ENSO modelling

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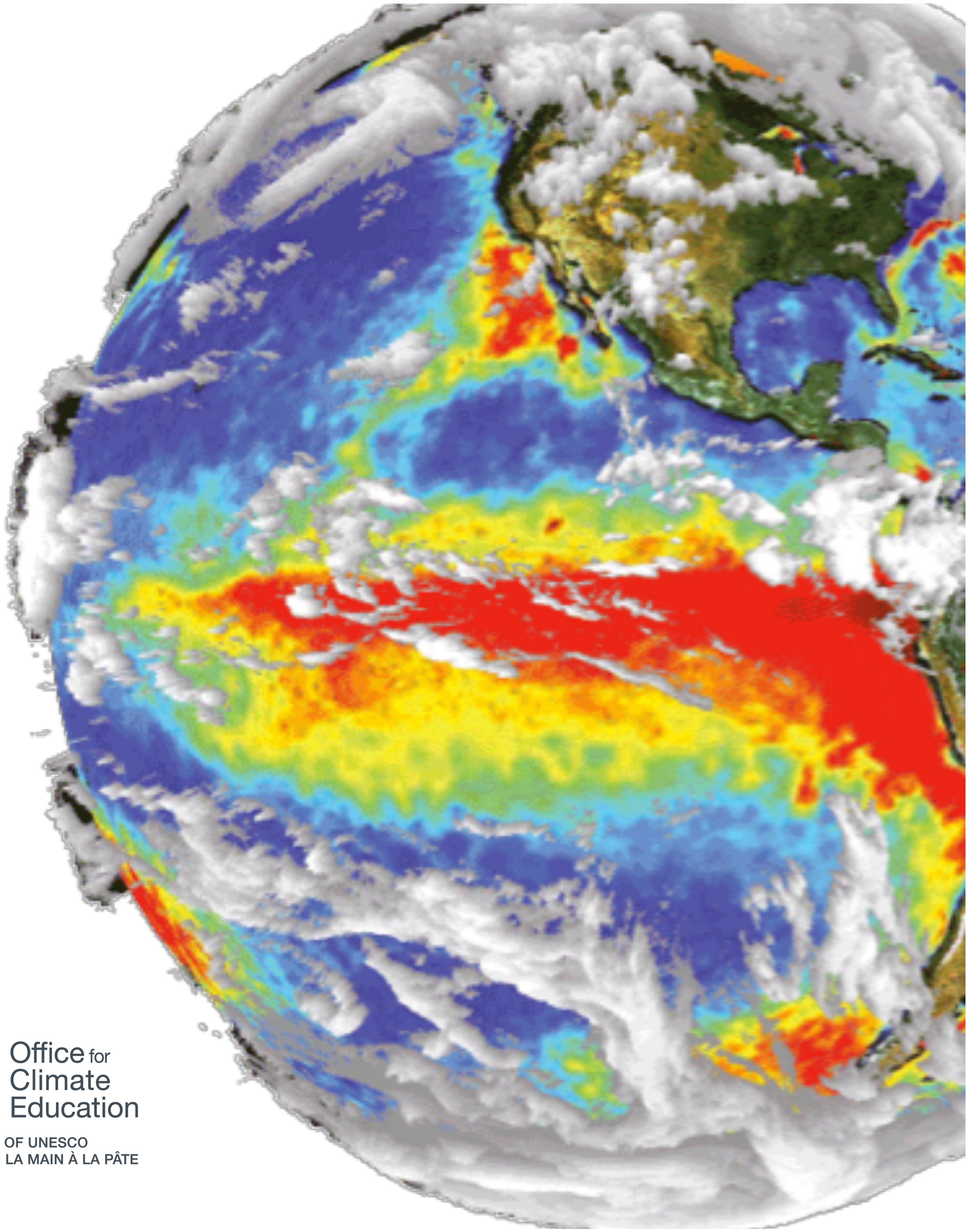
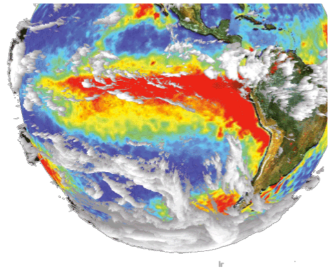


UNDER THE AUSPICES OF UNESCO
AND THE FOUNDATION LA MAIN À LA PÂTE

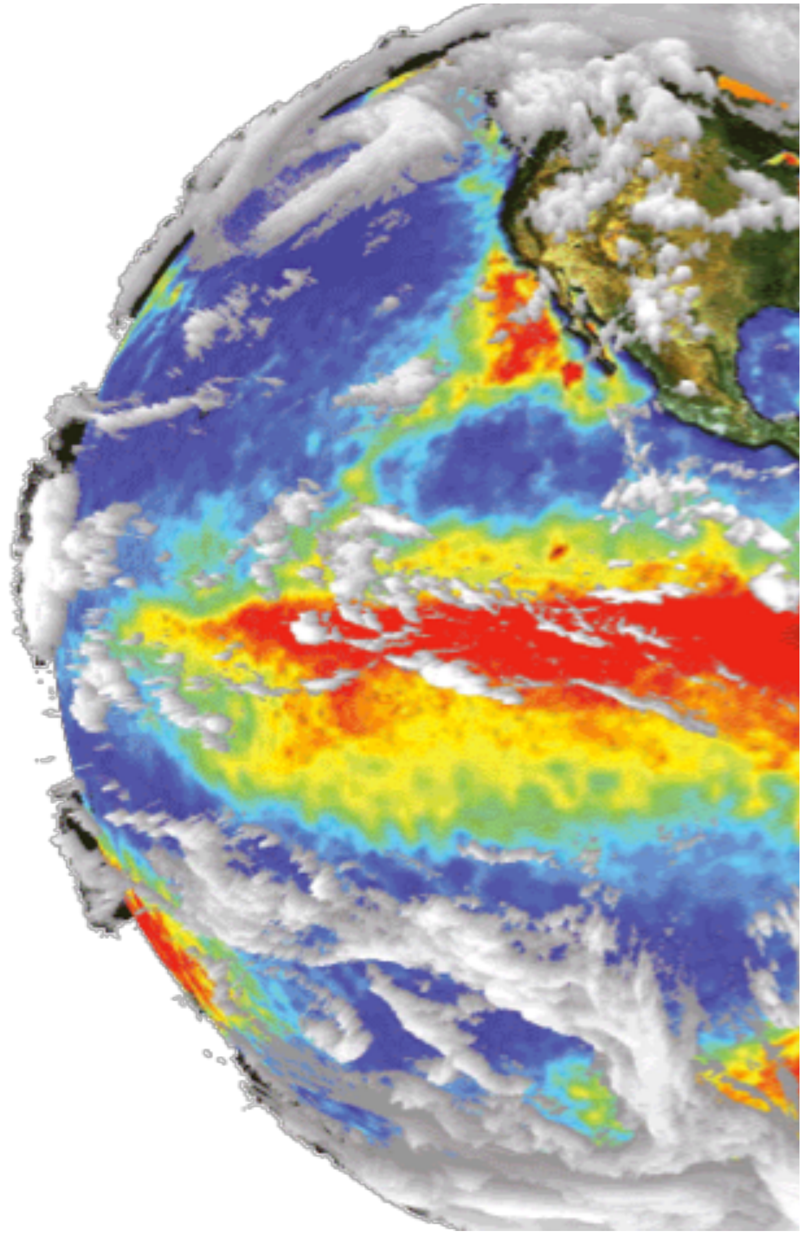


Outline

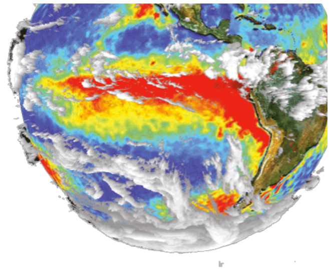
- Introduction
- Models for ENSO understanding
- Evaluation of ENSO in GCMs
- ENSO metrics
- Understanding sources of ENSO biases
- Challenges and opportunities

Introduction

- A bit of history : the TOGA decade
- Benefits of a hierachy of models
- GCMs



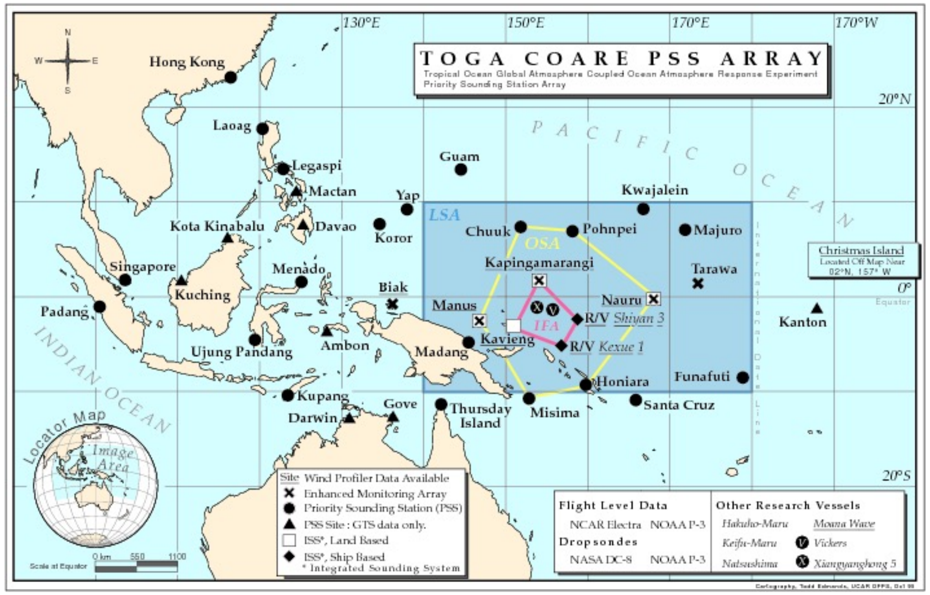
1990s : the TOGA revolution

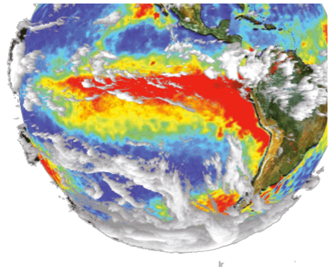


- A milestone for early GCMs development
- Improved resolution and physical parameterisations
- ENSO feedbacks

The TOGA Decade: Reviewing the Progress of El Niño Research and Prediction
Journal of Geophysical Research, 1998

David Anderson, Ed.

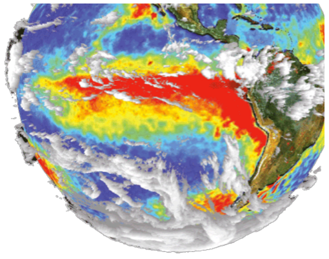


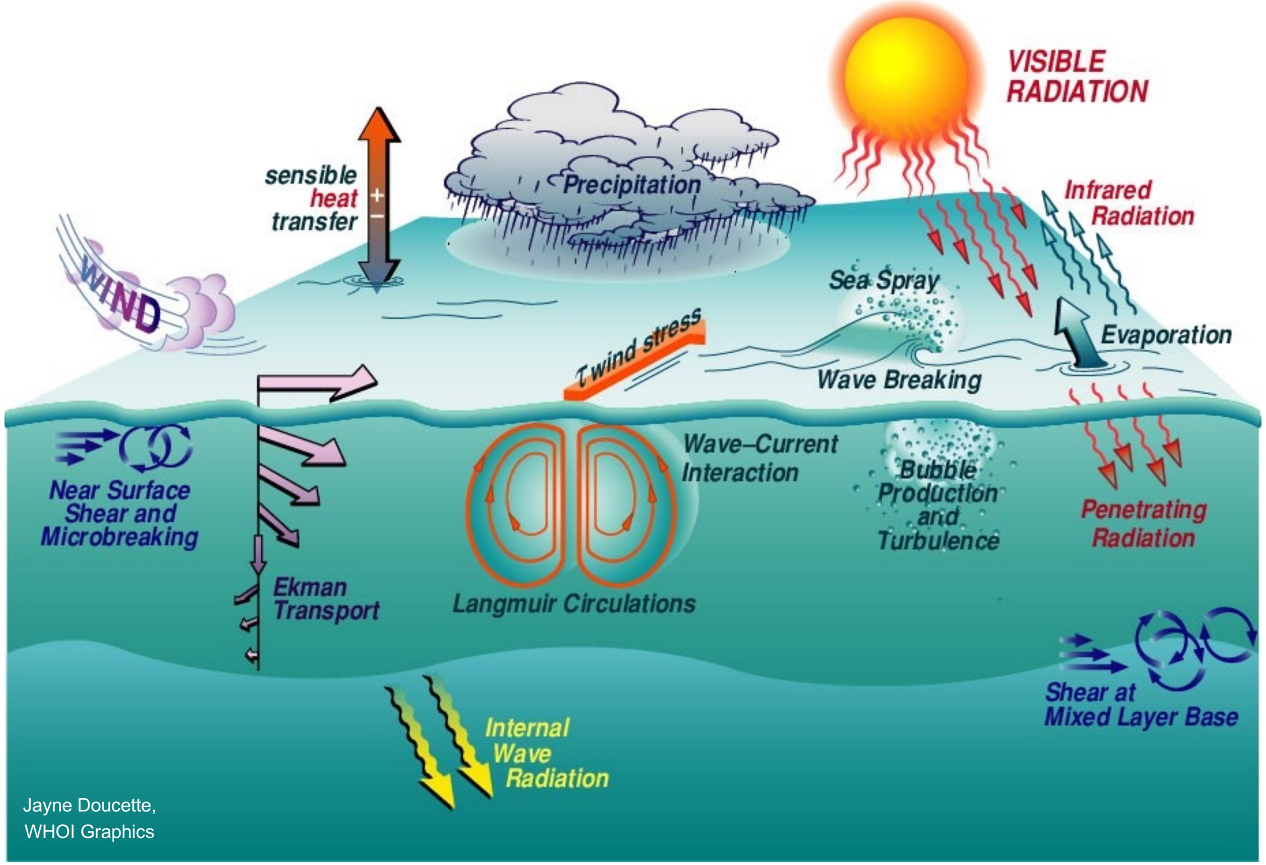


2000s: the CMIP era

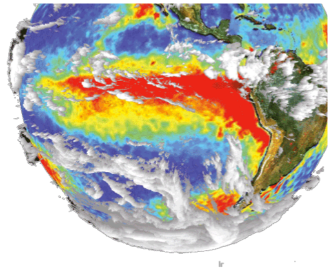
- CMIP3: first ENSO intercomparison
  - AchutaRao & Sperber, 2006; van Oldenborgh et al., 2005; Guilyardi 2006; Capotondi et al., 2006; Wittenberg et al., 2006
- More gradual improvement CMIP3 -> CMIP5 -> CMIP6
  - Bellenger et al., 2014; C. Chen et al., 2017; Stevenson et al. 2020
- Essential processes: deep convection and clouds, equatorial wave dynamics, upwelling, vertical mixing
- Role of resolution and physical parameterisations
- Role of intra-seasonal variability (MJO, WWE…)
- More complete view of ENSO feedbacks

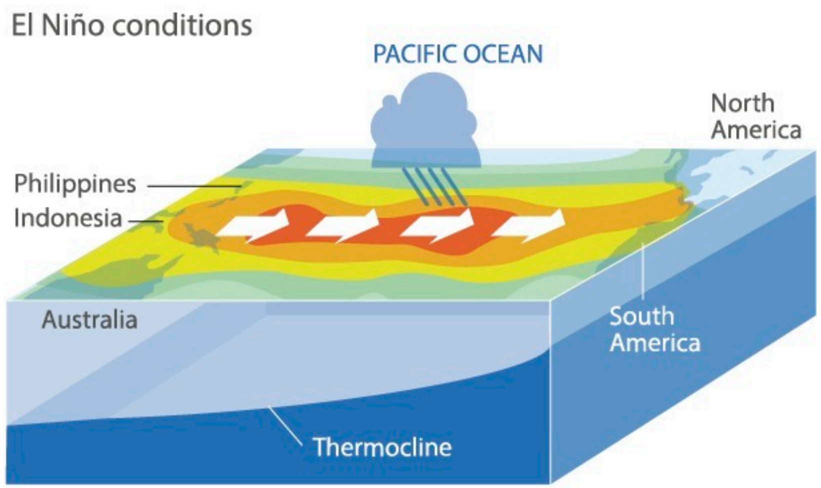
Parameterized air-sea interaction processes





ENSO feedbacks





Atmosphere response to SSTA

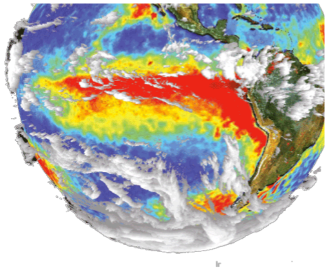
- Bjerknes wind stress feedback (μ)
- Heat flux response (α)

Ocean response to τ and HF anomalies

- Upwelling ("thermocline feedback")
- Zonal advection & Ekman feedbacks
- Wave dynamics
- Energy Dissipation

Non linear processes ("noise"):

- NL ocean dynamical
- Impact of WWE
- TIW stirring



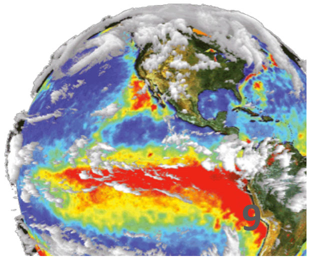
A hierarchy of models

- Simple models (harmonic oscillators, LIM,…)
- Intermediate complexity models (ICM)
- GCMs
- Differents goals and purpose:
  - Simple: theory and concepts, teaching tools, insights in sources of predictability
  - ICM: Easy to understand, versatile, limited in focus, difficult to relate to obs
  - GCM: Full complexity, expensive to develop and maintain, difficult to diagnose and understand, closer to observations
- Simpler models can be used to diagnose and understand more complex ones
- E.g. hybrid models, BWJ index

Bridging the gap between theory and GCMs

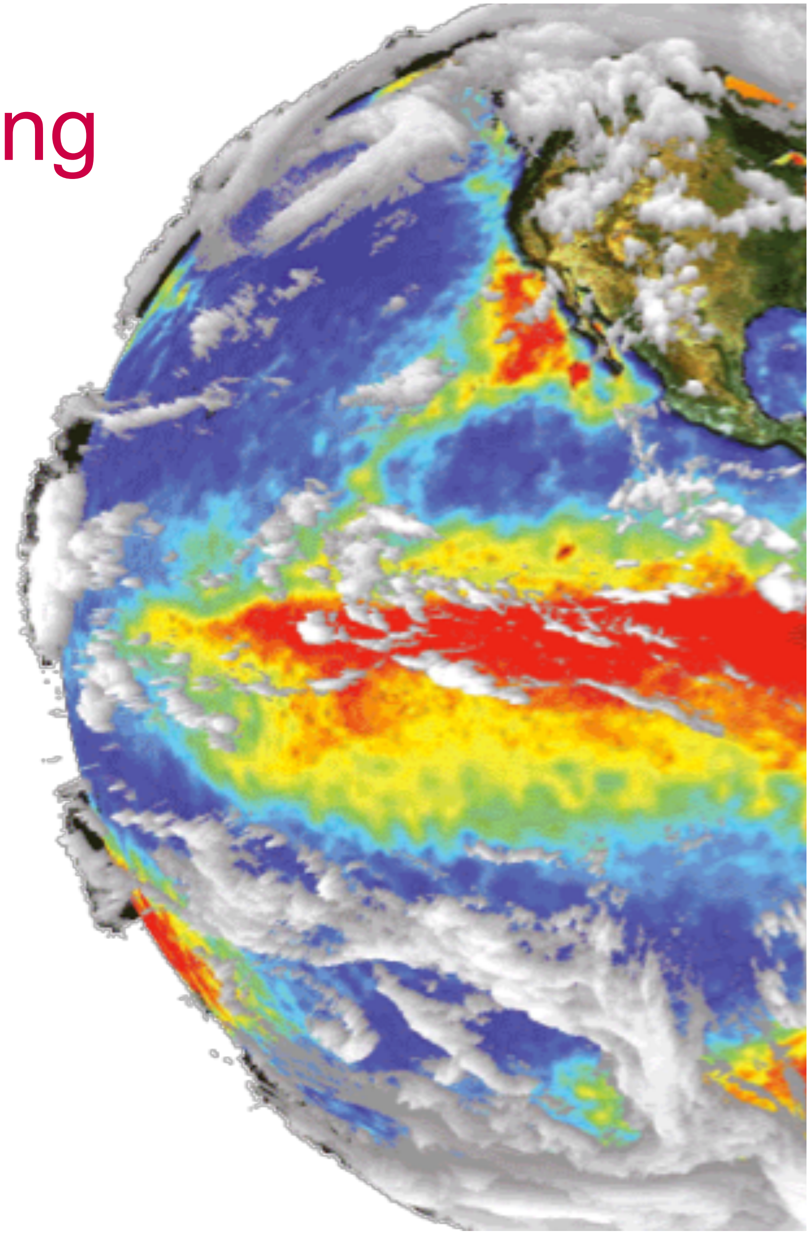
- Ensembles of opportunity provide a unique testbed for theory
- Disagreement -> model improvement but also theoretical improvement
- Many examples

The role of the atmosphere in ENSO

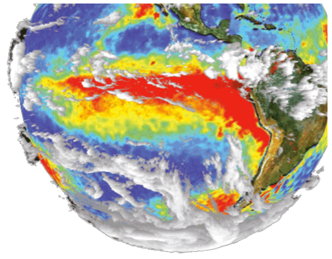


Models for ENSO understanding

Exploring the role of the atmosphere in ENSO:
Feedbacks, non-linearity and ENSO extremes

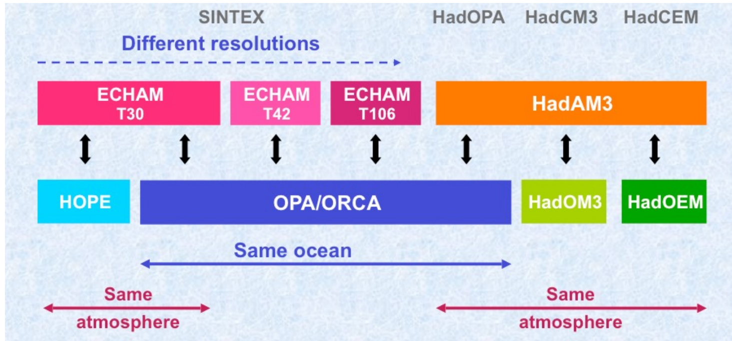


Atmosphere feedbacks during ENSO



Multi-model and sensitivity studies show that AGCM has a dominant role

(e.g. Schneider 2002, Guilyardi et al. 2004, Kim et al. 2008, Neale et al. 2008, Sun et al. 2008,...)



Two types of feedbacks:

Dynamical: Bjerknes feedback m

East-west SST gradient

Trade winds

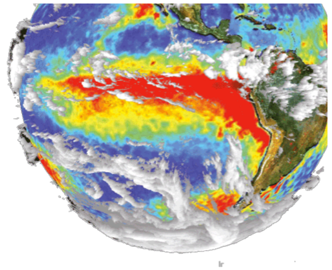
Equatorial upwelling in the east

Heat flux feedback a

SST increase in the east

Modified heat fluxes (SHF, LHF)

Guilyardi et al. (2004)



Role of atmosphere during ENSO

From a linear atmosphere to the driver of variability

1 - <u>Classical theory</u>:

Dynamical positive Bjerknes feedback: m

Negative heat flux feedback: a (SHF, LHF)

e.g.: the Bjerknes coupled-stability index for ENSO I_{BWJ}

Mean advection and upwelling (damping)

α : atmosphere heat flux feedback (local linear)

Zonal advection feedback

Ekman pumping feedback

Thermocline feedback

μ_a: Bjerknes feedback or linear "coupling strength"

$$\frac{\partial \langle T \rangle}{\partial t} = 2I_{BJ}\langle T \rangle + F[h],$$

$$2I_{BJ} = -\left(\frac{\langle \bar{u} \rangle}{L_x} + \frac{\langle -2y\bar{v} \rangle}{L_y^2} + \frac{\langle H(\bar{w})\bar{w} \rangle}{H_m}\right) - \alpha$$

$$+ \mu_a \beta_u \left\langle -\frac{\partial \bar{T}}{\partial x} \right\rangle + \mu_a \beta_w \left\langle \frac{\partial \bar{T}}{\partial z} H(\bar{w}) \right\rangle$$

$$+ \mu_a^* \beta_h \left\langle \frac{H(\bar{w})\bar{w}}{H_m} a \right\rangle,$$

$$\beta_u = \beta_{um} + \beta_{us}, \quad F = -\left\langle \frac{\partial \bar{T}}{\partial x} \right\rangle \beta_{uh} + \left\langle \frac{H(\bar{w})\bar{w}}{H_m} a \right\rangle.$$

Jin et al. (2006), Kim et al. (2010)

Linear stability analysis of recharged oscillator SST equation

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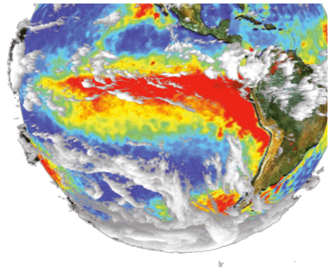
Role of atmosphere during ENSO



From a linear atmosphere to the driver of variability

2 - Dominant role of AGCM in coupled AOGCMs

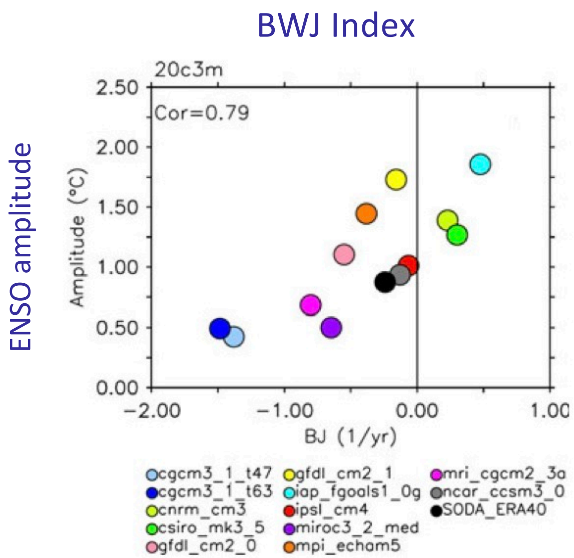
OGCM only modifies the amplitude

(Schneider 2002, Guilyardi et al. 2004, 2009, Kim et al. 2008, Neale et al. 2008, Sun et al. 2008, 2010)

e.g.: apply BWJ Index to the CMIP3 GCMs:

- BWJ Index correlated with ENSO amplitude !
- a major contributor to ENSO amplitude errors

Kim and Jin (2010), Guilyardi et al. (2009b)

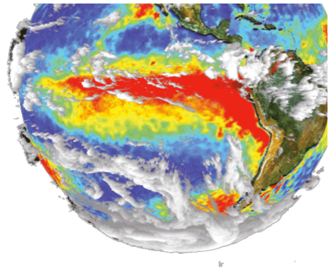


3 - The Southern Oscillation is an atmosphere mode

- Slab ocean El Niño, thermally coupled Walker mode (TCW)
- Mechanisms: MM, WES, cloud shortwave feedbacks, extra-tropical forcing
- Ocean role: amplify signal and 2-7 years power spectra in east Pacific

(Kitoh al 1999, Vimont et al. 2003, Chang et al. 2007, Dommenget 2010, Alexander et al. 2010, Terray 2011, Clement al. 2011)

Impact of atmosphere convection scheme on ENSO

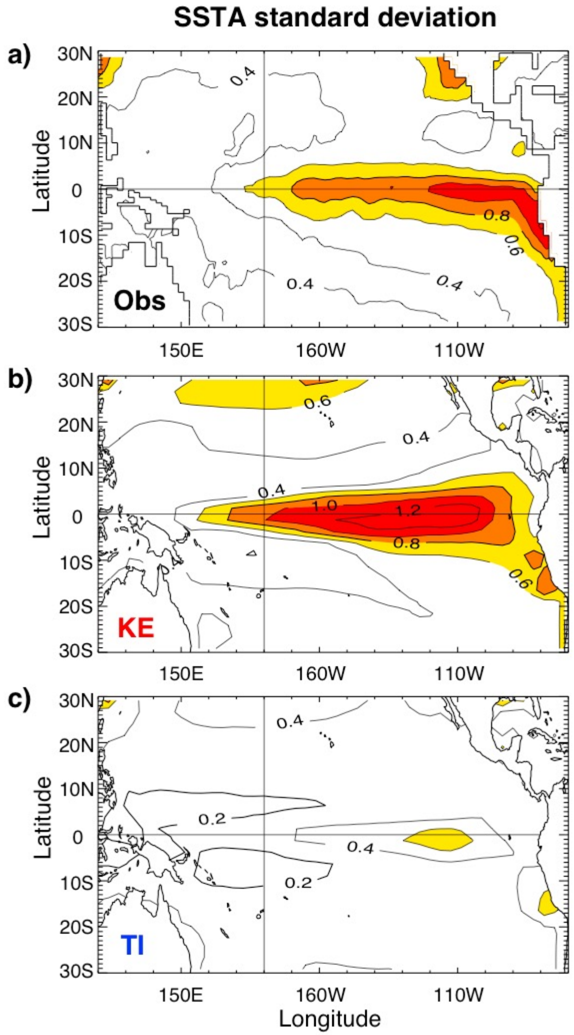


IPSL-CM4 model

Observations
(0.9 C) - HadiSST1.1

IPSL (KE)
Kerry Emanuel
(1.0 C) - in IPCC

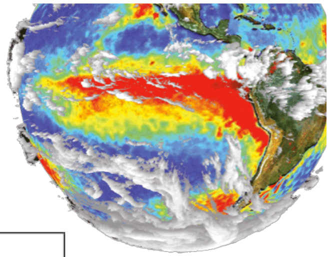
IPSL/Tiedke (TI)
(0.3 C) – old scheme



ENSO has
disappeared !
What role for α and μ ?

