Investigating Cloud-Snow Mask Algorithms on Sentinel-2 Time Series Satellite Images

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Abstract

The Sentinel-2 mission is a key Copernicus program, providing consistent coverage from two satellites with polar-orbiting, sun-synchronous orbits with a revisit time of 5 days at the equator. Each satellite delivers consistent, high-resolution (10-60 m) optical imagery, suitable for monitoring water bodies, especially for high-latitude, cloud- and snow-prone regions such as Iceland. This study evaluates the effectiveness of three cloud-snow masking approaches -(a) the MSK_CLDPRB and MSK_SNWPRB, which are probability-based masks, (b) the Scene Classification Layer (SCL) codes: 1,2,3,8,9,10,11 - in improving image usability for subsequent remote sensing analyses, and (c) a machine learning method which is using the CART algorithm trained on six spectral bands and SCL cloud-snow code labels from one image per year, applied through the entire collection. To focus on Iceland's challenging conditions, we investigated the Landeyjahöfn Harbour during February from 2019 to 2024. We assessed cloud-snow pixels' removal by each approach by computing the percentage of them. Results indicate that our SCL-based method outperformed either the machine learning or probability-based methods in percentage and number of removal pixels and has the advantages of being implemented into pre-processing workflows for studies in cloud- and snow-prone regions such as the Landeyjahöfn Harbour. This reiterates the strength and reliability of the SCL product based on the ESA multi-source classification algorithm, specific to Sentinel-2 Level-2A imagery. Our work represents a contribution to establishing effective cloud-snow masking over optical remote sensing images, as well as a perspective on AI infusion in the context of satellite imagery for water-related studies.

1. Introduction

Optical satellite imagery, obtained from Earth observation missions like Sentinel-2, encompassing critical such as land cover mapping, tracking climate change, cryosphere surveillance, and disaster management (e.g., flood and fire accident), heavily rely on the analysis of optical imagery captured by satellites which imaging over Earth's surface using solar energy reflected and transmitted into space like the Earth's albedo. For tracking Earth's dynamic processes, the availability of open-access Remote Sensing (RS) data has notably heightened the need for datasets prepared for immediate analysis. However, a significant challenge in optical RS is the widespread cloud presence of cloud which obscures approximately half of the Earth's surface at any given moment. Consequently, this extensive cloud cover limits direct observation of specific targets thereby detecting clouds is a prerequisite pre-processing step for subsequent tasks such as object detection and classification. There is a wide range of algorithms for cloud detection, which have been developed broadly categorized RS images detection into non-optical and optical by their applications. For optical imagery on most of the ground surfaces, clouds typically exhibit higher brightness and lower density.(Singh et al., 2022; Zhen et al., 2019).

In optical RS imagery, accurately identifying and masking features such as clouds and their shadows, water bodies, snow, and ice sheets is a crucial aspect of automated data processing. There are various methods which show results of different definitions for buffer zones in the classes of 1. cloud, 2. cloud shadow, 3. snow. To ensure precise classification, the interpreter labelled each feature carefully by visually the analysis of both true-colour and infrared false-colour imagery, as well as evaluating bottom-of-atmosphere (BOA) reflectance spectra. Detecting elements like clouds, cirrus, snow cover, and cloud-free regions is an important step in optical RS images analysis and is fundamental to effective atmospheric correction. The Sentinel-2 satellites, equipped with multi-spectral images from the Copernicus program, are specially designed for this goal, providing exceptional data across spatial resolution, global reach, spectral range, and revisit frequency (Hollstein et al., 2016; Zekoll et al., 2021).

Cloud and haze are frequent atmospheric interferences that can distort optical RS images, leading to reduced quality and impacting critical analyses on remote sensing applications, like land cover mapping, change detection, and data quantification. Due to this reason, two necessary pre-processing tasks are removing cloud and haze from imagery, and they have distinct optical characteristics requiring separate handling. Clouds typically obstruct all reflected radiation that is near, along the sensor's viewing path, making it common practice to replace cloud-covered regions with cloud-free pixels acquired at different moments to restore the surface's data, which has lost (Sun et al., 2017).

