Int J Appl Earth Obs Geoinformation 84 (2020) 101960

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

Tree species identification within an extensive forest area with diverse management regimes using airborne hyperspectral data

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ARTICLE INFO

Keywords:
Tree species classification
Hyperspectral images
The Białowieża Forest
HySpex
SVM

ABSTRACT

Information on tree species composition is crucial in forest management and can be obtained using remote sensing. While the topic has been addressed frequently over the last years, the remote sensing-based identification of tree species across wide and complex forest areas is still sparse in the literature. Our study presents a tree species classification of a large fraction of the Białowieża Forest in Poland covering 62 000 ha and being subject to diverse management regimes. Key objectives were to obtain an accurate tree species map and to examine if the prevalent management strategy influences the classification results. Tree species classification was conducted based on airborne hyperspectral HySpex data. We applied an iterative Support Vector Machine classification and obtained a thematic map of 7 individual tree species (birch, oak, hornbeam, lime, alder, pine, spruce) and an additional class containing other broadleaves. Generally, the more heterogeneous the area was, the more errors we observed in the classification results. Managed forests were classified more accurately than reserves. Our findings indicate that mapping dominant tree species with airborne hyperspectral data can be accomplished also over large areas and that forest management and its effects on forest structure has an influence on classification accuracies and should be actively considered when progressing towards operational mapping of tree species composition.

1. Introduction

Management of an extensive forest area with complex forest structure is challenging and requires detailed information about numerous forest inventory variables. One crucial variable is information on species composition. The latter is required for an efficient forest management (Heinzel and Koch, 2012; Jones et al., 2010), for improved modelling of other forest inventory variables (Ørka et al., 2013; Vauhkonen et al., 2014) and to plan biodiversity conservation measures (Nagendra, 2001). Tree species information can be obtained during field inventories, however, this requires a high level of manpower and is associated to high costs (Dalponte et al., 2008; Ghosh et al., 2014). Furthermore, in the field, species information is typically collected in sample plots or using rough, visual stand-wise estimates, while spatially continuous information is lacking. In heterogeneous forest stands obtaining exact information about the occurring species using field inventories is almost impossible (Immitzer et al., 2012). Lack of access to some parts of the investigated forest can further negatively affect field inventories. Remote sensing may enable to rapidly map dominant tree species over extensive forest areas and can provide information on inaccessible or protected forest areas within the study site (Potapov et al., 2008).

Many recent studies successfully mapped tree species using remote sensing data (i. a. Dalponte et al., 2012; Ghosh et al., 2014; Trier et al., 2018). The latest trends and advances have recently been summarized in Fassnacht et al., 2016a . One observation of the study was that studies based on hyperspectral data tend to consider more species and result in higher accuracies. While multispectral data were reported to have potential for tree species mapping (e.g. Key et al., 2001; Wolter et al., 1995), the continuous spectral information contained in hyperspectral data seems even more suitable to differentiate tree species with similar spectral properties. This has been reported in numerous studies (Dalponte et al., 2012; Ghosh et al., 2014; Goodenough et al., 2003; Wietecha et al., 2017). Focusing on the methodical approaches to derive the tree species maps, older studies applying hyperspectral data tend to use parametric classification algorithms, for instance Gaussian Maximum Likelihood (e.g. Martin et al., 1998) and classify forest communities rather than single tree species (Boschetti et al., 2007). More recent studies tend to use non-parametric classification algorithms (e.g. Dalponte et al., 2014; Ghosh et al., 2014; Jones et al., 2010)

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https://doi.org/10.1016/j.jag.2019.101960
Received 13 April 2019; Received in revised form 2 August 2019; Accepted 2 September 2019
Available online 27 September 2019

Table 1
Selected studies focusing on forest tree species recognition based on hyperspectral data. The size of the investigated areas, number of species classified, the applied sensor, the applied classification algorithm, the maximum observed overall accuracy as well as additionally applied data types are reported. When different methods were compared in the study, just the one identified as the best is mentioned in the table.

Study	*Area (ha)*	*No of species*	*Applied sensor*	*Algorithm*	*Overall Accuracy*	*Additional data*
Martin et al., 1998	400	11 (spec. and communities)	AVIRIS	Maximum Likelihood	75	no
Heinzel and Koch, 2012	1000	4	HyMap	SVM	88	LiDAR, CIR, texture
Dalponte et al., 2008	230	19	AISA Eagle	SVM	88	LiDAR
Dalponte et al., 2012	1 090	6	AISA Eagle	SVM	83	LiDAR
Ghosh et al., 2014	*Not specified*	5	HyMap, Hyperion	SVM, RF	82	LiDAR
Fassnacht et al., 2014	*Not specified*	4, 5, 6*	HyMap	SVM	65, 84, 86*	no
Jones et al., 2010	2 832	11	AISA Dual	SVM	72	LiDAR
Richter et al., 2016	218	10	AISA Dual	PLS-DA	78	no
Trier et al., 2018	*Not specified*	3	HySpex	Deep Neural Network	87	LiDAR
This study	62 000	7	HySpex	SVM	70	no

* different values for different test sites.

to differentiate individual species. The latter studies usually report high classification accuracies and provide solutions for local scales, often applying datasets covering comparably small extents (Table 1).

Analyses conducted on local scales (summarized in Table 1), often focus on the comparison of methods or smaller technical developments for improved species classification. Such studies are important to develop a sound understanding of the general potential of a given remote sensing data-type to classify tree species. However, the suitability of the presented approaches for operationally mapping tree species across larger areas is often not investigated (Fassnacht et al., 2016a). A further so far not frequently discussed factor is the complexity of the investigated forests. The complexity of a forest is on the one hand side described by the number of species occurring in it but on the other hand side also by the diversity of the forest stands in terms of age, degree of mixture and topography. Related to this, protected areas tend to be more heterogeneous and harbour a higher species richness than managed forests, which are often more uniform in structure, age and species composition (Paillet et al., 2010).

In earlier studies, tree species across areas from less than 1 to a few thousand hectare (Table 1) were classified with satisfactory results using airborne hyperspectral data (e.g. Heinzel and Koch, 2012; Jones et al., 2010). Many of those were conducted in temperate forests in Germany, Italy or boreal forests in northern Europe. The investigated forests differed in complexity and management. In Germany, the investigated areas were often located in managed forests, with comparably uniform forest structures where a single stand often contains only 1 or 2 dominant species. This may be one reason why authors reached very high accuracies even with medium spatial resolution hyperspectral data when classifying 4 (Heinzel and Koch, 2012) or 5 (Ghosh et al., 2014) tree species (Table 1). Other investigated areas, for example in Italy, were more complex in forest structure and data with finer spatial resolution were applied (Table 1). Studies of Dalponte et al. (2012, 2008) were conducted within protected and highly heterogeneous areas such as the forest *Bosco della Fontana* located in a natural reserve. Here, 19 tree species were classified. The majority of the species was classified with accuracies exceeding 70%. Authors reported a Kappa coefficient of the whole classification accounting to 88% (Table 1). Such studies focusing on highly heterogeneous forest areas with many tree species present over small areas benefit from finer resolution data to reduce problems related to mixed pixels (Dalponte et al., 2008; Jones et al., 2010). Most studies focusing on protected forests used data with 1–2 m spatial resolution (pixel size) which typically allows to obtain more than a single pixel per tree crown which in turn increases the fraction of pixels representing only a single species and hence reduces the mixed pixel problem. The mixed pixel problem typically occurs less in uniform, managed forests. Use of very high-resolution data is applicable on local scales, but when the extent of an area is large, apart from restrictions related to costs, new challenges may arise: flight missions to acquire the data last longer and the data might hence be acquired under differing illumination and weather conditions. Furthermore, the obtained dataset is likely to be large in size and challenging to process.

Summarizing the general trends of studies applying hyperspectral data to map tree species, protected areas were slightly more frequently examined than managed forests. However, large and complex forest areas under different management regimes have not yet been profoundly investigated and addressing such areas is hence still an important gap to fill in the current state of the art in remote sensing based tree species recognition (Fassnacht et al., 2016a).

