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Ocean productivity from space: Commentary

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Key Points:
- Models of oceanic Net Primary Production have improved over the last decades
- Coverage by satellite ocean color data is severely limited by clouds and low Sun elevation
- A combination of data from satellites, suborbital platforms, and autonomous profiling devices is needed

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Abstract Ocean color measurements from satellites have been used to estimate global oceanic productivity for about 30 years, but the approach still has many problems. A combination of more sophisticated satellite products with improved models has the potential of higher accuracy but in reality the improvement in accuracy during the last two decades has been minimal. Persistent cloud cover over the oceans and low Sun elevation over polar areas severely limit the potential of operational satellite ocean color measurements. A combination of remote measurements from both satellites and suborbital platforms as well as from a large number of autonomous devices in the ocean can overcome these limitations in the future.

Oceanic primary production is part of the "biological pump" that removes CO_2 from the upper ocean. Getting reliable estimates of the magnitude of this process [e.g., *Y. J. Lee et al.,* 2015] is therefore beyond pure academic interest. It may seem that using satellites to estimate primary production in the ocean is a novel development, but it is not. In the early 1980s, when investigators were able to see images of NASA's first ocean color sensor, the Coastal Zone Color Scanner, they realized the immense spatial variability or "patchiness" of phytoplankton distributions in the ocean. It became clear that the practice of estimating integrated production in the world's oceans by extrapolating a few time-consuming and hard to make in situ measurements to temporally and spatially variable oceans is doomed. Almost simultaneously, several researchers [*Eppley et al.,* 1985; *Platt,* 1986; *Perry,* 1986] proposed to use satellite images from space in conjunction with a model to estimate the net primary production (NPP, mg C m^{-2}) in the oceans. Now, over 30 years later, these models are still being developed and a recent paper by *Silsbe et al.* [2016] represents the state of the art of these efforts.

While significant progress has been made in the last 30 years, the problem is far from being solved. By now the number of different models and their variants proposed by researchers probably exceeds a hundred, but their accuracy is still questionable. Only a few of the multitude of NPP models are widely used, and the reasons for that are worth considering. In the 1990s the Vertically Generalized Production Model (VGPM) by *Behrenfeld and Falkowski* [1997a, 1997b] gained dominance due to its simple structure, excellent presentation, and robust performance. It became clear that making the models too complex by cramming many detailed equations describing poorly known processes into the models does not make the models perform better and can make their performance worse. Theoretically advanced and promising models often performed poorly when applied to real satellite data. For example, the Carbon based Productivity Model (CbPM) [*Behrenfeld et al.,* 2005] that followed VGPM to become the most influential model in the 2000s, performed worse than other models because of the sensitivity to poorly known input variables. Eppley [*Eppley et al.,* 1985] found that as a rule of thumb, the square root of the surface chlorophyll a concentration (mg m^{-3}) is approximately equal to NPP per day per square meter. It appeared that quite often the rule of thumb NPP estimate was more accurate than CbPM [e.g., *Kahru et al.,* 2009]. In a recent test of 32 different NPP models on Arctic data, none produced acceptable accuracy [*Z. Lee et al.,* 2015].

An impediment for progress in model improvement has been the fragmentation and poor accessibility of data sets of in situ measurements. The approach of *Saba et al.* [2011] to provide a freely available, quality-controlled data set is a great exception, and expanding and complementing this data set should be greatly encouraged. When applied to the *Saba et al.* [2011] data set, the recent CAFE model [*Westberry and Behrenfeld,* 2013; *Silsbe et al.,* 2016] performs reasonably well but does not provide a significant increase in accuracy compared to a model published 20 years earlier [*Antoine and Morel,* 1996]. In order for the CAFE or any other model to become the current standard NPP model of the decade like VGPM has been earlier, the model structure must be open and clearly documented. Most importantly, the model code should be available for implementation and modification by other researchers. Data products from the model should be accessible in order to compare the outputs of different implementations when applied to different data sets. The Ocean Productivity website of Oregon State University (http://www.science.oregonstate.edu/ocean.productivity) has been a great resource in providing access to global NPP data.

