Consortium for the Advancement of Marine Arctic Science (CAMAS)

Past, present, and future Arctic ocean-sea ice reanalyses: methodology and application for Arctic and global climate research

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Scope

(i) Big Picture / Historical introduction
- Brief cover of the history & methodology

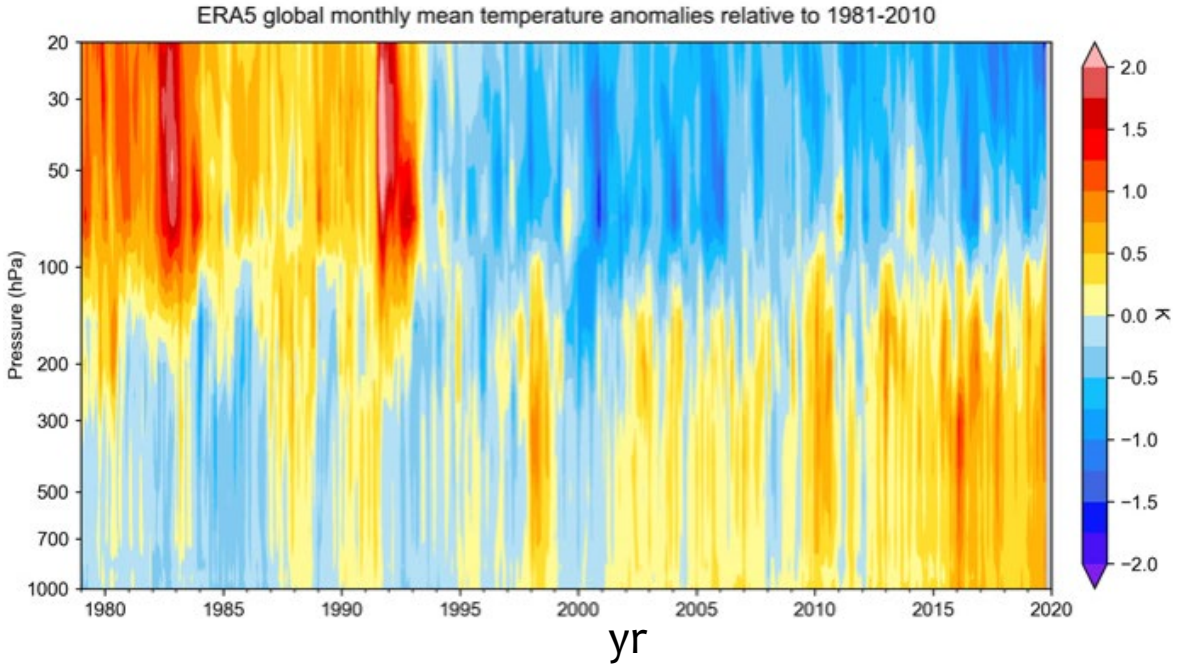
(ii) recent work in the community
- challenges, and successes of past/current Arctic ocean-sea ice reanalyses, incl. ASTE
- advantage / limitation of usage of reanalyses in Arctic and global climate research

(iii) Big Ideas for What Lies Ahead
- brief touch on advancement, future challenges and opportunities for methodology development and reanalysis products to serve the research community

(i) Climate Re-analysis: what is it?

A **climate reanalysis** gives a numerical description of the recent climate, produced by combining models with observations

Use [highly developed] **numerical models**[a] and **data assimilation** (DA) system[b] to 'reanalyse' archived observations, creating [global] [**model-data synthesis**] describing the recent history of the [atmosphere, land surface, and] oceans.



European Center for medium weather forecasting (ECMWF) Reanalysis v5

(i) Examples of high-latitude ocean-sea ice reanalyses

Atmospheric forcing:

- ASTE R1 (UT Austin, Nguyen et al., 2021)
- TOPAZ4 (NERSC, Sakov et al., 2012)
- PIOMASS (U. Washington, Zhang & Rothrock 2003)

