Current and Emerging Developments and Needs in S2S and S2D Prediction

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Canadian Centre for Climate Modelling and Analysis

Victoria, BC, Canada

- 347 Participants
- 224 Poster Presentations
- 144 Oral Presentations
- 92 Early Career Scientists
- 38 Countries
- 5 Days

Second International Conference on Subseasonal to Seasonal Prediction (S2S)

- *Mechanisms of S2S predictability*
- *Modelling issues in S2S prediction*
- *S2S ensemble predictions and forecast information*
- *S2S forecasts for decision making*
- *Land & Ocean initialization and processes*
- *Aerosols & Stratosphere*

Second International Conference on Seasonal to Decadal Prediction (S2D)

- *Mechanisms of S2D predictability*
- *Modelling issues in S2D prediction*
- *S2D ensemble predictions and forecast information*
- *S2D forecasts for decision making*
- *Hindcast and forecast quality assessment*
- *Frontiers in Earth system prediction*

Plenary cross-cutting themes:

- *Initialization, initialization shock and model error*
- *Research and operations*
- *Time scale interactions*

Synthesis article:

Merryfield et al., submitted to BAMS

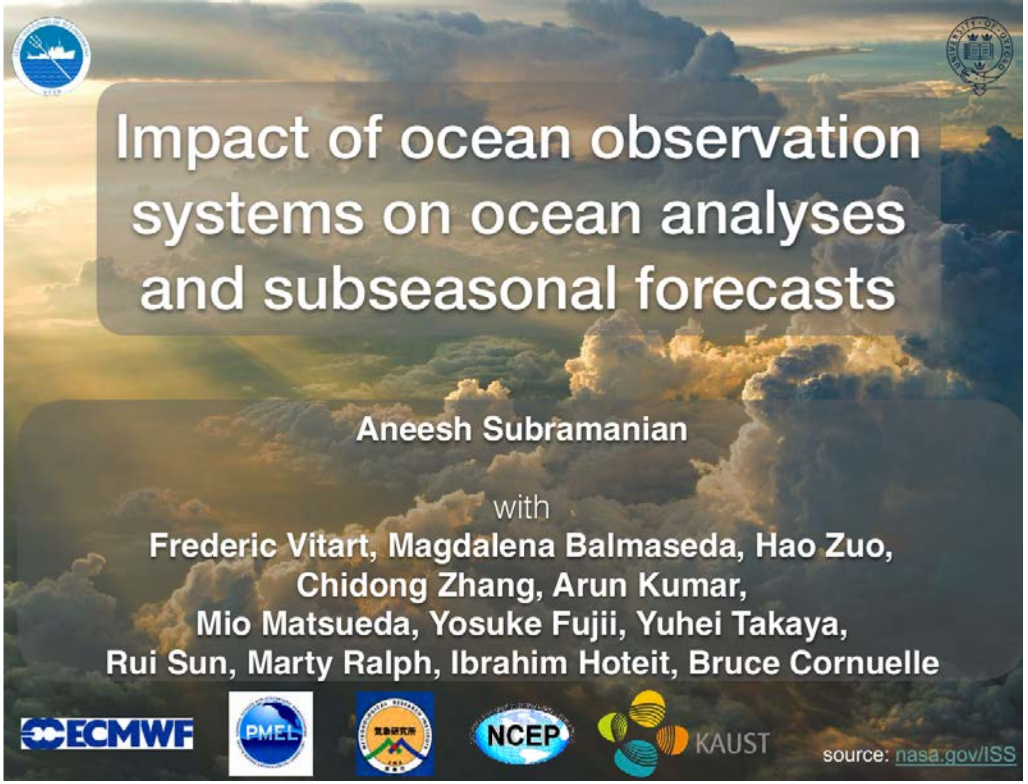
Contents of presentation

- Conference presentations of note (very selective)
- Perspectives on *understanding biases in prediction systems and key uncertainties that could be addressed by process studies to improve prediction*, informed by

  - 2018 S2S/S2D Conferences

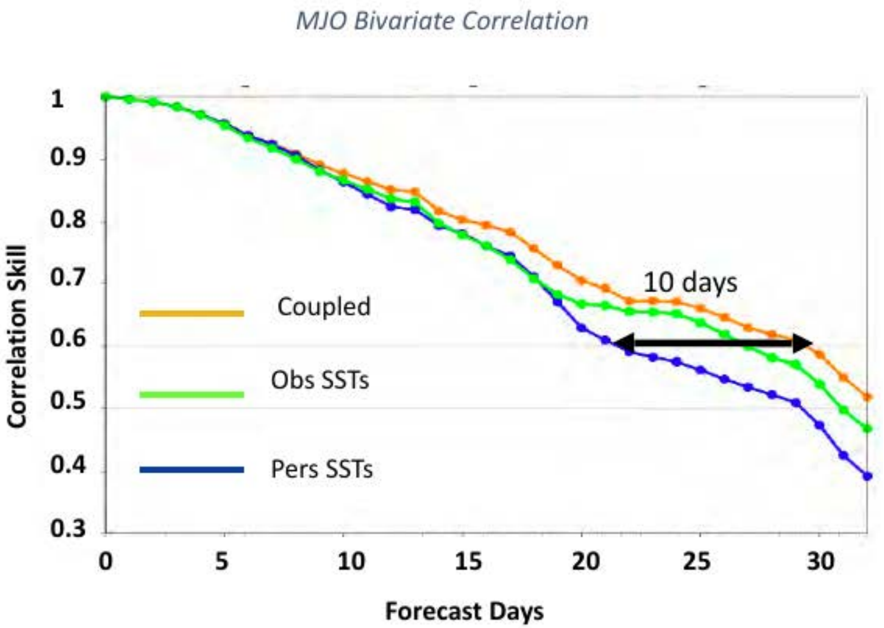
  - 2017 WGNE workshop on systematic errors in weather and climate models

  - personal observations



Ocean coupling improves MJO predictability

- Subseasonal forecasts of the MJO benefit significantly from coupling to the ocean (20 years of initialized forecasts)
- Ocean-atmosphere phase locking of anomalies and feedback act as a source of predictability on S2S timescales
- Understand coupled processes better to improve models and predictions on sub seasonal timescales



