

# Introduction to Data Assimilation, Subgrid-Scale Parameterization and Predictability

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# Outline

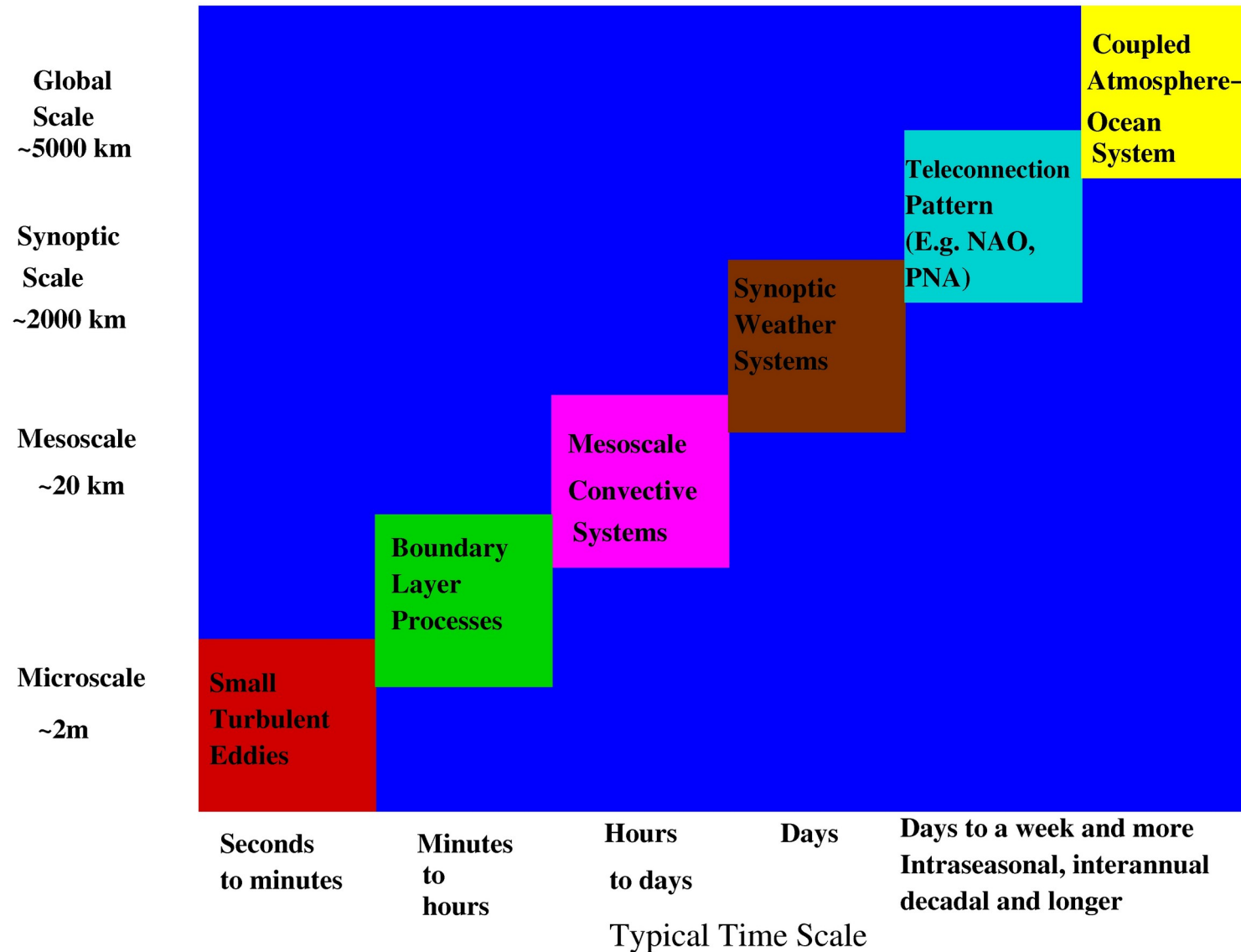
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- Dimension reduction
- Stochastic climate models

# Time Scales in the Climate System

Typical Sizes

Time and Space Scales in the Climate System



# Dimension Reduction

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# Dimension Reduction

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1) Simplification of the equations of motion via scale analysis:

