

Beyond the SCL: threshold optimisation of Cloud Probability and Cloud Score+ for cloud and shadow masking in Sentinel-2 imagery using CloudSEN12

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This is an original manuscript of an article published by Taylor & Francis in International Journal of Remote Sensing on 26 Oct 2026, available at: <https://doi.org/10.1080/01431161.2026.2747320>.

Please cite the published version.

ABSTRACT

Cloud and cloud shadow contamination in Sentinel-2 imagery must be accurately masked prior to any quantitative analysis, yet no previous study has systematically determined optimal thresholds for Cloud Probability (CP) and Cloud Score+ (cs and cs_cdf) or compared their performance against the Scene Classification Layer (SCL) for both cloud-only and joint cloud-and-shadow masking on a global reference dataset.

This study evaluates CP, CS+, and SCL for binary cloud masking (BCM) and binary cloud-and-shadow masking (BCSM) using 3,980 high-quality CloudSEN12 patches.

Optimal masking thresholds (OMT) were derived on a training subset ($n = 3,184$) by maximising median IoU, and five metrics were assessed on an independent test set ($n = 796$): IoU, precision, recall, F1-Score, and BOA.

For BCM, the OMTs were 38.1 (CP), 0.356 (cs), and 0.523 (cs_cdf). On the test set, cs_cdf achieved the highest performance (F1-Score = 82.8%, IoU = 70.7%), while SCL recorded the lowest values (F1-Score = 62.7%, IoU = 45.7%), driven by a severe recall deficit (52.9%) despite near-perfect precision (99.4%).

For BCSM, the OMTs shifted substantially: 10.2 (CP), 0.538 (cs), and 0.76 (cs_cdf) — the latter notably higher than values reported in previous studies, underscoring the need for recalibration when CS+ is used as a standalone masking tool. cs_cdf achieved the highest overall performance (F1-Score = 90.1%, IoU = 82.0%). A critical divergence emerged: CS+ products consistently improved from BCM to BCSM, reflecting their implicit shadow detection, while CP degraded (F1-Score = 73.4%) due to its cloud-only design, and SCL recorded the lowest values in both scenarios (BCSM: F1-Score = 58.8%). All pairwise differences were statistically significant (Friedman–Nemenyi, $p < 0.001$).

These results establish cs_cdf as the most effective product for joint cloud-and-shadow masking in Sentinel-2 imagery and provide threshold-specific, empirically grounded guidance for operational masking workflows.

Keywords: Sentinel-2; Cloud-and-shadow masking; Threshold optimisation

1. Introduction

The launch of the Sentinel-2A satellite in June 2015 marked a milestone in optical monitoring of the Earth's surface within the Copernicus Programme of the European

Space Agency (ESA) (European Space Agency (ESA) 2025a). Since then, the mission has generated a vast body of scientific literature, with over 240,000 publications by May 2026, underscoring its transformative impact on the remote sensing community. The mission has proven to be highly versatile, enabling its application across a wide range of studies, including the monitoring of earthquakes and volcanoes, heatwaves and wildfires, flood events, air quality, soil and vegetation dynamics, inland water bodies, ocean analyses, and the observation of ice and glaciers (European Space Agency (ESA) 2025b). The mission currently consists of three identical satellites—Sentinel-2A, Sentinel-2B, and Sentinel-2C—the latter launched in September 2024, which consolidates the operational continuity and temporal stability of the mission. Its success is underpinned by a combination of technical characteristics that are difficult to match, including global coverage, a five-day revisit period, fully open access to its products, and the MSI sensor, which acquires 13 spectral bands at 10, 20, and 60 m spatial resolutions, including four red-edge bands highly sensitive to vegetation (Copernicus 2026).

This spectral capability has fostered the development of numerous spectral indices (Sentinel-Hub 2025), while its compatibility with Landsat 8 has enabled an increase in the temporal density of multitemporal time series (Claverie et al. 2018). Nevertheless, the Sentinel-2 mission presents several relevant limitations: it lacks a thermal band, its historical record is still shorter than that of the Landsat family (NASA 2025), and, like any optical observation system, its imagery is frequently affected by the presence of clouds and cloud shadows. These atmospheric contaminants alter the surface reflectance recorded by the sensor and generate spurious values; therefore, they must be accurately identified and masked prior to any quantitative analysis or further processing.

Sentinel-2 products are distributed at two processing levels: Level-1C (L1C), which provides Top-of-Atmosphere (TOA) reflectance, and Level-2A (L2A), which

offers Surface Reflectance (SR). Both include not only the 13 native spectral bands but also several auxiliary bands related to cloud detection. These include QA60 (a binary cloud and cirrus mask) and the MSK_CLASSI bands (OPAQUE, CIRRUS, and SNOW_ICE), all at 60 m. L2A products also include the MSK_CLDPRB band at 20 m, which expresses the probability of cloud presence, and the Scene Classification Layer (SCL) at 20 m, which classifies each pixel into twelve categories, including cloud shadows, cloud medium probability, cloud high probability, and thin cirrus (Copernicus 2026). This classification is produced by the Sen2Cor algorithm (Main-Knorn et al. 2017), widely adopted in operational atmospheric-correction workflows. Both L1C and L2A products can be obtained directly from the Google Earth Engine cloud-based geospatial analysis platform (Gorelick et al. 2017), where they are available for large-scale access and processing (Google Earth Engine 2025c).

In addition to these native products, the Google Earth Engine platform provides two derived cloud-detection products: Cloud Probability (CP) (Google Earth Engine 2025b) and Cloud Score+ (CS+) (Google Earth Engine 2025a). The first is derived from the s2cloudless algorithm (Zupanc 2017; Skakun et al. 2022; Batič 2024), which is based on machine-learning techniques and provides a continuous band representing per-pixel cloud probability, with values ranging from 0 to 100. CS+, by contrast, is a recent method developed by Google Earth (V. Pasquarella 2023) that outputs two normalised bands ranging from 0 to 1 (cs and cs_cdf). The cs band measures spectral similarity to an ideally cloud-free pixel, while cs_cdf expresses the relative probability of being cloud-free based on the local history of values. Because CP and CS+ use the same scene identifiers as L1C and L2A, their integration into analytical workflows is immediate and reproducible. For both products, the user must define a threshold to determine which pixels are clouded or cloud-free.

The ensemble formed by QA60, MSK_CLASSI, MSK_CLDPRB, SCL, CP, and CS+ constitutes the operational foundation for cloud masking in Sentinel-2. However, scientific literature shows that their performance varies widely. The QA60 band, for example, was historically the first official cloud-detection mechanism, but multiple studies have documented its limitations: an Overall Accuracy (OA) of 86.5% and an omission error of 37.4% (Coluzzi et al. 2018), as well as OA of 78.16% and omissions of 25.35% in other cases (Li et al. 2022). This underdetection is attributed mainly to the band's low spatial resolution and its difficulty accurately delineating cloud edges and cirrus.

Later methods such as Sen2Cor have shown greater ability to identify thick clouds, but their performance remains highly dependent on scene characteristics. In a carefully annotated dataset, Sen2Cor achieved an OA of 88.55%, though with an omission error of 44.35% (López-Puigdollers, Mateo-García, and Gómez-Chova 2021). In specific studies, its performance ranged from detecting only 50% of visually verified thick clouds (Ibrahim et al. 2021) to achieving an F1-Score of 0.89 in the Amazon (Sanchez et al. 2020). However, this apparent strength coexists with frequent omissions of thin clouds and shadows: a Producer's Accuracy (PA) of 74.5% and a User's Accuracy (UA) of 97.3%, indicating high reliability when clouds are detected but a tendency to miss them (Tarrío et al. 2020). Variation across studies is a consistent pattern: the algorithm may achieve an F1-Score of 93.2% in homogeneous scenes but drop to 72.1% in heterogeneous ones (Cilli et al. 2020), revealing strong dependence on atmospheric and surface conditions.

The probabilistic approach of s2cloudless is also not without challenges. An evaluation using a 0.5 threshold reported a Precision of 0.161, Recall of 0.705, and F1-Score of 0.267 — results that indicate high commission error and limited performance

(Ebel et al. 2021). However, other studies show notably better metrics, including UA of 86.6% and PA of 79.9% (Wright et al. 2025) or an OA of 93.51% with an omission error of 18.77% (López-Puigdollers, Mateo-García, and Gómez-Chova 2021). In the Amazon, using a 70% threshold, PA was 0.75, UA was 0.59, and F1-Score was 0.66 (Sanchez et al. 2020). This heterogeneity demonstrates that s2cloudless performance depends heavily on evaluation conditions and, crucially, on the threshold used to convert the continuous probability band into a binary mask. Relatively small changes in this threshold can substantially affect metrics.

CS+, in contrast, has shown more stable and often superior behaviour. s2cloudless achieved an F1-Score of 0.92141, while CS+ reached 0.92124 (cs threshold = 0.50) and increased to 0.93545 (cs threshold = 0.65) (Gong et al. 2024). The cs_cdf band showed lower but still competitive results, with values of 0.87330 (threshold 0.50) and 0.90079 (threshold 0.65). Other studies reported F1-Scores between 0.946 and 0.951 for cs using a 0.50 threshold (Rifai and Harintaka 2024). Recent assessments revealed that CS+ can reach up to 89.4% cloud-free pixels with an omission error of 0.63%, while s2cloudless achieves 80.8% and presents an omission error of 15.4%, even after evaluating three different thresholds (0.35, 0.40, and 0.45) (Rodríguez-Puerta et al. 2024).

Finally, broader comparisons across methods have highlighted the moderate performance of traditional products such as MSK_CLDPRB (F1-Score = 0.36), the substantial improvement provided by s2cloudless (F1-Score = 0.58), and the intermediate performance of Sen2Cor (F1-Score = 0.41), while CS+ showed higher values when evaluating joint detection of clouds and shadows (F1-Score = 0.62) (Liang et al. 2024).

Together, these results reinforce two robust patterns: (i) classical methods such as QA60 and MSK_CLDPRB often exhibit high omission errors; and (ii) modern

probabilistic methods such as s2cloudless and CS⁺ depend critically on the threshold selected, especially in tropical or heterogeneous environments.

Against this backdrop, several recent studies have adopted CloudSEN12 (Aybar et al. 2022) as the reference dataset for evaluating cloud and shadow-masking algorithms. This global, multitemporal, and carefully annotated dataset includes 49,400 patches with four main classes (*clear*, *thick cloud*, *thin cloud*, *cloud shadow*) and has become a de facto benchmarking standard. Recent works (Wright et al. 2024; Cho et al. 2025; Y. Huang and Dewitt 2025; H. Huang et al. 2025; Wright et al. 2025; Zhang et al. 2025) have used it as reference data to validate segmentation methods, demonstrating its increasing relevance to the community. However, although the dataset has been used to compare products or train models, none of these studies systematically determined the optimal thresholds for CP or CS⁺, nor evaluated their combined performance with native products such as SCL.

