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Stochastic Convection Parameterizations

João Teixeira, Carolyn Reynolds (*), Kay Suselj & Georgios Matheou

Jet Propulsion Laboratory
California Institute of Technology
Pasadena, California

(*) Naval Research Laboratory
Monterey, California

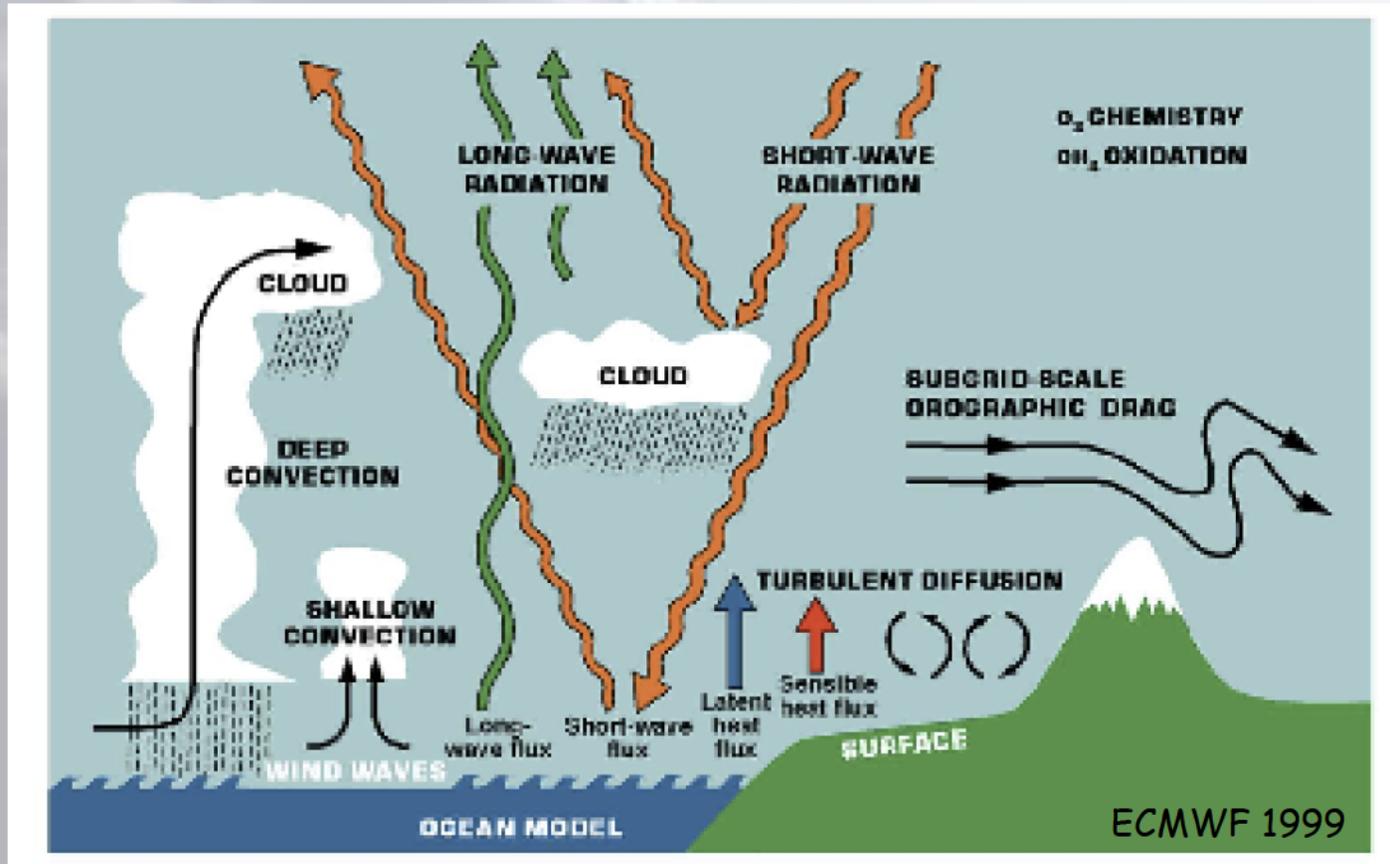


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Small-scale Processes in Atmospheric Models

It is not a simple computational fluid dynamics problem ...



... We need to represent radiation, clouds, turbulence, convection, gravity waves, surface interaction.



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Physical Parameterizations

1) Small-scale fluid dynamics:

- Turbulence and Convection (dry and moist)
 - Gravity waves
 - Clouds (phase transition / latent heat)
- Would be mostly solved if NWP models had resolutions of around 1-10m

2) Small-scale physical processes (NOT just fluid dynamics):

- Radiation Interaction
 - Cloud and aerosol microphysics
- Some of these equations are well-known but others not at all

3) Surface interaction can be (1) and (2) but also includes additional complexity (vegetation, biogeochemistry)



Physical Parameterizations: Example of radiation vs turbulence/convection

Turbulence and convection parameterization:

$$\frac{\partial \phi}{\partial t} = -\frac{\partial}{\partial z}(w\phi) \quad \Rightarrow \quad \text{Reynolds decomposition and averaging} \quad \Rightarrow \quad \frac{\partial \phi}{\partial t} = -\frac{\partial}{\partial z}(\overline{w\phi}) - \frac{\partial}{\partial z}(\overline{w'\phi'})$$

needs to be parameterized
due to non-linearity $w\Phi$



Radiation parameterization:

