Dealing with uncertainties in seasonal predictions

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Introduction – Sources of uncertainty

- Conceptual illustration : Uncertainties in weather predictions

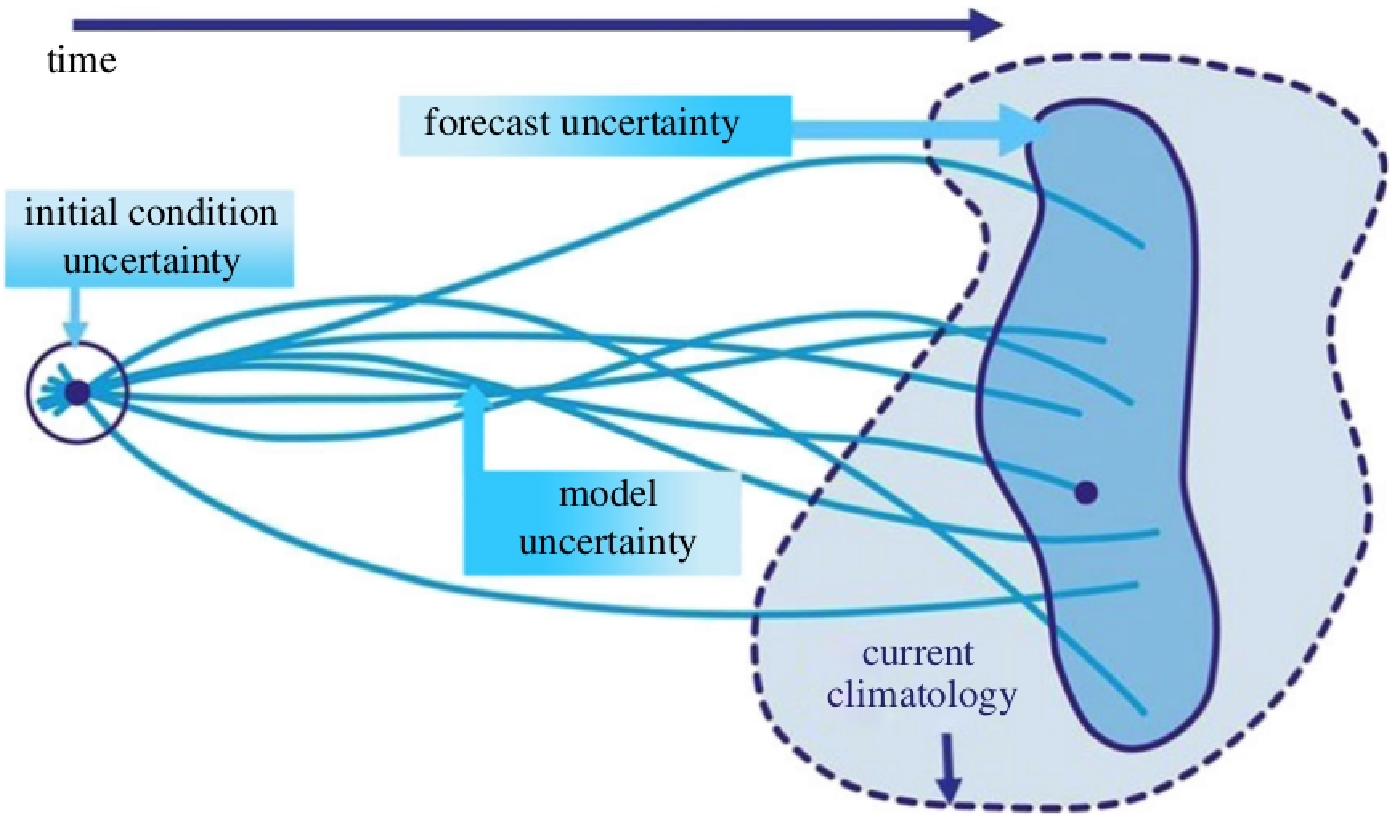


Figure 2 from Slingo and Palmer (2011) : illustration of sources of uncertainty in a probabilistic weather forecast

Introduction – Sources of uncertainty

- But in seasonal forecasts, there are additional sources of uncertainty

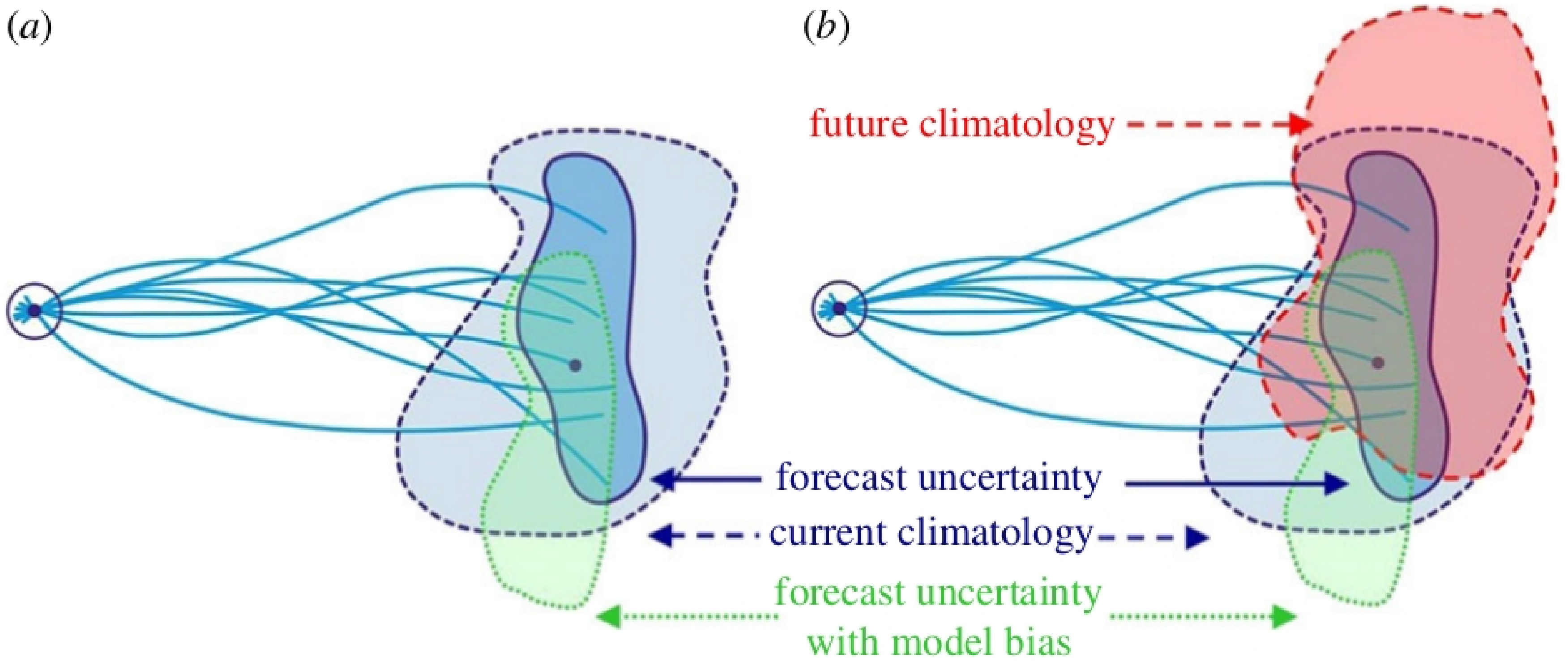


Figure 8 from Slingo and Palmer (2011) : illustration of sources of uncertainty in a probabilistic seasonal forecast with (a) model biases and (b) a changing climate

Introduction – Sources of uncertainty

Goal of this lecture :

- Provide an overview of the **different sources of uncertainty** in seasonal forecasting
- Discuss some **strategies used in state-of-the-art seasonal forecasting systems** to deal with these uncertainties

Lecture outline

- Dealing with uncertainties in initial conditions
- Dealing with uncertainties in numerical models
  - Multi-model approach
  - Stochastic perturbations
- Dealing with uncertainties in seasonal forecast evaluations
- Communicating uncertainties in seasonal forecasts

Lecture outline

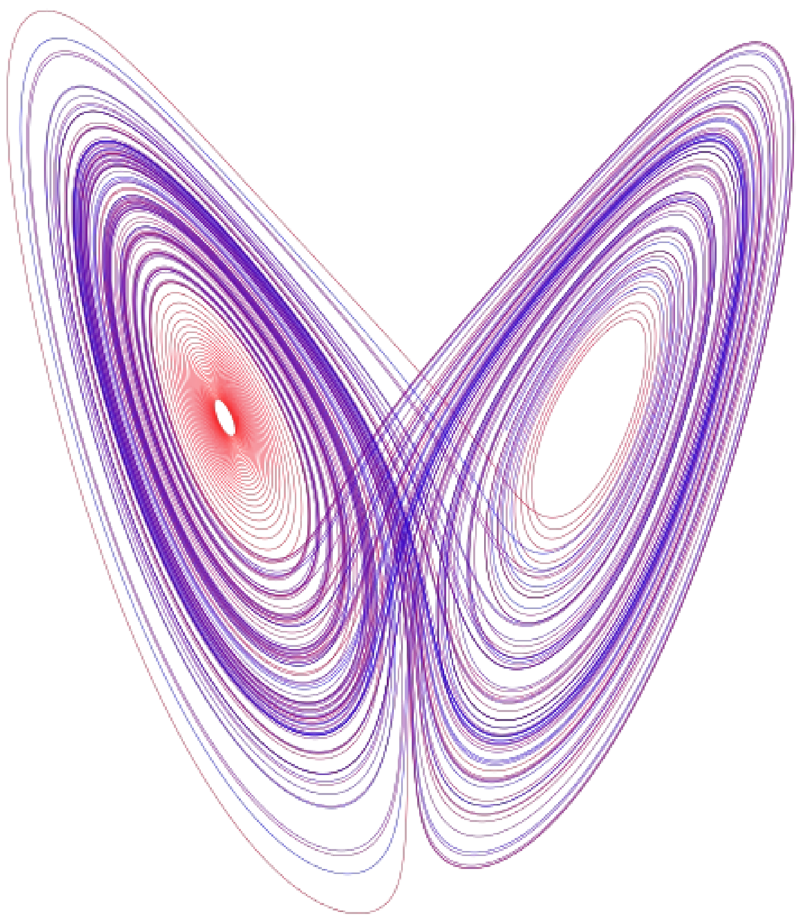
- **Dealing with uncertainties in initial conditions**

- Dealing with uncertainties in numerical models
  - Multi-model approach
  - Stochastic perturbations

- Dealing with uncertainties in seasonal forecast evaluations

- Communicating uncertainties in seasonal forecasts

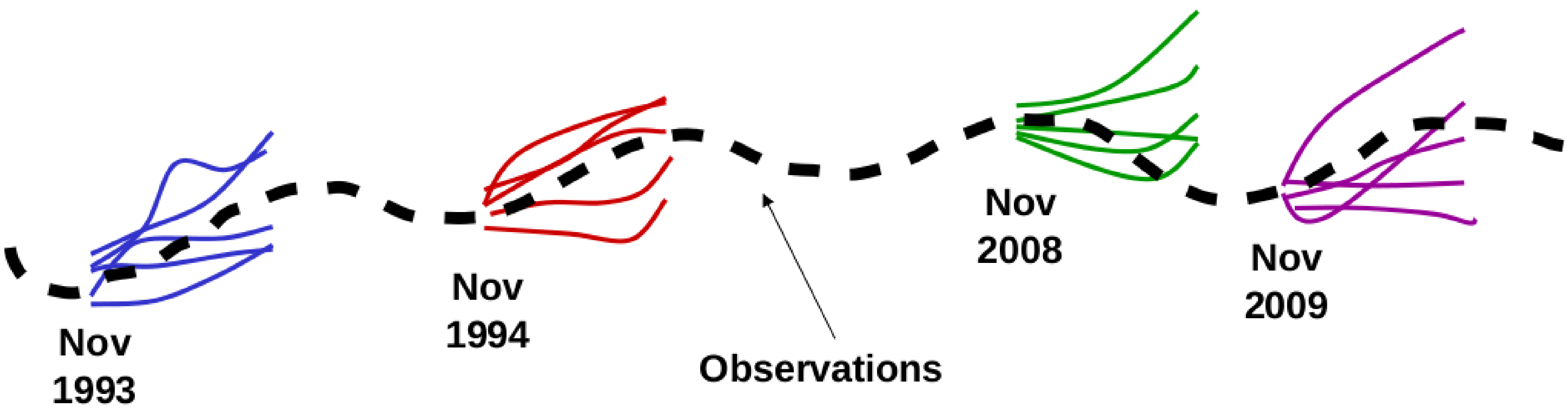
The Lorenz attractor (1963)