This methodological gap is significant. Both CP and CS⁺ offer valuable flexibility through threshold selection, but this flexibility also introduces operational uncertainty: different studies choose different thresholds—commonly within the 0.35–0.70 interval—producing heterogeneous results that hinder reproducibility. There is no consensus on which thresholds are optimal for each product or how they compare to native methods such as SCL when applied systematically to a global and heterogeneous dataset.

This uncertainty is further compounded by a particularly underexplored aspect: the use of CP and CS⁺ as standalone methods for the joint masking of clouds and cloud shadows. Most studies evaluating these products do so exclusively in the context of cloud masking, while their capacity to simultaneously identify shadows has received little systematic attention. In the few works addressing joint detection, CS⁺ typically appears as a preliminary mask within more complex methods — as in (Liang et al., 2024), where the `cs_cdf` band with the recommended threshold of 0.65 is used as a preprocessing step

within the TSMM method — without being evaluated as a final product in that context. CP, in turn, has not been assessed for joint masking in any of the reviewed studies. Furthermore, the cs band, which according to the official documentation is more sensitive to cloud edges and haze, has not been evaluated for this purpose either. This gap is relevant because CS+ was explicitly developed to evaluate pixel quality including both clouds and shadows, and because CP, as a continuous probability estimate, could in principle capture shadow-related spectral signatures — yet the potential of both products for joint detection remains largely unquantified.

Together, the general objective and specific objectives of this work are aimed at addressing a clearly identified gap in the literature: although CP and CS+ products offer flexibility for masking clouds and cloud shadows through threshold selection, previous studies have not determined the optimal values nor how they compare against native products such as SCL, either for cloud masking alone or for the joint masking of clouds and cloud shadows. This work contributes to filling that gap by (i) identifying optimal thresholds for CP and for the cs and cs_cdf bands of CS+ under both masking scenarios, and (ii) performing a comparative evaluation against SCL. Together, these contributions enable the establishment of reproducible operational recommendations for cloud and cloud shadow masking in Sentinel-2 imagery, grounded in systematic evidence from a global reference dataset.

2. Materials and methods

2.1 Software

Scripts were executed via Google Colaboratory (Colab; colab.google), a cloud-based Jupyter notebook environment, eliminating the need for local software installation. The CloudSEN12 dataset, Sentinel-2 imagery, CP, and CS+ products were accessed through

the Google Earth Engine (GEE) Python API directly from Colab. All data processing, threshold optimisation, and accuracy assessment were performed within Colab. Processed outputs were exported to Google Drive for subsequent analysis.

GEE (earthengine.google.com; Gorelick et al., 2017) is a cloud-based geospatial analysis platform that provides access to an extensive catalogue of satellite imagery and environmental datasets, enabling large-scale processing without local infrastructure requirements. GEE is widely applied in studies on climate change, deforestation, agriculture, water management, and environmental monitoring.

Figures displaying satellite patches were generated in QGIS 3.28.11 (Firenze). Additional figures were produced using Python 3.12.8 in the Spyder 6.0.3 IDE.

2.2 CloudSEN12 dataset

CloudSEN12 (CSen12) is a global-scale dataset developed for the semantic segmentation of clouds and cloud shadows in Sentinel-2 imagery (Aybar et al. 2022). The dataset comprises 49,400 patches and includes four semantic classes: *clear*, *thick cloud*, *thin cloud*, and *cloud shadow* (Table 1 and Figure 1). Its global coverage and wide geographic diversity make it particularly suitable for evaluating cloud masking products across heterogeneous atmospheric and surface conditions, as pursued in this study. CSen12 is freely available through GEE (<https://gee-community-catalog.org/projects/cloudsen12/>) or its official website (cloudsen12.github.io).

Table 1. Semantic classes defined in the CloudSEN12 dataset.

Code	Class	Description
0	Clear	Pixels without cloud and cloud shadow contamination.
1	Thick Cloud	Opaque clouds block all reflectance from the Earth's surface.
2	Thin Cloud	Semitransparent cloud that alters the surface spectral signal but still allows recognition of the background.
3	Cloud Shadow	Dark pixels are caused by thick or thin clouds.

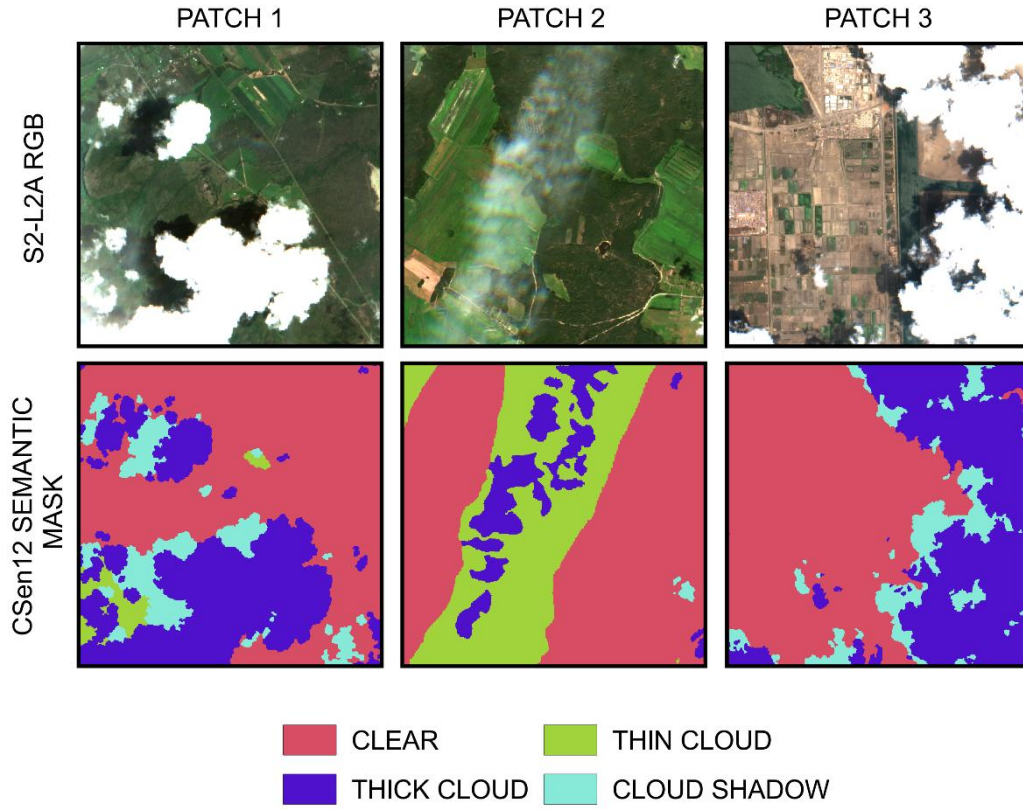


Figure 1. Examples of CSen12 patches with RGB images and semantic masks.

CSen12 encompasses diverse geographic regions spanning the 2018–2020 period. Each patch spans an area of $5,090 \times 5,090$ m and is structured into three annotation levels: *high-quality* (10,000 patches with complete pixel-level labels), *scribble* (10,000 patches with quick brush-stroke annotations), and *unannotated* (29,400 patches without manual labels). Annotations were produced by a team of 14 experts using interactive tools and active learning strategies. For each Region of Interest (ROI), five patches are included corresponding to different cloudiness levels: *cloud-free* (0%), *nearly clear* (0–25%), *low-cloud* (25–45%), *mid-cloud* (45–65%), and *fully cloudy* (>65%).

For this study, only *high-quality* patches were selected. Within this subset, only patches with *low-cloud* (25–45%) and *mid-cloud* (45–65%) cloudiness levels were retained, excluding *cloud-free* and *nearly clear* patches — which lack clouds — and *fully*

cloudy patches, where clear areas are minimal. Since each category comprises 2,000 patches, the selection yielded 3,980 patches in total (Figure 2). This selection ensures that all images contain both clear and cloud-covered areas simultaneously, which is essential for a robust evaluation of the analysed products. The selected patches were split into training (80%, $n = 3,184$) and test (20%, $n = 796$) subsets for threshold optimisation and accuracy assessment, respectively.

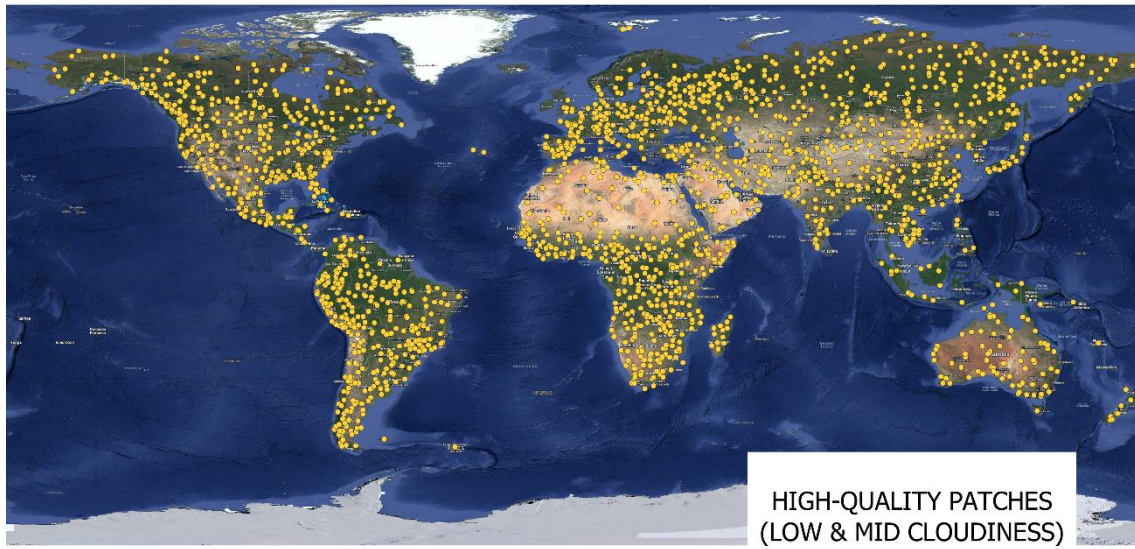


Figure 2. High-quality CSen12 patches with low and mid cloudiness.

2.3 Algorithmic background of evaluated products

This section provides a brief algorithmic description of the three Sentinel-2 products evaluated in this study. The SCL, generated by Sen2Cor, produces a discrete categorical output based on spectral thresholds and heuristic rules. CP, generated by s2cloudless, and CS+, developed by Google, both provide continuous per-pixel scores that quantify the likelihood of atmospheric occlusion, enabling flexible threshold-based masking. Understanding the underlying assumptions and methodological differences of each product is relevant to interpreting the threshold optimisation results presented in Section 3.

