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A computationally efficient approach to generate large ensembles of **coherent climate data for GCAM**

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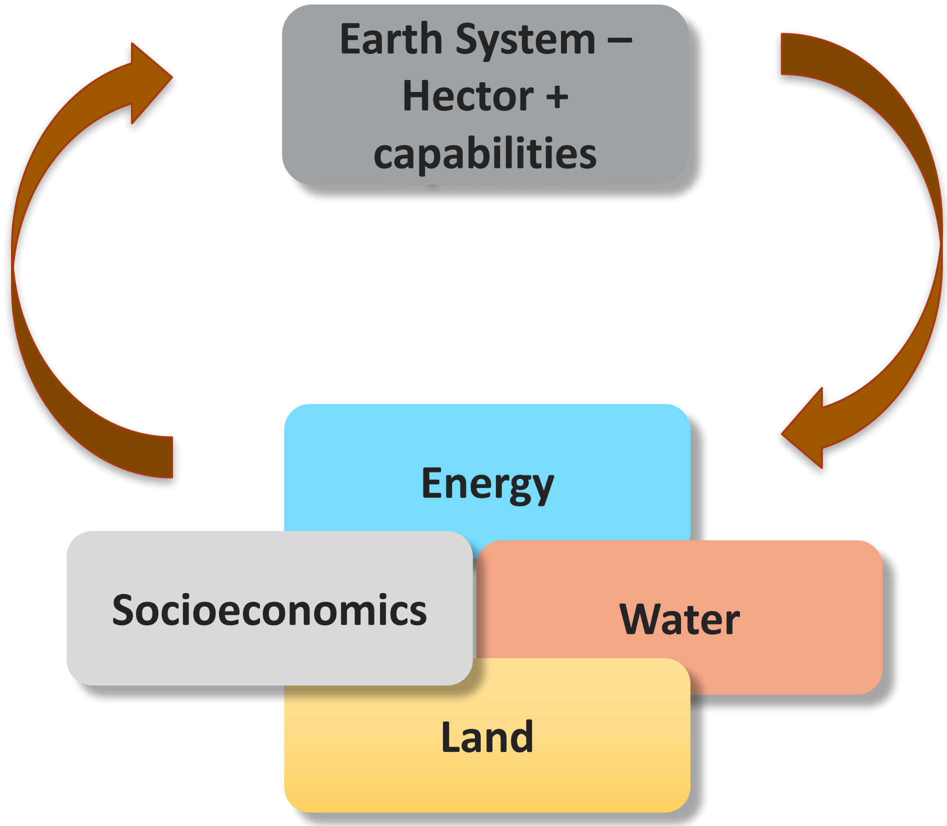
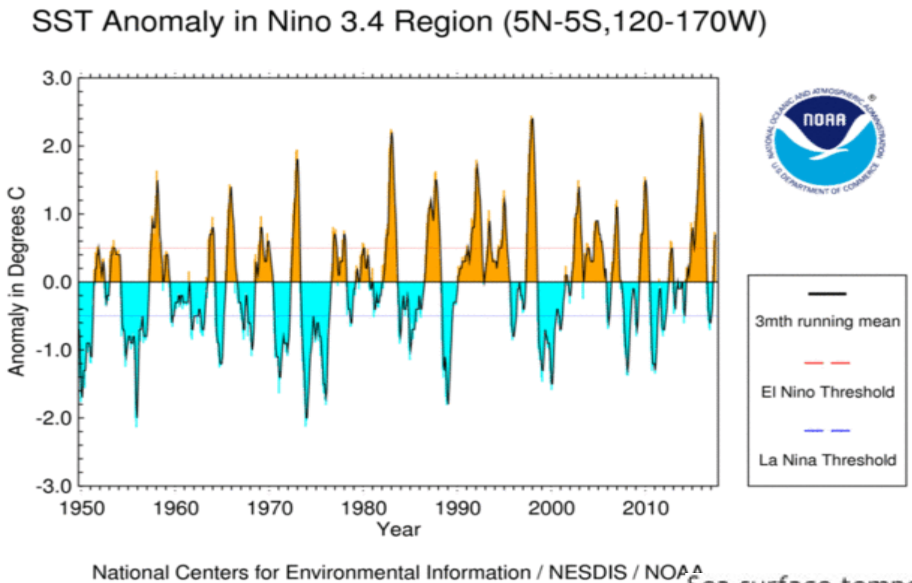
Fully integrated human-earth system framework

