) model to uncertain data

$$x(t) = a + b t$$

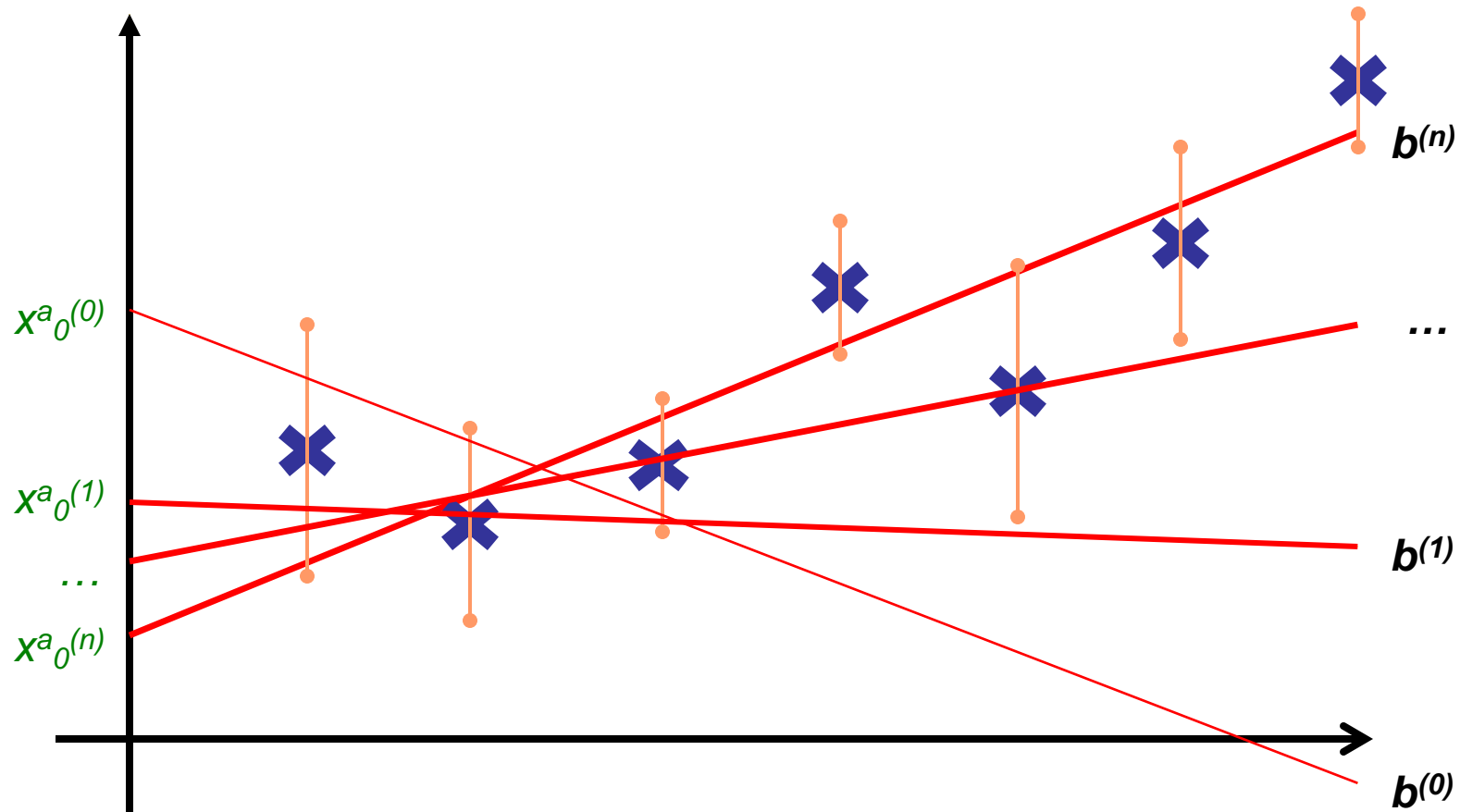
Think of ***b*** (slope) as model parameter; ***a*** (intercept) as “initial condition”



- for model $x(t) = a + b t$
 - vary slope (i.e., “model parameter”) b
 - model calibration



- for model $x(t) = a + b t$
 - vary constant (i.e., intercept) a
 - model “initialization”



- for model $x(t) = a + b t$, simultaneously vary
 - initial condition (i.e. “model state”) $x^a(0) = a$
 - and slope (i.e. “model parameter”) b

What do we mean by “validating the models”?

- **The purpose of Data Assimilation (or Bayesian inference):**
combine imperfect knowledge in model, data, and priors, for “optimal”
 - parameter estimation – calibration
 - state estimation – reconstruction
 - model initialization for prediction (the classic NWP problem of DA)
 - flux inversion (e.g., CO₂)
- **Data Assimilation comes with uncertainties too!**
 - Observation errors
 - Observational sampling: sparsity, inhomogeneity, ...
 - Approximation of error covariances needed
 - DA methods differ

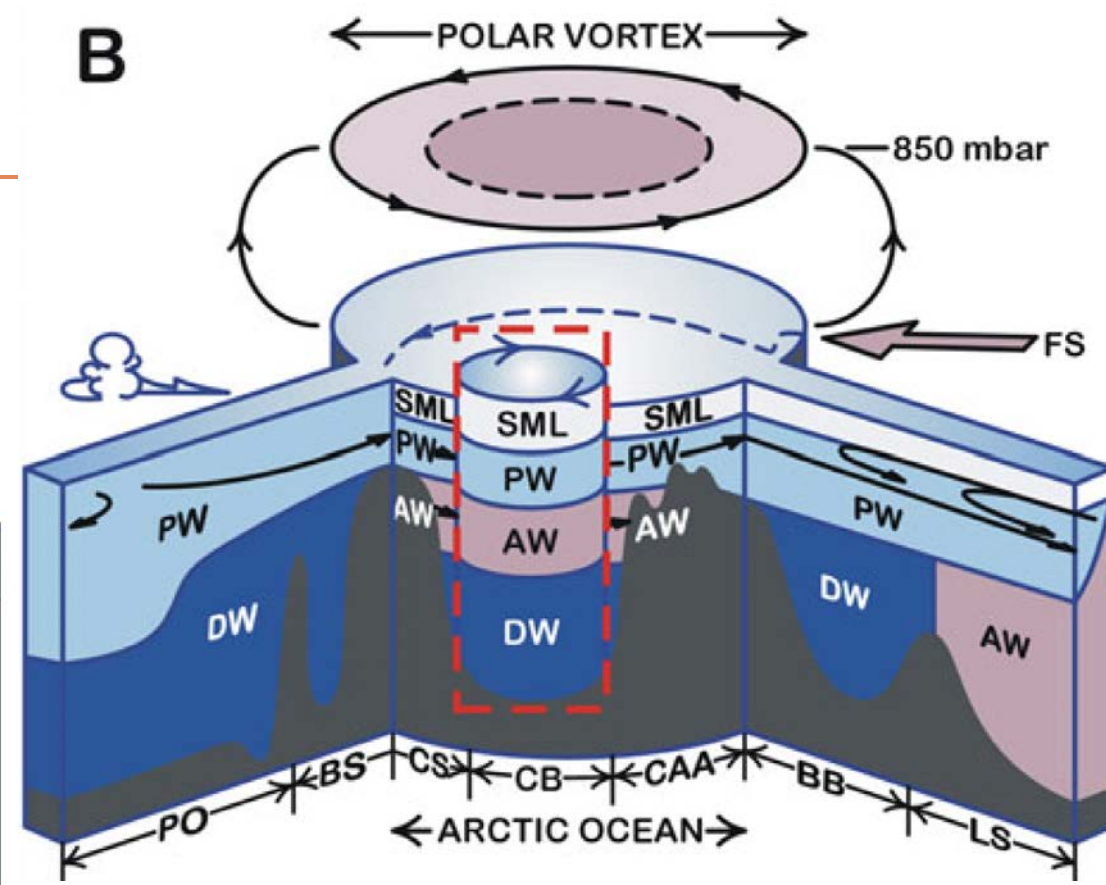
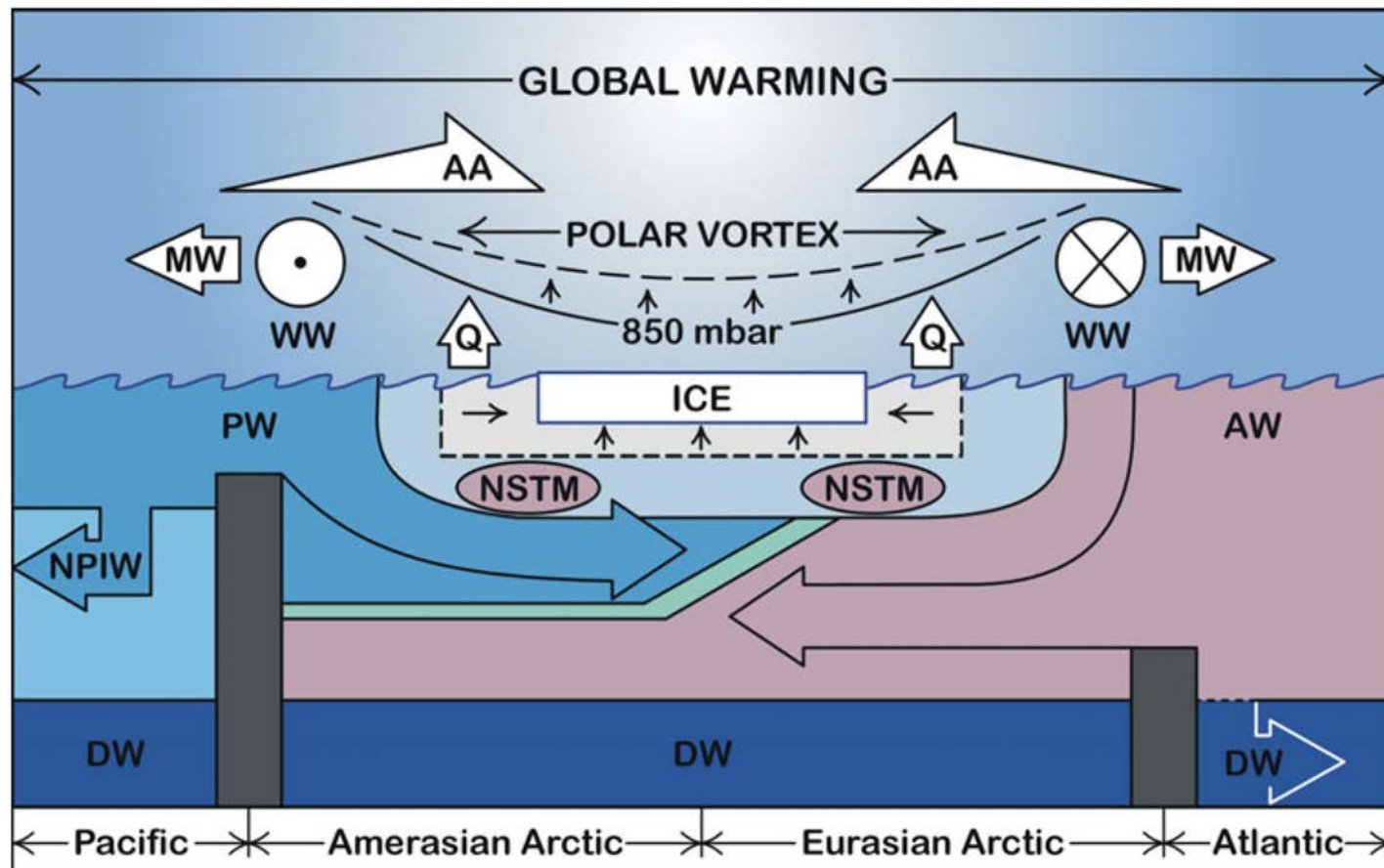
Let's come back to:

