

Surface Climate Decadal Predictability in a Multi-Model Collection of Large Ensembles

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The multi-model LE Repository

(Deser et al. 2020)

Modelling centre	Model version	Resolution (atmosphere/ocean)	Years	Initialization	No. of member
CCCma	CanESM2	-2.8°x2.8°/-1.4°x0.9°	1950-2100	Macro and micro	50
CSIRO	MK3.6	-1.9°x1.9°/-1.9°x1.0°	1850-2100	Macro	30
GFDL	ESM2M	2.0°x2.5°/1.0°x0.9°	1950-2100	Macro	30
GFDL	CM3	2.0°x2.5°/1.0°x0.9°	1920-2100	Micro	20
MPI	MPI-ESM-LR	-1.9°x1.9°/nominal 1.5°	1850-2100	Macro	100
NCAR	CESM1	-1.3°x0.9°/nominal 1.0°	1920-2100	Micro	40
SMHI or KNMI	EC-Earth	-1.1°x1.1°/nominal 1.0°	1860-2100	Micro	16

**Daily data from MPI are unavailable.*



How large is the forced predictability in daily TAS/precipitation in the near term?
How significant is the forced predictability compared to that produced by ENSO?



Relative Entropy

Shannon's information theory

- **Kullback-Leibler divergence**

$$D_{\text{KL}}(\mathbf{p} \parallel \mathbf{q}) = \int_X \mathbf{p}(\mathbf{x}) \log_2 \frac{\mathbf{p}(\mathbf{x})}{\mathbf{q}(\mathbf{x})} d\mathbf{x}$$

A way to compare distributions, but not a proper distance, as $D_{\text{KL}}(\mathbf{p} \parallel \mathbf{q}) \neq D_{\text{KL}}(\mathbf{q} \parallel \mathbf{p})$

1 bit of info: reduce uncertainty by 2

- **n-dimensional Gaussian distribution**

$$D_{\text{KL}}(\mathbf{p} \parallel \mathbf{q}) = \text{const} * \left\{ \ln \left[\frac{\det(\sigma_q^2)}{\det(\sigma_p^2)} \right] + \text{tr} \left[\sigma_p^2 (\sigma_q^2)^{-1} \right] + (\bar{\mu}^p - \bar{\mu}^q)^T (\sigma_q^2)^{-1} (\bar{\mu}^p - \bar{\mu}^q) - n \right\}$$

To quantify predictability limit:

Kleeman 2002 Branstator and Teng 2010, Teng and Branstator 2011, Teng et al. 2011, Branstator and Teng 2012, Branstator et al. 2012 (annual mean subsurface temp)

- **Jensen-Shannon divergence (JSD)**

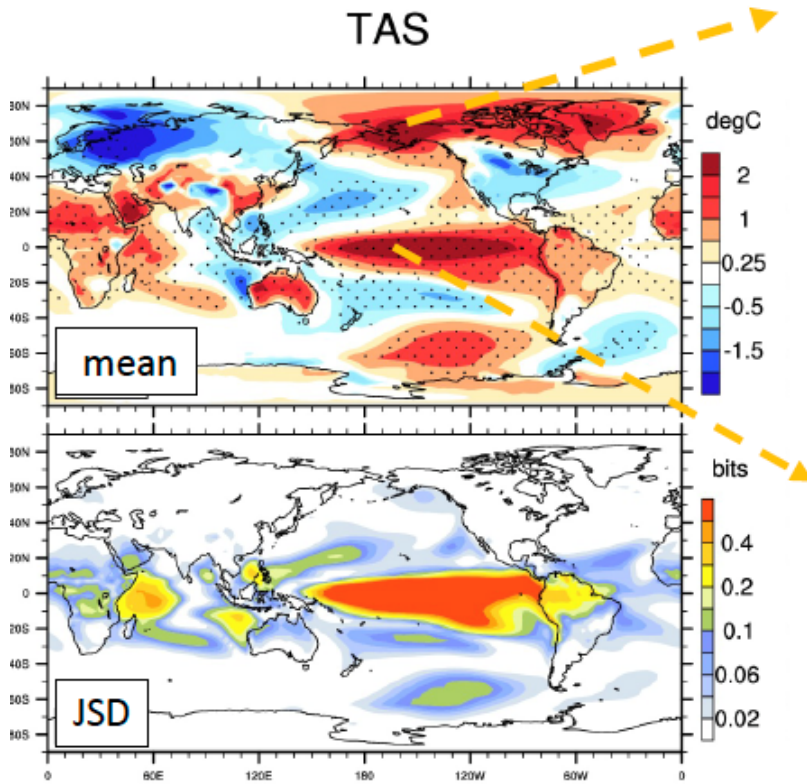
$$JSD(\mathbf{p} \parallel \mathbf{q}) = \frac{1}{2} D_{\text{KL}}(\mathbf{p} \parallel \mathbf{M}) + \frac{1}{2} D_{\text{KL}}(\mathbf{q} \parallel \mathbf{M}), \mathbf{M} = \frac{1}{2}(\mathbf{p} + \mathbf{q})$$