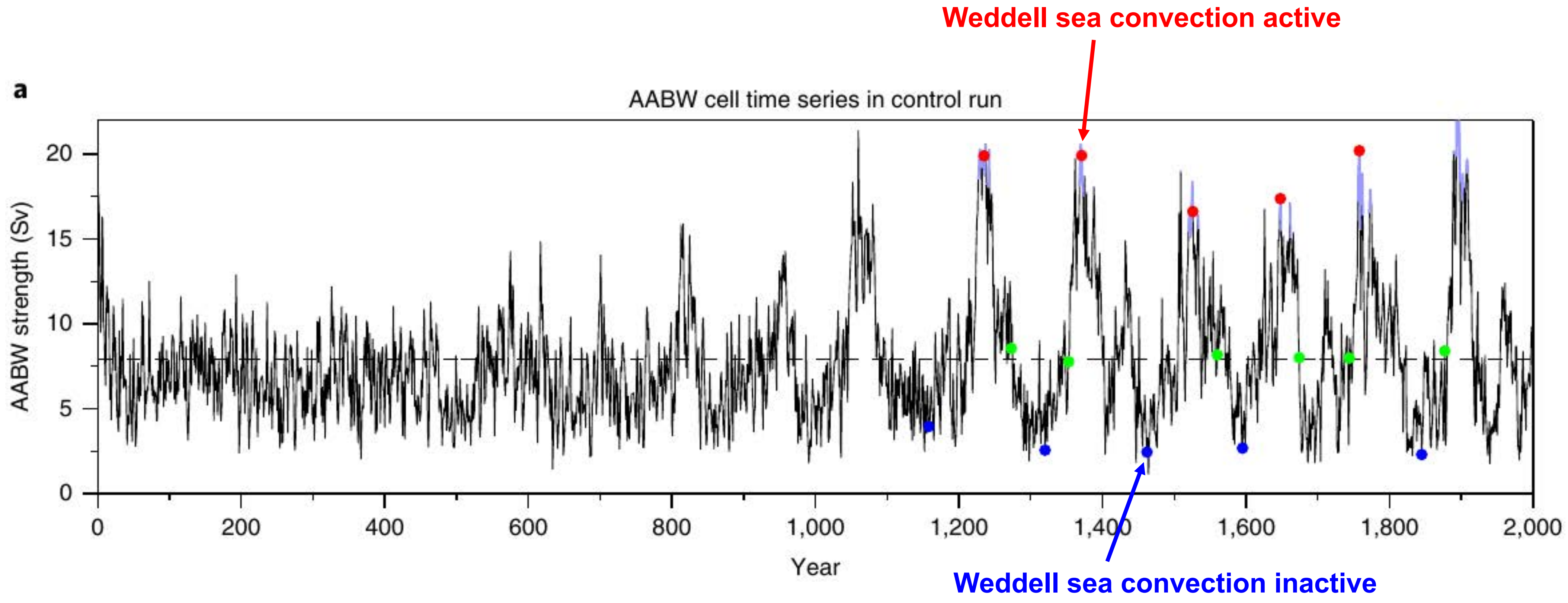
Subramanian, A., F. Vitart, C. Zhang, A. Kumar and M. A. Balmaseda 2018

- Ocean data assimilation helps improve forecast skill of some atmospheric variables on subseasonal timescales
- Further analysis is required to understand the systematic impact of ocean observations on improved process understanding and forecast skill for S2S timescales

nature climate change
ARTICLES
https://doi.org/10.1038/s41558-018-0350-3

Natural variability of Southern Ocean convection as a driver of observed climate trends

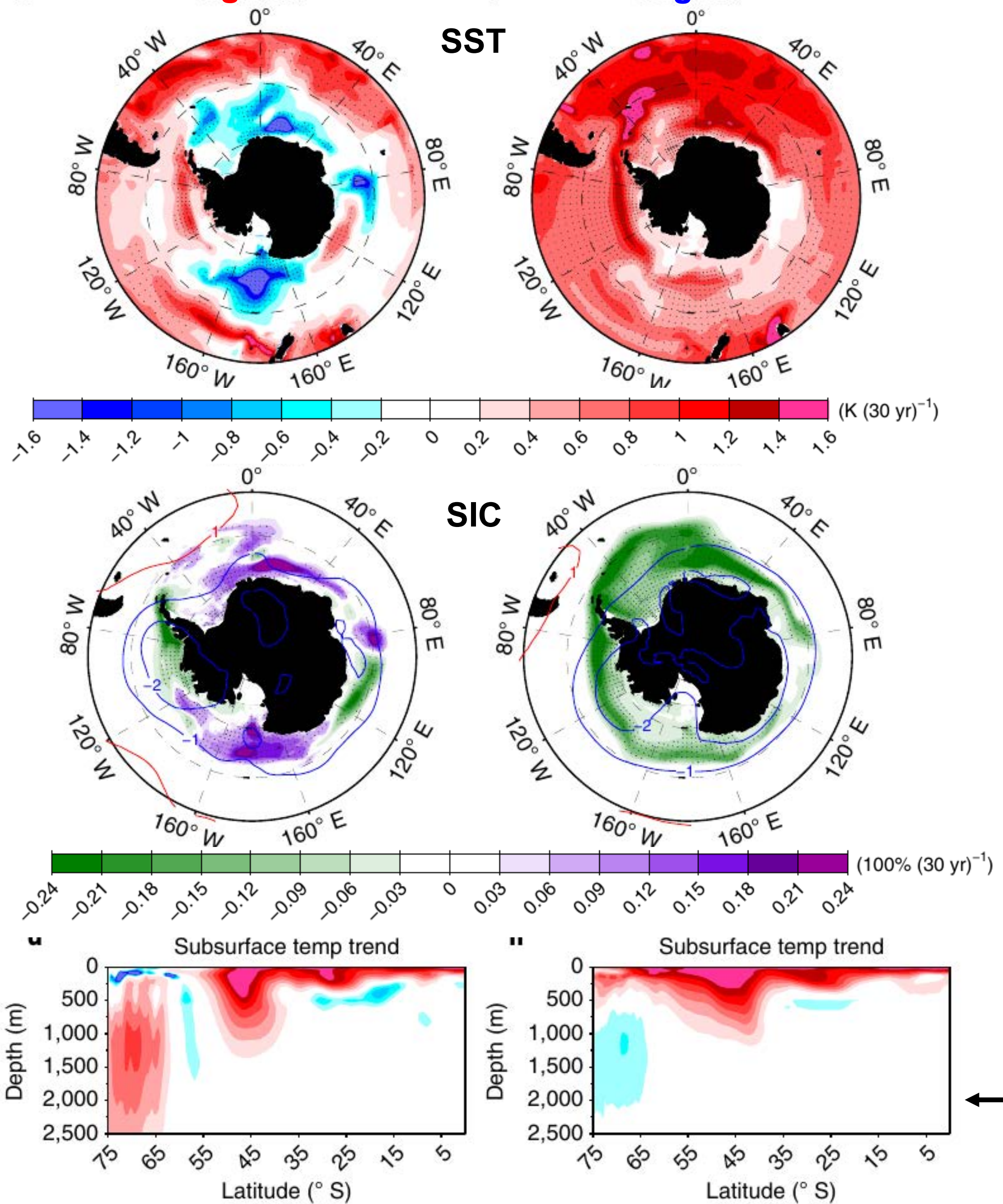
Liping Zhang[1,2*], Thomas L. Delworth[1,2], William Cooke[2,3] and Xiaosong Yang[2,3]



Composite 30y trends

Following active conv. | Following inactive conv.

