



Drivers of new optical water types in southwestern Patagonian fjords derived from ship-borne radiometry

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Abstract. This research aimed to take a step closer to a holistic assessment of the Optical Water Types (OWT) of the southwestern Patagonian fjords and channels. Using a participatory science approach, we collected high-frequency data from a Ferry Box system and TriOS radiometers on the Yaghán Ferry between 2022 and 2023, as it travelled from Punta Arenas to Puerto Williams, across the Chilean Patagonian fjords and channels. By combining ERA5 meteorological data with on-site water quality measurements such as turbidity, Chl-a, and CDOM, we identified the main factors driving nine unique OWTs, which, for the first time in Patagonia, were grouped using in situ measured reflectance data.

Importantly, this study does not aim to predict outcomes; instead, it focuses on statistically separating these OWTs and identifying their specific water-quality features as well as meteorological and potential land use forcings. To test the reliability of these groups, we used a Random Forest classifier to identify the main factors and key parameters for each water type. The results show that runoff, CDOM, and Chl-a are generally the main drivers of OWT differences, though each group has its own subtle influences, as shown by One-vs-Rest analysis. We found that working closely with community partners greatly improves our ability to monitor complex systems, such as the Patagonian fjords and channels. This research encourages the creation of inclusive, broad monitoring strategies that recognise the close connection between people and the environment, helping us better understand and protect these valuable areas.

1 Introduction

OWTs have been implemented to demarcate water types based on their bio-geo-optical properties (Prieur and Sathyendranath, 1981; Spyarakos, 2018) and can provide information about water constituents, such as CDOM, Chl-a, and TSM. These optical properties are derived from inherent and apparent optical properties (IOPs and AOPs) and from in situ radiometric measurements above and below the water surface. By classifying waters based



on specific optical signatures, OWT addresses the substantial variability present in diverse regional and environmental contexts. This classification is critical for selecting appropriate RS algorithms and improving the accuracy of bio-optical parameter retrievals (Bi and Hieronymi, 2024). This approach supports monitoring of biogeochemical processes and can thus contribute to understanding broader climate feedback mechanisms and to identifying distinct water types linked to specific environmental conditions (Spyrakos et al., 2018; Hieronymi et al., 2023; Lehmann, Moritz K. et al., 2018; Sent et al., 2025). As satellite technologies and data processing improve (Bresciani et al., 2022), the widespread adoption of OWT methodologies could yield significant advances in our understanding of ecosystem dynamics and their responses to climate change (Jackson, Sathyendranath and Mélin, 2017; Bi, Shun and Hieronymi, 2024).

Patagonian fjords constitute a distinctive and highly complex network of narrow channels and fjords that sustain rich coastal ecosystems and host highly diverse water masses, each with properties shaped by continental freshwater inputs from glacial melt and terrestrial runoff (Iriarte, Pantoja and Daneri, 2014). These waters receive nutrient-rich Subantarctic Surface Waters (nitrate and phosphate), fostering a productive environment and influencing local carbon cycling and biological productivity (Pérez-Santos, 2018; Vargas, 2018; Giesecke, 2021). The mixing of runoff with local marine water creates distinct water quality characteristics (Tamayo-Leiva et al., 2021), which are influenced by four principal water circulation mechanisms: density-driven flows from freshwater inputs, tidal forcing, wind forcing, and topographic effects (Nepf and Geyer, 1996; Valle-Levinson, Blanco and Frangópulos, 2006; Soto-Riquelme, Pinilla and Ross, 2023). Tidal forces explain 60-80% of the variance in some channels and generate intense mixing over submarine sills (Soto-Riquelme, Pinilla and Ross, 2023). Wind forcing can reverse surface outflow during winter months and modulate stratification seasonally (González, 2013). Topographic features, such as sills, can enhance mixing and act as transport barriers for deeper water masses (Valle-Levinson et al., 2006; Giesecke et al., 2021). Environmental factors such as seasonal light regime, water-column light penetration, macro- and micronutrient supply, water-column stratification, and freshwater influx are the main drivers of the dynamics of these fjord ecosystems (Torres, R., 2020; Alves-De-Souza, 2026). The influence of these mechanisms varies with local environmental conditions, and they ultimately shape ecosystem functioning by modulating nutrient and sediment transport, affecting light penetration, and modifying the biogeochemical properties of the euphotic zone (Crosswell, 2022).

Southern Patagonian channels (48-53° S) receive high loads of fine, silt-sized sediment created when glaciers grind bedrock, which are transported to fjords, playing a fundamental role in light limitation for primary producers (benthic and pelagic) (González et al., 2013; Alves-de-Souza et al., 2026), whereas intense stratification is dictated mainly by freshwater inflow to coastal environments. In fjords with land-terminating glaciers, fresh



water is transported mainly through the surface, creating shallow (a couple of centimetres) turbidity plumes that flow outside the fjords as quasi-laminar fluids (Meire, 2017; Giesecke, 2019). In fjords with marine-terminating glaciers, turbulent flow dominates due to subglacial discharge (Straneo and Cenedese, 2015), leading to the homogenisation of turbidity throughout the water column (Meire, 2017; Meire, 2023) and reducing vertical stratification (Giesecke et al., 2019). Meltwater and precipitation potentially introduce CDOM from peatlands and vegetated areas, which can account for up to 80% of total light absorption in the Pacific sector of southern Patagonia (Rain-Franco, 2019). By contrast, biological productivity might depend more on the chemical composition and bioavailability of macro- and micronutrients derived from continental runoff and their interactions with coastal marine waters (Torres et al., 2020). Continental weathering, erosion, and the leaching of macro- and micronutrients depend on land use, soil types, basin size and connectivity, and volcanic activity. These factors imprint distinct geochemical signatures on runoff (León-Muñoz, 2021) and have distinct impacts on autotrophic communities (Raudina, 2022). Suspended sediments from glacier melt and soil erosion can either support or limit marine productivity by modifying the underwater light environment (Oren and Gunde-Cimerman, 2007; Geraldès and Pinto, 2021; Efimova et al., 2023), as well as river inputs, depending on the surrounding geology and vegetation (Marín-Guirao, 2013). Southern Chilean rivers export an estimated 200×10^6 t/year of suspended sediments and 20×10^6 t/year of dissolved solids, volumes that rival those of major South American river basins, aside from the Amazon River (Milliman and Farnsworth, 2013).

Although runoff plays a key role in shaping the environmental state of the southwestern Patagonian fjords, available data remain scarce (Godoy et al., 2025). The relationship between runoff quality and nearshore marine attributes, such as geology, soils, vegetation, and climate, has not been systematically explored. This data gap is further exacerbated by limited water quality monitoring initiatives and the scarcity of hydrological time series, particularly in near-coastal zones. In the southwestern Patagonian fjords and channels, the system's complexity is intensified by glacier-ocean processes that affect hydrography, light and nutrient availability, carbonate chemistry (Vellojin, 2022), and air-sea gas exchange. Warming-driven glacier melt has notably altered the biogeochemistry and optical properties of the Magellan Strait during the Holocene (Aracena et al., 2015). Nevertheless, precipitation at the western section of southern Patagonia (~ 4000 mm yr⁻¹ with an increase of 200 mm per decade (Garreaud et al., 2013) dominates over the fresh water discharge of melting (Sauter, Arndt and Schneider, 2020), while the eastern section (Punta Arenas city) has experienced an overall decline in rainfall since the 1990s, particularly during spring and summer, along with an increasing trend in extreme drought events (González-Reyes, Jacques-Coper and Muñoz, 2021).



Monitoring subpolar coastal waters, particularly in the Southern Hemisphere, has long been challenging due to their remoteness, limited land connectivity, and low population density, which make long-term monitoring programs costly to implement and sustain. RS has transformed approaches to monitoring coastal waters, but retrieval accuracy can be highly variable and often unsatisfactory in optically complex waters such as the Patagonian fjords (Huovinen et al., 2020). Additional challenges include high cloud cover and the narrow width of fjords and channels, which limit the applicability of satellite sensors (Díaz, 2025); thus, relying solely on satellite RS is ineffective for consistent monitoring. In recent years, the potential value of an automated above- or near-surface approach for measuring water-leaving reflectance from water bodies has been demonstrated as an effective tool for validating satellite observations. Studies have shown that acquiring such reflectance data has helped extend understanding of spatial variations in reflectance across diverse water types and increased the temporal resolution of observations (Spyrakos et al., 2018; Hieronymi et al., 2023; Sent et al., 2025). The aforementioned has also significantly increased the number of matchups available for calibrating and validating satellite data. Furthermore, integrating in situ data collection via participatory monitoring (e.g., continuous monitoring on non-research vessels) with RS has become essential for obtaining reliable datasets that reflect the actual condition of these marine ecosystems (Hieronymi, Müller and Doerffer, 2017; Wilson et al., 2025). This study aims to develop a monitoring framework for the Southwestern Patagonian fjords, demonstrating that OWTs provide reliable spectral fingerprints associated with specific environmental drivers, offering predictive potential for ecosystems through continuous monitoring systems such as the FerryBox on board diverse platforms, thereby filling fundamental gaps in hard-to-reach environments.

2 Data and Methods

2.1 Study area

Chilean Patagonian fjords are a unique marine ecosystem characterised by recent glacial formation (Pleistocene) (Rozzi et al., 2024) (Fig 1a). They feature strong environmental gradients in oxygen, salinity, and nutrients governed by estuarine regimes (Tamayo-Leiva et al., 2021). The latitudinal gradient extends from northern Patagonia (41-45°S) to the Antarctic Polar Front (55°S) (Figs. 1a and 1b), with temperatures declining southward. Salinity decreases mainly in coastal areas towards the south, with maximum concentrations between 42 and 51°S. Beyond these latitudes, salinity increases towards the Antarctic Polar Front (Saldías, 2019). Antarctic Polar Front waters are characterised by low temperatures (<6°C), high salinity (33.7-34.5), and elevated oxygen levels (>6 ml L⁻¹) (Iriarte et al., 2014). Substantial variations in nutrient and turbidity distributions are closely linked to the seasonal and spatial diversity of biological communities in these fjords (Sepúlveda, Pantoja and



130 Huguen, 2011; Pérez-Santos et al., 2018). Moreover, Patagonian fjords have a paramount ecological importance supporting rich and unique marine assemblages with high diversity enhanced by their characteristic subantarctic location (Betti, 2021). These unique characteristics are critical for understanding broader ecological implications, such as carbon cycling.

135 2.2 FerryBox and TriOS Ramses data acquisition

Data for turbidity, Chl-a, and CDOM were acquired from mid-September 2022 until August 2023 by a FerryBox I system on board the Yaghán ferry (Fig. 2B). The FerryBox I (4H-Jena) is an autonomous measuring platform that uses Ships of Opportunity (SOOP) to collect seawater and analyse its chemical, physical, and biological properties (Petersen, 2014). It functions as a flow-through system that takes in water through an inlet in the vessel hull and pumps it into a measuring circuit containing a series of sensors. This system is installed in the machine room of the ferry Yaghan, which carries cargo and passengers approximately once a week between Punta Arenas and Puerto Williams along a ~520 km route, with a similar route on both the outbound and return legs of the trip (Fig. 1). During its trip, it continuously pumps water (~15 L min⁻¹) from about 1 m below the sea from the ship's starboard bow to an array of sensors (see www.starm.cl for more details). Parameters were measured at 1-minute intervals (approximately every 300 m, depending on ship speed) (Fig. 1). Information collected by the sensors is complemented with GPS and time (UTC) data and integrated into a single ASCII file containing the daily measurements recorded by the system.

A set of three TriOS radiometers, with a wavelength range of 320 to 950 nm and a 2.5 nm resolution, was mounted on the ferry's bridge (Fig. 2A) to measure remote sensing reflectance (*R_{rs}*) of the sea. One cosine collector irradiance sensor (RAMSES ACC; 180° field of view) was oriented vertically toward the sky to measure the total downwelling irradiance (*E_d*). Two Advanced Radiance Collector (RAMSES-ARC) sensors (7° field of view) were used: one pointed diagonally upward at approximately 45° to measure the radiance of skylight (*L_s*), and the other pointed downward toward the sea surface at approximately 45° to measure the total radiance from the water surface (*L_t*). Both radiance sensors were oriented toward the ship's starboard side to capture clear-sky conditions and undisturbed, unshaded water, respectively (according to the manufacturer's specifications). Only *R_{rs}* collected at solar zenith angles between 0 and 90 degrees were retained for further analysis.



Figure 1. Map of the Chilean Patagonia (a) (Google Satellite), and close-up of the study area (b) with the track covered by the FerryBox system on board the Yaghán ferry from Punta Arenas to Puerto Williams (orange line).



The lower base map was designed and developed by Esri | Powered by Esri, and the upper by Google © 2025 NASA, Map data © 2025 Google).

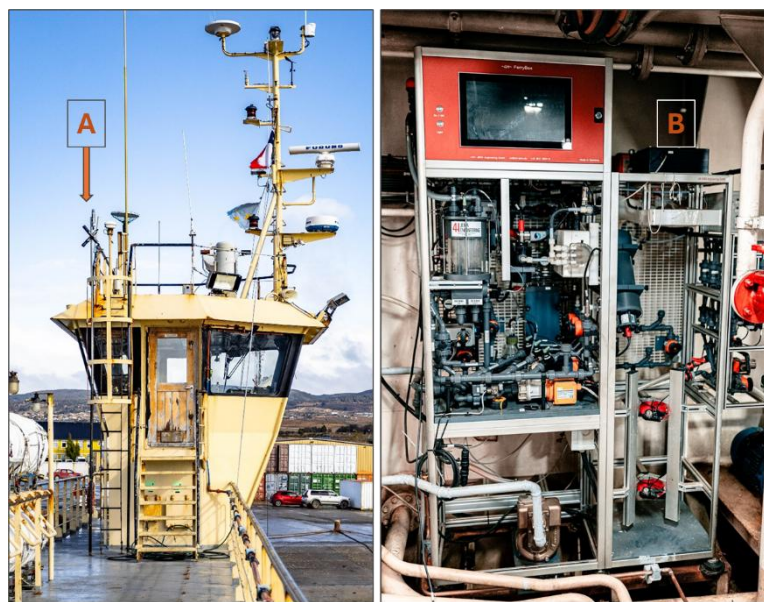


Figure 2. The TriOs Ramses radiometers (A) and FerryBox (B) system on board the ferry Yaghán.

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2.3 Meteorological data

To identify the dominant meteorological characteristics, a quantitative analysis of the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) Land Daily Aggregated dataset was performed. The ERA5 data include air temperature at 2 m, total precipitation, runoff, snowmelt, surface net solar radiation, and wind speed, with a spatial resolution of 11 km (more specifically 11132 m). All data for the study area (Fig. 1b) from 2022 to 2024 were obtained from Google Earth Engine (GEE). The mean value for each of the six meteorological variables (temperature, precipitation, runoff, snowmelt, wind speed, and surface radiance) was calculated for each cluster and then used in the analysis. To match each OWT to the appropriate environmental data, we used a spatiotemporal nearest-neighbour extraction algorithm implemented in Python using the xarray multidimensional data framework. For each *in situ* water sample, the algorithm searched the ERA5 grid (11x11 km) to find and extract meteorological values from the closest grid cell and the corresponding date.

