

# Lomb-Scargle Project

## CAP-384

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INPE

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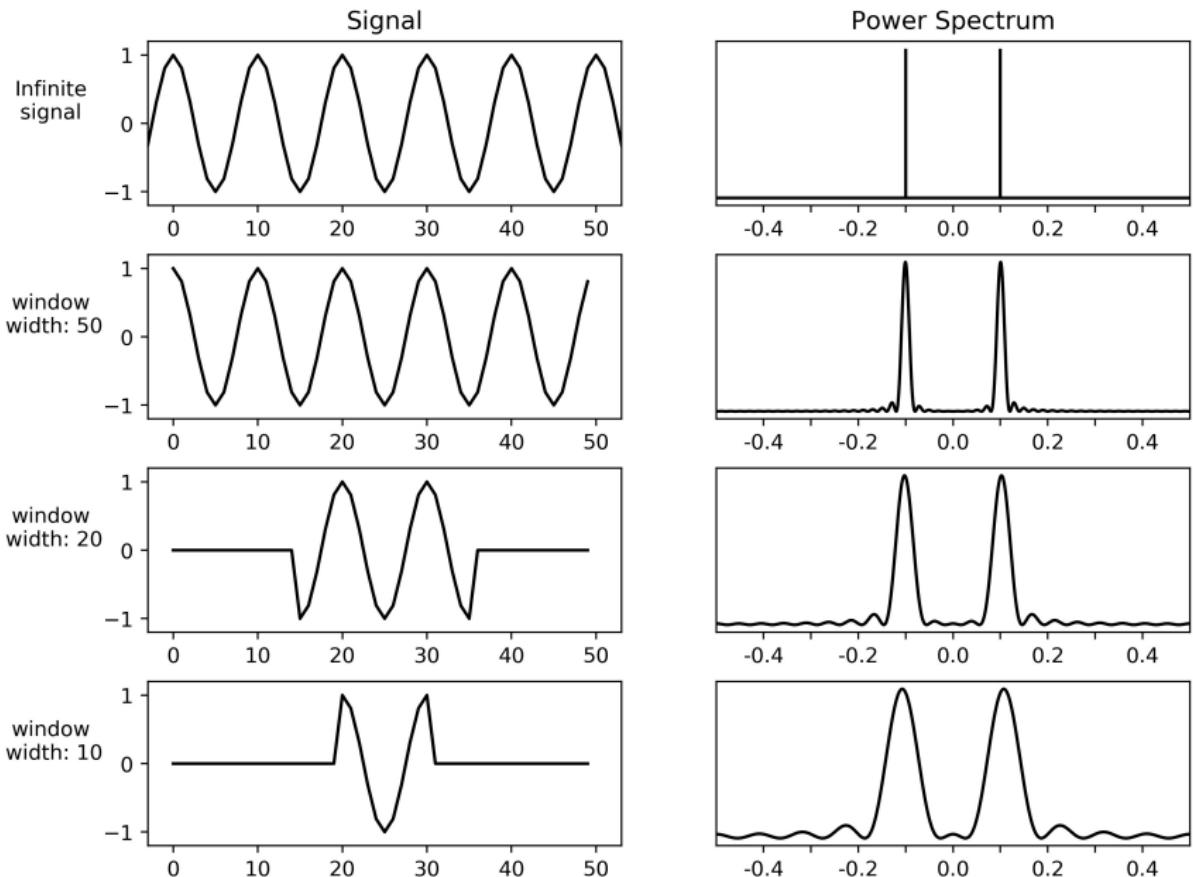
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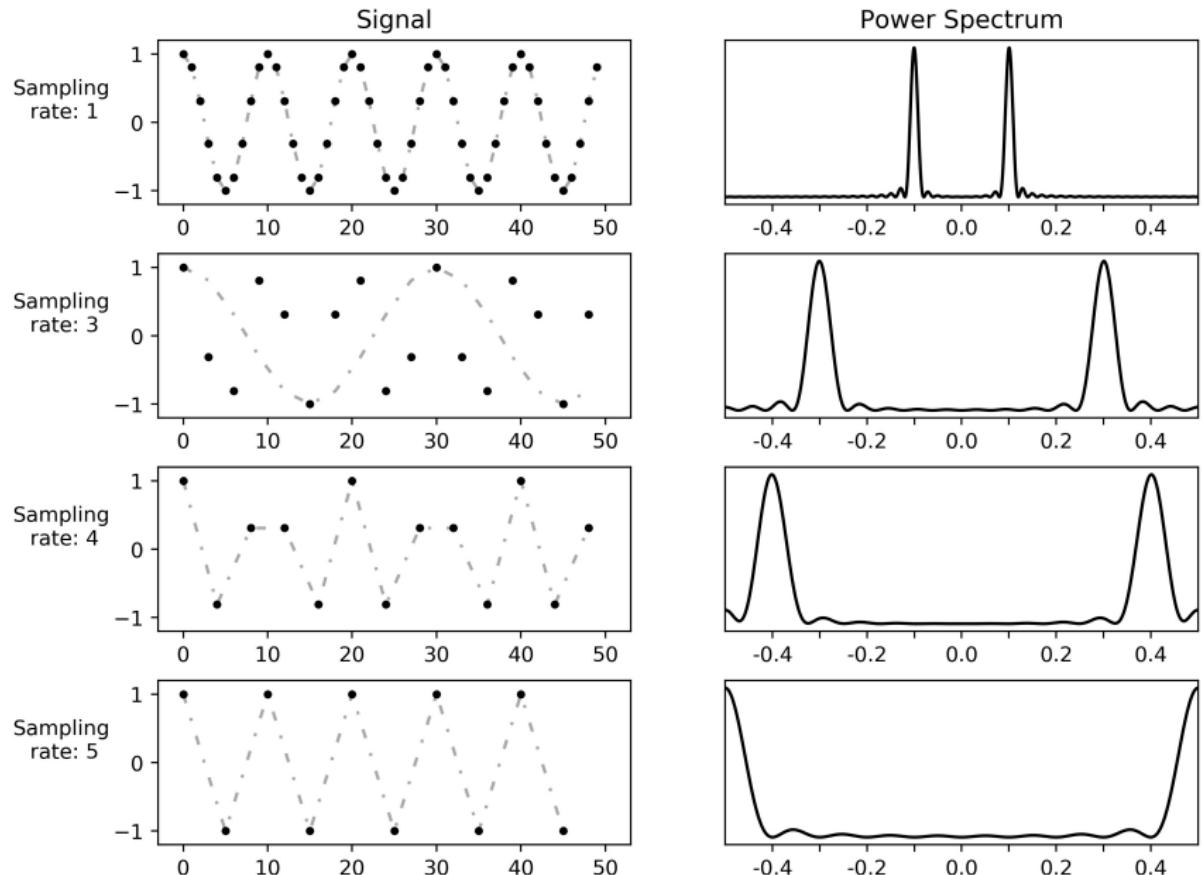
# An overview of the project

- Solar flux at 10.7 cm
- Indicator of Sun's magnetic activity, and one of the oldest records of our star
- Three sets of data downloaded (11/1963 a 07/2020):
  - ▶ Daily averages (20440 entries)
  - ▶ 27-day averages (672 entries)
  - ▶ Yearly averages (56 entries)
- Simulation of random sampling (two scenarios)
- Library astropy with LombScargle class was used
- Periodogram generated and analyzed under different conditions

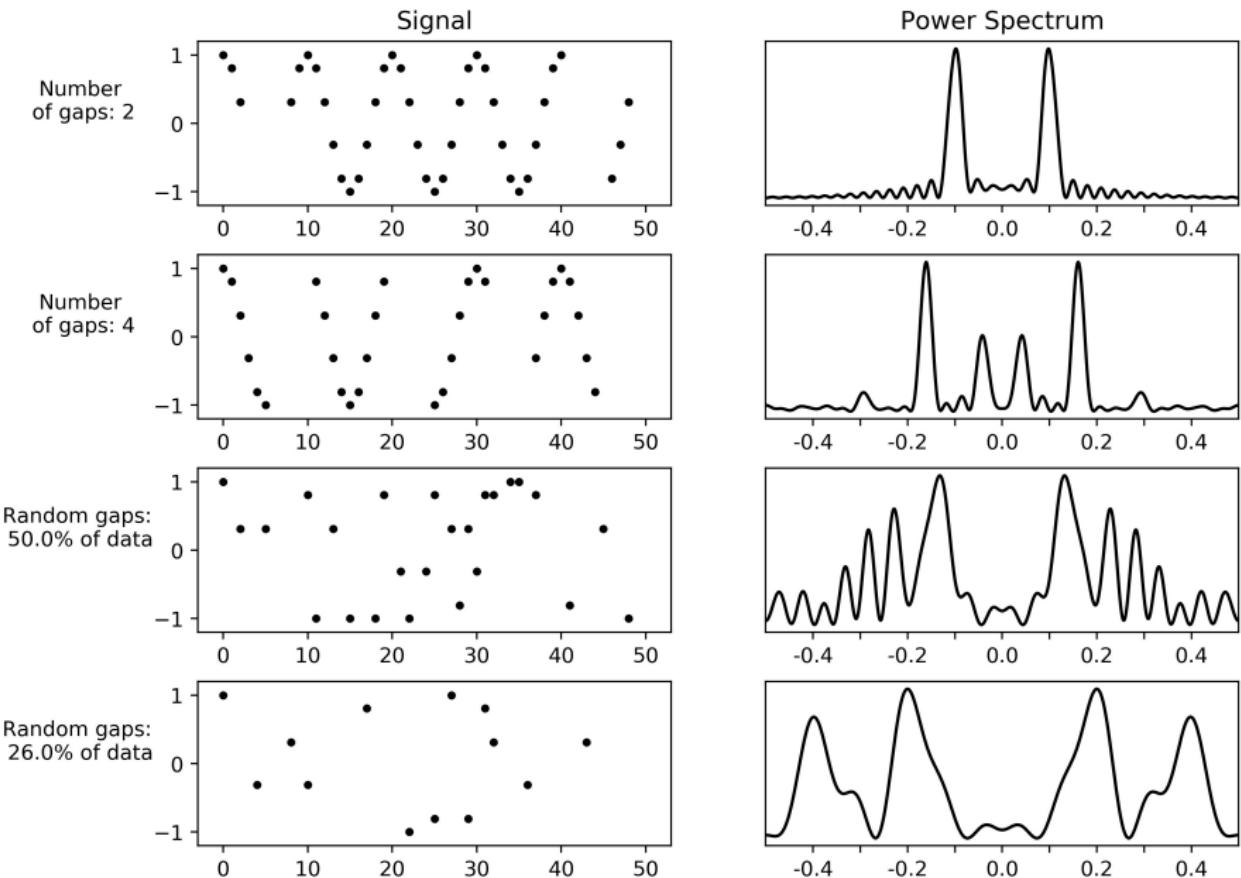
# Effects of finite sampling - spectral leakage



# Effects of sampling rate - aliasing (a kind of leakage)



# Effects of non-uniform sampling



# Lomb-Scargle periodogram

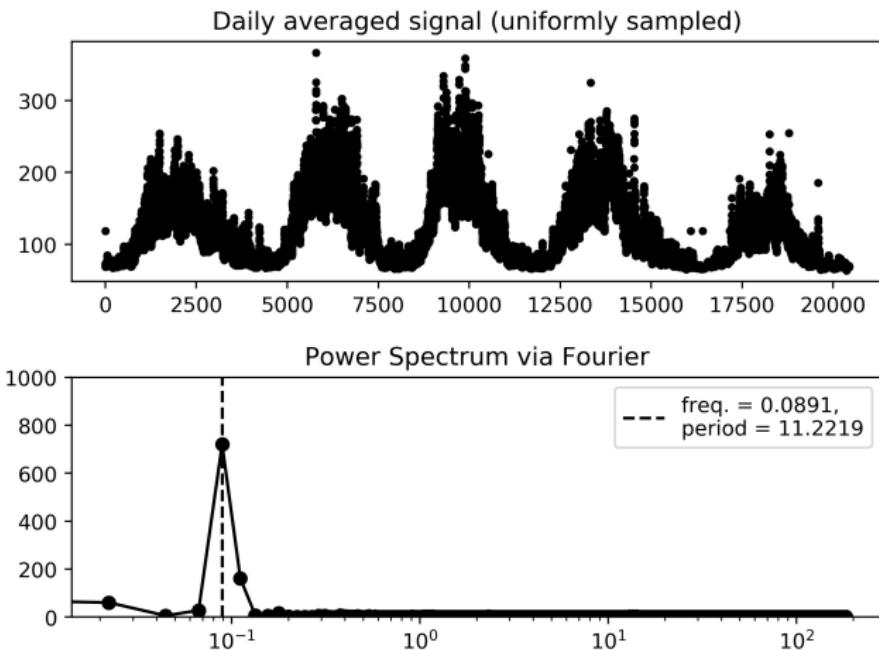
- Main tool for analysis of unevenly sampled temporal series
- Belongs to a set of tools of spectral analysis that explores the least squares method
- Estimates frequencies by fitting sinusoidal functions to the data
- Available via the library `astropy` (with  $O[N \log N]$  complexity) via the class `LombScargle`:

```
from astropy.timeseries import LombScargle  
frequency, power = LombScargle(t, f).autopower()
```

