https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Open Access Earth System Science Data Discussions

BGC-Argo+: Global biogeochemical Argo float data with secondary quality control and derived parameters

Seth M. Bushinsky[1], Zachary Nachod[1], Mathilde Jutras[1,2], Daniela König[1], Shannon McClish[1], and Charles Addey[1]

[1]Department of Oceanography, School of Ocean and Earth Science and Technology, University of Hawaiʻi at Mānoa, Honolulu, HI, USA
[2]Now at: Institut des sciences de la mer, Université du Québec à Rimouski, Rimouski, QC, Canada

Correspondence: Seth M. Bushinsky (seth.bushinsky@hawaii.edu)

Abstract. Biogeochemical Argo floats have quickly become the largest single source of ocean biogeochemical measurements. The vast amount of data collected and the long life-time, typically over 5 years, during which floats measure the ocean makes it challenging to provide consistently quality controlled data. We developed a set of automatic and manual outlier detection methods with a focus on oxygen, nitrate, and pH data that we applied to the 2,429 biogeochemical Argo floats with data available through the global data assembly centers that were deployed as of January 2025. The full biogeochemical dataset, named BGC-Argo+, is a uniform repository of profiles and gridded data to enable easy use of the global dataset for direct observational, mapping, or modeling uses. Data are available through an archived repository or at www.bgc-argo-plus.info, along with information on the outliers removed that should enable future improvements to the global dataset of biogeochemical float measurements.

1 Introduction

Measurements of dissolved oxygen concentrations date back to the 19th century (Winkler, 1888). Historically, the main source of ocean biogeochemistry measurements have been from discrete water samples taken from Nisken bottles, originally strapped directly onto cables lowered from the side of a ship. Rosettes of bottles are now typically used to sample throughout the water column, with instrument packages containing biogeochemical sensors for measuring tracers such as oxygen sent down with the sampling bottles and providing high resolution profiles of chemical tracers at each cast along a ship's track. The advent of autonomous vehicles equipped to carry oceanographic sensors has been changing the field over the past 3 decades. The most numerous autonomous vehicles used to observe ocean biogeochemistry are Argo profiling floats. Argo floats are profilers that typically conduct one profile from 2000 m to the surface every 10 days, transmit their data, then return to a park depth of 1000 m where they drift until the next profile (Wong et al., 2020; Roemmich et al., 2009).

Argo floats were initially deployed with conductivity-temperature-depth (CTD) sensors that provided information on ocean water properties and circulation. The first oxygen sensors were included on floats in 2002, with nitrate following in 2007 and pH in 2012 (Figure 1). Optical measurements that provide information on particle density and fluorescence, light sensors, and many other types of sensors have been deployed over time as well. In addition to the different quantities sampled, there have been changing sensor manufacturers, model types, and sensing approaches during the past two decades. Even for floats equipped with the same sensors, there have been many different approaches taken to quality controlling and adjusting the data. An added difficulty is that Argo floats are rarely recovered, making it impossible to conduct a post-deployment assessment of sensor drift.

The use of biogeochemical Argo float (BGC-Argo) data has progressed from individual or small scale projects where groups or users typically deployed each float they analyzed and were very familiar with the data (e.g. Uchida et al., 2008; Körtzinger et al., 2004; Martz et al., 2008) to basin and global scale studies combining data from dozens or hundreds of floats from a variety of projects and countries (e.g. Bushinsky et al., 2017; Dove et al., 2022; Sharp et al., 2022; Vives et al., 2025). All Argo data are freely available in near real-time, providing oceanographic data to anyone. The data are passed through several real-time quality checks and are expected to be evaluated and corrected within two years by the float Principal Investigator (PI) who purchased and deployed the float. However, despite significant efforts among different institutions and data centers, the continued development of sensors and evolving sensor adjustments and calibrations, along with the rapid expansion of the numbers of BGC-Argo floats in the ocean, has made quality control of individual floats/individual profiles and data types increasingly challenging. It is increasingly important that the entire BGC-Argo data array be assessed in a comprehensive manner such that the highest quality data be made available to users both within and outside the BGC-Argo community. In order for this data to be optimally useful as a global dataset, it is necessary for the float community to assess data quality and make it easily available for broader use.

In this work we follow the lead of two ship-based quality control and data-inter-comparability programs. The Global Ocean Data Analysis Project (GLODAP) uses crossovers between research cruises to create an internally consistent dataset of high-quality biogeochemical bottle data (Key et al., 2015; Olsen et al., 2016, 2020). The Surface Ocean CO_2 Atlas is a compendium of surface $p$$CO_2$ measurements with strict quality control and accuracy requirements. Both of these efforts have greatly increased the usability of these data by enabling researchers to access large amounts of shipboard data with a reasonable expectation that most bad data and outliers have been corrected or removed and that the data have gone through multiple levels of assessment by experts.

BGC-Argo data are fundamentally different than shipboard bottle measurements, both in terms of the quantity of data collected and the time over which measurements are returned. When an individual researcher on a research cruise has responsibility over a limited number of measurements and runs all samples themselves, there is a high initial level of oversight on the generation of data. BGC-Argo data undergo evaluation by individual researchers and automated routines at the Data Assembly Centers (DACs) that process Argo data, bringing a depth of knowledge on float and sensor types and broad consistency, but data are collected data over years and individual floats may not get the same degree of consistent attention as shipboard measurements.

In this manuscript we describe a secondary quality control approach for BGC-Argo data designed to remove and identify any outliers from the global BGC-Argo dataset, combining new routine data quality checks and a systematic outlier detection approach specifically adapted to Argo data. Our focus is on the oxygen, nitrate, and pH sensor data collected by BGC Argo floats. By analyzing all available data we are able to identify issues common throughout the dataset. Some of these issues have been

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

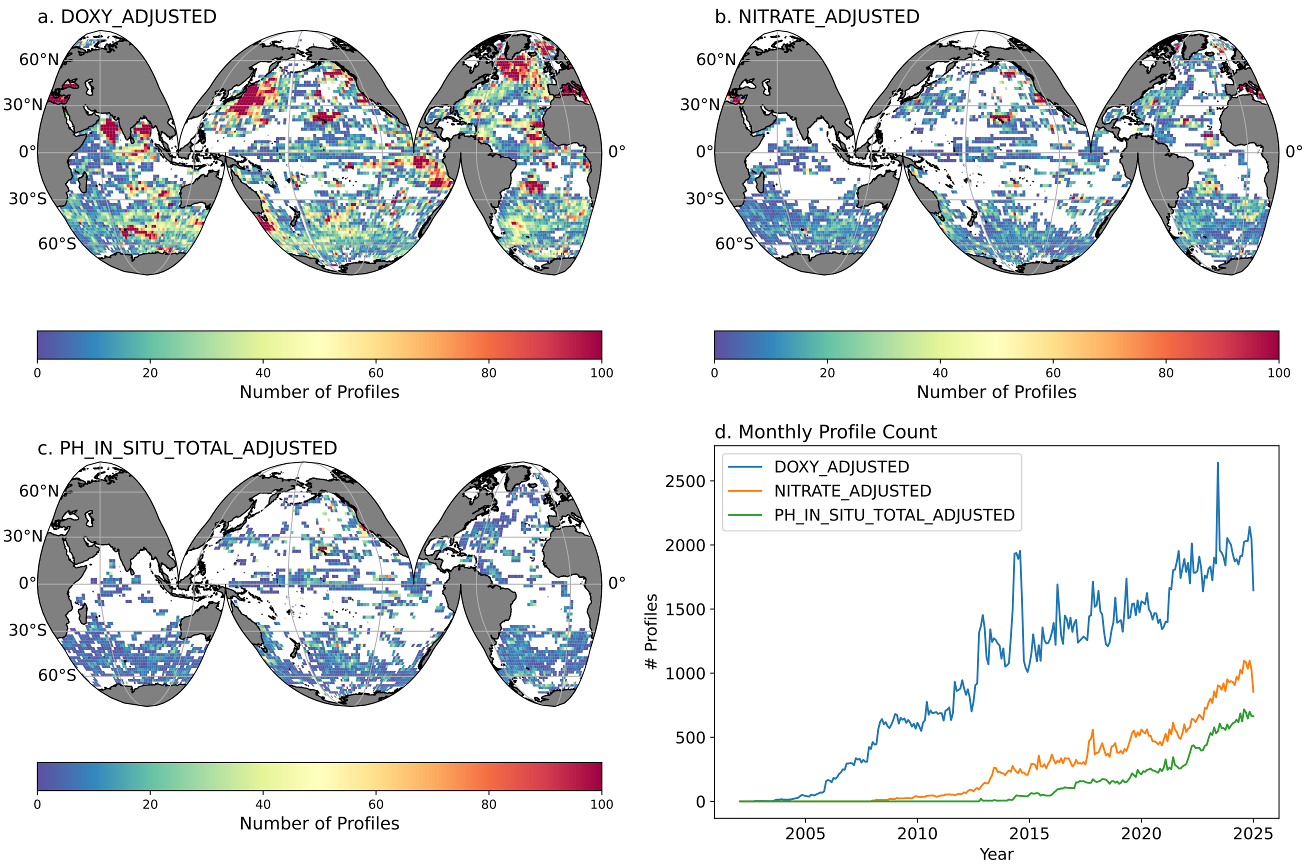


Figure 1. Biogeochemical Argo float profile density. Profiles marked as "ADJUSTED" with non-NaN data counted in 2°x 2° bins for (a) oxygen, (b) nitrate, and (c) pH. (d) Number of Argo profiles per month for oxygen, nitrate, and pH.

previously described but are still present, while others occur only occasionally and are likely to be missed without evaluation of large numbers of floats. Our goal is to: (1) improve the quality of the BGC-Argo dataset, (2) increase the accessibility and utility of the data, (3) raise awareness of quality control issues so that individual PIs and DACs have an easier time identifying and addressing them, and (4) make it easier to identify any future issues in the float dataset as they arise. To aid accessibility beyond simply bringing the data together and removing outliers, we also calculate commonly useful derived parameters such as density (neutral and potential), spiciness, mixed layer depth (MLD), oxygen saturation, and derived carbonate system parameters such as dissolved inorganic carbon (DIC), total alkalinity (TA), and $p\mathrm{CO_2}$. While some of these, especially the carbonate system parameters, are experimental and subject to on-going changes in calculation, we recognize that they are being widely calculated and used and believe it is worthwhile to provide these data calculated for the global dataset in a uniform manner.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

2 Data

Biogeochemical Argo profile data used in this study were identified by downloading a copy of the "argo_synthetic-profile_index.txt" file from the Global Ocean Data Assimilation Experiment (GODAE) FTP server. Floats with an oxygen, nitrate, pH, or other biogeochemical sensor were identified, along with the DAC where the data was stored. "Sprof" and "meta" NetCDF files were then downloaded on January 24, 2025 (2,429 floats total, Table 1).

Each DAC processes the physical (temperature, salinity, and pressure) and biogeochemical data after they are transmitted via satellite from a float. The exact processing steps performed may differ between DACs, but should follow the steps outlined in the Argo quality control manuals for different parameters (e.g. Thierry et al., 2025). When DACs process the raw data transmitted from floats, they perform a series of calculations to derive a concentration in common units. Depending on the sensor, these can include: correction of raw output to account for any sensor-specific pressure dependencies, conversion of raw output to concentration in common units, or applying additional tracer-specific corrections for temperature, salinity, and pressure.

For every profile, each variable in an Sprof file has one of three processing modes assigned to it that indicates the level of adjustment and quality control that has been performed prior to being distributed by the DACs: "Real Time", "Real Time Adjusted", and "Delayed Mode" (stored in the "PARAMETER_DATA_MODE" field). "Real Time" data refers to data typically available within 12-24 hours of a float profile that has only passed automated simple quality control tests. This data is still subject to errors in physical and biogeochemical parameters, such as sensor drift. If calibration data are available and applied to the data in real time, then an [PARAMETER]_ADJUSTED field will be filled and the data marked as "Real Time Adjusted". "Delayed Mode" data refers to data that has passed non-automated quality control from data experts (usually the float PIs or groups that deployed the float), typically performed within 1-2 years after a profile is taken. Data in the [PARAMETER]_ADJUSTED field are updated when delayed mode processing is applied.

3 Methods

Production of this secondary quality controlled dataset, which we call BGC-Argo+, followed the following steps and is outlined in Figure 2:

1. Download Sprof and Meta files, apply flags, filter out non-delayed mode data for most parameters, save to new "filtered" files.
2. Perform automatic removal of density inversions, near-surface data, bottom oxygen hooks.
3. Manual examination and removal of detectable outliers.
4. Calculation of derived physical and biogeochemical variables.
5. Saving of individual float files with original structure maintained, plus gridded datasets.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Open Access Earth System Science Data Discussions

3.1 Flag and mode filtering

Float information that may be relevant to understanding patterns in potential outliers or biases in the data, such as sensor models and oxygen calibration comments, was extracted from the meta files and stored in the data files. Oxygen sensors were further categorized by their calibration approach as "air_cal" or "not_air", depending on whether the float sensor was calibrated using in-air measurements or not (Bushinsky et al., 2025). All "ADJUSTED" sensor data with a quality control flag of 3 (Probably bad data that are potentially correctable) or 4 (Bad data) in the Sprof file were set to NaN values. At this point "[variable]_ADJUSTED_BGCArgoPlus" variables were created to preserve the original ADJUSTED data, allow easy comparison of differences, and to have one single variable type that includes all changes described in this study. All subsequent changes or removal of data only applies to these new "BGCArgoPlus" variables. The "POSITION_QC" variable was used to set latitude and longitude data to NaN where the quality control (QC) flag was 3 or 4.