Guilyardi et al. (2009b)

BS index for KE and TI



$$\frac{\partial \langle T \rangle}{\partial t} = 2I_{BJ}\langle T \rangle + F[h],$$

$$2I_{BJ} = -\left(\frac{\langle \bar{u} \rangle}{L_x} + \frac{\langle -2y\bar{v} \rangle}{L_y^2} + \frac{\langle H(\bar{w})\bar{w} \rangle}{H_m}\right) - \alpha$$

$$+ \mu_a \beta_u \left\langle -\frac{\partial \bar{T}}{\partial x} \right\rangle + \mu_a \beta_w \left\langle \frac{\partial \bar{T}}{\partial z} H(\bar{w}) \right\rangle$$

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$$\beta_u = \beta_{um} + \beta_{us}, \quad F = -\left\langle \frac{\partial \bar{T}}{\partial x} \right\rangle \beta_{uh} + \left\langle \frac{H(\bar{w})\bar{w}}{H_m} a \right\rangle.$$

	Dynamic damping	Thermodynamic damping (α)	Ocean feedbacks	**BJ Index**
KE	-0.46	-0.45	1.02	**0.11**
TI	-0.61	-1.33	0.52	**-1.42**
Change (%)	-30%	-200%	-50%	

Table 1. The BJ Index and its components for KE and TI simulations. The ocean feedbacks sums the zonal advective feedback, the thermocline feedback and the Ekman feedback (see Jin et al. 2006 for details). Units are 1/Yr.

Guilyardi et al. (2009b)

→ Linear theory: α dominant factor in TI/KE difference

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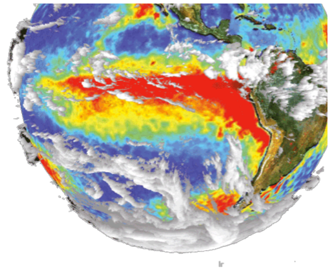
Impact of atmosphere convection scheme on ENSO – role of *α* and *μ*



	m	a	ENSO amplitude
Obs	~10/12	-18	0.9
KE	4	-5	1.0
TI	4	-20	0.3
	10^{-3} N.m^{-2}/C	W.m^{-2}/C	^{o}C

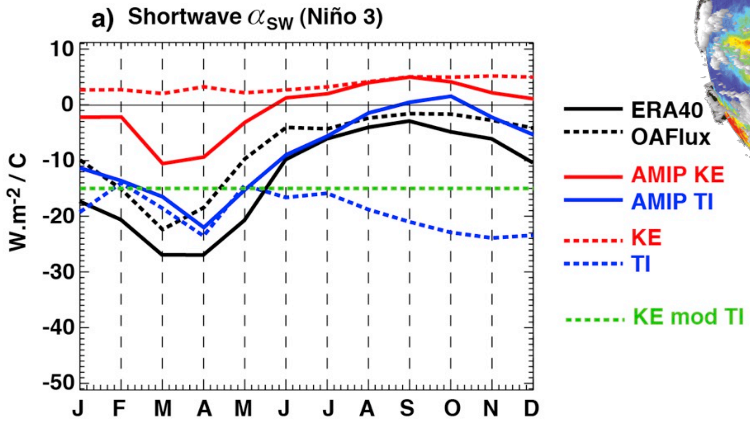
KE: error compensation !

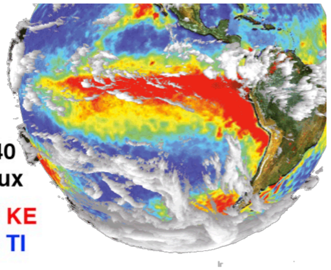
Due to shortwave feedback difference second half of the year (ENSO growth)

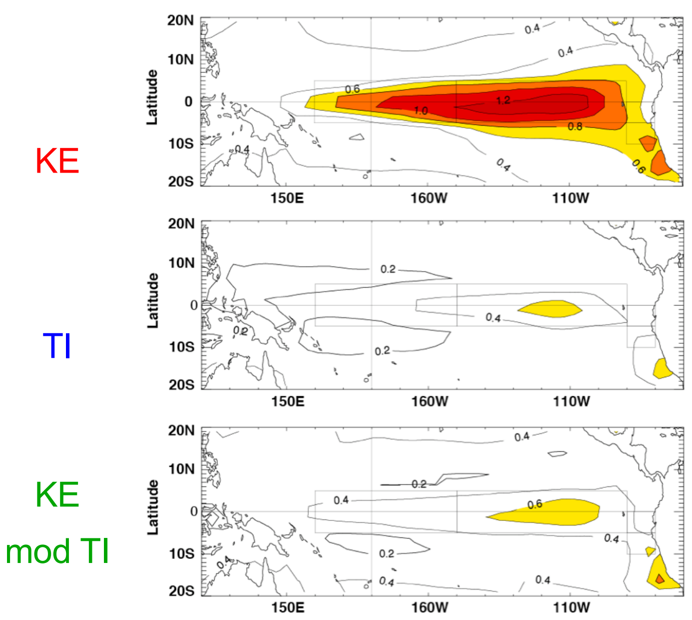
→ a_{sw} sensitive to atmosphere convection scheme in IPSL-CM4

Can we suppress ENSO in KE ?

- Perform KE run with increased a_{sw}
  - Interannual Flux Correction:
  - $SHF_O = SHF_{SC}^{KE} + a_{sw}^{mod}\,(SST_O - SST_{SC}^{KE})$
  - $a_{sw}^{mod} = -15\ W.m^{-2}$
  - Mean state (SC) unchanged







	m	a	El Niño Amplitude
Obs	~10	-18	0.9
KE	4	-5	1.0
TI	4	-20	0.3
KE mod TI	5	-21	0.4
	$10^{-3}\ N/m^2/C$	$W/m^2/C$	°C

ENSO gone as well !

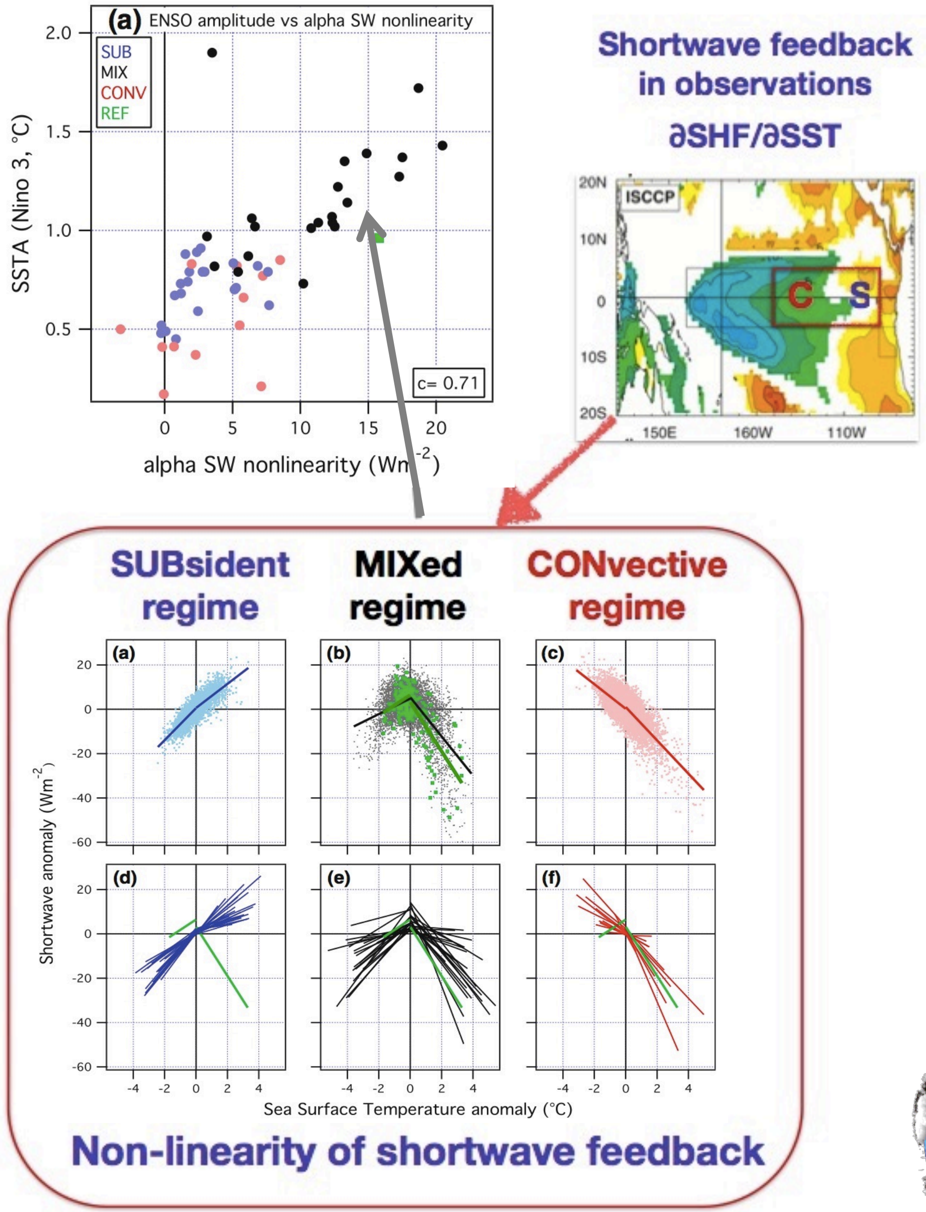
Extreme El Niño events related to atmosphere non-linearity

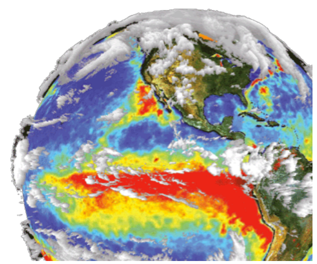
Two regimes in east Pacific

Only models with MIXed regime can simulate extreme El Niño events

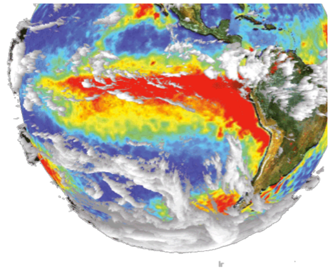
Only one third of models have a MIXed regime

This non-linearity is a key process-based metric



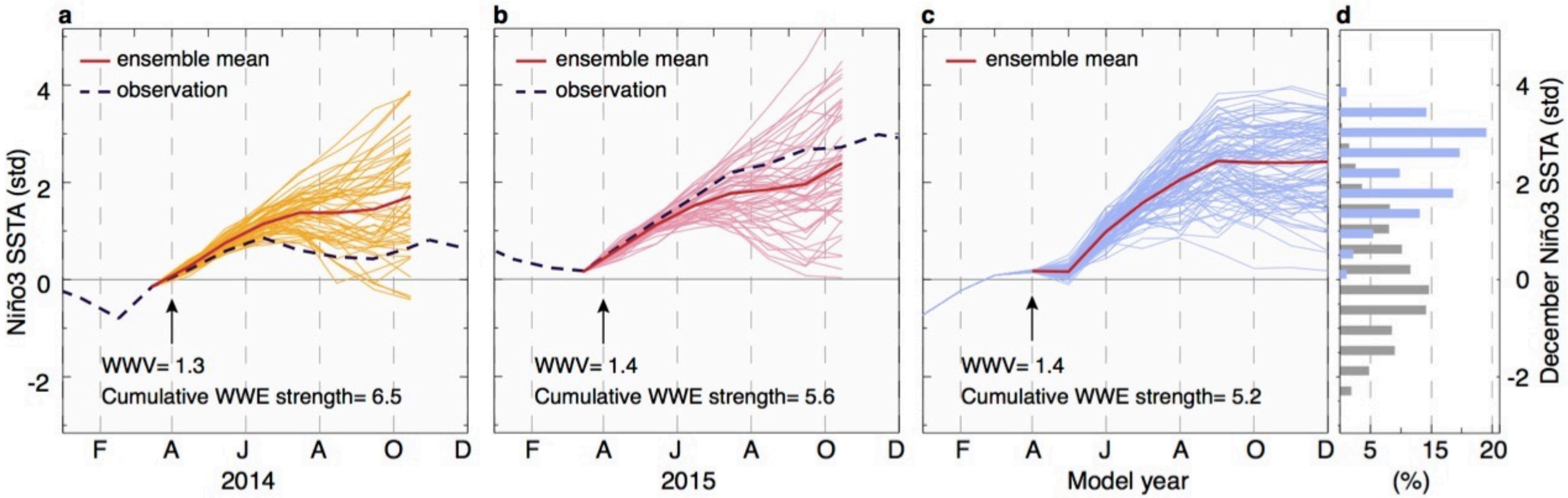


Extreme El Niño predictability as a function of WWE activity



Operational forecasts

Model study (CNRM-CM5)



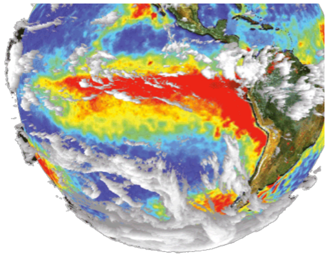
ECMWF April 2014 forecast

ECMWF April 2015 forecast

Model April forecast with same WWV and initial WWE

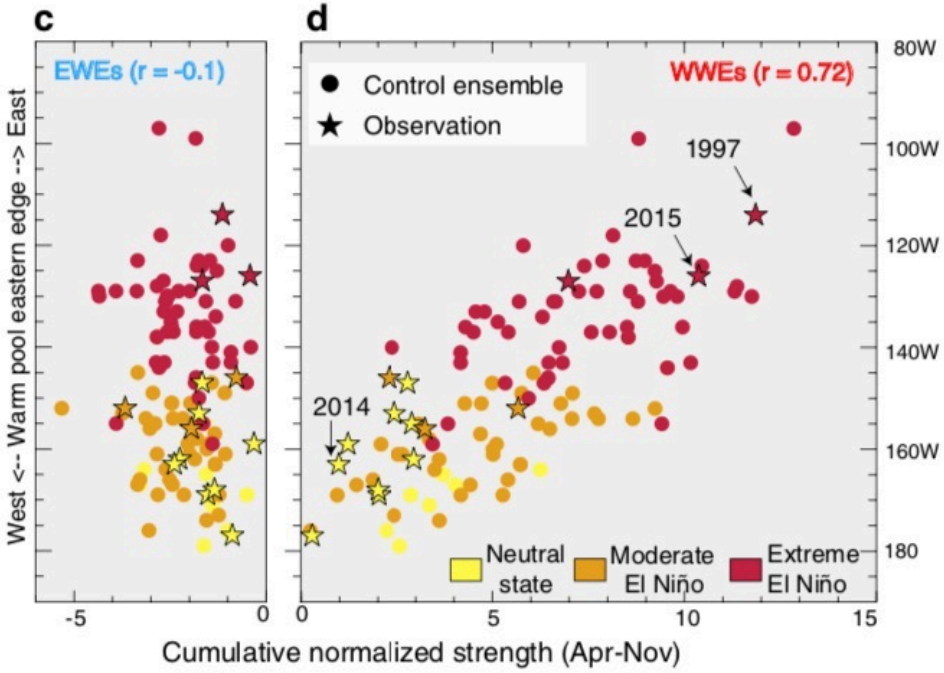
100 members

Influence of Westerly Wind Events stochasticity on El Niño amplitude: the case of 2014 vs. 2015 - *Puy et al. 2017*



Extreme El Niño predictability as a function of WWE activity

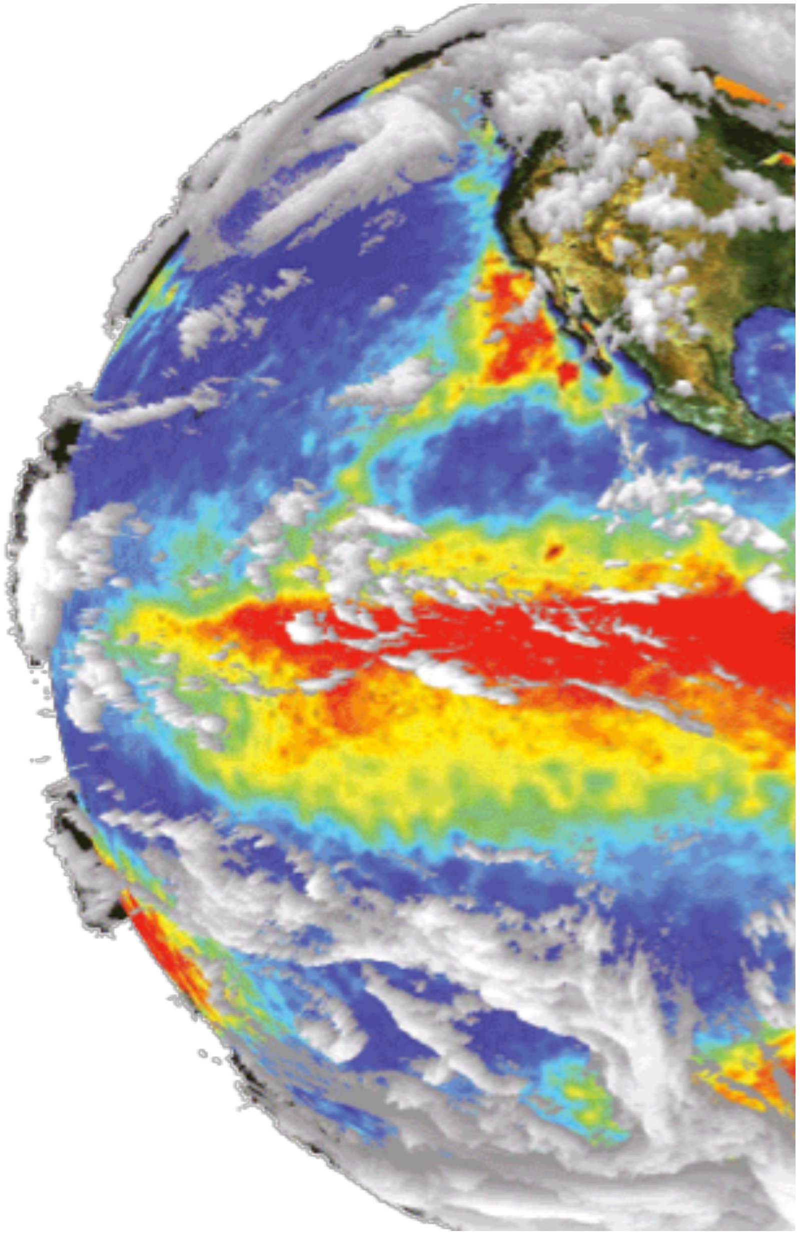
Cumulated WWE activity during growth phase directly influences ENSO amplitude via eastern displacement of WP edge



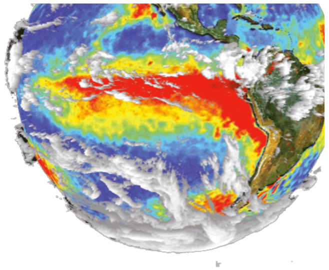
Influence of Westerly Wind Events stochasticity on El Niño amplitude: the case of 2014 vs. 2015 - *Puy et al. 2017*

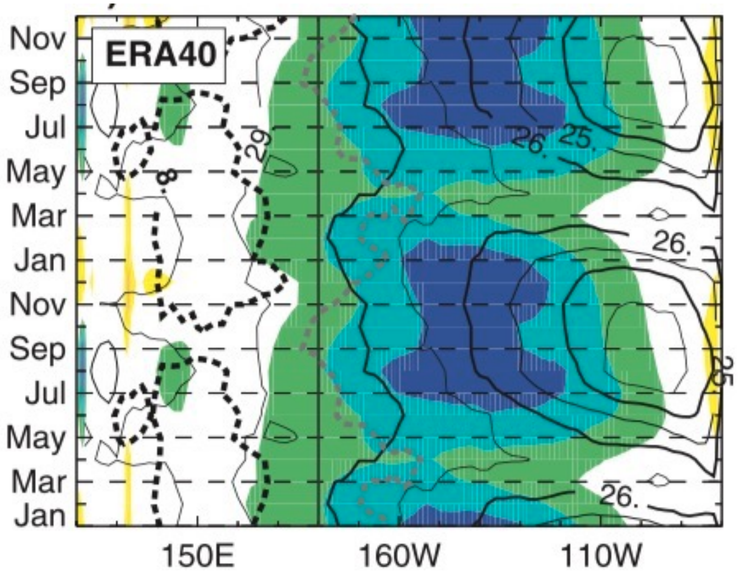
Evaluation of ENSO in GCMs

- ENSO influence is global: need to get it right
- Early need for ENSO evaluation
  - Tropical Pacific mean state
  - ENSO key biases and mechanisms
- From statistics to process-based metrics



ENSO as an anomaly to a mean state





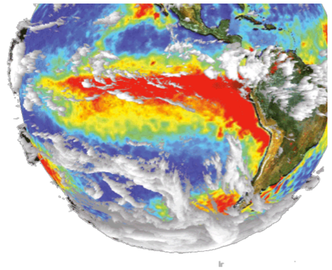
Hovmoeller of annual cycle along the equator (x2):

Wind stress (shading), SST (solid contours),
Precipitation (3 and 8 mm/day dashed)

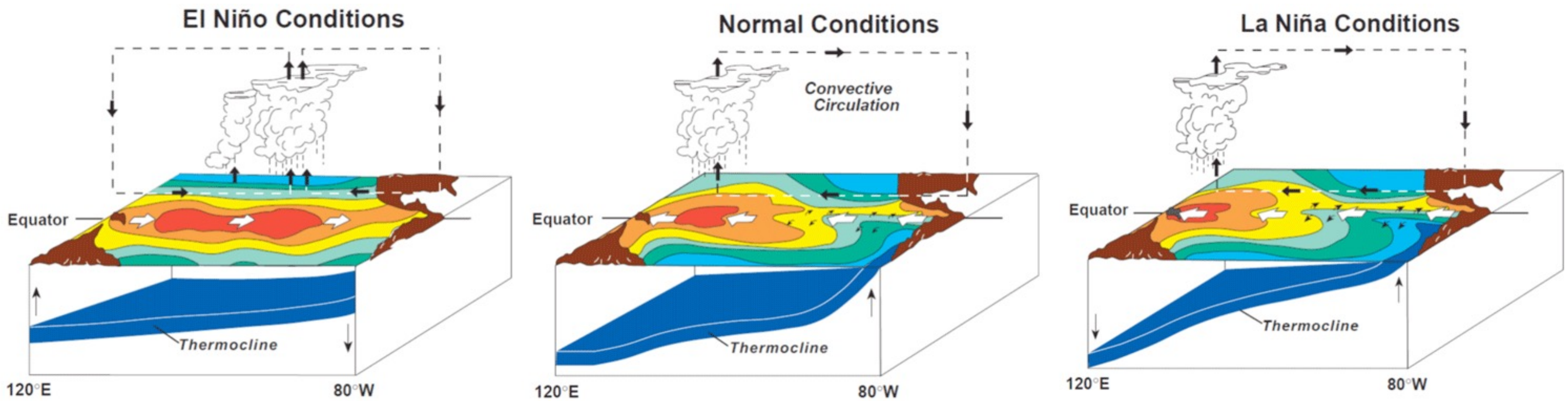
Annual cycle = background to ENSO

Northern Spring is “**El Niño** – like”

Northern Fall is “**La Niña** – like”



ENSO and the mean state



Complete disruption of Annual Cycle

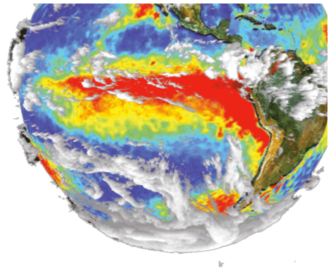
Amplification of Annual Cycle

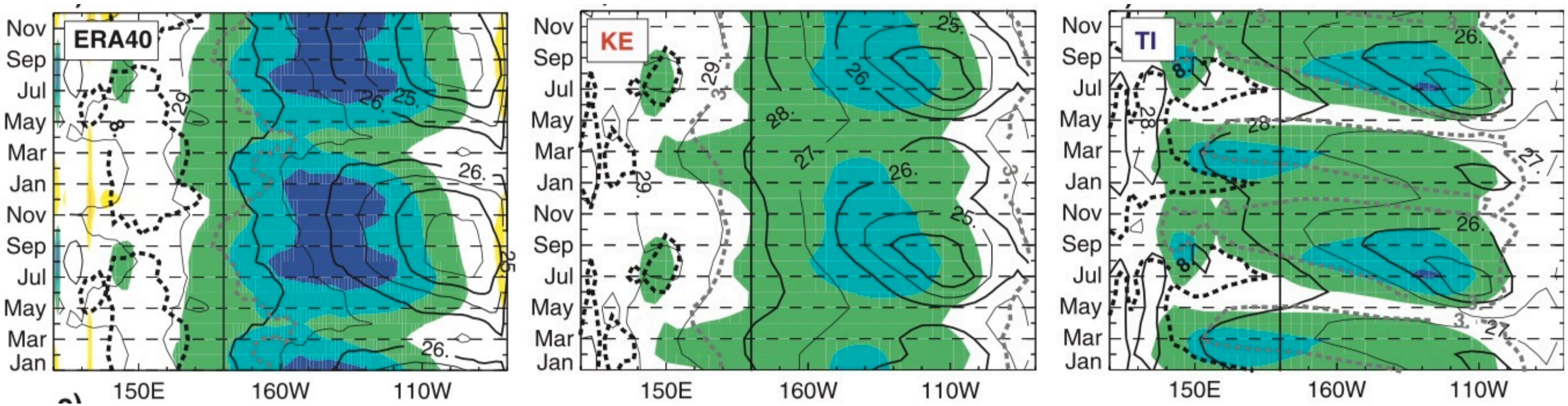
discharge

recharge

→ Evaluation of mean state and annual cycle is a first step

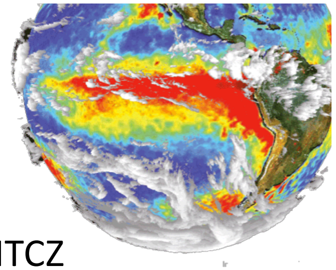
Models struggle to simulate mean state and annual cycle



