Royal Netherlands
Meteorological Institute
Ministry of Infrastructure and the Environment

Introduction to empirical models
(including relevant statistical concepts)

MedCOF Training Workshop
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Outline

1. Introduction
2. Teleconnections and the basis empirical seasonal prediction
3. Methods in empirical seasonal prediction
4. Empirical seasonal prediction in practice
5. Summary and outlook

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What is empirical prediction?

- "Empirical" – based on experience
- Using existing global data sets to construct hypotheses and prediction methods.
  - What do observations tell us about the workings of the climate system?
  - What is the maximum value we can extract from real world data?

- Eliciting statistical relationships to represent known physical processes in the climate system.
- Usually, the relationship between regional-scale anomalies in a target variable (the "predictand") and climate phenomena (the "predictors").

"Empirical" or "statistical"?

- Terms often used interchangeably:
- van den Dool (2007) asks:
  - Are we driven by intuition? (empirical)
  - Or to apply or develop a statistical methodology? (statistical)

- In seasonal prediction, it's usually the former…
  - The first step is always to understand physical relationships.
  - Then to find a statistical model that best represents these relationships.

Dynamical prediction… and its limitations

- Operational seasonal forecasting now a regular activity.
- Dynamical forecast systems remain the most important tool in producing predictions.
- However…
  - Development is inherently complex.
  - Forecast generation is computationally demanding.
  - Errors and biases limit model skill.

A place for empirical prediction

- An alternative to dynamical prediction systems.
- May serve as a **baseline** for dynamical models.
- Used to improve forecasts by limiting the effects of dynamical model biases.
  - Particularly so in regions where dynamical systems have known weaknesses.

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Different development…

…different output…

…systematic comparison difficult…

(more later…)

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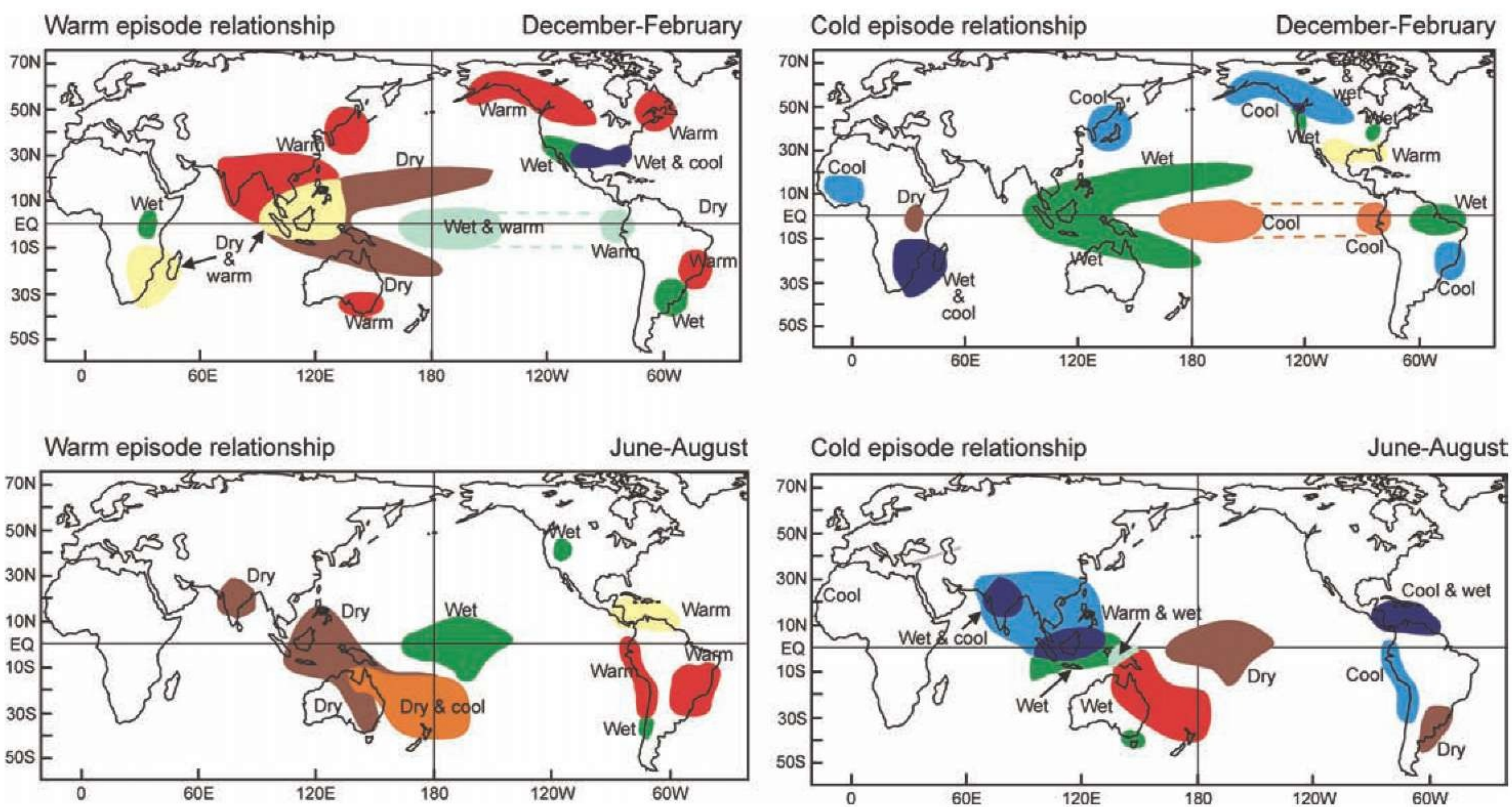
Teleconnections

- Atmospheric circulation exhibits sustainable variability on time scales from a few days to several years or even centuries.
- Recurring and persistent patterns of pressure and circulation anomalies across large vast geographical areas - teleconnections.
- Teleconnections typically form the basis for an empirical seasonal prediction model.
  - When we have existing knowledge of a teleconnection…
  - …we can develop an empirical model to represent it.

Known ENSO teleconnections



Lagged teleconnections

- Teleconnections often spoken about in simultaneous terms… which is not much use for prediction.
- In reality, an anomaly in the climate system may take days/ weeks/months to propagate.
- Regional climate anomalies associated with ENSO, for instance, may be predictable many months in advance.
- Empirical models often incorporate some lag – finding a link between the predictand and the predictor at some lead time.

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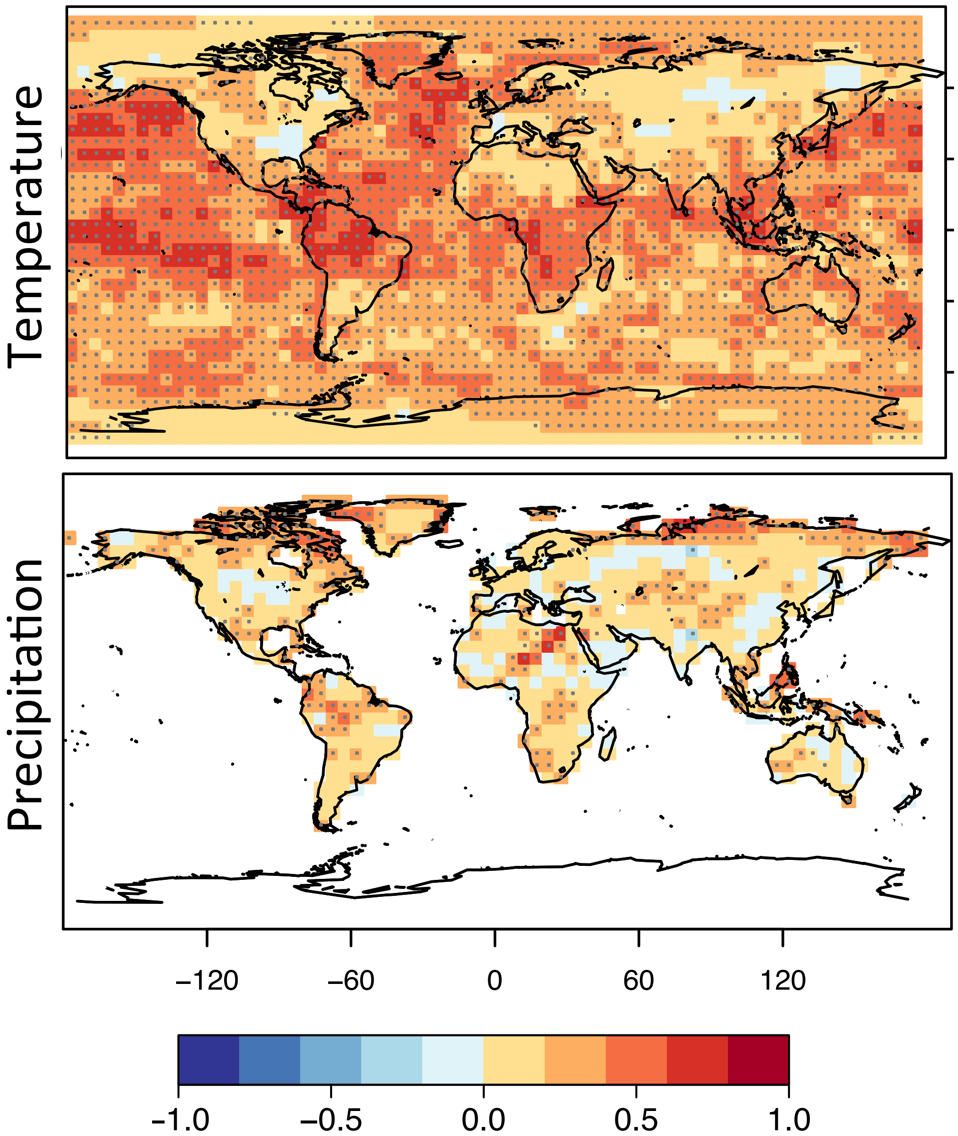
Persistence

- Empirical prediction at its most simple.
- **Persistence**: observations of a given variable at some lead time are taken as the forecast for that variable.
- Such forecasts have frequently performed better at short lead times than those simply prescribed by climatology.
- Often persistence is used as a reference method for other statistical methods.

Persistence – what is the best we can do?