# The analysis

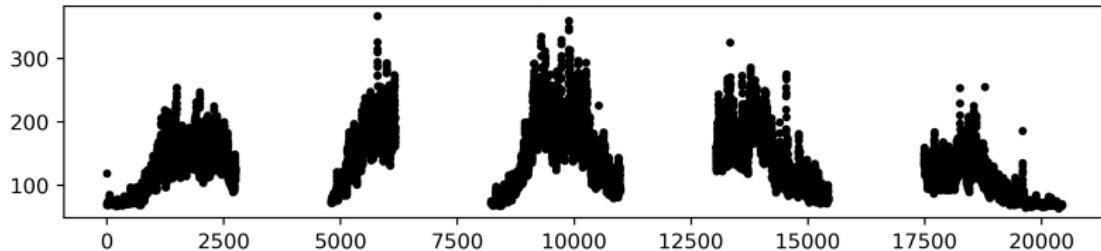
- Scenario 1
  - ▶ Gaps (of data) randomly placed in the original series
  - ▶ Size of gaps equal to 10% of data
  - ▶ Five number f gaps tested
- Scenario 2
  - ▶ Data randomly deleted from the original series
  - ▶ Deletion of a particular percentage
  - ▶ Five percentages are tested

# Power spectrum via FFT - the usual analysis

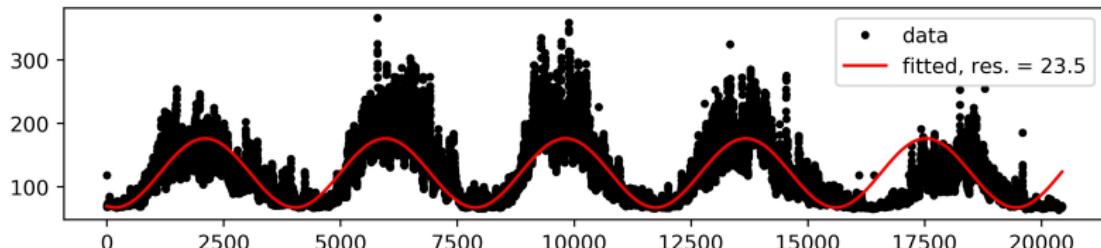
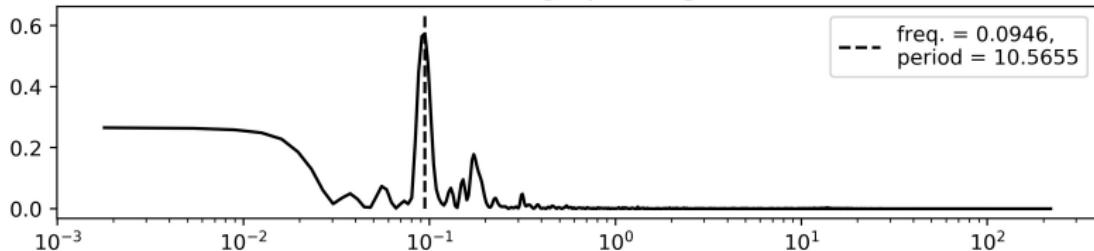


# Scenario 1 - daily averages

Data with 4 gaps - 60.0% of data

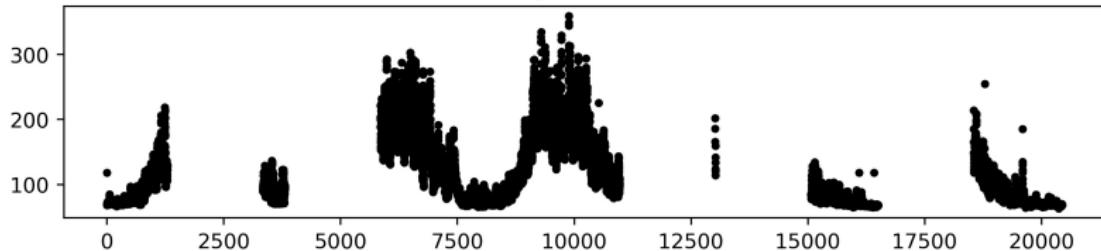


Lomb-Scargle periodogram

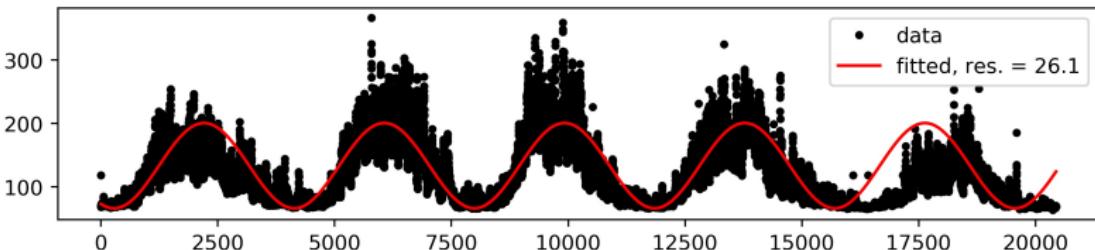
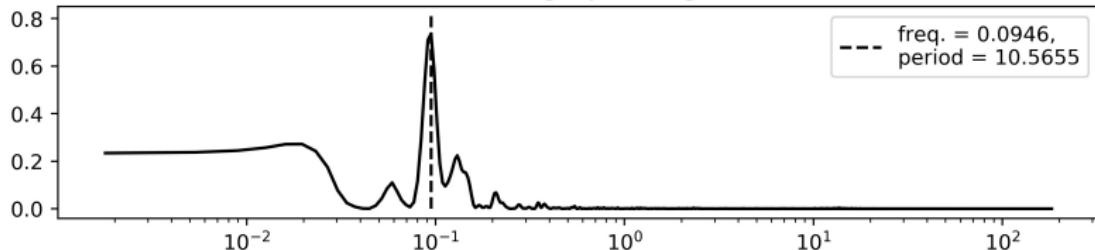


# Scenario 1 - daily averages

Data with 5 gaps - 50.0% of data

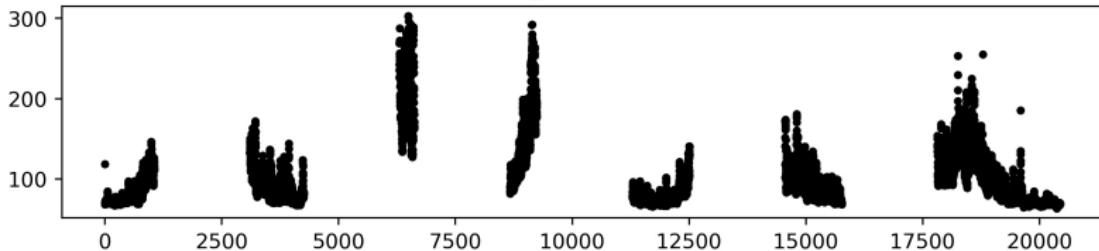


Lomb-Scargle periodogram

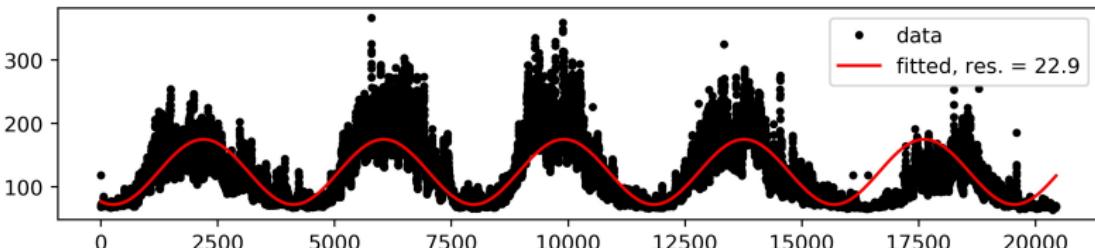
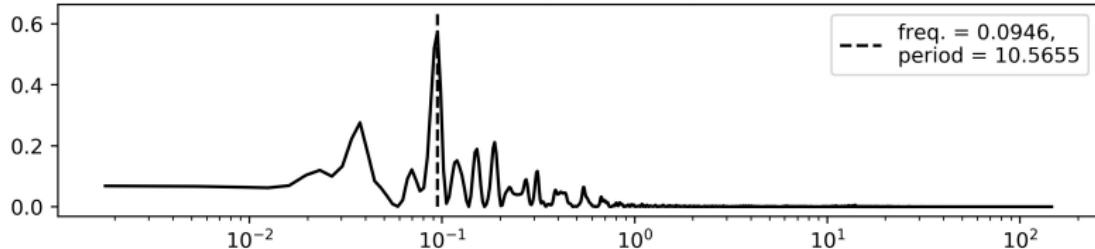


# Scenario 1 - daily averages

Data with 6 gaps - 40.0% of data

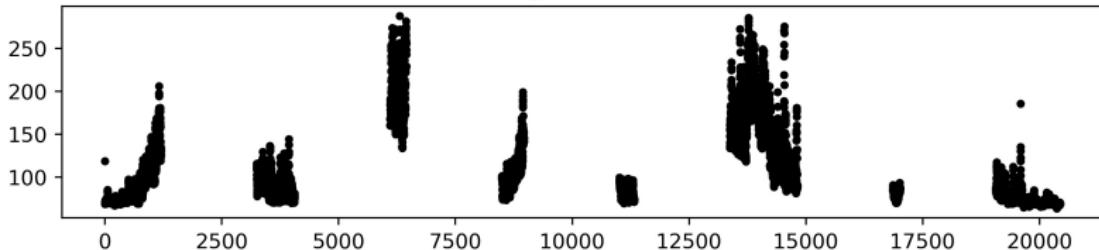


Lomb-Scargle periodogram

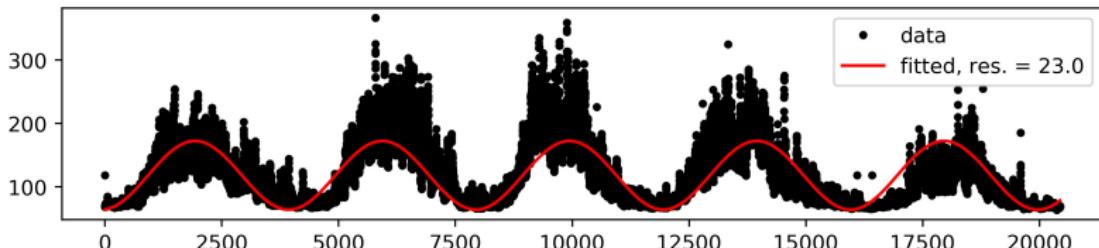
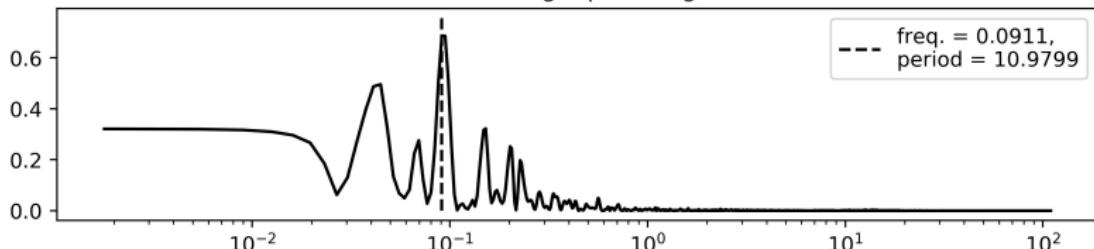


# Scenario 1 - daily averages

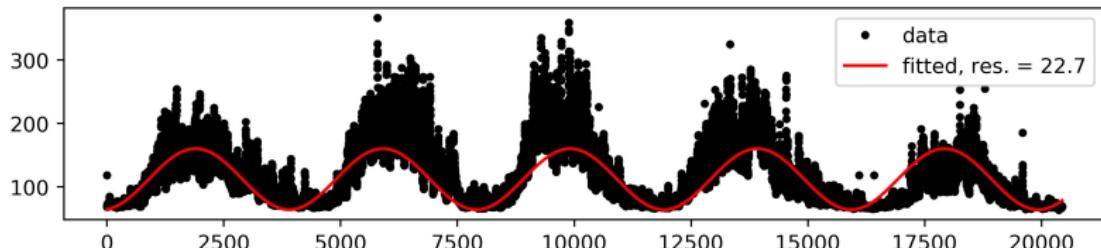
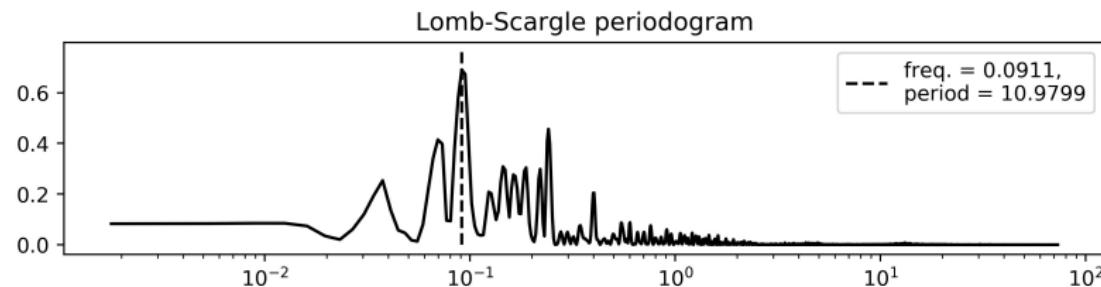
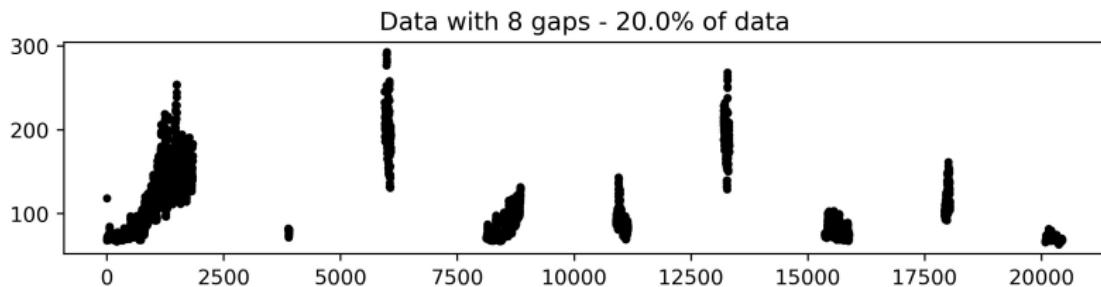
Data with 7 gaps - 30.0% of data



