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Hybrid Method for Cloud Detection Using Sentinel-2 Imagery and Spectral Indices

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ABSTRACT: Satellite imagery constitutes an extremely valuable source of information about the natural environment and the processes occurring on the Earth's surface. However, the availability of useful optical imagery is often significantly limited by atmospheric factors, most notably the presence of clouds. Cloud cover can completely hinder the interpretation of satellite images or lead to erroneous analysis results if not properly identified and filtered out. Moreover, not all clouds are easily detectable—thin cirrus clouds located above water bodies often remain unnoticed in basic RGB visualizations. This article aims to develop and validate an effective method for cloud identification using selected spectral bands and remote sensing indices, which was further tested on the coastal waters of Poland.

1 INTRODUCTION

Satellite remote sensing has become a vital tool for monitoring and analysing environmental processes across diverse spatial and temporal scales. Among the numerous satellite missions, the European Space Agency's Sentinel-2 program stands out for its high-resolution optical imagery and frequent revisit times, providing critical data for applications such as land cover mapping [1] and coastal zone management. However, the effectiveness of satellite imagery is often diminished by atmospheric interference, particularly cloud cover, which can obscure surface details, reduce image quality, and potentially distort analytical results. This challenge is especially pressing in consistently cloudy areas, like coastal regions, where accurate environmental analysis is crucial [2].

In maritime environments, optical satellite imagery is increasingly used to support coastal monitoring, hydrographic surveys, shoreline mapping, vessel detection, environmental hazard assessment, and navigation-related decision-making. However, cloud contamination significantly limits the availability and reliability of remotely sensed information. Therefore, accurate cloud detection constitutes an essential preprocessing step for maritime monitoring systems and navigation-support applications.

Accurately detecting clouds is a fundamental preprocessing step in remote sensing workflows. While thick clouds are generally identifiable in standard true-colour composites, thin cirrus clouds present a significant challenge due to their low optical thickness and partial transparency. These clouds are difficult to detect over water bodies, where the spectral contrast between clouds and the underlying surface is minimal.

Various cloud detection algorithms have been developed to address this challenge, including rule-based methods, thresholding techniques, and machine learning approaches. Among these, the Random Forest (RF) algorithm has gained popularity. Studies have demonstrated the effectiveness of RF-based methods in cloud detection tasks, particularly when combined with spectral indices that enhance the contrast between clouds and other surface features [3].

Spectral indices, such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Snow Index (NDSI), and Cloud Discrimination Index (CDI), are widely used to improve cloud detection accuracy. These indices take advantage of the unique spectral characteristics of clouds in contrast to vegetation, snow, and other land cover types, enabling more precise classification. The primary objective of this study is to develop and evaluate a hybrid cloud detection method that integrates selected spectral indices (NDVI, NDSI, CDI) with the Random Forest algorithm to enhance the accuracy of cloud identification in Sentinel-2 imagery over coastal areas. The proposed approach aims to address the limitations of existing methods in detecting thin cirrus clouds, particularly over water bodies, and to provide a reliable tool for preprocessing optical satellite data in environmental monitoring applications.

This article is structured into four main sections. The first section, Introduction, presents the motivation for addressing this research topic. The second section, Materials and Methods, describes the study area, data sources, preprocessing steps, training sample preparation, and the proposed hybrid method. The third section, Results, discusses the outcomes of applying the method to a cloud-affected Sentinel-2 scene over northern Poland. The article concludes with a general summary of the findings.

2 MATERIALS AND METHODS

2.1 *Study Area*

The satellite image shows the northern region of Poland, highlighting the coastal area of the Pomeranian Voivodeship. It includes part of the southern Baltic Sea, specifically Gdańsk Bay (Zatoka Gdańska), the Hel Peninsula (Półwysep Helski), and the shoreline extending westward toward the open Baltic Sea (Fig. 1). This location was selected for its frequent use as a measurement site.

