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# Bayesian probabilistic model for multi-year climate predictability

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## Introduction & Motivation

- Near-term climate ranging between 1 – 10 years is the combined result of a forced component and of the internal variability intrinsic to the climate system.
- Predictions on this time scale from dynamic climate models rely on initialization at the current observed climate, and time forward simulation with physical principles.
- We develop a Bayesian data-driven prediction system that uses the current climate state and tendencies, produces probabilistic forecasts, and provides probability distributions over the model parameters.
- Our modeling framework offers a novel tool for multi-year climate predictions independent from dynamic climate models, incorporating uncertainty quantification, and identifying climate modes and interactions that exhibit long-term predictability.

## Methods

We focus on global-scale 1940 – 2024 sea surface temperature (SST) over the oceans and 2m air temperature (T2m) over land from the ERA5 reanalysis product.

1. **Dimensionality reduction**: projecting climate variables on Laplacian eigenvectors.
   ⇨ time-evolving projection coefficients capturing the largest spatial scales (Fig. 1)

2. **Detrending and filtering**: 2nd order polynomial to remove trend in each Laplacian separately, 1/5 $\text{yr}^{-1}$ low-pass filter to enhance multi-year signal.
   ⇨ smooth and stationary time series used for model calibration (Fig. 1)

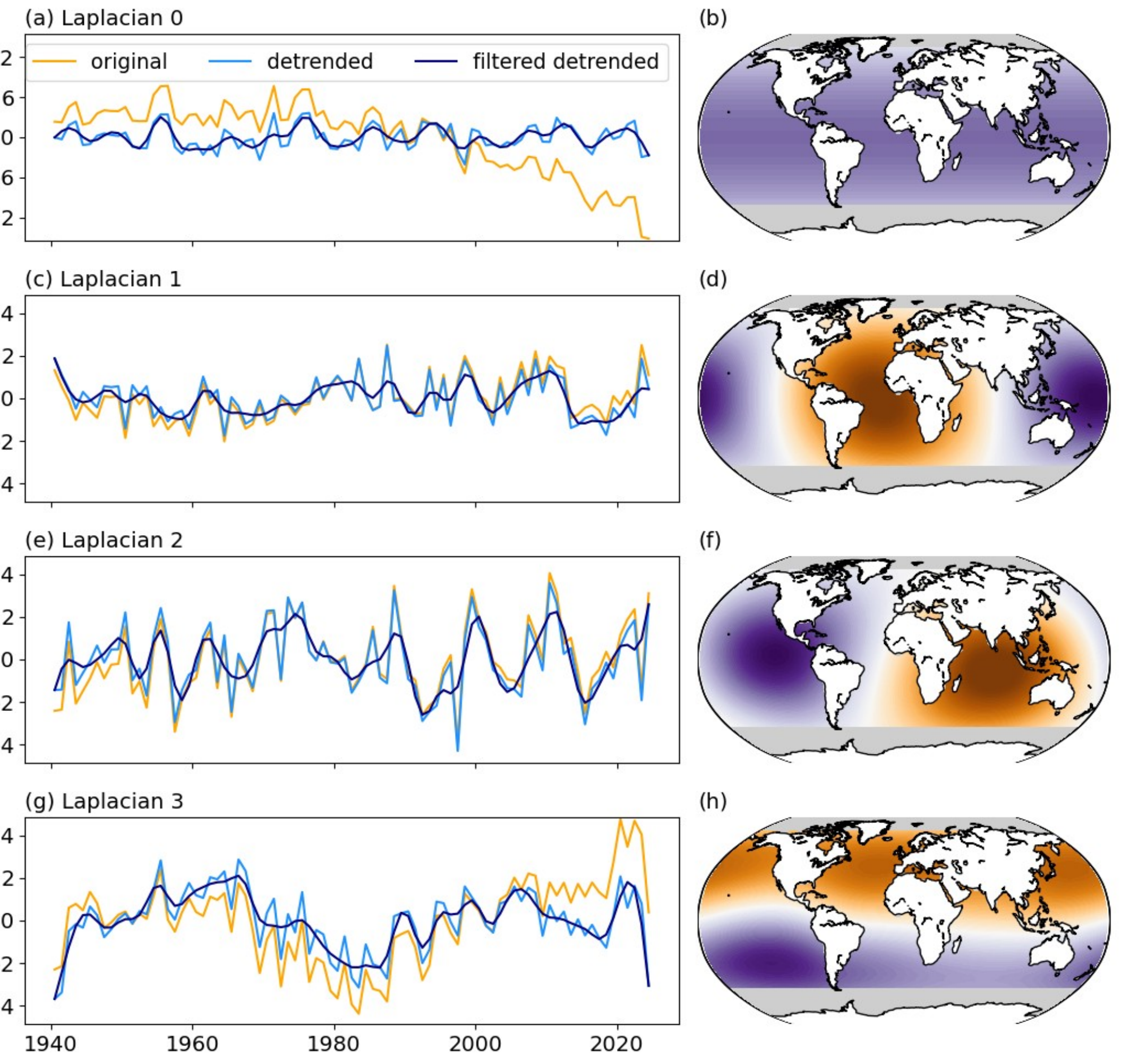

**Figure 1: Laplacian eigenvector and projection coefficient time series.** The time series (a,c,e,g) of the projection coefficients for the 4 leading Laplacian eigenvectors for the ocean domain, and their spatial patterns (b,d,f,h). Orange curves show raw projection coefficients, light blue detrended with 2nd order polynomial, and dark blue low-pass filtered with Butterworth filter of cutoff frequency 1/5 $\text{yr}^{-1}$ and order 3. The Laplacian eigenvectors are a set of orthogonal spatial patterns depending only on latitude-longitude coordinates. Projecting on a limited number of leading Laplacians systematically removes small-scale variability.

3. **Bayesian vector autoregression:** probabilistic multivariate time series model