Primitive Equations

→ Quasi-geostrophic equations

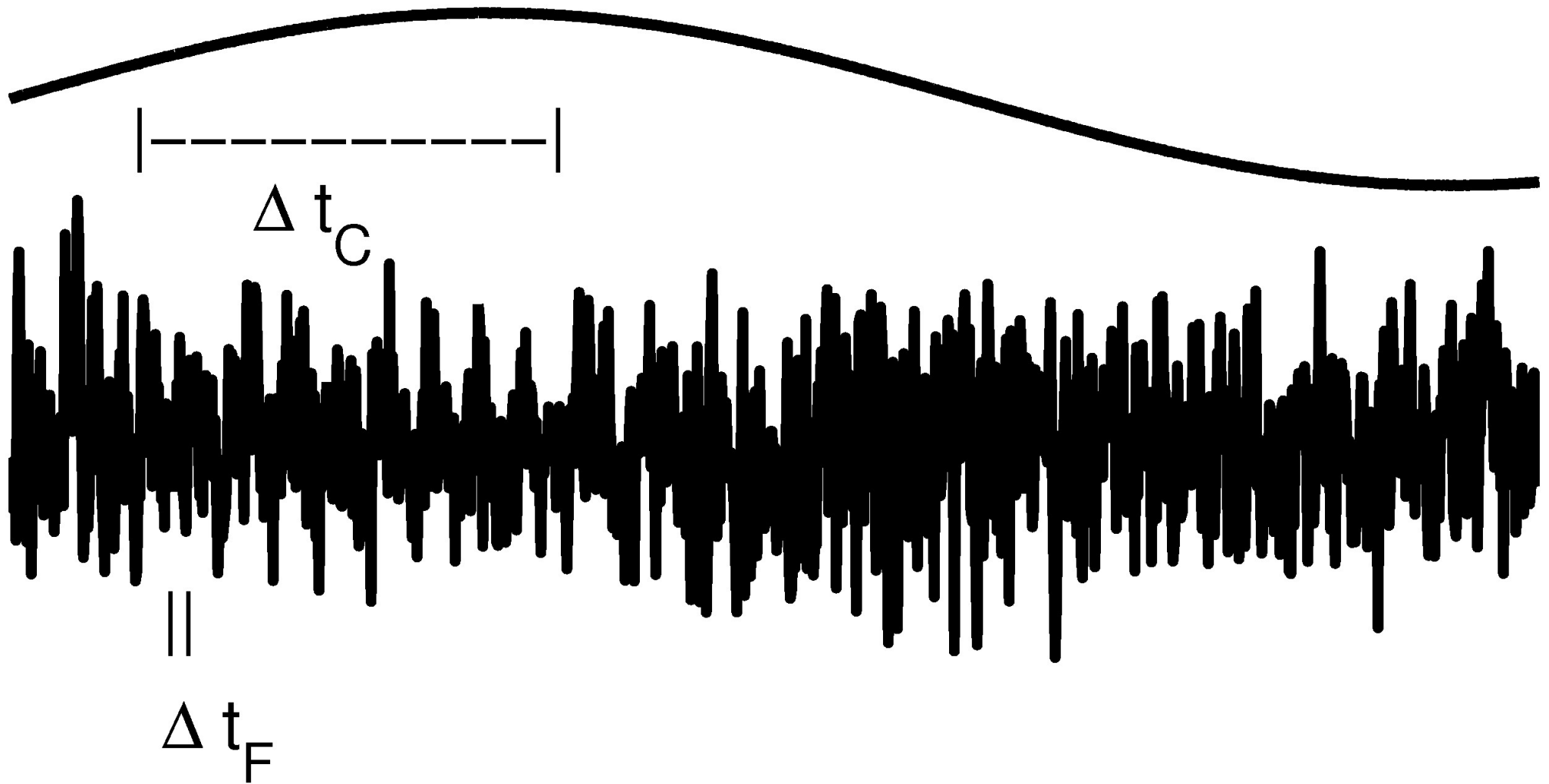
→ Barotropic equations

→ ...

2) Adiabatic elimination of fast modes

# Time Scale Separation

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# Dimension Reduction

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$$dx = f(x, y) dt$$

$$dy = \frac{1}{\epsilon} g(x, y) dt + \frac{1}{\sqrt{\epsilon}} h(x, y) dW$$

$\epsilon$ : Measure of time scale separation

# Dimension Reduction

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$$dx = f(x, y) dt$$

$$dy = \frac{1}{\epsilon} g(x, y) dt + \frac{1}{\sqrt{\epsilon}} h(x, y) dW$$

$\epsilon$ : Measure of time scale separation

$$\Rightarrow dx = \tilde{f}(x) dt + \tilde{g}(x) dW$$



# Example

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$$dx = ax \, dt + by \, dt$$

$$dy = -\frac{1}{\epsilon} cx \, dt + \frac{1}{\sqrt{\epsilon}} k \, dW$$

# Example

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$$dx = ax \, dt + by \, dt$$

$$dy = -\frac{1}{\epsilon} cx \, dt + \frac{1}{\sqrt{\epsilon}} k \, dW$$

Solve equation for  $y(t)$ :

$$y(t) = y(0) e^{\frac{-ct}{\epsilon}} + \frac{1}{\sqrt{\epsilon}} \int_0^t e^{\frac{-c(t-s)}{\epsilon}} k \, dW$$

