Submesoscale Anisotropic Marine Biological Variability near Bermuda: Ocean Color and SST

David M. Glover[a], Scott C. Doney[a], Norm Nelson[b], and Alise Wallis[c]

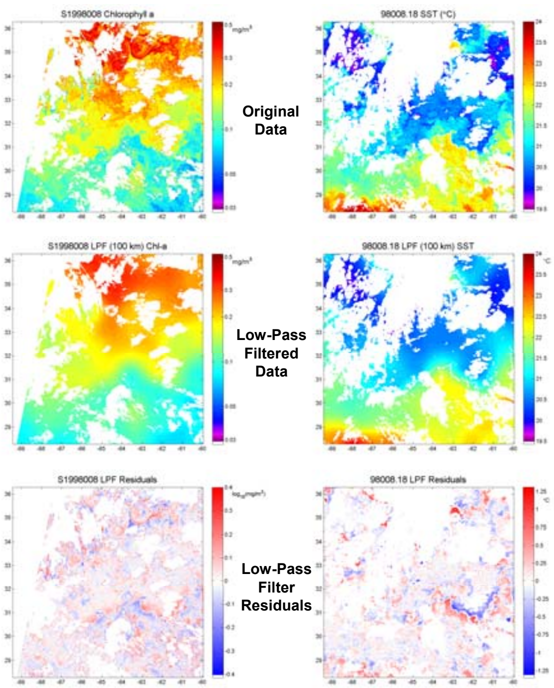
[a]Woods Hole Oceanographic Institution, [b]University of California, Santa Barbara, [c]Hunter College

Introduction

Submesoscale and mesoscale physical variability strongly modulate the structure, biomass, and rates of marine ecosystems and their functioning in the ocean. Characteristic time and space scales of key ocean physical-biological phenomena range from the submesoscale (0.3-10 km; day-week) to mesoscale (10-300 km; week-few months). In Doney et al. (2003), we characterized for the first time the geographical patterns of the magnitude and spatial-scales of mesoscale ocean biological variability globally for a single year. Now, we present interim results characterizing the submesoscale component of ocean color variability using variogram techniques applied to high spatial resolution (1 km), regional satellite data near Bermuda. In the previous work, using SeaWiFS standard mapped level 3 products, we were unable to resolve between a true geophysical signal in the submesoscale versus instrument and/or environmental noise; here we show that the submesoscale (<10km) accounts for approximately 50% of the total resolved variance, the remainder found at mesoscales. We can extend this analysis to remotely sensed, physical variables and introduce here geostatistical analyses of the spatial variability found in sea surface temperature (SST). On submesoscales, we present variograms of chlorophyll and SST data collected at near-coincident times and compare the results. The distribution of submesoscale variability among biological and physical variables provides important insights into the mechanisms of interaction between biological ecosystems and their physical environment. Quantification of anisotropic submesoscale variability is an essential first step in deriving physical-biological parameterizations that may deviate significantly from purely physical, conservative tracers.

Data

Matched data image pairs (SeaWiFS: Chl_a and AVHRR:SST) 8 Jan 1998



AVHRR and SeaWiFS

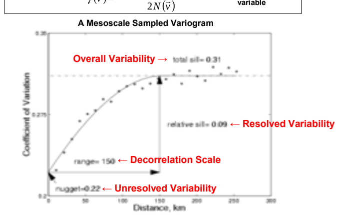
- SeaWiFS L3 LAC Reproc 4 data
- AVHRR MCSST from NOAA-12, -14, and -16
- 1.1 km, equal area pixels
- 880x880 km subsample centered near Bermuda
- Gridding was done with a nearest neighbor nudging technique
- Submesoscale (0.3-10 km, day-week)
- 1653 daily SeaWiFS images and 6572 6-hourly AVHRR images from 1998-2003
- Here only one image with >50% clear pixels in both AVHRR and SeaWiFS for clarity

Procedure

- Log transform the Chl_a data (not necessary for the SST data)
- Low pass filter (Gaussian 50 km half height width) log(Chl) and SST
- Create residuals by subtracting LPF from original data
- De-speckle residuals with Chauvenet's criterion
- Subsample residuals into 20x20 pixel sub-groups
- Create 2D variograms with FFT-based algorithm (Marcotte, 1996) of each 20x20 sub-group
- Convert variograms to coefficient of variation (CV) units
- Extract 1D variograms from 2D variograms in 72 directions
- Regress spherical model against extracted 1D variograms to obtain estimates of decorrelation scale, resolved and unresolved variability

Methods

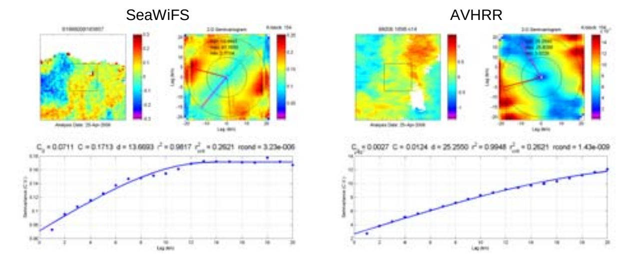
Semivariance: $\gamma(\vec{v}) = \dfrac{\sum[Z(\vec{x}) - Z(\vec{x}+\vec{v})]^2}{2N(\vec{v})}$ Z = regionalized variable



