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Ewa Głowienka[1], Nicole Zembol[2]

Forest Community Mapping Using Hyperspectral (CHRIS/PROBA) and Sentinel-2 Multispectral Images[3]

Abstract: The possibility to use hyperspectral images (CHRIS/PROBA) and multispectral images (Sentinel-2) in the classification of forest communities is assessed in this article. The pre-processing of CHRIS/PROBA image included: noise reduction, radiometric correction, atmospheric correction, geometric correction. Due to MNF transformation the number of the hyperspectral image channels was reduced (to 10 channels) and smiling errors were removed. Sentinel-2 image (level 2A) did not require pre-processing. Three tree genera occurring in the study area were selected for the classification: pine (*Pinus*), alder (*Alnus*) and birch (*Betula*). Image classification was carried out with three methods: SAM (Spectral Angle Mapper), MTMF (Mixture Tuned Matched Filtering), SVM (Support Vector Machine). For the CHRIS/PROBA image, the algorithm SVM turned out to be the best. Its overall accuracy (OA) was 72%. The poorest result (OA = 52%) was for the MTMF classifier. In the classification of Sentinel-2 multispectral image the best result was for the MTMF method: OA = 82%, kappa coefficient 0.7. For other methods, the overall accuracy exceeded 65%. Among the classified genera, the highest producer's accuracy was obtained for pine (PA = 96%), and the broad-leaf genera: alder and birch had PA ranging from 42% to 85%.

Keywords: hyperspectral, pre-processing, multispectral, Sentinel-2, CHRIS/PROBA, machine learning

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[1] AGH University of Science and Technology, Faculty of Geo-Data Science, Geodesy, and Environmental Engineering, Krakow, Poland, email: eglo@agh.edu.pl, https://orcid.org/0000-0001-7326-1592

[2] SATIM, Krakow, Poland, email: zembol.nicole@gmail.com

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1. Introduction

In the context of forest management, remote sensing represents a rich and important source of information on the Earth surface. Illegal logging, floods, droughts and fires are examples of threats that can be continuously monitored. Forested areas can be huge and thus the monitoring of forest communities and the inventory of plant species/generic composition with traditional field methods is costly and labor intensive – and sometimes even impossible to carry out. For many years, scientists have been conducting research related to the application of airborne [1–3] and satellite [4–9] remote sensing. Due to such applications, it is possible to study the tree stands and condition of vegetation in large areas without human intervention in the natural environment [10–13]. Since 2015, multispectral images of Sentinel-2 (S-2), Copernicus program are available with very good temporal (up to 2–3 days for middle latitudes) and spatial (10 m, 20 m) resolutions [14]. Moreover, the spectral characteristics of S-2 (13 spectral bands) make it a very valuable dataset for quasi-continuous monitoring of environmental changes [15], agricultural management [16] as well as for studying the structure and characteristics of forest communities [17, 18].

On the other hand, for at least two decades, hyperspectral data enable the acquisition of very detailed information related to ecology, agriculture, forestry, e.g., for the study of plant species compositions, crop diversity, or stand evaluation in forest areas [2, 3, 9, 11, 19, 20]. Hyperspectral images are characterized by rich spectral information obtained as a result of recording electromagnetic radiation in numerous and narrow spectral ranges (4–10 nm). Hyperspectral data from ESA's CHRIS/PROBA (Compact High Resolution Imaging Spectrometer/The Project for On-Board Autonomy) experimental mission, made a very valuable contribution to the study of vegetation and forests and their structure [21–24]. In the literature, many scientists have presented results on the classification and mapping tree stands based on hyperspectral data of much larger range and more possibilities of image analyses, compared to multispectral data [25–28].

The current study had two main objectives: (i) the application of hyperspectral (CHRIS/PROBA) and multispectral (Sentinel-2) data to determine the occurrence of specific species in a selected forest area; and (ii) the assessment and comparison of the level of classification accuracy obtained with two different types of classifiers in the context of species identification.