“Models enable us to ask WHAT-IF experiments”

– Fundamental question of **system sensitivity**

Local vs. remote influences

Carmack et al. (AMBIO, 2012)

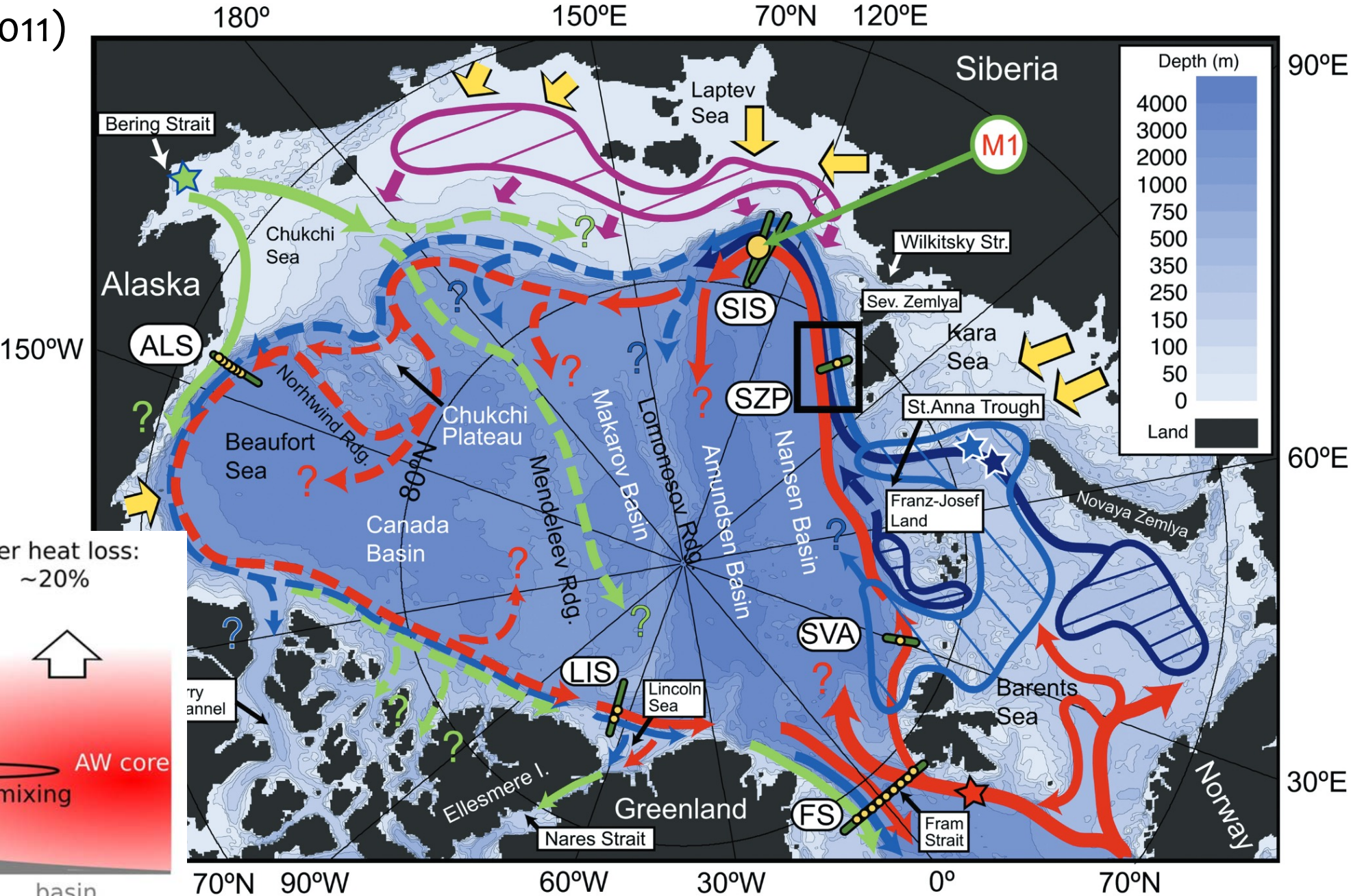


When we think about transport of heat vs. freshwater across the Arctic, we probably have different parts of “the circulation” in mind(?) E.g.:

- surface vs. depth
- locally vs. remotely forced

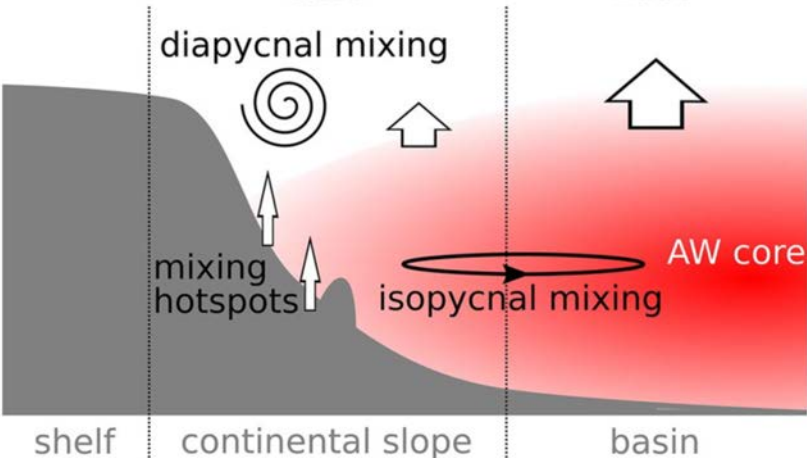
Arctic Circumpolar Boundary Circulation

Aksenov et al. (2011)



also Schulz et al., JGR, 2021

overall contribution to AW layer heat loss:
~80%
~20%



From conceptual drawings & correlation analysis
to dynamical reconstruction of
local vs. remote “drivers”

Case 1: Elucidating large-scale atmospheric controls on Bering Strait throughflow variability

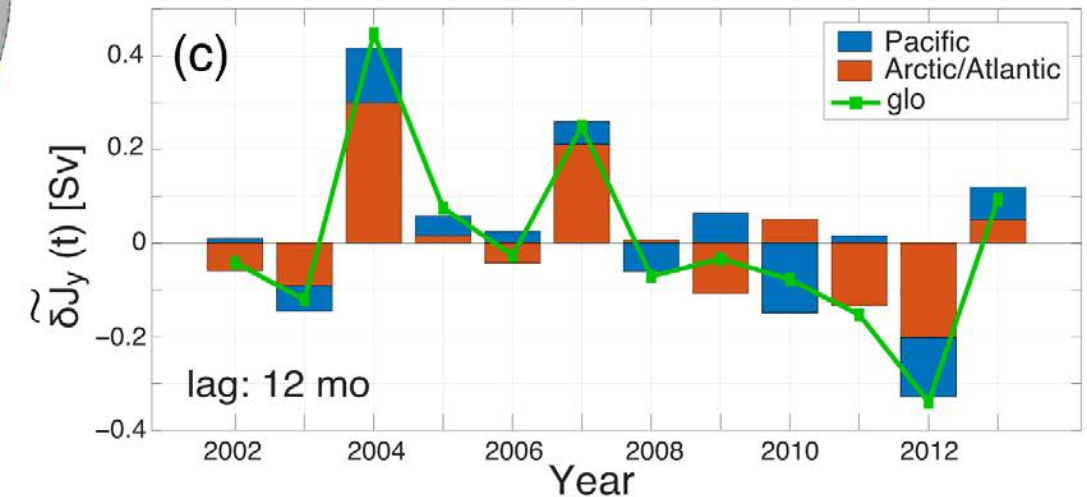
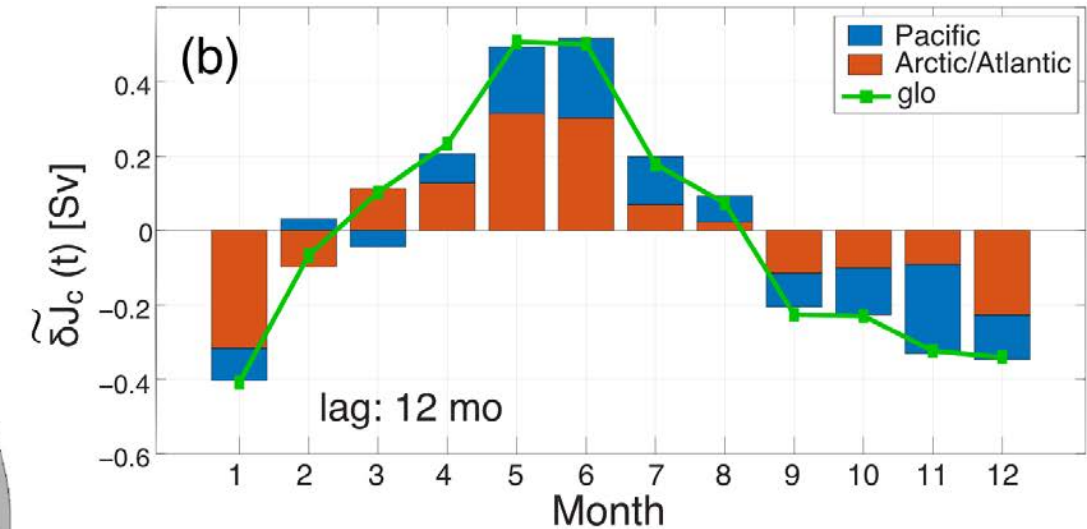
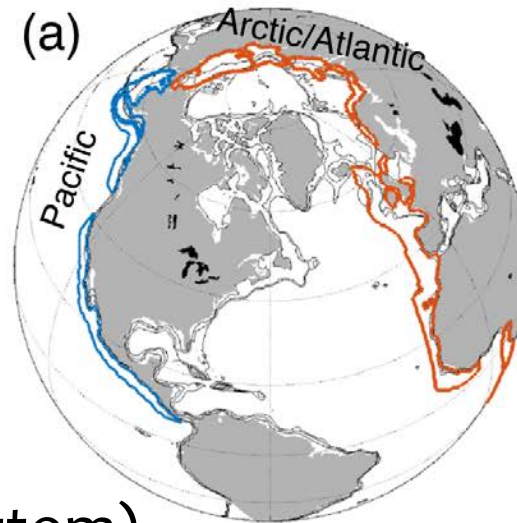
Nguyen et al. (JGR, 2020)

