Air parcel trajectory dispersion near the tropical tropopause

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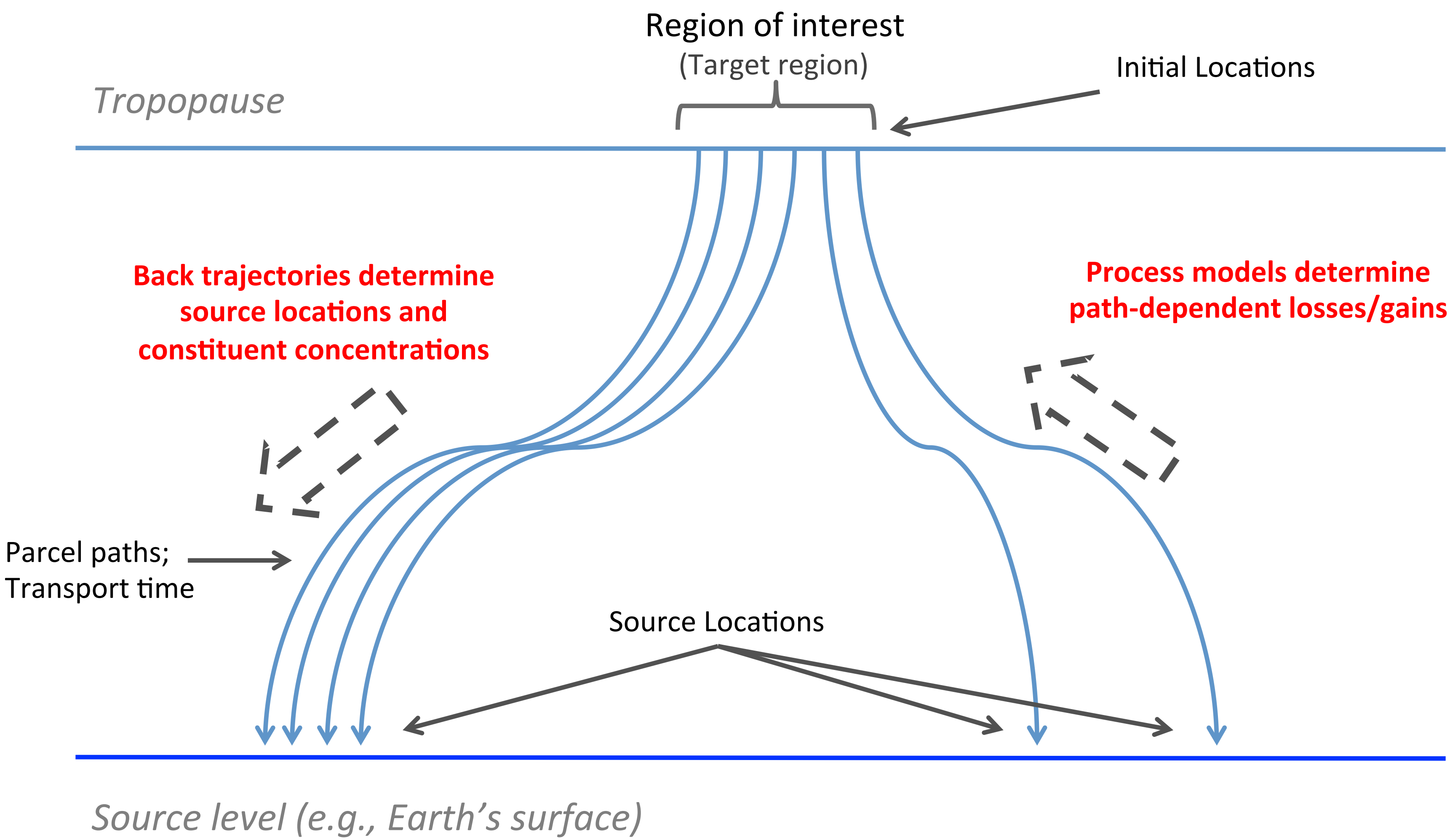
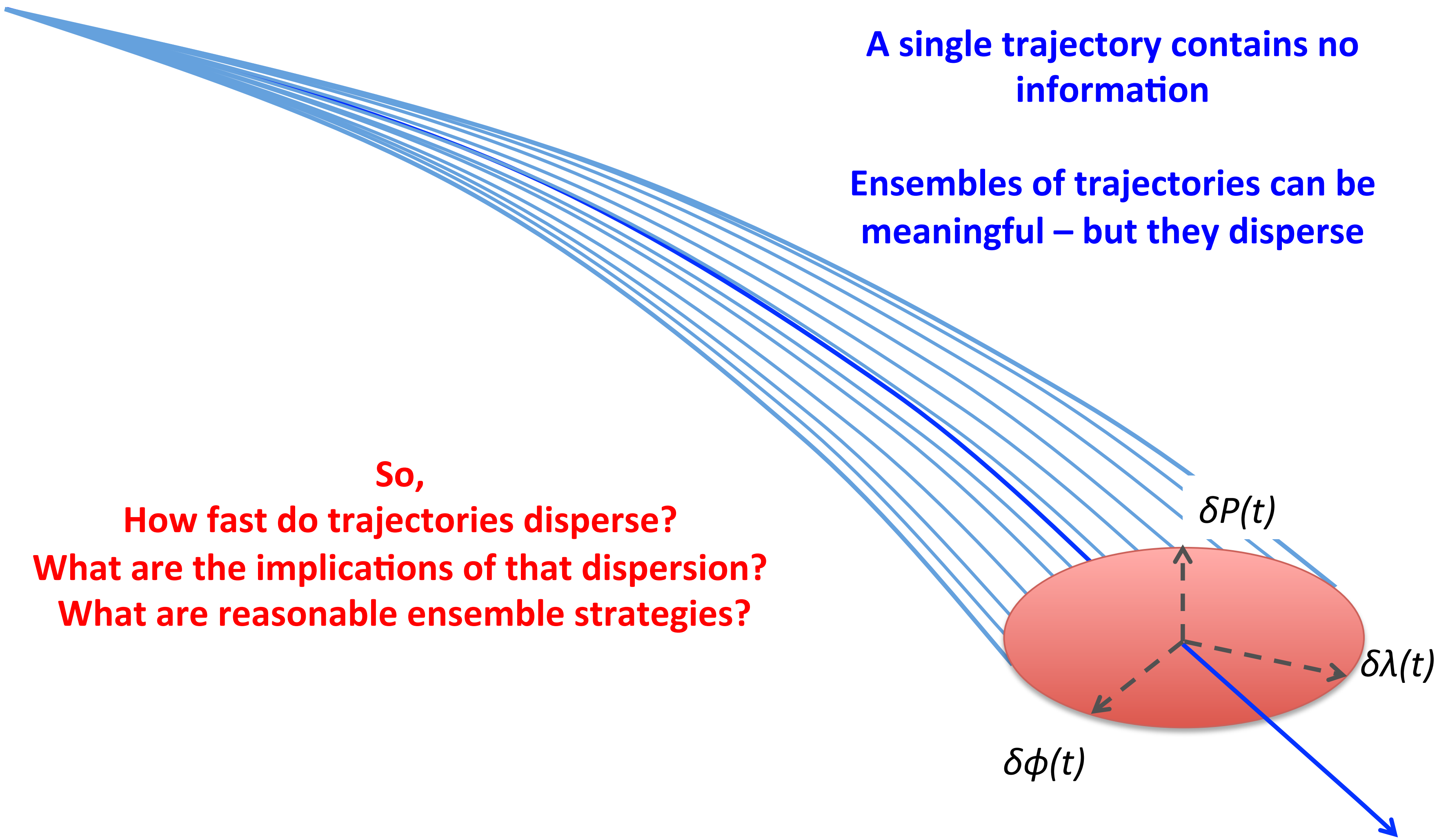
Overview

