Identifying and Accounting for Time-Correlated Noise

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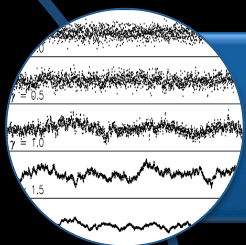
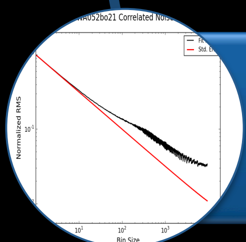
IRAC Data Challenge

2014 AAS - Boston

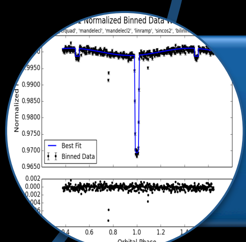
Overview of Discussion



How to identify time-correlated noise

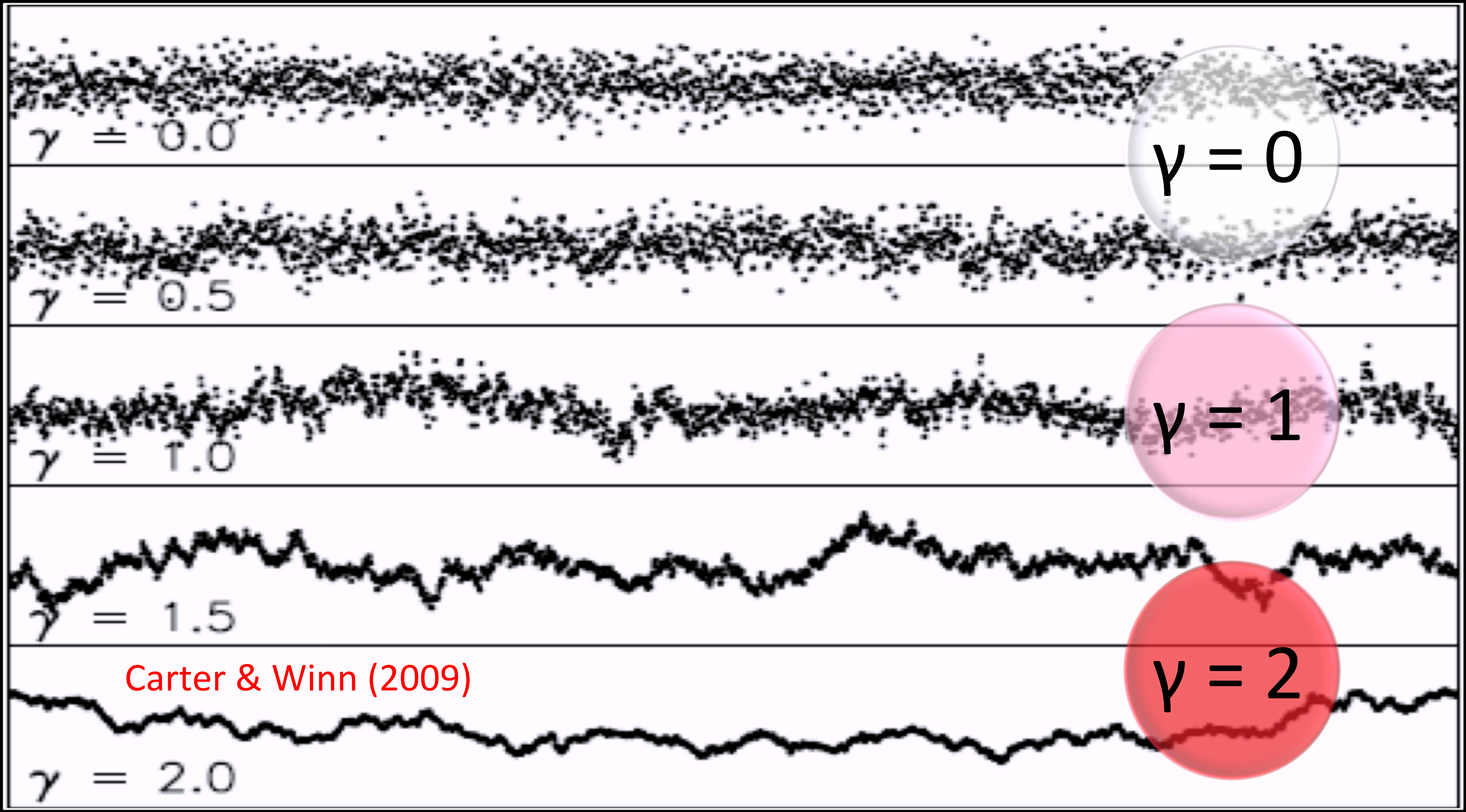


How to account for time-correlated noise in parameter uncertainty estimates



Compare results using simulated data

Examples of $1/f^{\gamma}$ Noise



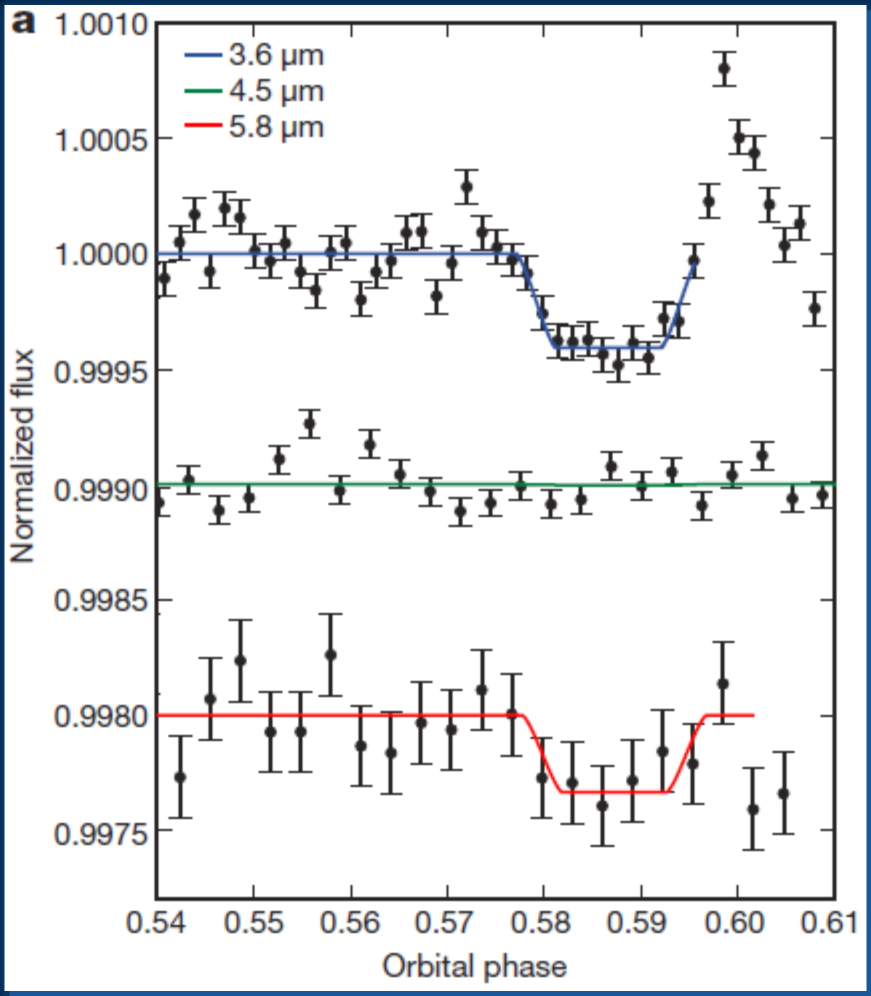
Carter & Winn (2009)

