Uncertainty Quantification of GNSS RO Retrieval Products

Chi O. Ao and Anthony J. Mannucci

Jet Propulsion Laboratory
California Institute of Technology, Pasadena, CA

CLARREO SDT Meeting, Nov. 29–Dec. 1, Hampton, VA

Status of CLARREO-related tasks from past year

1. RO bending angle climatology for high altitude initialization (Nov 2015)
   • Algorithm being implemented/tested at JPL processing system

2. Trends and variability of the tropical width from RO, reanalysis, and climate models (May 2016)
   • Paper in preparation
   • To be presented at AMS Annual Meeting 2017

3. Collaboration with Knuteson & Feltz (UW) on understanding biases between IR & RO strato temperatures.

4. obs4MIPs monthly-averaged RO temperature and geopotential height datasets have been released.
Motivation: Establishing GNSS RO as reference observations

• Following the GRUAN (GCOS Reference Upper Air Network) paradigm:
  ✓ Is traceable to an SI unit or an accepted standard
  ✓ Provides a comprehensive uncertainty analysis
  ✓ Is documented in accessible literature
  ✓ Is validated (e.g. by intercomparison or redundant observations)
  ✓ Includes complete meta data description
  ✓ Important to distinguish contributions from systematic error and random error
Existing works

*Kursinski et al., JGR, 1997*

- Comprehensive analysis of multiple error sources.
- Did not separate systematic and random errors
- Derived under limited sets of parameters.

*Scherlin-Pirscher et al., AMT, 2011*

- Separated systematic and random errors (plus sampling error estimates).
- Considered only climatological averages.

Independent uncertainty estimates specific to a retrieval system are desirable.
Approach to per datum uncertainty estimation

\[ \sigma_{tot}^2 = \sigma_{sys}^2 + \sigma_{ran}^2 \]

Random = noise that averages down as \( \sim 1/\sqrt{N} \), where \( N \) is the number of observations.

HF = High-frequency variations (uncorrelated noise from sample to sample)

LF = Low-frequency variations (from multipaths and possibly orbit/clock)
Estimating random errors

Estimate phase noise from the excess phase data:

• Detrend phase and compute standard deviation over an interval containing many data points (e.g., 1 sec = 50 pts)

• Propagate phase uncertainty through retrieval chain *(analytically or Monte Carlo)*

*This method accounts only for “high-frequency” noise. It will not capture “low-frequency” phase variations such as those from local multipath.*
Example 1: Phase to BA (Random)
Example 1: BA to N to T (Random)

BA Error

sigN/N in %

sigN x 10
Example 2: Phase to BA (Random)
Example 2: BA to N to T (Random)

BA Error

sigN/N in %
sigN x 10

~ 2x worse than Example 1

2012-02-18-00:33tsx_gps54
Estimating systematic errors

Consider largest error sources for $z > 10$ km

Residual (large-scale) ionospheric error

$Solar-max$ daytime condition $\sim 0.1$ micro-rad at all heights

+ High-altitude Abel initialization

Estimated based on residuals of exponential fit as $\pm X\%$ of best fit (typical values of $X$ is 10)

+ Hydrostatic initialization of $T$

Estimated assuming $\pm 5K$ uncertainty at 40 km initialization height
Example 1: Systematic, iono+ha
Example 2: Systematic, iono+ha
Example 2: Systematic, T init
Summary

• Progress towards per datum uncertainty characterization of RO retrieval products.
• Dominant error sources have been taken into account.
• Systematic iono error can be better estimated (currently only an upper bound).
• Lower troposphere error characterization needs additional work (modeling tracking error & noise propagation thru nonlinear retrieval).
• Uncertainty estimates need to be verified.
• Retrieval errors from non-spherical atmosphere were not considered here (but were in Kursinski et al. 1997); they can be interpreted as representation errors.