



Lecture 13: Discussion of Hinnov and Goldhammer (1991)

1. Geological setting
2. Cycles in the Latemar Limestone (space)
3. Potential origin of the Latemar cycles (time)
4. Testing the hypothesis: the data
5. Testing the hypothesis: the analysis

We acknowledge and respect the lək̓ʷəŋən peoples on whose traditional territory the university stands and the Songhees, Esquimalt and W̱SÁNEĆ peoples whose historical relationships with the land continue to this day.



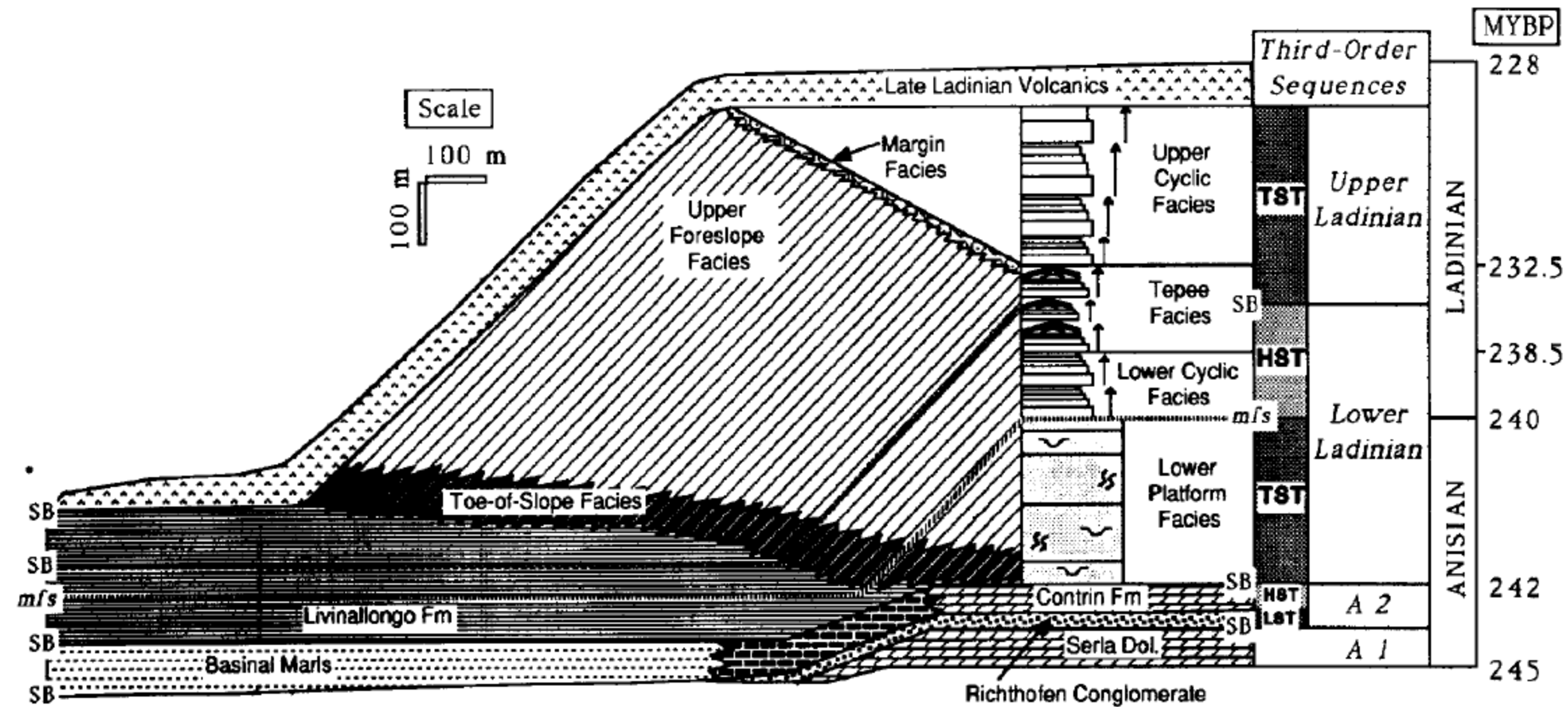
In [60]:

```
import random
def pick_group(class_list):
    if len(class_list)>0:
        picked=random.sample(class_list,2)
        [class_list.remove(p) for p in picked]
        print(' and '.join(picked))
    else:
        picked=[]
    return class_list,picked
```



Geological setting

- why would a platformal setting be especially sensitive to sea level changes?

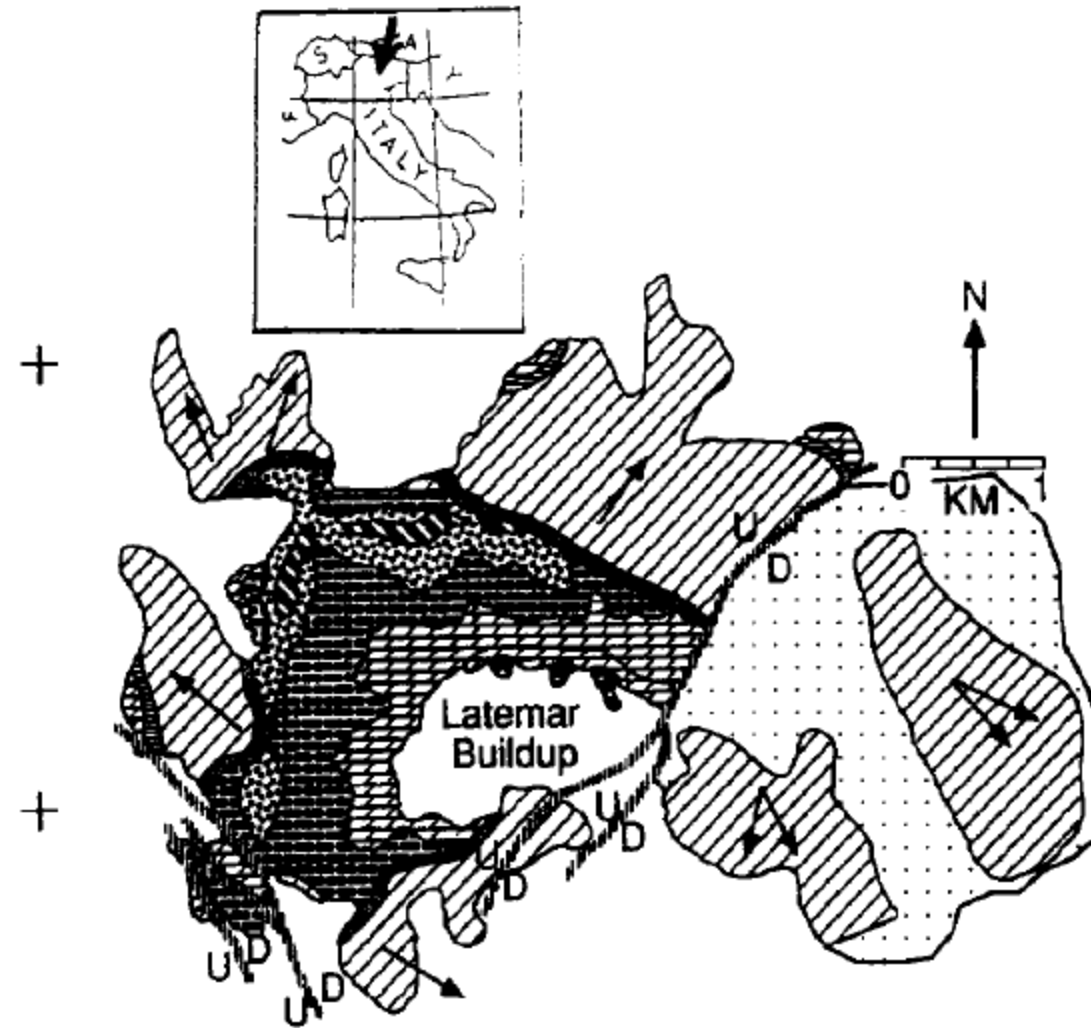


```
In [61]: class_list = ['Kai', 'Stacey', 'Grace', 'Liam', 'Matteo', 'Matthew', 'Noa', 'Izzy', 'Felix', 'Rhys', 'Andrea', 'Kristyn']
class_list, picked = pick_group(class_list)
```