Example Spitzer Light Curves

- Light curves with time-correlated noise show excess “bumps” or “wiggles”

- Possibly due to
  - Atmospheric extinction
  - Instrument artifacts
  - Astrophysical effects

- How to quantitatively identify and account for time-correlated noise?



Identifying Time-Correlated Noise

Compute χ_ν^2

- Look for $\chi_\nu^2 > 1$
- Requires reliable uncertainties

Covariance matrix

- Look for power in off-diagonal elements

Autocorrelation / FFT

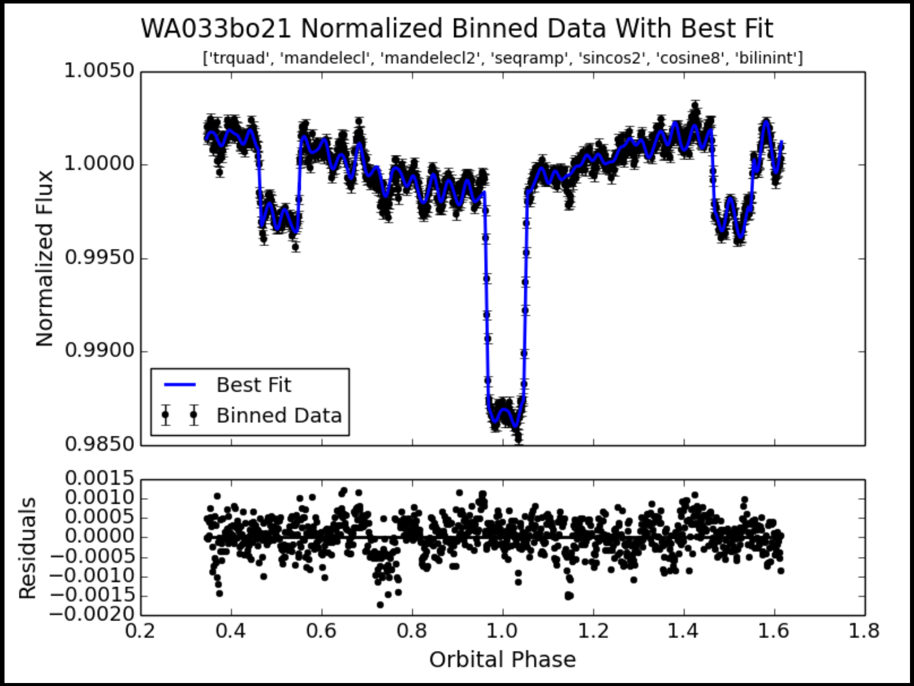
- Uncorrelated noise has equal power density at all *f*
- Look for peaks in the power density

