



### Introduction to Data Assimilation,

Subgrid-Scale Parameterization and

Predictability

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# **Outline for Today**

### Stochastic Parameterization Schemes

- ECMWF Model
  - Stochastic Physics
  - Stochastic Backscatter
- Empirical Approach (Wilks model)





In climate models we decompose tendencies into dynamical and physical components

$$dx = f(x)_{Dyn}dt + f(x)_{Phy}dt$$

- Dynamical components from resolved equations of motion
- Physical components from parameterizations of unresolved physical processes





## ECMWF Stochastic Physics scheme

$$\tilde{f}(x)_{Phy} = (1 + r\eta)f(x)_{Phy}$$
  
 $\eta \in [-1, +1]; r \in [0,1]$  tapers the perturbations to zero  
near the surface & in the stratosphere

- Stochastically perturbed physics tendencies (SPPT) scheme
- Simulates uncertainty due to sub-grid parametrisations
- Developed by Buizza et al. (1999)
  - Improved in 2009





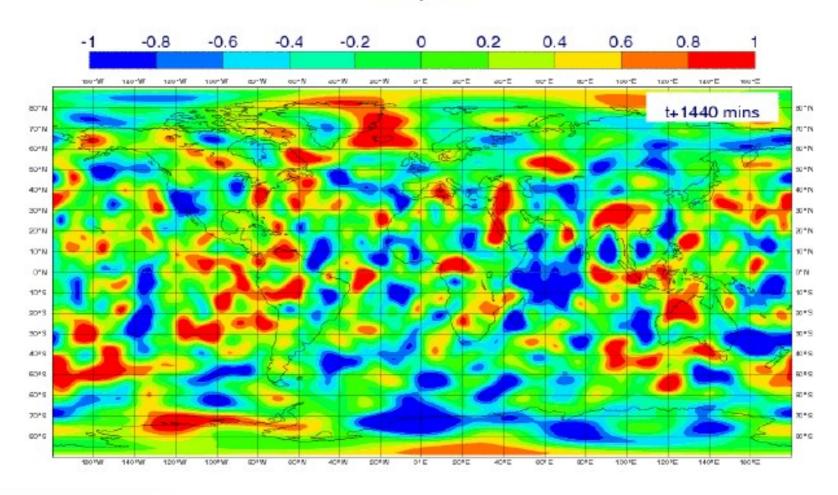
### **ECMWF** Stochastic Physics scheme:

### SPPT pattern

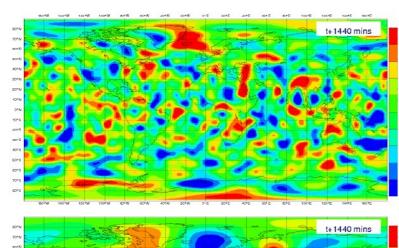
- 2D random pattern of spectral coefficients, r
  - Time-correlations: AR(1)
  - Space-correlations: Gaussian
- Applied at all model levels to preserve vertical structures



#### SPPT pattern

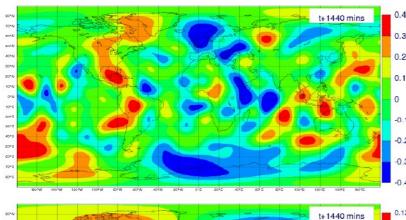




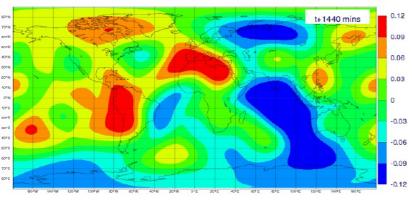


3 correlation scales:

