The relationship between small and resolved-scale variability in the Tropical Tropopause Layer

Characterizing unresolved variability for trajectory calculations

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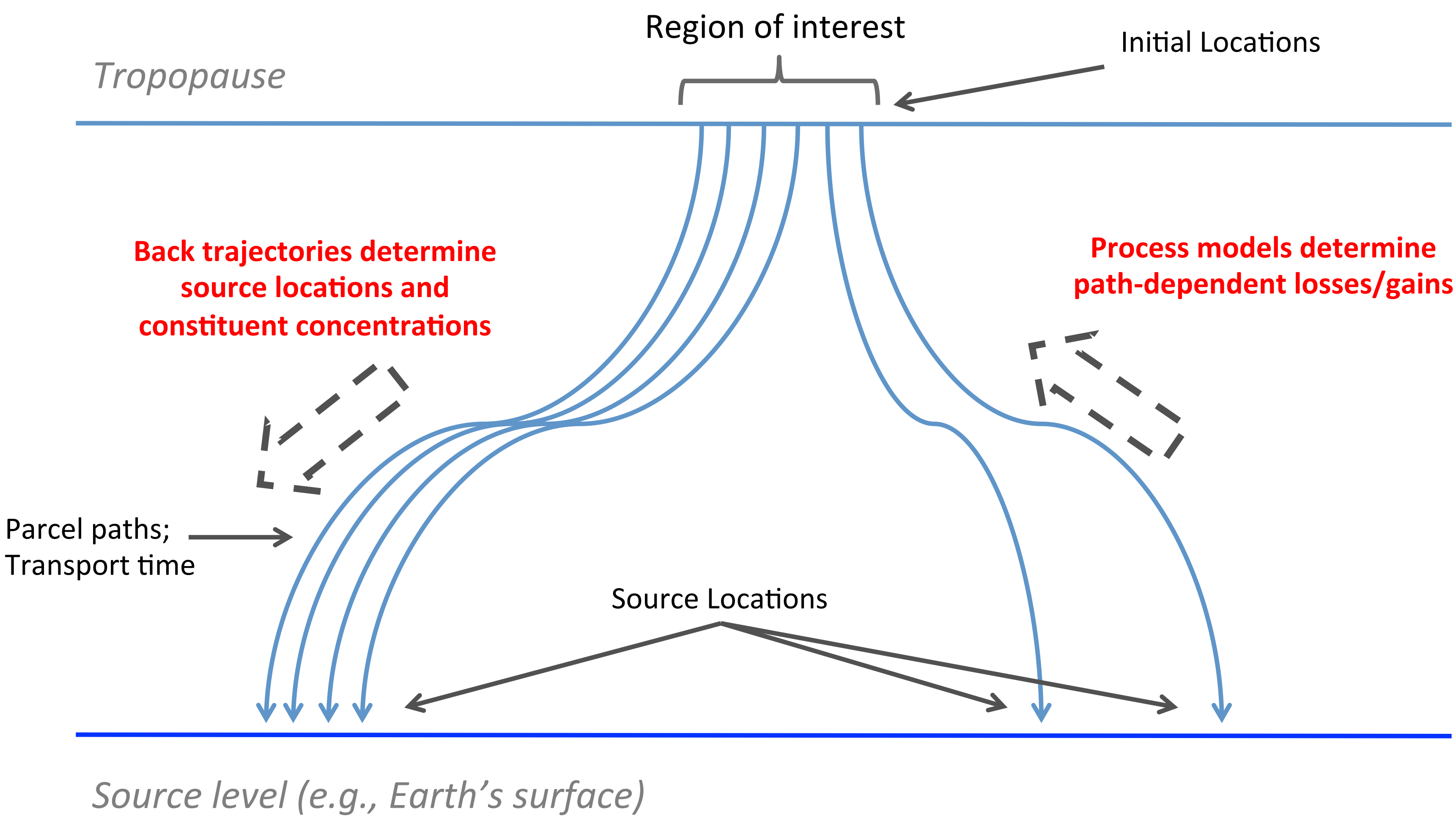
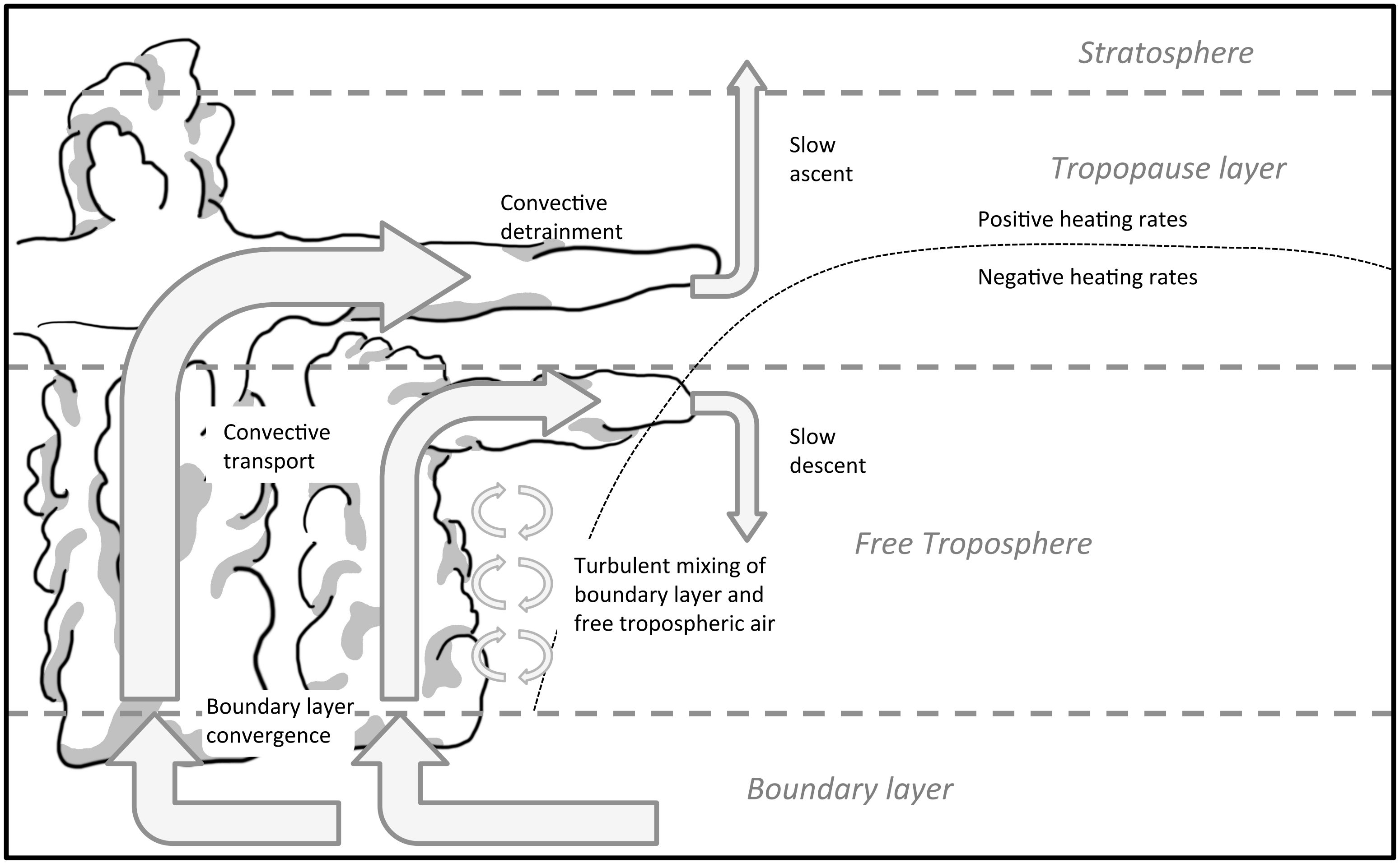
For process studies involving chemical concentrations, cloud formation, and dynamical interactions in the TTL

