Exploring and extending the limits of weather predictability?

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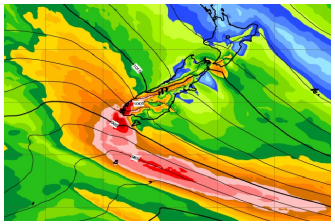
Arnt Eliassen's legacy for NWP

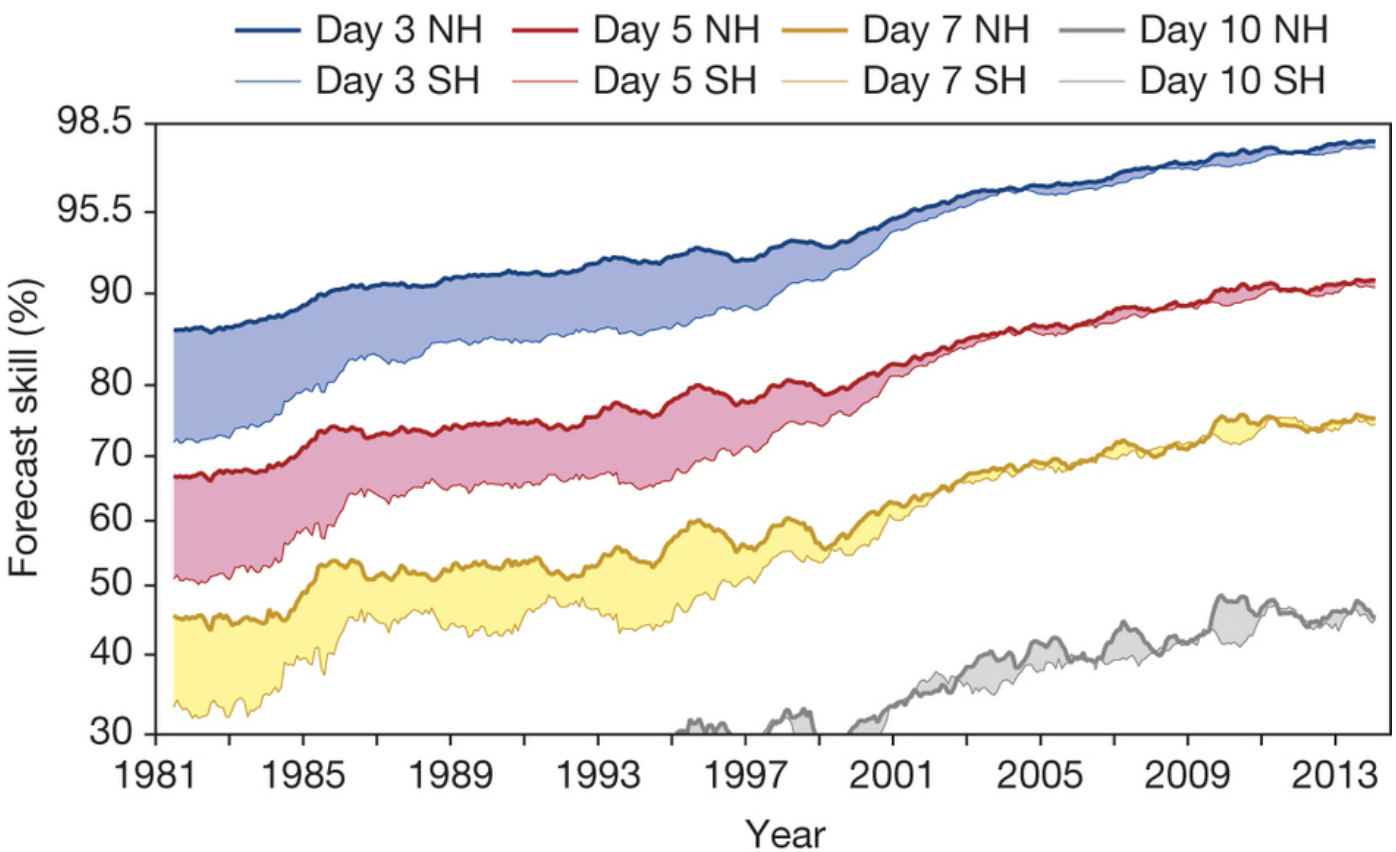
- ECMWF is an independent intergovernmental organisation supported by 34 states.
- ECMWF produces twice-daily global numerical weather forecasts
- Components of the forecasting system:
  - atmospheric GCM
  - land surface model
  - ocean GCM
  - ocean wave model
  - Perturbation models to represent uncertainty in the initial conditions and modelled processes



Evolution of forecast skill

The quiet revolution of numerical weather prediction

(Bauer, Thorpe & Brunet, Nature 2015)



Correlation between the forecasts and the verifying analysis of the height of the 500-hPa level, expressed as the anomaly with respect to the climatological height

Simmons & Hollingsworth (QJRMS 2002)

Factors influencing skill improvements

- **The forecast model has improved** through increased spatial resolution and more accurate description of physical processes
- **The assimilation of observation data has improved** substantially leading to a reduction in the initial state error
- **More observations have become available**, in particular satellite observations

Simple error growth model (*Lorenz, 1982; Dalcher and Kalnay, 1987, and Savijärvi, 1995*):

$$\frac{dE}{dt} = \left(\alpha E + \beta\right)\left(1 - \frac{E}{E_\infty}\right)$$

E … perturbation/difference between two realisations of the atmosphere

α … exponential growth rate of small perturbations due to initial condition sensitivity

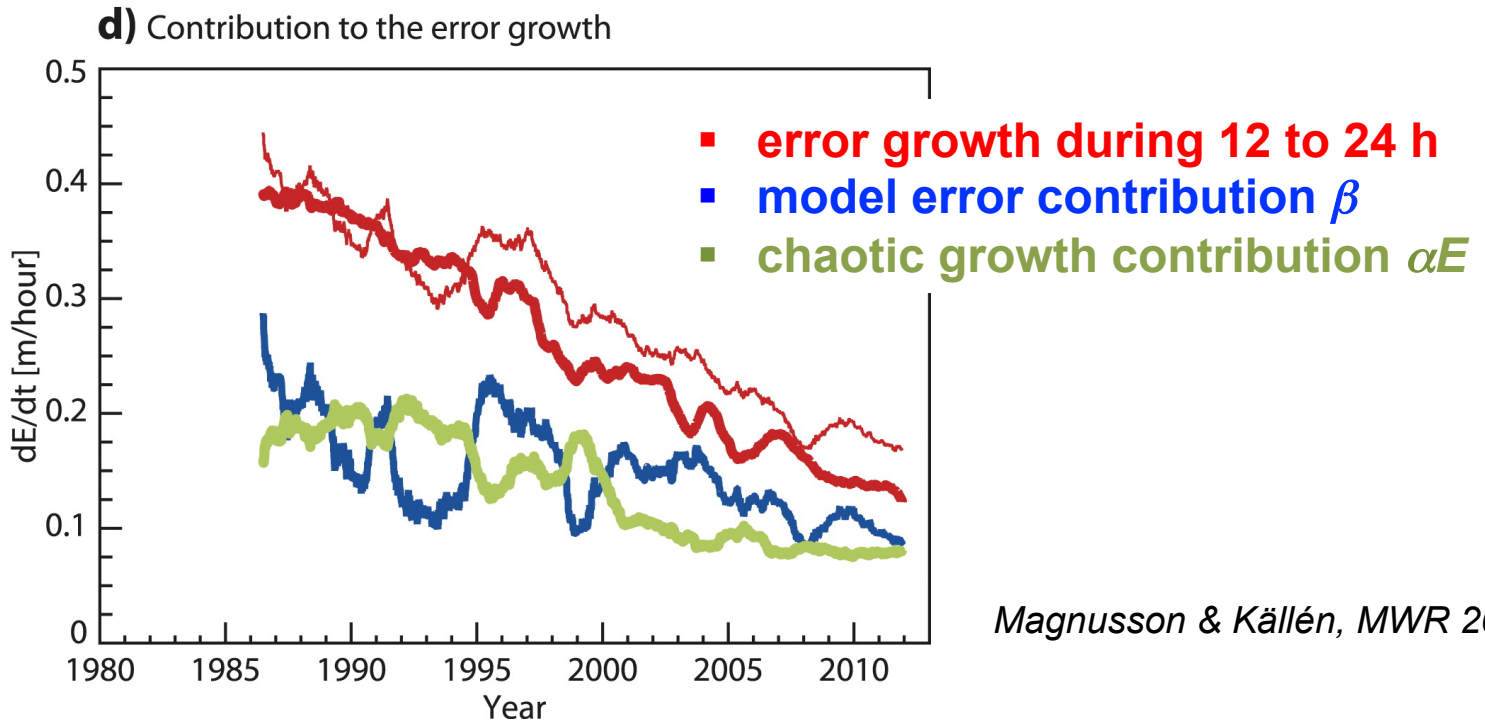
β … linear growth rate due to model error

E_∞ … climatological growth rate (asymptotic limit)

$E(t=0)$ … amplitude of initial perturbation = analysis error

Factors influencing skill improvements

Error growth estimation

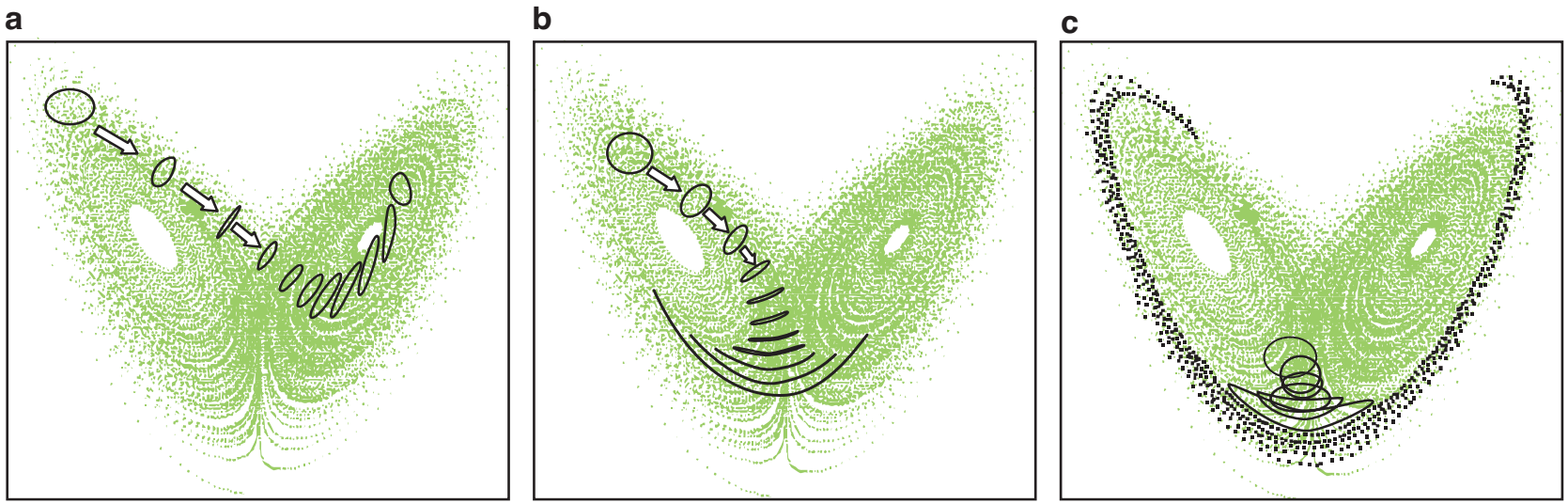


Magnusson & Källén, MWR 2013

- Total error growth decreased over time
- Largest contribution from decreased analysis error (αE)
- Contribution from model error term β

Scientific basis for ensemble forecasting

In a nonlinear system the growth of initial uncertainty is flow dependent – here illustrated with the Lorenz (1963) model.