Correlation between MAM and DJF climate anomalies (1961-2013).

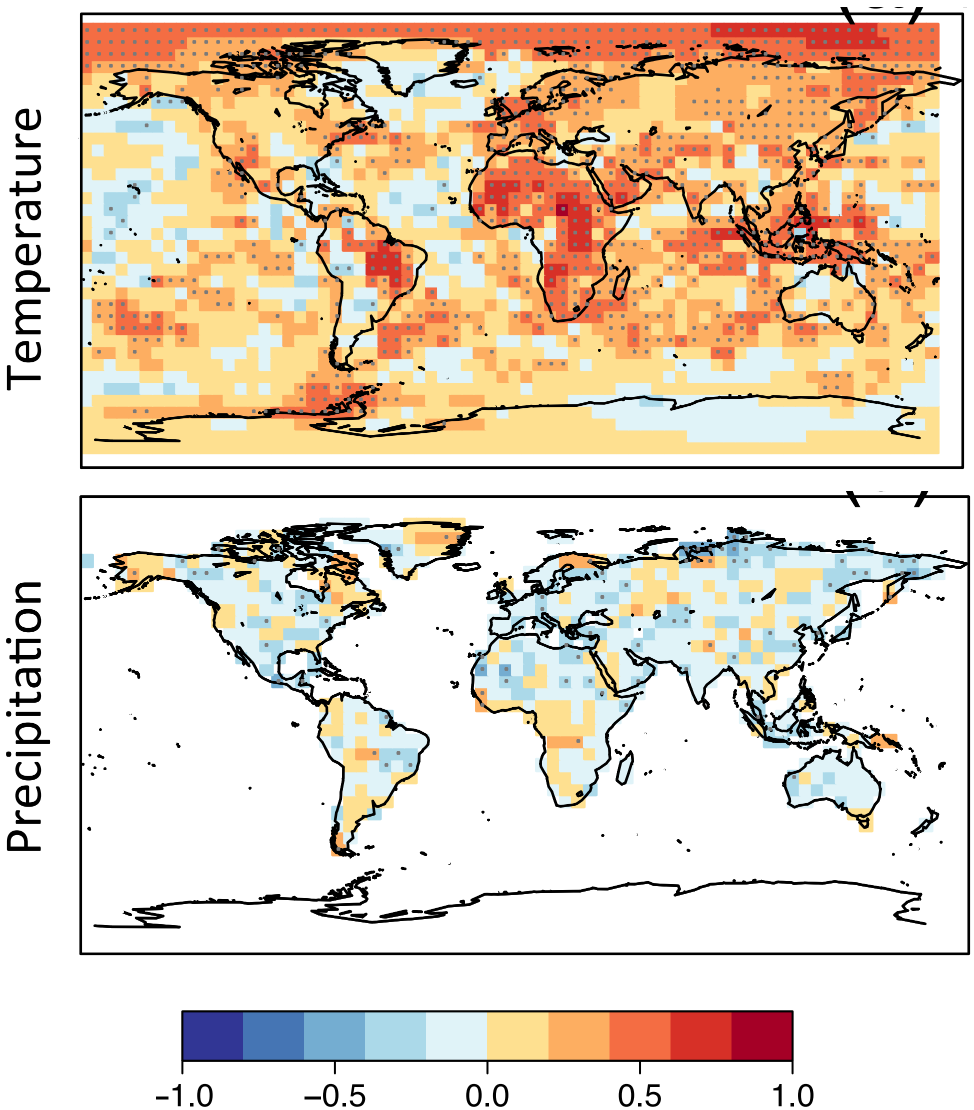
- Persistence usually skillful for temperature in the tropics... less so in other regions.
- For precipitation, skill is generally limited.

Linear regression

- Stronger skill usually comes from relating the temporal sequence of predictor and predictand events in the observed record by simple **linear regression**.
- For instance, a linear regression model may describe the relationship between soil moisture during March and temperature during April.
  - Dry soil -> decreased evaporation -> increased temperature.
  - Forecast for time *t* requires regression coefficients applied to soil moisture at time *t-1*.

- Other possibilities include making use of the predictive skill associated with long-term climate change.

Linear regression – global warming signal



Much discussion recently on the merits of using global warming signal as a source of skill.

Correlation between observed and predicted MAM climate (1961-2013) using greenhouse gas concentration as a predictor in a linear regression model.

- Useful, potentially for temperature.
- Precipitation dominated by climate system internal variability… alternative predictors needed!

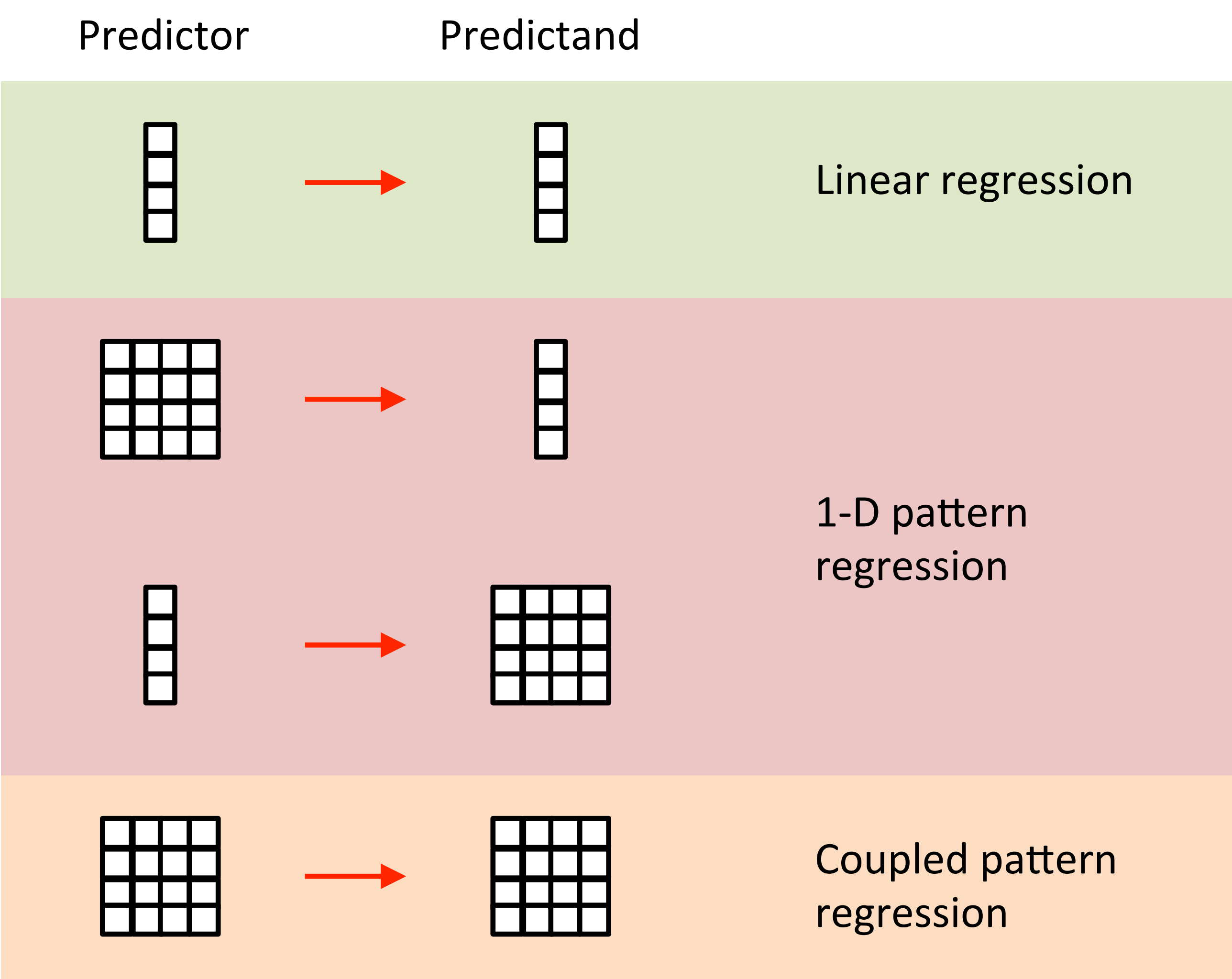
Non-local linear regression

- In seeking to represent teleconnections, “non local” linear regression is more suitable.
- For example, what is the linear relationship between European winter temperatures and Pacific SST from the preceding autumn.
- Often, we use climate indices to describe climate anomalies in remote regions:
  - ENSO: NINO3.4, NINO4.
  - Pacific Decadal Oscillation (PDO).
  - Indian Ocean Dipole (IOD)…. etc.