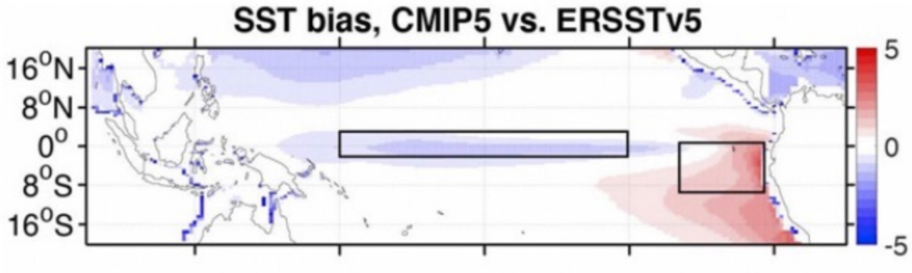


- Convection in AMIP TI too strong -> semi-annual cycle

Key biases – Tropical Pacific mean state

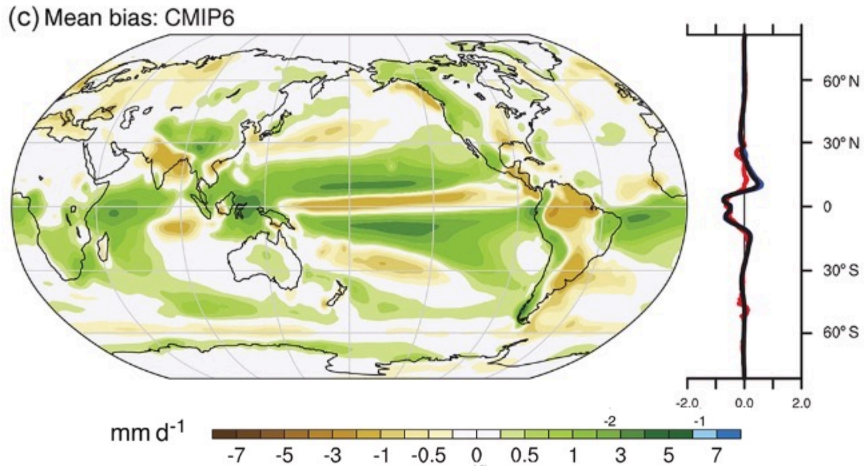


- Too strong Equatorial Cold Tongue (ECT) that extends too far west
- Warm SST bias near the coast of South America



Stevenson et al. 2020

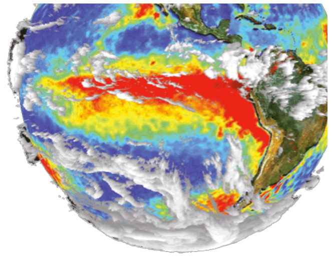
- Excessive “double” ITCZ
- SPCZ too zonal



Fasullo 2020

- Biases in the cloud regimes over the eastern and central Pacific
- Equatorial τ_x that is too strong or too weak
- Overly cyclonic wind stress off-equator (favour ECT)
- Equatorial Pacific dry bias
- Overly intense hydrologic cycle over the tropical Pacific
- Biases in the equatorial thermocline depth, intensity, sharpness, and zonal slope

Guilyardi et al. 2020

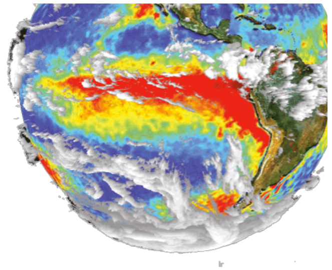


Key biases in ENSO

- Amplitude errors, which can also affect the skewness, diversity, and interdecadal modulation
- Errors in spectrum - too sharply peaked, and ENSO period too regular and biennial
- Too little synchronization of ENSO to the annual cycle, or a synchronization of ENSO to the wrong season
- Errors in the level of interdecadal modulation
- SSTA patterns and atmosphere response displaced too far west
- Too little skewness of ECT SSTAs toward warm events

Guilyardi et al. 2020

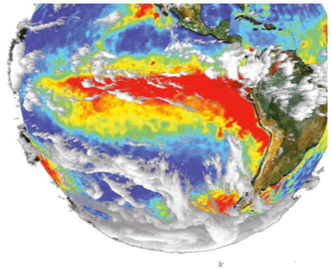
Key biases in ENSO mechanisms



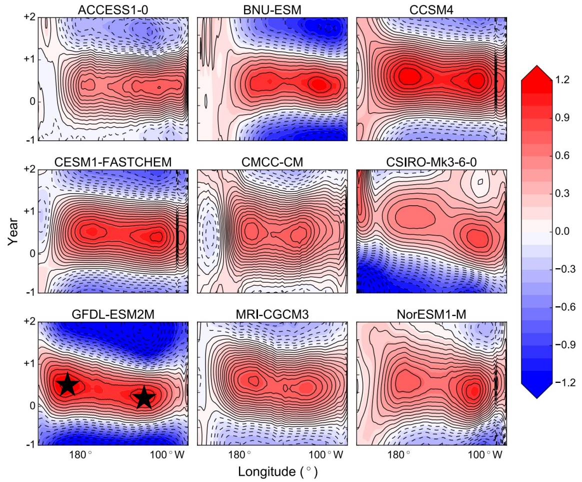
- Equatorial τ_x anomalies that are too weak, too far west, and too narrow in the meridional direction (reduced zonal wind feedback)
- Too little damping of SSTAs by surface heat fluxes, often due to a weak cloud shading response (a_{SW} problem)
- Insufficient cross-timescale linkage between ENSO, its intraseasonal precursors, and Pacific decadal modes, linked to biases in the background climatology
- Error compensations that can lead to right statistics for wrong physical reasons

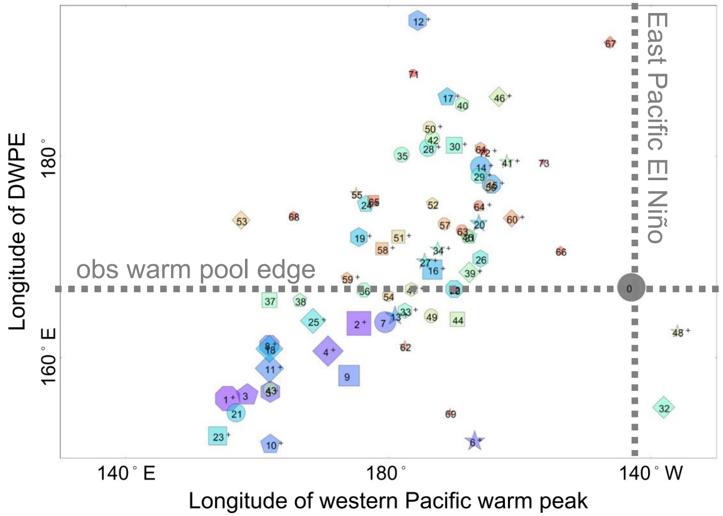
Guilyardi et al. 2020

Double-peaked El Niño SSTAs

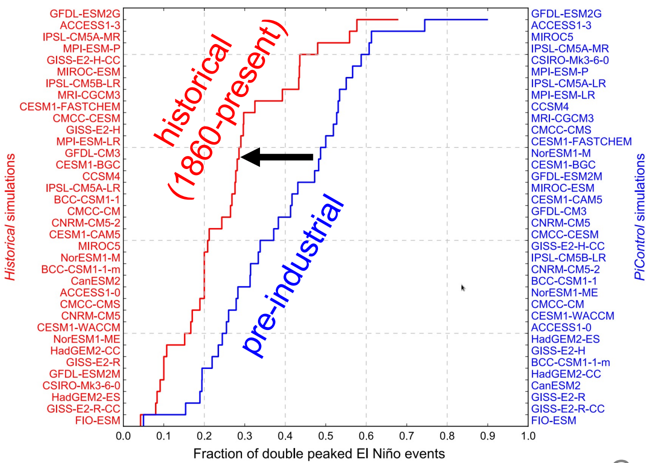


Composite El Niño in CMIP5 models
(equatorial SSTA)



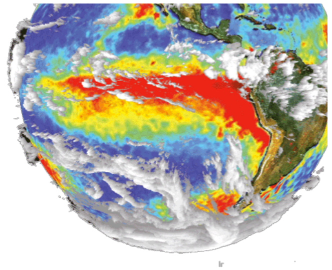


If warm pool is too far west, we get more **double-peaked El Niños** with western peaks that are **farther west**.



Present-day simulations show *fewer* double-peaked El Niños than pre-industrial.

Graham et al. (CD 2017)



CMIP5 rainfall responses to ENSO

Obs

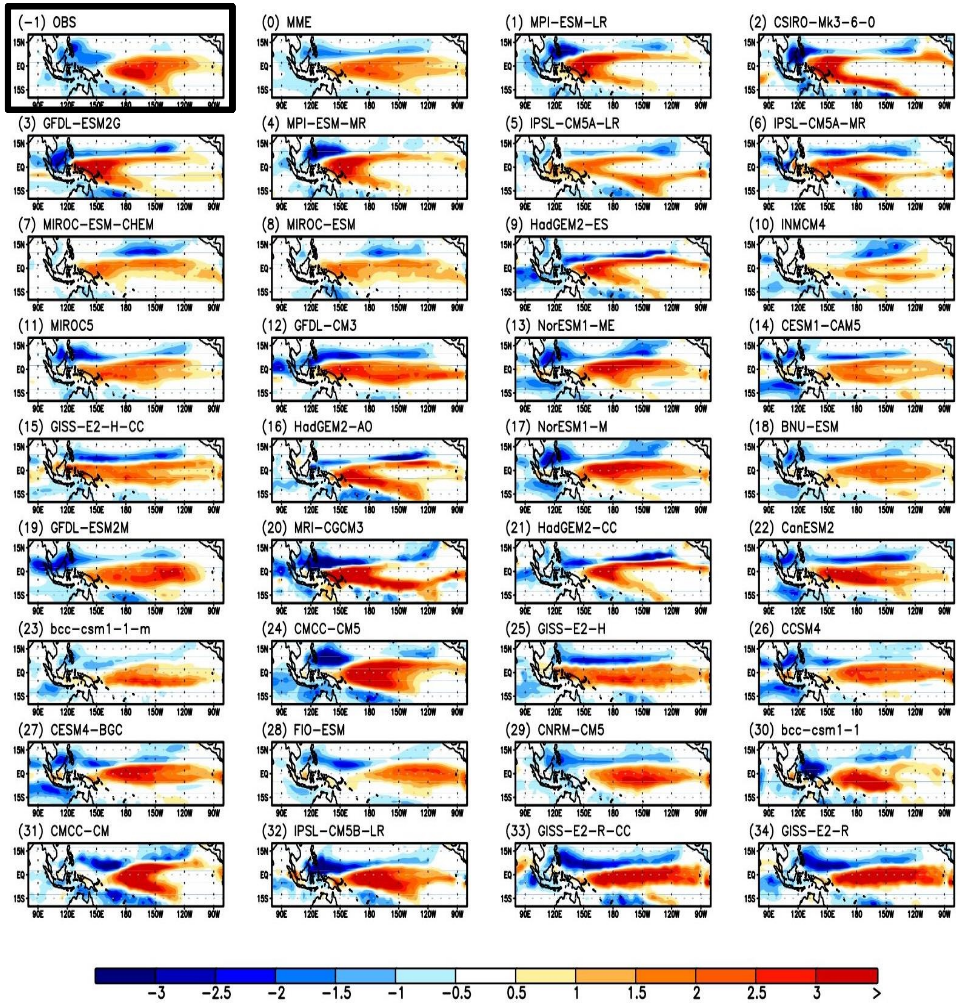


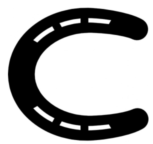
FIG. 1. The precipitation anomalies regressed onto the Niño-3.4 index during the December–February (DJF) season, in the observation (−1), multimodel ensemble (MME; 0), and each model (1–34; model numbers are given in Table 1). Note that the unit of the regression is mm day^{-1} °C^{-1}.

DJF regressions on NINO3.4 SSTA.

Obs show eastward & equatorward shift of deep convection during El Niño.

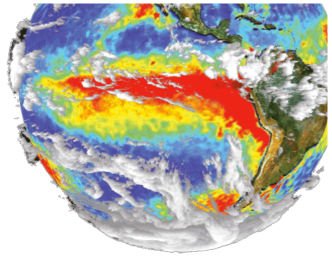
ECT cold SST bias → many **model** responses are too far west along the equator.

“Horseshoe” shape.



Ham & Kug (JC 2015)

CMIP5: SSTA zonal propagation linked to mean state



Warmer-ECT models show less **westward propagation** of equatorial SSTAs.

May be due to a **weaker westward SEC**, or weaker dT/dx & dT/dz curbing **zonal & Ekman feedbacks** relative to the thermocline feedback.

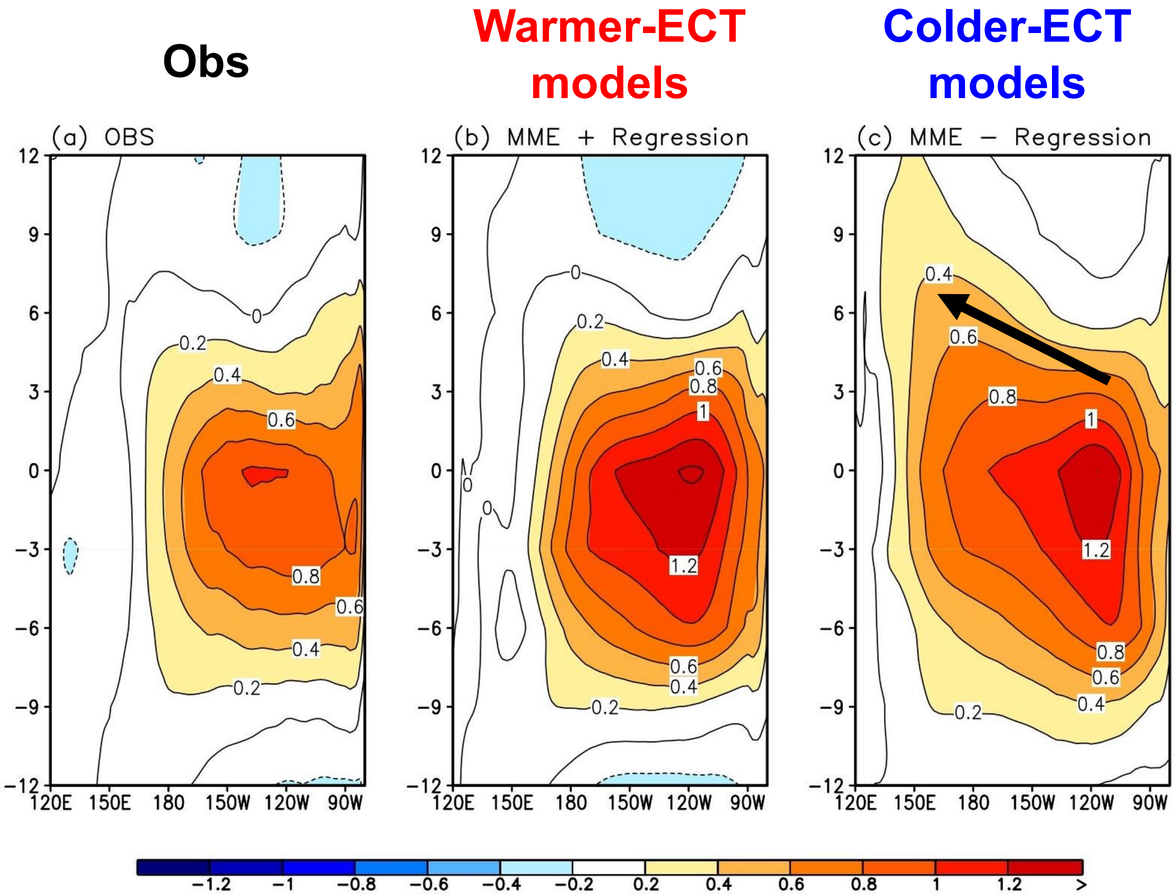
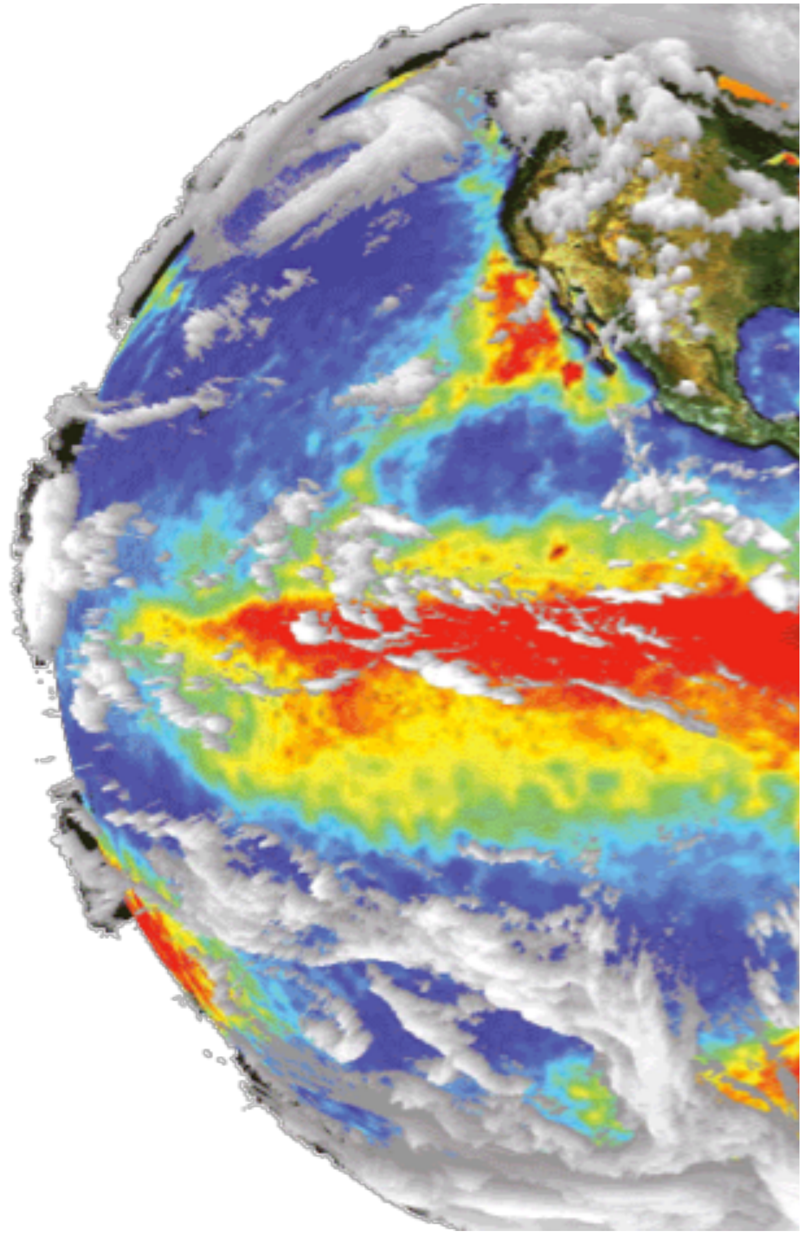


FIG. 6. (a) The observed equatorially averaged (5°S–5°N) ENSO-related SST anomalies from the preceding January (i.e., −12 on the y axis), to subsequent December (i.e., +12 on the y axis) of the ENSO peak season. Also shown is the regression of the intermodel differences of the equatorially averaged ENSO-related SST anomalies onto the first EOF PC from the preceding January to subsequent December of the ENSO peak season, which is (b) added to and (c) subtracted from the MME response of the Niño-3.4-regressed SST.

Ham & Kug (JC 2015)

ENSO metrics

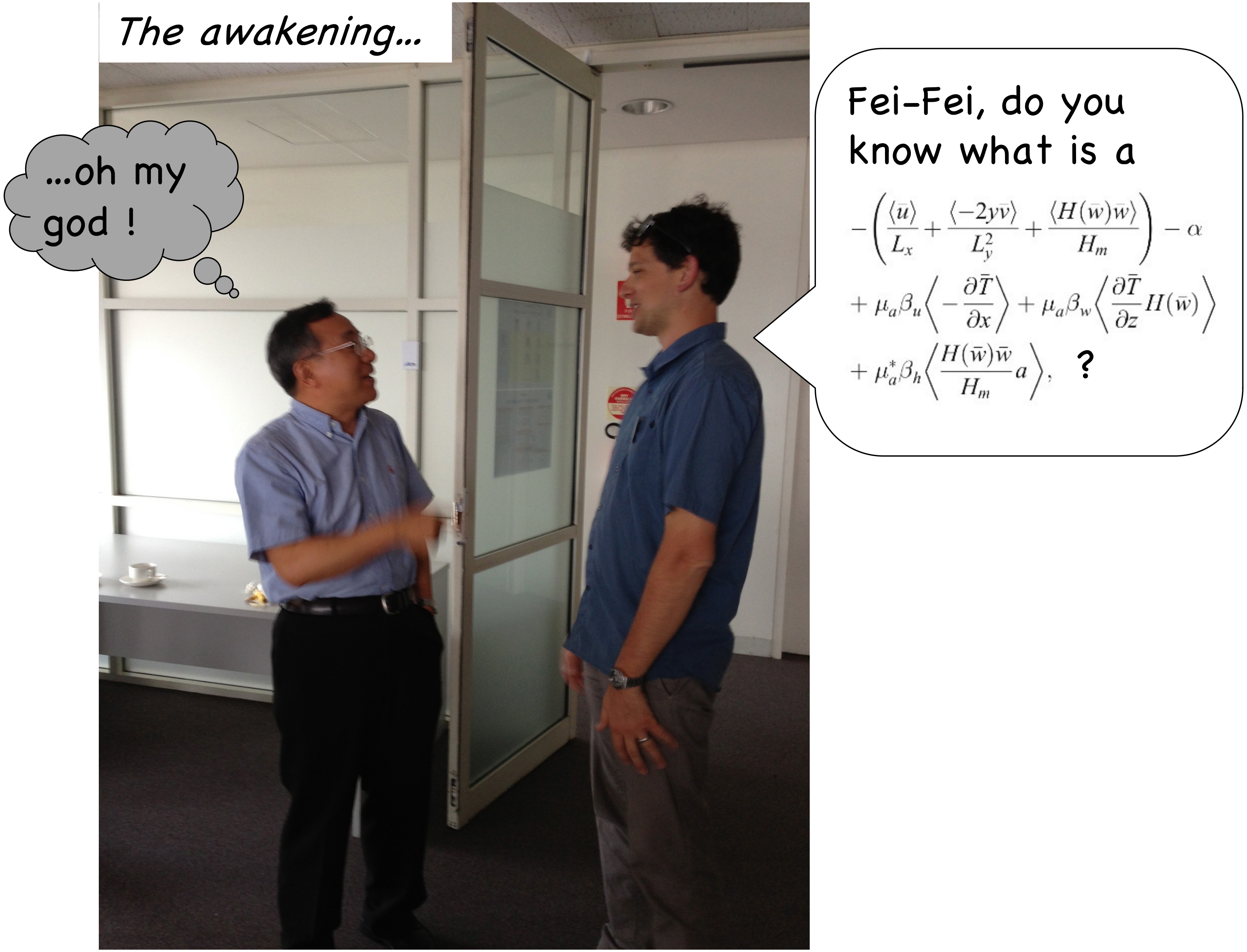
- Measure of distance between model and a reference
- Two main goals:
  - Guide model development
  - Help “non experts” assess ENSO
- Go beyond the *niño3 SSTA stdev* view
- CLIVAR context, WG, several papers
- Learning to use metrics f(Q, context)
- Dealing with unsufficient observations
- Benefits and risks



CLIVAR ENSO metrics work group

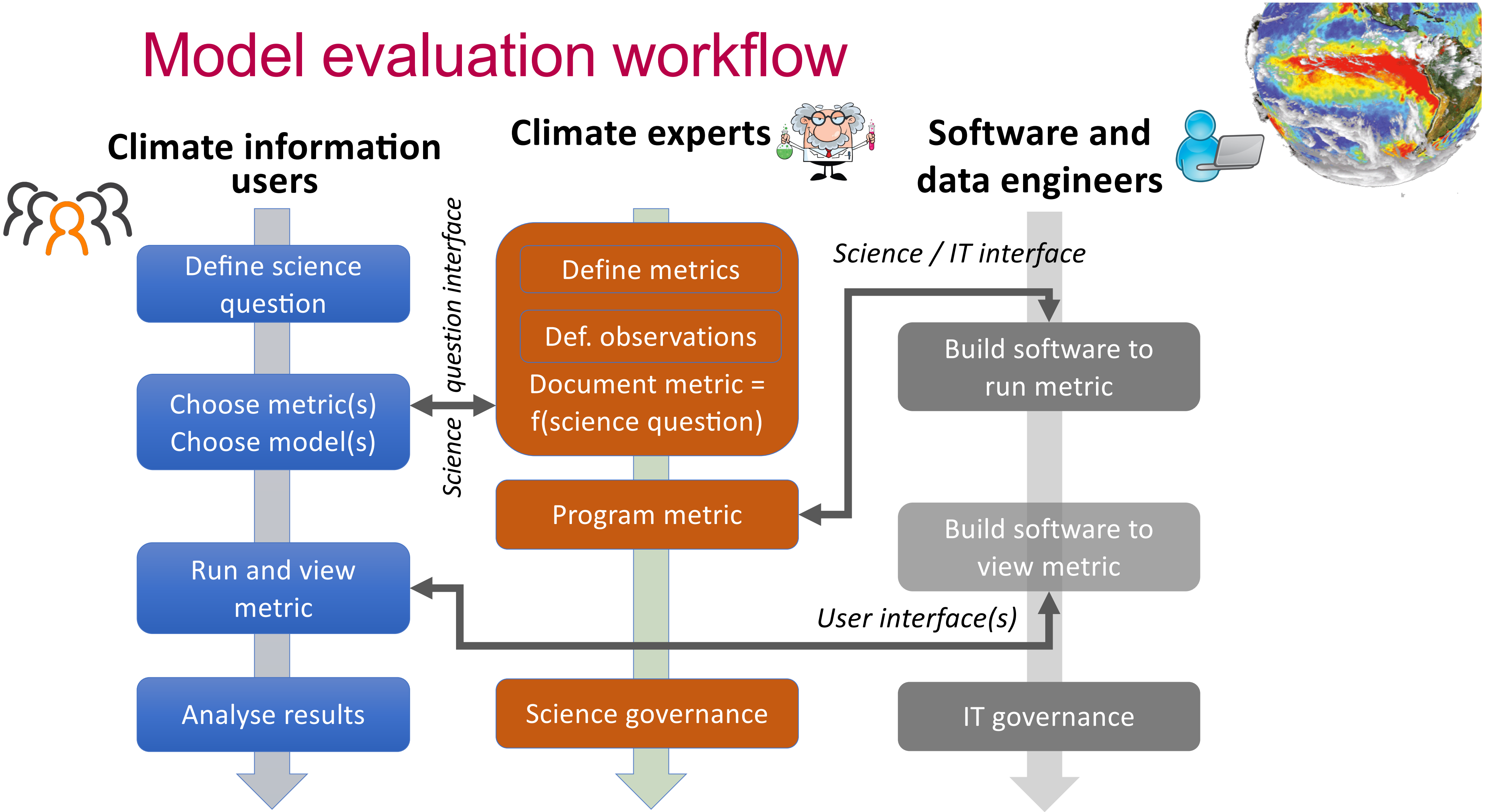
- Initiated via the CLIVAR Research Focus Development Team “ENSO in a changing climate” (2014-2018)
- Now coordinated by CLIVAR Pacific Region Panel (Andrew)
- (too?) many meetings (Paris, Pune, Hobart, San Francisco, Lijiang, Busan, Quayaquil,…)
- Led to a number of papers
- Great community adventure – now led by Yann and Andrew

From BJ to BWJ...



