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EXCELENCIA SEVERO OCHOA

What level of decadal prediction skill would be achievable given perfect initialisation?

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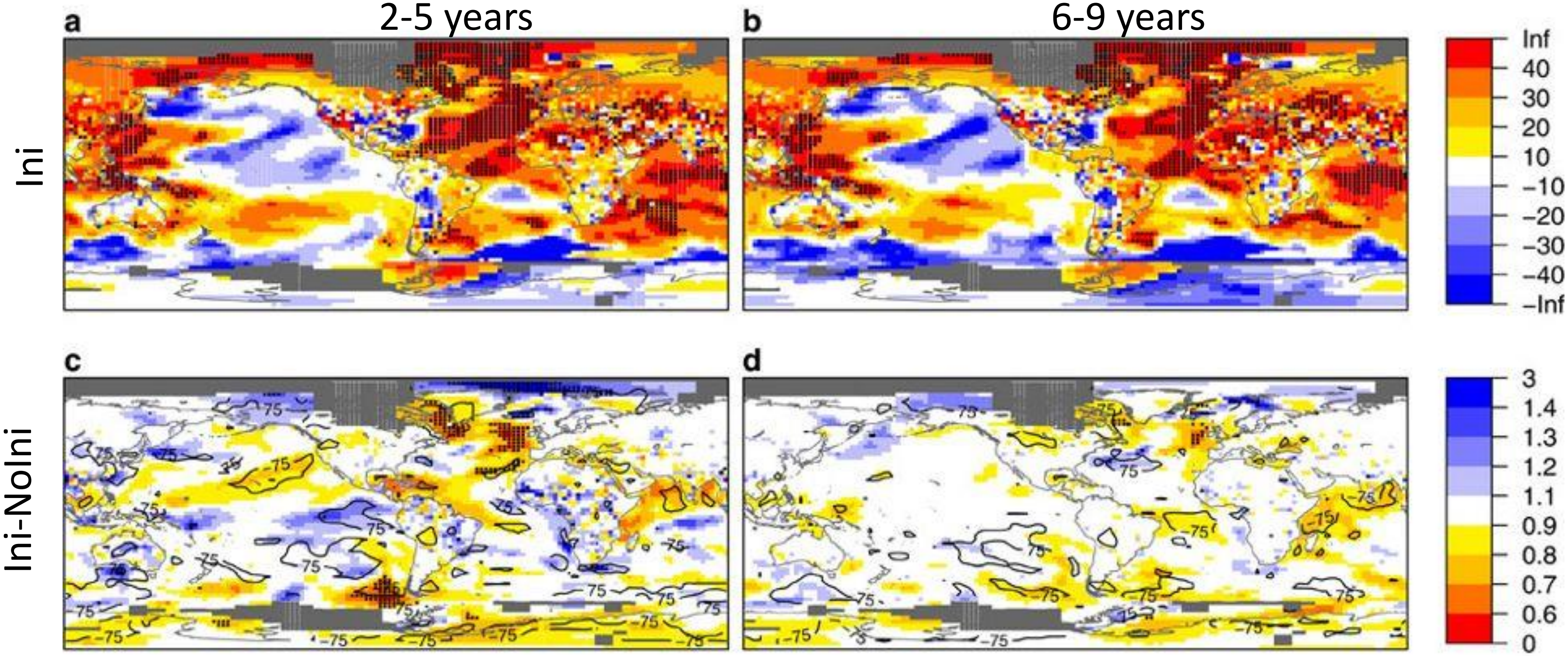
Forecast quality in decadal predictions – added value from initialization?

e.g. near-surface temperature in CMIP5 (RMSSS)



[Doblas-Reyes et al 2013]

→ Limited predictability from initialisation versus external forcing due to imperfect initialisation?

→ What level of skill may be achievable?

[Interesting scientific question, but also to important to manage expectations!]

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Perfect-model prediction experiments

How far can the model predict itself, starting from identical (almost) initial conditions?