The Sen2Cor processor generates Sentinel-2 Level-2A products through two main modules: scene classification and atmospheric correction. The SCL is a 12-class map produced at 20 m resolution that includes two cloud confidence classes (medium and high probability), thin cirrus, and cloud shadows (Louis and L2A Team 2021). Cloud detection relies on a sequential threshold algorithm that applies per-pixel spectral filters — including brightness thresholds, NDSI, NDVI, and band ratios across the visible, NIR, and SWIR regions— multiplicatively updating cloud probability at each step. Cirrus clouds are detected using B10 (1.375 μm), sensitive to upper-tropospheric scattering. Cloud shadow detection combines a radiometric branch based on a neural network identifying low-reflectance areas with a geometric branch that projects the cloud mask along the solar direction using an empirical top-cloud height distribution.

The s2cloudless algorithm (Zupanc 2017) is a pixel-based, single-scene cloud detection method for Sentinel-2 imagery developed by Sinergise. It operates on top-of-atmosphere (TOA) reflectance values from ten Sentinel-2 bands (B01, B02, B04, B05, B08, B8A, B09, B10, B11, and B12) and employs a LightGBM gradient boosting classifier trained on approximately 14 million pixels labelled using MAJA-derived cloud masks from 596 globally distributed tiles (Zupanc 2017). For each pixel, the model produces a continuous cloud probability value between 0 and 1, which constitutes the CP product. A binary cloud mask can be derived by thresholding this probability map, with a default threshold of 0.4 recommended to minimise cloud omission errors, optionally followed by morphological operations (convolution and dilation) to smooth boundaries and reduce salt-and-pepper effects (Skakun et al. 2022).

CS+ is a per-pixel quality assessment algorithm for Sentinel-2 imagery developed by Google, based on a weakly supervised deep learning approach (V. J. Pasquarella et al. 2023). Rather than treating cloud detection as a discrete classification problem, CS+

models each pixel as a linear combination of its true surface reflectance and atmospheric corruption, producing a continuous quality score on $[0, 1]$. The model is trained through a bootstrapping procedure that leverages an atmospheric similarity metric (ASIM) to automatically mine over 2.2 million Sentinel-2 video sequences, requiring only 900 sparsely annotated image pairs for fine-tuning (V. J. Pasquarella et al. 2023). Two output bands are provided: `cs`, an instantaneous atmospheric similarity score, and `cs_cdf`, its cumulative distribution through time, which is less sensitive to low-magnitude spectral changes and terrain shadows (V. Pasquarella 2023). In both cases, values approaching 1 indicate clear conditions and values approaching 0 indicate atmospheric occlusion.

Table 2 summarises the main algorithmic characteristics of the three evaluated products.

Table 2. Algorithmic characteristics of the evaluated Sentinel-2 quality assessment products.

Attribute	SCL (Sen2Cor)	Cloud Probability (s2cloudless)	Cloud Score+
Developer	ESA / Telespazio	Sinergise	Google
Output type	Categorical (12 classes, including No Data)	Continuous $[0-1]$	Continuous $[0-1]$
Spatial resolution	20 m	10 m	10 m
Temporality	Mono-temporal	Mono-temporal	Multi-temporal
Methodology	Spectral thresholds + heuristics	Gradient boosting (LightGBM)	Weakly supervised deep learning
Training data	Rule-based (no training)	~14M MAJA-labelled pixels	~2.2M auto-mined video sequences
Input bands	Multiple (VIS, NIR, SWIR, cirrus)	B01, B02, B04, B05, B08, B8A, B09, B10, B11, B12	All Sentinel-2 bands
Cloud shadow detection	Yes (geometric + radiometric)	No	Yes (implicit)
Cirrus detection	Yes (B10)	Yes (B10)	Yes (implicit)
Threshold adjustable	No	Yes	Yes

Despite sharing Sentinel-2 L1C imagery as a common input, the three products differ substantially in their underlying methodology, output type, and scope. SCL is the

only categorical product, assigning each pixel to a discrete class without providing a continuous measure of atmospheric contamination, which precludes threshold-based optimisation. CP and CS+ both produce continuous per-pixel scores that enable flexible masking through threshold adjustment, which is the central focus of this study. A key distinction between them is temporality: while CP operates on a single acquisition, CS+ incorporates multi-temporal support imagery to estimate atmospheric similarity, making it inherently less dependent on spectral heuristics.

2.4 Generation of cloud and cloud-and-shadow masks from CSen12 and the SCL

Prior to mask generation, SCL, CP, cs, and cs_cdf were spatially aligned to the CSen12 patch grid by reprojecting each image to the CRS, nominal scale, and pixel alignment of the corresponding CSen12 patch. This ensures that all comparisons are performed on an identical pixel grid, eliminating misalignment artefacts introduced by differences in native projection or pixel origin between products.

For each CSen12 patch, two binary mask types were generated from both the CSen12 semantic mask and the SCL: a *binary cloud mask* (BCM) and a *binary cloud-and-shadow mask* (BCSM), enabling the separate evaluation of cloud and joint cloud-and-shadow masking performance.

Thin cloud pixels were excluded from the cloud class and treated as non-cloud in this study. Unlike thick clouds, which completely block surface reflectance and are unambiguously invalid for spectral analysis, thin clouds are semitransparent and allow partial observation of the underlying surface, albeit with a distorted spectral signal. This spectral ambiguity makes thin cloud pixels inherently difficult to classify consistently, as evidenced by the lowest inter-annotator agreement reported for this class during the CSen12 quality control phase (producer's accuracy of 78%; (Aybar et al. 2022)). Visual

inspection of a subset of CSen12 patches provided additional empirical support for this decision: labelled thin cloud areas frequently showed poor spatial agreement with visually identifiable thin cloud features. Furthermore, several widely used cloud detection algorithms, including s2cloudless — the basis of the Cloud Probability product evaluated in this study — do not provide a dedicated thin cloud category ((Aybar et al. 2022), Table 5), making its inclusion in the evaluation inconsistent with the operational outputs of the assessed products.

From the CSen12 semantic mask, binary cloud masks (CSen12-BCM) were generated by assigning a value of 1 to pixels labelled as *thick cloud* (code 1) and a value of 0 to all remaining classes (*clear*, *thin cloud*, and *cloud shadow*). Binary cloud-and-shadow masks (CSen12-BCSM) were generated by assigning a value of 1 to pixels labelled as either *thick cloud* (code 1) or *cloud shadow* (code 3), and a value of 0 to all remaining classes.

From the SCL of the corresponding S2-L2A image, binary cloud masks (SCL-BCM) were generated by assigning a value of 1 to pixels classified as *cloud medium probability* (class 8) or *cloud high probability* (class 9) — which correspond to the *thick cloud* class in the CSen12 semantic mapping (Aybar et al., 2022, Table 5) — and a value of 0 to all other classes, including *thin cirrus* (class 10) (Figure 3). Binary cloud-and-shadow masks (SCL-BCSM) were generated by additionally including *dark area pixels* (class 2) and *cloud shadows* (class 3), resulting in a value of 1 for classes 2, 3, 8, and 9, and a value of 0 for all remaining classes.

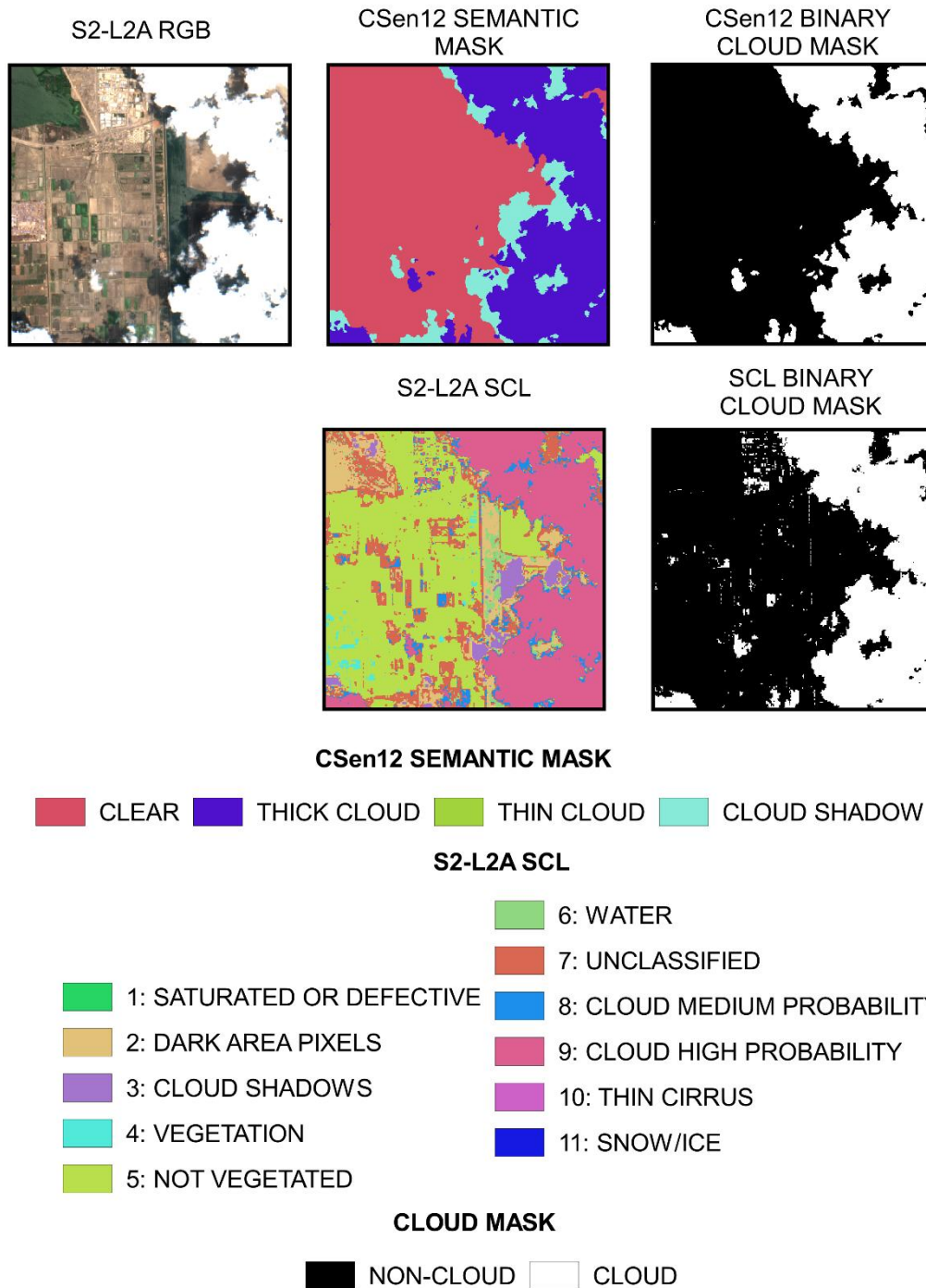


Figure 3. Conversion of the CSen12 semantic mask and SCL into binary cloud masks (CSen12-BCM and SCL-BCM).

