Use of Stochastic Modeling to improve predictions

Oklahoma, Oct 31-Nov 2 , 2018

Judith Berner

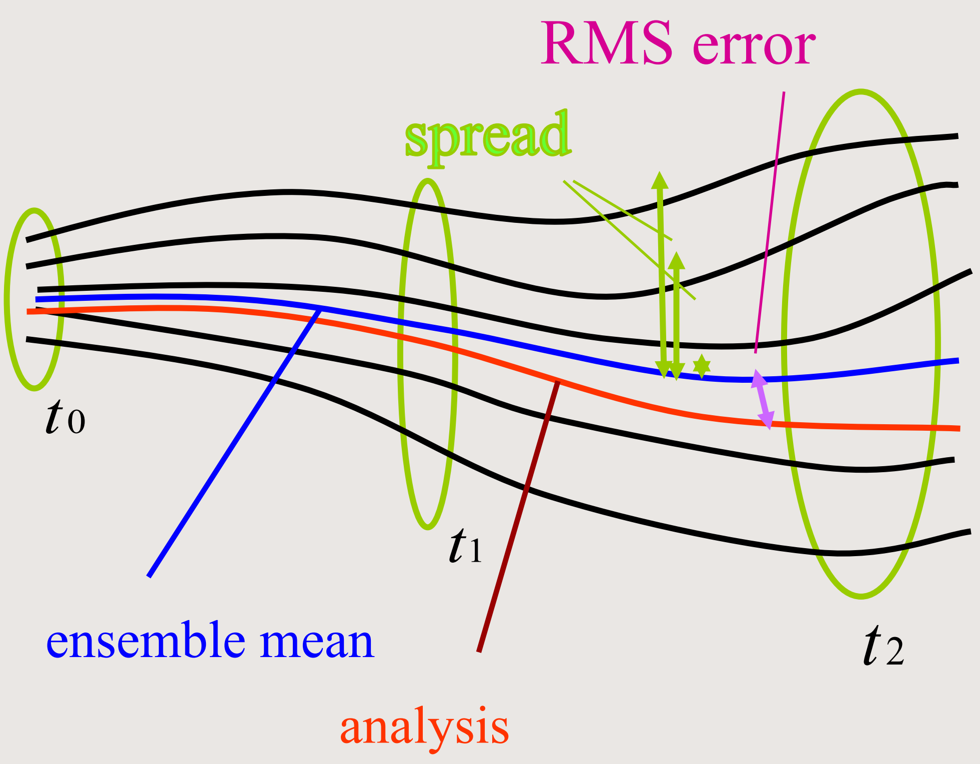
National Center for Atmospheric Research

Outline

- The need for uncertainty representations in ensemble forecasts
- Current stochastic parameterizations
- Next generation stochastic parameterizations

Representing initial uncertainty by an ensemble of states

- Forecast uncertainty in weather models:
  - Initial condition uncertainty
  - Model uncertainty
  - Boundary condition uncertainty
- Represent initial forecast uncertainty by ensemble of states
- Reliable forecast system: Spread should grow like ensemble mean error, if not we have model error



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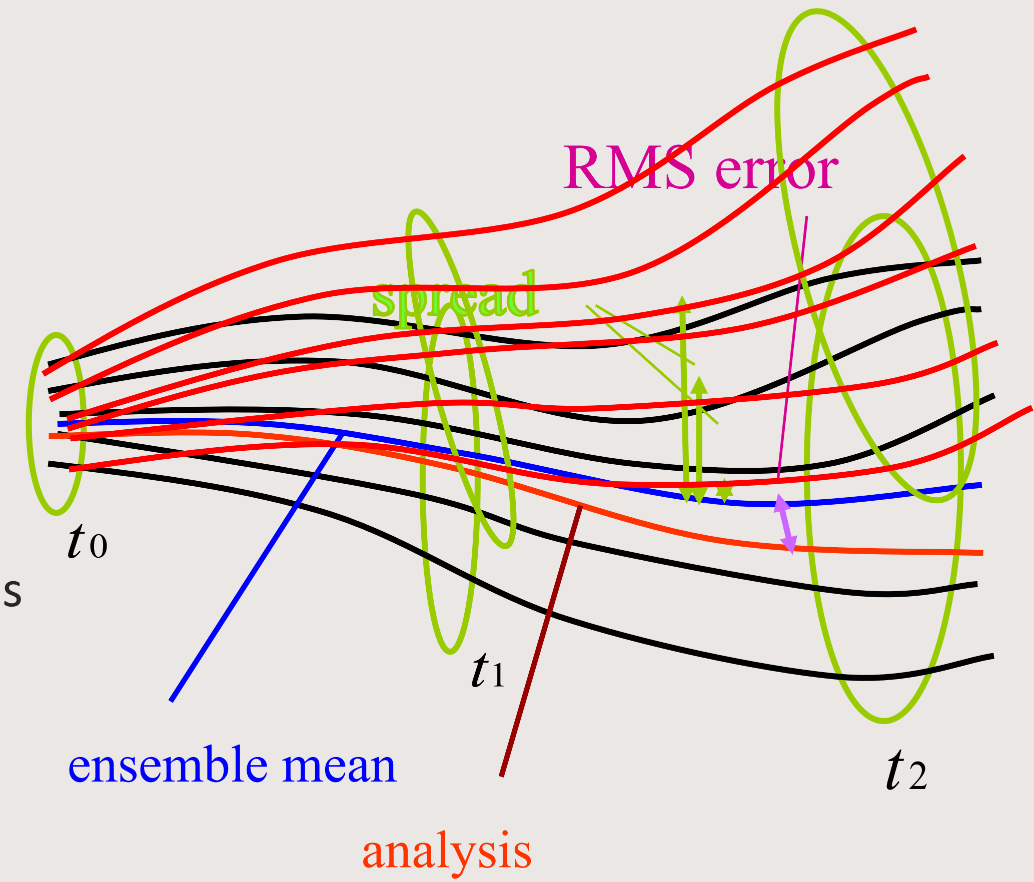
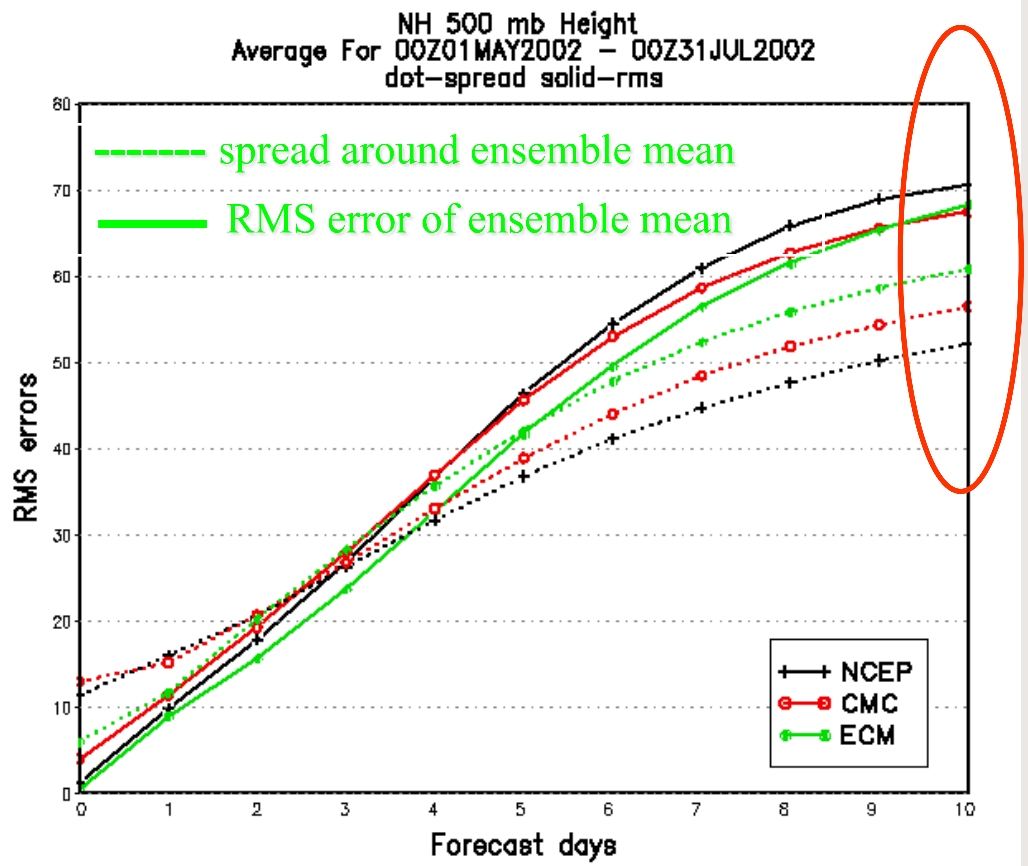