- Simple Climate Models (SCM) are great tools for multiple scenarios, quick analyses, and probabilistic assessments
- Earth System Models (ESM) are complex and therefore expensive to run under multiple scenarios
- How can we emulate the regional climate of the larger ESMs?

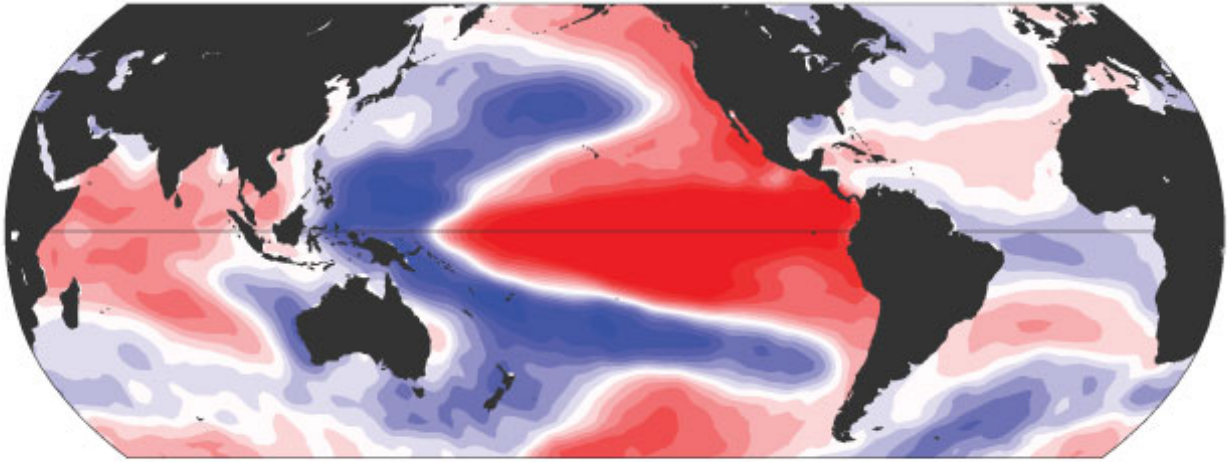


We want to produce coherent spatial and temporal climate data



- Existing methods to add in variability:
  - Stochastic noise
  - MCMC
  - Historical variability
  - Pattern scaling residuals
- These methods do not preserve spatial and temporal coherence

