ATOC5860 – Application Lab #4
Spectral Analysis of Timeseries
in class March 10 and March 15

ASK IF YOU HAVE QUESTIONS ☺

Notebook #1 – Spectral analysis of hourly surface air temperatures from Fort Collins, Colorado at Christman Field
ATOC5860_applicationlab4_fft_christman.ipynb

LEARNING GOALS:
1) Complete a spectral analysis using two different functions in Python (direct FFT from numpy and using scipy which has more options). Describe the results including an interpretation of the spectral peaks and an assessment of their statistical significance.
2) Contrast applying a Boxcar and a Hanning Window when calculating the power spectra. What are the advantages/disadvantages of these two window types? What are the implications for the resulting power spectra?

DATA and UNDERLYING SCIENCE:
In this notebook, you analyze two years (January 1, 2013 through December 31, 2014) of hourly surface temperature observations from Christman Field in Fort Collins, Colorado. Missing data have been already treated. The data are in .csv format and are called Christman_data_nomissing.csv.

Questions to guide your analysis of Notebook #1:

1) Look at your data. What are the autocorrelation and e-folding time of your data? What spectral peaks do you expect to find in your analysis and how much power do you think they will have?

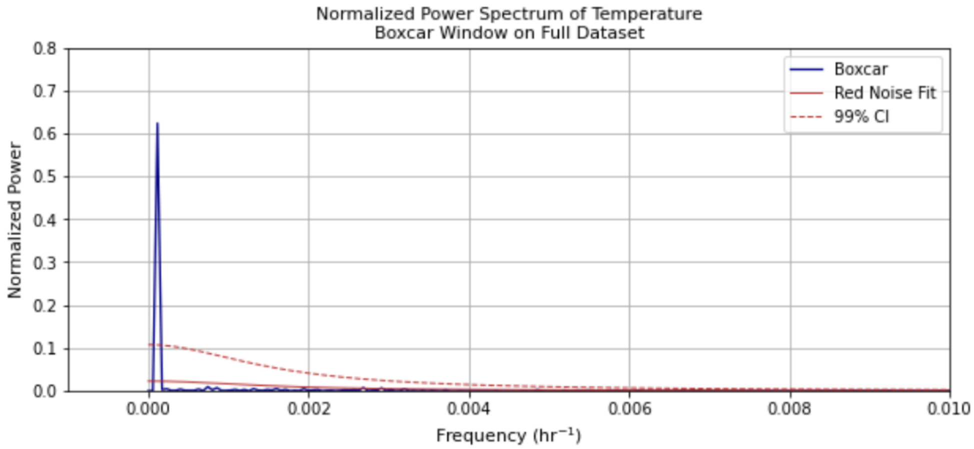
Temperature lag-1 autocorrelation = 0.99 (super red) and Te = 100.92 hours

I see seasonal temperature variability that would explain a lot of the variance (~9,000 hrs).

2) Calculate the power spectra using the Numpy method, which assumes a Boxcar window that is the length of your entire dataset. Graph the power spectra, the red noise fit to the data, and the 99% confidence interval. What statistically significant spectral peaks did you find? What do they represent? How did you assess the statistical significance (what is the null hypothesis that you are trying to reject)? Compare back to Barnes and Hartman notes to make sure all of the equations and functions in the notebook are working as you expect them too.

The null hypothesis is that there are no significant peaks of variance (no peaks above the 99% CI).

