

ENSO Metrics: Status & Next Steps



Presented by **Andrew Wittenberg**

with contributions from

Yann Planton, Jiwoo Lee, and the ENSO Metrics Team

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ENSO Metrics: Background



CLIVAR Research Focus: ENSO in a Changing Climate

<http://www.clivar.org/research-foci/enso>

2014-2018; then merged back into CLIVAR PRP

Co-chairs: E. Guilyardi (IPSL) & A. Wittenberg (NOAA GFDL)

Implementation & application: **Yann Planton** (IPSL/PMEL)

12 ENSO experts (France, US, Australia, Japan, Korea, UK)

Goals:

- Understand ENSO **processes** & **past/future changes**
- Develop **evaluation** protocol for ENSO in GCMs
- Target **obs** to improve models & projections

ENSO Performance: Andrew, Yann, Antonietta, Mike, Matt, Scott, ...

Teleconnections: Scott, Yann, Shayne, Cai, ...

Processes: Yann, Eric, Soon-Il, Fei-Fei, Tobias, ...

Community package liaisons:

PMP: **Jiwoo Lee** & Peter Gleckler (PCMDI)

ESMValTool: Veronika Eyring (DLR); Bryan Lawrence (NCAS); Barcelona (BSC)

CliMAF: Jérôme Servonnat (IPSL)

ENSO metrics strategy

Start with a small subset of **essential, simple** metrics.
Avoid getting bogged down with complexity
Aim more at model *users* than model developers.
Expand as code, interfaces, use-cases take shape.

Metrics (scalars) are first step in a **diagnostic hierarchy**
Useful for intercomparing models & metrics
Dive-down diagnostics: Scalar \rightarrow 1d \rightarrow 2d \rightarrow 3d
Want to see both “forest” and “trees”.

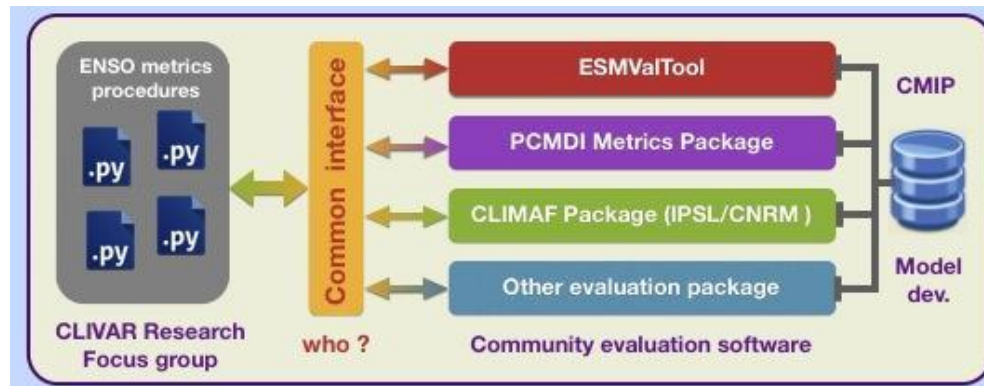


Account for:

- **Internal variability** (multiple historical ensemble members)
- **Obs uncertainties** (use multiple obs products, epochs)