Theory leads to

$$C_p \frac{\partial T}{\partial t} = -\frac{\partial}{\partial z} [F_R(T, q, l)]$$

But models have

$$C_p \frac{\partial \bar{T}}{\partial t} = -\frac{\partial}{\partial z} [F_R(\bar{T}, \bar{q}, \bar{l})]$$

This is incomplete



Complex non-linearities



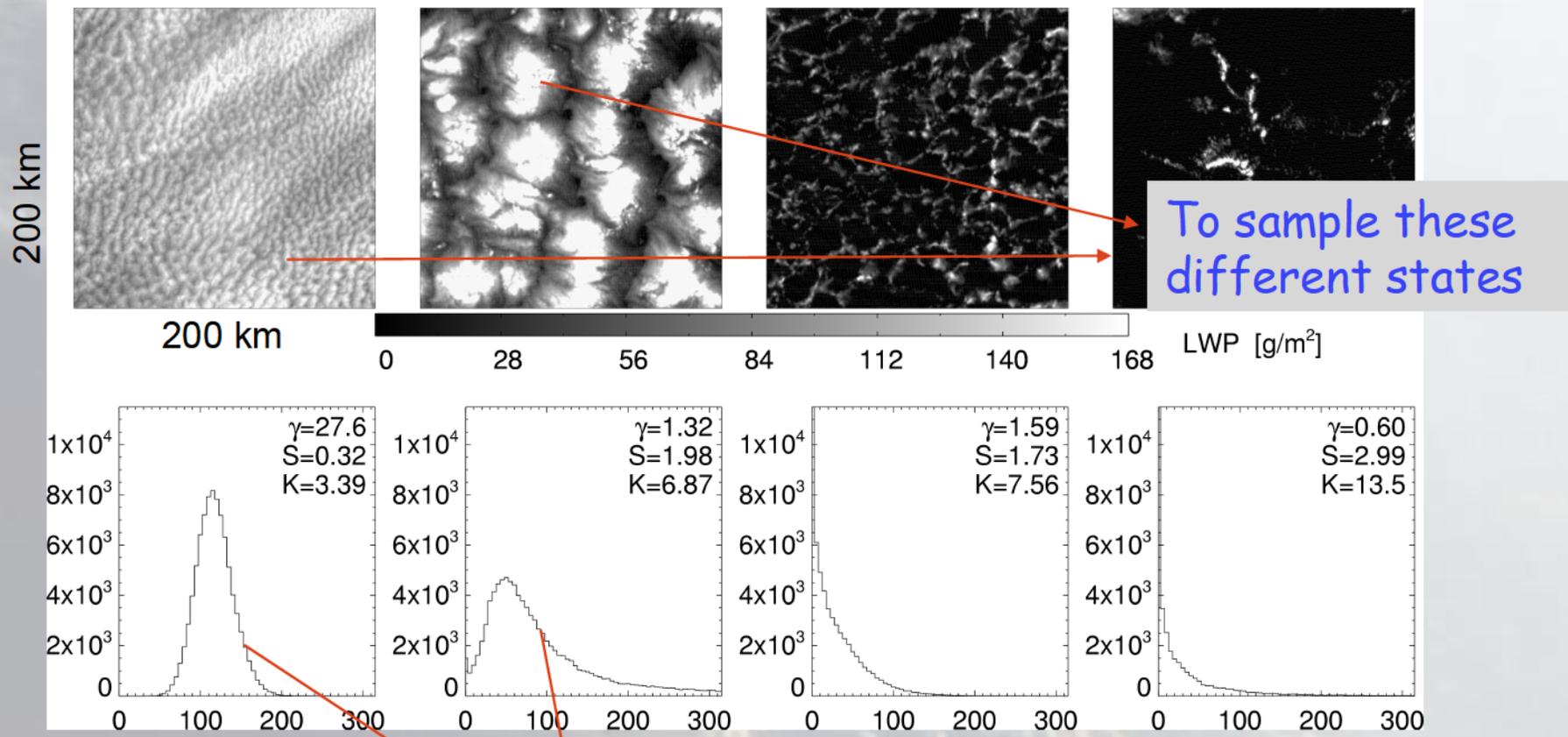
Stochastic approach





Need for stochastic approaches

Non-linearities in cloud-radiation interaction, cloud microphysics are too complex -> need stochastic approaches