$$\boldsymbol{y}(t) = \mathbf{A}_1\, \boldsymbol{y}(t - \Delta t) + \mathbf{A}_2\, \boldsymbol{y}(t - 2\Delta t) + \boldsymbol{\xi}(t)$$

$$\boldsymbol{\xi}(t) \sim \mathrm{N}(0, \boldsymbol{\Sigma})$$

$t$: time index (year)

$\boldsymbol{y}$: vector of the $m$ leading Laplacian projection coefficients

$\mathbf{A}_j$: j-lag autoregression coefficient matrix of dimensions $m{\times}m$

$\boldsymbol{\xi}$: $m$-dimensional residual noise

$\boldsymbol{\Sigma}$: noise covariance matrix of dimensions $m{\times}m$

4. **Inference task**: calibrate posterior probability distributions of $\mathbf{A}_1$ , $\mathbf{A}_2$ , $\boldsymbol{\Sigma}$
   ⇨ Sparse Bayesian algorithm for inference in large dimensions: Horseshoe+ prior
   (note: results shown with 20 and 10 Laplacians for SST and T2m, i.e, $m = 30$)

## Results: Model Performance

- Results are shown using 10-fold cross-validation for hindcasts over 1940 – 2024.
- Results are evaluated against raw SST and T2m data from each left-out cross-validation fold.
- Computation of a 800-member ensemble, starting every-year, with yearly prediction lead-time up to 5 years.
- Evaluation of:
  - deterministic skill ⇨ Anomaly Correlation Coefficient (ACC) of the ensemble mean
  - probabilistic skill ⇨ Ranked Probability Skill Score (RPSS) with tercile-based categories
- But much of the skill is associated with the forced increasing trend in temperature (see Fig. 2).
  ⇨ Evaluation of residual skill, i.e., after removing 2nd order polynomial at every grid cell (Figs. 3,4).
  ⇨ Isolates skill associated with internal climate variability (Figs. 3,4).
- Residual ACC:
  - 1-yr lead ⇨ largest over tropical oceans, widespread ocean and land skill (no land skill for persistence)
  - 5-yr lead ⇨ still skillful over most oceans and large land areas (zero skill for persistence)
  - 1-5-yr averaged lead ⇨ time-averaging enhances signal-to-noise ratio, and skill is high and widespread
- Residual RPSS:
  - probabilistic metric is more challenging
  - 1-yr lead skill mostly limited to tropical oceans, no skill remaining at 5-yr lead
  - here also 1-5-yr averaging increases performance
- Combining SST – T2m in the statistical modeling framework confers predictability from ocean-atmosphere coupling.

