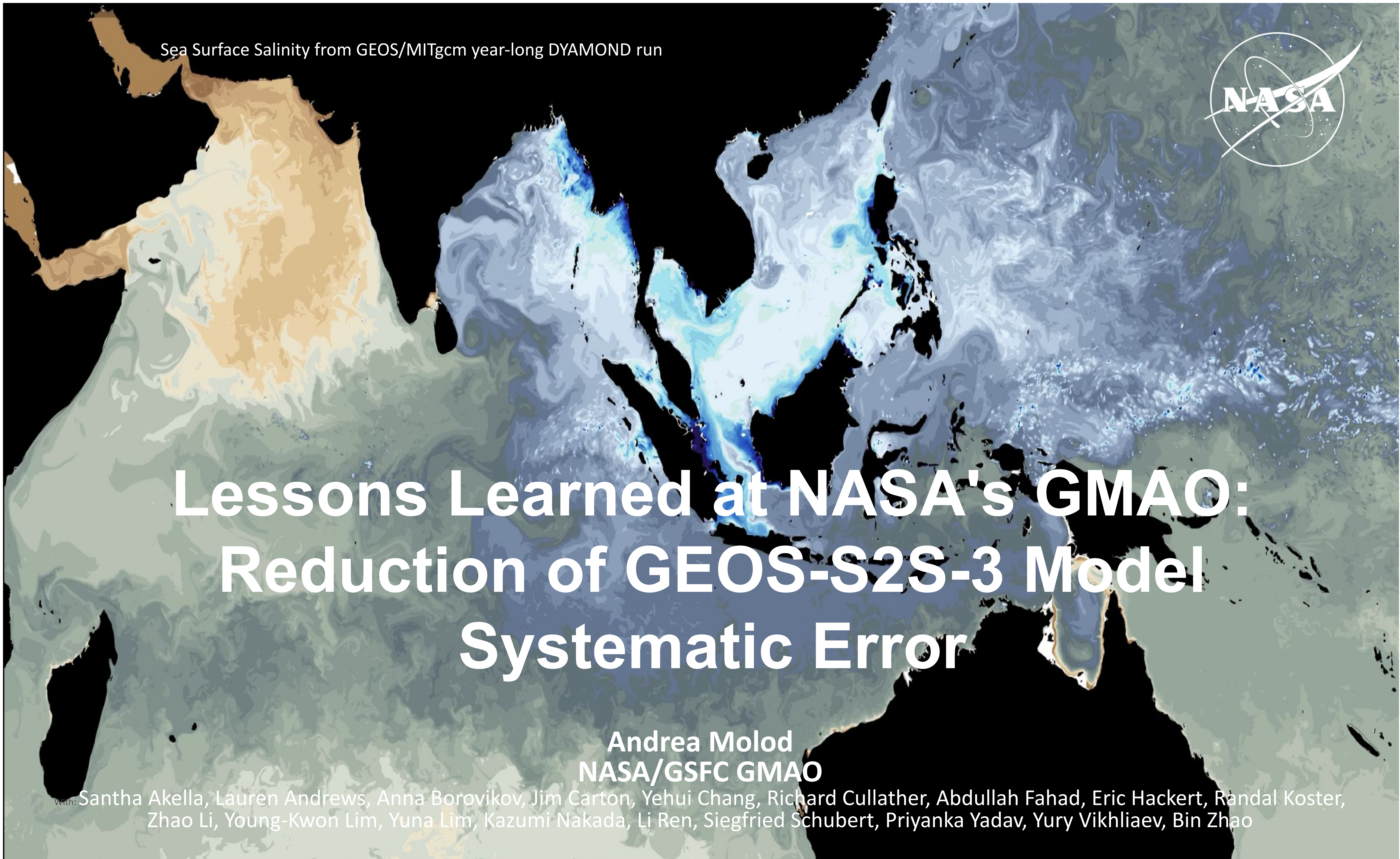

Sea Surface Salinity from GEOS/MITgcm year-long DYAMOND run

Lessons Learned at NASA's GMAO: Reduction of GEOS-S2S-3 Model Systematic Error

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GMAO's Model Error Correction Methods

1. Green's Functions objective parameter tuning: Implemented for GEOS-S2S-3, Included in development of next version, used in GMAO for wave model development. Results positive, can be improved further. Code was placed on github.

2. "Tendency Bias Correction" – *a priori* error correction – mixed results and thoughts for future

GEOS-S2S-3 Coupled Model and DA: Overview of System Characteristics

Model

- AGCM: Recent GMAO NWP (including aerosol model) + two-moment cloud microphysics
- OGCM: **MOM5, ~0.25 deg, 50 levels,**; **Ice Sheet runoff to proper location**
- **New "atmosphere-ocean interface layer" - diurnal warming and cool layer**
- Sea Ice: CICE-4.0
- Forecasts: **initialized from "GiOcean-NRT" assimilation, new perturbation/ensemble strategy;**
- Retrospective Forecasts: **initialized from "GiOcean" reanalysis, new perturbation/ensemble strategy;**

Coupled Ocean Data Assimilation System – Coupled Reanalysis "GiOcean" and "GiOcean-NRT"

- Atmosphere is "replayed" to "**GEOS_IT**"; precipitation correction over land, **modified to "regular replay"**
- **Aerosol is "replayed" to GEOS_IT analyzed aerosol optical depth using GAAS (Goddard Aerosol Assimilation System)**
- Penny et al. (2013) LETKF code/system, set here using **(updated)** static background error statistics;

Observations

- nudging of SST and sea ice fraction from GEOS-IT boundary conditions, **new technique for sea ice;**
- assimilation of *in situ* Tz and Sz including Argo, XBT, CTD, tropical moorings;
- assimilation of satellite along-track ADT (Jason, Saral, ERS, GEOSAT, HY-2A, CryoSat-2);
- sea ice concentration from the National Snow and Ice Data Center (NSIDC).
- **assimilation of SMOS, SMAP, Aquarius sea surface salinity**

GODDARD EARTH SCIENCES

1. GEOS-S2S-3 AOGCM: Model Tuning using the Green's Functions Method

Recipe:

1. Define a set of parameters to perturb.
2. Run a set of AOGCM experiments, perturbing one parameter at a time.
3. Define a set of observational targets and choose a "cost function".
4. Use the Green's functions methodology to choose the set of parameters that minimizes the cost. The computational cost of the minimization is negligible.
5. Assuming linearity, compute the projected cost reduction.
6. Run a new forward "optimized" experiment with optimized parameters and assess the optimized cost reduction.

Note: steps 3-6 can be repeated with different observational targets and cost functions without the need for additional GCM experiments.