ERA-interim/ERA5

MERRA2

JRA55

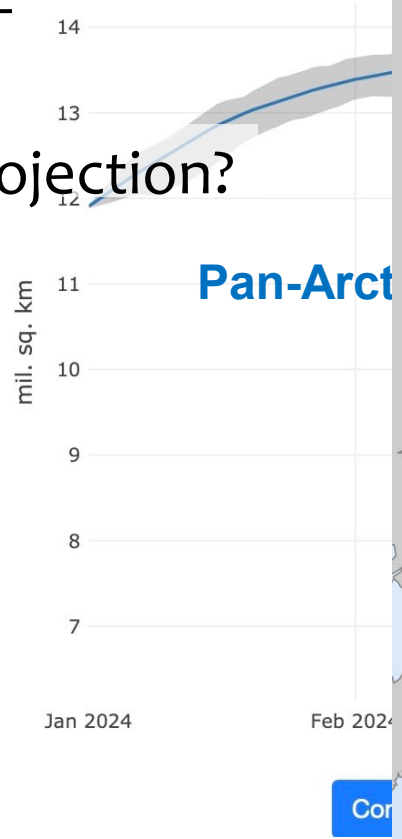
NCEP

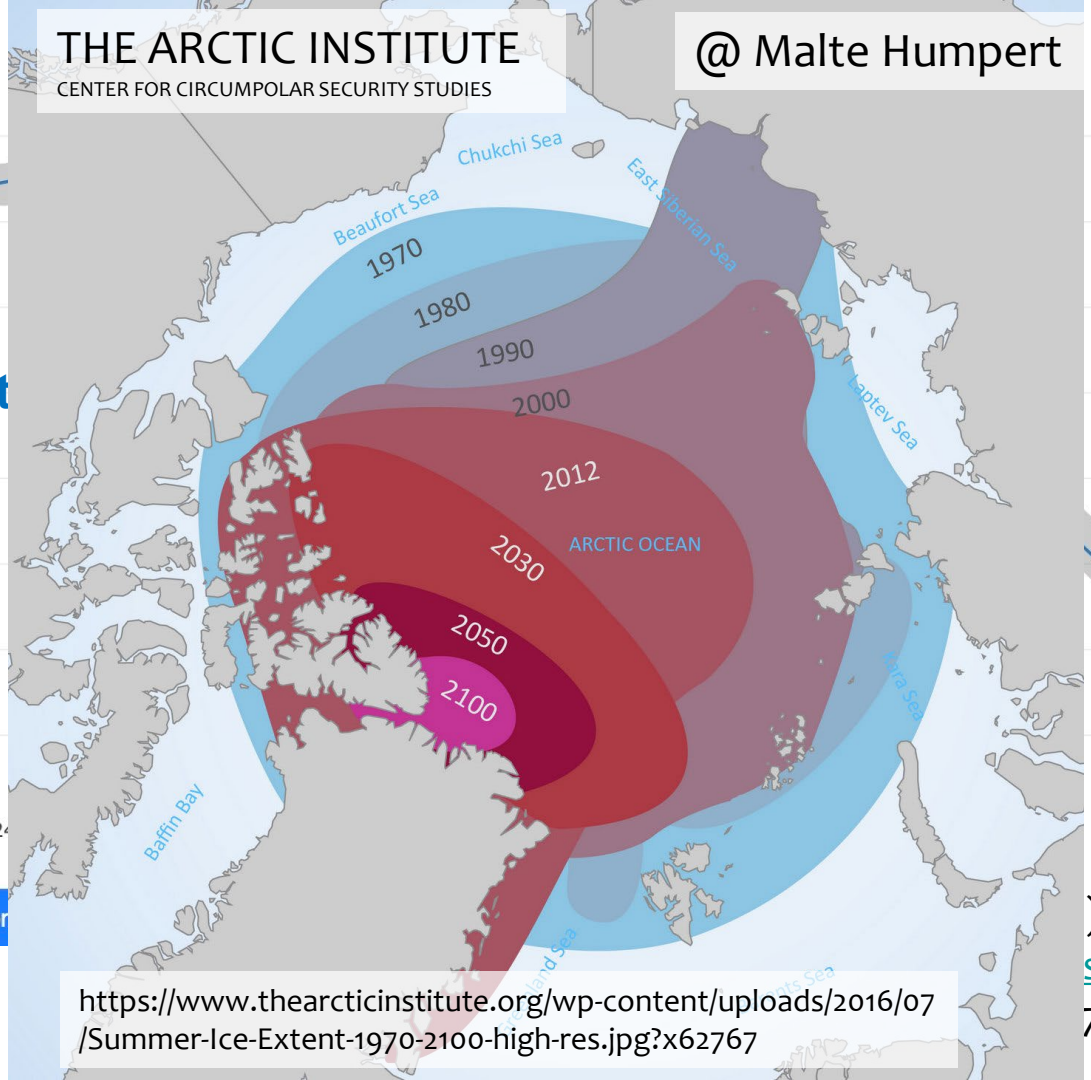
CORE-II, others

- ORAS5 (ECMWF, Zuo et al., 2018)
- SODA3 (U. Maryland, Carton et al., 2018)
  - RARE (Carton & Chepurin, 2023)
- GECCO3 (Hamburg Univ., Köhl 2020)
- ECDA3 (GFDL/NOAA)
- Others (e.g., Uotila et al., 2018, An asessement of ten ocean reanalyses in the polar regions)

(i) Identifying Scientific Goals

- Forecasting?
- Prediction/Projection?





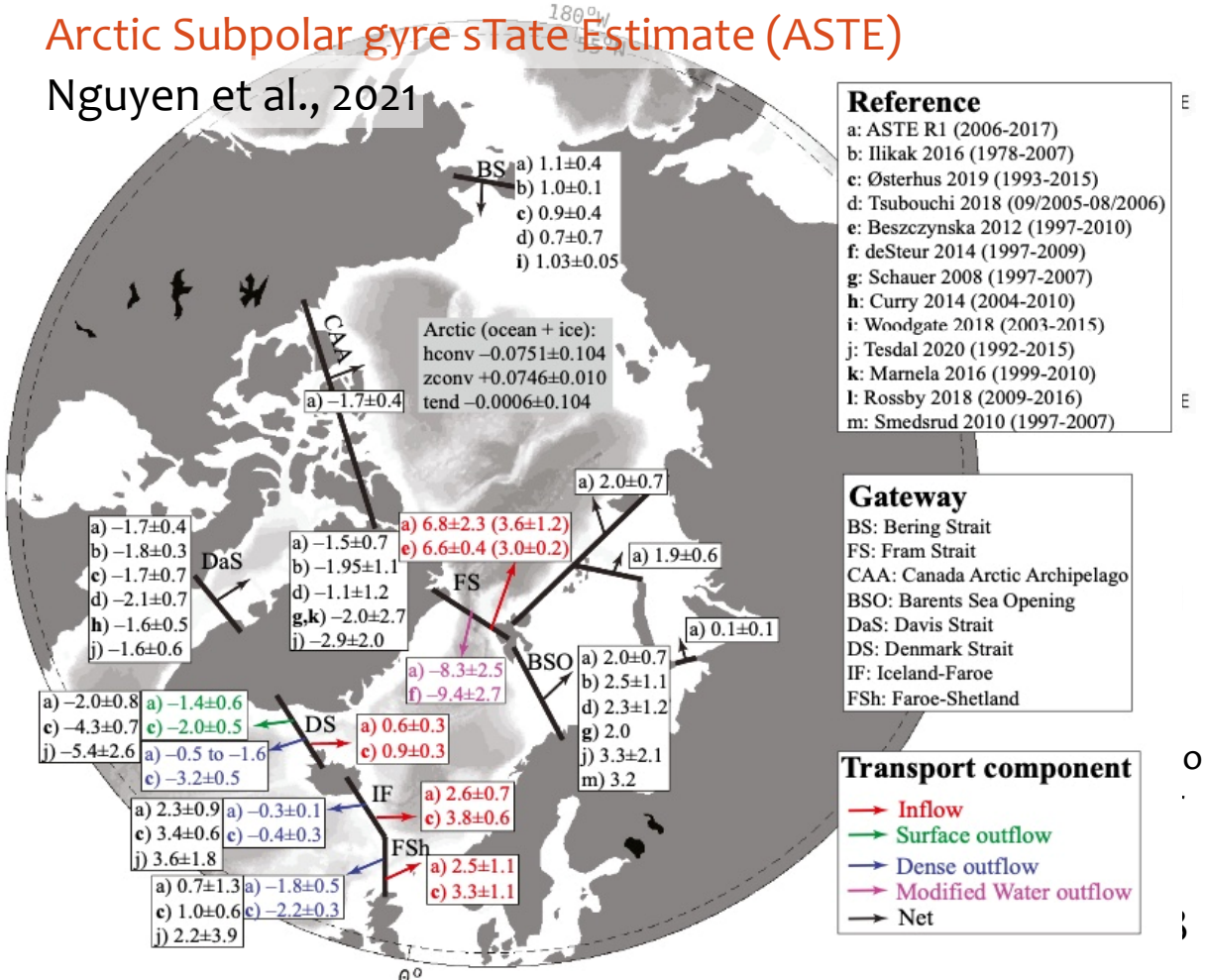
(i) Identifying Scientific Goals

Hindcasts

- filter method (sequential DA)
- smoother method (inverse/adjoint)