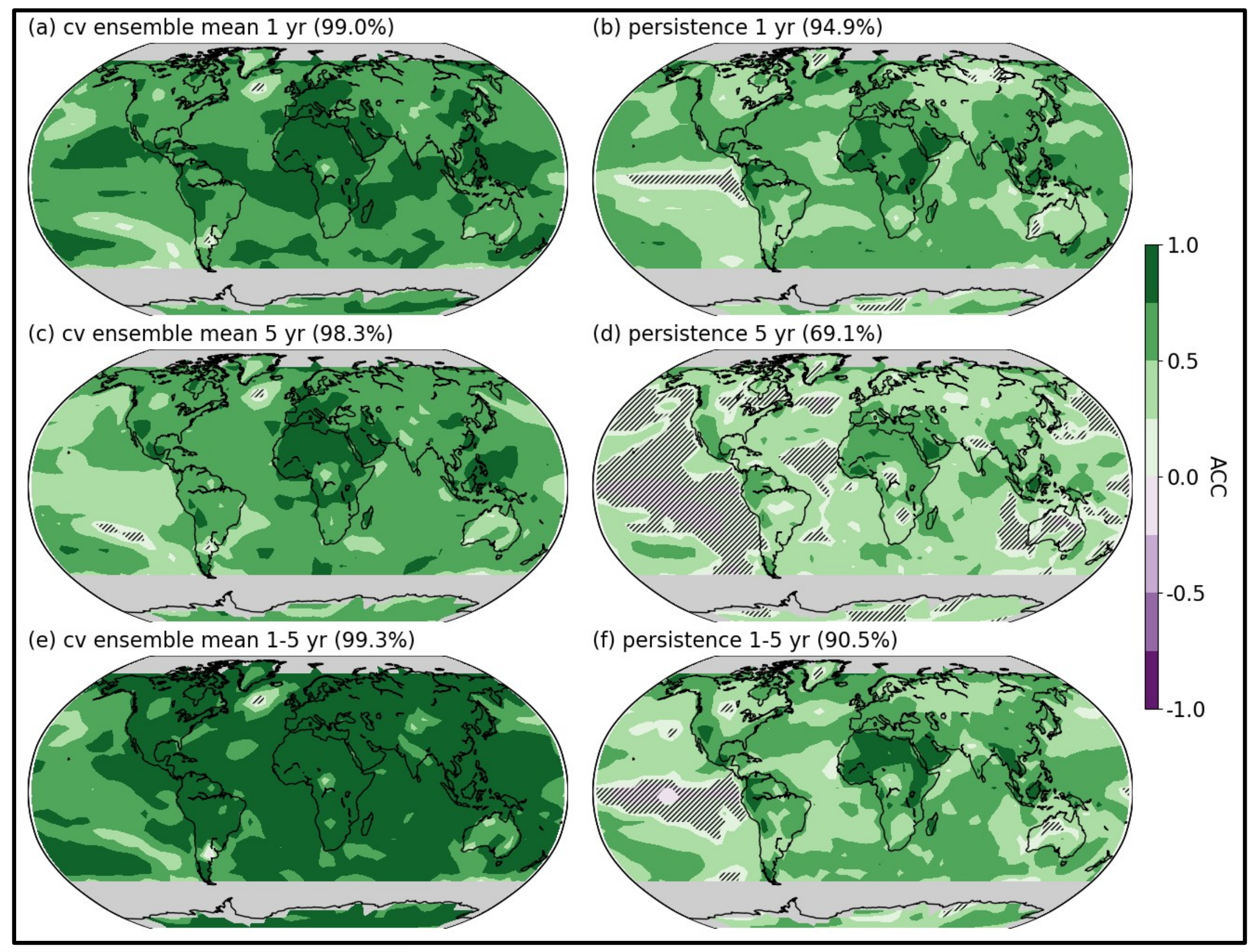

**Figure 2: Anomaly Correlation Coefficient.** 10-fold cross-validation (cv) of ensemble mean correlation with observed SST (over oceans) and T2m (over land) for hindcasts over 1940 – 2024. The ensemble mean (a,c,e) is compared with persistence benchmark (b,d,f). Lead-times are 1 yr, 5 yr, and averaged over 1-to-5 yr. No trend is removed, explaining much of the high and extensive skill. Hatching shows non-significance, controlling for a false discovery rate of 5%, significant area % given on top of panels. High-latitude oceans are excluded to avoid sea-ice.

