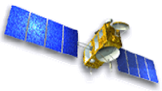
Use of fuzzy logic clustering analysis to address wave impacts on altimeter sea level measurements: Part I data classification



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I. Abstract

Each satellite ocean altimeter measurement must be corrected for surface waves to accurately retrieve a sea level estimate. This wave correction is developed through indirect empirical methods, but because it can not be directly determined using satellite data, it has been difficult to quantify the correction model's uncertainty, much less improve upon it. A new approach for assessing and improving this wave-induced sea state bias algorithm is described here based on fuzzy logic clustering analysis, data from a global ocean wave model, and direct averaging over the altimetric sea surface height anomaly field. These tools combine to provide an objective means to define regimes of nonlinear surface wave variability, to partition wave model and altimeter data into these classes, and subsequently to build class-specific wave correction models in the standard wave height wind speed data domain. Six regimes are objectively determined using input parameters related to the wave height, wave age, and variation in short-scale slope variance. This paper focuses mainly on method demonstration and on detecting and quantifying where the present-day global sea state bias model fails. Several new results emerge. Overall, the methodology yields results anticipated by numerous investigators over the past decades including regional impacts, the effect of swell, and expected ambiguity associated with wave age and steepness. A substantial portion of data samples exhibit range error magnitudes exceeding 0.5% in SWH. As importantly, these errors are not globally or randomly distributed and appear to impose systematic spatial and temporal sea level error in regions as diverse as the equatorial Pacific and Antarctic Circumpolar Current. The six classes combine to show positive skill in sea surface height variance reduction over a single global model. The analysis is applied equally to TOPEX and Jason-1 data with similar end results. This suggests that the wave physics underpinning the analysis could be divorced from inherent sensor differences, leading to a more universal cross-platform handling of this correction. Further refinement, including fuzzification, should extend this methodology to development of a robust operational solution.

This poster (Part I) sketches the methodology and a companion poster (Part II) presents resulting sea state bias error examination.

II. Methodology – objective classification of wind wave data into nonlinear wave provinces

Study Objectives:

- ❖ Exploit 6 hourly global wave model output to aid altimeter SSB model improvement
- ❖ Apply a fuzzy clustering analysis to partition the global ocean into regimes of wind wave nonlinearity
- ❖ Develop regime-based SSB models to assess the performance of the operational global SSB model

Concept of fuzzy clustering analysis for data classification:

Clustering analysis can partition a collection of related data points into a number of subgroups in which the data inside a subset (class, cluster, or regime) exhibit similarity to some objective degree. Traditional hard (or crisp) clustering analysis assigns each data sample to ONLY one class in a multi-dimensional parameter space under the assumption that boundaries between classes are well defined. A fuzzy cluster analysis allows for vagueness or noise when partitioning the data - a data point can now belong to numerous subsets. The method used here assigns each data sample a fuzzy set membership value for each different class where this class-specific membership value represents the likelihood that the sample belongs to that class.

Data compilation and classification inputs:

Global surface wind wave (WaveWatch 3) model-estimated wave parameters, ECMWF and blended NCEP/QSCAT winds, and altimeter (TOPEX and Jason1) measurements were all collocated by spatial and temporal interpolation onto the standard NASA/GSFC altimeter pathfinder locations. That is, all data are collocated along the TOPEX ground tracks for the years 2000-2003. Variables used for the objective clustering analysis are summarized in Table I.

Table I: Definition of three input variables for fuzzy logic clustering analysis

Variable	Definition	Data source
v1: Altimeter-derived significant wave height	H_{s_alt}	TOPEX , Jason1
v2: Ratio of windsea height (H_{sea}) to significant wave height	$D_S = H_{sea}/H_{s\_alt}$	Wave model
v3: Ratio of long-wave slope variance (mss_l) to total slope variance (mss_t)	$D_H = mss_l/mss_t$ $mss_l = (2\pi)^4/(g2\ m4)$: (where m4: 4th order moment) $mss\_t = R_{eff} / \sigma\text{-Ku}$ (where R_{eff}=0.45)	 Wave model TOPEX, Jason-1

Fuzzy clustering procedure (Moore et al., 2001)

The overall classification scheme is given in the flow chart shown below where we work with one year of data (T/p or Jason-1) for any realization.