This study examines the uncertainty associated with trajectory calculations in the Tropical Tropopause Layer (TTL). We use three different trajectory-ensemble strategies to estimate how fast trajectories launched back in time from the tropical tropopause disperse. Comparisons of dispersion from these different approaches, along with sensitivity calculations, allow us to estimate dispersion rates, constrain those rates, and draw conclusions that help us design trajectory experiments and interpret their results.

This schematic illustrates the potential diagnostic power of back-trajectories calculations. These calculations can, in principle, determine the sources of chemical constituents at the target location and defines parcel pathways over which process models can determine path-dependent losses and gains.



However, trajectory dispersion (both physical and that due to data uncertainty) limits their applicability. This schematic illustrates the dispersion of an ensemble of parcel trajectories and serves as a background for discussing related issues.



A single trajectory contains no information

Ensembles of trajectories can be meaningful – but they disperse

So,
How fast do trajectories disperse?
What are the implications of that dispersion?
What are reasonable ensemble strategies?

Dispersion is quantified in terms of the ensemble spread of trajectories (longitude $\delta\lambda$, latitude $\delta\phi$, and pressure δP) and how these terms grow with time.

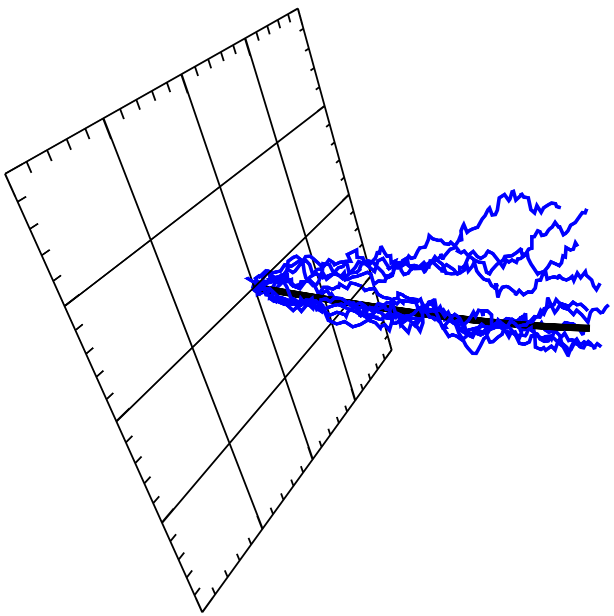
The following three slides describe the different ensemble types

- Ensemble #1: (Monte Carlo) Random perturbation to wind fields at each time step. This ensemble uses our most realistic representation of wind fields in which we combine the 'resolved' winds (space scales 2° and larger) from the ECMWF operational analysis with a stochastic model of unresolved wind fluctuations based on the observed multi-fractal behavior of wind fields at small scales. Uses data from 2013 for which ECMWF operational analysis data is available at NCAR.

- Ensemble #2: Perturbed initial parcel locations. This ensemble is based on traditional ensemble techniques in which the initial conditions are perturbed. Trajectories are calculated using the resolved winds only and are initially separated by 2° latitude and longitude. Uses data from 2013 (with some calculations from 2007).

- Ensemble #3: Multi-model ensemble. This ensemble is formed by trajectories calculated using different analysis data (ERA-interim, MERRA, CFSR, GFS) and different trajectory formulations (kinematic and diabatic). Calculations are based on resolved wind fields and each ensemble member is initialized at the same locations. Uses existing multi-model ensemble data for Jan-Feb 2007. Two of the ensemble members depend on diabatic heating rate data unavailable beyond 2008.

Ensemble #1: Monte Carlo simulations using random wind perturbations at each trajectory time step



(Potentially) the most realistic simulation of trajectories we have and the primary focus of this work

Use analysis data for resolved winds (ECMWF operational analysis smoothed to 2°)

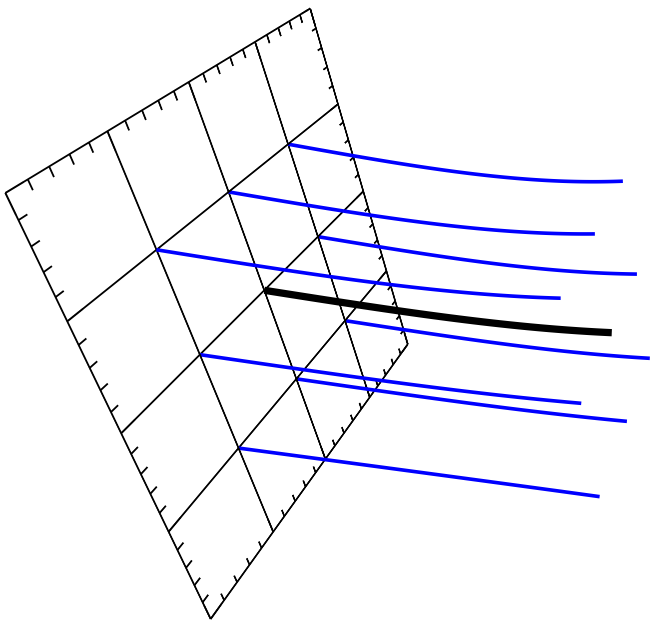
Stochastic model simulates unresolved wind fluctuations. Total wind fluctuations consistent with multiplicative cascades (multi-fractal); unresolved variance determined from variance at small resolved scales.

