Dynamic ecological provinces:
a biogeochemical and physiological template of the global ocean

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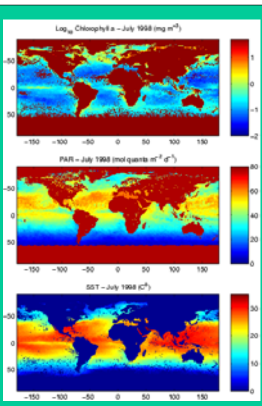
I. Introduction

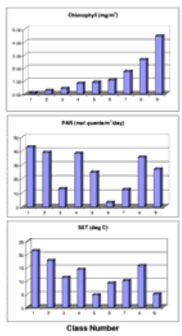
The concept of oceanic provinces has existed for almost a century (review in Longhurst 1998). Whether real or only conceptual, provinces provide a useful framework for understanding the mechanisms controlling biological, physical and chemical processes and their interactions. Criteria have been established for defining provinces based on physical forcings (Longhurst 1995), availability of light and nutrients (Fanning 1992), complexity of the marine food web, and other factors (Mueller and Lange 1989). The use of provinces for assessing marine primary production was saliently exemplified by Longhurst et al. (1995). In general, such classification systems reflect the heterogeneous nature of the ocean environment, and the effort of scientists to comprehend the whole system by understanding its homogeneous components.

If provinces are defined strictly on the basis of geospatial or temporal criteria (e.g., latitude zones, bathymetry, or season), the resulting maps exhibit discontinuities that are uncharacteristic of the ocean. While this may be useful for many purposes, it is unsatisfactory in that it does not capture the dynamic nature of ocean systems. Boundaries fixed in time and space do not allow us to observe inter-annual or longer-term variability that may result from climate change. Ideally, the criteria used to define provinces should be based on properties that can be measured remotely, but this is not always the case. Provinces may be based on other properties, such as trophic complexity, nutrient concentrations, or photosynthetic efficiencies (Platt and Sathyendranath, 1999) that are not amenable to remote sensing. In general, one can use satellite observations (e.g., ocean color, temperature) to guide a classification system, but other attributes of the classes or provinces may have to be inferred from statistical associations with an incumbent degree of uncertainty.

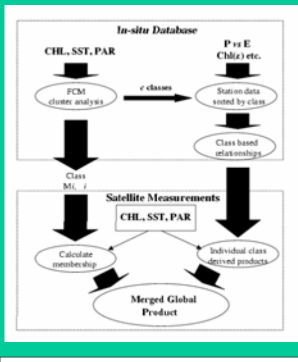
The presented study exploits the potential of using fuzzy logic as a means of classifying the ocean into objectively defined provinces using properties measurable from satellites. The properties we will use are the surface chlorophyll concentration (CHL), sea surface temperature (SST), and the above-water incident photosynthetic available radiation (PAR). It is generally accepted that these three properties are important determinants of primary productivity, but no universally reliable relationship exists to predict depth integrated primary production (IPP) from CHL, PAR, and SST. The single most important property, statistically, is CHL. The chlorophyll level is an index of the trophic state but CHL accounts for only about 30% of the variability in IPP (Balch et al, 1991). The next most important variable is PAR. In light-limited environments, the instantaneous rate of production (PP) is proportional to PAR, but PAR has a deceasing effect as PP approaches a light-saturated value, P_{max}. The next most important property is SST, because the maximum rate of photosynthesis (P_{max}) is influenced, in part, by the temperature. All these generalizations have informed PP models based on CHL, PAR, and SST. However, the physiological response of phytoplankton to their environment is not easily quantified with a single model, because the communities found globally have different responses. Consequently, the algorithms for estimating IPP from CHL, PAR, and SST are able to reproduce ^{14}C-measured IPP only to within about a factor of two (Campbell et al. 2002). Since the physiological response of phytoplankton to light and temperature depends on the community and its adaptation to its environment, we believe that it is not possible to parameterize these relationships with single universally reliable models. Our approach is to partition the ocean into provinces, each having a different domain of CHL, PAR, and SST, and to parameterize IPP models for these distinct environmental domains.

