Summary of χ pod Chameleon EQ14 Analysis

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1 Overview

- This document is an attempt to provide an overview/summary of what i've found in my χ pod analysis.
- The motivation/goal for all this work is to show if and how well the CTD- χ pod method works for estimating χ , ϵ , K_T , etc from fast temperature profiles.
- Before dealing with all the issues with the CTD deployments (depth loops, entraining water, rosette-induced turbulence), I wanted to verify that the method itself worked w/out these complications.
- The Chameleon microstructure profiler has both thermistor and shear probes, so this seemed like an ideal way to test the method. I would apply the χ pod method to the chameleon thermistor data only (ϵ_{χ}) , and compare to the 'true' results computed using the shear probes (ϵ) .
- I found that basically the estimates of χ agreed, but ϵ_{χ} was about an order of magnitude smaller than ϵ (Figure 1,2,3).
- The χ pod method requires an assume mixing efficiency, and uses the normal assumption that $\gamma = 0.2$. I computed gamma from the chameleon data (formula) and found that it was about an order of magnitude smaller than 0.2; hence the low epsilon estimates.
- Is gamma really different here? Am I calculating it wrong? What does gamma mean? Sasha found something similar previously, gives me a little more confidence that i'm not doing something wrong..
- One idea was that we should be computing gamma over patches, and it's meaningless outside of patches. Previous work has found gamma is close to 0.2 . So I tried computing patches and gamma. This can be a whole other can of worms (lots of choices to make in how to identify patches, compute N2, Tz etc), but I found I could get gammas close to 0.2 . And on a point-by-point basis, ϵ_{χ} agreed better with ϵ_{χ} . But then we have much fewer data points...
- Looked at whether averaging multiple profiles agreed better. Doesn't seem to make epsilon agree. However, gamma computed from average quantities is closer to 0.2?
- So, is gamma really small here, or am I just computing it wrong? Look at other locations/regimes?

2 Data and Processing

- ComputeChi_Chameleon_Eq14.m : Applies χ pod method to Chameleon profiles from EQ14.
- Sally shared w/ me Chameleon data that she and Jim processed. I ended up reprocessing it using a smaller fmax (7Hz) because it looked like the thermistor spectra rolled off much lower than the assumed 32Hz.

3 ?

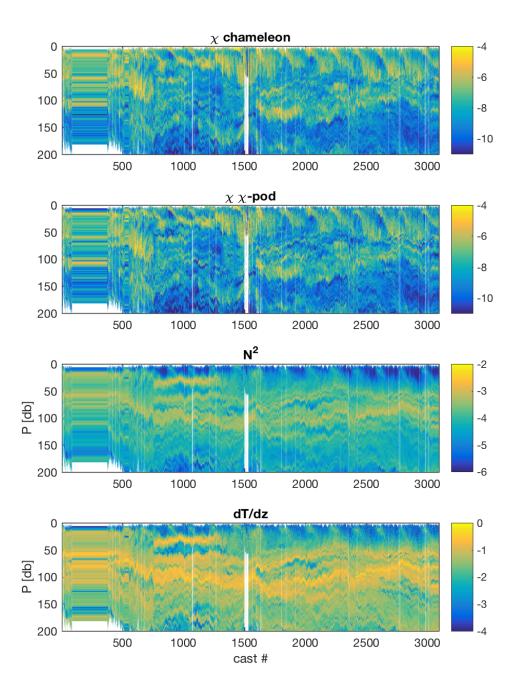


Figure 1: Comparison of χ from chameleon method and chi-pod method, for EQ14 chameleon profiles. Each profile was averaged in 2m bins.

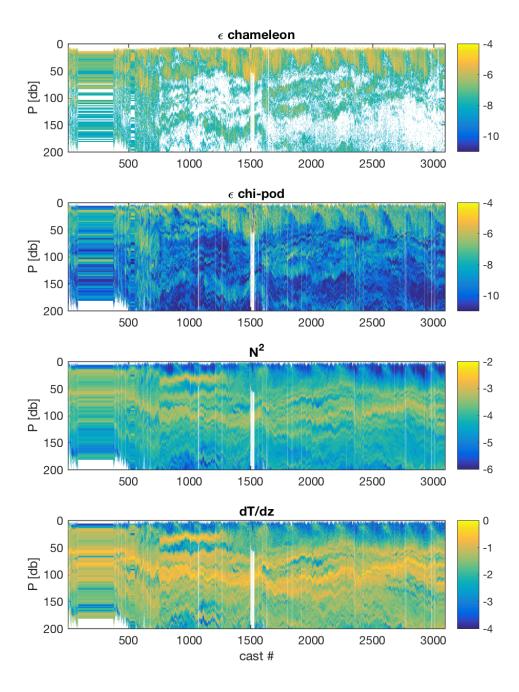
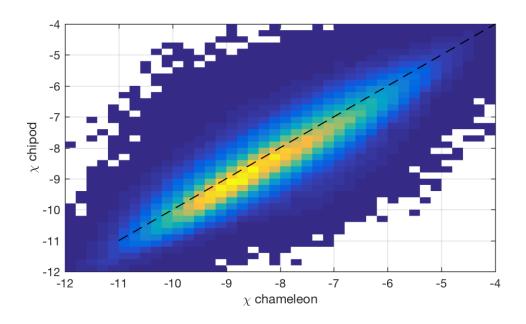