CESM1, consistent set-up to decadal hindcasts (just replacing real-world observations with a historical simulation, for both initialisation and evaluation):

- decadal simulations started from a historical reference run, 1^{st} Jan each year 1961-2005
- 5 ensemble members (perturbing air temperature with Gaussian noise order of magnitude 10^{-5}K)
- Historical runs (5 members CMIP5 hist) as un-initialised counterpart
- Compare skill for initialised/uninitialised runs, and perfect-model/real-world predictions (real-world hindcasts from CMIP5, *Yeager et al 2012*)
- (focus on near-surface temperature to illustrate the framework)

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Comparing the different prediction experiments

	The initialized perfect model predictions	The initialized real-world decadal hindcasts	The uninitialized climate predictions
Near surface temperature observations		The skill of real-world decadal hindcasts (iii)	The skill of the uninitialized real-world climate predictions (iv)
Perfect model temperature reference	The prediction skill of initialized perfect model (i)		The prediction skill of the uninitialized perfect model (ii)

Skill measures

Forecast accuracy: Mean Squared (error) Skill Score (MSSS)

$$\mathrm{MSSS}(\mathrm{H}, \bar{\mathrm{O}}, \mathrm{O}) = \mathrm{r}_{\mathrm{HO}}^2 - \left[\mathrm{r}_{\mathrm{HO}} - \frac{\mathrm{s}_{\mathrm{H}}}{\mathrm{s}_{\mathrm{O}}}\right]^2 - \left[\frac{\bar{\mathrm{H}} - \bar{\mathrm{O}}}{\mathrm{s}_{\mathrm{O}}}\right]^2$$

r_{HO}: sample correlation between the hindcasts and the observations
$\mathrm{S_H}^2$; $S_O{}^2$: the sample variances of the ensemble mean hindcasts and observations,
$\bar{O} = \sum_{j=1}^{n} O_j$: climatological forecast (where *Oj* represents the observations, or perfect-model reference respectively, over *j* = 1,...,*n* start times), $\bar{\mathrm{H}}$ the mean hindcast

Ensemble dispersion: Logarithmic Ensemble Spread Score (LESS)

$$LESS = \ln\left(\frac{\overline{\sigma_{\hat{H}}^2}}{\sigma_R^2}\right)$$

in which,

$\overline{\sigma_{\hat{H}}^2} = \frac{1}{n}\sum_{j=1}^{n} \frac{1}{m-1}\sum_{i=1}^{m}(\hat{H}_{ij} - \hat{H}_j)^2$ (average ensemble variance)

$\sigma_R^2 = \frac{1}{n-2}\sum_{j=1}^{n}\left(\hat{H}_j - O_j\right)^2$ (reference mean square error)

LESS <0: the ensemble is under-dispersive (i.e. overconfident)
LESS >0: the ensemble is over-dispersive (i.e. under-confident)