Use midpoint displacement to model a multiplicative cascade (has some very nice, practical properties)

Model parameters are constrained by values in existing literature, analysis of ECMWF operational analysis data, and measurement from MMS during ATTREX (sensitivity tests determine how well the calculations are constrained)

Ideally, Ensemble #1 represents physical dispersion from a volume 1 grid-spacing in diameter

Ensemble #2: Perturbed initial conditions



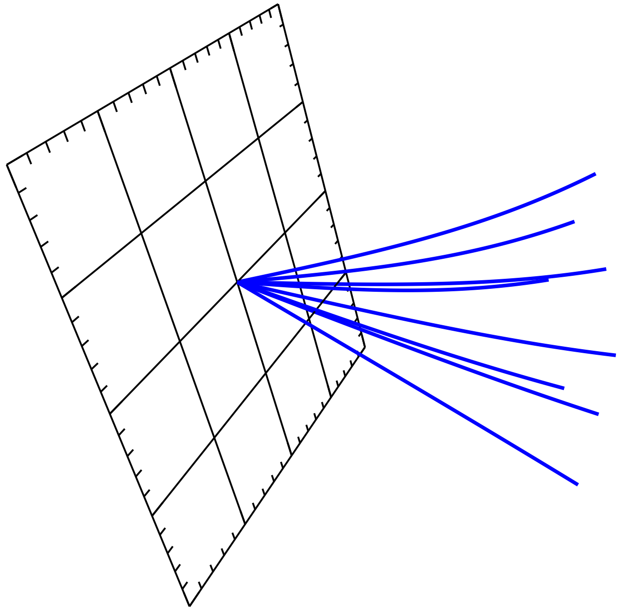
A common alternative to Ensemble #1

Displace initial locations (lat, lon) one grid spacing from unperturbed trajectory

Uses **resolved wind fluctuations** only

Represents dispersion by the resolved flow

Ensemble #3: Multi-model ensemble



Dispersion by inter-analysis differences of resolved winds

Each ensemble member uses **different forcing data** of trajectory approach

Uses **resolved wind fluctuations** only

Each member has **identical initial locations**

Some Important Results

Dispersion for Ensemble #1 is well constrained by observational estimates of model parameters

In terms of:

- Variance of unresolved fluctuations
- Predictability of small scale variance in terms of resolved variance
- Energy spectra
- Coherence (or lack thereof) between unresolved fluctuations of *u*, *v*, *w*, *T*

But, it is difficult to have confidence in vertical winds from either observations or analysis data

Dispersion for Ensemble #2 is not very sensitive to choice of forcing data
(ECMWF, ERA-interim, MERRA, GFS, CFSR)

Dispersion is largely a property of the resolved flow
Unresolved fluctuations provide 'initial' perturbations that grow via the resolved flow

Dispersion rates for the upper tropical tropopause are

Longitude: 3.1 ± 0.5°/d (i.e., ~310 km/d)
Latitude: 0.84 ± 0.1°/d
Pressure: 2.9 ± 0.3 mb/d

Ramifications and Conjecture I

Dispersion is large enough to **spread parcels throughout the tropics** within typical TTL transport times (30-60 d)

Ensemble #1 provides a **plausible estimate for physical dispersion** and represents fundamental limitations of trajectory calculations in the TTL

Ensemble #2 (perturbed initial locations) **is a reasonable cheap alternative to Ensemble #1** with sufficient temporal averaging; the initial spread should be ~1 resolved scale in diameter

Dispersion from systematic **analysis data error is** (somewhat) **separable from that due to random error**

Some Ramifications and Conjecture II

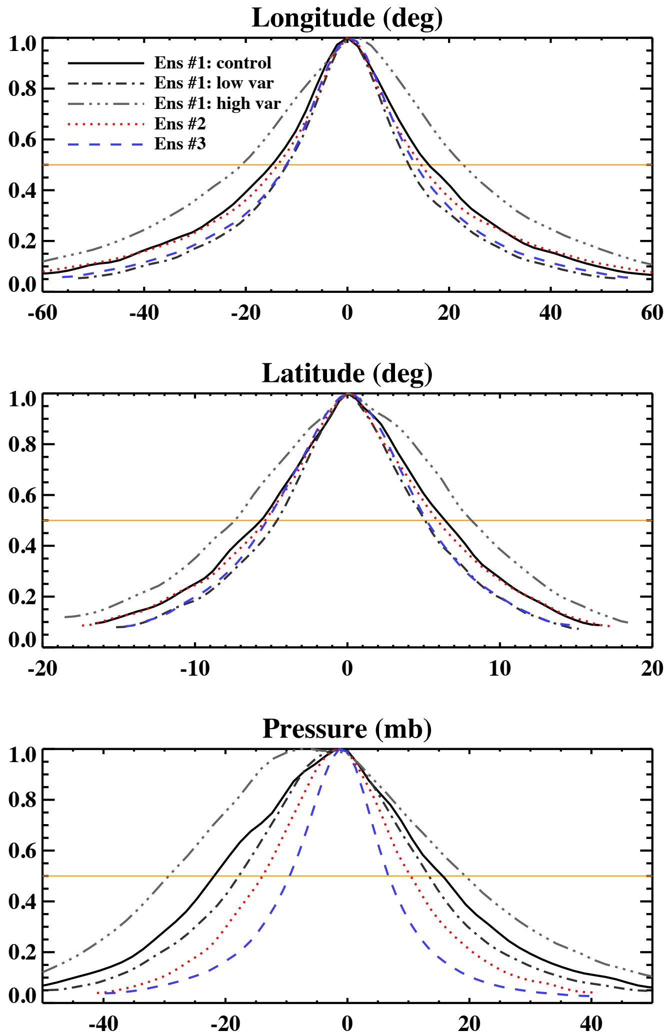
The **smallest (target) volume** that should be represented by back trajectories is determined by the **resolution of the forcing data**