The set of initial conditions (black circle) is located in different regions of the attractor in a), b) and c)
and leads to different error growth and predictability in each case.

Perfect ensemble prediction systems

What is a perfect ensemble?

- Perfect sampling of the underlying probability distribution of the true state of the atmosphere ("*TRUTH*")
- Over a large number of ensemble forecasts, the statistical properties of the true value X_{TRUTH} of any quantity X are identical to the statistical properties of a member X_j of the ensemble

In particular,

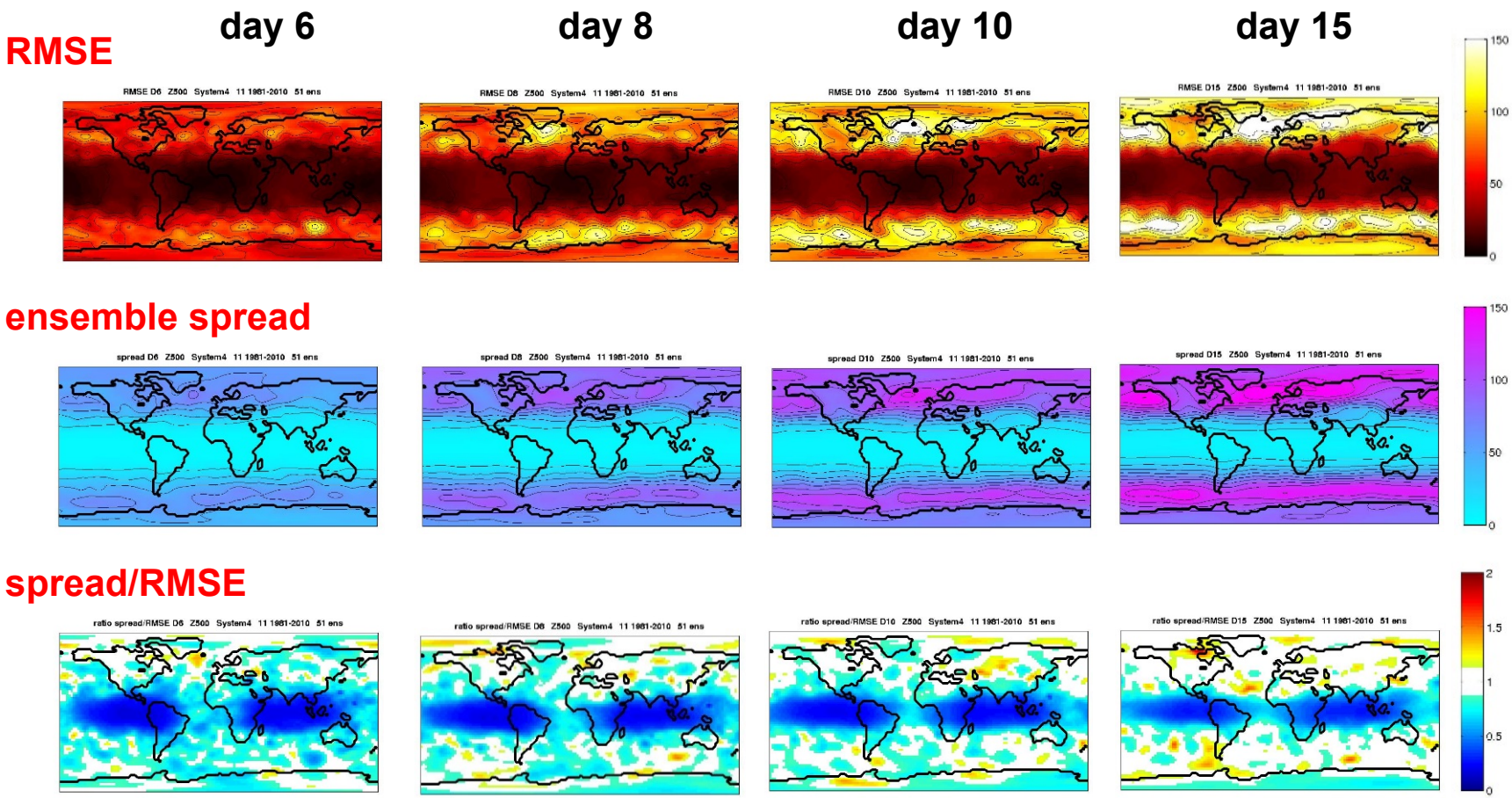
$$\underbrace{\overline{\left|X_j - X_{MEAN}\right|^2}}_{\text{ensemble variance}} = \underbrace{\overline{\left|X_{TRUTH} - X_{MEAN}\right|^2}}_{\text{mean squared error}}$$

X_{MEAN} … ensemble mean

The time-mean ensemble spread around the mean equals the time-mean RMSE of the ensemble mean.

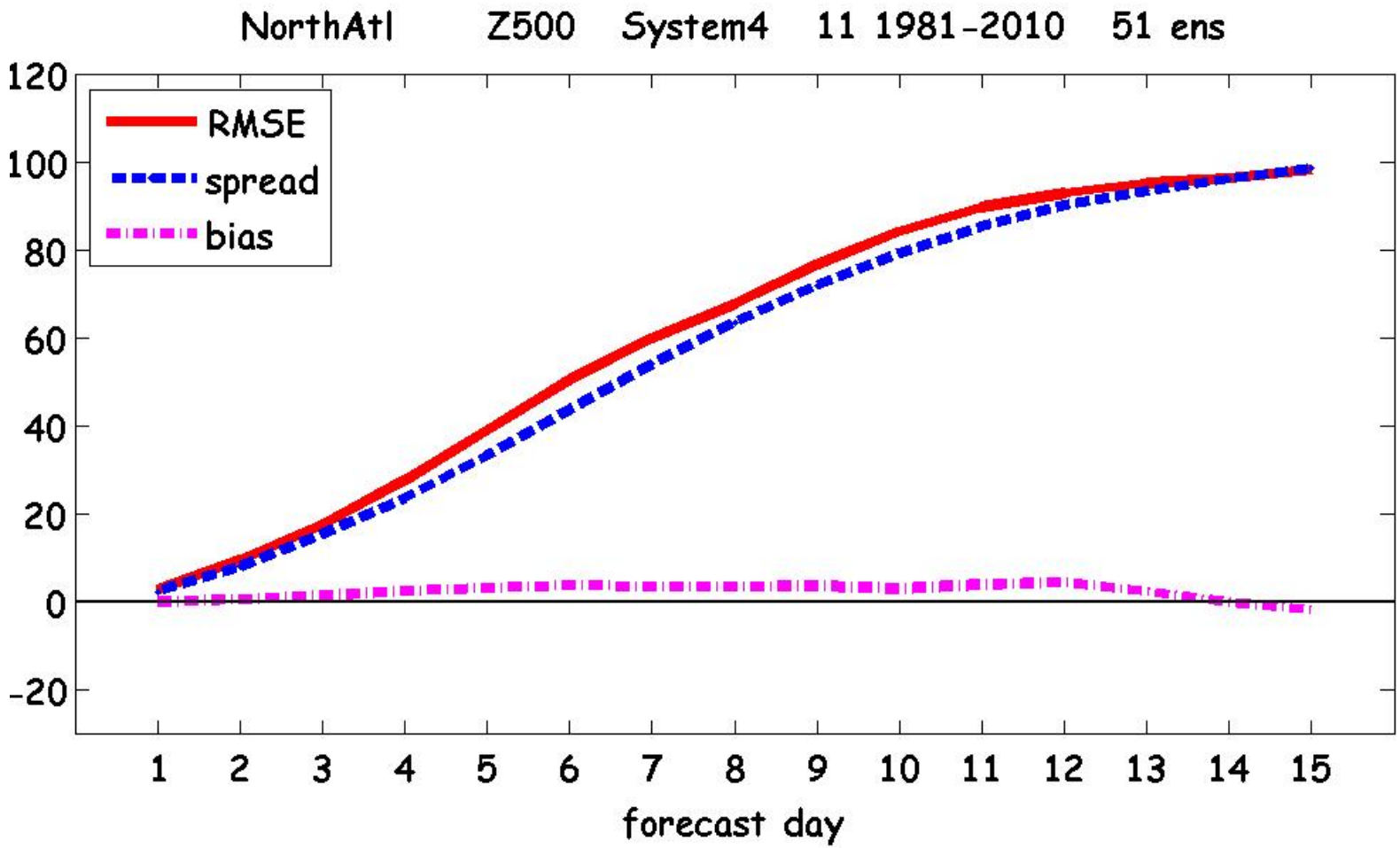
Error growth in the medium range

- Evolution of Z500 ensemble forecast error and spread from ECMWF's seasonal prediction System 4
- Statistics over 30-year retrospective forecasts from 1981-2010 initialised on the 1st November each year, 51 ensemble members

