Multi-frequency analysis of modeled-versus-observed variability in tropospheric temperature

2020 LLNL Women in Data Science Workshop

March 2nd 2020

Giuliana Pallotta
Joint work with Benjamin D. Santer

LLNL-PRES- 805278
This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract DE-AC52-07NA27344. Lawrence Livermore National Security, LLC

Lawrence Livermore National Laboratory

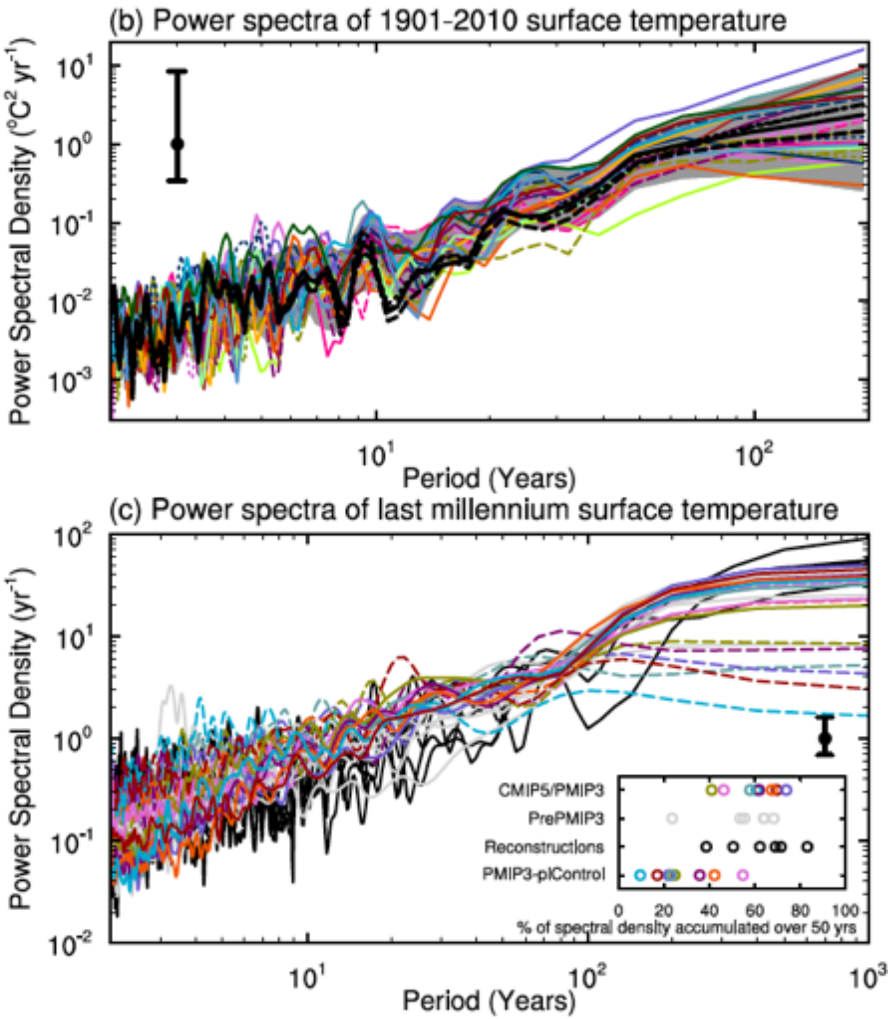
Motivation for the analysis

- An accurate assessment of how climate models reproduce the poorly observed low-frequency variability is a critical component of Detection & Attribution work.
- Specifically, recent claims have raised the question about climate models <u>underestimating</u> observed low-frequency variability. If that was confirmed, all the conclusions about the statistical significance of climate change signals in the observations would be spurious.
- Hence, studying the 'direction' in the bias of the estimate of internal variability in climate model simulations is crucial.

Our goals

- We want to analyze the **spectral features** of global-mean **mid-to-upper tropospheric temperature (TMT)** in simulated and observed time series.
- We want to study the directionality in the bias (deficit or surplus) of CMIP5 climate models in reproducing the low-frequency variability, poorly observed in satellite records.
- We want to identify the timescales where the differences in the shape of the spectra are more pronounced (high versus low frequencies)
- We want to assess how these model-versus-obs discrepancies are sensitive to different, plausible, analyst choices.

Relevant literature: 2013 IPCC report, Chapter 9, Evaluation of climate models



Power spectral density for 1901–2010 global mean surface temperature for both historical CMIP5 simulations and the observations (after **Jones et al., 2012**). The grey shading provides the 5 to 95% range of the simulations.

Power spectral density for Northern Hemisphere surface temperature from the CMIP5 PMIP3 last-millennium simulations (colour, solid) using common external forcing configurations (**Schmidt et al., 2012**), together with the corresponding pre-industrial simulations (colour, dashed), previous last-millennium AOGCM simulations.

Recent papers raising the underestimation issue

- Global-scale multidecadal variability missing in state-of-the-art climate models (Kravtsov et al. 2018)

"While climate models exhibit various levels of decadal climate variability and some regional similarities to observations, none of the model simulations considered match the observed signal in terms of its magnitude, spatial patterns and their sequential time development."

- Underestimated AMOC Variability and Implications for AMV and Predictability in CMIP Models (Yan et al. 2018)

"Using both observations and simulations from the Coupled Model Intercomparison Project Phase 3 and 5, here we show that most models underestimate the amplitude of low-frequency AMOC variability"

Sensitivity study: a multi-dimensional problem

- Satellite dataset (**RSS**, **STAR** and **UAH**) => 3
x
- Class of CMIP5 simulations (**HIST+RCP8.5** and **CTL**) => 2
x
- Externally forced signal (MMA, linear, quadratic and cubic) => 4
x
- Frequency band of interest (entire spectrum, high and low) => 3
x
- Statistical models (three AR(p), ARMA(1,1), four FARIMA(p,d,q))=> 8

