Climate Prediction Windows

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Outline

- Bayesian climate prediction & evidence
  - Modifying prediction using data
  - Huang et al. 2011: Rating data types
- Testing models' multi-decadal predictive capability
  - Multi-decadal prediction and sensitivity?
  - What data type contains the most information?
  - Are means or trends a better test?
  - Extracting maximum information from data
  - A tabulation
- Conclusions

Bayesian approach

$$P(\mathbf{y}\,|\,\mathbf{d}) \propto \int d\mathbf{x}\, P(\mathbf{d}\,|\,\mathbf{x}) \int d\theta\, P(\mathbf{x},\mathbf{y}\,|\,\theta)$$

Predictand — Data — Observable — Model physics

$$\mathbf{y}_{\text{most likely}} = \mathbf{y}_{\text{prior}} + \Sigma_{yx}\Sigma_{xx}^{-1}(\mathbf{d} - \mathbf{x}_{\text{hindcast}})$$

$$\Sigma_{yy,\,\text{posterior}} = \Sigma_{yy,\,\text{prior}} - \Sigma_{yx}\Sigma_{xx}^{-1}\Sigma_{xy}$$

$$= \sigma^2_{\text{prior}}(1-\rho^2)$$

Relevance of observable

Inter-model ***variance*** of observable

Uncertainty reduction

A few more concepts…

Inter-model variance = Natural variability + Irrelevant uncertain physics + **Relevant uncertain physics**

Evidence = Agreement of model **x** and data **d**

	Relevant	Irrelevant
Good evidence	Fine-tune prediction of a good model	Reassuring but uninteresting
Poor evidence	GREAT concern; future research desperately needed	Dismiss with mild concern

Ranking Data Types

Satellite Measurements

Data type	ρ	σ_ρ	$\Delta\hat{\sigma}$	$\Delta\hat{\mu}$
Total outgoing long-wave radiation	0.67	0.13	0.27	0.75
Radiance at 995 cm^{-1}	0.67	0.13	0.23	0.44
Dry pressure at 5.5 km	0.64	0.14	0.22	0.42
Radiance at 1,600 cm^{-1}	0.60	0.16	0.18	0.34
Radiance at 560 cm^{-1}	0.55	0.17	0.15	0.35
Reflected solar radiation	−0.47	0.19	0.13	0.32
Radiance at 500 cm^{-1}	0.44	0.20	0.09	0.30

In Situ Measurements

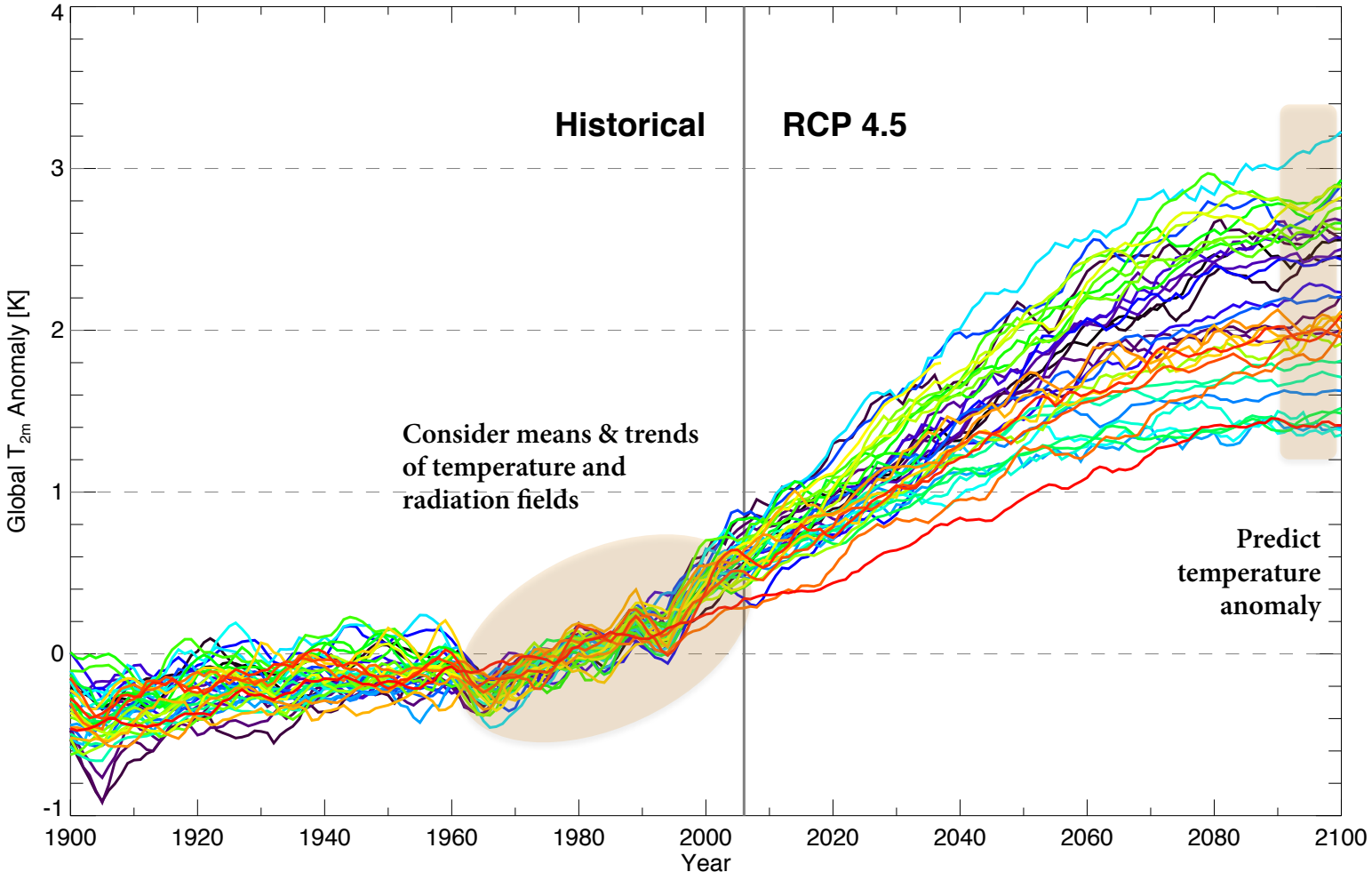
Data type	ρ	σ_ρ	$\Delta\hat{\sigma}$	$\Delta\hat{\mu}$
Geopotential height at 500 hPa	0.64	0.14	0.22	0.44
Surface air temperature	0.61	0.15	0.21	0.27
Upwelling long-wave radiation at surface	0.61	0.15	0.21	−0.47
Precipitable water	0.61	0.15	0.18	0.42
Geopotential height at 200 hPa	0.56	0.17	0.17	0.39
Air temperature at 500 hPa	0.53	0.17	0.15	0.44
Specific humidity at 500 hPa	0.45	0.19	0.10	0.43

Huang, Y., S. Leroy, and R. Goody, 2011: Discriminating between climate observations in terms of their ability to improve an ensemble of climate prediction. *Proc. Nat. Acad. Sci.*, **108**, 10405–10409.

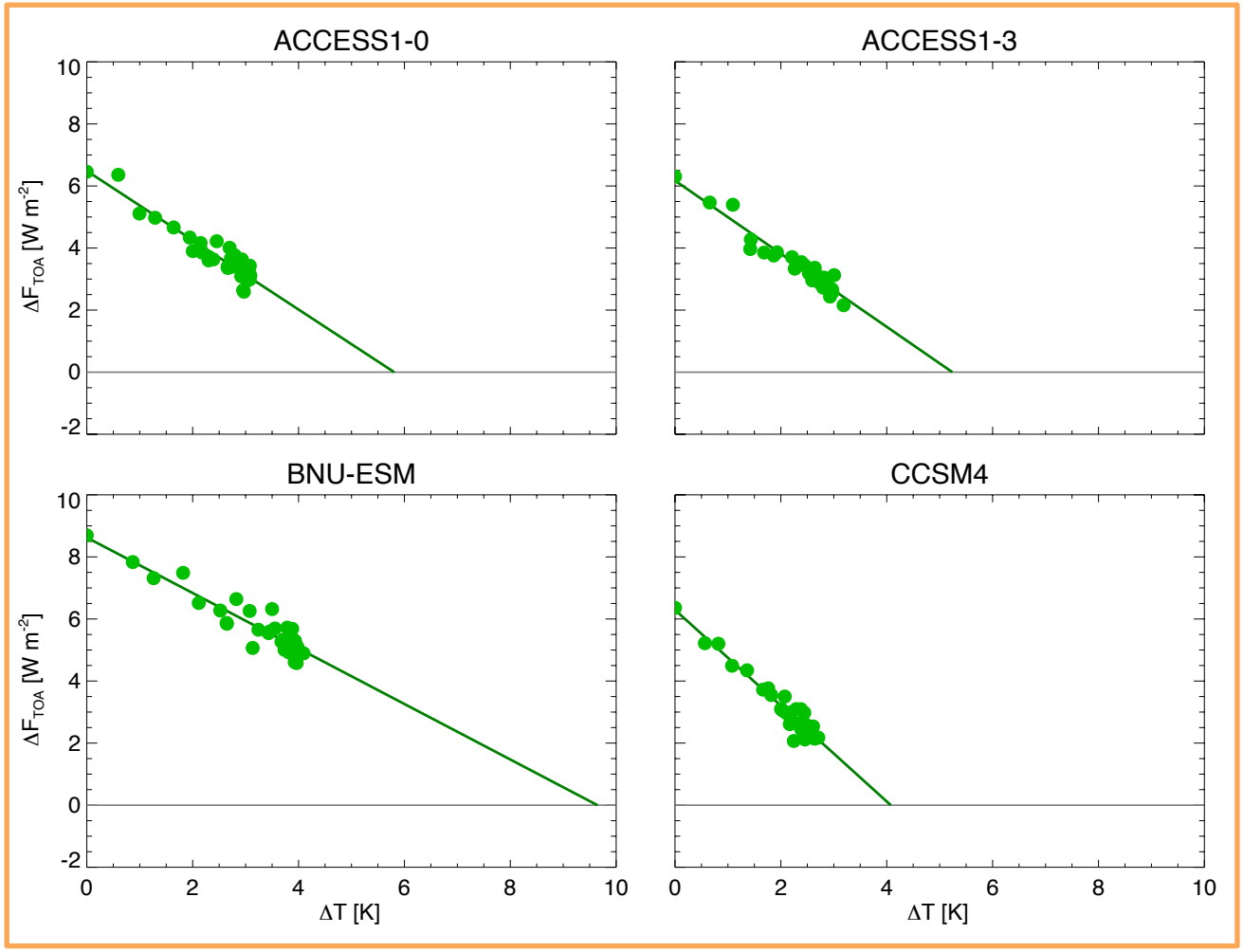
Next steps…

- **Strengthen conclusions by using more models**
  - Use CMIP5 archive (ca. 50 models)
- **Consider spatial dimension**
  - Expect global averages to wash out important information
  - Spatial dimension may compensate for missing information, e.g. radiative forcing
- **Consider information in temporal *trends* and temporal *means***
  - Check assumption that climate models ought to be tested by climate trends
  - Check that sensitivity is more closely related to radiation trends rather than to radiation means
- **Assume that we are testing atmospheric models only**
  - Model simulations will use prescribed sea surface temperature
  - Use CMIP5 historical runs with prescribed SST as simulated data

