

# Time series and error analysis with FOGMEx (`tsfit/tsview`), CATS and Hector

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Material from R. King, T. Herring, M. Floyd (MIT) and S. McClusky (now ANU)

# Issues in GPS Error Analysis

- What are the sources of the errors ?
- How much of the error can we remove by better modeling ?
- Do we have enough information to infer the uncertainties from the data ?
- What mathematical tools can we use to represent the errors and uncertainties ?

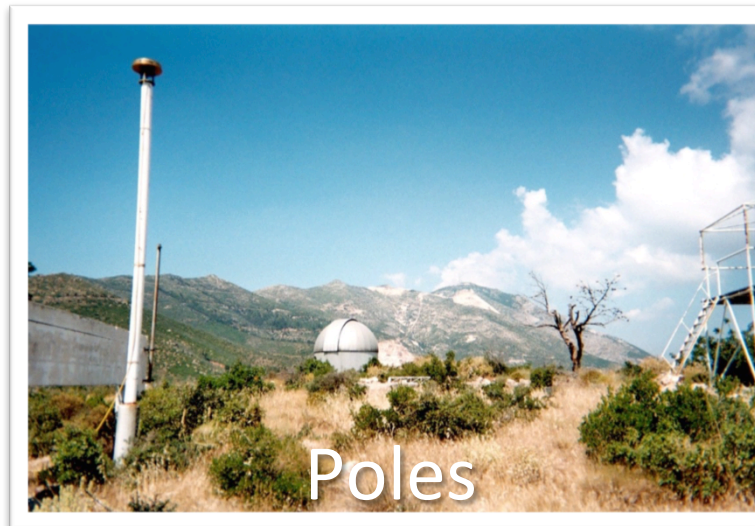
# Determining the Uncertainties of GPS Parameter Estimates

- Rigorous estimate of uncertainties requires full knowledge of the error spectrum—both temporal and spatial correlations (never possible)
- Sufficient approximations are often available by examining time series (phase and/or position) and reweighting data
- Whatever the assumed error model and tools used to implement it, external validation is important

# Sources of Error

- Signal propagation effects
  - Receiver noise
  - Ionospheric effects
  - Signal scattering ( antenna phase center / multipath )
  - Atmospheric delay (mainly water vapor)
- Unmodeled motions of the station
  - Monument instability
  - Loading of the crust by atmosphere, oceans, and surface water
- Unmodeled motions of the satellites

# Fixed antennas



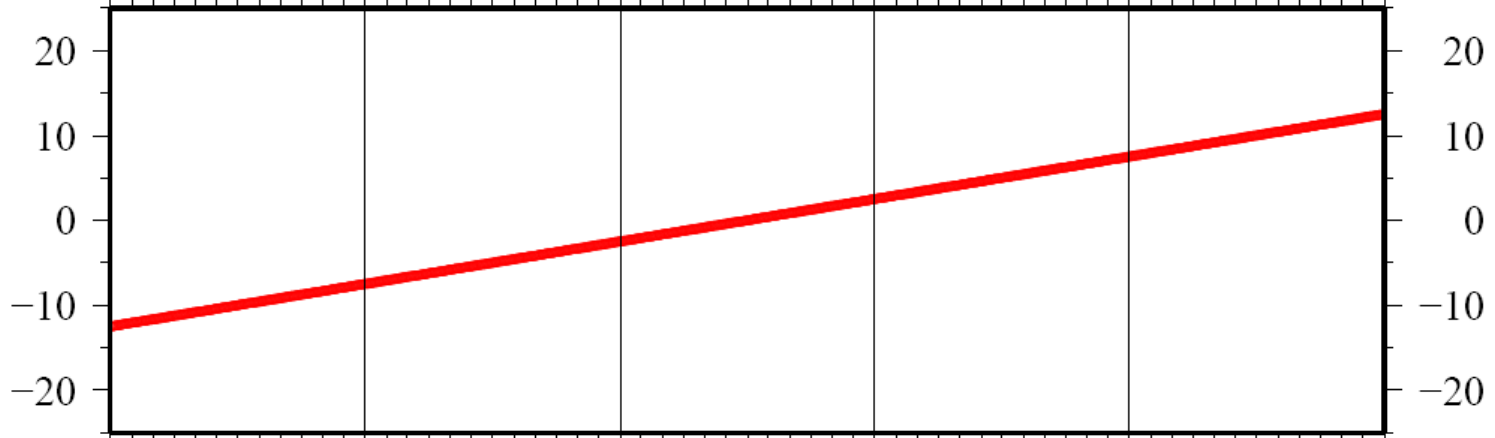
# Time series characteristics

# Time series components

observed position      (linear) velocity term

$$x^i = x_0^i + v^i (t - t_0)$$

↑  
initial position

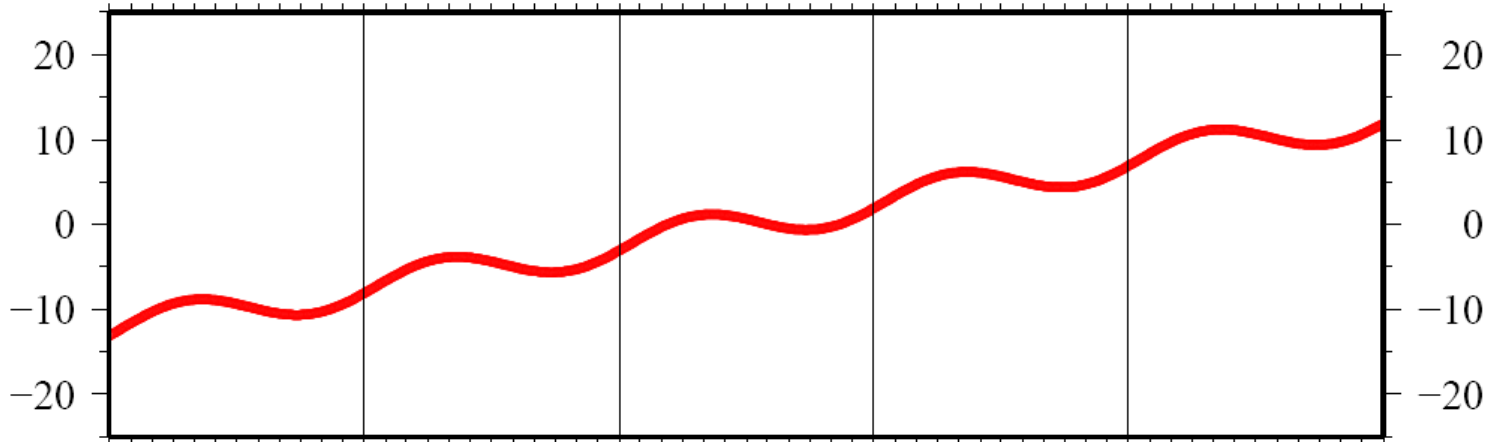


# Time series components

observed position      (linear) velocity term

$$x^i = x_0^i + v^i(t - t_0) + A_0^i \cos\left(\frac{2\pi(t - t_0)}{T_0} - \tau_0\right)$$

initial position      annual period sinusoid





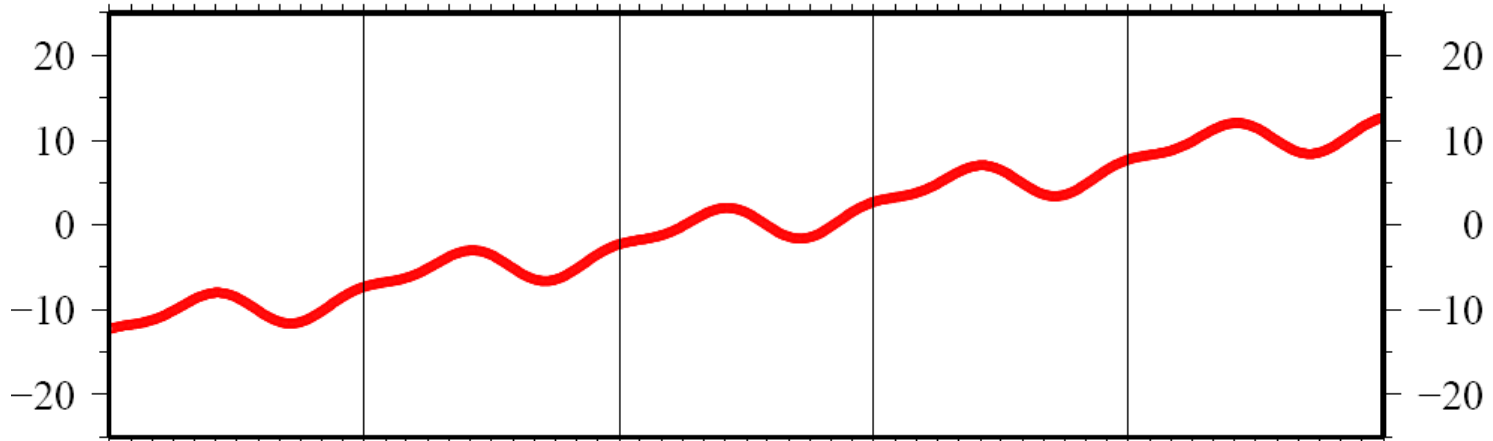
# Time series components

observed position      (linear) velocity term

$$x^i = x_0^i + v^i(t - t_0) + \underbrace{A_0^i \cos\left(\frac{2\pi(t - t_0)}{T_0} - \tau_0\right)}_{\text{annual period sinusoid}} + \underbrace{A_1^i \cos\left(\frac{2\pi(t - t_0)}{T_1} - \tau_1\right)}_{\text{semi-annual period sinusoid}}$$

initial position

seasonal term



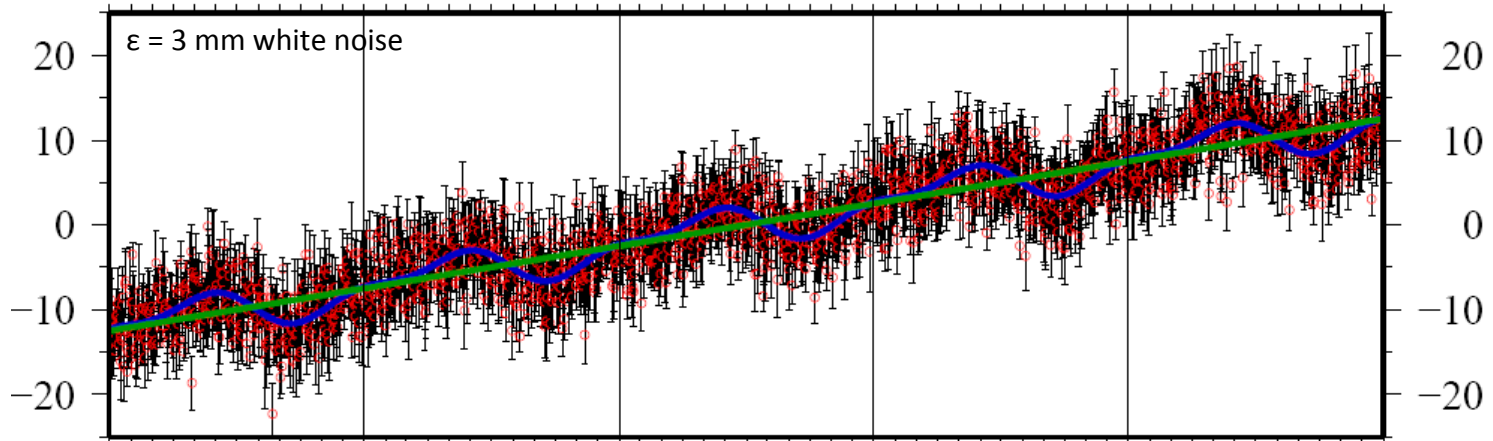
# Time series components

observed position      (linear) velocity term

$$x^i = x_0^i + v^i(t - t_0) + \underbrace{A_0^i \cos\left(\frac{2\pi(t - t_0)}{T_0} - \tau_0\right)}_{\text{annual period sinusoid}} + \underbrace{A_1^i \cos\left(\frac{2\pi(t - t_0)}{T_1} - \tau_1\right)}_{\text{semi-annual period sinusoid}} + \varepsilon$$