GEOS-S2S-3 AOGCM: Green's Functions Cost and Verification

Verification data "targets":

Variable	Dataset	Years
Ice fraction	MERRA-2	1996-2004
Net surface short-wave radiation	SRB	1997-2004
Downward long-wave radiation	SRB	1997-2004
Near surface temperature	HadCRUT4	1996-2004
Sea surface temperature	ECCO	1996-2004
Sea surface salinity	ECCO	1996-2004
THETA at 300m	ECCO	1996-2004
SALT at 300m	ECCO	1996-2004

Cost function:

$$J = \sum_{v}^{8} \sum_{s}^{4} \sum_{l}^{N_l} \left(\frac{x_{v,s,l} - y_{v,s,l}}{\sigma_{v,s}} \right)^2$$

- x - model
- y - observations
- σ - data error variance
- v - variable
- s - season
- l - location
- N_l - total grid cells

From: Strobach et al., 2022 GMD

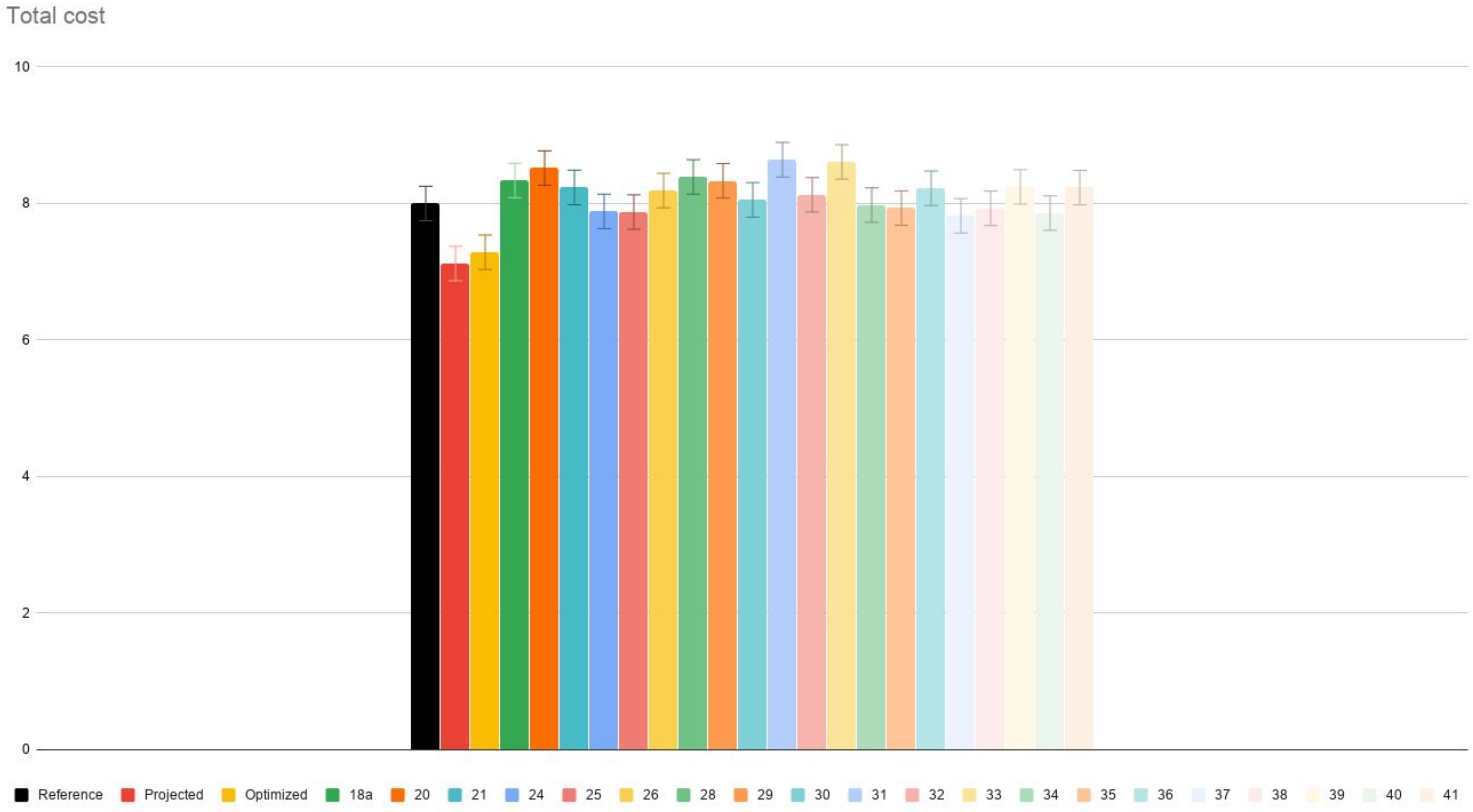
Optimized parameters

#	Parameter	Initial value	Perturbed value	Optimized value
1	DCRIT_DRIZZLE	0.2	0.3	0.21
2	LTS_LOW	19	20	19.4
3	CICE_AH_MAX	0.3	0.2	0.35
4	ALBICEV	0.73	0.82	0.77
5	ALBICEI	0.33	0.4	0.37
6	TURNRHCRIT	884	750	904
7	CQFACTOR	1	1.5	1.23
8	Charnok1	2.92E-3	2.19E-3	3.36E-3
9	Charnok2	-1.1E-8	-2.0E-8	-1.22E-8
10	XPFAC	1	1.2	1.05
11	SCLMFDFR	1	0.8	1.05
12	MINRHCRIT	0.9	0.85	0.91
13	MIN_EXP	0.6	0.8	0.69
14	MAX_EXP	1.5	1.7	1.44
15	TS_AUTO_ICE	4	3	4.49
16	BC_INFAC	1	0.5	0.74
17	DUST_INFAC	1	0.5	0.83
18	DCS	3.5E-4	3.0E-4	3.72E-4
19	UISCALE	1	0.9	0.97
20	KHRADFAC	0.85	0.5	0.92

In many cases the optimized parameters are outside the range of the default and perturbed values