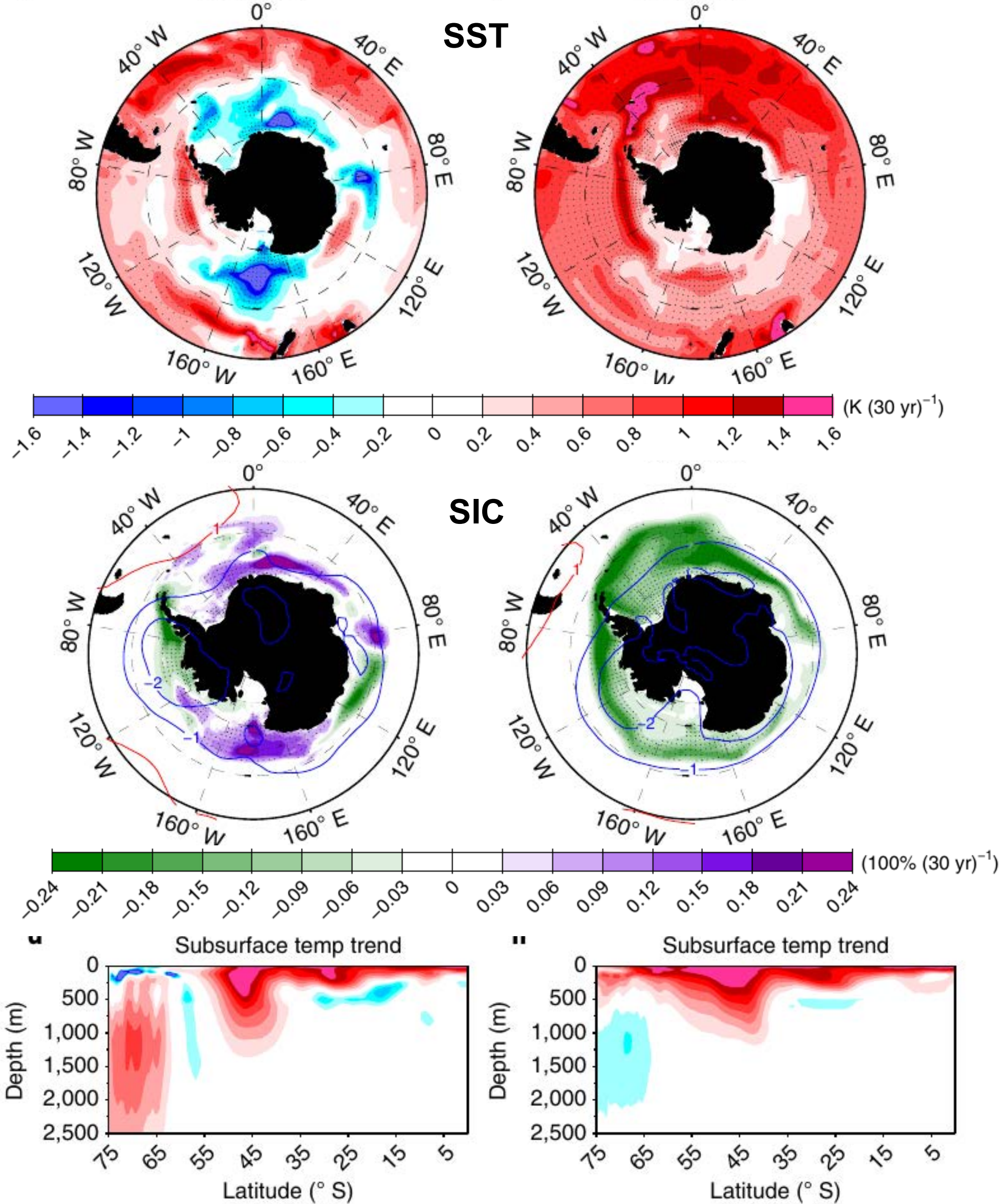
Zhang et al., *Nat. Clim. Change* (2019)

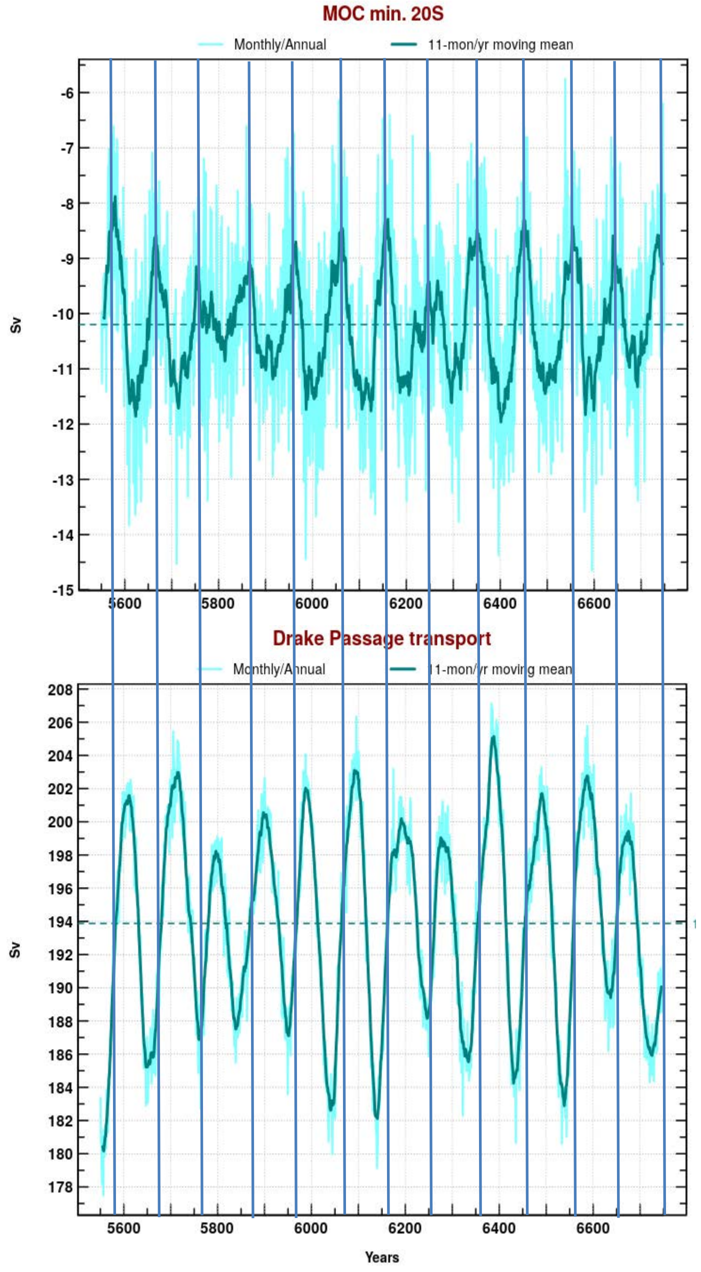


Deep high latitude ocean obs may be crucial for initializing (multi-)decadal predictions

Composite 30y trends

Following active conv. **Following inactive conv.**





~100 year oscillation involving AABW and Southern Ocean also seen in control run of CanESM5 (CCCma CMIP6 model)

↓

multi-model analysis/intercomparison would be of great interest

Are some key biases largely due to under-resolution of topographic effects?