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2.4 Data processing and analysis

2.4.1 Optical Water Types Classification



180 A functional data analysis (*fda*) approach (Levitin et al., 2007) was used to identify clusters that retain as much reflectance-spectrum information as possible in a computationally efficient manner. This method has previously been used successfully within Spyarakos et al. (2018) to derive meaningful OWTs. A key idea in FDA is that a series of observations, in this case, reflectance spectra, is treated as a noisy realisation of an underlying smooth process. That smooth process, or curve, is estimated using nonparametric statistical modelling, and the
185 resulting smooth curves become the observations of interest for subsequent analysis. This representation provides a low-dimensional summary that preserves the essential shape characteristics of the spectra.

Using the *fda* package in R, curves were fitted to the spectra using a natural cubic spline with 55 equally spaced basis functions. The basis dimension was selected to ensure that the full range of wavelengths was represented with approximately 1 basis function every 10 nm. A functional boxplot (Sun and Genton, 2011) was
190 next used to identify unusual observations, and, based on this, 44 (0.37%) curves were removed prior to further analysis to prevent clustering from being influenced by atypical spectra. Functional PCA (FPC) was applied to the remaining spectra to further reduce dimensionality and identify key features of variability in the data, in terms of both overall shape and mean reflectance level. By using the FPCA scores, we obtain a very low-dimensional representation of the curves ideal for subsequent clustering, as the scores are orthogonal. The first two FPCs
195 explained over 99% of the variability in the underlying data.

K-means clustering was applied to the FPCA scores for the curves. While many unsupervised classification approaches are available, K-means is a suitable choice as, unlike many other approaches, its computational cost scales linearly with the number of observations, and although iterative, it typically converges quickly and reliably.

2.4.2 Data analysis

200 The main dataset included *in situ* water-quality measurements (Turbidity, Chl-a, and CDOM). These were used to define and separate each OWT. To match each OWT to the appropriate environmental data, we used a spatiotemporal nearest-neighbour extraction algorithm using the xarray multidimensional data framework in Python (Hoyer and Hamman, 2017). For each water quality sample, the algorithm used its latitude, longitude, and
205 timestamp to search the ERA5 grid and extract meteorological values from the closest grid cell and the nearest hourly time.

To test for significant differences in environmental and meteorological parameters across the nine reflectance clusters, a one-way Analysis of Variance (ANOVA) was performed on the imputed dataset. The full



dataset was used to examine the distribution and sample size of each identified cluster. After the significant
 210 ANOVA result ($p < 0.05$), a Tukey's Honestly Significant Difference (HSD) post-hoc test was conducted to
 determine which specific cluster pairs were significantly different.

2.4.3 Seasonality and spatial distribution

215 We measured the spatial diversity of the classified OWTs along the transect using the Shannon-Wiener
 Index (H'). This index combines both richness, the total number of distinct OWTs, and evenness, the degree to
 which these OWTs are evenly distributed. A low H' score means the transect is mostly made up of one or a few
 OWTs, showing low diversity. A high H' score means there is a greater variety of OWTs that are more evenly
 distributed. To assess the patchiness of the OWTs, we also calculated the boundary transition rate. This is the
 220 average number of times different OWTs are encountered per 10 km of the transect. A low transition rate suggests
 large, continuous areas of the same OWT, indicating spatial stability. A high transition rate means boundaries
 between OWTs occur more often, indicating a more fragmented and complex water-mass structure.

We also tested whether there were significant links between the identified OWTs and the seasons. To do
 this, we used a chi-squared (χ^2) test of independence. We applied the test to a table showing how often each OWT
 225 cluster occurred in each season (summer, autumn, winter, and spring). The test checks whether the distribution of
 OWTs is independent of season. If the result is statistically significant ($p < 0.05$), it means that certain OWTs are
 more likely to be found in specific seasons.

To find the land-based factors influencing each OWT, we used a nearest-neighbour spatial analysis and
 then applied a resource selection function. We measured the straight-line distance from each marine observation
 230 ($N = 10,533$) to the centre of the closest land use area using a cKDTTree algorithm with projected UTM coordinates
 (Zone 19S). Land-use data were obtained from the National Forestry Corporation (CONAF, 2014), and we focused
 on eight categories, including Forests, Glaciers, and Urban areas. Since some land cover types are much more
 common (for example, Praderas y Matorrales make up over 55% of the study area), we used Manly's Selection
 Ratios (W_i) to measure the strength of the association between specific water types and different land uses (Eq.1)
 235 (Manly, 2008). The selection ratio for land use category i by OWT j is defined as:

$$w_i = \frac{o_{ij}}{p_i} \quad (\text{Eq. 1})$$

Where:

O_{ij} is the proportion of times OWT j is observed with land use i , which is considered the "used" resource. P_i shows
 how much of the total study area is land use i , or the "available" resource. If W_i is greater than 1, it indicates that



240 the OWT is more often found near this land use, suggesting a preference. If W_i is less than 1, it means the water type is avoided near that land use.

4.4.4 Random Forest

245 We used a Random Forest (RF) classifier (Breiman, 2001) to assess how well environmental parameters can predict the OWTs. RF is a type of machine learning algorithm that works well with complex, high-dimensional data. The analysis was structured in two phases: (1) a multi-class classification to assess overall model performance as well as to identify the general most important drivers for all OWTs, and (2) a One-vs-Rest (OvR) interpretation to identify the specific environmental drivers for each OWT. The primary model was a multi-class classifier trained
250 to predict the OWT cluster using ERA5 meteorological data (runoff, temperature, precipitation, surface radiance, and wind speed) and water quality parameters (turbidity, Chl-*a*, and CDOM) predictors. Before training, the predictor variables were standardised using a StandardScaler (Z-score standardisation) to remove scale differences among variables, and the model was configured with balanced class weights to account for potential class imbalance in the OWT clusters. The full dataset was randomly split into a training set (80%) to avoid overfitting
255 and a blind test set (20%) to ensure unbiased performance. The RF model was built with 500 trees to ensure a stable model (Breiman, 2001). A feature importance table and confusion matrix were generated to visualise the most important drivers and misclassification patterns. Standard classification metrics were computed, including accuracy and per-class precision, recall, and F1 Score.

For phase (2), we computed an OvR to understand the unique environmental signature of each OWT. The
260 latter involved training a separate binary RF classifier for each OWT (e.g., "Cluster 1" vs "All Other Clusters", "Cluster 2" vs "All Other Clusters", etc.) (Wang et al., 2024). By calculating feature importance for each of these binary models, we could identify the parameters most critical for distinguishing one water type from all others. All steps were performed in Python using the *scikit-learn* package.

265 4.4.5 OWT-Land use

We assessed how land ecosystems might relate to each OWT by running a high-resolution spatial proximity analysis. We matched each marine sampling station, grouped by OWT, to the closest land-use (Corporación Nacional Forestal, 2014) category using a distance-minimising computational method. We processed the data in Python, using *geopandas* and *scipy.spatial* libraries. To ensure accurate measurements and avoid high-latitude
270 distortions, we standardised and reprojected marine and land-use datasets into the Universal Transverse Mercator



(UTM) system. We used a spatial indexing algorithm based on a k-dimensional tree (cKDTree) to speed up the nearest-neighbour search in the large datasets. For each marine OWT coordinate, the algorithm found the closest land-use patch by calculating the minimum Euclidean distance. Additionally, we added a macro-category, sub-category, and exact distance (in meters) of each identified land patch to each marine station's record. This linked
275 dataset formed the basis for calculating standardised residuals and identifying statistically significant spatial relationships between coastal water signatures and nearby land environments. To test whether these observed matching rates reflected statistically significant ecological affinities, we calculated standardised residuals for each OWT-Land Use pair. In this context, standardised residual rates exceeding a threshold magnitude of 1.96 (equivalent to a 95% confidence level, $p < 0.05$) were considered statistically significant. Positive values above
280 +1.96 indicated a significant spatial preference, while negative values below -1.96 indicated significant spatial rejection between the water mass and the specific land use.

3 Results

285 3.1 Optical Water Types

Nine distinct clusters were identified in the Southwestern Patagonian Fjords in our study (Fig. 3). Optical clusters were distinguished by both spectral magnitude (brightness) and spectral shape (water constituents). Cluster 5 was the "brightest", with the highest mean reflectance and a strong peak at 543 nm in the yellow-green range.
290 Similar spectral peaks were observed for Clusters 4 (541 nm), 9 (537 nm), and 7 (536 nm). By contrast, Cluster 6 was the "darkest" water, with the lowest mean reflectance (peak at 495 nm) (Fig. 4).

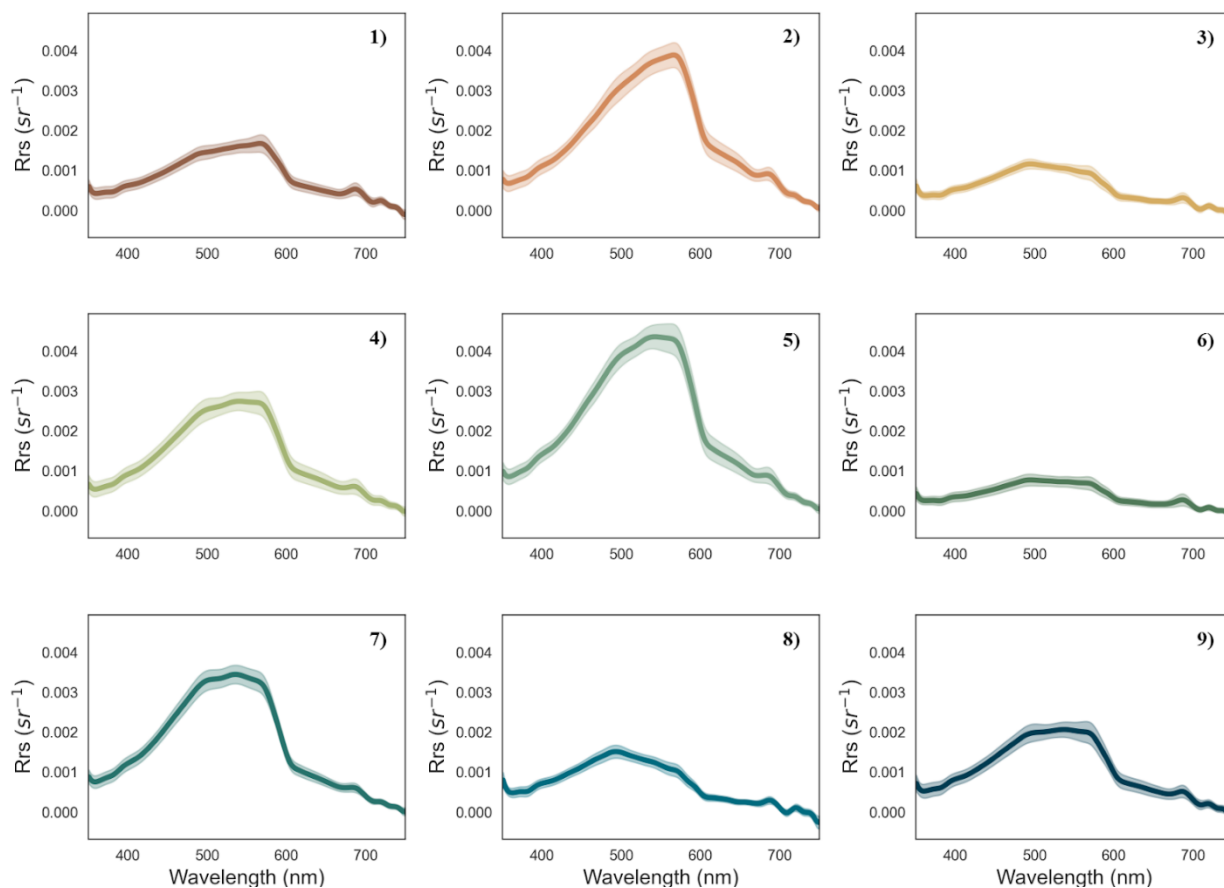
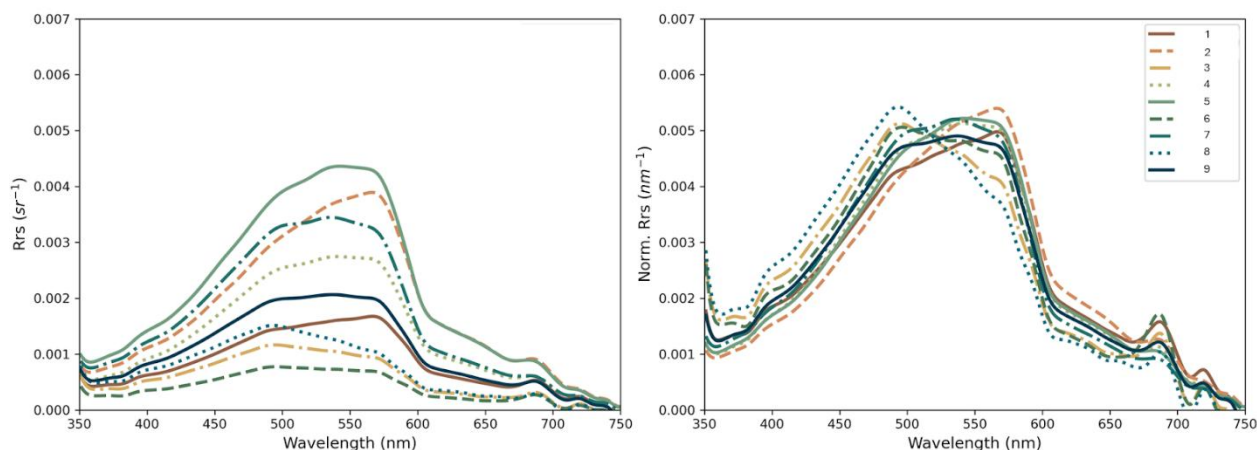


Figure 3. Mean reflectance per cluster (1-9) with shaded standard deviation.



295 Figure 4. Spectral curves for each optical cluster. The right figure was standardised by dividing by the spectral integral (Spyrakos et al., 2018).