Trajectories *can* help determine sources and path-dependent processes



However, errors in the winds used to calculate air-parcel trajectories cause substantial uncertainties



It’s convenient to categorize wind variations by scale

Large scales are better sampled by observations than small scales

Large scales (> 1000(0) km, 7 km, 1 month)

- Reliably represented in analysis data

Mid-range scales

- The problem child - Difficult to characterize
- Marginally resolved by observing networks
- Important for weather
- Require extensive sensitivity tests to characterize

Small scales (< 100 km, 2km, 1 d)

- Completely unresolved
- No hope of accurately reproducing
- Apparently have robust statistical properties

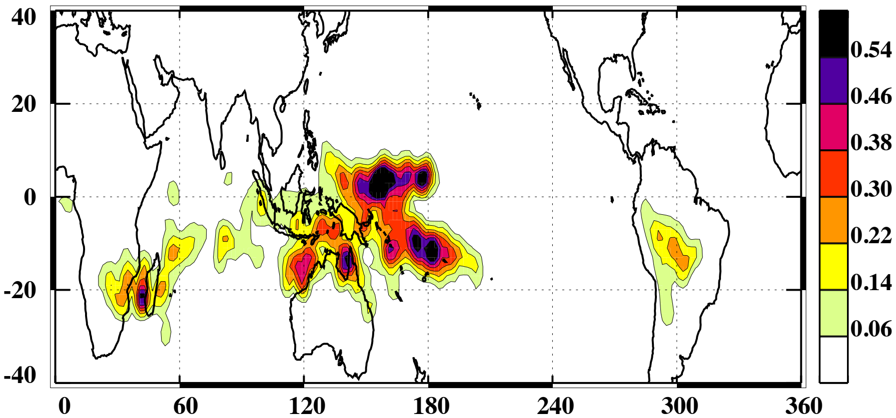
We will be simulating small-scale fluctuations in trajectory calculations with a multi-fractal random walk

Some statistics are not very resolution sensitive

(Errors generated by small scale fluctuations cancel in large ensembles)

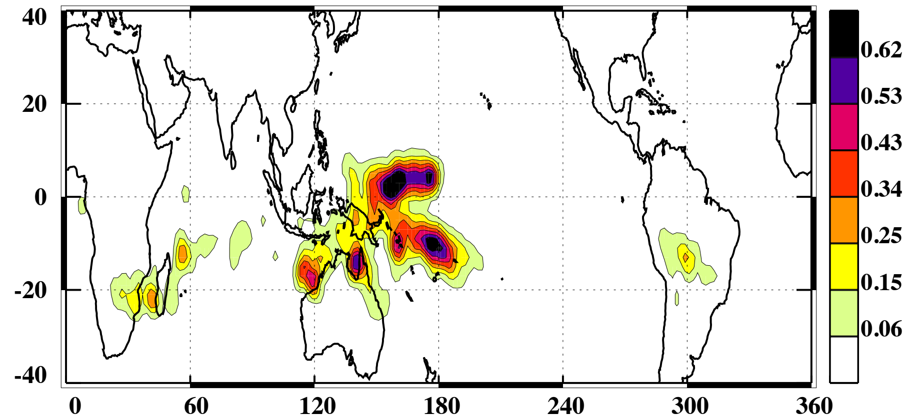
1/8° resolution

300 mb source fraction (per 1000)

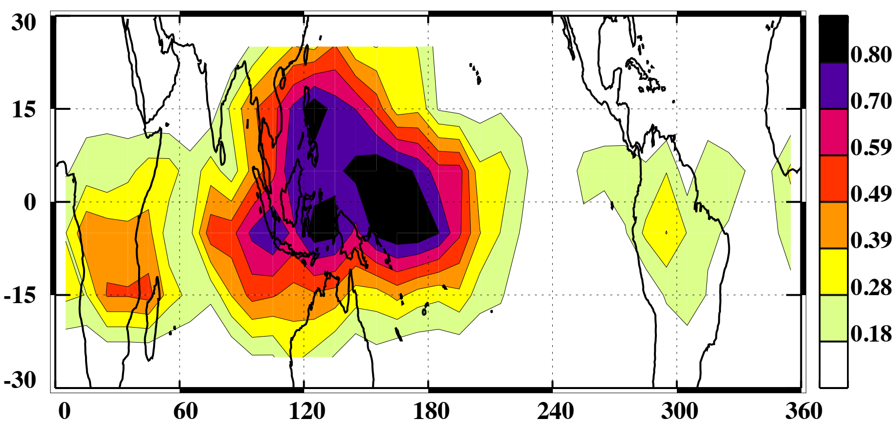


2° resolution

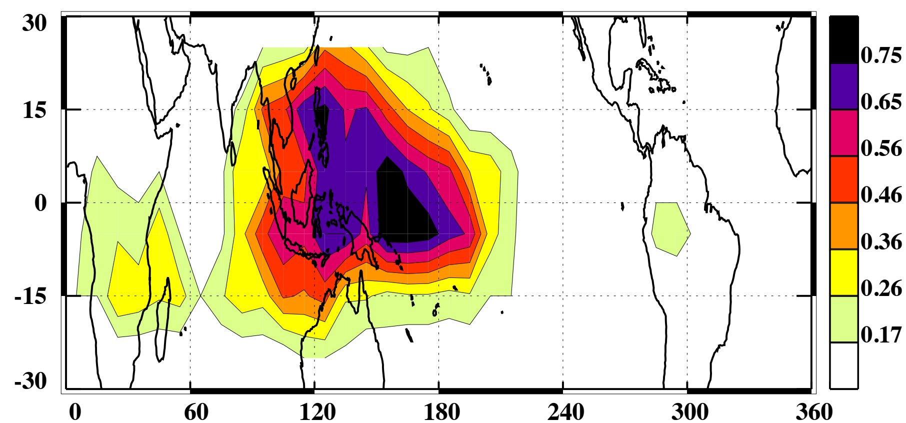
300 mb source fraction (per 1000)