# Example

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$$dx = ax \, dt + b \left[ y(0) e^{\frac{-ct}{\epsilon}} + \frac{k}{\sqrt{\epsilon}} \int_0^t e^{\frac{-c(t-s)}{\epsilon}} dW \right]$$

Time scale separation:  $\epsilon \rightarrow 0$

$$y(0) e^{\frac{-ct}{\epsilon}} \rightarrow 0 \text{ for } \epsilon \rightarrow 0$$

$$\frac{k}{\sqrt{\epsilon}} \int_0^t e^{\frac{-c(t-s)}{\epsilon}} dW \rightarrow \frac{k}{c} dW \text{ for } \epsilon \rightarrow 0$$

# Example

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Effective model:

$$dx = ax \, dt + \frac{bk}{c} dW$$

# Stochastic Climate Modeling

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$$d \vec{z} = F dt + L \vec{z} dt + B(\vec{z}, \vec{z}) dt$$

$$\vec{z} = (\vec{x}, \vec{y})$$

Slow modes

Fast modes

# Stochastic Climate Modeling

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$$d \vec{x} = F_1 dt + L_{11} \vec{x} dt + L_{12} \vec{y} dt + B_{11}^1(\vec{x}, \vec{x}) dt + B_{12}^1(\vec{x}, \vec{y}) dt + B_{22}^1(\vec{y}, \vec{y}) dt$$

$$d \vec{y} = F_2 dt + L_{21} \vec{x} dt + L_{22} \vec{y} dt + B_{11}^2(\vec{x}, \vec{x}) dt + B_{12}^2(\vec{x}, \vec{y}) dt + B_{22}^2(\vec{y}, \vec{y}) dt$$

Stochastic Modeling Assumption:

$$B_{22}^2(\vec{y}, \vec{y}) \approx -\frac{\Gamma}{\epsilon} \vec{y} + \frac{\sigma}{\sqrt{\epsilon}} d \vec{W}$$

Stochastic Process  
Ornstein-Uhlenbeck Process

# Stochastic Mode Reduction

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$$d x_1 = \frac{A_1}{\epsilon} x_2 y dt$$

$$d x_2 = \frac{A_2}{\epsilon} x_1 y dt$$

$$d y = \frac{A_3}{\epsilon} x_1 x_2 dt - \frac{\gamma}{\epsilon^2} y dt + \frac{\sigma}{\epsilon} dW$$

Energy conservation:  $A_1 + A_2 + A_3 = 0$

# Stochastic Mode Reduction

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$$y(t) = y(0) e^{-\frac{\gamma t}{\epsilon^2}} + \frac{A_3}{\epsilon} \int_0^t e^{-\frac{\gamma(t-s)}{\epsilon^2}} x_1 x_2 ds + g(t)$$

$$g(t) = \frac{\sigma}{\epsilon} \int_0^t e^{-\frac{\gamma(t-s)}{\epsilon^2}} dW$$

$$\epsilon \rightarrow 0 \quad y(0) e^{-\frac{\gamma t}{\epsilon^2}} \rightarrow 0$$

$$\frac{A_3}{\epsilon} \int_0^t e^{-\frac{\gamma(t-s)}{\epsilon^2}} x_1 x_2 ds \rightarrow \frac{A_3}{\gamma} x_1(t) x_2(t)$$

$$\frac{1}{\epsilon} g(t) \rightarrow \frac{\sigma}{\gamma} dW$$



# Stochastic Mode Reduction

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$$d x_1 = \frac{A_1 A_3}{\gamma} x_1 x_2^2 dt + \frac{\sigma}{\gamma} A_1 x_2 \circ dW$$

Stratonovich

$$d x_2 = \frac{A_2 A_3}{\gamma} x_1^2 x_2 dt + \frac{\sigma}{\gamma} A_2 x_1 \circ dW$$

$$d x_1 = \frac{A_1}{\gamma} \left[ A_3 x_2^2 + A_2 \frac{\sigma^2}{2\gamma} \right] x_1 dt + \frac{\sigma}{\gamma} A_1 x_2 dW$$

$$d x_2 = \frac{A_2}{\gamma} \left[ A_3 x_1^2 + A_1 \frac{\sigma^2}{2\gamma} \right] x_2 dt + \frac{\sigma}{\gamma} A_2 x_1 dW$$