576

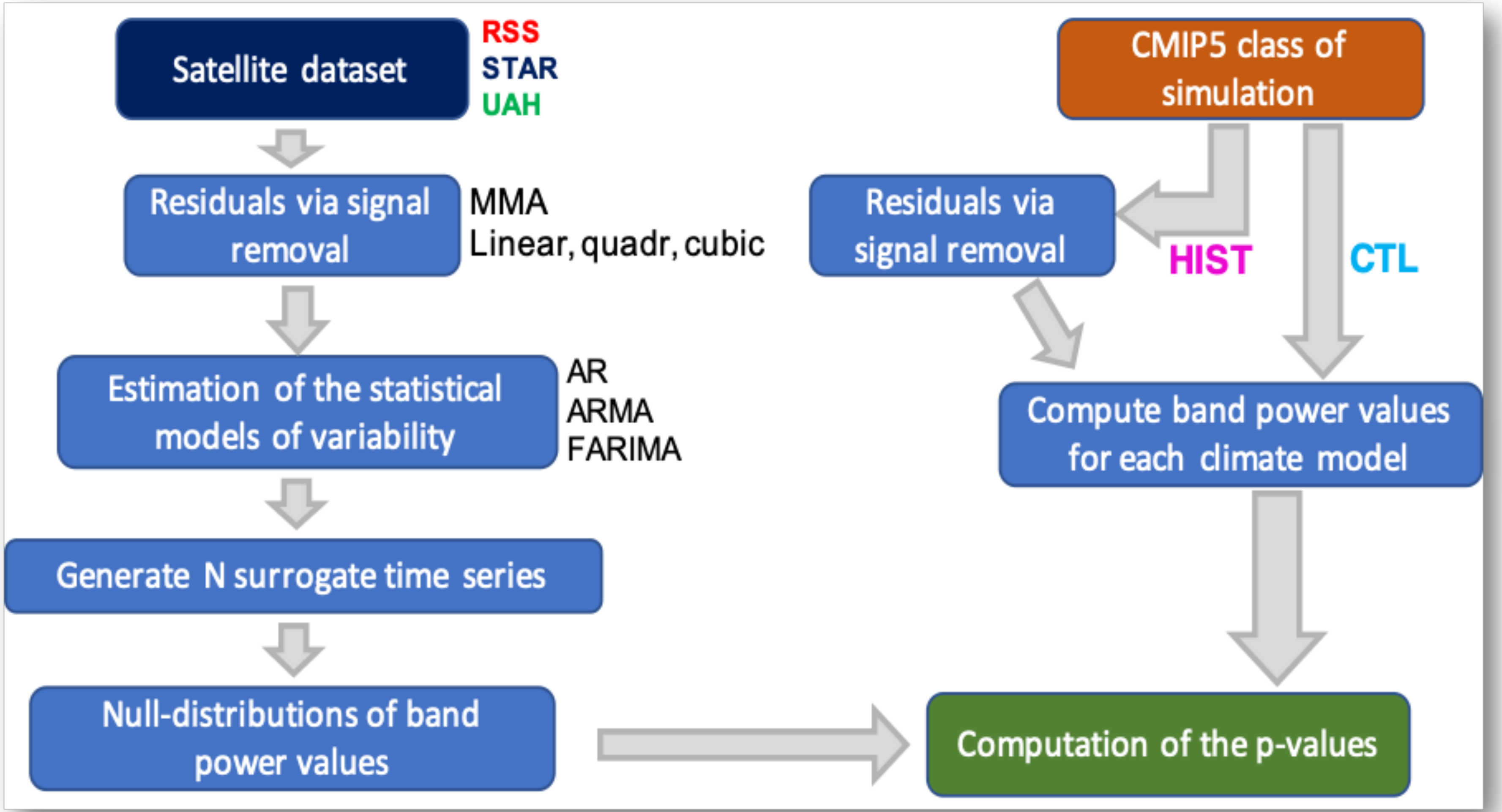
x

- Power spectral densities (normalized and not-normalized) => 2
x
- Metrics (TVD, Hurst Exponent, Coherence) => 3