Here, we focus on the Białowieża Forest in Poland. A highly heterogeneous and complex forest area which is differently managed in its distinct parts. One part is protected as a national park, with a strict protection reserve in its core-zone. Other parts of the Białowieża Forest are managed forests which again contain reserves with different levels of protection. We assume that such a high level of heterogeneity may influence the obtained classification accuracy (Smith et al., 2002). The aim of this study is hence to i) develop a workflow to map tree species composition of the extensive and complex Białowieża Forest area using airborne hyperspectral data, ii) and to investigate how different types of management due to different levels of protection in the area influence the classification results.

2. Materials and methods

2.1. Study area

2.1.1. Overview

The study was conducted in the Polish part of the Białowieża Forest. The Białowieża Forest covers an area of 1345 km^2, 592 km^2 in Poland and 753 km^2 in Belarus (Więcko, 1984). The Białowieża Forest is located in the north-east of Poland, on the North Podlasian Lowland, in the mesoregion of Bielsk Plain (Kondracki, 2002). The area has a temperate climate with both continental and Atlantic influences. The forest is a mosaic of forest communities stocked with differing dominant species. Coniferous and mixed coniferous forests cover 52% of the forest's area, wet deciduous forests 20%, rich mesic deciduous stands 15% and early successional stands with birch (*Betula* spp.) and aspen (*Populus tremula* L.) cover 13% of the Białowieża Forest (Jędrzejewska and Jędrzejewski, 1998). According to Faliński (1986) the dominant tree species are oaks (*Quercus robur* L. and *Quercus petraea* (Matt.) Liebl.), European hornbeam (*Carpinus betulus* L.), Norway spruce (*Picea abies* (L.) H.Karst) and Scots pine (*Pinus sylvestris* L.), followed by Black alder (*Alnus glutinosa* (L.) Gaertn.), Small-leaved lime (*Tilia cordata* Mill.), Norway maple (*Acer platanoides* L.), birch (*Betula pendula* Roth *and B. pubescens* Ehrh.) and European ash (*Fraxinus excelsior* L.). However, due to massive ash decline, the share of European ash has considerably decreased in recent years (Miścicki, 2016). Furthermore, ongoing bark beetle infestations (*Ips typographus* (L.)) changed the structure of spruce-dominated stands in the

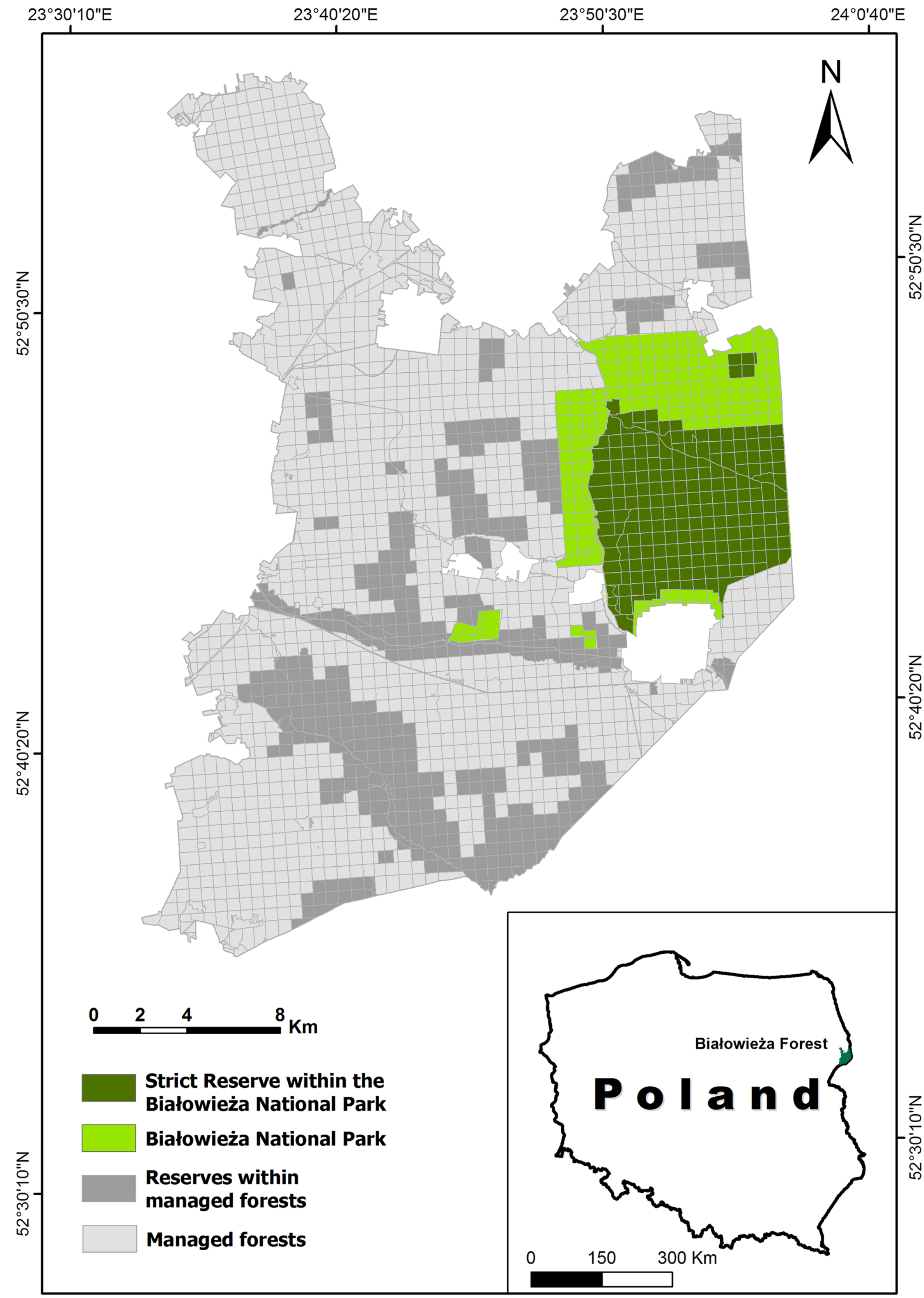

Fig. 1. Białowieża Forest study area subdivided into managed and protected areas.

Białowieża Forest (Stereńczak et al., 2019). The polish part of the forest is partially protected by Białowieża National Park and various reserves (see section 2.1.2). A large share of the Polish part of the Białowieża Forest area is managed within 3 forest districts: Białowieża, Hajnówka and Browsk. Nevertheless, many stands remain under different forms of protection (Fig. 1).

2.1.2. Different management regimes

The studied area is subject to a variety of management strategies and protection concepts (Fig. 1). Particular differences exist between the management of (1) the strict reserve, (2) the managed forests and (3) other protected areas (reserves). The strict reserve is a completely protected area. For a hundred years no management intervention has been conducted here, except for removing fallen trees from tracks. People are allowed to enter these parts of the forests just with a special permission or in a guided tour. In the managed forests the management regime follows the Polish state forests act. However, the management measures conducted in the close-to-natural stands of the Białowieża Forest are quite limited. One measure concerns the reconstruction of stands after disturbances. This is typically accomplished by planting tree species suitable for the local site conditions. That means that in many cases even the managed stands in the Białowieża Forest are more complex than a typical managed forest in Poland. Nevertheless, they are much more uniform than the protected parts of the Białowieża Forest. For example on nutrient-poor sites, mono-species stands are likely to occur. Within all of the protected zones, mono-species stands are very rare, and the few existing ones are small in extent. Generally, the management in the national park outside the core protection zone and the reserves in the managed part is quite similar. These areas are basically without management, except for measures against bark beetle infestations. In these areas, the expected species diversity is higher than in the managed forests. Both parts are protected for around 50 years, so some effects of former forest management are still visible. We hence assume a complexity gradient with highest complexity of species structure in the strict reserve area, a lower complexity in reserves and finally the lowest complexity in the managed part. Despite this assumed complexity gradient, all the species we analyse occur throughout the whole forest, even though with differing frequencies depending on the management regime (Fig. 2).