High atmospheric horizontal resolution eliminates the wind-driven coastal warm bias in the southeastern tropical Atlantic

Sebastian Milinski[1,2], Jürgen Bader[1,3], Helmuth Haak[1], Angela Cheska Siongco[1], and Johann H. Jungclaus[1]

GRL 2016

→ **helps near coast, but doesn't solve large offshore SST bias due to insufficient low-level clouds**

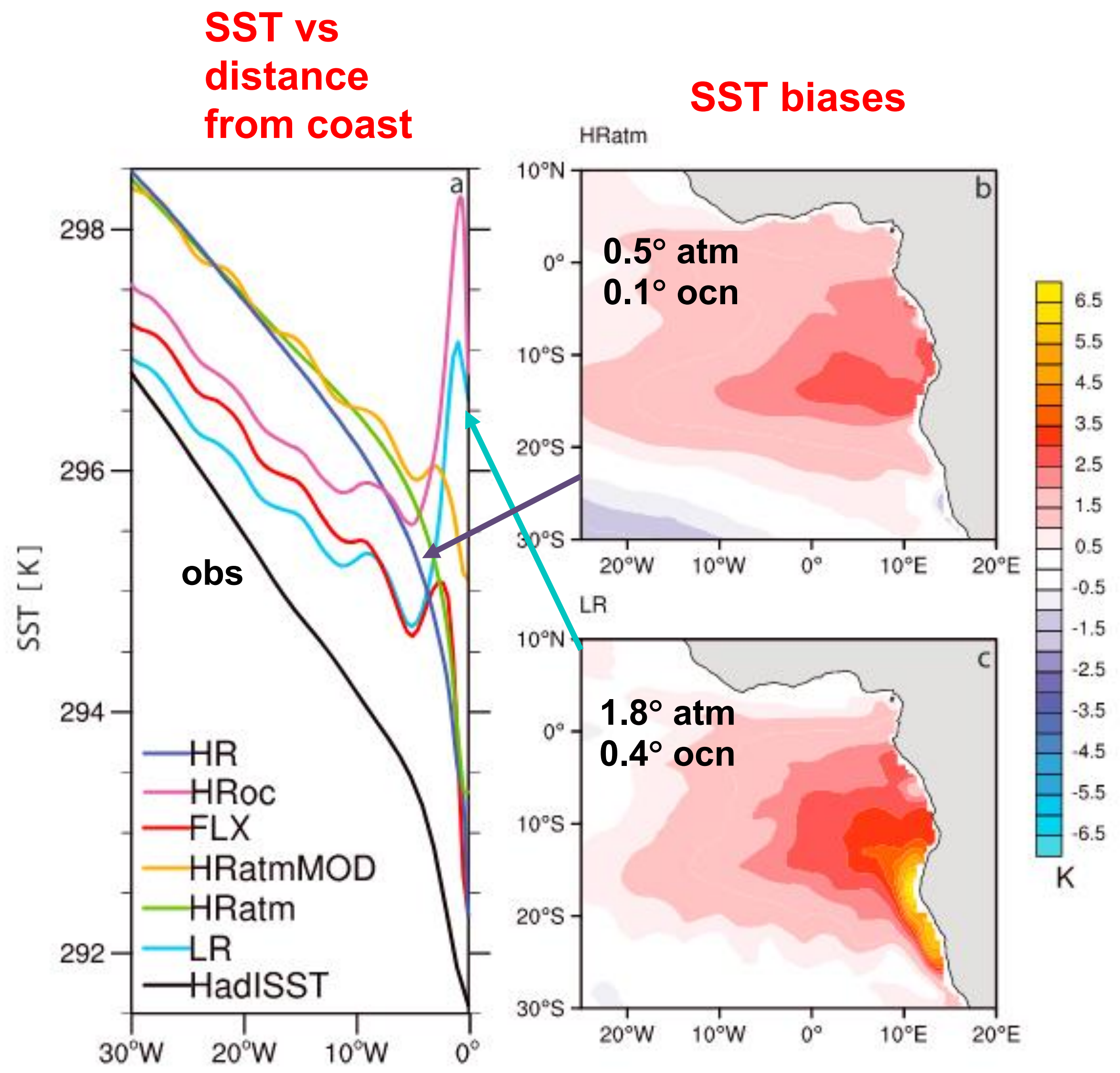
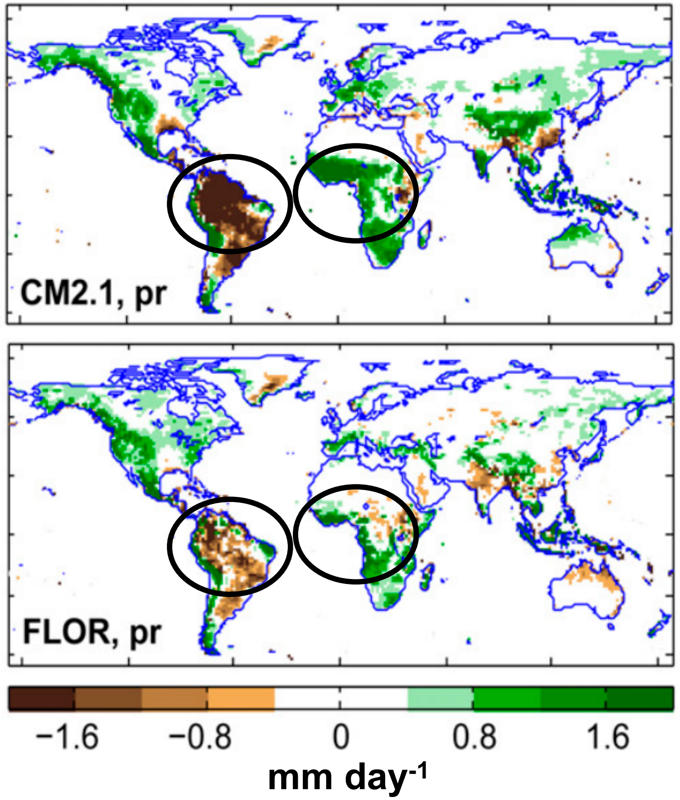


Figure 1. High atmospheric horizontal resolution eliminates coastal SST bias in the SETA region: (a) coast-following meridional mean of SST on model grid, averaged 15°S to 25°S; (b) time mean SST bias for HRatm (0.5° horizontal resolution); and (c) time mean SST bias for LR (1.8° horizontal resolution).

