Adjoints as a Tool for Observing System Design: with applications to AMOC

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Aims

- We aim to show that adjoint modelling is a powerful tool for:

  1. **Identifying critical observation uncertainties**

  2. **Exploring potential proxy information of observations**

Background: Adjoint Models

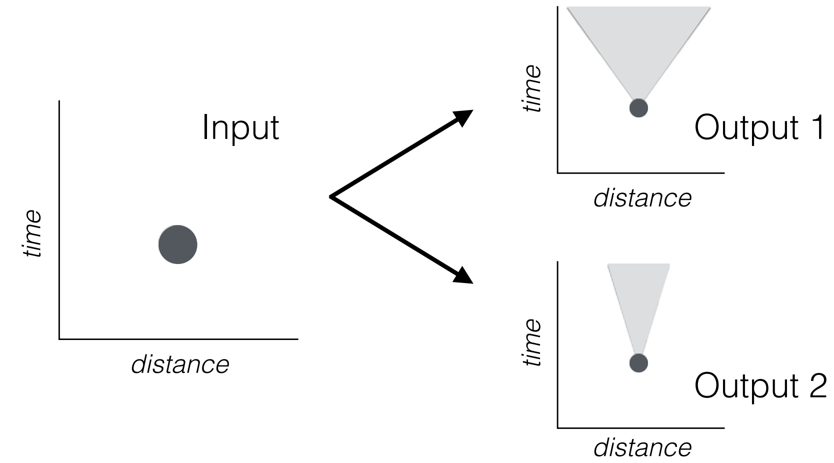
- The adjoint of an OGCM provides the **local linear sensitivity** of an output scalar Quantity of Interest (**QoI**) to all model controls (**x**) as a function of **control lead time** ($\mathrm{T}_{\mathrm{lead}}$):

$$\boxed{\frac{\partial \mathrm{QoI}}{\partial \mathbf{x}}(x, y, z, \mathrm{T}_{\mathrm{lead}}) \qquad \text{for} \;\; \mathbf{x} = \mathbf{x}_{\mathrm{boundary}} + \mathbf{x}_{\mathrm{initial}} + \mathbf{x}_{\mathrm{params}}}$$

- They reveal all viable **dynamical mechanisms** via which perturbations in **x influence** the QoI.

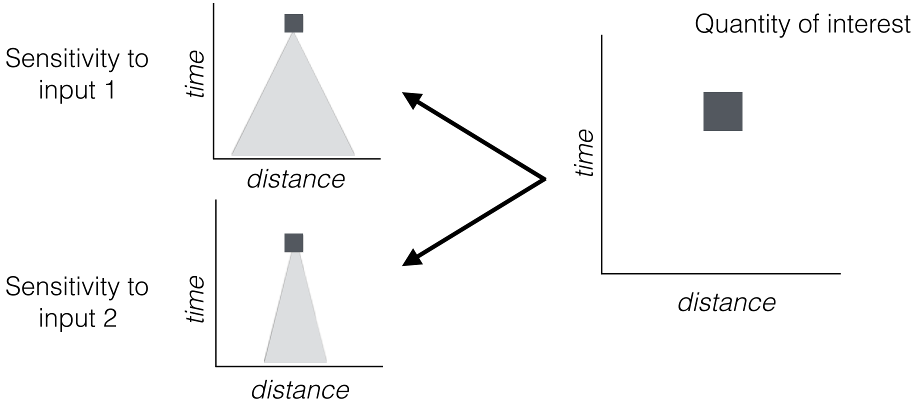
Background: Adjoint vs Forward Sensitivity

Forward sensitivity study



Result: **Impact of a single input perturbation on all model outputs**

Adjoint sensitivity study



Result: **Sensitivity of a single model output (QoI) to all model inputs**

Jones et al. , 2018

PART 1:

Adjoints applied to dynamical attribution

Aims

- We aim to show that adjoint modelling is a powerful tool for:

  1. **Identifying critical observation uncertainties**

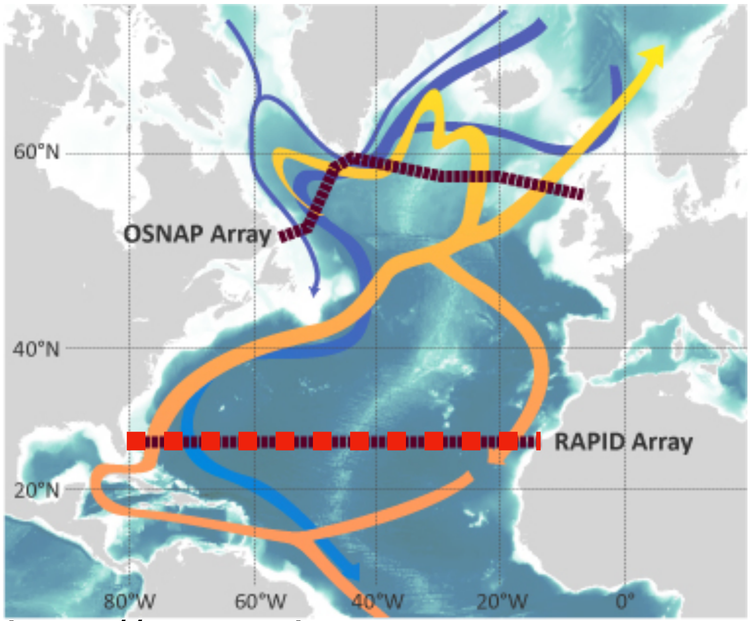
  2. **Exploring potential proxy information of observations**

Aims

- We aim to show that adjoint modelling is a powerful tool for:

1. **Identifying critical observation uncertainties**
case study: *key atmospheric uncertainties for* ***MOC***$_{\textbf{RAPID}}$ *estimates*

2. **Exploring potential proxy information of observations**

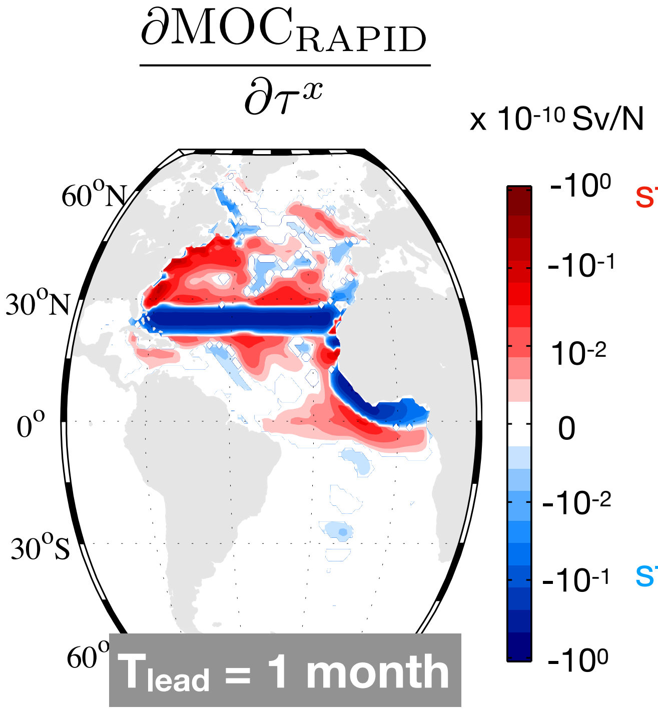


http://www.ukosnap.org

Model:
- Quasi-global (74°N and 78°S) MITgcm
- grid = 1°x1°, 33 levels
- forcing = NCEP II air-sea flux climatology
  + OMIP runoff climatology
  + restoring to SSS/SST climatology
  (all climatologies = 12 x monthly-mean repeating)
- subgrid = KPP mixing + GM eddy schemes

- **QoI = monthly-mean MOC**$_{\textbf{RAPID}}$
- **controls** = τ^x, τ^y, Q, (E-P)
- max T_{lead} = 15 years