As Earth observation technology continues to advance, RS imagery is now captured at diverse spatial, temporal, and spectral resolutions. However, these images are frequently compromised by atmospheric and weather-related factors- like clouds and snow. For the study of the land surfaces and water bodies, clouds are viewed as a form of interference that can obscure or lose vital ground data. Enhancing image quality, especially for thin cloud removal, is a significant step to It is a challenging process because images over land and water surfaces are covered by thin clouds, retaining both cloud characteristics and underlying surface details, involving radiative signatures and textural features (Shen et al., 2014).

One of the vital pre-processing steps in remote sensing image workflows is cloud removal. Most modern techniques rely on deep learning models, which demand large datasets of image pairs with or without clouds. However, collecting such real-world datasets is challenging, and models trained on synthetic data

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often struggle to perform well on natural scenes. Cloud-free imagery is usable data for analysing and investigating, particularly in high-latitude areas such as Iceland, where cloud cover is common, especially in winter. Therefore, improving cloud removal is an essential and high-value pre-processing task in studies that use visible-band RS data. Additionally, the process essentially acts as image reconstruction, driven by accurate cloud detection. Techniques for removing clouds are generally grouped into two categories: 1. single-image and 2. multi-temporal approaches. Time-series cloud removal in RS imagery, broadly adopted on platforms with big data like the GEE, which includes merging multiple same-path imagery to restore cloud-covered areas. Researchers have explored diverse restoration models, like spatial-temporal regression, low-rank decomposition, and deep learning. Even though time-series RS imagery removal can lead to variations in image tone and surface detail because of the temporal dynamics and seasonal fluctuations of such data, particularly in snowy and icy areas, where the clean images from clouds and snow parts are scarce, further compromising information quality (Tan et al., 2024; Wu et al., 2023).

Across much of the Earth's surface, clouds are typically identifiable by their high reflectance in visible wavelengths and their relatively low temperatures regions such as Iceland. However, distinguishing clouds from ice and snow sheets remains challenging, since both appear bright, and atmospheric temperature inversions above ice sheets often make the surfaces colder than the clouds themselves. Although cloud formations generally stand out in ice and snow sheets imagery. The main difficulty lies in accurately classifying them automatically, ensuring they're recognized as clouds and not misunderstood as features of the ice and snow sheets (Choi and Bindschadler, 2004).

The loss of information due to clouds and cloud shadows is a widespread issue, significantly impacting various subsequent research applications such as land cover and change detection, atmospheric variable estimation, and ocean parameter inversion. As a result, the detection of clouds and cloud shadows has become the primary challenge for many passive remote sensing satellite image production applications. The view angle of the satellite sensor and the illuminating angle are used to predict possible cloud shadow locations and select the one that has the maximum similarity with the potential cloud shadow mask. If the scene has snow, a snow mask is also produced. Due to the high spectral variability of clouds, cloud shadows, and the Earth's surface, automated, accurate separation of clouds and cloud shadows from normally illuminated surface conditions is difficult (Liang et al., 2024; Zhu and Woodcock, 2012).

A variety of techniques have been developed to effectively detect clouds and their shadows in Sentinel-2 Level-2A imagery. These approaches span classifying from binary data, which distinguishes cloud from non-cloud pixels, to advanced multi-class algorithms capable of identifying multiple classifications encompassing thick cloud, thin cloud, cloud shadows, and snow. The multiple-class algorithms are particularly useful, as they enable the extraction of land surface information from regions partially retrieved by the pixels that have thin clouds or through haze correction processes. Nonetheless, clouds can significantly impact the accuracy of land and water surface analysis in optical RS imagery, particularly within the short-wavelength bands of the visible spectrum. To mitigate this issue, our study introduces techniques to reduce the influence of cloud interference in visible-band images. Accurately detecting clouds is essential for processing optical RS imagery like Sentinel-2. Most current methods depend on numerous spectral thresholds across various bands, making them applicable only to certain satellite platforms. However, detecting clouds becomes particularly challenging when working with sensor data that offers limited spectral band availability (Wright et al., 2024; Yao et al., 2022; Zhang et al., 2023).

The European Space Agency (ESA) has developed a mission for the Copernicus plan under the European Union, which is a satellite called Sentinel-2. This satellite presents high-resolution, multi-spectral observations of all Earth surfaces at a repetitive orbit. The Level 2A is a fundamental product frequently used by Sentinel-2 users, offering surface albedo data following atmospheric correction and incorporating cloud and snow mask. The cloud/snow mask plays a critical role in enabling automated processing of Sentinel-2 Level-2A imagery, making precise validation of its performance essential (Baetens et al., 2019).