Arctic Subpolar gyre sTate Estimate (ASTE)

Nguyen et al., 2021



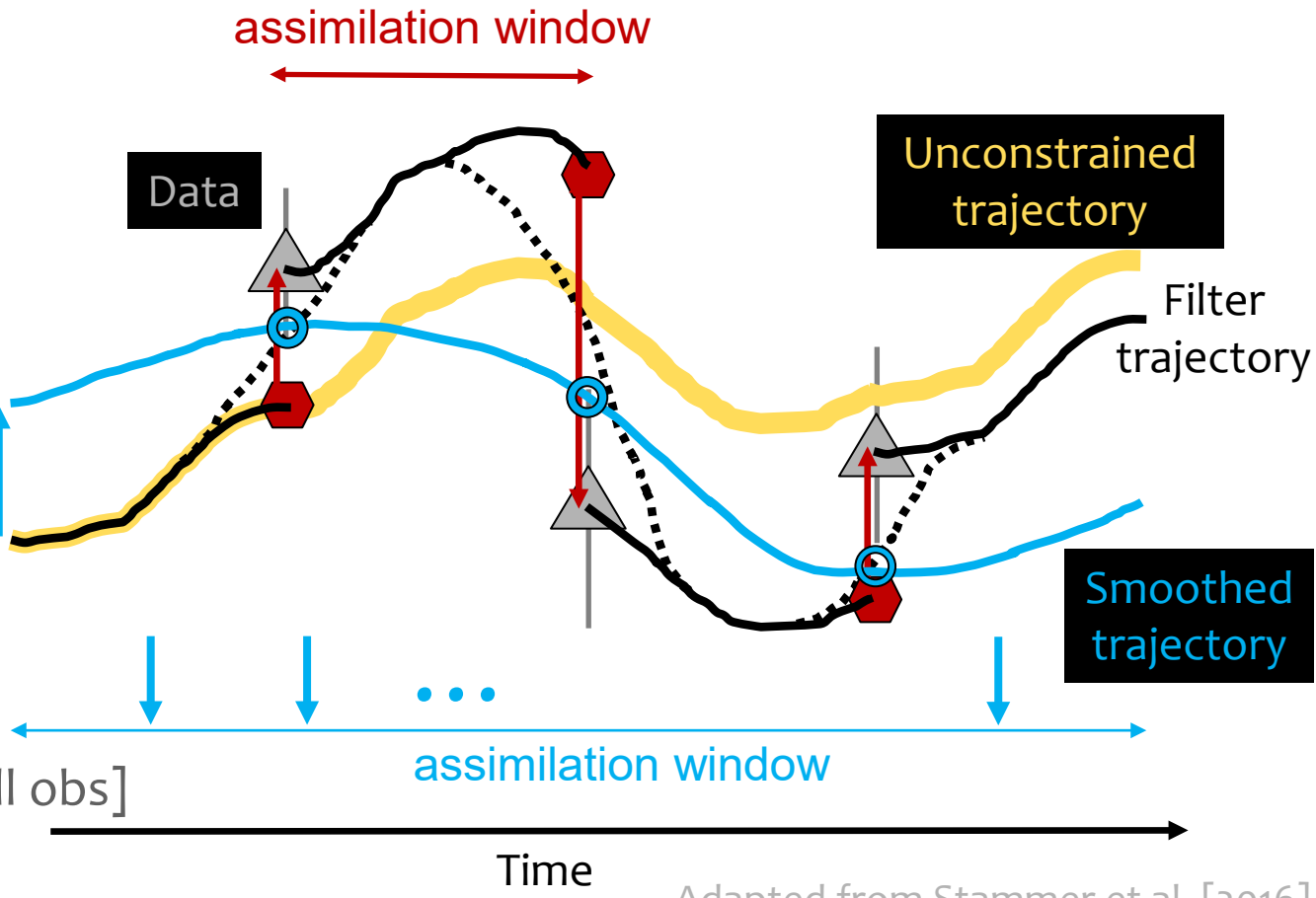
(i) Data assimilation [DA] Methodology

Filter method

- Sequential DA
- Short assimilation window
- Very good fit to where data exist
- Non-conservative

Smooth method

- Strict adherence to conservation laws
- Dynamically consistent → budget closure
- Approach agreement to within obs. uncertainty [Not guaranteed to fit all obs]



Adapted from Stammer et al. [2016]

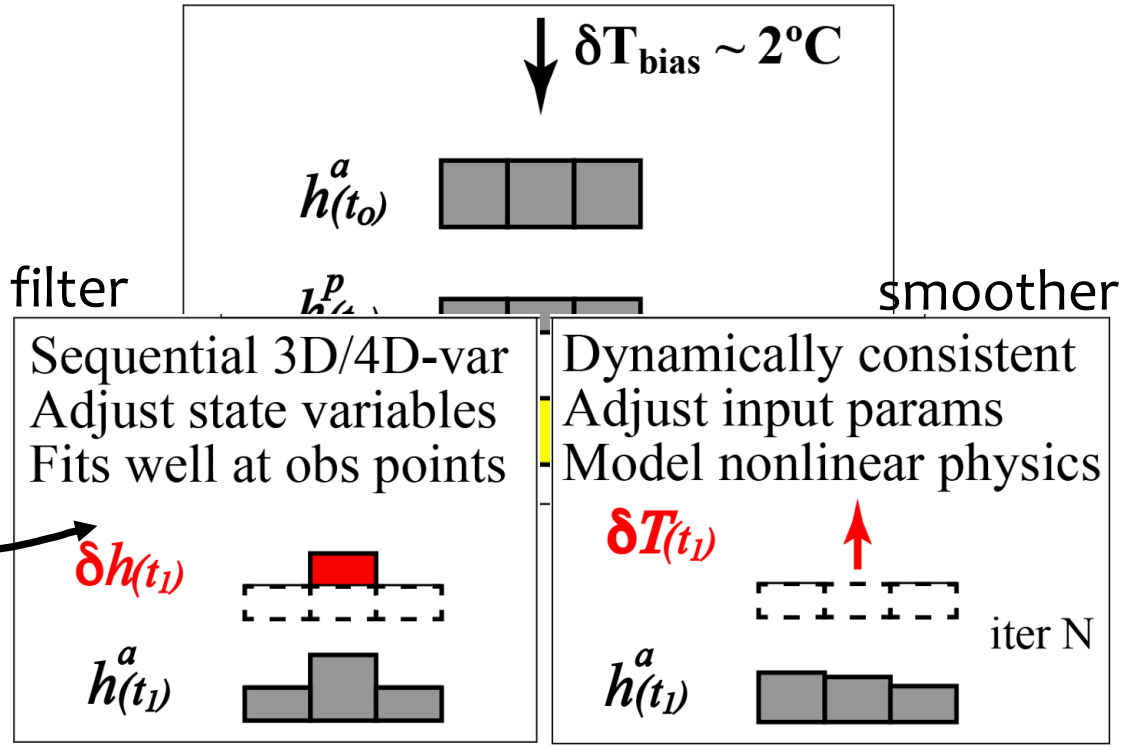
(ii) Impact of analysis increments

Example: ~2-6°C bias in T_{air}

→ forcing Arctic coupled ocean-sea ice Reanalyses:

