SYLWAN 166 (3): 194-210, March 2022
https://doi.org/10.26202/sylwan.2022011
Journal homepage: https://sylwan-journal.pl

ORIGINAL PAPER

Classification of ‘potential’ forests based on remote sensing data

Tomasz Hycza✉, Maciej Lisiewicz, Patryk Waraksa, Krzysztof Stereńczak

Forest Research Institute, Department of Geomatics, Sękocin Stary, Braci Leśnej 3, 05-090, Raszyn, Poland

ABSTRACT

The aim of this study is to estimate the area with forest vegetation that does not yet meet the criteria formulated in the FAO/UN definition (minimum height 5 m, minimum canopy cover 10%, minimum area 0.5 ha), but will potentially meet them in the future (5 years or more, depending on the individual site conditions), which means that (according to the definition) they also represent forest areas. The study was conducted in the Białowieża Glade. Tree species were classified individually and then divided into two groups: those that will reach a height of 5 m in the future and those that will not (grey willow, hawthorn). Hyperspectral (reduced with MNF transformation) and ALS-based features were used for classification with the SVM algorithm. Classification accuracy based on ALS data was better than that of hyperspectral data for individual species but similar for the two species groups – 95.5% (Kappa 87.5%). Information about species and height was used to perform the classification of a fishnet layer into ‘forests’, ‘potential forests’ and ‘non-forests’, with an accuracy of 96% (Kappa 87.7%). A map of forests and potential forest vegetation was created in the form of a thematic map, taking into account height, canopy cover, area of the complex and land use. This study provides new solutions in the context of climate change, deforestation and the need for reporting the forest area by individual countries (including Poland) to the FAO/UN.

KEY WORDS

species, classification, hyperspectral data, ALS data, potential forest area, reporting, FAO/UN forest definition

Introduction

Globally, there are various forest definitions. Some of them are formulated in national laws, others are international. The differences in forest definitions result from the different characteristics of forest vegetation around the world and the different forms of land use and forest management (Putz and Redford, 2009). There are also economic and political reasons why different countries consider certain areas to be forests (Sasaki and Putz, 2009). Poland (like many other countries) is required to its report forest area to the Food and Agriculture Organization of the United Nations (FAO/UN). For details, see the forest definitions of the 1991 Forest Act and the FAO/UN (Forest Resources Assessment 2004, 2007, 2012; Table 1). Post-agricultural areas with forest succession, which have not been officially reclassified from agricultural to forest lands, are not

✉e-mail: t.hycza@ibles.waw.pl

Received: 23 February 2022; Revised: 15 April 2022; Accepted: 27 April 2022; Available online: 17 June 2022

Table 1.
Criteria for delimiting forest areas

Variables	Act on Forests 1991 (Poland)	FAO/UN
Minimum area [ha]	0.1	0.5
Minimum height [m]	–	5
Minimum crown coverage [%]	–	10
Width of the forest complex [m]	–	–
Land intended for renovation	yes	yes
Land intended for natural succession	yes	yes
Hunting plots	yes	yes
Christmas tree plantations	yes	yes
Agricultural land (according to the land registry) with secondary succession	no	yes
Land related to forest management	yes	yes
Orchards and urban greenery	no	no

considered forests according to the Law on Forests, contrary to the FAO/UN definition, which does not refer to the official status of the land with forest vegetation (Jabłoński, 2015; Jabłoński *et al.*, 2017).

Aerial and satellite imagery have been successfully used since the early 2000s to estimate forested areas, with an 80% accuracy (Kunz *et al.*, 2000; Haapanen *et al.*, 2004; Wężyk and de Kok, 2005; Próchnicki *et al.*, 2006; Wang *et al.*, 2008; Pekkarinen *et al.*, 2009; McRoberts, 2011, 2012; Hościło *et al.*, 2015; Kolecka *et al.*, 2015; Thompson *et al.*, 2016; Szostak *et al.*, 2017). Using airborne scanner lasing (ALS) data makes it possible to obtain similar or better estimates of forest area (Castillo-Núñez *et al.*, 2011; McRoberts *et al.*, 2012; Pujar *et al.*, 2014; Kolecka *et al.*, 2015; Naesset *et al.*, 2016; Thompson *et al.*, 2016; Szostak *et al.*, 2017). However, there is a lack of studies that detect potential forest areas, namely areas covered with trees which do not reach the required height (5 m) and canopy cover (10%) but are expected to, in 5 years or more, depending on the individual site conditions (according to the FAO/UN definition).

To determine whether or not an area will become forest (as defined by the FAO/UN), it is critical to determine what tree species are present and whether they will reach the required height under certain growth conditions. In this context, remote sensing is useful for determining tree species composition over large areas (Potapov *et al.*, 2008; Fassnacht *et al.*, 2016).

Airborne laser scanner data are useful to perform species-based classification based on structural, spectral or intensity features (Yao *et al.*, 2012; Hovi *et al.*, 2016; Kamińska *et al.*, 2021; Michałowska and Rapiński, 2021). The highest overall accuracy of species classification based on the ALS data was achieved using the full waveform data (Hovi *et al.*, 2016). However, radiometric features also allow for a high accuracy (You *et al.*, 2020). Combining radiometric features with ALS elevation information could allow us to take advantage of the complementary benefits of the different information sets needed for species classification, thereby improving the overall accuracy by up to 93% (Zhang and Liu, 2012; Shi *et al.*, 2018; You *et al.*, 2020).

The continuous spectral information contained in hyperspectral data appears to be extremely useful for distinguishing tree species with similar spectral characteristics (Farreira *et al.*, 2016; Wietecha *et al.*, 2017). For example, Dalponte *et al.* (2012) achieved a higher classification accuracy for seven species and non-forest class, five groups of species and no forest class and two groups of species (coniferous, deciduous) and non-forest class using the SVM method (74.1-95.8%) compared to Random Forests (RF) (69.4-94.4%) performed on the hyperspectral and ALS data representing the study area in northern Italy. Similarly, Ghosh *et al.* (2014) achieved a higher accuracy using the SVM classifier method (81-92.7%) than RF (78-81.5%).The combination of LiDAR data with multispectral or hyperspectral imagery can further improve the classification accuracy (Liao *et al.*, 2018, 2019; Shi *et al.*, 2018, 2019; Yang *et al.*, 2019).

In this work, the SVM algorithm was used to perform supervised parametric pixel-based species classification of hyperspectral data and ALS features. Support Vector Machines (Vapnik, 1999) is a supervised, nonparametric machine learning algorithm and performs well on high-dimensional data, often outperforming other algorithms in comparative studies (Hughes, 1968; Melgani and Bruzzone, 2004; Dalponte *et al.*, 2008; Mountrakis *et al.*, 2011; Heinzel and Koch, 2013). The SVM classifier searches for the optimal hyperplane to discriminate between defined target classes, using kernels to expand the feature space (James *et al.*, 2013). The radial kernel tends to handle nonlinear data well (James *et al.*, 2013) and has been used in previous studies on tree species classification (*e.g.*, Fassnacht *et al.*, 2014; Ghosh *et al.*, 2014).

In this context, the aim of the present study is to classify tree species in the Białowieża Glade into two groups – those that will reach a height of 5 m and those that will not, with the goal to determine which dataset (hyperspectral or ALS) provides better classification results, to develop a methodology for mapping areas of potential forest vegetation and to estimate the area of potential forest vegetation in the Białowieża Glade.

Materials and methods

STUDY AREA. The Białowieża Glade (Fig. 1) is located in the heart of the Białowieża Forest, near the border to Belarus. The clearing is 14 km^2 in size and has the shape of a square, with a side length of 4 × 4 km. The Białowieża Glade is a perfect example of an area with abandoned agriculture, where secondary succession is in full swing. The most common species forming the succession are birch, aspen, alder, hornbeam and willow (Pabjanek, 2003).