$\text{MOC}_{\text{RAPID}}$ air-sea flux sensitivity

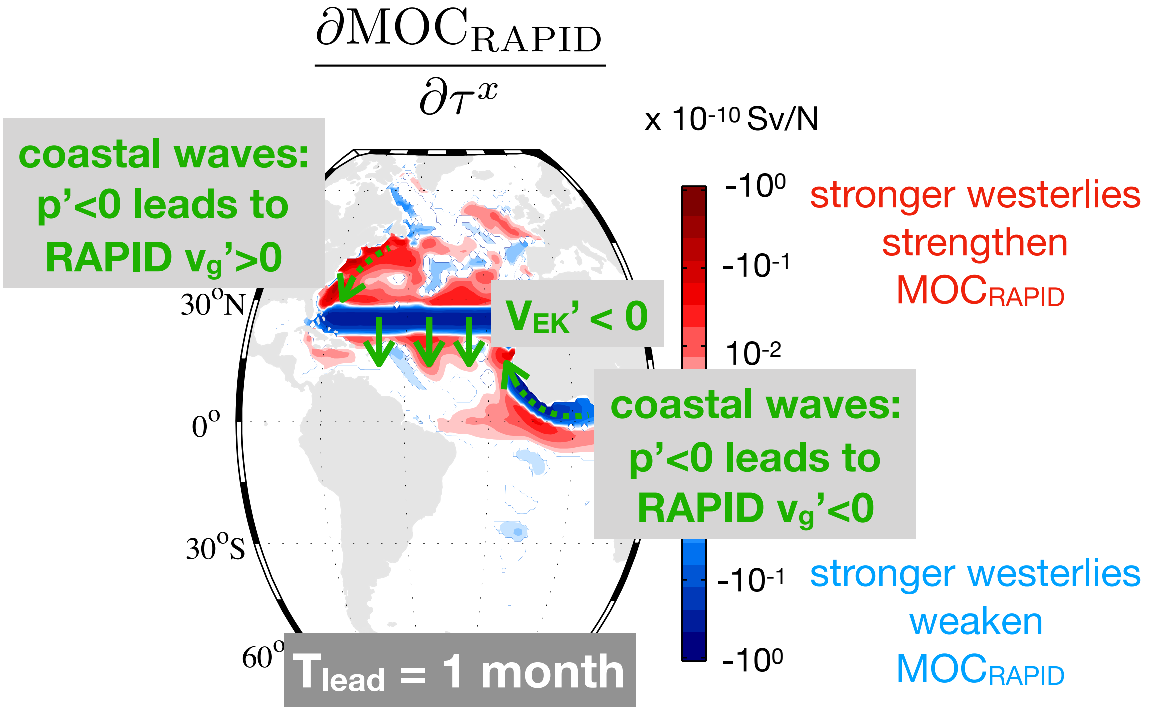


stronger westerlies strengthen $\text{MOC}_{\text{RAPID}}$

stronger westerlies weaken $\text{MOC}_{\text{RAPID}}$

Pillar et al. , 2016

MOC_{RAPID} air-sea flux sensitivity



Pillar et al. , 2016

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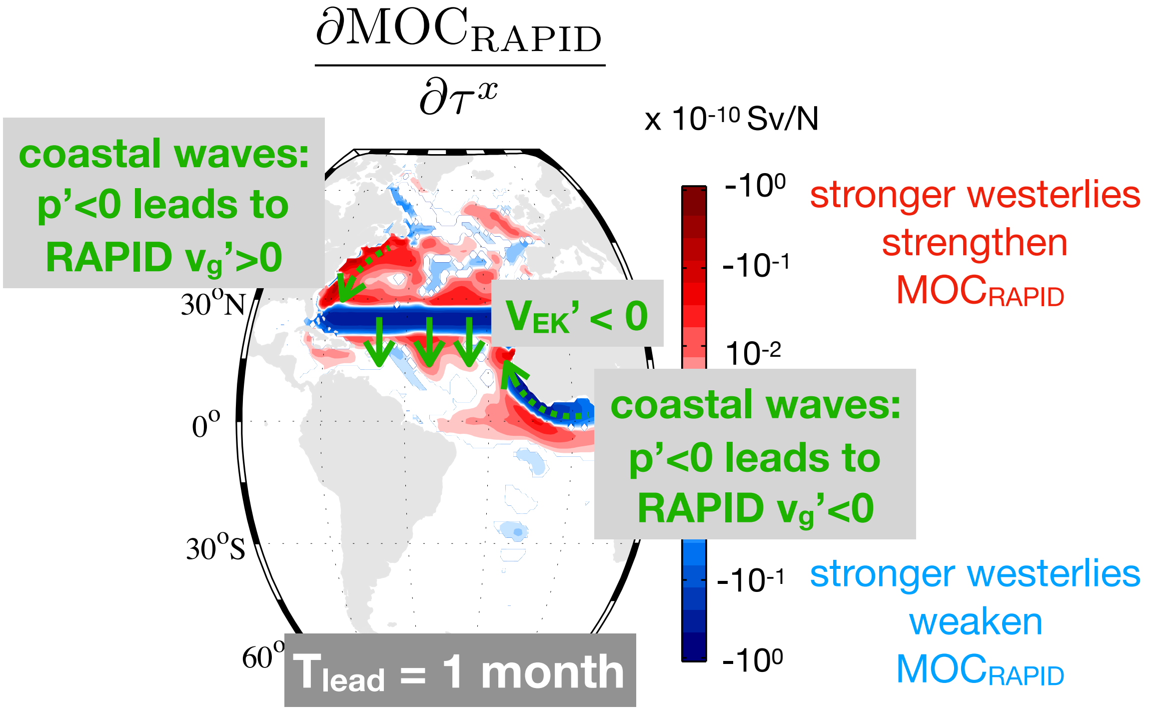

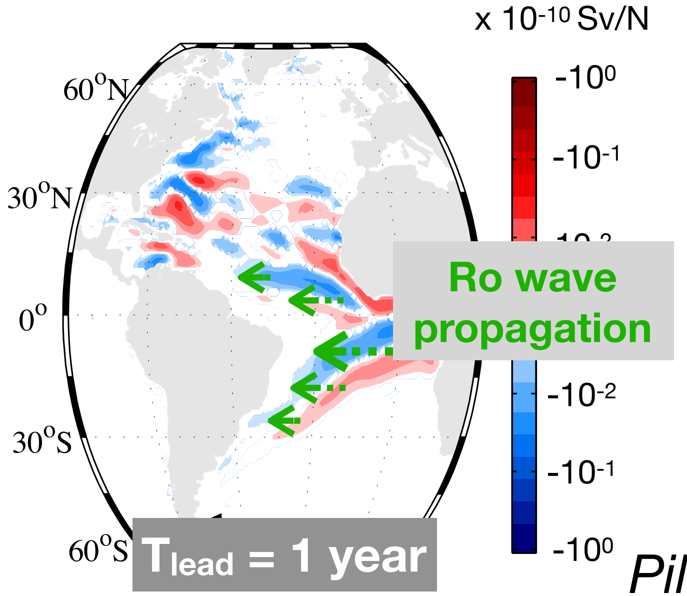

Pillar et al. , 2016

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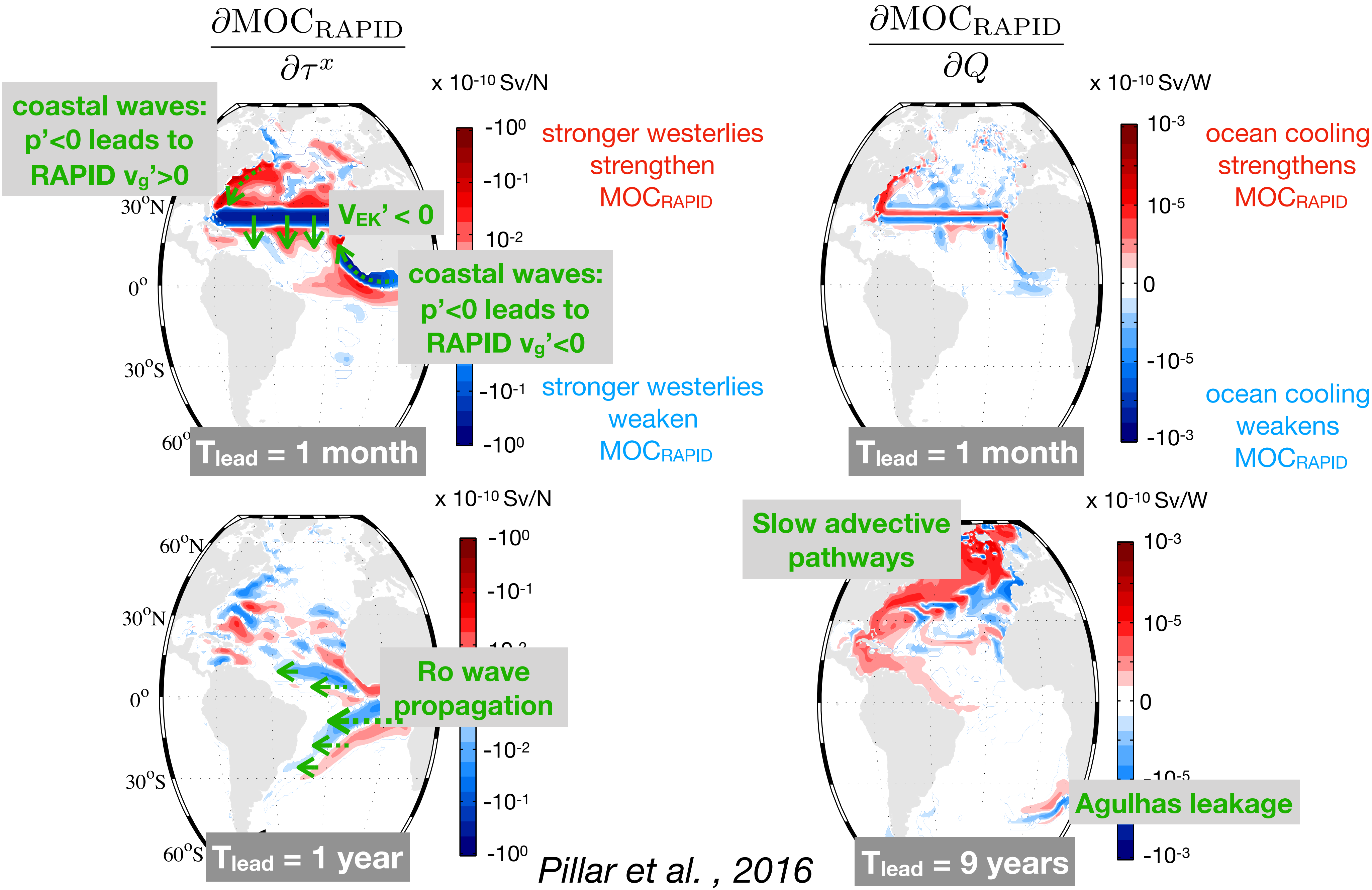
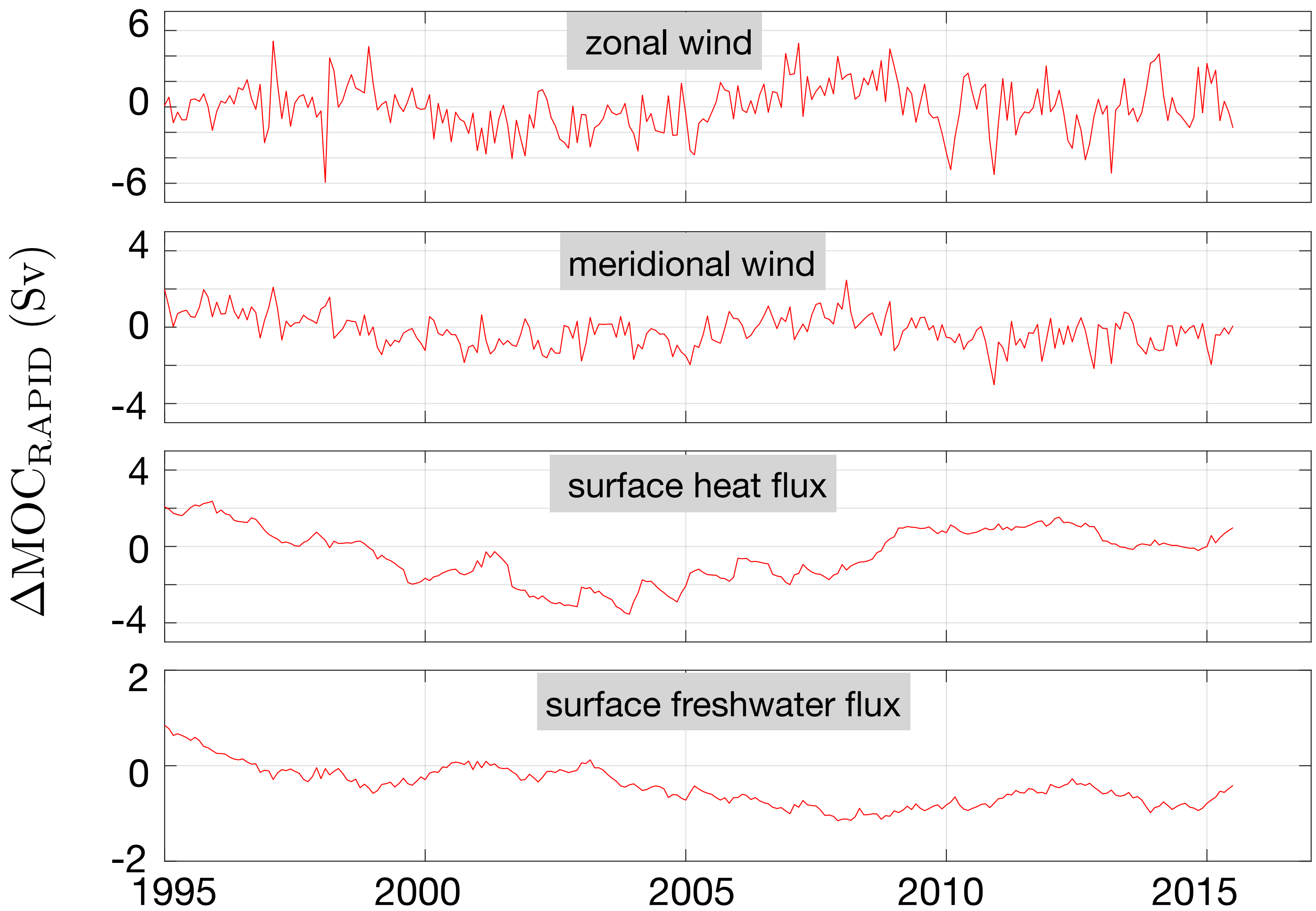