2. Study Area and Data

The study area is in the Warmia-Masuria Voivodeship (Province), on the border between the districts of Olsztyn, Szczytno and Nidzica. It is south-east of the city of Olsztynek (Fig. 1). It covers the area around lakes Omulew, Gim and Kiernoz Wielki.

The area is part of the Napiwodzko-Ramucka Forest. The predominant species occurring in the area is the Scotch pine (*Pinus sylvestris*). There are several forms of nature protection in the area; the whole forest is a protected landscape area.

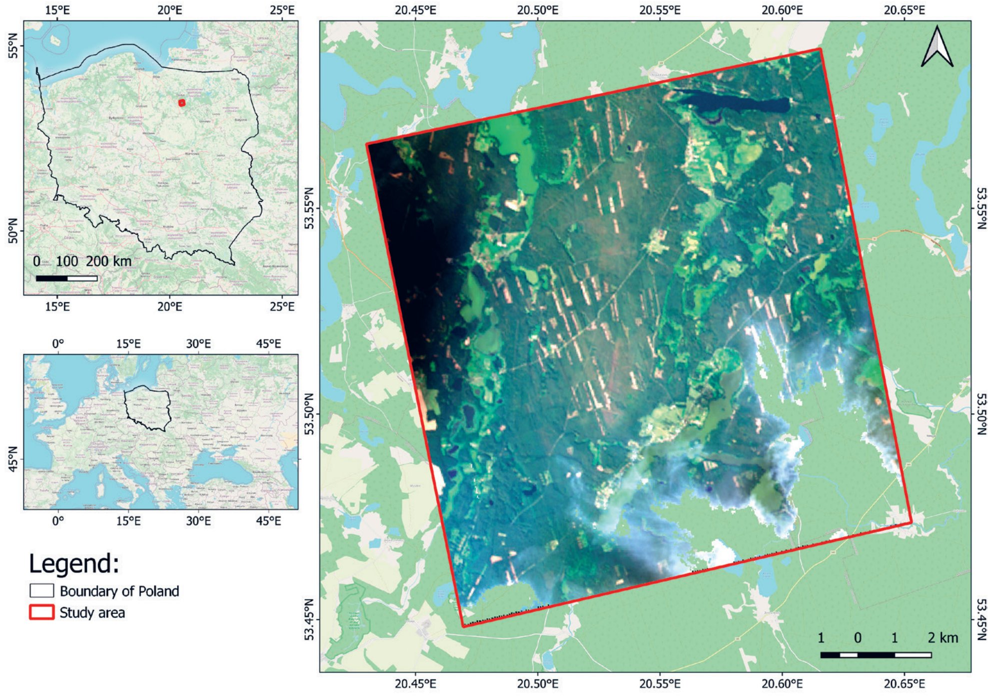


Fig. 1. The study area – the range of hyperspectral image CHRIS/PROBA – the base map OpenStreetMap

Source: www.openstreetmap.org

For the selected area, the set of hyperspectral data covering five scenes recorded in various angles: –55°, –36°, 0°, 36°, 55° was downloaded. Hyperspectral data of CHRIS (Compact High Resolution Imaging Spectrometer) sensor, put on satellite PROBA-1 (The Project for On-Board Autonomy), were obtained from the repository of the European Space Agency (ESA) [14]. The scene covered the area south of the Omulew Lake (Fig. 1) and was recorded on August 3, 2018 in the NADIR mode. The selected image had 62 spectral channels in Visible and Near Infrared (VNIR) (400–1050 nm) range, spatial resolution 34 m, processing level 1A [29].

Moreover, multispectral image from the MSI (MultiSpectral Instrument) sensor of the Sentinel-2 satellite records electromagnetic radiation in the range of VNIR and Short-Wave Infrared (SWIR). The Sentinel-2 image, processing level 2A, was obtained free of charge from SentinelHub [14]. The image was recorded on September 20, 2018 in 13 spectral channels of spatial resolution 10 m (VNIR), 20 m (SWIR1), 60 m (SWIR2).