We need to sample (Monte Carlo) these PDFs



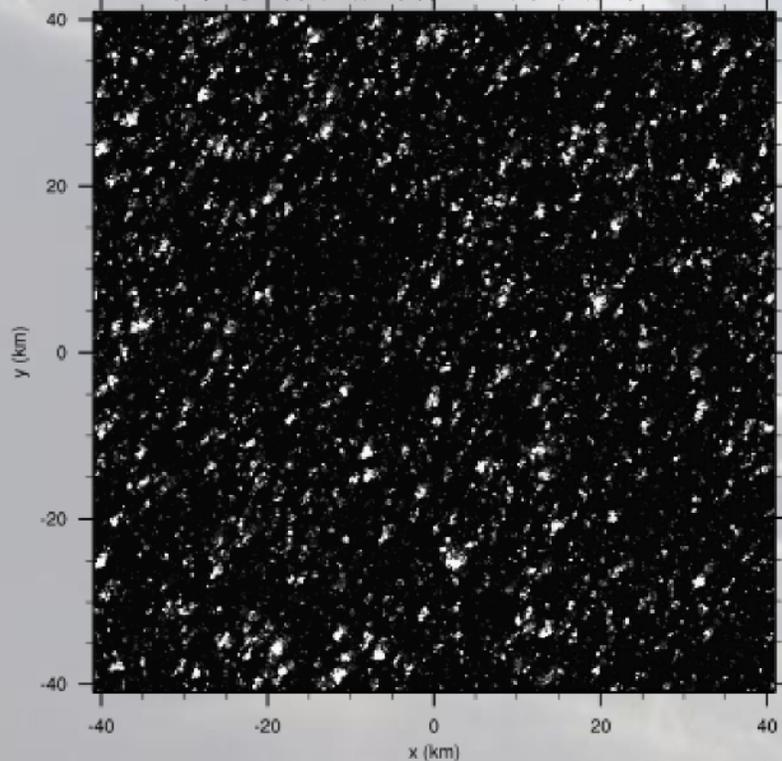
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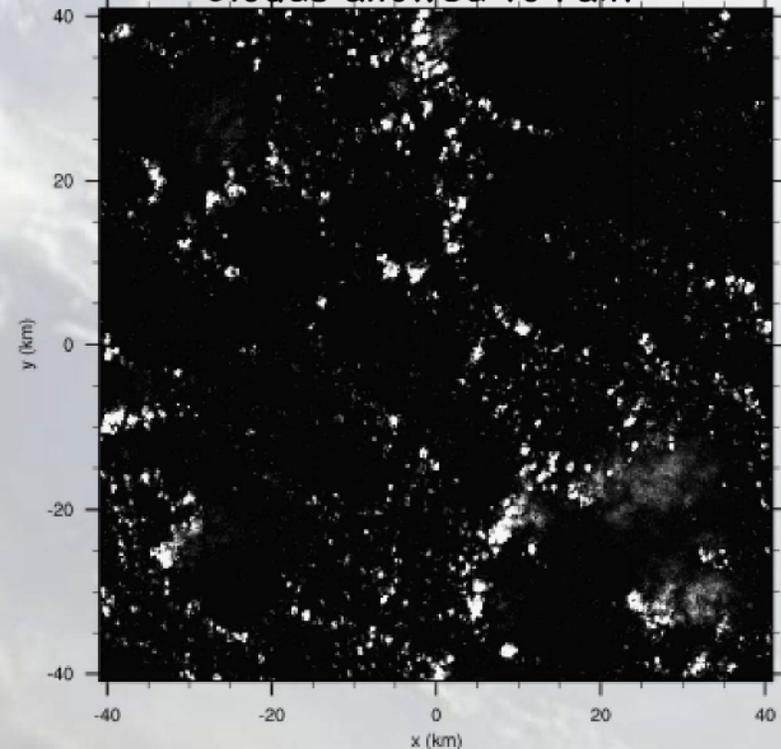
Large-Eddy Simulation (LES) models

- High-resolutions ($\sim 10\text{-}50\text{m}$) in all 3 dimensions
- Resolutions good enough to represent key dynamics in convection
- Closures still needed for scales $< 10\text{m}$ (but simpler to do)