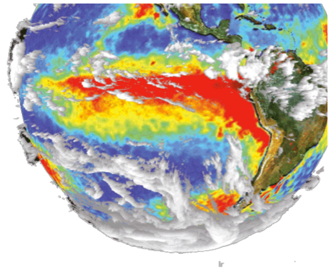


Model evaluation workflow



Articulate different actors, different expertise and expectations

Document science provenance of metric

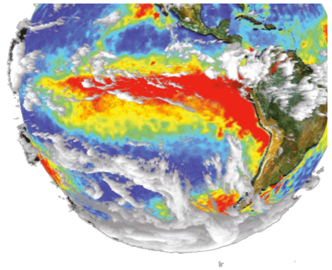


- What is the scientific question ?
- What are the related metrics?
- What are the reference “observations” ?

- Introduce concept of Metric collection (MC) to address specific science question

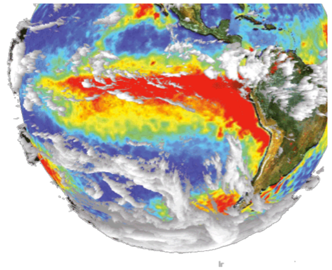
	Metric 1	Metric 2	Metric 3	Metric 4	Metric 5…
Collection Q1					
Collection Q2					
Collection Q3					
…					

First science questions for ENSO metrics



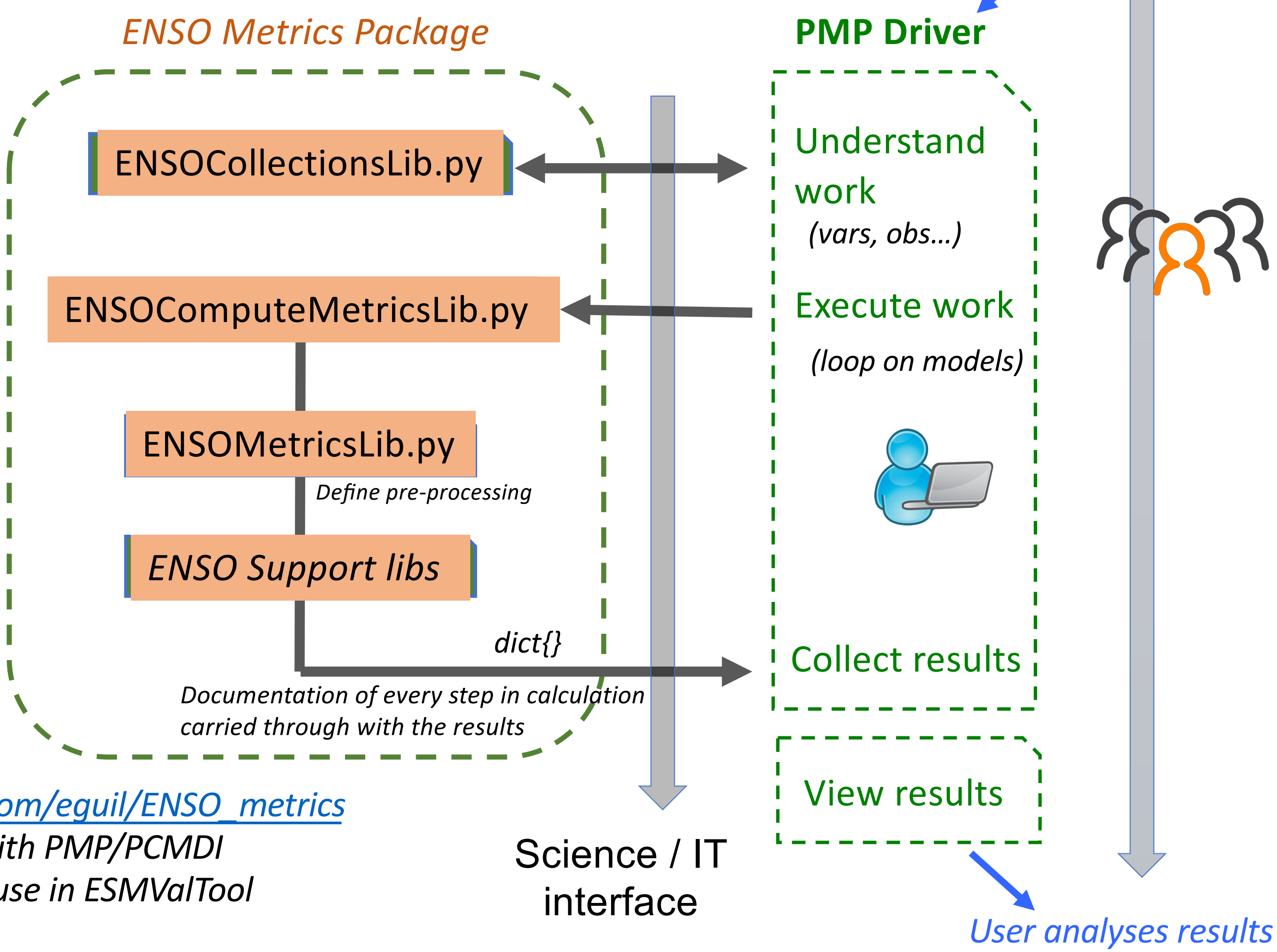
- **ENSO performance in historical**
  - Mean state incl. SC, ENSO characteristic space/time, diversity, decadal
  - Use ensemble or Picontrol to evaluate uncertainty
- **ENSO teleconnections in historical**
  - Metrics a la Scott (25 regions,…), RMS,…
- **ENSO processes** (right for right reasons)

Structure of pilot ENSO package



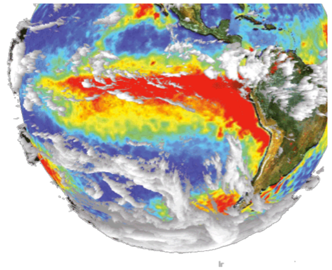
Engage with an IT infrastructure (driver), here PMP

User chooses metric collection and models



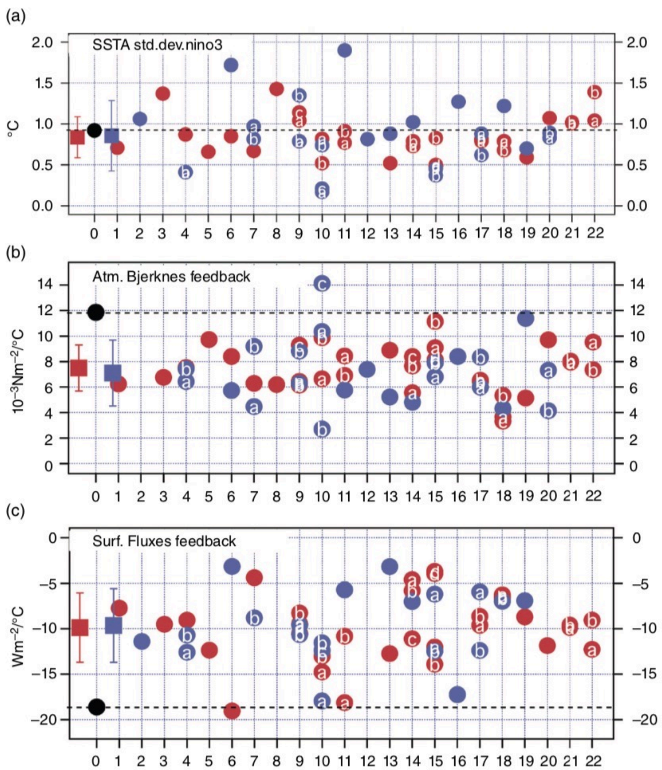
https://github.com/eguil/ENSO_metrics
Collaboration with PMP/PCMDI
Explore how to use in ESMValTool

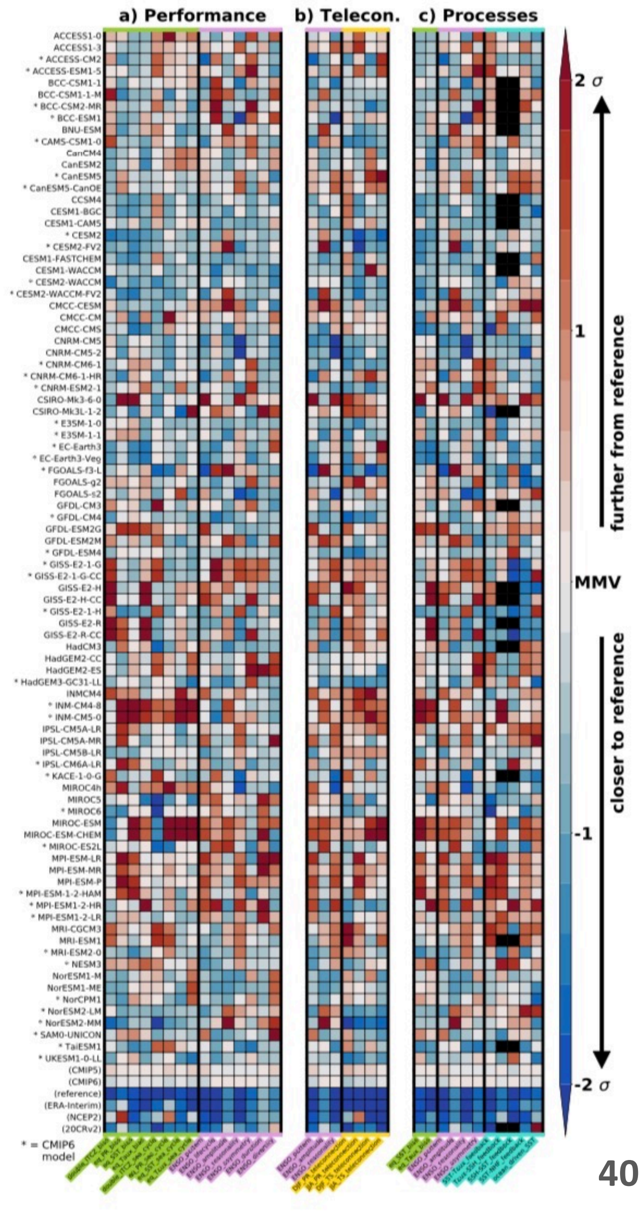
Some happy ENSO metrics team members



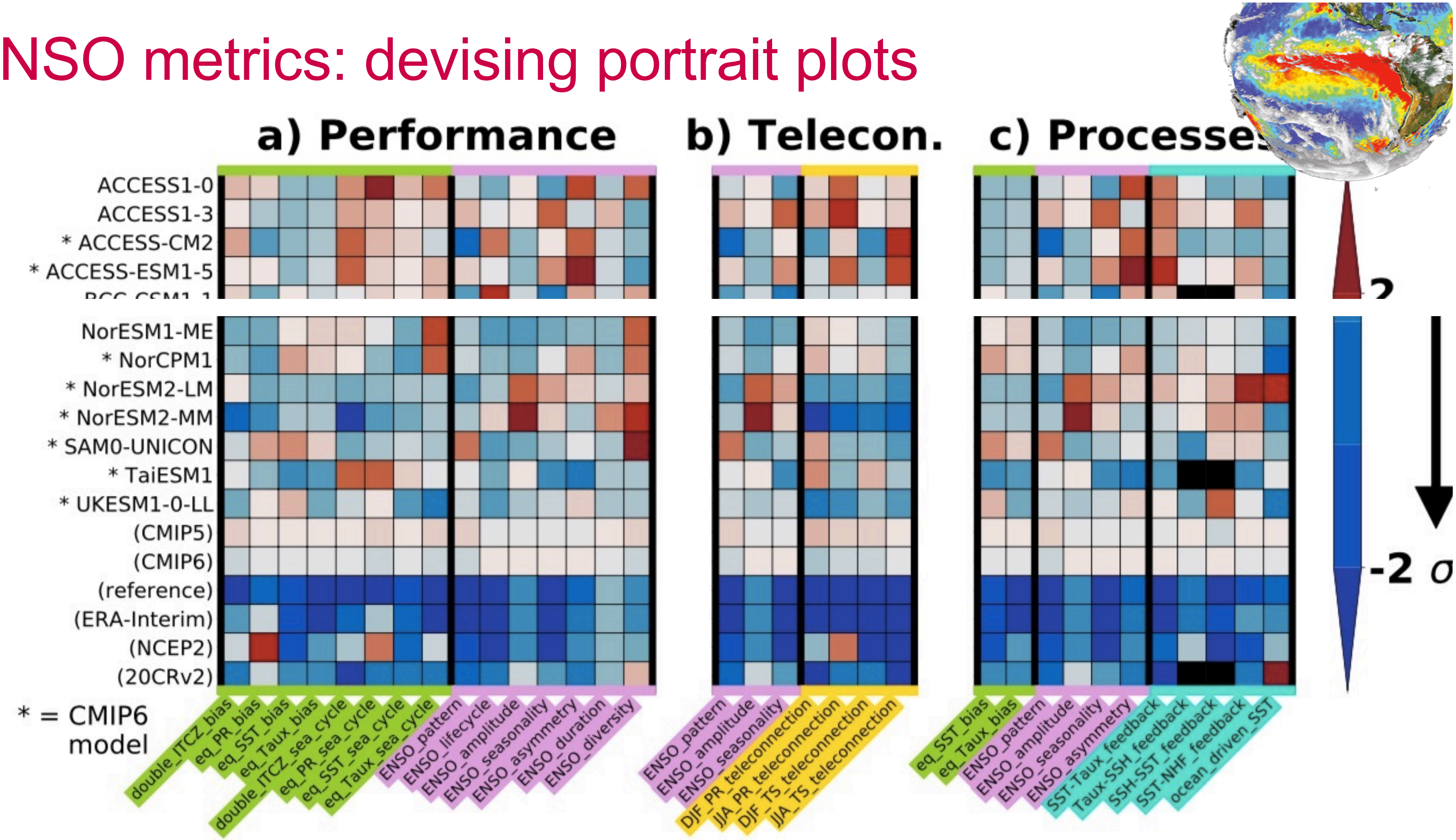
CMIP6 Model Analysis Workshop, Barcelona, 2019

ENSO metrics: devising portrait plots



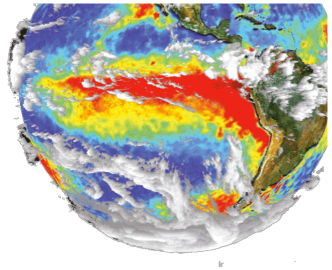


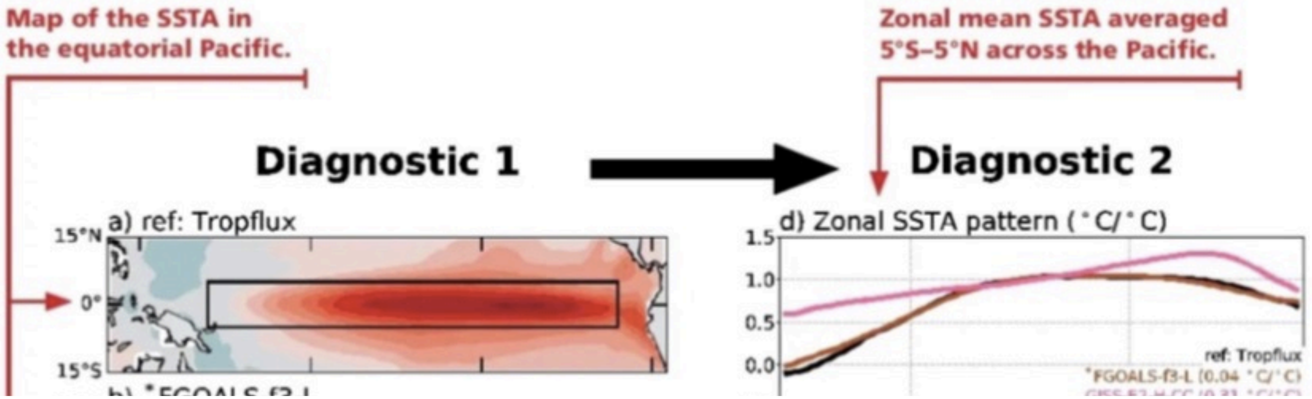
ENSO metrics: devising portrait plots



Planton et al. 2021 BAMS: Evaluating Climate Models with the CLIVAR 2020 ENSO Metrics Package

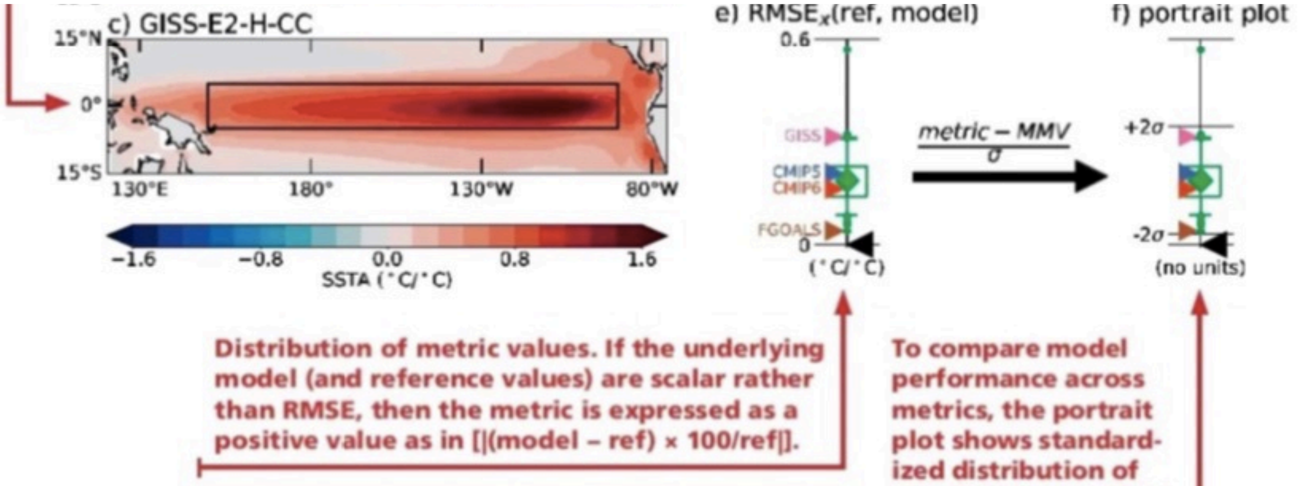
Building a metric for portrait plot





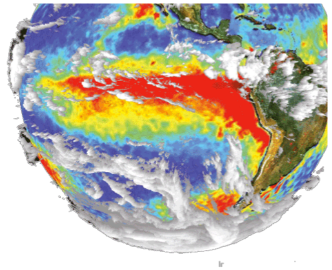
Program for Climate Model Diagnosis and Intercomparison

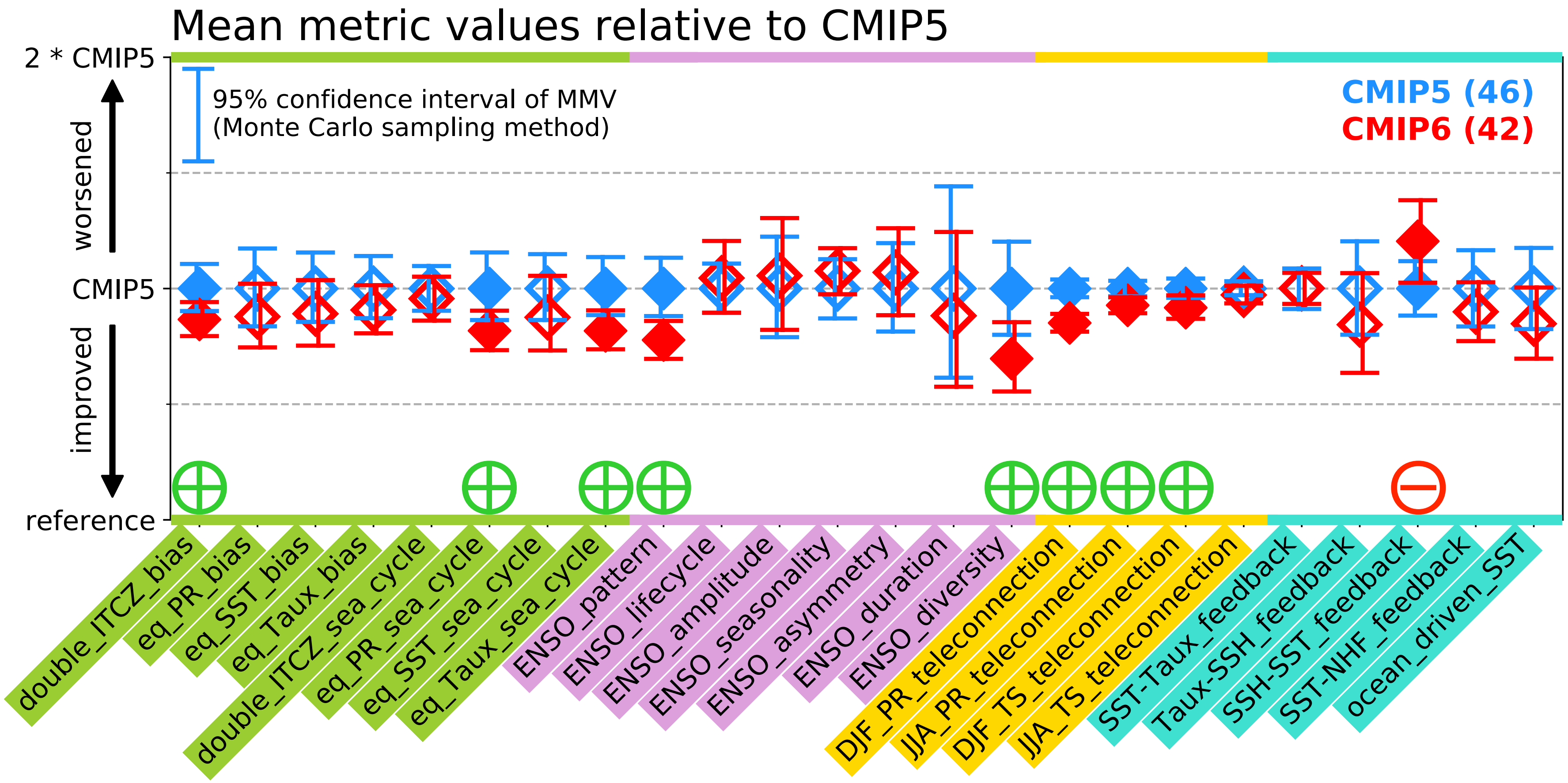
https://cmec.llnl.gov/results/enso/



Planton et al. 2021 BAMS: Evaluating Climate Models with the CLIVAR 2020 ENSO Metrics Package

CMIP5→6: 8 significantly improved
1 significantly degraded



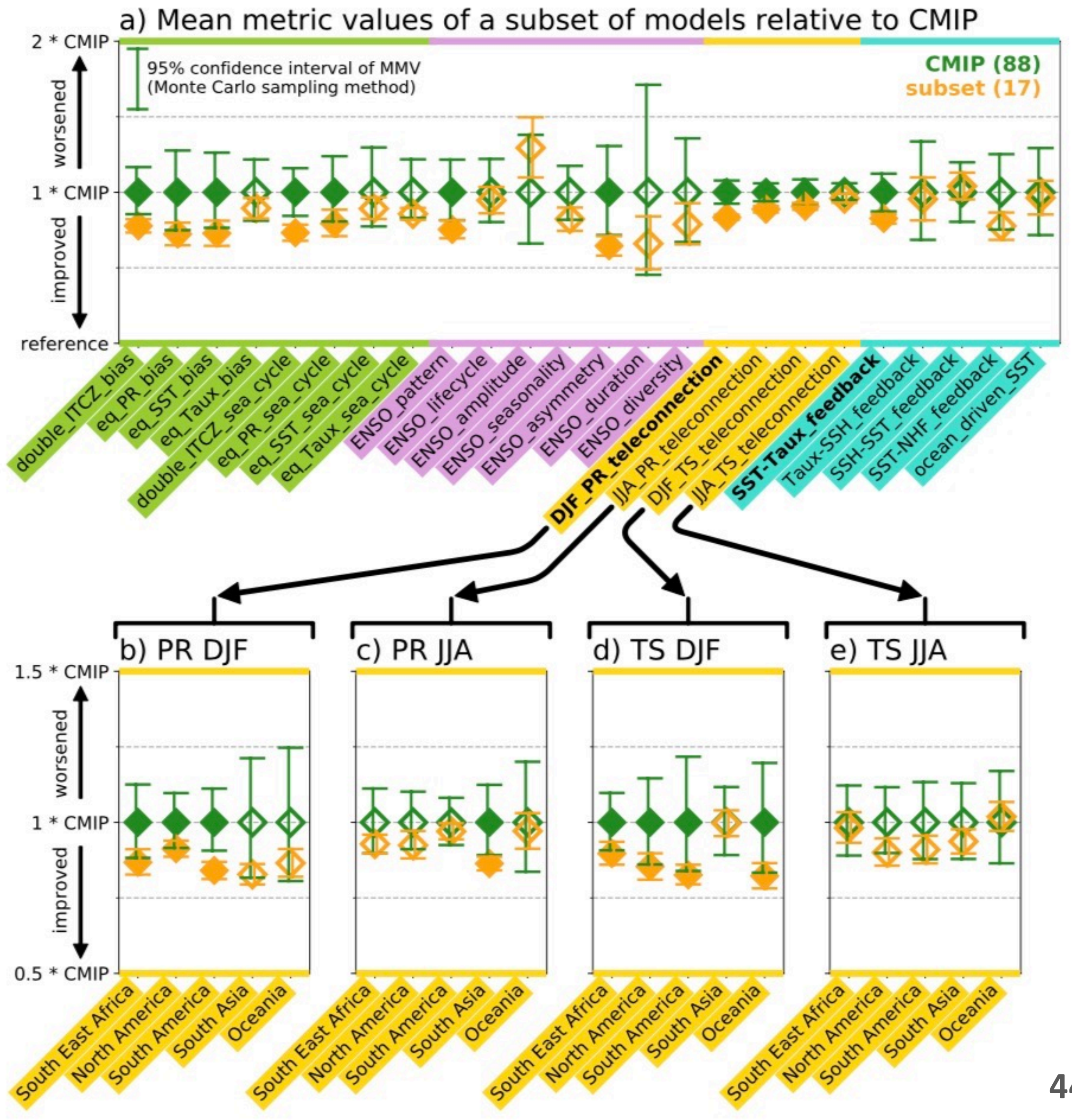


Planton et al. 2021 BAMS: Evaluating Climate Models with the CLIVAR 2020 ENSO Metrics Package