From: Strobach et al., 2022 GMD

GEOS-S2S-3 AOGCM: Green's Functions Total Cost

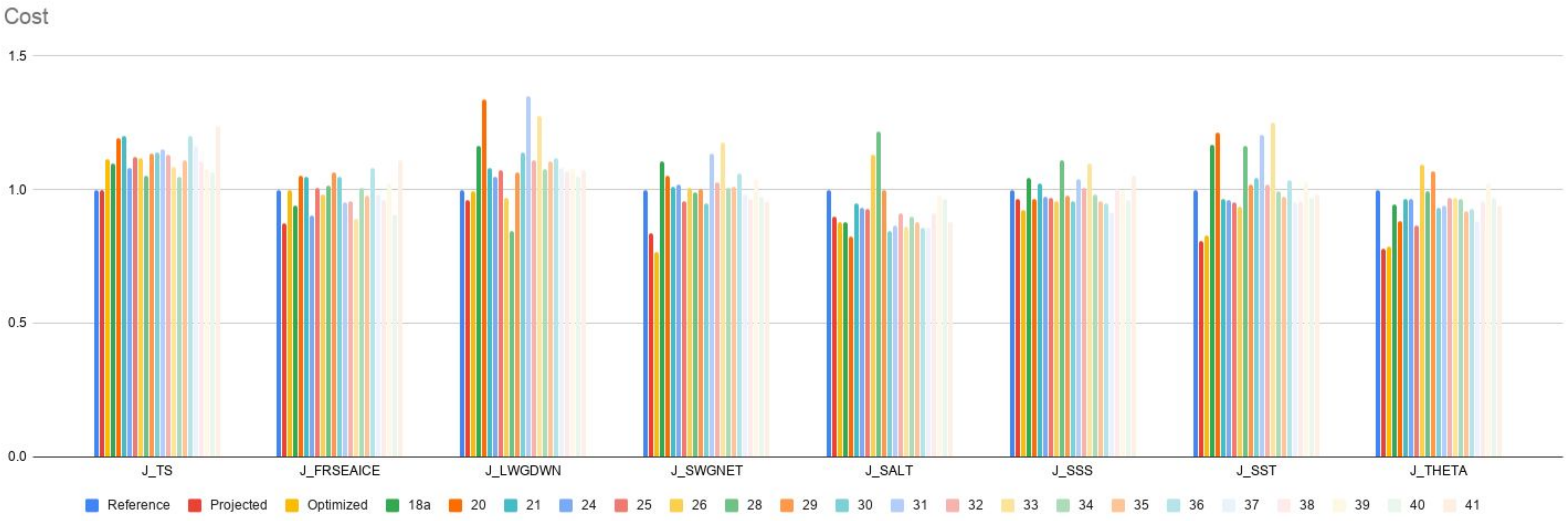


Cost was also assessed for each observational target individually. For this example all cost was reduced except for surface skin temperature over sea ice.

Ocean observational targets all showed reduced cost despite not including ocean model parameters in the optimization.

