



Improving seaweed cover estimation in high latitudes: a focus on kelp classification

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Abstract. Satellite remote sensing offers the most practical means of monitoring *Macrocystis pyrifera* kelp forests across the remote Strait of Magellan, but standard atmospheric correction workflows assume a plane-parallel atmosphere that becomes inaccurate at the high solar zenith angles (SZA) characteristic of subantarctic latitudes, introducing wavelength-dependent radiometric biases into spectral unmixing products. This study develops and validates a Kelp Fractional Cover (KFC) product for the full 70,000 km² extent of the Strait of Magellan by applying an empirical SZA correction to Sentinel-2 Level-1C imagery prior to endmember extraction, using bilinear spectral unmixing implemented through the R-based Endmember Composition Algorithm (RECA) and Google Earth Engine. Pure pixel spectra for kelp, water, and land were extracted from over a decade of cloud-filtered imagery across ten sampling zones, yielding 51,002 pure kelp pixels, and endmembers were applied via a pseudoinverse unmixing model to generate per-pixel fractional cover with an associated RMSE layer. Validation against 60 independently paired, tidally and temporally controlled SuperDove image comparisons across ten additional zones showed strong model performance, with a peak Mean Jaccard Index of 0.50, an area-based R² of 0.69, and a polygon-based Overall Accuracy of 0.94, converging within an optimal binarization threshold range of 0.27-0.35. A second analysis comparing corrected and uncorrected models in optically deep, kelp-free reference zones confirmed that uncorrected fractional cover estimates exhibited spurious seasonal oscillations in kelp and land fractions tracking the annual SZA cycle, an artifact that the correction substantially suppressed in both deep-water and coastal validation zones. These results demonstrate that accounting for SZA-driven radiometric distortion is a prerequisite, rather than an optional refinement, for producing temporally consistent kelp cover estimates at high latitudes, and that failing to do so risks misattributing illumination-geometry artifacts to genuine ecological change. The resulting decade-long KFC time series, publicly available at <https://doi.org/10.5281/zenodo.2187772> (Iribarren et al., 2026), provides a spatially consistent, regionally continuous monitoring tool for one of the most extensive and least disturbed kelp forest systems on Earth, supporting future integration with in situ and environmental covariate data.

1 Introduction

Macroalgae forests dominated by species of the order Laminariales (commonly known as Kelp) are among the most productive coastal ecosystems, supporting food webs by providing habitat, refuge, nursery, and contributing substantially to carbon



export to deep waters (Smale et al., 2013; Krause-Jensen and Duarte, 2016; Wernberg et al., 2019). In subantarctic regions of South America the giant kelp *Macrocystis pyrifera* is widely distributed forming exuberant submarine forests that cover more than 4,800 km² (Mora-Soto et al., 2020). The remoteness and climatic harshness of this region make field-based monitoring logistically difficult, making satellite remote sensing the most practical approach for observing spatial and temporal changes in kelp forests. In this context, attempts have been made to assess the distribution and abundance of *M. pyrifera* through aerial and satellite image-based mapping using Landsat and Sentinel-2 (Friedlander et al., 2018; Huovinen et al., 2020; Mora-Soto et al., 2020; Gonzalez-Aragon et al., 2025; Guajardo-Rubilar et al., 2026). Although these studies have substantially improved our understanding of the regional distribution of *M. pyrifera*, the reliable detection and quantification of kelp forests from satellite imagery remain challenging because of the spectral complexity of nearshore environments. Consequently, methodological developments have increasingly focused on approaches that can account for the mixed spectral signatures characteristic of coastal pixels.

While land cover classification in remote sensing contexts commonly relies on spectral indices such as the Normalized Difference Vegetation Index (NDVI; Tucker, 1979) or categorical classification methods, the analysis of kelp forests has increasingly favored Spectral Mixture Analysis (SMA), given that coastal environments present low spatial separability among components — algae, water, and land — which frequently co-occur within a single pixel even at the spatial resolution of sensors such as Sentinel 2 (10–20 m spatial resolution; Cavanaugh, 2011; Bell et al., 2015a; Bell et al., 2015b; Friedlander et al., 2018; Huovinen et al., 2020.). SMA addresses this by decomposing each pixel into the fractional contributions of its constituent endmembers (Keshava and Mustard, 2002).

Existing remote sensing products for the southern Chilean Patagonian region vary considerably in their spatial extent, temporal coverage, and methodological approach. Friedlander et al. (2018) applied Multiple Endmember Spectral Mixture Analysis (MESMA) to Landsat 8 OLI imagery at 30 m resolution, restricted to a single austral summer season (December 2016–March 2017) and to three discrete sub-regions—Francisco Coloane Marine Park, Cape Horn, and Diego Ramírez—covering only a fraction of the broader Strait of Magellan system. Huovinen et al. (2020) applied Spectral Mixture Analysis (SMA) to Sentinel-2 imagery at 10 m resolution in the Yendegaia Fjord over a two-year period (2016–2018), demonstrating the superior accuracy of SMA over vegetation indices in a single, highly localized fjord environment. Finally, Mora-Soto et al. (2020) produced a global binary presence/absence map of *M. pyrifera* in channels and fjords from this ecoregion using Sentinel-2 imagery composited over a four-year period (2015–2019) at 10 m resolution. However, this product provides no information on within-pixel fractional cover or temporal dynamics. Collectively, these studies either cover broad spatial extents without fractional information, or provide fractional cover estimates over limited, spatially isolated sites and narrow time windows. A systematic, high-resolution fractional cover product spanning the full extent of the Strait of Magellan and integrating multi-year time series — sufficient to characterize both seasonality and interannual trends — therefore remained absent for the Chilean subantarctic zone. Moreover, the accuracy and ecological interpretation of satellite-derived products ultimately depend on robust field validation. In particular, *in situ* measurements of kelp density, species-specific spectral signatures, and intrinsic pigment composition are needed, as these characteristics strongly influence the optical properties of kelp canopies and, consequently, their reflectance patterns. However, studies explicitly linking satellite-derived metrics with field observations remain scarce in the



southern South American subantarctic region (Gómez et al., 2025; Kaminsky et al., 2026), highlighting the need for integrated approaches combining remote sensing with ecological and bio-optical measurements, and validation at resolutions higher than those provided by the sensors used for prediction.

Several factors limit kelp cover estimation in this region. Persistent cloud cover reduces the availability of usable imagery (Garreaud et al., 2009; Hoskins and Valdes, 1990b), tidal variability complicates the detection of submerged canopy (Servicio Hidrográfico y Oceanográfico de la Armada de Chile, n.d.; Medeiros and Kjerfve, 1988b; Huovinen et al., 2020; Gómez et al., 2025), and high Solar Zenith Angles (SZA) introduce radiometric distortions that are not fully accounted for in standard atmospheric correction workflows (Xu et al., 2024). Standard atmospheric correction algorithms used in global ocean color and land surface processing — including those applied to Sentinel-2 Level-1C products — are based on look-up tables (LUTs) generated under the assumption of a plane-parallel atmosphere, which treats atmospheric layers as horizontally infinite and vertically homogeneous (He et al., 2018; Xu et al., 2023, 2024). This geometry is a reasonable approximation at low-to-moderate SZAs (typically $<70^\circ$), where photon path lengths through the atmosphere are short. However, at the latitudes of the Strait of Magellan ($\sim 52^\circ\text{S}$ - $\sim 54^\circ\text{S}$), SZAs can approach 85° during winter months, conditions under which the curvature of the Earth causes photons to traverse substantially longer and more oblique atmospheric paths than the plane-parallel model predicts (Korkin et al., 2020).

The radiometric consequences of this geometric mismatch are wavelength-dependent and non-trivial in magnitude. Xu et al. (2024) demonstrated, using a Monte Carlo vector radiative transfer model for a spherical-shell atmosphere, that Earth curvature effects on top-of-atmosphere radiances — quantified as the relative percentage difference between spherical-shell and plane-parallel TOA radiance simulations for the same solar-sensor geometry — at SZAs $>70^\circ$ can reach up to 5.36% for aerosol-dominated atmospheres and exceed 12% when molecule–aerosol interactions are considered at SZA = 80° . Critically, these errors are not spectrally uniform. At low-to-moderate SZAs, the curvature effect is markedly larger at 865 nm ($\sim 9.93\%$) than at 412 nm ($\sim 2.56\%$), reflecting the dominant role of optical thickness in attenuating the geometric distortion through multiple scattering (Xu et al., 2024). This pattern, however, reverses in terms of growth rate: as SZA increases toward 80° , sensitivity to SZA is inversely related to wavelength, the effect at 412 nm rises sharply to $\sim 7.47\%$ at high viewing zenith angles, while the corresponding increase at 865 nm is comparatively more modest, reaching $\sim 10.81\%$ (He et al., 2018; Xu et al., 2023, 2024). This means that, although the absolute magnitude of the Earth curvature effect remains larger at longer wavelengths, the rate of growth with increasing SZA is substantially steeper in the short wavelength spectrum, making this wavelengths disproportionately more sensitive to high-SZA geometry — a distinction with important implications for multi-spectral atmospheric correction algorithms.

Because atmospheric path length affects near-infrared bands more strongly than blue bands, solar zenith angle (SZA) variation can shift the apparent spectral signatures of kelp, water, and other surface components in ways unrelated to actual reflectance. When endmembers are extracted from images acquired under different SZA conditions across seasons, this illumination-driven variability introduces systematic inconsistencies in the endmember matrix. Consequently, when these endmembers are applied to unmix scenes acquired under varying geometries, fractional cover estimates may reflect differences in illumination as much as real changes in canopy extent or density.



In this study, we map kelp forest fractional cover in the Strait of Magellan using bilinear spectral unmixing of Sentinel-2 Level-1C imagery, incorporating a correction for wavelength-dependent radiometric effects from SZA at high latitudes. By applying this correction prior to endmember extraction, we derive spectral signatures from more radiometrically consistent data and improve the physical basis of the unmixing model. The resulting fractional cover product is validated against high-resolution SuperDove imagery to evaluate its ability to detect kelp occurrence and estimate canopy extent across the Strait of Magellan and surrounding subantarctic waters under different SZA conditions.

More broadly, this study aims to improve the reliability of kelp detection in high-latitude environments, where extreme solar geometry represents an important source of uncertainty in multi-spectral analyses. By reducing distortions, we can enhance the reliability of the spectral discrimination between floating kelp canopy and other coastal components, including intertidal macroalgae, vegetation, and terrestrial surfaces (Huovinen et al., 2020). Moreover, we demonstrate the artifacts arising from uncorrected data, showing the distinctive and biased patterns that are often included in current mapping endeavours. This is an essential effort not only for generating more accurate estimates of kelp fractional cover, but also for strengthening the transferability of remote-sensing approaches to subantarctic ecosystems characterized by complex coastal mosaics and strong seasonal variations in solar radiation.

2 Methodology

2.1 Study area

The study area was centered on the Strait of Magellan, bounded to the south by Mount Darwin, to the west by the western tip of the Brunswick Peninsula, to the north by the locality of Cóndor (Santa Cruz, Argentina), and to the east by the southeastern boundary of Garibaldi Fjord, spanning from $52^{\circ}7'57''\text{S}$, $72^{\circ}27'37''\text{W}$ to $54^{\circ}44'11''\text{S}$, $68^{\circ}55'21''\text{W}$ and covering an approximate area of $70,000 \text{ km}^2$ (Figure 1). This region was selected for two principal reasons. First, the subantarctic zone harbors the most spatially extensive *M. pyrifera* forests across its entire distribution range, many of which maintain largely pristine ecological conditions that maximize the probability of locating pixels with high spectral purity for endmember extraction (Mora-Soto et al., 2020, 2021). Second, the fragmented geography and extreme climatic conditions of the region impose severe logistical constraints on systematic field surveys, making satellite remote sensing a particularly valuable and perhaps the only viable tool for periodic monitoring of kelp forest dynamics at ecologically meaningful management. On the other hand, strong variation of tidal range (2–12m) along the strait (Medeiros and Kjerfve, 1988a; Gómez et al., 2025) poses a challenge for correct estimations of kelp cover.