Andrea and Kai



Geological setting



LEGEND		
Ladinian		Late Ladinian Volcanics
		Upper Cyclic Facies
		Tepee Facies
Ladinian & Anisian		Lower Cyclic Facies
		Latemar Margin Facies
		Latemar Foreslopes
Anisian		Livinallongo Fm (basinal carbonate)
		Lower Platform Facies
		Contrin Fm



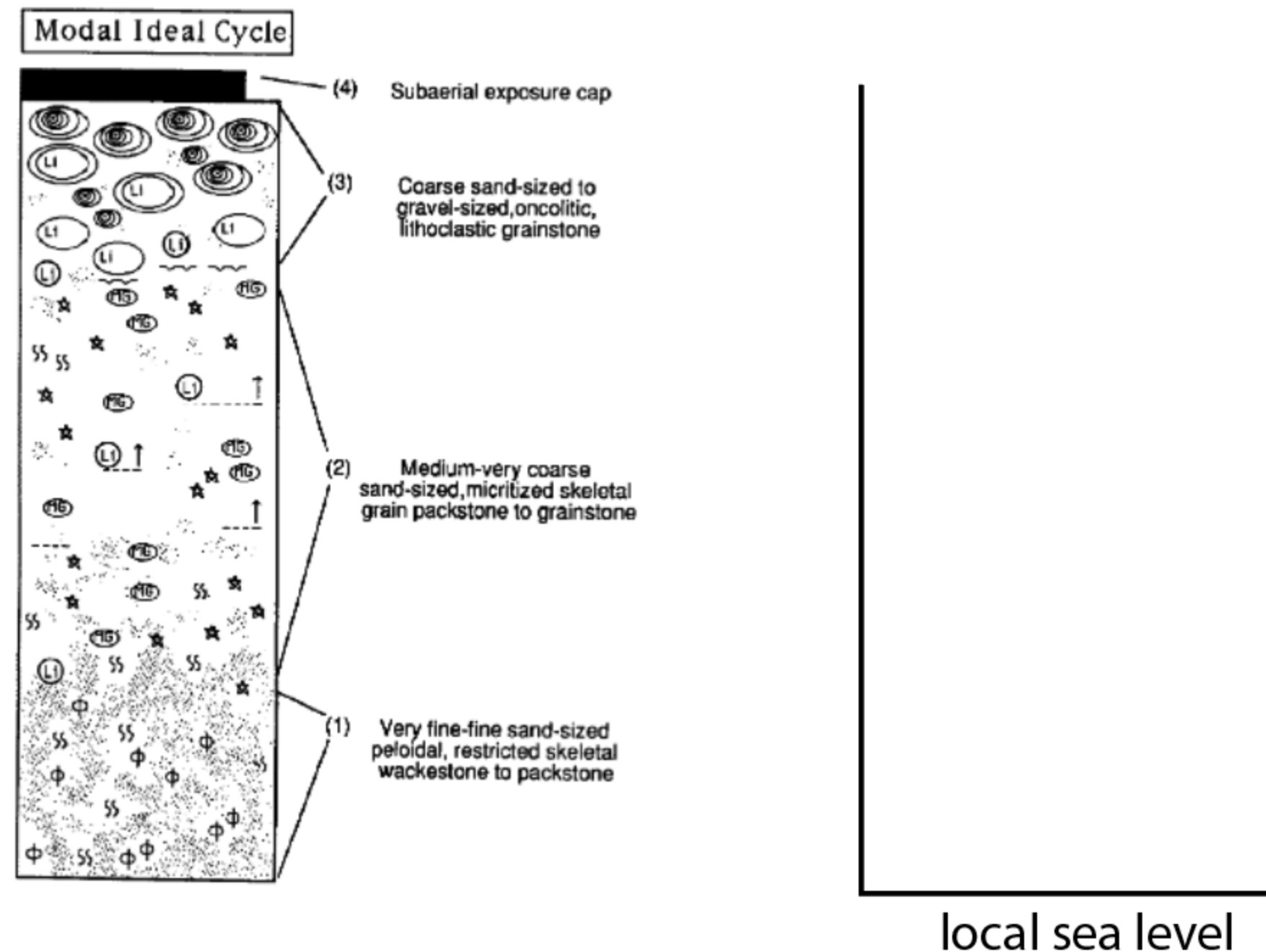
```
In [62]: class_list = ['Kai', 'Stacey', 'Grace', 'Liam', 'Matteo', 'Matthew', 'Noa', 'Izzy', 'Felix', 'Rhys', 'Andrea', 'Kristyn']  
class_list, picked = pick_group(class_list)
```

Grace and Rhys



An ideal cycles in the Latemar Limestone

- what do the authors think is happening to sea level during deposition?
- *"The absence of features indicating peritidal deposition between the subtidal member and vadose cap is conspicuous throughout the formation."*



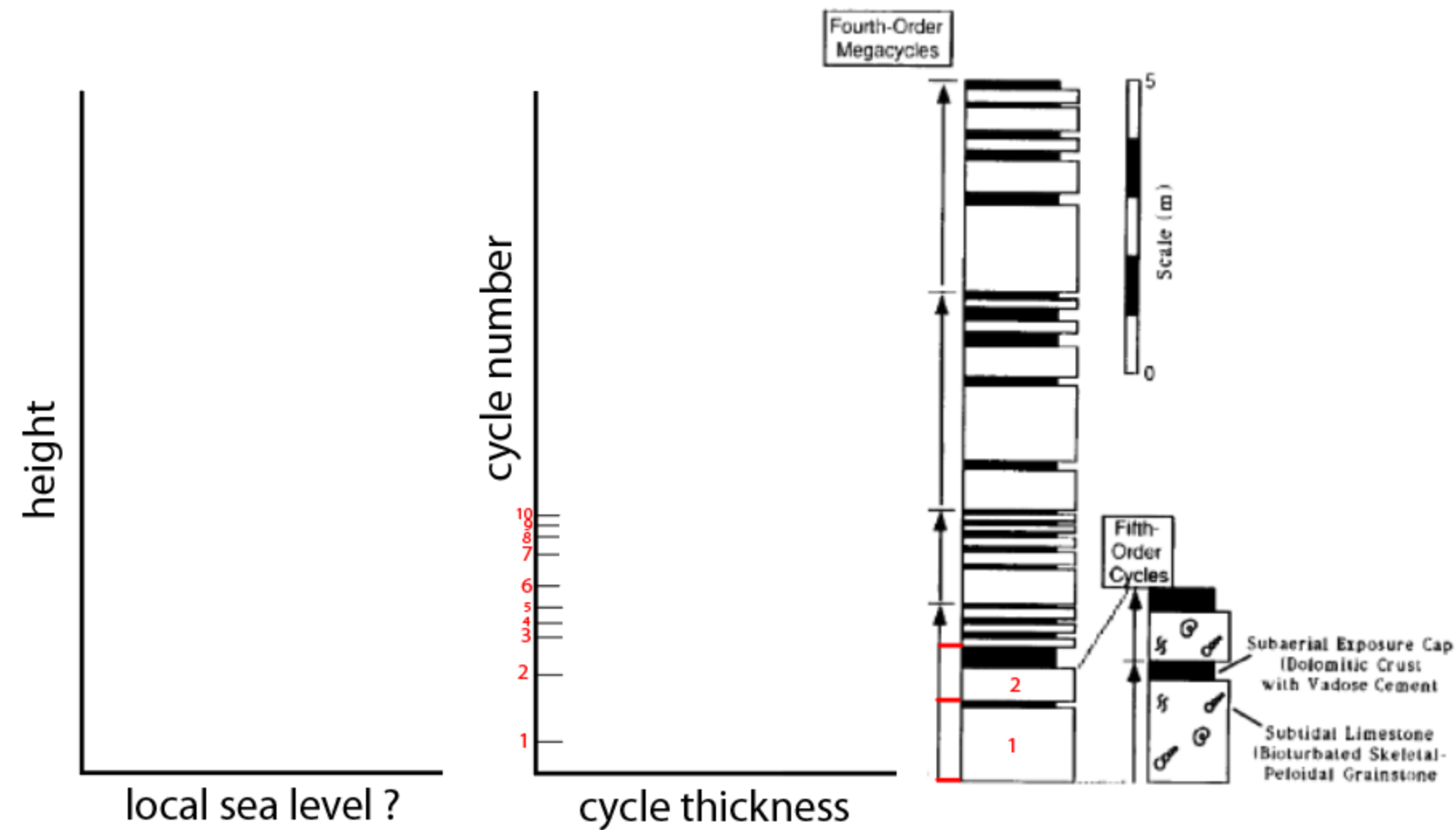
```
In [64]: class_list = ['Stacey', 'Liam', 'Matteo', 'Matthew', 'Noa', 'Izzy', 'Felix', 'Kristyn']  
class_list, picked = pick_group(class_list)
```