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# Reduced Order Models

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## 3 level QG Model (Marshall and Molteni 1993)

$$\frac{\partial q_1}{\partial t} = -J(\psi_1, q_1) - D_1(\psi_1, \psi_2) + S_1$$

$$\frac{\partial q_2}{\partial t} = -J(\psi_2, q_2) - D_2(\psi_1, \psi_2, \psi_3) + S_2$$

$$\frac{\partial q_3}{\partial t} = -J(\psi_3, q_3) - D_3(\psi_2, \psi_3) + S_3,$$

$$q_1 = \nabla^2 \psi_1 - R_1^{-2}(\psi_1 - \psi_2) + f$$

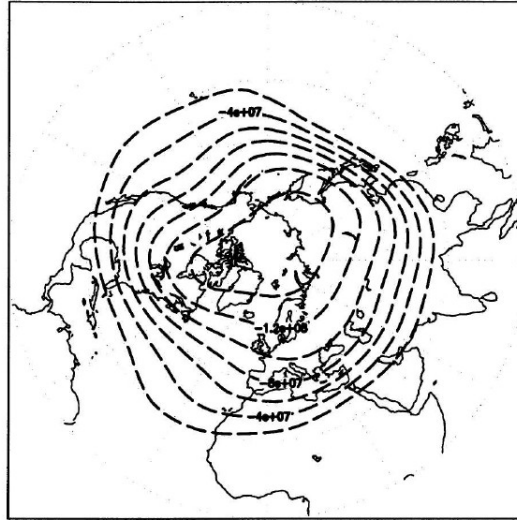
$$q_2 = \nabla^2 \psi_2 + R_1^{-2}(\psi_1 - \psi_2) - R_2^{-2}(\psi_2 - \psi_3) + f$$

$$q_3 = \nabla^2 \psi_3 + R_2^{-2}(\psi_2 - \psi_3) + f \left( 1 + \frac{h}{H_0} \right),$$

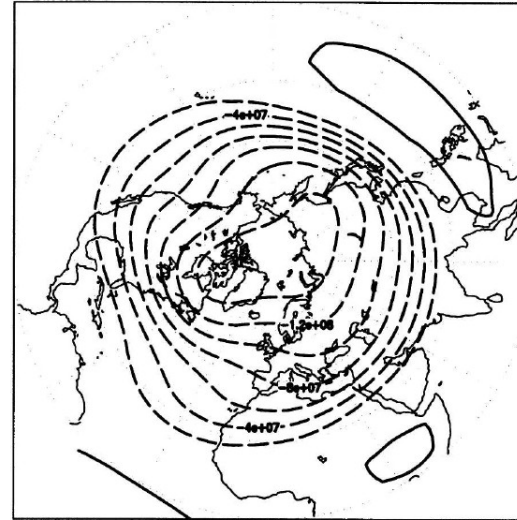
# Reduced Order Models

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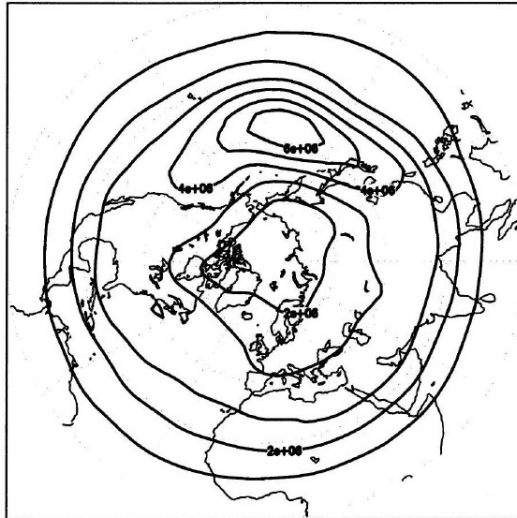
a) QGM



