

6TH MARCH 2026  
DEPARTMENT OF PHYSICS, FACULTY OF SCIENCE, UNIVERSITY OF SPLIT

PHOTOCLIM 3<sup>rd</sup> ANNUAL MEETING  
PRESENTATION OF THE RESULTS ACHIEVED DURING  
THE SECOND PROJECT YEAR

PROJECT FUNDED BY THE CROATIAN SCIENCE FOUNDATION IP-2022-10-8859

# Fragility of primary production under climate change



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# Fragility of marine photosynthesis under climate change

RESEARCH PROJECT

Phytoplankton primary production is arguably the oldest productive system on Earth

## Second year work plan

### List of deliverables:

- D13. Annual project work meeting
- D14. Filling data gaps in the local database
- D15. Creating time series of photosynthesis parameters
- D16. Creating time series of Gaussian parameters
- D17. Workshop on bioeconomic models in oceanography
- D18. Creating a theoretical framework for quantifying the discount rate of marine ecosystems
- D19. Workshop on primary production modeling
- D20. Educational materials on dynamic models of primary production
- D21. Training in primary production measurements at the Plymouth Marine Laboratory
- D22. Training in primary production modelling at the Plymouth Marine Laboratory
- D23. Attendance at conferences
- D24. Scientific publication
- D25. Scientific publication

## D13. Annual project work meeting

On the **20th February 2025** we had our Annual meeting at the Faculty of Science in Split.

### Meeting agenda

09:30 – 10:00 Gathering of participants

10:00 – 10:05 Opening remarks

10:05 – 10:30 Presentation of the results achieved in the first project year

    Presentation of the work plan for the remaining project period

    Presentation of the financial plan for the remaining project period

11:00 – 11:30 Coffee & Discussion

11:30 – 12:30 Planning of Project Activities for the Second Year

    Filling in data gaps

    Creating time series of photosynthesis parameters

    Creating time series of Gaussian parameters

    Software tools for data processing

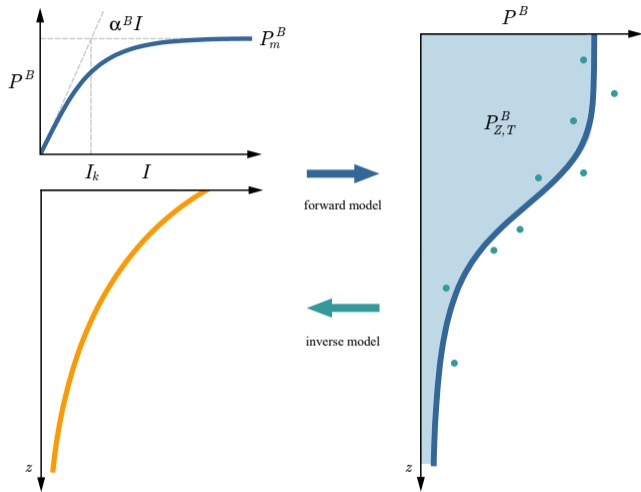
12:30 – 13:00 Planning of the workshop project - Modeling of primary production

13:00 – 15:00 Lunch

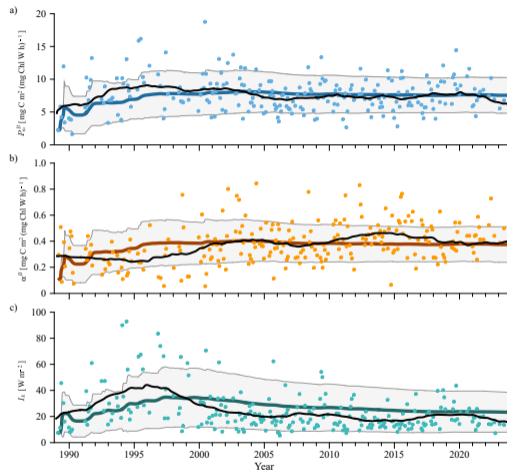
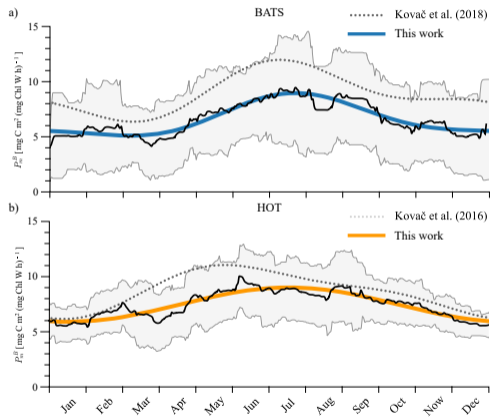
## D14. Filling data gaps in the local database

