Auxiliary Material

Appendix A. Model descriptions.

1. SAT,DI,WI model descriptions

Model 1: This model estimates NPP as:

$$\mathrm{NPP}\ [\mathrm{mgC\ m^{-2}\ d^{-1}}] = [(\mathrm{chl}_0\ [\mathrm{mg\ chl\ m^{-3}}])^{1/2}] \times 1000$$

[*Eppley et al.*, 1985]. It ignores any external forcing or changes in physiological state. While other models incorporate information regarding geography or forcing fields, this model assumes that the standing stock is sole determinant of photosynthetic rate. All biomass performs identically. This simplicity is inherently elegant because biomass is, for most of the ocean, an excellent indicator of nutrient supply and presence of light.

Model 2: This is the original Howard, Yoder, Ryan model [*Howard and Yoder*, 1997], which for many years was a standard MODIS algorithm. Maximum growth rate is parameterized as a function of SST according to *Eppley* [1972]. NPP is integrated to the MLD rather than to the euphotic depth.

Model 3: This is a variant of the original Howard, Yoder, Ryan model [*Howard and Yoder*, 1997] which integrates photosynthesis to the euphotic depth as defined in *Behrenfeld and Falkowski* [1997] rather than to the MLD [*Carr*, 2002].

Model 4: This model is based on the formulation obtained through dimensional analysis by *Platt and Sathyendranath* [1993]. The photosynthetic parameter (P^{B}_{max}) is assigned by combining a temperature-dependent relationship for the maximum growth rate [*Eppley*, 1972] with a variable carbon to chlorophyll ratio following the statistical relationship of *Cloern et al*. [1995].

Model 5: This model uses an artificial neural network to perform a generalized nonlinear regression of NPP on several predictive variables, including latitude, longitude, day length, MLD, SST, P^{B}_{opt} (computed according to *Behrenfeld and Falkowski* [1997]), PAR, and Chl-*a* [*Scardi*, 2000; *Scardi*, 2001].

Model 6: This Vertically Generalized Production Model (VGPM) [*Behrenfeld and Falkowski* 1997] variant uses the continuous function of *Morel and Berthon* [1989] to estimate total integrated Chl-*a*, which in turn is used to estimate the euphotic depth with the equations proposed by *Morel and Maritorena* [2001].

Model 7: This VGPM variant formulates P^{B}_{opt} as a function of SST and Chl-*a* [*Kameda and Ishizaka*, 2005; *Yamada et al.*, 2005]. The model is based on the assumption that phytoplankton consists of large and small phytoplankton groups, which have specific Chl-*a* productivities and temperature functions such that changes in Chl-*a* concentration depends on the abundance of large phytoplankton.

Model 8: The original VGPM developed by *Behrenfeld and Falkowski* [1997] is one of the most widely known and used NPP models. The maximum observed photosynthetic rate within the water column, P^{B}_{opt}, is obtained as a 7th-order polynomial of SST.

Model 9: This model only differs from Model 8 in that $P^B{}_{opt}$ is estimated as an exponential function of temperature following *Eppley* [1972].

Model 10: This model [*Tang et al*., 2008] uses support vector machine (SVM) as the nonlinear transfer function between ocean primary productivity and Chl-*a* concentration, euphotic layer depth, PAR, maximum carbon fixation rate and day length. The maximum carbon fixation was estimated by using a seventh-order polynomial function of SST [*Behrenfeld and Falkowski*, 1997]. The euphotic layer depth was estimated using the integrated chlorophyll [*Morel and Berthon*, 1989].

Model 11: This model is similar to Model 13 [*Tang et al*., 2008] except that the maximum carbon fixation rate was estimated as a SVM-based nonlinear function of SST, Chl-*a* and PAR.

2. SAT,DR,WI model descriptions

Model 12: In this model the depth-distribution of PAR is given by an empirical equation of light attenuation, which is determined by chl_0. The depth-distribution of Chl-*a* is determined by an empirical equation of PAR and Chl-*a* along the PAR depth-distribution line in a log scale with estimating a chlorophyll maximum up to 0.1 % depth of PAR. Total productivity is empirically estimated and integrated from surface to 1 %

euphotic zone and for a day light time as a function of SST, depth-dependent PAR, Chl-*a*, latitude, and seasons [*Asanuma*, 2006].