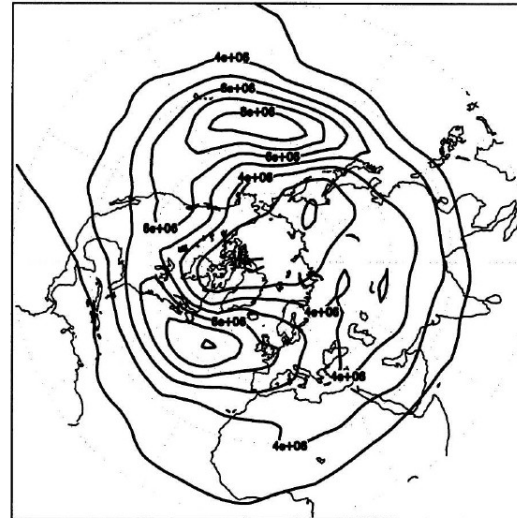
ECMWF



b) QGM

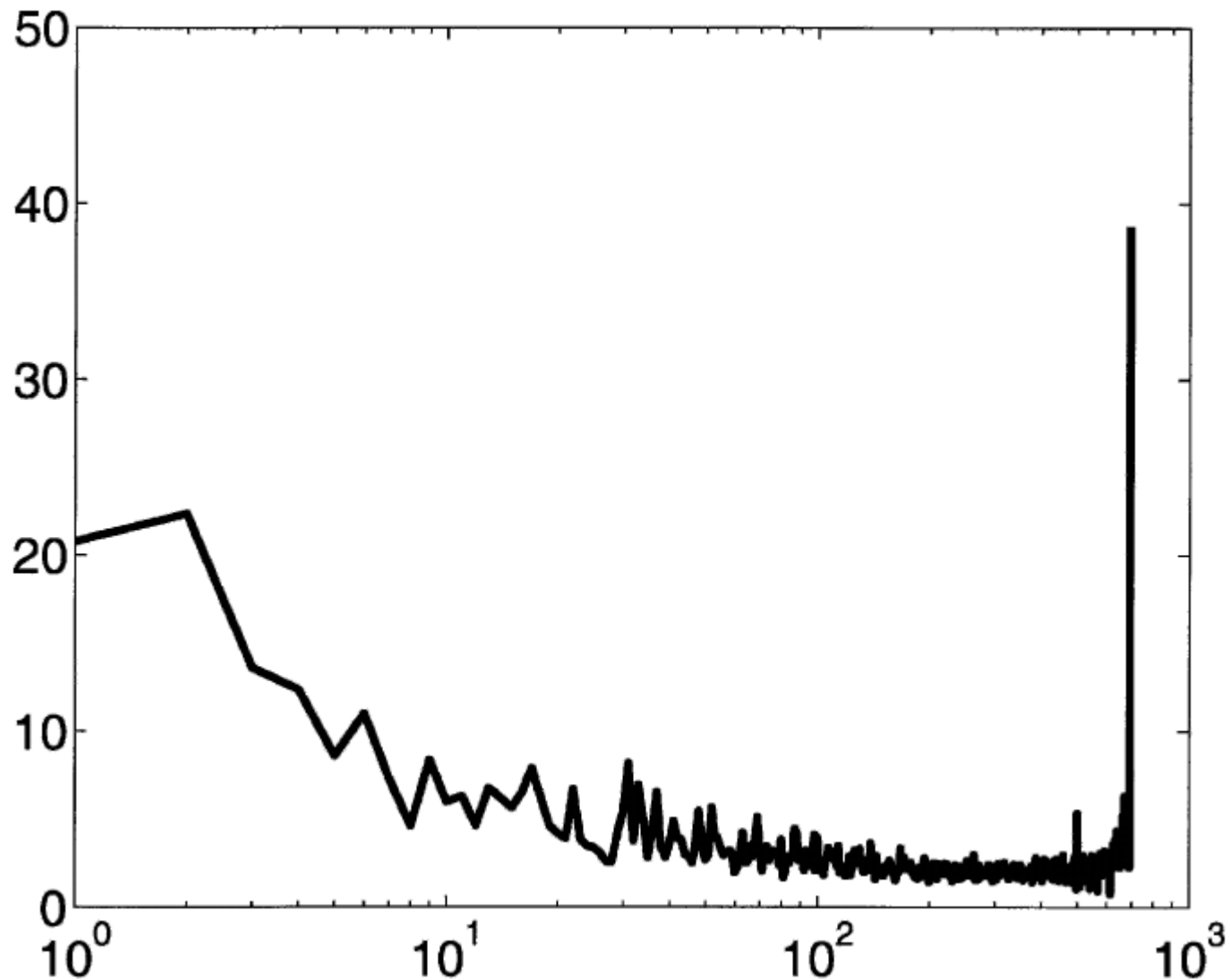


ECMWF



# Reduced Order Models

