

Data-Driven Adjacency Correction from High-Contrast Satellite Imagery Using Deep Water as a Natural Reference Target

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Abstract

The adjacency effect introduces spatial biases in high-resolution satellite imagery through atmospheric scattering of radiance from adjacent surfaces, particularly near sharp albedo contrasts such as ice-ocean boundaries. This study presents a data-driven approach for estimating the atmospheric point spread function directly from spaceborne observations over marine environments in both polar regions. Using optically deep ocean water as a natural reference target with known spatial homogeneity, an iterative inversion procedure minimizes reflectance variance to retrieve double Gaussian kernel parameters characterizing multi-scale scattering processes. The correction is sensor-agnostic and requires no external ground measurements or climatological aerosol profiles. The methodology is validated across Sentinel-2 MSI and EnMAP imagery capturing ice-ocean interfaces in diverse conditions over multiple acquisition dates. Results demonstrate that the adjacency effect extends over characteristic length scales of 2–12 km, with a short-range aerosol component (2 km) and long-range molecular scattering contribution (12 km). Corrected deep water reflectance exhibits improved spatial homogeneity consistent with expected values for open ocean waters, with RMSE reductions of 28–82 % across both sensors. Oceanographic features affected by the adjacency effect become apparent after correction, while snow surfaces exhibit improved uniformity. These findings have implications for polar region monitoring and processing pipelines, as current atmospheric correction schemes may underestimate adjacency effects at moderate to large distances from high-contrast boundaries.

1. Introduction

Optical terrestrial and aquatic remote sensing relies on high-spatial-resolution satellite imagery to monitor dynamic surface processes (Pan et al., 2022). As spatial resolution improves, however, the assumption of a horizontally homogeneous atmosphere breaks down near sharp boundaries between surfaces with contrasting optical properties (Lion et al., 2025). This phenomenon, known as the adjacency effect (AE), arises from atmospheric scattering of photons originating in surrounding bright or dark terrain into the sensor's instantaneous field of view (Bulgarelli et al., 2017). The result is a spatial blending of surface signals that degrades image contrast, blurs feature edges, and introduces significant biases in retrieved geophysical parameters at high-contrast interfaces, e.g., coastlines and ice margins (Lion et al., 2025).

The physical manifestation of the adjacency effect is governed by the atmospheric point spread function (PSF), which describes how radiance from a surface element spreads laterally due to molecular and aerosol scattering (Wu et al., 2023). Radiative transfer simulations show that AE magnitude depends strongly on aerosol optical depth (AOD), visibility, solar zenith angle, and viewing geometry (Ma et al., 2019, Houborg and Ceschia, 2017, Feng et al., 2017). Under clear atmospheric conditions with low aerosol loading, single scattering dominates the PSF core. In dusty or highly turbid atmospheres over complex terrain, however, multiple scattering contributions become critical (Jiang et al., 2016). Advanced Monte Carlo approaches have quantified these 3D radiative effects, revealing that topographic complexity and surface heterogeneity further modulate the spatial extent of atmospheric cross-talk (Zhao et al., 2013, Wu et al., 2023). Accurately characterizing the PSF therefore requires accounting for both the scattering phase function and the specific atmospheric state at the time of observation.

AE correction has historically been integrated into atmospheric correction pipelines using look-up tables or analytical approximations derived from models such as 6S or MODTRAN (Liang et al., 2001, Liang et al., 2002). Convolution-based methods apply a pre-calculated PSF kernel to surface-leaving radiance estimates to isolate the adjacently scattered component (Sei, 2015). These empirical or model-driven kernels work well over flat terrain but often fail to capture the spatial variability of atmospheric scattering conditions across large swaths or dynamic ice-covered regions (Castagna and Vanhellemont, 2025). Recent advancements have introduced sensor-generic closed-form expressions and data-driven iterative procedures aimed at reducing computational overhead while maintaining physical fidelity (Guzzi et al., 2021, Wu et al., 2024). Relying solely on modeled PSFs, however, can introduce systematic errors when the actual atmospheric state deviates from climatology or standard aerosol profiles, potentially biasing both surface reflectance retrieval and downstream aerosol products (Lyapustin and Kaufman, 2001).

Estimating an accurate AE kernel is especially critical in polar and high-latitude marine environments, where large areas of deep ocean water adjoin highly reflective drift or fast ice sheets (Zhang et al., 2022). These extreme albedo contrasts generate substantial adjacency effects observed from space (Paulino and Silva, 2022). Conventional atmospheric processors designed for mid-latitude vegetated or bare-soil targets often misinterpret the intense cross-scattering between ice and water as surface reflectance, or fail to accurately retrieve bottom-of-atmosphere values near the shoreline (Pan et al., 2022).