From: Strobach et al., 2022 GMD

Cost by variable



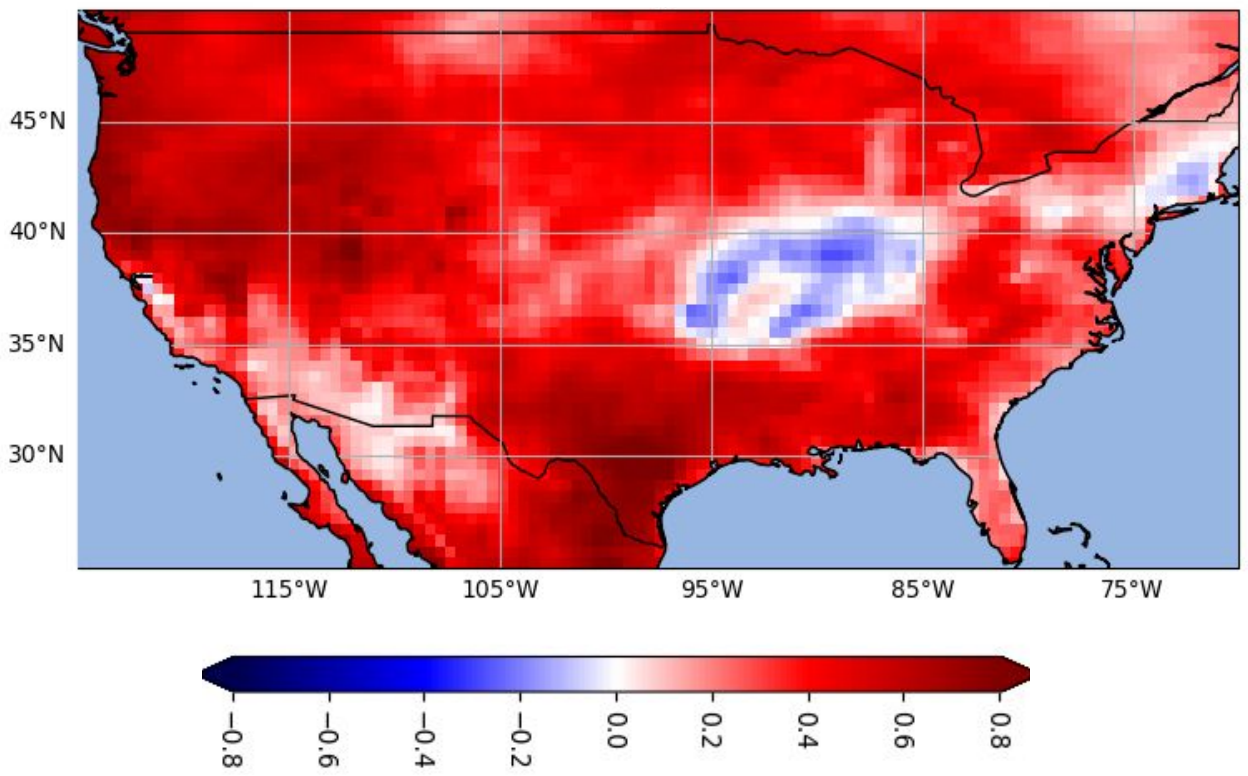
From: Strobach et al., 2022 GMD

GEOS-S2S-3: Forecast Evaluation – Impact of Green's Functions Tuning

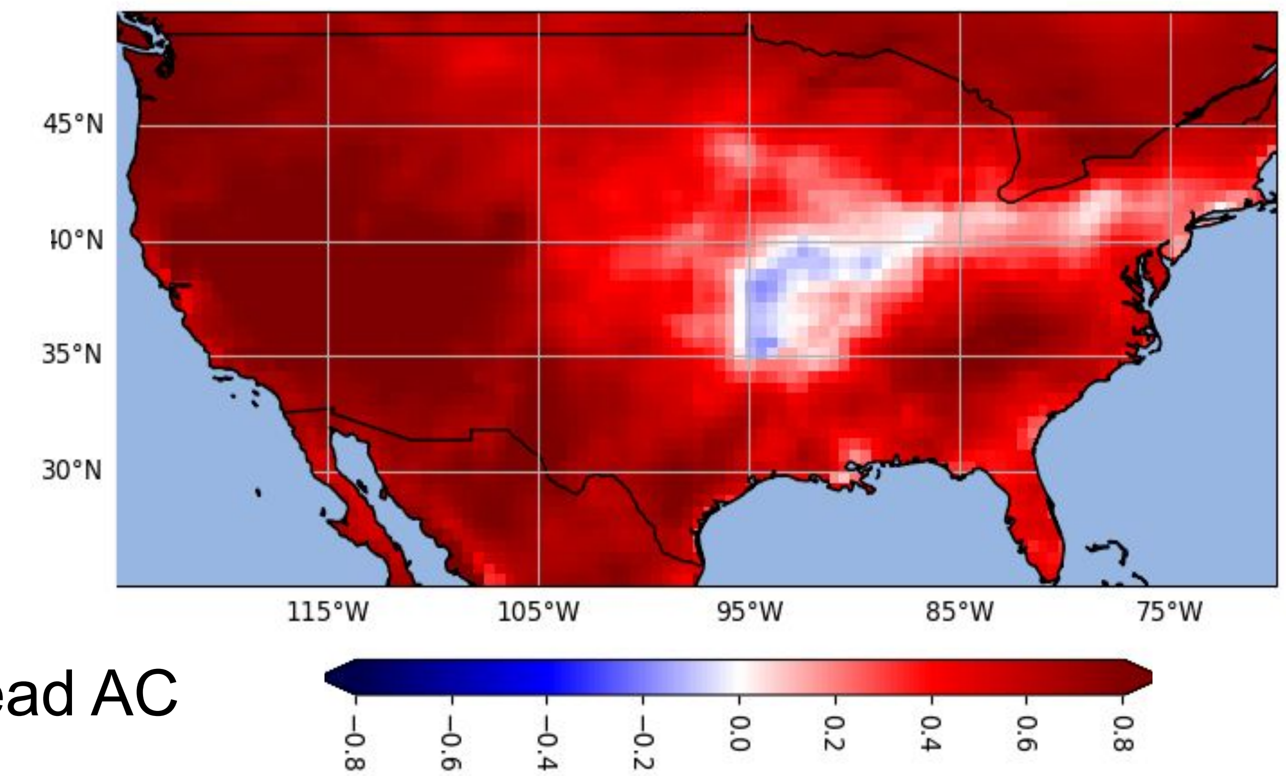
Results of Green's Functions Tuning:

- Improved long term bias (observational targets and other fields in time slice experiments
- Error "saturation" in shorter time (was 6 months for T2M, now 3 months)
- Improvement in boreal summer and winter skill at short lead times (<3 months)

GEOS-S2S-2



GEOS-S2S-3



June 1-month lead AC

Analysis of Zhao Li

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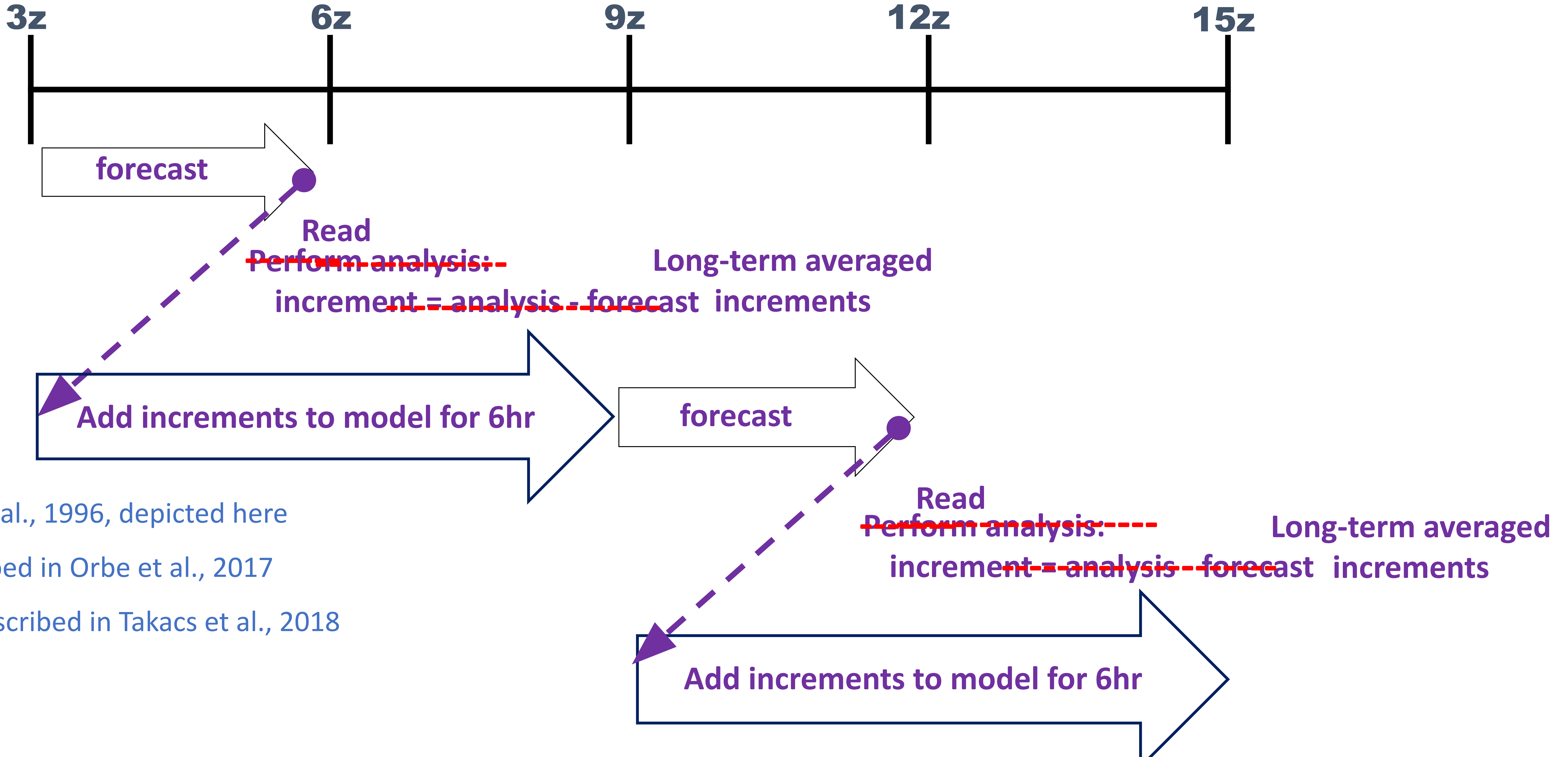
Green's Functions Tuning - Recap and Future Directions

- Use of GF method has so far used a simple cost function. As reported in Strobach et al., 2022 this has necessitated removing observational targets that "absorb all the error" at the expense of other targets. Use of alternative cost functions will be explored