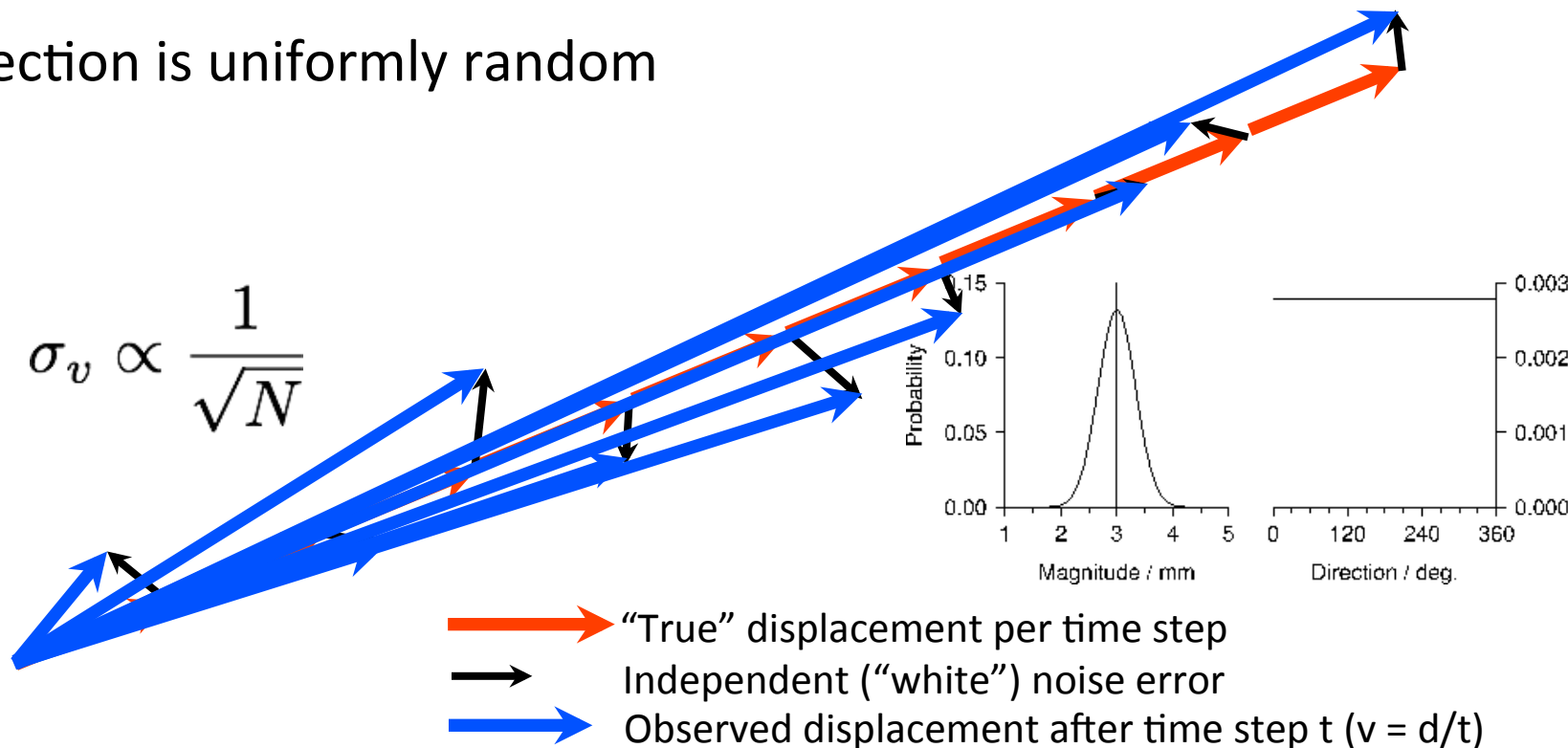
initial position

seasonal term



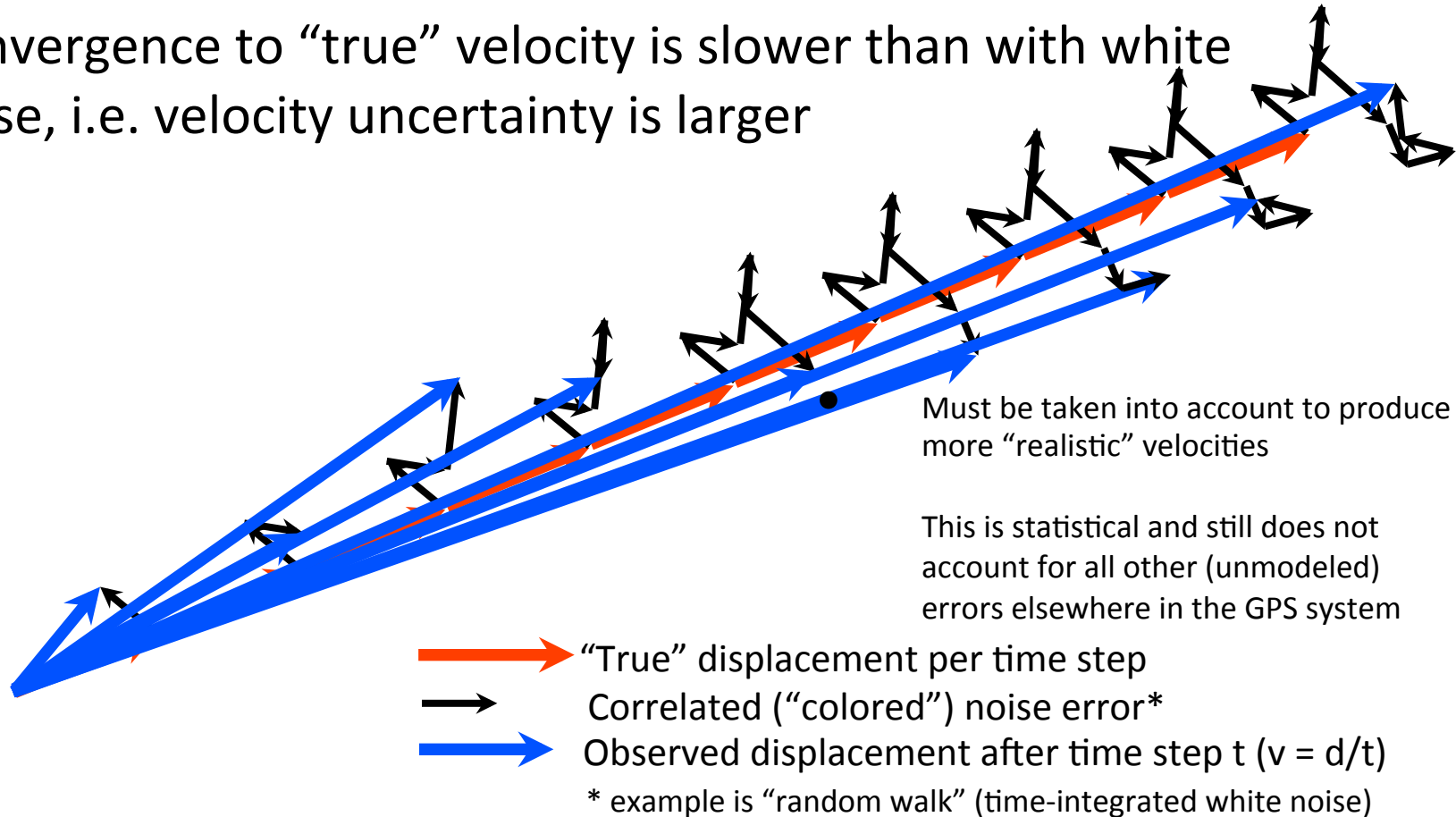
# “White” noise

- Time-independent (uncorrelated)
- Magnitude has continuous probability function, e.g. Gaussian distribution
- Direction is uniformly random

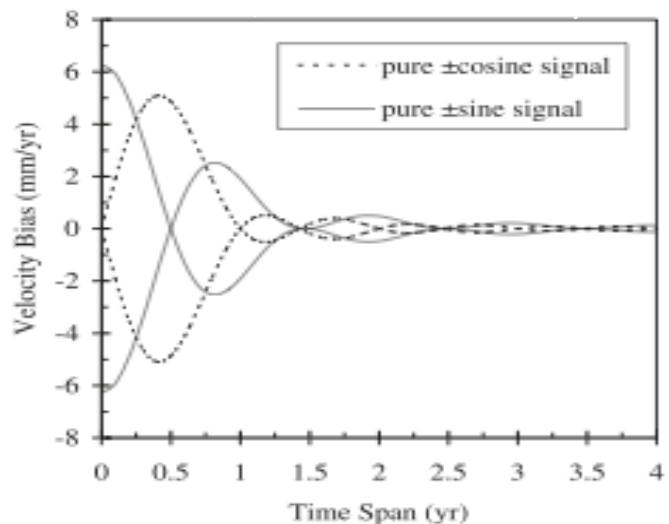


# “Colored” noise

- Time-dependent (correlated): power-law, first-order Gauss-Markov, etc
- Convergence to “true” velocity is slower than with white noise, i.e. velocity uncertainty is larger

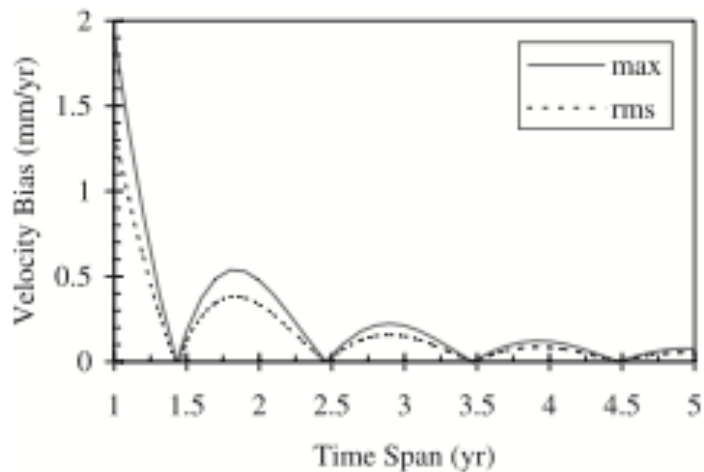


# Velocity Errors due to Seasonal Signals in Continuous Time Series



Theoretical analysis of a continuous time series by *Blewitt and Lavallee [2002]*

