

## Article

# Resolving Satellite and In Situ Mismatches in Net Primary Production Using High-Frequency In Situ Bio-Optical Observations in the Subpolar Northwest Atlantic

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## Highlights

### What are the main findings?

- Discrepancies were observed between profiler-based *in situ* and satellite-derived NPP estimates in the Central Labrador Sea, with the difference in photosynthetic parameterizations identified as a major contributing factor.
- Sensitivity analysis revealed unequal responses to input variables across NPP models, highlighting that some inputs may have larger influences on the discrepancy of NPP estimates than others.

### What are the implications of the main findings?

- Reconciling satellite and *in situ* NPP estimates require examining not only differences in model inputs, but also model-specific parameterizations and sensitivities to those inputs.
- Targeted ship-based P-I measurements, particularly outside the spring bloom, could better characterize seasonal variabilities in phytoplankton photosynthetic responses and improve the representation of seasonal variability in NPP estimates.

## Abstract

Net primary productivity (NPP) plays a central role in biological carbon pump (BCP) and global carbon cycling, but NPP estimates in high-latitude regions remain highly uncertain despite their disproportional contribution to the global carbon sink. Previous studies identified discrepancies among satellite- and *in situ*-derived NPP estimates, but the drivers of disagreement remain poorly resolved due to limited high-frequency observations. Here, we present continuous depth-resolved estimates of *in situ* NPP from the Central Labrador Sea (56°N) in the subpolar Northwest Atlantic, reconstructed from daily bio-optical profiles collected between May and November 2016, and a 40-year dataset of photosynthesis parameters derived from <sup>14</sup>C photosynthesis-irradiance (P-I) incubation experiments. Comparing with two satellite-based models showed satellite models overestimated NPP by factors of 2.5–4 from the study period. Statistical analyses identified the P-I parameterization as the most influential contributor to the disagreement between satellite and *in situ* NPP



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estimates. Given the importance of NPP to estimates of the biological carbon pump, our findings highlight the need for regionally appropriate P-I parameterization in NPP models, particularly in high-latitude regions.

**Keywords:** net primary production (NPP); primary production models; photosynthesis–irradiance parameters; bio-optical profiles; SeaCycler mooring; satellite; high-latitude oceans

## 1. Introduction

Marine primary productivity makes up 50% of global primary productivity and provides a baseline for estimation of the potential export and sequestration of biologically-metabolized carbon in the deep ocean [1,2]. Net primary productivity (NPP) describes the total amount of organic carbon produced within the euphotic zone ( $Z_{eu}$ ), defined by 1% of surface light level, after accounting for autotrophic respiration. Organic carbon produced by phytoplankton is either remineralized, grazed by higher trophic species, or transported into the interior ocean via gravitational sinking [3], eddy-mixing [4,5], the mixed-layer pump [6], and the vertical migration of animals [7,8], forming the bases of Biological Carbon Pump (BCP) [9]. It accounts for two-thirds of the vertical gradient of dissolved inorganic carbon concentration in the ocean, while the remaining one-third carbon dioxide ( $CO_2$ ) is sequestered through the solubility pump [10]. Marine carbon pumps contribute significantly to regulate atmospheric  $pCO_2$  at relatively low concentration, where their absence would make up to a difference of 200 ppm of atmospheric  $pCO_2$  [11], equivalent to 1560 Pg of  $CO_2$  in the ocean.

Several key metrics that are commonly used for estimating BCP, such as export ratio and efficiency, rely on the estimates of NPP [12]. Traditionally, NPP can be estimated from the photosynthetic rate of phytoplankton using incubation of seawater samples after addition of isotopic tracers during research cruises [13]. The decrease in ship-time opportunities in recent years has directly impacted the availabilities of *in situ* NPP measurements [14], hence remote sensing offers a complementary approach to achieving more comprehensive data coverage (in space and time).

Satellite-based approaches for NPP estimation are constrained by three factors: (1) restricted data availability due to detection constraints (e.g., cloud coverage, low light intensity), (2) the uncertainties arising from the conversion of  $R_{rs}$  to bio-optical parameters, and (3) the choice of NPP models. Insufficient sunlight, due to cloud coverage and the Earth's rotation and tilt, hinder the spatial coverage of satellite retrieval, particularly in high-latitude regions [15]. Its limited detection at depth (only up to and integrated over first optical depth,  $Z_{pd}$ ) also restricts the ability to resolve the vertical distribution of bio-optical parameters within the euphotic zone ( $\sim 4.6$  times deeper than  $Z_{pd}$ ) and limits the opportunity to observe subsurface phenomena, such as deep chlorophyll a (Chl-a) maxima [14,16]. Hence, satellite-based NPP models often incorporate assumptions about biomass distributions and ocean conditions (such as  $Z_{eu}$ ).

Even when retrieval of satellite data is optimal, the propagation of uncertainties through the pipeline of NPP estimation remains a significant challenge [14,17]. Furthermore, the choice of NPP models can lead to substantial bias in the estimation of BCP fluxes up to 100% difference [18]. Various model assumptions may not always align NPP estimates with actual biogeochemical processes in the ocean [17]. Despite these limitations, most models for carbon export estimations continue to rely on satellite-derived NPP data in their export calculations, due to the scarcity of alternative data sources.

Autonomous platforms equipped with *in situ* optical and biogeochemical sensors offer the potential to address gaps in observational data [19]. Unlike ship-based expeditions,

these platforms can offer year-round observations with higher vertical resolution, enhancing the spatiotemporal coverage of *in situ* optical observations and quality of NPP estimates. Several comparisons of NPP estimates have been conducted between satellite and *in situ* platforms, including measurements from profiling floats [20–22] and gliders [23]. Such comparisons, however, are not common in the central Labrador Sea, despite its crucial role in global carbon sequestration [24,25].

This study aimed to identify the key source of bias between *in situ* and satellite NPP estimates in the subpolar ocean. We present a high-frequency, depth-resolved *in situ* NPP time series in the central Labrador Sea, derived from daily bio-optical profiles collected by a moored profiler and photosynthetic variables compiled from an archive of ship-based measurements [26]. We then compared profiler-based *in situ* NPP with two sets of satellite-based NPP estimates: one from the regionally tuned BIO model [27,28] and one from the globally applied Vertical Generalized Productivity Model (VGPM) [29]. The VGPM model estimates NPP from satellite-derived chlorophyll-a, PAR, and SST, whereas the BIO model is a depth- and spectrally resolved model that uses chlorophyll-a (Chl-a) and PAR as satellite inputs but requires the assignment of photosynthetic parameters achieved by using satellite-based Chl-a and SST.

Using depth-resolved *in situ* observations that satellites cannot directly capture, this study evaluated how the representation of bio-optical properties and photosynthetic parameters influences NPP estimates. We identified the sources of NPP differences and determined responsible components in NPP models that can be improved to achieve higher consistency between satellite and profiler-based *in situ* observations. Reconciling the discrepancy between satellite and *in situ* NPP estimates is essential for obtaining more reliable NPP estimates, and for reducing uncertainties propagated to the assessment of the BCP, marine food webs, and carbon cycle.

## 2. Study Area

Located in the subpolar Northwest Atlantic (NWA), the Labrador Sea is a strong regional carbon sink, with net annual uptake estimates of  $\sim 3 \text{ mol C m}^{-3} \text{ year}^{-1}$  [25,30]. In winter, intense deep convection penetrates to a depth of up to  $\sim 2000 \text{ m}$  [31], forming deep water masses and supporting the ventilation of the interior ocean with oxygen [32,33]. Carbon- and nutrient-rich water, entrained from the interior into the surface ocean during convective mixing, plays a critical role in initiating highly productive spring blooms [34] and is fundamental for mediating and enhancing biological carbon export [35].

## 3. Materials and Methods

### 3.1. Data Availability

#### 3.1.1. In Situ Observations: Moored Profiler “SeaCycler”

*In situ* profiles of bio-optical data were collected at high temporal resolution from a moored profiler, the SeaCycler, in the Central Labrador Sea ( $56.82^\circ\text{N}$ ,  $52.22^\circ\text{W}$ , Figure 1). Profiles of bio-optical and biogeochemical parameters (Table S1), namely Chl-a concentration and photosynthetically active radiation, were measured in the upper 150 m of the water column every 20 h with vertical sampling intervals of approximately 0.1 m. A total of 209 bio-optical profiles (124 daytime and 85 night-time) between May and November 2016 were used to calculate *in situ* NPP. Profiles presented in this study were vertically averaged over 0.5 m depth intervals.

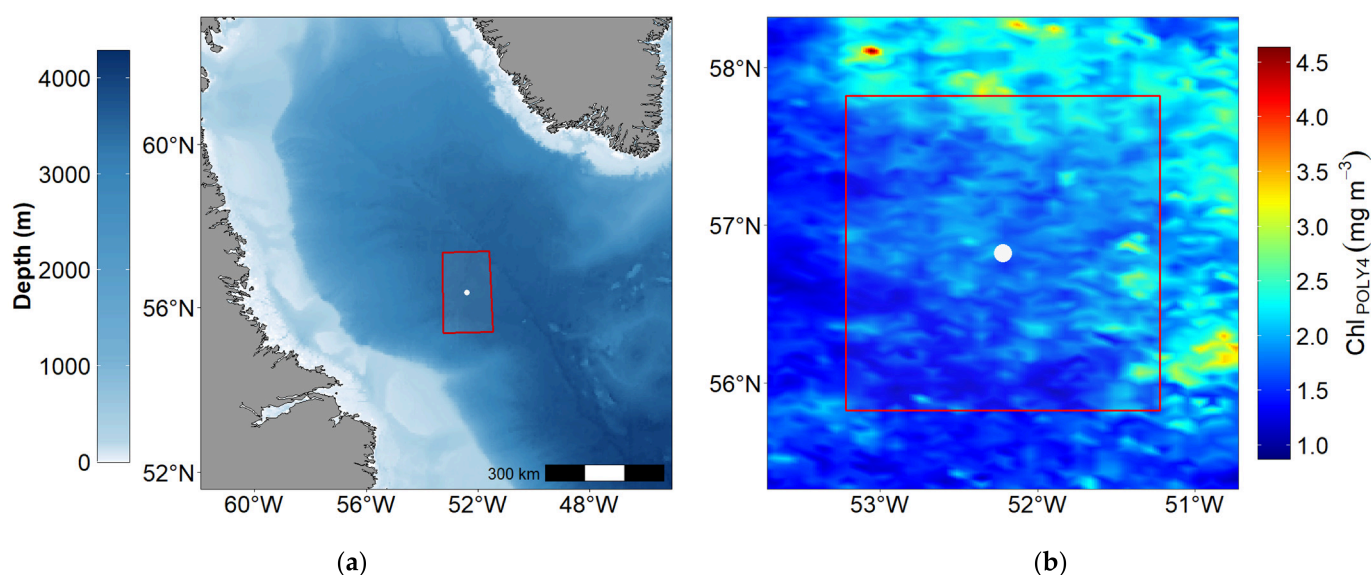


**Figure 1.** (a) The location of SeaCycler deployment (white dot) and the spatial coverage of remotely sensed data from MODIS-aqua satellite included in this study (red rectangle). (b) Satellite-based  $\text{Chl}_{\text{POLY4}}$  averaged over the observational period (May–November 2016) near the SeaCycler.

Chl-a concentration profiles were measured from Chl-a fluorescence signals at 695 nm using a WetLabs ECO fluorescence-backscattering-CDOM (model FLBB CD2K, WET Labs Inc., Philomath, OR, USA) sensor. Chl-a fluorescence was converted to Chl-a concentration based on the linear regression of Chl-a fluorescence against extracted Chl-a (i.e., Turner Fluorometry method). Non-photochemical quenching (NPQ) was mostly observed in the top 10 m of the water column due to exposure of phytoplankton biomass to high irradiance [36]. Hence, NPQ was corrected for surface Chl-a by applying a combined method using night-time ratio of Chl-a to backscattering ( $\text{Chl}:\text{b}_{\text{bp}}$ ) [37] and vertical extrapolation of subsurface signal to the top 10 m [38]. Data validation was carried out with shipboard *in situ* Chl-a measurements collected immediately after the deployment of SeaCycler. The performance of two satellite-based Chl-a products were assessed by comparing with profiler-based *in situ* Chl-a concentration ( $\text{Chl}_{\text{prof}}$ ).