- Use of GF method's observational targets will be expanded to include derived quantities such as Hadley cell mass streamfunction, Velocity Potential and Niño 3.4

2. Tendency Bias Correction (TBC)

IAU, "Replay" and TBC at GMAO: Flow Diagram

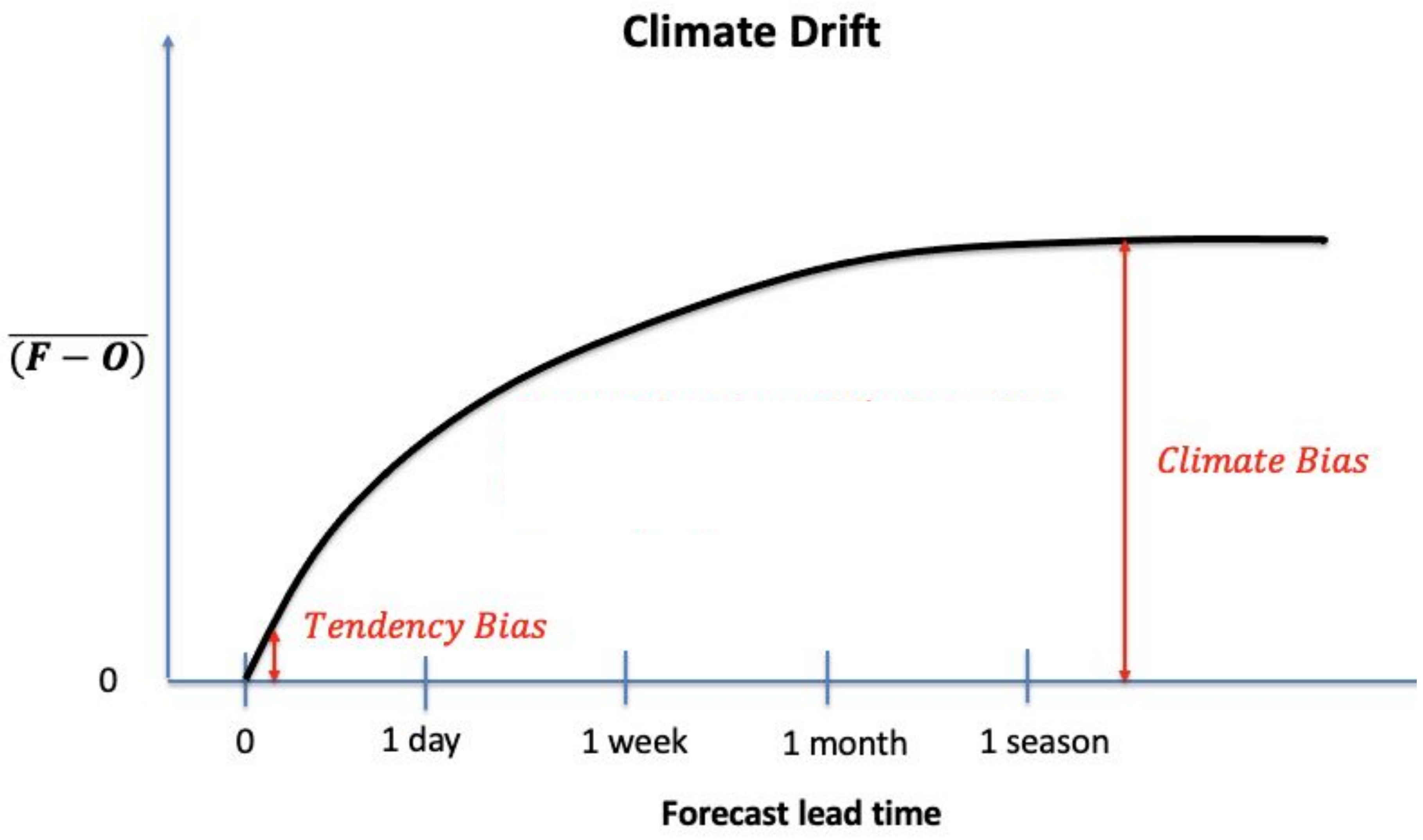


IAU of Bloom et al., 1996, depicted here

"Replay" described in Orbe et al., 2017

Updated IAU described in Takacs et al., 2018

Underlying Motivation/Questions



- Can we reduce the model's climate bias by correcting the initial drift or tendency bias?
- Does reduced climate bias manifest itself in increased forecast skill at subseasonal to seasonal lead times?

"Drift" refers to time mean differences between the model forecasts and observations (or reanalysis) that are functions of lead time.

The "tendency bias" and the model's climatological bias represent the two end points of the bias evolution or drift, with the former measuring how the model initially starts to drift away from the observed climate and the latter measuring where it ends up.