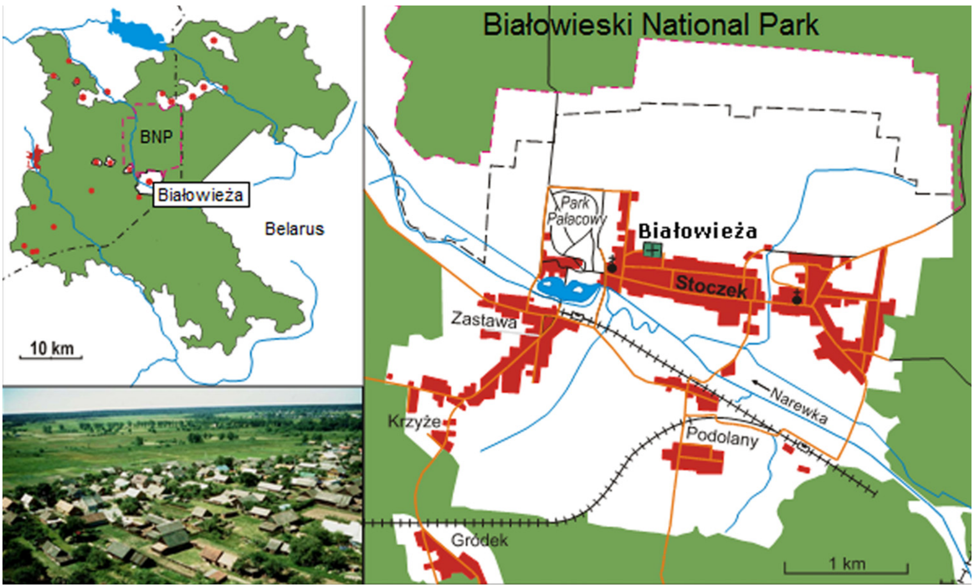

Fig. 1.
Study site-Białowieża Glade (Pabjanek, 2003)

Data. In August 2019, 40 hyperspectral flight strips were acquired using a HySpex VNIR-1800 and as SWIR-384 camera. The HySpex VNIR-1800 operates in the 0.4-1.0 µm spectral range, covered by 182 bands, and the HySpex SWIR-384 operates in the spectral range of 1.0-2.5 µm, covered by 288 bands and with 384 spatial pixels. Images were acquired with a spatial resolution of 2 m; both sensors provide images with a radiometric resolution of 16 bits (NorskElektroOptikk AS, 2019). Images from the two sensor systems were stacked, resulting in images with a spatial resolution of 2 m in 430 bands.

All pre-processing, namely orthorectification, geometric and atmospheric corrections, was performed by the data provider (MGGP AERO co.). The processing steps included a PARGE geometry correction based on GPS/IMU data. Subsequently, atmospheric correction was performed using the MODTRAN5 model implemented in the ATCOR4 software.

Airborne laser scanner data (ALS) were acquired in August 2019, using a Riegl VQ-780i full waveform system (RIEGL Laser Measurement Systems, Austria); the obtained point cloud had an average density of 19 pts/m^2. The entire Białowieża Forest was covered by 88 flight lines, with a 20% side overlap. Data were collected with a maximum scan angle of ±60° and a laser beam size of 0.25 m. A digital terrain model (DTM) and a digital surface model (DSM) were created from the ALS data (both with a resolution of 0.5 m).

The data were created for the project LIFE+ – ForBioSensing PL 'Comprehensive Monitoring of Stand Dynamics in the Białowieża Forest using Remote Sensing Techniques'. The entire area of the Białowieża Glade was classified with the adjacent buffer zone of the Białowieża Forest stand in a width of 100 m.

Areas without forest vegetation extraction. Areas with a canopy height model (CHM) (created on the basis of the ALS point cloud) of less than 1 m were excluded from the analysis because we did not classify cropland, meadows and pastures. Areas without vegetation were also excluded from the analysis, using a vegetation mask based on the mNDVI705 vegetation index (Sims and Gamon, 2002) calculated on the basis of hyperspectral data using spectral bands of 750, 705 and 445 nm. All pixels with mNDVI705 index values below 0.44 were excluded. The threshold was derived using visual assessment and has been shown to reliably distinguish areas with and without forest vegetation throughout the Białowieża Forest by Modzelewska *et al.* (2020). The equation is as follows:

$$\text{mNDVI705} = (750\text{ nm} - 705\text{ nm}) / (750\text{ nm} + 705\text{ nm} - 2 \cdot 445\text{ nm})$$

Rivers, ponds, water bodies, cultivated land, cemeteries, roads, debris, telephone poles, parking lots, landfills, apiaries, raspberry fields, currant fields, orchards and parks (*i.e.*, agricultural or municipal land) were excluded from further analysis of land area as defined by the FAO/UN with a vector layer representing the Land and Buildings Evidence Map. Some of the areas could have been already extracted in the previous step as the mask layers overlap.

The remaining land, cropland, grassland (possibly abandoned), fallow land, wasteland, plantations, forest edges, trees and other green areas were included in the analysis (Fig. 2).

ALS feature extraction. Classification features were derived from height measurements of ALS ('structural features') and the ALS intensity distribution ('intensity features'). Intensity and some of the structural features were calculated only for ALS points above the mean half of the highest ALS point (H=Hmax/2) recorded in a given segment (Kamińska *et al.*, 2018). Intensity features were calculated only up to the first returns. Structural features related to tree height were omitted due to overfitting the model to classify two groups (trees up to 5 m and over 5 m).

As many of the characteristics were highly correlated, Pearson´s correlation coefficient was used to determine pairwise correlations. Starting with the most important variable and moving to the less important ones, highly correlated characteristics (r>0.9) were systematically removed, leaving a set of the 15 most important and uncorrelated predictors. Table 2 provides an overview of all 15 features used in the classification.

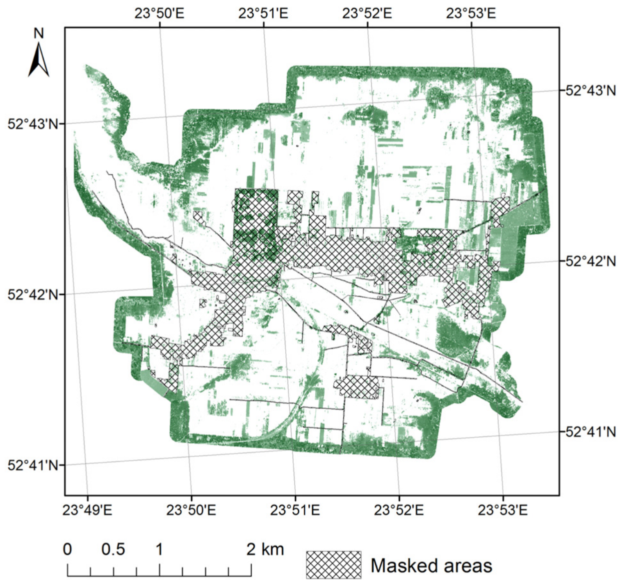

Fig. 2.
The hyperspectral image after masking

Table 2.
Features derived from the ALS data

Feature	Description
Structural features	
H_{cv}	The coefficient of variation of all returns above half height of the segment from the point cloud
$H_{dist\_1\_2}$	The mean of the distance between the first and second return of each point
CanRR	The canopy relief ratio of points for all returns above half height of the segment from the point cloud: (avg(X)-min(X))/(max(X)-min(X))
P_{FRAH}	The percentage of first returns above half height of the segment in relation to first returns from the whole point cloud
P_{ARAH}	The percentage of all returns above half height of the segment in relation to first returns from the whole point cloud
R_{crown}	The ratio of the number of points at a distance of ±25 cm from CHM to all points classified as vegetation
R_{s_all}	The ratio of the first or single return points to all return points classified as vegetation
R_{g_all}	The ratio of points classified as the ground to all return points
Intensity features	
I_{max}	The maximum of the intensity values
I_{mode}	The mode of the intensity values
I_{sd}	The standard deviation of the intensity values
I_{IQR}	The inter-percentile range of the intensity values
I_{kurt}	The kurtosis of the intensity values
I_{p10}	The 10th percentile of the intensity values
I_{p90}	The 90th percentile of the intensity values