For oxygen, nitrate, and pH data we only retained the Delayed Mode data, setting profiles in the other modes to NaN. This step ensured that only the highest quality data is present the new dataset. It is likely that some "Real Time Adjusted" profiles contain good data or data that can be salvaged, and these will be considered for addition to the dataset in future updates.

We did not perform the same steps for pressure, temperature, or salinity, as our experience was that bad data in the "ADJUSTED" data fields for these physical parameters were already removed by the time any BGC data was put into Delayed Mode. Likewise we did not remove non-Delayed Mode data for other biogeochemical parameters (such as fluorescence, backscatter, or irradiance) as the vast majority of those did not appear to ever be set into Delayed Mode and were not the focus of the outlier removal approach described below.

There were 2,429 individual floats with Sprof files in the downloaded dataset. Of these, we evaluated those with valid (i.e. non-NaN), delayed mode oxygen, nitrate, or pH data. For oxygen, of the 2,244 floats equipped with oxygen sensors, 1,901 had valid data in the 'DOXY_ADJUSTED' field (Table 1). Of those 1,901 floats with valid oxygen data, 1,381 floats had at least one profile marked as delayed mode, 519 contained real time adjusted profiles but no delayed mode data, and 4 floats only contained real time data. There is a lag in the number of profiles set to delayed mode, with some real time and real time adjusted profiles existing in the oxygen dataset going back to 2004 (Figure 3). 807 floats have been deployed with nitrate sensors, with 715 containing valid adjusted data, 619 with delayed mode profiles, 96 with real time adjusted but no delayed mode, and zero with all real time. 724 floats have been deployed with pH sensors, with 532 containing valid adjusted data, 480 with delayed mode profiles, 52 with real time adjusted but no delayed mode, and zero with all real time.

3.2 Automated outlier detection

As we examined the BGC-Argo files for outliers, we identified several categories of common errors for which we developed automated detection algorithms. Our first automated step was for any above surface and near-surface measurements to be removed. In-air measurements are used for in-situ calibration of oxygen sensors and should not be present in the main float profiles. However, a significant number of floats contained data at the top of profiles that sharply deviated from clear mixed

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

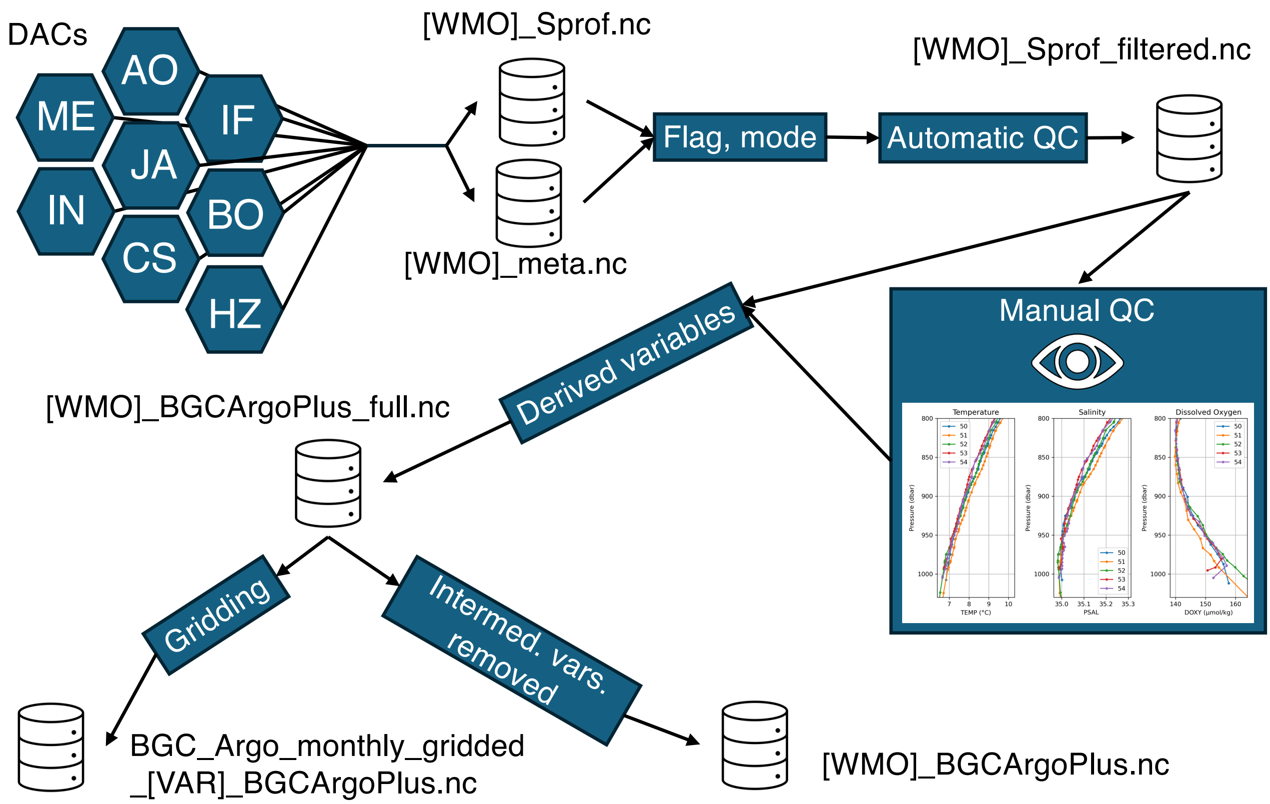


Figure 2. Schematic of data processing for the creation of the BGC-Argo+ dataset. All biogeochemical Argo float data are downloaded from the global Data Assembly Centers (DACs). Relevant meta data are added to the float profile data (Sprof), then filtered using data quality flags and passed through our automatic quality control process (Section 3.2). Profiles were then examined manually to identify and flag outliers, which were removed from the dataset. Derived variables (physical parameters such as potential and neutral density, carbonate system variables, etc.) were calculated from the quality controlled dataset and stored as “[WMO]_BGCArgoPlus_full.nc" files. Finally, intermediate variables needed only for the various processing steps were removed for external distribution (“[WMO]_BGCArgoPlus.nc"). Oxygen, nitrate, and DIC data were additionally gridded by month, latitude, longitude, and depth and stored in separate files.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

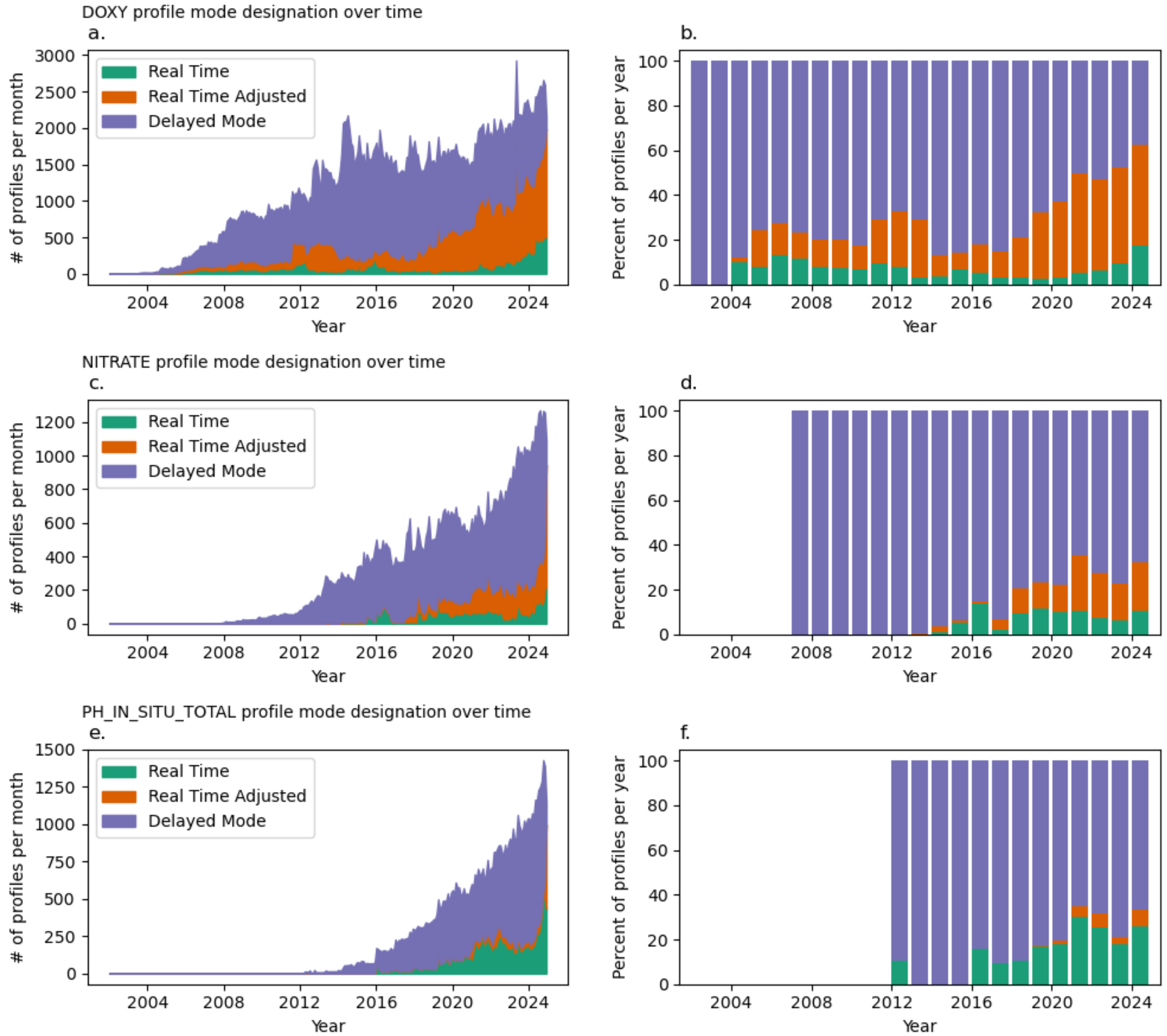


Figure 3. Argo float profile mode for oxygen, nitrate, and pH. Profiles are labeled "Real Time", "Real Time Adjusted", or "Delayed" mode. We only assessed delayed mode profiles for this work, marking all non-delayed mode profiles to "NaN" values.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Table 1. Numbers of floats and profiles with different sensors and data modes

Numbers of floats with sensor[2] types:

	TEMP	PSAL	PRES	DOXY	NITRATE	PH_IN_SITU_TOTAL	BBP	CHLA	PAR
Total Floats	2,429	2,429	2,429	2,244	807	724	1,129	1,144	356
"ADJUSTED"	2,039	2,029	2,039	1,901	715	532	958	1,100	124
Any DM	1,608	1,594	1,608	1,381	619	480	93	54	124
RTA but no DM	402	406	402	519	96	52	865	1,097	0
All RT	29	29	29	4	0	0	15	2	0

Numbers of profiles with sensor types:

	TEMP	PSAL	PRES	DOXY	NITRATE	PH_IN_SITU_TOTAL	BBP	CHLA	PAR
Total profiles	332,914	332,914	332,914	323,788	91,118	68,650	166,412	274,706	68,844
"ADJUSTED"	293,142	281,321	293,822	277,543	73,037	34,199	114,952	238,696	26,299
DM	241,618	240,046	241,618	210,880	67,756	46,278	17,042	8,960	26,873
RTA	50,944	50,944	50,944	84,123	11,534	2,536	95,344	227,258	0
RT	5,604	5,604	5,604	2,708	401	541	8,299	9,409	586

[1] DM = Delayed Mode, RTA = Real Time Adjusted, RT = Real Time

[2] TEMP = Temperature, PSAL = Salinity, PRES = Pressure, DOXY = Oxygen, NITRATE = Nitrate, PH_IN_SITU_TOTAL = pH, BBP = Backscatter, CHLA = Chlorophyll, PAR = Photosynthetically Active Radiation

layer (ML) mean values, often with associated pressures that were ≤ 0 db (example shown in Figure 4), which may be due to wave action that brings the top of the float up above the surface briefly. This problem has been noted in the Argo O_2 quality control manual for PROVOR/ARVOR floats (one of the three main types of Argo floats) due to the optode being suspected of measuring a mix of air/water (Thierry et al., 2025). The quality control manual recommends that data with a pressure <=1db for bin-averaged data and <=0.5 db for spot sampled data be flagged as "probably bad data" (QC flag = 3).

Based on our experience from the first several hundred floats that we examined, we determined that these outliers were not all removed and were still common in some floats, necessitating an automated approach to handle these outliers. A 2 db threshold was set, with any data at a lower pressure set to NaN. This threshold corresponds to the depth where near-surface data begins to substantially deviate from the mean oxygen concentrations between 7 and 12 db, which we assume to be part of the well-mixed upper layer (Figure A3).