rms *vs* bin size

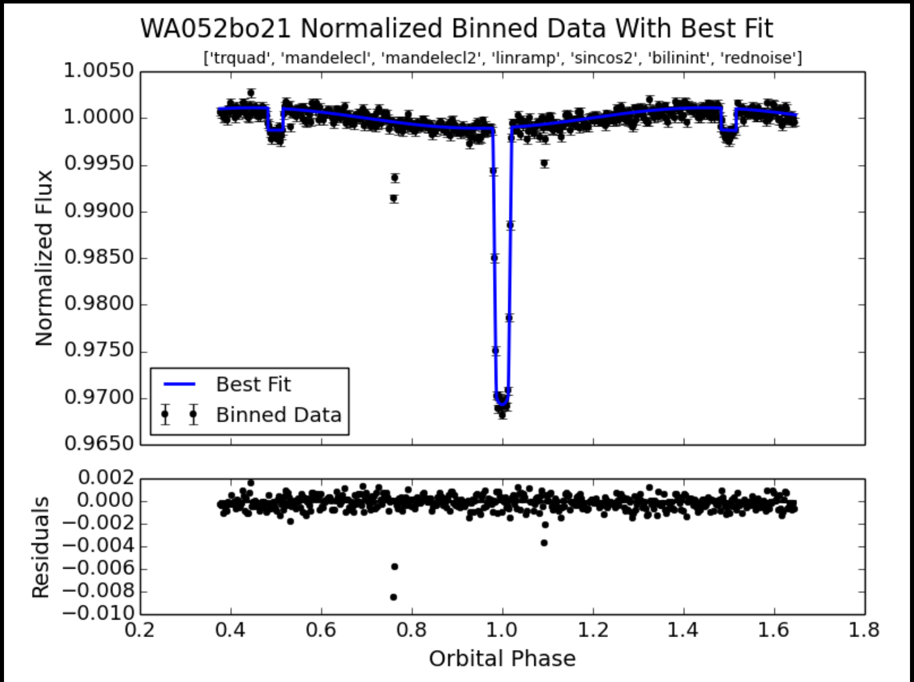
- Uncorrelated noise follows $\sigma/\sqrt{n}$ with increasing *n*
- Look for deviation from $\sigma/\sqrt{n}$ when binning