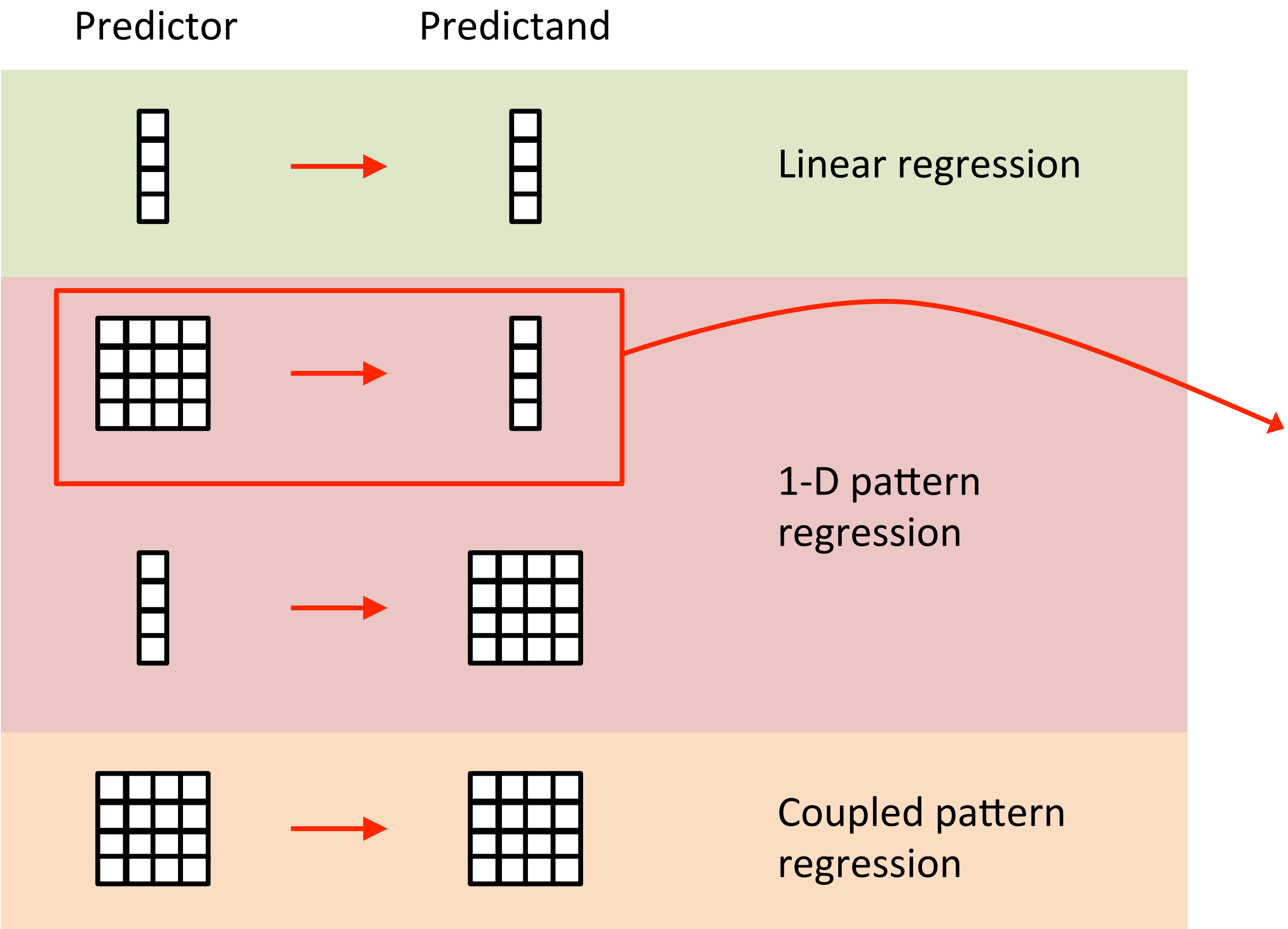
Pattern-based regression

- More complex methods seek to find patterns of variability in spatial fields of climate data.
- EOF analysis is common method of reducing data into several 'modes'.
- The linking of a time series of spatial patterns with, either, a time series at a given location or, alternatively, another time series of patterns.
- For examlple, the time series of one or mode EOF modes may be used to fit a (multiple) linear regression model to estimate the predictand.

Pattern-based regression



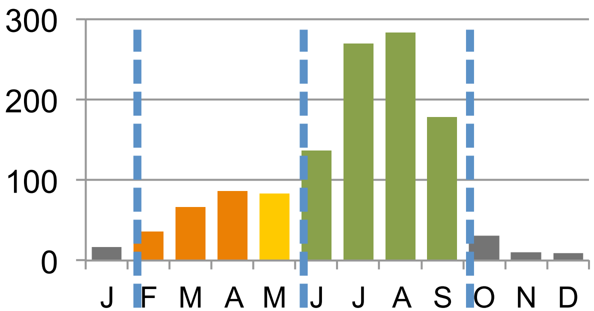
Pattern-based regression

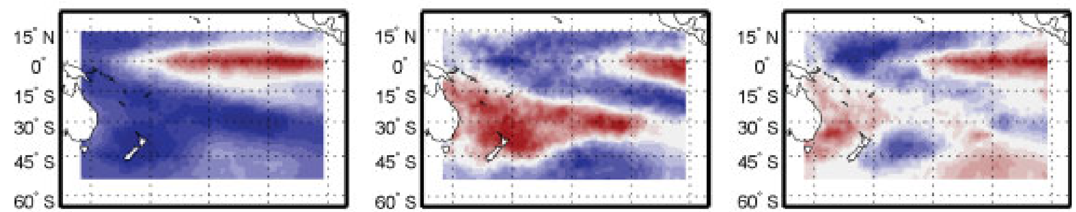


Example:
Forecasting spring rains in Ethiopia

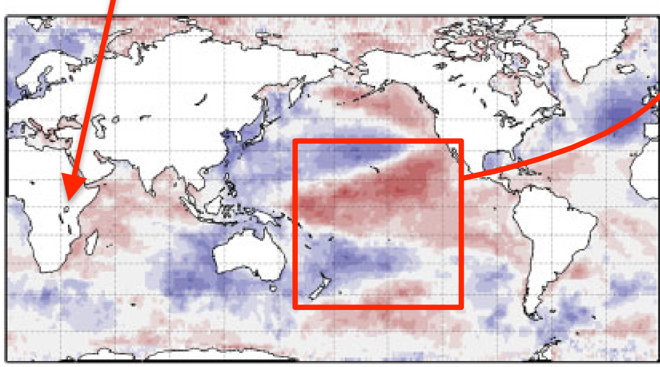
Pattern-based regression – example

Forecasting spring rains in Ethiopia

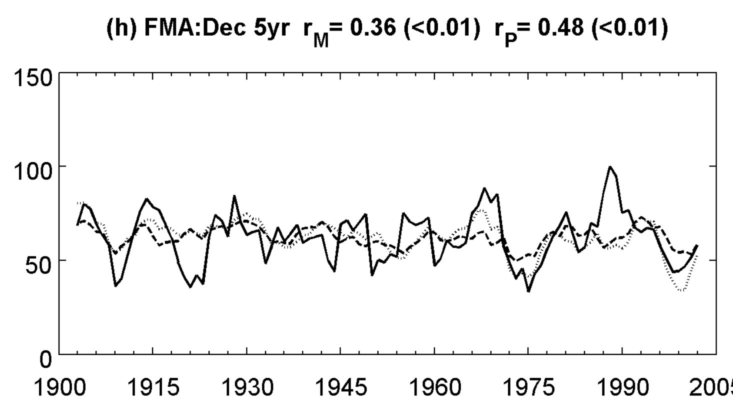




Leading EOFs used to estimate Ethiopia spring precip.

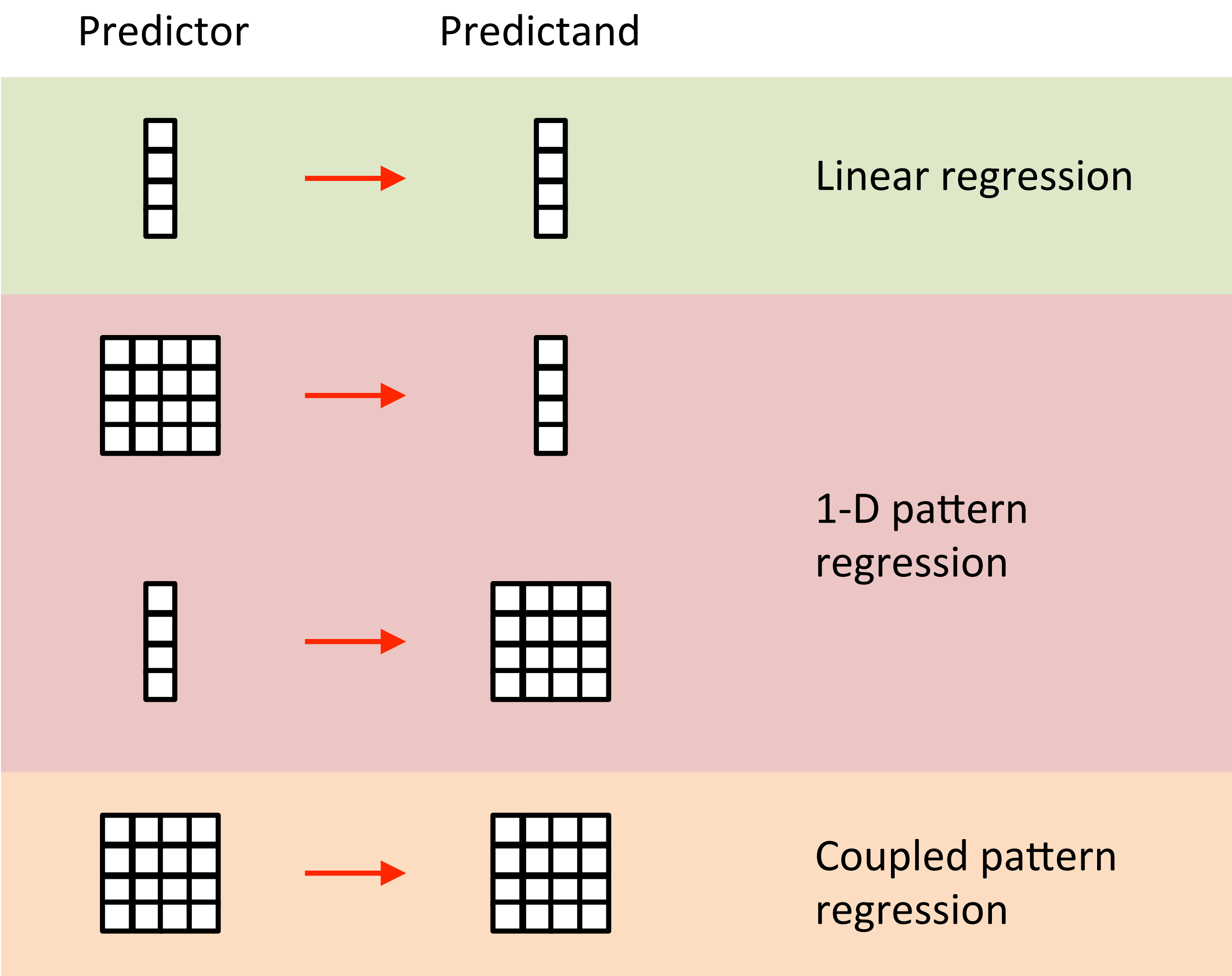


Correlation between Ethopia precip and SST (1901-2010).



Eden *et al*. (2014) Int. J. Climatol.

