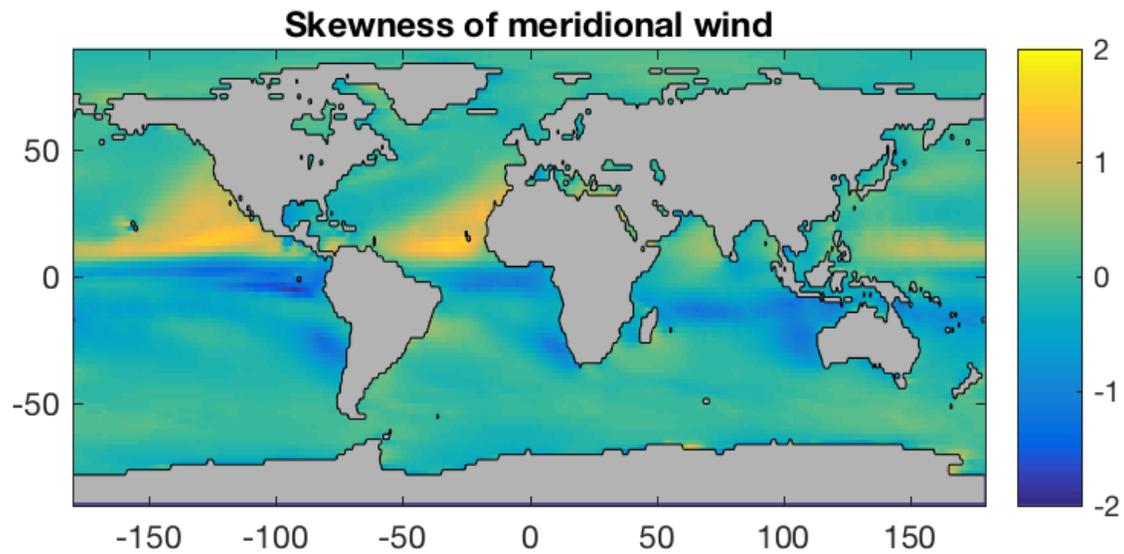
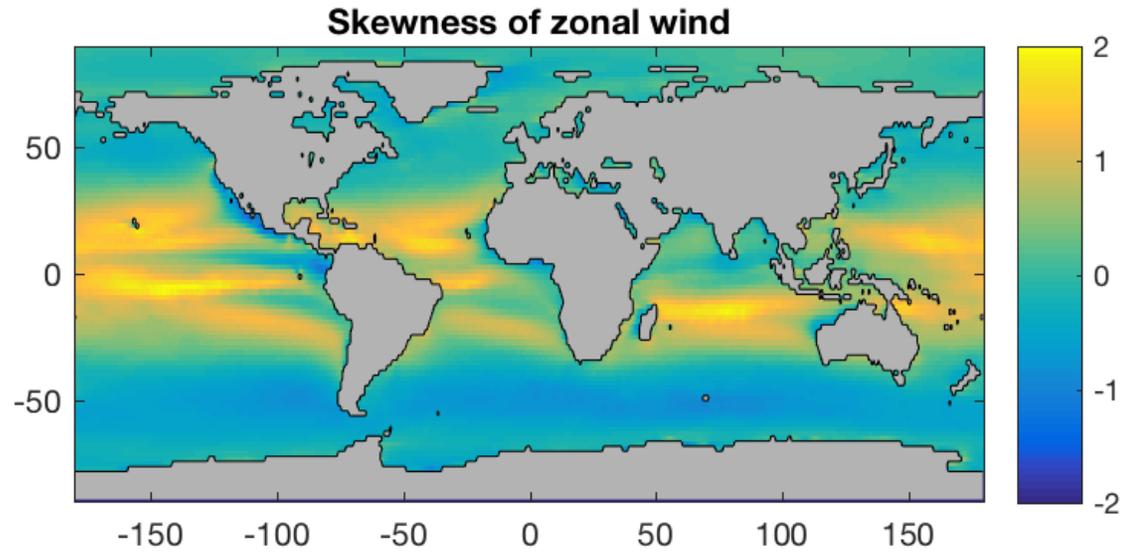