CMIP5: History and Projection

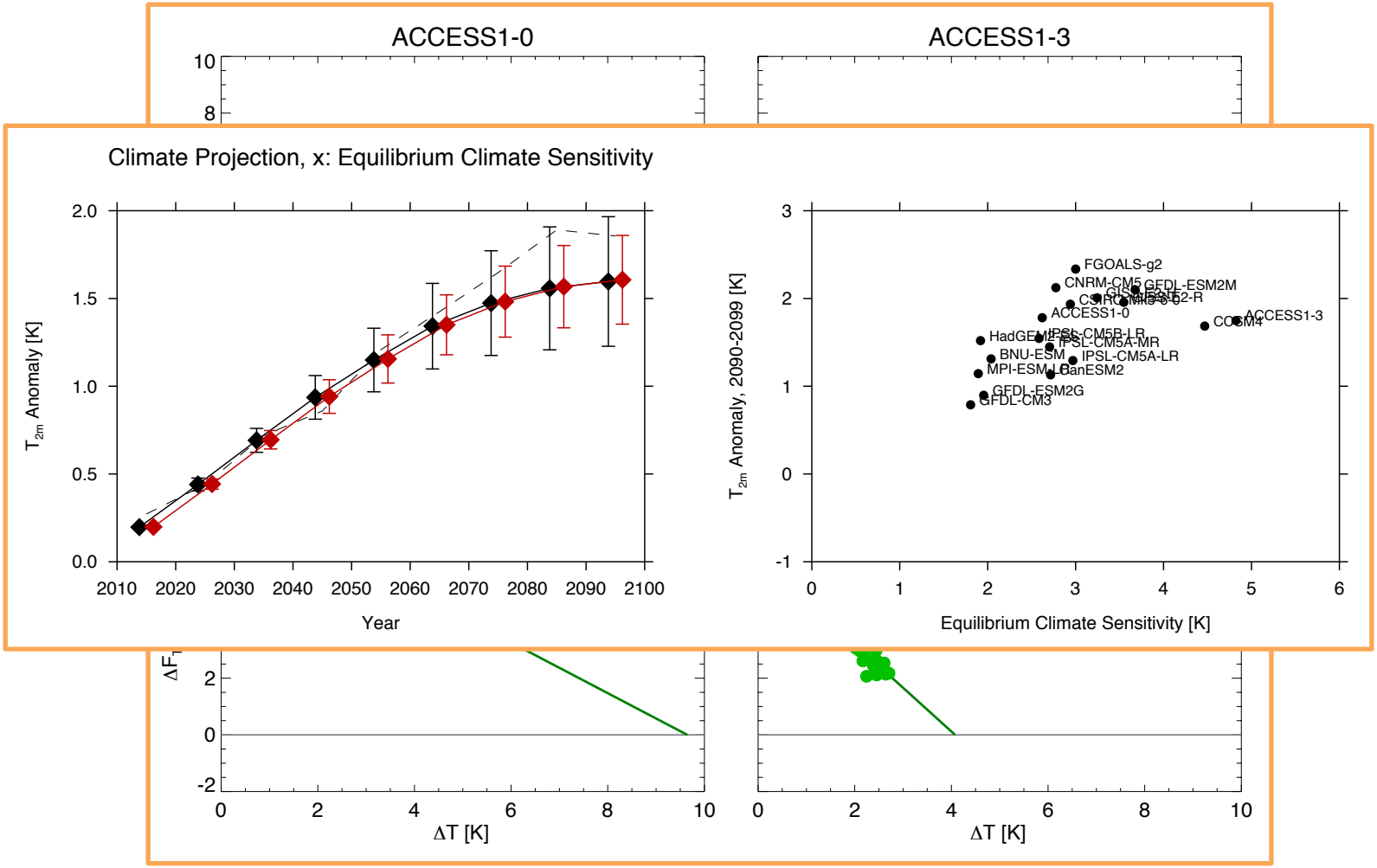


Sensitivity and climate prediction



Andrews, T., J.M. Gregory, M.J. Webb, and K.E. Taylor, 2012: Forcing, feedbacks and climate sensitivity in CMIP5 coupled atmosphere-ocean climate models. *Geophys. Res. Lett.*, **39**, doi:10.1029/2012GL051607.

Sensitivity and climate prediction



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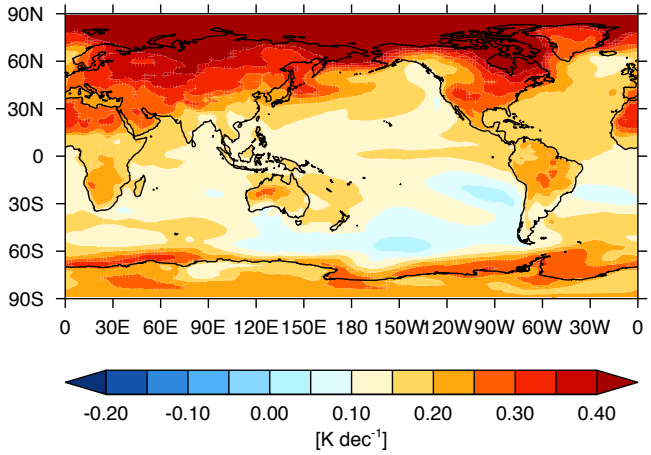
Temperature as Data

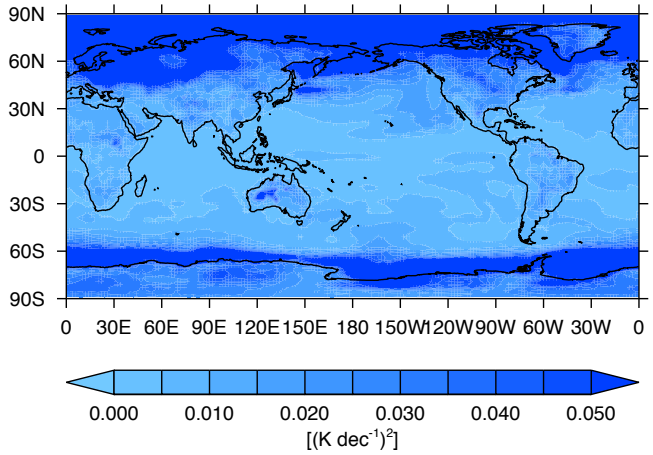
$$\mathbf{y}_{\text{most likely}} = \mathbf{y}_{\text{prior}} + \Sigma_{yx}\Sigma_{xx}^{-1}(\mathbf{d} - \mathbf{x}_{\text{hindcast}})$$

$$\Sigma_{yy,\,\text{posterior}} = \Sigma_{yy,\,\text{prior}} - \Sigma_{yx}\Sigma_{xx}^{-1}\Sigma_{xy}$$

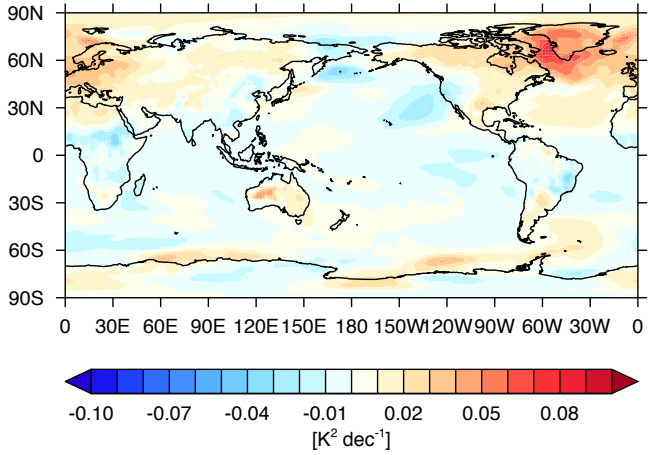
Ensemble Mean x



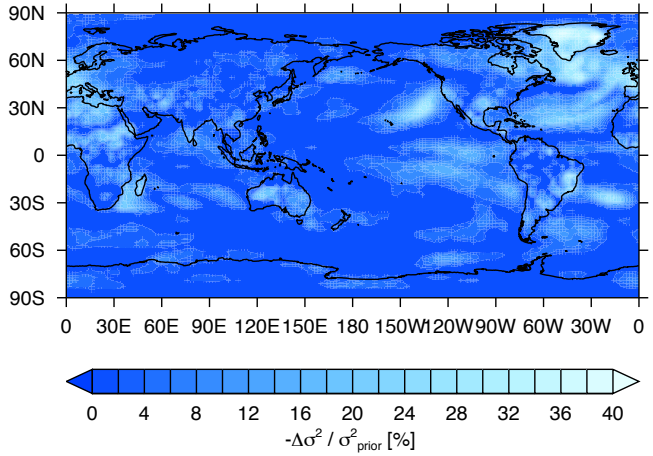
Ensemble Variance x



Relevance (Σ_{xy})

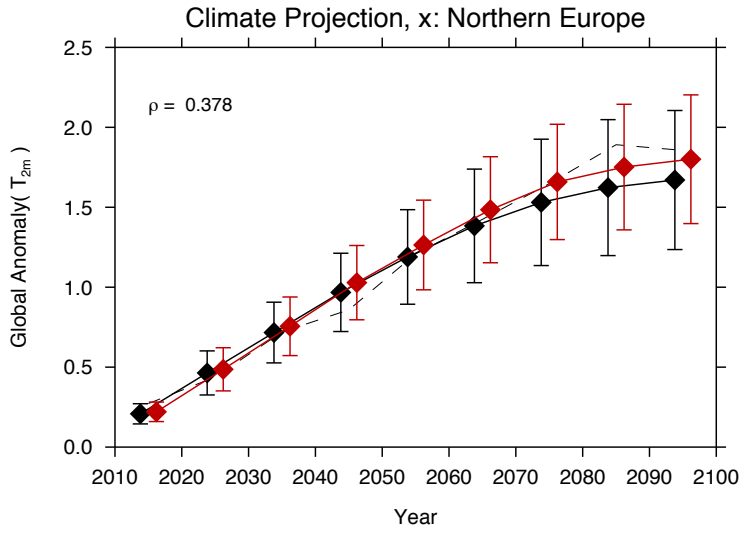


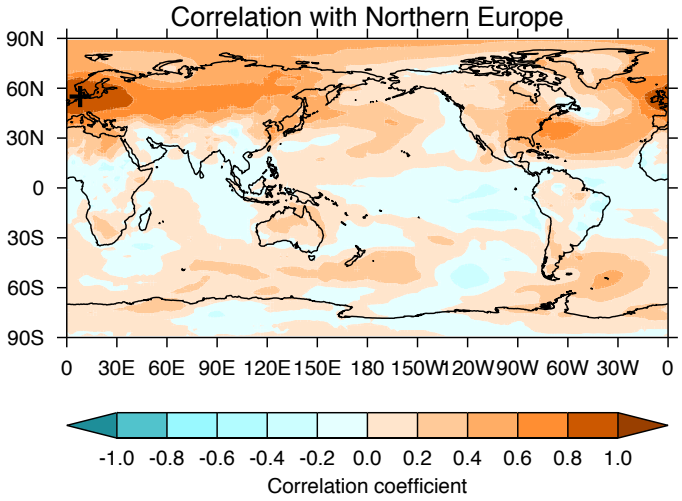
Uncertainty Reduction

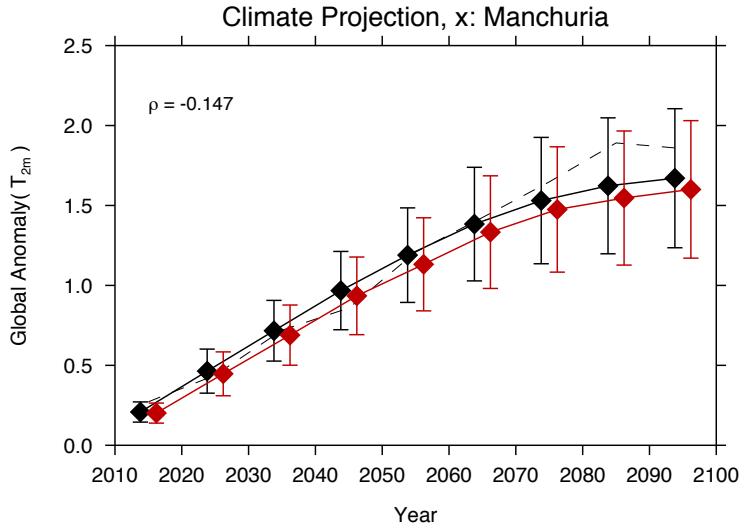


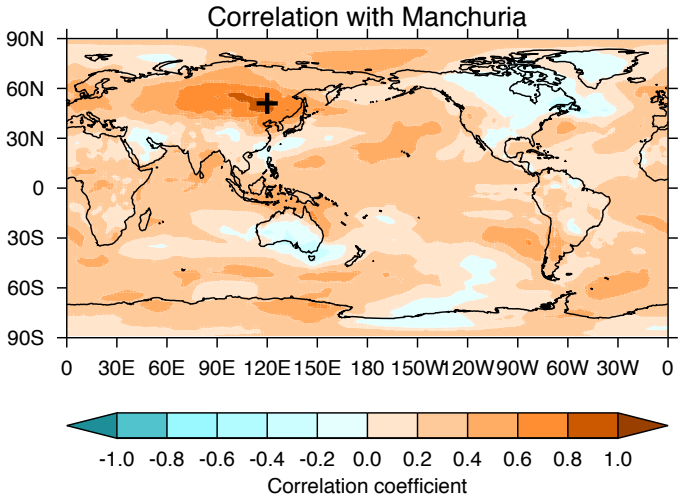
Improved prediction

Data: temperature trend (1970-2005)