 $\frac{1}{2}$  i) 6 hours, 500 km,  $\sigma = 0.52$ 



 $^{\circ}_{\circ}$ ii) 3 days, 1000 km,  $\sigma = 0.18$ 



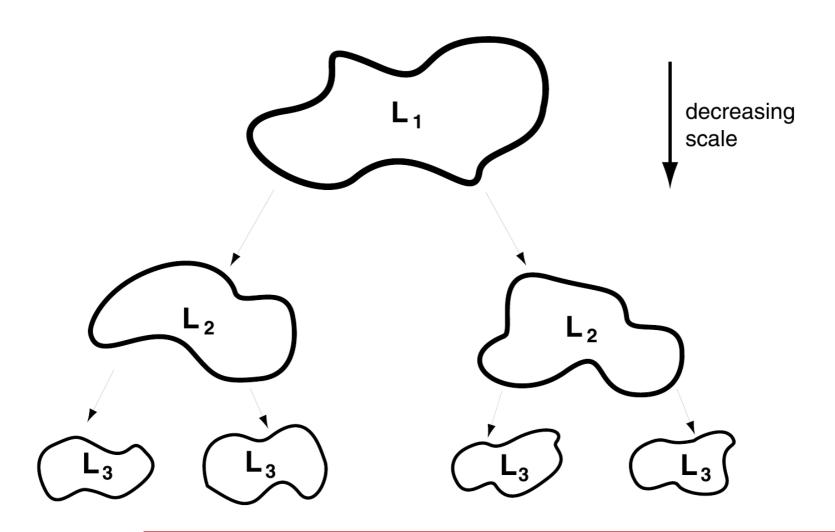
 $\sigma = 0.06$  iii) 30 days, 2000 km,  $\sigma = 0.06$ 





## **Energy Spectra**

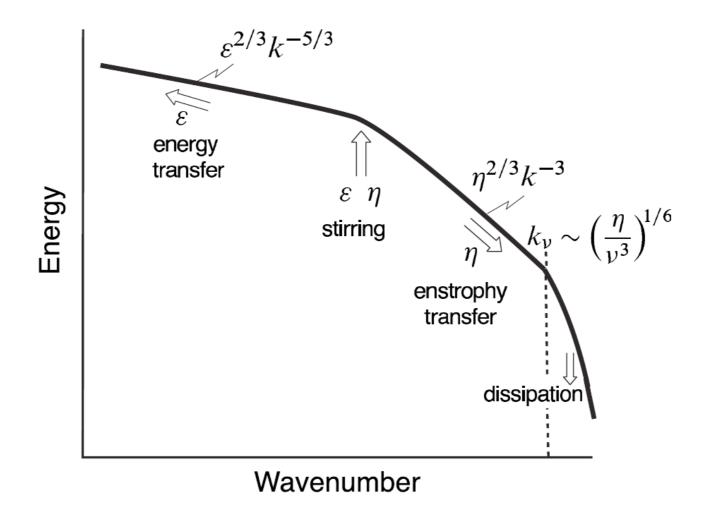
### Energy cascade





# **Energy Spectra**

#### Two Dimensional Turbulence



- Attempting to simulate a process otherwise absent from the model
  - upscale transfer of energy from sub-grid scales
- Represents backscatter of Kinetic Energy (KE) by adding perturbations to U and V via a forcing term to the streamfunction

$$F_{\varphi} = \left(\frac{b_R D_{\text{tot}}}{B_{\text{tot}}}\right)^{1/2} F^*$$



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#### where

- F\* is a 3D random pattern field,
- B<sub>tot</sub> is the mean KE input by F\* alone,
- D<sub>tot</sub> is an estimate of the total dissipation rate due to the model,
- $b_R$  is the backscatter ratio a scaling factor.





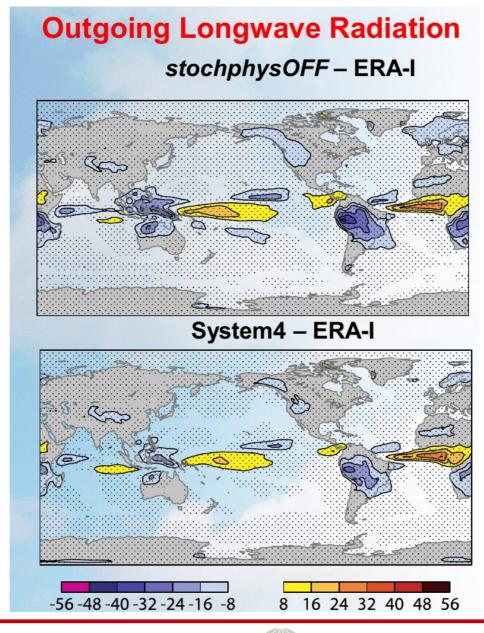
### 3D random pattern field F\*:

- First-order auto-regressive [AR(1)] process for evolving F\*
  - $F^*(t + \Delta t) = \phi F^*(t) + \rho \eta(t)$
- where  $\phi = \exp(-\Delta t \tau)$  controls the correlation over timestep  $\Delta t$ ;
- and spatial correlations (power law) for wavenumbers define ρ for random numbers η
- vertical space-(de)correlations: random phase shift of η between levels



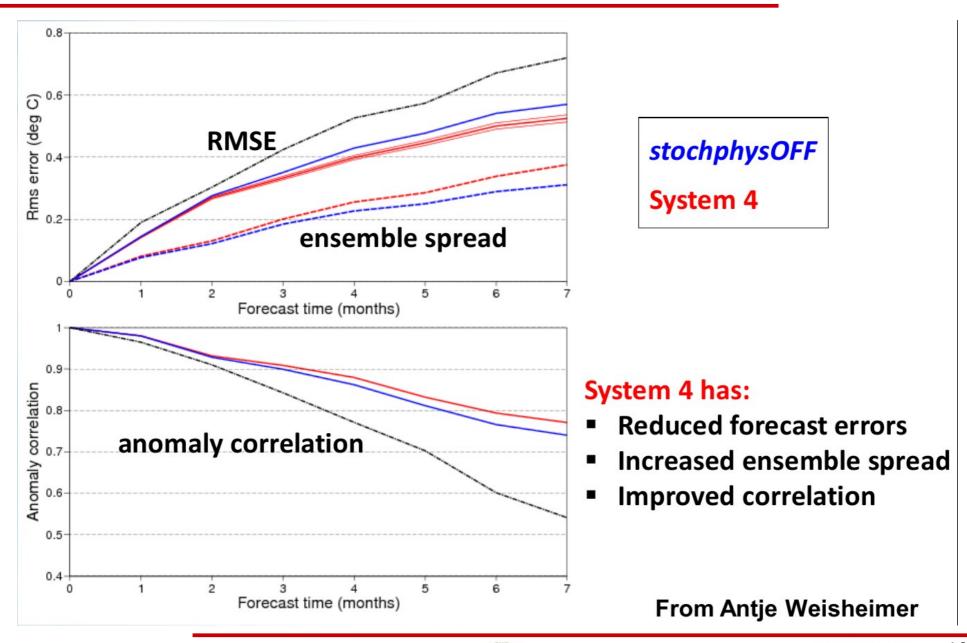
- Adding SPPT + SKEB perturbations:
  - increases ensemble "spread" (= ensemble standard deviation), i.e. ensemble members describe greater region of the parameter space
  - some reduced ensemble mean errors
- In the extra-tropics:
  - SPPT and SKEB each have a similar impact, i.e. perturbations are successfully adopted and evolved by the model
  - Experiments: perturbations in days 0-5 contribute most effect















#### 2-Level Lorenz-96 Model

$$\frac{\mathrm{d}X_k}{\mathrm{d}t} = -X_{k-1}(X_{k-2} - X_{k+1}) - X_k + F - \frac{hc}{b} \sum_{j=J(k-1)+1}^{kJ} Y_j; \quad k = 1, \dots, K$$
(1a)

$$\frac{\mathrm{d}Y_j}{\mathrm{d}t} = -cbY_{j+1}(Y_{j+2} - Y_{j-1}) - cY_j + \frac{hc}{b}X_{\mathrm{int}[(j-1)/J]+1}; \quad j = 1, \dots, JK. \quad (1b)$$