Written in **Python**

Powerful, flexible
Plugs into community efforts



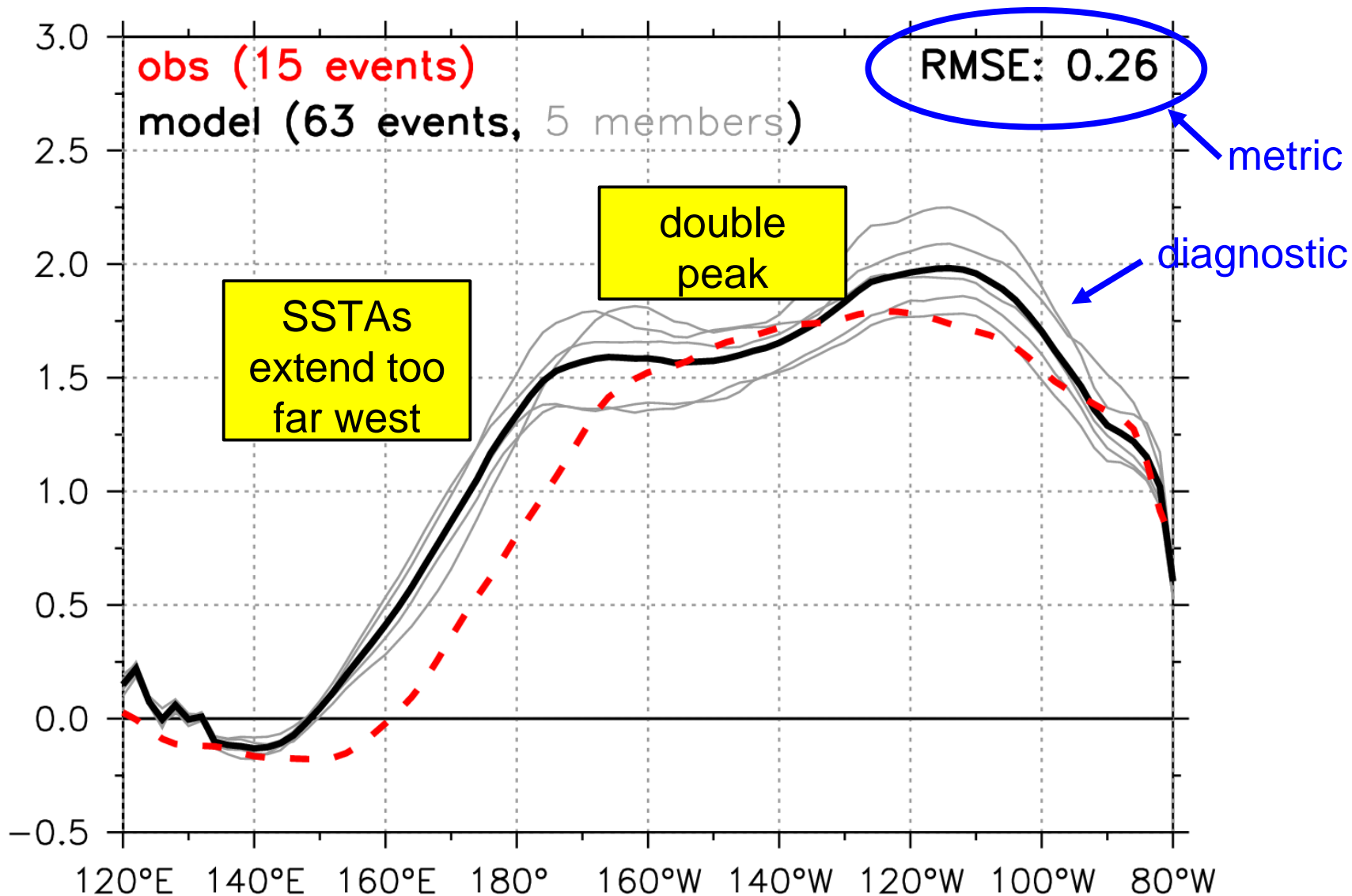
Metric Requirements

1. **Documentation:** Whys & hows of metric and collection
2. Math **definition** of metric (positive scalar “distance”)
3. Input data **frequency** (monthly, daily, ...) and **grid** (1x1 lat/lon, region, etc.)
4. **Obs** (as many as possible) and **epoch** to use
5. Literature **reference** to show robustness/utility of metric
6. **Sample size** (duration or ensemble) needed for metric to make sense
7. Dive-down **diagnostics** (e.g. the spatial maps used to compute RMSE)
8. **Normalization** to use for multi-model intercomparison (single color bar)

Warm events: SSTA ($^{\circ}\text{C}$, $y=0$, $t=\text{Dec}(0)$)