Izzy and Noa



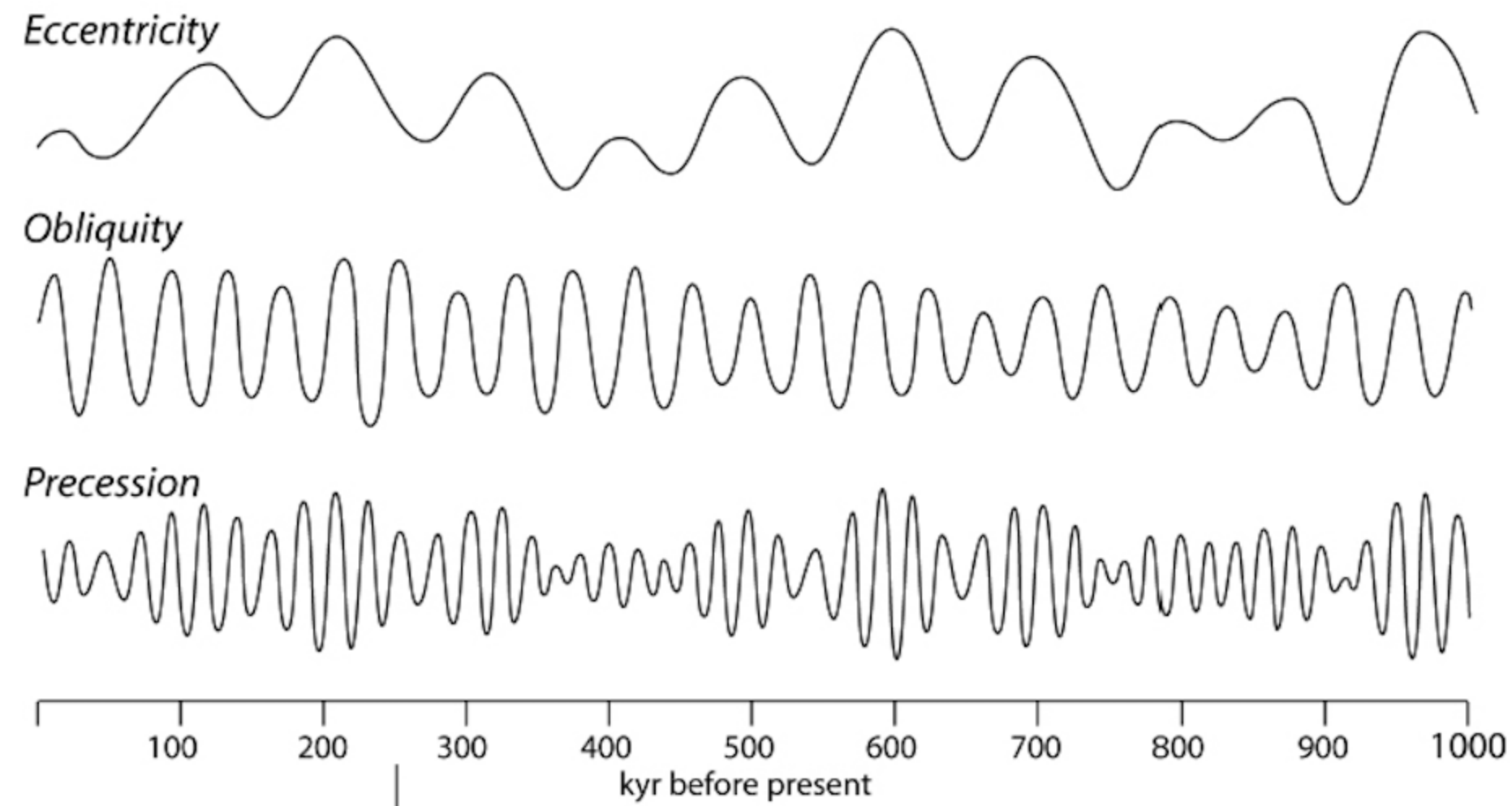
Nested cycles in the Latemar Limestone

- where is the *ideal Latemar cycle* on this plot?
- what is happening to **cycle thickness** up section?
- what do the authors think is happening to sea level?



What is the proposed driver of cyclicity?

- what is driving an *ideal cycle*?
- what is driving the *bundling of cycles* into groups of five?

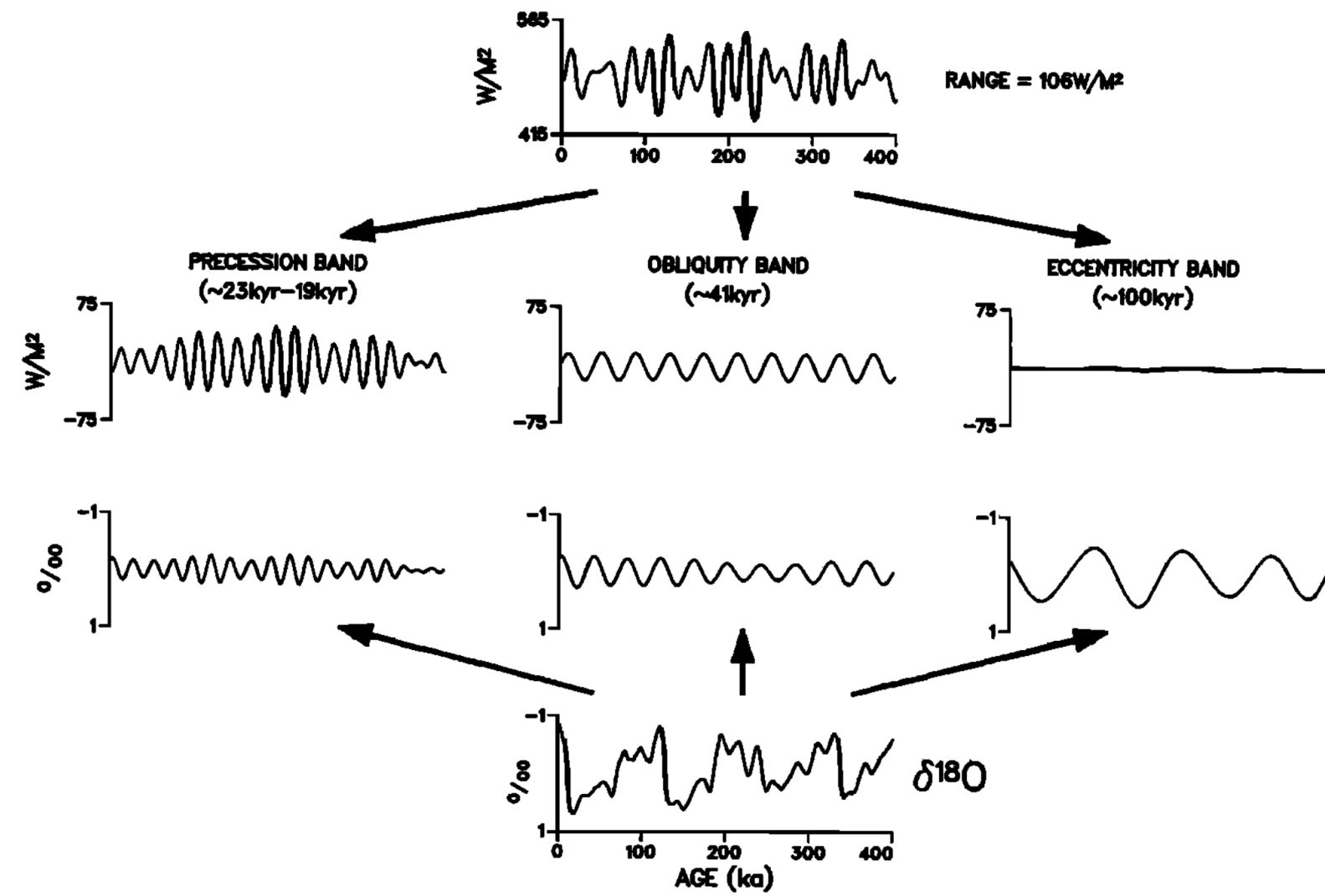


```
In [65]: class_list = ['Stacey', 'Liam', 'Matteo', 'Matthew', 'Felix', 'Kristyn']  
         class_list, picked = pick_group(class_list)
```