$$\tilde{\delta J}(t) = \sum_k \tilde{\delta J}_k(t) = \sum_k \int_{t_0}^t \int_{x_1} \int_{x_2} \frac{\partial J}{\partial \Omega_k}(x_1, x_2, \alpha - t) \delta \Omega_k(x_1, x_2, \alpha) dx_1 dx_2 d\alpha,$$

Reconstruction of origins of

- seasonal cycle (top)
- interannual variability (bottom)

of volume transport through Bering Strait ($= J$)

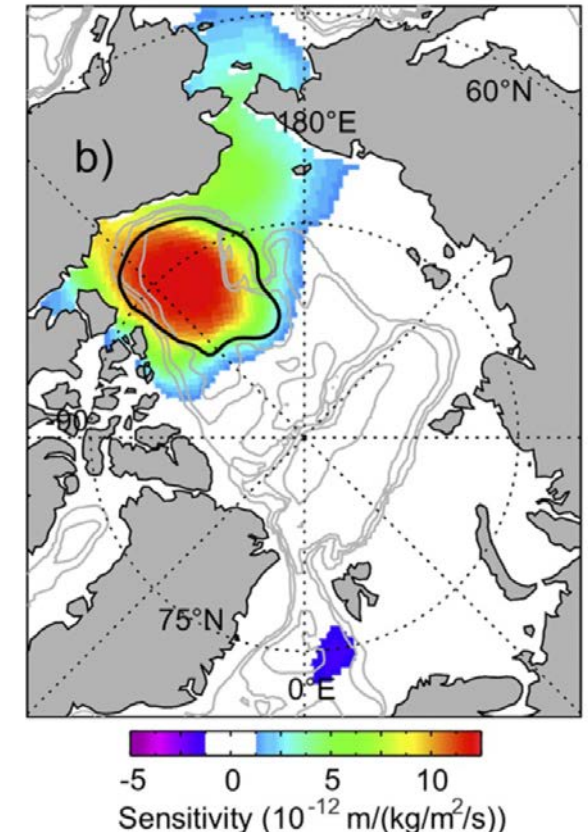
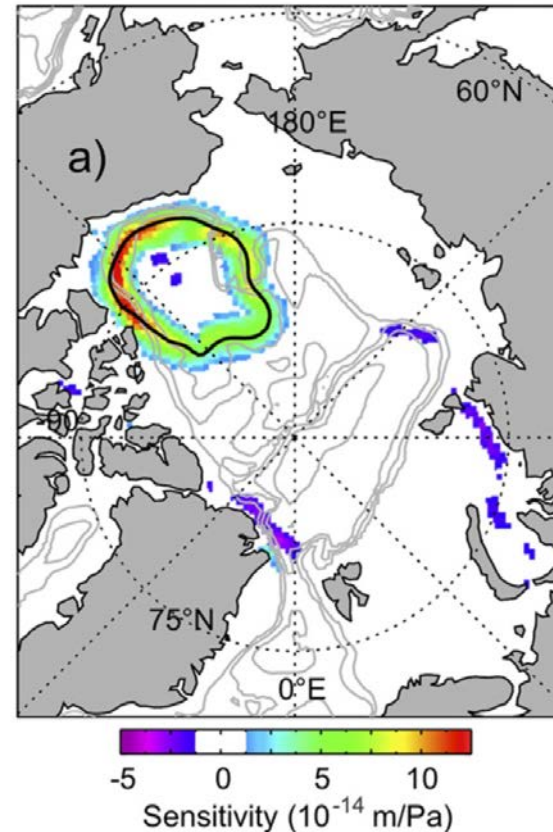
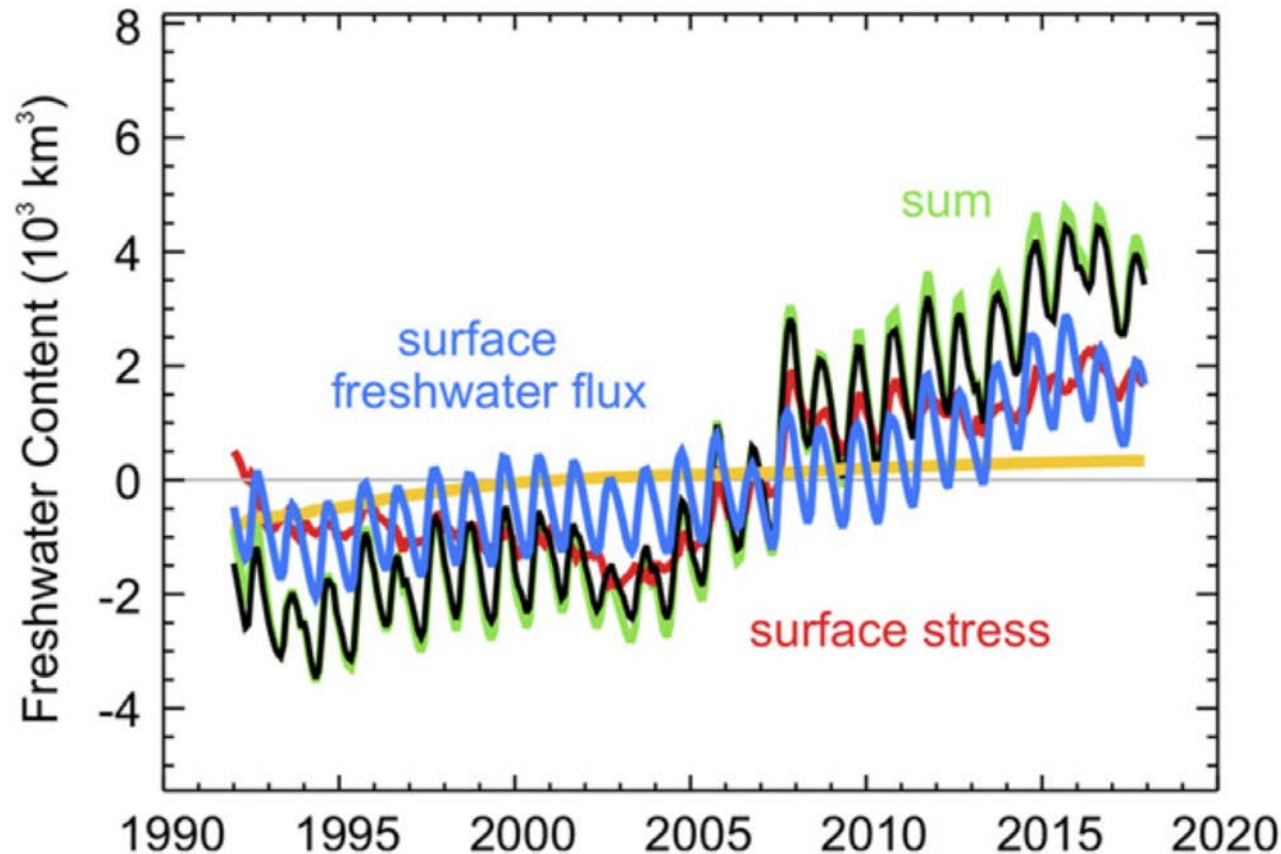


Case 2: Causal Mechanisms of Sea-level and Freshwater Content Change in the Beaufort Sea

Fukumori et al. (JPO, 2021)