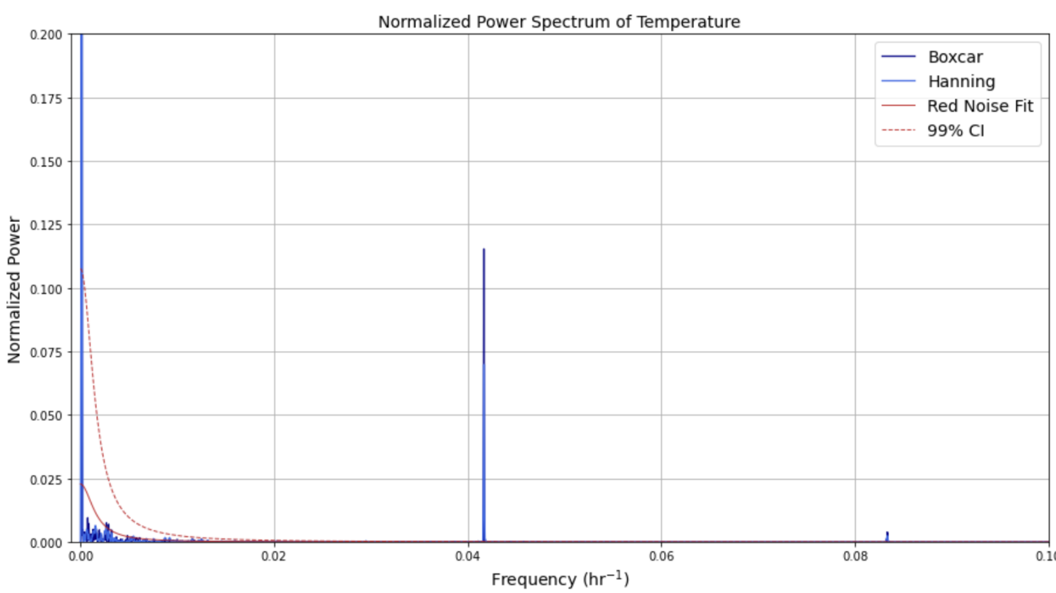
For the first method: 0.00011 hr^{-1} (1, annual year cycle), 0.42 hr^{-1} (1 day diurnal cycle) and 0.83 hr^{-1} (1 hour).



3) Calculate the power spectra using the scipy method. Check that you get the same result as you got using the Numpy method. Next – compare the power spectra obtained using both a Boxcar window and a Hanning window. Assume a window length that is the entire length of the dataset. Do you get the same statistically significant peaks when applying the Hanning window and the Boxcar window? How do they differ? Can you explain why?

For the second method: 0.00011 hr^{-1} (1 year cycle) and 0.42 hr^{-1} (1 day). This are the same significant peaks

The boxcar method leads to higher peak values, while the Hanning window smooths out the peaks! This is because the Hanning method intentionally smooths out.



4) If time – take a look at other surface meteorological variables in the dataset. Do you obtain similar spectral peaks?

Dewpoint temperature mirrors the temperature, but other variables do not vary on the same features.

5) Question: Are you seeing power at 12-hour frequencies when looking at temperature? Maybe it is atmospheric tides? Or is it some kind of spectral ringing artifact? Unsolved mysteries of ATOC7500 Objective Data Analysis…

This was very confusing to us as well!

Notebook #2 – FFT analysis using Dome-C Ice Core Data
ATOC5860_applicationlab4_fft_EPICA.ipynb

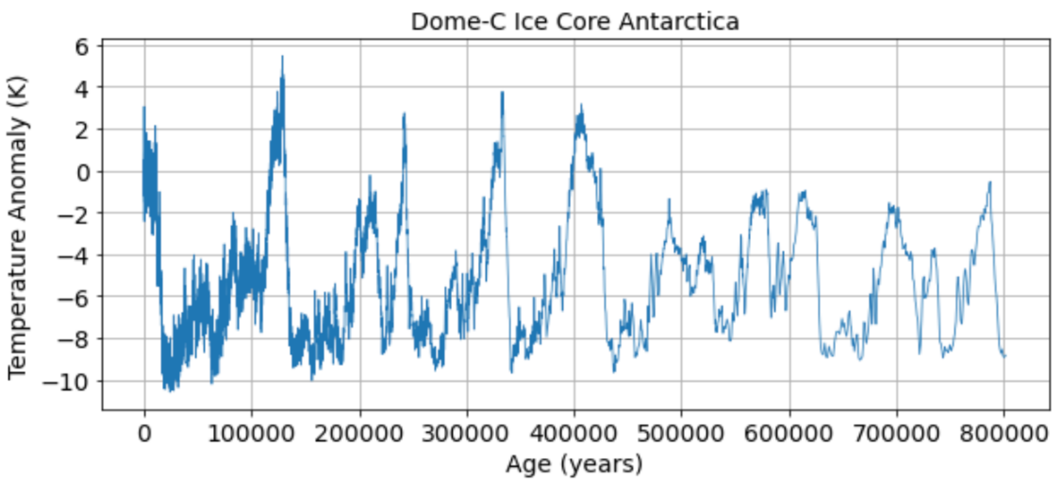
LEARNING GOALS:
1) Calculate power spectra of a dataset available on a non-uniform temporal grid. Describe the results including an interpretation of the spectral peaks and an assessment of their statistical significance.
2) Contrast applying a Boxcar and a Hanning Window when calculating the power spectra. What are the advantages/disadvantages of these two window types? What are the implications for the resulting power spectra?
3) Apply a Hanning Window with various window lengths - What are the advantages/disadvantages of changing the window length and the implications for the resulting power spectra in terms of their statistical significance and temporal precision?
4) Apply a Hanning Window with various window lengths and use Welch's method (Welch's Overlapping Segment Analysis, WOSA). How does WOSA change the results and why?