*In situ* profiles of photosynthetically active radiation (PAR, integrated irradiance between 400 and 700 nm) were inferred from daily profiles of downwelling irradiance ( $E_d$ ) at 490 nm. The diffuse attenuation coefficient at 490 nm ( $K_d(490)$ ) was calculated by regressing (Type II linear model) the log-transformed  $E_d(490)$  against depth within the top 20 metres of the profiles (median  $R^2 = 0.997$ ), with fewer than 5% of observations have residuals exceeding  $\pm 2$  standard deviations. Finally,  $E_d(490)$  was then converted to spectral  $E_d(\lambda)$ , with  $\lambda$  ranging between 400 nm and 700 nm, using a radiative transfer simulation [39]. Profiles of PAR were computed by integrating  $E_d$  spectrally from 400 nm to 700 nm at each depth.

### 3.1.2. MODIS-Aqua Satellite Data

Remotely sensed marine bio-optical parameters were derived from  $R_{\text{rs}}$  measured by the Moderate Resolution Imaging Spectroradiometer onboard the Aqua satellite (MODIS-Aqua) provided by NASA's ocean color website. Satellite PAR was retrieved from Top-of-Atmosphere radiances (TOA) by applying a conversion algorithm [40] to calculate daily integrated PAR (unit: Einstein  $\text{m}^{-2} \text{d}^{-1}$  or mol photon  $\text{m}^{-2} \text{d}^{-1}$ ). TOA radiance was corrected for atmospheric layers to obtain  $R_{\text{rs}}$ , then converted to bio-optical variables using ocean-colour retrieval algorithms. Application of ocean colour algorithms to retrieve Chl-a varied with water properties. The Color Index (CI), an empirical band difference

approach, is suitable for retrieving low Chl-a concentration ( $<0.3 \text{ mg m}^{-3}$ ) [41,42]. The Ocean Colour series (OCx), an empirical band ratio approach, is used to retrieve from high Chl-a concentration (up to  $100 \text{ mg m}^{-3}$ ) water [43,44].

The Chl-a product provided by NASA was processed with the combined implementation of CI and OCx algorithms (OCI) [42]. However, this approach contains systematic biases at the regional scale despite overall satisfactory performance at the global scale [45]. Therefore, this study evaluated an alternative NPP output using the satellite Chl-a product processed by the “POLY4” algorithm, a regionally tuned version of the OCx model with coefficients optimized for the Northwest Atlantic [45], which is better aligned with shipboard *in situ* Chl-a measurements (Figure S5). In this study, SeaCycler was spatially matched to all satellite observations within a  $2^\circ$  radius of its location ( $56.82^\circ\text{N}$ ,  $52.22^\circ\text{W}$ ).

### 3.2. Primary Production Models

#### 3.2.1. In Situ NPP: The Webb Model

The photosynthetic-irradiance (P-I) parameters ( $P_{\max}^B$ ,  $\alpha^B$ ,  $\beta^B$ ) used in this study were derived from the Amiran-tanh model [46,47]:

$$P^B = P_{\max}^B \tanh\left(\frac{\alpha^B I}{P_{\max}^B}\right) \tanh\left(\left(\frac{P_{\max}^B}{\beta^B I}\right)^\gamma\right), \quad (1)$$

where  $P^B$  represents the Chl-a normalized photosynthetic rate ( $\text{mg C} [\text{mg chl-a}]^{-1} \text{h}^{-1}$ ) measured under varying irradiance levels,  $I$  ( $\text{W m}^{-2}$ ). The superscript  $B$  denotes normalization to Chl-a concentration ( $\text{mg chl-a m}^{-3}$ ),  $P_{\max}^B$  corresponds to the maximum photosynthetic rate (same unit as  $P^B$ ).  $\alpha^B$  represents the photosynthetic efficiency under minimal light levels ( $\text{mg C} [\text{mg chl-a}]^{-1} \text{h}^{-1} [\text{W m}^{-2}]^{-1}$ ),  $\beta^B$  represents the photoinhibition rate at high light level (same unit as  $\alpha^B$ ) and  $\gamma = \cosh^2(1) \approx 2.38$  is a fitting constant. The model was fitted to an archive of *in situ*  $^{14}\text{C}$  incubation data ( $n = 128$ ) collected during a series of cruises across the Labrador Sea between 1977 and 2019 [26] using the piCurve R package [47,48]. The photoinhibition term ( $B$ ) was omitted in our study, as only 9.6% of total P-I curves exhibited minor photoinhibition, and no satellite-based approach reliably captures this effect.

*In situ* NPP was estimated using the Webb model [49] and depth-resolved Chl-a and PAR profiles derived from the moored profiler:

$$\text{NPP}_{\text{Webb}} = \int_0^{Z_{\text{eu}}} \text{Chl}_{\text{prof}}(z) \times P_{\max}^B \left(1 - e^{-\frac{\text{PAR}(z)\alpha^B}{P_{\max}^B}}\right) \times \text{DL} \, dz, \quad (2)$$

where  $z$  (m) is the depth,  $\text{PAR}$  ( $\text{W m}^{-2}$ ) is depth-resolved PAR,  $\text{Chl}_{\text{prof}}$  ( $\text{mg chl-a m}^{-3}$ ) is depth-resolved Chl-a concentration, and  $\text{DL}$  is the number of hours of daylight between sunrise and sunset computed for each day at the location of the SeaCycler [50]. Although discrete measurements of P-I parameters showed some variability with depth, the sensitivity analysis in the Webb model (Figure S3) suggested that the magnitude of depth-integrated NPP was less influenced by the depth variability of P-I parameters (up to 12.5%, Figure S3c) than the seasonality of P-I parameters (up to 250%, Figure S3c). Therefore,  $P_{\max}^B$  and  $\alpha^B$  in this model are assumed to be constant with depth and averaged monthly to maximize the temporal coverage. The depth-integrated NPP was calculated by integrating depth-resolved NPP from surface to  $Z_{\text{eu}}$  (Equation (2), Figure S7).

#### 3.2.2. Satellite-Based Global Model: Vertical Generalized Productivity Model (VGPM)

The Vertical Generalized Productivity Model (VGPM) is a chlorophyll-based productivity model [29] that uses satellite-derived surface Chl-a, PAR, and SST to estimate column-integrated NPP using the following equations:

$$\text{NPP}_{\text{VGPM}} = \text{Chl}_{\text{OCI}} \times P_{\text{opt}}^B \times \frac{0.66125 \times \text{PAR}}{\text{PAR} + 4.1} \times Z_{\text{eu}} \times \text{DL}, \quad (3)$$

$$P_{\text{opt}}^B = \sum_{i=0}^7 a_i \left( \frac{\text{SST}}{10} \right)^i, \quad (4)$$

where optimal photosynthesis capacity,  $P_{\text{opt}}^B$  (unit:  $\text{mg C (mg Chl)}^{-1} \text{ h}^{-1}$ ), is the daily integrated production measurement as a 7-degree polynomial function of sea surface temperature (SST) based on a global relationship [29],  $\text{Chl}_{\text{OCI}}$  is the NASA Chl-a product processed by the OCI algorithm [42] and  $\text{PAR}$  refers to the satellite-derived photosynthetic active radiation. NPP is integrated from surface to the depth of the modeled euphotic zone ( $Z_{\text{eu}}$ ) from the Case I water model [51] with the assumption of constant NPP with depth. In this study, daily  $\text{NPP}_{\text{VGPM}}$  was computed using daily measurements of satellite Chl-a, PAR and SST from MODIS-Aqua and modeled  $Z_{\text{eu}}$  (Figure S9).

### 3.2.3. Satellite-Based Regional Model: Bedford Institute of Oceanography (BIO)

A regional primary productivity model is applied for the Labrador Sea [27] that was an update from the Platt model [28] to derive NPP:

$$\text{NPP}_{\text{BIO}} = \text{Chl}_{\text{POLY4}} \int_0^{24} \int_0^{Z_{\text{eu}}} \frac{\Pi(z, t)}{\sqrt{1 + \left( \frac{\Pi(z, t)}{P_{\text{max}}^B} \right)^2}} dz dt, \quad (5)$$

$$\Pi(z, t) = \int_{400}^{700} \alpha^B(\lambda) I(\lambda, z, t) d\lambda, \quad (6)$$

where  $I(\lambda, z, t)$  is the depth and wavelength-dependent light field with the subsurface light modeled using a direct and diffuse component of the irradiance in a clear sky scenario [52]. Hourly estimates of spectrally dependent surface light were scaled up to the daily measurement of surface PAR from the MODIS-Aqua satellite, and propagated at depth with a vertical resolution of 0.5 m. This primary production model uses the satellite Chl-a product derived from the POLY4 algorithm ( $\text{Chl}_{\text{POLY4}}$ ) for the NWA region [45].

Data gaps of satellite Chl-a were filled using the Data Interpolating Empirical Orthogonal Functions (DINEOF) approach [53], applied over the extended Northwest Atlantic region (39–82°N, 42–95°W). Within the 2° spatial window surrounding SeaCycler, an average of 88.5% of satellite Chl-a pixels were missing, with daily percentages of missing pixels ranging from 9.5% to 100% (Figure S6). The Root Mean Squared Logged Error (RMSLE) between observed and reconstructed pixels is 0.157 (mean absolute error = 17.1%), similar to the RMSLE expected during previous matchup exercises between *in situ* and satellite-derived Chl-a products [45,54]. For pixels with data coverage less than 0.5%, the mean RMSLE increased to 0.188, corresponding to a mean absolute error of 40%.

Similar to the *in situ* NPP, regional P-I parameters ( $P_{\text{max}}^B$ ,  $\alpha^B$ ) were derived from fitting the same P-I Model (Equation (1)) to *in situ*  $^{14}\text{C}$  incubation experiments carried out across the Labrador Sea between 2014 and 2022 [26], using the R package “piCurve” [47,48]. The broadband  $\alpha^B$  is then multiplied by normalized phytoplankton absorption, resulting in the spectrally dependent value (Equation (6)).

Unlike the monthly averaged climatology used by the Webb model, the BIO model uses satellite data, i.e., Chl-a and SST, to infer the P-I parameters based on ecological considerations. Devred et al. [27] found that phytoplankton community structure, as indicated by pigment signature, may be used to inform on P-I parameters. By applying a cluster analysis to a dataset of 211 pigment measurements derived from High-Performance Liquid Chromatography (HPLC), four regimes were identified: (1) diatom-dominated on the LS shelves, (2) a low Chl-a biomass in the Basin, (3) a mixed-population (including both *diatom* and *phaeocystis* spp.) in the Basin, and (4) high-*phaeocystis* spp. biomass in the basin. Each of these four trophic regimes was assigned a set of  $P_{\text{max}}^B$  and  $\alpha^B$  derived from shipboard P-I measurements. Since these regimes exhibited distinctive signatures in

SST and Chl-a, satellite-derived SST and Chl-a were used to classify each pixel into a trophic regime and assigned the corresponding P-I parameters (Figure S8).

### 3.3. Study Design

This study compared NPP time series from *in situ* and satellite models with respect to both magnitude and seasonal variability. NPP was expressed as surface and depth-integrated values to assess how vertical extrapolation influences the magnitude of depth-integrated estimates. Surface NPP was treated as a baseline, representing the shared observational layer for both satellite and profiler data. Of the three NPP models evaluated, profiler-based *in situ* NPP<sub>Webb</sub> was selected as the reference to compare with two satellite-derived NPP estimates because it was constrained by high-frequency, depth-resolved observations of Chl-a and PAR. The Chl-a profiles were validated with shipboard *in situ* Chl-a measurements and corrected for non-photochemical quenching, providing a better representation of temporal and vertical variability that cannot be observed by satellite. Additionally, the Webb model uses a mathematical formulation comparable to that of the BIO model, reducing the differences from the impact of model choices and providing a direct comparison between both estimates.