- Lorenz (1963) : Introduction of chaos theory in meteorology
- Very simple model (non-linear equations)
- Small errors in initial conditions could lead to very large uncertainties in the time evolution on the Lorenz attractor
- Depending on the initial phase, the growth of uncertainty (and hence predictability) differs greatly.
- Limits of predictability in a deterministic framework : typically 10-15 days

Consequence : ensemble prediction

- Probabilistic weather forecasts : generated with small random perturbations to the atmospheric initial conditions
- Conversely, when dynamical seasonal forecasts were first developed, these were constructed as ensemble forecasts



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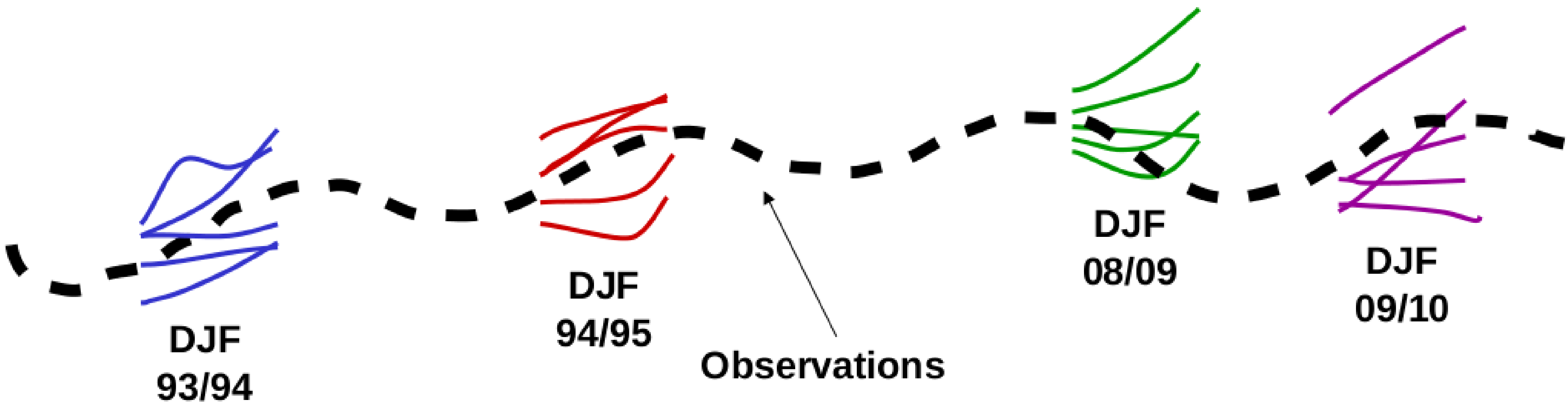

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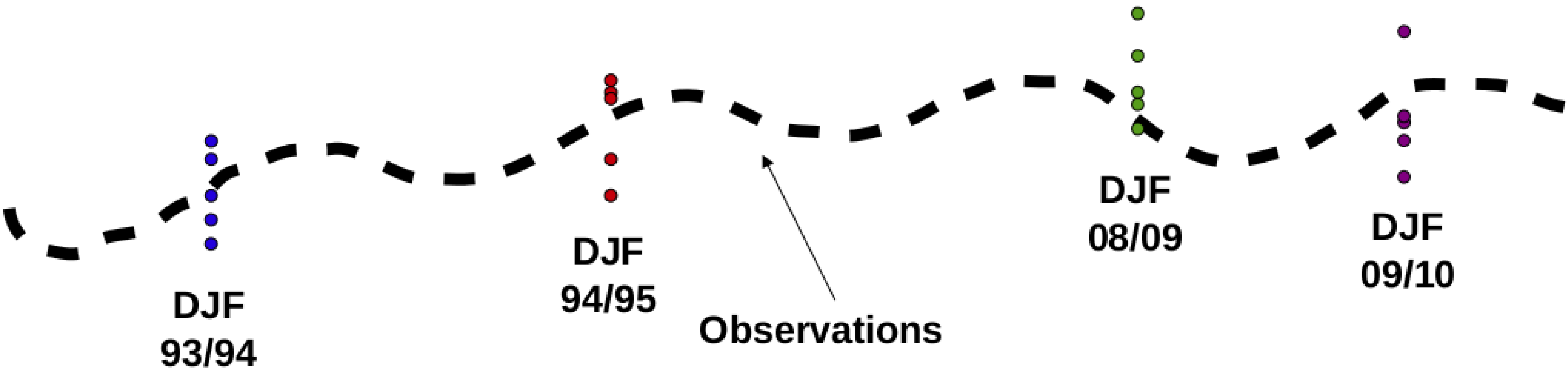


Consequence : ensemble prediction

- Global reanalyses for the atmosphere, land, ocean provide initial conditions over a range of past years ; corresponding analyses are used for real time initialization
- Ensemble generation techniques for initialization vary depending on the institute, but generally use one of the following:
  - **Lagged initialization**: (*Hoffman and Kalnay, 1983)* ensemble members are initialized using different sets of initial conditions separated by 6 hours, one day, one week… or combinations of these for the atmosphere / ocean
  - **Initial condition perturbation**: *(Kalnay, 2003)* atmosphere or ocean (re)analysis + small perturbation
  - **Ensemble assimilation** : similar to the previous method, but members directly derived from the members of an ensemble assimilation technique

Consequence : ensemble prediction

- Examples :
  - ECMWF SEAS5: atmosphere and some land fields are perturbed using EDA perturbations from 2015, as well as leading singular vector perturbations ; ocean fields are from a 5-member OCEAN5 analysis + SST pentad perturbations (Johnson et al. 2019)
  - CFSv2: lagged initialization with 4 runs per day every five days for the 9-month forecasts, 1 run per day for 1-season forecasts (Saha et al. 2014)
  - Météo-France System 6: lagged initialization with start dates on the 20th, 25th of the previous month, 1 control member on the 1st

Lecture outline

Dealing with uncertainties in initial conditions

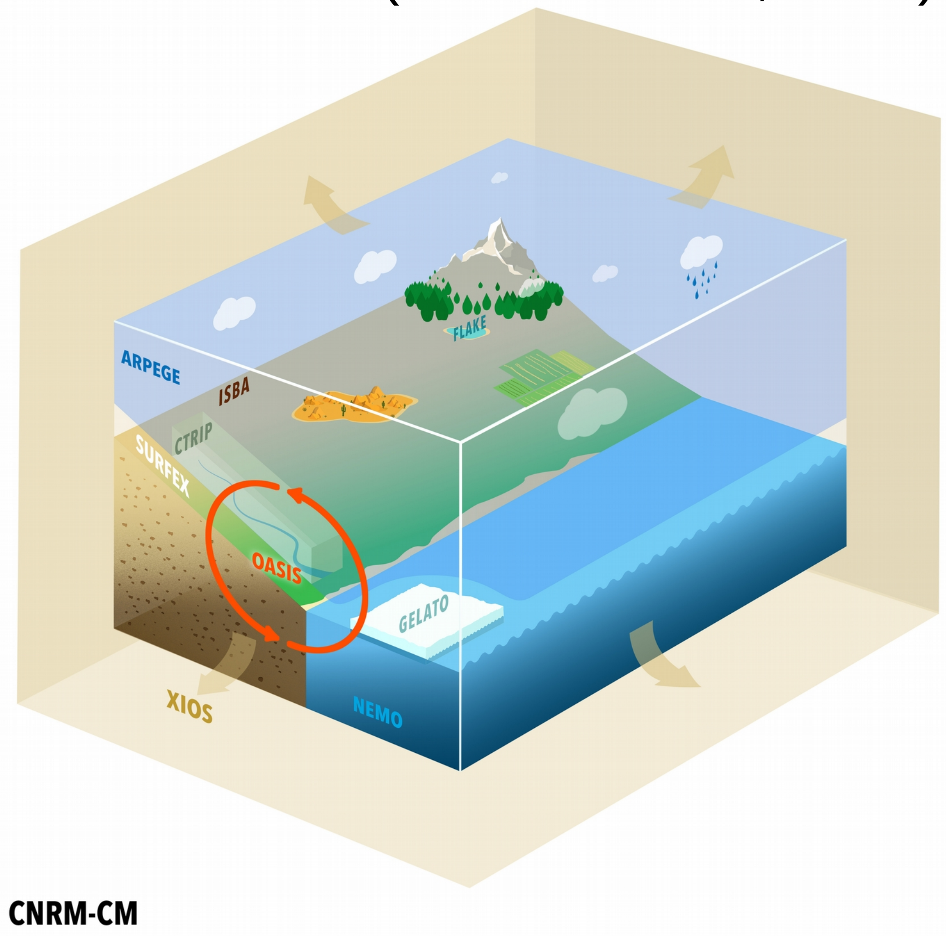
- **Dealing with uncertainties in numerical models**
  - **Multi-model approach**
  - **Stochastic perturbations**

Dealing with uncertainties in seasonal forecast evaluations

Communicating uncertainties in seasonal forecasts

Uncertainties in numerical models

- Example: CNRM-CM model co-developed by CNRM and CERFACS (Voldoire et al., 2019)



Atmosphere: ARPEGE Climat climate model, typically run at resolutions ~1.4° (~0.5° in System 6)

Land surface: SURFEX interface

Ocean: NEMO v3.6 on ORCA1 tripolar grid

Coupler: OASIS MCT

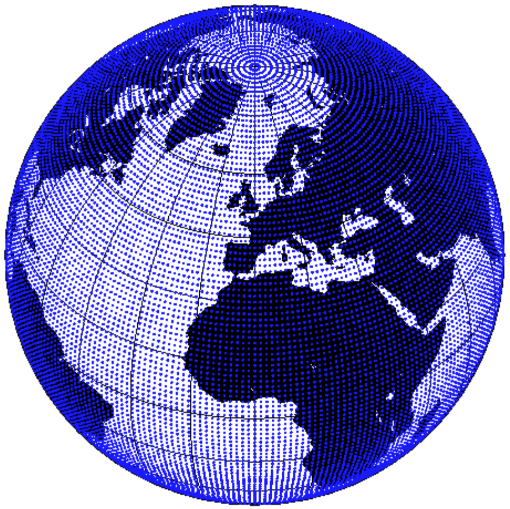
Uncertainties in numerical models

- Numerical models are implemented on finite grids

  → numerical approximations of the equations defining the time evolution of physical fields (e.g. Navier-Stokes equations for ocean and atmosphere) : time stepping, splitting of integration of seperate tendencies...

  →sub-grid scale phenomena often need to be parameterized in GCMs (e.g. triggering of convection…)

  → example : lower resolution models have a coarser topography and don’t represent well the impact of orography on large-scale flow



Uncertainties in numerical models

- Coupling different model components inevitably leads to further sources of model uncertainty
  - Representing fluxes between components
  - Coupling frequency of GCMs is restricted by computational costs
  - Limited availability of reference data (field campaigns)

Uncertainties in numerical models

- These model limitations inevitably lead to model-dependent and flow-dependent errors that are difficult to correct *a posteriori* in seasonal forecasts

- So how can we deal with these sources of uncertainty?