2.2. Data

2.2.1. Remote sensing data

The flight campaign took place between 24–27 th August 2015. Forty hyperspectral flight stripes were acquired with a HySpex VNIR-1800 and a SWIR-384 camera. HySpex VNIR-1800 operates in the spectral range of 0.4–1.0 µm which is covered by 182 bands. The scanning sensor has 1800 spatial pixels. During the flight campaign images with 2.5 m spatial resolution were acquired. HySpex SWIR-384 operates in the spectral range of 1.0–2.5 µm covered by 288 bands and with 384 spatial pixels. Images with 5 m spatial resolution were acquired. Both sensors provide images with a radiometric resolution of 16 bit (Norsk Elektro Optikk AS, 2019). The images of the two sensor systems were stacked resulting in images with a spatial resolution of 5 m in 451 bands. All the pre-processing, consisting of orthorectification, geometric and atmospheric corrections were executed by the data provider. The processing steps included a PARGE geometric correction based on GPS/IMU data. Then, atmospheric correction was conducted using the MODTRAN5 model implemented in ATCOR4 software.

LiDAR data were acquired on July, 2-5th, 2015 with a full-waveform Riegl LMS-Q680i scanner. The data were acquired with a maximum scan angle of ± 30° and a footprint size of a laser beam equal to 0.25 m. The obtained point cloud has an average density of 6 pts./m^2. The whole area was covered with 135 flight stripes with 40% side-overlap. From the ALS data, a digital terrain model (DTM) and a digital surface model (DSM) were generated (resolution of both – 0.5 m).

2.2.2. Field campaign

The field campaign was conducted from July to October 2015. A set of 685 circular plots distributed throughout the whole area of the Białowieża Forest was collected. Each plot covers an area of 500 sq. meters. The centre of each plot was precisely located with a real-time kinematic (RTK) or a static-mode, geodetic-class global navigation satellite systems tool (RMSE = 0.096 m). All the trees within the plot were located according to their distance (ultrasonic rangefinder) and azimuth (azimuth compass) from the plot's centre. For all trees in the plot we recorded tree species, tree height, crown length and diameter at breast height (DBH). For each tree, its potential visibility from above was noted and the information supported the subsequent decision in the office whether a given tree is suitable to be used as a reference tree or not (only trees assigned a good or intermediate visibility were checked in office).

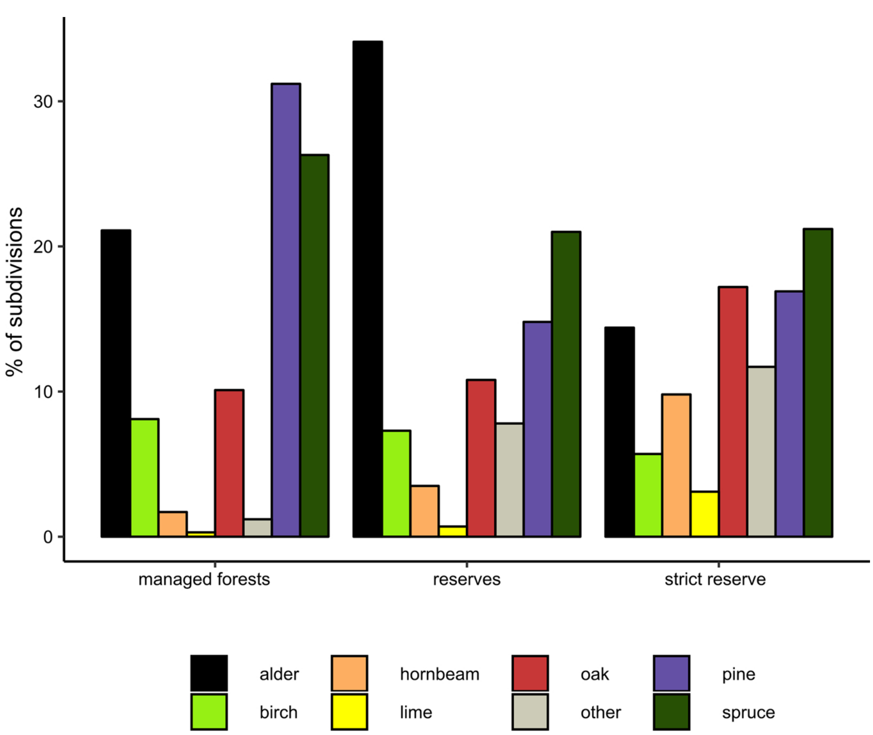

Fig. 2. Share of main species (dominant) in subdivisions stratified into different management regimes. (Low values for lime and hornbeam do not mean that they do not occur – those species grow as co-dominant species in stands with oak as a main species.) The plot bases on forest inventory data held by the Polish State Forests National Forest Holding.

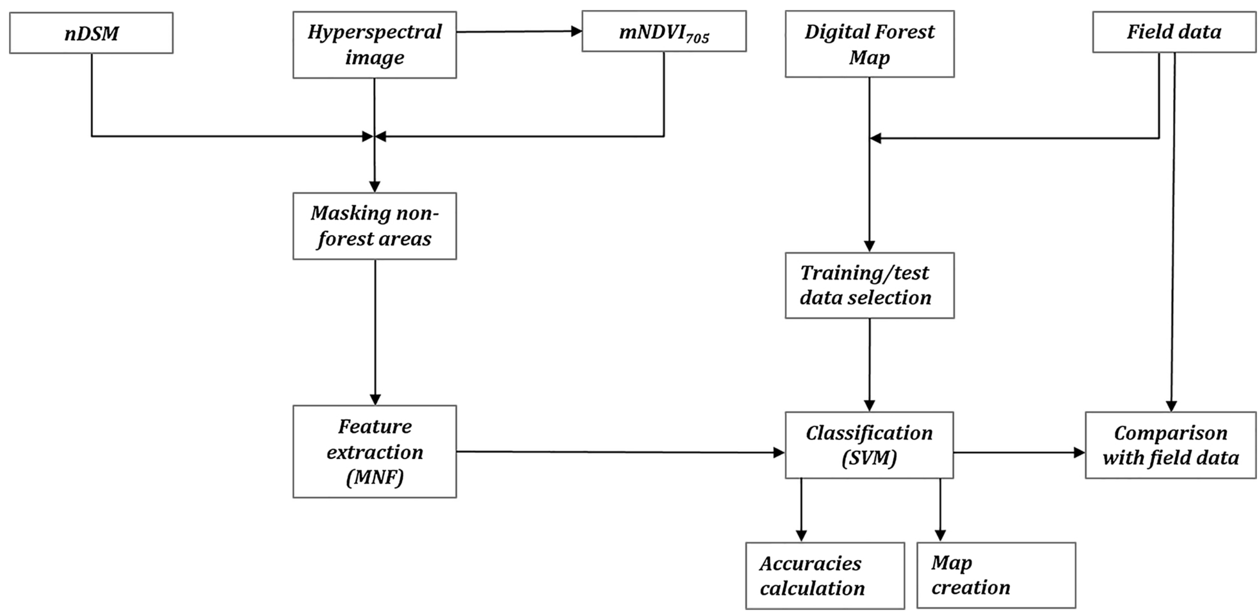

Fig. 3. Work-flow of the tree species classification and validation.

2.3. Workflow

As input data we used hyperspectral images, vegetation indices calculated from the hyperspectral images and the nDSM derived from LiDAR. After masking non-forest areas and applying a feature extraction, we conducted the supervised classification trained with trees identified in the hyperspectral images using the reference data collected in the field and a digital forest map. The results were then compared to data acquired from forest inventory plots (Fig. 3).

