Dynamics of island mass effect. Part I: detecting the extent

Guillaume Bourdin[1*], Lee Karp-Boss[1], Fabien Lombard[2], Gabriel Gorsky[2], and Emmanuel Boss[1]

[1]School of Marine Sciences, University of Maine, Orono, USA
[2]Laboratoire d'Océanographie de Villefranche-Sur-Mer, Sorbonne Université, France

Correspondence: Guillaume Bourdin (guillaume.bourdin@maine.edu)

Abstract. In the vast Pacific Ocean, remote islands and atolls induce mesoscale and sub-mesoscale processes that significantly impact the surrounding oligotrophic ocean, collectively referred to as the Island Mass Effect (IME). These processes include nutrient upwelling and phytoplankton biomass enhancement around islands, creating spatial and temporal heterogeneity in biogeochemical properties. Previous algorithms developed for detecting IME using satellite data are based on monthly or longer averages of satellite derived chlorophyll *a* concentrations. As such, they tend to underestimate the true extent of this phenomenon because they do not take into account sub-mesoscale and short term temporal variations and because of the sensitivity of the detection algorithm to single pixel variability. Here we present a new approach that enhances satellite data recovery by merging products from multiple sensors and applying the POLYMER atmospheric correction. By integrating modeled~~modelled~~ surface currents with higher temporal resolution satellite observations, we dynamically track chlorophyll *a* enhancements associated with IME and the advection of detached patches and filaments over distances exceeding 1000 km from their source. Our findings, applied to four island groups in the South Pacific, suggest that the ecological influence of IME on the oligotrophic ocean is much larger than previously recognized. This work provides a foundation for improved mechanistic understanding of IME and suggests broader implications for ocean ecology in subtropical regions. The approach developed here could be also be applied in studies on biological responses to other mesoscale and sub-mesoscale processes in other parts of the world's oceans.

1 Introduction

The Pacific Ocean is the largest ocean on our planet, covering approximately one-third of Earth's surface. Embedded in this vast open ocean are remote islands and atolls that are a source of perturbations to the open ocean ecosystem. As winds and currents interact with island topography, they induce mesoscale processes (i.e. local upwelling, eddies) that form at the~~ir~~ downstream wake ~~downstream~~ of islands. These in turn alter vertical and horizontal fields of temperature, light, and nutrients (Eden and Timmermann, 2004; Dong et al., 2007; Hasegawa et al., 2009; De Falco et al., 2022, and references therein). In most cases, increased chlorophyll *a* concentration ([Chla], see Table 1 for definitions of all acronyms and variables used in this manuscript) is observed in the vicinity of islands, likely triggered by nutrient inputs from land and/or upwelling of nutrient-rich deep water around islands (Shiozaki et al., 2014; Gove et al., 2016; Caputi et al., 2019). This phenomenon, known as Island Mass Effect (IME), alters the growth and mortality rates of plankton species and introduces spatio-temporal heterogeneity in biogeochemical properties in the surrounding oligotrophic ocean. Signatures and

effects of these IMEs can be detected hundreds of kilometers away from islands around which they were initiated (Messié et al., 2020, 2022). The first study on IME evaluated the enhancement of carbon fixation as a measure of productivity near Oahu island (Hawaii) relative to the background ocean (BO), which was defined as the furthest station along a transect

30 (in that case, 30 km away from the island's shore; Doty and Oguri, 1956)(in that case, 30 km away from the island's shore). This approach assumed that the IME was confined to an area located between the island's shore and the location of "BO station" (Doty and Oguri, 1956). The first basin-scale study of IME used in situ chlorophyll fluorescence measurements (Dandonneau and Charpy, 1985) and showed ubiquitous enhancements of chlorophyll fluorescence in the vicinity of large islands in the western Pacific (e.g. Vanuatu, Fiji, Tonga and Samoa islands).

35 The limited accessibility to vast areas in the South Pacific Ocean make ocean color remote sensing approaches well-suited for basin-scale studies of IME. Using long term averages of [Chla] from ocean color remote sensing data (July 2002 to June 2012), Gove et al. (2016) showed that IME is a nearly-ubiquitous phenomenon across the Pacific Ocean. The authorsThey estimated the magnitude of IMEs by looking at changes in [Chla] within a ∼30 km wide band around each island's 30 m isobath, relative to BO reference pixels located just outside this band (Gove et al., 2013, 2016). In practice, this detection method uses the same

40 quantitative approach as Doty and Oguri (1956) and accurately assesses the magnitude of the [Chla] enhancement associated with IME as long as the BO reference pixels are outside the region affected by IME. This assumption is reasonable for small islands (most islands in Gove et al. (2016) were smaller than a 30 km equivalent spherical diameter) and when using multi-year averages of [Chla] that tend to highlight only locations with permanent [Chla] enhancement (see below). A more recent basin-scale study of IME aimed to capture more complex spatial heterogeneity around islands by defining a specific [Chla] contour

45 to delineate the extent of IME, allowing the detection of IME to extend further than 30 km away from the 30 m isobath (Messié et al., 2022).

Generally speaking, approaches for the detection of IME from remotely sensed [Chla] require a full or nearly full pixel data recovery over the entire study area for an accurate delineation of the extent of IME. Messié et al. (2022) used yearly and monthly averages of 4 km spatial resolution [Chla] maps for their basin-scale estimation of IME. While this temporal and

50 spatial averaging enables the production of gap-less [Chla] maps, it reduces the ability to detect fine-scale heterogeneity in space and time (Lee et al., 2018), only highlighting [Chla] enhancement observable at the same location over the time frame of the averaging period and therefore generally confined to regions directly adjacent to islands. Indeed, determining the spatial extent of the biological response of IME and its effect on the ecology and bio-geochemistry of the adjacent oligotrophic ocean is challenging due to its spatial heterogeneity and the transient nature of phytoplankton responses to perturbations (Messié et al.,

55 2020; Cassianides et al., 2020). Surface ocean properties, as observed by satellite sensors, are advected by wind and currents across a kilometer-wide pixel on a timescale of a few hours. Therefore, observations of the ocean using yearly averages only capture spatial patterns due to dominant winds and currents over this time frame, ignoring spatial and temporal heterogeneity caused by short-term wind and current variability. Thus, a more accurate quantification of IME extent and dynamics requires temporal averaging of satellite data over shorter time scales (e.g. to resolve mesoscale variability up to two weeks) and tracking

60 the evolution of IMEs over space and time using surface currents data (Cassianides et al., 2020). Ideally, daily observations of the entire global ocean would provide the necessary temporal resolution to track IMEs. In reality, satellite measurements of

Table 1. Table of notation

SPSG	South Pacific Subtropical Gyre
IME	Island Mass Effect
BO	Background Ocean
IME_M	Island Mass Effect zone delineated with the Messié et al. (2022) algorithm
IME_D	Dynamic Island Mass Effect zone delineated with the algorithm developed in this study
IME_T	Total Island Mass Effect zone delineated with the algorithm developed in this study. $IME_M + IME_D = IME_T$
BO_M	Background ocean zone relative to IME_M zone, defined as: BO_M area == IME_M area, located outside of IME_M zone, and closest to the 30 m isobath
BO_T	Background ocean zone relative to IME_T zone, defined as: BO_T area == IME_T area, located outside of IME_T zone, and closest to the 30 m isobath
$[Chla]$	Total chlorophyll a concentration ($mg.m^{-3}$)
c_{p660}	Particulate beam attenuation coefficient at 660 nm (m^{-1})
chl_min	Minimum $[Chla]$ detected in the first pixel band adjacent to the 30 m isobath (shallow pixel polygon) of each island
chl_max	Maximum $[Chla]$ detected in the first pixel band adjacent to the 30 m isobath (shallow pixel polygon) of each island
chl_{5th}	5th percentile $[Chla]$ of the IME_T predicted zone
chl_{95th}	95th percentile $[Chla]$ of the IME_T predicted zone
$\Delta[Chla]_{IME_T-BO_T}$	IME_T [Chla] enhancement: ~~computed as~~ $[Chla]_{IME_T} - [Chla]_{BO_T}$ ($mg.m^{-3}$)
$\Delta[Chla]_{IME_M-BO_M}$	IME_M [Chla] enhancement: ~~computed as~~ $[Chla]_{IME_M} - [Chla]_{BO_M}$ ($mg.m^{-3}$)
$\sum[Chla]_{IME_T}$	IME_T surface-area integrated~~surface-integrated~~ [Chla] ($mg.m^{-1}$)
$\sum[Chla]_{IME_M}$	IME_M surface-area integrated~~surface-integrated~~ [Chla] ($mg.m^{-1}$)
$\Delta\sum[Chla]_{IME_T-BO_T}$	IME_T surface-area integrated~~surface-integrated~~ [Chla] enhancement: ~~computed as~~ $\sum[Chla]_{IME_T} - \sum[Chla]_{BO_T}$ ($mg.m^{-1}$)
$\Delta\sum[Chla]_{IME_M-BO_M}$	IME_M surface-area integrated~~surface-integrated~~ [Chla] enhancement: ~~computed as~~ $\sum[Chla]_{IME_M} - \sum[Chla]_{BO_M}$ ($mg.m^{-1}$)
$\underline{SEM^f_{[Chla]_{IME_T}}}$	Standard error of mean associated with $[Chla]_{IME_T}$ ($mg.m^{-3}$; see appendix B)
$SEM^f_{\Delta[Chla]_{IME_T-BO_T}}$	Standard error of mean associated with $\underline{\Delta[Chla]_{IME_T-BO_T}}$~~$\sum[Chla]_{IME_T-BO_T}$~~ ($mg.m^{-3}$; see appendix B)
$SEM^f_{\Delta\sum[Chla]_{IME_T-BO_T}}$	Standard error of mean associated with $\Delta\sum[Chla]_{IME_T-BO_T}$ ($mg.m^{-1}$; see appendix B)

the ocean surface in visible and near-infrared wavelengths are often obstructed by clouds or affected by sun-glint, limiting the extent of data recovery at the necessary temporal scales.

Here, we present a method to increase satellite data recovery to improve spatial and temporal resolution of satellite observa-
tions by merging products from up to five different satellite sensors and using an atmospheric correction that is less sensitive to
glint and adjacency effect. These merged products reveal frequent occurrences of higher [Chla] patches that are detached from
islands and advected offshore (referred to as "delayed IME" in Messié et al., 2020). The higher temporal resolution achieved
allows a more accurate estimation of [Chla] accumulation as a proxy for phytoplankton biomass accumulation (termed as
"blooms") associated with IMEs. Building upon the work of Messié et al. (2022), we integrate modeled~~modelled~~ surface cur-
rents to develop a dynamic algorithm for the detection of IME. We applied this algorithm to four island groups in the South
Pacific Ocean (i.e. Rapa Nui, Society Islands, Samoa, and Fiji) over a six-month period and show that accounting for detached
patches significantly increases estimates of total [Chla] stocks associated with IME in the area of study. This implies that IME
has a much larger impact on the oligotrophic ocean than previously estimated.

2 Method

2.1 Level-2 ~~Level-3 multi~~-satellite products computation~~composites~~

The use of a single satellite sensor often results in maps with significant gaps in data due to intermittent cloud cover or
glint (which depends on satellite-specific viewing angle). To address this, we have adapted NASA Ocean Color's process-
ing strategy to produce level 3 custom-made composite products from level-1A (L1A) top-of-the-atmosphere radiance. We
merged data collected by three different sensor types (Moderate Resolution Imaging Spectroradiometer - MODIS, Visible
Infrared Imaging Radiometer Suite - VIIRS, and Ocean and Land Colour Instrument - OLCI) onboard up to six~~five~~ polar-
orbiting satellites (Aqua, Terra, SNPP, JPSS1, Sentinel-3a, and 3b). By taking advantage of their different overpass times,
swaths, and viewing geometry, we decreased the impact of clouds and glint on data recovery. Additionally, we applied the
POLYMER atmospheric correction (Steinmetz et al., 2011) to further improve data recovery in areas impacted by glint and
adjacency effect (e.g. close to shore and clouds~~, see Steinmetz et al., 2011~~). POLYMER is an atmospheric correction based on
a spectral matching method to decompose the top of the atmosphere (TOA) signal into an atmospheric model and an ocean
reflectance model. A three-term polynomial fit is used to model the atmospheric reflectance with the first term accounting for
non-spectral scattering such as sun glint, and the last term accounting for adjacency effect from clouds and white surfaces
(Steinmetz et al., 2011). By utilizing the entire TOA spectrum and accounting for adjacency effects and residual glint in its
polynomial fit terms, this method improves the retrieval of high-quality data around clouds and from pixels affected by sun glint
compared to standard atmospheric correction methods (Frouin et al., 2009, 2012). The POLYMER atmospheric correction was
initially developed for the Medium Resolution Imaging Spectrometer sensor (MERIS) but was adapted to produce consistent
ocean color products between MODIS, VIIRS, and OLCI sensors among others (Steinmetz and Ramon, 2018).~~The conceptual~~
~~diagram of the processing pipeline, from level-1 to level-3, is shown in Fig. A1.~~
Most operational level-3 products are available at spatial resolutions of 4 or 9 km. While this resolution is usually sufficient
to capture important mesoscale spatial features in the open ocean, it does not resolve sub-mesoscale features like fronts, small
eddies, and filaments around islands. Additionally, bottom reflectance in coastal waters prevents data recovery closer than 4

or 9 km from shore at these spatial resolutions. Moreover, it is a common practice in coastal studies to remove at least one neighboring pixel around shallow areas to limit the impact of adjacency effects and ensure no contamination from bottom reflectance. Therefore, the closest data recovered with a 4 km spatial resolution is most often centered at least 6 km away from the 30 m isobaths. However, most islands in the ocean are smaller than 2 km^2. For instance, the median island area in the 2593 km x 2593 km region analyzed around the Fiji Archipelago is ~0.06 km^2 with ~ 86% of all islands smaller than 2 km^2. Therefore, having the closest pixel 6 km away from shore, and a pixel size that is at least twice the size of ~ 86% of islands, limits our ability to accurately quantify their IME (see example around Niue island Fig. A2). With the approach presented here, we can maximize data recovery close to shore while keeping the nominal resolution of 1 km of the operational MODIS and VIIRS level-2 (L2) products. Ideally, we would produce this type of multi-satellite composite for the entire Pacific Ocean, but we had to limit our study area to four case-studies around islands of interest due to computational and data storage capacity limitations. In each case, the maps were large enough (i.e. > 1200 km x 1200 km area) to capture the full extent of the IME around the group of islands studied and were limited to a maximum size of 2600 km x 2600 km area.