### 3.4. Model Sensitivity and Time Series Analysis

Sensitivity analysis was conducted to assess the impact of model inputs (Table 1) on depth-integrated NPP by applying a systematic 10% increase on each individual input parameter and computing the percentage difference in NPP:

$$|S_{\text{NPP model}}|(\%) = \left| \frac{\text{NPP}_{10\% \text{ increase in a parameter}} - \text{NPP}_{\text{Baseline}}}{\text{NPP}_{\text{Baseline}}} \right| \times 100\%, \quad (7)$$

**Table 1.** Summary of NPP model inputs used in this study. Schematic flowcharts of NPP models (Figures S7–S9) are provided in the Supplementary Materials.

| Variables                                                                                                      | NPP Models                                                                                                                                                                                                                                                                             |                                                                                                    |                                                                                                                                                                                                                                                                             |
|----------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                                                                                                                | Webb                                                                                                                                                                                                                                                                                   | VGPM                                                                                               | BIO                                                                                                                                                                                                                                                                         |
| Chl-a                                                                                                          | <b>Chl<sub>prof</sub></b><br><i>In situ</i> Chl-a profiles measured by SeaCycler, validated with shipboard <i>in situ</i> Chl-a measurement and corrected for non-photochemical quenching. [37,38]                                                                                     | <b>Chl<sub>OCI</sub></b><br>MODIS-aqua satellite Chl-a product processed by the OCI algorithm [42] | <b>Chl<sub>POLY4</sub></b><br>- MODIS-aqua satellite Chl-a processed by OCx algorithm, with coefficients tuned by the “POLY4” model for Northwest Atlantic [45]<br>- Observational gaps are filled by the DINEOF method [53]                                                |
| PAR                                                                                                            | <i>In situ</i> E <sub>d</sub> (490) profiles converted to PAR profiles using a radiative transfer simulation. [39]                                                                                                                                                                     | Satellite PAR                                                                                      | Modeled subsurface light field [52] and scaled up to measured satellite surface PAR.                                                                                                                                                                                        |
| Photosynthetic Parameters<br>(P <sub>max</sub> <sup>B</sup> , α <sup>B</sup> , P <sub>opt</sub> <sup>B</sup> ) | - Ship-based incubation data from AZOMP time series between 1977 and 2019 [26].<br>- P-I curves are estimated using the R package “piCurve” [48]<br>- P <sub>max</sub> <sup>B</sup> and α <sup>B</sup> are spatially averaged within a 2-degrees bin surrounding SeaCycler’s location. | P <sub>opt</sub> <sup>B</sup> is computed as a function of satellite SST [29]                      | - Ship-based incubation data from AZOMP time series between 2014 and 2022 [26].<br>- P-I curves are estimated using the R package “piCurve” [48]<br>- P <sub>max</sub> <sup>B</sup> and α <sup>B</sup> are selected based on the criteria of four characterized biomes [27] |

Table 1. Cont.

| Variables | NPP Models                                                                  |                                       |                                                                                                                                             |
|-----------|-----------------------------------------------------------------------------|---------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
|           | Webb                                                                        | VGPM                                  | BIO                                                                                                                                         |
| $Z_{eu}$  | Defined as 1% surface PAR using profiler-based <i>in situ</i> PAR profiles. | Chl-based empirical relationship [51] | Defined as 1% surface PAR, with light attenuation at each depth modeled as a function of absorption and scattering in the water column [52] |

The sensitivity of the Webb model was evaluated with *in situ* profiling data, including PAR,  $Chl_{prof}$ ,  $\alpha^B$  and  $P_{max}^B$ . For satellite-based models, the BIO model sensitivity was tested with satellite PAR,  $Chl_{POLY4}$ ,  $\alpha^B$  and  $P_{max}^B$ ; while the VGPM model sensitivity was tested with SST, surface  $Chl_{OCI}$ , and PAR. Due to the limited ability of satellite optical sensors to detect subsurface features, the assumption of constant Chl-a concentration in the satellite-based model was tested by replacing  $Chl_{POLY4}$  to depth-resolved  $Chl_{prof}$  in the BIO model and regressing the new depth-integrated output ( $NPP_{BIO, chl-prof}$ ) with original  $NPP_{BIO}$ . This was, however, not tested in the VGPM model for two reasons: (1) depth-integrated  $NPP_{VGPM}$  is estimated from surface Chl-a with a vertically generalized assumption rather than depth-resolved Chl-a profiles; therefore,  $Chl_{prof}$  cannot be substituted into VGPM in the same manner as in BIO without modifying the model formulation; and (2) VGPM does not explicitly use the P-I terms ( $P_{max}^B$ ,  $\alpha^B$ ) that were used in Webb and BIO.

To identify model inputs that have the most influence on NPP differences, two complementary statistical approaches were used: (1) stepwise multilinear regression (MLR) of the differences between satellite- and profiler-derived NPP estimates against the differences of input variables; and (2) variable importance analysis using RMSE permutation tests. The absolute logarithmic difference of depth-integrated NPPs between satellite-based models and the Webb model ( $\Delta NPP_{VGPM-Webb}$ ,  $\Delta NPP_{BIO-Webb}$ ) were regressed against the corresponding absolute differences of input variables as predictors:

$$\Delta NPP_{VGPM-Webb} = b_0 + b_1 \Delta Chl + b_2 \Delta PAR + b_3 P_{opt}^B + b_4 P_{max}^B + b_5 \alpha^B + b_6 t, \quad (8)$$

$$\Delta NPP_{BIO-Webb} = b_0 + b_1 \Delta Chl + b_2 \Delta PAR + b_3 \Delta P_{max}^B + b_4 \Delta \alpha^B + b_5 t, \quad (9)$$

Bidirectional stepwise regression (forward and backward) was conducted using Akaike information criterion (AIC) to evaluate different combinations of predictors in the regression model through iterative addition and removal of variables. This approach aims to identify the optimal regression model with the lowest AIC score that presents the best balance between the goodness of fit and model complexity statistically [55].

The relative importance of each predictor in the regression model was further assessed by permutation-based variable importance analysis, implemented with the vip R package [56]. The values of each predictor were randomly shuffled while the remaining predictors were unchanged, and RMSE was calculated from the predictions and observed values of the original fitted model. This process was repeated 1000 times for each predictor to generate a range of RMSE values for each predictor. Predictors with larger increases in RMSE were considered more influential in explaining the variability in  $\Delta NPP$  within the fitted regression model. Their relative importance reported by the mean increase in RMSE are summarized in a Variable Importance Plot (VIP).

To investigate the impact of P-I parameters on  $\Delta NPP_{BIO-Webb}$ , depth-integrated  $NPP_{webb}$  was recalculated with the satellite-based (i.e., SST and Chl-a) assignment of P-I parameters as used in the BIO model ( $NPP_{Webb*}$ ), where the parameters were spatially and temporally matched with the profiler location and measurement time. A new time-series

of depth-integrated  $NPP_{Webb^*}$  was computed and compared against depth-integrated  $NPP_{BIO}$ . Multilinear regression analysis was applied the differences of  $NPP_{Webb^*}$  and  $NPP_{BIO}$  ( $\Delta NPP_{BIO-Webb^*}$ ) using Equation (9) but without the P-I parameters, and the contribution of the remaining variables was presented in a variable importance plot.

## 4. Results

### 4.1. Bio-Optical Observations

The seasonal trend of satellite PAR is comparable to *in situ* PAR for most of the year (Figure 2a), with a moderately correlated linear relationship, except in June, early August and late September 2016 (Figure 2b, slope = 0.943). During these periods, satellite PAR was overestimated compared to *in situ* PAR, with a maximum difference of 40 mol photons  $m^{-2} d^{-1}$  (Figure 2b).

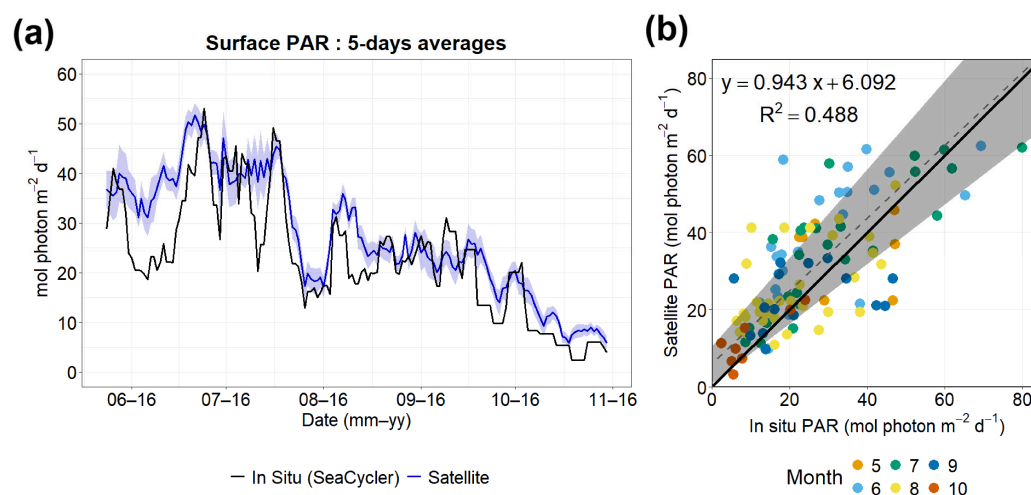


**Figure 2.** (a) 5-days averages of surface PAR from *in situ* (black, converted from  $W m^{-2}$  to mol photon  $m^{-2} d^{-1}$ ) and satellite-based products (blue). (b) Linear relationship between satellite and *in situ* PAR.

The seasonal trend of sea-surface Chl-a concentration shows moderate agreement between satellite-derived and *in situ* products (Figure 3a). A large phytoplankton bloom ( $>5 mg m^{-3}$ ), occurring between mid-June and early July with a peak of Chl-a concentration at  $\sim 9 mg m^{-3}$ , was captured by both *in situ*  $Chl_{prof}$  and satellite-derived  $Chl_{POLY4}$ . Satellite-derived  $Chl_{OCI}$  captured only 50% of the concentration observed by the former two products (Figure 3a). Subsurface Chl-a structures were observed deeper than  $Z_{pd}$  (Figure 3b).

Following the peak bloom in late June, spikes of Chl-a (seen as higher concentration of Chl-a in bright yellow, Figure 3b) were submerged deeper than the seasonal MLD (dashed line), likely attributable to sinking phytoplankton. In mid-July, deep Chl-a maxima were detected by  $Chl_{prof}$  between seasonal MLDs and  $Z_{eu}$ , and beyond the maximum depth detectable by the satellite ( $Z_{pd}$ ).

*In situ*  $Chl_{prof}$  exhibits a weak linear correlation with  $Chl_{OCI}$  (Figure 3c, slope = 0.973, intercept =  $-0.837$ ,  $R^2 = 0.47$ ), but a stronger fit with regionally tuned  $Chl_{POLY4}$  (Figure 3d, slope = 1.129, intercept =  $-0.569$ ,  $R^2 = 0.54$ ).  $Chl_{POLY4}$  aligns more closely with the 1:1 line between June and August, whereas both satellite-based products displayed increasing bias from  $Chl_{prof}$  starting in September and becoming most pronounced in October (Figure 3c,d), confirming the challenges of retrieving Chl-a at low solar angles.