2.4. Forest mask and subsetting

As a first step, bands covering wavelengths at the end of the spectral range of the sensors which were affected by noise were removed (bands 432–450). This led to a dataset with 431 bands covering the spectral range between 416 and 2400 nm. We furthermore excluded the parts of the images that covered the area of around 100 m from its border as these areas showed a higher level of noise. Next, we applied forest masks on the stripes to extract all pixels covered with tree canopies. This step was important for the subsequent minimum noise fraction (MNF) transformation (see section 3.4). MNF includes a principal component analysis (PCA) which transforms the dataset along some main axes of information. By excluding all other land cover classes, the MNF/PCA will stress differences between species instead of differences between forested areas and other land cover areas (Ghosh et al., 2014). To exclude non-forest areas a combination of LiDAR data and a vegetation index was used. Applying both datasets was found most effective as the vegetation index excluded dead trees effectively but did not deal well with some canopy gaps covered with non-forest vegetation. Hence, the LiDAR data was used to exclude all vegetated areas with heights below 2 m. As vegetation index we applied the $mNDVI_{705}$ (Sims and Gamon, 2002). All pixels with index values below 0.44 were excluded. The threshold was derived based on a visual assessment and proofed to be reliable throughout the BF.

$$mNDVI_{705} = (R_{750} - R_{705})/(R_{750} + R_{705} - 2 * R_{445})$$

As mentioned before the whole area of interest was covered with 40 stripes. Classifying each of the stripes separately would be time consuming and nearly impossible due to insufficient number of reference trees per individual stripe. However, merging all stripes in one mosaic was not feasible either as such a mosaic would be vast in data size and its parts would differ in radiometry, hampering the classification success. Hence, sets of neighbouring stripes were merged into 8 mosaics covering selected parts of the Białowieża Forest (Fig. 4). During the process of merging, three criteria were taken into account: image radiometry, date of acquisition and the flight direction during the collection of the stripes. Slight differences in radiometry of stripes were excluded in the following process of the MNF transformation. Images acquired on different dates were not merged together to keep differences in radiometry low. We also avoided merging horizontal stripes with vertical ones.

2.5. MNF transformation

Hyperspectral data are highly informative, however, the spectrally contiguous bands are inter-correlated, which can hamper the classification success. To obtain uncorrelated components from the hyperspectral data we applied an MNF transformation (Green et al., 1988). Applying MNF bands as input to classification algorithms instead of the original hyperspectral bands gave better results in numerous studies (e.g. Ghosh et al., 2014; Fassnacht et al., 2014; Zhang and Xie, 2012). MNF uses cascaded PCA transformations to separate information and noise. In the first step, noise and information are separated, and then new, uncorrelated components are arranged following the eigenvalues in a decreasing order. MNF bands are divided into 2 categories, initial components that have eigenvalues higher than 1 typically contain relevant information while those having eigenvalues lower than 1 are typically noisy (Vincheh and Arfania, 2017). Here, each of the eight mosaics were transformed individually with the MNF algorithm and the resulting MNF components were visually screened. During that process, we found that also within components having eigenvalues higher than 1 some noisy bands occurred (e.g. containing stripping and illumination effects). Those were excluded and only the remaining components were used as an input to the classification. Some components were constantly informative across the stripes, e.g. components 1 and 11 while others were found to be constantly noisy, e.g. component 2. Finally, for all images the majority of components between 4 to 14 were selected as input to the classification.

2.6. Reference data

We considered the most common species (Pine, Spruce, Alder, Oak,

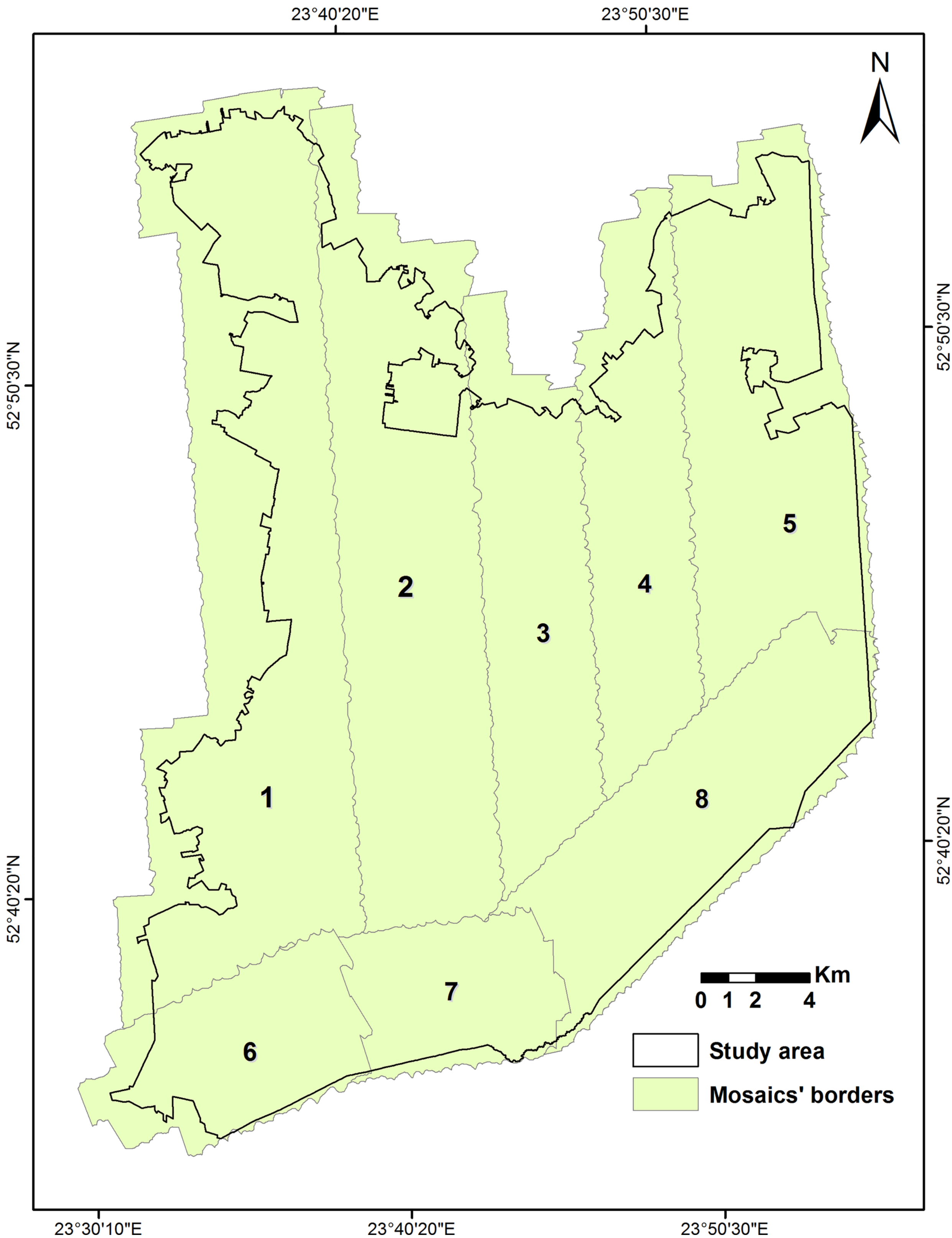

Fig. 4. Mosaics' borders. 40 stripes were mosaicked into 8 mosaics (IDs 1–8 as indicated in the map).

Birch, Lime and Hornbeam) of the Białowieża Forest area for the classification. The remaining species were summarized in the class "other broadleaves". Each of the mosaicked images was classified separately with its own set of training and test points. The reference sets were individually adapted to the corresponding classified area, its complexity and its particular species share (Table 2). The training and test sets were selected based on the trees' locations from the field inventory and a digital forest map provided by the Polish State Forests. To precisely select training/test data, additional high-resolution CIR images (0.5 m ground pixel) and a LiDAR based nDSM were used. The final numbers of

Table 2
Number of training pixels per class per classified image. The smallest of the classified images (Image 6) covered an area with very few stands containing lime and hornbeam, so it was eventually classified into 6 classes, without lime and hornbeam.

Class Image ID	1	2	3	4	5	6	7	8
Other	90	103	64	57	198	85	72	51
Birch	121	83	96	78	222	58	64	125
Oak	130	79	115	80	249	55	88	104
Hornbeam	111	89	70	68	202	–	72	175
Lime	115	80	89	89	201	–	50	75
Alder	234	79	110	104	401	74	67	197
Pine	206	102	125	78	287	53	73	100
Spruce	135	91	104	77	195	59	67	97

reference pixels available per species are summarized in Table 2.