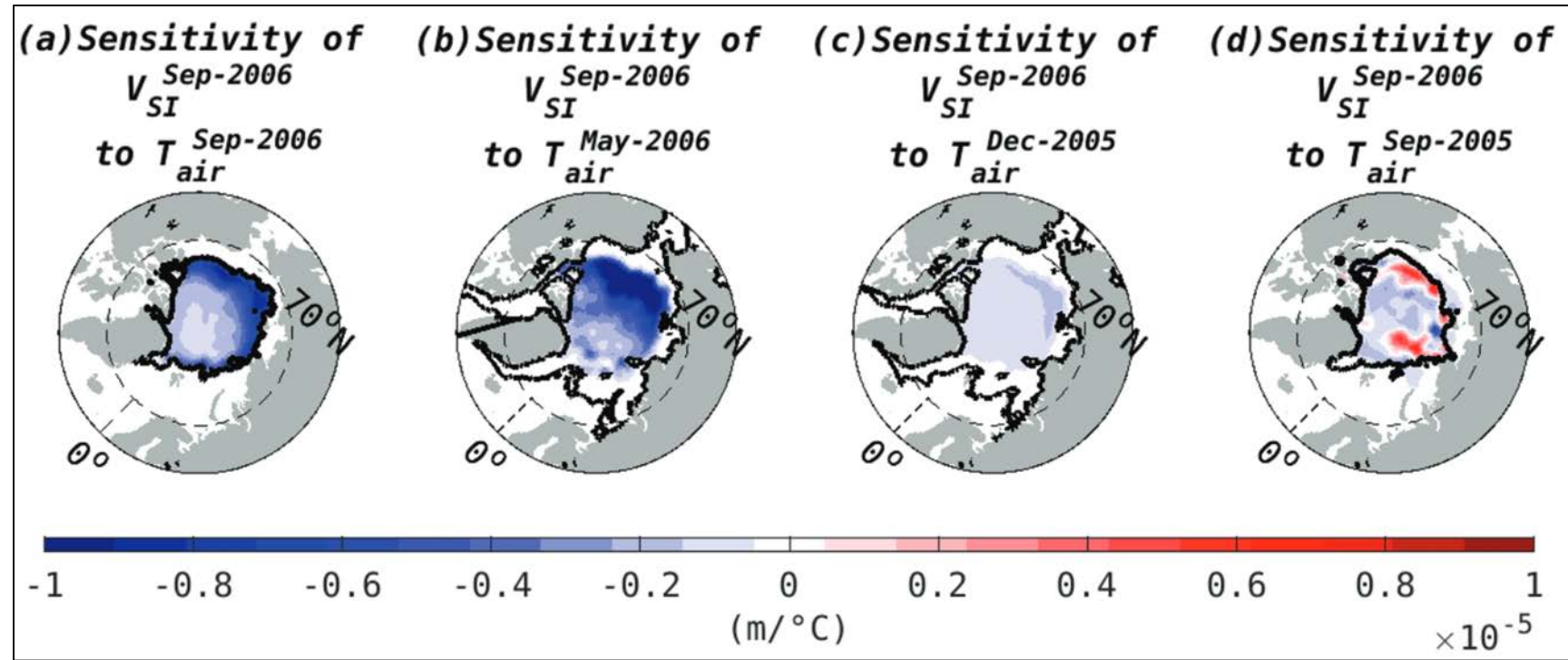
Reconstruction based on
space-time resolved sensitivity
patterns of J to different
surface forcings

$$\delta J(t) \approx \sum_i \sum_{\mathbf{r}} \sum_{\Delta t} \left. \frac{\partial J}{\partial \phi_i}(\mathbf{r}, \Delta t) \right|_{t_g} \delta \phi_i(\mathbf{r}, t - \Delta t).$$

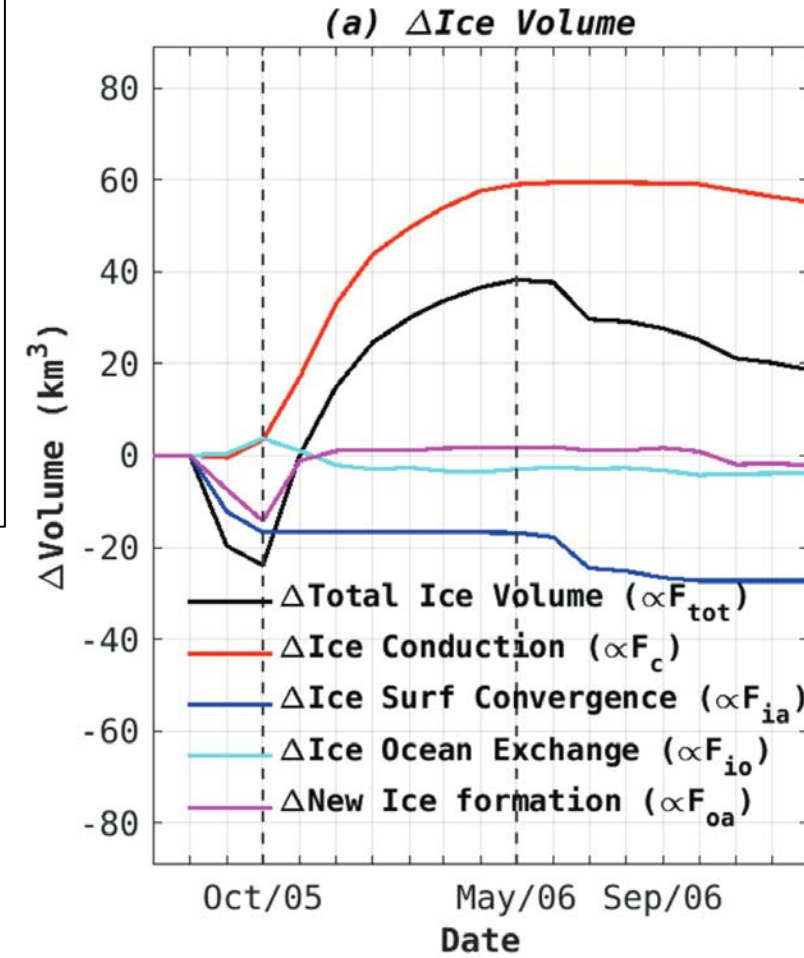


Case 3: Role of snow cover in modulating Arctic sea ice growth

Bigdeli et al. (GRL, 2020)

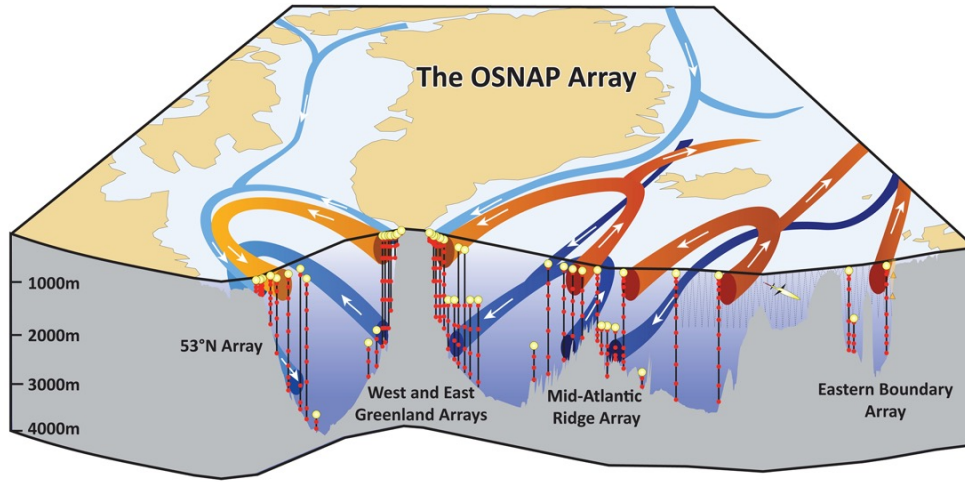


snow-melt-conductivity feedback



(How) can we use sensitivity information for quantitative observing system design?

Ocean Observing Systems



... are crucial for understanding the ocean's role in climate
... but are difficult & expensive to build and maintain

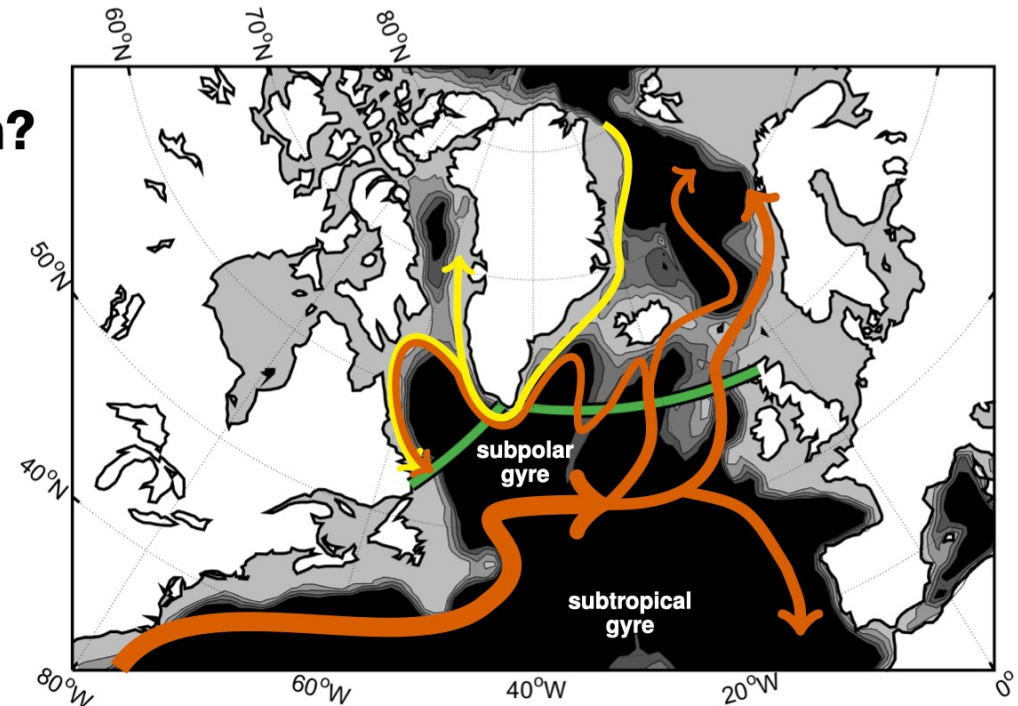
Overturning in the Subpolar North Atlantic Program (OSNAP)

<http://www.o-snap.org>

Lozier et al., 2019

How can ocean models inform observing system design?

