# Sea Level Variability, Attribution, and Prediction Using ECCO

2024 ECCO Annual Meeting

**Andrew Delman**[1], Ou Wang[2], Tong Lee[2], Thomas Frederikse[3], Renee Collini[4], Ichiro Fukumori[2], Emily Becker[5], Benjamin Kirtman[5],

[1]University of California Los Angeles, Los Angeles, CA, USA

[2]Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA

[3]Planet, Haarlem, The Netherlands

[4]The Water Institute, Baton Rouge, LA, USA

[5]University of Miami, Coral Gables, FL, USA

**Primary contact:** andrewdelman@g.ucla.edu

ECCO Estimating the Circulation and Climate of the Ocean

National Aeronautics and Space Administration

NASA

NATIONAL ACADEMIES *Sciences Engineering Medicine*

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# Two Studies of Sea Level Using the ECCO Framework

- **Study 1: Where are there robust regional trends and multidecadal variability in relative sea level (global mean removed)? What forces these trends & variability?**
  - Uses a suite of ECCOv4 release 5 forward simulations, with various forcings (wind stress, heat flux, freshwater flux) replaced by their seasonal climatologies
  - Spatial focus: Global scope, regional variations
  - Timescale focus: > 10 years

- **Study 2: What forcings contribute to monthly/seasonal sea level variability along the U.S. Gulf Coast, and how can the ECCO state estimate improve predictions of this variability?**
  - Uses ECCOv4 release 4 *adjoint sensitivities* of sea level (either at a single grid cell or along a coastal region) to reconstruct and hindcast sea level variations
  - Spatial focus: Single location or coastal region
  - Timescale focus: 1-12 months

- Despite the differences in method and focus, these studies both exploit unique benefits of ECCO (data-optimized surface fluxes, adjoint capability) to understand local and remote forcing of sea level variability

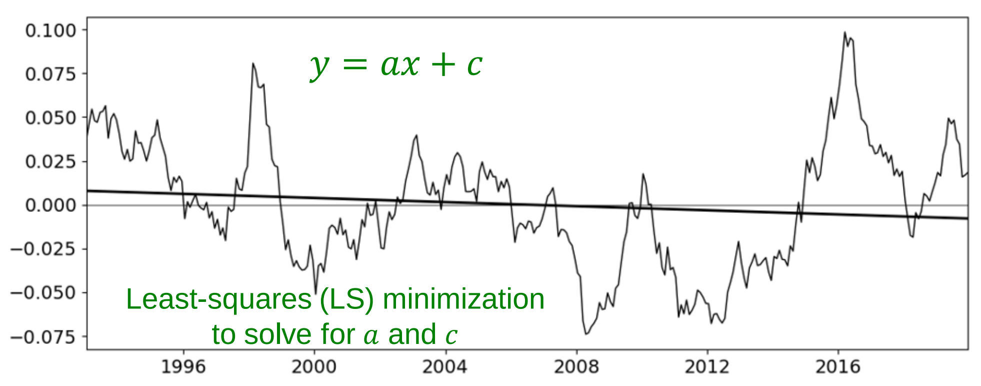
# Study 1: Regional sea level trends & multi-decadal variability

- ECCOv4 release 5 simulations were carried out (1993-2019) with each type of forcing replaced by seasonal climatology, to assess the impact of non-seasonal forcing on relative sea level (RSL)

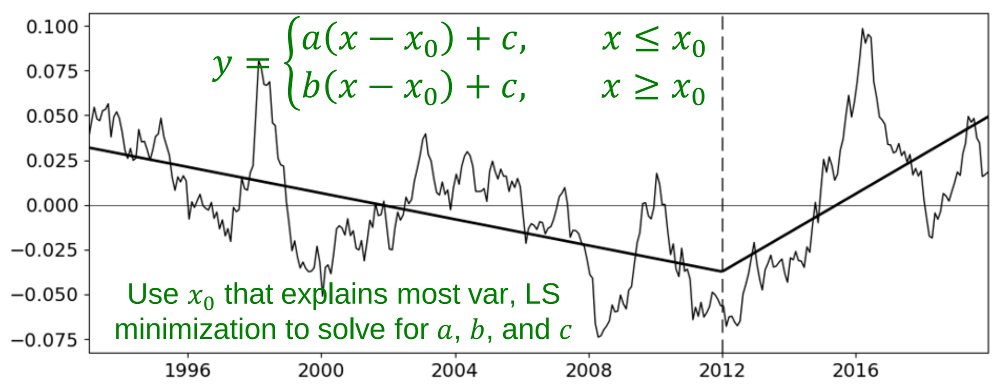
| Simulation | Forcings | | |
|---|---|---|---|
| | Wind str | Heat | Freshwater |
| All forcing | All | All | All |
| Clim only wind | Seas clim | All | All |
| Clim only heat | All | Seas clim | All |
| Clim only freshwater | All | All | Seas clim |

- Two types of regression applied to assess RSL time series: **linear trend** and **trend reversal** ("V" regression)

Linear trend, altimetry, NE tropical Pacific (150-110 W, 5-25 N)