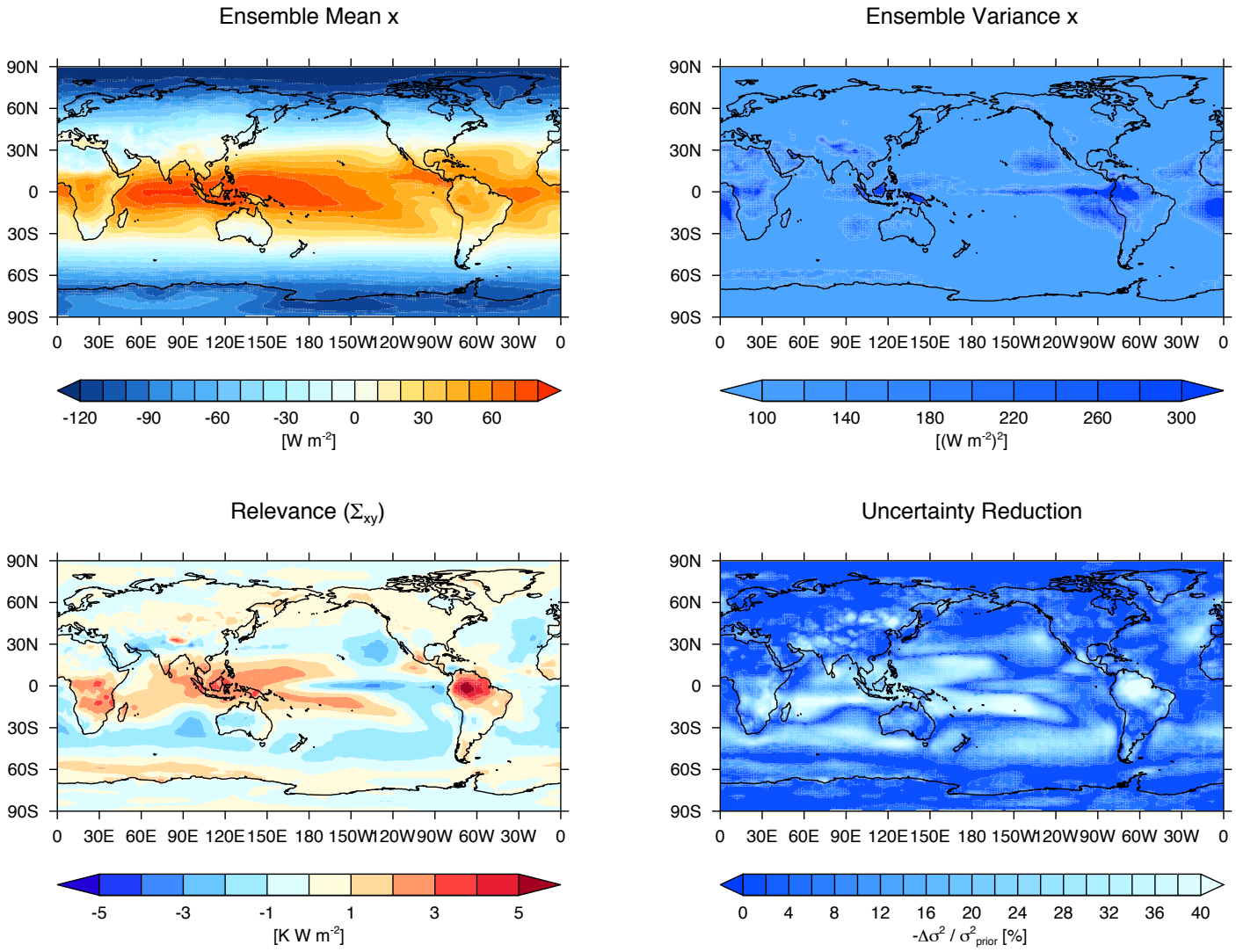




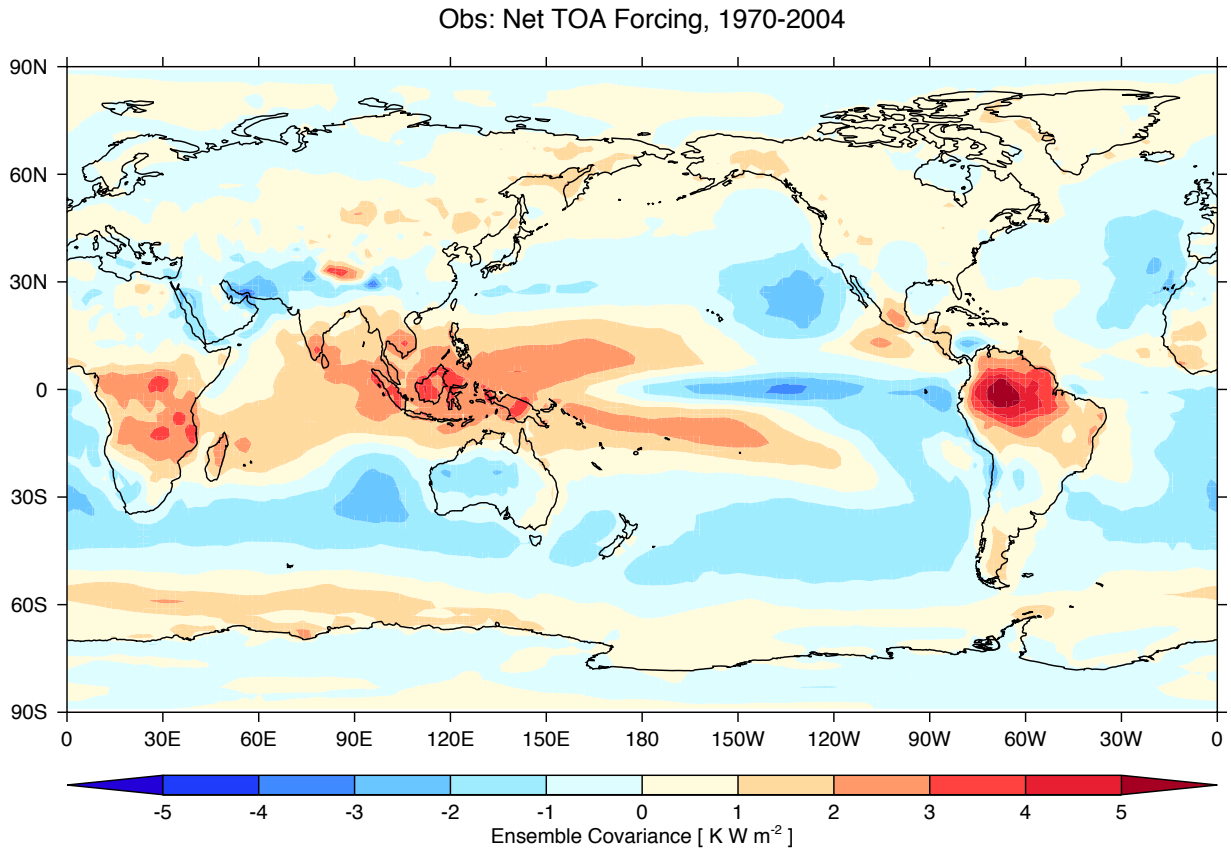




Diagnostics: Net TOA radiation

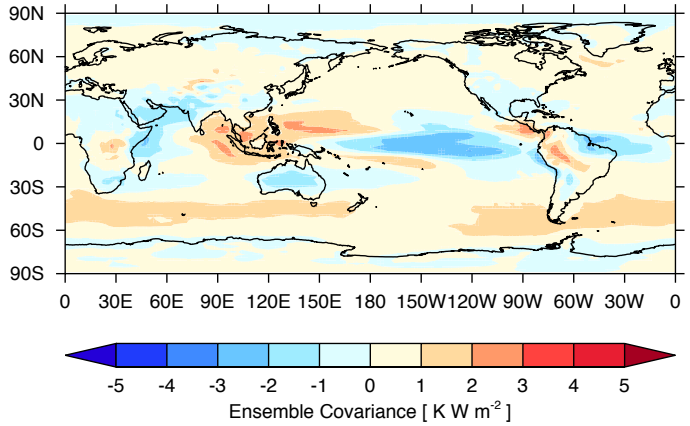


Mean radiance decomposition

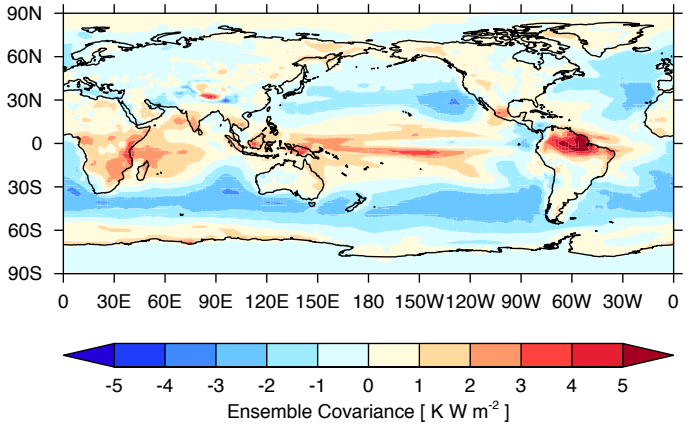


Mean radiance decomposition

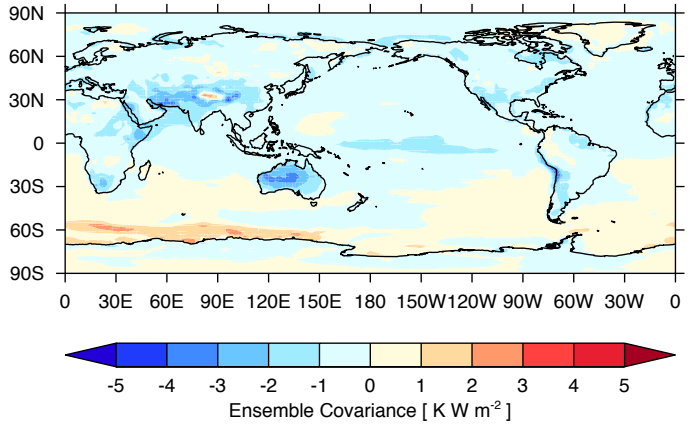
Obs: Net TOA Longwave Forcing, 1970-2004



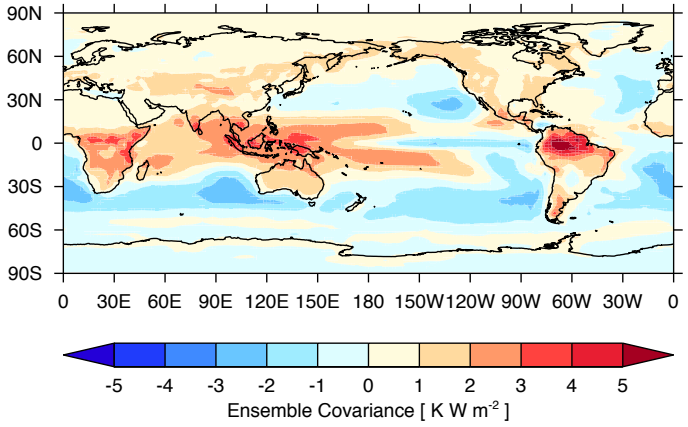
Obs: Net TOA Shortwave Forcing, 1970-2004



Obs: TOA Clear-sky Forcing, 1970-2004

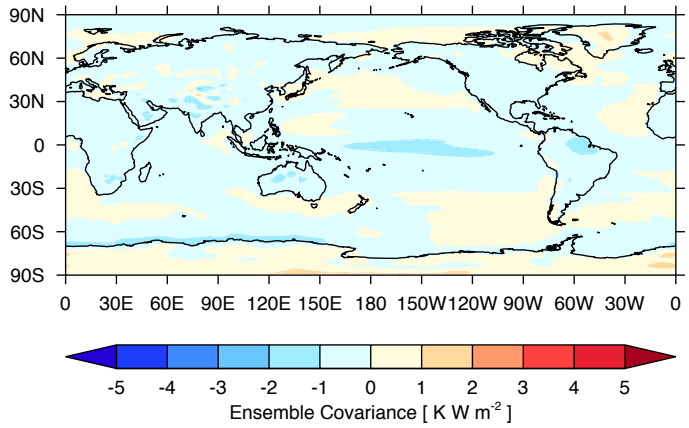


Obs: TOA Cloud Forcing, 1970-2004

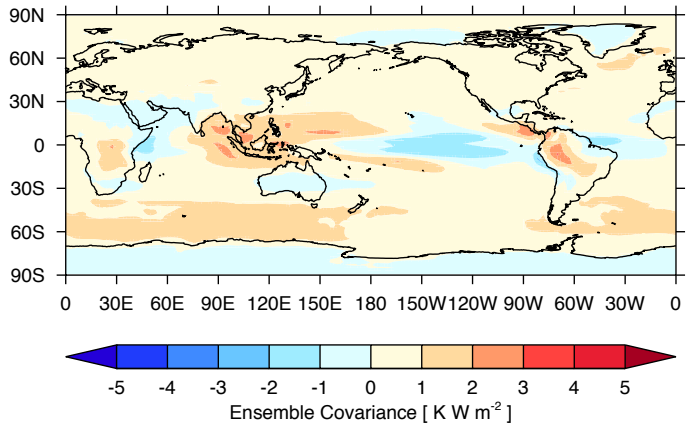


Mean radiance decomposition

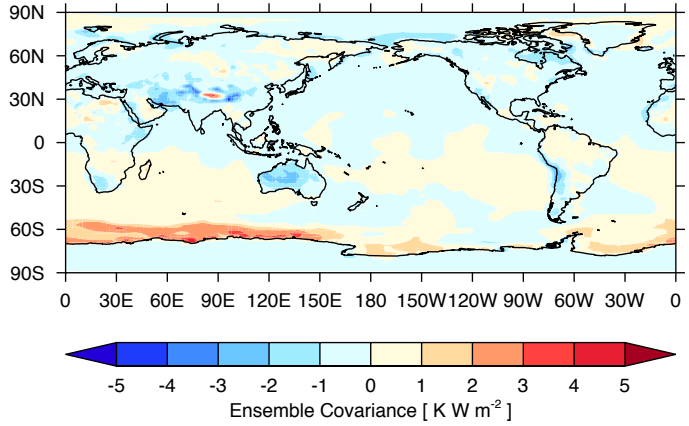
Obs: TOA Longwave Clear-sky Forcing, 1970-2004



