
Exploring the Weather-Climate Connection: Probabilistic Climate Dynamics

Part II: Stochastic Climate Models

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Overview

- Why is climate complex?

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- Modelling the climate system

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- Case Study II: Stochastic dynamics of sea-surface winds.

Introduction: Stochastic Climate Models

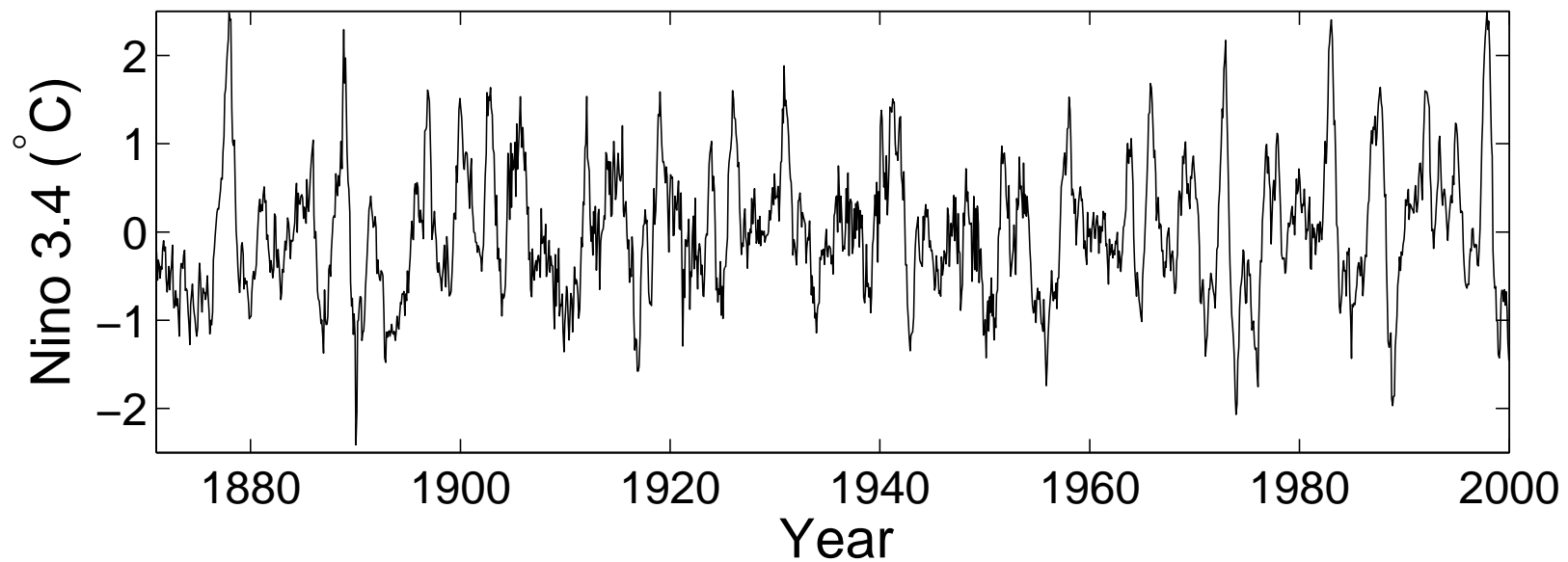
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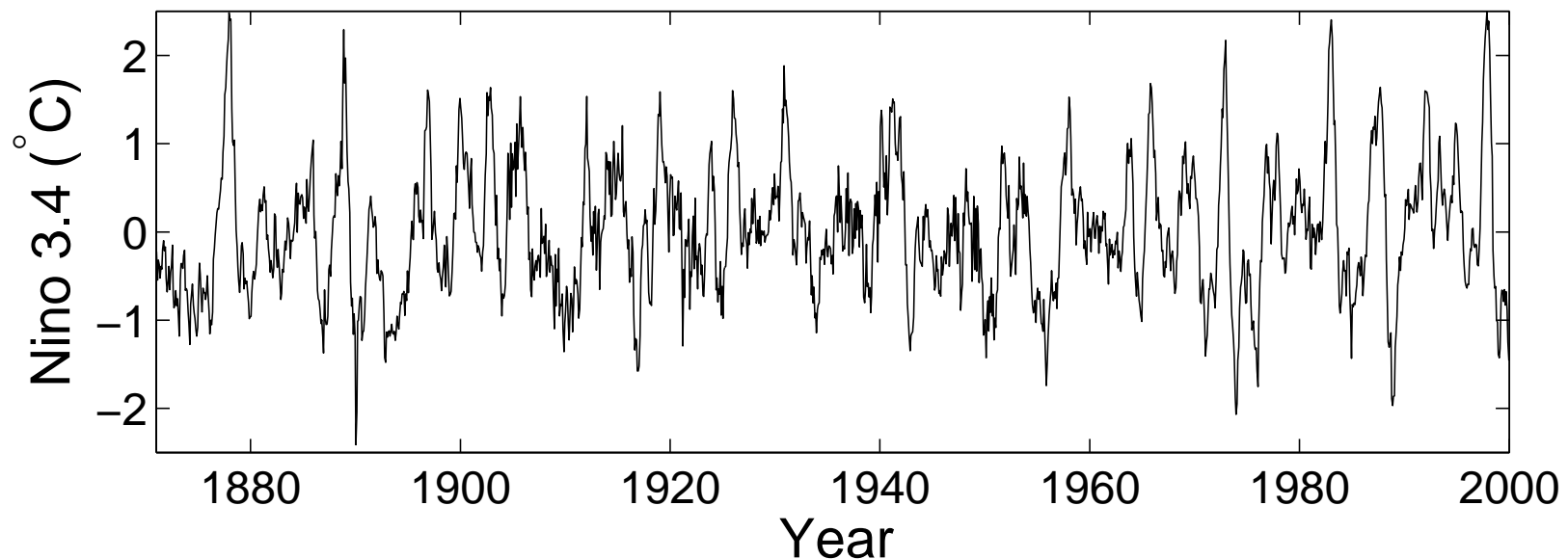
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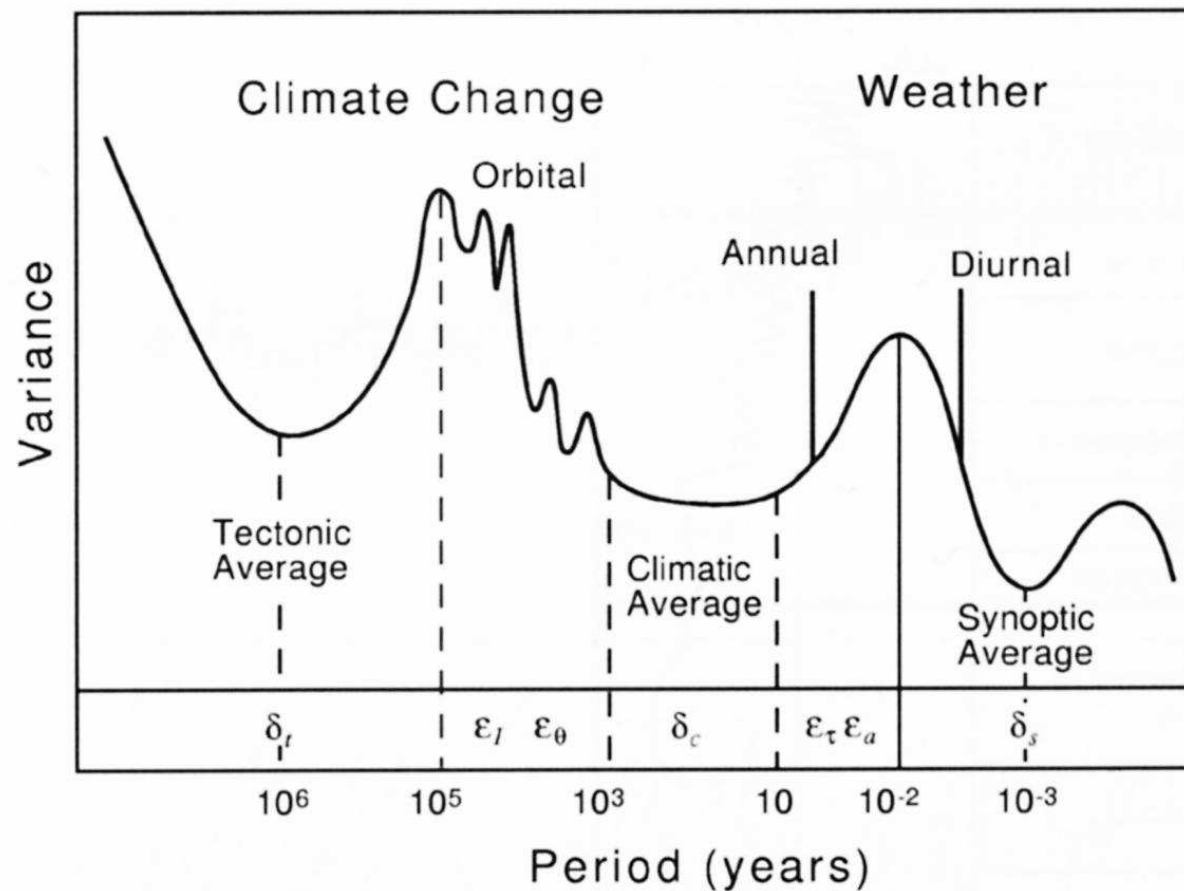
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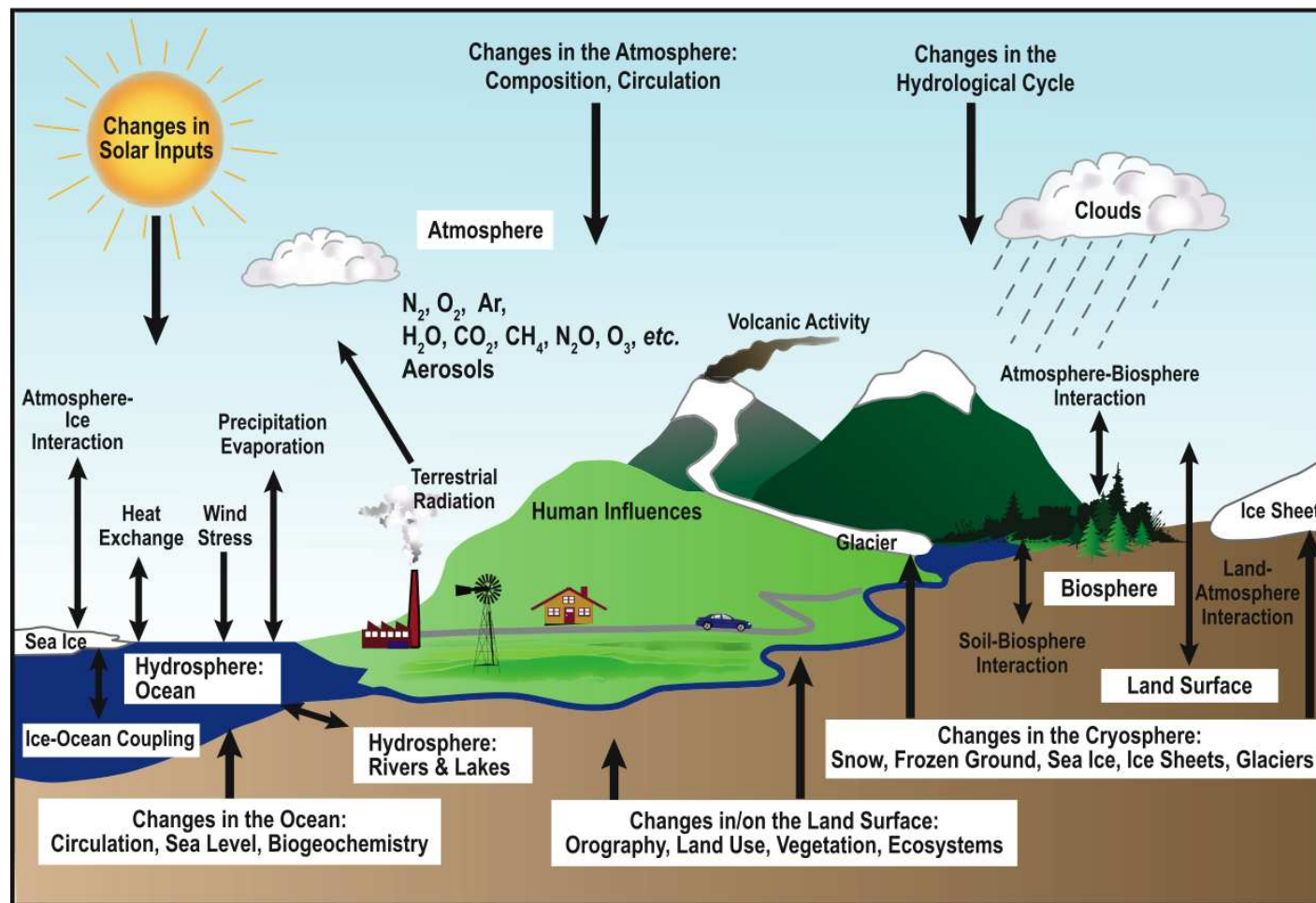
- Natural to model dynamics as interaction between **deterministic** and **random** (turbulent) parts of flow \Rightarrow stochastic climate models