2.1.1 Level-3 satellite products computation

All analyses for this study were conducted using the University of Maine's high-performance Linux computing cluster following the processing pipeline shown in Fig. A1. We downloaded level-1 (L1A) top-of-the-atmosphere radiance of MODIS-Aqua, MODIS-Terra, VIIRS-SNPP, and VIIRS-JPSS1 via NASA's common metadata repository application programming interface (CMR API), and and the resampled 1 km spatial resolution OLCI-S3a and OLCI-S3b data via the Copernicus Data Space Catalogue API using the Python download utility "getOC" (see reference for GitHub: Haëntjens and Bourdin, 2017). We built two sets of satellite data. We downloaded the first set of images along the entire *Tara* Pacific transect (May 2016 to October 2018 see Gorsky et al., 2019; Lombard et al., 2023) and used it to compute sensor specific calibration coefficients based on correlation with continuous in situ data (see section 2.2). We refer to it as the 'calibration dataset'. The second set of images, referred to as the 'study dataset', consisted of six-month long time-series of satellite images in the vicinity of islands of interestall MODIS and VIIRS level-1 (L1A) images in the vicinity of islands of interest from the Ocean Color repository, and OLCI level-1 images from the Copernicus repository. We processed all downloadedthese L1A images into atmospherically corrected level-2 remote sensing reflectance (R_{rs}) data using the POLYMER algorithm (version v4.17beta2; Steinmetz, 2023) and ancillary data from the European Centre for Medium-Range Weather Forecasts reanalysis model version 5 model (i.e. ERA5). We removed bad quality data pixels by applying the flags and recommendations of POLYMER (see reference POLYMER flags)(Steinmetz et al., 2011). For comparison, we also generated the standard NASA R_{rs} using the atmospheric correction of SeaDAS (i.e. "l2gen") using the Ocean Color Science Software (OCSSW) V2022.3, and applying the Ocean Color default flags (see reference NASA OBPG flags). Subsequently, we projected each satellite image of the study dataset onto the same equally spaced 1 km spatial resolution plate-carré reference grid specific to each studied region using nearest-neighbor interpolations from Python's SciPy library. We estimated [Chla] from all POLYMER and l2gen R_{rs} data using the OCx algorithm (i.e. chl_ocx; O'Reilly and Werdell, 2019) and the CI-OCx

blended algorithm (i.e. chlor_a; Hu et al., 2019; O'Reilly and Werdell, 2019).~~Subsequently, we projected each satellite image onto the same equally spaced one kilometer spatial resolution plate-carré reference grid using nearest-neighbor interpolation. We estimated [Chla] using the CI-OCx blended algorithm based on the most recent update of the color index algorithm~~

135 ~~(Hu et al., 2019) and the OCx algorithm (O'Reilly and Werdell, 2019). We computed surface-area integrated~~surface-integrated ~~[Chla] as a metric for two dimensional phytoplankton biomass in metric tons of Chla per depth meter~~ ($mt.m^{-1}$) ~~by summing the [Chla] of each pixel within a predefined zone (i.e. here, the zone influenced by IME) multiplied by the area of that pixel:~~

$$\sum[Chla]_{IME} = \sum_{n=1}^{N_{pixel_{IME}}} [Chla]_n \times area_{pixel_n} \tag{1}$$

140 ~~**2.1.2 In situ data**~~

2.2 In situ data and match-ups

We calibrated remote sensing products to minimize inter-sensor variability and biases using in situ data collected during the *Tara* Pacific Expedition (Gorsky et al., 2019; Lombard et al., 2023). We measured hyperspectral~~hyper-spectral~~ absorption (a) and attenuation (c) quasi-continuously near islands with a SeaBird ACs spectrophotometer mounted in an underway flow-

145 through system. We computed particulate absorption and attenuation coefficients (i.e., a_p and c_p) by referencing these sensor measurements to hourly samples taken through a 0.2μm filter (Dall'Olmo et al., 2009; Slade et al., 2010; Boss et al., 2019). Particulate beam attenuation at 660 nm (c_{p660}) was used as a proxy for particulate organic carbon (Gardner et al., 2006; Cetinić et al., 2012). We estimated absorption specific to Chla-containing~~[Chla]-containing~~ particles using the line-height of the a_p peak at 676 nm (a_{p676LH}; Boss et al., 2013). We collected surface samples daily around 10:30 am local time for pigment

150 analysis via high-pressure liquid chromatography (HPLC; see Gorsky et al., 2019; Lombard et al., 2023). We then estimated [Chla] from a_p by applying the well-constrained linear relationship between the logarithm of a_{p676LH} amplitude and the logarithm of total [Chla] estimated from HPLC (Fig. B2.a).

~~**2.1.3 In situ and satellite match-ups**~~

155

We performed match-ups between the calibrated [Chla] estimated from the underway system and the [Chla] estimated from satellites to choose the best algorithm (i.e. least noisy or biased) to compute [Chla] from satellite R_{rs}. ~~We downloaded L1A top-of-the-atmosphere radiance from MODIS-Aqua, MODIS-Terra, VIIRS-SNPP, VIIRS-JPSS1, OLCI-S3a, and OLCI-S3b along the entire *Tara* Pacific transect (May 2016 to October 2018 see Gorsky et al., 2019) with the python download utility~~

160 ~~"getOC" (https://github.com/OceanOptics/getOC) and processed them into atmospherically corrected level-2 R_{rs}. We then derived products following the same scheme as the level-3 products aforementioned but without re-projecting, nudging, or merging the products to keep each satellite's native resolution (Fig. A1). For comparison, we also generated the standard NASA R_{rs} using the atmospheric correction of SeaDAS (i.e. "l2gen") using the Ocean Color processor (OCSSW) V2022.3. We then estimated [Chla] from these R_{rs} using the same blended CI-OCx algorithm (i.e. chlor_a; Hu et al., 2019) and the simple OCx~~

165 algorithm (i.e. chl_ocx; O'Reilly and Werdell, 2019). We matched thesethree different [Chla] products (i.e. chlor_a_polymer, chl_ocx_seadas, chlor_a_seadas) with the calibrated [Chla] estimated from the underway system following Bailey and Werdell (2006). We extracted and averaged underway [Chla] measurements within a ±3-hour period of each satellite overpass (i.e. Aqua and SNPP 13:30, Terra 10:30, Sentinel 3a and 3b 10:00, JPSS1 14:20 local time at the equator), and satellite data from the 25 closest pixels to underway data locations, following the application of recommended Level-2 masks. We computed

170 median coefficients of variation of R_{rs}normalized water-leaving radiance (nLw) for bands between 412 and 555 nm and for the aerosol optical thickness at 865 nm for each match-up and tested several homogeneity thresholds and minimum number of unmasked pixels to maximize the number of valid match-ups without introducing noise to the in situ-satellite correlations (Bailey and Werdell, 2006). Only match-ups with a minimum of 7 unmasked pixels and coefficients of variation lower than 0.15 were kept (Fig. B2 b, c, and d). We compared the parameters of the robust linear regressions of valid match-ups to

175 choose for the best [Chla] derivation methods (Table B1). We found 33% more valid match-ups with [Chla] computed using POLYMER R_{rs} (N = 428) than valid match-ups with [Chla] computed using SeaDAS R_{rs} (N = 321). [Chla] computed with the blended CI-OCx using POLYMER R_{rs} showed, on average, the highest coefficient of determination ($\overline{R^2}_{chlor\_a\_polymer} = 0.78 \pm 0.05$), slopes closest to 1 ($\overline{slope}_{chlor\_a\_polymer} = 0.99 \pm 0.10$), and intercepts closest to 0 ($\overline{intercept}_{chlor\_a\_polymer} = -0.06 \pm 0.10$) when compared to in situ [Chla]. In contrast, the normalized root mean square error of the correlation between

180 in situ [Chla] and [Chla] computed with the blended CI-OCx using POLYMER R_{rs} ($\overline{nRMSE}_{chlor\_a\_polymer} = 21.81 \pm 6.34\%$) was higher than with the other two [Chla] computed using SeaDAS R_{rs} ($\overline{nRMSE}_{chlor\_a\_seadas} = 16.55 \pm 1.70\%$ and $\overline{nRMSE}_{chl\_ocx\_seadas} = 20.94 \pm 3.18\%$). Considering the smaller bias (slope closer to 1 and intercept closer to 0) and better data recovery (higher number of valid match-up) associated with the computation of [Chla] with the blended CI-OCx algorithm applied on POLYMER R_{rs}, we choose this method for the rest of the analysis to minimize differences between sensors while

185 maximizing valid pixel recovery. Despite the well-documented degradation of the MODIS sensor onboard the Terra satellite and its potential impact on climate studies (Lyapustin et al., 2014; Xiong et al., 2019; Xiong and Butler, 2020), our analysis found no significant indication of reduced data quality in [Chla] estimates derived from MODIS-Terra R_{rs}. Correlations between in situ [Chla] and MODIS-Terra-derived [Chla] showed performance metrics (R^2, $nRMSE$, slope, and intercept) comparable to those of other satellite sensors used in this study (Table B1 and Fig. B2 b, c, and d). These findings suggest that the extensive

190 correction and calibration efforts applied to MODIS-Terra data effectively mitigate the impacts of solar diffuser degradation, changes in scan mirror reflectance, and increased polarization sensitivity (Lyapustin et al., 2014). As a result, MODIS-Terra data can be reliably incorporated into the multi-satellite merged product used in this study.

2.1.4 Satellite products adjustment and merging

195 ### 2.3   Level-3 multi-satellite products merging

We followed a similar merging strategy to that of Copernicus' multi-satellite Global Ocean Colour processor (i.e. GlobColour): each sensor's satellite product was derived separately before merging them (Garnesson et al., 2019), rather than the strategy of the Ocean-Colour Climate Change Initiative (i.e. OC-CCI) which mergesmerging reflectances before calculating the products

(Sathyendranath et al., 2019). This method offers two important advantages:; (1) it does not require any band shifting procedure to merge R_{rs} between sensors with different spectral bands~~simulations of the 510 nm band, which are not available on VIIRS and MODIS~~, and (2) it benefits from sensor-specific algorithm coefficients that account for variability in R_{rs} across sensors to produce consistent products (Garnesson et al., 2019). To improve consistency and minimize the differences across satellite sensors, we individually calibrated the [Chla] data from each sensor with the underway in situ [Chla] measurements (using parameters from their respective robust linear regressions, see Table B1) to produce "calibrated" products before merging them. This nudging method reduced the inter-satellite variability and improved the spatial smoothness of the binned products. Since [Chla] was calibrated to in situ data, the bias associated with the estimation of [Chla] from each satellite was centered, and likely reduced, to the bias of in situ data. For each study area, we binned the calibrated data temporally to reconstruct full satellite images. Time-series of 8-day periods~~medians~~ were the smallest temporal binning we could achieve to recover nearly full satellite images in all the studied regions for six-month long time-series. Before computing the merged products~~median~~ of a given 8-day period and a given region, we grouped all re-projected level-2 images and removed outliers (see appendix C). To minimize the weight of outliers on the end level-3 products, the binning was performed with medians instead of averages. We produced a six-month long time-series of level-3 8-day medians of [Chla] for each of the four case-studies presented here. Each case-study region was centered geographically on an island sampled during the *Tara* Pacific Expedition, and each six-month time-series was centered temporally on the day of in situ sampling (Gorsky et al., 2019; Lombard et al., 2023). We propagated errors associated with [Chla] estimation, nudging, and merging throughout each step to represent the final [Chla] uncertainty denoted as the standard error of mean (i.e. SEM) of the merged product ($SEM^{f}_{[Chla]_{IME}}$; see appendix B). We used this final uncertainty to determine if the [Chla] enhancement associated with an IME was significant or not.

2.1.5 Spatial resolution ~~Most operational level-3 products are available at spatial resolutions of 4 or 9 km. While this resolution is usually sufficient to capture important mesoscale spatial features in the open ocean, it does not resolve sub-mesoscale features like fronts, small eddies, and filaments around islands. Additionally, bottom reflectance in coastal waters prevents data recovery closer than 4 and 9 km from shore at these spatial resolutions. Moreover, it is a common practice in coastal studies to remove at least one neighboring pixel around shallow areas to limit the impact of adjacency effects and ensure no contamination from bottom reflectance. Therefore, the closest data recovered with a 4 km spatial resolution is most often centered at least 6 km away from all 30 m isobaths. However, most islands in the ocean are smaller than 2 km^2. For instance, the median island area in the 2593 km x 2593 km region analyzed around the Fiji Archipelago is ~0.06 km^2 with ~86% of all islands smaller than 2 km^2. Therefore, having the closest pixel 6 km away from shore, and a pixel size that is at least twice the size of ~86% of islands, limits our ability to accurately quantify their IME (see example around Niue island Fig. A2). With the approach presented here, we can maximize data recovery close to shore while keeping the nominal resolution of 1 km of the operational MODIS and VIIRS level-2 (L2) products. Ideally, we would produce this type of multi-satellite composite for the entire Pacific Ocean, but we had to limit our study area to four case-studies around islands of interest due to computational and data storage capacity limitations. In each case, the maps were large enough (i.e. > 1200 km x 1200 km area) to capture the full extent of the IME around the group of islands studied and were limited to a maximum size of 2600 km x 2600 km area.~~

2.4 Island Mass Effect Detection

2.4.1 Bathymetry, island, and submerged reef databases

We created masks at 1 kmone kilometer spatial resolution denoting land (land mask) and areas shallower than 30 m depth (shallow mask) for the studied areas using the General Bathymetric Chart of the Oceans (GEBCO) database (GEBCO Bathymetric Compilation Group, 2022). Since a large number of islands and reefs are smaller than the spatial resolution of the GEBCO database (i.e. 15 arc-seconds corresponding to 463 m at the equator), we utilized the 30 m spatial resolution global island database (Sayre et al., 2019, 2020) to refine the land and shallow masks for the study areas. We then extended the shallow mask by one additional pixel to ensure all shallow pixels are masked. Subsequently, we merged the global island database and the submerged reef database from Messié et al. (2022) into a single database. To ensure accuracy, we automatically verified all island centroids to confirm their alignment with a land pixel on the land mask and to ensure their associated land polygon was not significantly smaller than the reported island area in the global island database. Similarly, we automatically checked all submerged reef centroids to confirm their alignment with a shallow mask pixel and to ensure their associated shallow mask polygons were not significantly smaller than the reported reef area in the Messié et al. (2022) database. We manually corrected any discrepancies that were identified when comparing to the bathymetry data and saved the corrections for reference. For simplicity, the term "islands" in this study also refers to submerged seamounts or reefs shallower than 30 m depth.