  Two strategies discussed here:

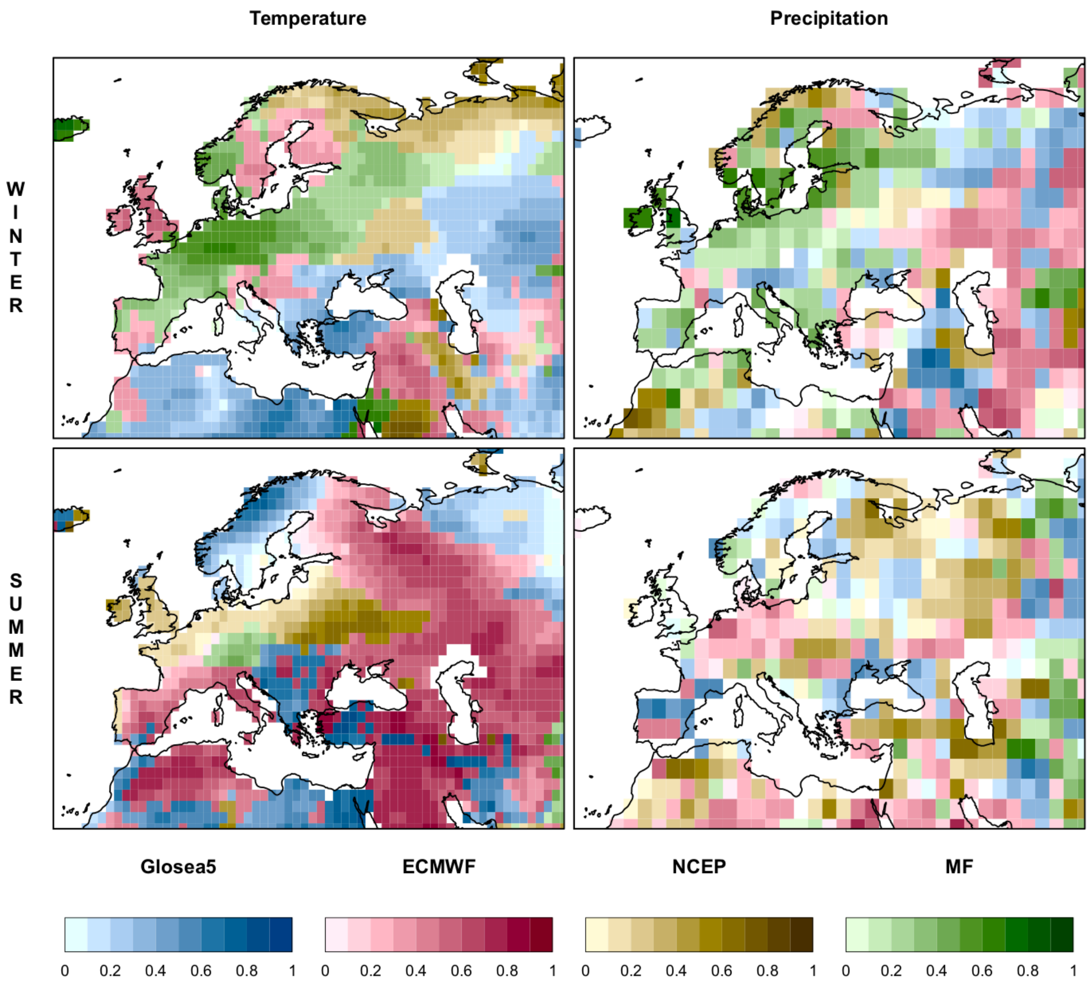
  - Multi-model approach: use several models as a means of quantifying errors related to model choices
  - Stochastic methods: introduce in-run perturbations accounting for model error

Multi-model approach

- Seminal papers: Krishnamurti et al. 1999 & 2000, Doblas-Reyes et al. 2000, Hagedorn et al. 2005
- Simple idea: combining ensemble forecasts from different, independant models as a way of estimating the uncertainty resulting from model error

- 3 straightforward ways to construct a multi-model ensemble:
  - Equally weighted members (Hagedorn et al. 2005)
  - Multi-model mean (equally weighted models)
  - Weighted ensemble, with weights depending on model performance for given criteria over the hindcast period

Multi-model mean



- Assumption: no particular model is more likely to represent the truth than any other in the multi-model
- Works well if levels of performance are similar

Fig. 3 from Mishra et al. 2019 showing at a gridpoint level the system with highest correlation, and correlation value, for EUROSIP hindcasts for DJF and JJA at lead times 2-4 months.

Weighted ensemble

- Several methods to determine weights have been applied in past studies:
  - Minimization of Ignorance score (Weigel et al. 2008)
  - Bayesian approaches (e.g. forecast assimilation, Stephenson et al. 2005)
  - Multiple linear regression techniques
  - Using correlation as weights (Mishra et al. 2019)
- Due to very short verification periods, and some co-linearity between the different forecasts, there is a large uncertainty in the weights derived from such techniques.
- To avoid over-fitting of some techniques, cross-validation is necessary, and if possible, separating learning and verification periods.

Some results (Batté and Déqué 2011, ENSEMBLES project)

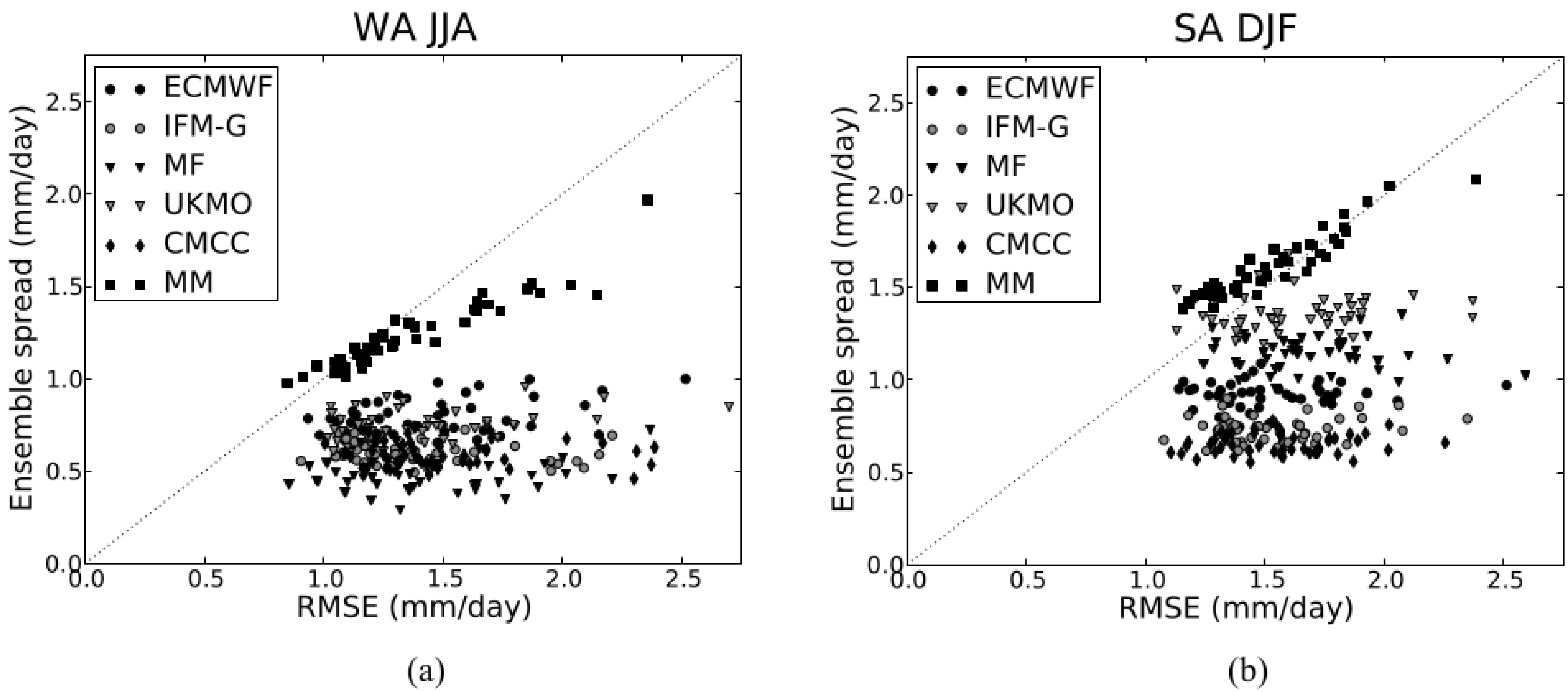


Fig. 6 from Batté and Déqué 2011 showing the RMSE vs ensemble spread of single models and multi-model ensemble (equal weights) for the ENSEMBLES project 1960-2005 seasonal hindcasts for JJA precipitation over West Africa (a) and DJF precipitation over southern Africa (b)

Some results (Mishra et al. 2019, EUROSIP)

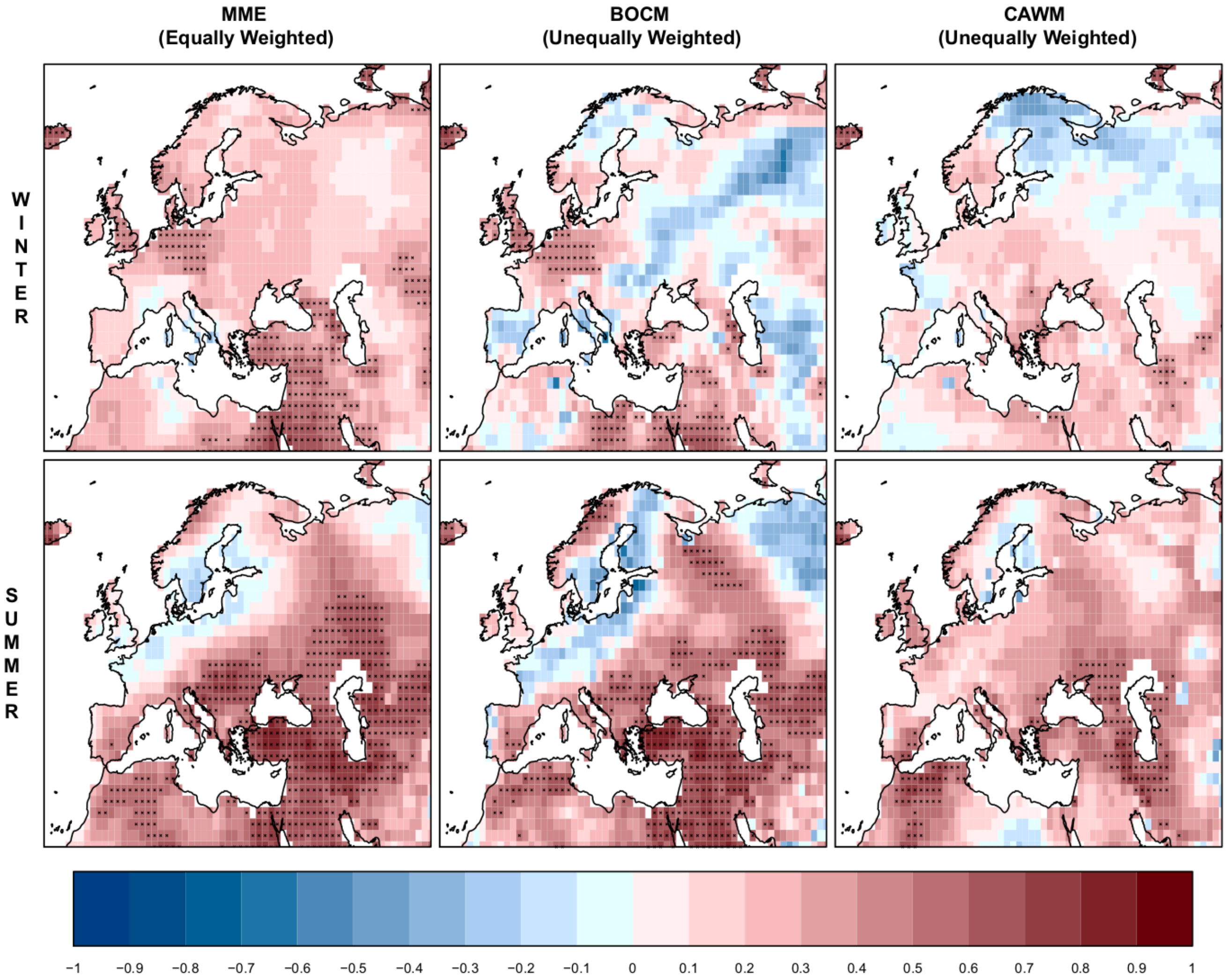
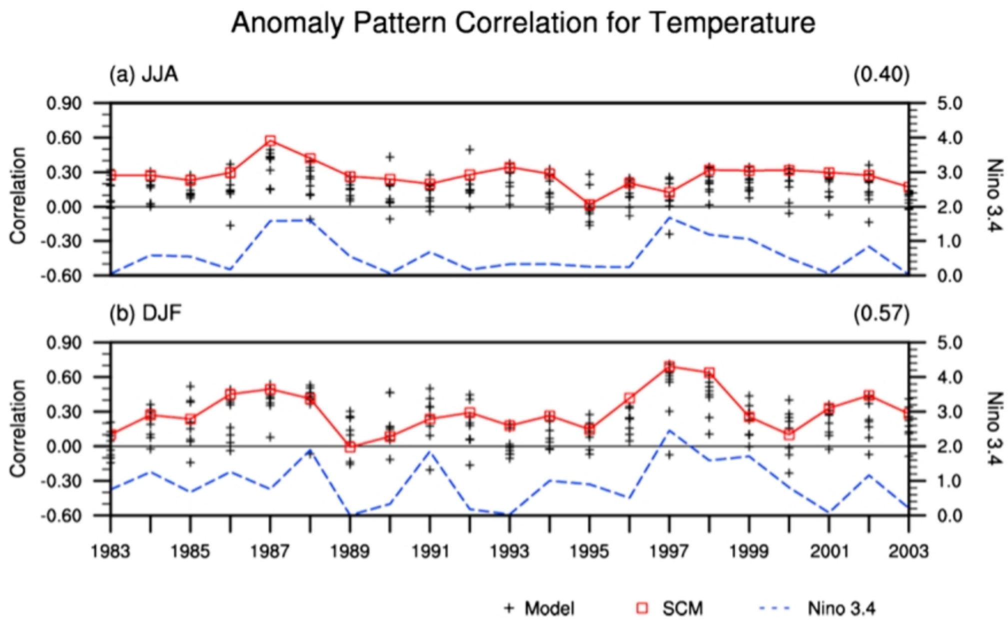
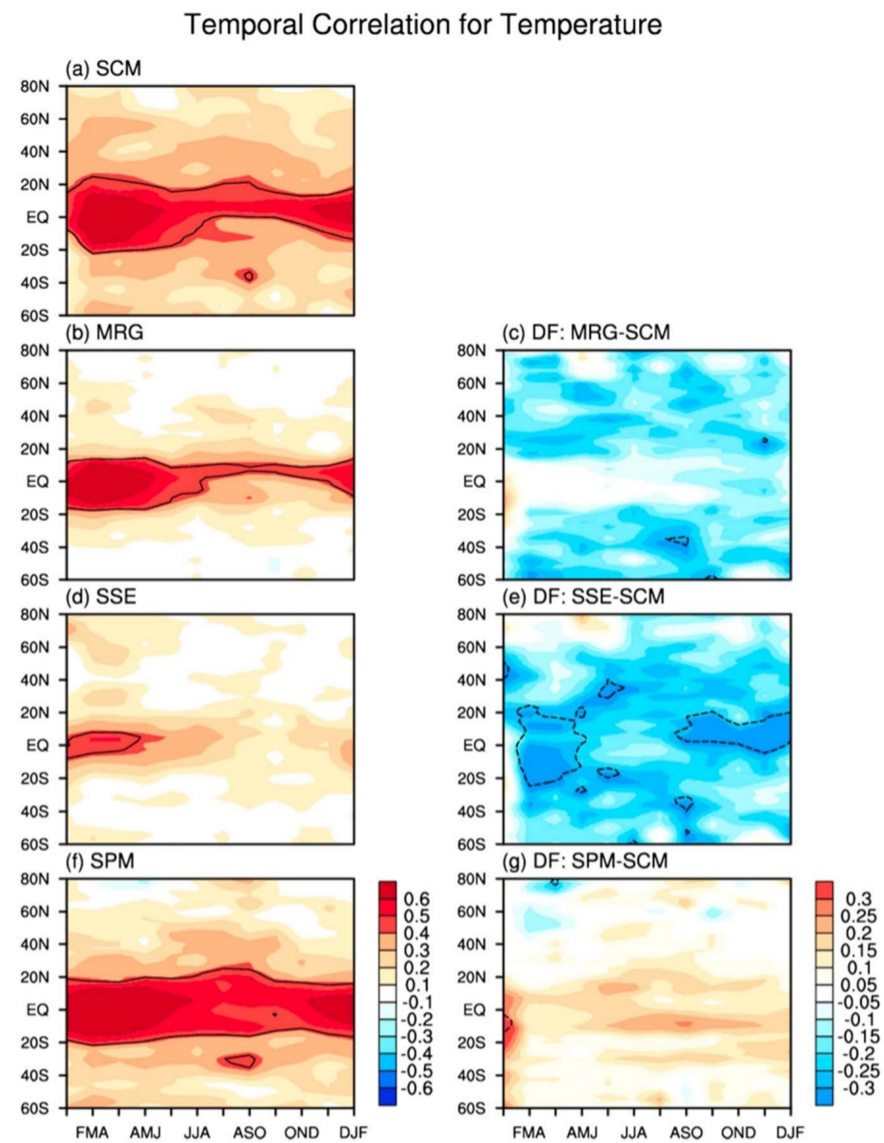