Fraction with sources at 100 mb



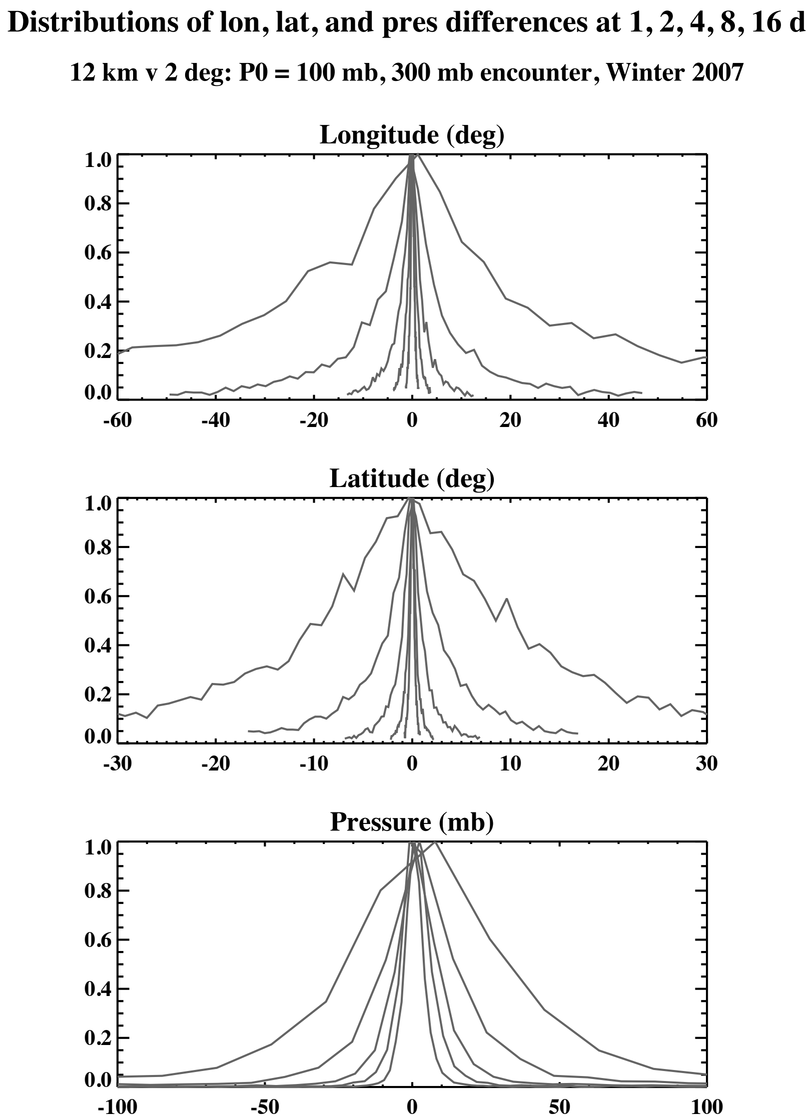
Fraction with sources at 100 mb



Amplitude ratio = 1.40 Source pattern correlation = 0.74 Influence correlation = 0.96

Some statistics are sensitive to resolution

Unresolved variations lead to trajectory dispersion away from the actual parcel path



At 16 d trajectories have dispersed:

~ 20° in longitude
~ 10° in latitude
~ 25 mb in pressure

Based solely on resolution

What can we do about this problem?

- We can't recreate actual small scale variations but we can estimate the associated uncertainties
- We can determine which statistics are more likely robust
- We can develop more efficient (and robust) trajectory strategies
  - Choosing optimal ensembles
  - Choosing optimal 'resolved' scales

The Overall Strategy

Characterize small-scale wind variability with observations

Airborne observations

- In situ observations
- Measure small-scale variations (1 - 20 Hz; 200 – 10 m)
- Small sample size
- Must filter affect of plane’s motion
- Flight path is 1 dimensional (a mixture of 4 Eulerian dimensions)
- Samples a limited region of phase space

High resolution analysis data

- Agree with airborne observations?
- Find systematic behavior
- Large sample size
- No direct observations – but based on equations of motions
- Affected by assimilation shock
- Affected by damping at smallest scales