#### Reduced Lorenz-96 Model

$$\frac{\mathrm{d}X_k^*}{\mathrm{d}t} = -X_{k-1}^*(X_{k-2}^* - X_{k+1}^*) - X_k^* + F - g_U(X_k^*); \quad k = 1, \dots, K.$$

$$g_U(X_k) = b_0 + b_1 X_k + b_2 X_k^2 + b_3 X_k^3 + b_4 X_k^4 + e_k,$$



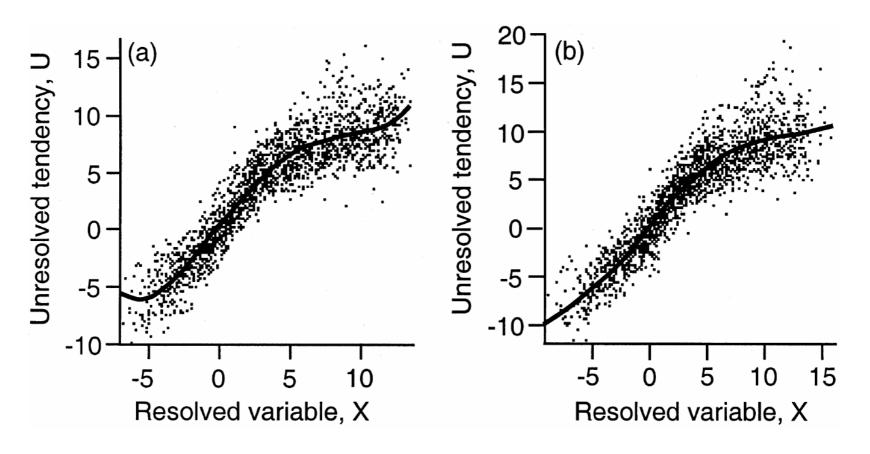


Figure 2. Scatterplots of the unresolved tendency U (Eq. (3)) as a function of the resolved variable X to which it applies, together with the regression functions constituting the deterministic part of the parametrizations  $g_U(X)$  (Table 1 and Eq. (4)), for forcings: (a) F = 18 and (b) F = 20.

TABLE 1. PARAMETRIZATION REGRESSION PARAMETERS AND DIAGNOSTICS

| $b_0$ | $b_1$ | $b_2$ | $b_3$              | $b_4$ | $s_e$ | $R^2$          |
|-------|-------|-------|--------------------|-------|-------|----------------|
| <br>  |       |       | -0.0130 $-0.00713$ |       |       | 87.6%<br>86.3% |

See text for details.



#### Reduced Lorenz-96 Model

$$\frac{\mathrm{d}X_k^*}{\mathrm{d}t} = -X_{k-1}^*(X_{k-2}^* - X_{k+1}^*) - X_k^* + F - g_U(X_k^*); \quad k = 1, \dots, K.$$

$$g_U(X_k) = b_0 + b_1 X_k + b_2 X_k^2 + b_3 X_k^3 + b_4 X_k^4 + e_k,$$

### AR(1) representation

$$e_k(t) = \phi e_k(t - \Delta) + \sigma_e(1 - \phi^2)^{1/2} z_k(t).$$



#### Reduced Lorenz-96 Model

$$\frac{\mathrm{d}X_k^*}{\mathrm{d}t} = -X_{k-1}^*(X_{k-2}^* - X_{k+1}^*) - X_k^* + F - g_U(X_k^*); \quad k = 1, \dots, K.$$

### Residuals:

$$U(t) = [-X_{k-1}(t)\{X_{k-2}(t) - X_{k+1}(t)\} - X_k(t) + F] - \left\{\frac{X_k(t + \Delta t) - X_k(t)}{\Delta t}\right\}$$



# Today's Exercise

Implement Wilks Scheme in Lorenz-96 Model Compare deterministic with stochastic scheme

K=8; J=32; F=18

h=1; c=10; b=10

 $\Delta t = 0.0001$ 

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|   | $b_0$ | $b_1$ | $b_2$ | $b_3$              | $b_4$ | $s_e$ | $R^2$          |
|---|-------|-------|-------|--------------------|-------|-------|----------------|
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$$\sigma_{\rm e} = s_{\rm e} \; ; \; \Phi = 0.984$$