2.5 Threshold optimisation for cloud and cloud-and-shadow masking using CP and

CS+

Threshold optimisation was performed for CP and CS+ (cs and cs_cdf) to determine the optimal masking threshold (OMT) for each product and masking type — cloud and cloud-and-shadow — yielding six product–mask type combinations to evaluate, as summarized in Table 3. SCL was excluded from threshold optimisation as it produces a categorical output that does not allow continuous threshold adjustment (Section 2.3).

This study extends the threshold optimisation framework introduced in a previous work (Cal 2026), where the Cloud Shadow Detection Index (CLOSDI) was developed and evaluated for cloud shadow masking in Sentinel-2 imagery using the CSen12 dataset.

Table 3. Product–mask type combinations evaluated in this study.

Product	Type	Acronym
CP	Binary cloud mask	CP-BCM
cs		CS-BCM
cs_cdf		CDF-BCM
CP	Binary cloud-and-shadow mask	CP-BCSM
cs		CS-BCSM
cs_cdf		CDF-BCSM

The CP product is natively expressed on a 0–100 scale. Since the cs and cs_cdf bands of CS+ are natively expressed on a 0–1 scale, their values were multiplied by 100 prior to all processing steps to match the CP scale, facilitating direct comparison between products and improving readability of results. For each product–mask type, threshold values were evaluated in increments of 1 (1 to 99). For each threshold evaluation, binary masks were generated for all training patches (3,184) across each product–mask type and compared against the corresponding CSen12 reference mask (CSen12-BCM / CSen12-BCSM).

For CP, a pixel is classified as cloud or cloud-and-shadow if its value is greater than or equal to the threshold. For cs and cs_cdf, the logic is reversed: a pixel is classified

as cloud or cloud-and-shadow if its value is less than or equal to the threshold, given that lower values indicate either reduced atmospheric similarity to a clear reference (cs) or a lower ranked quality relative to the historical distribution of scores for that pixel (cs_cdf). The effect of varying threshold values on the resulting mask is illustrated using cloud masking as an example in Figure 4.

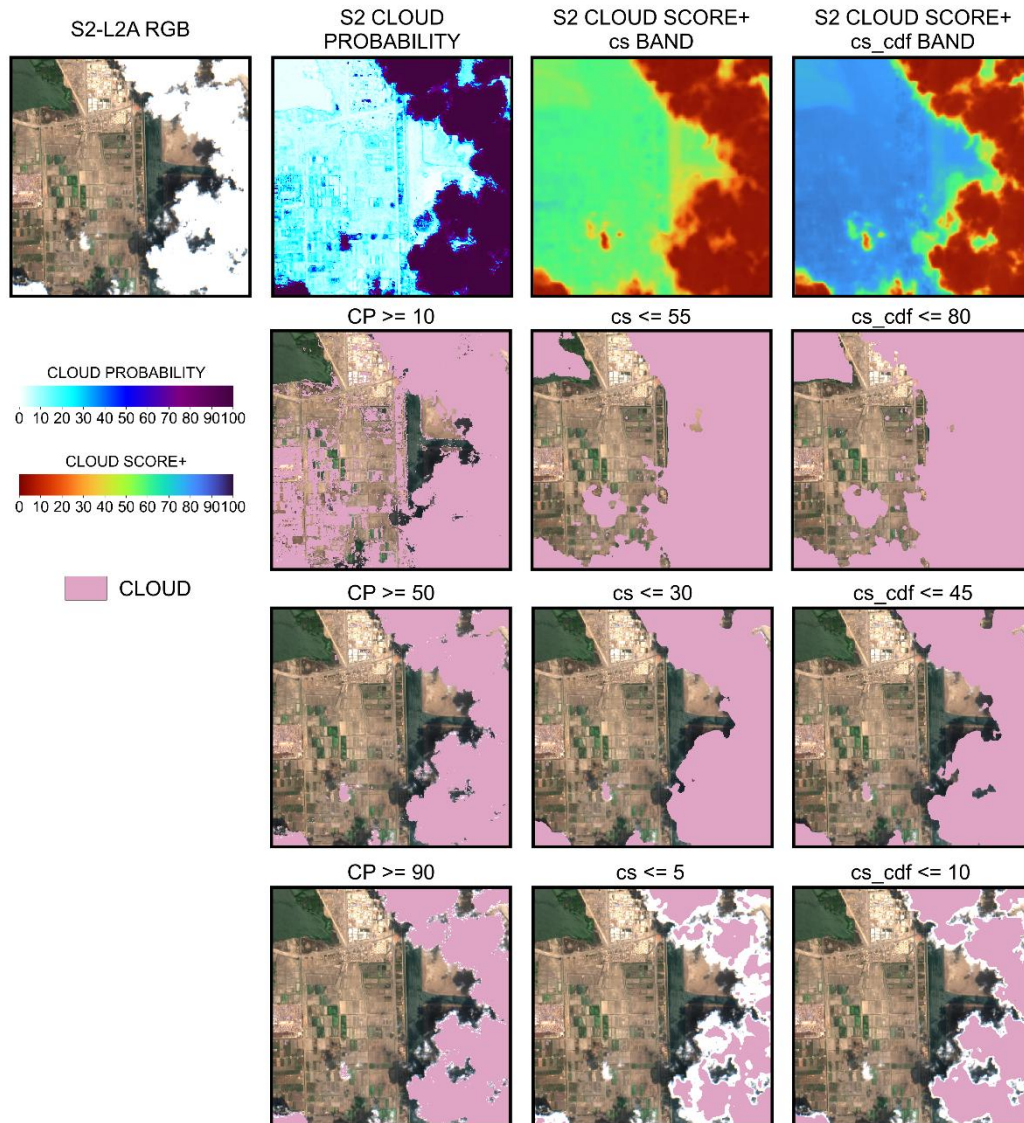


Figure 4. Effect of varying thresholds on cloud masking for CP, cs, and cs_cdf over a representative CSen12 patch.

Performance at each threshold was quantified using the Jaccard index (da Fontoura Costa 2021), also known as the intersection over union (IoU) (Wei and Hu 2024), a metric that measures the overlap between a generated mask and a reference mask (Eq. 1). For two binary masks A and B, IoU is defined as:

$$IoU = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

where a value of 0 indicates no overlap and 1 denotes perfect correspondence. IoU values are expressed as percentages throughout this study. This metric has been widely used in recent studies on satellite image segmentation (Nambiar et al. 2022; Mazza et al. 2021; Montero et al. 2023). Figure 5 illustrates the IoU calculation applied to a reference binary cloud mask and an evaluated binary cloud mask.

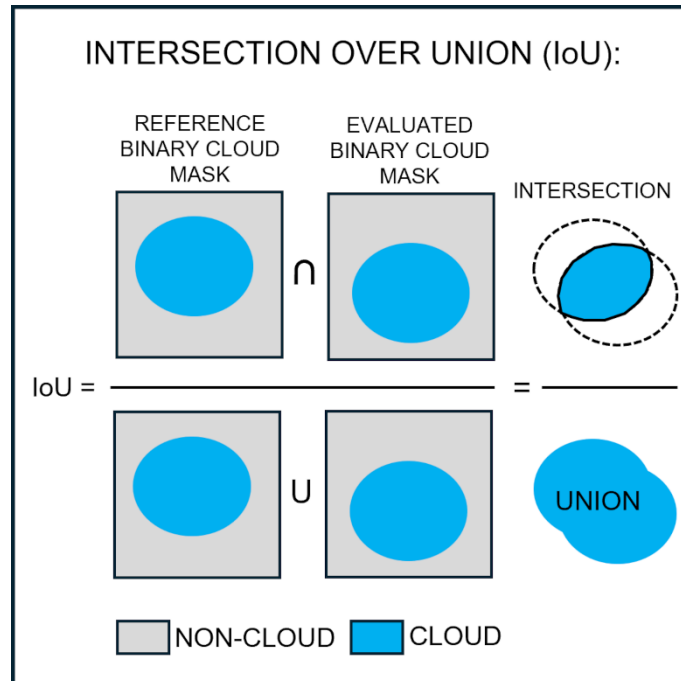


Figure 5. Illustration of the IoU calculation between a reference and an evaluated binary cloud mask.

For each product–mask type combination, the median IoU across all training patches was computed at each evaluated threshold value, yielding a median IoU–threshold curve. These curves were then fitted using a smoothing spline (UnivariateSpline, SciPy; (Virtanen et al. 2020)), and the threshold corresponding to the maximum IoU of the fitted curve was selected as the OMT for each product–mask type combination, yielding six OMT values for subsequent evaluation on the test set (796 patches).

On the test set, the CSen12-derived masks (CSen12-BCM and CSen12-BCSM) were used as reference to evaluate the performance of each product–mask type — using its respective OMT — and the SCL-derived masks (SCL-BCM and SCL-BCSM). Five commonly used metrics were computed: IoU (Eq. (1)), precision (Eq. (2)), recall (Eq. (3)), F1-Score (Eq. (4)), and balanced overall accuracy (BOA) (Eq. (5)), where TN denotes true negative pixels. Precision and recall are also known as user's and producer's accuracy, respectively, in the remote sensing literature (Aybar et al. 2022). Precision, recall, and F1-Score were calculated following previously established criteria (Sokolova and Lapalme 2009), whereas BOA was adopted as specified in the CSen12 benchmark (Aybar et al. 2022). The complete training and testing workflows are illustrated in Figures 6 and 7, respectively.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - Score = 2 \cdot \frac{P \cdot R}{P+R} \quad (4)$$

$$BOA = 0.5 \cdot \left(R + \frac{TN}{TN+TP} \right) \quad (5)$$

where TP , FP , and FN denote true positive, false positive, and false negative, respectively.