Trend reversal (V regression), altimetry, NE tropical Pacific (150-110 W, 5-25 N)



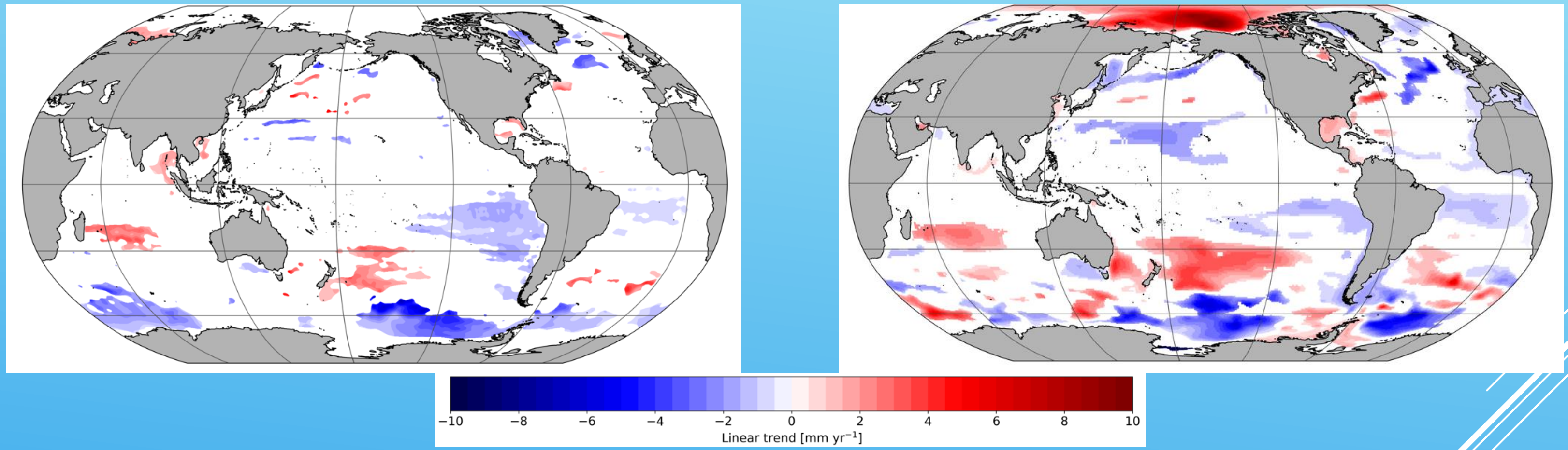

- Bootstrap analysis (n = 20000) used to assess whether trends and trend reversals are likely to be distinct from (rather than artifacts of) higher-frequency interannual variability

# Study 1: Regional sea level trends & multi-decadal variability

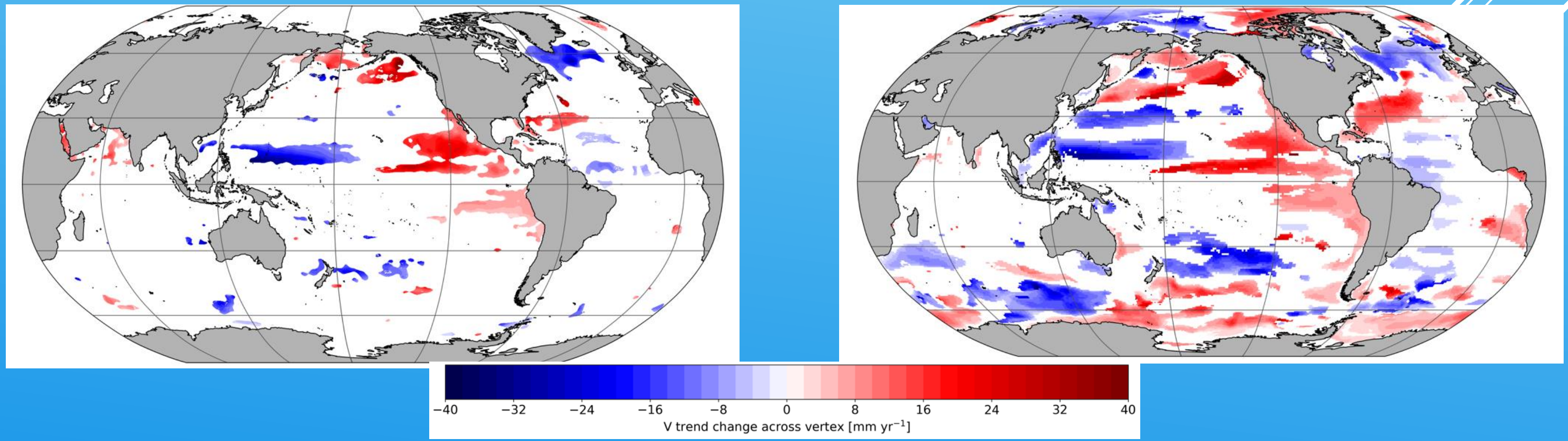
- Relative sea level (RSL) comparison of satellite altimetry observations vs. ECCOv4r5 all forcing simulation
- Only regions where $p < 0.1$ (based on bootstrap analysis of randomly-generated interannual variability) are shaded