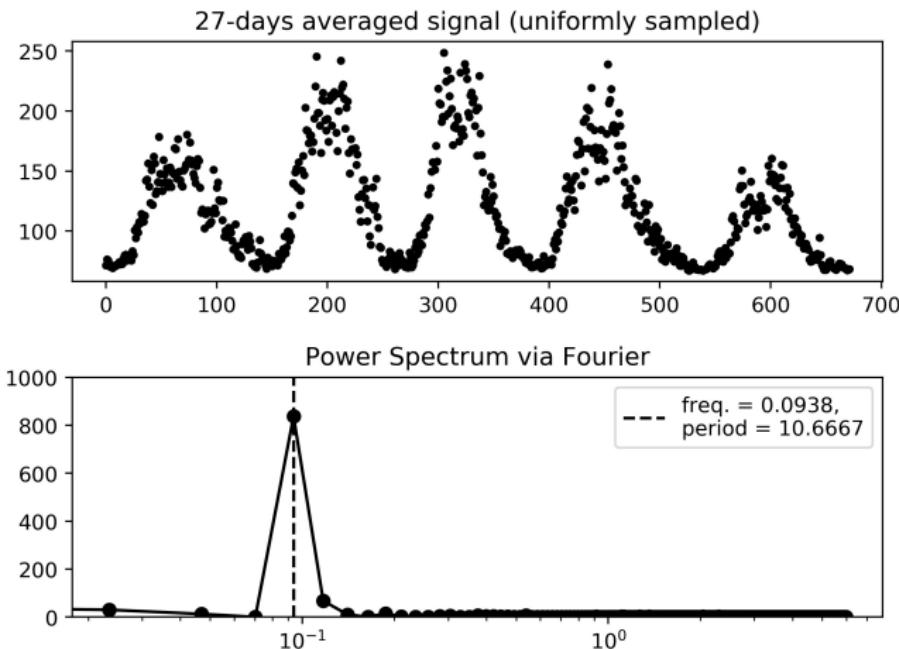
Lomb-Scargle periodogram



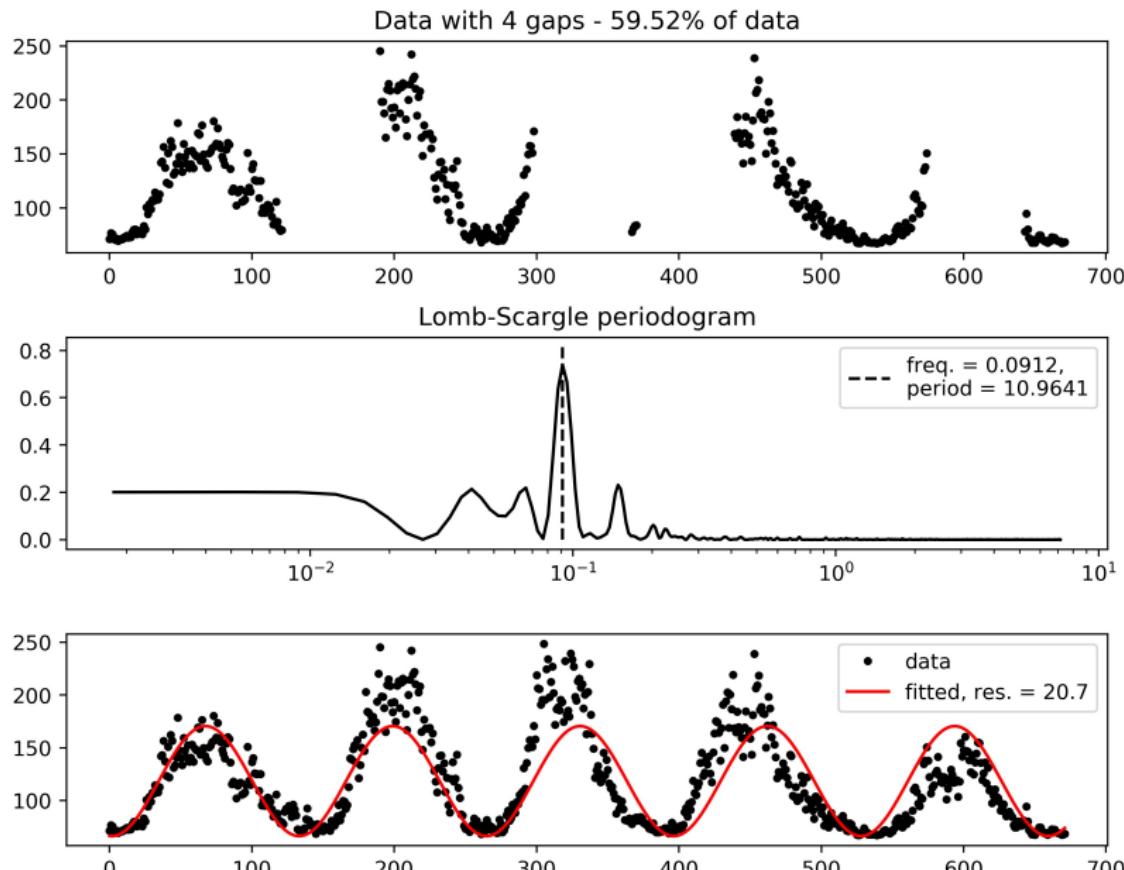
## Scenario 1 - daily averages



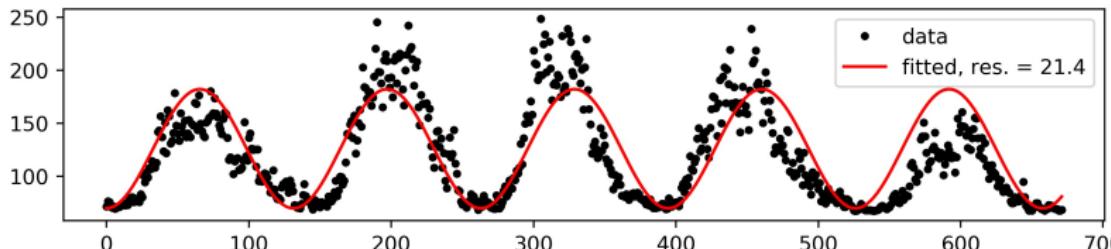
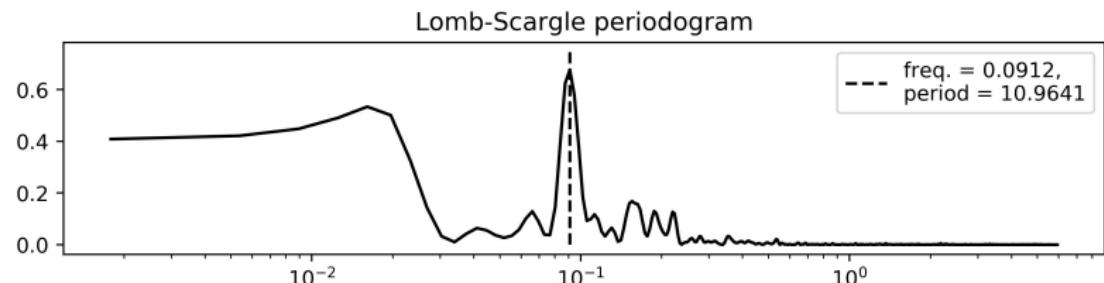
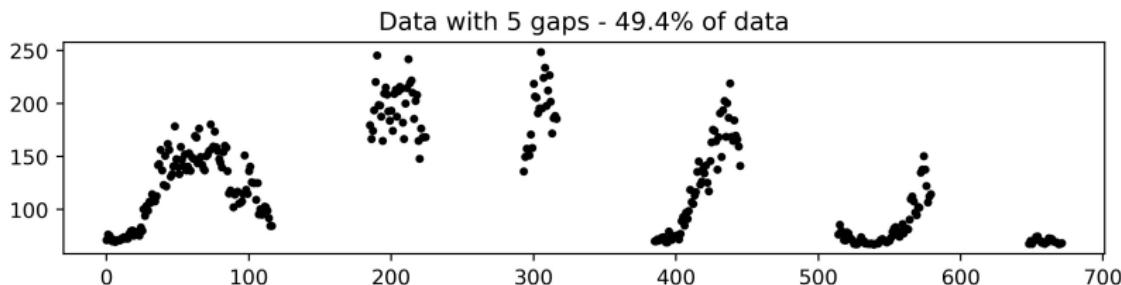
# Power spectrum via FFT - the usual analysis



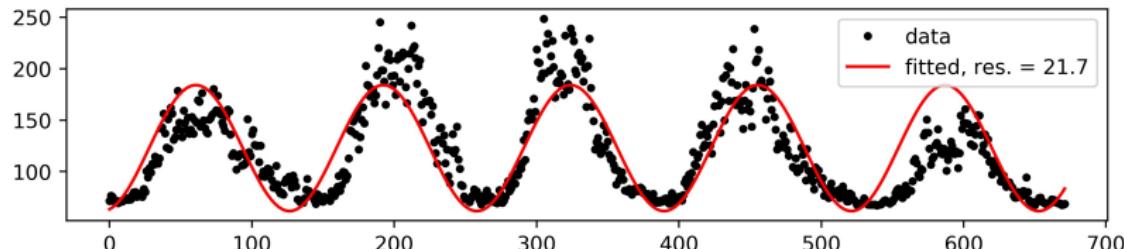
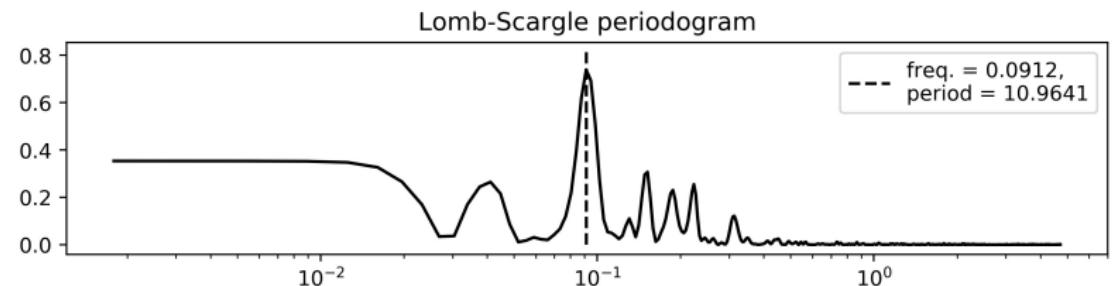
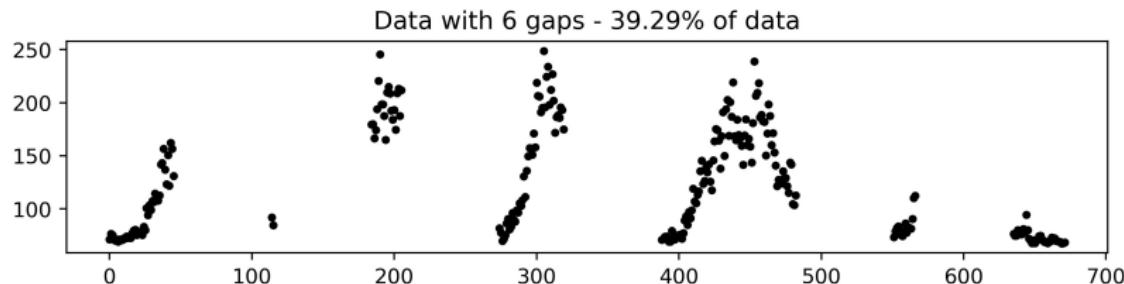
# Scenario 1 - 27-day averages