Fig. 10 from Mishra et al. 2019 showing near-surface temperature anomaly correlation with ERA-Interim in winter and summer EUROSIP multi-model hindcasts (1992-2012), using 3 different multi-model combination methods.

Some results (Min et al. 2014, APCC)





Figs. 4 and 6 from Min et al. (2014)
Top: surface temperature pattern correlation vs NCEPv2 for individual models (crosses) and the MME (red squares) for JJA and DJF APCC hindcasts over 1983-2003. The dashed blue line is the absolute value of the Nino 3.4 index.
Right: zonal mean time correlation for surface temperature with NCEPv2 for multi-model mean (SCM) and several multi-model weighting techniques.

Stochastic perturbations

- Assumption: seperation between predictable processes and unresolved scales that are represented by noise (Hasselmann, 1976)

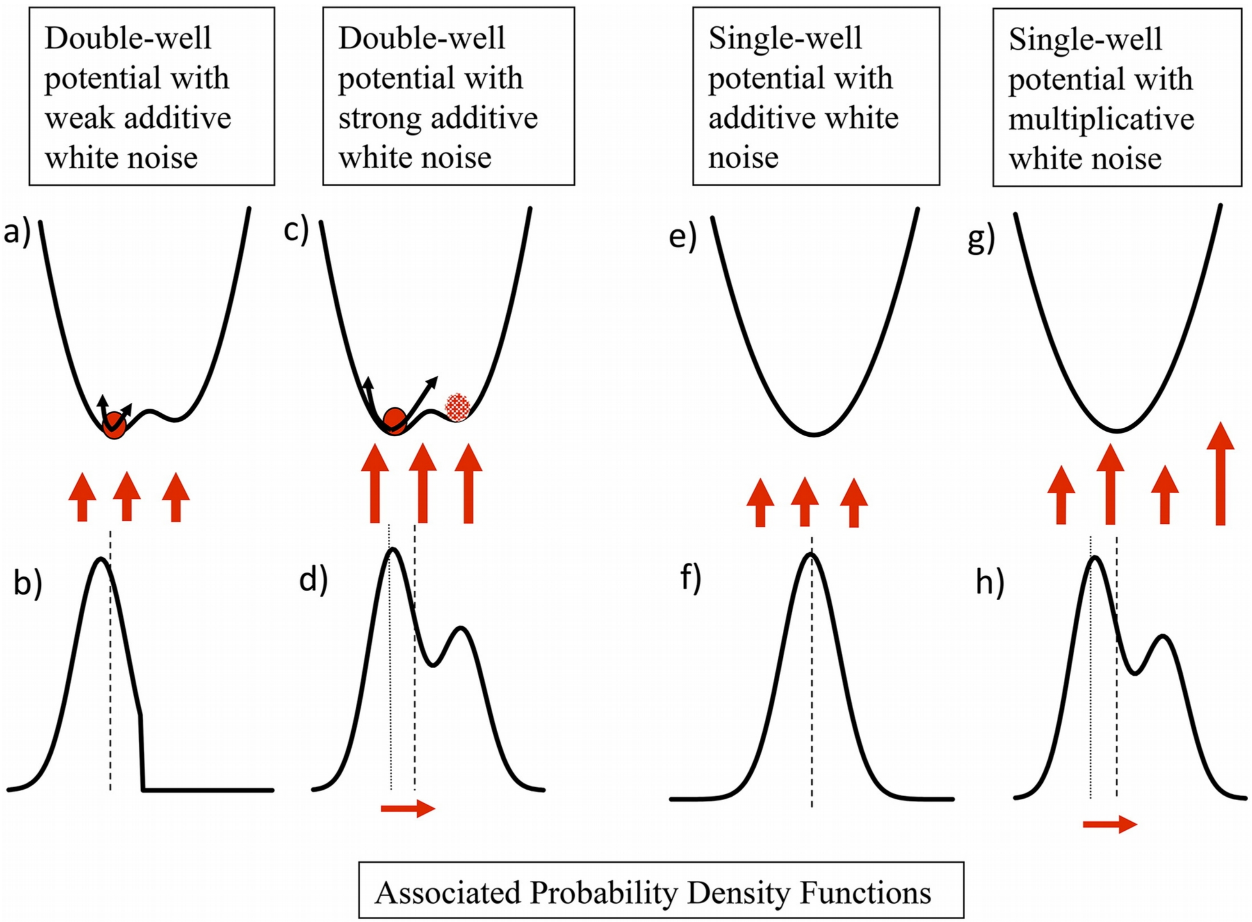


Fig. 1 from Berner et al. (2017) illustrating the effects of additive or multiplicative (state-dependent) white noise on simple systems, and associated PDFs obtained.

Stochastic perturbations

- Review paper on stochastic parameterizations in weather and climate models: Berner et al. (2017)

- Most common approaches in S2D forecasting:
  - Random perturbation (white noise or other)
  - Upscaling/backscatter algorithms
  - Approaches close to random flux corrections

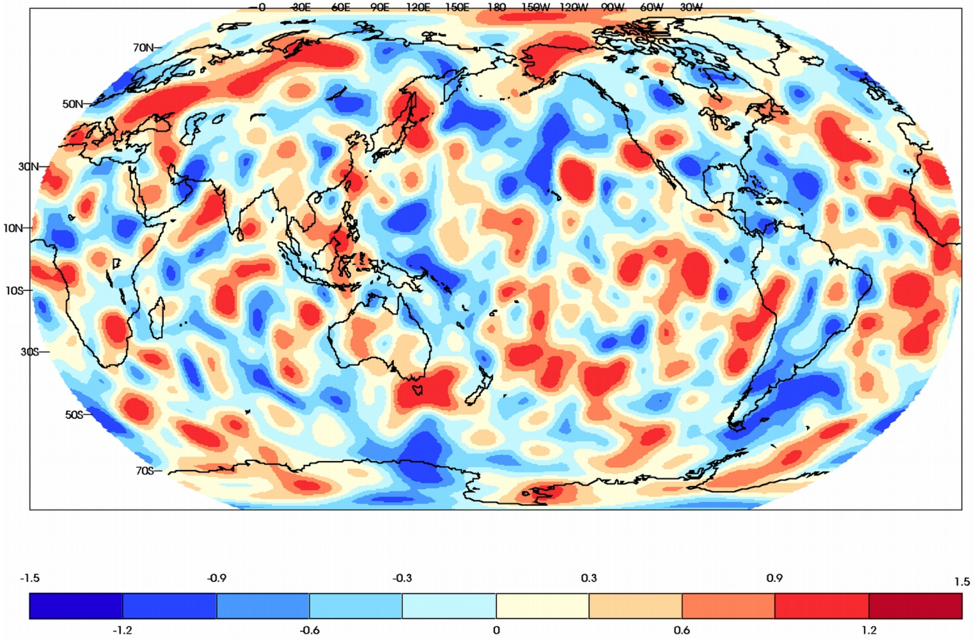
- Not only restricted to the atmosphere ***(focus in this talk)***
  - Sea ice (e.g. Jüricke et al. 2013)
  - Ocean (e.g. Zanna et al. 2018)
  - Land surface (e.g. MacLeod et al. 2016)

SPPT : Stochastically Perturbed Parameterization Tendencies

- Introduced by Buizza et al. (1999) into the IFS (ECMWF)
- Empirical method, straightforward to implement
- Time and space correlated multiplicative noise perturbs the net tendencies of the physical parameterizations in the atmospheric model

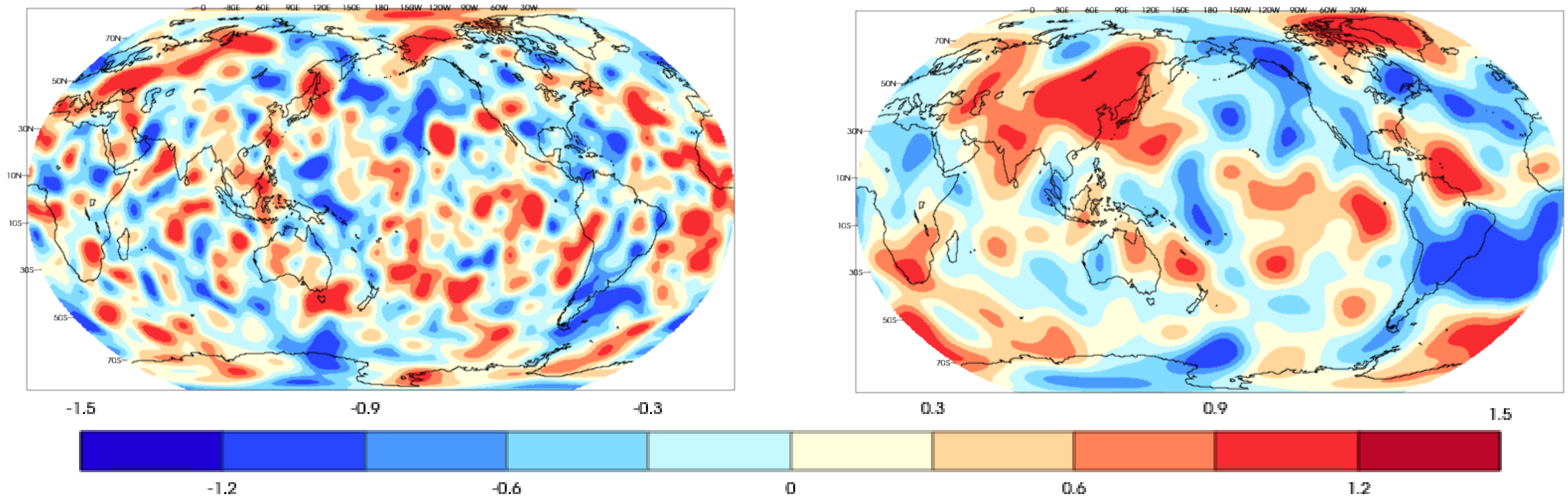
$$X_p = (1+r)X \; ; \; X = u, v, T, q$$

Spectral coefficients of *r* are defined by an AR(1) process forced with gaussian random numbers. The same *r* is used for all variables and model levels.