→Where to map this error/bias in atmospheric

- "extra" heat sink
- Artificial temporal/spatial jumps/trends related to data availability

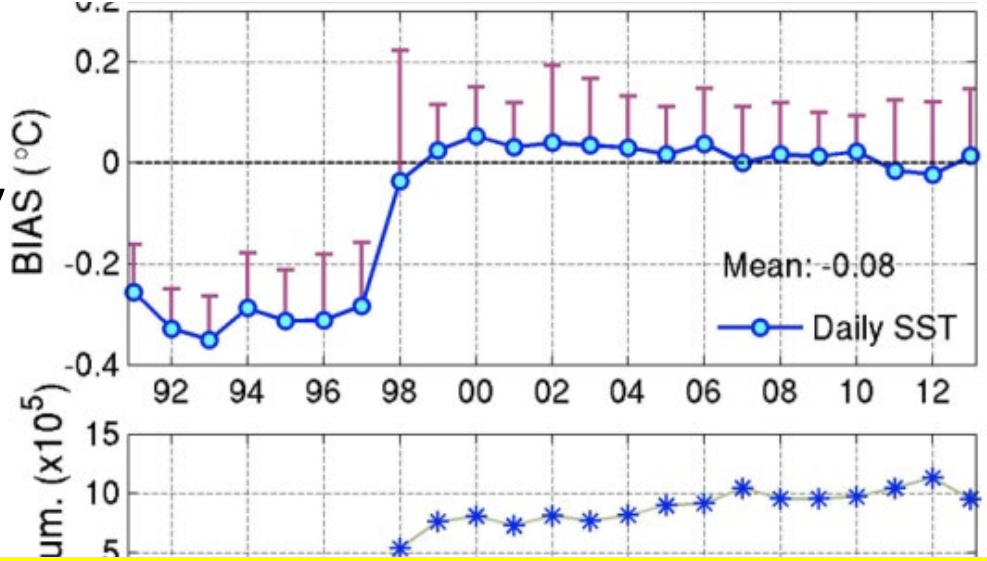


Not "matching" obs fully

(ii) Impact of analysis increments (inhomogeneous obs system)

- create artificial temporal/spatial jumps/ trends due to data availability
  (Xie et al., 2017, TOPAZ4)

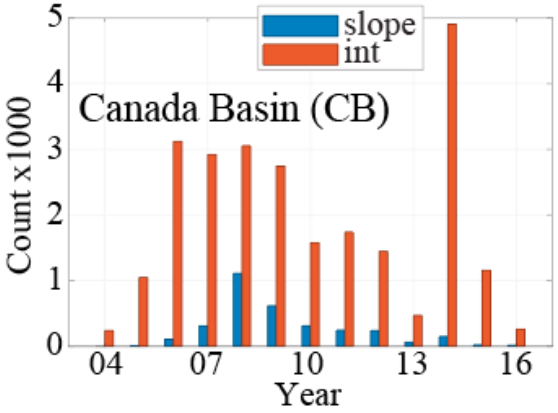
- create shock waves
  (Sivareddy et al., 2017)

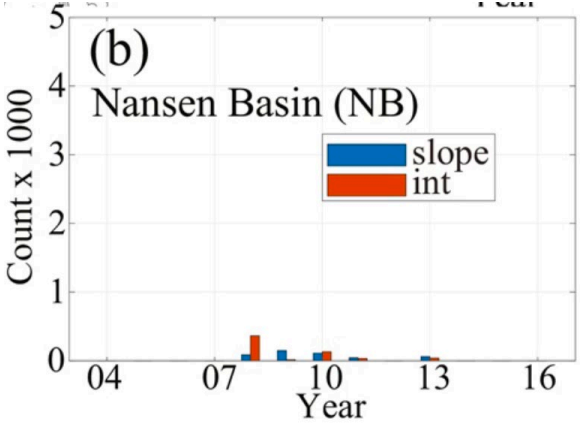


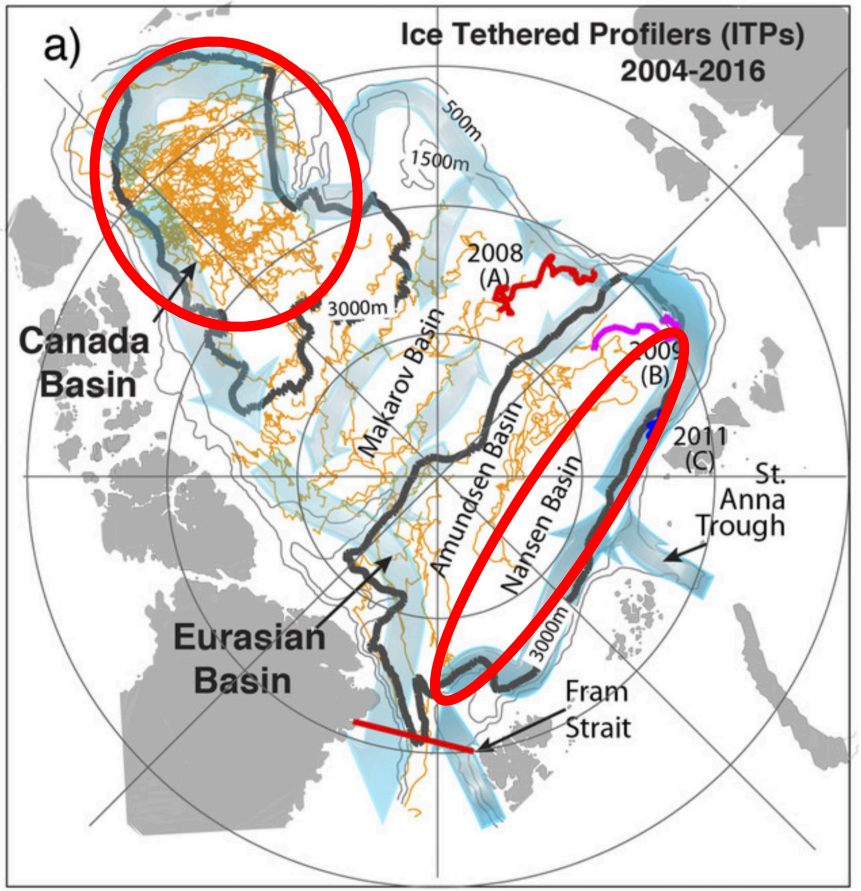
similation systems, that such shocks are generated in the ocean at the lateral boundaries of the d buoy network. They thrive and propagate westward as Rossby waves along these boundaries.