Using metrics

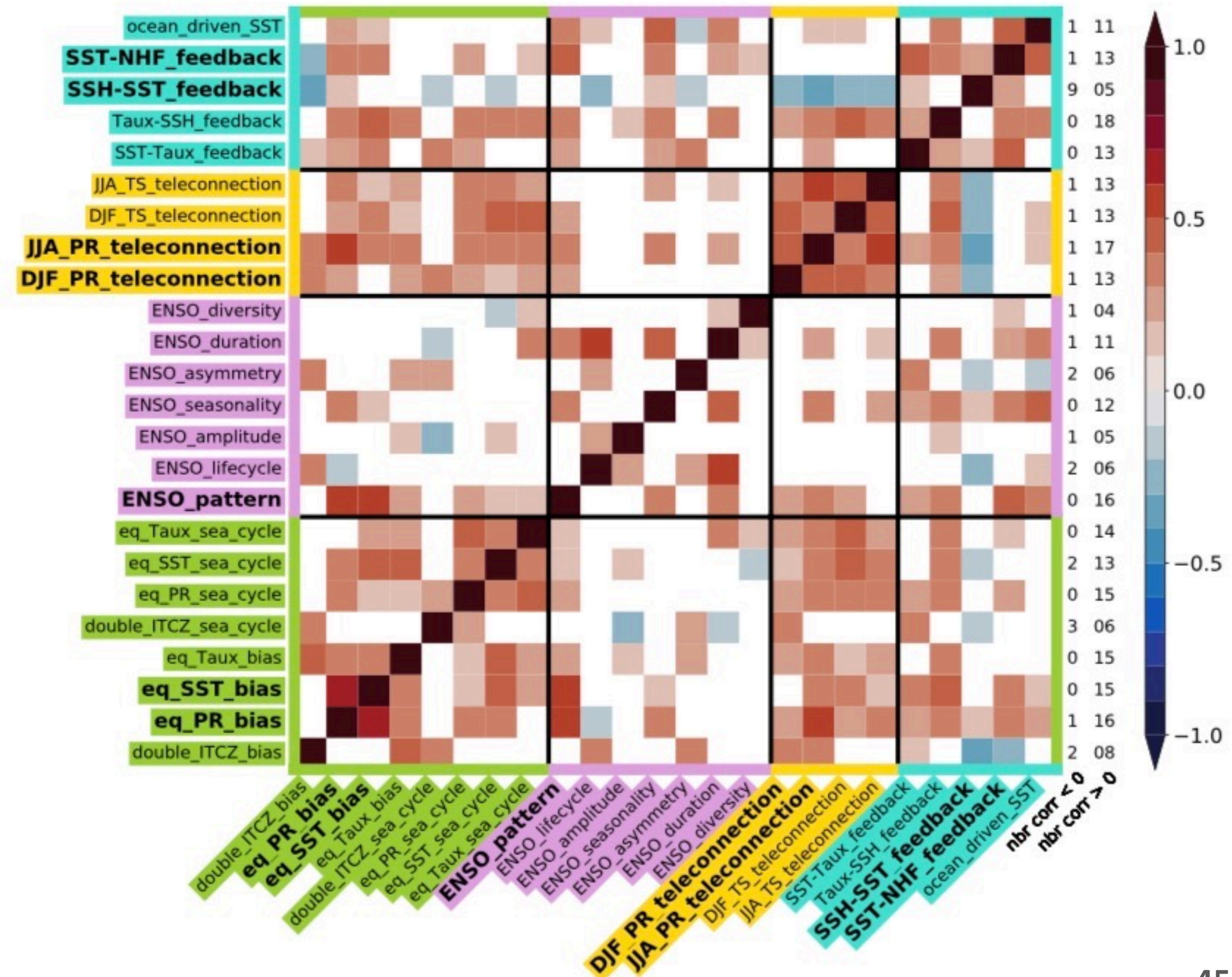
Address numerous questions

- Sub-sample models



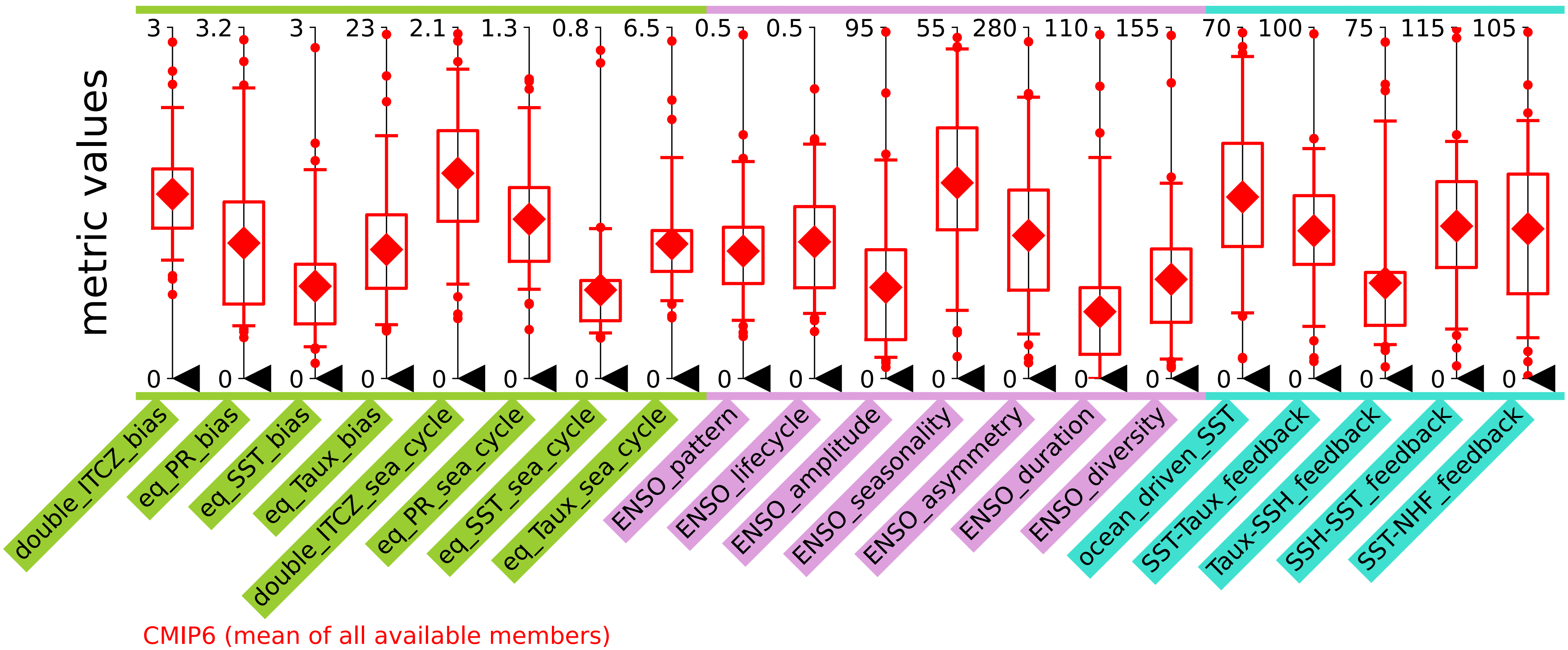
Metrics correlations

Intriguing correlations



How to take into account observations uncertainties in metrics ?

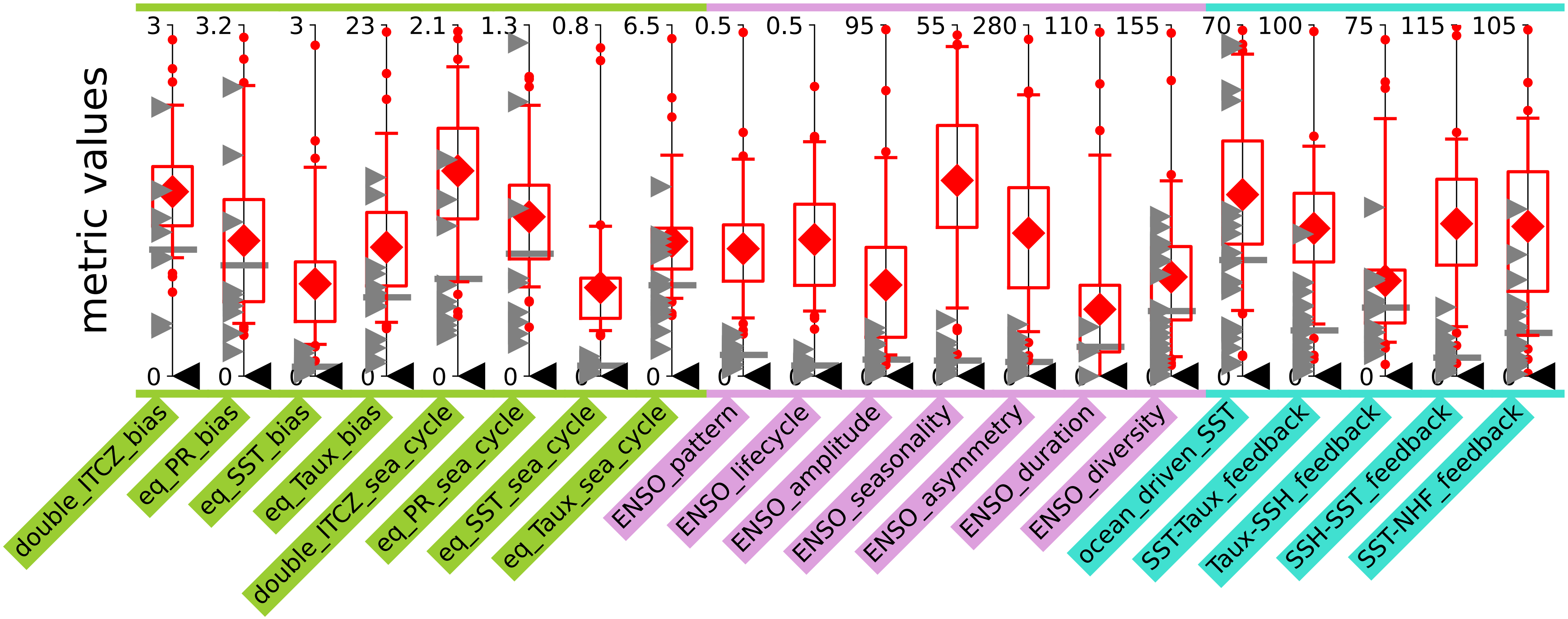
Some models are far away from the reference



Reference: AVISO (SSH), GPCPv2.3 (PR), OISSTv2 (SST), TropFlux (Taux & heat fluxes)

Planton et al. (2021)

Large observational uncertainties

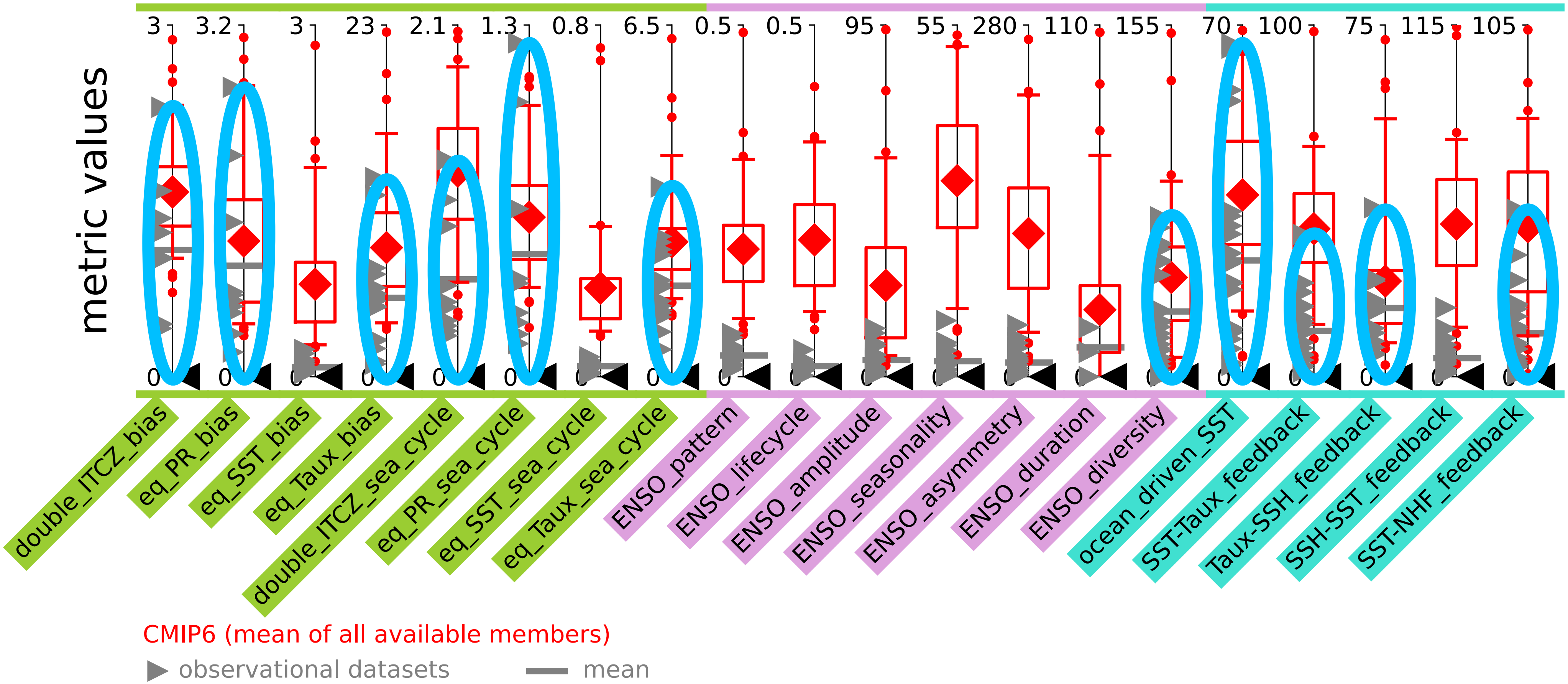


CMIP6 (mean of all available members)

▶ observational datasets — mean

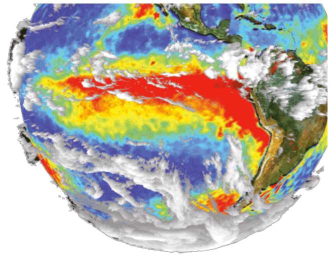
Reference: AVISO (SSH), GPCPv2.3 (PR), OISSTv2 (SST), TropFlux (Taux & heat fluxes)

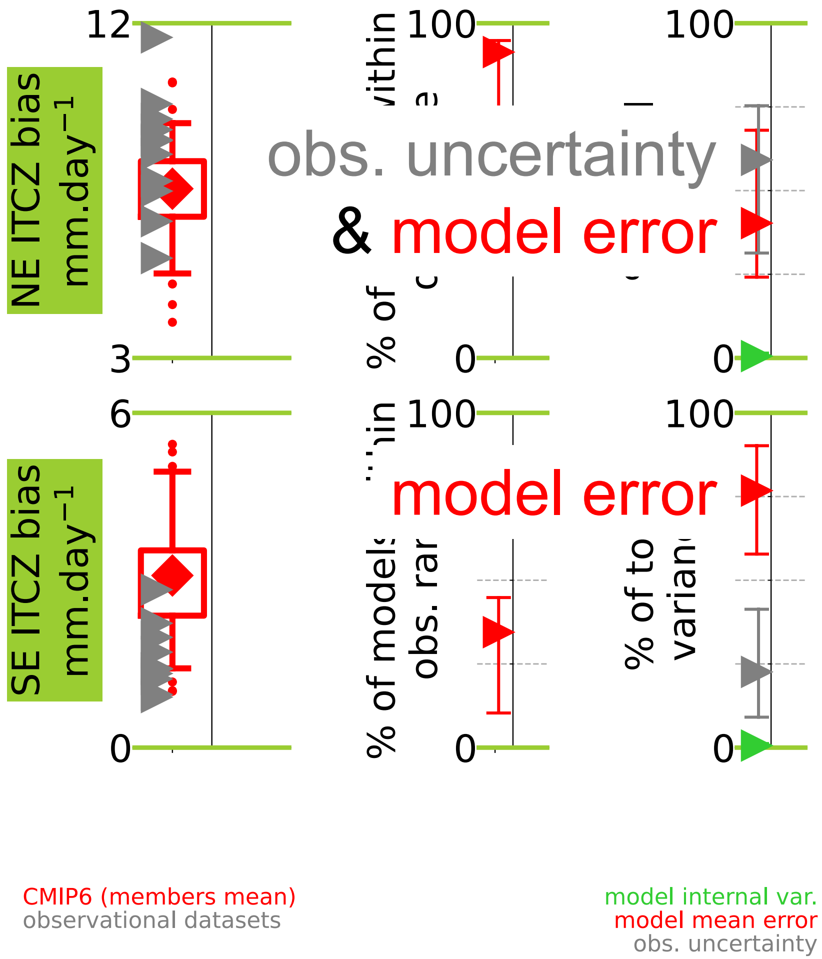
Large observational uncertainties

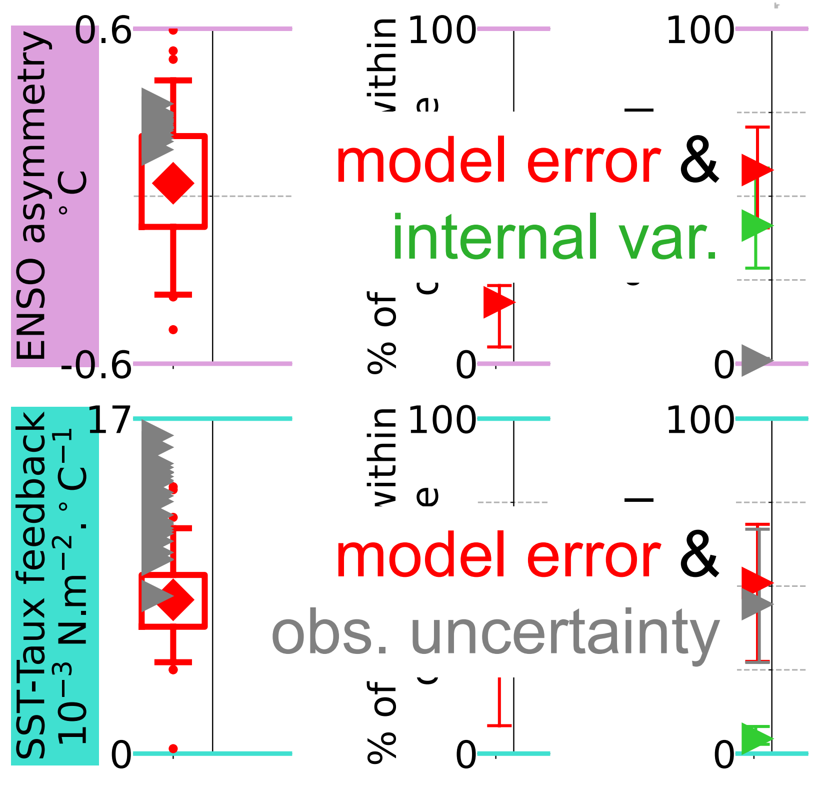


Reference: AVISO (SSH), GPCPv2.3 (PR), OISSTv2 (SST), TropFlux (Taux & heat fluxes)

Large model errors, but in some cases obs. uncertainty or internal variability are as large

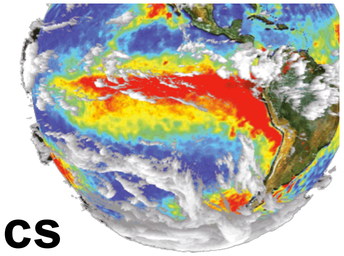




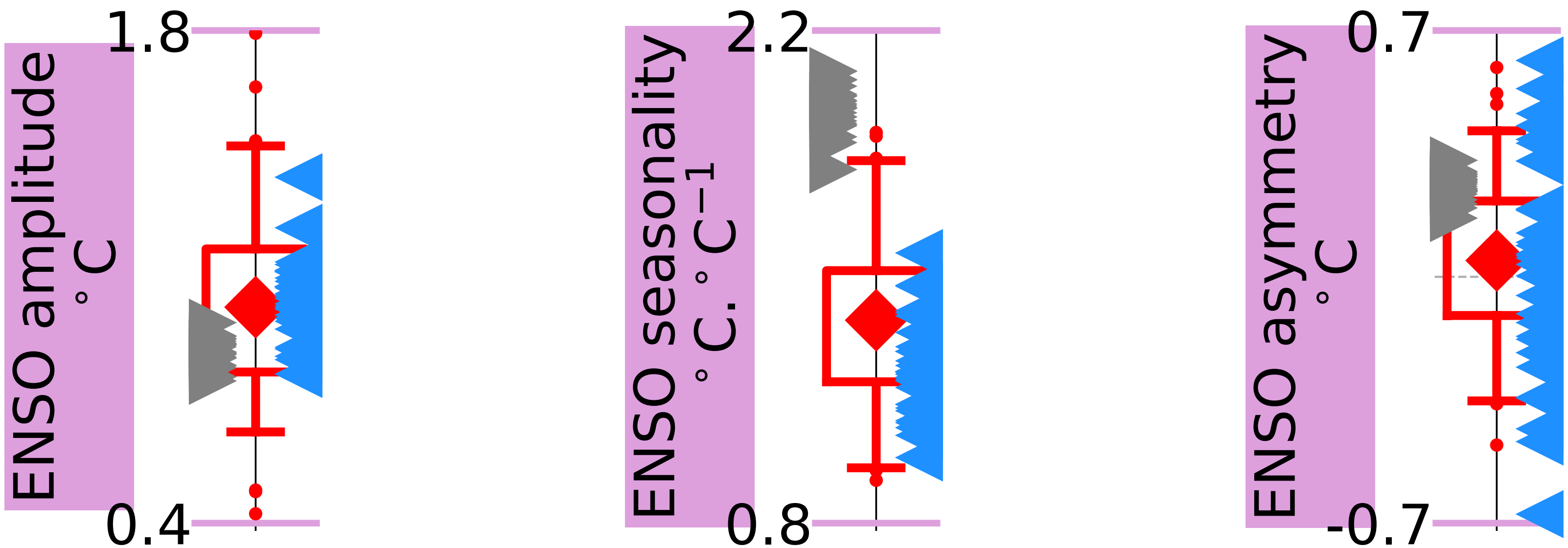


bootstrap: obs / model / member

Observations for metrics

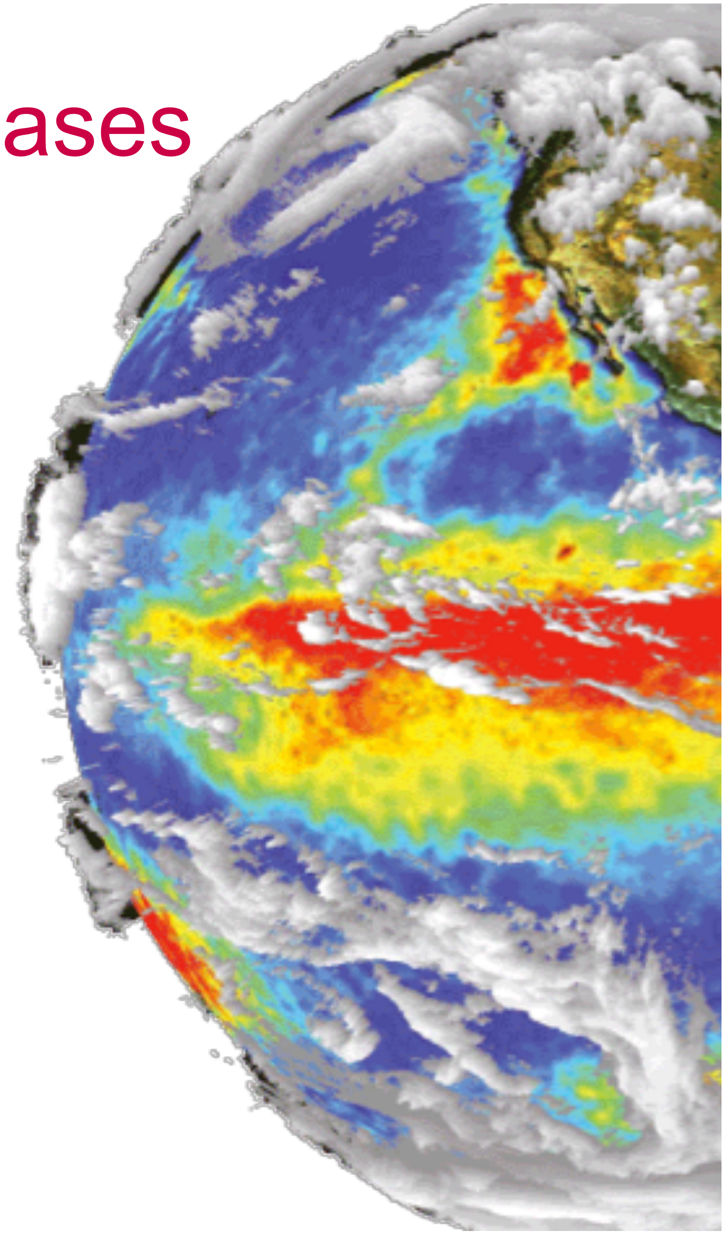


- **Obs. uncertainties large compared to mod. error in 50% of the metrics**
- **SST bias (cold tongue bias) is the clearest model error**
- **Large observation uncertainties in precipitation and feedbacks**
- **Obs4MIPS integrated into ENSO metrics package**



Understanding sources of ENSO biases

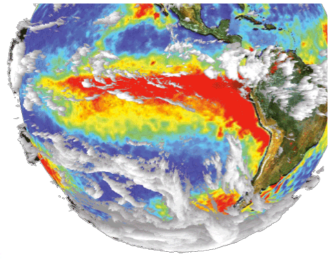
- How to disentangle sources of models errors in a highly coupled, non-linear, and multi-time scales phenomenon such as ENSO ?
- Dedicated simulations with artificially modified feedbacks or change of physics, but…
- Use of initialised simulations



Using initialized simulations to diagnose the growth of systematic biases in GCMs

- Seasonal hindcasts make it possible to distinguish fields that are affected by errors from the beginning of the simulation (wind patterns, precipitation, mixed layer depth) and those which respond to the previous one (SST, thermocline depth and zonal wind in the west Pacific).
- Seasonal/decadal time scale:
  - Tropical Atlantic: B. Huang et al. (2007)
  - Tropical Pacific : B. Vannière et al. (2013, 2014), J. Shonk et al. (2016)
- Decadal/longer time scale:
  - Tropical Atlantic: T. Toniazzo & S. Woolnough (2013)
  - North Atlantic & AMOC : B. Huang et al. (2015)

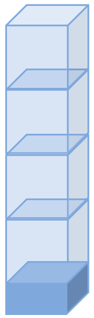
+ many other studies, eg Kim et al. 2017 (ENSO growth and BSI), Hermanson et al. 2018 (comparing seasonal forecast systems), Shonk et al, 2018 (Western Pacific ITCZ drift), Brient et al. 2019 (marine strato cumulus), Ding et al. 2020…

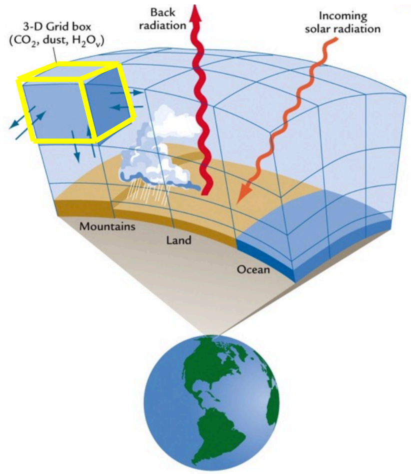


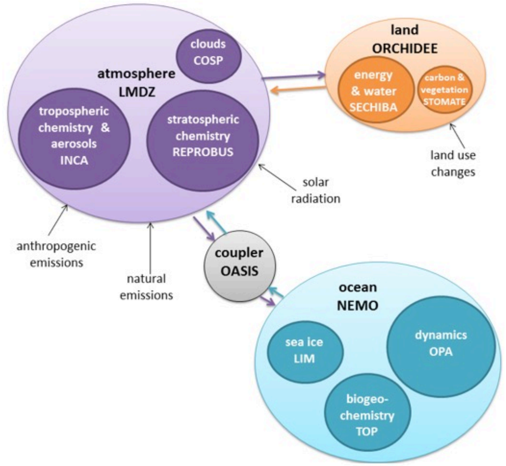
“Classical” CGCMs development path

Parameterization | **Component** | **Coupled model**

Model development process







Step 1
Parameterization constrained against field campaigns observation

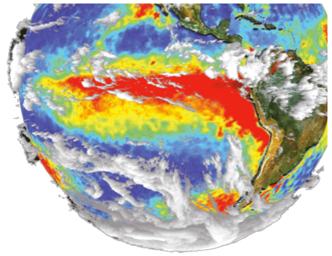
Step 2
Tuning of component, adjustment of large scale balance

Step 3
Tuning of coupled model to balance global energy budget and exchanged fluxes

EVALUATION — EVALUATION — EVALUATION

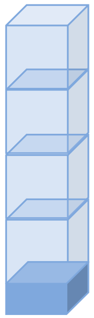
- Each step generates biases
- Source in coupled model is difficult to identify because of **bias compensation**, **feedback amplification** and **non-linearities**
- This development strategy does not allow to predict the coupled model SST biases