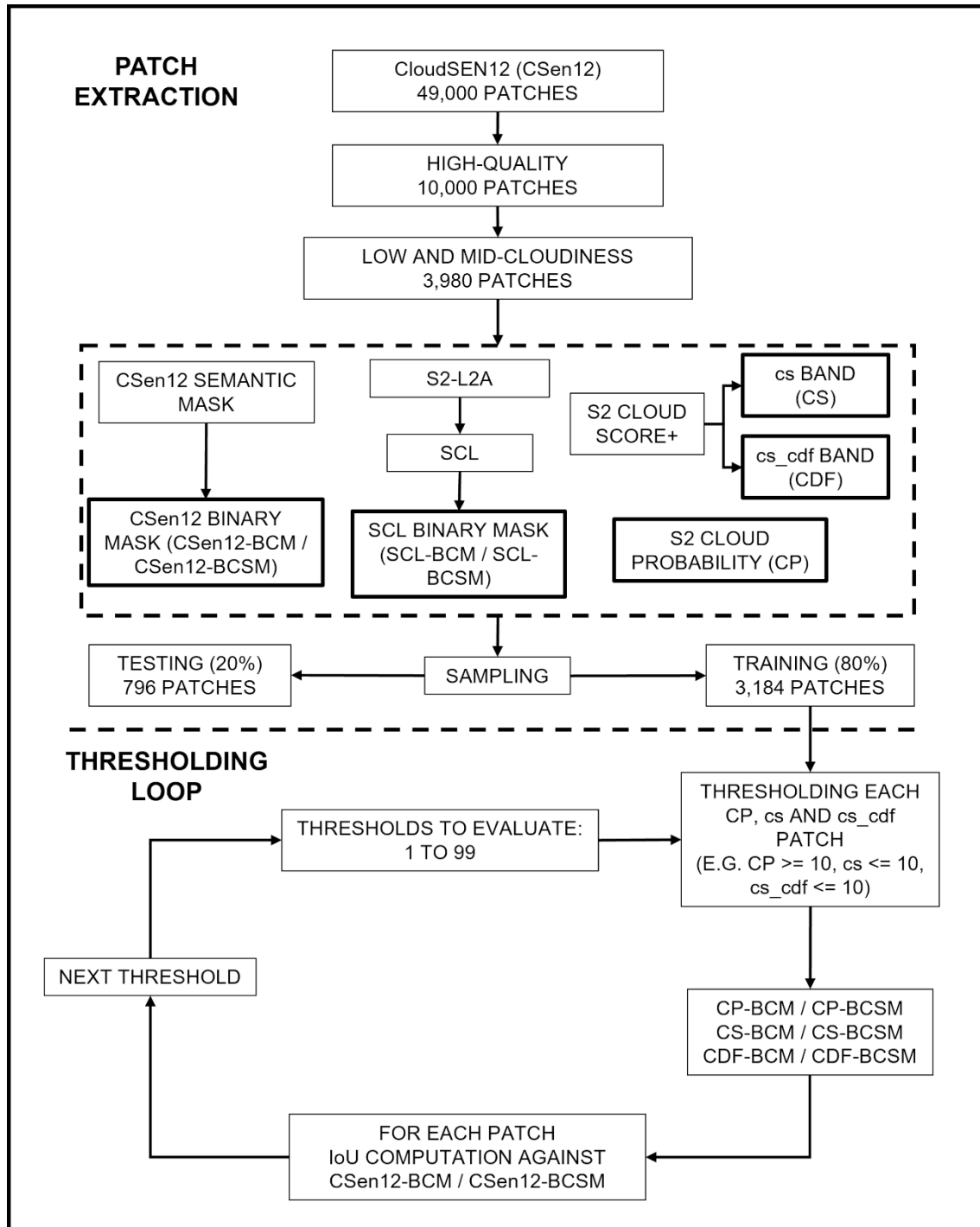


Figure 6. Workflow of the training procedure and OMT search for CP, cs, and cs_cdf products.

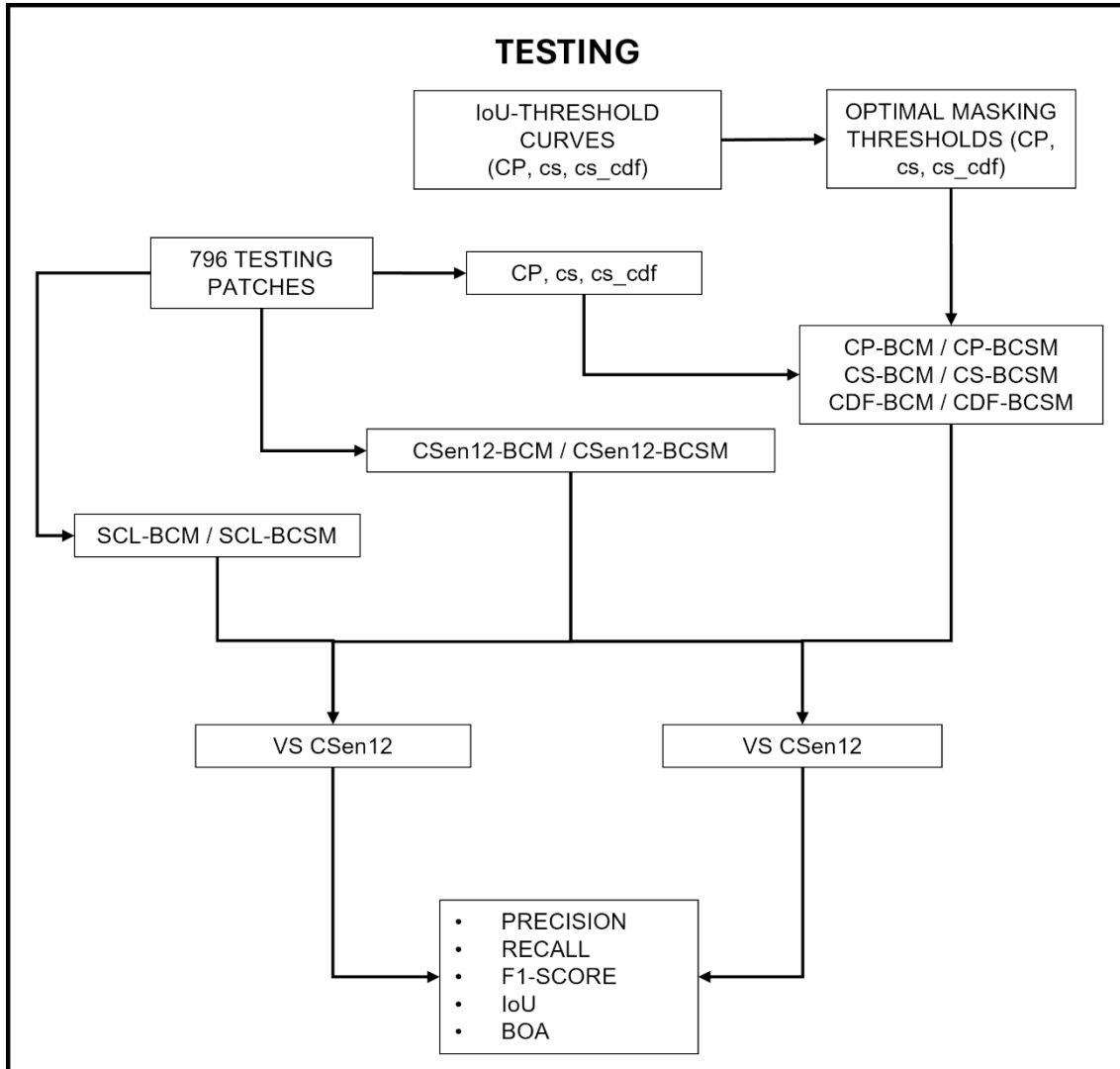


Figure 7. Workflow of the performance evaluation on the test set for CP, cs, cs_cdf, and SCL products.

3. Results and discussion

The results and discussion are organised into two subsections. Section 3.1 presents the OMTs obtained for each product–mask type using the training subset. Section 3.2 reports the performance metrics for cloud and cloud-and-shadow masking evaluated on the test subset, comparing CP, cs, and cs_cdf — applied using the OMTs derived in Section 3.1 — and the SCL-derived masks against the C Sen12 reference masks.

3.1 Optimal masking thresholds

The IoU–threshold curves and OMTs obtained for each product–mask type are shown in Figure 8 and summarised in Table 4.

For cloud masking (BCM), the OMT for CP-BCM was 38.1 (IoU = 63.5), for CS-BCM was 35.6 (IoU = 66.8), and for CDF-BCM was 52.3 (IoU = 70.3), with CDF-BCM achieving the highest IoU among the three products. The IoU–threshold curves for CS-BCM and CDF-BCM exhibited a characteristic shape: IoU values were near zero below a threshold of approximately 5, after which they rose sharply to their respective optima, followed by a rapid decline that stabilised at around IoU = 30 at high threshold values. In contrast, the CP-BCM curve showed a fundamentally different behaviour — starting at approximately IoU = 30 at the lowest threshold, rising gradually and steadily to its optimum, and then declining smoothly to approximately IoU = 20 at the highest threshold. This gradual and relatively symmetric profile confirms the notably flat region around the CP-BCM optimum, indicating low sensitivity to threshold selection over a broad range (approximately 20–50). CS-BCM exhibited a sharper and more asymmetric curve, suggesting greater sensitivity to threshold choice, while the CDF-BCM curve was shifted to the right relative to CS-BCM, indicating that `cs_cdf` requires higher threshold values to reach its optimum.

For cloud-and-shadow masking (BCSM), the OMT for CP-BCSM was markedly lower at 10.2 (IoU = 58.8), indicating that CP classifies a large proportion of pixels as cloud-and-shadow at low threshold values, which may result in overmasking in this scenario. The CS-BCSM and CDF-BCSM curves shared a similar shape to their BCM counterparts — near-zero IoU below threshold 5, a sharp rise to the optimum, followed by a rapid decline — but stabilised at a considerably higher IoU floor of approximately 50, reflecting the greater contribution of cloud shadow pixels to the combined mask. The

CP-BCSM curve, by contrast, started at approximately $\text{IoU} = 50$ at the lowest threshold, reached its optimum rapidly at 10.2, and then declined steadily to approximately $\text{IoU} = 15$ at the highest threshold. For CS-BCSM and CDF-BCSM, the OMT increased substantially relative to their BCM counterparts — 53.8 ($\text{IoU} = 77.4$) and 76.0 ($\text{IoU} = 81.8$), respectively — with both products achieving considerably higher IoU values than in the cloud-only scenario. This pattern suggests that CS+ products are better suited for joint cloud-and-shadow masking than for cloud masking alone, whereas CP shows the opposite trend, with BCM outperforming BCSM in terms of IoU .

A notable difference in curve shape was observed between the two masking scenarios. For BCM, the IoU –threshold curves exhibited a relatively flat region around the optimum, indicating stable performance over a broad threshold range. This stability was most pronounced for CP-BCM, whose curve remained nearly flat between approximately 20 and 50, suggesting that cloud masking with CP is particularly robust to threshold choice. CS-BCM and CDF-BCM showed somewhat sharper and more asymmetric curves, though still exhibiting a broader optimum region than their BCSM counterparts. In contrast, BCSM curves were markedly more peaked, with IoU declining sharply on both sides of the optimum, indicating that threshold selection is substantially more critical when cloud shadows are included in the masking scenario. This pattern suggests a general hierarchy of threshold sensitivity: $\text{CP-BCM} < \text{CS-BCM} \approx \text{CDF-BCM} < \text{CS-BCSM} \approx \text{CDF-BCSM} < \text{CP-BCSM}$, with CP-BCSM being the most sensitive given its very low OMT of 10.2.