Cloud cover limits the effectiveness of Earth observation via optical RS images, making fast and precise cloud detection a crucial level in generating reliable remote sensing products. Due to the shortage of robust cloud detection methods on the Google Earth Engine (GEE) cloud platform, this study focuses on cloud-prone areas and compares cloud detection approaches for Sentinel-2 imagery by integrating support vector machines with the CART algorithm to have an effective and highly accurate cloud detection model. The method's detection performance was evaluated against existing techniques like QA60 and mask probability, which use both visual assessment and quantitative metrics. Persistent cloudiness in snowfield areas poses a major challenge in acquiring high-quality RS imagery (Li et al., 2022; Lu, 2007).

The limitation of available cloud-free observations for mapping shorelines in Icelandic harbours is one of the major challenges, which are often disrupted by frequent cloud cover. Additionally, requires identification of a suitable selection method for classifying in mapping shorelines based on observing the cloud-snow masks. However, to address these issues, this study aimed to rapidly identify cloud and snow covers by assessing various cloud-snow mask algorithms and machine-learning techniques applied to Sentinel-2 Level-2A imagery. In particular, we evaluated three cloud-snow masking algorithms integrated within GEE and assessed the suitability of broadly used machine-learning classifiers (classification and regression tree, decision tree) for analysing cloud-snow filtered images (Gao et al., 2024).

Decision tree is commonly employed in data processing to construct predictive models that estimate the value of a target variable based on multiple input features. Among these, Classification and Regression Tree (CART) algorithms are widely utilized in fields such as RS, Statistics, etc. The initial section of the paper presents an overview of the superiority Scene Classification Layer (SCL) method. Furthermore, the supervised CART model is applied to handle missing or incomplete data for filtering images from clouds and snow. (Bhargava et al., 2016; Kori and Kakkasageri, 2023).

Over the past decade, Sentinel-2 optical imagery has played a vital role in various land cover and land use mapping studies utilizing machine learning (ML). The most significant component in the process is the SCL, which has been crucial for identifying and excluding heavily cloud-covered imagery. The SCL product offers pixel-wise scene classification for each associated Sentinel-2 imagery.

In this work, we present an assessment based on the information contained in the SCL data. The research question that drags us is how much clean data, e.g., cloud-snow-free, in a time series, are we actually feeding into ML models. While our initial approach focused on analysing cloud and snow coverage in individual satellite scenes, we ultimately conducted a broader evaluation based on labels within the SCL. Furthermore, this study implements three different methods for generating cloud-snow free composites and compares them both visually and quantitatively (based on the percentage of removal pixels) for the time series 2019 to 2024 for February. We investigate this month because the Landeyjahöfn Harbour is closed during the winter season, and February is typically one of the coldest and most atmospherically challenging months. During this time, cloud cover is often at its peak, and snow cover is extensive in the study area. However, there isn't a suitable imagery time-series Sentinel-2 collection for the months December and January, and it is difficult to obtain clear optical imagery in cloud- snow- prone regions. Therefore, this research focuses on detecting and removing clouds and snow from images and comparing the approaches to evaluate the best technique for having cloud/snow-free imagery collection (Sanchez et al., 2024). The novelty of this study, beyond its regional focus, lies in the comparative evaluation of three distinct cloud-snow masking approaches—MSK_CLDPRB/MSK_SNWPRB, SCL codes, and a CART-based machine learning method—which have not been previously compared to determine the most effective technique. The most important part of this comparison is the analysis of the differences across the three classification outputs, which highlights the practical implications of each masking strategy for remote sensing applications.