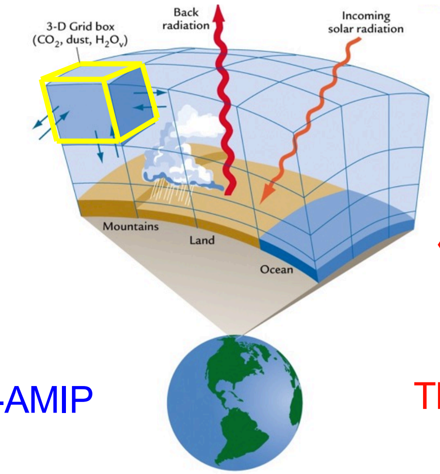
Working backwards

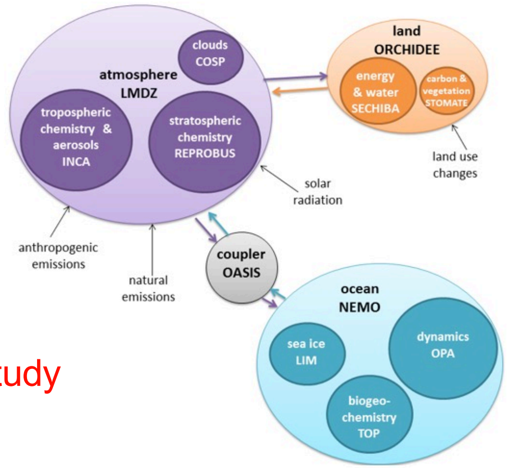


Parameterization | **Component** | **Coupled model**

Model development process







e.g. T-AMIP

This study

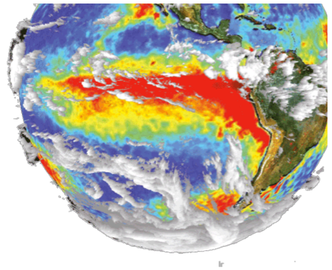
"Fast" physics errors

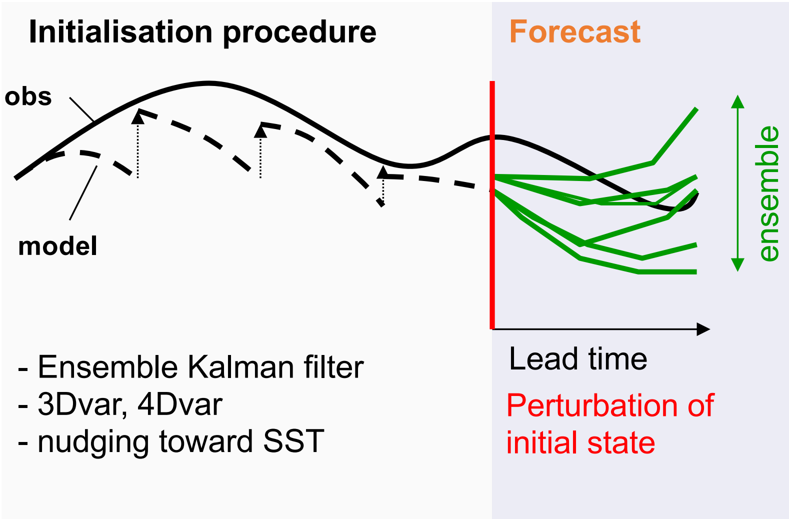
Atmosphere and ocean component errors

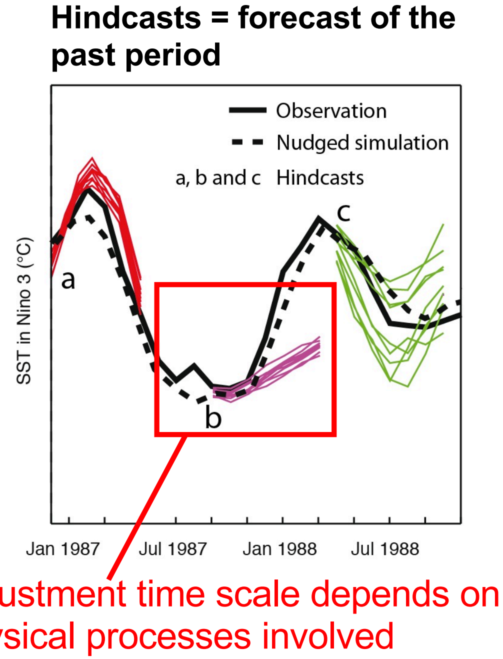
Long term coupled errors

↳ Use "reverse engineering" to attribute a **particular** bias of the coupled model to a component and back to a **specific** parameterisation

Using initialised simulations to understand model errors





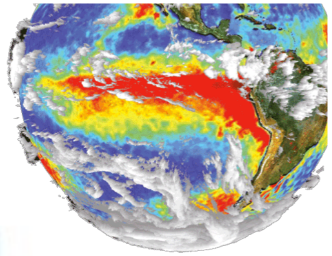


Hindcasts:

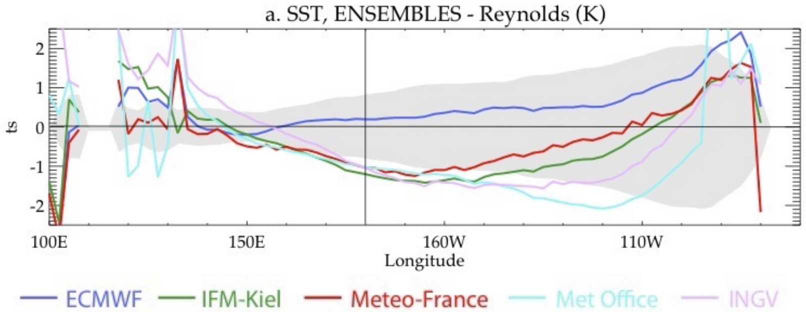
↳ Help distinguish time scale and location of error growth

↳ Help propose hypothesis for error source

Using seasonal hindcasts: a new strategy to understand GCM systematic errors

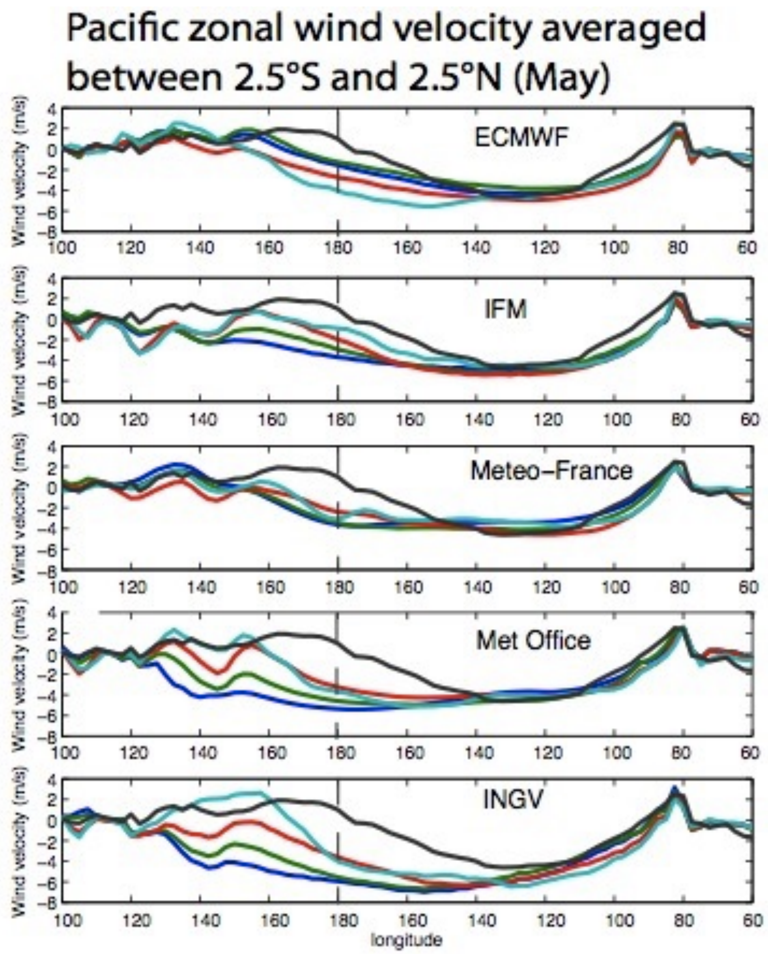


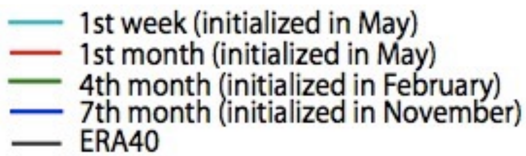
Cold tongue SST error (after 5-7 months)



ENSEMBLES stream 2 seasonal hindcasts

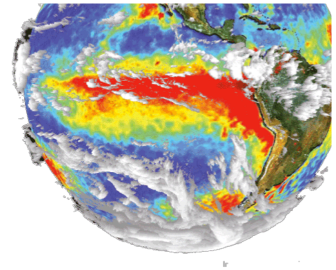
- Wind stress errors at equator present after one week
- Responsible for cold bias at equator

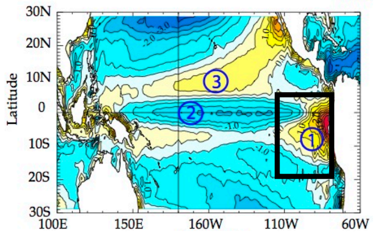




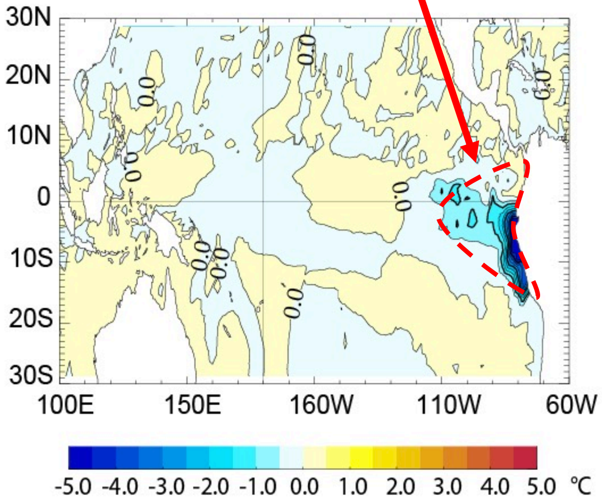
Vannière et al. 2011

Using additional simulations to demonstrate the source of error



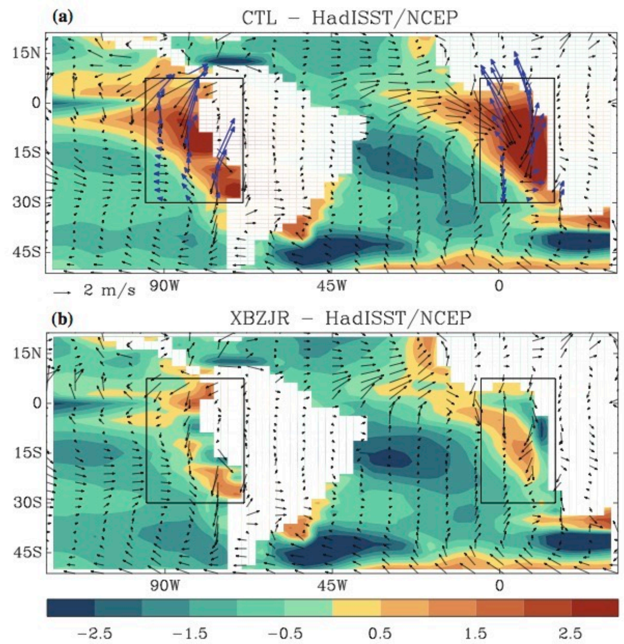


Oceanic simulation forced with fixed flux : impact of meridional wind correction



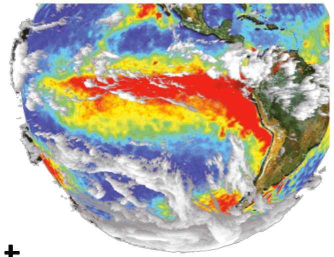
Vannière et al. (2014)

Coupled simulation with wind correction



Toniazzo and Woolnough (2013)

Can we devise a systematic experimental approach ?

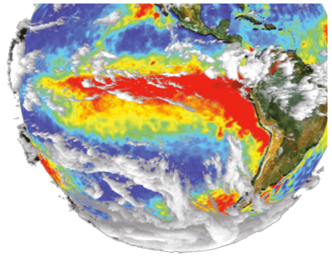


Vannière et al (2014) proposed a systematic approach to investigate the root cause of a SST bias in a climate model

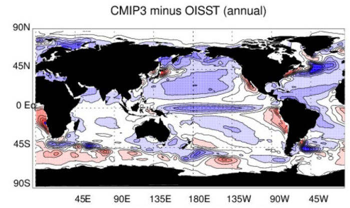
5 steps for 'solving the case':

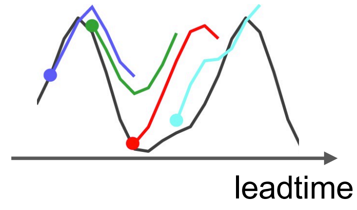
1. Identify the location and seasonality of the SST bias
2. Examine the time scales over which errors develop in different variables and link them together to build a chain of causality
3. Find whether the origin of the bias is local or remote
4. Determine if an atmospheric field or an oceanic field is at fault
5. Investigate whether the error is caused by the direct effect of that field, or by coupled feedbacks

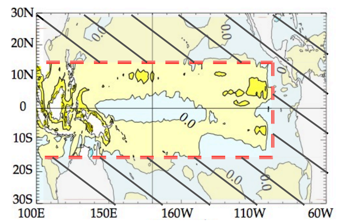
Associated experiments in support of approach

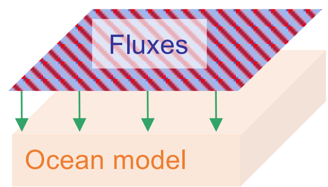


The 5 steps	Associated experiments
S1 **Location / seasonality**	**Historical or control experiment**
S2 **Time scale / chain of causality**	**Seasonal to decadal hindcasts**
S3 **Local or remote**	**Regionally restored experiments**
S4 **Atmospheric / oceanic field responsible for the bias**	**Ocean-only forced experiments**
S5 **Direct effect / amplification by coupled feedbacks**	



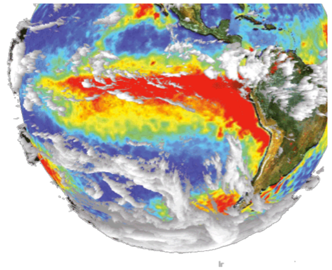






Vannière et al. (2014)

Identifying the origin of SST mean state biases in the tropical Pacific in IPSLCM5A-LR



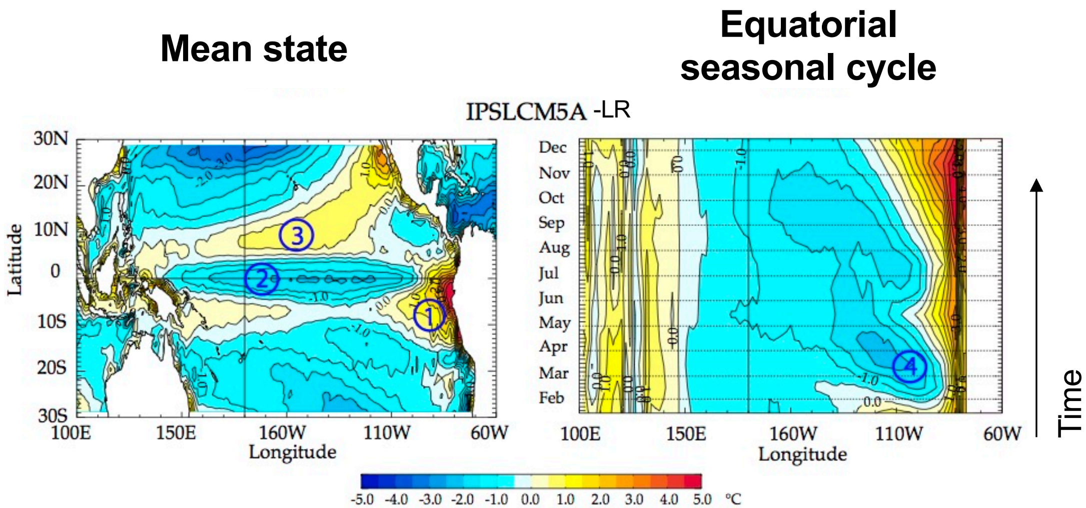
Approach is applied to **cold tongue bias** in IPSL-CM5A-LR (S1)

① Warm bias in the east Pacific

② Cold tongue bias

③ Warm bias on both side of the equator

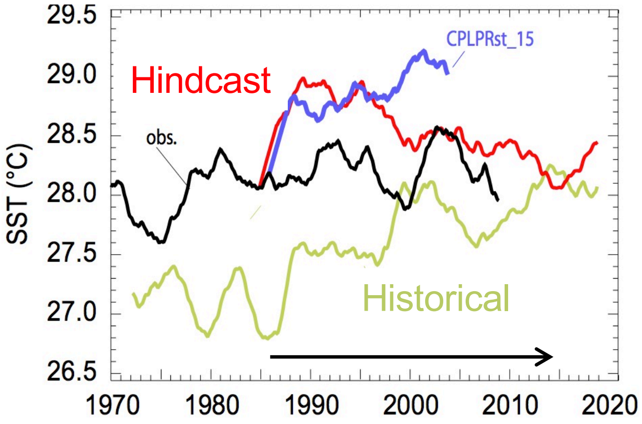
④ Spurious spring upwelling bias

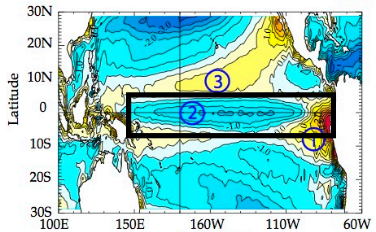


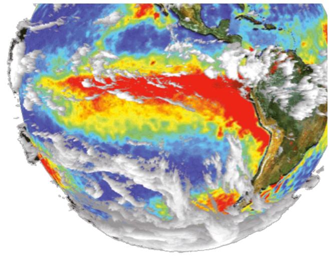
Vannière et al. (2014)

Cold tongue bias origin

> S2 : Time scale → Cold tongue bias



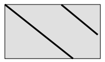


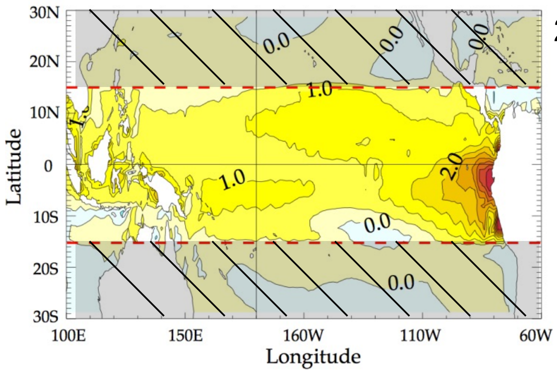


- ✓ It takes 30 years for the cold tongue bias to appear at the equator
- ✓ Hypothesis : ocean slow dynamics

> S3 : Geographical origin → Cold tongue bias

CPLPrst_15: Initialised simulation restored toward observed SST in midlatitudes





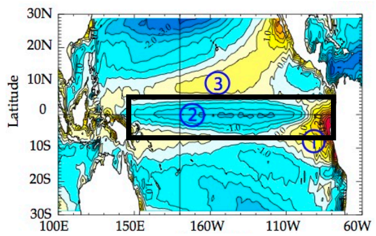
20-yr leadtime

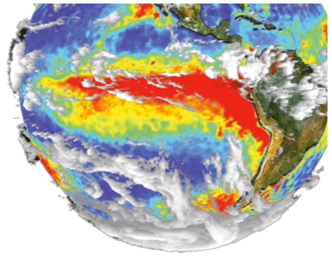
- ✓ SST corrected in mid-latitudes
  - ⇒ no development of the cold tongue bias

Vannière et al. (2014)

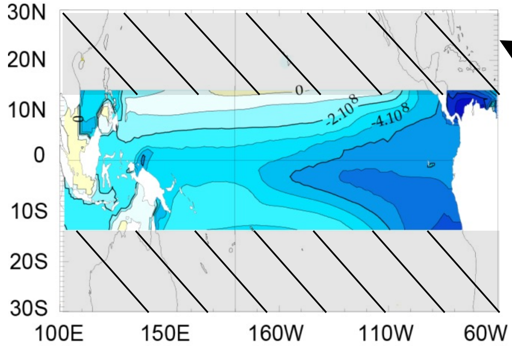
Cold tongue bias origin

> S4 : Ocean only simulation → reproduce cold tongue bias





Ocean only simulation (bulk) 300m heat content



Nudging toward the hindcast mid-latitudes cold bias

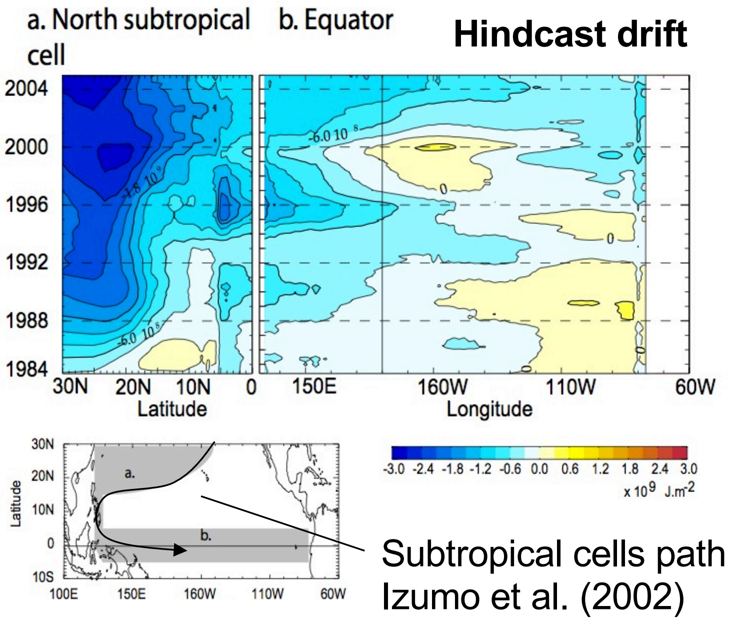
30 years leadtime

Experiment	Equatorial cooling trends of the 300m HTC ($J.m^{-2}.mth^{-1}$)
Hindcast	$-1.35\ 10^6$
Ocean only with SST restoring	$-1.73\ 10^6$
Ocean only without SST restoring	$0.1\ 10^6$

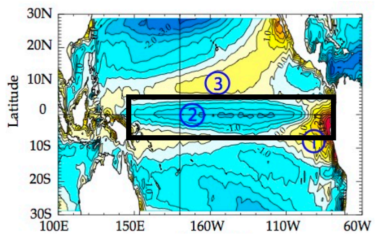
- ✓ When the midlatitudes cold SST bias is prescribed in an ocean-only experiment, the cold tongue bias develops at the equator
- ✓ The cooling trend is similar to that simulated by the control hindcast

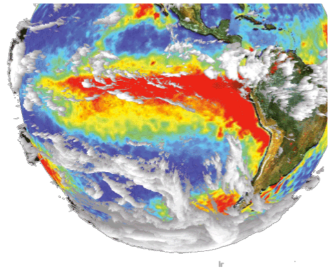
Vannière et al. (2014)

Cold tongue bias origin



Subtropical cells path according to Izumo et al. (2002)



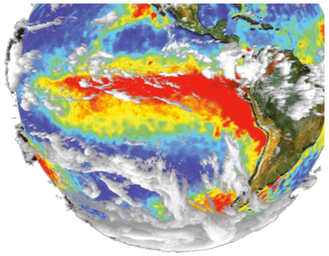


A possible cause of the midlatitude cold bias propagation is the advection by subtropical cells

Differs from other sources of the cold tongue bias (Vannière et al. 2013)

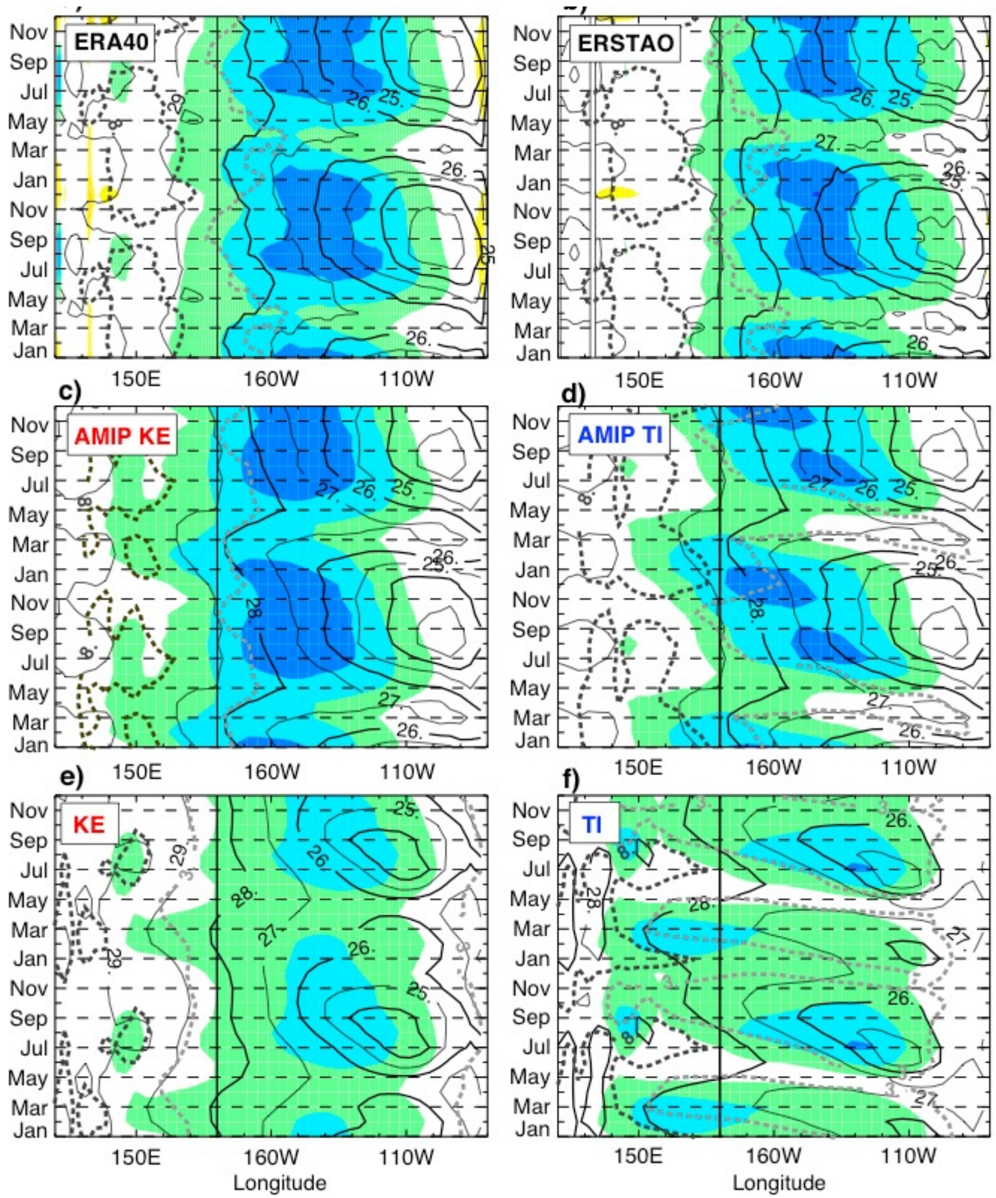
- Bjerknes feedback (Met Office)
- Atmospheric component wind errors (INGV)
- or otherwise proposed in many studies

Vannière et al. (2014)

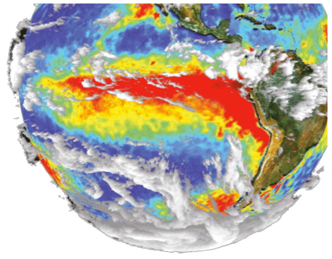


Using initialized simulations to diagnose the growth of systematic biases in GCMs - summary

- New approaches needed to address SST systematic errors
- Strategy to relate **coupled errors** to the **errors in one component** independently of the coupling:
  - 5 step 'case solving' approach
  - Requires range of dedicated simulations, including initialized
  - Proof of concept from several studies (tropical Pacific and Atl.)
  - Further benefits/costs to explore:
    - Apply during model development phase
      - cheap (300 years)
      - need to develop a 'tool box', i.e. several types of
    - Precise types of simulations will depend on 'case' i.e. SST bias – no 'standard' set
  - Can't be directly applied to SST interannual variability biases (ex: ENSO) but can be applied to ENSO mechanisms and feedbacks (not shown)
  - AMIP/T-AMIP is the starting point in the tropics - SST errors initially due to fast atmosphere biases



Mean seasonal cycle at Eq.