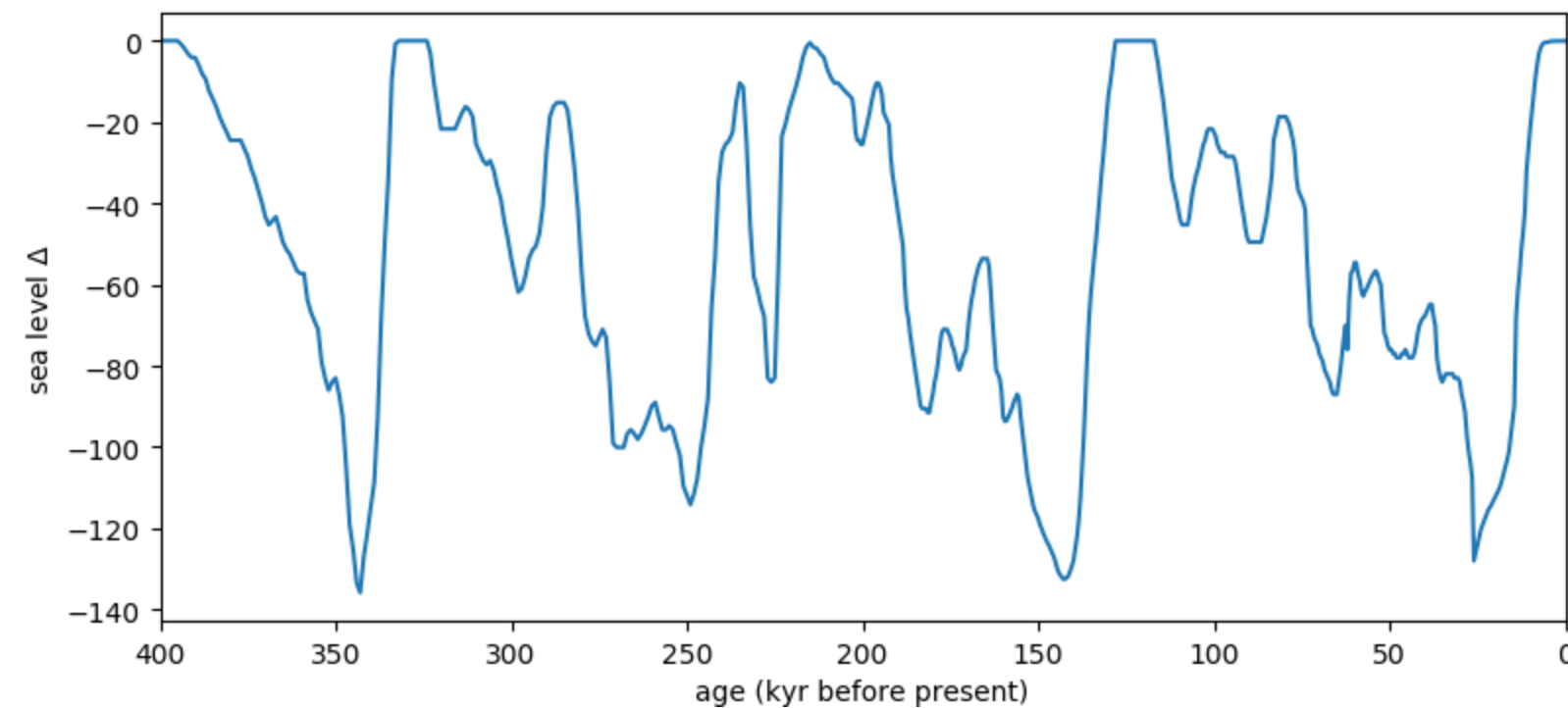
Matthew and Matteo



Q ↓ 65°N JUNE



But then why are the bundles asymmetric (according to the authors)?



```
In [ ]: class_list = ['Kai', 'Stacey', 'Grace', 'Liam', 'Matteo', 'Matthew', 'Noa', 'Izzy', 'Felix', 'Rhys', 'Andrea', 'Kristyn']
        class_list, picked = pick_group(class_list)
```

