Wavelet Analysis of Sea Surface Temperature, Precipitation, and Nutrient Loads in the Little River Watershed: A Continuous ENSO Approach

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Introduction

The El Niño/Southern Oscillation (ENSO) is a low-frequency global climate phenomenon with strong effects on southeastern US weather patterns. ENSO phase has been shown to have predictable effects on precipitation and stream flow, as well as nutrient loads in runoff. In monitoring and research efforts during the last century, ENSO indices have emerged as one of the most consistent for describing low-frequency climate variability on both global and regional scales (Ropelewski and Halpert, 1986).

Objectives:

• Understand the relationship between Sea Surface Temperatures and precipitation, flow, and nutrient loads in the Little River Watershed.

• Explore the low-frequency oscillations and inter-annual variability in nutrient loading as a non-stationary process via wavelet analysis.

•Understand the fine temporal scale dynamics of continuous nutrient load time series with relation to SST's.

• Isolate the relevant reconstructed components from the wavelet analysis to be used in a predictive tool.

•Eventually use SST anomalies (as manifested through ENSO phase) as a predictor for monthly and seasonal nutrient loading, and thus as a best management practice tool.

Materials and methods

Field Site: The Little River Watershed in Tifton, Georgia, is a Coastal Plain watershed, characterized by broad, flat alluvial flood plains with low-gradient, poorly defined channels, sandy soils, extensive riparian buffers and slow moving streams.

Hydraulic relationships that apply in much of the U.S. do not apply for the Coastal Plain. Existing models often rely on empirical algorithms to represent processes that are not well understood, making wavelet analysis appealing, as there are few pre-existing assumptions.

Figure 1. The Little River Watershed is 334 km², (30-40% agricultural). All analysis was done on sub-basin K, a 16.8 km² area in the north, with the most nutrient data available of any of the basins. The Southeast Watershed Research Lab has collected hydraulic, nutrient and climatic data continuously since 1965.

Wavelet Analysis: Decomposes a time series into time and frequency space. (Torrence & Compo, 1998)

- Finds long term periodic trends and localized variations of power.
- No imposed scale, can visualize El Niño in the 3-7 year period.
- Useful for finding patterns in non-stationary, low-frequency data.
- No assumed physical relationships.

Coherence/Cross-Wavelet Analysis: (Grinsted et al, 2001)

• Finds regions where two time series co-vary w/ high power.

•Visualization of phase behavior between series.

The Wavelet Transform $W_n(s)$: For every time series, X_n, there is a wavelet function localized in time and space.

Morlet Wavelet: $\Psi_0(\eta) = \pi^{-1/4} e^{i\omega\eta} e^{-\eta^2/2}$ (eq.1)

Wn(s) is applied to the function (the convolution of X_n and $\Psi_0(\eta)$, summed between 0 and the number of points in X_n), into Fourier space.

$$W_n(s) = \sum_{n'=0}^{N-1} x_{n'} \psi^{*}[(n'-n)\delta t / s] \qquad \text{(eq. 2)}$$

The Wavelet Power Spectrum: $|W_n(s)|^2$, and the amplitude and phase at each point, is normalized and visualized against red noise (AR-1 or Markov process)

The Cross-Wavelet Spectrum: Using two time series X and Y, with wavelet transforms $W^X_n(s)$ and $W^Y_n(s)$, the cross-wavelet spectrum is:

$$W^{XY}_n(s) = W^X_n(s) * W^{Y*}_n(s) \qquad \text{(eq.3)}$$

The cross-wavelet power, $| W^{XY}_n(s) |$, indicates areas of high common power between X and Y.

Reconstructed Components: The original time series can be reconstructed from the Wavelet Transform using deconvolution, as the sum of the real part of the transform over all scales. The scale of interest can be isolated and used to make predictions.

$$X_n = \frac{\delta j \delta t^{1/2}}{C_\delta \Psi_0(0)} \sum_{j=0}^{J} \frac{\Re\{Xn(aj)\}}{aj^{1/2}} \qquad \text{(eq.4)}$$

Results

Discrete Anomalies: Identifying ENSO via discrete yearly labels is a common method of data analysis. However, in dealing with long geophysical time series with large pooled variances (i.e. nutrient load), it is difficult to establish formal significance. These figures show discrete ENSO anomalies averaged over all years, with little fine temporal resolution.

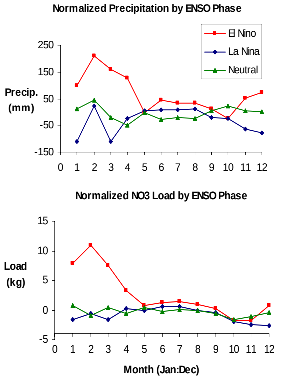

Figure 2. Monthly precipitation and NO_3 anomalies are shown for each discrete ENSO phase. It is apparent that El Nino winters show greater precipitation and nutrient runoff than other months and phases.