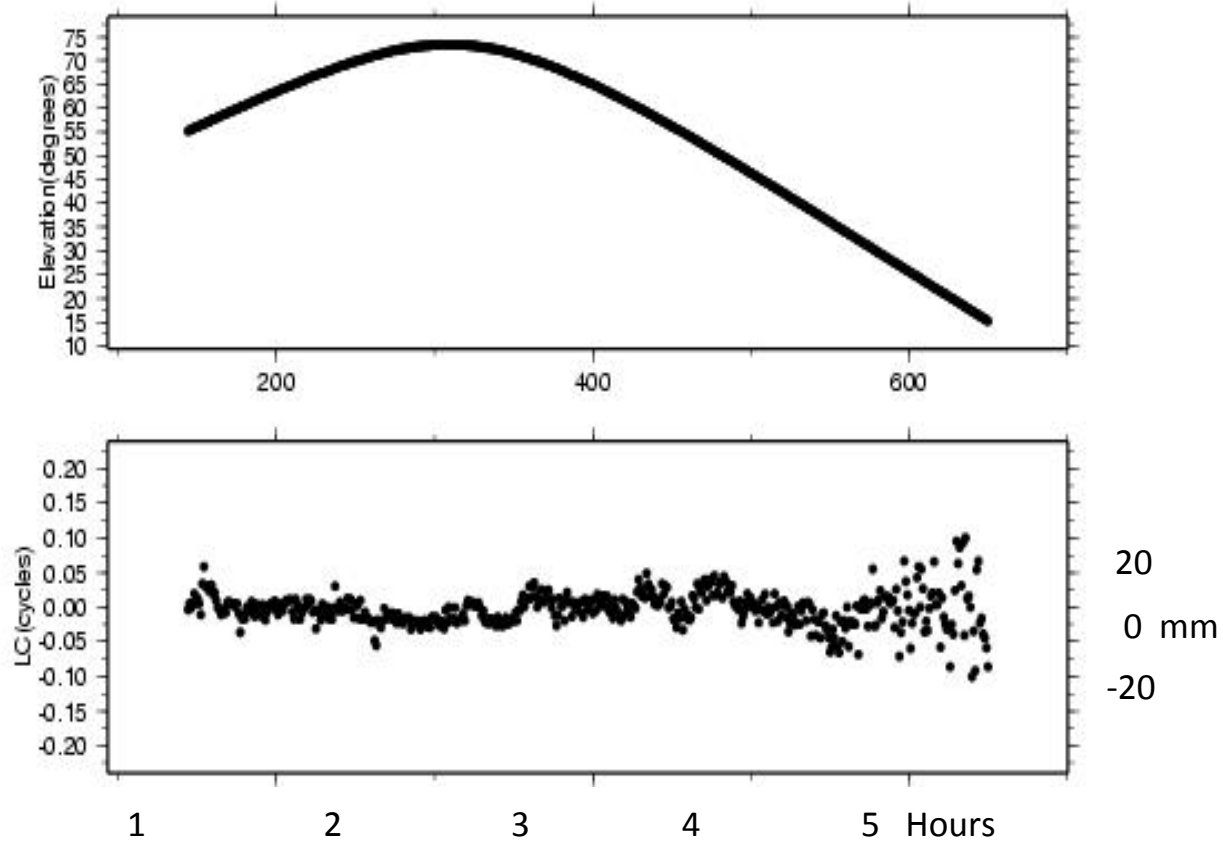
*Top:* Bias in velocity from a 1mm sinusoidal signal in-phase and with a 90-degree lag with respect to the start of the data span



*Bottom:* Maximum and rms velocity bias over all phase angles

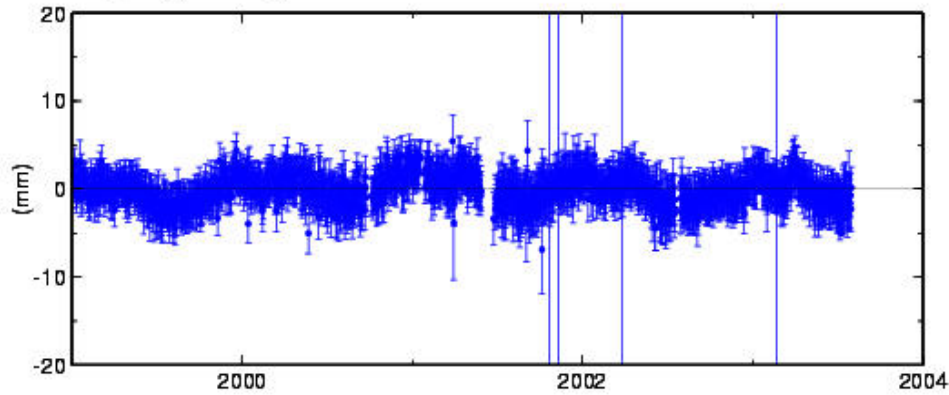
- The minimum bias is NOT obtained with continuous data spanning an even number of years
- The bias becomes small after 3.5 years of observation

# Characterizing Phase Noise

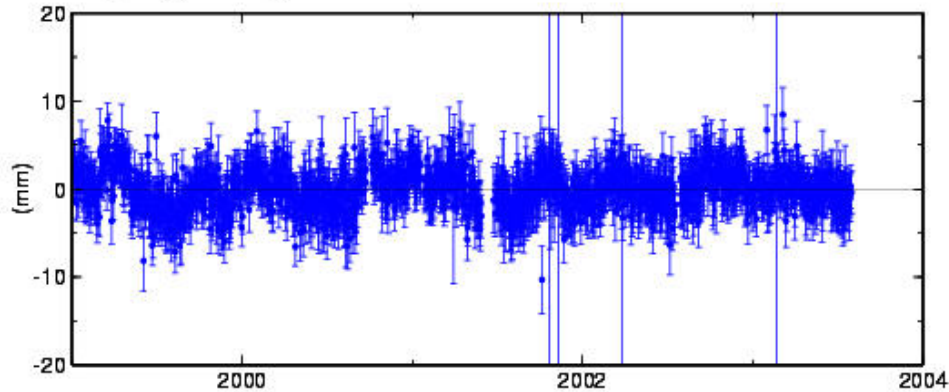


Elevation angle and phase residuals for single satellite

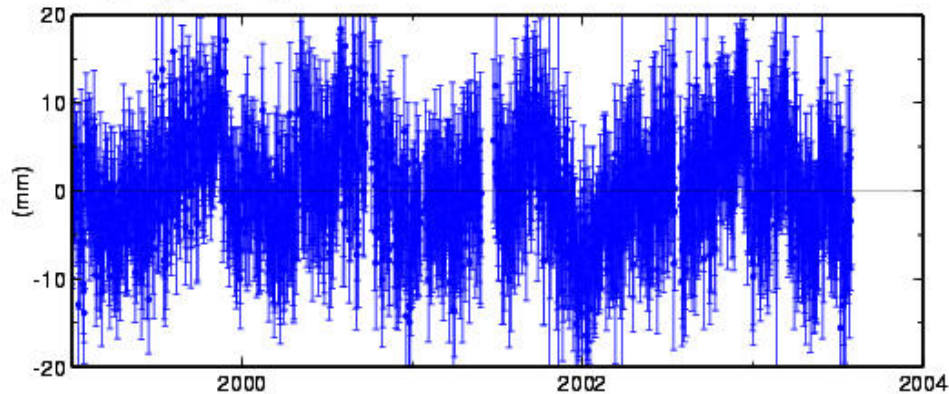
BURN North Offset 4762193.218 m  
rate(mm/yr)=  $1.39 \pm 0.04$  nrms= 0.69 wrms= 1.5 mm # 1578



BURN East Offset 19785454.795 m  
rate(mm/yr)=  $-1.43 \pm 0.05$  nrms= 0.86 wrms= 2.1 mm # 1578

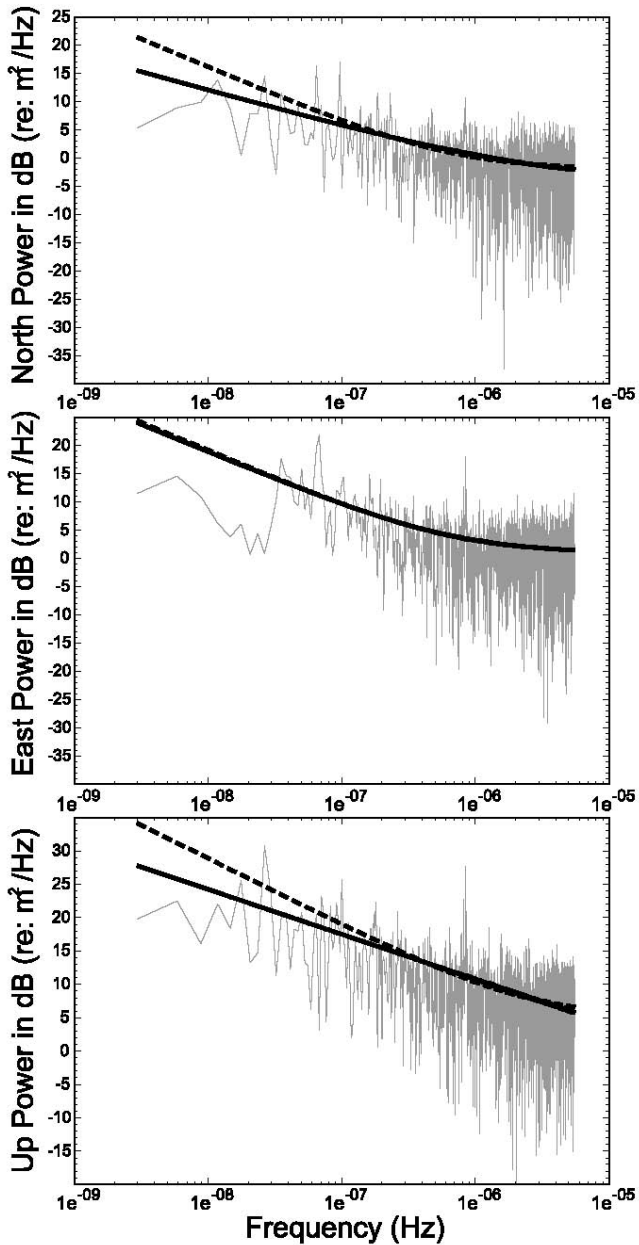


BURN Up Offset 1180.839 m  
rate(mm/yr)=  $-1.62 \pm 0.13$  nrms= 0.79 wrms= 5.5 mm # 1578



## Characterizing the Noise in Daily Position Estimates

Note temporal  
correlations of  
30-100 days and  
seasonal terms



## Spectral Analysis of the Time Series to Estimate an Error Model

Figure 5 from *Williams et al* [2004]: Power spectrum for common-mode error in the SOPAC regional SCIGN analysis. Lines are best-fit WN + FN models (solid=mean ampl; dashed=MLE)

Note lack of taper and misfit for periods > 1 yr



# Summary of Spectral Analysis Approach

- Power law: slope of line fit to spectrum
  - 0 = white noise
  - -1 = flicker noise
  - -2 = random walk
- Non-integer spectral index (e.g. “fraction white noise”  $\rightarrow 1 > k > -1$  )
- Good discussion in Williams [2003]
- Problems:
  - Computationally intensive
  - No model captures reliably the lowest-frequency part of the spectrum

# CATS (Williams, 2008)

- Create and Analyze Time Series
- Maximum likelihood estimator for chosen model
  - Initial position and velocity
  - Seasonal cycles (sum of periodic terms) [optional]
  - Exponent of power law noise model
- Requires some linear algebra libraries (BLAS and LAPACK) to be installed on computer (common nowadays, but check!)