symmetric, smoothed ([0,1]) version of KLD

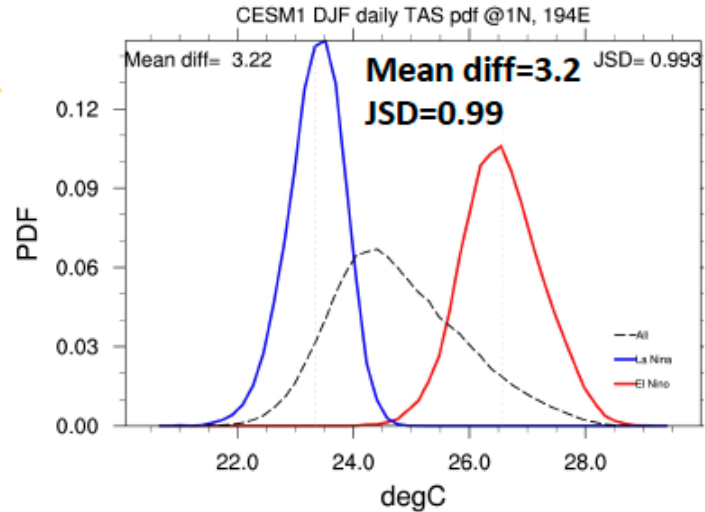
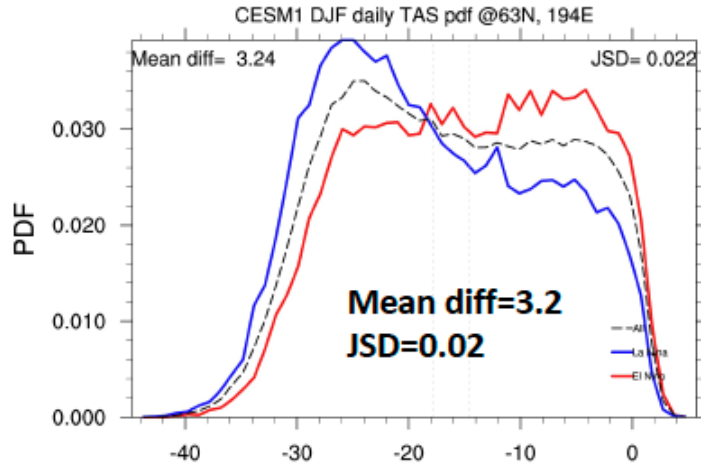
- **Cost function for machine learning tasks, but has not been widely used in climate research**