(ii) Arctic Observational distribution bias

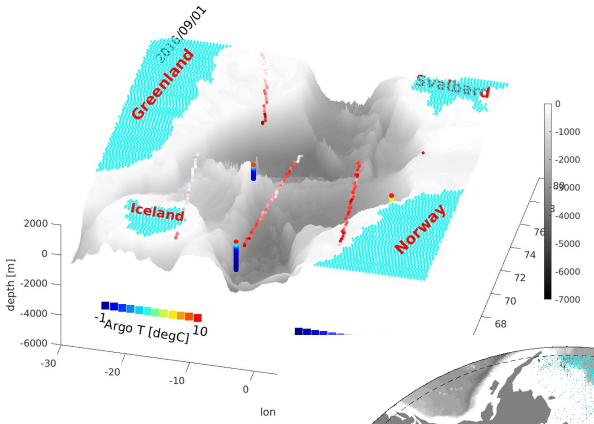
(Nguyen et al. 2020, 2021)







(ii) Data assimilation: combining observations and model



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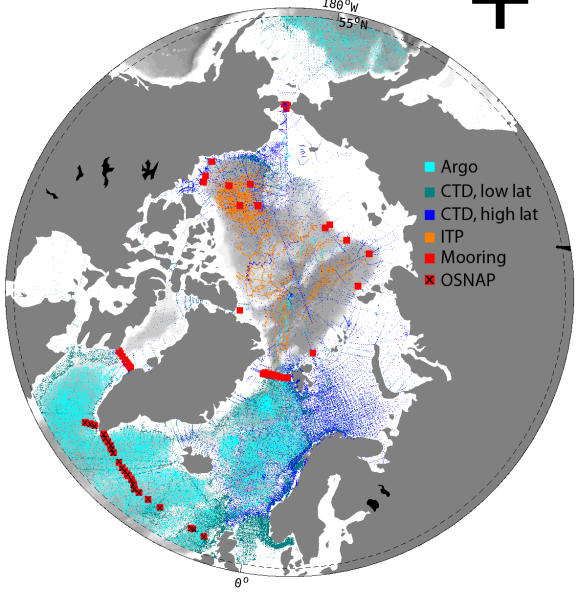
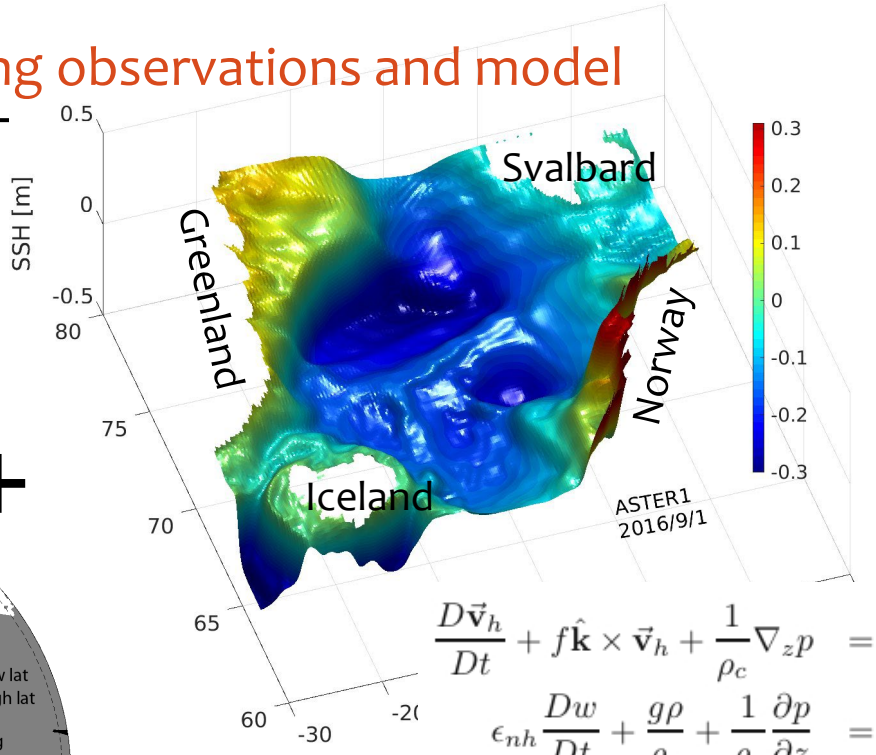