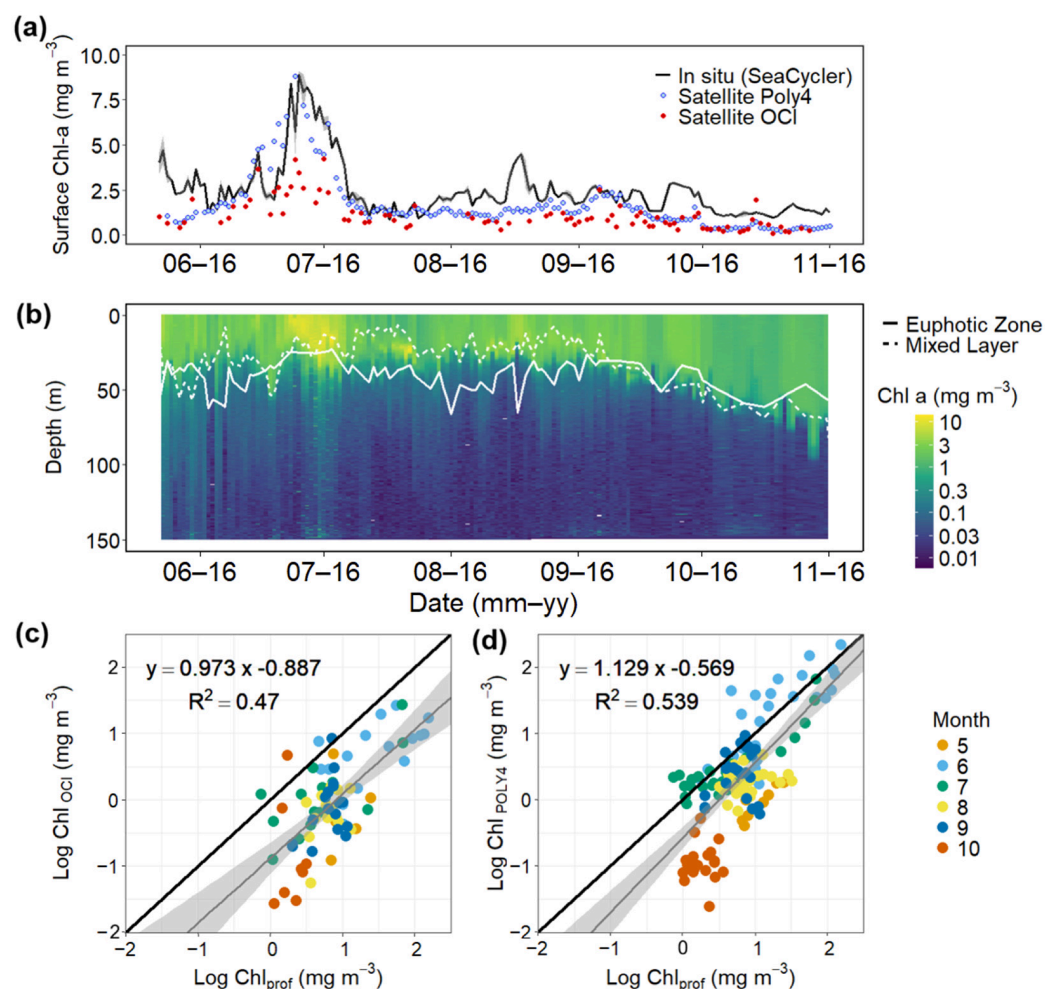


**Figure 3.** (a) Time series of surface Chl-a concentration for  $\text{Chl}_{\text{prof}}$ ,  $\text{Chl}_{\text{OCI}}$  and  $\text{Chl}_{\text{POLY4}}$ . Surface  $\text{Chl}_{\text{prof}}$  is an average from the sea surface to the first optical depth ( $Z_{\text{pd}} = 1/k_{490}$ ), approximately 10 m on average over the seasons. (b) Time series of depth-resolved  $\text{Chl}_{\text{prof}}$ . Solid white line is the seasonal euphotic depth (1% surface PAR) and dotted white line is the seasonal mixed layer depth (0.03 kg m<sup>-3</sup> deviation from surface density). Surface concentration of *in situ*  $\text{Chl}_{\text{prof}}$  was plotted against satellite-based (c)  $\text{Chl}_{\text{OCI}}$  and (d)  $\text{Chl}_{\text{POLY4}}$  with colors categorized by months (May–October). The equations indicate their linear relationships with uncertainty at 95% confident intervals (grey). The performance of  $\text{Chl}_{\text{OCI}}$  and (d)  $\text{Chl}_{\text{POLY4}}$ .

#### 4.2. Photosynthetic-Irradiance (P-I) Parameters

In the VGPM model, NPP output incorporates the daily optimized photosynthetic capacity ( $P_{\text{opt}}^{\text{B}}$ ) based on an empirical relationship with remotely sensed SST. As a result, the seasonal cycle of  $P_{\text{opt}}^{\text{B}}$  directly follows the SST (Figure 4a).  $P_{\text{opt}}^{\text{B}}$  was the lowest at  $\sim 1.8 \text{ mg C (mg chl-a)}^{-1} \text{ h}^{-1}$  in May 2016 and highest at  $\sim 4 \text{ mg C (mg chl-a)}^{-1} \text{ h}^{-1}$  in late August 2016 when SST was the highest.

In the satellite-based BIO model, the per-pixel satellite-based  $P_{\text{max}}^{\text{B}}$  and  $\alpha^{\text{B}}$  are higher than the monthly averages used in the *in situ*-based Webb model, with a growing discrepancy later in the year (Figure 4b,c). The difference in  $P_{\text{max}}^{\text{B}}$  between the two models increased from  $\sim 2 \text{ mg C (mg chl-a)}^{-1} \text{ h}^{-1}$  in May 2016 to the largest difference of  $\sim 4 \text{ mg C (mg chl-a)}^{-1} \text{ h}^{-1}$  in October 2016 (Figure 4b). Similarly, the difference in  $\alpha^{\text{B}}$  increased from  $\sim 0.01 \text{ mg C (mg chl-a)}^{-1} \text{ h}^{-1} (\text{W m}^{-2})^{-1}$  in May 2016 to  $\sim 0.06 \text{ mg C (mg chl-a)}^{-1} \text{ h}^{-1} (\text{W m}^{-2})^{-1}$  in October 2016 (Figure 4c).

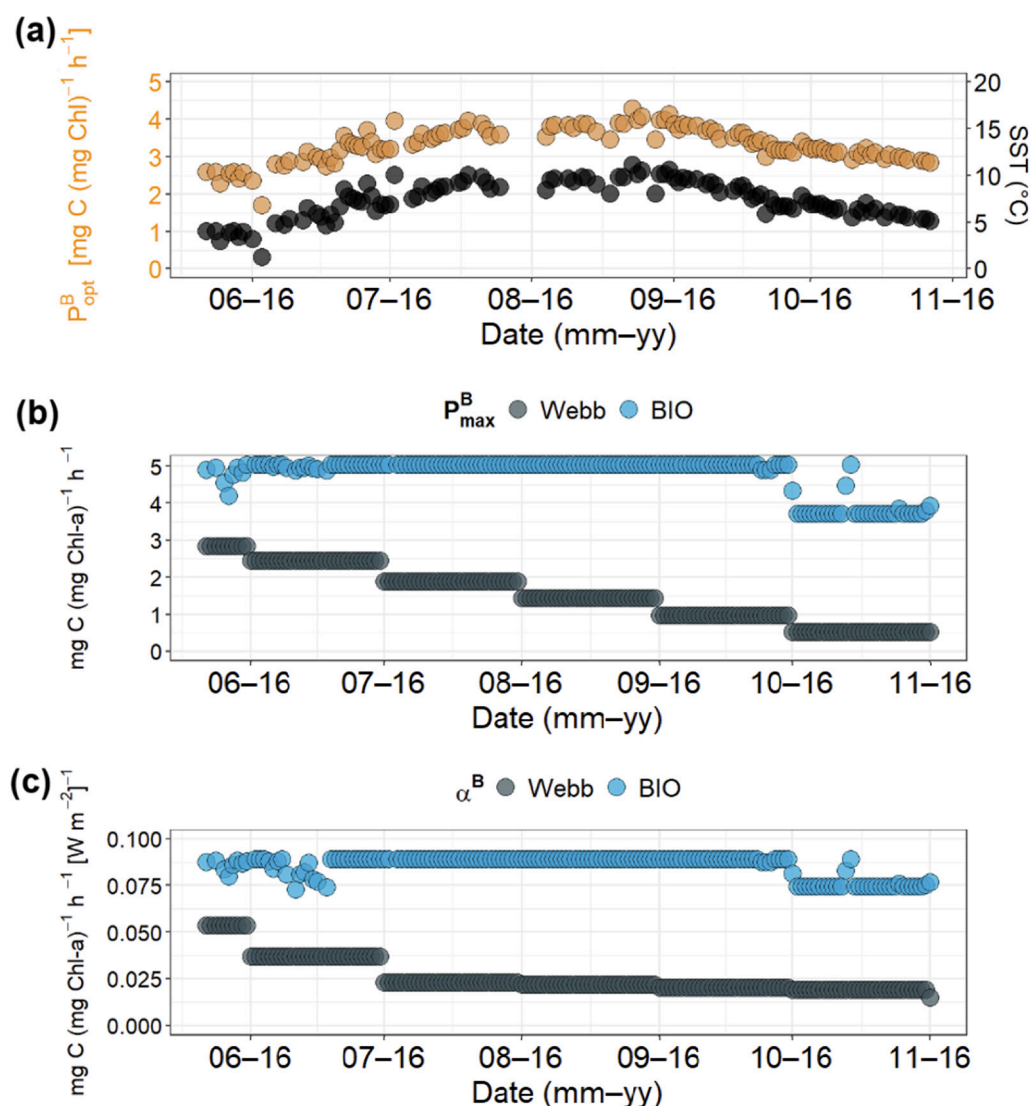


**Figure 4.** (a) Empirical daily optimized photosynthetic rate ( $P^B_{opt}$ ) computed from satellite SST data for the VGPM model. Time series of P-I parameters: (b)  $P^B_{max}$  and (c)  $\alpha^B$  for *in situ* Webb model and satellite-based BIO model. The Webb model is based on monthly averages of the P-I data archives between 1979 and 2019, while the BIO model is based on spatially assigned P-I data archives between 2014 and 2022.

#### 4.3. Net Primary Production (NPP)

##### 4.3.1. Comparison of NPP Time Series: Surface and Depth-Integrated Values

Surface  $NPP_{BIO}$  exhibits the highest values throughout the time series (except in May 2016) (Figure 5a), followed by  $NPP_{Webb}$  and  $NPP_{VGPM}$ . Surface  $NPP_{BIO}$  reached its peak at  $\sim 55 \text{ mmol C m}^{-3} \text{ d}^{-1}$  in late June 2016, contributing to the largest difference of  $\sim 36 \text{ mmol C m}^{-3} \text{ d}^{-1}$  seen between surface  $NPP_{Webb}$  and  $NPP_{BIO}$  (Figure 5e). In mid-September,  $NPP_{BIO}$  was 4.5 times higher than  $NPP_{Webb}$  ( $\Delta NPP_{BIO-Webb, \text{Surface}} = \sim 9 \text{ mmol C m}^{-3} \text{ d}^{-1}$ ). The difference between surface  $NPP_{Webb}$  and  $NPP_{VGPM}$  ( $\Delta NPP_{VGPM-Webb, \text{Surface}}$ ) remained generally within  $2.5 \text{ mmol C m}^{-3} \text{ d}^{-1}$  except in May, and from late June to early July when it reached about  $5 \text{ mmol C m}^{-3} \text{ d}^{-1}$  (Figure 5c). This resulted from  $NPP_{VGPM}$  underestimating the peak of the phytoplankton bloom, leading to a lower estimate than  $NPP_{Webb}$  by up to  $\sim 10 \text{ mmol C m}^{-3} \text{ d}^{-1}$ .