- Idea:**
- Use oceanic teleconnections that propagate observational constraints over long distances and can be exposed via the adjoint state
 - Combine adjoint-based estimation framework with adjoint-based sensitivity analysis



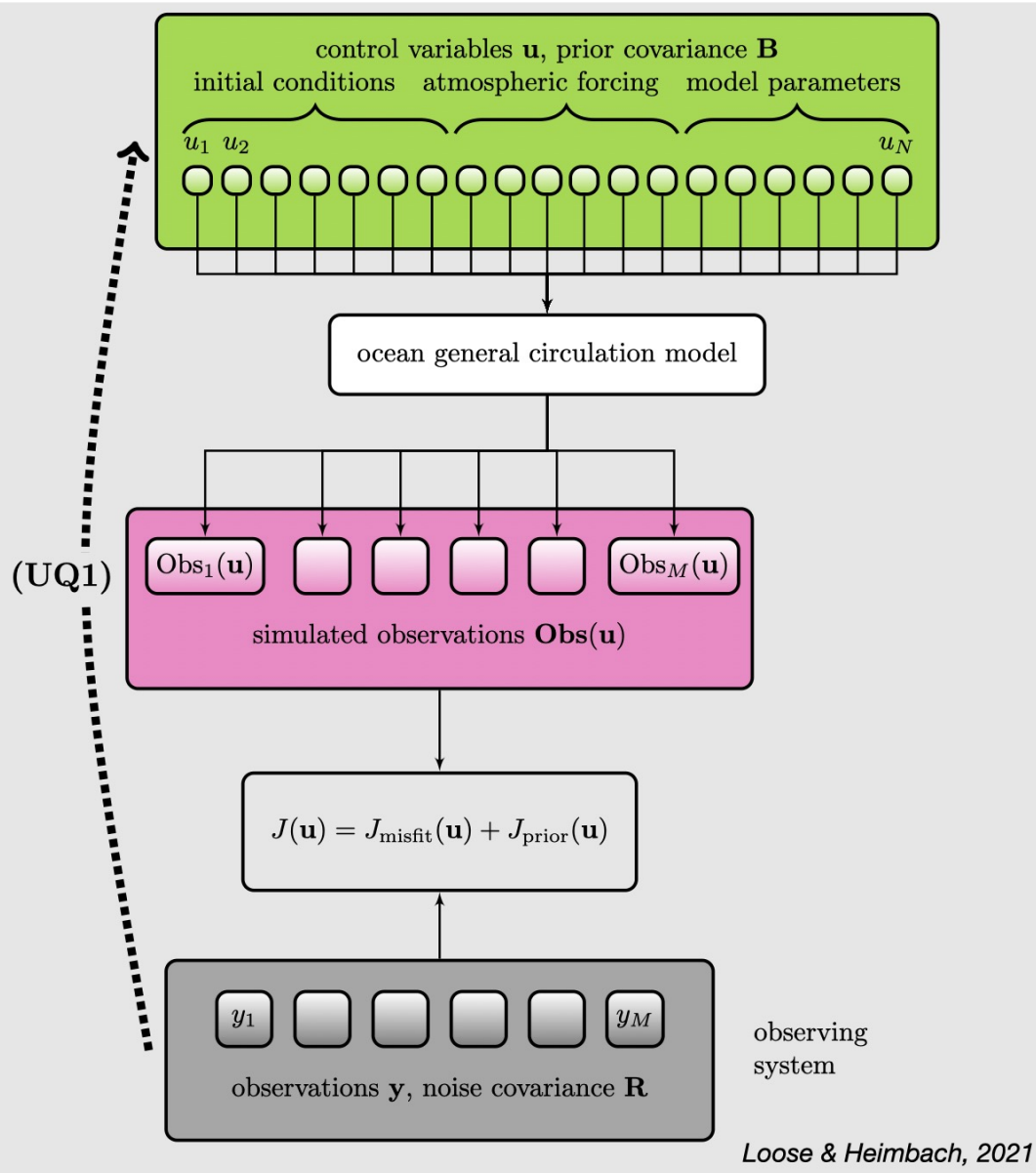
— OSNAP array — warm Atlantic waters — cold Arctic waters

→ Quantitative design of ocean observing systems

Uncertainty Quantification (UQ)

(UQ1): Inverse uncertainty propagation

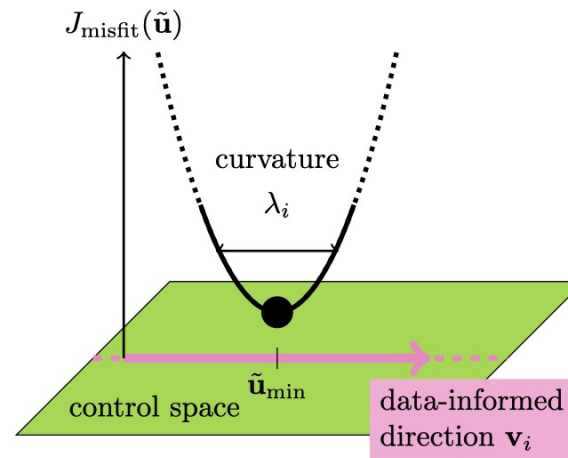
From prior to posterior uncertainty



Observations Simulated observations First guess

$$J(\mathbf{u}) = \underbrace{\frac{1}{2}(\mathbf{y} - \text{Obs}(\mathbf{u}))^T \mathbf{R}^{-1} (\mathbf{y} - \text{Obs}(\mathbf{u}))}_{J_{\text{misfit}}(\mathbf{u})} + \underbrace{\frac{1}{2}(\mathbf{u} - \mathbf{u}_0)^T \mathbf{B}^{-1} (\mathbf{u} - \mathbf{u}_0)}_{J_{\text{prior}}(\mathbf{u})}.$$

Uncertain model inputs Observation uncertainties Prior uncertainties



Hessian of cost function J

$$\mathbf{H}_J \approx \sum_{i=1}^M \lambda_i \mathbf{v}_i \mathbf{v}_i^T$$

Thacker, 1989

posterior uncertainty ~ inverse Hessian of J

Uncertainty Quantification (UQ)

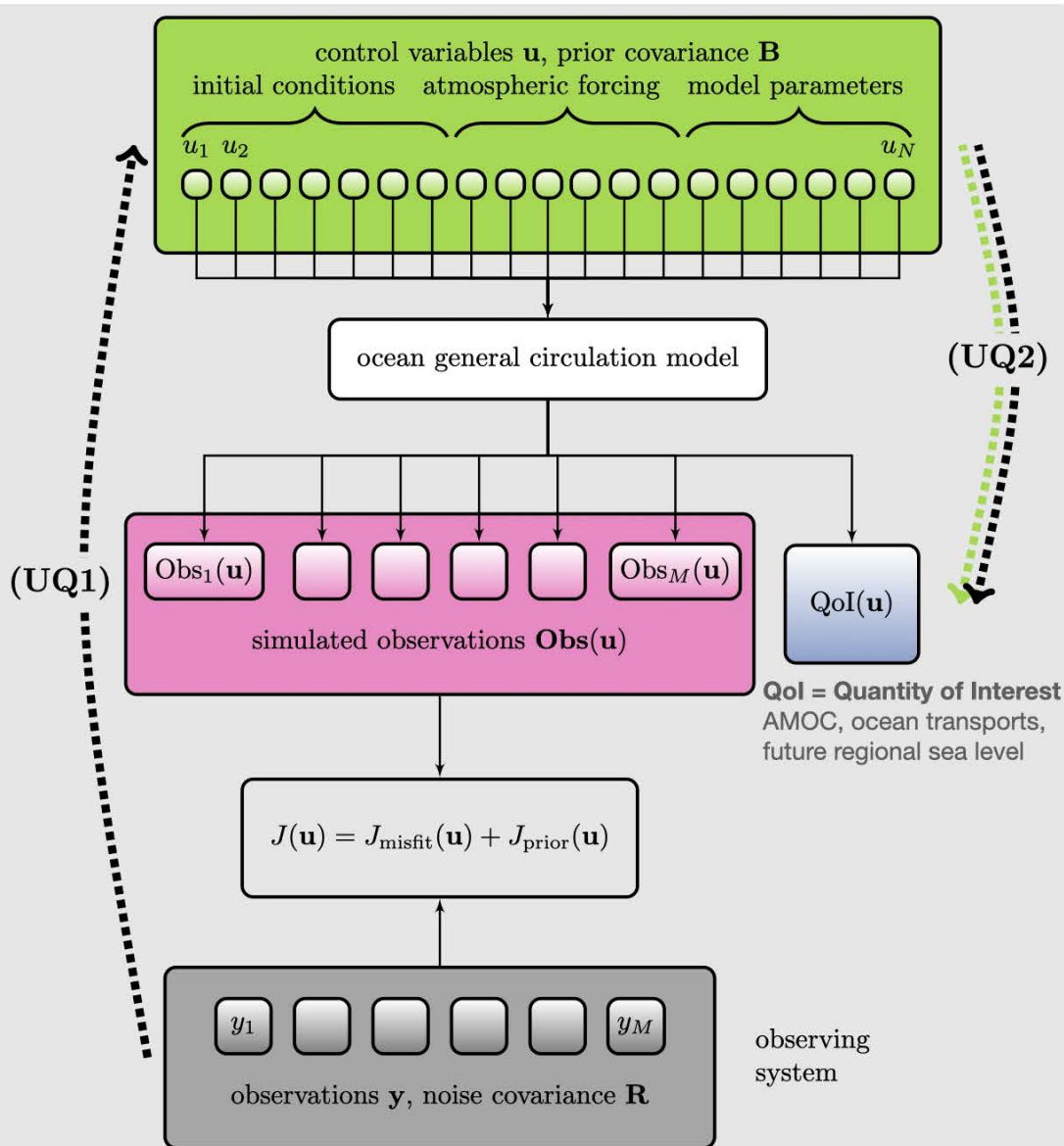
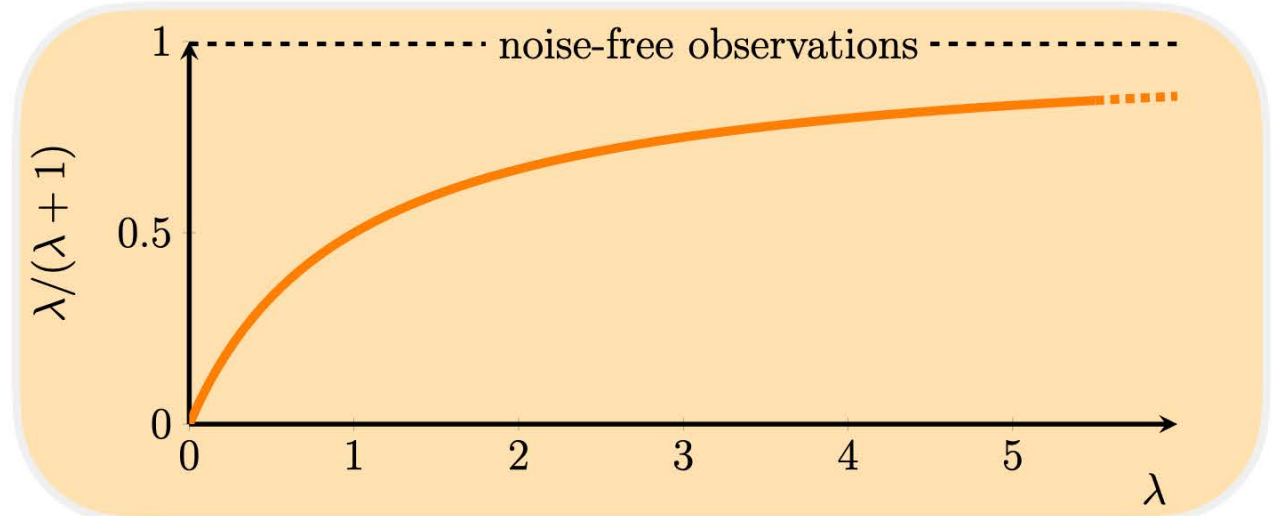
(UQ2): Forward uncertainty propagation

