UNIVERSITY OF Southampton

The 2nd Summer School of the Hel.A.S.
Nuclear activity in galaxies

– AGN variability –

Dimitrios Emmanoulopoulos

11–15 July 2016, Athens, Greece

My profile

Poisson distribution

$\Gamma(\alpha, z_0, z_1)$ distribution Frequency Domain Global Optimization

Cross–Spectrum Power–Spectrum

Time Domain General Relativity AGN

Analytical Methods

Time–delays Time Series Model Fitting

VHE Astrophysics

Wavelets Photon Statistics χ^2

Response Function

Quantum Gravity Monte Carlo Accretion disk

Covariance Convolution

Sampling Irregularities

Bayesian analysis Black holes

Outline

- What is a Black Hole?
- Problems in astrophysical time series.
- Development of new methods.
- Extraction of astrophysical information.

Time Series (in general)

- The only model-independent tool that provides information about a system.

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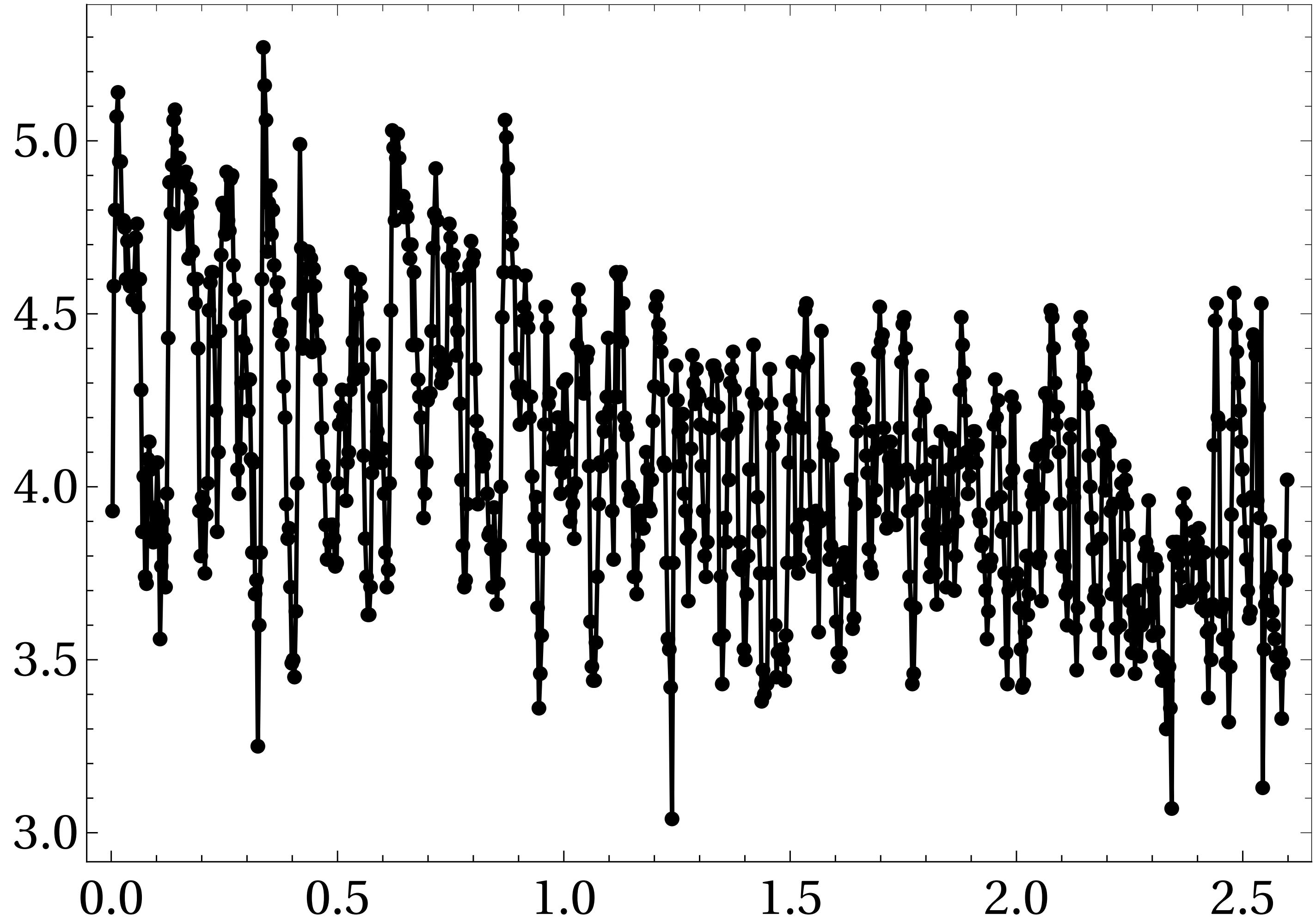
- Through modelling, this information is mapped into a system's property.

Time Series (in general)



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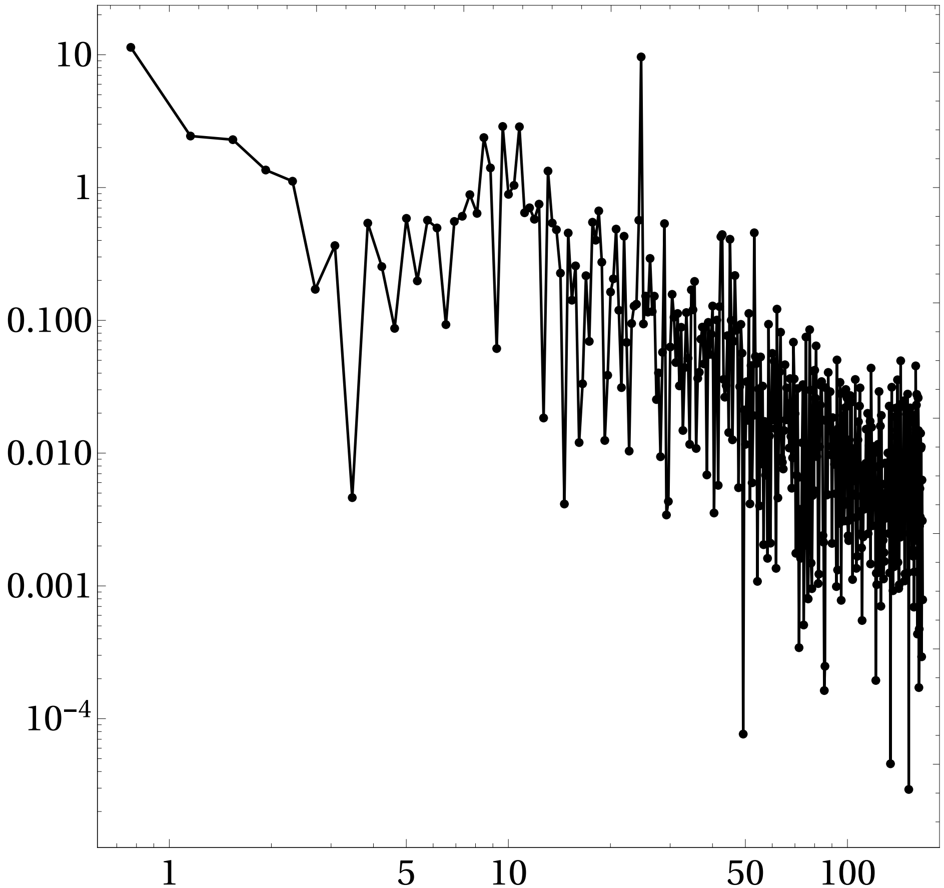

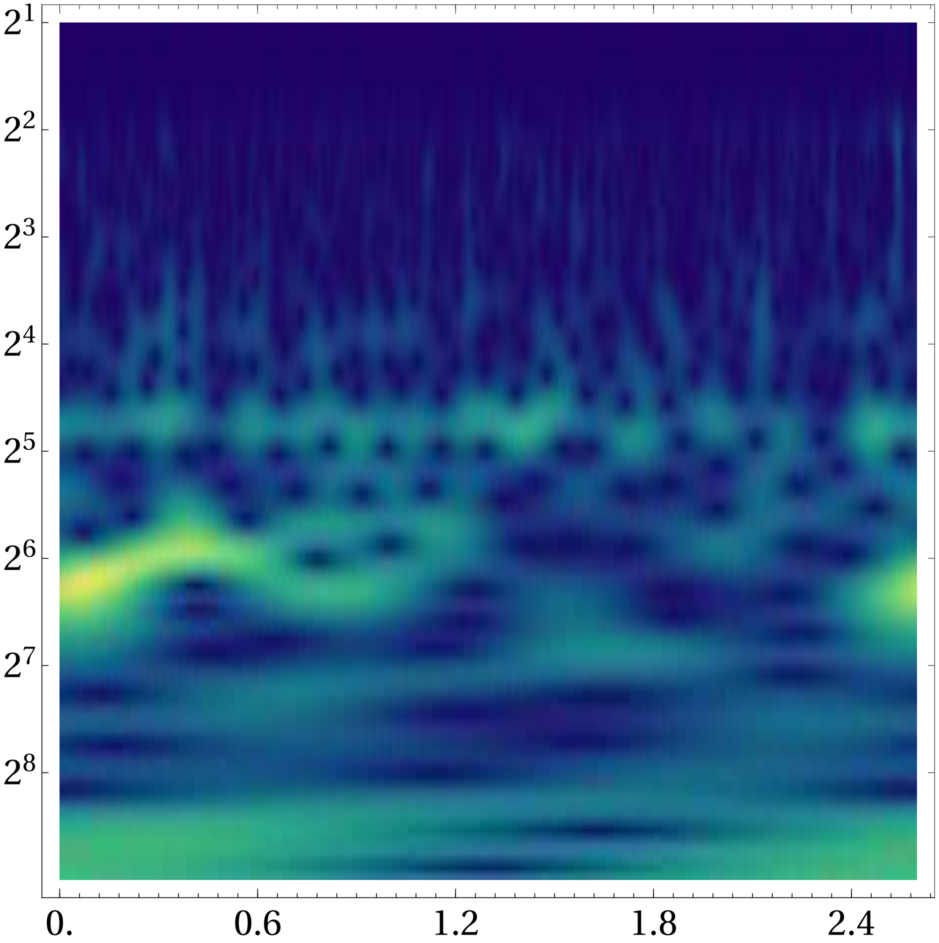

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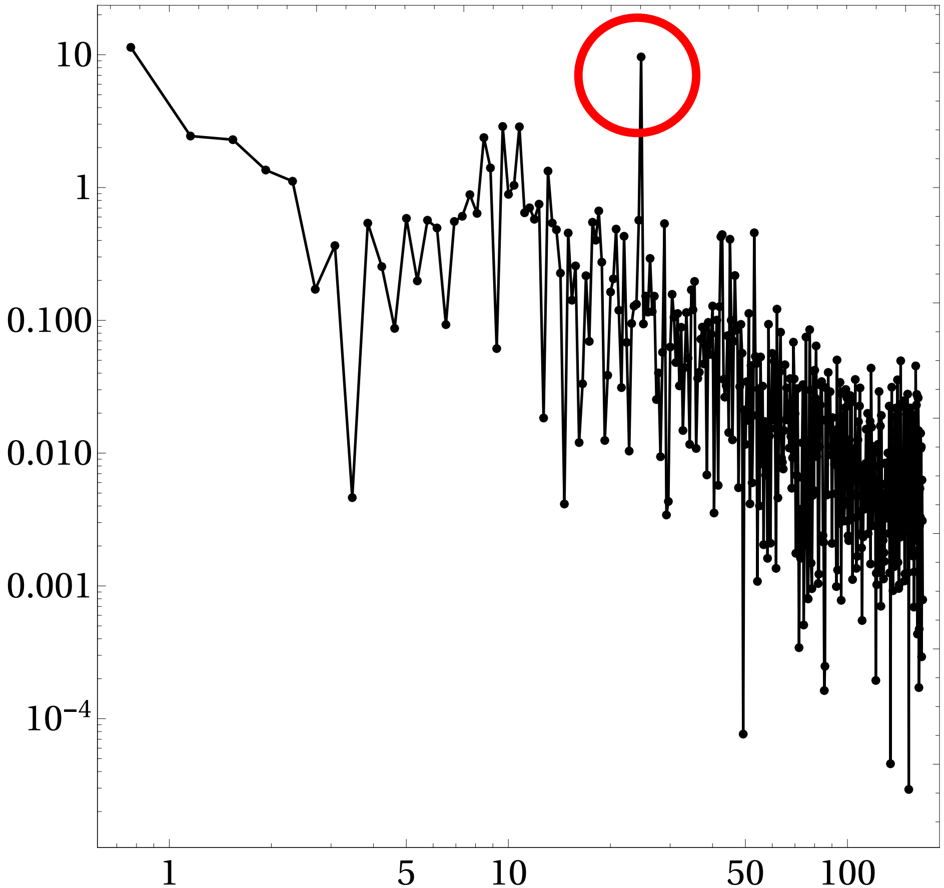

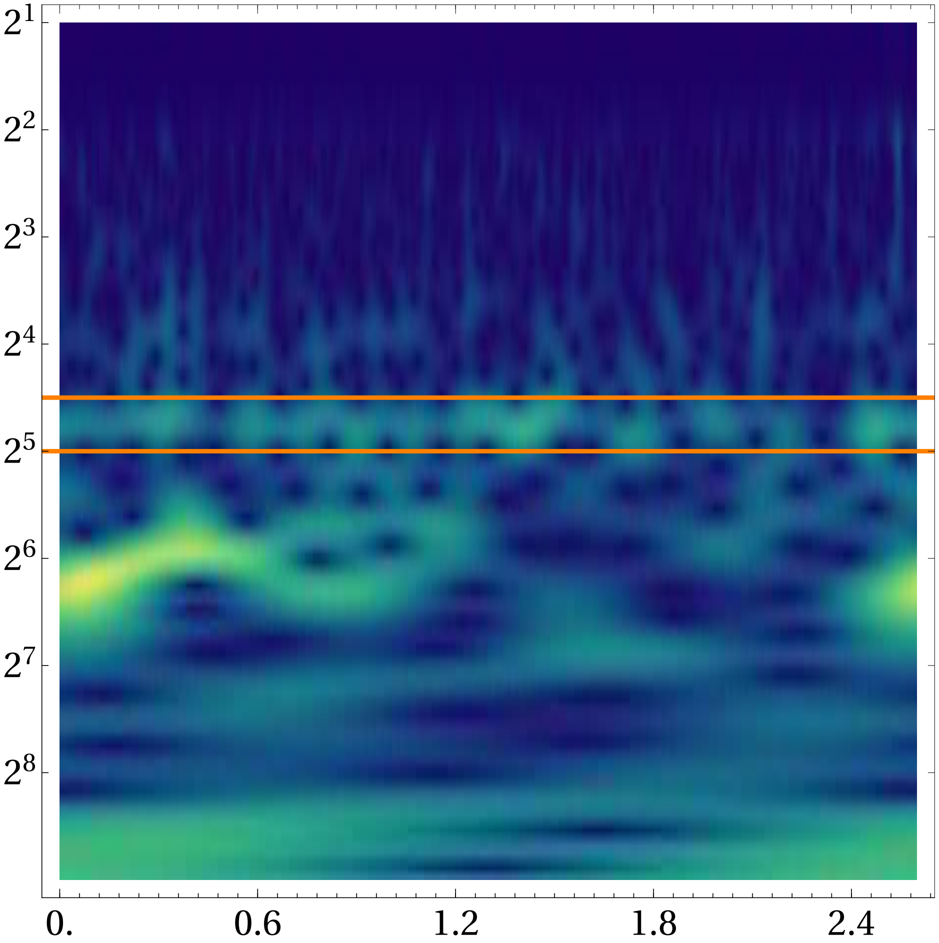

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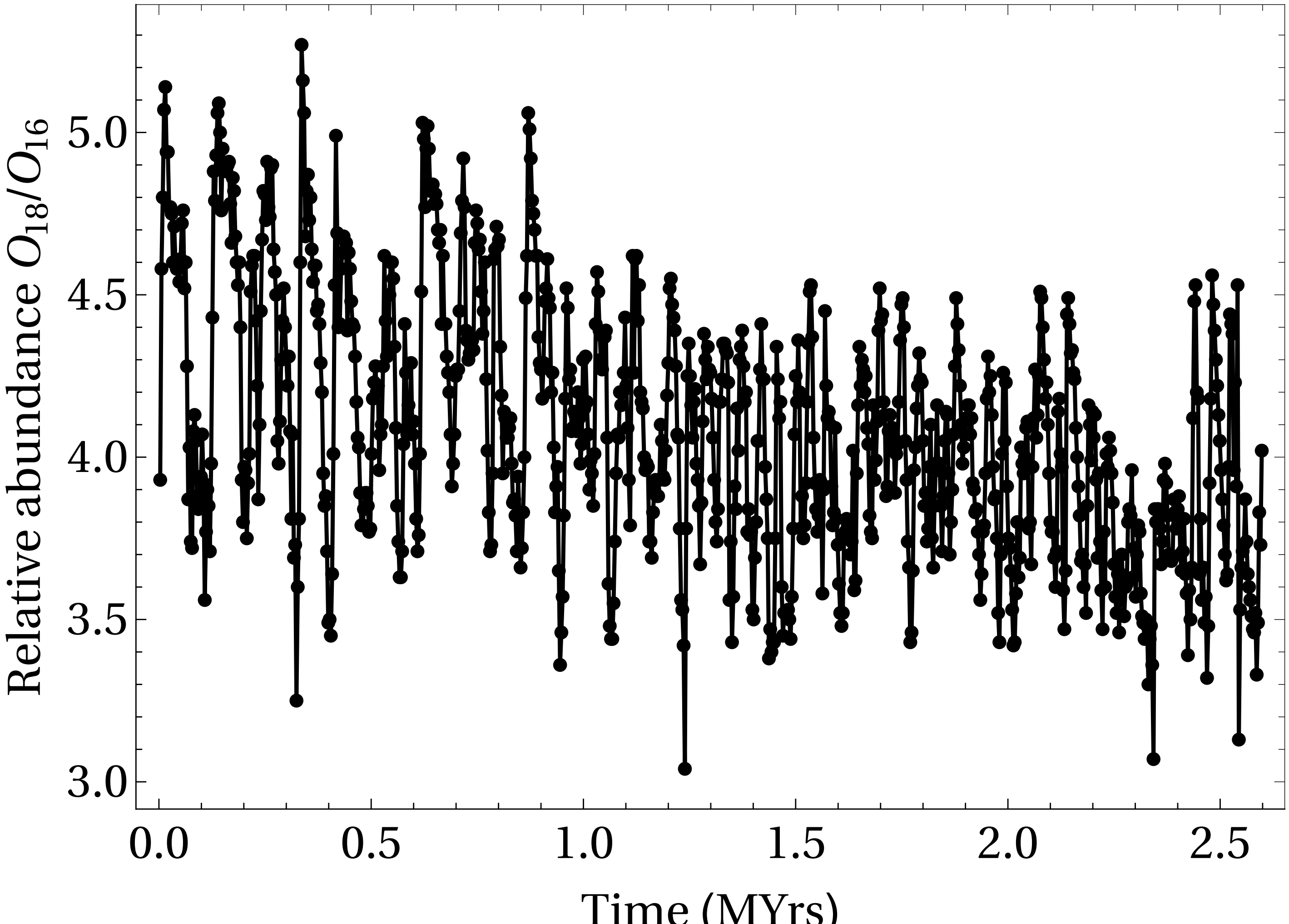

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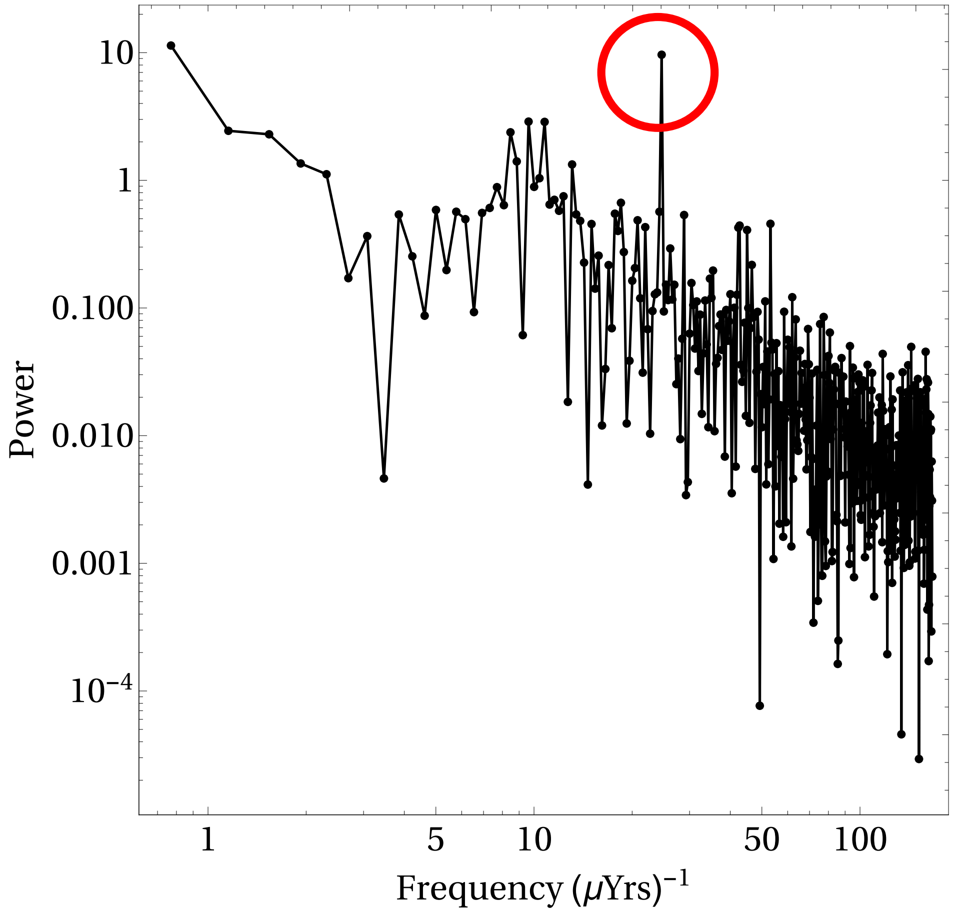
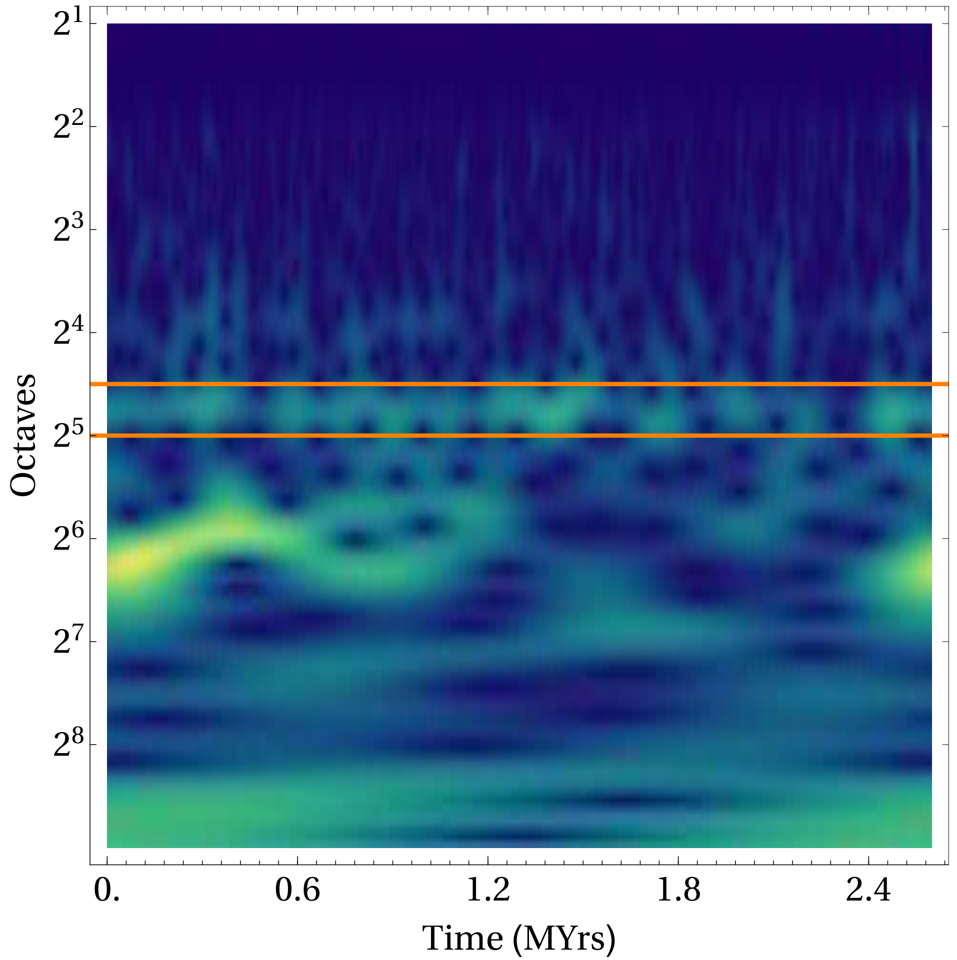




41 kYrs periodicity (Obliquity)

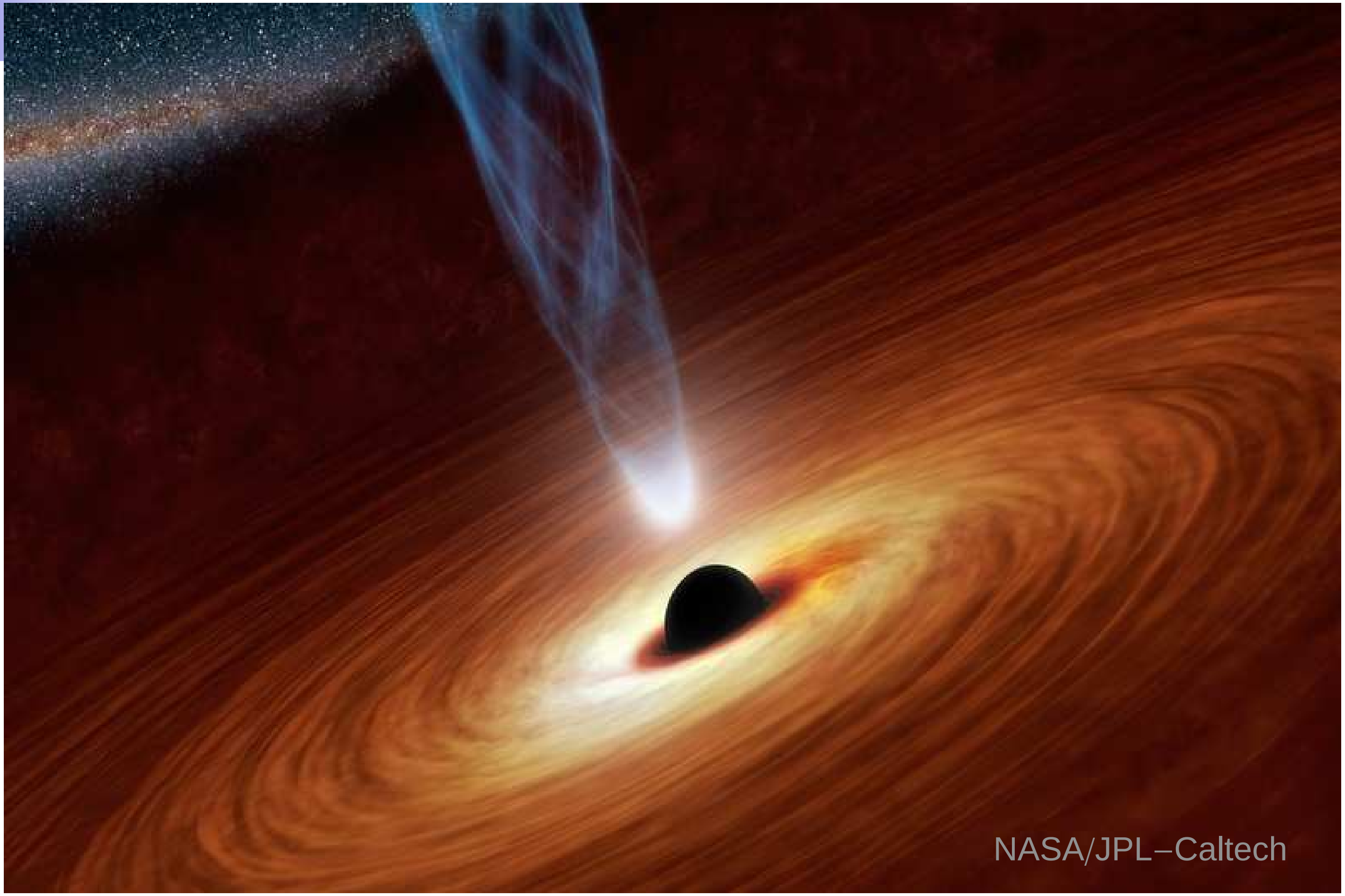
What is a Black Hole?

Luminosity$= (2 \times 10^{10}) \cdot (4 \times 10^{26}\ \mathrm{W}) = 8 \times 10^{36}$ W

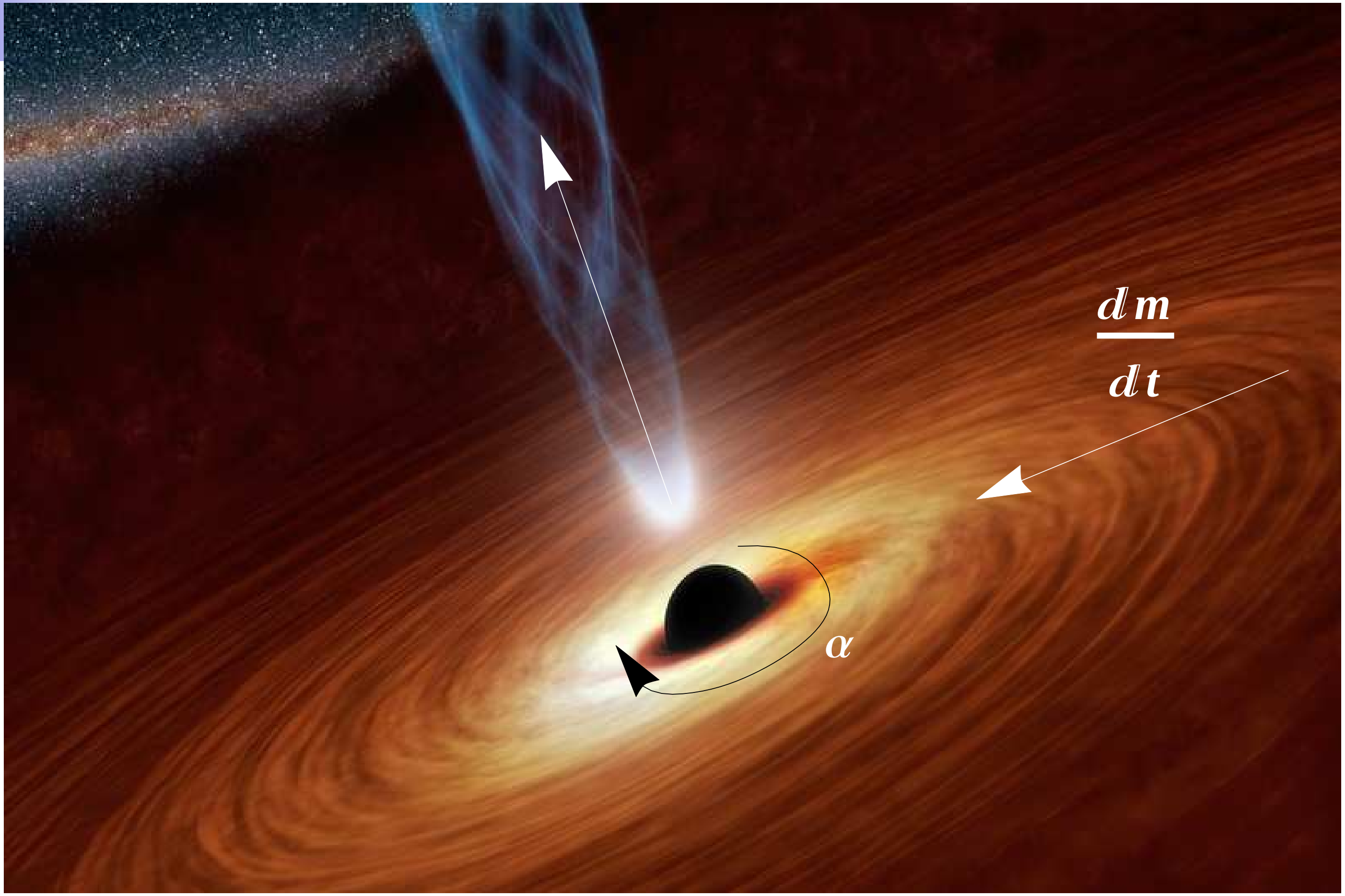
What is a Black Hole?

Luminosity$= 10^{44} - 10^{47}$ W

What is a Black Hole?

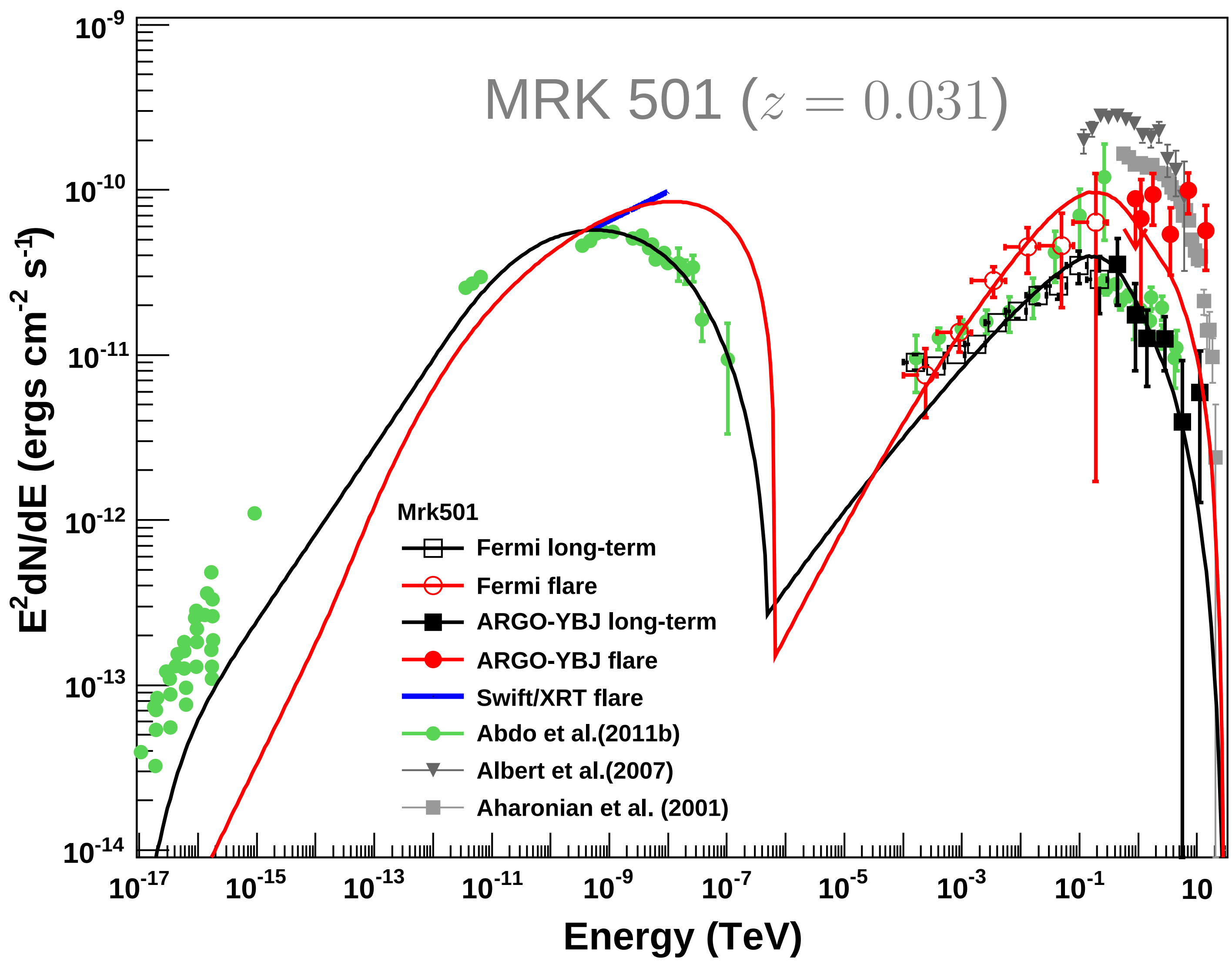


What is a Black Hole?



What is a Black Hole?

Radiation in the entire Elec.Magn. spectrum.



SongZhan Chen (2013), Science China Physics, Mechanics & Astronomy, **56**, 1

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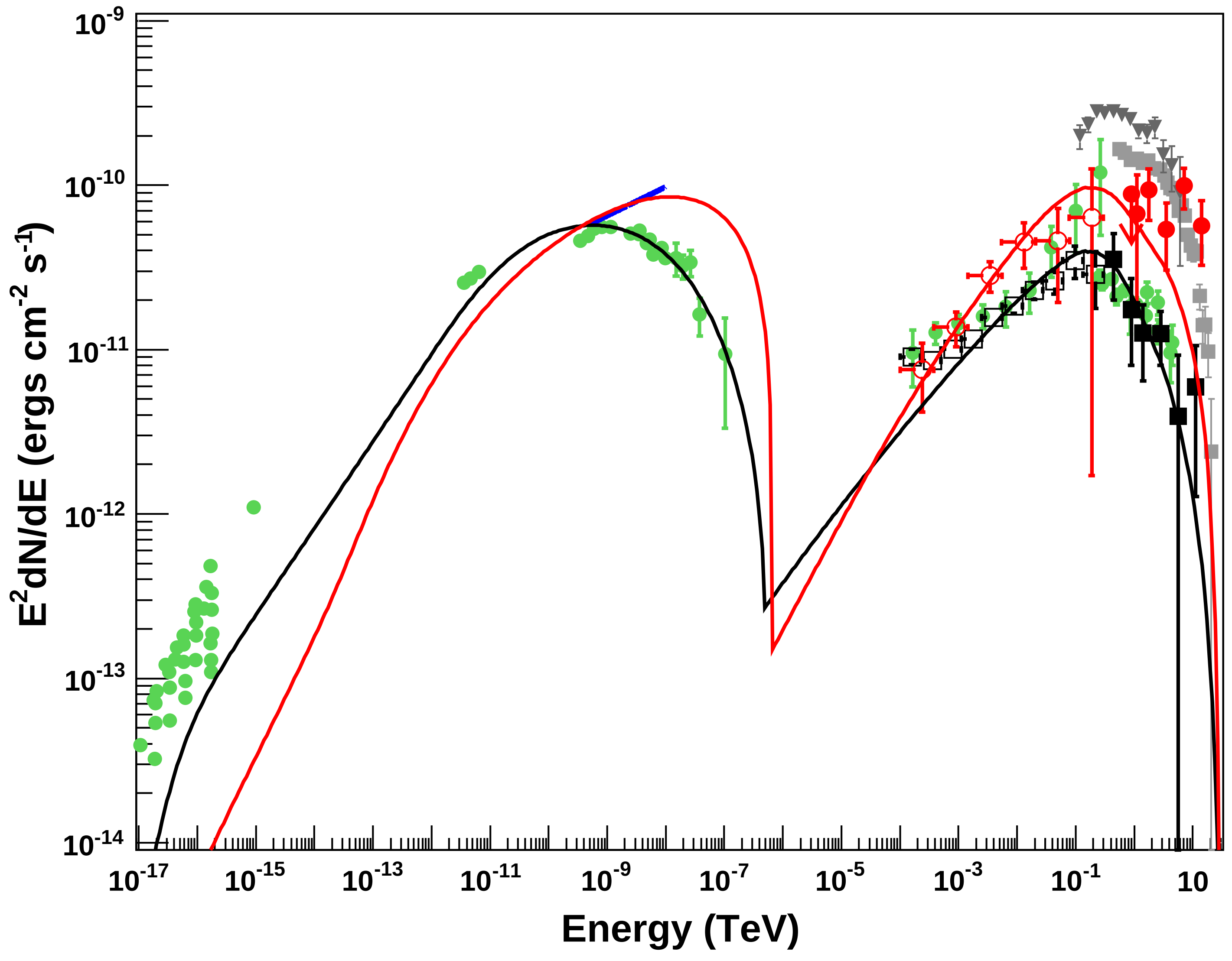
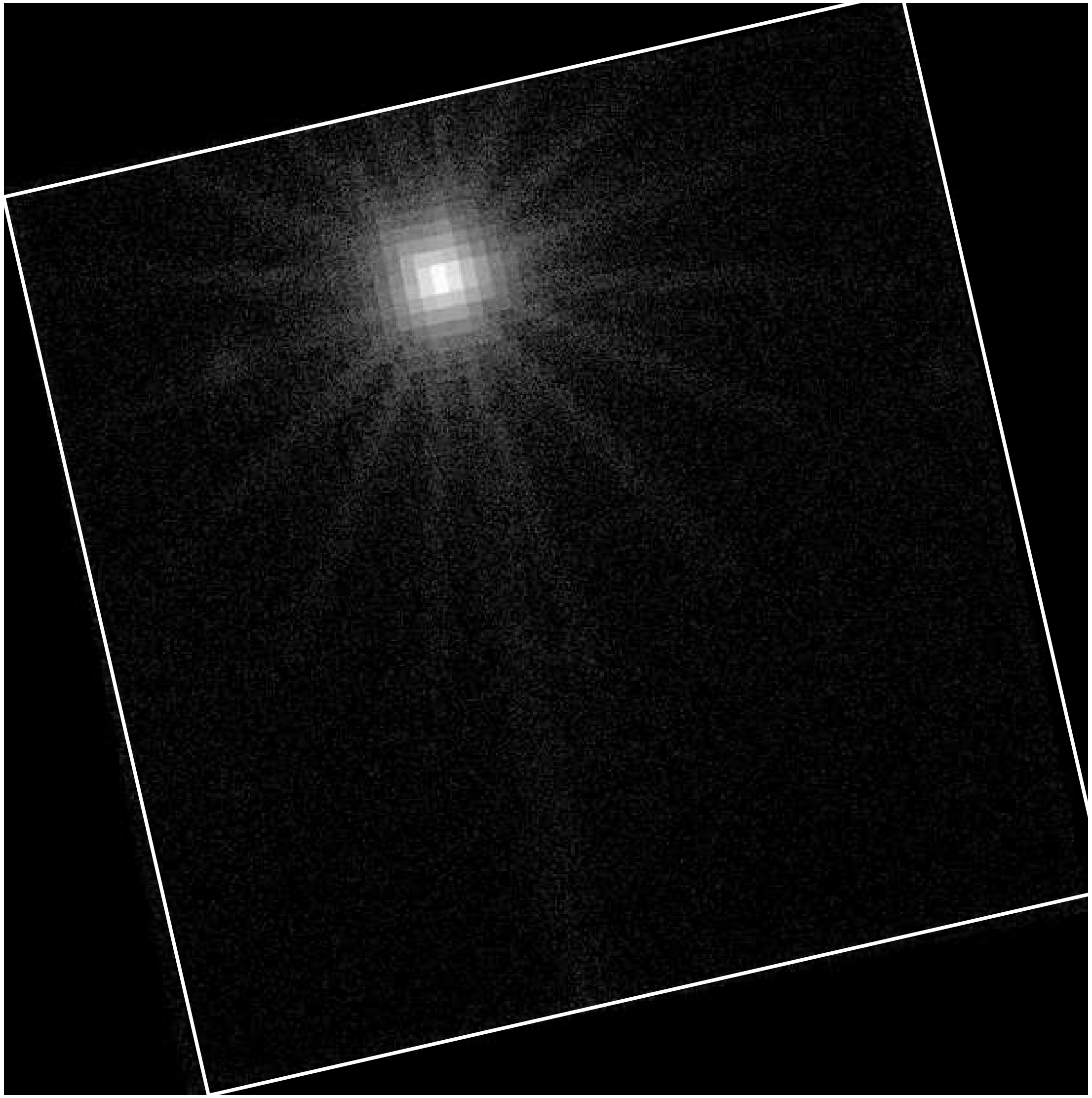


What do we really observe?