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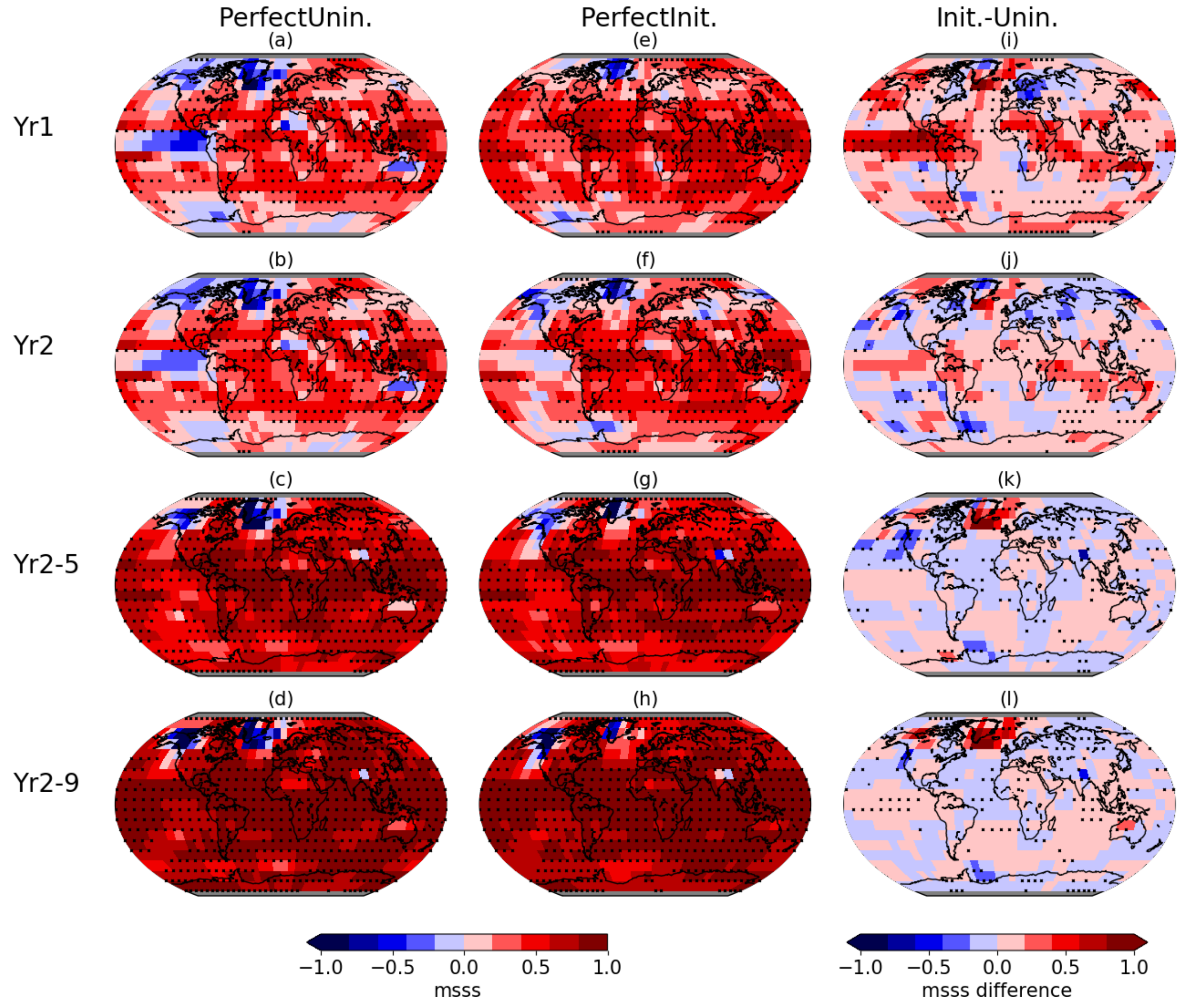
MSSS in initialized and un-initialized perfect-model predictions