From posterior to QoI uncertainty

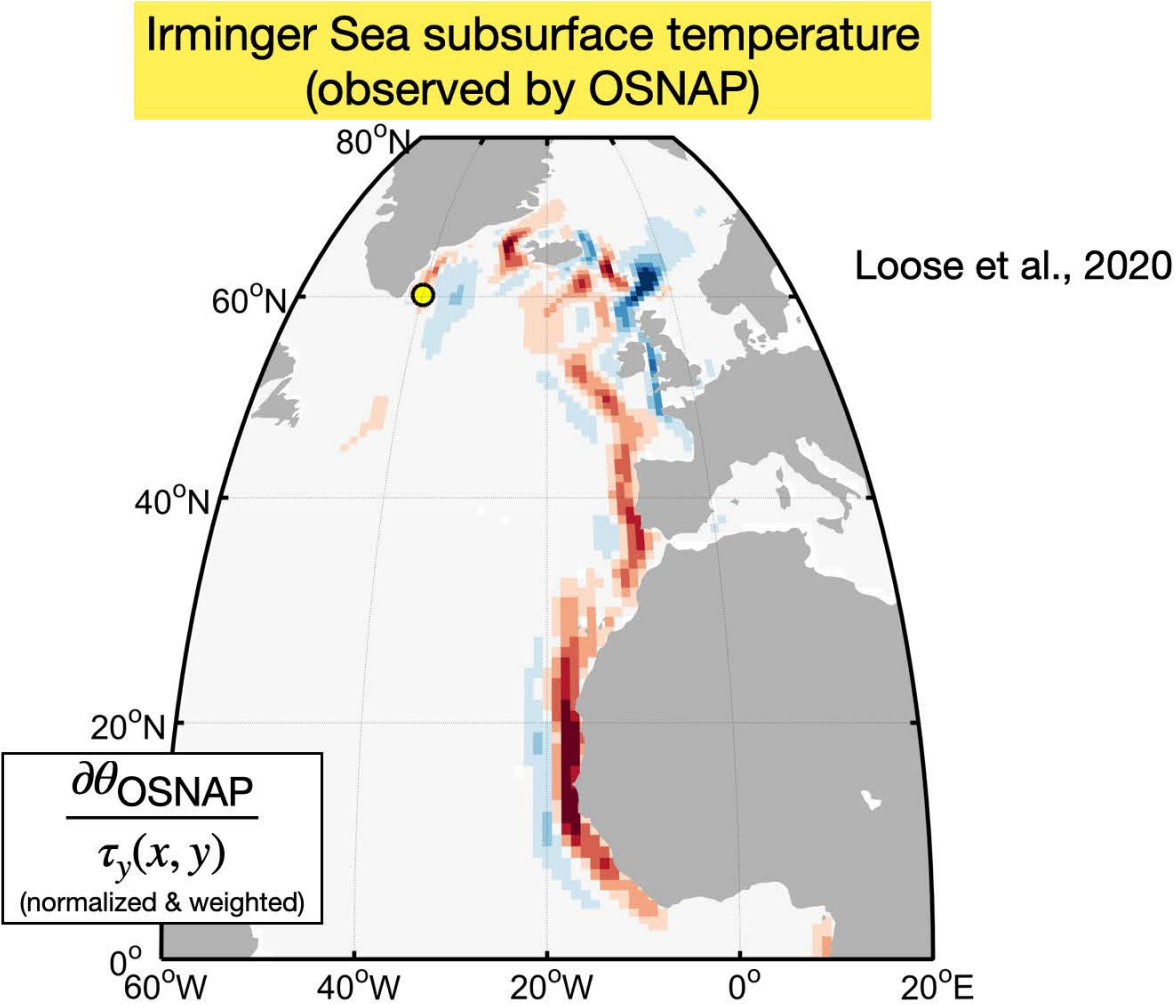
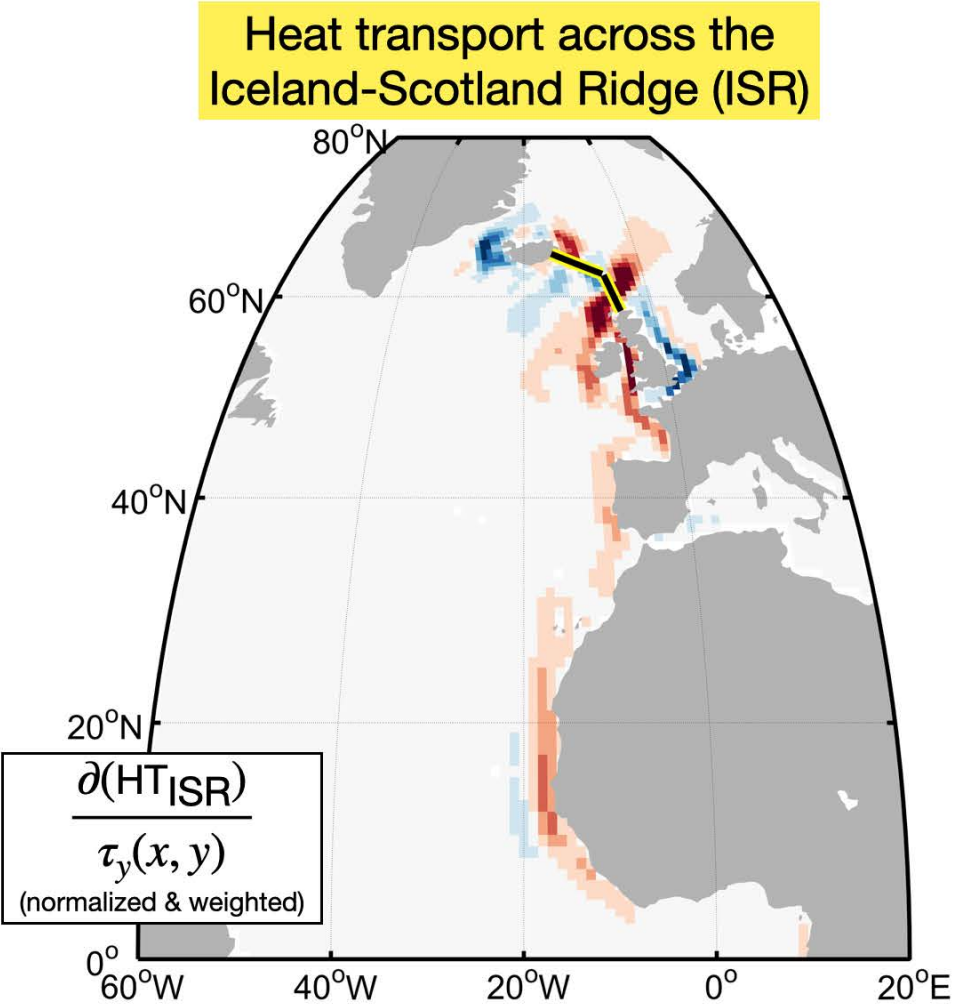
Uncertainty reduction in quantity of interest (QoI) by observing system:

$$\sum_{i=1}^M \frac{\lambda_i}{\lambda_i + 1} (\mathbf{q} \bullet \mathbf{v}_i)^2 \in [0, 1) \quad \text{where} \quad \mathbf{q} = \frac{\mathbf{B}^{T/2} \nabla_u \text{QoI}}{\|\mathbf{B}^{T/2} \nabla_u \text{QoI}\|}$$

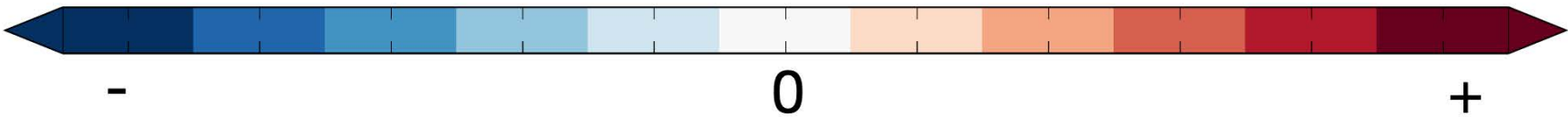
$(\mathbf{q} \bullet \mathbf{v}_i)^2$ = Degree of shared adjustment mechanisms between observing system and QoI