**Altimetry (JPL MEaSUREs)** | **ECCOv4r5 all forcing**

**Linear trend**



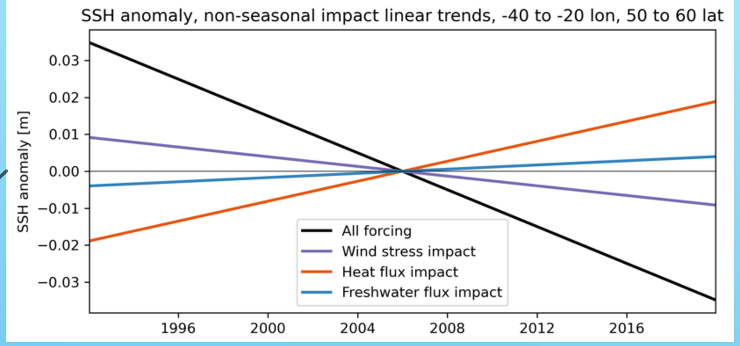

**Trend reversal (multidecadal variability)**

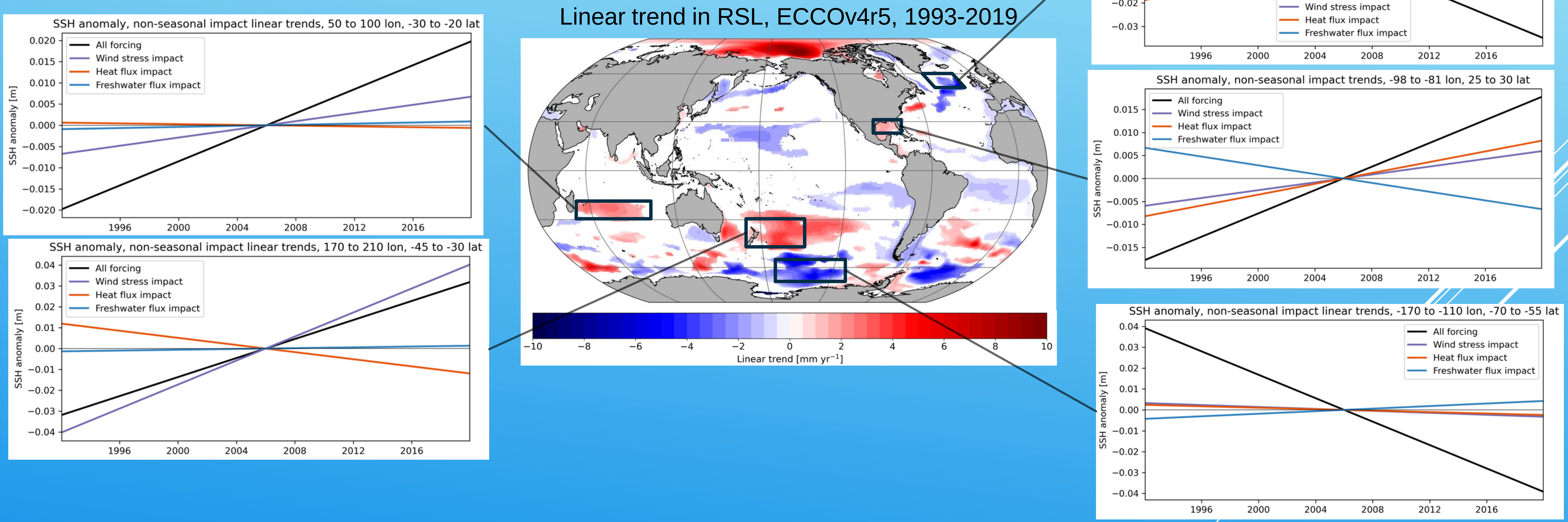



- More robust RSL linear trends in the Southern Hemisphere, more multidecadal variability in the Northern Hemisphere

# Study 1: Regional sea level trends & multi-decadal variability

- Can look at impacts of non-seasonal forcing by taking the difference of the simulations: all forcing – clim only wind, all forcing – clim only heat