To prepare test and control samples, the data of vector BDOT 10k (Baza Danych Obiektów Topograficznych – Database of Topographic Objects) were applied. The database (updated March 2019) is available free of charge in vector shapefile format from geoportal.gov.pl [30]. It is a database containing vector representation of topographic objects with their description at a scale of 1:10,000. The "PTLZ" layer, including land cover objects (wooded and forested areas), was taken for the analysis.

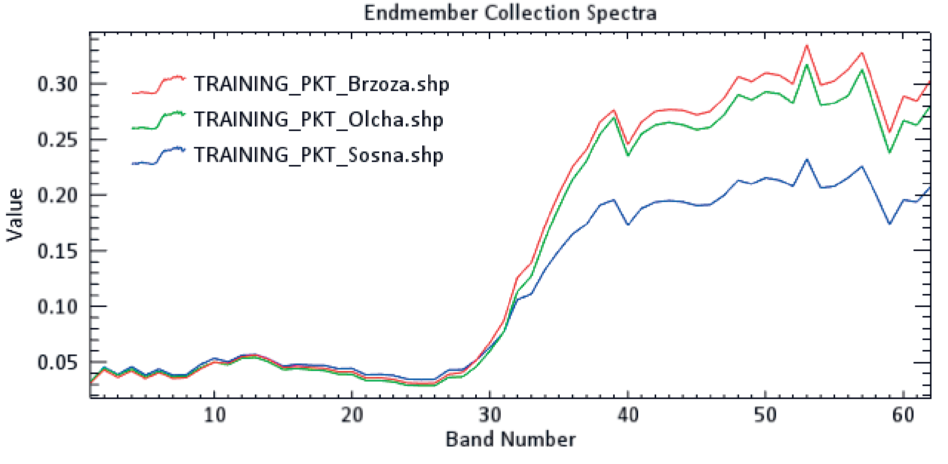
3. Methods

The processing of satellite data for the classification of forest communities was carried out in several stages, depending on the level of image processing. In case of the data of Sentinel-2 (level 2A), the obtained image was ready for the analysis (after radiometric, atmospheric and geometric correction. Channels of VNIR and SWIR1 range (10 channels) were combined in one image file and re-sampled to 20-meter resolution. We excluded three channels with 60-meter resolution (band 1 – Coastal aerosol, band 9 – Water vapour, band 10 – Cirrus) from the analysis as they were not useful for the purposes of a forest survey. In the case of the CHRIS/PROBA images (level 1A), it was necessary to carry out further stages of pre-processing, e.g., noise reduction [31], masking of clouds and atmospheric correction [32]. These procedures were carried out in ESA SNAP Toolbox. Additionally, Cross-Track Illumination Correction was carried out in ENVI for lines with the function of polynomial of third degree [33]. In the final stage of pre-processing, a geometric correction in CATALYST Professional software using a math model was carried out. Seven ground control points (GCPs), regularly distributed throughout the image, were used. The terrain coordinates of GCPs were obtained from an aerial orthophotomap and a digital elevation model (SRTM-Shuttle Radar Topography Mission). As a result of aerotrangulation, the following accuracies were obtained: RMS = 3.41 m, RMSX = 2.03 m, RMSY = 2.74 m. Orthorectification was performed using the cubic convolution interpolation method.

The study area was limited to forest areas. To carry out this, a mask covering the cloud-covered part of the image was also applied. Then, data redundancy reduction and elimination of channels affected by radiometric "smile" errors were performed. For this purpose, the image was transformed using the Minimum Noise Fraction (MNF) procedure [33, 34] implemented in ENVI software. After careful analysis, a set of 10 channels (1, 2, 4, 6, 7, 12, 11, 15, 17, and 18) containing the largest amount of spectral information and the least noise were selected from the image containing 62 channels after MNF transformation. It is an approach known from literature [27, 35–37] and used in the preprocessing of hyperspectral images, which are subjected to classification. This approach makes it possible to reduce the number of channels and thus counteract the Hughes effect.