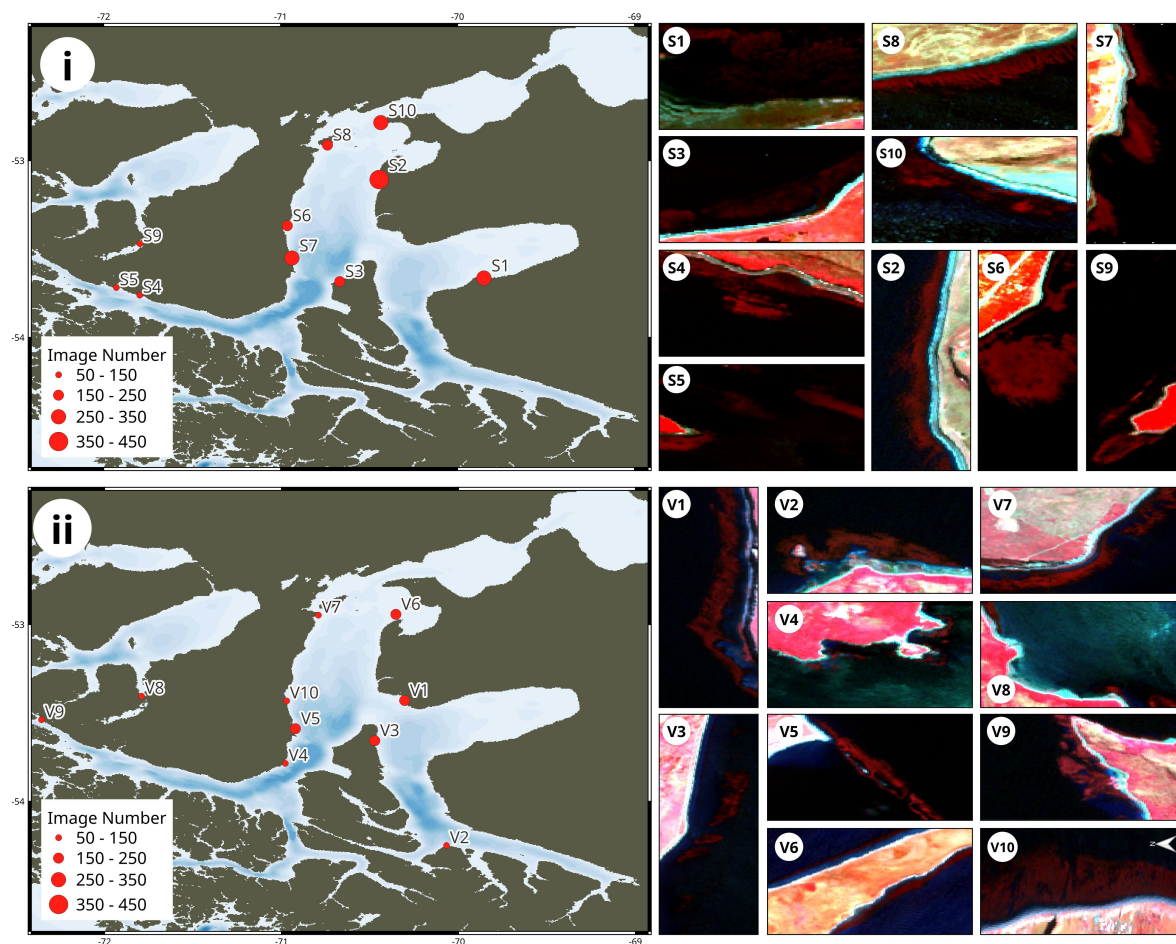


Figure 1. Spatial distribution and Sentinel-2 image examples of the reference study areas used for kelp forest pure pixel extraction and fractional cover validation. Panel I shows the sampling areas used for pure pixel extraction, with red points indicating the location of each area, and point size representing the number of available Sentinel-2 images remaining after cloud filtering. Panel II shows the independent validation areas, with example false-color composites for each area (R: near-infrared band, G: red band, B: green band), where photosynthetically active vegetation, including kelp forests, are highlighted in red tones. All areas are 1.5 km^2 , with dimensions, ~ 2250 by ~ 700 m and ~ 1150 by ~ 1350 m, for vertical and horizontal areas, respectively.

2.2 General Workflow

The methodological framework for generating fractional kelp cover imagery includes four sequential stages: (i) cloud-filter and SZA correction of Sentinel-2 images; (ii) extraction of spectrally pure pixel values; (iii) construction of a bilinear spectral unmixing model using the R-based Endmember Composition Algorithm (RECA; Seidel and Hlawitschka, 2015) and application of the resulting endmembers via a pseudoinverse function within Google Earth Engine (GEE; Gorelick et al., 2017) to produce



per-pixel fractional cover maps; and (iv) validation of the fractional cover estimates through comparison with independently delineated kelp extents derived from very high-resolution satellite imagery (Figure 2).

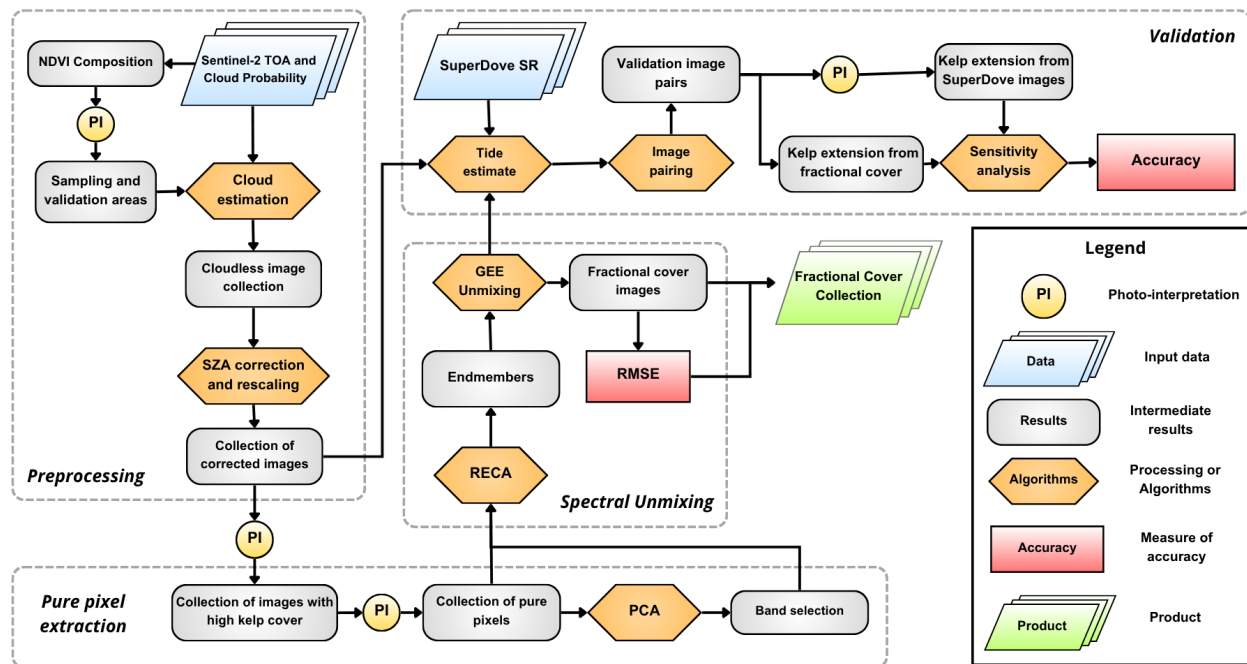


Figure 2. Schematic workflow for generating fractional kelp cover imagery from Sentinel-2 data, following four sequential stages: (i) cloud filtering and solar zenith angle (SZA) correction of Sentinel-2 Level-1C top-of-atmosphere (TOA) reflectance imagery; (ii) extraction of spectrally pure pixel values for kelp, water, and land surface components; (iii) construction of a bilinear spectral unmixing model using the R-based Endmember Composition Algorithm (RECA; Seidel & Hlawitschka, 2015) and application of the derived endmembers via a pseudoinverse function within Google Earth Engine to produce per-pixel Fractional Cover Collection; and (iv) validation of FMC estimates through comparison with kelp extents independently delineated from very high-resolution SuperDove imagery. Dashed boxes delimit the four main stages of the workflow.

2.3 Data preprocessing

2.3.1 Input data

130 The reference imagery used for endmember extraction and fractional cover mapping was the Sentinel-2 Level-1C collection available in GEE, consisting of orthorectified and radiometrically corrected top-of-atmosphere (TOA) reflectance images produced by the European Space Agency (ESA, 2015–present). Sentinel-2 Level-1C products provide 13 spectral bands spanning the visible, near-infrared, and shortwave infrared portions of the spectrum, with spatial resolution varying between 10 and



60 m depending on the spectral band. For external validation, fractional cover estimates were compared against kelp extents,
 135 photo-interpreted and manually delineated from SuperDove imagery (Planet Labs Inc.), a very high-resolution multispectral
 constellation whose spatial detail far exceeds that of Sentinel-2, providing a robust and independent reference for assessing
 model accuracy. The 13 Sentinel-2 spectral bands used in this work include coastal aerosol ($B1$, 443 nm, 60 m), blue ($B2$, 490
 nm, 10 m), green ($B3$, 560 nm, 10 m), red ($B4$, 665 nm, 10 m), vegetation red edge bands ($B5$, 705 nm, 20 m; $B6$, 740 nm, 20
 m; $B7$, 783 nm, 20 m), near-infrared ($B8$, 842 nm, 10 m; $B8A$, 865 nm, 20 m), water vapor ($B9$, 945 nm, 60 m), cirrus ($B10$,
 140 1375 nm, 60 m), and shortwave infrared bands ($B11$, 1610 nm, 20 m; $B12$, 2190 nm, 20 m).

2.3.2 Data Correction

To correct for the effect of solar zenith angles (SZA) on Sentinel-2 surface reflectance, we fitted a model to reference local data
 in order to capture the variability of this partially enclosed study area. For this, a transect was defined between both ends of
 the Strait of Magellan between the Atlantic and Pacific Oceans, following the central axis of the strait's main channel, a route
 145 that generally corresponds to the deepest waters of the strait. Along this transect, 37 circular zones with a radius of 1 km were
 spaced 10 km apart using their centroids, ensuring a spatially representative sample of the study area (Figure A1). According
 to GEBCO bathymetric data (GEBCO Compilation Group, 2026), the selected zones span a depth range of between 20 m, at
 their shallowest point in the northeastern portion of the strait, and 578 m at their deepest point, with a median depth of 77
 m. Hereafter, these zones are referred to as "deep-water zones" to distinguish them from the zones used for model fitting and
 150 unmixing endmember sampling and from the validation zones, both of which are coastal and located in shallow waters. For
 each zone, images were filtered using the Sentinel-2 Cloud Probability product with a maximum cloud probability threshold of
 25% and a maximum cloud pixel proportion of less than 1%, retaining only images with near-complete surface visibility. For
 each retained image, the SZA was calculated based on the centroid of each circular zone and the acquisition time of the scene
 using the R *suncalc* package and its *getSunlightPosition* function (Thieurmél and Elmarhraoui, 2022). Using these values, a
 155 per-band quadratic regression model was fitted to characterize the relationship between SZA and the median reflectance of each
 band across the image collection. The residuals of this initial fit were then used to classify the data into usable and unusable
 observations, using the 95th percentile of the absolute residual values as a threshold. A second quadratic regression model was
 subsequently fitted only using the observations classified as usable, with the aim of reducing the influence of noise in the data.
 The resulting model describes reflectance as a smooth polynomial function of the solar zenith angle (Figure 3).

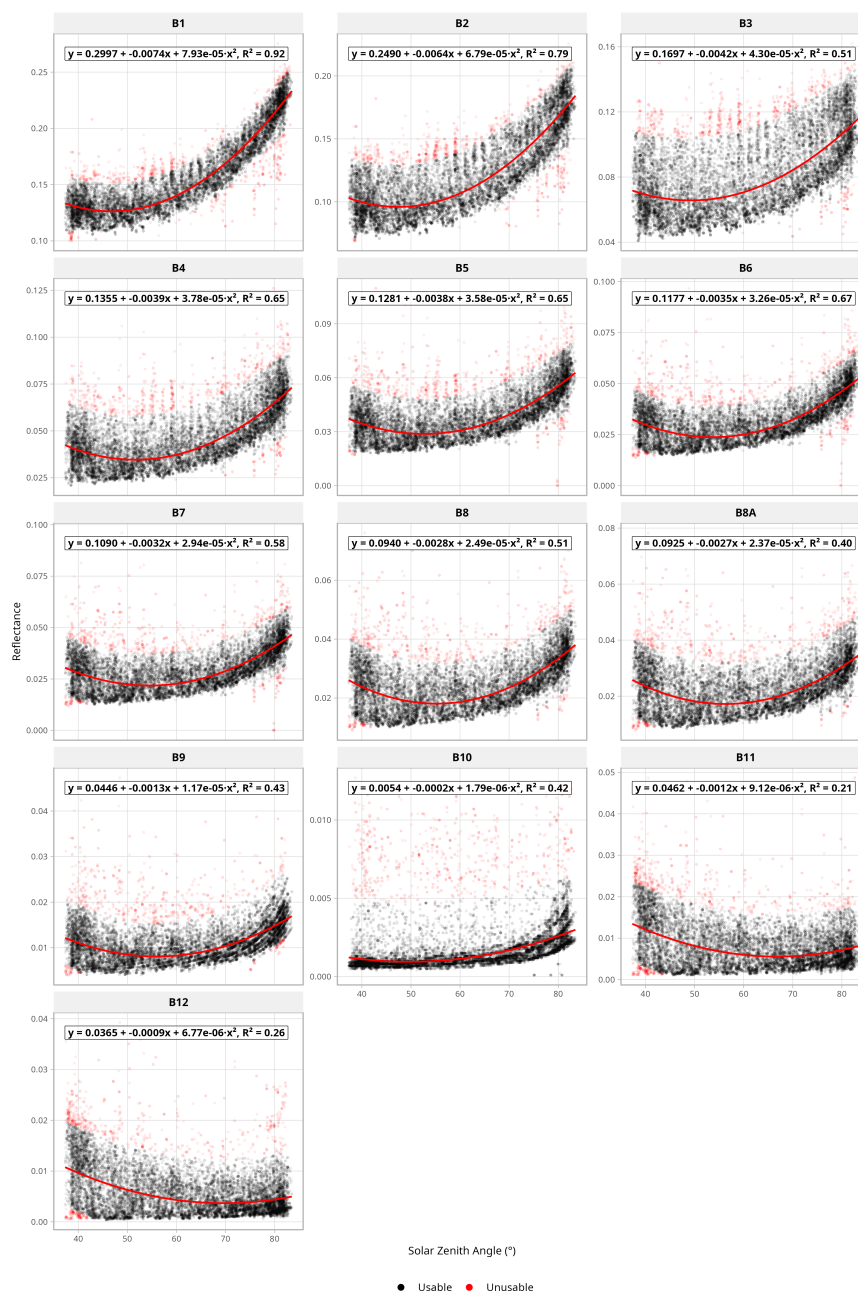


Figure 3. Quadratic regression models relating Solar Zenith Angle (SZA) to top-of-atmosphere (TOA) reflectance for each Sentinel-2 spectral band (B1–B12), derived from cloud-free imagery collected along a deep-water transect through the Strait of Magellan. Each panel shows median band reflectance as a function of SZA (°), with black dots denoting observations with absolute residuals below the 95th percentile, while red dots are observations outside this range. The red curve shows the fitted quadratic model ($y = a + bx + cx^2$), with the corresponding equation and coefficient of determination (R^2) displayed in each panel. The reflectance axis excludes the top 0.1% of the data for better visualization given highly asymmetric distributions.