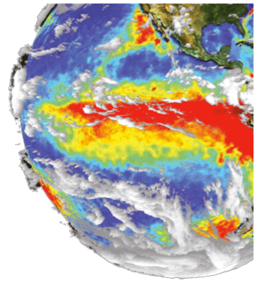
- Wind stress (shading)
- SST (solid contours)
- Precipitation (3 and 8 mm/day dashed)

- AMIP KE performs rather well
- Convection in AMIP TI too strong

- Biases amplified in coupled mode
- Semi-annual cycle in TI
- Equinoctial Central American monsoon too strong in TI (Braconnot et al. 2007)

66

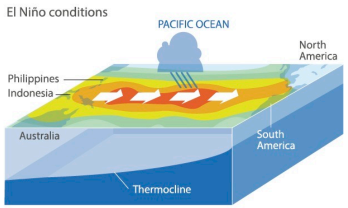
Large ensembles – a new horizon for ENSO

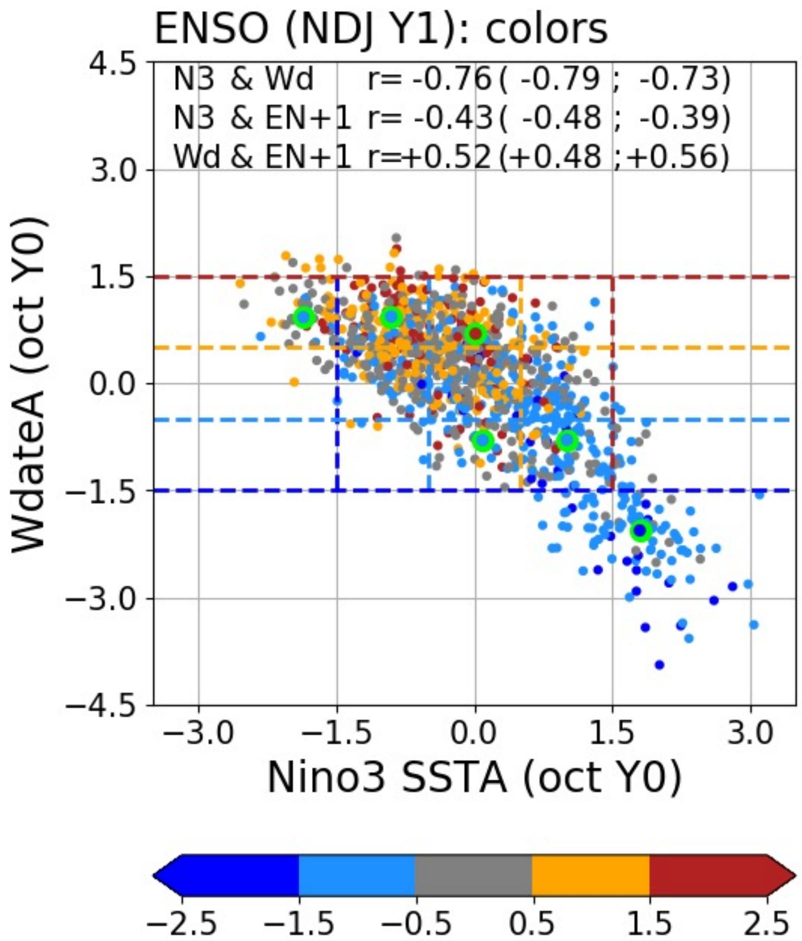


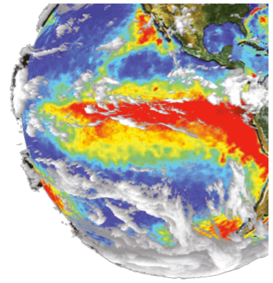
- ENSO precursors
- Distinguish external forcing from internal variability
- Better comparison with observations during historical period
- How well do models simulate ENSO? How well do we know ENSO?

Planton et al. 2022, Lee et al. 2021, Maher et al. 2020

ENSO precursors: the role of recharge





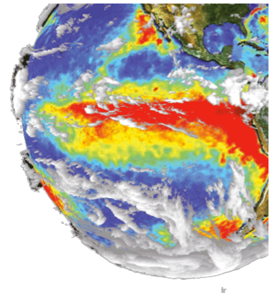


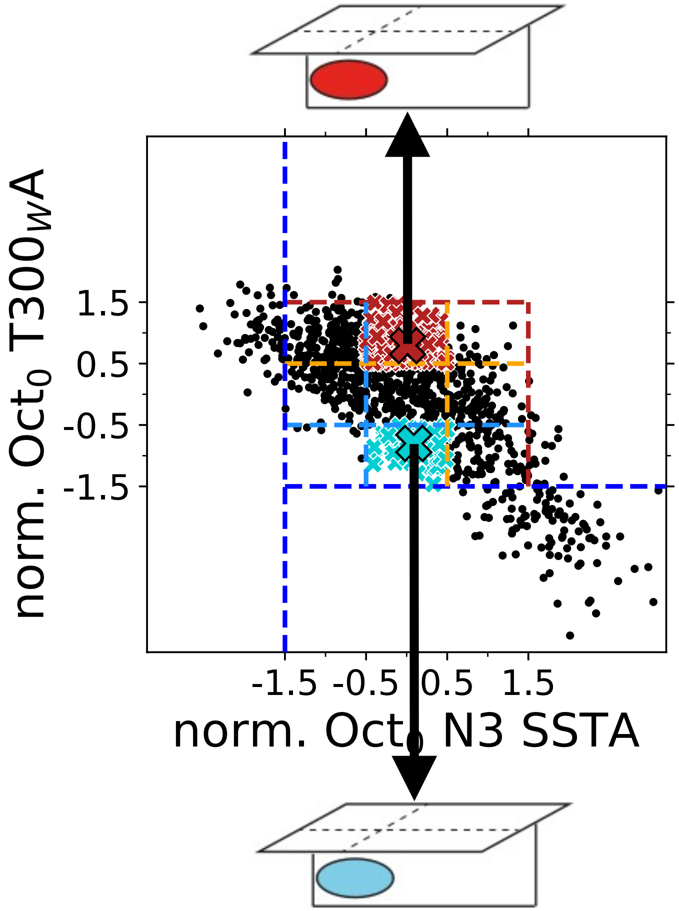
6 restarts:

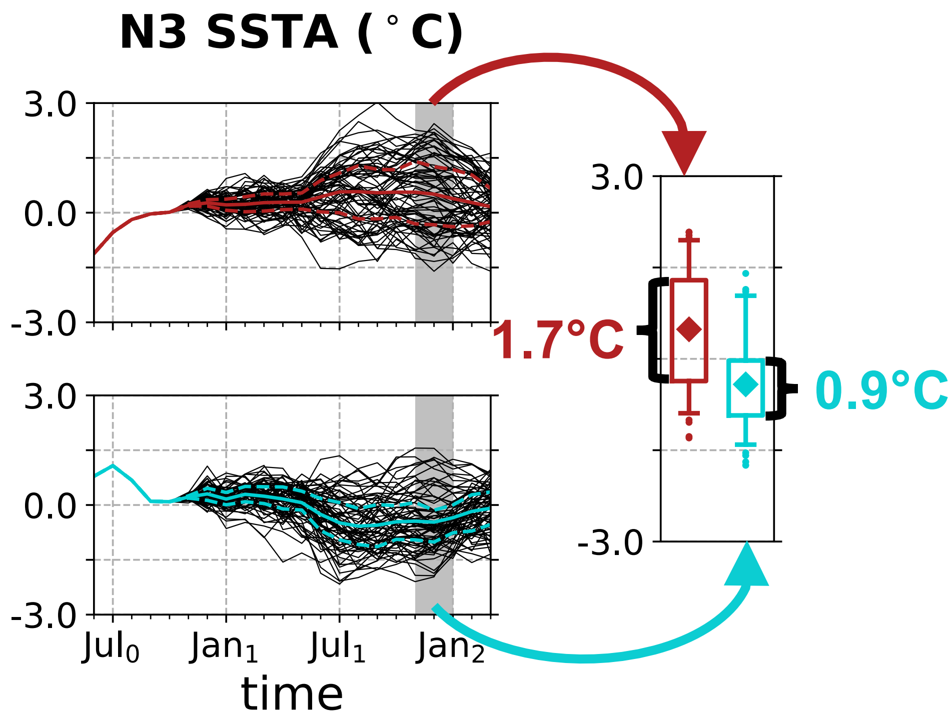
- 3 recharged
- 3 discharged
- median value of each box
- opposite two by two
- 70 members / ensemble

Planton et al. JC 2021

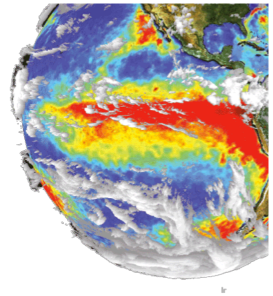
3 pairs of initial conditions were chosen to create ensemble experiments

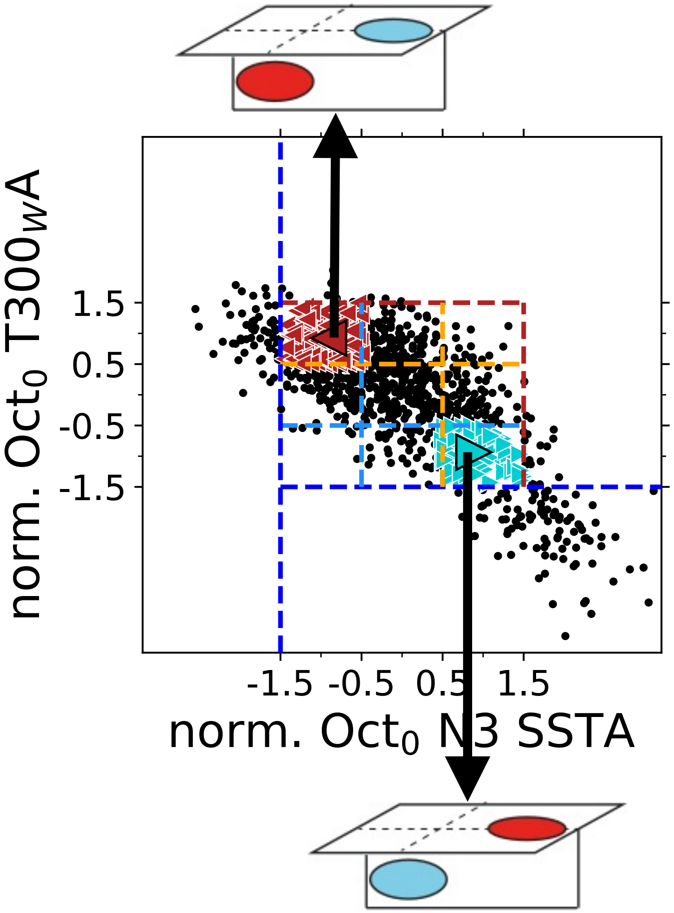


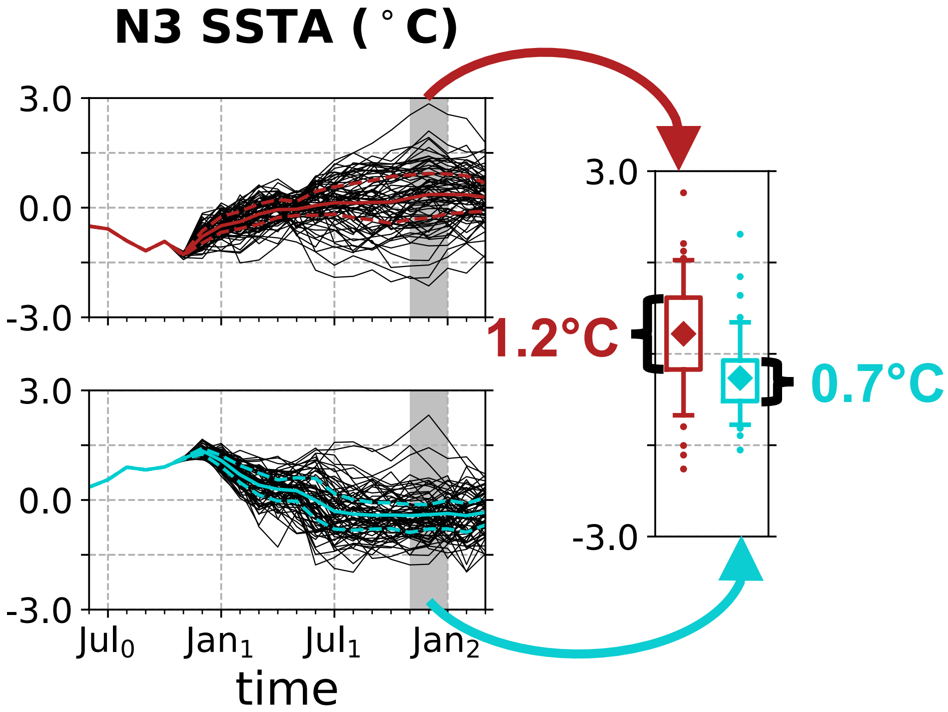




3 pairs of initial conditions were chosen to create ensemble experiments







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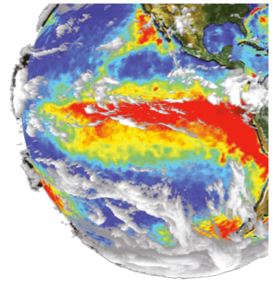
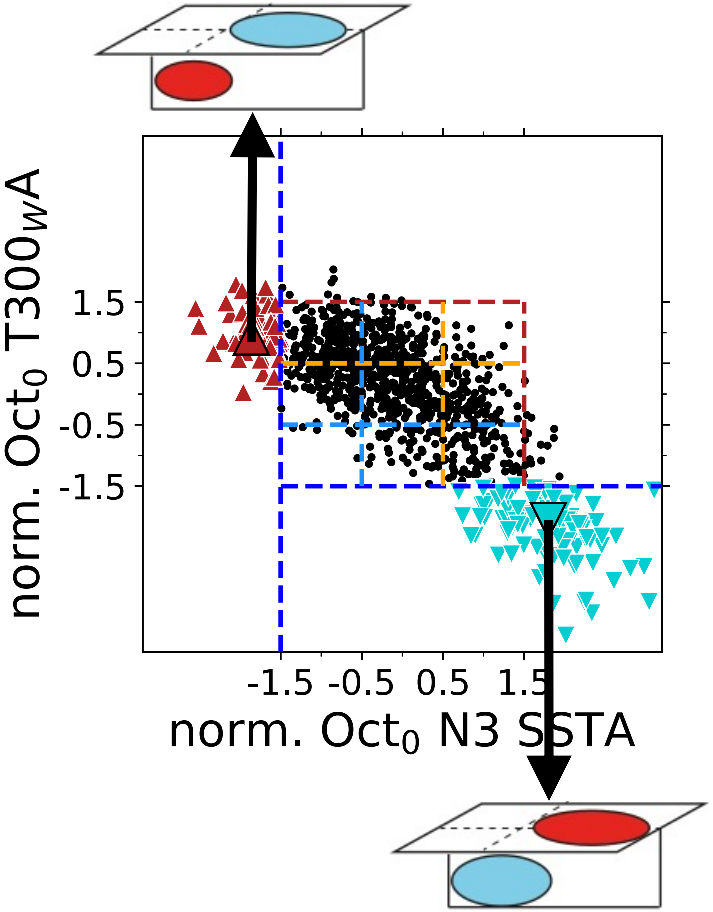
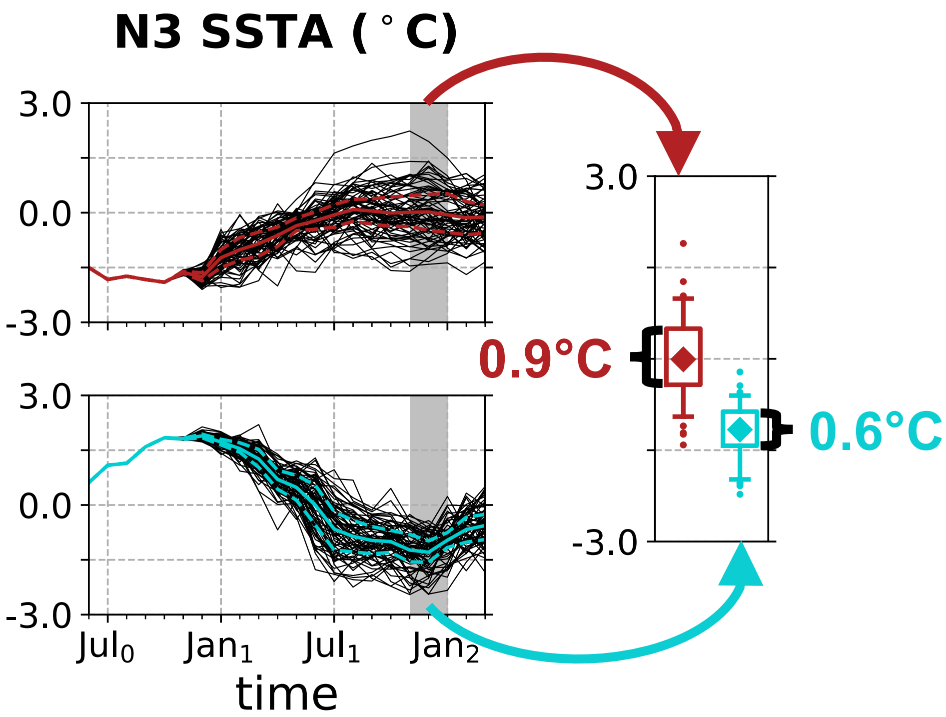
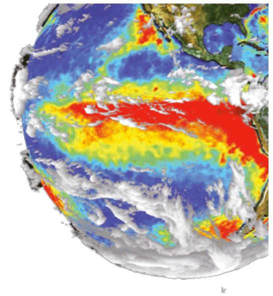
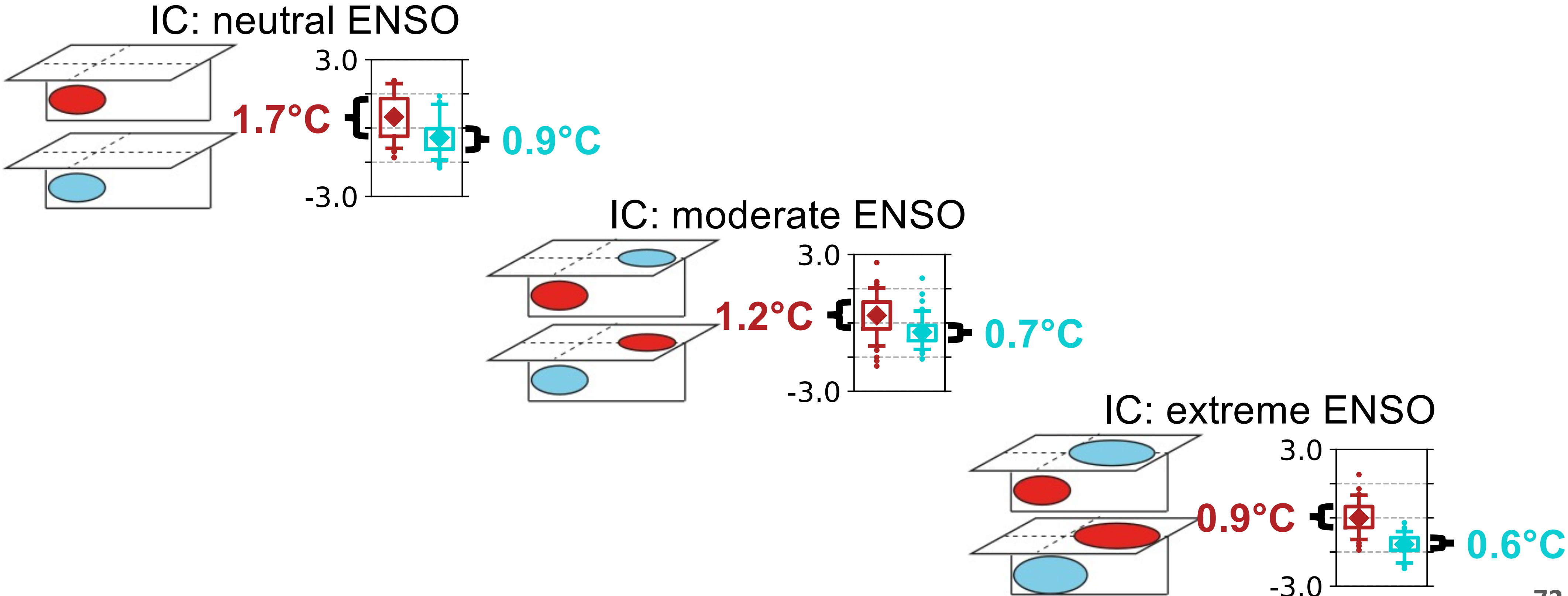






In this experimental setup, the outcome after a recharge is less predictable in every pair of experiments





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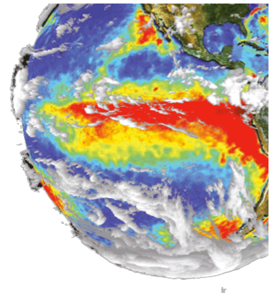
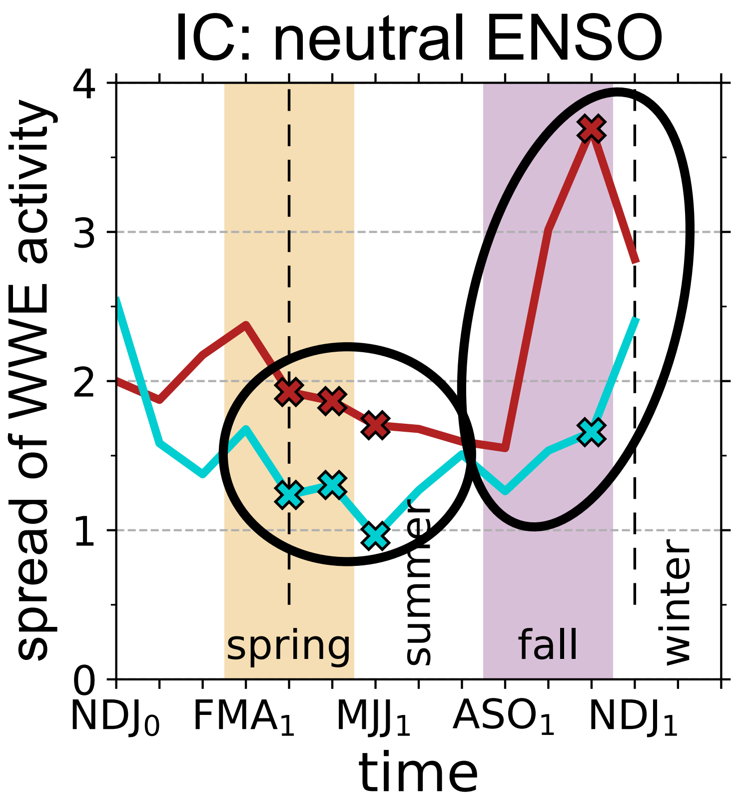
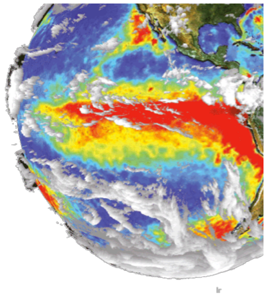




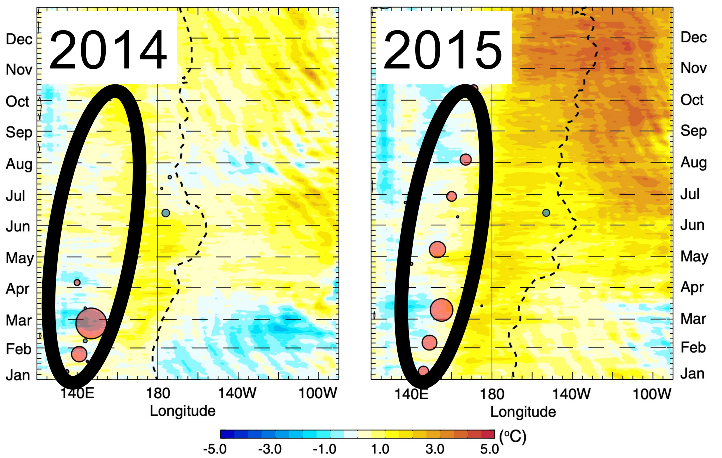
spread of WWE activity larger after a recharge than a discharge

Planton et al. JC 2021

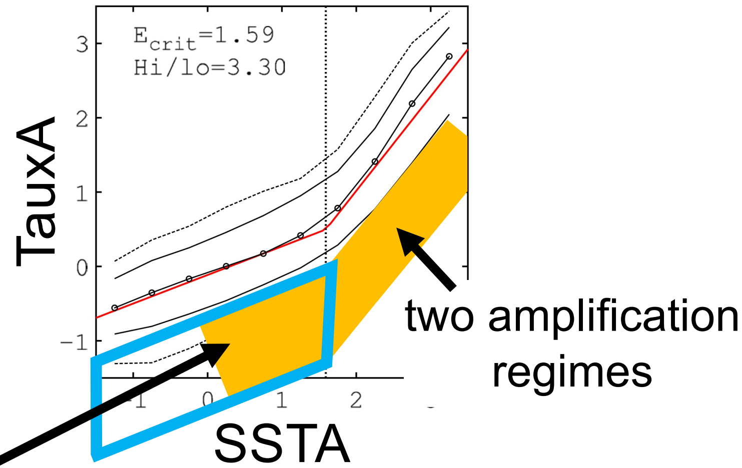
In conclusion, we found that the outcome after a recharge is less predictable due to WWE activity and the wind stress feedback nonlinearity



the spread of WWE activity after a recharge is larger, enhancing SSTA spread



the wind stress feedback after a recharge is stronger, enhancing SSTA spread



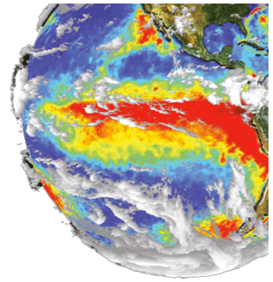
Planton et al. JC 2021

Geophysical Research Letters®

RESEARCH LETTER
10.1029/2021GL095041

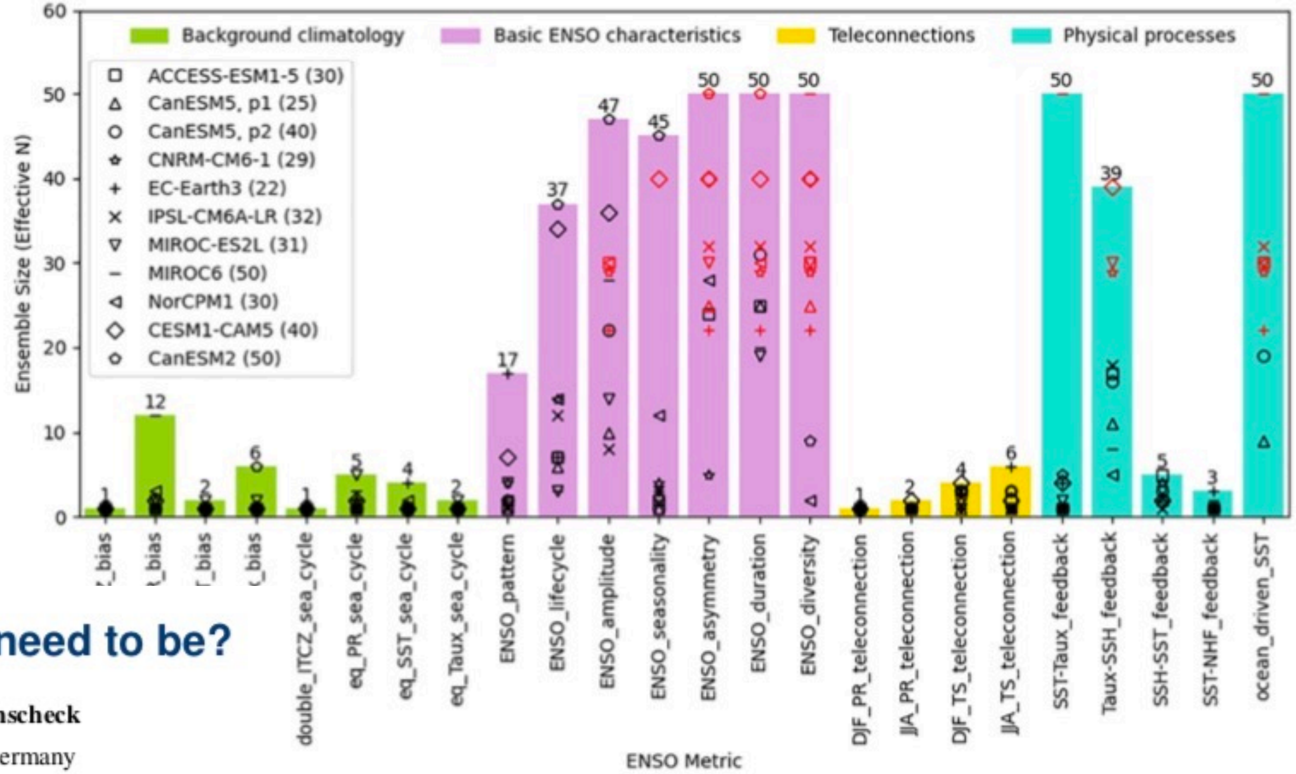
Robust Evaluation of ENSO in Climate Models: How Many Ensemble Members Are Needed?