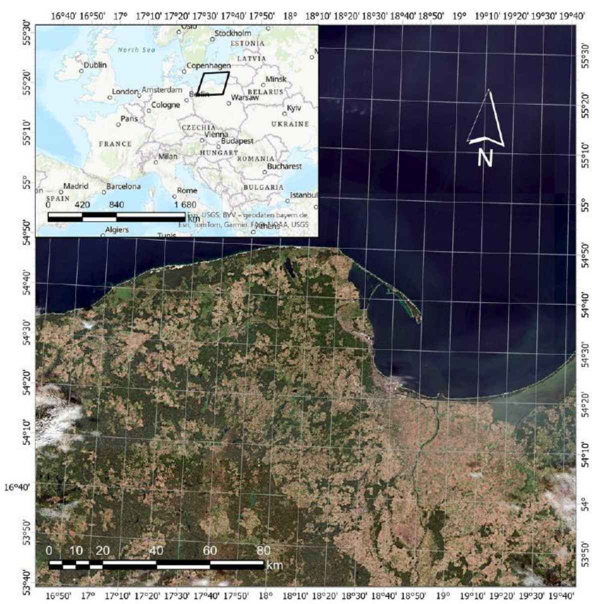

Figure 1. Location of the study area in northern Poland.

The Gulf of Gdańsk is an important maritime area characterized by intensive shipping traffic, port operations, hydrographic surveys, and coastal management activities. Reliable satellite-based observations are therefore important for supporting marine monitoring and navigation-related applications. The region features a variety of surface types, including forests, urban areas, the coastal waters of the Gulf of Gdańsk, and parts of the Vistula Lagoon. This land–water diversity, combined with dynamic environmental conditions, makes it a valuable yet challenging area for geospatial analysis. One of the major challenges in the remote sensing of this region is the frequent cloud cover, especially during the autumn and winter months. In Gdynia, December is the cloudiest month, with the sky being overcast or mostly cloudy about 69% of the time [4]. These conditions significantly limit the availability of cloud-free optical satellite imagery, underscoring the need for a cloud extraction method.

2.2 *Data used*

To establish and validate the proposed method, we utilized multispectral satellite imagery obtained from the Sentinel-2 mission. Developed by the European Space Agency (ESA) as part of the Copernicus program, Sentinel-2 is a multispectral Earth observation mission [5]. It offers high-resolution optical imagery tailored for applications including land-use mapping, vegetation monitoring, water quality assessment, and coastal zone studies.

The Sentinel-2 satellites are equipped with the MultiSpectral Instrument (MSI), which collects imagery across 13 spectral bands ranging from the visible and near-infrared (VNIR) to the short-wave infrared (SWIR) region. These bands vary in spatial resolution—10 m, 20 m, and 60 m—depending on their wavelength and intended application (European Space Agency) [6]. The spectral characteristics of the Sentinel-2 bands used in this study are summarized below (Tab. 1):

Table 1. Sentinel-2 Spectral Band Characteristics [6]

Band	Description	Spatial Resolution [m]	Central Wavelength [nm]
B1	Ultra Blue	60	443
B2	Blue	10	490
B3	Green	10	560
B4	Red	10	665
B5	Red Edge (VNIR)	20	705
B6	Red Edge (VNIR)	20	740
B7	Red Edge (VNIR)	20	783
B8	Near Infrared (NIR)	10	842
B8a	Narrow NIR (VNIR)	20	865
B9	Water Vapour (SWIR)	60	940
B10	Cirrus (SWIR)	60	1375
B11	SWIR	20	1610
B12	SWIR	20	2190

In this study, Sentinel-2 Level-2A satellite imagery was used to develop and test the proposed methodology. Specifically, an image acquired on September 6, 2024, covering the northern part of Poland and its surrounding water bodies, was selected as the primary dataset. The methods primarily utilized the spectral bands: Band 2 (Blue, 490 nm), Band 3

(Green, 560 nm), Band 4 (Red, 665 nm), Band 8 (Near-Infrared, 842 nm), and Band 11 (Short-Wave Infrared, 1610 nm) [6].