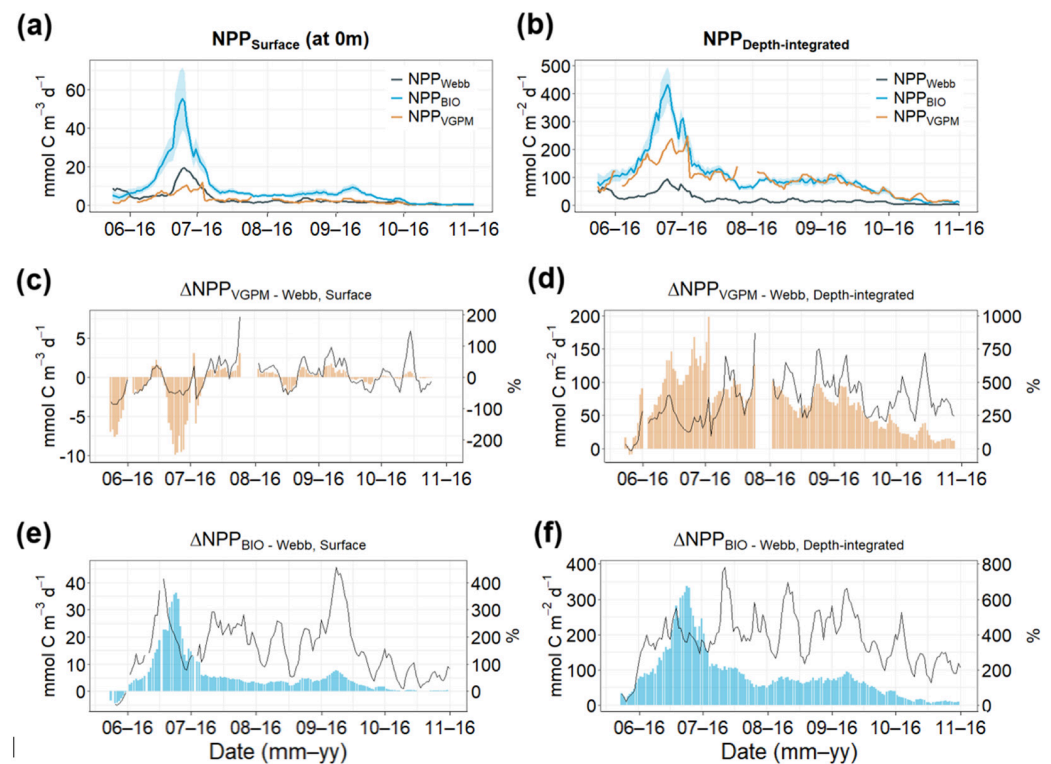


**Figure 5.** Time series in 5 days rolling averages for all (a) surface and (b) depth-integrated NPPs. Between  $NPP_{VGPM}$  and  $NPP_{Webb}$ , the differences were computed in absolute (orange bars) and percentage (black line) values for (c) surface ( $\Delta NPP_{VGPM-Webb, Surface}$ ) and (d) depth-integrated ( $\Delta NPP_{VGPM-Webb, Depth-integrated}$ ) time series. Similarly, the difference between  $NPP_{BIO}$  and  $NPP_{Webb}$  was computed in absolute (blue bars) and percentage (black line) values for (e) surface ( $\Delta NPP_{BIO-Webb, Surface}$ ) and (f) depth-integrated ( $\Delta NPP_{BIO-Webb, Depth-integrated}$ ) time series.

Depth-integrated  $NPP_{VGPM}$  and  $NPP_{BIO}$  were higher than  $NPP_{Webb}$  over the entire observation period (Figure 5b). The difference between depth-integrated  $NPP_{VGPM}$  and  $NPP_{Webb}$  (Figure 5d) was the highest in early July ( $\Delta NPP_{VGPM-Webb, Depth-integrated} \approx 200 \text{ mmol C m}^{-2} \text{ d}^{-1}$ ), contrasting with the negative difference (satellite—*in situ*) that was observed between surface NPP values (Figure 5c). The difference between depth-integrated  $NPP_{BIO}$  and  $NPP_{Webb}$  (Figure 5f) was highest in late June ( $\sim 300 \text{ mmol C m}^{-2} \text{ d}^{-1}$ ), consistent with the timing of the maximum difference in surface NPPs between two models (Figure 5e). Despite the magnitude of  $\Delta NPP_{BIO-Webb}$  being large, the seasonal trends of  $\Delta NPP_{BIO-Webb}$  were similar for both surface and depth-integrated NPPs (Figure 5e,f).

#### 4.3.2. Model Sensitivity

The Webb model was most sensitive to  $Chl_{prof}$  with  $|S_{Webb}|$  equals to 10% throughout the time series (Figure 6a,b). Surface PAR and  $\alpha^B$  had identical sensitivities towards  $NPP_{Webb}$  ( $5\% < |S_{Webb}| < 10\%$ ), resulting from the set-up of the Webb model that similarly impacted both variables (Equation (2)). Surface  $P^B_{max}$  was the least sensitive parameter in this model with  $|S_{Webb}|$  remaining below 5%. No visible seasonal trend was observed in the sensitivity of the Webb model, where the changes of  $NPP_{Webb}$  from all input variables seemed to be randomly distributed.

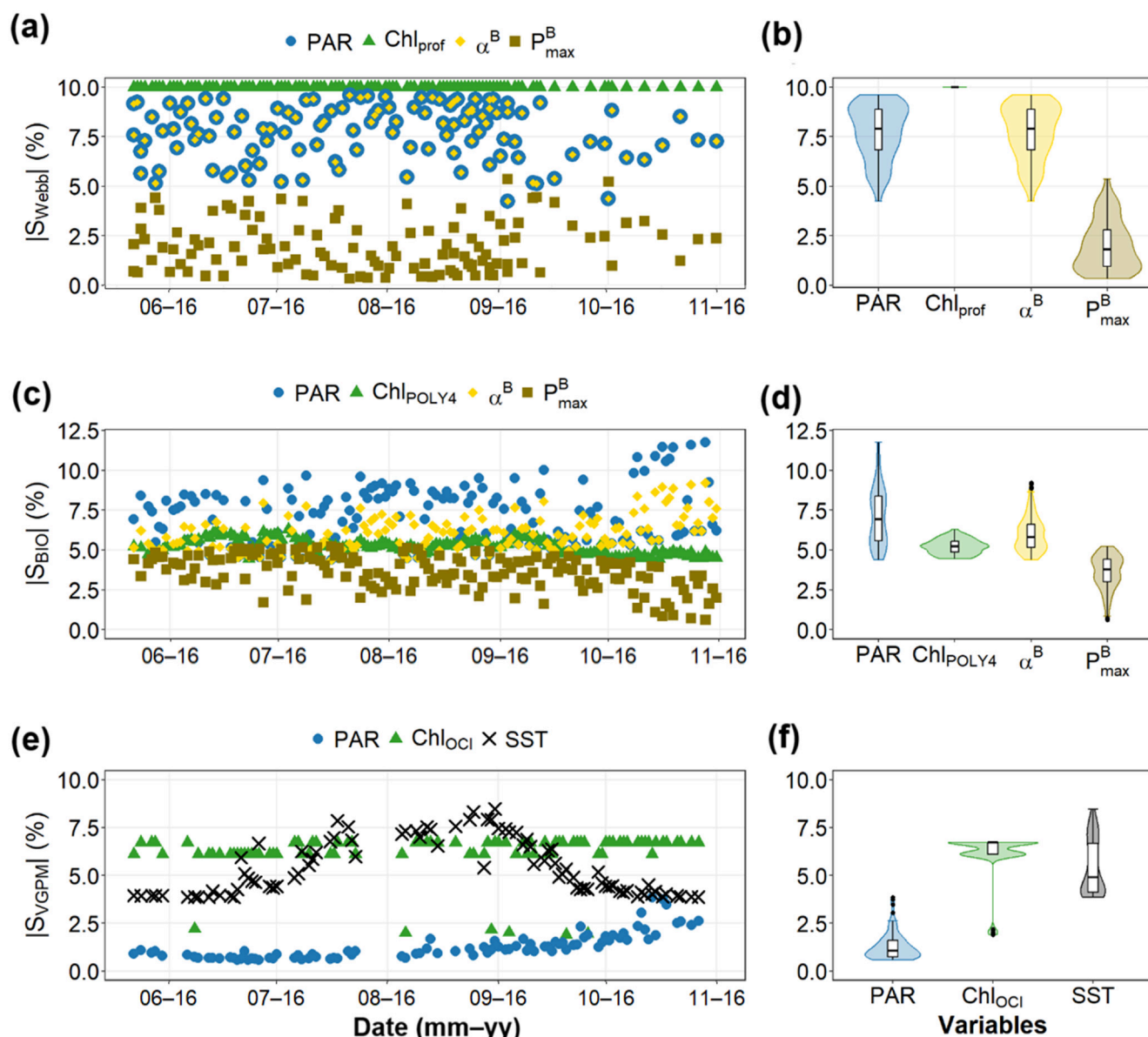


**Figure 6.** Model sensitivity (%) was assessed for (a,b)  $NPP_{Webb}$ , (c,d)  $NPP_{BIO}$ , and (e,f)  $NPP_{VGPM}$ . Relative changes in NPP were calculated in response to a 10% increase in each input variable, with all other inputs unchanged. Temporal model sensitivities are shown in (a,c,e), while the range of model sensitivity categorized by input variables are displayed in (b,d,f).

The BIO model was most sensitive to surface PAR ( $5\% < |S_{BIO}| < 12\%$ ), followed by  $\alpha^B$  ( $5\% < |S_{BIO}| < 9\%$ ),  $Chl_{POLY4}$  ( $5\% < |S_{BIO}| < 7\%$ ) and least by  $P_{max}^B$  ( $1\% < |S_{BIO}| < 5\%$ ) (Figure 6c,d). The increase of  $NPP_{BIO}$  by  $Chl_{POLY4}$  was mostly stable around 5% throughout the time series. However, the BIO model seemed to be temporally sensitive to the change of PAR,  $\alpha^B$  and  $P_{max}^B$ . After the beginning of October 2016,  $NPP_{BIO}$  showed higher sensitivity to PAR and  $\alpha^B$ , but lower sensitivity to  $P_{max}^B$  (Figure 6c). During productive seasons, characterized by high net primary productivity (NPP) values and shallower Chl-a maxima depths ( $<40m$ ), the change in  $NPP_{BIO}$  remained minimal as revealed by including the *in situ* Chl-a vertical profile in the BIO model (Figure S4). Pronounced shifts (up to  $\sim 50\%$ ) are observed during periods of low productivity that are associated with deeper Chl-a maxima ( $>40m$ ).

The VGPM model was most sensitive to SST ( $4\% < |S_{VGPM}| < 8\%$ ), followed by  $Chl_{OCI}$  ( $5\% < |S_{VGPM}| < 7\%$ ) and PAR ( $1\% < |S_{VGPM}| < 4\%$ ) (Figure 6e,f). A significant seasonal

trend could be seen for the sensitivity of SST in the model, with warmer temperatures resulting in higher percentage changes in  $NPP_{VGPM}$  (Figure 6e). Model sensitivity of VGPM to  $Chl_{OCI}$  was similar to that of the BIO model to  $Chl_{POLY4}$ , except for six “outliers” where  $|S_{VGPM}|$  was between 1.8% and 2.2%. Moreover, model sensitivity to PAR increased after the beginning of October 2016, which was also observed in the BIO model.

#### 4.3.3. Source of NPP Differences

For  $\Delta NPP_{VGPM-Webb}$ ,  $\alpha^B$  was the leading predictor with the highest importance score of  $0.13 \pm 0.04$  followed by  $P_{opt}^B$  with a score of  $0.081 \pm 0.031$ , while the importance of time,  $P_{max}^B$ ,  $\Delta Chl_{OCI-prof}$  and  $\Delta PAR$  were negligible (Figure 7a). The best model selected by AIC included  $P_{opt}^B$  and  $\alpha^B$  as the predictors (AIC = −36.4), while all other models displayed higher AIC values ( $\Delta AIC > 1$ ; Table 2). The final model explained 34.5% of the variance in  $\Delta NPP_{VGPM-Webb}$  ( $p < 0.001$ ; Table 3). The correlation with  $\alpha^B$  was moderately negative with coefficient of  $b = -30.82 \pm 13.28$  ( $p$ -value = 0.024), whereas the correlation with  $P_{opt}^B$  was marginally positive ( $\beta = 0.54 \pm 0.31$ ,  $p = 0.083$ ). No clear correlation is found in the intercept of  $\Delta NPP_{VGPM-Webb}$  ( $0.43 \pm 1.35$ ,  $p = 0.75$ ).