2.4.2 IME contour delineation

The [Chla] contour value delineating the IME was determined in three successive steps to dynamically detect detached IME patches. The first step used the method from Messié et al. (2022) to detect IMEs on each 8-day composite map of the time-series (see Fig. 1.a: step 1). This method defines the [Chla] contour value with an iterative process starting from the highest (chl_max) to the lowest [Chla] (chl_min) values detected one pixel away from the 30 m isobath of each island and ending when a set of specified conditions were met. These conditions include: (1) when [Chla] values fall below chl_min, (2) when the IME mask touches the domain borders or a continent masks, and (3) when regions with [Chla] exceeding 80% of the chl_max are detected farther than 150 km away from the 30 m isobath. This 150 km threshold was set to allow for the detection of water masses that were detached from an island and advected offshore (denoted as "detached IMEs") but, at the same time, to prevent potential bias by accounting for non-IME related [Chla] variability far from the island. We observed that this algorithm performed well when the IME is directly adjacent to the 30m isobath of an island and when the IME is spatially homogeneous, with the highest [Chla] values typically located near the island and decreasing with distance from shore (similar to the IME detected on monthly or yearly satellite averages; Messié et al., 2022). Therefore, this method is valuable as the first step for detecting the strongest IME signal that surrounds an island, referred to in this study as IME_M (Fig. 1.a: step 1). However, this approach underestimates the entire extent of an IME when applied on 8-day [Chla] products because it fails to detect elevated [Chla] patches that have been detached from their originating IME or when pixels with $[Chla] > 0.8 * chl\_max$ were detected more than 150 km from the island of origin. Detached IMEs, typically comprised of dynamic filaments and eddies that are quickly advected away from

islands, are detectable on 8-day averaged satellite products, but often not captured using monthly or yearly averages such as the products used by Messié et al. (2022). We therefore extended the method proposed by Messié et al. (2022) by adding another set of detection protocols, here called step 2 and step 3. We utilized modeled daily surface currents (i.e. global ocean ensemble physics reanalysis products provided by Copernicus Marine Services; European Union-Copernicus Marine Service (2019)) to predict the general locations of IME patches that detach from islands (Fig. 1 step 2). For clarity, we refer to the detached IME area obtained with this approach as IME_D (Fig. 1 step 3). The sum of both IME_M and IME_D areas (i.e. total IME) is referred to as IME_T. The following sequence was applied to detect IMEs in each 8-day median composite of the time-series (Fig. 1):

Step 1: Detection of IME_M (Messié et al., 2022, Fig. 1.a).

Step 2: Prediction of the general location of IME_D by applying the average current u and v vectors from the previous 8-day period (t = -1) to the location of IME_T detected at t = -1 (Fig. 1.d). When step 2 is performed on the first 8-day median of the time-series (t = 0), the surface current at t = 0 is applied to the IME_M detected at t = 0 instead (Fig. 1.b).

Step 3: Delineation of IME_D and IME_T using a second round of [Chla] value iteration ranging from the 95th to the 5th percentiles of [Chla] measured within the predicted zone and only keeping the patches that overlap with the predicted zone location as explained below.
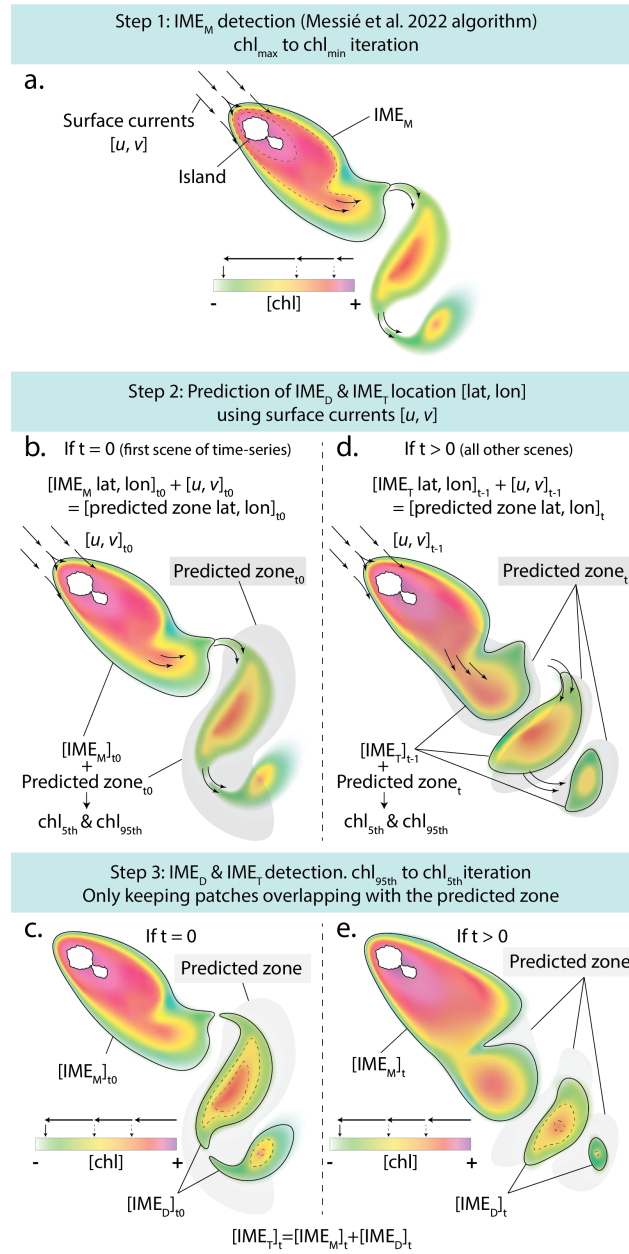
Figure 1. Island mass effect detection method. **a.** Step 1: $[\text{IME}_M]_{t_0}$ detection following the method from Messié et al. (2022), **b.** step 2 at t = 0 (first image of the time-series): prediction of the detached IME ($[\text{IME}_D]_{t_0}$) location applying t_0 surface currents ($[u,v]_{t_0}$) to $[\text{IME}_M]_{t_0}$ location, **c.** step 3 at t = 0: detached IME contour detection ($[\text{IME}_D]_{t_0}$) iterating from the 95th to 5th percentile of [Chla] (chl_{95th} and chl_{5th} respectively) detected within the $[\text{IME}_M]_{t_0}$ and the t_0 predicted zone, **d.** step 2 at t > 0 (rest of the time-series): prediction of $[\text{IME}_D]_t$ location applying t_{-1} surface currents ($[u,v]_{t_{-1}}$) to the total IME location detected on the previous image ($[\text{IME}_T]_{t_{-1}}$), **e.** step 3 at t > 0: $[\text{IME}_D]_t$ contour detection iterating from chl_{95th} and chl_{5th} detected within the $[\text{IME}_T]_{t_{-1}}$ and the t predicted zone.

Step 3 of the detection involves a second round of [Chla] iteration which is based on the IME_M detection method but adapted to the higher resolution satellite composites. First, we modified the detection of the [Chla] range, defining the range of iteration for a given IME, to better capture the dynamic range in [Chla] of the entire IME while avoiding potential biases in pixels adjacent to the island due to bottom reflectance and adjacency effect. We performed the [Chla] iteration from the 95th to the 5th [Chla] percentiles of the entire predicted zone (chl_{95th} and chl_{5th}) instead of performing the [Chla] iteration from chl_max to chl_min of the first pixel band around the 30 m isobath of each island. Additionally, the iteration step size was automatically defined to always correspond to 30 [Chla] steps within the [Chla] range of the entire predicted zone (from chl_{95th} to chl_{5th}). The number of [Chla] iteration steps (i.e. 30 iterations) was optimized by trial and error to better detect IME around Rapa Nui, where the [Chla] dynamic range is the lowest and where a small change in [Chla] contour has the most impact on the IME surface detected. Similarly to the IME_M detection, once the [Chla] contour value was found, the iteration was performed again starting at the preceding iteration but with an iteration step size divided by 10 in order to delineate the IME patch more accurately. As a result, the [Chla] iteration step value ranged from 10^{-4} to 10^{-1} mg m^{-3} which, in low dynamic range regions, is smaller than the 10^{-3} mg m^{-3} step value used in Messié et al. (2022), and smaller than the accuracy of absolute [Chla] retrieval from satellites (10^{-1} mg m^{-3}, discussed below). This smaller [Chla] iteration step value improved the performance of the detection algorithm around islands in regions with a very low dynamic range in [Chla] (e.g. Rapa Nui). We also modified the conditions to stop the [Chla] iteration, removing the condition that stopped the [Chla] iteration when pixels with $[Chla] > 0.8 * chl\_max$ are located more than 150 km away from the studied island to allow the detection of detached IME further than 150 km away from the island (i.e. condition number 3; Messié et al., 2022). Additionally, instead of stopping the [Chla] iteration when the IME touched the domain border, the IME was considered to be exiting the domain and the iteration was stopped when, for a given [Chla] contour, more than 25% of the predicted pixel location overlapped with a chlorophyll patch touching the border. This modification improved detection of IME by tolerating a small proportion of the IME patch to be advected near the domain border while still stopping the iteration when the [Chla] contour becomes too low and includes features that are not part of the IME. We also added a condition to stop the IME_D [Chla] iteration when the IME_D [Chla] contour intersected an IME_D contour associated with another island. Finally, as in Messié et al. (2022), the BO reference zones associated with each IME zone (i.e. IME_M, IME_D, and IME_T) were defined as the area equal to the size of the corresponding IME zone but located outside of the IME zone, closest to the shallow mask (i.e. BO zone associated with IME_M denoted as BO_M and BO zone associated with IME_T denoted as BO_T, Table 1). We computed surface-area integrated [Chla] as a proxy for surface phytoplankton biomass integrated over entire IME and BO zones in two-dimensional metric tons of chlorophyll a ($mt.m^{-1}$) by summing the [Chla] of each pixel within IME and BO zones multiplied by the area of that pixel:

$$\sum [Chla]_{IME} = \sum_{n=1}^{N_{pixel_{IME}}} [Chla]_n \times area_{pixel_n} \tag{2}$$

The difference in average [Chla] and $\sum [Chla]_{IME_T}$ between the IME and their corresponding BO reference zone were computed to estimate the biomass increase associated with an IME relative to the BO (i.e. $\Delta [Chla]_{IME_T - BO_T}$ and $\Delta \sum [Chla]_{IME_T - BO_T}$ respectively). The [Chla] enhancement attributed to a given IME was deemed significant when

both the mean and integrated values were above their uncertainty, e.g. $\Delta[Chla]_{IME_T - BO_T} - SEM^f_{\Delta[Chla]_{IME_T-BO_T}} > 0$
or $\Delta \sum[Chla]_{IME_T-BO_T} - SEM^f_{\Delta \sum[Chla]_{IME_T-BO_T}} > 0$. Examples of IME zones detected on the six-month long map
time-series around Fiji/Tonga and Samoa/Niue (Fig. 2, Fig. 3 and Bourdin, 2025)(Fig. 2 and Fig. 3) show contours outlining
the IME_M (i.e. red contours), the extension of the algorithm to detect the IME_D (i.e. bluegreen contours), and their associated
320   BO_T zones (i.e. white circlesblue contours). The same analysis was performed around Rapa Nui and the Society Islands, and
are accessible at Bourdin (2025).
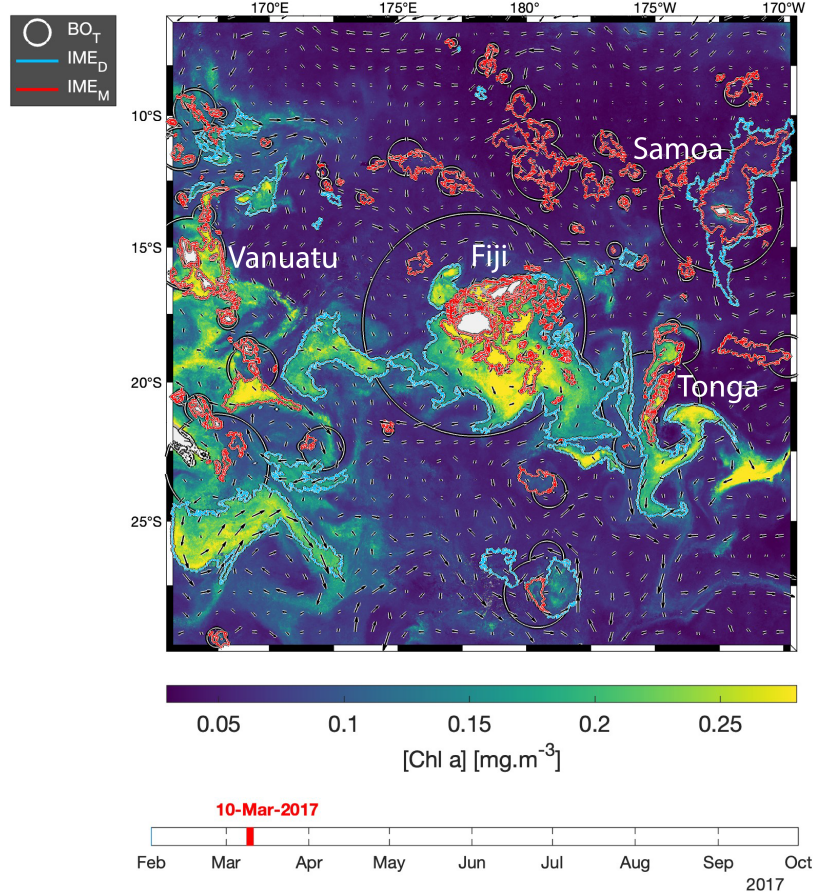
Figure 2. Snapshot of six-month long time series of 8-day multi-satellite composites of total chlorophyll *a* concentration ([Chla]) around
Fiji and Tonga archipelagos. The IME_M (Messié et al., 2022) contours are delineated in red, the IME_D contours added in this study are
delineated in bluegreen, and the BO_T zones associated with each IME_T area areis delineated with white circlesin light blue. Overlaid arrows
represent modeled surface current. Entire six-month animated time series accessible in video supplements or at Bourdin (2025).
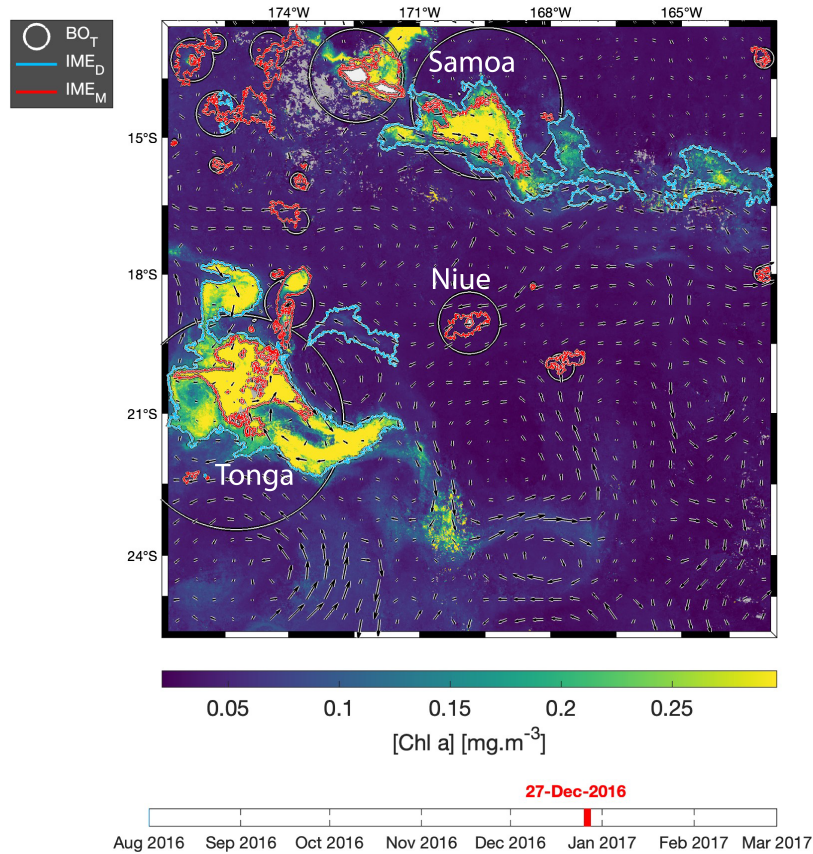
Figure 3. Snapshot of six-month long time series of 8-day multi-satellite composites of total chlorophyll *a* concentration ([Chla]) around Samoa(north of the map), Tonga(east of the map), and Niue(center of the map). The IME$_M$ (Messié et al., 2022) contours are delineated in red, the IME$_D$ contours added in this study are delineated in bluegreen, and the BO$_T$ zones associated with each IME$_T$ area areis delineated with white circlesin light blue. Overlaid arrows represent modeled surface current. Entire six-month animated time series accessible in video supplements or at Bourdin (2025).