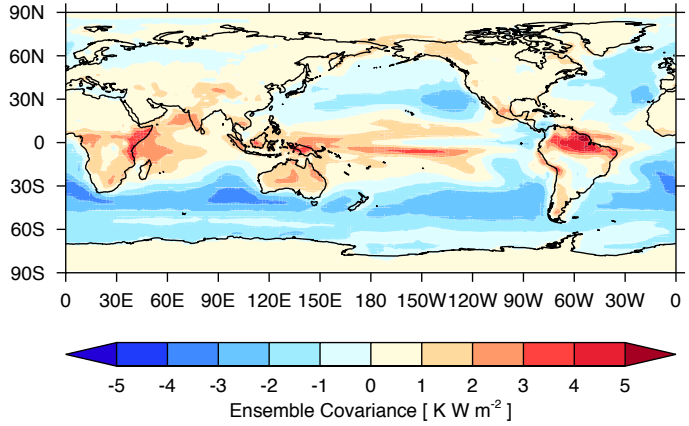
Obs: TOA Longwave Cloud Forcing, 1970-2004



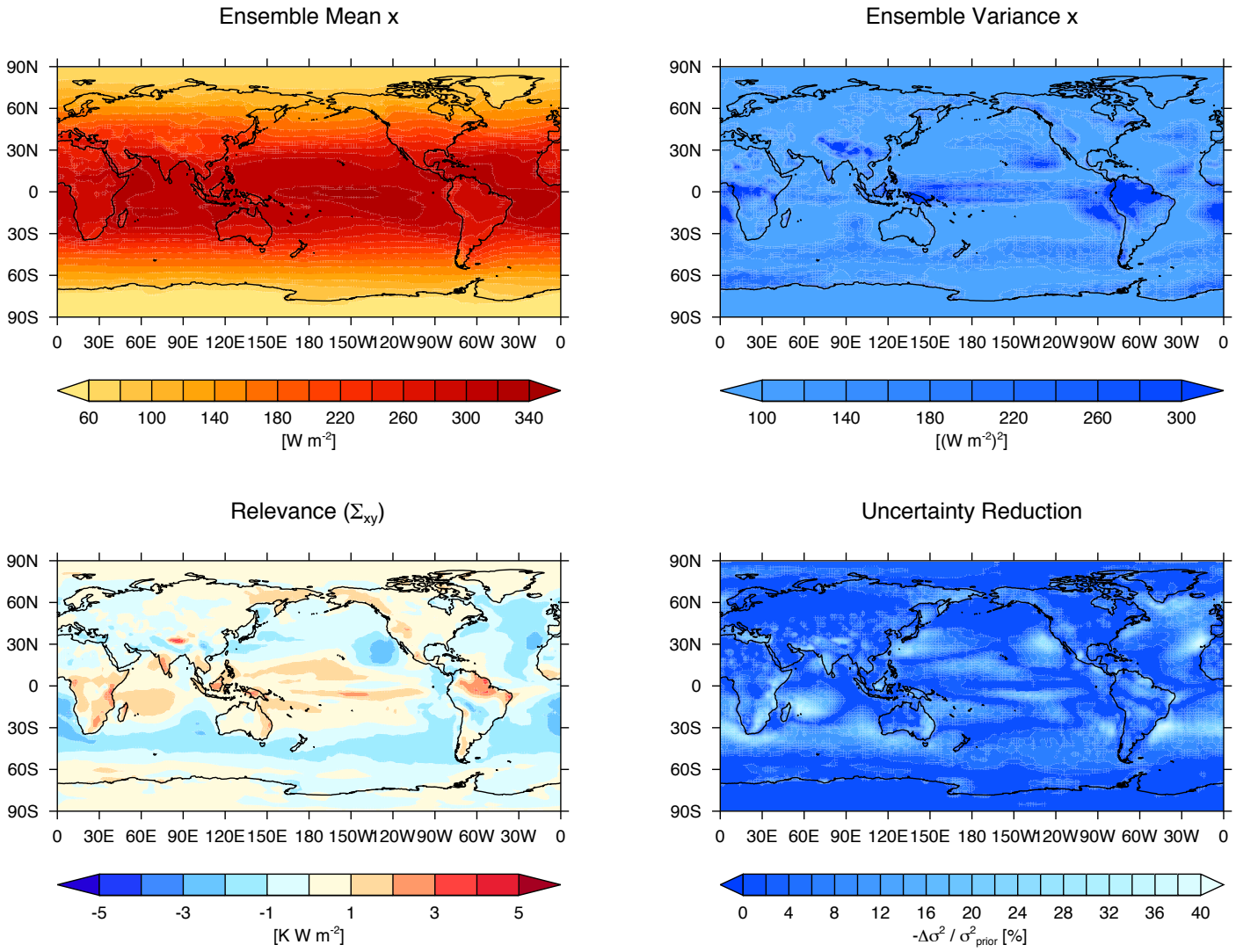
Obs: TOA Shortwave Clear-sky Forcing, 1970-2004



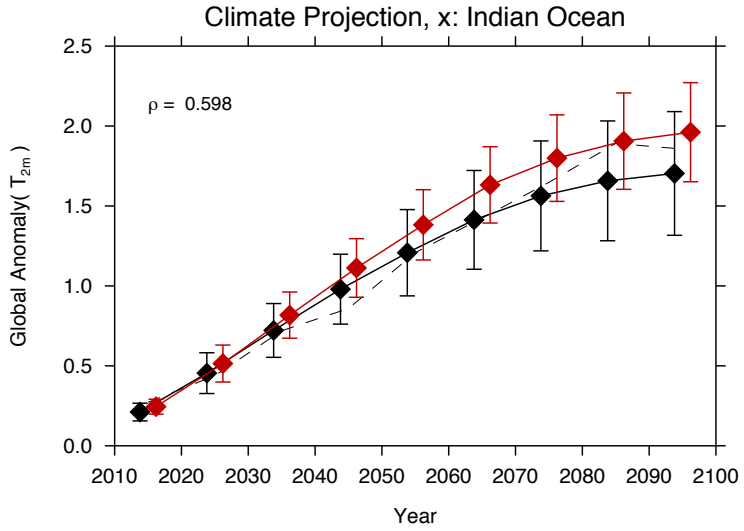
Obs: TOA Shortwave Cloud Forcing, 1970-2004