Clouds not allowed to rain



Clouds allowed to rain



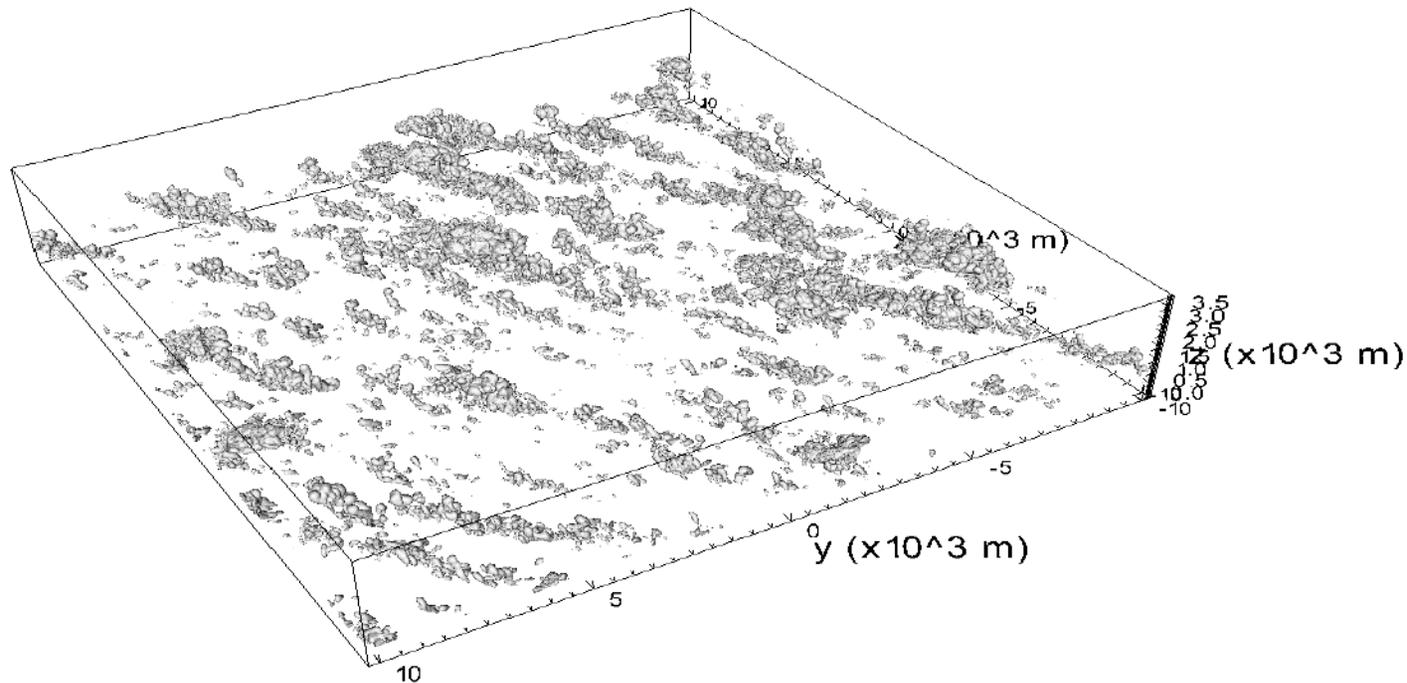
Matheou et al., MWR, 2011



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Moist convection

Representing moist convection with stochastic plumes leads to more realistic results



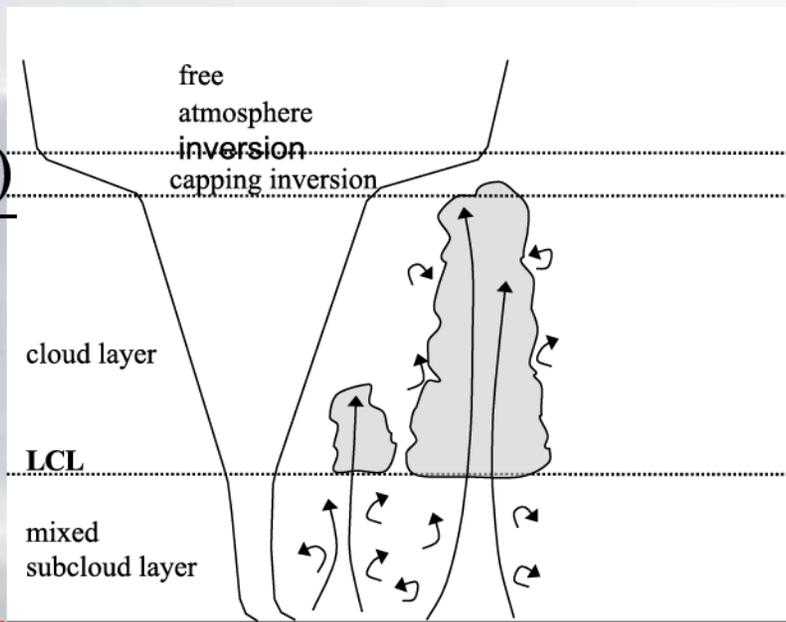
LES provides detailed statistics about cloud structure



Mass Flux Model for Cumulus Mixing

$$\left(\frac{\partial \bar{\phi}}{\partial t} \right)_{conv} = - \frac{\overline{\partial w' \phi'}}{\partial z} \approx - \frac{\partial M(\phi_u - \bar{\phi})}{\partial z}$$

Originally proposed by Arakawa 1969, Betts 1973



$$\frac{\partial \phi_u}{\partial z} = -\varepsilon(\phi_u - \bar{\phi}) \text{ for } \phi \in \{\theta_1, q_t\}$$

$$M = \sigma_u w_u$$

$$\frac{1}{2} \frac{\partial w_u^2}{\partial z} = -b\varepsilon w_u^2 + a \frac{g}{\theta_0} (\theta_{v,u} - \bar{\theta}_v)$$

Lateral entrainment rate: $\varepsilon = \frac{1}{w_u \tau} \approx \frac{1}{h_c}$

Constant τ : Neggers et al 01; Cheinet and Teixeira, 03.

Constant h : Siebesma 97

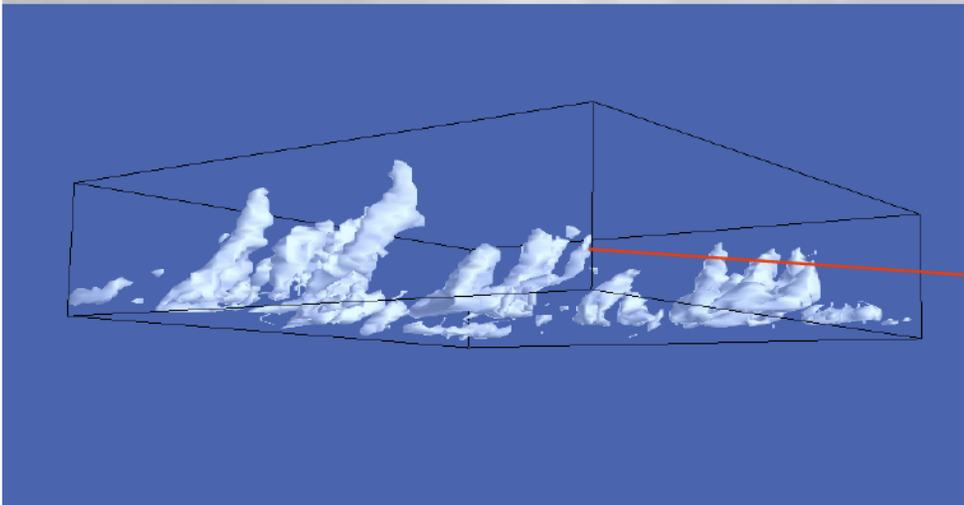
σ_u is the u-draft/core area fraction - not to be confused with cloud fraction