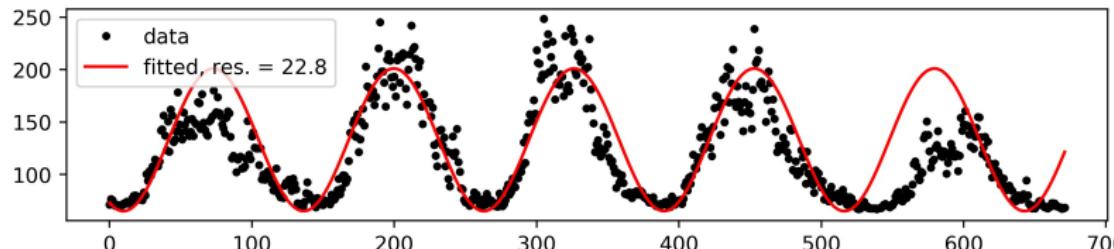
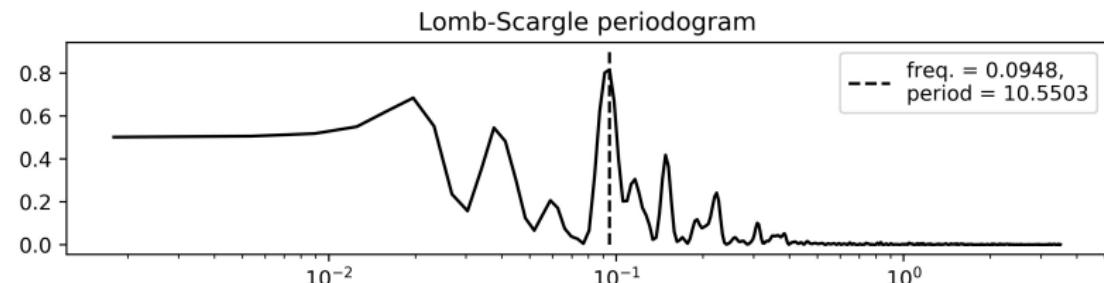
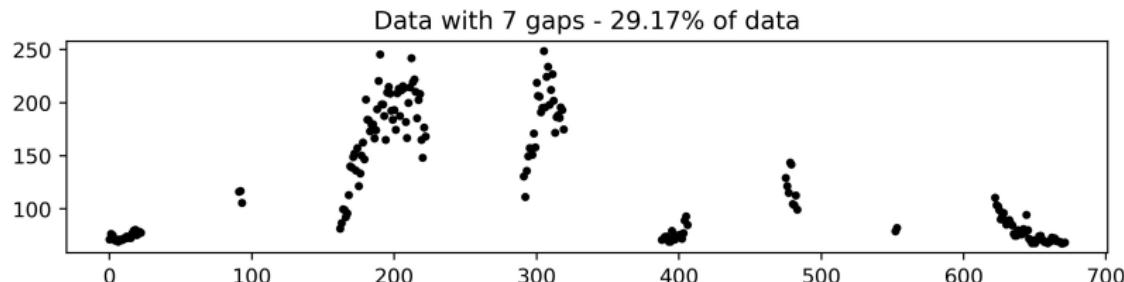
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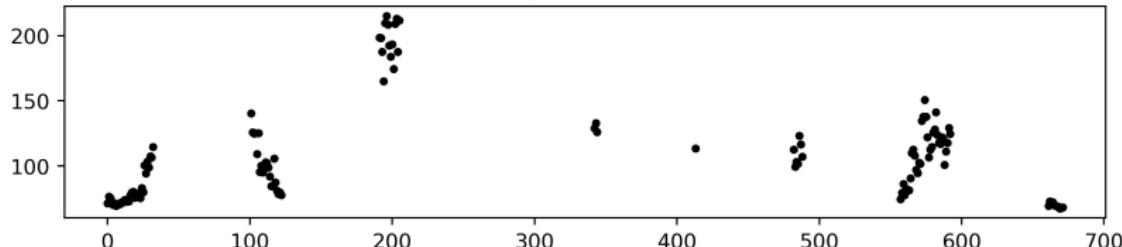


# Scenario 1 - 27-day averages

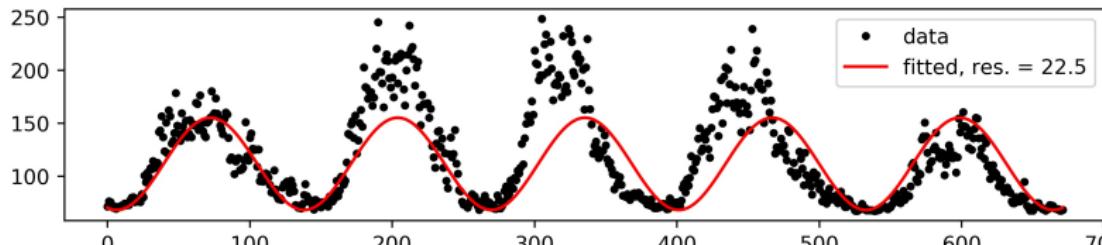
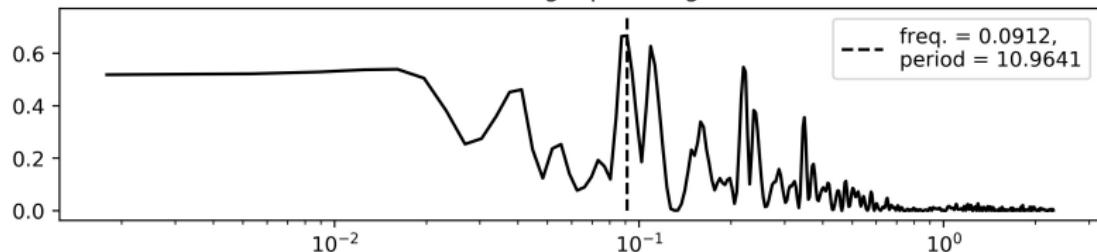


# Scenario 1 - 27-day averages

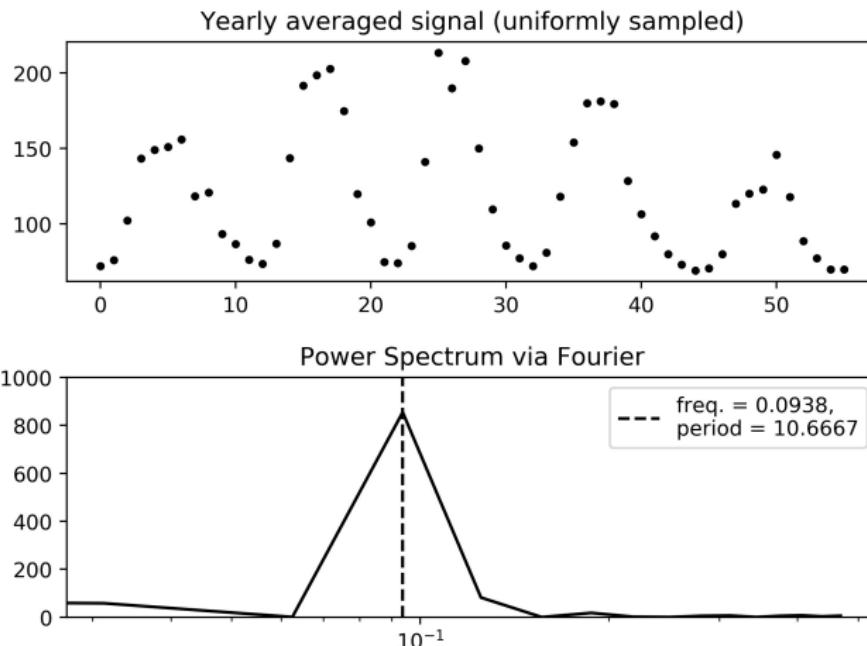
Data with 8 gaps - 19.05% of data



Lomb-Scargle periodogram

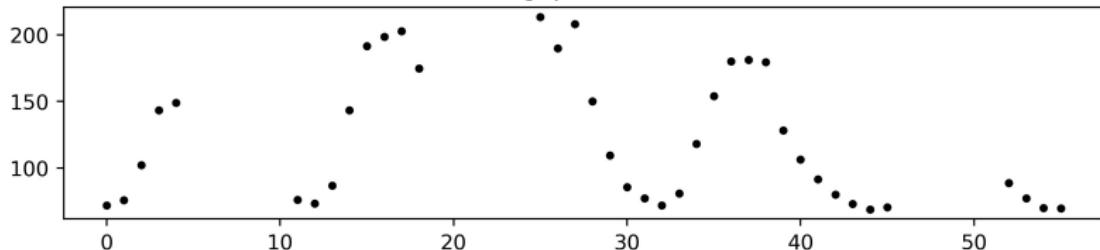


# Power spectrum via FFT - the usual analysis

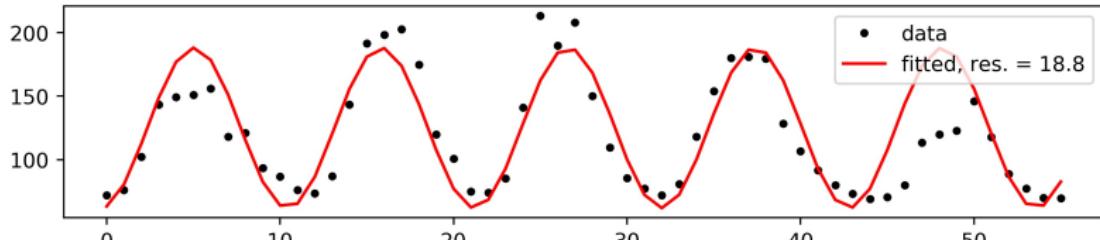
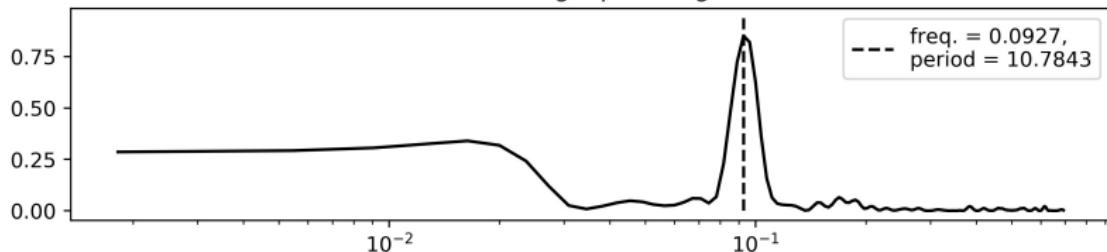


# Scenario 1 - yearly averages

Data with 3 gaps - 67.86% of data

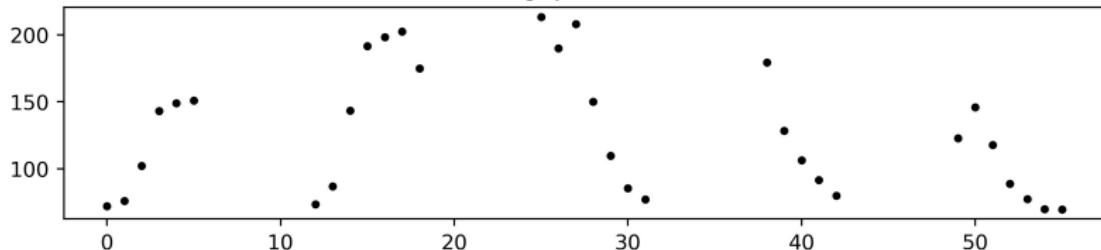


Lomb-Scargle periodogram

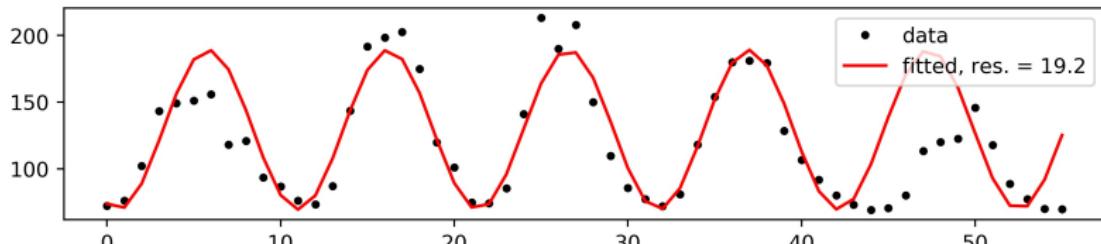
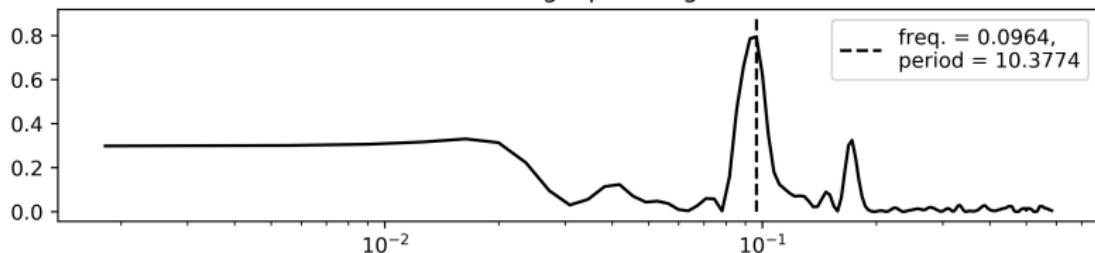


# Scenario 1 - yearly averages

Data with 4 gaps - 57.14% of data

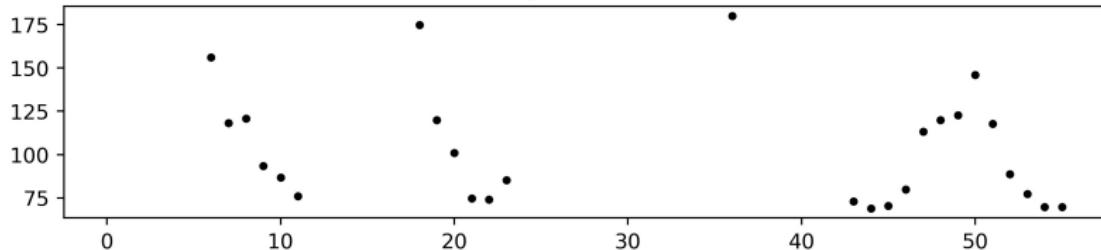


Lomb-Scargle periodogram

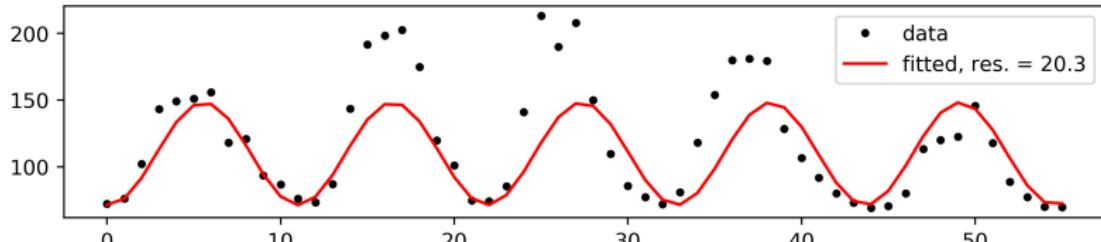
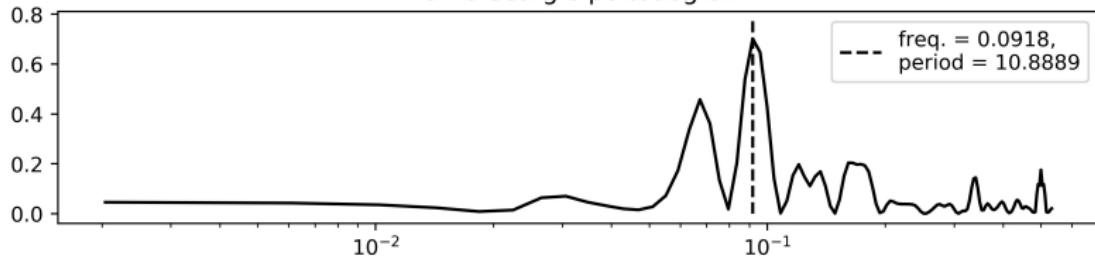