SPPT

- Results with EC-Earth → Batté and Doblas-Reyes (2015)
- 2 types of patterns used :
  - similar combination of time/space scales as ECMWF (System 4) → SPPT3
  - combination of two larger time/space scales to favor monthly and seasonal time scales → SPPT2L



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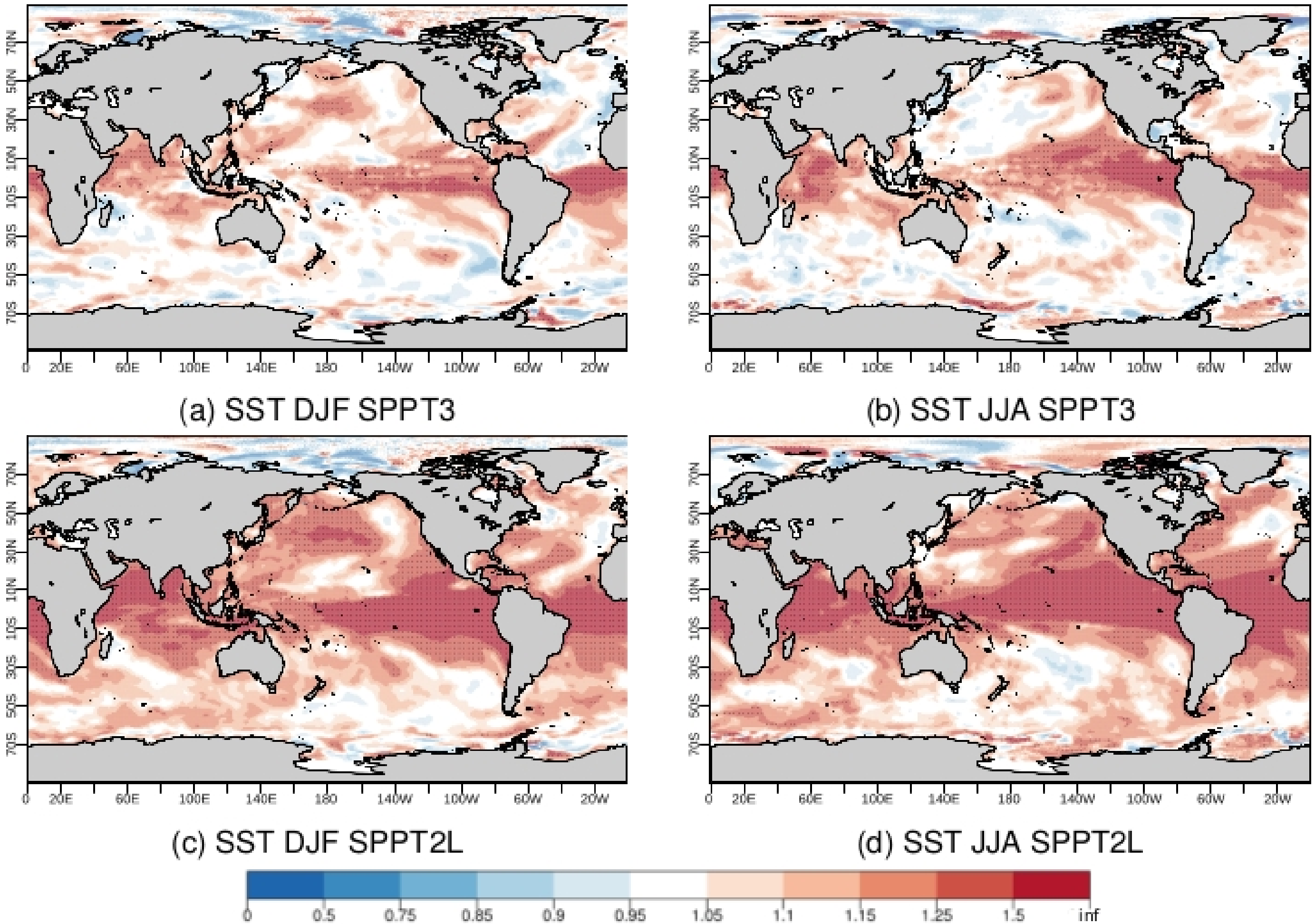
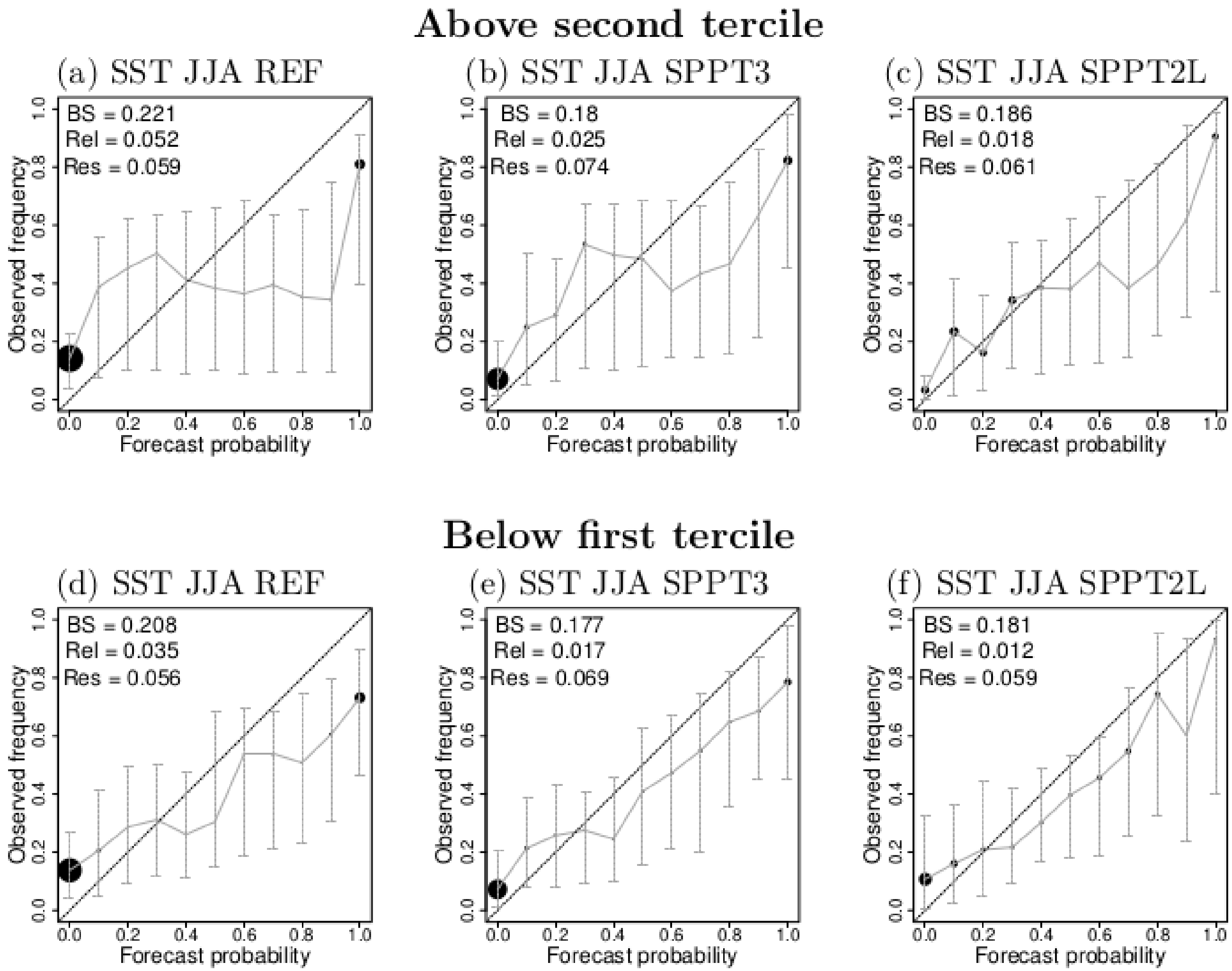


Impact of SPPT on the spread of SST re-forecasts with EC-Earth3 : relative spread with respect to a reference experiment with initial perturbations only.

Adapted from fig. 5 from Batté and Doblas-Reyes (2015)

SPPT

- Results with EC-Earth → Batté and Doblas-Reyes (2015)



Impact of SPPT on the Brier score and reliability / resolution components for Nino 3.4 SST re-forecasts with EC-Earth3.

Adapted from figs. 10-11 from Batté and Doblas-Reyes (2015)

Stochastic backscatter scheme (SKEB)

- References: Shutts (2005), Berner et al. (2009)
- Aim: account for upscale energy transfer from unbalanced flow (convection, gravity waves), as well as turbulence
- Formulation: perturbation of streamfunction
- Introduced in ECMWF seasonal prediction System 4 with SPPT

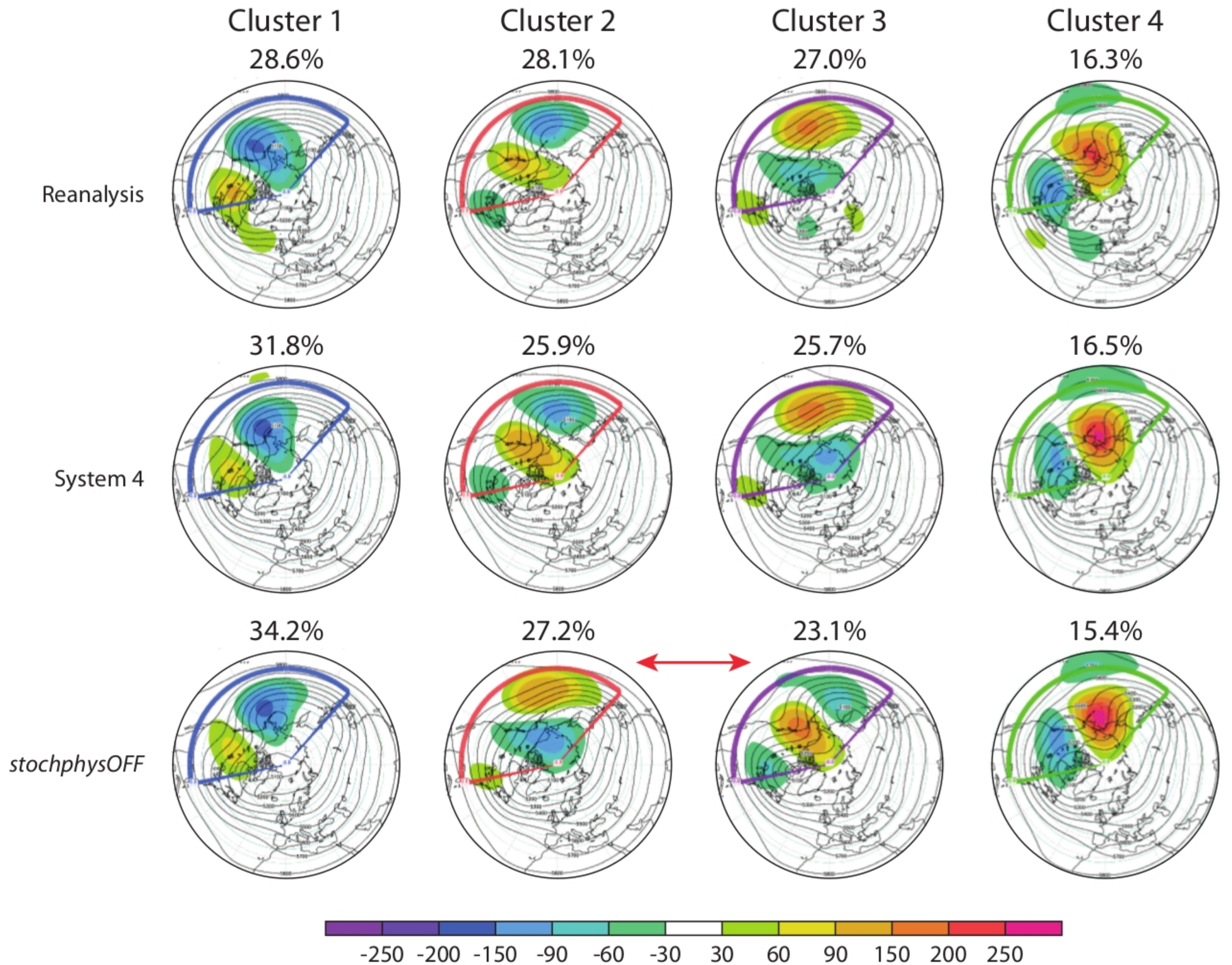
- Similar schemes have been used at NWP scales (ECMWF, UK MetOffice...)