# Hector (Bos et al., 2013)

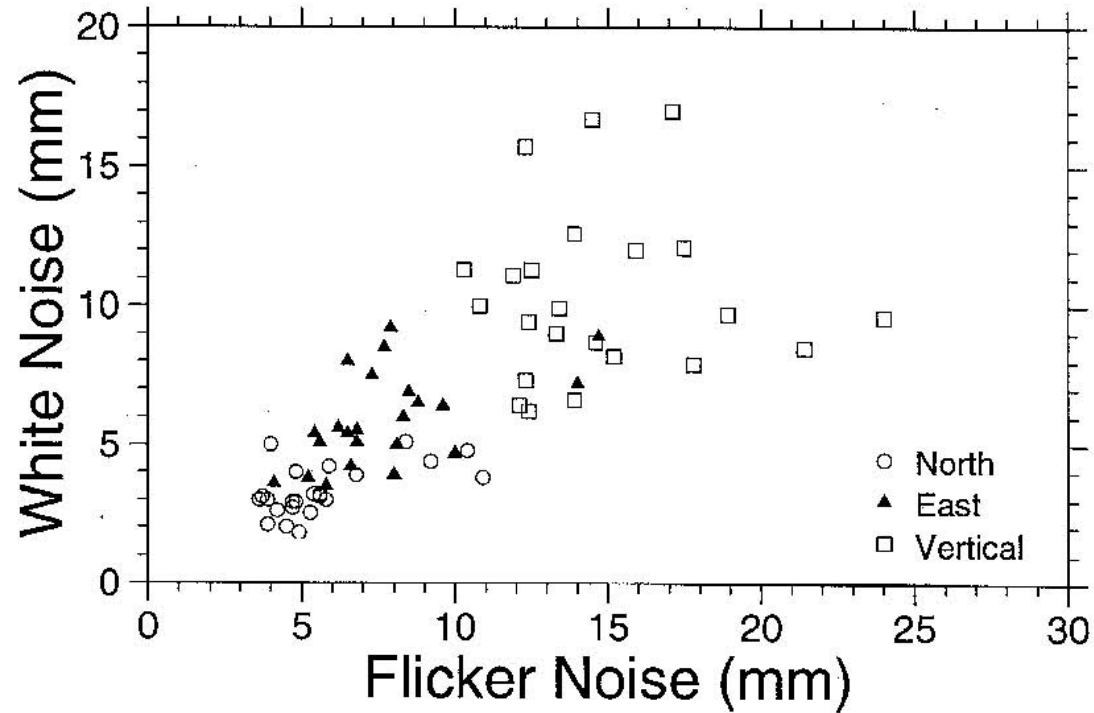
- Much the same as CATS but faster algorithm
- Maximum likelihood estimator for chosen model
  - Initial position and velocity
  - Seasonal cycles (sum of periodic terms) [optional]
  - Exponent of power law noise model
  - Also
- Requires ATLAS linear algebra libraries to be installed on computer
- Linux package available but tricky to install from source due to ATLAS requirement

# sh\_cats/sh\_hector

- Scripts to aid batch processing of time series with CATS or Hector
- Requires CATS and/or Hector to be pre-installed
- Outputs
  - Velocities in “.vel”-file format
  - Equivalent random walk magnitudes in “mar\_neu” commands for sourcing in globk command file
- Can take a *long* time!

Short-cut (Mao et al, 1998):

Use white noise statistics ( wrms) to predict the flicker noise



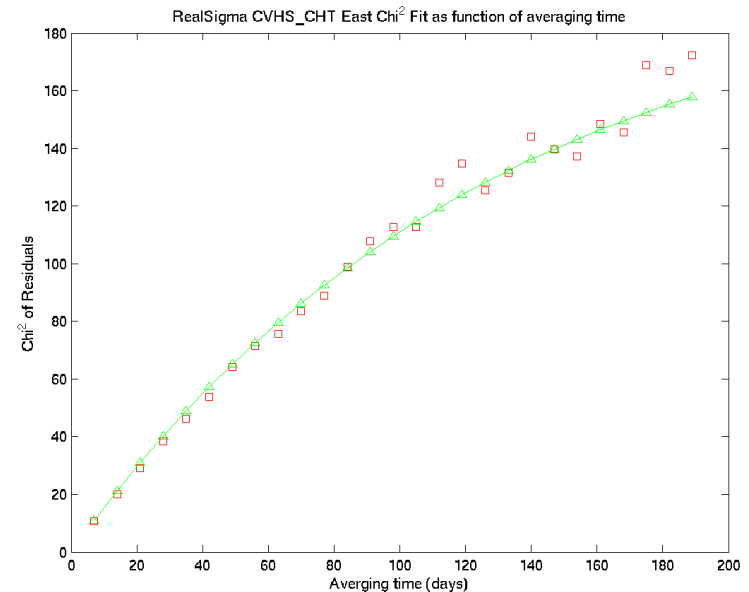
White noise vs flicker noise from *Mao et al.* [1999] spectral analysis of 23 global stations

# “Realistic Sigma” Algorithm for Velocity Uncertainties

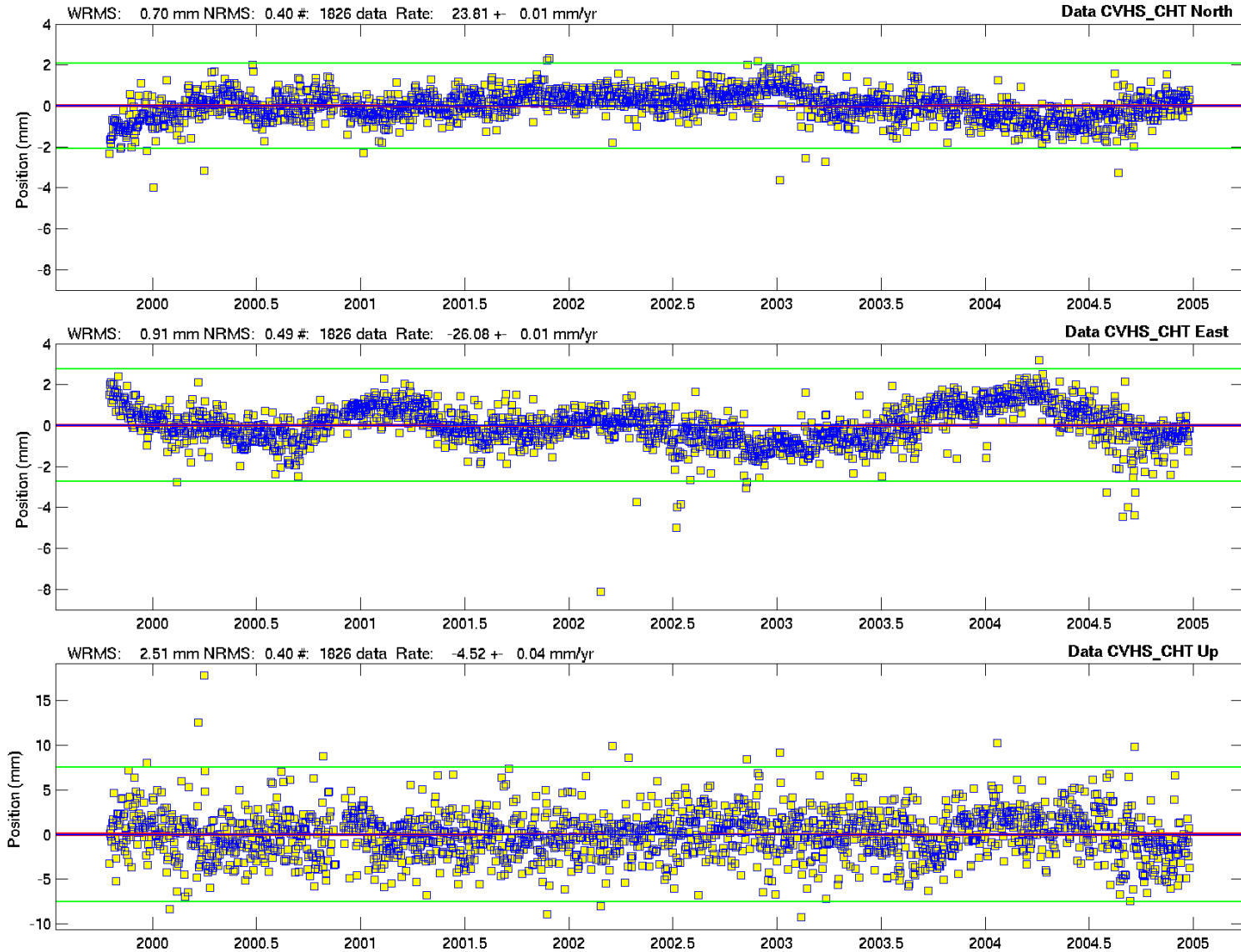
- Motivation: computational efficiency, handle time series with varying lengths and data gaps; obtain a model that can be used in *globk*
- Concept: The departure from a white-noise ( $\sqrt{n}$ ) reduction in noise with averaging provides a measure of correlated noise.
- Implementation:
  - Fit the values of  $\chi^2$  vs averaging time to the exponential function expected for a first-order Gauss-Markov (FOGM) process (amplitude, correlation time)
  - Use the  $\chi^2$  value for infinite averaging time predicted from this model to scale the white-noise sigma estimates from the original fit
  - and/or
  - Fit the values to a FOGM with infinite averaging time (i.e., random walk) and use these estimates as input to *globk* (`mar_neu` command)

# Extrapolated variance (FOGMEx)

- For independent noise, variance  $\propto 1/\sqrt{N_{\text{data}}}$
- For temporally correlated noise, variance (or  $\chi^2/\text{d.o.f.}$ ) of data increases with increasing window size
- Extrapolation to “infinite time” can be achieved by fitting an asymptotic function to RMS as a function of time window
  - $\chi^2/\text{d.o.f.} \propto e^{-\sigma\tau}$
- Asymptotic value is good estimate of long-term variance factor
- Use “real\_sigma” option in `tsfit`