Caveat: the resolution is determined more by the observational data assimilated into the analysis data than the resolution of the assimilation model (or the resolution of the data that is provided)

The **smallest source volume** that should be analyzed is determined by the **dispersion space scales**

There is no point in analyzing time scales smaller than those dynamically-linked to the space scales associated with dispersion

These panels are normalized histograms of dispersion for 10 day trajectories. Shown are differences from the ensemble mean for 69,000 – 87,000 (depending on the ensemble type) trajectories from 252 topical locations (10° separation between initial locations) and 34 start times during boreal winter (Jan-Feb).



Gray, dark gray, black – random perturbation ensembles (3 amplitudes: small amplitude, control, large amplitude)

Red – ±2° initial position spread

Blue – multi-model ensemble

Average dispersion growth at 10 d (short enough to obtain a 'linear' estimate); based on the standard deviation of Ensemble 1 histogram)

Longitude: 3.1°/d (i.e., ~310 km/d) ; Latitude 0.84°/d; Pressure 2.9 mb/d

All 3 ensembles have similar dispersion growth – although Ensemble #1 has stronger vertical dispersion

Ensemble #1 is not very sensitive to reasonable changes of multi-fractal parameters

Precise knowledge of these parameters is not necessary for obtaining a useful estimate of dispersion growth

Estimates of 10 d horizontal dispersion from Podglajen et al 2014 are 300-1000 km/d

The next 3 slides shows maps of 10 d dispersion rates as a functions of initial parcel location.

The first slide shows longitude dispersion for the three ensembles plus an additional ensemble #2 calculation using ERA-interim data during 2007. The main point is that there are similarities between spatial patterns from Ensembles #1 and #2 but these are different from Ensemble #3. This lower right panel demonstrates that the differences with ensemble #3 are not due to inter-annual variability.

The second slide shows different Ensemble #2 calculations (using different analysis data) from 2007. This slide demonstrates the degree to which spatial patterns of dispersion from Ensemble #2 are robust.

Latitude dispersion patterns (not shown) are different that longitude dispersion – but comparisons among the different ensemble types lead to the same conclusions as those from the longitude comparisons.

The third slide shows the strong similarity between patterns of vertical dispersion. This similarity is presumably due to the strong connection between vertical dispersion and tropical convection.

Addresses the question: Which locations near the tropopause have experienced the greatest dispersion (have the widest source regions)?

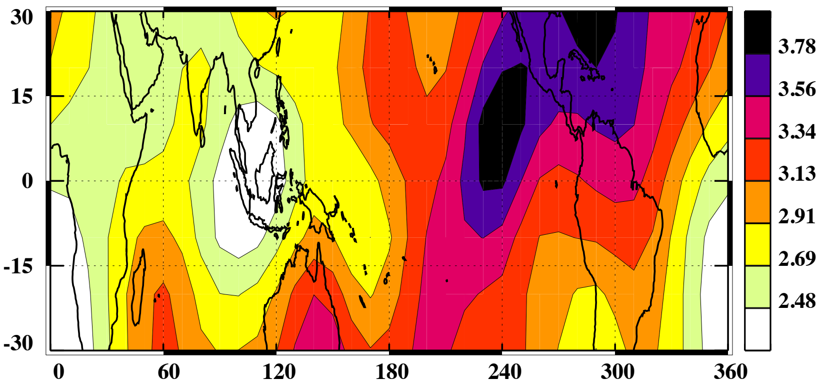
Exposes differences among the types of ensembles