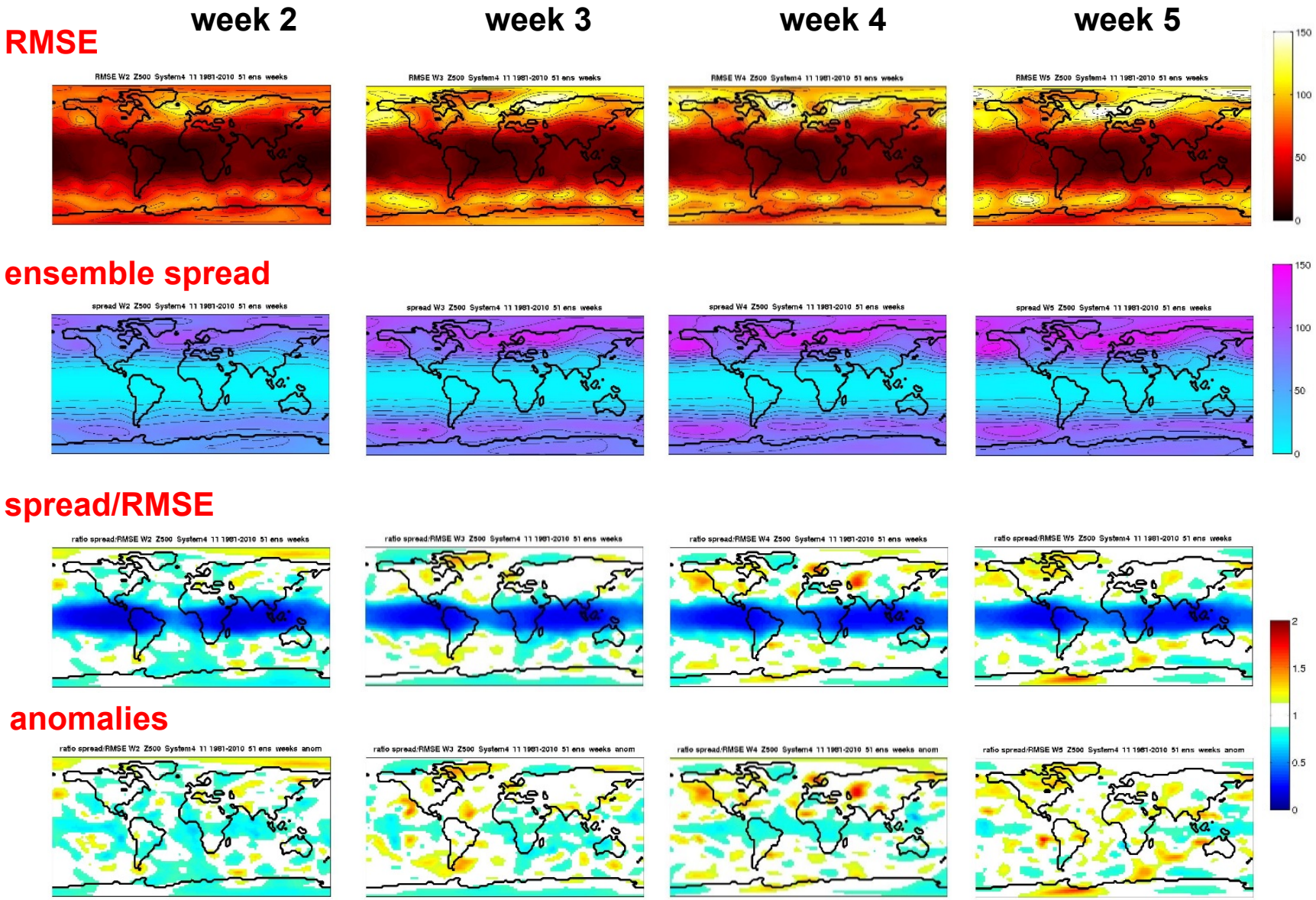


Error growth in the medium range

Z500 North Atlantic region

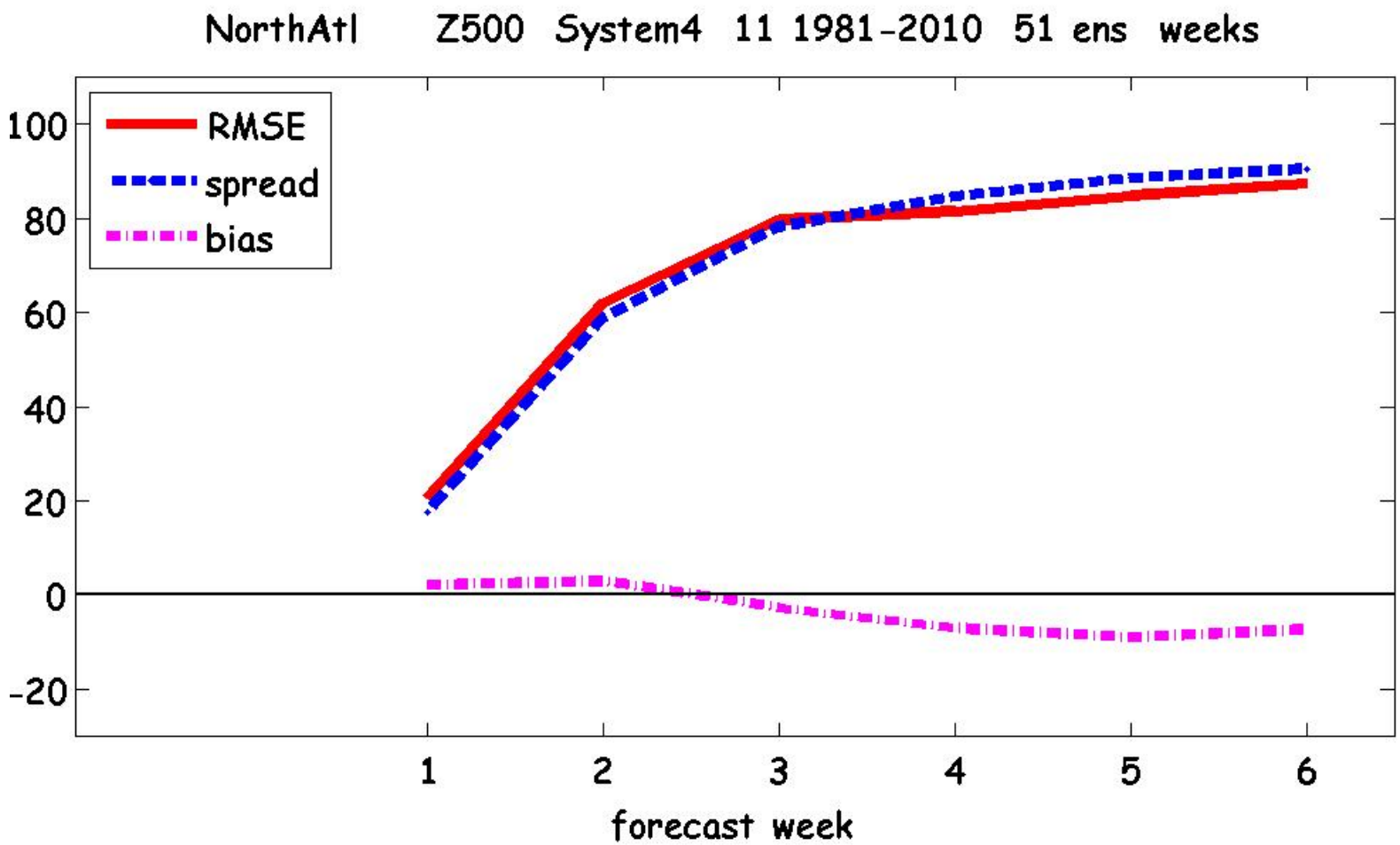


Error growth in the sub-monthly range

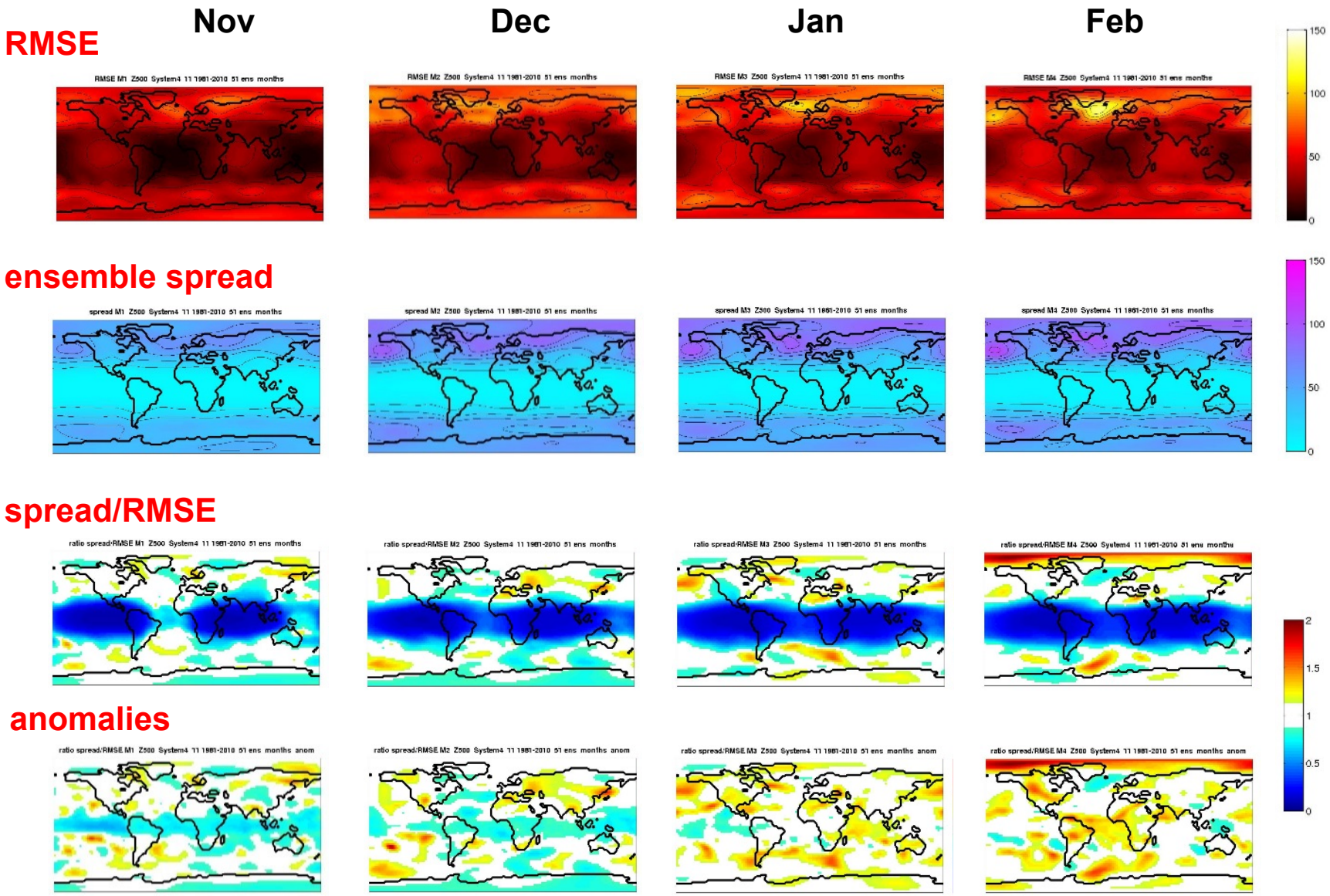


Error growth in the sub-monthly range

Z500 North Atlantic region

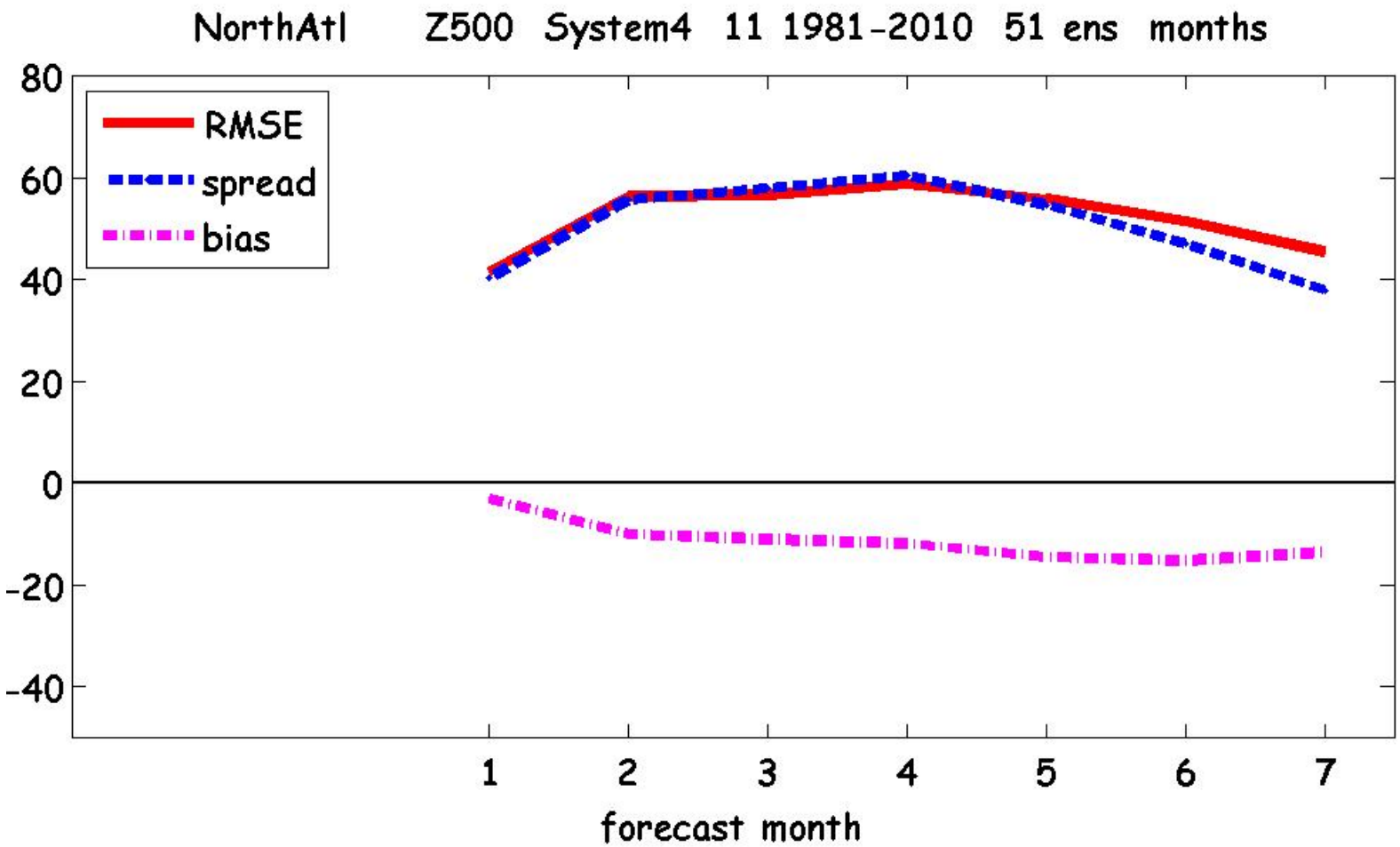


Error growth in the sub-seasonal range



Error growth in the sub-seasonal range

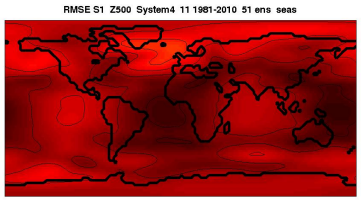
Z500 North Atlantic region



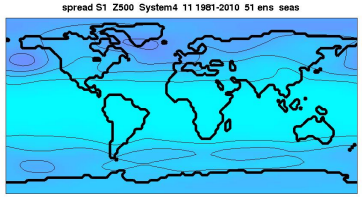
Errors at seasonal time scales

DJF

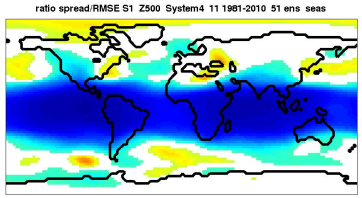
RMSE



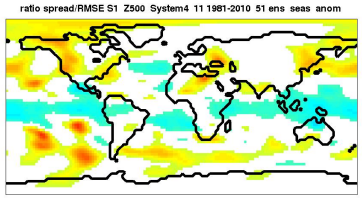
ensemble spread

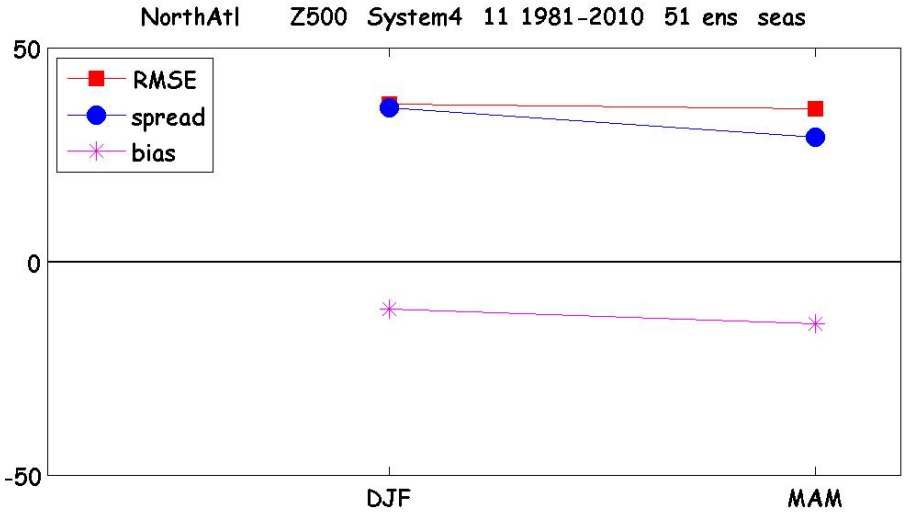


spread/RMSE