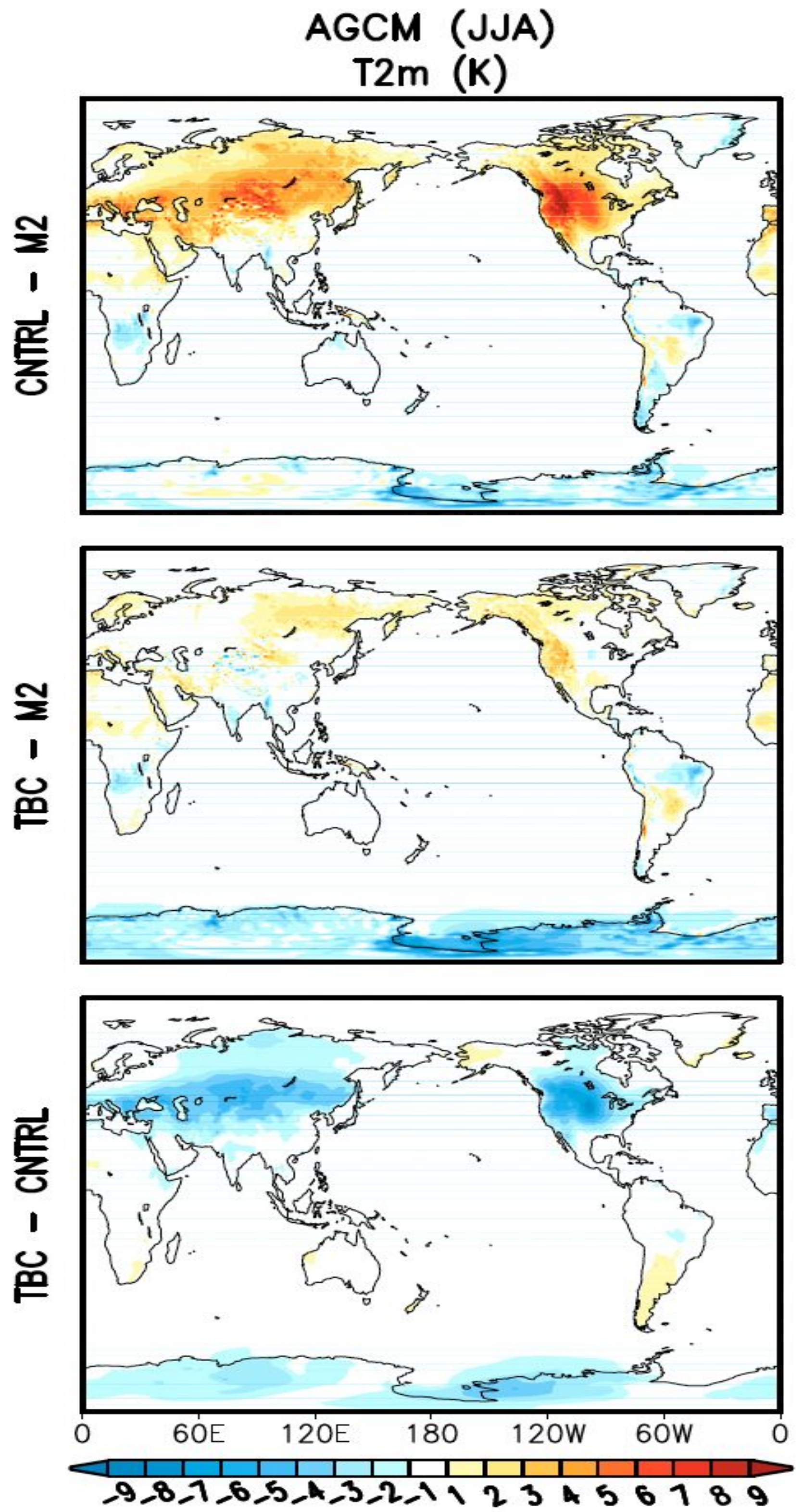
Atmospheric Correction in Atmospheric Model

<u>Experiment:</u>
Long "AMIP" simulation (~37 years using an atmospheric model forced with observed sea surface temperatures) with MERRA-2 AGCM and MERRA-2 analysis increments used to compute TBC terms

<u>Results:</u>
Time mean climate root mean squared error is reduced. Also improved interannual variability and seasonality.

Little impact on systematic error in other (diagnostic) fields such as cloud cover and precipitation.

Little impact on forecast skill



Chang et al., 2019

(Similar experiments and outcome shown in Kharin and Scinocca, 2012)

Atmospheric Correction in Coupled Model

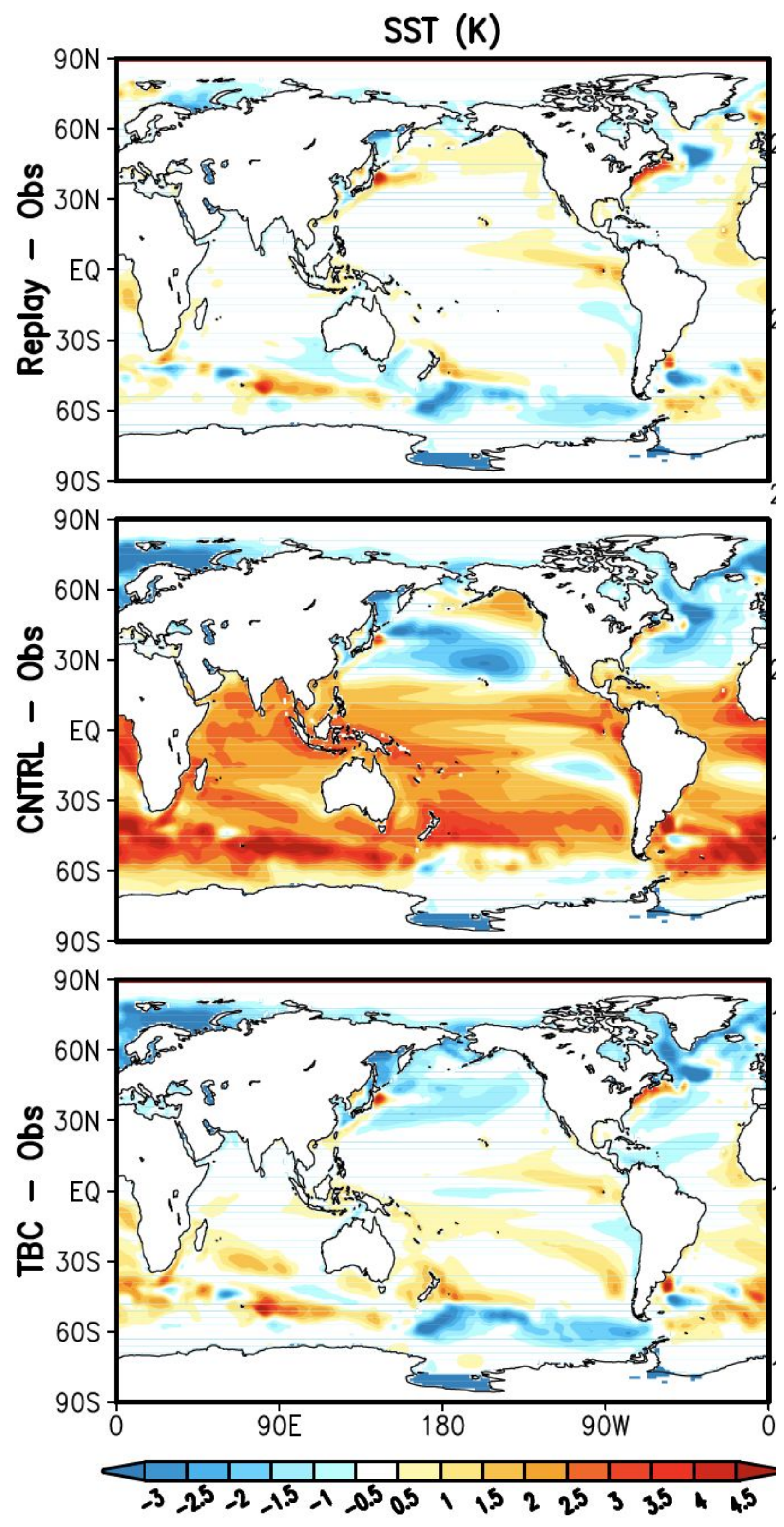
Experiment

Long coupled simulation in which atmosphere is "replay"ed to MERRA-2. TBC terms are interannual averages of replay increments at each 6-hour interval. Since the experiment is only correcting atmospheric quantities, the ocean is only indirectly constrained by the TBC.