Why is Climate Complex? Coupling Across Scales

- Climate system displays variability over broad range of space and time scales



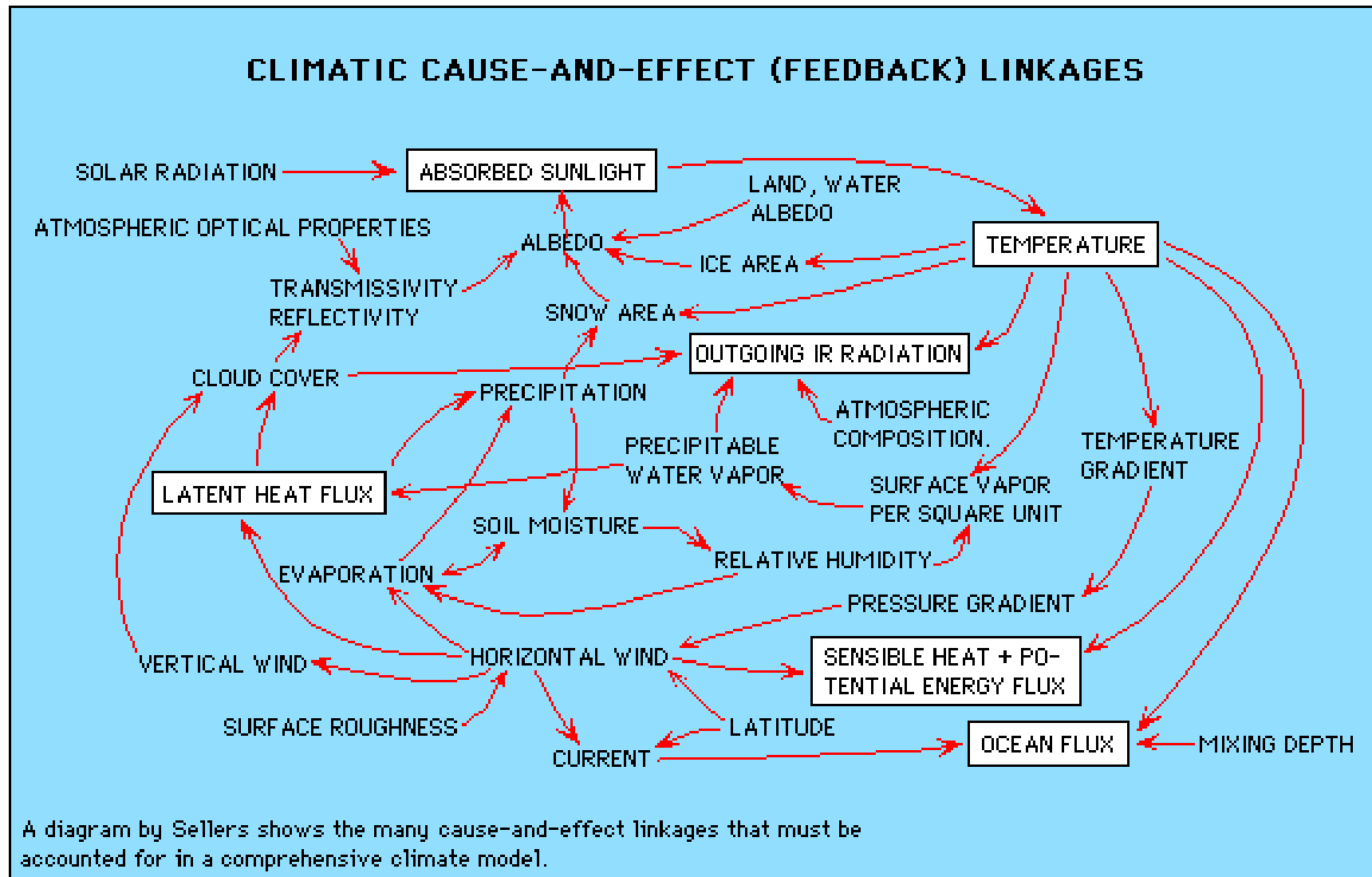
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From IPCC AR4 <http://www.ipcc.ch>

FAQ 1.2, Figure 1

Why is Climate Complex? Feedback Loops

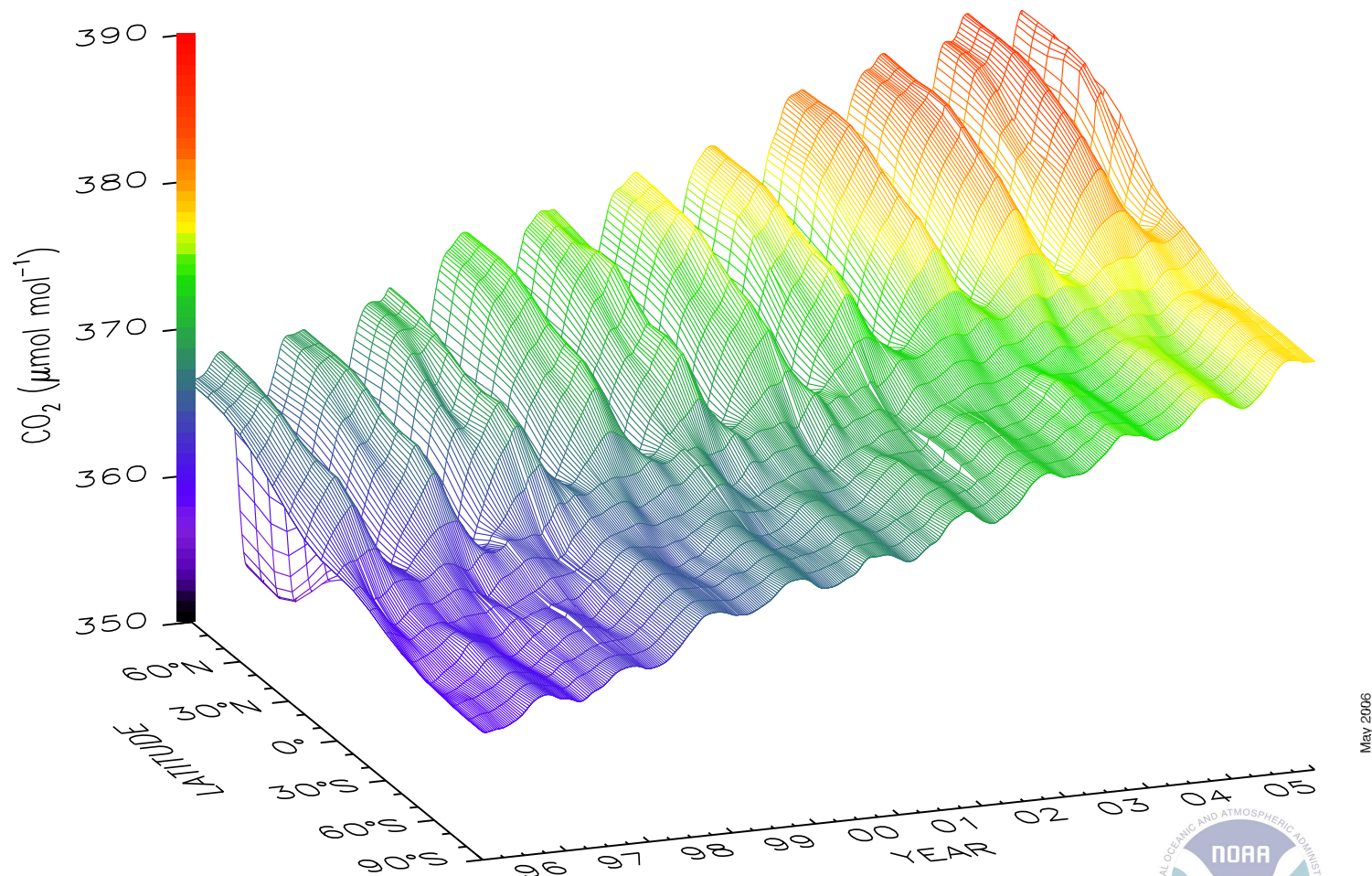


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From <http://eesc.columbia.edu/courses/ees/slides/climate/>

Why is Climate Complex? Non-Stationarity

Global Distribution of Atmospheric Carbon Dioxide
NOAA ESRL GMD Carbon Cycle



Three dimensional representation of the latitudinal distribution of atmospheric carbon dioxide in the marine boundary layer. Data from the GMD cooperative air sampling network were used. The surface represents data smoothed in time and latitude. Contact: Dr. Pieter Tans and Thomas Conway, NOAA ESRL GMD Carbon Cycle, Boulder, Colorado, (303) 497-6678 (pieter.tans@noaa.gov, <http://www.cmdl.noaa.gov/ccgg>).