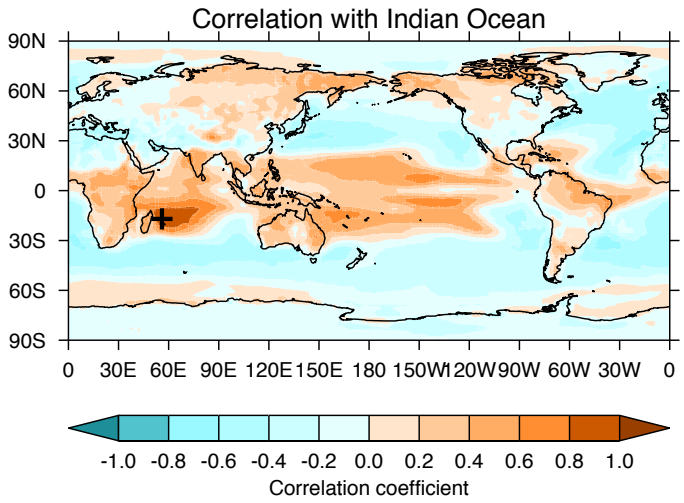


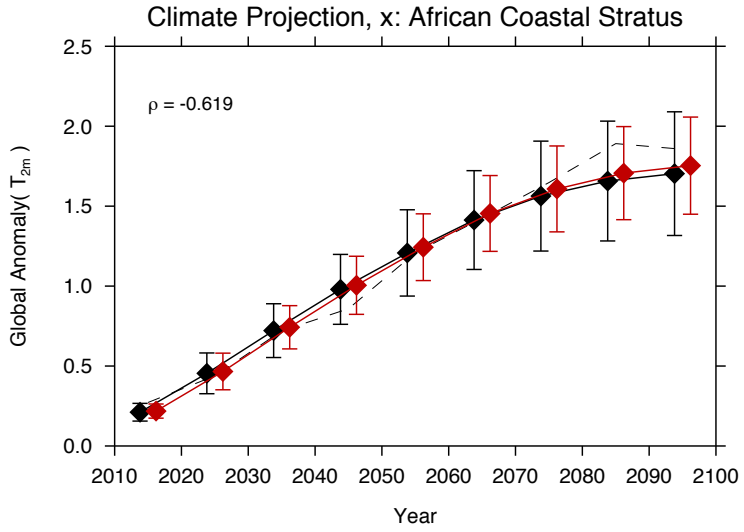
Diagnostics: Net TOA shortwave

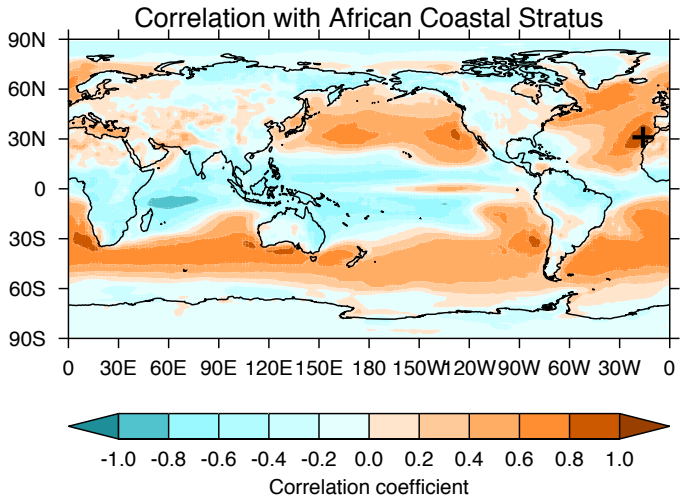


Improved prediction: Net shortwave

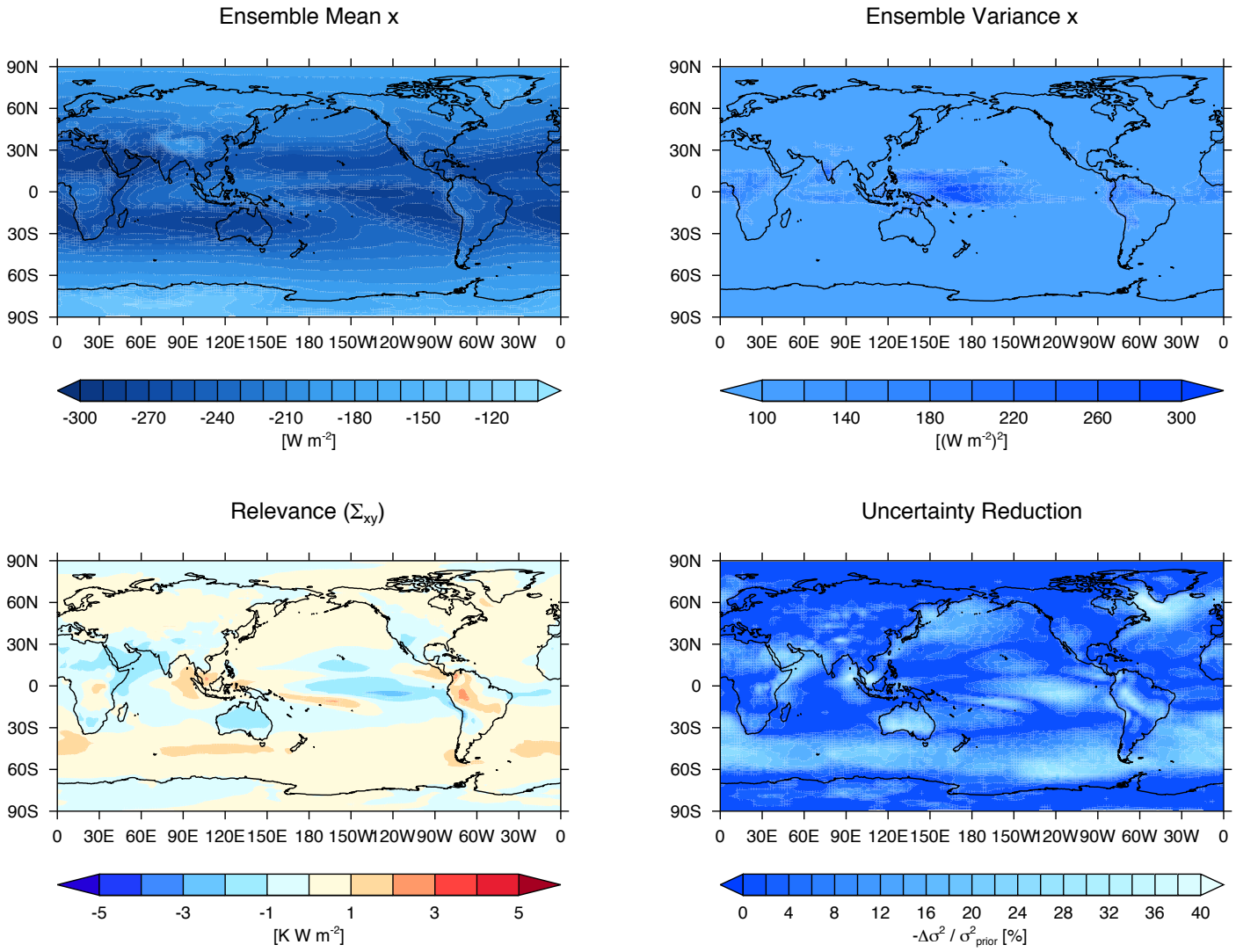




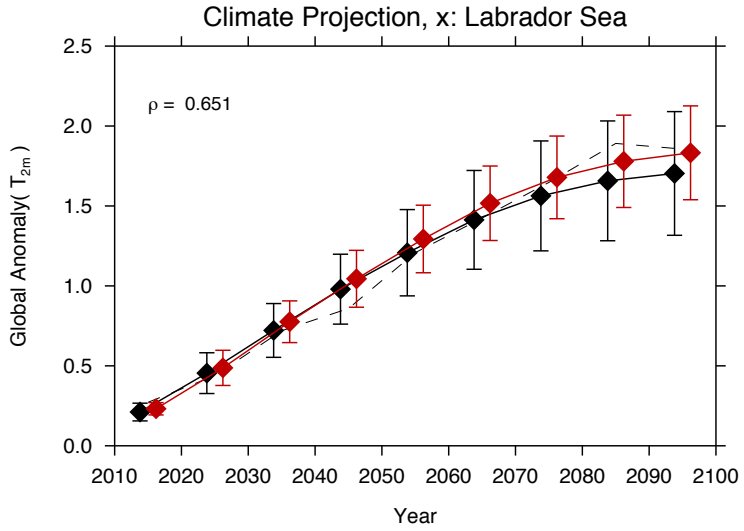


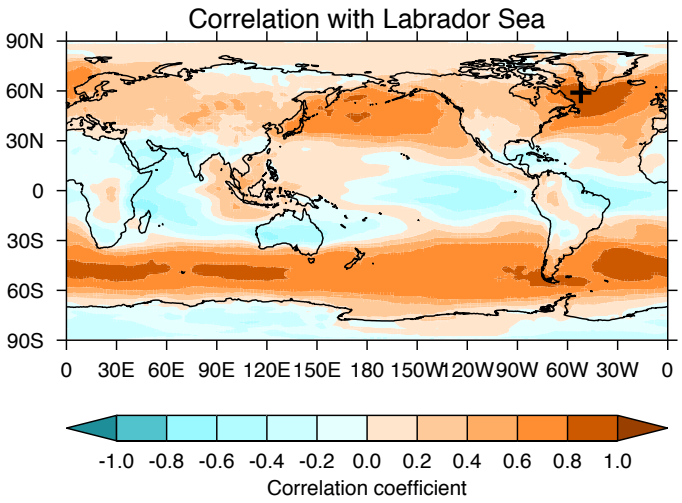


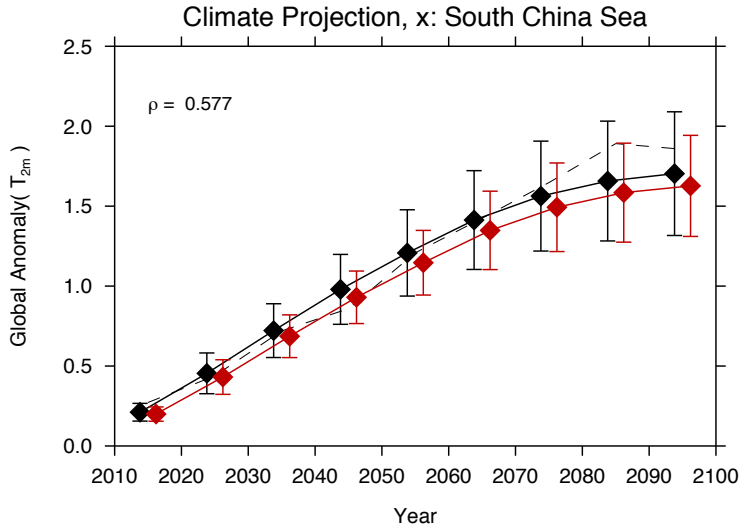
Diagnostics: TOA longwave

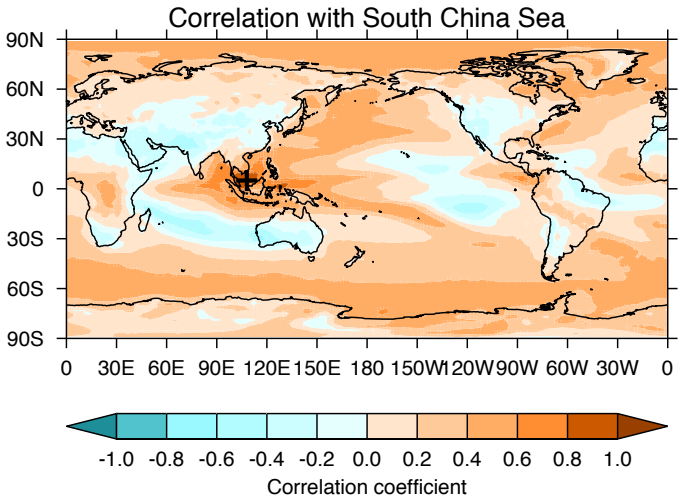


Improved prediction: TOA longwave









EOF Decomposition

$$\sigma^2_{\text{posterior}} = \sigma^2_{\text{prior}} \left(1 - \rho^2\right)$$

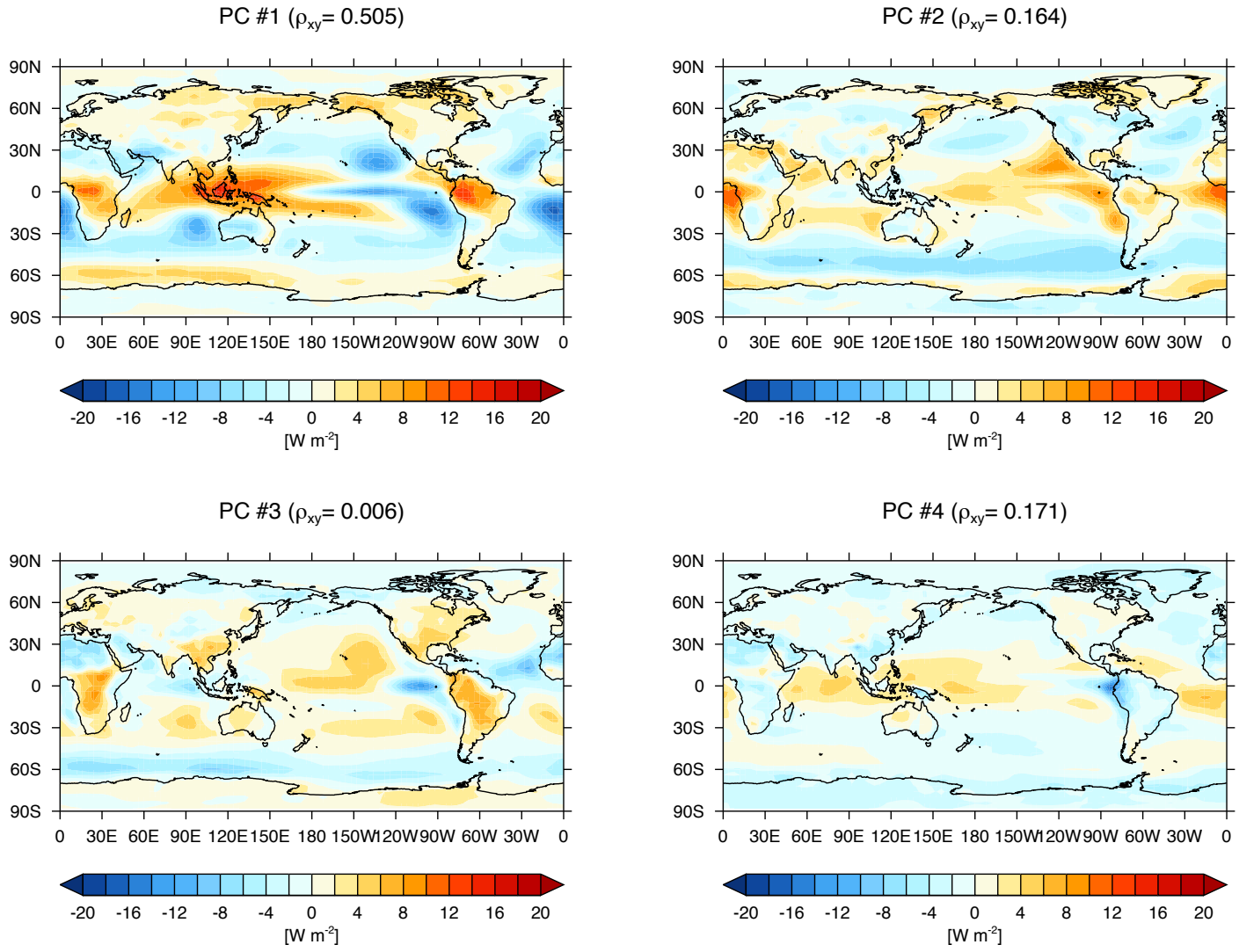
$$\Sigma_{xx} = \sum_{\mu} \lambda_\mu \, \boldsymbol{e}_\mu \, \boldsymbol{e}_\mu^T$$

$$\rho^2 = \sum_{\mu} \frac{\left(\boldsymbol{e}_\mu \cdot \Sigma_{xy}\right)^2}{\sigma^2_{\text{prior}} \, \lambda_\mu} = \sum_{\mu} \rho^2_\mu$$