2. Study Area and Methodology

2.1 Flowchart

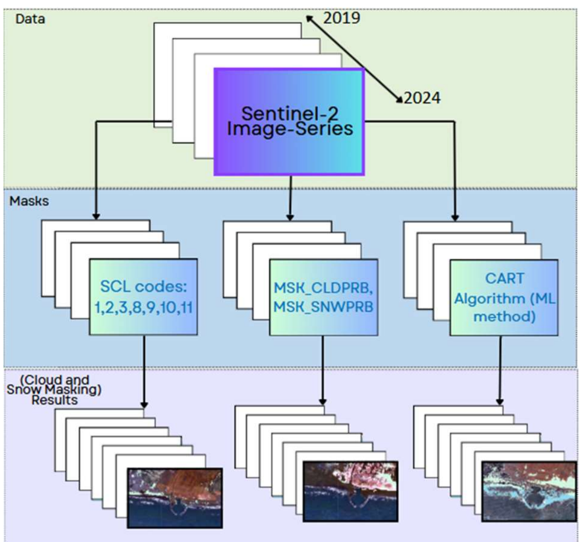


Figure 1. Flowchart describes the methodology parts

Figure 1 illustrates details of methodology by the steps from downloading Sentinel-2 Level-2A image series to applying three cloud-snow masks over 6 years (2019-2024) in a 2-kilometer buffer centered on the Landeyjahöfn Harbour in Iceland.

2.2 Data

The Landeyjahöfn Harbour is located along Iceland's sandy southern shoreline, a region marked by powerful wave activity and continuous sand movements due to sedimentary processes. This harbour opened in 2010 and since then frequently faced winter closures because sediment build-up reduces the water depth needed for safe navigation. Even though regular bathymetric mapping and monitoring of oceanographic conditions are conducted, it is still necessary to have a deep understanding of sediment dynamics to enable proactive dredging aligned with weather predictions. These intense wave activities and the straight, sandy nature of Landeyjahöfn Harbour, lacking protective fjords, make its construction incredibly challenging. Remarkably, aside from Landeyjahöfn, there isn't a single active harbour between Þorlákshöfn and Höfn í Hornafirði, despite this stretch of coastline spanning nearly 370 kilometres. Figure 2 shows an outline of the Landeyjahöfn Harbour from Google Earth platform (Viðarsdóttir, 2019).

Figure 2. An overview of Landeyjahöfn Harbour in Iceland

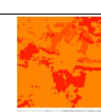
2.3 Masks

Sentinel-2 images provide valuable information about the land surface, but their quality is severely affected by cloud and snow cover. Therefore, to effectively filter clouds and snow cover in high latitude areas such as Iceland from Sentinel-2 Level-2A imagery, we offer three masking approaches were evaluated for each February month of the years 2019 to 2024: (a) Scene Classification Layer (SCL) (b) Probability Masks (Cloud and Snow) (c) a Machine Learning (ML) method based classifier employing the CART algorithm which presented in Table 1.

Sentinel-2 Masks Details	Description
SCL	Scene Classification Layer, based on Sen2Cor processor. Code-list: 1,2,3,8,9,10,11
MSK_CLDPRB	Cloud probability (%); values greater than are considered cloud
MSK_SNWPRB	Snow probability (%); values greater than are considered snow
CART Algorithm	Classification and Regression Trees, Machine Learning Algorithm based on SCL

Table 1. Sentinel-2 masks with their descriptions

(a) SCL: This method utilizes the predefined scene classification codes embedded within the SCL band to detect and exclude cloud- and snow-affected pixels. The SCL map in Level-2A product is generated based on data processed from atmospheric correction. We used seven codes of the SCL algorithm for filtering clouds and snow, which are specifically detailed in Table 2 with their application in classifying and their typical color in Sentinel-2 Level-2A imagery.

SCL code	Classification	Typical color	Display
1	Saturated or defective	Red	
2	Dark area pixels	Dark gray	

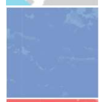
3	Cloud shadows	Brown	
8	Cloud medium probability	Light gray	
9	Cloud high probability	White	
10	Thin cirrus	Bright blue	
11	Snow	Pink	

Table 2. SCL classification codes details

The SCL band offers a spatial resolution of 20 meters and is exclusively available in Sentinel-2 Level-2A products to help identify and mask cloud, shadow, and snow, which are important for producing clean imagery.

(b) Probability Masks (MSK_CLDPRB (cloud probability mask) and MSK_SNWPRB (snow probability mask)): This technique is a replacement for the QA60 band method, which is no longer available in the Copernicus/S2_SR imagery collection from around late 2021. Probability masks were provided probabilistic assessments of Sentinel-2 Level-2A: the cloud probability quantifies the likelihood of cloud and snow presence on a pixel-by-pixel basis, enabling subtler differences and a flexible threshold-based filtering approach compared to categorical classification. These probability bands are often visualized using JPEG2000 format images, which encode cloudiness and snow levels per pixel, on a scale from 0 to 100 percent. Due to this encoding, probability masks can be more effective in conditions of clouds, haze, or snow boundaries rather than a simple binary classification.