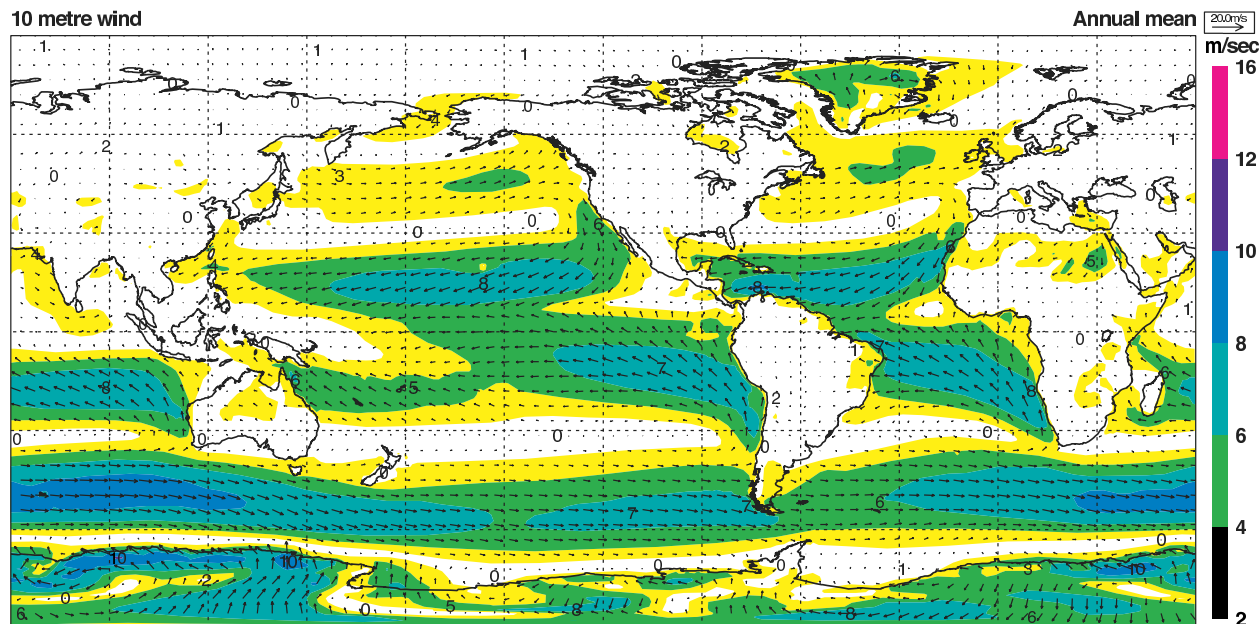
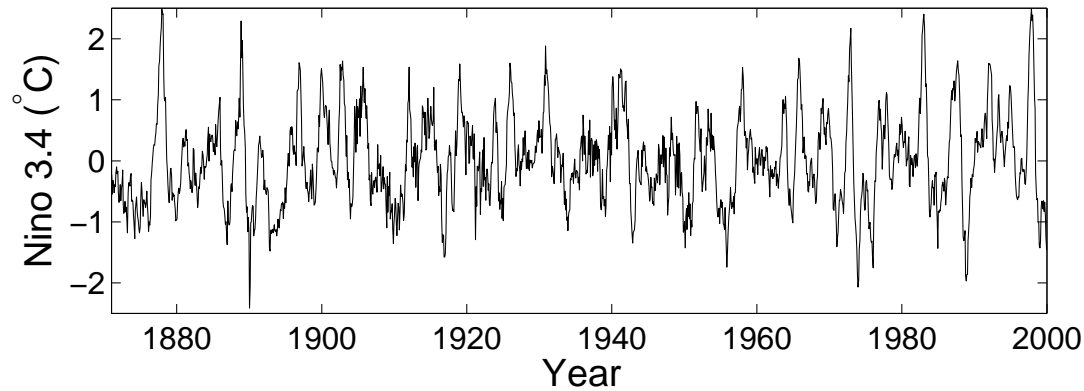


May 2006



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Why is Climate Complex? Data: Too Much & Not Enough



From ERA-40 Project Report Series 19

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- Climate models represent physical (+ biogeochemical) processes, typically through consideration of **budgets** of “**conserved quantities**”

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- ⇒ strong physical coupling of processes across different space and time scales

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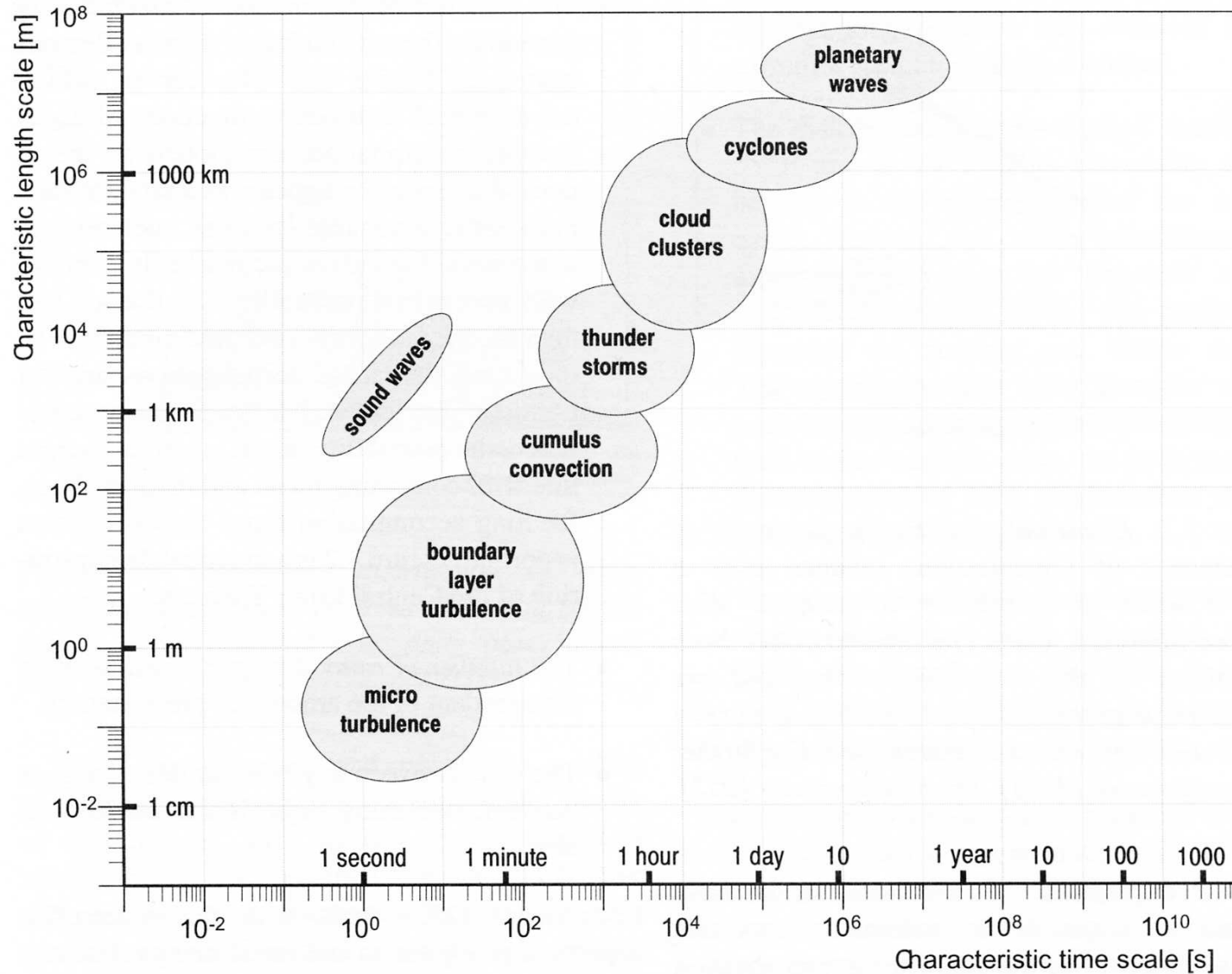
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- ⇒ “subgrid-scale parameterisations” (closure)