To address this challenge, we propose a methodology for estimating the PSF directly from spaceborne observations of high-contrast ice-ocean tiles. Deriving the PSF from large-scale in-situ spectral measurements to constrain aerosol properties and

surface reflectance simultaneously is unfeasible in remote polar regions (Ma et al., 2006, Martins et al., 2017). To circumvent this need, we exploit the radiometric properties of optically deep water bodies (e.g., open ocean) as natural reference targets. In the visible to shortwave infrared spectrum, deep water exhibits extremely low surface-leaving reflectance that attenuates rapidly with depth (Pan et al., 2022). Over large homogeneous patches, the true surface reflectance is therefore spatially invariant. Any observed spatial heterogeneity in such regions we attribute primarily to the adjacency effect—specifically, atmospheric scattering of photons from nearby bright surfaces (such as ice or land) into the sensor’s field of view (Bulgarelli et al., 2017). The goal becomes isolating and removing this scattering-induced variability to recover a spatially homogeneous background signal. Our approach uses 20–60 m spatial-resolution spaceborne imagery from Sentinel-2 MSI and EnMAP over tiles containing high-contrast boundaries between drift/fast ice and deep ocean water. We employ an iterative inversion strategy constrained by the homogeneity of the deep water pixels, allowing for self-consistent estimation of the PSF directly from the satellite tile itself without requiring external ground measurements. We detail the mathematical framework for a per-band estimating the PSF from high-resolution imagery applicable to multi- and hyperspectral sensors, evaluate its performance over drift and fast ice boundaries, and demonstrate improvements in surface reflectance homogeneity over deep water targets. In this study, we aim to estimate the atmospheric PSF directly from spaceborne observations without external measurements, validate the correction across multiple sensors (Sentinel-2 and EnMAP), and demonstrate improved spatial homogeneity of deep water reflectance after correction.

2. Methodology

The theoretical foundation of our adjacency correction approach follows the atmospheric radiative transfer formulations established by (Richter, 1990). Specifically, we employ Eq. 10 from (Richter, 1990):

$$\rho_c = \rho + q(\rho - \bar{\rho}), \quad (1)$$

where ρ_c = local surface reflectance
 ρ = observed surface reflectance
 q = diffuse-to-direct transmittance ratio
 $\bar{\rho}$ = mean surrounding surface reflectance

This equation relates the observed surface reflectance ρ to the actual local surface reflectance ρ_c and the surrounding terrain contributions $\bar{\rho}$, modulated by atmospheric transmittance terms q . Within our spectral modeling, all wavelength-dependent effects are encapsulated within a scaling factor q (see e.g. Fig. 4). This parameter is derived from Radiative Transfer Model (RTM) simulations that account for AOD, water vapor, surface topography, and viewing and illumination geometry at the point and time of observation. The spatial component of the adjacency effect, described by the PSF, is thus treated independently of spectral signature and atmospheric properties.

We impose the following constraint on our correction: for spatially homogeneous ρ , the corrected reflectance must satisfy $\rho_c = \rho$. Adapting Eq. (1) gives:

$$\rho_c = \rho + q \sum_{i=1}^n c_i (\rho - K_i * \rho), \quad (2)$$

where K_i = averaging kernel
 i = kernel index
 $*$ = spatial convolution

Equation (2) satisfies this constraint automatically if all kernels are normalized such that $K_i * 1 = 1$.

For efficient PSF estimation from satellite imagery, we parameterize the averaging kernel for $\bar{\rho}$ using a Gaussian mixture model:

$$K_i(r) = A_i \exp\left(-\frac{r^2}{2\sigma_i^2}\right), \quad (3)$$

where r = spatial distance from the target pixel
 σ_i = characteristic length scale
 A_i = normalization constant

The Gaussian form provides an unbiased approximation to physically more complex kernel functions while satisfying the normalization constraint and allowing flexibility in the spatial extent of scattering effects. We focus on a double Gaussian kernel ($n = 2$), which introduces four free optimization parameters: two magnitude coefficients (c_1, c_2) controlling the weight of each scattering contribution, and two characteristic length scales (σ_1, σ_2) representing the spatial extent of photon scattering. The two Gaussian components correspond to distinct physical scattering mechanisms: the shorter-range component (smaller σ) captures aerosol scattering, while the longer-range component (larger σ) represents molecular (Rayleigh) scattering (Tanre et al., 1981, Vermote et al., 1997).