Results

Various improvements to the climate bias of the mean state, stationary waves and related transients, and more realistic ENSO variability and associated teleconnections

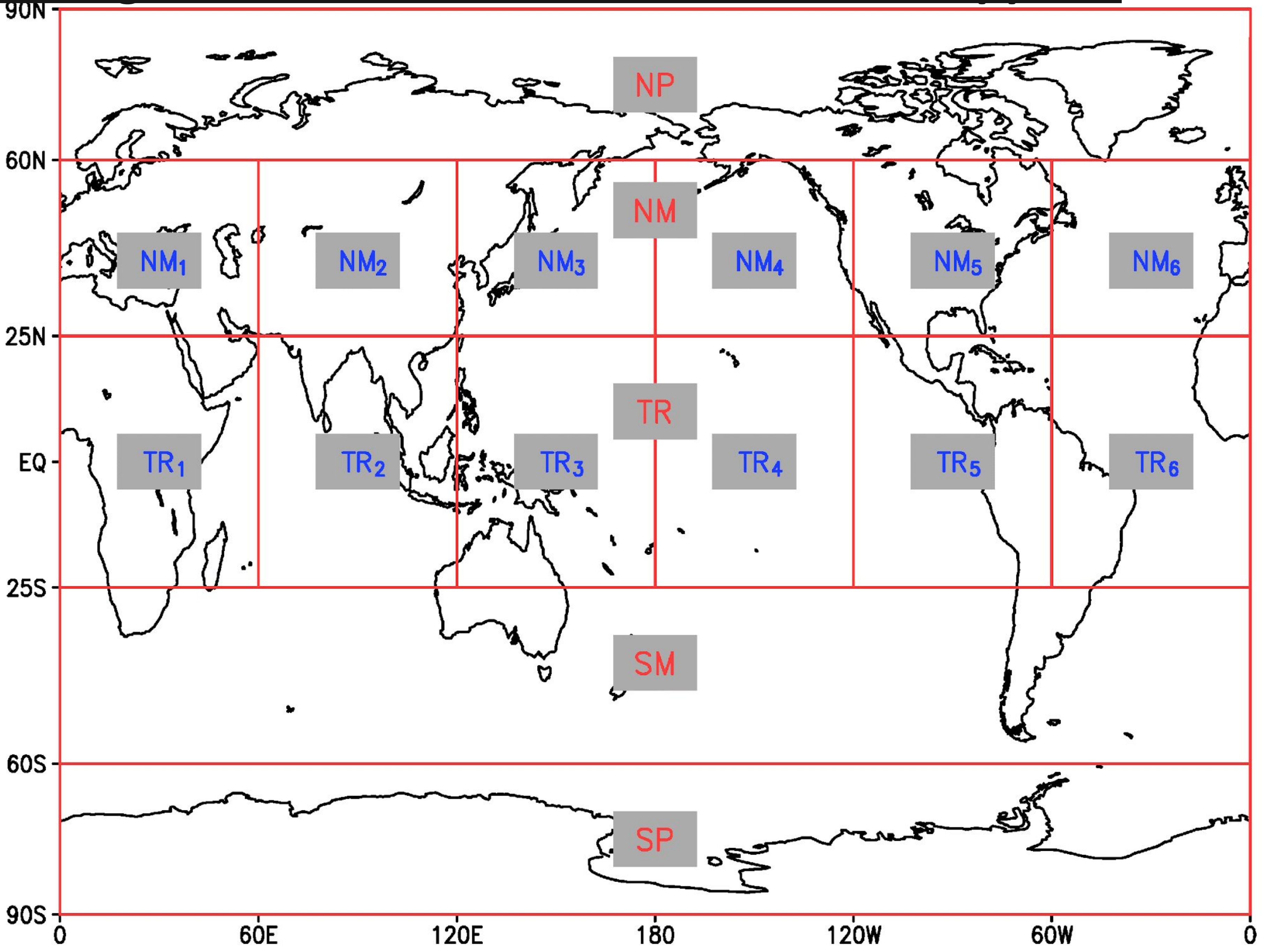
TBC-related skill improvements were rather modest at best at both subseasonal and seasonal time scales. The modest improvements were at subseasonal scales, for eddy heights over the Pacific–North American region and T2m over North America.



Chang et al., 2019

"Regional TBC" – Find Source of model error

The Regions Over Which Corrections were Applied



Regional TBC and Replay: A Tool for Addressing Model Error

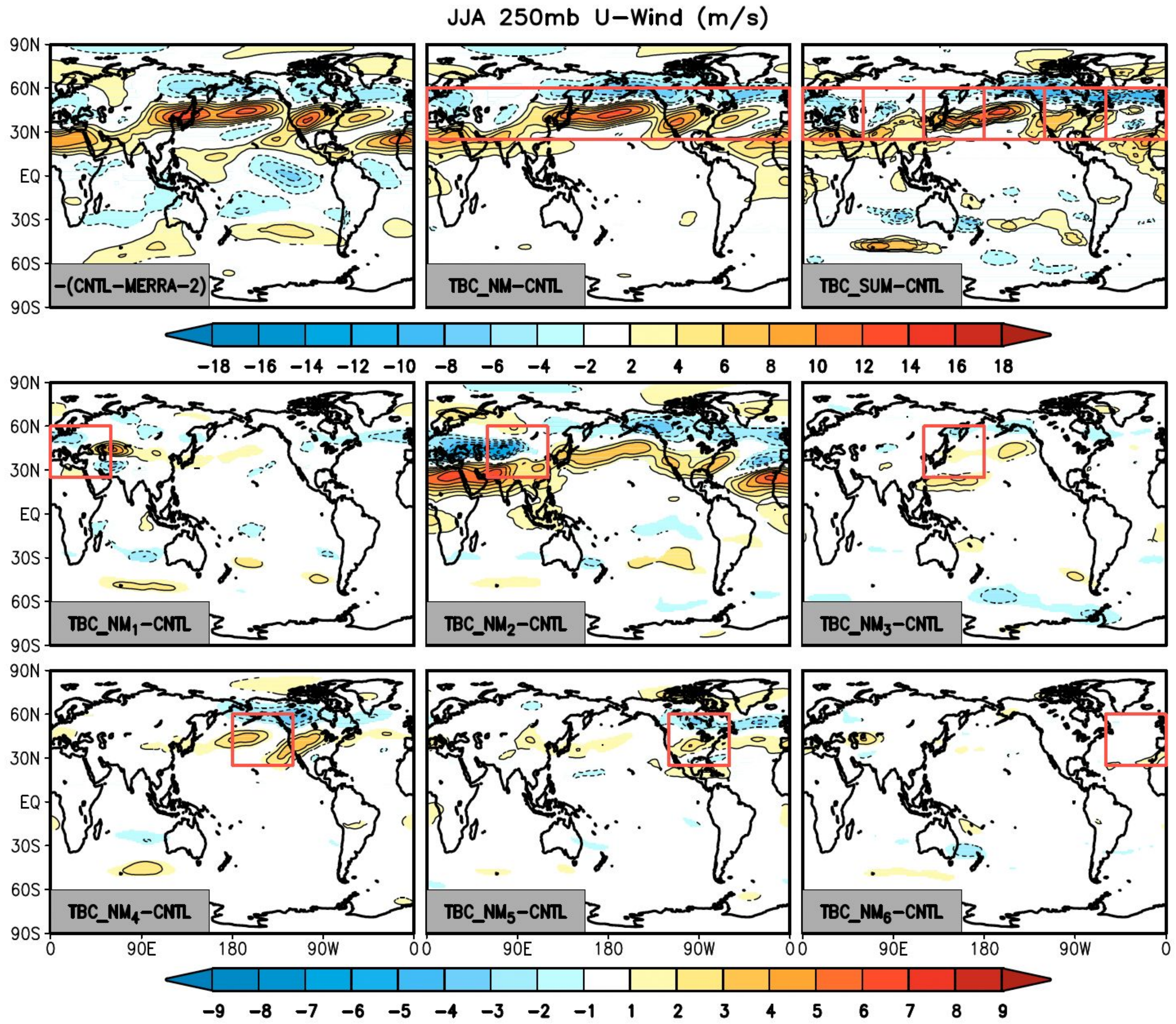
TBC corrections were applied together and separately in the regions shown here.