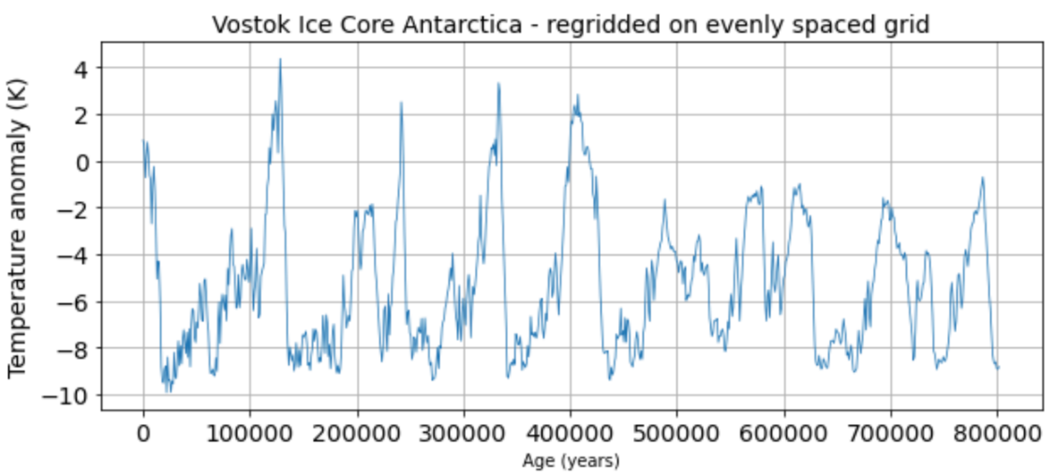
DATA and UNDERLYING SCIENCE:
In this notebook, you will perform a power spectral analysis of the temperature record from the Dome-C Ice Core, taken at 75 South and 123 East (Jouzel et al. 2007). The temperature data go back ~800,000 years before present. They are unevenly spaced in time. The data are available on-line here, courtesy of the NOAA Paleoclimatology Program and World Data Center for Paleoclimatology:
ftp://ftp.ncdc.noaa.gov/pub/data/paleo/icecore/antarctica/epica_domec/edc3deuttemp2007.txt More information on the data is available at:
https://www.ncdc.noaa.gov/paleo-search/study/6080

Questions to guide your analysis of Notebook #2:

1) Look at your data and pre-process for FFT analysis: Power spectra analysis assumes that input data are on an evenly spaced grid. The Dome-C temperature data are not uniformly sampled in time. Regrid the Dome-C temperature data to a

uniform temporal grid in time. Plot the data before and after re-gridding to make sure the re-gridding worked as expected.





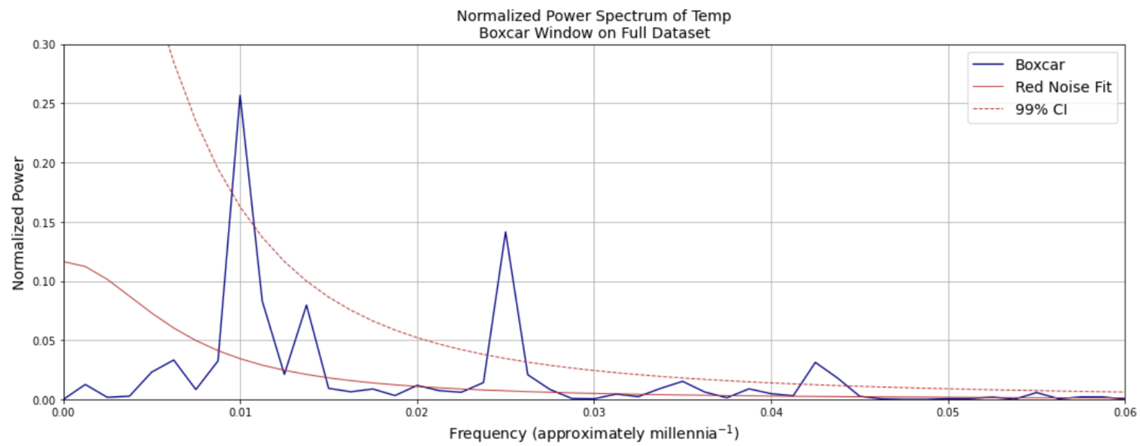
2) Signal and Noise: What is the autocorrelation and e-folding time of your data? What spectral peaks do you expect to find in your analysis and how much power do you think they will have? *Hint: Think back to the Petit 1999 Vostok ice core dataset discussed in class.*