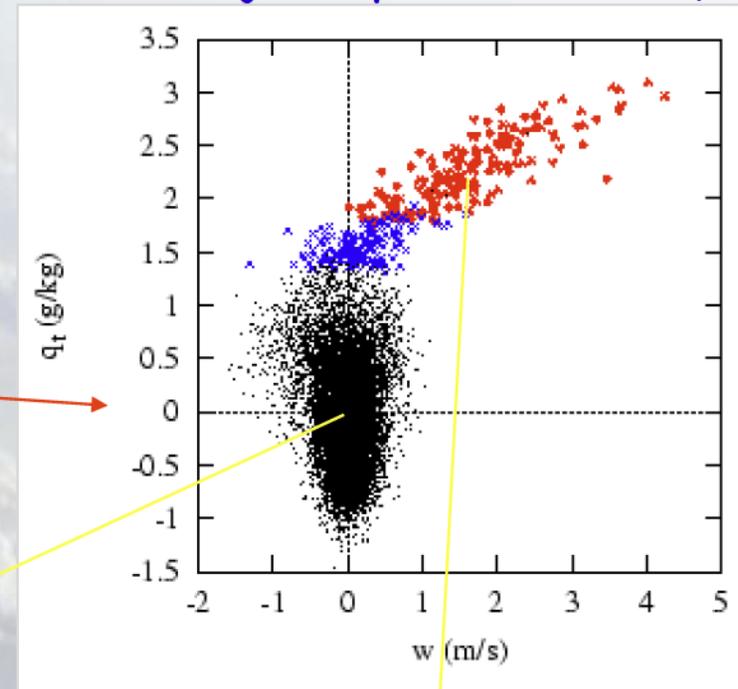
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LES models and Eddy-Diffusivity/Mass-Flux (EDMF) Parameterization

Large Eddy Simulation (LES) model
- BOMEX shallow cumulus case



Bimodal joint pdf of w and q_t



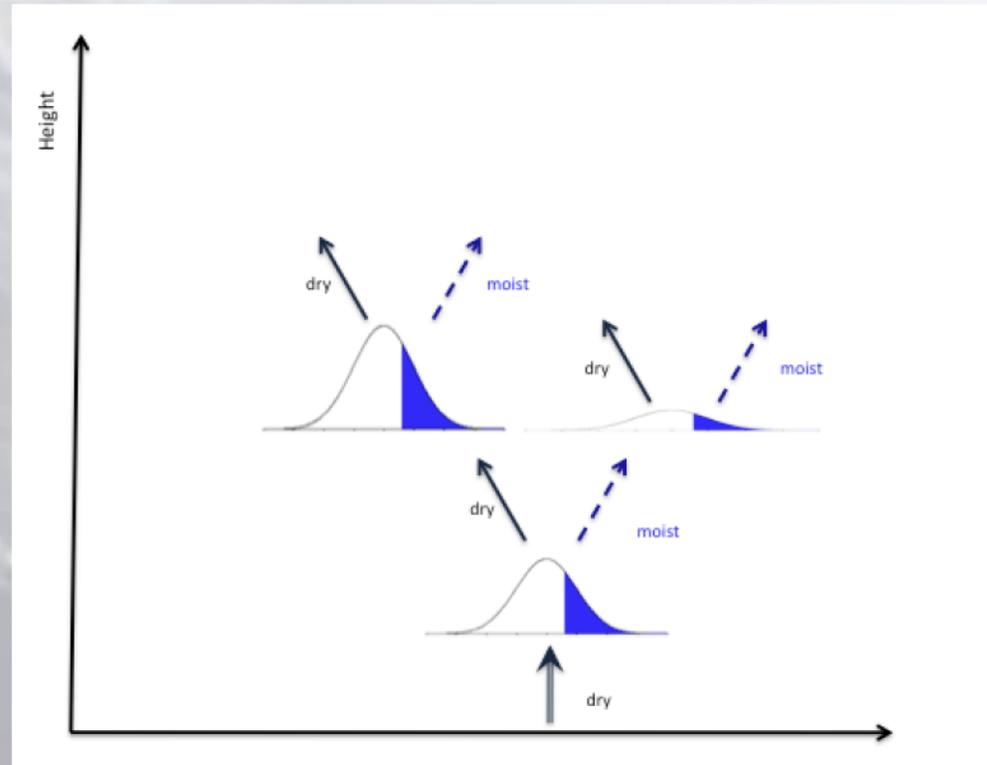
Well mixed sub-cloud layer:
Eddy-Diffusivity (ED) mixing

Cloud core updrafts:
Mass-Flux (MF) transport



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Stochastic Plume EDMF: using PDF of updraft properties



Suselj et al., JAS, 2012

- 1) Estimate PDF of plume/updraft properties (T , q , w)
- 2) Sample PDF to generate a variety of plumes (diff. properties)
- 3) Integrate different plumes in the vertical

Produces more realistic results than purely deterministic parameterization



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Stochastic Nature of Parameterizations in Ensemble Prediction