Enhancement of Sea Surface Wind Skewness by Filtering

Adam Monahan

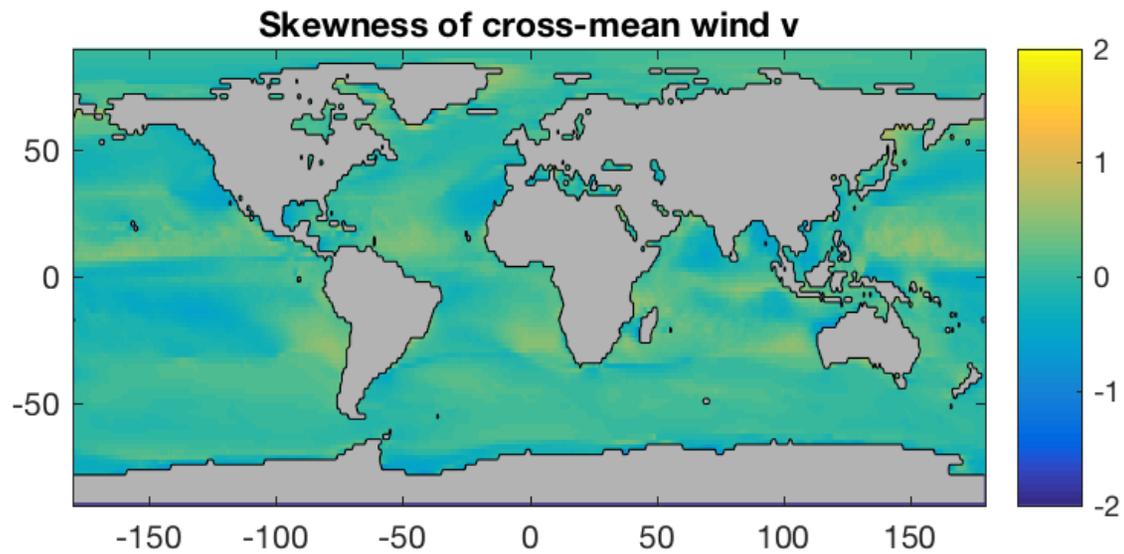
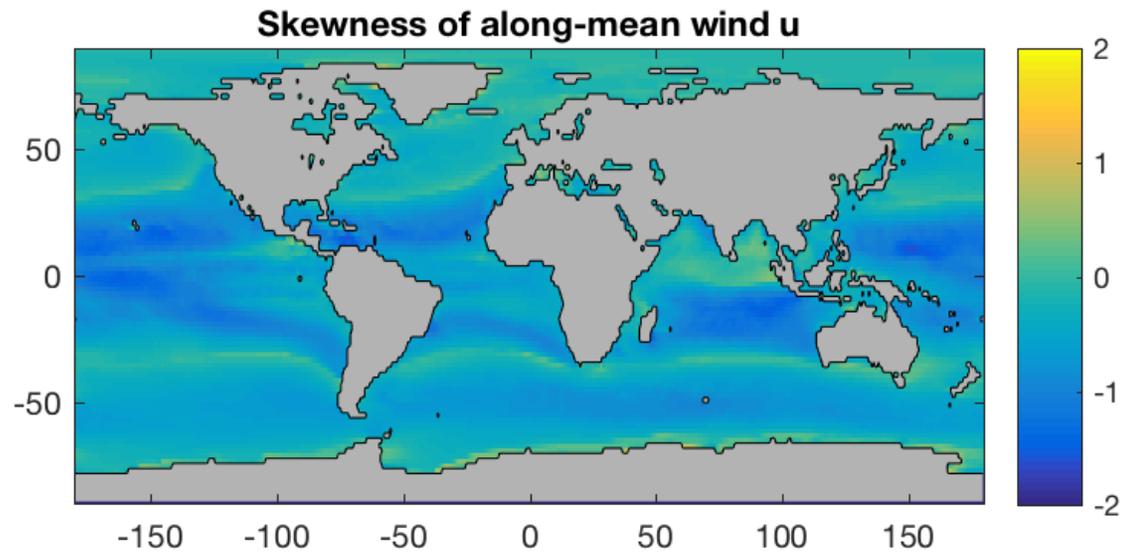
monahana@uvic.ca

School of Earth and Ocean Sciences, University of Victoria
Victoria, BC, Canada

Skewness of sea surface wind components



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Simple model of sea surface wind variability

- Idealized momentum budget of surface layer of depth h :

$$\begin{aligned}\frac{d}{dt}u &= \langle \Pi_u \rangle - \frac{c_d}{h}(u^2 + v^2)^{1/2}u + \eta_u \\ \frac{d}{dt}v &= -\frac{c_d}{h}(u^2 + v^2)^{1/2}v + \eta_v\end{aligned}$$

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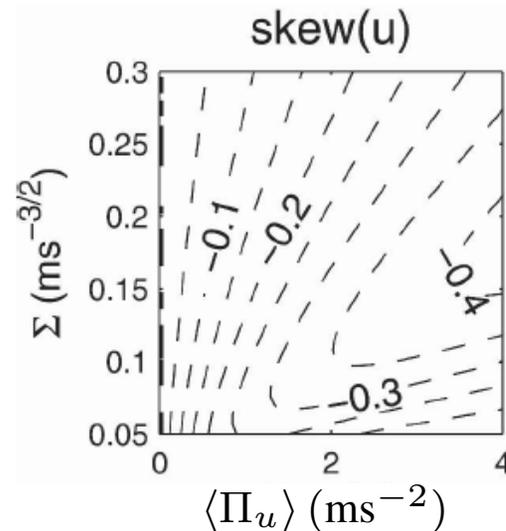
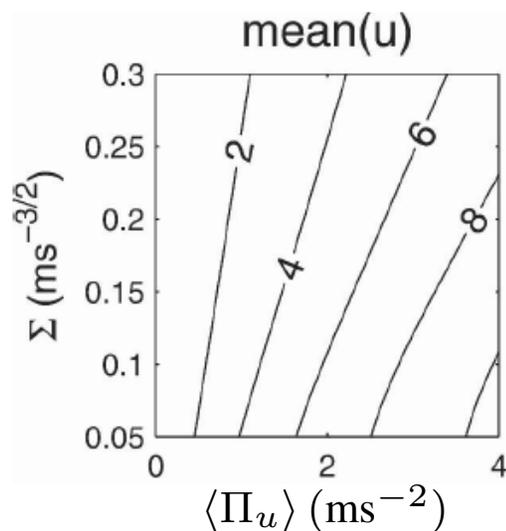
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Correlated Additive-Multiplicative (CAM) noise