Model 13: Photosynthesis per unit Chl-*a* was determined using an optimality-based model of nitrogen allocation and photoacclimation [*Armstrong*, 2006]; the optimality criterion was derived based on the photosynthesis model of *Geider et al.* [1998]. Photoacclimation and nitrogen allocation were determined as a function of light and temperature; therefore both PAR and SST were used in the productivity algorithm. Maximum photosynthetic rates were based on NPP estimated for *T. weissflogii* in *Armstrong* [2006], and were assumed to have *Eppley* [1972] temperature dependence; photoacclimation parameters were also as in Armstrong [2006]. Through the photoadaptation algorithm, Chl-*a* reflects nitrogen status, so that no assumptions about nutrient limitation are needed. Chl-*a* concentration was assumed constant over the photic zone and equal to surface Chl-*a*, so that light decreases exponentially with depth. Photic zone depth (1% light) was determined from Chl-*a* concentration and assumed extinction coefficients. The photic zone was assumed to be well mixed and cells were assumed to be photoacclimated to the light level at the middle of the photic zone (10% of surface illumination light. Column productivity is the integral over the photic zone of (photosynthesis/Chl-*a*) x Chl-*a*.

Model 14: This is a variant of Model 13 where the photic zone was divided into two equal depth (photoacclimation) zones (10%-100% and 1%-10% surface illumination, respectively), and separate photoacclimation parameters were calculated for the upper and lower parts of the photic zone (31.6% and 3.16% surface illumination, respectively).

Model 15**:** The Ocean Productivity from Absorption and Light (OPAL) model generates profiles of chlorophyll estimated from surface chlorophyll based on *Wozniak et al*. [2003] and uses the absorption properties in the water column to vertically resolve estimates of light attenuation in approximately 100 strata within the euphotic zone. Absorption by pure water is assumed to be a constant value over PAR wavelengths; chlorophyll-specific phytoplankton absorption is parameterized empirically [*Bricaud et al*., 1998]; absorption by photosynthetic pigments is distinguished from total absorption; and absorption by colored dissolved organic matter (CDOM) is calculated according to *Kahru and Mitchell* [2001]. The chlorophyll-specific phytoplankton absorption is used to calculate productivity, while absorption by photosynthetic pigments, water, and CDOM are used to vertically resolve light attenuation. SST, which is used as a proxy for seasonal changes in the phytoplankton community, is related to the chlorophyll-specific absorption coefficient. The quantum efficiency is obtained from a hyperbolic tangent and a constant φmax. Productivity is calculated for the 100 layers in the euphotic zone and summed to compute the integral daily productivity.

3. SAT,DR,WR model descriptions

Model 16: This is a spectral light-photosynthesis model published by *Morel* [1991]. It is formulated using Chl-*a* specific wavelength-resolved absorption and quantum yield

[*Antoine and Morel*, 1996]. Temperature dependence is given by the parameterization of $P^B{}_{max}$, which follows *Eppley* [1972]. The Chl-*a* profile is determined to be well-mixed or stratified according to the ratio of MLD and the euphotic depth, and if stratified, assigned a gaussian profile as in *Morel and Berthon* [1989]. Mean photo-physiological parameters are from *Morel et al.* [1996]. The model is run in its `satellite' version *Antoine et al.* [1996], where NPP is the product of integral biomass, the daily irradiance, and ψ^*(the cross-section of algae for photosynthesis per unit of areal Chl-*a* biomass). Lookup tables for ψ^* were previously generated using the full DR,WR model, and are used to increase computational efficiency.

Model 17: This is a variant of Model 16 that considers separately the micro-, nano-, and pico-phytoplankton size classes to determine NPP (specific parameterizations for the Chl-*a* vertical profile [*Uitz et al.,* 2006] and for the photo-physiological parameters [*Uitz et al.,* 2008]).

Model 18: This model follows that of *Platt and Sathyendranath* [1988] as implemented at global scale by *Longhurst et al.* [1995]. It uses biogeographical provinces to define the values of the parameters to describe the light-photosynthesis curve and the Chl-*a* depth profile. Photosynthetic parameters were updated using an extended data set provided by the Bedford Institute of Oceanography and an extensive literature review. Spectral surface irradiance is first estimated independently with the model of *Gregg and Carder* [1990] combined with a correction for cloud cover and then scaled to match the PAR values provided for the exercise. Spectral light is subsequently propagated in the water column with a bio-optical model with updated parameterizations of the inherent optical properties. All changes to the original implementation of *Longhurst et al.* [1995] are detailed by *Mélin* [2003].