Pillar et al. , 2016

Externally Forced MOC$_{\text{RAPID}}$ Variability

$$\Delta\mathrm{MOC}_{\mathrm{RAPID}}(t,F) = \sum_{\mathrm{T_{lead}}}^{15\ \mathrm{yrs}} \int\int \frac{\partial \mathrm{MOC}_{\mathrm{RAPID}}}{\partial F}(x,y,\mathrm{T_{lead}})\Delta F(x,y,t-\mathrm{T_{lead}})\,dx\,dy$$

$\Delta F =$ **NCEPII** monthly anomalies about the seasonal climatology

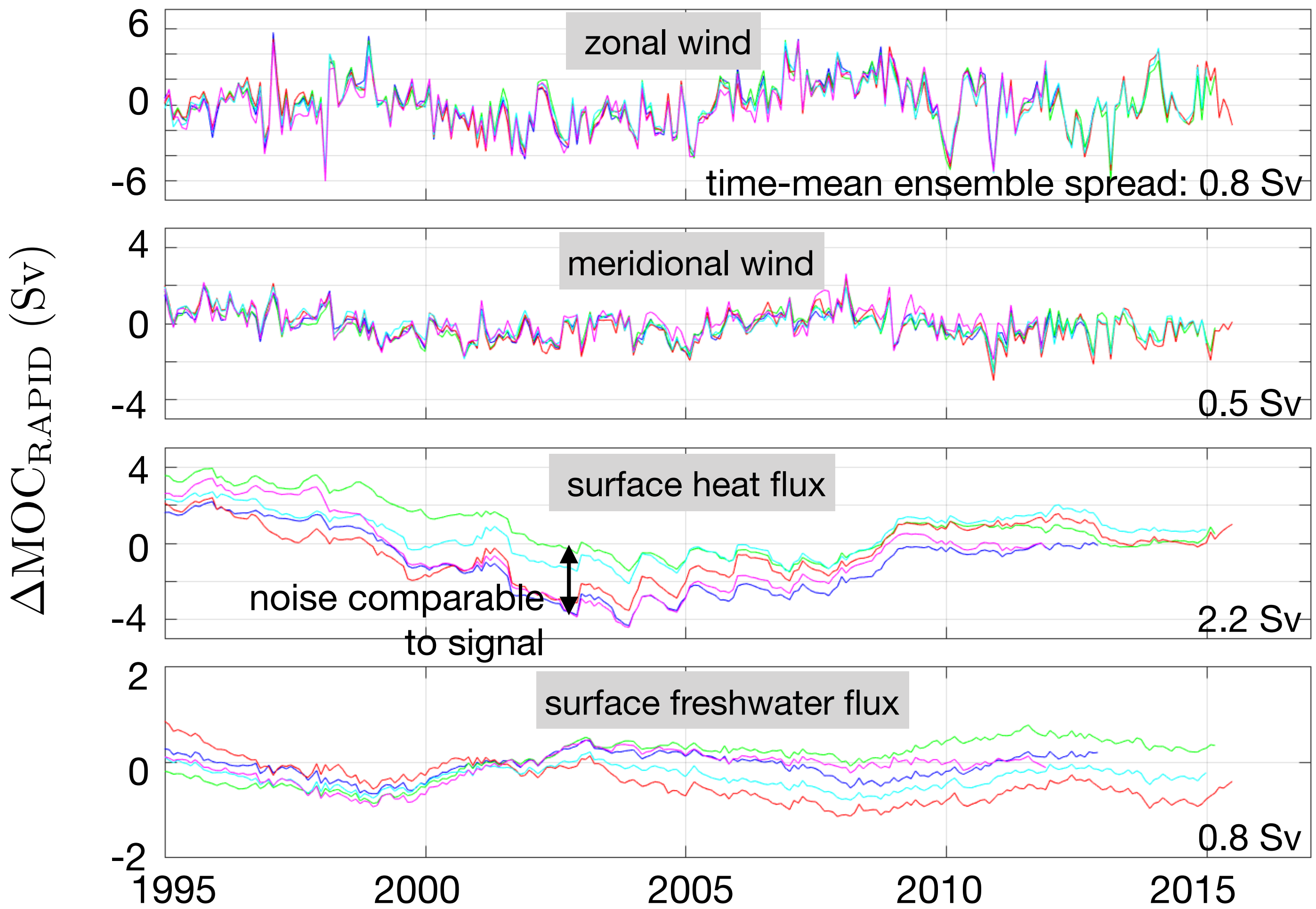


Pillar et al. , 2016

Externally Forced $\text{MOC}_{\text{RAPID}}$ Uncertainty

$$\Delta \text{MOC}_{\text{RAPID}}(t, F) = \sum_{\text{T}_{\text{lead}}}^{15 \text{ yrs}} \int\int \frac{\partial \text{MOC}_{\text{RAPID}}}{\partial F}(x, y, \text{T}_{\text{lead}}) \Delta F(x, y, t - \text{T}_{\text{lead}})\, dx\, dy$$

$\Delta F =$ **NCEPII**/ **NCEPI**/ **ERA-INT**/ **JRA55**/ **20CR** monthly anomalies



Pillar et al. , 2018

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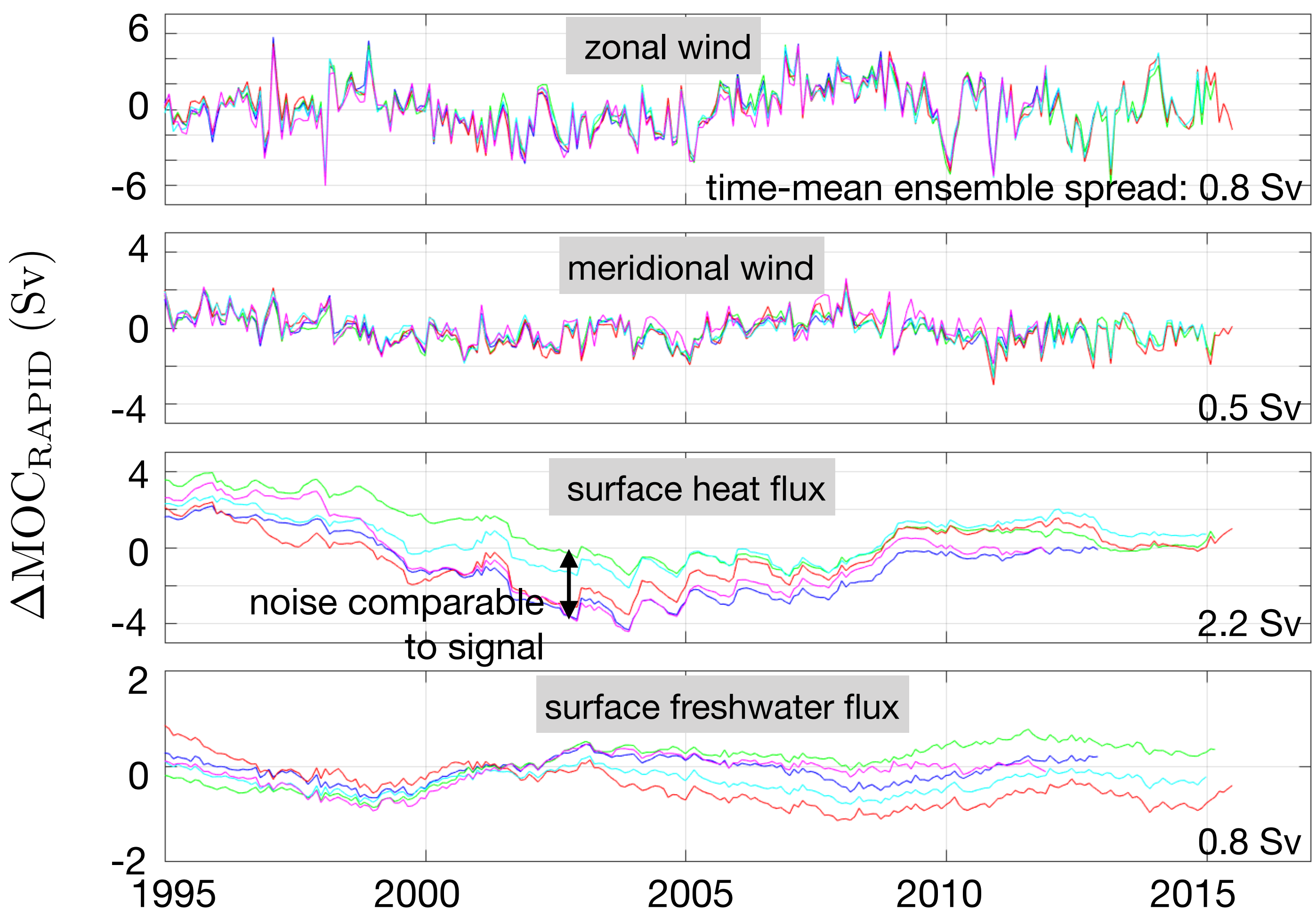


Key flux uncertainty?

(1) WHEN in time?

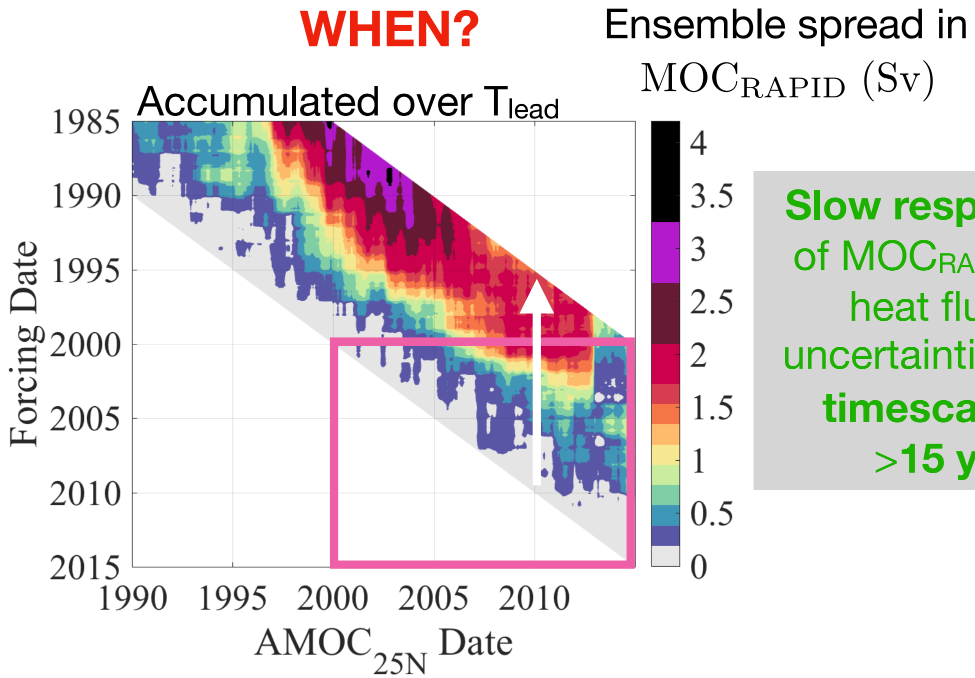
(2) WHERE in space?