Pattern-based regression – coupled patterns



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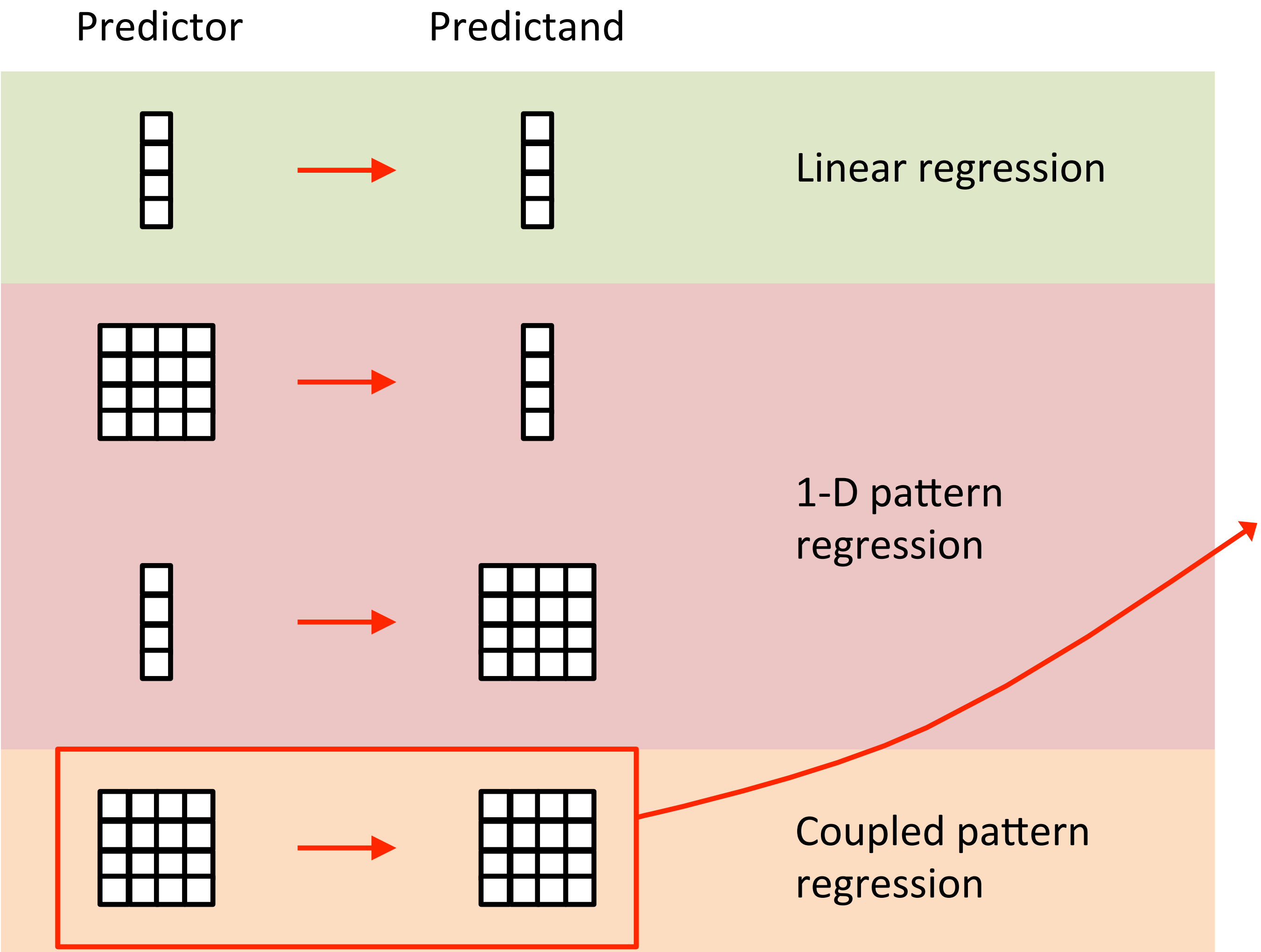

Methods include:

- Canonical correlation analysis (CCA)
- Maximum covariance analysis (MCA).
- Linear inverse models (LIM)

Much literature on the merits of each!

Generally more appropriate over limited region where meteorology is well-understood.

Towards probabilistic prediction…

- **Deterministic** vs **probabilistic** prediction.
- Whereas an *individual* deterministic forecast can be often be judged right or wrong, this is not possible for probabilistic forecasts.
- For comparison with probabilistic output from dynamical model ensembles, empirical prediction must also be probabilistic.

- More in the next section…

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Development of a global empirical prediction system

SPECS (Seasonal-to-decadal climate Prediction for the improvement of European Climate Services)

Work package 5.1: Building a prototype empirical prediction system for surface air temperature and precipitation:

- Seasonal prediction (led by KNMI)
- Decadal prediction (led by University of Reading)

Development of a global empirical prediction system

SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

Design brief:

- Global applicability with emphasis on Europe
- Exploit the long-term trend as an important source of skill
- Probabilistic output; act as a benchmark for dynamical forecast systems as well as a forecast system in its own right.

System built on lagged multiple linear regression.

- Seasonal (three-month) forecasts produced at one month lead time.
- Predictors: CO_2 equivalent; indices describing modes of variability, locally-varying predictors.
- Predictor selection based on physical principles to fullest extent.

Predictor selection and model fitting

CO_2 equivalent

Predictors describing internal variability

$$x = \alpha + \beta \boxed{C} + \sum_{i=1}^{n} (\Phi_i \boxed{F_i}) + \epsilon$$

Predictor selection and model fitting

CO_2 equivalent

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$$x = \alpha + \beta \boxed{C} + \sum_{i=1}^{n} (\Phi_i \boxed{F_i}) + \epsilon$$

- Nino3.4
- PDO
- AMO
- QBO
- IOD
- Local SST
- Persistence

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Persistence

Predictor selection

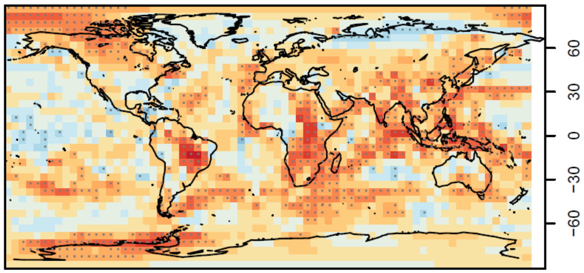
$$x = \alpha + \beta C + \sum_{i=1}^{k} (\Phi_i \boxed{F_i^S}) + \boxed{\epsilon}$$

Residuals from model fit randomly sampled and added to estimate to produce forecast ensemble

Forecast generation and verification

- Hindcasts produced for 1961-2013 compared with observations.
- Data from all previous years used to generate hindcast.
- System design facilitates framework used in verification of dynamical system output.
- Deterministic output:
  - Correlation
  - RMSE
- Probabilistic output:
  - Verification skill scores, including continuous rank probability skill score (CRPS) (R package: SpecsVerification)
  - Skill scores generated with respect to a reference forecast, generated from randomly sampling the climatology (sample size = 51).

Predictor selection

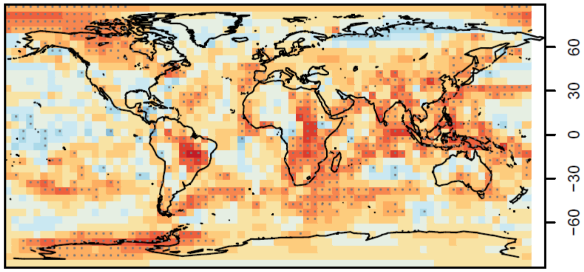


CO2EQV

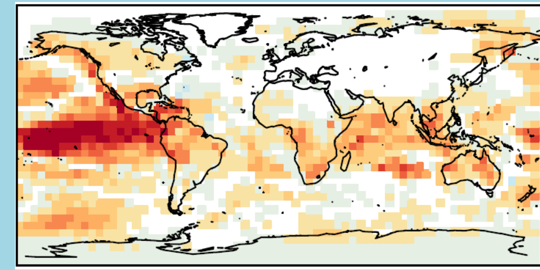
Correlation between observations predictions for DJF surface air temperature (1961-2014).

Linear regression model with one predictor: CO_2-equivalent (CO2EQV).

Predictor selection



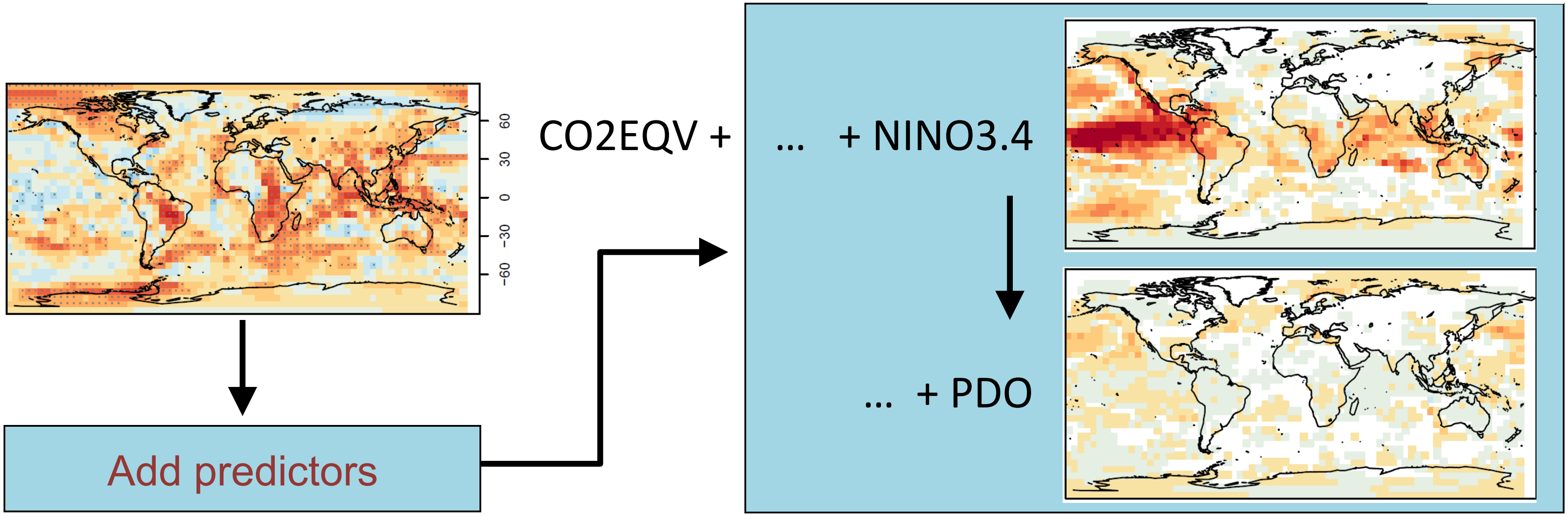
CO2EQV + … + NINO3.4



Add predictors

What is the incremental correlation gained by adding additional predictors?