anomalies





Probabilistic forecasting for decision making

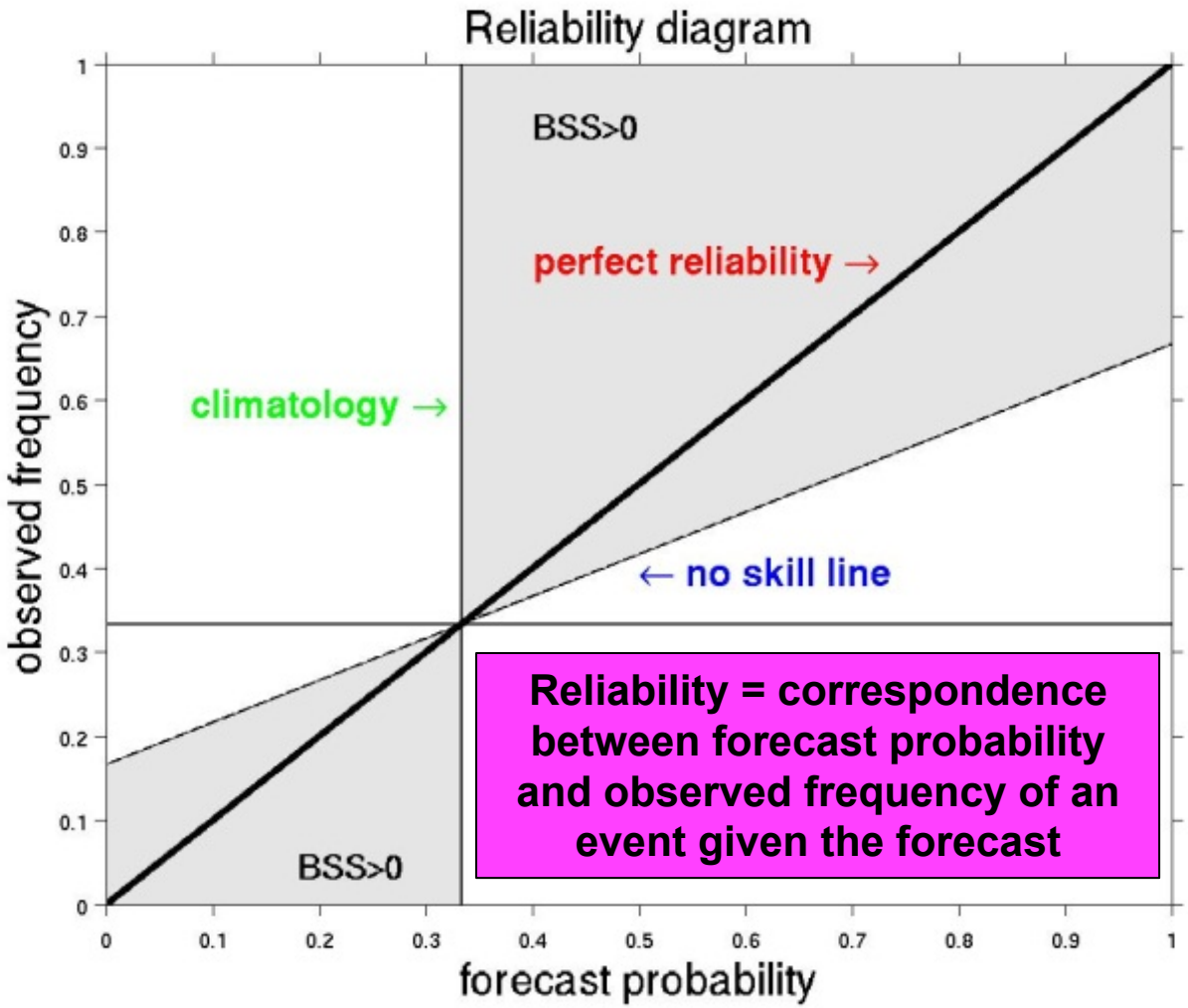
Example: Agronomists to advice farmers on the type of crop to plant in the coming season

- crop yield $C = C(X)$ with X … meteorological variables
- seasonal forecast probability distribution $\rho(X)$
- climatological distribution $\rho_C(X)$
- expected crop yield: $\langle C \rangle = \int_X C(X)\rho(X)dX$
- climatological crop yield expectation: $\langle C \rangle_C = \int_X C(X)\rho_C(X)dX$
- if $\rho(X) \approx \rho_C(X)$ → climatological (reliable) information
- if $\rho(X) \neq \rho_C(X)$ → differences in expected crop yield → decisions

It is essential that $\rho(X)$ must be reliable as otherwise the advice can be misleading!