Figure 2: Comparison of ϵ from chameleon method and chi-pod method, for EQ14 chameleon profiles. Each profile was averaged in 2m bins. Values of below chameleon noise floor (-8.5) have been naned out



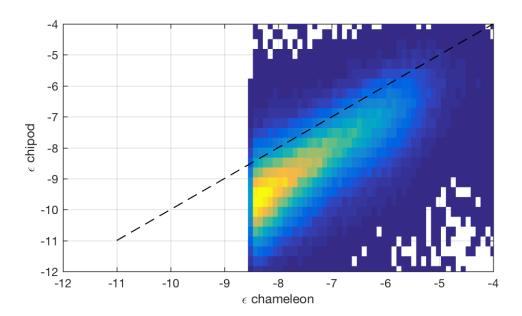


Figure 3: Comparison of χ ϵ from chameleon method and chi-pod method, for EQ14 chameleon profiles. Each profile was averaged in 2m bins. Values of below chameleon noise floor (-8.5) have been naned out

4 Comparing individual estimates of ϵ

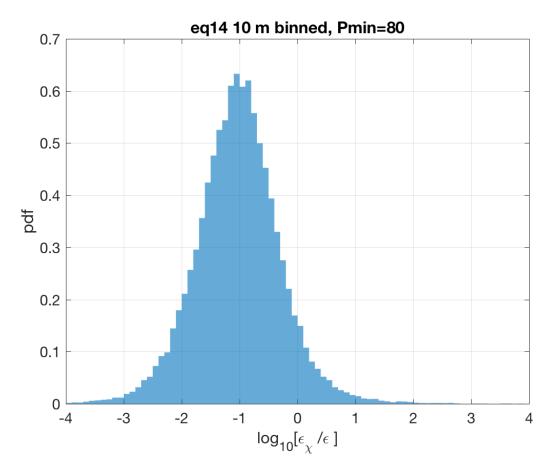


Figure 4: EQ14: Histogram of the ratio of ϵ estimates from χ pod method to the chameleon values, for χ pod method applied to 1m binned profiles, and applied to just patches. Estimates for each profile were averaged in 10m depth bins.

5 Normalized eps vs chi plots

Assuming that

$$\gamma = \frac{N^2 \chi}{2\epsilon < T_z > 2} \tag{1}$$

, plotting $[\chi/t_z^2]$ vs $[\epsilon/N\hat{2}]$ should follow a straight line with slope equal to $2\gamma.$

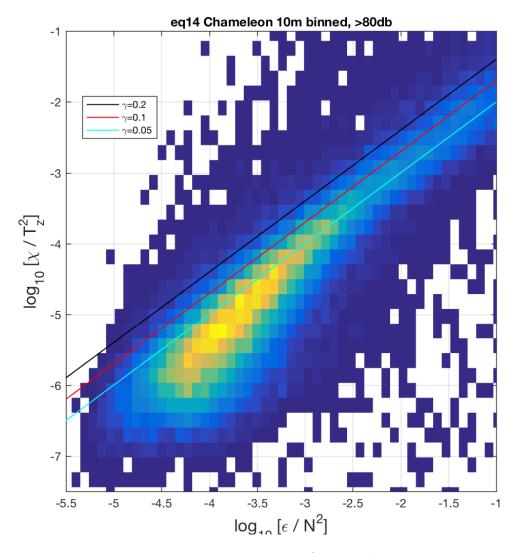


Figure 5: EQ14: 10m binned chameleon $\epsilon/N\hat{2}$ vs χ/t_z^2 for *below 80db*. Lines show different values of γ . Values of ϵ below noise floor ($log_{10}\epsilon < -8.5$) are discarded also.

6 Averaging many profiles of ϵ

Figure 6 shows one example. A folder with many profiles is located at: https://github.com/OceanMixingGroup/Analysis/tree/master/Andy_Pickering/eq14_patch_gamma/figures/chi_eps_profiles_40profavgs. In general, it seems that averaging profiles does not change the comparsion much; ϵ_{χ} is still biased low.

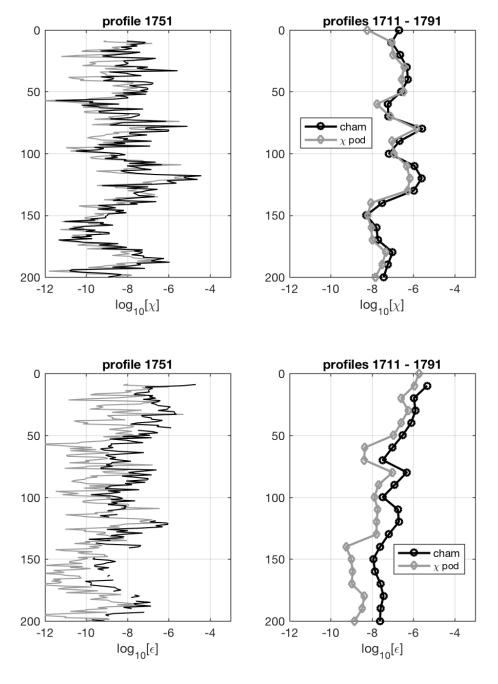


Figure 6: Example of averaging multiple profiles together. Left panels show a single profile from chamleeon and chi-pod method. Right panels show average of +/- 40 profiles, averaged in 10m depth bins.