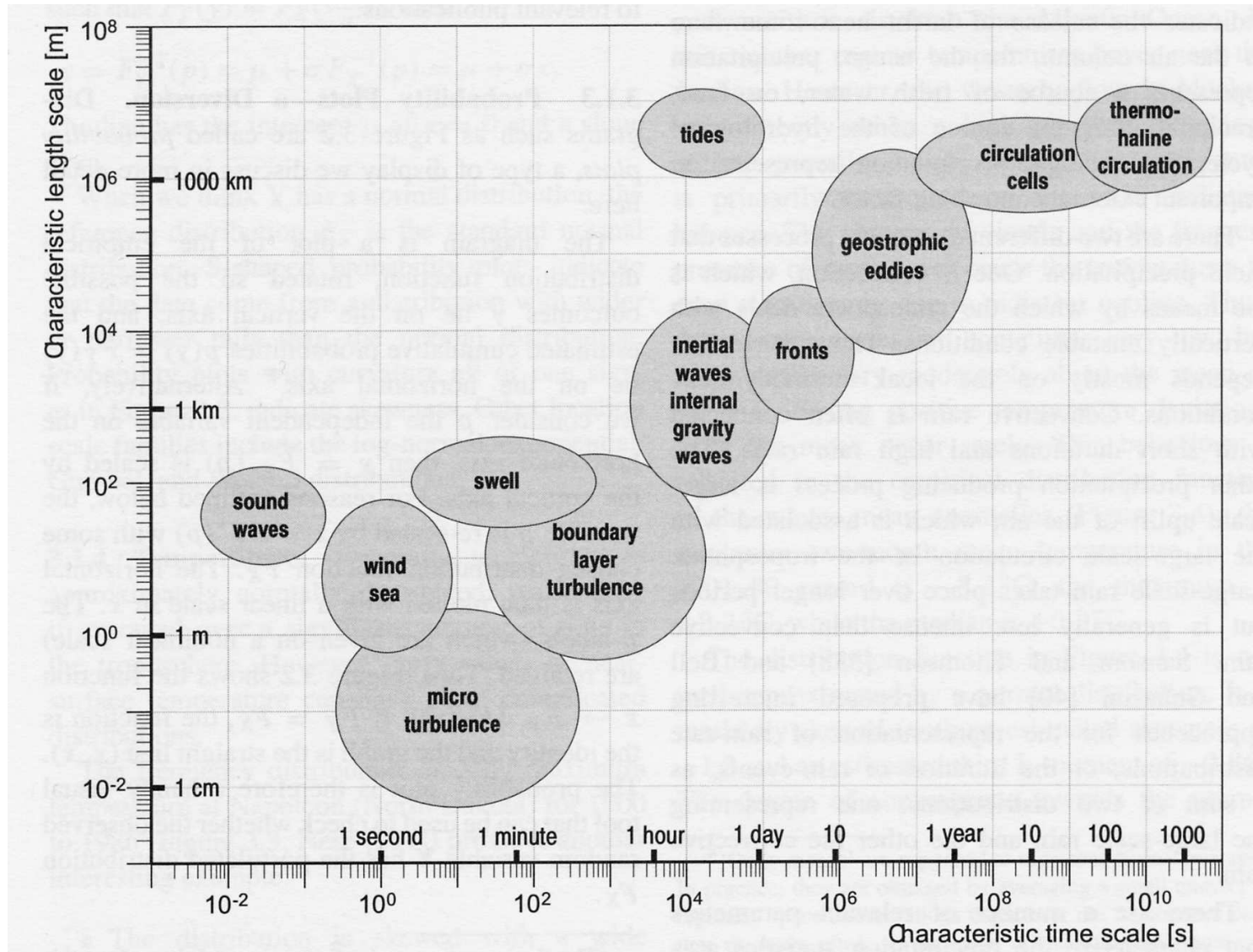
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From von Storch and Zwiers, 1999

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- coarse-graining results not only in unresolved *scales*, but also unresolved *processes* (e.g. internal gravity waves, convection, cloud microphysics)

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- Formally write “weather-climate” dynamics as multiscale system

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$$\frac{d}{dt}\zeta = [D\bar{f}(\bar{\mathbf{x}})]\zeta + \sigma(\bar{\mathbf{x}})\dot{\mathbf{W}}$$

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- “Hasselmann approximation”** (stochastic)

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⇒ semi-analytical reduced model

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- Fast/slow decomposition not unique;
“one person’s noise is another person’s signal”

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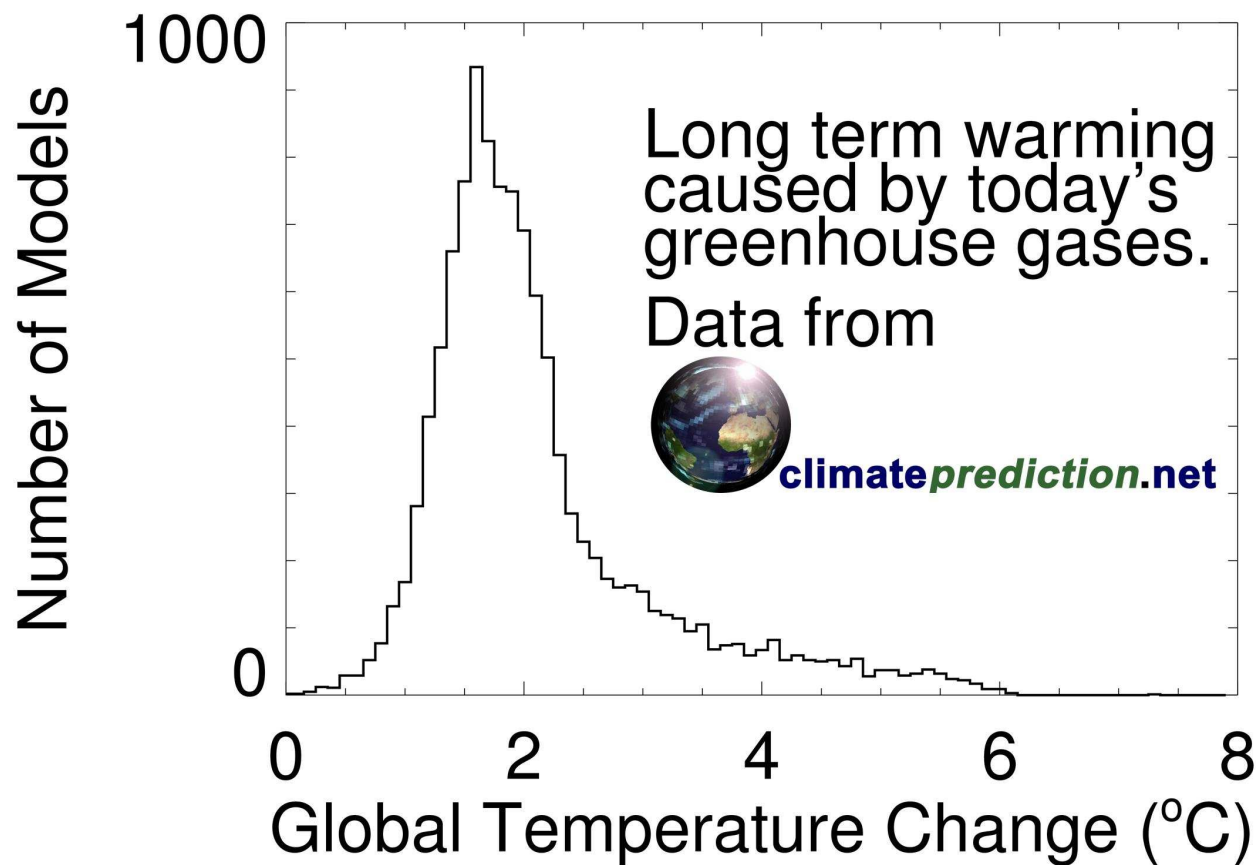
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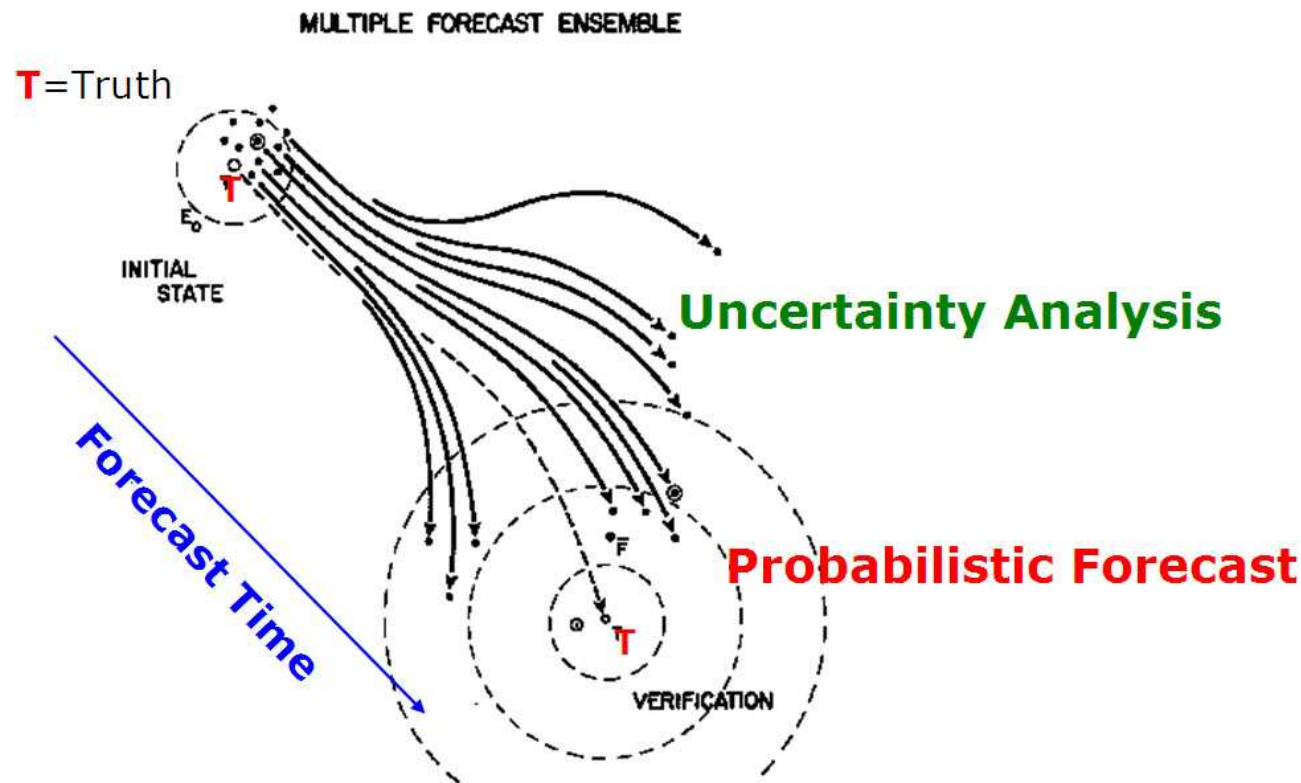
Parameter Uncertainty: Ensemble Prediction

- climateprediction.net uses idle private CPUs to integrate ensembles with different parameter settings



Initial Condition Uncertainty: Ensemble Forecasting

- Model uncertainties can also include initial conditions



UVic

http://chrs.web.uci.edu/images/ensemble_large_atmo.jpg

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- rates of biological activity sensitive to ocean temperature

Bulk Surface Mixed Layer Model

■ Dynamics of local SST:

$$\frac{\partial T}{\partial t} = -\mathbf{v} \cdot \nabla T + \frac{F_{sh}(t)}{h(t)} + \frac{F_{lh}(t)}{h(t)} + \frac{\overline{w'T'}|_{z=h}(t)}{h(t)} + \frac{F_{sw}(t)}{h(t)} - \sigma(\epsilon T^4 - \epsilon_a T_a^4)$$

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where

T

sea-surface temperature (SST)