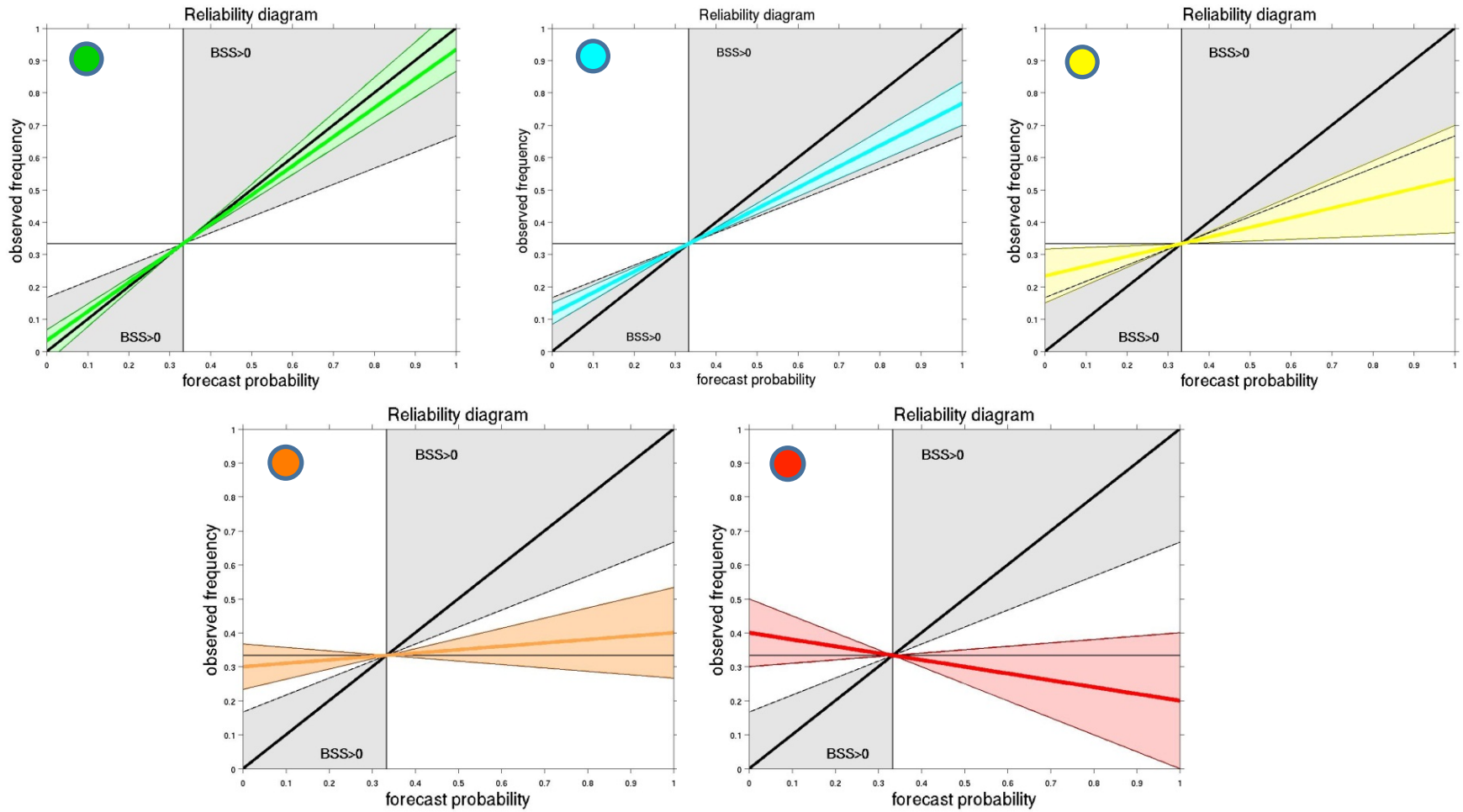
Forecast reliability

Suppose an event *E* has a forecast probability of 70%. The forecasting system is said to be *reliable* if the observed frequency of *E* is, within its uncertainty, also 70%.



Reliability = correspondence between forecast probability and observed frequency of an event given the forecast

Reliability categories



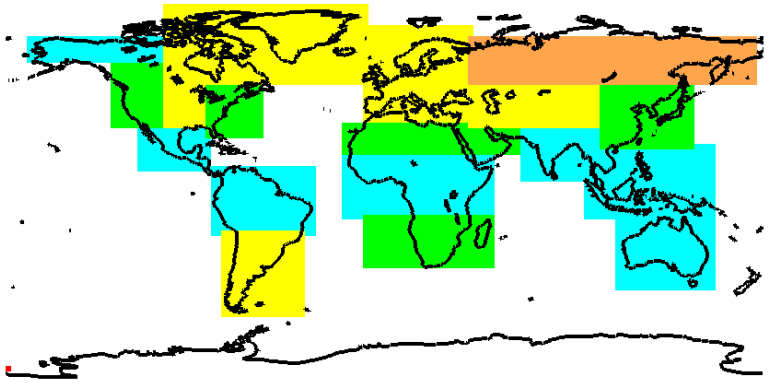
perfect **still useful** **marginally useful** **not useful** **dangerous**

(Weisheimer & Palmer, JRSI 2014)

How reliable are ECMWF's seasonal forecasts?

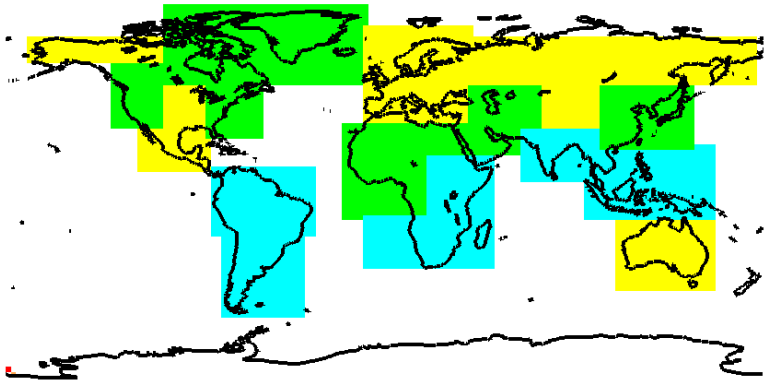
cold DJF

S4 DJF 2to4 1981-2010 167 lower terciles



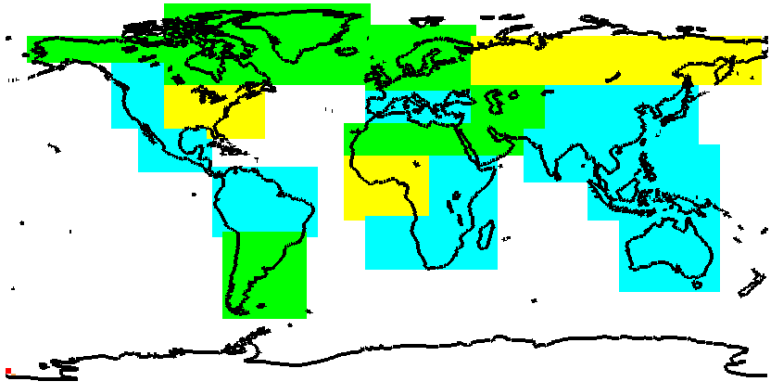
warm DJF

S4 DJF 2to4 1981-2010 167 upper terciles



cold JJA

S4 JJA 2to4 1981-2010 167 lower terciles



warm JJA

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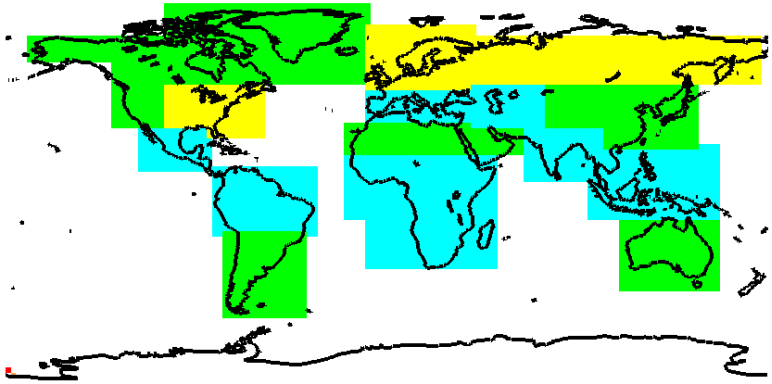

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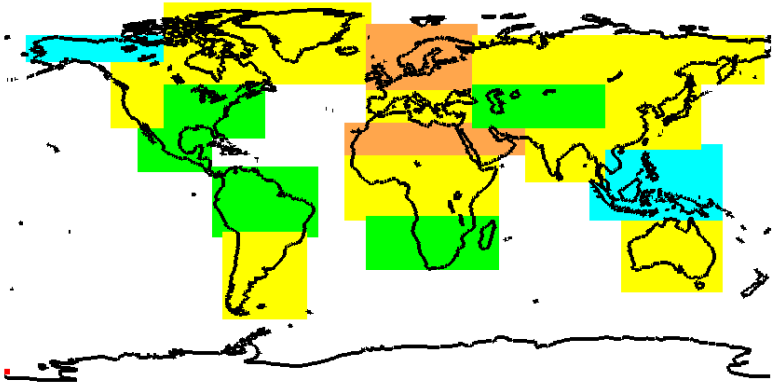
(Weisheimer & Palmer, JRSI 2014)

How reliable are ECMWF's seasonal forecasts?

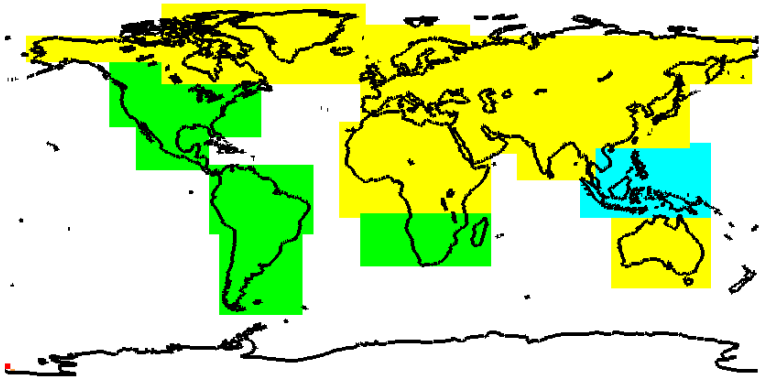
dry DJF

S4 DJF 2to4 1981-2009 228 lower terciles



wet DJF

S4 DJF 2to4 1981-2009 228 upper terciles



dry JJA

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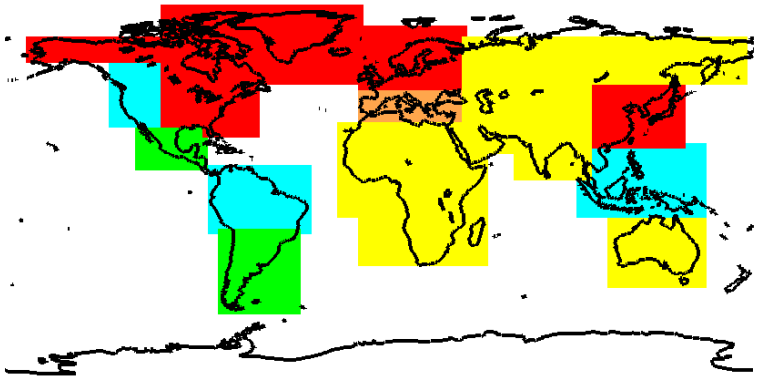