Another example: tropical precipitation and ENSO biases

annual mean precipitation bias

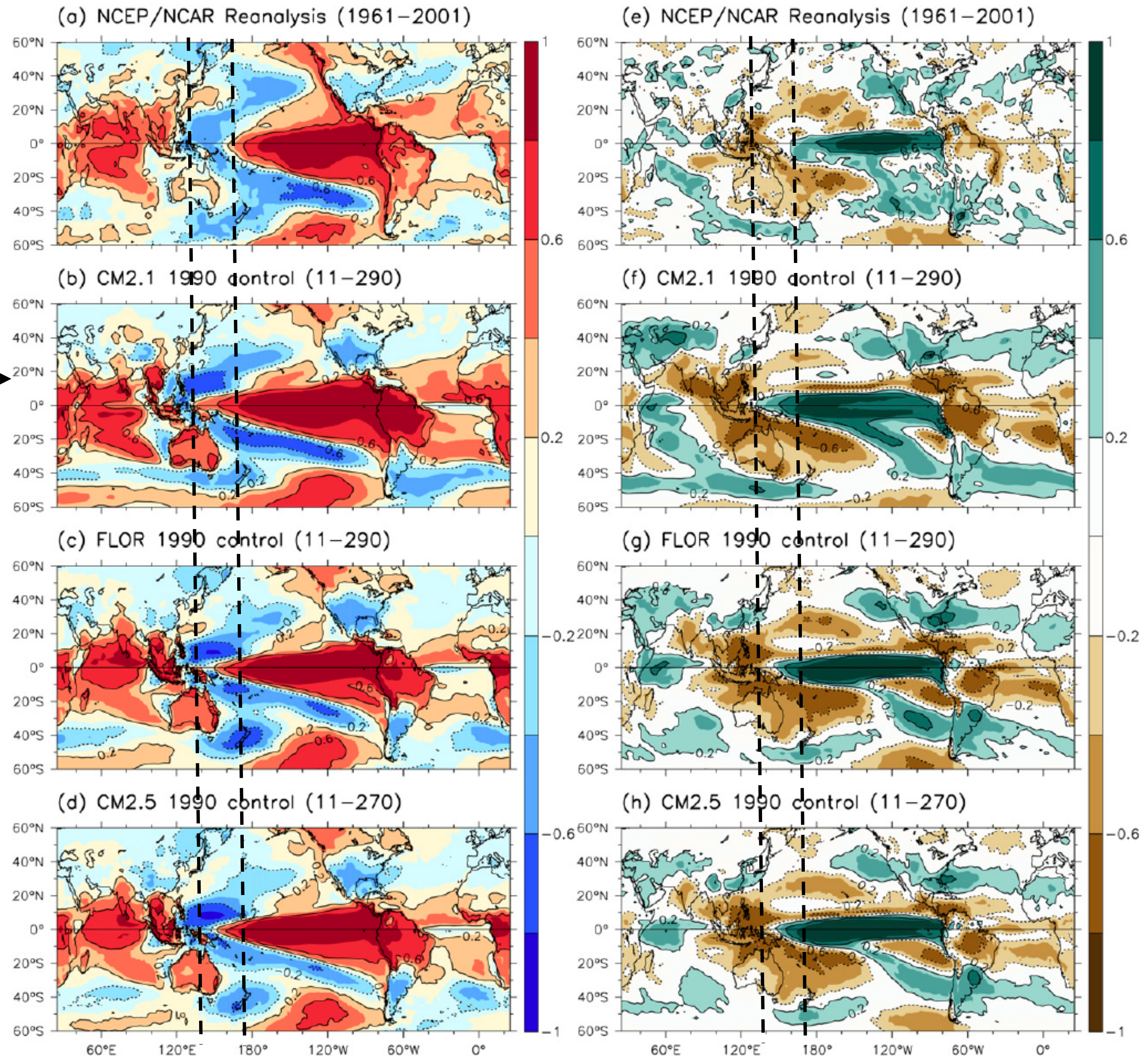


← 200 km atm → 1° ocn

← 50 km atm → 1° ocn

50 km atm → 1/4° ocn

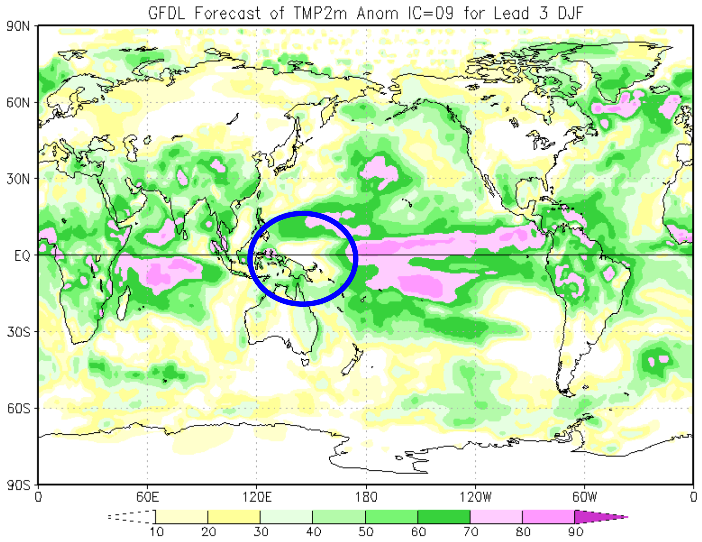
Correlation of temperature and precipitation anomalies w/ Niño3



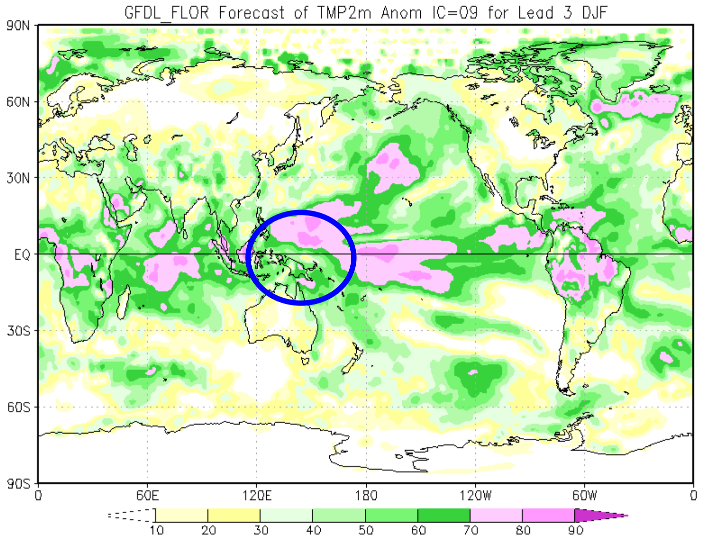
Jia et al., *J. Clim.* (2015)