<b>Stončica</b>	1962	
<b>Kaštelanski zaljev</b>	1962	
<b>Bermuda Atlantic Time Series</b>	1988	<a href="http://bats.bios.edu">bats.bios.edu</a>
<b>Hawaii Ocean Time Series</b>	1988	<a href="http://hahana.soest.hawaii.edu/hot/hot-dogs">hahana.soest.hawaii.edu/hot/hot-dogs</a>
<b>Cariaco</b>	1996	<a href="http://imars.marine.usf.edu/car">imars.marine.usf.edu/car</a>
Monterey Bay	1988	<a href="http://www.mbari.org/bog">www.mbari.org/bog</a>
La Coruña	1990	<a href="http://www.seriestemporales-ieo.com">www.seriestemporales-ieo.com</a>
Western Channel Observatory	1992	<a href="http://www.westernchannelobservatory.org.uk">www.westernchannelobservatory.org.uk</a>

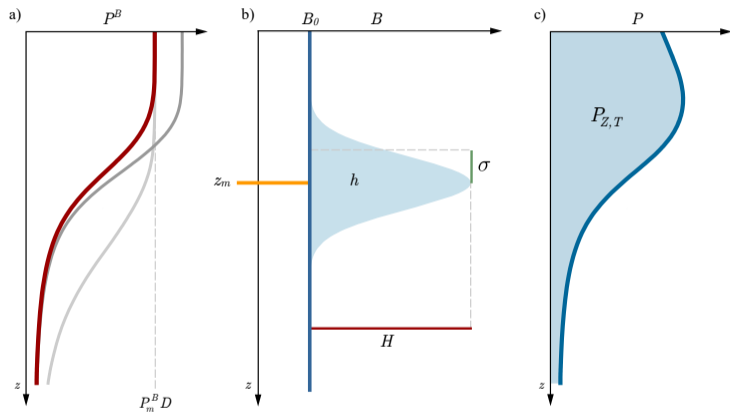
## D15. Creating time series of photosynthesis parameters



## D15. Creating time series of photosynthesis parameters



# D15. Creating time series of Gaussian parameters



## D17. Workshop on bioeconomic models in oceanography

On the 5th September at the Faculty of Science we have held the **Bioeconomical models in oceanography workshop**. The workshop hosted experts from physics, biology and economics, which together discussed the topic of sustainable usage of marine resources in a changing world.

A detailed report from the workshop can be found here:

[www.photoclim.org/news/workshop-on-bioeconomical-models-in-oceanography](http://www.photoclim.org/news/workshop-on-bioeconomical-models-in-oceanography)

## D17. Workshop on bioeconomic models in oceanography



## Bioeconomic interpretation of primary production models

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**Under review in Ecological Modelling**

## D19. Modelling primary production workshop

From the 27th to 31st October we have held the **Modelling primary production workshop**. The theme of the workshop was primary production modelling with a strong emphasis on parameter estimation methods for fine tuning of primary production models.

A detailed report from the workshop can be found here:

<https://www.photoclim.org/workshops/modelling-primary-production/>

## D19. Modelling primary production workshop



D20. Educational material on primary production modelling

Our second educational material is now available for download!

# MODELLING PRIMARY PRODUCTION

<https://www.photoclim.org/education/>

## D20. Educational materials on dynamic models of primary production

Following (3.16) and integrating the previous expression (over time and depth) yields the mixed layer production:

$$P_{Z_m, T} = \int_0^{Z_m} \int_0^D P(z, t) dt dz = \frac{B \alpha^B I_T}{K} (1 - e^{-KZ_m}), \quad (5.2)$$

where  $I_T$  stands for the total available light energy at the surface received during one day:

$$I_T = \int_0^D I_0(t) dt. \quad (5.3)$$

Now assume, in line with Figure 21, a depth-independent, biomass-specific, loss rate  $L^B$ , such that the total loss  $L(z, t)$  at each depth and time is given by:

$$L(z, t) = BL^B, \quad (5.4)$$

where  $L^B$  is the loss rate per unit biomass in the broadest sense (respiration, grazing), which can be parametrized in numerous ways [62]. Integrating this expression (over time and depth) yields mixed layer losses as:

$$L_{Z_m, T} = \int_0^{Z_m} \int_0^D L(z, t) dt dz = BL_T^B Z_m, \quad (5.5)$$

with  $L_T^B = 24 L^B$ , where the 24 comes due to integration over the entire day. We stress that temporal integration is carried out over daylight hours for primary production and over 24 hours for the loss term.

Following Sverdrup [58] the **critical depth**  $Z_c$  (m) is defined as the depth for which the following holds:

$$P_{Z_c, T} = L_{Z_c, T}, \quad (5.6)$$

or stated explicitly for Sverdup's model:

$$\frac{\alpha^B I_T}{K} (1 - e^{-KZ_c}) = 24 L^B Z_c. \quad (5.7)$$

The obtained equation is a transcendental one. Luckily, it is solvable using the Lambert W function, but prior to presenting the exact solution we will first interpret this expression.