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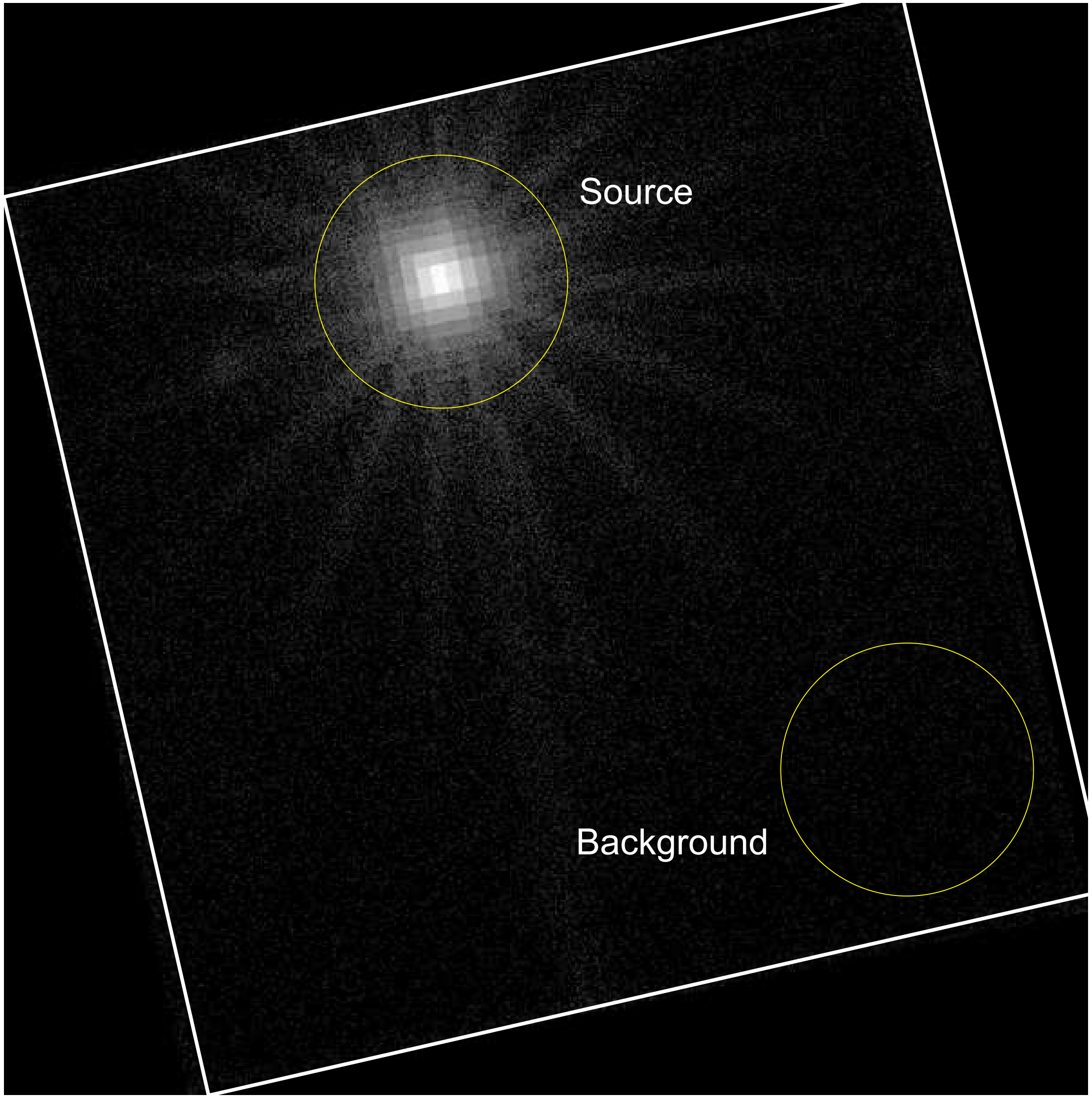
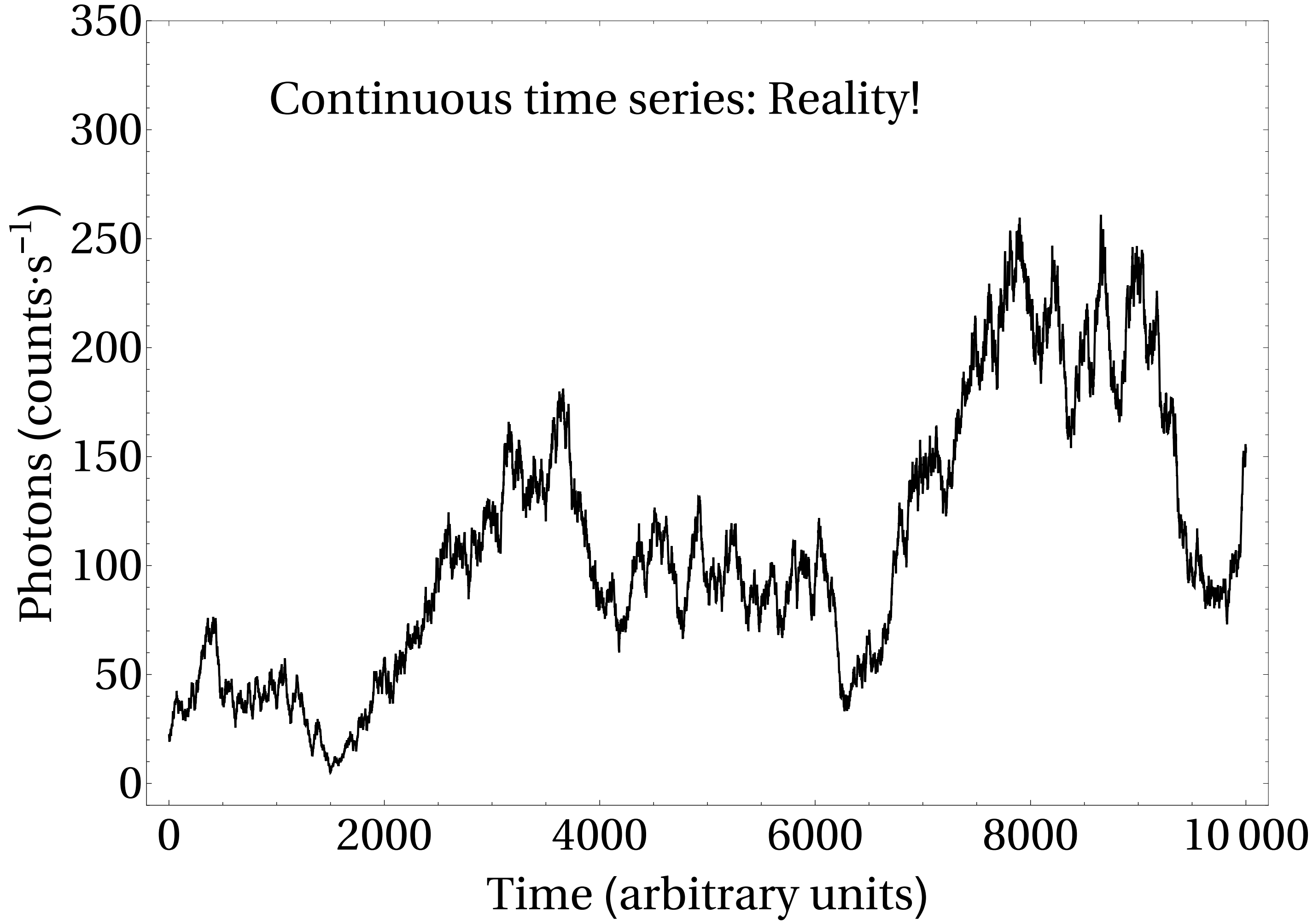


Data-set problems



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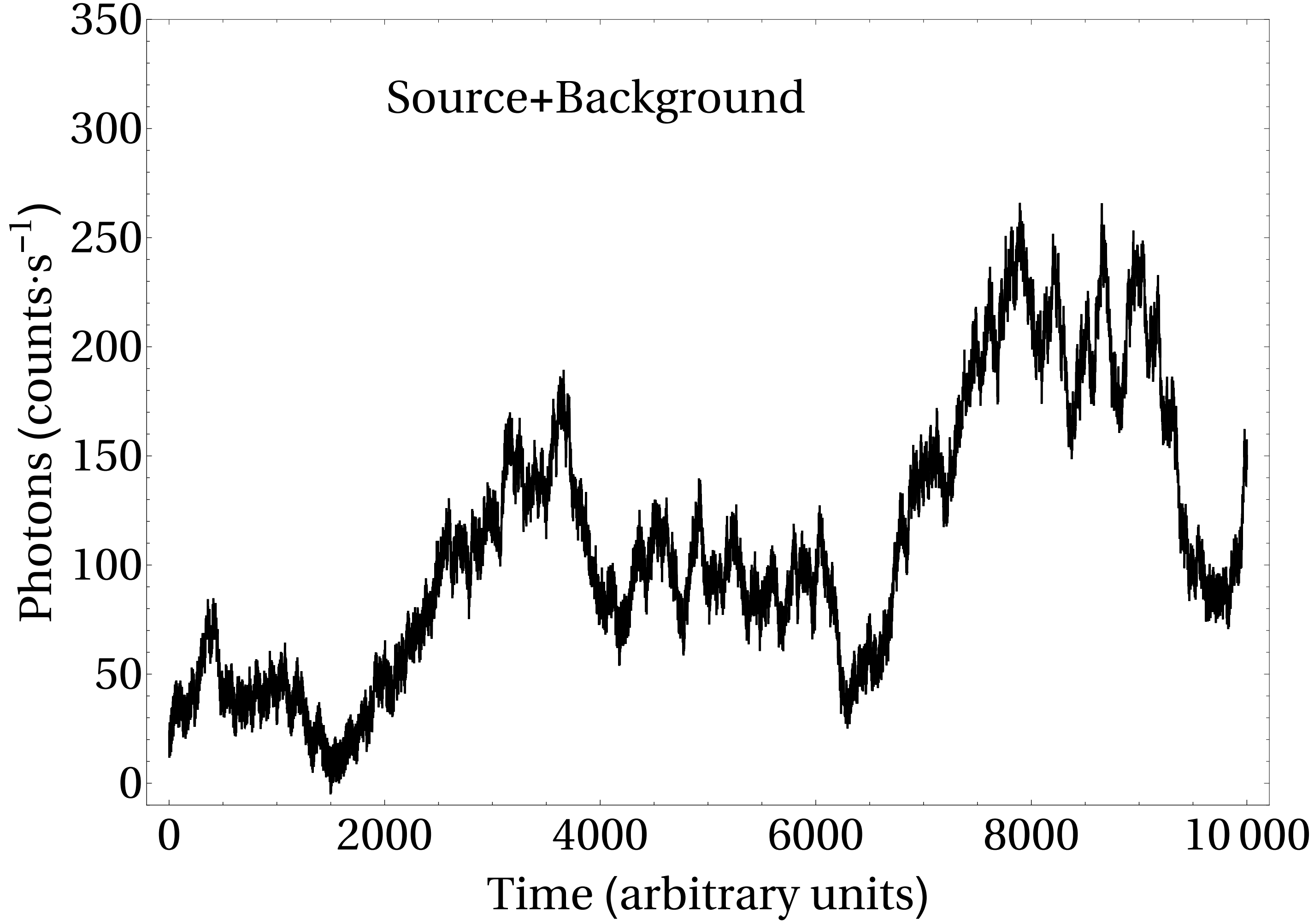

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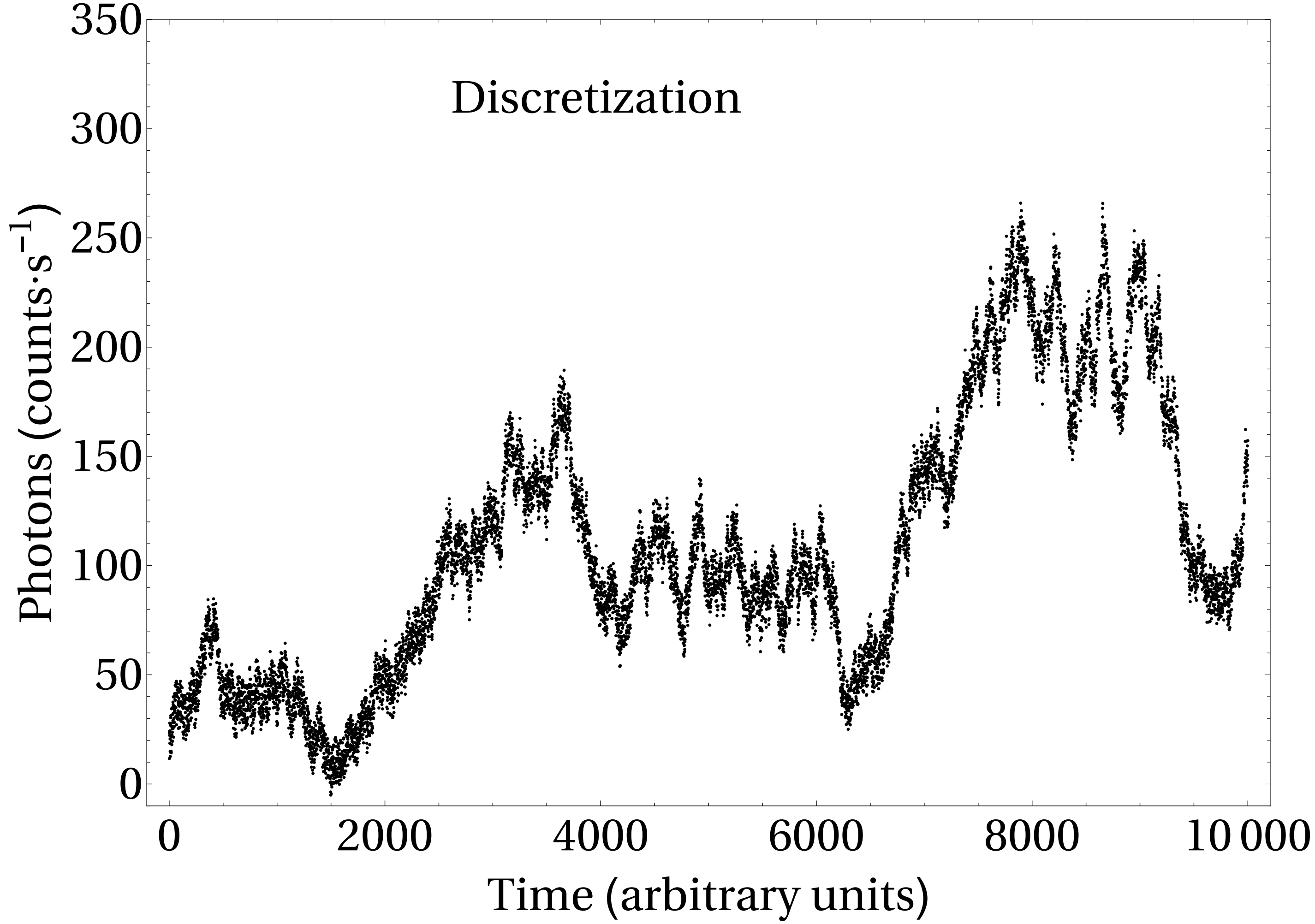

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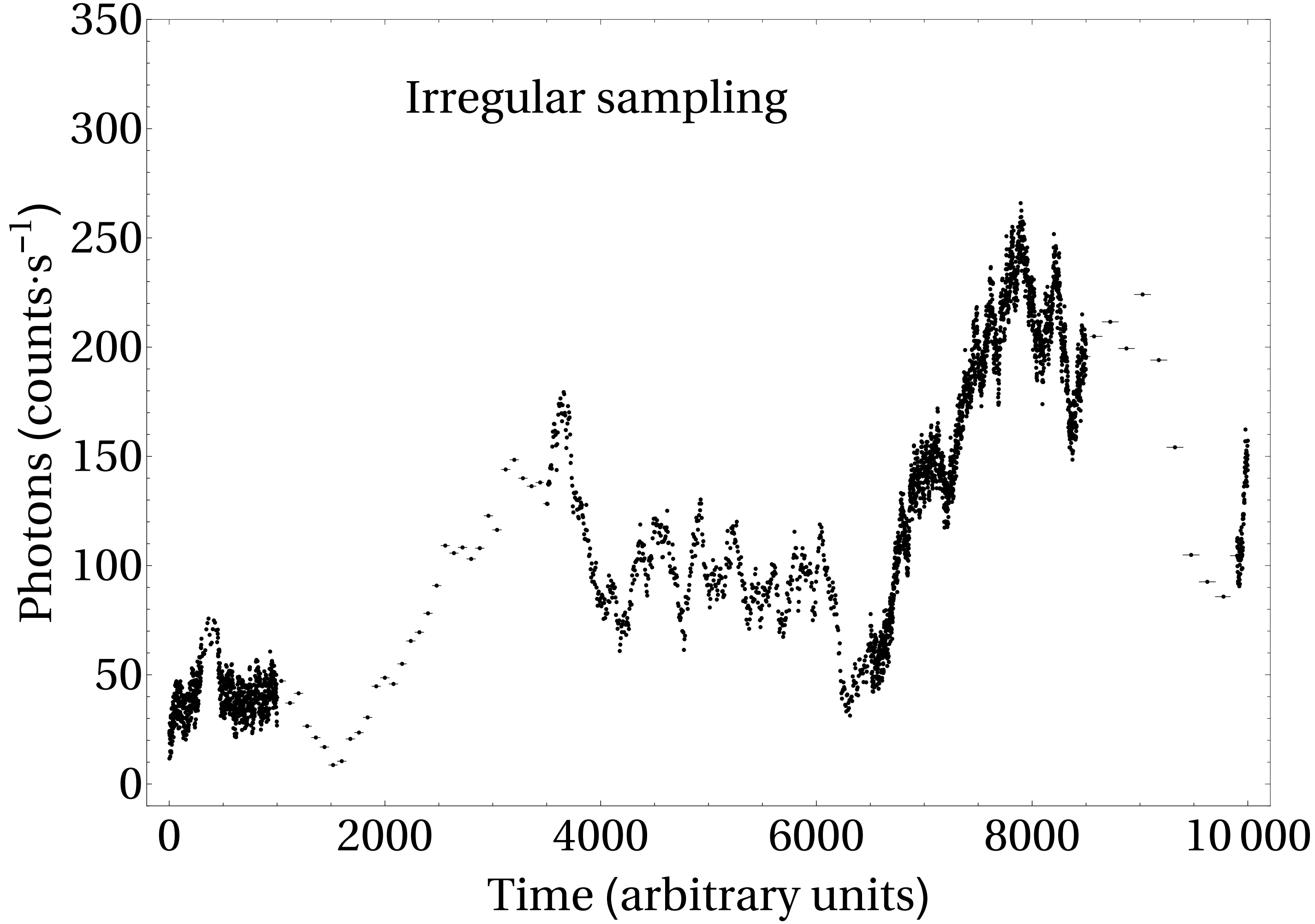

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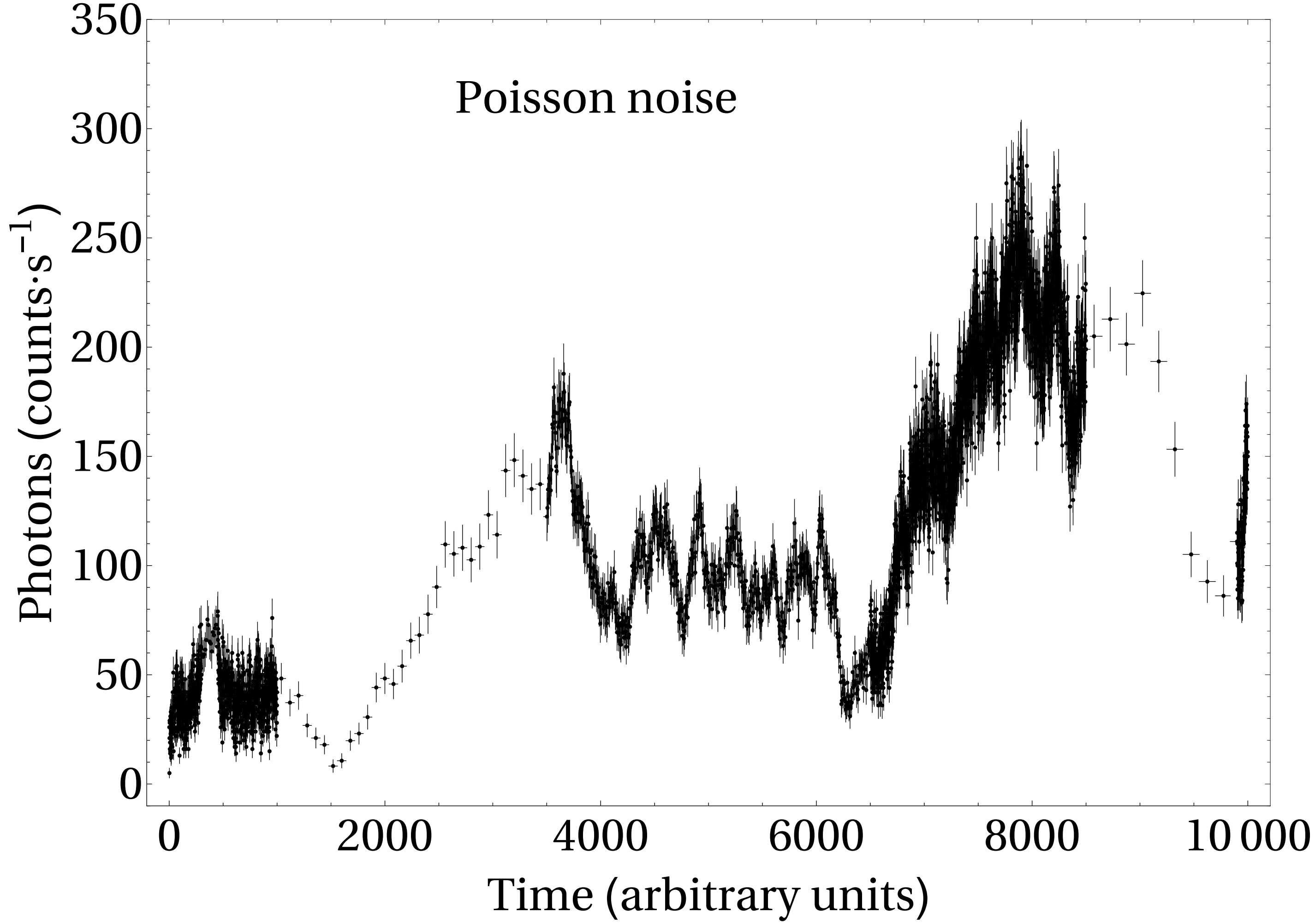

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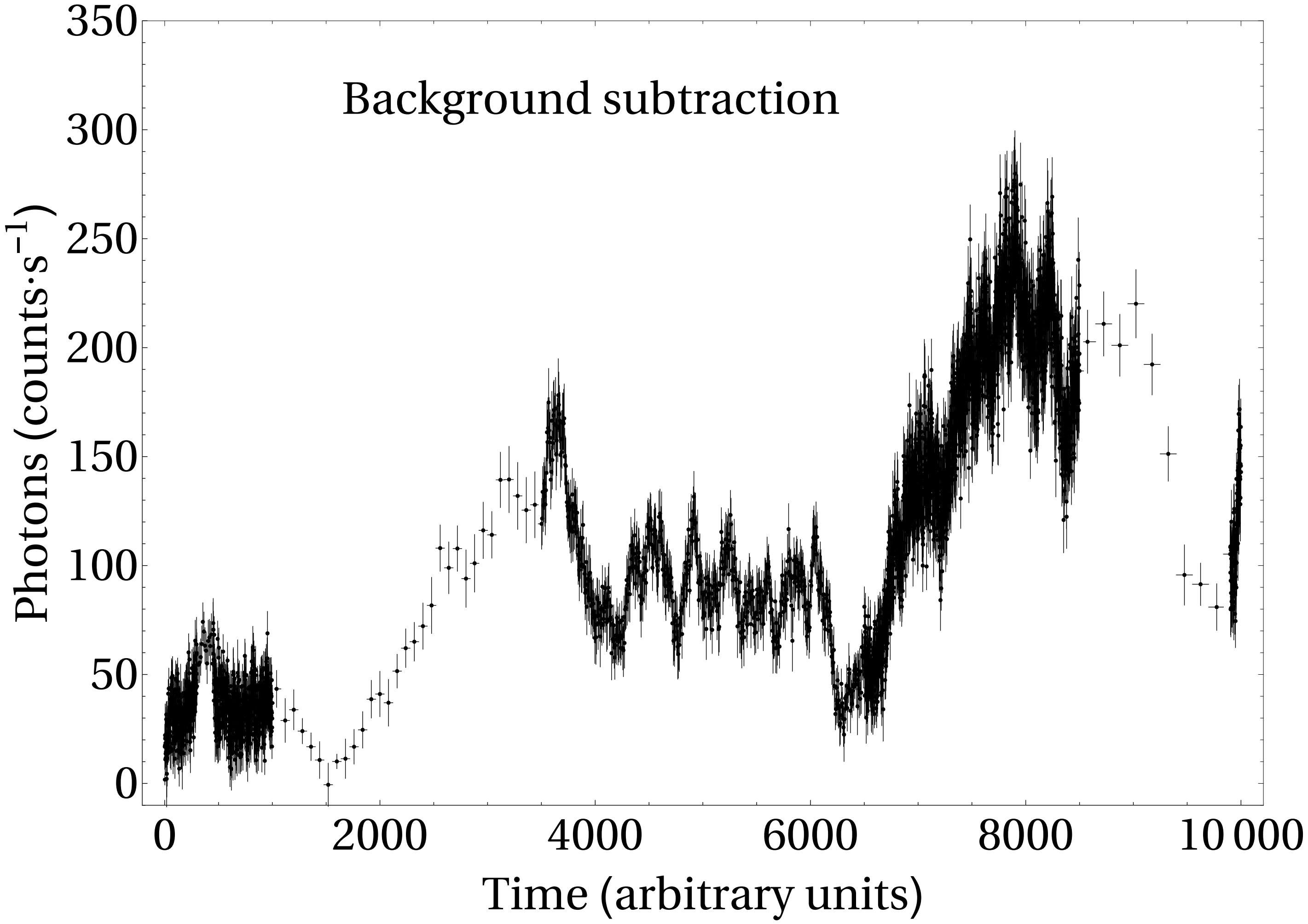

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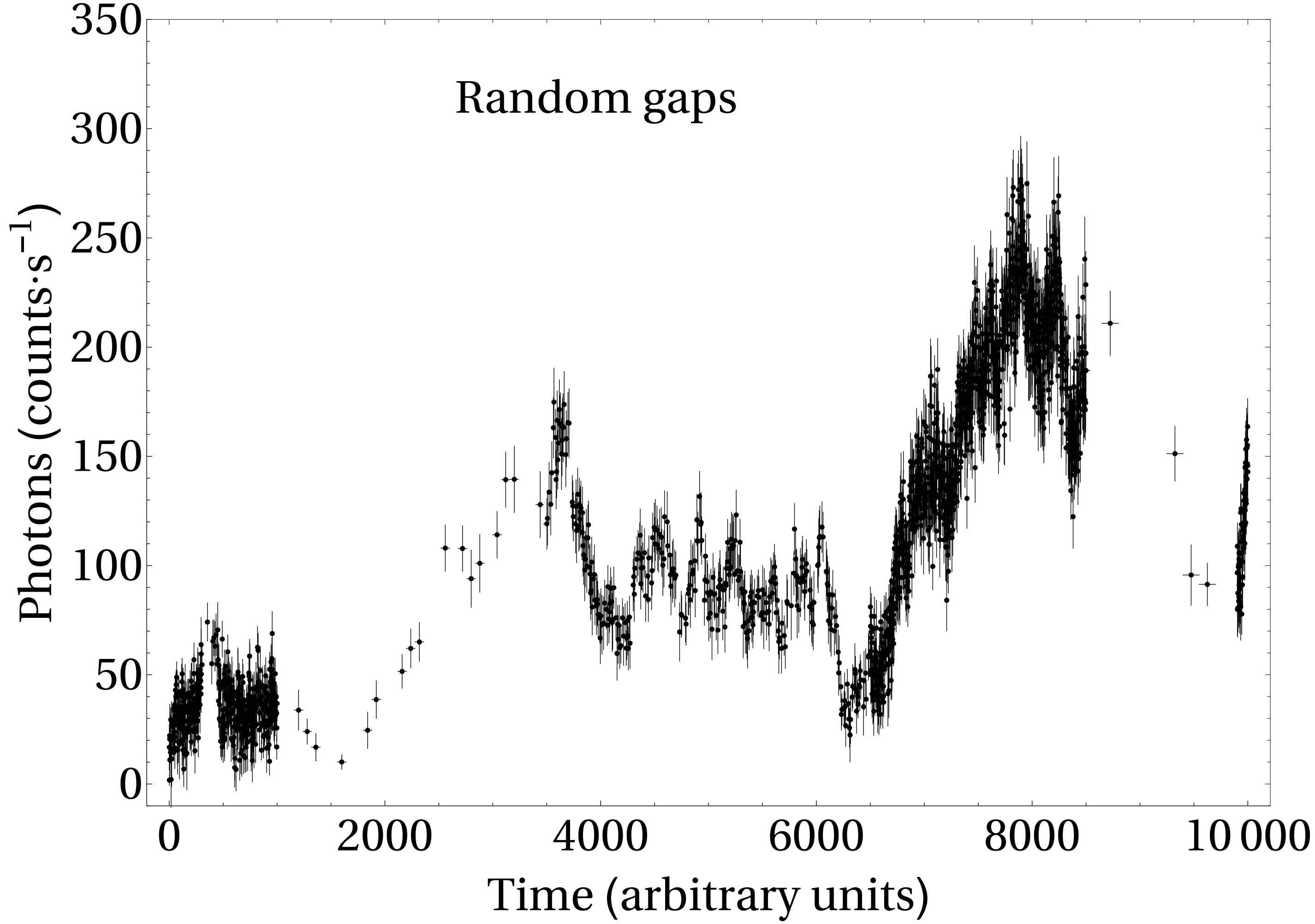

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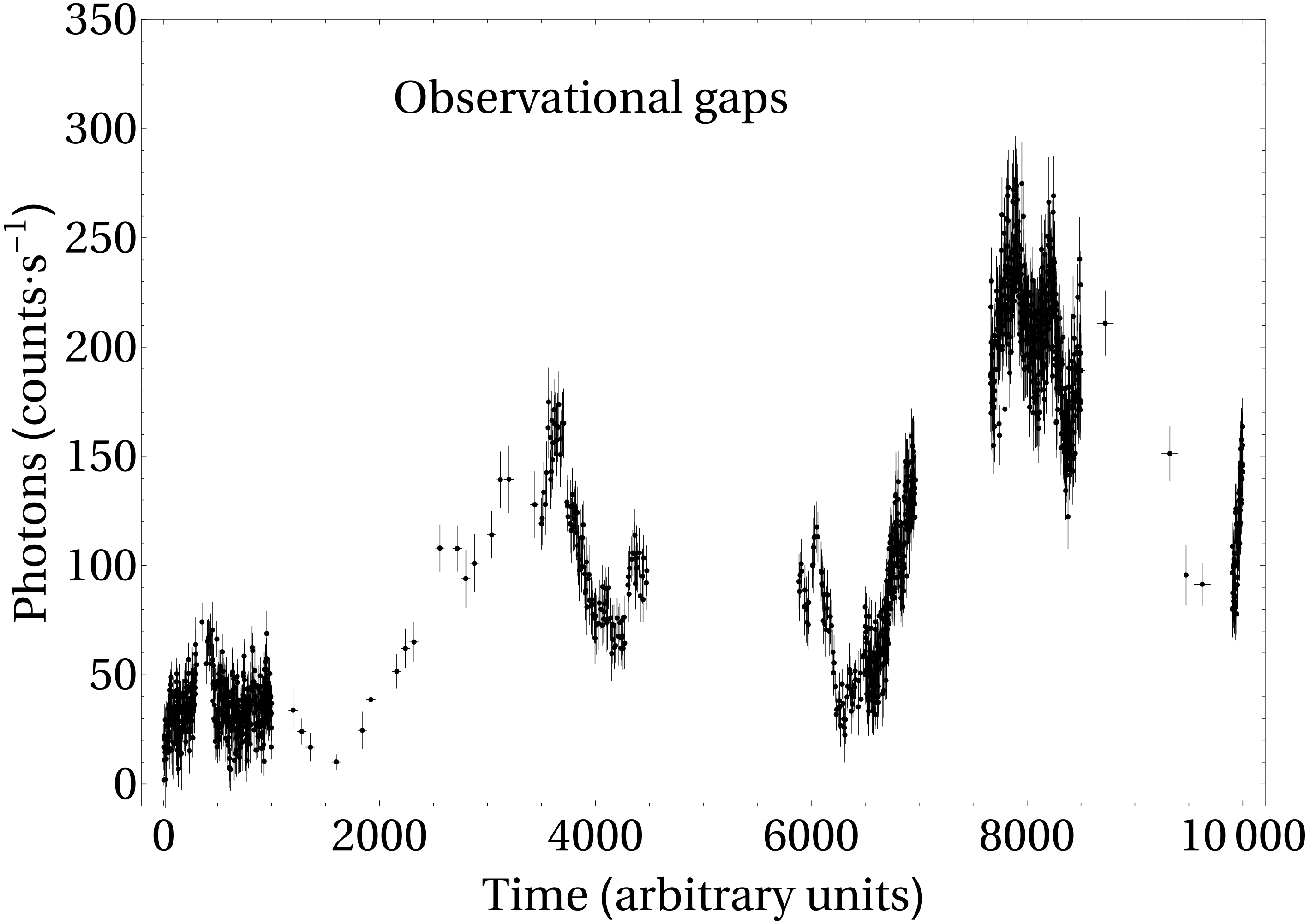

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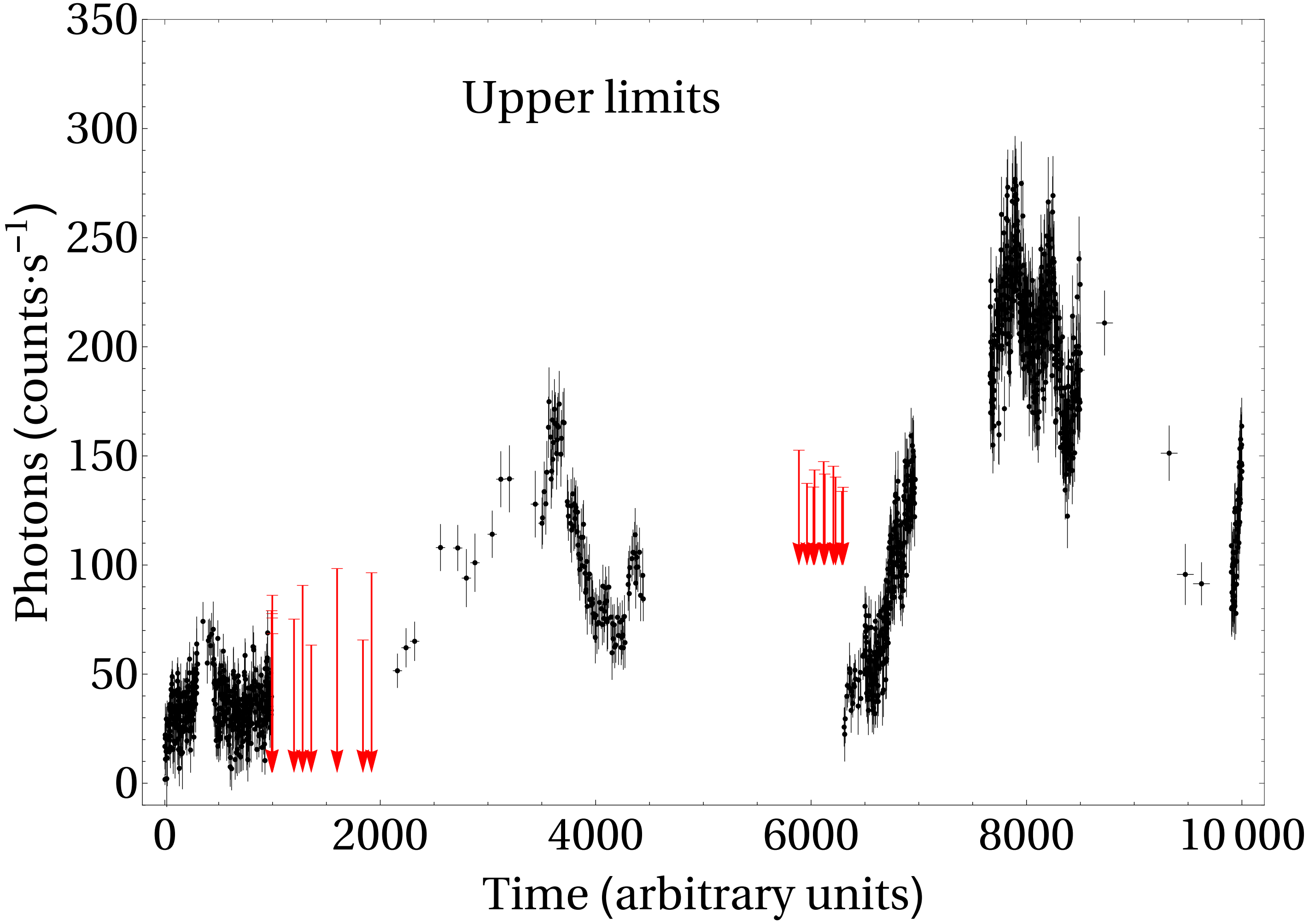

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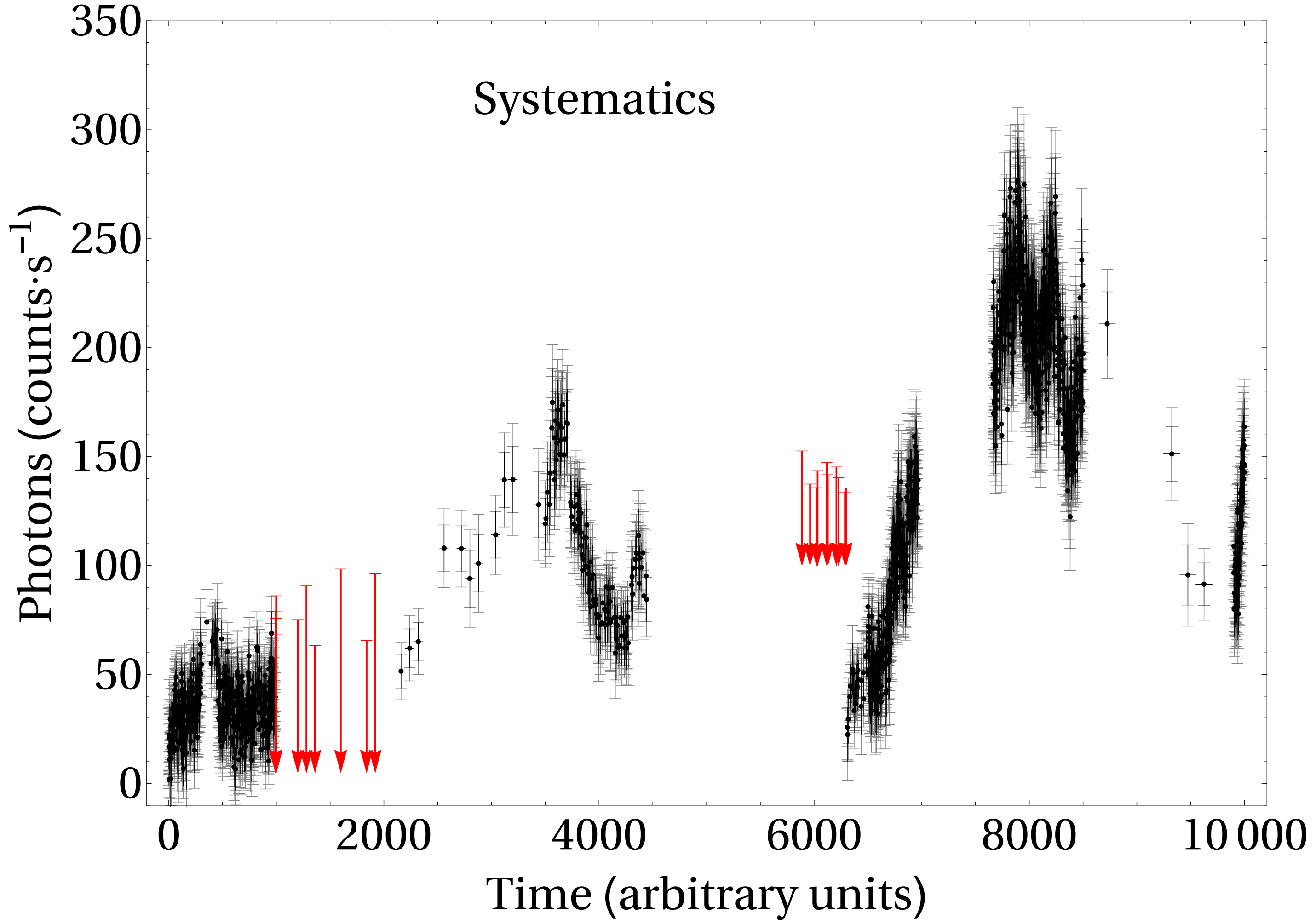

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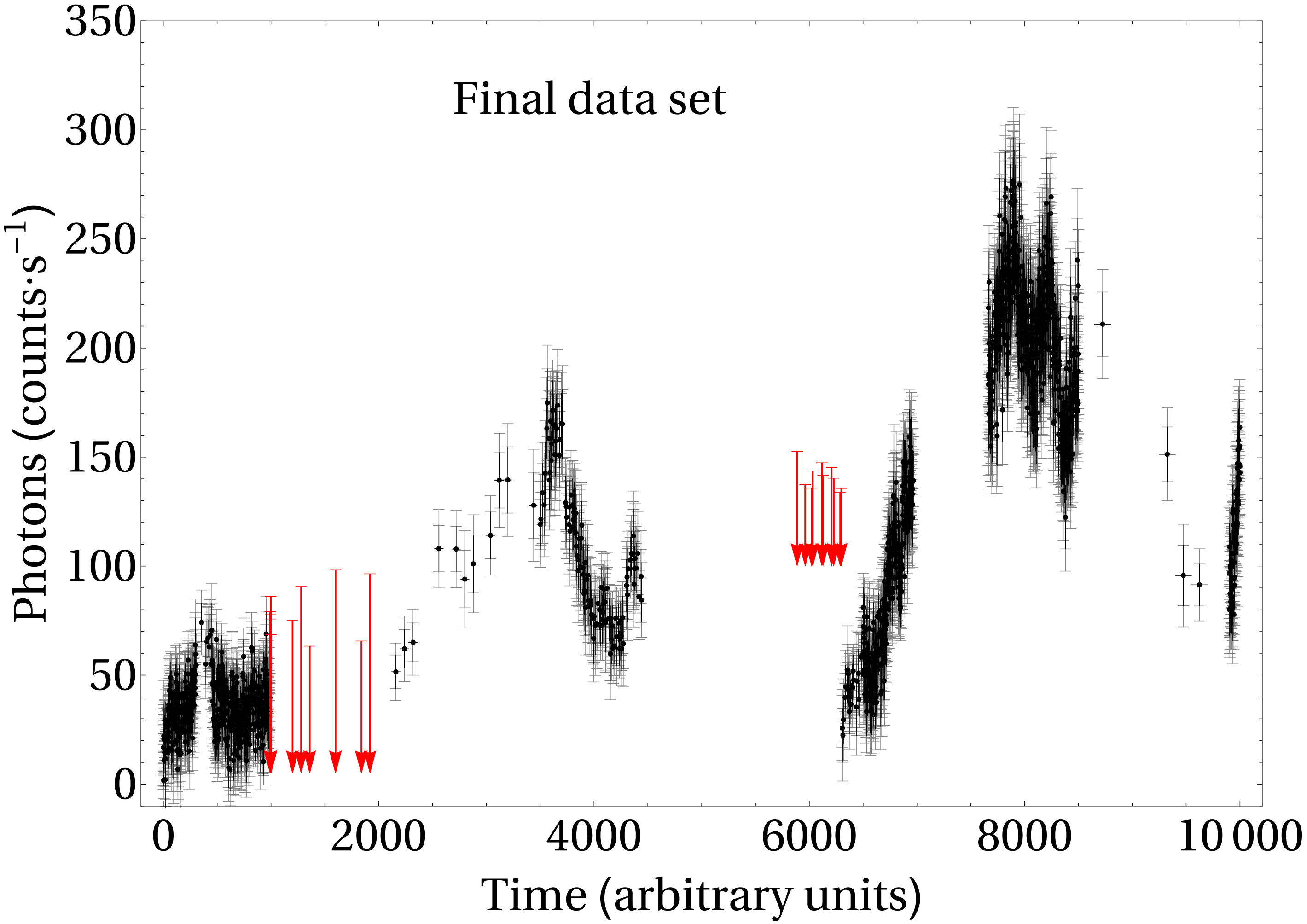

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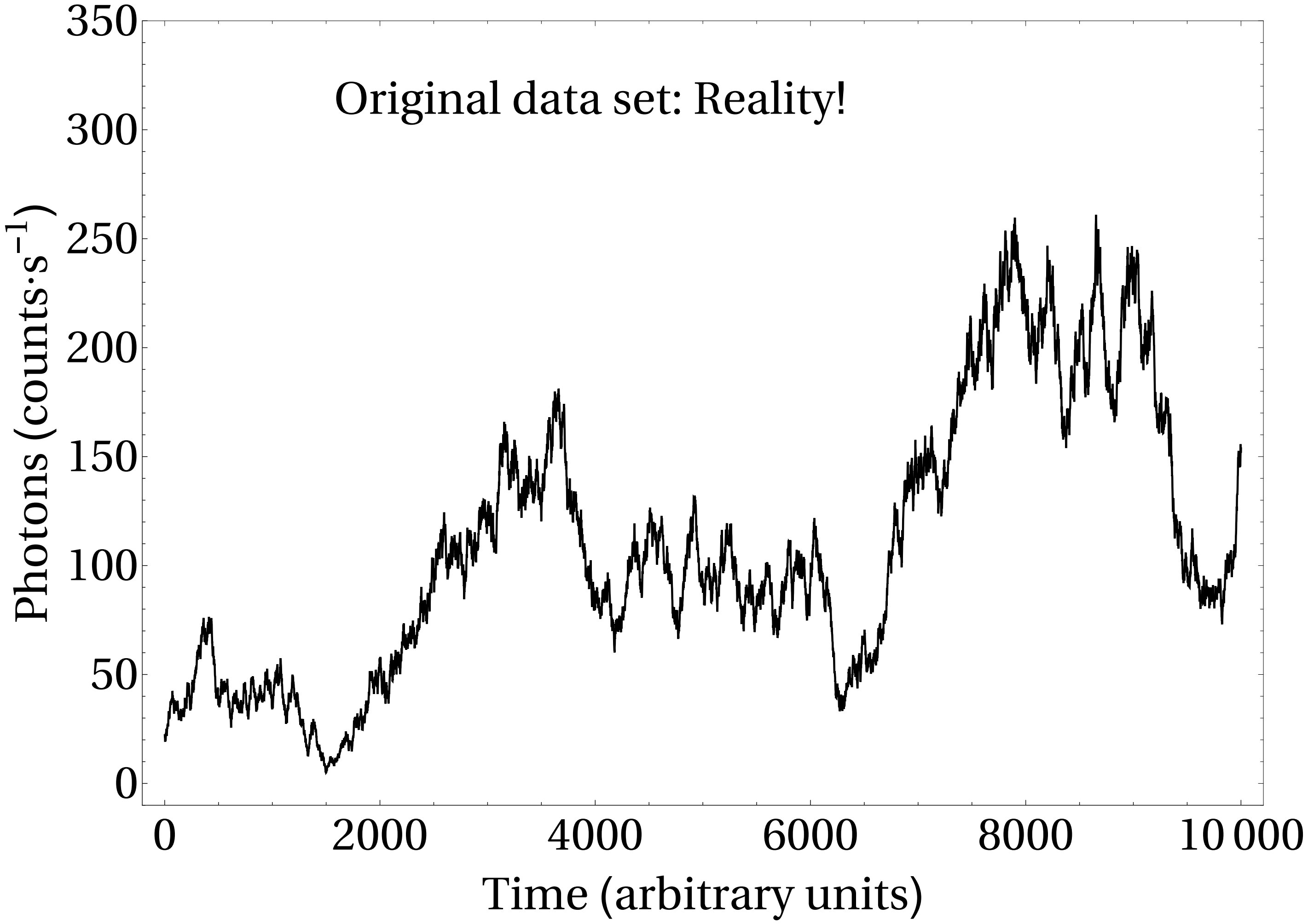

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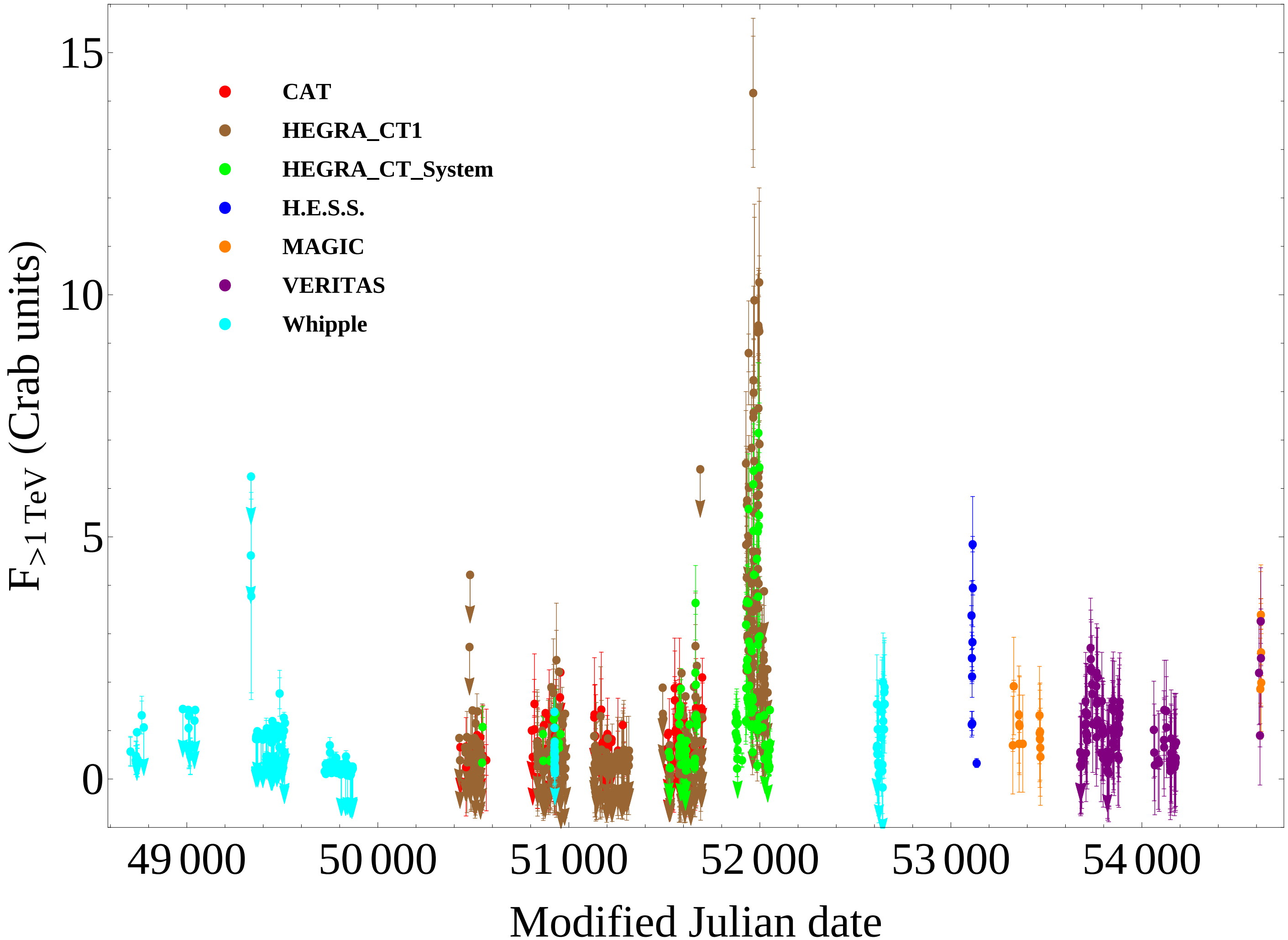