For parameterizations:

Ensemble and deterministic prediction are essentially different

In ensemble prediction systems:

- Parameterizations should be viewed as stochastic
- But within the context of current parameterizations
(without imposing artificial stochastic terms)

Parameterizations:

- Typically used to predict the evolution of grid-mean quantities
- Can also provide estimates of higher moments
(can be used to constrain random sampling)



Stochastic parameterizations in ensemble systems: a methodology

Methodology for stochastic parameterizations

A variable after being updated by a parameterization (e.g. moist convection) can be written:

$$\phi_{conv}^{stoch} = \bar{\phi}_{conv} + \varepsilon$$

$\bar{\phi}_{conv}$ - mean value of the variable after convection

ϕ_{conv}^{stoch} - stochastic value after convection

ε - normally distributed stochastic variable with
mean $\mu(\varepsilon) = 0$
standard deviation $\sigma(\varepsilon) = \sigma_{\phi,conv}$

$\sigma_{\phi,conv}$ - standard deviation due to moist convective processes

After discretizing the first term on the rhs, the following equation is obtained

$$\phi_{conv}^{stoch} = \bar{\phi} + \Delta t \left(\frac{\Delta \bar{\phi}}{\Delta t} \right)_{conv} + \varepsilon$$

$\bar{\phi}$ - mean value before the moist convection parameterization



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Stochastic convection: a simple approach

Assuming standard deviation proportional to convection tendency leads to:

$$\frac{\phi_{conv}^{stoch} - \bar{\phi}}{\Delta t} = (1 + \eta\beta) \left(\frac{\Delta \bar{\phi}}{\Delta t} \right)_{conv}$$

β - constant of proportionality

η - normally distributed stochastic variable with mean $\mu(\eta) = 0$

and standard deviation $\sigma(\eta) = 1$

(Teixeira & Reynolds, MWR, 2008)

Simple vertical correlation: single random number per column

No horizontal or temporal correlations:

- Simpler
- Perturbations assumed much smaller than grid-size
- Variance already possesses a certain degree of correlation
- Physically unclear how to construct correlations

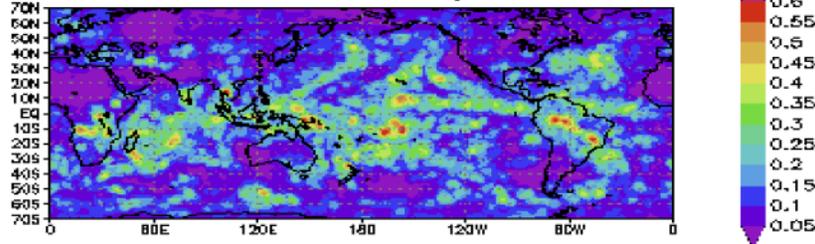


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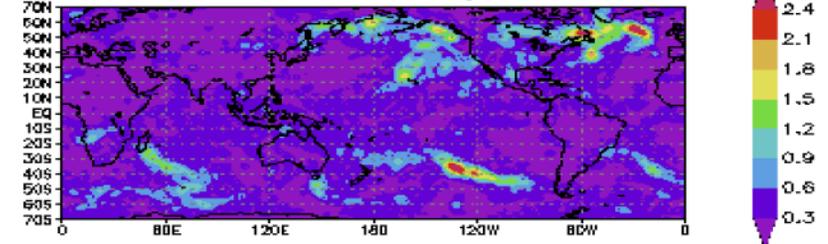
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US Navy NOGAPS ensemble spread due to stochastic physics only: 850 hPa Temperature

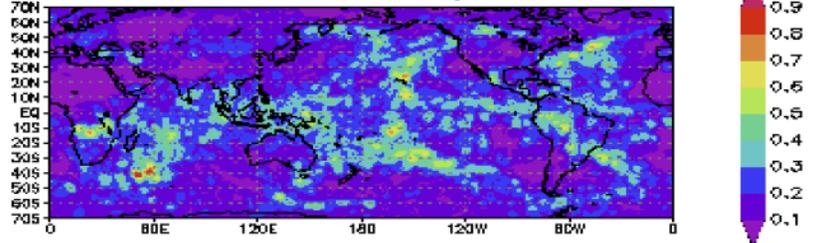
ENS STDEV: Stoch. Terms Only: 850-hPa T, 24h



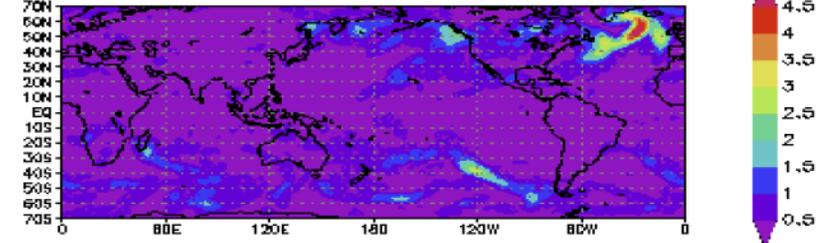
ENS STDEV: Stoch. Terms Only: 850-hPa T, 96h