Sample Light Curves

WASP-33

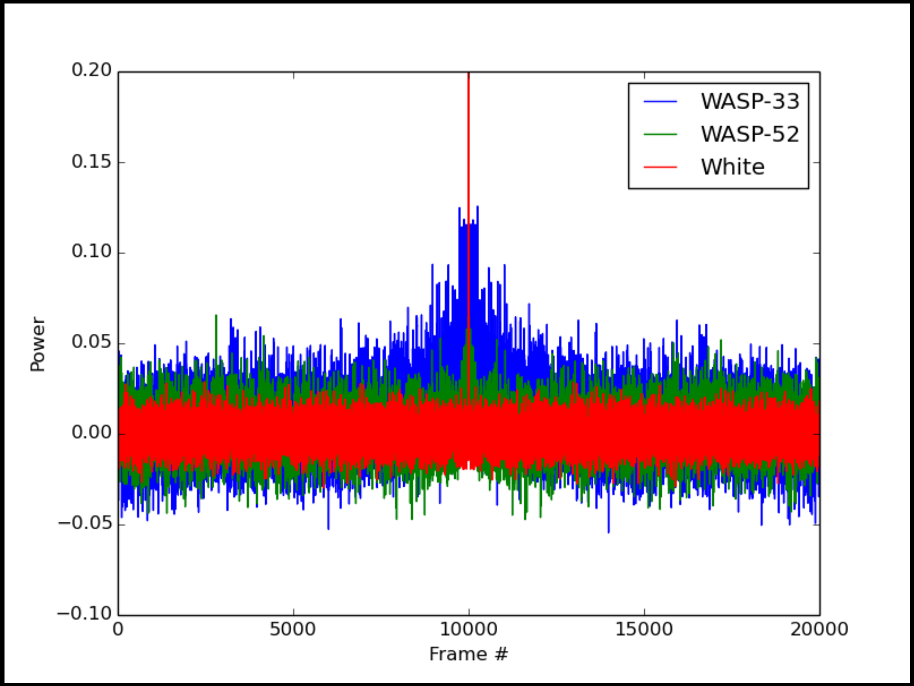


WASP-52

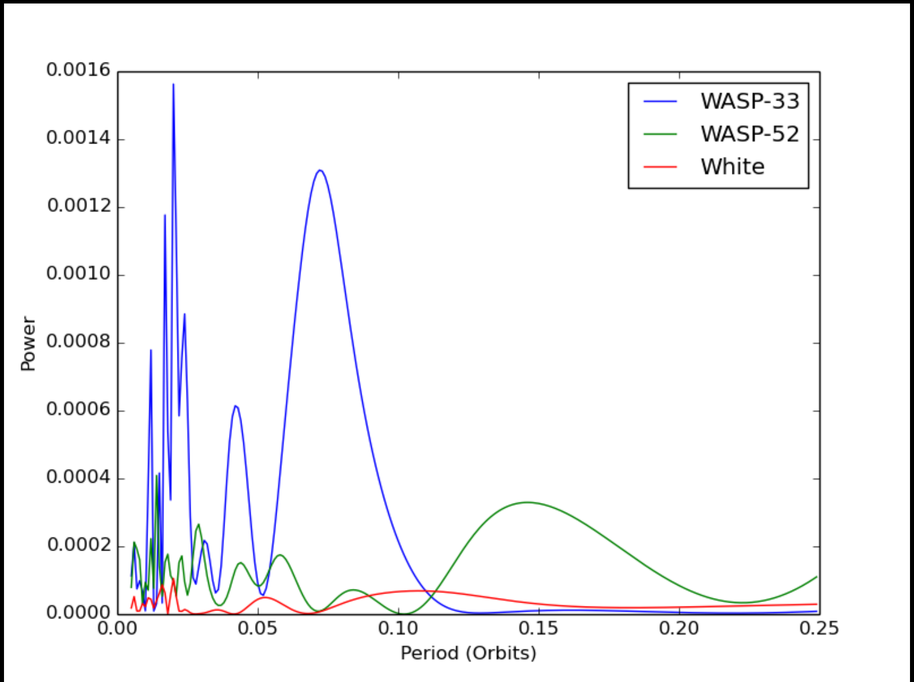


Autocorrelation / FFT

Autocorrelation

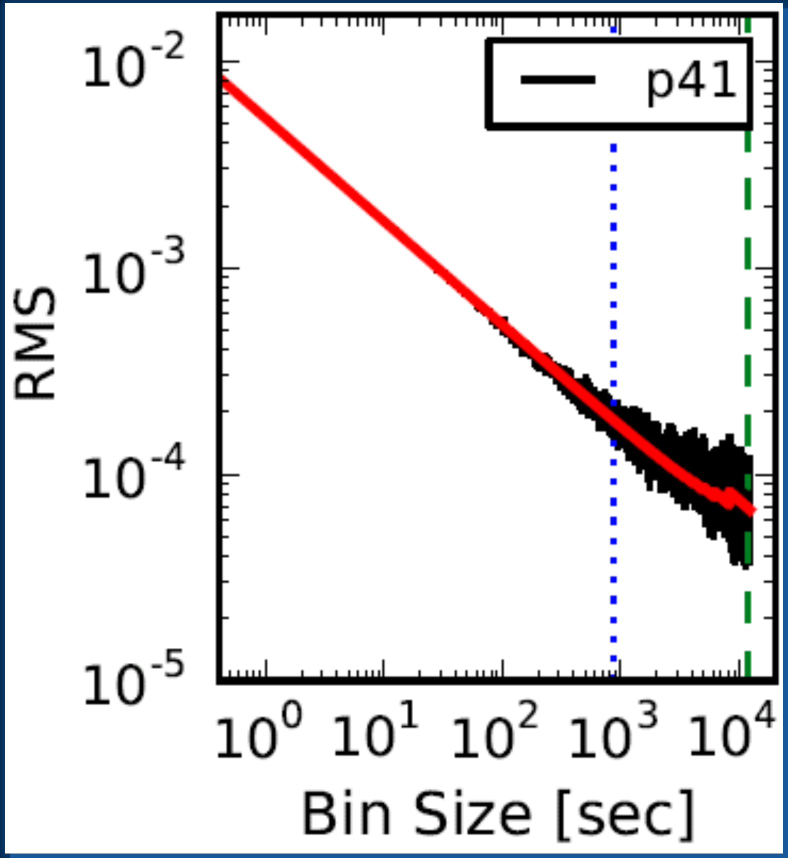


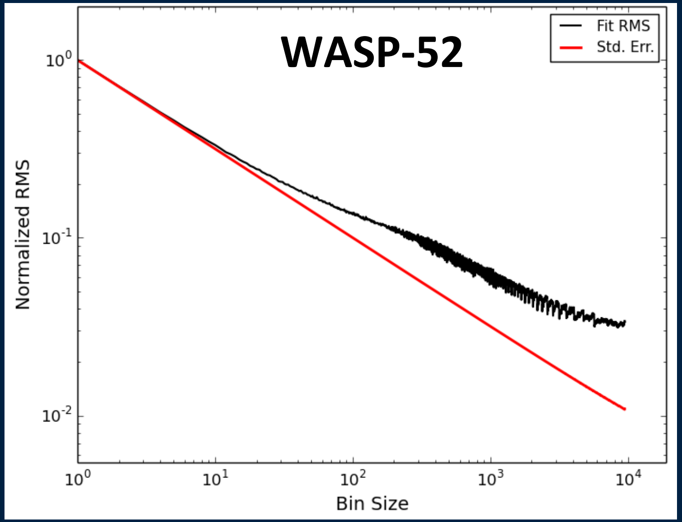
Lomb-Scargle (FFT)

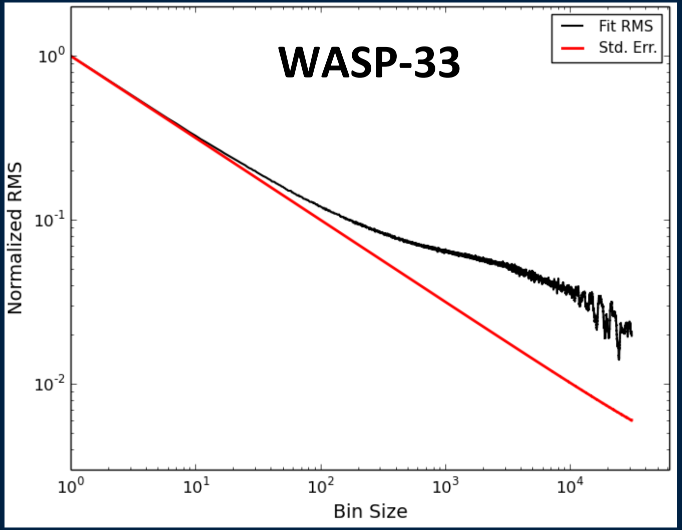


RMS vs Bin Size

White Noise







Accounting for Time-Correlated Noise

(DE)MCMC

- Assumes Gaussian-distributed uncorrelated noise