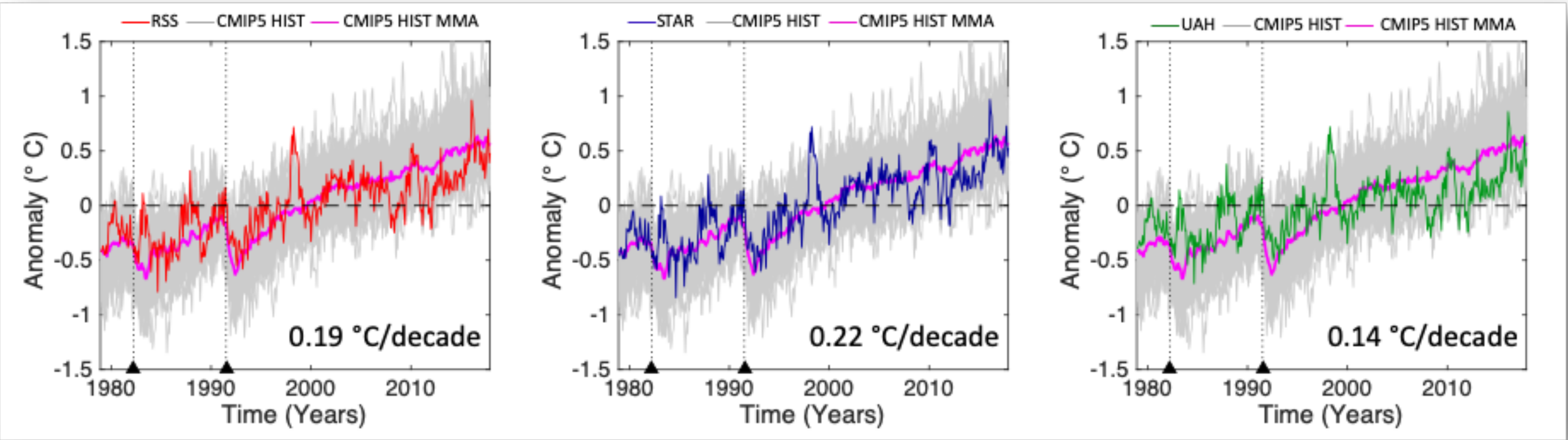
Work in progress

3456

Workflow of the sensitivity analysis

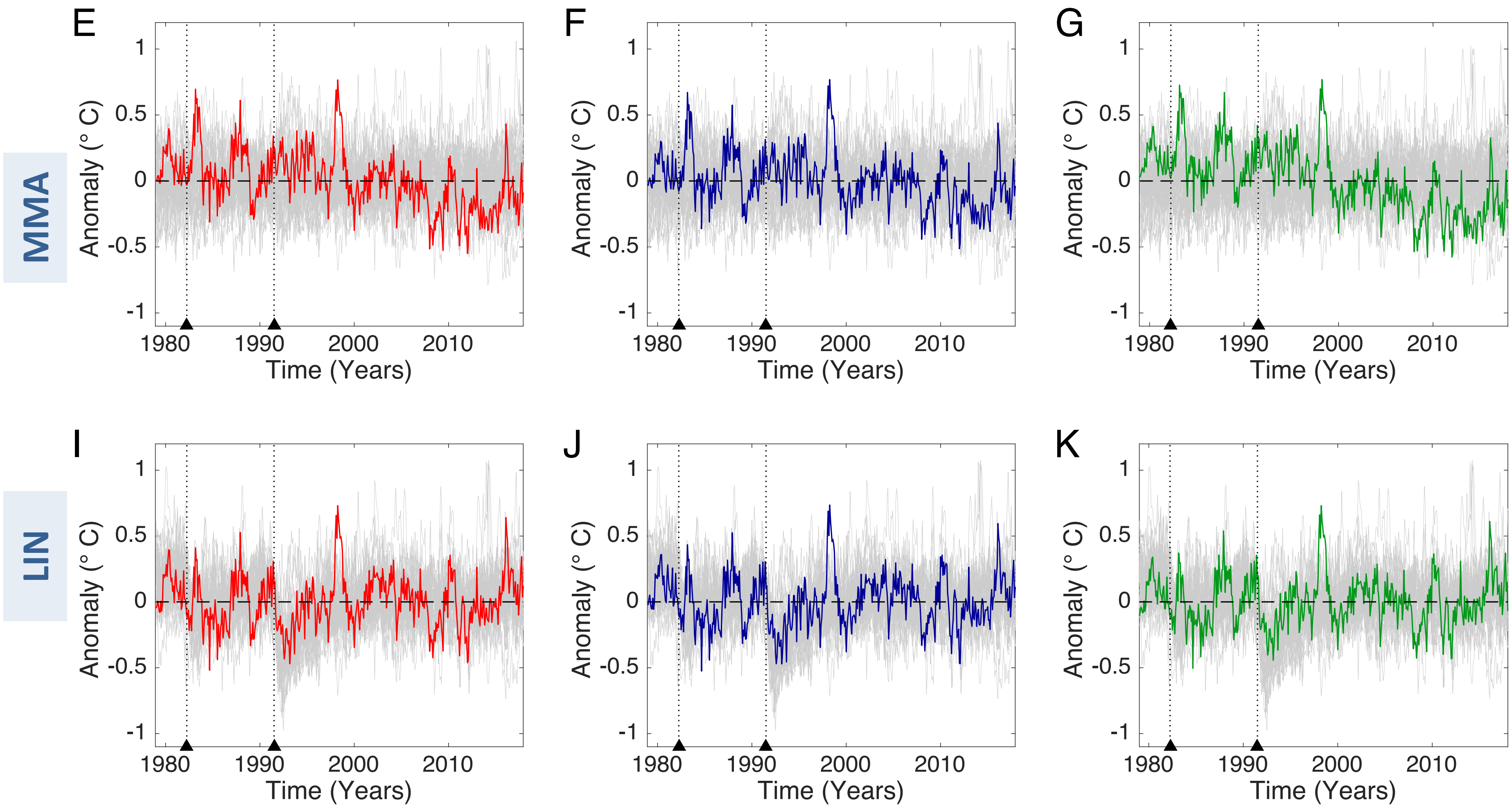


TMT observed and simulated time series



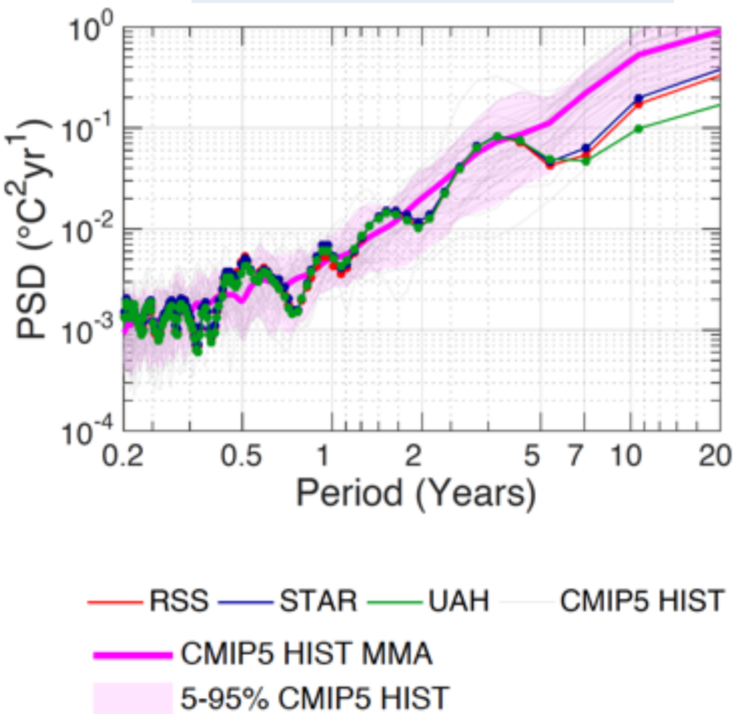
Anomalies calculated over the satellite era (January 1979-December 2018).

Estimating an externally forced signal



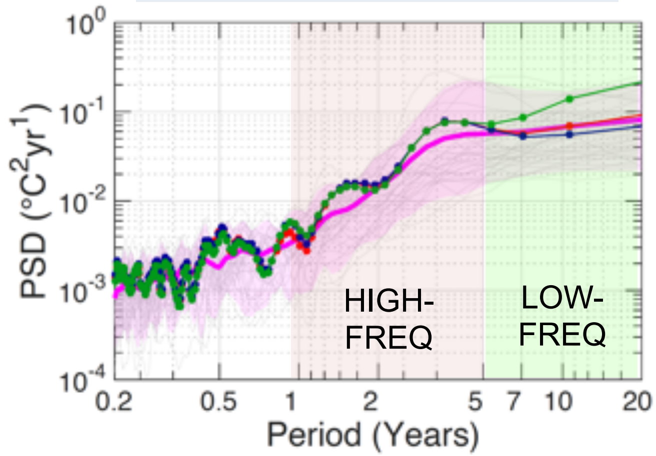
Power spectral densities for the HIST+RCP8.5