Stochastic perturbations in ECMWF forecasts

- Results with ECMWF Sys4 (Weisheimer et al. 2014)

ECMWF System 4 stochastic physics (SPPT + SKEB) impact on North Pacific / American region winter (DJF) weather regime frequency and patterns for hindcasts initialized on 1st of November 1981-2010.

Fig. 9 from Weisheimer et al. (2014)



At CNRM : stochastic perturbations of model dynamics

- Idea:
  - Use atmospheric relaxation (nudging) as a means of estimating model error in the prognostic variables

$$\frac{\partial X}{\partial t} = M(X) + \frac{X^{\text{ref}} - X}{\tau}$$

  - Run relaxed re-forecasts to build a population of model error estimates
  - Apply randomly sampled model error corrections back into the model during the seasonal forecast integration

$$\mathbf{X}(t + \Delta t) = \mathbf{X}(t) + \mathbf{M}(\mathbf{X}(t), t) + \delta\mathbf{X}$$

- References: Batté and Déqué (2012, 2016)

At CNRM : stochastic perturbations of model dynamics

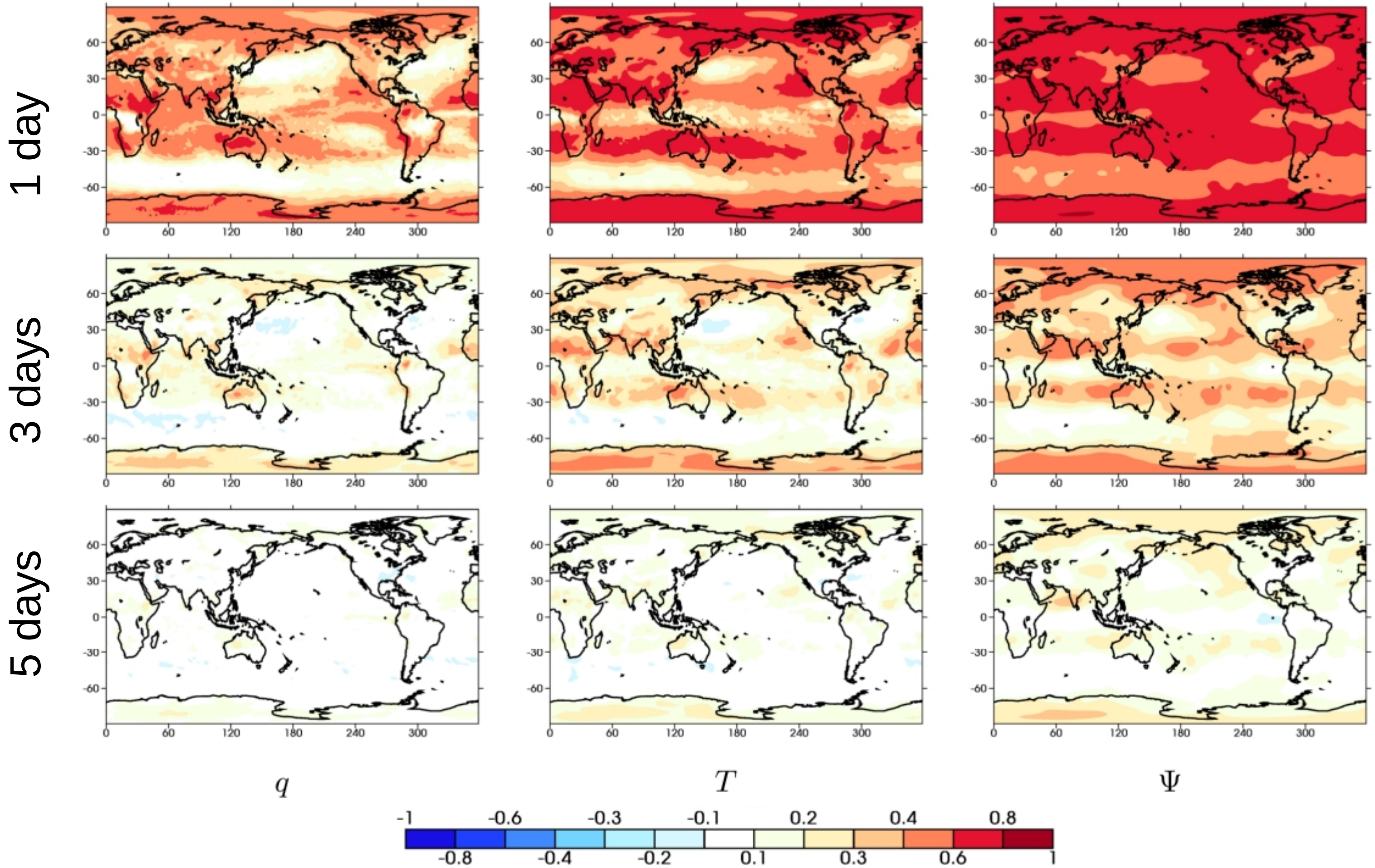
- Each ensemble member has it's own set of model corrections, thus generating ensemble spread

- The amplitude of the perturbations depend (although not linearly) on the strength of the relaxation in the 1st step run

- Different ways to draw random model corrections among the sample:
  - Series of consecutive days → example: 5 days
  - Using monthly mean corrections
  - Randomly changing corrections every 6 hours / every day...

At CNRM : stochastic perturbations of model dynamics

- Batté and Déqué (2016): Impacts of these perturbations on CNRM-CM (pre-CMIP6 version of ARPEGE-Climate)



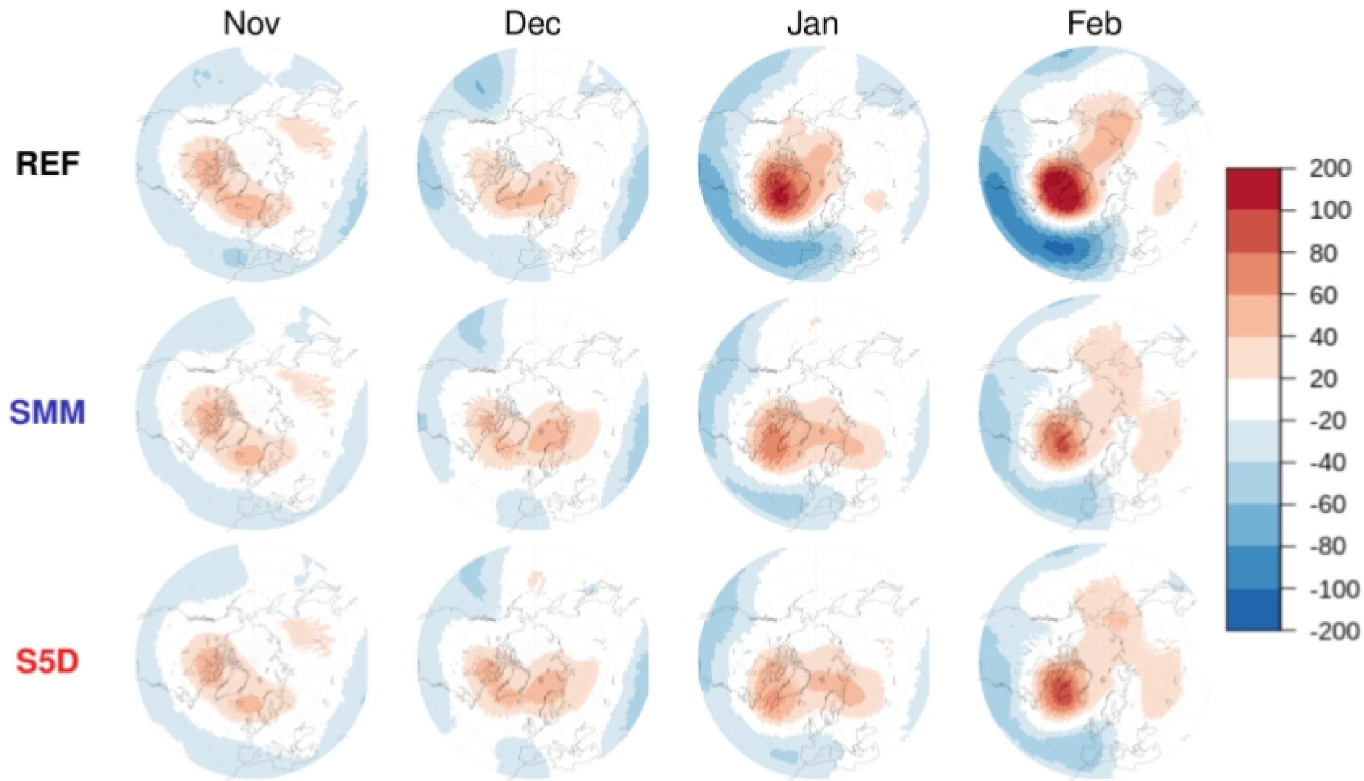
Auto-correlation of 850 hPa specific humidity, temperature, and 500 hPa streamfunction at lags of 1, 3 and 5 days.

Fig. 3 from Batté and Déqué (2016)

At CNRM : stochastic perturbations of model dynamics

- In Batté and Déqué (2016), 3 sets of experiments (NDJF 1979-2012) are compared. REF with initial perturbations only, SMM with monthly mean perturbations, and S5D with perturbations drawn from 5 consecutive days

Impact of stochastic perturbations on systematic errors for Z500 ; biases develop more slowly in the SMM and S5D experiments



At CNRM : stochastic perturbations of model dynamics

Run	NAO+ Freq.	NAO+ Length	Blocking Freq.	Blocking Length	NAO- Freq.	NAO- Length	Atl. Ridge Freq.	Atl. Ridge Length	NAO index r
ERA-I	32.1%	9.48	24.4%	7.14	18.8%	9.27	16.6%	5.85	-
REF	26.5%	8.28	23.4%	6.56	24.0%	8.90	16.8%	6.41	0.41
SMM	28.0%	8.36	23.8%	6.78	21.8%	9.35	17.1%	6.38	0.38
S5D	28.0%	8.35	23.8%	6.97	21.9%	9.16	17.1%	6.38	0.54

- As for Weisheimer et al. (2014), improvements are found in weather regime representation with the introduction of these perturbations.
- The NAO correlation is also improved, although differences are not significant.

Lecture outline

Dealing with uncertainties in initial conditions

Dealing with uncertainties in numerical models

- Multi-model approach
- Stochastic perturbations

- **Dealing with uncertainties in seasonal forecast evaluations**

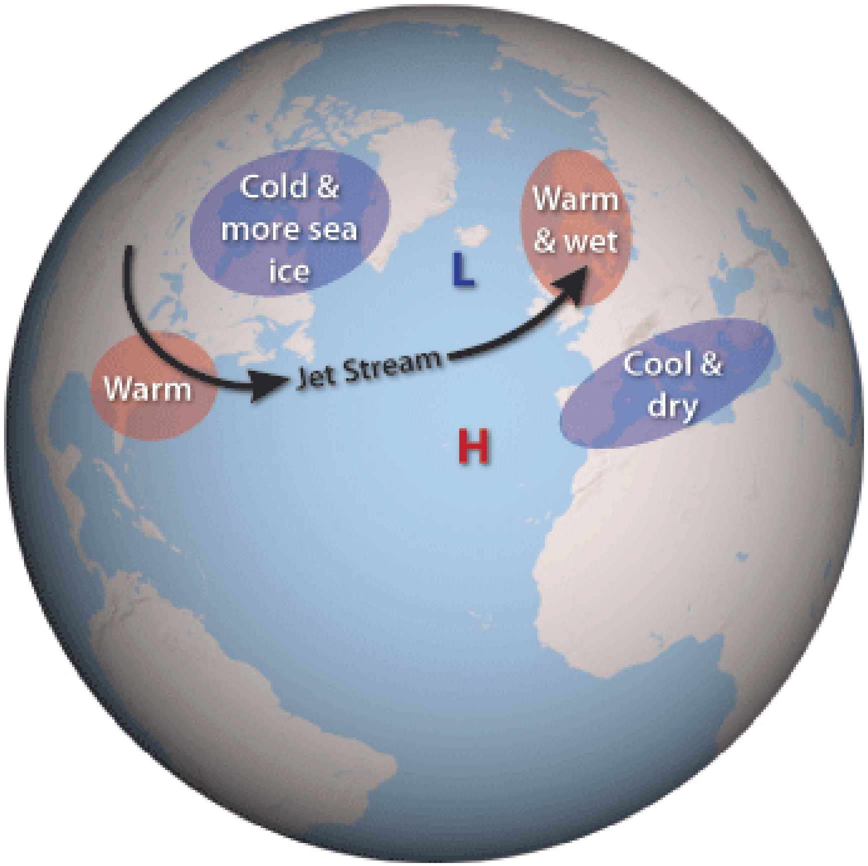
Communicating uncertainties in seasonal forecasts