Next, potential density was calculated and density inversions that exceeded -0.025 kg m^{-3} were identified in the upper 600m. While it is possible that density inversions in the ocean may briefly exist (Ruddick and Richards, 2003), large density inversions are not realistic and create a problem for mixed layer depth calculations. This density threshold was chosen because it was just below the 0.03 kg m^{-3} potential density threshold used for calculating MLD (see Section 3.4). Below this threshold density inversions would be less likely to bias MLD calculations, though they can still impact analyses of data separated into

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Open Access Earth System Science Data Discussions

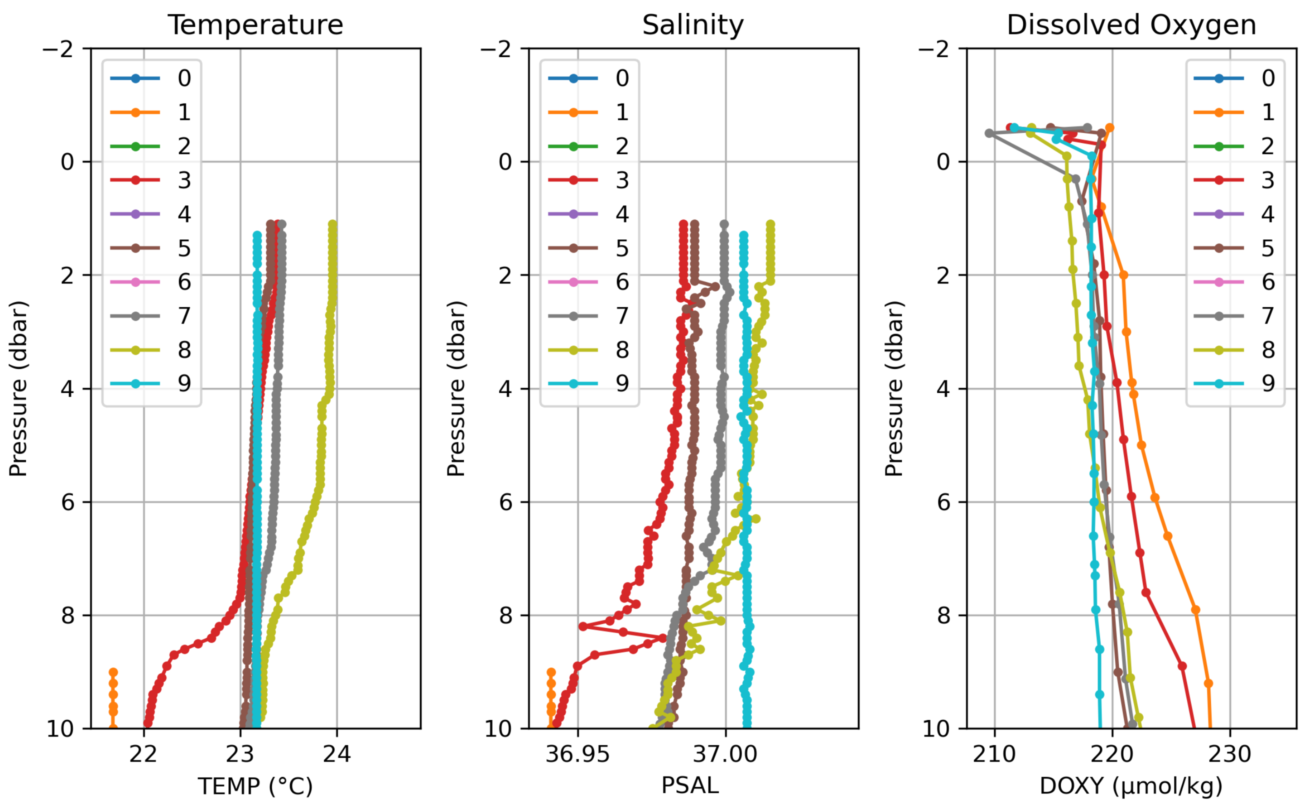


Figure 4. Air measurement example. Oxygen data include samples at a pressure of < 0 db that display a significant departure from the values measured in the rest of the mixed layer.

density bins. The density inversions we observed were almost always caused by a spike in the salinity sensor, so only salinity was set to NaN values at each density inversion point.

The final step in the automated outlier detection step was to look for and remove "hooks" that appear in the bottom of some oxygen profiles. These hooks are a known issue with float oxygen profiles that the Argo oxygen quality control manual suggests should be removed during delayed-mode quality control (Thierry et al., 2025). However, after examination of floats began, it was apparent that many bottom hooks remained in the adjusted oxygen data (Figure 5).

To identify these hooks, the mean and standard deviation of the oxygen change with depth (dO_2/dz) was calculated for the bottom 300 m of each profile, excluding the last three measurements. We exclude the last several points because a large oxygen change at the bottom of the profile can bias the mean and standard deviation, making it difficult to detect hooks. Any measurements yielding an oxygen change more than 3 SD from the mean were set to NaN (example for a single profile shown in Figure A2).

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

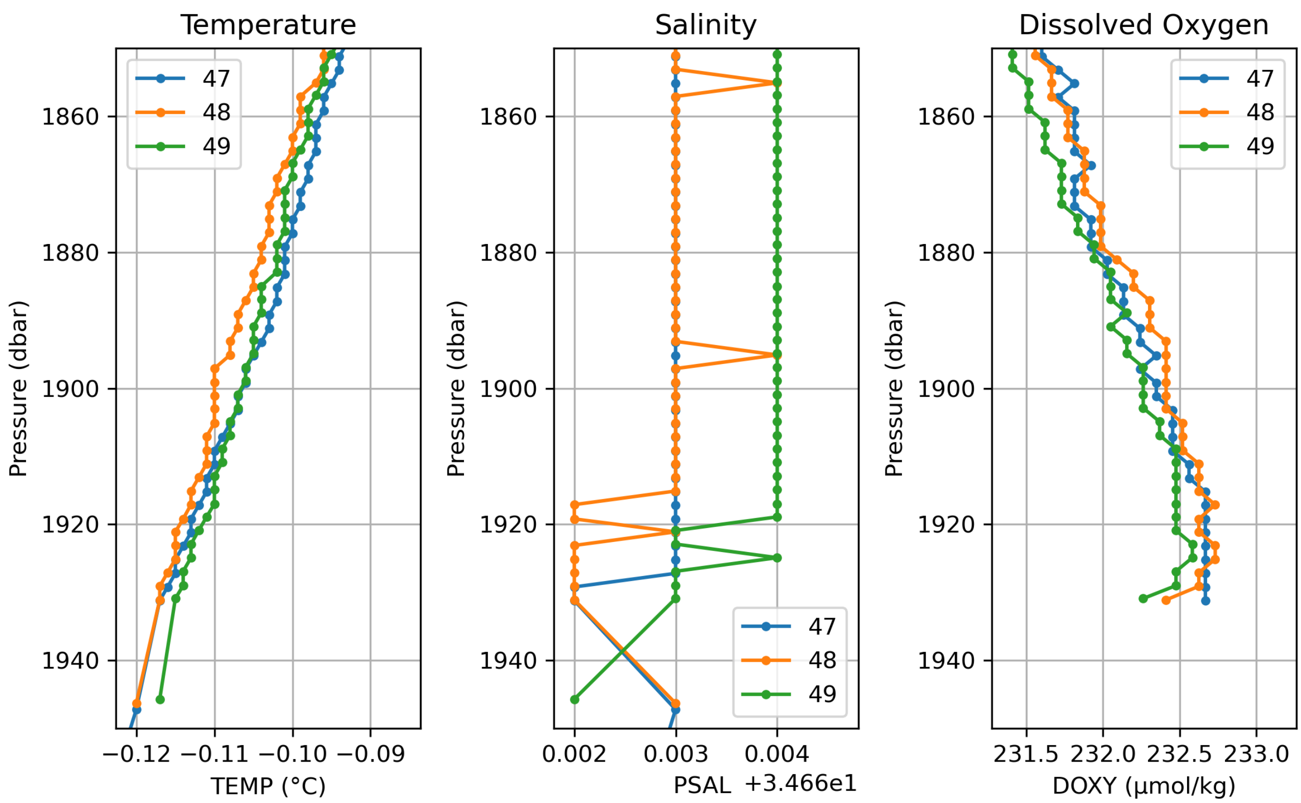


Figure 5. Bottom hook example for float 5901744, profiles 47-49. For these profiles the automated detection removed bottom points for profiles 48 and 49, but not 47.

3.3 Manual outlier detection

Float data was manually assessed for outliers by visually inspecting groups of float profiles and time series of float data in depth bins using an interactive tool that allowed manual data point selection (Figures A6 and A7). This tool displayed groups of several individual profiles and multiple time series at vertical levels. Available oxygen, nitrate, and pH data were viewed next to temperature and salinity to aid in distinguishing between real signals in the water column, for example when a float crosses a frontal boundary and there are simultaneous shifts in physical and biogeochemical variables, from outliers in individual parameters. This tool is available as part of the code for this data product.

Our goal was to have all float profiles reviewed by at least one, and preferably two people in order to increase our confidence that outliers were found.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

3.4 Derived parameter calculations

To increase the utility of the float data in this dataset, we calculated a range of derived physical and biogeochemical parameters (Table 3). For some of these parameters there are multiple different ways to calculate these values, so care should be taken when relying on these derived calculations.

3.4.1 Physical parameters and oxygen saturation

We used the Gibbs Seawater Python toolbox (GSW, McDougall and Barker (2011), specific functions listed in parentheses) to calculate potential density (sigma0), spiciness (spiciness0), conservative temperature (Θ), and depth (z_from_p) at each point. Neutral density was calculated using the EOS-80 seawater properties Matlab toolbox (eos_legacy_gamma_n script) via the Python Matlab engine (Jackett and McDougall, 1997).

Mixed layer depth was calculated for each float profile, following the de Boyer Montégut et al. (2004) criteria of a 0.03 kg m^{-3} σ_θ change from a reference depth of 10m or the shallowest depth available (necessary for under ice floats). For specific regions or applications a different MLD might be desired, but this represents a reasonable first estimate for a global dataset.

Oxygen saturation concentration was calculated using the Garcia and Gordon (1992) solubility through the GSW toolbox (O2sol_SP_pt).

3.4.2 Carbonate system parameters

Float pH data are often used to estimate carbonate system parameters (e.g. Bushinsky et al., 2019; Gray et al., 2018; Williams et al., 2018; Prend et al., 2022). In order to constrain the full carbonate system, at least two parameters out of TA, pH, $p\mathrm{CO_2}$, and DIC must be determined. Typically, float pH is paired with alkalinity estimates derived from ship-measured relationships (Williams et al., 2017). Float-based $p\mathrm{CO_2}$ and DIC estimates provided by the SOCCOM project initially used alkalinity based on a multiple linear regression (LIAR, Carter et al., 2016; Johnson et al., 2017) and more recently have switched to a method that averages alkalinity calculated from a neural network and multiple linear regression (Carter et al., 2021), which we followed here.

Using the alkalinity estimates, we then calculated DIC and $p\mathrm{CO_2}$ from measured pH and estimated TALK using the PyCO2sys Python package (Humphreys et al., 2024). The best approach to estimating $p\mathrm{CO_2}$ from float data has been the subject of significant debate. A central issue is whether float pH, measured with an ion-sensitive field effect transistor (ISFET) can be treated the same as the spectrophotometric pH measurements that are more commonly made on discrete samples and that have been used to determine carbonate system coefficients (Takeshita et al., 2020). Williams et al. (2016) corrected for differences in the pH sensor measurements by instituting a pH-dependent correction to float pH that was only used for $p\mathrm{CO_2}$ calculations. A recent working group report found that there is considerable uncertainty in the best way to institute this correction, therefore recommending that no correction be applied until further experiments and assessments point to a better method (Carter et al., 2023). However, crossover comparisons between float $p\mathrm{CO_2}$ and nearby ship-based measurements remain better with the correction applied than without. For the current dataset we continue to apply the Williams et al. (2016) correction as that has been most commonly used to date and, for now, provides the highest accuracy $p\text{CO}_2$. Future dataset versions will adopt new methods of estimating $p\text{CO}_2$ from floats as they demonstrate improved accuracy.

Another recent development that also impacts $p\text{CO}_2$ estimates from floats is the identification of a bias in float deep oxygen measurements that propagates through to float pH, DIC, $p\text{CO}_2$, and nitrate (Bushinsky et al., 2025). This bias has been adjusted in a DAC-dependent manner (Gouretski et al., 2024) but the float-dependent nature of the biases shown in (Bushinsky et al., 2025) requires a per-float correction scheme. Determination of the best approach to correct for this oxygen bias and its impact on pH, DIC, and $p\text{CO}_2$ is outside the scope of our current secondary QC approach and will be included in future BGC-Argo+ versions once established. Researchers using the carbonate system parameters included here should do so with care and understand that these are estimates under development. However, there is enough interest in these estimates and sufficient complexity in performing these calculations that we think it makes sense to provide our calculations of these parameters, especially since possible biases and uncertainty have been quantified (Bushinsky et al., 2025).

3.5 Final delivered dataset

Final BGC-Argo+ files are saved as “[WMO]_BGCArgoPlus.nc". These files preserve the original format of the “Sprof" files and the original data for ease of analysis and comparison. Lists of each removed data point are separately stored in text files. Oxygen, nitrate, and DIC data are also stored at monthly gridded 1x1°resolution and the same depth levels used by GLODAP.