- Linear SDE with correlated additive & multiplicative noise terms:

$$\frac{d}{dt}x = \left(Lx - \frac{1}{2}Eg \right) + (Ex + g) \circ \dot{W}_1 + b\dot{W}_2$$

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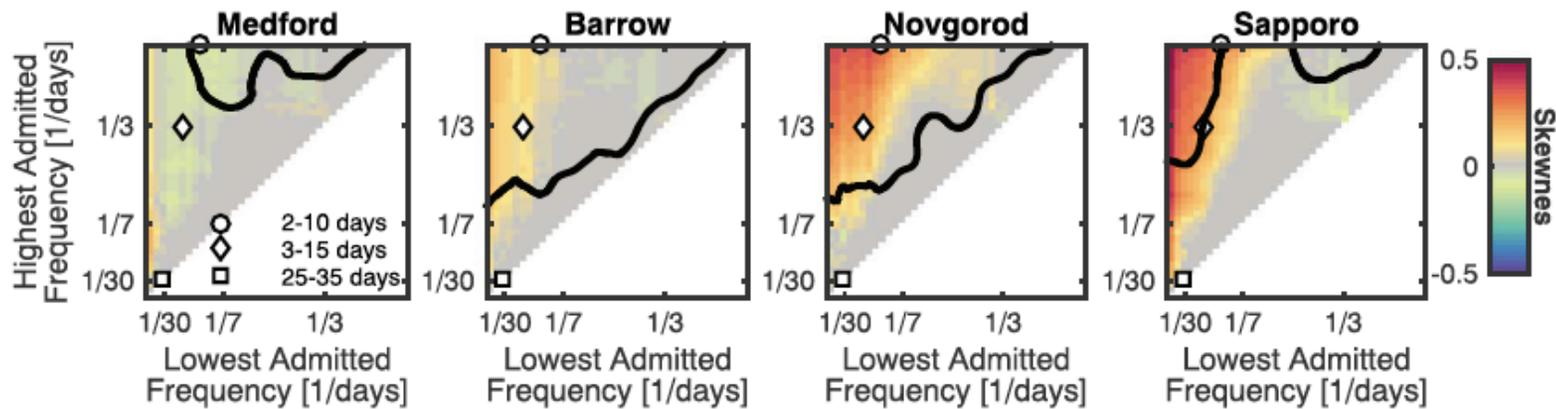
- Has been proposed as a generic model for non-Gaussianity in atmosphere/ocean variables

Skewness of bandpass-filtered temperatures

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Skewness of bandpass-filtered temperatures

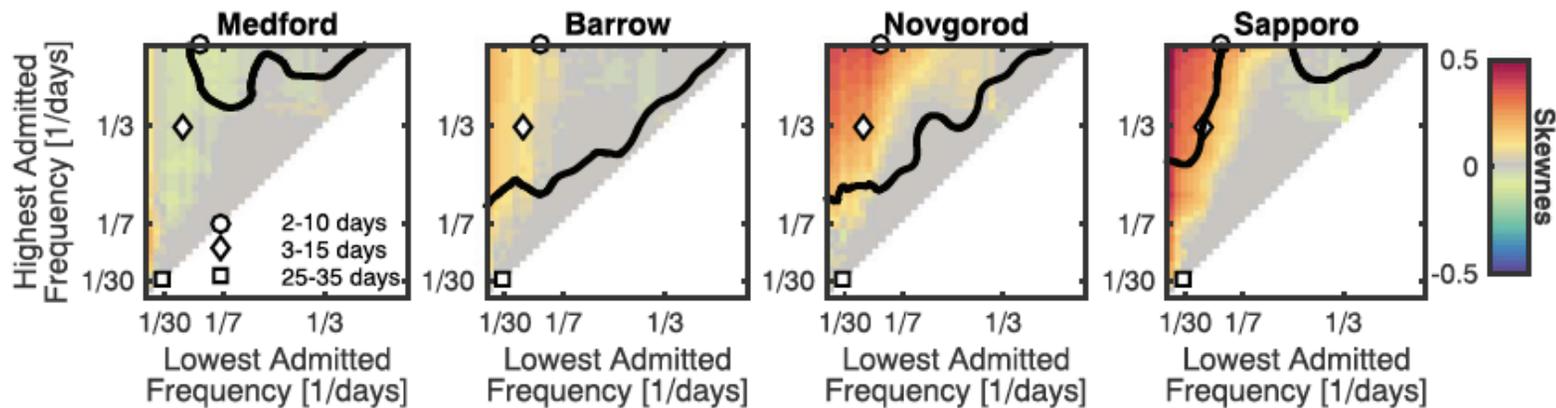
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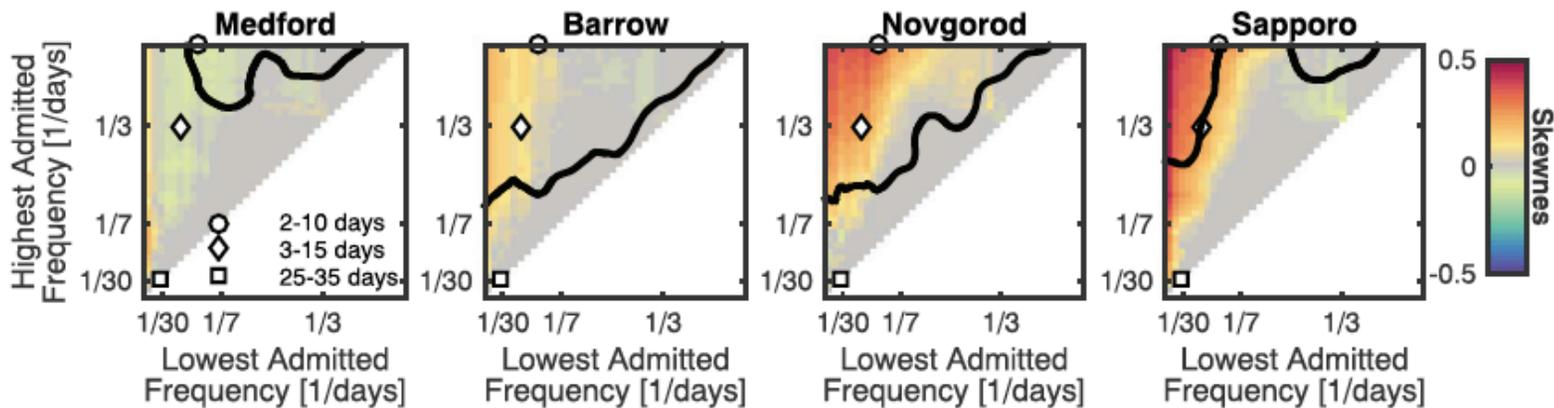