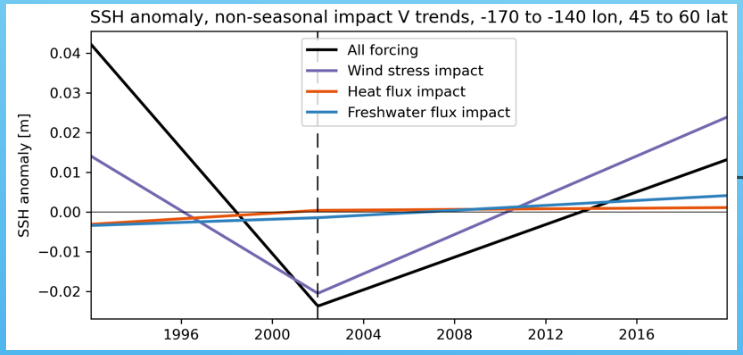


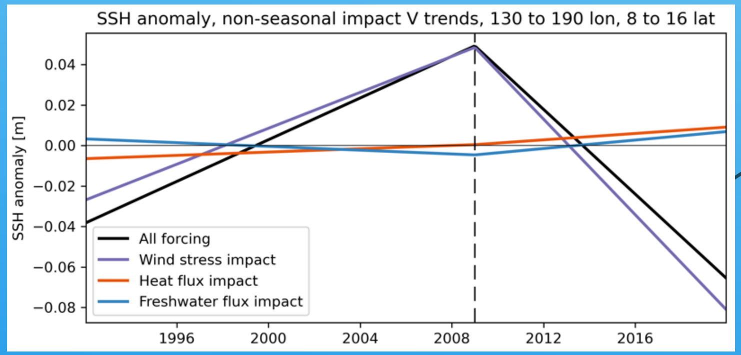




- Non-seasonal wind stress forcing explains more linear trends than the other forcings
- Non-seasonal heat flux sometimes occasionally has substantial contribution (e.g., Gulf of Mexico)

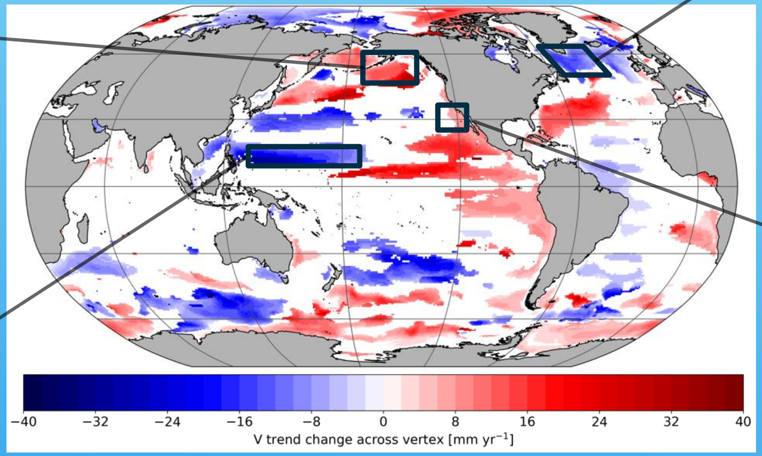
# Study 1: Regional sea level trends & multi-decadal variability

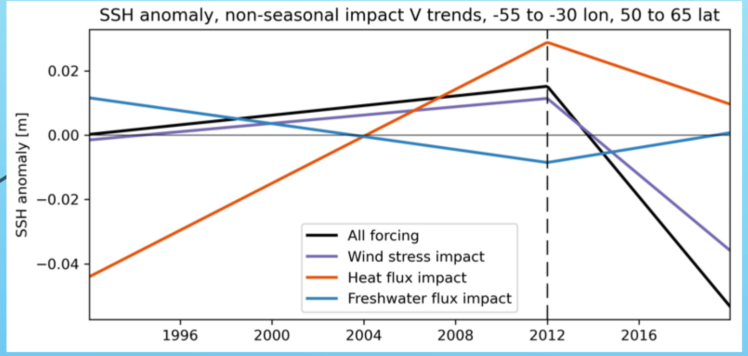
- Impacts of non-seasonal forcing: trend reversal/change (multi-decadal variability)

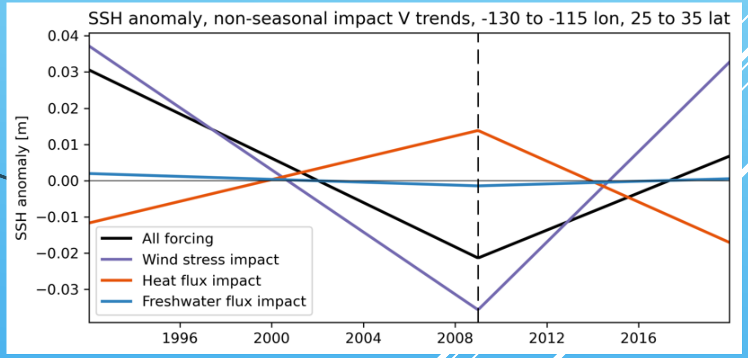



Trend reversal/change in RSL, ECCOv4r5, 1993-2019




- Non-seasonal wind stress forcing explains most RSL trend reversals
- Non-seasonal heat flux can also contribute substantially to multi-decadal variability (e.g., North Atlantic), or compensates (e.g., coast of California/Baja California)

# Study 2: Adjoint sensitivity-based prediction of seasonal sea level variations

- Adjoint sensitivities of sea level can be convolved with surface forcings to reconstruct and predict RSL variations for a given location (Pensacola, FL in the examples shown here)

RSL at a location

$$S_p(x, y, t, \tau) = \frac{\partial \eta(t)}{\partial F_p\,(x, y, t - \tau)}$$

Adjoint sensitivity

Forcing (surface flux) at various locations & lead times

RSL reconstruction

$$\eta'\,(t) = \sum_{p=1}^{4} \iiint S_p(x, y, t, \tau) \cdot F'_p\,(x, y, t - \tau)\, dx\,dy\,d\tau$$

From ECCOv4r4 From ECCOv4r4, reanalysis (e.g., ERA5), or seasonal prediction model