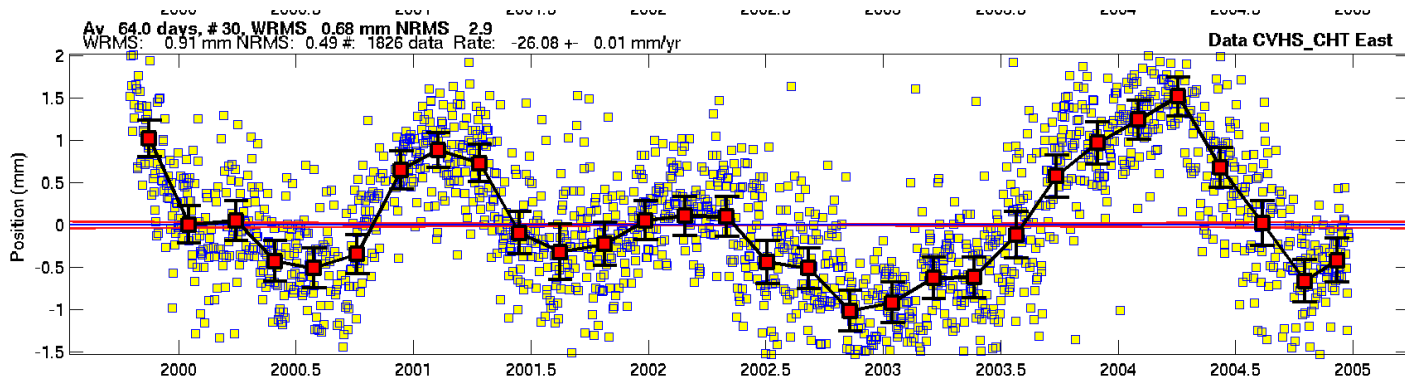


# Understanding the RS algorithm: Effect of averaging on time-series noise

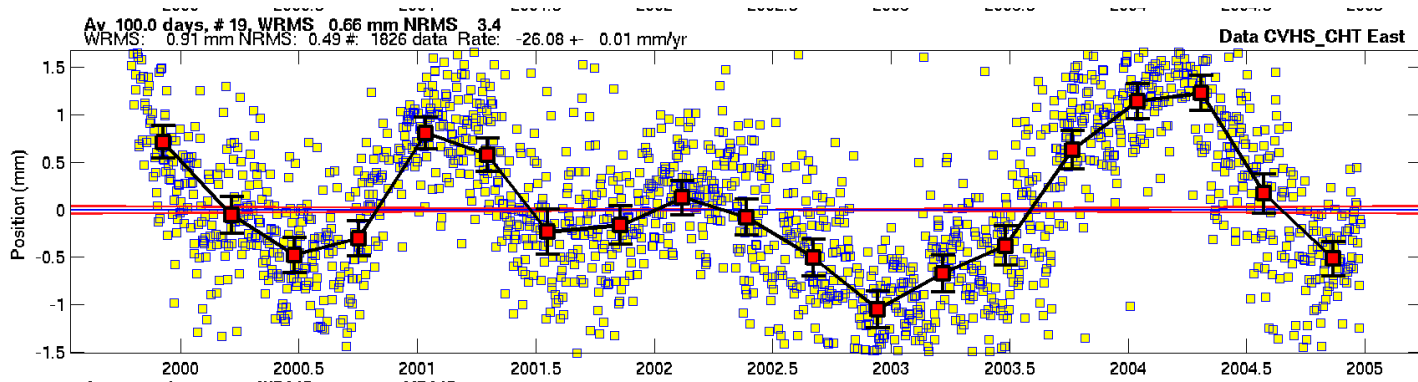




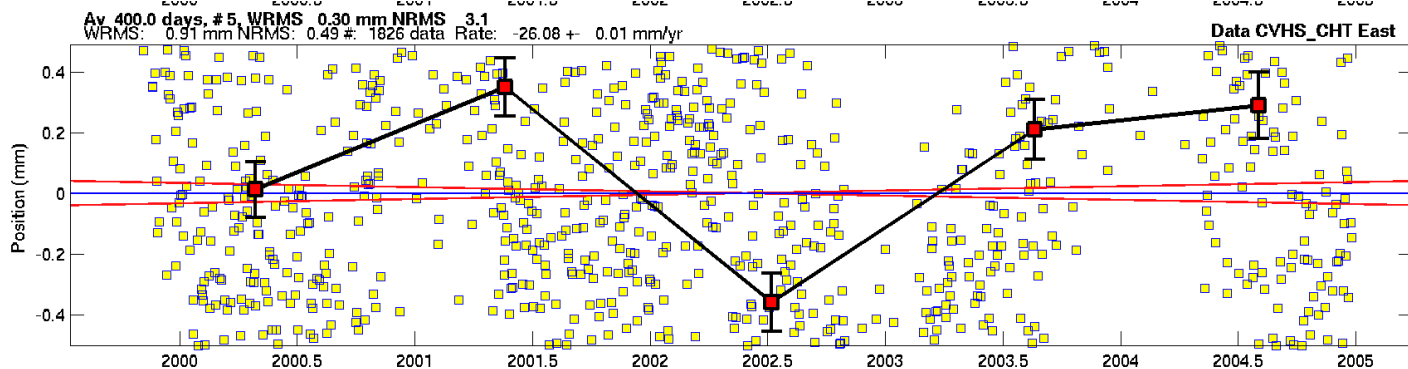
# Same site, East component ( daily wrms 0.9 mm nrms 0.5 )