2.4.3 Detecting IME around neighboring islands

In the case of neighboring islands, it is important to define which island, among a group of islands within a common IME$_M$ patch, contributes the most to the IME$_M$ (referred to as the "lead island"). In Messié et al. (2022), the lead island was defined as the island with the highest chl_min value detected on the first pixel band adjacent to its shallow mask polygon. In our study the 8-day median composite product maps are more spatially heterogeneous than monthly or yearly averages used in Messié et al. (2022) and therefore chl_min values may not be the best indicator to assign a lead island. Moreover, the first pixel band adjacent to the shallow mask, from which the chl_min value is extracted, is the most likely to be impacted by adjacency effect and bottom reflectance, leading to potential mis-assignment of the lead island. For example, the six-month map time-series around Fiji shows regions of enhanced [Chla] that have been advected in different directions around the archipelago with the

largest bloom always centered on Fiji's two largest islands (i.e. Viti Levu = 10912 km^2 and Vanua Levu = 5817 km^2; Fig. 2). When applying the IME_M criteria, the lead island was assigned to smaller islands (e.g. Koro Island = 105 km^2, Yalewa Kalou Island = 0.2 km^2) or to a 20 km^2 submerged reef in 19% of the realizations in this time series. Likewise, when applying the IME_M criteria on Society Islands' IME, the lead island was assigned to small islands in 24% of the 8-day frames in the time-series although the bloom was always centered on Tahiti. Based on observations of the time-series of [Chla] maps, we found that for large islands (> 100 km^2), the largest IMEs, in terms of area and magnitude [Chla], are generally located around islands with the largest land area. For that reason, in our dynamic model the lead island was reassigned after the IME_M detection (step 1; Fig. 1.a) following a different ranking (see below), which was also later used as the order of detection of the IME_D (Fig. 1 step 3). All islands of a specific study region were first sorted by 100 km^2 increments of land area categories (e.g. smaller than 100 km^2, between 100 km^2 and 200 km^2, etc.), then within each category they were further sorted by increments of 10 km^2 30 m isobath area sub-categories (representing the reef area). Thus, land area is ranked higher than reef area only when islands are larger or equal to 100 km^2. We further ranked islands within each land area category and reef area sub-category using their IME intensity based on chl_{95th} values, rounded to the closest 0.1 mg m^{-3}. Finally, islands of similar rounded land area, rounded reef area, and rounded chl_{95th} were ranked by their calculated IME_M area. The IME_T detection was performed following this ranking order, thus for a given IME_T zone encompassing multiple islands, the lead island was defined as the top ranked island in the IME_T zone. Once all IME_T detections were performed, the "lead islands" assigned by this ranking were verified to ensure that among all islands associated with a given IME_T patch, the lead island was indeed selected as the first island in the ranking previously defined. Considering the complexity of the currents around archipelagos, we acknowledge that although a single lead island was assigned to a given IME_T, the enhancement in [Chla] associated with IMEs could originate from the influence of multiple islands. For instance, the IME associated with Fiji was a combination of IMEs of all islands and submerged reefs of the archipelago which was also often mixed with the substantial IME influence of the Tonga archipelago. Therefore, IMEs of all islands and reefs associated with archipelagos were combined into "archipelagos IME", such as the "Fiji-Tonga" IME example (Fig. 2), to track the evolution of the combined IME over the six-month time-series produced (i.e. 88 islands and 140 submerged reefs; Fig. 5). Likewise, the IME_T associated with Samoa encompassed the IMEs of Savaii, Upolu, and Tutuila Islands and all the other small islands and reefs contained within the IME_T patch detected around the archipelago (i.e. 7 islands and 38 submerged reefs; Fig. 4). The IME around Society Islands in French Polynesia were also combined into one large IME that encompassed the Society Islands themselves, the Tuamotu Archipelago, and all small islands and reefs located in the large IME zone detected around Tahiti (i.e. 176 islands and 34 submerged reefs; Fig. E2). The IME_T associated with Rapa Nui encompassed Rapa Nui and Sala y Gómez islands and two submerged reefs (Fig. E1).

3   Assessment

3.1   Benefit of multi-sensor composites

Observation and tracking of water masses in the ocean from space is challenging due to glint and clouds that significantly reduce the amount of data recovered from satellite ocean color sensors. Furthermore, even without clouds or glint, uncertainties
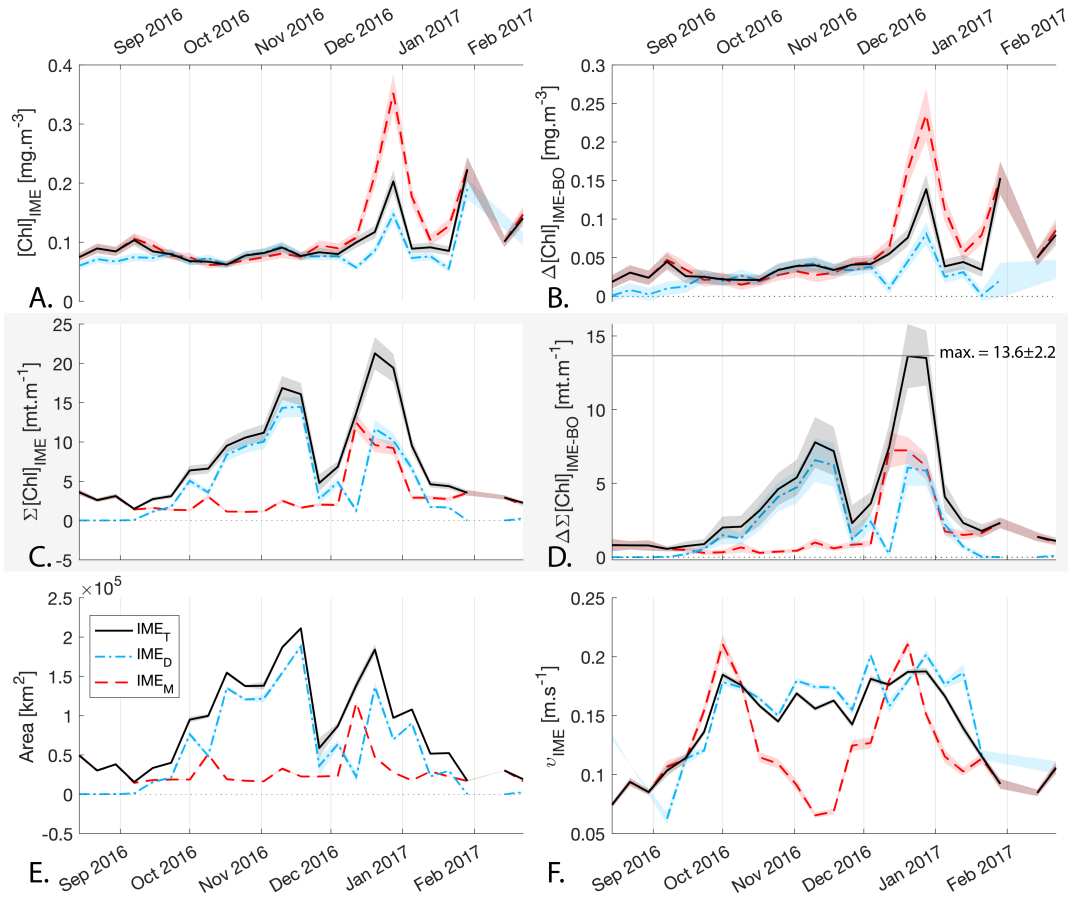
Figure 4. Six-month long time series of satellite derived IME properties of the IME zones (IME_M = red dashed line, IME_D = ~~blue green~~ blue dash-dotted line, and IME_T = black solid line) detected around Samoa (Savaii, Upolu, and Tutuila). **A:** Average chlorophyll a concentration within the IME zones ($[Chla]_{IME}$), **B:** difference in average [Chla] between each IME zones and their respective BO zones ($\Delta[Chla]_{IME-BO}$), **C:** IME surface-area integrated chlorophyll a ($\sum[Chla]_{IME}$), **D:** difference in IME and BO surface-area integrated chlorophyll a ($\Delta\sum[Chla]_{IME-BO}$)~~A and C: average of properties within the IME zones, B and D: difference between properties within each IME zones and their associated BO zones. A and B: chlorophyll a concentration ([Chla]), B and C: IME integrated chlorophyll a ($\sum[Chla]_{IME}$)~~, **E:** IME zone area, **F:** surface current velocity.

associated with satellite retrieval remain substantial mainly due to atmospheric gases (Gilerson et al., 2022). This impact is
365 even larger in oligotrophic and ultra-oligotrophic regions where less light is reflected back to the satellites by the ocean in comparison to the atmosphere. Merging data from multiple satellites with different overpass times and viewing angles offers several advantages: (1) changing cloud coverage over time may allow zones masked by clouds in the morning to be visible in the afternoon; (2) observing the ocean from varying viewing angles improves data recovery by minimizing the impact of sun-glint; (3) assuming no bias, combining data from sensors with different inherent uncertainties likely reduces the overall
370 uncertainty of the merged product; and (4) as atmospheric properties (other than clouds) change over time, merging data from
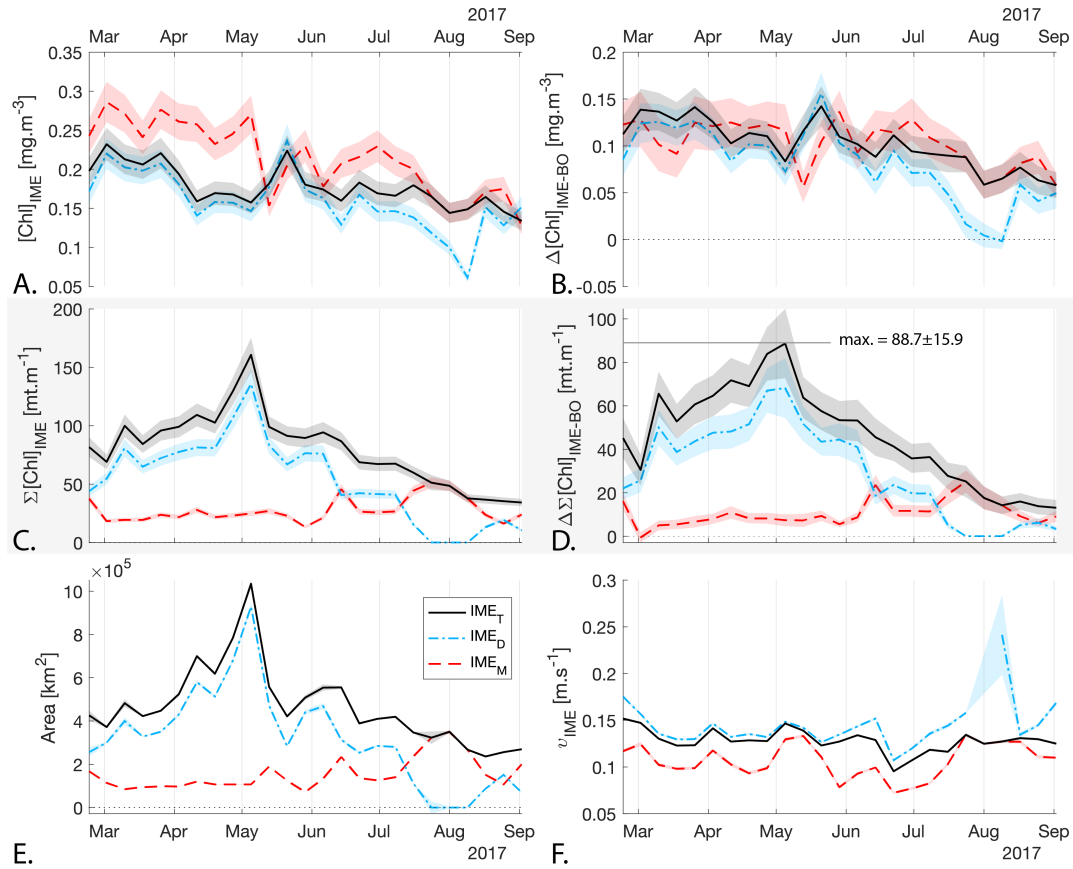
Figure 5. Six-month long time series of satellite derived IME properties of the IME zones (IME_M = red dashed line, IME_D = ~~blue green~~ blue dash-dotted line, and IME_T = black solid line) detected around Fiji and Tonga archipelagos combined. **A:** Average chlorophyll a concentration within the IME zones ($[Chla]_{IME}$), **B:** difference in average [Chla] between each IME zones and their respective BO zones ($\Delta[Chla]_{IME-BO}$), **C:** IME surface-area integrated chlorophyll a ($\sum[Chla]_{IME}$), **D:** difference in IME and BO surface-area integrated chlorophyll a ($\Delta\sum[Chla]_{IME-BO}$)~~A and C: average of properties within the IME zones, B and D: difference between properties within each IME zones and their associated BO zones. A and B: chlorophyll a concentration ([Chla]), B and C: IME integrated chlorophyll a ($\sum[Chla]_{IME}$)~~, **E:** IME zone area, **F:** surface current velocity.

multiple overpass times can further decrease the relative uncertainty of the final product. Moreover, the correction of adjacency effect and glint by the POLYMER atmospheric correction further increases data recovery and reduces uncertainties around clouds and in glint impacted areas. By merging products from multiple satellites, we maximized the amount of data available at a given time and location (~10 measurements per pixels in average for a given 8-day period). Recovery of sufficient data for binning was critical to identify and remove outliers, and obtain smooth level-3 products. ~~To further minimize the weight of outliers on the end level-3 products, the binning was performed with medians instead of averages.~~ This method allowed a

375

gap-less and smooth coverage of the zones analyzed during six month time-series at an 8-day frequency, and therefore improve the detection of sub-mesoscale currents, filaments, and eddies associated with IME.