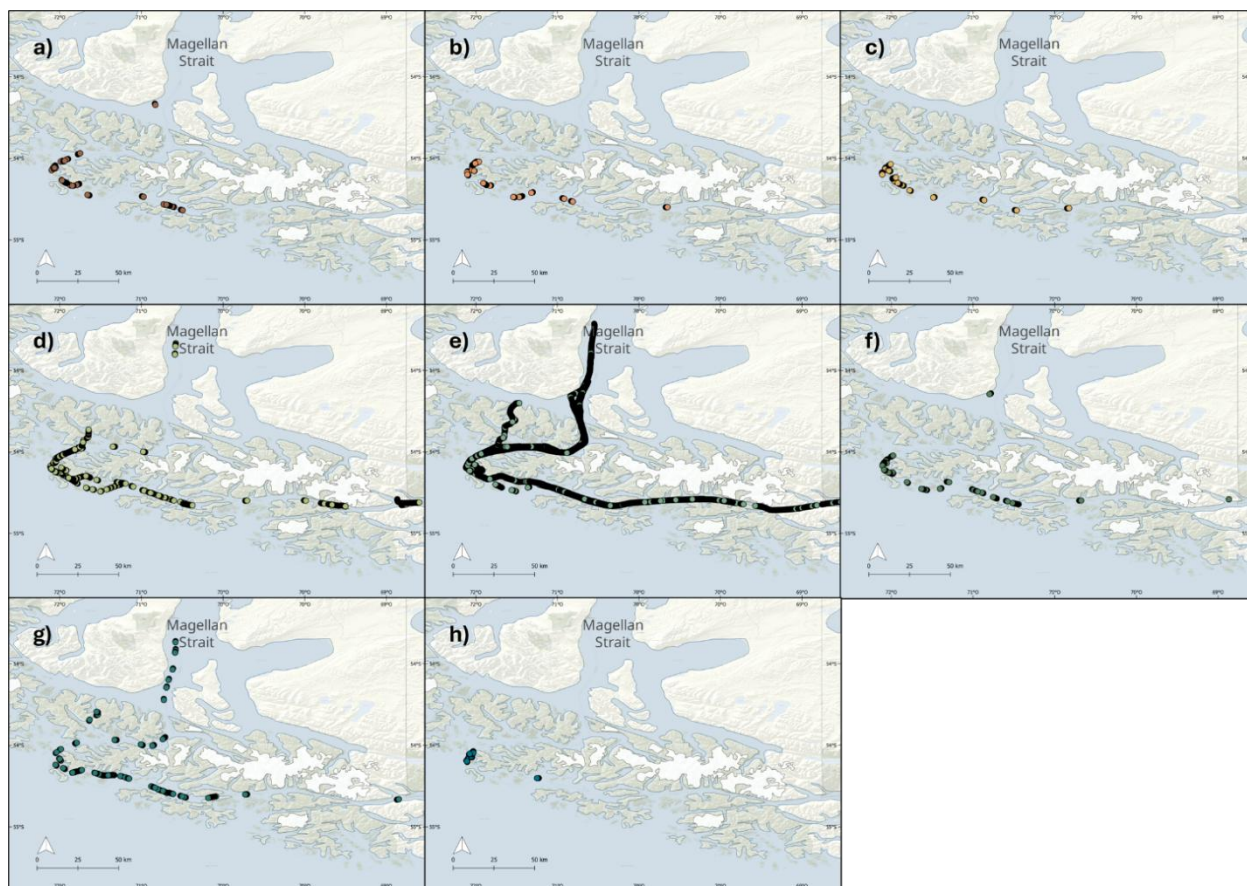


Figure 5. Spatial distribution of OWT: 1(a), 2 (b), 3 (c), 4 (d), 5 (e), 6 (f), 7 (g) and 9 (h) throughout the Southwestern Patagonian Fjords (Punta Arenas to Puerto Williams, the Yaghán Ferry route) from 2022 to 2023. The base map was designed and developed by Esri | Powered by Esri.

3.2 Water quality and meteorological parameters

A statistical summary of the biogeochemical and environmental parameters for the eight clusters is presented in Table 1 and Figure 6. Cluster 8 was not included due to lack of data for water quality parameters. The distributions highlight distinct characteristics for each cluster. For the biogeochemical parameters, Cluster 7 exhibited the highest median turbidity (4.987 NTU) (Fig. 6c), whereas Clusters 3 (0.467 NTU) and 2 (0.487 NTU) had the lowest. The widest range was seen in Cluster 5, which recorded the highest maximum turbidity (10.625 NTU). For Chl-a, Cluster 7 again showed the highest median concentration ($0.193 \mu\text{g L}^{-1}$) (Fig. 6b), while Clusters 9 ($0.085 \mu\text{g L}^{-1}$) and 3 ($0.09 \mu\text{g L}^{-1}$) showed the lowest.



Cluster 5 demonstrated the most extreme variability (Fig. 6), with a maximum Chl-a value ($1.014 \mu\text{g Chl-a L}^{-1}$) higher than all other clusters (e.g., Cluster 7 max $0.711 \mu\text{g Chl-a L}^{-1}$; Cluster 4 max $0.39 \mu\text{g Chl-a L}^{-1}$). Median CDOM was highest in Cluster 3 (0.006 RU) (Fig. 6a) and lowest in Clusters 5 and 9 (0.002 RU). Like its Chl-a and turbidity, Cluster 5 exhibited high variability in CDOM, with a maximum value (0.286 RU) that was an order of magnitude greater than that of most clusters ($\leq 0.031 \text{ RU}$). Cluster 7 also showed a high maximum for CDOM (0.149 RU). Environmental parameters also varied by cluster. Temperature medians ranged from 3.751°C (Cluster 6) to 8.13°C (Cluster 4) (Fig. 6e). Notably, Clusters 4, 5, and 7 were the only OWTs to record sub-zero minimum temperatures (min -1.472 , -0.705 , and -0.431°C , respectively). Cluster 5 also recorded the highest maximum temperature (12.586°C). Runoff medians were broadly similar ($4\text{--}5 \text{ m d}^{-1}$) (Fig. 6f), though Clusters 5 and 4 showed the highest maximums (11 and 9 m d^{-1} , respectively). Surface radiation was highest in Cluster 6 (Table 2). Cluster 6 also had a minimum radiation level significantly higher than those of the other groups (Fig. 6g). Precipitation medians were highest in Clusters 1, 2, and 9 (14 m d^{-1}) and lowest in Cluster 7 (2 m d^{-1}) (Fig. 6d). Finally, wind speed medians were consistent across all clusters ($2.259\text{--}2.373 \text{ m s}^{-1}$), though Clusters 1 and 5 experienced the highest maximum wind speeds (5.156 m s^{-1}) (Fig. 6h).

Table 1. Summary of descriptive statistics for the meteorological and water quality data associated with each of the optical clusters identified in this study.

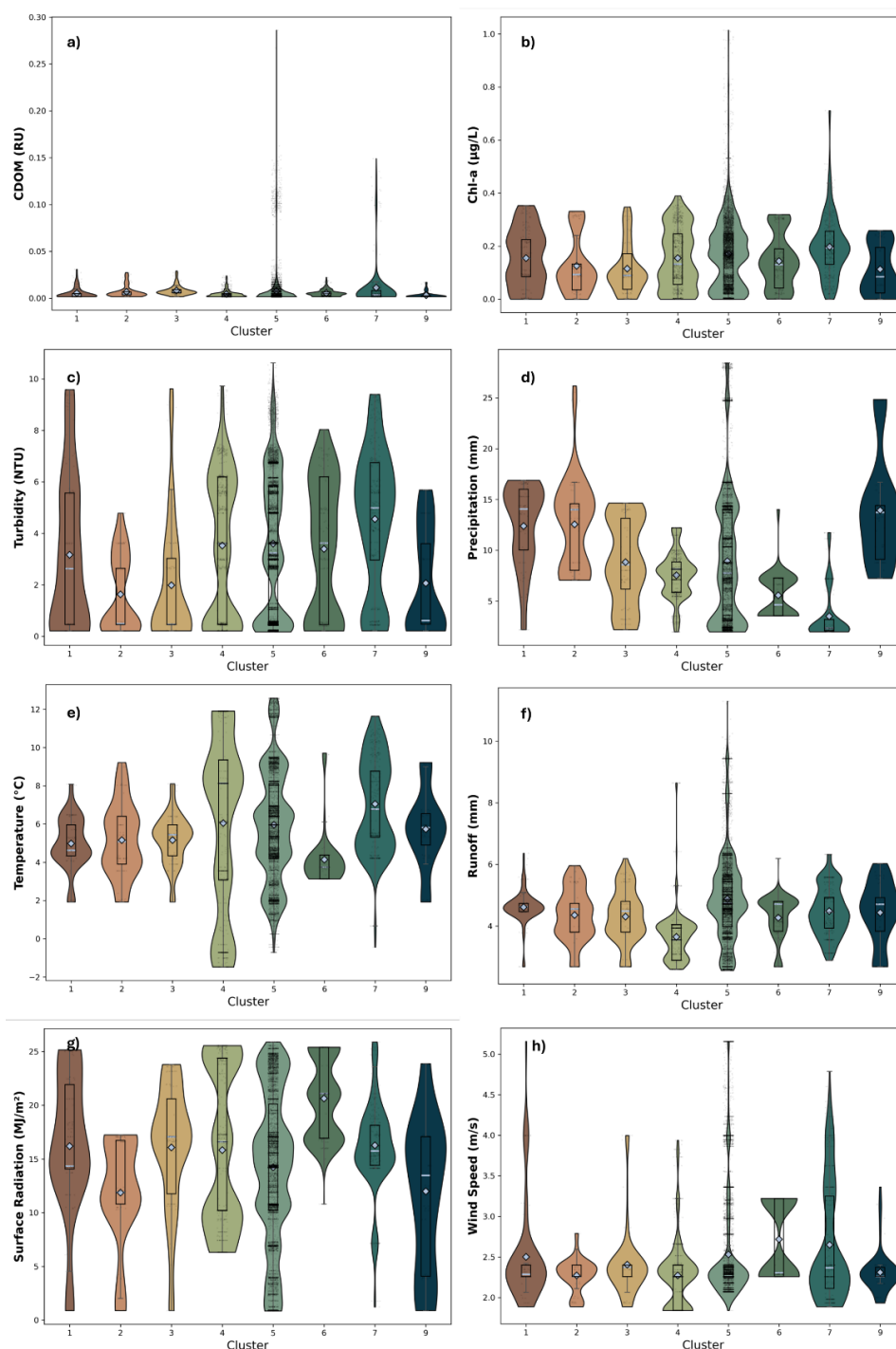
Parameter	Stats	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 9
		(N = 140)	(N = 111)	(N = 121)	(N = 936)	(N = 8536)	(N = 236)	(N = 389)	(N = 64)
Turbidity (NTU)	Median	2.634	0.487	0.467	3.602	3.236	3.626	4.987	0.609
	Min	0.213	0.213	0.215	0.212	0.176	0.213	0.214	0.213
	Max	9.588	4.789	9.618	9.728	10.625	8.036	9.406	5.688
Chl-a ($\mu\text{g/L}$)	Median	0.154	0.093	0.09	0.132	0.17	0.13	0.193	0.085



CDOM (RU)	Min	0	0	0.001	0	0	0.001	0	0
	Max	0.353	0.332	0.348	0.39	1.014	0.32	0.711	0.259
	Median	0.003	0.005	0.006	0.003	0.002	0.005	0.003	0.002
Runoff (mm d⁻¹)	Min	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	Max	0.031	0.027	0.029	0.024	0.286	0.022	0.149	0.017
	Median	5	5	4	4	5	5	4	5
Temperature (°C)	Min	3	3	3	3	3	3	3	3
	Max	6	6	6	9	11	6	6	6
	Median	4.628	5.083	5.434	8.13	5.958	3.751	6.771	5.817
Precipitation (mm d⁻¹)	Min	1.928	1.928	1.928	-1.472	-0.705	3.137	-0.431	1.928
	Max	8.092	9.221	8.111	11.91	12.586	9.709	11.645	9.221
	Median	14	14	9	8	8	5	2	14
	Min	2	7	2	2	2	2	2	7



SurfRad (MJ/m²)	Max	17	26	15	12	28	14	12	25
	Median	14.33	11.89	17.05	16.59	14.38	21.09	15.74	13.45
	Min	0.88	0.88	0.88	6.31	0.86	10.8	1.22	0.88
Wind Speed (m/s)	Max	25.15	17.24	23.8	25.55	25.89	25.4	25.89	23.87
	Median	2.287	2.259	2.373	2.259	2.259	2.306	2.365	2.259
	Min	1.888	1.888	1.888	1.841	1.841	2.259	1.887	1.934
	Max	5.156	2.79	3.997	3.937	5.156	3.221	4.787	3.363



330 Figure 6. Rain plots for water quality and meteorological parameters per cluster (1-9): (a) CDOM [RU]; (b) Chl-*a* [$\mu\text{g L}^{-1}$]; (c) Turbidity [NTU]; (d) Precipitation [mm d^{-1}]; (e) Temperature [$^{\circ}\text{C}$]; (f) Runoff [mm d^{-1}]; (g) Surface



Radiance [MJ/m]; and (h) Wind speed [m s^{-1}]. The blue line represents the mean, while the blue diamond represents the median. Cluster 8 was excluded from this analysis due to a lack of data points.

335 3.3 ANOVA and Tukey HSD

The ANOVA and Tukey HSD analyses were performed on the full dataset (10533 rows). Significant differences ($p < 0.05$) were detected among clusters for Chl-a, turbidity, and CDOM, as well as for all meteorological variables, except for temperature. Tukey's post hoc tests showed significant pairwise differences
340 between clusters (Fig. 7).

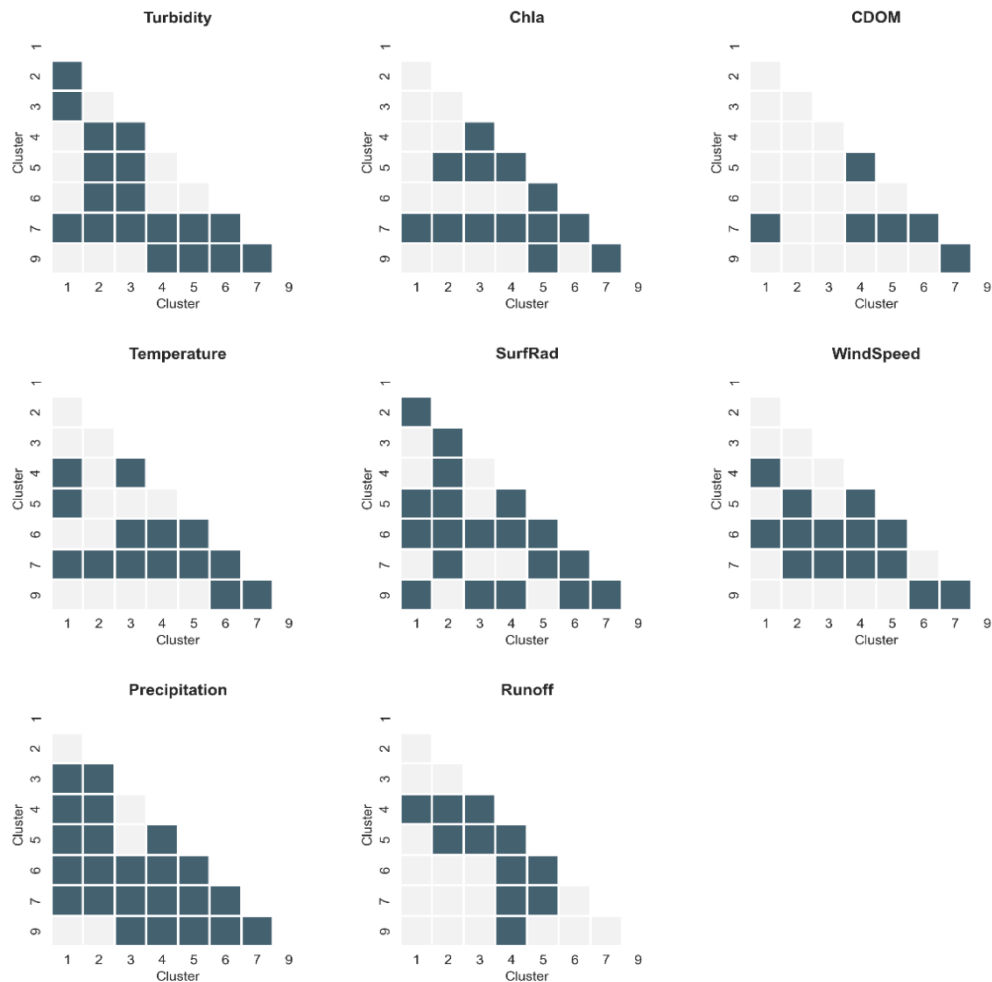


Figure 7. Pairwise comparison matrices from the Tukey HSD post-hoc tests ($p < 0.05$) for all eight water and meteorological variables. Each panel compares 8 clusters (1, 2, 3, 4, 5, 6, 7, and 9). A dark blue square indicates a statistically significant difference between a cluster pair for that variable, while a light grey square indicates no significant difference.