$-\mathbf{v} \cdot \nabla T$

horizontal advective tendency

$h(t)$

mixed layer (ML) depth

$F_{sh}(t) = c_h ||\mathbf{u}|| (T_a - T)$

surface “sensible heat” flux

$F_{lh}(t) = c_h ||\mathbf{u}|| (q_a - q_s(T))$

surface “latent heat” flux

$\overline{w'T'}|_{z=h}(t)$

turbulent fluxes at ML base

$F_{sw}(t)$

surface shortwave (solar) heating

$\sigma(\epsilon T^4 - \epsilon_a T_a^4)$

net surface longwave cooling

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with spectrum

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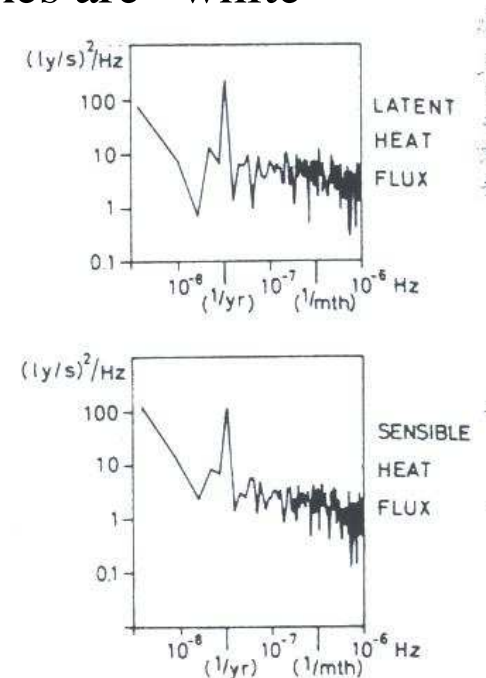
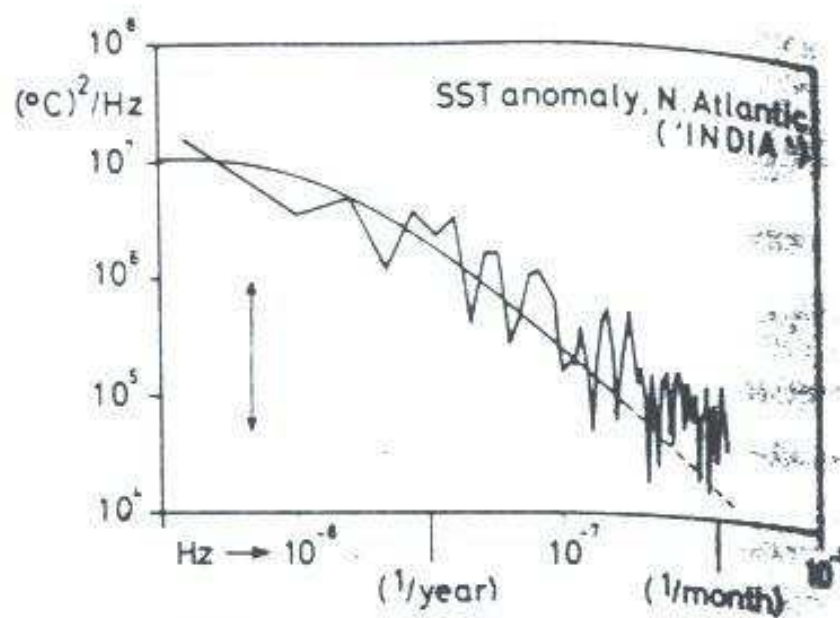
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- “Slow” local surface ocean dynamics ⇒ red-noise response to “fast” atmospheric forcing



What do we learn about SST variability?

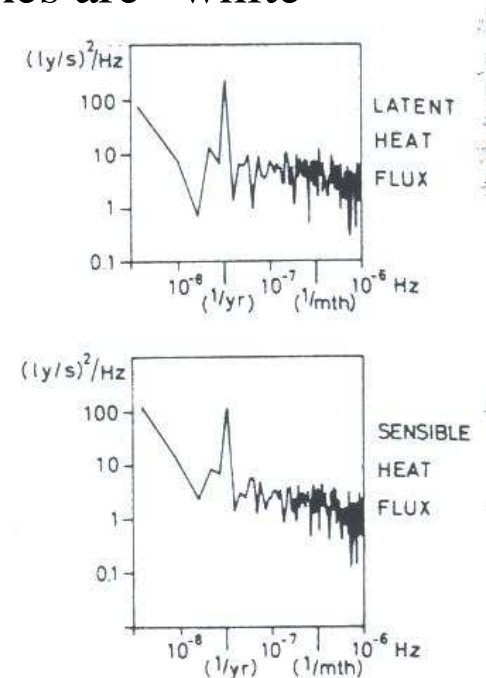
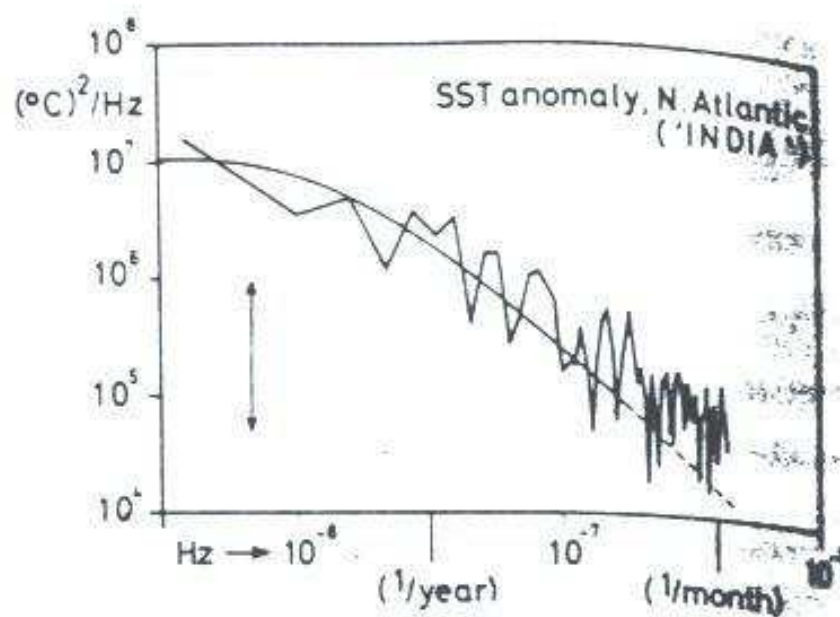
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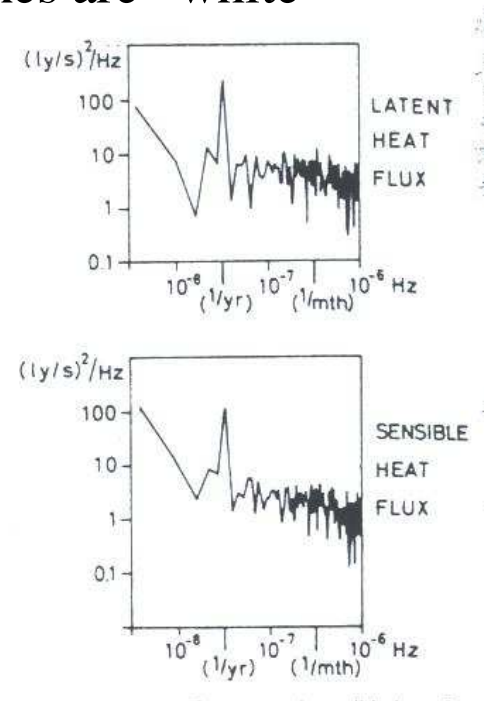
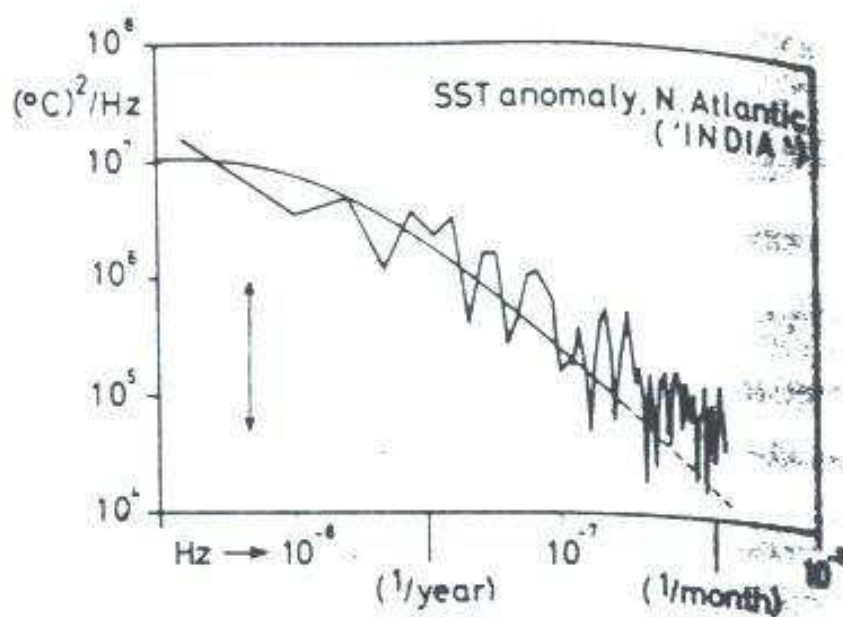


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- Generalisation with multiplicative noise effects explains slight non-Gaussianity of SST



UVic

(c.f. Sura, Newman, & Alexander *J. Phys. Oceanogr.*, 2006)