The inversion strategy uses high-contrast tiles captured by Sentinel-2 and EnMAP sensors, focusing on regions where deep open ocean water abuts high-albedo ice margins. The input data for each sensor was processed from Level-1C top-of-atmosphere radiance to Level-2A bottom-of-atmosphere reflectance using PACO (Python-based Atmospheric Correction) (de los Reyes et al., 2020) with its adjacency correction module disabled, providing pre-corrected surface reflectance as the starting point for our iterative inversion. While the ice margin itself is inherently heterogeneous, we assume that large areas of optically deep ocean exhibit negligible intrinsic spectral variance under uniform solar illumination. Any heterogeneity within a pixel cluster over deep water is therefore attributed entirely to atmospheric cross-talk from adjacent bright surfaces—i.e., the adjacency effect. Tiles (Table 3) were selected based on the presence of (i) clearly delineated ice-water boundaries, (ii) sufficient open ocean area (at least 10 km $\times$ 10 km) to establish a homogeneous reference, and (iii) no cloud cover.

Starting from an initial PSF (with initial parameters set to $\sigma_1 = 1$ km, $\sigma_2 = 6$ km, $c_1 = 0.05$, $c_2 = 0.1$ based on preliminary visual analysis of the uncorrected reflectance), we iteratively adjust the double Gaussian kernel parameters ($c_1, c_2, \sigma_1, \sigma_2$) to minimize the spatial variance of the corrected deep water reflectance using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (Broyden, 1970, Fletcher, 1970, Goldfarb, 1970, Shanno, 1970). At each iteration, the adjacency contribution is computed via Eq. (2) and subtracted from the observed reflectance; if residual variance remains, the kernel parameters are refined. Although local minima in parameter space are theoretically possible, the optimization consistently converges to physically meaningful PSF parameters across all test tiles. To measure

the variance in water reflectance, we compute the RMSE with respect to a homogeneous reference equal to the deep-ocean-water reflectance from the same tile. Convergence is achieved when the gradient of RMSE with respect to the kernel parameters vanishes.

The deep water reflectance is automatically obtained per-band as the 5th percentile over all water pixels. For tiles without large open waters (e.g. DT110541.03), we assume 2 % deep water reflectance (Pan et al., 2022).

3. Results

We apply our iterative inversion procedure (Eq. (2)) to a set of high-contrast Sentinel-2 MSI and EnMAP tiles containing ice-ocean boundaries. Minimizing the spatial variance of corrected deep water reflectance allows us to simultaneously estimate the double Gaussian PSF parameters and derive corrected surface reflectance for each tile. The tiles shown in Figs. 1 and 2 are the ones used for PSF parameter estimation.

Before correction, artificial brightening of deep water near the ice margin caused by the adjacency effect is visible in both the Sentinel-2 and EnMAP tiles (Figs. 1 and 2, left columns). After correction, the deep water exhibits spatially homogeneous reflectance across both sensors, with values near the ice converging to those observed far from any bright targets ($\sim 2\%$). Without adjacency correction, water reflectance at the ice interface is overestimated by approximately 8 % instead of the expected $\sim 2\%$, representing a fourfold overestimation (6 percentage points excess; visible in the colormaps and profile plots of Fig. 1 and 2). Water reflectance structures affected by the adjacency effect become apparent after correction (see, e.g., T52DDN in Fig. 1), and the line profiles (right columns) illustrate how the adjacency effect extends over long ranges and is substantially reduced by our approach (see orange line in Fig. 1). The Sentinel-2 detector striping artifact over water remains unchanged in all tiles, as it originates from the detector rather than atmospheric scattering. A similar trend is observed for snow surfaces: although spatial homogeneity is not imposed as a constraint (since snow cannot reasonably be assumed spatially homogeneous), the corrected snow reflectance exhibits improved uniformity. Prior to correction, an apparent decrease in snow reflectance toward deep water—the inverse of the water brightening effect—is visible and largely removed by our approach, yielding values consistent with expectations, though verification with in-situ data is not possible.

The double Gaussian model converges to a two-scale structure of atmospheric scattering across both sensors (Figs. 1, 2). For Sentinel-2, the shorter-range component is $\sigma_1 = 2.0$ km and the longer-range component is $\sigma_2 = 11.6$ km. The corresponding EnMAP-derived parameters show a similar double Gaussian structure but with smaller length scales ($\sigma_1 = 1.6$ km, $\sigma_2 = 7.9$ km), see Table 1:

Table 1. Gaussian kernel parameters from Sentinel-2 and EnMAP.