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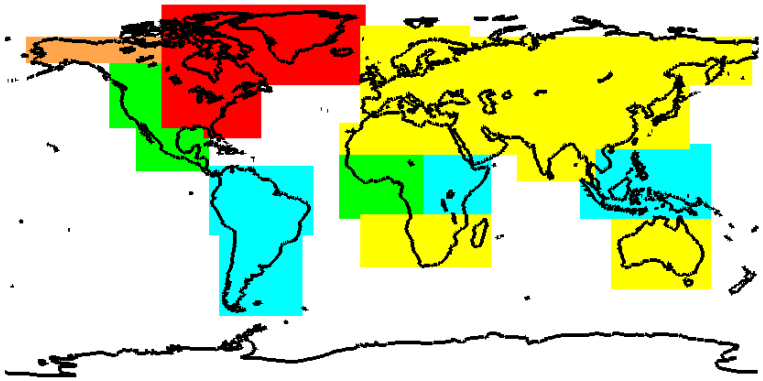
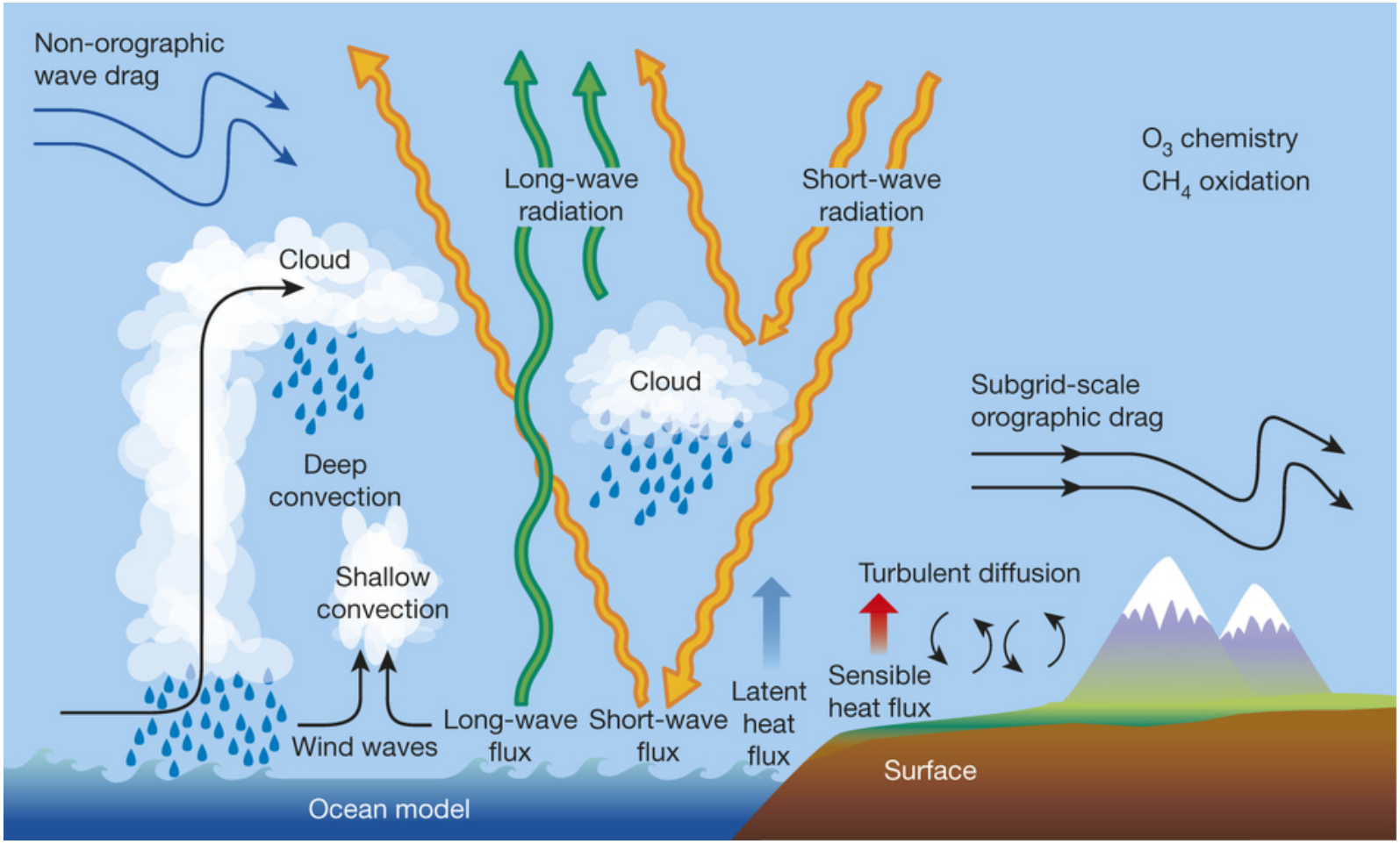


perfect | still useful | marginally useful | not useful | dangerous

(Weisheimer & Palmer, JRSI 2014)

Parameterised physical processes



Better forecasts through an element of randomness?

Deterministic parametrisations are inconsistent with the scaling symmetries in the Navier Stokes equations and the observed power law behaviour in the atmosphere.

Stochastic parametrisations:

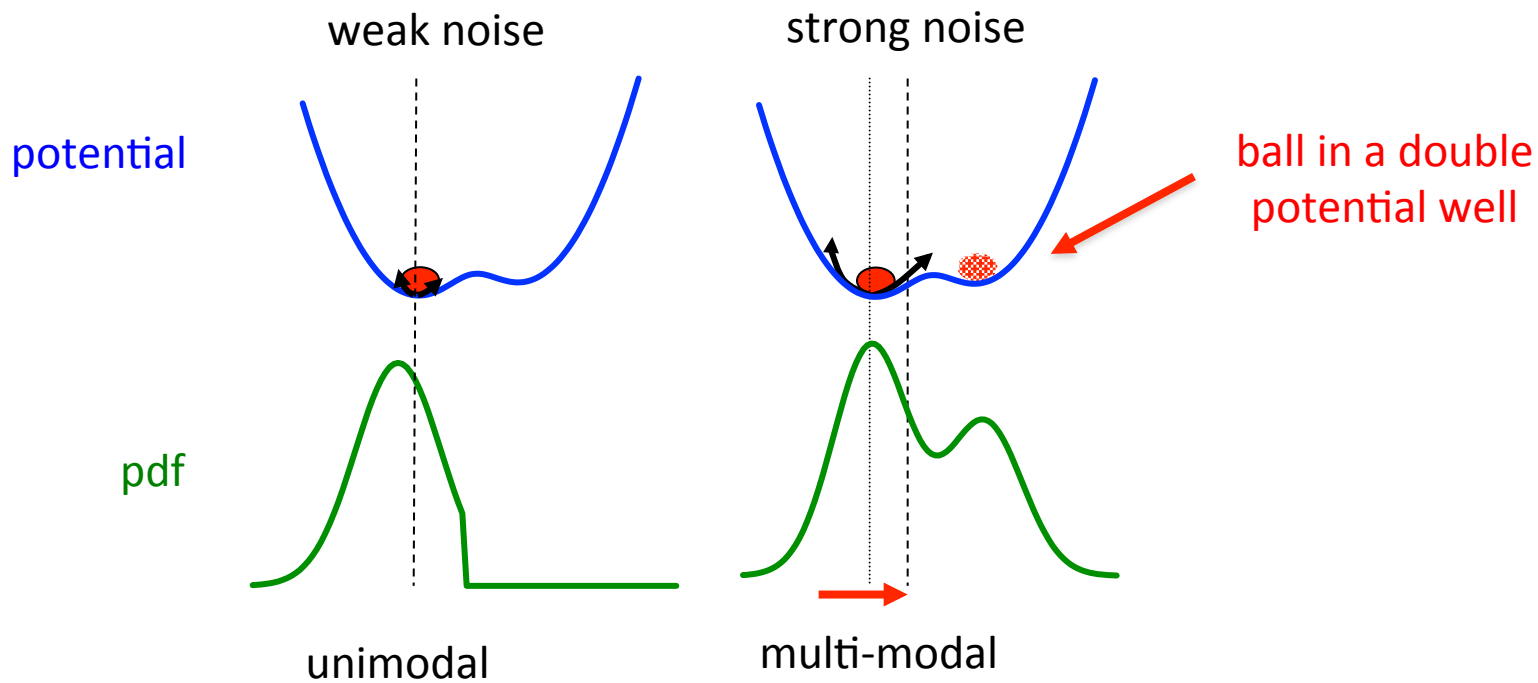
- Provide specific stochastic realisations of the sub-grid flow, not some assumed bulk average effect
- Describe the sub-grid tendency in terms of a probability distribution constrained by the resolved-scale flow
- Parametrisation development can be informed by coarse-graining budget analyses of very high resolution (e.g. cloud resolving) models

Palmer (QJRMS 2012), Towards the probabilistic Earth-system simulator: A vision for the future of climate and weather prediction.

Effects of stochastic noise

Conceptual understanding from simplified models

- Modifications of the mean climate through noise-induced drift
- Noise-enhanced variability
- Noise activated regime transitions



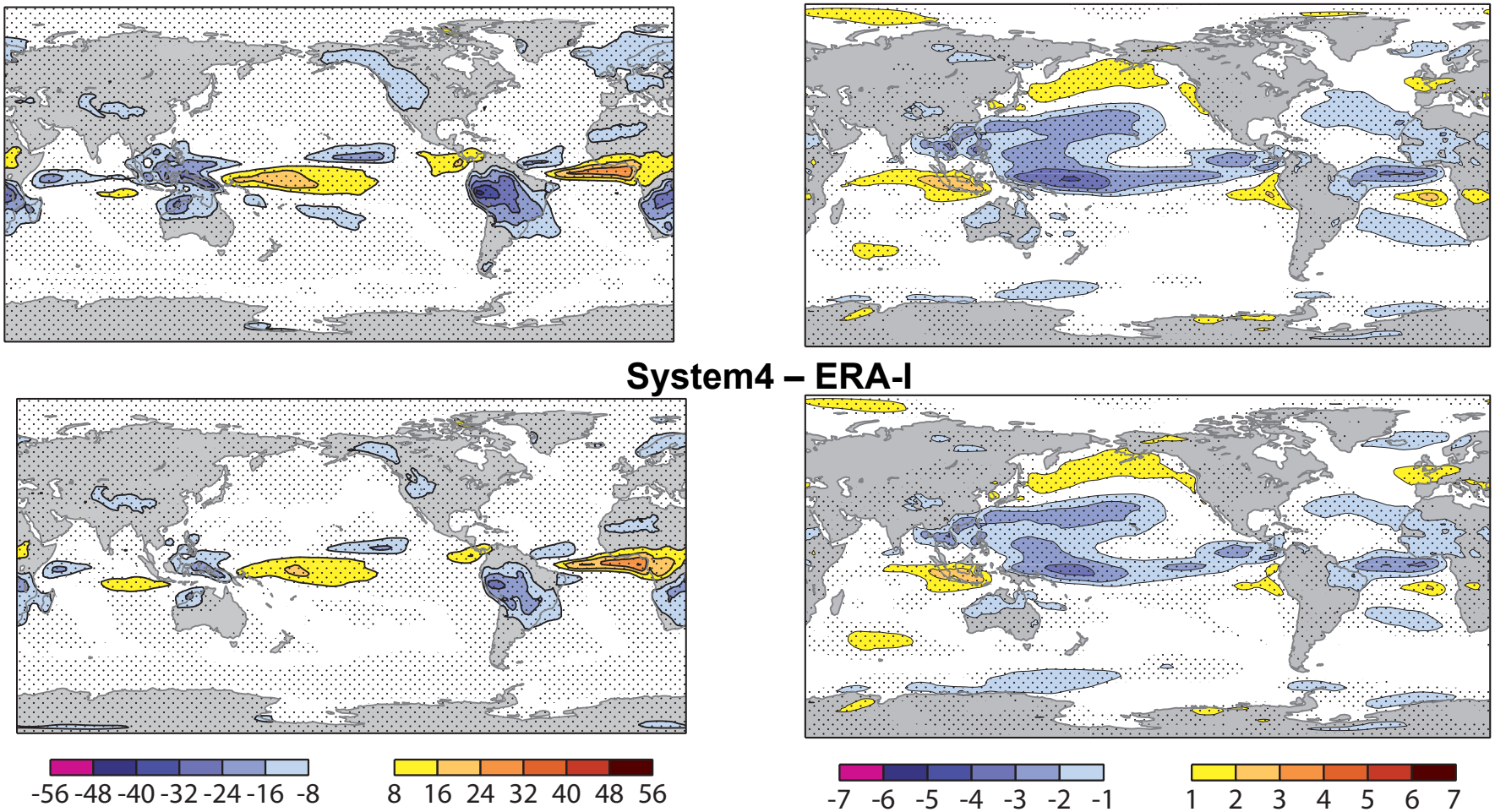
Stochastically perturbed physical tendency (SPPT) scheme