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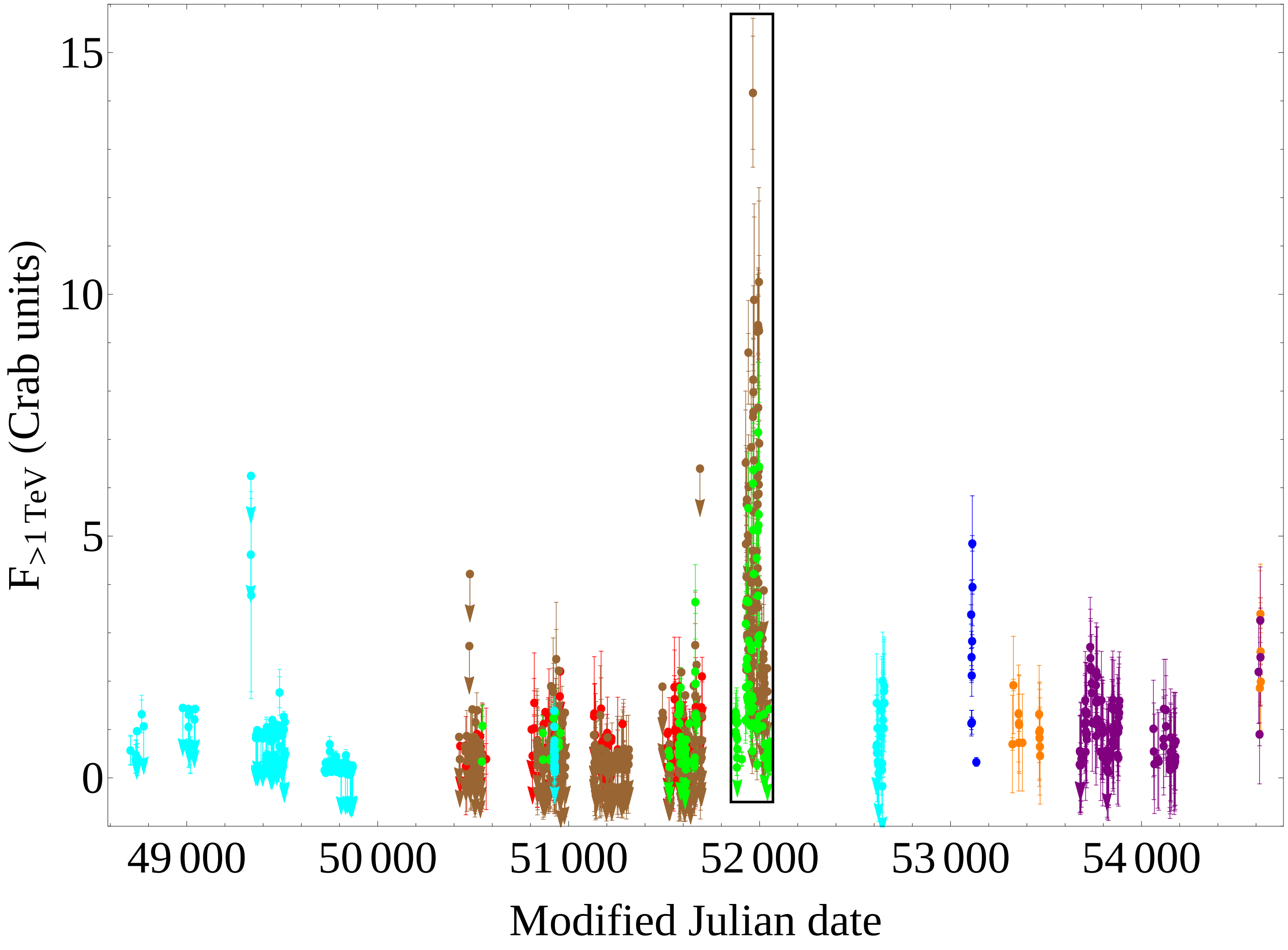

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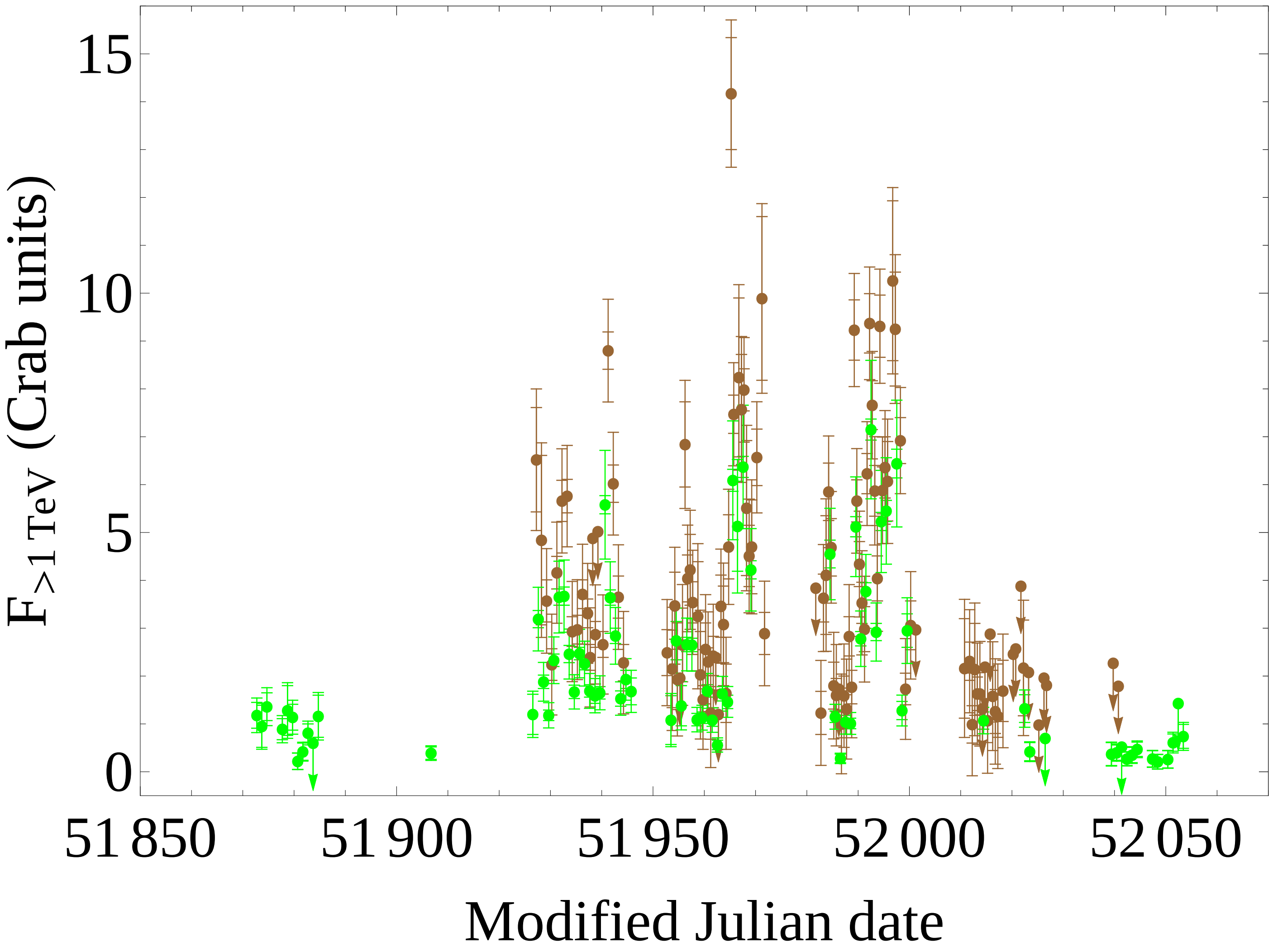

Methodological problems

For a set of observations x_i measured at t_i ($i = 1, \ldots, N$)

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$$\text{Periodogram} = |DFT(f_j)|^2 = \left| \sum_{i=1}^{N} x_i e^{2\pi i f_j t_i} \right|^2$$

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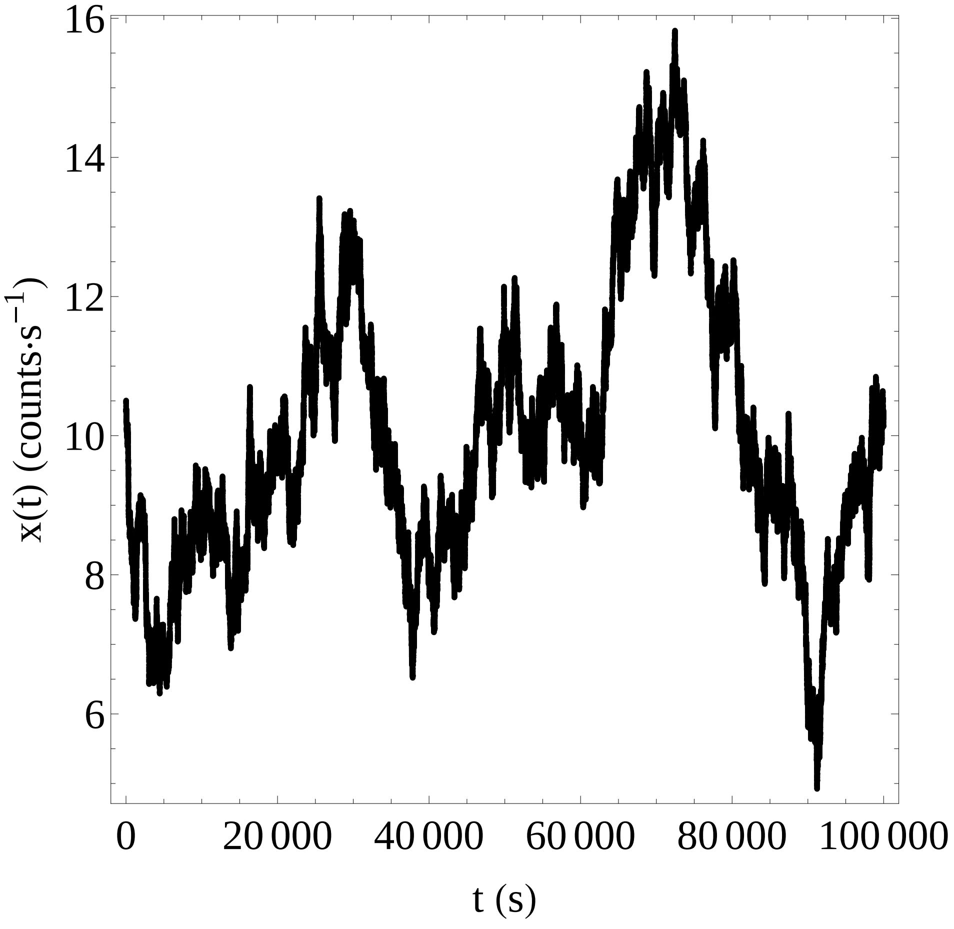
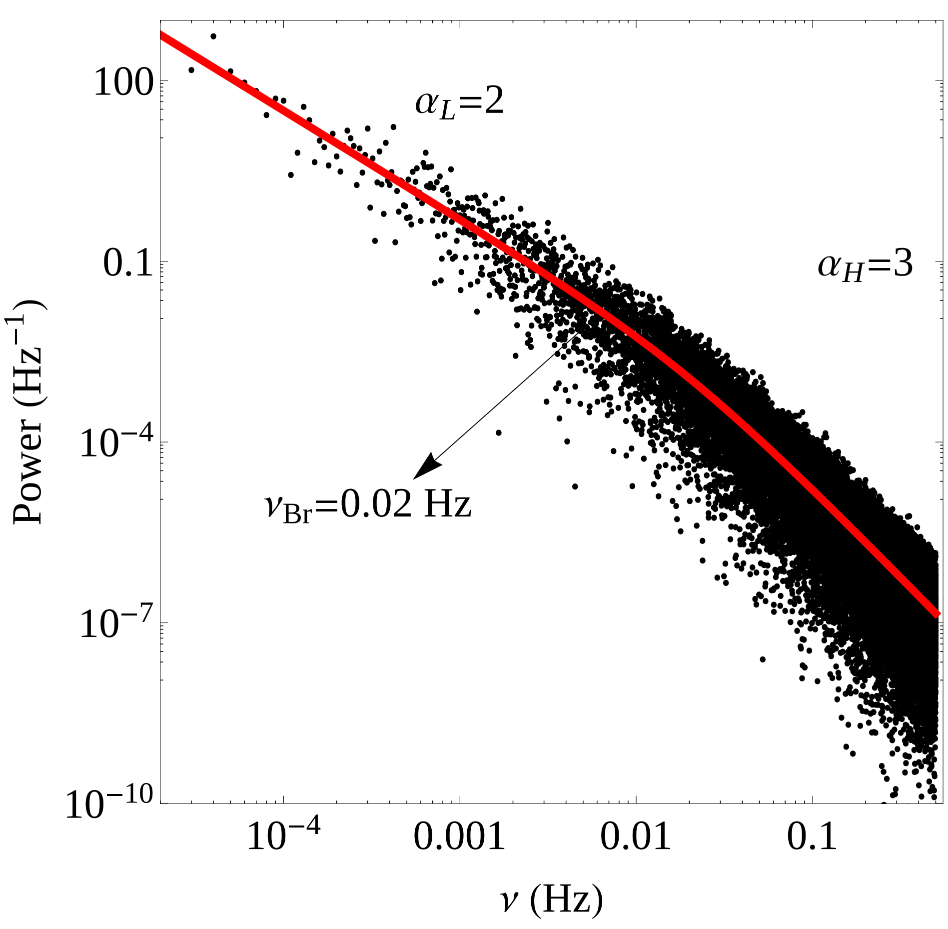
Fitting a model to the Periodogram $\longrightarrow$ PSD, $P(\nu)$

Methodological problems

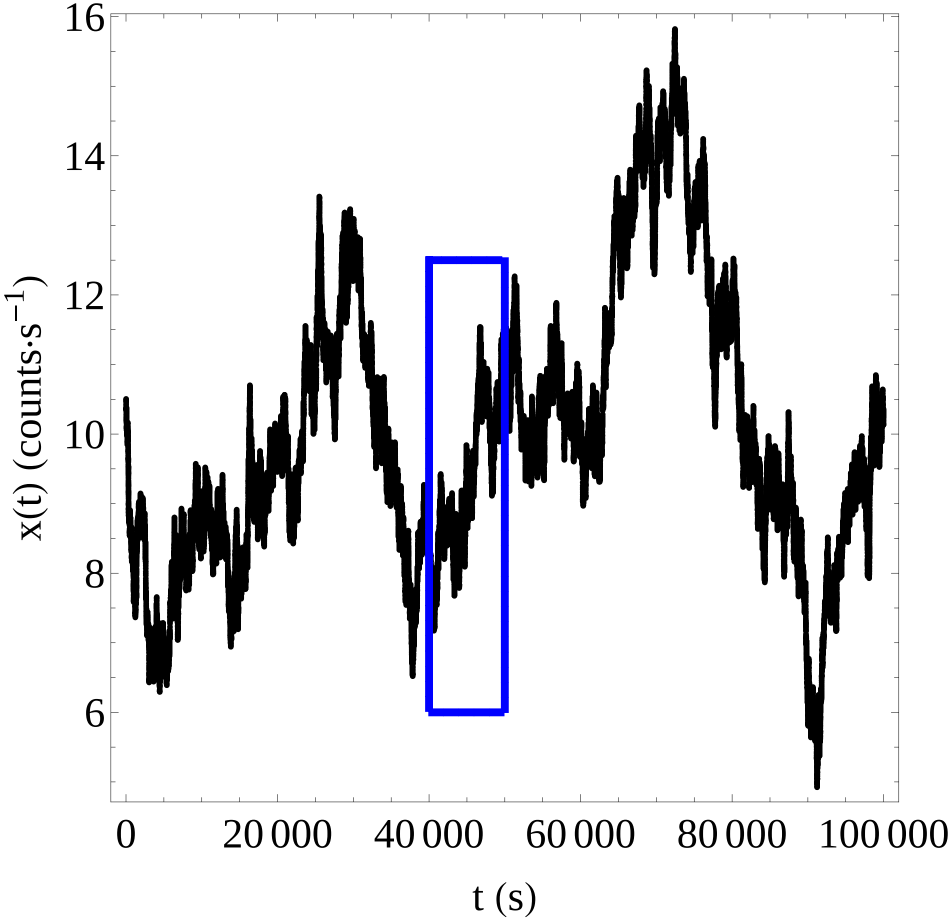
Original light curve

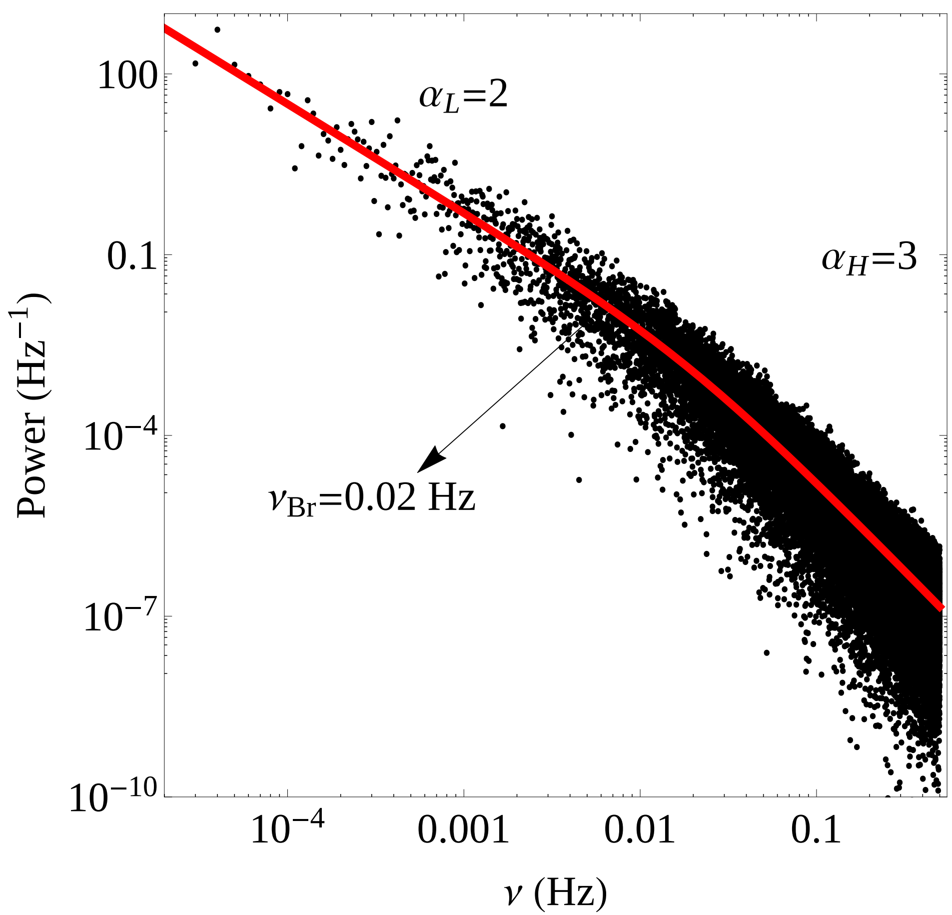




Methodological problems

Light curve segment





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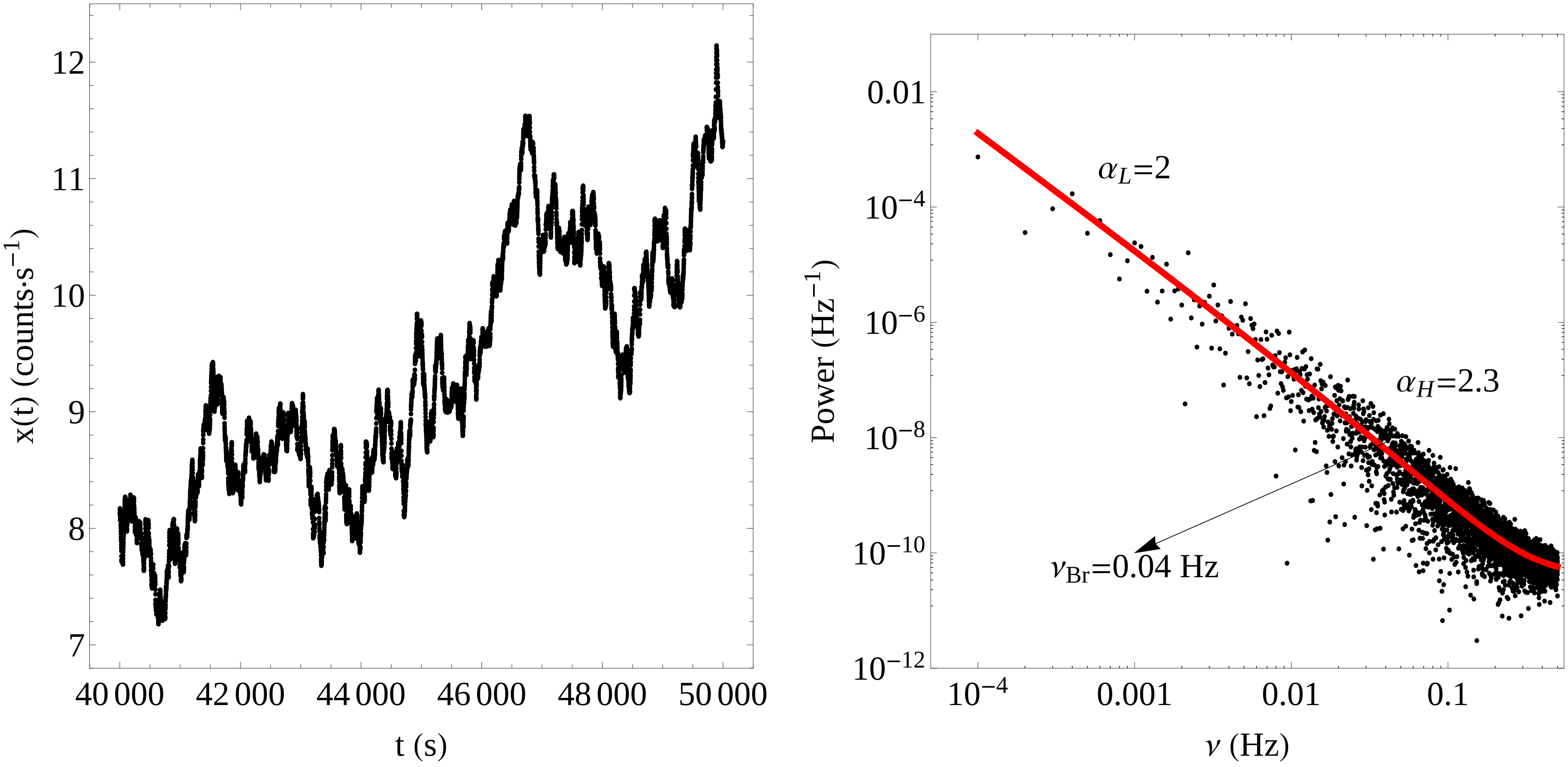
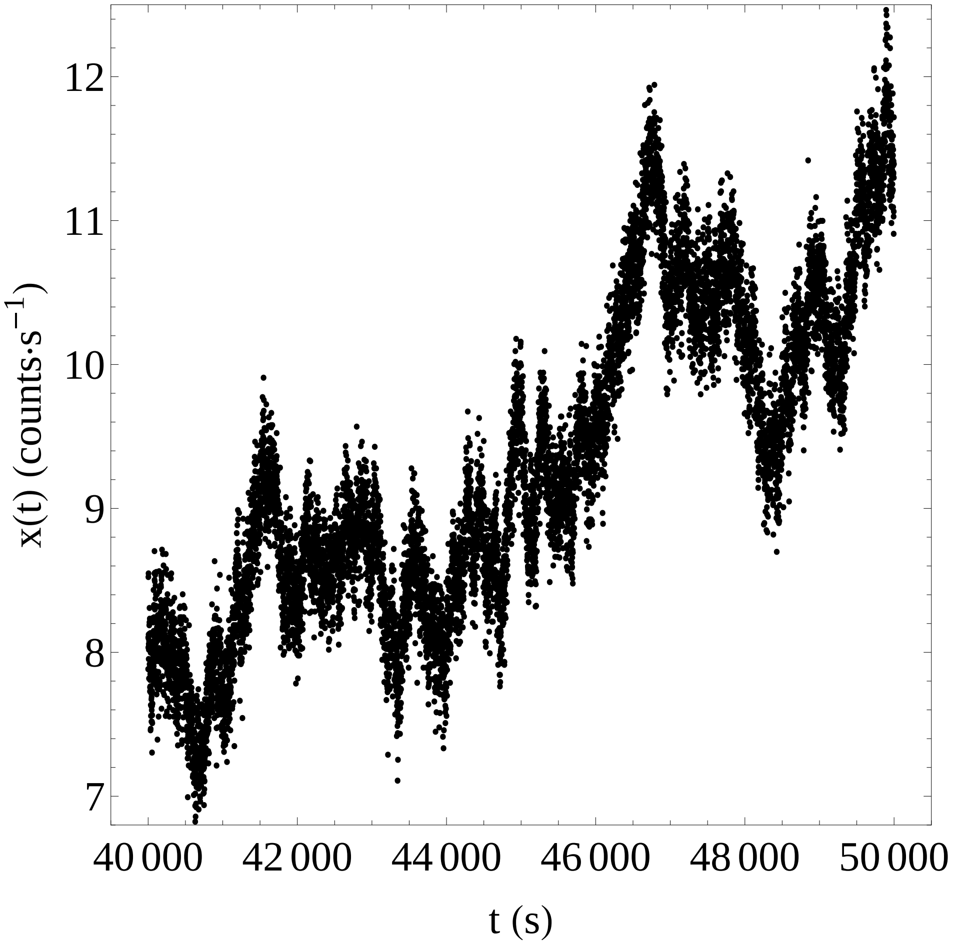
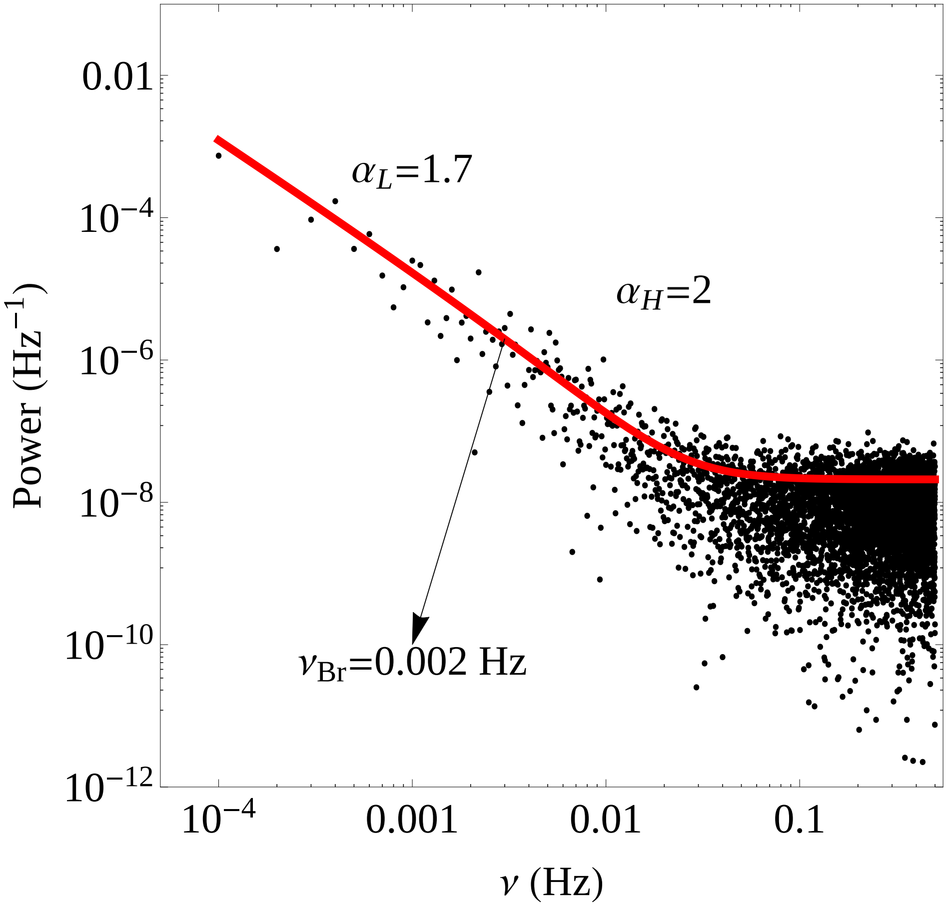


Methodological problems

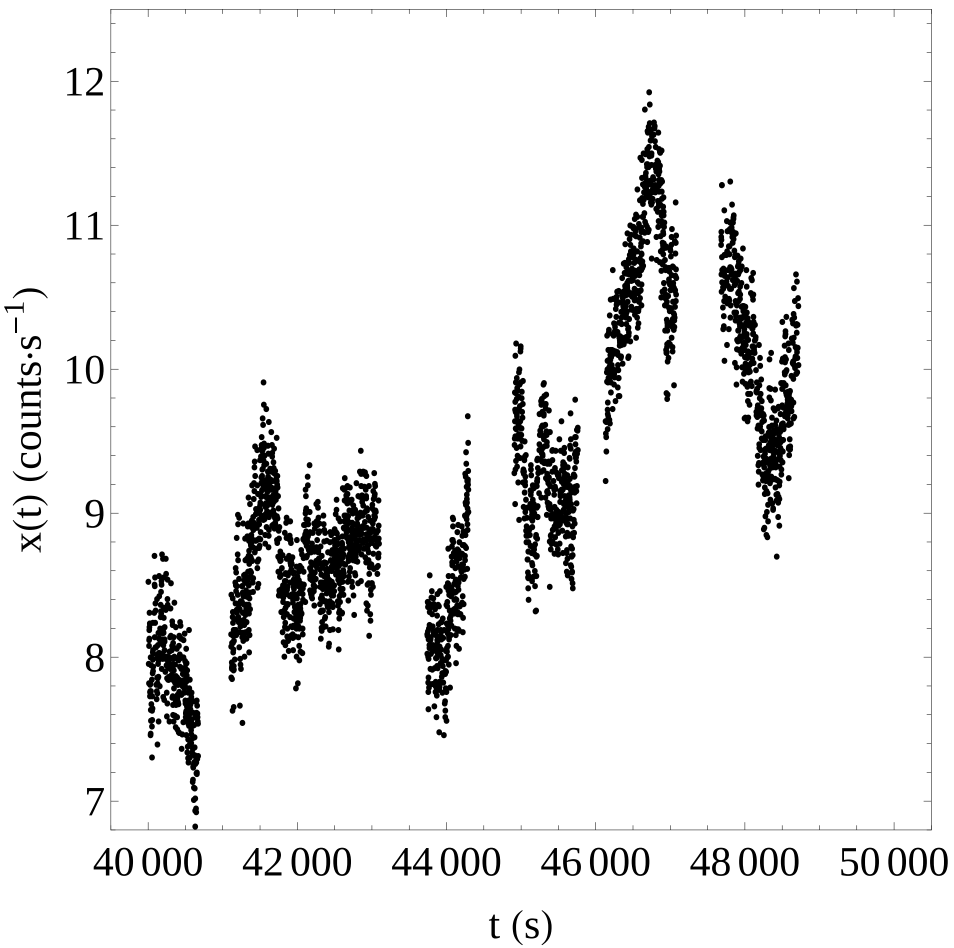
Light curve segment + Poisson noise

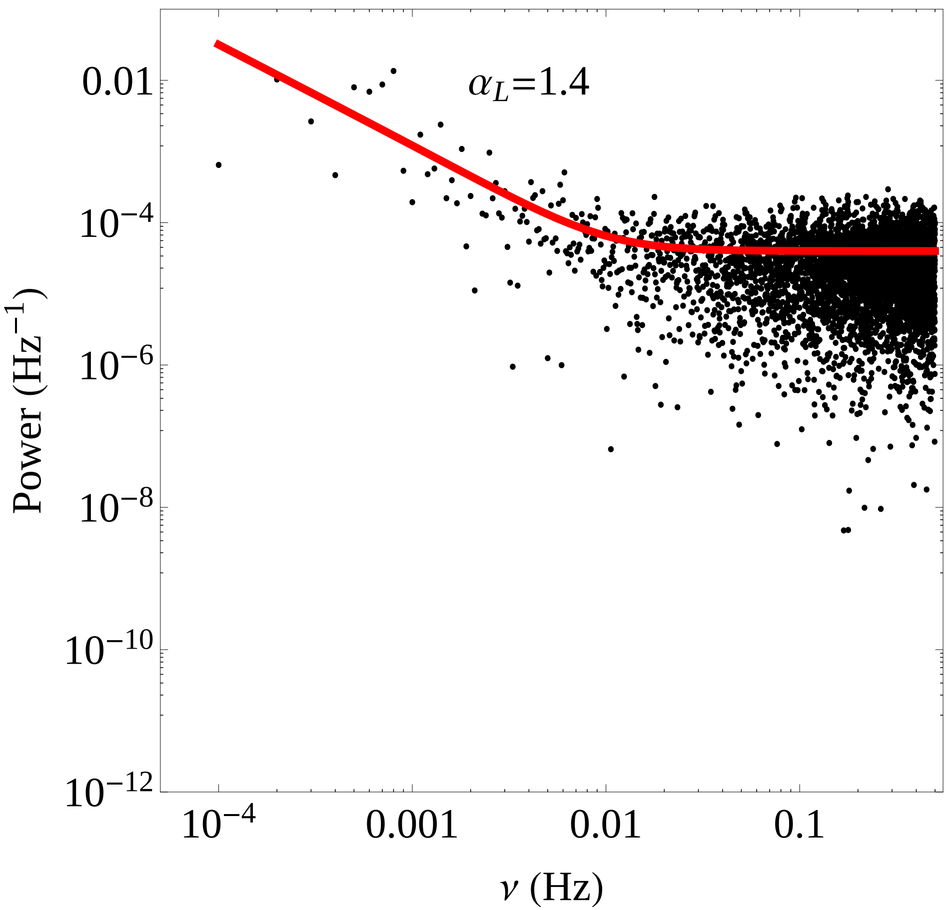




Methodological problems

Light curve segment + Poisson noise + Missing data





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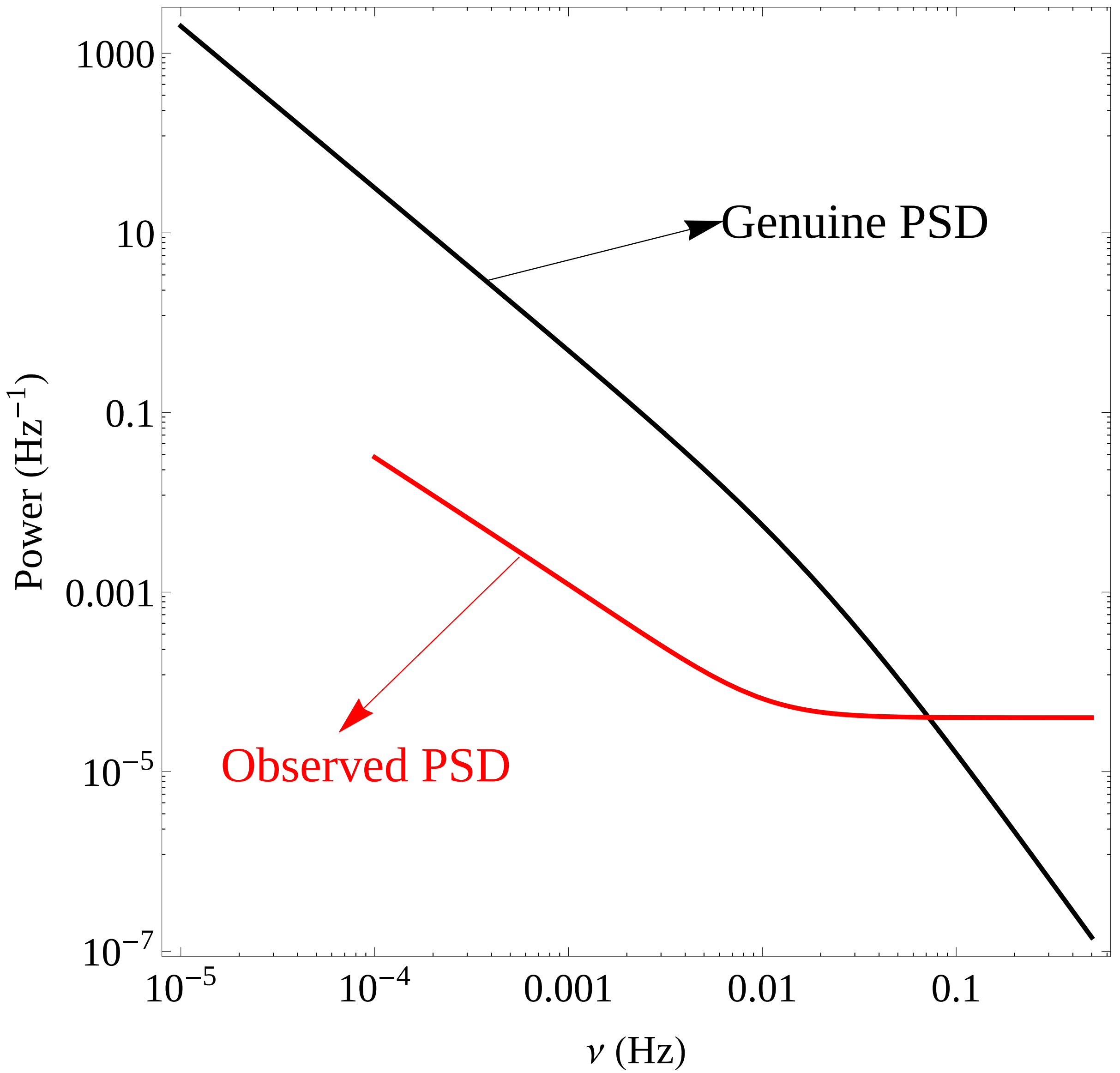

Monte Carlo approach

- <u>PSD model</u> $\longrightarrow$ Artificial time series (e.g. 10000)

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- Repeat the process for another PSD model.

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- PSD model $\longrightarrow$ Artificial time series (e.g. 10000)
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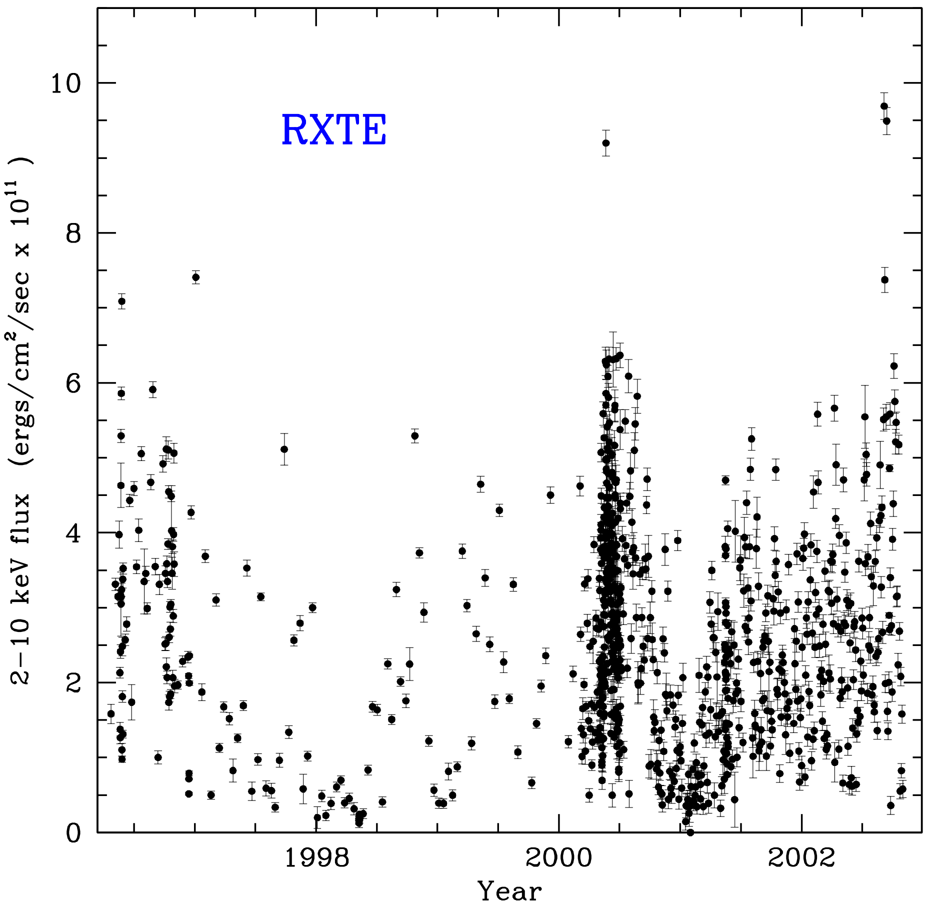
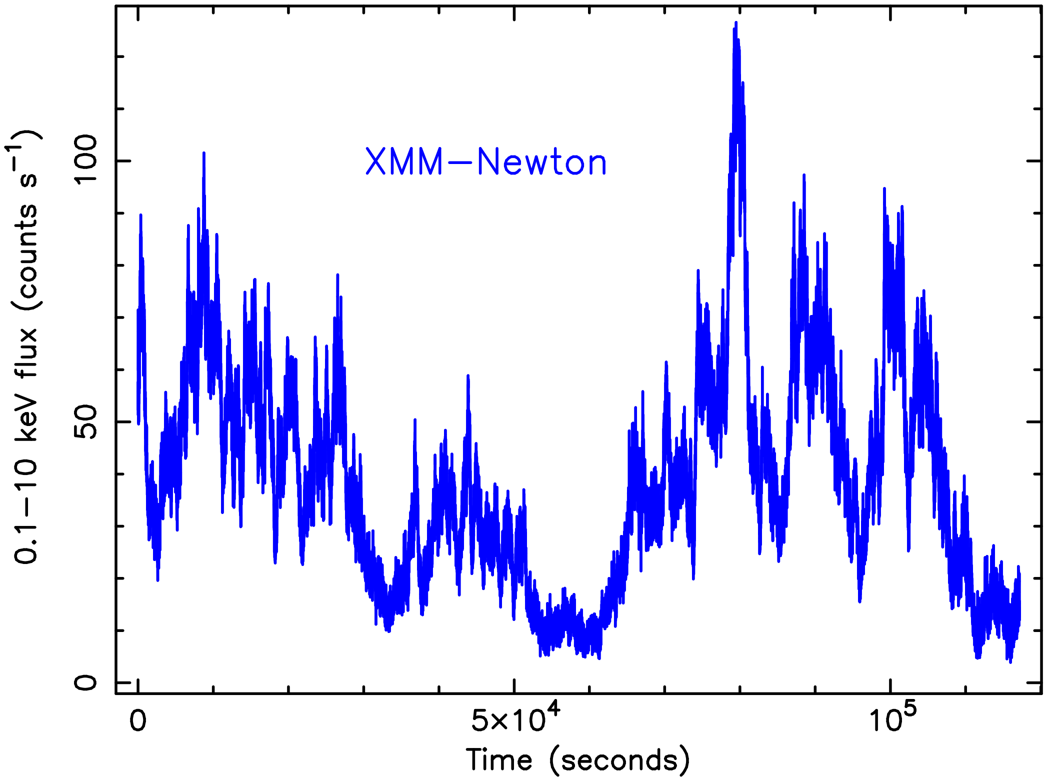
- 'Dirty' periodograms $\longrightarrow$ $\langle$'Dirty' periodogram$\rangle$
- Fit to the observed 'dirty' periodogram.
- Repeat the process for another PSD model.
- Establish a 'goodness-of-fit' criterion.