	Sentinel-2		EnMAP	
	c_i	σ_i [km]	c_i	σ_i [km]
$i = 1$	0.093	2.0	0.071	1.6
$i = 2$	0.097	11.6	0.077	7.9

Optimization of both datasets yielded consistently similar magnitude coefficients, with $c_1 \approx c_2$ across all tiles and sensors

(Table 1). This convergence allows us to simplify the correction (Eq. (2)) to

$$\rho_c = \rho + qc \sum_{i=1}^n (\rho - K_i * \rho), \quad (4)$$

where $c = (c_1 + c_2)/2$

Across all tiles, the value of c is 0.095 for Sentinel-2 and 0.074 for EnMAP. In this simplified formulation (4), all correction terms $\rho - K_i * \rho$, i.e. the difference between observed reflectance and its weighted surroundings, contribute equally to the correction. The parameter c effectively corrects inaccuracies in the factor q .

Table 2. RMSE over water with respect to spatially homogeneous reflectance in absolute pre- and post-correction reflectance, and relative decrease of RMSE.

ID	RMSE		Relative
	Pre [%]	Post [%]	Decrease [%]
T27CVU	2.27	1.33	41.5
T30DWH	4.03	1.36	66.2
T52DDN	2.84	1.00	64.6
T51DWH	3.08	1.84	40.3
T48DWM	2.22	1.27	42.7
T46DEN	1.39	0.86	37.9
T33XWL	10.22	1.82	82.2
T46DEM	2.63	0.90	65.6
T30DWJ	2.90	1.68	42.0
T50DPM	2.39	1.45	39.5
T28XEQ	1.60	1.01	36.9
T01WFR	1.75	1.14	34.6
DT101342.05	2.46	1.55	37.2
DT107949.04	2.25	0.93	58.4
DT110541.03*	4.72	1.63	65.4
DT110574.04	2.33	1.07	53.9
DT110574.05	1.51	1.08	28.2
DT168868.07	2.20	1.58	28.4

*Uses 2 % deep water reference reflectance

Table 2 summarizes the performance of our correction across all datasets, reporting both absolute RMSE values (relative to a spatially homogeneous reference reflectance over water) and relative improvement percentages. The weighted averaged RMSE across all tiles is the metric minimized during kernel parameter optimization.

For Sentinel-2, uncorrected tiles exhibit RMSE values in the range 1.4–4.0 %, which are reduced to 0.9–1.8 % following correction, corresponding to a relative improvement of 35–82 %. The EnMAP dataset shows a similar trend: uncorrected RMSE values (1.5–4.7 %) are generally reduced to 0.9–1.6 %, corresponding to relative improvements of 28–65 %.

Across both sensors, RMSE values decrease from 2–4 % (uncorrected) to $\sim 1.5\%$ (corrected). The magnitude of improvement scales with the proportion of water pixels affected by the AE within each tile: tiles dominated by open water exhibit smaller gains, as both the adjacency effect and its correction are inherently weaker in those cases.

Figure 3 compares corrected versus uncorrected water reflectance for Sentinel-2 (band 1) and EnMAP (band 9). In both panels, points lie predominantly below the 1:1 line, indicating