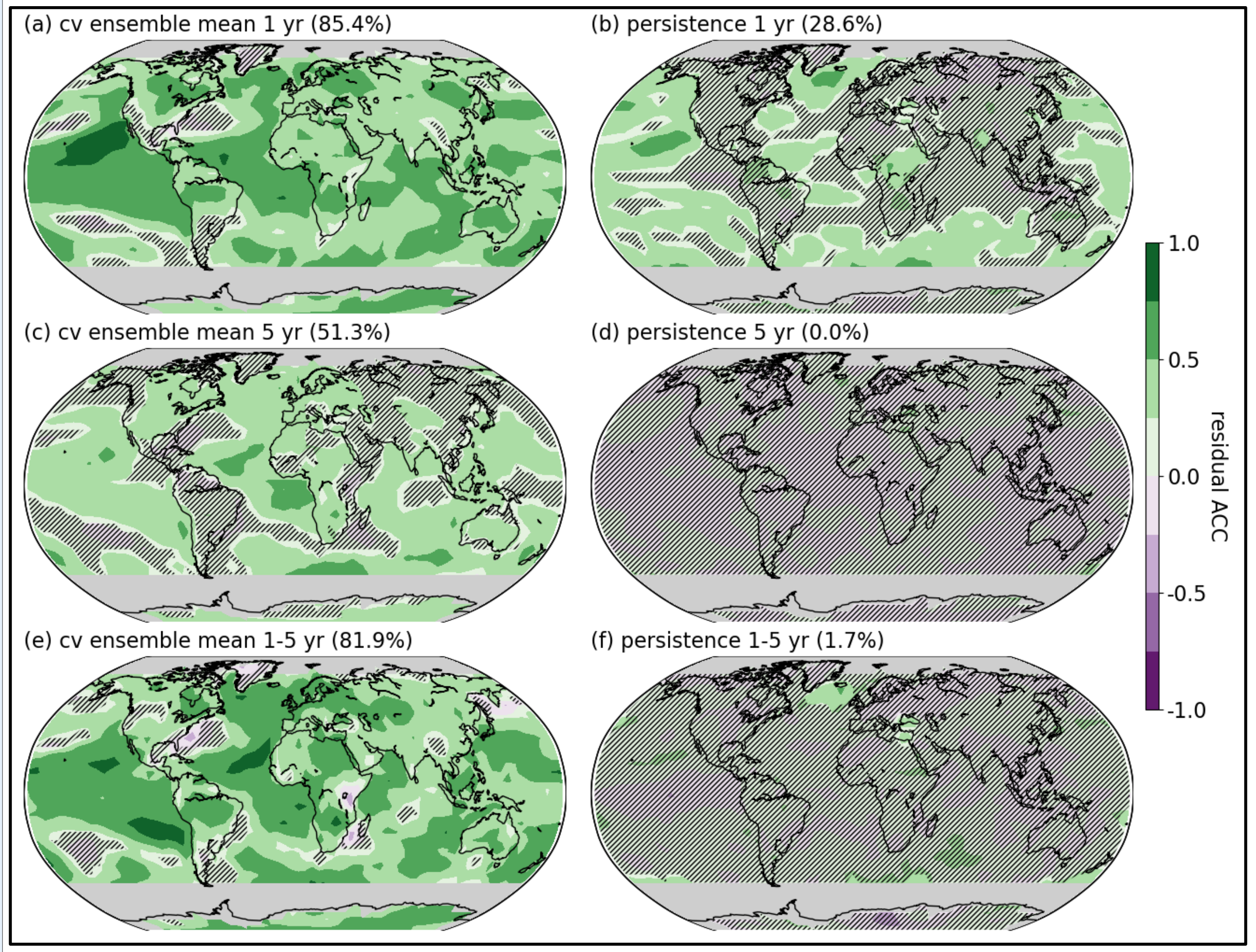

**Figure 3: Residual Anomaly Correlation Coefficient.** Same as Fig. 2, but quadratic 1940 – 2024 trend is removed at each grid cell prior to evaluation. The cross-validated (cv) ensemble mean skill is highest over tropical oceans, generally higher over oceans than land, decreases with lead time, but still marked at 5-yr lead time even over some land areas. Time averaging (e) improves the signal-to-noise ratio (see also Fig. 5).