ALS DATA CLASSIFICATION PROCESS. To classify tree species based on ALS data, we used individual tree segments delineated according to the method of Stereńczak *et al.* (2020). Polygonal layers representing crowns of individual trees (with a given area and height) created for the project LIFE+ – ForBioSensing PL 'Comprehensive Monitoring of Stand Dynamics in the Białowieża Forest using Remote Sensing Techniques' were used for the analyses. The segmentation method uses the CHM and adaptive kernel windows in relation to tree height; taller trees were smoothed with a larger kernel window and shorter trees with smaller kernel windows. In total, three groups of trees were defined with respect to height for coniferous and deciduous tree species. Evaluation of the results shows that the method works well for dominant trees in the sample and can be used to accurately detect trees divided into coniferous, deciduous and mixed trees, namely 85%, 85% and 75%, respectively.

We adopted a threshold/minimum of 30 samples (one for each segment representing a single tree) per species and ultimately included 317 trees of 10 species in the study (30 to 33 per species). We tested different values in the fitting process with the specific optimal parameters based on the highest overall classification accuracy. To avoid overfitting the classification model, a five-fold cross-validation was performed, repeated 20 times, and the mean classification accuracy indices were determined. Classification and optimisation were performed using the Caret package in R (R Core Team, 2021). Classification 1 was performed for 10 tree species individually, and the results were aggregated into two species groups (those that will reach a height of 5 m and those that will not), referred to Classification 2.

HYPERSPECTRAL DATA MINIMUM NOISE FRACTION TRANSFORMATION. Although hyperspectral data are highly informative, spectrally contiguous bands are correlated with each other, which can affect the classification success. To obtain uncorrelated components from hyperspectral data, we applied minimum noise fraction (MNF) transformation (Green *et al.*, 1988). In previous studies, using MNF bands as input to classification algorithms instead of the original hyperspectral bands has led to better results (Zhang and Xie, 2012; Fassnacht *et al.*, 2014; Ghosh *et al.*, 2014).

The MNF uses cascaded PCA transformation to separate information and noise. In the first step, noise and information are separated, and subsequently, the new and uncorrelated components are arranged in decreasing order according to the eigenvalues. The MNF bands are divided into two categories, where the first components with eigenvalues above 1 typically contain relevant information, whereas those with eigenvalues below 1 are typically noisy (Vincheh and Arfania, 2017). Finally, the components 1 to 19 (eigenvalues 2) were selected as input for classification.

HYPERSPECTRAL DATA CLASSIFICATION PROCESS. The reference pixels for the classification of hyperspectral data were divided into 50% training (150) and 50% (150) test pixels (2×15 points for each class) to obtain a high classification accuracy. The reference pixels were located in areas in which particular species represented the vegetation, determined during the field inventory performed in April 2021. No more than one point represented a homogenous forest patch, and we avoided the location of points in areas with a mixed species composition.

Classification 3 was performed for 10 tree species individually (Hornbeam – *Carpinus* L., Alder – *Alnus* Mill., Oak – *Quercus* L., Willow – *Salix caprea* L., Poplar – *Populus* L., Grey Willow – *Salix cinerea* L., Hawthorn – *Crataegus* L., Birch – *Betula* L., Pine – *Pinus* L., Spruce – *Picea* A. Dietr.), whereas Classification 4 was performed for the six species groups created based on the similarity/closeness of the spectral profiles (Hornbeam+Alder, Oak+Willow+Poplar, Grey Willow, Hawthorn, Birch, Coniferous) (Fig. 3). The results of Classification 4 (six species groups) were aggregated into two species groups ('Forest species' and 'Non-forest species') and referred to as

Classification 5. The parameters for the SVM classification were kernel type: radial basis function, gamma in kernel function: 1, penalty parameter: 100, pyramid level: 0, classification probability threshold: 0.

Estimating the area of 'potential forests'. Geometric vegetation parameters (height, crown projection area – area under the single tree crown, minimum complex area – polygon representing a single forest complex) were used to classify the area with forest vegetation (Hycza *et al.*, 2021); land use information was not used. Polygons representing individual tree crowns from segmentation were provided with information on their height and crown projection area, and the area with forest vegetation was calculated according to the FAO/UN definition.

The area for which percent cover was calculated was artificially generated by dividing the entire area to be analysed into a 0.01 ha (10×10 m) fishnet and dividing the total area of polygons representing tree canopies with a height of at least 5 m by the area of the fishnet (Straub *et al.*, 2008). The fishnets were created to produce a thematic map representing the vegetation of the entire study area with and without forest, as defined by the FAO/UN. The fishnets with woody vegetation ≥5 m and canopy cover ≥10% were classified as 'forest', and those with woody vegetation <5 m now but ≥5 m in the future and canopy cover ≥10% were classified as 'potential forests'. All other fishnets were classified as 'non-forest' (Fig. 4).

Accuracy estimation of 'forests', 'potential forests' and 'non-forests' was conducted using a series of 120 test points representing the three classes above, manually established in the study

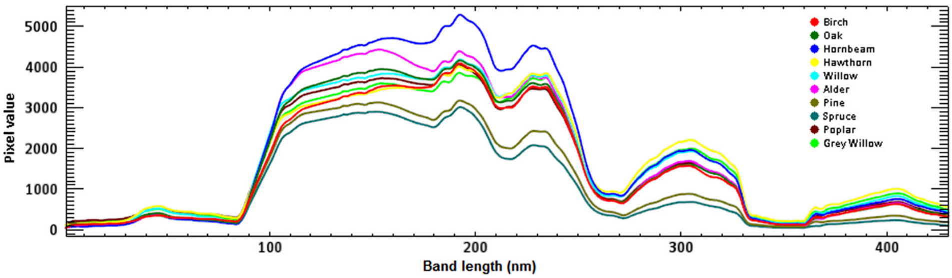

Fig. 3.
Spectral profiles for the individual species

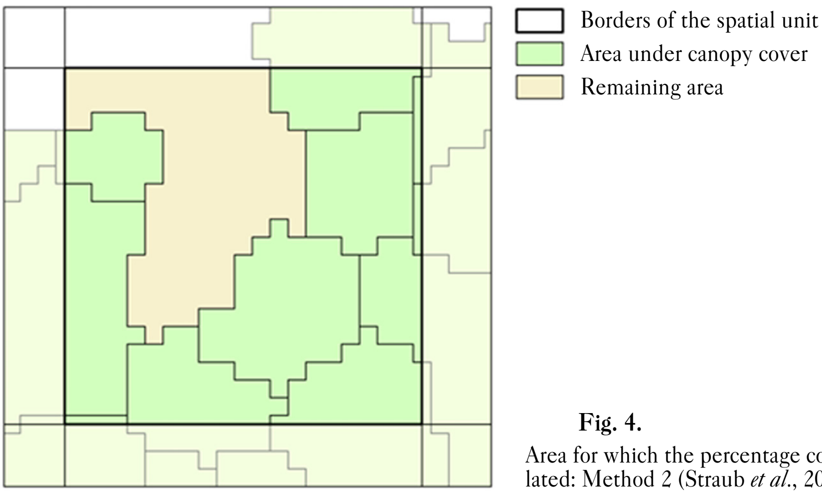

Fig. 4.
Area for which the percentage cover was calculated: Method 2 (Straub *et al.*, 2008)

area using the orthophotomap, the canopy height model and data from the site inventory conducted in April 2021. The results of the accuracy assessment are presented in Table 4.