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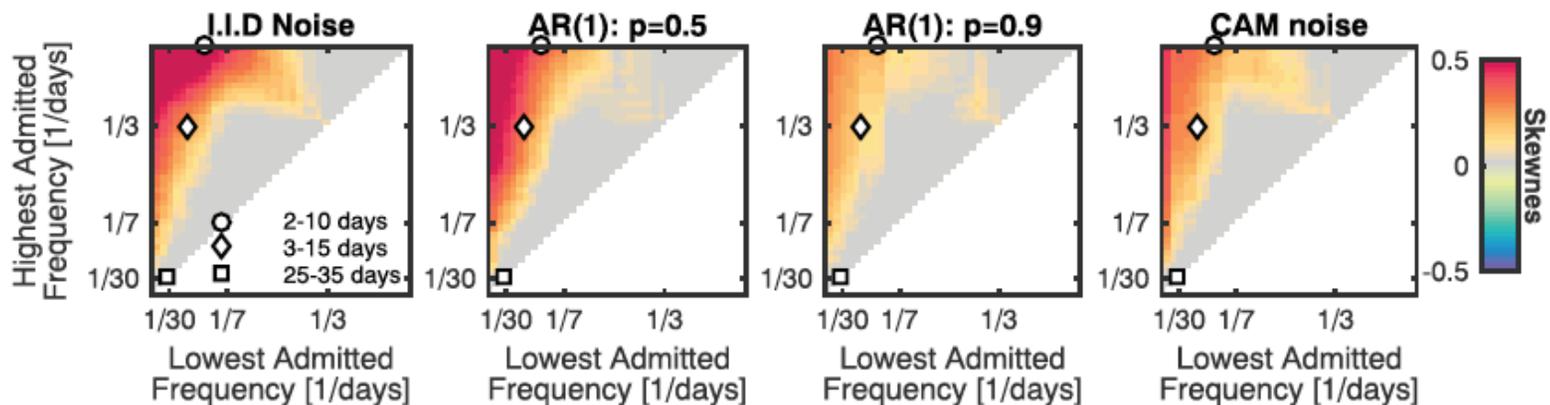
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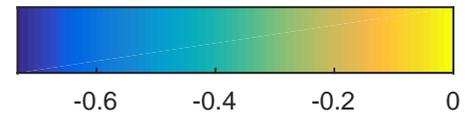
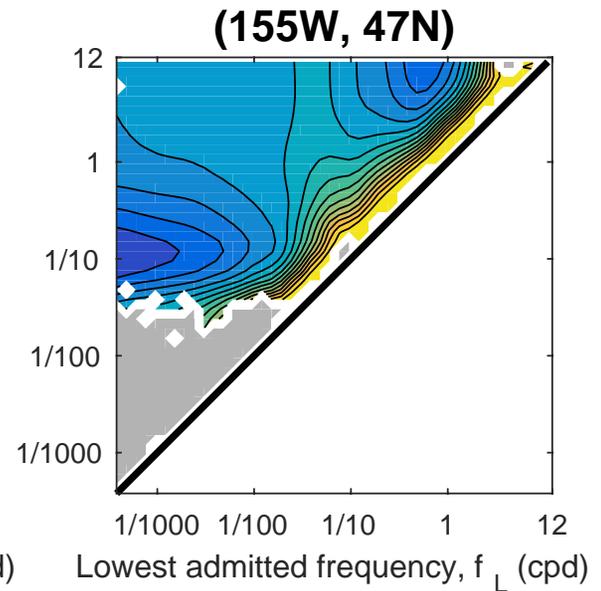
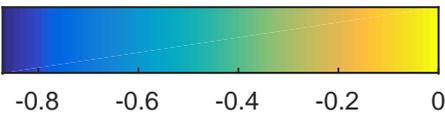
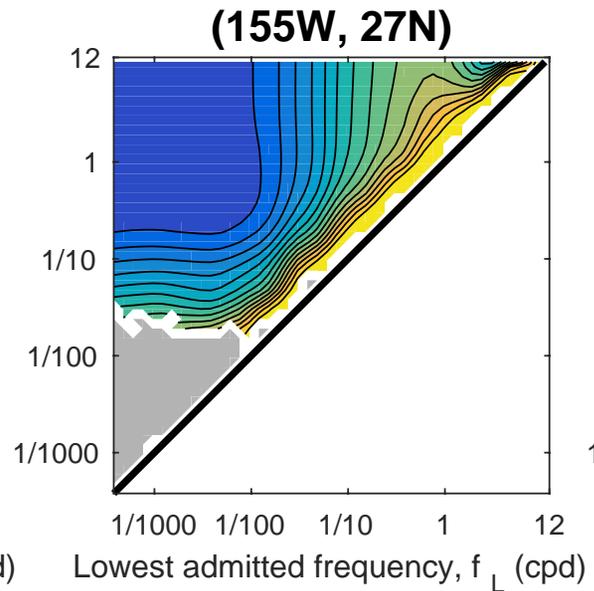
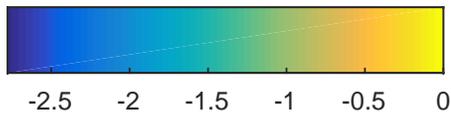