Model 19: This model is an implementation of the *Morel* [1991] model in which the depth distribution of Chl-*a* is assumed constant throughout the water column. The broadband incident PAR is spectrally resolved using a look-up-table generated from a single run of the *Gregg and Carder* [1990] marine irradiance model where the effects of clouds and aerosols are essentially linearly scaled. The model uses 60-minute time and 10-m depth steps at 5-nm wavelength resolution when run using the global datasets [*Smyth et al.,* 2005].

Model 20: This model [*Ondrusek et al*., 2001] derives spectral irradiance from PAR using *Tanré et al*. [1990], and assumes a vertically uniform Chl-*a* profile. Quantum yield is parameterized as a maximum value times both a light dependent term [*Bidigare et al*., 1992; *Waters et al*., 1994] and a temperature dependent term. Temperature dependence was assumed to be sigmoidal, and was based on a vertical profile of temperature derived from SST and MLD.

4. CBSAT model descriptions

Model 21: The Carbon-based Production Model (CbPM) represents a new approach to NPP assessment that utilizes satellite information on both surface Chl-*a* and particulate backscatter (bbp) at 443 nm, which is converted into phytoplankton carbon biomass (*C*) [*Behrenfeld et al*., 2005]. This expanded information set allows the ratio of Chl-*a*:C to be calculated and related to phytoplankton growth rates (*m*), such that NPP is then calculated as the product of *C* and *mu*. In the current application of the CbPM, not all field data were provided with bbp so phytoplankton C was estimated using 'typical values' derived from SeaWiFS data for a given sample location. This lack of coincident field bbp data compromises the performance of the CbPM in the current model-field data comparison. Vertical structure in this version of the CbPM is as assumed in Model 8.

Model 22: This model represents an expansion in both the physiological attributes of the original CbPM (Model 21) and the space- and time-resolution of the model, and is described in detail in *Westberry et al*. [2008]. The model requires surface Chl-*a* concentration data and particulate backscatter coefficients (bbp) at 443 nm. As with Model 21, execution of this model for the current study required the estimation of bbp from the SeaWiFS record, as not all of the coincident field data for bbp were available. Vertical structure in Chl-*a* concentration in this model is driven primarily by photoacclimation of cellular Chl-*a*, with additional adjustments made for changes in nutrient stress through the water column.

5. BOGCM model descriptions

Model 23: This model is that of *Dutkiewicz et al.* [2005] updated to include cycling of carbon, alkalinity, and oxygen [*Bennington et al*., 2009; *Koch et al*., 2009]. The model considers the fate of phosphorus, iron, silicon, carbon, and oxygen as they pass from dissolved inorganic form to phytoplankton, to zooplankton, and to detritus in both dissolved and sinking particulate forms. The model includes two phytoplankton functional groups (diatoms and other small phytoplankton) and one zooplankton class. Phytoplankton growth is limited by multiple nutrients (phosphate, iron, and silicic acid) and light. Temperature modifies growth rates according to *Eppley* [1972]. The ecosystem model is coupled to the MIT general circulation model [*Marshall et al*., 1997a, 1997b] configured to the North Atlantic region with 0.5° resolution and forced by daily NCEP reanalysis products.

Model 24: The Pelagic Interaction Scheme for Carbon and Ecosystem Studies (PISCES) ocean biogeochemical model simulates the biogeochemical cycling of carbon, oxygen, nitrate, phosphate, iron, and silicate [*Aumont and Bopp*, 2006]. The model has twenty-four compartments. Four living pools are represented: two phytoplankton size classes/groups (nanophytoplankton and diatoms) and two zooplankton size-classes (microzooplankton and mesozooplankton). Phytoplankton growth can be limited by 5 different nutrients: Nitrate, ammonium, phosphate, silicate and iron. For all living compartments, the ratios between C, N and P are kept constant, but the internal contents in Fe and Chl-*a* of both phytoplankton groups and in Si of diatoms are prognostically simulated as a function of the external concentrations in nutrients and of the light level. There are three non-living compartments for organic matter: semi-labile dissolved organic matter (with timescales of several weeks to several years), small and big sinking particles. The two particle size-classes differ by their sinking speeds (3 m day^{-1} for the small size-class and 50 to 200 m day^{-1} for the large size-class).