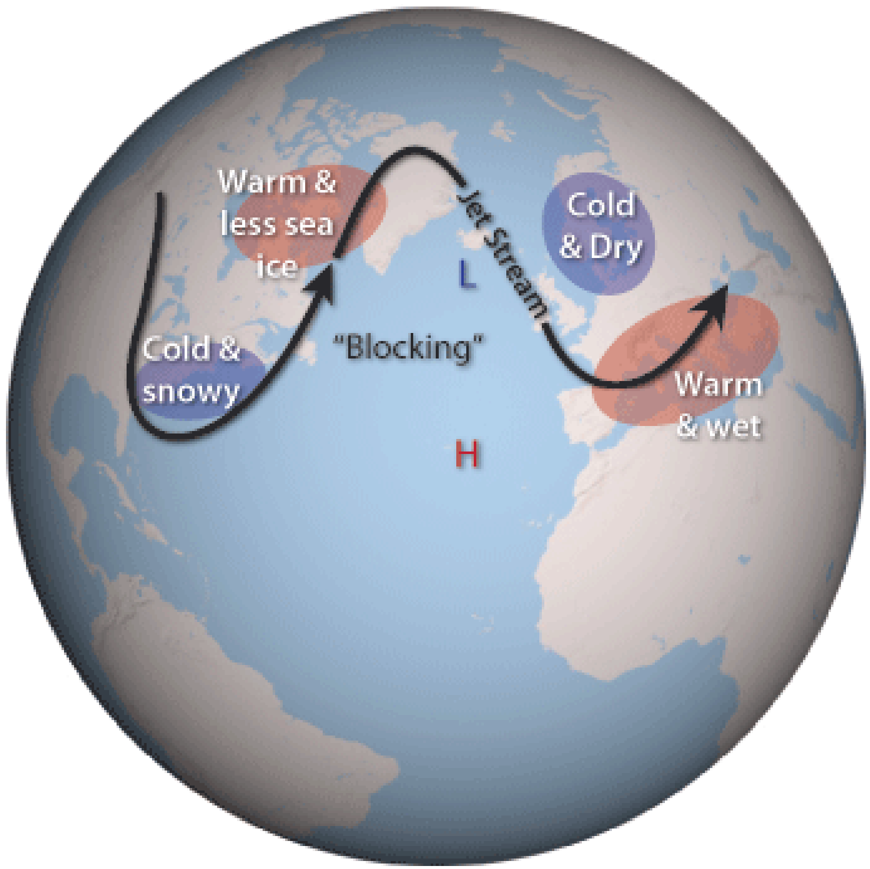
Scores, noise, and how to deal with this

- See A. Munoz and D. Hudson's lectures
- Verification: comparison between re-forecast (past cases) and reference data (observations, reanalyses)
- Limited samples mean that verification metrics are necessarily uncertain
- But a larger number of past cases means going back to periods when reference data was sparse and also more uncertain!
- Some methods can provide some insight into the uncertainty in the skill evaluations of seasonal forecasts:
  - Sub-sampling of ensemble members / years
  - Bootstrap
  - Statistical significance tests → but beware of over-interpretation! (see Wilks, 2016)

Illustration: the North Atlantic Oscillation

NAO+ | **NAO-**





Mean impacts observed during positive and negative NAO phases in winter.
Source: UK Met Office, adapted from Gardiner and Herring (NOAA)

Recent studies show promising skill...

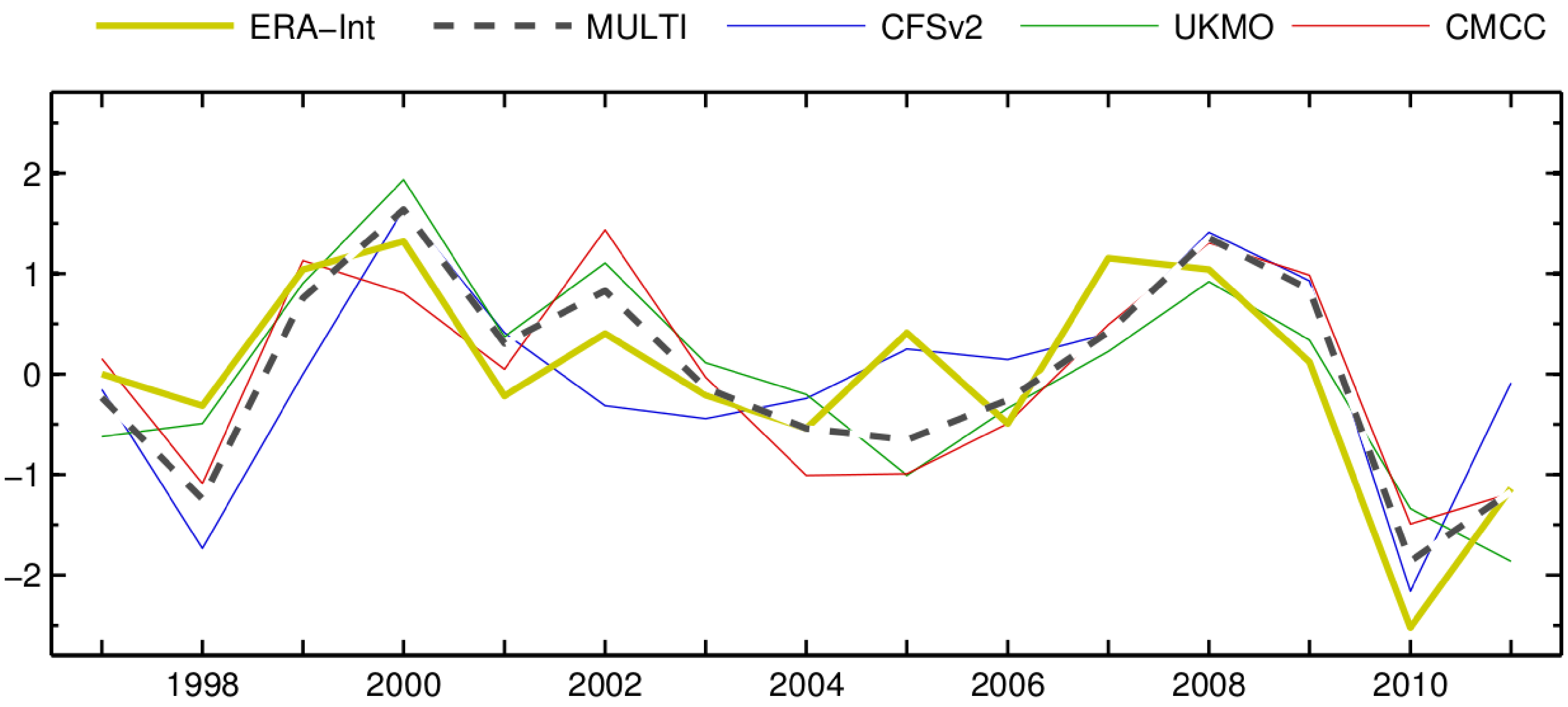
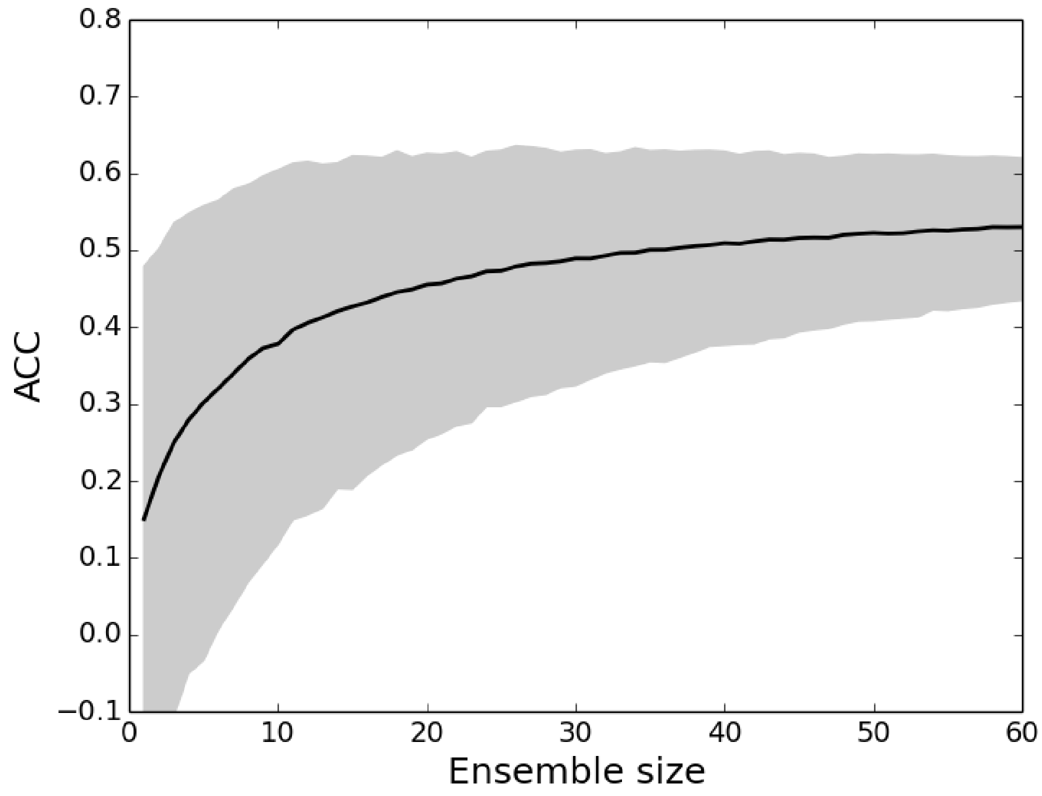


Fig. 1 from Athanasiadis et al. (2017) showing ERA-Interim and re-forecast DJF NAO index (Nov. initializations) computed following Li and Wang (2003).
The multi-model correlation is 0.85.

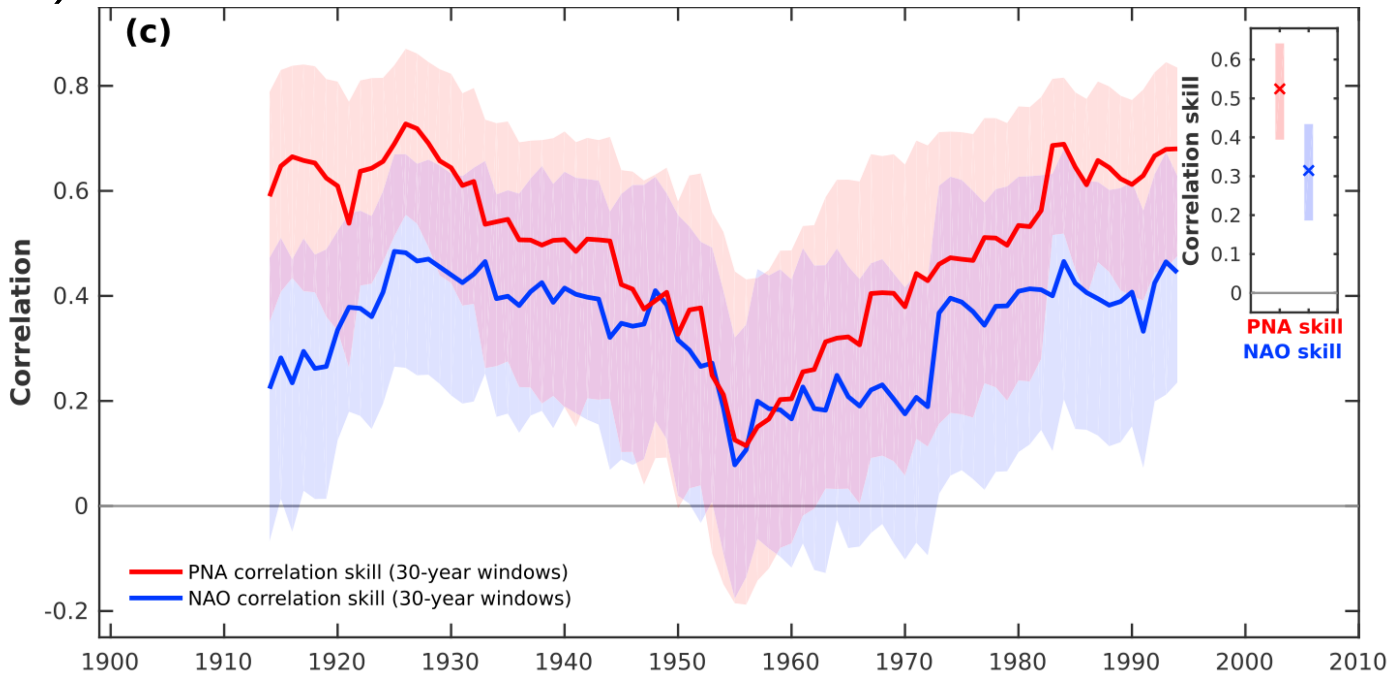
Uncertainties in evaluation of NAO predictability

- Ensemble size and signal-to-noise issues
  - How many ensemble members are necessary to represent the intrinsic variability of the phenomena?
  - What are the the confidence intervals around the estimates?