Underdispersivness of ensemble systems



Buizza et al., 2005

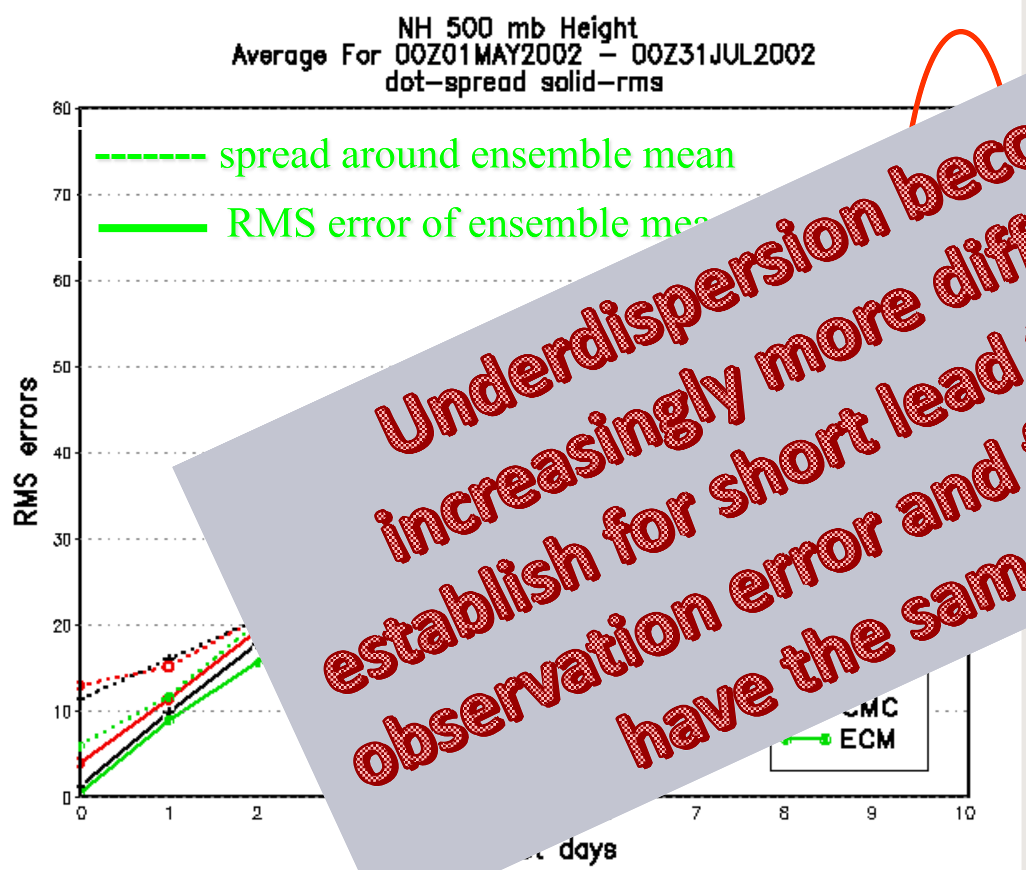
The RMS error grows faster than the spread

- Ensemble is unreliable and overconfident

- Underdispersion is a form of **model error**

- ***Forecast error = initial error + model error + boundary error***

Underdispersivness of ensemble systems



Buizza et al., 2005

Underdispersion becomes increasingly more difficult to establish for short lead times, since observation error and forecast error have the same order

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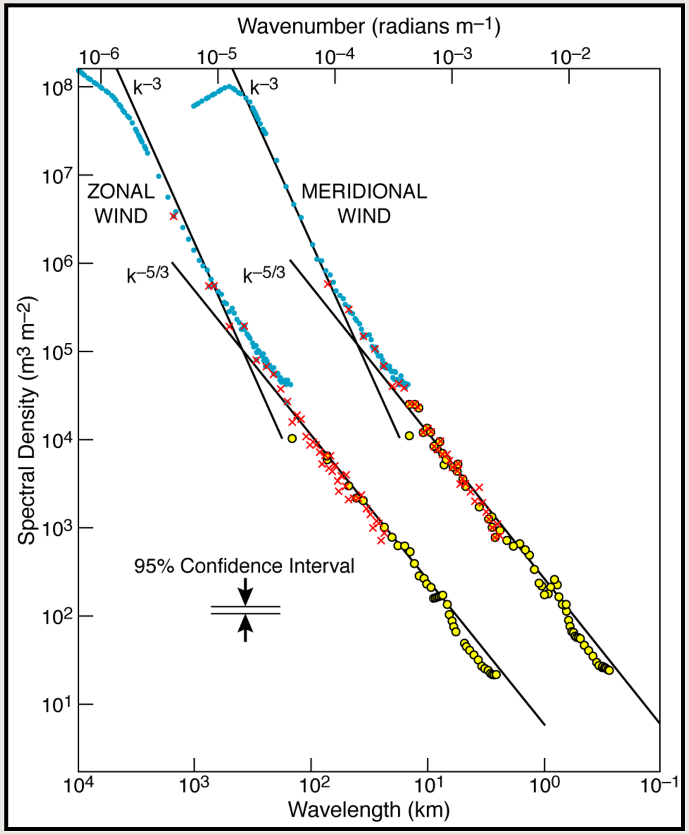
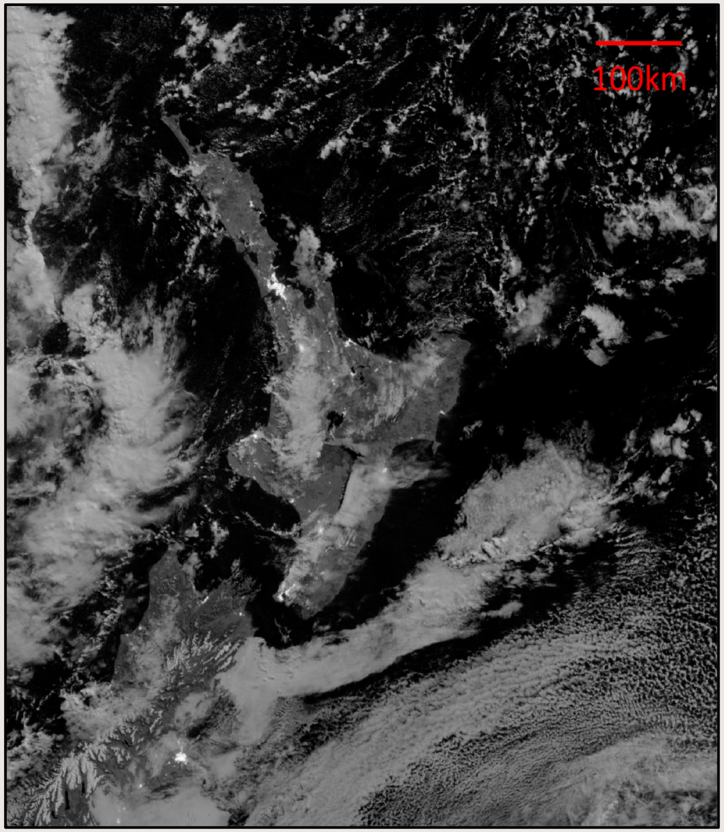
➢ ***Forecast error = initial error + model error + boundary error***

Kinetic energy spectra



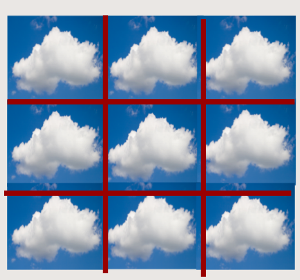


Nastrom and Gage, 1985

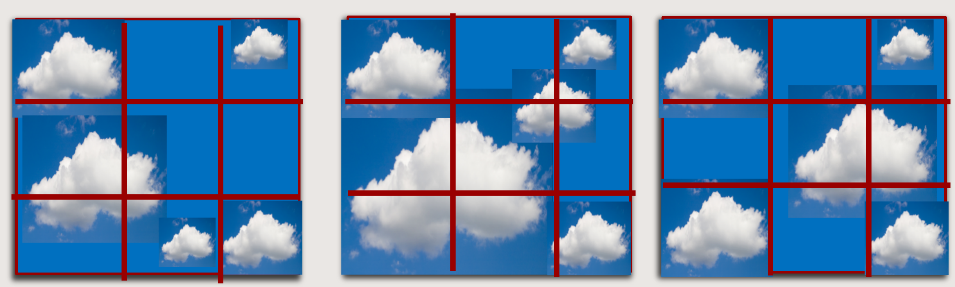
Stochastic parameterizations

- No separation of scales
- Grid-scale variables cannot fully constrain subgrid-scale motion
- Stochastic parameterization scheme: describes the subgrid-scale motion in terms of a pdf constratined by the resolved flow
- Provides stochastic realizations of the subgrid-flow, not some assumed bulk scale flow

Equilibrium



Stochastic realizations



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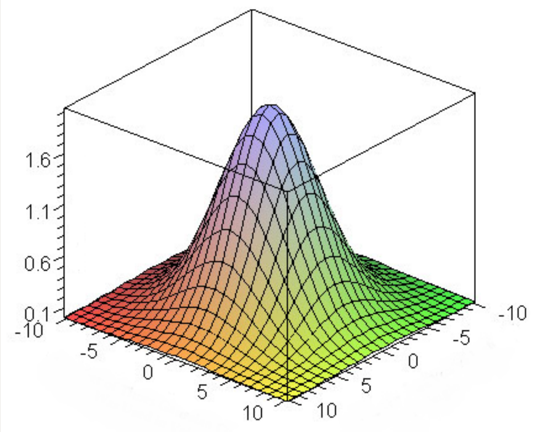
Stochastically perturbed tendency scheme (SPPT)

Rationale: Especially as resolution increases, the equilibrium assumption is no longer valid and fluctuations of the subgrid-scale state should be sampled (Buizza et al. 1999, Palmer et al. 2009, Berner et al. 2015)