Results

CLASSIFICATION INTO SPECIES. The images after MNF transformation and, in particular, the first 19 bands of the image and the 15 most important ALS features were subjected to the Support Vector Machine (SVM) classification algorithm. The results of the classification accuracy analysis are shown in Table 3.

The accuracy of Classification 4 (ALS data into 10 species) was 81.5% (Kappa 79.4%), with producer's and user's accuracy values >71% for particular species. The accuracy of Classification 3 (hyperspectral data into 10 species) was 67.3% (Kappa 63.7%). Pine and poplar were falsely classified as other species, and the producer's accuracy of willow was only 5%. The accuracy of Classification 4 (hyperspectral data into six groups) was 93.5% (Kappa 87.5%). Both producer's and user's accuracy were >85% (except for hawthorn), reaching 100% for coniferous species. The accuracy of Classifications 2 and 5 (into two groups) was similar with 95-96%.

Figure 5 shows the classification results for the selected part of the Białowieża Glade. Forest species were correctly classified, regardless of their height and age. Young spruce and mature forest vegetation were classified as 'forest species'. Grey willow, which does not reach a height of 5 m, was classified as a 'non-forest species'.

ESTIMATING THE AREA OF 'POTENTIAL FOREST' . Table 4 shows the area of networks representing forests, potential forests and no forests. In the Białowieża Glade, the class of 'forests' occupied 742.9 ha (HI) and 683.3 ha (ALS), and the class of 'potential forests' occupied 34.6 ha (HI) and 36.2 ha (ALS). The class of 'non-forests' occupied 1,034.8 ha (HI) and 1,092.7 ha (ALS). This means that more fishnets are classified in the 'forests' class with the hyperspectral data than with the ALS data.

Figure 6 shows the results of estimating the areas of 'forests', 'potential forests' and 'non-forests', based on the network thematic map, and reflects the actual condition shown in Figure 5. Mature trees were represented as 'forests', whereas young spruce trees were represented as 'potential forests' and grey willows as 'non-forests'.

ACCURACY ASSESSMENT OF 'FORESTS', 'POTENTIAL FORESTS' AND 'NON-FORESTS' AREA ESTIMATION. Accuracy estimation of 'forests', 'potential forests' and 'non-forests' was performed using a set of 120 test points representing these classes. The results of the accuracy estimation are presented in Table 5. Slightly better results (92.5%) were obtained with the hyperspectral data set than with the ALS data (90%). When classifying hyperspectral data, the producer's accuracy for 'potential forests' was 80%, and the user's accuracy was 97%. When classifying ALS data, the producer's accuracy for 'potential forests' was 72.5%, and the user's accuracy was 96.7%.

The areas of 'forests', 'potential forests' and 'non-forests' could not be compared with the data from a local database because the 'Forest law' of 1991 does not include the definition of a 'potential forest', therefore this kind of class does not exist in any database.

Discussion

The aim of this study was to classify the tree species in the Białowieża Glade into species that will not reach a height of 5 m (hawthorn, grey willow) and other species that will reach a height of 5 m when mature. This is important in the context of estimating and reporting potential for-

Table 3.
Classification results

	Classification 1	
	Overall accuracy [%]	Kappa coefficient [%]
	81.45	79.35
	Producer's accuracy [%]	User's accuracy [%]
Alder	73.5	73.9
Birch	89.5	77.5
Grey willow	88.5	89.0
Hawthorn	79.8	77.0
Hornbeam	95.1	92.0
Oak	73.0	75.1
Pine	89.8	89.8
Spruce	79.7	93.9
Poplar	68.0	85.6
Willow	71.0	61.5
	Classification 2	
	Overall accuracy [%]	Kappa coefficient [%]
	95.49	87.51
	Producer's accuracy [%]	User's accuracy [%]
Forest species	97.0	97.1
Non-forest species	90.5	90.4
	Classification 3	
	Overall accuracy [%]	Kappa coefficient [%]
	67,34	63.74
	Producer's accuracy [%]	User's accuracy [%]
Alder	90	75
Birch	80	100
Grey willow	100	50
Hawthorn	75	78.95
Hornbeam	95	82.61
Oak	45	81.82
Pine	0	0
Spruce	100	50
Poplar	0	0
Willow	5	100
	Classification 4	
	Overall accuracy [%]	Kappa coefficient [%]
	93.47	81.76
	Producer's accuracy [%]	User's accuracy [%]
Alder+Hornbeam	98.31	85.29
Birch	100	95.24
Coniferous	100	100
Grey willow	85	94.44
Hawthorn	65	92.86
Oak+Poplar+Willow	95	100
Classification 5		
	Overall accuracy [%]	Kappa coefficient [%]
	95.98	87.71
	Producer's accuracy [%]	User's accuracy [%]
Forest species	96.86	98.09
Non-forest species	92.5	88.1

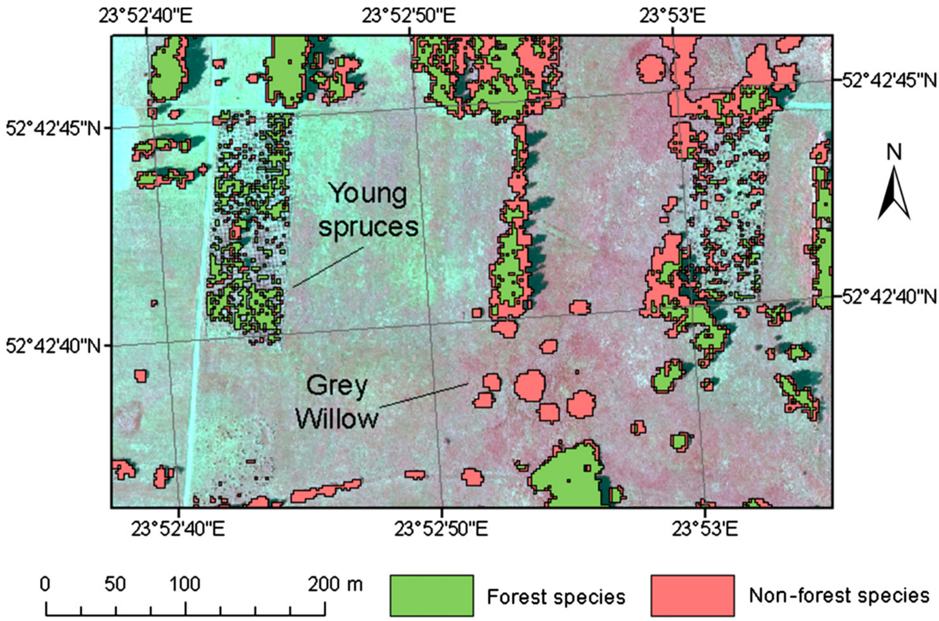

Fig. 5.
Classification results (two classes; based on hyperspectral data)

Table 4.
Area of fishnets representing 'forests', 'potential forests' and 'non-forests'

Class	Hyperspectral data (ha)	ALS data (ha)
Forests	742.9	683.3
Potential forests	34.6	36.2
Non-forests	1,034.8	1,092.7

est area according to the FAO/UN definition of forest. However, this issue is poorly addressed in the existing literature.