4 Results and Discussion

Overall, 100% of floats were reviewed by at least one person, 66.8% of floats (926 floats) were reviewed by at least two people, and 11.1% of floats (154 floats) were reviewed by three people. Particular focus was given to floats with pH data. Oxygen measurements had the greatest number of outliers removed, with >17,000 profiles from 505 floats having at least one oxygen measurement manually removed, >49,000 profiles from 460 floats with surface measurements removed, and >11,000 profiles from 252 floats with data removed due to detected bottom oxygen hooks (Figure 6, Table 2). We count numbers of profiles and floats rather than individual observations in order to limit biases in our interpretation of outlier frequency due to differences in the number of samples per profile for different sensors, float types, or sampling schemes. Many of the "Manual Removals" (Table 2) were for individual spikes in data, for instance where one biogeochemical measurement changed value by a significant amount without an accompanying change in any other biogeochemical or physical measurement. Removal of bottom oxygen hooks were found through the automated algorithm and counted in the "Bottom Oxygen Check", but an additional 15,978 profiles, or 92% of the oxygen profiles with manual removals, included removal of the deepest points in a profile, indicating that the majority of the manual oxygen removals were also due to bottom oxygen hooks. These points were either removed individually or, once it was established that many or all of the oxygen profiles in a given float included bottom oxygen hooks, were removed all at once for a given set of profiles or an entire float. The large number of manual bottom book removals indicates that a less strict removal condition (i.e. removing more points that are likely bottom oxygen hooks) should be used in future automated checks.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Temperature measurements had the second most number of outliers removed, almost entirely through surface removal. Salinity was next, again primarily due to removal of surface data, plus identified density inversions (almost 2,000 profiles from 564 floats).

Manual removals accounted for the most nitrate and pH floats with outliers removed (267 and 172 floats, respectively), while surface removals impacted a larger number of nitrate and pH profiles (8,440 and 1,780, respectively). Bottom "hooks" were seen in pH profiles, with 860 profiles containing removals of the deepest measurements, or 72% of all pH manual removals. It does not seem this issue with pH has been demonstrated previously. It may be related to water flow past the pH sensor and whether the water is actively being pumped. Step changes in the pH data were often observed at 1,000 db in floats where the pump is off from 2,000 - 1,000 db before being turned on for the upper 1,000 db of the profile, but this was not flagged.

Another common reason for flagging biogeochemical data for removal was when there was an obvious difference in the first profile's measurements that was not present in temperature, salinity, or other biogeochemical parameters, indicating some equilibration or "wetting" time had not been reached for that sensor prior to sampling. The first oxygen profile for a float was removed 20 times, 53 times for nitrate, and 49 times for pH.

One interesting, though infrequent outlier type was when an oxygen sensor in the mixed layer appeared to have an anomalously slow response time for a single profile (Figure A4). This slow change was noticeable because temperature and salinity showed clearly uniform mixed layer signatures, as did surrounding oxygen profiles. Our conclusion is that some sticky organic matter, such as a salp, adhered to the oxygen sensor at some point in the profile below the mixed layer. This greatly slowed, though did not stop, the response of the oxygen sensor but was apparently washed away prior to subsequent profiles. We therefore refer to these outliers as "goo covered".

A much more common issue were anomalous spikes in sensor response at the base of the mixed layer, most commonly in nitrate or pH measurements (Figure A5). These seemed to coincide with a sharp transition in temperature or salinity, perhaps indicating a lag between the conditions experienced by the sensor and those used for processing the raw signal into nitrate concentrations or pH. These differed from other noisy nitrate profiles, which were also sometime observed, as they were limited to the base of the mixed layer or other sharp gradients. Where these spikes were obvious, we removed them, but there is often a high degree of variance in biogeochemical properties at the base of the mixed layer and many of these spikes were likely missed. However, given their location in the water column these seem less likely to bias most analyses than biases that are widespread across many depths or present within the mixed layer. Nitrate measurements are often slightly negative in the mixed layer in subtropical regions where we would expect nitrate concentrations close to zero. While we did remove significant negative (and positive) spikes, we did not remove negative nitrate concentrations. When mean ML nitrate is below zero in regions or times when it should be zero, it is likely that nitrate data for that float should be adjusted accordingly, but for now we make no adjustment in these situations.

The depths with the greatest numbers of profiles with outliers removed are at the surface (<10 db) and in the 1500-2000 db bin, followed by 750-1000 db, which matches the prevalence of surface removals and of bottom oxygen hooks, as profiles most often begin at 2000 db, followed by 1000 db (Figure 7).

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Open Access Earth System Science Data Discussions

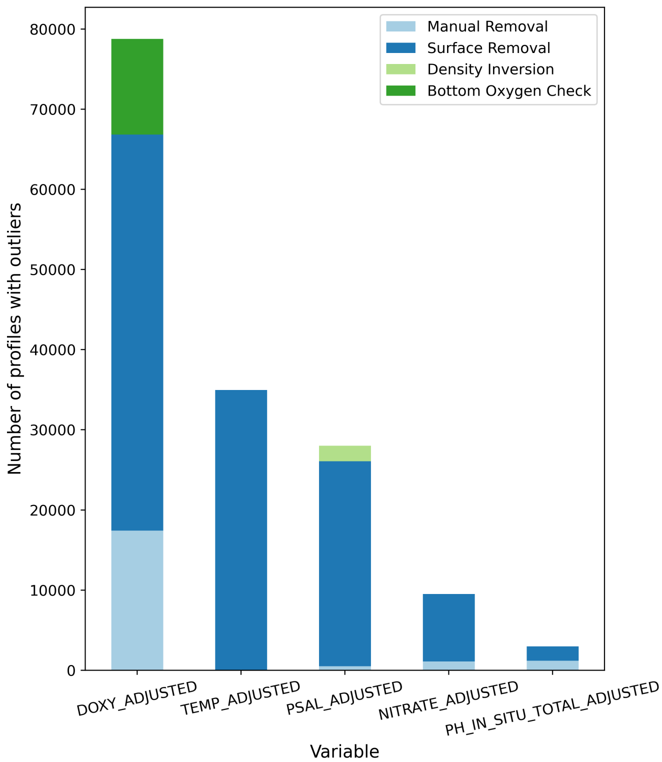


Figure 6. Numbers of float profiles with at least one point removed, separated by sensor and method of removal. Outliers in the Surface Removal, Density Inversion, and Bottom Oxygen Hook categories were removed automatically, while all points removed by individual researchers are included in "Manual Removal". Note that many of the manual removals for oxygen and pH were also associated with anomalous measurements at the base of their profiles (bottom hooks), but were not captured by the automatic detection algorithm.

Outliers also do not seem to be spatially uniform. For instance, surface removals of oxygen data are far more common in the Atlantic and Indian oceans than in the Pacific (Figure 8) and appear to be on floats processed by the IF, IN, and BO data centers, with a smaller number processed by AO and HZ. Bottom oxygen hooks seem most prevalent in the Southern Ocean and in the North Atlantic. This could reflect differences in sensor types deployed by different programs, differences in post-processing, or regions where there is more of a difference in oxygen between the park depth and the maximum sampling depth. While such an analysis is beyond the scope of this manuscript, the collected outliers and their associated metadata are available in the data repository for this work or through the BGC-Argo+ website to help analyze the data by different metadata groupings.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Table 2. Numbers of floats (profiles) with data removed for each variable and reason

Variable	Manual Removal	Surface Removal	Density Inversion	Bottom Oxygen Check
DOXY_ADJUSTED	506 (17,829)	460 (49,422)	0 (0)	252 (11,922)
TEMP_ADJUSTED	22 (36)	321 (34,933)	0 (0)	0 (0)
PSAL_ADJUSTED	179 (514)	255 (25,550)	564 (1,957)	0 (0)
NITRATE_ADJUSTED	267 (1,107)	81 (8,440)	0 (0)	0 (0)
PH_IN_SITU_TOTAL_ADJUSTED	172 (1,231)	76 (1,780)	0 (0)	0 (0)

Table 3. Variables added to the BGCArgoPlus files

Variable name	Description
TALK_BGCArgoPlus	Alkalinity estimated from ESPER Mixed, which is an average of ESPER neural network and ESPER multiple linear regression (Carter et al. 2023)
DIC_BGCArgoPlus	DIC calculated from float PH_IN_SITU_TOTAL_ADJUSTED_BGCArgoPlus and TALK_BGCArgoPlus.
sigma0	Potential Density calculated using gsw.SA_from_SP, gsw.CT_from_t, gsw.sigma0
cons_temp	Conservative temperature calculated using gsw.CT_from_t
spiciness0	Spiciness calculated using using gsw.SA_from_SP, gsw.CT_from_t, gsw.spiciness0
gamma	Neutral density calculated using EOS-80 seawater properties Matlab toolbox (eos_legacy_gamma_n script) via the Python Matlab engine (Jackett and McDougall, 1997)
depth	Depth calculated using gsw.conversions.z_from_p
MLD	MLD calculated using De Boyer Montegue et al. 2004 (modified to work w/ under ice data as well)
DOXY_SAT	The saturation concentration of oxygen using Garcia and Gordon 1992 using the gsw 'O2sol_SP_pt' Python package. Assumes standard atmospheric pressure.

4.1 The impact of applying a secondary quality control to float data

The importance of using a secondary quality controlled dataset such as BGC-Argo+ will depend on the question being asked and the amount of data used for analysis. One of the strengths of floats or other autonomous platforms is that the quantity of data gathered is often much greater, and spread widely through space and time, than can be achieved through shipboard measurements. Therefore, random outliers will be unlikely to impact results or interpretation of analyses employing large numbers of floats. However, analyses that rely on a small number of floats or profiles will be more subject to biased results if individual outliers exist in the data. Similarly, analyses that follow a single float through time and interpret changes in observed quantities may be significantly influenced by a single bad profile or data point. For example, pCO_2 from an individual float could be compromised (Figure 9) by a bad first profile, but the overall dataset is less likely to have issues if outliers are random and larger numbers of data are used, assuming biases such as presented in Bushinsky et al. (2025) are addressed.

4.2 Comparison to other approaches

There have been other efforts to perform a secondary quality control on the float biogeochemical dataset. Gouretski et al. (2024) took a comprehensive approach to filter out bad data from float, shipboard, and CTD oxygen datasets covering the period of 1920 to 2023 (IAP

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

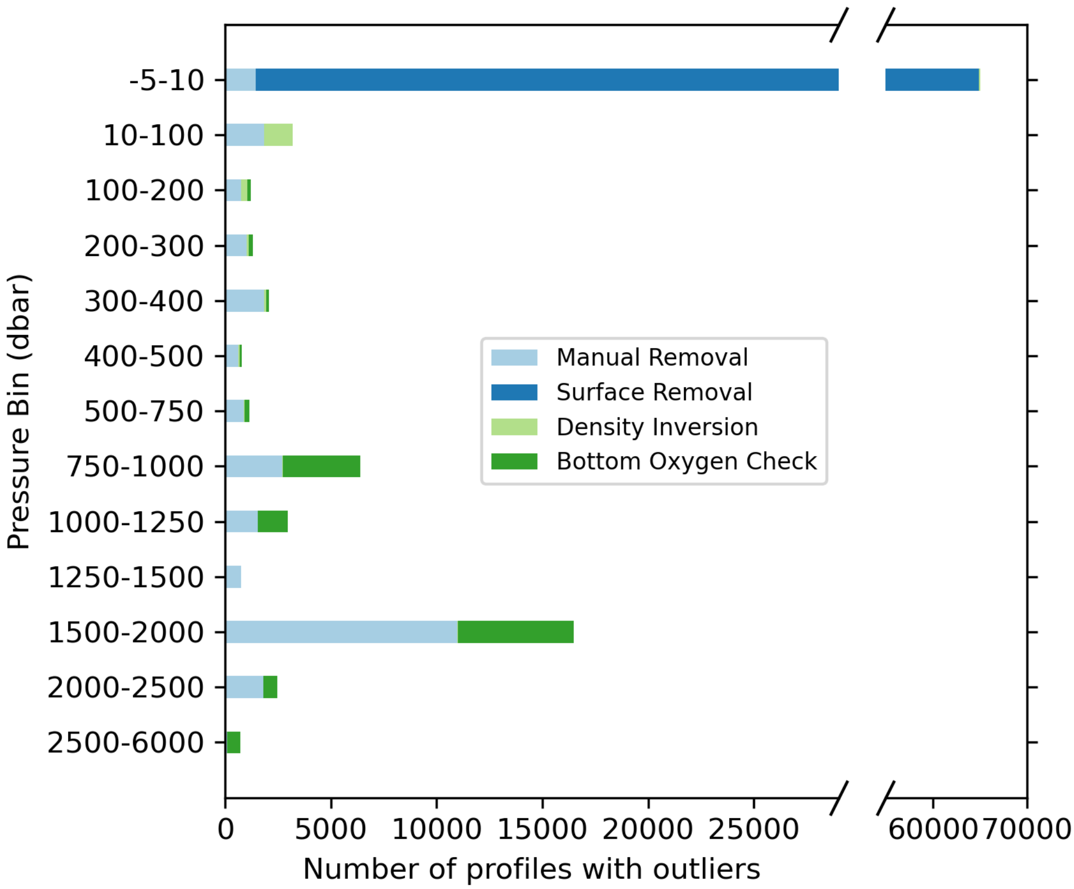


Figure 7. Numbers of profiles with outliers removed for all sensors, binned by pressure, and separated by outlier type.