Sea surface temperature anomaly patterns

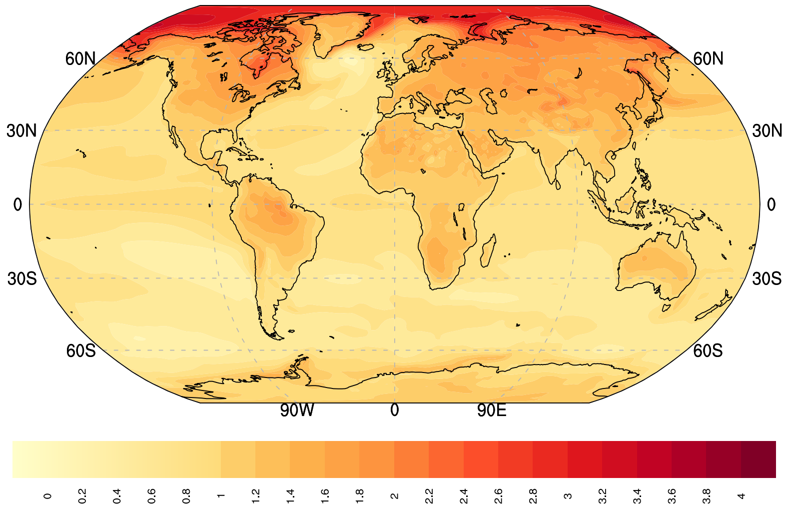


Classic ENSO signal

Step 1: Mean Climate – Pattern Scaling

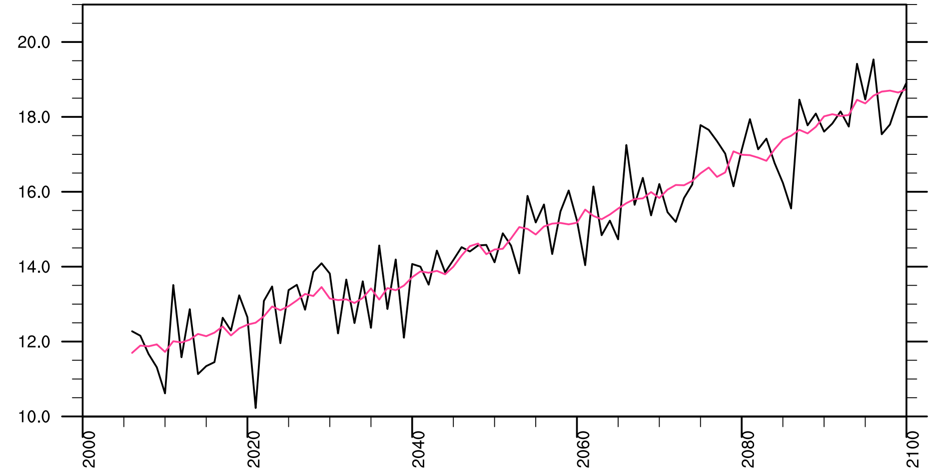
$$\mathrm{T}_{\mathrm{local}} = \alpha + \beta\,\mathrm{T}_{\mathrm{global}} + \epsilon$$

Pattern of Global Mean Temperature Change



Annual average TAS patterns in °C / °C.

Mid-Atlantic Temperature Change



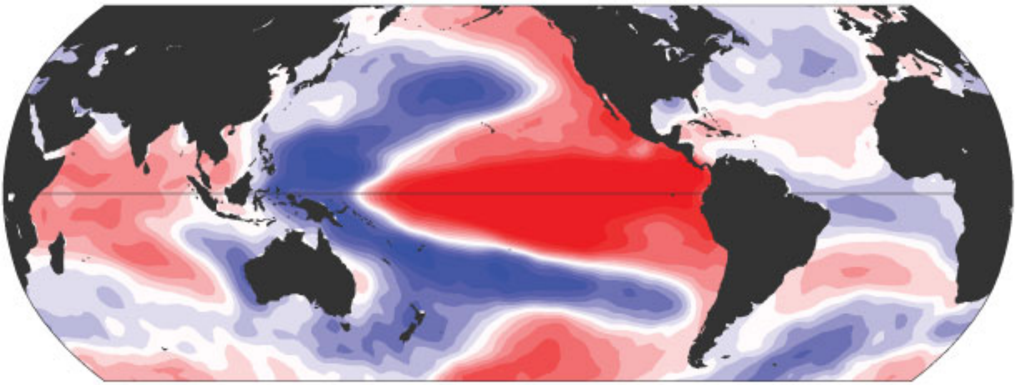
Actual (black line) and pattern predicted (red line) annual average TAS time series in °C.