Predictor selection



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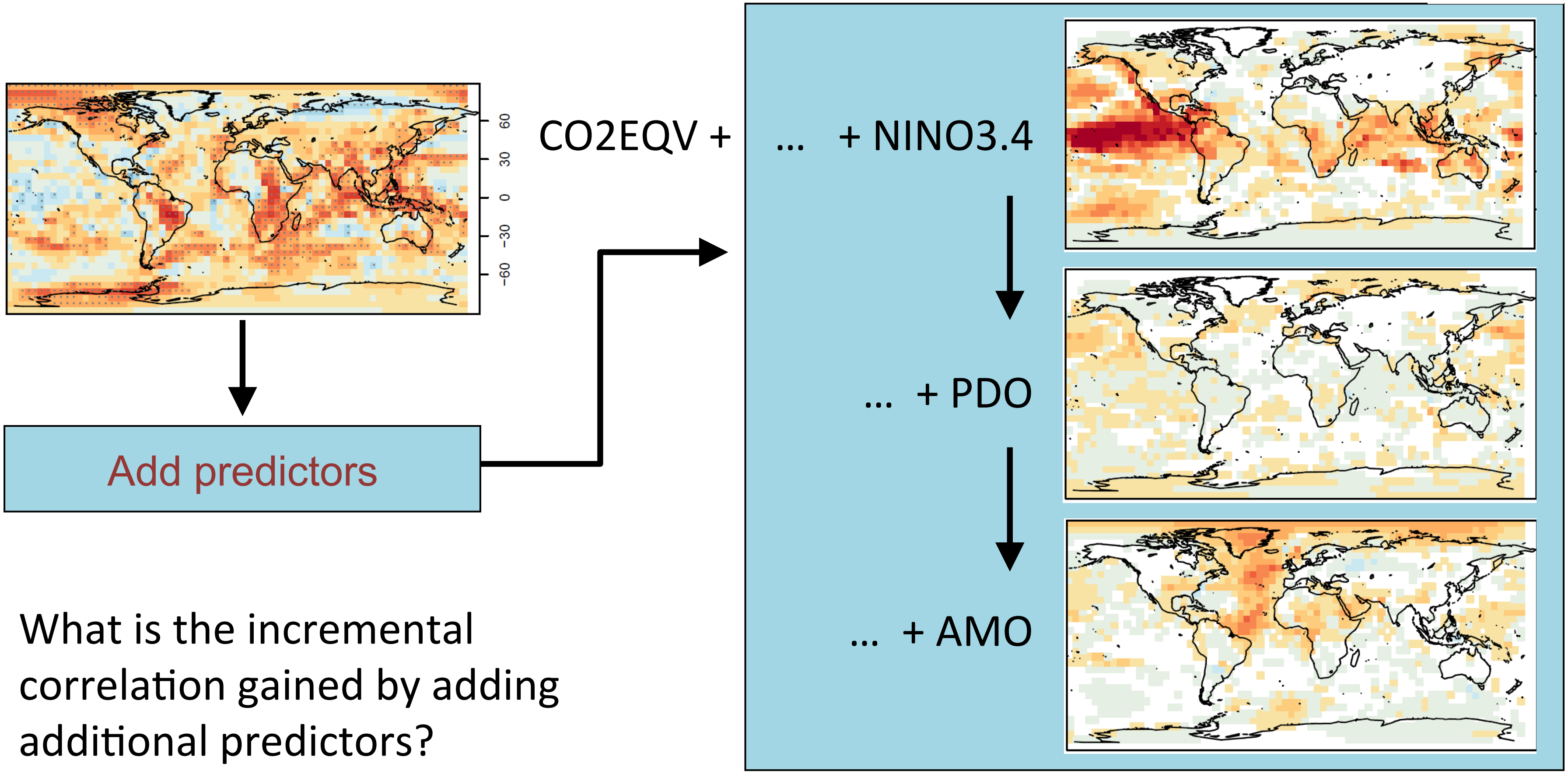

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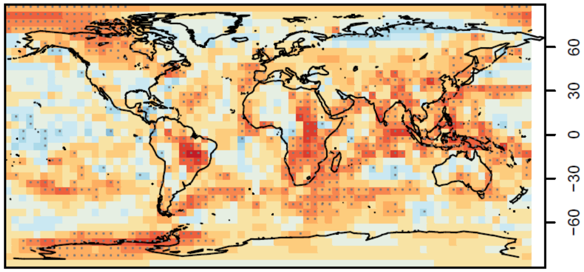
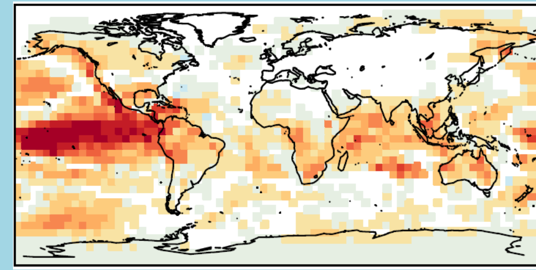
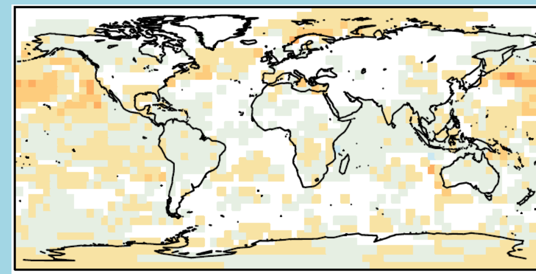


Add predictors

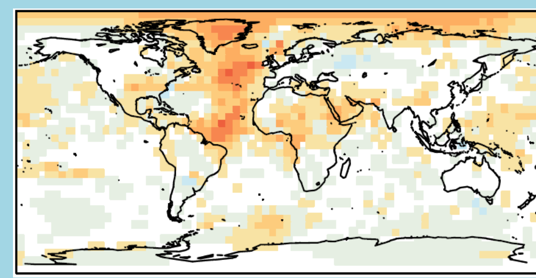
CO2EQV + … + NINO3.4



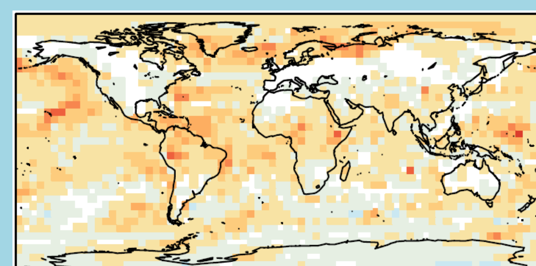
… + PDO



… + AMO



… + PERS



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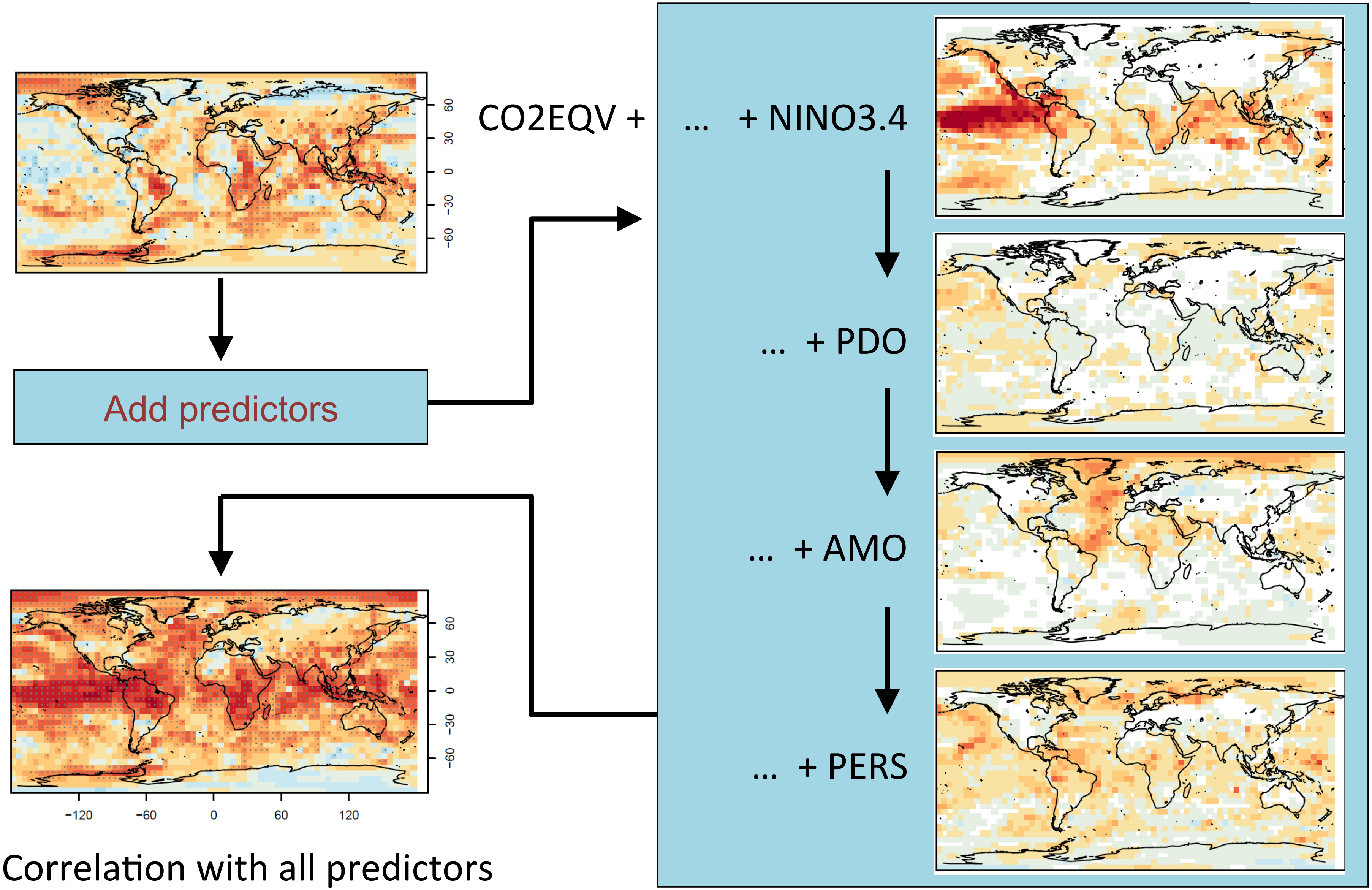