Based on color compositions from MNF channels and vector data, the BDOT, training and control samples were prepared for the classification and accuracy estimation. For the districts of: Olsztyn, Szczytno, and Nidzica, the traverses of the BDOT layer representing the same tree genus were aggregated. Three genera of trees occurring in the biggest clusters were selected for the classification. These were: birch (*Betula*), alder (*Alnus*) and pine (*Pinus*). Due to too small area (<1%) and the lack of the possibility to make training/control parcels of a sufficient number of pixels, other genera: beech (*Fagus*), ash (*Fraxinus*), linden (*Tilia*), larch (*Larix*)) were rejected. On the other hand, the clusters of oak (*Quercus*) and spruce (*Picea*) were eliminated because of the thick cloud cover in the area where these genera occurred in the Chris image. Based on the prepared training samples, spectral curves were generated (Fig. 2).

a)



b)

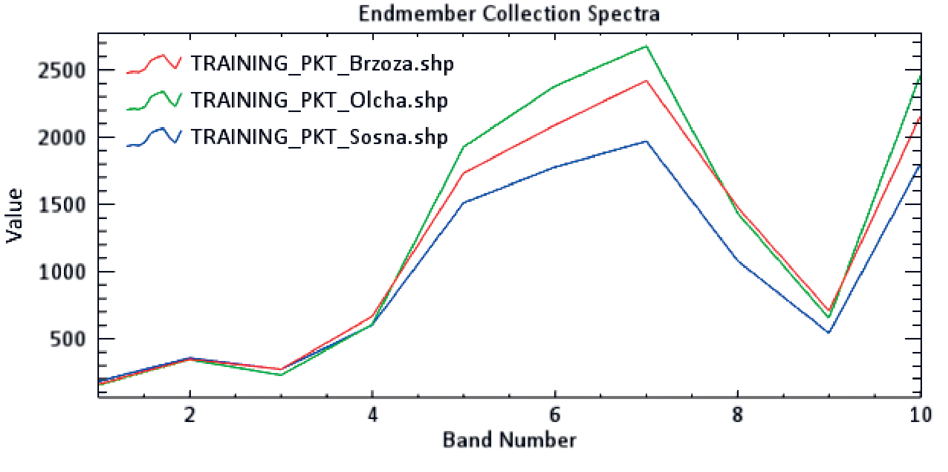


Fig. 2. Spectral curves of the classified genera of trees, based on images of: a) CHRIS/PROBA; b) Sentinel-2

Images of CHRIS/PROBA and Sentinel-2 were classified by two types of classifiers using ENVI software. The first type includes methods based on the comparison of spectral curves of each image pixel with the pattern curves representing the data of the given class. These are methods dedicated to the classification of hyperspectral images with much higher spectral resolution than in multispectral images. The Spectral Angle Mapper (SAM) [35, 36] method was applied, based on the comparison of spectral angles between the pattern vector and the vector of the examined pixel. The spectral curves generated for pine, birch, and alder were used. Based on testing, spectral angle values of 0.5 radian and 0.2 radian were used for the CHRIS/PROBA and Sentinel-2 images, respectively.

The second method was the Mixture Tuned Matched Filtering (MTMF) method [36, 37]. This algorithm defines the linear spectral combination of fractions/components of each pixel. As an input file for MTMF classification, the image after MNF transformation (10 selected channels) and reference spectral curves transformed to MNF space were used.

The second type of classification method used in this study is a machine learning (ML) method: Support Vector Machine (SVM) [38, 39]. ML algorithms are "universal approximators", they learn the behavior of the system from a set of training data and do not require prior knowledge of the nature of the relationships between the data [38]. These methods have been very popular in recent years for image classification.