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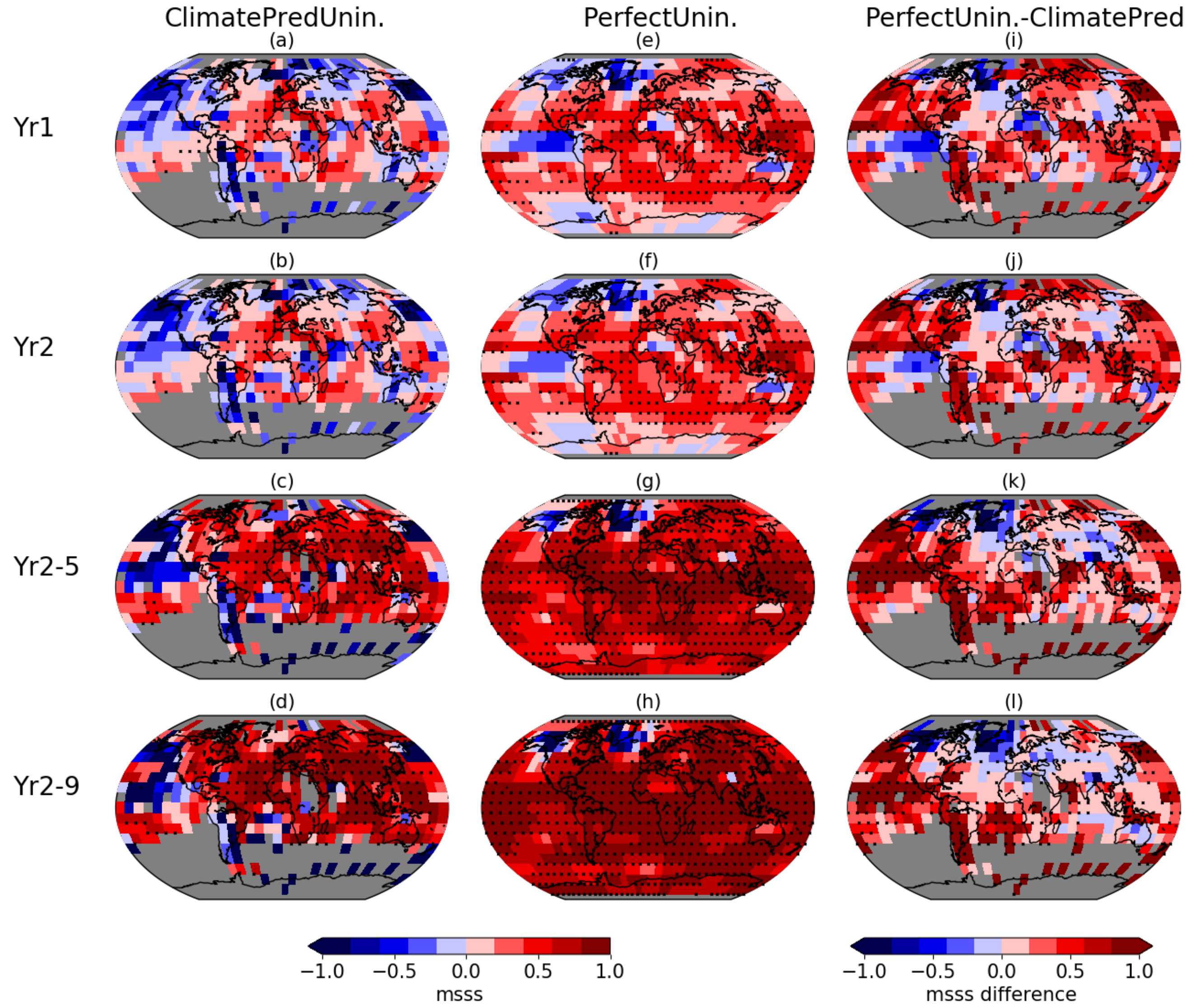