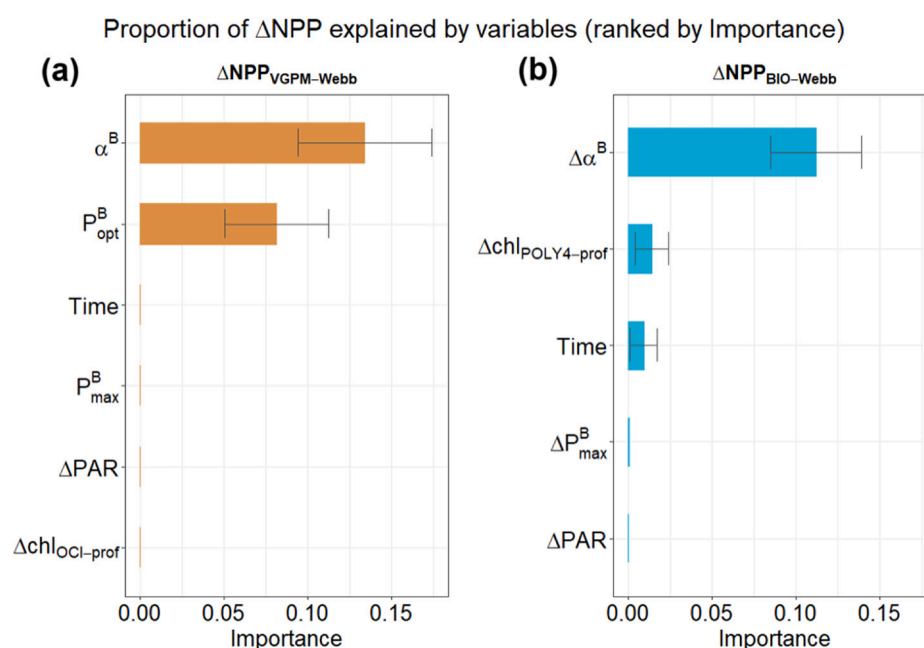


**Figure 7.** Variable Important Plot of predictors sorted by the most to least importance for the regression models (a)  $\Delta NPP_{VGPM-Webb}$  and (b)  $\Delta NPP_{BIO-Webb}$ .

**Table 2.** Regression models of  $\Delta NPP_{VGPM-Webb}$ ,  $\Delta NPP_{BIO-Webb}$  and  $\Delta NPP_{BIO-Webb^*}$  ranked by AIC. Model in the first rank is chosen to be the final regression model with the lowest AIC score.  $\Delta AIC$  is the difference of AIC score between the selected model and the final model (ranked first).

| Rank                     | Models                                                                                                | AIC Score | $\Delta AIC$ |
|--------------------------|-------------------------------------------------------------------------------------------------------|-----------|--------------|
| $\Delta NPP_{VGPM-Webb}$ |                                                                                                       |           |              |
| 1                        | $\Delta NPP \sim P_{opt}^B + \alpha^B$                                                                | −36.4     | 0            |
| 2                        | $\Delta NPP \sim \text{time} + P_{opt}^B + \alpha^B$                                                  | −34.68    | 1.72         |
| 3                        | $\Delta NPP \sim \text{time} + \Delta Chl_{OCI-prof} + P_{opt}^B + \alpha^B$                          | −32.86    | 3.54         |
| 4                        | $\Delta NPP \sim \text{time} + \Delta Chl_{OCI-prof} + P_{opt}^B + P_{max}^B + \alpha^B$              | −31.18    | 5.22         |
| 5                        | $\Delta NPP \sim \text{time} + \Delta Chl_{OCI-prof} + \Delta PAR + P_{opt}^B + P_{max}^B + \alpha^B$ | −29.18    | 7.22         |

Table 2. Cont.

| Rank                              | Models                                                                                                                | AIC Score | $\Delta$ AIC |
|-----------------------------------|-----------------------------------------------------------------------------------------------------------------------|-----------|--------------|
| $\Delta$ NPP <sub>BIO–Webb</sub>  |                                                                                                                       |           |              |
| 1                                 | $\Delta$ NPP $\sim \Delta\alpha^B$                                                                                    | −58.66    | 0            |
| 2                                 | $\Delta$ NPP $\sim$ time + $\Delta\alpha^B$                                                                           | −58.33    | 0.33         |
| 3                                 | $\Delta$ NPP $\sim$ time + $\Delta$ Chl <sub>POLY4-prof</sub> + $\Delta\alpha^B$                                      | −57.32    | 1.34         |
| 4                                 | $\Delta$ NPP $\sim$ time + $\Delta$ Chl <sub>POLY4-prof</sub> + $\Delta P_{\max}^B$ + $\Delta\alpha^B$                | −55.33    | 3.33         |
| 5                                 | $\Delta$ NPP $\sim$ time + $\Delta$ Chl <sub>POLY4-prof</sub> + $\Delta$ PAR + $\Delta P_{\max}^B$ + $\Delta\alpha^B$ | −53.34    | 5.32         |
| $\Delta$ NPP <sub>BIO–Webb*</sub> |                                                                                                                       |           |              |
| 1                                 | $\Delta$ NPP $\sim$ time + $\Delta$ Chl <sub>POLY4-prof</sub>                                                         | −61.92    | 0            |
| 2                                 | $\Delta$ NPP $\sim$ time + $\Delta$ Chl <sub>POLY4-prof</sub> + $\Delta$ PAR                                          | −59.98    | 1.94         |

Table 3. Statistical result of the final regression model for  $\Delta$ NPP<sub>VGPM–Webb</sub>,  $\Delta$ NPP<sub>BIO–Webb</sub> and  $\Delta$ NPP<sub>BIO–Webb\*</sub>.

| Model                             | Adjusted R <sup>2</sup> | RSE  | p-Value | Predictor                          | Estimate ( $\beta$ ) | p-Value |
|-----------------------------------|-------------------------|------|---------|------------------------------------|----------------------|---------|
| $\Delta$ NPP <sub>VGPM–Webb</sub> | 0.345                   | 0.70 | <0.001  | Intercept                          | 0.43 ± 1.35          | 0.75    |
|                                   |                         |      |         | $P_{\text{opt}}^B$                 | 0.54 ± 0.31          | 0.083   |
|                                   |                         |      |         | $\alpha^B$                         | −30.82 ± 13.28       | 0.024   |
| $\Delta$ NPP <sub>BIO–Webb</sub>  | 0.105                   | 0.74 | <0.001  | Intercept                          | 0.15 ± 0.42          | 0.728   |
|                                   |                         |      |         | $\Delta\alpha^B$                   | 24.76 ± 6.97         | <0.001  |
| $\Delta$ NPP <sub>BIO–Webb*</sub> | 0.054                   | 0.72 | 0.025   | Intercept                          | 82.17 ± 30.25        | 0.008   |
|                                   |                         |      |         | Time                               | −0.0048 ± 0.0017     | 0.008   |
|                                   |                         |      |         | $\Delta$ Chl <sub>POLY4-prof</sub> | −0.121 ± 0.079       | 0.133   |

$\Delta\alpha^B$  was the most influential predictor in the model of  $\Delta$ NPP<sub>BIO–Webb</sub> with an importance score of  $0.11 \pm 0.03$ , followed by  $\Delta$ Chl<sub>POLY4-prof</sub> and time with significantly lower scores of  $0.014 \pm 0.010$  and  $0.009 \pm 0.008$ , respectively (Figure 7b). The contributions of  $\Delta P_{\max}^B$  and  $\Delta$ PAR were considerably less important for the model. The best regression model of  $\Delta$ NPP<sub>BIO–Webb</sub> only included  $\Delta\alpha^B$  as the lone predictor (AIC = −69.93), as indicated by AIC selection (Table 2). However, the final model only explained 12.7% of the variance in  $\Delta$ NPP<sub>BIO–Webb</sub> (Adjusted R<sup>2</sup> = 0.105,  $p < 0.001$ ; Table 3).  $\Delta$ NPP<sub>BIO–Webb</sub> was strongly correlated with  $\Delta\alpha^B$  ( $\beta = 24.76 \pm 6.97$ ,  $p < 0.001$ ). The model intercept was not significantly different from zero ( $0.15 \pm 0.42$ ,  $p = 0.728$ ), indicating no detectable offset in modelled  $\Delta$ NPP<sub>BIO–Webb</sub> when  $\Delta\alpha^B = 0$ .

#### 4.3.4. Impact of the Assignment of P-I Parameters on NPP Agreement

To demonstrate the impact of the P-I parameters to  $\Delta$ NPP<sub>BIO–Webb</sub>, the regression model was recomputed with a new set of NPP<sub>webb</sub> which used the same P-I parameters as the BIO model (denoted as NPP<sub>webb\*</sub>). This improved the agreement between the BIO and the updated Webb models (Figure 8b). The slope of correlation increased from 0.862 (Figure 8a) to 0.998 (Figure 8b), indicating a near-perfect proportional relationship between NPP<sub>webb\*</sub> and NPP<sub>BIO</sub>. The intercept (on log<sub>10</sub> scale) was reduced from 1.879 (Figure 8a) to 0.147 mmol C m<sup>−2</sup> d<sup>−1</sup> (Figure 8b), suggesting a significant reduction in systematic bias. Despite this, the coefficient of determination (R<sup>2</sup>) decreased slightly from 0.682 (Figure 8a) to 0.603 (Figure 8b), NPP<sub>webb\*</sub> was overall better aligned with NPP<sub>BIO</sub> except for some outliers in October 2016.

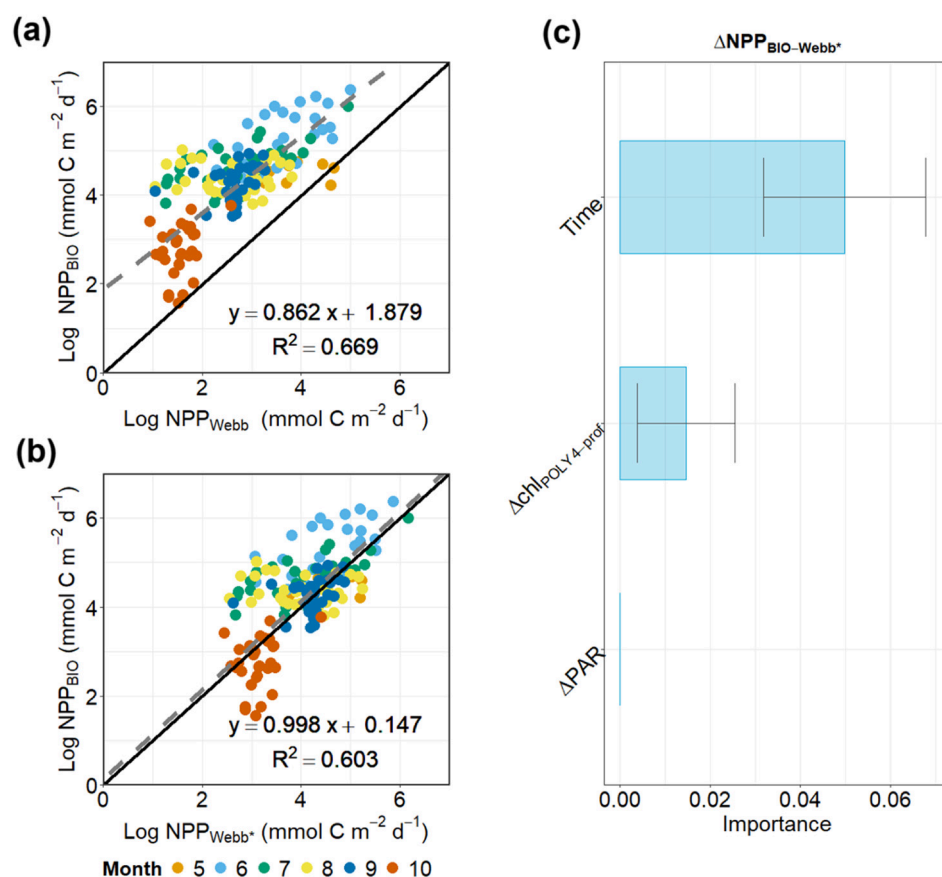


**Figure 8.** Linear relationship between  $\text{NPP}_{\text{BIO}}$  and  $\text{NPP}_{\text{webb}}$ : (a) depth-integrated  $\text{NPP}_{\text{webb}}$  from monthly averages of P-I parameters, and (b) updated depth-integrated  $\text{NPP}_{\text{webb}}$  using the P-I parameters assigned in  $\text{NPP}_{\text{BIO}}$  (denoted as  $\text{NPP}_{\text{Webb}^*}$ ). (c) The Variable Importance analysis ranked by importance score for the regression model of  $\Delta\text{NPP}_{\text{BIO-Webb}^*}$ .