Original time series

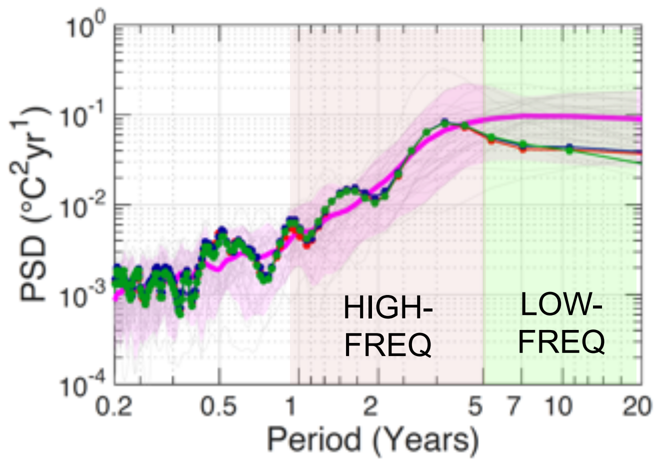


Residuals

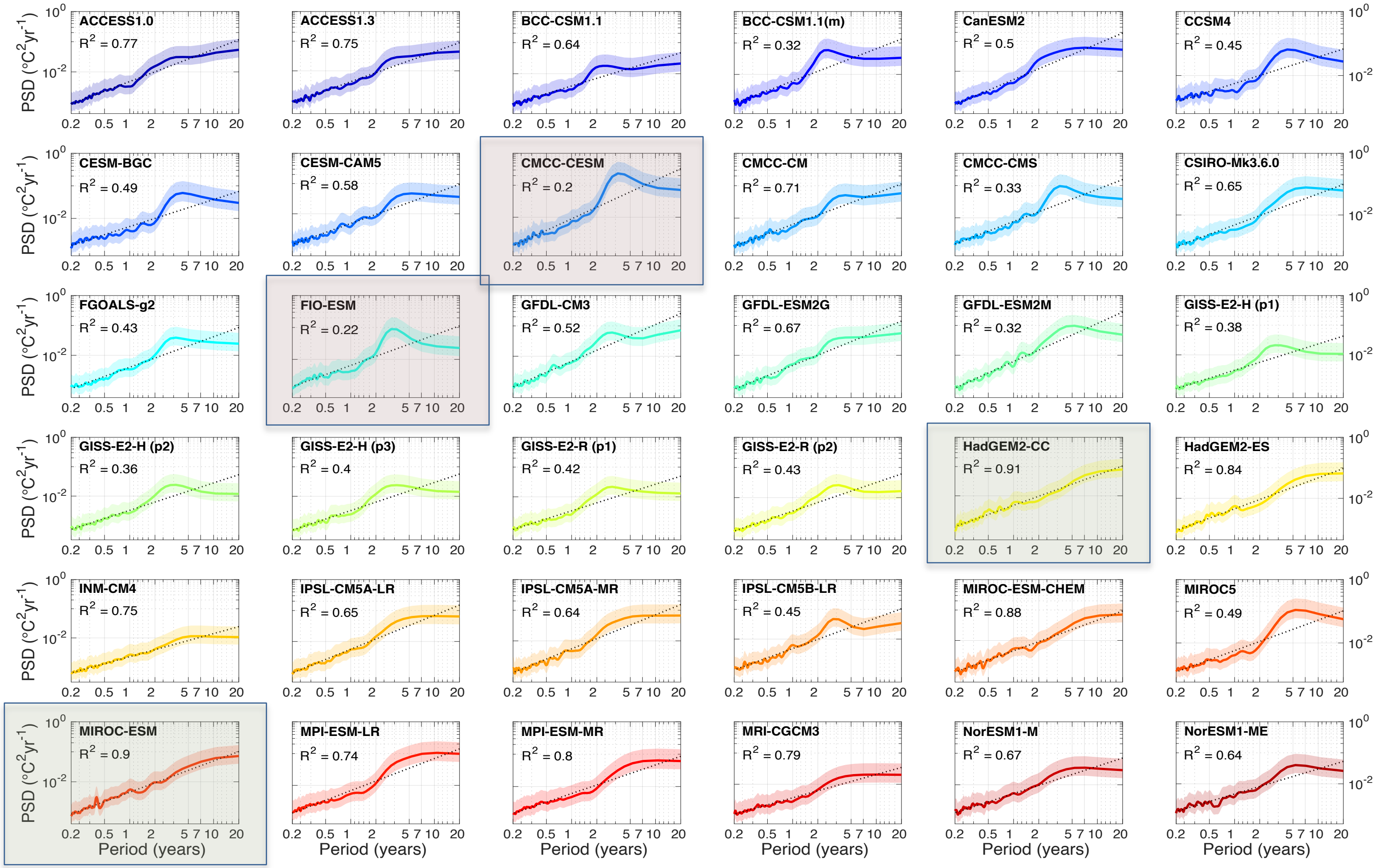
MMA



LIN

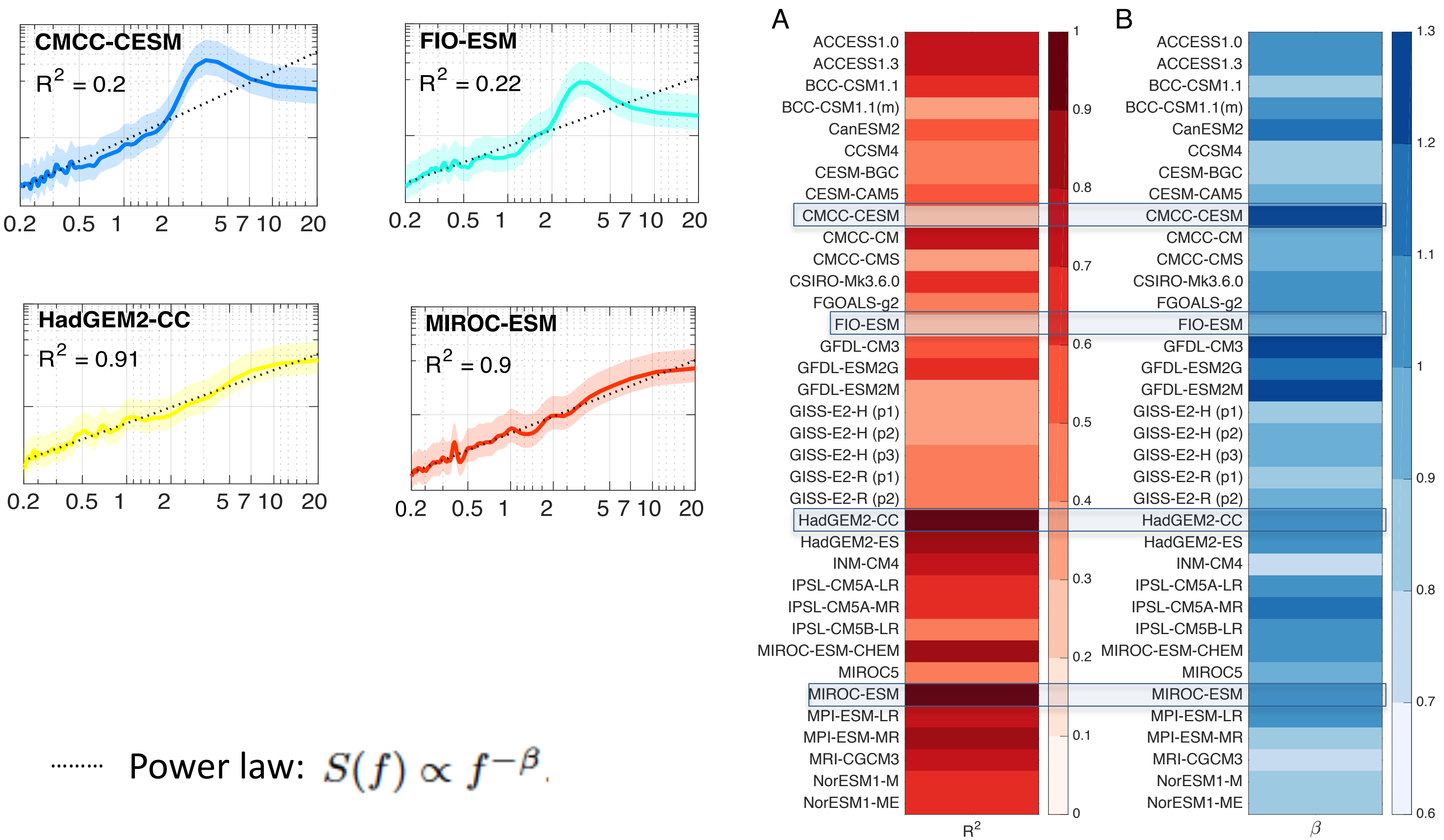


Power spectral densities for the control runs



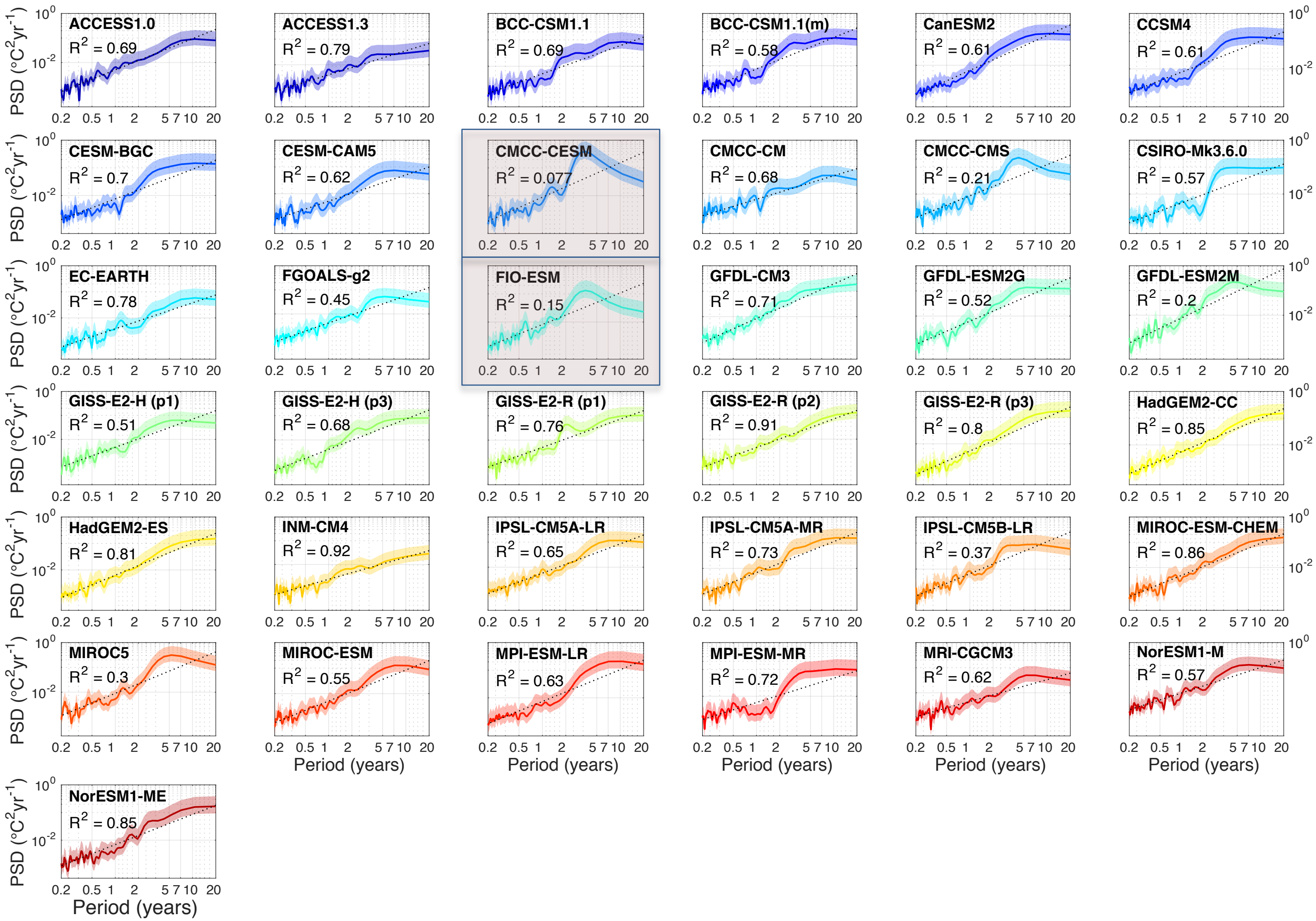
Power law estimate: $S(f) \propto f^{-\beta}$.