- SL can also be predicted using this methodology, where the forcings at lead times $\tau > \tau_0$ are taken either from seasonal climatology only (**anomalies from "past forcing" only**) or from prediction models (**hybrid prediction**)

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Adjoint sensitivity

RSL at a location

Forcing (surface flux) at various locations & lead times

$$\eta'(t) = \sum_{p=1}^{4} \iiint S_p(x, y, t, \tau) \cdot F_p'(x, y, t-\tau)\, dx\, dy\, d\tau$$

RSL reconstruction

From ECCOv4r4

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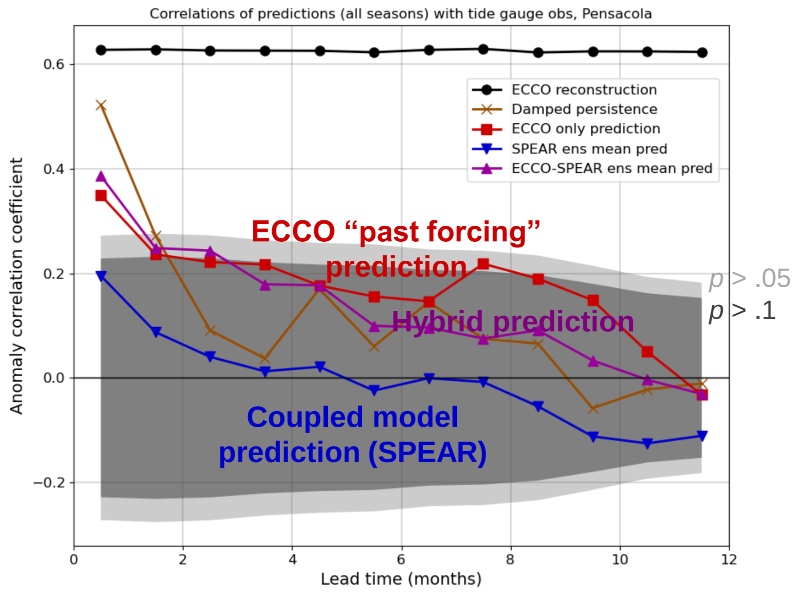


Predictions using ECCO adjoint sensitivities ("past forcing" only and hybrid) perform better than many coupled model predictions of RSL (e.g., SPEAR at left)

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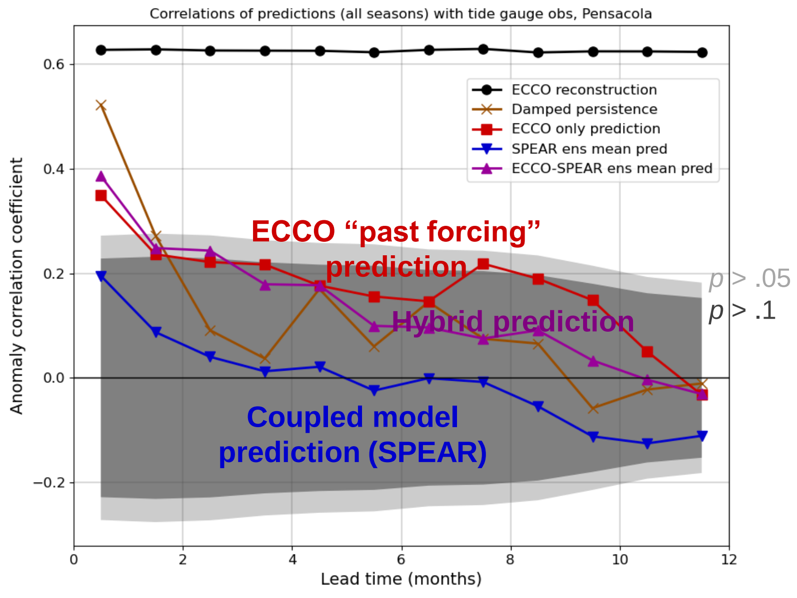
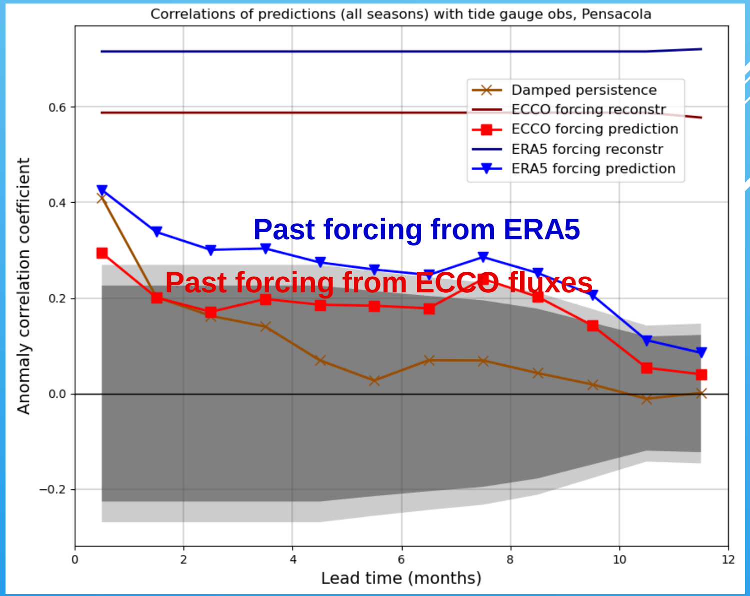