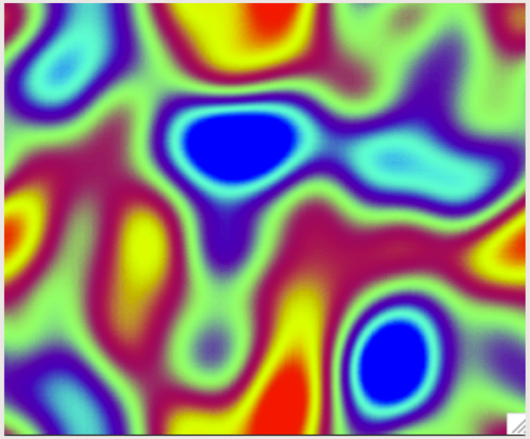


$$\frac{\partial X}{\partial t} = D_X + (r+1)P_X$$

Local tendency for variable X

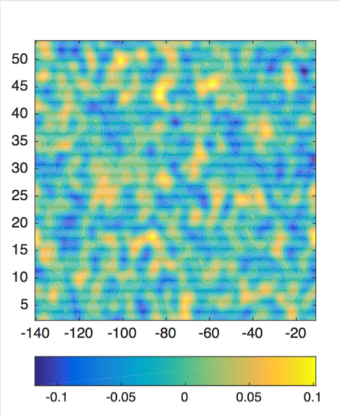
Dynamical tendencies => Resolved scales

Physical tendencies => Unresolved scales

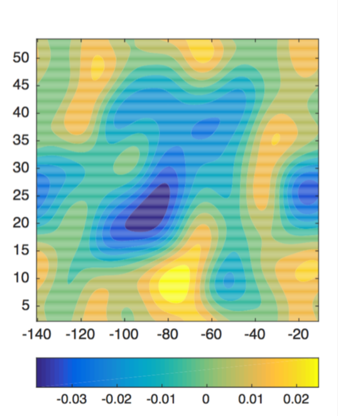


- Perturbs accumulated U,V,T,Q tendencies from physical parameterizations packages
- Same pattern for all tendencies to minimize introduction of imbalances

Stochastic parameter(izations) perturbations (SPP)



Perturbed parameter in MYNN PBL Scheme	Name	magnitude
Turbulent Mixing length	el	30%
Subgrid Cloud fraction	cldfra_bl	20%
Thermal and Moisture Roughness Length	CZIL	30%
Prandtal Number's limit set to 2.5	Prlimit	1
Perturbed parameter in RUC LSM Scheme	**Name**	**magnitude**
Soil Moisture	SMOIS	20%



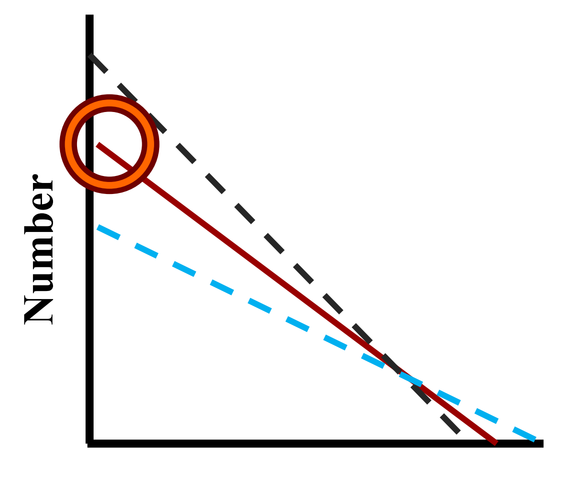
Stochastic pattern perturbs parameters @ 15km and 3km

- (Closure tendencies in GF convection scheme)
- Turbulent mixing length, subgrid cloud fraction, thermal and moisture roughness lengths in MYNN PBL
- Soil moisture, leaf index, etc in RUC LSM

Jankov et al., et al 2016, 2018

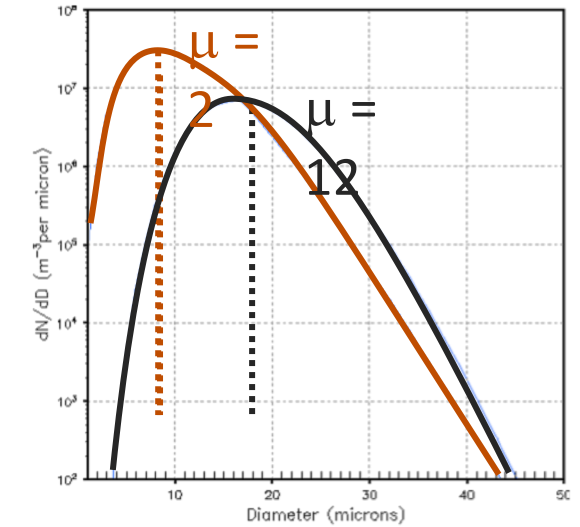
SPP to Thompson microphysics scheme

A.) Graupel Y-intercept parameter



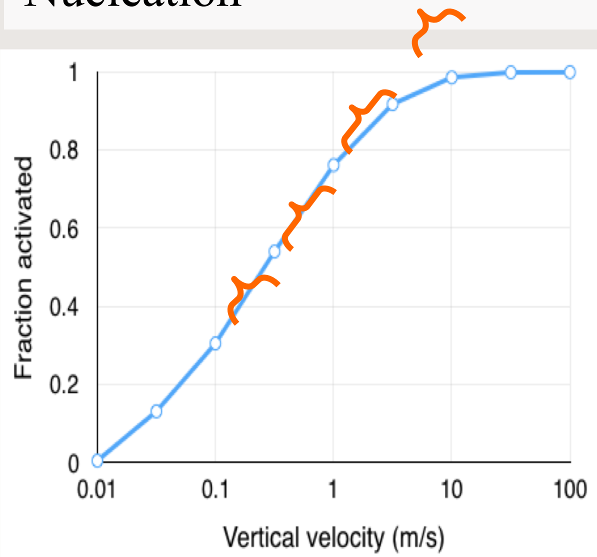
+/- 1.5 orders of magnitude (m^{-4})

B. Cloud water gamma dist.shape)



+/- 3 always constrained [2,15]

C.) Cloud Condensation Nucleation

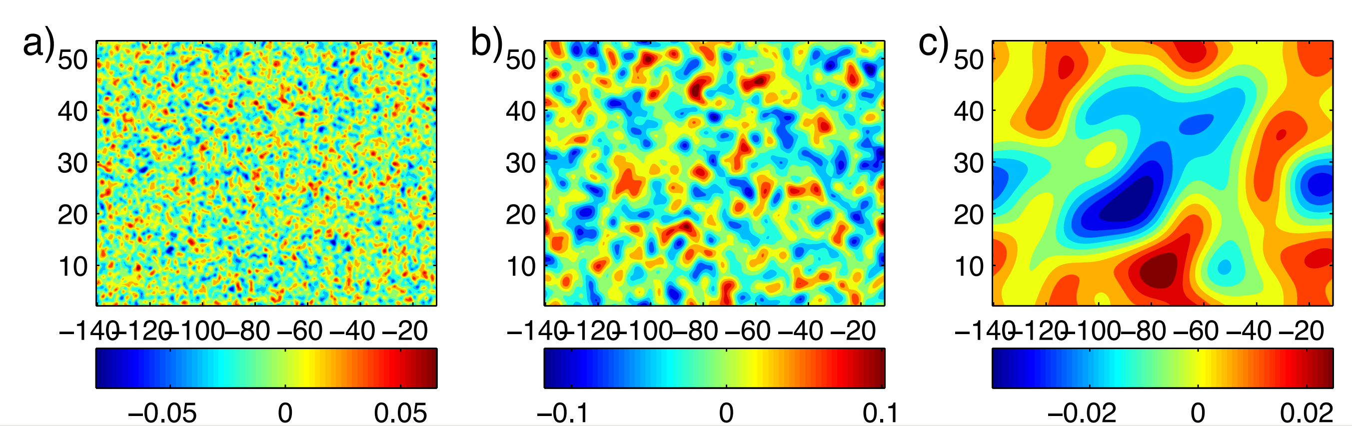


W perturbed up to + 0.35 m/s

With Greg Thompson, Jason Otkin, Sarah Griffin, Maria Frediani Fanyou Kong

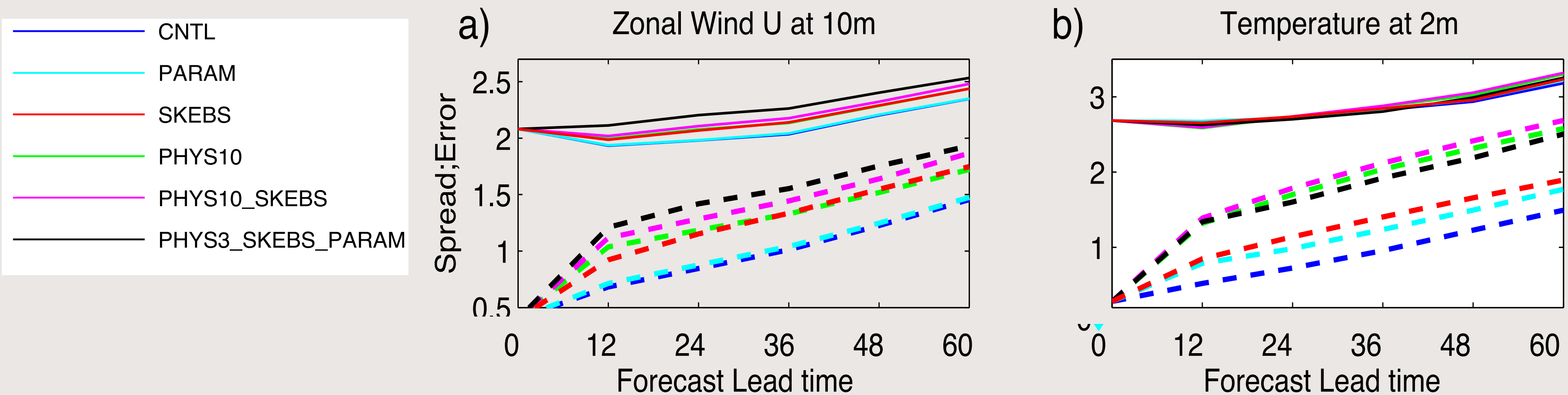
Stochastic pattern generator: Spatio-temporal correlations