detrended, smoothed with 5mo triangle

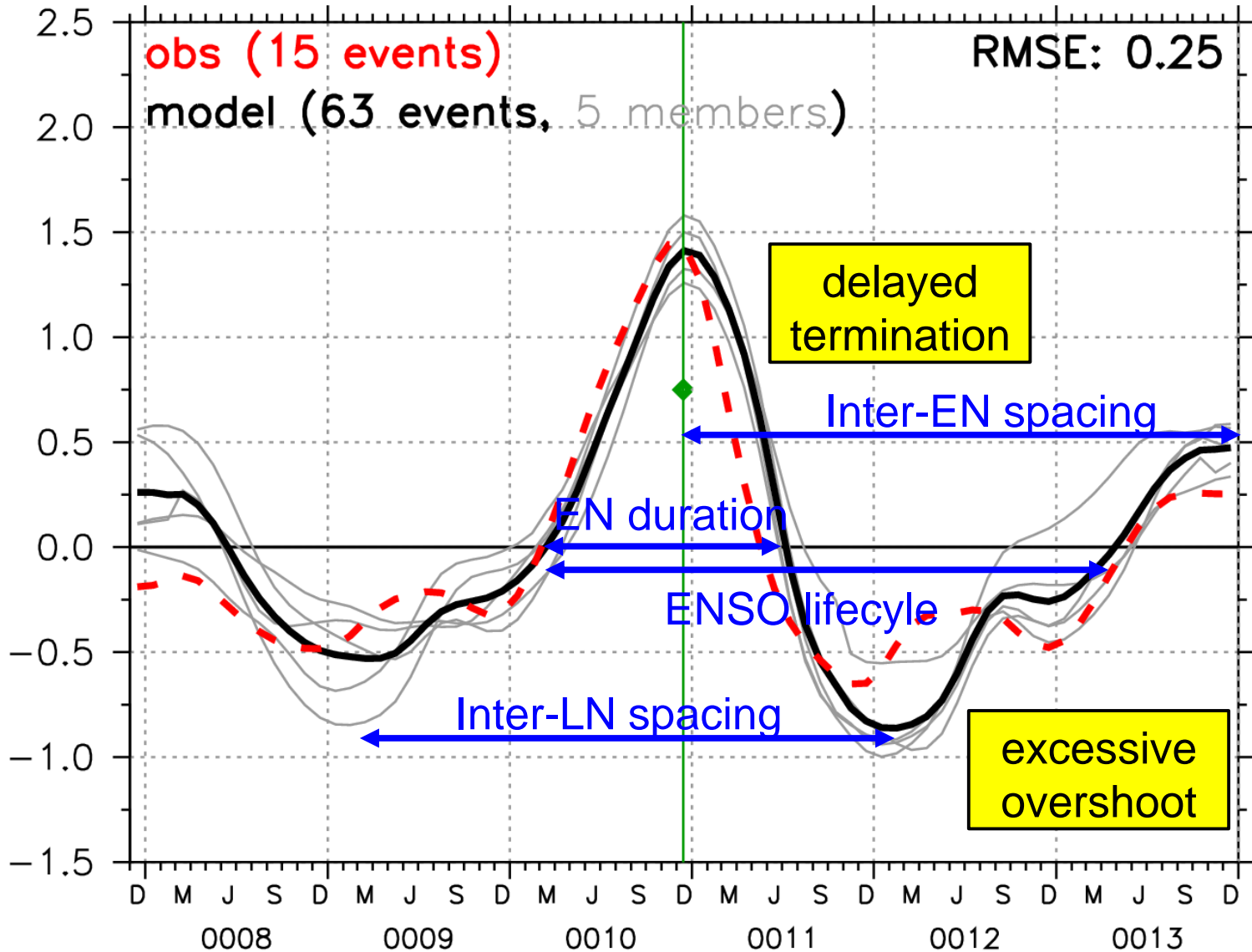
1961–2016 composite, **Dec(0) NINO3 SSTA $> 0.75^{\circ}\text{C}$**



Warm events: NINO3 SSTA (°C)

detrended, smoothed with 5mo triangle

1961–2016 composite, Dec(0) NINO3 SSTA > 0.75°C



ENSO performance

RMSE-based metrics

- Colors: *relative* to median value of metric (last column)
- Numbers: metric value

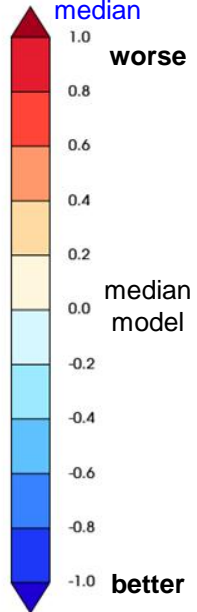
metrics

ENSO_perf, Rmse

numbers: RMSE relative to obs
(perfect score is 0)

Number: Metric value, Color: Normalized by median (each row)