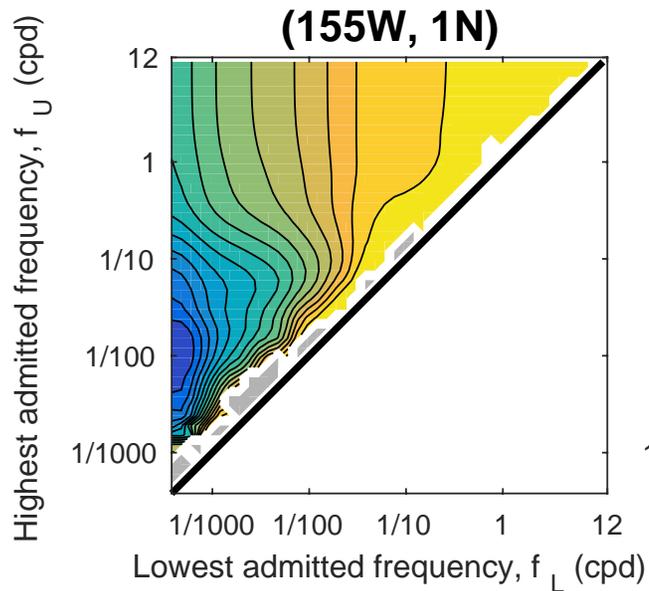
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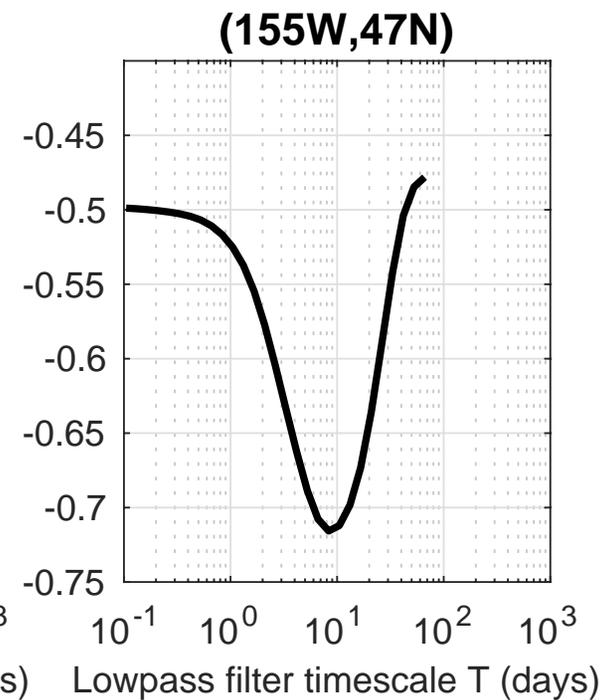
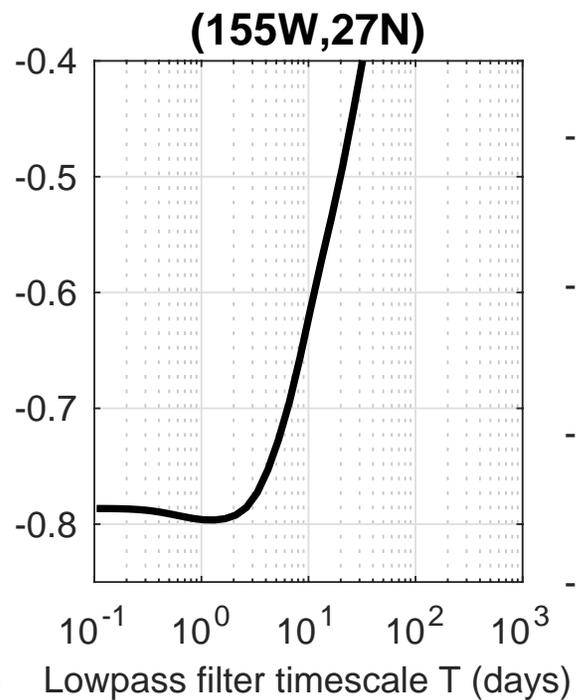
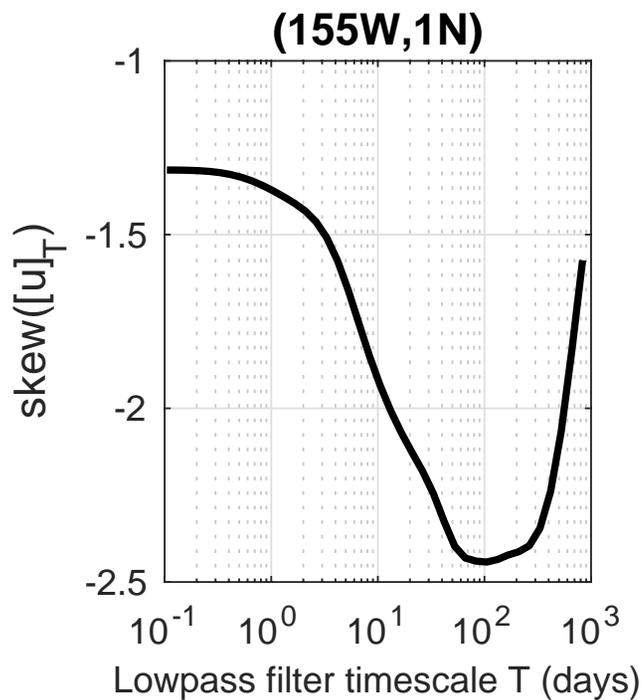
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- Bandpass filter using forward-backward Butterworth filter