64-d avg  
wrms 0.7 mm  
nrms 2.0

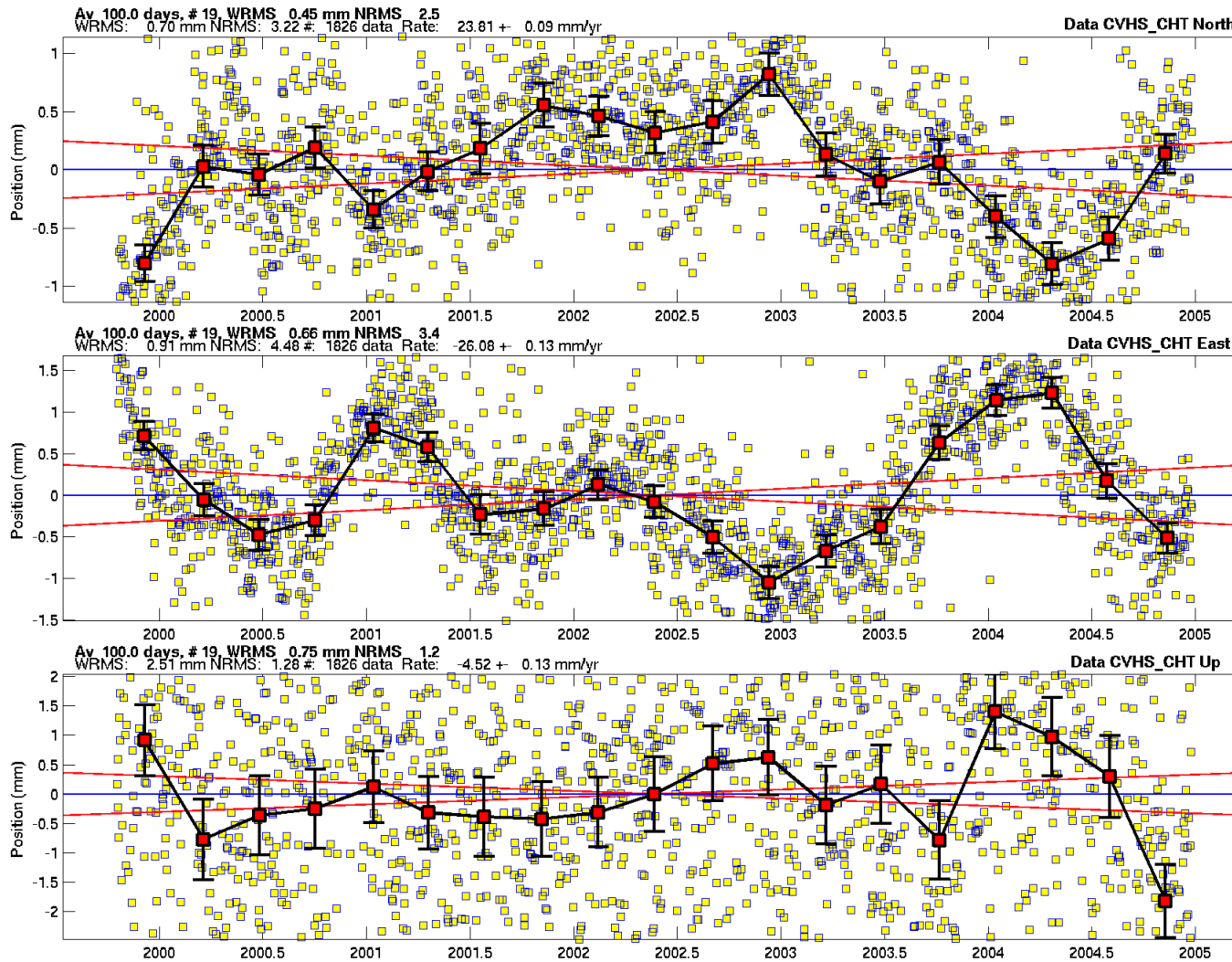


100-d avg  
wrms 0.6 mm  
nrms 3.4



400-d avg  
wrms 0.3 mm  
nrms 3.1

# Using TSVIEW to compute and display the “realistic-sigma” results

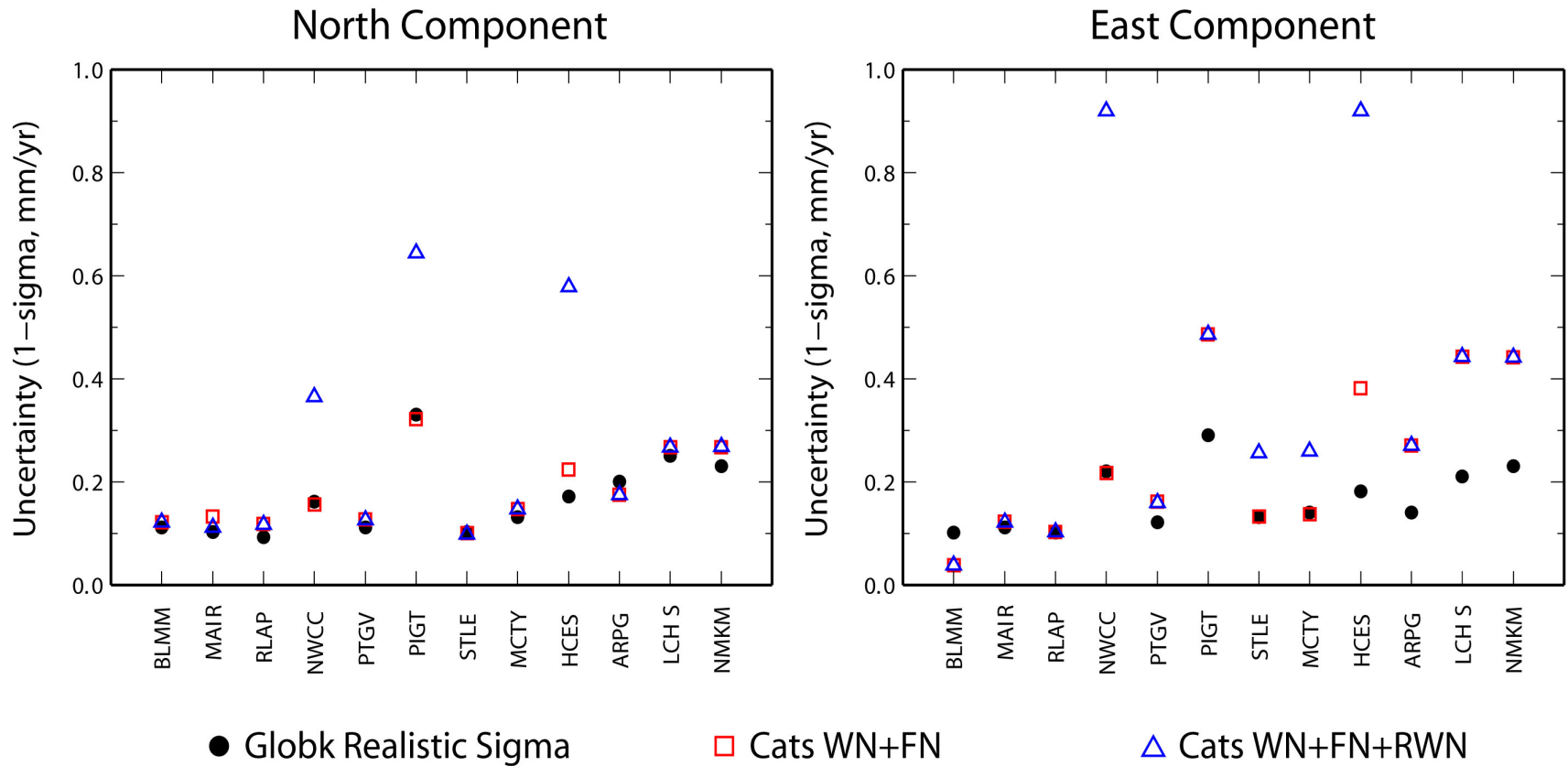


Note rate uncertainties with the “realistic-sigma” algorithm :

0.09 mm/yr N  
0.13 mm/yr E  
0.13 mm/yr U

Red lines show the 68% probability bounds of the velocity based on the results of applying the algorithm.

# Comparison of estimated velocity uncertainties using spectral analysis (CATS) and Gauss-Markov fitting of averages (GLOBK)



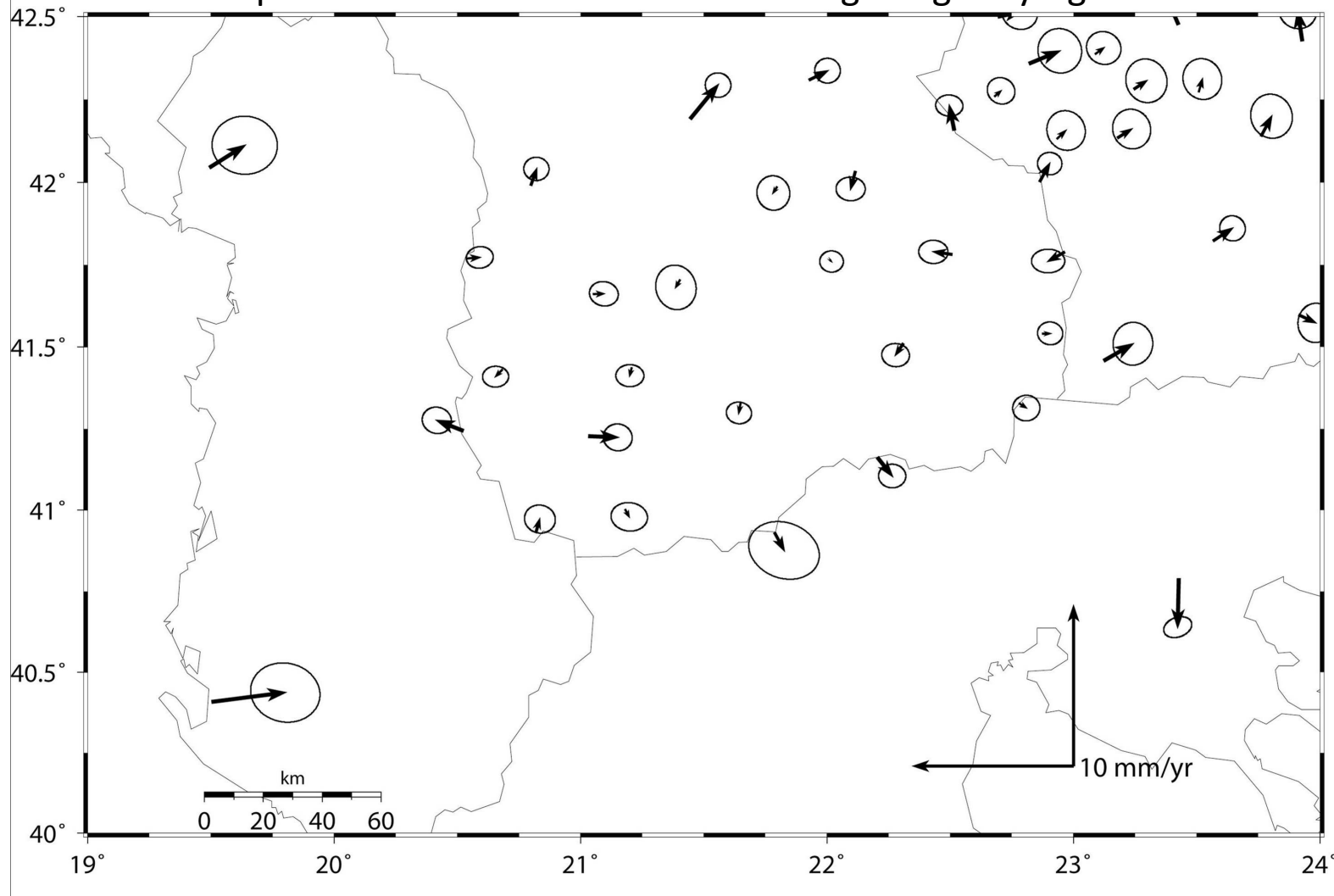
Plot courtesy E. Calais

# Summary of Practical Approaches

- White noise + flicker noise (+ random walk) to model the spectrum [Williams et al., 2004]
  - White noise as a proxy for flicker noise [Mao et al., 1999]
  - Random walk to model to model an exponential spectrum [Herring “realistic sigma” algorithm for velocities]
  - “Eyeball” white noise + random walk for non-continuous data
- 
- Only the last two can be applied in GLOBK for velocity estimation
  - All approaches require common sense and verification

# External validation of velocity uncertainties by comparing with a model

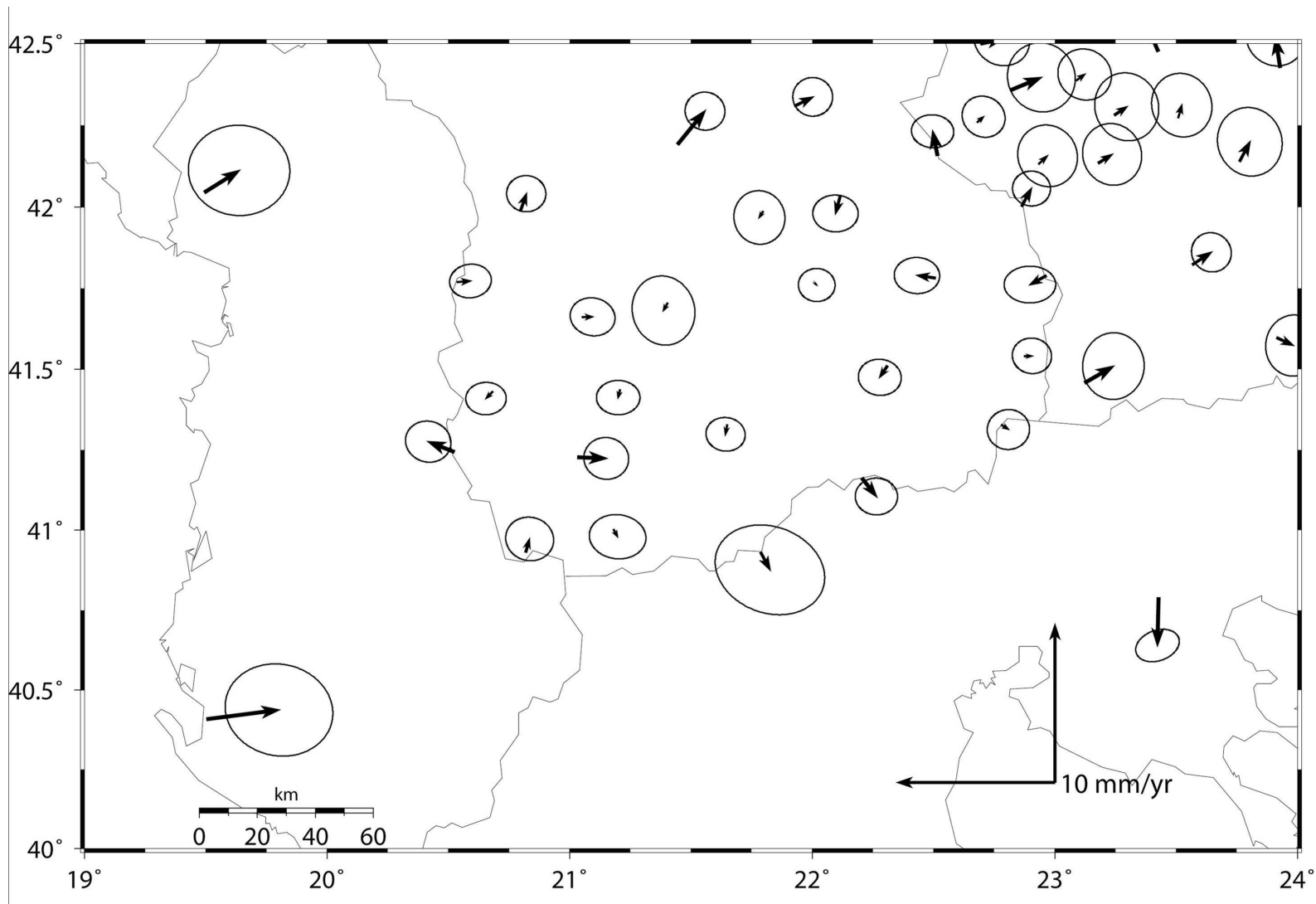
- Simple case: assume no strain within a geologically rigid block