Application

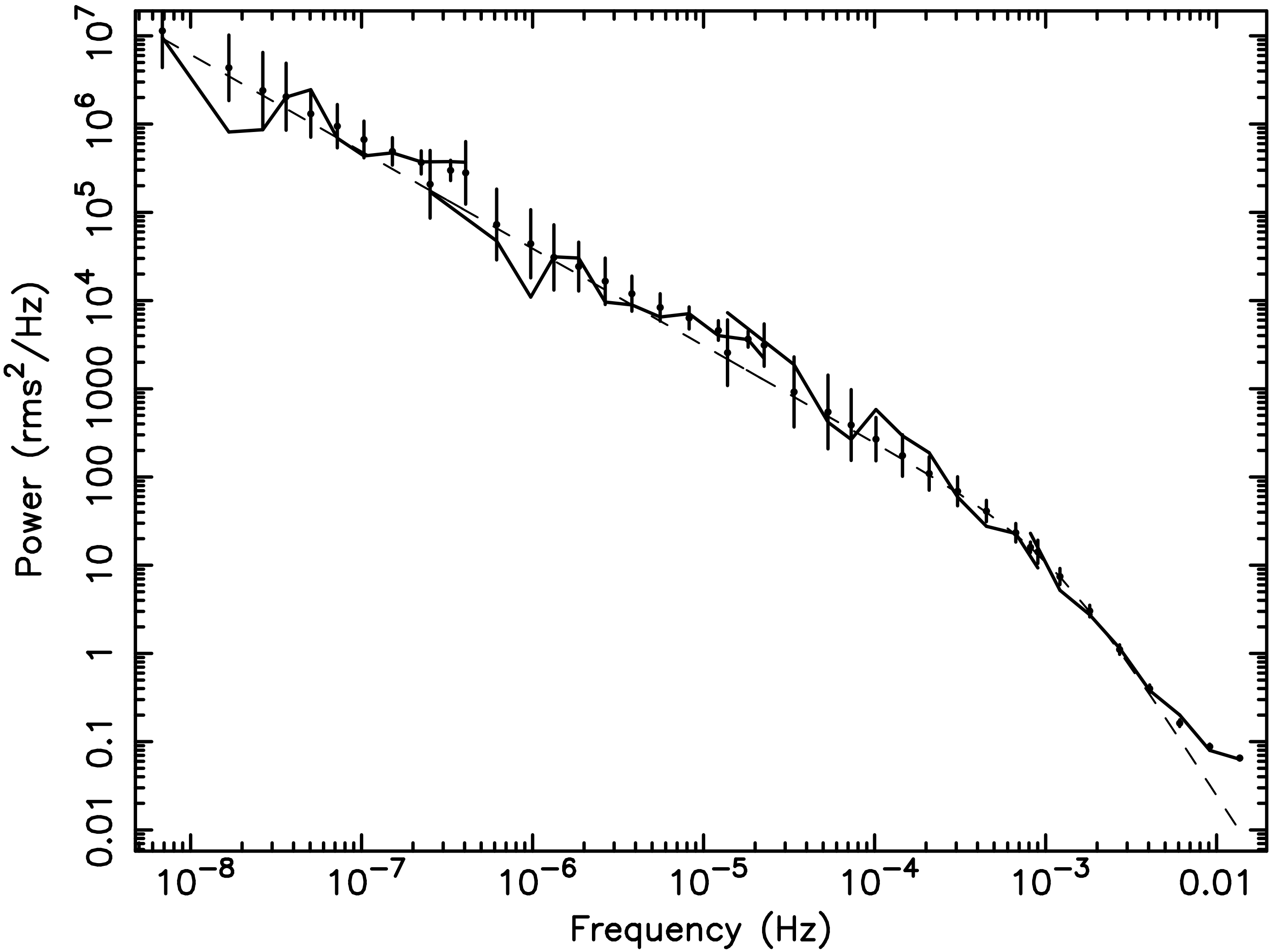
NGC 4051





McHardy et al. 2004, MNRAS, **348**, 783

Application



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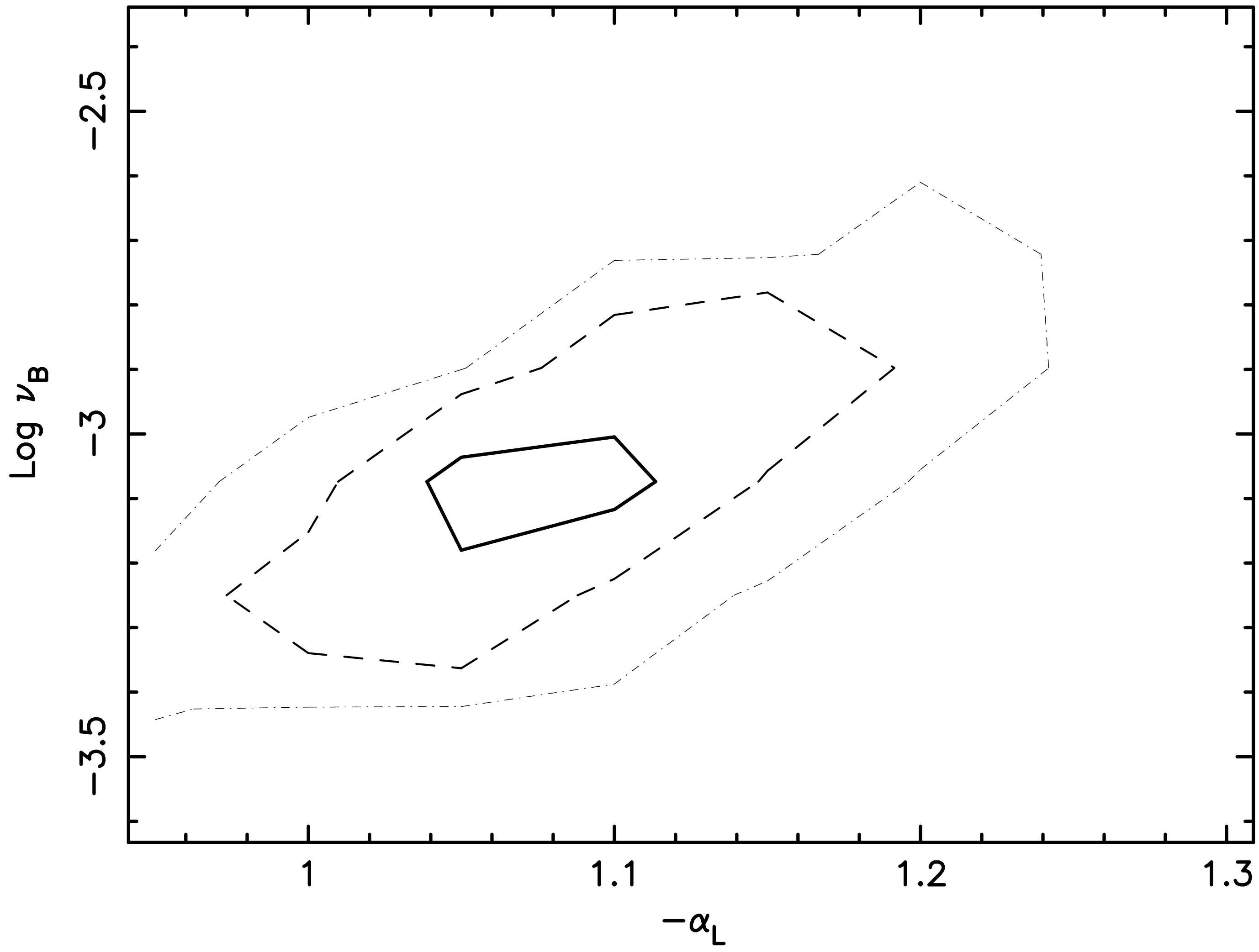

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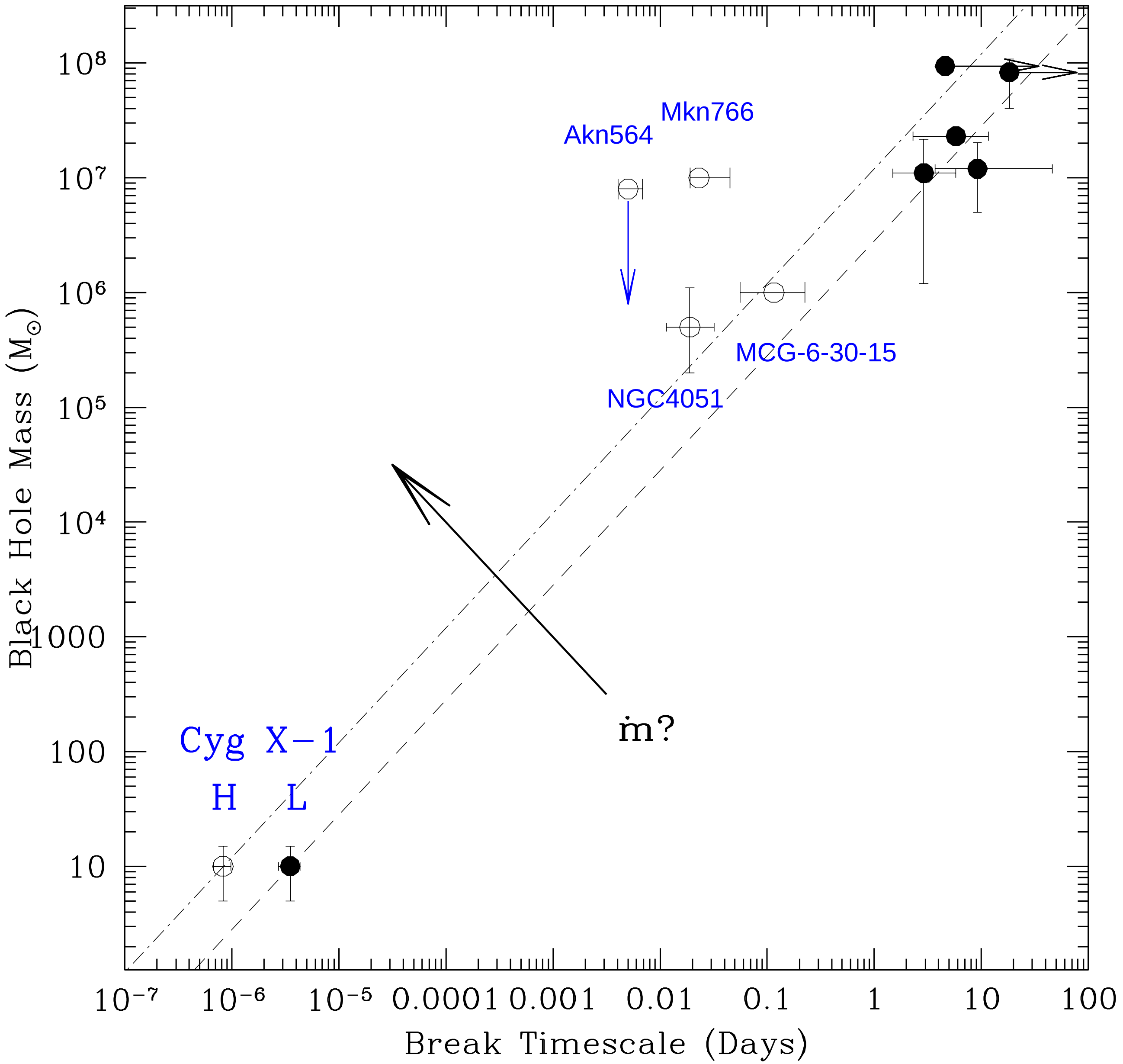


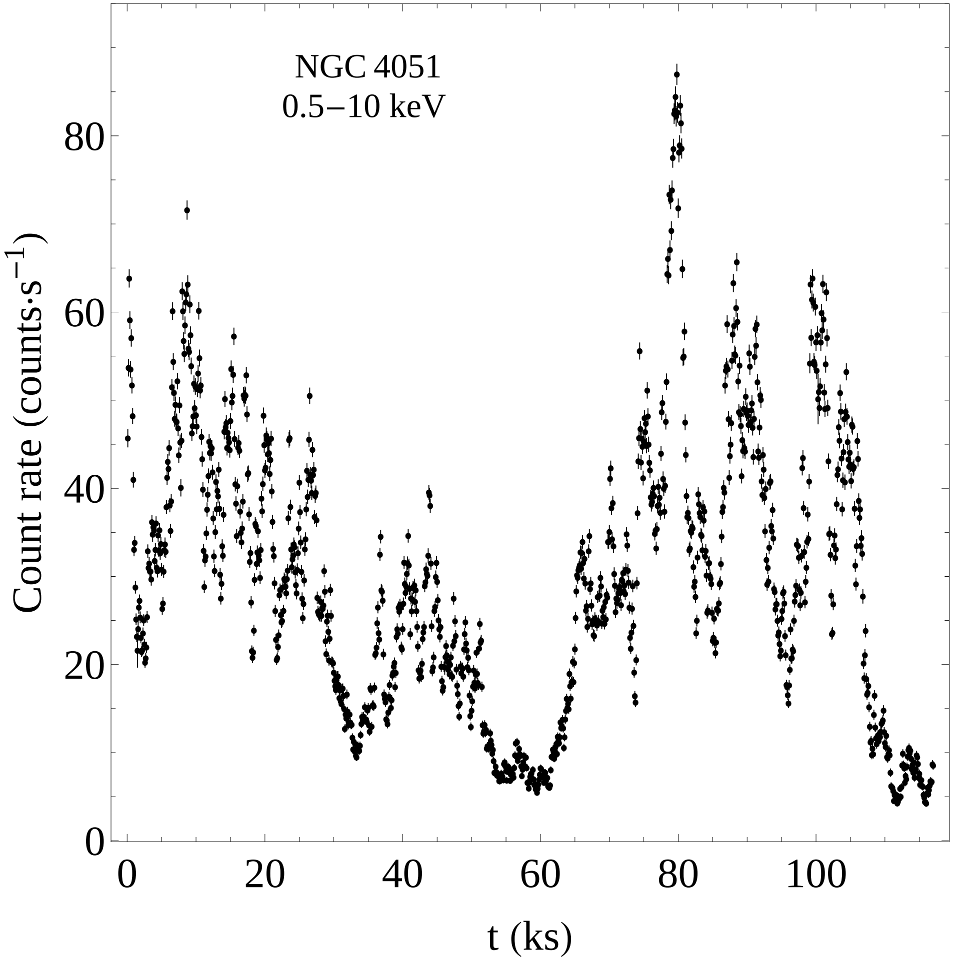
Monte Carlo problems

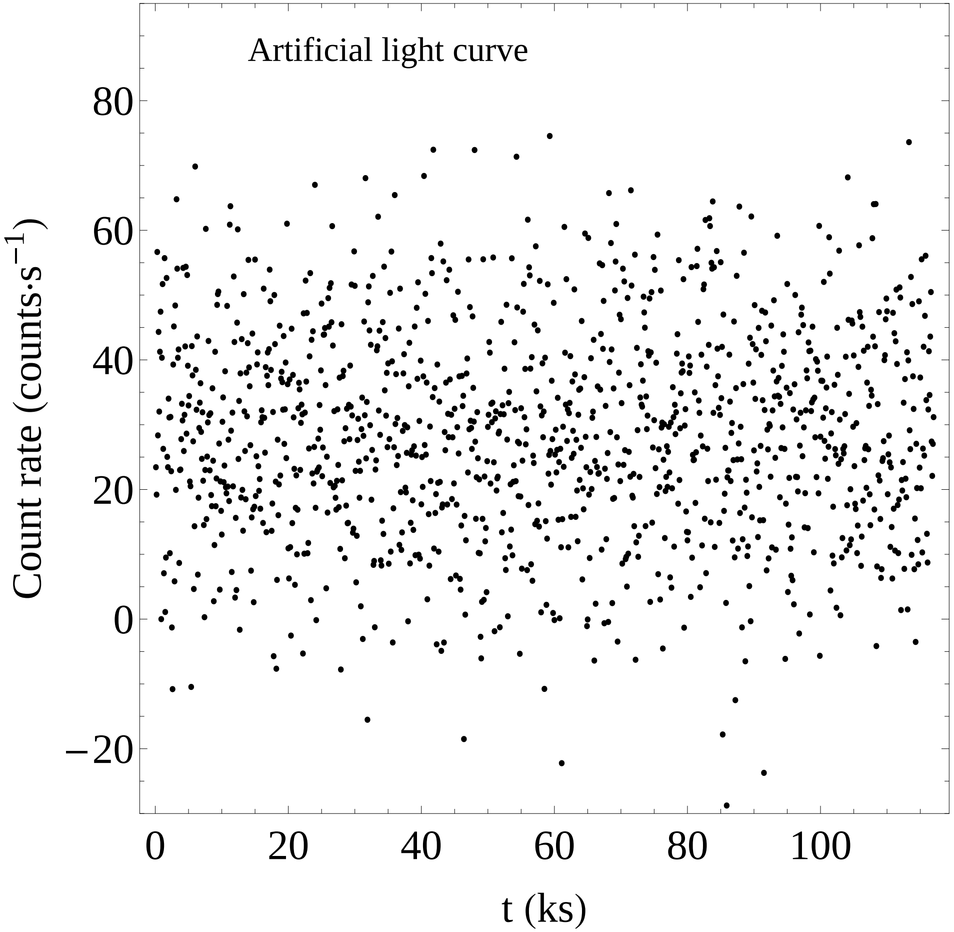
1) White noise: Random number generator

PSD always flat

Monte Carlo problems

1)White noise: Random number generator





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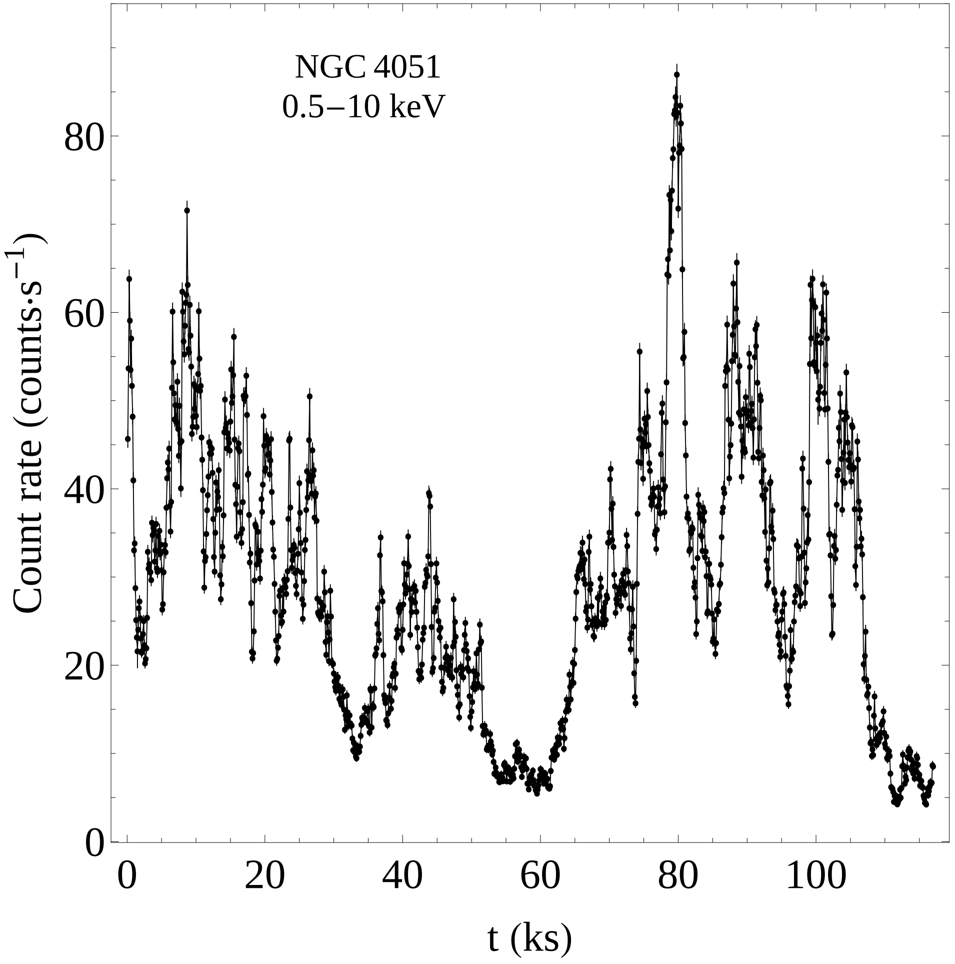

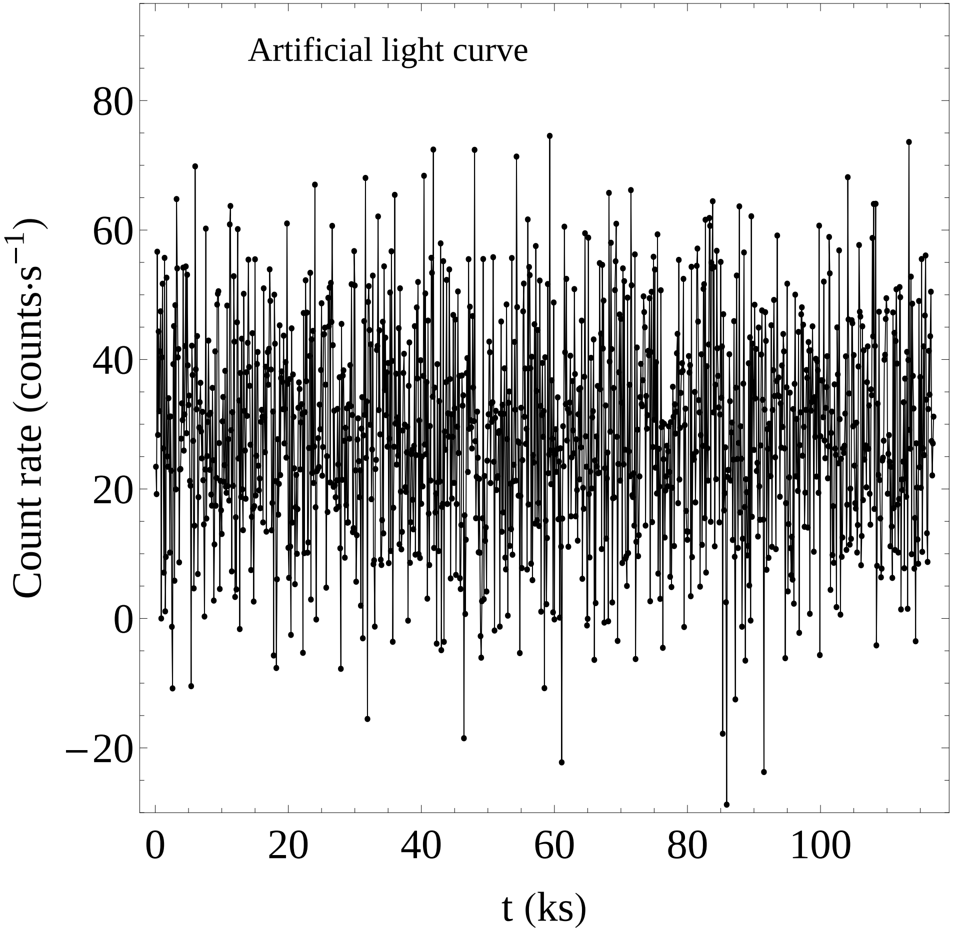

Monte Carlo problems

2)Done, C. et al. 1992, ApJ, **400**, 138

Phase randomisation BUT fixed amplitude

$$x(t) \sim \sum \sqrt{P(\nu)} \cos(2\pi\nu t + \phi)$$

with $\phi \in [0, 2\pi]$

Monte Carlo problems

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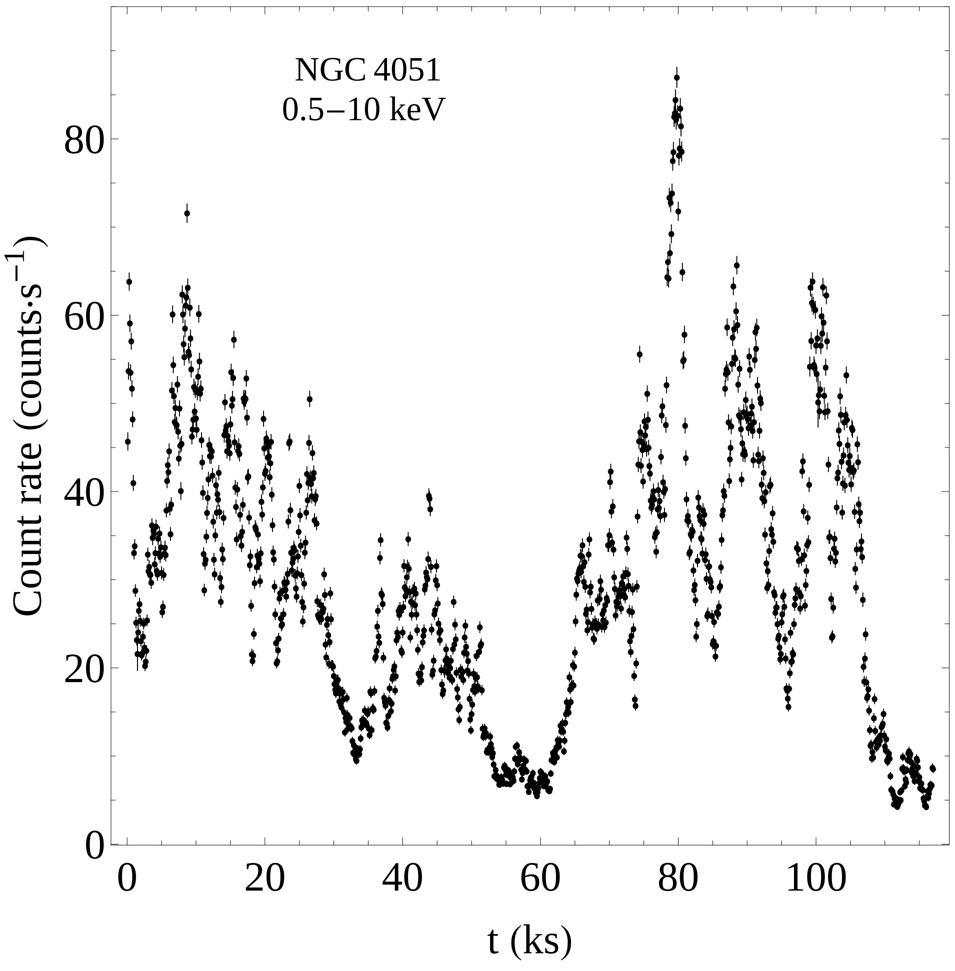

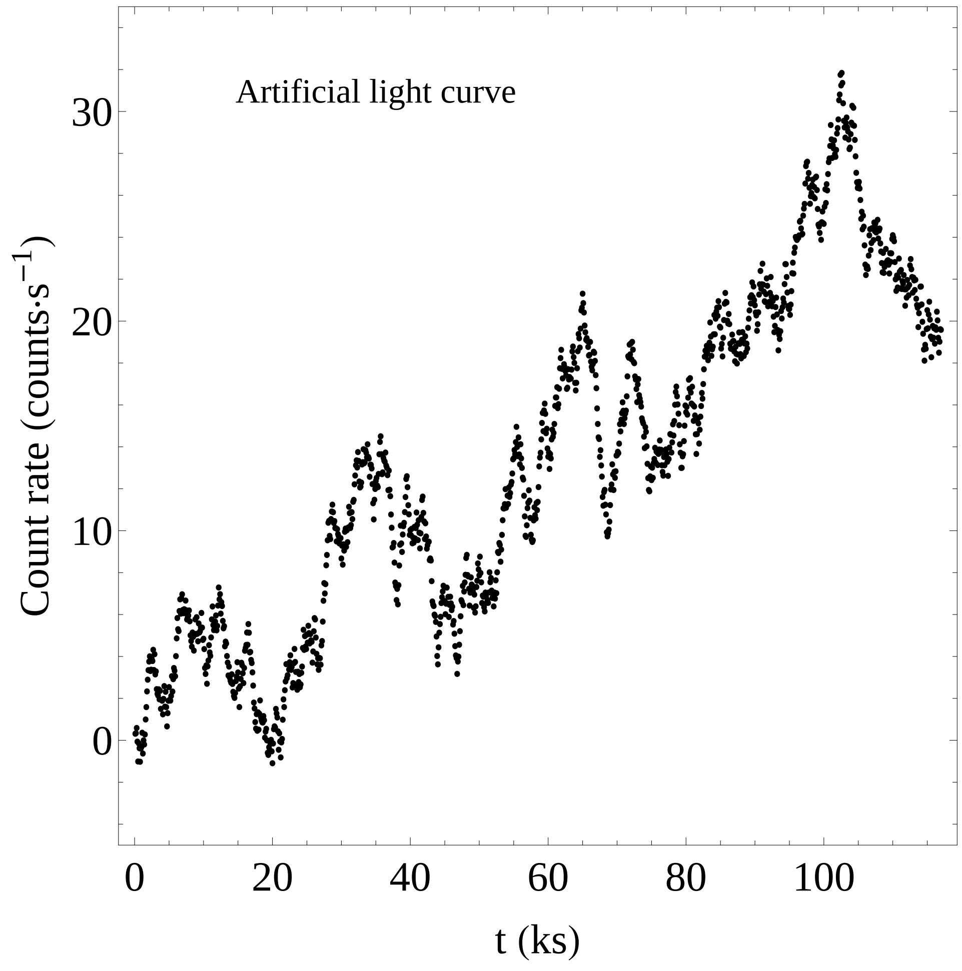

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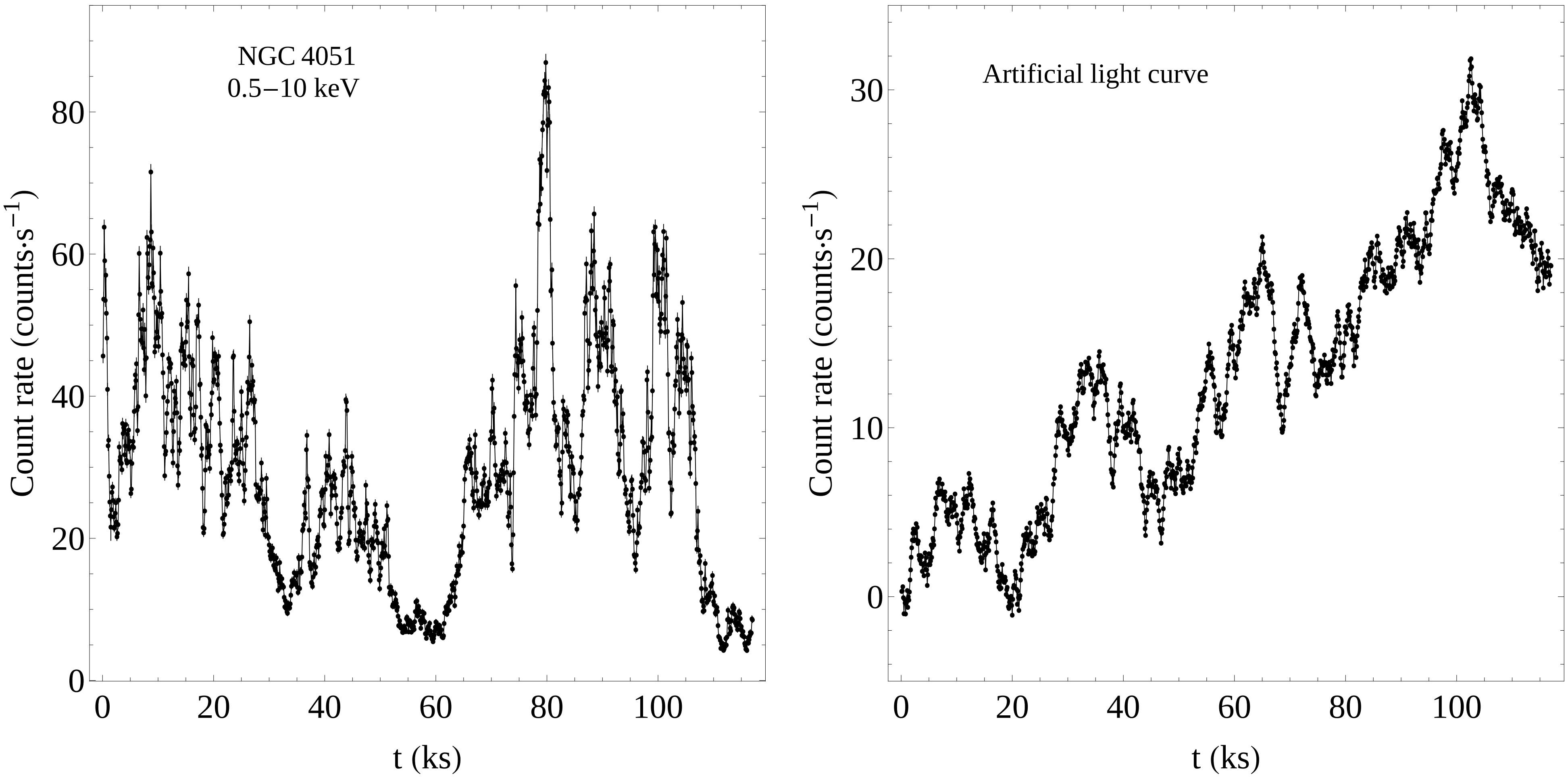

Monte Carlo problems

3)Timmer & König 1995, A&A, **300**, 707

Phase randomisation AND Amplitude randomisation

$$FT_{x(t)}(\nu) = \mathcal{N}(0, \frac{1}{2}P(\nu)) + i\mathcal{N}(0, \frac{1}{2}P(\nu))$$

Monte Carlo problems

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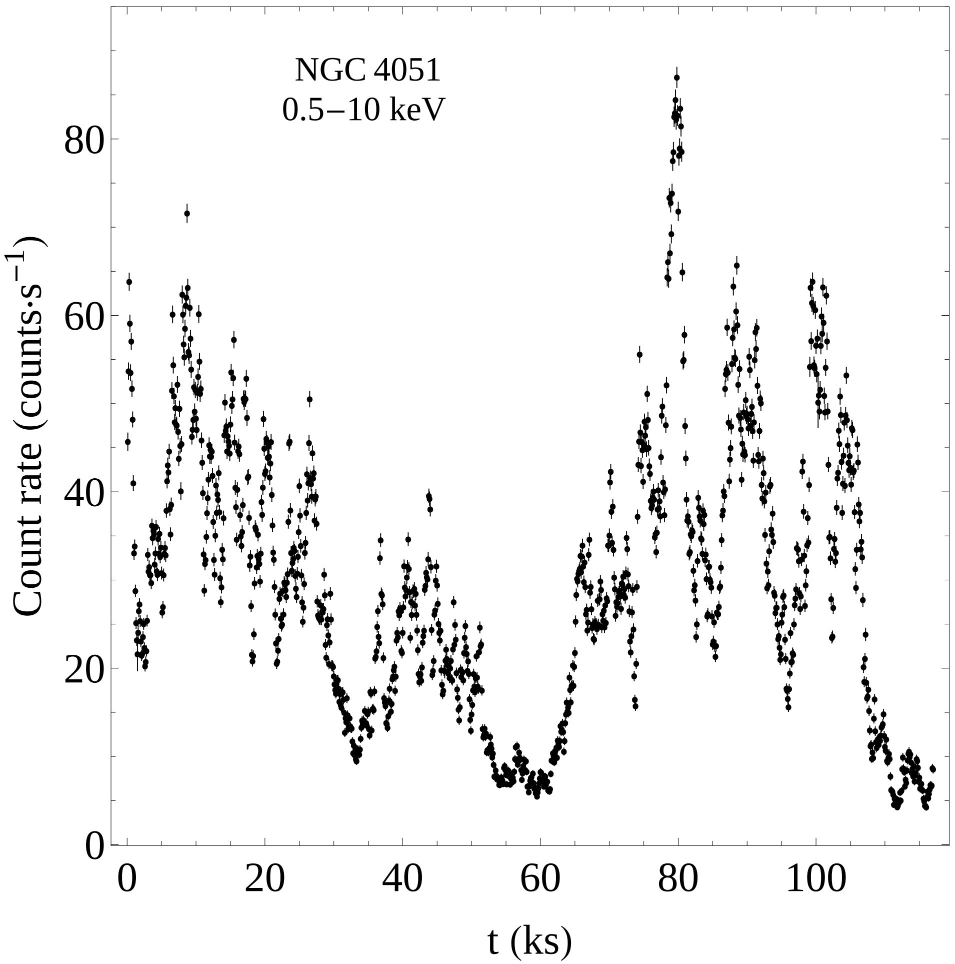

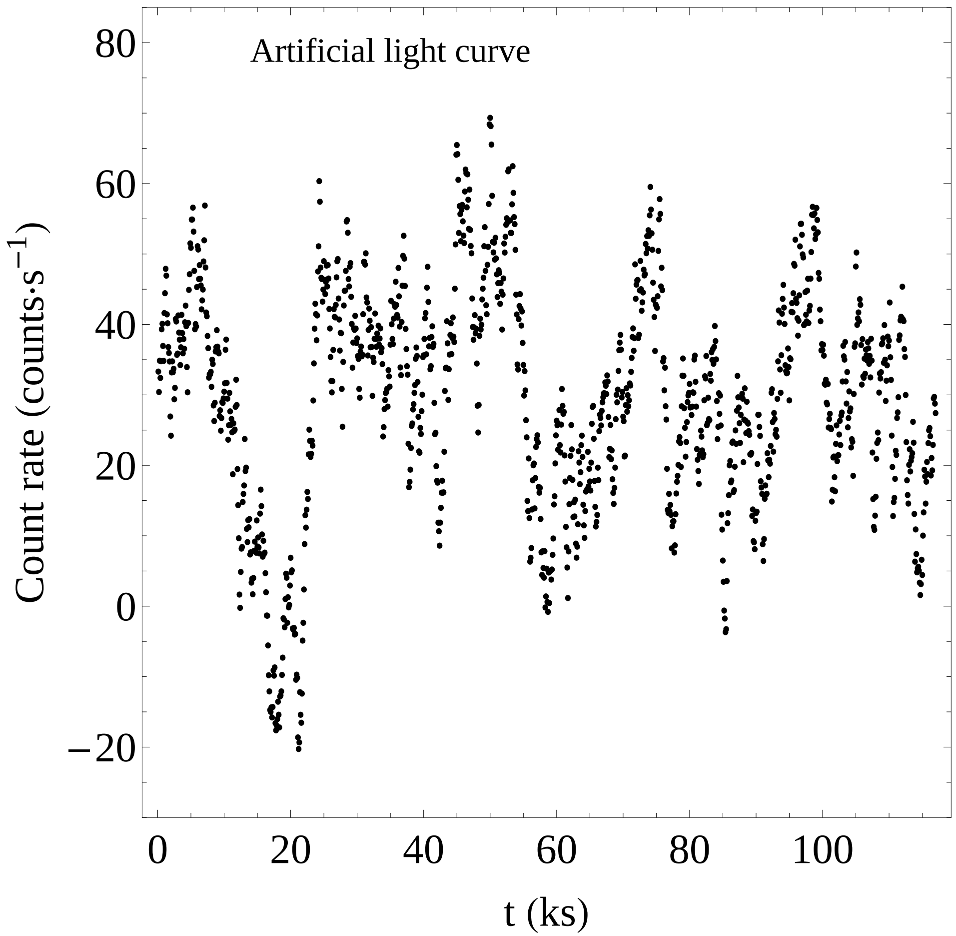

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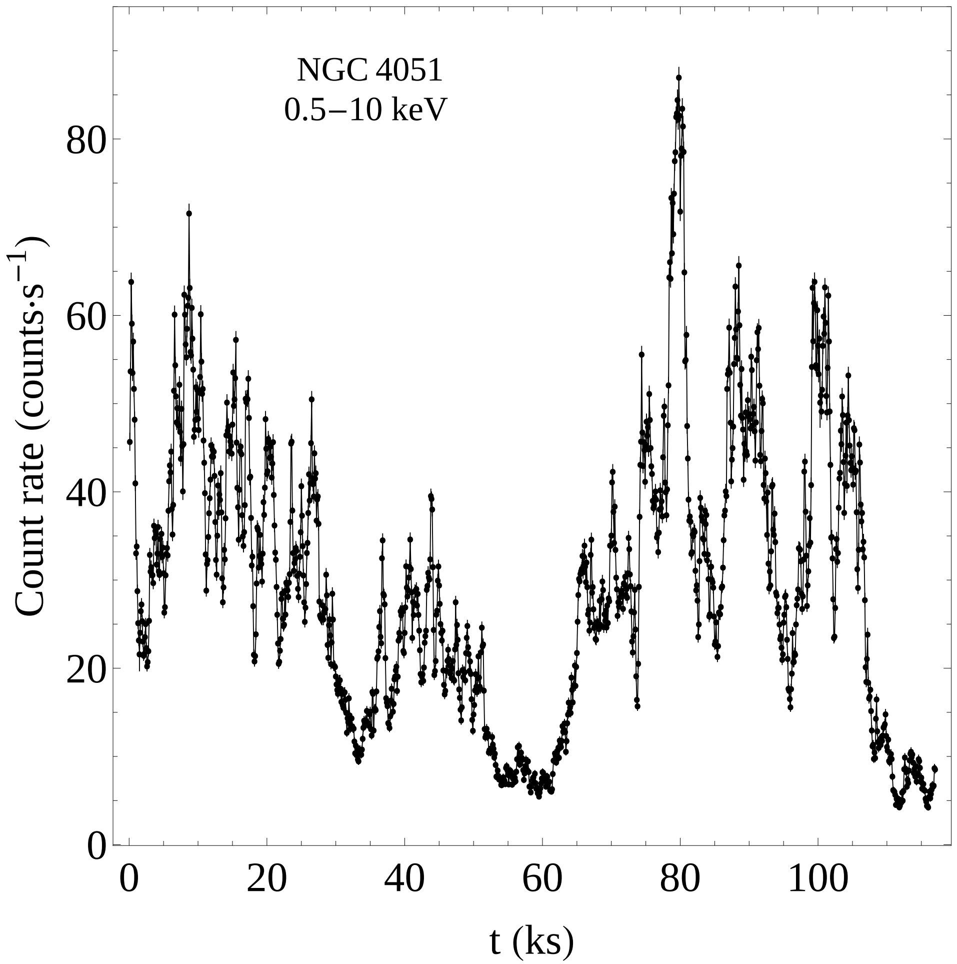

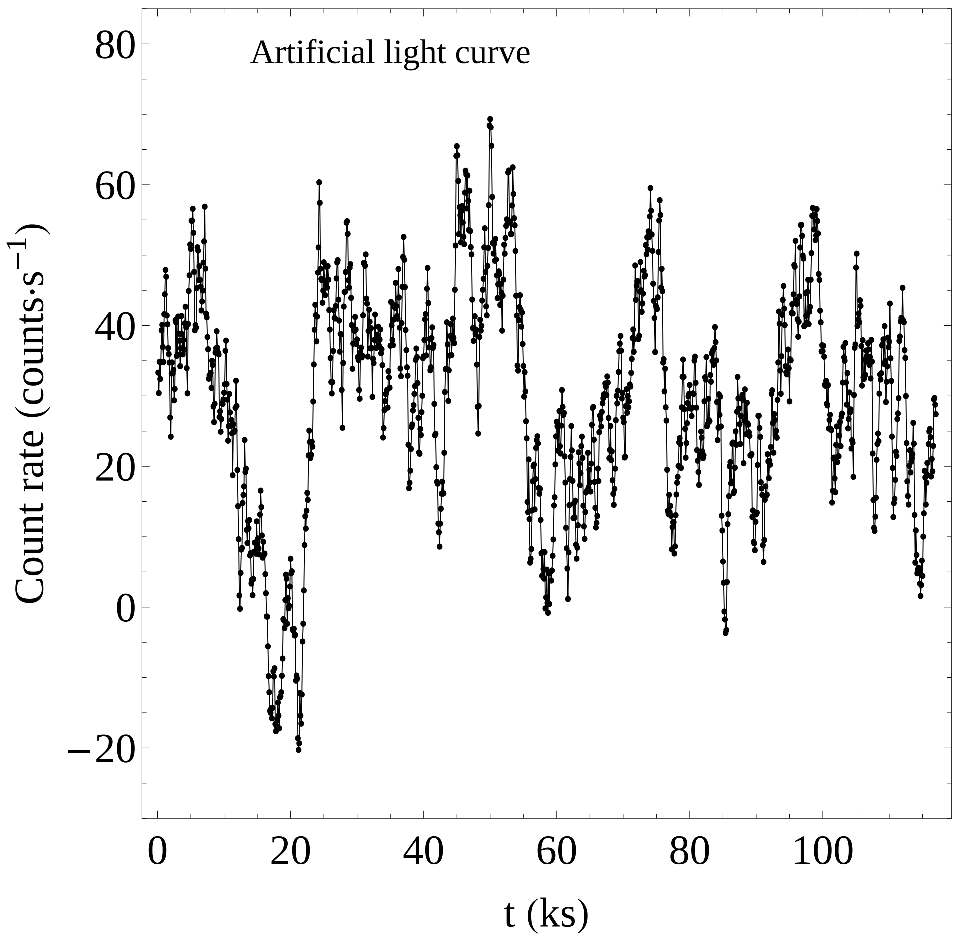

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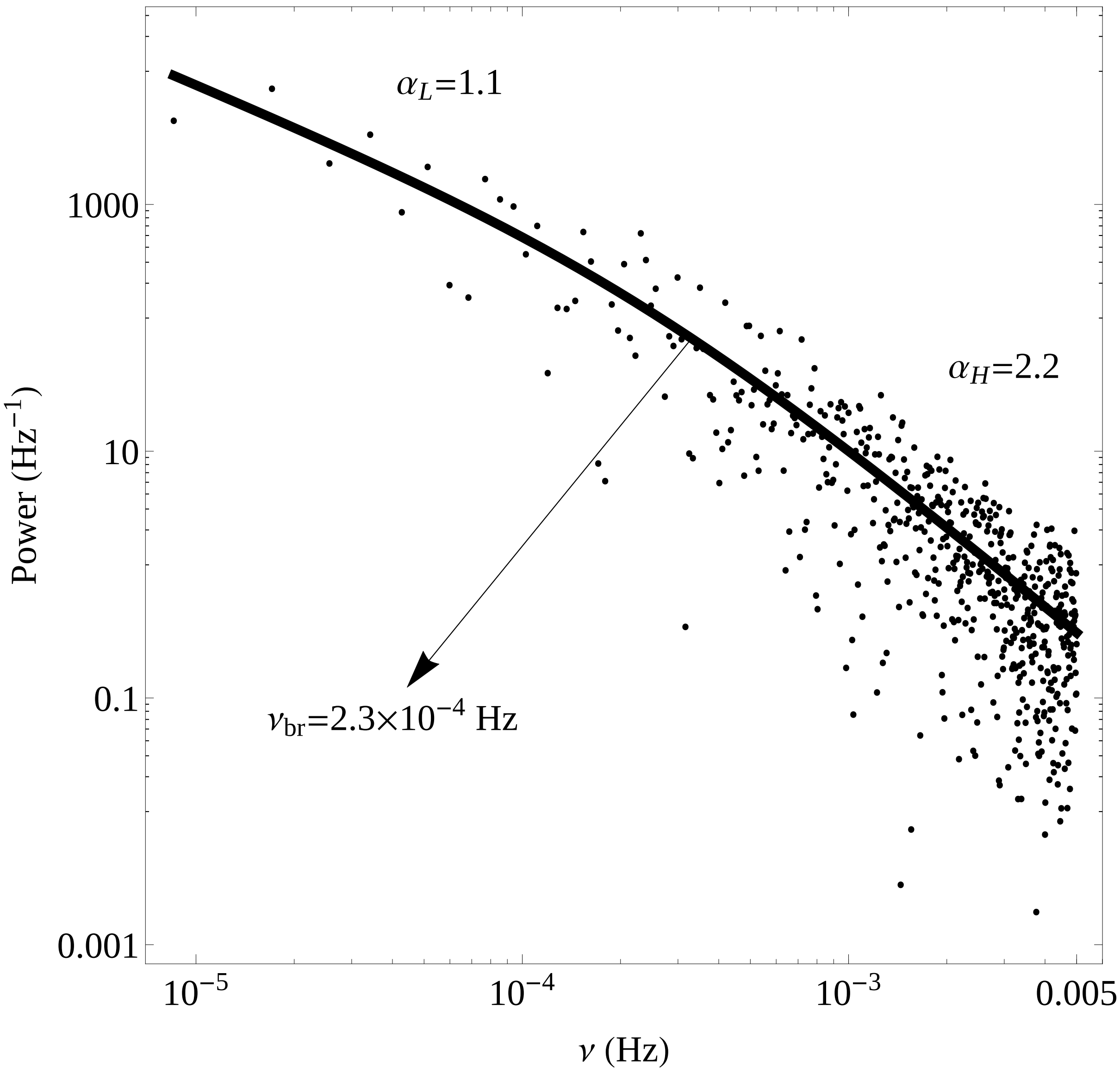

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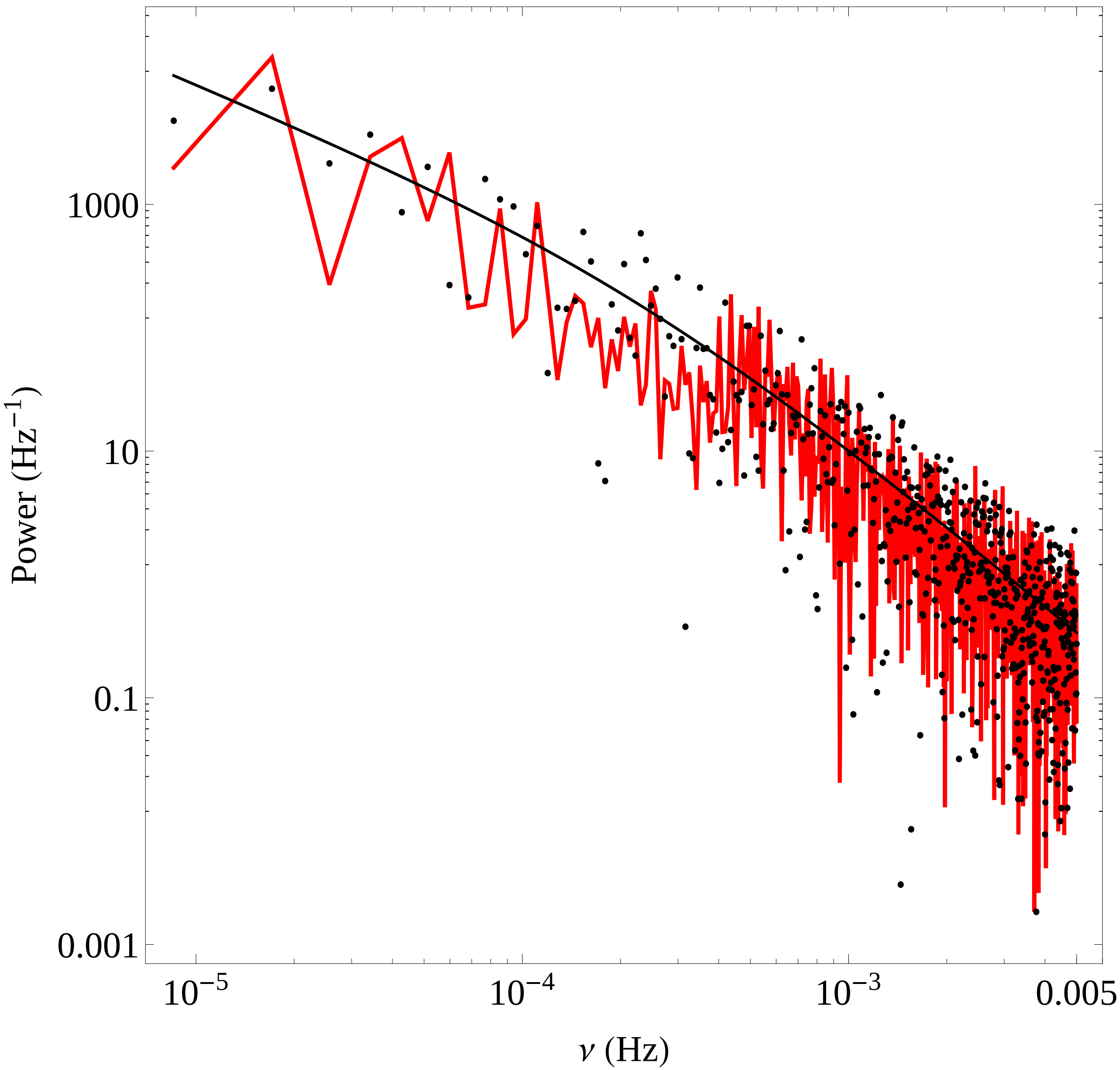

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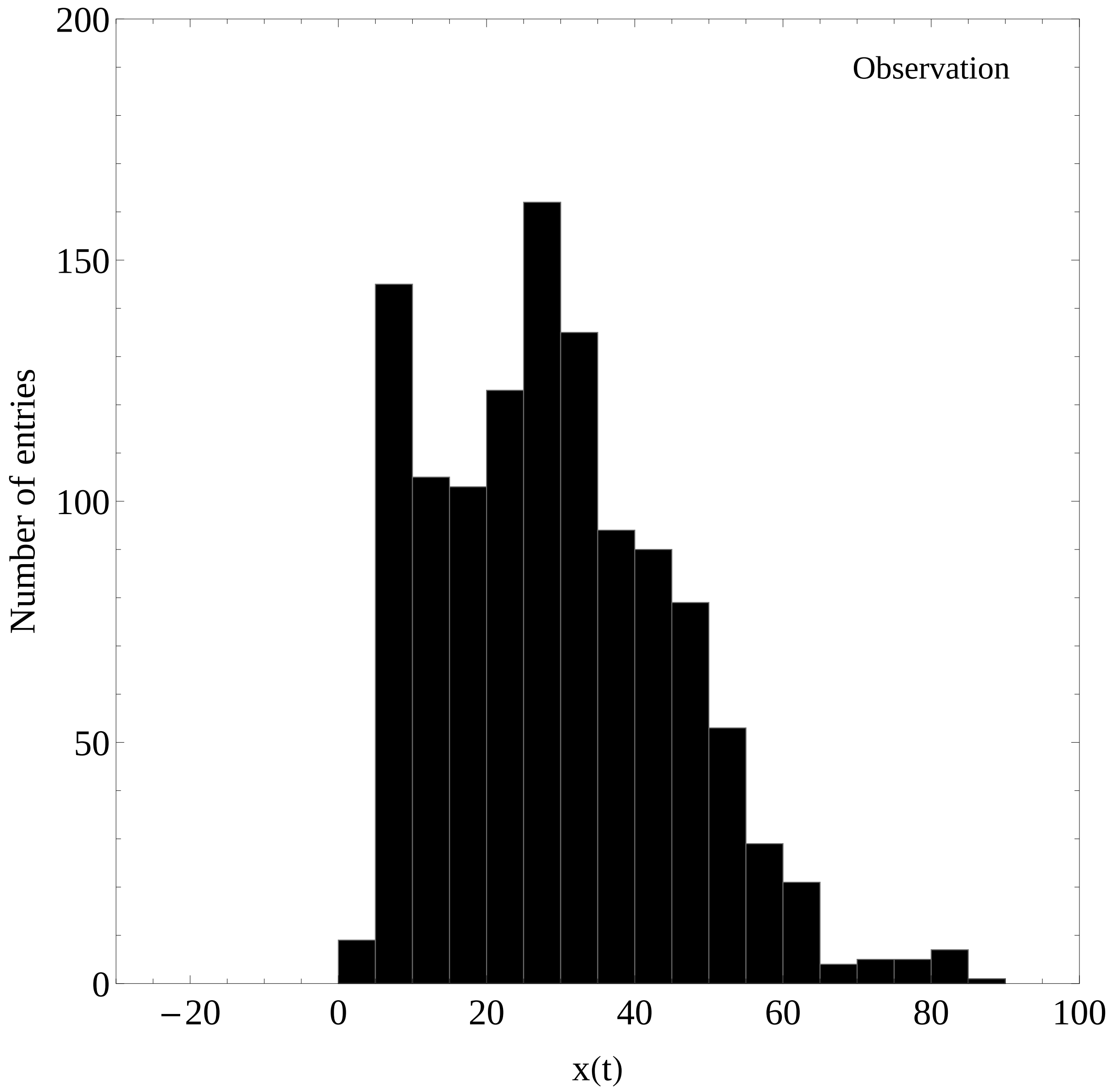

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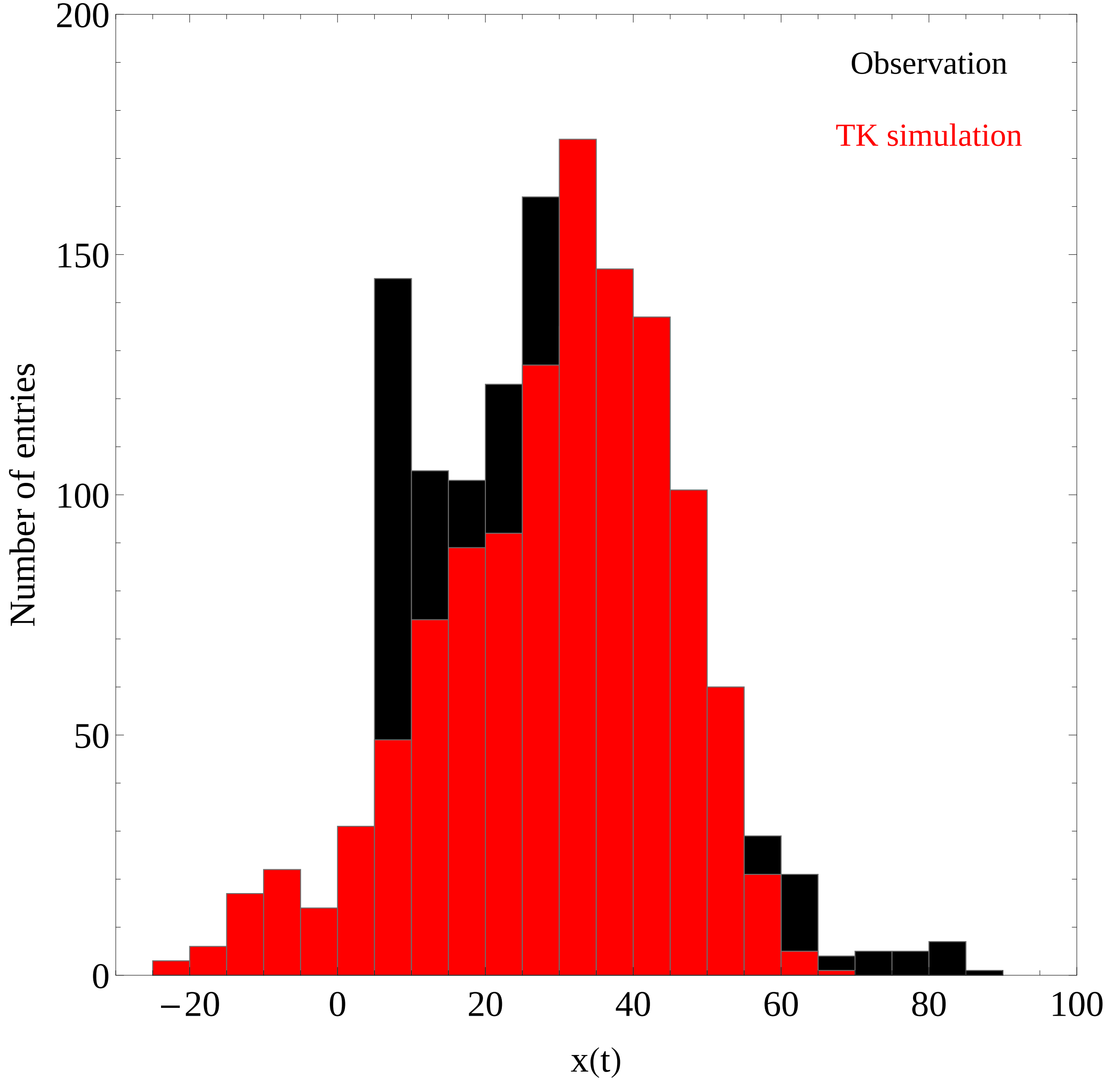


Monte Carlo problems

Few times that **Normality** is a problem!