For both image types (hyperspectral and multispectral), the SVM algorithm was applied and assuming the following parameters: kernel type RBF (Radial Basis Function), with a probability threshold of 0.6 for CHRIS/PROBA and 0.1 for Sentinel-2.

The accuracy of classification was estimated based on the Confusion Matrix and the following parameters: overall accuracy (OA), producer accuracy (PA), and user accuracy (UA), kappa coefficient, omission error (OE) and commission error (CE) [40].

4. Results and Discussion

The results of SAM, MTMF, and SVM classification made for the hyperspectral image are presented in Figure 3. The results obtained with three classifiers (SAM, MTMF, SVM) for the multispectral image are presented in Figure 4. The parameters of estimated accuracy of classification can be seen in Tables 1 and 2.

The hyperspectral images were classified with varying accuracy depending on the classifier used. The OA accuracy value ranged from 53% (MTMF) to almost 72% (SVM) (Tab. 1). In the SAM and MTMF classification images (Fig. 3), a noticeable "zonality of classes" can be observed, which may be caused by remaining error "smile". SVM method proved to be much less sensitive to this type of interference.

SAM method in the classification of the hyperspectral image achieved the overall accuracy of 62% (kappa = 0.5). In the case of the accuracy of the classification of subsequent trees, the best classified was pine, for which the producer's accuracy was 70%. Much lower producer's accuracy was obtained for birch (58%) and alder (52%). The omission errors in case of broad-leaf trees were over 42%, while the commission errors were around 20% (Tab. 1).