colors:
medians
from
inter-model
median



SeasonalSstLonRmse (C)	0.26	0.22	0.22	0.20	0.19	0.19	0.21	0.18	0.13	0.15	0.16	0.17	0.24	0.18	0.21	0.21	0.17	0.33	0.22	0.13	0.28	0.08	0.31	0.29	0.27	0.27	0.14	0.18	0.15	0.16	0.16	0.45	0.10	0.13	0.21	0.26	0.32	0.19	0.22	0.56	0.56	0.21	0.20	0.22	0.17	0.10	0.22	0.20	
SeasonalSstLatRmse (C)	0.13	0.18	0.20	0.22	0.16	0.17	0.21	0.16	0.19	0.19	0.19	0.08	0.15	0.20	0.43	0.45	0.27	0.20	0.24	0.19	0.46	0.22	0.25	0.25	0.17	0.17	0.15	0.19	0.21	0.19	0.18	0.39	0.36	0.33	0.22	0.31	0.40	0.09	0.21	0.29	0.29	0.27	0.39	0.26	0.24	0.21	0.24	0.21	
SeasonalPrLatRmse (mm/day)	1.21	1.29	1.60	1.76	1.77	1.84	1.42	1.80	1.59	0.64	0.68	1.44	1.45	1.44	1.02	1.05	1.00	1.06	0.99	2.30	1.62	1.86	1.08	1.13	0.81	0.82	2.01	2.08	1.65	1.50	1.57	1.11	1.48	1.52	1.21	0.86	1.35	0.75	0.68	0.38	0.38	1.62	1.67	1.59	1.51	1.44	1.33	1.44	
NinoSstTsRmse_2 (C)	0.30	0.36	0.34	0.53	0.48	0.36	0.37	0.25	0.27	0.30	0.40	0.85	0.37	0.28	0.21	0.26	0.36	0.23	0.24	0.28	0.35	0.76	0.30	0.33	0.30	0.32	0.74	0.49	0.37	0.33	0.41	0.32	0.36	0.31	0.28	0.30	0.34	0.82	0.70	0.44	0.43	0.47	0.42	0.45	0.20	0.28	0.39	0.34	
NinoSstTsRmse_1 (C)	0.26	0.40	0.36	0.44	0.45	0.36	0.37	0.24	0.26	0.24	0.38	0.70	0.40	0.28	0.23	0.26	0.35	0.22	0.24	0.26	0.33	0.64	0.29	0.32	0.29	0.28	0.74	0.48	0.37	0.34	0.44	0.29	0.35	0.30	0.29	0.30	0.33	0.77	0.70	0.42	0.47	0.49	0.44	0.41	0.18	0.28	0.38	0.35	
NinoSstLonRmse_2 (C)	0.28	0.44	0.50	0.46	0.48	0.26	0.52	0.27	0.45	0.56	0.48	0.72	0.57	0.28	0.16	0.21	0.78	0.46	0.40	0.31	0.62	0.76	0.61	0.44	0.47	0.60	0.24	0.23	0.47	0.36	0.41	0.75	0.51	0.56	0.39	0.45	0.51	0.77	0.57	0.80	0.70	0.51	0.59	0.52	0.15	0.24	0.47	0.47	
NinoSstLonRmse_1 (C)	0.19	0.37	0.32	0.30	0.36	0.26	0.49	0.29	0.39	0.42	0.42	0.48	0.43	0.28	0.15	0.21	0.88	0.45	0.36	0.32	0.62	0.61	0.47	0.39	0.35	0.38	0.22	0.23	0.35	0.32	0.34	0.63	0.44	0.54	0.27	0.46	0.46	0.64	0.53	0.59	0.57	0.55	0.50	0.49	0.16	0.24	0.41	0.39	
NinaSstTsRmse_2 (C)	0.36	0.36	0.54	0.63	0.32	0.34	0.25	0.33	0.29	0.31	0.28	0.67	0.35	0.33	0.41	0.39	0.34	0.37	0.32	0.44	0.39	0.49	0.45	0.46	0.36	0.39	0.62	0.33	0.37	0.33	0.39	0.39	0.36	0.38	0.35	0.39	0.44	0.49	0.40	0.45	0.42	0.36	0.37	0.31	0.30	0.31	0.39	0.37	