160 While the SZA correction removes most of the atmospheric influence on measured reflectance, it also introduces negative
 values to data. In order to prevent this, and homogenize the data for endmember extraction, we applied a final correction using
 two sequential steps: First, residuals between the modeled and observed reflectance values were calculated for each band;
 second, a linear stretching was applied to restore the corrected values to the radiometric range of each band, using a floor and
 ceiling. Per-band floors and ceilings were calculated as the 1st and 99th percentiles of the total samples of pixels used for
 165 endmember extraction (Table A1), thus normalizing the range of values across the study area and incorporating the *ad-hoc*
 variability of our focal study system.

2.4 Pure pixel extraction

Spectral unmixing analysis is based on the decomposition of the multidimensional space between endmembers, which repre-
 sent the noiseless spectral signatures of pure components that are naturally mixed in a system (Keshava and Mustard, 2002).
 170 The purity and noiselessness of real endmembers are only found in laboratory conditions; therefore, approximation algorithms
 to estimate their values are often used. The unmixing phase of the analysis involves resolving the combinations on the linear
 multidimensional space between endmembers found on observational data. The accuracy of the endmember estimation funda-
 mentally conditions the quality of the fractional cover estimates produced by the unmixing model, as any systematic bias in the
 spectral signatures will propagate directly into the estimated fractions (Keshava and Mustard, 2002; Bioucas-Dias et al., 2012).
 175 For estimating the endmembers we generated a collection of pure pixels. A pure pixel is defined as a spatial unit whose recorded
 reflectance is dominated by a single surface component, thereby providing their representative spectral signature (Boardman,
 1993; Ren et al., 2026). Accordingly, identifying image locations where the surface cover is as spectrally homogeneous as
 possible is a critical prerequisite for the analysis. Within the study area, ten rectangular sampling zones of approximately 1.5
 km² were delineated for pure pixel extraction, and ten additional zones of equivalent dimensions were independently selected
 180 for model validation, both sets ensuring a spatially uniform distribution across the study region (Figure 1). All twenty zones
 were selected following the same reference information consisting of a Sentinel-2 composite of the maximum values of annual
 mean NDVI for the 2015–2024 period, allowing for the identification of significant algal cover in at least one year of the study
 period. NDVI was used as the primary indicator of photosynthetically active kelp presence at the surface, consistent with its
 established effectiveness for detecting kelp patches in coastal environments (Tucker, 1979; Cavanaugh et al., 2010; Nijland
 185 et al., 2019; Huovinen et al., 2020; Mora-Soto et al., 2020).

A cloud filtering procedure was first applied to the full Sentinel-2 image collection intersecting the sampling areas for the
 period between August 19, 2015 and March 29, 2025. Cloud masking was performed using the Sentinel-2 Cloud Probability
 product generated with the *Sentinel Hub Cloud Detector* Python library (Skakun et al., 2022), whereby all pixels with a cloud
 probability exceeding 50% were dropped. In order to avoid overestimating cloud cover due to confusion between snow and
 190 clouds or due to cloud presence over adjacent land areas, we used a water mask (including pixels with kelp), to generate grids
 of equidistant points spaced by 0.002 degree points within each sample and validation zones. We used this grid to calculate
 the proportion of non-cloud pixels to the total amount of pixels within the water mask. Each zone had between 35 and 49
 grid points depending on the water cover within them. Only images with an estimated cloud pixel proportion below 10% were



retained for further processing (Appendix A2). Following cloud filtering, 689 images were retained for spring, 611 for autumn,
 195 527 for summer, and 463 for winter. From this pooled collection, images exhibiting the highest kelp density were manually
 selected through photointerpretation of NIR–Red–Green false-color composites (Sentinel-2 bands *B8*, *B4*, and *B3*), together
 with maps of NDVI and Normalized Difference Water Index (NDWI, Gao, 1996) (Campbell and Wynne, 2011; Ghazouani
 et al., 2019), irrespective of the acquisition season (day of year). For each image, we manually delineated polygons of spatial
 clusters of pixels exhibiting the highest kelp canopy cover. As part of this photointerpretation process, pixels located in close
 200 proximity to the coastline were deliberately excluded from polygon delineation, since their spectral signature is more likely
 to be affected by mixed contributions from intertidal substrate, emergent vegetation, or shadow effects associated with the
 shoreline, rather than representing a spectrally pure kelp canopy signal. We then extracted the image values for all intersecting
 pixels within these polygons, creating a collection of pure kelp pixels. Similarly, pure water and land surface pixels were
 extracted using fixed polygons defined for each zone, considering their temporal stability across the study period. In total,
 205 51,002 pure kelp pixels were collected (Table A2), to which, an equal number of water and land pixels (51,002 per class) were
 randomly sampled using their corresponding fixed polygons to avoid class imbalance.

A Principal Component Analysis (PCA) was then applied to the combined spectral dataset to evaluate the separability of
 the three components of kelp, water and land, and to select the spectral bands to input on the unmixing model. The first two
 principal components jointly explained 89.1% of the total variance in the dataset and produced a clear spatial separation among
 210 the kelp, water, and land surface clusters (Figure 4). Given that *B1* (443 nm) is primarily sensitive to aerosol scattering and *B10*
 (1375 nm) to cirrus cloud absorption, both bands represent potential sources of atmospheric noise for the spectral unmixing
 model, consequently they were excluded from the analysis. Their exclusion, however, does not compromise the discrimination
 of the components, as these are precisely the two bands that contribute less to explaining the variance captured by the first
 two principal components (Figure A2); the remaining ten bands — *B2* through *B9*, *B11*, and *B12* — were retained as model
 215 inputs. Prior to endmember estimation, the spectral values of each pixel were normalized by dividing each band by the sum
 of all retained bands, such that the resulting values summed to one. This transformation converts absolute reflectance values
 into relative proportions of reflectance across bands, which is required as the spectral unmixing algorithm used in this work
 operates on compositional data (Weltje, 1997; Seidel and Hlawitschka, 2015).

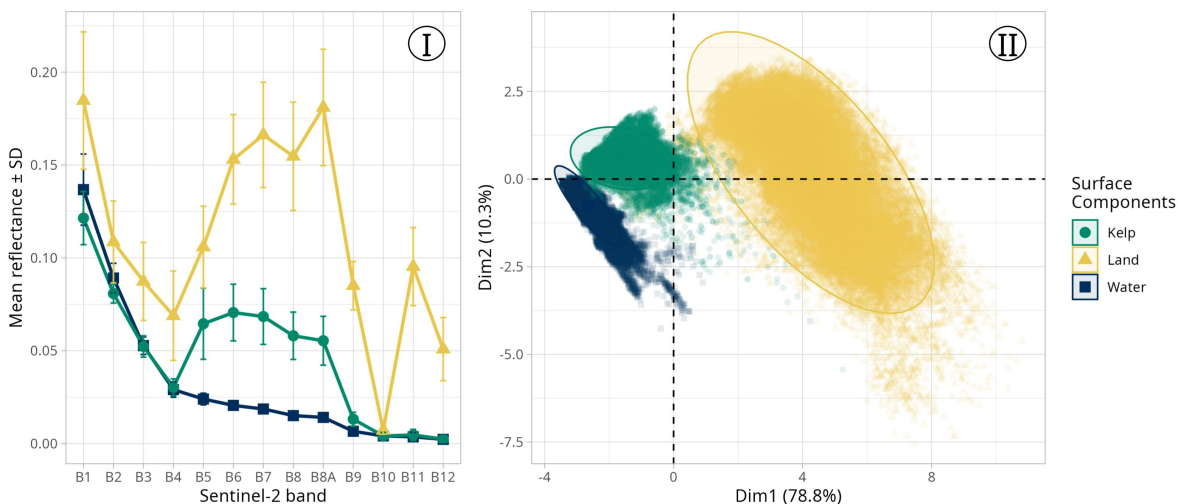


Figure 4. Panel I shows the mean spectral reflectance profiles ($\pm$ SD) of pure pixels extracted from solar zenith angle (SZA)-corrected Sentinel-2 imagery for the three analyzed components. Reflectance values are shown across the Sentinel-2 spectral bands for kelp, land, and water classes. Panel II shows the principal component analysis (PCA) of pure pixel spectral values derived from the same SZA-corrected imagery, showing the clustering and spectral separability among the three surface components based on the first two principal dimensions.

2.5 Spectral unmixing model

220 Endmember estimation was performed using the R-based Endmember Composition Algorithm (RECA; Seidel and Hlawitschka, 2015), which operationalizes the End Member Modeling Algorithm (EMMA) originally described by Weltje (1997) as pseudocode. RECA implements a bilinear spectral unmixing approach, a designation that reflects the simultaneous estimation of two sets of unknowns: the endmember composition matrix and the mixing proportion matrix. The algorithm was executed with default values of convexity error threshold of -6, a maximum of 10,000 iterations, and a standard weighting exponent of

225 1, as recommended by Weltje (1997).

Once the endmembers for kelp, water and land surface were obtained, the spectral unmixing model was applied to each SZA-corrected Sentinel-2 image in GEE using the pseudoinverse function *unmix*. Prior to unmixing, the reflectance values of each pixel were normalized to sum one, since the endmembers produced by RECA are expressed as relative proportions of reflectance. Two physical constraints were imposed during the inversion: (i) a sum-to-one constraint, ensuring that the estimated

230 fractions represent mutually exclusive coverage proportions at the pixel level; and (ii) a non-negativity constraint, precluding physically meaningless negative abundance values. The result of applying the model to each image is a three-band raster layer in which each band contains the estimated fractional cover of one component — kelp, water, and land — for every pixel. The internal consistency of the model was assessed by computing the per-pixel Root Mean Square Error (RMSE) between the original reflectance values and those reconstructed from the linear combination of endmembers weighted by their respective



fractions, as formalized in equations (1) and (2). The RMSE assumes that the reflectance of each pixel for n components is defined as:

$$R_b = \sum_{i=1}^n R_{i,b} F_i + \varepsilon_b \quad (1)$$

where R_b is the reflectance for band b , $R_{i,b}$ is the value of endmember i in band b , F_i is the fraction of endmember i , and ε_b is the residual error in band b . From this, the RMSE is calculated across m bands as:

$$RMSE = \left[m^{-1} \sum_{b=1}^m \varepsilon_b^2 \right]^{1/2} \quad (2)$$

The RMSE layer was incorporated into the final fractional kelp cover product as a spatially explicit indicator of model fit, flagging pixels where surface compositions not represented by the three-endmember model may have introduced systematic reconstruction errors.

2.6 Annual composite generation and public dataset

To generate a spatially continuous, decade-long Kelp Fractional Cover (KFC) product for public release, the validated spectral unmixing workflow described above was applied to annual Sentinel-2 composites spanning the full study area. For each year from 2015 to 2025, all Sentinel-2 Level-1C images intersecting the study area were filtered using the Sentinel-2 Cloud Probability product (Skakun et al., 2022), retaining pixels with a cloud probability below 25%, consistent with the threshold applied during pure-pixel extraction. Annual periods were defined from 1 July to 30 June of the following year rather than by calendar year, to avoid splitting the austral summer growing season across two composites (Mora-Soto et al., 2022). For each period, a per-pixel median composite was calculated from all retained images and corrected for solar zenith angle following the empirical quadratic model described in Sect. 2.3.2, using the mean SZA of the contributing scenes. Corrected reflectance was linearly stretched to the per-band 1st–99th percentile range and normalized to sum to one across bands prior to inversion. The three-endmember bilinear unmixing model (kelp, water, land) was applied using the pseudoinverse `unmix` function in GEE, under sum-to-one and non-negativity constraints, producing per-pixel fractional cover for the three components together with the associated per-pixel RMSE layer (Eq. 2.5) as an indicator of local model fit. Owing to GEE export size limitations, each annual composite was processed and exported in spatial tiles that were subsequently mosaicked. Fractional cover and RMSE values were rescaled from their native 0–1 range to a 0–10000 integer range and stored as 16-bit GeoTIFFs to reduce file size while preserving four decimal digits of precision upon rescaling.