# Scenario 1 - yearly averages

Data with 5 gaps - 46.43% of data

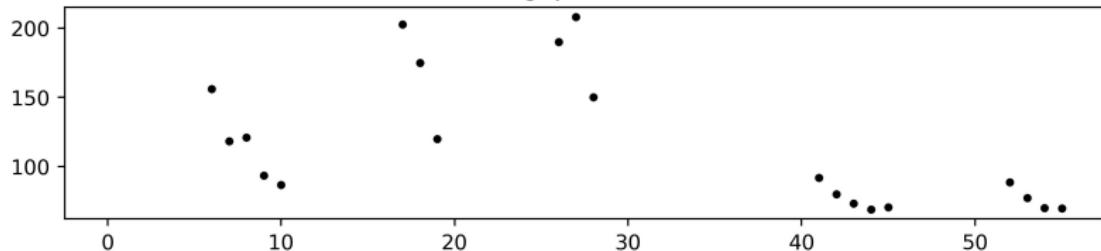


Lomb-Scargle periodogram

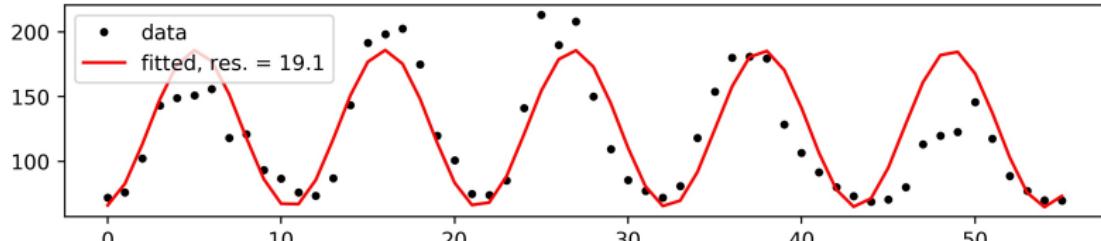
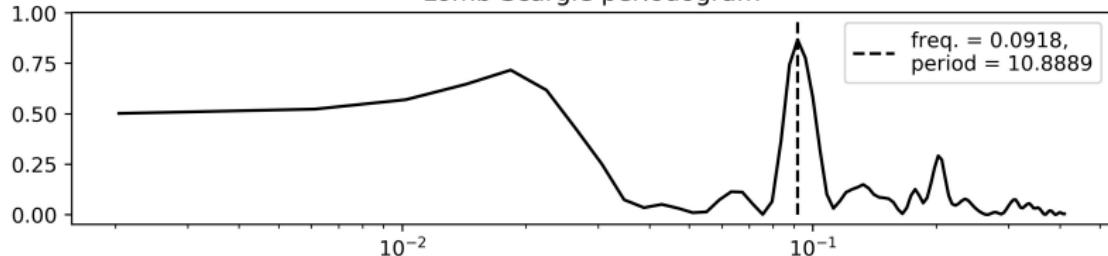


# Scenario 1 - yearly averages

Data with 6 gaps - 35.71% of data

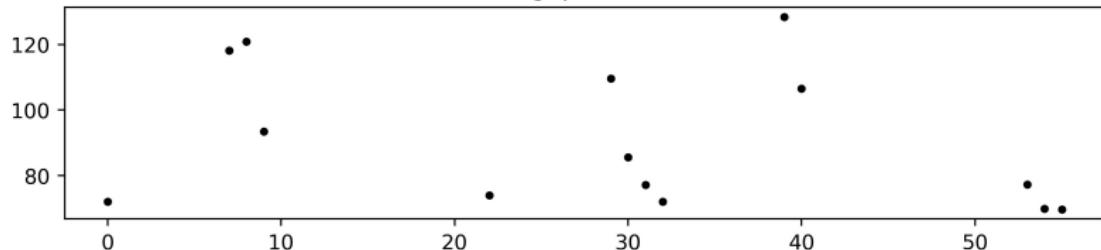


Lomb-Scargle periodogram

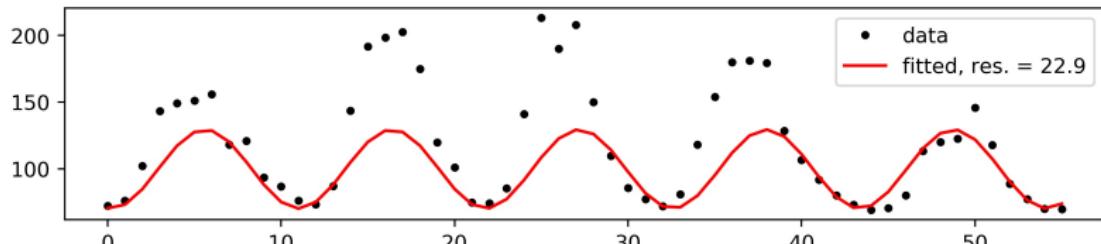
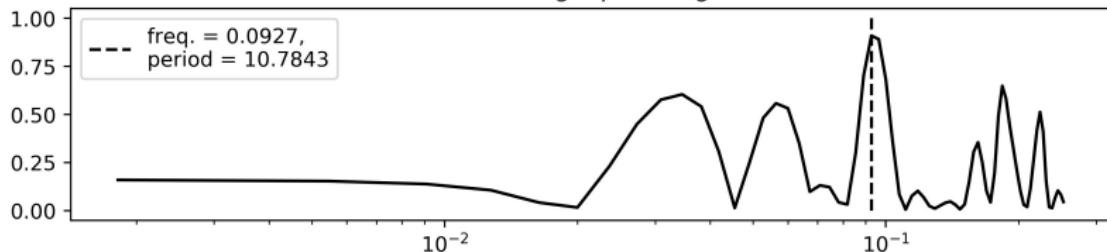


# Scenario 1 - yearly averages

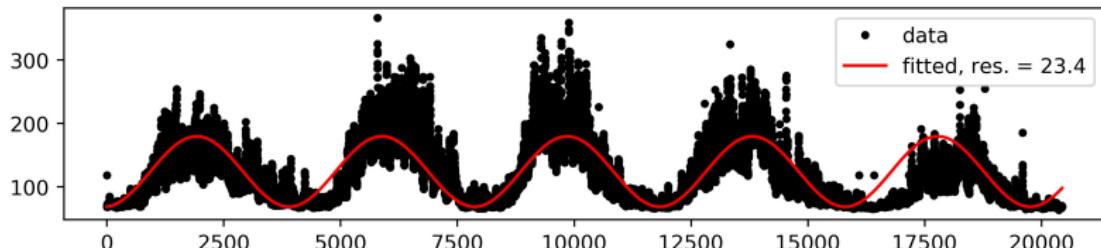
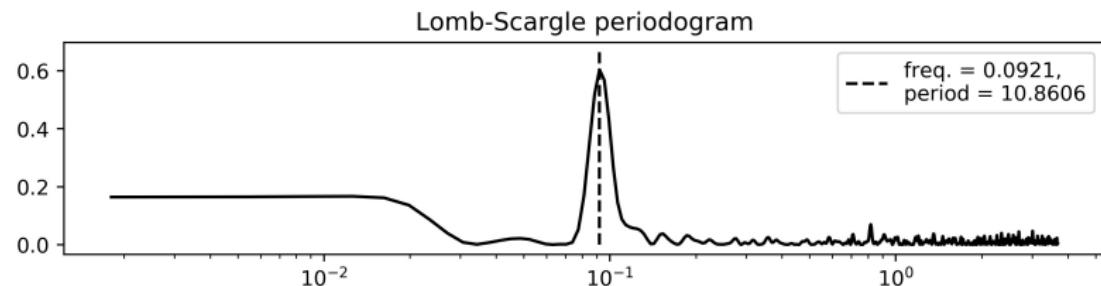
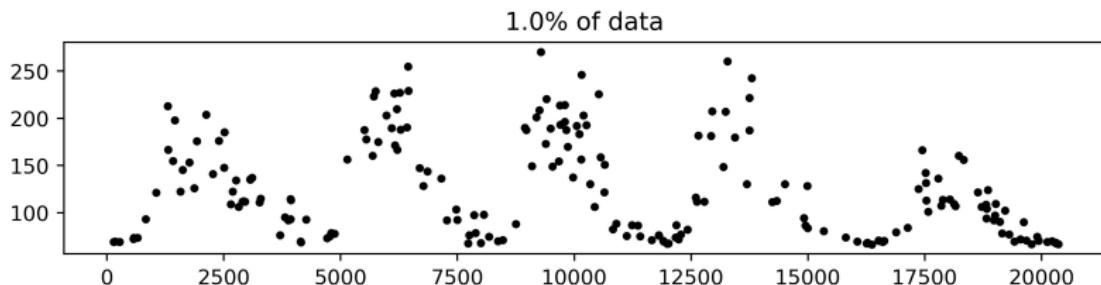
Data with 7 gaps - 25.0% of data



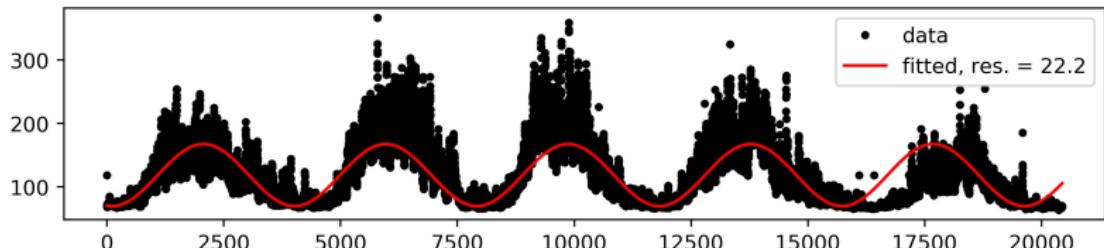
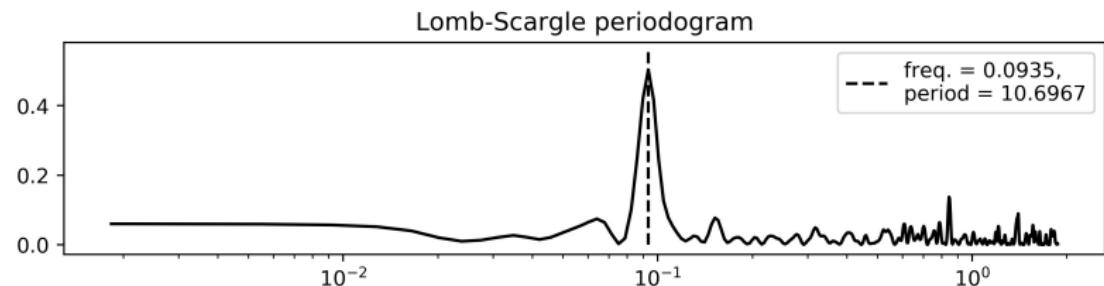
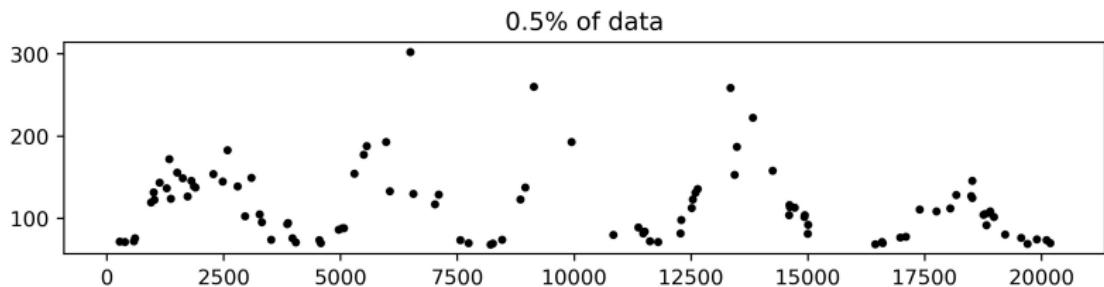
Lomb-Scargle periodogram