It is worth noting that among the species in the study area, only hawthorn and grey willow do not reach the maximum height of 5 m, of which the latter is genetically closely related to willow, which will reach the height of 5 m. The other species, including oak, birch, hornbeam, pine, spruce, poplar and alder, largely exceeded a height of 5 m when mature. We did not hold on rigidly to the 5-year criterion because the definition contains the following statement: 5 m or more, depending on the individual site conditions. Classification of the ALS data into 10 species was significantly better (81.4%) than classification using the hyperspectral data (67.3%). Classification of the hyperspectral data into two species groups was slightly better (96%) than classification of the ALS data (95%). The less species/group of species were classified, the higher the classification accuracy. The species classification accuracy (two classes) achieved in this study (95%-96%) is similar to that of Dalponte *et al.* (2009, 2012, 2013) – 95.8% (three classes), Ghosh *et al.* (2014) – 96.5%, Ghiyamat *et al.* (2013) – 92.6% (three classes) and Forzieri *et al.* (2012) – 85% (four classes), although it was carried out for very young trees.

In terms of the cost-benefit ratio, the ALS data seem to be more useful than the hyperspectral data, providing more reliable results for single species classification and almost the

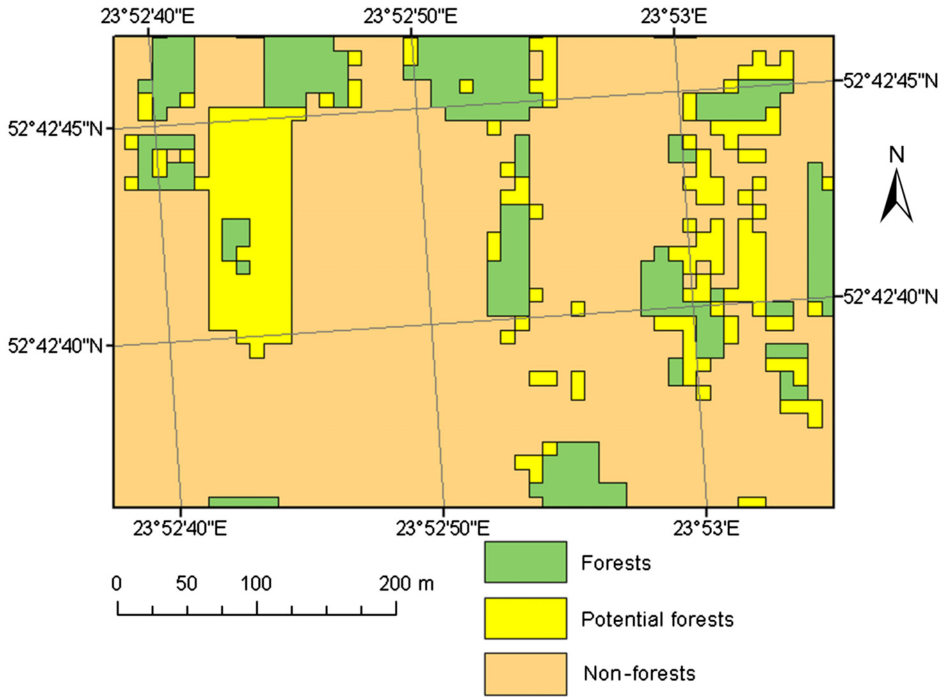

Fig. 6.
Map of 'forests', 'potential forests' and 'non-forests' (based on hyperspectral data)

Table 5.
Accuracy of the estimation of 'forests', 'potential forests' and 'non-forests'

Class	Hyperspectral data [%]	ALS data [%]
Overall accuracy	92.5	90.0
Kappa	88.8	85.0
Forests	Producer's accuracy – 100.0	Producer's accuracy – 100.0
	User's accuracy – 95.2	User's accuracy – 100.0
Potential forests	Producer's accuracy – 80.0	Producer's accuracy – 72.5
	User's accuracy – 97.0	User's accuracy – 96.7
Non-forests	Producer's accuracy – 97.5	Producer's accuracy – 97.5
	User's accuracy – 86.7	User's accuracy – 78.0

same accuracy for the classification of the two specific species groups. This may be the result of a better spatial resolution of the ALS data or the three-dimensional specificity of the analysis. In the case of willow, it is possible that the spectral profile of willow and grey willow is similar because they are closely related biologically but are relatively different morphologically. Since the ALS data are at least half the cost of the hyperspectral data, do not have as many limitations in acquisition when weather conditions are considered and provide similar results, they are more efficient.

Sophisticated methods for estimating forest area include object segmentation and supervised classification (Pekkarinen *et al.*, 2009; Szostak *et al.*, 2017), but few of them consider the geometric characteristics of forest vegetation – height (Kolecka *et al.*, 2015; Thompson *et al.*, 2016) and canopy cover (Kolecka *et al.*, 2015) – mentioned in the international forest definitions, with an overall accuracy of 95%. However, their partial values (1 m, 2-20% canopy cover) do not match the values (5 m, 10%) given in the forest definitions formulated by the FAO/UN.

The methodology presented by Straub *et al.* (2008) was used to estimate the forest area. For this purpose, the authors used a grid of squares with a defined fishnet area and divided the area of forest vegetation (≥5 m, ≥10%) by the area of the fishnet, obtaining an accuracy of 97.7%. This approach is more methodologically correct than that proposed by Wang *et al.* (2008) and has a lower degree of complexity (and thus workload) than the method presented by Eysn *et al.* (2010, 2012). Hycza *et al.* (2021), when comparing these methods, reached the same conclusion.

The advantage of the presented method for estimating potential forest area is that it does not depend that much on the type of dataset or spatial resolution, as long as it is possible to perform species classification. However, the larger the pixels or the lower the density of the ALS point cloud, the lower the classification accuracy, which may lead to unacceptable generalisation. Estimation of areas with forest vegetation has been addressed in numerous publications, but no publications were found that estimate potential forest areas. However, the methodology based on tree height (or potential height), canopy cover (or potential canopy cover) and area of the forest complex (or potential forest) can be used to perform this type of analysis. Nevertheless, future forest development is not a simple issue that can be easily projected through image classification.

The height criterion was fully considered in this study. In estimating the forest area, not only trees above the selected threshold were considered but also lower trees that have the potential to reach the threshold and were identified based on information about their species, obtained through species classification. We must, however, keep in mind that the same tree species growing in different conditions reach different sizes, and therefore, local/regional conditions must be taken into account when implementing the results of this work.

There is also the criterion of minimum canopy area (=10%), which was not fully considered in the study. We can identify individual trees and classify them according to their species, but it is extremely difficult to estimate the canopy area that will be reached when the trees are mature enough. Each species has its own characteristics, but the area and height of the tree crown depend on competition, microclimate, soil, moisture and other site characteristics. For this reason, we classified the nets according to the presence of potential woody vegetation without attempting to estimate the future canopy area. However, this is not impossible if one has a suitable database of average species canopy sizes corresponding to the various conditions at the study site.

Conclusions

The accuracy of the classification based on ALS data was higher for individual species but similar for the two groups of species (95.5%, Kappa coefficient 87.5%) compared to the accuracy of the classification based on hyperspectral data 96% (Kappa coefficient 87.7%). A map of the forest and potential forest vegetation was created, showing the potential of remote sensing data for predicting changes in forest area due to plant development. The proposed method allowed the delineation of ‘forests’, ‘potential forests’ and ‘non-forests’ on the Białowieża Glade with an accuracy of 90%-92.5% (Kappa coefficient 85-88.8%).The estimation accuracy obtained for ‘forests’ and ‘potential forests’ was high but cannot be compared with other results since no relevant studies were found.

The results presented in the study can support reports to the FAO/UN on forest area. Estimation of potential forest area is important according to international definitions, taking into account land use and its future development, even without current forest vegetation. This, in turn, is important in the context of reporting and estimating carbon stocks and biodiversity to mitigate climate impacts.

Authors' contributions

T.H. – performed the literature review, conceptual plan, field inventory, analysis, text writing and editing; M.L. – performed the analysis based on ALS data and text editing; P.W. – performed the field inventory; K.S. – provided data and performed the conceptual planning and text editing.