7 Effects of averaging in different-sized depth bins

I tried making plots of normalized chi vs eps, and scatterplots of chi-pod vs chameleon epsilon, for data averaged in different-sized depth bins (for each profile, not across profiles). They don't seem to change.

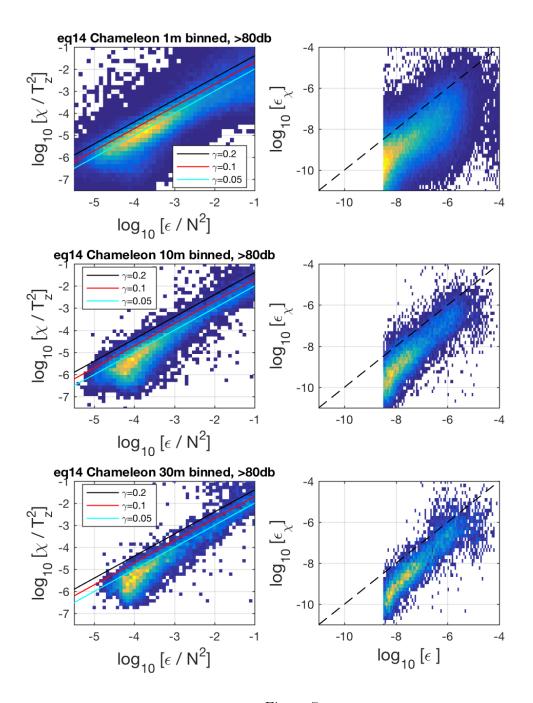


Figure 7:

8 Effects of averaging different numbers of profiles

I tried making plots of normalized chi vs eps, and scatterplots of chi-pod vs chameleon epsilon, for data averaged across different numbers of profiles. This doesn't seem to change either, which is strange because it looked like when I plotted average profiles they were matching better for more averaging....

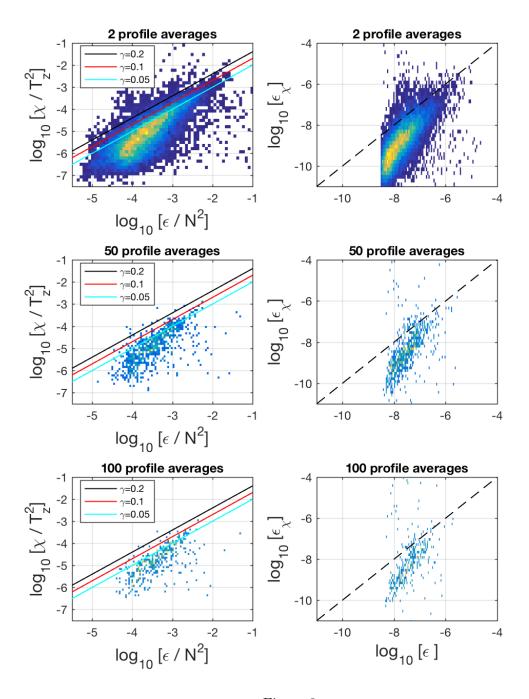


Figure 8:

9 γ computed from averaged quantities

If we compute gamma from time-averaged N^2, T_z, χ, ϵ do we get $\gamma = 0.2$ (or a different gamma)? Estimates from the averaged data are larger (Figures ??,9) but still slightly less than 0.2.

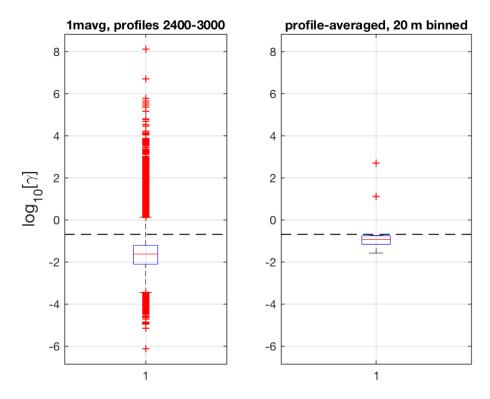


Figure 9: Boxplots of $log_{10}[\gamma]$ for a set of profiles from EQ14. Left is for all 1m avg data. Right is for data from all profiles averaged in 10m bins. Horizontal dashed line indicates $\gamma = 0.2$.

10 Summary

- Inidivudal (and 10m binned) χ pod estimates of ϵ are biased low compared to Chameleon values
- γ computed from averaged (across profiles) N^2 , T_z , χ , and ϵ is larger, but not quite 0.2 (mean is around 0.1?)