Evidence that model biases impact forecast skill

temperature correlation skill

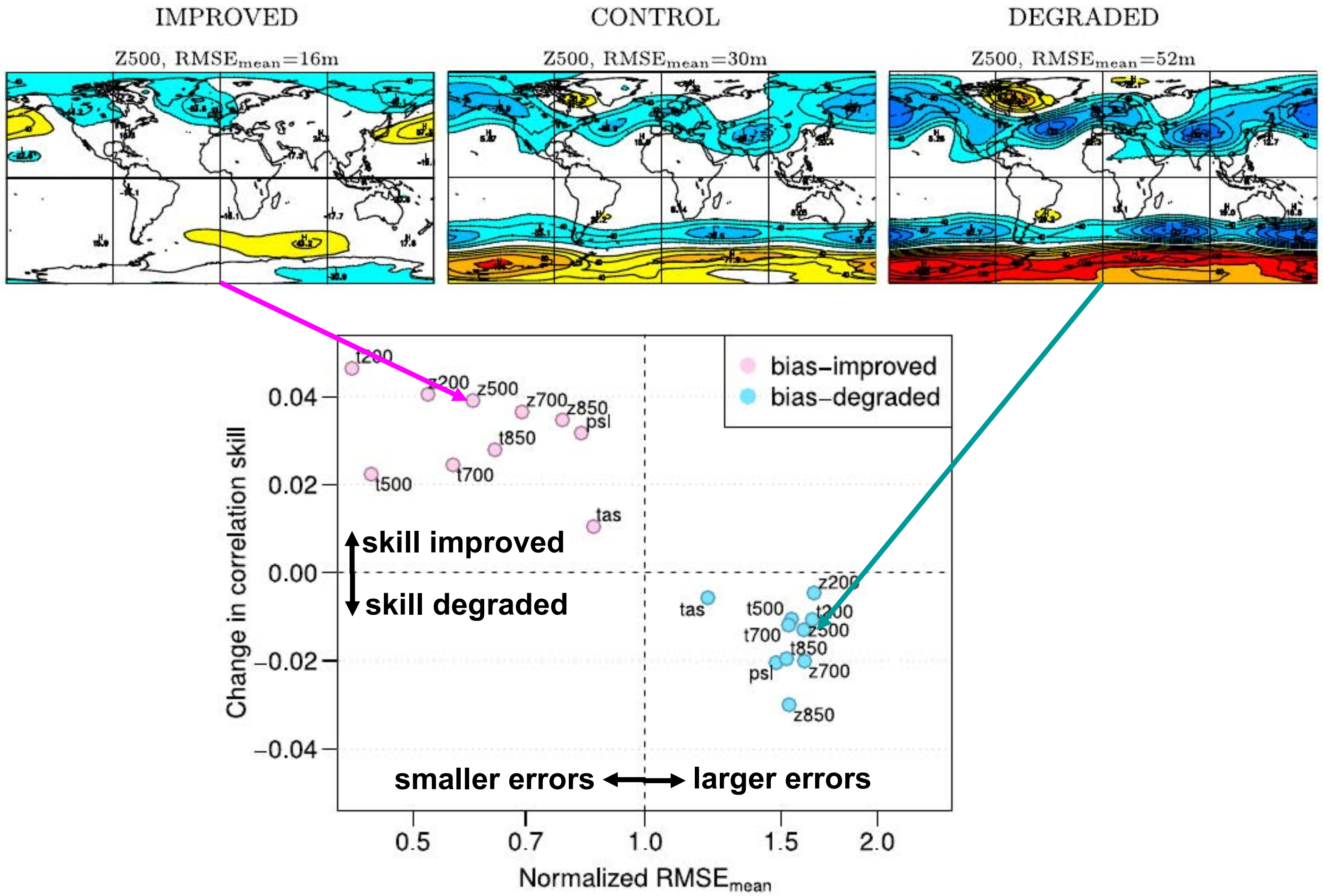


← **GFDL CM2.1**
200 km atm
1° ocn



← **GFDL FLOR**
50 km atm
1° ocn

Apply model tendency adjustments estimated from nudging to obs



https://www.cpc.ncep.noaa.gov/products/NMME/

Kharin and Scinocca, *GRL* (2012)

Non Linear and Non Stationary Forecast Errors:

Time to revise the forecast strategy?

Magdalena A. Balmaseda
Frederic Vitart

ECMWF, Shinfield Park, RG2 9AX, Reading, UK

- It is possible to produce **more skilful predictions at extended and seasonal range by correcting model bias** during forecast phase
- It is possible **to design a consistent framework for treatment of model bias**:
  - estimation of model bias during data assimilation phase using observational constrain.
  - bias estimate applied during forecast phase. Complementary to stochastic physics
  - This should produce improved forecast, easier to calibrate .
- The nudging residuals provide a starting point for experimentation

[Also: **assimilation increments** are potentially a powerful tool for diagnosing origins of model error]

ECMWF

An approach for assessing development of model errors

- In long-term historical simulations and projections, initial conditions are mostly “forgotten” → difficult to diagnose origins of model errors
- S2S/S2D predictions are (mostly) initialized from model states close to observations → development of model errors can be tracked
- A WCRP Working Group on Subseasonal to Inderdecadal Prediction (WGSIP) project aims to facilitate systematic intercomparisons of such behavior

  Project web page: https://www.wcrp-climate.org/wgsip-projects/lrftip

  S2D Conference poster: https://www.wcrp-climate.org/images/WCRP_conferences/S2S_S2D_2018/pdf/Programme/posters/presentations/posters_C1/P-C1-07-Merryfield.pdf