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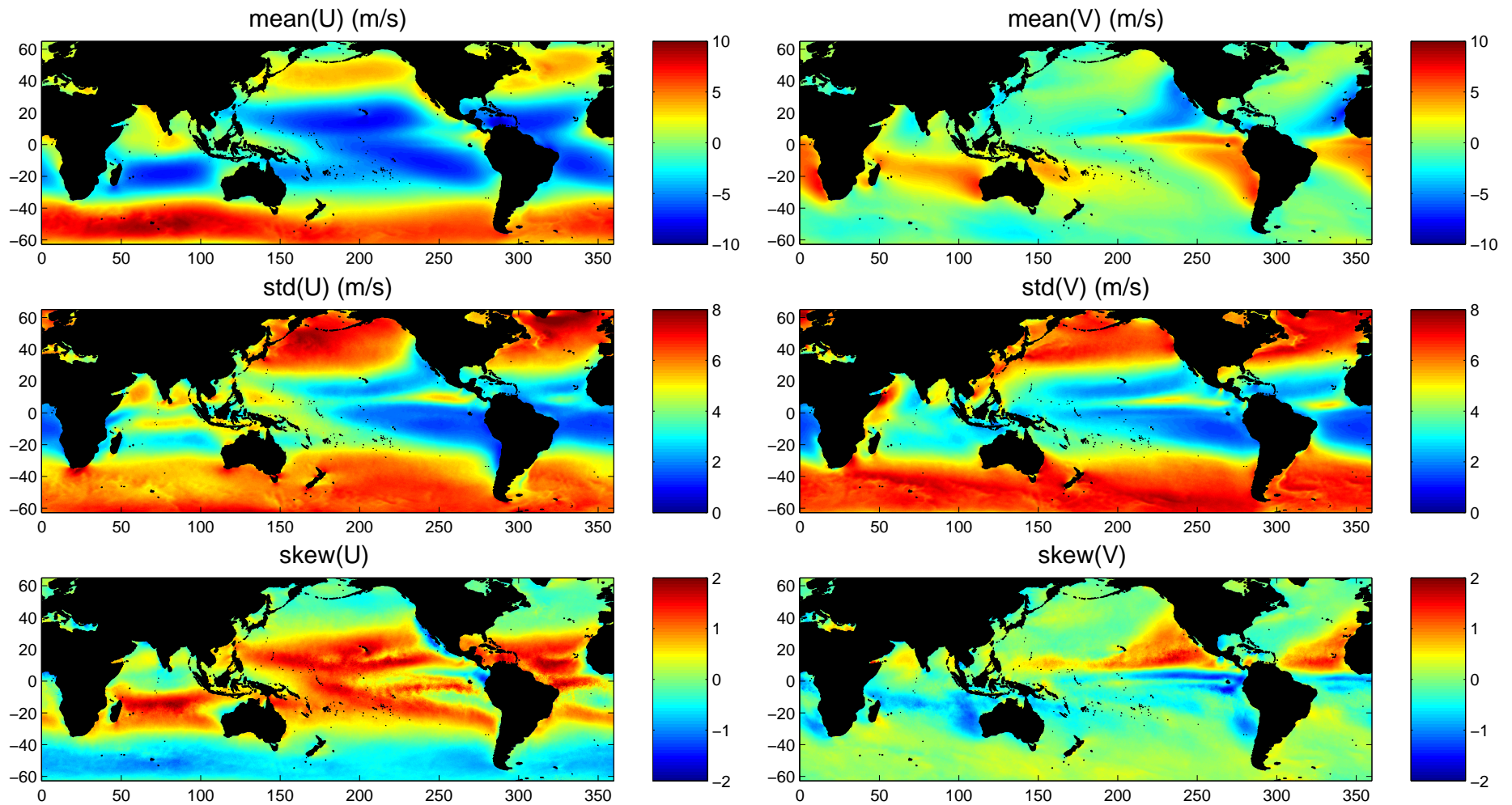
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- generation rate scales as cube of wind speed; extreme events important

Vector Wind Moments

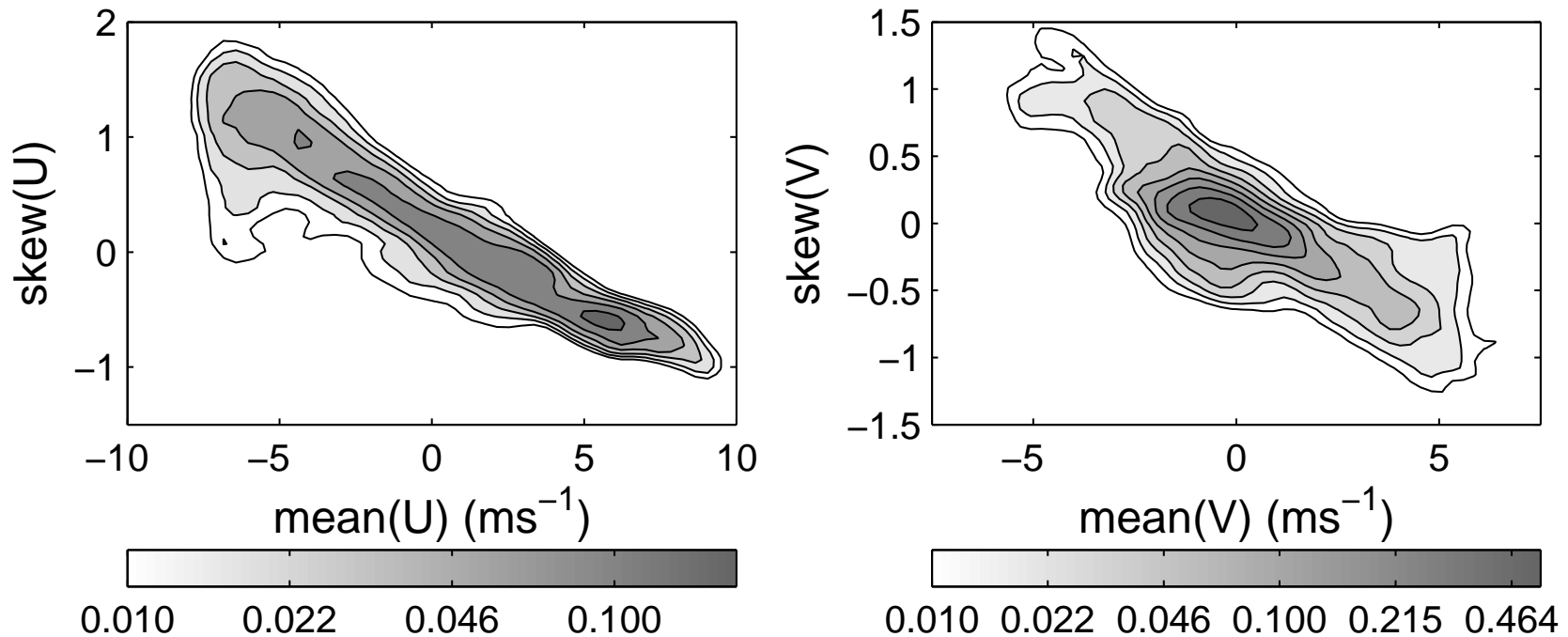


Zonal Wind

Meridional Wind

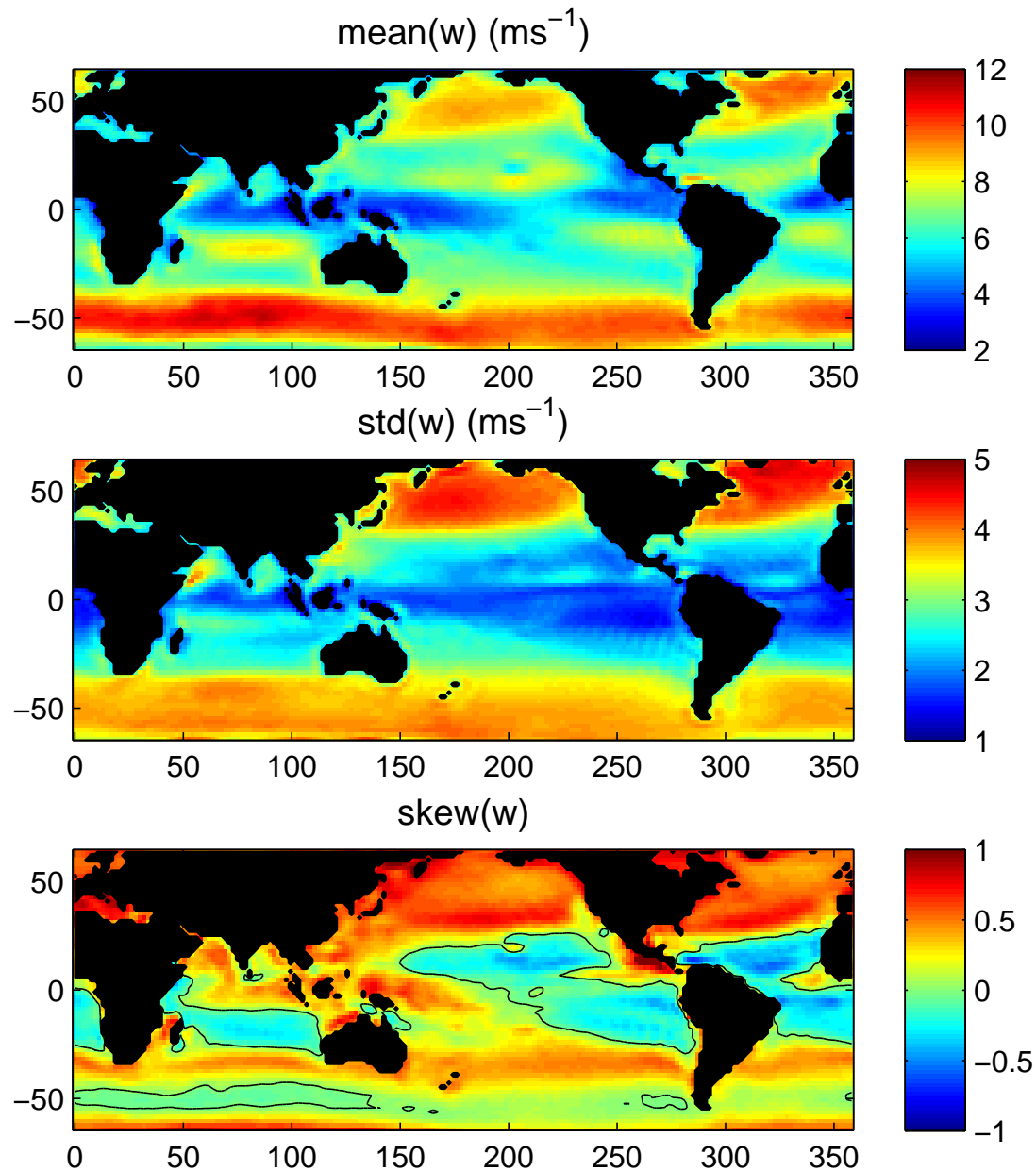
Mean and Skewness of Vector Wind

- Joint pdfs of mean and skew for zonal and meridional winds



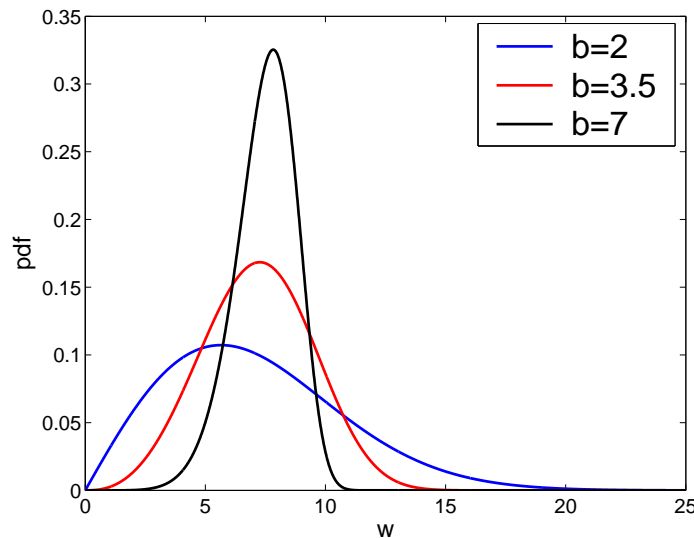
(note logarithmic contour scale)