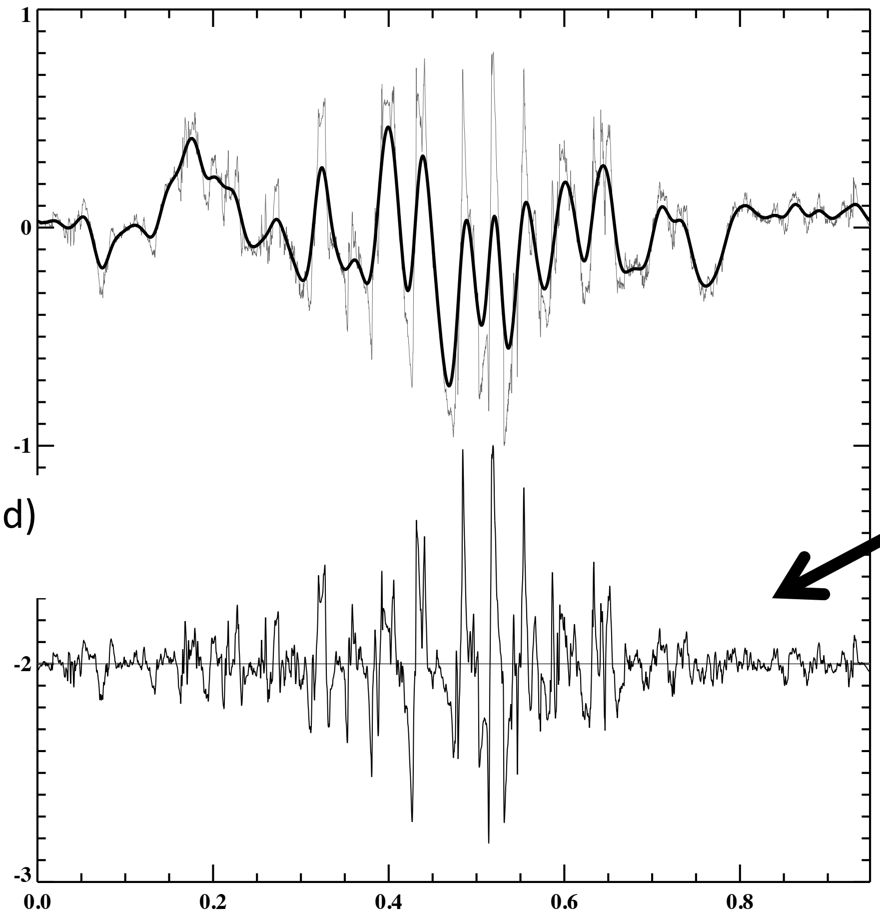
Examine the impact on trajectory calculations

- Create random small-scale deviations to resolved flow
- Perform large ensembles to understand uncertainties

Sample zonal wind variations

Total zonal wind
Smoothed (resolved)

Small scale (unresolved) deviations



Time (days)

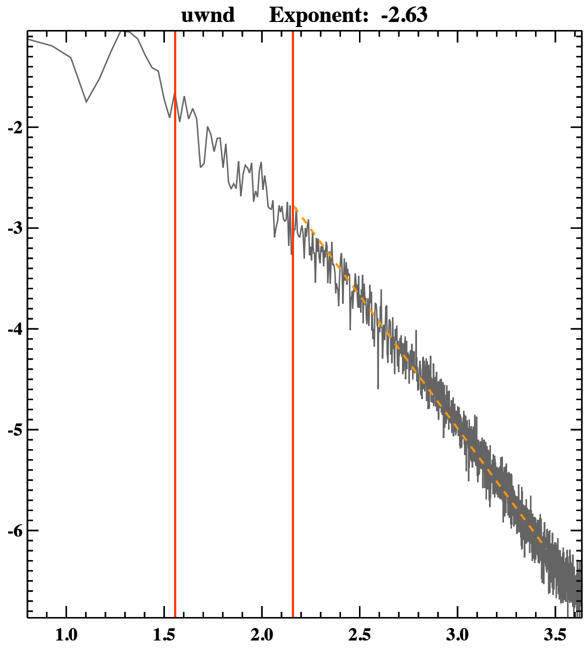
This is what we want to characterize and simulate with a multi-fractal random walk