Step 2: EOF - Preserve Spatial Correlation

$$\epsilon = \sum \phi_{xy} \, \psi_t$$

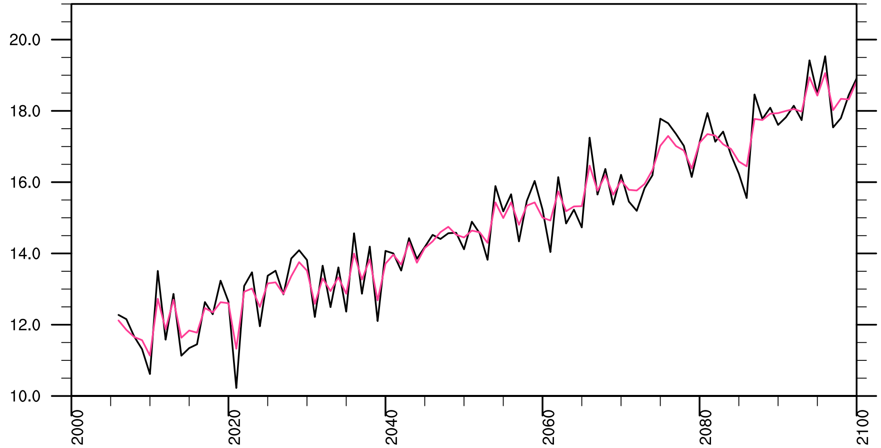
- ϕ_{xy} is the spatial component
- ψ_t is the temporal component
- First 50 EOFs capture ~99% of the variance
- We can reproduce the variability – but it's only 1 realization.

Sea Surface Temperature Anomaly



Classic ENSO signal

Mid-Atlantic Temperature Change



Actual (black line) and pattern predicted with 1st 50 EOFs (red line) annual average TAS time series in °C.

Step 3: FFT – Preserve Temporal Correlation

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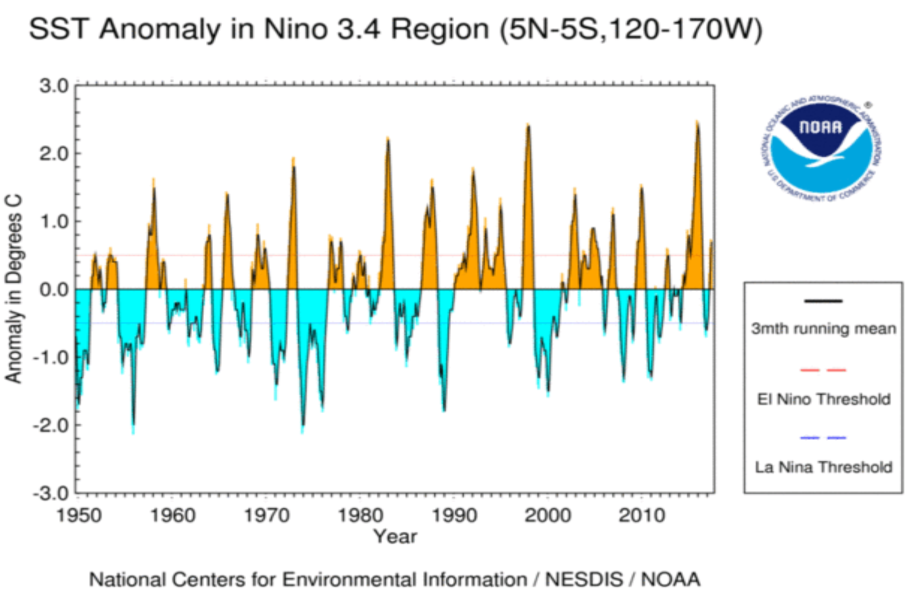
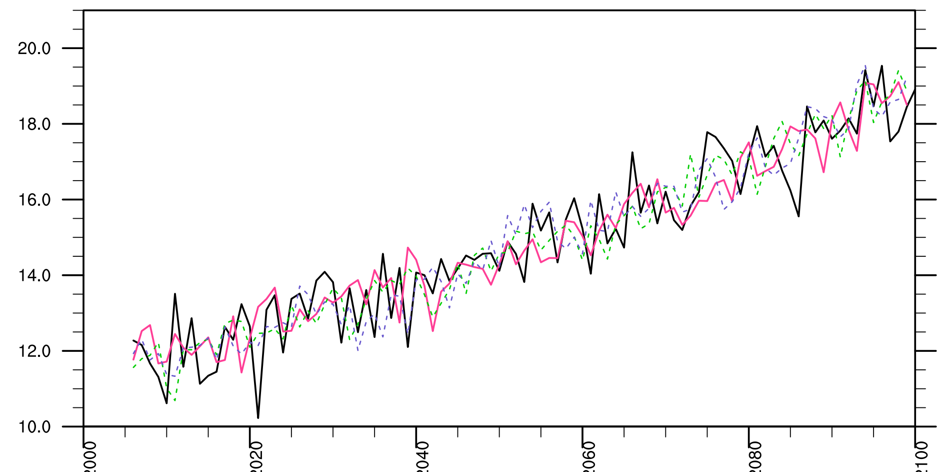
$$\epsilon = \sum \phi_{xy}\,\psi_t$$