3.2   IME detection algorithm refinement

380   Time-series of remote sensing maps (Bourdin, 2025) and their snapshots (Fig. 2, Fig. 3) reveal the complexity of currents around islands and the rather chaotic advection patterns of IME into the open-ocean and between islands (Fig. 2 and Fig. 3). The four case studies were located in the South Pacific Subtropical Gyre (SPSG) where geostrophic currents are low and mesoscale and sub-mesoscale currents interact with island topography from variable directions. In this region, the "upstream" sides of islands also show enhanced [Chla] which suggests IME water masses are advected in all directions around islands

385   (e.g. Fig. A2). Under these conditions and contrary to the assumption in Messié et al. (2022), there are generally no strict upstream pixels directly adjacent to an island. Consequently, defining the lower end of the [Chla] iteration as the minimum [Chla] detected in the first pixel band around the shallow pixel mask may result in an overestimation of the lower threshold of the [Chla] iteration, and thus an underestimation of the IME area. Therefore, to better capture the local range in [Chla] and to avoid potential remaining impact of adjacency effect and bottom reflectance on satellite retrievals, we extracted the range of the

390   [Chla] iteration from the entire predicted zone of the IME location. In addition, to improve robustness and reduce sensitivity to noise, we used the 95th to the 5th percentiles instead of the maximum and minimum [Chla] values. By construction, all IME [Chla] were higher than the [Chla] of their respective BO zones, however, while mean [Chla] of all IME_T zones were significantly higher than their BO_T counterparts (i.e. $\Delta[Chla]_{IME_T - BO_T} - uncertainty > 0$; Fig. 4, Fig. 5, Fig. E1, Fig. E2), IME_M [Chla] were not significantly higher than their BO_M counterparts in several occurrences in the eastern SPSG

395   (i.e. $\Delta[Chla]_{IME_M - BO_M} - uncertainty < 0$; Fig. E1, Fig. E2). This suggests that the larger relative uncertainty in [Chla] retrieval and the very low dynamic range in [Chla] in this region (Fig. E1) prevented accurate delineation of the entire IME zone using the [Chla] iteration step size of the IME_M algorithm. To improve IME detection in ultra-oligotrophic regions, we used a dynamic [Chla] iteration step size as a function of the regional [Chla] dynamic range instead of a fixed step size. This adaptive iteration step size resulted in a smaller step size in ultra-oligotrophic regions than the value used in Messié et al.

400   (2022), and smaller than the accuracy of [Chla] retrieval from satellites. While a 0.01 mg m^{-3} iteration step is appropriate for accurately delineating IME in mesotrophic regions (Messié et al., 2022), it represents most of the [Chla] variability of ultra-oligotrophic regions (Fig. A2). Satellite measurements may exhibit a notable relative uncertainty when retrieving absolute [Chla], particularly in oligotrophic regions. This is mostly due to the atmospheric contribution being significantly larger than the contribution of the water-leaving radiance to the top-of-atmosphere radiance measured by satellites (Gilerson et al., 2022).

405   However, given that these Pacific Ocean regions are distant from major sources of absorbing aerosols, atmospheric properties are expected to be relatively uniform within a specific satellite image (i.e. MODIS images cover 600 km^2 at the equator). Consequently, the precision of the signal necessary to delineate spatial patterns in [Chla] is expected to be higher than the accuracy of retrieved [Chla]. An advantage of this iterative method is that it does not rely on absolute values of [Chla] to delineate IME, but rather on spatial increases in [Chla] around islands. Indeed, reducing the step size of the [Chla] iteration

410 improved the performance of the detection algorithm around small islands and in ultra-oligotrophic regions where the dynamic range of [Chla] is very low (e.g. Rapa Nui).

In the current study, we adjusted the satellite measurements of [Chla] to best match in situ values and improve our confidence in accurately retrieving absolute [Chla]. We note that a similar IME delineation accuracy can be achieved, even without in situ data, by nudging [Chla] of all satellite sensors to one of them to minimize inter-sensor heterogeneity and obtain spatially

415 homogeneous composites. Even though this method may introduce a bias towards the satellite sensor chosen as reference, this bias will be equivalent to the bias associated with the use of a single satellite sensor, and, since for the detection of IME we do not rely on absolute [Chla] values, we expect to achieve a similar accuracy in mapping the extent of IME.

3.3 Detached IME detection

When quantifying IME, one challenge is to only account for [Chla] increases associated with this phenomena and not with

420 other mesoscale processes. Messié et al. (2022) solved this problem by stopping the [Chla] iteration when pixels with $[Chla] > 0.8 * chl\_max$ are located more than 150 km away from the 30m isobath of an island. When comparing IME_T and IME_M contours on the same 8-day median [Chla] products, we found that this restriction was the primary reason the IME_M algorithm underestimated the IME area. With the higher resolution time series obtained here, we show that pixels with the highest [Chla] within an IME, are heterogeneously distributed and frequently detected further than 150 km from the 30 m isobath. A

425 detection of such pixel with the IME_M algorithm will result in the termination of the iteration process before the entire IME is detected. Therefore, in this study, we adapted and improved the IME detection algorithm of Messié et al. (2022) to work with the spatial and temporal heterogeneity of our level-3 merged satellite products. We removed this aforementioned condition and minimized accounting for potential [Chla] increases due to non-IME related processes by using modeledmodelled surface currents to select and track only the high [Chla] patches that were advected away from islands and submerged reefs. We

430 nonetheless expect a potential overestimation of IME where processes not associated with IME trigger [Chla] accumulation in the surface ocean away from an island and advect this water mass from the open ocean, around an island, and towards the open ocean again downstream of the island (e.g. advection of continental coastal processes, equatorial upwelling, etc.). In these regions, clustering water masses based on more properties than just [Chla] may help differentiate between non-IME [Chla] increases and IME patches. This clustering method was initially explored in this study using Self-Organizing Maps (SOM;

435 Vesanto and Alhoniemi, 2000) to delineate IME zones based on [Chla], back-scattering coefficient (b_{bp}), SST, the ratio of [Chla] and b_{bp}, and phytoplankton physiological stress indicators (not shown). While the SOM clustering accurately delineated the IME zones in regions with sufficient dynamic range (e.g. in the western SPSG, around Fiji, or Samoa), the method often failed in the ultra-oligotrophic regions (e.g. in the eastern SPSG around Rapa Nui) where the signal-to-noise ratio of b_{bp} and the physiological stress indices were too low to delineate IME zones as accurately as the iterative [Chla] method. Therefore,

440 because this study also focuses on regions with relatively low dynamic ranges, we decided not to use the SOM clustering method; nonetheless it could be a good alternative or complement method in regions under continental or upwelling influence where the [Chla] iteration method might overestimate IME. In the four case studies presented here, the high temporal resolution products show that most, if not all, increases in [Chla] initiated close to islands or submerged reefs. The mixed layer depth in

the SPSG is almost exclusively shallower than 80 m, which is significantly shallower than the nutricline in most of the gyre

445 ($\sim$150-220 m; Longhurst, 2007; Raimbault et al., 2008). It implies that wind-driven divergence in this region generally upwells nutrient-deplete water from above the nutricline. In this context, islands and shallow submerged topography may provide the most significant perturbations in this strongly stratified system, with the potential to introduce nutrients to the euphotic zone and trigger phytoplankton blooms as large as the IME zones observed.

3.4 IME detection method validation

450 Consistent with satellite imagery, IME_M and IME_D zones were characterized by elevated underway [Chla] and c_{p660} in comparison to the BO_T zones in all four cases studied (Fig. 6, Fig. D1, Fig. D2, and Fig. D3). Both variables collected with the underway system increased steeply on the inbound transect to Fiji (left hand side panel of Fig. 6) and decreased gradually on the outbound transect (right hand side panel of Fig. 6). Southward currents were the dominant surface currents on the western side of Fiji during the 16-day period overlapping with in situ sampling. The pattern shown along the outbound transect indicates

455 the demise and/or dilution of the bloom as it was advected south of Fiji. The increase in [Chla] and c_{p660} was ubiquitous near shore and was captured by the satellite IME_T detection algorithm. In comparison, the IME_M algorithm detected the strongest [Chla] increase within IMEs (Fig. 6, Fig. D1, Fig. D2, Fig. D3) but often missed the [Chla] gradient from IME to background ocean (e.g. outbound transect from Society Islands Fig. D2), and systematically missed the IME_D (e.g. inbound transect to Samoa Fig. D3 and departure from Fiji Fig. 6).

460 3.5 Extent of IME using different algorithms

Similarly, the IME zones detected during the six-month time-series around Fiji/Tonga, Samoa/Niue, Rapa Nui, and the Society Islands (Fig. 2, Fig. 3, and Bourdin, 2025) suggest that the IME_M detection algorithm generally performs well in capturing the core of an IME as long as the associated [Chla] distribution is concentric on the island with the highest [Chla] located close to shore. In all four case studies, the IME_M algorithm generally failed to capture the full extent of the IME area at

465 8-day observation frequency (i.e. IME_M area $\ll$ IME_T area; Fig. 7 and Table 2). To compare the IME_M algorithm to the one developed here, we calculated the absolute and percent differences in mean [Chla], detected IME area, and surface-area integrated [Chla]~~surface-integrated chlorophyll a~~ ($\sum[Chla]$) derived from the two approaches applied on the same 8-day median [Chla] products (Fig. 7 and Table 2). [Chla] averages in IME_M zones were equivalent or higher than in the IME_T zones (Fig. 7 and Table 2) because the minimum value of the [Chla] used in the iteration to find the IME_T contour was always

470 lower than the minimum value used in the IME_M algorithm. Therefore, when different from the IME_T contour, the IME_M contour was always located closer to the island shore where [Chla] is generally higher than in the rest of the IME_T zone, explaining the negative differences in average [Chla] between IME_T and IME_M (Table 2, Fig 7). The area and surface-area integrated [Chla]~~surface-integrated chlorophyll a~~ were largely underestimated in IME_M in comparison to IME_T in all four case studies (Fig. 7 and Table 2). For instance, the large bloom event that developed around Fiji between March and May 2017

475 detected in the IME_T zone was not detectable in the IME_M zone. The IME_T also captured a nearly continuous increase in biomass around the Society Islands while it was only intermittently captured by the IME_M contour (Fig. 7). In each case, the
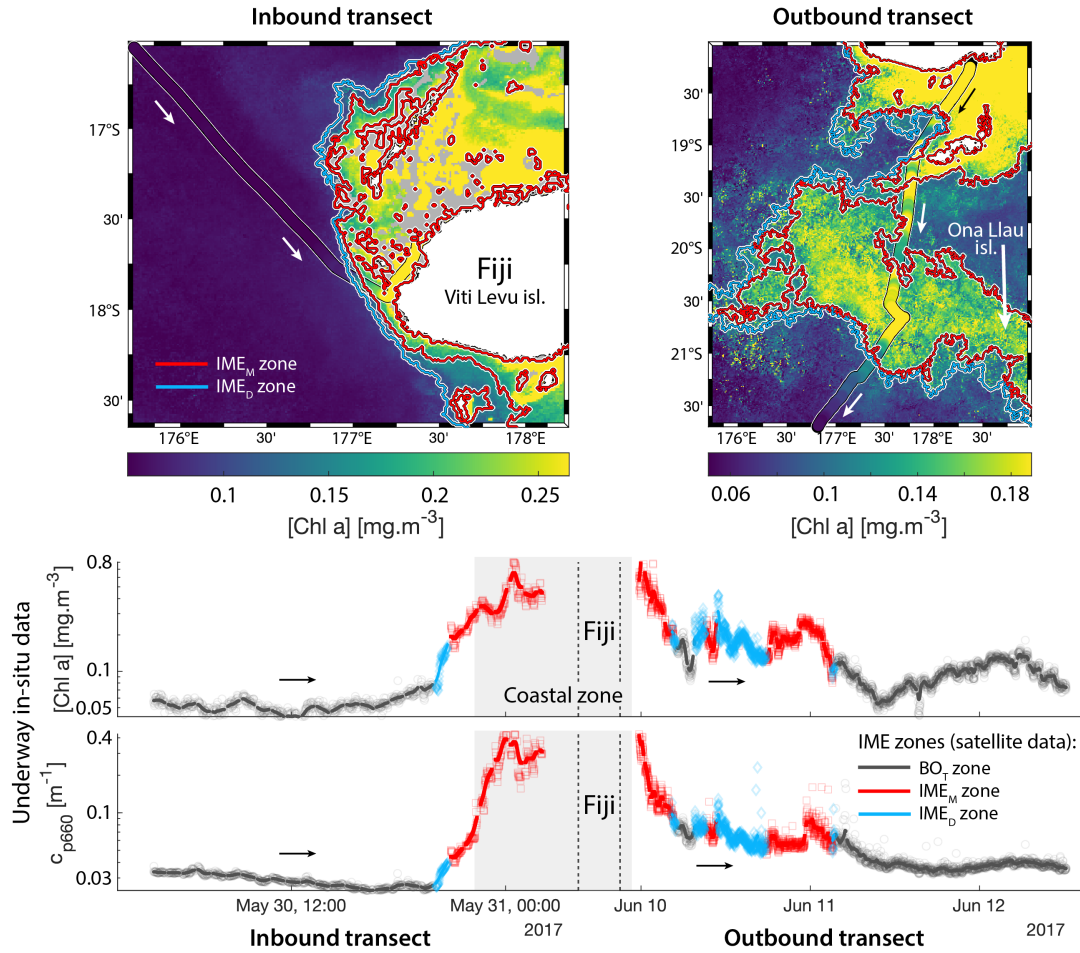
Figure 6. Validation of the extent of IME using in situ underway data around Fiji archipelago. **Top row**: 8-day median Chlorophyll *a* [Chla] at the time of sampling along the transect inbound to Fiji (top left panel) and at the time of sampling along the transect outbound from Fiji (top right panel). [Chla] measured in situ with the underway system are overlaid on the satellite data background, **middle row**: Chlorophyll a concentration ([Chla]), **bottom row**: beam attenuation at 660 nm (proxy for particulate organic carbon). Data sampled with the underway system during the transect sailing towards Fiji (**left**) and sailing away from Fiji (**right**). Data colored when located within the IME zones detected on the overlapping 8-day satellite composite (BO_T = black circle, IME_M = red square, or IME_D = bluegreen diamond). The underway data points are minute binned and the solid lines are smoothed underway data. The smoothing was performed applying a 2h low-pass digital filter to the minute binned data. The grey patch highlights the time *Tara* was sailing in coastal water (< 6 nautical miles away from a submerged reef or coast).