Across all combinations, CDF-BCM and CDF-BCSM consistently achieved the highest IoU , followed by CS and CP. The addition of cloud shadows to the masking scenario substantially improved performance for CS+ products but reduced it for CP, highlighting fundamental differences in how these products respond to cloud shadow

contamination, and underscoring the particular suitability of `cs_cdf` for joint cloud-and-shadow masking in Sentinel-2 imagery.

The OMTs identified in this study can be contextualised against thresholds reported in the literature, with the caveat that most previous studies evaluated CP and CS+ exclusively for cloud masking. For CP-BCM, the OMT of 38.1 — equivalent to 0.381 in the 0–1 scale used in some studies — falls within the range commonly used in the literature (0.35–0.70; see Introduction), though toward the lower end, suggesting that relatively permissive thresholds are optimal for cloud masking in a globally distributed dataset. Notably, this value is close to the default threshold of 0.4 recommended by the algorithm developers to minimise cloud omission errors (Skakun et al. 2022), confirming that the default value performs near-optimally for cloud masking on the CSen12 dataset. For CS-BCM, the OMT of 35.6 — equivalent to 0.356 in the native 0–1 scale of CS+ — is below the 0.50–0.65 range reported for `cs` in previous studies (Rifai and Harintaka 2024; Gong et al. 2024), while for CDF-BCM the OMT of 52.3 — equivalent to 0.523 in the native 0–1 scale — is close to the 0.50 threshold used by (Gong et al. 2024). For the cloud-and-shadow masking scenario, direct comparisons are more limited. The only reviewed study using `cs_cdf` for joint detection is (Liang et al. 2024), who applied a threshold of 0.65 as a preprocessing step within the TSMM method. The OMT identified here for CDF-BCSM was 76.0 — equivalent to 0.76 in the native 0–1 scale — notably higher than the 0.65 threshold applied by (Liang et al. 2024), suggesting that when `cs_cdf` is used as a standalone product for joint masking, a more conservative threshold is required to maximise overlap with expert-labelled masks.

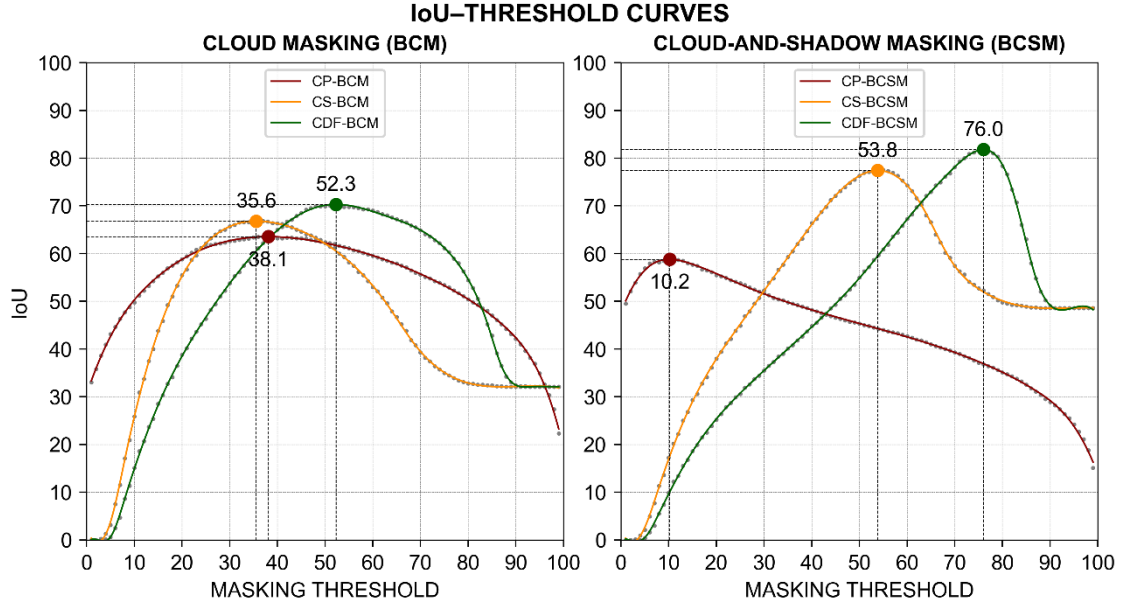


Figure 8. IoU-threshold curves for cloud and cloud-and-shadow masking.

Table 4. Optimal masking thresholds (OMT) and IoU at OMT for each product-mask type combination.

Product-mask type	OMT	IoU at OMT
CP-BCM	38.1	63.5
CS-BCM	35.6 (0.356)	66.8
CDF-BCM	52.3 (0.523)	70.3
CP-BCSM	10.2	58.8
CS-BCSM	53.8 (0.538)	77.4
CDF-BCSM	76.0 (0.76)	81.8

Note: Values in parentheses correspond to the native 0–1 scale of CS+ products.

3.2 Cloud and cloud-and-shadow masking performance

Median performance metrics for each product-mask type combination on the test set are shown in Figure 9 and summarised in Table 5.

For cloud masking, SCL-BCM achieved the highest precision (99.4%) but the lowest recall (52.9%), reflecting its highly conservative masking behaviour — it correctly identifies the clouds it detects but omits a large proportion of actual cloud pixels. In contrast, CP-BCM, CS-BCM, and CDF-BCM showed a more balanced performance

across all metrics. CDF-BCM achieved the highest median F1-Score (82.8%), IoU (70.7%), and BOA (85.5%) among all evaluated products, followed closely by CS-BCM (F1-Score = 80.3%, IoU = 67.0%, BOA = 83.8%) and CP-BCM (F1-Score = 76.8%, IoU = 62.3%, BOA = 81.4%). SCL-BCM recorded the lowest F1-Score (62.7%), IoU (45.7%), and BOA (73.5%), confirming its limited effectiveness for cloud masking when evaluated against expert-labelled CSen12 masks. Visual inspection of test patches suggested that CS-BCM and CDF-BCM partially masked cloud shadow areas in addition to clouds — a behaviour that, while beneficial in the BCSM scenario, introduces false positives in the BCM evaluation where shadows are not part of the reference mask, likely constraining the BCM performance of these products.

Visual inspection of a subset of test patches further revealed that CP, cs, and cs_cdf frequently masked thin cloud pixels, despite the fact that thresholds were optimised exclusively against thick cloud and cloud shadow reference masks. This suggests that the continuous scores provided by these products capture thin cloud contamination to some degree, even without explicit optimisation for this class, and supports the exploration of thin cloud detection as a direction for future work.

For cloud-and-shadow masking, SCL-BCSM again achieved the highest precision (98.3%) but the lowest recall (48.1%), with performance degrading further relative to BCM. CP-BCSM showed a notable improvement in recall compared to CP-BCM (89.5% vs. 84.9%), though at the cost of a slight decrease in precision (72.5% vs. 88%). CDF-BCSM achieved the highest median values across all metrics — F1-Score of 90.1%, IoU of 82.0%, and BOA of 87.0% — representing a substantial improvement over its BCM counterpart and over all other evaluated products. CS-BCSM also performed strongly (F1-Score = 87.3%, IoU = 77.5%, BOA = 85.2%), further confirming the suitability of CS+ products for joint cloud-and-shadow masking. SCL-BCSM recorded the lowest

overall performance, with an F1-Score of 58.8%, IoU = 41.6%, and BOA of 70.0%. These results can be partially contextualised against Liang et al. (2024), the only reviewed study evaluating CS+ for joint cloud-and-shadow masking, who reported an F1-score of 62%, a precision of 78%, and a recall of 57% for `cs_cdf` with a threshold of 0.65 on the CSen12 dataset. Direct comparability is however limited, as their cloud class combines thick and thin clouds and their shadow class combines deep and shallow shadows, whereas the present study excludes thin clouds from both masking scenarios.

A consistent pattern emerged across both masking scenarios: all products improved their F1-Score, IoU, and BOA when transitioning from BCM to BCSM, with the exception of SCL, which degraded in all metrics. This divergence highlights a fundamental difference in how these products respond to the inclusion of cloud shadows — CS+ products benefit substantially from the joint masking scenario, whereas SCL, which relies on predefined class thresholds, fails to adapt. The performance gap between CDF-BCSM and the remaining products was notably wider in BCSM than in BCM, underscoring the particular suitability of `cs_cdf` for joint cloud-and-shadow masking in Sentinel-2 imagery.

The IoU distributions across the 796 test patches, summarised in Table 6 and illustrated in Figure 10, provide additional insight beyond the median values reported in Figure 9. All products exhibited a minimum IoU of 0, indicating that complete masking failure occurs in some patches regardless of the product — a result consistent with the inherent variability of a globally distributed dataset. Conversely, maximum IoU values were high across all products (92.8–100.0), suggesting that under favourable conditions all products perform well.

The interquartile range ($IQR = Q3 - Q1$) reveals important differences in consistency. SCL showed the widest IQR in both masking scenarios (BCM: 48.0; BCSM:

41.3), reflecting greater variability in performance across patches. In contrast, CDF-BCSM exhibited the highest Q1 (57.6) and Q3 (90.2) among all combinations, indicating that even in the lower quartile of its distribution, performance remains at an acceptable level — a particularly relevant property for operational applications.

All products displayed a negatively skewed IoU distribution, as evidenced by the consistently larger distance between the median and Q1 compared to the distance between Q3 and the median. This pattern indicates that while most patches achieve relatively high IoU values, a tail of poorly performing patches exists for all products. This lower tail is most pronounced for SCL-BCM (median – Q1 = 29.0) and least pronounced for CDF-BCSM (median – Q1 = 24.3), suggesting that CDF-BCSM produces more consistent masking across diverse scene conditions.

While the OMTs identified in this study provide a robust starting point for operational masking, the IoU distributions shown in Figure 10 reveal that performance varies considerably across individual patches, with minimum values of 0 observed for all products. This variability suggests that in specific contexts — such as scenes dominated by particular surface types, unusual atmospheric conditions, or specific geographic regions — manual fine-tuning of the threshold above or below the OMT may be warranted to better balance commission and omission errors according to the requirements of the application.

For CS and CDF products, the median, Q1, and Q3 were consistently higher in BCSM than in BCM, reinforcing the pattern identified in Section 3.1 that CS+ products benefit from the joint cloud-and-shadow masking scenario. For SCL and CP, the opposite trend was observed, with lower median IoU values in BCSM than in BCM. For SCL, this degradation reflects its rigid reliance on predefined class thresholds, which limits its ability to adapt to the joint masking scenario. For CP, the IoU decrease despite improved

recall suggests a tendency toward overmasking when cloud shadow pixels are included in the reference.