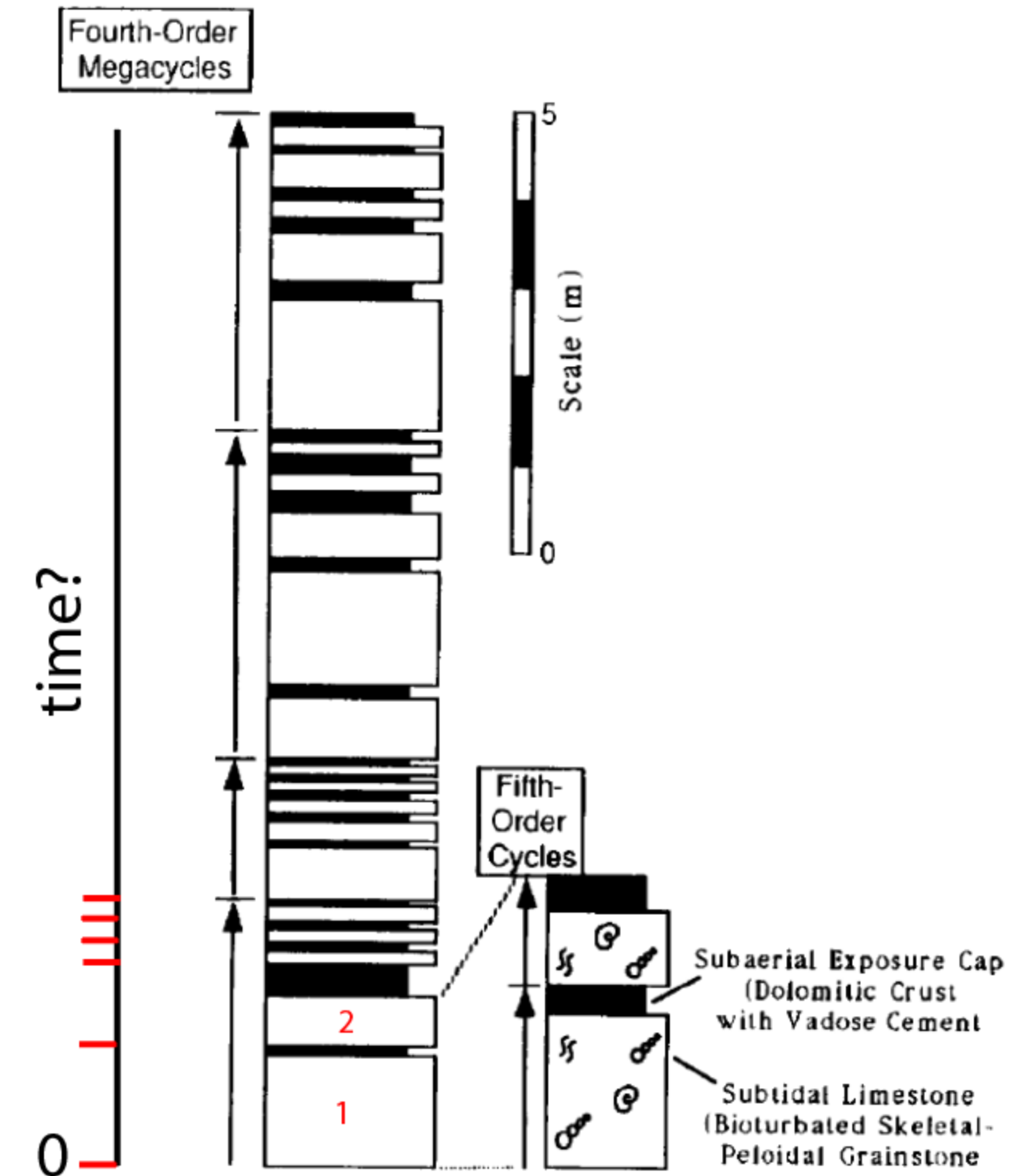
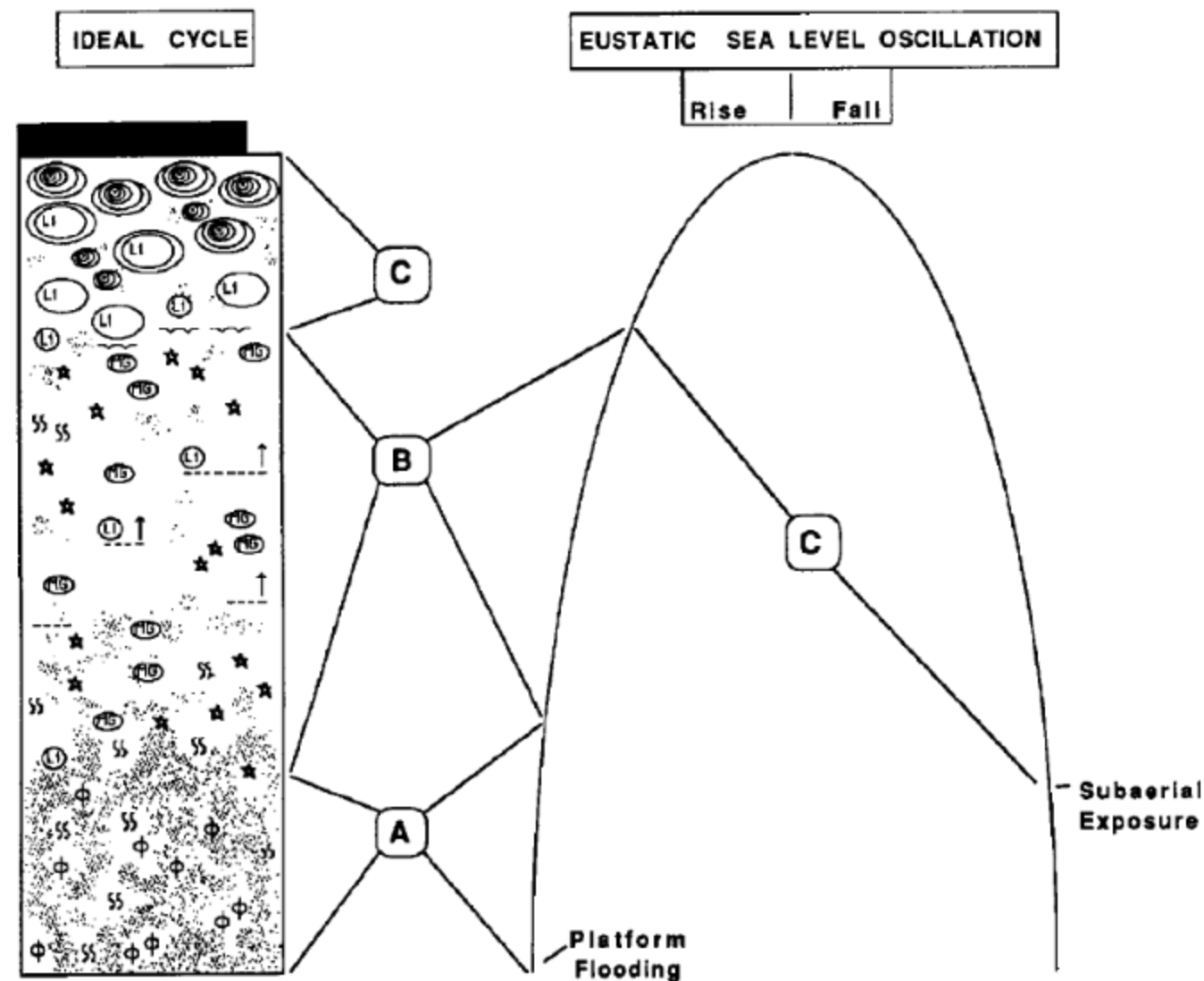


```
In [ ]: class_list = ['Kai', 'Stacey', 'Grace', 'Liam', 'Matteo', 'Matthew', 'Noa', 'Izzy', 'Felix', 'Rhys', 'Andrea', 'Kristyn']  
class_list, picked = pick_group(class_list)
```

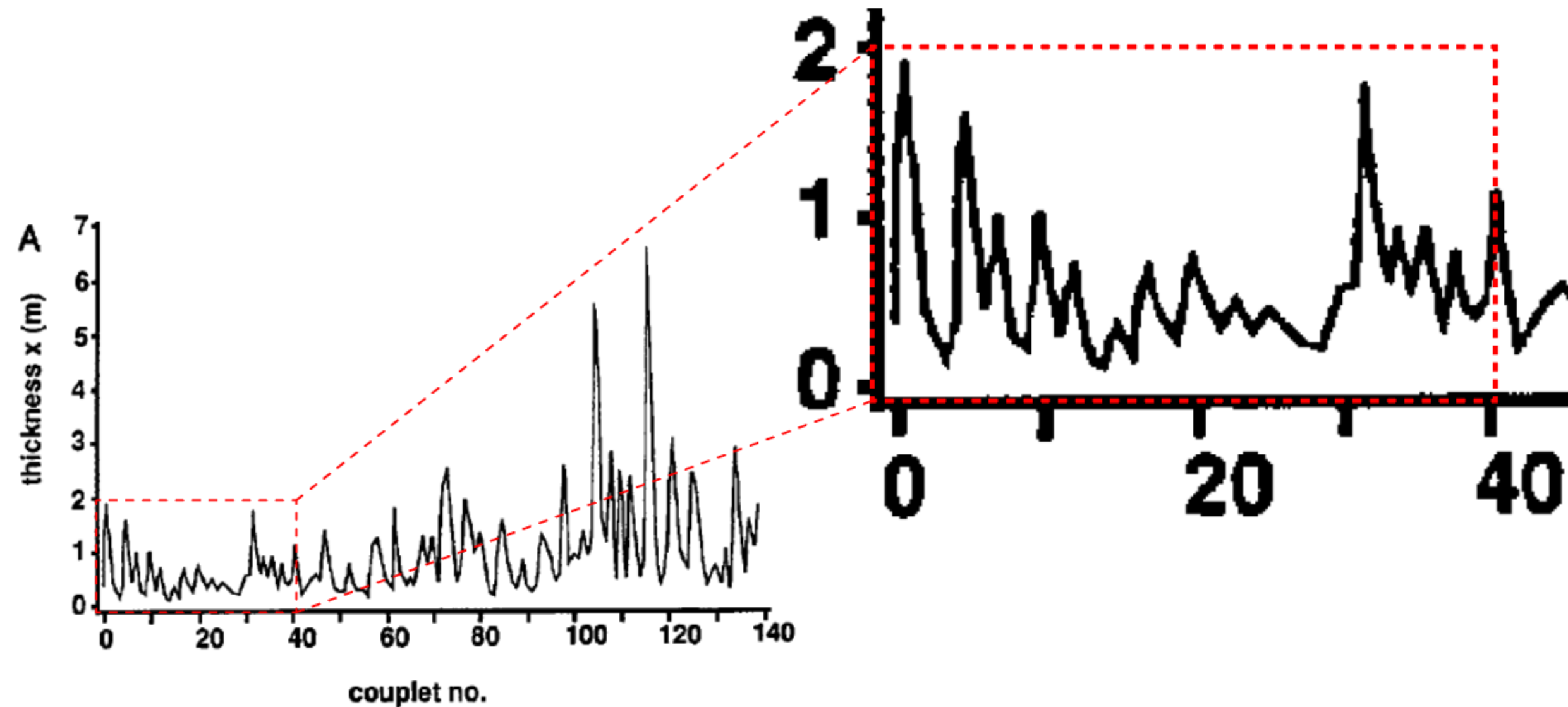


How then is time distributed in the Latemar succession?