GMT plot at  
70%  
confidence

17 sites in  
central  
Macedonia:  
4-5 velocities  
pierce error  
ellipses

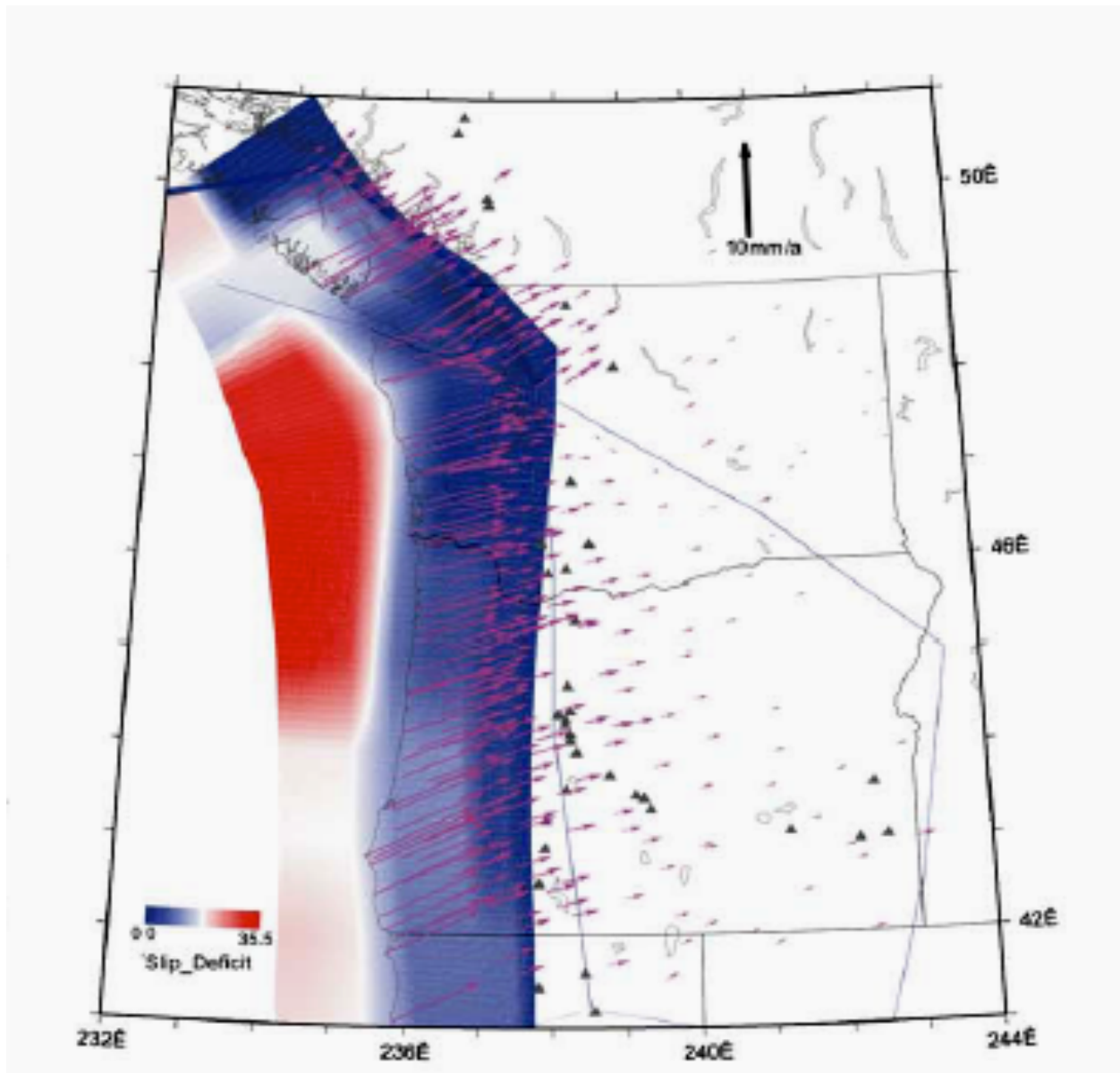
.. same solution plotted with 95% confidence ellipses



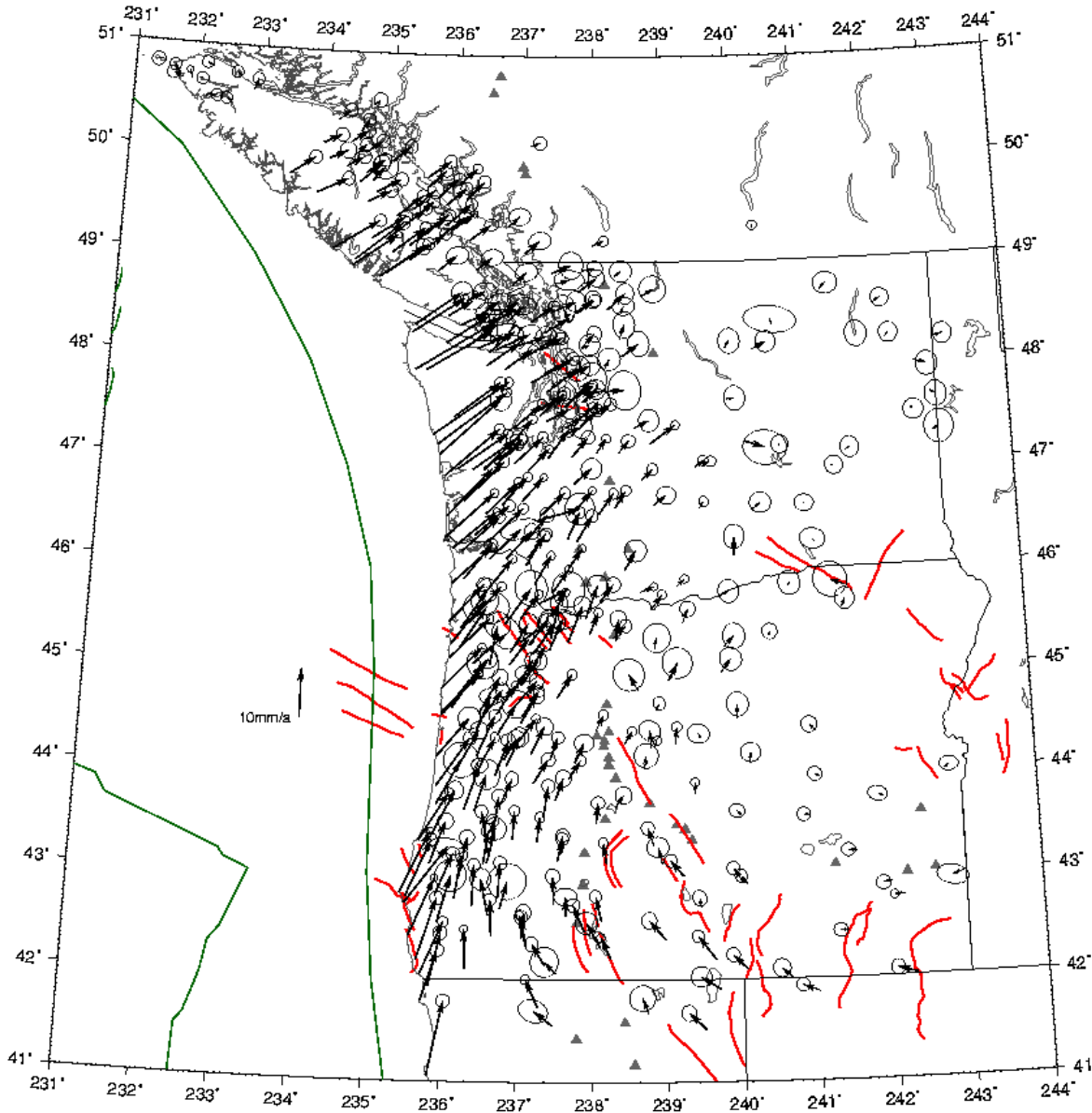
1-2 of 17  
velocities  
pierce error  
ellipses

# External validation of velocity uncertainties by comparing with a model

- a more complex case of a large network in the Cascadia subduction zone



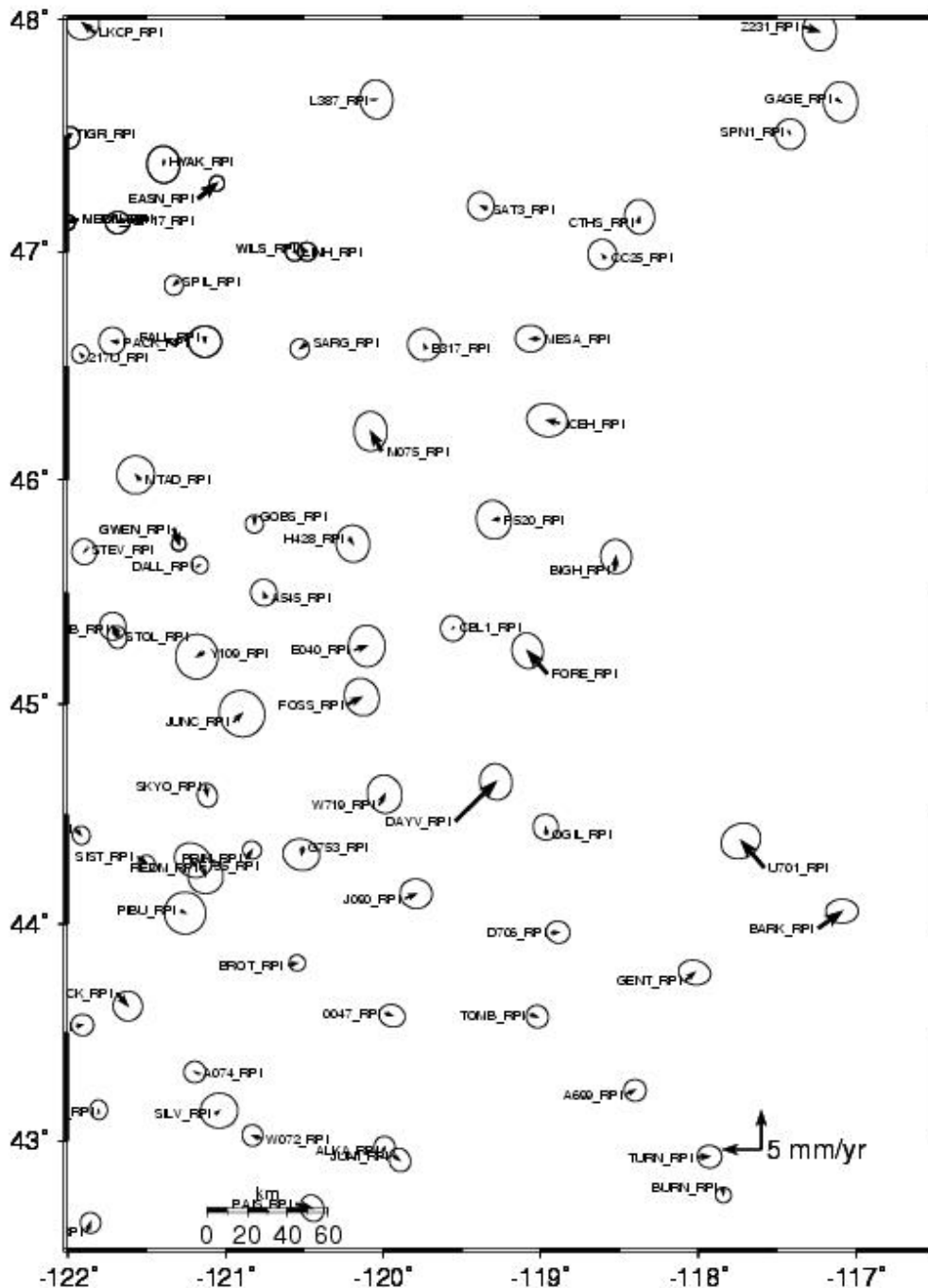
Colors show slipping and locked portions of the subducting slab where the surface velocities are highly sensitive to the model; area to the east is slowly deforming and insensitive to the details of the model