Focus on space and time origins of heat-driven MOC$_{\mathrm{RAPID}}$ ensemble spread

Pillar et al. , 2018

Critical Heat-Flux Uncertainties?

WHEN?



Slow response of MOC_{RAPID} to heat flux uncertainties on **timescales >15 yr**

WHERE?

Pillar et al. , 2018

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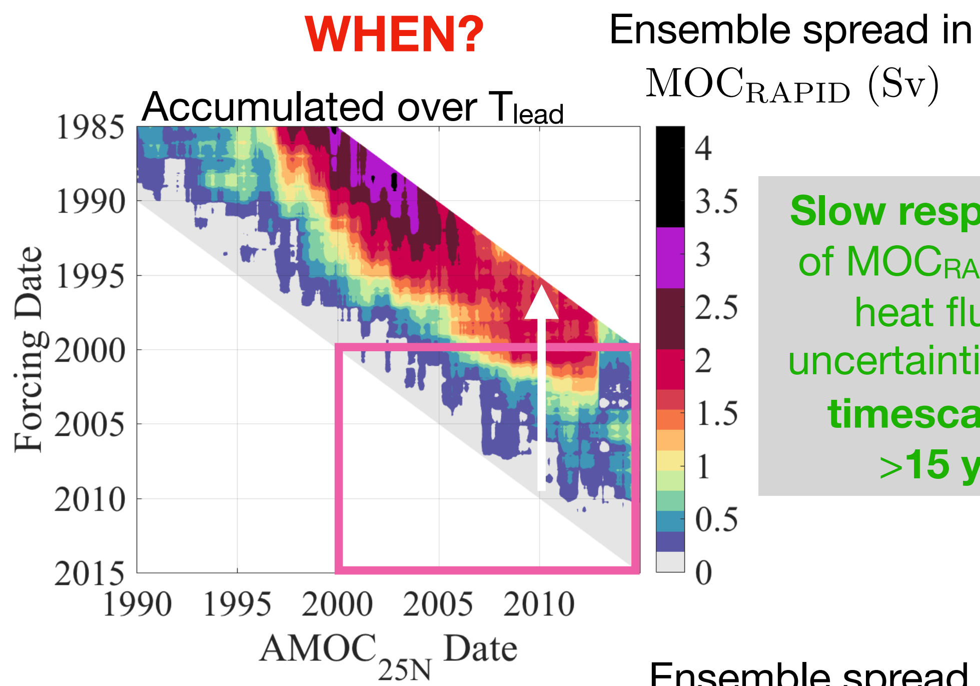

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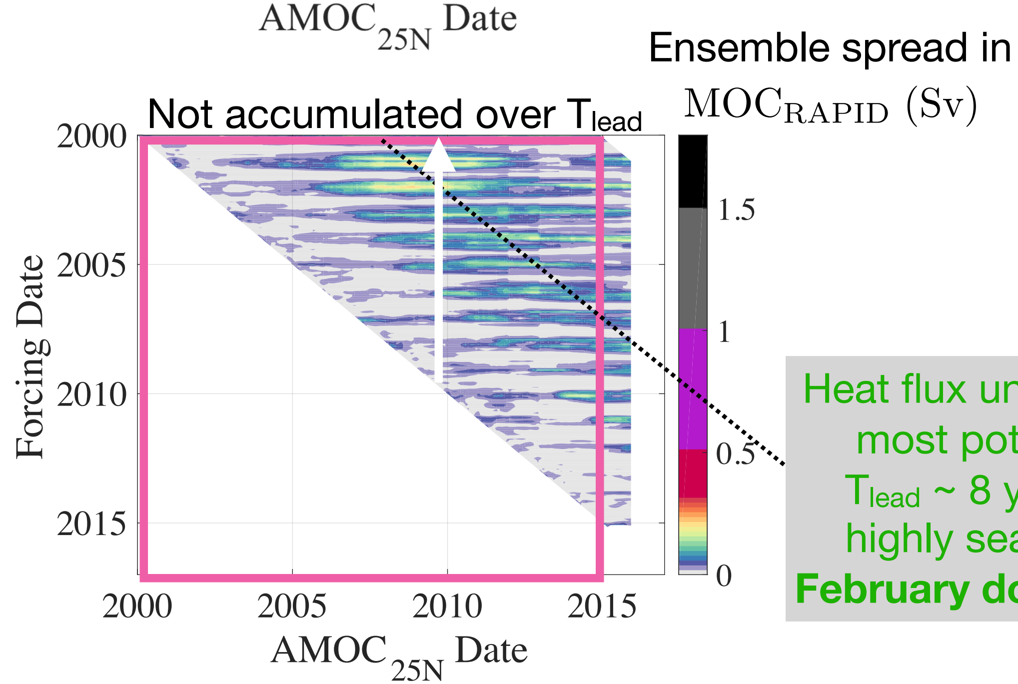


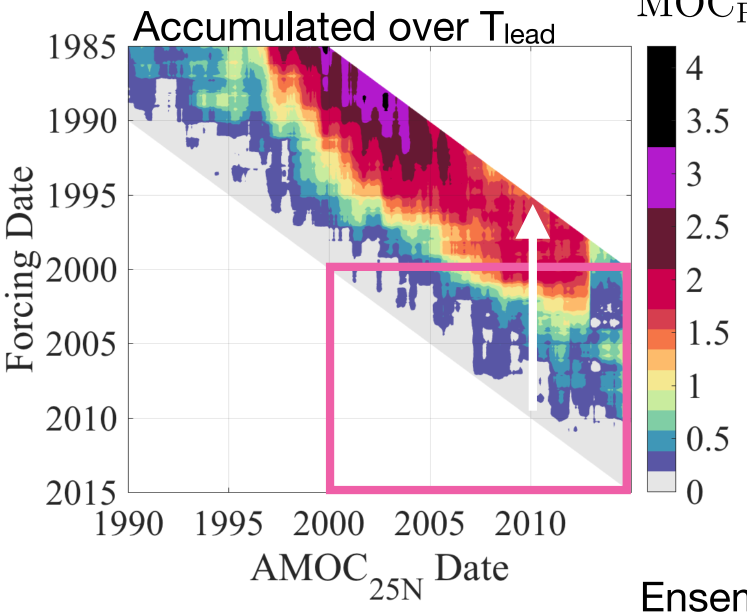
Heat flux uncertainty most potent at T_{lead} ~ 8 yrs and highly seasonal: **February dominates**

Pillar et al. , 2018

Critical Heat-Flux Uncertainties?

WHEN?

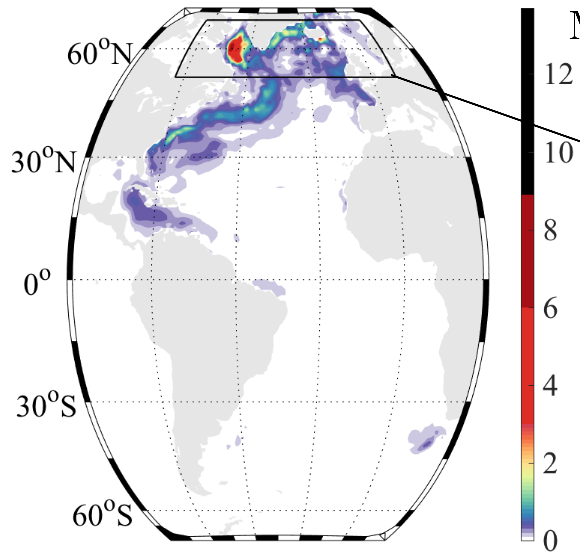
Ensemble spread in $\mathrm{MOC_{RAPID}}$ (Sv)



Slow response of $\mathrm{MOC_{RAPID}}$ to heat flux uncertainties on **timescales** >**15 yr**

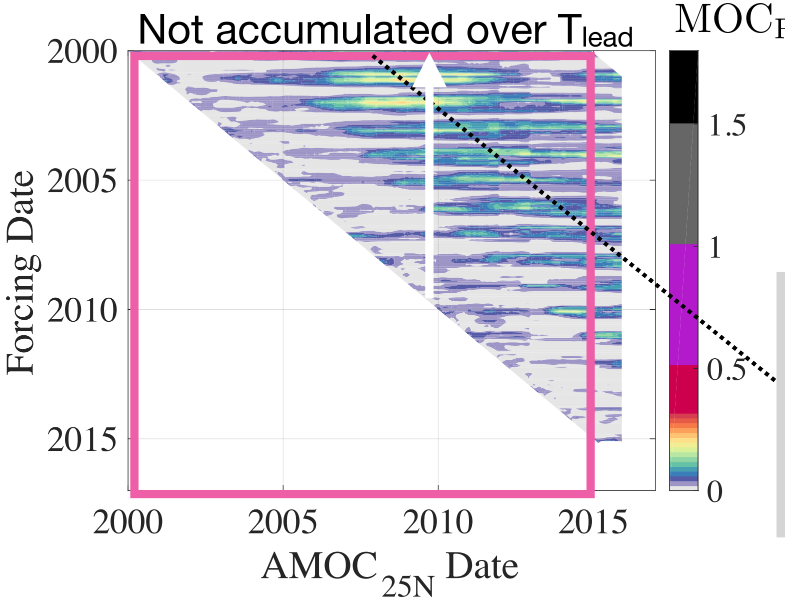
WHERE?

Time integrated (17yrs) ensemble spread in $\mathrm{MOC_{RAPID}}$ (Sv)



~50% of ensemble spread in heat-driven $\mathrm{MOC_{RAPID}}$ from **SPG.** Most potent uncertainty is over **Labrador Sea**

Ensemble spread in $\mathrm{MOC_{RAPID}}$ (Sv)



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Pillar et al. , 2018

Critical Heat-Flux Uncertainties?