Wavelet Power Spectra and Analysis

ENSO events were seen in the 3-7 year period of the SST spectra, as expected. Years with greater power were seen in the known strong El Nino years (1986, 1997). Precipitation spectra seem to match SST in terms of temporal power and periodicity. Interestingly, NO_3 load does not correlate as well, although it shows similar periodicity, and a more extended range of significant years.

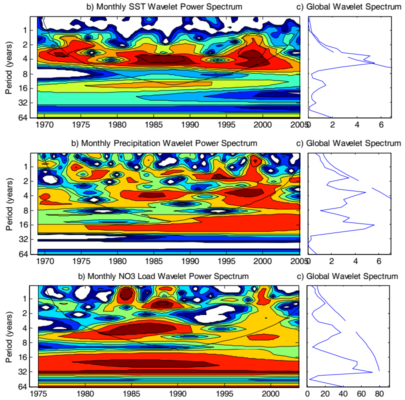

Figure 3. Significant regions are inside the black-line cone of influence. Red/orange denote high power, while blue/white are low power. The global spectrum is integrated across all years, and shows the dominant periods.

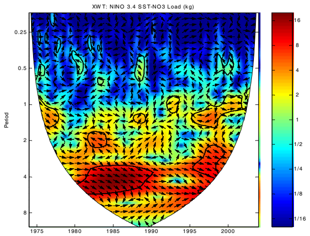

Figure 4. Cross-Spectra analysis between SST and NO_3 load time series.

Again, high power is seen (red) in the 3-7 year period, indicating that SST and nutrient loads share high-power and are in-phase during strong ENSO events in the expected periodicity.

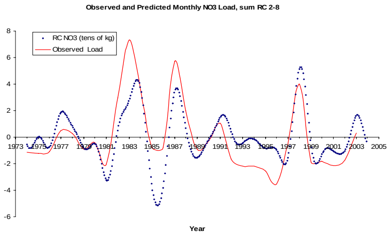

Figure 5. Reconstructed components summed from periods 2-8 years for NO3 load. (6/25 years used)

Reconstructed Components

•Using the RC's of interest, we can capture a large percentage of the original time series variance using only the fraction of the data, showing the significance of the period isolated.

•These can be used to build predictive models within and between different variables that have demonstrated cross-spectral correlation in our analyses.

• The model will take recent SST's as input, and output predictions of nutrient loads for a particular region, avoiding errors associated with modeling physical processes.

Conclusions

In classifying ENSO phase discretely, we have previously shown that it is very difficult to assign formal significance to resulting nutrient loads (Keener et al, 2007). Additionally, discrete labels fail to capture monthly or finer temporal resolution variability, monthly anomaly causing events, or anomaly relative weakness or strength. By using wavelet analysis and continuous measures of sea surface temperature to predict nutrient loads, it is possible to reduce process-based error and obtain a more detailed picture of the temporal lags involved.

In the monthly wavelet power analysis and cross-spectral analysis, both SST, precipitation, NO_3, and P loads were found to share high power in the 3-7 year band that ENSO signals are known to occupy. This indicates that the ENSO low-frequency signal could be used as a predictor for nutrient loads.

Differences in the regions of high power in the time domain can be explained by nutrients taking longer or shorter times to flush into the slow moving streams in Coastal Plain ecosystems, meaning that after a large precipitation event, an immediate response in nutrient loads could be seen, and after a dry ENSO event, nutrient flushes into the system may initially lag but could be ultimately large if an intense storm occurred at the right time. Land use changes are also being explored for causative effects on relevant time series.

Literature cited

Grinsted A., Moore J.C., Jevrejeva S., (2004). *Application of the cross wavelet transform and wavelet coherence to geophysical time series.* Geophysics, 11 : 561-566.

Keener V.W., Ingram K.T., Jacobson B., Jones J.W. 2007 (under review). *Effects of historical climate variability and El-Niño/Southern Oscillation on simulated monthly and seasonal phosphorus loading in south Florida.*

Ropelewski, CF, Halpert, MS. 1986. *North American precipitation and temperature patterns associated with the El Niño/Southern Oscillation (ENSO*). Mon. Weather Rev, 114: 2352-2362.

Torrence, C., and G.P. Compo (1998), *A practical guide to wavelet analysis*. Bulletin of the American Meteorological Society, *79(1)*, 61-78.

For further information

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