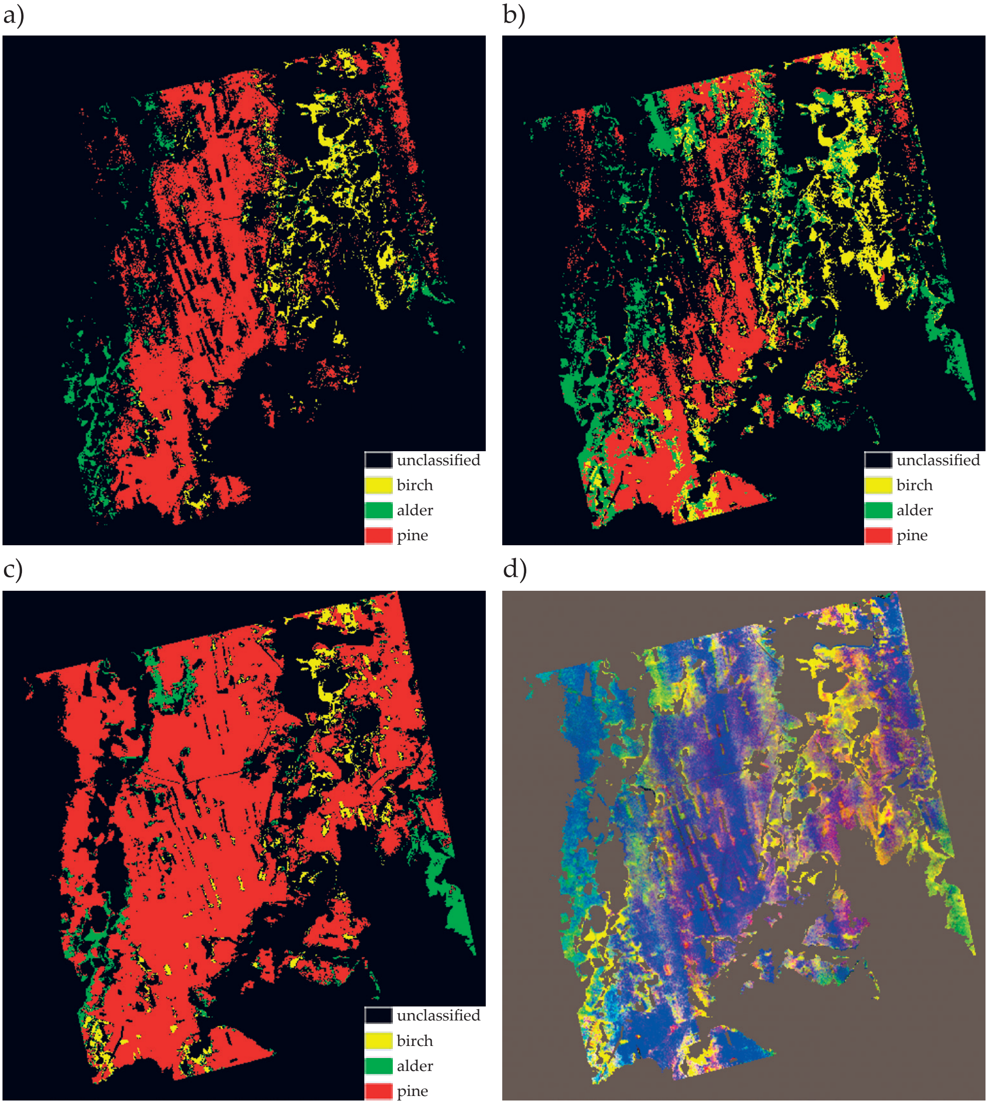


Fig. 3. The result of the classification of the CHRIS/PROBA hyperspectral image with different methods: SAM (a), MTMF (b), and SVM (c); color composition made of the fraction image obtained in MTMF classification: R – pine, G – alder, B – birch (d)

The classification with the MTMF method gave the lowest values of total accuracy (53%). A large part of the image was attributed to the class of unclassified areas. One should notice very low producer's accuracy (PA = 52%) for the pine class, which for SVM classifiers gave the best results (above 90%). In the case of broad-leaf trees, the alder achieved the highest level of accuracy among all the tested classifiers (PA = 64%). This was due to a large commission error (EC = 47%) while simultaneously being underestimated for the birch class, for which the omission error was as high as 58% (Tab. 1).

The SVM machine learning methods obtained values of overall accuracy at a level of 72% [9]. The best classified genus occurring in the studied area was pine (*Pinus*), for which the producer's accuracy was as high as 96% for SVM [12]. The lowest producer's accuracy was obtained in both methods for alder – about 50%. In case of the second broad-leaf genus (birch) – the producer's accuracy was 54% for the SVM classifier (Tab. 1).

Table 1. The results of the classification accuracy assessment of the CHRIS/PROBA image

Classifier	Type of tree	Overall accuracy (OA) [%]	Kappa	Producer accuracy (PA) [%]	User accuracy (UA) [%]	Error of omission (EO) [%]	Error of commission (EC) [%]
SAM	pine	62.1	0.5	70.5	100.0	29.6	0.0
	alder			52.0	81.3	48.0	18.8
	birch			57.7	79.0	42.3	21.1
MTMF	pine	52.6	0.4	52.3	95.8	47.7	4.2
	alder			64.0	53.3	36.0	46.7
	birch			42.3	84.6	57.7	15.4
SVM	pine	71.6	0.6	95.5	91.3	4.6	8.7
	alder			48.0	80.0	52.0	20.0
	birch			53.9	87.5	46.2	12.5

In the case of the classification of the Sentinel-2 multispectral image (Fig. 4, Tab. 2), the highest accuracy was reached with MTMF, for which the overall accuracy equaled 82%, the kappa coefficient was 0.72. The lowest overall accuracy of S-2 image was obtained for the SAM classifier (OA = 65%, kappa = 0.5).

It was worth noticing that the SVM and SAM classifiers reached very similar levels of classification accuracy to those in case of hyperspectral image – the difference was only 1% and 4%, respectively. This can result from similar image parameters obtained after preprocessing – both images contained 10 channels.