- How long does one cycle last? How about 5 cycles?



Testing the hypothesis: how are they going to do it?



```
In [66]: class_list = ['Stacey', 'Liam', 'Felix', 'Kristyn']  
         class_list, picked = pick_group(class_list)
```

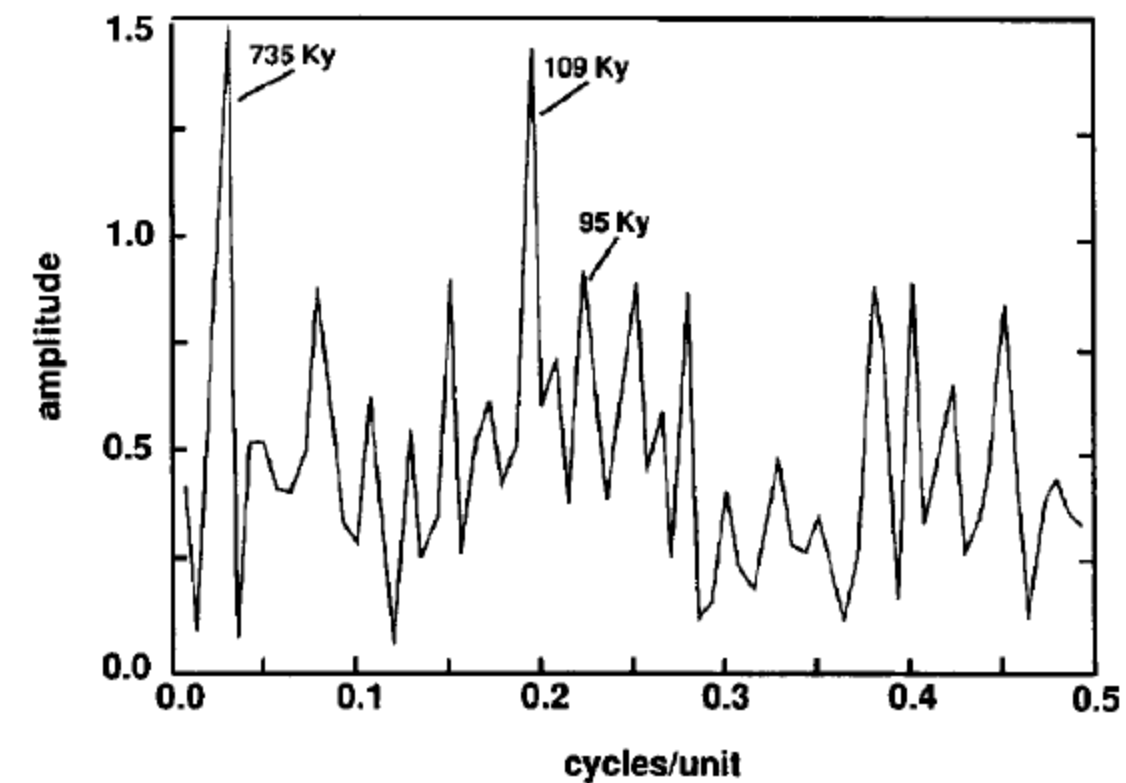
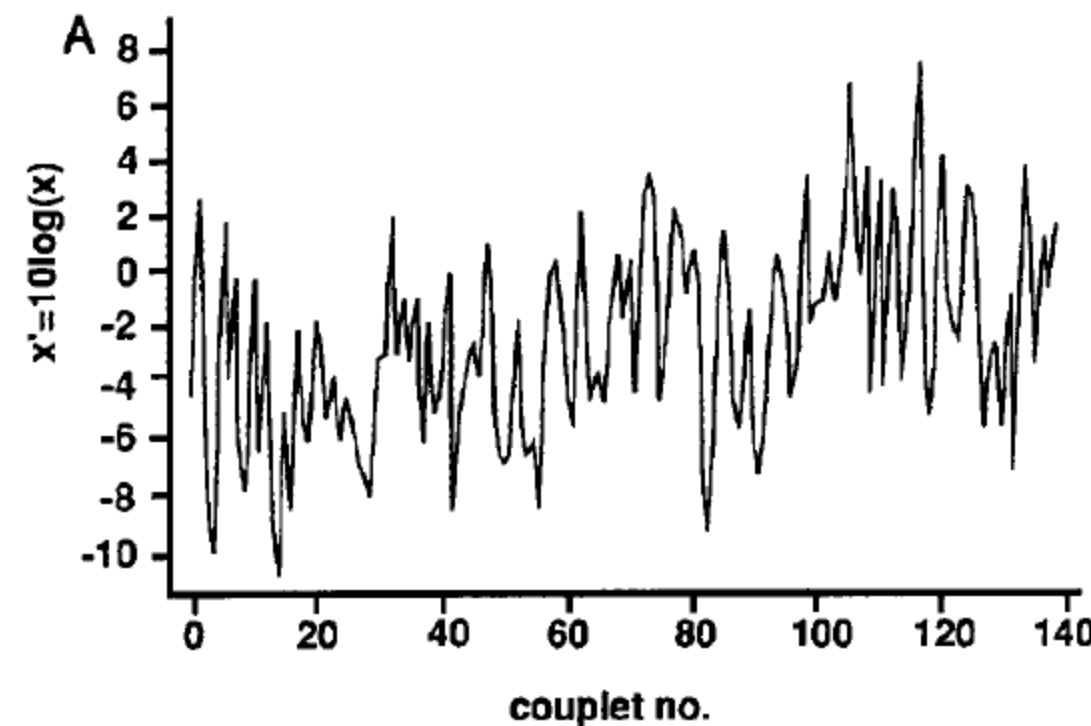
Felix and Stacey



Testing the hypothesis: the analysis

Authors need to accomplish two things:

- show that a 5:1 bundling of cycles is a significant feature of the data (**easier**)
 - in other words, are there cycles in space?
- make the case that 1 bundle = precession and 5 bundles = eccentricity (**way, way harder**)
 - do the cycles require a **cyclic (in time)** forcing?



