Towards improved analysis of short mesoscale sea level signals from satellite altimetry

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Abstract. Altimeter measurements are characterized by a dramatic drop in signal-to-noise ratio below about 100 km wavelength, making it very challenging to analyze small mesoscale variability in SSH. CMEMS therefore provides low-pass filtered products to mitigate the problem and more innovative and suitable noise filtering methods are left to users seeking to unveil small-scale altimeter signals. Here, a fully data-driven approach is applied successfully to provide robust estimates of noise-free sea level anomaly signals. The method combines Empirical Mode Decomposition (EMD), to best analyze non-stationary and non-linear processes, and an adaptive noise filtering technique inspired by Discrete Wavelet Transform decompositions. It is found to better resolve the distribution of SLA variability in the 30-120 km mesoscale wavelength band, with a practical uncertainty variable attached to the denoised SLA estimates. Measurements from the Jason-3, Sentinel-3 and Saral/AltiKa missions are processed and analyzed, and their energy spectral and seasonal distributions characterized in the small mesoscale domain. In anticipation of the upcoming SWOT mission data, the SASSA data set (Satellite Altimeter Short-scale Signals Analysis, Quilfen and Piolle, 2021) of denoised SLA measurements for three reference altimeter missions already yields valuable opportunities to evaluate global small mesoscale kinetic energy distributions (Quilfen et al., 2022. Earth Science System Data, 14) .

EMD denoising of SLA measurements

EMD is a method for decomposing signals into a small number of scale-dependent components based on the local characteristic sampling scale of the data, called intrinsic modulation functions (IMF), each modulated in amplitude and frequency (Figure 1). Applied to a Gaussian noise signal, EMD provides a set of IMFs with a predictable distribution of noise energy, which decreases rapidly with increasing IMF rank: ~ 59, 20.5, 10.3, 5.2 % of total energy for the first four IMFs (~ 95% of the total noise energy). Noise and real signals IMFs share the same frequency bands (Figure 2) , allowing each IMF in a processed data segment to be tested and denoised against a well-predicted noise variance level (Figure 1). A single threshold parameter is tuned to calibrate the entire method (Figure 3).

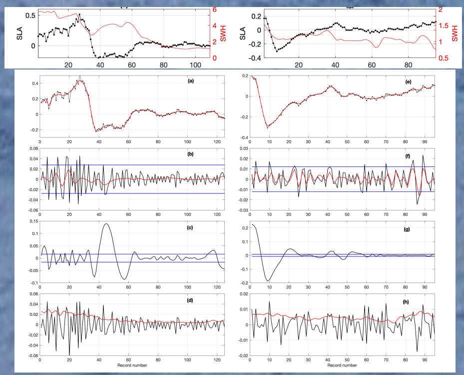


Figure 1. SARAL data segments (Gulf Stream) for cycle 106 and passes 53 (left) and 597 (right). Top panels: SLA and SWH; Panels (a) and (e): noisy (black) and denoised (red) SLA; panels (b) and (f): IMF1 (black), real signal (red) retrieved from wavelet denoising of IMF1, and thresholds (blue) applied in IMF1 denoising; panels (c) and (g): IMF2 (black) and thresholds (blue) applied in IMF2 denoising; panels (d) and (h): noise (black) retrieved from IMF1 and uncertainty (red) attached to the denoised SLA. All units in meters on the y axis

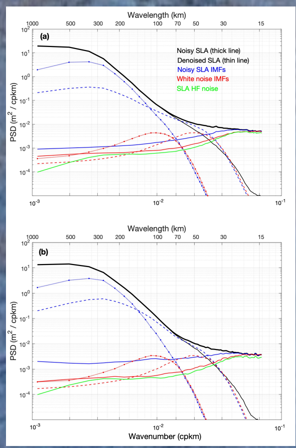


Figure 2:Mean PSD of the first three IMFs (first = solid; second = dashed; third = dotted) for white noise (red curves) and SARAL 1Hz SLA along-track measurements (blue curves), and mean PSD of the corresponding noisy (thick black line) and denoised (thin black line) SLA measurements. The PSD is the average of PSDs computed over all data segments covering the years 2016–2018, for the Agulhas (10–35° W; 33–45° S, a) and Gulf Stream (72–60° W; 44–32° N, b) regions. The green line is for the PSD of the SLA high-frequency noise estimated from the SLA's IMF1 (solid blue line)

Denoising scheme calibration

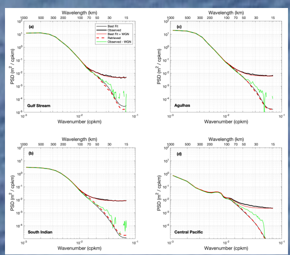


Figure 3. Mean PSD (2016-2018) of SARAL SLA : observed (thick black), best fit (thin black), best fit plus WGN (red), retrieved (dashed red), and observed minus WGN (green). WGN estimated in the range 15–25 km.