Bandpass-filtered skew(u)

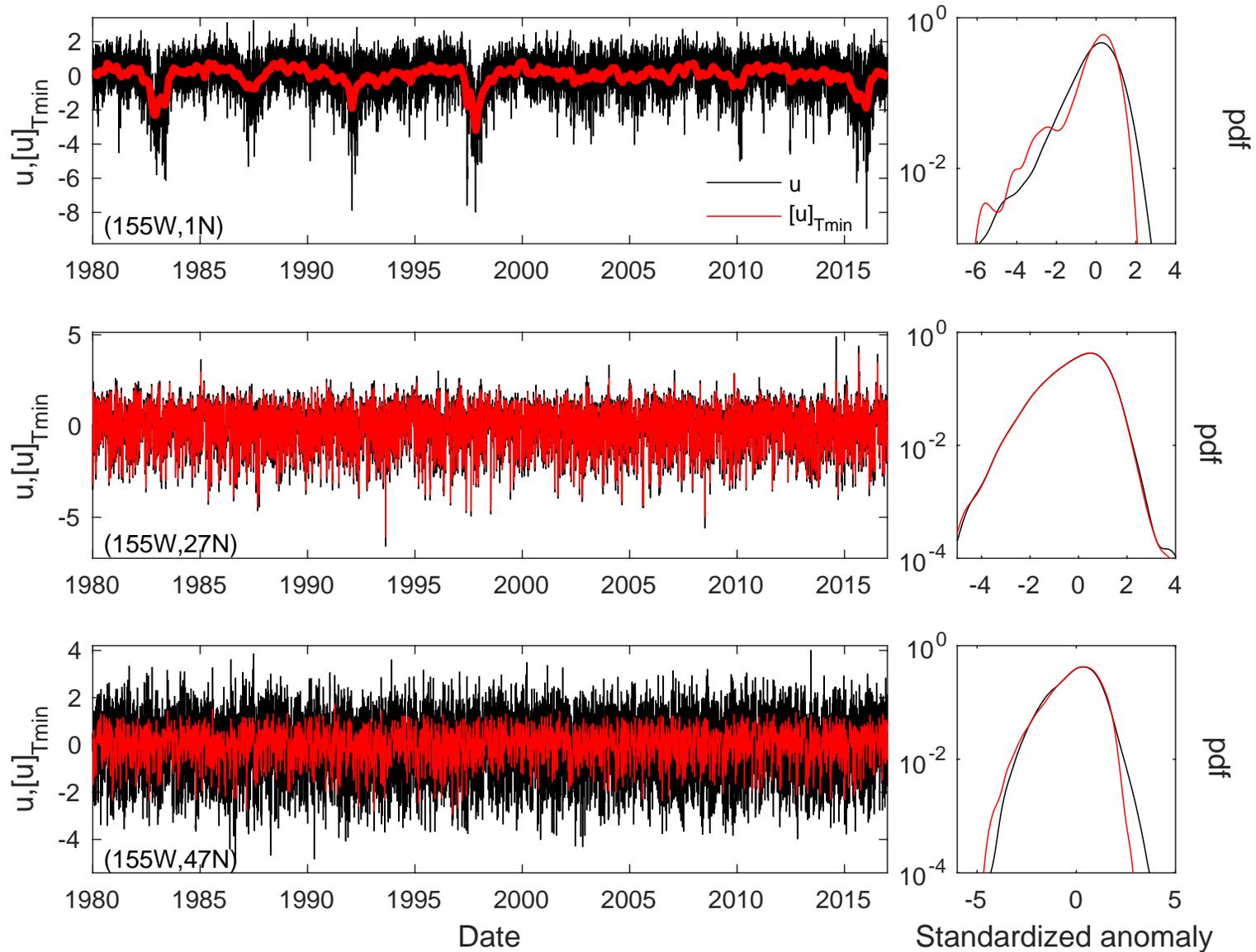


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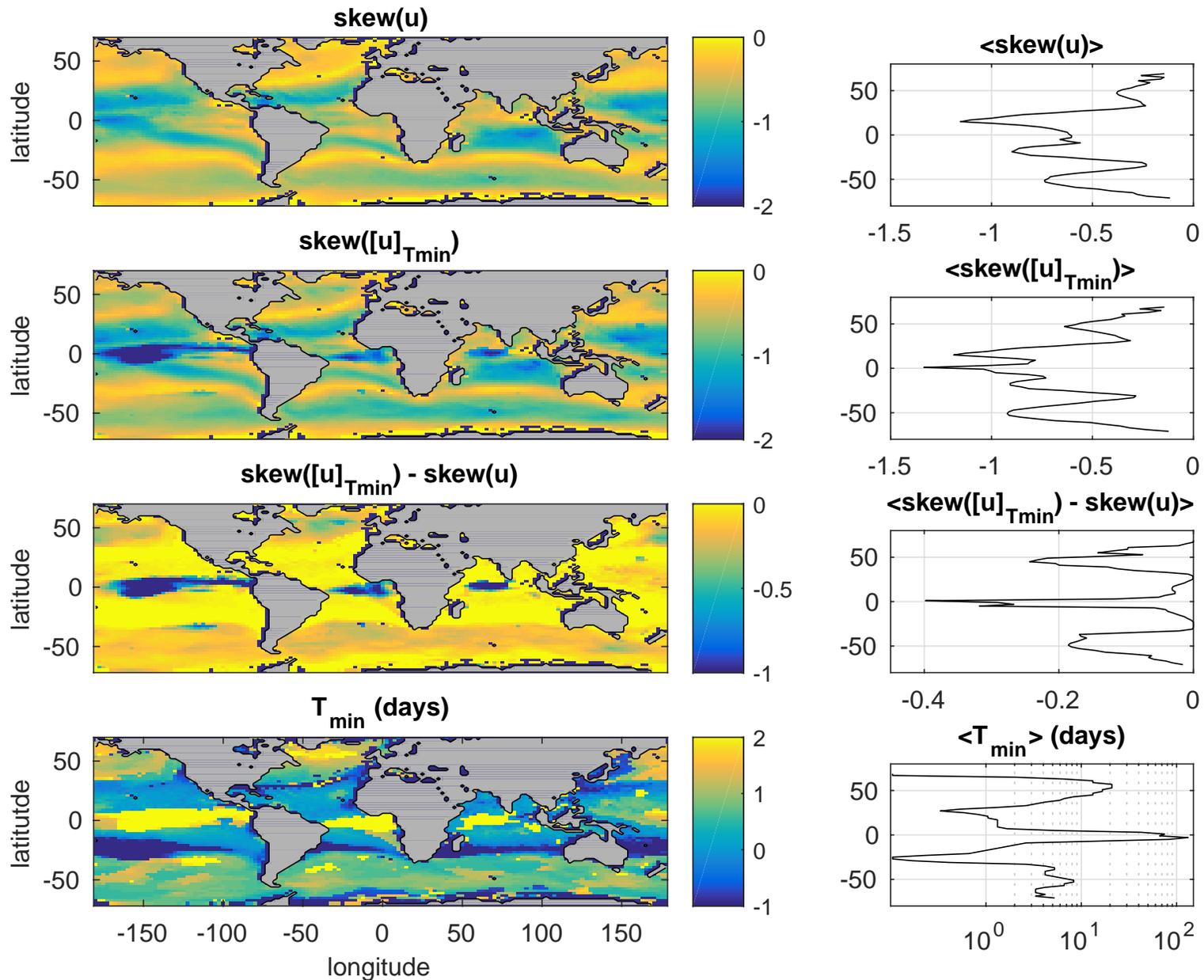


$$T = f_c^{-1}$$

Raw and lowpass-filtered time series



Spatial distribution



Timescales of idealized model

- Idealized near-surface momentum budget:

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- Model (η_u, η_v) as red-noise process

$$\begin{aligned}\frac{d}{dt}\eta_u &= -\frac{1}{\tau}\eta_u + \frac{\sigma}{\tau}\dot{W}_1 \\ \frac{d}{dt}\eta_v &= -\frac{1}{\tau}\eta_v + \frac{\sigma}{\tau}\dot{W}_2\end{aligned}$$