Predictions using ECCO adjoint sensitivities ("past forcing" only and hybrid) perform better than many coupled model predictions of RSL (e.g., SPEAR at left)

At this location, using ERA5 forcings yields slightly better predictions than using ECCO fluxes

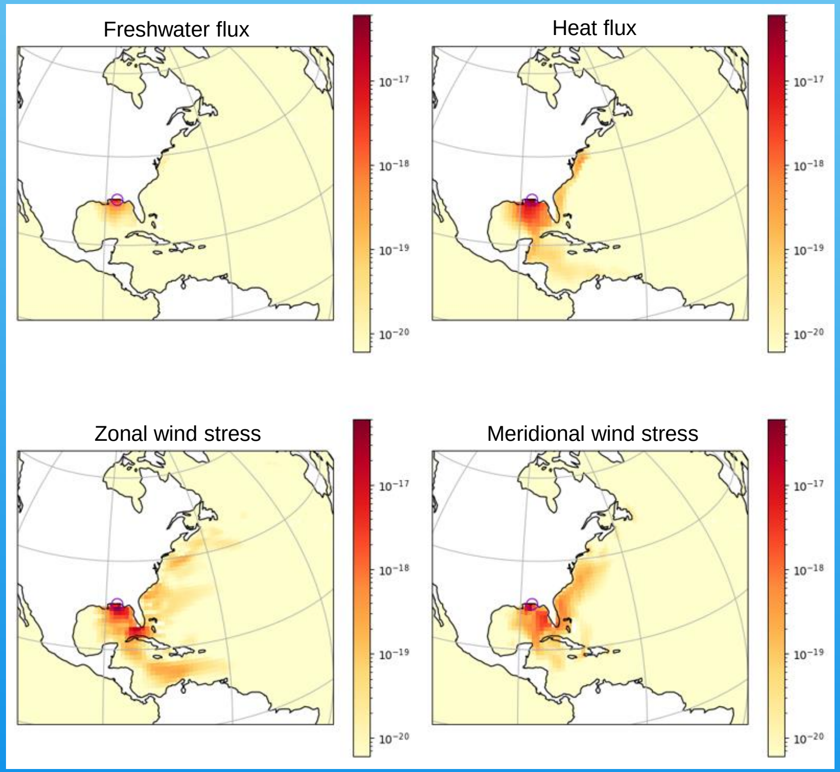


# Study 2: Adjoint sensitivity-based prediction of seasonal sea level variations

- You may recall in a previous slide that Gulf of Mexico sea level has been rising faster than the global mean – ECCOv4r5 simulations suggested that both wind stress & heat flux were contributing substantially
- What about at shorter timescales (SL contributions forced with 0-12 month lead times)?