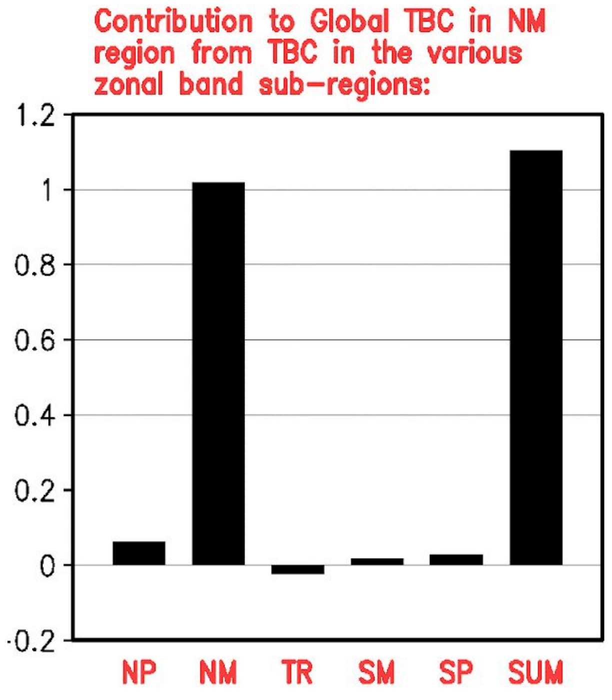
Experiments were performed with the GEOS AGCM forced with observed SST and run for the period 1980-2017. A TBC experiment was also conducted in which the increments were applied globally. In addition, a **CNTRL** run was made without any correction terms.

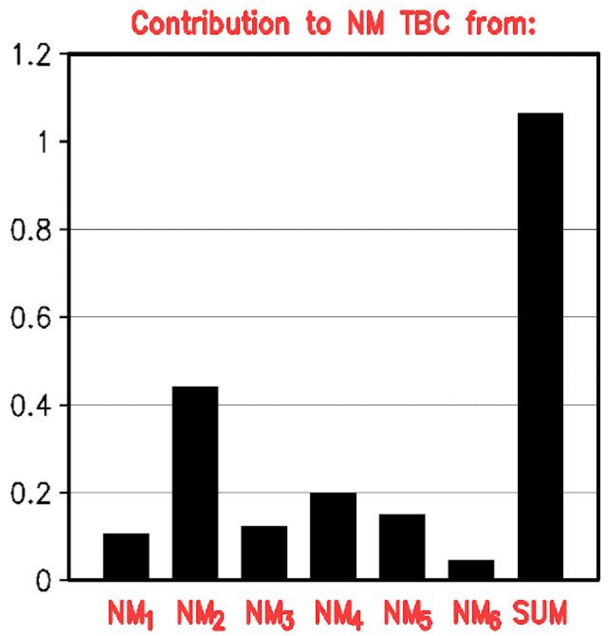
Schubert et al., 2019

Regional TBC – Source of model error (cont'd)

JJA 250mb U-wind: TBC







Upper left panel is (CNTRL-MERRA-2). The other panels are the experiments (TBC-CNTRL) for the regions shown by the red boxes. The upper right map is the sum of the results of the 6 NM regions. The bar graphs are the normalized spatial inner products from the various experiments.

Key results: much (87%) of the AGCM long term bias in the NM region can be corrected by the TBC in that region, and much of that (>40%) is achieved by the correction over the Tibet region (NM_2). Results are similar for T2M and precipitation in JJA

Schubert et al., 2019

TBC – What Works and What Does Not

Why is there little or no impact on forecast skill after demonstrating that TBC can significantly reduce climate bias?

The connection between forecast skill and the quality of a model's climate (including variability) is not straightforward, though it seems plausible that a model with a better long-term climate should have better forecast skill. However…. Some possible obstacles are:

- The "true" errors cannot be represented by a simple constant forcing term and are, in fact, state dependent (e.g., Leith 1978; Danforth et al. 2007)

- Correcting climate drift (which is a function of forecast lead time) can presumably only lead to improved forecast skill if a substantial amount of the bias (and its correction) occurs before all predictability is lost. The two time scales (associated with drift development and predictability) serve to define a window of forecast leads during which TBC can be expected to have an impact on skill.

TBC Results – Motivation for Future Directions

Q: Can we reduce the model's climate bias by correcting the initial drift or tendency bias?
A: Yes, this has been shown for atmosphere (Chang et al., 2019, Kharin and Scinocca, 2012), ocean (Lu et al., 2022) and coupled models (Chang et al 2019, Merryfield et al., 2022) and assimilation systems (Lu et al., 2020)

Q: Does reduced climate bias manifest itself in increased forecast skill at subseasonal to seasonal lead times?
A: Marginal increased skill at best, some potential promise for coupled TBC

Future Directions with TBC in GMAO

1. Use atmospheric replay increments and ocean IAU increments, both derived by ML to include model state dependance, to estimate TBC terms.
2. Use in weakly coupled assimilation with goal of improving Mean Analysis Error
3. Use in forecasts initialized from coupled assimilation to evaluate impact on skill