El Nino vs. La Nina in CESM1 1800-yr piconrol



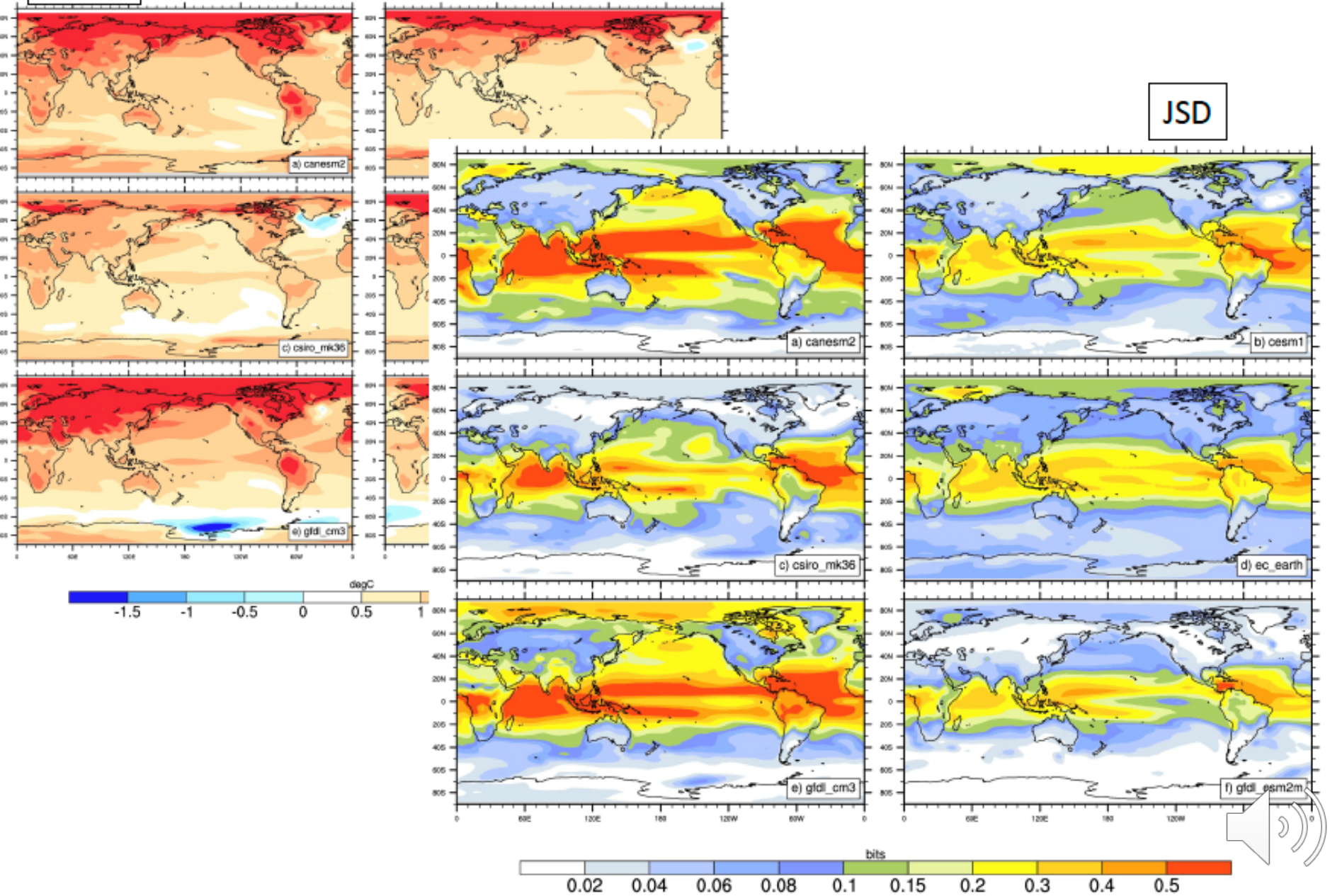
based on 280 El Nino, 247 LaNina



TAS 2028-2032 vs. 1980-2000

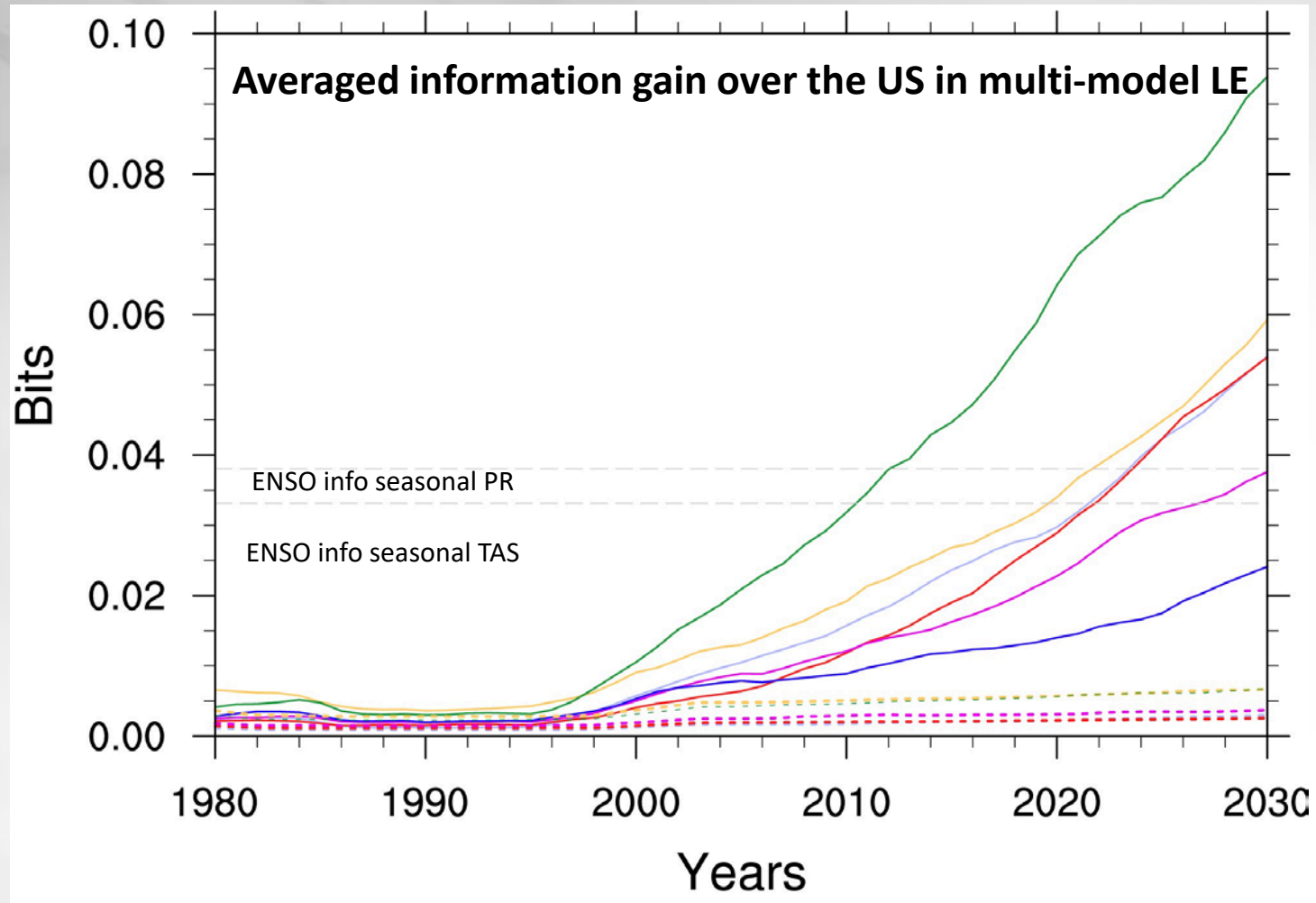
Mean

JSD





How significant is the forced predictability compared to that produced by ENSO?



With relative entropy we can quantify and compare predictability (of both forced and initial-value) on S2D time scales