**Variance contributions** (per unit area) to reconstruction, with ERA5 forcings 1980-2023

$$\left\langle \int S_p F_p' \, d\tau \right\rangle^2$$



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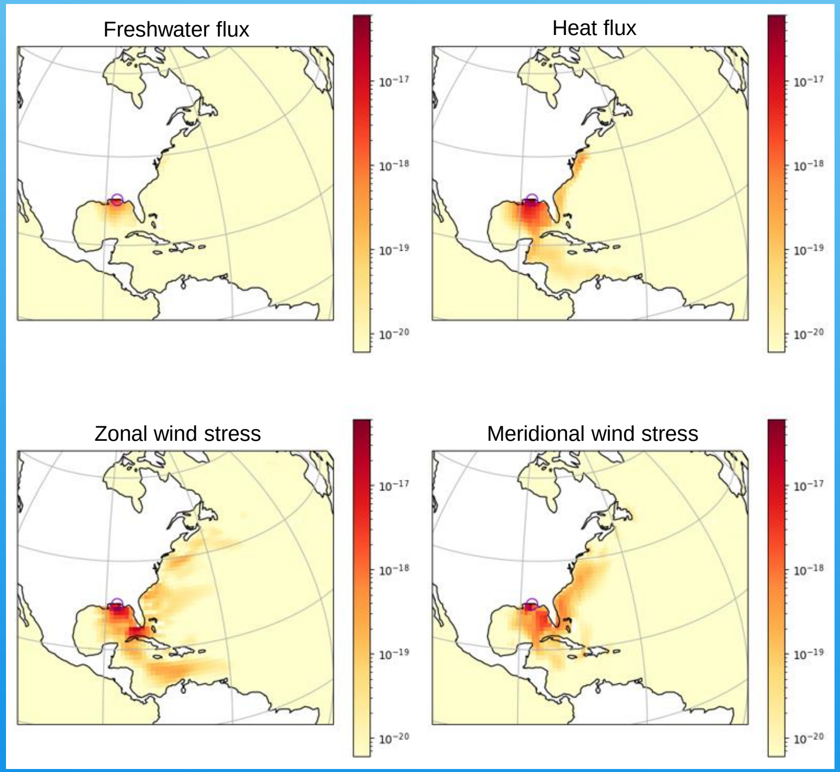
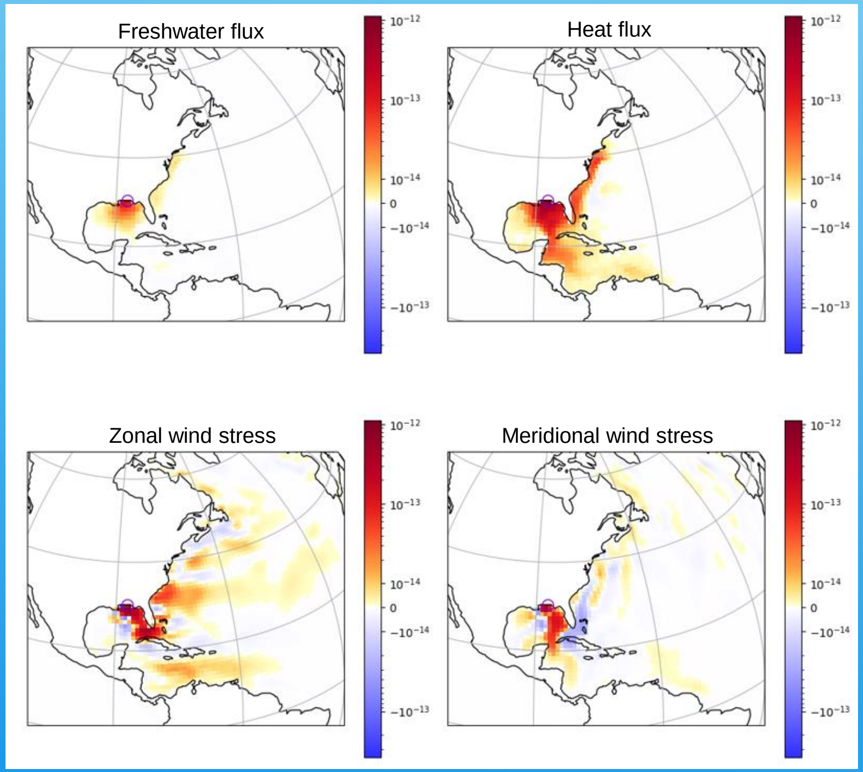



**Variance explained** (per unit area) of reconstruction

$$1 - \frac{\left\langle \eta' - \int S_p F_p' \, d\tau \right\rangle^2}{\langle \eta' \rangle^2}$$



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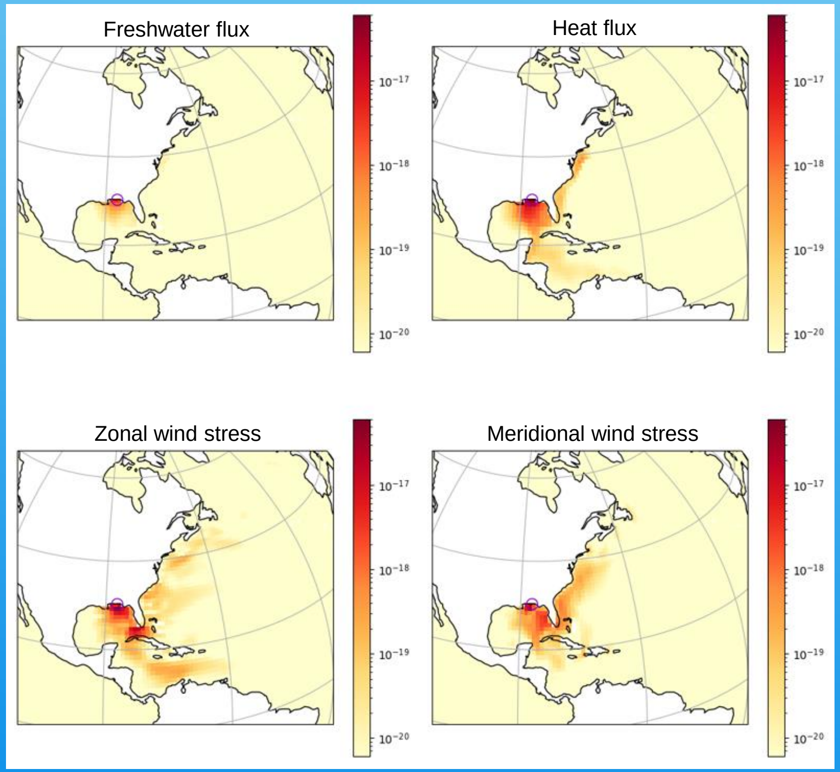