Jiwoo Lee[1], Yann Y. Planton[2], Peter J. Gleckler[1], Kenneth R. Sperber[1], Eric Guilyardi[3,4], Andrew T. Wittenberg[5], Michael J. McPhaden[2], and Giuliana Pallotta[1]



Key Points:

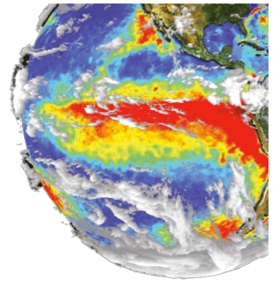
- To estimate the ensemble size required to characterize the ENSO simulation, ensemble members of



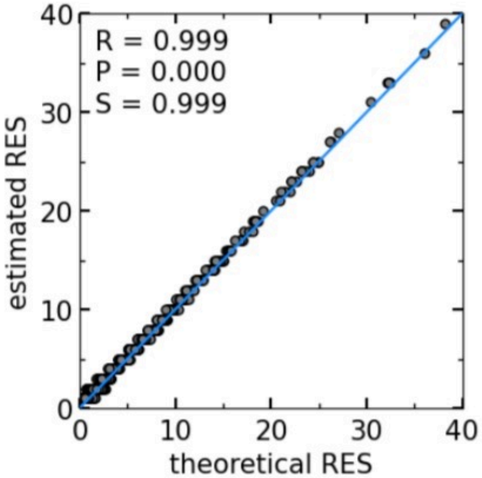
How large does a large ensemble need to be?

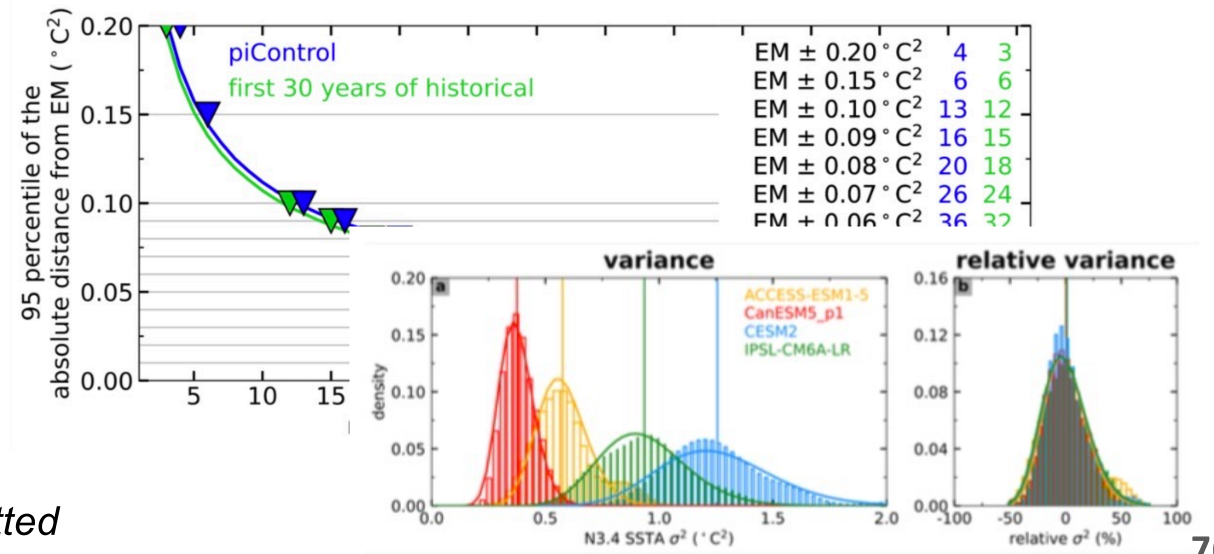
Sebastian Milinski, Nicola Maher, and Dirk Olonscheck
Max Planck Institute for Meteorology, Hamburg, Germany

Detecting ENSO Variance Changes in a Warmer World



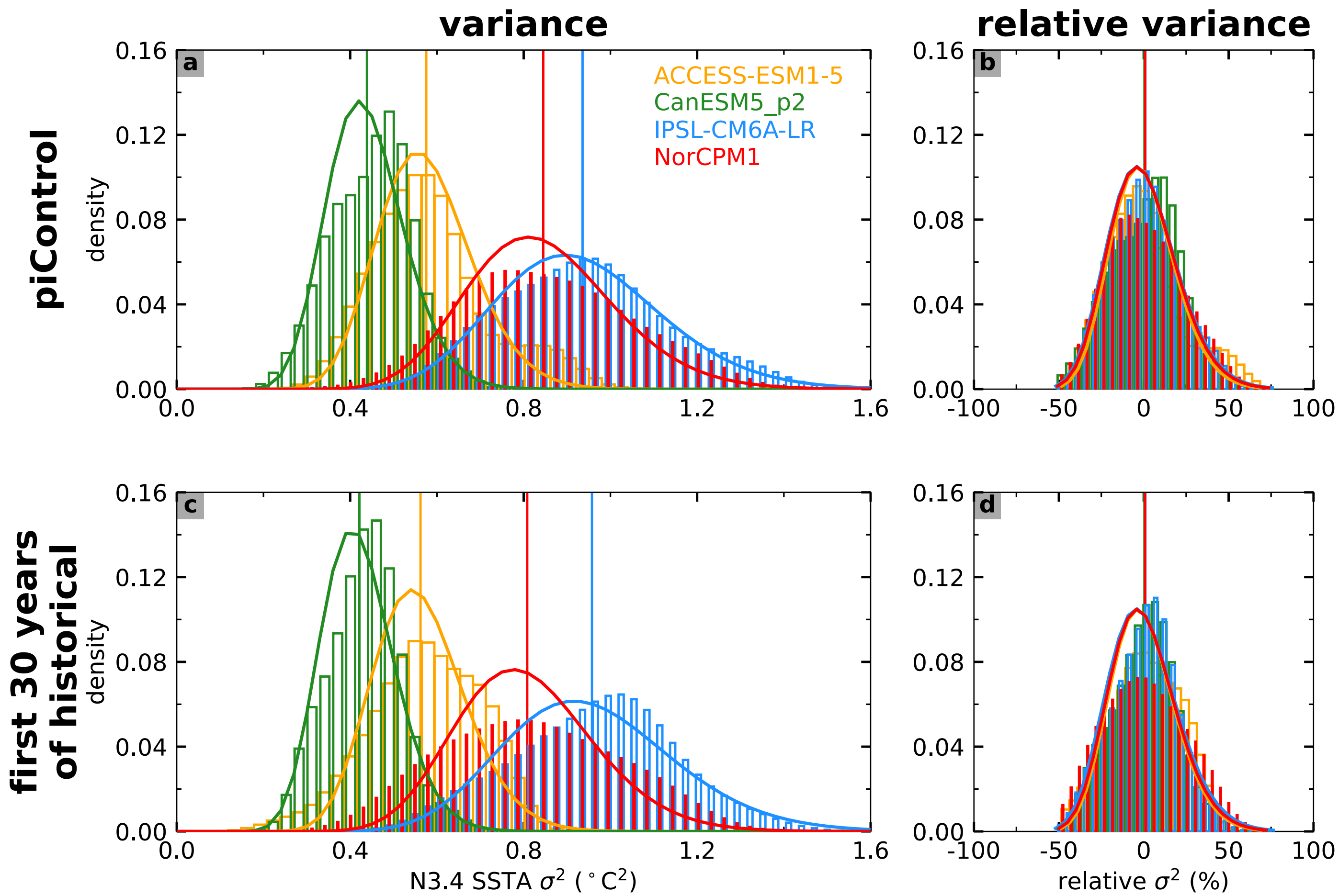
- required ensemble size (RES) depends linearly on the ensemble-variance simulated by the models and increases with the square of the desired absolute accuracy of ensemble-mean variance.





Atwood et al. 2017, Planton et al. 2022, submitted

The modulation of ENSO in CMIP6 large ensembles is χ^2 distributed

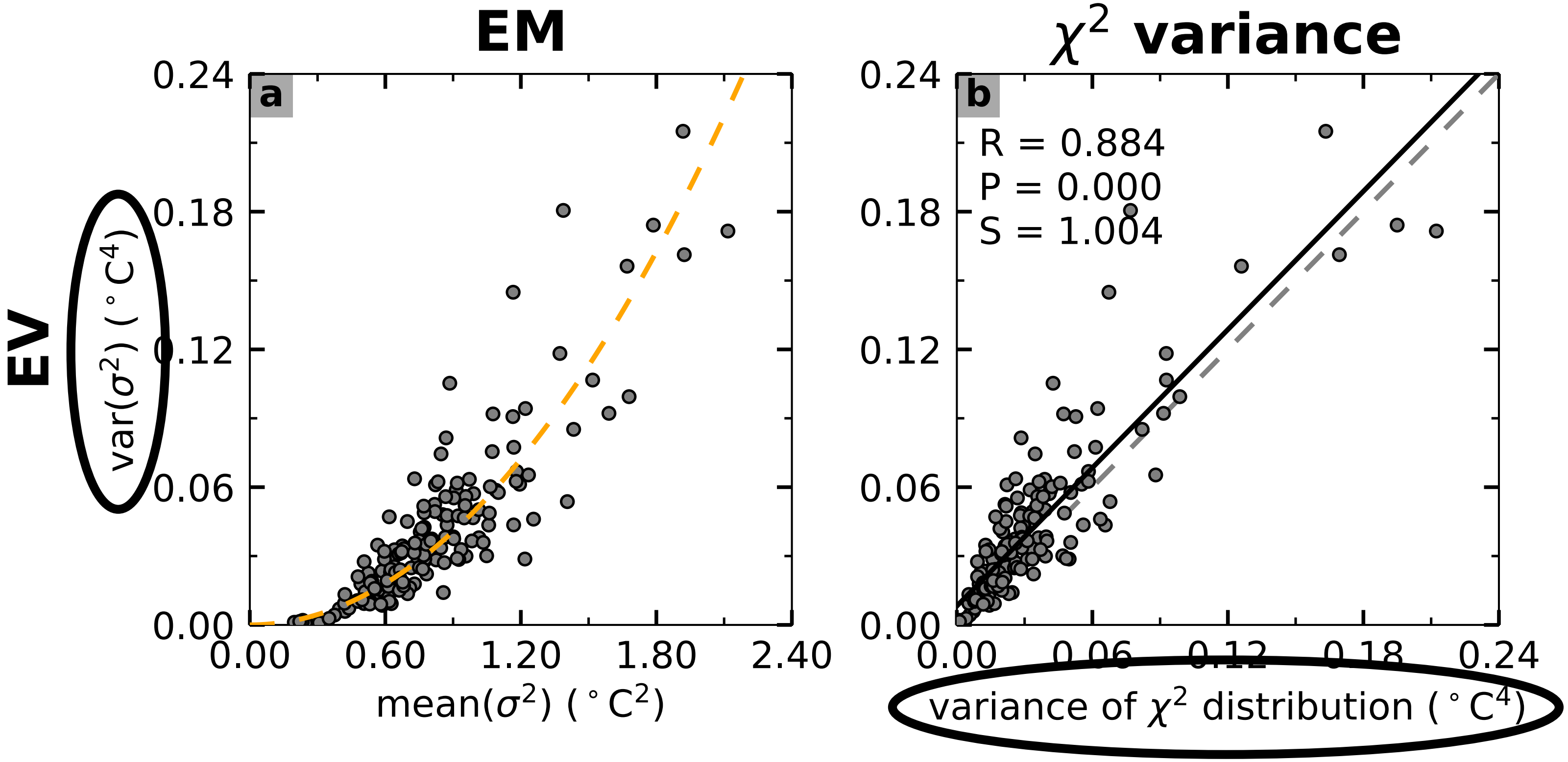


Atwood et al.’s results reproductible with CMIP6 piControl and large ensembles of historical

Planton et al. 2022, submitted

CMIP6's interannual variability close to that expected of χ^2

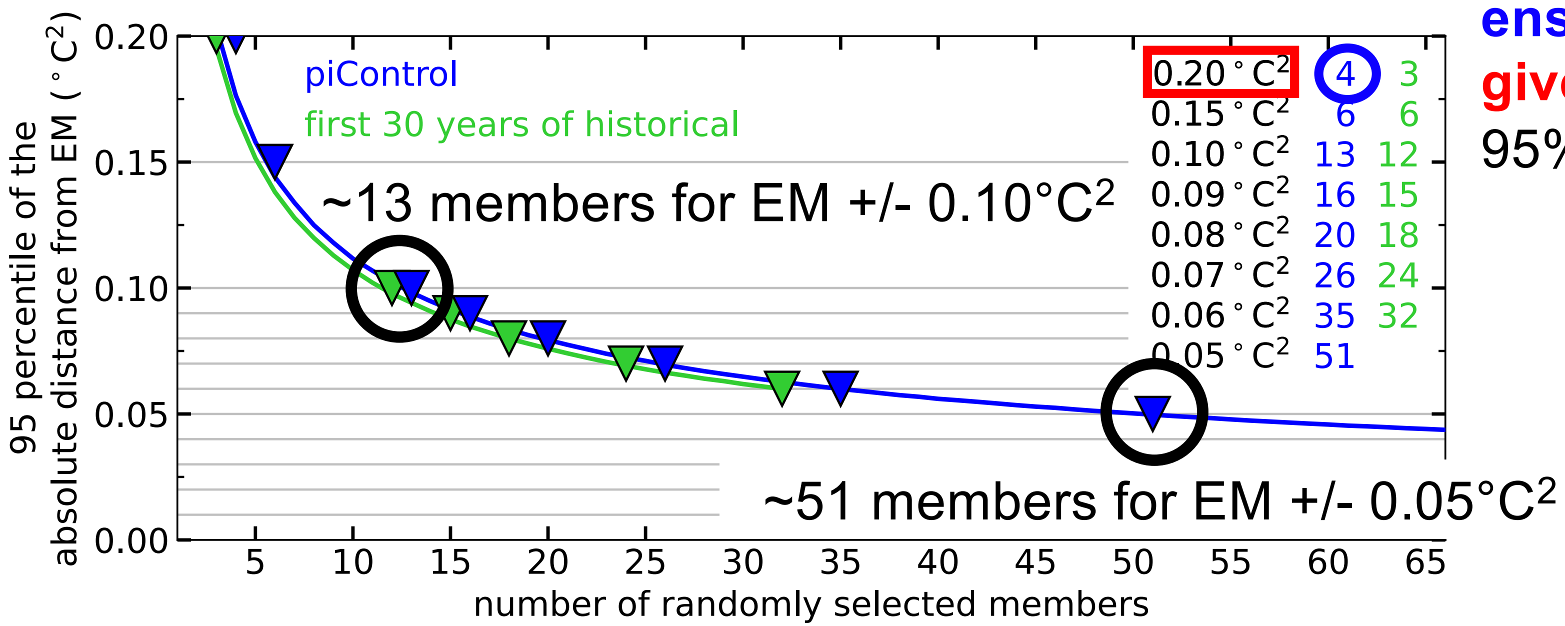
ensemble variance = internal variability



expected variance if χ^2 distributed

Planton et al. 2022, submitted

Strong increase of the required ensemble size with the desired level of accuracy



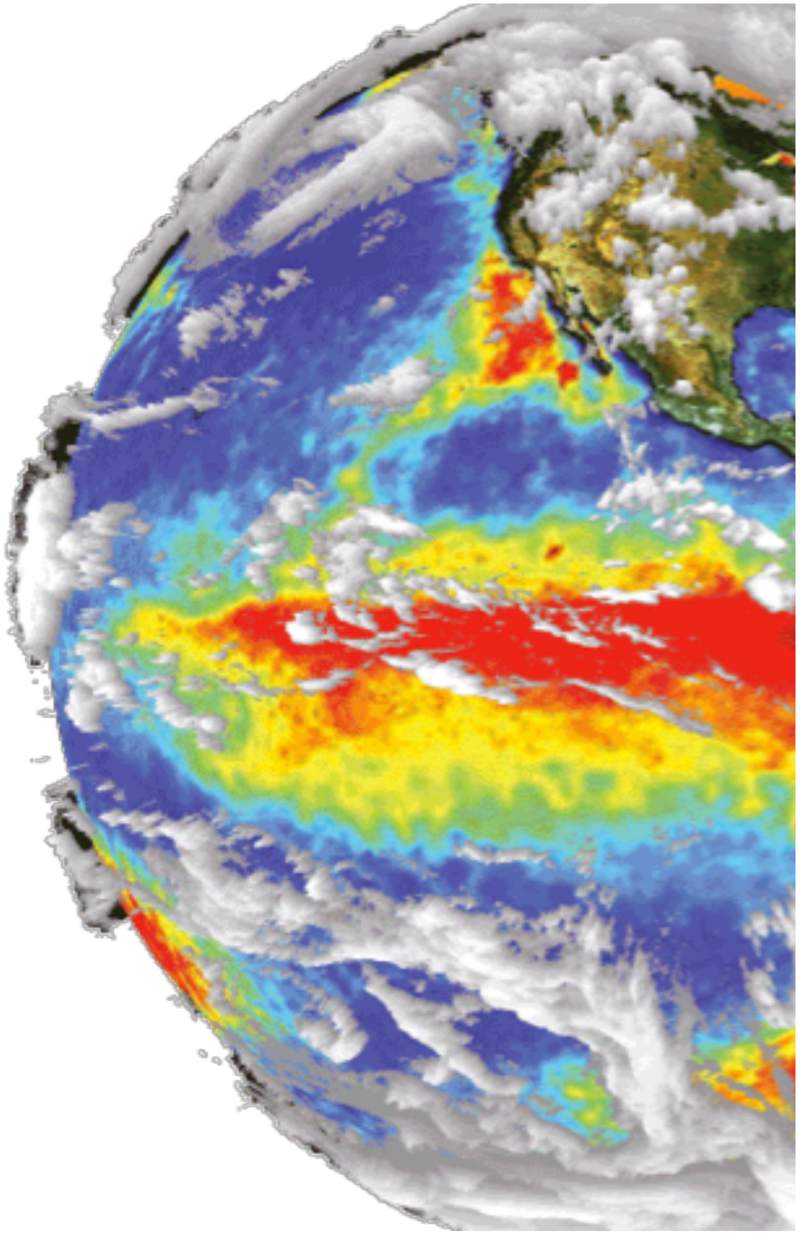
ensemble size to obtain **given accuracy** at the 95% confidence level

Planton et al. 2022, submitted

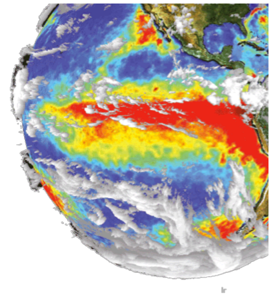
Methodology similar to:
Lee et al. 2021 GRL: Robust Evaluation of ENSO in Climate Models: How Many Ensemble Members Are Needed?

Challenges and opportunities in ENSO modelling

- Model improvement
- Using ensembles
- Using observations
- Metrics and the street lamp syndrome
- Modelling strategies



CGMs progress over the past 15+ years

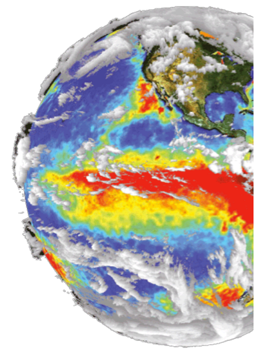


1. Virtually all CMIP-class CGCMs now have a recognizable ENSO.
   - A major target of model development.
2. Improved ENSO **amplitude, spectrum, and spatial diversity**.
   - But substantial biases and inter-model differences remain.
3. Most models now capture the **dominant** ENSO mechanisms.
   - But often not the right balance, and next-order feedbacks are missed.
4. Improvements have been **incremental** and hard-won.
   - Comprehensive models target *multiple* phemonena & scientific questions.
   - Finite resources → force compromises during development/tuning.
5. Ocean/atmosphere **grid refinements** and **improved physics** have helped a lot.
   - Enabled by faster computers.
   - Often reduce mean biases, improve ENSO teleconnections & extremes.
   - But require careful retuning & additional development.
6. Large ensembles (SMILEs) are helping address new questions
   - Distinguish external forcing from internal variability
   - Role of NL and ISO
   - Better comparison with observations and assess uncertainty

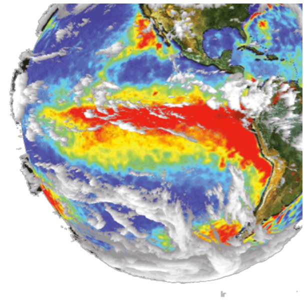
Adapted from Andrew Wittenberg

Areas primed for progress in the next 5-10 years of CLIVAR (2015)

- Improve the understanding of different physical processes that influence ENSO characteristics (frequency, amplitude, diversity,…).
- Synthesize existing ENSO evaluation methods in GCMs including bridges to theory and use of initialised simulations.
- Propose ENSO evaluation protocols and develop a strategy for coordinated ENSO analysis/metrics of CMIP models; develop and maintain an interactive website (including contribution to CMIP6).
- Sustain observing systems for ENSO research and prediction; and identify new observations needed to better constrain ENSO processes, both for the current climate and for past climates.
- Improve the understanding of how ENSO might change in the future.
- Enhance international collaboration between observationists and modelers for studies of ENSO
- Enhance applications of ENSO analysis and forecast products for targeted user communities.
- Build research capacity by contributing to the development of the next generation of talents dealing with ENSO science and prediction.



Models are both fun and demanding



- Our only tools to test understanding and provide forecasts / projections
- Help test and challenge theory
- Need careful evaluation = f(science question, obs)
- Accuracy, i.e. size of ensemble is also f(science question)
- Metrics are an exciting development
- Danger of the street lamp syndrome
- Carefully devise experiments for specific question and understand the limits
- Engage with other communities (theory, model, obs, impacts…)

Advance notice for later discussion !

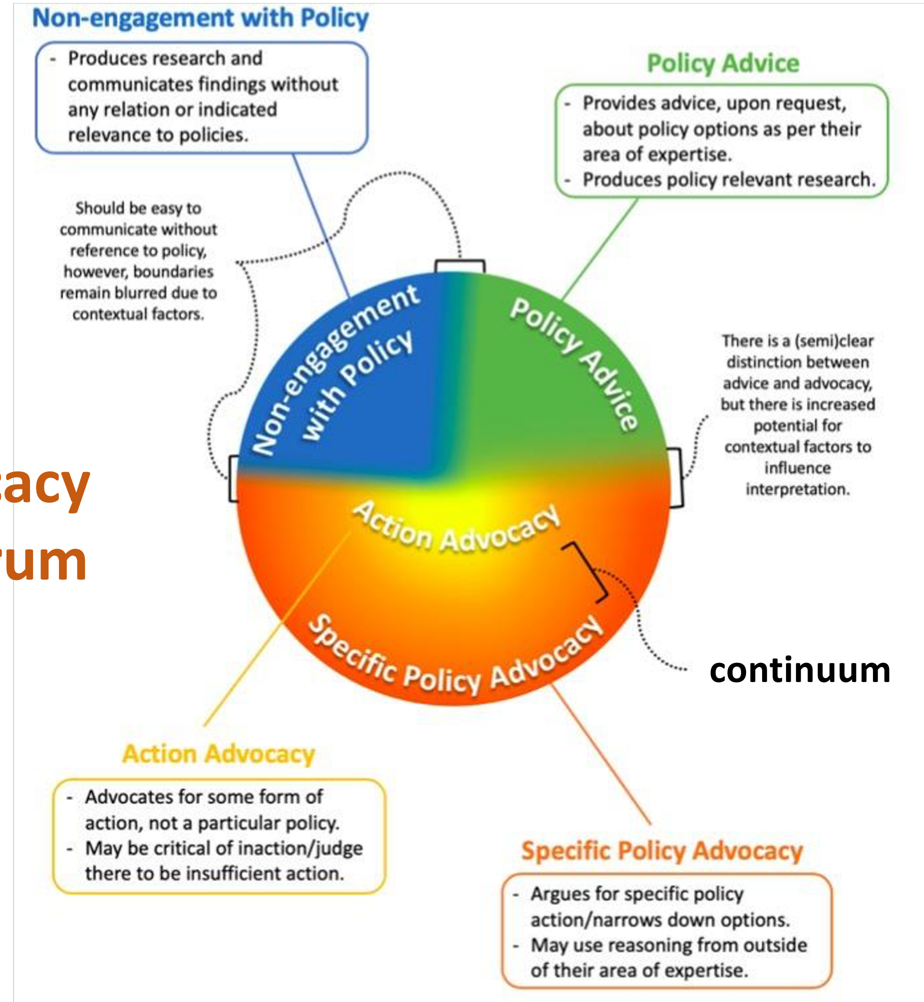
Ethics of advocacy/engagement of climate scientists in society

- New issue for environmental scientists (e.g. climate science)
- Scientist vs. expert vs. citizen vs. activist ?
- Neutrality, values-based, trust, credibility, legitimacy ?
- Naive, manipulated, irrelevant ?
- Technocracy vs. democracy ?
- Public good vs, private interests, medias, politicians ?
- Which hat to wear? Which advocacy?
- Cf. COVID and numerous historical examples (Manhattan project, bio-ethics,…)

Research integrity vs. reserch ethics ?

How should climate change scientists engage in policy advocacy ?

Advocacy spectrum



Contextual factors :

- Influences perception
- Miss goal on target
- Miss target (« stealth advocacy »)

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