Correlation with all predictors

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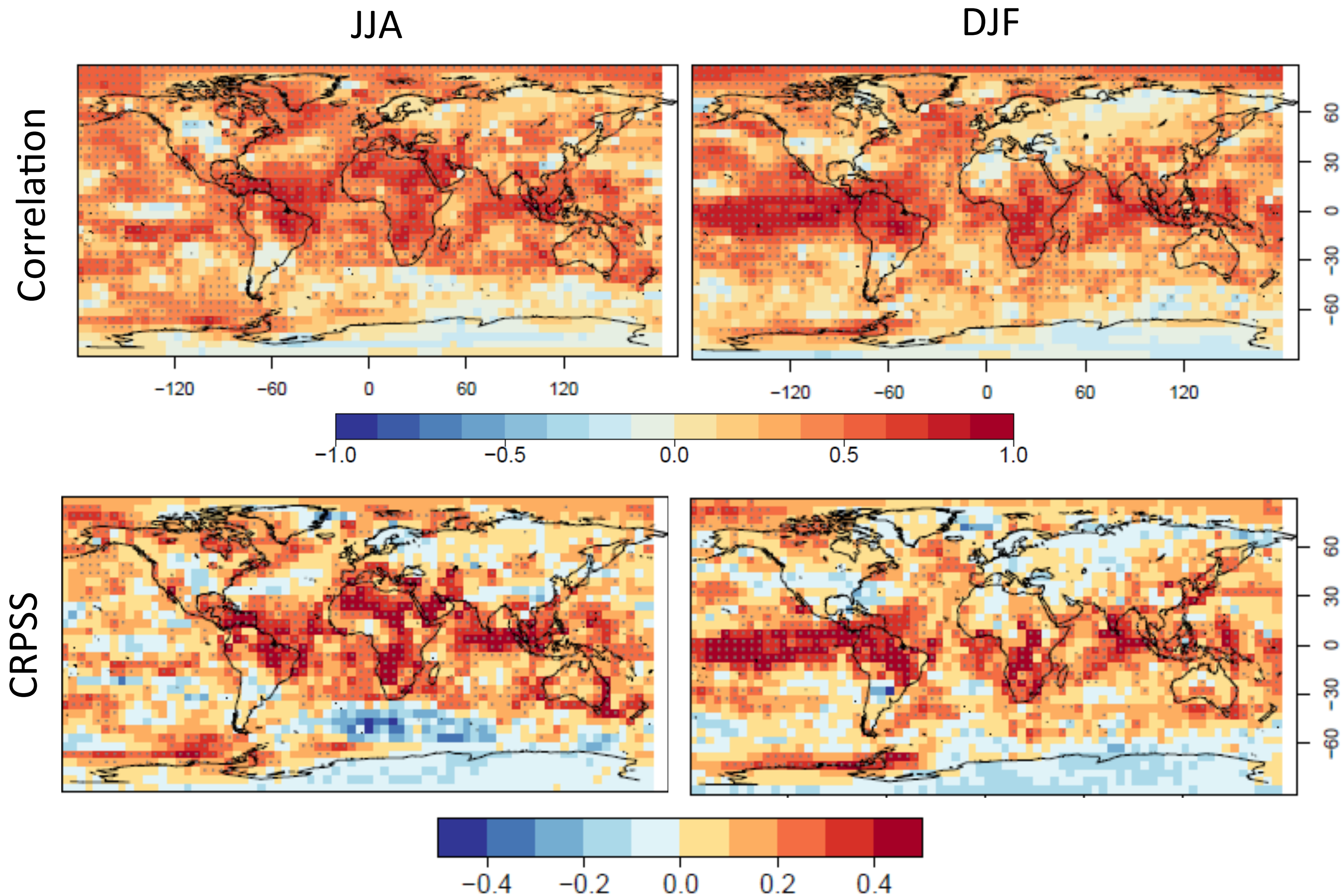
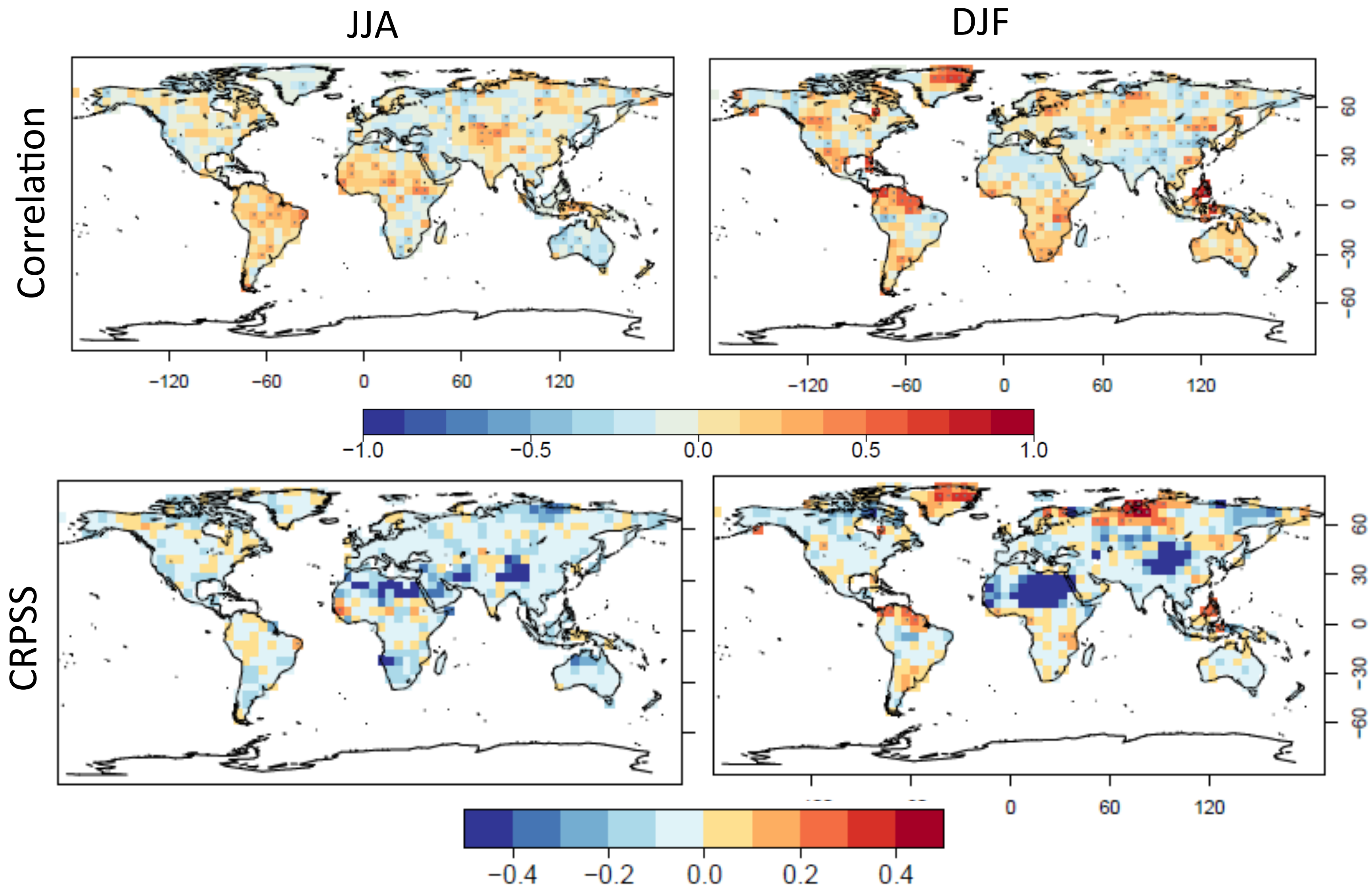
Forecast skill: surface air temperature



Forecast skill: precipitation



Prediction system: summary

Prediction system produces good skill in many regions

SAT: Interannual variability is well-represented throughout the tropics and in a number of extra-tropical regions:

- Parts of Europe, particularly during spring and summer
- Southern Africa, eastern Australia
- Spatial for correlation and CRPS patterns broadly similar