- Underestimates parameter uncertainties when data are correlated

Time-Averaging

- Pont et al. (2006), Winn et al. (2007,2008)
- Multiply (DE)MCMC uncertainties by β parameter

Residual Permutation

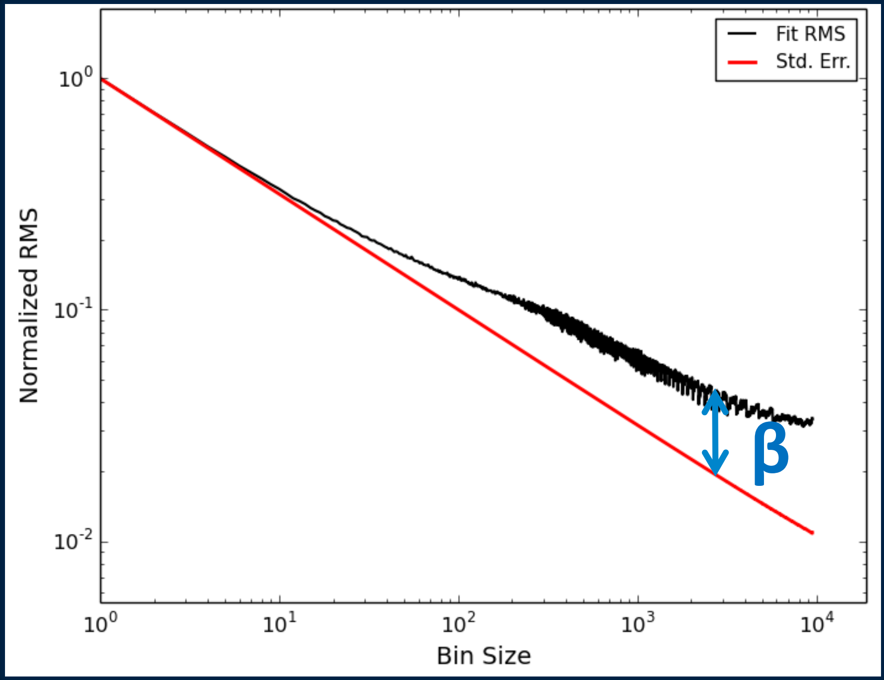
- Find best fit, permute residuals in time, add residuals to best-fit model, repeat
- Can generate up to *n* artificial datasets while preserving time-correlated noise