285 hereafter). They performed multiple statistical checks on the float data, for example removing values far outside of local climatological values, or that exceed reasonable supersaturation values. They also apply a per-DAC correction to float oxygen data that addresses biases between shipboard and float oxygen data, similar to the biases seen in (Bushinsky et al., 2025).

The IAP float oxygen dataset is interpolated to regular depth levels from 0 to 2000 db, making it difficult to identify specific points that have been removed. However, we can at least compare the number of oxygen profiles per month present in each dataset (Figure A8). The primary cause for differences in profiles between our dataset and IAP is that we remove profiles with the "Real Time Adjusted" data mode, though there will be other differences due to the differing approaches to dataset quality control. We recommend that all future secondary quality controlled datasets maintain the original data format to make it easier to compare between different versions of the same float data.

Looking forward, combining a statistical approach such as the IAP method with the types of outliers caught in this in-depth assessment of individual profiles may offer the most robust way to detect and remove bad data. One important point in our approach is that we considered

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

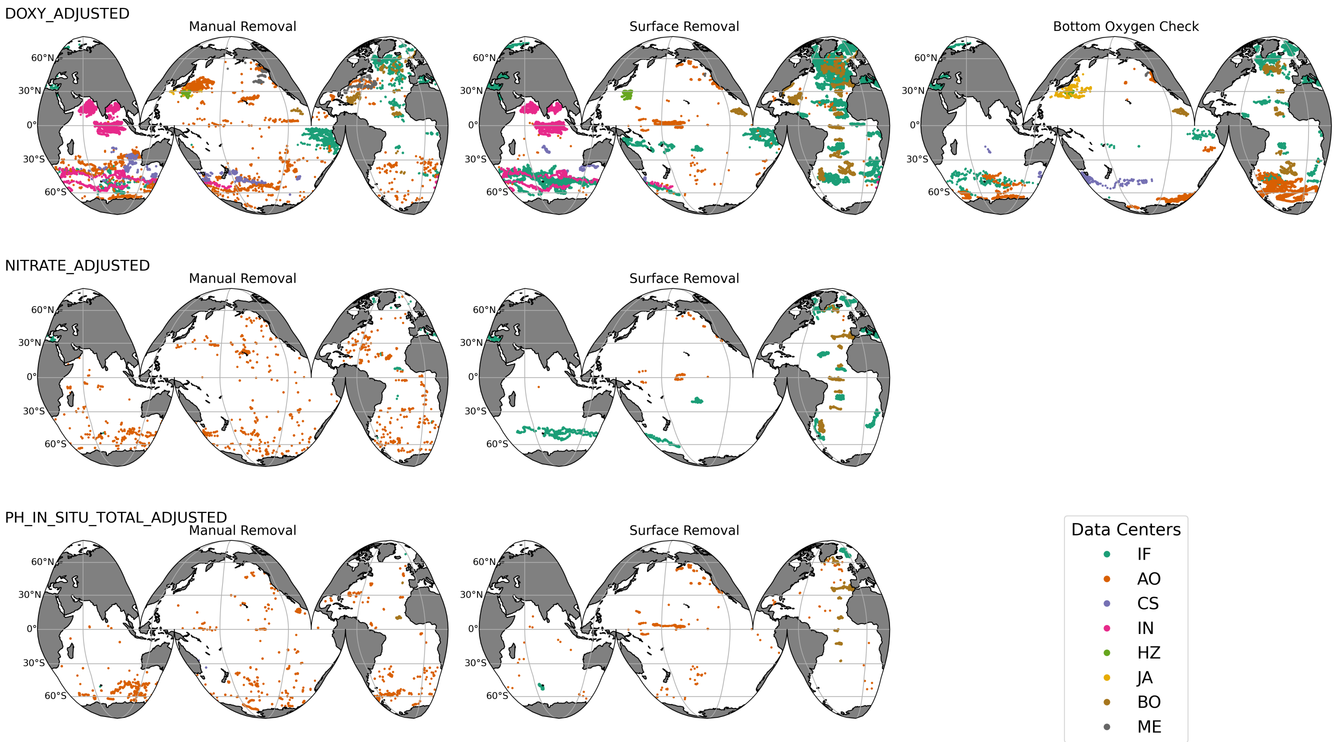


Figure 8. Locations of profiles for oxygen, nitrate, and pH sensors with variables removed. Clusters of removals, such as those for surface or bottom oxygen hooks, likely correspond to different projects and processing by different data centers. Note that outlier groupings may occur due to differences in measurement frequency (at times, some floats profiled more frequently than 10 days) or due to overall differences in profile density (Figure 1).

multiple physical and biogeochemical variables at once, which can help to distinguish unexpected variability from bad data. We additionally evaluated nitrate and pH data, though those could also be approached from a statistical point of view. One of the main reasons to manually examine float data (or any data) is to discover features or flaws that may be hidden by viewing data in aggregate. This could be examples of novel biogeochemical signatures or unknown sensor issues, but regardless, they can only be discovered through careful examination of the original data.

5 Practicalities and Caveats

At a minimum, our goal with manual quality control was to have at least one person look at every float profile to assess whether the data passed at least a cursory examination by an expert when viewed in a way where outliers were most likely to stand out. While this was accomplished, there are several factors to consider with this approach. One point is that our group is comprised of open-ocean oceanographers. This, combined with the increased natural variability found in coastal areas or inland seas may mean that we have missed more bad data in those regions.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

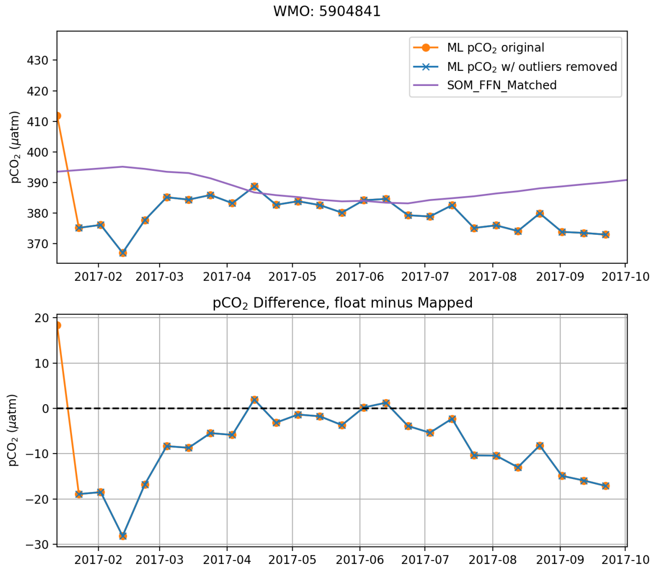


Figure 9. Example of the impact of a bad 1st profile removal for float 5904841. Top: mixed layer pCO_2 plotted vs. time, both original (orange) and once outliers have been removed (blue). Output from a mapped pCO_2 product trained on SOCAT data (SOMFFN, Landschützer et al. (2013)) is plotted for comparison (purple). The difference in pCO_2 between the float-estimated mixed layer pCO_2 and SOM-FFN (bottom) shows the large and anomalous difference between the first profile's pCO_2 estimate and the rest of the time series.

We aimed to be conservative, so this likely means that there are data points that should be removed that we did not, but it may be that points were removed that should have been retained. Similarly, there may be useful information, even in "bad" data. For example, if a particle or organism briefly interferes with a sensor and created an outlier that we then removed (such as in our "goo covered" oxygen profiles), it is possible that a different researcher would be interested in those data as signals. Also, as previously mentioned, there is likely a subset of the near real time adjusted data that could or should be included in some types of analyses.

Our process for outlier detection is time consuming and inherently subjective. It certainly could be sped up, and perhaps improved, through adoption of algorithms or artificial intelligence tools trained on the outlier dataset we have generated. However, we believe it is important for researchers to be engaged at every step of the way, and development of these tools requires initial steps such as manual outlier detection to build a dataset identifying outliers and good data. Furthermore, it is essential to maintain continued vigilance for new problems as they arise.

6 Code and data availability

The BGC-Argo+ data is archived at https://doi.org/10.5281/zenodo.19709012 (Bushinsky et al., 2026b) and can also be accessed through the website developed for this project: www.bgc-argo-plus.info. The profile data used in this study were collected and made freely available by the International Argo Program and the national programs that contribute to it (https://argo.ucsd.edu, https://ocean-ops.org). Original data files are available from ftp://ftp.ifremer.fr/ifremer/argo/dac or ftp://usgodae.org/pub/outgoing/argo/dac. All processing, outlier detection, and manuscript plotting code is available at https://doi.org/10.5281/zenodo.19705310 (Bushinsky et al., 2026a).

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

7 Conclusions

Our goal for this study was to: (1) produce a dataset as free from outliers as possible to enable ease of use of float biogeochemical data, (2) to identify common problems in the float biogeochemical data so that they can be removed in the future at the individual PI level or at the DAC processing steps, and (3) provide a dataset with increased utility and derived variables to increase the accessibility of oceanographic float data for the wider community. This unified dataset can also be used to identify broader issues about sensor performance can be recognized when data is aggregated globally, as opposed to by individual deployment groups or DACs.

Appendix A: Appendix

A1 Optical data

We did not perform a secondary QC on the optical data as we did not have the experience necessary to do so. These data are included unchanged in BGC-Argo+. Spatial profile density and monthly profile counts are shown in Figure A1.

A2 Float outlier detection figures

Examples of outlier detections and data used to determine different outlier detection thresholds are shown here. The oxygen depth derivative threshold approach for one of the example bottom hook profiles in Figure 5 is shown in Figure A2.

To determine what pressure to use for removal of surface data, for every oxygen profile we compared the mean oxygen concentration difference between four pressure ranges (7 to 4 db, 4 to 2 db, 2 to 0 db, and 0 to -2 db) and the mean from 7 to 12 db. We then averaged the results for each float (Figure A3). From this, we saw an increase in the mean oxygen difference between near-surface data and the 7 to 12 db mean in the 2 to 0 db and 0 to -2 db bins.

Manual outliers were found and recorded using the tool shown in Figure A6. Examples of other types of outliers removed in the dataset are anomalously slow oxygen sensor response in the mixed layer (Figure A4) and spikes in nitrate (and sometimes pH), often observed at the base of the mixed layer (Figure A5).

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

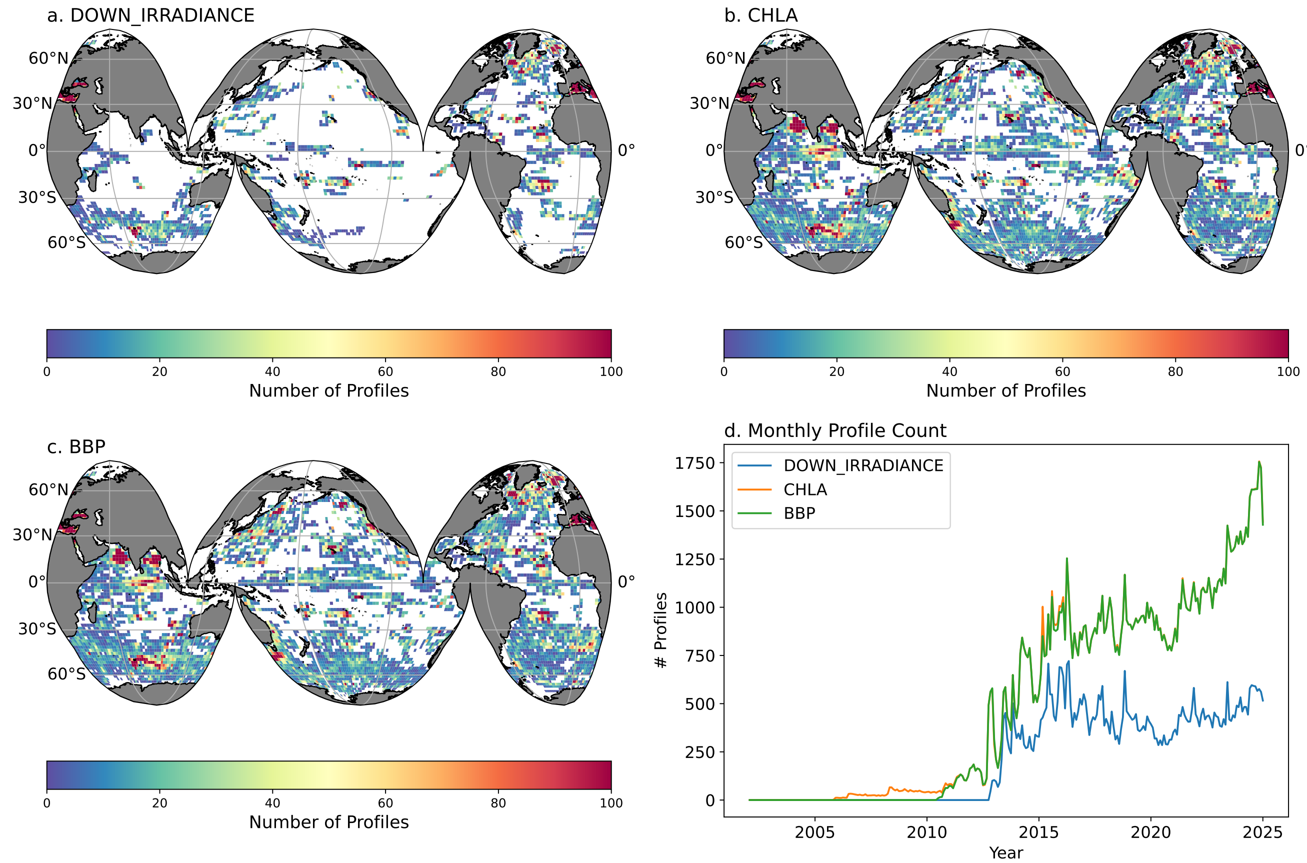


Figure A1. Biogeochemical Argo float profile density. Profiles non-NaN data counted in 2°x 2° bins for (a) downwelling irradiance, (b) chlorophyll, and (c) backscatter. (d) Number of Argo profiles per month vs. time. Profile counts include sensors of any wavelength. For floats with multiple sensors of a given type (i.e. both BBP700 and BBP532) only the first sensor of that type was counted.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