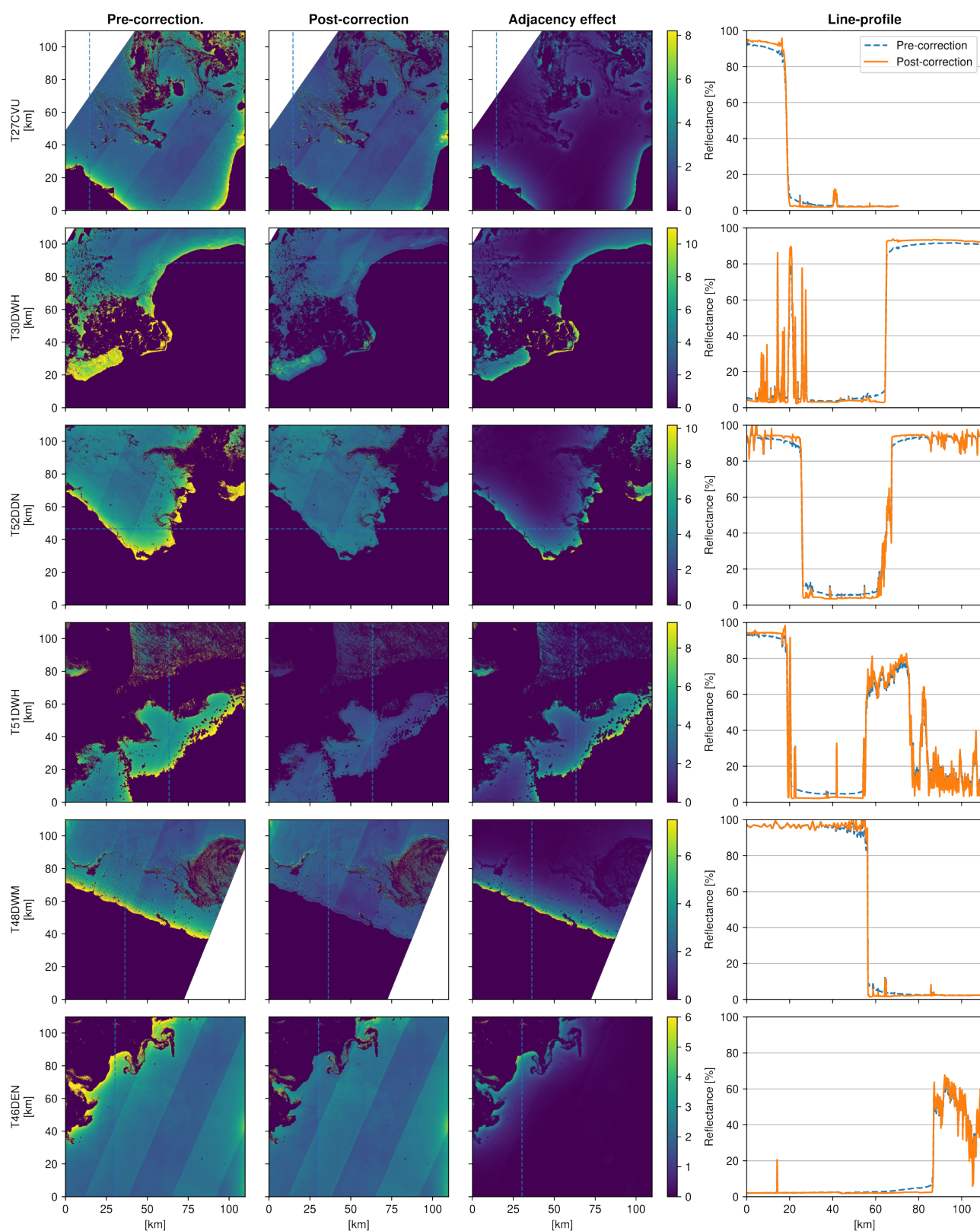


Figure 1. An illustrative selection of corrected Sentinel-2 tiles. From left to right: colormap of Band 1 around 442 nm pre- and post-correction, estimate of the adjacency effect (in reflectance), and line profile corresponding to the dashed line. The land reflectance is masked in the colormaps for illustration purposes.