2.3 *Preprocessing*

As an initial step, a review and analysis of commonly used spectral indices was conducted to identify those that are most suitable for cloud detection in multispectral satellite imagery. These indices are frequently utilized in remote sensing to enhance the spectral contrast between various surface types, such as vegetation, soil, water, snow, and clouds. Several indices were assessed based on literature sources and preliminary testing with Sentinel-2 imagery, including:

- NDVI (Normalized Difference Vegetation Index) – used to identify vegetated areas and marine algae monitoring [7-8],
- NDWI (Normalized Difference Water Index) – useful in distinguishing water bodies from land [9], the delineation of open water features [10], and cloud-covered areas.
- NDSI (Normalized Difference Snow Index) – often used to discriminate between snow and clouds as well as bright land features [11],
- BI (Brightness Index) – highlights bright surfaces, such as clouds and bare soil [12],
- CDI (Cloud Displacement Index) – developed to improve cloud detection by analysing spectral dissimilarities over time or across bands [13].

Based on the literature review and empirical analysis of Sentinel-2 data in the study area, the following three spectral indices were selected for the proposed cloud detection method: NDVI, NDSI, and CDI.

The NDVI is calculated as follows [7-8]:

$$\frac{NIR - RED}{NIR + RED} \tag{1}$$

where:
NIR–recording in the near-infrared range (the so-called NIR band),
RED– recording in the green-light range (so-called red band).

NDVI values close to 1 indicate the presence of healthy vegetation, while negative values suggest the presence of water, clouds, or snow. In the case of water bodies, NDVI values are often similar to those of clouds, which may lead to classification challenges in such areas.

The Normalized Difference Snow Index is calculated using the following formula [11]:

$$\frac{GREEN - SWIR}{GREEN + SWIR} \tag{2}$$

where:
GREEN – reflectance in the green-light range (so-called green band),
SWIR – reflectance in the short-wave infrared range (so-called SWIR band),

High NDSI values typically indicate snow or clouds, as both reflect strongly in the visible spectrum (especially green) but absorb more in the SWIR range. This makes NDSI particularly useful for distinguishing bright surfaces such as snow and clouds from other land covers.

A simplified formulation of CDI can be expressed as [13]:

$$\frac{BLUE - SWIR}{BLUE + SWIR} \tag{3}$$

where:
BLUE – reflectance in the blue-light range (so-called blue band).

This index is particularly effective for separating clouds from bright non-cloud surfaces.

2.4 *Training samples preparation*

For supervised classification, a set of training samples was manually prepared using a point-based approach, which is one of the simplest and most effective methods for collecting labelled data in remote sensing analysis. Each point represents a pixel with a known class and is used to guide the classification algorithm in distinguishing between different surface and atmospheric conditions.

Three classes were defined to represent different cloud conditions:

- Class 0 – No Cloud: points were placed over cloud-free areas such as open water, vegetation, and urban surfaces.
- Class 1 – Thin Clouds: samples were collected from light, semi-transparent clouds, especially cirrus formations.
- Class 2 – Thick Clouds: points were placed on bright, dense cloud formations with strong reflectance.

To ensure balanced representation and reduce bias, points were distributed evenly across the entire image, avoiding excessive clustering in specific regions. For each class, a minimum of 30 to 50 points should be collected, which is considered a good practice for achieving reliable classification accuracy. Once the training points were digitized, pixel values were extracted from selected input layers, including both spectral bands and calculated indices. The input features included:

- Spectral bands: B2 (Blue), B3 (Green), B4 (Red), B8 (NIR), and B11 (SWIR)
- Spectral indices: NDVI, NDSI, and CDI

These raster layers were stacked, and their pixel values at each training point's location were extracted to build the training dataset.

2.5 *Hybrid cloud detection approach*

In this study, a hybrid approach was implemented for cloud detection by combining spectral indices and Sentinel-2 spectral bands with a supervised classification algorithm. The method integrates physically based indicators with data-driven machine learning to improve classification accuracy in spectrally complex environments, such as coastal zones (Fig. 2).