Longitude dispersion

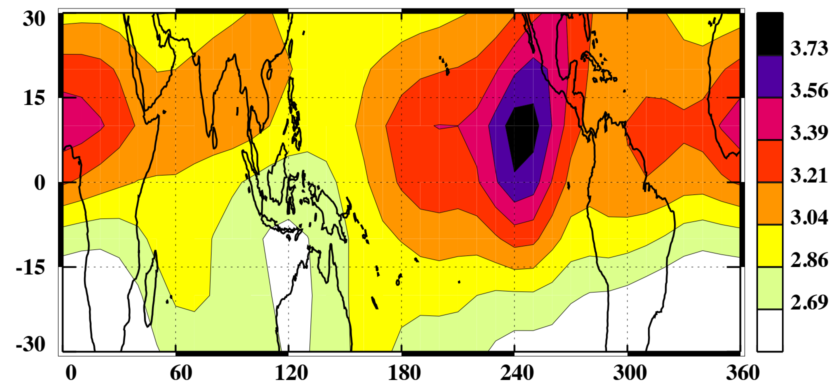
Ensembles #1 and #2 have similar spatial patterns and amplitudes of dispersion

Ensemble #3 has more discrepancies

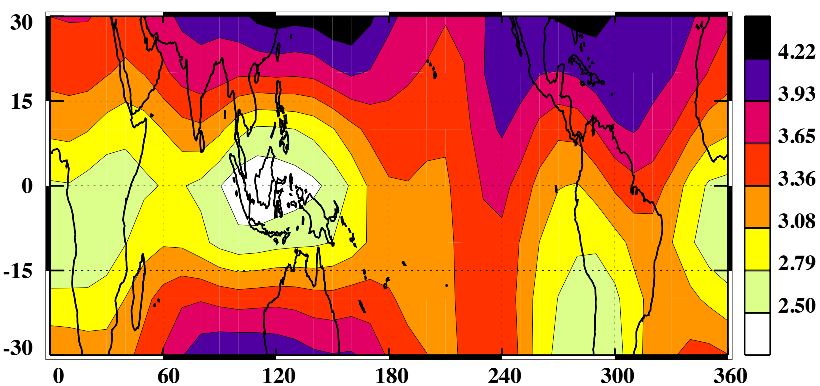
Ensemble #1 (ECWMF 2°; J-F 2013)



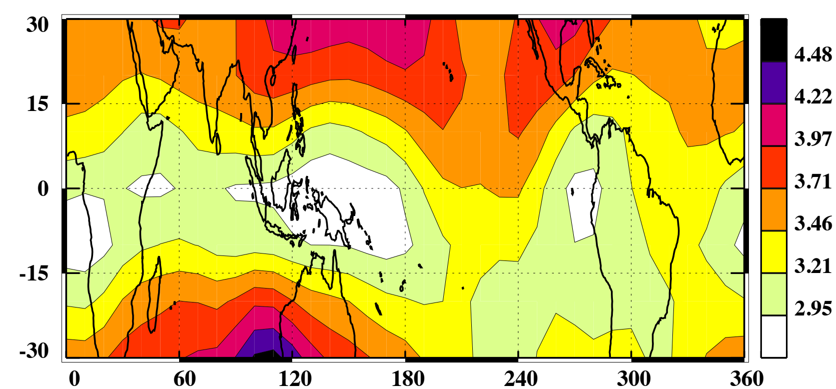
Multi-model ensemble (#3; J-F 2007)



Ensemble #2 (ECWMF 2°; J-F 2013)



Ensemble #2 (ERA-interim; J-F 2007)