Component relevance

Component variance

EOFs: Net TOA radiation



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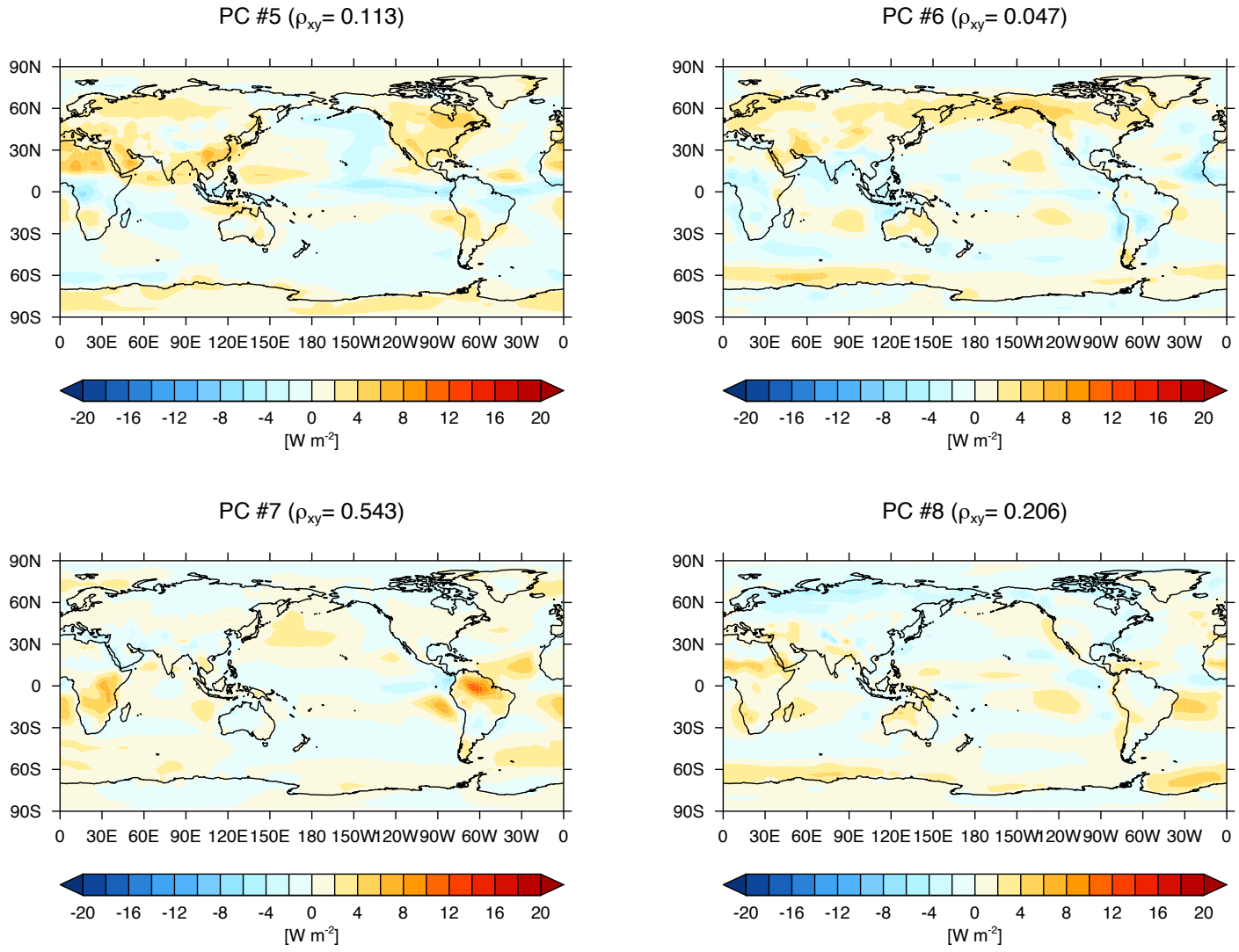
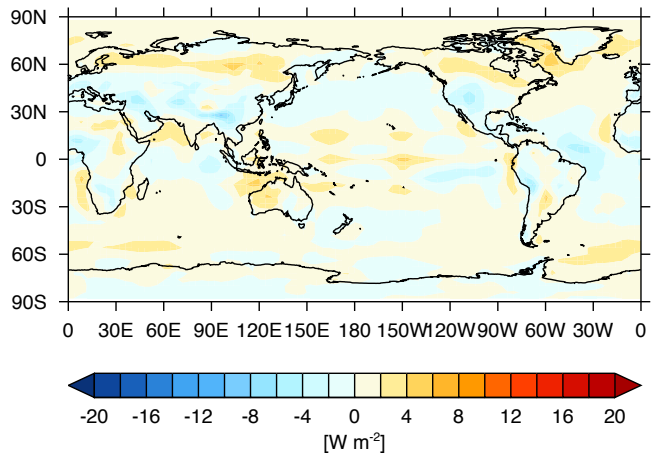
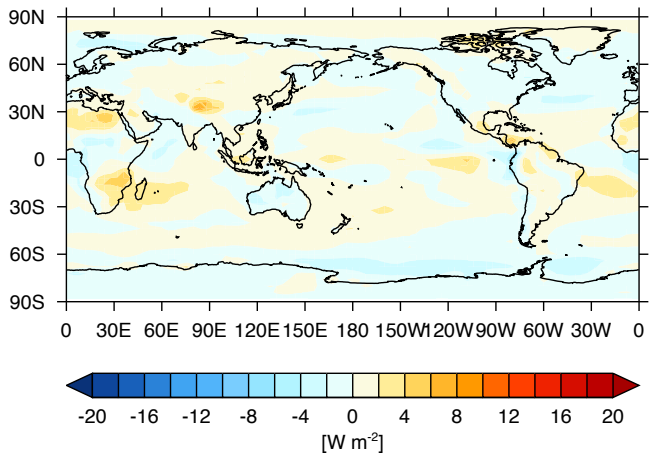


EOFs: Net TOA radiation

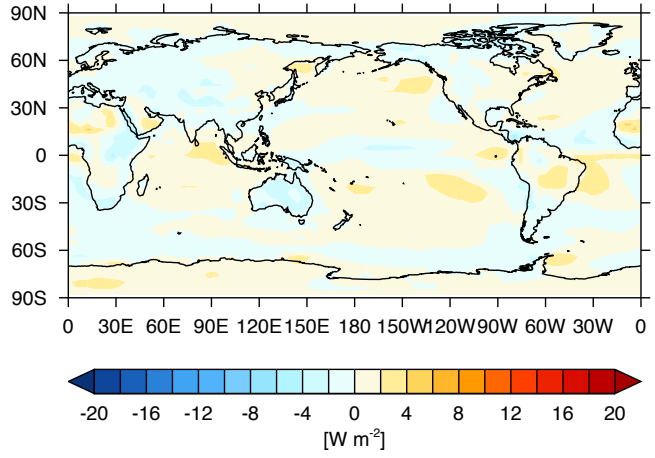
PC #9 (ρ_{xy}= 0.072)



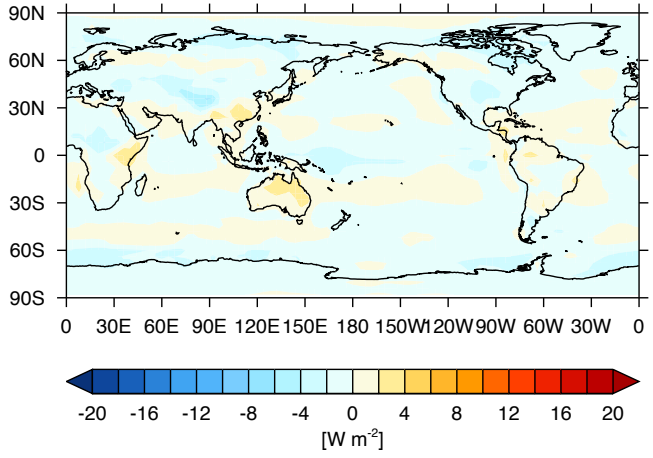
PC #10 (ρ_{xy}= 0.335)



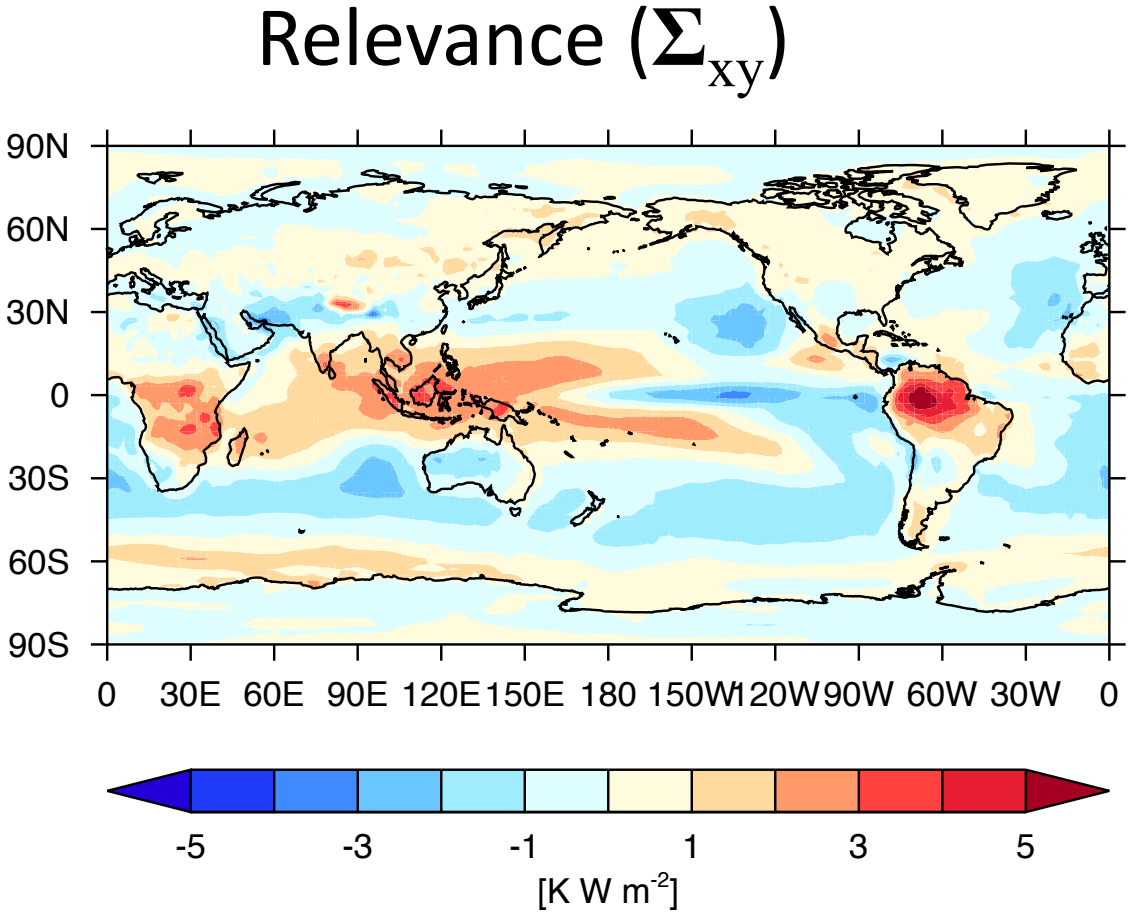
PC #11 (ρ_{xy}= 0.191)



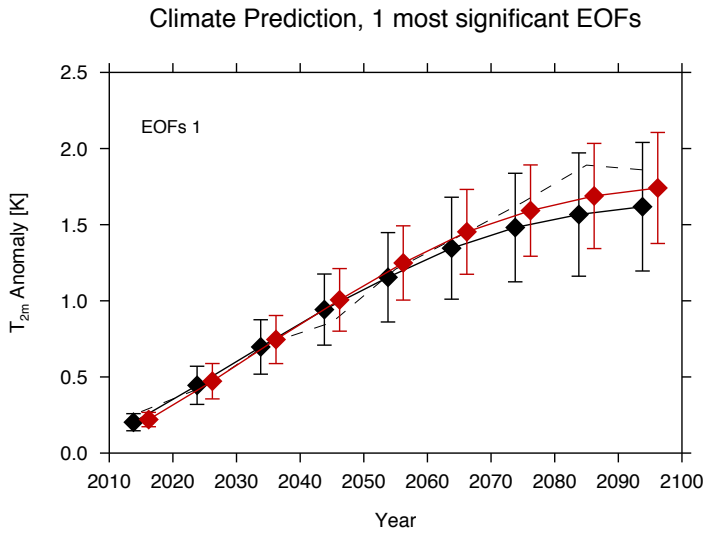
PC #12 (ρ_{xy}= 0.003)