Sensitivity maps identify shared adjustment mechanisms & pathways

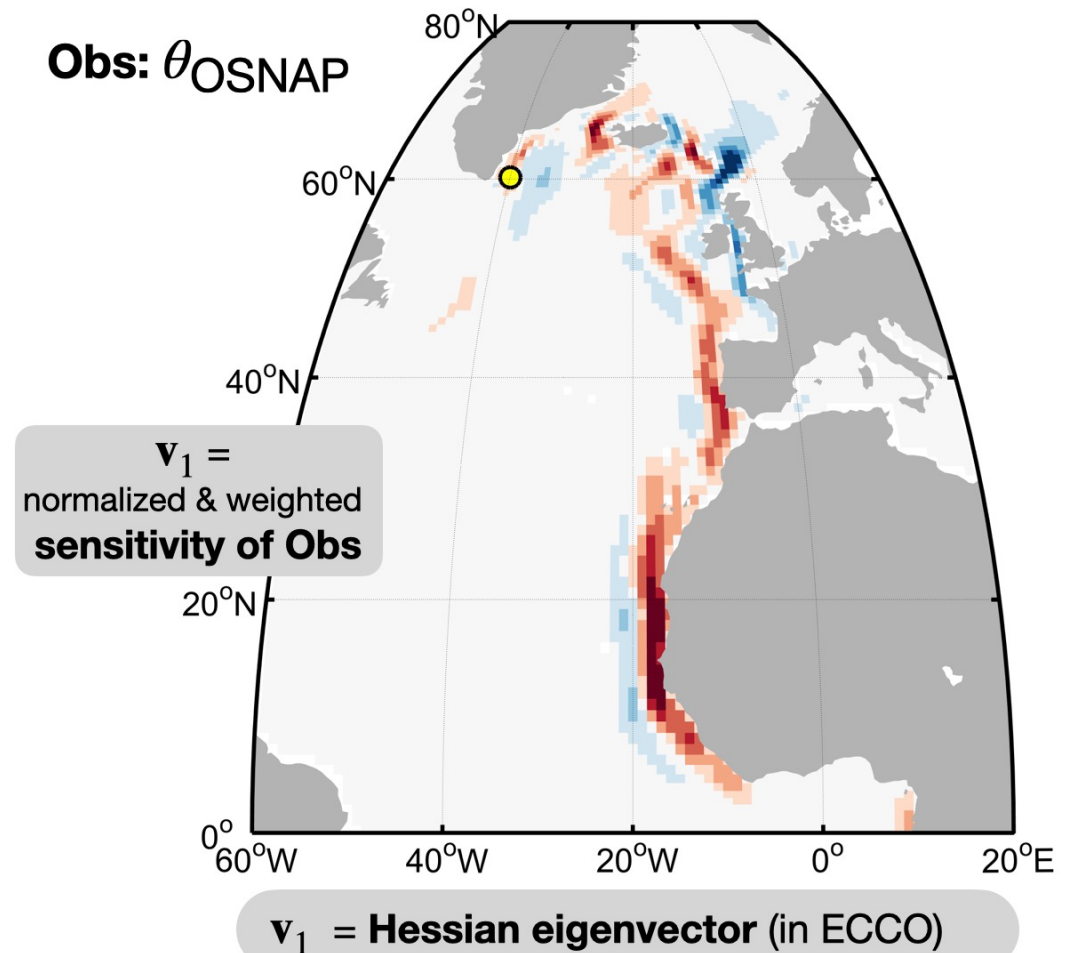
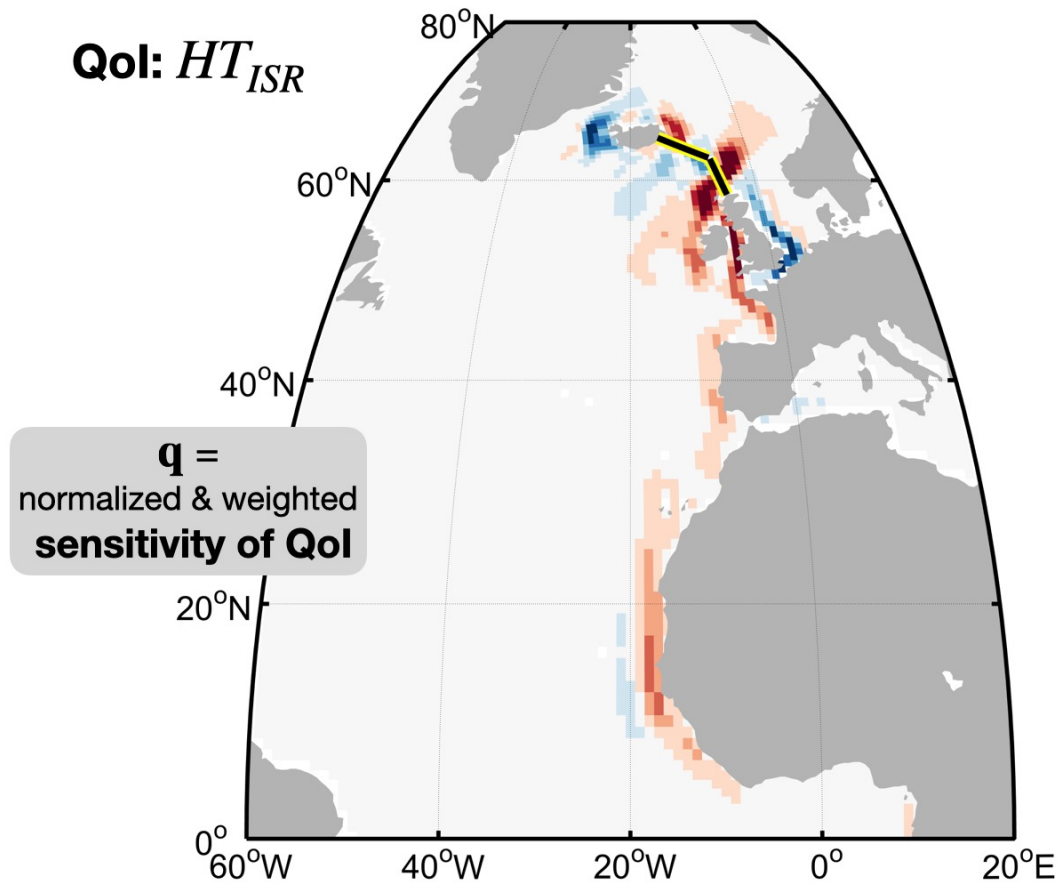


Sensitivity to meridional wind stress τ_y



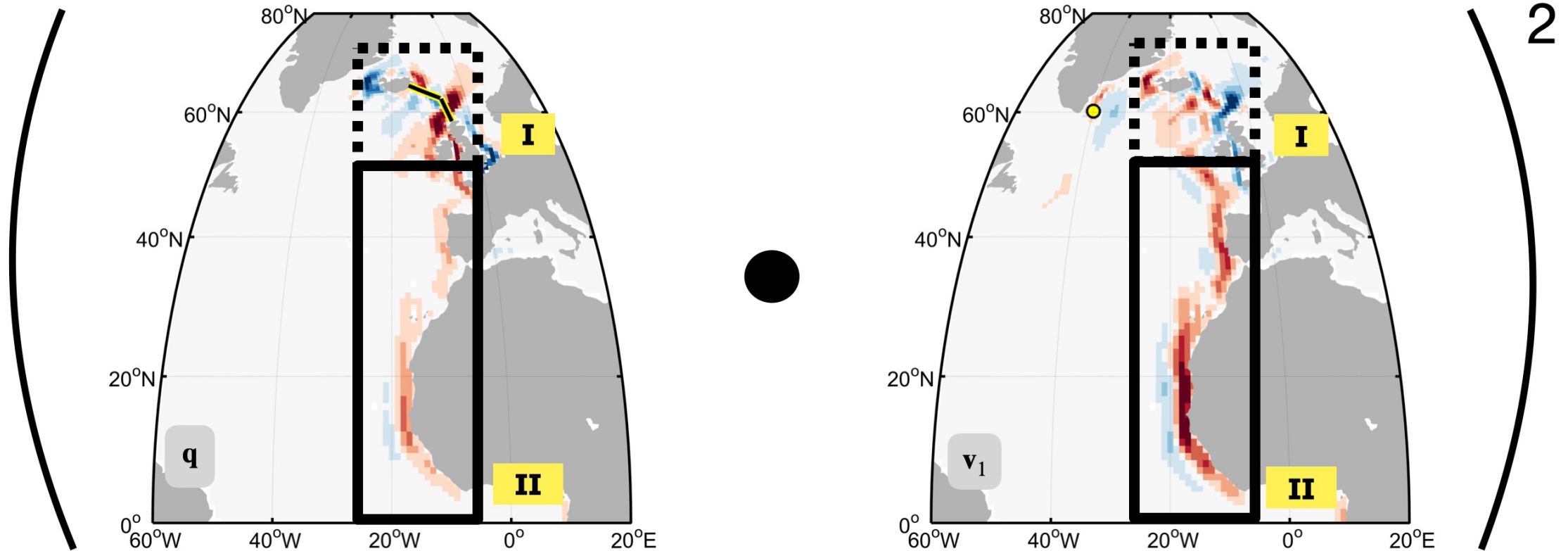
Computed with
MITgcm adjoint
model

Sensitivity maps re-interpreted in the context of UQ



$(\mathbf{q} \bullet \mathbf{v}_1)^2$ = uncertainty reduction in HT_{ISR} by noise-free θ_{OSNAP} observation