Aims to simulate model uncertainty due to physical parametrisations

- Net parameterised physical tendency: $X = [X_U, X_V, X_T, X_Q]$ from
  - Radiation
  - Gravity wave drag
  - Vertical mixing
  - Convection
  - Cloud physics
- Perturbed with multiplicative noise $r \in [-1,1]$: $X_{pert} = (1 + \mu r) X$
- Univariate random number r is described through a spectral AR(1) pattern which is smooth in space and time
- Perturbations are Gaussian distributed and truncated at ±2σ
- Tapered perturbations near the surface and in the stratosphere with $\mu \in [0,1]$

Impact of stochastic parametrisations

OLR | ***stochphysOFF* – ERA-I** | **zonal wind 850hPa**

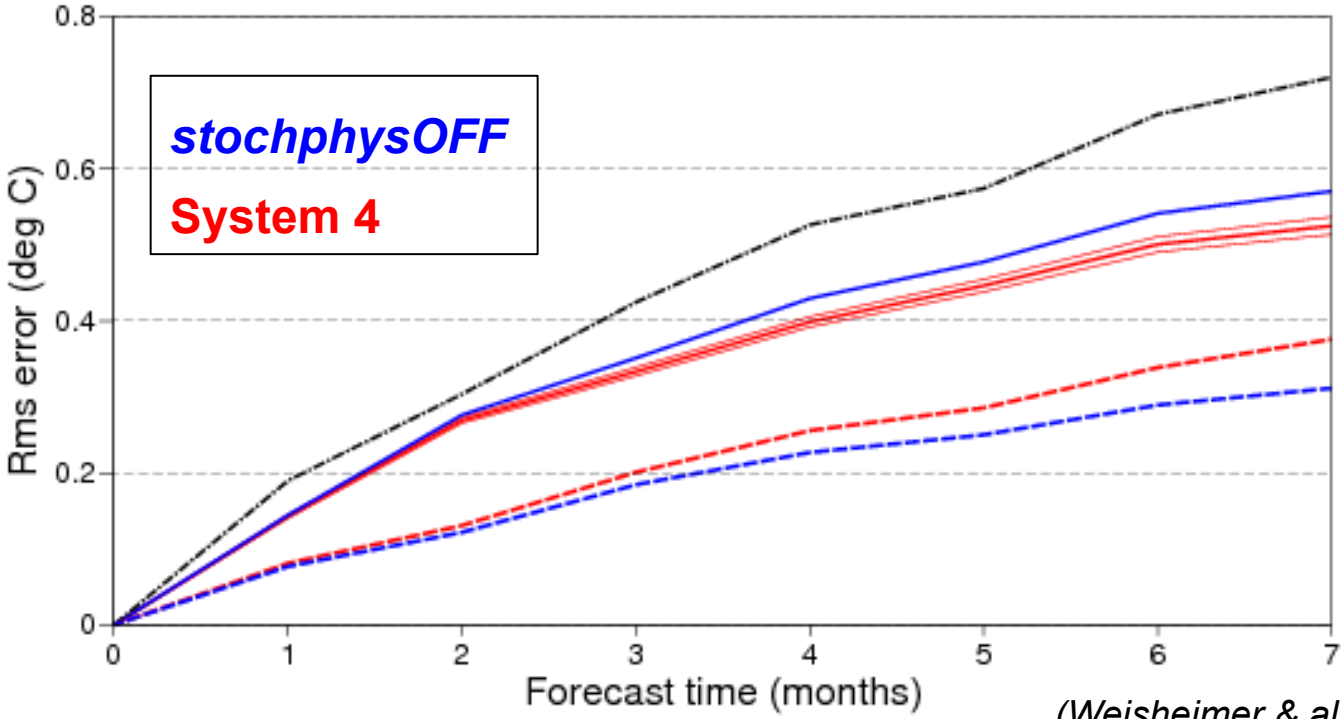


(Weisheimer & al., PhilTransA 2014)

- ✓ Reduction of overly active tropical convection
- ✓ Reduced westerly wind biases over tropical West Pacific

Impact of stochastic parametrisations

ENSO forecast quality: Nino3.4 SST



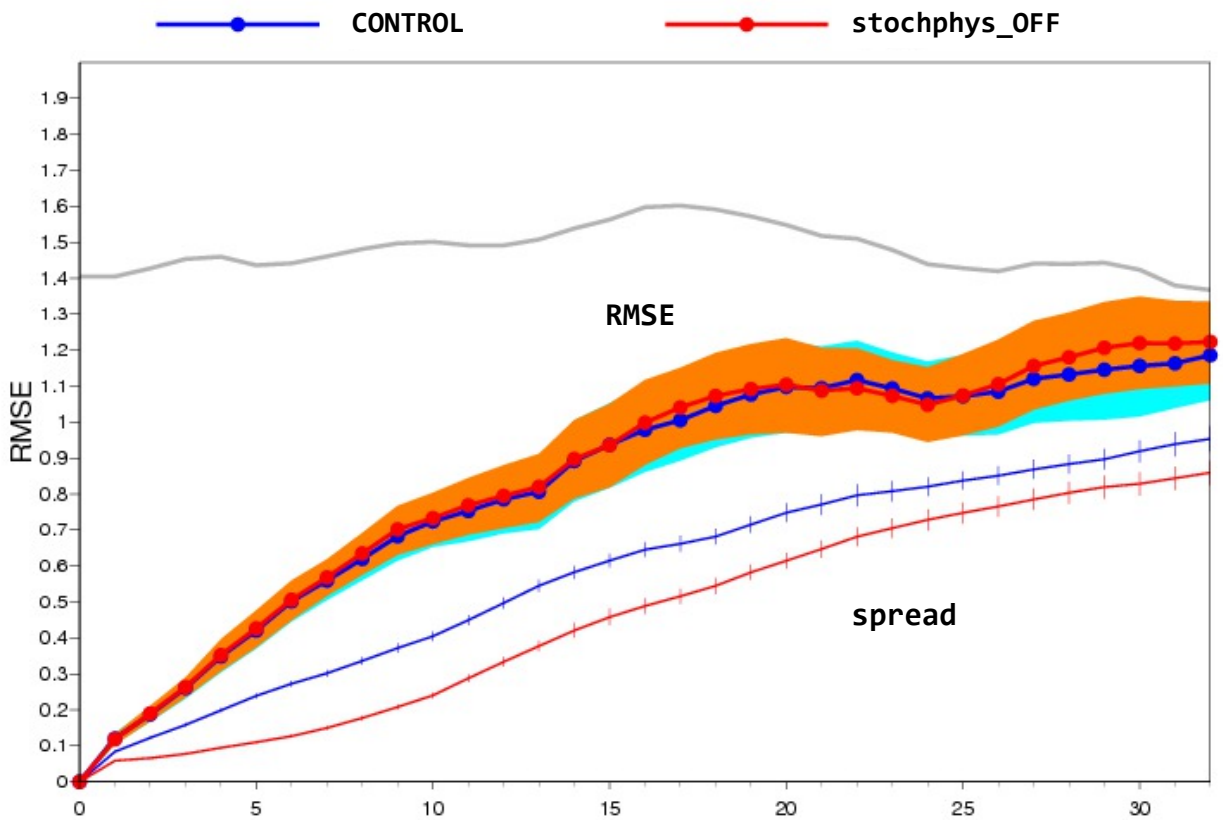
(Weisheimer & al., PhilTransA 2014)

System 4 (with stochastic parametrisations) has:

- **Reduced forecast errors**
- **Increased ensemble spread**
- **Improved correlations**

Impact of stochastic parametrisations

MJO forecasts on sub-seasonal timescales



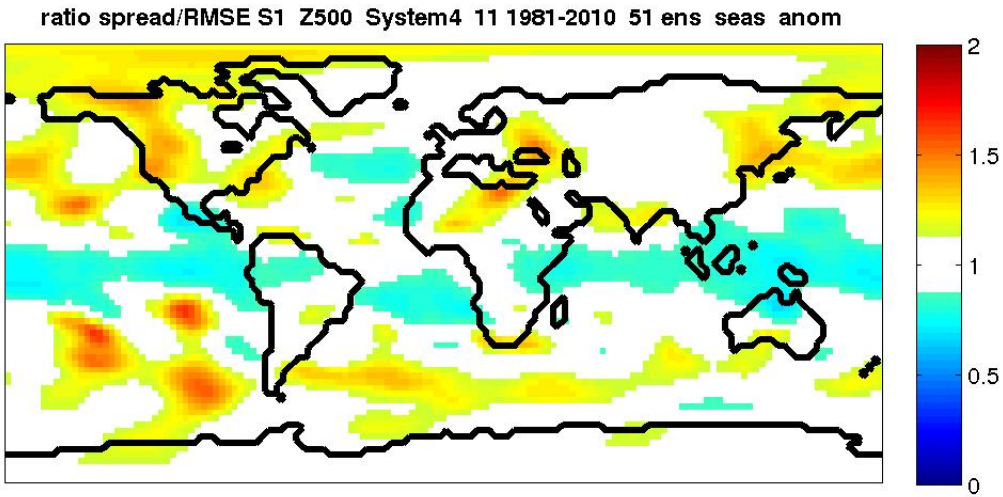
Significant increase in tropical spread leading to improved probabilistic forecasts