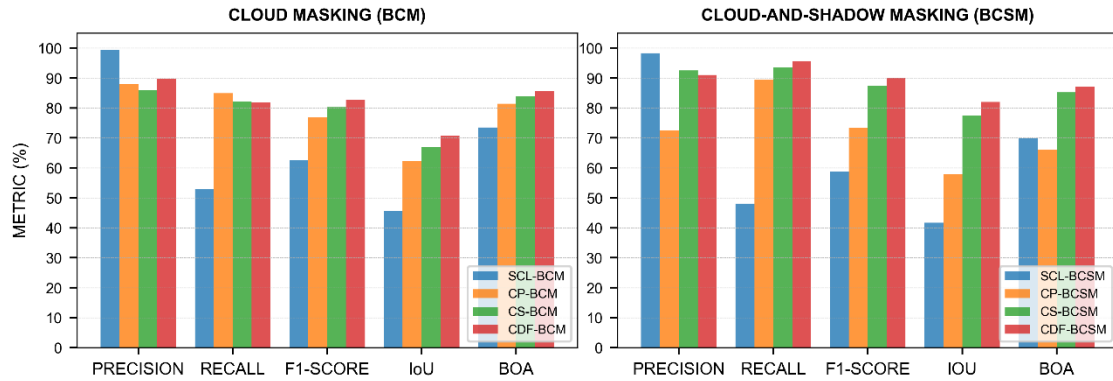


Figure 9. Median performance metrics for cloud and cloud-and-shadow masking at optimal thresholds, evaluated on the CSen12 test set.

Table 5. Median performance metrics for cloud and cloud-and-shadow masking at optimal thresholds, evaluated on the CSen12 test set.

Product-mask type	Precision	Recall	F1-Score	IoU	BOA
CDF-BCM	89.7	81.8	82.8	70.7	85.5
CS-BCM	86.0	82.2	80.3	67.0	83.8
CP-BCM	88.0	84.9	76.8	62.3	81.4
SCL-BCM	99.4	52.9	62.7	45.7	73.5
CDF-BCSM	91.0	95.7	90.1	82.0	87.0
CS-BCSM	92.6	93.6	87.3	77.5	85.2
CP-BCSM	72.5	89.5	73.4	57.9	66.1
SCL-BCSM	98.3	48.1	58.8	41.6	70.0

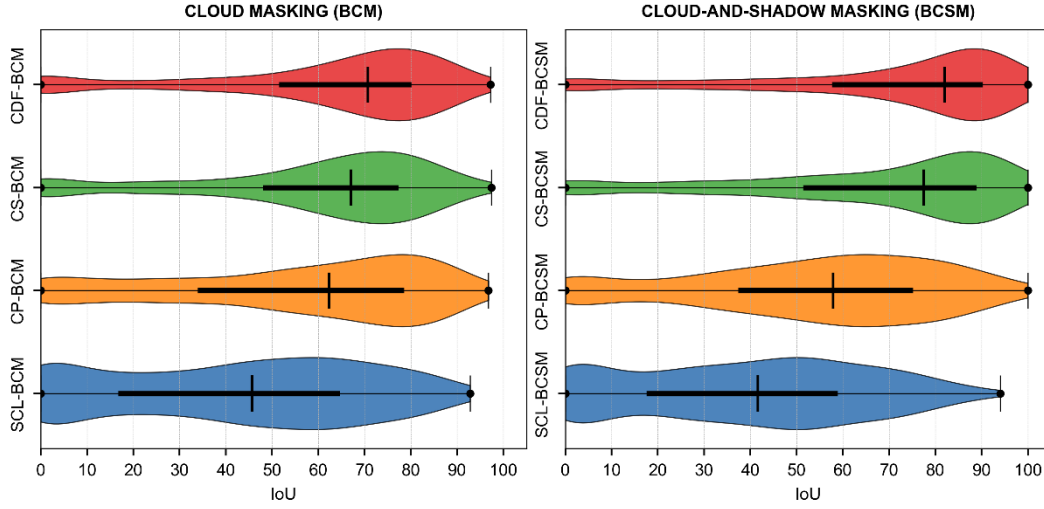


Figure 10. IoU distribution for cloud masking and cloud-and-shadow masking across all test patches.

Table 6. IoU descriptive statistics for cloud and cloud-and-shadow masking on the test set.

Product-mask type	Minimum	Q1	Median	Q3	Maximum
CDF-BCM	0.0	51.5	70.7	80.1	97.2
CS-BCM	0.0	48.0	67.0	77.3	97.4
CP-BCM	0.0	33.9	62.3	78.5	96.8
SCL-BCM	0.0	16.7	45.7	64.7	92.8
CDF-BCSM	0.0	57.6	82.0	90.2	100.0
CS-BCSM	0.0	51.4	77.5	88.8	100.0
CP-BCSM	0.0	37.3	57.9	75.1	100.0
SCL-BCSM	0.0	17.5	41.6	58.8	94.0

To statistically compare the four products across the 796 test patches, the Friedman test was applied as a non-parametric omnibus test for detecting overall differences in IoU rankings across multiple conditions, followed by the Nemenyi post-hoc test for pairwise comparisons. This approach is preferred over parametric alternatives such as ANOVA, as it makes no assumptions about normality or homogeneity of variance. The negatively skewed IoU distributions observed across all products (Figure 10) confirm that these assumptions are not met in the present data. The Nemenyi test controls the

family-wise error rate across all pairwise comparisons, making it appropriate when all products are compared against each other rather than against a single control (Demšar 2006).

The Friedman test confirmed statistically significant differences among products in both masking scenarios ($p < 0.001$). Post-hoc Nemenyi analysis (Figure 11) revealed that for cloud masking, CDF-BCM significantly outperformed all other products, while CP-BCM and CS-BCM were statistically equivalent ($p = 0.594$), both significantly outperforming SCL-BCM. For cloud-and-shadow masking, all pairwise comparisons were statistically significant ($p < 0.001$), with products forming a complete performance hierarchy: CDF-BCSM $>$ CS-BCSM $>$ CP-BCSM $>$ SCL-BCSM. Notably, the equivalence between CP and CS observed in the cloud-only scenario dissolved entirely under joint masking, where *cs_cdf* emerged as a distinctly superior product. The magnitude of rank differences visible in Figure 11 further indicates that these statistical differences reflect meaningful practical separations in masking performance, particularly between CDF-BCSM and the remaining products in the BCSM scenario.

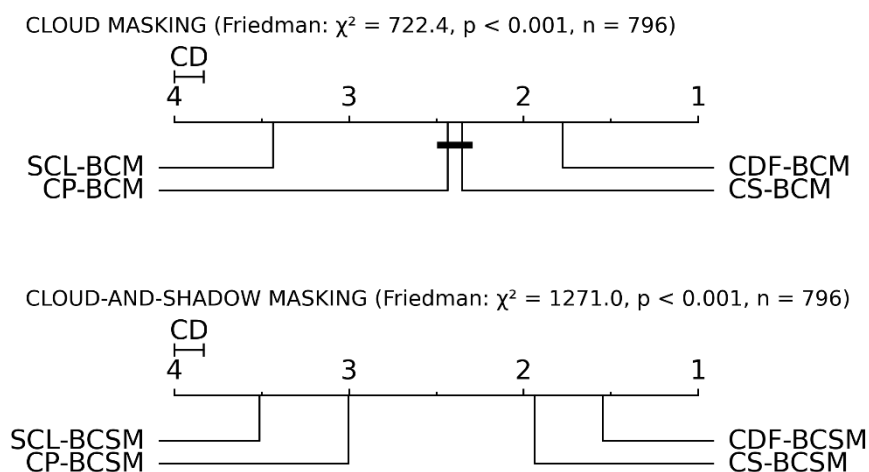


Figure 11. Critical difference diagrams comparing product performance for cloud and cloud-and-shadow masking based on IoU (Friedman–Nemenyi test, $n = 796$, $\alpha = 0.05$). Horizontal bars connect products with no statistically significant difference.

Figures 12 and 13 illustrate representative examples from the test set for BCM and BCSM respectively, providing qualitative insight into the spatial patterns of agreement and disagreement between products and the CSen12 reference masks.

The performance differences observed across products can be partly understood in terms of their underlying algorithmic characteristics described in Section 2.3. SCL's consistently high precision but low recall across both masking scenarios reflects the conservative nature of its rule-based spectral thresholds: by design, only pixels that clearly exceed predefined brightness and spectral criteria are classified as cloud, resulting in low commission errors but substantial omission of cloud and shadow pixels that fall below those thresholds. This rigidity, combined with the absence of any learning component, limits SCL's ability to generalize across the diverse surface and atmospheric conditions represented in the globally distributed CSen12 dataset.

The contrasting behaviour of CP and CS+ products in the BCSM scenario — where CS+ improved substantially while CP degraded — is consistent with their algorithmic differences in cloud shadow handling. CP is a cloud-only detector that does not model shadow as a distinct atmospheric effect; when applied to BCSM, its low OMT of 10.2 indicates that a large fraction of pixels must be masked to achieve maximum overlap with the reference, leading to overmasking of non-shadow areas and reduced precision.

CS+, by contrast, implicitly detects cloud shadows as part of its quality assessment framework through the ASIM-based training, which exploits the temporal contrast

between shadowed and clear acquisitions of the same location. This allows `cs` and `cs_cdf` to assign low quality scores to shadow-affected pixels without requiring explicit geometric shadow projection, which likely explains their substantially higher performance in the BCSM scenario. The superiority of `cs_cdf` over `cs` in both masking scenarios is consistent with its cumulative distributional nature: by integrating information across the historical score distribution for each pixel, `cs_cdf` is less sensitive to transient spectral anomalies and provides a more stable separation between clear and contaminated observations.