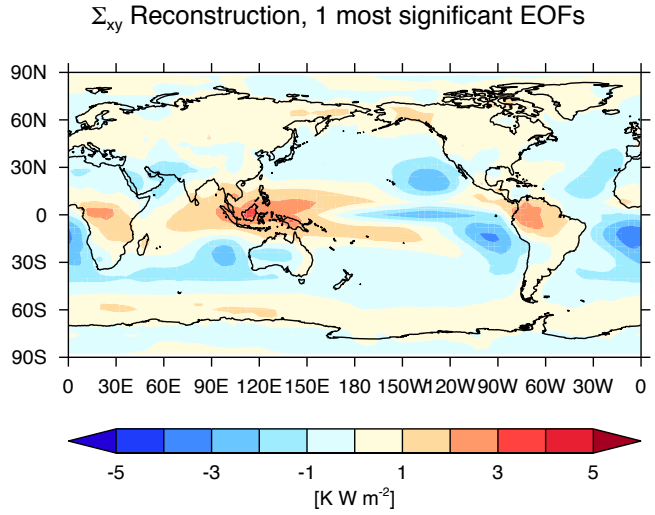


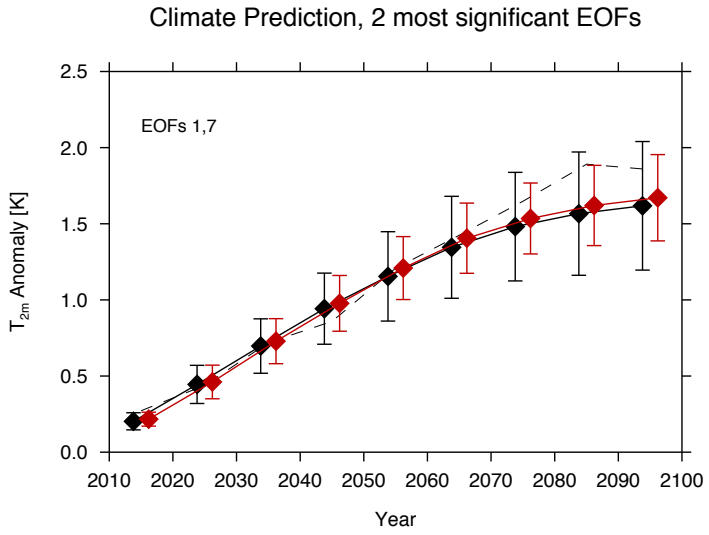
Improved prediction using EOFs

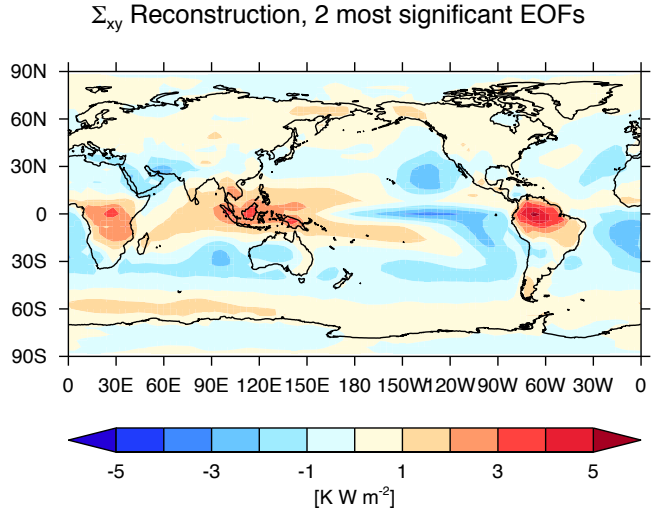


Improved prediction using EOFs

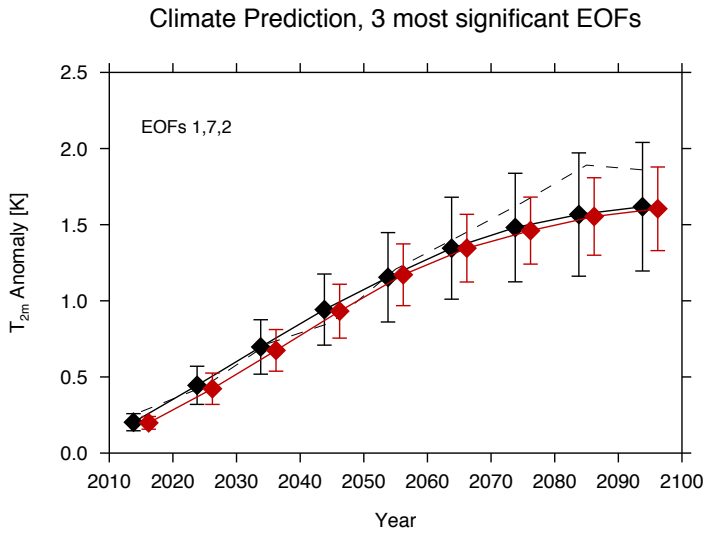


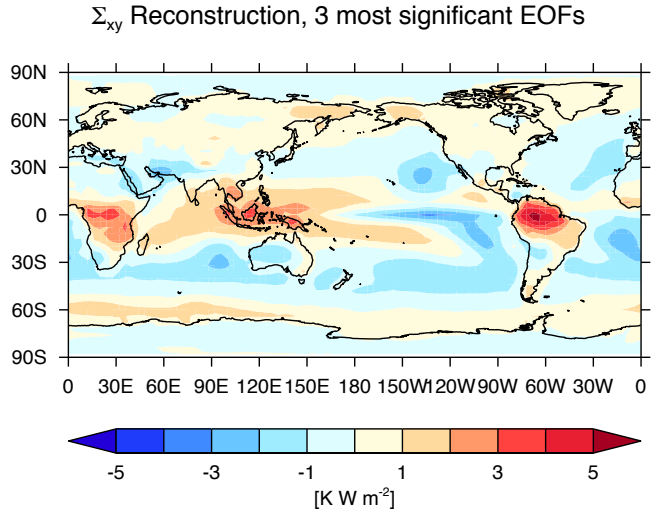


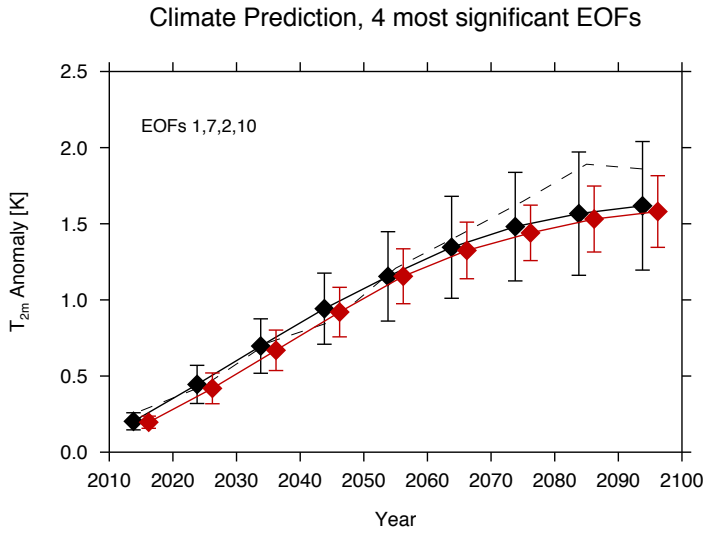


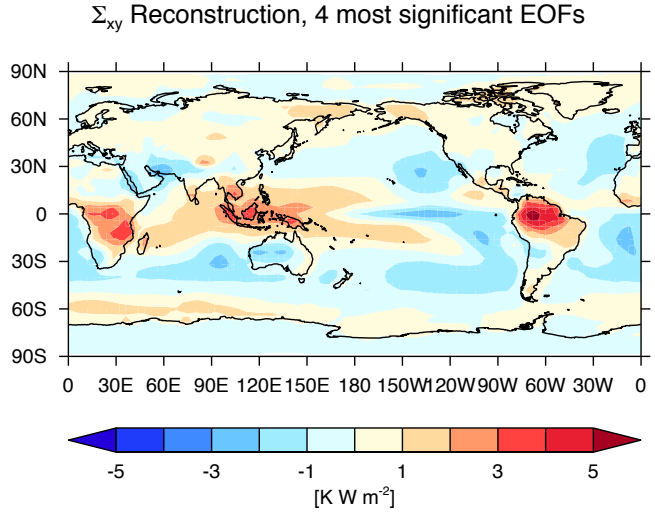


Improved prediction using EOFs

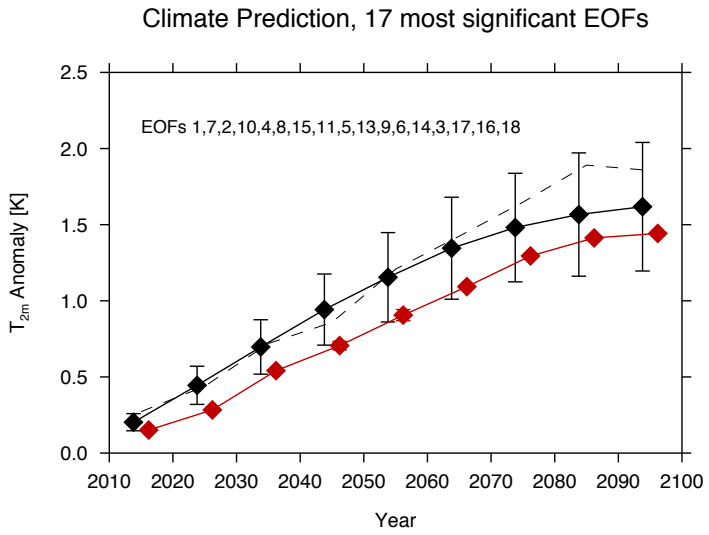


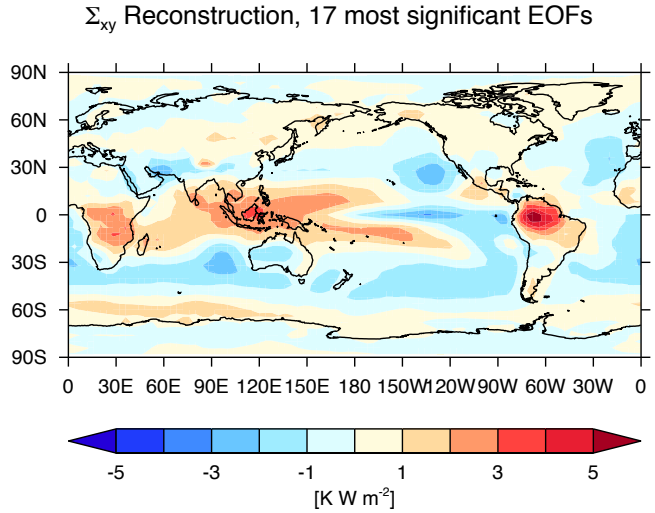


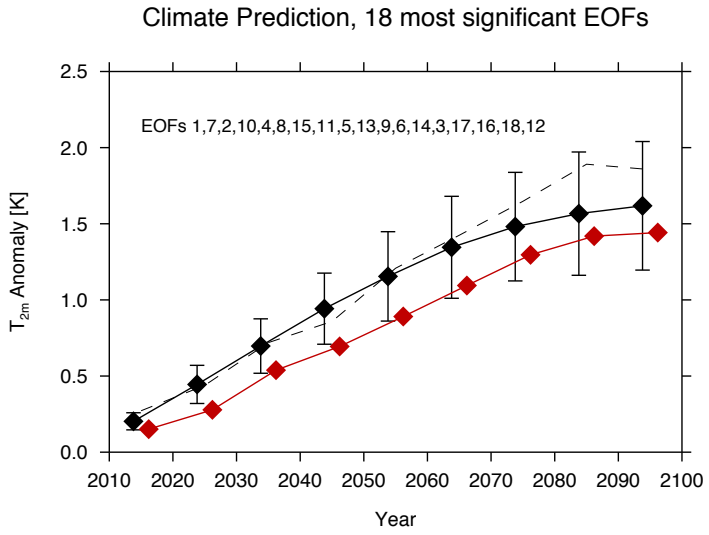


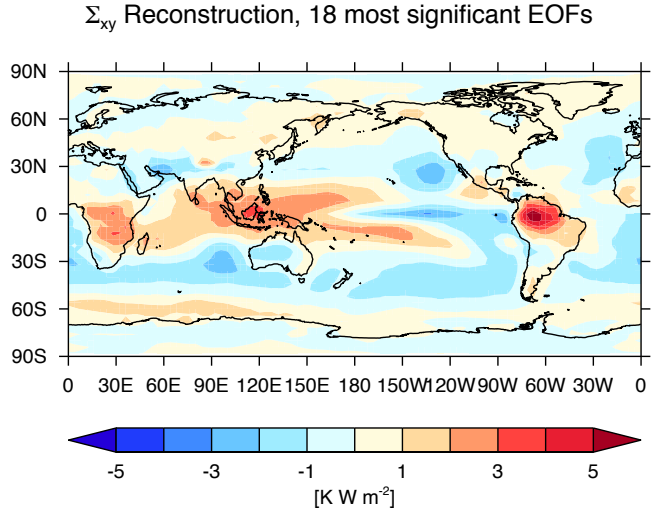


Improved prediction using EOFs

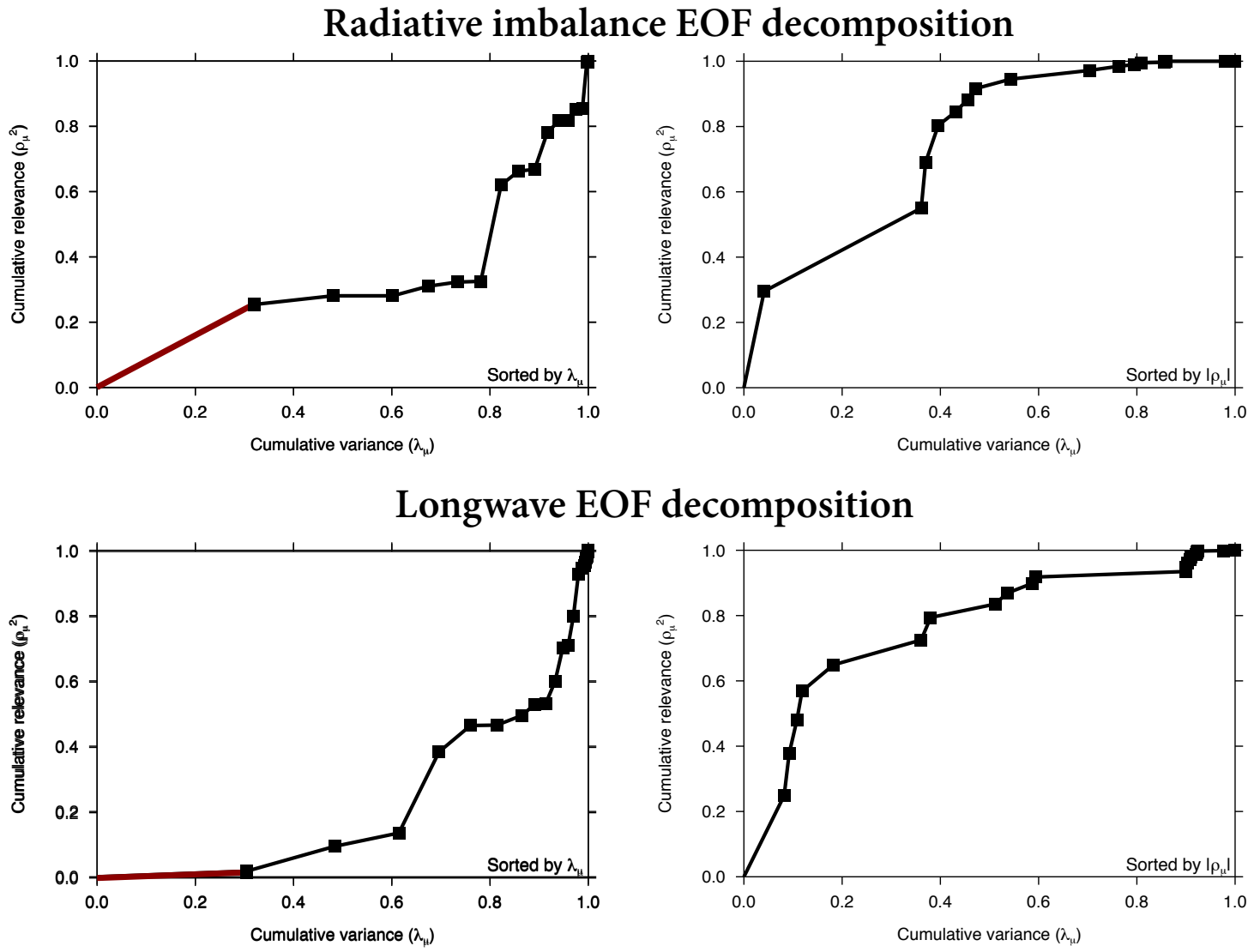








Variance and relevance spectra

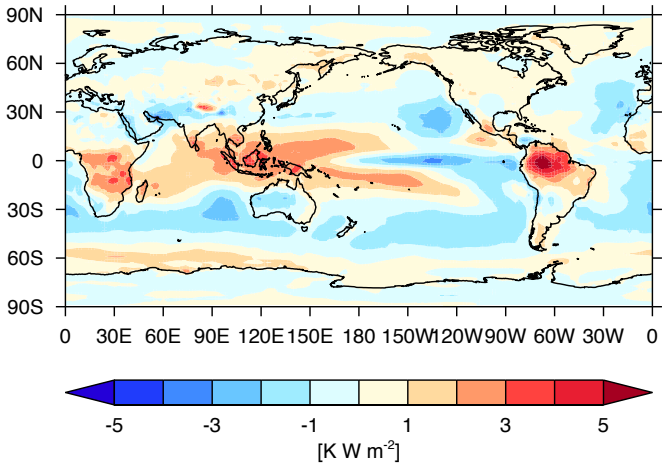


Prediction improvement: All data types

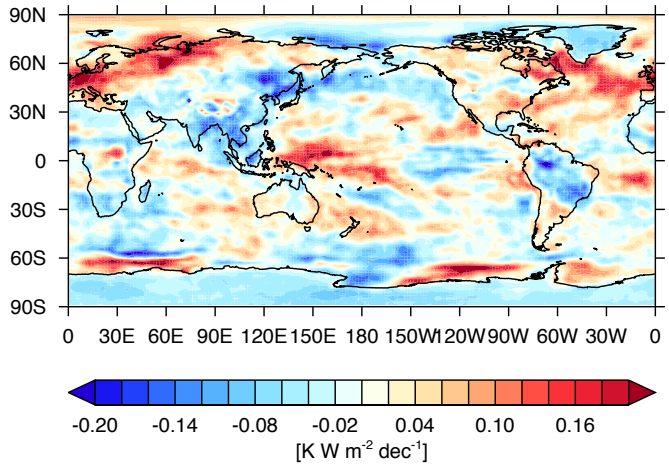
Data type	Global	EOF 1		EOF 2	
	ρ	% variance	ρ	% variance	ρ
Longwave	0.070	30.5	0.131	17.9	0.276
Longwave trend	-0.311	19.8	0.312	10.5	0.309
Shortwave	-0.103	33.2	0.285	14.7	0.235
Shortwave trend	0.360	14.4	0.419	9.5	0.397
Temperature	0.053	26.9	0.261	15.5	0.060
Temperature trend	0.081	22.6	0.137	12.2	0.240

Observation-prediction covariances

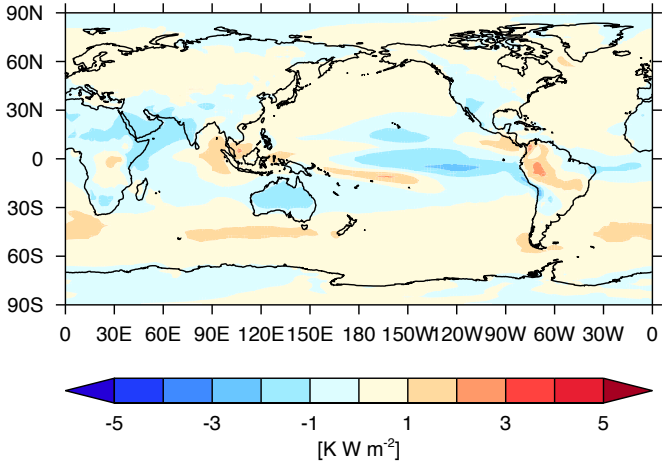
Σ_{xy} of Net TOA Forcing



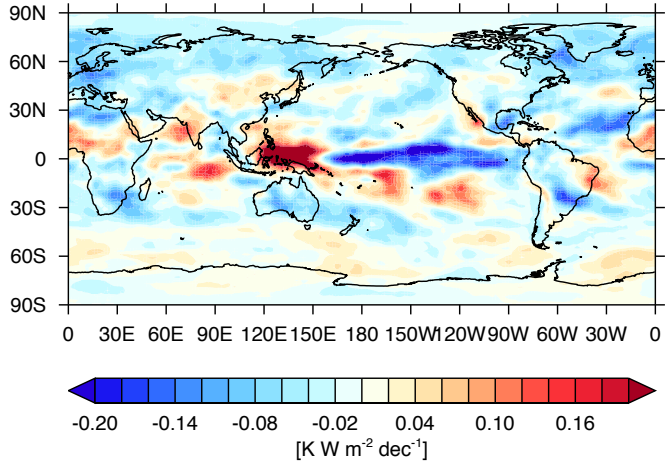
Σ_{xy} of Net TOA Forcing Trend



Σ_{xy} of TOA Longwave

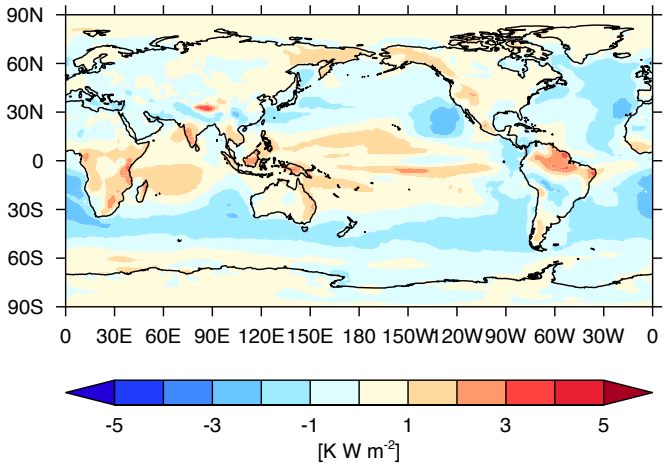


Σ_{xy} of TOA Longwave Trend

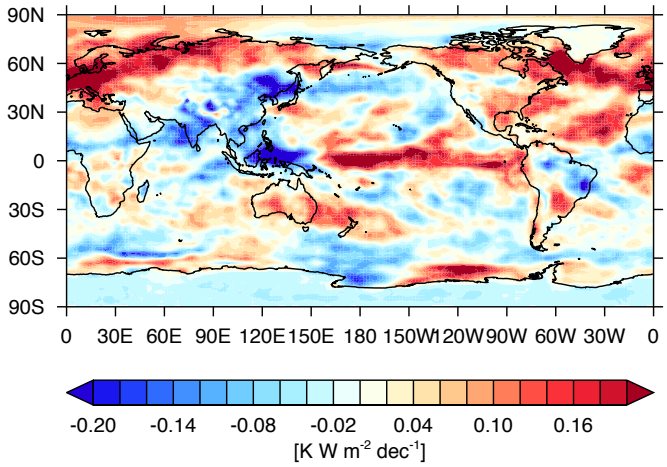


Observation-prediction covariances

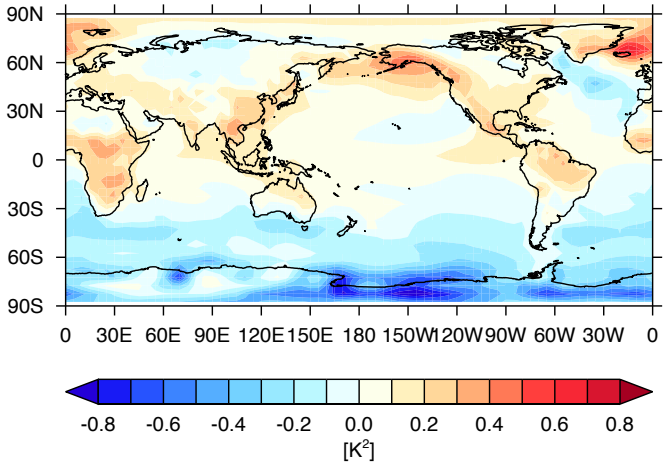
Σ_{xy} of Net TOA Shortwave



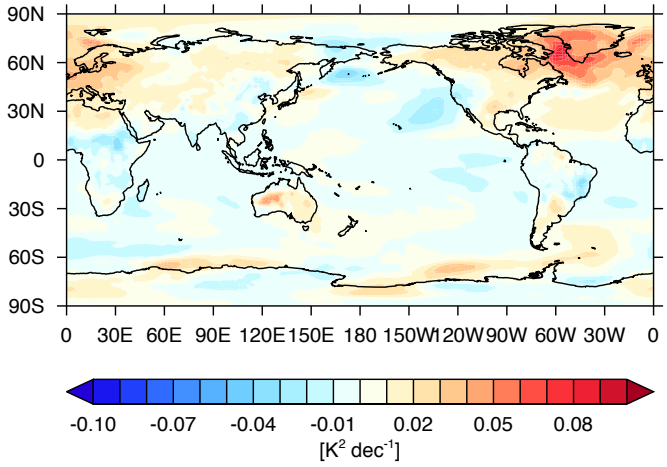
Σ_{xy} of Net TOA Shortwave Trend



Σ_{xy} of Surface Air Temperature