3.4 Optical Water Types, meteorological characteristics, and water quality parameters

The seasonal distribution of each OWT was analysed by the chi-squared test, which revealed a highly significant association between seasons and clusters $\chi^2(21) = 185.7, p < 0.001$. This result indicates that the distribution of OWTs is strongly season-dependent. This result provides robust statistical confirmation that the composition of OWT in the Patagonian fjords exhibits strong seasonal variability. For example, Cluster 4 showed



a strong association with summer (res = +2.11) and autumn (res = +2.30), and a strong disassociation from winter (res = -4.97) and spring (res = -5.77). Contrastingly, Cluster 7 was mostly winter type (res = +3.04) that strongly avoided autumn (res = -4.94). Other clusters also showed clear preferences: Cluster 6 was associated with summer (res = +2.25), while Cluster 2 (res = +3.49) and Cluster 5 (res = +2.56) were associated with spring. Cluster 1 showed a preference for autumn (res = +1.95) followed by spring (res = + 0.98), and Cluster 3 showed no significant seasonal preference.

Table 2. Post-hoc test results for the chi-squared standardised residuals test, showing the positive and negative association of each cluster per season.

Cluster	Autumn	Spring	Summer	Winter	Seasonality
1	1.95	0.98	-0.71	-1.92	Autumn
2	0.14	3.49	-0.96	-1.71	Spring signature
4	2.3	-5.77	2.11	-4.97	Autumn/Summer
5	0.22	2.56	-1.39	2.18	Spring/Winter
6	-1.52	-3.49	2.25	-2.5	Summer signature
7	-4.94	-2.01	1.96	3.04	Winter signature
9	0.52	-2.48	0.92	-1.3	Summer/ Autumn

The Shannon analysis revealed a clear seasonal progression in our data, from a stable, homogeneous winter with the lowest mean_H (0.77) and change rate (0.290) to a dynamic, patchy summer with the highest mean_H (0.463) and change rate (2.049). In between, spring was characterised by a low cluster diversity (mean_H = 0.256) but a high change rate (1.182). Lastly, Autumn was the opposite of Spring, with a low change rate of 0.409 and high diversity of optical water types (mean_H = 0.354).

3.5 Random Forest Model

375 The Random Forest model achieved a high overall accuracy of 97.5% and an F1 Score of 0.877, indicating
a strong predictive relationship between environmental conditions and optical water-type characteristics. The
model showed excellent performance for both dominant and several rare water types. However, performance was
lower than that of the rarest clusters, which exhibited lower values. The confusion matrix (see Appendix A, Fig.
A1) shows high recall for clusters 1, 4, 5, and 6. It also highlights that the primary source of error was the
380 misclassification of rarer water types, notably clusters 2, 3, 7, and 9.

To identify the key environmental drivers that distinguish the water-type clusters, a general feature-
importance analysis was conducted (see Appendix A, Fig. A2). Results indicate that runoff, CDOM, and Chl-a
were the most important predictors overall. Nevertheless, the specific drivers per cluster gave variable principal
forcings for each OWT, as shown in Figure 8.

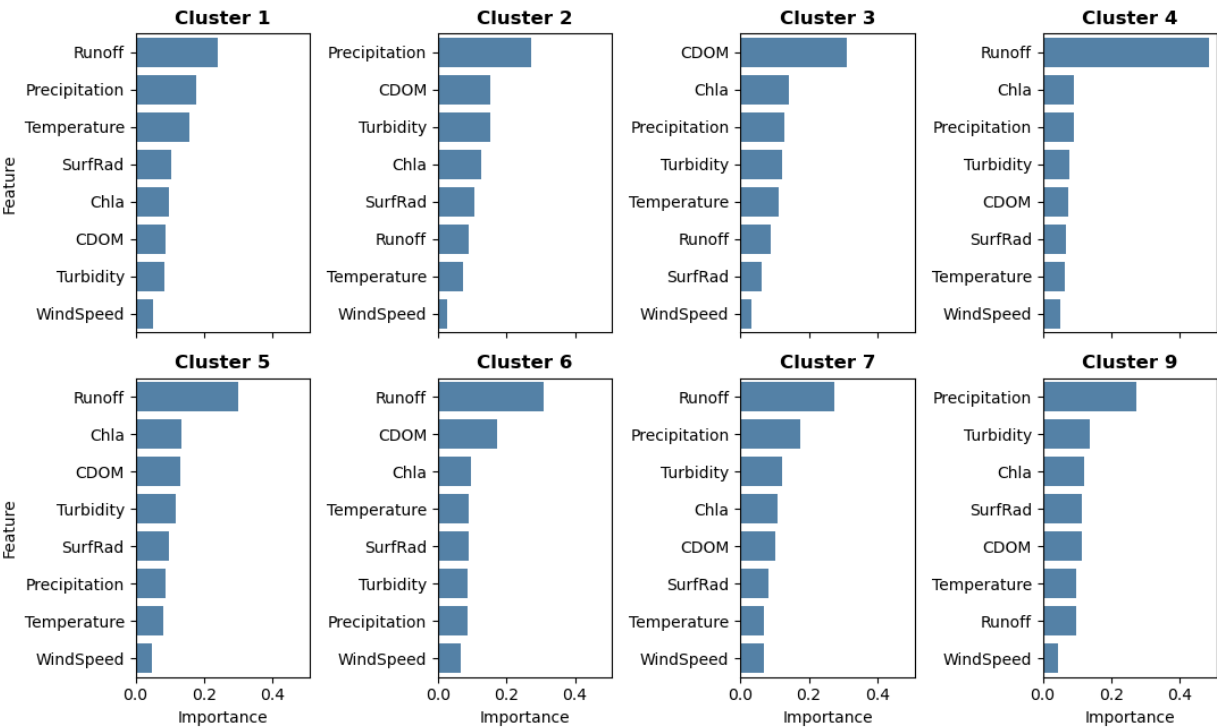


Figure 8. OWTs' environmental feature importance from the OvR analysis.

Table 3 summarises the main features for each OWT found in this study. OWT 1 was characterised by low median
temperature, high runoff and precipitation, and productive waters (Table 3), while OWT 7 showed the lowest mean



precipitation but was the warmest, most biologically active and turbid, exhibiting the highest Chl-a. In contrast, OWT 9 represented the oligotrophic type, associated with high rainfall together with OWTs 1 and 2, the latter with the lowest surface radiation. OWT 3 and 6 showed the "Highest" and "High" CDOM values (Table 3), respectively, both with warm temperatures, and OWT 6 with the highest surface radiation (Table 3 and Fig. 7). OWT 5, by comparison, showed high Chl-a concentrations but low CDOM.

Table 3. Summary of drivers for each cluster (from OvR) with its key water quality characteristics from descriptive statistics (median).

OWT	Main Drivers	Water Quality Characteristics	OWT description
1	Runoff Precipitation	Turbidity: Medium CDOM: Low Chl-a: High	Warm freshwater type. Its combination of high runoff and warm temperature suggests it could be a seasonal (e.g., summer) meltwater plume.
2	Precipitation CDOM	Turbidity: Low CDOM: High Chl-a: Low	Precipitation-OM type. Rain washes high levels of OM from soils and sediments into the fjord.
3	CDOM	Turbidity: Low CDOM: Highest Chl-a: High	High-CDOM water. Likely from a specific terrestrial source or river. Its CDOM value is its single most unique feature.
4	Runoff	Turbidity: Highest CDOM: Medium Chl-a: Medium	Glacial/river plume type. This is the dominant freshwater cluster, defined by its massive runoff signature. This likely corresponds to a significant river or glacial melt outlet.
5	Runoff Chl-a	Turbidity: High CDOM: Very Low Chl-a: High	Marine/winter type. Its water quality is likely representative of runoff-mixed, marine-dominated, or winter- and spring-dominated conditions. An event of Chl-a maximum felt within this OWT.
6	Runoff CDOM	Turbidity: Medium CDOM: High Chl-a: Medium	Summer-type water. Dark waters with high CDOM are associated with thawing and runoff.
7	Runoff Precipitation	Turbidity: Highest CDOM: Medium Chl-a: Highest	Productive waters with the highest turbidity. Dominant in winter, associated with high runoff and precipitation events.
9	Precipitation Turbidity	Turbidity: Low CDOM: Very Low Chl-a: Lowest	Oligotrophic type. Heavy rain event linked to low turbidity, CDOM, and Chl-a, suggesting dilution.



4. Discussion

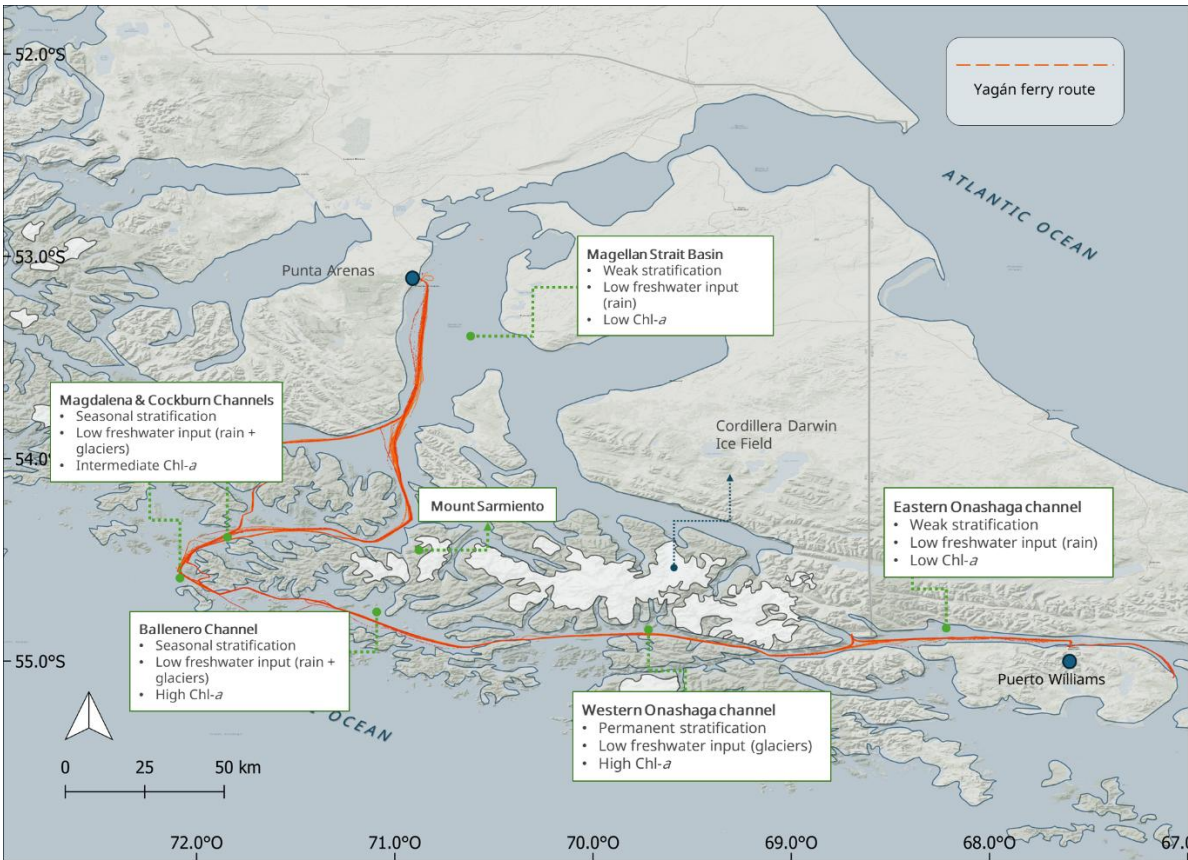
4.1. Exploring the Characteristics of the OWT

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OWT were clearly distinguished by their magnitude (Fig. 2), although some exhibited similar spectral shapes, indicating comparable water constituents (Fig. 5). Cluster 5 demonstrated the highest mean reflectance and a pronounced peak at 543 nm in the yellow-green range. This yellow-green peak likely indicated elevated concentrations of suspended matter, including phytoplankton and scattering materials (Schalles, 2006). Similarly, clusters 4, 9, and 7 exhibited strong peaks in the green spectral range, with cluster 7 displaying the highest Chl-a concentrations among all clusters. These clusters (5, 4, 9, and 7) also showed similarity in the SAM analysis (see Appendix C, Fig. C1). In contrast, Cluster 6 represented the darkest water type, predominantly observed in summer. This dark OWT exhibited the lowest mean reflectance, with a peak at 495 nm, likely due to high concentrations of absorbing materials such as CDOM. Notably, OWT 3 spectra also exhibited dark water properties, but this type was primarily present in spring (Table 3) and was associated with lower mean Chl-a, turbidity, and runoff, but higher mean precipitation than OWT 6 (Table 2). Although CDOM concentrations were lower for OWT 6 than for OWT 3, it is suggested that the very high surface radiation observed for OWT 6 may have caused significant CDOM photobleaching, thereby reducing the signal of this absorbing component. In contrast, the high concentration of CDOM in OWT 3, likely sourced from the adjacent land (Fig. 6), may have persisted for longer periods due to lower surface radiation intensity. Notably, the area covered by OWT 6 lies within a region of dense peat bogs (Cape Froward, Fig. 6f), which may have contributed to the darker waters and low reflectance values observed for this cluster. Clusters 8, 6, and 3 were grouped together in the SAM analysis, forming a distinct subcategory of organic matter (OM)-absorbing water (see Appendix C, Fig. C1), supported by the proximity of wetlands and peat bogs, which are recognised as significant OM sources (Fig. 6) (Frey et al., 2009; Opdal, Anders Frugård et al., 2023). It is important to note that the initial FerryBox water quality data indicated that Cluster 2 had low turbidity (Table 2). However, the spectral analysis (see Appendix C, Fig. 1) revealed that it was one of the brightest targets, suggesting the presence of highly scattering materials and highlighting inconsistencies between the FerryBox turbidity results and the recorded bio-geo-optical properties. This highlights the need for broader in situ measurements to improve potential data inconsistencies.