Competing interests

The authors declare that they have no conflicts of interest.

Funding

The analyses used data from the LIFE+ ForBioSensing PL 'Comprehensive Monitoring of the Dynamics of Stands in the Białowieża Forest using Remote Sensing' conducted in the Forest Research Institute in 2014-2022 and financially supported by the European Commission (agreement no. LIFE13 ENV/PL/000048) and the National Fund for Environmental Protection and Water Management (agreement no. 485/2014/WN10/OP-NM-LF/D).

References

Castillo-Núñez, M., Sánchez-Azofeifa, A., Croitoru, A., Rivard, B., Calvo-Alvarado, J., Dubayah, R.O., 2011. Delineation of secondary succession mechanisms for tropical dry forests using LiDAR. *Remote Sensing of Environment*, 115: 2217-2231. DOI: https://doi.org/10.1016/j.rse.2011.04.020.

Dalponte, M., Bruzzone, L., Gianelle, D., 2008. Fusion of hyperspectral and LIDAR remote sensing data for classification of complex forest areas. *IEEE Transactions on Geoscience and Remote Sensing*, 46: 1416-1427. DOI: https://doi.org/10.1109/TGRS.2008.916480.

Dalponte, M., Bruzzone, L., Gianelle, D., 2012. Tree species classification in the southern Alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images and LIDAR data. *Remote Sensing of Environment*, 123: 258-270. DOI: https://doi.org/10.1016/j.rse.2012.03.013.

Dalponte, M., Bruzzone, L., Vescovo, L., Gianelle, D., 2009. The role of spectral resolution and classifier complexity in the analysis of hyperspectral images of forest areas. *Remote Sensing of Environment*, 133 (11): 2345-2355. DOI: http://dx.doi.org/10.1016/j.rse.2009.06.013.

Dalponte, M., Řrka, H.O., Ene, L.T., Gobakken, T., Nésset, E., 2013. Tree crown delineation and tree species classification in boreal forests using hyperspectral and ALS data. *Remote Sensing of Environment*, 140: 306-317 DOI: https://doi.org/10.1016/j.rse.2013.09.006.

Eysn, L., Hollaus, M., Schadauer, K., Pfeifer, N., 2012. Forest Delineation Based on Airborne LIDAR Data. *Remote Sensing*, 4 (3): 762-783. DOI: https://doi.org/10.3390/rs4030762.

Eysn, L., Hollaus, M., Vetter, M., Mücke, W., Pfeifer, N., Regner, B., 2010. Adapting alpha-shapes for forest delineation using ALS Data. 10th International Conference on LiDAR Applications for Assessing Forest Ecosystems – Silvilaser 2010, 14-17 September, Freiburg, Germany, 10 pp. DOI: https://doi.org/10.13140/2.1.2460.2887

Farreira, M.P., Zanotta, D.C., Zortea, M., de Souza Filho, C.R., 2016. Mapping tree species in tropical seasonal semi-deciduous forests with hyperspectral and multispectral data. *Remote Sensing of Environment*, 179: 66-78. DOI: https://doi.org/10.1016/j.rse.2016.03.021.

Fassnacht, F.E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L.T., Straub, C., Ghosh, A., 2016. Review of studies on tree species classification from remotely sensed data. *Remote Sensing of Environment*, 186: 64-87. DOI: https://doi.org/10.1016/j.rse.2016.08.013.

Fassnacht, F.E., Neumann, C., Förster, M., Buddenbaum, H., Ghosh, A., Clasen, A., Joshi, P.K., Koch, B., 2014. Comparison of feature reduction algorithms for classifying tree species with hyperspectral data on three central European test sites. *IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing*, 7 (6): 2547-2561. DOI: https://doi.org/10.1109/JSTARS.2014.2329390.

Forest Resources Assessment, 2004. Working Paper 83. Global Forest Resources Assessment Update 2005, Terms and Definitions.

Forest Resources Assessment, 2007. Working Paper 135. Specification of National Reporting Tables for FRA 2010.

Forest Resources Assessment, 2012. Working Paper 180. Forest Resources Assessment Update 2015, Terms and Definitions.

Forzieri, G., Moser, G., Catani, F., 2012. Assessment of hyperspectral MIVIS sensor capability for heterogeneous landscape classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 74: 175-184. DOI: https://doi.org/10.1016/j.isprsjprs.2012.09.011.

Ghiyamat, A., Shafri, H.Z.M., Mahdiraji, G.A., Shariff, A.R.M., Mansor, S., 2013. Hyperspectral discrimination of tree species with different classifications using single- and multiple-endmember. *International Journal of Applied Earth Observation and Geoinformation*, 23: 177-191. DOI: https://doi.org/10.1016/j.jag.2013.01.004.

Ghosh, A., Fassnacht, F.E., Joshia, P.K., Koch, B., 2014. A framework for mapping tree species combining hyperspectral and LiDAR data: Role of selected classifiers and sensor across three spatial scales. *International Journal of Applied Earth Observation and Geoinformation*, 26: 49-63. DOI: https://doi.org/10.1016/j.jag.2013.05.017.

Green, A., Berman, M., Switzer, P., Craig, M.D., 1988. A transformation for ordering multispectral data in terms of image quality with implications for noise removal, *IEEE Transactions on Geoscience and Remote Sensing*, 26 (1): 65-74. DOI: https://doi.org/10.1109/36.3001.

Haapanen, R., Ek, A.R., Bauer, M.E., Finley, E.O., 2004. Delineation of forest/non forest land use classes using nearest neighbor methods. *Remote Sensing of Environment*, 89 (3): 265-271, DOI: https://doi.org/10.1016/j.rse.2003.10.002.

Hościło, A., Mirończuk, A., Lewandowska, A., Gąsiorowski, J., 2015. Inventory of the actual forest cover of the country using the existing photogrammetric data. Final Report. Warsaw: Institute of Geodesy and Cartography, 24 pp. Available from https://bip2.lasy.gov.pl/pl/bip/px_dg~rdlp_poznan~nadl_turek~lesistosc_polski___wyniki_badan_2015_rok.pdf [accessed: 01.03.2022].

Hovi, A., Korhonen, L., Vauhkonen, J., Korpela, I., 2016. LiDAR waveform features for tree species classification and their sensitivity to tree- and acquisition related parameters. *Remote Sensing of Environment*, 173: 224-237. DOI: https://doi.org/10.1016/j.rse.2015.08.019.

Hughes, G.F., 1968. On the mean accuracy of statistical pattern recognizers. *Transactions on Information Theory*, 14: 55-63. DOI: https://doi.org/10.1109/TIT.1968.1054102.

Hycza, T., Stereńczak, K., Kamińska, A., 2021. The use of remote sensing data to estimate land area with forest vegetation cover in the context of selected forest definitions. *Forests*, 12: 1489. DOI: https://doi.org/10.3390/f12111489.

James, G., Witten, D., Hastie, T., Tibshirani, R., 2013. An introduction to statistical learning. New York: Springer, 426 pp. DOI: https://doi.org/10.1007/978-1-4614-7138-7.

Jabłoński, M., 2015. Definicja lasu w ujęciu krajowym i międzynarodowym oraz jej znaczenie dla wielkości i zmian powierzchni lasów w Polsce. *Sylwan*, 159 (6): 469-482. DOI: https://doi.org/10.26202/sylwan.2014264.

Jabłoński, M., Korhonen, K.T., Budniak, P., Mionskowski, M., Zajączkowski, G., Sućko, K., 2017. Comparing land use registry and sample based inventory to estimate forest area in Podlaskie, Poland. *iForest*, 10: 315-321. DOI: https://doi.org/10.3832/ifor2078-009.