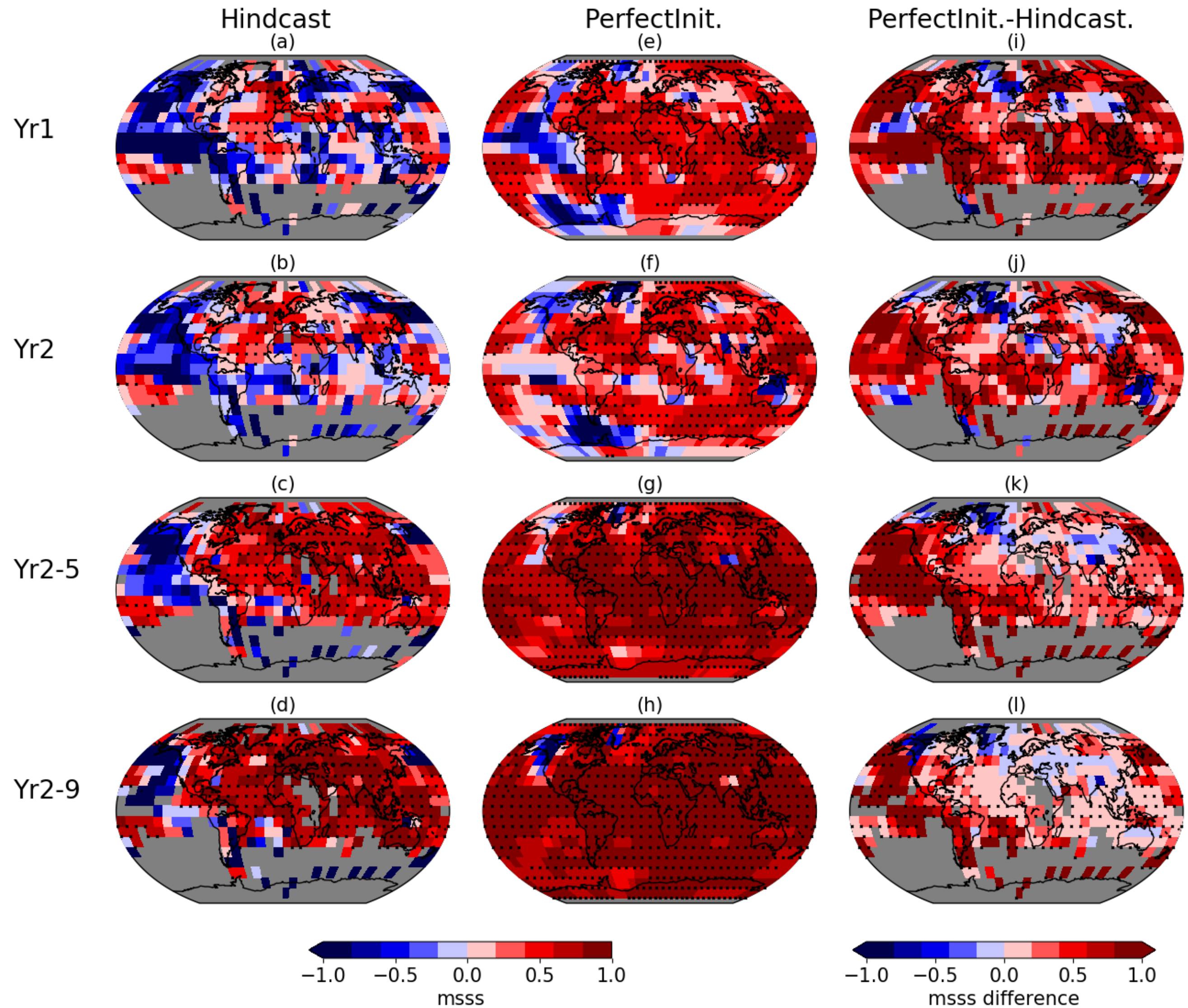
[added value from initialization?]