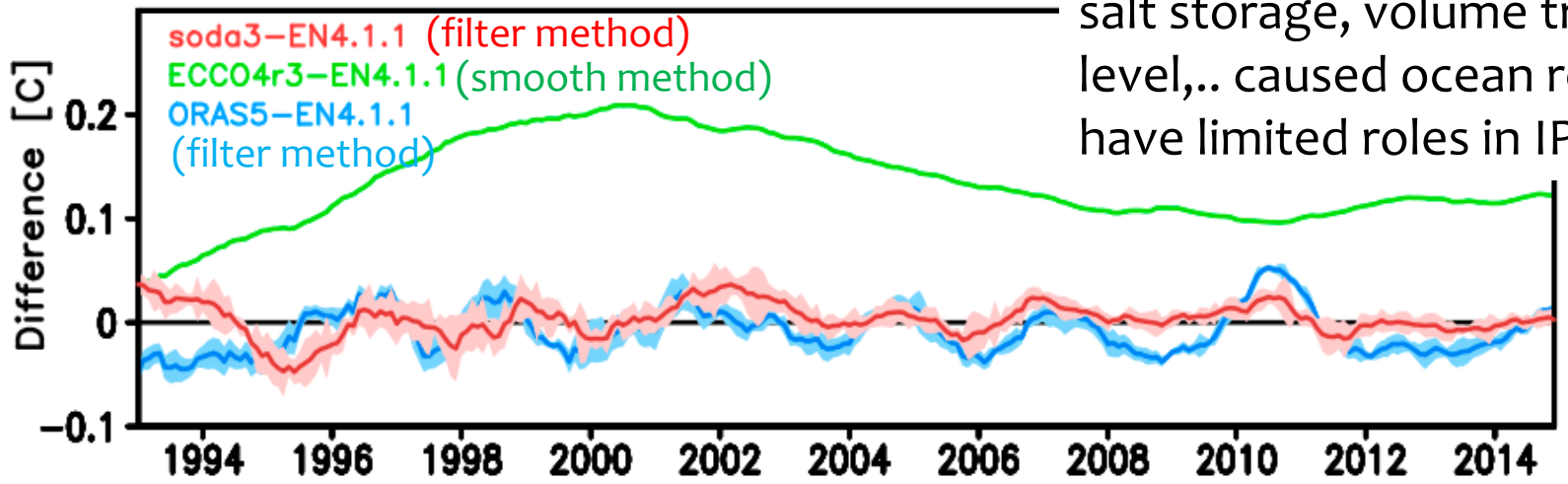


$$
\begin{aligned}
\frac{D\vec{\mathbf{v}}_h}{Dt} + f\hat{\mathbf{k}} \times \vec{\mathbf{v}}_h + \frac{1}{\rho_c}\nabla_z p &= \vec{\mathcal{F}} \\
\epsilon_{nh}\frac{Dw}{Dt} + \frac{g\rho}{\rho_c} + \frac{1}{\rho_c}\frac{\partial p}{\partial z} &= \epsilon_{nh}\mathcal{F}_w \\
\nabla_z \cdot \vec{\mathbf{v}}_h + \frac{\partial w}{\partial z} &= 0 \\
\rho &= \rho(\theta, S) \\
\frac{D\theta}{Dt} &= \mathcal{Q}_\theta \\
\frac{DS}{Dt} &= \mathcal{Q}_s
\end{aligned}
$$

(ii) Investigation of changes

Carton et al., 2019

"Concerns of biases in .. heat and salt storage, volume transports, sea level,.. caused ocean reanalyses to have limited roles in IPCC.. "



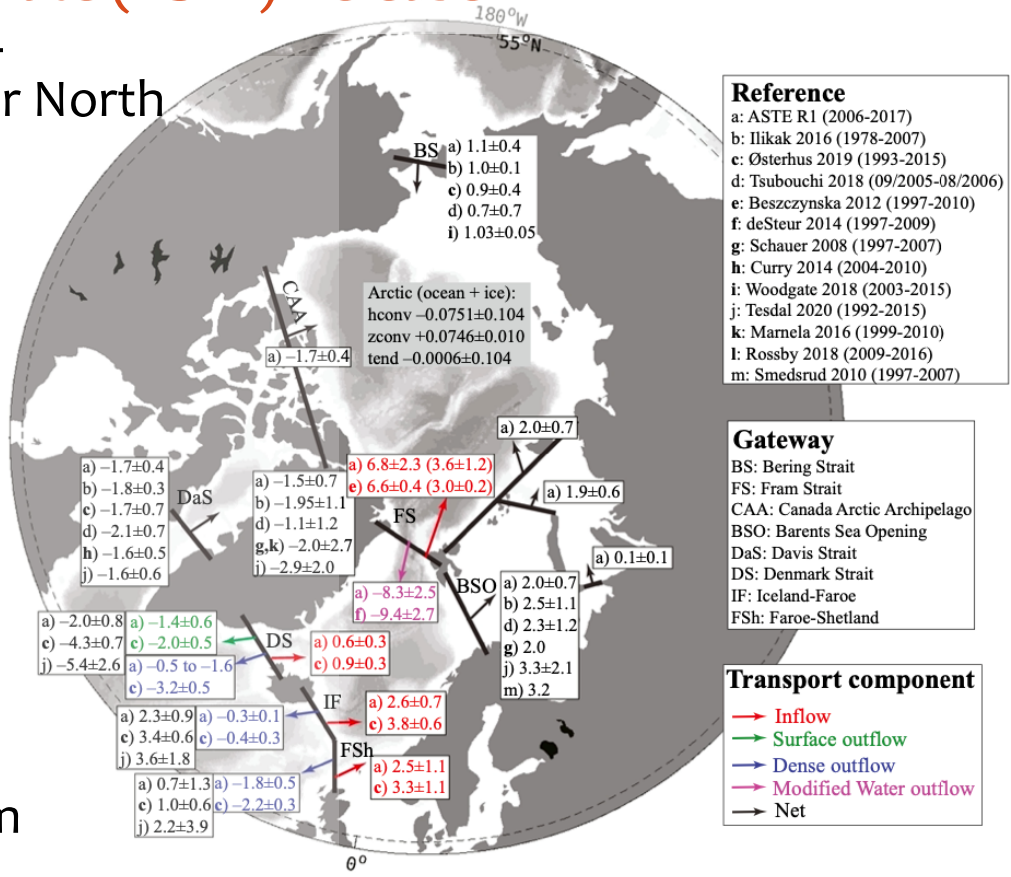
"To evaluate bias and accuracy of the reanalyses **only** where observations are actually available…"

"Following the examination of misfits, we explore interannual to decadal variability of global and regional ocean heat content **changes**."

(ii) Arctic Subpolar gyre sTate Estimate (ASTE) Release 1

The first of its kind for Arctic & subpolar North Atlantic ocean-sea ice reanalysis:

- (multi-)decadal, for climate studies
- Fit to diverse > 10^9 satellite & high-latitude in situ observations
- Model dynamics – interpolator where there is no data
- Adjoint-based non-sequential
  - → **Dynamically consistent**
  - → **Budget closures** for mass, heat, salt, momentum
- Accounts for **uncertain input parameters** (surface forcing, internal mixing, initial conditions)



(Nguyen et al. 2021)

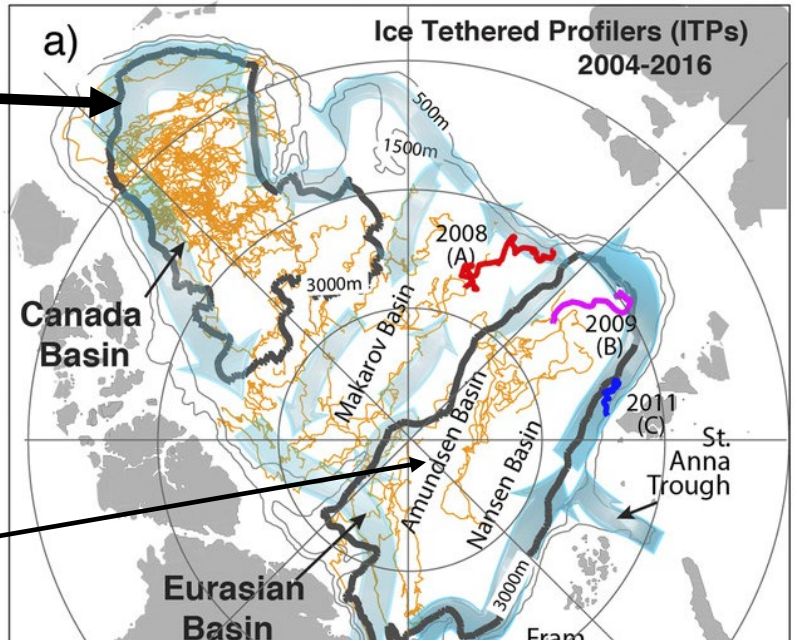
(iii) Challenges: ASTE Release 1: Persistent bias

