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Dominant spatial variability scales from observations around the Hawaiian Islands

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ABSTRACT

We utilize a variety of available observations with a semivariogram technique to quantify the oceanic variability around the Hawaiian Islands. The Hawaiian Islands have a significant impact on the North Pacific circulation, and quantifying the characteristics of the variability is important for understanding the eddy energy, as well as required for statistical techniques to work with the data, such as optimal interpolation, data assimilation, etc. Both satellite sea surface height and temperature data are used to determine horizontal scales of variability, while Argo profiles, ship-borne profiles, and autonomous Seagliders provide estimates of the vertical scales. In the lee of the islands, satellite data reveal an increase in horizontal variability attributed to enhanced eddy activity that persists for over 1000 km westward; however, only within 400 km of the immediate lee the horizontal length scales are greatly reduced. Further west, length scales increase significantly indicating a change in the generation mechanism for eddy variability and where eddies merge and coalesce. The meridional length scale gradient is found to be larger than previous results and more representative of the gradient of the first baroclinic mode of the internal Rossby radius. Vertical length scales are shown to increase in the lee, with vertical temperature variability doubled from the windward side.

1. Introduction

Ocean dynamics occur over a wide range of time and space scales. Interannual and planetary dynamics occur at the largest scales, while smaller motions include local tides, surface waves, and ocean mixing. In general, the ocean is dominated by mesoscale fluctuations on time scales between 20 and 150 days and spatial scales between 50 and 500 km (Wyrtki et al., 1976; Danztler, 1977; Richman et al., 1977) that decrease poleward from the tropics (Mercier and Colin de Verdiere, 1985; Lee and Niiler, 1987). Applying autocorrelation to very advanced high-resolution radiometer (AVHRR) infrared data, Krause et al. (1990) estimated eddy scales in the North Atlantic that matched the Rossby radius of the first baroclinic mode. Similarly, Stammer (1997) and Chelton et al. (1998) used along-track TOPEX/Poseiden altimeter data to estimate global eddy spatial scales finding that eddy scales outside the tropics vary proportionally (though not identically) to the internal Rossby radius of deformation.

The Hawaiian Islands (Fig. 1) are located in the southern portion of the North Pacific Gyre in the presence of nearly persistent northeastward trade winds. The island chain has a significant effect on both ocean currents and winds (Xie et al., 2001). The mountain peaks on the islands of Maui and Hawai'i penetrate the trade wind inversion layer forcing the wind to flow around the islands creating a large wake region of weakened flow (Smith and Grubisic, 1993). An active and intense eddy field lies in the wake region, driven primarily by the wind stress curl and intrinsic instabilities in the ocean flow (Calil et al., 2008; Yoshida et al., 2010). Fig. 1 shows a map of eddy kinetic energy (EKE) from geostrophic currents (provided by AVISO) calculated from a combination of altimetry missions from 2000 through 2008. The effects of the islands on the ocean flow can be seen in the increase in EKE found leeward of the island chain.

With such dynamical variation, the Hawaiian Islands pose a difficult challenge to determine the dominant characteristics of oceanic variability. Understanding this variability is important for quantifying the circulation and it is also crucial for determining the decorrelation scales that are applicable for optimal interpolation, data assimilation, or state-estimation problems. In this paper, we present a robust method to determine the spatial variability that is applicable in both the horizontal and vertical. We apply the semivariogram method (Journel and Huijbregts, 1978; Kitanidis, 1997; Banerjee et al., 2004) to multiple years of satellite sea surface height (SSH) and temperature (SST) data along with *in situ* temperature and salinity profiles. Spectral analysis is also commonly used to compute spatial scales from

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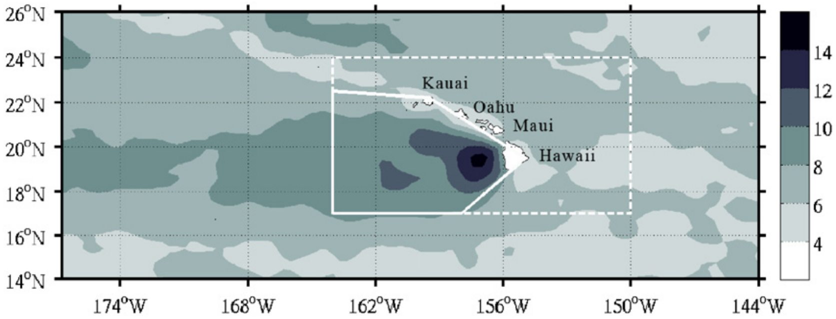

Fig. 1. The Hawaiian Islands, with leeward (solid white line) and windward (dot–dash white line) regions defined for semivariogram calculation. Contour levels show mean EKE levels for 2000 through 2008 from the AVISO absolute geostrophic velocity product.