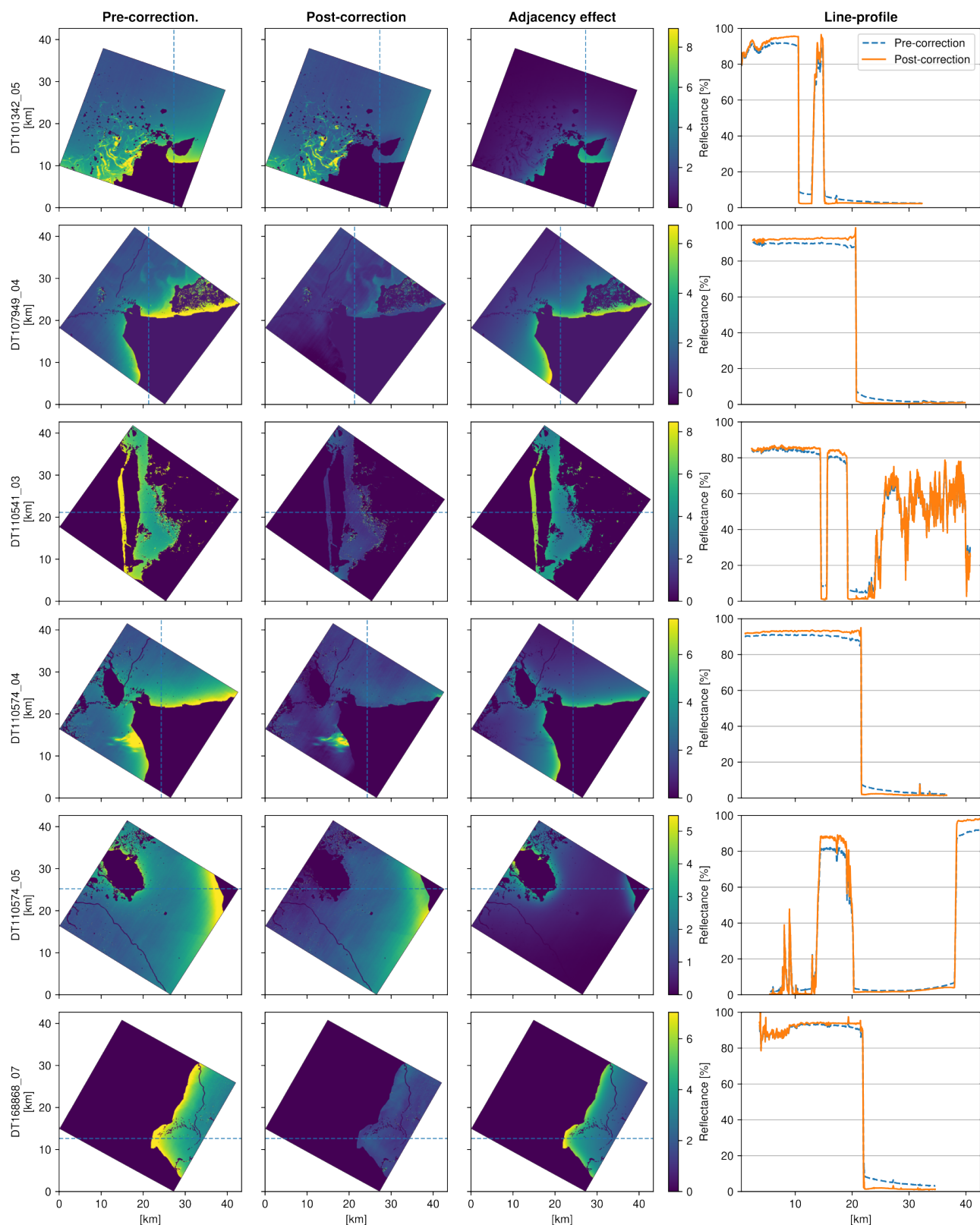


Figure 2. The same as Fig. 1, but for Band 9 (459 nm) of EnMAP.

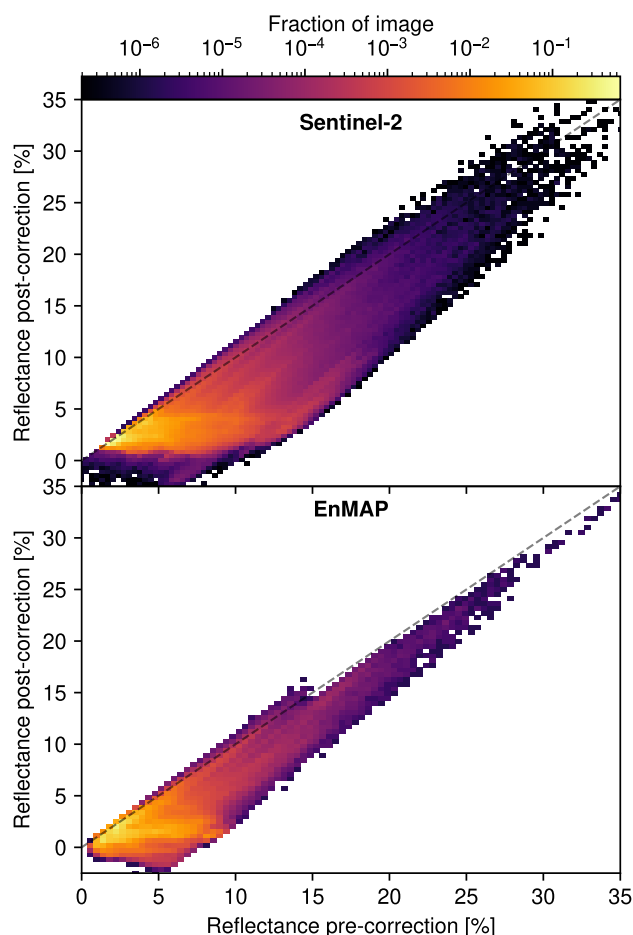


Figure 3. Heatmap of the corrected vs. uncorrected reflectance over water for the selection of Sentinel-2 and EnMAP tiles in Fig. 1 and Fig. 2, respectively.

that photons scattered from adjacent bright terrain inflate the observed signal and are removed by correction. The majority of water reflectances shift from 2–10 % to approximately 2–5 %, consistent with expected values for deep ocean water (Paulino and Silva, 2022). The two panels exhibit similar distributions despite differences in spatial resolution, spectral band selection, and acquisition conditions.

4. Discussion

The optimized PSF parameters reveal a two-scale structure of atmospheric scattering common to both sensors: a short-range component ($\sigma_1 \approx 2$ km) associated with aerosol scattering, and a longer-range component ($\sigma_2 \approx 10$ km) corresponding to molecular (Rayleigh) scattering (Tanre et al., 1981, Vermote et al., 1997). The consistency of this double Gaussian structure across both sensors supports the physical basis of our parameterization.