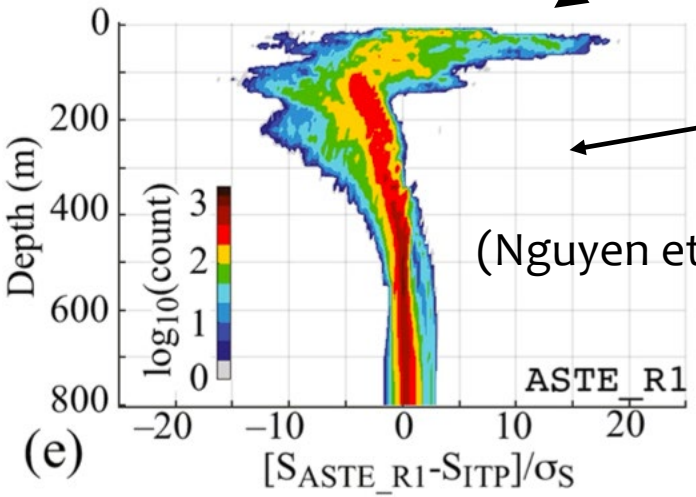
(Nguyen et al. 2020)

Observations distribution bias

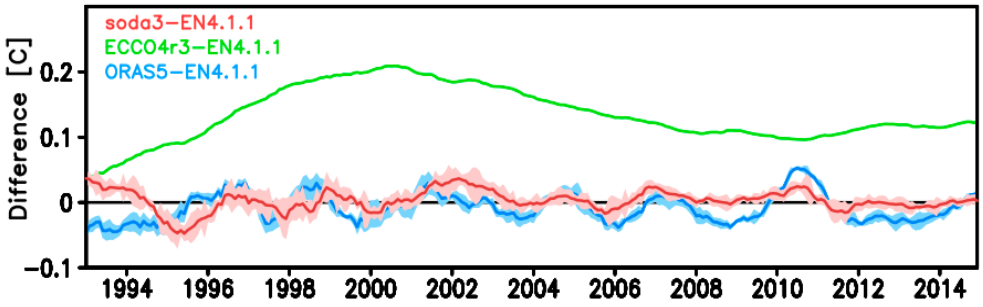
→ non-unique ways to improve uncertain / highly unconstrained input parameters

→ persistent reanalysis errors/biases





(Nguyen et al. 2021)



(iii) Opportunities – rethinking about "biases"

Biases exist for [many] reasons
→ opportunities for improvement:

- analysis increments: mapping into missing physics
- Observing network assessment & design ←→ inverse-based method
- machine-learning methods ←→ emphasis on conservations

(iii) Observing network assessment & design

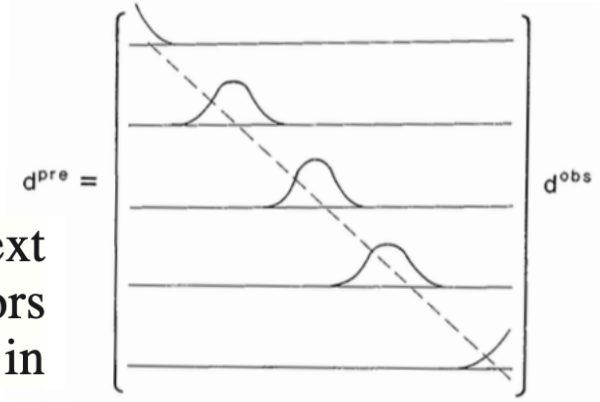
Moore et al., 2011

diagnostic tools, we find that more than 90% of the observations assimilated into the model provide redundant information. This is a

Menke 1989, Geophysical Data Analysis: Discrete Inverse Theory

The rows of the data resolution matrix describe how well neighboring data can be independently predicted, or *resolved*.