The Sentinel-2 image achieved overall accuracy at a very good level: SAM (65%), SVM (73%), MTMF (82%). One can state that the multispectral image can be successfully applied in the classification of forest communities and other forms of land cover [6, 17, 18]. A great advantage of this type of data is their processing level 2A, which significantly reduces the duration and costs of work. Temporal resolution of Sentinel-2 images (2–3 days) gives the opportunity to monitor forest communities in large areas, e.g., for national parks, in which human intervention in natural environment is forbidden [41].

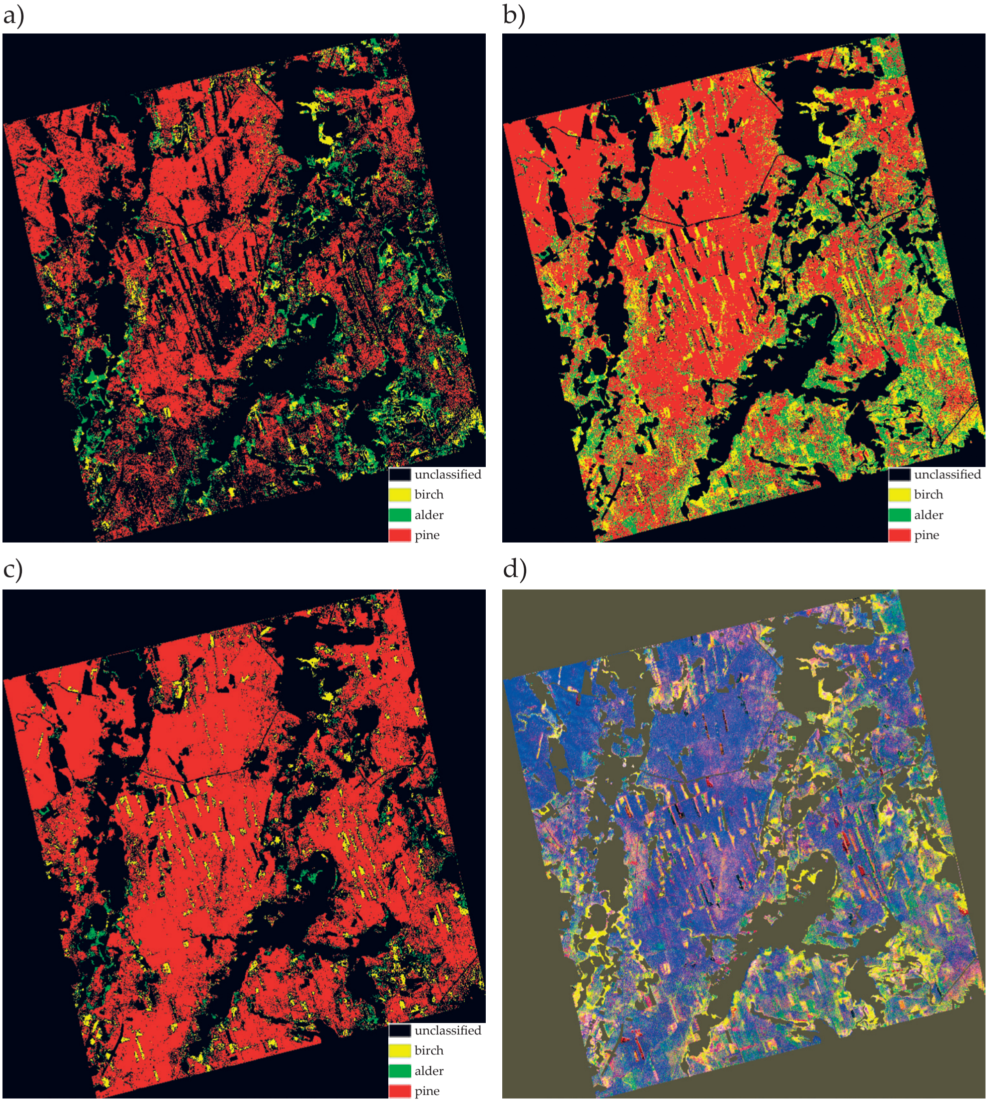


Fig. 4. The results of the classification of multispectral image Sentinel-2 with methods: SAM (a), MTMF (b), and SVM (c); color composition made of the fraction image obtained in MTMF classification: R – pine, G – alder, B – birch (d)