Uncertainties in evaluation of NAO predictability

- Length of the hindcast
  - Under- or over-estimation of NAO predictability in the last decades? (Eade et al. 2014, Shi et al. 2015)
  - Role of multi-decadal variability in recent levels of skill? (O’Reilly et al. 2017)



Correlation of NAO and PNA indices with ERA-20C in atmosphere-only winter re-forecasts over 1900-2010 with IFS forced by HadISST (Source : O’Reilly et al. 2017)

Lecture outline

Dealing with uncertainties in initial conditions

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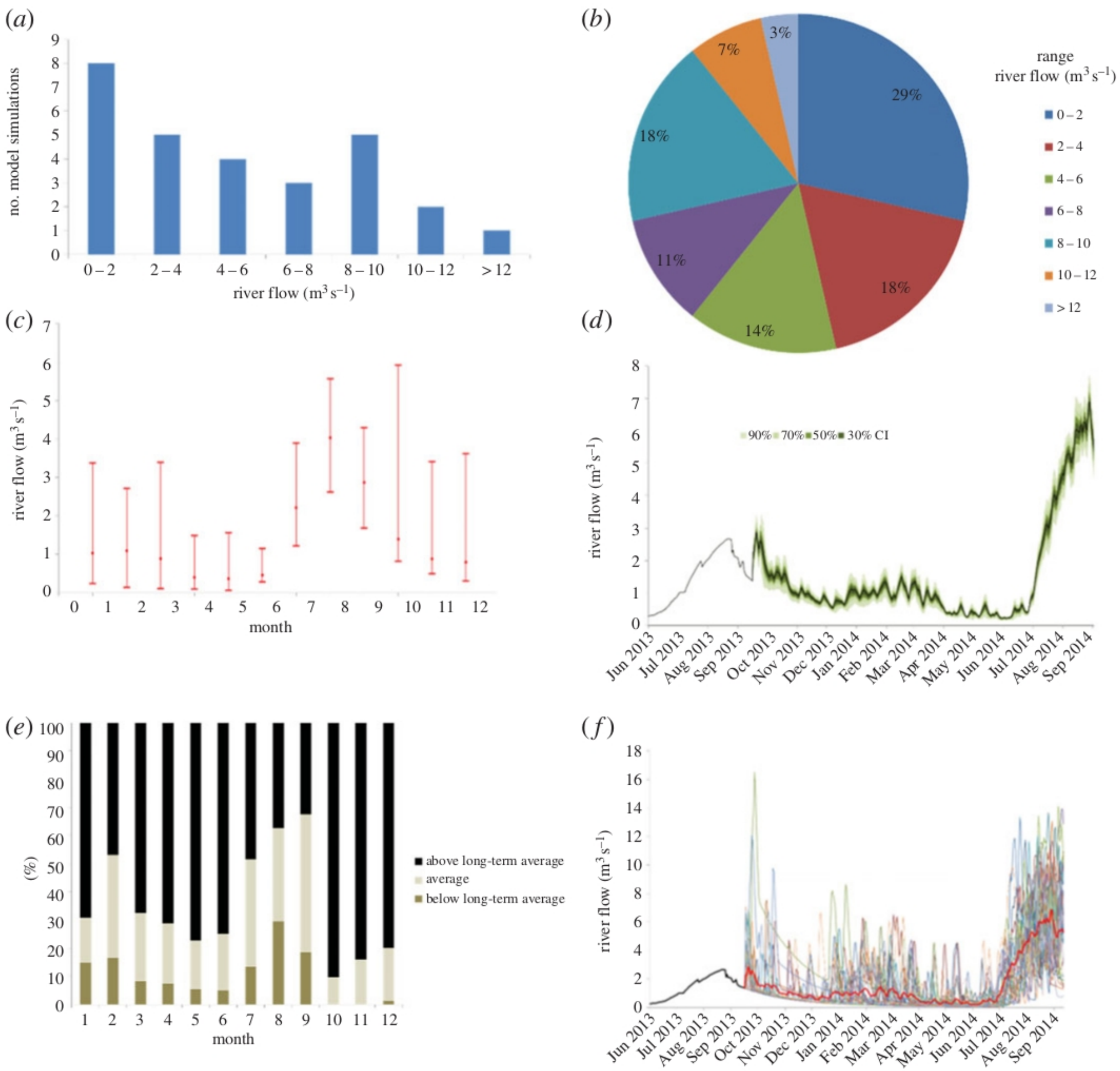
- Multi-model approach
- Stochastic perturbations

Dealing with uncertainties in seasonal forecast evaluations

- **Communicating uncertainties in seasonal forecasts**

Communication of uncertainty is key!



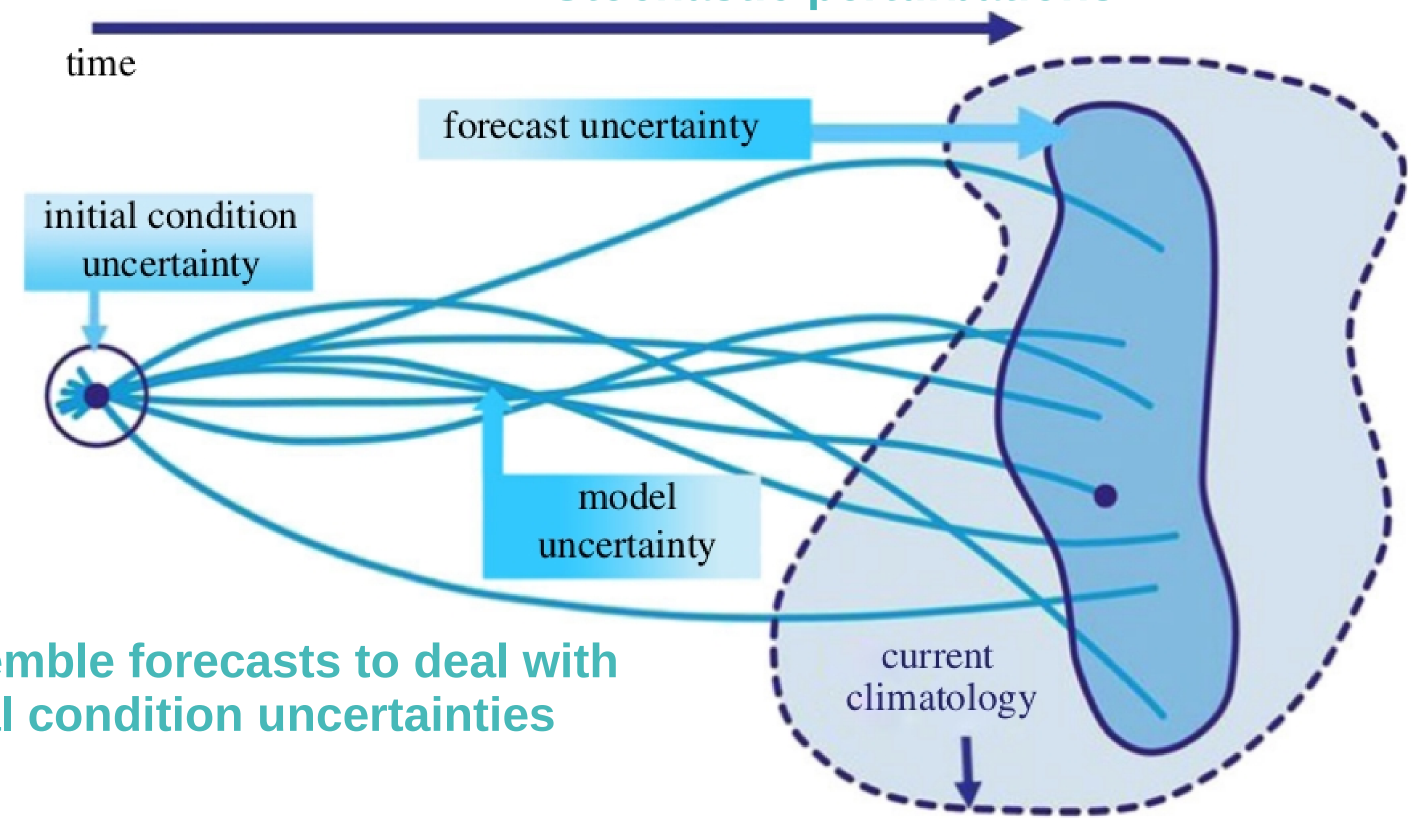
But how you communicate it may not be very straightforward...

Example: 6 different ways of providing ensemble seasonal forecasts of river flows to potential users.

Adapted from Fig.1 of Taylor et al. (2015)

Conclusion – Dealing with uncertainties

Model uncertainty:
- MME approach
- Stochastic perturbations



Verification uncertainty:
- Robust ensemble sizes and re-forecast length (not easy...)
- Estimates of levels of uncertainty

Ensemble forecasts to deal with initial condition uncertainties

Figure 2 from Slingo and Palmer (2011) : illustration of sources of uncertainty in a probabilistic weather forecast

Thanks a lot for your attention!

Further reading...

On ensemble forecasting:

- Hoffman and Kalnay (1983) Lagged average forecasting, an alternative to Monte Carlo forecasting. *Tellus*, 35A: 100-118.
- Kalnay (2003) Atmospheric predictability and ensemble forecasting. In *Atmospheric Modelling, Data Assimilation and Predictability*, chapter 6. Cambridge University Press.
- Lorenz (1963) Deterministic nonperiodic flow. *J. Atm. Sc.*, 20: 130-141.
- Slingo and Palmer (2011) Uncertainty in weather and climate prediction. *Phil. Trans. R. Soc. A* 369: 4751–4767.

On GCMs / seasonal forecasting systems:

- Johnson, Stockdale, Ferranti et al. (2019) SEAS5 : the new ECMWF seasonal forecast system. *Geosci. Model Dev.*, 12, 1087-1117.
- Saha et al. (2014) The NCEP Climate Forecast System Version 2, *J. Climate*, 27: 2185-2208.
- Voldoire et al. (2019) Evaluation of CMIP6 DECK experiments with CNRM-CM6-1, *J. Adv. Mod. Earth Sys.*, accepted.

Further reading...

On multi-model ensembles:

- Athanasiadis et al. (2017) A multi-system view of wintertime NAO seasonal predictions. *J. Climate,* 30: 1461-1475.
- Batté and Déqué (2011) Seasonal predictions of precipitation over Africa using coupled ocean-atmosphere general circulation models : skill of the ENSEMBLES project multi-model ensemble forecasts. *Tellus*, 63A: 283–299.
- Doblas-Reyes et al. (2000) Multi-model spread and probabilistic seasonal forecasts in PROVOST. *Q. J. Roy. Meteorol. Soc.* 126 (567): 2069-2087.
- Hagedorn et al. (2005) The rationale behind the success of multi-model ensembles in seasonal forecasting – I. Basic concept. *Tellus,* 57A(3): 219-233.
- Krishnamurti et al. (1999) Improved weather and seasonal climate forecasts from multimodel superensembles. *Science*, 285(5433): 1548-1550.
- Krishnamurti et al. (2000) Multimodel ensemble forecasts for weather and seasonal climate. *J. Climate,* 13(23):4196–4216.
- Mishra et al. (2019) Multi-model skill assessment of seasonal temperature and precipitation forecasts over Europe. *Clim. Dyn.*, 52(7-8): 4207-4225.
- Min et al. (2014) Assessment of APCC multimodel ensemble prediction in seasonal climate forecasting: Retrospective (1983–2003) and real-time forecasts (2008–2013), *J. Geophys. Res. Atmos.*, 119: 12,132–12,150.
- Stephenson et al. (2005) Forecast assimilation : a unified framework for the combination of multi-model weather and climate predictions. *Tellus,* 57A(3): 252-264.
- Weigel et al. (2008) Can multi-model combination really enhance the prediction skill of probabilistic ensemble forecasts? *Q. J. Roy. Meteorol. Soc.* 134: 241-260.

Further reading...

On stochastic perturbations:

- Batté and Déqué (2012) A stochastic method for improving seasonal predictions, *Geophys. Res. Lett.*, 39: L09707.
- Batté and Déqué (2016) Randomly correcting model errors in the ARPEGE-Climate v6.1 component of CNRM-CM: applications for seasonal forecasts. *Geosci. Model Dev.*, 9: 2055–2076.
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- Berner et al. (2009) A spectral stochastic kinetic energy backscatter scheme and its impact on flow-dependent predictability in the ECMWF Ensemble Prediction System, *J. Atmos. Sci.,* 66: 603–626.
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Further reading...

On signal-to-noise issues, evaluation and communication of uncertainties:

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