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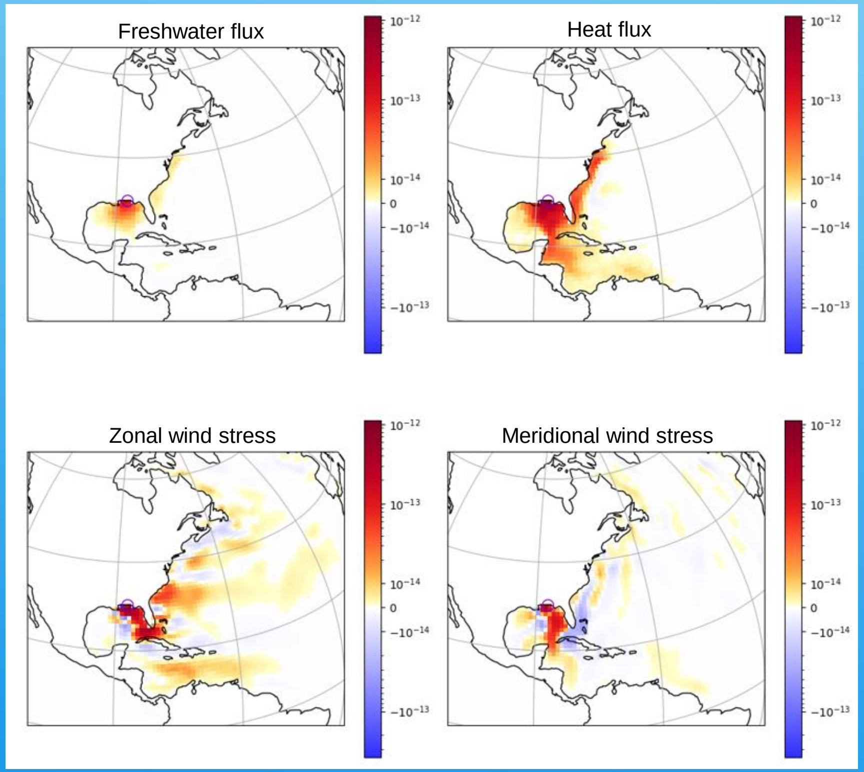
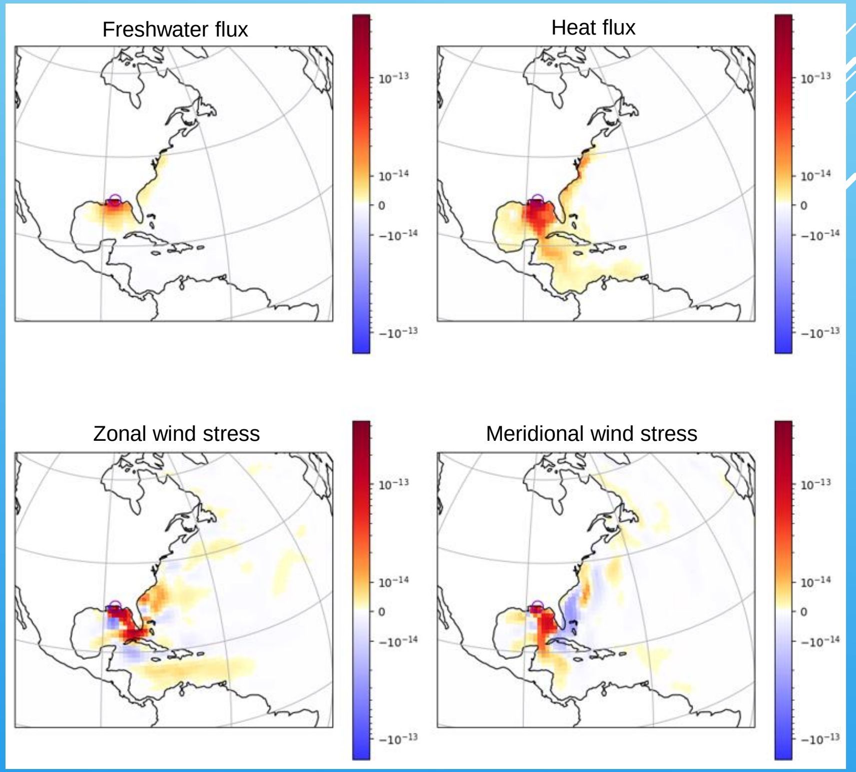



**Variance explained** (per unit area) of tide gauge obs

$$1 - \frac{\left\langle \eta'_{\mathrm{obs}} - \int S_p F_p' \, d\tau \right\rangle^2}{\langle \eta'_{\mathrm{obs}} \rangle^2}$$



# Takeaways

**Study 1: Regional sea level trends & multi-decadal variability**

- Linear trends of relative sea level (either from anthropogenic forcing or >30 years variability) are more prevalent in the Southern Hemisphere.
- More decadal to multi-decadal (10-30 years variability) in the Northern Hemisphere.
- Wind stress is responsible for most regional RSL trends/multi-decadal variability, with heat flux sometimes also contributing or counter-acting the wind stress contribution.

**Study 2: Adjoint sensitivity-based prediction of seasonal sea level variations**

- Adjoint sensitivities from the ECCOv4 state estimate can remove biases in coupled prediction models, leading to more accurate predictions of sea level on monthly-seasonal timescales.
- In the Gulf of Mexico region, these predictions can be done with comparable or better skill using ERA5 forcing …good news for potential operational applications.
- With adjoint, we can do "validation" assessments not just of the prediction time series, but of the contributions from individual flux types/lead times/locations.

- Questions or ideas? Please reach out to me at: andrewdelman@g.ucla.edu.