underestimation of IME_M compared to IME_T was variable over time, suggesting the criteria used to delineate the extent of the IME_M are sensitive to noise in a given satellite image and thus depends on the spatial smoothness of the [Chla] map used to delineate the IME_M. The modification of these criteria in the IME_T algorithm reduced its sensitivity to single pixel variability.
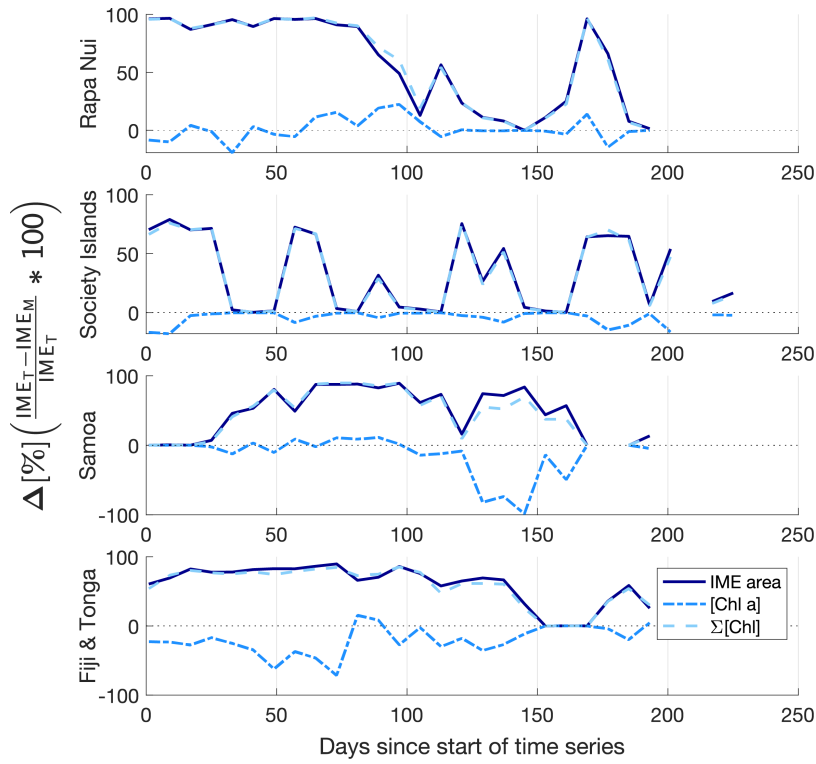
Figure 7. Differences (%) in IME area (solid line), chlorophyll ~~a~~ a concentration ([Chla]; dash-dotted line), and IME surface-area integrated [Chla]~~surface-integrated chlorophyll a~~ ($\sum[Chla]_{IME}$; dash line) estimated by the IME$_M$ and IME$_T$ algorithms for the four case studies (Rapa Nui, Society Isl., Samoa, Fiji-Tonga)

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3.6 IME quantification metric

The [Chla] enhancement associated with IME was quantified as the difference between surface-area integrated ~~surface-integrated~~ [Chla] in a given IME zone and surface-area integrated~~surface-integrated~~ [Chla] in the respective BO zone (chosen to have the same surface area, see Methods) to better represent the total Chla enhancement. In all four cases, the surface-area integrated~~surface-integrated~~ [Chla] enhancement associated with IME$_T$ relative to their BO$_T$ counterparts was significant during the entire six-month time-series (i.e. $\Delta\sum[Chla]_{IME_T-BO_T} - uncertainty > 0$) except for two 8-day occurrences around Rapa Nui.

It should be emphasized that [Chla] can be associated with large uncertainties as a measure of phytoplankton biomass due to photo-acclimation, a process of intra-cellular pigment adjustment in response to changes in light and nutrient conditions (Cullen, 1982; Geider et al., 1998). This is especially the case in regions with increased mesoscale activity and upwelling such as those adjacent to islands. When low-light adapted cells with larger intra-cellular [Chla] are upwelled to the surface, satellites can measure an apparent increase in [Chla] that is not necessarily associated with an increase in biomass (Hasegawa et al.,

Table 2. IME_M and IME_T detection methods comparison summary: six month mean and standard deviation of differences

Variables	Island group	Δ [IME_T - IME_M]	$\Delta[\%]$
	Rapa Nui	$7 \times 10^{-4} \pm 5.7 \times 10^{-3} mg.m^{-3}$	$1 \pm 10\%$
	Society Isl.	$-2.2 \times 10^{-3} \pm 3.2 \times 10^{-3} mg.m^{-3}$	-4±6%
$[Chla]_{IME}$	Samoa	$-1.7 \times 10^{-2} \pm 3.9 \times 10^{-2} mg.m^{-3}$	-14±30%
	Fiji&Tonga	$-3.6 \times 10^{-2} \pm 3.6 \times 10^{-2} mg.m^{-3}$	-21±21%
	Rapa Nui	$7 \times 10^{4} \pm 6.3 \times 10^{4} km^{2}$	$58 \pm 39\%$
	Society Isl.	$2.2 \times 10^{5} \pm 2.2 \times 10^{5} km^{2}$	33±32%
IME area	Samoa	$5.7 \times 10^{4} \pm 5.8 \times 10^{4} km^{2}$	49±35%
	Fiji&Tonga	$3.1 \times 10^{5} \pm 2.2 \times 10^{5} km^{2}$	60±28%
	Rapa Nui	$4.1 \pm 4.1 mt.m^{-1}$	$58 \pm 27\%$
	Society Isl.	$10.4 \pm 11.7 mt.m^{-1}$	32±31%
$\sum[Chla]_{IME}$	Samoa	$4.6 \pm 4.9 mt.m^{-1}$	45±34%
	Fiji&Tonga	$52.3 \pm 35.2 mt.m^{-1}$	58±27%

2008). In all case studies presented here, the increased [Chla] detected in IME zones was associated with increased c_{p660}, which is a proxy of total organic biomass (including phytoplankton biomass) that is not impacted by photo-acclimation (Behrenfeld and Boss, 2006). This observation provides confidence that detected IME zones were indeed associated with spatial increases

495 in phytoplankton biomass around islands. When investigating the ecological consequences of IME, it is important to note that both satellite data and our underway measurements only describe surface ocean properties and do not inform about the vertical distribution of biomass in IME zones. Gove et al. (2016) showed that the increase in [Chla] associated with IME propagated below the surface and suggested this increase in [Chla] represented a strong increase in biomass at depth. Although strong subsurface chlorophyll maximums (SCM) are generally measured in subtropical regions, most of the SCM signal is often due

500 to photo-acclimation to low light availability at depth and only associated with a moderate increase in biomass (Kitchen and Zaneveld, 1990; Fennel and Boss, 2003; Furuya, 1990).

3.7 The utility of capturing IME's temporal dynamics

The high temporal resolution products revealed the high spatial and temporal heterogeneity of IME and frequent connectivity between IME zones of distant islands. This dynamic IME detection method permitted tracking in time the accumulation of

505 chlorophyll *a* standing stock in surface waters, which suggested frequent temporal increases in phytoplankton biomass in addition to the spatial increase in phytoplankton biomass already detected around islands. For instance, the accumulation of integrated [Chla] in IME zones suggests the occurrence of two distinct blooms in Samoa's IME zone and a large bloom in Fiji-Tonga's IME zone. These blooms were sustained for weeks while being advected off-shore and eventually detached from the island they originated from (Fig. 2 and Fig. 3). The first one around Samoa was initiated around mid-September 2016 and was

510 advected southward towards Niue (see area and $\Delta[Chla]_{IME_T - BO_T}$ increases; Fig. 4). The integrated [Chla] of this bloom

continued to increase after the water mass detached from Samoa and persisted near Niue until the end of November 2016 (i.e. ∼10 weeks after detaching from Samoa; Fig. 3 and Fig. 4). The second bloom detected in Samoa's IME initiated around November 22nd 2016 was advected east, detaching from the archipelago and reaching a maximum surface-area integrated surface-integrated [Chla] enhancement relative to BO of 13.6 $mt.m^{-1}$ before ending around January 24th 2017 (Fig. 3, Fig.

515 4). A third bloom observed in the same region detached from Tonga and was detected more than ∼1300 km east of the island. Phytoplankton biomass can continue to accumulate in advected water masses even without an additional influx of nutrients. For example, if the rate of horizontal dilution of a bloom with its surrounding oligotrophic waters reduces encounter rates, and hence grazing pressure, phytoplankton biomass will continue to accumulate even if the remaining nutrients only support a low growth rate (as long as the growth rate exceeds the grazing rate; Lehahn et al., 2017). Interestingly, both bloom initiation events

520 detected around Samoa were synchronised with a sudden increase in the average surface current velocity within the IME_M zone. The increased current interacting with the island topography may have promoted sub-mesoscale and mesoscale mixing and the upwelling of nutrient and trace metal enriched water to the surface close to shore. The current data overlaid on the [Chla] map time-series also show increased surface current close to shore when and where each of the three blooms started to detach from their island of origin (Bourdin, 2025). This suggests that when IME water parcels were detached from their source

525 of nutrients (i.e. the island) and diluted into the surrounding oligotrophic ocean, the phytoplankton biomass in the growing patch continued to accumulate due to a reduction of grazing while using the limited nutrient supply advected with it. This dynamic emphasizes the fact that although phytoplankton blooms in IME zones are triggered by local enrichment of macro-nutrients and trace metals near islands (Messié et al., 2020, 2022; Gove et al., 2016, 2013; De Verneil et al., 2017; Hasegawa et al., 2009; Caputi et al., 2019; Palacios, 2002; Signorini et al., 1999), they are also tightly controlled by loss processes such as

530 grazing. In the case of Fiji-Tonga, the IME surface-area integrated surface-integrated [Chla] enhancement relative to the BO (i.e. $\Delta \sum [Chla]_{IME_T-BO_T}$) increased up to 88.7±15.8 $mt_{[Chla]}.m^{-1}$, covered an area up to ∼1 million km², with a longitudinal extent of ∼2000 km. The IME surface-area integrated surface-integrated [Chla] decreased from May 5th to September 2nd to finally reach pre-bloom values again in August 2017, approximately five months after the bloom initiated; Fig. 5). In contrast to the Samoa case study, no apparent increase in current speed was detected near Fiji or Tonga during the period covered by

535 the time series. In this case, the timing of this large bloom observed around the Fiji and Tonga archipelagos coincided with the annual *Trichodesmium* spp. blooms observed in this region during the austral summer (Dandonneau and Gohin, 1984; Dupouy et al., 2000). The high underwater volcanic activity characteristic of this region can supply significant amount of trace metals directly into the euphotic zoneand support these large blooms of *Trichodesmium* spp. (Bonnet et al., 2023; Guieu et al., 2018; Berman-Frank et al., 2001; Lory et al., 2022; Rubin et al., 2011). These known shallow hydrothermal vents were systematically

540 located within the detected IME zone associated with Tonga and Fiji suggesting the detected IME is likely a combined effect of islands and shallow hydrothermal vents in this region. The longer generation time of *Trichodesmium* spp., which allows surface currents to spread them horizontally, and their ability to partially escape grazing pressure may explain why these blooms can be maintained for five months and cover a significant area of ∼1 million km² (Capone et al., 1997; Messié et al., 2020). These two case studies show how the dynamic detection of IME provides information about IME phenology and about island connectivity

545 in comparison to a frozen field observation of the ocean for which all maps are independent of each other.

4 Conclusions

The method developed here describes the history of a given IME with finer resolution, and highlights dynamics that are not detectable using monthly and yearly average remote sensing products. Such a method is essential for improving our mechanistic understanding of IME (e.g. whether the cause is island runoff or upwelling) and the ecological succession within IMEs. De Falco et al. (2022) highlight the uniqueness of interactions between a given island topography and surrounding wind and current flows, suggesting that phytoplankton responses depend on these interactions. Here we show that IMEs are highly dynamic, they can induce large coherent blooms that can sustain for month while being advected more than 1000 km away from their source. These advected IMEs seed the oligotrophic ocean and other islands with water masses characterized by higher phytoplankton abundance and potentially different species composition than the surrounding oligotrophic ocean such as the *Trichodesmium* blooms in the south-west Pacific ocean. This analysis reveals a broader spatial extent of IMEs in subtropical regions, suggesting that islands have a greater impact on food web dynamics and biogeochemical processes in these areas, which are traditionally considered oligotrophic. This detection method can also be adapted to track water masses with specific optical properties being advected in upwelling regions or in river plumes. We suggest that future studies use more satellite variables than just [Chla] in regions where processes other than the one studied can cause elevated surface [Chla] to better discriminate the underlying processes.

We demonstrated the importance of using gap-less high temporal and spatial resolution satellite products and modeled surface currents to identify and track sub-mesoscale filaments and eddies associated with IME around islands in the subtropical Pacific Ocean. We minimized satellite uncertainties by augmenting the number of observations and maximized data recovery by using all available NASA and ESA polar-orbiting ocean color satellites. At the current dawn of global hyperspectral ocean color sensing, we recommend having sensors with different overpass times when planning for new ocean color satellites as part of the future constellation to help maximize coverage and understand the dynamic of mesoscale and sub-mesoscale processes in the Ocean.

Code and data availability. HPLC data is accessible on BCO-DMO repository. In situ underway optical data can be accessed on Tara Pacific SeaBASS repository. The satellite binning software package used to create custom level-3 multi-satellite products from level-2 satellite data, to remove outliers, to nudge, and propagate uncertainties is accessible at Bourdin (2024). Level-3 multi-satellite composites data, downloaded current data, the dynamic IME detection algorithm software, and its main outputs for each case study, including island databases for all region and their IME and BO masks, are available at Bourdin (2025).

Author contributions. TPC supported the collection of in situ data and logistics and G.G., F.L., and E.B. designed and coordinated in situ sampling. G.B. collected and processed underway in situ data. G.B. designed the satellite merging method and the dynamic IME detection method. G.B., L.K.B., and E.B. assessed the method and wrote the original draft. All authors have read and reviewed the manuscript.