Power law fit in the control runs

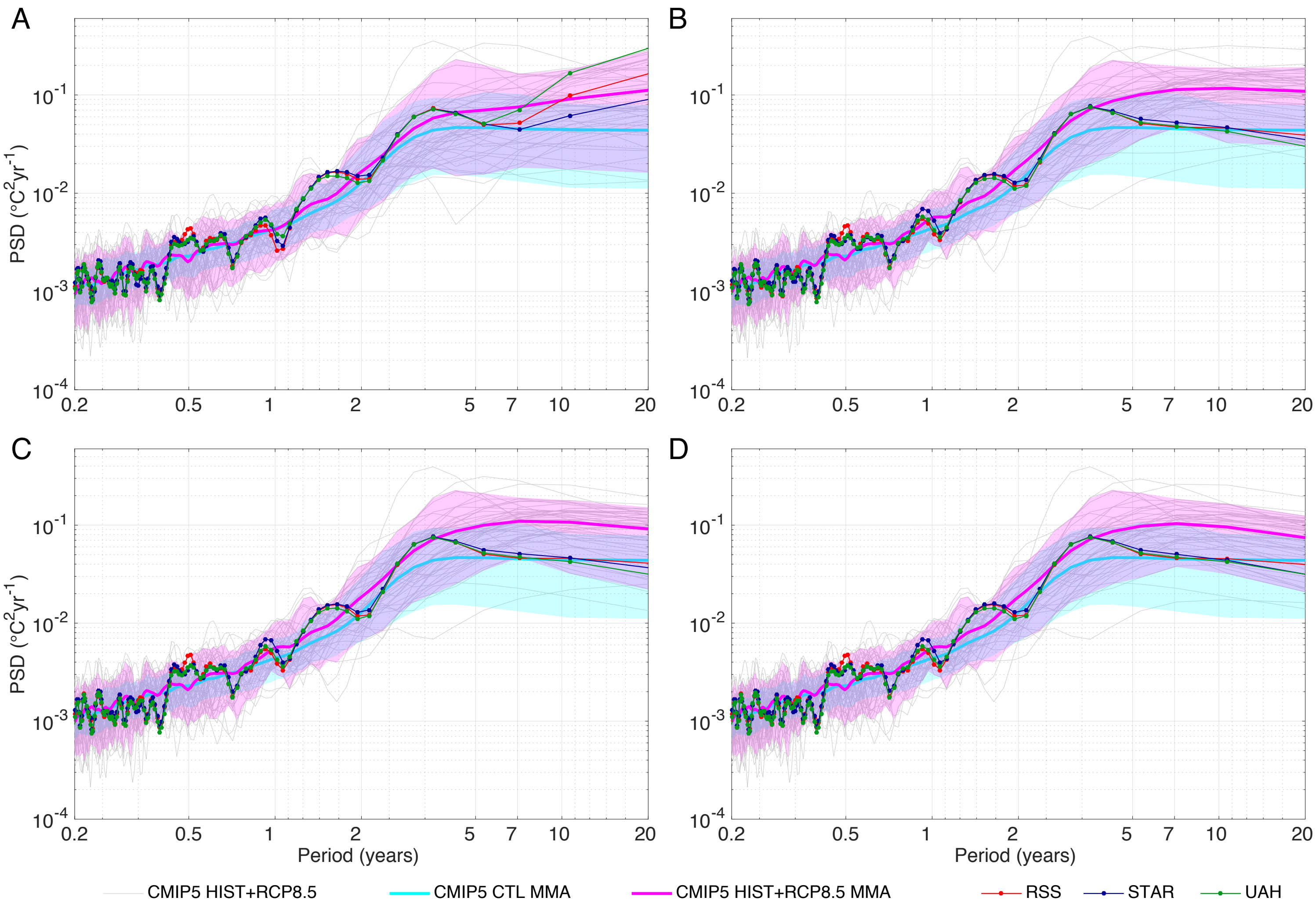


.... Power law: $S(f) \propto f^{-\beta}$.