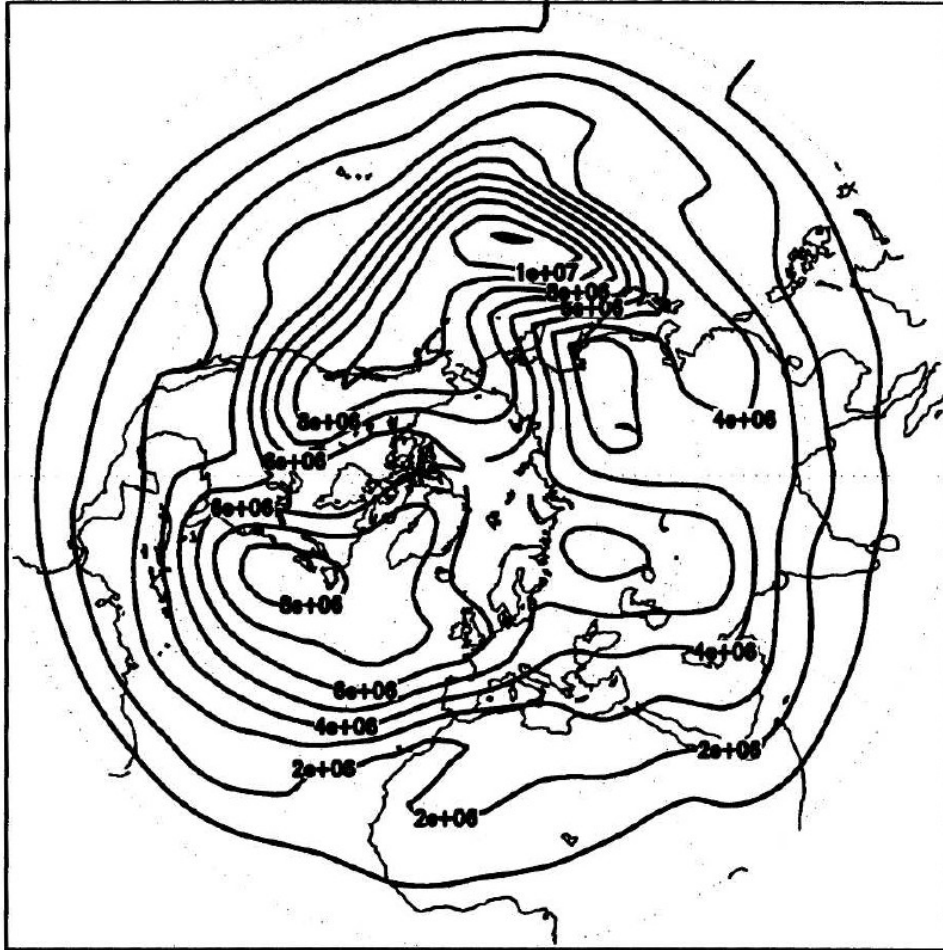
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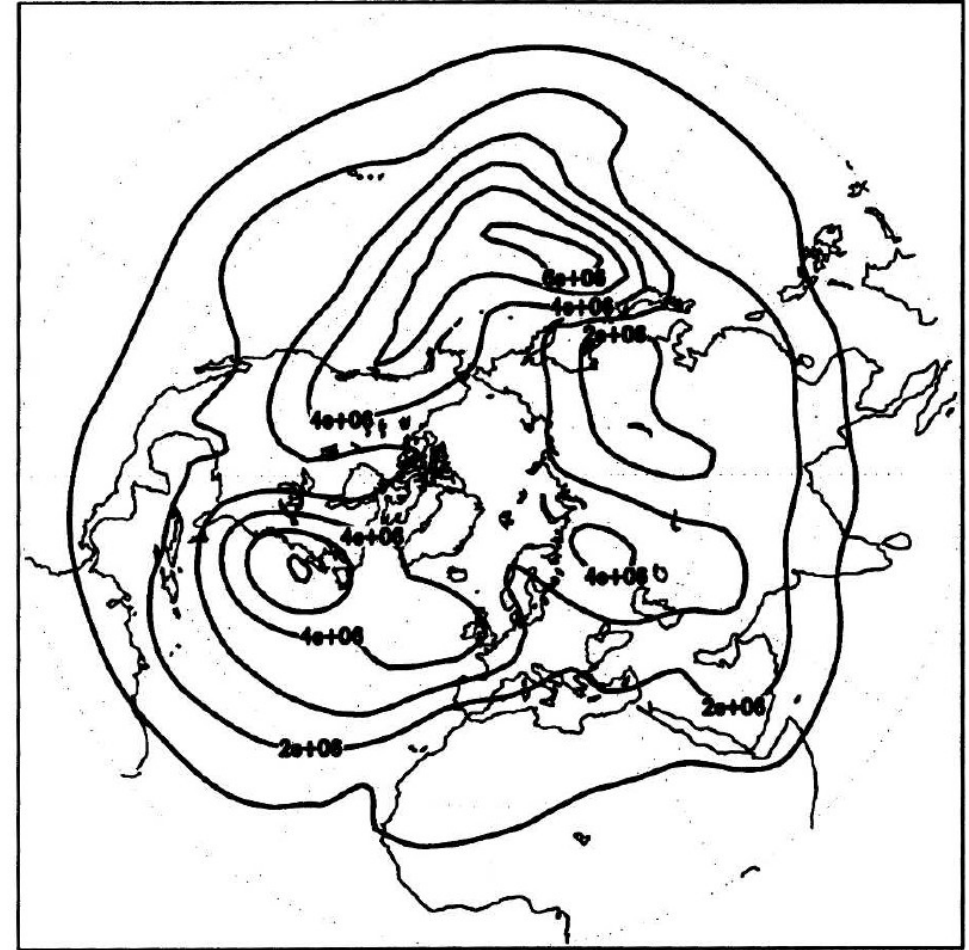
# Reduced Order Models