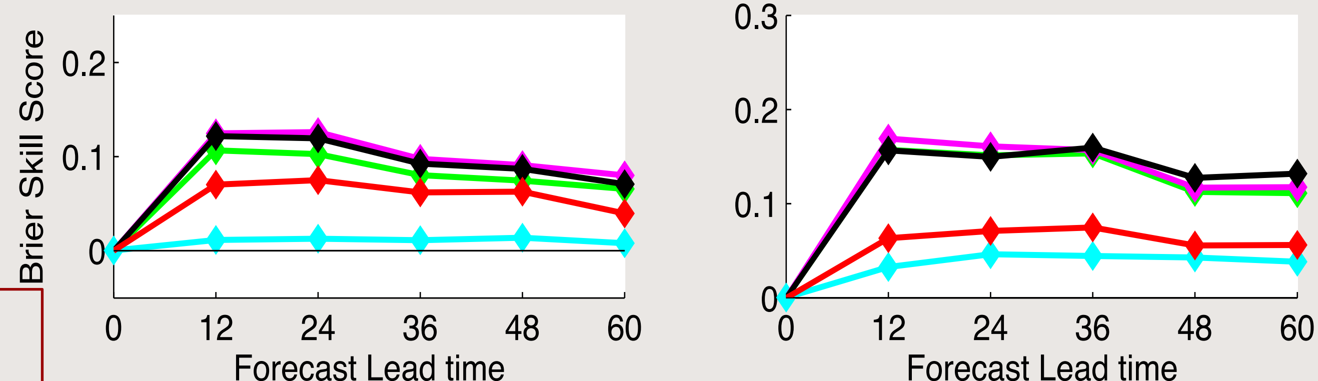
User defined: magnitude, spatial, and temporal time scales



fine scale ⟷ broad scale

Brierscore skill score near the surface





$$\mathrm{BSS}_{\mathrm{exp}} = \frac{\mathrm{BS}_{\mathrm{ref}} - \mathrm{BS}_{\mathrm{exp}}}{\mathrm{BS}_{\mathrm{ref}}}$$

Brier skill measures probabilistic skill in regard to a reference (here CNTL). Verified event: μ<x<μ+σ

Berner et al., et al 2015

Limited vs unlimited predictability in Lorenz 1969

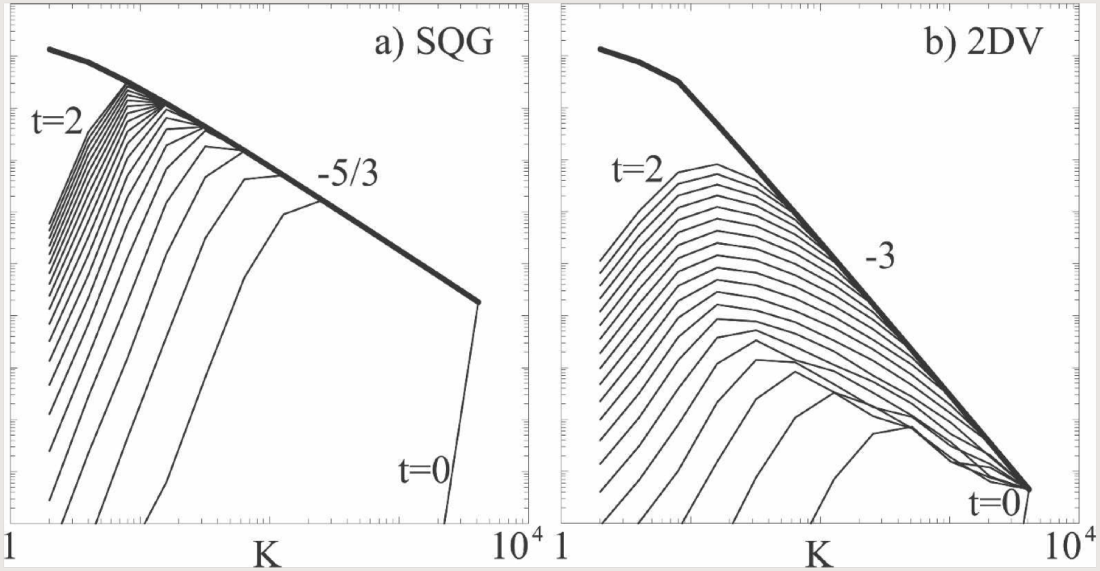
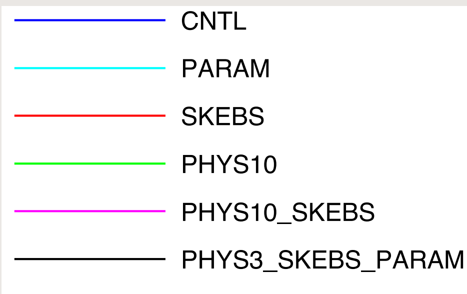


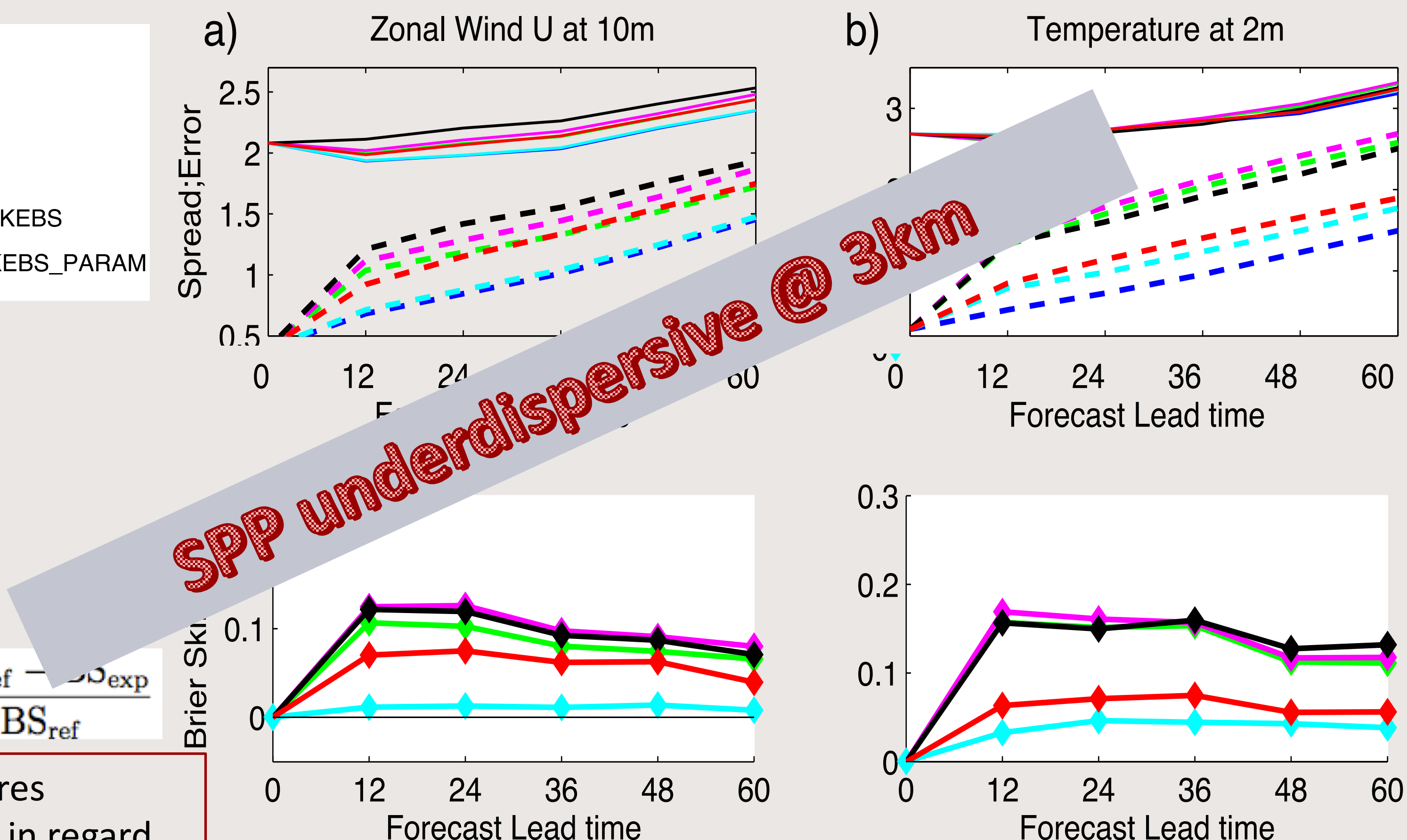
FIG. 1. Error energy per unit wavenumber, $K^{-1}Z(K,t)$ for $t = 0, 2$ in steps of 0.1 for (a) SQG turbulence and (b) 2DV turbulence. The heavy solid line indicates the base-state kinetic energy spectra per unit wavenumber, $K^{-1}X(K)$, which has a $-5/3$ slope for SQG and a -3 slope for 2DV.