data resolution matrix

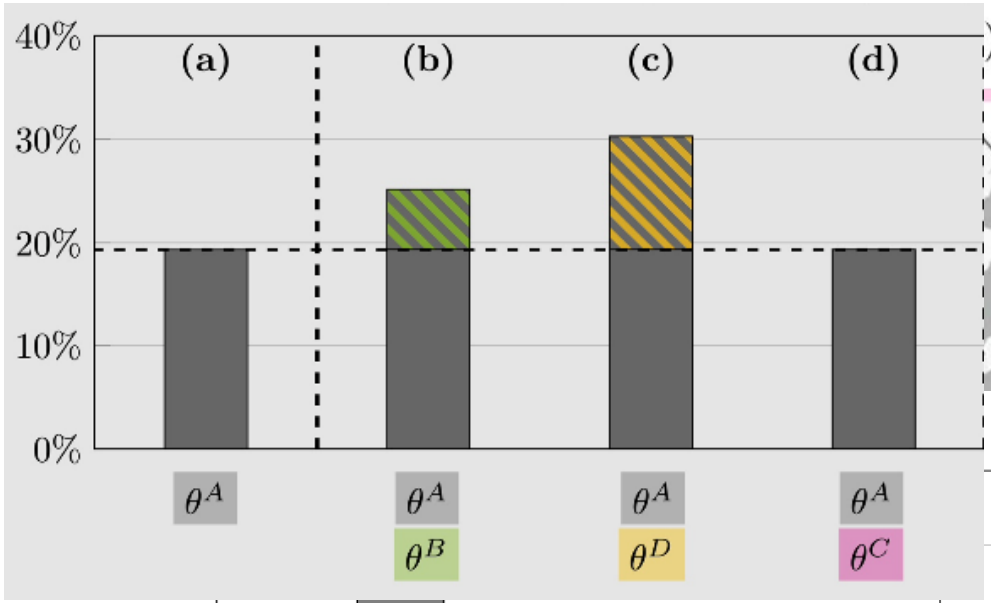


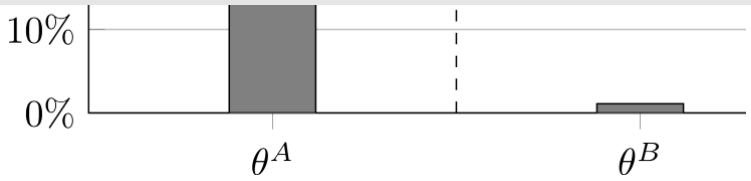
Köln & Stammer, 2004

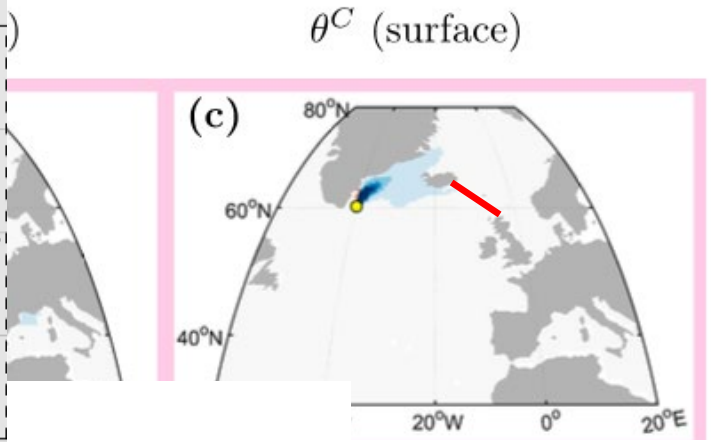
the design problem was discussed here in the context of optimal observations that emerge as singular vectors from the data resolution matrix. It was shown that in

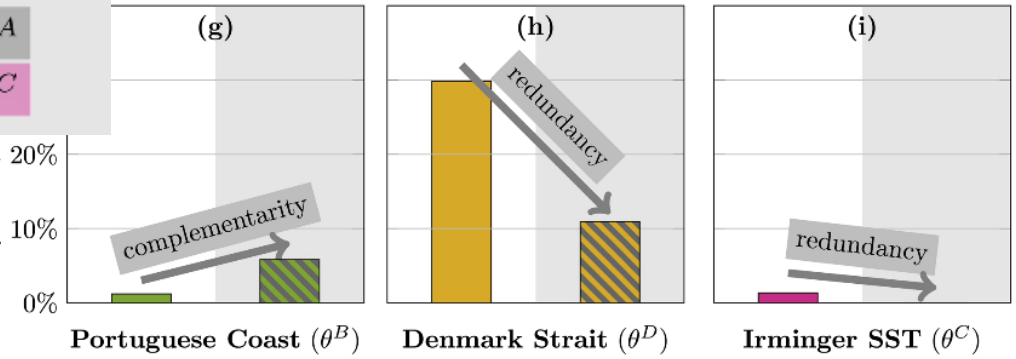
(iii) Observing network assessment & design

Loose 2020, Loose et al., 2020, 2021: Dynamical Proxy Potential









(iii) Machine learning (with emphasis on conservation)

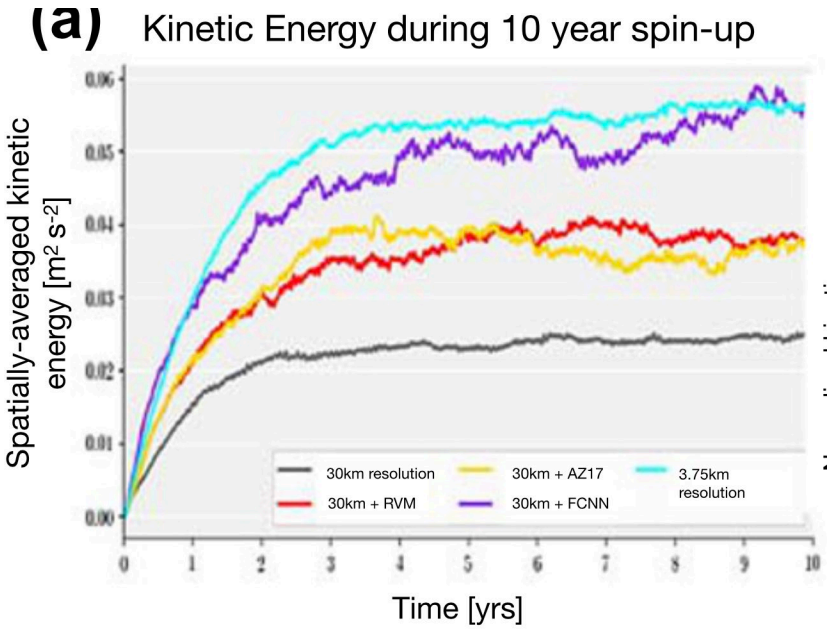
Machine learned physics
Zanna & Bolton, 2020,
Bolton & Zanna, 2023

3.1 Discovering Eddy Momentum Parameterizations

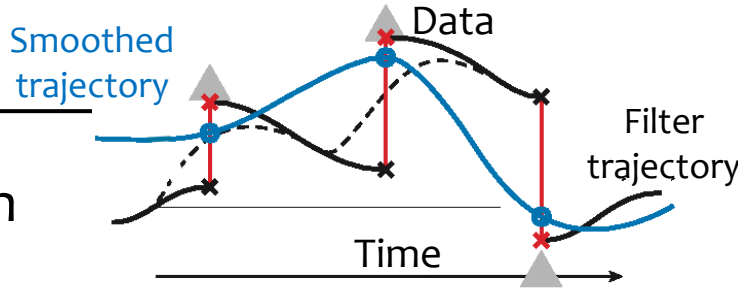
For constructing the library of functions to reveal expressions for the eddy momentum forcing, we write the spatial derivatives of the velocity field using the following basis functions

$$\zeta = \overline{v}_x - \overline{u}_y, \qquad \sigma = \overline{u}_x + \overline{v}_y,$$

$$D = \overline{u}_y + \overline{v}_x, \qquad \tilde{D} = \overline{u}_x - \overline{v}_y,$$



Summary



- observations are valuable but alone often can not inform large-scale or full-depth dynamics
- Models are incredibly powerful tools to “connect the dots”, filling in between sparse observations
- Reanalyses: combine of obs and models through data assimilation
- Emphasis on dynamical consistency (non-sequential, conserving) or goodness of fit (sequential, non-conserving)
- Be knowledgeable what you are using:
  - Understand your “assessment” of reanalyses where data exist
  - Understand usage in studying circulation / budget / changes

Summary

- ASTE:
  - The first of its kind for Arctic & subpolar North Atlantic ocean-sea ice reanalysis:
  - utilizes conservation laws as dynamical interpolator between sparse obs
- Persistent biases exist in ASTE → opportunities to improve reanalyses
- Inverse-based methods are a powerful technique to aide calibration of model's parameters, observational redundancy, and network design

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