2.7. Classification process

To classify the tree species, we implemented the Support Vector Machines (SVM) algorithm (Vapnik, 1999). SVM is a supervised, non-parametric, machine learning algorithm. It has been found to perform well with high dimensional data and frequently outperformed other algorithms in comparative studies (Melgani and Bruzzone, 2004; Dalponte et al., 2008; Heinzel and Koch, 2012; Mountrakis et al., 2011). During the classification, the SVM classifier seeks the optimal hyper-plane to distinguish between the defined target classes. The SVM uses *kernels* to enlarge the feature space (James et al., 2000). Here we applied a radial kernel. The radial kernel tends to deal well with non-linear data (James et al., 2000) and has been used in some former works concerning tree species classification (e.g. Ghosh et al., 2014; Fassnacht et al., 2014). The SVM was trained using the *e1071* package in R (Meyer et al., 2019). Gamma and cost parameters were optimized during a 10-fold cross validation. For the majority of the classified images the values for gamma and cost were 0.1 and 1, respectively. In a few cases, the values deviated slightly (Appendix 1). Iterative classifications were executed 100 times using unbalanced sets of training pixels (Table 1). Within each iteration the reference pixels were split into 70% training and 30% test pixels to obtain the classification accuracies. To obtain the final classification maps we applied an SVM model trained using all reference pixels of a given image to the a raster stack containing the selected MNF components. The classified images for the mosaics covering the eight parts of the area (Fig. 4) were merged into one map of the whole area. In the overlapping areas, pixels from the image with lower error (higher accuracy) were selected to produce the map.

2.8. Comparison of accuracies in differently managed areas

In order to evaluate whether managed and protected areas show differences in classification accuracies, we compared overall accuracies and Kappa Coefficient's values obtained within those areas (Table 3). For this step we collected a completely independent set of validation pixels from the reference data (Table 2). These points were not used in the process of training and were distributed throughout the whole forest area, hence covering all three management regimes as defined above. For each of the areas, the species share in the validation set was comparable to the actual species share in the area.

Table 3
Accuracies of differently managed areas.

Management regime	OA	Kappa	No of points
strict reserve	0.64	0.53	298
reserves	0.66	0.56	321
managed forest	0.77	0.70	401

2.9. Comparison of classified species shares to inventory plots

As an additional independent validation, we compared the obtained classification maps with the actual tree species cover within inventory plots of the area. To do this, we adopted the approximated tree crown delineation method developed by Wietecha et al. (2019). Within each inventory plot, the crown cover of the trees (see section 2.2.2) was calculated and drawn as a circle around the stem position. The radius of the circle bases on species-specific formulas (relation height ∼ crown area). The general formula was as follows:

$$r = \sqrt{ae^{bh}/\pi}$$

where:
r = radius
a, b – model parameter
e – natural exponential base
h – height of a tree measured in the field.
The parameters of the formula were derived for each of the analysed species applying data of 100 tree crowns manually delineated from CIR images. Further details are described in the work of Wietecha et al. (2019). Fig. 5 presents an example plot. The obtained layer with crown areas was intersected with the classification result. The crown areas of the main tree species (the most frequent in the plot) and for species cover proportions derived from the classification maps were compared.

3. Results

3.1. Overall accuracy

The classification process resulted in a thematic map of the most common forest tree species in the Białowieża Forest (Fig. 6).

The overall accuracies for each classified image oscillated between 0.69 and 0.8 while Kappa values varied from 0.64 to 0.77 (Fig. 7). The accuracies for the eight images are mostly comparable and only slightly higher for image 6 which was classified into only 6 instead of the 8 classes used for the other images (Fig. 7).

Fig. 5. Approximated tree crowns within one of the inventory plots.

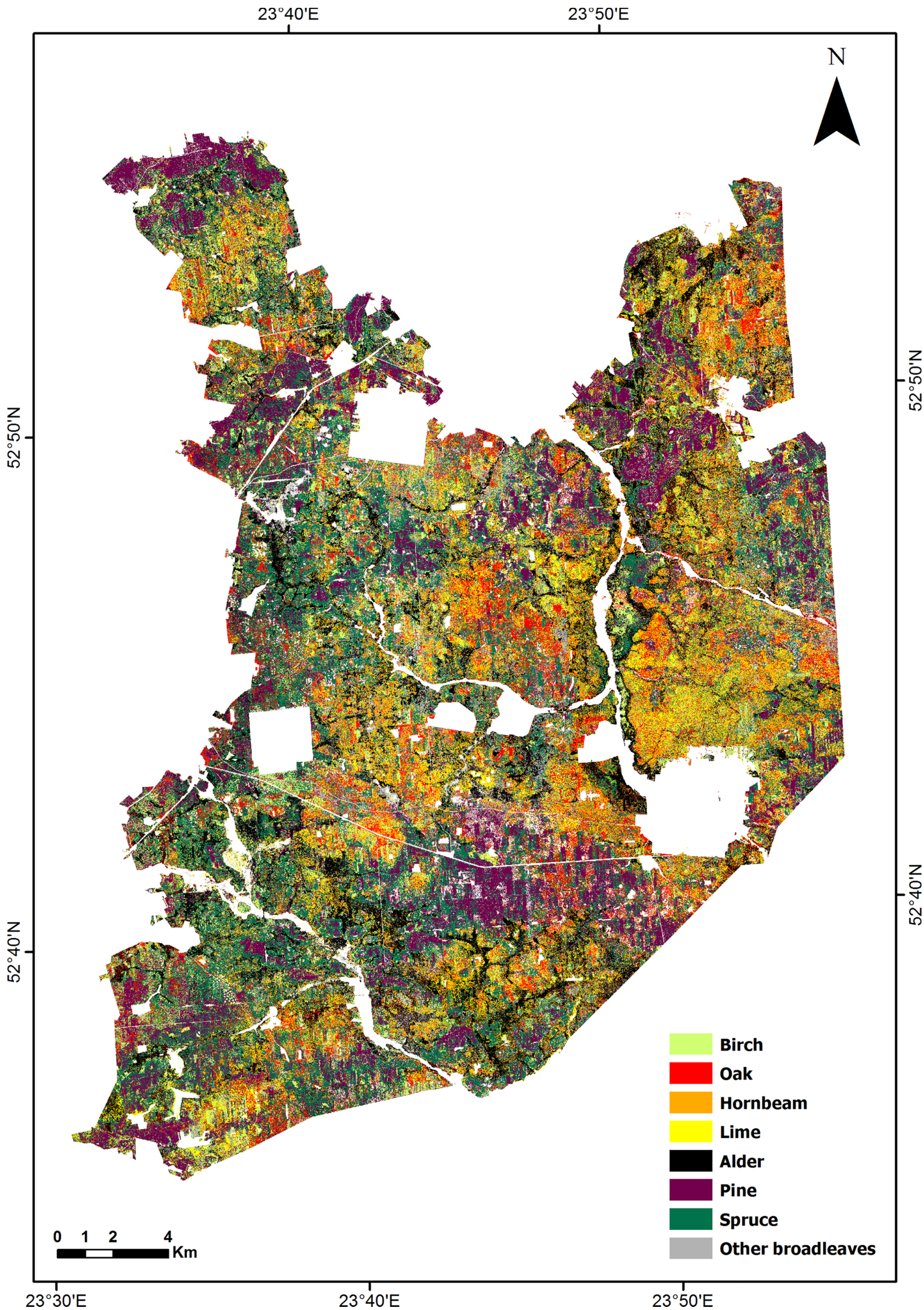

Fig. 6. The thematic map of species composition covering the whole investigated area.