Rotunno and Snyder, 2008

2DV – 2D Vorticity equation
SQG - surface quasi-geostrophic equations

Brierscore skill score near the surface





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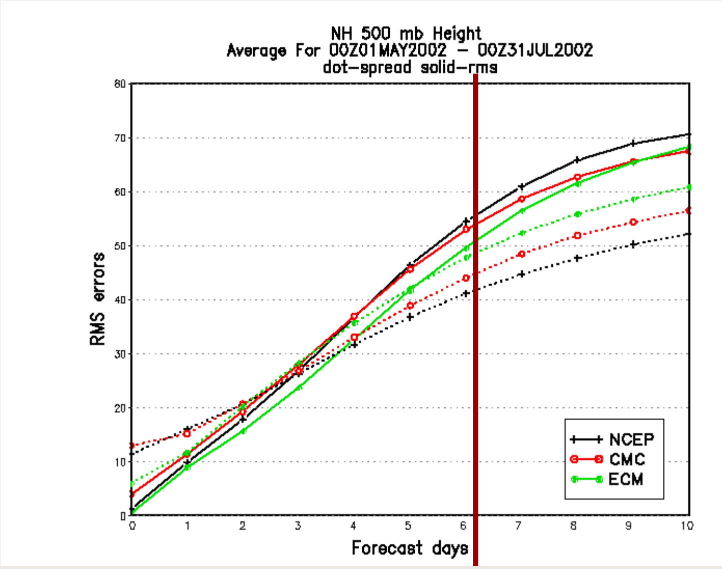

- Is it sufficient to represent instantaneous uncertainty (SPP) or do we need to include “memory term”, which represents the integrated effect from past model errors (SPPT, SKEBS)?
- Larger spatial scales due to upscale error-growth?

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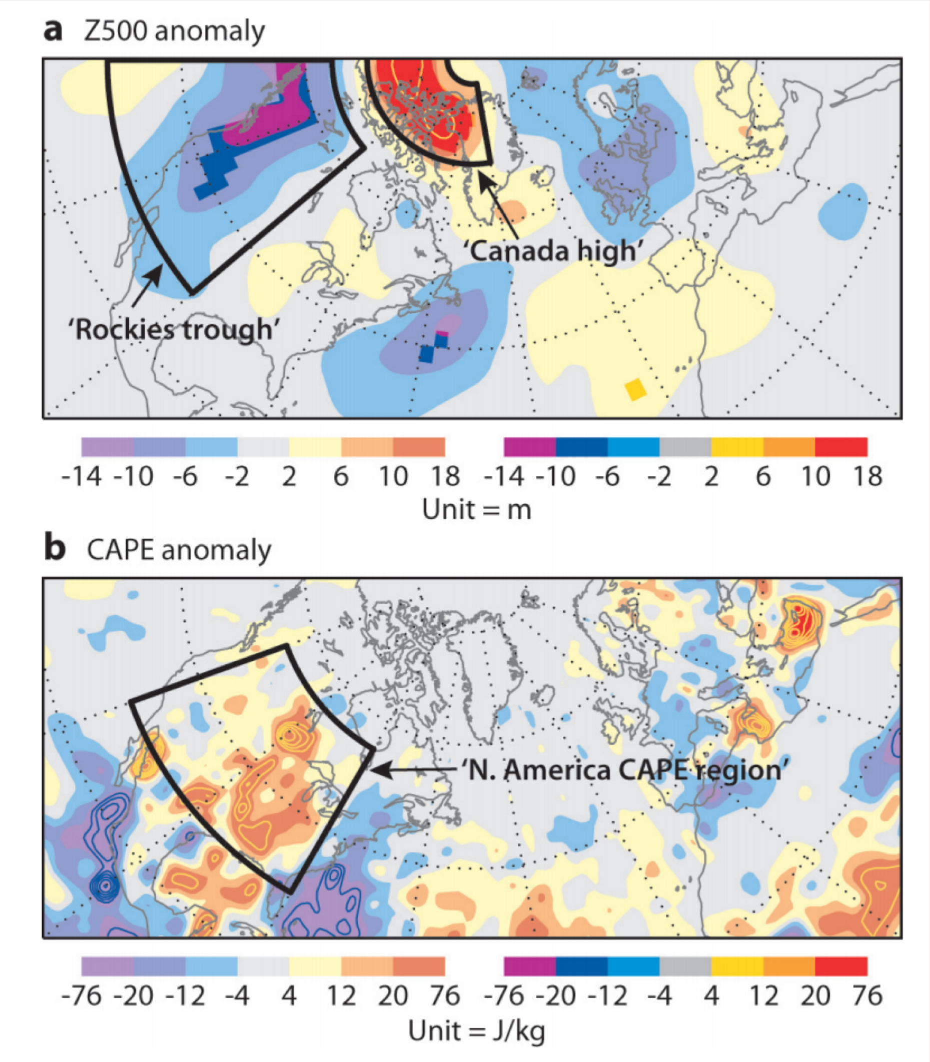
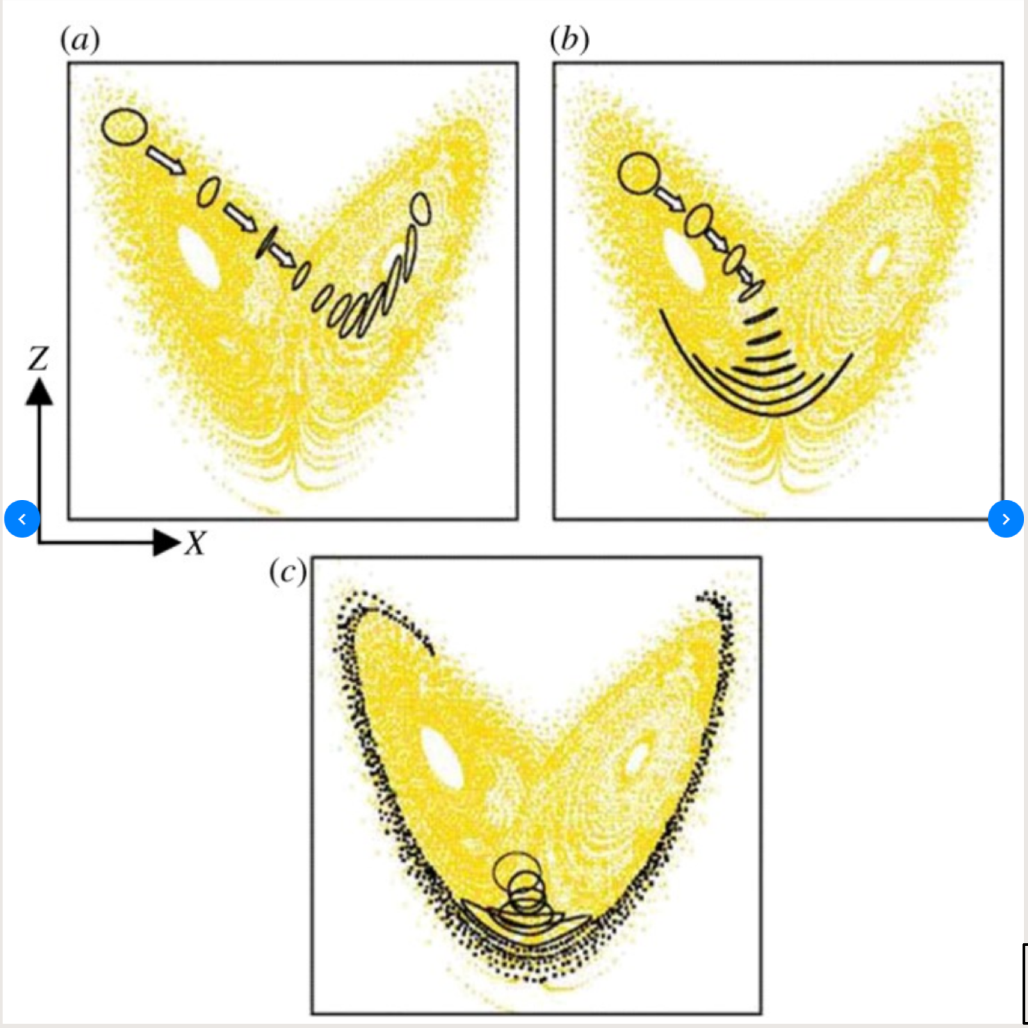
Upscale error growth



Rodwell et al. 2013

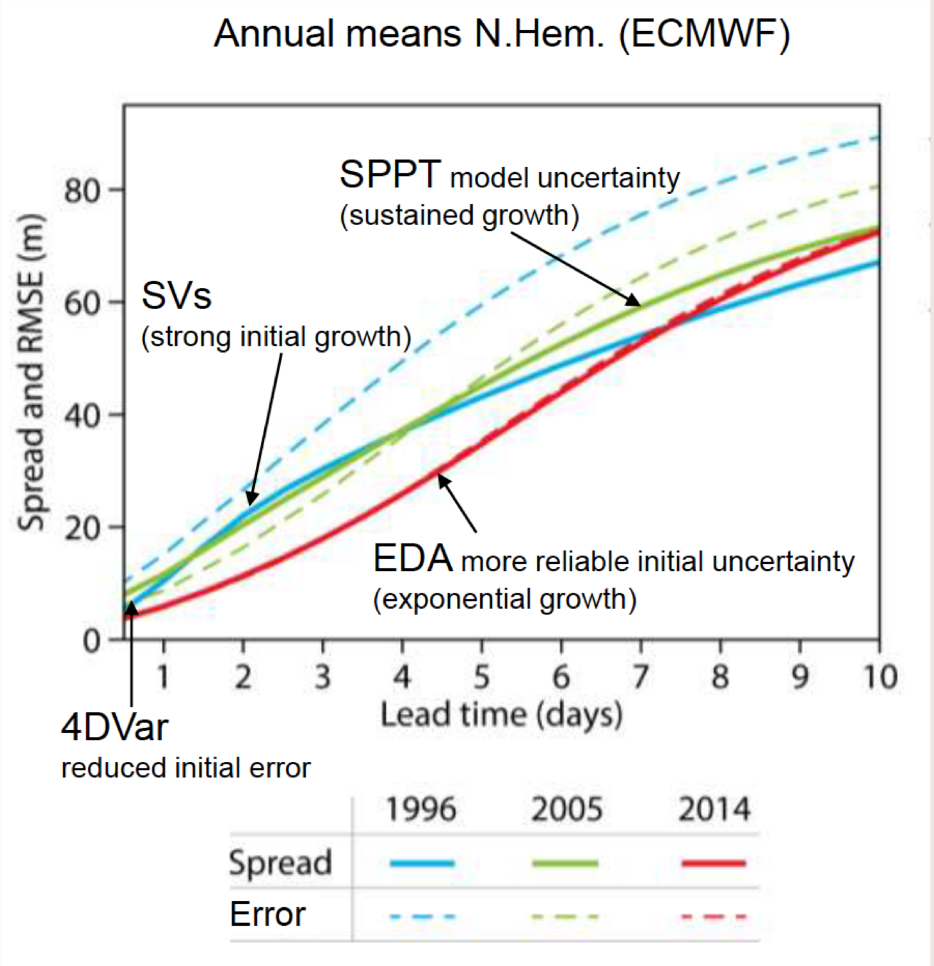
Flow-dependent error growth



Palmer, 2001

Spread and error

- Better Spread-error agreement (better obs, initial conditions, forecast model and uncertainty schemes
- Allows for a reduction of initial condition perturbations (important for short-range weather forecasts)
- Spread curve becomes exponential !