For active mixing proceeding exactly to the critical depth  $Z_m = Z_c$ , mixed layer production equals losses and therefore no biomass accumulation takes place. In order for biomass accumulation to take place, production needs to exceed losses:

$$\frac{\alpha^B I_T}{K} (1 - e^{-KZ_m}) > 24 L^B Z_m, \quad (5.8)$$

which occurs when mixing does not proceed to the critical depth  $Z_m < Z_c$ . If mixing proceeds beyond the critical depth  $Z_m > Z_c$  losses dominate:

$$\frac{\alpha^B I_T}{K} (1 - e^{-KZ_m}) < 24 L^B Z_m, \quad (5.9)$$

and biomass accumulation will not take place. To know which condition is satisfied we proceed to solve (5.7) to obtain  $Z_c$ .

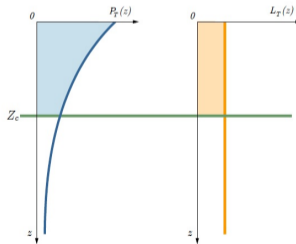


Figure 22: Graphical representation of the critical depth  $Z_c$  (green line) as the depth at which vertically integrated production (blue surface) equals vertically integrated losses (orange surface).

## D20. Educational materials on dynamic models of primary production

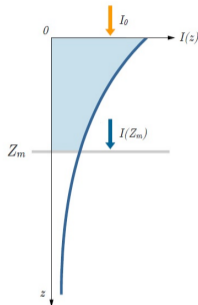


Figure 28: Irradiance at the mixed layer depth  $I^*(Z_m)$  (blue arrow) calculated using expression (6.8), based on surface irradiance (orange arrow) attenuated due to water and mixed layer biomass.

Combining the previous two expressions we derive the following expression for average biomass at steady state:

$$B^* = \frac{K_w}{k_B} \left( \frac{C}{Z_m} - 1 \right). \quad (6.14)$$

It is important to note that this result is general and does not depend on the specific formulation of the photosynthesis irradiance function. The production light relation, as dictated by the photosynthesis irradiance

function determines  $C$  and therefore  $B^*$ . We stress that  $C$  is the optically uncoupled critical depth and is the solution to:

$$\int_0^C p^B(I) dz = L^B C, \quad (6.15)$$

under irradiance attenuated only due to water:

$$\frac{dI}{dz} = -K_w I, \quad (6.16)$$

implying that biooptical coupling is not present in the model. With no biooptical coupling irradiance at  $C$  is simply:

$$I(C) = I_0 \exp(-K_w C). \quad (6.17)$$

By expressing  $I^*(Z_m)$  from (6.13) at steady state, we arrive at:

$$I^*(Z_m) = I_0 \exp(-K_w C). \quad (6.18)$$

We observe that irradiance at the mixed layer depth at steady state equals the irradiance at the optically uncoupled critical depth:

$$I^*(Z_m) = I(C). \quad (6.19)$$

This result was already demonstrated for the linear photosynthesis irradiance model (5.32). Here we see it is generalized to any photosynthesis irradiance function.

Finally, having derived the solution for average steady state biomass, it is straightforward to find the total steady state biomass, by simply multiplying (6.14) with the mixed layer depth (Figure 29):

$$B_z^* = \frac{K_w}{k_B} (C - Z_m). \quad (6.20)$$

According to this expression total steady state biomass is proportional to the depth difference between the optically uncoupled critical depth and the mixed layer depth. In case of a mixed layer approaching zero the solution gives:

$$\lim_{Z_m \rightarrow 0} B_z^* = \frac{K_w}{k_B} C. \quad (6.21)$$

This is a finite quantity, in comparison to the solution for average steady state biomass (6.14), which diverges when  $Z_m$  goes to zero.

# D20. Educational materials on dynamic models of primary production

## 7.3 THE EFFECT OF SINKING ON THE BIOMASS PROFILE

Let us assume the phytoplankton sink with a sinking speed  $w$  ( $\text{m s}^{-1}$ ). For now, assume that biomass is conserved, such that neither production nor losses affect  $B$ . In this case we can write:

$$B(z, t + \Delta t) = B(z - w\Delta t, t) \quad (7.17)$$

This expression states that biomass at depth  $z$  and time  $t + \Delta t$  came from depth  $z - w\Delta t$  and time  $t$  (Figure 39). In the limit of small  $\Delta t$ , Taylor series expansion of both sides around  $B(z, t)$  gives:

$$B(z, t) + \frac{\partial B}{\partial t} \Delta t \approx B(z, t) - w \frac{\partial B}{\partial z} \Delta t. \quad (7.18)$$

Cancelling terms on both sides yields the advection equation:

$$\frac{\partial B}{\partial t} + w \frac{\partial B}{\partial z} = 0. \quad (7.19)$$

The exact solution to this equation, under no flux boundary condition at the surface, is set by the initial condition  $B_0(z)$  and reads:

$$B(z, t) = B_0(z - wt). \quad (7.20)$$

It is important to stress that the shape of the initial condition does not change with time, it simply gets advected with depth. Therefore, the ultimate fate of any phytoplankton is to sink out of the photic zone (Figure 39).