Model 25: The Biogeochemical Elemental Cycling (BEC) ocean model simulates the biogeochemical cycling of carbon, oxygen, nitrate, phosphate, iron, silicate, and alkalinity. The ecosystem has multiple, potentially growth limiting nutrients (nitrogen, phosphorus, silicon, and iron) and four phytoplankton groups (diatoms, diazotrophs, coccolithophores, and picophytoplankton) [*Moore et al*., 2002, 2004; *Doney et al*., 2009]. Growth rates can be limited by available nutrients and/or light levels. Full carbonate chemistry, as well as sinking particulate and semi-labile dissolved organic pools are included in a global, 3D context without nutrient restoring [*Moore et al*., 2004]. The BEC runs within the coarse-resolution ocean component of the Community Climate System Model [*Yeager et al*., 2006], driven with time-varying atmospheric forcing from NCEP reanalysis and satellite data products [*Doney et al*., 2007].

Model 26: This is the model of *Dutkiewicz et al*. [2009], which is a slightly modified version of that of *Follows et al*. [2007]. For the physical circulation the MITgcm [*Marshall et al*., 1997b] is used, constrained to be consistent with altimetric and hydrographic observations in a relatively course resolution (1 x 1 degree horizontally, 24 levels). Inorganic and organic forms of nitrogen, phosphorus, iron and silica are transported, and 78 phytoplankton types as well as two simple grazers are resolved. The relatively large number of phytoplankton types are initialized each with physiological traits and functionalities stochastically chosen from plausible ranges. A subset of the virtual organisms persist at high abundances, according to their ability to locally compete for resources and susceptibility to predation, among many other factors. In this way the phytoplankton community 'self-assembles'. The simulation uses only a climatological annual cycle, so no attempt is made to capture interannual variability. Because carbon is not resolved in this model, a fixed C:P ratio of 117 to 1 is used to calculate NPP in terms of carbon.

Model 27: In this NASA Ocean Biogeochemical Model (NOBM) variant [*Gregg*, 2008], National Oceanographic Data Center (NODC) data for 1979-2004 were assimilated using the Conditional Relaxation Analysis Method. The assimilation affected the model representations of total Chl-*a* (sum of the 4 phytoplankton groups), but not the individual community distributions directly. Primary production was affected by the change in total Chl-*a*, as well as by indirect effects such as subsurface irradiance resulting from absorption and scattering by the changed Chl-*a* field.

Model 28: The NOBM simulates four phytoplankton groups (diatoms, chlorophytes, cyanobacteria, and coccolithophores) and four nutrients (nitrate, ammonium, silica, and iron) [*Gregg and Casey*, 2007]. The model is approximately 0.8° resolution with 14 vertical layers in quasi-isopycnal configuration. The model was forced by monthly mean winds and shortwave radiation from NCEP for 1979-2004.

Model 29: The ocean biogeochemical cycles is based on the Hamburg Oceanic Carbon Cycle (HAMOCC5) model [*Maier-Reimer et al.*, 2005]. The model contains over 30 biogeochemical tracers, which include dissolved inorganic carbon, total alkalinity, oxygen, nitrate, phosphate, silicate, iron, phytoplankton, and zooplankton. Two major classes of phytoplankton functional groups are simulated in the model: diatoms and coccolithophores. In addition to temperature, and light, the primary production is also co-limited by nitrate, phosphate, and iron concentrations. The HAMOCC5 model is coupled online with the Bergen Climate Model (BCM), which is simulated based on historical CO2 forcing. The ocean model has approximately 2.5^{o} horizontal resolution with 35 isopycnic vertical layers. More detail description of the model is discussed in *Tjiputra et al*. [2010].

Model 30: This model uses physics from the Modular Ocean Model 4 with the *Griffies et al*. [2005] scenario of 1 degree nominal resolution, climatological forcing. The biological model represents a mixotrophic microbial community (no explicit zooplankton) with a variable combination of autotrophs, heterotrophs and mixotrophs. By using a minimal base model of a mixotrophic population together with adaptively varying investments in autotrophy and heterotrophy, model complexity is restricted to a minimum: the model has just 12 parameters, which were tuned exclusively for BATS over the period 1989-1993 with the 1D General Ocean Turbulence Model.