MSSS un-initialized real-world and perfect-model predictions



[inconsistencies model vs. obs?]

MSSS initialized real-world hindcasts and perfect-model prediction



[total margin of possible improvement?]

Compare areas with increased/decreased skill

	Lead year	Significant improvement ($p<0.1$)	Significant negative difference
Initialized perfect model vs 'uninitialized' perfect model	1	35%	--
	2	15%	5%
	2-5	--	12%
	2-9	13%	9%
Uninitialized perfect model vs uninitialized climate predictions	1	29%	--
	2	27%	--
	2-5	45%	--
	2-9	44%	5%
Initialized perfect model vs decadal hindcasts	1	48%	--
	2	29%	--
	2-5	61%	--
	2-9	54%	--

Effect of initialisation

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	2-9	54%	--

Inconsistencies
Model - observations

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Overall possible improvement
If perfect-model skill was achievable

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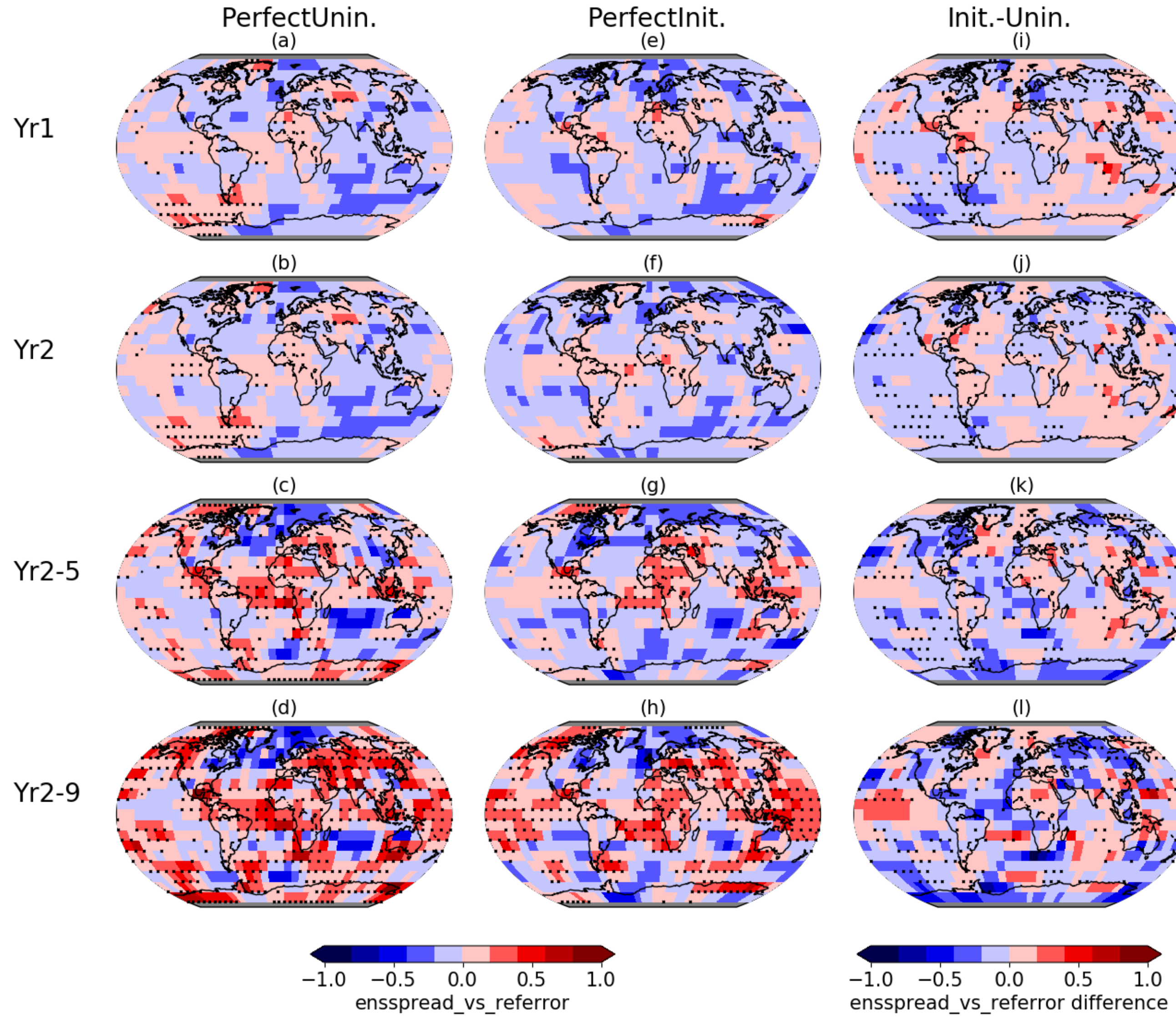
LESS in initialized and un-initialized perfect-model predictions



