# CHARACTERIZING THE MODIS CHLOROPHYLL PRODUCT UNCERTAINTY

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## Abstract

Empirical chlorophyll products derived from NASA's ocean color satellite programs have a nominal uncertainty of ± 35%. This metric has been hard to assess, in part because the data sets for evaluating performance do not reflect the true distribution of chlorophyll in the global ocean. A new technique is introduced that characterizes the chlorophyll uncertainty associated with distinct optical water types, and shows that for much of the open ocean the relative error is under 35%. This technique is based on a fuzzy classification of remote sensing reflectance into eight optical water types for which error statistics have been calculated. The error statistics are based on a data set of coincident MODIS Aqua satellite radiances and in situ chlorophyll measurements. The chlorophyll uncertainty is then mapped dynamically based on fuzzy memberships to the optical water types. The uncertainty maps are thus a separate, companion product to the standard MODIS chlorophyll product.

## Overall Schematic

- The overall scheme requires 3 steps (Figure 1).
- *Step 1* involves finding the 'class' centers for different optical water types. This uses a cluster analysis on an in situ data set of remote sensing reflectance.
- *Step 2* involves characterizing the error for each optical water type. This requires an independent chlorophyll validation matchup data set with satellite imagery.
- *Step 3* is the operational stage where ocean color imagery is classified to the different optical water types, and error properties can be spatially mapped via the classification.

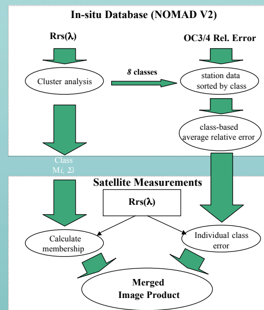


Figure 1. Flow chart schematic of method.

## Step 1 - Optical water type characterization

- A cluster analysis was performed on a data set (~2400 observations) of remote sensing reflectance from NASA's global bio-optical data set (NOMADv2) to determine and characterize the properties of reflectance 'classes' (or *optical water types*).
- *Eight* optical water types were identified and judged as the optimal number based on validity tests of the cluster analysis (Figure 2).
- These statistical properties of the optical water types form the basis for the *fuzzy membership function*.

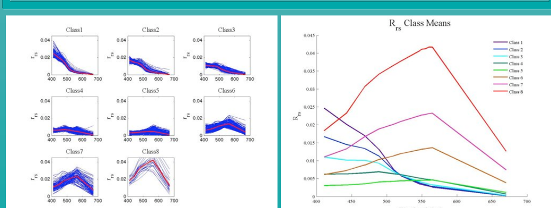

Figure 2. *Left*: cluster analysis results for remote sensing reflectance from the NOMADv2 data set (~2400 observations). Eight clusters were deemed 'best' for this data set based on validity function analysis (see paper). *Right*: Mean remote sensing reflectance spectra for the eight optical water types.

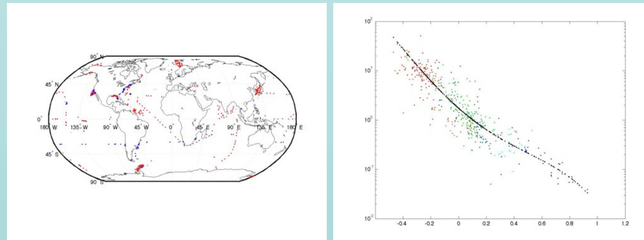

Figure 3. *Left*: Geographic location of the Aqua chlorophyll validation data set of 541 matchup points between in situ chlorophyll and co-located, simultaneous satellite measurements (assembled by OBPG at NASA). *Right*: The distribution of matchup data with the predicted Aqua chlorophyll from the OC3 algorithm (color-coded by optical water type).

## Step 2 - Chlorophyll uncertainty characterization

- An independent data set of in situ chlorophyll measurements were matched to MODIS satellite data and formed the Aqua validation data set (541 points) assembled by NASA (Figure 3 - left).
- These data were classified to the 8 optical water types, and error statistics were computed between measured chlorophyll and satellite-precidected chlorophyll (Figure 3 - right) on each subset of data for the different optical water types (Table 1).
- These calculations form the representative error characteristics for each water type, which can then be mapped.

| Optical Water Type | Average relative error (%) | RMS log error | Bias log error | # of points |
|---|---|---|---|---|
| 1 | 18 | 0.080 | -0.004 | 8 |
| 2 | 31 | 0.220 | -0.072 | 30 |
| 3 | 43 | 0.251 | -0.066 | 19 |
| 4 | 57 | 0.266 | 0.042 | 44 |
| 5 | 59 | 0.303 | 0.058 | 94 |
| 6 | 61 | 0.353 | -0.014 | 166 |
| 7 | 60 | 0.264 | 0.084 | 145 |
| 8 | N/A | N/A | N/A | 0 |

Table 1. Uncertainty statistics of the eight optical water types for the MODIS *Chl* product as characterized using the Aqua validation data set.

## Step 3 - Map generation

- A *fuzzy membership function* was created for the eight water types, which allows any observation of remote sensing reflectance to be classified into one or more of the eight water types. Membership values are permitted to take on values between 0 and 1, and to have membership to multiple water types.
- Ocean color data can be classified according to this method, and an global monthly image from May 2005 from Aqua classified to the 8 classes is shown in Figure 4 (top).
- These memberships serve as weighting factors when normalized for the class-specific error characteristics, which can then be mapped at the same scale (figure 4 bottom).

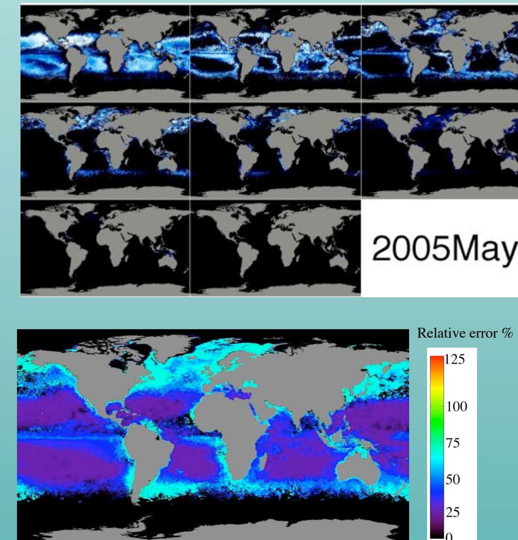


Figure 4. *Top*: Spatial distribution of the 8 optical classes for a monthly composite image from May 2005 (Aqua). These are depictions of the fuzzy memberships to each class (white is high membership, blue intermediate, and black no membership). *Bottom*: The subsequent relative error map produced from Table 1 weighted by the normalized fuzzy memberships.

## Conclusions

- Optical classification provides a mechanism to map specific water types from ocean color imagery based on remote sensing reflectance.
- Error characteristics are not uniform over the range of natural conditions in the oceans.
- Validation data sets provide a means to independently characterize the performance of satellite-derived products.
- Combining validation sets with the classification methodology provides a framework to map error properties in a dynamic scheme and unified to a common set of optical classes.