Power spectral densities for the HIST+RCP8.5: Linearly detrended residuals

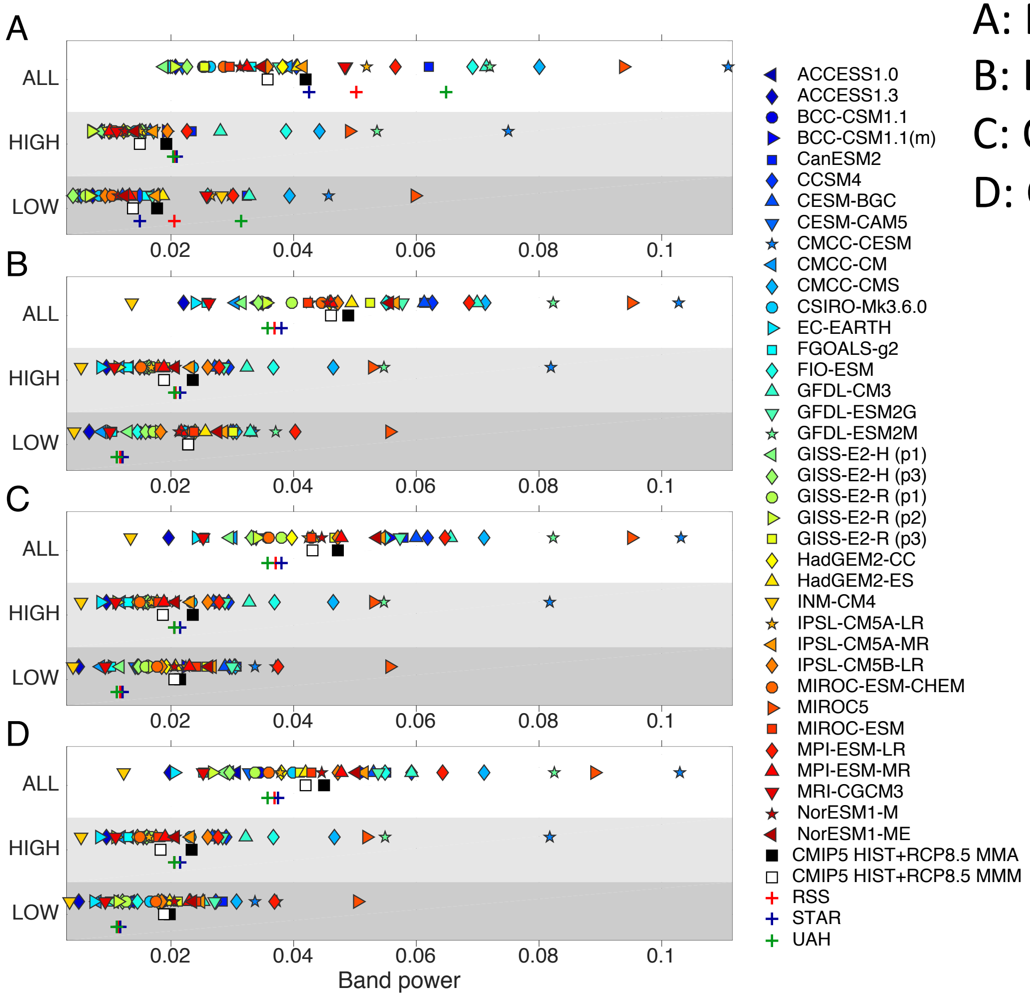


Comparing ensemble-averaged spectra



A: MMA
B: Linear
C: Quadratic
D: Cubic

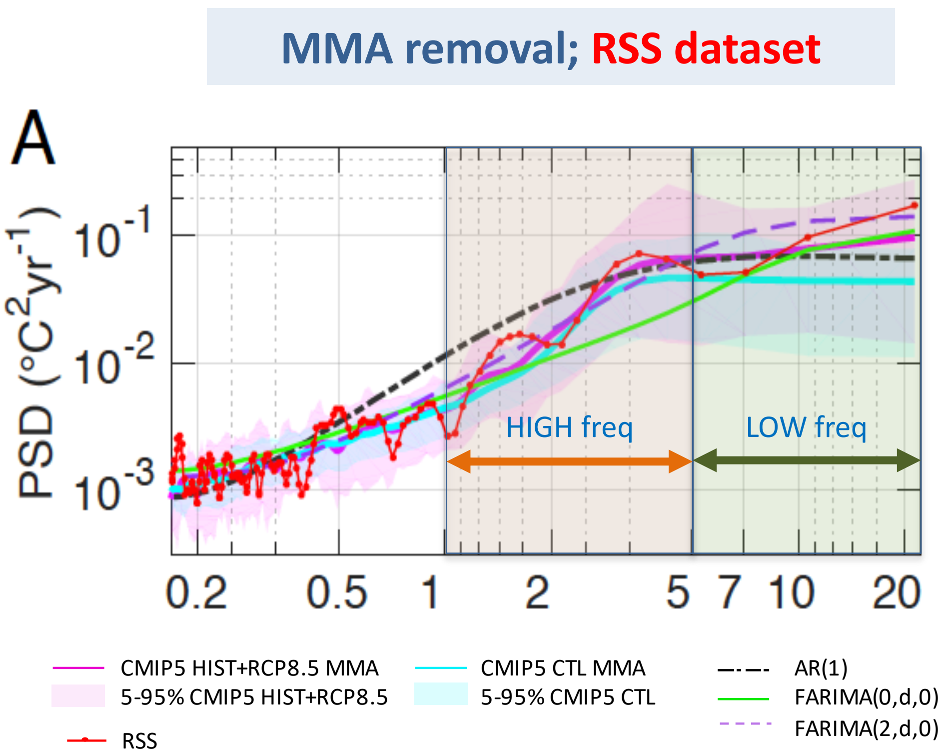
Comparing simulated and observed band power



A: MMA
B: Linear
C: Quadratic
D: Cubic

Metrics:
- Cross-correlation (time-domain)
- Total variational distance(TVD) (normalization, no sign, whole spectrum)
- Coherence (sensitive to the phasing of peaks in power)
- **Band power** (easy to use and understand)

Spectral densities from the statistical models of the climate internal (observed) variability