Testing the hypothesis: the analysis

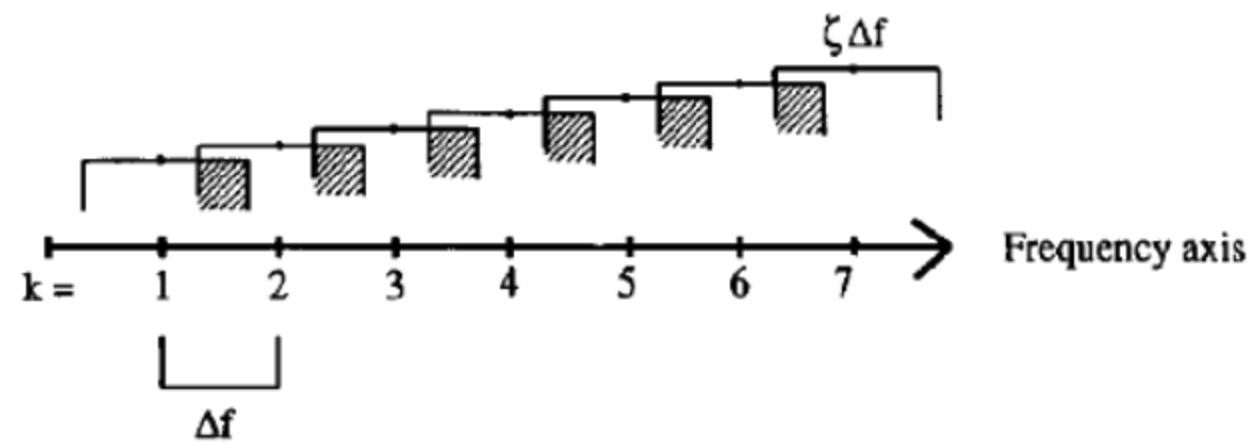
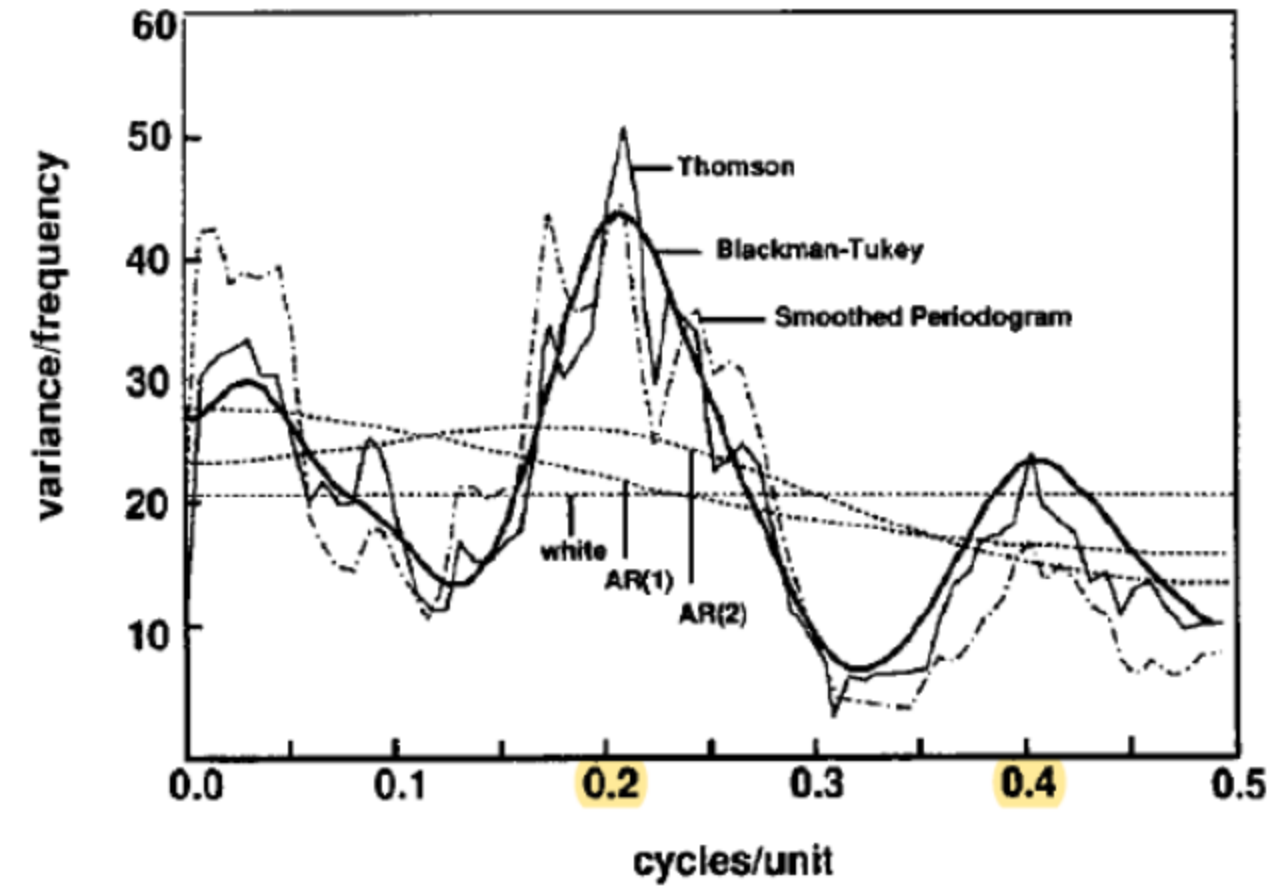
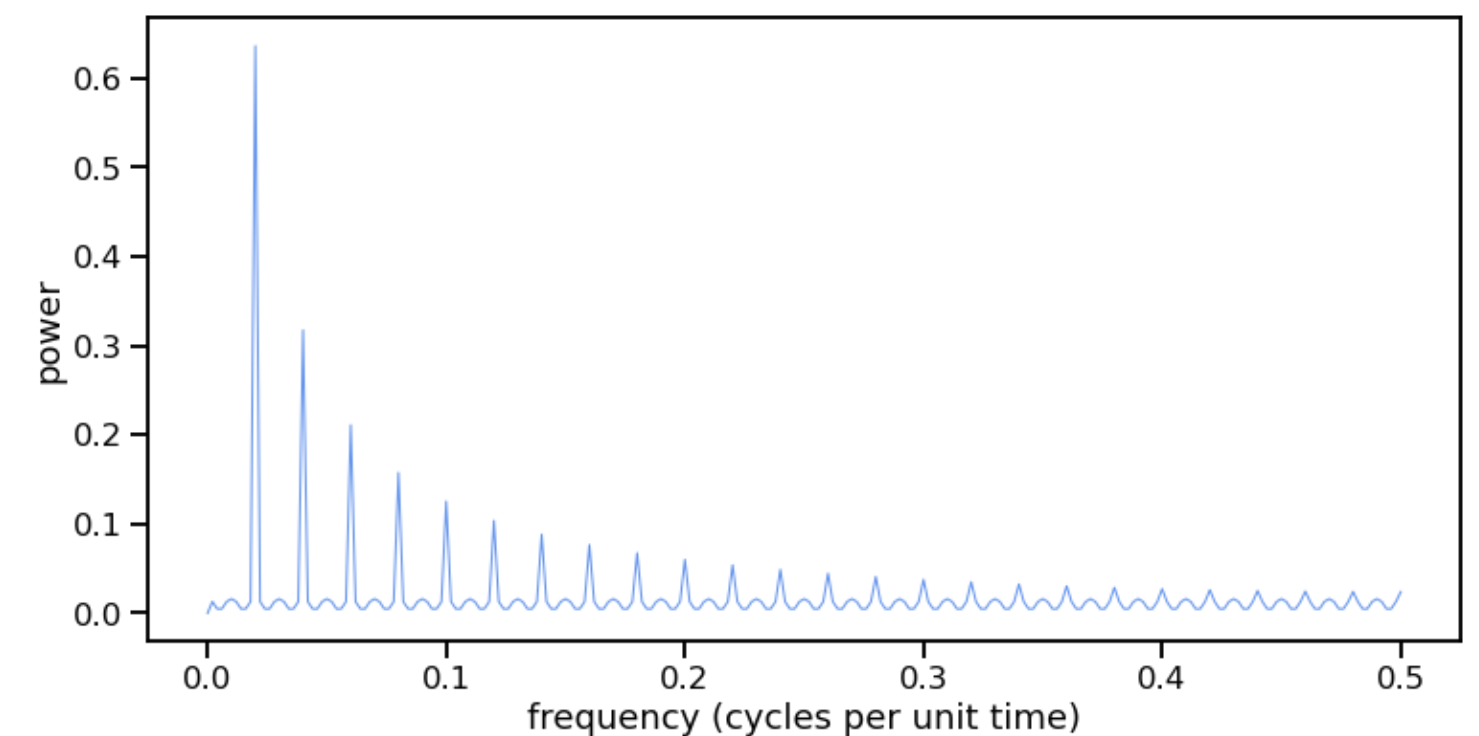
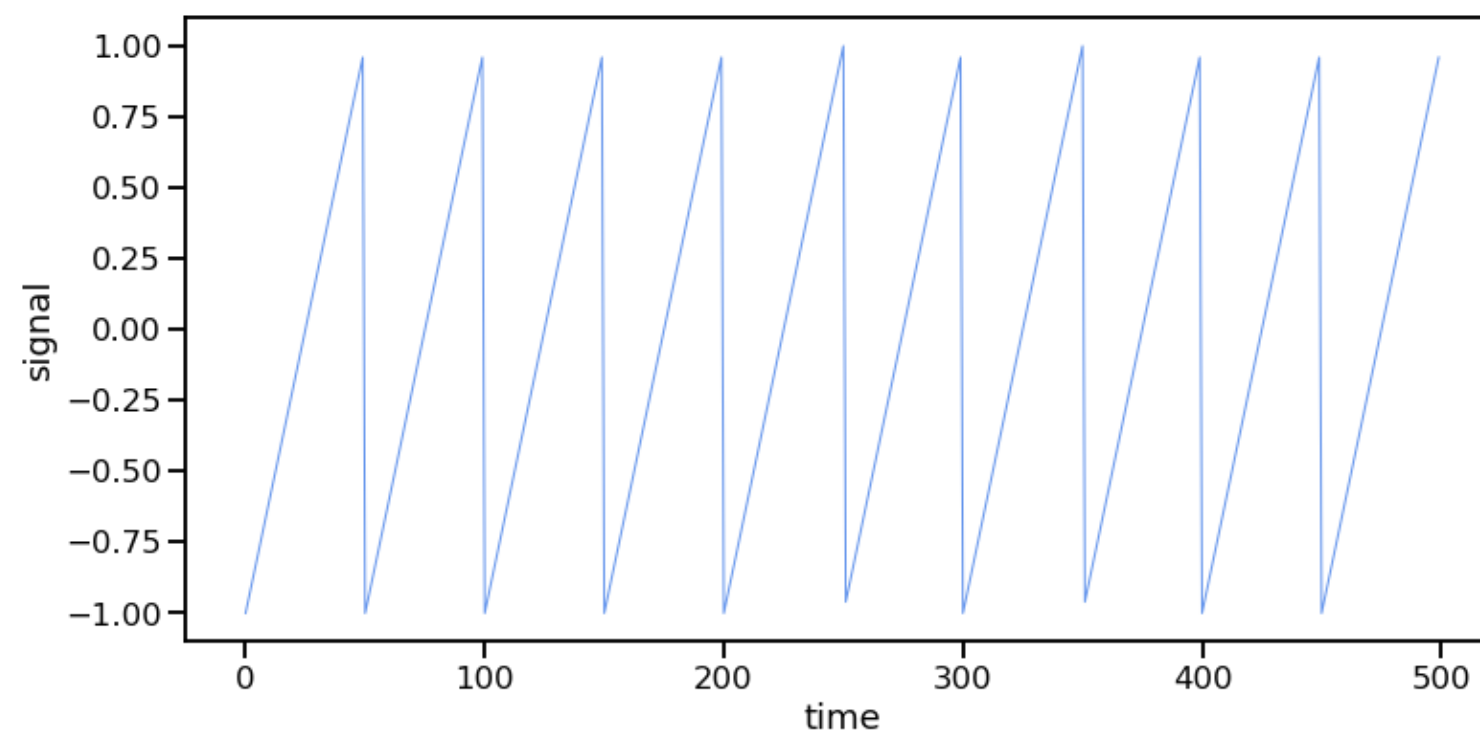