Monte Carlo problems

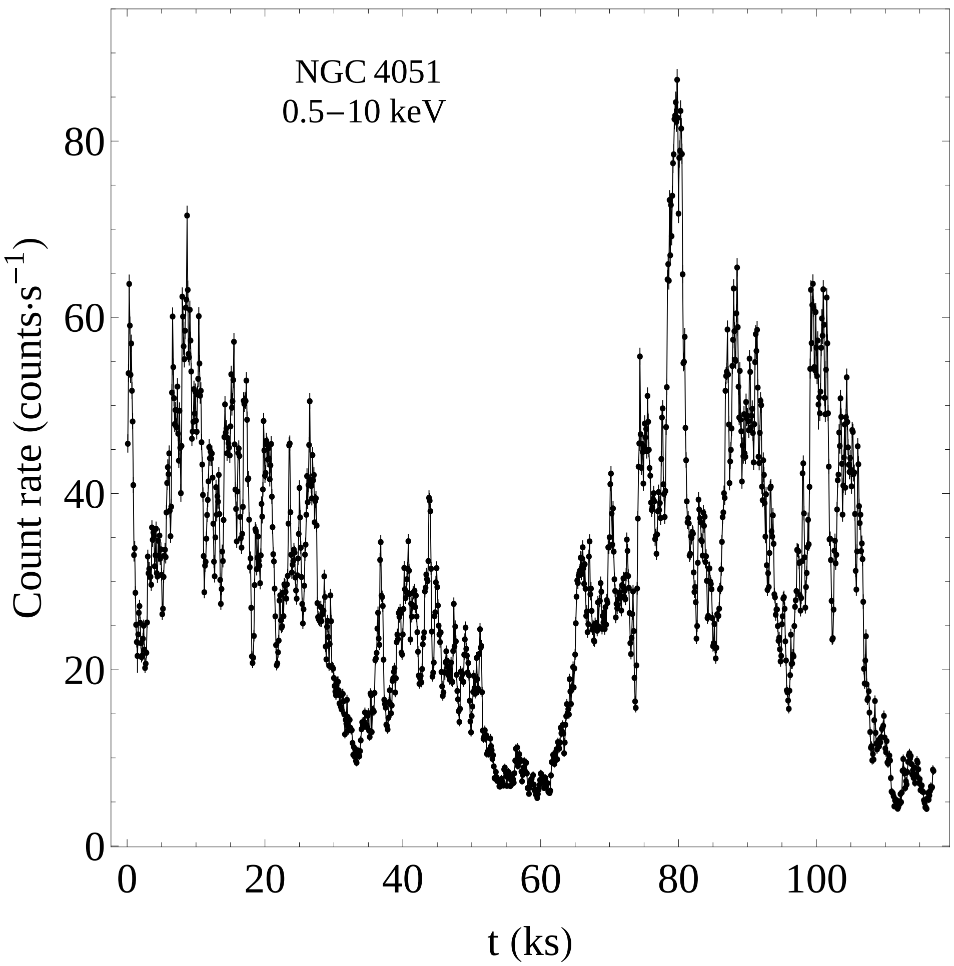
Few times that **Normality** is a problem!

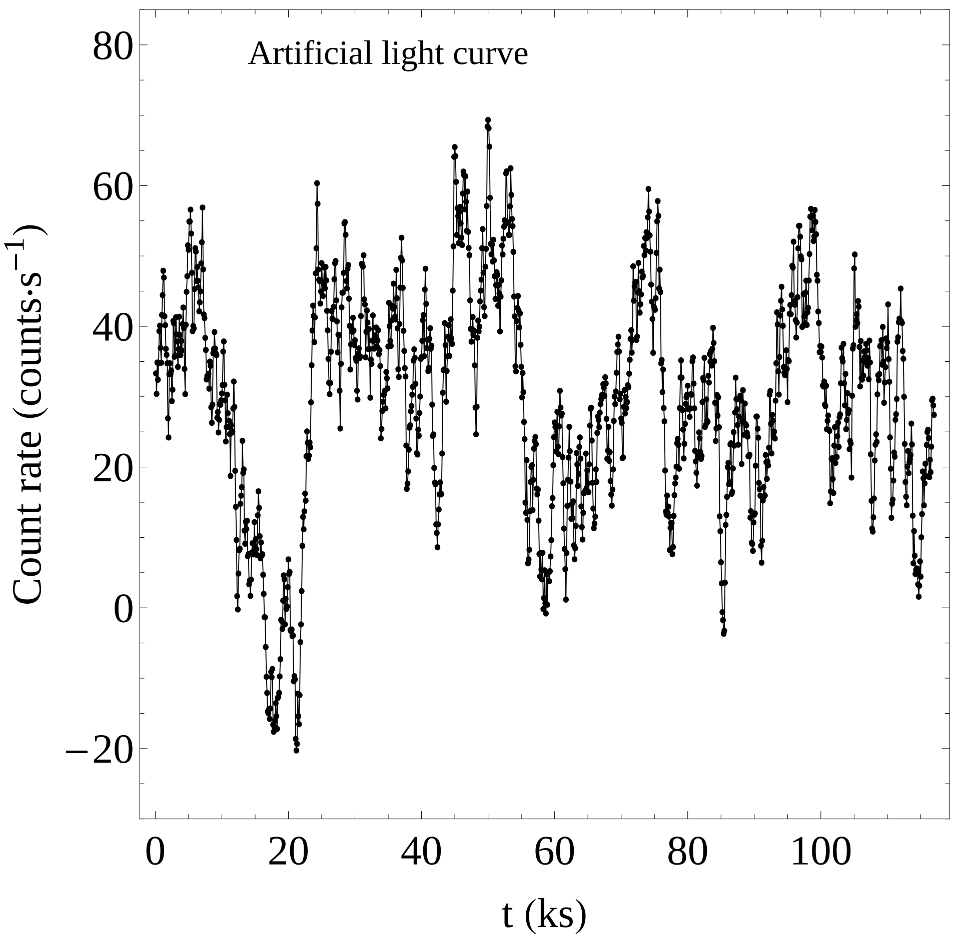
- Wrong underlying probability distribution.
- Physically unrealistic artificial light curves.

The underlying physical flux distribution is always defined for positive flux values.

Monte Carlo problems

Few times that **Normality** is a problem!





Simulating realistic light curves

Emmanoulopoulos et al. 2013, MNRAS, **433**, 907

+

Out[23]=

Generating artificial light curves:Revisited and updated

The numerical code

Dimitrios Emmanoulopoulos[†]

[†]Physics and Astronomy, University of Southampton, SO17 1BJ, Southampton, United Kingdom
D.Emmanoulopoulos@soton.ac.uk

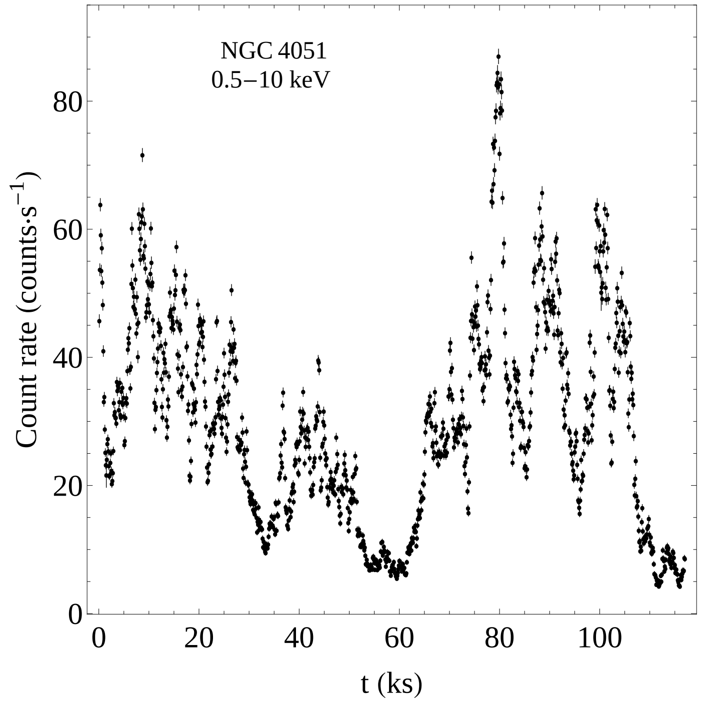
Abstract

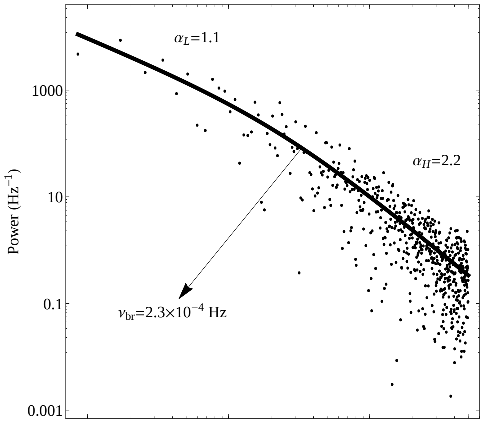
This notebook presents the entire methodology for the production of artificial light curves as presented in § 3.1 in the corresponding MNRAS paper. As it is done in the paper (
Newton (obs ID: 0109141401), for the production of a single artificial light curve having the same statistical and variability properties as the observed light curves. The method
described in the MNRAS paper. As in any time series methodology we caution the readers that the outputs of the method depends ONLY in the input parameters and thus the

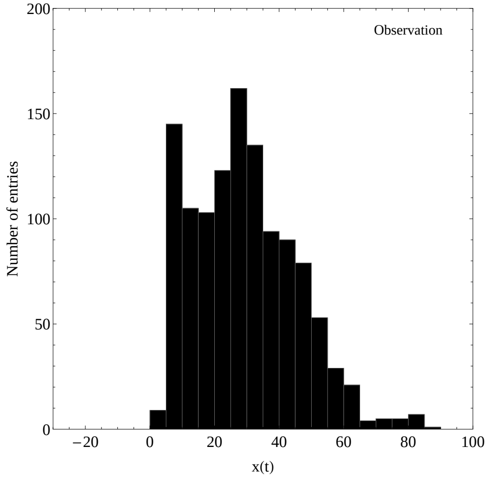
For all the astrophysical fields!

Simulating realistic light curves

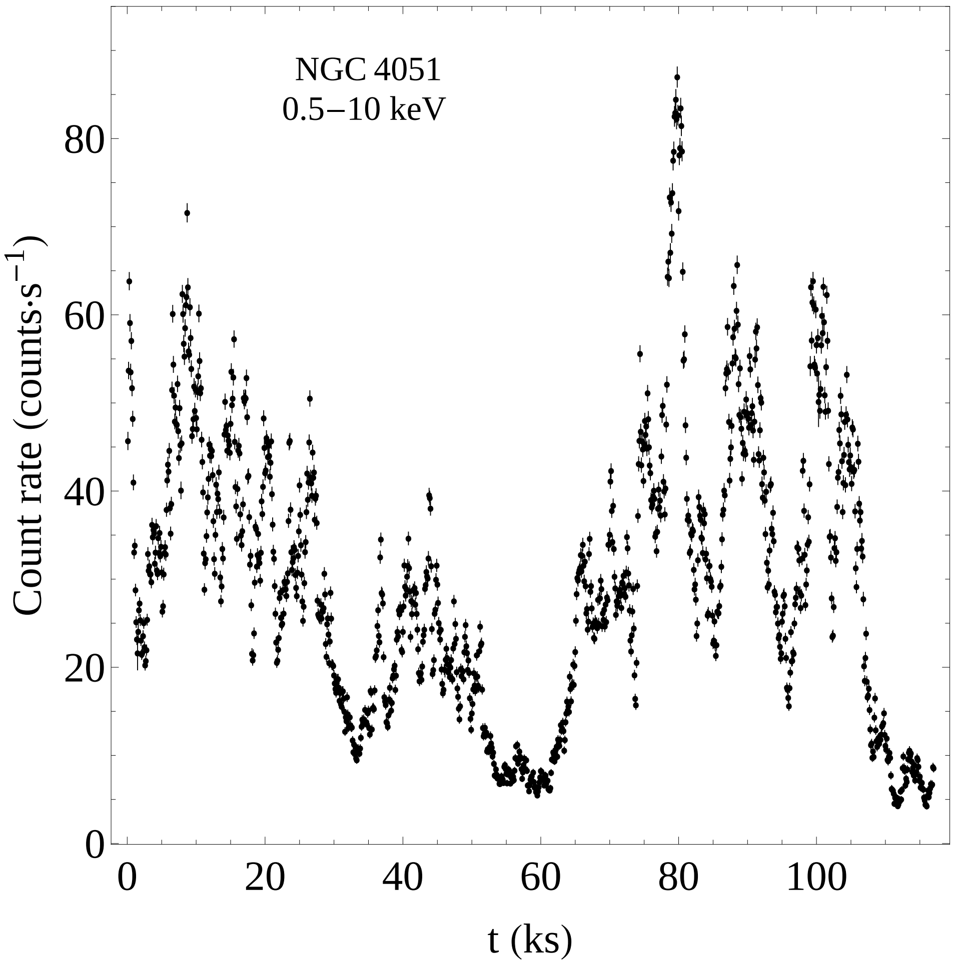
We randomize amplitudes and phases in an iterated fashion.