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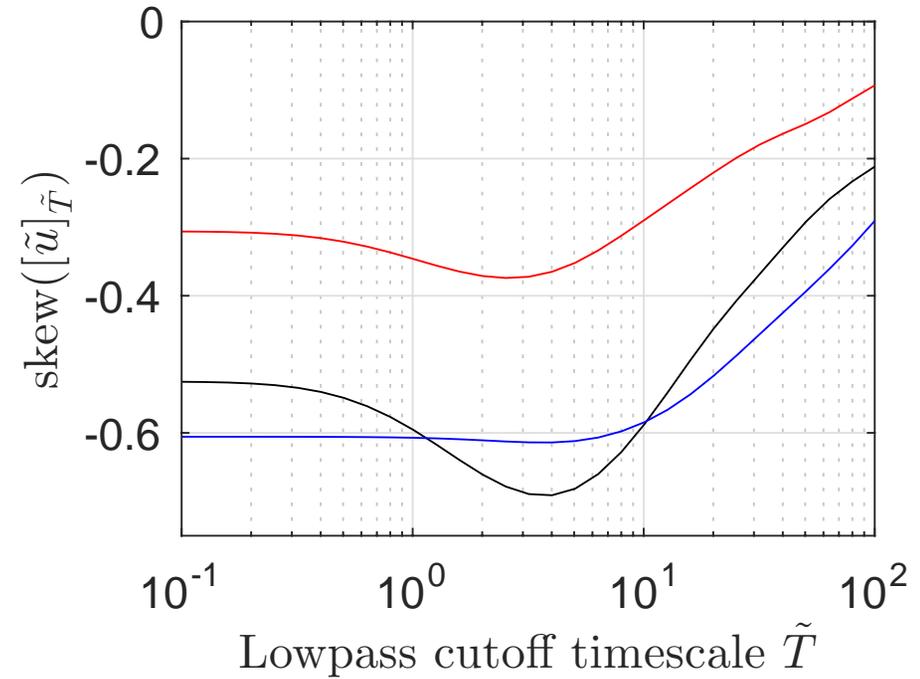
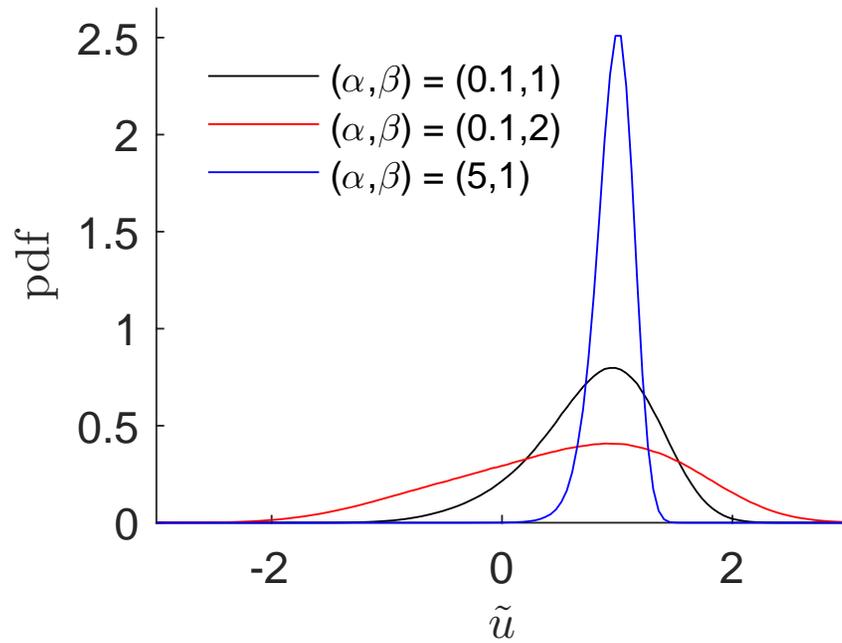
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⇒ System characterized by two non-dimensional parameters:

$$\alpha = \frac{\tau}{\theta}$$

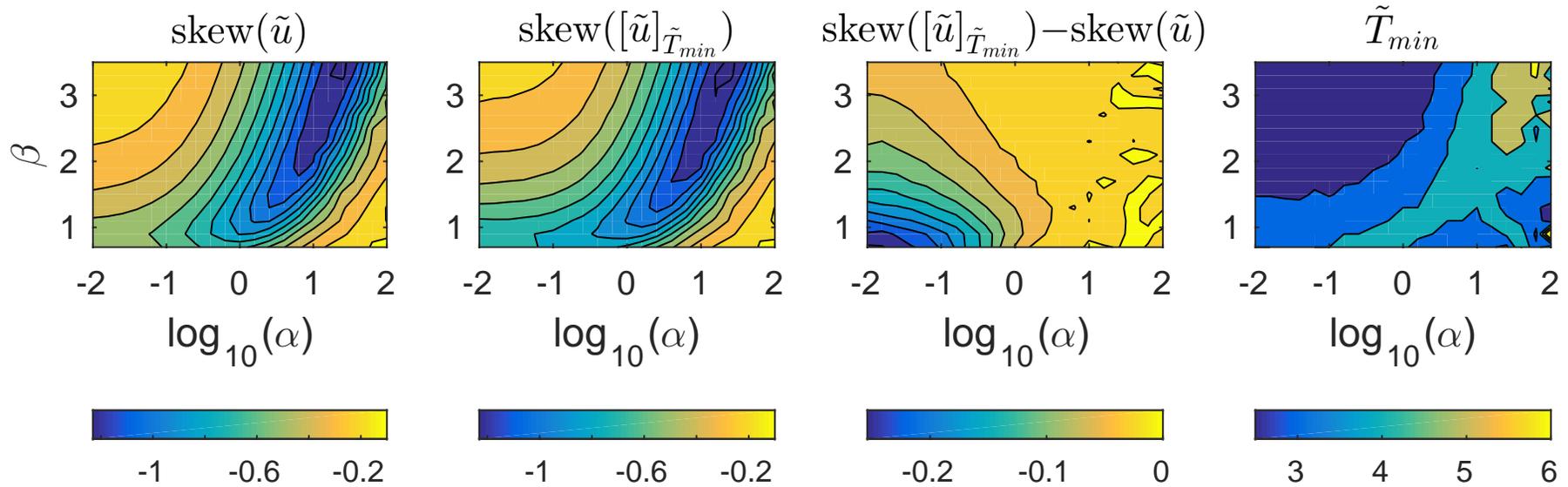
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