A binary kelp forest extent layer was additionally derived from each annual fractional cover composite by applying the following pixel-wise criteria: kelp fraction greater than 0.35 (3500 in the scaled layer), land fraction below 0.10 (1000 scaled),



and surface elevation below 5 m based on the SRTM Digital Elevation Model (Farr et al., 2007). The kelp fraction threshold of 0.35 corresponds to the binarization cutoff that jointly maximized the area-based coefficient of determination and polygon-based Overall Accuracy during validation (Sect. 2.7), while the elevation constraint follows the 5 m threshold adopted to
 265 exclude terrestrial pixels without erroneously removing shallow-water kelp canopy. Continental lagoons with elevation at or below sea level within the strait were additionally masked from the binary layer to prevent false positives associated with these enclosed water bodies, which are spectrally and topographically indistinguishable from coastal kelp habitat using elevation and fractional cover alone.

The resulting dataset — comprising, for each of the eleven annual periods (2015–2025), a fractional cover and RMSE com-
 270 posite (`KelpWaterLandUnmix_<year>.tif`) and a binary kelp extent layer (`KelpForestExtent_<year>_binary.tif`), both at 10 m spatial resolution — was deposited in a public repository to support independent reuse, long-term monitoring, and integration with in situ and environmental covariate data (Iribarren et al., 2026).

2.7 Validation

Validation of the fractional cover estimates was conducted through two complementary approaches to assess model perfor-
 275 mance, regarding the predicted spatial extent of kelp cover and the SZA correction improvements to data.

The first approach evaluated the ability of the SZA-corrected model to accurately detect and estimate the spatial extent of kelp forests. We compared estimated Kelp Fractional Cover (KFC) values against photointerpreted and manually delineated kelp extents using SuperDove imagery across ten dedicated validation zones, selected using the same criteria used for the endmember sampling areas described in section 2.4. We used the period spanning from March 13, 2020 to July 4, 2025,
 280 which is constrained by the operational overlap between the Sentinel-2 and SuperDove missions (Figure A3). The same cloud filtering procedure applied to the sampling areas was performed to both image collections in the validation zones. Because tidal ranges can be of up to 10 m in parts of the study area (Servicio Hidrográfico y Oceanográfico de la Armada de Chile, n.d.), considerably affecting exposed shore area, we estimated the tidal level for each candidate image pair using the empirical ocean tide model *EOT20* (Hart-Davis et al., 2021). Validation Sentinel-2–SuperDove image pairs were then assembled by
 285 sequentially applying four selection criteria: (i) the difference in acquisition time of day between paired images could not exceed one hour in order to minimize variations in solar illumination geometry; (ii) the difference in acquisition date could not exceed ten days in order to limit the influence of phenological or storm-driven changes in kelp cover between observations; (iii) within each validation zone, no individual Sentinel-2 or SuperDove image could be used in more than one pair in order to ensure independence among pairs and spatial representativeness of the validation dataset; and (iv) after the first three criteria
 290 were met, a subset of six pairs per zone exhibiting the smallest estimated tidal difference were retained (Figure A4). This procedure yielded a total of 60 image pairs: 27 in summer, 15 in autumn, 5 in winter, and 13 in spring (Figures A3 & A4).

For each SuperDove image, the spatial extent of kelp cover was delineated manually through photointerpretation of true-color and NIR–Red–Green false-color composites together with NDVI maps, producing multiple polygons for each scene. For each corresponding paired Sentinel-2 image, the spectral unmixing algorithm was applied to derive the KFC layer. We masked
 295 this layer to restrict the analysis to the marine domain by retaining all pixels with a surface elevation lower than 5 m, based on



the SRTM Digital Elevation Model (Farr et al., 2007). A threshold of 5 m, rather than 0 m, was adopted because of erroneous exclusions of water zones with kelp in one of the study areas, while for the remaining zones the use of 5 m instead of 0 m did not substantially alter the resulting coastline. Since the reference kelp delineations from SuperDove represent presence-only spatial extents, the continuous KFC values were binarized at varying fraction thresholds as part of a sensitivity analysis.

300 The correspondence between the binarized KFC extents and the manually delineated reference areas was evaluated using three complementary metrics: (i) the mean Jaccard spatial overlap index from all image pairs, which quantifies the similarity between two spatial extents as the ratio of their intersection to their union; (ii) the coefficient of determination (R^2) of the linear regression between the two sets of area measurements (Sentinel-2 and SuperDove); and (iii) the polygon-based Overall Accuracy (OA), derived from a confusion matrix framework and defined as the proportion of correctly classified polygons over
 305 the total number of polygons. Producer's Accuracy (PA) and User's Accuracy (UA) were additionally computed from the same confusion matrix to characterize commission and omission errors, respectively, though these metrics were not included in the threshold sensitivity analysis.

The second approach evaluated the capacity of the SZA correction to remove solar zenith angle-driven artifacts from the fractional cover estimates. For this purpose, we compared the aggregated time series of resulting fractional cover estimates,
 310 both with and without the application of the SZA correction. We explored the temporal behavior of these estimations for both the validation areas and along the transect areas presented in section 2.3.2. Both unmixing approaches were then independently applied to the full image collection available for the deep-water sampling zones used to fit the SZA regression: the unmixing with endmembers obtained from corrected pure pixel values was applied to the corrected images, while the unmixing with endmembers obtained from uncorrected pure pixel values was applied to the uncorrected images. For each image and each
 315 zone, the mean fractional cover of each component — kelp, water, and land — was computed over the deep-water pixels. Because these zones are located in open, optically deep waters devoid of kelp or land surfaces, the fractional cover of the kelp and land components should theoretically remain negligible and invariant through time if the model is free from SZA-induced bias. Any systematic temporal variation in these fractions — in particular a seasonal pattern consistent with the annual SZA cycle — would therefore indicate residual contamination attributable to illumination geometry rather than to true surface
 320 cover. The monthly distributions of mean fractional cover for both models were compared to assess the degree to which the SZA correction stabilizes the spectral unmixing output and reduces spurious temporal variability in deep-water predictions. To further evaluate the effect of the SZA correction in coastal environments — and, consequently, in areas where kelp forests are present — the same analysis was extended to the ten validation zones described in the first approach. Images were selected following the same filtering criteria applied to the deep-water sampling zones, retaining only those with a cloud probability
 325 below 25% and a maximum cloud pixel proportion of less than 1% over the water portion of each image. For each image and each validation zone, the mean fractional cover of each spectral component was computed, and the monthly distributions of both the corrected and uncorrected models were compared. This complementary assessment allowed us to examine whether SZA-induced artifacts persist or are amplified in optically shallower, structurally heterogeneous coastal settings relative to the open-water baseline.



330 3 Results

3.1 Preprocessing

A total of 2,016 cloud-free Sentinel-2 images were available across the ten sampling areas, from which 219 images were selected based on quality and suitability for endmember estimation (see Table A3). Image selection showed a clear seasonal bias, with most acquisitions concentrated in summer, followed by spring, limited representation in autumn, and almost no
 335 usable winter imagery due to persistent cloud cover. The filtering process yielded 51,002 pure kelp pixels overall, although the contribution varied notably among sites, ranging from 2.2% (S9) to 21.7% (S7). Areas S7, S4, S6, and S2 provided the largest contributions to the endmember dataset, with a combine 70.6% of the data, while the rest of the areas contributed comparatively fewer pixels. This uneven distribution reflects both spatial variability in kelp presence among sites and differences in image availability and quality across the study region.

340 3.2 Pixel values extraction

The spectral characteristics of extracted pixels for endmember calculation exhibited distinct reflectance patterns and variability across the 13 spectral bands analyzed (Figure 4). The land fraction displayed the highest overall reflectance values, particularly in the near-infrared and shortwave infrared regions ($B8A$: mean $\pm$ SD = 0.181 ± 0.032 , $B7$: mean $\pm$ SD = 0.166 ± 0.029), while also showing the greatest variability across most bands (SD range: 0.002–0.037). In contrast, the water fraction
 345 demonstrated consistently low reflectance across all bands, with values ranging from 0.004 ($B10$) to 0.137 ($B1$) and exhibiting relatively low variability (SD range: 0.001–0.019), characteristic of its spectral absorption properties. The algae fraction showed intermediate reflectance values with notable peaks in visible blue ($B1$: mean $\pm$ SD = 0.121 ± 0.014) and near-infrared bands ($B6$: mean $\pm$ SD = 0.071 ± 0.015 , $B7$: mean $\pm$ SD = 0.068 ± 0.015), reflecting the typical chlorophyll absorption and scattering features. Thermal bands ($B10$, $B11$, $B12$) exhibited minimal reflectance across all fractions (means <0.010), with
 350 the land fraction showing the highest thermal response in $B11$ (mean $\pm$ SD = 0.095 ± 0.021). The distinct spectral signatures and moderate variability observed within each endmember fraction confirm their suitability for spectral unmixing analysis.

3.3 Endmembers

The endmember estimation with SZA corrected pure pixel data reached the convexity error threshold of -6 after 517 iterations. Negative values accounted for only 0.47% of the mixing proportions generated from the pure-pixel sample, indicating a strong
 355 model fit and that only a minimal proportion of sample points fell outside the mixing polytope defined by the endmembers (Weltje, 1997). The endmember values for kelp, water, and land, expressed as relative reflectance proportions, are presented in Figure 5, and available in Table A3.

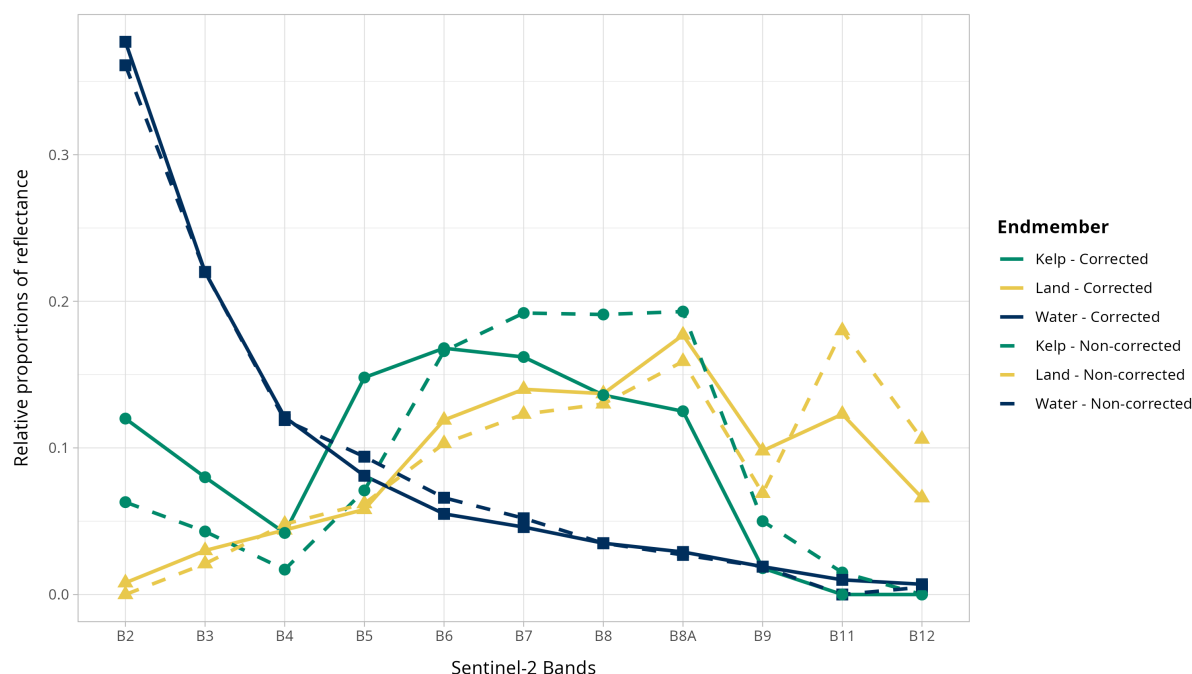


Figure 5. Estimated kelp, water, and land endmembers derived from the RECA spectral unmixing algorithm using SZA-corrected pure pixels and non-SZA-corrected pure pixels, expressed as relative reflectance proportions across Sentinel-2 spectral bands.

The estimated endmembers presented clearly distinguishable spectral signatures for water, kelp, and land. The water endmember exhibited a monotonic decrease in reflectance from the blue band (B2) toward the SWIR region (B12), whereas the kelp endmember showed a pronounced increase in the near-infrared region (B7–B8A). In contrast, the land endmember exhibited higher relative reflectance values in the shortwave-infrared region, particularly in the first SWIR band (B11), and lower values in the blue (B2) and green (B3) bands. These differences in spectral shape indicate that the selected bands collectively contributed to the spectral separability of the analyzed components.

3.4 Fractional cover estimations

The spectral unmixing model produced spatially coherent fractional cover estimates for the three defined components — kelp, water, and land — across all processed Sentinel-2 scenes, with per-pixel fractions responding consistently to the known distribution of surface types within the study area. Across the image collection, pixels spatially coincident with the coastal land margin systematically exhibited elevated land fraction values, reflecting the spectral dominance of terrestrial reflectance, while pixels located within the aquatic domain were characterized by the predominance of water and kelp fractions, with the spatial extent of kelp-dominated signal delineating discrete and spatially coherent patches within the marine environment. The three output bands behaved as mutually complementary spatial discriminators: the land fraction effectively separated terrestrial from aquatic pixels, while the kelp and water fractions resolved the internal structure of the aquatic domain according to the



presence or absence of kelp canopy. Figure 6 illustrates this general behavior for a representative scene acquired on February 4, 2019 over sampling zone 6, showing the RGB composite of fractional outputs — with the Red, Green, and Blue channels encoding the land, kelp, and water fractions, respectively, on a scale from 0 to 1 — alongside the filtered composite obtained by retaining only pixels with a land fraction ≤ 0.3 , which isolates the aquatic domain and enhances the visualization of spatial variability in kelp fraction.