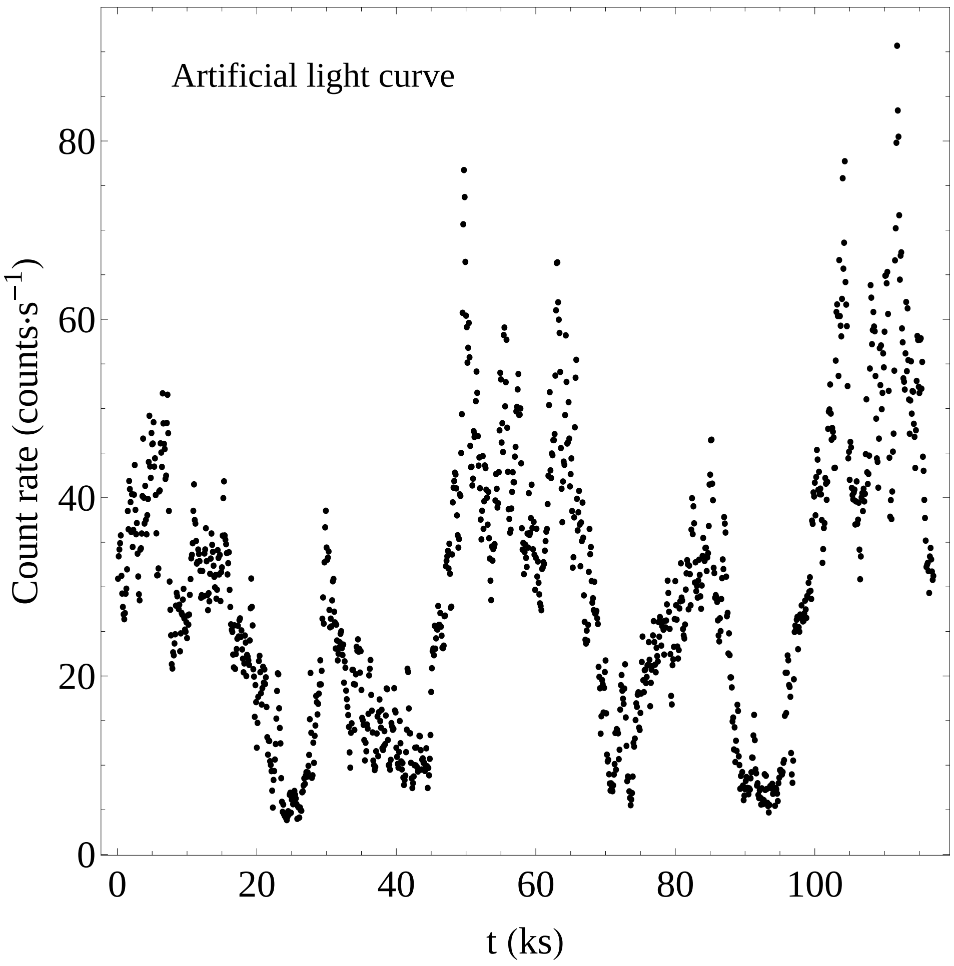




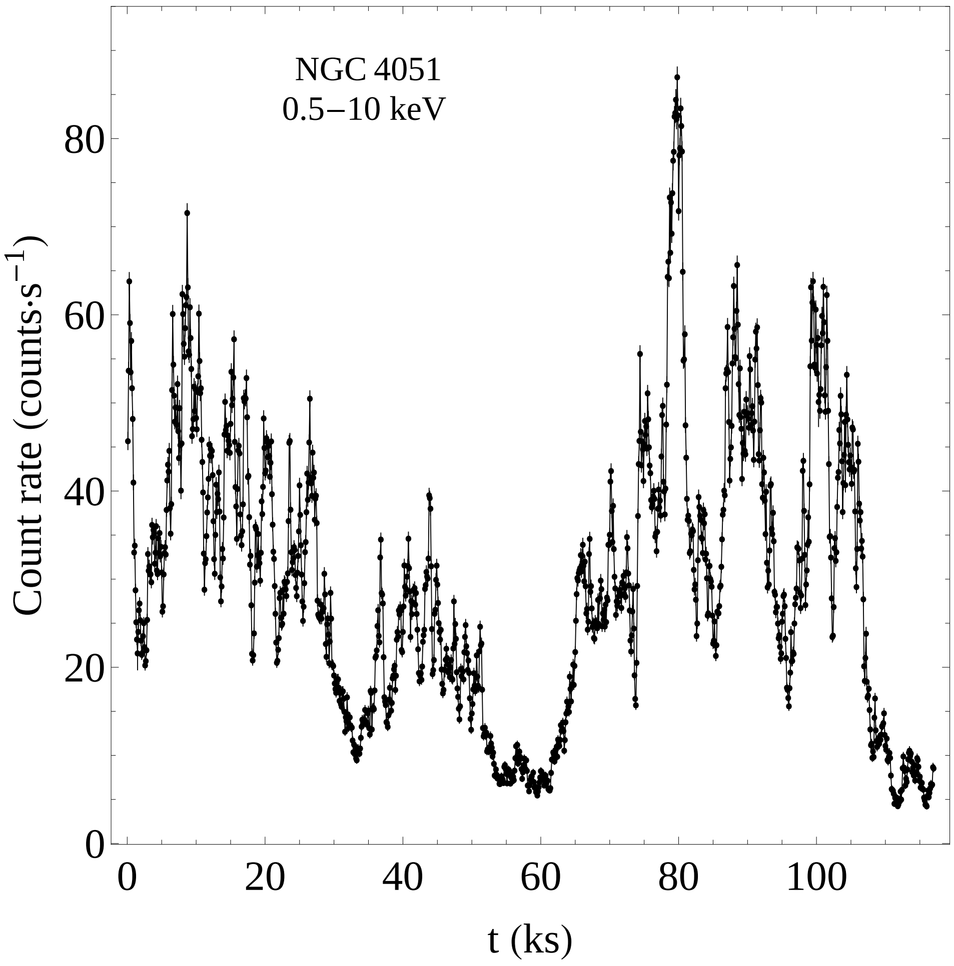


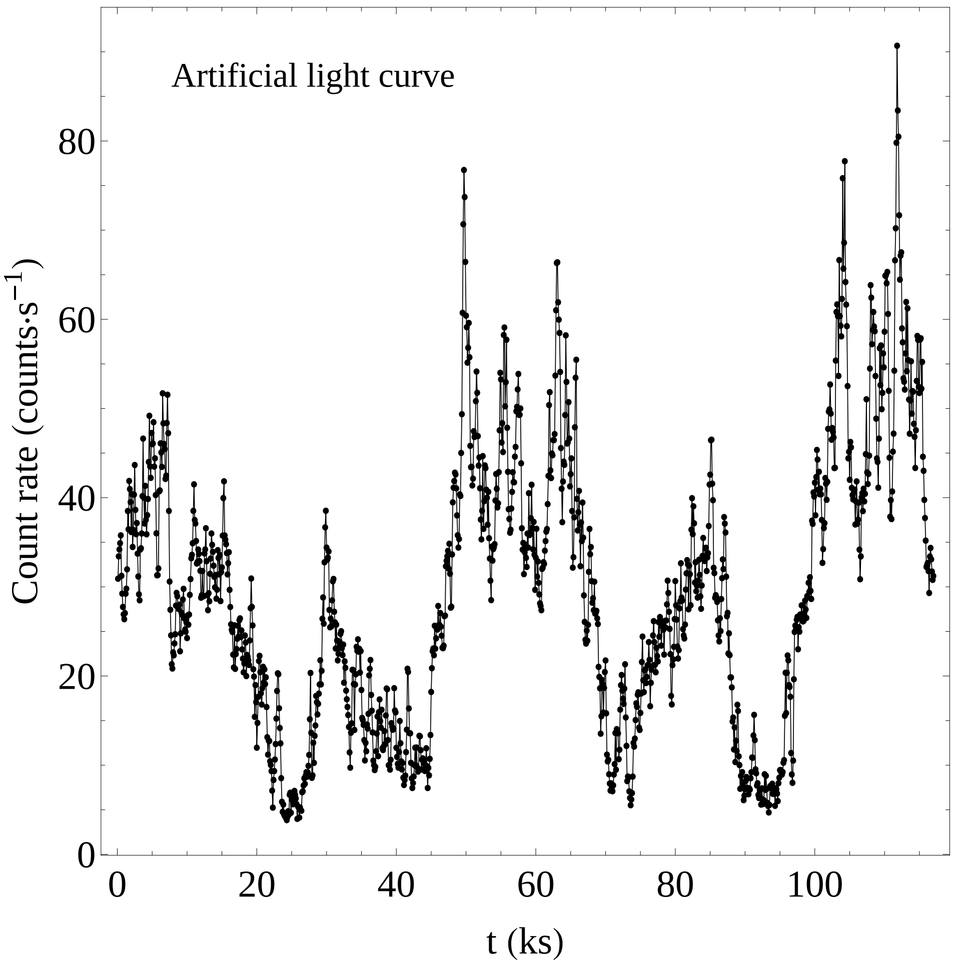
Simulating realistic light curves



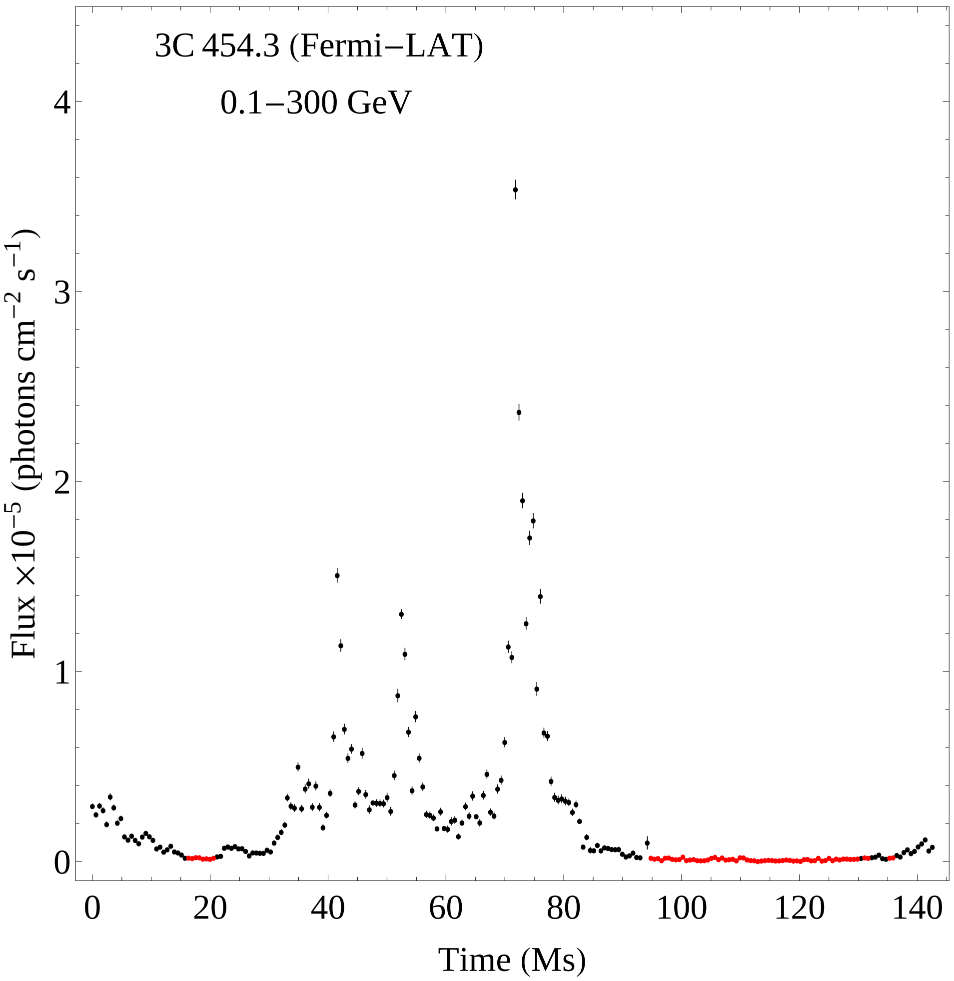


Simulating realistic light curves

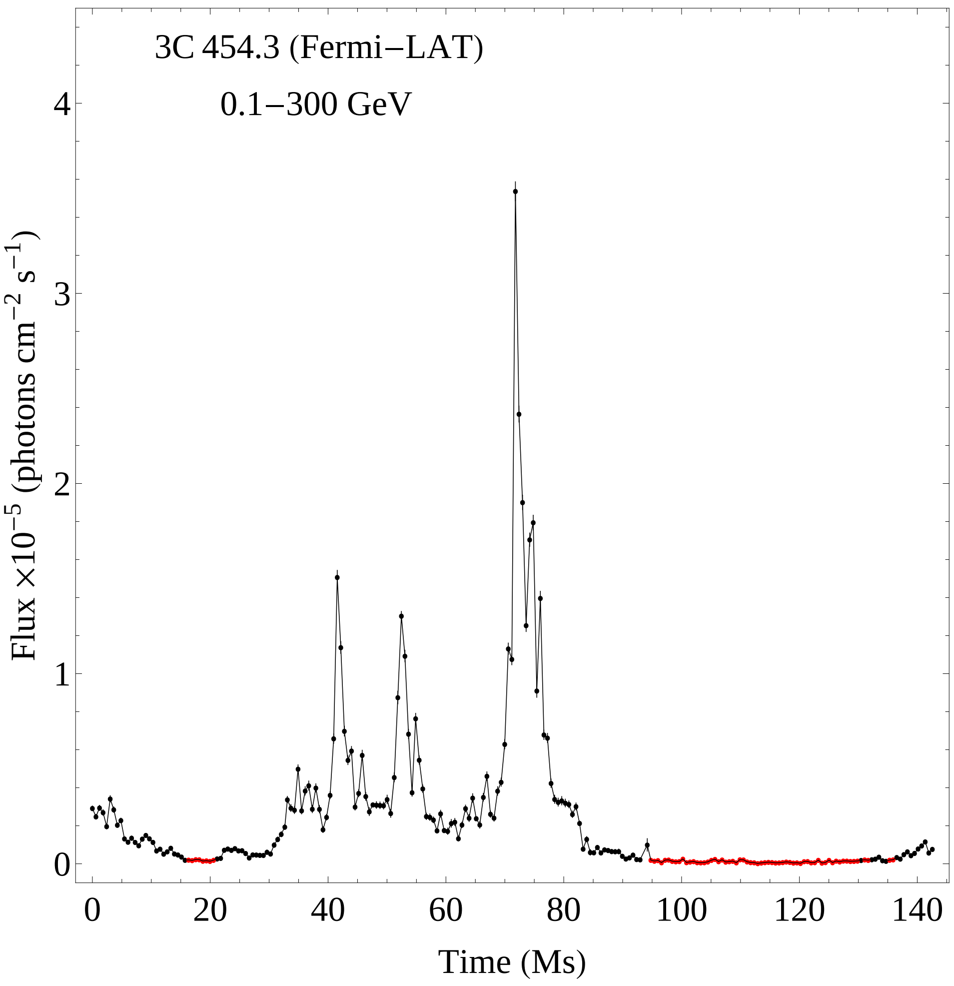


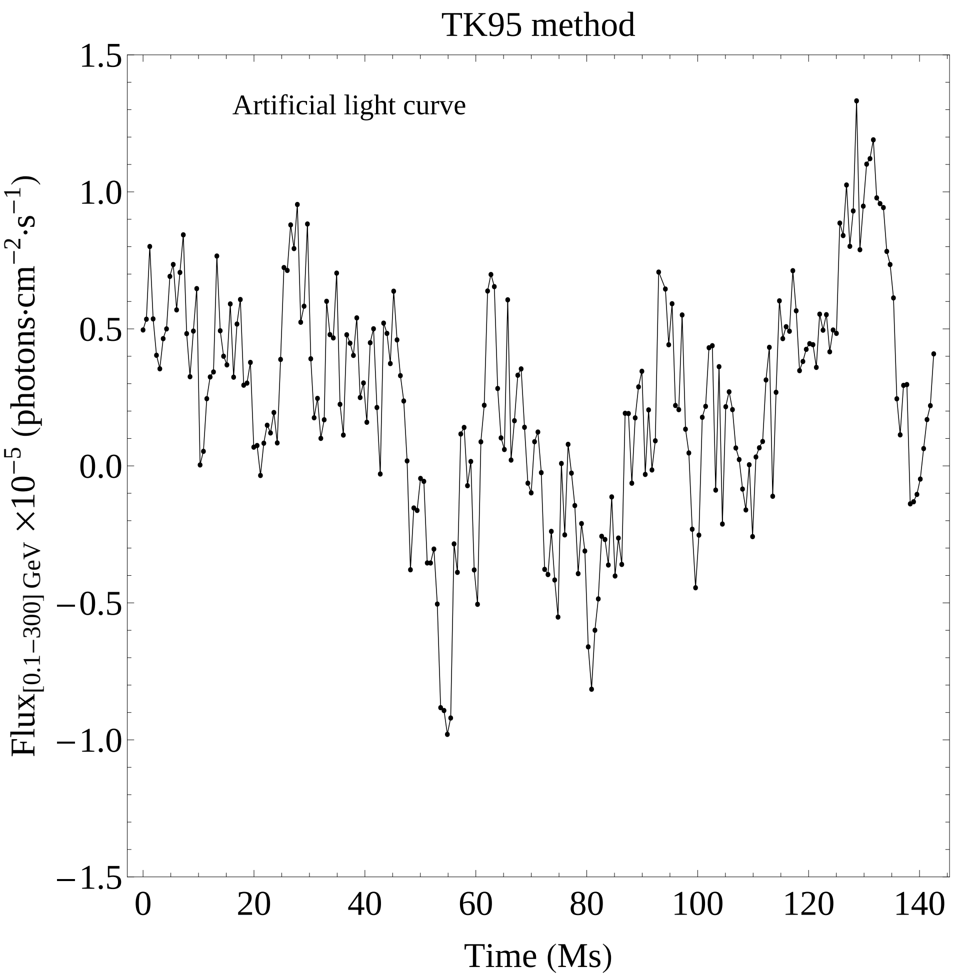


Simulating realistic light curves

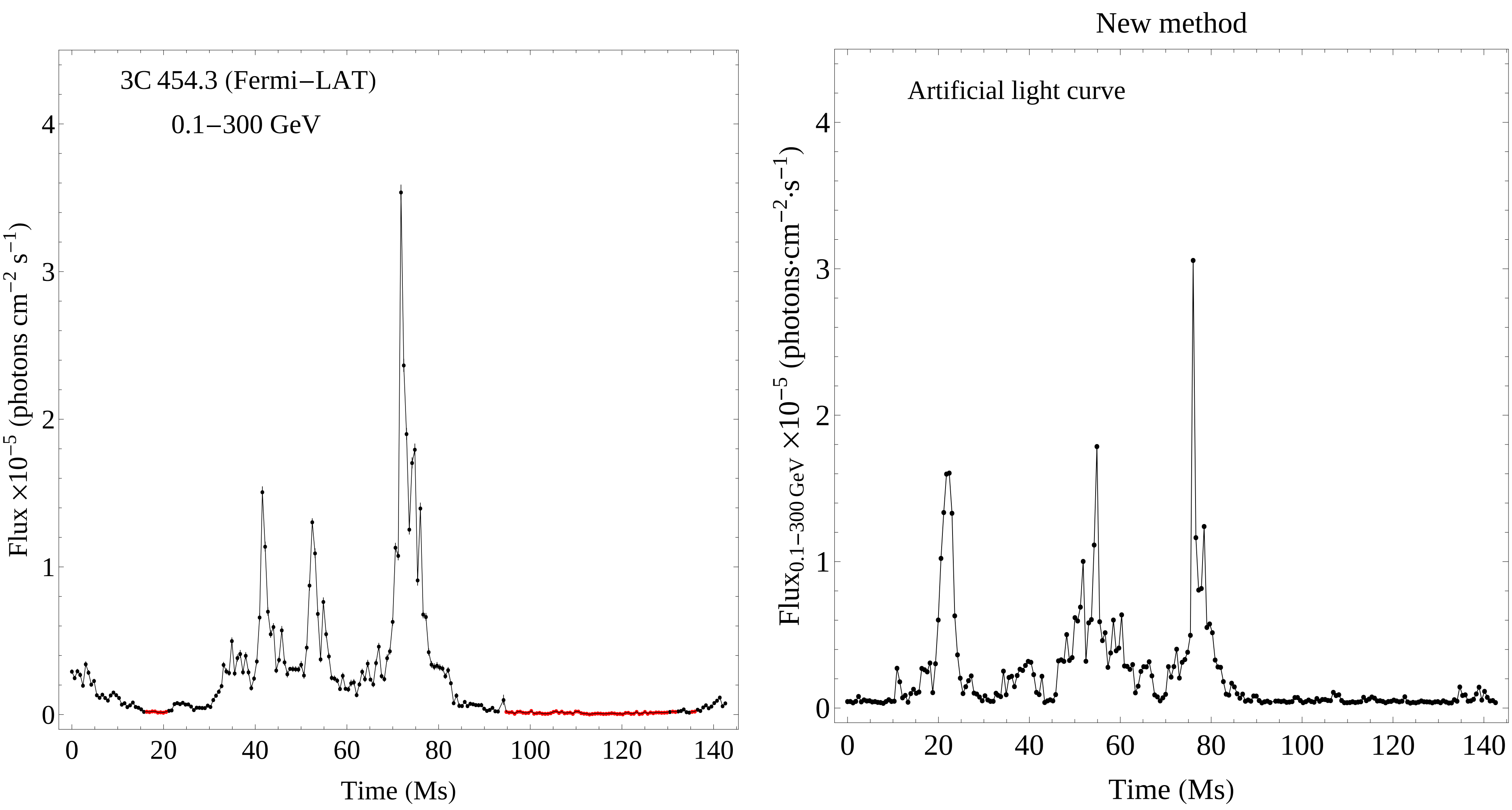


Simulating realistic light curves

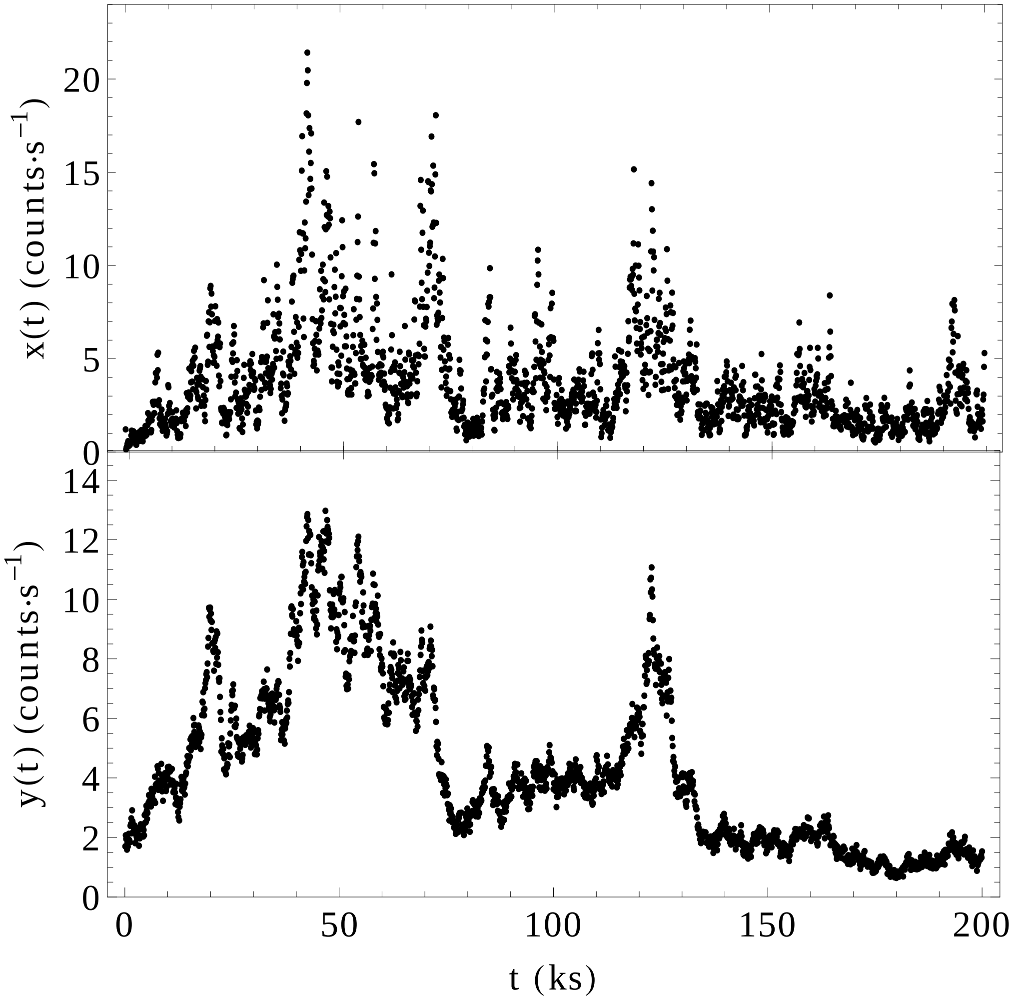




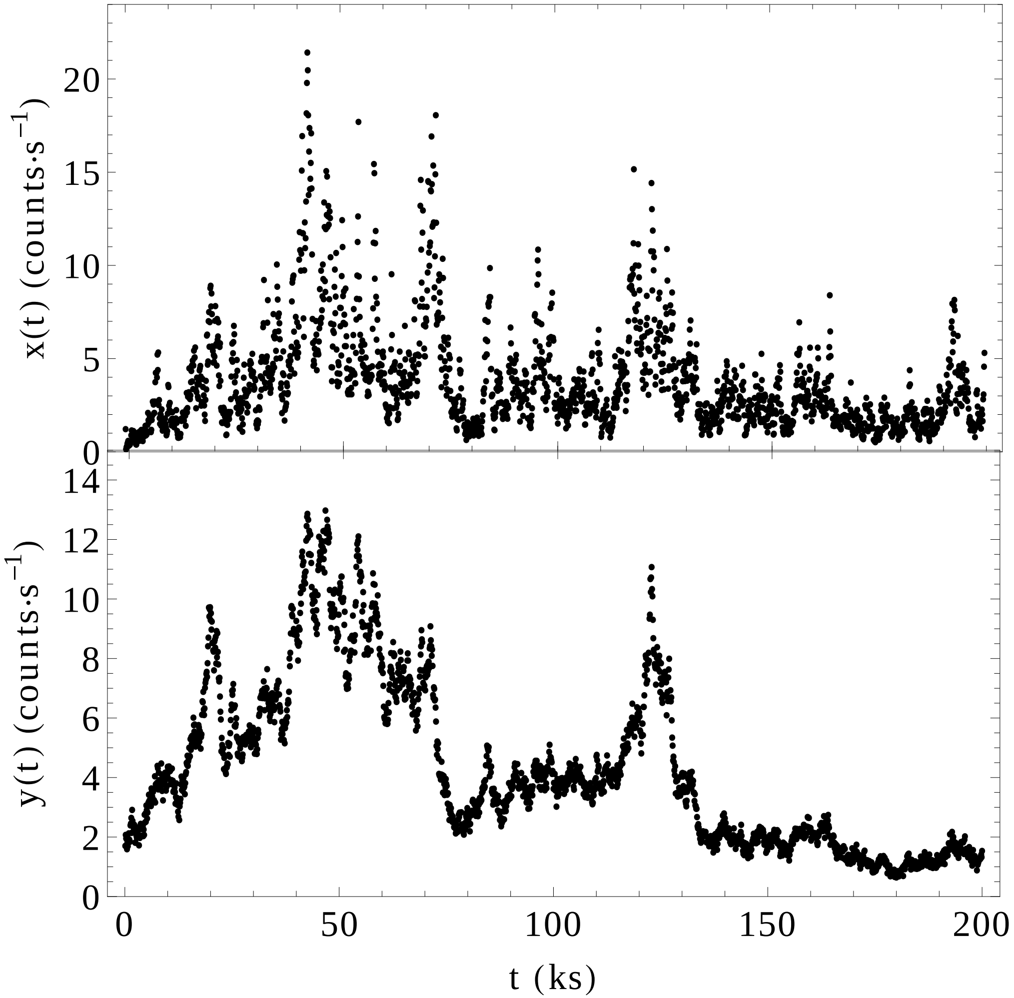
Simulating realistic light curves

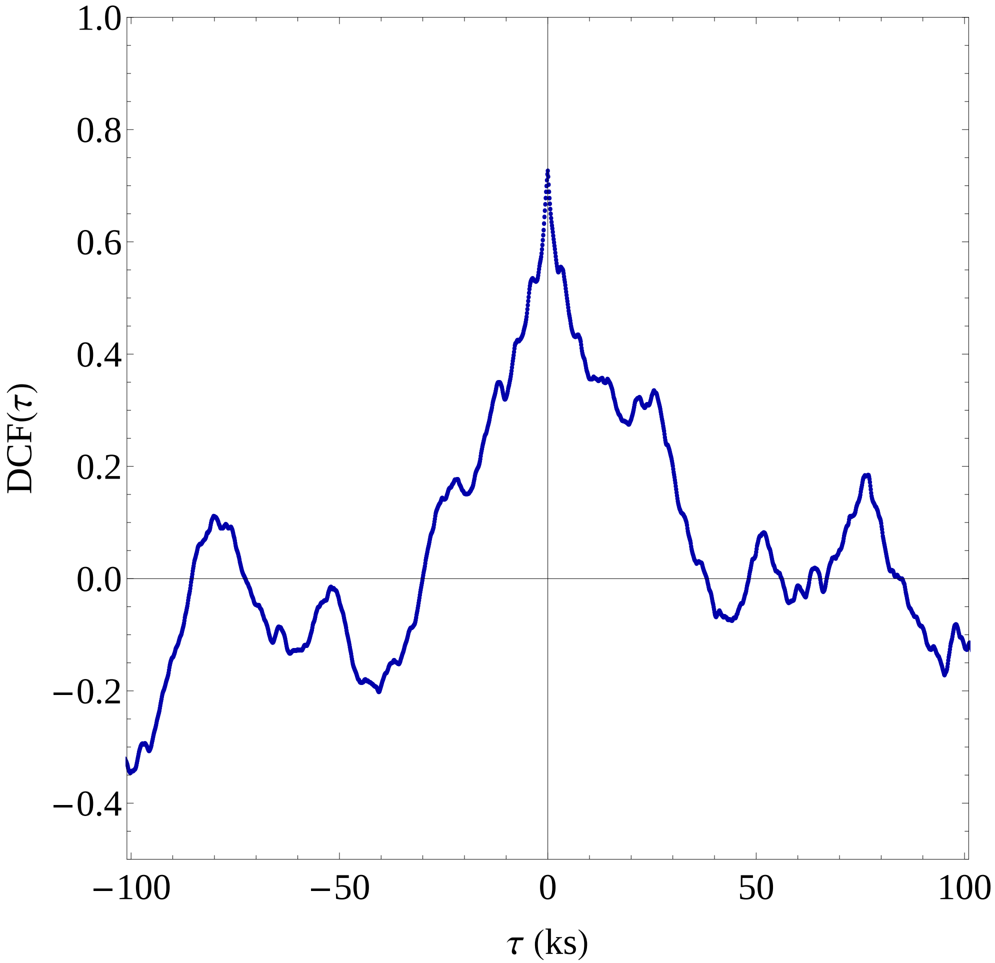


Simulating realistic light curves

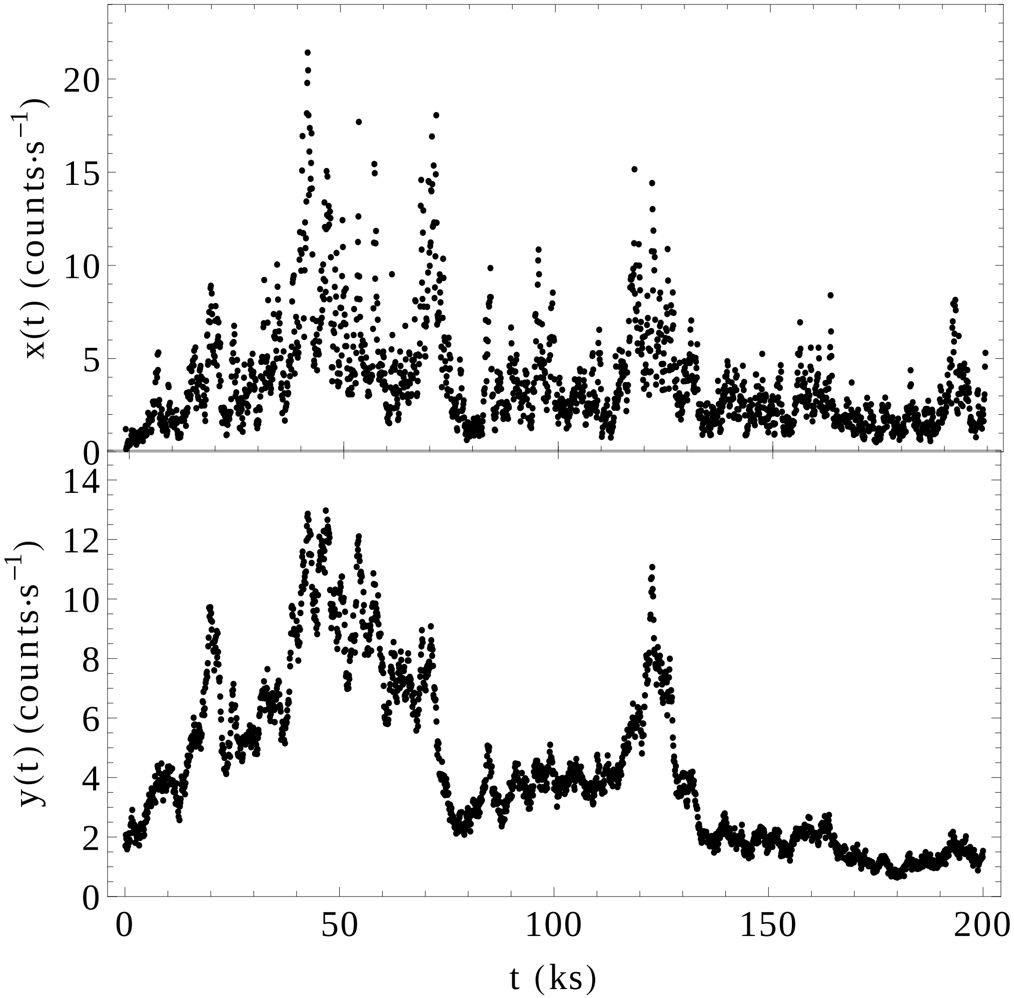


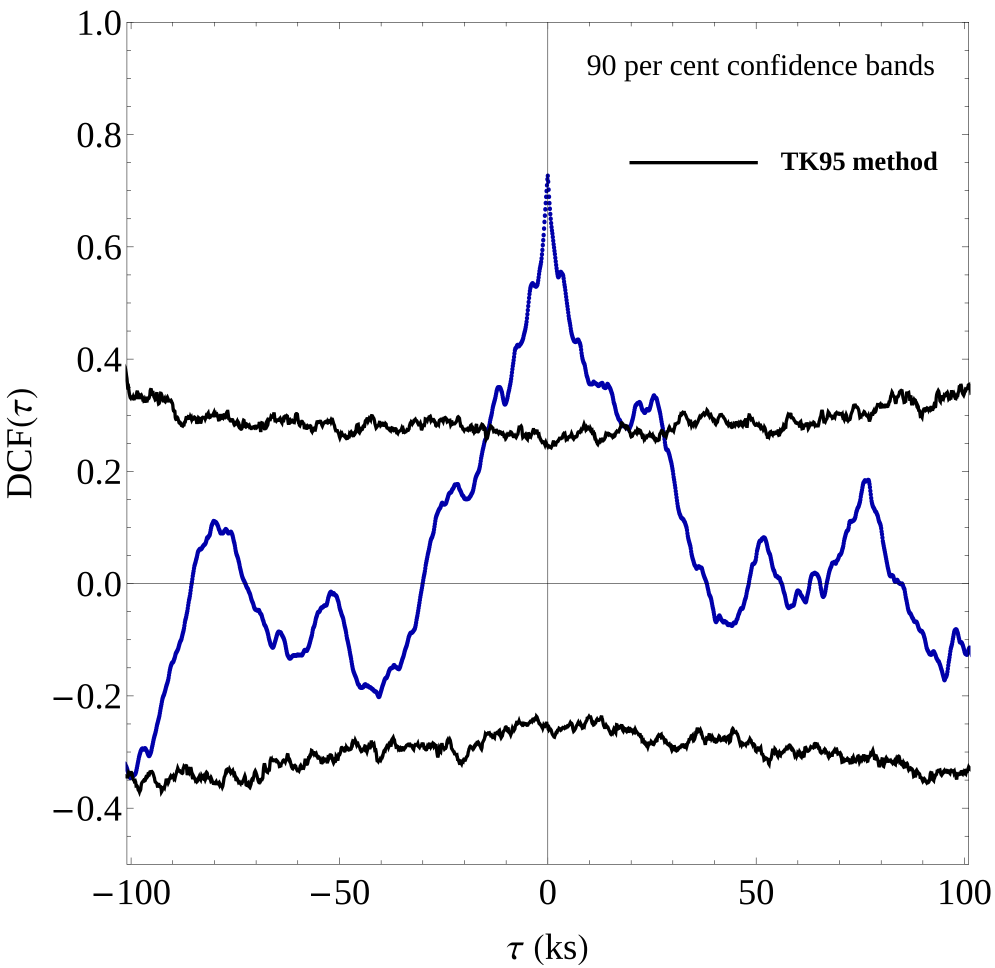
Simulating realistic light curves



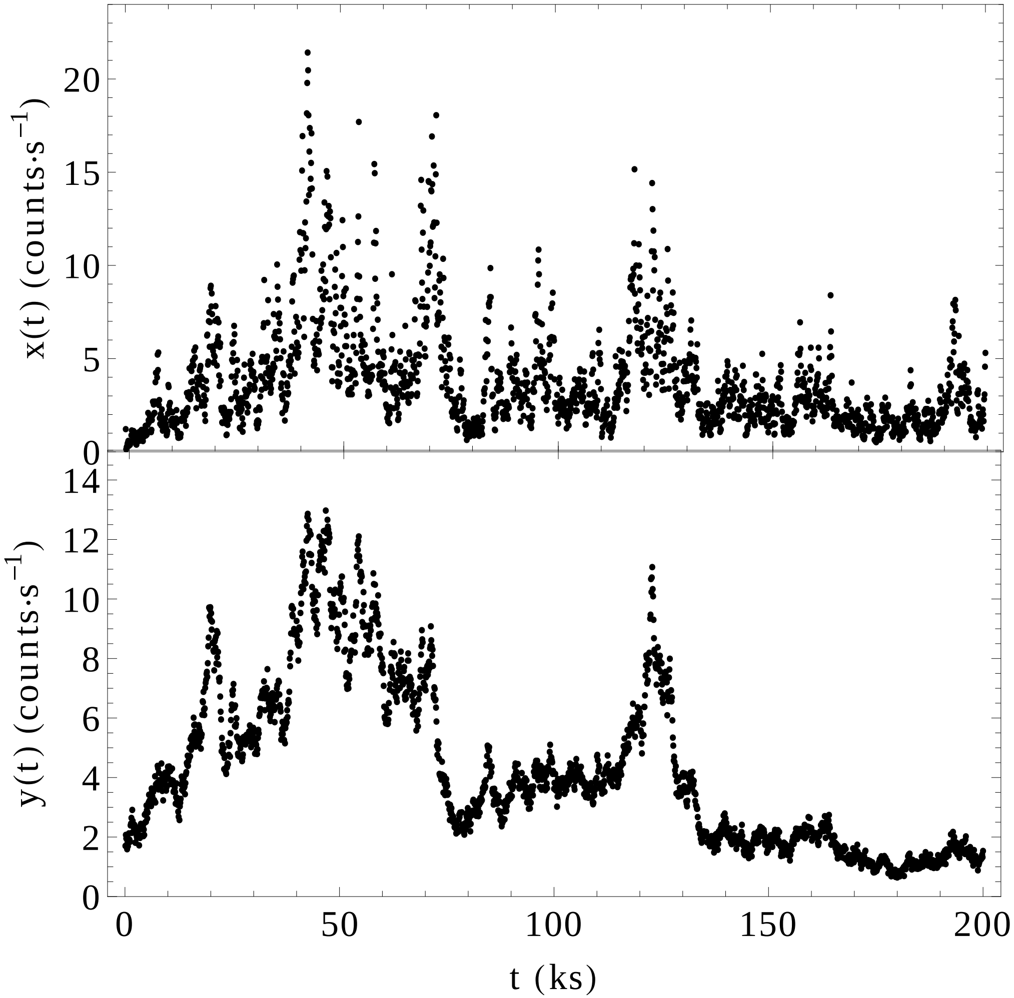


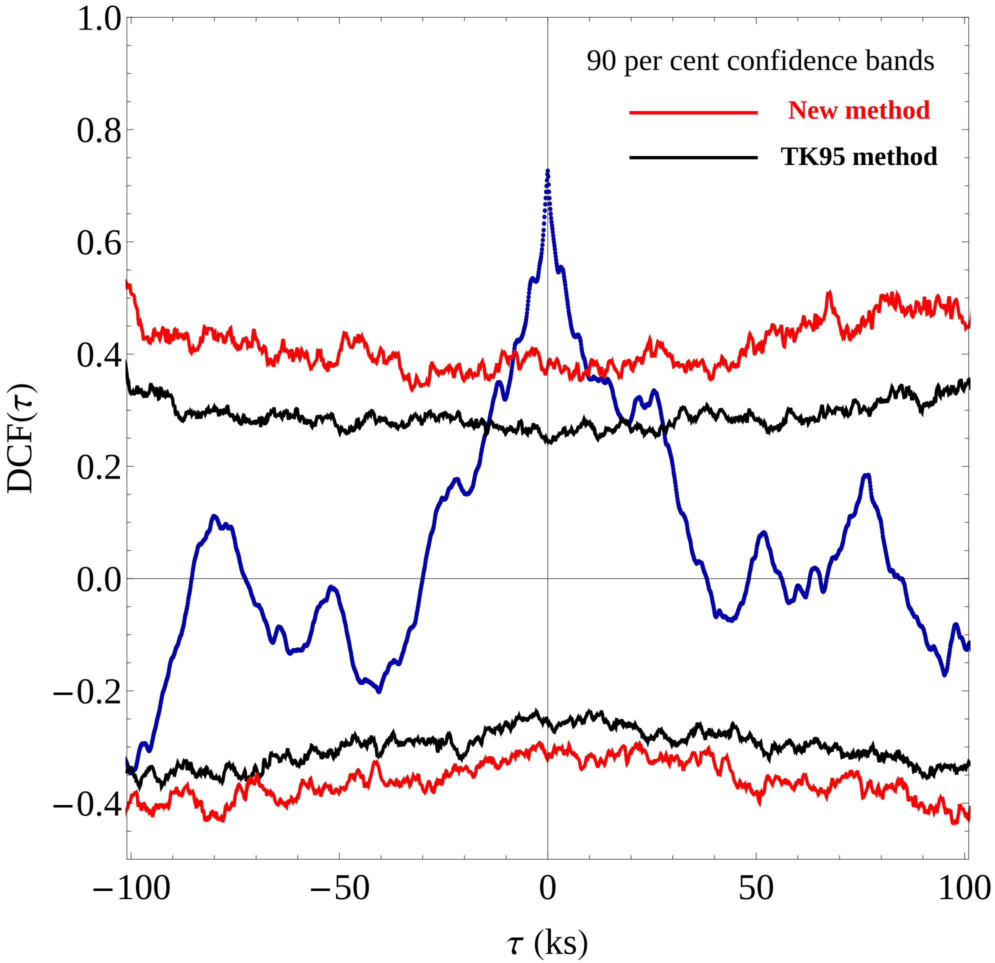
Simulating realistic light curves



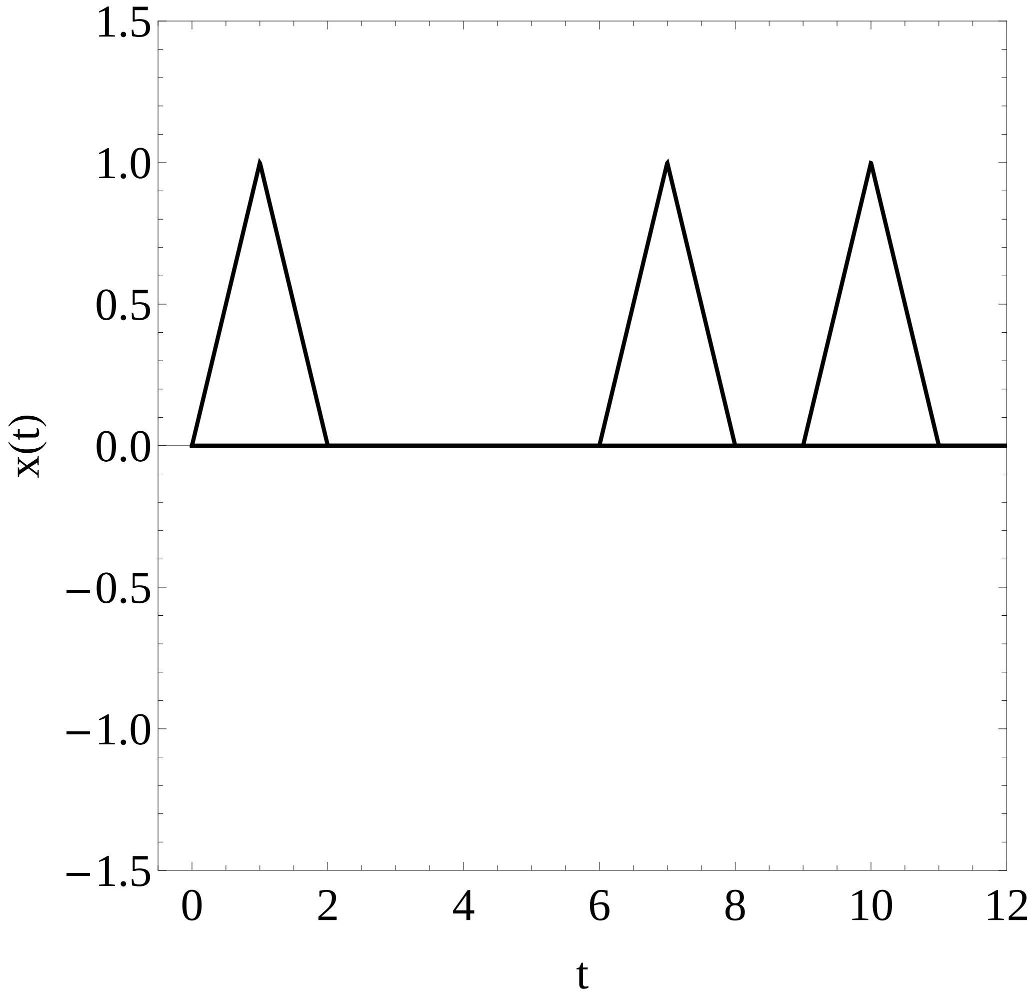


Simulating realistic light curves



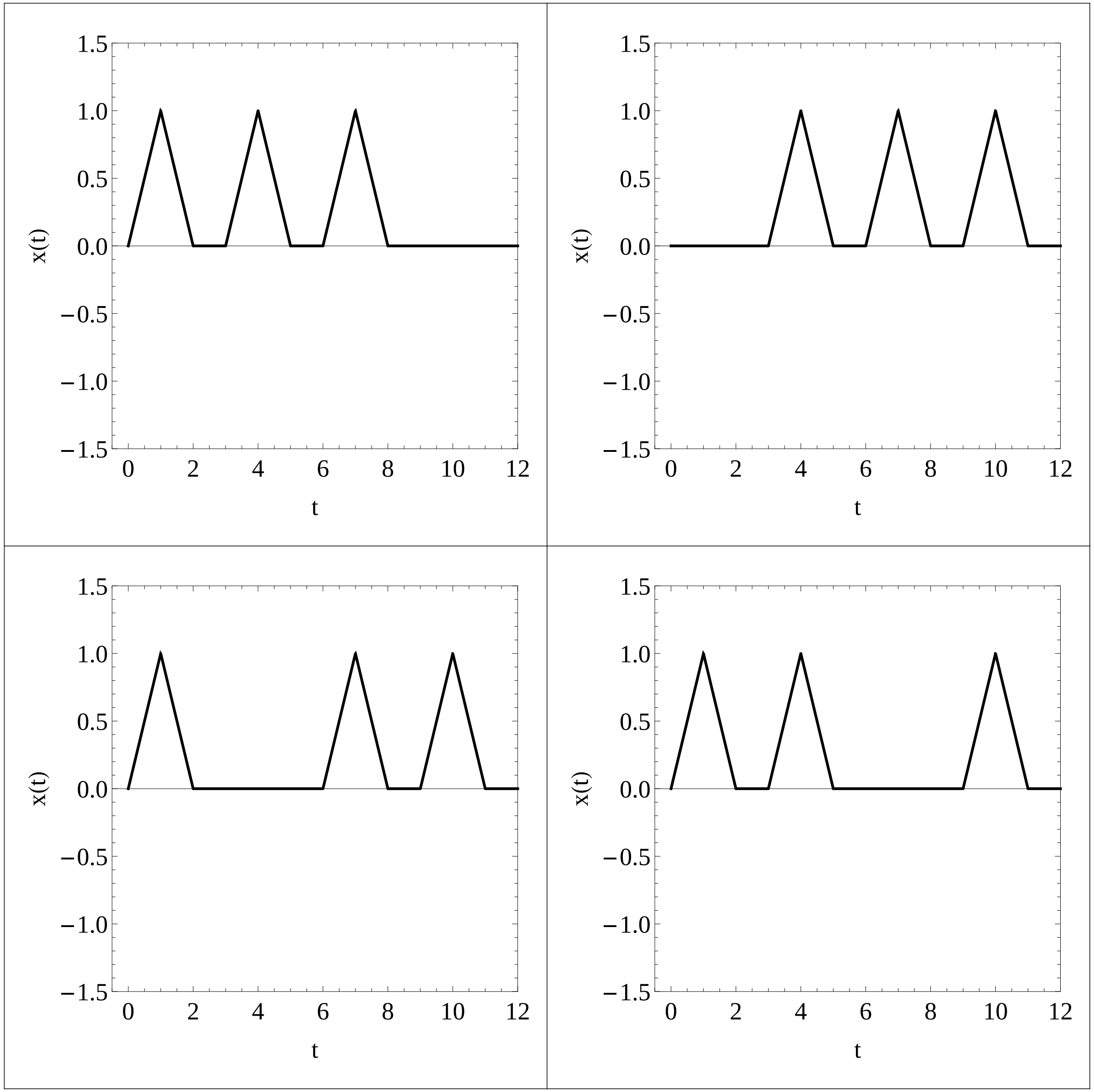


Additional material



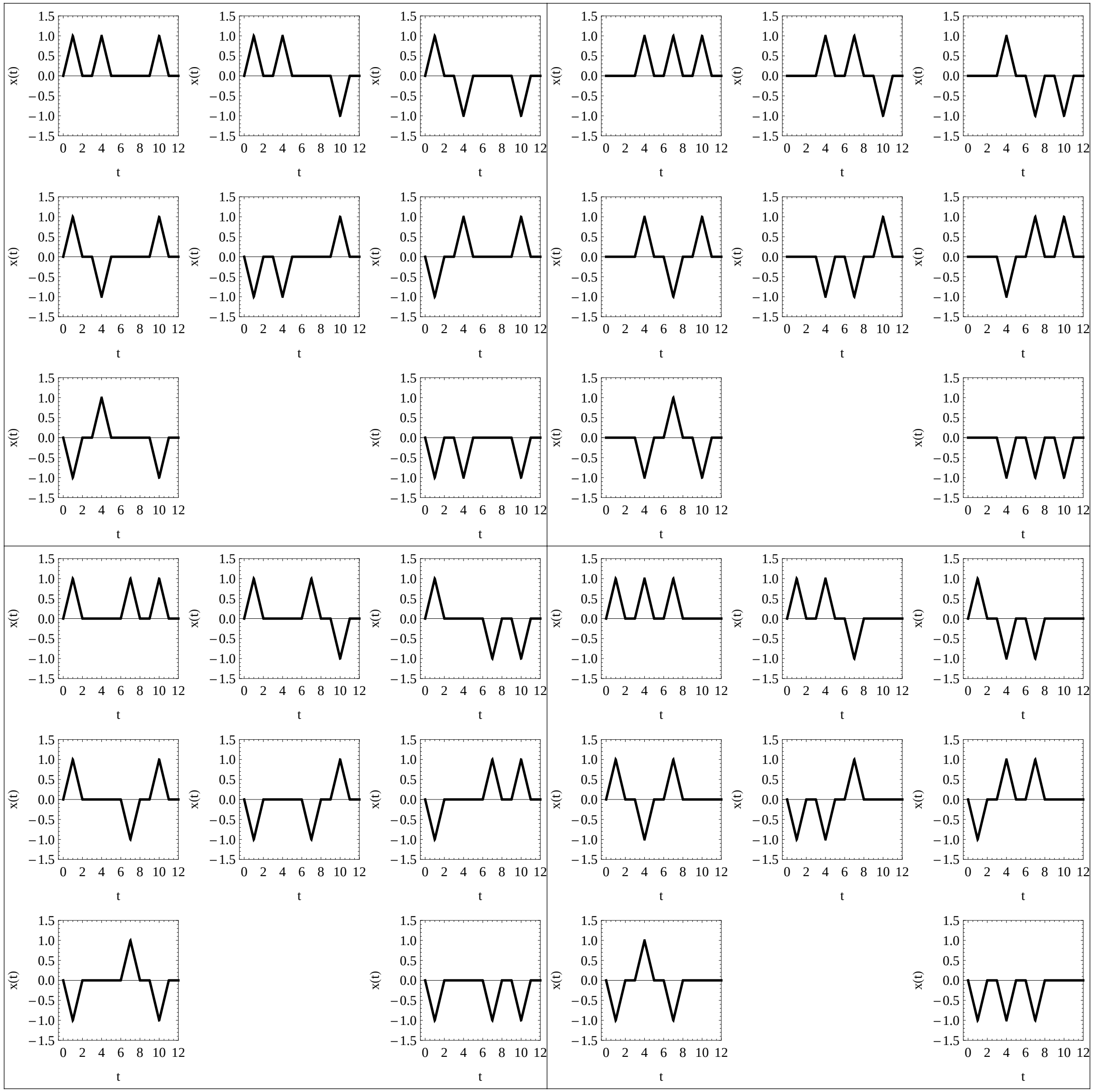
Additional material

Bursty' chance coincidence=25%



Additional material

‘Gaussian’ chance coincidence$\simeq$3%



Wide applicability...

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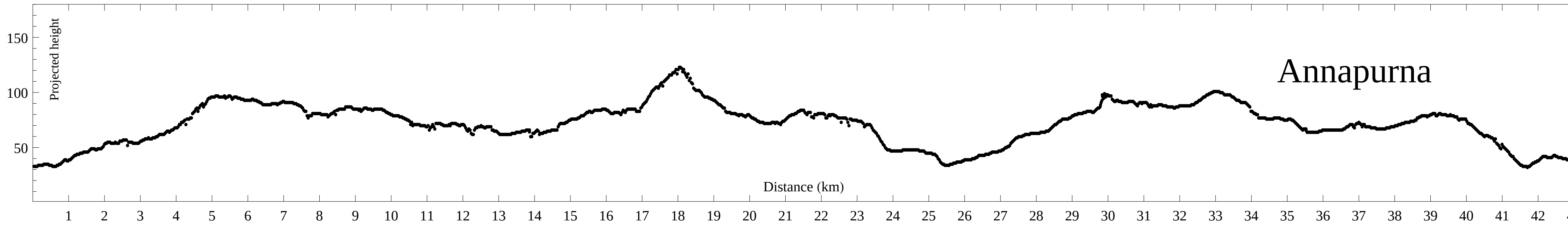
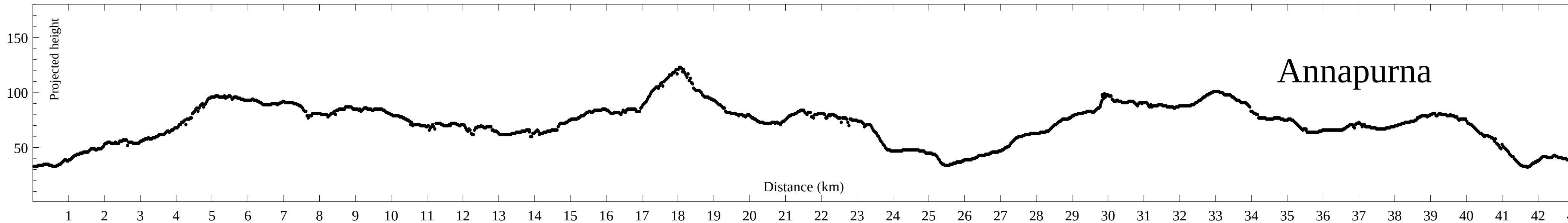
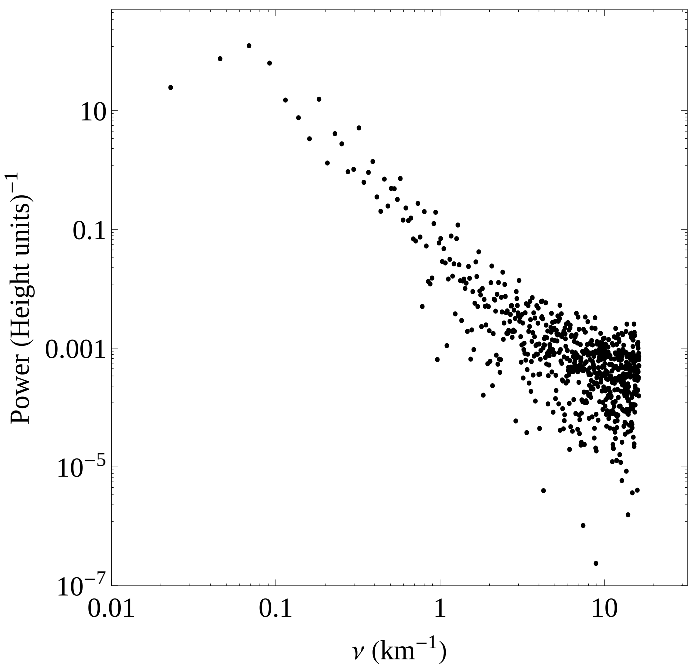
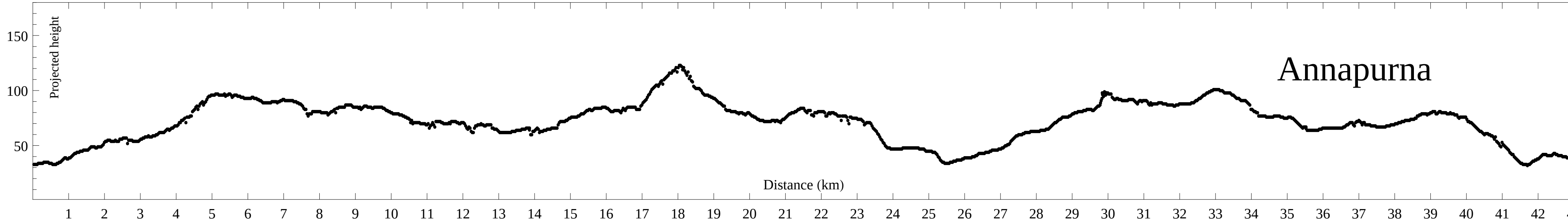


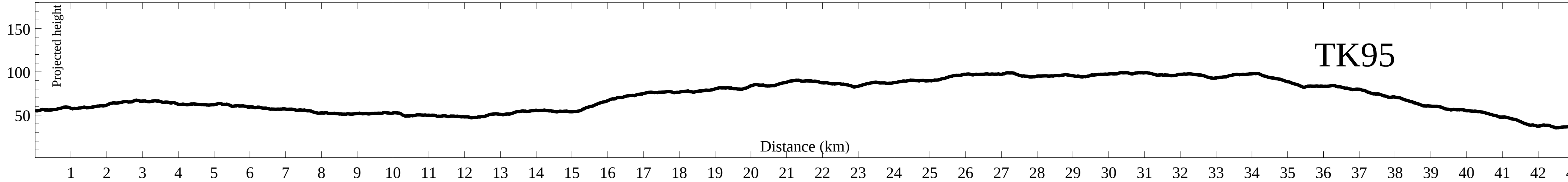
Wide applicability...



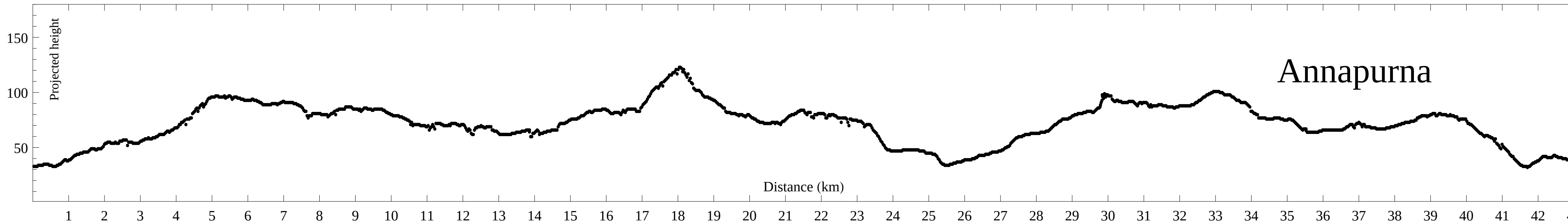


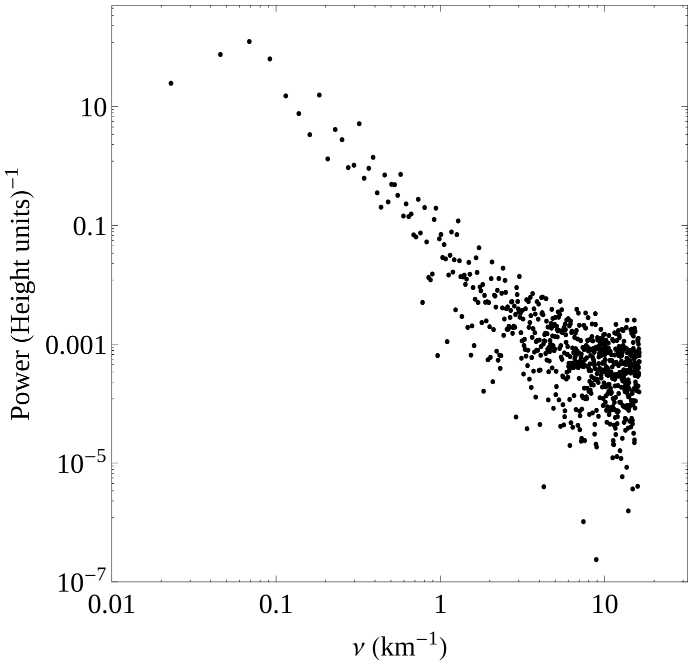
Wide applicability...

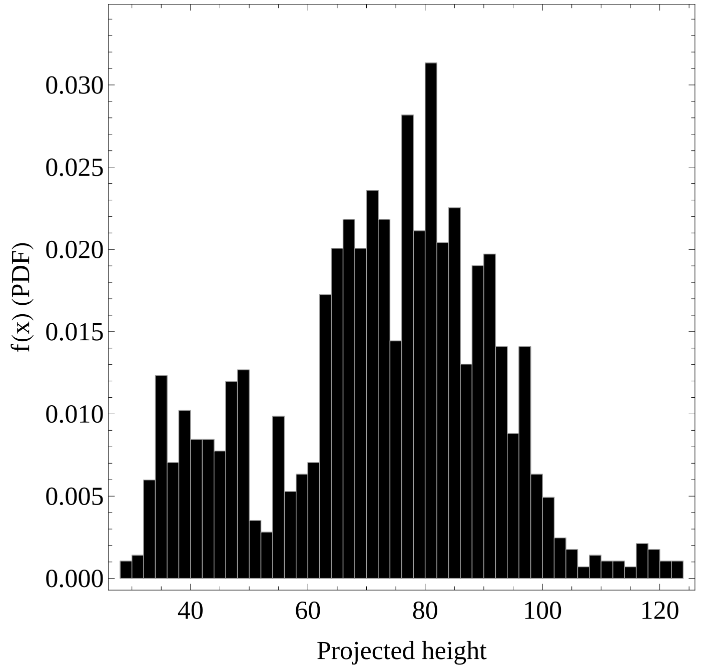




Wide applicability...







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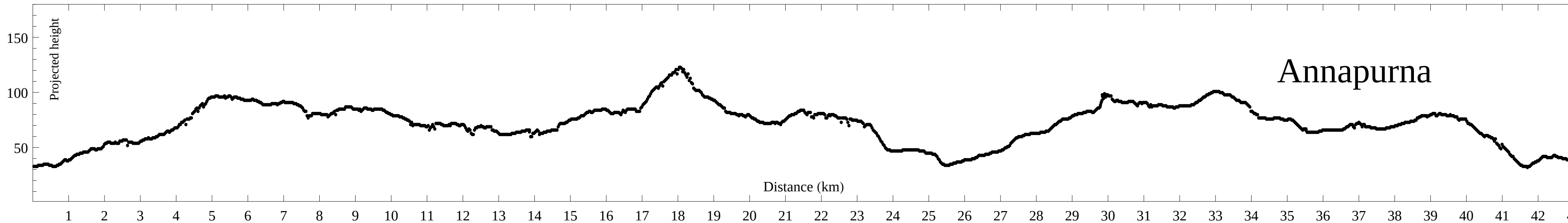

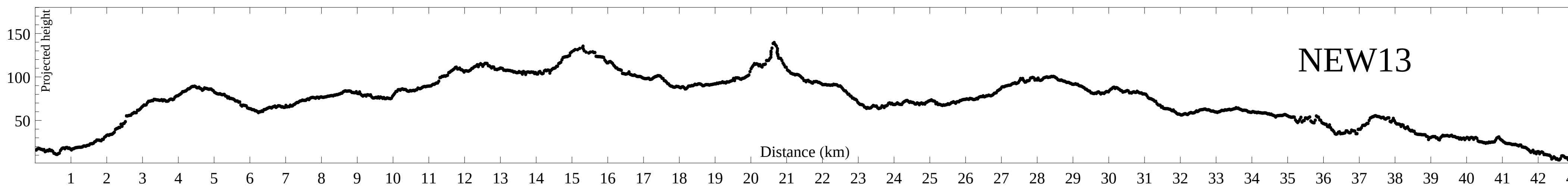

More realistic light curves appropriate for timing studies

and not only...

General Remarks

A proper time-series analysis method should:

- Describe the properties of the underlying physical jet-process and not the properties of a single realization i.e. observed data set.
- The error estimation, of a given physical quantity, should be representative of its underlying statistical distribution.

What is SF?

$$SF(\tau) = \left\langle \left(x(t+\tau) - x(t)\right)^2 \right\rangle$$

What is SF?

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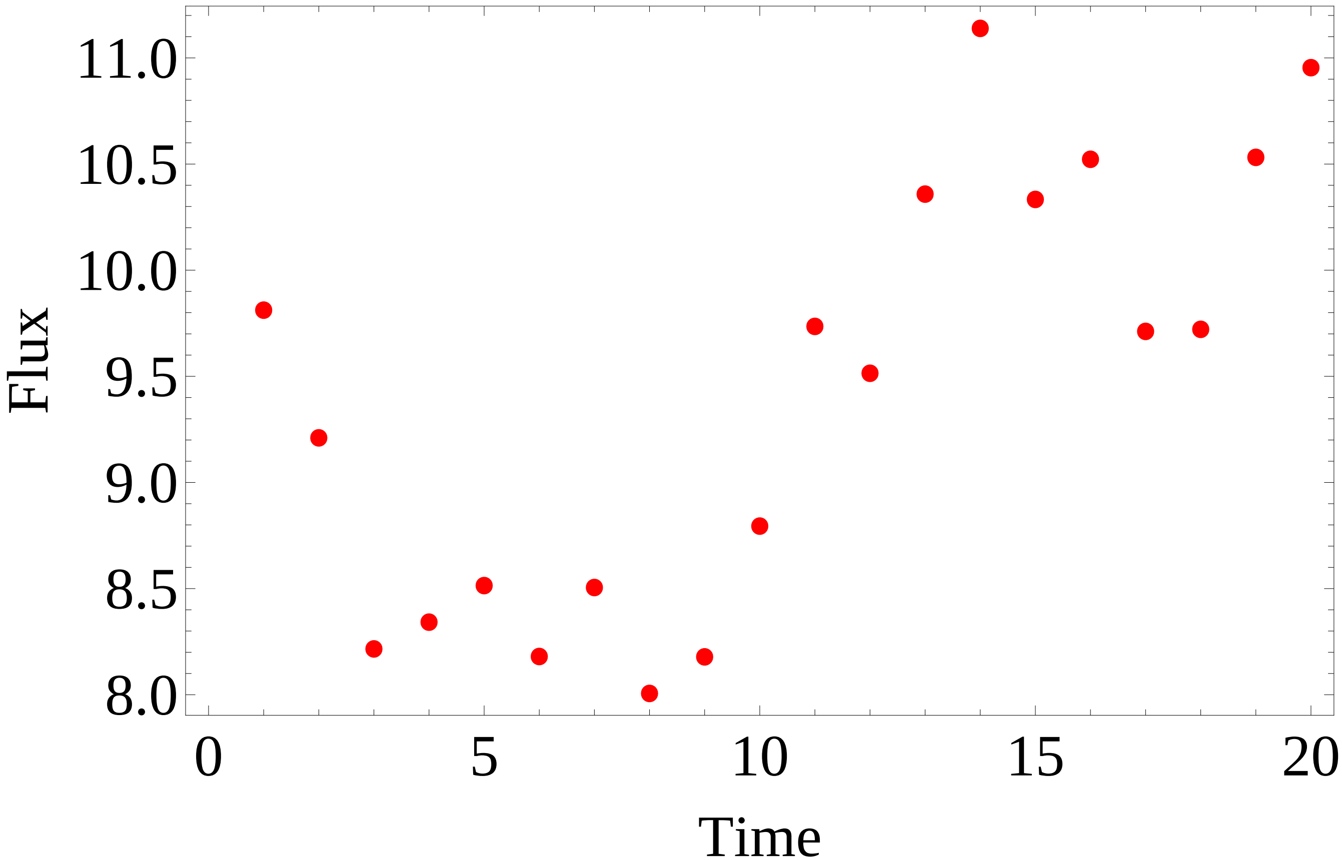
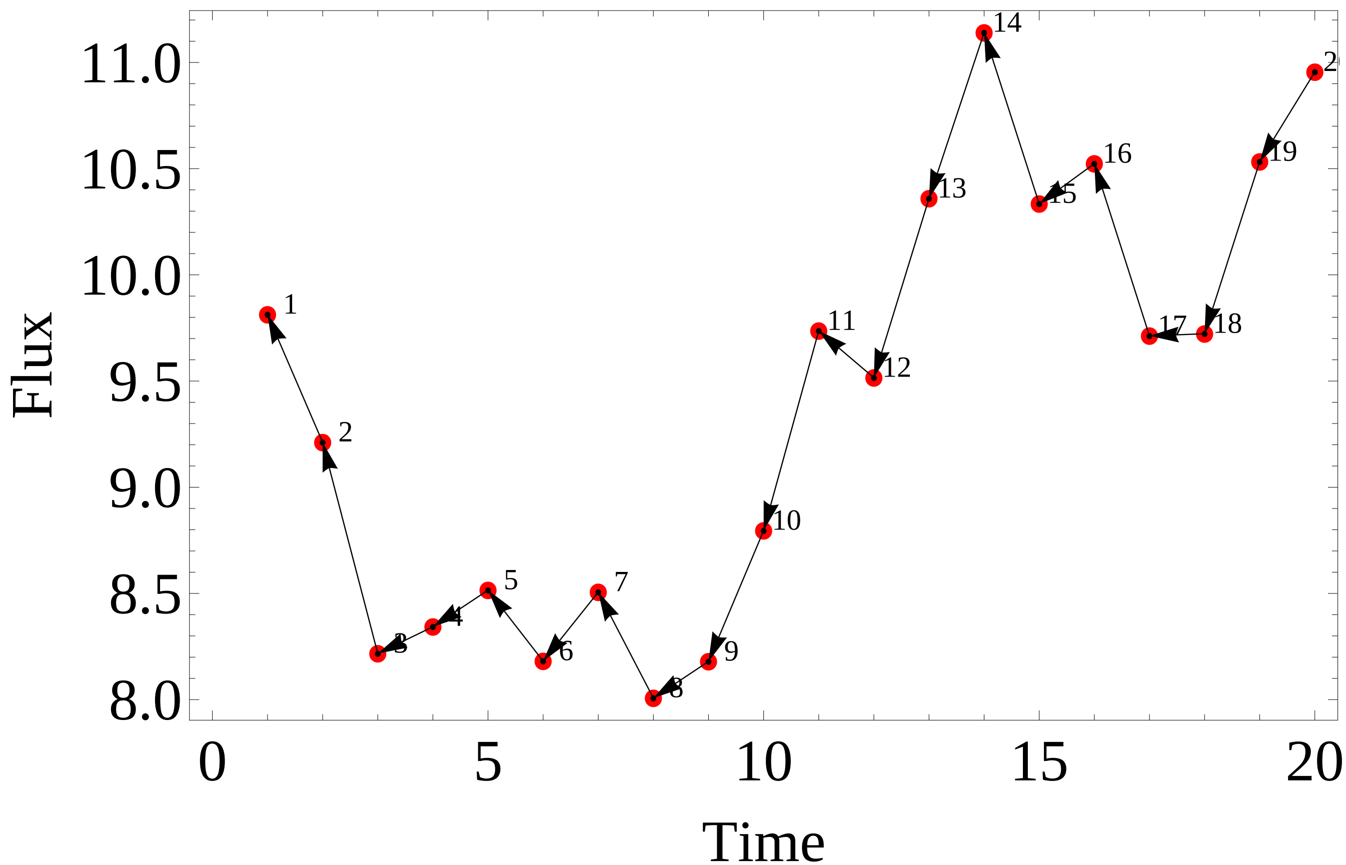


What is SF?

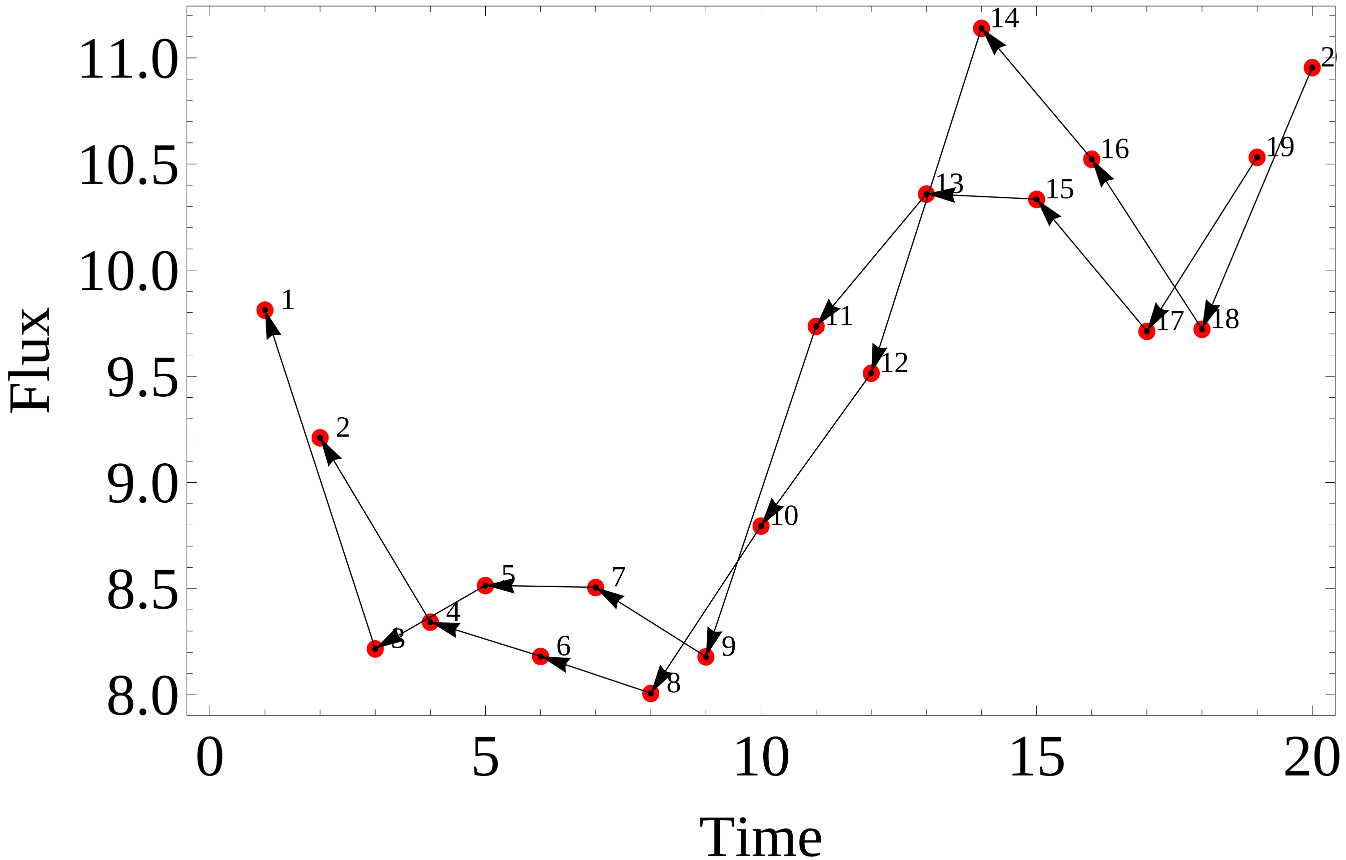
$$SF(\tau) = \left\langle (x(t+\tau) - x(t))^2 \right\rangle$$



$\tau = 1$

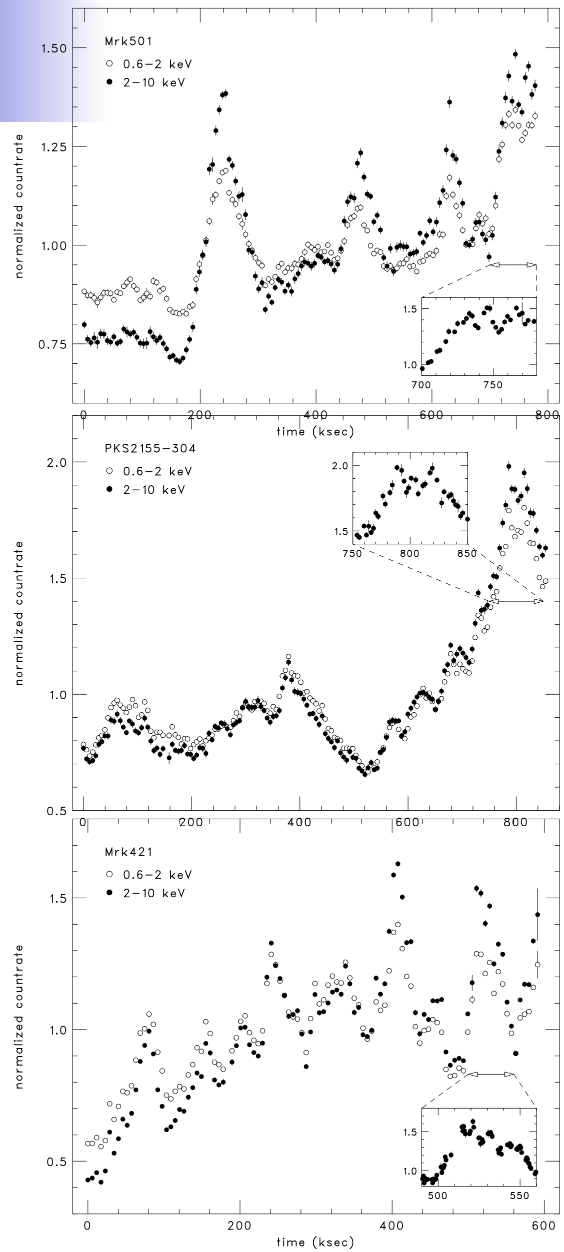
What is SF?