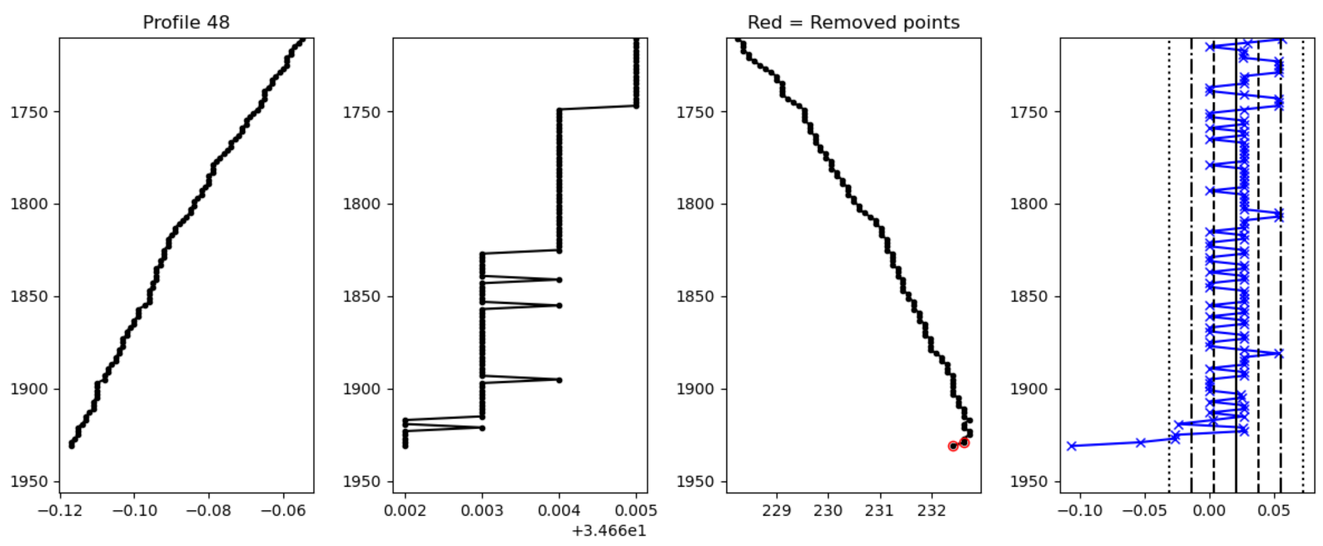


Figure A2. Bottom oxygen filtering example. Float 5901744, profile 48.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

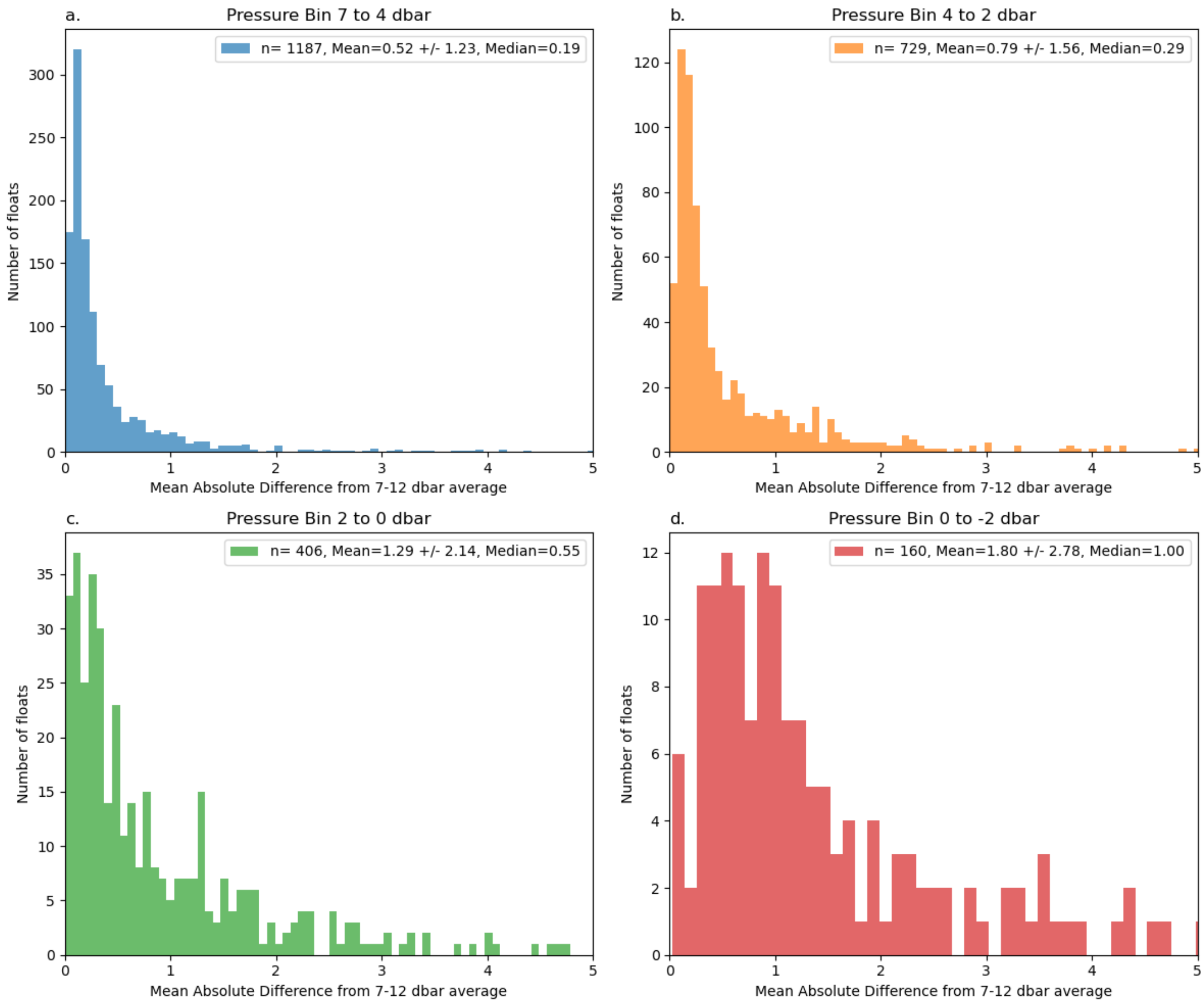


Figure A3. Comparison between different parts of the upper 12 dbar DOXY profiles.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

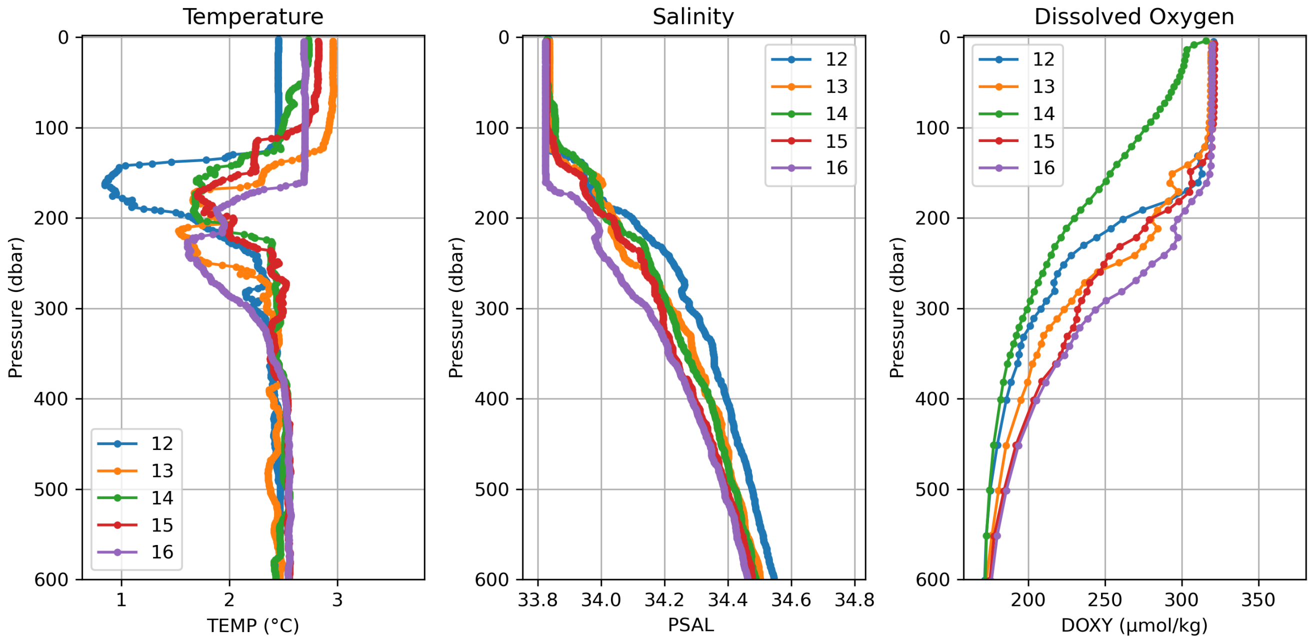


Figure A4. Example of slow oxygen response in the mixed layer. Oxygen in profile 14 displays an abnormally slow response when transitioning from lower oxygen at 600 db, where it agrees with the other oxygen profiles, to a mixed layer concentration. Surrounding profiles 12, 13, 15, and 16 all display a uniform vertical oxygen concentration, while profile 14 only reaches the same concentration just below the sea surface. We hypothesize that the optode was covered by "goo" (organic matter of unknown origin) that temporarily limited the oxygen response for that profile.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