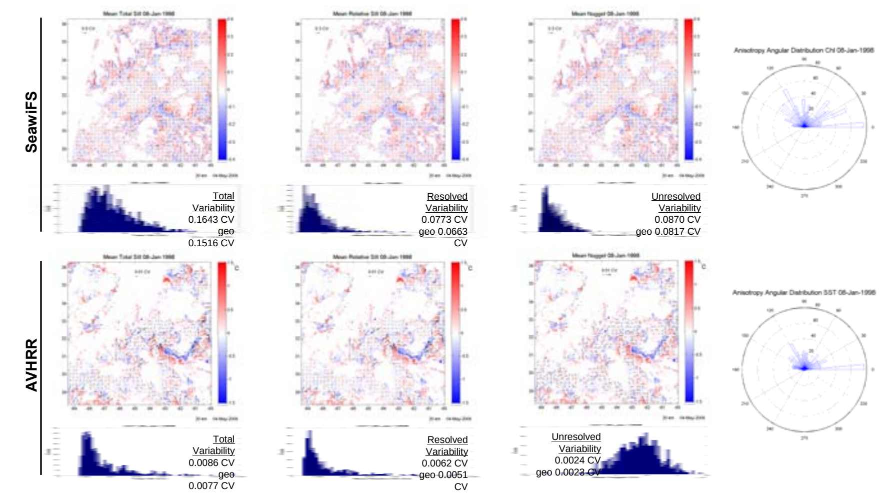
Geostatistics

The semivariogram or structure function $\gamma(\vec{v})$ measures the local spatial variation of geophysical data $Z(\vec{x})$, describing how samples are related with vector distance $\vec{v}$ (Chilès and Delfiner, 1999). The semivariogram is closely related to the covariance function. In general, two neighboring points are more likely to have similar values than sample pairs farther apart. Thus the semivariogram (covariance) function will have low (high) values at small spatial lags, increasing (decreasing) with distance. Beyond some distance, the data points can often be assumed to be uncorrelated or independent, in which case the semivariogram approaches a uniform variance while the covariance function goes to zero.

Results

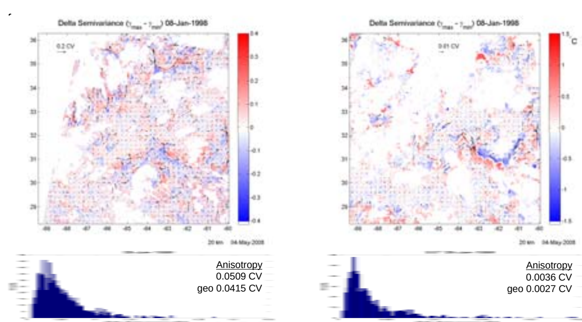


If we zoom in on the same 20x20 pixel sub-group for both SeaWiFS and AVHRR, we can generate the following diagnostic plots showing the residuals, the extraction of the 1D semivariances from the 2D variograms, and the progression of the 1D regressions. The upper left panel shows a close-up of the 20x20 residual field (box within frame). The upper right panel shows the 2D variogram (note the direction of the minimum trough is not the same for Chl_a and SST. The lower panel shows an example of the extracted 1D semivariances and the non-linear least square fit of a spherical model variogram curve to those data points. Note: if either the SeaWiFS or AVHRR data has isotropic variability, their 2D variograms would have **circular symmetry.**



The panels above show the distribution and magnitu the total, resolved and unresolved variability in SeaW ocean color and AVHRR SST data and the angular distribution of the vectors. Although the level of varial in AVHRR data is considerably lower than variability i SeaWIFS data, the pattern we observed in our mesoscale study (Doney *et al*., 2003) is repeated for both data streams in the submesoscale: Approximate half the total variability is resolved and the other half unresolved.

The panels to the right display a measure of the anisotropic variability in SeaWiFS and AVHRR data. Angular distribution is the same as the above figures. Higher values of anisotropic variability are associatec with strong submesoscale features still apparent in th residual fields. Differences in magnitude and associa may be due to the passage of time (~2.5 hours), futu work with MODIS 1 km data should remove this uncertainty.



Summary

- The amount of variability (in coefficient of variation space) is lower for AVHRR-derived SST than for SeaWiFS-derived chlorophyll, but
- As in the previous mesoscale study, approx. half the total variability is resolved geophysical variability, the remainder variability is due to sub-grid scale processes or noise for both data sources and
- Anisotropy is spatially linked to the presence of eddies, fronts and filaments

References

Chilès, J-P. and P. Delfiner, 1999, *Geostatistics, Modeling Spatial Uncertainty*, Wiley Inter-science series in Probability and Statistics, New York, NY, 695 pp.

Doney, S.C., D.M. Glover, S.J. McCue, and M. Fuentes, 2003, Mesoscale variability of Sea-viewing Wide Field-of-view Sensor (SeaWiFS) satellite ocean color: Global patterns and spatial scales, *J. Geophys. Res.*, **108**(C2), 3024, doi:10.1029/2001JC000843.

Marcotte, D. 1996, Fast variogram computation with FFT, *Computers and Geosciences*, **22**(10), 1175-1186.