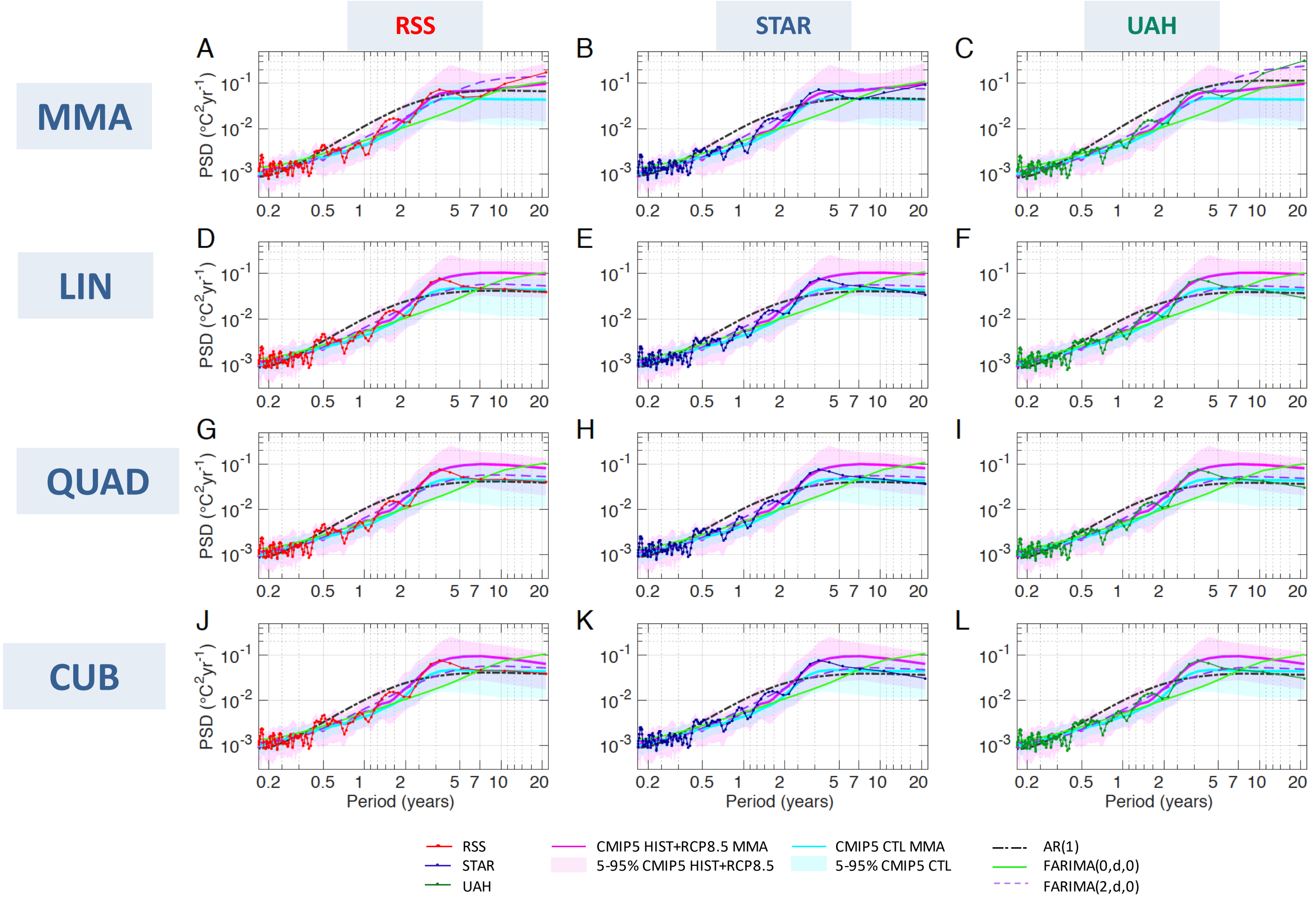
ALL: entire spectrum

HIGH: frequencies from 1 to 5 years

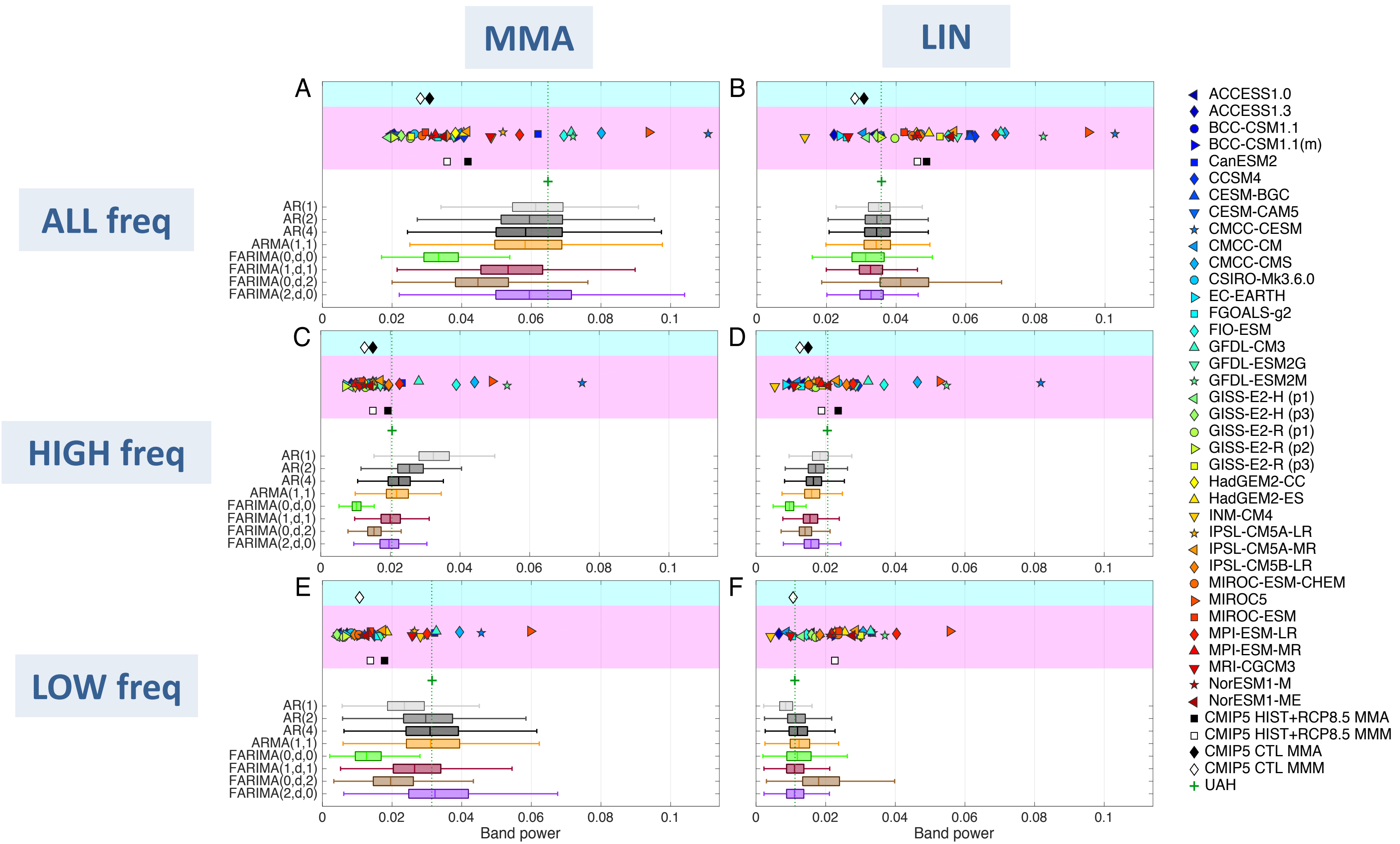
LOW: frequencies from 5 to 20 years

- We investigated three families of models with different short- and long-memory features;
- We applied an objective criterion (AIC) to select the best fitting models in each family; here we show the best FARIMA model **FARIMA(2,d,0)**;
- We generated 10,000 surrogate timeseries for each statistical model;
- We computed the power spectral densities by applying the Welch method (Hamming window, 50% overlap);
- We computed the band power values for each frequency band of interest.

Spectral densities from the statistical models of the climate internal (observed) variability



Empirical distributions of band power from the surrogate models with UAH reference



Probability that CMIP5 HIST+RCP8.5 simulations have larger band power than observations

		MMA (ALL)	MMA (HIGH)	MMA (LOW)	LIN (ALL)	LIN (HIGH)	LIN (LOW)	QUAD (ALL)	QUAD (HIGH)	QUAD (LOW)	CUB (ALL)	CUB (HIGH)	CUB (LOW)	Average
RSS	AR(1)	0.28	0.18	0.48	0.71	0.51	0.90	0.67	0.50	0.89	0.62	0.51	0.86	0.59
	AR(2)	0.30	0.22	0.36	0.71	0.56	0.82	0.67	0.55	0.80	0.63	0.55	0.75	0.58
	AR(4)	0.31	0.28	0.33	0.71	0.61	0.79	0.68	0.61	0.76	0.63	0.61	0.72	0.59
	ARMA(1,1)	0.31	0.27	0.33	0.71	0.60	0.79	0.68	0.60	0.77	0.63	0.60	0.72	0.58
	FARIMA(0,d,0)	0.54	0.77	0.55	0.76	0.91	0.78	0.74	0.91	0.76	0.69	0.91	0.71	0.75
	FARIMA(1,d,1)	0.33	0.30	0.35	0.74	0.64	0.82	0.71	0.63	0.80	0.67	0.63	0.75	0.61
	FARIMA(0,d,2)	0.35	0.47	0.37	0.55	0.73	0.58	0.51	0.72	0.54	0.47	0.72	0.49	0.54
	FARIMA(2,d,0)	0.29	0.30	0.28	0.74	0.63	0.82	0.71	0.62	0.80	0.67	0.62	0.75	0.60
STAR	AR(1)	0.39	0.24	0.65	0.70	0.51	0.90	0.67	0.51	0.89	0.63	0.52	0.87	0.62
	AR(2)	0.41	0.28	0.50	0.71	0.56	0.82	0.67	0.56	0.80	0.64	0.57	0.77	0.61
	AR(4)	0.42	0.32	0.47	0.71	0.59	0.80	0.68	0.59	0.78	0.64	0.60	0.75	0.61
	ARMA(1,1)	0.42	0.34	0.46	0.71	0.61	0.79	0.68	0.61	0.76	0.64	0.62	0.73	0.61
	FARIMA(0,d,0)	0.54	0.77	0.54	0.75	0.90	0.77	0.72	0.90	0.75	0.67	0.90	0.70	0.74
	FARIMA(1,d,1)	0.42	0.33	0.47	0.74	0.63	0.82	0.71	0.63	0.81	0.68	0.64	0.78	0.64
	FARIMA(0,d,2)	0.35	0.48	0.38	0.54	0.71	0.57	0.49	0.70	0.53	0.46	0.71	0.48	0.53
	FARIMA(2,d,0)	0.40	0.30	0.45	0.74	0.61	0.83	0.71	0.61	0.81	0.68	0.63	0.78	0.63
UAH	AR(1)	0.18	0.14	0.28	0.74	0.55	0.91	0.71	0.54	0.90	0.65	0.54	0.87	0.58
	AR(2)	0.19	0.18	0.19	0.75	0.60	0.83	0.72	0.60	0.82	0.66	0.59	0.77	0.57
	AR(4)	0.20	0.22	0.18	0.75	0.63	0.82	0.72	0.62	0.80	0.66	0.62	0.75	0.58
	ARMA(1,1)	0.20	0.23	0.17	0.75	0.65	0.80	0.72	0.65	0.78	0.67	0.65	0.73	0.58
	FARIMA(0,d,0)	0.54	0.77	0.55	0.78	0.92	0.80	0.76	0.92	0.77	0.72	0.92	0.73	0.77
	FARIMA(1,d,1)	0.24	0.27	0.23	0.78	0.68	0.84	0.76	0.67	0.83	0.71	0.67	0.78	0.62
	FARIMA(0,d,2)	0.33	0.45	0.35	0.58	0.75	0.60	0.54	0.74	0.56	0.50	0.74	0.50	0.55
	FARIMA(2,d,0)	0.19	0.28	0.16	0.78	0.66	0.84	0.75	0.66	0.83	0.70	0.65	0.78	0.61
	Average	**0.34**	**0.35**	**0.38**	**0.72**	**0.66**	**0.79**	**0.68**	**0.65**	**0.77**	**0.64**	**0.65**	**0.73**	**0.61**