Now assume that during  $\Delta t$  production and losses also affect  $B$ . Equation (7.17) now becomes:

$$B(z, t + \Delta t) = B(z - w\Delta t, t) \left[ 1 + \frac{1}{\chi} \left( P^B(z - w\Delta t, t) - L^B \right) \Delta t \right]. \quad (7.21)$$

This expression states that during sinking, production acts to increase biomass and losses act to decrease biomass. Phytoplankton that started off at depth  $z - w\Delta t$  and time  $t$  will experience production given by  $B(z - w\Delta t, t)P^B(z - w\Delta t, t)$  and losses given by  $B(z - w\Delta t, t)L^B$ . Once

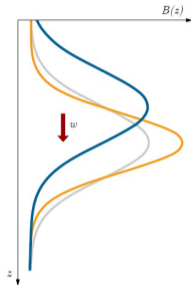


Figure 39: Subjected to sinking the phytoplankton will simply be “washed out” out of the photic zone. Each phytoplankton cell increases its depth due to sinking  $w$  (red arrow). The biomass profile gets advected with depth (grey curve), but it also changes shape due to production and losses during sinking (orange curve).

again, in the limit of small  $\Delta t$ , Taylor series expansion of both  $B(z, t)$  and  $P^B(z, t)$  gives:

$$B(z, t) + \frac{\partial B}{\partial t} \Delta t \approx B(z, t) - w \frac{\partial B}{\partial z} \Delta t + \frac{1}{\chi} \left[ B(z, t) - w \frac{\partial B}{\partial z} \Delta t \right] \left[ P^B(z, t) - w \frac{\partial P^B}{\partial z} \Delta t \right] \Delta t + \frac{1}{\chi} \left[ B(z, t) - w \frac{\partial B}{\partial z} \Delta t \right] L^B \Delta t. \quad (7.22)$$

## D21. and D22. Training

**Marija Bačeković Kolođer** attended the following training programs:

**12th to 16th May 2025.**

Training in primary production measurements at the Plymouth Marine Laboratory

**8th to 16th September 2025.**

Training in primary production modelling at the Plymouth Marine Laboratory

## D23. Attendance at conferences: IOCS 2025



Robert Brewin gave a keynote lecture titled Aquatic Carbon from Space. Shubha Sathyendranath was part of the Planning Committee. Žarko Kovač presented a poster titled: Towards analysis ready primary production data, while Marija Bačeković Koloper presented a poster titled: Bayesian Estimation of Photosynthesis–Irradiance Parameters for Marine Phytoplankton.

## D24. Scientific paper on time series of photosynthesis parameters

### Time series of photosynthesis parameters

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**Under review in Journal of Geophysical Research: Oceans**

# D24. Scientific paper on time series of photosynthesis parameters

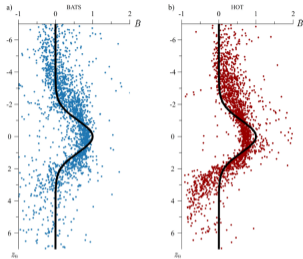


Figure 4. Comparison of modelled (black curve) versus measured chlorophyll *a* depth for: a) BATS (blue points) and b) HOT (red points). The black curve corresponds to the Gaussian function with zero mean and unit standard deviation. In order to show the chlorophyll measurements on the same plot, all data were normalized as described in detail in the text. The coefficient of determination for BATS is 85.92% and for HOT is 89.49%.

model is adequate to describe the measurements and subsequently the optimal parameter values are well suited for modelling primary production at these two stations, with the proviso that the parameters be paired with the same model that was used to retrieve them (Kowal et al., 2017b). In this instance, the model used here falls in the class of non-spectral models for light penetration and photosynthesis, with the exponential function (11) used to describe the photosynthesis irradiance curve (Platt et al., 1980).

To highlight the overall fit of daily production with depth (12) we proceeded to normalize primary production data in a similar fashion as was done for the chlorophyll data, as shown in Figure 4. The procedure for normalization of production data is given in great detail in Kowal et al. (2018). In short, the goal of normalization allows for a direct comparison of the  $f_p$  function (13) with measured daily production at each individual depth. The results are provided in the Supplementary material (Supplementary figures 3 and 4). As can be seen from the Supplementary figure the normalized data fitting well the model displays a mismatch as predicted by (13) and the model displays no bias.