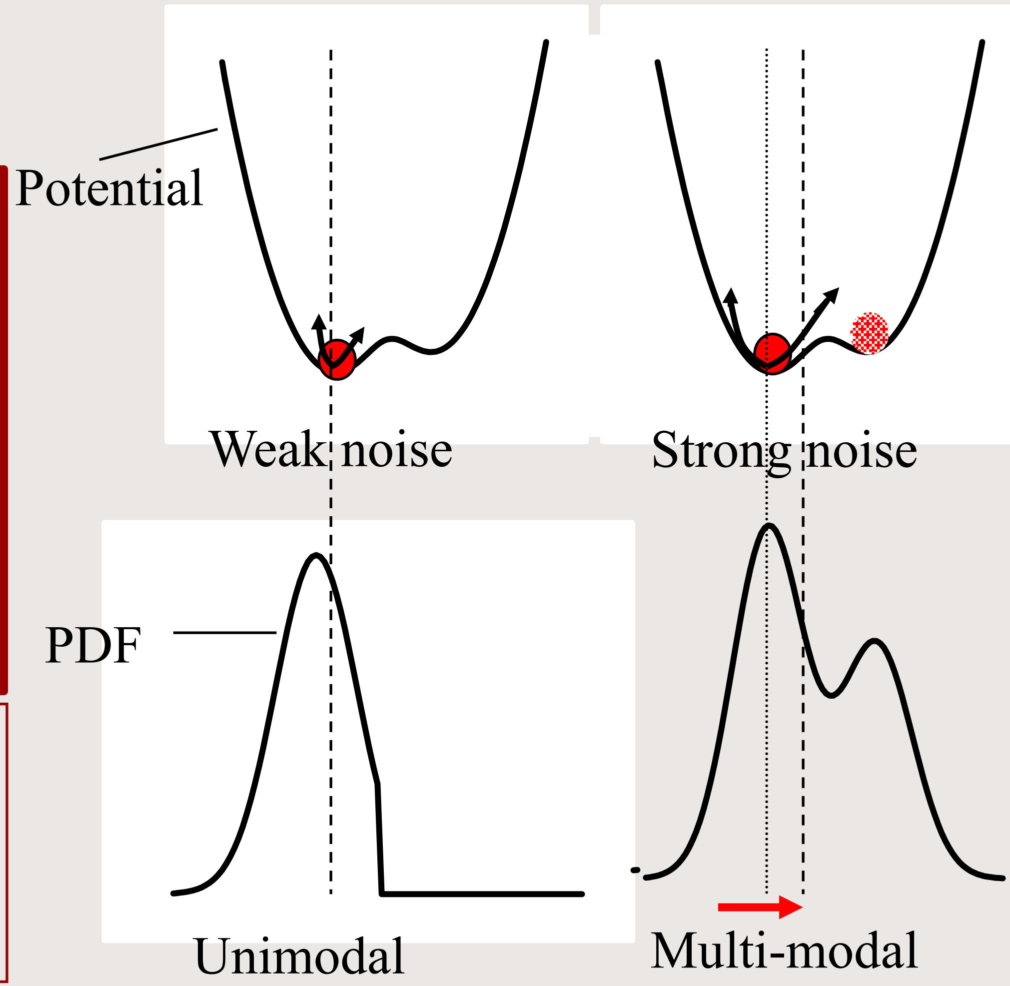


Curtosy Mark Rodwell

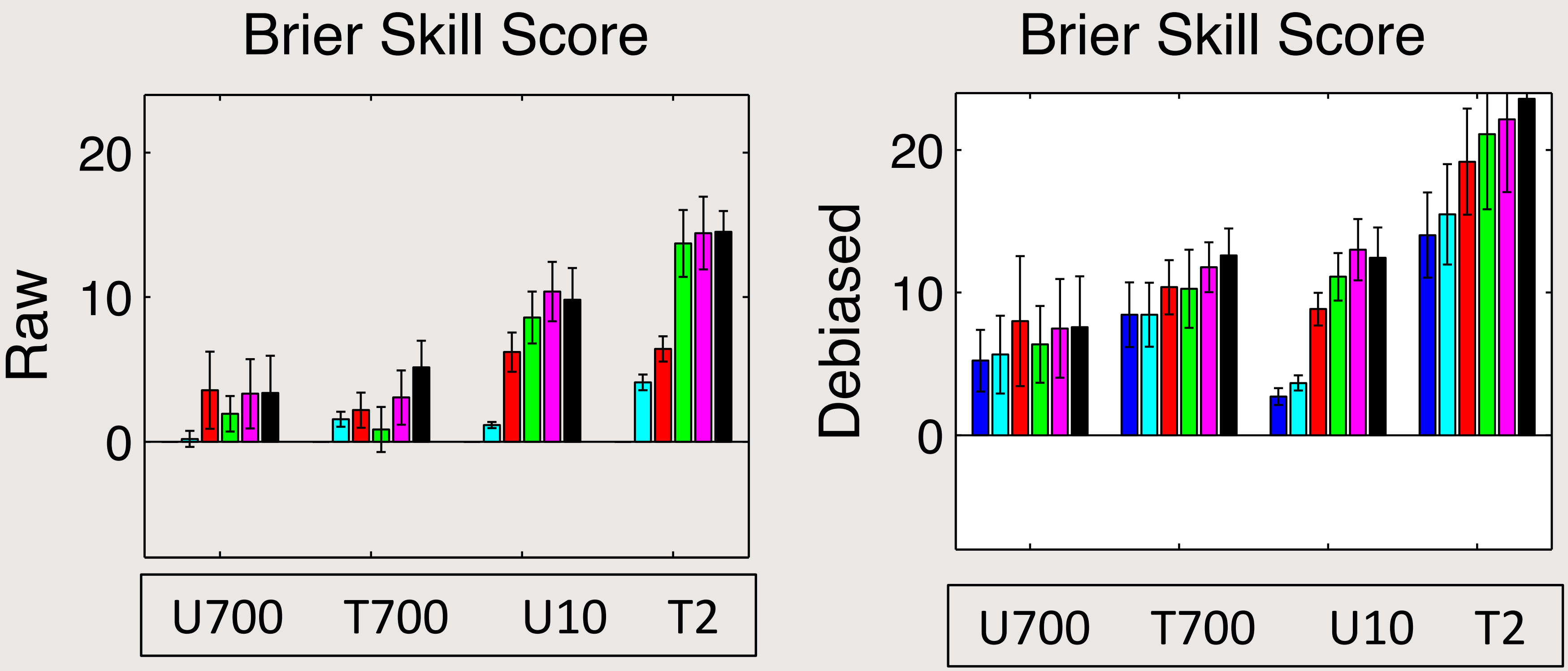
Potential of stochastic parameterizations to reduce model error

- Stochastic parameterizations can change the mean and variance of a PDF
  - Impacts variability
  - Impacts mean bias

Berner et al. 2017 "Stochastic Parameterizations: Toward a new view of weather and climate", Bulletin of the American Meteorological Society (BAMS)



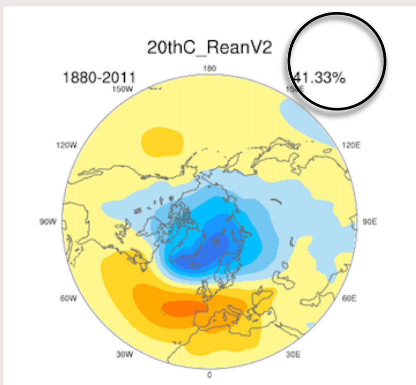
Importance of bias

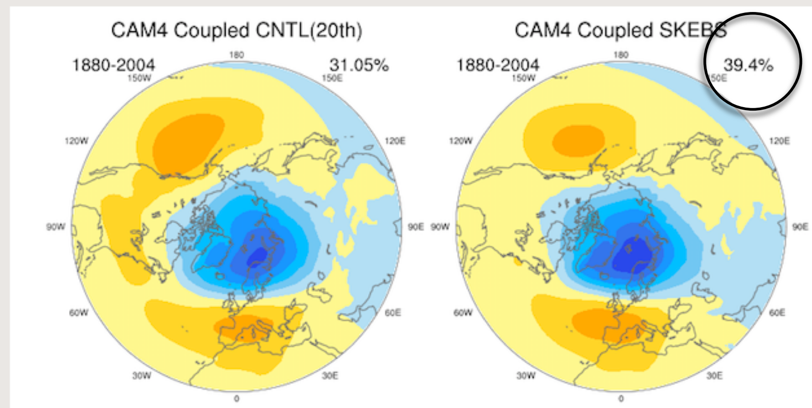


Impact of Stochastic Parameterizations on low-frequency modes in CESM

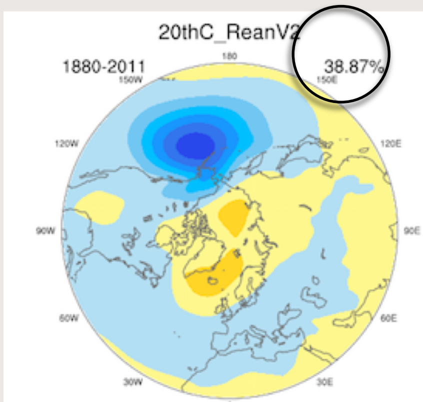
- Important for subseasonal to seasonal forecasting