Uncertainty reduction via oceanic teleconnections

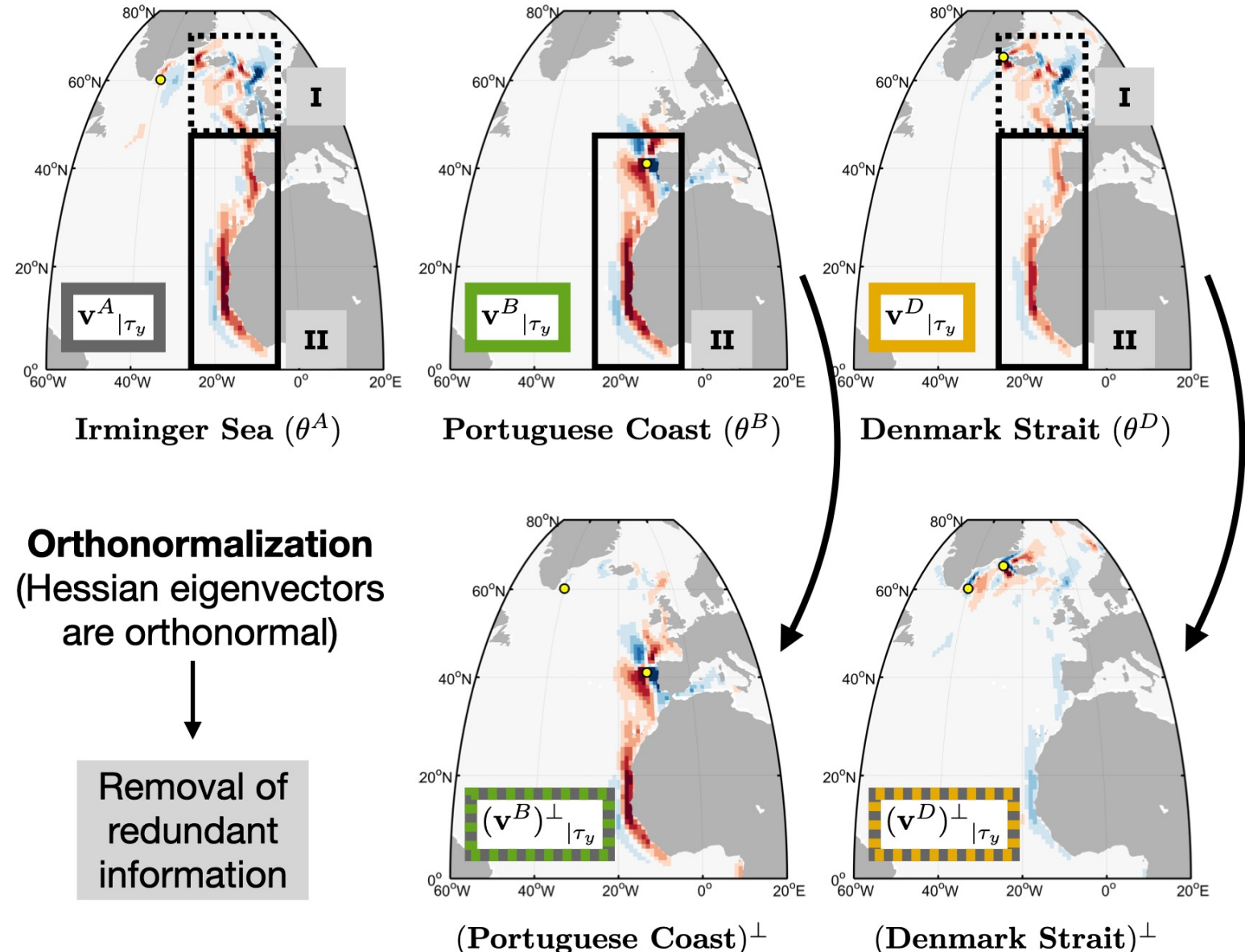


Uncertainty reduction in HT_{ISR} by noise-free θ_{OSNAP} observation:

$$(\mathbf{q} \bullet \mathbf{v}_1)^2 = (\underbrace{[\mathbf{q} \bullet \mathbf{v}_1]_+}_{\text{II}} + \underbrace{[\mathbf{q} \bullet \mathbf{v}_1]_-}_{\text{I}})^2 = (0.15 + (-0.59))^2 = (-0.44)^2 = 19\%$$

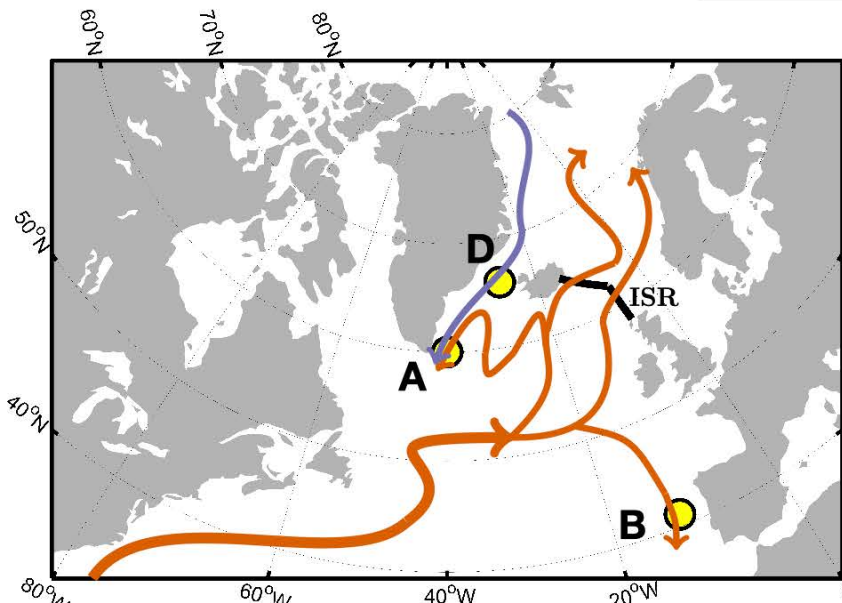
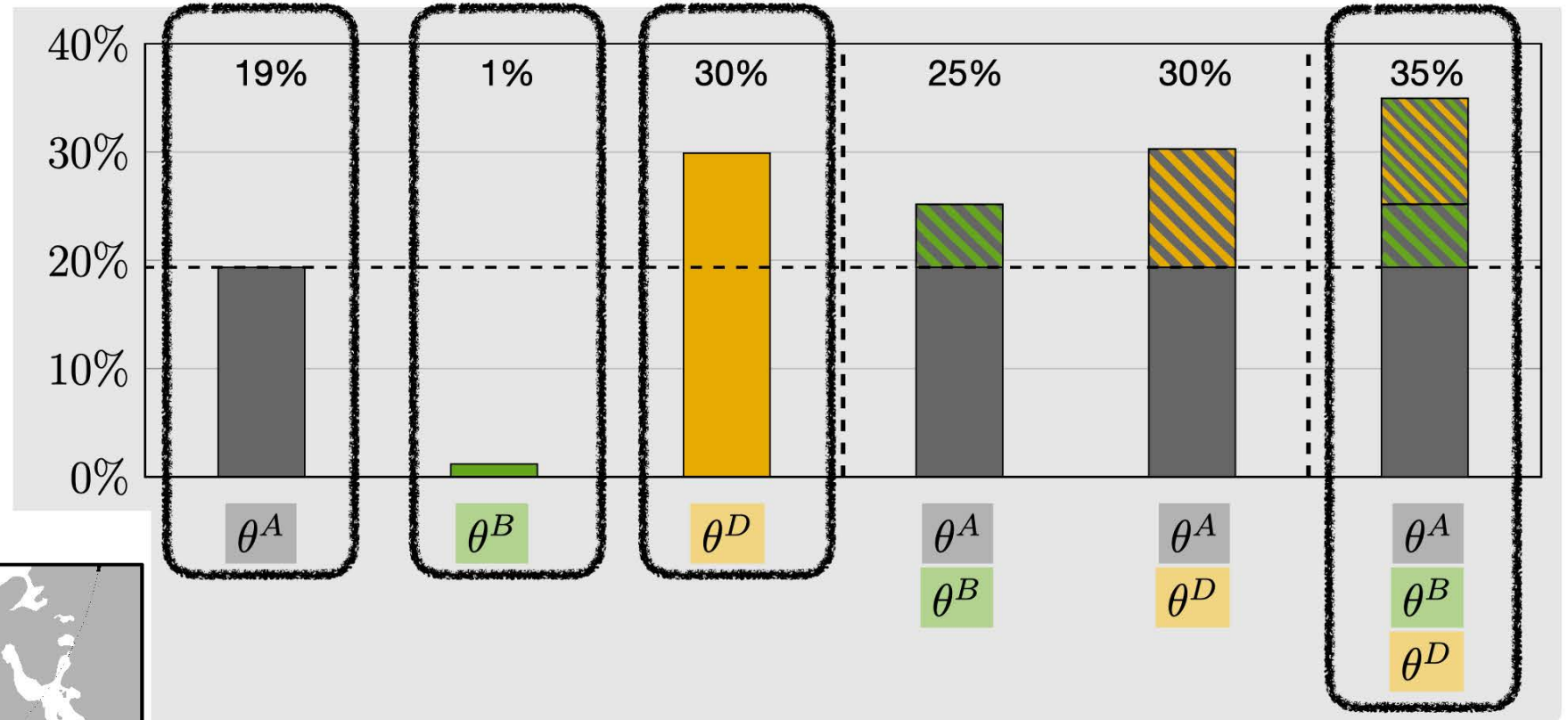
- Shared adjustment mechanisms lead to large uncertainty reduction
- BUT: destructive interference is possible

Assessing data redundancy vs. complementarity



Assessing data redundancy vs. complementarity

Uncertainty reduction in HT_{ISR} by noise-free observations



- Adding observation A (in the Irminger Sea) to observation D (in Denmark Strait) gives no extra information due to **data redundancy**
- Observation A (in the Irminger Sea) and observation B (off Portugal) show **data complementarity**

Conclusion: try to formulate what are we after?

- Documenting "circulation changes" in response to climate change?
 - What "circulation"?
 - Can we develop compelling metrics?
- Assessing ...
 - freshwater storage, transports, changes?
 - heat storage, transports, changes?
 - changes in biogeochemical cycles and ecosystems (some of which constrained by the physics)?

Those are likely different (different sources, different key depths, ...)
- Air-ice-ocean interactions
 - Relevant for both near-surface atmosphere & ocean
 - Both poorly observed / constrained