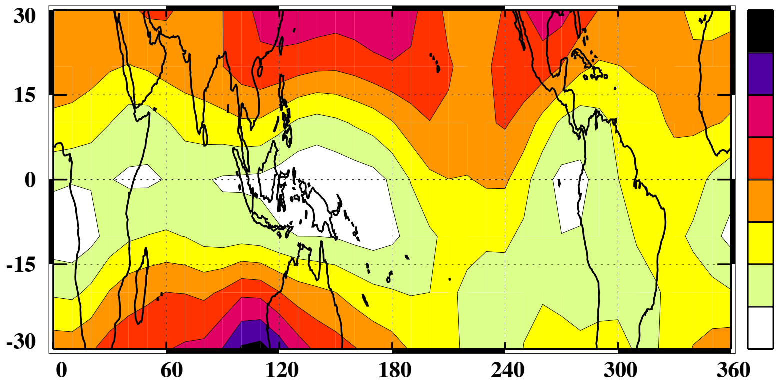


Discrepancies with the multi-model are not just due to inter-annual variability

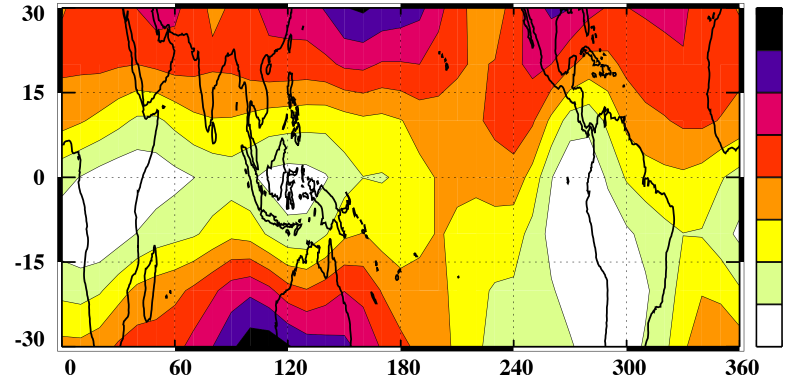
Longitude dispersion

Ensemble #2 results are robust to changes of forcing data

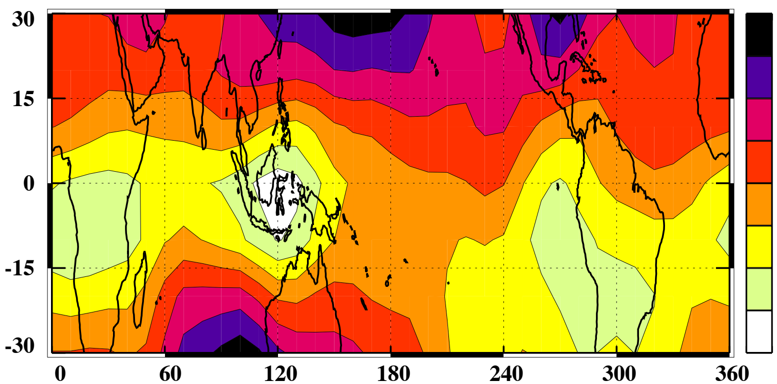
ERA ensemble (J-F 2007)



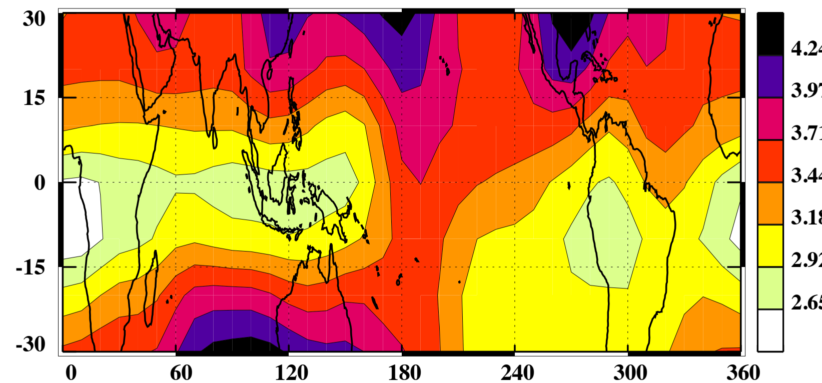
MERRA ensemble (J-F 2007)



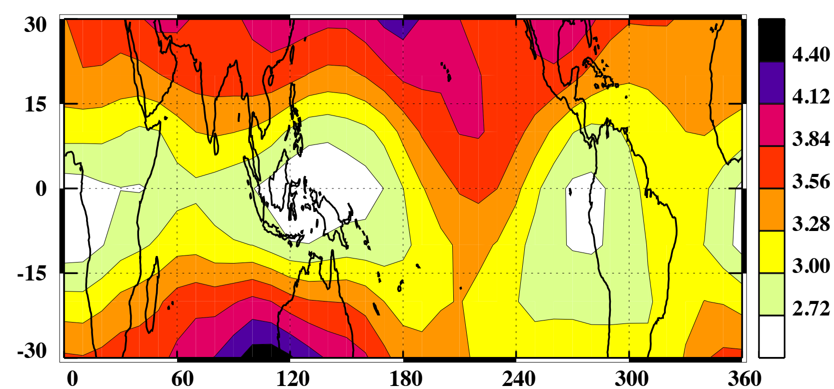
CFSR (J-F 2007)



GFS (J-F 2007)