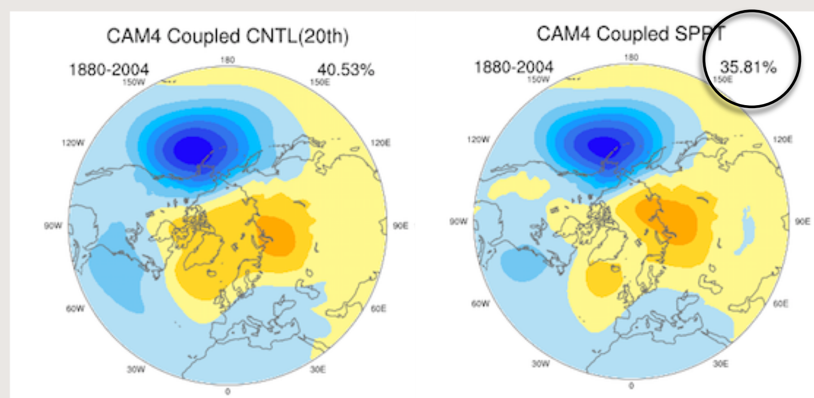
NAO





PNA





Summary

- Development is away from “ad hoc” schemes and toward more “process-based” uncertainty representations in close collaborations with parameterization developers.
- As horizonal resolution increases will it be sufficient to represent instantaneous uncertainty (e.g. through SPP) instead of more integrative model-error schemes (not yet there)
- Upscale error-growth of mesoscale processes should be studies process-based as well as statistically (spread/error)

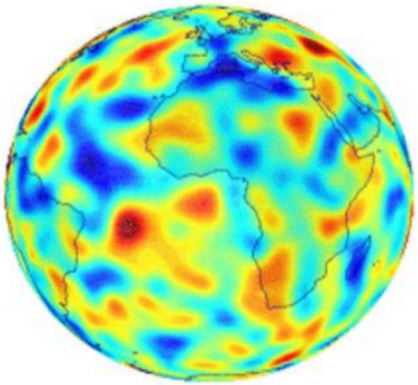
- **Stochastically Perturbed Parametrisation Tendencies (SPPT)**
  - represents random errors due to model's physical parametrisation schemes
- Implemented in models worldwide

$$T = D + (1+e)\sum_{i=1} P_i$$

T – Total tendency
D – Dynamics tendency
P – Physics tendency

Pattern correlated in space & AR(1) in time:

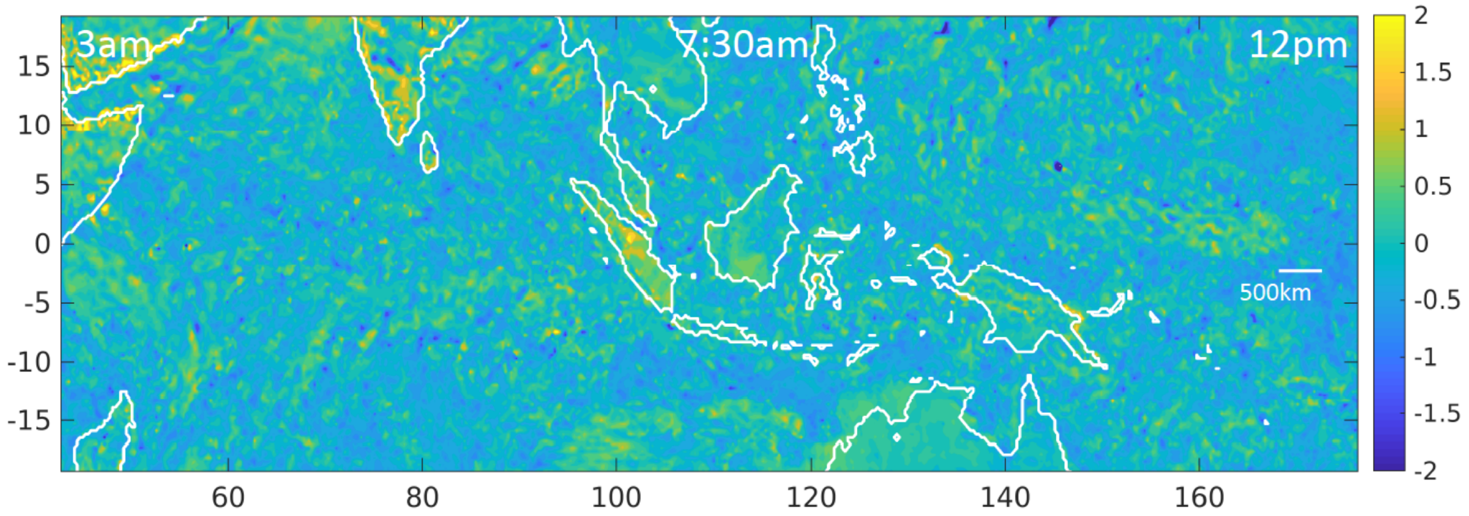
σ	L (km)	τ (days)
0.52	500	0.25
0.18	1000	3
0.06	2000	30



All schemes are perturbed using same pattern.
All variables perturbed using same pattern.
Pattern constant in height

Palmer et al, 2009.
ECMWF Tech Memo 598

Snapshot of optimal SPPT ‘e’ perturbation

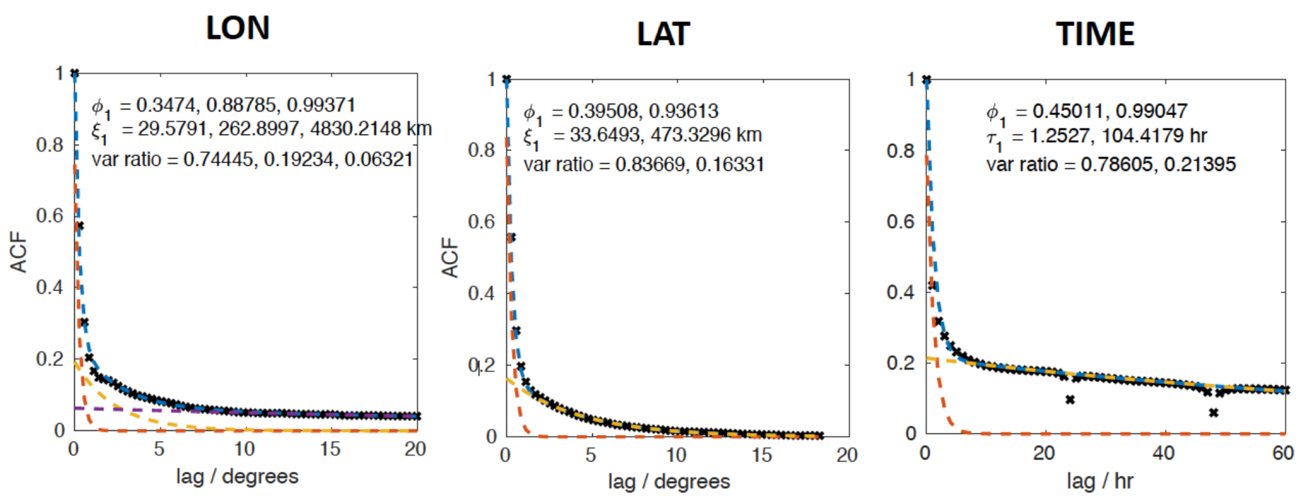


$$T - D - \sum_i P_i - b(P) = e \sum_i P_i$$

Calculate best fit ***e*** as a function of position for a single time step

$\Rightarrow$ Snapshot of optimal stochastic perturbation at a given time

Spatial and temporal correlation



- Model temporal and spatial correlation scales as arising from a sum over several scales
- Iteratively fit each scale, long to short