Regression analysis was performed for the difference between  $\text{NPP}_{\text{Webb}^*}$  and  $\text{NPP}_{\text{BIO}}$  ( $\Delta\text{NPP}_{\text{BIO-Webb}^*}$ ) against time,  $\Delta\text{Chl}_{\text{POLY4-prof}}$  and  $\Delta\text{PAR}$ , using Eq. 9 without  $\Delta\text{P}_{\text{max}}^{\text{B}}$  and  $\Delta\alpha^{\text{B}}$  components. After AIC selection, time ( $\beta = -0.0048 \pm 0.0017$ ,  $p = 0.008$ ) and  $\Delta\text{Chl}_{\text{POLY4-prof}}$  ( $\beta = -0.121 \pm 0.079$ ,  $p = 0.133$ ) were retained while  $\Delta\text{PAR}$  was removed from the final model (AIC = −61.92; Table 2). Interestingly, time ranked first with an important score of  $0.05 \pm 0.02$  as the most influential variable for  $\Delta\text{NPP}_{\text{BIO-Webb}^*}$  (Figure 8c), followed by  $\Delta\text{Chl}_{\text{POLY4-prof}}$  ranked second with an importance score of  $0.015 \pm 0.011$ , three times less important than time, while the impact of  $\Delta\text{PAR}$  in  $\Delta\text{NPP}_{\text{BIO-Webb}^*}$  was negligible.

## 5. Discussion

Comparisons of satellite-based productivity models have been previously carried out during round-robin exercises on a global scale and in the Arctic regions [57–61]. However, there are very few comparisons performed using *in situ* NPP derived from a mooring equipped with bio-optical sensors. In this study, profiler-based *in situ*  $\text{NPP}_{\text{Webb}}$  was compared with two satellite-derived NPP estimates (VGPM, BIO). Using this comparison framework, we evaluated model sensitivity to input variables and examined the differences in these variables associated with the disagreement among NPP estimates. While several satellite-based primary production models exist, the study was limited to two models: the VGPM and the BIO model.

### 5.1. What Drives the Model Most?

Chl-a concentration exerts the strongest influence on  $NPP_{Webb}$  among other inputs, while satellite-based models are from 40 to 50% less sensitive to Chl-a concentration than the Webb model. Although *in situ*  $Chl_{prof}$  was better correlated with  $Chl_{POLY4}$  than  $Chl_{OCI}$  in the top 10 m of the water column, both BIO and VGPM models have similar ranges of sensitivity to Chl-a concentration (i.e., about 6%). This is assumed to be tied to the vertical resolution of Chl-a between *in situ* and satellite products. Both BIO and VGPM models assume constant Chl-a concentrations in the water column and do not consider the subsurface structure of Chl-a. Although efforts have been carried out to derive Chl-a vertical profiles in the water column using a statistical approach [28], these were not implemented in the current study.

In other regions, such as the Arctic, the incorporation of Chl-a maxima reduced the error of satellite-based NPP estimates by 25% [62]. By substituting  $Chl_{prof}$  into  $NPP_{BIO}$ , an increase of ~50%  $NPP_{BIO}$  was observed at lower NPP estimates that associated with Chl-a maxima deeper than 40 m (Figure S4), suggesting that the vertical structure of Chl-a may affect satellite-based NPP estimates. A correction factor of 0.83 (Figure S4) on NPP outputs could be considered for satellite NPP models in this region during the seasons when deep Chl-a maxima and low productivity have been observed.

The BIO model is largely driven by PAR and  $\alpha^B$ , which the Webb model also shares similar sensitivity to both variables. At higher latitudes, light intensity is significantly reduced compared to the lower latitudes. As the light penetration in the euphotic zone changes seasonally, the light availability could be the limiting factor of phytoplankton growth at high latitude, particularly in spring when nutrients in the water column are plentiful. Therefore, it would be reasonable that both models are more sensitive to  $\alpha^B$  than  $P^B_{max}$ , since PAR in the Labrador Sea is rarely sustained at high enough intensity for the photosynthetic rate to reach saturation at  $P^B_{max}$ .

In contrast, although the VGPM model is mostly driven by Chl-a, its sensitivity to SST surpassed that of Chl-a from mid-July to September. Unlike other parameters, the model sensitivity to SST exhibited a pronounced seasonal pattern, whereas the sensitivity trend of other parameters remained relatively random and flat over time. Based on the model configuration, Figure 7 in Behrenfeld and Falkowski [29] showed that  $P^B_{opt}$  shifted only ~2 mg C (mg chl-a)<sup>-1</sup> h<sup>-1</sup> over the range of SST between 0 and 8 °C, while the change was more dramatic for water above 8 °C. This pattern coincided with the sudden increase of  $|S_{VGPM}|$  after SST increased past 8 °C (Figure 6e), suggesting that the seasonal pattern is related to the nonlinear temperature dependence of  $P^B_{opt}$  in the model. Therefore, the VGPM model revealed distinct photosynthetic responses compared with the Webb and the BIO models.

### 5.2. What Causes the NPP Difference?

The magnitude of differences between depth-integrated  $NPP_{Webb}$  and  $NPP_{BIO}$  was largely attributed to the methods used to assign P-I parameters within the timeframe of this study. In the BIO model, P-I parameters are selected based on oceanographic consideration revealed by both satellite-derived Chl-a concentration and sea surface temperature, while the Webb model used a monthly climatology based on a large archive (128 data points) surrounding the location of SeaCycler in the Labrador Sea. This led to large differences of P-I parameters (Figure 4b,c) and created a considerable gap between  $NPP_{Webb}$  and  $NPP_{BIO}$  that is strongly correlated to  $\Delta\alpha^B$  (Figure 7b). Comparatively, the impact of  $\Delta P^B_{max}$  was not as important as  $\Delta\alpha^B$  on NPP due to limited available light for photosynthesis in high latitude regions. While  $\Delta Chl_{POLY4-prof}$  and  $\Delta PAR$  may contribute to  $\Delta NPP_{BIO-Webb}$ , their influences were less significant comparing to  $\Delta\alpha^B$ . The agreement between depth-integrated  $NPP_{Webb}$

and  $NPP_{\text{BIO}}$  improved significantly when the same set of P-I parameters were assigned to both models (Figure 8b). This demonstrates that the difference of *in situ* and satellite-based NPPs could be minimized with a better characterization of P-I parameters in the region, especially for periods outside the bloom season when the data are scarce.

When applied the same set of P-I parameters in the BIO and Webb model, time became the most influential factor in  $\Delta NPP_{\text{BIO-Webb}}$ . While Chl-a and PAR were ecologically relevant, their lower importance score indicated that time captured much of the variability observed in  $\Delta \text{Chl}_{\text{POLY4-prof}}$  and  $\Delta \text{PAR}$ . The temporal variability was linked to limited satellite detection in the later season, notably around mid-September, when PAR began to drop below  $20 \mu\text{mol photons m}^{-2} \text{d}^{-1}$ . This was supported by the outliers in October observed from the comparison of Chl-a (Figure 3d) and NPP (Figure 8b), as well as the heightened sensitivity of NPP to the change of satellite PAR in the BIO and VGPM model around the same time (Figure 6). Although satellite data were gap-filled using the DINEOF method, persistently lower data coverage, such as in later months or more northern areas, resulted in higher estimate errors (Figure S6).

The discrepancy between  $NPP_{\text{VGPM}}$  and  $NPP_{\text{Webb}}$ , however, told a different story. A lack of consistency in temporal patterns was observed in  $\Delta NPP_{\text{VGPM-Webb}}$  for both surface and depth-integrated time series (Figure 5c,d). This is due to increasing bias in the SST-dependent  $P^{\text{B}}_{\text{opt}}$ , and the absence of the  $\alpha^{\text{B}}$  term in the VGPM model (Figure 7a). The empirical relationship between SST and  $P^{\text{B}}_{\text{opt}}$  has been considered the Achilles' heel of the VGPM model [63,64]. Numerous studies have reported poor agreement between *in situ* and satellite  $P^{\text{B}}_{\text{opt}}$  [60,63], suggesting the sole dependency of  $P^{\text{B}}_{\text{opt}}$  on SST oversimplified the complexity within  $P^{\text{B}}_{\text{opt}}$ . Since the VGPM model itself is quite sensitive to SST (Figure 6e,f), this led to the findings of the unexplained pattern in  $NPP_{\text{VGPM}}$  during non-bloom periods when SST rarely varied. As a result,  $P^{\text{B}}_{\text{opt}}$  might not be well suited for large-scale application at the Labrador Sea, as the photosynthetic response was biased towards regions with warmer water. Moreover,  $\alpha^{\text{B}}$  as a key influencer of  $\Delta NPP_{\text{VGPM-Webb}}$  highlighted its importance of accurately representing photosynthetic efficiency under lower PAR conditions, particularly in high-latitude regions where there is limited available light during the winter and early spring. This suggests that incorporating  $\alpha^{\text{B}}$  in the NPP model may be more important than relying primarily on the optimal growth rate as portrayed by the VGPM model.

### 5.3. Why VGPM and BIO Produce Different NPP Estimates?

The major difference between the VGPM and BIO models lie in the representation of photosynthetic terms, the use of different Chl-a retrieval algorithms and the treatment of light field propagation within the model. The VGPM model used the photosynthetic rate  $P^{\text{B}}_{\text{opt}}$  derived from a global empirical relationship with SST [65], which does not account for other key variables that could affect photosynthetic efficiency (e.g., Chl-a, PAR, nutrients). The BIO model adopted per-pixel assignment of  $\alpha^{\text{B}}$  and  $P^{\text{B}}_{\text{max}}$  using SST and Chl-a as predictors based on a clustering analysis of phytoplankton community composition and trophic levels [27]. Moreover, the VGPM model did not include  $\alpha^{\text{B}}$ , a key parameter to describe photosynthesis at low light conditions. The BIO model not only included  $\alpha^{\text{B}}$  but adjusts for spectral dependence by assuming its spectral shape resembles the shape of the phytoplankton absorption spectrum (Equation (6)). These configuration differences explained why the VGPM model was more responsive to SST (Figure 6f), whereas the BIO model displayed stronger sensitivity to  $\alpha^{\text{B}}$  (Figure 6d).

Although the VGPM and BIO models utilized raw data from the MODIS-Aqua satellite, they applied different Chl-a retrieval algorithms (OCI and POLY4). The regionally tuned  $\text{Chl}_{\text{POLY4}}$  in the BIO model better reproduced the June-July bloom than global  $\text{Chl}_{\text{OCI}}$  in the VGPM model (Figure 3c). Since the relative error of NPP is highly correlated to the

errors of surface Chl-a concentration [57], regionally tuned products can therefore reduce the propagation of Chl-a retrieval errors down to the NPP estimates.

More importantly, both models differed in the propagation of surface observations throughout the euphotic zone. The VGPM model extrapolates all variables from the surface to depth by assuming they are constant within the euphotic zone. While the BIO model maintains the assumption of constant Chl-a concentration and photosynthetic parameters throughout the water column, it resolved the subsurface light field using a radiative transfer model [52] by modelling light attenuation in the water column as a function of absorption and scattering by water, phytoplankton, colored dissolved organic matter (yellow substances), and detritus [27]. As a result, the BIO model exhibited in average 6 times more sensitive to PAR than the VPGM model (Figure 6d,f), indicating that the BIO model captured the role of light availability in regulating NPP more realistically.

#### 5.4. Which Is More Important: Good Modeling or Good Data?

Our study demonstrated that the impact of an input variable on NPP is determined by its magnitude, its representation within the model and the model's sensitivity to changes in that variable. Consequently, mismatches among NPP estimates may arise not only from the differences in the magnitude of input variables, but from the extent to which these differences propagate through the models. The comparison between Webb and BIO models provided a clear example. The P-I parameters assigned by the two models differed substantially over the same periods, because both models also showed strong sensitivity to  $\alpha^B$ , the differences of  $\alpha^B$  have the most influence on the divergence between  $NPP_{Webb}$  and  $NPP_{BIO}$ . When both models are applied with matching P-I parameters, their NPP estimates become more consistent with each other, supporting the discrepancy of P-I parameters passed down to the difference of their NPP estimates. In this case, improving the agreement of their P-I parameters has greater impacts than other input variables.