The effective range derived from Sentinel-2 data (~ 12 km) matches the findings by (Bulgarelli and Zibordi, 2018), but extends beyond the typical range assumed for the adjacency effect in atmospheric correction schemes (Richter, 1998, Castagna and Vanhellemont, 2025). Even the EnMAP-derived estimate, while shorter, remains substantially larger than conventional assumptions. This discrepancy indicates that current algorithms may contribute to underestimation of adjacency effects at mod-

erate to large distances from high-contrast boundaries, particularly in polar and high-latitude marine environments where such interfaces are frequently encountered.

Given the long length scales (kilometers) over which the adjacency effect extends, finite-sized remote sensing tiles will inherently suffer from incomplete correction at their edges (Castagna and Vanhellemont, 2025). For example, tile T46DEN (Fig. 1) exhibits brightening along its right edge due to AE contributions originating from terrain outside the sensor’s field of view; such out-of-frame sources cannot be corrected. Similarly, in DT110574_05 (Fig. 2), only a small fraction of the ice mass is captured within the tile boundary. The correction consequently underestimates the full adjacency effect that would arise if the entire (presumably much larger) ice body were visible.

The bidirectional reflectance distribution function (BRDF) of ice and water surfaces introduces angular dependencies in the observed radiance, but these effects average out over a large ensemble of tiles with diverse viewing geometries (Castagna and Vanhellemont, 2025). Natural variability in ocean optical properties—chlorophyll concentration gradients, colored dissolved organic matter (CDOM) distributions, and suspended sediment concentrations—can also introduce apparent spatial heterogeneity in deep water reflectance (Paulino and Silva, 2022). Sun glint, sky glint, and small-scale features such as thermal fronts and internal waves may contribute further to observed variability. These oceanographic effects typically manifest at length scales smaller than the characteristic 2–12 km scales of atmospheric scattering; their influence on observed reflectance is therefore averaged out by the PSF, which reduces their potential to bias the estimated PSF parameters.

A notable limitation in this study is the limited number of Sentinel-2 ($N = 12$) and EnMAP ($N = 6$) tiles used for PSF parameter estimation. EnMAP, being a tasking mission, is inherently constrained by its availability of suitable ice-water tiles captured under cloud-free conditions. A more automated selection of suitable ice-water tiles without clouds could be achieved using bathymetry maps to identify potential deep waters; however, automatically analyzing the distribution of ice—particularly small fragments as opposed to large ice extents—is beyond the scope of this study. Tiles composed predominantly of pure ice and open water also make direct estimation of AOD from imagery particularly challenging. Restricting the analysis to Cryosphere tiles does not cover the full range of atmospheric conditions found around the globe, particularly with regards to aerosol types (e.g., dust, biomass burning), which can significantly influence scattering properties and PSF characteristics. This constraint on tile availability limits the statistical robustness of the derived PSF parameters and highlights the need for future validation over diverse geographic regions and atmospheric regimes.

This study covers an extreme dynamic range (2 % water reflectance to near 100 % snow reflectance) and assumes a linear correction in reflectance (Richter, 1990). Verifying this assumption with tiles exhibiting smaller contrast differences would be valuable, but spatially homogeneous reference targets on the scale of tens of kilometers are difficult to find outside of deep waters. Coastlines are typically unsuitable for this purpose: shallow water and water depth gradients mimic the adjacency effect, making reliable separation between AE and water depth variations impossible. This limitation highlights the need for additional validation strategies that can assess linearity across a broader range of surface reflectance conditions.

5. Conclusions

This paper presents a data-driven methodology for estimating the atmospheric PSF and correcting the AE in high-resolution satellite imagery. The approach is sensor-agnostic and requires only high-contrast tiles containing regions that can be assumed spatially homogeneous, such as deep open ocean. By leveraging the known radiometric properties of these reference targets, our iterative inversion approach estimates PSF parameters directly from the observed tile without requiring external ground measurements or climatological data. We demonstrated this approach using a double Gaussian kernel parameterization; however, the methodology is general and does not mandate a specific functional form—any kernel parameterization that satisfies the normalization constraint can be employed, providing flexibility for adaptation to different atmospheric conditions or scattering regimes.

The simplified correction (Eq. (4)) introduces a magnitude coefficient c that effectively rescales the diffuse-to-direct transmittance ratio q derived from RTM simulations. Further studies should investigate whether q and c can be rigorously separated, i.e., whether the spectral and atmospheric components are truly captured by q , or whether c compensates for additional effects not accounted for in the RTM parameterization. Notably, the original correction formulation (Eq. (1)) may overestimate the adjacency effect via the diffuse-to-direct transmittance ratio; the observed $c < 1$ suggests that this overestimation is corrected by the magnitude coefficient.