Kamińska, A., Lisiewicz, M., Stereńczak, K., Kraszewski, B., Sadkowski, R., 2018. Species-related single dead tree detection using multi-temporal ALS data and CIR imagery. *Remote Sensing of Environment*, 219: 31-43. DOI: https://doi.org/10.1016/j.rse.2018.10.005.

Kamińska A., Lisiewicz M., Stereńczak K., 2021. Single tree classification using multi-temporal ALS data and CIR imagery in the mixed old-growth forest in Poland. *Remote Sensing*, 13: 5101. DOI: https://doi.org/10.3390/rs13245101.

Kolecka, N., Kozak, J., Kaim, D., Dobosz, M., Ginzler, Ch., Psomas, A., 2015. Mapping Secondary Forest Succession on Abandoned Agricultural Land with LiDAR Point Clouds and Terrestrial Photography. *Remote Sensing*, 7: 8300-8322. DOI: https://doi.org/10.3390/rs70708300.

Kunz, M., Nienartowicz, A., Deptuła, M., 2000. Teledetekcja satelitarna wtórnych lasów na gruntach porolnych na przykładzie Zaborskiego Parku Krajobrazowego. *Fotointerpretacja w Geografii*, 31: 122-128.

Li, Q., Wong, F., Fung, T., 2019. Classification of Mangrove Species Using Combined WordView-3 and LiDAR Data in Mai Po Nature Reserve, Hong Kong. *Remote Sensing*, 11: 2114. DOI: https://doi.org/10.3390/rs11182114.

Liao, W., Van Coillie, F., Gao, L., Li, L., Chanussot, J., 2018. Deep Learning for Fusion of APEX Hyperspectral and Full-waveform LiDAR Remote Sensing Data for Tree Species Mapping. *IEEE Access*, 6: 68716-68729. DOI: https://doi.org/10.1109/ACCESS.2018.2880083.

Melgani, F., Bruzzone, L., 2004. Classification of Hyperspectral Remote Sensing Images with Support Vector Machines. *IEEE Transactions on Geoscience and Remote Sensing*, 42 (8): 1778-1790. DOI: https://doi.org/10.1109/TGRS.2004.831865.

McRoberts, R.E., 2011. Satellite image-based maps: Scientific inference or pretty pictures. *Remote Sensing of Environment*, 115: 715-724. DOI: https://doi.org/10.1016/j.rse.2010.10.013.

McRoberts, R.E., Gobakken, T., Naesset, E., 2012. Post-stratified estimation of forest area and growing stock volume using lidar-based stratifications. *Remote Sensing of Environment*, 125: 157-166. DOI: https://doi.org/10.1016/j.rse.2012.07.002.

Michałowska, M., Rapiński, J., 2021. A review of tree species classification based on airborne LiDAR data and applied classifiers. *Remote Sensing*, 13: 353. DOI: https://doi.org/10.3390/rs13030353.

Modzelewska, A., Kamińska, A., Fassnacht, F.E., Stereńczak, K., 2020. Multitemporal hyperspectral tree species classification in the Białowieża Forest World Heritage site. *An International Journal of Forest Research*, 94 (3): 464-476. DOI: https://doi.org/10.1093/forestry/cpaa048.

Mountrakis, G., Im, J., Ogole, C., 2011. Support vector machines in remote sensing: a review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66: 247-259. DOI: https://doi.org/10.1016/j.isprsjprs.2010.11.001.

Naesset, E., Orka, H.O., Solberg, S., Bollandsas, O.M., Hansen, E.H., Mauya, E., Zahabu, E., Malimbwi, R., Chamuya, N., Olsson, H., Gobakken, T., 2016. Mapping and estimating forest area and aboveground biomass in miombo woodlands in Tanzania using data from airborne. *Remote Sensing of Environment*, 175: 282-300. DOI: https://doi.org/10.1016/j.rse.2016.01.006.

Pabjanek, P., 2003. Kształtowanie zapustów leśnych w warunkach puszczańskich polany osadniczej. Doctoral dissertation, University of Warsaw (msc.).

Pekkarinen, A., Reithmaier, L., Strobl, P., 2009. Pan-European forest/non-forest mapping with Landsat ETM+ and CORINE Land Cover 2000 data. *Journal of Photogrammetry and Remote Sensing*, 64: 171-183. DOI: https://doi.org/10.1016/j.isprsjprs.2008.09.004.

Potapov, P., Yaroshenko, A., Turubanova, S., Dubinin, M., Laestadius, L., Thies, C., Aksenov, D., Egorov, A., Yesipova, Y., Glushkov, I., Karpachevskiy, M., Kostikova, A., Manisha, A., Tsybikova, E., Zhuravleva, I., 2008. Mapping the world's intact forest landscapes by remote sensing. *Ecology and Society*, 13 (2): 51. DOI: https://doi.org/10.5751/ES-02670-130251.

Próchnicki, P., 2006. Wykorzystanie GIS i teledetekcji jako narzędzi do analizy sukcesji zakrzewień w Narwiańskim Parku Narodowym. *Roczniki Geomatyki*, 4 (2): 127-134.

Pujar, G.S., Reddy, P.M., Reddy, C.S., Jha, C.S., Dadhwal, V.K., 2014. Estimation of trees outside forests using IRS high resolution data by Object Based Image Analysis. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 9-12 December 2014, Hyderabad, India, pp. 623-629.

Putz, F.E., Redford, K., 2009. The Importance of defining 'forest': tropical forest degradation, deforestation. Long-termp shifts, and further transitions. *Biotropica*, 42 (1): 10-20. DOI: https://doi.org/10.1111/j.1744-7429.2009.00567.x.

R Core Team, 2021. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org.

Sasaki, N., Putz, F.E., 2009. Critical need for new definitions of 'forest' and 'forest degradation' in global climate change agreements. *A Journal of Society and Conservative Biology*, 2 (5): 226-232. DOI: https://doi.org/10.1111/j.1755-263X.2009.00067.x.

Sims, D., Gamon, J., 2002. Relationship between leaf pigment con- tent and spectral reflectance across a wide range species, leaf structures and development stages. *Remote Sensing of Environment*, 81: 337-354. DOI: https://doi.org/10.1016/S0034-4257(02)00010-X.

Shi, Y., Skidmore, A., Heurich, M., 2018. Important LiDAR metrics for discriminating forest tree species in Central Europe. *ISPRS Journal of Photogrammetry and Remote Sensing*, 137: 163-174. DOI: https://doi.org/10.1016/j.isprsjprs.2018.02.002.

Shi, Y., Skidmore, A., Holzwarth, S., Heiden, U., Pinnel, N., Zhu, X., Heurich, M., 2018. Tree species classification using plant functional traits from LiDAR and hyperspectral data. *International Journal of Applied Earth Observation and Geoinformation*, 73: 207-219. DOI: https://doi.org/10.1016/j.jag.2018.06.018.

Shi, Y., Skidmore, A., Heurich, M., 2019. Improving LiDAR-based tree species mapping in Central European mixed forests using multi-temporal digital aerial colour-infrared photographs. *International Journal of Applied Earth Observation and Geoinformation*, 84: 101970. DOI: https://doi.org/10.1016/j.jag.2019.101970.

Stereńczak, K., Kraszewski, B., Mielcarek, M., Piasecka, Ż., Lisiewicz, M., Heurich, M., 2020. Mapping individual trees with airborne laser scanning data in an European lowland forest using a self-calibration algorithm. *International Journal of Applied Earth Observations and Geoinformation*, 93: 102191. DOI: https://doi.org/10.1016/j.jag.2020.102191.

Straub, C., Weinacker, H., Koch, B., 2008. A fully automated procedure for delineation and classification of forest and non-forest vegetation based on full waveform laser scanner data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 37: 1013-1019.