It was also assumed that, due to higher spectral resolution (number of channels), better results would be obtained for the CHRIS/PROBA hyperspectral image. The lower accuracy of classification obtained for the MTMF classifier may be attributed to various factors. One has to regard the difference in spectral ranges, in which CHRIS/PROBA and S-2 were recorded. The lack of channels in SWIR spectral range, could be an important reason lowering the accuracy of classification [6, 17]. This is especially the case with the MTMF classifier, which is based on the analysis of spectral curves.

Moreover, an important aspect in the context of the assessment of the possibility of using the CHRIS/PROBA hyperspectral image is cloud cover and differences in illumination, which cause significant deformations in the spectral answer given by the subsequent objects [42]. Most probably, the pre-processing and MNF transformation were insufficient to obtain a noise-free image. The effect of smiling was visible in the images after the classification (SAM, MTMF).

Table 2. The results of the classification accuracy assessment of the Sentinel-2 image

Classifier	Type of tree	Overall accuracy (OA) [%]	Kappa	Producer accuracy (PA) [%]	User accuracy (UA) [%]	Error of omission (EO) [%]	Error of commission (EC) [%]
SAM	pine	72.6	0.6	61.4	100.0	38.6	0.0
	alder			84.0	75.0	16.0	25.0
	birch			53.9	87.5	46.2	12.5
MTMF	pine	82.1	0.7	93.2	95.4	6.8	4.7
	alder			60.0	83.3	40.0	16.7
	birch			84.6	68.8	15.4	31.3
SVM	pine	65.3	0.5	90.9	97.6	9.1	2.4
	alder			52.0	86.7	48.0	13.3
	birch			61.5	94.1	38.5	5.9

Certainly, the difference in spatial resolution of the images (CHRIS – 34 m, Sentinel-2 – 20 m) also influenced the classification results. The crown width for the box birch is 5–10 m, black alder and limber pine reach a width of about 2 m [43]. The spectral reflectance value of a single pixel may represent an averaging of the spectral characteristics of several or even a dozen trees. It depends on the species of trees, their vegetative state, age, canopy closure, or factors related to terrain [44]. Thus, the smaller field pixel dimension improves the quality of forest community classification.

5. Conclusion

The supervised classification achieved the best result for the Sentinel-2 multispectral image with the application of MTMF method. The obtained overall accuracy was 82%, the kappa coefficient equaled 0.7. The results of overall accuracy for the hyperspectral image were 10% lower. The best result was for the SVM classifier, where OA = 72% and kappa coefficient was 0.6. Definitely worse classification results were obtained for the methods based on spectral curves. This can be caused by sensitivity of these methods to radiometric errors, which, despite pre-processing could not be totally eliminated. Among the three classified genera (pine, alder, birch), the best results were obtained for pine (producer's accuracy over 90%). Probably, the important factor influencing such a result was the habitat advantage of that species (above 95% of the study area). Additionally, the spectral curves of broad-leaf trees (alder and birch) have a very similar course, which could cause mistakes in the classification and a decrease in the producer's accuracy for these genera. Nevertheless, one can state that the results of overall accuracy were quite satisfactory, both for the CHRIS/PROBA hyperspectral, and Sentinel-2. Undoubtedly, the CHRIS/PROBA hyperspectral is a source of great information potential referring to the forms of land cover. Nonetheless, the authors plan a deeper analysis of a larger number of the images of the same area, of higher radiometric homogeneity of the area, obtained during cloudless days. The results obtained will make a reference point in future analyses using a similar set of image data.

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