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Figure 9. Some environmental characteristics and names of the southwestern Patagonian channels. The base map was designed and developed by Esri | Powered by Esri

4.2 Assessing the Link to Environmental Drivers

430

We found that OWT varies strongly by season, confirmed by the chi-squared test (Table 2). The results provided robust statistical evidence that Patagonian fjord waters exhibit strong seasonal variability. The most common cluster was OWT 5, suggesting it represents the water baseline in southwestern Patagonian fjords and indicating that this area has overall high turbidity, as expected due to the strong influence of glaciers, runoff, and frequent precipitation and wind events (Table 3). Cluster 4 was also dominant, but mainly during autumn, as was Cluster 1, with high runoff and wind speed suggesting that precipitation and melting events delivered large amounts of particles, as indicated by high turbidity. Other OWTs, such as 6 and 9, appeared mainly during summer, with high temperatures and precipitation, especially cluster 9, which induced water dilution. Clusters 3 and 2 were rare and primarily occurred in spring, when CDOM was high.

435



A primary hotspot of high optical diversity (H') and high seasonal variability was identified between the
440 Monte Sarmiento and the Magdalena and Cockburn channels. We attribute this dynamism to the location's unique
oceanography and geomorphology, which functions as a central convergence zone. This area is subject to strong,
tidally driven exchange between the Pacific Ocean and the Strait of Magellan, and a complex interaction with
coastal water masses and the archipelago (Giesecke et al., 2021; Valle-Levinson, Blanco and Frangópulos, 2006).
The Magdalena Channel Island system (Fig. 9) is rich in peatlands, mostly, while the Onashanaga channel (Oc)
445 known as Beagle Channel introduces waters heavily influenced by marine-terminating glaciers at the western
section of the Oc. These glaciers deliver significant amounts of freshwater and fine sediments (rock flour) towards
the western section of the Oc, with inputs peaking during the summer melt season (Giesecke et al., 2021).

The high diversity and rapid change around the Magdalena and Cockburn channels suggest a strong
convergence and tidal mixing among these multiple, optically distinct water masses (Valle-Levinson et al., 2006;
450 Giesecke et al., 2021). For example, marine and fresh waters (Pacific/Strait), high-CDOM terrestrial runoff
(peatbogs and tundra), and turbidity coming from fresh glacial meltwater. On the other hand, the Oc was identified
as a second key area, presenting a different optical signature. While this region's overall diversity was lower, it was
heavily dominated by clusters 4, 6, and 7 (Figs. 5 and 9). The dominance of these specific OWT, which are
characteristic of high turbidity and Chl-a, demonstrates the local influence of glacial melting. This effect was most
455 pronounced in summer, aligning with expected peak meltwater discharge.

Spring exhibited low cluster diversity but a high rate of change, suggesting a rapid turnover of OWT. This
might be related to the high heterogeneity of freshwater discharge, particularly the strong increase in meltwater
discharge during spring, leading to rapid changes in optical water properties (OWP). In addition, the observed
460 variability may be associated with patchy phytoplankton blooms along the track, given that spring is typically
characterized by the highest phytoplankton biomass and bloom activity in the region (Almandoz et al., 2011;
Cadaillon et al., 2024). In contrast, autumn was more stable, which could be related to lower phytoplankton growth
and the absence of large phytoplankton blooms. During this period, the phytoplankton community is usually
dominated by pico- and nanophytoplankton, resulting in relatively low Chl-a concentrations. Additionally, this
465 season was also characterised by high diversity, suggesting multiple constituent sources (e.g., peatlands, rivers,
glaciers, and oceanic waters) (Fig. 10). In addition, the lower freshwater discharge associated with decreasing
atmospheric temperatures may contribute to greater stability in the OWP. Finally, the combination of cold waters,
low precipitation and reduced solar radiation during the austral winter appears to induce stable conditions, as
evidenced by the very low diversity and rate of change of the OWT. This condition is further exacerbated during



470 winter, when shorter daylight duration and colder temperatures result in more stable and less productive conditions, with reduced phytoplankton biomass and lower meltwater discharge. Cluster 4 appears to represent the primary glacial meltwater plume. This is supported by three characteristics: 1) its geographic location, which was consistently found at the head of tidewater glaciers (Fig. 10); 2) its highest mean turbidity; and 3) its seasonal trend, which showed a significant positive association with summer/autumn, aligning with the regional melt season.

475 Closely related to the aforementioned is Cluster 1, which we interpreted as a seasonal, shallow runoff water lens. The combination of high runoff and warmer temperatures associated with this cluster suggests it captures the distinct seasonal freshwater signature during the warmest months, distinguishable from the direct, sediment-laden discharge of Cluster 4. The terrigenous and precipitation-driven signatures differ from those of glacial plumes; our results distinguish OWT, likely driven by terrestrial runoff and precipitation. Cluster 2 appears to represent a
 480 precipitation-high turbid type. The association with precipitation suggests that rainfall may be eroding the surrounding soils into the fjord. Contrastingly, Cluster 3 represented a high-CDOM water type; as CDOM is its most distinctive feature, this cluster was likely linked to a mixture of allochthonous sources, such as discharges from peatlands and other OM-rich materials, but also autochthonous OM from algae, suggested by a moderate Chl-a concentration (Table 2). Cluster 6 shared some of Cluster's 3 optical characteristics, but with even "darker" waters
 485 in the system, potentially driven by higher concentrations of mixed materials indicated by high turbidity (Table 2). Notably, Cluster 6 showed the coldest mean temperatures, potentially strengthening stratification and causing the concentration of light-absorbing materials at the surface. Cluster 7 represented the OWT with the highest turbidity and high Chl-a, potentially indicating areas of intense production and sediment resuspension (Table 4). In contrast, Cluster 9 appeared to represent the oligotrophic type, where rain was linked to CDOM, Chl-a and low turbidity in
 490 comparison to Cluster 2, suggesting that under specific conditions (e.g., rock-dominant areas) fresh inputs may result in dilution, rather than high turbidity (e.g., low-biomass and low sediment surface waters).

4.3 Assessing OWT as environmental indicators

495 A key objective of this work was to determine whether these characterised OWT could serve as predictable fingerprints of their environmental drivers. To assess this, we employed a Random Forest (RF) classifier. The model demonstrated a strong ability to resolve the dominant water types (F1-scores > 0.90), suggesting that the link between these OWTs and their environmental drivers (e.g., runoff, CDOM, Chl-a) is stable and learnable. The OvR analysis further validated our characterisations by identifying specific drivers for each cluster. However, the
 500 model's performance was much lower for rare classes. This highlights that while our framework can suggest the



presence of rare OWTs, its ability to predict them is constrained by data reliability. Despite these limitations, the importance of the OvR supports our interpretations. The progression from a stable winter to a patchy summer, as revealed by the Shannon analysis, clearly demonstrates the strong influence of seasonality on Patagonian OWT (Fig. 10a), a finding consistent with the Random Forest model (see Appendix A, Fig. A1).

505

Table 4. Integrated summary of the dominant characteristics per OWT. The summary includes dominant water-quality properties associated with land-use and meteorological contexts.

OWT	WQ	Associated Land Use	Meteorological context	Process
7 Anthropogenic signature	Highest Chl-a Highest Turbidity	Wetlands and urban/industrial	Spring: Very dry (-5.0mm) & Warm (+1.2°C) Winter: Dry & Cold	Spring warmth combined with dry conditions might create water column stability. High nutrient inputs from wetlands and urban runoff likely trigger the intense algal blooms observed.
4 Glacial Plume	Highest Turbidity Medium CDOM	Forests and agricultural sites	Spring: Wet (+6.0mm) Runoff: Negative (-0.0005)	High spring precipitation might fall as snow on forests, leading to a negative immediate runoff anomaly. Turbidity might be driven by physical mixing of the agricultural sites (deforested) rather than a direct meltwater pulse.
1 Warm Freshwater	High Chl-a Low CDOM	Shrublands and grasslands	Autumn: Runoff Peak (+0.0008) Temp: Warm (+0.5°C)	High autumn flow runoff events, possibly draining open coastal plains and shrublands via runoff carrying nutrients to support primary production.
9 Oligotrophic	Lowest Chl-a Low Turbidity	Shrublands	Autumn: Wet (+2.0mm) Temp: Very Cold (-2.0°C)	An anomalous storm event was captured in autumn, with heavy precipitation and runoff likely rapidly washing the substrate, diluting water constituents.
5 Marine Baseline	High Turbidity Very Low CDOM	Barren land, grasslands and shrublands	Winter: Very dry (-5.8 mm) Temp: Freezing (-3.7°C)	Extreme cold and continuous runoff, lack of precipitation. High turbidity due to barren land inputs.
3 High-CDOM	Highest CDOM High Chl-a	Shrublands	Spring: Heavy rain (+7.3mm) Temp: Cold (-1.3°C)	Rejected all other land categories. Its dominance in spring suggests a thaw influence, during which melted snow leaches the shrubland soil, transporting nutritious components into the fjords, supporting primary productivity and autochthonous CDOM.



2 Precipitation- OM	Low Turbidity* High CDOM	Grasslands and shrublands	Spring: Heavy rain (+7.5mm)	This OWT rejected forests. Extreme precipitation might represent the erosion of soil and sediments transported into the fjord in areas lacking the root shield of forests.
6 Summer Thaw	Medium Turbidity High CDOM	Wetlands	Summer:Stable Autumn:Wet/Cold flush	Darkest OWT with a significant statistical link to Wetlands. It might represent seasonal thawing and drainage of peatlands, releasing organic-rich water during the warmer months.

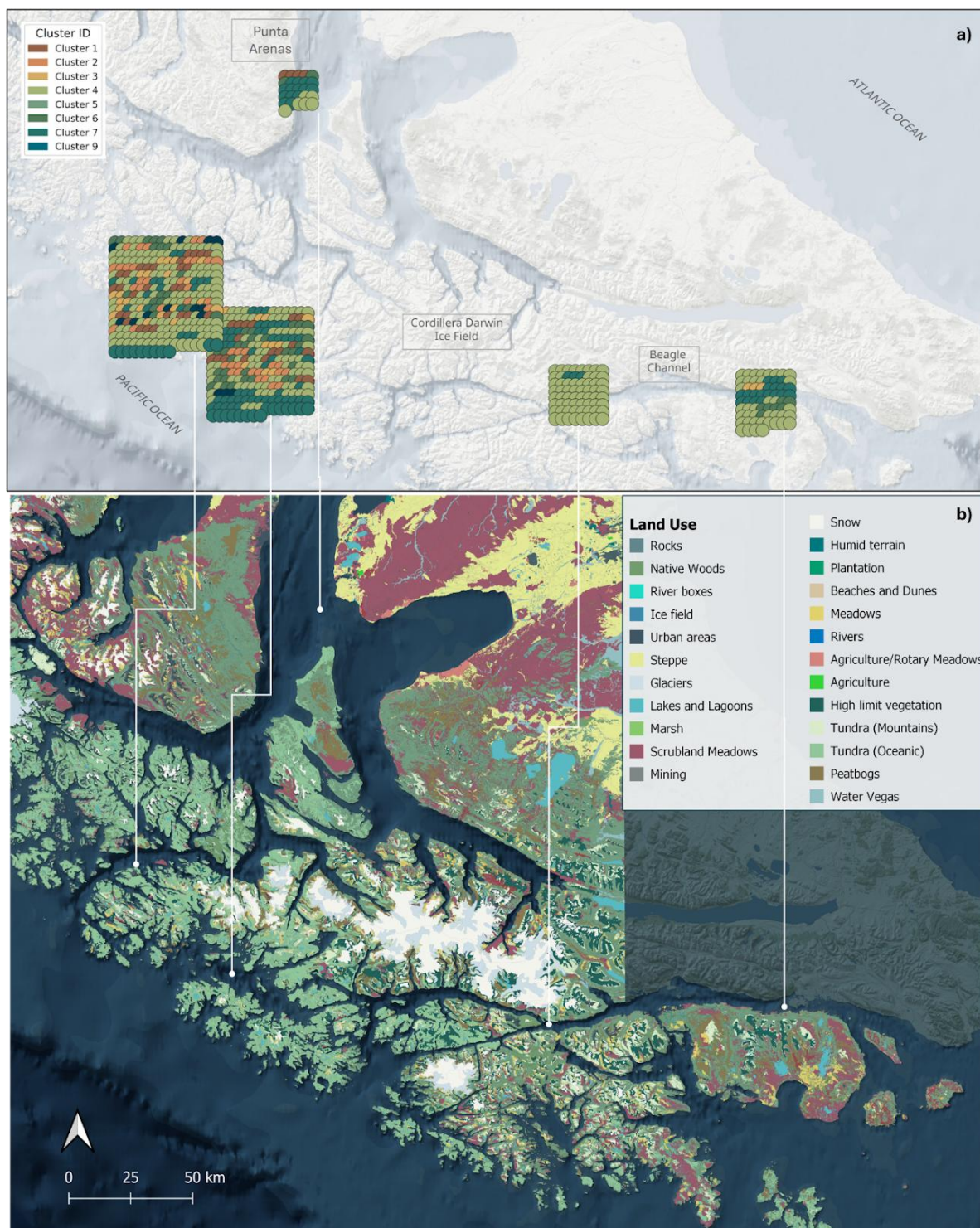




Figure 10. OWT dominance location for all seasons (a) per land-use (b). The distance considered to count for each dominant cluster by area was 0.01 decimal degrees. The base map was designed and developed by Esri | Powered by Esri

515 Further integration of OWT with seasonal land-use analysis revealed a highly complex coastal ecosystem driven by diverse near-shore linkages. After correlating the dominant OWT with specific land-cover uses, we identified three primary mechanisms controlling the bio-geo-optical variability of the region: (A) Runoff sediment transport, (B) Organic material pulses from thaw and (C) anthropogenic activity and coastal runoff events. Runoff sediment-dominated OWTs were identified for clusters 1, 4, and 5; anthropogenic and background coastal runoff
 520 events for cluster 7, and organic material pulses for clusters 2, 3 and 6 (Fig. 10).

Baseline (OWT 5): Runoff emerged as the most significant feature. This cluster was identified as the main system baseline, representing the region's dominant optical signature (Fig. 5e). It was characterised by high turbidity (Median 3.236 NTU) and very low CDOM (Median 0.002 RU. It was widespread along most of the
 525 coastline, with high prevalence in adjacent Barren Land (92.1%), Shrublands (87.5%), and Forests (67.4%). Because of this dominance, which obscures other signals, its direct statistical associations are limited, displaying only a slight positive relationship with Forests (Score 1.7) and Urban and Industrial Areas (Score 1.0) in the global analysis. The cluster's broad presence indicates that runoff and the continuous transport of inland materials across seasons primarily shape the south-western Patagonian fjords (Fig. 8).

530 Transition waters (OWT 4): Runoff was the defining variable for this cluster; it showed one of the highest maximum runoff levels (9 m d⁻¹) among the clusters (Table 2) and a significant seasonal variability. After excluding background from OWT 5, this cluster shows a strong ecological association, with the study's strongest positive relationship with Forests (Score 4.4) and a secondary association with Croplands (Score 2.4). It also shows
 535 a strong statistical rejection of Wetlands (Score -2.3) (Figs. 5d and 10b). These findings indicate that OWT 4, defined by its seasonality and transitional characteristics, is associated with basins containing stabilising vegetative cover, such as forests and low-impact agricultural grasslands, which might buffer runoff impacts.