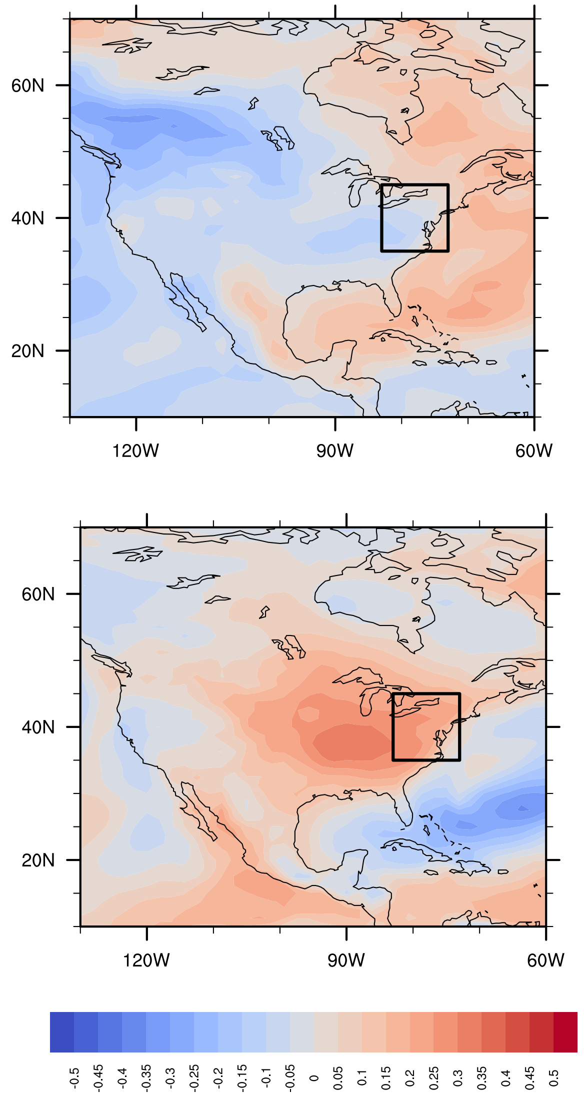
- Fast Fourier Transform to ψ_t
- Decompose the time series into the frequencies that make it up (magnitudes and phases)
- Randomizing the phase will maintain the temporal autocorrelation but with random timing





Actual (black line) and pattern predicted with 1^{st} 50 FFT/S EOFs (magenta line) annual average TAS time series in °C. Dashed lines represent 2^{nd} and 3^{rd} realization.