Wind Speed Moments



Wind Speed pdf: Weibull distribution

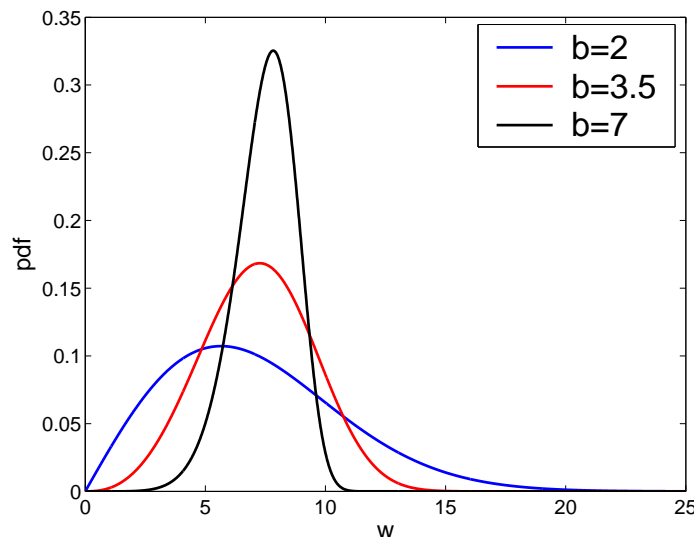
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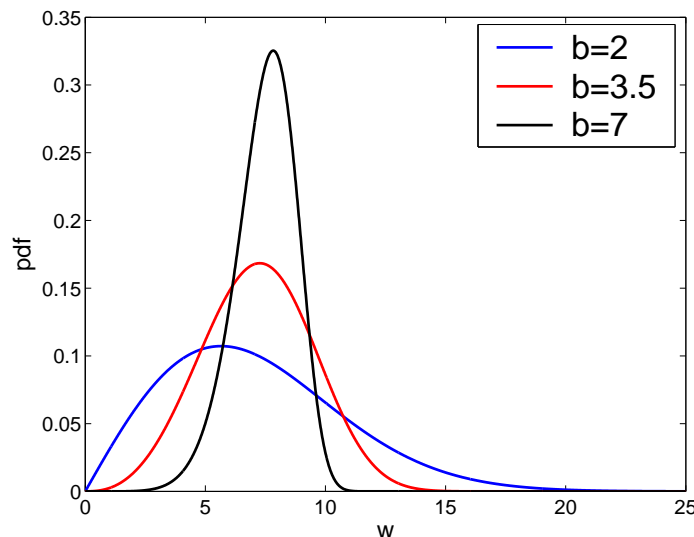


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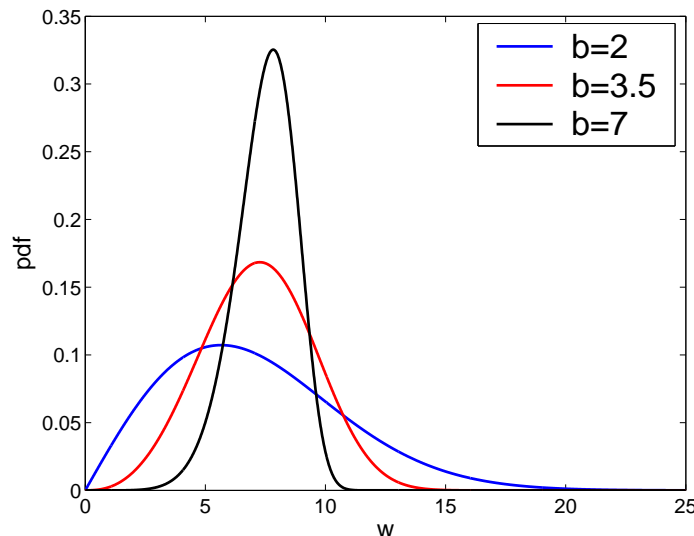


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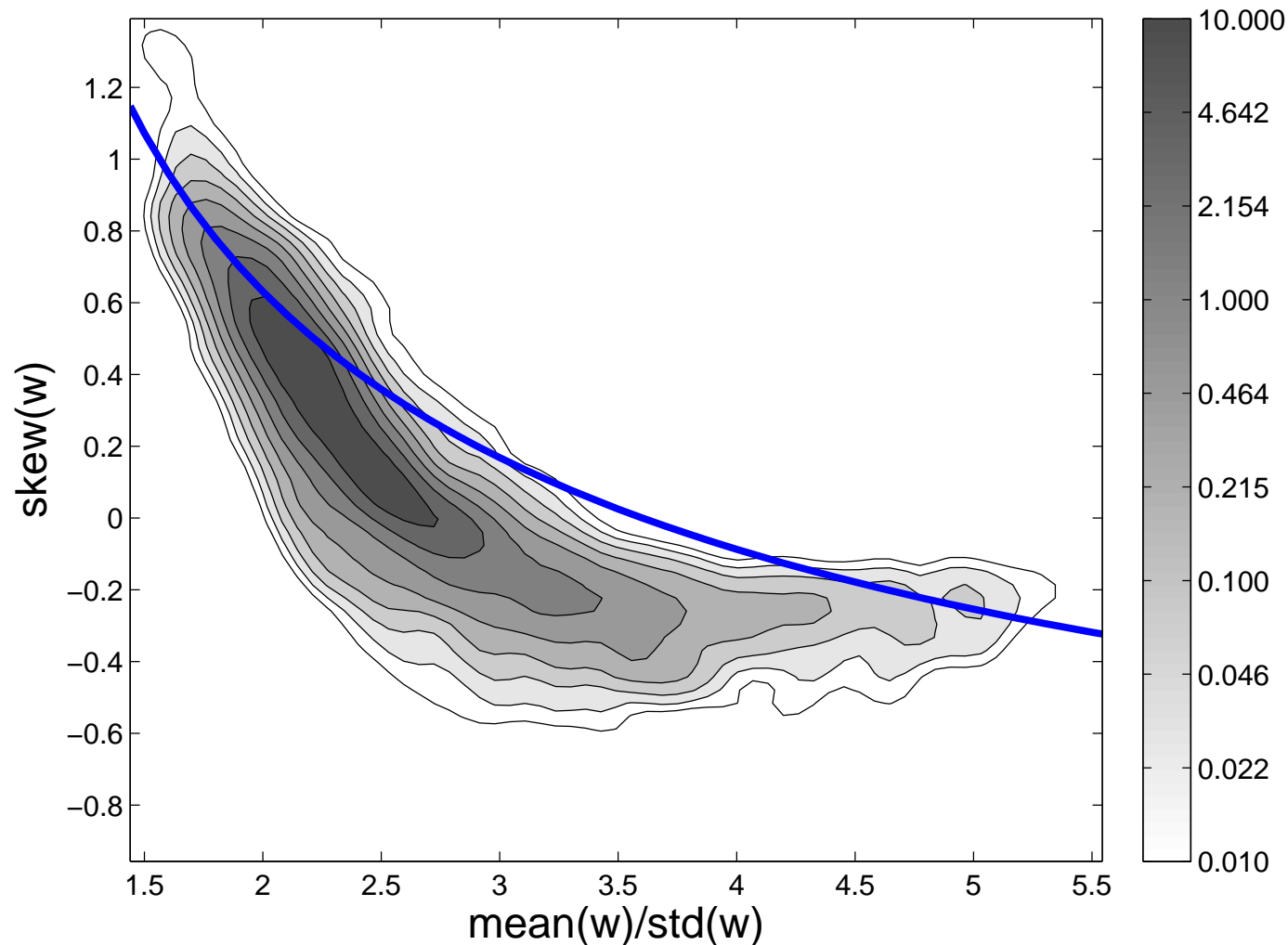
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- $p_w(w)$ is unimodal



Wind Speed pdfs: Observed

- Observed speed moments fall around Weibull curve



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UVic

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- Flux parametrised in terms of \mathbf{u} by bulk drag formula:

$$\tau_s = \rho_a c_d w \mathbf{u}$$

where $w = \|\mathbf{u}\|$ is the wind speed.

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$$\Pi_v(t) = \sigma \dot{W}_2(t)$$

where \dot{W}_i is Gaussian white noise

$$\langle \dot{W}_i(t_1) \dot{W}_j(t_2) \rangle = \delta_{ij} \delta(t_1 - t_2)$$

Mechanistic Model: SDE

- Decomposing Π into mean and fluctuations:

$$\begin{aligned}\Pi_u(t) &= \langle \Pi_u \rangle + \sigma \dot{W}_1(t) \\ \Pi_v(t) &= \sigma \dot{W}_2(t)\end{aligned}$$

where \dot{W}_i is Gaussian white noise

$$\left\langle \dot{W}_i(t_1) \dot{W}_j(t_2) \right\rangle = \delta_{ij} \delta(t_1 - t_2)$$

we obtain stochastic differential equation

$$\begin{aligned}\frac{du}{dt} &= \langle \Pi_u \rangle - \frac{c_d}{h} w u - \frac{W_e}{h} u + \sigma \dot{W}_1 \\ \frac{dv}{dt} &= -\frac{c_d}{h} w v - \frac{W_e}{h} v + \sigma \dot{W}_2\end{aligned}$$

Mechanistic Model: pdf

- Solution of associated Fokker-Planck equation for stationary pdf:

$$p_{uv}(u, v) = \mathcal{N}_1 \exp \left(\frac{2}{\sigma^2} \left\{ \langle \Pi_u \rangle u - \frac{W_e}{2h} (u^2 + v^2) - \frac{1}{h} \int_0^{\sqrt{u^2 + v^2}} c_d(w') w'^2 dw' \right\} \right)$$