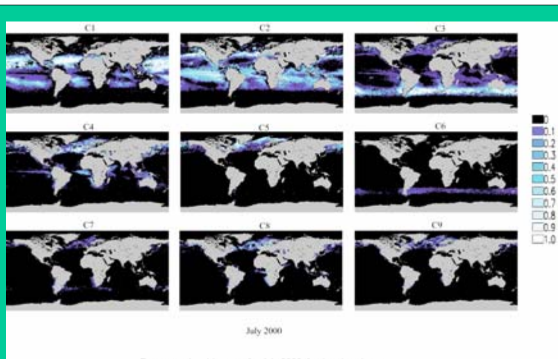
We have identified nine domains based on in-situ CHL, SST, and PAR measurements associated with a large geographically-diverse primary productivity data set. These domains where subsequently mapped globally using satellite ocean color and temperature data. Thus mapped the domains represent spatially coherent and seasonally dynamic provinces. The use of satellite data to map provinces accommodates their dynamic variability as province maps can be updated with each image that is processed. We propose to adopt this classification as the basis for parameterizing class-specific relationships among variables that are not remotely sensed and those that are amenable to remote sensing (e.g., SST, CHL, PAR). Once the class-specific relationships have been specified, they will be applied within each province as determined by satellite observations, and the derived properties will then be recomposed into a single blended map based on weighted fuzzy memberships to the provinces (Moore et al. 2001).





Plot showing the mean values of the 3 variables in each of the nine classes. The classes themselves have been ordered so that chlorophyll increases in concentration from class 1 to class 9.





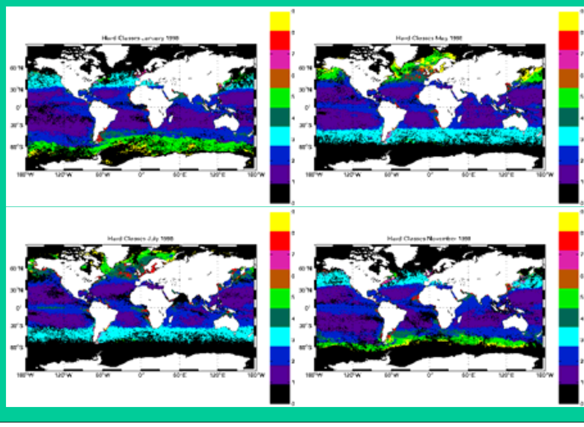
Fuzzy membership maps for July 2000, for the nine classes

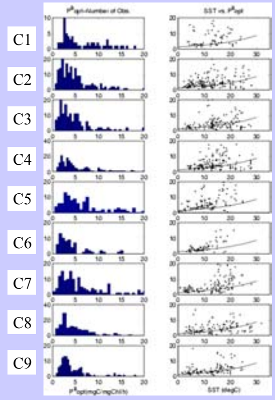
II. Use of fuzzy logic to define ocean provinces

Fuzzy logic was first introduced by Zadeh (1965) as a mathematical way to represent vagueness and imprecision inherent in data. The idea behind fuzzy sets simply states that an object can have partial *membership* to more than one set. This concept is a departure from classical set theory, which maintains that an object belongs exclusively to only one set. The degree of belonging to any given set is expressed mathematically by a *membership function* which ranges from 0 to 1. In fuzzy set theory, full membership to exclusively one set is still permitted, and thus it is a superset of classical set theory.

We have applied this approach to a large in-situ primary productivity data set (largely drawn from the data of Behrenfeld and Falkowski, 1997) in which we identified nine classes based on the ranges of CHL, SST, and PAR within the data set. Our original purpose was to evaluate the performance of primary productivity algorithms within different environmental *niches*. Subsequently, the classification was applied to monthly composited satellite data of CHL, SST, and PAR to map the global distribution of the nine classes. The resulting classes were spatially coherent and logically distributed within any given month, and yet temporally dynamic from month to month. The nine classes thus "scaled up" to represent nine large-scale dynamic provinces (see table below).

	SST	PAR	CHL	Province
Class 1	High	High	V. Low	Sub Tropical Gyres
Class 2	High	High	Low	Tropical
Class 3	Medium	Low	Low	Temperate Deep MLD
Class 4	Medium	High	Medium	Temperate High Nutrient
Class 5	Low	Medium	Medium	Polar
Class 6	Medium	V. Low	Medium	High Lat, Low Light
Class 7	Medium	Low	High	Enclosed Temperate seas
Class 8	Medium	High	High	Upwelling/ River Plumes
Class 9	Low	Medium	V. High	High-Mid Lat, Coastal Blooms