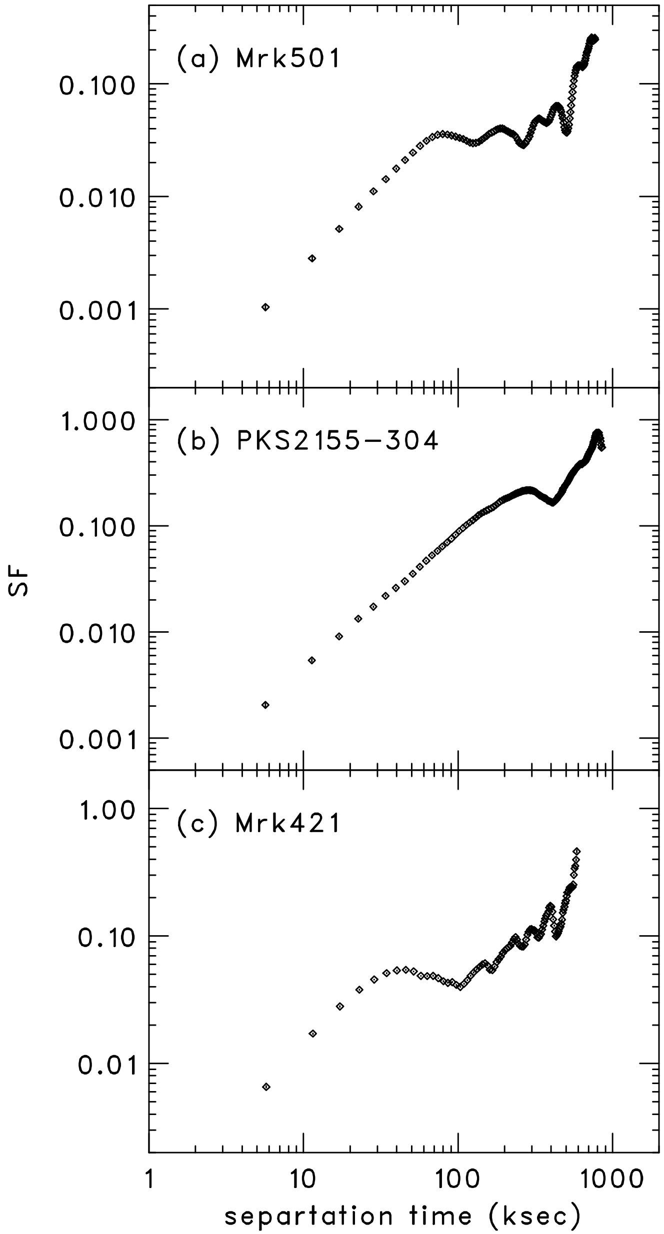
$$SF(\tau) = \left\langle \left(x(t+\tau) - x(t)\right)^2 \right\rangle$$



$\tau = 2$

SF and blazars





Tanihata et al. (2001), Apj, **563**, 569

SF and blazars

THE ASTROPHYSICAL JOURNAL, 563:569–581, 2001 December 20

VARIABILITY TIMESCALES OF TeV BLAZARS OBSERVED IN THE *ASCA* CONTINUOUS LONG-LOOK X-RAY MONITORING

CHIHARU TANIHATA,[1,2] C. MEGAN URRY,[3] TADAYUKI TAKAHASHI,[1,2] JUN KATAOKA,[4] STEFAN J. WAGNER,[5] GREG M. MADEJSKI,[6] MAKOTO TASHIRO,[7] AND MANABU KOUDA[1,2]

Received 2001 June 10; accepted 2001 August 17

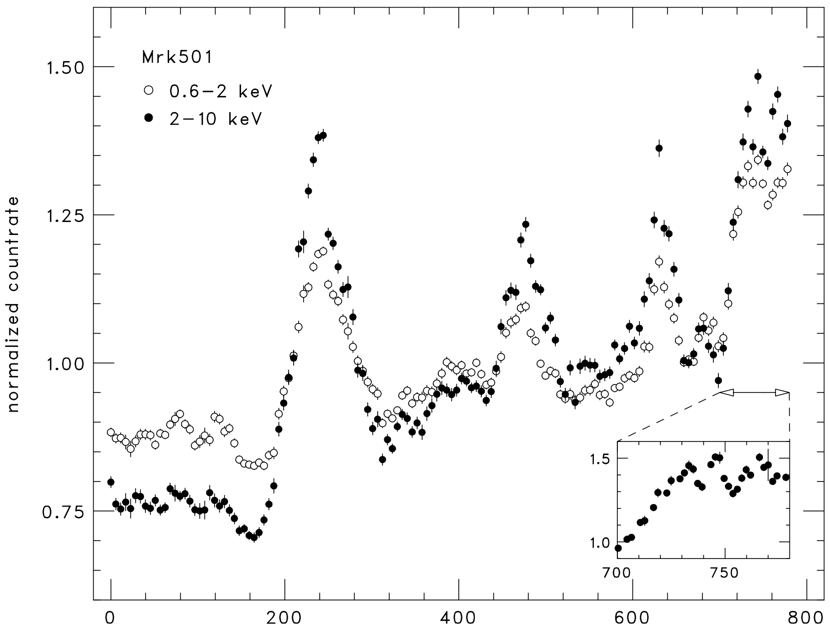
ABSTRACT

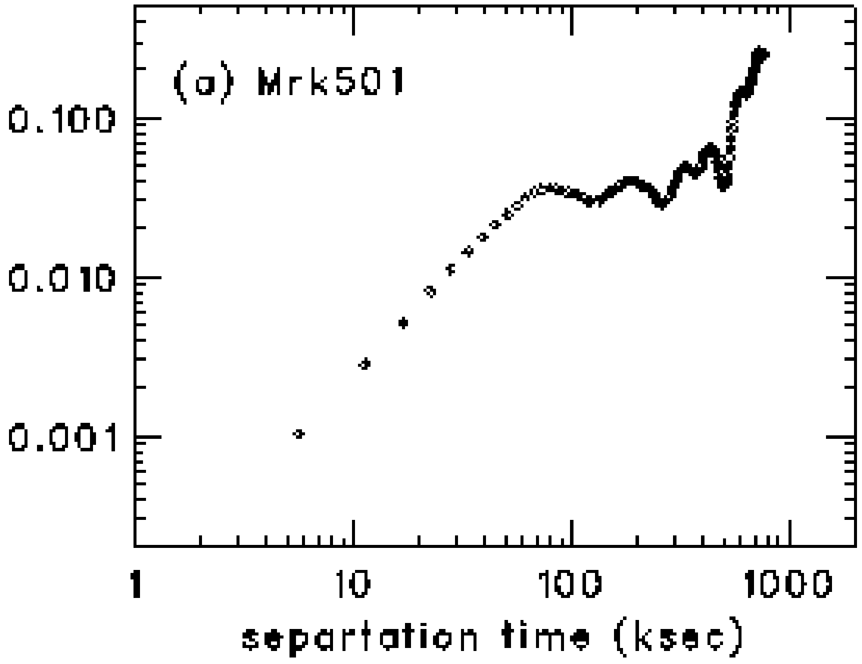
Three uninterrupted, long (lasting respectively 7, 10, and 10 days) *ASCA* observations of the well-studied TeV-bright blazars Mrk 421, Mrk 501, and PKS 2155−304 all show continuous strong X-ray flaring. Despite the relatively faint intensity states in two of the three sources, there was no identifiable quiescent period in any of the observations. Structure function analysis shows that all blazars have a characteristic timescale of ~1 day, comparable to the recurrence time and to the timescale of the strong-

Is this really the case?

SF simulations: Length

MRK 501





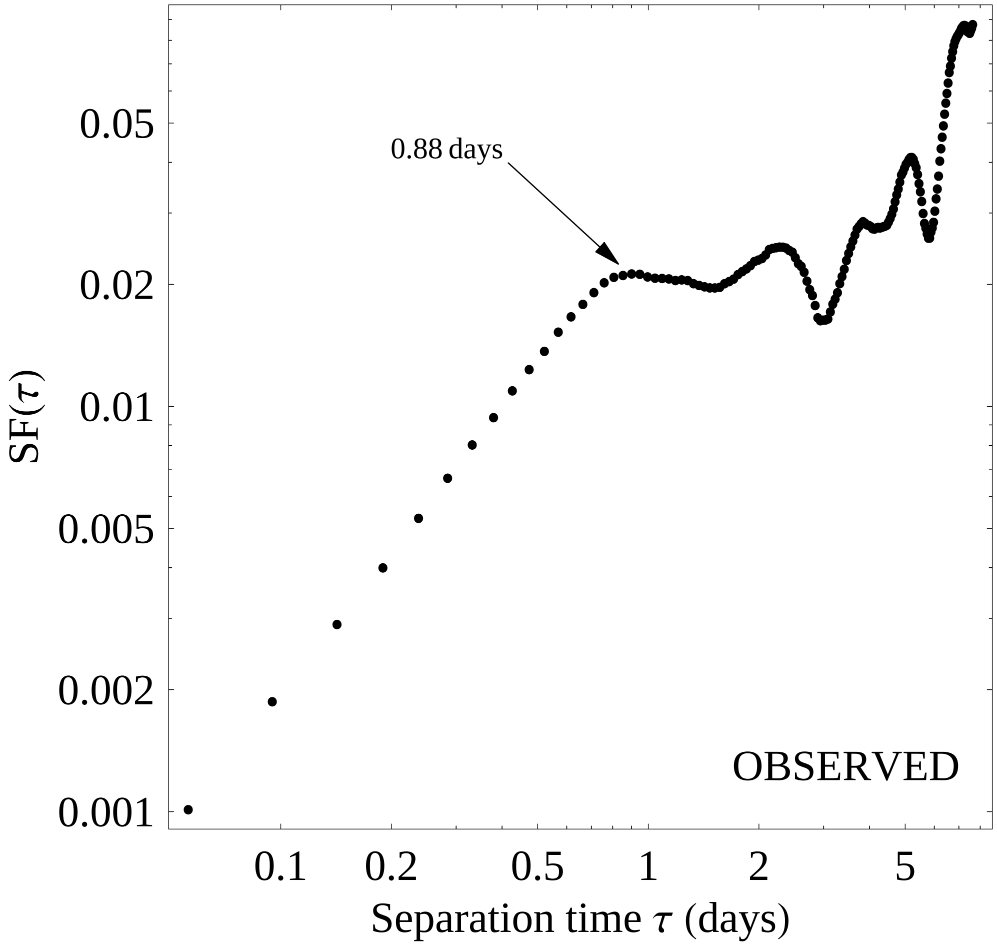
SF simulations: Length

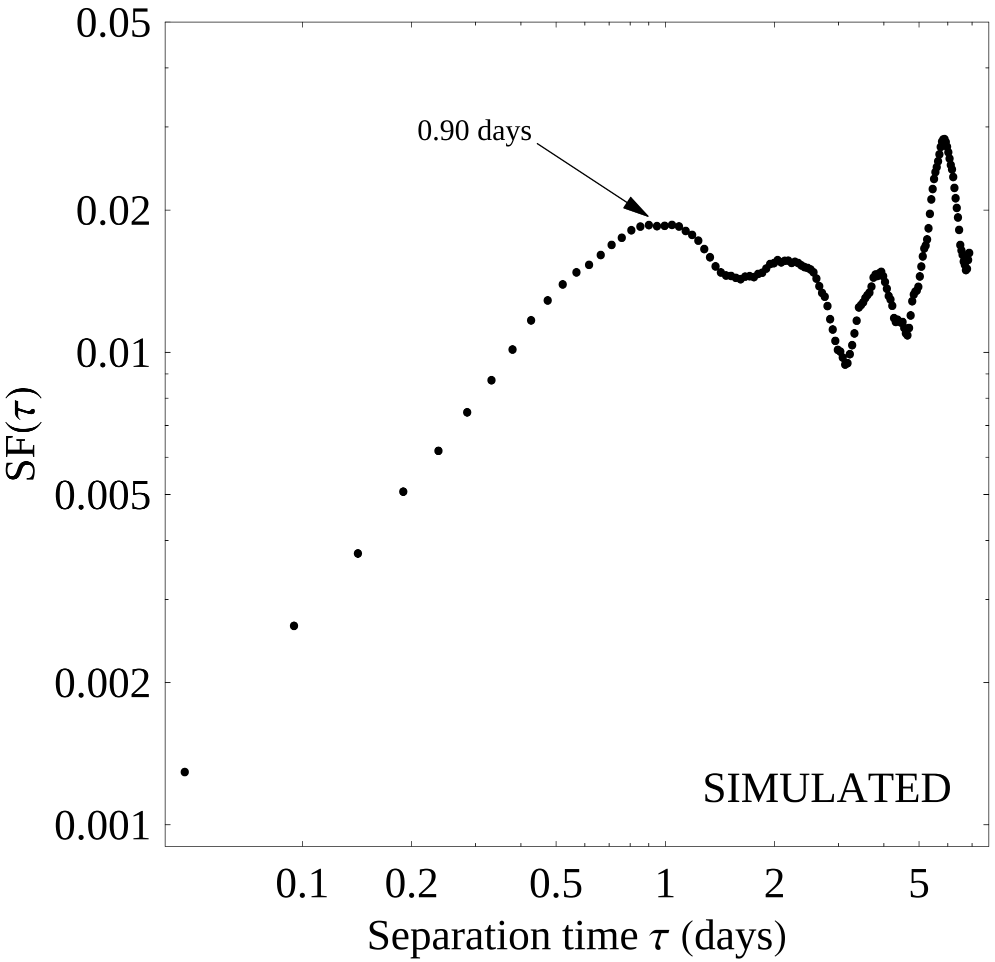
Construction of artificial light curves with NO characteristic time scales.

(Timmer J., Koening M., (1995), A&A, **339**, 41)

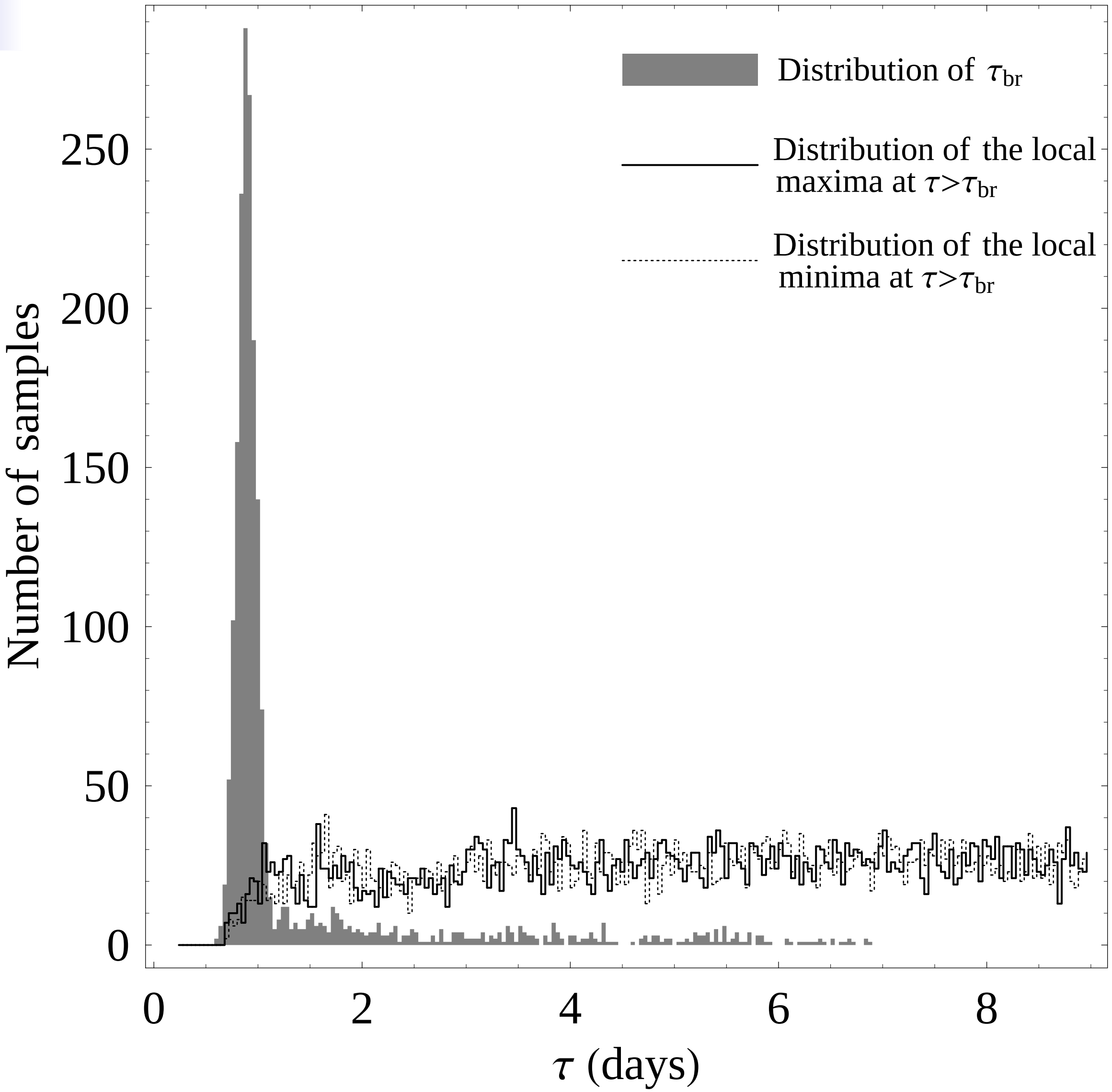
The data sets have the same statistical behaviour as the observations i.e. same PSD $\propto \nu^{-1.8}$.

SF simulations: Length





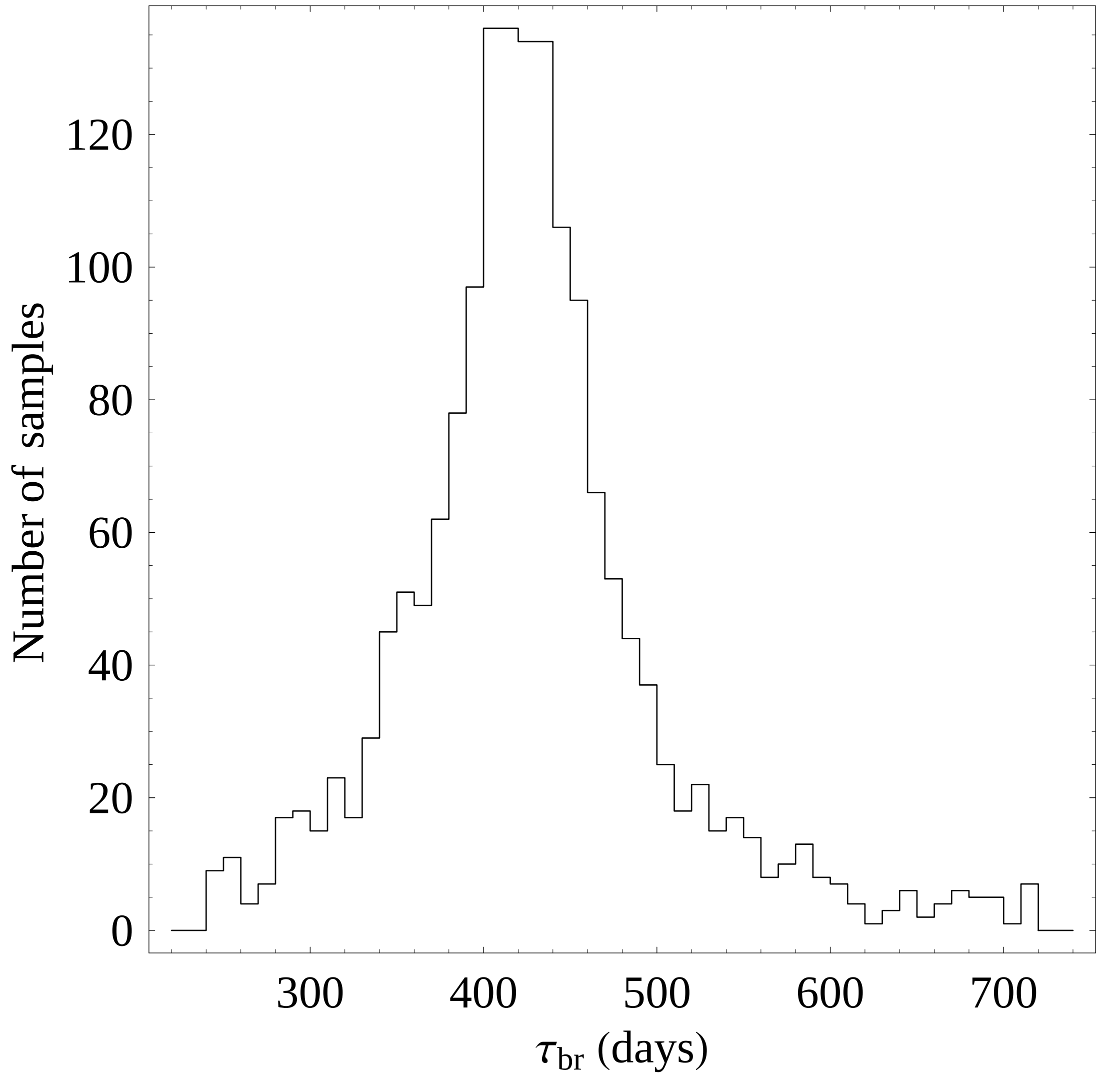
SF simulations: Length



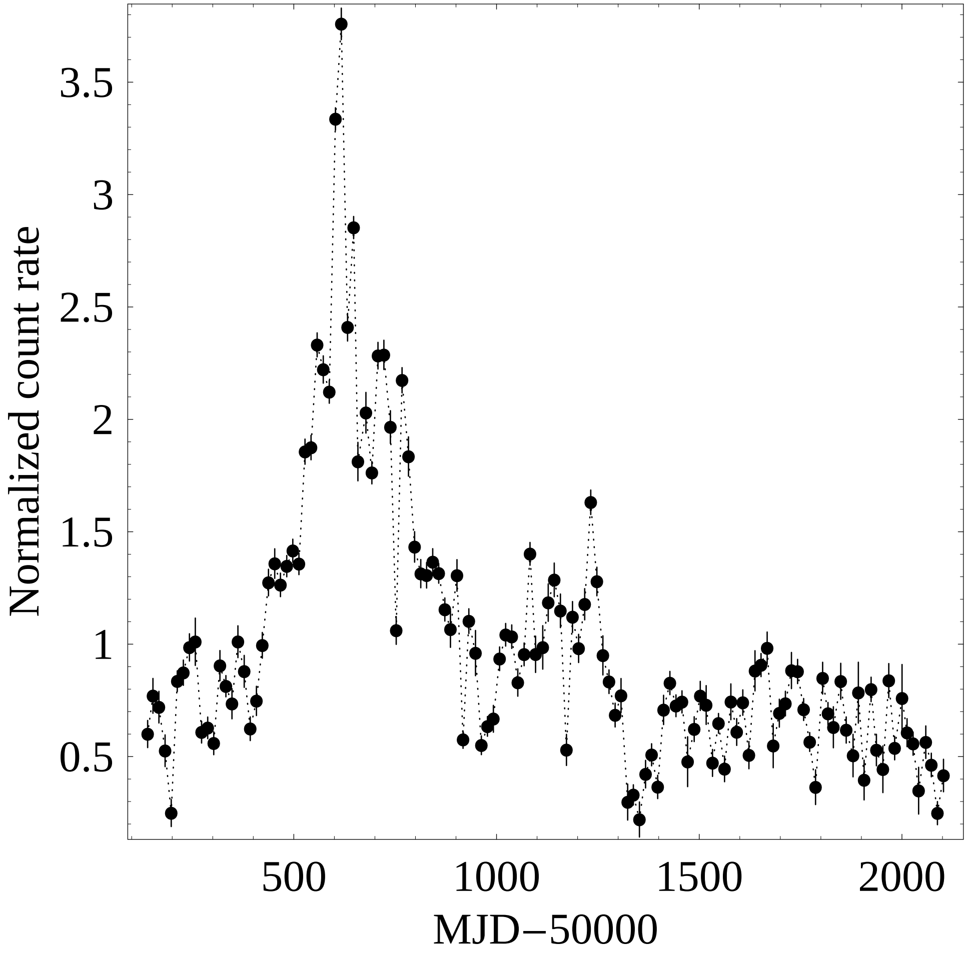
Emmanoulopoulos et al. (2010), MNRAS., **404**,931–946

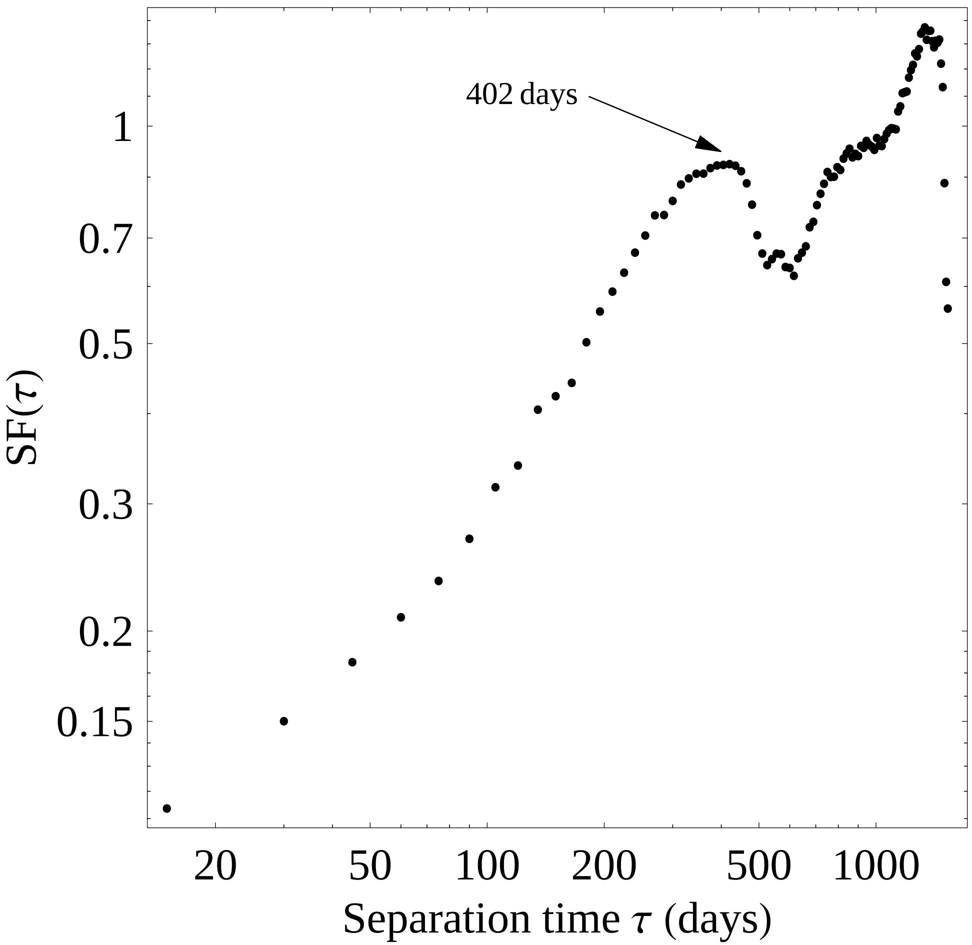
SF simulations: Length

What about longer data sets?



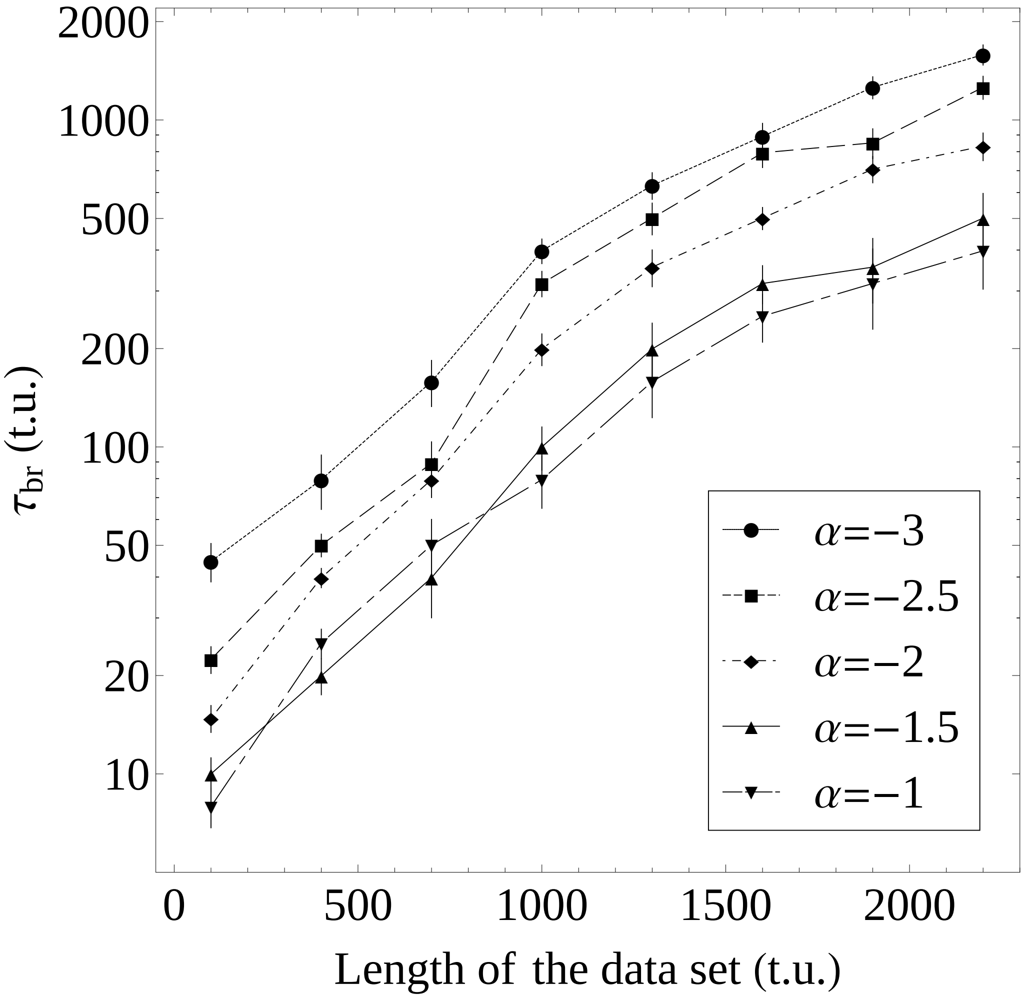
SF simulations: Length





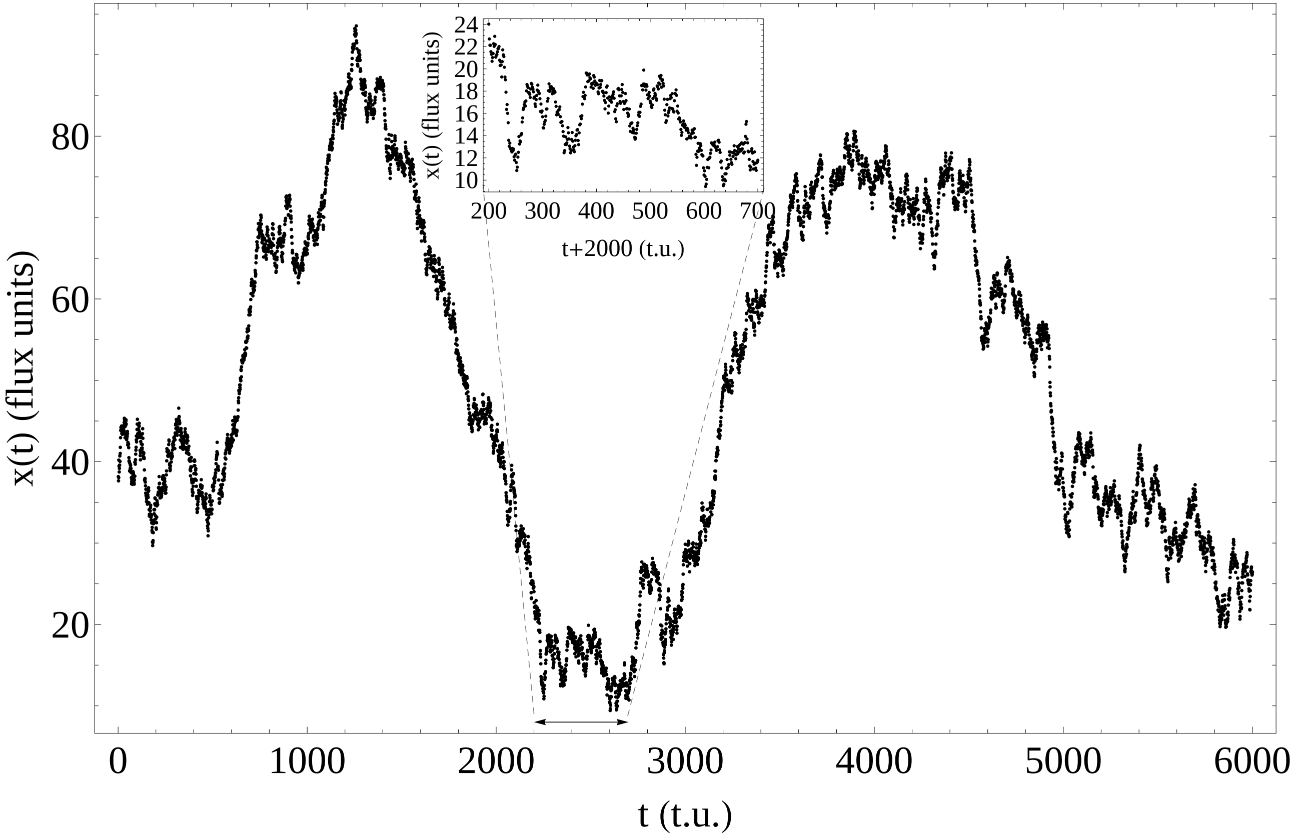
Mrk 501: ASM data set

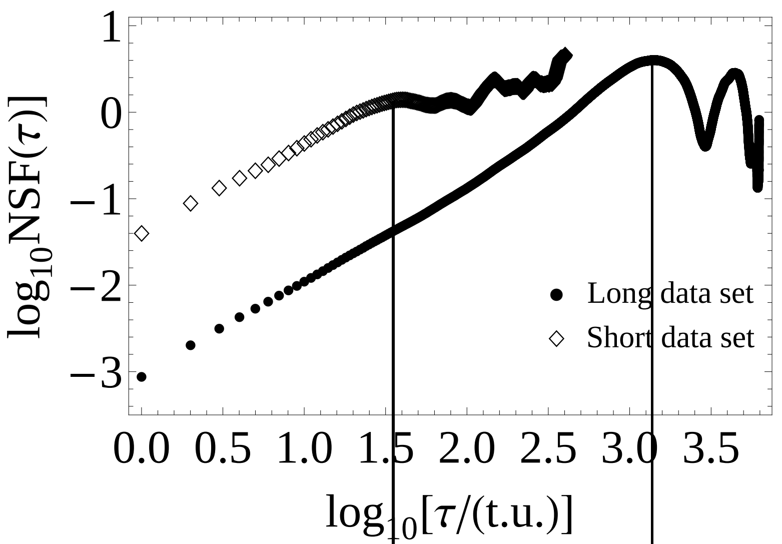
SF simulations: Length



Emmanoulopoulos et al. (2010), MNRAS., **404**,931–946

SF simulations: Length



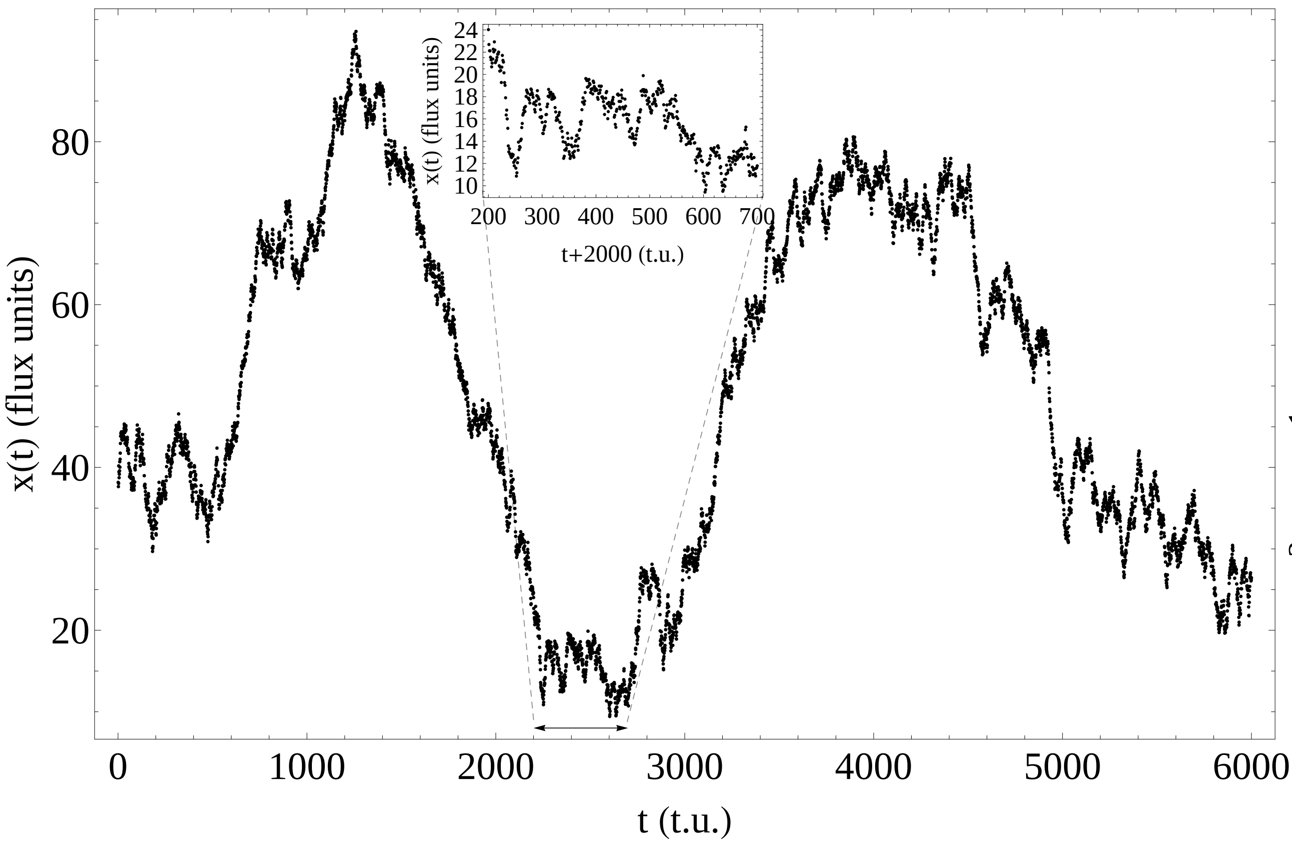


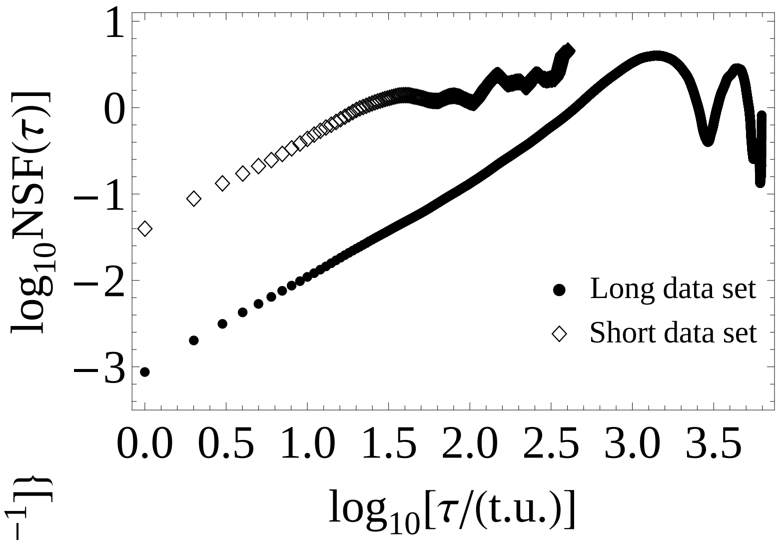
$R_1 \leq 10^{18}$ cm $R_2 \leq 10^{21}$ cm

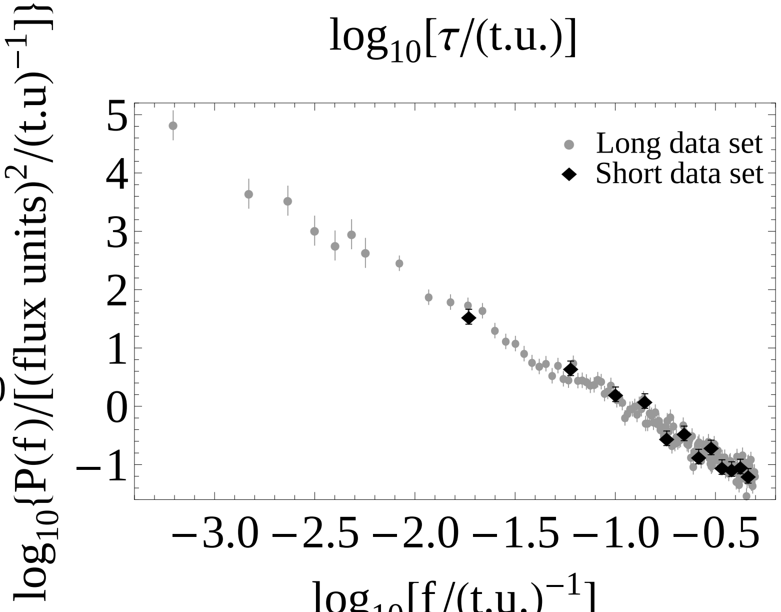
Misinterpretation:

Different jet-properties

SF simulations: Length

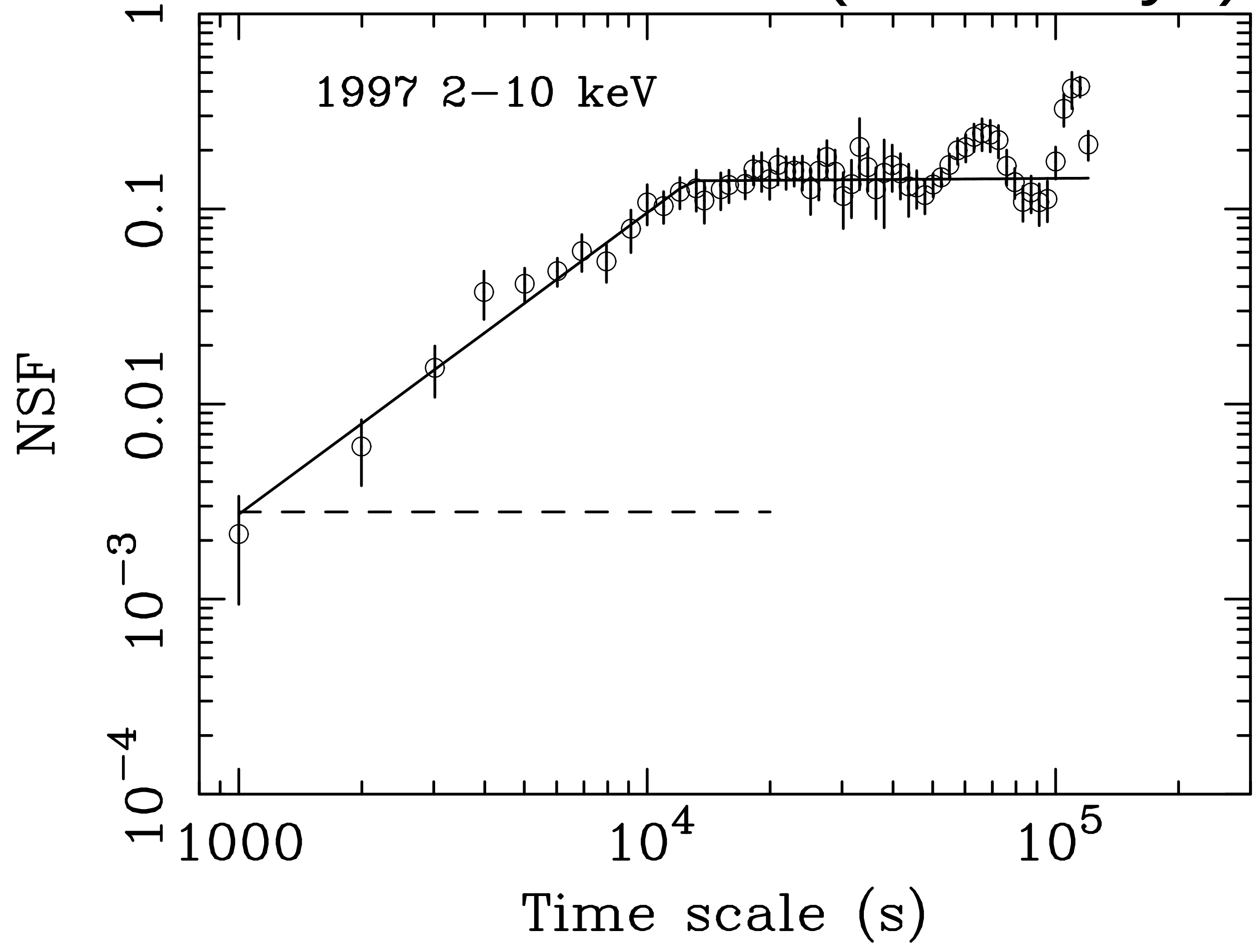






Fitting procedures

PKS 2155-304 (~ 1.3 days)



Zhang Y. H. et al. (2002), **572**:762-785

Fitting procedures

$$SF_{\mathrm{M}}(\tau; C, \tau_{\max}, \beta_1, \beta_2) = \begin{cases} C\left(\frac{\tau}{\tau_{\max}}\right)^{\beta_1} & \tau \leq \tau_{\max} \\ C\left(\frac{\tau}{\tau_{\max}}\right)^{\beta_2} & \tau > \tau_{\max} \end{cases}$$

Under the assumptions of Gaussianity and Independency

$$\chi^2 = \sum_{i=1}^{N} \left[\frac{SF(\tau_i) - SF_{\mathrm{M}}(\tau_i; C, \tau_{\max}, \beta_1, \beta_2)}{\sigma_i}\right]^2$$

and we minimize it...