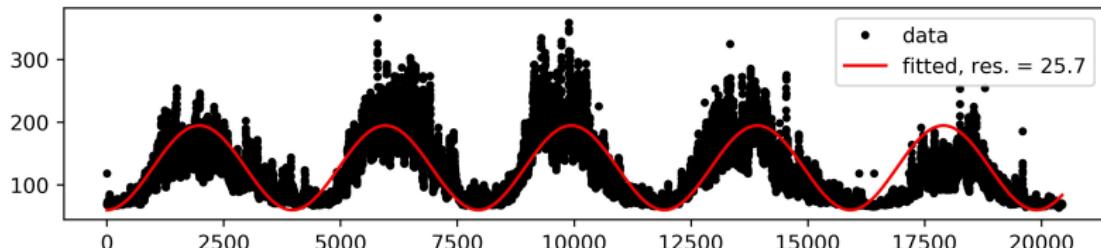
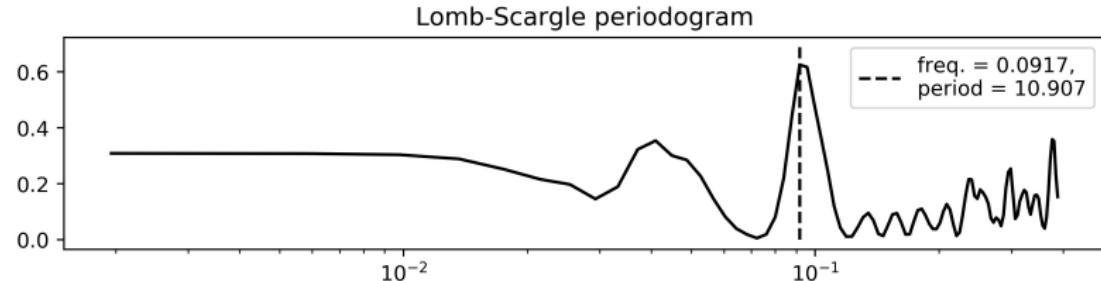
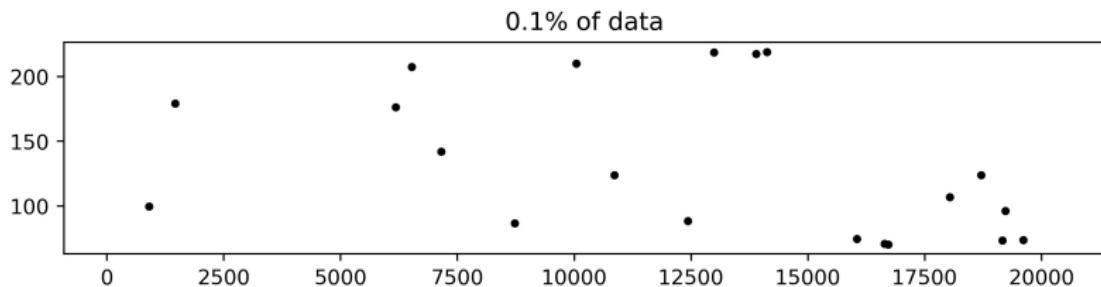
## Scenario 2 - daily averages



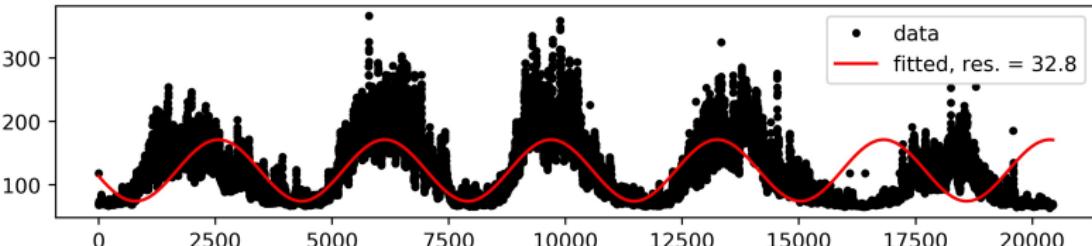
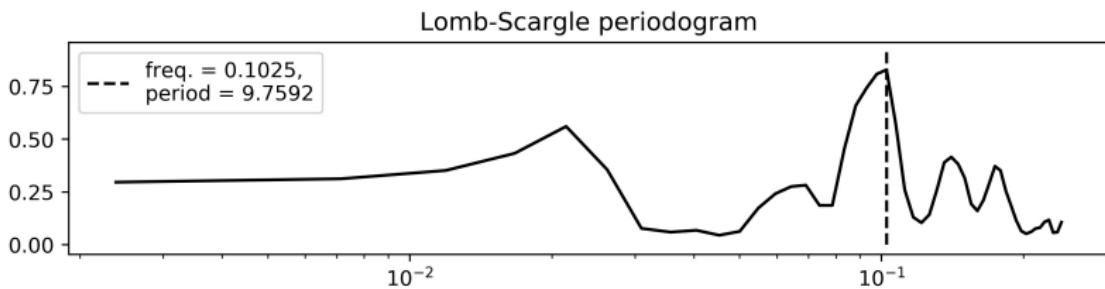
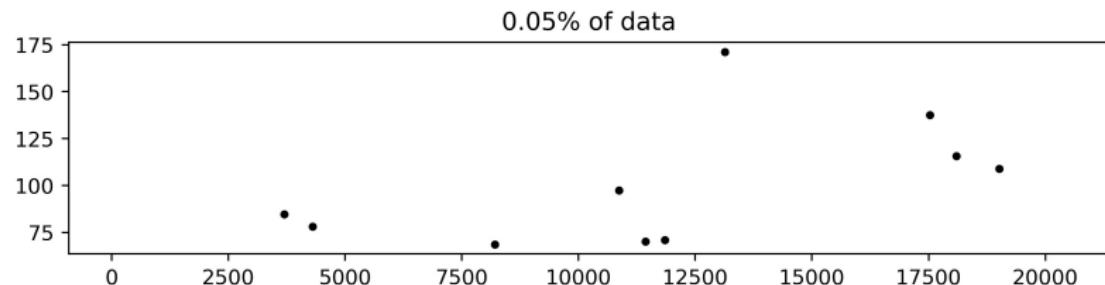
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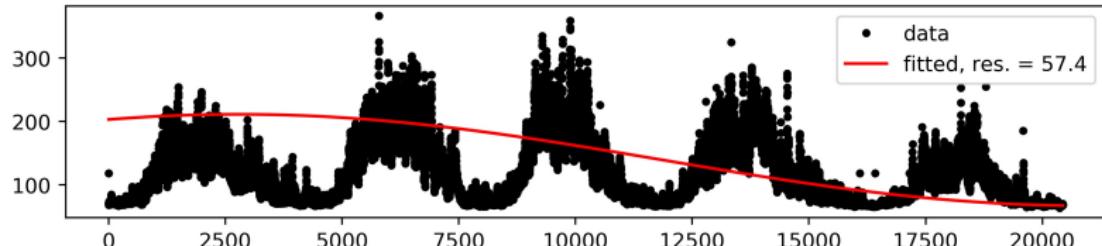
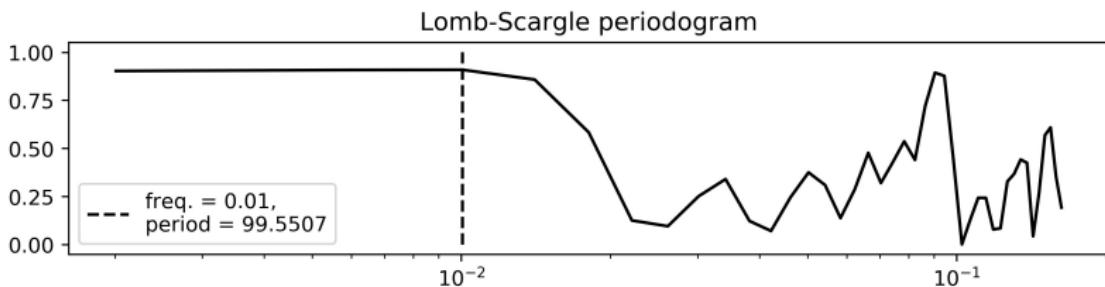
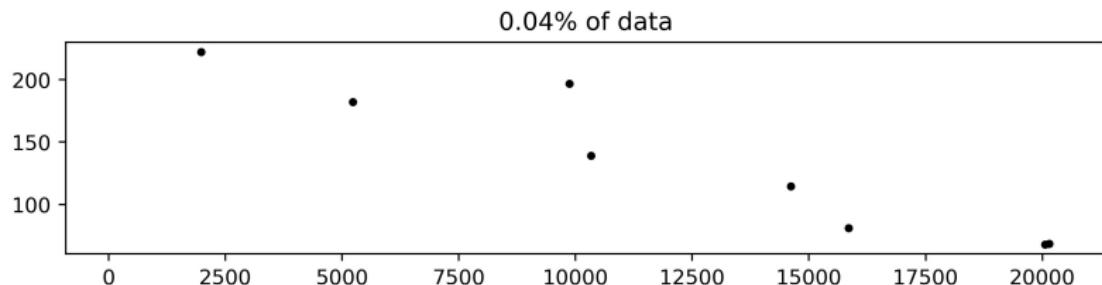
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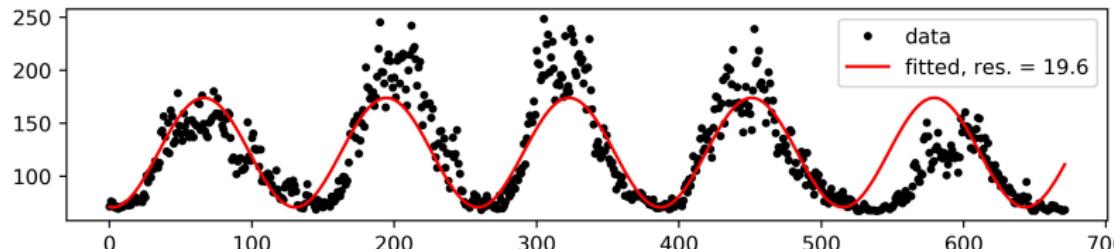
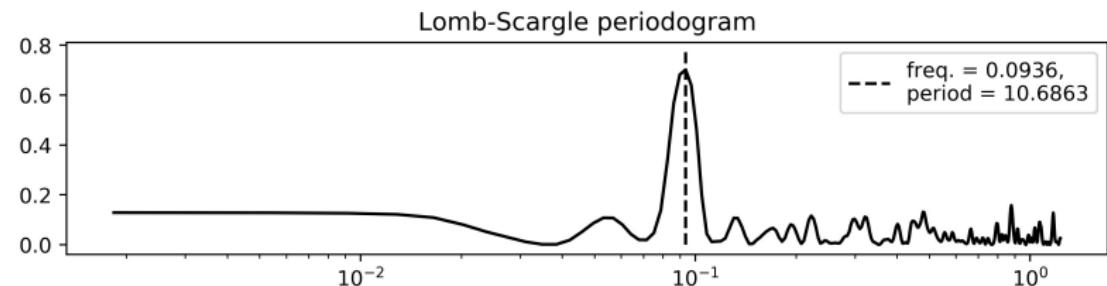
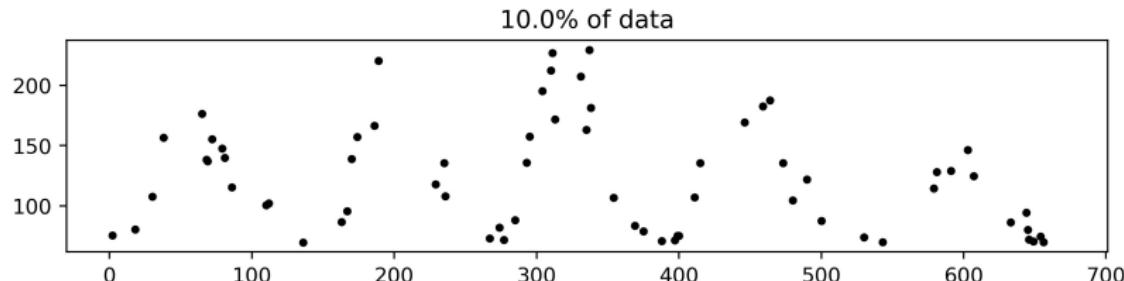
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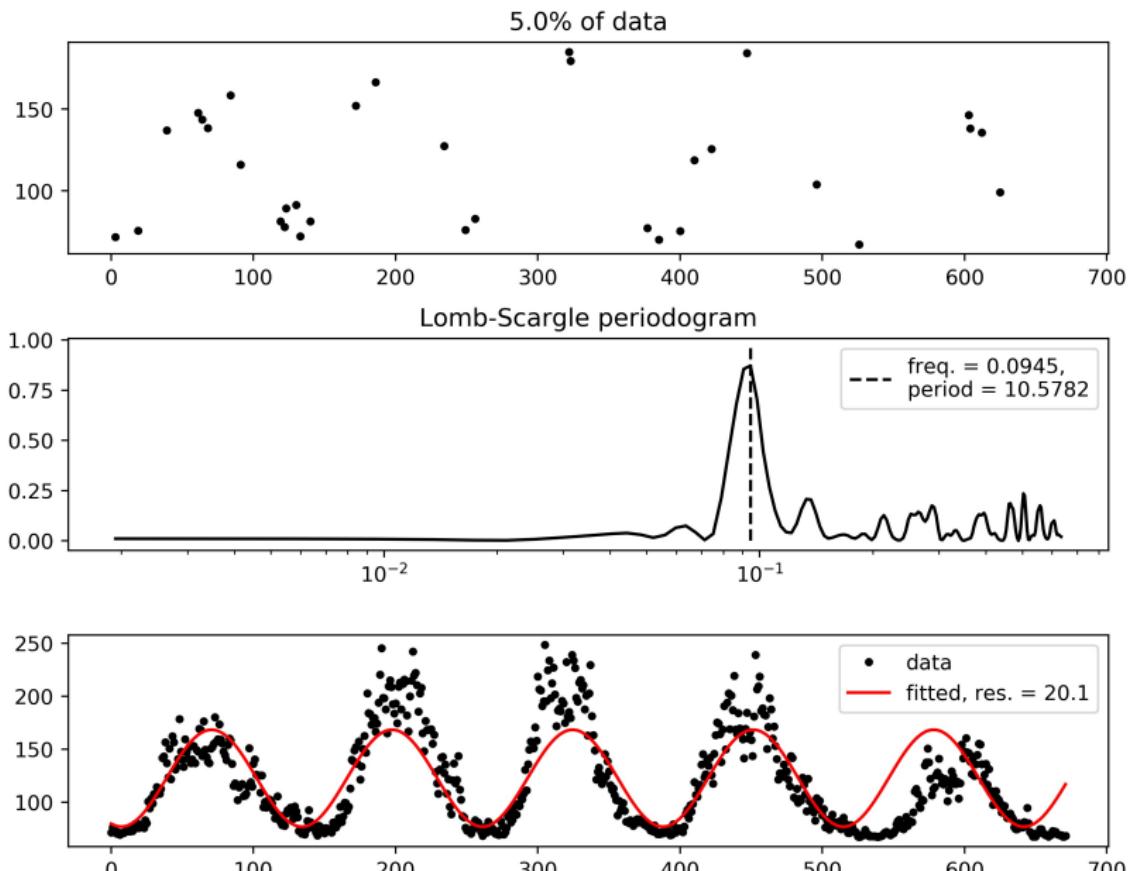
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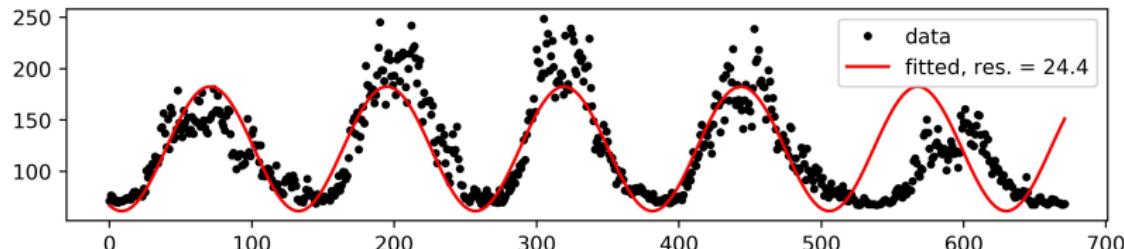
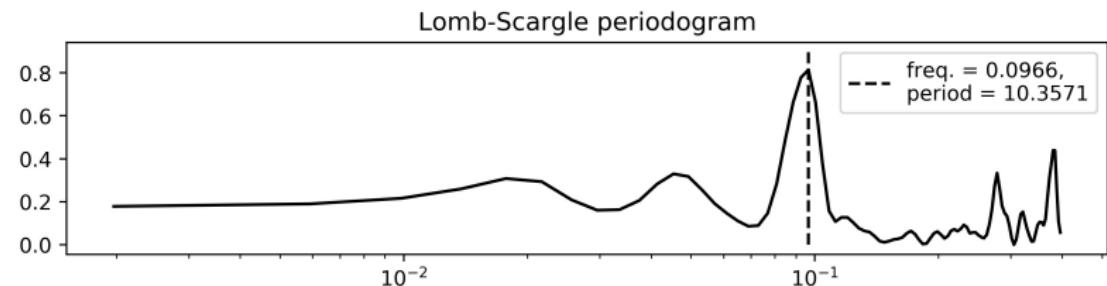
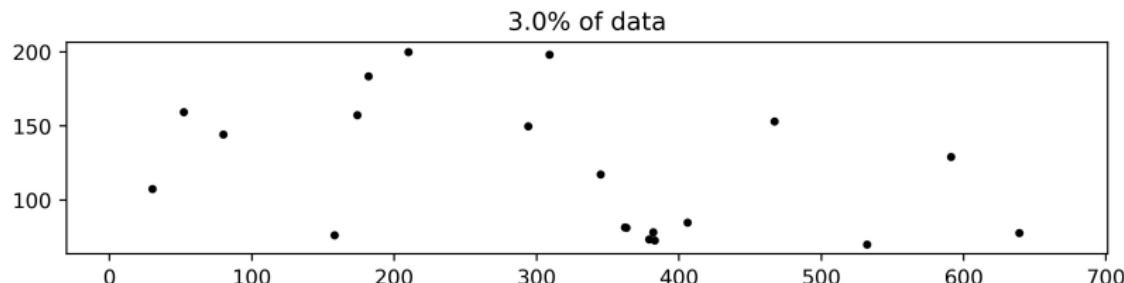
## Scenario 2 - 27-day averages