Competing interests. The authors declare no competing interests

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Appendix A: Satellite merging pipeline

590   MODIS, VIIRS, and OLCI L1A radiance data were processed with SeaDAS l2gen and POLYMER algorithms to produce atmospherically corrected level-2 R_{rs} data. Low-quality data pixels were removed by applying the recommended atmospheric correction flags on their respective R_{rs} data. Every scene was then projected onto the same equally spaced 1 km~~one-kilometer~~ spatial resolution plate-carré reference grid using nearest-neighbor interpolation before [Chla] computation. Each satellite [Chla] were nudged to best match in situ values before merging them into 8-day median composites (Fig. A1).
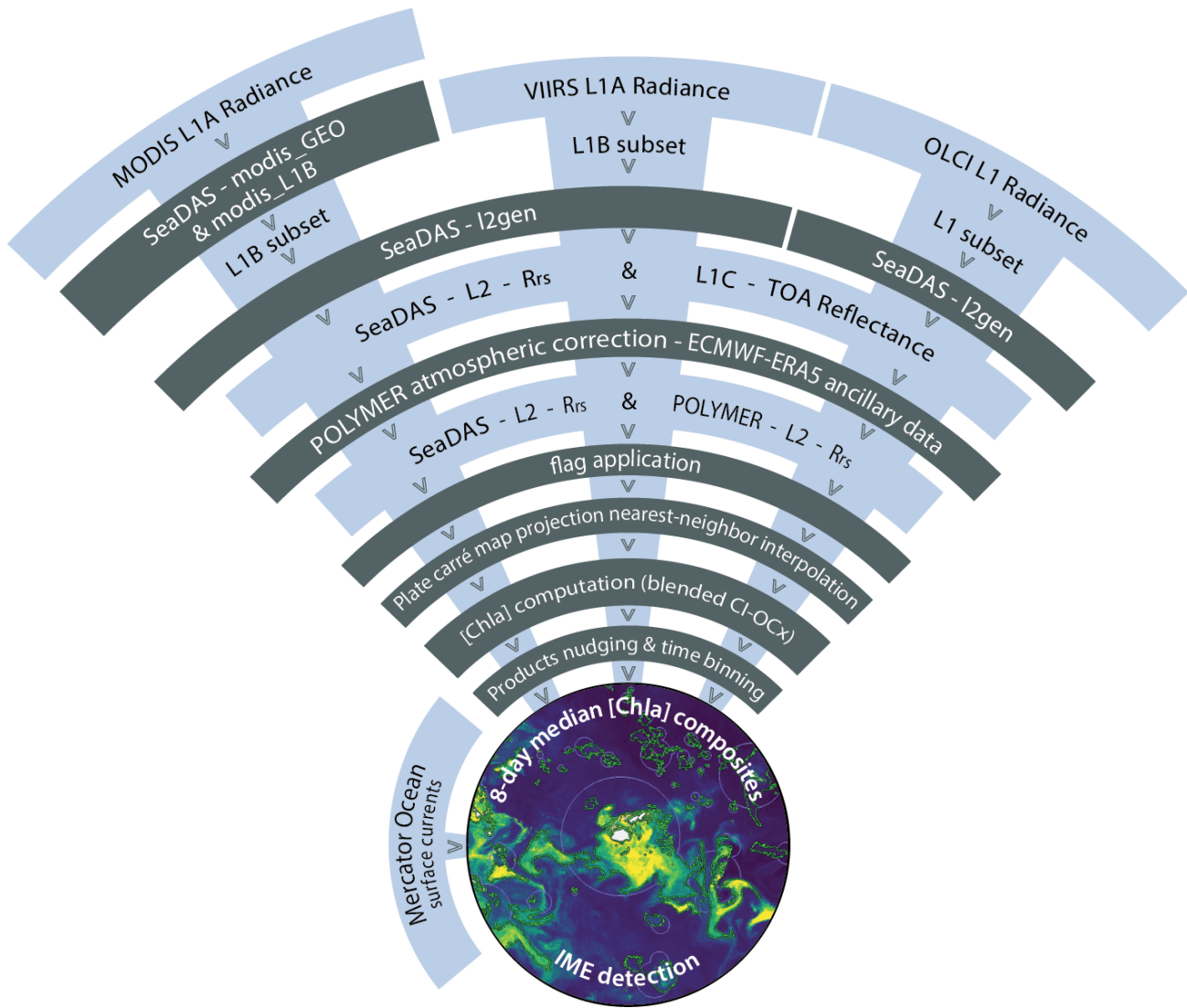
Figure A1. Satellite composite production flowchart.
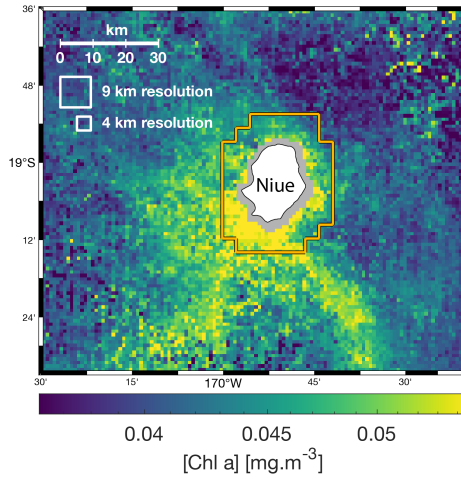
Figure A2. Multi-satellite composite of [Chla] around Niue island (2016-09-11 to 2016-09-18) at 1 km spatial resolution. The white squares represent the 4 and 9 km resolution pixel sizes of the level-3 NASA and the ~~orange~~red contour represents the shallow pixel mask at 4 km spatial resolution.

Appendix B: Uncertainty estimates

The 8-day merged products represent a composite of multiple overpasses and satellites that included $\sim$120 ocean color images (daytime) for a $\sim$2500 km^2 square region around the Fiji archipelago. Therefore, each pixel of the merged product is a median of n number of observations of the original images with standard deviations ($\sigma_{V_{bin}}$) representing the temporal variability of a variable V in a given pixel during each 8-day period and the variability between sensors after nudging. The number of non-flagged observations ($n_{V_{bin}}$) used to bin each merged pixel was generally sufficient, with 8-day long periods and an operational constellation of five to six satellites, to produce smooth merged [Chla] products. For example, the median number of non-flagged [Chla] observations used to bin each pixel was $n_{bin_{[Chla]}} = 10$ for the entire time series around Fiji, with less than 2.5% of the pixels binned with less than 3 non-flagged observations (Fig. B1).

Known uncertainties were propagated from in situ data to satellite [Chla] end-products. HPLC derived [Chla] and in situ a_p spectra were measured along track. The error associated with the computation of [Chla] from the underway system was estimated by the normalized root mean square error ($nRMSE_{udw}$ in %) of the relation between the underway chlorophyll line height (a_{p676LH}) and total [Chla] measured from HPLC during the *Tara* Pacific expedition (Fig. B2.a).

The error associated with the computation of [Chla] from satellites was estimated by the $nRMSE_{sat}$ of the relation between the underway chlorophyll line height (a_{p676LH}) and [Chla] obtained from each satellite sensor along the transect of the *Tara* Pacific expedition (Fig. B2 (b), (c), and (d)). The uncertainties of binned satellite end-products were computed as follows:

$$\sigma_V = \sqrt{\sigma_{Vbin}^2 + \sum_{n=1}^{n_c}(\tilde{V} \times nRMSE_c)^2} \tag{B1}$$
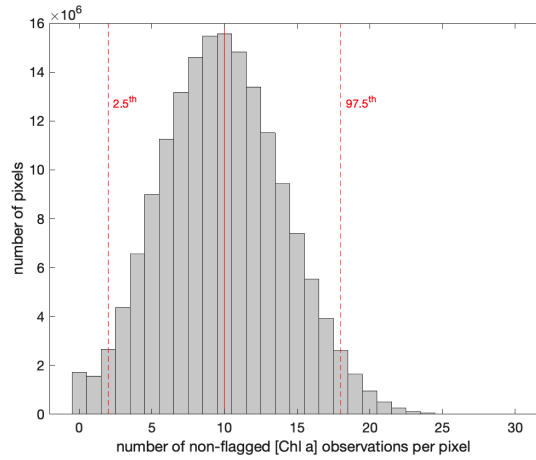
Figure B1. Distribution of the number of valid [Chla] (i.e. not flagged) observations per merged pixel over each 8-day period along the six-month time-series around the Fiji archipelago (2017-02-18 to 2017-09-05).

Table B1. Robust correlations parameters of match-ups between satellite and in situ underway data

Variables	Satellite sensor	R^2	nRMSE [%]	Slope	Intercept	N
POLYMER R_{rs} Blended CI-OCx [Chla] (chlor_a)	MODISA	0.78	24.38	1.09	-0.01	111
	MODIST	0.81	20.48	1.08	-0.01	96
	VIIRSN	0.82	16.18	0.90	-0.19	109
	VIIRSJ1	0.70	31.47	1.02	0.05	27
	OLCI	0.79	16.56	0.89	-0.13	85
SeaDAS R_{rs} Blended CI-OCx [Chla] (chlor_a)	MODISA	0.74	18.59	0.84	-0.27	85
	MODIST	0.71	16.61	0.70	-0.43	67
	VIIRSN	0.70	16.17	0.81	-0.56	92
	VIIRSJ1	0.84	17.37	1.15	0.14	22
	OLCI	0.81	13.99	1.01	-0.10	55
SeaDAS R_{rs} OCx [Chla] (chl_ocx)	MODISA	0.66	20.00	0.71	-0.32	85
	MODIST	0.67	19.30	0.75	-0.35	67
	VIIRSN	0.62	25.97	1.20	-0.50	92
	VIIRSJ1	0.74	21.76	1.36	0.19	22
	OLCI	0.70	17.65	0.80	-0.11	55

With $\tilde{V}$ the binned variable, n_c the number of calibration/correction, and $nRMSE_c$ the $nRMSE$ associated with each of the n_c correction. The standard error of the mean of the adjusted satellite end-products of each pixel were computed as follows:

$$SEM_V = \frac{\sigma_V}{\sqrt{n_{V_{bin}}}} \tag{B2}$$
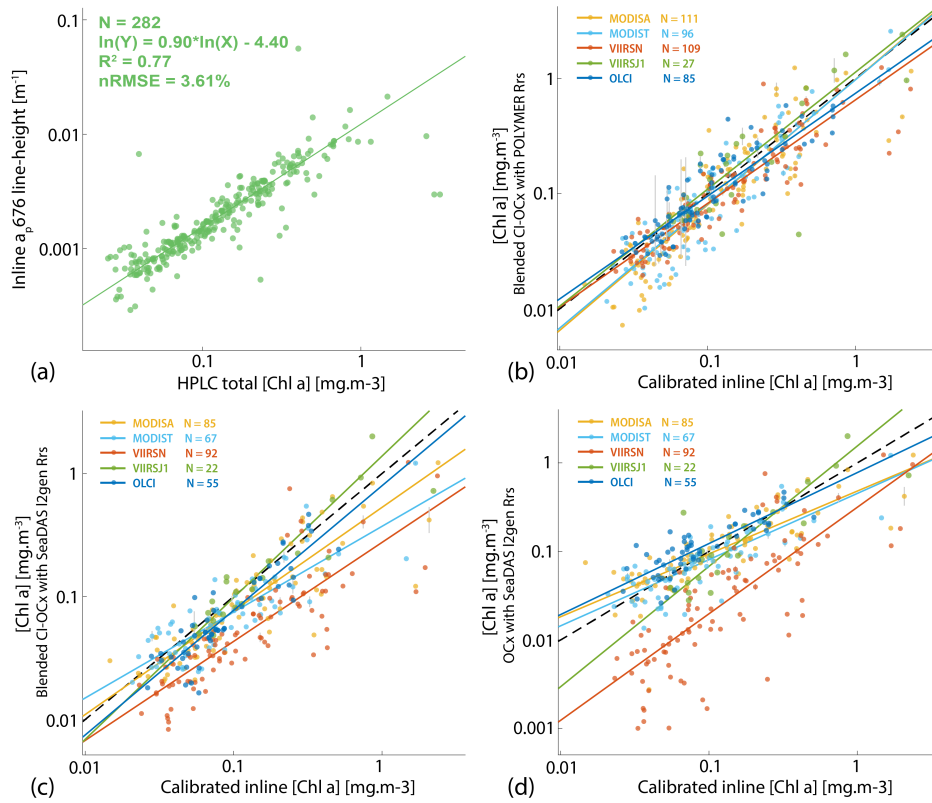
Figure B2. Robust linear regressions between [Chla] measured from HPLC and a_p Chla absorption peak at 676 nm measured from the underway system (a), and between calibrated [Chla] estimated from a_p underway measurements and [Chla] estimated from satellite data using the blended CI-OCx algorithm on POLYMER R_{rs} (b), the blended CI-OCx algorithm on l2gen R_{rs} (c), and the OCx algorithm on l2gen R_{rs} (d). In situ measurements were conducted during the *Tara* Pacific expedition (May 2016 to October 2018).

615 The final uncertainty estimate associated with [Chla] within entire IME or BO zones ($SEM^f_{[Chla]_{IME}}$) as presented in Fig. E1, Fig. E2, Fig. 4, and Fig. 5 were expressed as the average standard error of the mean of the adjusted [Chla] within entire IME or BO zones:

$$SEM^f_{[Chla]_{IME}} = \frac{\overline{\sigma}_{[Chla]_{IME}}}{\sum n_{[Chla]_{bin_{IME}}}} + S_{[Chla]_{unc}} \times \overline{[Chla]}_{IME} \tag{B3}$$

With $\sum n_{[Chla]_{bin_{IME}}}$ the total number of [Chla] observations within the IME zone before merging and $S_{[Chla]_{unc}}$ the weighted

620 bias associated with the computation of the slopes of the regressions between in situ [Chla] and each satellite [Chla] estimates. $S_{[Chla]_{unc}}$ was computed as follows:

$$S_{[Chla]_{unc}} = |1 - S_{[Chla]sat}| \times \frac{n_{M_{sat}}}{N_{M_{tot}}} \tag{B4}$$

With $S_{[Chla]sat}$ the slope of the relation between in situ [Chla] and [Chla] of a given satellite, $n_{M_{sat}}$ the number of valid match-ups of the same satellite, and $N_{M_{tot}}$ the total number of valid match-ups. $S_{[Chla]_{unc}}$ represents the maximum bias associated

with the computation of the merged satellite [Chla] which we assume to be equivalent to the potential likelihood bias of the merged satellite [Chla]. Assuming enough valid match-ups with each satellite, $S_{[Chla]_{unc}}$ is a conservative estimate of the bias associated with the slopes computation because the merging method forces each satellite [Chla] to agree with in situ data using sensor-specific corrections, which likely reduces the bias of the merged product. IME area uncertainties ($\sigma_{A_{IME}}$) were computed during the detection of the IME [Chla] contours as the difference in IME area between the last two iterations of [Chla] contours:

$$\sigma_{A_{IME}} = A_{IME_{cChl_f}} - A_{IME_{cChl_{f-1}}} \tag{B5}$$

With $A_{IME_{cChl_f}}$ the IME area at the final IME contour value and $A_{IME_{cChl_{f-1}}}$ the IME area at the previous contour value. Therefore, $\sigma_{A_{IME}}$ represents the area detection resolution associated with the size of the step of [Chla] iteration. The uncertainties associated with the estimation of IME surface-area integrated~~surface-integrated~~ [Chla] ($\sum[Chla]_{IME}$) were computed as follows:

$$SEM^f_{\sum[Chla]_{IME}} = \sum[Chla]_{IME} \times \sqrt{\left(\frac{SEM^f_{[Chla]_{IME}}}{\overline{[Chla]}_{IME}}\right)^2 + \left(\frac{\sigma_{A_{IME}}}{A_{IME}}\right)^2} \tag{B6}$$