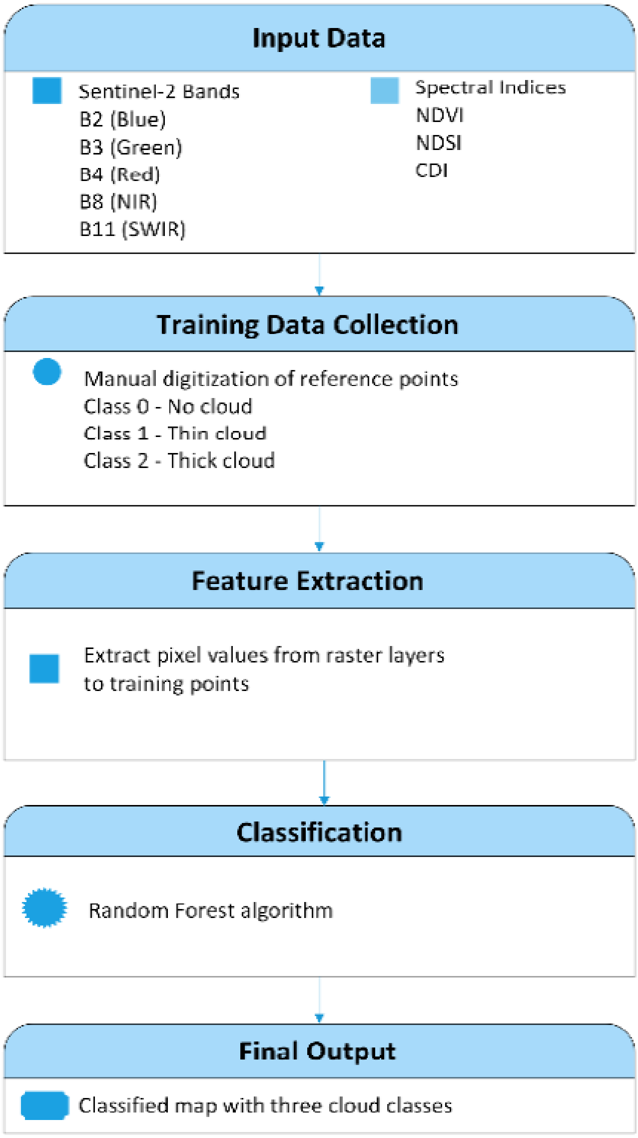

Figure 2. Hybrid Cloud Detection Workflow.

The Random Forest (RF) algorithm was chosen as the classification method because of its well-documented robustness, high performance, and resistance to overfitting in remote sensing applications [11-12]. Random Forest is an ensemble learning approach that constructs multiple decision trees during training and outputs the class that represents the mode of the predictions made by the individual trees. It is especially effective in managing high-dimensional input data and heterogeneous feature sets.

In this study, the RF model was trained using a feature set that included the previously mentioned spectral indices—NDVI, NDSI, and CDI—along with Sentinel-2 spectral bands: Band 2 (Blue), Band 3 (Green), Band 4 (Red), Band 8 (NIR), and Band 11 (SWIR). This feature combination was chosen based on its proven relevance for distinguishing between cloud types and cloud-free surfaces, particularly in coastal and mixed land-water regions.

To evaluate the performance of the classification model, the confusion matrix, precision, and recall were calculated for each class based on the confusion matrix. Precision (P) is defined as the proportion of correctly predicted instances of a given class to the total number of cases predicted as that class:

$$\frac{TP}{TP+FP} \tag{4}$$

where:
TP (True Positives) – the number of points that were correctly classified as belonging to the target class,
FP (False Positives) – the number of points that were incorrectly classified as belonging to the target class, when in fact they belong to a different one.

Recall (R) is defined as the proportion of correctly predicted instances of a given class to the total number of actual cases of that class in the reference dataset:

$$\frac{TP}{TP+FN} \tag{5}$$

where:
FN (False Negatives) – the number of points that truly belong to the target class but were incorrectly classified as belonging to another class.