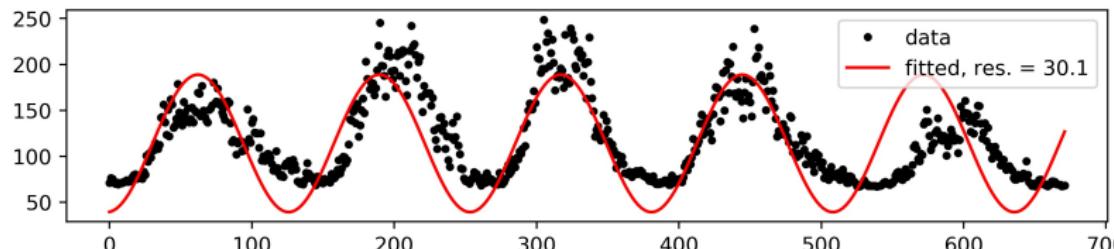
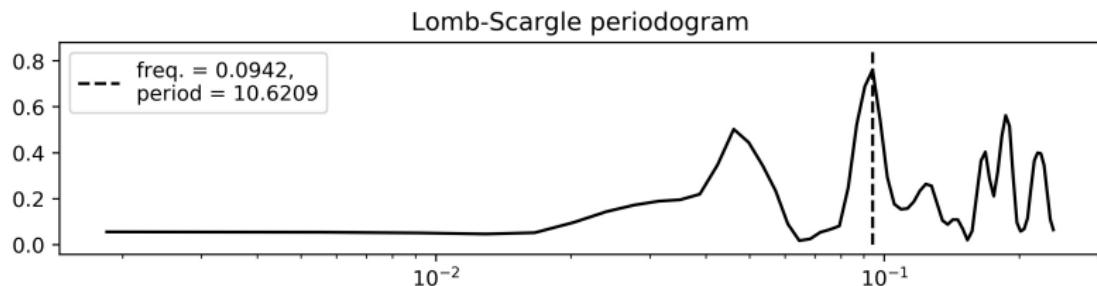
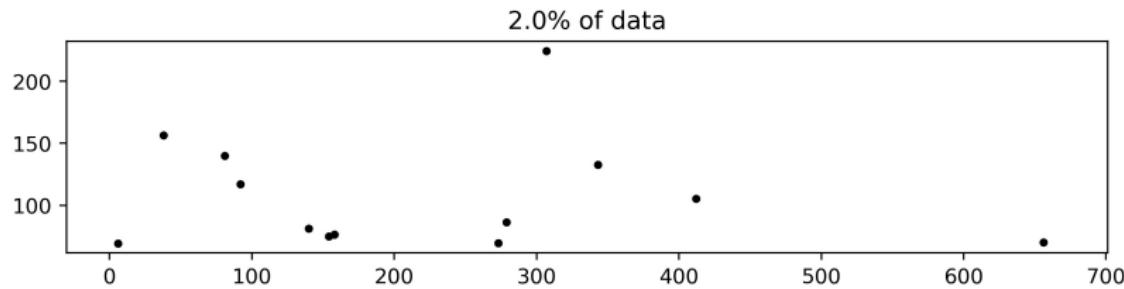
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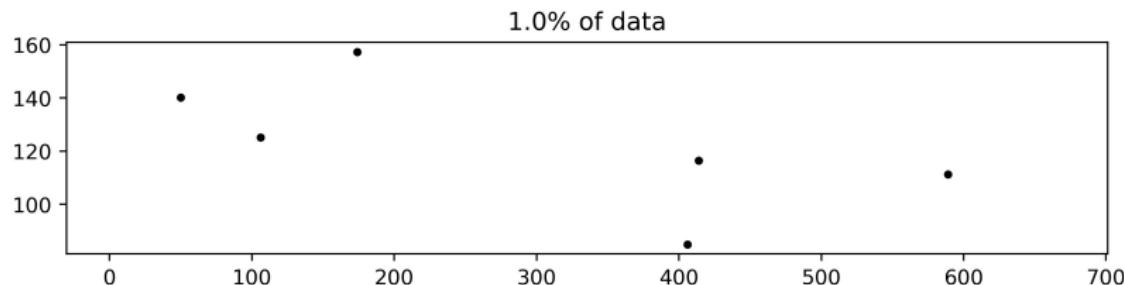
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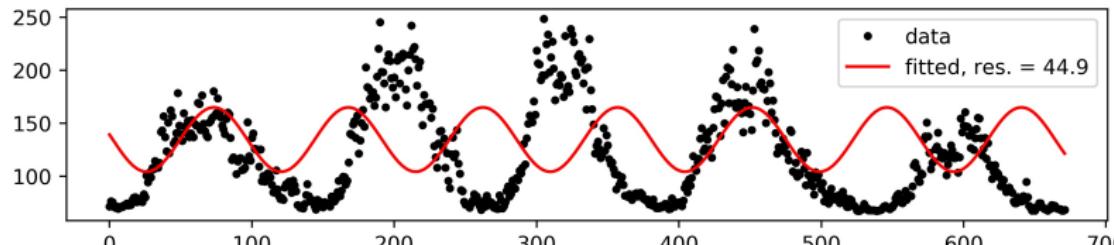
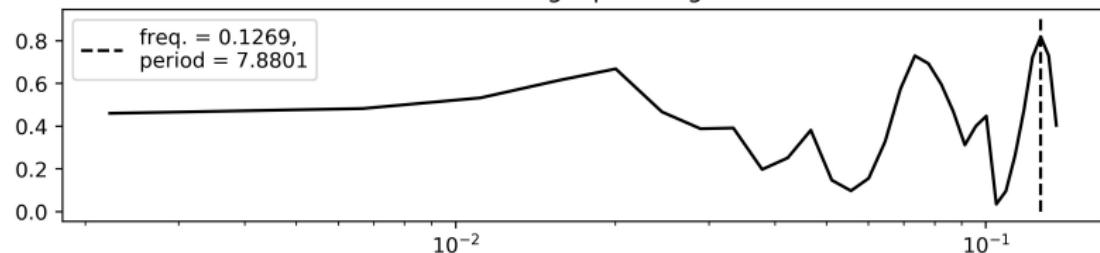
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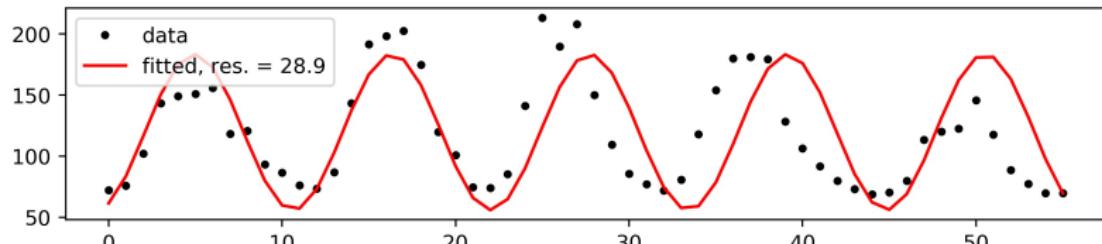
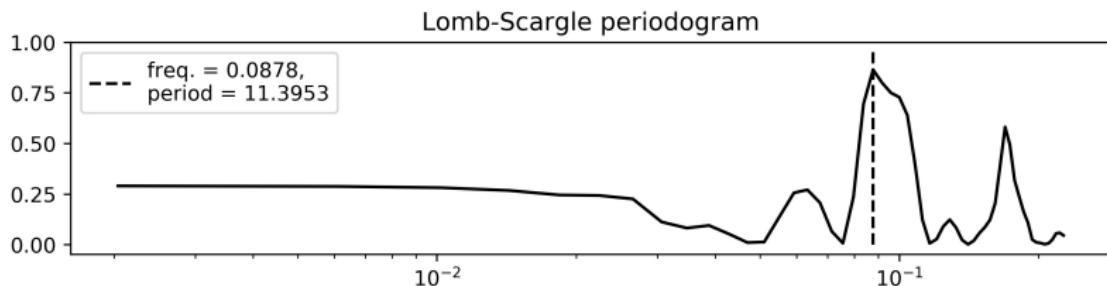
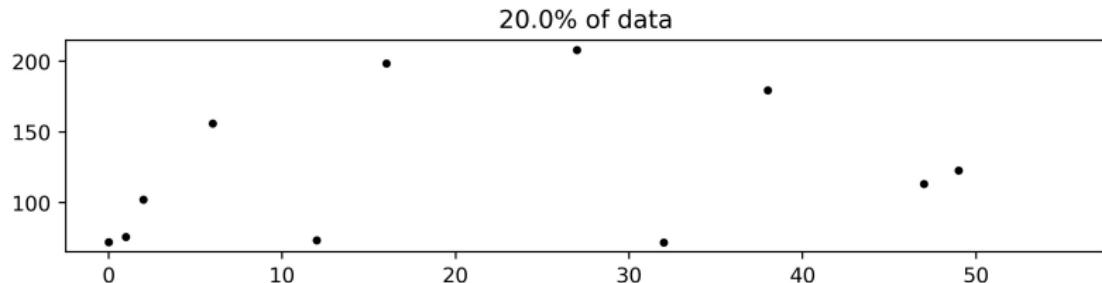
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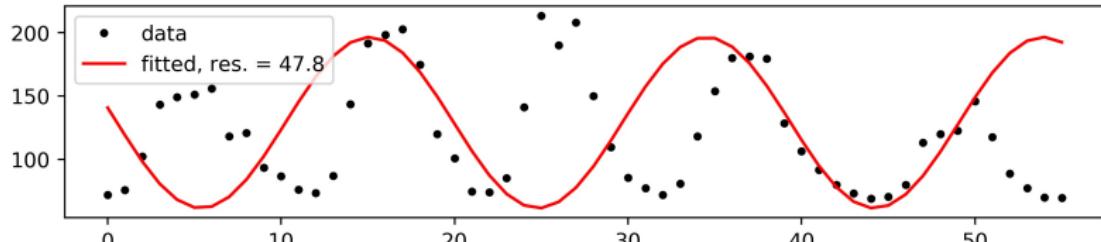
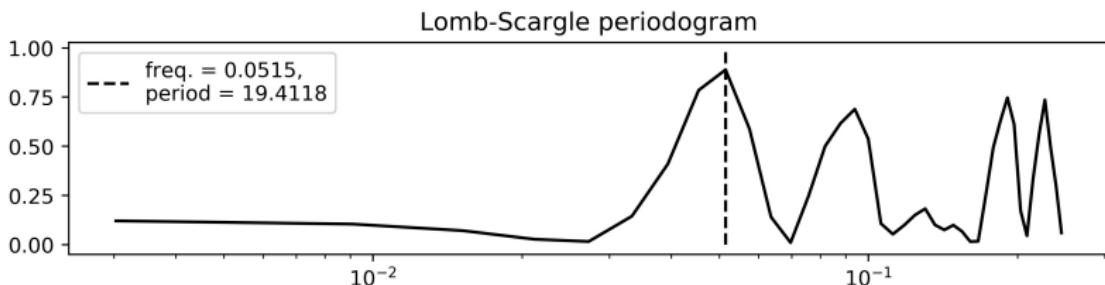
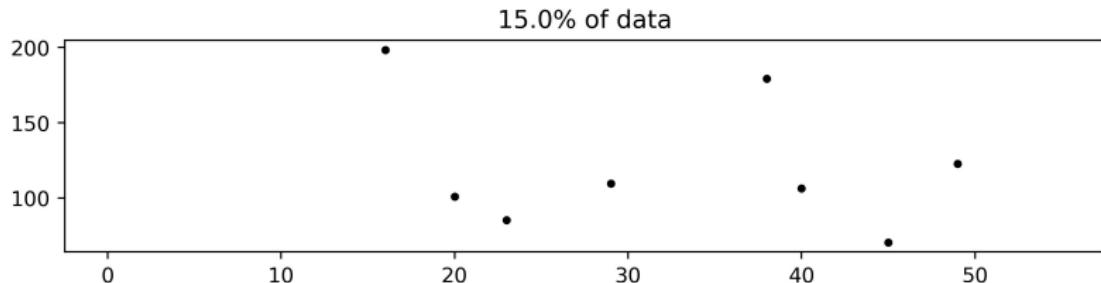
Lomb-Scargle periodogram