Model 31: This model makes use of a BOGCM coupled to a simple plankton ecosystem model that drives biogeochemical cycles. The physical model used is OCCAM, a global, medium–resolution, primitive equation, finite difference BOGCM (a ¼º high–resolution version is described in *Marsh et al*., [2005]). OCCAM's vertical resolution is 66 levels (with thickness ranging from 5 m at the surface to 200 m at the abyssal seafloor), with a horizontal resolution of typically 1º (~100 km). OCCAM's prognostic variables are temperature, salinity, velocity and free–surface height. The biogeochemical cycles of nitrogen, carbon, oxygen and alkalinity are embedded within OCCAM, and are driven primarily by a nitrogen–based nutrient–phytoplankton–zooplankton–detritus (NPZD) model [*Oschlies*, 2001], with the other cycles coupled via standard OCMIP-2 protocols [*Najjar and Orr*, 1999]. Simulations are forced at the surface with high resolution spatial and temporal data for the period January 1958 to December 2004 inclusive. A minor variant of this coupled physical–biogeochemical model is described in *Yool et al.* [2007].

Model 32: The PlankTOM5 model is a three phytoplankton, two zooplankton, three detritus, three nutrient Dynamic Green Ocean Model. It has variable Fe:C, Chl-*a*:C and Si:C ratios, fixed N:C:O, variable $CaCO_3$:C in large particulate detritus, and fixed $CaCO_3$:C in coccolithophores, resulting in 25 state variables. It has ballasting of large particulate detritus by $CaCO_3$ and SiO_2, a steady state photosynthesis model, denitrification in low oxygen zones and a surface N_2-fixation scheme that conserves the N content of the ocean. It is embedded in the NEMOv2.3 OGCM, initialized with observations, and forced by daily NCEP reanalysis. The model was run from 1948-2007 [*Buitenhuis et al*., unpublished].

Model 33: The Tracers of Phytoplankton with Allometric Zooplankton (TOPAZ) model. This prognostic ocean biogeochemistry/ecology model considers 25 tracers including three phytoplankton groups, two forms of dissolved organic matter, heterotrophic biomass, and dissolved inorganic species for coupled C, N, P, Si, Fe, $CaCO_3$, O_2 and lithogenic cycling with flexible N:P:Fe stoichiometry. The model includes such processes as gas exchange, atmospheric deposition, scavenging, N_2 fixation and denitrification. Loss of phytoplankton is parameterized through the size-based relationship of *Dunne et al*. [2005], river inputs, and sediment processes. This biogeochemistry was run in the Modular Ocean Model version 4 [*Griffies et al*., 2005] with 50 vertical z-coordinate layers and a nominally 1° global resolution horizontal B-grid with tri-polar coordinates to resolve the arctic and finer detail of 1/3° near the equator. The model was forced with 6-hourly and interannually varying forcing from the atmospheric reanalysis of *Large and Yeager* [2004].

Model 34: The PELAGOS model (PELAgic biogeochemistry for Global Ocean Simulations, [*Vichi et al.,* 2007*a*,*b*] is a global ocean implementation of the Biogeochemical Flux Model (BFM, http://bfm.cmcc.it) embedded in the OPA 8.2 GCM and forced with 6-hourly ECMWF analysis (1958-2006). It implements variable nutrient:carbon and chl:carbon ratios for all the lower trophic level functional groups (3 phytoplankon, 3 zooplankton and bacteria) and organic components (detrital and dissolved organic matter) for a total of 48 prognostic variables.

6. 1D-ECO model descriptions

Model 35: In this model [*Salihoglu et al.,* 2008] autotrophic growth is represented by three algal groups and the cell quota approach is used to estimate algal growth and nutrient uptake. The model includes two zooplankton, nitrate, phosphate, silicate, ammonium, DON, DOP and two detritus compartments. Atmospheric nitrogen deposition, N_2 fixation and denitrification processes are considered. The simulated surface light field, which provides input to the underwater light field, is obtained from a clear sky spectral irradiance model [*Gregg and Carder*, 1990] that is corrected for cloud cover effects using the NCEP PAR data. Time-varying mixed layer depth is taken to be the depth at which the change in σ_t over 1 m depth exceeds 0.05 kg m^{-3}. The σ_t is estimated using the temperature and salinity time-series from the BATS cruises.

Model 36: This model is the same as Model 35 with the exception of MLD source. In this case, the model used the same MLD we provided ocean color models.

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