Fitting procedures

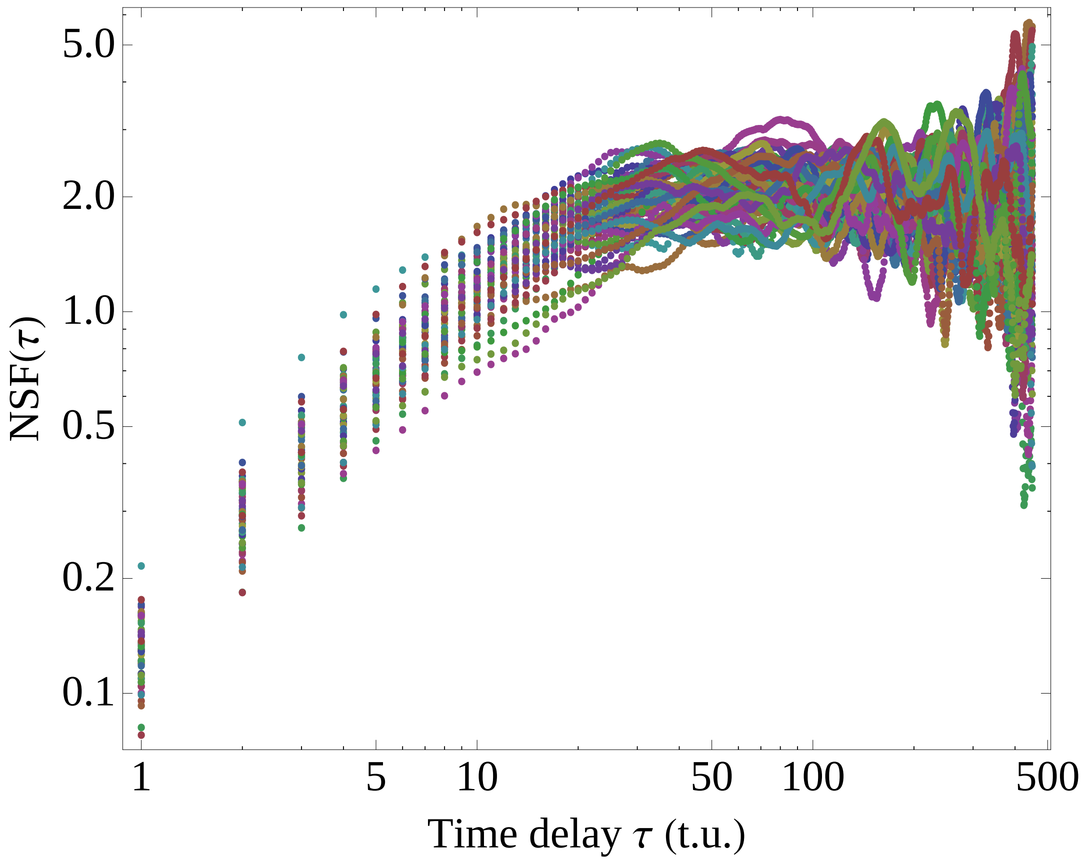
2000 light curves, 500 t.u. long, PSD index -2.

- Estimation of SF slope: β, $\delta\beta$

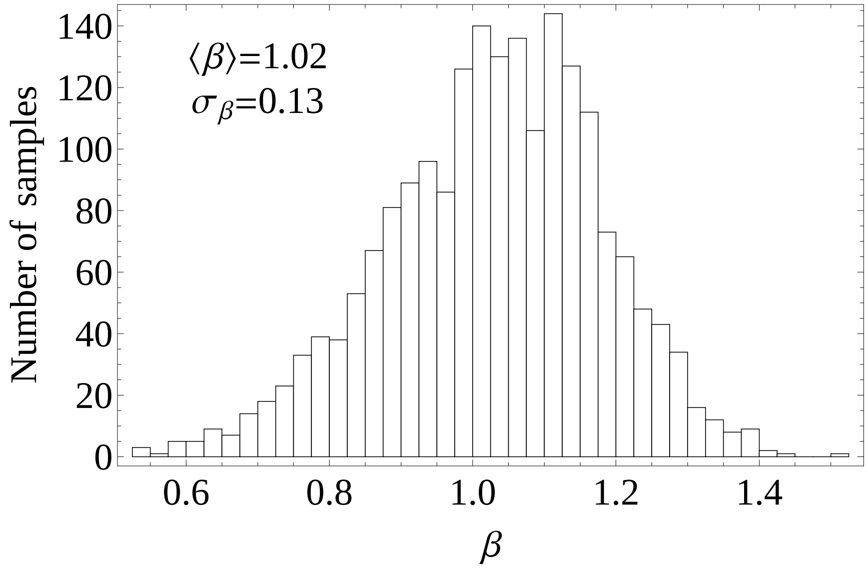
Fitting procedures

2000 light curves, 500 t.u. long, PSD index -2.

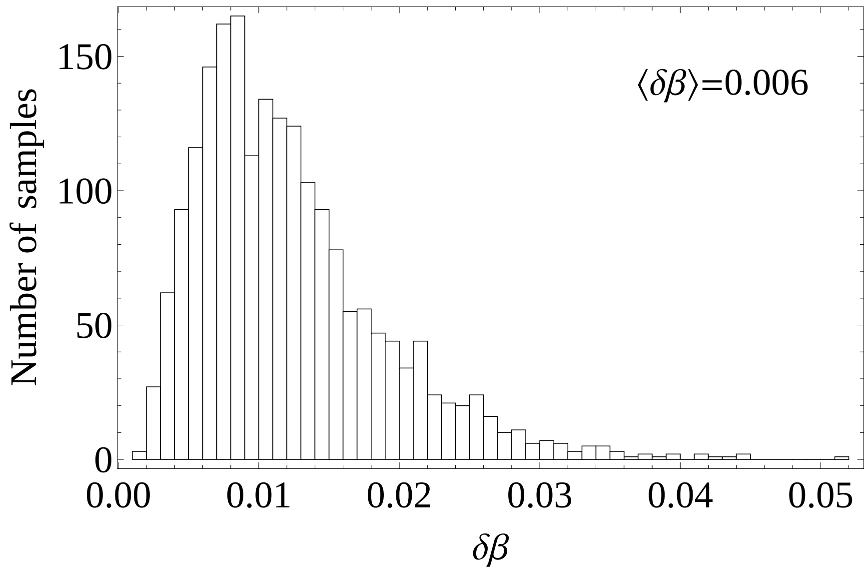
- Estimation of SF slope: β, $\delta\beta$



Fitting procedures

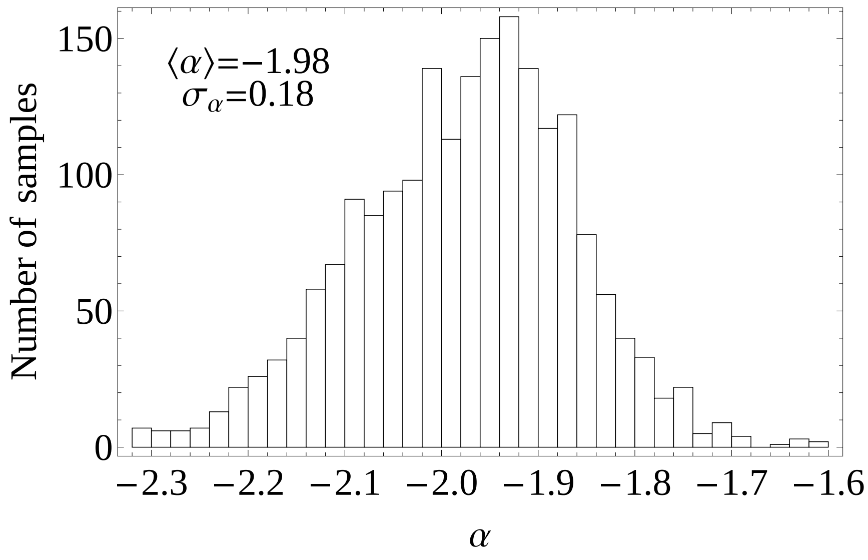


Distribution of fitted SF-slopes.

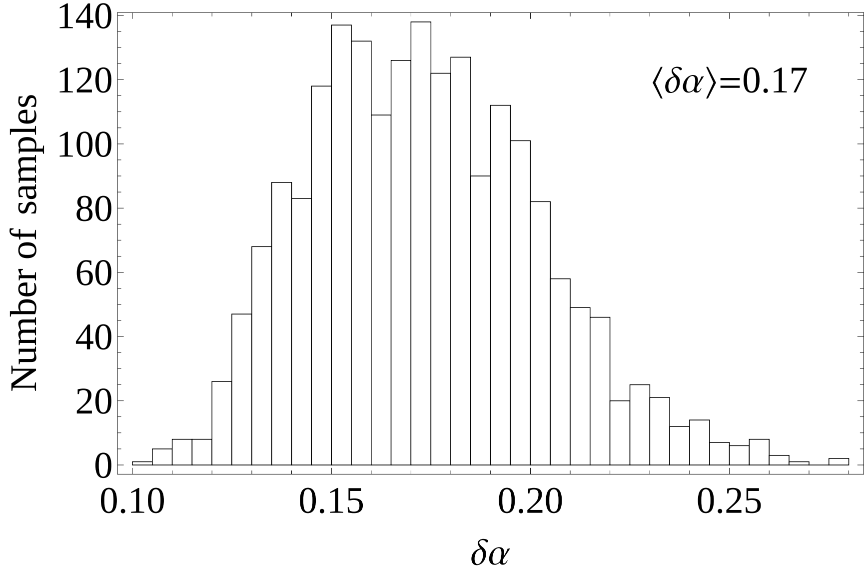


Distribution of derived errors on individual SF-slopes.

Fitting procedures



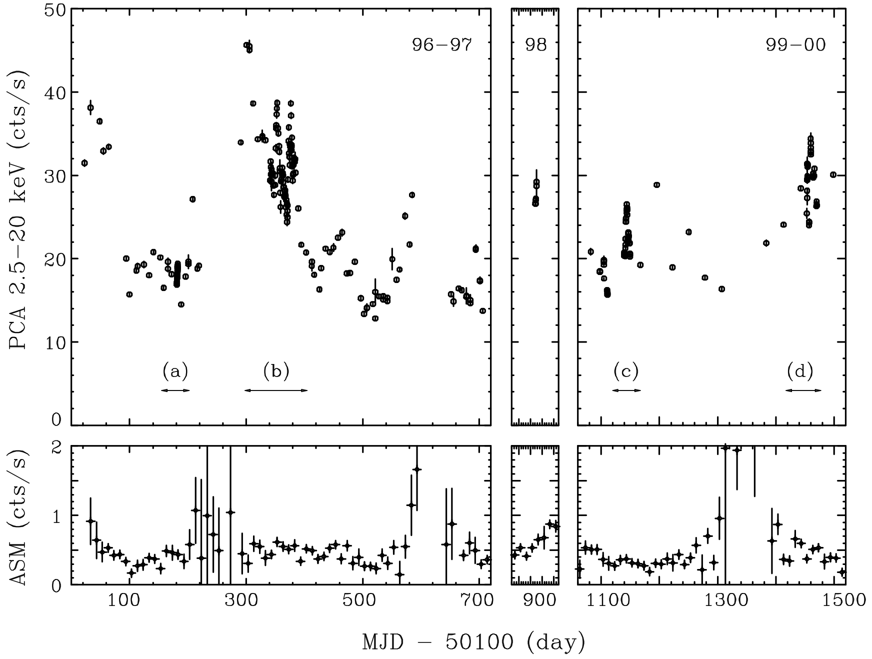
Distribution of fitted periodogram-slopes.

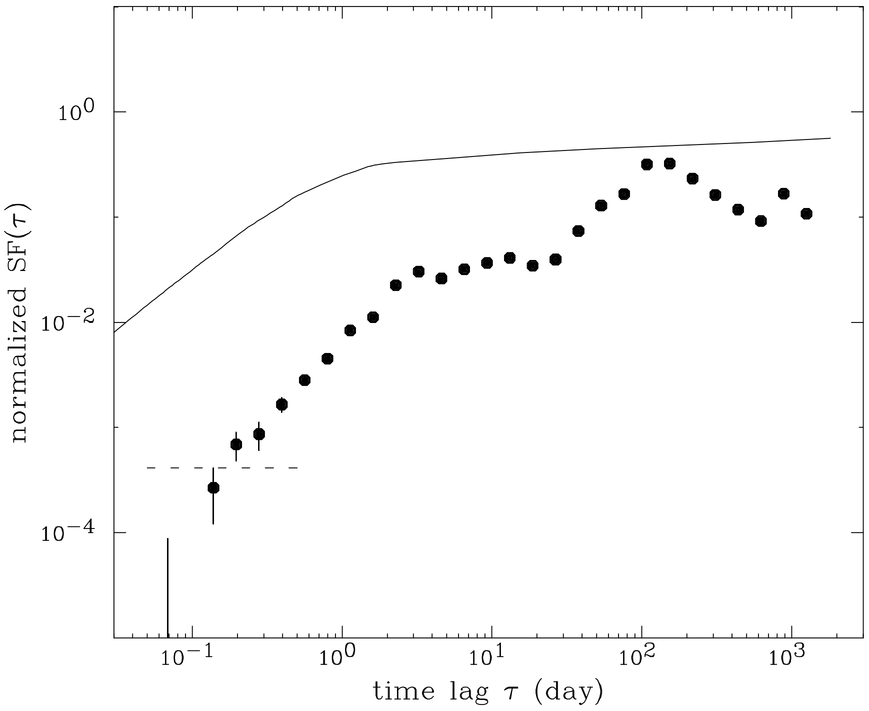


Distribution of derived errors on individual periodogram-slopes.

Gappy data sets

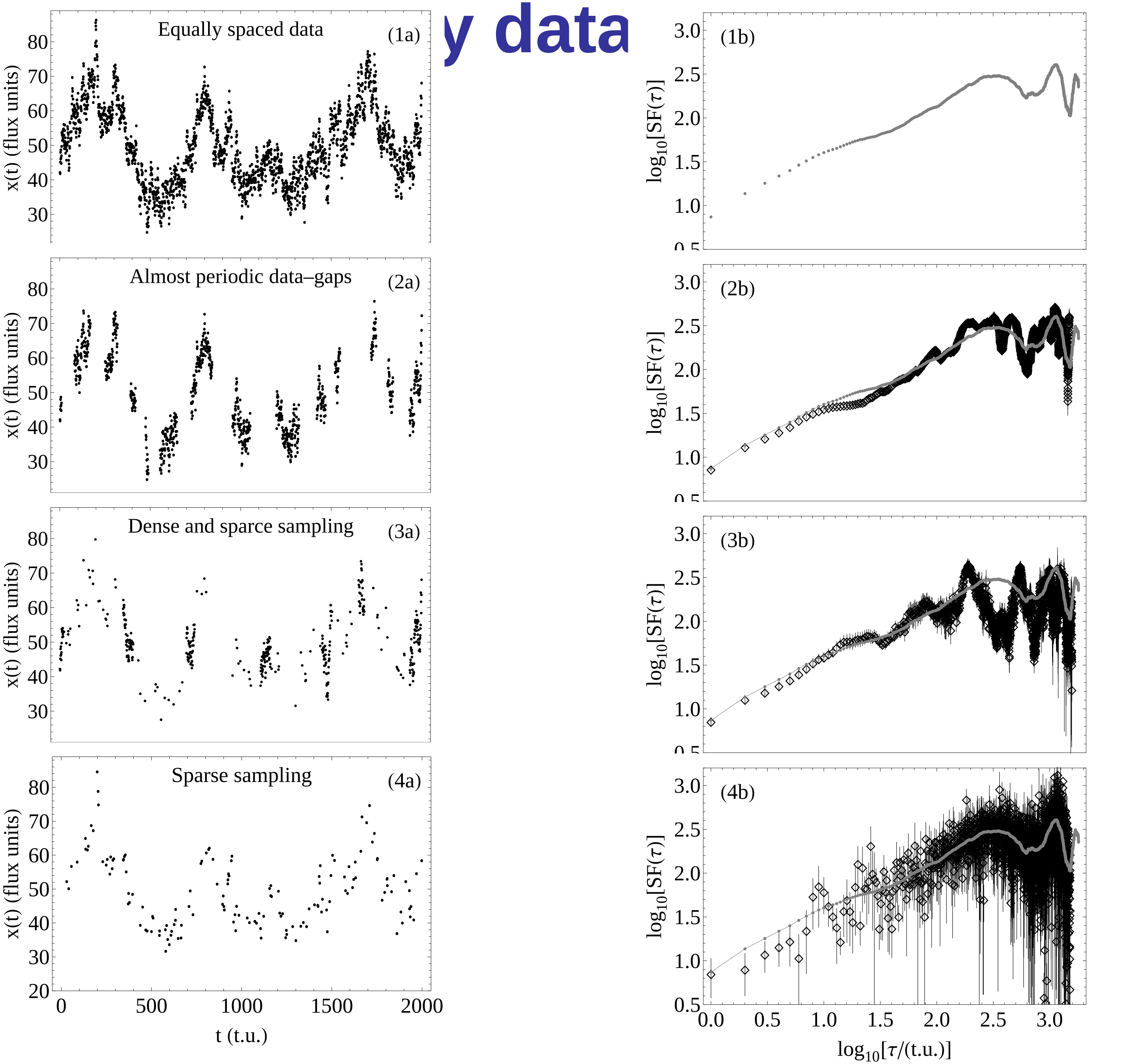
3C 273





Kataoka et al. (2000), MNRAS,**336**, 932–944

y data



Equally spaced data
(1a)
Almost periodic data–gaps
(2a)
Dense and sparce sampling
(3a)
Sparse sampling
(4a)
x(t) (flux units)
t (t.u.)
0
500
1000
1500
2000
20
30
40
50
60
70
80
(1b)
(2b)
(3b)
(4b)
$\log_{10}[SF(\tau)]$
$\log_{10}[\tau/(t.u.)]$
0.0
0.5
1.0
1.5
2.0
2.5
3.0

Gappy data sets

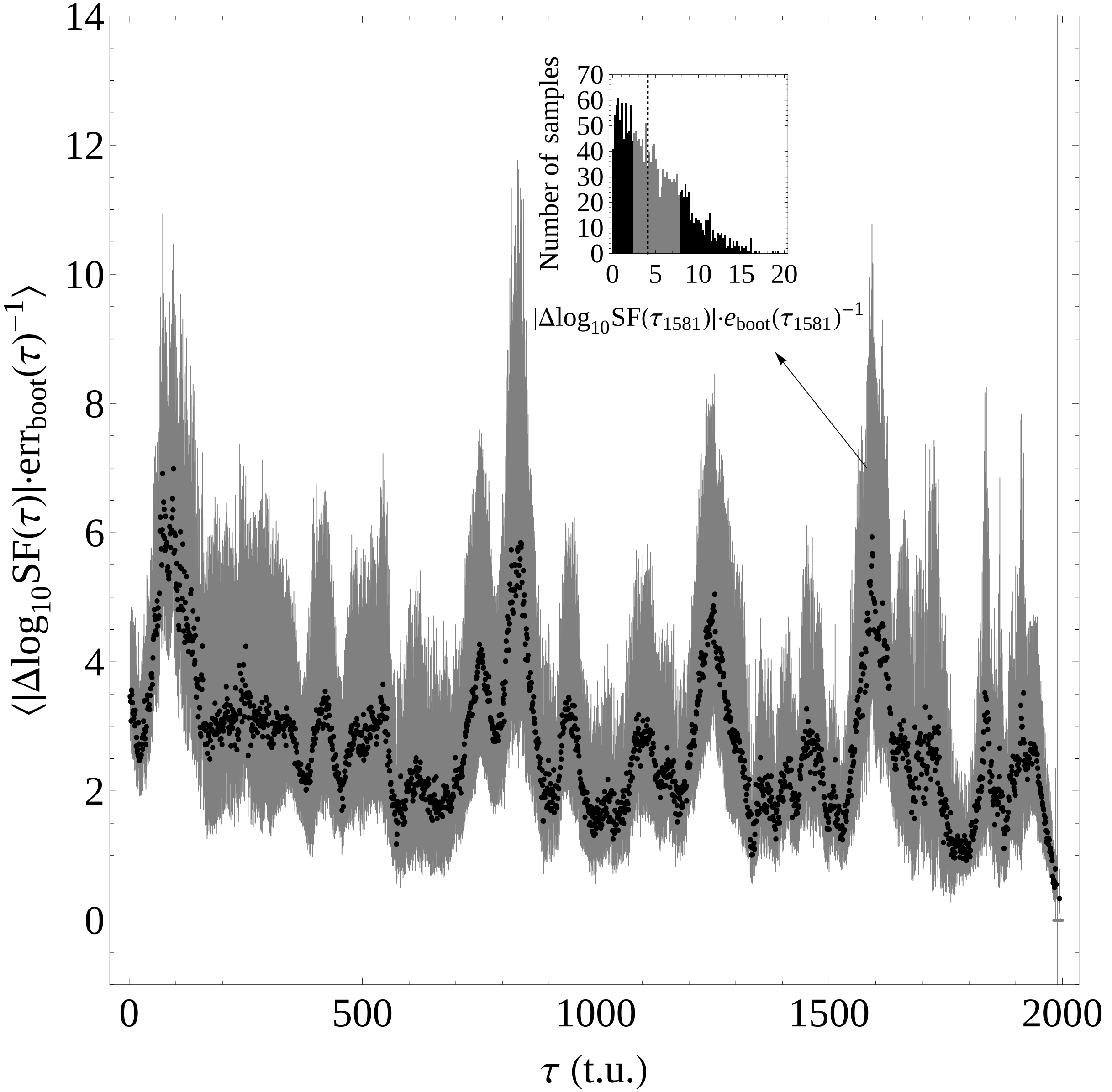
Bootstrap method for a given gappy-pattern

e.g. Czerny et al. (2003) MNRAS, **342**, 1222-1240

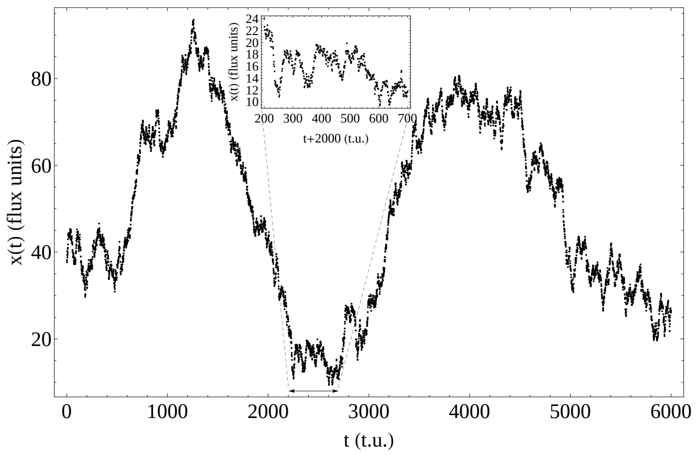
For each SF bin i:

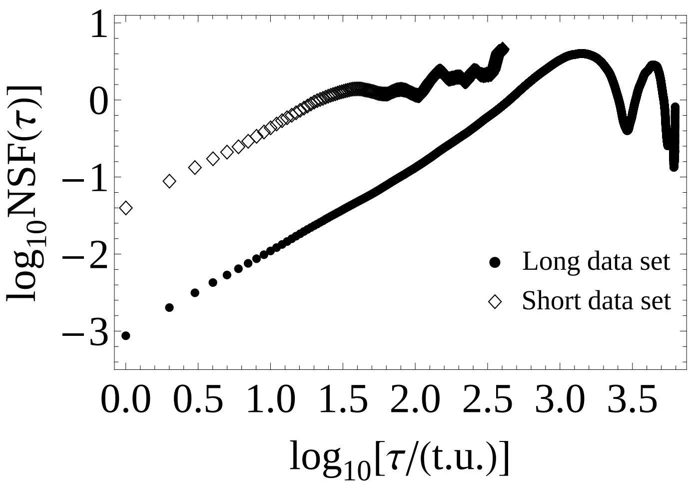
$$\left\langle \frac{|SF^i_{\mathrm{gappy,btstrp}} - SF^i_{\mathrm{continuous}}|}{err_{\mathrm{bootstrap^i}}} \right\rangle$$

Gappy data sets

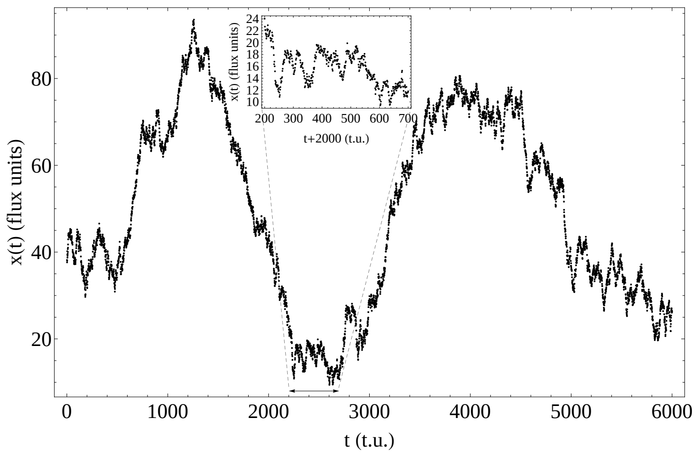


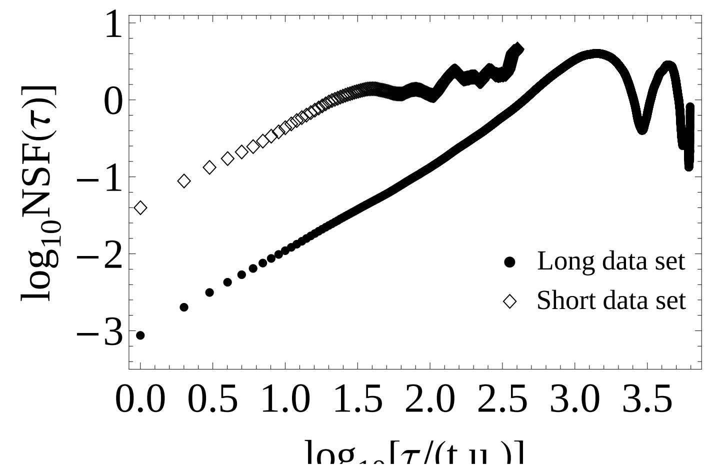
Visual Conclusions

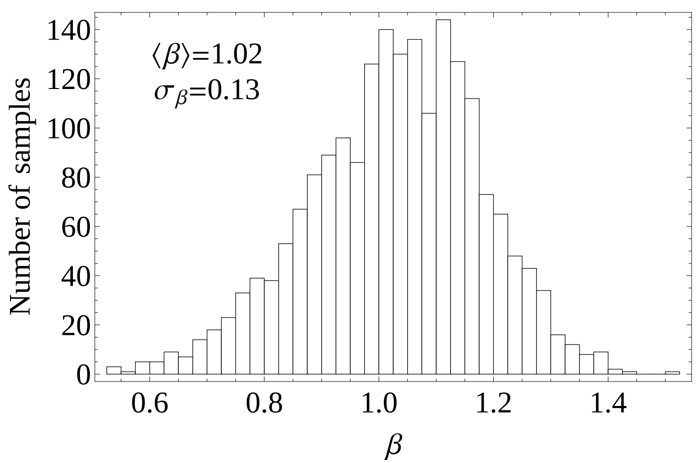


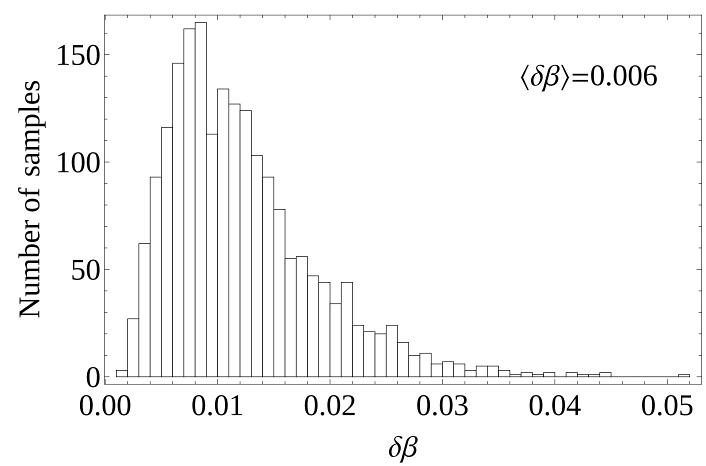


Visual Conclusions

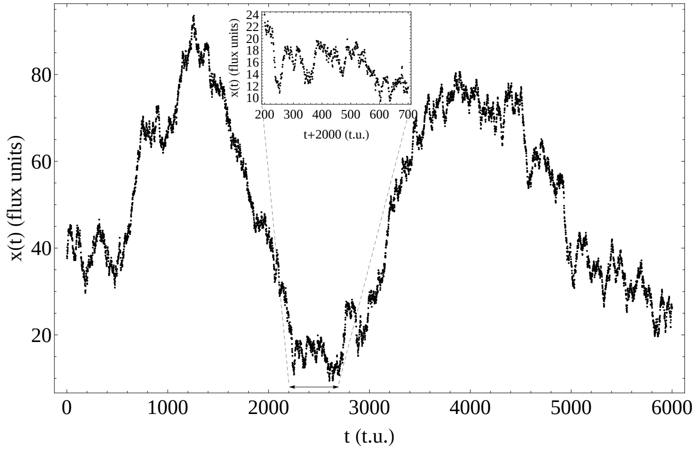


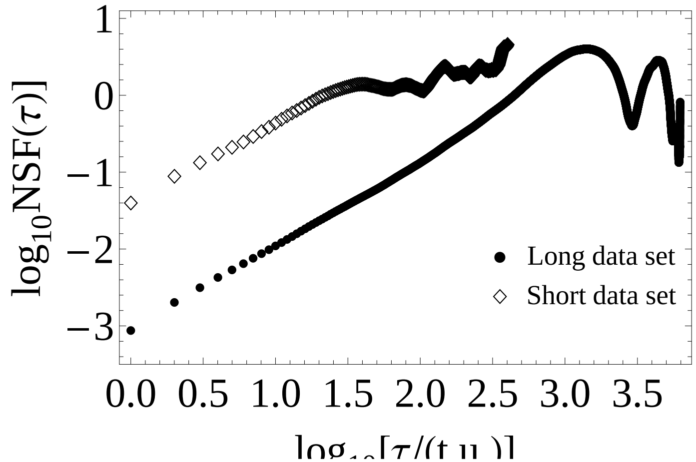


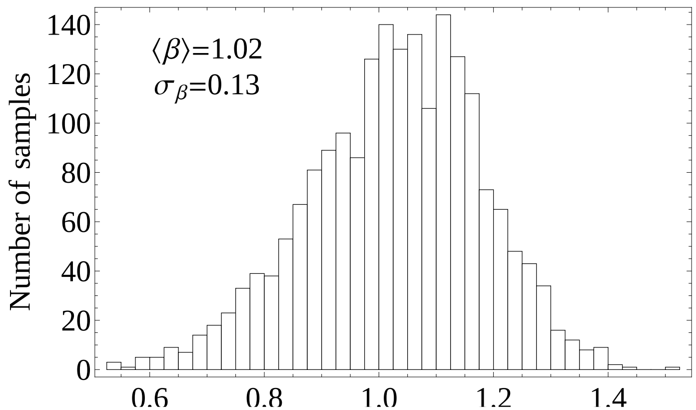


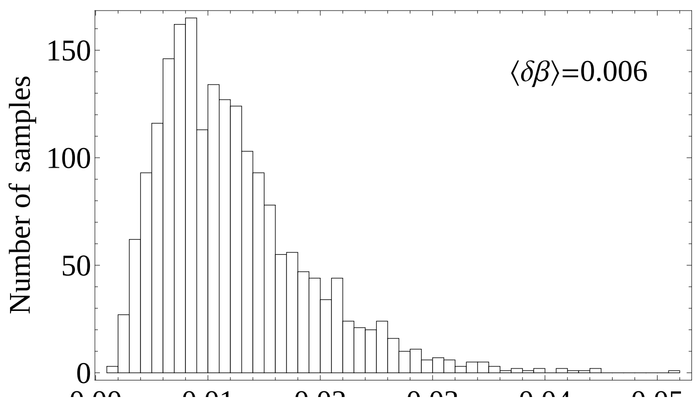


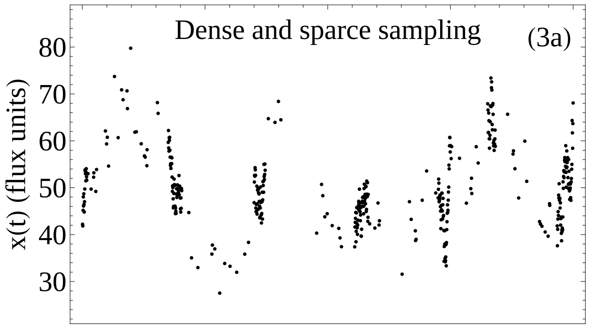
Visual Conclusions

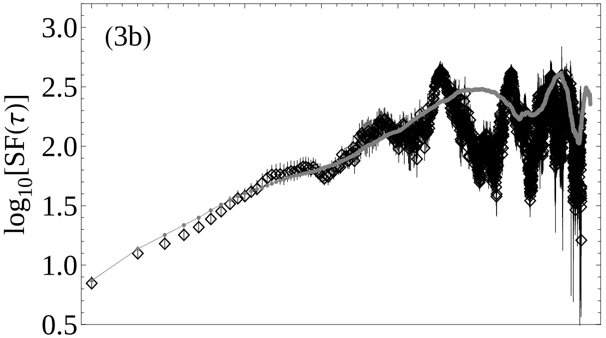












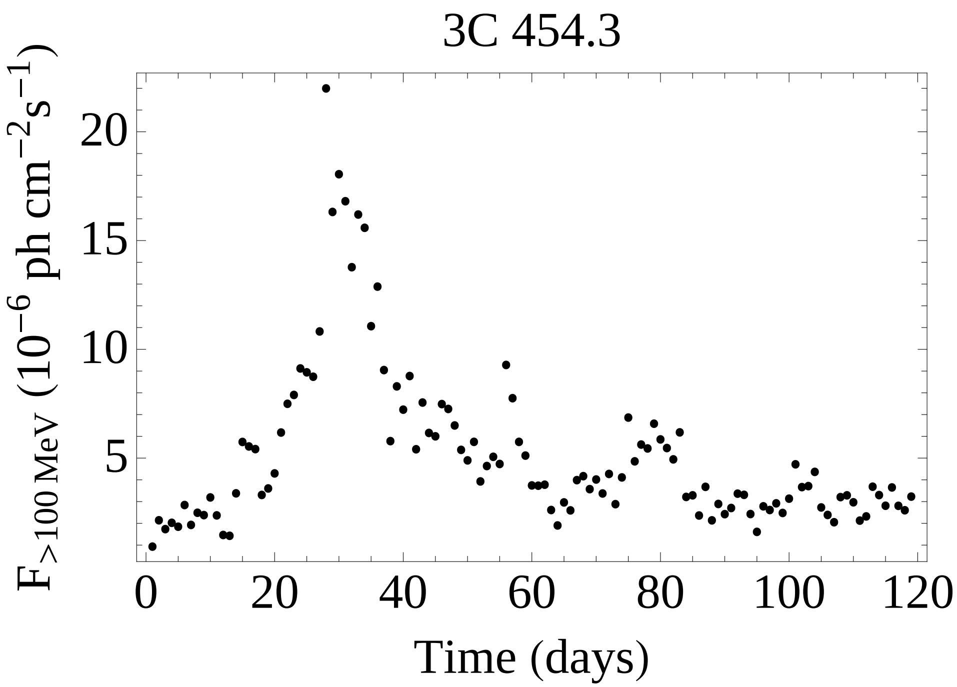
Thank you!

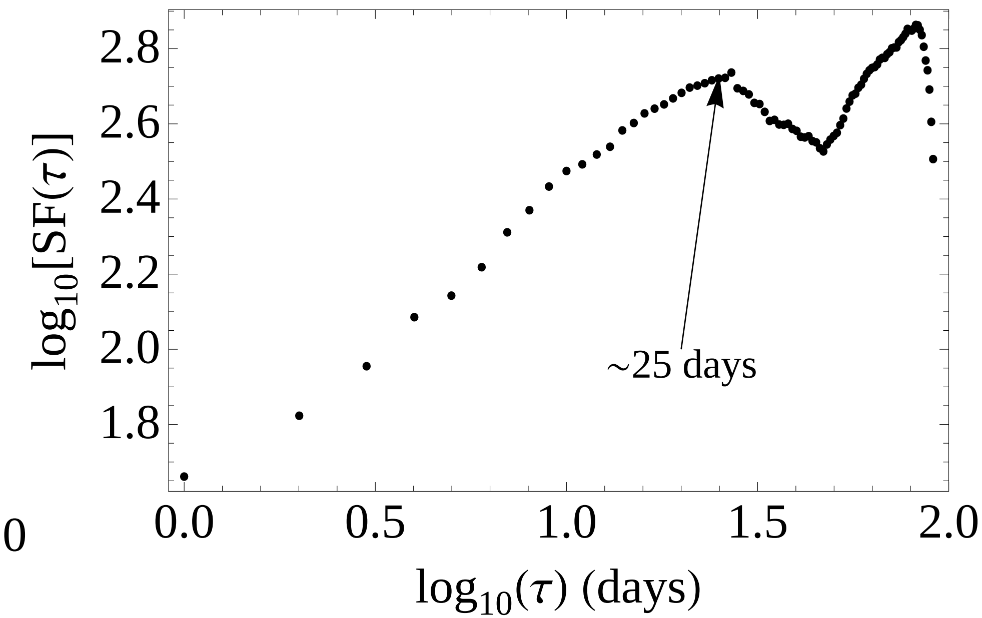
Additional Material

- FERMI data
- PSD of triangular-shots
- SF and PSD relation
- Generilized Gaussian distribution
- Statistically independent points

FERMI data

An example for the FERMI data



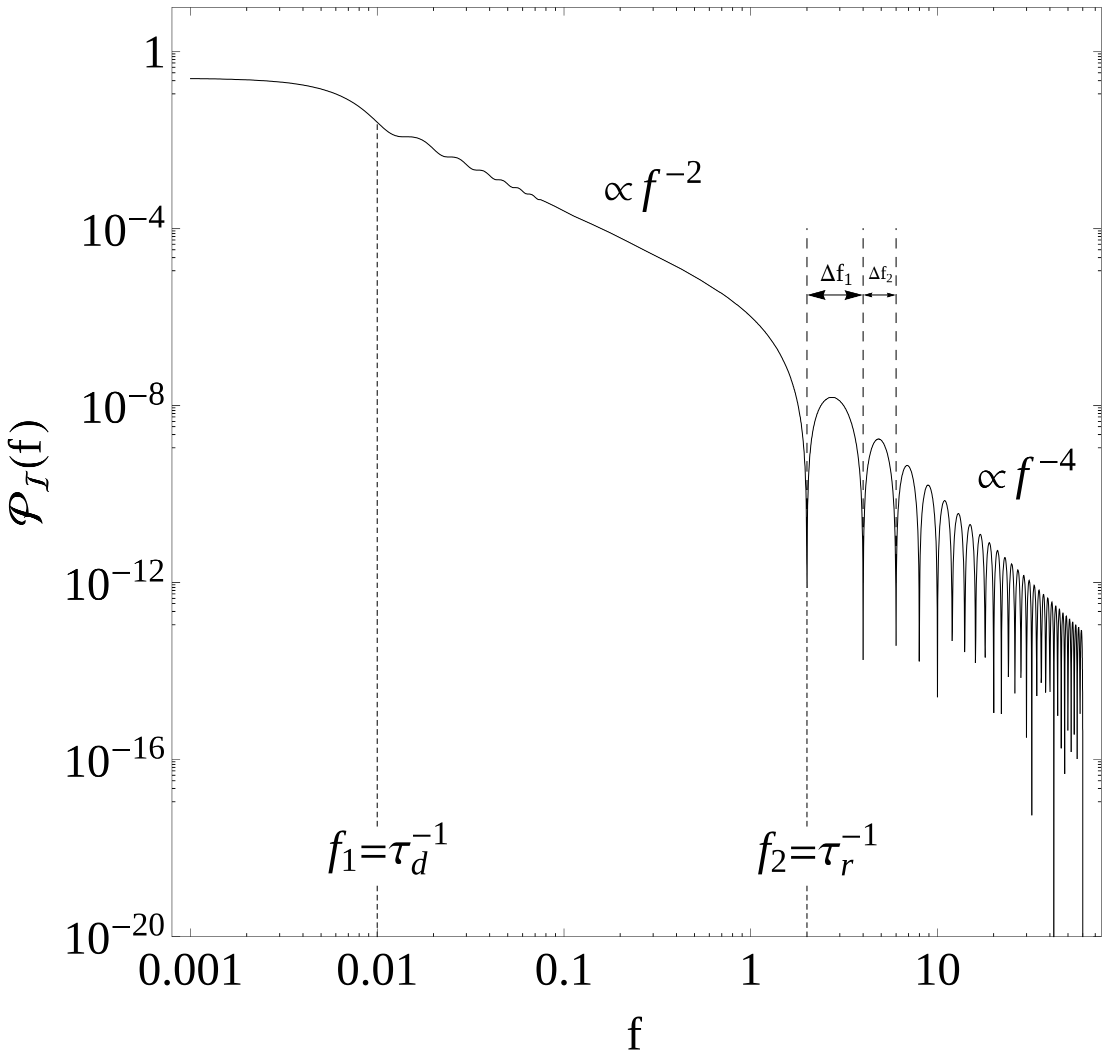


Ackermann et al. arXiv:1007.0483v2

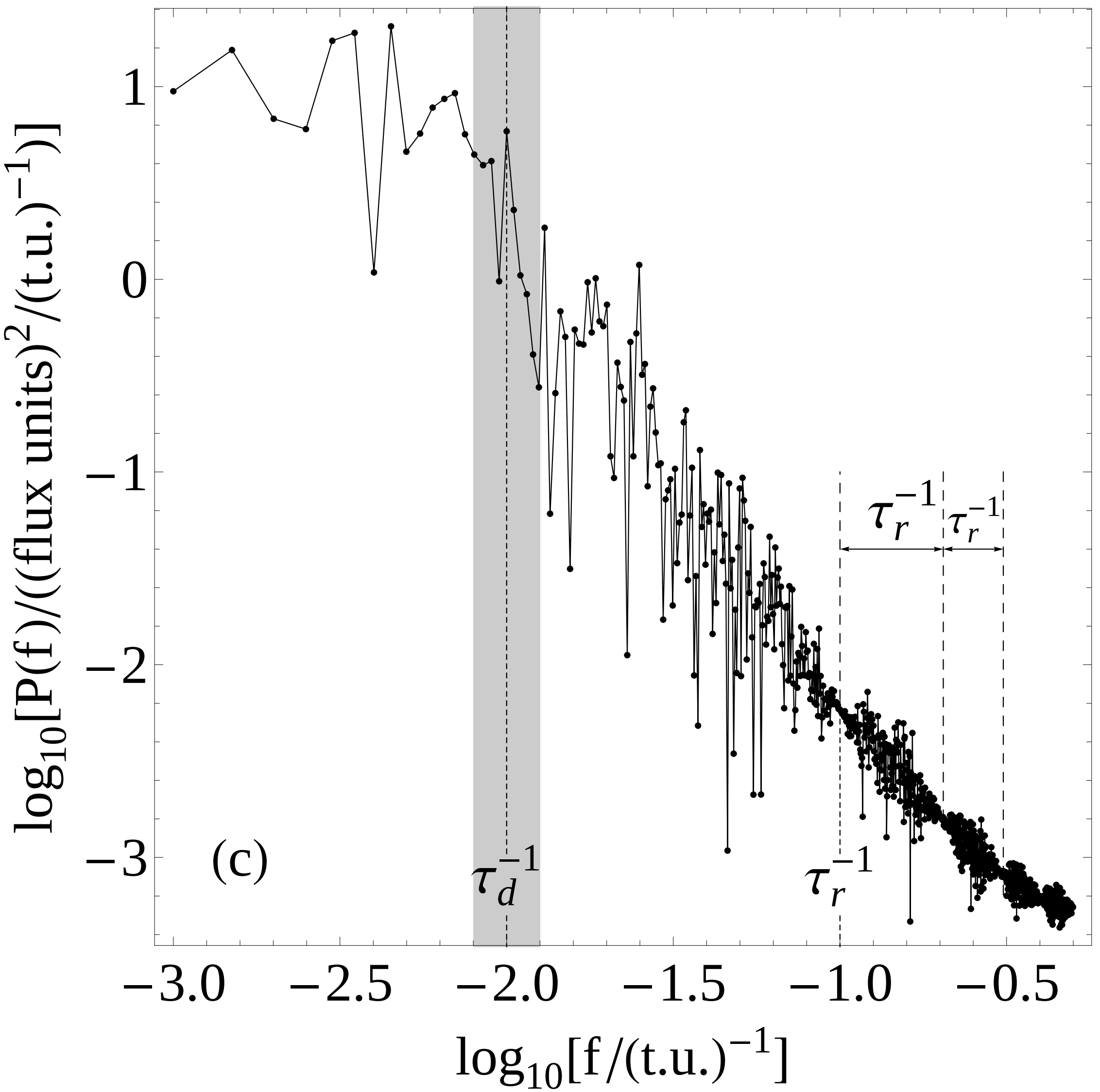
PSD of triangular-shots

$$
\begin{aligned}
\mathcal{P}_{\mathcal{I}}(f) \;&=\; \frac{I_0^2}{8\pi^4 t_\mathrm{d}^2 t_\mathrm{r}^2 f^4}\{t_\mathrm{d}^2 + t_\mathrm{d} t_\mathrm{r} + t_\mathrm{r}^2 - \\
&\quad (t_\mathrm{d} + t_\mathrm{r})\left[t_\mathrm{r}\cos(2\pi t_\mathrm{d} f) + t_\mathrm{d}\cos(2\pi t_\mathrm{r} f)\right] + \\
&\quad t_\mathrm{d} t_\mathrm{r}\cos(2\pi(t_\mathrm{r} + t_\mathrm{d})f)\} \;\; \text{for } t_\mathrm{r} \neq 0 \;\&\; t_\mathrm{d} \neq 0
\end{aligned}
$$

PSD of triangular-shots



PSD of triangular-shots



SF and PSD relation

$$SF(\tau) = -2^{\lambda}\kappa\pi^{\lambda-1}\Gamma(1-\lambda)\sin\left(\frac{\lambda\pi}{2}\right)\tau^{\lambda-1}$$

1. stationarity, also called “weakly stationarity”i.e. mean value and autocovariance function independent of time translations.
2. zero mean data set.
3. The frequency range f should vary from 0 to ∞.
4. The PSD should be given from a power-law form with index $1 < \lambda < 3$.

Generilized Gaussian distribution

$$y_{\mathrm{M}}(\tau_i) = SF_{\mathrm{M}}(\tau_i; C, \tau_{\max}, \beta_1, \beta_2)$$

$$P_i\big(SF(\tau_i)\big) = \frac{1}{|\Sigma_i|^{\frac{1}{2}}(2\pi)^{\frac{N}{2}}} e^{-\frac{1}{2}[SF(\tau_i)-y_{\mathrm{M}}(\tau_i)]^{\mathrm{T}}\Sigma^{-1}[SF(\tau_i)-y_{\mathrm{M}}(\tau_i)]}$$

Statistically independent points

$$SF_{\mathrm{M}}(\tau; C, \tau_{\max}, \beta_1, \beta_2) = \begin{cases} C\left(\frac{\tau}{\tau_{\max}}\right)^{\beta_1} & \tau \leq \tau_{\max} \\ C\left(\frac{\tau}{\tau_{\max}}\right)^{\beta_2} & \tau > \tau_{\max} \end{cases}$$

Single $SF(\tau_i)$ probability $\rightarrow$ Gaussianity assumption

$$P_i\Big(SF_{\mathrm{M}}(\tau_i; C, \tau_{\max}, \beta_1, \beta_2)\Big) = \frac{1}{\sigma_i\sqrt{2\pi}} e^{-\frac{1}{2}\left[\frac{SF(\tau_i) - SF_{\mathrm{M}}(\tau_i; C, \tau_{\max}, \beta, \beta_2)}{\sigma_i}\right]^2}$$

Ensemble $SF(\tau)$ probability $\rightarrow$ Independency assumption

$$P(C, \tau_{\max}, \beta_1, \beta_2) = \prod_{i=1}^{N}\left(\frac{1}{\sigma_i\sqrt{2\pi}}\right) e^{-\frac{1}{2}\sum_{i=1}^{N}\left[\frac{SF(\tau_i) - SF_{\mathrm{M}}(\tau_i; C, \tau_{\max}, \beta_1, \beta_2)}{\sigma_i}\right]^2}$$

Statistically independent points

$$\chi^2 = \sum_{i=1}^{N} \left[\frac{SF(\tau_i) - SF_{\mathrm{M}}(\tau_i; C, \tau_{\max}, \beta_1, \beta_2)}{\sigma_i} \right]^2$$