

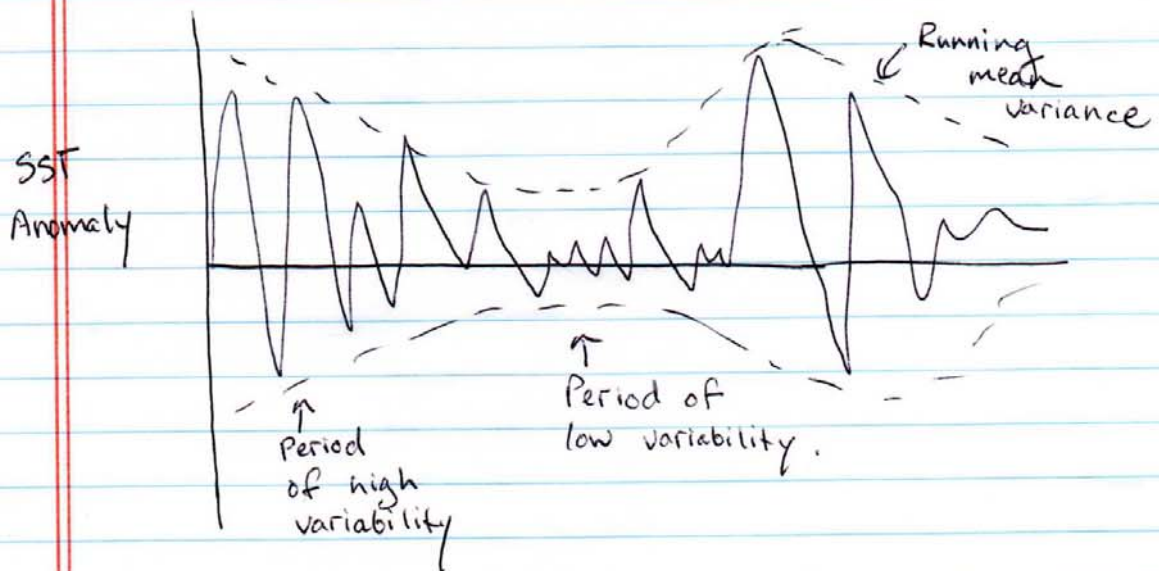
Wavelet Analysis

Ref: Torrence and Compo BAMS Article
"A Practical Guide to Wavelet Analysis"
+ web references (has code too!)

Motivation: Many time series exhibit non-stationarity in their statistics.

A series may contain periodic signals, but these may vary in frequency and time (and typically do!)

Niño example



If we do just a plain spectral analysis, we'll completely miss how the spectral power is changing with time!

Could just look at specific time windows for Fourier analysis...

Disadvantages:

- 1) The choice of the length of the window is arbitrary and will have windowing issues. Ideally want to allow for variety of scales.
- 2) Low frequencies are lost by chopping up the time series.
- 3) Assumes the signal can be broken down into sines and cosines.

Idea behind wavelets:

Decompose time series into time / frequency space simultaneously. So have 2 pieces of info:

- Amplitude of periodic signals
- How amplitude varies with time (phase)

Wavelet function replaces the sinusoidal functions.

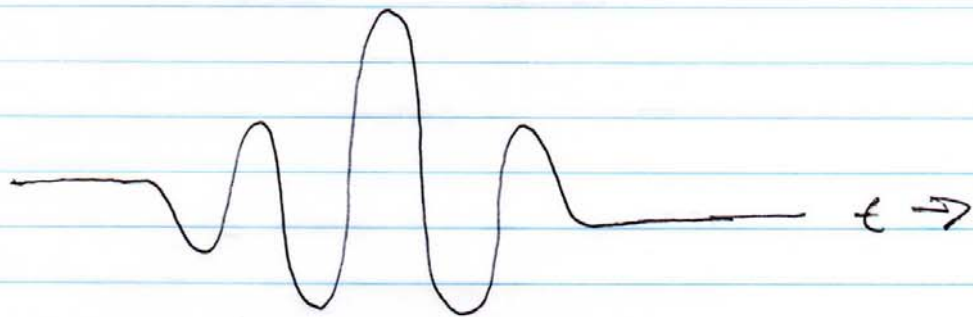
Wave packet (for an individual wavelet) has finite duration and a specific frequency.

Considerations for wavelets:

- Orthogonal or not orthogonal
- Complex or real
- Width
- Shape.

Many types of wavelets. Examples: Morlet, Mexican Hat (looks like sombrero), Paul.

Most commonly used is Morlet



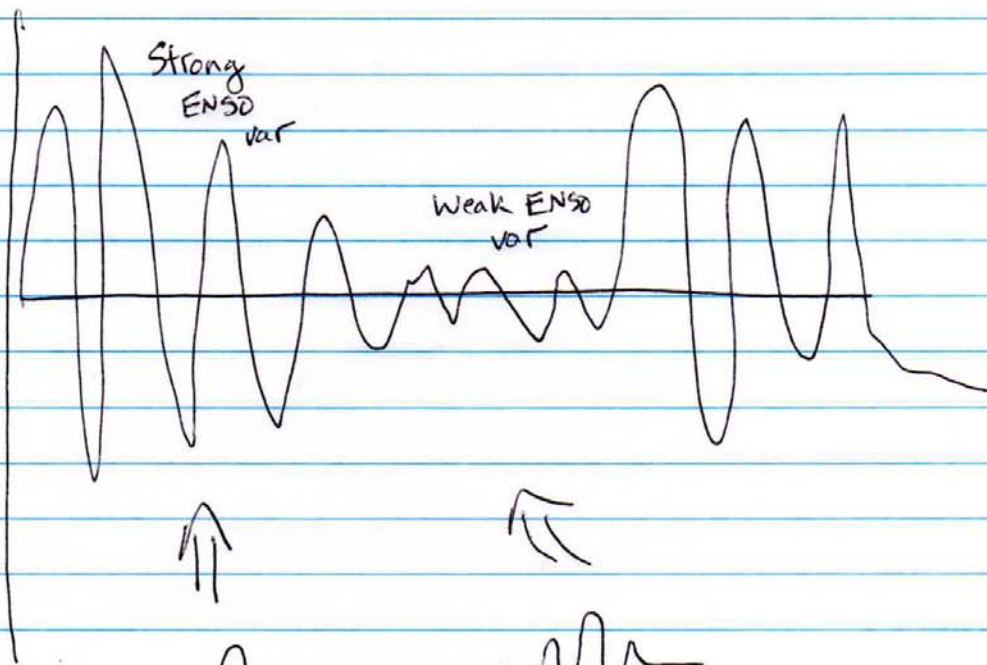
Characteristics of Morlet wavelet:

- Just a sine wave multiplied by a Gaussian. (center of wave corresponds to peak in bell curve)
- Width of the wavelet corresponds to the desired frequency. wider, the longer period is.

"Slide" the wavelet along the time series to construct a new time series of the projection amplitude vs. time.

Back to Nino example

Wavelet with corresponding period = 5 yrs.



Wavelet projects strongly here (large amplitude)

Wavelet projects weakly here (small amplitude)

Equation for the Morlet wavelet

$$\psi_0(\eta) = \pi^{-1/4} e^{-\eta^2/2} e^{i\omega_0\eta}$$

$\uparrow$ $\nwarrow$
Gaussian part Wave part

η = (non-dimensional) time

ω_0 = wave number (i.e. width of wavelet)

$\psi_0(\eta)$ = Wavelet function.

Since the wavelet function is complex, it contains both amplitude + phase info.

Wavelet transform ($W_n(s)$)

For a (time) series x_n ! (n = time)

$$W_n(s) = \sum_{n'=0}^{N-1} x_{n'} \psi^* \left[\frac{(n'-n)s}{s} \right]$$

The convolution of a time series with a scaled and translated version of the wavelet.

s = given frequency scale.

($>$ lowest possible frequency & often multiple of it)

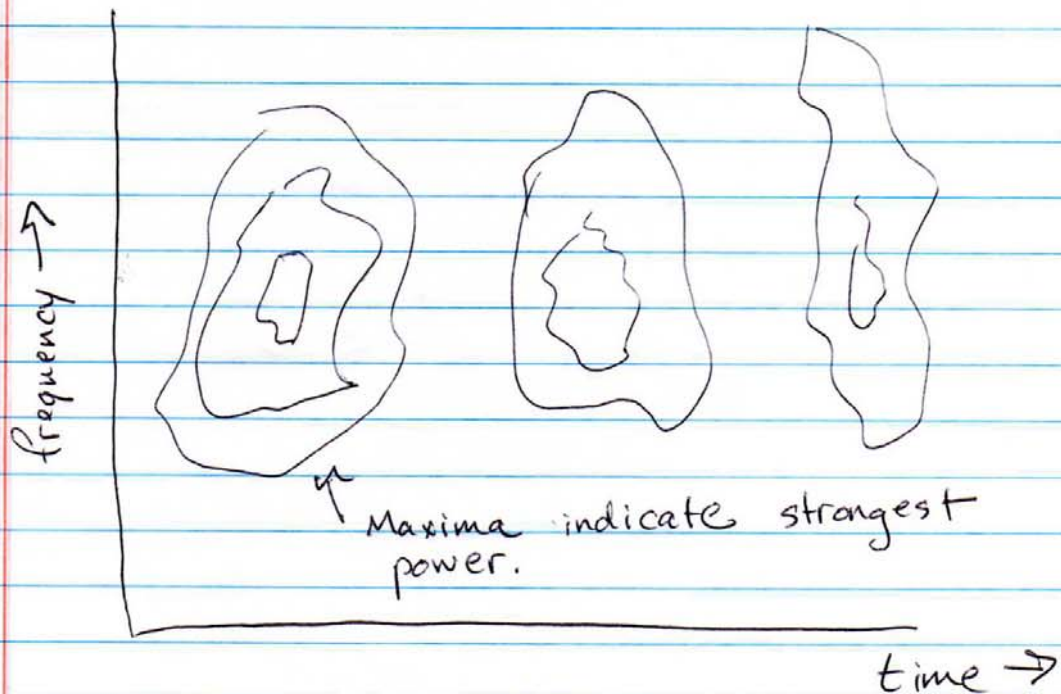
n = localized time index.

From this can construct a two-dimensional picture of the wavelet transform as a function of frequency and time.

Plot $W_n^2(s)$: Power spectrum

$W_n(s)$: Actual oscillations of the wavelets with phasing.

Wavelet power spectrum



The power spectrum is typically normalized by the total variance of the time series (σ^2)

Other notes

Cone of influence : Region of wavelet spectrum in which edge effects become important. Defined via e-folding time for autocorrelation each freq. scale. Typically shown as hatched region.

Red noise spectrum

Most rigorous way is via Monte-Carlo technique:

- Construct many, many AR(1) time series (i.e. using a Markov model)
- Compute wavelet power spectra for each time series.
- Avg. all the results to get background red noise spectrum.

(Best to do this way because it accounts for χ^2 dist)

Significance

Similar to spectral analysis, multiply the red noise spectrum by χ^2 value for the desired confidence interval (div. by $\frac{1}{2}$ to remove dof factor)

Global = values obtained by averaging data from wavelet analysis over given freq. for all times.