3.2. Particular species recognition

Pine, spruce and alder are classified with high accuracies (Fig. 8). Regardless of the location, pine is predicted with the best producer's and user's accuracies (0.79-0.93 PA; 0.84-0.94 UA). The second top-classified tree species tends to be alder. Slightly lower results are

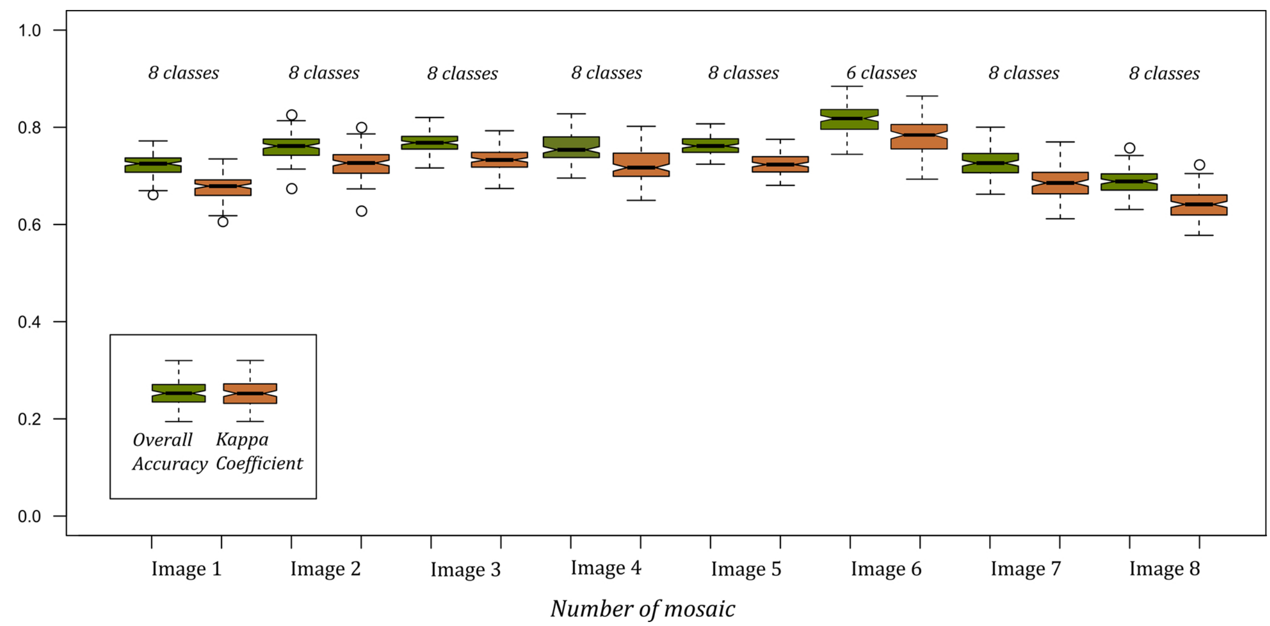

Fig. 7. Overall accuracies and Kappa coefficient values for the eight images covering the entire study area. Boxplots show the accuracy ranges obtained during the iterative data-splits into 70% training and 30% validation data (100 iterations).

obtained for spruce. Deciduous trees generally show lower accuracies. Classes of birch and oak reach good accuracies, slightly lower than alder. Birch has slightly higher accuracies than oak. Comparably lower producer's and user's accuracies are obtained for hornbeam, lime and other species (Fig. 8). Furthermore, alder, pine and oak are classified with good stability (accuracies on the same level for all images). Lower stability rates are observed for birch and spruce. Hornbeam and lime are even less stable. The class of other broadleaves is the least stable one.

3.3. *Differently managed areas*

The obtained accuracies differ for areas with different management strategy (Table 3). In managed forests, accuracies were higher than in the protected areas. However, the results for the two types of protected areas (strict reserve and another protected parts) are comparable (Table 3).

In general, single species accuracies are the highest in the managed part of the Białowieża Forest area. Here, conifer species and alder are reaching best accuracies. Alder has also high accuracy in the protected areas. In the strict reserve – hornbeam, pine and lime are classified with the best accuracies. Oak, hornbeam and lime are underestimated in the managed forests; birch, spruce and pine in reserves; spruce in the strict reserve. Overestimated classes are lime in the managed part, lime and spruce in reserves and the class of other broadleaves is overestimated in all types of the forest (Table 4).

3.4. *Comparison with inventory plots*

The recognition of the main tree species in the inventory plots shows generally moderate performances. Just pine trees are properly classified regardless of the management strategy. Compared to other species, alder and pine are more accurately classified when being a main species in a plot. In managed forests, spruce is also well recognized, while in protected areas the accuracies are rather poor. In the strict reserve, deciduous trees are classified more accurately than in the managed or other protected stands (Table 5).

Considering species cover proportions – coniferous trees are generally underestimated, more in preserved parts than in managed. Especially spruce is underestimated in the strict reserve part. Lime and other broadleaves are overestimated in all parts. In the strict reserve, oak is overestimated, while in reserves and managed forests alder is slightly underestimated (Fig. 9).

4. Discussion

This study presents an approach to classify tree species in the wide and complex Białowieża Forest which is one of the most diverse, impenetrable and close to natural forests in Europe. We obtained satisfying results for the majority of the seven classified species even though the absolute accuracies varied with species and location. We particularly found that the type of management influences the classification results. We observed better classification results for managed parts than for reserves and the strict reserve areas (Table 4).

The type of management in a given area seems to play a key role for the classification success. Managed forests are supposed to be more organised and less heterogeneous, especially when compared with the preserved part of the Białowieża Forest. Comparing specific species accuracies, alder is classified with high accuracy, irrespective of the area's management, while coniferous species, mainly spruce, are rather underestimated in both managed and protected areas. However, the underestimation rate is notably higher in reserves and strict reserve area (Fig. 9). A possible reason for this, is the higher degree of mixture in the preserved forests.

Spruce trees grow individually and are scattered throughout the strict reserve stands (Faliński, 1986). Spruces' crowns are typically rather narrow and cover less area of a pixel than the wide crowns of broadleaf trees (Caudullo et al., 2016). This may result in overestimation of broadleaved species particularly in stands with oaks, hornbeam or lime and underestimation of spruce trees with smaller crowns as we can assume that the majority of mixed pixels are classified as broadleaf trees, even if some pixels also cover a certain fraction of spruce canopy. The same mechanism might apply for individual pine trees surrounded by broadleaf trees. However, in some open pine stands also a different kind of problem occurs. Here, the trees density is so low that the understorey signal of broadleaf species causes misclassification of pine trees. This problem may also occur in single-species stands. The majority of single-species stands in the Białowieża Forest are the result of tree planting activities where mostly pine, spruce and oak stands were established in the managed part of the forest (Faliński, 1986).