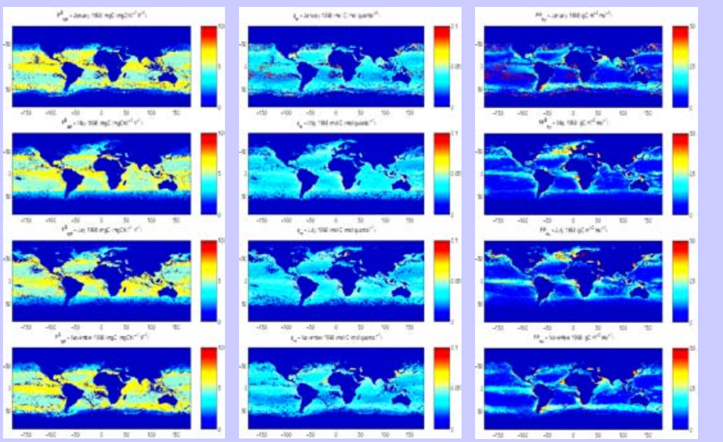


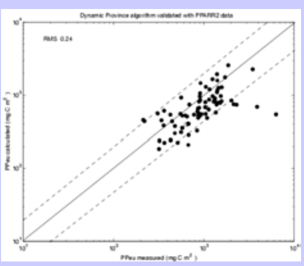


III. Primary Production Modeling

In the development of algorithms and models that use remotely sensed data as input (e.g. primary production), there are certain aspects of the models that are not directly detectable by remote sensing, e.g., in the case of primary production modeling, the photosynthetic parameters of the P-E curve and the vertical biomass profile. These properties often vary considerably at the global scale in a complex non-linear fashion; thus their parameterization becomes complex. There have been two alternative approaches used to represent these variables or processes (Platt et al. 2000). One approach is to use climatological averages of parameters within predetermined provinces (e.g. Longhurst et al., 1995). While this province approach is based on oceanographic insight into the processes that control the geographic distribution of the variables (Longhurst, 1995), the prescribed provinces tend to be static, varying at most seasonally, and are separated by fixed boundaries. They are unsatisfactory in that they do not capture the dynamic nature of the ocean environment and do not allow for temporal variability in the location of provinces. A second approach is to parameterize statistical relationships between satellite-measured variables and the desired quantity (e.g. Pmax or PBopt as a function of SST). However, these functions often tend to be complex non-linear functions (e.g. Behrenfeld and Falkowski 1997) and are only valid within the bounds of the data set used for the parameterization.

The method proposed here provides a marriage between these two contrasting approaches. In using the satellite data and fuzzy memberships, variables computed according to class-specific relationships can be seamlessly reconstructed into global maps. We have observed that the individual classes themselves are extremely dynamic, information that would be lost in a static biogeographical classification. On the other hand, by restricting the task to modeling variability within individual classes, the high degree of non-linearity in relationships at global scales is reduced (may even be nearly linear) when considered on a class-specific basis. Thus, this approach capitalizes on the combined advantages of using satellite and in-situ data, reproducing the quantitative variability of the in-situ measured variables (especially when inaccessible to remote sensing) with the synoptic and dynamic continuity provided by the remote sensing data.





Prototype Dynamic Province based PP model

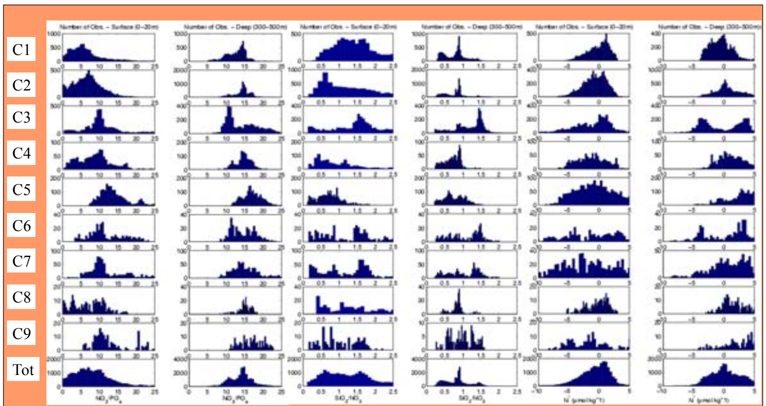
As a demonstration of the potential of the presented dynamic provinces in parameterizing primary production algorithms a simple Depth Integrated Model has been formulated and is described below. The algorithm is at present being compared with more than 15 others in the third round of the Primary Production Algorithm Round Robin (PPARR-3). Primary production itself is estimated through:

$$PP = 12000\,\phi\,\overline{E}_0\,Chl\,\overline{a}_{ph}{}^{*}$$

Where $a_{ph}{}^{*}$ is the phytoplankton specific absorption coefficient, E_0 is the average water column available radiation to the chosen depth of integration (MLD or euphotic depth). This variable includes a parameterized conversion of the satellite measured downwelling irradiance (as in II.) to scalar irradiance the relevant quantity in light photosynthesis models. The final term ϕ is the the quantum yield which is estimated as:

$$\phi = \phi_m \frac{E_k}{E_0}\left[1 - e^{-\frac{E_0}{E_k}}\right]$$

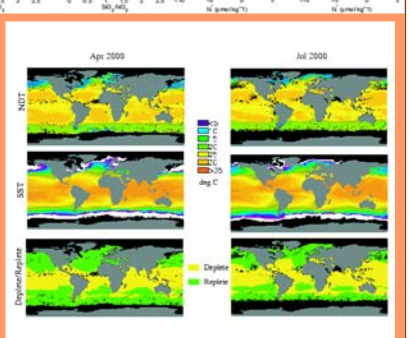
Here E_k is the irradiance at the onset of saturation (which we calculate as a function of E_0 – an aspect of the parameterization which will also become class specific) and ϕ_m is the maximum quantum yield which we estimate as $\phi_m=(P^B{}_m/E_k)a_{ph}{}^{*}$. Herein lies the effect of $P^B{}_{opt}$ on the computed primary production. At present we estimate $P^B{}_{opt}$ as a function of SST for the classes which have a mean temperature less than 10 deg.C and mean class values are used for classes with mean temperature above 10 deg. C. The fuzzy memberships (as shown in II.) are then used to recompose the blended $P^B{}_{opt}$ product. Example products for $P^B{}_{opt}$, ϕ_m and PP_{eu} are shown above. On the left is a preliminary validation of this algorithm with the PPARR-2 dataset (Campbell et. al. 2002) the RMS obtained is in good agreement with those of the best algorithms resulting for the original PPARR-2 experiment.



IV. Nutrient Biogeochemistry

A further application of the proposed dynamic province is in the biogeochemical study of nutrients and how these interact with and limit primary productivity. Here we show distribution functions (obtained from the nutrient climatology of Louanchi and Najjar 2000) of specific biogeochemically relevant variables and how they vary from one province to another. These variables include the ratio NO_3/PO_4, the ratio SiO_2/NO_3 and the quasi conservative tracer N* (Gruber and Sarmiento1997) as a useful indicator of nitrogen fixation and denitrification.

Additionally for the identification of limiting nutrients, our approach is to determine the nutrient depletion temperature within each province for the limiting nutrient(s). It is now recognized that large areas of the ocean are limited by nutrients other than nitrogen; this has been effectively modeled recently by Keith Moore and coworkers (Moore et al. 2002). Whilst in the past nitrate depletion temperatures have been developed as a means of identifying areas of nutrient depletion (Kamykowski and Zentara 1986), now there is sufficient data to map out depletion temperatures for different nutrients. Our analysis will be undertaken in two successive steps: first, after grouping nutrient data into classes based on the statistics described above, we will determine which if any is the limiting nutrient (recognizing that Si might be limiting diatom production but not the whole autotrophic community). The second step will be to plot concentrations of the limiting nutrients identified in the first step against the mixed layer temperature. The intercept of this regression (i.e., the temperature corresponding to a zero or threshold nutrient concentration) provides us with the depletion temperature for the limiting nutrient in that province. We fully expect, however, that there will be provinces where nutrients are not limiting (e.g., Class 4 or Class 8). Information about the limiting nutrient and the nutrient depletion temperature will enable us to map regions as being nutrient-replete vs. nutrient-deplete.



Two monthly composites for April and July 2000, illustrating nitrate depletion temperatures processed based on class estimated values, the respective SST images and maps highlighting where SST is higher or lower than NDT, here termed the nitrate deplete/replete map.

V. Conclusions

It is apparent that synoptic satellite data provide an appropriate means of extrapolating quantities measured in-situ but not directly measurable from satellite to global scale. However, the use of any single satellite data source is not likely to reproduce the necessary variability of the complex processes typical of biological and physiological variability associated with pelagic production. We believe that the use of fuzzy logic as a means of both classifying multiple-satellite data sets and blending derived products is a relevant tool to address these issues.

A prototype primary production algorithm parameterized based on nine global dynamic provinces has shown to perform as well as the best algorithms in a previously undertaken Round Robin experiment.

Future work will address in much more detail in the use of such a classification scheme in parameterizing primary production algorithms. Specifically the following items will be addressed.

•A fully depth and wavelength resolved model will be implemented

•Models describing the vertical distribution of biomass will be parameterized for each class.

•Variability of photosynthetic parameters $P^B{}_m$ an E_k will be investigated for each class.

•Variability in the required depth for integration of the light field as a function of either the euphotic depth or the mixed layer depth will be investigated

•Use provinces to study both the light and nutrient limitation of primary production in biogeographically distinct regions.

•The relationship between phytoplankton functional groups (from models and in-situ data) and the observed biogeochemical characteristics (as in IV.) of each class.

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