Conclusions

- Main finding: most CMIP5 climate models do not (on average) underestimate the (poorly) observed low-frequency variability;
- Lessons learned about sensitivities:
  - The choice of the functional form of the signal and of the dataset has implications for the significance of the results
  - Two commonly used statistical models of short-term and long-term memory (i.e., AR(1) amd FARIMA(0,d,0)) have deficiencies in capturing the shape of the observed natural variability spectrum.

Main References

- **Pallotta** G., B. D. Santer: Multi-frequency analysis of model-versus-observed variability in tropospheric temperature. *Under review*, 2020
- Santer B.D., J. Fyfe, S. Solomon, J. Painter, C. Bonfils, G. **Pallotta**, M. Zelinka: Quantifying stochastic uncertainty in detection time of human-caused climate signals. PNAS Oct 1, 2019 116 (40) 19821-19827
- Santer B. D., Po-Chedley S., Zelinka, M., Cvijanovic I., Bonfils C., Durack, P., Fu Q., Kiehl, J., Mears, C., Painter, J., **Pallotta, G.**, Solomon, S., Wentz, F., and Zou C.Z. Human Influence on the Seasonal Cycle of Tropospheric Temperature, 2018, *Science*, vol. 361, 6399

Funding acknowledgement

- Work at LLNL was performed under the auspices of the U.S. Department of Energy under contract DE-AC52-07NA27344 through the Regional and Global Model Analysis Program.

Extra-slide: Probability that CMIP5 CTL simulations have larger band power than observations

		MMA (ALL)	MMA (HIGH)	MMA (LOW)	LIN (ALL)	LIN (HIGH)	LIN (LOW)	QUAD (ALL)	QUAD (HIGH)	QUAD (LOW)	CUB (ALL)	CUB (HIGH)	CUB (LOW)	Average
RSS	AR(1)	0.07	0.05	0.15	0.25	0.14	0.33	0.25	0.14	0.33	0.26	0.14	0.33	0.20
	AR(2)	0.09	0.09	0.07	0.27	0.16	0.23	0.27	0.16	0.23	0.28	0.16	0.23	0.19
	AR(4)	0.10	0.12	0.06	0.27	0.19	0.20	0.28	0.19	0.20	0.28	0.19	0.20	0.19
	ARMA(1,1)	0.10	0.12	0.06	0.27	0.18	0.20	0.28	0.18	0.20	0.28	0.18	0.21	0.19
	FARIMA(0,d,0)	0.34	0.41	0.21	0.38	0.44	0.22	0.38	0.44	0.22	0.38	0.44	0.22	0.34
	FARIMA(1,d,1)	0.12	0.14	0.07	0.31	0.20	0.23	0.32	0.20	0.23	0.32	0.20	0.23	0.21
	FARIMA(0,d,2)	0.14	0.23	0.09	0.16	0.24	0.10	0.16	0.24	0.10	0.16	0.24	0.10	0.16
	FARIMA(2,d,0)	0.09	0.14	0.04	0.31	0.19	0.23	0.31	0.19	0.23	0.32	0.20	0.24	0.21
STAR	AR(1)	0.17	0.11	0.28	0.25	0.14	0.33	0.25	0.14	0.34	0.27	0.15	0.35	0.23
	AR(2)	0.19	0.14	0.17	0.26	0.16	0.23	0.27	0.16	0.23	0.29	0.17	0.25	0.21
	AR(4)	0.20	0.16	0.14	0.27	0.18	0.21	0.27	0.18	0.21	0.29	0.18	0.23	0.21
	ARMA(1,1)	0.20	0.17	0.14	0.27	0.19	0.20	0.27	0.19	0.20	0.29	0.19	0.21	0.21
	FARIMA(0,d,0)	0.34	0.41	0.21	0.35	0.42	0.21	0.35	0.42	0.21	0.35	0.42	0.21	0.33
	FARIMA(1,d,1)	0.20	0.16	0.14	0.31	0.19	0.24	0.31	0.20	0.24	0.34	0.21	0.26	0.23
	FARIMA(0,d,2)	0.15	0.23	0.09	0.14	0.23	0.09	0.14	0.23	0.09	0.15	0.23	0.09	0.16
	FARIMA(2,d,0)	0.18	0.15	0.13	0.31	0.19	0.24	0.31	0.19	0.24	0.34	0.20	0.26	0.23
UAH	AR(1)	0.03	0.01	0.04	0.30	0.16	0.35	0.30	0.16	0.35	0.30	0.16	0.35	0.21
	AR(2)	0.04	0.05	0.01	0.32	0.18	0.25	0.32	0.18	0.25	0.32	0.18	0.25	0.19
	AR(4)	0.04	0.08	0.01	0.32	0.19	0.23	0.32	0.20	0.23	0.32	0.20	0.23	0.20
	ARMA(1,1)	0.04	0.08	0.01	0.32	0.21	0.21	0.32	0.21	0.22	0.32	0.21	0.22	0.20
	FARIMA(0,d,0)	0.35	0.42	0.21	0.41	0.46	0.24	0.41	0.46	0.24	0.41	0.46	0.24	0.36
	FARIMA(1,d,1)	0.06	0.11	0.03	0.37	0.22	0.26	0.38	0.22	0.26	0.38	0.22	0.26	0.23
	FARIMA(0,d,2)	0.13	0.21	0.08	0.18	0.25	0.10	0.18	0.25	0.10	0.18	0.25	0.10	0.17
	FARIMA(2,d,0)	0.04	0.12	0.01	0.37	0.21	0.26	0.37	0.21	0.26	0.37	0.21	0.26	0.23
	Average	**0.14**	**0.16**	**0.10**	**0.29**	**0.22**	**0.22**	**0.29**	**0.22**	**0.23**	**0.30**	**0.22**	**0.23**	**0.22**