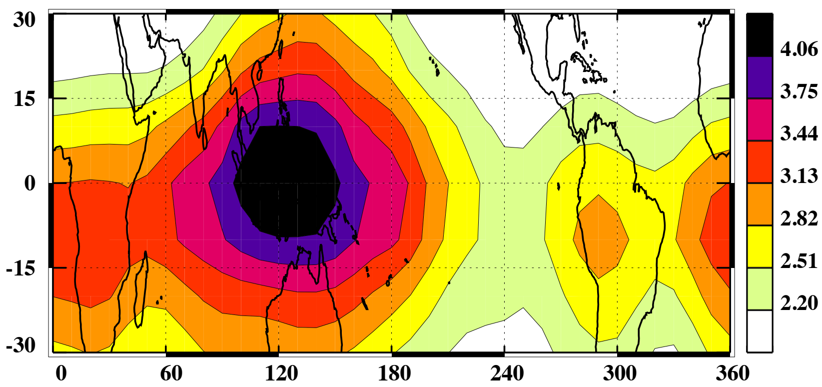
ERA-interim; Yang et al. heating
(J-F 2007)



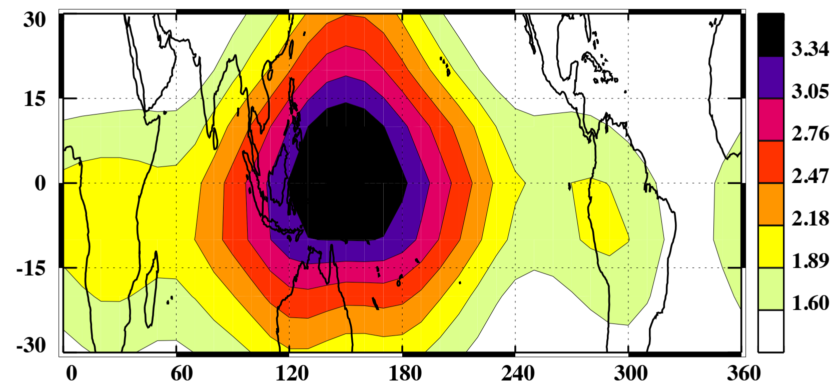
Vertical dispersion is similar among all Ensembles

and related to convection

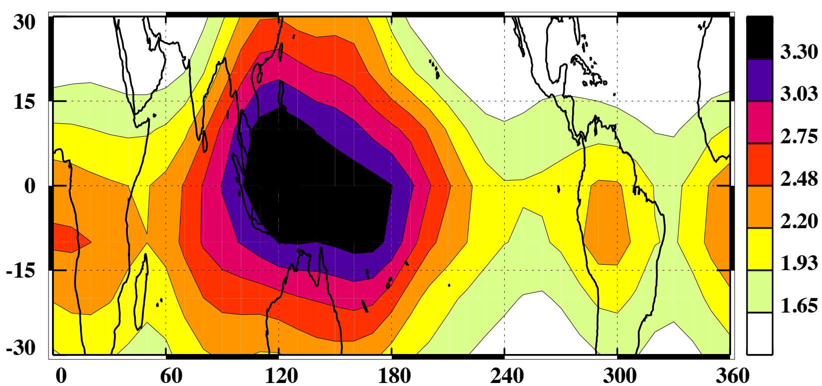
Ensemble #1 (ECWMF 2°; J-F 2013)



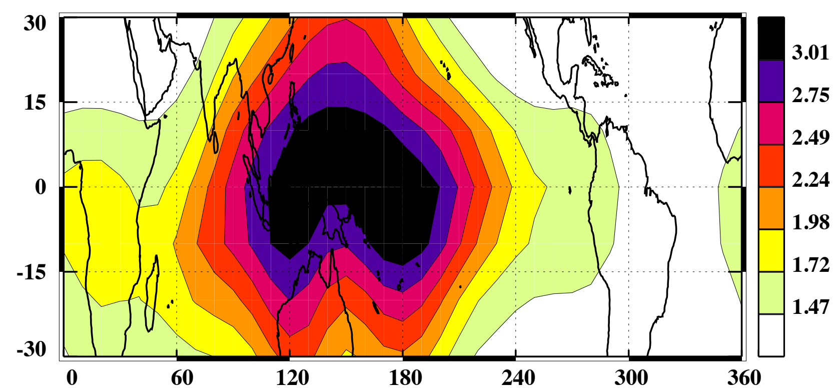
Multi-model ensemble (#3; J-F 2007)



Ensemble #2 (ECWMF 2°; J-F 2013)



Ensemble #2 (ERA-interim; J-F 2007)



Reiteration of important properties of dispersion

Dispersion is due primarily to **large-scale flow**

Dispersion is **not very sensitive to** specification of **small-scale noise**

Dispersion is **not very sensitive to** choice of **forcing data**

Despite systematic differences in the forcing data

Hence, the earlier conjectures