We have also checked the model data mismatch over

time to see if there is evidence of a temporal bias. We found no temporal bias, implying that the parameters are suitable for a time-series analysis, which is treated in the next section.

### 3.2 Seasonal cycle

The seasonal cycle of parameters at both stations are examined first, followed by an analysis of the entire time series. As already mentioned, due to the lack of sufficient PAR data we were not able to estimate reliably the seasonal cycle of the initial slope and the photoadaptation parameter at BATS. For it was possible for the HOT time series, and the photoadaptation parameter was derived from the initial slope and the assimilation number.

The irregular sampling intervals, with the average monthly frequency (Figure 1a) and gaps in the data (Figures 1b and 1c), make the estimation of the mean, median and variance for each month difficult. For a given month, calculations imply taking all the values that were measured in that given month over all the years. However, for an ocean station which is sampled at irregular intervals and has gaps, such as the two stations here, this procedure may result in erro-

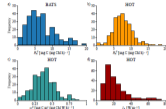


Figure 5. Histograms of the recovered photosynthesis parameters at BATS and HOT: a) Histograms of the assimilation number at BATS, b) Histograms of the assimilation number at HOT. c) Histograms of the initial slope at BATS. The initial slope and the photoadaptation parameter were not estimated at BATS due to a lack of optimal data needed to accurately estimate their values.

neous estimation of the seasonal cycle. The reason is that, if there is significant variability at time scales shorter than one month, the sampling at irregular intervals may yield results that may be more noisy than the original data. Also, as evident by the tails in the distributions of parameters (Figures 4 and 5) there is higher probability than normal for low or high parameter values. Due to these reasons, we may get erroneous estimates of the mean, median or variance for a given month using this approach.

To tackle these problems we estimated the mean seasonal cycle of parameter values by calculating the mean value for each day of the year, taking into account data collected 15 days prior and 15 days post a given day, over all years, following the approach of Kowal et al. (2016b) and Kowal et al. (2018b). In this manner, the effect on the estimation of the mean on that day, caused by sparse data is minimized. The results are shown in Figure 7. At BATS the assimilation number  $P_{max}^0$  has a minimum in March and maximum in July. At HOT the minimum in  $P_{max}^0$  is in January and the maximum is in June. The initial slope  $\alpha^0$  did not have a strong seasonal cycle at HOT, while at BATS we were unable to estimate it due to the lack of optimal data. Seasonal cycles of watercolumn production at both stations, estimated in the same manner, are given in the Supplementary material (Supplementary figures 1 and 2).

In comparison to the previous results of Kowal et al. (2018b), obtained on a ten-year shorter time series at BATS, the seasonal cycle of the assimilation number is rather similar in phase, albeit with a larger amplitude (Figure 7a). For BATS the difference in the magnitude is pronounced throughout the year and during the maximum in July the difference is most pronounced. At HOT the difference from Kowal et al. (2016b) results occur both in phase and in amplitude (Figure 7.b). The prior observed maximum was in May and now we observe it in July. Apart from the phase shift in the maximum, a significant difference in the amplitude is not observed over the entire year.

The photoadaptation parameter  $A_0$  did not have a clearly defined seasonal cycle earlier but was observed to model the Kowal et al. (2016b). However, the minimum in January

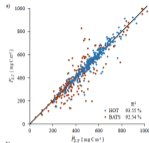


Figure 6. Model versus data comparison for: a) watercolumn production  $P_w$  and b) normalized watercolumn production  $P_w/P_0$  at both stations. Ticks mark the measured variable, whereas the model variable is without a tick. Data from BATS are given in red and data from HOT are given in blue. The coefficient of determination  $R^2$  for each station is given in the bottom right corner.

and a maximum in June were also observed in this work (not shown). It is important to stress that the photoadaptation parameter is the ratio of the assimilation number to the initial slope (14), with the initial slope being a rather small number in comparison with the assimilation number. Therefore, a small error in the estimated value of the initial slope may lead to a large error in the estimated value of photoadaptation parameter. Since the optimization of the assimilation number by the inverse method is more robust than the estimation of the initial slope (Kowal et al., 2017b), the error in the estimation of the initial slope has a stronger effect on the photoadaptation parameter.