Together, precision and recall provide a comprehensive view of classification performance, striking a balance between the trade-off between false positives and false negatives.

3 RESULTS

The first step in evaluating the effectiveness of the proposed cloud detection method involved a visual and analytical assessment of the spectral index outputs. The three selected indices—NDVI, NDSI, and CDI—were used with the Sentinel-2 imagery to highlight various surface characteristics relevant to cloud detection.

The first index analysed is the NDVI, which is commonly used to identify vegetated areas by utilizing the spectral contrast between the red and near-infrared bands (Fig. 3).

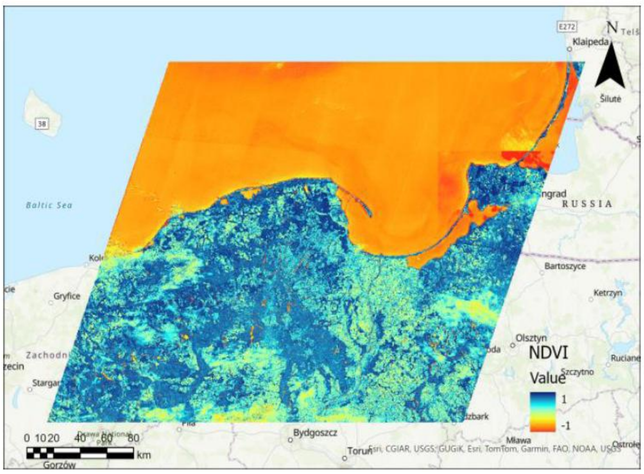

Figure 3. The map presents the NDVI values over the coastal and inland areas of northern Poland.

The NDVI effectively highlights vegetated areas (green to blue), but it cannot reliably differentiate between clouds and water surfaces, nor can it detect thin clouds with high confidence. These findings support the decision to use the NDVI only as part of a hybrid approach, complemented by indices such as

NDSI and CDI, which are more sensitive to cloud characteristics.

The next index assessed in this study is the NDSI (Fig. 4).

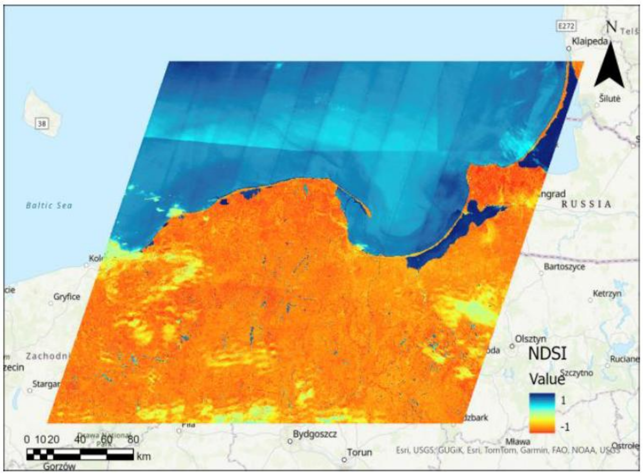

Figure 4. NDSI distribution across the study area based on Sentinel-2 imagery (06.09.2024).

This result confirms that NDSI is more sensitive to the presence of optically thick clouds, particularly in regions where NDVI struggled to differentiate clouds from water surfaces. However, the index may still have difficulty with thin cirrus clouds or high-altitude haze, which do not create a strong contrast in green versus SWIR reflectance. Therefore, further enhancement is accomplished with the Cloud Displacement Index (Fig. 5).