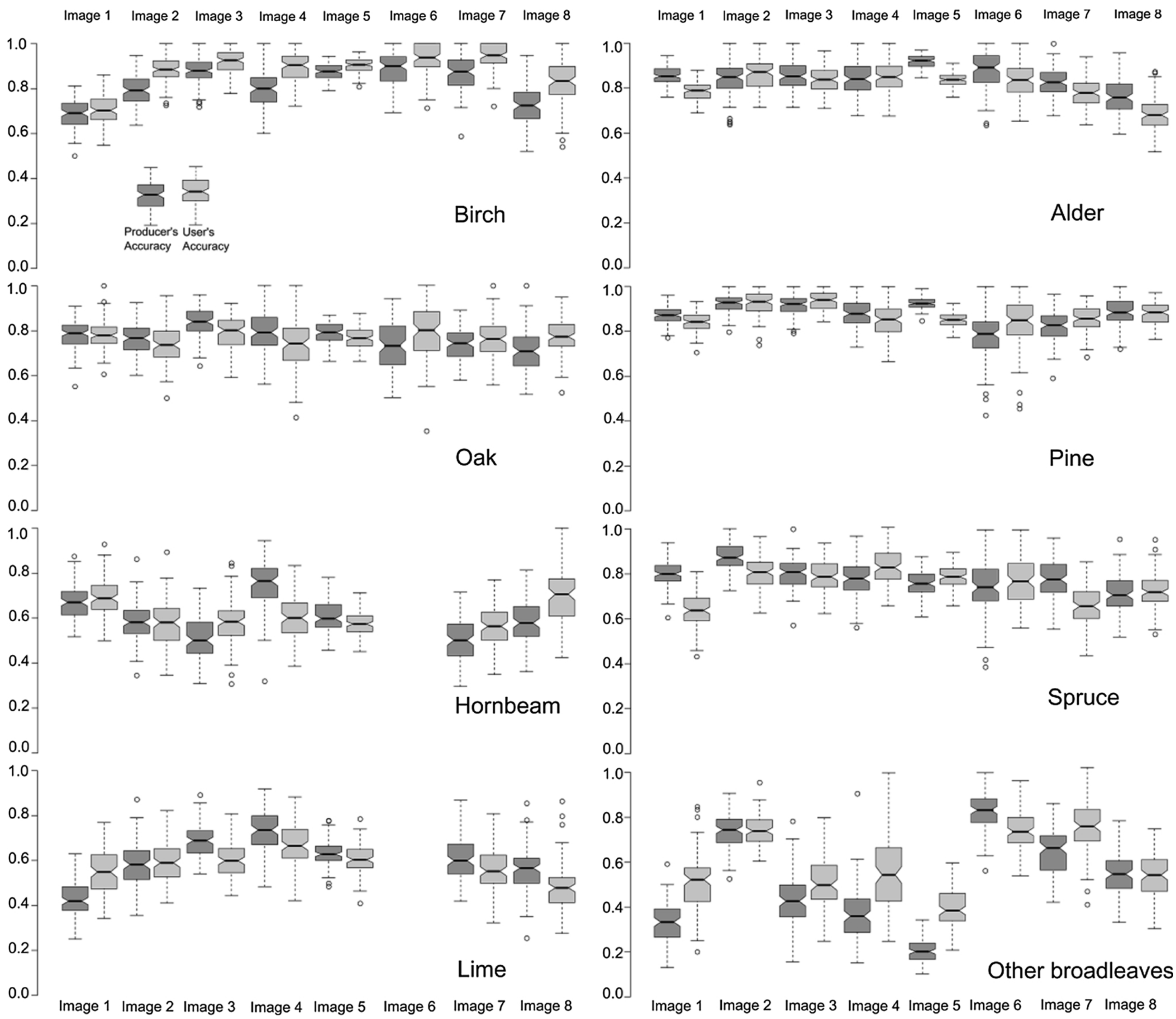

Fig. 8. Producer's and user's accuracies for specific species. Explanations follow those of Fig. 7.

Table 4
Single classes accuracies in differently managed areas.

	managed forests		reserves		strict reserve	
class	PA (OE)	UA (CE)	PA (OE)	UA (CE)	PA (OE)	UA (CE)
Birch	0.68	0.74	0.50	0.94	0.61	0.70
Oak	0.58	0.86	0.67	0.61	0.63	0.67
Hornbeam	0.56	0.71	0.93	0.70	0.68	0.72
Lime	0.55	0.33	0.89	0.48	0.73	0.66
Alder	0.83	0.82	0.83	0.79	0.68	0.63
Pine	0.90	0.86	0.64	0.70	0.71	0.67
Spruce	0.79	0.84	0.51	0.62	0.57	0.69
Other	0.87	0.43	0.77	0.40	0.29	0.22

Contrarily, the reserves are covered with much more diverse, multi-layered and multispecies stands.

Broadleaf stands in the Białowieża Forest generally have a higher degree of mixture and more tree species. In most of Białowieża Forest's rich sites, hornbeam is present in the stands' second layer. Due to that, more mixed pixels are present and may increase the chance of misclassifications. From the group of broadleaf species, alder is classified with the best accuracy. This might be related to the stand structure of alder stands, which are often composed of mostly alder trees with only few admixtures. Hence, intermixture and heterogeneity of these stands is lower than in other broadleaf stands (Faliński, 1986). The opposite can be stated for oak-hornbeam forests which often show a notable mixture with lime and other tree species (Faliński, 1986). The high intermixture and the similar spectral signal of those broadleaf species causes increased error rates.

Hence, stand heterogeneity is likely to be the essential difference between managed and preserved forests which drives also the accuracy differences between these management types. Managed forests' stands, especially with coniferous species as dominant species, are rather uniform: many stands are stocked with 60% or more share of one dominant species, some co-dominant species and admixtures. Multispecies and heterogeneous stands are not that common in managed forests (Fig. 10). In our results, we observed an about 10% higher overall accuracy for the managed stands as compared to the preserved parts. Similarly, Dalponte et al. (2009) reported around 10% higher accuracy for the less complex forest area investigated in their study. The more heterogeneous and mixed the stands are, the more difficult is the species recognition. Earlier studies focusing on managed areas (featuring many pure stands with only one dominant species) often reported very high overall accuracies exceeding 80 or even 95% when classifying 4–5 tree species (Fassnacht et al., 2014; Ghosh et al., 2014; Heinzel and Koch, 2012). In our study 8 classes were considered and the accuracy

Table 5
The amount of inventory plots with correctly classified main tree species.

	all stands		managed forests		reserves		strict reserve	
Main tree species on the plot	No of plots (reference)/ Accurately classified	% of correctly classified plots	No of plots (reference)/ Accurately classified	% of correctly classified plots	No of plots (reference)/ Accurately classified	% of correctly classified plots	No of plots (reference)/ Accurately classified	% of correctly classified plots
Birch	44/**23**	52%	17/**10**	59%	13/**3**	23%	14/**10**	71%
Oak	42/**25**	60%	17/**10**	59%	16/**9**	56%	9/**6**	67%
Hornbeam	100/**60**	60%	12/**5**	42%	29/**17**	59%	59/**38**	64%
Lime	31/**12**	39%	2/**1**	50%	5/**0**	0%	24/**11**	46%
Alder	143/**107**	75%	44/**32**	73%	66/**49**	74%	33/**26**	79%
Pine	94/**76**	81%	57/**43**	75%	21/**19**	90%	16/**14**	88%
Spruce	167/**95**	57%	82/**59**	72%	45/**16**	36%	39/**19**	49%
Other	35/**20**	57%	11/**7**	64%	13/**7**	54%	11/**6**	55%

within the managed forests is slightly lower (77%).

One limiting factor in our study when comparing our accuracies to previous works conducted in preserved areas is the coarser spatial resolution (pixel size) of the data we used. Spatial resolution may be an important limiting factor, the more limiting, the more diverse the forest is. At a spatial resolution of 5 m, mixed pixel issues are expected to be frequent in a diverse forest. The average crown sizes in the investigated forest is 24.6 sq. m which equals almost exactly a single pixel's area (25 sq. m). Assuming that in many cases the centre of a pixel is not spatially coinciding with the centre of a tree, a high number of mixed pixels can be expected. However, in the case of our study it would be challenging to acquire and analyse hyperspectral data of higher spatial resolution due to the extensive area. Former works applying hyperspectral data were based on resolutions from 1 to up to 30 m. On preserved, heterogeneous areas, often 1 or 2 m data were applied for comparably small areas (Dalponte et al., 2012; Jones et al., 2010; Richter et al., 2016); in these studies, all issues related to mixed pixels and between stripes errors were less pronounced. In the studies of managed forests, authors used data with lower spatial resolution, from 3 to 4 to 5–8 m (Fassnacht et al., 2014; Ghosh et al., 2014) and one study even obtained good results with 30 m (Ghosh et al., 2014). However, these results were obtained for comparably homogeneous forest stands often consisting of a single species. Hence, the interplay between spatial resolution and the area's heterogeneity, has an important impact on the classification results. As found by Dalponte et al. (2013), higher spatial resolution is required to classify heterogeneous forest area with good accuracies. In our study some parts of the forested areas were more, some others less heterogeneous (Fig. 10). So, the acquisition of an intermediate spatial resolution might have been sub-optimal for some of the individual stands but seemed to be a good compromise to classify both heterogeneous and more homogeneous stands with reasonable accuracies.