Velocities and  
70% error  
ellipses for 300  
sites observed by  
continuous and  
survey-mode  
GPS 1991-2004

Test area (next  
slide) is east of  
238E

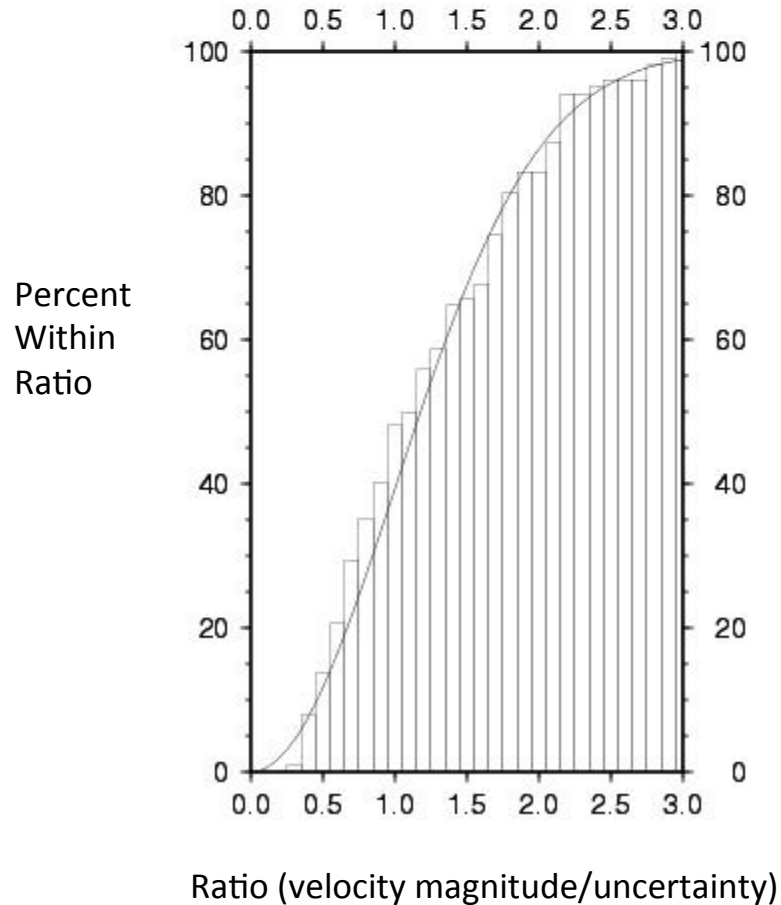




Residuals to elastic block model for 73 sites in slowly deforming region

Error ellipses are for 70% confidence:  
 13-17 velocities pierce their ellipse

## Statistics of Velocity Residuals

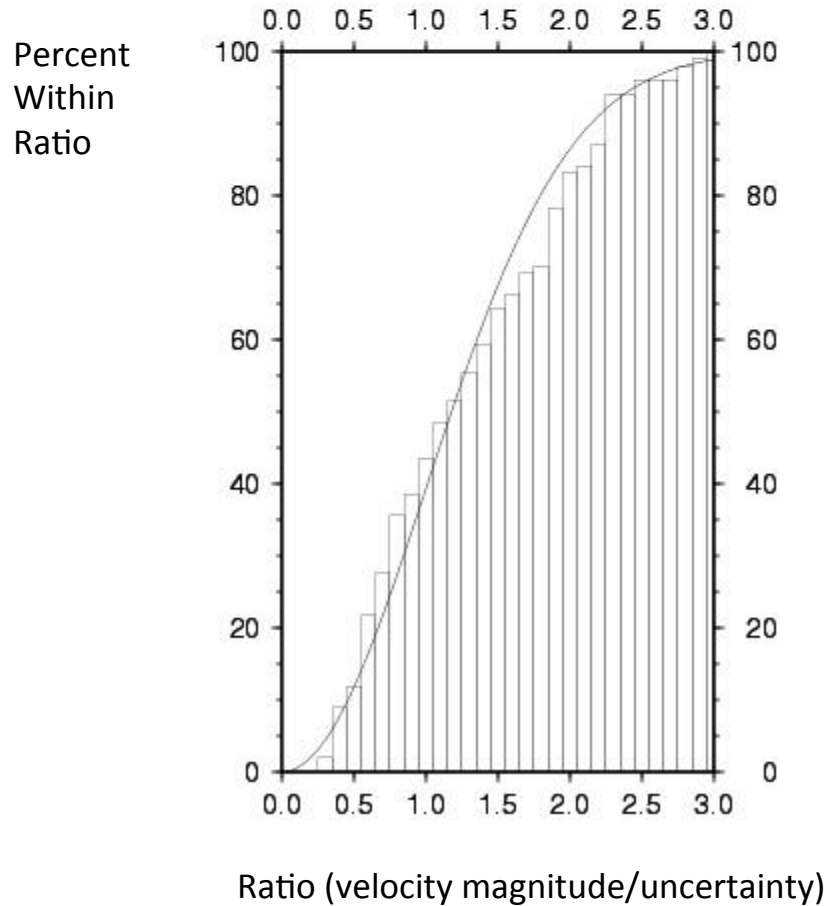


Cumulative histogram of normalized velocity residuals for Eastern Oregon & Washington ( 70 sites )

Noise added to position for each survey:  
0.5 mm random  
1.0 mm/sqrt(yr)) random walk

Solid line is theoretical for a chi distribution

# Statistics of Velocity Residuals



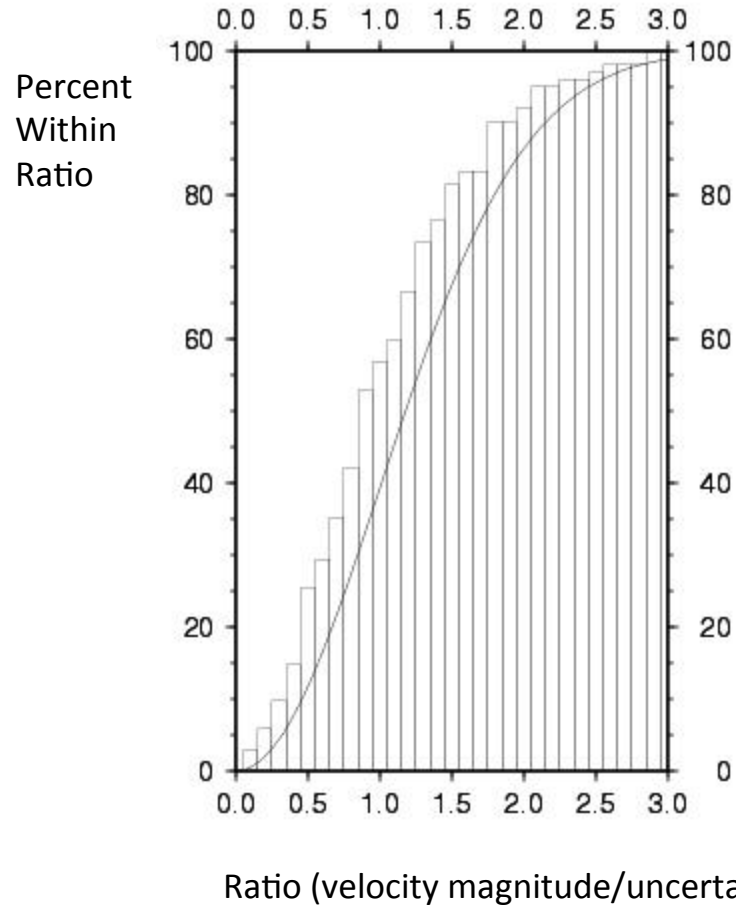
Same as last slide but with a smaller random-walk noise added :

0.5 mm random  
0.5 mm/yr random walk

( vs 1.0 mm/sqrt(yr)) RW for 'best' noise model )

Note greater number of residuals in range of 1.5-2.0 sigma

## Statistics of Velocity Residuals



Same as last slide but with larger random and random-walk noise added :

2.0 mm white noise  
1.5 mm/sqrt(yr) random walk

( vs 0.5 mm WN and 1.0 mm/sqrt(yr))  
RW for 'best' noise model )

Note smaller number of residuals in all ranges above 0.1-sigma

# Summary

- All algorithms for computing estimates of standard deviations have various problems: Fundamentally, rate standard deviations are dependent on low frequency part of noise spectrum which is poorly determined.
- Assumptions of stationarity are often not valid
- “Realistic sigma” algorithm is a convenient and reliable approach to getting velocity uncertainties in *globk*
- Velocity residuals from a physical model, together with their uncertainties, can be used to validate the error model

# Tools for Error Analysis in GAMIT/GLOBK

- GAMIT: AUTCLN reweight = Y (default) uses phase rms from postfit edit to reweight data with constant + elevation-dependent terms
- GLOBK
  - rename ( eq\_file) \_XPS or \_XCL to remove outliers
  - sig\_neu adds white noise by station and span; best way to “rescale” the random noise component; a large value can also substitute for \_XPS/\_XCL renames for removing outliers
  - mar\_neu adds random-walk noise: principal method for controlling velocity uncertainties
  - In the gdl files, can rescale variances of an entire h-file: useful when combining solutions from with different sampling rates or from different programs (Bernese, GIPSY)
- Utilities
  - tsview and tsfit can generate \_XPS commands graphically or automatically
  - grw and vrw can generate sig\_neu commands with a few key strokes
  - “Realistic sigma” algorithm implemented in tsview (MATLAB) and enfit/enfum; sh\_gen\_stats generates mar\_neu commands for globk based on the noise estimates
  - sh\_plotvel (GMT) allows setting of confidence level of error ellipses
  - sh\_tshist and sh\_velhist (GMT) can be used to generate histograms of time series and velocities.

# References

## **Spectral Analysis**

- Langbein and Johnson [J. Geophys. Res., 102, 591, 1997]  
Zhang et al. [J. Geophys. Res., 102, 18035, 1997]  
Mao et al. [J. Geophys. Res., 104, 2797, 1999]  
Dixon et al. [Tectonics , 19, 1, 2000] Herring [GPS Solutions, 7, 194, 2003]  
Williams [J. Geodesy, 76, 483, 2003]  
Williams et al. [J. Geophys. Res. 109, B03412, 2004]  
Langbein [J. Geophys. Res., 113, B05405, 2008]  
Williams, S. [GPS Solutions, 12, 147, 2008]  
Bos et al. [J. Geod., 87, 351-360, 2013]

## **Effect of seasonal terms on velocity estimates**

- Blewitt and Lavallee [J. Geophys. Res. 107, 2001JB000570, 2002]

## **Realistic Sigma Algorithm**

- Herring [GPS Solutions, 7, 194, 2003]  
Reilinger et al. [J. Geophys. Res., 111, B5, 2006]

## **Validation in velocity fields**

- McClusky et al. [J. Geophys. Res. 105, 5695, 2000]  
McClusky et al. [Geophys. Res. Lett., 28, 3369, 2000]  
Davis et al. [J. Geophys. Res. Lett. 2003GL016961, 2003]  
McCaffrey et al., [Geophys J. Int., 2007.03371, 2007]