PRECIP: Few areas of notable skill are found

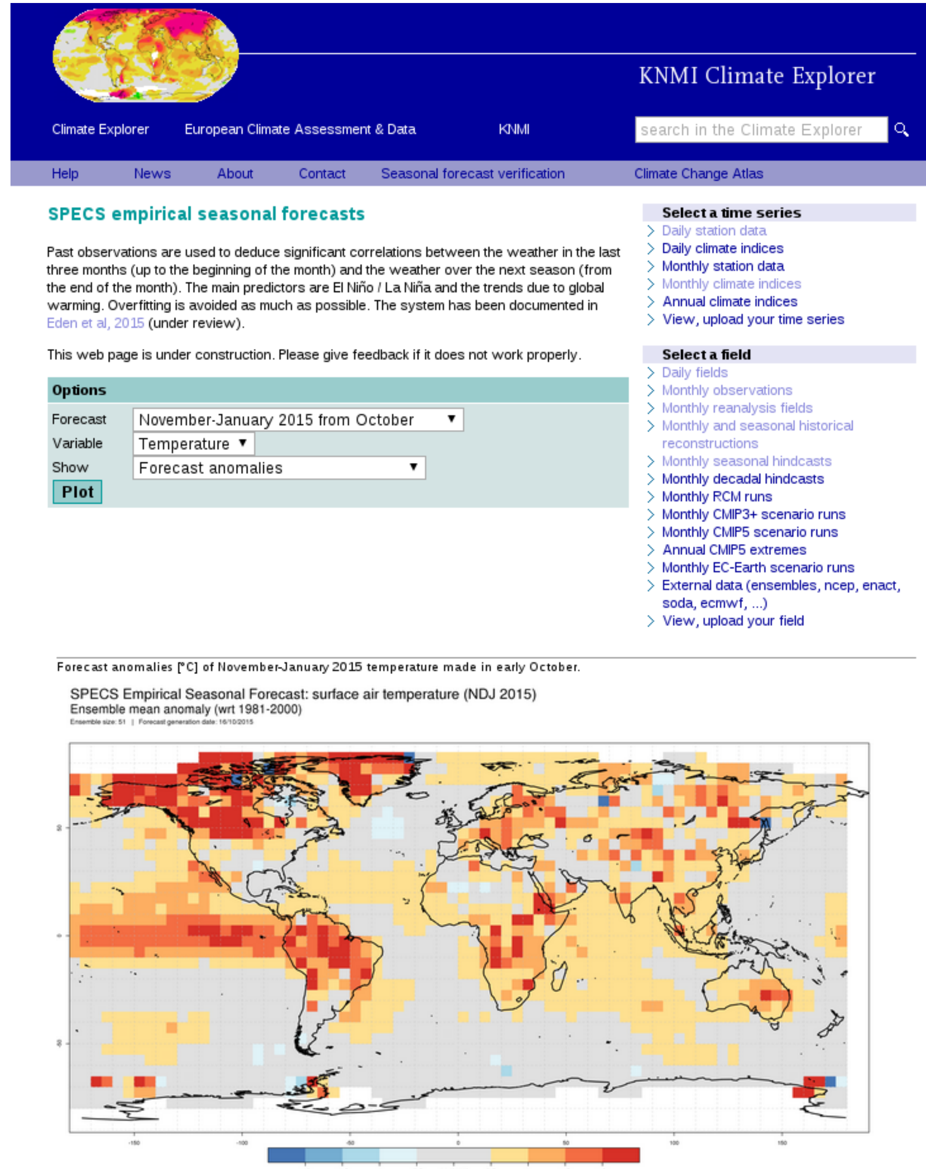
- Correlation in regions with known ENSO teleconnection is strong.
- Probabilistically, system does not perform better than the climatological ensemble throughout most of the world

Forecast dissemination

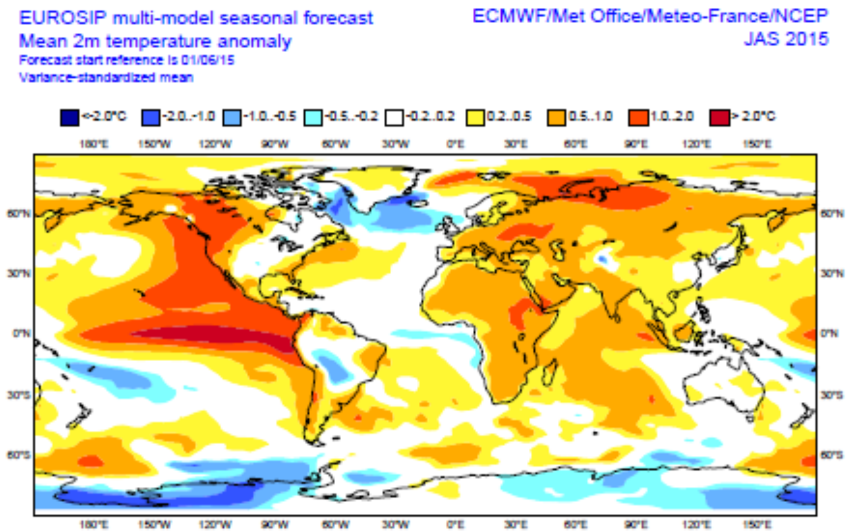
- Forecasts made as soon as predictor data is made available.
  - In practice, between 5th and 10th of each month.
  - e.g. Forecast for November, made between 5-10th October using predictor data from July-August-September (i.e., one month lead).
- Forecasts and verification statistics made available on KNMI Climate Explorer.

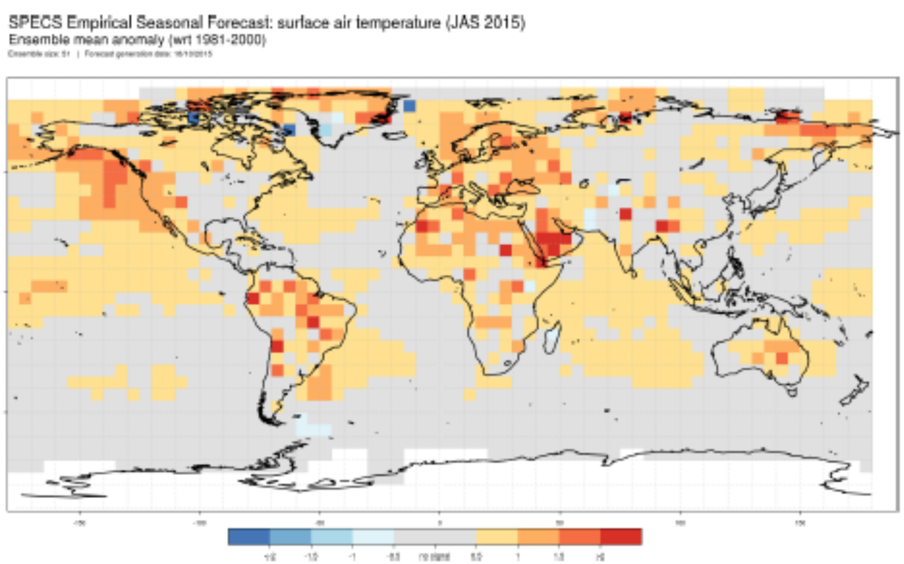
  climexp.knmi.nl/spes.cgi

- Forecast/hindcast netcdf files available for download.



Comparison with dynamical forecasts





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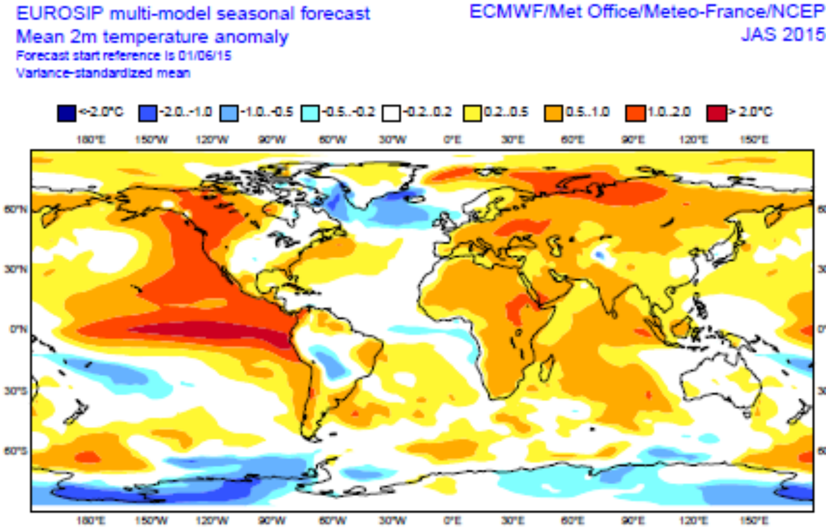