Szostak, M., Hawryło, P., Piela, P., 2017. Using of Sentinel-2 images for automation of the forest succession detection. *European Journal of Remote Sensing*, 51 (1): 142-149. DOI: https://doi.org/10.1080/22797254.2017.1412272.

Thompson, S.D., Nelson, T.A., Giesbrecht, I., Frazer, G., Saunders, S.C., 2016. Data-driven regionalization of forested and non-forested ecosystems in coastal British Columbia with LiDAR and RapidEye imagery. *Applied Geography*, 69: 35-50, DOI: https://doi.org/10.1016/j.apgeog.2016.02.002.

Vapnik, V.N., 1999. An overview of statistical learning theory. *IEEE Transactions on Neural Networks*, 10 (5): 988-999. DOI: https://doi.org/10.1109/72.788640.

Vincheh, Z.H., Arfania, R., 2017. Lithological mapping from OLI and ASTER multispectral data using matched filtering and spectral analogues techniques in the Pasab-e-Bala Area, Central Iran. *Open Journal of Geology*, 7 (10): 1494-508. DOI: https://doi.org/10.4236/ojg.2017.710100.

Wang, Z., Boesch, R., Ginzler, C., 2008. Integration of high resolution aerial images and airborne Lidar data for forest delineation. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 37: 1203-1207.

Wężyk, P., de Kok, R., 2005. Automatic mapping of the dynamics of forest succession on abandoned parcels in south Poland. In: J. Strobl, ed. Angewandte Geoinformatik. Heidelberg: Herbert Wichman Verlag, pp. 774-779.

Wietecha, M., Modzelewska, A., Stereńczak, K., 2017. Airborne hyperspectral data for the classification of treespecies a temperate forests [Wykorzystanie lotniczej teledetekcji hiperspektralnej w klasyfikacji gatunkowej lasów strefy umiarkowanej]. *Sylwan*, 161 (1): 3-17. DOI: https://doi.org/10.26202/sylwan.2016101.

Yao, W., Krzystek, P., Heurich, M., 2012. Tree species classification and estimation of stem volume and DBH based on single tree extraction by exploiting airborne full-waveform LiDAR data. *Remote Sensing of Environment*, 123: 368-380. DOI: https://doi.org/10.1016/j.rse.2012.03.027.

Yang, G., Zhao, Y., Li, B., Ma, Y., Li, R., Jing, J., Dian, Y., 2019. Tree species classification by employing multiple features acquired from integrated sensors. *Journal of Sensors*, 2019: 3247946. DOI: https://doi.org/10.1155/2019/3247946.

You, H., Lei, P., Li, M., Ruan, F., 2020. Forest species classification based on three-dimensional coordinate and intensity information of airborne LiDAR data with random forest method. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-3/W10: 117-123. DOI: https://doi.org/10.5194/isprs-archives-XLII-3-W10-117-2020.

Zhang, C., Xie, Z., 2012. Combining object-based texture measures with a neural network for vegetation mapping in the Everglades from hyperspectral imagery. *Remote Sensing of Environment*, 124: 310-320. DOI: https://doi.org/10.1016/j.rse.2012.05.015.

Zhang, Z., Liu, X., 2012. Support vector machines for tree species identification using LiDAR-derived structure and intensity variables. *Geocarto International*, 28: 1-15. DOI: https://doi.org/10.1080/10106049.2012.710653.

STRESZCZENIE

Klasyfikacja gruntów „potencjalnie" leśnych na podstawie danych teledetekcyjnych

Niektóre definicje lasów są sformułowane w prawie poszczególnych krajów, inne mają charakter międzynarodowy. Różnice w zapisach wynikają z odmiennych cech roślinności leśnej oraz różnych form użytkowania gruntów i gospodarki leśnej (Putz i Redford, 2009). Polska zobowiązana jest do raportowania powierzchni gruntów leśnych do Organizacji ds. Wyżywienia i Rolnictwa (FAO/ONZ) (Forest Resources Assessment, 2004, 2007, 2012). Grunty porolne z sukcesją wtórną nie są w Polsce uznawane za lasy (ze względu na użytkowanie gruntu), w przeciwieństwie do definicji FAO/UN (Jabłoński, 2015, Jabłoński i in., 2017) (tab. 1). Aby stwierdzić, czy dany grunt stanie się gruntem leśnym w ciągu 5 lat, kluczowe jest określenie, jakie gatunki drzew tam występują.

Celem badań jest określenie, który zestaw danych (zobrazowania hiperspektralne i dane z lotniczego skanowania laserowego) daje lepsze wyniki klasyfikacji na dwie grupy gatunków: te, które osiągną 5 m wysokości i te, które takiej wysokości nie osiągną, a także opracowanie metodyki mapowania powierzchni gruntów „potencjalnie" leśnych na przykładzie Polany Białowieskiej (ryc. 1-2).

Do klasyfikacji zobrazowania hiperspektralnego i danych z chmury punktów z lotniczego skanowania laserowego (tab. 2) wykorzystano algorytm Support Vector Machine (Vapnik, 1999).

Klasyfikację zdjęcia hiperspektralnego przeprowadzono dla 10 gatunków drzew (grab *Carpinus* L., olcha *Alnus* Mill., dąb *Quercus* L., wierzba iwa *Salix caprea* L., topola *Populus* L., wierzba szara *Salix cinerea* L., głóg *Crataegus* L., brzoza *Betula* L., sosna *Pinus* L., świerk *Picea* A.

Dietr.), 6 grup wyznaczonych na podstawie krzywych spektralnych (ryc. 3) (grab+olcha, dąb+wierzba+topola, wierzba szara, głóg, brzoza, sosna+świerk). Wyniki drugiej klasyfikacji zagregowano w 2 grupy gatunkowe (te, które osiągną wysokość 5 m i te, które takiej wysokości nie osiągną). Klasyfikację chmury punktów z lotniczego skanowania laserowego przeprowadzono dla 10 gatunków drzew i 2 grup gatunków.

Klasyfikacja danych ALS na 10 gatunków przyniosła lepsze wyniki (81,4%) niż klasyfikacja ze zobrazowania hiperspektralnego (67,3%). Klasyfikacja zobrazowania hiperspektralnego na 2 grupy gatunków okazała się natomiast minimalnie lepsza (96%) niż klasyfikacja danych ALS (95%). Im mniejsza liczba klas, tym wyższa była dokładność klasyfikacji (tab. 3, ryc. 5).

Powierzchnia, dla której obliczane jest pokrycie przez korony, została sztucznie utworzona poprzez podzielenie całego obszaru na siatkę kwadratów o powierzchni 0,01 ha (10×10 m) i podzielenie powierzchni poligonów reprezentujących korony drzew o wysokości co najmniej 5 m przez powierzchnię pola podstawowego (Straub i in., 2008) (ryc. 4). Na tej podstawie utworzono kartogram, w którym poszczególne oczka siatki reprezentują grunty leśne, „potencjalnie" leśne i nieleśne (ryc. 6).

Dokładność szacowania powierzchni gruntów leśnych, „potencjalnie" leśnych i nieleśnych została przeprowadzona przy użyciu zestawu 120 punktów referencyjnych. Nieco lepsze wyniki (92,5%) uzyskano w przypadku klasyfikacji danych hiperspektralnych niż danych ALS (90%). W pierwszym przypadku dokładność producenta dla „lasów potencjalnych" wyniosła 80%, a użytkownika 97%. W drugim przypadku dokładność producenta wyniosła 72,5%, a użytkownika 96,7% (tab. 4-5).

Szacowanie powierzchni gruntów leśnych (w tym „potencjalnie" leśnych) jest ważne w kontekście raportowania, szacowania zasobów węgla, monitorowania bioróżnorodności i łagodzenia skutków zmian klimatu.