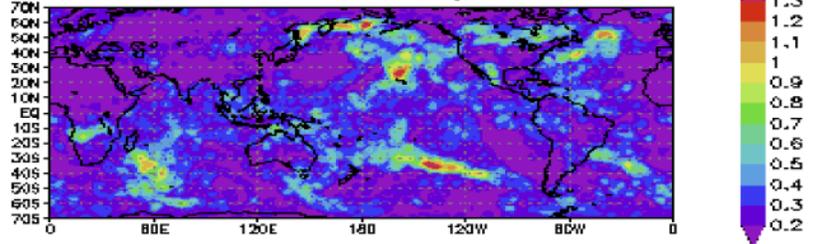
ENS STDEV: Stoch. Terms Only: 850-hPa T, 48h



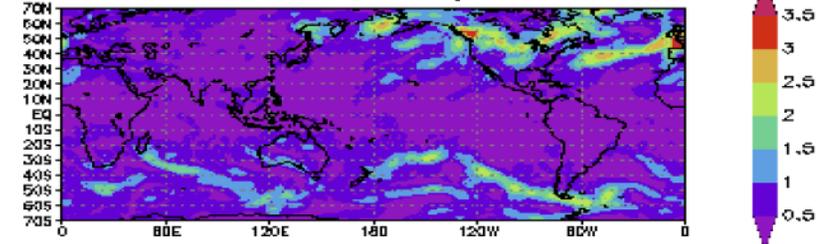
ENS STDEV: Stoch. Terms Only: 850-hPa T, 120h



ENS STDEV: Stoch. Terms Only: 850-hPa T, 72h



ENS STDEV: Stoch. Terms Only: 850-hPa T, 144h



- Perturbations grow in time
- At 24 h: mostly in Tropics/Sub-tropics
- At 144 h: mostly in Mid-latitudes
- Similar for U at 250 and 850 hPa, Z at 500 hPa

(Teixeira & Reynolds, MWR, 2008)



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Simple stochastic convection approach in Navy's ensemble prediction system

NOGAPS stochastic convection after 5 to 10 days:

- Saturation in Tropics
- Synoptic (sub-synoptic) peak in NH Extra-tropics

Stochastic Convection:

- Is able to produce substantial ensemble spread in the Tropics
- Produces sizeable impact in ensemble spread in the extratropics

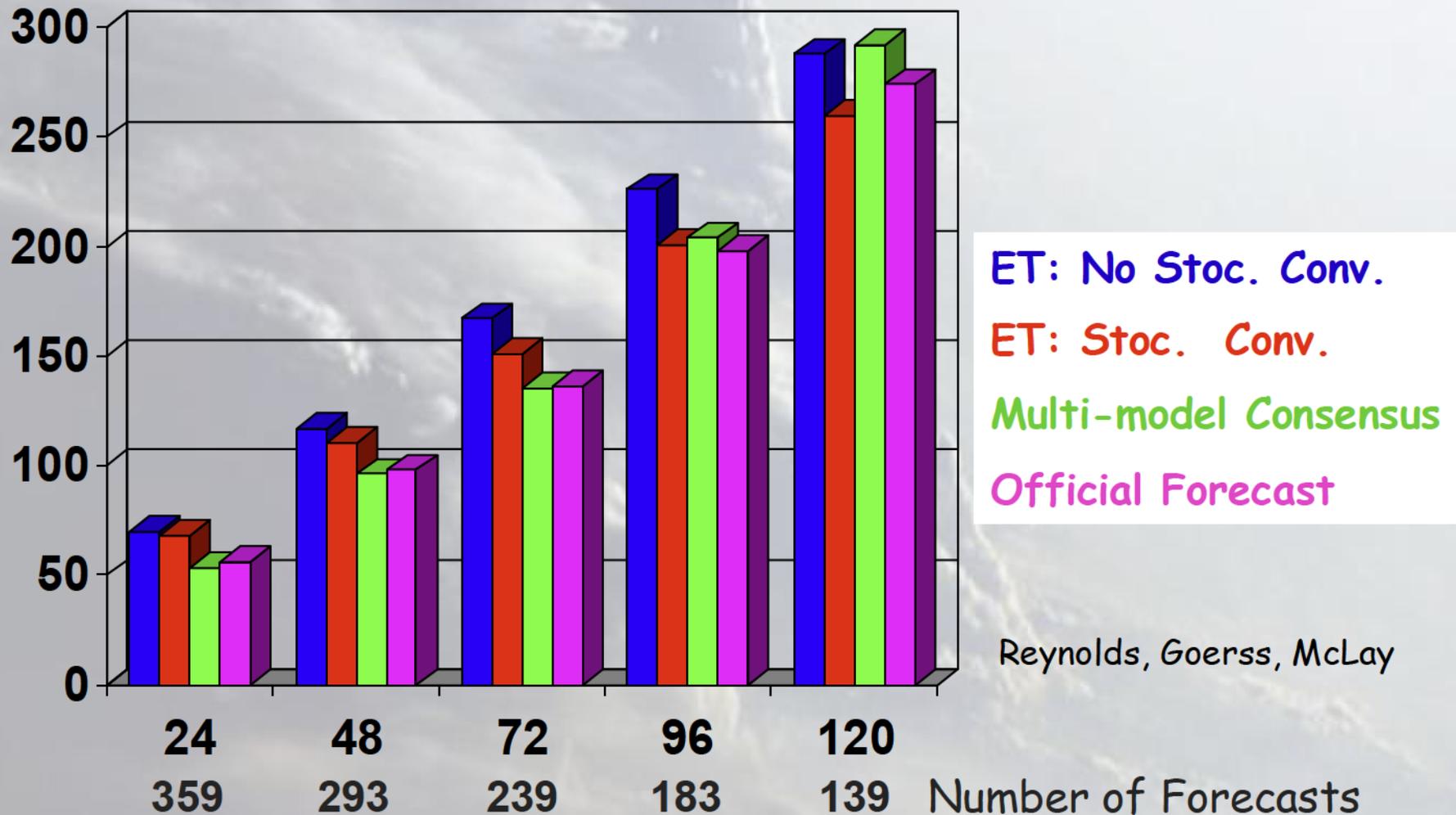
Initial-condition + stochastic convection show promising increase in ensemble spread and decrease in number of outliers in the Tropics