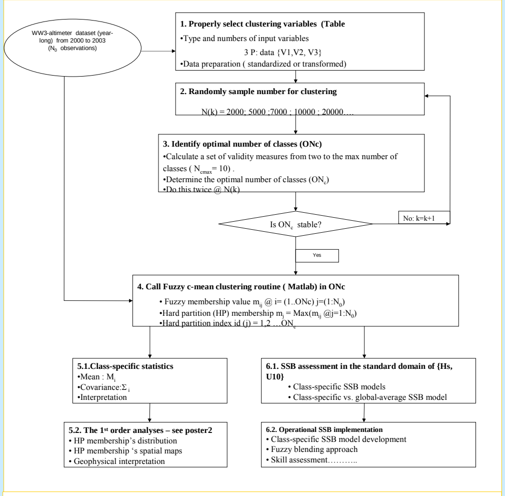

Figure 1: Flowchart of the fuzzy logic clustering scheme for wind-wave classification and SSB modeling efforts

III. Classification results – six wind wave nonlinearity regimes

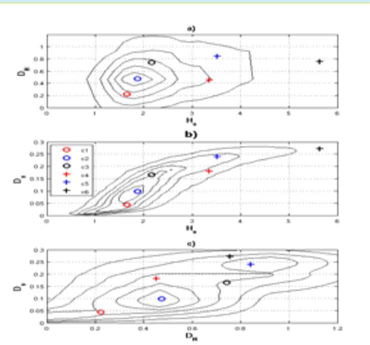

Figure 2: Centroid values for the six class centers are shown in the respective 2D parameter spaces representing the inputs of $\{H_{salt}, D_H, D_S\}$. The corresponding contours represent the 2D data probability distribution with the innermost being the most populated.

The three wave parameters $\{Hs\_alt, D_H, D_S\}$ defined in Table I were selected for input to the classifier specifically for the objective of operational SSB improvements. Hs_alt is a first order SSB correlative; D_H is a measure of wave field maturity (i.e. close to pseudo inverse wave age - the higher it is, the younger the wave is); $D_S = mss\_l/mss\_t$ is a ratio providing the relative magnitude of longer vs. short wave sea surface slope (the lower D_s, the more significant the surface roughness contribution from short waves). These input selections drive a classification with some physical basis for examining SSB variability. Through an extensive training method as shown in Figure 1, the optimal number of clusters identified using a set of validity functions is 6. The prescribed order from class 1 to class 6 is based on ascending values in wave height.

Results for one annual scale fuzzy clustering analysis is shown in Figures 2-4 using the year 2000 dataset of TOPEX and wave model output driven by ECMWF winds.

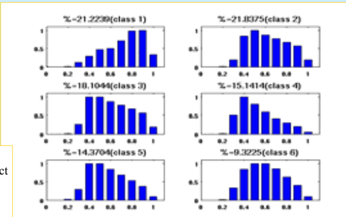

Figure 3. Fuzzy membership value probability distribution for each class along with the percentage of class-specific data points with respect to the total data. Note that each data samples's membership value lies between 0 and 1 for each class and the 6-class sum of all membership values for that data sample is equal to 1.

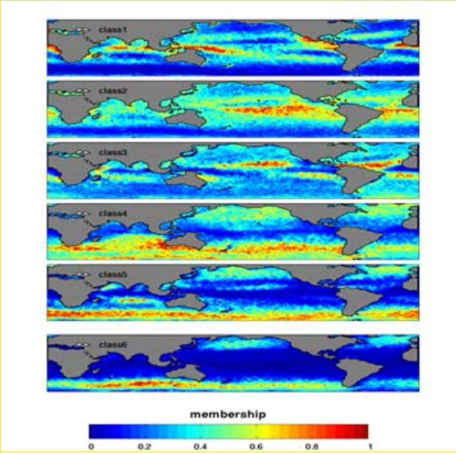

Figure 4. An annually averaged (over a 2-by-2 degree region) spatial map of the max-normalized membership values. The higher the images membership value for a class in a given location, the more likely this class occurs frequently in that location.

VI. Conclusions

❖ A new approach has been developed for synthesizing all available wind wave information to assign each altimeter data sample over the global ocean to belong to wave nonlinearity-based regimes.

❖ Fuzzy logic implicitly deals with the data vagueness and noise that make the SSB problem difficult to resolve. It also provides a generic tool for objectively classifying large amounts of ocean satellite data.

❖ Assessment of regime-based SSB models versus the global-average SSB model shows the new methodology will support operational SSB improvement (See poster Part II)

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