Erosion events (OWT 2): Precipitation and CDOM were the most significant features. This cluster is primarily
 540 associated with Shrublands (Score 1.9, excluding the dominant cluster) and is strongly rejected by Forests (Score -3.0) (Figs. 5b and 10b). This pattern suggests that storm-driven precipitation may erode shrubland and grassland soils. Consequently, Cluster 2 likely represented the physical transport of soil and light-absorbing components,

e.g., organic matter, into the fjord during intense precipitation events in regions lacking the structural root protection provided by dense forests.

545

The anthropogenic signal (OWT 7): This cluster provided the most direct evidence of human impact (Fig. 10b). It was characterised as productive/turbid, with the highest median Chl-a values ($0.193 \mu\text{g L}^{-1}$) and the second-highest CDOM concentration (0.149 RU) (Table 2). It showed the strongest standardised association with Wetlands (Score 4.8, excluding OWT 5). Notably, OWT 7 is the only water type with a strong positive association with
 550 Urban and Industrial Areas (Score 2.6) (see Appendix E, Fig. E1). Additionally, the RF OvR showed runoff followed by precipitation as the main drivers for this OWT, reinforcing the role of strong runoff events in washing anthropogenically linked components into the marine system.

Superficial water (OWT 1): Runoff and precipitation were the most influential features for this OWT. It showed
 555 the strongest association with Shrublands (Score 2.8, excluding OWT 5) and the highest level of rejection of Forests (Score -4.7) in the study. This OWT showed high autumn runoff and was associated with water bodies and shrublands from spring through autumn (see Appendix C, Table C1 and Appendix E, Fig. E1), possibly draining open coastal plains via runoff, as indicated by the RF OvR analysis. The lack of significant turbidity (Median 2.634 NTU) or CDOM (Median 0.003 RU) may have led a moderate water dilution, favouring light availability and,
 560 therefore, phytoplankton growth (Median Chl-a $0.154 \mu\text{g L}^{-1}$) during rainfall events.

Summer water (OWT 9): Precipitation was the most significant feature for this OWT. Spatial analysis revealed a moderate positive association with Shrublands (Score 1.4, excluding OWT 5) and a rejection of Wetlands (Score -2.1). An anomalous autumn storm event, characterised by heavy precipitation and runoff, likely caused rapid
 565 substrate washing and the formation of a mixed, clearer water type that defined the ecosystem's summer water (see Appendix D, Fig. D1). This might have reduced sediment transport, producing a mixed, clearer water type (median turbidity 0.609 NTU) that characterised the ecosystem's summer water. Nevertheless, we interpret the results for this cluster with caution because this rare water type was less predictable (F1-score = 0.833), an expected consequence of the class imbalance in our dataset (Support = 13). However, the model achieved perfect precision
 570 (1.000) for Cluster 9.

Dark water (OWT 6): Runoff and CDOM were the most significant features for this cluster. Cluster 6 demonstrated a strong association with Wetlands (Score 2.3) and a minor association with Shrublands (Score 1.1),



excluding the dominant matrix (OWT 5). It consistently rejected Forest areas (Score -3.1) and had the lowest median temperature (3.75°C) (Fig. 5f). The underlying mechanism appears to be summer thaw, which might flush coastal wetlands and release a pulse of "black water" rich in allochthonous dissolved organic matter but low in sediment, resulting in an optically dark environment (Fig. 5f and 9). Rodríguez-Flórez et al. (2023) support this, finding that Oc during winter was enriched with land-recalcitrant organic carbon, fuelling heterotrophic activity in surface waters of the eastern Oc (Fig. 10).

Local productive water (OWT 3): CDOM was the most significant feature for this cluster. This cluster is moderately and exclusively associated with Shrublands (Score 1.0, excluding OWT 5) and avoided all other terrestrial categories. Its spring prevalence suggests influence from thaw events, during which melted snow leaches shrubland soils and transports organic components into the fjord. CDOM was the primary predictor for Cluster 3, followed by Chl-a, suggesting that the source of OWT 3 CDOM is mainly autochthonous/derived, in contrast to OWT 6, whose strongest predictors were runoff and CDOM. Maltis et al. (2023) found organic carbon indicators of post-bloom activity during spring, supporting fresh labile organic material in the euphotic layers of the Oc, consistent with our findings for OWT 3 (Fig. 5 and 9).

5 Conclusions

The waters of the southwestern Patagonian fjords can be effectively characterised as distinct OWT, rather than as isolated variables. Nine clusters were identified, with Cluster 5 representing the region's baseline water type, providing a robust framework for interpreting fjord dynamics. Runoff, CDOM, and Chl-a were identified as the primary drivers of OWT variability, alongside a pronounced seasonal signal. Summer exhibited the greatest diversity of water types, while winter showed the least diversity and the most stable conditions.

This study provides a characterisation of OWT, linking them to both their biogeochemical properties and environmental drivers (Figs. 5 and 10). This approach represents an innovative contribution to regional monitoring and demonstrates the potential of participatory scientific collaboration with local sectors, such as the marine transportation system (FerryBox on board the Yaghán Ferry). However, gaps, above all in water-quality parameters, require further attention to improve the reliability of each OWT. A recommended next step is to include glacial runoff data for each OWT and to test the application of the proposed OWT framework to satellite imagery, which could offer an improved method for mapping OWT at broader temporal scales. A significant challenge in assessing land-ocean optical interactions in the south-western Patagonian fjords is the profound lack of *in-situ* terrestrial hydrological and meteorological infrastructure. Hyper-glaciated regions within our study area, most notably the



Cordillera Darwin and the Santa Inés Ice Field, represent extreme ungauged catchments. Consequently, global reanalysis models like ERA5 struggle to accurately capture localized runoff pulses in these highly fragmented, steep micro-basins, often underrepresenting the true magnitude of runoff discharge. Urgent actions are needed to implement programs to account for these data gaps in the region.

610 These findings indicate an innovative pathway to developing an operational monitoring tool by applying an integrated framework to historical or real-time satellite imagery. This approach would enable high-resolution mapping of these highly important waters and facilitate the tracking of climate-driven and hydrological changes in this remote ecosystem.

615 Appendix A

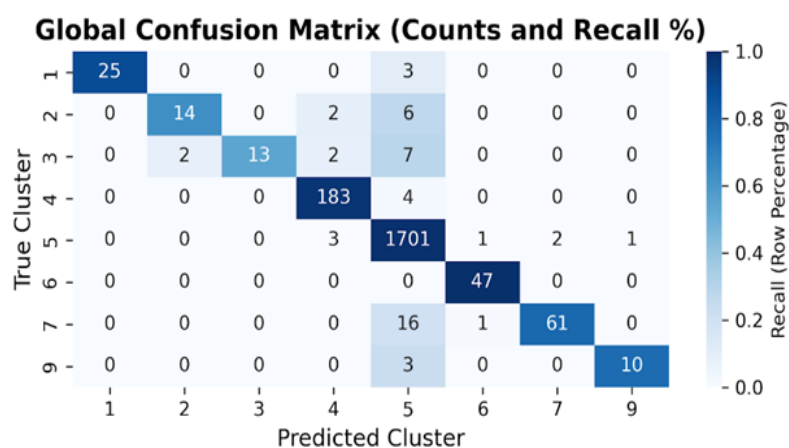


Figure A1. Random Forest confusion matrix

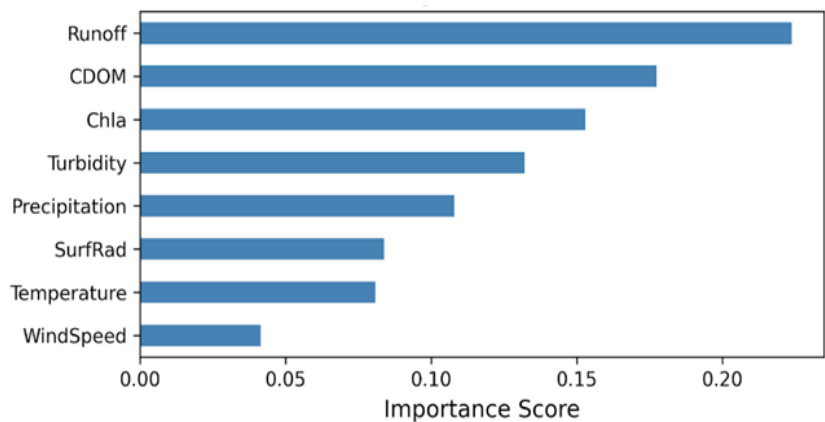


Figure A2. General parameter importance derived from the Random Forest model (500 estimators).

Appendix B

SAM analysis

Clustering of the SAM similarity scores identified four primary OWTs, defined by a spectral angle distance threshold of 0.10 radians. Most of the data were grouped into a large, spectrally similar cluster (Group A: clusters 1, 4, 5, 7, 9) and a smaller secondary group (Group B: clusters 3 and 6). Two clusters (2 and 8) exhibited distinct spectral signatures, joining the main groups only at distances greater than 0.10 radians, and were therefore classified as independent water types (Groups C and D, respectively) (left figure). Similarity dendrogram for all the sub-optical clusters obtained by SAM analysis: A (1, 4, 5, 7 and 9), B (3 and 6), C (2) and D (8). Finally, the spectral signatures of the two dominant regimes identified by the SAM analysis (right picture).

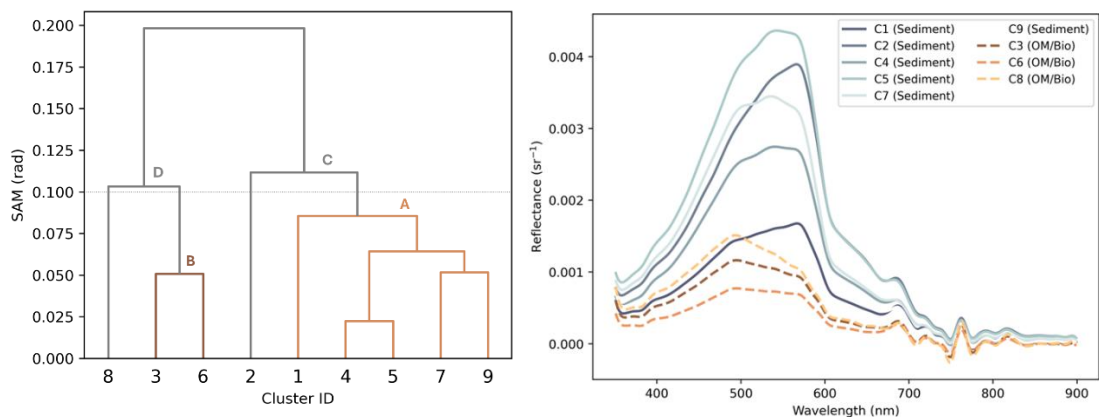


Figure B1. Main clusters identified by the SAM analysis (left) and spectral curves for each cluster group (right) distinguished by colour (blue: sediment, orange: organic matter/biological).

Appendix C

Table C1. Descriptive statistics for water quality and meteorological parameters per season.



Period	Cluster	N	Turbidity (NTU)	Chl-a (µg/L)	CDOM (RU)	Temp (°C)	SurfRad (MJ/m ²)	Wind (m/s)	Precip (m)	Runoff (m)	
2022 Summer	1	63	5.96 ± 2.08	0.21 ± 0.004	± 0.004	± 5.69	± 20.34 ± 4.98	4.79	± 0.0087	± 0.0050	±
				0.05	0.003	0.78		0.40	0.0054	0.0000	
	2	25	3.85 ± 0.48	0.14 ± 0.004	± 0.004	± 5.59	± 12.23 ± 3.81	-	0.0170	± 0.0060	±
				0.05	0.002	2.22			0.0022	0.0000	
	3	34	5.12 ± 2.22	0.16 ± 0.008	± 0.008	± 5.82	± 17.33 ± 5.36	4.54	± 0.0089	± 0.0050	±
				0.06	0.005	1.11		0.00	0.0057	0.0000	
	4	545	5.63 ± 1.52	0.23 ± 0.004	± 0.004	± 6.30	± 18.28 ± 6.80	1.61	± 0.0083	± 0.0030	±
				0.08	0.004	4.01		1.38	0.0061	0.0010	
2022 Spring	5	4705	5.70 ± 1.62	0.23 ± 0.004	± 0.004	± 6.79	± 16.50 ± 6.96	4.38	± 0.0086	± 0.0050	±
				0.07	0.004	3.31		2.44	0.0080	0.0010	
	6	142	5.28 ± 1.39	0.20 ± 0.005	± 0.005	± 6.85	± 19.78 ± 5.72	3.93	± 0.0076	± 0.0050	±
				0.07	0.004	2.92		3.79	0.0065	0.0000	
	7	272	6.03 ± 1.58	0.21 ± 0.004	± 0.004	± 6.42	± 20.20 ± 4.67	6.82	± 0.0049	± 0.0050	±
				0.07	0.003	2.71		1.97	0.0046	0.0010	
	9	27	4.27 ± 1.00	0.21 ± 0.005	± 0.005	± 7.67	± 11.27 ± 6.98	-	0.0152	± 0.0050	±
				0.04	0.005	2.10			0.0054	0.0000	
2022 Spring	1	17	2.64 ± 0.02	0.33 ± 0.018	± 0.018	± 5.55	± 19.61 ± 0.00	-	0.0208	± 0.0050	±
				0.01	0.005	0.00			0.0000	0.0000	
	2	22	2.63 ± 0.02	0.32 ± 0.018	± 0.018	± 5.55	± 19.61 ± 0.00	-	0.0208	± 0.0050	±
				0.01	0.006	0.00			0.0000	0.0000	
	3	13	2.66 ± 0.03	0.32 ± 0.020	± 0.020	± 5.55	± 19.61 ± 0.00	-	0.0208	± 0.0050	±
				0.02	0.006	0.00			0.0000	0.0000	
	4	35	2.67 ± 0.04	0.20 ± 0.016	± 0.016	± 7.32	± 22.23 ± 2.77	1.42	± 0.0208	± 0.0040	±
				0.14	0.005	1.79		0.42	0.0000	0.0000	
2022 Spring	5	891	2.87 ± 0.24	0.28 ± 0.011	± 0.011	± 7.20	± 18.57 ± 4.57	1.03	± 0.0090	± 0.0050	±
				0.21	0.009	1.48		0.34	0.0083	0.0010	
	6	6	2.64 ± 0.01	0.30 ± 0.016	± 0.016	± 4.49	± 19.53 ± 0.07	-	0.0189	± 0.0050	±
				0.01	0.005	0.07			0.0012	0.0000	
	7	25	3.17 ± 0.08	0.45 ± 0.003	± 0.003	± 7.58	± 12.77 ± 1.46	-	0.0021	± 0.0050	±
				0.16	0.001	0.58			0.0000	0.0010	