NinaSstTsRmse_1 (C)	0.28	0.27	0.54	0.63	0.34	0.32	0.26	0.35	0.28	0.37	0.30	0.53	0.31	0.35	0.43	0.38	0.24	0.38	0.31	0.47	0.30	0.45	0.41	0.43	0.28	0.34	0.57	0.37	0.30	0.26	0.29	0.31	0.31	0.31	0.34	0.36	0.35	0.46	0.41	0.38	0.28	0.30	0.30	0.31	0.28	0.28	0.35	0.33	
NinaSstLonRmse_2 (C)	0.34	0.43	0.45	0.40	0.31	0.25	0.35	0.22	0.32	0.48	0.33	0.38	0.51	0.17	0.23	0.19	0.52	0.26	0.31	0.38	0.47	0.52	0.52	0.38	0.47	0.38	0.31	0.28	0.33	0.33	0.30	0.60	0.46	0.51	0.39	0.30	0.39	0.44	0.37	0.80	0.71	0.40	0.50	0.36	0.29	0.28	0.39	0.38	
NinaSstLonRmse_1 (C)	0.31	0.31	0.30	0.37	0.28	0.25	0.33	0.22	0.32	0.37	0.36	0.15	0.31	0.05	0.22	0.21	0.57	0.28	0.30	0.47	0.37	0.43	0.33	0.48	0.23	0.21	0.34	0.22	0.32	0.32	0.33	0.33	0.35	0.32	0.36	0.22	0.29	0.31	0.41	0.34	0.47	0.42	0.34	0.32	0.33	0.33	0.28	0.32	0.32
BiasTauxLonRmse (1e-3 N/m2)	7.73	6.44	5.29	5.96	5.56	5.93	6.36	4.59	6.08	7.19	12.37	4.33	9.12	7.84	9.13	6.31	12.05	5.01	14.41	5.88	21.20	22.23	17.94	18.17	10.51	5.22	8.85	6.27	6.65	4.67	8.04	9.70	12.59	2.85	9.40	3.72	3.75	8.84	9.72	9.13	9.53	9.57	9.15	8.44					
BiasTauxLatRmse (1e-3 N/m2)	6.10	10.70	3.69	4.02	5.40	3.57	6.03	2.81	4.41	5.76	8.55	3.11	7.81	6.88	8.71	8.24	7.18	3.34	7.95	6.61	15.40	14.45	9.31	9.48	11.13	10.11	7.22	6.99	7.14	7.37	9.81	5.46	8.38	5.56	7.14	11.11	10.87	8.70	6.94	9.01	8.18	8.65	7.67	7.59					
BiasSstLonRmse (C)	0.64	0.62	0.98	0.59	0.37	0.34	1.06	0.30	0.62	0.30	0.36	0.65	0.27	0.23	0.94	1.12	2.74	1.09	1.03	1.09	1.67	1.24	0.86	1.02	1.03	1.03	0.63	0.43	0.79	1.19	1.18	1.40	1.42	1.01	0.58	1.68	0.80	1.06	1.04	2.16	2.14	1.71	1.43	1.81	0.82	1.02	1.01	1.02	
BiasSstLatRmse (C)	0.61	0.49	0.67	1.24	0.43	0.49	0.69	0.45	0.48	0.49	0.58	1.25	0.55	0.62	0.52	0.73	1.58	0.36	0.23	0.80	1.33	0.67	0.99	1.10	1.02	1.02	1.15	0.77	0.65	0.99	0.99	0.85	1.12	0.83	0.29	1.14	0.63	0.78	0.91	1.65	1.64	1.15	1.12	1.21	0.97	1.23	0.86	0.81	
BiasPrLonRmse (mm/day)	0.58	1.38	1.38	1.29	1.62	1.59	1.87	1.50	1.87	1.27	1.91	1.60	1.69	1.62	1.06	1.19	3.99	1.77	0.89	2.22	3.38	2.00	1.49	1.43	1.66	1.66	1.20	1.36	1.25	1.07	1.38	2.69	3.27	3.47	1.41	3.71	1.71	2.04	1.03	1.92	1.87	3.96	3.52	4.06	0.81	0.86	1.88	1.62	
BiasPrLatRmse (mm/day)	1.67	1.36	2.52	3.27	1.47	1.58	1.51	1.47	1.85	0.89	1.15	2.46	2.05	2.11	1.93	1.82	1.28	0.89	1.92	2.27	2.35	2.35	3.46	3.44	2.38	2.39	2.66	2.32	1.15	0.98	1.09	2.36	1.91	1.79	1.62	1.35	1.46	0.87	0.34	0.80	0.79	2.01	2.11	1.94	1.33	1.29	1.79	1.80	