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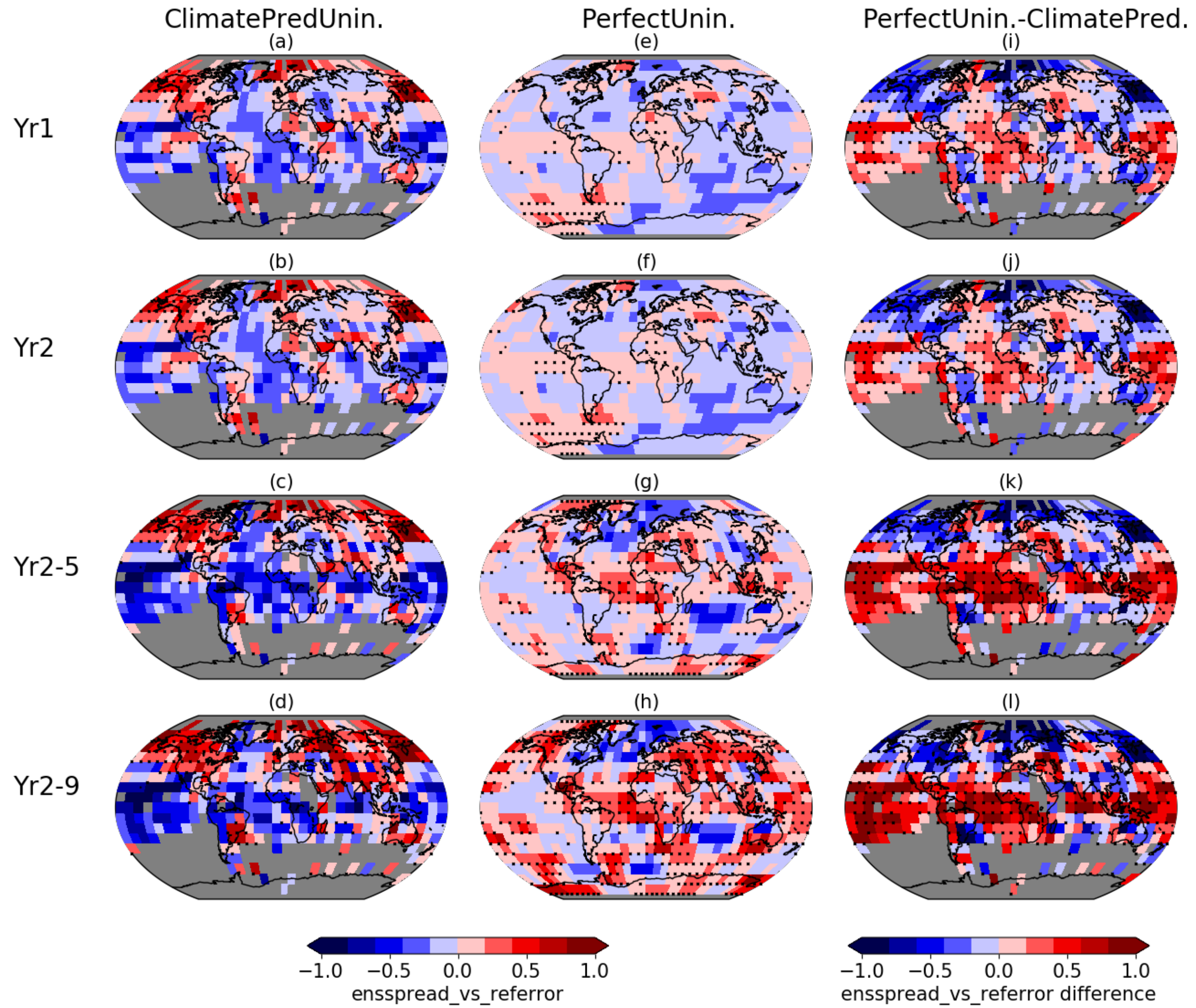
[no clear effect from initialization!]