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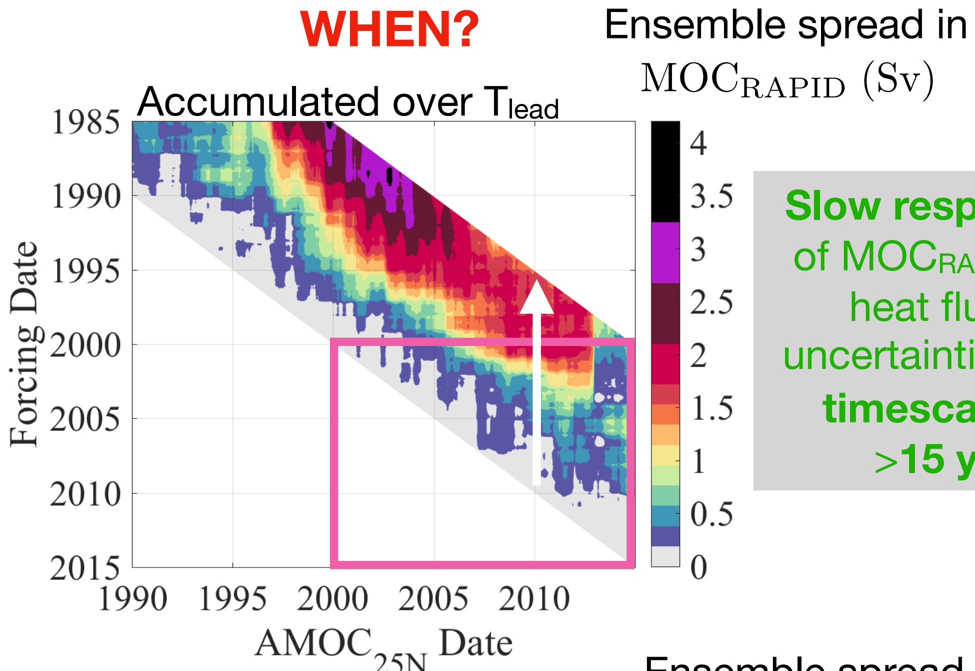
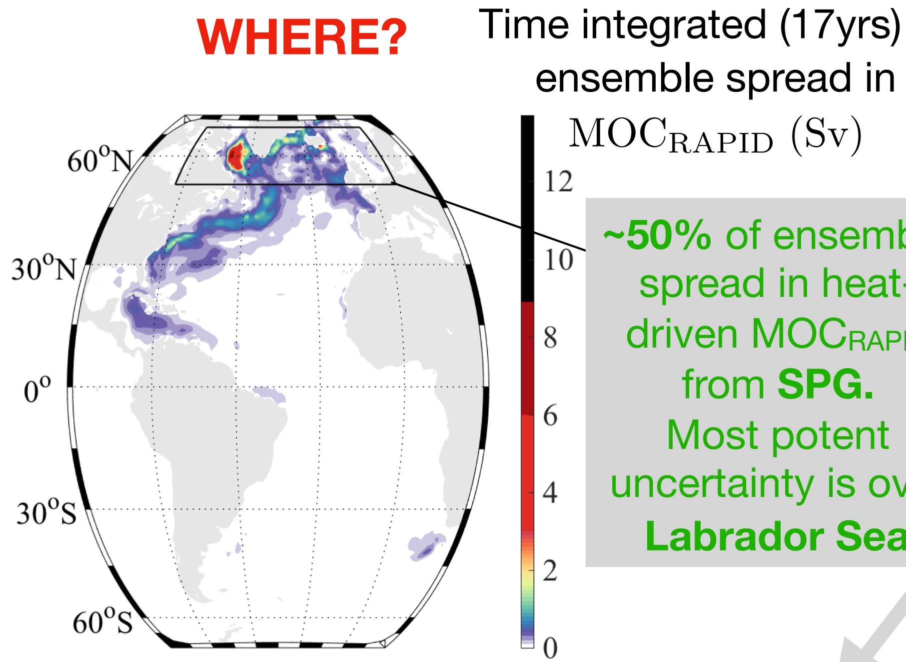
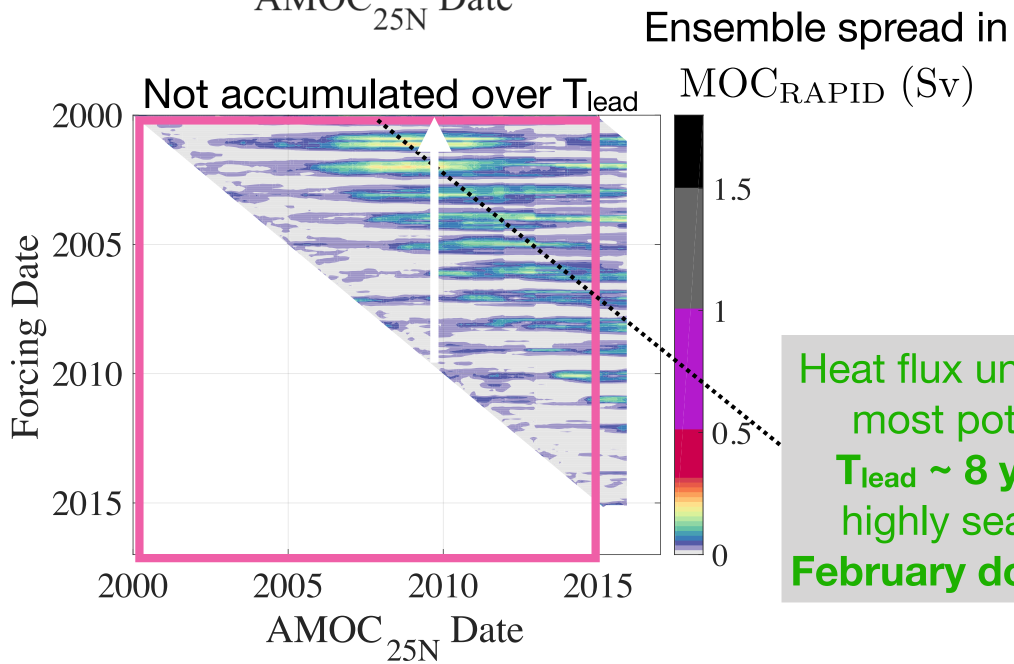


Slow response of MOC_{RAPID} to heat flux uncertainties on **timescales** >**15 yr**

WHERE?



~50% of ensemble spread in heat-driven MOC_{RAPID} from **SPG.** Most potent uncertainty is over **Labrador Sea**



Heat flux uncertainty most potent at **T_{lead} ~ 8 yrs** and highly seasonal: **February dominates**

UNCERTAINTY REDUCTION TARGETS

Supports importance of initialised LSW anomalies for decadal prediction *(e.g., Yeager and Robson 2017)*

Pillar et al. , 2018

PART 2:

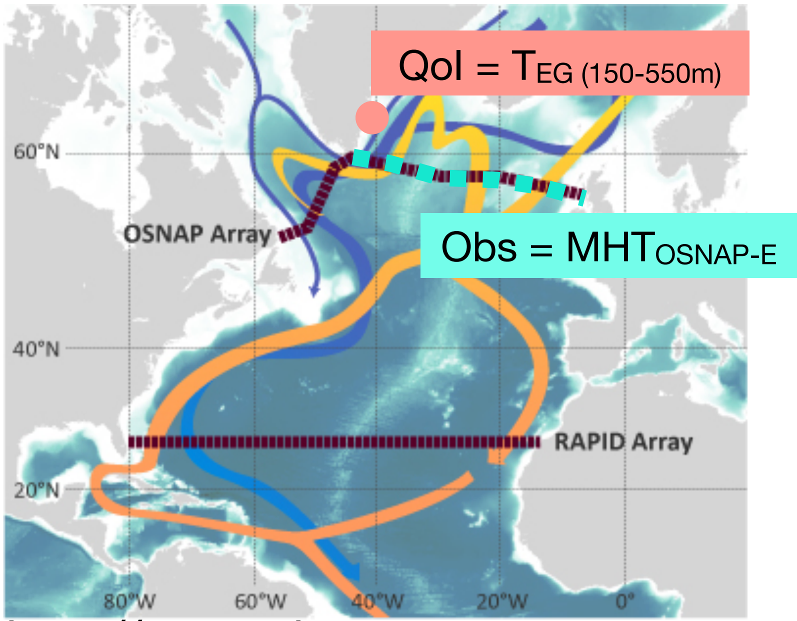
Adjoints applied to observing system design

Aims

- We aim to show that adjoint modelling is a powerful tool for:

1. Identifying critical observation uncertainties
case study: key *atmospheric uncertainties* for **MOC$_{RAPID}$** estimates

2. **Exploring potential proxy information of observations**



http://www.ukosnap.org

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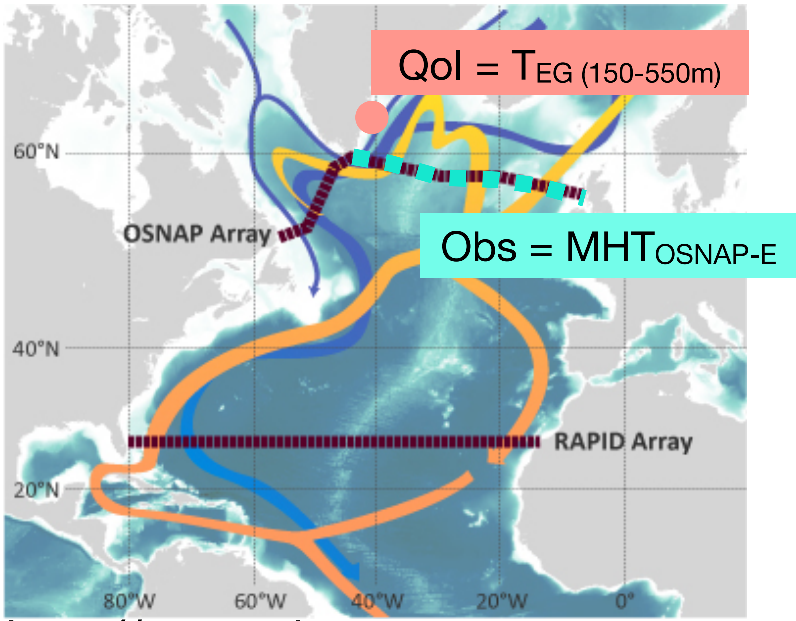
1. Identifying critical observation uncertainties
case study: *key atmospheric uncertainties for* **MOC_{RAPID}** *estimates*

2. **Exploring potential proxy information of observations**
case study: *constraints on* ***T_{EG}*** *provided by* ***$MHT_{OSNAP\text{-}E}$*** *(Loose et al. 2018)*



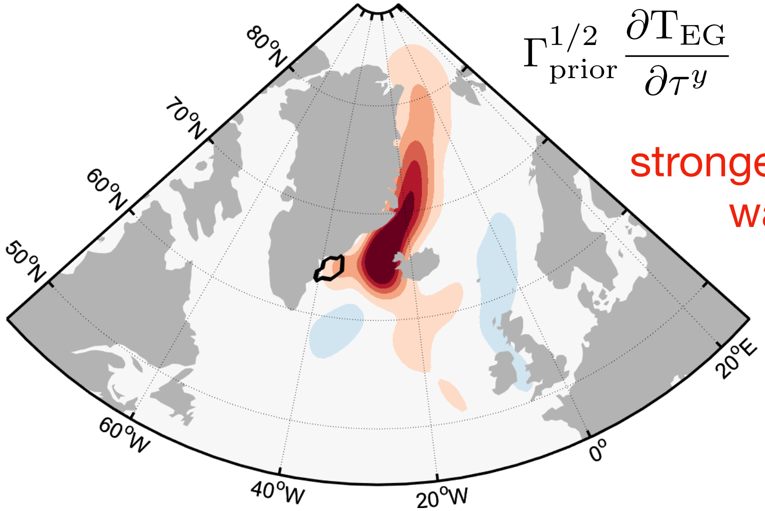
http://www.ukosnap.org

Inverse Modelling Framework:
- Global MITgcm in ECCOv4 *(Forget et al., 2015)*
- grid = 1°x1°, 50 levels
- forcing = optimised atmospheric state (1992-2011) with bulk formulae
- subgrid = KPP mixing + GM eddy schemes

