

# Use of fuzzy logic clustering analysis to address wave impacts on altimeter sea level measurements: Part II results



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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. Part I sketched the methodology and this poster presents resulting sea state bias error examination.

## II. First-pass SSB analysis for 6 nonlinear wave classes using hard partitioning

### Objective

Our objective is to combine wave model and altimeter data to improve the sea state bias correction at each data point

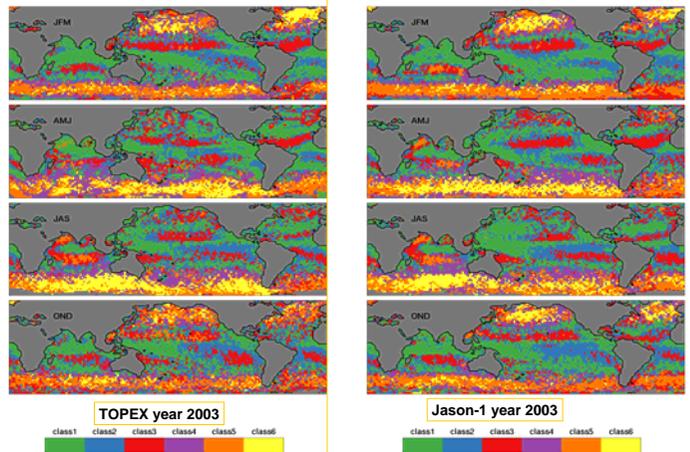
### Approach

- In Poster I we defined a method for assigning all altimeter data samples fuzzy membership values (from 0 to 1) in 6 possible wave nonlinearity regimes
- Here we revert to hard class divisions by grouping the data into their class of maximum membership value (simple max. threshold)
- These hard classes are used as a step in the overall SSB correction process. This poster provides observed sea state bias for the case of 6 hard boundaries. We calculate SSB models just as for the operational method using a bin-averaging approach (Vandemark et al. 2002). The hypothesis is that these 6 new SSB models will allow assessment of:
  - quantitative SSB differences from the global-average operational SSB model
  - the physics driving under- and over-corrections
  - a means to map where these errors occur
  - efficacy of eventual switch back to fuzzy combination of six model solutions as an operational approach to SSB correction

### Mapping of all six wind wave provinces, seasonally-averaged

The figure provides one view of the temporal and spatial variability of the data divisions based on combined wave model and altimeter data. Some points of note:

- Jason-1 and T/P are giving quite similar clustering results
- These wind-wave provinces are dynamic and seasonal and basin-scale shifts are evident at all latitudes (e.g. see Arabian Sea, trade wind belts)
- Spatial intermingling of classes gives some indication that class assignments are likely to coexist (or be vague) over much of the ocean much of the time
- The dynamics seen amongst the low Hs classes (1-3, green-blue-red) suggests that a single SSB algorithm could indeed be multi-valued at lower latitudes.



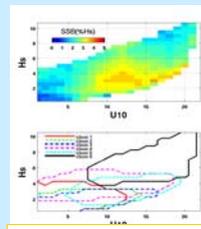
**Fig. 1** Seasonally-averaged mapping of our regimes of wave nonlinearity (see Poster I). Color for each pixel means that class x had the highest total membership value for that location over the season. In a rough sense (see Poster I Fig. 2) the classes can be assigned to wave development categories as follows:  
**Low wave height classes (1-3):** 1 = swell-dominated 2 = mixed sea 3 = young steep seas  
**Moderate wave height classes (4-5):** 4 = older seas/mix 5 = young steep seas  
**Extreme wave height (6):** 6 = high seas

### CLASS-BASED SSB MODELS AND COMPARISON TO THE GLOBALLY AVERAGED RESULT

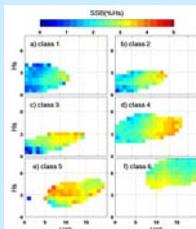
These figures use the direct averaging approach over one year of data to provide sea state bias estimates versus the operational coupled altimeter-derived Hs and wind speed. This is done for all data (the global average in Fig. 2) and then for the hard-class subsets 1-6 (Fig. 3). The difference between each class-based solution and the global average is given in Figure 4. This SSB "anomaly" figure provides some interesting results that quantitatively affirm much of what has been suggested in the past decade(s) of SSB modeling and field experiment work:

- the swell-dominated sea (class 1) SSB falls below the benchmark by as much as 1% on an average over a year of data
- the SSB for young seas at lower wave heights and winds speeds (class 3) are much greater
- young steep seas at higher Hs (class 5) show similar excess

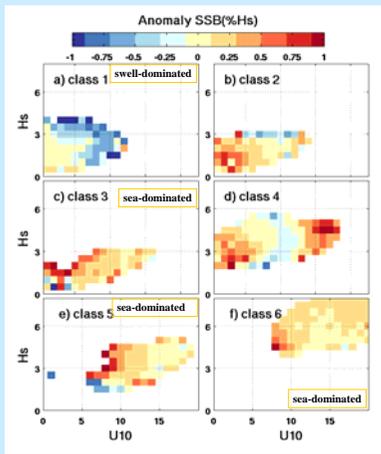
**Most important, from an empirical and operational standpoint what is most promising is that we can see where the present 2 parameter (Hs, U10) algorithm is likely to fail.**



**Fig. 2** Annually-averaged TOPEX altimeter sea state bias estimate (upper) and 90% probability for where the 6 hard class subset samples lie in (Hs, U10) data space (lower).



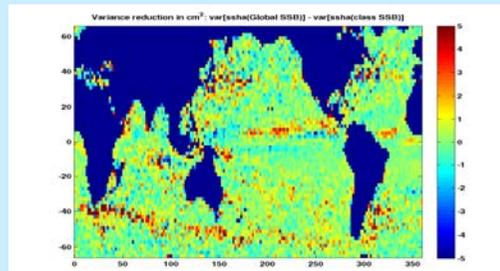
**Fig. 3** Class-based SSB models for TOPEX altimeter using same method as for the global-average (Fig. 2)



**Fig. 4** Difference between the class (Fig. 3) and global-average (Fig. 2) SSB models of Figs. 2 and 3. Note that red (blue) indicates that the class-based solution substantially over (under) estimates the nominal operationally-implemented solution.

### Preliminary look at global class-based SSB correction

The figure below indicates the potential of a classification-based approach to highlight and perhaps correct for wave-induced errors in the dynamic topography that are not being removed with the present-day SSB algorithms. We used the hard class subset SSB models of Fig. 3 to provide a point-by-point SSB correction for the entire year 2000. We then calculated the sea surface height for all TOPEX data applying both class-based and the global SSB corrections. The sea surface height variances at each location for the two realizations are differenced to give the result below. Our hard classification, direct averaging methods, and [Hs,U10] parameterization only lead to a crude first-cut SSB model but the significant amount of positive values (red) are where this class-based solution appears to outperform the single global algorithm. Note the western boundary current areas, Arabian Sea, the Agulhas current, and ITCZ are all highlighted.



**Fig. 5** Improvement (red) in sea surface height correction obtained with simplistic class-based SSB model versus the global-average two parameter SSB model.

## III. Summary

- A new approach has been developed for synthesizing all available wind wave information to partition the global ocean into wave nonlinearity-based regimes
- Physics of the sea state bias are now easier to ascertain from the on-orbit data and our work with Jason-1 and TOPEX suggests that both satellites show similar SSB anomaly (Fig.4) behavior, i.e. both platforms are subject to wave-induced electromagnetic bias impacts regardless of the tracker.
- Assessment of regime-based SSB models versus the global-average SSB model shows the new methodology should support SSB improvement in the near future

### References

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### Acknowledgments

The authors wish to recognize the help of H. Tolman and Paul Wittmann in the wave model (WaveWatch III) implementation. The research is sponsored by NASA's Science Directorate. H. Feng also acknowledges financial support from GEST/NASA-GSFC.



## Ocean Surface Topography Science Team Meeting

Venice, Italy, 16-18 March, 2006