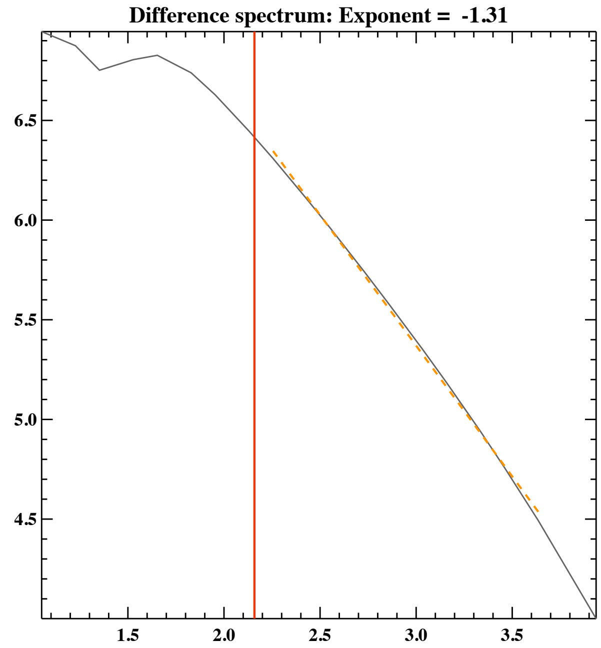
Why multi-fractals?

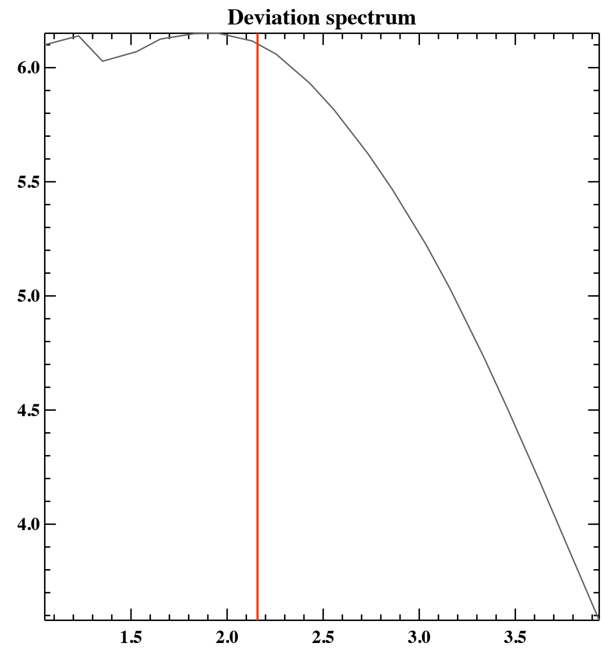
- Complex systems (non-linear, high order) like the atmosphere self-organize into structures that are best (so far) described with multi-fractals

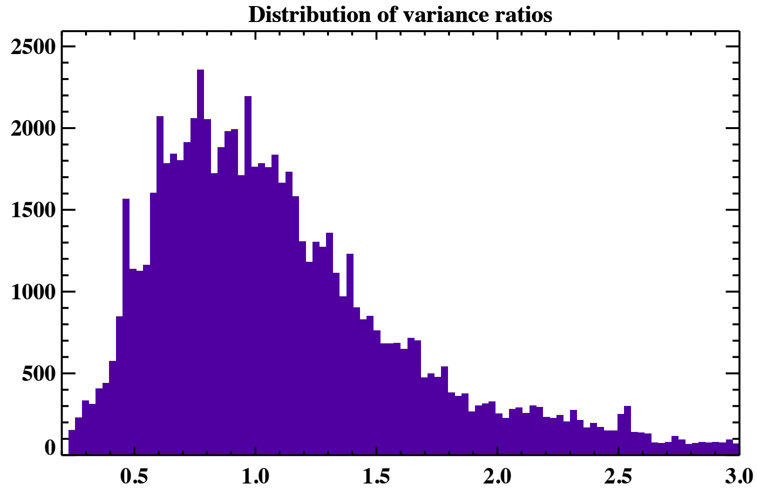
ATTREX data: zonal wind – are these data multifractal?