2023 Summer	1	38	0.47 ± 0.01	0.07	± 0.002	± 6.51	$\pm 16.56 \pm 2.65$	-	0.0122	± 0.0040	$\pm$
				0.03	0.001	0.82			0.0008	0.0010	
	2	52	0.47 ± 0.03	0.07	± 0.004	± 6.50	$\pm 15.42 \pm 3.52$	-	0.0116	± 0.0040	$\pm$
				0.03	0.002	0.71			0.0015	0.0000	
	3	61	0.46 ± 0.01	0.07	± 0.007	± 6.74	$\pm 15.15 \pm 3.73$	-	0.0115	± 0.0040	$\pm$
				0.03	0.002	0.67			0.0014	0.0010	
	4	236	0.48 ± 0.05	0.06	± 0.004	± 6.56	$\pm 14.42 \pm 4.04$	2.36	± 0.0105	± 0.0040	$\pm$
				0.03	0.001	1.18		0.07	0.0023	0.0000	
	5	1788	0.49 ± 0.06	0.07	± 0.002	± 6.21	$\pm 12.91 \pm 4.18$	2.21	± 0.0083	± 0.0040	$\pm$
				0.05	0.002	0.91		0.10	0.0034	0.0010	
	6	71	0.47 ± 0.05	0.05	± 0.006	± 7.12	$\pm 13.21 \pm 3.82$	2.27	± 0.0088	± 0.0040	$\pm$
				0.04	0.002	1.69		0.04	0.0026	0.0010	
				0.07	± 0.013	± 5.98	$\pm$		0.0072	± 0.0040	$\pm$
	7	63	0.50 ± 0.07	0.05	0.017	0.77	11.94 ± 3.89	-	0.0033	0.0010	
				0.05	± 0.002	± 6.40	$\pm$		0.0117	± 0.0040	$\pm$
	9	29	0.53 ± 0.08	0.03	0.000	0.27	16.61 ± 2.05	-	0.0018	0.0010	
2023				0.00	± 0.005	± 7.44	$\pm$		0.0109	± 0.0050	$\pm$
Autumn	1	22	0.21 ± 0.00	0.00	0.000	0.09	3.42 ± 0.01	-	0.0005	0.0000	
				0.00	± 0.004	± 5.03	$\pm$	8.49	± 0.0114	± 0.0050	$\pm$
	2	12	0.21 ± 0.00	0.00	0.000	1.13	6.10 ± 1.25	0.00	0.0002	0.0000	
				0.00	± 0.006	± 6.08	$\pm$	4.08	± 0.0087	± 0.0050	$\pm$
	3	13	0.23 ± 0.01	0.00	0.000	1.52	4.83 ± 1.80	0.00	0.0021	0.0010	
				0.00	± 0.004	± 6.18	$\pm$	7.50	± 0.0100	± 0.0040	$\pm$
	4	120	0.22 ± 0.01	0.00	0.001	1.56	4.25 ± 1.60	2.12	0.0015	0.0000	
				0.00	± 0.002	± 3.67	$\pm$	6.04	± 0.0100	± 0.0060	$\pm$
	5	894	0.22 ± 0.02	0.00	0.000	1.86	4.20 ± 2.57	3.35	0.0031	0.0010	
				0.00	± 0.005	± 4.55	$\pm$	8.49	± 0.0115	± 0.0050	$\pm$
	6	17	0.21 ± 0.00	0.00	0.000	0.00	6.64 ± 0.00	0.00	0.0000	0.0000	
				0.00	± 0.017	± 4.26	$\pm$	6.98	± 0.0102	± 0.0040	$\pm$
	7	9	0.23 ± 0.01	0.00	0.001	0.35	6.68 ± 0.06	1.79	0.0016	0.0000	
				0.00	± 0.002	± 4.55	$\pm$	8.49	± 0.0115	± 0.0050	$\pm$
	9	8	0.21 ± 0.00	0.00	0.000	0.00	6.64 ± 0.00	0.00	0.0000	0.0000	



2023				0.14	± 0.110	± 1.72	±	7.52	± 0.0032	± 0.0050	±
Winter	5	258	1.11 ± 0.14	0.04	0.021	0.99	2.39 ± 0.69	0.47	0.0011	0.0010	
				0.17	± 0.112	± 2.19	±		0.0026	± 0.0030	±
	7	20	1.06 ± 0.02	0.05	0.015	1.09	2.58 ± 0.57	-	0.0010	0.0000	

640 **Appendix D**

Table D1. Seasonal meteorological anomalies per optical cluster.

Season	Cluster	Precip. (m)	Temp. (°C)	Runoff (m)	Surf. Radiation (MJ/m ²)
Autumn	1	+0.00029	+0.47	+0.0008	-9.25
	2	+0.00056	-1	+0.0001	-9.12
	3	-0.001	-1	+0.0004	-8.56
	4	+0.00005	-1	+0.0002	-7.66
	5	+0.00039	-2	+0.0006	-6.75
	6	+0.00173	-2	+0.0004	-5.51
	7	+0.00017	-1	+0.0000	-7.3
	9	+0.00199	-2	+0.0003	-5.49
Spring	1	+0.00656	-1	+0.0004	+3.55
	2	+0.00747	-1	+0.0002	+3.68
	3	+0.00732	-1	+0.0004	+3.01
	4	+0.00603	+0.52	0	+5.74
	5	-0.001	+0.57	+0.0002	+2.81
	7	-0.005	+1.17	+0.0005	-0.21
Summer	1	0	+0.08	0	+1.40
	2	+0.00033	+0.19	0	+0.28
	3	-0.001	+0.02	0	+1.16
	4	0	+0.08	0	+0.48
	5	0	+0.35	0	+0.88



	6	+0.00006	+0.17	0	+0.25
	7	-0.001	+0.37	0	+1.00
	9	0	+0.06	0	-0.1
Winter	5	-0.006	-4	+0.0000	-9.23
	7	-0.005	-3	0	-10.19

Appendix E

645

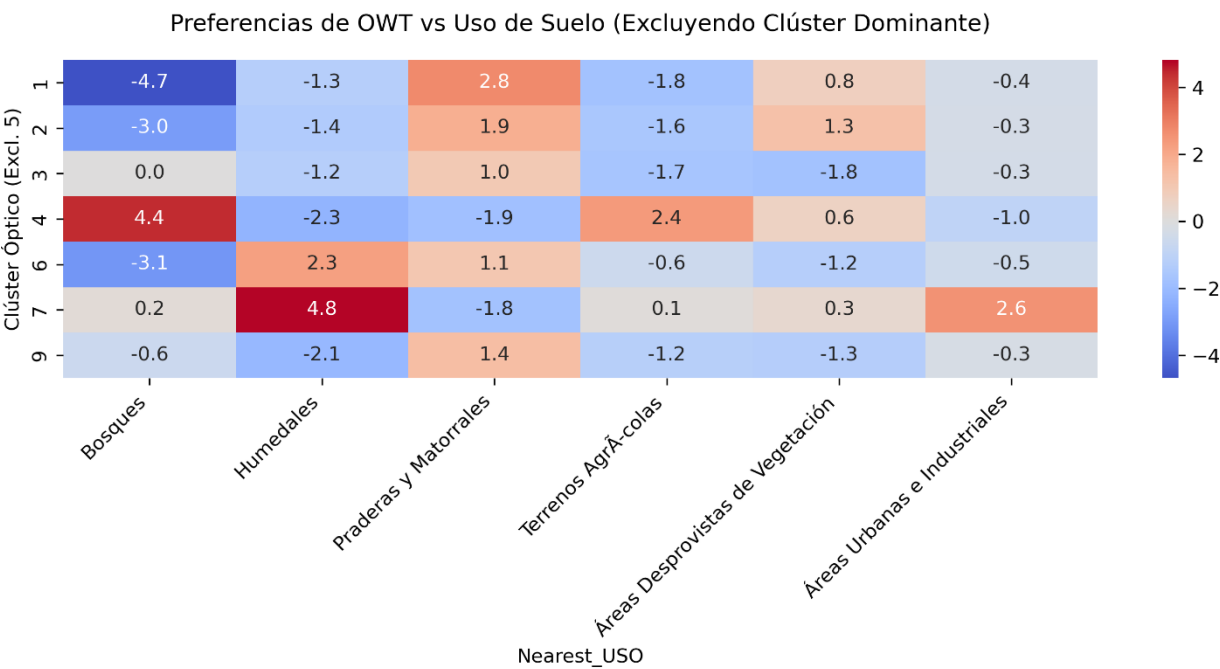


Figure E1. Habitat preference per OWT, excluding dominant cluster 5.

Code and data availability

650

Data is openly available at <https://data.mendeley.com/datasets/4m2c7w4bcw/2>. Aguilar Vega, Ximena; Giesecke, Ricardo; O'Donnell, Ruth; Jiang, Dalin; Spyrakos, Evangelos (2026), “Drivers of new optical water types in



southwestern Patagonian fjords derived from ship-borne radiometry”, Mendeley Data, V2, doi: 10.17632/4m2c7w4bcw.2

Supplement link

655 The link to the supplement will be included by Copernicus, if applicable.

Author contributions

XAV: Conceptualization, Visualization, Investigation, Software, Validation, Formal analysis, Writing - review & editing, Data curation, Methodology, Writing - original draft, Resources. RO: Resources, Validation, Formal analysis, Methodology, Data curation. DJ: Resources, Validation, Formal analysis, Data curation. RG: Funding acquisition, Project administration, Investigation, Resources, Data curation, Writing - review & editing. 660
JI: Writing - review & editing. JW: Funding acquisition, Project administration, Investigation, Resources review & editing. OZ: Funding acquisition, Project administration, Investigation, Resources. ES: Resources, Supervision, Writing - review & editing, Methodology, Validation, Data curation.

Competing interests

665 The authors declare that they have no conflict of interest.

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References

1. Aguilar Vega, Ximena; Giesecke, Ricardo; O'Donnell, Ruth; Jiang, Dalin; Spyarakos, Evangelos (2026),
690 “Drivers of new optical water types in southwestern Patagonian fjords derived from ship-borne
radiometry”, Mendeley Data, V2, doi: 10.17632/4m2c7w4bcw.2
2. Almandoz, G. O., Hernando, M. P., Ferreyra, G. A., Schloss, I. R., & Ferrario, M. E. (2011). Seasonal
phytoplankton dynamics in extreme southern South America (Beagle channel, Argentina). *Journal of Sea
Research*, 66(2), 47-57.
3. Anand, R., Mehrotra, K., Mohan, C. K., and Ranka, S.: Efficient classification for multiclass problems
695 using modular neural networks, *IEEE T. Neural Network.*, 6, 117–
124, <https://doi.org/10.1109/72.363444>, 1995.
4. Breiman, L. Random Forests. *Machine Learning* 45, 5–32 (2001).
<https://doi.org/10.1023/A:1010933404324>
5. Bertrand, S. (2025) 'Biogeochemistry of Riverine Organic Matter Inputs to the Patagonian Fjords and
700 Implications for Fjord Organic Carbon Budgets', *Journal of Geophysical Research: Biogeosciences*,
Available at: <https://doi.org/10.1029/2024jg008531>.



6. Bi, S. and Hieronymi, M. (2024) 'Holistic optical water type classification for ocean, coastal, and inland waters', *Limnology and Oceanography*, 69(7), pp. 1547–1561 Available at:
<https://doi.org/10.1002/lno.12606>.
- 705 7. Bresciani, M., Giardino, C., Fabbretto, A., Pellegrino, A., Mangano, S., Free, G. and Pinardi, M. (2022) 'Application of new hyperspectral sensors in the remote sensing of aquatic ecosystem health: Exploiting PRISMA and DESIS for four Italian lakes', *Resources*, 11(2), pp. 8.
8. Betti, F. (2021) 'Hard-Bottom Megabenthic Communities of a Chilean Fjord System: Sentinels for Climate Change?', *Frontiers in Marine Science*, 8(2021) Available at:
710 <https://doi.org/10.3389/fmars.2021.635430>.
9. Alves-De-Souza, C. (2026) 'Phytoplankton realized niches along the continental shelf and inner seas of Chilean Patagonia', *Progress in Oceanography*, 244 Available at:
<https://doi.org/10.1016/j.pocean.2026.103707>.
10. Aracena, C., Aracena, C., Lange, C.B., Lange, C.B., Iriarte, J.L., Iriarte, J.L., Iriarte, J., Rebolledo, L.,
715 Rebolledo, L., Pantoja, S. and Pantoja, S. (2011) 'Latitudinal patterns of export production recorded in surface sediments of the Chilean Patagonian fjords (41–55°S) as a response to water column productivity', *Continental Shelf Research*.
11. Cadaillon, A., Iachetti, C. M., Giesecke, R., Lepio, V. V., Malits, A., & Schloss, I. R. (2024). Rapid change in plankton community structure during spring along the eastern Beagle Channel. *Journal of Marine Systems*, 241, 103906.
- 720 12. Castillo-Llarena, A., Prange, M. and Rogozhina, I. (2025) 'Orbital and millennial-scale forcing of the Patagonian Ice Sheet throughout the Last Glacial Cycle', *Nature communications*, 16(1) Available at:
<https://doi.org/10.1038/s41467-025-64614-5>.
13. Corporación Nacional Forestal, CONAF (2014). 68073 - Región de Magallanes y Antártica Chilena,
725 Sistema de Información Territorial (SIT CONAF). Recuperado de <https://sit.conaf.cl/>
14. Cuevas, L. A., Tapia, F. J., Iriarte, J. L., González, H. E., Silva, N., and Vargas, C. A. (2019). Interplay between freshwater discharge and oceanic waters modulates phytoplankton size-structure in fjords and channel systems of the Chilean Patagonia. *Prog. Oceanogr.* 173, 103–113. doi: 10.1016/j.pocean.2019.02.01
- 730 15. Crosswell, J.R. (2022) 'Geophysical controls on metabolic cycling in three Patagonian fjords', *Progress in Oceanography*, 207 Available at: <https://doi.org/10.1016/j.pocean.2022.102866>.
16. Díaz, P.A. (2025) 'Unveiling the 2017 *Karenia* Bloom in NW Chilean Patagonia by Integrating Remote Sensing and Field Data', *Microorganisms*, 13(11) Available at:
<https://doi.org/10.3390/microorganisms13112440>.
- 735 17. Efimova, T., Churilova, T., Skorokhod, E., Suslin, V., Buchelnikov, A. S., Glukhovets, D., ... & Moiseeva, N. (2023). Light absorption by optically active components in the arctic region (august 2020) and the possibility of application to satellite products for water quality assessment. *Remote Sensing*, 15(17), 4346.
18. Garreaud, R.D., Garreaud, R.D., López, P., Lopez, P., Minvielle, M., Minvielle, M., Rojas, M. and Rojas, M. (2013) 'Large-Scale Control on the Patagonian Climate', *Journal of Climate*, .
- 740