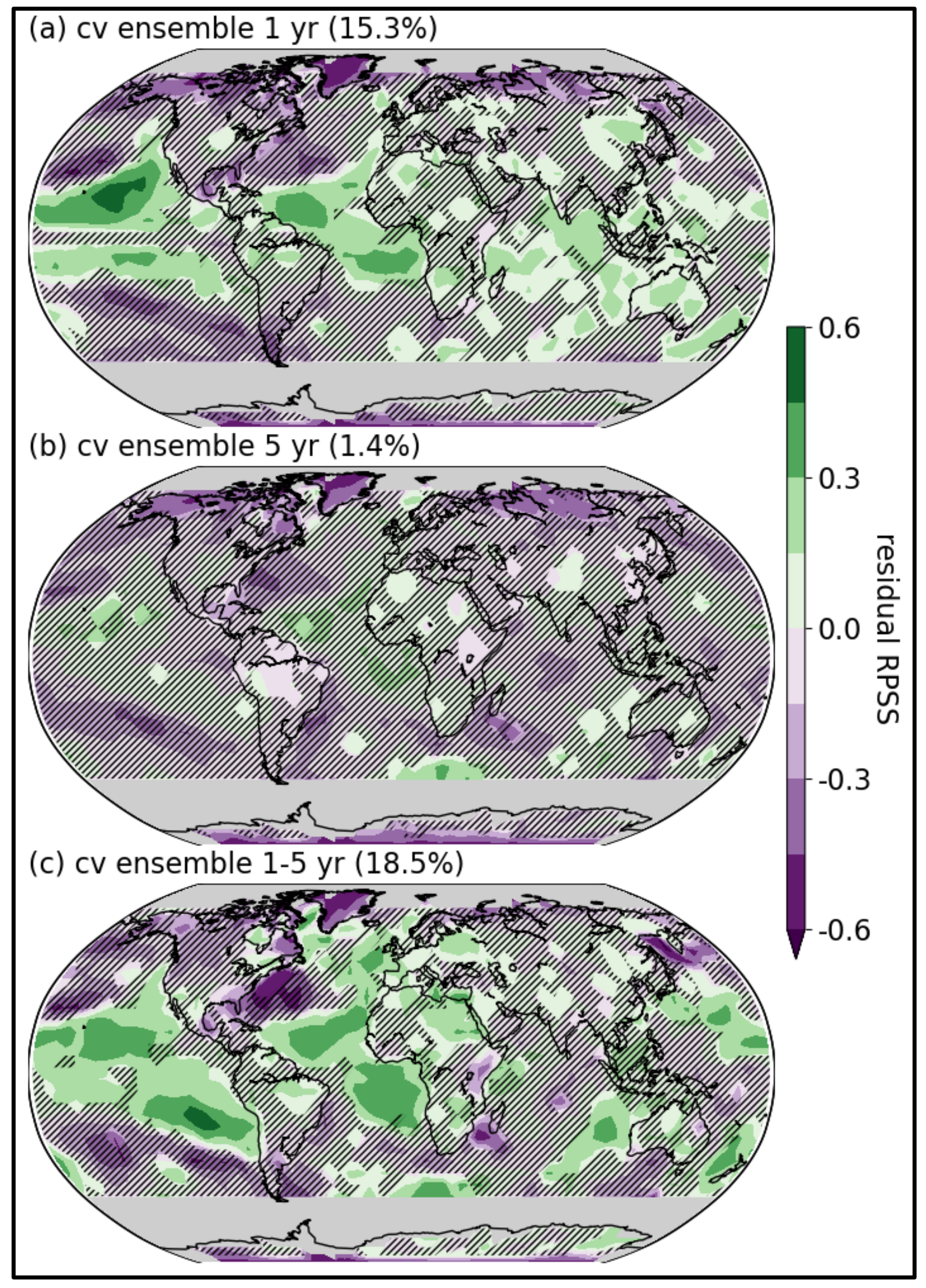

**Figure 4: Residual Ranked Probability Skill Score of detrended series.** Using tercile categories, against reference of climatology. At 1-yr lead, skillful areas are mostly limited to tropical oceans, and vanish at 5-yr lead.