- **QoI = 5yr-mean T_{EG} (150-550m)**
- **Obs = 5yr-mean $MHT_{OSNAP\text{-}E}$**
- controls = τ^x, τ^y, $R_{SW\downarrow}$, $R_{LW\downarrow}$, q, T_{atm}, P

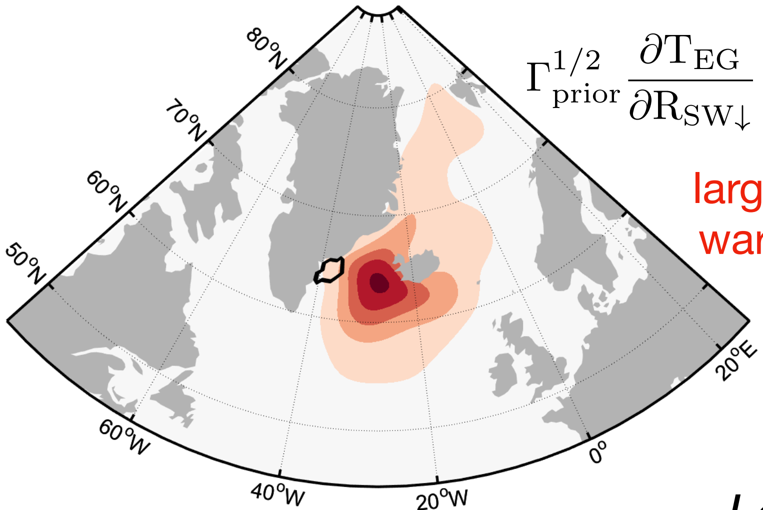
T_{EG} Forcing Sensitivity

Linear sensitivities for QoI (T_{EG})
(prior weighted and normalised)



$$\Gamma_{\text{prior}}^{1/2} \frac{\partial \mathrm{T_{EG}}}{\partial \tau^y}$$

stronger southerlies
warm T_{EG}



$$\Gamma_{\text{prior}}^{1/2} \frac{\partial \mathrm{T_{EG}}}{\partial \mathrm{R_{SW\downarrow}}}$$

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Loose et al. , 2018

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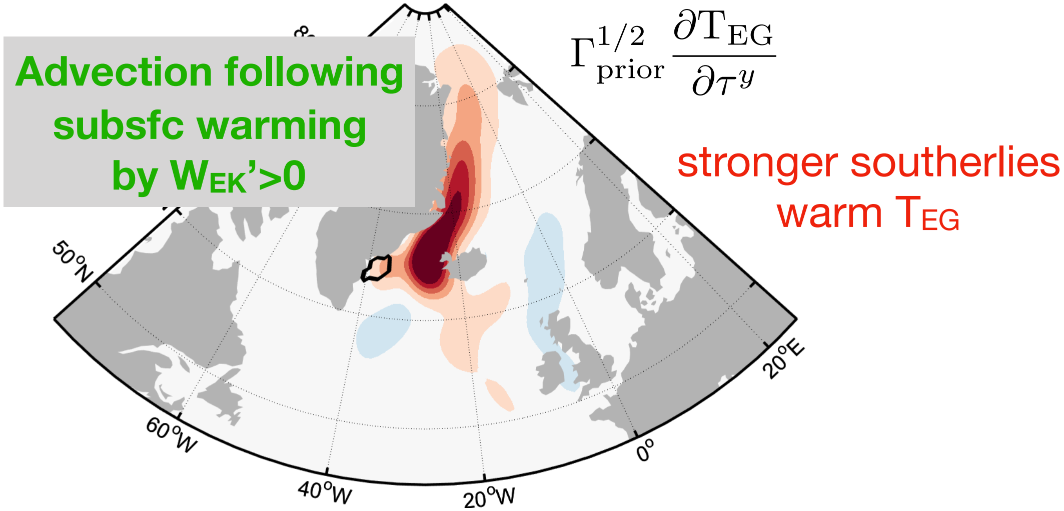
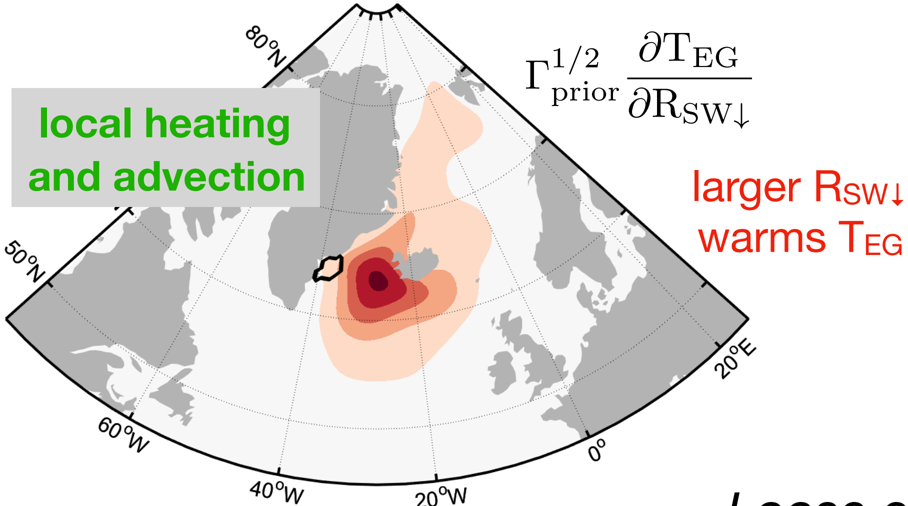


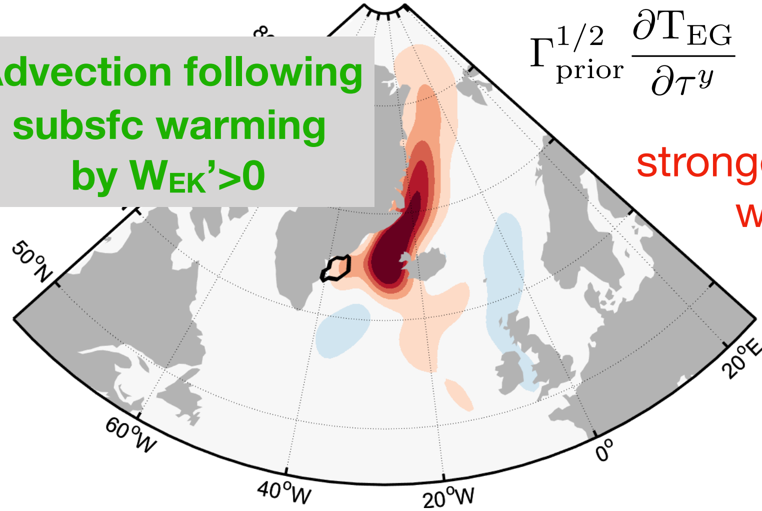


Loose et al. , 2018

T_{EG} vs. $MHT_{OSNAP\text{-}E}$ Forcing Sensitivity

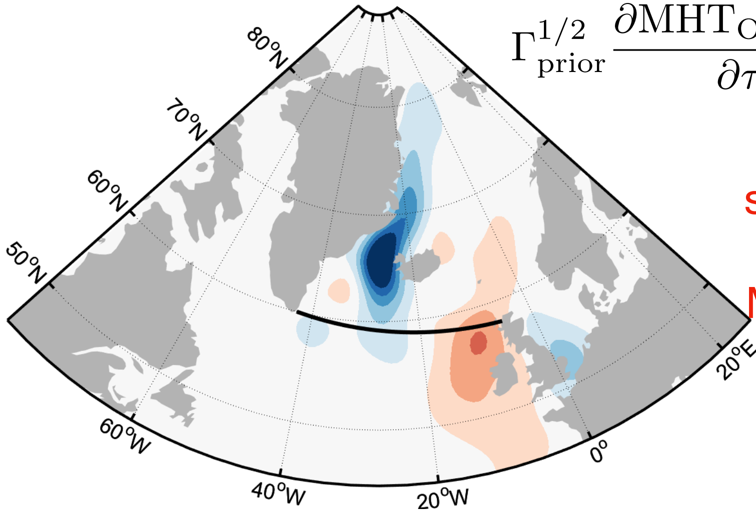
Linear sensitivities for QoI (T_{EG})
(prior weighted and normalised)

Linear sensitivities for Obs ($MHT_{OSNAP\text{-}E}$)
(prior weighted and normalised)



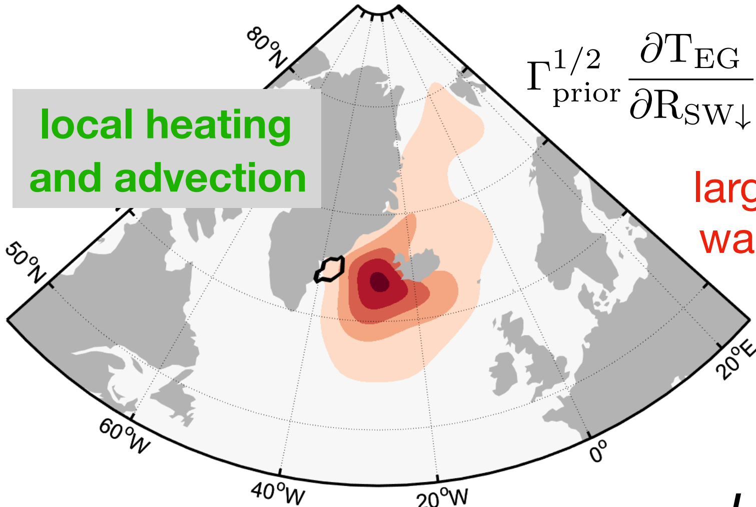
$$\Gamma^{1/2}_{\text{prior}} \frac{\partial \text{T}_{\text{EG}}}{\partial \tau^{y}}$$

stronger southerlies warm T_{EG}



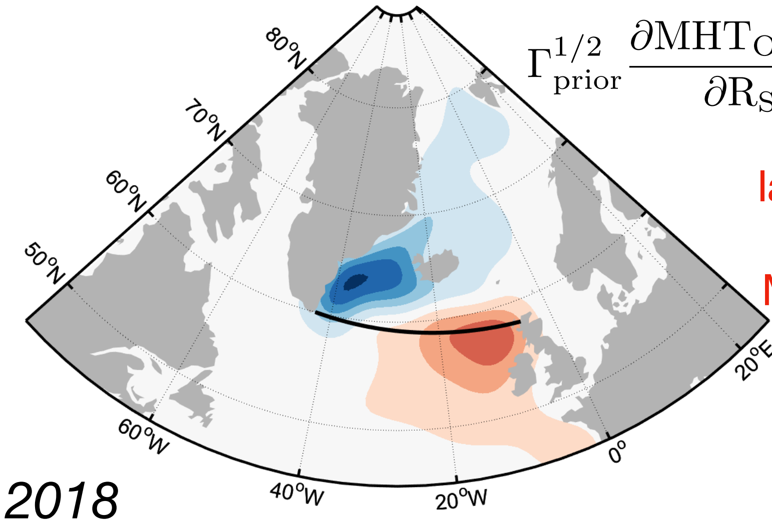
$$\Gamma^{1/2}_{\text{prior}} \frac{\partial \text{MHT}_{\text{OSNAP-E}}}{\partial \tau^{y}}$$

stronger southerlies increase $MHT_{OSNAP\text{-}E}$



$$\Gamma^{1/2}_{\text{prior}} \frac{\partial \text{T}_{\text{EG}}}{\partial \text{R}_{\text{SW}\downarrow}}$$

larger $R_{SW\downarrow}$ warms T_{EG}



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larger $R_{SW\downarrow}$ increases $MHT_{OSNAP\text{-}E}$