Mechanistic Model: pdf

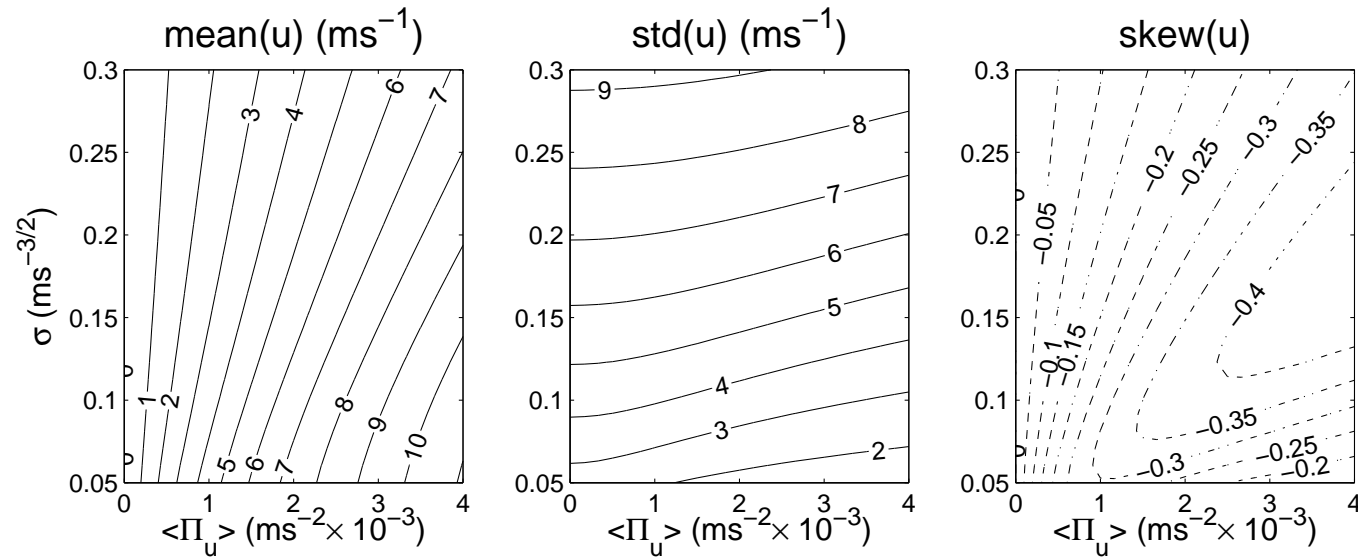
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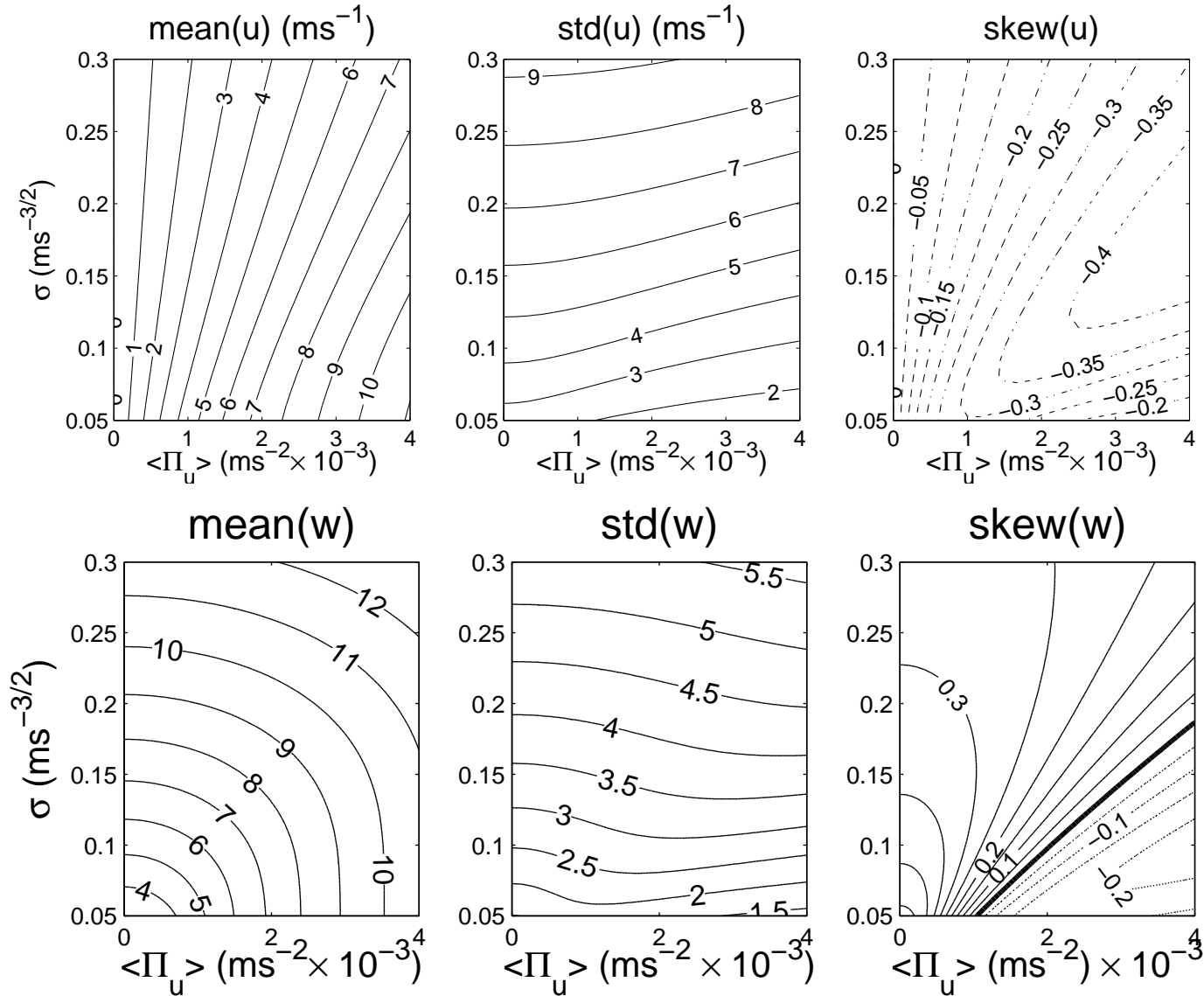
- Changing to polar coordinates and integrating over angle gives wind speed pdf:

$$p_w(w) = \mathcal{N} w I_0 \left(\frac{2 \langle \Pi_u \rangle w}{\sigma^2} \right) \exp \left(-\frac{2}{\sigma^2} \left\{ \frac{W_e}{2h} w^2 + \frac{1}{h} \int_0^w c_d(w') w'^2 dw' \right\} \right)$$

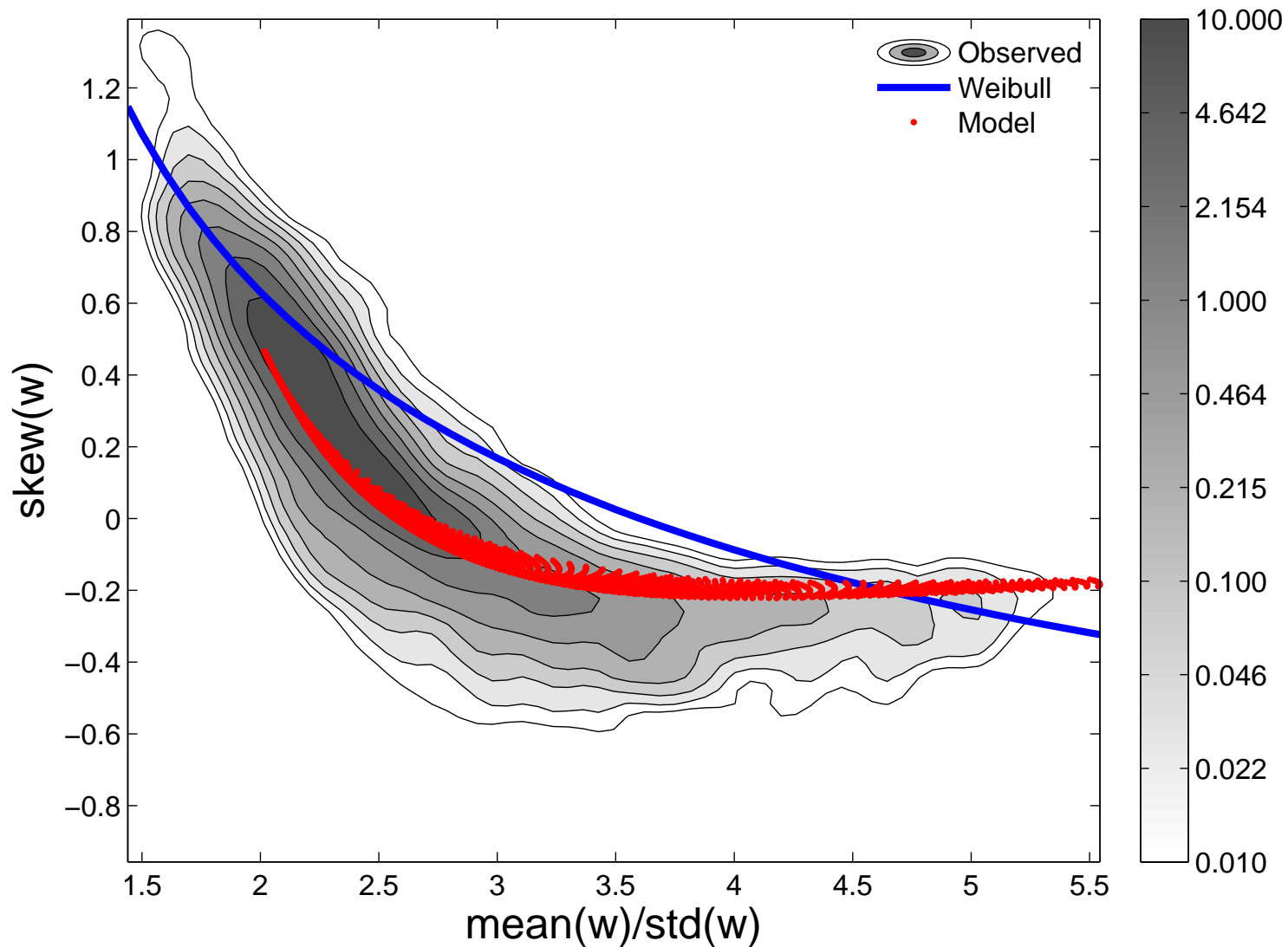
Mechanistic Model: Predictions



Mechanistic Model: Predictions



Mechanistic Model: Comparison with Observations



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