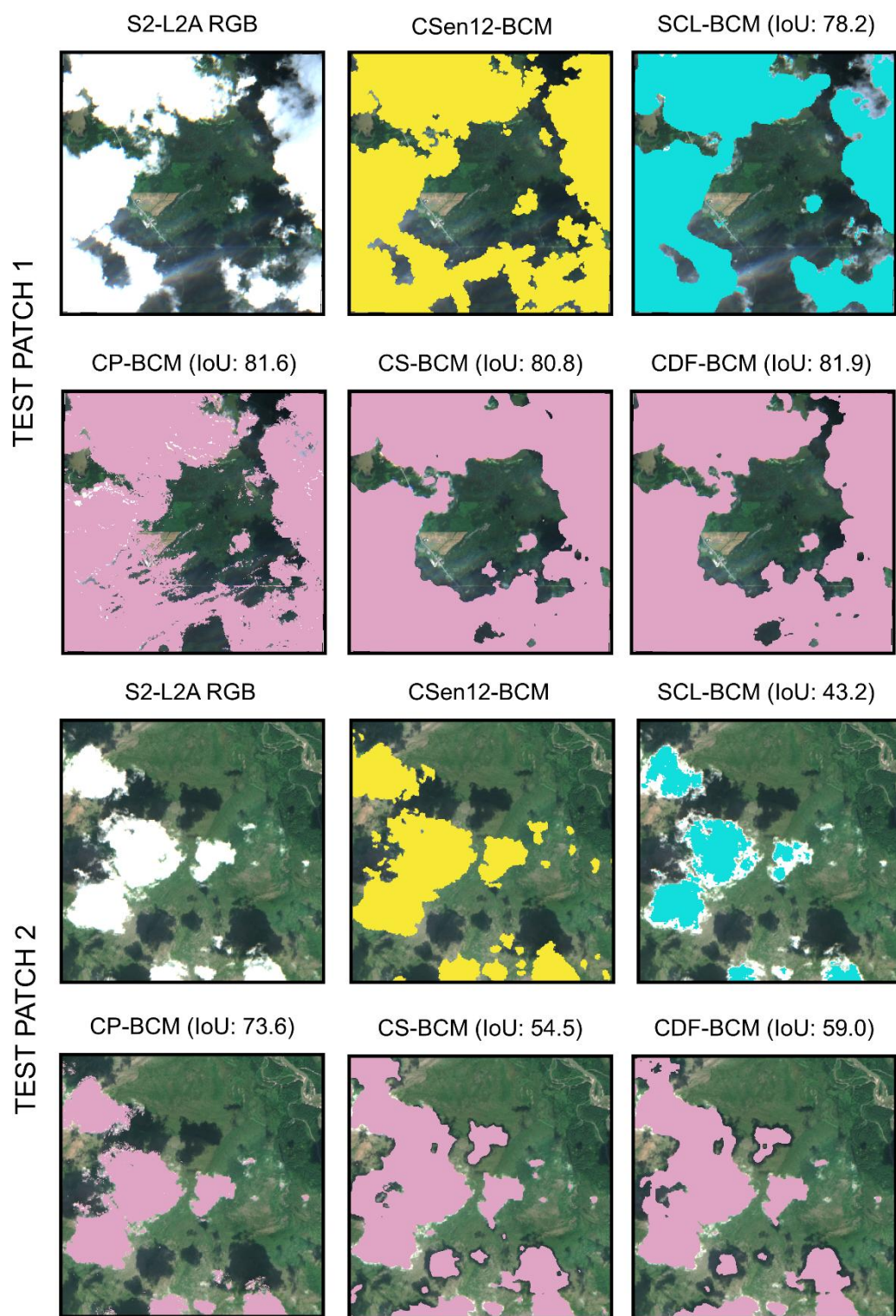


Figure 12. Cloud masking results for two representative test patches, with IoU shown for each product.

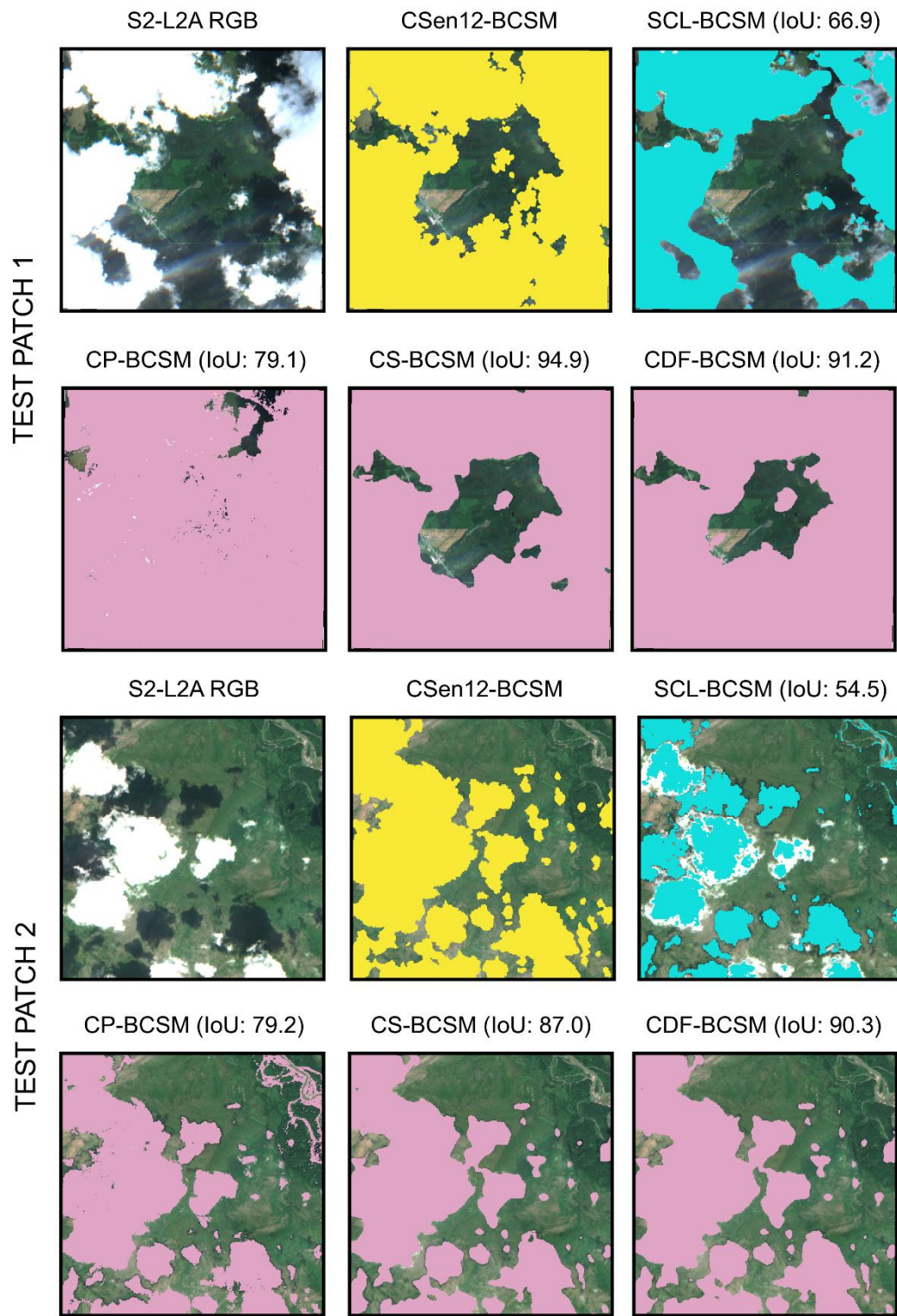


Figure 13. Cloud-and-shadow masking results for two representative test patches, with IoU shown for each product.

4. Conclusions

This study evaluated the performance of three Sentinel-2 quality assessment products — Cloud Probability (CP), Cloud Score+ (cs and cs_cdf), and the Scene Classification Layer (SCL) — for cloud and joint cloud-and-shadow masking using the CSen12 dataset as reference. Threshold optimisation was performed for CP, cs, and cs_cdf using a training subset of 3184 high-quality patches with low and mid cloudiness levels, and performance was assessed on an independent test set of 796 patches using IoU, precision, recall, F1-Score, and BOA.

Among the six product–mask type combinations evaluated, CDF-BCSM achieved the highest overall performance (F1-Score = 90.1%, IoU = 82.0%), confirming cs_cdf as the most effective product for joint cloud-and-shadow masking in Sentinel-2 imagery. CS+ products (cs and cs_cdf) consistently improved their performance when transitioning from cloud-only to joint masking, a behaviour attributable to the implicit cloud shadow detection embedded in the ASIM-based training framework. CP, by contrast, showed the opposite trend, with performance degrading in the BCSM scenario due to its cloud-only design, which leads to overmasking when shadow pixels are included in the reference. SCL recorded the lowest performance in both scenarios, reflecting the limitations of its rule-based spectral threshold approach in a globally distributed and heterogeneous dataset.

The optimal masking threshold for CP-BCM (38.1, equivalent to 0.381 in the native 0–1 scale) was found to be close to the default value of 0.4 recommended by the algorithm developers, providing independent empirical confirmation that this default performs near-optimally for cloud masking on the CSen12 dataset. For CS+ products, the optimal thresholds for joint cloud-and-shadow masking were notably higher than those reported in previous studies, suggesting that more conservative thresholds are required

when cs and cs_cdf are used as standalone masking products rather than as preprocessing steps within larger workflows.

These findings have practical implications for users selecting cloud and cloud shadow masking strategies for Sentinel-2 time-series analysis. When only cloud masking is required, cs_cdf with its optimal threshold provides the best balance between commission and omission errors. When cloud shadows must also be masked, cs_cdf emerges as clearly superior, with statistically significant advantages over all other evaluated products. SCL, despite its widespread operational use, showed limited effectiveness against expert-labelled masks, particularly in its ability to detect cloud-covered pixels, and its categorical output precludes the threshold flexibility offered by CP and CS+.

Beyond masking performance, CP and CS+ offer an additional practical advantage over SCL: both products are natively generated at 10 m resolution, compared to the 20 m native resolution of SCL, providing finer delineation of cloud and shadow boundaries — a relevant consideration for applications requiring spatial precision.

These results provide actionable guidance for Sentinel-2 users requiring robust cloud and cloud shadow masking, and highlight cs_cdf as the most effective product for joint masking applications.

Future work could investigate the optimisation of masking thresholds specifically targeting thin cloud detection, given that visual inspection of test patches suggests that CP and CS+ products capture thin cloud contamination to some degree even without explicit optimisation for this class.

Author contributions

Adrián Cal: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. Guadalupe Tiscornia: Conceptualization, Writing – review & editing, Supervision.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Declaration of generative AI use

The authors used Claude (Anthropic) to enhance the clarity of the writing, including corrections to grammar, syntax, style, and readability, and to ensure that the text adhered to British English standards during the preparation of this work. Following the use of this tool, the authors reviewed and edited the content as necessary and assume full responsibility for the final published article.

Data Availability Statement

Sentinel-2 imagery, Cloud Probability, and Cloud Score+ were obtained from Google Earth Engine. The CloudSEN12 dataset is publicly available at <https://gee-community-catalog.org/projects/cloudsen12/> and its official website (cloudsen12.github.io).

Acknowledgements

The authors gratefully acknowledge the institutional support of the Instituto Nacional de Investigación Agropecuaria (INIA, Uruguay) and the availability of open-access resources, such as the Google Earth Engine platform and CloudSEN12 dataset, which made this research possible. The authors also thanks the remote sensing research community for their continuous efforts to promote open and reproducible science.

Funding

This research did not receive any specific grants from funding agencies in the public, commercial, or not-for-profit sectors. This work was carried out as part of the authors' regular activities at the Instituto Nacional de Investigación Agropecuaria (INIA, Uruguay).

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