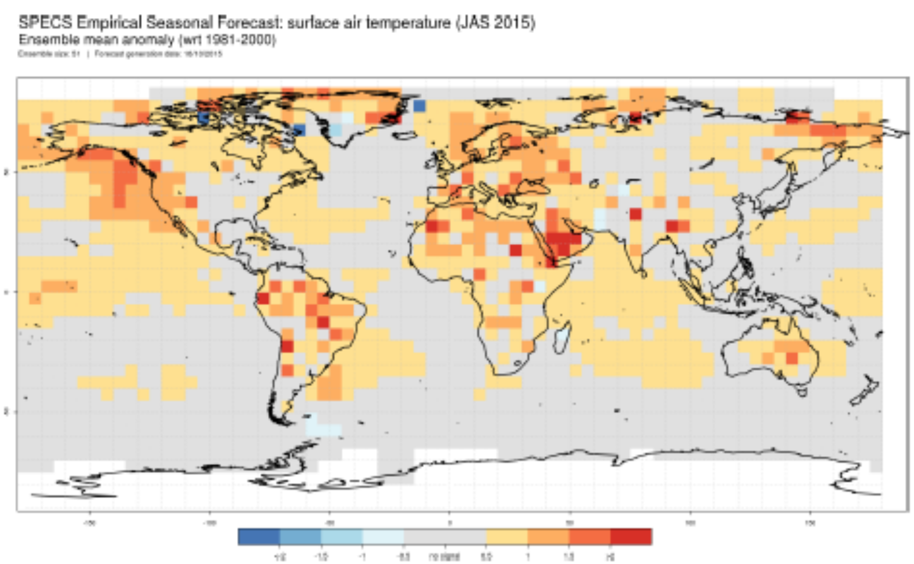

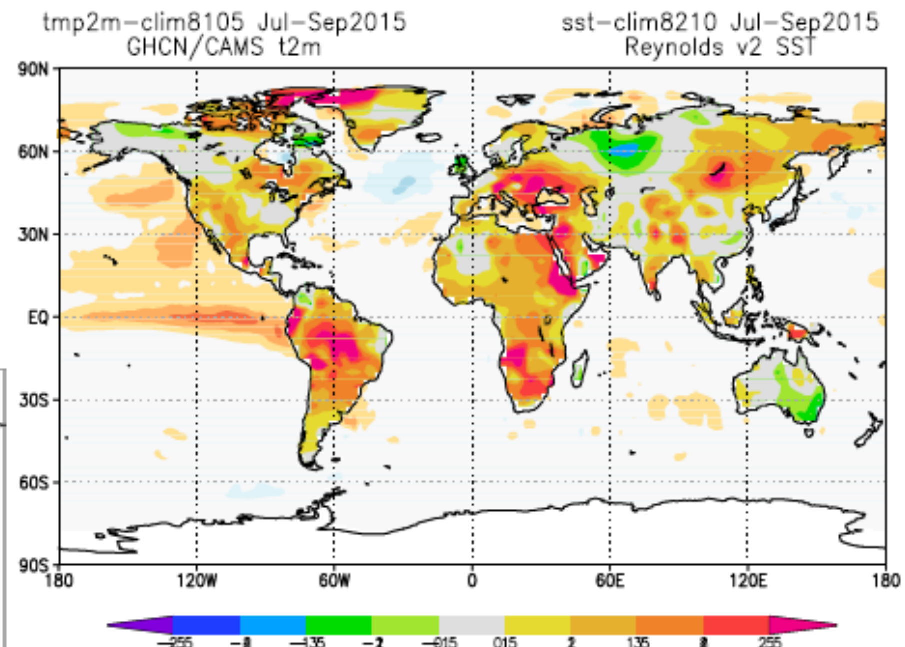

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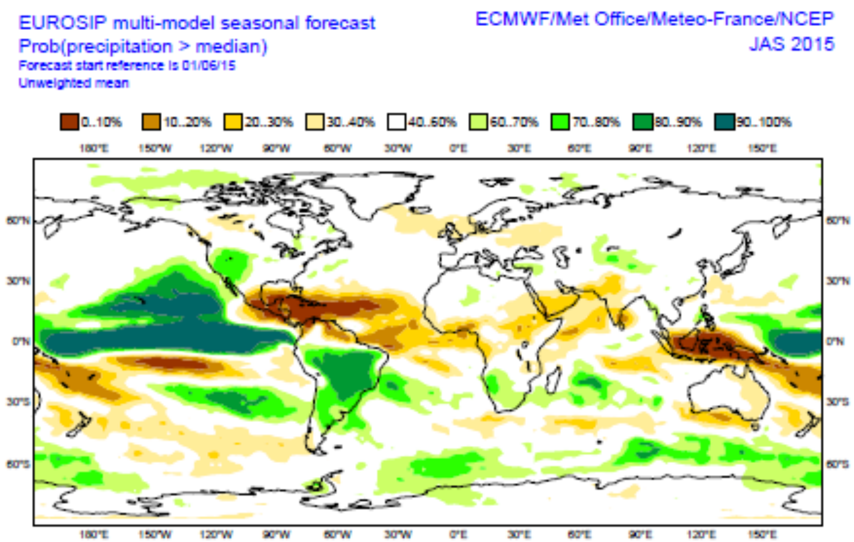

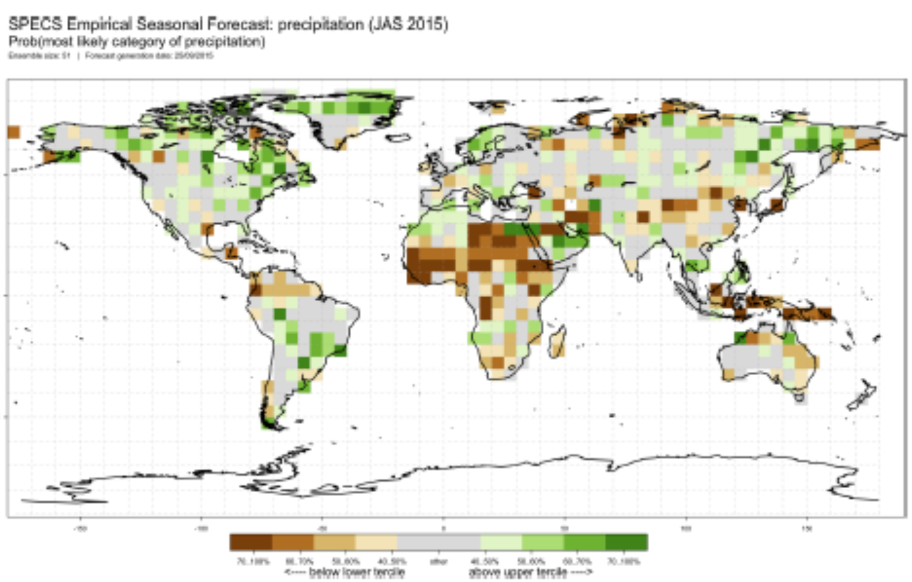

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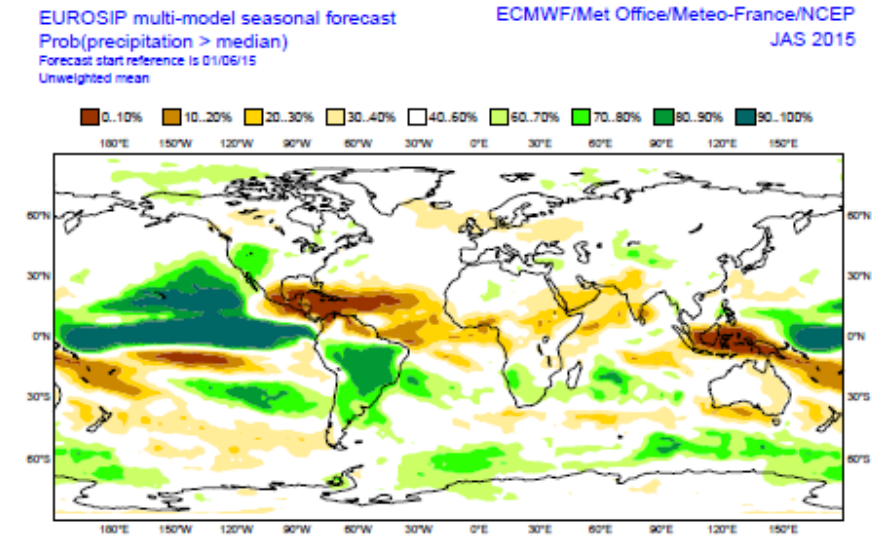

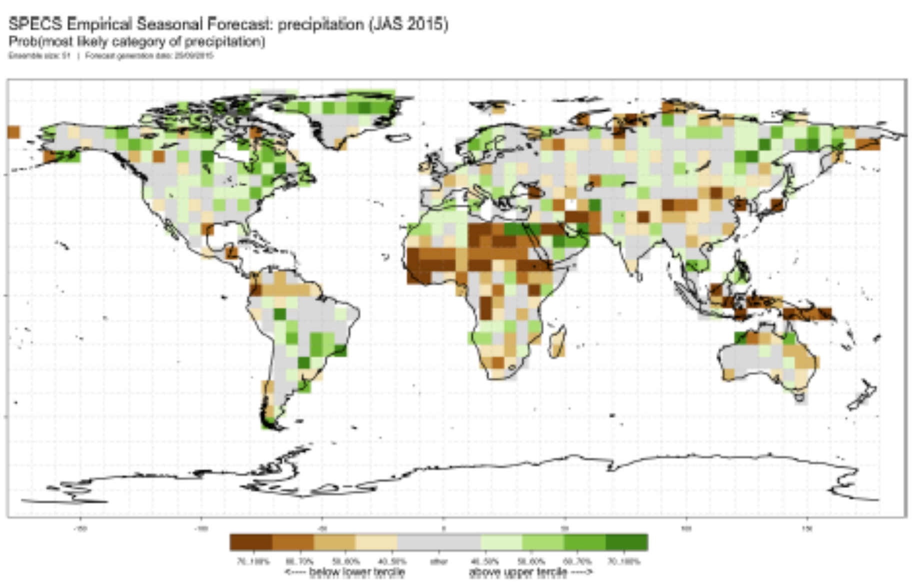

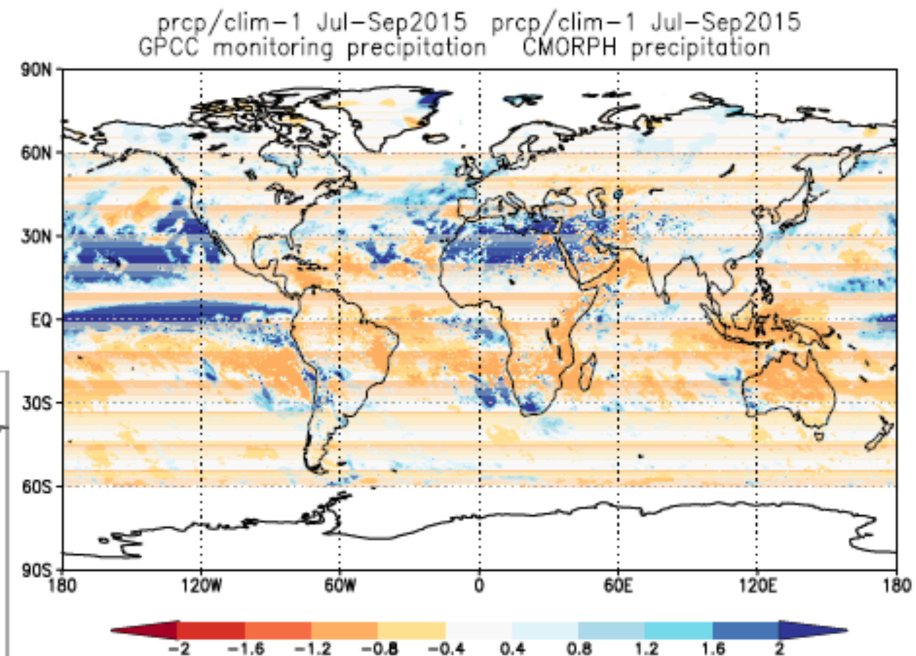

Further development

- Prediction system presented and validated in Eden et al. (2015), Geosci. Model Dev. (in review)
- Further model development based on feedback from users.
  - Alternative methods of ensemble generation.
  - Additional forecast information to made available via Climate Explorer.
  - Higher resolution forecasts forthcoming.

- A model for decadal prediction built with the same principles has also been developed (Suckling *et al*., Clim. Dynamics., submitted).

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Summary and outlook

- Dynamical models are process-based and can resolve non-linear terms – an inherent advantage over empirical models that are (usually) linear.
- However, when the processes involved in seasonal prediction are also linear, dynamical methods may have no clear advantage.
- Thus, empirical methods continue to play an important role:
  - As an often credible alternative to dynamical models.
  - As a benchmark for aiding the development of dynamical models.

- Is there scope for greater communication and collaboration among dynamical and empirical forecast-makers?

Thank you

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