different
composite
thresholds

models

* = CMIP6

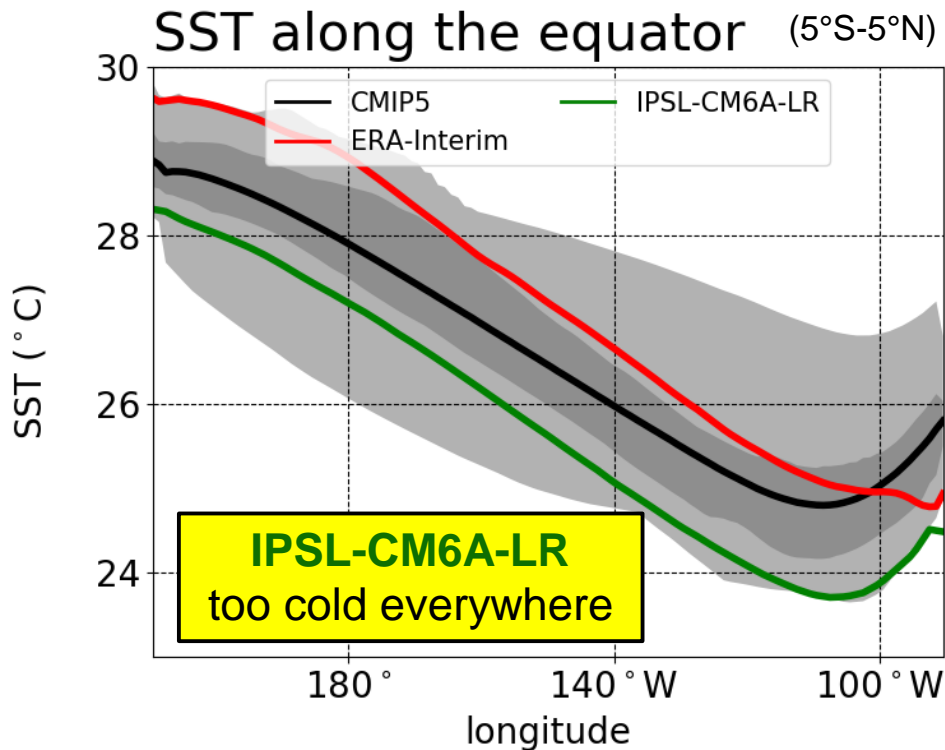
Dive-down diagnostics: Annual-mean SST

Metric:

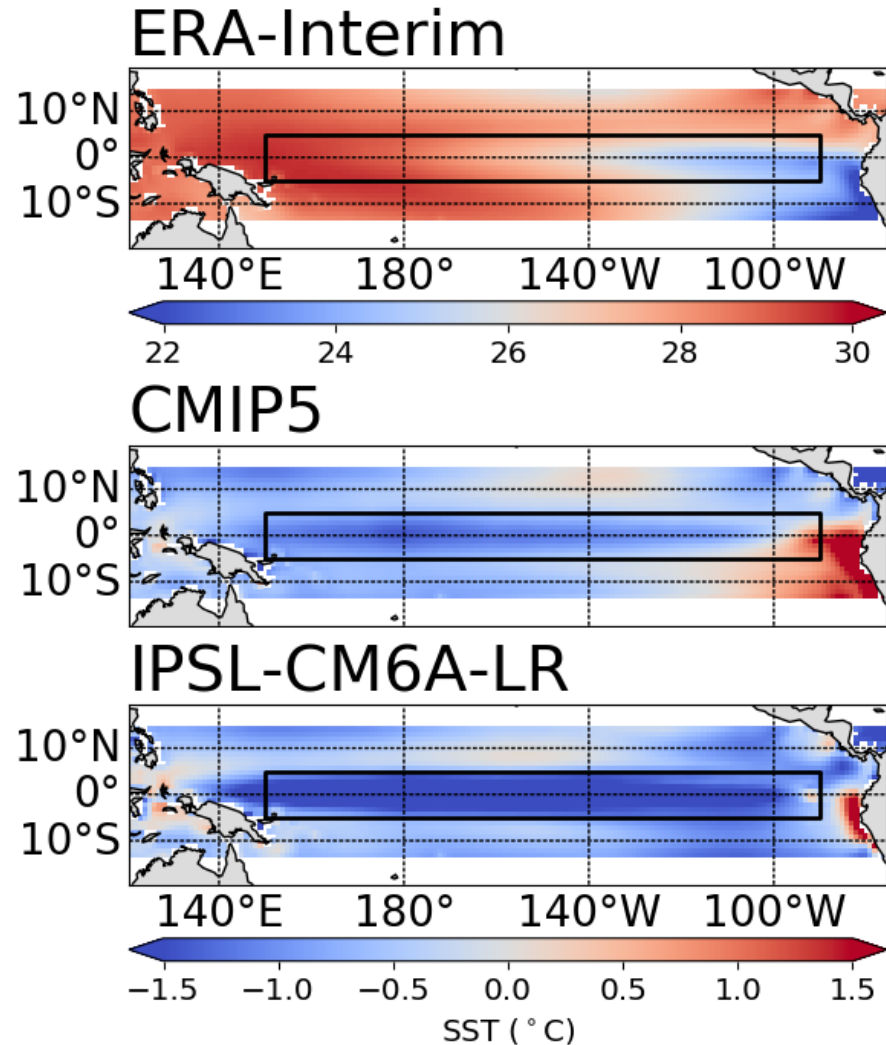
RMSE(obs, model)

IPSL-CM6A-LR = 1.6°C

Dive-down level 1:



Dive-down level 2:



ENSO Metrics: Public Release & Documentation

[Planton et al. \(BAMS 2021\)](#)

“Evaluating climate models with the CLIVAR 2020 ENSO metrics package.”