Wavelet Technique

- Carter & Winn (2009)
- Computes likelihood in a wavelet basis with a nearly diagonal covariance matrix

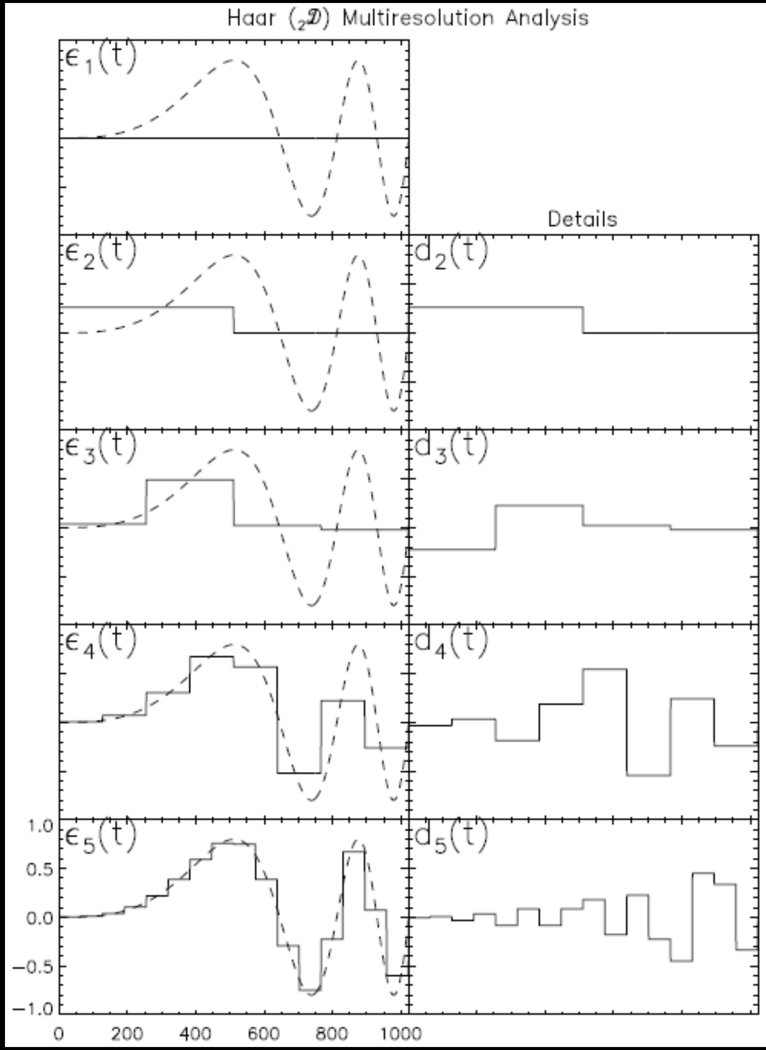
Time-Averaging Technique

- Compute β
  - Ratio between measured and predicted rms values
- β can be bin size dependent
  - What length scale do you choose?



Wavelet Technique

- Transform light curve residuals into wavelet domain
- With a suitable wavelet basis, covariance matrix is nearly diagonal
- Assumes noise sources have power spectral density that varies as $1/f^{\gamma}$
- Increasing γ → longer-range correlations



Wavelet Technique

- Want to maximize likelihood in wavelet domain

$$\mathcal{L} = \left\{ \prod_{m=2}^{M} \prod_{n=1}^{n_0 2^{m-1}} \frac{1}{\sqrt{2\pi\sigma_W^2}} \exp\left[-\frac{\left(r_n^m\right)^2}{2\sigma_W^2} \right] \right\} \times \left\{ \prod_{n=1}^{n_0} \frac{1}{\sqrt{2\pi\sigma_S^2}} \exp\left[-\frac{\left(\bar{r}_n^1\right)^2}{2\sigma_S^2} \right] \right\}$$