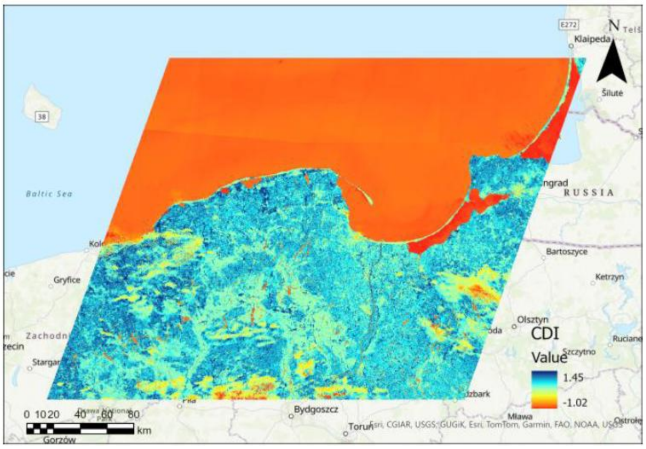

Figure 5. CDI distribution over the study area based on Sentinel-2 imagery (06.09.2024).

The CDI map confirms its role as a vital component in hybrid cloud detection, especially for distinguishing clouds from spectrally similar surfaces like snow, sand, or water. Its inclusion in the classification model greatly improves the identification of both thin and thick clouds, which NDVI or NDSI alone may not fully capture.

Based on the generated spectral index maps (NDVI, NDSI, CDI) and the reference true colour image (Fig. 6), the process of identifying training data (Fig. 7) was initiated.

Figure 6. Analysed area in true colour.

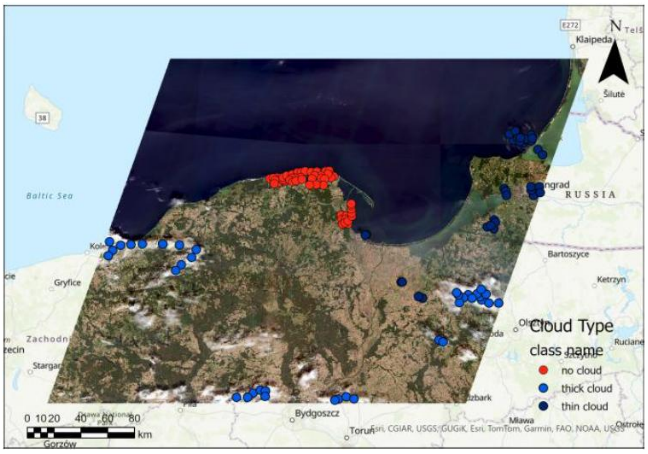

Figure 7. Distribution of training points for cloud classification.

After constructing the classification model, it was then applied to the entire Sentinel-2 scene to generate a complete cloud cover map (Fig. 8).

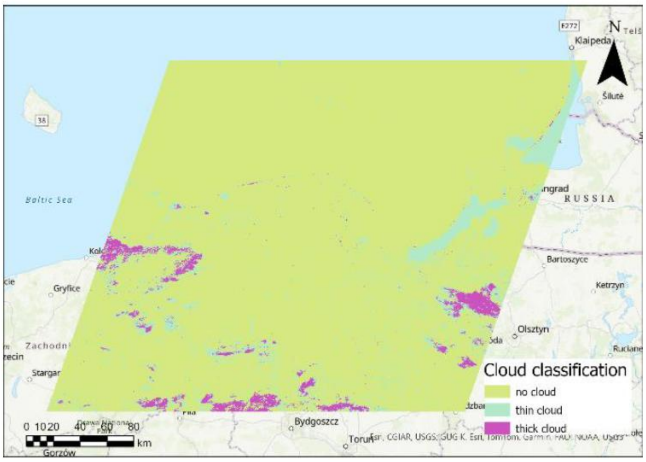

Figure 8. Cloud classification applied to the entire Sentinel-2 scene acquired over the Gdańsk Bay.

In the next stage of the study, the cloud classification map underwent validation. A confusion matrix (Fig. 9) was used to assess the model's performance.