- Documents & demonstrates the package
- **CMIP6 models mostly outperform CMIP5, except for some process metrics** (e.g., the h → SST coupling worsened)

CMIP5/6 ENSO Metrics summary

<https://pcmdi.llnl.gov/research/metrics/ens0>

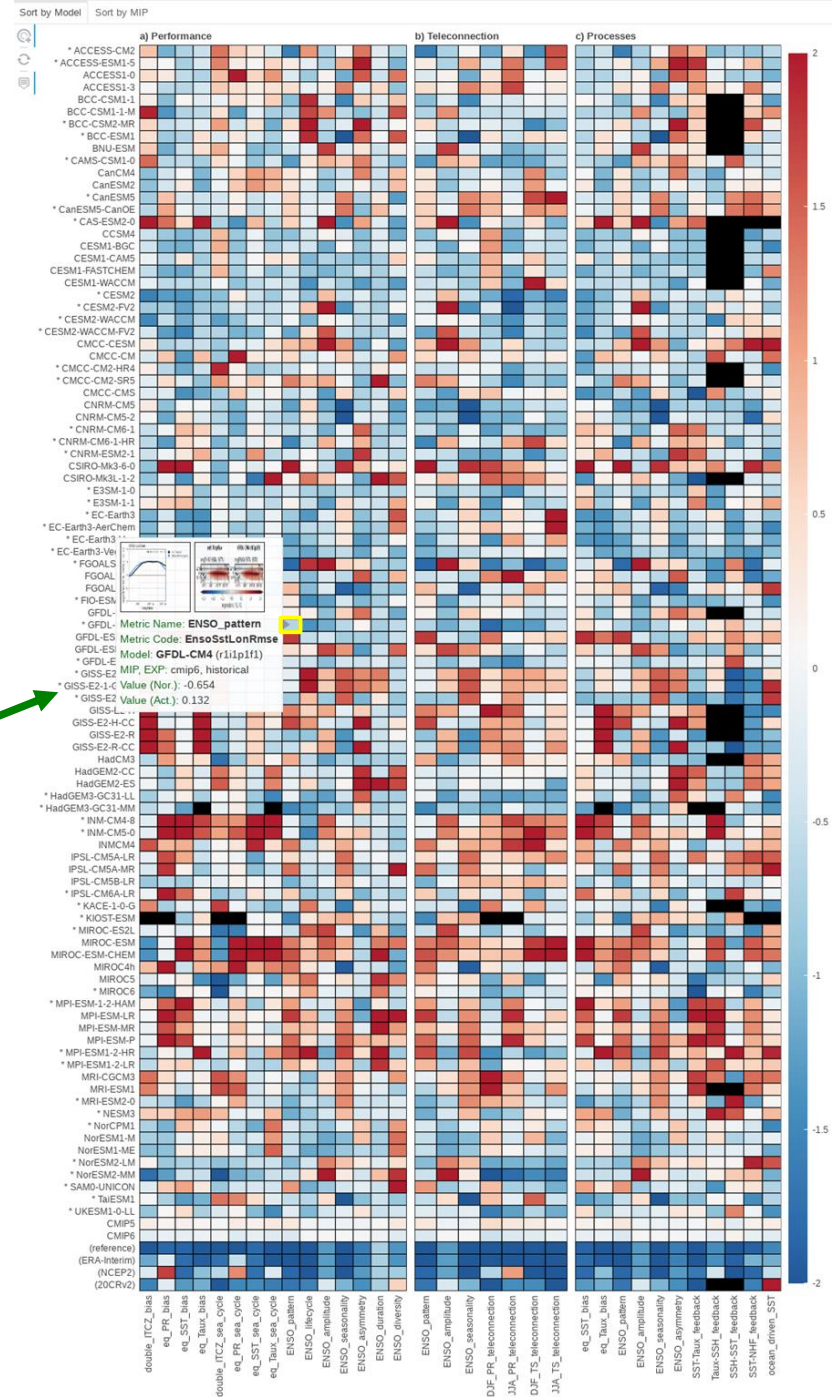
- **Interactive** dive-down diagnostics
- Pre-computed model metrics for download ([JSON](#) & [Excel](#))

Wiki:

https://github.com/CLIVAR-PRP/ENSO_metrics/wiki

Software:

https://github.com/CLIVAR-PRP/ENSO_metrics



Recent studies using the ENSO Metrics Package

[Lee et al. \(GRL 2021\)](#): “Robust evaluation of ENSO in climate models: How many **ensemble members** are needed?”