LESS un-initialized real-world and perfect-model predictions



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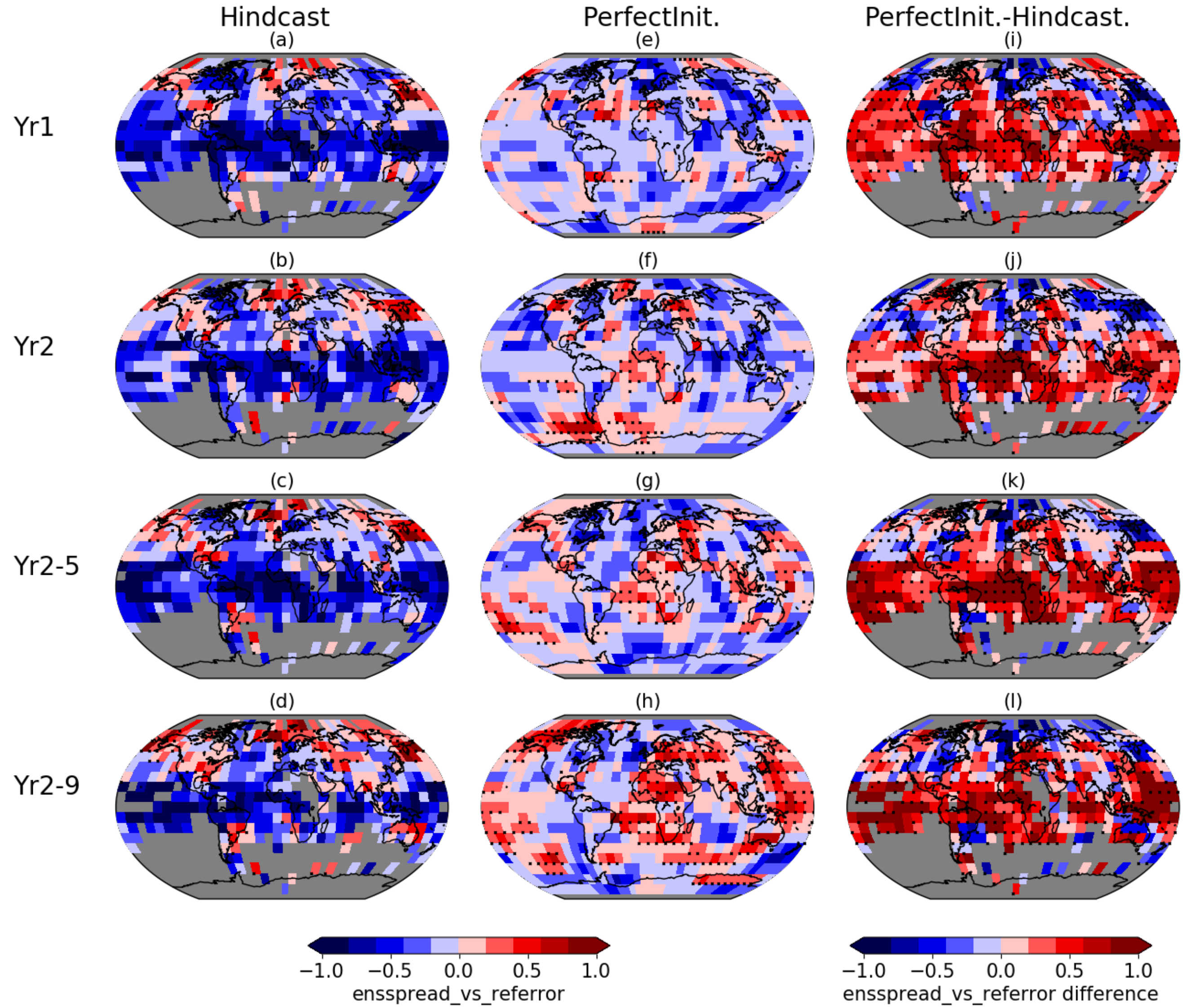
[inconsistencies model vs. obs?]

LESS initialized real-world hindcasts and perfect-model prediction



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[pattern/differences very similar between initialized/un-initialized]

Summary + Concluding thoughts

- perfect-model experiments can be useful to determine the limits of achievable prediction skill (illustrated for tas, but similarly applicable to other variables…)
- Helps to better understand predictability (initialisation versus external forcing), and to manage expectations
- Added value from initialisation until ~2-3 years forecast time
- (ideal) initialisation does not appear to affect ensemble dispersion

- Run similar experiments with different models to understand in how far predictability patterns are model-dependent

→ run such perfect-model predictions complementary to DCPP-A real-world hindcasts??!

[Caveat: predictability of real world may be different to predictability within model missing key processes? Improved models more/less predictable?
→ Perfect-model benchmark informs us what skill is achievable with our existing models (the same used to make predictions!) given ideal initialisation]

(Larger ensemble sizes to e.g. better estimate robustness of skill differences, reliability, etc.)

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Thank you

Liu, Donat, Taschetto, Doblas-Reyes, Alexander, England: A framework to determine the limits of achievable skill for interannual to decadal climate predictions, *JGR-Atmosphere* (revised)

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