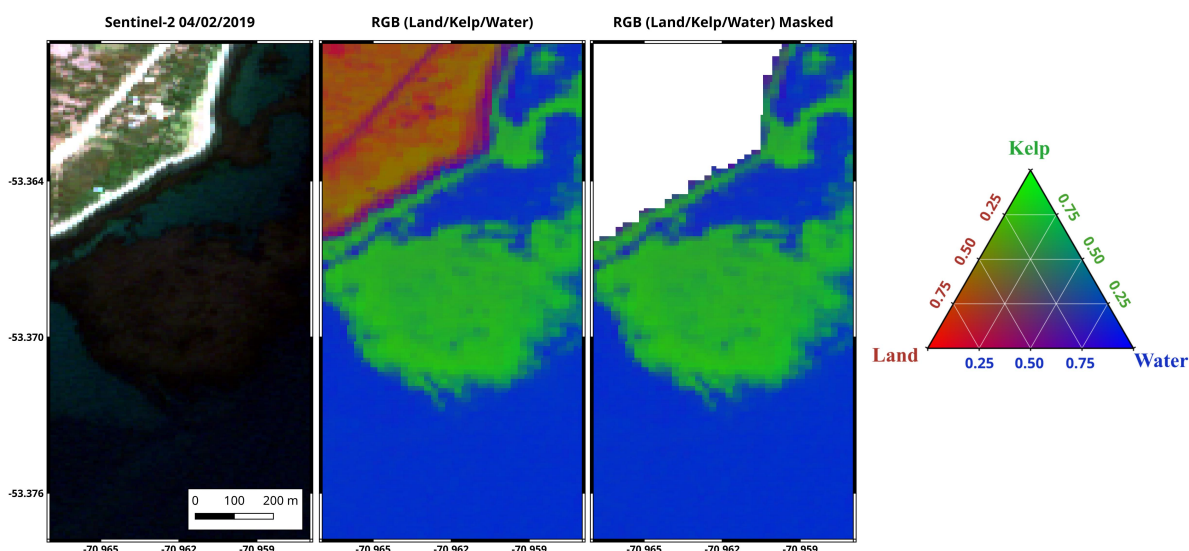


Figure 6. Example of the application of the spectral unmixing model to sampling zone 6. (Left) True-color composite of the input image, displayed with a 3–97% linear contrast stretch. (Center) RGB composite of the modeled endmember fractions, with the Red, Green, and Blue channels representing the land, Kelp, and water fractions, respectively (color scale from 0 to 1). (Right) Filtered fraction composite retaining only pixels with a land fraction ≤ 0.3 , isolating the aquatic domain for improved visualization of kelp and water fraction.

3.5 Validation outcomes

The sensitivity analysis of the binarization threshold for the kelp fraction revealed a consistent pattern across both validation metrics, with their respective maxima occurring within a narrow KFC range (Figure 7). The Mean Jaccard Index reached its peak of 0.50 at a threshold of 0.27, reflecting the best overall spatial overlap between the binarized KFC extents and the manually delineated SuperDove reference polygons. The R^2 of the area-based linear regression attained its maximum of 0.69 at a slightly higher threshold of 0.35, indicating the strongest correspondence between the two area measurements at that cutoff value. Notably, the polygon-based Overall Accuracy (OA) also reached its maximum of 0.94 at a threshold of 0.35, further corroborating the suitability of this cutoff in terms of correct classification of kelp presence and absence polygons. The convergence of both spatial and area-based optima within the 0.27–0.35 range, together with peak values of 0.50, 0.69, and 0.94 for the Jaccard Index, R^2 , and OA, respectively, indicates a satisfactory and consistent model capability to determine kelp



forest extent across the validation zones. A binarization threshold within this range is recommended for subsequent analyses, as it represents a balanced operating point at which the Jaccard Index remains near its peak with negligible decline relative to its maximum, while R^2 and OA are substantially higher than at the Jaccard-optimal threshold.

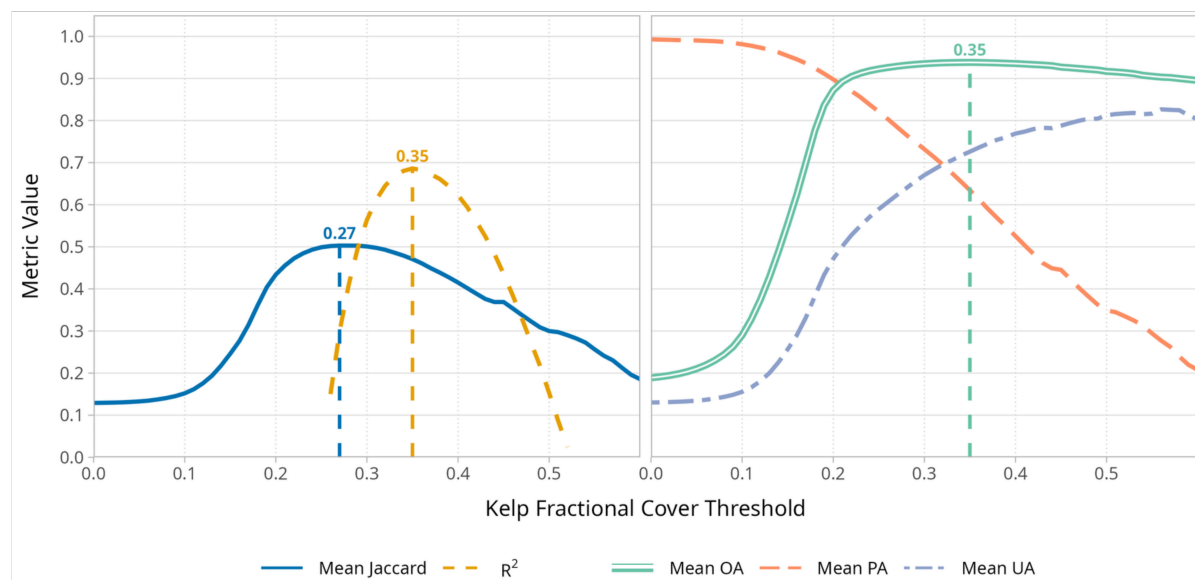


Figure 7. Sensitivity analysis of Kelp Fractional Cover (KFC) thresholds used to binarize SZA-corrected Sentinel-2-based fractional cover maps for validation against manually delineated SuperDove kelp extents. The left panel shows model performance evaluated using the mean Jaccard spatial overlap index and the coefficient of determination (R^2) between estimated and reference kelp areas across 60 SuperDove/Sentinel-2 image pairs. The right panel presents polygon-based classification accuracy metrics, including means Overall Accuracy (OA), Producer's Accuracy (PA), and User's Accuracy (UA) for image pairs. Only the threshold for OA is displayed. Dashed lines indicate the thresholds maximizing each metric.

Figure 8 shows a subset of the 60 validation image pairs, consisting of one randomly selected pair for each month of the year, except June due to the lack of Sentinel-2 images. Moreover, examples of the visual comparison between the binarized KFC layers, generated using a threshold of 0.3, and their corresponding SuperDove images with manually delineated reference polygons, are presented.

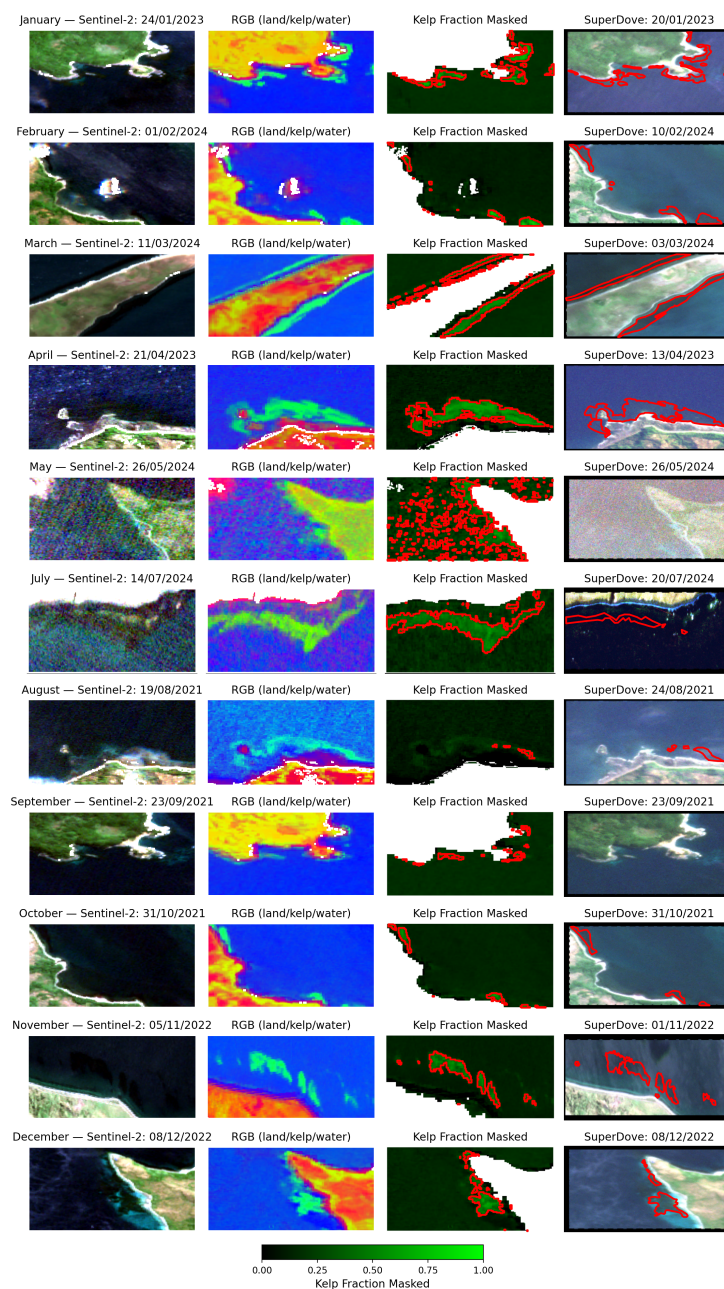


Figure 8. Monthly examples of the validation dataset (June absent due to the lack of Sentinel-2 images). Each row shows four columns: (1) Sentinel-2 true-color image after SZA correction; (2) RGB composite representing the fractional-cover outputs of the unmixing model (land/kelp/water, as in Figure 6); (3) Kelp fractional cover (KFC) with the altitude mask shown in white and red polygons derived by binarizing the kelp fraction using a threshold of 0.35; and (4) SuperDove true-color image with manually delineated kelp-extent polygons in red. Images were randomly selected for each month. For visualization purposes, each band was linearly stretched using the 2nd and 98th percentiles.



395 On the second validation step, the endmembers derived from the uncorrected pure pixels were found to be somewhat similar to those obtained from the SZA-corrected reflectance values (Figure 5, Table A3), with a almost equal water endmember, but different land and kelp endmembers. While maintaining similar patterns along the spectral range, the land endmember with slightly higher values in the SWIR region (B_{11} and B_{12}), and the kelp endmember with lower values in the visible range (B_1 , B_2 and B_3) and higher values in the region of the NIR (B_8). This non-corrected endmember estimation converged after
 400 299 iterations, with negative mixture proportions accounting for 0.816% of the total mixing proportions generated from the pure pixel sample. This indicates also a good model fit and a minimal proportion of sample points falling outside the mixing polytope (Weltje, 1997).

The unmix application of each set of endmembers to their respective image collections — non-corrected endmembers applied to non-SZA-corrected images, and SZA-corrected endmembers applied to corrected images — revealed a consistent reduction
 405 in seasonal variability across all spectral components in the corrected approach, in both the deep-water sampling zones and the coastal validation zones (Figure 9). In the non-corrected model, the kelp, land, and water fractions all exhibited marked monthly fluctuations in the deep-water zones — where no actual kelp or land surface is present — with the land component displaying a considerable oscillation, reaching median values that exceed 0.20 during austral summer months and dropping near 0.05 in winter. This pattern is consistent with a systematic SZA-driven artifact, as the deep-water zones are expected to
 410 yield negligible and temporally stable kelp and land fractions in the absence of illumination-geometry bias. Following the SZA correction, the monthly distributions of all three components in the deep-water zones became substantially more stable, with interquartile ranges markedly reduced and seasonal trends largely suppressed. Although the corrected model produced a higher overall RMSE relative to the non-corrected version, the RMSE distributions were considerably more uniform across months, indicating that the correction trades a reduced apparent fit for a more consistent and artifact-free spectral decomposition.
 415 The same stabilizing effect of the SZA correction was observed in the coastal validation zones, where the land and water fractions followed patterns largely analogous to those in the deep-water areas. However, the kelp fraction in the validation zones exhibited a distinct seasonal signal that was absent in the deep-water zones under both the corrected and non-corrected models, which is expected based on the ecological processes of kelp.