Along the lines of Kowal et al. (2016b) and Kowal et al. (2018b), we fitted a sum of two sine functions to the seasonal cycles of the assimilation number: first with an annual period and the second with a semi annual period (Figure 7). For HOT only one sine function was sufficient to model the seasonal cycle, namely the one with the annual period, while

## A new global dataset of photosynthesis parameters

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**Under review in Earth System Science Data**

# D25. Scientific paper on the determination of photosynthesis parameters from a global database

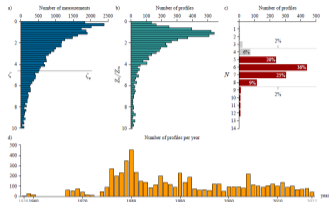


Figure 1. Plot of auxiliary variables. a) Histogram of measurement depths expressed as optical depths. Each individual measurement is treated as one entry. Depthwise size  $C_e$  is highlighted by the grey line. b) Histogram of the ratio between the optical depth and the stated layer depth. Here each profile is treated as one entry. c) Histogram of profiles with a given number of measurement depths. The two grey arrows indicate that percentage order to all the profiles below or above the grey line. d) This series of the number of measured production profiles per year globally.

values of photosynthesis parameters, the measured production profile has to have a minimal number of depths to vertically resolve the shape of the normalized production profile. As demonstrated by Kowal et al. (2016a) the normalized production profile (6) is uniquely determined by the photosynthesis parameters, whereas normalized daily water-column production (9) is not. This is because the normalized water-column production is an integral of the normalized production profile (Figure 1) and therefore loses the degree of freedom that are present in the production profile, which enable the estimation of photosynthesis parameters. Therefore, a given pair of photosynthesis parameters may not be an exact match for the normalized production profile, but it may be a good match for water-column production.

We have analyzed the distribution of profiles with respect to the number of measurement depths per profile, as shown in Figure 4a. The highest number of profiles has 6 measurement depths, which is adequate for successful parameter estimation. The total number of profiles with 6 or more measurement depths accounts for 72% of the measured profiles. Around 20% of the profiles have 5 measurement depths, which is on the limit for successful parameter estimation. In order to use as much of the available data as possible, we have opted to use those profiles as well in parameter estimation. The remainder 8% of profiles have less than 5 measurement depths. In other words, out of the 6984 profiles, 473. For these profiles, it is not feasible to estimate both parameters, and therefore we opted to exclude them. On the other end, some profiles have measurements

from 9 to 14 depths (which is excellent), but these account for less than 2% of all the profiles.

Looking at the temporal distribution of measurements, as shown in Figures 1d, the observations start in 1968, but there is a gap from 1961 till 1966, with another gap year in 1973. After 1973, there is a surge in data collection, with the highest number of profiles being measured in 1980 and in the neighboring years. Afterwards, the global number of measured profiles is of the order of 100 per year. This is arguably very low, highlighting the value of such measurements, given the high demand for photosynthesis parameters in remote sensing applications and in ecosystem models. With this in mind, we now proceed to describe the application of the inverse model and the obtained results.

## 4 Results

As a first step in the application of the inverse model we have analyzed primary production profiles for signs of vertical homogeneity in photosynthesis parameters, by testing whether they meet condition (12), and if so for how many depths. Out of the total 5611 profiles with more than 4 measurement depths, 968 profiles do not violate this condition at all, 2407 profiles violate it at one depth, 1409 at two depths and 747 at three or more depths. We have at first applied the inverse model on all profiles only to find that those profiles which strongly violate the vertical homogeneity condition result in outlier values for photosynthesis parameters. Therefore, we focus on those profiles for which

the vertical homogeneity condition is not violated, or violated at one or two depths. In total there are 4864 such profiles. This accounts for 86% of the original 6984 profiles in the Matusz & Scudlitz (2021) dataset.

Distributions of photosynthesis parameters obtained from these profiles are provided in Figure 5. The obtained parameter values are within the expected ranges than for reported in the literature (Kowal et al., 2017b; Botman et al., 2018; Amirian et al., 2025). The estimated values of the initial slope  $\alpha^0$  range from about 0 to 0.6  $\text{mg C}(\text{mg CHl})^{-1}(\text{W m}^{-2})^{-1}$  with only handful parameter values above the upper limit. The majority of values of the assimilation number  $P^0$  are found to be below 10  $\text{mg C}(\text{mg CHl})^{-1} \text{h}^{-1}$ , with the bulk of the estimates being above 0 and below 5  $\text{mg C}(\text{mg CHl})^{-1} \text{h}^{-1}$ , consistent with conventional photosynthesis-irradiance experiments. Neither of these parameters are normally distributed, being positively skewed and exhibiting long tails. The mean and median of the initial slope  $\alpha^0$  being 0.101 and 0.130  $\text{mg C}(\text{mg CHl})^{-1}(\text{W m}^{-2})^{-1} \text{h}^{-1}$ , respectively, with the mean and median of the assimilation number  $P^0$  being 4.135 and 2.736  $\text{mg C}(\text{mg CHl})^{-1} \text{h}^{-1}$ , respectively. Given the information on the values of the initial slope and the assimilation number it is straightforward to calculate the photosynthesis parameter, defined as:

$$I_0 = \frac{P^0}{\alpha^0}$$

The photosynthesis parameter describes how phytoplankton adjust their light-harvesting capacity to ambient light conditions (Reynolds, 2006; Kirk, 2011). It represents the irradiance at which phytoplankton transition from light limited to light saturated photosynthesis (Jassby & Platt, 1976) and is also a measure of the light level to which phytoplankton have adapted (Zemanov, 1997). Distribution of the photosynthesis parameter is also given in Figure 5. It is positively skewed with a long tail. The tail of the photosynthesis parameter values are found below 50  $\text{W m}^{-2}$ . The mean and the median are 20.862 and 11.615  $\text{W m}^{-2}$ , respectively.

We stress here that the objective of this study was not to provide an interpretation of this specific dataset, but rather to increase the number of photosynthesis parameters available for usage in primary production models. A comprehensive interpretation of the estimated parameter values would necessitate a detailed oceanographic analysis and knowledge regarding, or local biogeochemical processes, which falls outside the scope of the present work and is a potential course for future research. To facilitate this, we provide the obtained parameter values in a table, published online at <https://zenodo.org/records/17923417> (Kowal et al., 2025). Along with each estimated pair of photosynthesis parameters we provide the original profile number given by Matusz & Scudlitz (2021) so that the parameter values can be traced back to the profiles from which they had been estimated. We also give the date of each profile, along with coordinates. To be more precise we also provide the following: date (year, month, day), latitude, longitude, initial slope  $\alpha^0$ , assimilation number  $P^0$  and the original profile number from Matusz & Scudlitz (2021), each given in a separate column. We only provide parameter values in which both parameters were estimated successfully, in line with the limitations set by the experiment and the inverse procedure, described in detail in (Kowal et al., 2016a). We

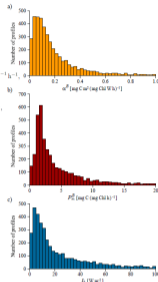


Figure 5. Histograms of the obtained photosynthesis parameters: a) Distribution of the initial slope  $\alpha^0$ , b) Distribution of the assimilation number  $P^0$ , c) Photosynthesis parameter  $I_0$ . The horizontal axis shows parameter values, and the vertical axis indicates the percentage of profiles within each interval of those values.

also flag the values where the inverse procedure did not converge, or local biogeochemical processes, which falls outside the scope of the present work and is a potential course for future research. To facilitate this, we provide the obtained parameter values in a table, published online at <https://zenodo.org/records/17923417> (Kowal et al., 2025).

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## D26. Additional result: Project application accepted

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Improving early warnings of marine tipping points using satellites, models, and in-situ data.

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## D27. Additional result: New project application

A new project application to the COST call Open Call Collection OC-2025-1 called the **Pan-European Research Alliance for Antifragile Systems Methods (MANTIS)** was submitted. Associates from 13 countries participated in the project application. The project team includes Žarko Kovač, whose role is the application of stochastic models in the study of antifragility of primary production in the sea. The project provides financial resources for networking with foreign partners on topics close to the PHOTOCCLIM project.

D28. Additional result: Scientific paper under review

## **Island Trapped Waves Enhance Primary Production in Idealized Numerical Models**

Jasen R. Jacobsen<sup>1,\*</sup>, Christopher A. Edwards<sup>1</sup>, Žarko Kovač<sup>2</sup>, Hrvoje Mihanović<sup>3</sup>, Zrinka Ljubešić<sup>4</sup>

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Under review in *Marine Ecology Progress Series*