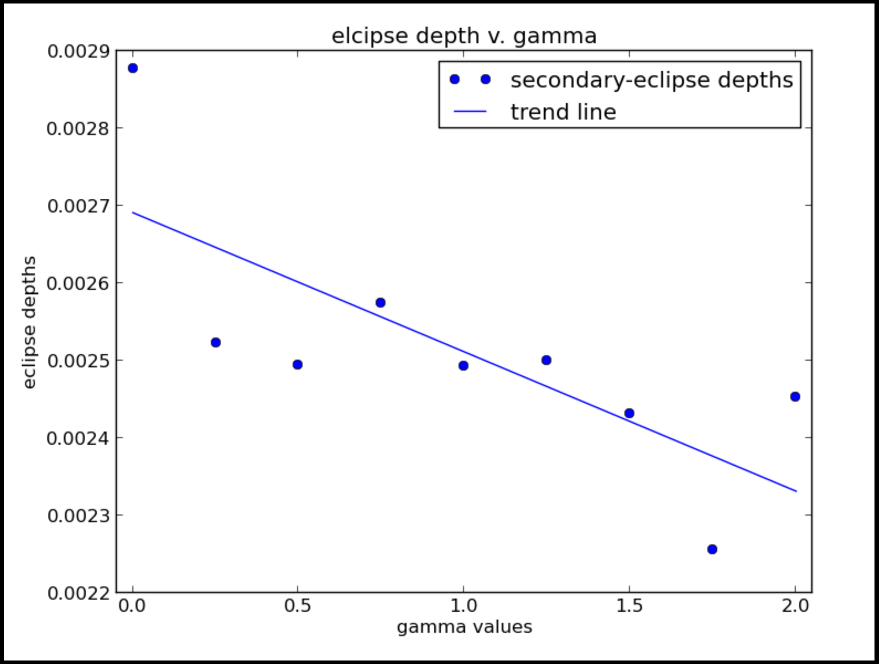
$$\sigma_W^2 = \sigma_r^2 2^{-\gamma m} + \sigma_w^2$$
$$\sigma_S^2 = \sigma_r^2 2^{-\gamma} g(\gamma) + \sigma_w^2$$

- 3 noise parameters: σ_r , σ_w , γ

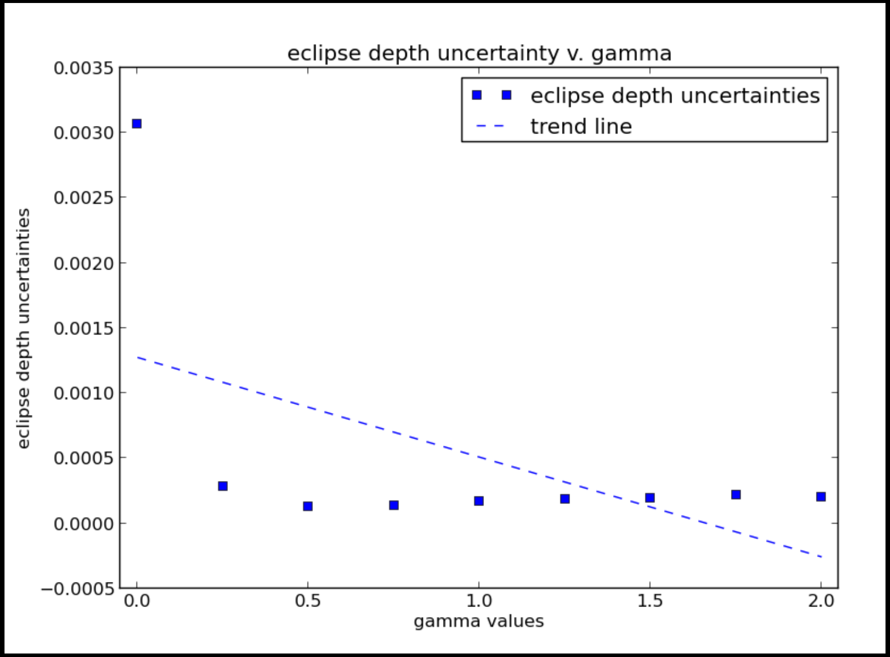
- Drawbacks
  - Errors in noise and transit parameters are correlated
  - Some wavelets work better than others
  - Unstable MCMC at low γ values