Σ_{xy} of Surface Air Temperature Trend



Conclusions

- It is possible to optimize by spatial fingerprinting.
- Indications point toward mean state being more important than trends for verifying atmospheric models for multi-decadal prediction.
- Indications point toward top-of-atmosphere shortwave being more important than top-of-atmosphere longwave and surface air temperature for verifying atmospheric models for multi-decadal prediction.
- Truncating EOFs in Gaussian regression is an unsolved problem.
- It will be necessary to work with much larger ensembles in the future.

Activities

- "Modeling": Information content, reanalysis
  - Huang, Y., S.S. Leroy, and R.M. Goody, 2011: Discriminating between climate observations in terms of their ability to improve an ensemble of climate predictions. *Proc. Nat. Acad. Sci.*, **108**, 10405–10409.
  - Leroy, S.S., and M.J. Rodwell, 2014: Leveraging highly accurate data in diagnosing errors in atmospheric models. *Bull. Amer. Meteor. Soc.*, In Press.
  - Leroy, S.S., G. Redaelli, and B. Grassi, 2014: Climate prediction windows: Optimizing the discrimination of climate models using data. In Preparation.
- Radio occultation
  - Leroy, S.S., C.O. Ao, and O. Verkhoglyadova, 2012: Mapping GPS radio occultation by Bayesian interpolation. *J. Atmos. Ocean. Tech.*, **29**, 1062–1074.
  - M.E. Gorbunov, A. Shmakov, S.S. Leroy, and K.B. Lauritsen, 2011: COSMIC radio occultation processing: Cross-center comparison and validation. *J. Atmos. Ocean. Tech.*, **28**, 737–751.
  - Verkhoglyadova, O., C.O. Ao, and S.S. Leroy, 2014: Deriving winds from GNSS radio occultation data. In Preparation.