

A new approach to estimating observational uncertainty in the MSU/AMSU datasets



A Brute force Monte-Carlo analysis

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Motivation for a new analysis

- Uncertainty is critical for all climate related applications
- Most previous work has focused on:
 - uncertainty in global scale long-term trends or
 - has been narrowly focused on regional radiosonde comparisons
- However, many applications or intercomparison efforts
 are focused on regional analysis or short time scales
- Little information on the uncertainty on these time/space scales



This Analysis

- "Ground up" uncertainty analysis based on estimates of uncertainty at each processing step
- Brute-force Monte-Carlo approach
- Results are in the form of random gridded realizations of the error
- The random realizations can be processed using the same code/methods as is used to process the actual data for the study in progress
- Thus uncertainty estimates available for all space/time scales



Sources of uncertainty for MSU/AMSU

- Instrument noise
- Sampling
- Errors in diurnal adjustment
- Calibration errors

- The effect of these on the merging process
 - merging parameters (which are intended to fix calibration errors) are deduced from intersatellite differences
 - Errors in differences can lead to errors in merging parameters
- Other, unknown errors... probably are small???



Sampling Noise



Sampling for 1 day, 1 satellite (TMT, TTS, or TLS)



Time series for the a single point in the North Pacific (40N, 170W)





Sampling Uncertainty in MSU Channel 2

Uncertainty is largest in the mid latitudes, where interesting weather and gaps in satellite coverage combine to give large errors.

The sampling uncertainty tends to be strong correlated in space, with the errors in nearby pixels similar.

Tends to not be correlated over month-to-month time scales, so the *direct* effect on long term trends is small.





Diurnal Adjustment

Local Measurement times drift – need to adjust measurements or the local diurnal cycle will alias into long term trend.

We use a model based adjustment derived from CCM3. Errors in this adjustment were unknown.

Compare adjustments with adjustment derived from other models



CCM3, HADGEM1 and CMAM

Remote Sensing Systems

For TMT and TLT, we now have 1 additional model. We obtained monthly averaged hourly data from a HADGEM1 diagnostic run.

For TTS and TLS, we also have results from CMAM.







Diurnal Adjustment Uncertainty

- Crude guess at uncertainty from inter-model differences
- Uncertainty is correlated in space and time
 - Dry, land areas have large uncertainty
 - Large seasonal cycles in uncertainty
- Errors in diurnal adjustment lead to changes in the merging parameters.
 - Calibration target temperatures (a prognostic variable for calibration adjustments) have large seasonal signals.
 - Errors in diurnal cycles lead to latitude dependent changes in intersatellite offsets.
- Changes (Errors) in merging parameters in turn lead to spatially and temporally correlated errors.

Too Complex to Represent with Traditional Statistical Metrics! USE MONTE CARLO.



The Plan

- 1. Start with a gridded monthly dataset of all zeros. Each satellite's data is valid only for months when that satellite was actually observing. (144x72x384x10)
- 2. For each valid satellite/month, add in a random realization of the sampling uncertainty.
- 3. Then add in a realization of the diurnal uncertainty. diurnal adjustment = sqrt(2)/2 a∆diur a is a zero-mean random variable with unit variance ∆diur is the difference between the CCM3 and HADGEM1 adjustments
- 4. Perform merge using same method as we use for the real data.
- Repeat a large number (right now 400) of times to get numerous realizations of the expected errors.
 (144x72x396x400) 2 GB large but manageable.



Advantages

- **Spatial** and **Temporal** correlations in sampling and diurnal uncertainty automatically included.
- If the above do a good job of describing the real intersatellite differences, then the effects of sampling and diurnal error on the merging parameters are correctly included.
- Dataset can be interrogated in a number of ways to estimate uncertainty for various numerical products and experiments.



Comparison of After-the-Merge Intersatellite Differences





Std. dev. of monthly average intersatellite differences in real MSU channel 2 data.





Std. dev. of monthly average intersatellite differences in simulated MSU channel 2 data.





Example monthly error TMT, January 2003, Realization 0







Example monthly error TMT, January 2003, Realization 1







Spatial Dependence of Temporal Correlation of after-the-merge intersatellite differences





Errors in Trends, TLT, 1979-2008







Correlation of Errors in Trends between different realizations, TLT, 1979-2008







Example: Long Term Trends

- Compare trend uncertainty in 3 weightings
 - Global Average
 - Tropical (20S to 20N)
 - Continental USA





Trends in error realizations TMT, 1979-2008





Example 2 Comparison with Homogenized Radiosondes

Sample both real data and error realizations at the radiosonde locations Analyze Sampled Error Time Series to determine uncertainty estimate





Radiosonde Comparison: TLT





Radiosonde Comparison: TLS





Summary and Availability

Monte Carlo analysis provides information about uncertainty on all space and time scales.

This uncertainty information should be used for all intercomparison and climate change analysis using our data.

Will be on our website after we submit the paper -- if you want access before that, send me an email.