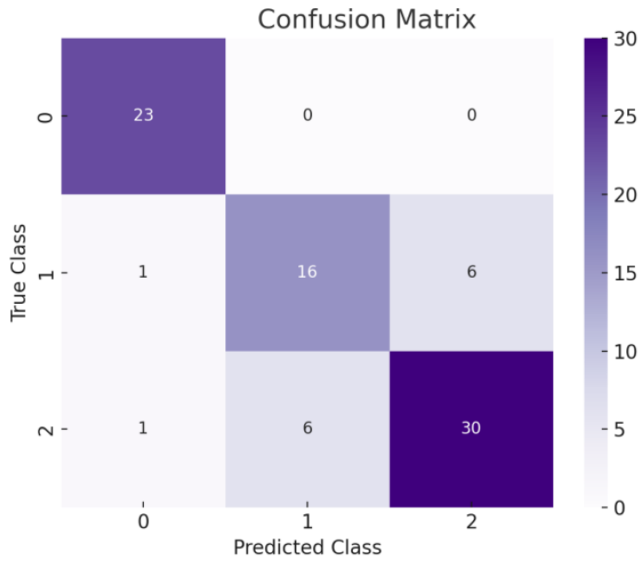

Figure 9. Confusion matrix showing the classification results of the cloud detection model. Class 0 represents cloud-free areas, class 1 corresponds to thin clouds, and class 2 refers to thick clouds.

The confusion matrix shows that the classifier performed exceptionally well in distinguishing cloud-free areas (class 0), achieving a perfect classification with 23 correctly identified samples and no misclassifications. Thin clouds (class 1) were classified correctly in 16 instances, while 1 instance was misclassified as class 0 and 6 as class 2, indicating some spectral overlap with both neighbouring categories. For thick clouds (class 2), the model achieved 30 correct classifications, with minor confusion: 1 sample was misclassified as class 0, and 6 as class 1. Overall, the classifier demonstrated high accuracy across all categories, though further refinement could enhance the discrimination between thin and thick clouds.

To quantitatively evaluate the classification model, precision and recall were calculated for each class (Tab. 2).

Table 2. Precision and recall values calculated for each class based on the confusion matrix.

Class	Precision	Recall	Sample
0 – no clouds	0.92	1.00	23
1 – thin clouds	0.73	0.70	23
2 – thick clouds	0.83	0.81	37

The evaluation metrics indicate that the model excelled in identifying cloud-free areas (class 0), achieving both high precision (0.92) and perfect recall (1.00), which means that no cloud-free samples were misclassified. For thick clouds (class 2), the model also demonstrated strong performance, with balanced precision (0.83) and recall (0.81), suggesting dependable detection of dense cloud structures.

The lowest precision and recall were observed for thin clouds (class 1), with values of 0.73 and 0.70, respectively. This result suggests that thin clouds are more challenging to classify accurately, likely due to their lower spectral contrast and partial transparency, which can create confusion with both clear sky and thick cloud classes. Incorporating additional spectral indices or training samples may improve the classification of this category in future work.

4 CONCLUSIONS

This study demonstrated the effectiveness of a hybrid cloud detection method that combines selected spectral indices (NDVI, NDSI, CDI) with Sentinel-2 spectral bands and a supervised learning approach using a machine learning algorithm (Random Forest). The proposed approach enabled accurate identification of various cloud types over a spectrally complex coastal region in northern Poland.

The results indicated that the model excelled in detecting cloud-free areas, achieving a precision of 0.92 and a perfect recall of 1.00. Thick clouds were also classified reliably (precision = 0.83; recall = 0.81), while thin clouds posed the greatest challenge due to their spectral similarity to both clear skies and thick clouds (precision = 0.73; recall = 0.70). These findings emphasize the importance of combining spectral indicators with effective classification techniques to reduce misclassification in complex land–water environments.

The method's simplicity, flexibility, and relatively low computational cost make it suitable for operational maritime applications, including coastal monitoring, hydrographic data preprocessing, shoreline mapping, vessel detection support, and navigation-related environmental monitoring. By improving the reliability of cloud-free Sentinel-2 products, the proposed approach may support safer and more efficient decision-making in coastal and marine environments. Future research may explore integrating additional spectral features, time series analysis, or deep learning-based models to enhance the detection of optically thin clouds and haze layers.

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