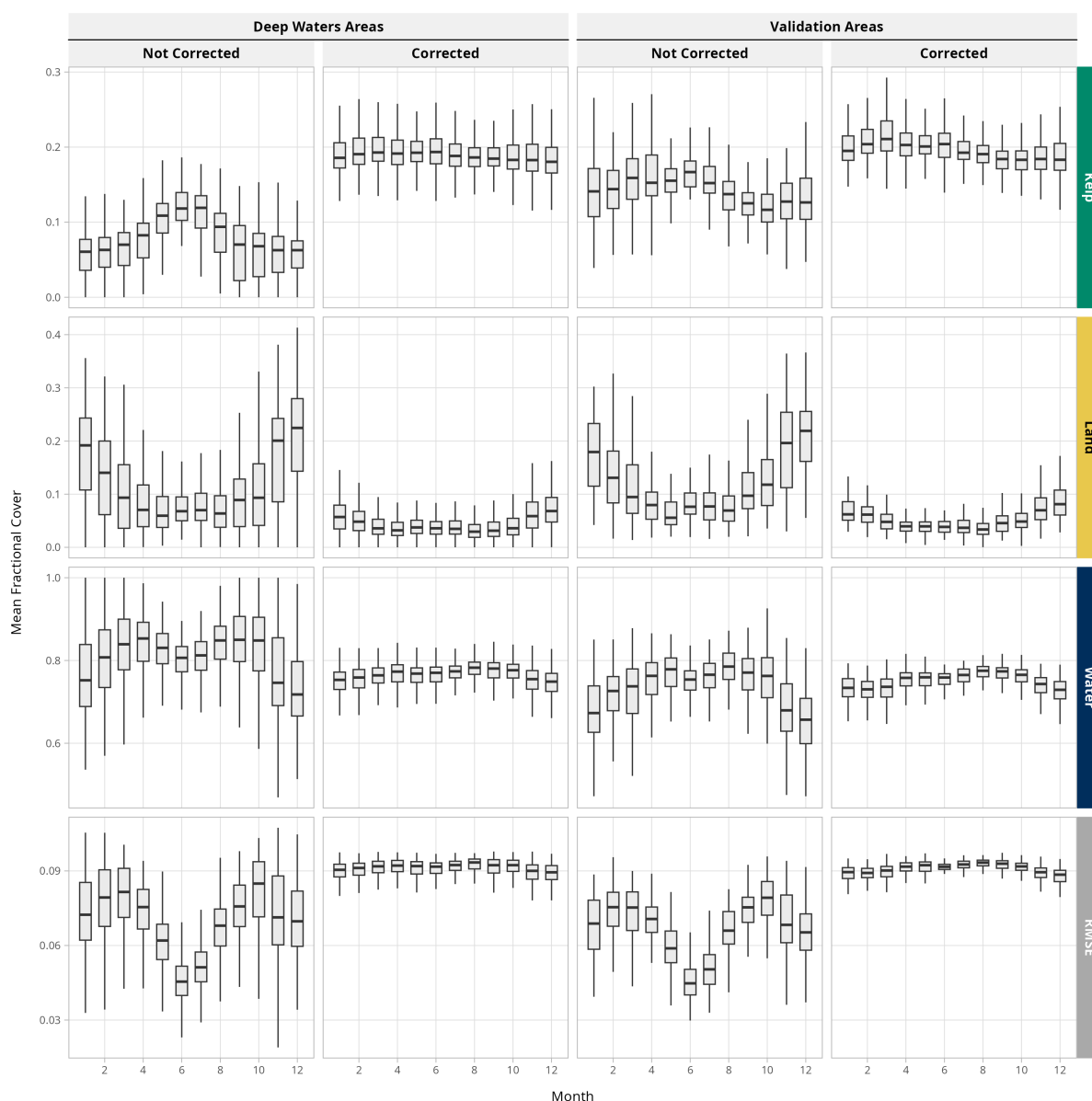


Figure 9. Monthly distributions of mean fractional cover for the kelp, land, water, and RMSE components, estimated from the spectral unmixing model applied independently to deep-water sampling zones and coastal validation zones across all available Sentinel-2 images in the study area. Results are shown before (Not Corrected) and after (Corrected) solar zenith angle (SZA) correction, for both the deep-water zones (both left columns) and the ten validation zones (both right columns). For each image and each zone type, the mean fractional cover of each component was computed over the corresponding pixel sets. Both model versions were fitted using their respective endmember spectral values — derived from uncorrected pure pixels for the uncorrected model, and from SZA-corrected pure pixels for the corrected model — and applied to their corresponding image collections.



3.6 Decadal kelp fractional cover product

Application of the validated unmixing model to annual Sentinel-2 composites yielded a continuous, spatially explicit Kelp Fractional Cover (KFC) time series spanning eleven annual periods (2015–2025) across the full $\sim 70,000 \text{ km}^2$ extent of the Strait of Magellan. Binarization at the optimal threshold (kelp fraction > 0.35 , land fraction < 0.10 , elevation $< 5 \text{ m}$) produced annual maps of kelp forest extent consistent with the persistent, spatially extensive distribution of *Macrocystis pyrifera* previously reported for this sub-Antarctic region (Mora-Soto et al., 2020, 2021). Cloud filtering at a 25% maximum cloud probability threshold (Skakun et al., 2022) resulted in uneven image availability across years and seasons, with fewer usable scenes typically retained during austral winter months owing to persistent cloud cover (Garreaud et al., 2009; Hoskins and Valdes, 1990a); this constrains, but does not preclude, the interpretation of interannual comparisons in the resulting composites. The per-pixel RMSE layer accompanying each annual fractional cover composite identified areas of elevated reconstruction error concentrated near the coastline and in zones of complex substrate mixing, consistent with the presence of surface types (e.g., intertidal macroalgae, exposed rock, sediment plumes) not explicitly represented by the three-endmember model (Keshava and Mustard, 2002; Bioucas-Dias et al., 2012).

4 Discussion

The results of this study demonstrate two interrelated advances in the remote sensing of subantarctic kelp forests. First, an empirical correction for the wavelength-dependent radiometric effects of solar zenith angle (SZA) effectively suppressed a systematic source of illumination-geometry bias that — to our knowledge — has not previously been quantified or corrected in kelp remote sensing workflows operating at high latitudes (Friedlander et al., 2018; Huovinen et al., 2020; Mora-Soto et al., 2020). Second, a bilinear spectral unmixing framework applied across the full spatial extent of the Strait of Magellan over a multi-year Sentinel-2 archive produced continuous, per-pixel Kelp Fractional Cover (KFC) estimates at regional scale, with validation performance that remained robust and internally consistent across sites, seasons, and acquisition geometries. The following sections first assess the empirical performance of the KFC product against independent validation data and published benchmarks, then examine the methodological basis of the SZA correction that underpins it, and finally address the main limitations and broader ecological implications of the framework.

The quantitative performance of the KFC product is most directly assessed through the validation metrics, which require interpretation against both the structural constraints of the validation design and the benchmarks reported by comparable prior studies. The results — a peak Mean Jaccard Index of 0.50, an area-based R^2 of 0.69, and a polygon-based Overall Accuracy of 0.94, all converging within a binarization threshold range of 0.27–0.35 — are examined in turn against each of these reference frames. The high OA of 0.94 is, on its own, an insufficient basis for evaluating model performance: in coastal binary classification problems, this metric is well known to be magnified by the overwhelming dominance of the non-kelp background class, which structurally biases it toward high values regardless of the spatial precision of kelp detection (Foody, 2020; Douzas et al., 2019). The Jaccard Index, by penalizing both omission and commission errors relative to the union of predicted and observed extents, provides a more demanding and ecologically meaningful measure of spatial correspondence (Contini et al.,



2025; Krasnodębska et al., 2025). In this regard, the Jaccard value of 0.50 obtained here represents a moderate result (Marquez et al., 2022; Marzuki et al., 2024), though one that must be evaluated against structural constraints inherent to the validation design: the resolution disparity between the Sentinel-2-derived KFC layer (10 m) and SuperDove (3.7 m) generates irreducible
 455 geometric discordances at the sub-pixel scale; residual tidal offsets within retained image pairs alter exposed canopy area between acquisitions (Huovinen et al., 2020; Servicio Hidrográfico y Oceanográfico de la Armada de Chile, n.d.; Medeiros and Kjerfve, 1988b); residual atmospheric effects — including undetected cloud edges, aerosol gradients, and cloud shadows — can locally suppress or distort the spectral signal in either sensor’s imagery (V’arnai et al., 2013; Christensen et al., 2017; Aybar et al., 2022); and the maximum ten-day temporal separation criterion does not preclude storm-driven detachment events
 460 altering true canopy extent between acquisitions (Ebeling et al., 1985; Dayton et al., 1992). These constraints collectively impose a ceiling on achievable Jaccard values that lies substantially below unity regardless of model performance.

With this framework established, the present results are broadly consistent with published benchmarks, where direct metric comparisons are constrained by differences in validation designs. Mora-Soto et al. (2020) reported Producer’s and User’s accuracies of 73.1% and 76.4%, respectively, figures broadly consistent with the OA and area-based R^2 obtained here, though
 465 their estimates were derived from spatially extensive UAV surveys aggregated over a four-year composite period rather than from temporally and tidally controlled individual scene pairs. Huovinen et al. (2020), the closest methodological analogue, reported overall SMA accuracies of 66–82% within a single fjord environment and noted a sharp decline in classification agreement at fractional cover values below 0.50 — a threshold sensitivity pattern consistent with what is observed here. The present study extends this line of work to the full spatial extent of the Strait of Magellan, where the diversity of sites, seasons,
 470 and acquisition geometries provides a broader empirical basis for evaluating model consistency than was possible in either prior framework.

The cross-site and cross-seasonal robustness documented above reflects, in part, the properties of the SZA correction that underpins the spectral unmixing framework — a correction whose validity rests critically on the representativeness of the deep-water reference zones from which it was empirically derived. Reference zones for SZA-based reflectance correction were
 475 selected from deep-water areas within the main channel of the Strait of Magallanes, where bottom reflectance contributions to the water-leaving radiance signal are negligible and, unlike coastal zones, kelp forest coverage is absent — a relevant distinction given the strong spectral signature of macroalgae in surface reflectance. The optical environment of the strait is, however, inherently heterogeneous. In this area, predominate marked gradient in turbidity from glacial and terrigenous inputs (Palacios et al., 2021; Gómez et al., 2025) and pronounced variations in phytoplankton, non-pigmented particles, and chromophoric
 480 dissolved organic matter, each prevailing in distinct sectors, while episodic phytoplankton blooms, and variable wind-driven mixing further modulate surface optical properties across the spatial and temporal scales (Hamam’e and Antezana, 1999; Lutz et al., 2016; Soto et al., 2024) These characteristics constitute factors that must be considered when interpreting correction outputs, rather than sources of systematic error *per se*. Critically, confining the reference zones to the strait itself ensures that the atmospheric column above the reference pixels — including aerosol optical depth, water vapor, and ozone concentration —
 485 remains spatially consistent with the imagery being corrected (Wang et al., 2021; Ruddick et al., 2000), a condition that could not hold if open-ocean reference areas were used in a region of high subantarctic atmospheric variability (Pereira et al., 2004;



dos Santos et al., 2020; Mansilla et al., 2023; Laguarda and Osorio, 2025). The local representativeness of these reference zones therefore constitutes a meaningful methodological advantage for reflectance correction, despite the optical complexity of the underlying waters. More broadly, the magnitude of the SZA-driven bias corrected here scales with solar zenith angle itself, implying that studies comparing kelp cover across latitudinal gradients that span regions of consistently high SZA ($>70^\circ$) are exposed to the same source of error, and should account for it explicitly rather than attribute uncorrected geometry-driven artefacts to genuine spatial differences in canopy extent.

A first fundamental limitation of the present study concerns the explanatory scope of the validation framework: the SuperDove-based validation operates exclusively in the binary domain, confirming the model's capacity to detect kelp presence and estimate canopy extent, but providing no basis for evaluating whether continuous KFC values are quantitatively meaningful as measures of within-pixel canopy density in an ecological sense. In spectral mixture analysis, fractional abundance corresponds to actual surface cover only under the assumption that endmember spectra are radiometrically representative and that mixing is strictly linear at the pixel scale (Boardman, 1993; Keshava and Mustard, 2002); for floating kelp canopies, the three-dimensional canopy structure, vertical light attenuation, and variable sub-surface frond contributions further decouple spectral fraction from areal cover in ways a binary validation cannot detect (Huovinen et al., 2020). Establishing whether KFC values carry quantitative biophysical meaning would require *in situ* measurements across a gradient of canopy densities with complementary field spectroscopy, neither of which currently exists for the subantarctic Patagonian system at the required spatial scale. In the absence of such calibration, the KFC product is most appropriately interpreted as a spatially and temporally consistent index of canopy presence and relative abundance, suitable for detecting spatial gradients, seasonal dynamics, and interannual trends, rather than as a calibrated biophysical variable directly convertible to canopy density or biomass.

A second, distinct limitation concerns the seasonal representativeness of the endmember extraction dataset. With pure kelp pixels available from only one of ten sampling areas during winter, the endmember matrix disproportionately represents spring, summer, and autumn canopy conditions — an imbalance imposed by persistent cloud cover and reduced kelp density in winter imagery (Hoskins and Valdes, 1990b; Garreaud et al., 2009; Huovinen et al., 2020). If kelp spectral properties vary seasonally due to changes in pigmentation, biomass density, epiphyte load, or senescence state, the current endmembers may inadequately represent winter canopy reflectance, potentially introducing season-dependent biases in fractional cover estimates. Resolving whether model performance is stable across seasons would similarly require dedicated winter reference imagery with complementary field spectroscopy. Together, these two limitations define the conditions under which the KFC product should currently be used and the data acquisitions that would most directly extend its utility, while also framing the interpretive context for the temporal patterns detectable within the existing record.