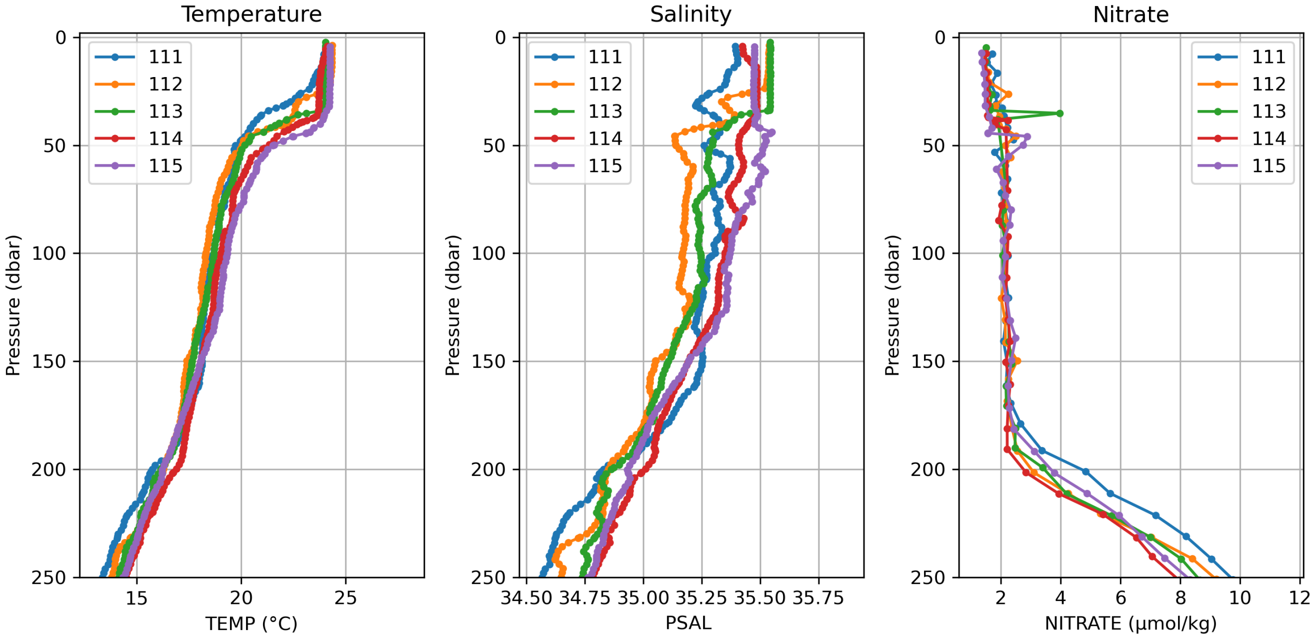
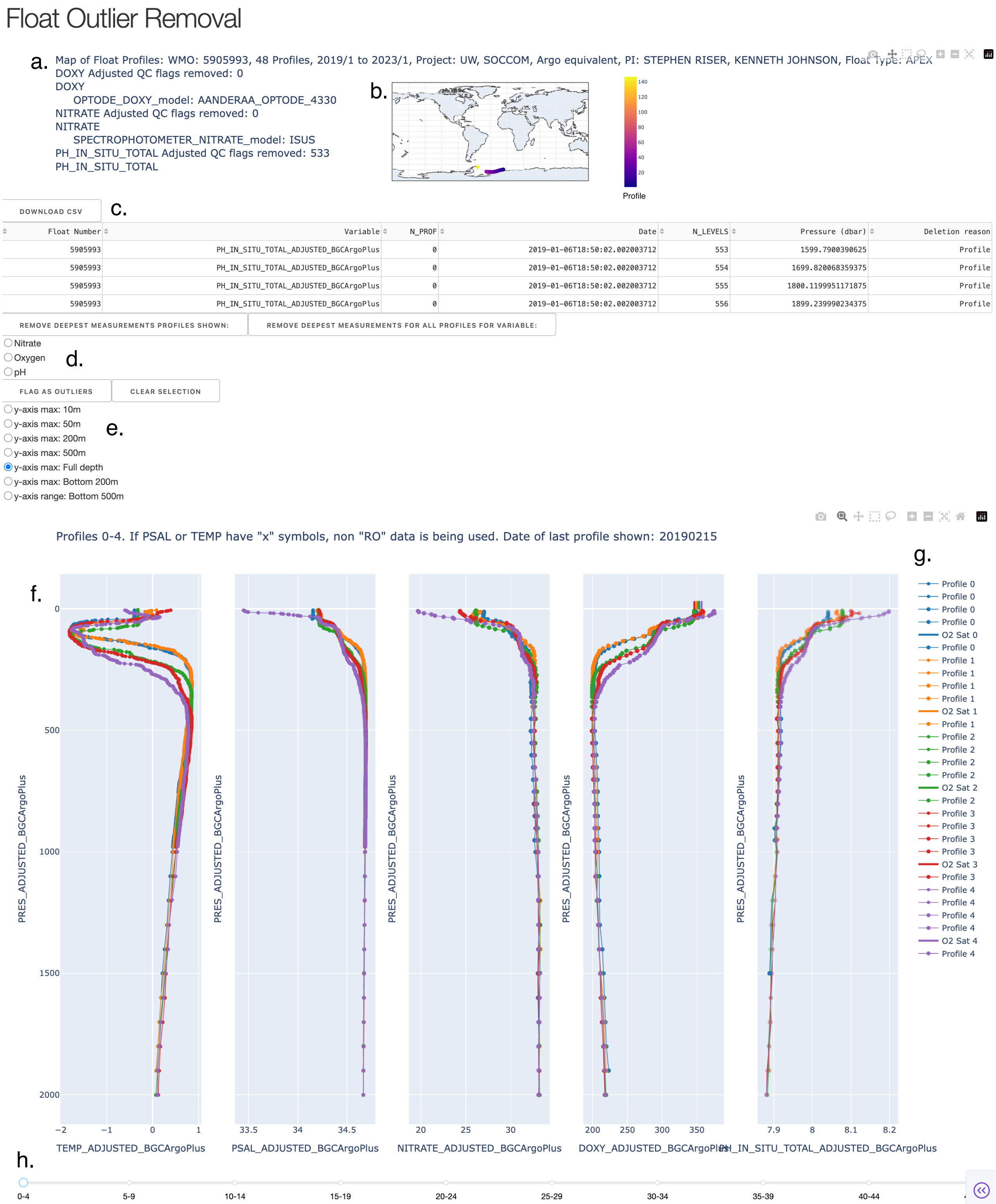


Figure A5. Example of a mixed layer nitrate spike in profile 113.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Open Access Earth System Science Data Discussions



https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Open Access Earth System Science Data Discussions

Figure A6. (Prior page). Screenshot of the top of the outlier detection tool. (a) Basic information about the float, including WMO, number of profiles collected, project, PI, float type. Numbers of data points removed due to QC flags and biogeochemical sensor types are also included to provide context for outlier detection. (b) Map of float profile locations, colored by profile number. Map is interactive (zoom/scroll). (c) Any points manually identified will be added to the table here, which contains sufficient information to identify them for subsequent removal. When review of the float is done, clicking "DOWNLOAD CSV" will store this information in a comma delimited text file. (d) If bottom hooks are identified in different parameters the parameter can be selected using the radio button to the left and either all bottom data points for the profiles shown or all bottom data points for every profile in the deployment will be flagged for removal. (e) Different default y-axes can be chosen. (f) Profiles shown in groups of 5. Individual or groups of points can be selected for removal. Once points are identified, clicking the "FLAG AS OUTLIERS" button will add the points to the table and remove them from the figures shown here. Colored vertical lines near 0 db lines in the oxygen plot indicate the saturation concentration calculated from temperature and salinity. (g) individual profiles can be chosen or hidden to make it easier to examine or select points. (h) A slider for selecting different profiles. Once the slider is selected, arrow keys can be used to navigate between groups of profiles.

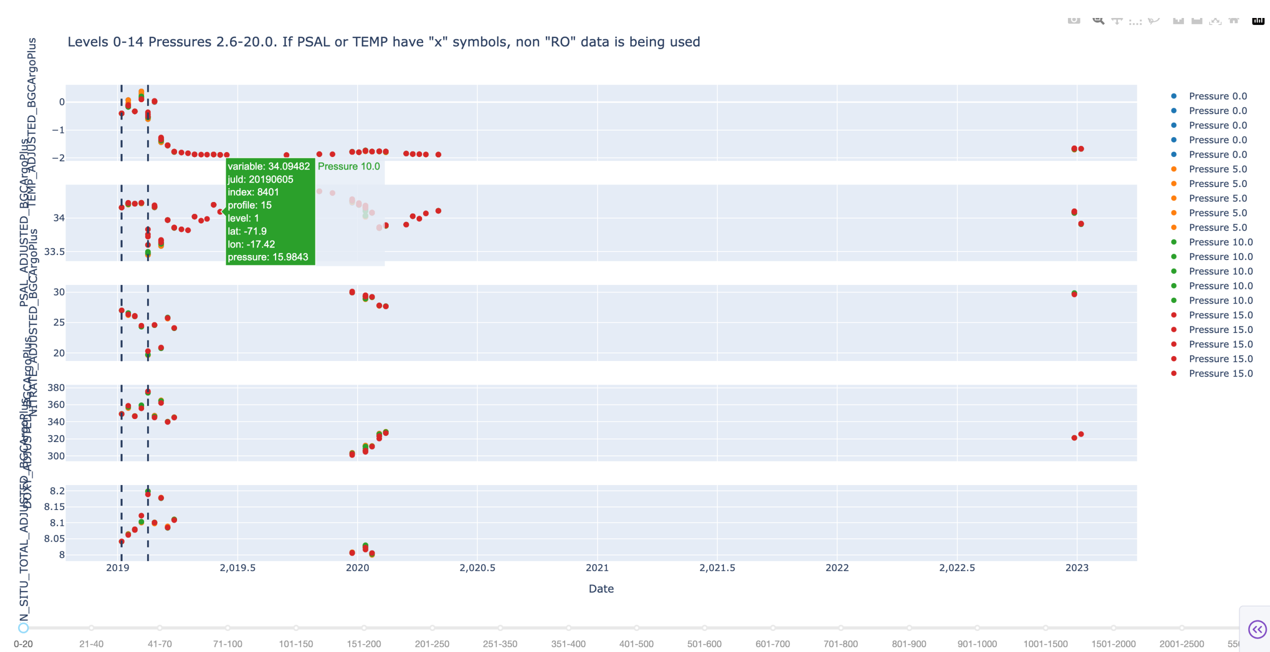


Figure A7. Screenshot of the bottom portion of the outlier detection tool. Plots are similar to the profiles shown in Figure A6 but are instead time series of data available in different depth ranges. Different depth ranges can be selected using the slider. Vertical dashed lines in each plot indicate the profiles shown above. Points removed from time series figures will also be added to the outlier detection table above and removed from both profile and time series subplots.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Open Access Earth System Science Data Discussions

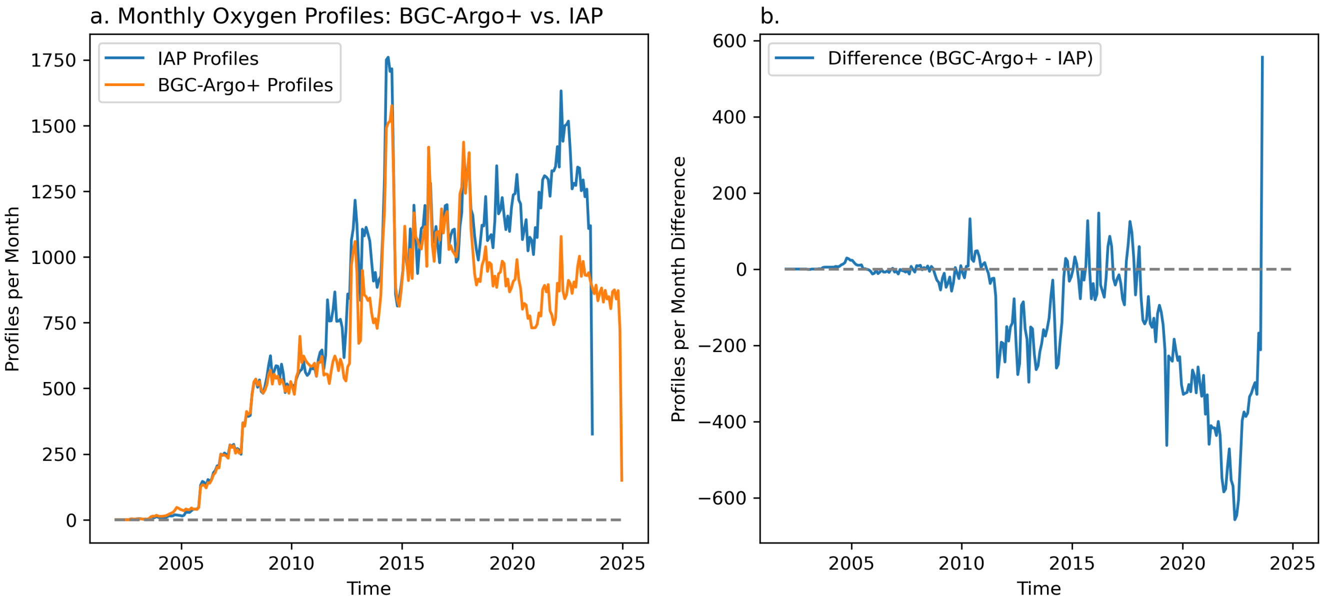


Figure A8. a. Comparison between the number of Argo oxygen profiles per month in the BGC-Argo+ and IAP datasets. The primary cause of differences (b.) in the number of profiles per month for each dataset is the exclusion of Real Time Adjusted data from the BGC-Argo+ dataset. Other differences are due to differences in which profiles are removed in each dataset. It is not currently possible to compare the number of individual samples removed between datasets.

Author contributions. SB conceived of this work and administered the project. Software for data processing and outlier detection was developed by SB, ZN, MJ, DK, and SM. Outlier detection work was carried out by all co-authors. SB prepared the manuscript with contributions from all co-authors.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. The Argo Program is part of the Global Ocean Observing System (Argo, 2000). Two individual projects that contributed a significant amount of data used in this study are: The Southern Ocean Carbon and Climate Observations and Modeling (SOCCOM) Project funded by the National Science Foundation, Division of Polar Programs (NSF PLR -1425989 and OPP-1936222), supplemented by NASA, and the Global Ocean Biogeochemistry Array (GO-BGC) Project funded by the National Science Foundation, Division of Ocean Sciences (NSF OCE-1946578). SMB and this work was primarily funded by the NOAA Climate Program Office's Climate Observations and Monitoring, Climate Variability and Predictability, and Global Ocean Monitoring and Observation programs (NA21OAR4310260) and received support from Schmidt Sciences, LLC (InMOS). The authors would like to thank Ari Essunfeld for sharing his knowledge on Python interactive tools. This is SOEST contribution number XXXX.

References

Bushinsky, S., Nachod, Z., Jutras, M., König, D., McClish, S., and Addey, C.: BGC-Argo+ Processing and Outlier Detection Code, https://doi.org/10.5281/zenodo.19705310, 2026a.

Bushinsky, S., Nachod, Z., Jutras, M., König, D., McClish, S., and Addey, C.: BGC Argo+, v0.1 2026_04, https://doi.org/10.5281/zenodo.19353191, 2026b.

Bushinsky, S. M., Gray, A. R., Johnson, K. S., and Sarmiento, J. L.: Oxygen in the Southern Ocean From Argo Floats: Determination of Processes Driving Air-Sea Fluxes, Journal of Geophysical Research: Oceans, 122, 8661–8682, https://doi.org/10.1002/2017JC012923, iSBN: 8653282898678, 2017.

Bushinsky, S. M., Landschützer, P., Rödenbeck, C., Gray, A. R., Baker, D., Mazloff, M. R., Resplandy, L., Johnson, K. S., and Sarmiento, J. L.: Reassessing Southern Ocean Air-Sea CO2 Flux Estimates With the Addition of Biogeochemical Float Observations, Global Biogeochemical Cycles, 33, 1370–1388, https://doi.org/10.1029/2019GB006176, 2019.