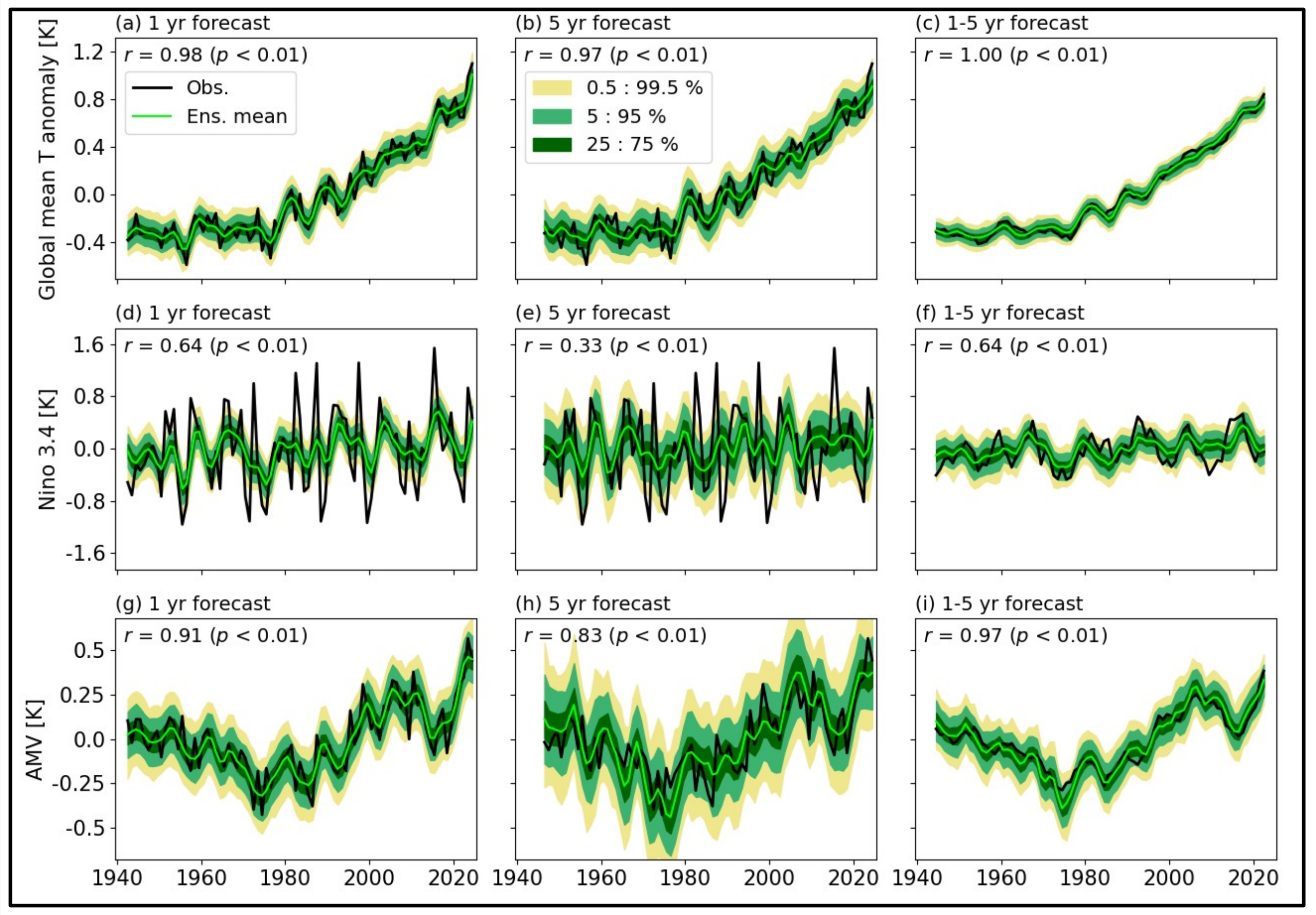

**Figure 5: Hindcasts of climate indices.** Ensemble (800 members) mean (green) and ranges for hindcasts of (a,b,c) global mean temperature, (d,e,f) El Niño 3.4 index, and (g,h,i) Atlantic Multidecadal Variability index, and observations (black). Hindcasts are shown at (a,d,g) 1-yr lead, (b,e,h) 5-yr lead, and (c,f,i) 1-5-yr averaged lead; *r* is the correlation coefficient. Notice that 1-yr lead ensemble uncertainty is well-calibrated for global mean and AMV, but over-confident for El Niño 3.4, and uncertainty increases with lead-time for all indices. Time-averaging enhances signal-to-noise ratio, improving the agreement between observed and ensemble mean variability, as well as calibration of the ensemble spread.