Appendix C: Outliers removal

Bio-optical variables in the ocean, including [Chla], generally follow a log-normal distribution (Campbell, 1995) with fewer high values forming a heavy-tail in the high end of the dynamic range. After appropriate flagging, low quality data pixels impacted by sun glint, adjacency effect, and bottom reflectance are rare and account for a few pixels scattered on either end of the log-normal distribution and beyond realistic values for a given region (generally $< 1^{st}$ percentile or $\gg 99^{th}$ percentile; Fig. C1). Computing the median of these pixels can result in noisy merged products when they are the only available data over a given 8-day period and at a given location (i.e. pixel). Consequently, to improve consistency of the level-3 merged products, rare outliers of a given variable were removed from all re-projected level-2 images of a given 8-day period and a given region based on the distribution of all individual x measurements (i.e. pixels). First, we grouped all the re-projected level-2 images of a given variable, 8-day period, and region together, and applied a log normal transformation to the data:

$$x_t = \ln(x - \min(x) + 1) \tag{C1}$$

We partitioned x_t into N bins of width W defined using the Freedman-Diaconis rule that is more suited to a heavy-tailed distribution due to its low sensitivity to outliers (Freedman and Diaconis, 1981):

$$W = 2 \times \frac{IQR(x_t)}{\sqrt[3]{n}} \tag{C2}$$

Where IQR is the inter-quartile range and n is the number of observations in the data x_t. The minimum number of pixels per bin threshold (n^b_{min}) was computed as a rounded fraction of n of a given variable (i.e. horizontal line in Fig. C1):

$$n^b_{min} = \lfloor n \times 10^{-6} \rceil \tag{C3}$$
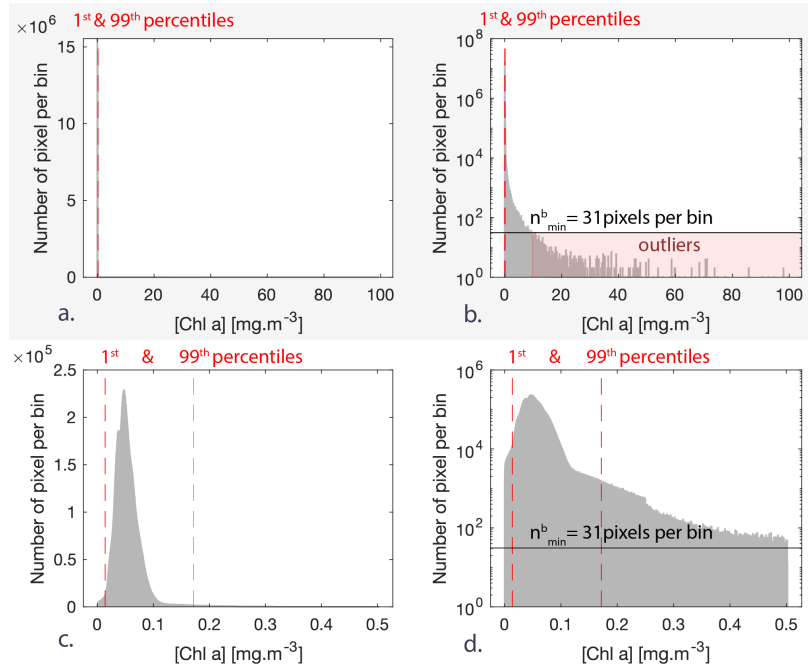
Figure C1. Example distribution of all valid [Chla] (i.e. not flagged) observations from all satellite sensors merged (i.e. MODISA-Aqua, MODIS-Terra, VIIRS-SNPP, OLCI-S3A) from 2016-09-19 01:00 to 2016-09-26 21:30 UTC (8-day period) around Niue and Samoa (77 satellite images merged) before outlier removal (subplots (a) and (b)), and after outlier removal (subplots (c) and (d)). The number of pixels per bin are displayed on a linear scale on subplots (a) and (c) and on a log base 10 scale on subplots (b) and (d). The dashed lines represent the 1st and the 99th percentiles, the solid horizontal line represents the cut-off value in pixel per bin for outlier removal (n_{min}^{b}), and the red shaded area highlights the pixels removed.

The lower-end threshold t_L was determined by finding the first bin with less pixels than n_{min}^{b} (i.e. gap in normal distribution), going from the median $\tilde{x}$ to x_{min} ($x_{min} \leq t_L < \tilde{x}$). Similarly, the higher-end threshold t_H was determined by finding the first bin with less than n_{min}^{b} pixels per bin, going from $\tilde{x}$ to x_{max} ($\tilde{x} < t_H \leq x_{max}$). This threshold detection was iterated up to 15 times or until t_L and t_H did not change from one iteration to the other. Any re-projected level-2 pixel from a given 8-day period, region, and variable falling out of the range (t_L, t_H) were deleted before computing the medians of the merged level-3 products.

 Appendix D: Rapa Nui, Society Isl., and Samoa validation transects
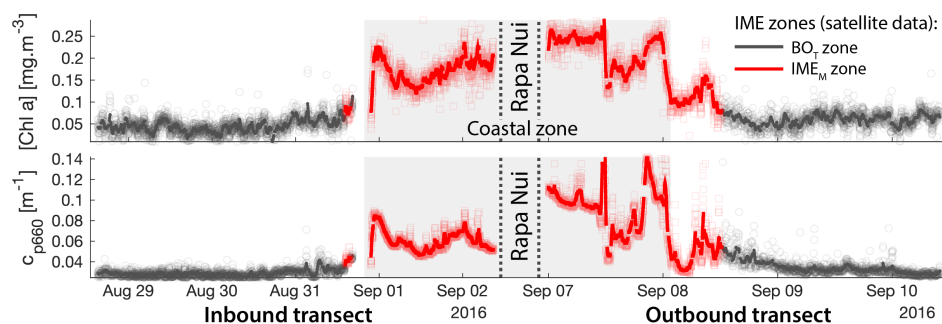
Figure D1. Validation of the IME extent using in situ underway data around Rapa Nui. **Top row**: Chlorophyll a~~a~~ concentration ([Chla]), and **bottom row**: beam attenuation at 660 nm (proxy for particulate organic carbon). Data sampled with the underway system during the transect sailing towards Rapa Nui (**left**) and sailing away from Rapa Nui (**right**). Data colored when located within the IME zones detected on the overlapping 8-day satellite composite (BO_T = black circle or IME_M = red square). The points are minute binned underway data and the solid lines are smoothed underway data. The smoothing was performed by applying a 2h low-pass digital filter to the minute binned data. The grey patch highlights the time *Tara* was sailing in coastal water (< 50 m depth).
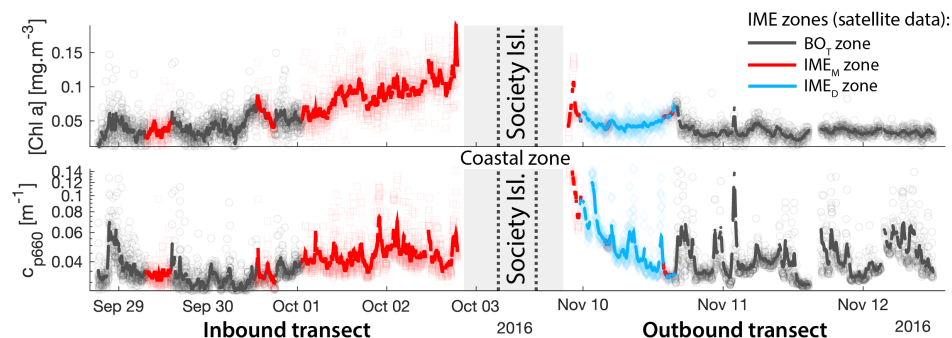
Figure D2. Validation of the IME extent using in situ underway data around Society Islands in French Polynesia. **Top row**: Chlorophyll a ~~a~~ concentration ([Chla]), **bottom row**: beam attenuation at 660 nm (proxy for particulate organic carbon). Data sampled with the underway system during the transect sailing towards Society Islands (**left**) and sailing away from Society Islands (**right**). Data colored when located within the IME zones detected on the overlapping 8-day satellite composite (BO_T = black circle, IME_M = red square, or IME_D = blue~~green~~ diamond). The points are minute binned underway data and the solid lines are smoothed underway data. The smoothing was performed applying a 2h low-pass digital filter to the minute binned data. The grey patch highlights the time *Tara* was sailing in coastal water (< 50 m depth).
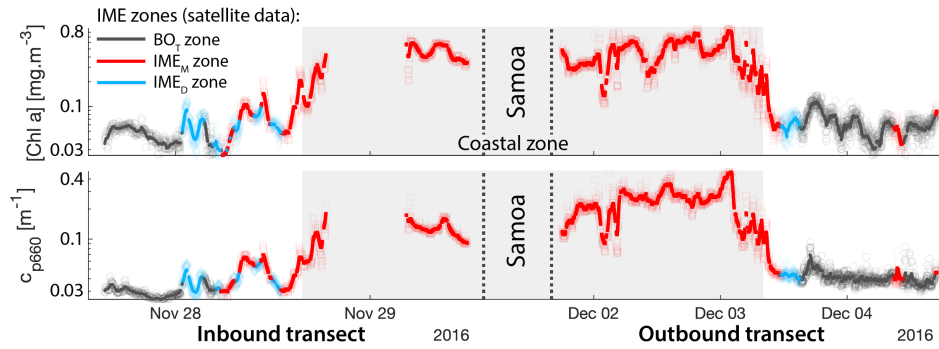
Figure D3. Validation of the IME extent using in situ underway data around Samoa. **Top row**: Chlorophyll *a*~~a~~ concentration ([Chla]), and **bottom row**: beam attenuation at 660 nm (proxy for particulate organic carbon). Data sampled with the underway system during the transect sailing towards Samoa (**left**) and sailing away from Samoa (**right**). Data colored when located within the IME zones detected on the overlapping 8-day satellite composite (BO_T = black circle~~, or~~ IME_M = red square, or IME_D = blue diamond). The points are minute binned underway data and the solid lines are smoothed underway data. The smoothing was performed by applying a 2h low-pass digital filter to the minute binned data. The grey patch highlights the time *Tara* was sailing in coastal water (< 50 m depth).

Appendix E: Rapa Nui and Society Isl. time-series
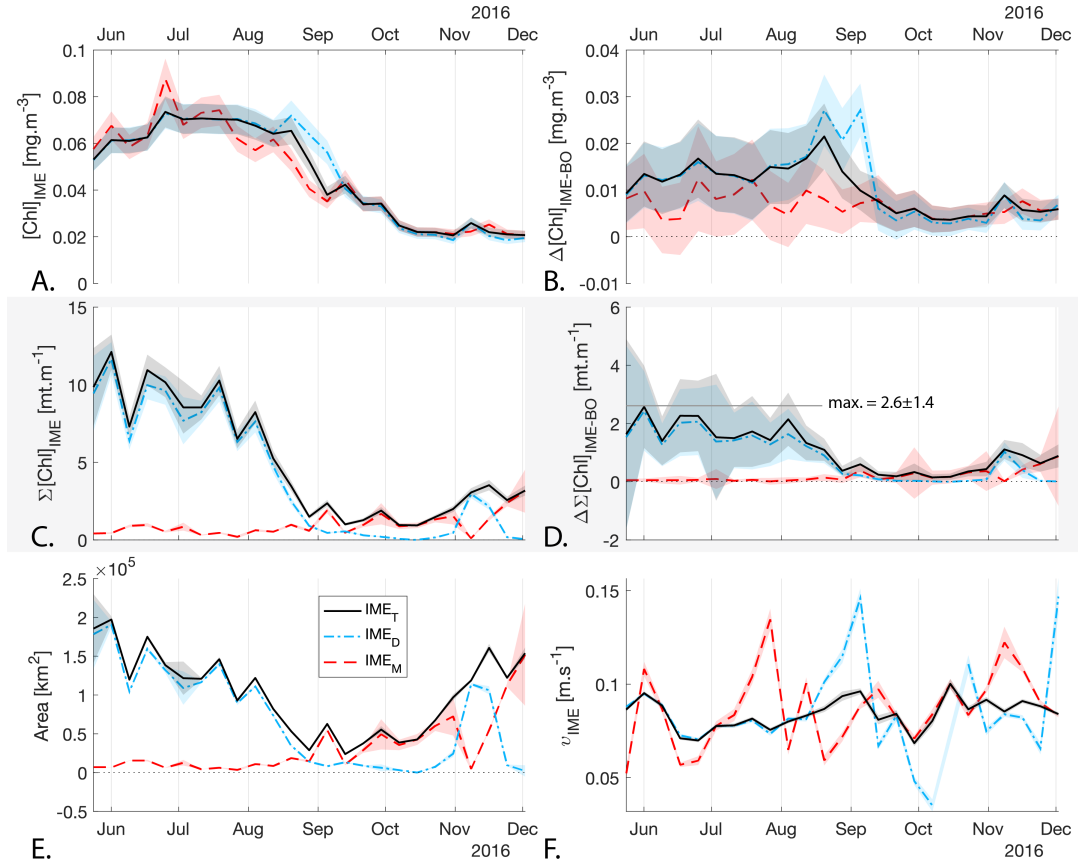
Figure E1. Six-month long time series of satellite derived IME properties of the IME zones (IME$_M$ = red dashed line, IME$_D$ = blue green dash-dotted line, and IME$_T$ = black solid line) detected around Rapa Nui. **A:** Average chlorophyll a concentration within the IME zones ($[Chla]_{IME}$), **B:** difference in average [Chla] between each IME zones and their respective BO zones ($\Delta[Chla]_{IME-BO}$), **C:** IME surface-area integrated chlorophyll a ($\sum[Chla]_{IME}$), **D:** difference in IME and BO surface-area integrated chlorophyll a ($\Delta\sum[Chla]_{IME-BO}$) ~~A and C: average of properties within the IME zones, B and D: difference between properties within each IME zones and their associated BO zones. A and B: chlorophyll a concentration ([Chla]), B and C: IME integrated chlorophyll a ($\sum[Chla]_{IME}$)~~, **E:** IME zone area, **F:** surface current velocity.

Figure E2. Six-month long time series of satellite derived IME properties of the IME zones (IME_M = red dashed line, IME_D = ~~blue green~~ blue dash-dotted line, and IME_T = black solid line) detected around Society Islands in French Polynesia. **A:** Average chlorophyll a concentration within the IME zones ($[Chla]_{IME}$), **B:** difference in average [Chla] between each IME zones and their respective BO zones ($\Delta[Chla]_{IME-BO}$), **C:** IME surface-area integrated chlorophyll a ($\sum[Chla]_{IME}$), **D:** difference in IME and BO surface-area integrated chlorophyll a ($\Delta\sum[Chla]_{IME-BO}$)~~A and C: average of properties within the IME zones, B and D: difference between properties within each IME zones and their associated BO zones. A and B: chlorophyll a concentration ([Chla]), B and C: IME integrated chlorophyll a ($\sum[Chla]_{IME}$)~~, **E:** IME zone area, **F:** surface current velocity.

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