What makes our study unique is the analysis of an exceptionally complex and large forest area. Our results provide accurate recognition of the most frequent species in the Białowieża Forest. The recognition rate on the inventory plots is acceptable for the dominant species on the plot and proper for species composition on the plots with slight over/underestimation of certain species. Probably the main limitation of our results in terms of practical use of the species maps would be the underestimation of spruce which is one of the most frequent species in the analysed forest. Related to this, the frequent overestimation of some broadleaves, mainly lime, oak and the other broadleaves class may also limit the usefulness of the created species maps. Some of the over and underestimation issues might be addressed by enhancing the spatial resolution of the data used. It should improve species recognition in the parts of high heterogeneity, e.g. the strict reserves. However, using 1–2 m data would meaningfully complicate the analysis of such a wide area and, for the majority of the forest the high spatial resolution is not

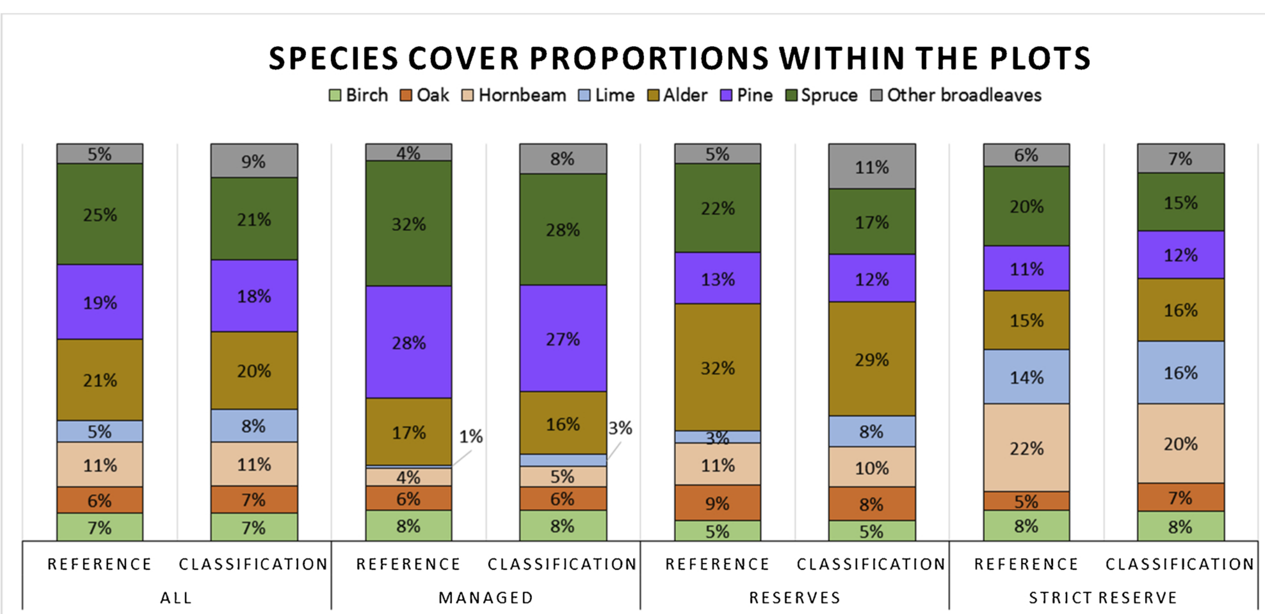

Fig. 9. Comparison of species cover proportions within the inventory plots with the obtained classification maps. Reference values are approximated via crown cover estimates (section 2.8) within all the inventory plots (section 2.2.2).

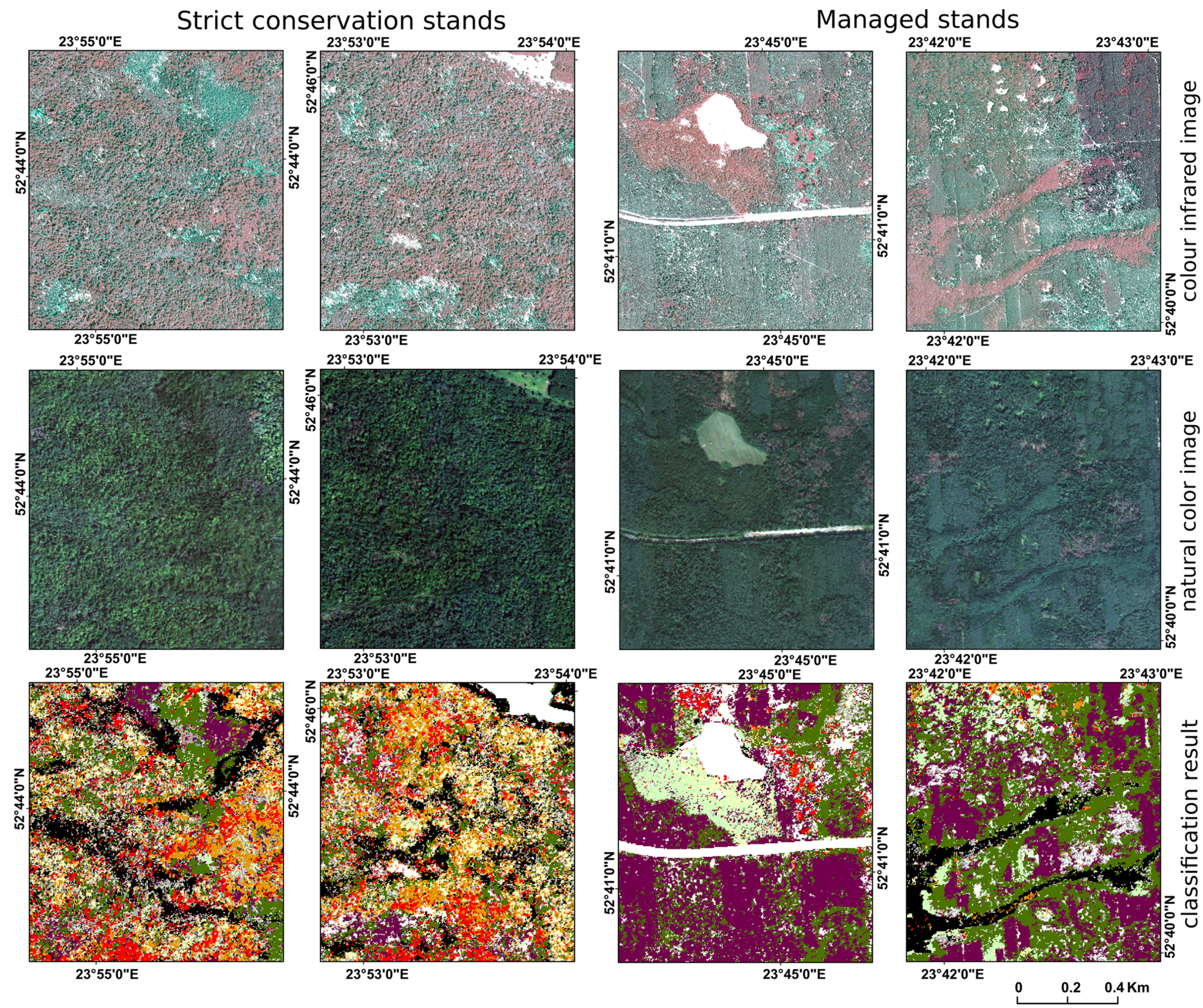

Fig. 10. The differences between stands' diversity of preserved (in the strict reserve area) and managed forests shown on high resolution colour infrared images, natural colour composition of hyperspectral images and the classification results.

absolutely necessary.

Here, we wanted to investigate what level of accuracy we can reach using a single set of hyperspectral images, without any additional data (also considering the costs of the data acquisition). Nevertheless, the results may be improved by applying multitemporal datasets or by fusing the hyperspectral data with LiDAR data. Using data acquired in different stages of growing season might also help (Richter et al., 2016; Tagliabue et al., 2016), especially in classifying the most diverse areas. LiDAR data may be useful in some cases by adding information on species-specific structural attributes (Kamińska et al., 2018). Future research should investigate the mentioned topics, particularly also with datasets covering large forest areas.

5. Conclusions

In this research, we assessed the potential of hyperspectral imagery to map a highly heterogeneous forest area composed of preserved and managed forests. The seven dominant and most frequent tree species in the investigated area were classified with moderate to good accuracies depending on the species. Conifer species were generally better recognized than broadleaved species. We observed that in case of the Białowieża Forest the management regime affects the forest species composition and its diversity, which in turn also influences the obtained classification results. Particularly heterogeneous stands (mostly located in preserved and highly protected forest areas) with high species intermixture were challenging to classify. One likely reason for this was the pixel size of 5 m which in the examined forest area led to a high number of mixed pixels. Obtained results might be used for further analysis of ecological issues and the development of management plans in the area.

Declaration of Competing Interest

None.

Acknowledgments

The study was financially supported by the project LIFE +ForBioSensing PL "Comprehensive monitoring of stand dynamics in the Białowieża Forest supported by remote sensing techniques", supported by European Commission under European Union financial instrument LIFE+(agreement no. LIFE13 ENV/PL/000048) and Polish National Fund for Environmental Protection and Water Management (agreement no. 485/2014/WN10/OP-NM-LF/D).

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jag.2019.101960.

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