- For **CMIP5/6 & LEs**, need $N \geq 50$ to constrain ENSO baseline & process metrics
- Less for climatology ($N \geq 6$) & ENSO teleconnections ($N \geq 12$)
for 95% of N-ensemble means (of 1979-2018 metrics) to fall within 10% of actual mean metric

[Xu et al. \(JC 2022\)](#): “The Andes affect ENSO statistics”

- Elevate the Andes to more realistic levels in CESM_1.2.2
 - better (more LN-like) troPac climate
 - weaker ENSO; more asymmetric, irregular, evaporatively-damped

Planton et al. (in prep for JAMES): “Detecting ENSO variance changes in a **warmer world.**”

- **CMIP6** historical runs: Sample size to detect past & future ENSO amplitude changes?
Need 5 – 9 members, for ensemble-mean 30yr variance to fall within 15% of actual long-term variance
- If ENSO strengthens → more decadal modulation → later detection
- Quiet/hyperactive ENSO decades can aid earlier detection

Lee et al. (in prep for GMD): “Diversifying objective summaries of Earth system model performance: An overview of the **PCMDI Metrics Package (PMP).**”

- A section is devoted to the **ENSO metrics**

Community Connections

CLIVAR/ICTP ENSO Summer School

Yann Planton developed & ran student tutorials, applying package to CMIP6
→ supported the [WCRP Academy Lighthouse Activity \(LHA\)](#)

Jiwoo Lee joined the CMIP7 Climate Model Benchmarking Task Team

→ Actively promoting the CLIVAR ENSO Metrics via the PMP framework

Connections with other community efforts

[PMP](#), [ESMValTool](#), [CliMAF](#), [MDTF](#)

[ES-Doc](#) & [Comparator](#): model resolution, lineage, parameterization schemes

Tropical Pacific Observing System (TPOS)

Obs targeting + new reference data

Next Steps for ENSO Metrics

Leverage recent enhancements

- Added more **obs datasets** to test robustness (Planton et al., in prep)
- **Index statistics**: mean, stddev, skewness, d.o.f. → significance
- **Wait times** between ENSO events: mean, stddev, skewness, PDFs, transition probabilities

New metrics in development

- ENSO regional **teleconnections**: regressions, composites (per [McGregor et al. 2022](#))
- New ENSO **process metrics** (per [Chen et al. JC 2021](#))
 - BWJ indices, ML heat budget, nonlinear dynamical heating (NDH)
- Model-analogs as metrics of ENSO **evolution, predictability, forecast skill**
 - Applied to NMME & CMIP5 historical: Ding et al. ([JC 2018](#); [GRL 2020](#))
 - Applied to CMIP6 & LE, historical & future: Lou et al. (subm. & in prep.)
 - + ongoing work at NOAA PSL & GFDL
- CLIVAR PRP Working Group on **Conceptual Models of ENSO**

New & proposed projects:

- Impact of **climate change** on ENSO (Planton, Lee, et al., in prep)
- EqPac **upwelling & mixing** in CGCMs (Wittenberg et al., NOAA CVP), funded 2023-25
- Dynamical ENSO metrics & **emergent constraints** (Jin et al., NOAA MAPP), submitted

Action Items for PRP

1. **Feedback** on metrics, interfaces, development, dissemination
2. Recommend **observational** references
 - Latest *gridded* products, reanalyses
 - How to best characterize obs uncertainties?
 - Best epochs to use?
3. Recommended **realizations** for model & obs (epochs, ensemble sizes)
4. Ideas for new metrics
 - **Expand** existing collections: e.g. connect to **conceptual models**
 - **New collections**: Climate change, teleconnection processes, impacts, ...
5. Ideas for applications & tiering of metrics
 - Model evaluation & **selection/weighting**
 - Physical **links** among metrics; **emergent constraints** for future change
6. Resources: **Postdocs**, web/data techs, funding opportunities, ...