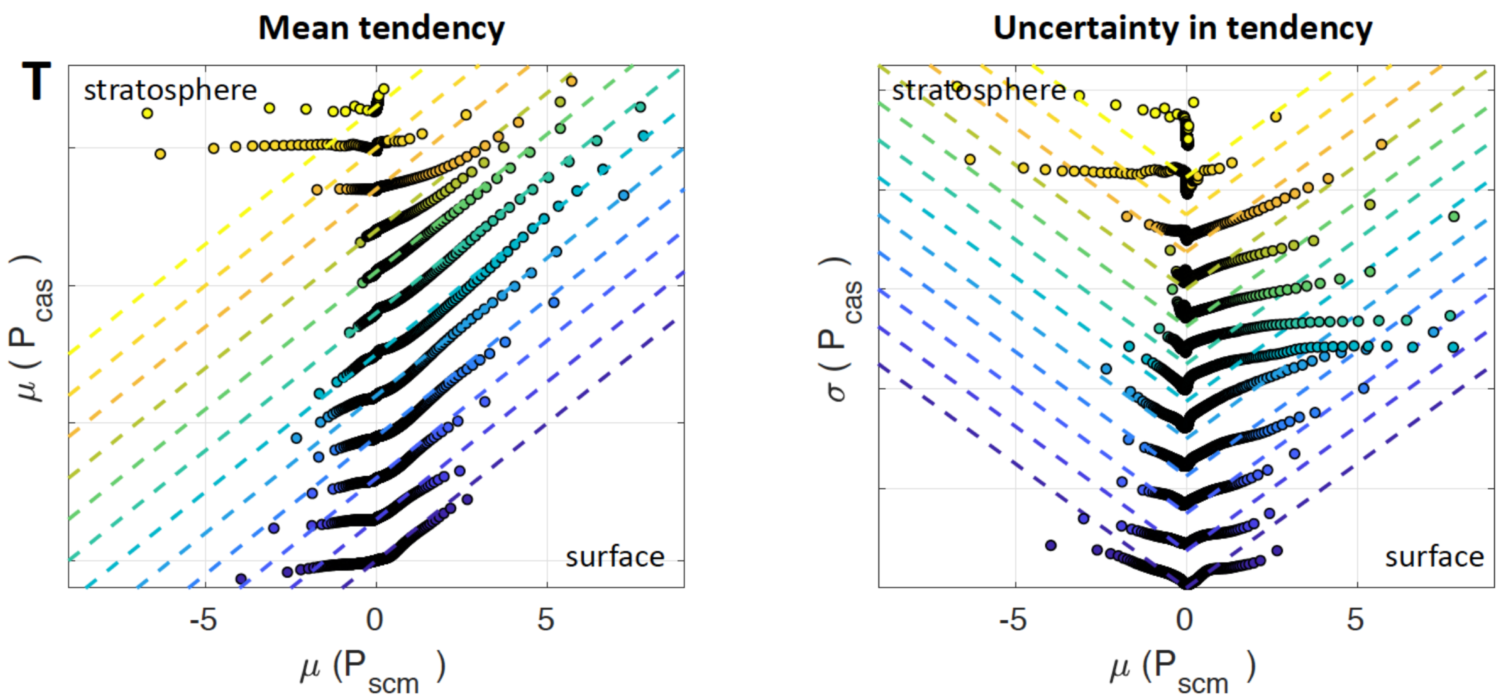
First scale: ~ grid scale
Second scale: ~ 200–400 km
Ocean provides spatial correlations

NEW:

σ	L (km)	τ
0.35	32	1 hr
0.17	370	4.5 d
0.10	(2000)	(30 d)

- + **skewness**?

T-tendency



Data grouped by level.

Dark blue: levels 91—87 (ground—995 hPa)

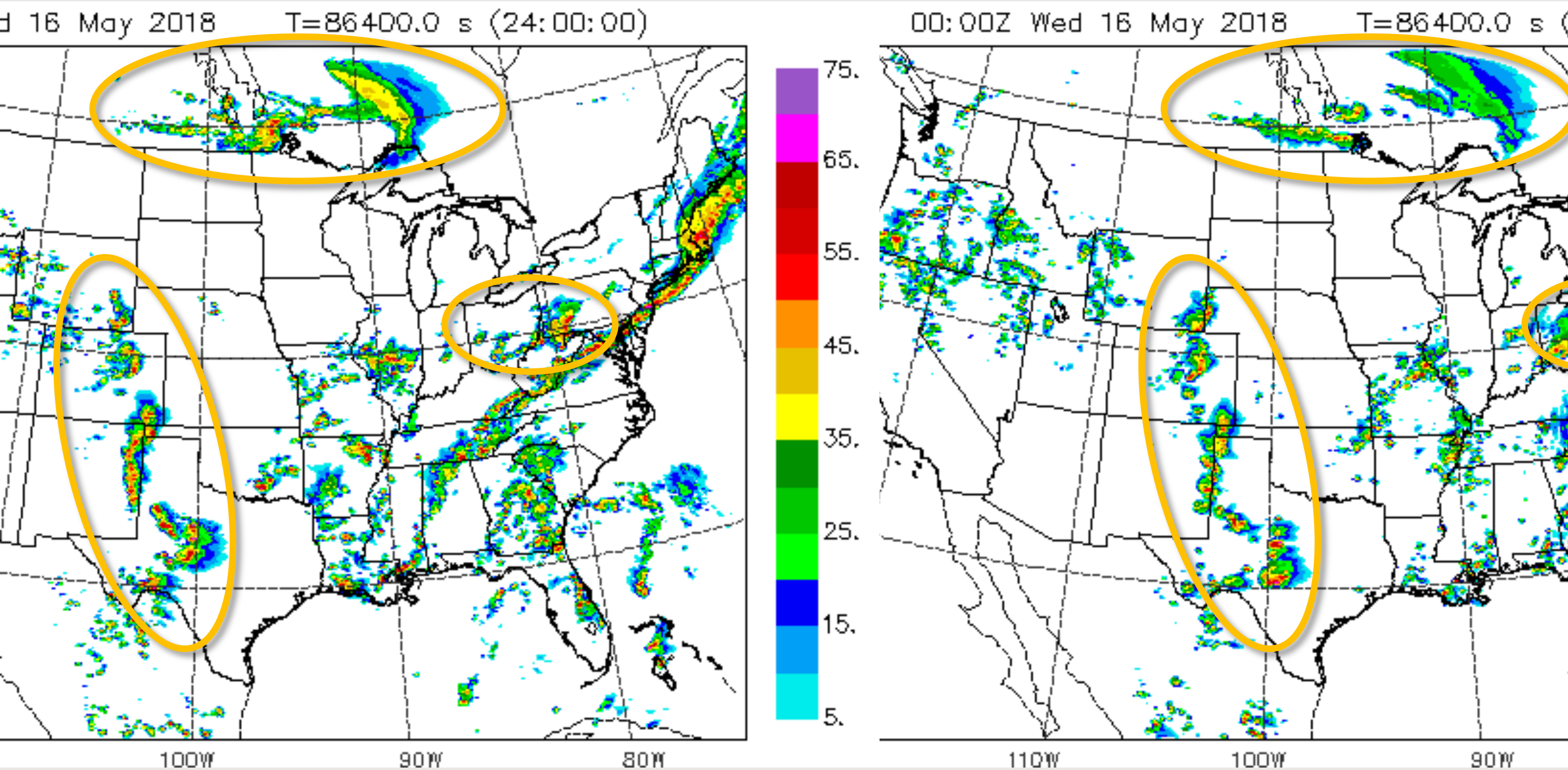
Yellow: levels 32—36 (86—60 hPa)

New 2018 HWT Example

18 Spring Experiment

Control

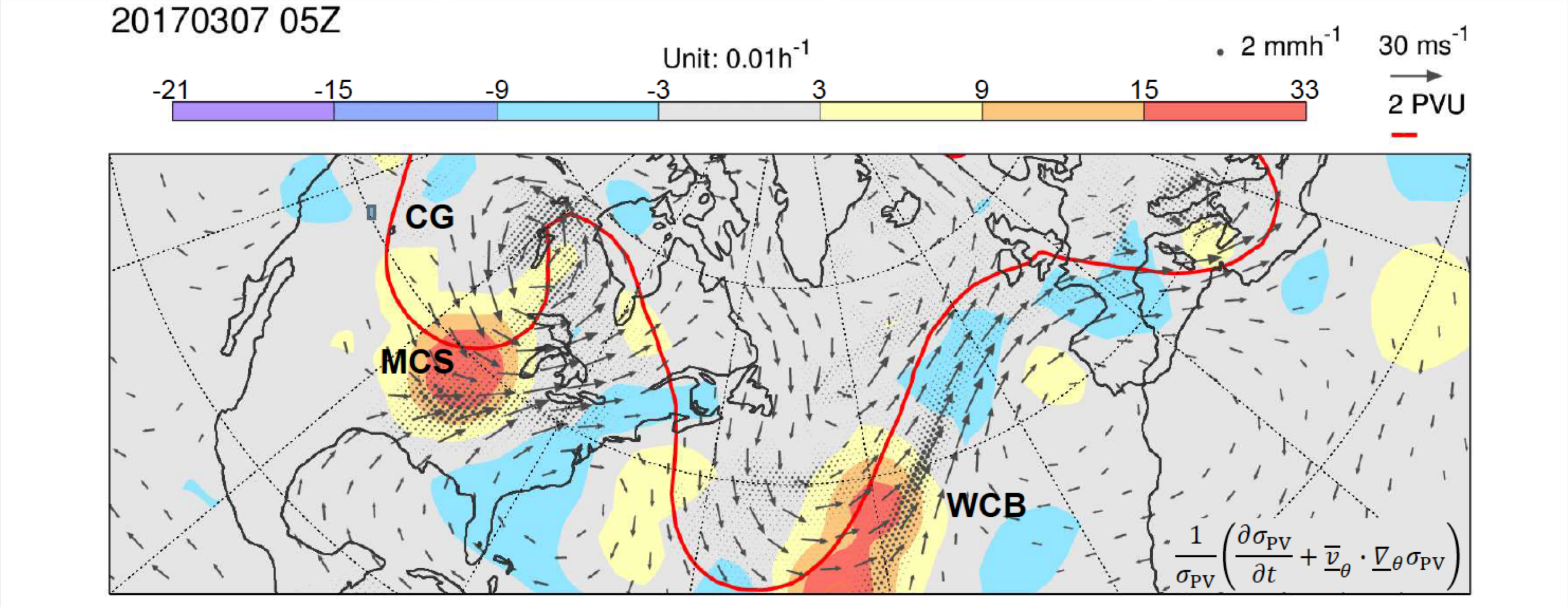
SPP_MP=7



"

Lagrangian" growth-rate (following EnsMn horizontal flow) for EDA

background $\sigma PV315$



PV_{315}=2 & $\underline{v}_{850}$ from control forecast, precipitation is ensemble-mean. 1d running-mean gives 12h-integrated growth rate with any diurnal cycle removed. T21 smoothed

Rodwell et al. 2018