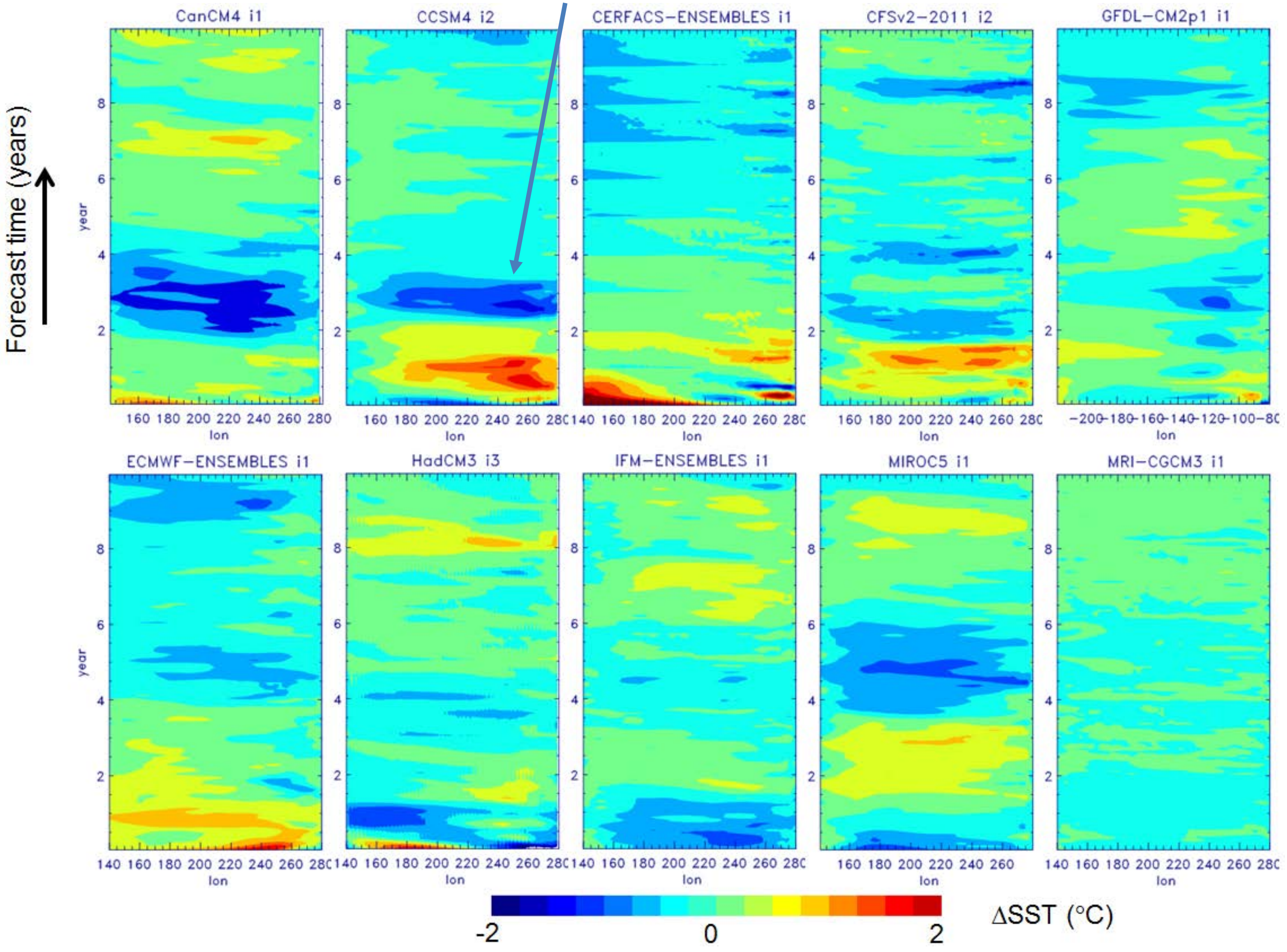
- Objectives are to

  - Provide a **resource for systematic studies** of the development of model errors

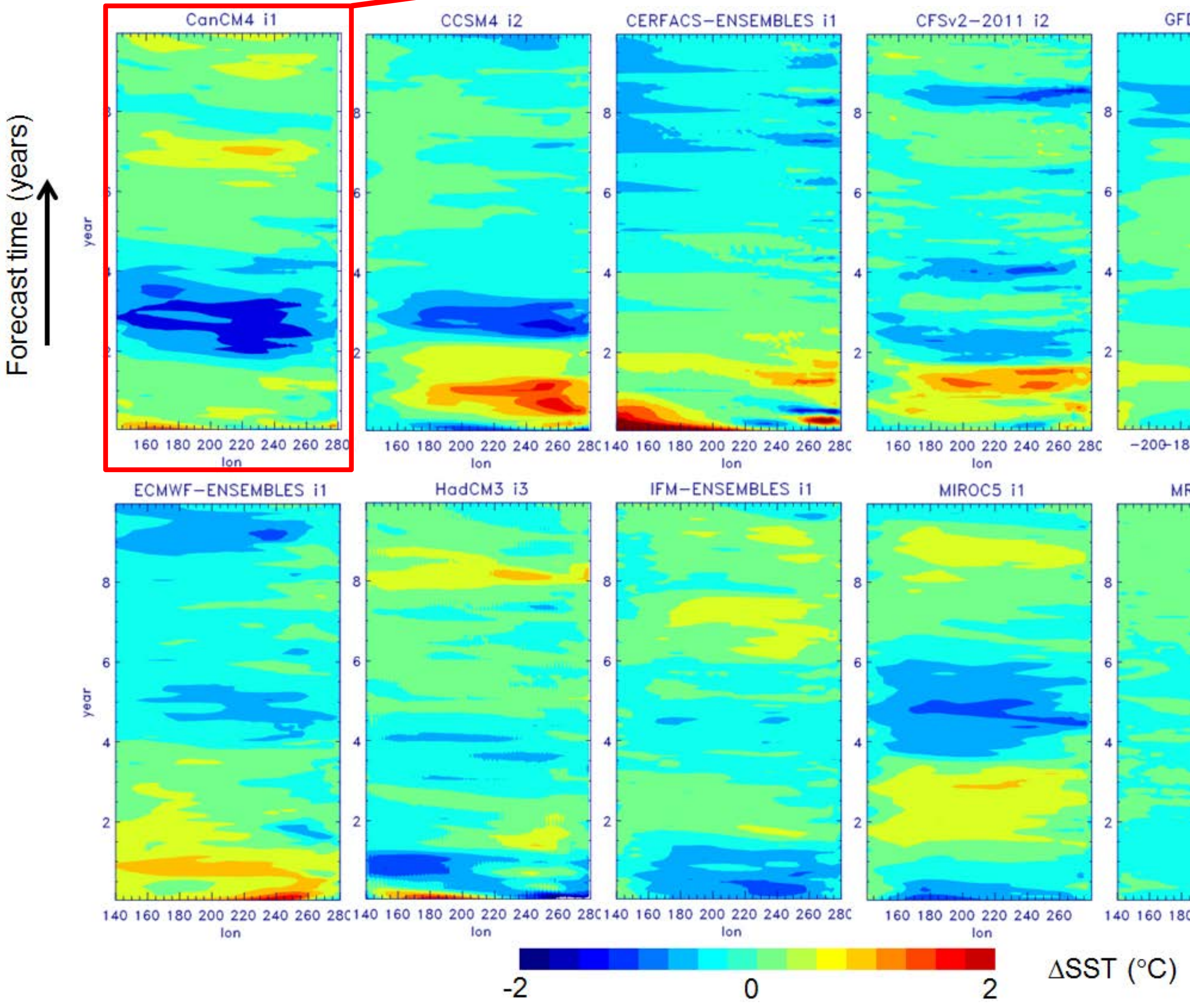
  - Develop a **set of standard diagnostics** for describing error development (“shock” & “drift”)