Temp lag-1 autocorrelation = 0.96 and Te = 25.0. This indicates that there is a lot of red noise. I expect power on certain time scales as I know there are consistent variations.

3) Use Boxcar Window to calculate power spectra: Calculate the power spectra using the Numpy method, which assumes a Boxcar window that is the length of your entire dataset. Graph the power spectrum, the red noise fit to the data, and the 99%

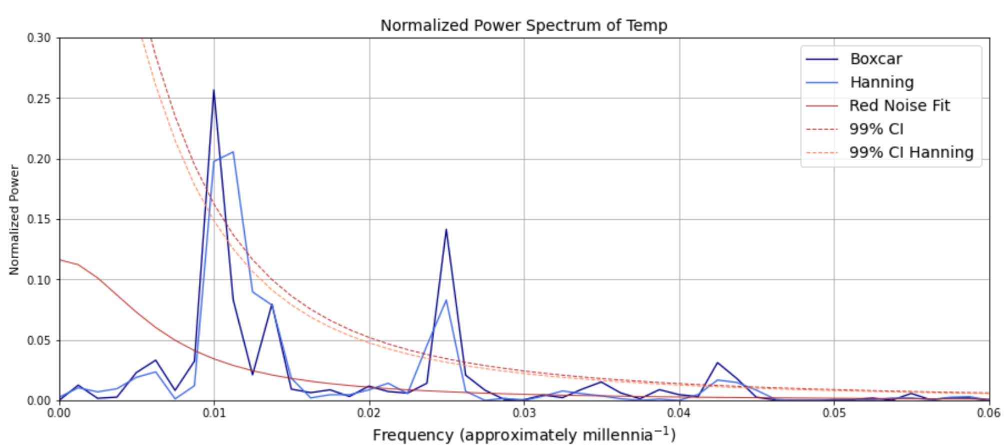
confidence interval. What statistically significant spectral peaks did you find? What do they represent?

We found three significant peaks at: 100,328 years, 40,131 years, and 22932-23,607 years. These are the Milankovitch cycles.



4) <u>Compare Boxcar Window vs. Hanning Window</u>: Calculate the power spectra using the SciPy method. Compare the results obtained using a Boxcar window that is the length of your entire dataset to those obtained using a Hanning window that is the length of your entire dataset. Graph the power spectrum, the red noise fit to the data, and the 99% confidence interval. What statistically significant spectral peaks did you find? What do they represent? What are the differences between the results obtained using the Boxcar window and the Hanning window? Is the intuition that you gained by looking at Fort Collins temperatures the same as what you are seeing here with Dome-C temperature records? Why or Why not?

The Hanning window does again lead to a decline in the power of the peaks, but the same peaks do appear! The intuition from the Fort Collins dataset is similar leading to decline peaks