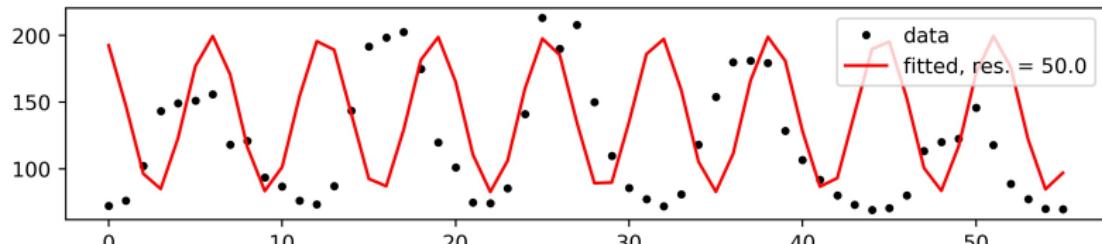
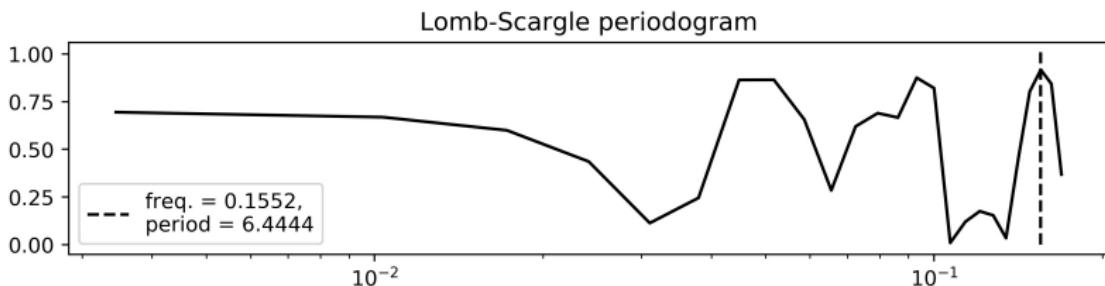
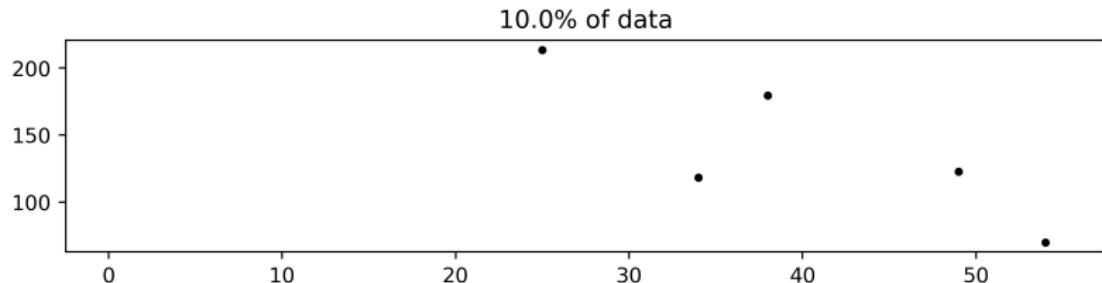
## Scenario 2 - yearly averages



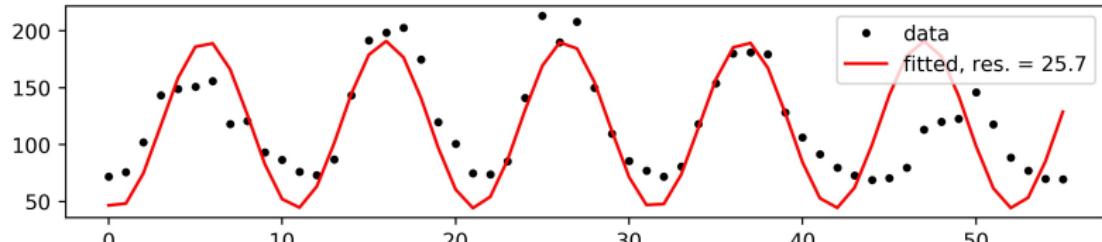
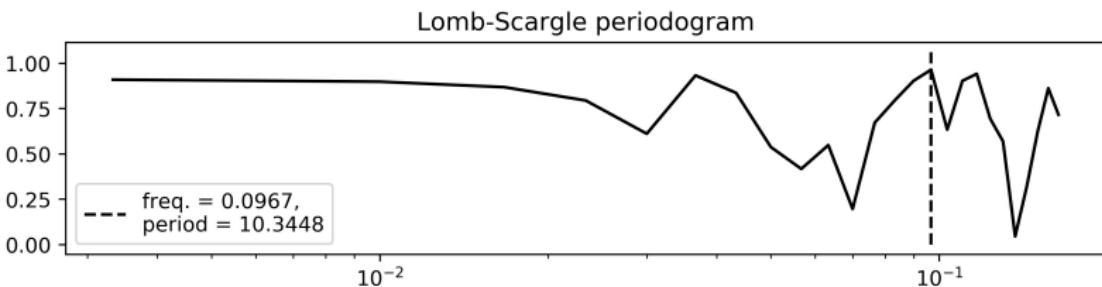
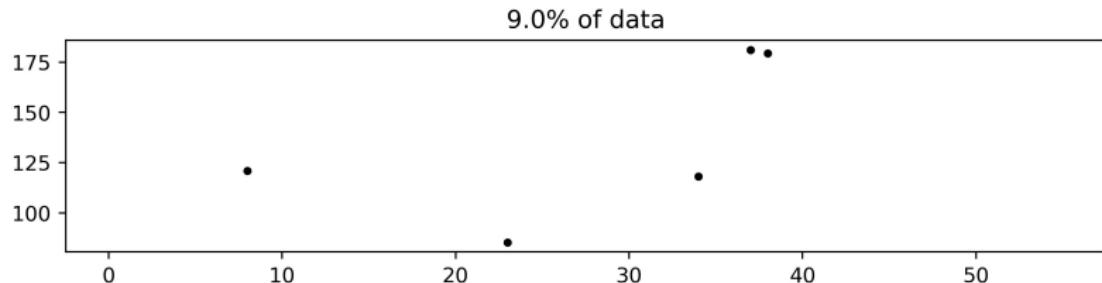
## Scenario 2 - yearly averages



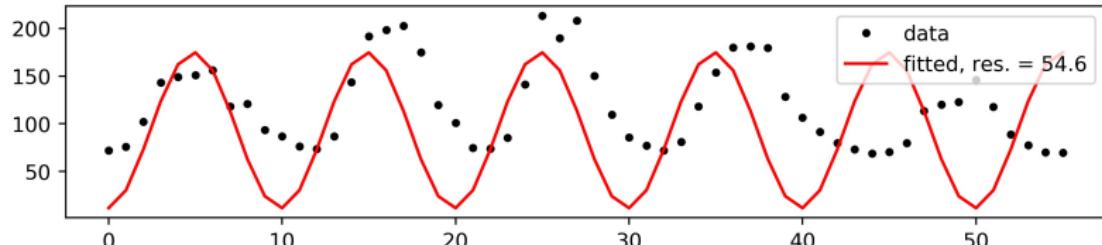
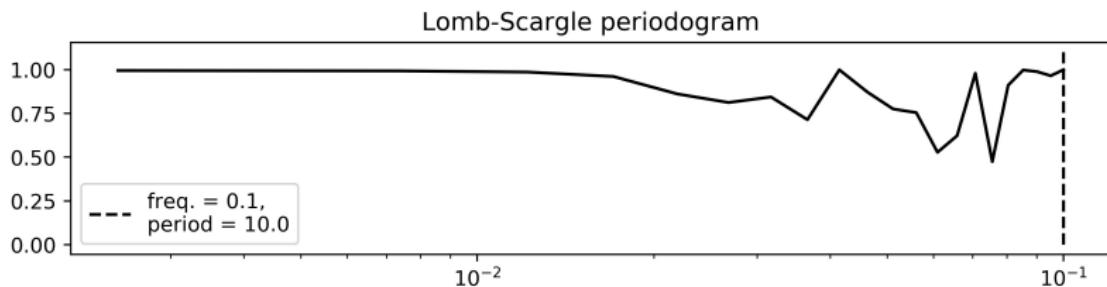
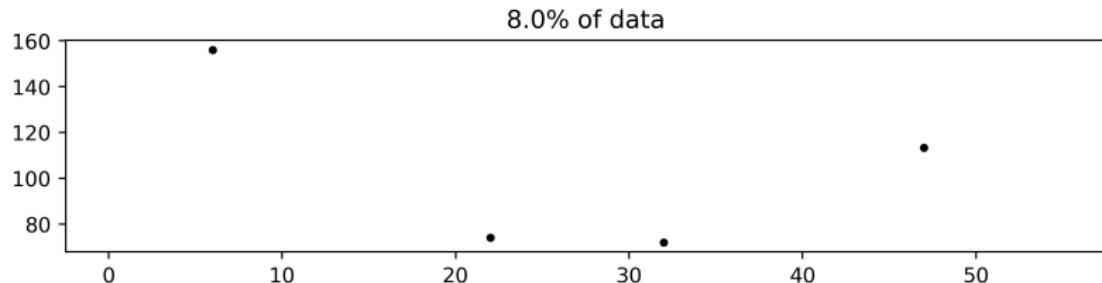
## Scenario 2 - yearly averages



## Scenario 2 - yearly averages



## Scenario 2 - yearly averages



## Final remarks

- Effects of sampling discussed
- Experiments undertaken with two scenarios of uneven sampling
- Lomb-Scargle periodogram introduced and applied via `LombScargle` class (from Python's package `astropy`)
- Parameter `nyquist_factor` tuned during analysis
- The tool was successfully implemented

# Links

Source of the data:

[omniweb.gsfc.nasa.gov/form/dx1.html](http://omniweb.gsfc.nasa.gov/form/dx1.html)

Documentation of the tool (astropy's LombScargle class):

[docs.astropy.org/en/stable/timeseries/lombscargle.html](http://docs.astropy.org/en/stable/timeseries/lombscargle.html)

This project's repository:

[github.com/leosattler/projeto-lomb-scargle.git](https://github.com/leosattler/projeto-lomb-scargle.git)

Thank you!