Future work should assess the transferability of the estimated PSF parameters across diverse atmospheric conditions and lower-resolution sensors (e.g. Sentinel-3 SLSTR). The consistency of results across two sensors with different spatial resolutions supports the sensor-independent formulation of our approach. Our findings indicate that the adjacency effect at ice-water boundaries extends over 2–12 km from the contrast interface, farther than assumed in many correction schemes. These findings have implications for polar and high-latitude marine environment monitoring, where water reflectance near ice margins may be overestimated if the adjacency effect is not accounted for.

The proposed approach enables empirical adjacency effect characterization using only spaceborne observations, eliminating the requirement for field measurements and providing a pathway for incorporating physics-based corrections into processing frameworks for high-resolution satellite imagery.

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Appendix

Figure 4 illustrates the diffuse-to-direct transmittance ratio q derived from MODTRAN (Berk et al., 2014) radiative transfer simulations as a function of wavelength for varying AOD conditions. The ratio q increases monotonically with AOD due to enhanced atmospheric scattering across all spectral regions. Based on the atmospheric conditions observed across the tiles listed in Table 3, we infer a typical AOD of approximately 0.06 at 550 nm, consistent with clear polar marine atmospheric conditions. Outside the strong water vapor absorption bands, q exhibits negligible sensitivity to variations in the total water vapor column; the corresponding curves are therefore not shown in Fig. 4.

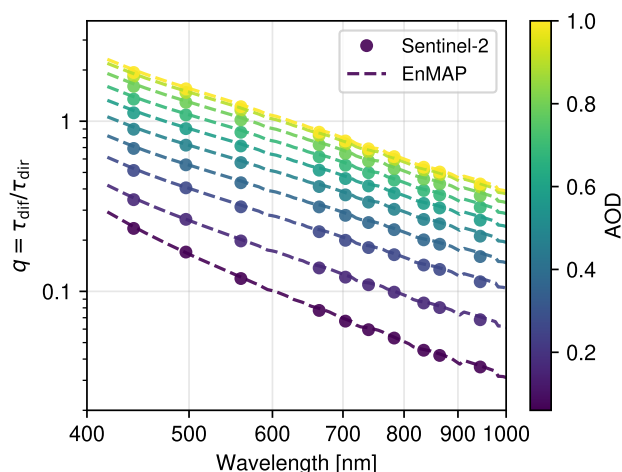


Figure 4. Illustrative diffuse-to-direct transmittance ratio q derived from MODTRAN (total water vapor column of 0.4 g/cm^2) for Sentinel-2 and EnMAP spectral bands as a function of wavelength for different AOD values.

Table 3. Tile identifiers for the Sentinel-2 and EnMAP scenes used in this study.

ID	Filename
T33XWL	S2A_MSIL1C_20160429T132722_N0500_R024_T33XWL
T46DEM	S2B_MSIL1C_20200113T025559_N0500_R003_T46DEM
T46DEN	S2B_MSIL1C_20200113T025559_N0500_R003_T46DEN
T30DWH	S2B_MSIL1C_20231128T085009_N0510_R078_T30DWH
T30DWJ	S2B_MSIL1C_20231128T085009_N0510_R078_T30DWJ
T27CVU	S2B_MSIL1C_20250106T094019_N0511_R007_T27CVU
T52DDN	S2B_MSIL1C_20251130T003459_N0511_R116_T52DDN
T51DWH	S2B_MSIL1C_20251216T005509_N0511_R059_T51DWH
T48DWM	S2B_MSIL1C_20260129T021549_N0511_R117_T48DWM
T50DPM	S2B_MSIL1C_20260210T011529_N0512_R002_T50DPM
T28XEQ	S2B_MSIL1C_20260627T170849_N0512_R112_T28XEQ
T01WFR	S2B_MSIL1C_20260705T231549_N0512_R087_T01WFR
DT110541_03	ENMAP01-___L1C-DT0000110541_20250113T214303Z_003_V010502
DT101342_05	ENMAP01-___L1C-DT0000101342_20241116T002633Z_005_V010501
DT107949_04	ENMAP01-___L1C-DT0000107949_20241225T102640Z_004_V010502
DT110574_04	ENMAP01-___L1C-DT0000110574_20250114T104402Z_004_V010502
DT110574_05	ENMAP01-___L1C-DT0000110574_20250114T104402Z_005_V010502
DT168868_07	ENMAP01-___L1C-DT0000168868_20251204T220757Z_007_V010505