(c) Machine Learning Classifier: In a third method, we use ML Algorithm – the Classification and Regression Tree (CART)- which is a supervised decision tree method, for pixel-wise classification of clouds and snow. This model differs from traditional thresholding or probability-based filtering, which was trained using SCL codes, particularly those corresponding to cloud and snow classifications, as reference labels, enabling automatic masking with adaptive thresholding and rule-based learning. The CART-based approach allows dynamics modeling of cloud-snow distributions that may exceed band-based masking in regions with variable atmospheric conditions. The output mask is typically validated against original reference images of the study area from February 2019 to 2024.

Year/Index	Cloud and Snow Pixels Removed (Probability Mask)	Cloud and Snow Removed Percentage (Probability Mask)	Cloud and Snow Pixels Removed (SCL Mask)	Cloud and Snow Removed Percentage (SCL Mask)	Cloud and Snow Pixels Removed (CART Algorithm)	Cloud and Snow Removed Percentage (CART Algorithm)
2019	3050	4.37%	2627	3.76%	5617	8.05%
2020	153	0.22%	12473	17.87%	20363	29.18%
2021	3304	4.73%	6585	9.43%	6628	9.50%
2022	27908	39.99%	34909	50.02%	14616	20.94%
2023	53081	76.05%	65229	93.46%	60948	99.68%
2024	15510	22.22%	21372	30.62%	5649	8.09%

Table 3: Number and percentage of cloud and snow removed pixels from the free of mask Sentinel-2 images

2.4 Results

To evaluate the effectiveness of each method, we analyzed the number and percentage of removed pixels for cloud and snow from 2019 to 2024 with designing a function to quantitatively measure how effective a cloud and snow masking methods are from original Sentinel-2 imagery by counting the number of pixels identified in the cloud-snow removal pixels and finally divided them by total original pixels. Table 3 indicates the number and percentage of pixels that the SCL-based method has removed of cloud and snow compared to the probability mask and CART algorithm approaches. The results present variations of effectiveness among the three cloud-snow masking methods throughout the study period. The SCL-based approach consistently showed strong results in terms of cloud and snow pixel removal, generally outperformed the probability-based mask, and demonstrated robust capabilities when compared to the CART algorithm in specific years.

The composite metric-absolute pixel counts and relative removal percentage was a key part of the tracking of cloud-snow masking method performance over time. The relative visualizations in Figure 3 and Figure 4 reflect an interpretable illustration of how effectively each cloud-snow masking method was adapted for utilize from 2019 to 2024.

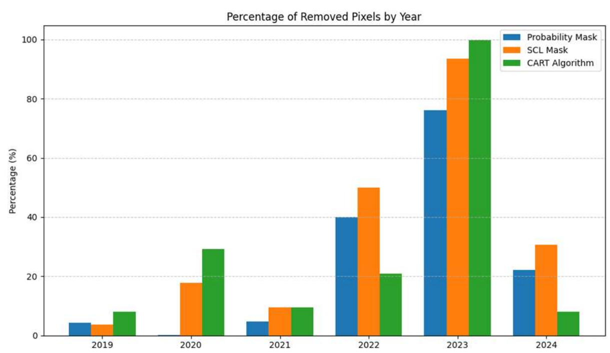


Figure 3. The bar chart of the percentage of removed pixels by year

The findings in Figure 3 demonstrate that the SCL mask approach had the highest overall cloud and snow removal efficiency during the six-year study period. This method maintained its total cloud and snow removal performance at percentage rates of 50.02% in 2022 and 30.62% in 2024. These correspond to its best seasonal performance months, respectively, of February 2022 and 2024, when cloud-snow coverage is expected to be higher during the winter months. Although, CART algorithm achieved the maximum percentage (reported separately as 99.68% in February 2023), it was less consistent across six years with more abrupt fluctuations than the SCL Mask, with a relatively consistent recommendation and approach to cloud-snow removal. Lastly, the Probability Mask exhibited fewer overall pixel removals and more variability over time than the SCL method, indicating less longevity and usability in its completion.