FIG. 12.—Illustration of correlation between adjacent frequency estimates comprising a smoothing window of $K = 7$, and modified by a spectral window of bandwidth $\zeta \Delta f$. The shaded regions indicate regions of correlation; the sum of frequency spaces indicated by the unshaded areas equals $(K - 1)(\zeta - 1) + 2$.



Overtone

```
In [67]: #make some white noise
N=500
t = np.arange(0.0, 500, 1)
meas=scipy.signal.sawtooth((2*np.pi*t)/50)
mf=fft(m meas - np.mean(m meas))
tf,power,results=fft_axes(mf,N,N,1)
#plot
fig1=plt.figure(1,figsize=(27,6))
ax1=fig1.add_subplot(121)
ax1.set_xlabel('time')
ax1.set_ylabel('signal')
ax1.plot(m meas, '-', lw=1, color='#6495ED')
ax1=fig1.add_subplot(122)
ax1.plot(tf,power, '-', lw=1, color='#6495ED')
ax1.set_xlabel('frequency (cycles per unit time)')
ax1.set_ylabel('power')
```



Noise: red or white?

```
In [ ]: from scipy.fftpack import fft
import matplotlib.pyplot as plt
import numpy as np
from scipy import signal
import pandas as pd
import seaborn as sns
sns.set_context('talk')
%matplotlib inline

def fft_axes(yf,T,N,dt):

    if N % 2==0:
        xf=np.hstack((np.arange(0,1/(2*dt),1/T),(N//2)/T))
        power=2.0/N *np.abs(yf[0:len(xf)])
    else:
        xf=np.arange(0,1/(2*dt),1/T)
        power=2.0/N *np.abs(yf[0:len(xf)])

    results=pd.DataFrame(zip(xf,power),columns=['freq','power'])
    results=results.sort_values(by=['power'],ascending=False)

    return xf,power,results
```




```
In [ ]: #make some white noise
N=500
t = np.arange(0.0, 500, 1)
meas=np.random.uniform(size=500)
#periodic signal
amp=0.0 #amp=0.065 #amp=0.13
ang_freq=0.02
meas=meas + amp*np.sin(ang_freq* 2*np.pi*t)
#fft
mf=fft(m meas - np.mean(m meas))
tf,power,results=fft_axes(mf,N,N,1)
#plot
fig1=plt.figure(1,figsize=(27,6))
ax1=fig1.add_subplot(121)
ax1.set_xlabel('time')
ax1.set_ylabel('signal')
ax1.plot(m meas, '-', lw=1, color='#6495ED')
ax1=fig1.add_subplot(122)
ax1.plot(tf,power, '-', lw=1, color='#6495ED')
# ax1.annotate('our signal',(ang_freq,power[tf==ang_freq][0]),xytext=(50, 0), textcoords='offset points',fontsize=16,arrowprops=
ax1.set_xlabel('frequency (cycles per unit time)')
_=ax1.set_ylabel('power')
```



```

In [ ]: #make some red noise
t = np.arange(0.0, 500, 1)
meas=np.random.randint(-1,2,500)
meas=np.cumsum(meas)
#periodic signal
amp=2 #amp=2
ang_freq=0.02
meas=meas + amp*np.sin(ang_freq * 2*np.pi*t)
#fft
mf=fft(meas - np.mean(meas))
tf,power,results=fft_axes(mf,N,N,1)
#plot
fig1=plt.figure(1,figsize=(27,6))
ax1=fig1.add_subplot(121)
ax1.set_xlabel('time')
ax1.plot(meas,'-',lw=1,color='#6495ED')
ax1=fig1.add_subplot(122)
# ax1.plot(tf,power,'-',lw=1,color='#6495ED')
ax1.plot(np.log10(tf[1:]),np.log10(power[1:]),'- ',lw=1,color='#6495ED')
# ax1.annotate('our signal',(np.log10(ang_freq),np.log10(power[tf==ang_freq][0])),xytext=(50, 0), textcoords='offset points',font
ax1.set_xlabel('frequency (cycles per unit time)')
_=ax1.set_ylabel('power')

```

```

In [ ]: #make some white noise
N=100
t = np.linspace(0.0, N, 100000)
meas=2*np.sin((2*np.pi*t)/50)+np.cos(2*np.pi*t/10)

#plot
fig1=plt.figure(1,figsize=(27,6))
plt.plot(t,meas+t/5)

```

```

In [ ]:

```