Wavelet Technique

Eclipse Depth *vs* γ

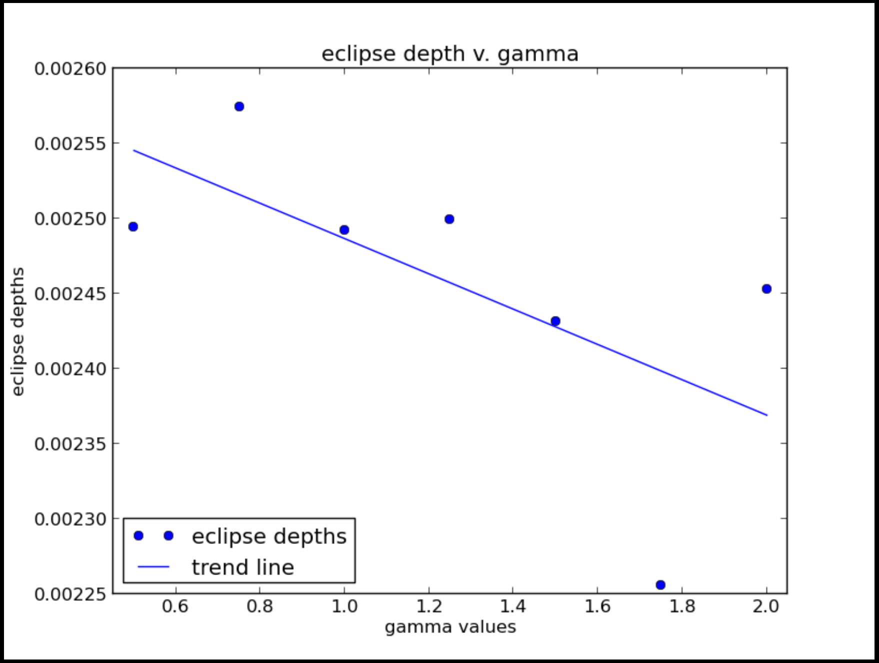


Eclipse Depth Err *vs* γ

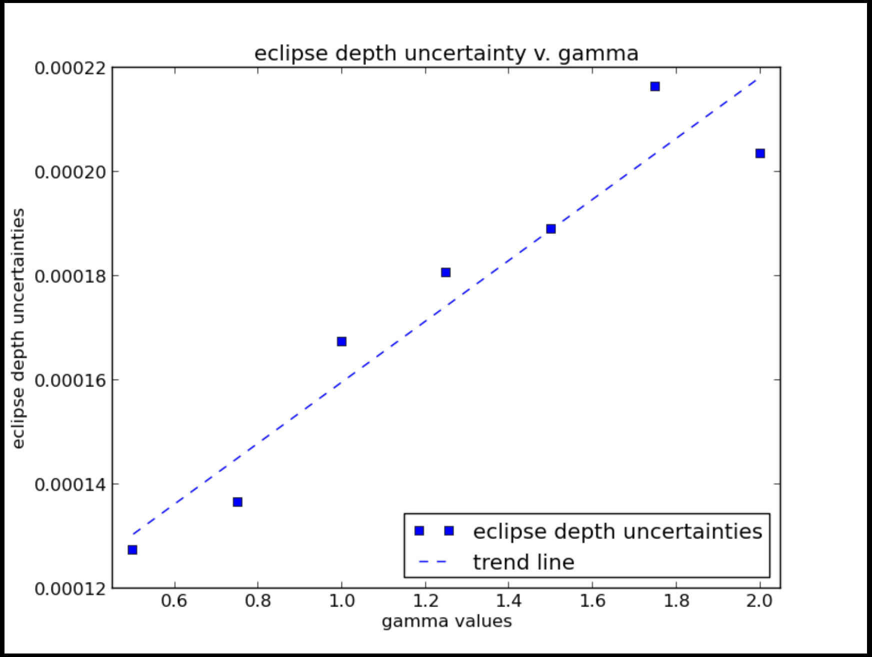


Wavelet Technique

Eclipse Depth *vs* γ



Eclipse Depth Err *vs* γ



Simulated Data (WASP-52)

- Applied each method to simulated WASP-52 dataset
- Compared eclipse depths and uncertainties
- Tests show that some uncertainties may be overestimated

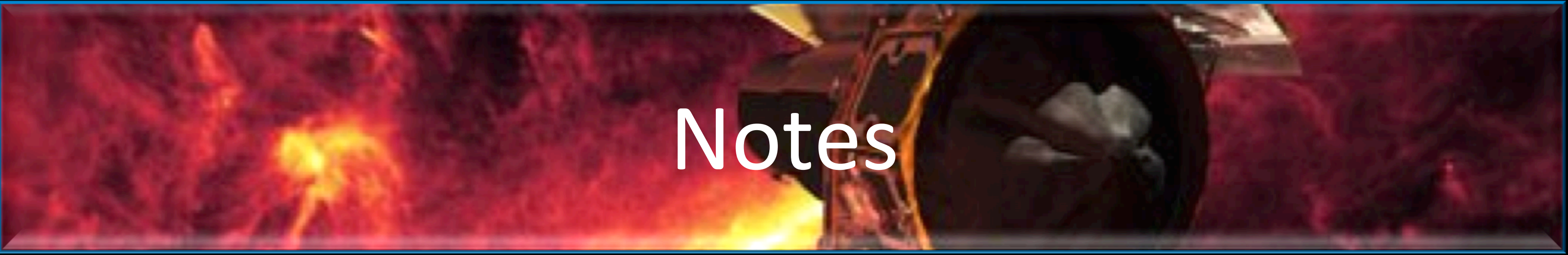
Method	Ecl. Depth (%)	Ecl. Depth Err (%)
(DE)MCMC	0.248	0.013
Time-Avg	0.248	0.036
Res. Perm.	0.297	0.007
Wavelet (γ=1.4)	0.250	0.021

Conclusions

- Identifying time-correlated noise
  – Lomb-Scargle
  – rms *vs* bin size

- Accounting for time-correlated noise
  – Need further testing to determine which method produces the most reliable uncertainties
  – Apply multiple techniques, compare uncertainties

Bonus Slides



Notes

- Show BLISS map projections?
- Due to residual systematics or unmodeled astrophysical signal(s)

$$\beta=\sqrt{1+(\square_{r}/\square_{w})}$$