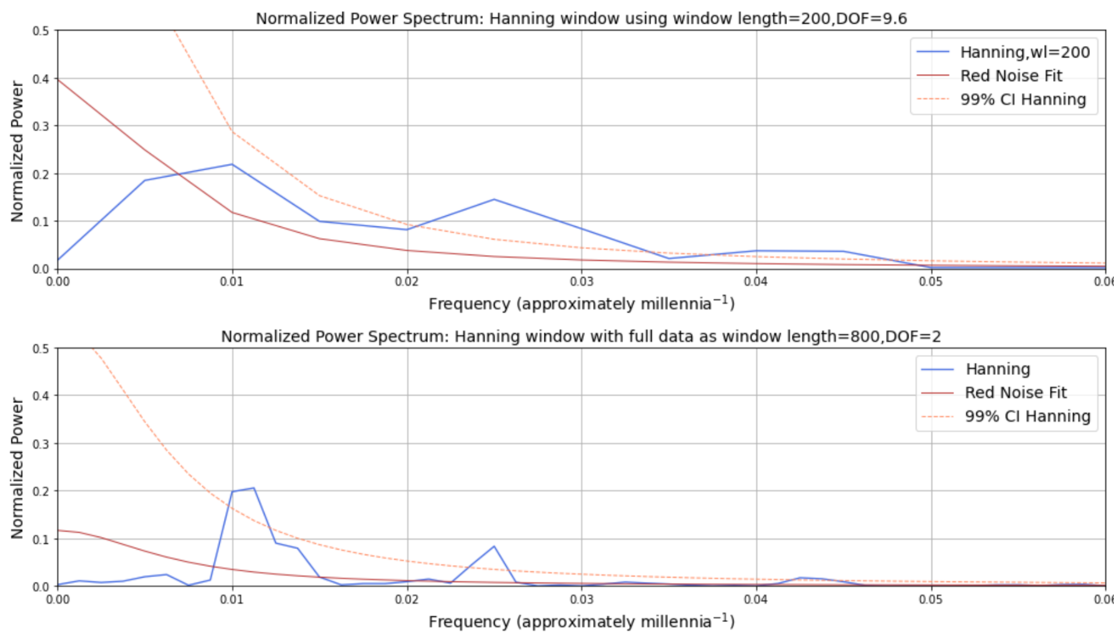


5) <u>Hanning Window with different window lengths:</u> Using the SciPy method, compare the power spectra obtained using Hanning window with different window lengths. Graph the power spectra, the red noise fit to the data, and the 99% confidence interval. Did you find any statistically significant spectral peaks? How does decreasing the window length affect the temporal precision of the spectral peaks and their statistical significance? Did you find the classic tradeoff between 1) high spectral/temporal resolution but low quality statistics, and 2) high quality statistics but low spectral/temporal resolution?

With the shorter window, we found a significant variation at 40,000 years and 23,000 years.

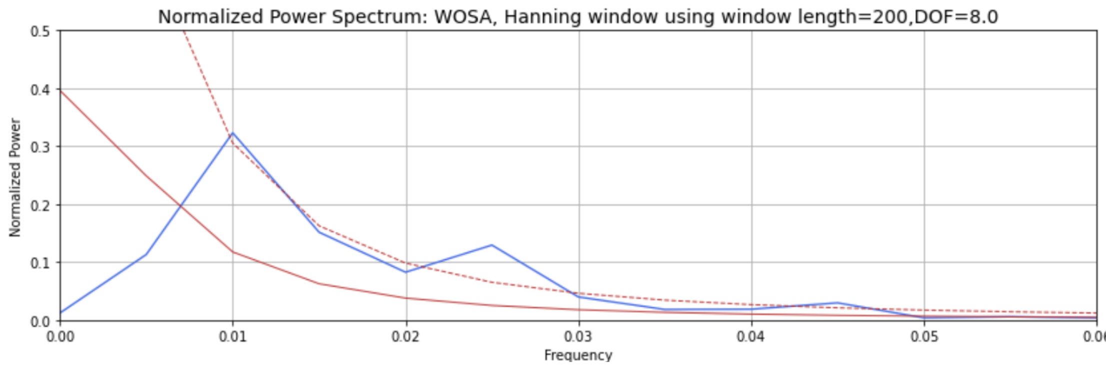
With the longer window, we found a significant variation at 100,000 years, 40,000 years and 23,000 years.

Decreasing the window length leads to less precise measurements but increases significance. I think we found the classic mix up of precision vs resolution!



5) <u>Add WOSA (Welch Overlapping Segment Averaging):</u> Having found what you think is a good balance between precision in the identification of the spectral peaks and statistical significance – Try applying WOSA (Welch Overlapping Segment Averaging) in addition to using the Hanning Window with different window lengths. How does this change your results?

With the WOSA, we find the same peaks, but they are less significant. It seems the WOSA method leads to more “spread out” results.



Normalized Power Spectrum: WOSA, Hanning window using window length=200,DOF=8.0
Normalized Power
Frequency
0.0
0.1
0.2
0.3
0.4
0.5
0.00
0.01
0.02
0.03
0.04
0.05
0.06