Step 4: Reconstruct Multiple Realizations of Local Temperature

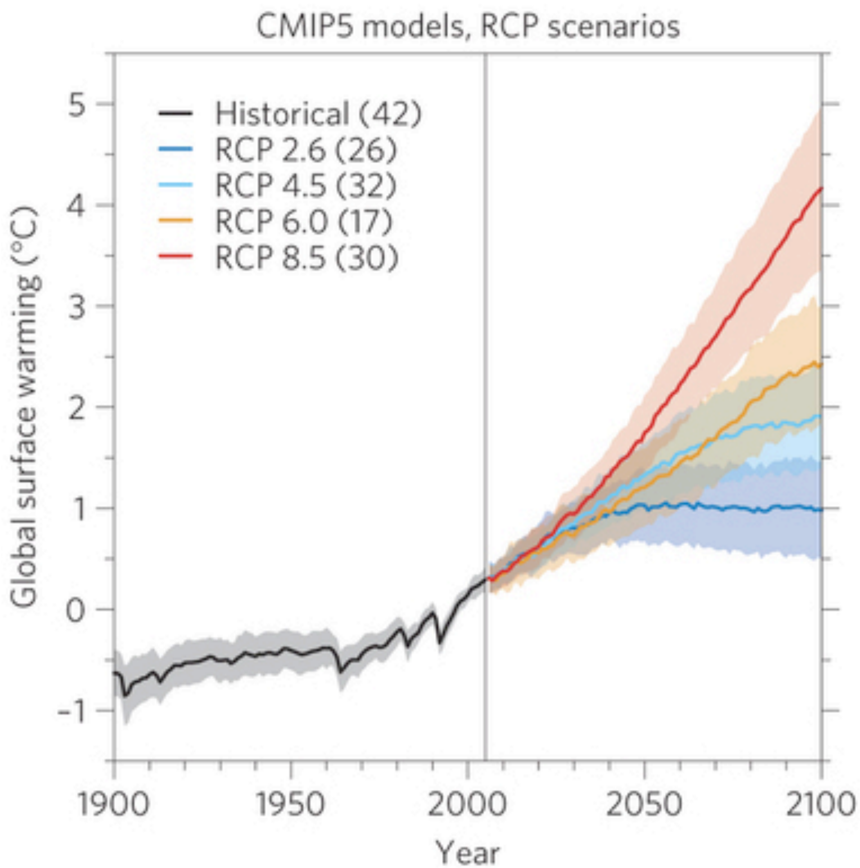


$$\mathrm{T}_{\mathrm{local}} = \alpha + \beta\, \mathrm{T}_{\mathrm{global}} + \epsilon$$

- Multiple the pattern by global mean temperature change (Hector), add the y-intercept, and add in the reconstructed residuals.
- We have the model response, and the spatial and temporal variability preserved, with some introduced randomness
  - Time slice (e.g., 2050) with spatial coherence
  - Spatial slice (e.g., Mid-Atlantic) with temporal coherence