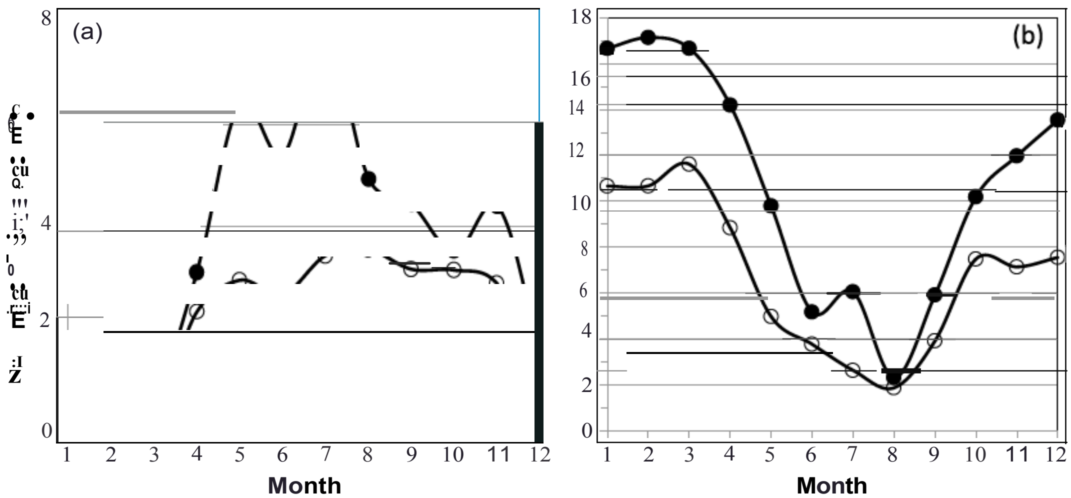

Figure 1. Average number of days with ocean color data per month off (a) northeast Vietnam and (b) northwest of the Philippines from a single satellite sensor (SeaWiFS, open circles) and a combination of two sensors (SeaWiFS and MODJS-Aqua, filled circles).

While model improvement must continue, the practical application of these models faces major obstacles that are barely discussed and often just ignored. It is typical to apply NPP models to satellite data composited over monthly time periods as daily or higher-resolution satellite data are not available. However, photosynthesis is a nonlinear process and results from applying a model to monthly mean data is not equal to the mean of the results from applying the same model to temporally frequent data sets. Days can be very different in terms of solar radiation and other variables. Some areas of the world ocean are cloudy most of the time and rarely have any ocean color data; others have extreme seasonal differences in the number of clear days when ocean color data can be obtained. Figure 1 shows two examples of the number of days per month of available ocean color data from one or two satellite sensors. In the first region (coastal Vietnam) intense cloudiness during the winter months (December to March) allows less than 2 days and sometimes less than 1 day per month of ocean color retrievals. In the second region (NW off the Philippines) the period of January to March is very clear (up to 17 days of ocean color data per month), but only 2 days of ocean color data per month can be obtained in August. It is obvious that monthly composites based on data from only a few days per month are unreliable and that composites over shorter time periods inevitably miss a lot of areas due to clouds. Additional restrictions are caused by the low Sun elevation over high-latitude oceans. The total area of open

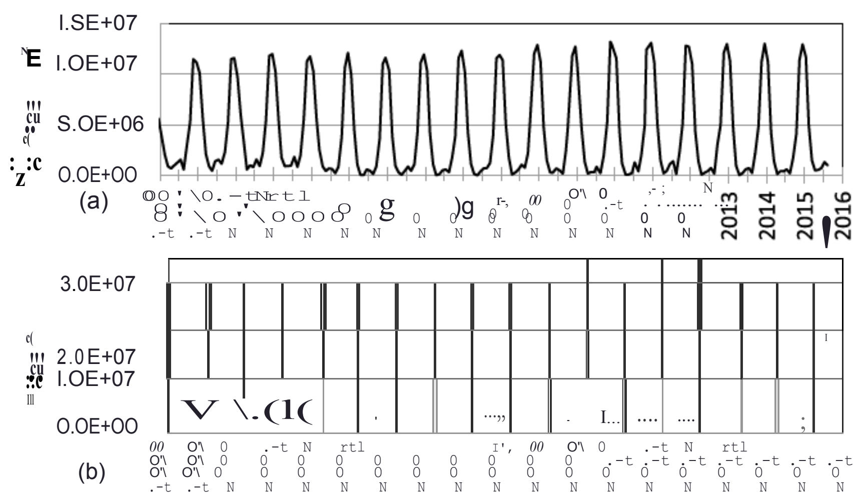

Figure 2. Total area of missing ocean color data (monthly composites merged from multiple satellite sensors) in open water areas in the (a) Northern and (b) Southern Hemispheres.