A persistent limitation shared across current macroalgae remote sensing frameworks — including the present one — is the inability to differentiate between seaweed species at the pixel level using broad-band multispectral imagery. While distinct spectral signatures have been documented for the major photosynthetic pigment groups, the ubiquitous presence of chlorophyll-*a* across all macroalgal taxa generates overlapping absorption features in the red (≈ 680 nm) and blue (≈ 450 nm) spectral regions that multispectral sensors such as Sentinel-2 cannot resolve at the inter-species level (Stekoll et al., 2006; Huovinen et al., 2020; Douay et al., 2022). Taxonomic discrimination relies instead on accessory pigments whose absorption features are



group-specific. For instance, fucoxanthin and chlorophyll-c are characteristic of Ochrophyta (brown algae, including kelps), phycoerythrin and phycocyanin are exclusive to Rhodophyta (red algae), and green algae (Chlorophyta) are distinguished by chlorophyll-b and neoxanthin (Douay et al., 2022). These pigment-level differences produce phylum-scale spectral contrasts that, under controlled conditions and using narrow-band sensors, are detectable. In practice, however, these distinctions are mostly unresolvable using broad-band satellite data only. Multispectral resampling analyses confirm that the narrow absorption features diagnostic of accessory pigments are lost when spectra are convolved to the bandwidth configurations of Sentinel-2 MSI or Landsat OLI, whose spectral windows — typically 20–60 nm wide — collapse the inter-pigment contrast necessary for sub-phylum classification (Bannari et al., 2022). In addition, seasonal variation in pigment concentration driven by changes in photosynthetic activity, epiphyte load, and light history can exceed inter-specific spectral differences, reducing the temporal reproducibility of any classification approach and introducing an additional confounding source of variability if not enough data is available (Selvaraj et al., 2021a, b).

Within this broader constraint, certain within-habitat reflectance contrasts remain exploitable for coarser taxonomic stratification. Huovinen et al. (2020) reported disproportionately elevated reflectance in intertidal macroalgae relative to floating kelp, a pattern attributable to the emerged condition of intertidal fronds, reduced water-column attenuation, and structural differences in canopy architecture that collectively shift the effective spectral footprint relative to submerged canopies. This intertidal–subtidal reflectance asymmetry offers a basis for separating emerged assemblages from floating canopies and could, in principle, be exploited to distinguish communities dominated by different macroalgal functional types if complemented by targeted habitat stratification. In the Strait of Magellan, where *M. pyrifera* constitutes the dominant floating canopy and intertidal zones support distinct assemblages of furoids and crustose red algae, such stratification represents a tractable near-term extension of the present framework (Olmedo-Masat et al., 2020). Full taxonomic resolution at the species level would ultimately require airborne or satellite hyperspectral data — from forthcoming missions such as NASA’s Surface Biology and Geology (SBG), Portable Remote Imaging Spectrometer (PRISM) or ESA’s Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) — combined with region-specific spectral libraries for both floating and submerged matters (Hu, 2022; Vahtmäe et al., 2025). A prime example of this requirement is the approach by Olmedo-Masat et al. (2020), who developed a localized spectral library specifically for classifying the macroalgal assemblages present in Patagonian waters.

The residual seasonal signal detected in coastal fractional cover estimates — most conservatively interpreted as reflecting genuine kelp phenological variability consistent with summer biomass peaks reported for southern populations (Van Tussenbroek, 1989; Huovinen et al., 2020) — illustrates both the ecological potential and the current interpretive limits of the framework. The satellite record can detect temporally structured canopy dynamics at regional scale, and discrimination of recurrent phenological cycles from interannual variability or hydrodynamic disturbance will constitute a critical next step in leveraging the full potential of this approach. A more rigorous assessment of the temporal signal would further require an explicit analysis of its spatial drivers, as the pooled analysis aggregates coastal sectors that may differ substantially in their local phenological regimes — differences in fetch, freshwater influence, tidal exposure, or propagule supply that could generate spatially heterogeneous seasonal trajectories obscured by regional averaging. Integrating fractional cover estimates with in situ observations of canopy density and seasonal condition would improve interpretation of the temporal variability detected, particularly



regarding canopy turnover and phenological processes (Dayton, 1985; Van Tussenbroek, 1989; Steneck and Johnson, 2013; Wernberg et al., 2019; Gómez et al., 2025). Incorporating environmental covariates — such as tidal height, water turbidity, wave exposure, freshwater input, and herbivory pressure — may further explain part of the spatial and temporal heterogeneity observed across coastal sectors of the Strait of Magellan (Dayton, 1985; Gómez et al., 2025), and provide a useful framework for evaluating local canopy removal and regeneration dynamics (Ebeling et al., 1985; Dayton et al., 1992).

The public release of the decadal KFC and binary kelp extent dataset extends the utility of this study beyond methodological validation, offering a ready-to-use monitoring resource for a region where sustained field-based observation remains logistically prohibitive (Mora-Soto et al., 2020, 2021). Unlike previous efforts that produced either presence-only maps over multi-year composites (Mora-Soto et al., 2020) or fractional cover restricted to single seasons or localized fjords (Friedlander et al., 2018; Huovinen et al., 2020), the annual cadence and sub-pixel resolution of this product make it directly comparable to long-term Landsat- and UAV-based kelp canopy time series developed for other regions, such as California's decades-long giant kelp record (Bell et al., 2020; Cavanaugh et al., 2021), and thus enable analogous interannual and phenological analyses for Patagonian *Macrocystis pyrifera* forests. The inclusion of a per-pixel RMSE band alongside the fractional cover layers allows downstream users to flag or filter pixels affected by land-cover types not explicitly modeled by the three-endmember unmixing scheme (Keshava and Mustard, 2002; Bioucas-Dias et al., 2012), an important safeguard given the compositional and spectral complexity of nearshore Patagonian environments (Lutz et al., 2016). Because the binary layer was calibrated against an optimal Jaccard-based threshold (Krasnodębska et al., 2025), it is best suited to extent- and area-based queries, whereas the fractional layer retains the sub-pixel abundance information necessary to detect gradual canopy thinning or expansion, including responses to regional glacier retreat and freshwater input (Dussaillant et al., 2019; Meier et al., 2018) or to marine cold-spell events shown to affect Patagonian kelp forests (Mora-Soto et al., 2022). Future work coupling this dataset with in situ bio-optical and density measurements (Palacios et al., 2021; Gómez et al., 2025) would further strengthen the ecological interpretability of the fractional cover signal across this extensive and comparatively undisturbed kelp forest system.

Together, these methodological and observational advances would strengthen the utility of the monitoring framework for long-term observation of one of the least disturbed kelp forest systems currently documented worldwide (Mora-Soto et al., 2021), at a time when kelp forests globally are experiencing widespread distributional and structural change (Wernberg et al., 2019) and subantarctic Patagonia is undergoing accelerating climatic shifts, including continued glacial retreat (Meier et al., 2018; Dussaillant et al., 2019; Palacios et al., 2021).

5 Conclusions

High-latitude kelp remote sensing has operated under an unexamined assumption: that standard atmospheric correction adequately normalizes the spectral data from which endmembers are extracted and fractional cover is estimated. This study shows that this assumption does not hold. At the latitudes of the Strait of Magellan, solar zenith angles routinely reach values at which the plane-parallel atmospheric model underlying Sentinel-2 Level-1C processing introduces wavelength-dependent radiometric errors of sufficient magnitude to produce systematic, seasonally structured artifacts in fractional cover estimates —



artifacts that would otherwise be interpreted, or misinterpreted, as real temporal variability in canopy extent. Correcting for this geometry prior to endmember extraction is therefore not an optional refinement: it is a prerequisite for producing temporally consistent kelp cover products in this and analogous high-latitude systems.

These findings have implications beyond the Strait of Magellan. Studies comparing kelp forest distribution and dynamics across latitudinal and temporal gradients should explicitly account for solar zenith angle, particularly when SZA exceeds approximately 70°, where radiometric distortions become sufficiently large to bias fractional cover estimates. Failing to account for these effects risks attributing differences driven by acquisition geometry to ecological variation, potentially confounding comparisons among regions or seasons.

In addition to these methodological implications, this study delivers a practical monitoring product: a continuous, per-pixel Kelp Fractional Cover time series across the full spatial extent of the Strait of Magellan, derived from a decade-long Sentinel-2 archive and validated against independent very high-resolution imagery under controlled tidal and temporal pairing conditions. Validation across 60 image pairs yielded a peak Mean Jaccard Index of 0.50, an area-based R^2 of 0.69, and a polygon-based Overall Accuracy of 0.94, with optimal binarization within a threshold range of 0.27–0.35 — collectively confirming that the framework reliably detects kelp presence and estimates canopy extent at regional scale. The KFC product constitutes a spatially consistent index of canopy dynamics suitable for monitoring, not a calibrated biophysical variable, and should be used accordingly until in situ spectral data across a canopy density gradient become available for quantitative calibration.

The monitoring capacity this framework provides is directly relevant to a system for which no continuous, spatially explicit record of canopy dynamics has previously existed. The Strait of Magellan hosts the largest known stands of *Macrocystis pyrifera* on Earth, under conditions that have until recently remained largely pristine (Mora-Soto et al., 2021), yet the phenological dynamics of these forests at regional scale remain less studied. The archive-based, regionally continuous nature of the KFC product positions it as a practical foundation for that characterization — one that, combined with complementary field observations of canopy condition and the integration of environmental covariates such as tidal height and water turbidity, could enable the discrimination of recurrent seasonal dynamics from interannual variability and hydrodynamic disturbance across the full extent of this ecologically and biogeochemically significant system.



APPENDIX: Additional figures

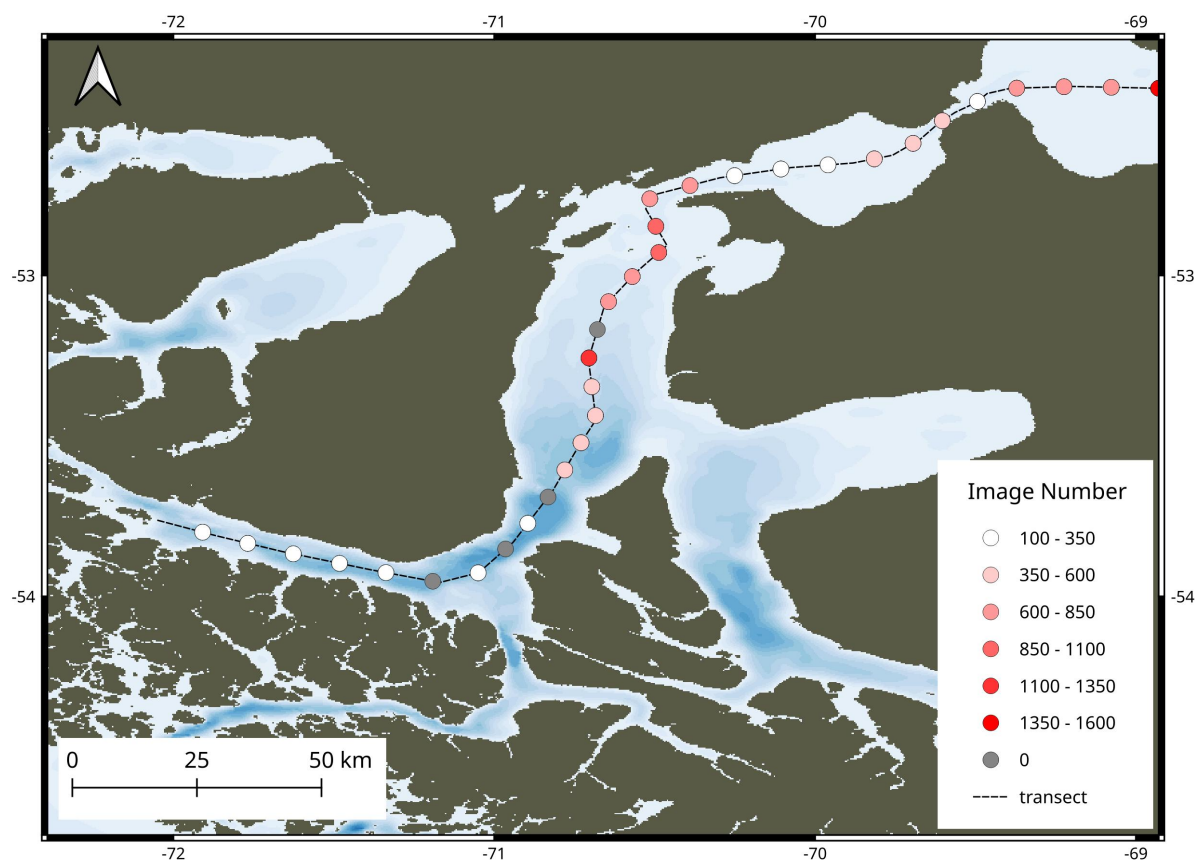


Figure A1. Location of the 37 circular correction zones (1 km radius) distributed at 10 km intervals along a transect between the Atlantic and Pacific entrances of the Strait of Magellan. The color gradient represent the number of Sentinel-2 images after filter, using the Sentinel-2 Cloud Probability product with a cloud probability threshold of 25% and a maximum cloud pixel proportion of less than 1%. The median of each image was used to fit the per-band quadratic SZA correction models. Zone boundaries are not shown to scale.