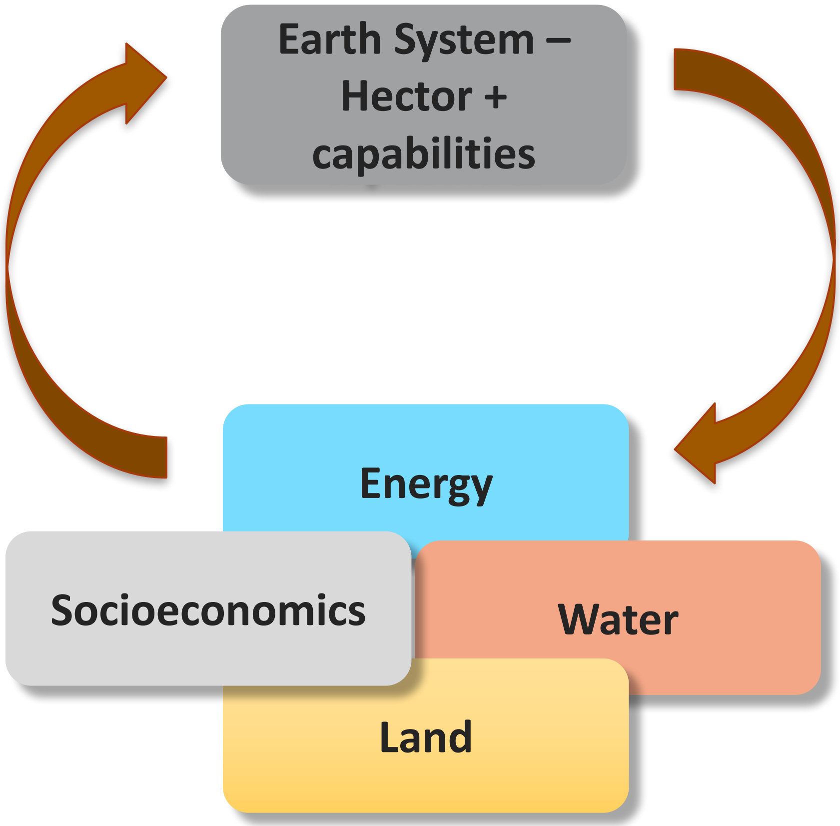
ESM benefits without the ESM costs

- Combination of Hector and regional climate information
  - Run any emission scenario
- Datasets with coherent temporal and spatial characteristics of the underlying ESM – without having to run it!
- Multiple climate realization at a minimal cost
  - <1 minute on a laptop vs. months of supercomputing



Broader implications and future work

- GCAM impacts
  - Land
  - Water resources
  - Energy supply and demands
- Modify this approach to use multiple predictors – both temperature and precipitation
  - Other local variables of interest
- Check out mean climate patterns at https://github.com/JGCRI/CMIP5_patterns
- Release the code to produce the synthetic realizations this winter – stay tuned!



Questions?

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Method to Generate Synthetic Model Realizations

1. Emulate model behavior (pattern scaling)
   - $$\mathrm{T}_{\mathrm{local}} = \alpha + \beta\,\mathrm{T}_{\mathrm{global}} + \epsilon$$
     - T_{global} is the GMT time series (1-D); T_{local} is the gridded time series (3-D); ϵ is the residual term (3-D); α is the y-intercept; β is the regression slope (2-D)

2. Preserve spatial variability (decompose residuals through EOF analysis)
   - $$\epsilon = \sum \phi_{xy}\,\psi_t$$
     - ϕ_{xy} is the spatial basis function (2-D) of the residuals
     - ψ_t is the corresponding EOF projection coefficient (1-D)

3. Preserve temporal correlation (apply Fast Fourier Transform/Synthesis with randomized phase to ψ_t)
   - Bochner-Khinchin-Wiener theorem (Box and Jenkins, 1970):
     - Relationship between power spectral density (PSD) and autocorrelation
     - PSD is based on squared magnitude of the FFT
     - Phase from FFT can then randomized to produce multiple ψ_t s