## Results: Parameter Inference

Estimation of 1800 lag-coefficients ($\mathbf{A}_1$ , $\mathbf{A}_2$) and 435 entries for the covariance matrix ($\boldsymbol{\Sigma}$).

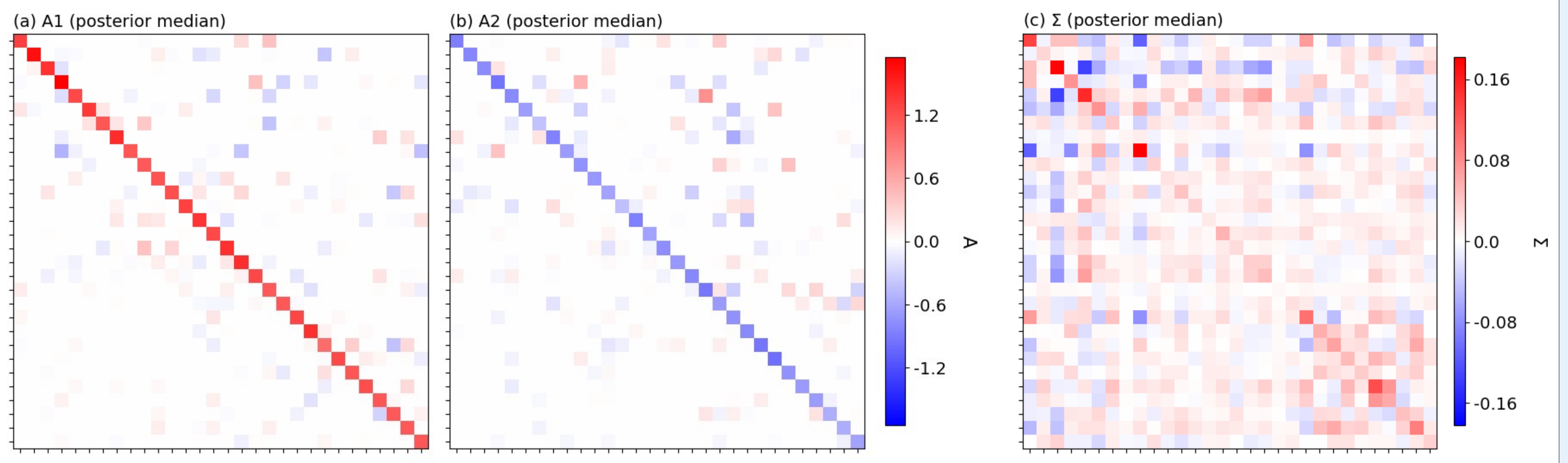

**Figure 6: Median of Posterior Distributions.** Posterior median for the lag-1 (a, $\mathbf{A}_1$) and lag-2 (b, $\mathbf{A}_2$) autoregression coefficient matrices, and for the covariance matrix ($\boldsymbol{\Sigma}$). The SST-specific entries are in the upper-left 20×20 corners, and the T2m-specific entries in the lower-right 10×10 corners. In a,b, diagonal entries represent self-lagged effects, below-diagonal entries large- to small-scale effects, and above-diagonal entries small- to large-scale effects.

## Discussion Points and Conclusions

- Bayesian model allows generation of ensembles of statistically-consistent members.
- High skill of ensemble mean at multi-year lead time SST and land T2m predictions.
- Model is calibrated in a reduced subspace with filtered data, but evaluated with raw data.
- Bayesian framework ⇨ sampling of parametric uncertainty and aleatoric uncertainty.
- Sparsity-promoting methods constrain high-dimensional model space with 85 yr of data.
- Can we use this modeling framework to address questions related to:
  - signal-to-noise paradox?
  - investigate SST – T2m lagged interactions (and other variables)?
  - quantification of predictability of climate modes?
  - compare predictability in observations versus dynamic climate models?
- This work is still in progress: we welcome comments, ideas, and insights.

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