A single threshold parameter is first set to calibrate the entire method for Saral (Figure 3): a best-fit value is determined for different regions by finding the best fit, in the 100-30 km wavelength range, between the average PSD of noisy data and the one calculated as the sum of the PSD of the denoised data and the estimated local WGN. A value averaged over the regions is then computed to process the global data-set. The recovered denoised PSDs obtained using this configuration are shown as dashed red curves in Figure 3, and compared to the mean PSD obtained by subtracting the average HF noise from the average noisy PSD (green curves). Once calibrated for Saral, the method for Sentinel-3 and Jason-3 data is calibrated to fit the Saral results, Figure 4.

Consistency for the various altimeters

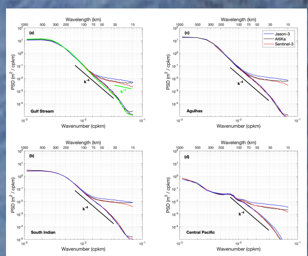


Figure 4: Mean PSD (2016-2018) of observed and denoised 1Hz SLA. The green curve in panel (a) shows the PSD of denoised Sentinel-3 SLA for the hypothesis of a Gaussian pink noise (k−1 slope, green solid line).

Comparison / other schemes

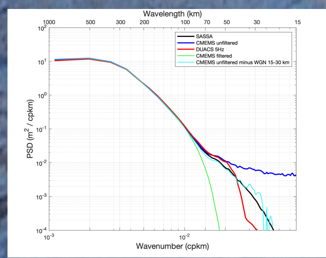


Figure 5. Mean PSD of SARAL 1Hz SLA. Gulf Stream region.

A comparison is presented with the official CMEMS products and with the experimental 5Hz products proposed in the SSALTO/DUACS project that include several improvements over the CMEMS processing and intend to prepare for SWOT. The SASSA products show much better agreement with the expected PSD (black and cyan curves) due to the adaptative EMD approach that filters noise consistently across the wavelength range.

SSH seasonal variability

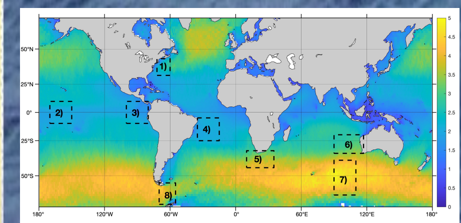


Figure 6. Yearly averaged SWH (m).Dashed black boxes show the eight areas analyzed in Figure 7

Seasonal variability in the small mesoscale is difficult to analyze from standard altimeter measurements, as sea state conditions strongly shape the SSH noise. As shown in Figure 1, a strength of the EMD approach is that the dependence of HF noise on SWH is truly captured in the IMF1 allowing it to be filtered out. However, residual errors related to high SWH may remain in the noise-free data, and thus Figure 7 shows the seasonal analysis also tested with high SWH discarded from the analysis. Only 3 regions among those selected thus appear to experience significant seasonal variability, namely the Gulf Stream, west of Australia and the tropical region east of Brazil. These results deserve to be analyzed in more detail.

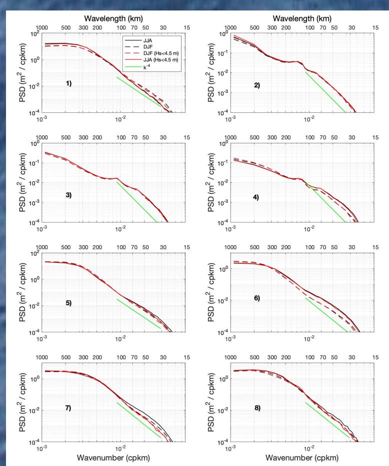
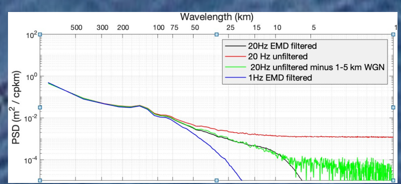


Figure 7. Mean PSD of AltiKa 1Hz denoised SLAs in boreal summer (JJA) and boreal winter (DJF). Eight regions selected as shown in Figure 6.

Improved analysis of small mesoscale variability with Sentinel-3 Peachi products



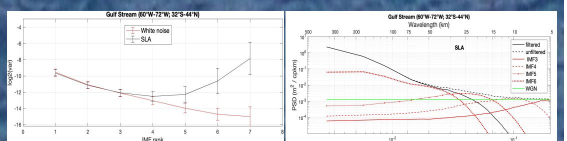


Figure 8; top: mean PSDs of Sentinel-3 20Hz SLA, central Pacific, (from Peachi products in LR-RMC mode); bottom: IMFs variance as a function of IMF rank (left) and associated PSDs (right), Gulf Stream

The SAR processing of Sentinel-3 in LR-RMC mode has several attracting features to provide a useful dataset for SWOT preparation and analysis: high resolution data at 20Hz free of hump artifact and surface wave effects, and with reduced noise dependence on SWH. These features are also favorable for applying EMD to further recover SSH variability in the small mesoscale range 15-50 km, accounted for in the IMF5 which is significantly different from pure noise, as shown in Figure 8, bottom panels.