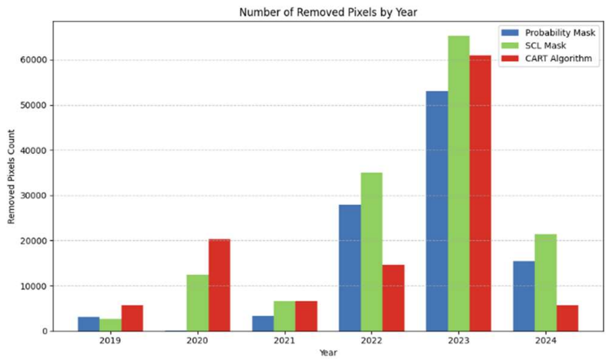


Figure 4. The bar chart of the number of removed pixels by year

Figure 4 supports the same trend observed in the percentage analysis. The SCL approach removed a greater number of pixels in most years, like a significant peak in 2023 (65229). Though the CART algorithm closely matches SCL in some years, its pixel count lacks consistent growth, reinforcing the conclusion that SCL provides more reliable coverage. The Probability–based approach yields comparatively lower pixel counts in all years except 2023.

The SCL method was best performing but remained competitive and effective throughout the time series, while the probability-based mask clearly defined some effectiveness (e.g., 76.05% in February 2023), generally exhibited lower removal percentages compared to either the SCL or CART methods.

3. Conclusion and Decision

Our research strategically selected a study period – February months from 2019 to 2024- characterized by persistent cloud cover and frequent snowfall in the high-latitude region of the Landeyjahöfn Harbour in Iceland, to rigorously evaluate the robustness and effectiveness of three cloud-snow masking algorithms: Probability-based mask, SCL-based classification, and CART ML algorithm. By focusing on the most atmospherically challenging conditions, this evaluation serves as a stress test for algorithmic reliability under adverse environmental scenarios. If an approach performs well in February from the winter season, when cloud and snow prevalence is high, it can be considered suitable for dependable pre-processing. Accurate cloud and snow masking is a fundamental requirement for reliable RS assessments, particularly for trustworthy Earth observation analyses in optically complex areas where reflectance distortions can compromise data integrity.

This study conducted a quantitative assessment using Sentinel-2 Level-2A imagery to compare three distinct cloud-snow masking methods: probability-based, SCL-based, and a CART machine learning algorithm, from February 2019 to 2024. Our findings show that the SCL-based cloud and snow masking method consistently eliminated a greater number of pixels by total and the percentage of area across most of the study period than the other approaches. The CART algorithm method can model complex and non-linear relationships between bands, which probability masks may overlook. This ML algorithm did remove the most pixels in some years and reached a removal rate of 99.68% in 2023; However, in contrast, the SCL-based approach provided to be highly competitive and consistently robust, notably achieving a 93.46% removal rate in the same year while also leading in 2022 and 2024, without the need for complex training data.

These findings underscore the strength of the multi-source classification logic that the SCL offers worldwide filtering technique performance for cloud and snow detection in similar environments. Overall, the strength and consistency provided by the SCL-based method with regard to the seven-year period of cloud and snow masking approaches clearly demonstrates the inherent reliability of the multi-source classification technique used by ESA to produce the SCL product for Sentinel-2 Level-2A imagery. This should position the SCL-based method with considerable implementation benefits for pre-processing into operational workflows for remote sensing (RS) studies in cloud- and snow-prone environments. While machine learning cloud-snow masking approaches require extensive training data and computational resources for model development and application, the SCL product is also readily available from the Sentinel-2 Level-2A data, making it a highly efficient and easy-to-implement method for cloud-snow masking operations.

This study represents a significant contribution towards developing efficient and reliable cloud-snow masking strategies over optical RS images. Beyond the scope of simple pixel masking, the demonstrated reliability of the SCL approach opens doors for more sophisticated applications in water monitoring and land cover changes. The shown effectiveness of the SCL-based method provides a useful insight on how to enhance pre-processing workflows, especially in the context of advanced analytical methods, including AI infusion, and water studies. This reiterates the importance of using robust, immediately available data as part of pre-processed satellite products, which can streamline research and policy efforts by adding value to Earth observation data, making it usable in dynamic and challenging environments such as the Landeyjahöfn Harbour in Iceland.

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