Unlike the BIO model, the VGPM model derives the photosynthetic response through the SST-dependent  $P^B_{opt}$  term rather than  $\alpha^B$ . Although the VGPM model showed high sensitivity to  $P^B_{opt}$ , but the influence of  $\alpha^B$  from the Webb model was comparatively stronger on  $\Delta NPP_{VGPM-Webb}$  (Figure 7a). As a result, the discrepancy of  $NPP_{VGPM}$  and  $NPP_{Webb}$  cannot be solely explained by the differences in the magnitude of input variables. Instead, it reflects the impact of model parameterization on photosynthetic rates that would be appropriate for the region, which  $\alpha^B$  matters more than  $P^B_{opt}$  in this case. The contradictory patterns of NPP differences between the comparisons of satellite and profiler-based NPPs further suggest that similar discrepancies in NPP estimates may result from different sources of bias.

Our findings suggest that neither “good data” or “good model” alone is sufficient to be an independent solution. Regional observations can provide more representative inputs for NPP models; however, their benefits depend on the ability of the models to translate those inputs and the associated regional processes into realistic NPP estimates. Hence, reconciling *in situ* and satellite NPP estimates requires considering both the regional validity of model inputs and the model-specific responses of NPP to those inputs, especially when the model sensitivity varies seasonally or nonlinearly. Priority should be given to those inputs that differ significantly with regional observations and exert a strong influence on the NPP estimates.

#### 5.5. Limitations and Recommendations

Overall, this study was limited to chlorophyll-based primary productivity models. By examining the strength and weakness of each model, our goals were to emphasize the importance of using regional data sources for NPP models and to assess the applicability

of model outputs within the Labrador Sea. Although SeaCycler provided high-frequency, depth-resolved observations, our results are based on chlorophyll-based models evaluated at a single site in the Labrador Sea. The observed NPP discrepancies and the contributing factors may differ in other areas of the Labrador Sea, such as the boundary-current regions on the Labrador Shelf and the Greenland Shelf [66,67]. To evaluate the broader applicability of our findings, similar comparisons should be conducted in other regions across the subpolar Northwest Atlantic, over different observational periods, and using additional NPP models.

We recognized the limitation of using monthly climatology of P-I parameters in the estimates of  $NPP_{Webb}$ , as the 40-years dataset were unequally distributed over the seasons due to ship time restriction. In fact, most measurements were made in spring (May–June), resulting in a bias of seasonal distribution in our dataset. Improved seasonal coverage of ship-based P-I parameters [14], particularly outside the bloom seasons, is therefore necessary to improve model robustness. Similarly, the BIO model is regionally tuned to the Labrador Sea and more challenging to apply at synoptic scales, given the spatio-temporal variation in photosynthetic parameters. However, new approaches based on machine learning may solve the issue [68].

In the past 20 years, newer productivity models, such as carbon-based (CbPM) and absorption-based (AbPM) models, were developed as an improvement upon the VGPM model [69,70]. Most productivity models started to use globally based empirical relationships to estimate NPP that may be sufficient for global studies but may not necessarily be suitable for regional-scale studies. Therefore, applying global relationships to biogeochemically heterogeneous regions without adequate validation data might lead to poorly established proxies and inaccurate NPP estimates. An important lesson from this study is that reliable regional NPP estimates require both well-characterized regional parameters and a model that appropriately translates those parameters into NPP. For the Labrador Sea, the immediate priorities are to improve regional and seasonal characterization of P-I parameters, evaluate the suitability of SST-dependent  $P^B_{opt}$  in the region and consider include depth-resolved Chl-a profiles in satellite NPP estimates. Particularly, the limited availability of P-I measurements outside spring bloom restricts the characterization of seasonal variability of phytoplankton physiology. Carr et al. [56] emphasized the need for improved parameterization of  $P^B_{max}$  and a deeper understanding of the influence of sea surface temperature (SST) on photosynthesis, suggesting a potential update to the relationship between SST and  $P^B_{opt}$ , particularly to better represent high-latitude regions.

Future research should prioritize observation strategies that improve regional and seasonal observations in the NPP models. Long-term, high-frequency and depth-resolved observations from fixed moorings can provide continuous characterization of seasonal and short-term variability from bio-optical and biogeochemical properties, including spectral irradiance, phytoplankton absorption, dissolved oxygen, and carbonate variables, such as total alkalinity, pH, and  $pCO_2$ . Mobile platforms, such as biogeochemical Argo floats, can extend these observations across broader spatial gradients. Targeted ship-based sampling should remain essential to providing direct P-I measurements. Together, these complementary approaches could fill temporal, spatial, and vertical gaps that currently limit the development and evaluation of regional NPP models. These observations can also support hybrid modelling approaches that integrate multiple data sources and environmental variables to estimate P-I parameters where direct measurements are sparse. Incorporating phytoplankton community structure and a range of environmental factors, such as SST, light, and nutrients, into model frameworks can provide a more ecologically representative basis for assigning P–I parameters across diverse marine ecosystems [71].

## 6. Conclusions

This study presents a comparative analysis of net primary productivity (NPP) time series derived from two satellite-based models and a profiler-based *in situ* model in the Central Labrador Sea between May and November 2016. Satellite-based estimates ( $NPP_{BIO}$  and  $NPP_{VGPM}$ ) exceeded profiler-based  $NPP_{Webb}$  estimates, although the mechanisms associated to these NPP differences are distinct.  $\alpha^B$  and SST-dependent  $P^B_{opt}$  are important contributors to the difference between  $NPP_{VGPM}$  and  $NPP_{Webb}$ ; while the difference of assigned  $\alpha^B$  has the most influence on the disagreement between  $NPP_{Webb}$  and  $NPP_{BIO}$ . Assigning a common set of P-I parameters improved the agreement between  $NPP_{Webb}$  and  $NPP_{BIO}$ , demonstrating the importance of photosynthetic parameter assignments in our study.

Future improvements should prioritize regional characterization of model inputs that strongly drive the model on NPP estimates. In the central Labrador Sea, improving the characterization of seasonal variability in  $\alpha^B$  across seasons should be prioritized. The issue of limited availability of P-I measurements outside the spring bloom season should be addressed, as this may introduce additional uncertainties into the estimates of seasonal NPP used for characterizing regional carbon cycle. Increasing ship-based measurements across different seasons would help capture the temporal variability of the P-I parameters. Similar comparisons of NPP estimates are recommended at other sites across the subpolar NWA, over longer observational periods, with the inclusion of various NPP models.

Addressing these gaps requires observation strategies designed to constrain the sources of uncertainty in NPP estimates. Fixed moorings can provide long-term, high frequency and depth-resolved observations, while mobile platforms can extend the spatial coverage. These observations can further support the development of modeling techniques that integrate environmental drivers, such as sea surface temperature (SST), Chl-a, nutrient concentrations, and phytoplankton community structure, to predict P-I parameters where data coverage is currently limited.

Since NPP defines the production of organic carbon that can contribute to export, uncertainties in NPP estimates can propagate into the estimates of carbon export and may introduce systematic biases. Given the Labrador Sea's role as a major CO<sub>2</sub> sink, this study highlights the need to better constrain the variability of phytoplankton physiology to improve carbon budget estimates. Improving parameter characterization will improve estimates of NPP, and strengthen the assessment its role in carbon export, ecosystem dynamics, and ocean biogeochemical cycles.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18213681/s1>, Figure S1: Monthly, full depth averages of P-I parameters; Figure S2: Monthly, 10m binned (for top 30m) averages of P-I parameters; Figure S3: Sensitivity analysis of NPP to  $P_{Bmax}$  and  $\alpha^B$  under different temporal and depth averaging scenarios; Figure S4: Linear correlation between original ( $NPP_{BIO}$ ) and updated depth-integrated NPP from the BIO model using *in situ* Chl<sub>prof</sub> from SeaCycler ( $NPP_{BIO,Chlprof}$ ); Figure S5: Shipboard *in situ* versus satellite-derived chl-a for NASA generic OCI algorithm, the POLY4 algorithm for valid pixels and the POLY4 algorithm with both valid and DINEOF “reconstructed” pixels; Figure S6: Percentage of valid pixels of satellite retrieval over the study period for the area of interest; Figure S7: Schematic diagram for profiler-based Webb model; Figure S8: Schematic diagram for satellite-based BIO model; Figure S9: Schematic diagram for satellite-based VGPM model; Table S1: A list of sensors equipped on the SeaCycler mooring during 2016 deployment.; Table S2: The robustness of  $NPP_{Webb}$  estimates assessed by Monte Carlo simulation.

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writing—review and editing, K.K., E.D., S.C., M.M.A., and A.J.I.; visualization, K.K.; supervision, D.W.R.W.; project administration, K.K.; funding acquisition, D.W.R.W. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** VGPM model data are available from the Ocean Productivity website maintained by Oregon State University (<https://orca.science.oregonstate.edu/>, accessed on 20 October 2026). MODIS-Aqua POLY4 chlorophyll-a (Chl-a) data are available through the CIOOS Atlantic repository ([https://catalogue.cioosatlantic.ca/dataset/ca-cioos\\_f869feaf-4534-4f81-8276-a1bd08c488a9](https://catalogue.cioosatlantic.ca/dataset/ca-cioos_f869feaf-4534-4f81-8276-a1bd08c488a9), accessed on 20 October 2026). The code for the BIO model is available on the Github page (<https://github.com/BIO-RSG>, accessed on 20 October 2026) of the Satellite Ocean Colour and Phytoplankton Ecology Group (SOPhyE) at the Bedford Institute of Oceanography, Dartmouth, Canada. The SeaCycler data and the code for the Webb model will be available in a public repository.

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## Abbreviations

The following abbreviations are used in this manuscript:

|                               |                                                                                                                                          |
|-------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Chl <sub>OCI</sub>            | Satellite Chl-a estimated by OCI ocean colour algorithms (mg m <sup>-3</sup> )                                                           |
| Chl <sub>POLY4</sub>          | Satellite Chl-a estimated by POLY4 ocean colour algorithms (mg m <sup>-3</sup> )                                                         |
| Chl <sub>prof</sub>           | Depth-resolved Chl-a observed by SeaCycler mooring (mg m <sup>-3</sup> )                                                                 |
| E <sub>d</sub> (λ)            | Downwelling irradiance measured at λ (W m <sup>-2</sup> nm <sup>-1</sup> )                                                               |
| K <sub>d</sub> (λ)            | Diffuse attenuation coefficient of downwelling irradiance at λ (m <sup>-1</sup> )                                                        |
| NPP <sub>Webb</sub>           | Net Primary Production from the Webb model (Equation (2))                                                                                |
| NPP <sub>VGPM</sub>           | Net Primary Production from the VGPM model (Equation (3))                                                                                |
| NPP <sub>BIO</sub>            | Net Primary Production from the BIO model (Equation (5))                                                                                 |
| PAR                           | Photosynthetic Active Radiation (mol photon m <sup>-2</sup> d <sup>-1</sup> )                                                            |
| P <sup>B</sup> <sub>opt</sub> | Optimal photosynthetic capacity (mg C [mg chl-a] <sup>-1</sup> h <sup>-1</sup> )                                                         |
| P <sup>B</sup> <sub>max</sub> | Maximum photosynthetic rate normalized by Chl-a (mg C [mg chl-a] <sup>-1</sup> h <sup>-1</sup> )                                         |
| SST                           | Sea Surface Temperature (°C)                                                                                                             |
| α <sup>B</sup>                | Photosynthetic efficiency under minimal light levels (mg C [mg chl-a] <sup>-1</sup> h <sup>-1</sup> [W m <sup>-2</sup> ] <sup>-1</sup> ) |
| λ                             | Wavelength (nm)                                                                                                                          |

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