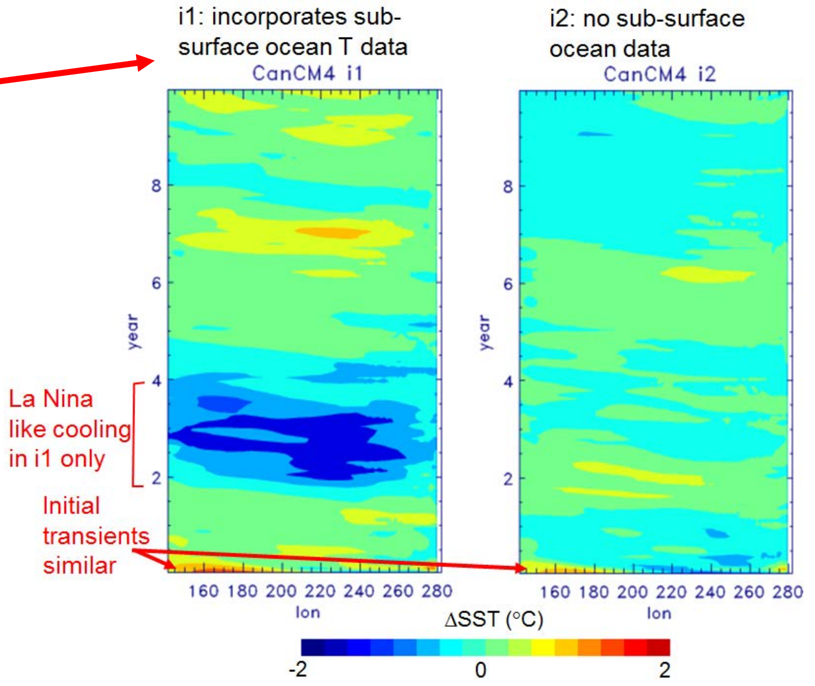
Development of equatorial Pacific SST biases in decadal predictions

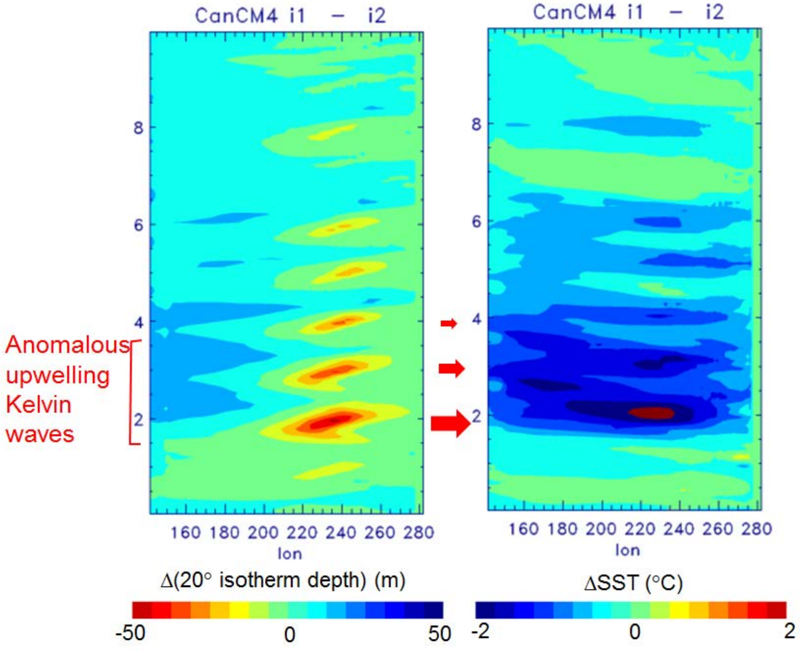
due to spurious changes in NCEP/NCAR reanalysis wind stress (Teng et al. *Clivar Exchanges* 2017)



Development of equatorial Pacific SST biases in decadal predictions







5th WGNE workshop on systematic errors in weather and climate models

June 19-23, 2017, Montréal, Québec, Canada

SYSTEMATIC ERRORS IN WEATHER AND CLIMATE MODELS

Nature, Origins, and Ways Forward

***BAMS* 2018**

Ayrton Zadra, Keith Williams, Ariane Frassoni, Michel Rixen, Ángel F. Adames, Judith Berner, François Bouyssel, Barbara Casati, Hannah Christensen, Michael B. Ek, Greg Flato, Yi Huang, Falko Judt, Hai Lin, Eric Maloney, William Merryfield, Annelize Van Niekerk, Thomas Rackow, Kazuo Saito, Nils Wedi, and Priyanka Yadav

Errors addressed in presentations:

- convective precipitation—diurnal cycle (timing and intensity); the organization of convective systems; precipitation intensity and distribution; and the relationship with column-integrated water vapor, SST, and vertical velocity;
- cloud microphysics—errors linked to mixed-phase, supercooled liquid cloud, and warm rain;
- precipitation over orography—spatial distribution and intensity errors;
- MJO modeling—propagation, response to mean errors, and teleconnections;
- subtropical boundary layer clouds—still underrepresented and tending to be too bright in models; their variation with large-scale parameters remains uncertain; and their representation may have a coupled component/feedback;
- double intertropical convergence zone/biased ENSO—a complex combination of westward ENSO overextension, cloud–ocean interaction, and representation of tropical instability waves (TIW);
- tropical cyclones—high-resolution forecasts tend to produce cyclones that are too intense, although moderate improvements are seen from ocean coupling; wind–pressure relationship errors are systematic;
- surface drag—biases, variability, and predictability of large-scale dynamics are shown to be sensitive to surface drag; CMIP5 mean circulation errors are consistent with insufficient drag in models;
- systematic errors in the representation of heterogeneity of soil;
- stochastic physics—current schemes, while beneficial, do not necessarily/sufficiently capture all aspects of model uncertainty;
- outstanding errors in the modeling of surface fluxes; errors in the representation of the diurnal cycle of surface temperature;
- errors in variability and trends in historical external forcings;
- challenges in the prediction of midlatitude synoptic regimes and blocking;
- model errors in the representation of teleconnections through inadequate stratosphere–troposphere coupling; and
- model biases in mean state, diabatic heating, SST; errors in meridional wind response and tropospheric jet stream impact simulations of teleconnections.

→ Need
- Improved treatments of cloud microphysics and boundary layer processes to reduce uncertainties in low-cloud radiative feedbacks
- Process studies leading to reduced tropical convection and rainfall biases in convection-permitting models
- Improved treatments of coupled processes → model physics at root of long-term predictability, development of coupled data assimilation

Conclusions

- Model biases have gradually improved over time, but remain problematic
- Same issues have persisted over time: tropical SST/precipitation biases, ENSO westward extension, insufficient low clouds over eastern subtropical oceans, precipitation diurnal cycle…
- Some biases evidently due to insufficient resolution for capturing topographic influences on atmosphere and ocean
- Others surely sue to inadequate parameterizations
- Systematic intercomparisons of bias development in coupled prediction models may provide clues (likewise for data assimilation increments)

Also,

- Simulation and S2S prediction of MJO remains problematic in many models
- A pervasive issue in S2D prediction is a "signal to noise paradox" (Scaife and Smith, npj Atmospheric Sci. 2018) $\rightarrow$ *some predictable signal in models are weaker than in real world*