Loose et al. , 2018

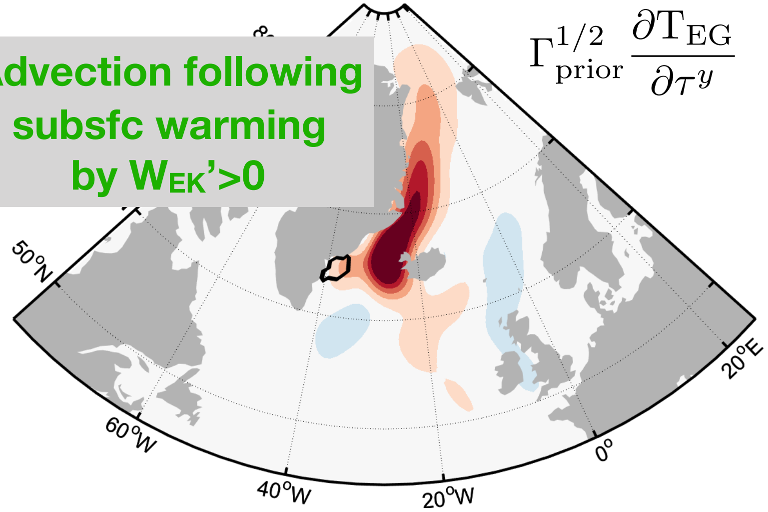
T_{EG} vs. $MHT_{OSNAP\text{-}E}$ Forcing Sensitivity

Linear sensitivities for QoI (T_{EG})
(prior weighted and normalised)

Linear sensitivities for Obs ($MHT_{OSNAP\text{-}E}$)
(prior weighted and normalised)

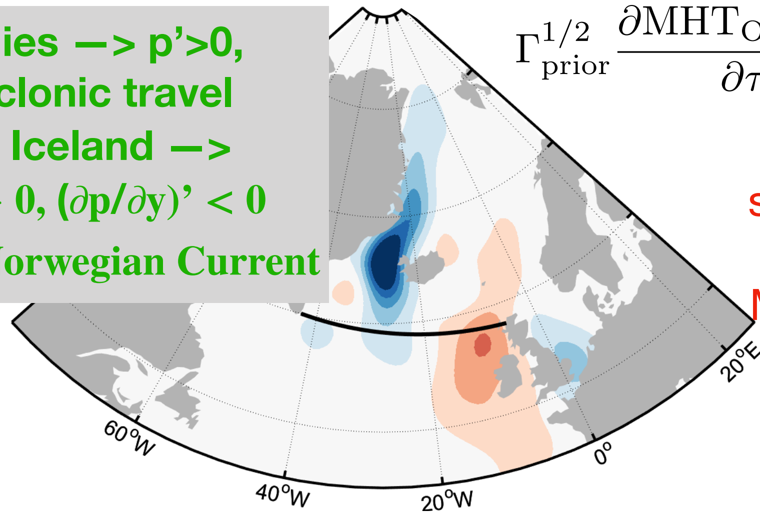
$$\Gamma_{\text{prior}}^{1/2}\frac{\partial T_{EG}}{\partial \tau^y}$$

Advection following subsfc warming by W_{EK}'>0



$$\Gamma_{\text{prior}}^{1/2}\frac{\partial MHT_{OSNAP\text{-}E}}{\partial \tau^y}$$

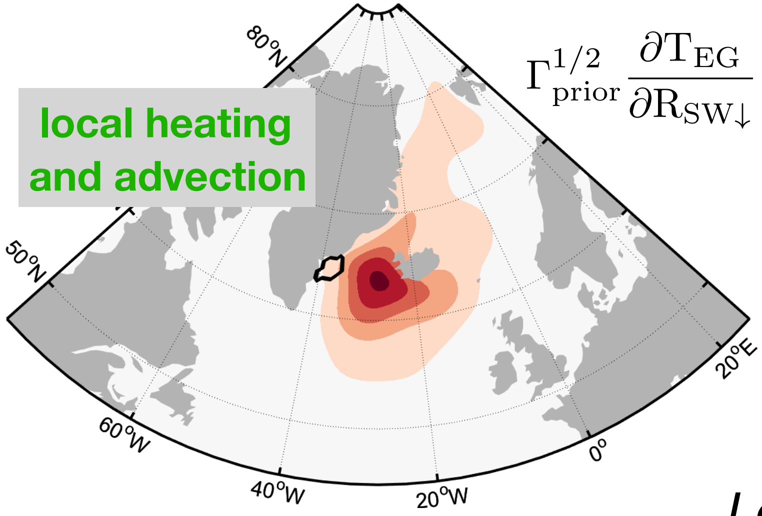
northerlies —> p'>0,
anti-cyclonic travel
around Iceland —>
$(\partial p/\partial x)' > 0$, $(\partial p/\partial y)' < 0$
= stronger Norwegian Current



stronger southerlies increase $MHT_{OSNAP\text{-}E}$

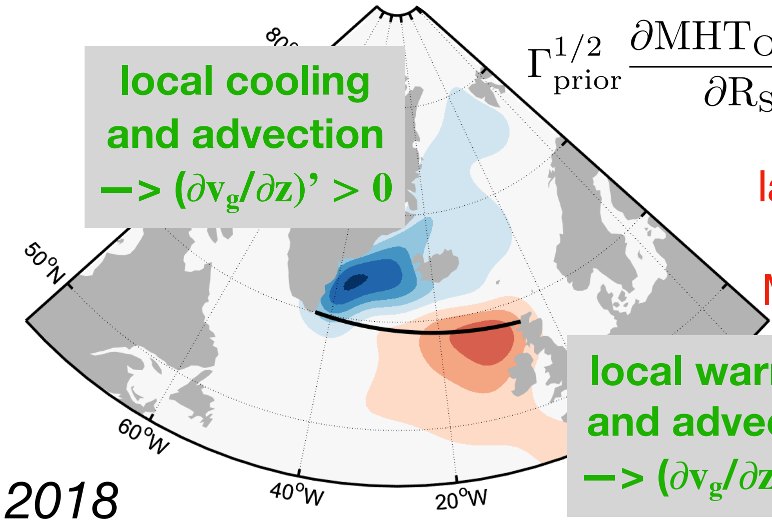
$$\Gamma_{\text{prior}}^{1/2}\frac{\partial T_{EG}}{\partial R_{SW\downarrow}}$$

local heating and advection



$$\Gamma_{\text{prior}}^{1/2}\frac{\partial MHT_{OSNAP\text{-}E}}{\partial R_{SW\downarrow}}$$

local cooling and advection
—> $(\partial v_g/\partial z)' > 0$



larger $R_{SW\downarrow}$ increases $MHT_{OSNAP\text{-}E}$

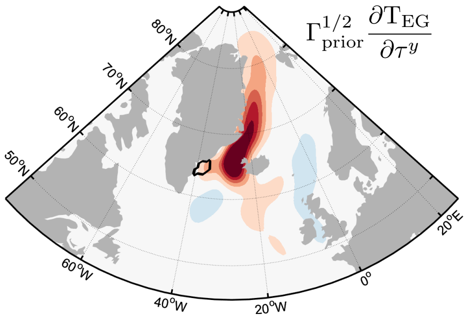
local warming and advection
—> $(\partial v_g/\partial z)' > 0$

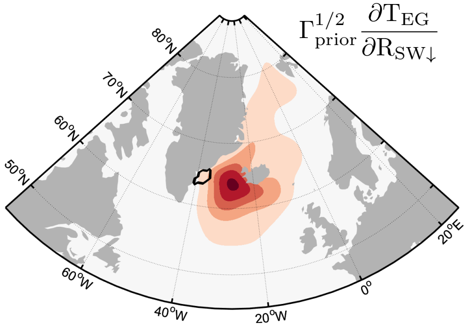
Loose et al. , 2018

T_{EG} vs. $MHT_{OSNAP-E}$ Forcing Sensitivity

Linear sensitivities for QoI (T_{EG})
(prior weighted and normalised)
≈ information required to reduce QoI uncertainty

Linear sensitivities for Obs ($MHT_{OSNAP-E}$)
(prior weighted and normalised)
≈ information transmitted by the observing system





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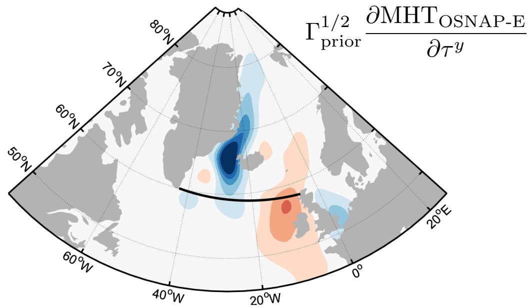
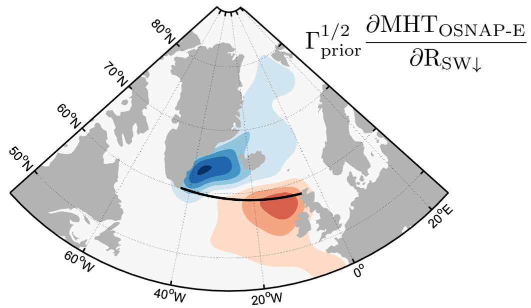
sensitivity to remaining controls

Strong projection implies Obs provides strong constraint on QoI

Strongest projection for τ^y and $R_{SW\downarrow}$





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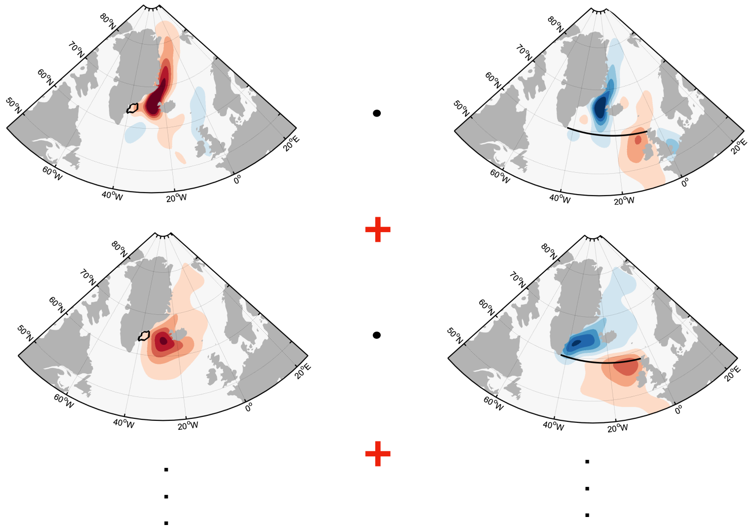
sensitivity to remaining controls