Stochastic physics and spread-skill

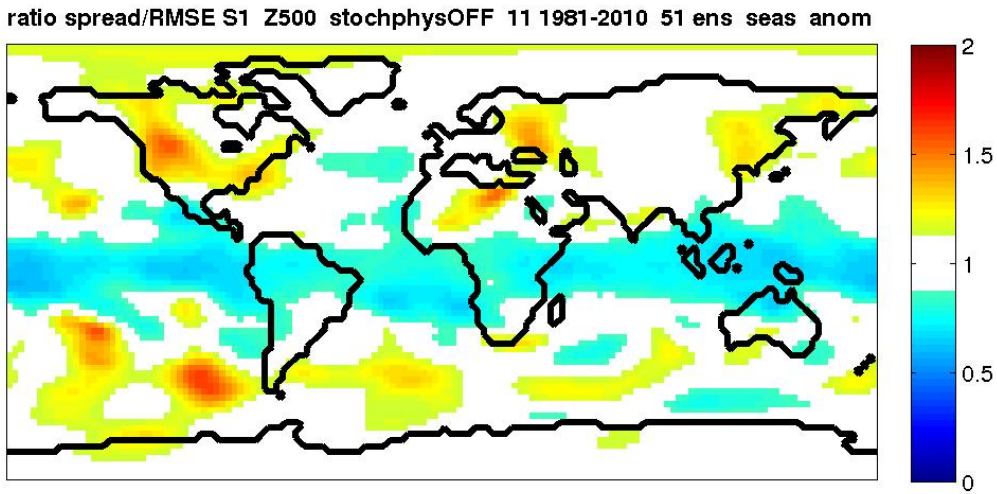
Ratio ensemble spread / RMSE

DJF

with stochastic parametrisations

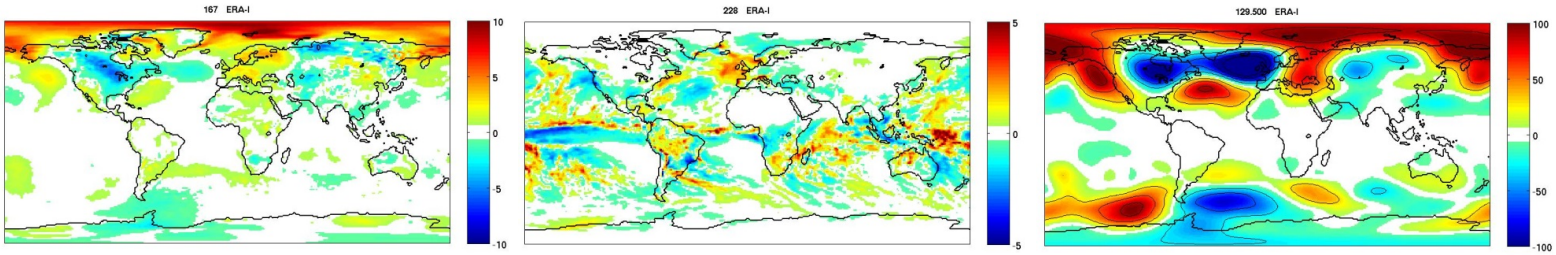


without stochastic parametrisations



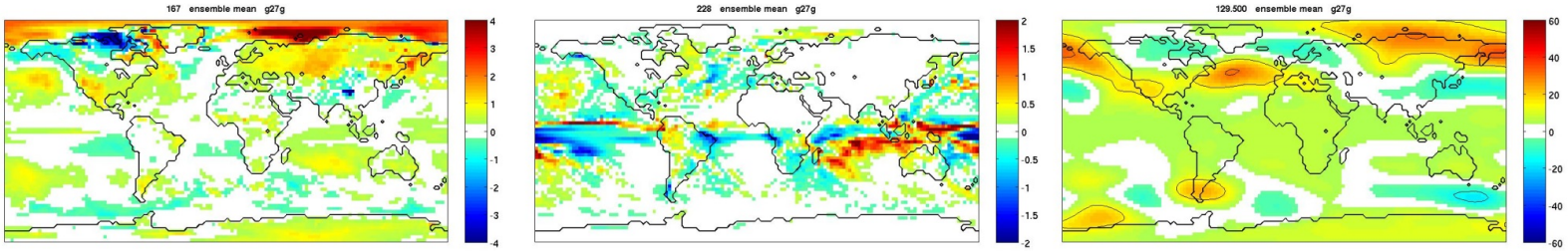
Tropical impact in the winter 2013/14

2m temp **precipitation** **Z500**

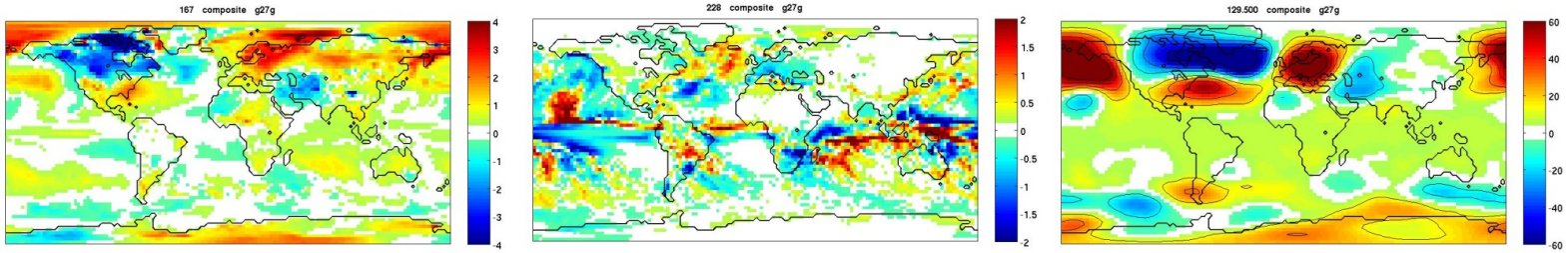


What were the drivers for these extreme mid-latitude conditions?

Seasonal forecasts from System 4 (ensemble mean anomaly):



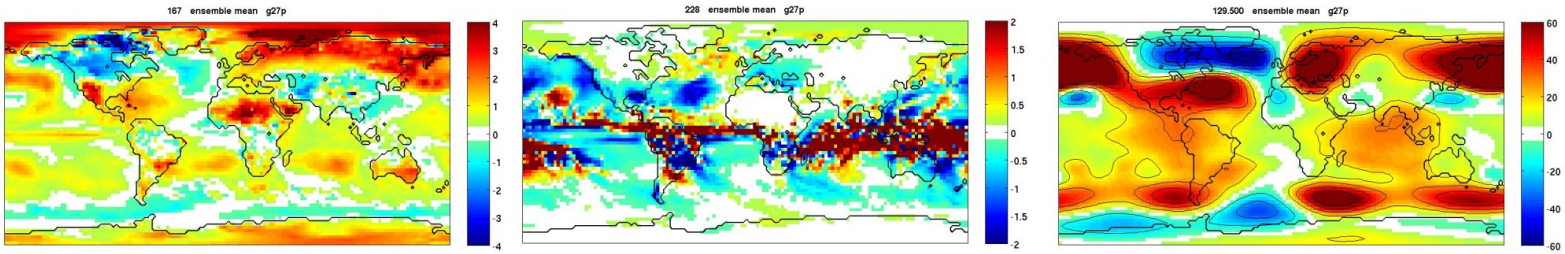
Composite of “good” members (15%):



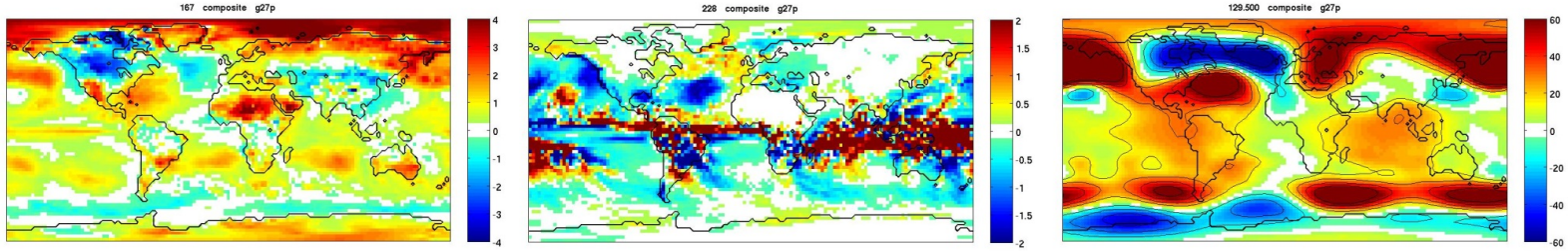
Tropical impact in the winter 2013/14

Relaxation/nudging of the tropical atmosphere ±20° towards ERA-I

ensemble mean anomaly



composite of “good” members (40%)



Tropics influence substantially the weather and climate of the extratropics
→ need for reducing model and forecast errors

Summary

Arnt Eliassen pioneered, together with John v. Neumann, Jules Charney and others, the era of numerical weather prediction which is nowadays a well established and recognised part of our every day life.

His legacy continues to live through the operation of a unique and unparalleled international institution where scientific and computational forces were joined to provide the best possible weather forecasts.

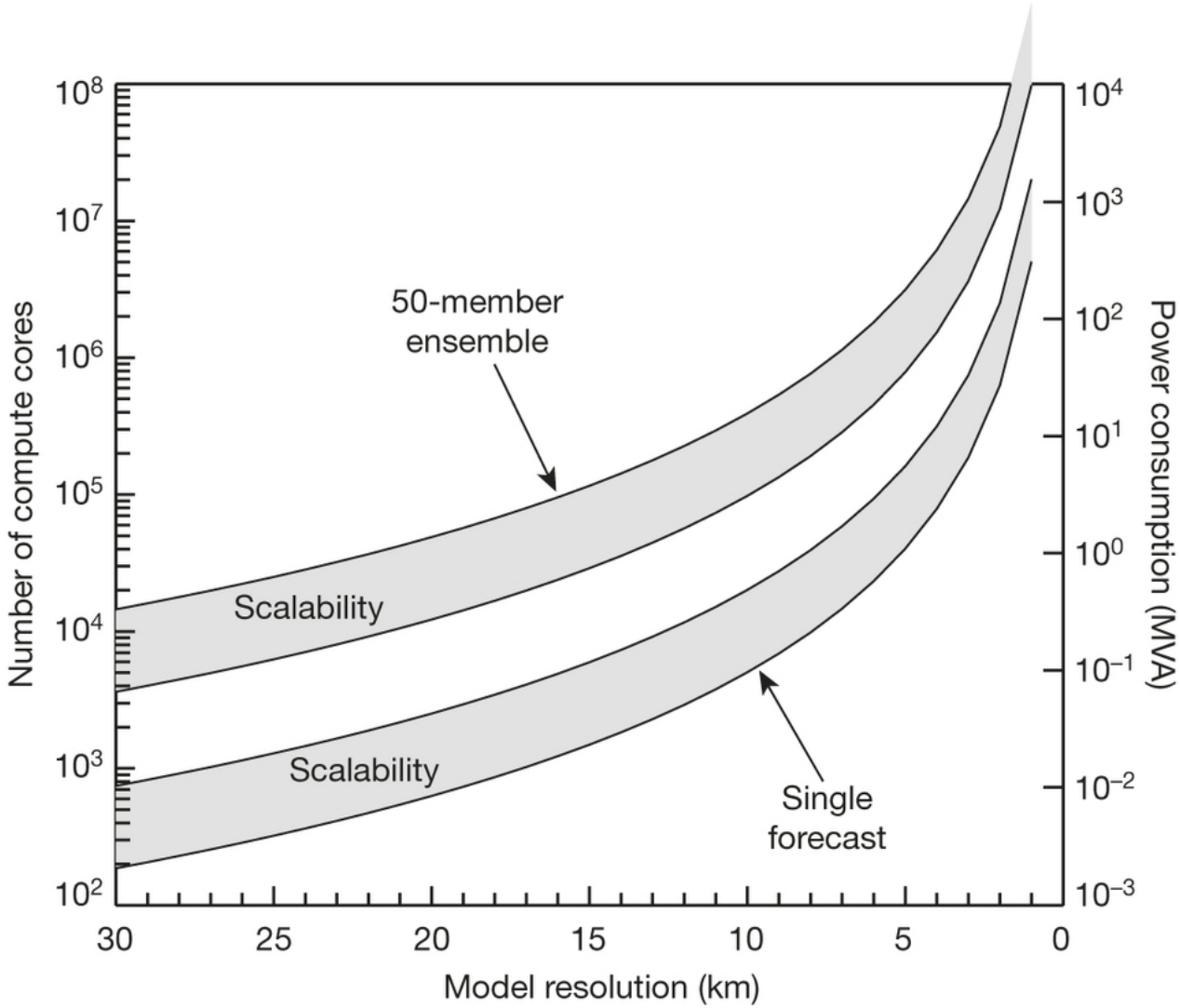
Numerical weather forecasts have gone through a “quiet revolution” with steady skill increases for nearly 40 years due to improved forecast models, more accurate initialisation and the growing observational coverage.

The useful forecast range has increased and operational forecasts now also include the prediction climate anomalies several months and seasons ahead.

Reliability is essential for the use of our forecasts in real-life decision making.

Future challenges include further improvements of the models, including the explicit representation of model imperfectness, and highly parallel scale-adoptive computing.

Scalability



(Bauer, Thorpe and Brunet, Nature 2015)