oceanographic data, however it is not used because the method has problems with missing data and spectral slopes can be misinterpreted (Fasham, 1978). Geostatistical techniques, such as the semivariogram or the closely related autocorrelation method, proved less detailed information, but are more robust for geophysical data (Chelton and Schlax, 1991). The semivariogram method was chosen over the autocorrelation method to avoid using the “zerocrossing” of the autocorrelation function as a length scale estimate, which does not always exist. From the semivariogram we can also calculate the geophysical variability captured by the observations and the unresolved variance that provides an estimate of the measurement error. Because the eddy field dominates the variability of the ocean, we utilize anomaly data to limit the effect of large-scale mean dynamics in the statistics and to focus on the mesoscale. In Section 2, we present the semivariogram method and its application. In Sections 3 and 4, we present the results from the satellite and *in situ* data before concluding.

2. Concepts and definitions

Combining spatially and temporally sparse data to determine the variability characteristics (actual variability and the length scale of decorrelation) is a difficult challenge. The semivariogram function describes the covariance of sparsely distributed data as a function of distance (Banerjee et al., 2004), and has been used successfully for ocean dynamics (Seuront and Lagadeuc, 1997; Doney et al., 2003; Milliff et al., 2003; Powell et al., 2008).

The semivariogram is defined as

$$\gamma(h) = \tfrac{1}{2}E\left[(z(x+h)-z(x))^2\right], \tag{1}$$

where E is the linear expectation, h is the lag distance, $z(x)$ represents the data value at a given location, x, and $\gamma(h)$ is defined as the semivariogram function (the term variogram is used for $2\gamma(h)$). Thus, the semivariogram is the mean squared difference of all values within h distance of x. Because values are scattered spatially, no value of h is consistent, so a range of distances are used to bin the data: $h = h_o \pm \delta h$. These lag bins provide enough data such that the E operator is significant.

Data residuals are first computed for all available lag distances within the data and binned. Binning sizes were chosen to be as small as possible, while maintaining significant and consistent sample numbers per bin. Once computed, the set γ (Eq. (1)) is considered the empirical semivariogram composed only of observed data.

A statistical model is commonly fit to the computed empirical semivariogram for a mathematical representation of the variance (Journel and Huijbregts, 1978). This statistical model provides a tool for describing how a measurement varies as it is perturbed from its location. There are many mathematical models that may fit the semivariogram (exponential, circular, etc.), and after experimentation we found that a stationary Gaussian model (Kitanidis, 1997) most consistently represented the empirical semivariograms.

The Gaussian model:

$$\Gamma(h) = C_o + (\sigma^2 - C_o)(1-\exp(-h^2/L^2)) \tag{2}$$

is fit to the empirical semivariogram, $\gamma(h)$, values using linear least-squares to solve for the model parameters C_o, σ^2, and L. The “nugget”, Co, gives the zero-lagged or unresolved variance. The upper limit of the variance, σ^2, is called the “sill” and represents the value at which the data is no longer correlated. The lag distance, h, between C_o and σ^2 is estimated by L. Because the Gaussian function decays asymptotically, this “range” is estimated by (Kitanidis, 1997)

$$\alpha \approx 7L/4. \tag{3}$$

To generate the characteristics of the variability the observational data is used with predetermined lag bins to compute the empirical semivariogram. The modeled semivariogram is generated by fitting the Gaussian model (Eq. (2)) to the empirical semivariogram. From this fit, we generate our estimates of the unresolved variance (hereafter measurement error), C_o, and the maximum variance (hereafter variability), σ^2. The difference between the sill and the nugget is attributed to the geophysical variability captured by the observations. The length scale over which the geophysical variability is significant is the range, α. As the range is exceeded and the variance reaches σ^2, two observations are considered randomly correlated.

We now turn our attention to employ this semivariogram method on a variety of data to determine the measurement error, variability, and length scales around the Hawaiian Islands.

3. Horizontal variability and length scales

To analyze the horizontal variability and length scales around the Hawaiian Islands we use four years of satellite sea surface height and temperature data from 2004 through 2007. We chose this period because of the availability of satellite altimetry data. At least two satellites are required to map the ocean; however with additional satellites the resolution of SSH measurements is greatly enhanced (La Traon et al., 2001). During this time there are four satellite altimeters available, until the failure of Topex/Poseidon in 2006. While altimetry data is better suited to capture eddy size and fluctuations, SST has also been shown to be an indicator of eddy scale (Krause et al., 1990).

We analyze the along-track sea level anomaly product (SLA) produced by Ssalto/Duacs and distributed by AVISO (with support from CNES) from the altimeters onboard the TOPEX/Poseidon,