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Atlantic 2005 - TC Forecast Error (nm)

Stochastic Convection significantly improves NOGAPS ET performance

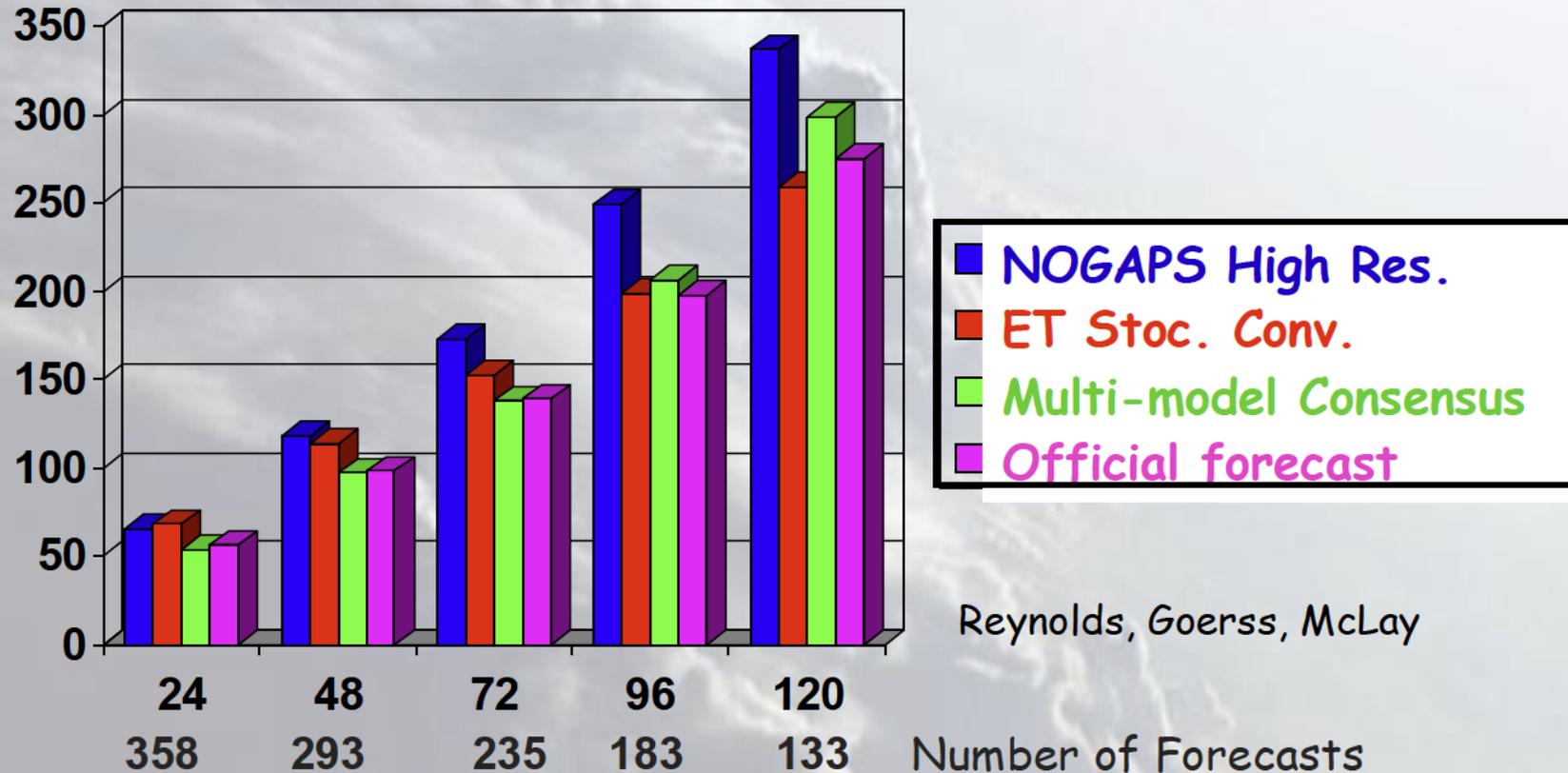




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Atlantic 2005 - TC Forecast Error (nm)



Reynolds, Goerss, McLay

NOGAPS ET with stochastic convection better than high-res deterministic model, and competitive with official forecast at 96 and 120 hours



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Summary

- Sub-grid scale physical processes possess complex non-linearities
- Some parameterizations need to be stochastic (e.g. radiation-cloud interaction, cloud microphysics) EVEN in deterministic models
- Moist convection parameterizations using plumes (mass-flux) are more realistic if stochastic
- Simple stochastic convection parameterizations produce improvements in hurricane forecasts with NOGAPS ensemble system
- Stochastic physics and resolution independent parameterizations