Loose et al. , 2018

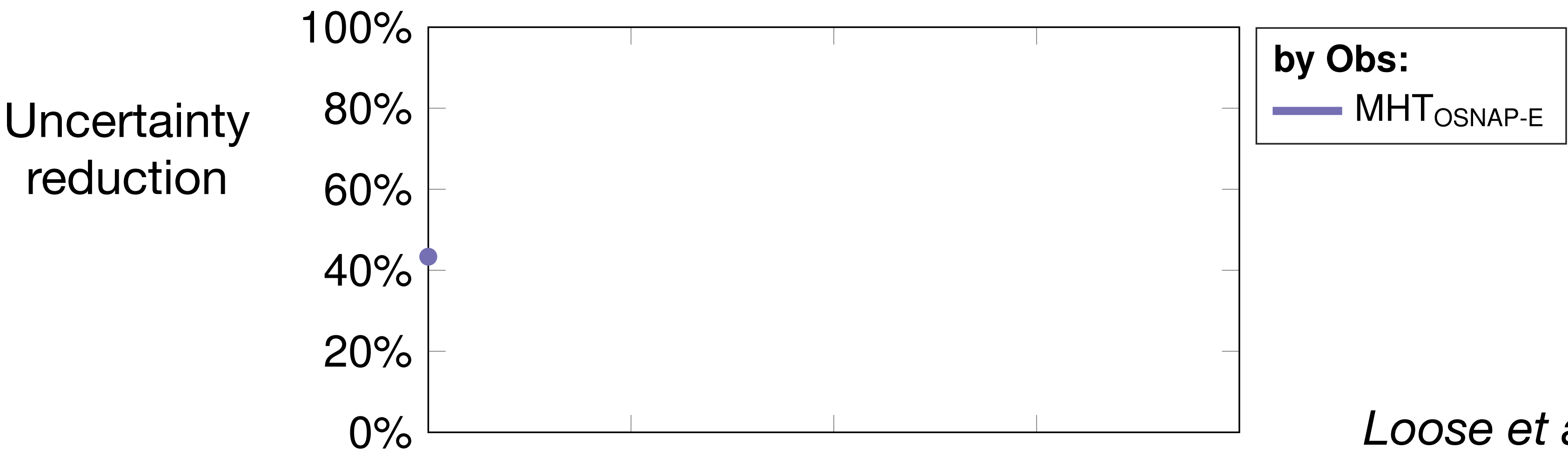
Exploring Proxy Potential of Existing Arrays

Uncertainty reduction $\propto \left(\Gamma^{1/2}_{\text{prior}} \frac{\partial T_{\text{EG}}}{\partial \mathbf{x}}\right)^{\mathsf{T}} \bullet \left(\Gamma^{1/2}_{\text{prior}} \frac{\partial \text{MHT}_{\text{OSNAP-E}}}{\partial \mathbf{x}}\right)$

Accumulate projection for all controls



continue for remaining controls



Loose et al. , 2018

Exploring Proxy Potential of Existing Arrays

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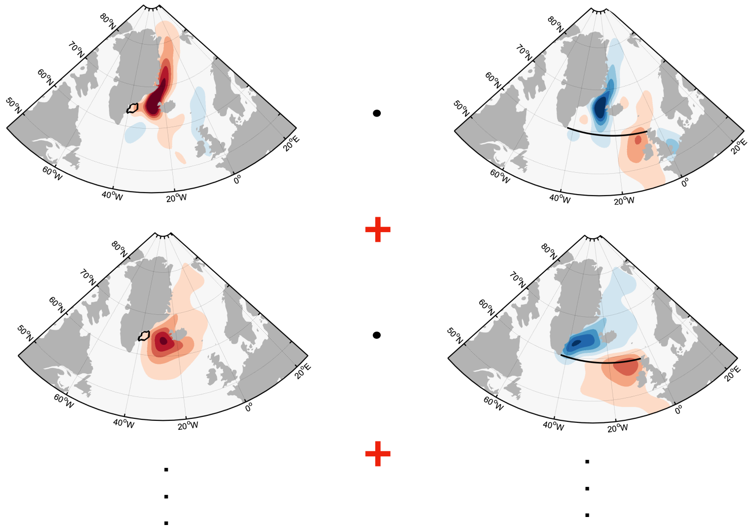

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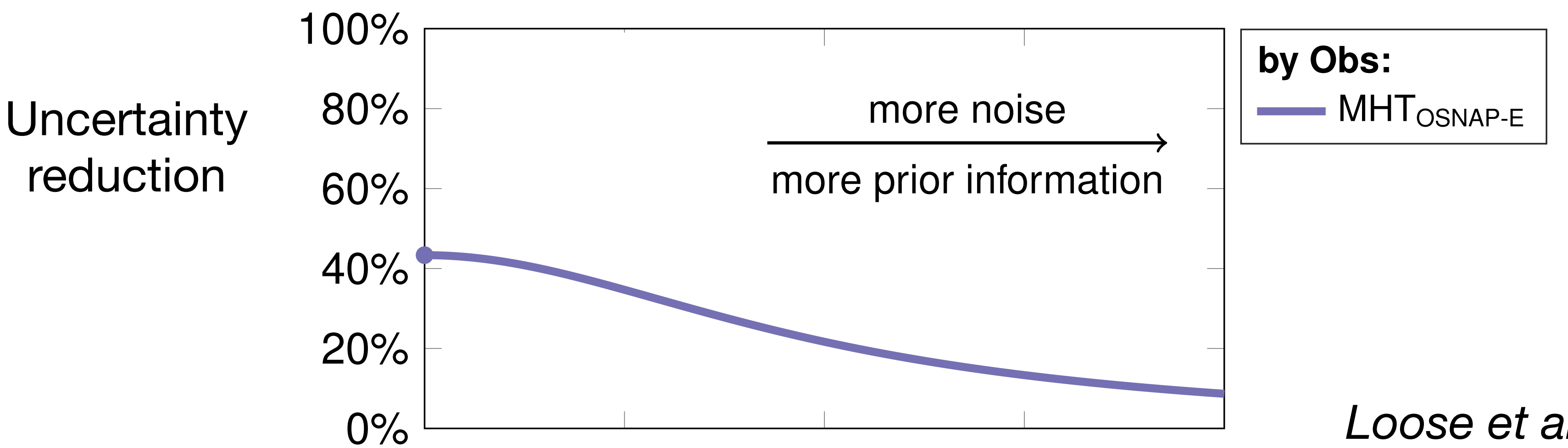

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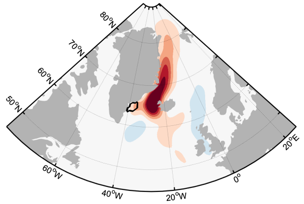
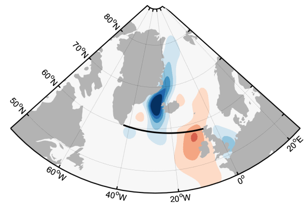
 $\cdot$ 

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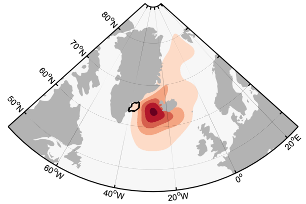
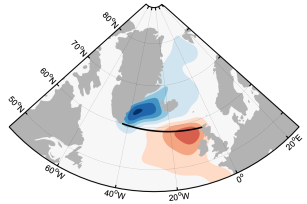
 $\cdot$ 

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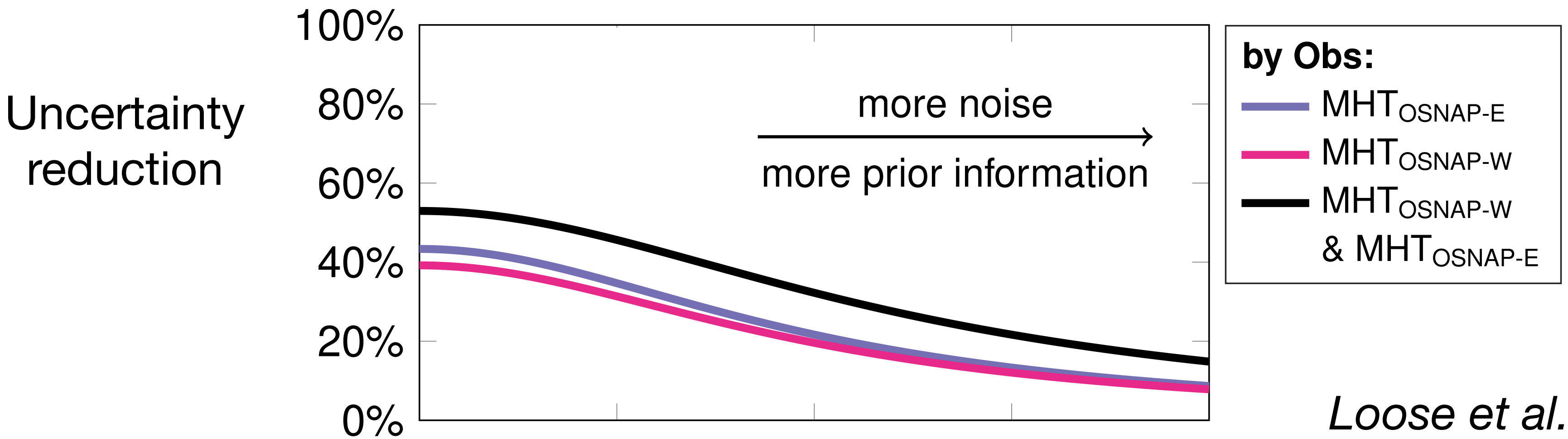
continue for remaining controls



Loose et al. , 2018

Conclusions

- Adjoint modelling is a powerful tool for:

  (1) Identifying critical observation uncertainties
  - sensitivities reveal key space-time origins of most potent uncertainties

  (2) Exploring potential proxy information of observations
  - sensitivities allow comparison of information required to monitor QoI and information transmitted by the observing system.

Case Study Results:

(1) Critical air-sea flux uncertainty for $\text{MOC}_{\text{RAPID}}$ = Lab. Sea. winter heat flux

(2) OBSERVED $\text{MHT}_{\text{OSNAP-E}}$ is a useful proxy for UNOBSERVED subsurface T_{EG}

- Benefits of adjoint-based approach include:

  - ☑ unambiguous dynamical attribution of uncertainty impacts
  - ☑ nesting within inverse modelling framework (view full space/time context)
  - ☑ quantitative strategy for observing system design
  - ☑ includes quantification of role of observation noise and prior uncertainty
  - ☑ assessment of complementarity in systems of multiple observations

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