water (i.e., with no ice) with missing ocean color data in monthly composites reaches ~11 million km^2 in the Northern Hemisphere during boreal winter and ~30 million km^2 in the Southern Hemisphere during austral winter (Figure 2). While we can assume that NPP is low over the winter season at high latitudes, not all of this area is under polar night conditions and even low NPP per area multiplied by the large area is a big number. It is obvious that satellite ocean color has severe limitations not just by missing large areas of the ocean surface due to clouds and low Sun angle but also due to missing the vertical dimension of the ocean. The way to fill these gaps is through a combination of data from satellites, suborbital drones, and a large number of autonomous profiling devices with smart sensors. However, the high cost and problems with merging disparate data sets remain problematic. The Biochemical-Argo program [*Johnson and Claustre*, 2016] is an ambitious program aiming to cover the world oceans with biological sensors, but obtaining reliable measurements from autonomous devices is not easy and their spatial coverage will not be comparable to that of remote sensing. In the near-term, models like CAFE applied to interpolated and extrapolated satellite data remain the best option to get global productivity estimates.

References

Antoine, D., and A. Morel (1996), Ocean primary production: 1. Adaptation of a spectral light-photosynthesis model in view of application to satellite chlorophyll observations, *Global Biogeochem. Cycles*, *10*, 43–55, doi:10.1029/95GB02831.

Behrenfeld, M. J., and P. G. Falkowski (1997a), A consumer's guide to phytoplankton primary productivity models, *Limnol. Oceanogr.*, *42*, 1479–1491.

Behrenfeld, M. J., and P. G. Falkowski (1997b), Photosynthetic rates derived from satellite based chlorophyll concentration, *Limnol. Oceanogr.*, *42*, 1–20.

Behrenfeld, M. J., E. Boss, D. A. Siegel, and D. M. Shea (2005), Carbon-based ocean productivity and phytoplankton physiology from space, *Global Biogeochem. Cycles*, *19*, GB1006, doi:10.1029/2004GB002299.

Eppley, R. E. Stewart, M. Abbott, and U. Heyman (1985), Estimating ocean primary production from satellite chlorophyll: Introduction to regional differences and statistics for the southern California Bight, *J. Plankton Res.*, 7, 57–70.

Johnson, K. S., and H. Claustre (2016), Bringing biogeochemistry into the Argo age, *Eos*, 97, doi:10.1029/2016EO062427.

Kahru, M., R. Kudela, M. Manzano-Sarabia, and B. G. Mitchell (2009), Trends in primary production in the California Current detected with satellite data, *J. Geophys. Res.*, *114*, C02004, doi:10.1029/2008JC004979.

Lee, Y. J., et al. (2015), An assessment of phytoplankton primary productivity in the Arctic Ocean from satellite ocean color/in situ chlorophyll-a based models, *J. Geophys. Res. Oceans*, *120*, 6508–6541, doi:10.1002/2015JC011018.

Lee, Z. J. Marra, M. J. Perry, S. Sathyendranath, and M. Kahru (2015), Estimating oceanic primary productivity from ocean color remote sensing: A status assessment, *J. Mar. Syst.*, *149*, 50–59, doi:10.1016/j.jmarsys.2014.11.015.

Perry, M. J. (1986), Assessing marine primary production from space, *BioScience*, *36*(7), 461–467.

Platt, T. (1986), Primary production of the ocean water column as a function of surface light intensity: Algorithms for remote sensing, *Deep-Sea Res. Part A*, *33*, 149–163.

Saba, V. S., et al. (2011), An evaluation of ocean color model estimates of marine primary productivity in coastal and pelagic regions across the globe, *Biogeosciences*, *8*, 489–503, doi:10.5194/bg-8-489-2011.

Silsbe, G. M., M. J. Behrenfeld, K. H. Halsey, A. J. Milligan, and T. K. Westberry (2016), The CAFE model: A net production model for global ocean phytoplankton, *Global Biogeochem. Cycles*, *30*, GB5521, doi:10.1002/2016GB005521.

Westberry, T. K., and M. J. Behrenfeld (2013), Oceanic net primary production, in *Biophysical Applications of Satellite Remote Sensing*, chap. 8, edited by J. M. Hanes, pp. 205–230, Springer, Berlin.