## D29. Additional result: Scientific paper under review

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Abstract

Discussion

Metrics



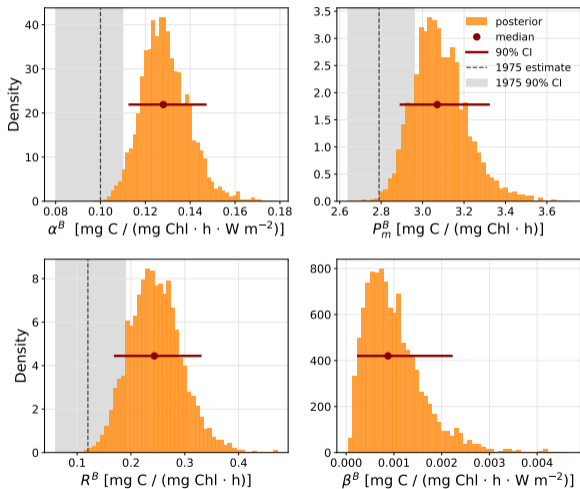
29 Dec 2025

### Modelling primary production: multitude of theories, or multitude of languages?

Jozef Skákala [✉](#), Shubha Sathyendranath, Yuri Artioli, Deep S. Banerjee, Heather Bouman, Robert J. W. Brewin, Momme Butenschön, Stefano Ciavatta, Stephanie Dutkiewicz, Yanna Fidai, David Ford, Grinson George, Karen Guihou, Bror Jönsson, Marija Baččković Koloper, Žarko Kovač, Lekshmi Krishnakumary, Gemma Kulk, Charlotte Laufkötter, Gennadi Lessin, Jann Paul Mattern, Angélique Melet, Alexandre Mignot, David Moffat, Fanny Monteiro, Mayra Rodriguez Bennadji, Cécile Rousseaux, Ranjini Swaminathan, Osvaldo Ulloa, and Jerry Tjiputra

Under review in Ocean Science

## D30. A new method for parameter estimation implemented



## D31. New digitized historical data collected

In collaboration with **Dr. Andrew Erwin** and **Dr. Mohammad Amirian** from **Dalhousie University in Canada**, access to digitized historical data of experimental measurements of the dependence of photosynthesis on light has been achieved. We now have access to a digitized **dataset totaling 107,256 individual incubations.**

## Primary production measurements in the Adriatic during 2025

In situ primary production measurements were conducted at the following stations:

### **Kašetla bay:**

20.1., 28.2., 28.3., 11.4., 14.5., 23.7., 28.8., 4. 10., 29. 10., 20. 11., 11. 12.

### **Stončica station:**

21.1., 24.2., 29.3., 12.4., 24.7., 31.8., 19.11., 10. 12.

## JGR Oceans

### RESEARCH ARTICLE

10.1029/2024JC021415

#### Key Points:

- Interaction of phytoplankton with the underwater light field sets up a bio-optical feedback mechanism creating constants of motion
- A new differential equation shows that the light intensities at both the compensation depth and the critical depth are constants of motion
- Mixed-layer depth acts as the bifurcation parameter, and the critical depth is identified as the bifurcation point


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## Critical Times for the Critical Depth Theory

Žarko Kovač<sup>1</sup>  and Shubha Sathyendranath<sup>2</sup>

<sup>1</sup>Faculty of Science, University of Split, Split, Croatia, <sup>2</sup>National Centre for Earth Observations, Plymouth Marine Laboratory, Plymouth, UK

**Abstract** Critical Depth Hypothesis is arguably one of the longest standing biophysical theories in oceanography and is the earliest mathematically formulated theory aimed at explaining the phenomenon of phytoplankton blooms. It introduces a depth horizon, termed the critical depth, at which the integrated primary production from the surface to that depth equals the integrated loss terms within the same layer. In mixed layers deeper than the critical depth, losses dominate photosynthesis and vice versa. A related horizon in case of weak mixing is the compensation depth, where the rate of photosynthesis matches the loss rate. In this paper, the effect of phytoplankton light attenuation on the critical depth is examined, showing that it creates a bio-optical feedback in the model. A new differential equation, derived for the time evolution of the compensation depth reveals that the light intensities at both the compensation depth and the critical depth are constants of motion. Exact solutions for average and total mixed layer biomass at steady state are derived, and their stability properties are analyzed. An existence of a bio-optical bifurcation is shown, in which the mixed layer depth acts as the bifurcation parameter and the critical depth is identified as the bifurcation point. Transients between steady states are also explored, and it is shown that the relation between the initial condition and the final steady state is paramount in determining whether a shallowing or deepening of the mixed layer will lead to a rise or a decline in biomass over time.

# Papers published in 2025

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## Simulating vertical phytoplankton dynamics in a stratified ocean using a two-layered ecosystem model

Qi Zheng<sup>1</sup>, Johannes J. Viljoen<sup>1</sup>, Xuerong Sun<sup>1</sup>, Žarko Kovac<sup>2</sup>, Shubha Sathyendranath<sup>3</sup>, and Robert J. W. Brewin<sup>1</sup>

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**Abstract.** Phytoplankton account for around half of planetary primary production and are instrumental in regulating ocean biogeochemical cycles. Around 70 % of the oceans is characterized by either seasonal or permanent stratification. In such regions, it has been postulated that two distinct planktonic ecosystems exist, one that occupies the nutrient-limited surface mixed layer and another that resides below the mixed layer in a low-light, nutrient-rich environment.

using two vertically separated planktonic ecosystems. Nevertheless, simulating the ecosystem in the subsurface layer was more challenging than the ecosystem in the surface mixed layer as less is known about model parameters and processes due to a lack of measurements, suggesting that more work is needed to study controls on subsurface planktonic communities.

Published in Biogeosciences



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Thank you!