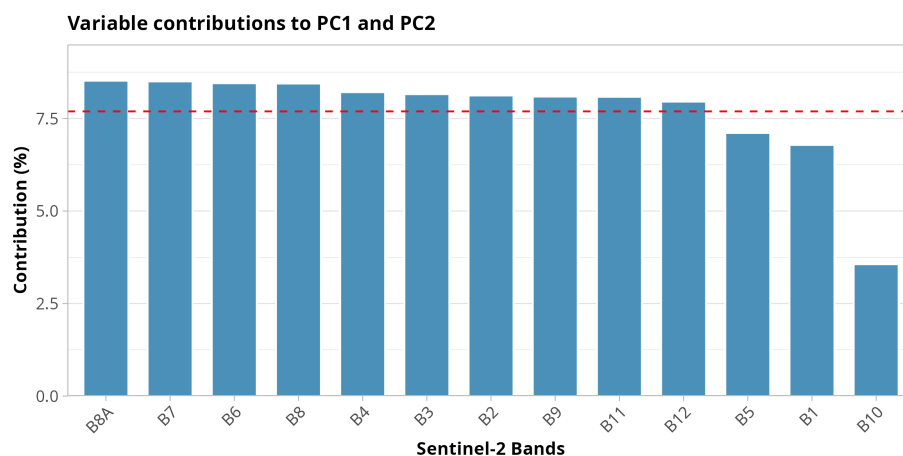


Figure A2. Contribution of Sentinel-2 spectral bands to the first two principal components (PC1 and PC2) derived from the principal component analysis (PCA) of pure pixel values extracted from SZA-corrected imagery. Bar heights represent the percentage contribution of each spectral band to the explained variance of the first two PCA dimensions. The red dashed line indicates the expected average contribution threshold under equal variable contribution. Bands exceeding this threshold contributed more strongly to the spectral discrimination among the analyzed components.

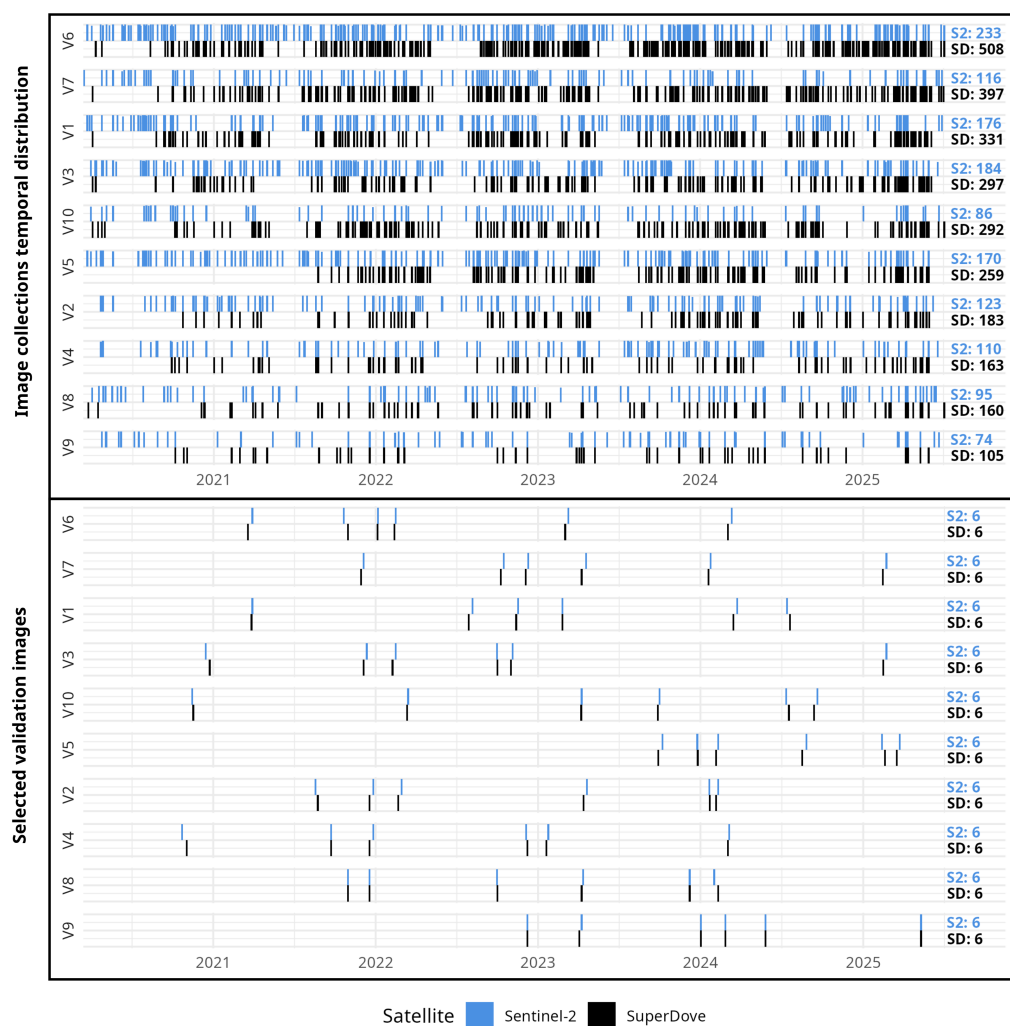


Figure A3. Temporal distribution of Sentinel-2 (blue) and SuperDove (black) imagery across the overlapping acquisition period for the ten validation zones (V1–V10). The top panel shows the complete image collections available for each validation zone, with the total number of Sentinel-2 (S2) and SuperDove (SD) images indicated on the right side of each panel. Validation zones are ordered from top to bottom according to the number of available SuperDove images. The bottom panel shows the subset of Sentinel-2 and SuperDove image pairs selected for the validation analysis. The selection criteria for the validation pairs are described in the main text.

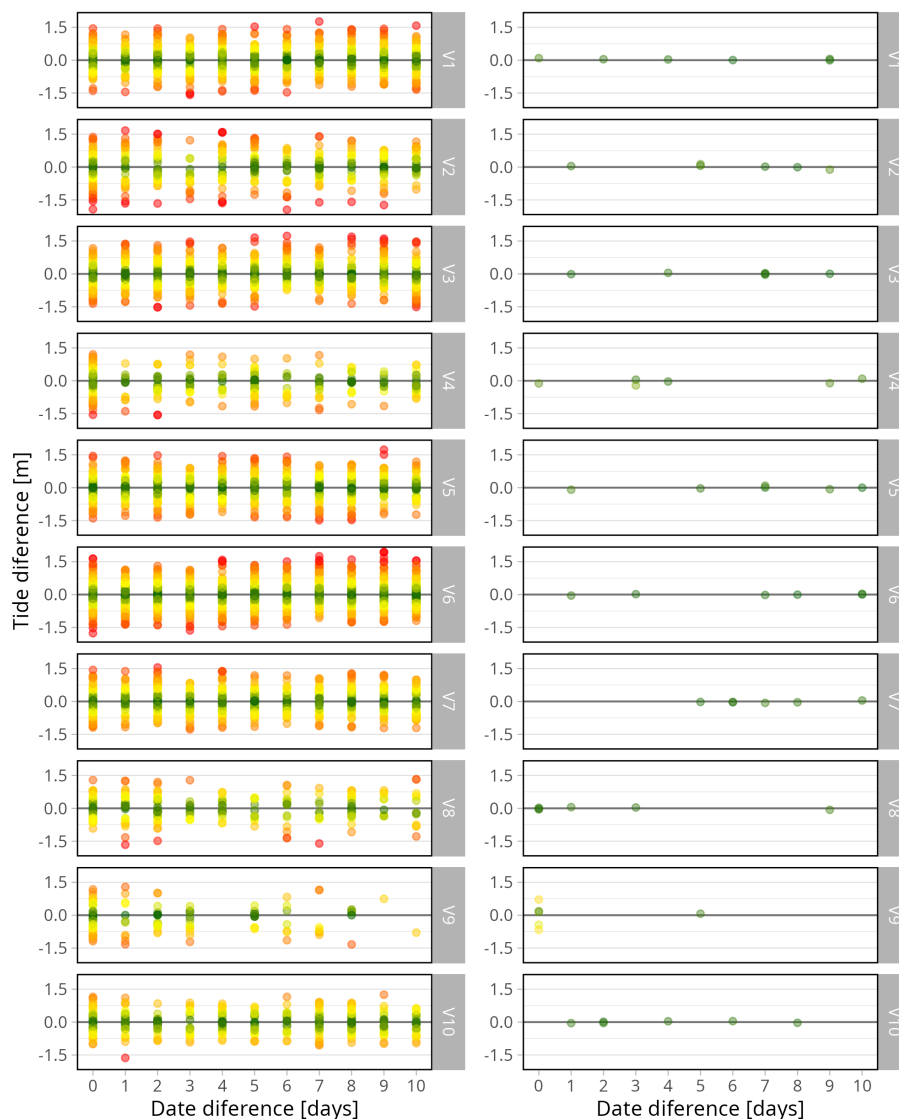


Figure A4. Temporal differences (days) and tidal differences (m), estimated using the EOT20 tidal model, between Sentinel-2 and SuperDove image pairs used for validation analyses across the ten validation areas (V1–V10). The left panels show all Sentinel-2 and SuperDove image combinations acquired within a maximum temporal separation of 10 days, while the right panels show the subset of image pairs selected for the validation analysis. Point colors represent tidal differences between acquisition times. The selection criteria for the validation pairs are described in the main text.



615 APPENDIX: Additional tables

Table A1. Percentile values used to the stretching step in the SZA correction for Sentinel-2 TOA imagery

Band	1st percentile	99th percentile
B1	0.1070	0.2760
B2	0.0746	0.2250
B3	0.0455	0.1760
B4	0.0242	0.1610
B5	0.0204	0.1610
B6	0.0179	0.2140
B7	0.0160	0.2380
B8	0.0127	0.2370
B8A	0.0114	0.2580
B9	0.0052	0.1070
B10	0.0005	0.0110
B11	0.0015	0.1430
B12	0.0001	0.0921



Table A2. Summary of Sentinel-2 image availability, selected images, and pure kelp pixels extracted for each sampling area.

Area	Coordinates	Total images	Cloud-free images	Selected images	Summer images	Autumn images	Winter images	Spring images	Pure kelp pixels	Contribution (%)
S1	-69.851, -53.664	1125	341	24	10	2	0	12	2206	4.3
S2	-70.443, -53.108	1197	355	18	2	7	3	6	7085	13.9
S3	-70.666, -53.684	1114	226	22	9	7	0	6	3624	7.1
S4	-71.796, -53.761	1100	148	19	12	4	0	3	9894	19.4
S5	-71.928, -53.718	1102	131	13	8	4	0	1	4141	8.1
S6	-70.962, -53.368	589	153	12	8	2	0	2	7950	15.6
S7	-70.936, -53.551	1123	298	23	11	8	0	4	11067	21.7
S8	-70.735, -52.912	608	179	9	2	6	0	1	2185	4.3
S9	-71.795, -53.470	1147	130	7	5	0	0	2	1121	2.2
S10	-70.434, -52.785	1136	343	14	6	3	0	5	1729	3.4
Total		10241	2304	161	73	43	3	42	51002	100



Table A3. Relative spectral reflectance proportions of the Sentinel-2 endmembers derived from non-corrected and SZA-corrected imagery.

Sentinel-2 Band	From non-corrected images			From corrected images		
	Land	Kelp	Water	Land	Kelp	Water
B2	0.000	0.063	0.361	0.008	0.120	0.377
B3	0.021	0.043	0.220	0.030	0.080	0.220
B4	0.048	0.017	0.119	0.044	0.042	0.121
B5	0.062	0.071	0.094	0.058	0.148	0.081
B6	0.103	0.166	0.066	0.119	0.168	0.055
B7	0.123	0.192	0.052	0.140	0.162	0.046
B8	0.130	0.191	0.035	0.137	0.136	0.035
B8A	0.159	0.193	0.027	0.177	0.125	0.029
B9	0.069	0.050	0.019	0.098	0.018	0.019
B11	0.180	0.015	0.000	0.123	0.000	0.010
B12	0.106	0.000	0.005	0.066	0.000	0.007

Data availability

The annual (1 July–30 June) Kelp Fractional Cover dataset generated in this study, comprising per-pixel kelp, water, and land fractional cover with an associated RMSE band, and a derived binary kelp forest extent layer (thresholds: kelp fraction > 0.35, land fraction < 0.10, elevation < 5 m), at 10 m spatial resolution for the Strait of Magellan and surrounding areas (2015–2025), is publicly available as GeoTIFF files at <https://doi.org/10.5281/zenodo.2187772> (Iribarren et al., 2026).

Author contributions.

Joseba Iribarren: Conceptualization, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualization. **Gerardo E. Soto:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data Curation, Writing - Review & Editing, Visualization, Supervision, Project administration. **Pirjo Huovinen:** Conceptualization, Methodology, Investigation, Writing - Review & Editing, Supervision, Funding acquisition. **Ivan Gómez:** Conceptualization, Investigation, Writing - Review & Editing, Supervision, Funding acquisition

Competing interests.

The authors declare no conflicts of interests.



630 *Acknowledgements.* This project was supported by the ANID grant FONDECYT numbers 1241571 and 1242028, and FONDAP IDEAL number 15150003.

Portions of the manuscript text were revised with the assistance of generative artificial intelligence tools to support language editing. The authors, for whom English is not a first language, used these tools to improve linguistic clarity. All outputs were critically reviewed and edited, and the authors take full responsibility for the final content.



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