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a) QG-Model



b) S-MTV





# Reduced Order Models

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a) QG-Model

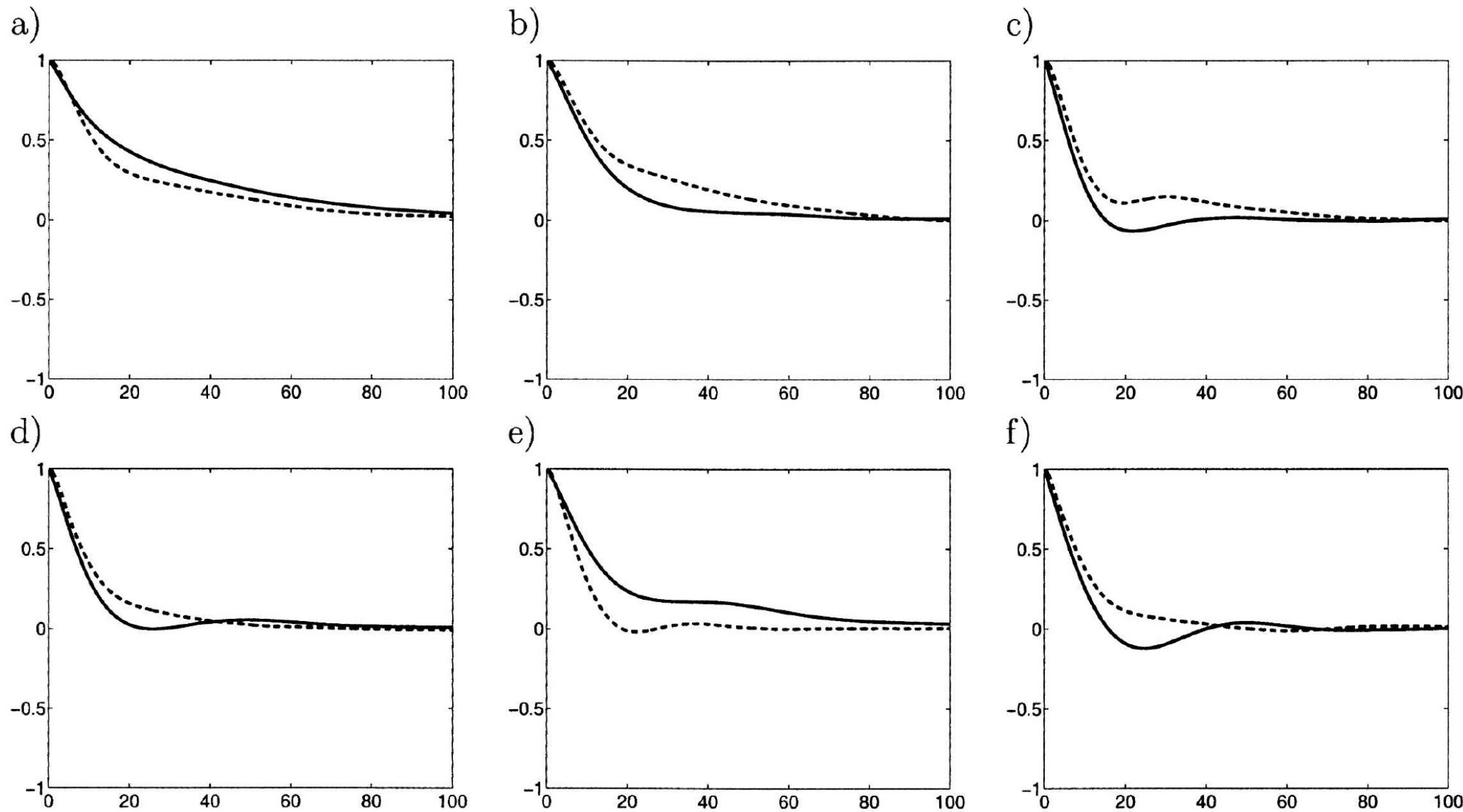


b) S-MTV



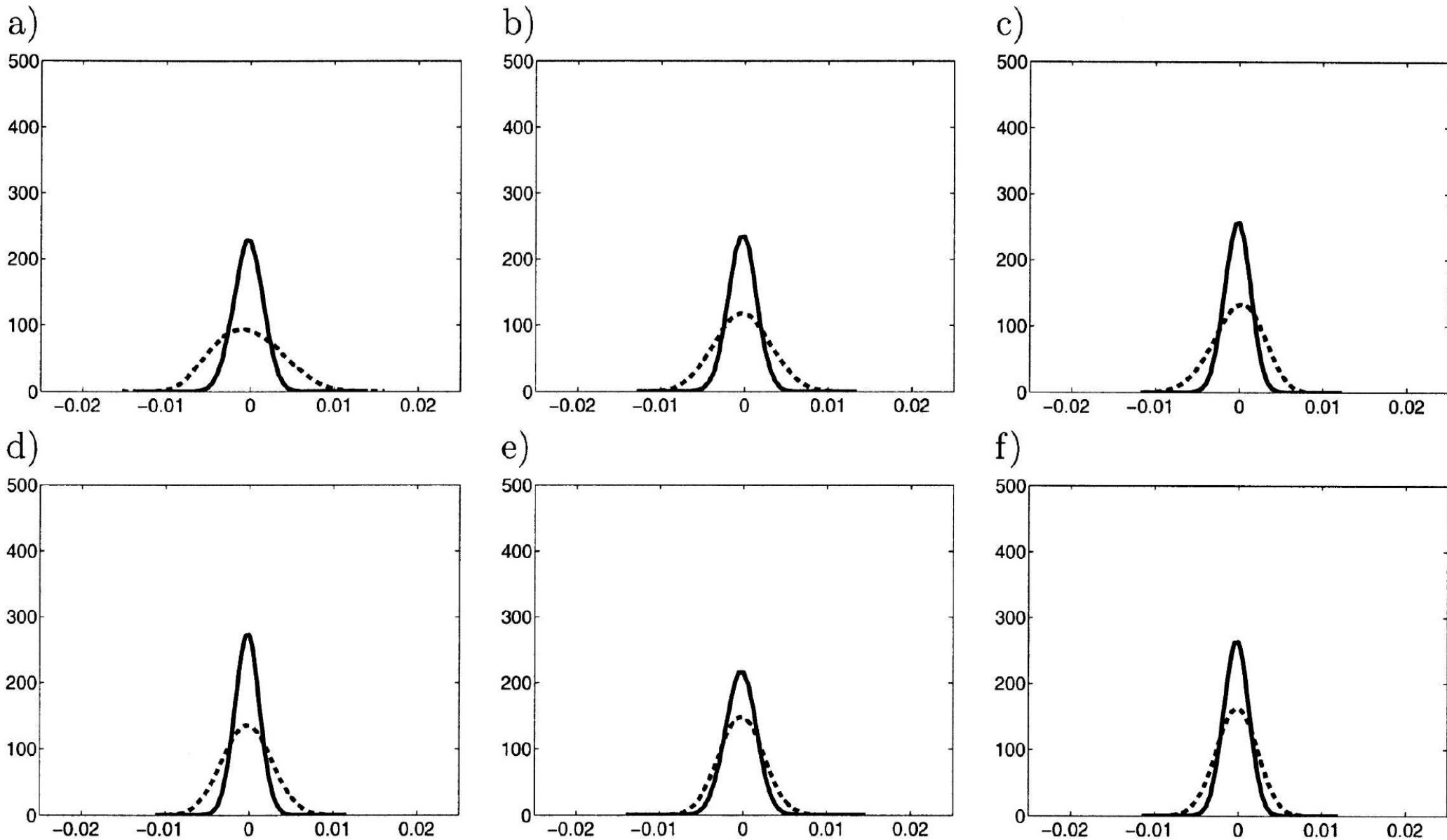
# Reduced Order Models

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# Reduced Order Models

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# Exercise

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$$d x_1 = \frac{A_1}{\epsilon} x_2 y dt$$

$$d x_2 = \frac{A_2}{\epsilon} x_1 y dt$$

$$d y = \frac{A_3}{\epsilon} x_1 x_2 dt - \frac{\gamma}{\epsilon^2} y dt + \frac{\sigma}{\epsilon} dW$$

$$A_1 = 0.5 \quad \gamma = 1$$

$$A_2 = 0.5 \quad \sigma = 1$$

$$A_3 = -1 \quad \epsilon = 0.1$$

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$$d x_1 = \frac{A_1}{\gamma} \left[ A_3 x_2^2 + A_2 \frac{\sigma^2}{2 \gamma} \right] x_1 dt + \frac{\sigma}{\gamma} A_1 x_2 dW$$

$$d x_2 = \frac{A_2}{\gamma} \left[ A_3 x_1^2 + A_1 \frac{\sigma^2}{2 \gamma} \right] x_2 dt + \frac{\sigma}{\gamma} A_2 x_1 dW$$

Use 4-th order  
Runge-Kutta for  
deterministic part  
and Euler forward  
for stochastic part

Compute Autocorrelation function  
and Probability Density Function  
for comparison

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