19. Garzón-Cardona, J.E., Martínez, A.M., Koch, B.P., Krock, B., Palma, E.D., Kong, X. and Lara, R.J. (2023) 'Sources and distribution of dissolved organic matter and inorganic nitrogen in waters of the southern Patagonian shelf and northern Drake Passage (51–56°S, 64–69°W)', *Journal of Marine Systems*, 241.
- 745 20. Giesecke, R. (2021) 'General Hydrography of the Beagle Channel, a Subantarctic Interoceanic Passage at the Southern Tip of South America', *Frontiers in Marine Science*, 8(2021) Available at: <https://doi.org/10.3389/fmars.2021.621822>.
21. Giesecke, R., Höfer, J., Vallejos, T. and González, H.E., 2019. Death in southern Patagonian fjords: copepod community structure and mortality in land-and marine-terminating glacier-fjord systems. *Progress in Oceanography*, 174, pp.162-172.
- 750 22. Giesecke, R., Martín, J., Piñones, A., Höfer, J., Garcés-Vargas, J., Flores-Melo, X., Alarcón, E., Durrieu de Madron, X., Bourrin, F. and González, H.E., 2021. General hydrography of the Beagle Channel, a subantarctic interoceanic passage at the southern tip of South America. *Frontiers in Marine Science*, 8, p.621822.
- 755 23. Godoy, C.C., Iachetti, C.M., Diodato, S.L., Friesen, S.L. and Bruno, D.O. (2025) 'Spring-summer temporal dynamics of the zooplankton community in a flooded inlet of a sub-Antarctic river (Tierra del Fuego National Park)', *Continental Shelf Research*, , pp. 105633.
24. González, H.E. (2013) 'Land-ocean gradient in haline stratification and its effects on plankton dynamics and trophic carbon fluxes in Chilean Patagonian fjords (47-50°S)', *Progress in Oceanography*, Available at: <https://doi.org/10.1016/j.pocean.2013.06.003>.
- 760 25. González-Reyes, Á, Jacques-Coper, M. and Muñoz, A.A. (2021) 'Seasonal precipitation in south-central Chile: Trends in extreme events since 1900', *Atmósfera*, 34(4), pp. 371–384.
26. Geraldès, V. and Pinto, E. (2021) *Mycosporine-Like Amino Acids (MAAs): Biology, Chemistry and Identification Features* MDPI AG.
- 765 27. Hieronymi, M., Bi, S., Müller, D., Schütt, E.M., Behr, D., Brockmann, C., Lebreton, C., Steinmetz, F., Stelzer, K. and Vanhellemont, Q. (2023) 'Ocean color atmospheric correction methods in view of usability for different optical water types', *Frontiers in Marine Science*, 10.
28. Huovinen, P., Huovinen, P., Ramírez, J., Ramírez, J., Palacios, M., Palacios, M., Palacios, M., Gómez, I. and Gómez, I. (2020) 'Satellite-derived mapping of kelp distribution and water optics in the glacier impacted Yendegaia Fjord (Beagle Channel, Southern Chilean Patagonia).', *Science of The Total Environment*, .
- 770 29. Hoyer, S. and Hamman, J. (2017) 'xarray: ND labeled arrays and datasets in Python',
30. Iriarte, J.L., Pantoja, S. and Daneri, G. (2014) *Oceanographic Processes in Chilean Fjords of Patagonia: From small to large-scale studies* Elsevier BV, pp. 1.
- 775 31. Iriarte, J.L., González, H.E. and Nahuelhual, L. (2010) 'Patagonian Fjord Ecosystems in Southern Chile as a Highly Vulnerable Region: Problems and Needs', *AMBIO*, 39(7), pp. 463.
32. Jackson, T., Sathyendranath, S. and Mélin, F. (2017) 'An improved optical classification scheme for the Ocean Colour Essential Climate Variable and its applications', *Remote Sensing of Environment*, 203, pp. 152–161 Available at: <https://doi.org/10.1016/j.rse.2017.03.036>.



- 780 33. Kruse, F. A., Lefkoff, A. B., Boardman, J. W., Heidebrecht, K. B., Shapiro, A. T., Barloon, P. J., &
Goetz, A. F. (1993). The spectral image processing system (SIPS)—interactive visualization and analysis
of imaging spectrometer data. *Remote sensing of environment*, 44(2-3), 145-163.
34. Lehmann, M.K., Nguyen, U., Allan, M. and Van der Woerd, H.J. (2018) 'Colour classification of 1486
lakes across a wide range of optical water types', *Remote Sensing*, 10(8), pp. 1273.
- 785 35. León-Muñoz, J. (2021) 'Climate and Land Cover Trends Affecting Freshwater Inputs to a Fjord in
Northwestern Patagonia', *Frontiers in Marine Science*, 8 Available at:
<https://doi.org/10.3389/fmars.2021.628454>.
36. Levitin, D.J., Nuzzo, R.L., Vines, B.W. and Ramsay, J.O. (2007) 'Introduction to functional data
analysis.', *Canadian Psychology/Psychologie canadienne*, 48(3), pp. 135.
- 790 37. Malits, A., Monforte, C., Iachetti, C., Gereá, M., & Latorre, M. (2023). Source characterization of
dissolved organic matter in the eastern Beagle Channel from a spring situation. *Journal of Marine
Systems*, 240, 103863.
38. Manly, B.F. (2008) *Statistics for environmental science and management* Chapman and Hall/CRC.
39. Meire, L. (2023) 'Impact of glacial meltwater on the biogeochemistry of a West Greenland fjord system',
795 *Biogeosciences*, 20(8), pp. 1521–1540 Available at: <https://doi.org/10.5194/bg-20-1521-2023>.
40. Meire, L. (2017) 'Marine-terminating Glaciers Sustain High Productivity in Greenland Fjords', *Global
Change Biology*, 23(12), pp. 5344–5357 Available at: <https://doi.org/10.1111/gcb.13801>.
41. Milliman, J.D. and Farnsworth, K.L. (2013) *River discharge to the coastal ocean: a global synthesis*
Cambridge University Press.
- 800 42. Montero, P. (2011) 'Seasonal variability of primary production in a fjord ecosystem of the Chilean
Patagonia: Implications for the transfer of carbon within pelagic food webs', *Continental Shelf Research*,
Available at: <https://doi.org/10.1016/j.csr.2010.09.003>.
43. Montero, P., Montero, P., Pérez-Santos, I., Pérez-Santos, I., Daneri, G., Daneri, G., Gutiérrez, M.H.,
Gutiérrez, M.H., Igor, G., Igor, G., Seguel, R., Seguel, R., Seguel, R., Purdie, D.A., Purdie, D.A.,
805 Crawford, D.W. and Crawford, D.W. (2017) 'A winter dinoflagellate bloom drives high rates of primary
production in a Patagonian fjord ecosystem', *Estuarine Coastal and Shelf Science*, .
44. Nepf, H.M. and Geyer, W.R. (1996) 'Intratidal variations in stratification and mixing in the Hudson
estuary', *Journal of Geophysical Research: Oceans*, 101(C5), pp. 12079–12086 Available at:
<https://doi.org/10.1029/96jc00630>.
- 810 45. Oren, A. and Gunde-Cimerman, N. (2007) *Mycosporines and mycosporine-like amino acids: UV
protectants or multipurpose secondary metabolites?* Oxford University Press (OUP), pp. 1.
46. Pérez-Santos, I. (2018) 'Turbulence and Hypoxia Contribute to Dense Biological Scattering Layers in a
Patagonian Fjord System', *Ocean Science*, 14(5), pp. 1185–1206 Available at: [https://doi.org/10.5194/os-
14-1185-2018](https://doi.org/10.5194/os-14-1185-2018).
- 815 47. Petersen, W. (2014) 'FerryBox systems: State-of-the-art in Europe and future development', *Journal of
Marine Systems*, 140, pp. 4–12.
48. Prieur, L. and Sathyendranath, S. (1981) 'An Optical Classification of Coastal and Oceanic Waters Based
on the Specific Absorption Spectra of Phytoplankton Pigments, Dissolved Organic Matter, and Other



- Particulate Materials', *Limnology and Oceanography*, 26(4), pp. 671–689 Available at:
<https://doi.org/10.4319/lo.1981.26.4.0671>.
49. Rain-Franco, A. (2019) 'Variability of chromophoric dissolved organic matter in three freshwater-influenced systems along central-southern Chile', *Progress in Oceanography*, 174, pp. 154–161.
 50. Rodríguez-Benito, C.V., Navarro, G. and Caballero, I. (2020) 'Using Copernicus Sentinel-2 and Sentinel-3 data to monitor harmful algal blooms in Southern Chile during the COVID-19 lockdown', *Marine Pollution Bulletin*, 161.
 51. Rodríguez-Flórez, C. N., Paczkowska, J., Martín, J., Gil, M. N., Flores-Melo, X., & Malits, A. (2023). Terrigenous dissolved organic matter input and nutrient-light-limited conditions on the winter microbial food web of the Beagle Channel. *Journal of Marine Systems*, 239, 103860.
 52. Raudina, T.V. (2022) 'Seasonal and spatial variations of dissolved organic matter biodegradation along the aquatic continuum in the Southern Taiga bog complex, Western Siberia', *Water*, 14(23).
 53. Rodríguez-Flórez, C. N., Paczkowska, J., Martín, J., Gil, M. N., Flores-Melo, X., & Malits, A. (2023). Terrigenous dissolved organic matter input and nutrient-light-limited conditions on the winter microbial food web of the Beagle Channel. *Journal of Marine Systems*, 239, 103860.
 54. Rozzi, R., Rosenfeld, S., Armesto, J. J., Mansilla, A., Núñez-Ávila, M., & Massardo, F. (2024). Ecological Connections Across. Conservation in Chilean Patagonia: Assessing the State of Knowledge, Opportunities, and Challenges, 323.
 55. Saldías, G.S. (2019) 'Freshwater structure and its seasonal variability off western Patagonia', *Progress in Oceanography*, Available at: <https://doi.org/10.1016/j.pocean.2018.10.014>.
 56. Saldías, G.S., Figueroa, P.A., Carrasco, D., Narváez, D.A., Pérez-Santos, I. and Lara, C., 2024. Satellite-derived variability of sea surface salinity and geostrophic currents off Western Patagonia. *Remote Sensing*, 16(9), p.1482.
 57. Sauter, T., 2020. Revisiting extreme precipitation amounts over southern South America and implications for the Patagonian Icefields. *Hydrology and Earth System Sciences*, 24(4), pp.2003–2016. <https://doi.org/10.5194/hess-24-2003-2020>
 58. Schalles, J.F. (2006) *Remote sensing of aquatic coastal ecosystem processes: Science and management applications*, pp. 27–79.
 59. Sent, G., Spyarakos, E., Jackson, T., Atwood, E.C., Brotas, V., Groom, S. and Brito, A.C. (2025) 'Can optical water types be used as ecological indicators? Insights from a temperate estuary', *International Journal of Applied Earth Observation and Geoinformation*, 144, pp. 104880.
 60. Sepúlveda, J., Pantoja, S. and Huguen, K.A. (2011) 'Sources and Distribution of Organic Matter in Northern Patagonia Fjords, Chile (~44–47°S): A Multi-Tracer Approach for Carbon Cycling Assessment', *Continental Shelf Research*, 31(3–4), pp. 315–329 Available at: <https://doi.org/10.1016/j.csr.2010.05.013>.
 61. Spyarakos, E. (2018) 'Optical types of inland and coastal waters', *Limnology and Oceanography*, 63(2), pp. 846–870 Available at: <https://doi.org/10.1002/lno.10674>.
 62. Soto-Riquelme, C., Pinilla, E. and Ross, L. (2023) 'Wind influence on residual circulation in Patagonian channels and fjords', *Continental Shelf Research*, 254 Available at: <https://doi.org/10.1016/j.csr.2022.104905>.



63. Straneo, F., Sutherland, D.A., Stearns, L., Catania, G., Heimbach, P. and Moon, T. (2019) 'The case for a
860 sustained Greenland ice sheet-ocean observing system (GrIOOS)', *Front. Mar. Sci.*, 6 Available at:
<https://doi.org/10.3389/fmars.2019.00138>.
64. Sun, Y. and Genton, M.G. (2011) 'Functional boxplots', *Journal of computational and graphical statistics*,
20(2), pp. 316–334.
65. Torres-valdés, S., Tsubouchi, T., Bacon, S., Naveira-garabato, A.C., Sanders, R., McLaughlin, F.A.,
865 Petrie, B., Kattner, G., Azetsu-scott, K. and Whitledge, T.E. (2013) 'Export of nutrients from the Arctic
Ocean', *Journal of Geophysical Research: Oceans*, 118(4), pp. 1625.
66. Torres, R. (2020) 'Freshwater runoff effects on the production of biogenic silicate and chlorophyll-a in
western Patagonia archipelago (50–51°S)', *Estuarine, Coastal and Shelf Science*, 241 Available at:
<https://doi.org/10.1016/j.ecss.2020.106597>.
- 870 67. Torres, R., Torres, R., Torres, R., Frangópulos, M., Frangópulos, M., Hamamé, M., Hamamé, M.,
Montecino, V., Montecino, V., Maureira, C., Maureira, C., Pizarro, G., Pizarro, G., Reid, B., Reid, B.,
Valle-Levinson, A., Valle-Levinson, A., Blanco, J.L.S. and Blanco, J.L. (2011) 'Nitrate to silicate ratio
variability and the composition of micro-phytoplankton blooms in the inner-fjord of Seno Ballena (Strait
of Magellan, 54°S)', *Continental Shelf Research*, .
- 875 68. Torres, R., Torres, R., Torres, R., Pantoja, S., Pantoja, S., Harada, N., Harada, N., González, H.E.,
González, H.E., Daneri, G., Daneri, G., Frangópulos, M., Frangópulos, M., Rutllant, J.A., Rutllant, J.A.,
Duarte, C.M., Duarte, C.M., Ruíz-Halpern, S., Ruiz-Halpern, S., Mayol, E., Mayol, E., Fukasawa, M. and
Fukasawa, M. (2011) 'Air-sea CO₂ fluxes along the coast of Chile: From CO₂ outgassing in central
880 northern upwelling waters to CO₂ uptake in southern Patagonian fjords', *Journal of Geophysical
Research*, .
69. Valle-Levinson, A., Blanco, J.L. and Frangópulos, M. (2006) 'Hydrography and frontogenesis in a glacial
fjord off the Strait of Magellan', *Ocean Dynamics*, 56(3), pp. 217–227 Available at:
<https://doi.org/10.1007/s10236-005-0048-8>.
- 885 70. Vargas, C.A. (2018) 'Influence of Glacier Melting and River Discharges on the Nutrient Distribution and
DIC Recycling in the Southern Chilean Patagonia', *Journal of Geophysical Research: Biogeosciences*,
123(1), pp. 256–270 Available at: <https://doi.org/10.1002/2017jg003907>.
71. Vellojin, J.P. (2022) 'Understanding the implications of hydrographic processes on the dynamics of the
carbonate system in a sub-Antarctic marine-terminating glacier-fjord (53 S)', *Frontiers in Marine Science*,
9.
- 890 72. Wilson, H. (2025) 'Unlocking the global benefits of Earth Observation to address the SDG 6 in situ water
quality monitoring gap', *Frontiers in Remote Sensing*, 6(2025) Available at:
<https://doi.org/10.3389/frsen.2025.1549286>.
73. Zhang, Z., Chen, P., Zhang, S., Huang, H., Pan, Y., & Pan, D. (2025). A Review of Machine Learning
Applications in Ocean Color Remote Sensing. *Remote Sensing*, 17(10), 1776.
895 <https://doi.org/10.3390/rs17101776>