Bushinsky, S. M., Nachod, Z., Fassbender, A. J., Tamsitt, V., Takeshita, Y., and Williams, N.: Offset Between Profiling Float and Shipboard Oxygen Observations at Depth Imparts Bias on Float pH and Derived p CO_2, Global Biogeochemical Cycles, 39, e2024GB008 185, https://doi.org/10.1029/2024GB008185, 2025.

Carter, B. R., Williams, N. L., Gray, A. R., and Feely, R. A.: Locally interpolated alkalinity regression for global alkalinity estimation, Limnology and Oceanography: Methods, 14, 268–277, https://doi.org/10.1002/lom3.10087, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/lom3.10087, 2016.

Carter, B. R., Bittig, H. C., Fassbender, A. J., Sharp, J. D., Takeshita, Y., Xu, Y.-Y., Álvarez, M., Wanninkhof, R., Feely, R. A., and Barbero, L.: New and updated global empirical seawater property estimation routines, Limnology and Oceanography: Methods, 19, 785–809, https://doi.org/10.1002/lom3.10461, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/lom3.10461, 2021.

Carter, B. R., Sharp, J. D., Dickson, A. G., Álvarez, M., Fong, M. B., García-Ibáñez, M. I., Woosley, R. J., Takeshita, Y., Barbero, L., Byrne, R. H., Cai, W., Chierici, M., Clegg, S. L., Easley, R. A., Fassbender, A. J., Fleger, K. L., Li, X., Martín-Mayor, M., Schockman, K. M., and Wang, Z. A.: Uncertainty sources for measurable ocean carbonate chemistry variables, Limnology and Oceanography, p. lno.12477, https://doi.org/10.1002/lno.12477, 2023.

de Boyer Montégut, C., Madec, G., Fischer, A. S., Lazar, A., and Iudicone, D.: Mixed layer depth over the global ocean: An examination of profile data and a profile-based climatology, Journal of Geophysical Research, 109, C12 003, https://doi.org/10.1029/2004JC002378, 2004.

Dove, L. A., Balwada, D., Thompson, A. F., and Gray, A. R.: Enhanced Ventilation in Energetic Regions of the Antarctic Circumpolar Current, Geophysical Research Letters, 49, e2021GL097 574, https://doi.org/10.1029/2021GL097574, 2022.

Garcia, H. E. and Gordon, L. I.: Oxygen solubility in seawater: Better fitting equations, Limnology and Oceanography, 37, 1307–1312, https://doi.org/10.4319/lo.1992.37.6.1307, 1992.

Gouretski, V., Cheng, L., Du, J., Xing, X., Chai, F., and Tan, Z.: A consistent ocean oxygen profile dataset with new quality control and bias assessment, Earth System Science Data, 16, 5503–5530, https://doi.org/10.5194/essd-16-5503-2024, 2024.

Gray, A. R., Johnson, K. S., Bushinsky, S. M., Riser, S. C., Russell, J. L., Talley, L. D., Wanninkhof, R., Williams, N. L., and Sarmiento, J. L.: Autonomous Biogeochemical Floats Detect Significant Carbon Dioxide Outgassing in the High-Latitude Southern Ocean, Geophysical Research Letters, 45, 9049–9057, https://doi.org/10.1029/2018GL078013, 2018.

Humphreys, M. P., Cala, B. A., Schiller, A. J., Sandborn, D., Gregor, L., Pierrot, D., van Heuven, S. M. A. C., Lewis, E. R., and Wallace, D. W. R.: PyCO2SYS: marine carbonate system calculations in Python, https://doi.org/10.5281/zenodo.3744275, 2024.

Jackett, D. R. and McDougall, T. J.: A Neutral Density Variable for the World's Oceans, Journal of Physical Oceanography, 27, 237–263, https://doi.org/10.1175/1520-0485(1997)027<0237:ANDVFT>2.0.CO;2, 1997.

Johnson, K. S., Plant, J. N., Coletti, L. J., Jannasch, H. W., Sakamoto, C. M., Riser, S. C., Swift, D. D., Williams, N. L., Boss, E., Haëntjens, N., Talley, L. D., and Sarmiento, J. L.: Biogeochemical sensor performance in the SOCCOM profiling float array, Journal of Geophysical Research: Oceans, 122, 6416–6436, https://doi.org/10.1002/2017JC012838, iSBN: 8653282898678, 2017.

Key, R., Olsen, A., van Heuven, S., Lauvset, S., Velo, A., Lin, X., Schirnick, C., Kozyr, A., Tanhua, T., Hoppema, M., Jutterström, S., Steinfeldt, R., Jeansson, E., Ishi, M., Perez, F., and Suzuki, T.: Global Ocean Data Analysis Project, Version 2 (GLODAPv2), ORNL/CDIAC-162, NDP-093, https://doi.org/10.3334/CDIAC/OTG.NDP093_GLODAPv2, place: Oak Ridge, Tennessee, 2015.

Körtzinger, A., Schimanski, J., Send, U., and Wallace, D.: The ocean takes a deep breath., Science (New York, N.Y.), 306, 1337, https://doi.org/10.1126/science.1102557, 2004.

Landschützer, P., Gruber, N., Bakker, D. C. E., Schuster, U., Nakaoka, S., Payne, M. R., Sasse, T. P., and Zeng, J.: A neural network-based estimate of the seasonal to inter-annual variability of the Atlantic Ocean carbon sink, Biogeosciences, 10, 7793–7815, https://doi.org/10.5194/bg-10-7793-2013, 2013.

Martz, T. R., Riser, S. C., and Johnson, K. S.: Ocean metabolism observed with oxygen sensors on profiling floats in the South Pacific, Limnology and Oceanography, 53, 2094–2111, https://doi.org/10.4319/lo.2008.53.5_part_2.2094, 2008.

McDougall, T. J. and Barker, P.: Getting started with TEOS-10 and the Gibbs Seawater (GSW) Oceanographic Toolbox, https://www.teos-10.org/pubs/Getting_Started.pdf, 2011.

Olsen, A., Key, R. M., Van Heuven, S., Lauvset, S. K., Velo, A., Lin, X., Schirnick, C., Kozyr, A., Tanhua, T., Hoppema, M., Jutterström, S., Steinfeldt, R., Jeansson, E., Ishii, M., Pérez, F. F., and Suzuki, T.: The Global Ocean Data Analysis Project version 2 (GLODAPv2) – an internallyconsistent data product for the world ocean, Earth System Science Data, 8, 297–323, https://doi.org/10.5194/essd-8-297-2016, 2016.

Olsen, A., Lange, N., Key, R. M., Tanhua, T., Bittig, H. C., Kozyr, A., Azetsu-scott, K., Becker, S., Brown, P. J., and Carter, B. R.: GLODAPv2.2020 - the second update of GLODAPv2, Earth System Science Data Discussions, https://doi.org/10.5194/essd-2020-165, 2020.

Prend, C. J., Gray, A. R., Talley, L. D., Gille, S. T., Haumann, F. A., Johnson, K. S., Riser, S. C., Rosso, I., Sauvé, J., and Sarmiento, J. L.: Indo-Pacific Sector Dominates Southern Ocean Carbon Outgassing, Global Biogeochemical Cycles, 36, e2021GB007 226, https://doi.org/10.1029/2021GB007226, 2022.

Roemmich, D., Johnson, G. C., Riser, S., Davis, R., Gilson, J., Owens, W., Garzoli, S., Schmid, C., and Ignaszewski, M.: The Argo Program: Observing the Global Ocean with Profiling Floats, Oceanography, 22, 34–43, https://doi.org/10.5670/oceanog.2011.65, iSBN: 1042-8275, 2009.

Ruddick, B. and Richards, K.: Oceanic thermohaline intrusions: observations, Progress in Oceanography, 56, 499–527, https://doi.org/10.1016/S0079-6611(03)00028-4, 2003.

Sharp, J. D., Fassbender, A. J., Carter, B. R., Johnson, G. C., Schultz, C., and Dunne, J. P.: GOBAI-O $_2$: temporally and spatially resolved fields of ocean interior dissolved oxygen over nearly two decades, preprint, ESSD – Ocean/Chemical oceanography, https://doi.org/10.5194/essd-2022-308, 2022.

Takeshita, Y., Johnson, K. S., Coletti, L. J., Jannasch, H. W., Walz, P. M., and Warren, J. K.: Assessment of pH dependent errors in spectrophotometric pH measurements of seawater, Marine Chemistry, 223, 103 801, https://doi.org/10.1016/j.marchem.2020.103801, 2020.

https://doi.org/10.5194/essd-2026-311
Preprint. Discussion started: 12 May 2026

Thierry, V., Bittig, H., and Team, T. A.-B.: Argo quality control manual for dissolved oxygen concentration, Argo-BGC group, https://doi.org/10.13155/46542, version Number: 2.2, 2025.

Uchida, H., Kawano, T., Kaneko, I., and Fukasawa, M.: In Situ Calibration of Optode-Based Oxygen Sensors, Journal of Atmospheric and Oceanic Technology, 25, 2271–2281, https://doi.org/10.1175/2008JTECHO549.1, 2008.

Vives, C. R., Schallenberg, C., Strutton, P. G., Bendtsen, J., Richardson, K., and Boyd, P. W.: The Contribution of Deep Chlorophyll Maxima to Net Primary Production in the Southern Ocean, Global Biogeochemical Cycles, 39, e2024GB008 327, https://doi.org/10.1029/2024GB008327, 2025.

Williams, N., Juranek, L., Feely, R., Russell, J., Johnson, K., and Hales, B.: Assessment of the carbonate chemistry seasonal cycles in the Southern Ocean from persistent observational platforms, Journal of Geophysical Research: Oceans, 123, 1–20, https://doi.org/10.1029/2017JC012917, 2018.

Williams, N. L., Juranek, L. W., Johnson, K. S., Feely, R. A., Riser, S. C., Talley, L. D., Russell, J. L., Sarmiento, J. L., and Wanninkhof, R.: Empirical algorithms to estimate water column pH in the Southern Ocean, Geophysical Research Letters, 43, 3415–3422, https://doi.org/10.1002/2016GL068539, 2016.

Williams, N. L., Juranek, L. W., Feely, R. A., Johnson, K. S., Sarmiento, J. L., Talley, L. D., Dickson, A. G., Gray, A. R., Wanninkhof, R., Russell, J. L., Riser, S. C., and Takeshita, Y.: Calculating surface ocean pCO2 from biogeochemical Argo floats equipped with pH: An uncertainty analysis, Global Biogeochemical Cycles, 31, 591–604, https://doi.org/10.1002/2016GB005541, iSBN: 08866236, 2017.

Winkler, L. W.: Die Bestimmung des im Wasser gelösten Sauerstoffes, Berichte der deutschen chemischen Gesellschaft, 21, 2843–2854, https://doi.org/10.1002/cber.188802102122, _eprint: https://chemistry-europe.onlinelibrary.wiley.com/doi/pdf/10.1002/cber.188802102122, 1888.

Wong, A. P. S., Wijffels, S. E., Riser, S. C., Pouliquen, S., Hosoda, S., Roemmich, D., Gilson, J., Johnson, G. C., Martini, K., Murphy, D. J., Scanderbeg, M., Bhaskar, T. V. S. U., Buck, J. J. H., Merceur, F., Carval, T., Maze, G., Cabanes, C., André, X., Poffa, N., Yashayaev, I., Barker, P. M., Guinehut, S., Belbéoch, M., Ignaszewski, M., Baringer, M. O., Schmid, C., Lyman, J. M., McTaggart, K. E., Purkey, S. G., Zilberman, N., Alkire, M. B., Swift, D., Owens, W. B., Jayne, S. R., Hersh, C., Robbins, P., West-Mack, D., Bahr, F., Yoshida, S., Sutton, P. J. H., Cancouët, R., Coatanoan, C., Dobbler, D., Juan, A. G., Gourrion, J., Kolodziejczyk, N., Bernard, V., Bourlès, B., Claustre, H., D'Ortenzio, F., Le Reste, S., Le Traon, P.-Y., Rannou, J.-P., Saout-Grit, C., Speich, S., Thierry, V., Verbrugge, N., Angel-Benavides, I. M., Klein, B., Notarstefano, G., Poulain, P.-M., Vélez-Belchí, P., Suga, T., Ando, K., Iwasaska, N., Kobayashi, T., Masuda, S., Oka, E., Sato, K., Nakamura, T., Sato, K., Takatsuki, Y., Yoshida, T., Cowley, R., Lovell, J. L., Oke, P. R., Van Wijk, E. M., Carse, F., Donnelly, M., Gould, W. J., Gowers, K., King, B. A., Loch, S. G., Mowat, M., Turton, J., Rama Rao, E. P., Ravichandran, M., Freeland, H. J., Gaboury, I., Gilbert, D., Greenan, B. J. W., Ouellet, M., Ross, T., Tran, A., Dong, M., Liu, Z., Xu, J., Kang, K., Jo, H., Kim, S.-D., and Park, H.-M.: Argo Data 1999–2019: Two Million Temperature-Salinity Profiles and Subsurface Velocity Observations From a Global Array of Profiling Floats, Frontiers in Marine Science, 7, 700, https://doi.org/10.3389/fmars.2020.00700, 2020.