Putting It All Together and Example Data

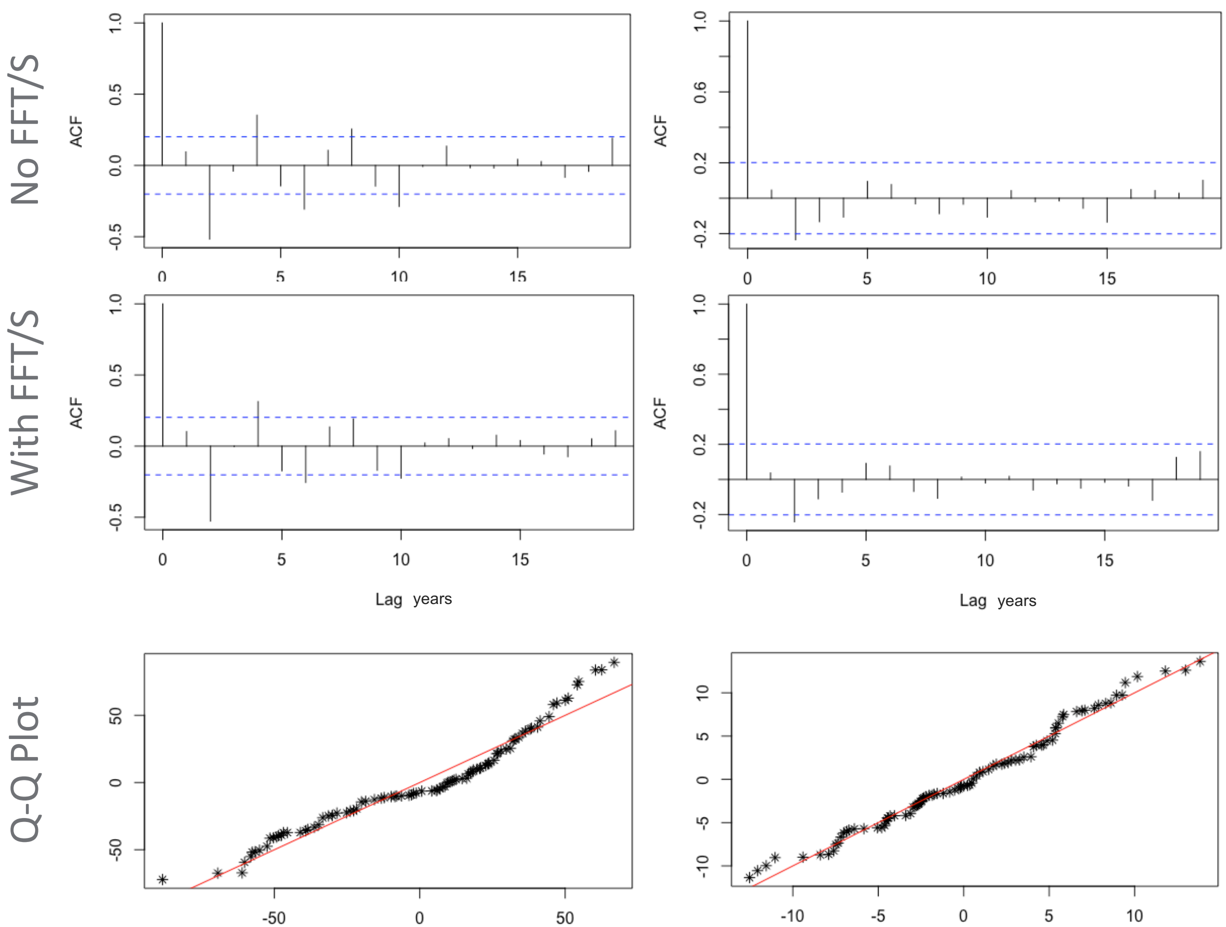
4. Generate multiple sets of residuals (Multiply ϕ_{xy} (from step 2) by transformed ψ_t (from step 3), and then sum to generate new ϵs).
   - Repeat steps 3 & 4 as many times as wanted

5. Reconstruct T_{Local} (Use α (y-intercept), β (pattern), and T_{global} from step 1 and add ϵ from step 4)
   - $\mathrm{T}_{\mathrm{local}} = \alpha + \beta\,\mathrm{T}_{\mathrm{global}} + \epsilon$

- Data
  - CMIP5 models: ACCESS1-0, CCSM4
  - Forcing scenario: rcp8.5, 2006-2100
  - Climate variable: temperature at surface (TAS)

Results: Autocorrelation and Quantiles of FFT/S EOFs

Model 1 EOF 1 ψ_t | Model 1 EOF 50 ψ_t



Kolmogorov-Smirnov test:
D = 0.143, p-value = 0.251

Kolmogorov-Smirnov test:
D = 0.059, p-value = 0.9899

- Temporal autocorrelation is preserved
- And…
- The distributions are not significantly different