13 flights; Winter 2013, 2014

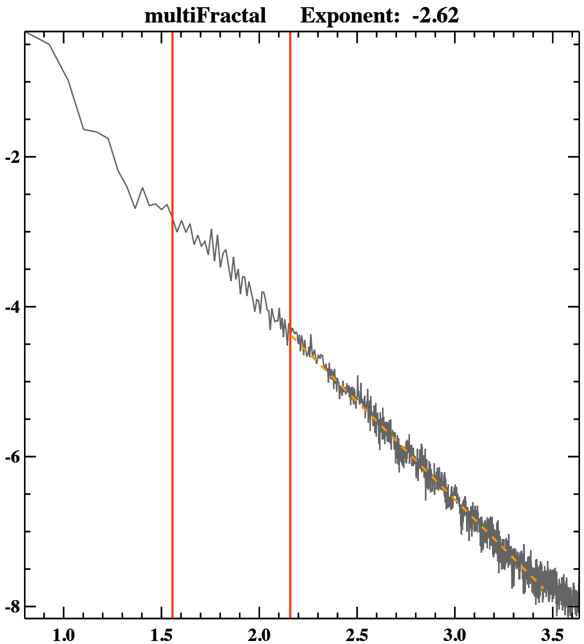


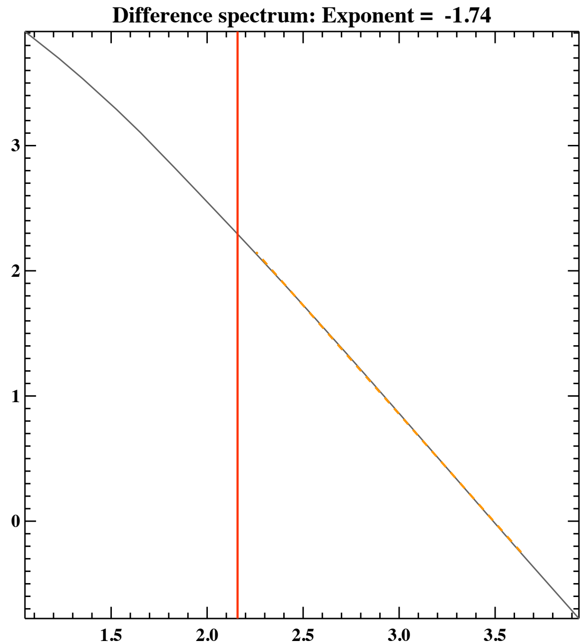


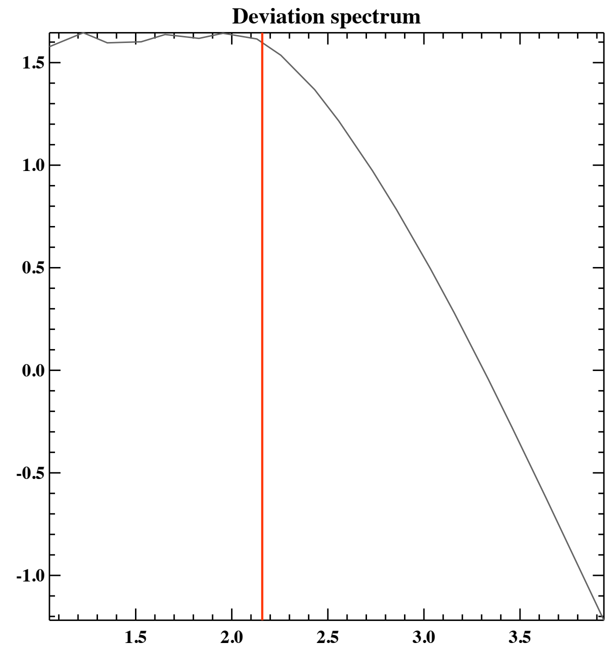


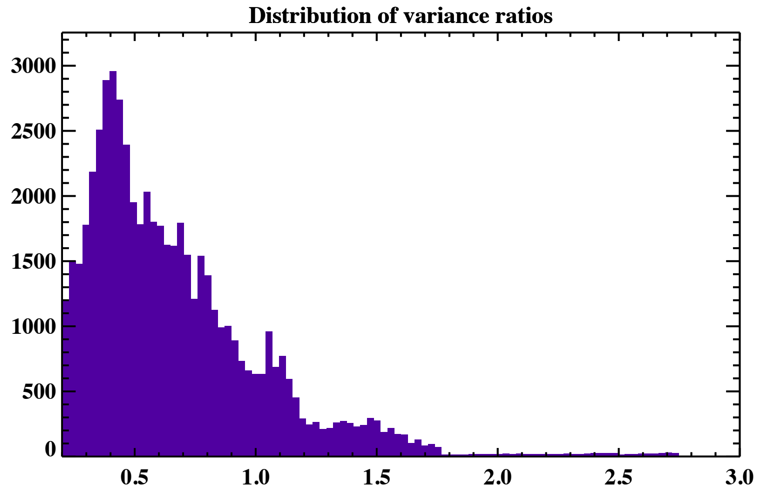


Multi-fractal random walk





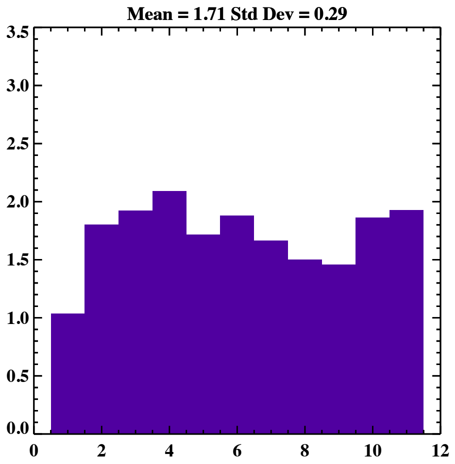


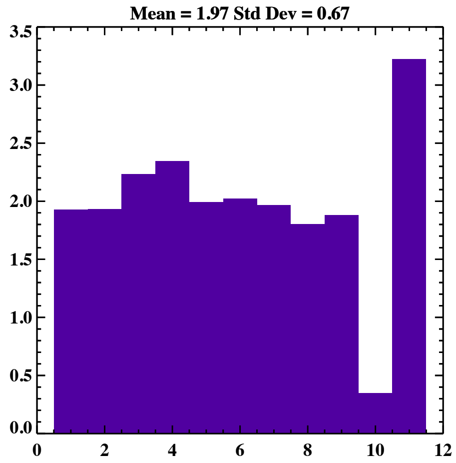


Separating horizontal and vertical components

Effective power spectrum exponents (β)

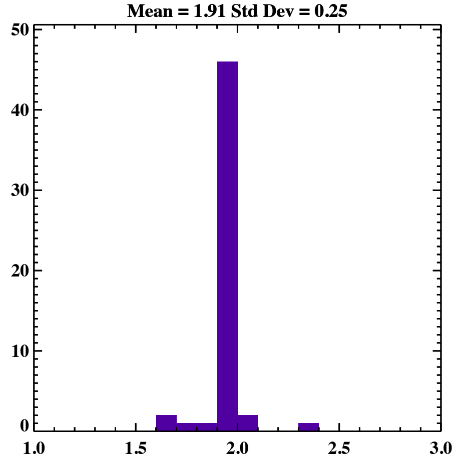
From individual flights (11)

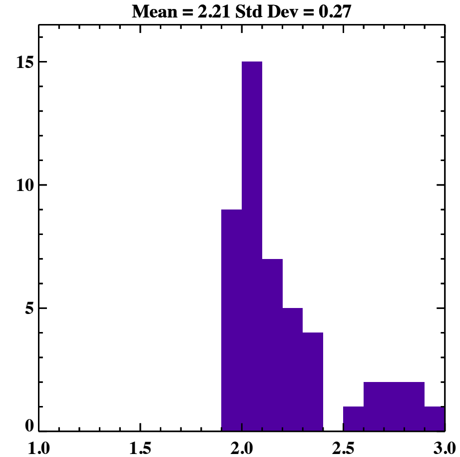




	Horizontal	Vertical
From All Flights	1.97 (0.25)	2.39 (0.27)
From Lovejoy et al	1.67	2.5

From Random combinations of 3 flights (55)





Horizontal

Vertical

Summary
Simulating deviations from resolved flow
What we want to know

- We want to know wind deviations δu' as functions of Δx, Δy, Δz, Δt
  - Δt is one time step
- We want a 'local' measure of δu'
- We want to know the uncertainty of δu'

Summary

Issues with obtaining relevant statistics from ATTREX data

- With ATTREX data we have δu' as a function of Δr
  - Where Δr is a mixture of Δx, Δy, Δz, Δt

- δu' is different dependencies on Δx, Δy, Δz, Δt
  - How do we separate them?

- (Related question) How do we account for the motion of the aircraft from the statistics?
  - How about measurement error?

Two analysis components
Conclusions

- Examine statistics of δu'
  - Statistics of δu have a power law dependence on Δr
  - We can compare Δr based statistics with those in high resolution ECMWF data
    - Then use ECMWF for the remainder of the analysis
    - Use sensitivity testing to account for uncertainties
  - **Δx dependence dominates δu (as it does for trajectories)**
  - This allows us to model δu' based on resolved variance
    - We know the variance of the deviations (as functions of Δr
    - Model with a multifractal random walk
  - We can examine the ratio of 'mid-scale' variance to small-scale variance to determine the uncertainty of our variance estimates

- How to separate dependencies

– **Flight irregularities (dips) don't hinder the analysis, they help**
  - By providing a better sample of phase space
  - We would like to see greater variations in flight paths

– So far, we have had some success in separating Δx, Δz

– Δt is problematic – too closely related to Δx
  - Δx=v Δt

Conclusions

- We are developing simulations of small scale fluctuations to better understand trajectory uncertainties
- We are using small samples of observed small scale fluctuations in airborne data to understand large samples of model-derived small-scale fluctuations in analysis data (not shown here)
- Unlike other studies (e.g., Lovejoy, Tuck, and Schertzer) – our analysis benefits from erratic flight paths (i.e., dips)
  - But still has substantial sampling issues (in phase space)